FOOD TRADE SYSTEM UNDER CRISES IN A METACOUPLED WORLD

By

Nan Jia

A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

Fisheries and Wildlife – Doctor of Philosophy
Environmental Science and Policy – Dual Major

2025

ABSTRACT

In an increasingly interconnected world, food trade systems are increasingly exposed to overlapping crises—including pandemics, geopolitical conflicts, and climate change. These disruptions reveal persistent vulnerabilities in global supply chains and demand a cross-scale understanding of food trade resilience. This dissertation applies the metacoupling framework—which integrates human–nature interactions within (intracoupling), between neighboring (pericoupling), and between distant (telecoupling) systems—to examine food trade dynamics under multiple crises across spatial and temporal scales.

Chapter 2 presents a systematic review of 455 peer-reviewed studies and identifies major gaps in existing research. While most studies focus on national-scale trade or intracoupled systems, few consider spillover systems or interactions across multiple coupling types. Based on this gap, the chapter synthesizes fragmented resilience indicators into a unified assessment framework, structured around human- and nature-related drivers.

Chapter 3 develops a multi-dimensional evaluation framework to assess food trade resilience before and after the COVID-19 pandemic. By disaggregating five indicators—Bonilla index, centrality, connectivity, trade disruptions, and supply chain diversity—into adjacent and distant trade components, the study reveals stark inequalities in resilience, particularly in low-income countries with limited diversification and infrastructure.

Chapter 4 constructs a rapid assessment framework to estimate the impacts of the Russia–Ukraine war on winter cereals trade in 2022. Leveraging remote sensing-based cropland data, trade statistics, and network metrics, the study shows a sharp decline in trade connectivity and the emergence of new trade pathways, exposing the fragility of current supply chains in conflict-affected regions.

Chapter 5 extends the analysis to the global wheat trade over three decades (1991–2022). Using a combination of network analysis, structural change modeling (SCM), and generalized additive models (GAM), the chapter quantifies long-term trends in trade resilience. The results show widening disparities across income groups, with distant trade growing in dominance and low-income countries remaining disproportionately vulnerable to both acute and chronic crises. Together, these chapters advance theoretical and empirical understanding of food trade resilience under multiple crises. By integrating metacoupling theory with remote sensing, network science, and quantitative modeling, this dissertation provides a cross-scale perspective on the evolving structure of global wheat trade and offers actionable insights for enhancing global food system resilience.

This work is dedicated to my family, co-authors, and my dear friends, Mengting Wang, Zhimeng Jiang, Yongqing Ye, and others who helped me without whose constant and unconditional support this dissertation was not possible.

ACKNOWLEDGEMENTS

The journey to complete this dissertation and my Ph.D. studies has been an amalgam of challenges, happiness, excitement, and achievements. Reaching this point would have been impossible without the tremendous support, encouragement, and guidance from my advisor, mentors, collaborators, friends, and family.

Firstly, I extend my heartfelt thanks to my advisor, Dr. Jianguo (Jack) Liu, who provided a remarkable platform for collaboration and offered me complete freedom to explore every possibility. His dedication to students’ work is unparalleled, often extending his support well into the late hours after a long day's work. Despite his busy schedule, he prioritized providing timely feedback on my manuscripts. As his research assistant, I felt that he dedicated more to my development than I could possibly contribute to return. His mentorship has imparted invaluable lessons that I will carry forward in my career and life, aiming to support my future students and perpetuate this spirit of dedication.

I am also immensely grateful to my committee members for their support and advice throughout my Ph.D. training. I thank Dr. Kenneth Frank for his inspirational guidance in my research design and for generously sharing his course materials and code, which enhanced my understanding of our methods and experimental designs. My appreciation extends to Dr. Emilio Moran for his invaluable advice on becoming a successful researcher. Dr. Andrés Viña deserves special thanks for numerous individual meetings that deepened my understanding of remote sensing data and methodologies, helping me transition from exploring 'what' to understanding 'why' in my research. His critiques have always been critical, constructive, and thought-provoking.

Further, I would like to acknowledge the members of the Center for Systems Integration and Sustainability (CSIS) at Michigan State University. Special thanks to Yuqian, Jincheng, Nick, Xiang and Michelle for the helpful tips and resources that eased my Ph.D. journey. Gratitude also goes to Yinshuai, Wen, Jie, Xiang and Nick for dedicating their valuable time to assist with my research projects, and to Sue, James, and Shuxin for their exceptional support in science communication, software, and data management. A special mention to Jill, the first person I met at MSU and the kindest soul I've encountered, for her extensive support throughout my program. I appreciatively acknowledge the backing from the Environmental Science and Policy Program (ESPP), Kellogg Biological Station Long-Term Ecological Research (KBS LTER) Program, MSU Cloud Computing Fellowship, Michigan AgBioResearch, Asian Studies Center, and other funding sources.

Huge thanks to Yingjie Li, Ruishan Chen, Hongbo Yang, Yue Dou, and Xutong Wu, who play as both mentors & friends, for providing me with many opportunities outside of MSU. Thanks to my dear friends, Mengting, Zhimeng, Yongqing, Yuqian, Yurong, Keyi, and many others who brought so much fun to this journey. You have given me the strength to hold on in times of trouble and to accompany me through the most challenging parts of this journey. You have supported me whenever I doubted myself and lost my confidence, so I could find myself again. You were there for me on all the important, but lonely days, and I thank you for being there and feeling loved by you guys. Any achievement that I made from the completion of this dissertation is equally theirs. Finally, I want to thank my family for their unconditional support and love.

Lastly, I acknowledge that all contents of this dissertation were originally drafted by myself, and a Large Language Model (LLM) was used to help polish the English expression for improved clarity and native fluency.

PREFACE

The chapters in this dissertation were conceptualized as separate papers and written collaboratively with co-authors. While this research principally represents my own work, I use the pronoun we throughout the dissertation as an acknowledgment of the contributions of my collaborators, without whose contributions and guidance this dissertation would not be possible.

TABLE OF CONTENTS

CHAPTER 1: INTRODUCTION

1.1 Background

In an increasingly interconnected global environment, the dynamics of international food trade are profoundly influenced by multiple crises, from global pandemics to geopolitical conflicts (Davis et al., 2021; Hallegatte, 2019; Liu et al., 2013a; Young et al., 2006). Notably, the COVID-19 pandemic and the Russia–Ukraine conflict represent critical disruptions that underline the importance of resilience within food trade networks (Abay et al., 2023; Behnassi and El Haiba, 2022; Falkendal et al., 2021; Fan et al., 2021). These events underscore the urgent need to understand the immediate and extended impacts of such crises on global food systems, particularly for essential commodities like winter cereals.

The COVID-19 pandemic brought widespread disruption to global supply chains, altering consumer demand, restricting labor mobility, and introducing financial volatility that impacted food security worldwide (Charlton, 2022; Laborde et al., 2020). These disruptions require a systematic evaluation of food trade resilience across spatial scales and trade distances. It is essential to quantify the shifts in network performance before and after the pandemic to reveal the structural vulnerabilities and adaptive capacities of the global food trade system (Carlson et al., 2021).

The Russia–Ukraine conflict has introduced another layer of complexity to the global food trade (Feng et al., 2023; Laber et al., 2023; Van Meijl et al., 2024). As two of the world's leading exporters of winter cereals, the war has substantially disrupted their production and trade routes, with ripple effects extending into global food prices and supply stability. This situation calls for the integration of satellite observations with trade modeling to simulate and assess the potential spatial and structural consequences of such geopolitical tensions.

Beyond short-term disruptions, the compounded and cascading impacts of multiple crises—both health-related and geopolitical—highlight the systemic risks embedded in modern food trade networks. These interconnected networks are shaped by complex feedbacks and spillovers across sending, receiving, and indirectly affected systems (Davis et al., 2021; Distefano et al., 2018; Gephart and Pace, 2015; Gomez et al., 2021). Understanding these dynamics is crucial to developing strategies that enhance trade resilience and support global food security in an era of compounding uncertainty.

This dissertation addresses these challenges by applying the metacoupling framework to evaluate the resilience of global wheat trade under multiple crises. Chapter 2 offers a systematic review of 455 studies and identifies critical gaps in existing resilience assessments, particularly the neglect of spillover systems and cross-scale interactions. Chapter 3 introduces a framework to assess resilience across adjacent and distant trade systems before and after the COVID-19 pandemic, revealing disparities between income groups. Chapter 4 simulates the 2022 Russia–Ukraine war's impact on winter cereal trade using satellite-derived cropland data and trade network metrics. Finally, Chapter 5 examines long-term structural changes in the global wheat trade network from 1991 to 2022, using network analysis, structural change modeling (SCM), and generalized additive models (GAM) to uncover income-based disparities and shifts in trade roles over time.

Together, these chapters provide theoretical and empirical insights for understanding the spatial, structural, and temporal dimensions of food trade resilience. By integrating network analysis, remote sensing, and systematic review within a metacoupling framework, this research offers practical tools and policy-relevant findings for improving the resilience of global food systems.

1.2 Theoretical Framework

To uncover the various human-nature interactions and their effects at multiple scales, the metacoupling framework originated. The principle and framework of metacoupled (Liu, 2017a) are developed based on telecoupling's research on the interaction between distant systems (Liu et al., 2013a) which aims to qualify the impacts of distant connections such as global trade (Herzberger et al., 2019a), gas emission (Yao et al., 2018), cropland soil erosion with distant drivers (Wang et al., 2021). The metacoupling framework has a comprehensive consideration of the interactions and impacts between the focal system and the adjacent systems with support through the integration of a series of interdisciplinary concepts and theories (Liu et al., 2019a). Each metacoupled system integrates three profound complex systems through flows at different scales. There are five main components of each sub-framework, system, flows, causes, agents, and effects, Figure 1.2 is the specific structure of the intra-, peri- and telecoupled systems.

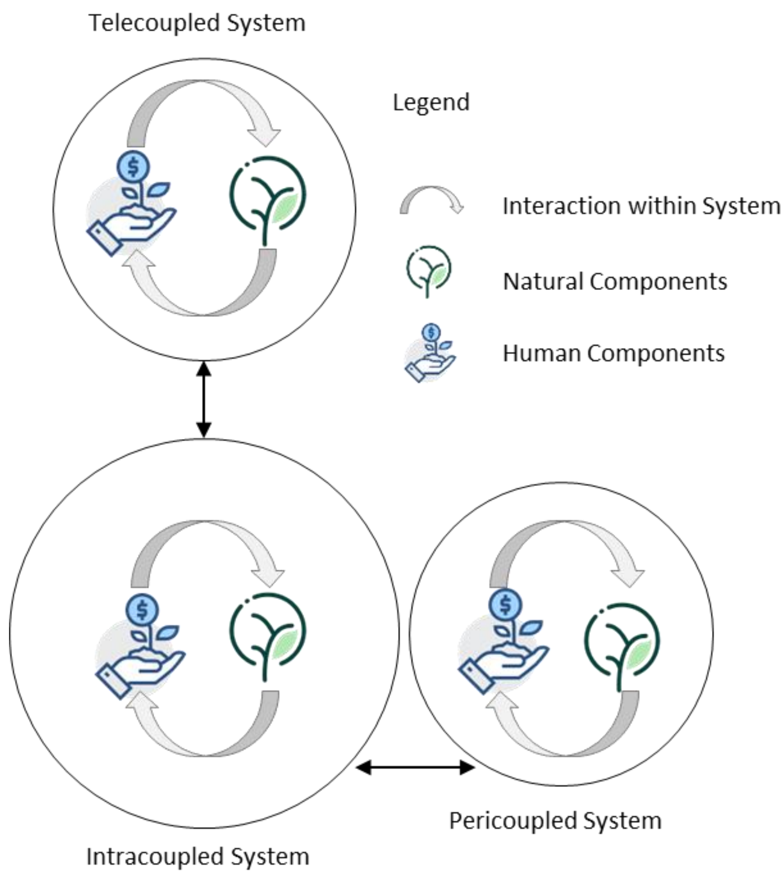


Figure 1. 1 Metacoupling framework (adapted from Liu 2017).

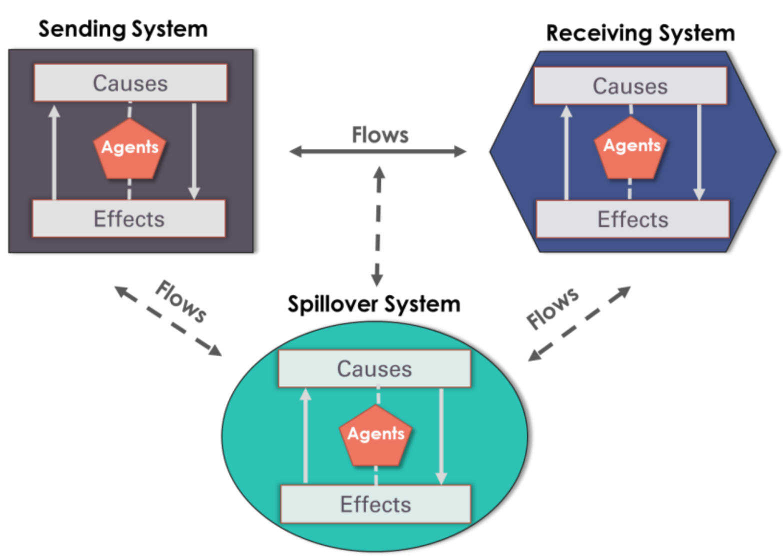


Figure 1. 2 System structure of tele-, peri- and intracoupled systems which include sending, receiving spillover systems, causes, agents, effects, and flows.

This thesis consists of four research chapters (Chapters 2 through 5) organized according to the structure in Figure 1.3.

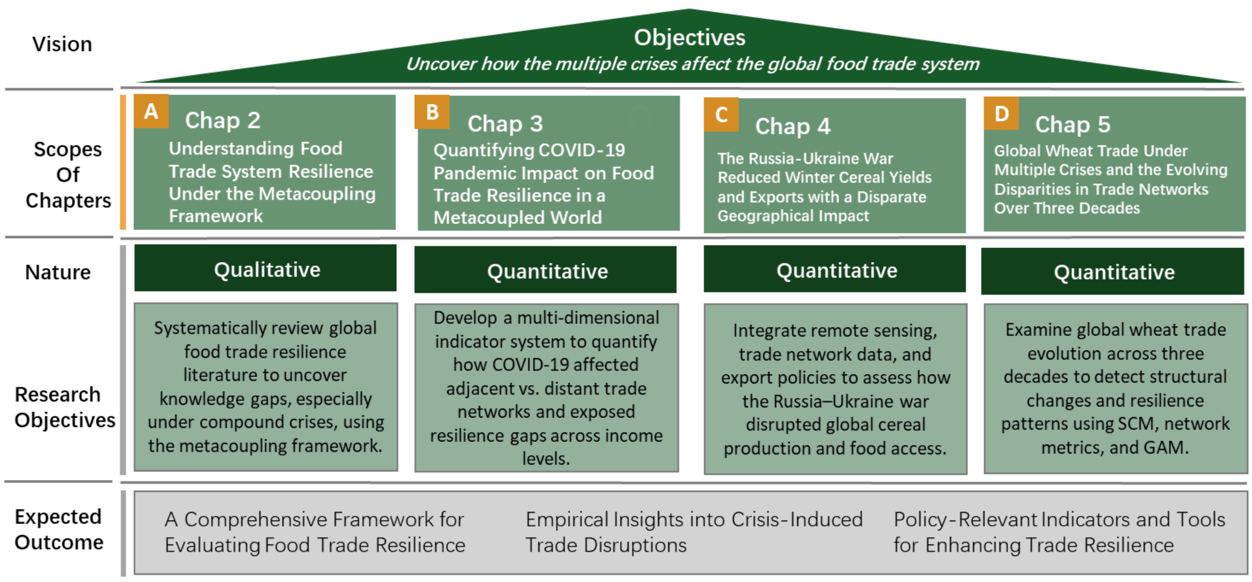


Figure 1. 3 Interrelations among four research chapters of the proposed dissertation research on the complex effect of metacoupling processes on a coupled human and natural system.

1.3 Goals and Objectives

This dissertation aims to deepen our understanding of how global food trade systems—particularly wheat trade—respond to multiple types of crises. It does so by applying the metacoupling framework to assess resilience across spatial and temporal scales, using both qualitative and quantitative approaches. The four core chapters each address a specific aspect of this broader goal.

Chapter 2 provides a systematic literature review and meta-analysis of 455 peer-reviewed studies related to food trade resilience. The objective is to evaluate how existing research addresses different spatial scales and the main components of food trade systems, including sending, receiving, and spillover systems. This chapter also synthesizes the indicators used in current assessments and proposes a new classification based on human- and nature-related drivers to guide future resilience evaluations.

Chapter 3 examines how the COVID-19 pandemic affected global food trade, with a focus on both adjacent and distant trade relationships. This chapter develops a quantitative framework to evaluate trade resilience using five indicators—Bonilla index, centrality, connectivity, trade disruption, and supply chain diversity. It incorporates globally available datasets on political, economic, demographic, institutional, and supply chain factors, and analyzes how different income groups experienced and responded to disruptions between 2019 and 2020.

Chapter 4 builds a rapid assessment framework to estimate the impact of the 2022 Russia–Ukraine war on winter wheat trade. Using a combination of satellite-derived cropland data and international trade statistics, this chapter compares trade network structure in 2022 with pre-war patterns from 2021. The analysis is carried out at multiple spatial scales to capture uneven impacts across regions and income groups.

Chapter 5 extends the analysis to a longer time frame by constructing a global wheat trade network from 1991 to 2022. This chapter applies network analysis, scenario simulation, structural change modeling (SCM), and generalized additive models (GAM) to evaluate how the structure and resilience of the wheat trade system have evolved. Special attention is given to income group disparities and the effects of multiple crisis events (e.g., financial crisis, COVID-19, export bans). The objective is to identify long-term structural changes and highlight persistent inequalities in global food security.

CHAPTER 2: UNDERSTANDING FOOD TRADE SYSTEM RESILIENCE UNDER THE METACOUPLING FRAMEWORK

2.1 Abstract

Resilience of international food trade systems, threatening global food security. Here we utilize the metacoupling framework (which integrates socioeconomic and environmental dimensions across multiple adjacent and distant geographic regions and scales), in conjunction with a systematic review of existing studies, to identify potential research gaps. Through a systematic review of 455 peer-reviewed articles, this study highlights the unbalanced nature of existing research, which often overlooks the interconnectedness of food trade systems at national, regional, and global scales. Our analysis reveals that there is an insufficient focus on spillover systems, which have been discussed the least among the main components (systems, agents, causes, effects, and flows) of the metacoupling framework. In addition, there is a large lack of research on the complex dynamics across multiple geographical scales and the interdependencies among the different components. Our findings emphasize the necessity for future research to incorporate all metacoupling components, thereby enhancing the robustness and effectiveness of current efforts to sustain global food security amidst multiple crises.

2.2 Introduction

Global food systems are linked through intensive and complex food trade networks. These networks create dependencies among nations and states that can mitigate or exacerbate the effects of external crises, which differ based on how and where crises enter the network (Hertel et al., 2020; Smith & Glauber, 2020; Wood et al., 2023). The complex interplay of climate change, geopolitical tensions, and global pandemics underscores the need to better understand these systems, which is integral to ensuring food security and sustainability worldwide.

Existing research has made an attempt to analyze the resilience of food trade networks, showing that it may increase supply diversity—referring to the variety of geographic sources, product types, and transportation pathways—but also may grow the dependence on food imports, which reduces the resilience of the system (Kummu et al., 2020; Thow, 2009; Thow & Hawkes, 2009). Food production capacity, scale, and diversity are key factors that guarantee a food system's own resilience, as they directly influence its ability to absorb crises, adapt to changes, and recover from disruptions (Coopmans et al., 2021; Fan et al., 2021). Moreover, these factors are essential for sustaining the resilience of global and regional food trade systems by supporting stable supply chains, reducing dependency on a few producers, and enhancing the overall adaptability of interconnected markets. Greater connectivity and self-organization within local systems not only enhance their ability to respond to crises but also strengthen the overall resilience of the global food trading system by enabling faster recovery, resource-sharing, and adaptive responses to disruptions (Berkhout et al., 2023; Coopmans et al., 2021; Miralles et al., 2017). This local-level adaptability plays a crucial role in stabilizing regional and global supply chains, highlighting how resilience at smaller scales contributes to the robustness of the entire food trade network. However, much of this research remains fragmented by either focusing on only local supply chains in isolation or measuring the extensive global trade networks through harmonized assessment metrics. Therefore, an integrated framework that bridges all these cross-scale studies is needed. The metacoupling framework represents a sophisticated and integrative conceptual model that incorporates socioeconomic and environmental interactions within a single coupled human and natural system and across neighboring and distant systems (Liu, 2017; Liu et al., 2021). This framework is structured by three systems: sending, receiving, and spillover – see Figure 1. Each system has five main components: systems (usually defined using political or geographic boundaries; flows, such as the transfer of information and commodities; agents, the facilitators of the flows and include traders and policymakers among others; causes, the underlying reasons for the flows; and effects, the outcomes resulting from the flows (Figure 2. 1).

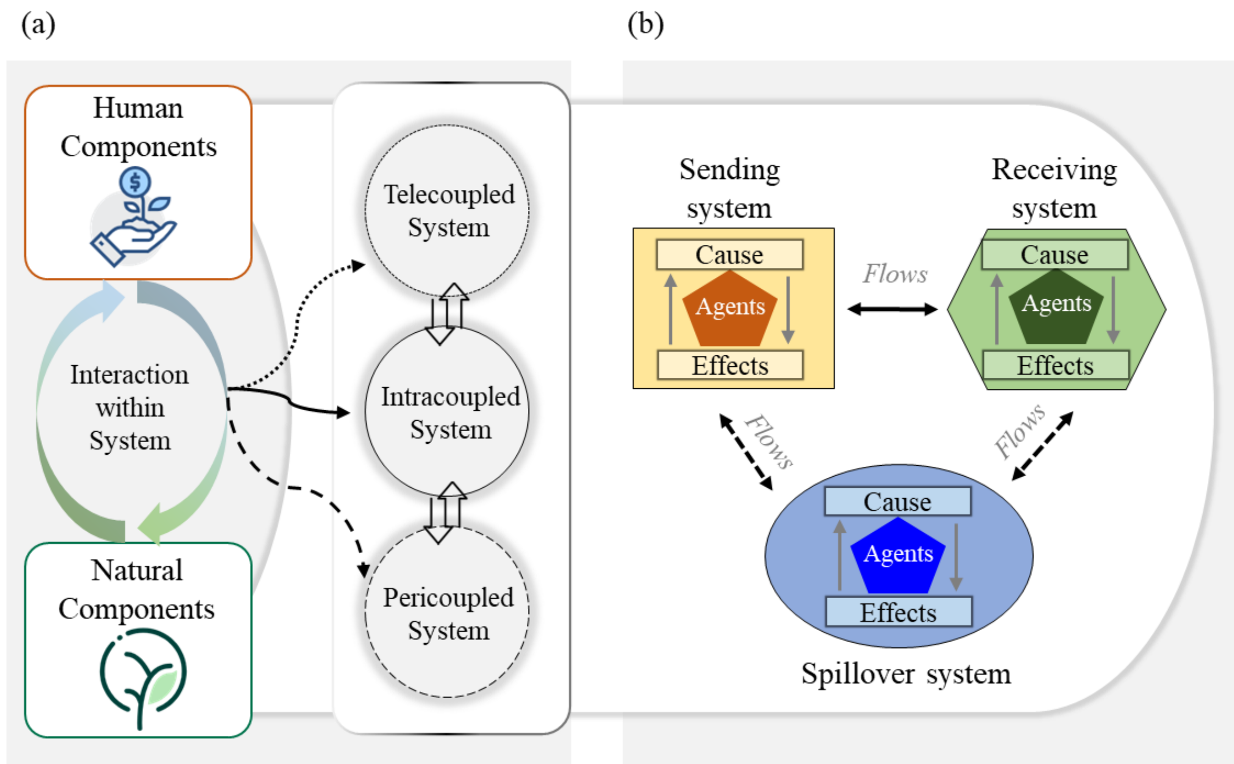


Figure 2. 1 Metacoupling framework (a) and the components of each system (b). The three circles represent the three scales of coupled human and natural systems (a). The ribbon arrows embody human-nature interactions, the green plants represent natural components, and the hand icon indicates human components (adapted from Liu, 2017 (page 1 Figure 2.1). (b) shows the general conceptual framework of coupling human-nature interactions between two or more coupled systems (from Liu et al., 2013 (page 3 Figure 2)) illustrates five main components and interrelationships: systems (sending, receiving, spillover), flows, agents, causes, and effects.

In global food trade networks, the sending and receiving systems can be importing and exporting countries, with the sending system being the exporter and the receiving system being the importer. Spillover systems are those that affect or are affected by the exchanges between sending and receiving systems. Despite their significance, spillover effects remain an underexplored dimension in resilience studies, often being overlooked in traditional assessments of food trade systems. These spillover effects can take various forms, including indirect economic repercussions, environmental degradation, and policy-driven shifts in trade patterns, among others. Understanding these dynamics is crucial for developing a more comprehensive framework for food trade resilience.

By illuminating the interactions within and between national and global food trade systems through the concepts of intracoupling (human–nature interactions within a system), pericoupling (human–nature interactions between adjacent systems), and telecoupling (human–nature interactions between distant systems), the framework provides a comprehensive perspective that is largely absent from the existing literature (Jia et al., 2024). For example, intracoupling can be observed in domestic food supply chains within countries such as China or the United States, where internal production, distribution, and consumption interact (Herzberger et al., 2019). Pericoupling occurs in regional trade between neighboring countries, such as Russia and China (Herzberger et al., 2019). Telecoupling is evident in the global soybean trade, where Brazil and the USA export large quantities to China, creating long-distance dependencies that influence food security and environmental sustainability in all three nations (Sun et al., 2018). The interplay among these coupled systems underscores the complexity of global food trade and highlights the need for resilience frameworks that go beyond simplistic assessments of supply and demand. In particular, resilience assessments must consider not only direct trade linkages but also assess how systemic disruptions, such as geopolitical shifts, climate-induced supply chain breakdowns, and regulatory interventions, cascade across these networks.

In addition, while existing research has begun to identify key factors affecting food system resilience, such as diversification in food trade supply and food production forms, adaptation, and the strength of socioecological linkages, consensus on how these factors should be integrated and assessed in the context of food trade is still missing (Kummu et al., 2020; Toth et al., 2016). Given this backdrop, our systematic review seeks to address major gaps by employing the metacoupling framework as a conceptual lens to examine the existing literature on food trade system resilience. This study represents the first step of a two-stage research agenda, where we systematically review existing resilience assessments, analyze their limitations, and propose a metacoupling-based evaluation framework. The second step, which will be presented in the next chapter, involves an empirical case study to operationalize this framework and test its applicability in a real-world food trade system.

Combining existing studies with the metacoupling framework helps us identify knowledge gaps in existing studies. As depicted in Figure 2.1, we scanned all the articles for the components in the intracoupled (focal) system, pericoupled (adjacent) system(s), and telecoupled (distant) system(s) that were addressed at national, regional, and global scales: agents; flows; receiving, sending, and spillover systems; effects; and causes. By categorizing the research according to the metacoupling domains—intra-, peri-, and telecoupling—this investigation provides a critical analysis of the coverage and depth of studies into the five main components of the framework, highlighting the diversity of factors in resilience assessment, and promoting a more comprehensive understanding of the resilience of the food trade system. This first stage of the research is crucial because it establishes a structured foundation for integrating metacoupling into resilience assessments, ensuring that the subsequent empirical application is informed by a thorough understanding of existing research gaps. Food system resilience in this study refers to the ability of these networks to absorb, adapt to, and recover from crises—such as climate change, geopolitical tensions, or pandemics—while continuing to ensure food availability, accessibility, and stability.

2.3 Methodology

2.3.1 Data Retrieval

We utilized the widely recognized systematic review methodology, referred to as the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) approach (Figure 2. 2) (Moher et al., 2010). This method guided us in gathering, reviewing, and selecting relevant studies that fall within the ambit of our research objectives, as elaborated in Section 2.3.2.

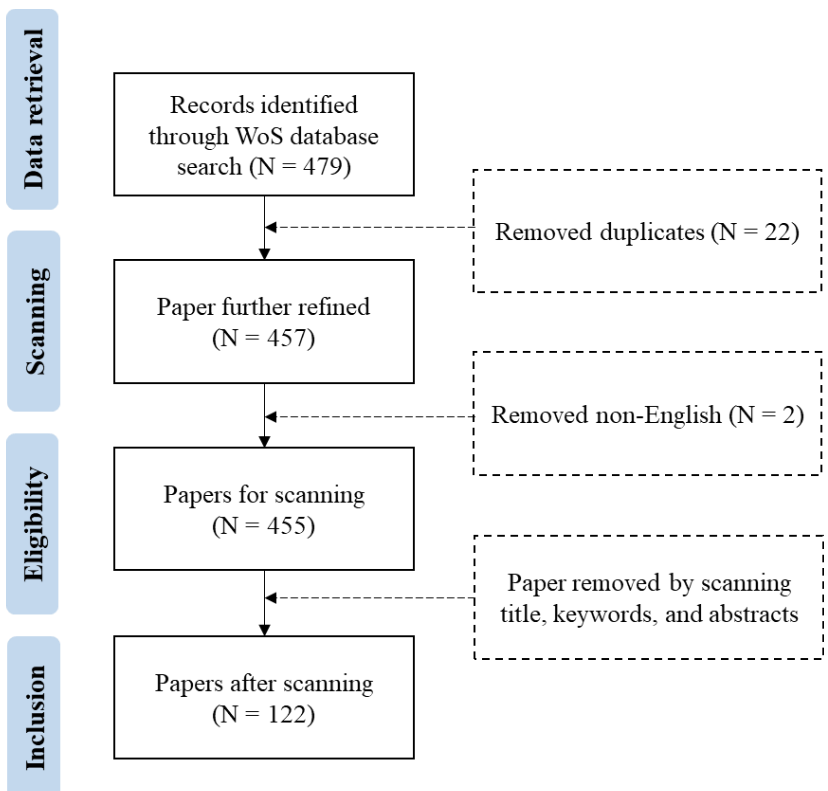


Figure 2. 2 PRISMA workflow for paper selection and scanning.

For the review, we collected relevant articles from the Web of Science (WoS) by utilizing the tailored search terms “(#1 OR # 2).”

#1: TS = (((food* OR crop*) NEAR/5 trade) NEAR/5 (resilienc* OR vulnerab*))

#2: TS = (((food* OR crop*) NEAR/5 (trade system)) NEAR/5 (resilienc* OR vulnerab*))

The WoS search strategy employs Boolean and proximity operators to refine literature retrieval. In the specified search queries, the NEAR/5 operator ensures that key terms appear within a defined proximity to each other, allowing for a more targeted yet comprehensive identification of relevant studies. The NEAR/5 operator instructs the database to retrieve records in which the specified terms appear within five words of each other, in any order. This approach enhances the relevance of search results by capturing literature where these concepts are closely related while allowing for slight variations in word arrangement.

The first query, TS = (((food OR crop) NEAR/5 trade) NEAR/5 (resilienc* OR vulnerab*))**, identifies studies where the term food or crop appears within five words of trade, and this combined phrase then appears within five words of resilience or vulnerability, including variations such as resiliency and vulnerabilities. The use of wildcard (*) ensures inclusivity of multiple word forms, thereby broadening the scope while maintaining relevance. This query is designed to capture research discussing the resilience or vulnerability of food or crop trade in a structured manner.

The second query, TS = (((food OR crop) NEAR/5 (trade system)) NEAR/5 (resilienc* OR vulnerab*))**, follows a similar logic but introduces the term trade system instead of trade. This distinction refines the search by emphasizing systemic perspectives on food and crop trade rather than individual trade transactions. Consequently, this query prioritizes studies that examine the structural resilience or vulnerabilities within food trade systems, ensuring a focus on broader trade networks and interdependencies. In total, we compiled 479 publications related to the topic search (TS) used. Some of these papers were duplicated, and some were written in non-English languages, so we excluded these two groups. Finally, the research results as of March 16, 2024, showed that 455 papers were obtained. The paper list was downloaded with parameters containing the published year, article title, journal, authors, keywords, times cited (all databases), DOI, research areas, and unique WoS ID.

2.3.2 Scanning Papers with Expertise Knowledge

Our goal was to evaluate how the current literature represents the different elements of the Metacoupling framework. A pre-selected set of 455 papers was used as input. Articles that assessed trade dynamics and were human-centered were included in the selection, which revolved around quantitative and qualitative analyses of food and crop trade. Literature review articles that focused only on biophysical properties or technical aspects, and/or did not take trade into account were excluded.

Table 2. 1 Inclusion and exclusion criteria for scanning papers

Inclusion criteria (related to food/crop trade and discussion about resilience/vulnerability)	**Exclusion criteria (not related to food/crop trade and no discussion about resilience/vulnerability)**
• Quantitative/qualitative studies (including evaluation framework) • Predict/estimate trade dynamics/ socioeconomic aspects of food/crop trade • Social sensing / social media: application of non-technical aspects to study food trade (supply chain; production; export quantity; production such as fertilizer import; food price; climate factors) • Public health • Economic activities (e.g., food prices) • Political activities (agents; stakeholders, political economy; legitimation)	• Outline of study progress/review papers • Physical aspects of soil quality and climate features without considering effects on human/society • Focus on food/crop system not related to trade • Remote sensing/algorithms: production prediction, data/method development, etc. • Survey/workshop participants to study food economics

2.4 Statistical Outline of Food Trade Resilience in a Metacoupled World

This section summarizes the levels of quantitative and qualitative distribution, study areas, and types of couplings covered in food trade system resilience studies through Sankey diagrams

(Figure 2.3(a)). The results show that there are more quantitative studies than qualitative ones, with a total of 87 quantitative and 35 qualitative studies screened as inputs for the final scan (122 in total). The top research regions with the most frequent research on the resilience of the food trade system include the globe, the United States of America, the United Kingdom, Mexico, India, Indonesia, and China.

We categorized these study areas as global, regional (more than one country but less than global), and national (one country or smaller spatial scale). The trend in the proportion of studies at different scales is similar in quantitative and qualitative studies (Figure 2.3(b)), with national-scale studies being the most prevalent in both types of studies (42.53% [37 papers] quantitative, 48.57% [17 papers] qualitative), followed by global-scale studies (39.08% [34 papers] quantitative, 25.71% [9 papers] qualitative) and regional scale studies (18.39% [16 papers] quantitative, 25.71% [9 papers] qualitative).

As seen in Figure 2.3(c), concerns about the resilience of the food trade have increased over time. In 2020, 9 papers discussed resilience, increasing to 23 in 2021, 25 in 2022, and 21 in 2023. This interesting trend may be related to the outbreak of the COVID-19 global pandemic in 2020, when social distancing and travel embargoes, among others, led to the disruption of food trade, thus triggering concern among scholars (Gren, et al, 2024).

The proportions involving intra-, peri-, tele-, and metacoupling varied across study scales (Figure 2.3 (b)). Specifically, at the national scale, quantitative and qualitative studies have similar distribution trends across the four coupling types, with intracoupling accounting for the highest percentage, followed by metacoupling. More articles consider telecoupling than pericoupling in quantitative studies. In qualitative studies, however, there are as many studies considering tele- and pericoupling. At the regional scale, both quantitative and qualitative studies consider telecoupling the most, followed by meta-, intra-, and pericoupling. At the global scale, large variability emerges in terms of quantitative and qualitative studies covering different coupling types. Specifically, quantitative studies of meta- and telecoupling have a larger share of global-scale studies, while intra- and pericoupling have fewer. In qualitative studies, tele- and intracoupling have a slightly higher share, but overall, the four types have similar shares.

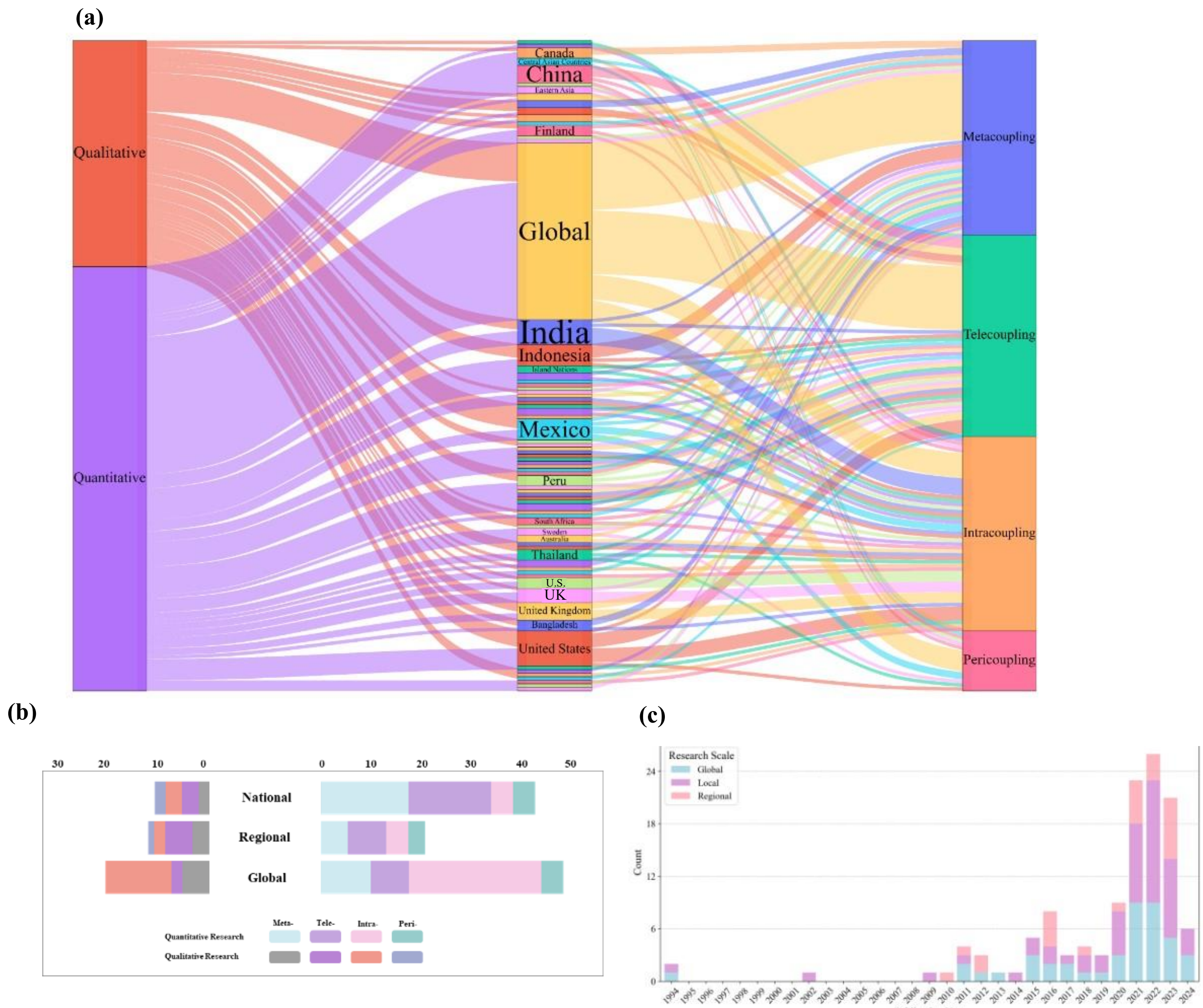


Figure 2. 3 Distribution of food trade resilience research by methodology, geographical focus, and coupling types. (a) Sankey diagram representing the flow of qualitative and quantitative studies across different regions and coupling types (meta-, tele-, intra-, and pericoupling); (b) Bar chart comparing the distribution of studies by coupling type across different geographical scales; (c) Temporal distribution chart showing the number of studies published from 1990 to 2024 (data for 2024 was as of March 13th). This highlights the increase in post-2020 research.

2.5 Components in Coverage in Food Trade Resilience

2.5.1 National-scale Components Coverage

At the national scale, the research usually involved domestic food trade flows, including both the distribution of domestically produced foods from their place of origin to points of consumption and the internal movement of imported foods from entry points (such as ports or distribution centers) to consumers. Since some studies involved research on multiple different systems and different components, these different components were counted repeatedly, so their total may exceed the total number of articles involved. At the national scale, the components of the focal (the country under the study), adjacent (neighboring countries or regions with direct trade links, and distant (non-contiguous countries or regions engaged in food trade) systems were discussed a total of 283 times (times means the total number they were discussed) across the analyzed studies, indicating that national-scale discussions of food trade resilience were more frequent than those at regional and global scales (Figure 2.4). One series of studies at the national scale considered an entire country as a system, and the trade flows under consideration took place within the focal system (Adiga et al., 2022; Horn et al., 2022; Nava et al., 2023; Syfongxay et al., 2022; Willer & Aldridge, 2023). Thus, the country in study can be defined as an intracoupling system. The focal system and its main components were discussed 166 times, with the focal system being discussed the most, including 56 times as the junction point of three different systems (Figure 2.4). Furthermore, the receiving system was discussed 23 times, the sending system 31 times, and the spillover system was only discussed twice. Flows were discussed 33 times, the most of any single component. Four of the five components—agents, causes, effects, and flows—were discussed in a more balanced way. The limited discussions of spillover systems reflect insufficient attention to spillover effects in trade, which can indirectly trigger price fluctuations, contribute to environmental degradation, and exacerbate socioeconomic and ecological challenges. For example, disruptions in trade flows—such as export bans or supply chain crises—can create price volatility by limiting food availability in some regions while causing oversupply in others (Jia et al., 2024). Similarly, shifts in agricultural production driven by trade demands can lead to deforestation, soil depletion, and water overuse, particularly in regions with less stringent environmental regulations. Additionally, trade-induced spillovers can widen socioeconomic inequalities by creating food accessibility disparities or displacing small-scale farmers from local markets (Arouri et al., 2012; Hou & Zhu, 2022; Nordin & Sek, 2019; Y.-J. Zhang et al., 2008).

Alternatively, if provinces/cities/counties within a country are considered as the focal system, their neighboring provinces/cities/counties are considered adjacent systems, and geographically noncontiguous areas are considered distant systems (Mastronardi et al., 2022; Rothwell et al., 2016; Thanichanon et al., 2018). The components of adjacent systems were discussed 51 times, and the components of distant systems were discussed 66 times. The limited focus on spillover systems observed in studies of the focal system was also evident in research on adjacent and distant systems, where spillover effects received comparatively little attention. Interestingly, we found that the distribution of the other components in studies of adjacent and distant systems was not as balanced as the distribution within the focal system. Furthermore, both the adjacent and distant sytems lacked adequate attention to agents (discussed twice in adjacent systems and three times in distant systems). We believe this little attention to agents may be due to the need for fieldwork and additional data collection challenges for some researchers (Elsig, 2011).

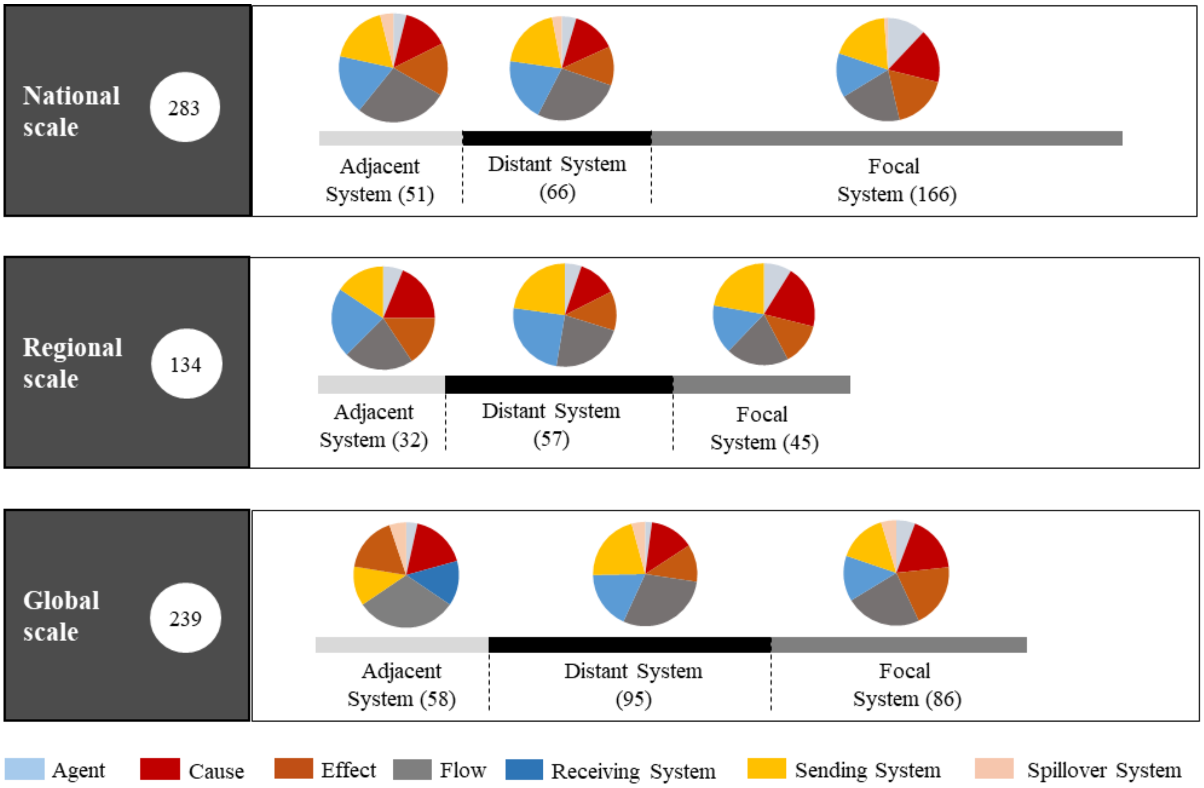


Figure 2. 4 Share of discussions of components in adjacent, distant, and focal systems at national, regional, and global scales. All numbers in the figure indicate the frequency of discussions on each component across the analyzed studies. Since some studies address multiple components and cover both national and regional scales, the total count exceeds the number of individual studies (122).

2.5.2 Regional Scale Components Coverage

Regional-scale studies examine food trade dynamics within politically or economically connected regions. These may include trade within political blocs, such as the European Union, or among countries influenced by shared policies, such as those in the Belt and Road Initiative. Regional studies can also focus on trade between countries with similar dietary habits, cultural practices, or historical connections, such as Canada and the United States (Chepeliev et al., 2023; Hu et al., 2023; Larochez-Dupraz & Huchet-Bourdon, 2016; Maggio et al., 2016; Qinghua et al., 2023; Rabbi et al., 2023). These studies typically analyze the movement of food from producers to consumers within the region, covering both intra-regional trade (e.g., food exchange among

EU member states) and inter-regional trade (e.g., food exports from these regions to external markets).

The frequency of discussion of the five main components of the metacoupling framework related to regional scale was the lowest of the three research scales, at only 134 times (Figure 2.4). Papers describing research at the regional scale did not discuss spillover effects, whereas papers covering research at both national and global scales discussed them. Next, of all components examined, agents were the least discussed in focal/adjacent/distant systems. This may be due to the challenges of acquiring agent data and the complexity of analysis in regional-scale studies. Specifically, among focal systems, the most discussed system was still the sending system, which was studied 10 times. At the regional scale, studies most frequently examined causes and effects, each discussed nine times, indicating a strong focus on the factors driving food trade and its socioenvironmental consequences. However, research on adjacent systems was notably limited, with only 32 instances across all components, suggesting that interactions between neighboring regions are understudied. Within adjacent systems, flows and receiving systems were the most frequently examined (seven times each), while sending systems and effects were addressed less often (five times each), and agents were rarely considered (only twice). In contrast, distant systems received the most attention, with 57 mentions, likely because regional trade is often analyzed as a whole in relation to external markets. This trend aligns with the emphasis on receiving systems (14), sending systems (13), and flows (14) in the literature. Despite this, a critical gap remains in the study of spillover systems, which received less attention than other components across all scales. Given their potential role in price volatility, environmental degradation, and unintended socioeconomic consequences, the lack of research on spillover effects represents a major gap in understanding food trade resilience.

2.5.3 Global Scale Components Coverage

Globalization studies are different from national- and regional-scale studies because they include all countries and regions of the world. Therefore, the use of uniform, publicly available data is usually required, and few studies are able to take into account nationally localized data and characteristics. Influenced by this feature, agents were the least addressed in the use of globalized trade data to measure and assess trade (system) resilience, whether in focal systems (discussed twice), adjacent systems (discussed twice), or distant systems (discussed five times). Twenty studies focused on food trade flows within the focal system, making it the second most frequently studied component after the combined analysis of all three system types—receiving (12 studies), sending (13 studies), and spillover (4 studies). Concerns about causes and effects were addressed 15 and 17 times, respectively, and overall, global-scale studies had similar levels of concern for the components of the focal system, with the exception of agents and the spillover system. Only 58 studies of adjacent systems dealt with their components. The most discussed components were receiving systems (7) and sending systems (10). Spillover systems were discussed three times, which shows that global studies usually focus on the parties directly involved in food trade and less on the scope of spillover effects. Of the remaining four components, the most important was flows, discussed 18 times, implying the highest level of attention was paid to the type of food trade in global-scale studies.

Distant systems were the most frequently discussed among the three types, appearing 95 times across the studies evaluated. Among the components, flows (28), receiving systems (17), and sending systems (20) received the most attention. However, spillover effects were examined in only three studies, highlighting a large gap in understanding spillover dynamics in global-scale studies.

2.6 Indicators of Food Trade Resilience

While quantitative studies often incorporate resilience assessment frameworks, there is no standardized approach that systematically integrates key indicators across different coupling scales. Existing studies tend to focus on isolated aspects of resilience, such as economic trade dependencies or environmental vulnerabilities, without fully capturing the interconnected nature of food trade within the coupled human and natural systems (CHANS) framework. To address this gap, we propose a new framework that categorizes resilience indicators comprehensively and integrates them into a unified structure that reflects the complexity of food trade resilience.

An important feature of the reviewed quantitative studies on food trade system resilience is the use of indicator-based frameworks. We identified 87 indicators across 40 studies, which we categorized into human-related and nature-related factors (Table 2.2). Nature-related factors include biophysical drivers (e.g., soil quality, water availability, biodiversity) and environmental drivers (e.g., climate and weather, elevation, natural resource degradation). These indicators are critically important for understanding long-term sustainability and can sometimes cause sudden, large-scale disruptions. Weather and climate extremes such as hurricanes and earthquakes can have immediate and devastating impacts, rapidly halting infrastructure, disrupting transportation, and triggering cascading failures across trade networks. Their role in shaping the resilience of food systems is especially pronounced in regions vulnerable to climate variability and ecological stress.

However, the empirical focus of this dissertation centers on crises that are primarily human-driven, including the COVID-19 pandemic, the 2008 global financial crisis, and the 2010 Russian wheat export ban. These events were characterized by rapid shifts in trade flows, policy decisions, and institutional responses, making social, economic, and political indicators more directly relevant for the analysis. As such, the analytical framework employed here emphasizes variables that are more responsive over short to medium timescales. This focus does not diminish the importance of environmental or biophysical factors, but rather reflects the thematic scope of the study. Future research—particularly those examining climate extremes, natural disasters, or compound socio-environmental shocks—should incorporate a broader suite of environmental indicators to capture the full spectrum of resilience dynamics in food trade systems. Integrating these factors into metacoupling analyses could offer valuable insights into how ecological feedbacks reshape global trade, especially under conditions of accelerating environmental change.

To fill this knowledge gap, we classified the assessment indicators used in food trade system resilience into broad categories and subcategories. Since CHANS encompasses both human and natural systems, the broad categories include human-related factors and nature-related factors. Human-related factors include innovation and research drivers, economic and market drivers, political and institutional drivers, and demographic and supply chain indicators (Table 2.2). Nature-related factors are categorized into biophysical drivers and environmental drivers (Table 2.2). By merging these existing indicators into a comprehensive framework, we provide a structured approach to resilience assessment that accounts for both human and environmental dimensions. Integrating these fragmented indicators into a unified system allows for a more holistic evaluation, offering a systematic way to assess vulnerabilities, identify intervention points, and improve the adaptability of food trade systems in response to crises and disruptions.

Table 2. 2 Assessment frameworks are classified into broad and secondary categories

Broad category	**Subcategories**	**Example factors**	**Number of publications**	**Selected referenced studies**
Human-related factors	Innovation and research drivers	Technology; infrastructure; innovation	4	(Lehikoinen et al., 2021)
	Economic and market drivers	Livelihoods and income; markets, firms, and trade; land tenure; food prices; GDP	26	(Nava et al., 2023; Saman & Alexandri, 2018; Willer & Aldridge, 2023)
	Political and institutional drivers	Governance frameworks; policy; institutional support; civil strife and conflict; social move ban; export ban; trade partner	11	(Gephart et al., 2016; González-Mon et al., 2023; Yu et al., 2023)
	Sociocultural drivers	Social norms and traditions; social stratification; women's empowerment; diet habit	6	(González-Mon et al., 2023; Yu et al., 2023)
	Demographic	Population; changing age profiles; migration	1	(Suweis et al., 2015)
	Supply chain	Storage and trade; historical export quantity; retail and marketing; industries; transportation	17	(Marchand et al., 2016; Nava et al., 2023; Nicholson et al., 2021)
Nature-related factors	Biophysical drivers	Soil quality; water availability; biodiversity	10	(Karakoc & Konar, 2021; Lehikoinen et al., 2021; Mastronardi et al., 2022)
	Environmental drivers	Climate and weather; topography and land use; pests and diseases; natural resources degradation	12	(Larochez-Dupraz & Huchet-Bourdon, 2016; Yu et al., 2023)

Some of the 40 studies considered more than one aspect of the indicator factors, so the sum of all indicator counts resulted in a final tally of 87. Of all the subcategories, economic and market drivers (26) had the largest share, reaching 29.89% of the number of times all indicators were considered, which is particularly consistent with the food trade. Supply chain, the second-highest subcategory, was covered 17 times, accounting for 19.54% of the total, which may be determined by the fact that any trade process needs to be supported by a supply chain. Third in the ranking was environmental drivers (12 studies, 13.79%), with factors such as climate and weather, topography and land use, pests and diseases, and natural resource degradation, which are the main factors to be considered when studying the dynamics of food production (Pimentel, 2018; Ray et al., 2019; Wirsenius et al., 2010).

Political and institutional drivers, discussed 11 times, are also an important subcategory for measuring the resilience of the food trade (system), which typically includes governance frameworks, policy, institutional support, civil strife and conflict, social movility bans, export bans, trade partners, and so on. These factors can largely affect food accessibility. Biophysical drivers, a set of physiological and biochemical indicators that determine the productivity of the land, is an important determinant of the amount of output, at the very beginning of the food trade, and was discussed 10 times, accounting for 11.49%. Other indicators such as sociocultural drivers (6), innovation and research drivers (4), and demographics (1) were considered less in this literature, possibly influenced by a number of factors, such as the difficulty of obtaining data, the complexity of the analyses, etc., which may explain the lack of attention paid to these dimensions in the existing literature.

2.7 Implications of the Metacoupling Framework for Food Trade Resilience Evaluation

In light of the increasing frequency of multiple crises—ranging from environmental crises to economic and social disruptions—understanding the resilience of food trade networks is paramount. The metacoupling framework provides a robust methodology for tracing the interdependencies and vulnerabilities within global food trade systems (Liu, 2017). By evaluating the flows of commodities across sending, receiving, and spillover systems, this framework delineates how disturbances in one region can propagate and amplify across the network, thus exacerbating vulnerabilities, not only in regions heavily reliant on food imports but also in those dependent on critical inputs for food production, such as fertilizers, seeds, and agricultural equipment (Kummu et al., 2020). Furthermore, the framework can help explicitly understand and balance the proportions of intracoupling, pericoupling, and telecoupling, which is essential for enhancing resilience by identifying overdependencies, diversifying trade linkages, and strengthening adaptive capacities across different scales.

Given the limitations of existing resilience assessment measures identified in our review, we propose the development of new, integrated indicators within the metacoupling framework to better capture the complexity of food trade systems. Current measures often fail to account for the multi-scale interactions between sending, receiving, and spillover systems, limiting their ability to provide a comprehensive assessment of trade resilience. By incorporating new indicators that explicitly address these interactions, our framework offers a more robust approach to understanding and enhancing resilience in global food trade networks. We propose a series of measurable indicators designed to assess the status of the system's resilience, ensuring a more comprehensive evaluation within the metacoupling framework.

In addition, there is a need to develop new metrics in future research, such as a coupling strength index, which aims to quantify the intensity of interactions among intra-, peri-, and telecoupled systems. Such an index could help assess the robustness of the connections within and between systems, offering a systematic approach for evaluating resilience in food trade networks. For instance, a coupling strength index to measure the intensity of interactions among intra-, peri-, and telecoupled systems could help identify the robustness of connections within and between systems. In the metacoupling framework, high coupling strength indicates that a system can withstand crises and disruptions because of its strong interactions and well-connected nature. Countries with high coupling strength can maintain their food trade flows in the face of crises, thereby keep a high resilience level.

Incorporating the metacoupling framework into existing resilience assessment models can profoundly enhance the analysis of food trade dynamics (Liu et al., 2021). For instance, traditional studies often neglect the intricate dynamics of spillover systems, where indirect effects of policy changes or economic activities can lead to environmental degradation and socioeconomic instability in distant regions (Zhang et al., 2023). By integrating these dimensions, the framework facilitates a more holistic understanding of the agents involved—from traders to policymakers—and the underlying causes driving these complex interactions. A comprehensive approach is essential for addressing the often fragmented nature of current resilience assessments and for fostering a more interconnected understanding of global food security.

The integration of the metacoupling framework enables a nuanced examination of resilience factors such as food supply and transportation diversification and adaptation, viewing them not as isolated elements but as interconnected components within a complex network (Fan et al., 2021). Future work should develop and evaluate new practices and policies that not only address immediate needs within individual systems but also consider their potential impacts on global food security (Smith & Glauber, 2020). These could include trade diversification strategies to reduce dependency on single suppliers, adaptive tariff adjustments to stabilize food prices, sustainability incentives to promote environmentally responsible production, and cross-border cooperation frameworks to enhance resilience against supply chain disruptions. Promoting sustainable practices in food production and enhancing cooperation between different systems (focal, adjacent and distant systems discussed in the study) may help mitigating the risk of adverse spillover effects, thereby fostering a more resilient food trade network capable of withstanding future crises. Integrating the metacoupling framework into food trade resilience evaluation represents a large advancement in this regard, offering a detailed and holistic analysis that is essential for understanding and enhancing the sustainability of global food systems in an increasingly interconnected world.

2.8 Conclusion

This systematic review critically examined the current status of food trade resilience research through the lens of the metacoupling framework. By categorizing and analyzing studies across intra-, peri-, and telecoupling domains, we identified major gaps in the literature, particularly regarding the integration and comprehensive assessment of spillover systems and agents. These findings highlight the need for a more holistic understanding of the resilience of global food trade systems.

The application of the metacoupling framework revealed that many existing studies fail to capture the intricate dynamics and interdependencies that shape global food trade. Instead of treating national, regional, and global scales as isolated layers, a more integrated approach is needed to address how disruptions cascade through different systems. Focusing on the connections and flows between sending, receiving, and spillover systems allows researchers and policymakers to better anticipate and mitigate the impacts of socioeconomic and environmental crises on global food security.

While this review provides a comprehensive examination of food trade resilience through the metacoupling perspective, it is important to acknowledge several limitations. One limitation stems from the inherent complexity of the metacoupling framework itself. Although it offers a broad and integrative view, its operationalization and quantification can be challenging, especially in data-scarce environments. In such cases, while quantitative applications may be limited, qualitative analysis based on the framework can still provide valuable insights. Another limitation relates to the focus on published academic literature, which may overlook grey literature and on-the-ground practices that offer important perspectives on resilience strategies not yet fully captured in academic discussions. Recognizing these limitations points to opportunities for future work to expand data sources and refine methodologies to better capture the intricacies of global food trade resilience.

This study serves as the foundation for a broader research effort to integrate the metacoupling framework into empirical assessments of food trade systems. By systematically reviewing and categorizing existing research, we establish the groundwork for the second phase of this project, which involves operationalizing the proposed framework in real-world case studies. The insights gained here not only refine the conceptual basis for future analysis but also inform the development of measurable indicators and practical assessment methodologies aimed at supporting the resilience of food trade systems under multiple crises.

CHAPTER 3: QUANTIFYING THE IMMEDIATE IMPACTS OF COVID-19 PANDEMIC ON FOOD TRADE RESILIENCE IN A METACOUPLED WORLD

3.1 Abstract

The COVID-19 pandemic has exposed critical vulnerabilities in the global food trade system, emphasizing the importance of resilience across diverse income levels and spatial scales. This study develops a comprehensive evaluation framework to assess food trade resilience, integrating economic, political, socio-cultural, and logistical dimensions. By disaggregating five key indicators—Bonilla index, centrality, connectivity, global trade disruptions, and supply chain diversity—into adjacent and distant trade components, we offer a nuanced understanding of how spatial proximity influences trade resilience dynamics. Our findings reveal stark disparities: low-income countries demonstrate acute vulnerabilities, especially in adjacent trade networks, due to limited diversification and infrastructural deficiencies. In contrast, high-income countries exhibit greater adaptive capacity, with diverse supply chains and robust trade networks buffering against global disruptions. Notably, adjacent trade dependencies in regions such as North Africa deteriorated largely, while distant trade networks demonstrated relative stability. These insights underscore the unequal impacts of global crises and highlight the critical need for targeted strategies to enhance resilience in the most vulnerable regions. By leveraging this integrated framework, our study provides actionable insights for policymakers to strengthen global food trade systems in the face of mounting uncertainty.

3.2 Introduction

Building upon the systematic review and integrated indicator framework established in Chapter 2, this chapter applies the framework to evaluate the impacts of the COVID-19 pandemic on global food trade system resilience. While Chapter 2 identified major gaps in the fragmented application of resilience indicators and synthesized a comprehensive framework, this chapter operationalizes these indicators to assess real-world shifts during a large-scale global crisis.

The COVID-19 pandemic has underscored the vulnerability of international food trade networks, disrupting production, distribution, and consumption patterns across countries and regions (Dodds & Pippard, 2013). The pandemic-induced restrictions on labor mobility, transportation, and international trade led to supply shortages, logistical bottlenecks, price fluctuations, and increased food insecurity, particularly in nations heavily dependent on food imports (Arndt et al., 2020; Béné, 2020; Mena et al., 2022). These cascading disruptions highlighted the critical importance of resilience in food trade systems—their capacity to absorb shocks, adapt to evolving conditions, and recover while ensuring food availability, accessibility, and affordability. Despite the growing recognition of food trade resilience as a critical research area, previous studies often focused on isolated factors, such as economic dependencies, supply chain vulnerabilities, or governance challenges (Gephart et al., 2016; Ingram, 2011; Grassia et al., 2022). Few assessments have systematically integrated these dimensions into a unified analytical framework, particularly one capable of capturing the spatial heterogeneity and transboundary nature of trade network resilience. As discussed in Chapter 2, this lack of integration hampers efforts to fully understand how disruptions cascade through interconnected food systems across different spatial scales.

To address this gap, this chapter utilizes the comprehensive indicator framework developed through the meta-analysis of 455 studies in Chapter 2. Specifically, the framework incorporates economic, political, demographic, socio-cultural, and supply chain dimensions, providing a multi-faceted basis for resilience assessment. By applying this framework to the global food trade system before and during the COVID-19 pandemic (2019–2020), we aim to offer empirical insights into how different income groups and trade linkages—adjacent versus distant—responded to a major global shock.

The scientific questions of this chapter aims to answer are: (1) How did the COVID-19 pandemic impact the resilience of global food trade systems? What is the differences among income groups? (2) How did adjacent and distant trade relationships respond differently to the COVID-19 disruption? and (3) Which human-related drivers contributed most to the changes in food trade resilience during COVID-19?

Through this analysis, we seek to advance understanding of how global food trade networks absorb and adapt to large-scale crises, and to inform strategies aimed at enhancing the resilience of food systems in an increasingly interconnected and crisis-prone world.

3.3 Methodology

3.3.1 Integrated Framework for Food Trade (System) Resilience

This study adopts the integrated indicator framework developed in Chapter 2, which synthesizes insights from a systematic review of 455 peer-reviewed studies on food trade resilience, and there are 38 publications that include the indicators for evaluating the food trade system resilience (Figure 3.1). The framework consolidates fragmented indicators into six thematic categories—Innovation and Research, Economy and Market, Policy and Institution, Society and Culture, Demographic, and Supply Chain—providing a comprehensive structure for resilience evaluation across spatial and income dimensions.

Building on this foundation, we selected 25 distinct indicators representing critical drivers of food trade system resilience. These indicators capture the economic, political, socio-cultural, demographic, and logistical factors shaping the capacity of food trade networks to absorb and adapt to crises. Each indicator's directionality—whether it positively or negatively influences resilience—was determined based on the existing literature (e.g., Larochez-Dupraz & Huchet-Bourdon, 2016; Diserens et al., 2018; Gephart et al., 2016; González-Mon et al., 2023; Karakoc & Konar, 2021).

The COVID-19 pandemic period (2019–2020) provides an ideal context for applying this framework, allowing us to assess temporal changes in resilience outcomes under a major external shock. We applied the framework to disaggregate resilience performance into adjacent and distant trade components, enabling the examination of spatial heterogeneity across countries of different income levels.

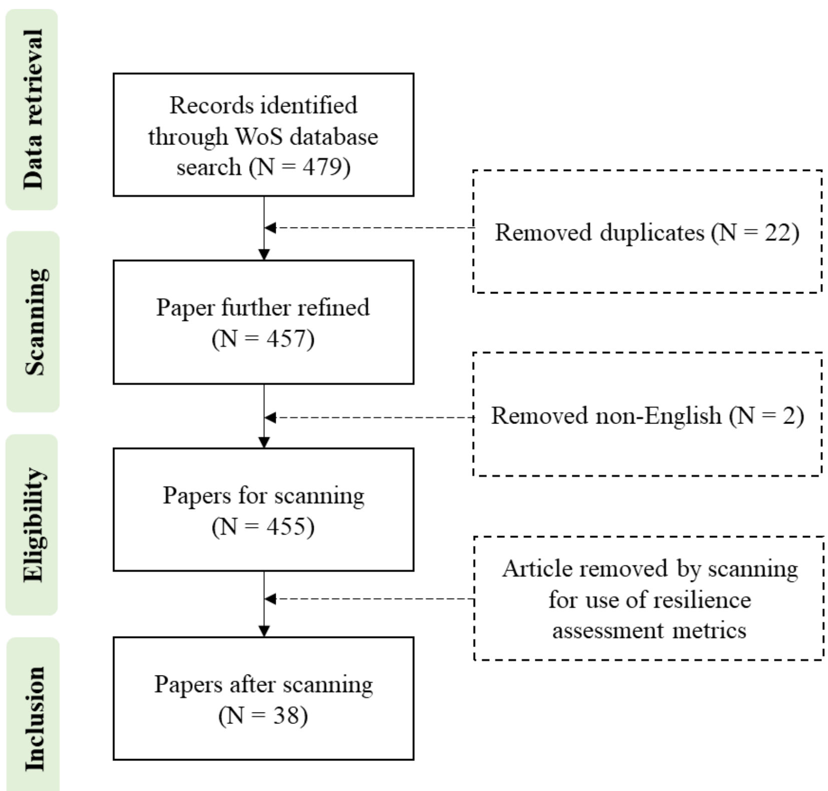


Figure 3. 1 PRISMA workflow for paper selection and scanning.

3.3.2 Building Food Trade (System) Resilience Evaluate Indicators

From the reviewed literature, data on resilience indicators were systematically extracted. We identified 25 distinct indicators, the broad category, indicators' name, description of each indicator, and positive or negative to food resilience and resources are all listed in Table 3.1. The extraction aimed to capture the commonly discussed indicators that are utilized to measure food trade resilience and the diverse metrics employed across different studies. These indicators were then integrated into a single framework to facilitate a structured analysis of food trade resilience. The framework categorized the indicators into six thematic groups: "Innovation and Research", "Economy and Market", "Policy and Institution", " Society and culture", "Demographic", and "Supply Chain". In this study, we have included a separate category "Innovation and research" for indicators that do not have a direct product, are derived from the literature, and need to be calculated using raw data.

Table 3. 1 Selected indicators for food trade resilience framework

Broad category	**Indicators**	**Description**	**Positive /Negative**	**Reference study**
Innovation and research	Bonilla Index (BI)	An indicator representing the vulnerability of food security to trade. It measures the ratio of national food import expenditure to the value of total exports.	-	(Larochez-Dupraz & Huchet-Bourdon, 2016)
	Connectivity of food trade network	Trade connections (Here use trade quantity)	+	(Diserens et al., 2018; Gephart et al., 2016; González-Mon et al., 2023; Karakoc & Konar, 2021; Lehikoinen et al., 2021)
	Centrality of food trade network	Key role of countries in connecting global trade flows, use betweenness centrality of food trade network	+	(Grassia et al., 2022)
Economy and market	Exchange Rate (E)	The exchange rate plays a role in determining the cost of food imports, as it affects the domestic price of imported goods.	+	(Larochez-Dupraz & Huchet-Bourdon, 2016; Saman & Alexandri, 2018)
	World Food Prices (Pw)	Changes in global food prices directly impact food trade resilience by affecting the cost of imports and the income from exports.	-	(Larochez-Dupraz & Huchet-Bourdon, 2016; Nisar et al., 2023; Saman & Alexandri, 2018; Travnikar & Bele, 2022)
Economy and market	GDP	GDP of a country	+	(Yu et al., 2023)
	Income levels	Average earnings, influencing purchasing power and food demand.	+	(Kahiluoto et al., 2012; Yu et al., 2023)
	Energy dependence	Reliance on energy sources for food production and transportation.	-	(Rabbi et al., 2023)

Table 3.1 (cont'd)

Economy and market	Export Growth Rate	Yearly monthly growth rate	+	(Nisar et al., 2023)
	Production diversity	Variety of food types cultivated in domestic agricultural systems.	+	(Kahiluoto, 2020; Nicholson et al., 2021; Seekell et al., 2017)
Policy and institution	Trade Dependencies	The dependency on food imports	-	(Chatzopoulos et al., 2021; Fridman et al., 2021; Gephart et al., 2016; Hadida et al., 2022; Hellegers, 2022; Lehikoinen et al., 2021; Marchand et al., 2016; Nicholson et al., 2021; Suweis et al., 2015; Travnikar & Bele, 2022)
	Political stability	Consistency in governance affecting trade policies and relationships.	+	(Hellegers, 2022)
	Domestic Food Production	Domestic food production capacity	+	(Hadida et al., 2022; Ingram, 2011; Marchand et al., 2016; Willer & Aldridge, 2023)
	Domestic consumption	Consumption of food within a country's borders, affects availability.	-	(Prasetyo et al., 2021)
	Trade partner diversity	Variety of countries involved in food imports and exports.	+	(Gephart et al., 2016; Lehikoinen et al., 2021)
	Trade diversification	Expanding variety of traded food products and markets.	+	(Grassia et al., 2022; Hadida et al., 2022; Marchand et al., 2016)
Society and culture	Exposure to crises	Population affected by crises, here used total people	-	(Gephart et al., 2016)
	Affordability	Accessibility of food products relative to income levels.	+	(Ingram, 2011)
	Diet preference	Preferential choices influencing demand for specific food products.	-	(Ingram, 2011)
Demographic	Population growth	Increase in the number of people impacting food demand.	-	(Suweis et al., 2015)
	Food availability	Sufficient supply of food products for consumption and trade.	+	(Suweis et al., 2015)
	Human development index (HDI)	Measure of a country's development based on health and education.	+	(Harris et al., 2022)
	Calorie supply	Average daily calorie intake per person, reflecting food availability.	+	(Fridman et al., 2021; Ingram, 2011; Nicholson et al., 2021)
Supply chain	Global Trade Disruptions	Trade decrease quantity	-	(Bassett et al., 2021; Rabbi et al., 2023)
	Supply chain diversity	Variety of routes and sources in food distribution networks.	+	(Bassett et al., 2021; Carlson et al., 2021; Mastronardi et al., 2022)

3.3.3Bonilla Index

The Bonilla Index (BI) is a representative indicator reflecting the vulnerability of food accessibility to trade, as it measures the ratio of national food import expenditure to the value of total exports (Diaz-Bonilla et al., 2000). Introduced by Larochez-Dupraz and Huchet-Bourdon (2016), the BI is used to assess how dependent a country's food accessibility is on its ability to engage in global trade.

Usually, a higher BI value indicates greater food vulnerability, as a large portion of a country's export earnings is required to cover its food import needs. While a lower BI value indicates a more resilient food trade system, with less dependency on external food supplies relative to export revenue.

BI can be further nuanced by applying the framework of metacoupling, which accounts for human-nature interactions such as trade within and across adjacent and distant countries (Liu 2017, 2023) and dividing trade flows into two categories: trade with adjacent countries and trade with distant countries. In this context and in the description of the other indicators in this article, all references to 'adjacent' mean that the two countries or regions share a border, while 'distant' means that the two countries or regions do not share a border. This distinction is important because trade with adjacent countries typically involves lower transportation costs, and shorter supply chains, making it inherently more resilient to disruptions. In contrast, distant trade introduces more risk, as it involves longer and more complex supply chains that are often subject to greater logistical and geopolitical vulnerabilities. By applying the telecoupling framework (Liu et al. 2013), which examines interactions across long distances, this division helps us understand the broader impacts of distant trade dependencies.

The formula for BI is given by:

$$BI = \frac{V_{mf}}{V_x} = \frac{Q_{mf} \cdot P_{mf}^d}{Q_x \cdot P_x^d} \quad (1)$$

Where V_{mf} is the value of food imports in national currency; V_x is the value of total exports in national currency; Q_{mf}: quantity of food imports; Q_x: quantity of total exports; P_{mf}^d, P_x^d: domestic aggregated prices in national currency for food imports and total exports.

While the total BI is separated into its adjacent and distant components as:

$$BI_{total} = BI_{adj} + BI_{dis} \quad (2)$$

Where BI_{adj} is the BI value calculated through adjacent countries' food trade, BI_{dis} is the BI value calculated through distant countries' food trade.

The importance of the BI lies in its ability to highlight the economic pressures and potential risks faced by countries heavily reliant on food imports. The BI offers a comprehensive understanding of food accessibility by considering both import spending and export capacity. This indicator is particularly relevant for countries with limited domestic food production capabilities and those prone to external economic crises. It enables policymakers to identify and mitigate risks associated with food trade, thereby enhancing overall food security and stability. Given that the BI encompasses both import dependency and export performance, it makes sense to use it to measure the food trade's resilience. This dual consideration ensures that the assessment of food security is not one-dimensional but rather reflects the broader economic context in which trade occurs.

3.3.4 Connectivity and Centrality of the Food Trade Network

Connectivity and betweenness centrality are widely accepted indicators in network analysis. They are essential indicators for analyzing the structural resilience and robustness of the food trade network. Connectivity measures the degree to which nodes (countries) are linked within the network, reflecting the overall integration and potential for trade diversification in the global food trade system (Pósfai, 2016). Betweenness centrality assesses the extent to which a node lies on the shortest path between other nodes, indicating its role in facilitating trade flows and controlling information dissemination within the network (Freeman, 1977).

These indicators are important for identifying primary countries that maintain the stability and efficiency of the food trade network. A well-integrated network with numerous trade routes is reflected in high connectivity, which improves resilience by offering backup routes in the event of disruptions. Betweenness centrality highlights the crucial role that certain countries play in maintaining the continuity of trade flows and preventing localized crises by connecting seemingly unconnected areas of the network.

In this study, we also separate the connectivity and centrality into adjacent trade and distant trade categories. This is because when impacted by crisis events, for example, the Russia-Ukraine War, adjacent countries' trade and distant countries' trade are impacted differently (Chai et al., 2024). Thus, instead of the traditional construction of a trade network and simultaneous evaluation of connectivity and centrality, in this study, we construct an adjacent country trade network and a distant country trade network to calculate the separate connectivity and centrality and use the sum of adjacent and distant networks' metrics as the total value.

The formula for betweenness centrality $C_B(v)$ of a node v is given by:

$$C_B(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}} \tag{3}$$

Where σ_{st} is the total number of shortest paths from node s to node t, and $\sigma_{st}(v)$ means the number of those paths that pass-through node v (Freeman, 1977). This measure is crucial for understanding the strategic importance of countries within the food trade network and for developing policies that enhance global food security by ensuring robust trade linkages (Pósfai, 2016; Freeman, 1977).

$$C_{B_{total}} = C_{B_{adj}} + C_{B_{dis}} \quad (4)$$

Where $C_{B_{adj}}$ is the betweenness centrality value calculated through adjacent countries' food trade, $C_{B_{dis}}$ is the betweenness centrality value calculated through distant countries' food trade. Conducting connectivity and betweenness centrality as indicators contributes to measuring food trade resilience, as they reflectthe structural dynamics of trade networks and help identify systemic strengths and vulnerabilities. These indicators provide insights into the network's capacity to withstand disruptions and adapt to changing conditions, making them indispensable tools for policymakers and researchers focused on food security.

3.3.5 Supply Chain Indicators

1) Global trade disruptions

Global trade disruptions largely impact the resilience of food trade networks. These disruptions can arise from various factors, including geopolitical tensions, natural disasters, pandemics, and economic sanctions, among others. To understand the effects of such disruptions, we calculated the progress in food trade resilience by comparing the current trade network with the previous trade network. This comparison involves a subtraction method, analyzing changes in trade flows, connectivity, and centrality metrics to identify disruptions and their impacts on the food trade system.

We can measure the degree of disruptions and determine which trade routes and countries are most impacted by comparing the current and historical networks. We can then monitor the modifications to trade patterns with this strategy, including fluctuations in trade volume, changes in trading partners, and changes in the centrality of important nodes as:

$$C_{td} = N_c - N_p \quad (5)$$

Where N_c is the food trade network of the current year, while N_p is the food trade network of the previous year.

Here, we also used the separate adjacent and distant components to calculate the degree of total global trade disruptionas:

$$C_{td_{total}} = C_{td_{adj}} + C_{td_{dis}} \quad (6)$$

Where $C_{td_{adj}}$ is the global trade disruptions value calculated through adjacent countries' food trade, $C_{td_{dis}}$ is the global trade disruptions value calculated through distant countries' food trade.

2) Supply chain diversity

Supply chain diversity is an indicator of enhancing the resilience of a country's trade system. A diverse supply chain ensures that when one supply route or mode of transportation is disrupted, alternative routes and modes can be utilized to compensate for the shortfall. This adaptability is essential for maintaining the steady flow of goods and mitigating the impact of trade disruptions. Therefore, it is important for importing countries to employ a variety of import modes and distribute their imports as evenly as possible across different types of food and transportation methods.

To quantify supply chain diversity, we consider three components: the mode of import, the type of food imported, and the uniformity of distribution. The formula for supply chain diversity as:

$$D_{sc} = T_{fi} * M_{fi} * E \quad (7)$$

Where D_{sc} is supply chain diversity; T_{fi} is type of food imported; M_{fi} is mode of import; E in this context, measures the evenness of the distribution of imports across different categories. It is calculated using the formula for evenness (E), which is derived from the Shannon index as:

$$E = \frac{H}{Hmax} = \frac{H}{\ln S} \quad (8)$$

Where H is the Shannon index calculated from the distribution of imports, $Hmax$ is the maximum possible Shannon index, and S is the number of different import categories (e.g., different modes of transport or types of food).

The value of E ranges from 0 to 1, where values closer to 1 indicate a more even distribution of imports across the different categories, thereby reflecting higher uniformity. High uniformity in the context of supply chain diversity suggests that the imports are well-balanced across various modes and types, reducing the vulnerability to disruptions in any single supply chain.

Considering that supply chains also involve supplying countries at different distances, supply chain indicators can also be divided into adjacent and distant countries as:

$$D_{sc_{total}} = D_{sc_{adj}} + D_{sc_{dis}} \tag{9}$$

Where $C_{td_{adj}}$ is the supply chain diversity value calculated through adjacent countries' food trade, $C_{td_{dis}}$ is the supply chain diversity value calculated through distant countries' food trade.

This metric provides a comprehensive measure of a country's trade resilience by considering the diversity and balance of its import strategies. By promoting diverse and balanced import practices, countries can enhance their ability to withstand and quickly recover from global trade disruptions.

3.3.6 Food Trade Resilience Score Construction

To quantify the resilience of national food trade systems, we constructed a composite index by aggregating 26 indicators across six thematic dimensions: Innovation and Market, Policy and Institution, Demographic, Supply Chain, Socio-cultural, and Environmental. Each indicator was first normalized individually using min–max normalization to ensure comparability across different units and measurement ranges. This standardization allowed for the integration of diverse metrics into a single evaluative framework.

The final resilience score for each country was calculated as the unweighted sum of the 26 normalized indicator values. This method preserves the contribution of each indicator and reflects the overall structural capacity of a country to maintain stable food trade under external crises. The resulting score captures multidimensional attributes of food system resilience and enables cross-country and cross-year comparisons without imposing additional scaling constraints. All indicators, including their definitions, data sources, and normalization procedures, are documented in Table S3.1.

3.4 Data

This study utilizes a comprehensive suite of indicators across six thematic categories to assess the resilience of global food trade systems. Data were meticulously gathered from several global databases to ensure a robust analysis.

3.4.1 Innovation and Research

To assess the market structure and innovation capacity within global food trade systems, we examined two key indicators: the Bonilla Index (BI), trade connectivity and centrality metrics of trade network. BI and trade coennectivity were calculated using Food and Agriculture Organization (FAO) trade data, capturing each country’s degree of trade dependency and the overall volume and intensity of its trade relationships. These metrics reflect the robustness and integration of a country's market position. While Centrality of Trade Network was Derived from the United Nations Commodity Trade Statistics Database (UN Comtrade) database to examine the interconnectedness of countries in the global trade network.Centrality measures indicate how central or influential a country is in facilitating flows between other nations, providing insight into market innovation, adaptability, and systemic importance. Together, these indicators help characterize both structural resilience and the capacity for market adaptation under crisis conditions.

3.4.2 Economy and Market

To evaluate the economic dimensions of innovation and market adaptability in global food trade, we included several macroeconomic indicators. Exchange rate data, sourced from XE.com, were used to standardize trade values across different national currencies, enabling consistent cross-country comparisons of trade activity. World food price trends, captured through the FAO Food Price Index, and national GDP data from the World Bank were incorporated to assess overall economic conditions that shape trade behavior and resilience. Additionally, income level classifications (from the World Bank) and energy dependence data (from the International Energy Agency) were used to evaluate a country's financial capacity and vulnerability to energy-related trade disruptions. These indicators collectively reflect the structural and economic context within which countries innovate and operate their food trade systems.

3.4.3 Political and Institution

Political stability and domestic food systems play a critical role in shaping market performance and innovation capacity in food trade. Political stability, derived from the World Bank’s Worldwide Governance Indicators, reflects the degree of governance predictability and institutional reliability that underpins trade relationships and market confidence. A stable political environment fosters conditions for policy innovation and consistent trade regulation, both of which are essential for resilient and responsive markets. In parallel, domestic food production and consumption data, drawn from FAO statistics, offer insight into national self-sufficiency and internal demand structures. Countries with strong domestic production and stable consumption patterns are often better positioned to innovate and buffer against external trade crises, thereby reinforcing market stability under crisis conditions.

3.4.4 Society and Culture

Affordability and diet preferences, drawn from the Global Food Prices Database and FAO dietary data, reflect the socio-cultural drivers that shape consumption behavior and influence food trade patterns. These factors determine demand diversity across countries and affect how markets respond to changing economic and cultural conditions, especially during disruptions.

3.4.5 Demographic

Population growth and the Human Development Index (HDI) provide critical demographic context for understanding food trade dynamics. Population data from the UN World Population Prospects and HDI scores from the United Nations Development Programme capture trends in human capital, development, and demand pressure—factors that influence trade volumes, infrastructure needs, and the capacity for innovation in food systems

3.4.6 Supply Chain

Within the Innovation and Market domain, global trade disruptions and supply chain diversity serve as key indicators of systemic adaptability. Using UN Comtrade and FAO trade data, we analyzed the structural flexibility of countries' food trade systems and their exposure to external disruptions. Supply chain diversity captures the range and distribution of trade partners, reflecting a country's ability to reroute food flows when disruptions occur. The global trade disruption metric quantifies the extent and frequency of trade interruptions, offering insight into the stability of market linkages. Together, these indicators reflect how innovation in logistics, sourcing strategies, and trade partnerships contribute to a more resilient and responsive food trade system.

3.4.7 Income Level and Annual Carbon Emission Data

To incorporate socioeconomic and environmental dimensions into our assessment of food trade resilience, we utilized national income classifications and annual carbon emissions data as contextual variables. These indicators offer important perspectives on the structural characteristics and environmental pressures that may shape countries' resilience capacities.

The classification of countries by income level was based on the World Bank's official methodology for fiscal years 2024–2025, which organizes countries into four income groups—low, lower-middle, upper-middle, and high—based on Gross National Income (GNI) per capita using the Atlas method (World Bank, 2023). This classification was consistently applied to both 2019 and 2020 to facilitate comparative analysis, recognizing that while income categories may evolve annually, a fixed classification improves interpretability of resilience differences across time.

National carbon dioxide (CO_2) emission data were obtained from the Emissions Database for Global Atmospheric Research (EDGAR), version 7.0, published by the European Commission's Joint Research Centre (Crippa et al., 2022). This dataset provides harmonized and high-resolution estimates of CO_2 emissions from fossil fuel combustion and industrial processes. We extracted total national CO_2 emissions (in megatonnes per year) for 2019 and 2020 to align with the period of trade data used in the study. These data allowed us to examine whether countries with higher emissions levels demonstrated distinctive resilience patterns, particularly under stress conditions such as the COVID-19 pandemic.

The integration of income level and emissions data supports a more comprehensive analysis of trade resilience, highlighting the intersection between economic status, environmental exposure, and systemic vulnerability.

3.5 Results

3.5.1 Global Food Trade System Resilience Impacted by COVID-19

The analysis of global food trade resilience for 2019 and 2020 illustrates distinct spatial patterns in the ability of regions to sustain and manage their food trade networks under challenging conditions. Food trade resilience was measured using a composite index that combines our 6 categories of indicators as shown in Table 3.1. In 2019 (Figure 3.2. (a)), the highest levels of resilience were predominantly visible in European countries, particularly in Russia, which has a resilience score of about 10.66, followed by Germany (9.97), Italy (9.27), and Poland (9.12). North American countries such as Canada (9.04) and the United States (8.64) also exhibited high resilience. These high resilience scores might have been obtained due to advanced logistics, diversified food sources, and robust economic conditions. Russia's leading resilience score reflected a combination of factors, including its dominant role as a global wheat exporter, state-supported logistics infrastructure, and proactive trade policies. Its capacity to pivot toward non-Western markets amid geopolitical tensions and its relatively self-sufficient food production system further strengthened its trade stability.

In Asia, China (8.89) and India (8.27) ranked among the most resilient nations, reflecting the scale and diversity of their agricultural production and trade networks. China's resilience, driven by substantial investments in infrastructure, large-scale food production, and large economic growth, placed it among the top resilient countries. India similarly showed high resilience due to its strong agricultural sector and extensive trade market. Conversely, lower resilience scores were markedly noticeable in Central Africa, including countries such as the Democratic Republic of the Congo and Chad, with resilience scores of about 1.83 and 0.97, respectively. These countries faced large challenges related to logistics, political instability, and limited economic diversification, which severely hindered their food trade resilience. South Asia, with countries like Afghanistan (1.54) and Nepal (5.16), also exhibited lower resilience indices, reflecting infrastructure deficiencies and economic constraints. Similarly, parts of South America, including Venezuela (0.41) and Bolivia (4.16), showed low resilience scores due to political and economic instability.

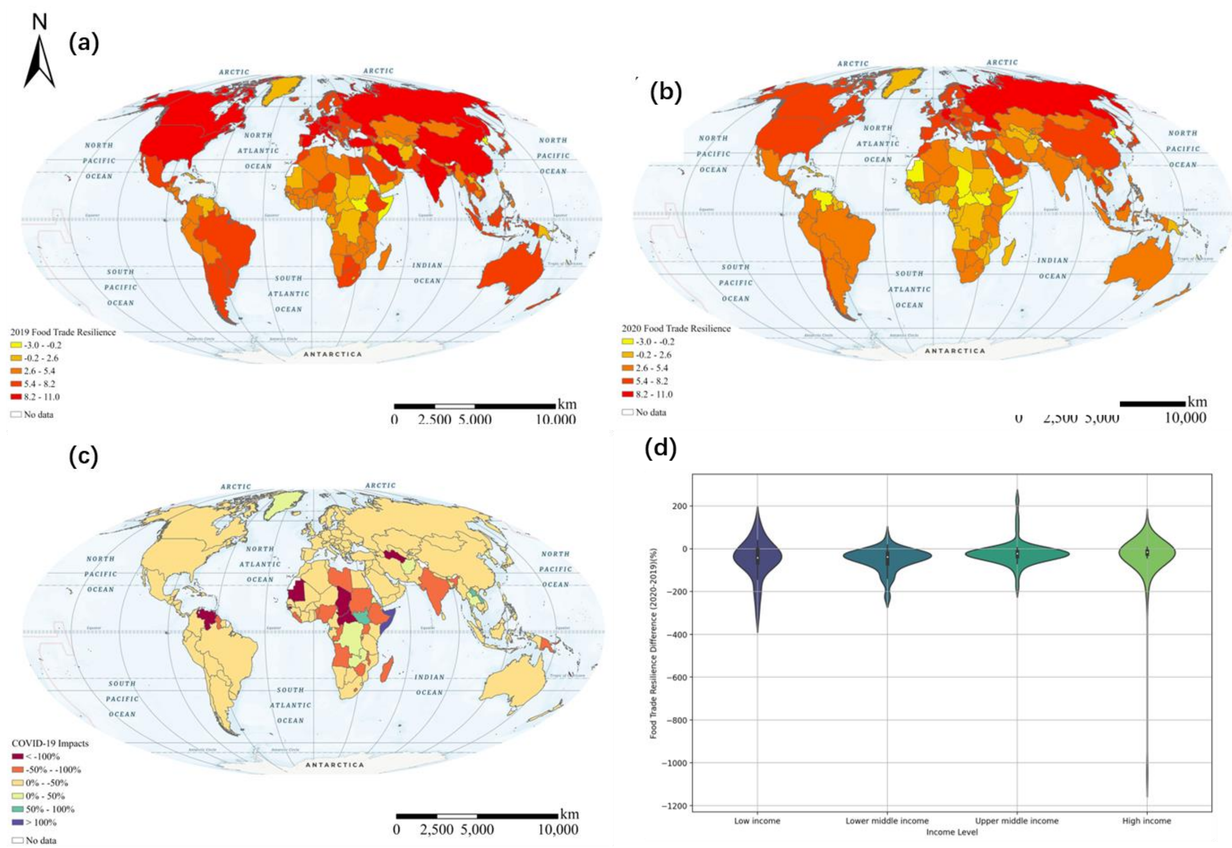


Figure 3. 2 Global food trade resilience and relative changes across income levels. Panels (a) and (b) illustrate the food trade resilience scores in 2019 and 2020, respectively, based on a composite index integrating multiple economic, social, and logistical indicators. Panel (c) shows the percentage change in food trade resilience from 2019 to 2020, capturing the relative impact of the COVID-19 pandemic at the national level. Panel (d) displays the distribution of relative resilience changes across among low-, middle-, and high-income, using violin plots to visualize the spread and central tendencies of percentage changes within each income level (https://blogs.worldbank.org/en/opendata/world-bank-country-classifications-by-income-level-for-2024-2025).

In 2020 (Figure 3.2 (b)), the overall pattern of food trade resilience showed some shifts, primarily influenced by the COVID-19 pandemic. The pandemic had widespread impacts on "Innovation and Research", "Economy and Market", "Policy and Institution", " Society and culture", "Demographic", and "Supply Chain" (for the category details, please see Table 3.1). Europe continued to show strong resilience, but countries experienced varying degrees of impact due to lockdown measures, supply chain disruptions, and changes in trade policies, with Germany and Russia scoring approximately 8.91 and 9.21. Despite pandemic-related trade uncertainties, Russia's food trade network remained highly resilient, likely supported by its continued grain export capacity, limited dependence on external suppliers, and state-managed trade systems that buffered against logistical shocks. The United States and Canada maintained high resilience scores, with slight adjustments reflecting the pandemic's impact on their food trade systems. The United States scored approximately 6.52, and Canada scored approximately 7.69 in 2020, indicating a slight decrease. China's resilience score for 2020 showed some decline due to trade restrictions caused by the pandemic, among other things, but China (5.82) remained somewhat resilient, driven by continued investments in infrastructure and a quicker economic recovery than expected from the initial pandemic impact.

Differences were observed in regions with previously lower resilience. Central African countries, such as the Democratic Republic of the Congo (5.22), saw further declines in resilience due to exacerbated logistical challenges and economic pressures (Figure 3.2 (b)) (Balike Dieudonné Z, 2021). South Asian countries like Afghanistan (3.76) experienced additional setbacks in resilience, influenced by pandemic-induced restrictions and economic constraints. The pandemic accelerated technological innovations and research in food production and supply chain management (Kafi, et al., 2023). However, regions with limited access to these advancements saw a widening resilience gap. Economic contractions and market disruptions were widespread, affecting countries' abilities to maintain stable food trade networks (Engemann& Jafari, 2022; Aday&Aday, 2020; Ihle, et al., 2020). Developed countries with diversified economies showed better resilience compared to those reliant on limited trade partners (Kummu, et al., 2020). Government's responses to the pandemic, including trade policies and support measures, largely impacted food trade resilience (Arita, et al., 2022). Regions with proactive and adaptive policies managed better compared to those with less effective responses (Adger, et al., 2011). The pandemic influenced socio-cultural factors, including changes in consumption patterns and public health measures, impacting food availability and distribution (Supplementary file 1). Population dynamics, such as urban-rural migration and changes in labor availability, affected food production and trade (Supplementary file 1). Countries with more flexible labor markets showed better adaptability (Bernal-Verdugo, et al., 2012). Disruptions in global supply chains were a major factor affecting resilience (Supplementary file 1). Countries with diverse and robust supply chains managed better compared to those with heavily disrupted networks.

The impact of COVID-19 on global food trade resilience varied largely across countries, as measured by the food trade resilience difference (Kubatko, et al., 2023). India, a lower-middle-income country, exhibited one of the most pronounced declines in food trade resilience, with a difference in -3.54 (Figure 3.2 (c)). This substantial decrease underscores the severe disruptions faced by India, likely driven by large supply chain interruptions, logistical challenges, and restrictions on global trade due to the pandemic (Priyadarshini, et al., 2021). The country's heavy reliance on agricultural exports and the limited capacity to buffer against such large-scale disruptions exacerbated the impact (Foong, et al., 2023). Brazil, an upper-middle-income country, showed a resilience decline of 1.50, reflecting moderate impacts on its food trade during the pandemic (Figure 3.2 (c). While Brazil faced challenges in sustaining its trade flows, the extent of the impact was less severe compared to countries like India. Brazil's diverse agricultural production and its relatively resilient export markets helped cushion the blow, though logistical issues and domestic pandemic management still posed large challenges (Szymczak, et al., 2020). In contrast, the United Arab Emirates (ARE), a high-income country, experienced a slight improvement in resilience, with a difference of 0.46 (Figure 3.2 (c)). This indicates that the UAE's food trade network maintained a higher degree of stability, possibly due to its robust infrastructure, diversified trade partnerships, and the ability to quickly adapt to changing global trade dynamics. The UAE's strategic investments in food security and logistics may have also played a role in mitigating the impact.

Interestingly, Hungary, a high-income country, demonstrated a large increase in resilience, with a difference of 1.33 (Figure 3.2 (c)). This positive change suggests that Hungary's food trade system adapted effectively to the pandemic, potentially benefiting from shifts in global trade dynamics. Hungary's strong trade infrastructure, unique logistics system construction, and effective policy responses contributed to its ability to not only withstand but also improve its food trade resilience during the crisis (Gyuris, 2022). These examples illustrate the varied impacts of COVID-19 on food trade resilience across different countries and income levels. The geographical distribution of these changes, as shown in Figure 3.2, highlights the disparities in how countries managed to cope with the pandemic's challenges. Factors such as economic structures, trade dependencies, crisis management capabilities, and strategic investments in infrastructure and food security played critical roles in determining resilience outcomes (Supplementary file 1, Table 3.1).

3.5.2 Impacts of Key Indicators on Food Trade Resilience During COVID-19

Figure 3.2(d) illustrates the distribution of food trade resilience differences due to the COVID-19 pandemic across various income levels. The resilience difference is calculated as the change in food trade resilience from 2019 to 2020, reflecting the pandemic's impact on each country's ability to maintain stable food trade. Lower-middle-income countries exhibit the widest distribution of negative changes, indicating large variability and greater susceptibility to the pandemic's disruptions. This variability is likely due to less diversified economies and weaker healthcare and trade infrastructures, which exacerbated the impact of global trade disruptions. Conversely, high-income countries showed a relatively narrower distribution with smaller negative changes and even slight improvements, highlighting their more robust economic structures and better crisis management capabilities.

Furthermore, Figure 3.3 provides additional context by comparing the average values of various resilience indicators across different income levels for the years 2019 and 2020. Figure 3.3(a) presents the average values of key indicators affecting food trade resilience for 2019 and 2020. Indicators such as trade diversification, production diversity, and domestic food production saw notable declines in lower-middle-income countries. This decline indicates that these countries struggled to maintain diverse and stable food production and trade networks amidst the pandemic. Lower-middle-income countries also experienced large drops in political stability and trade dependencies, further correlating with the broader distribution of negative resilience changes observed in Figure 3.2(d). Figure 3.3(b) provides detailed information showing the shifts in resilience indicators across different income levels between 2019 and 2020. It illustrates that high-income countries generally maintained or slightly improved their resilience indicators, such as GDP and food availability. In contrast, lower and lower-middle-income countries showed substantial declines in several indicators, including energy dependence and export growth rate. These shifts highlight the disparities in resilience dynamics, reinforcing that lower income countries faced more pronounced challenges due to their limited capacity to adapt to global disruptions. In terms of the connectivity of food trade networks, there was a general downward trend in trade between distant countries. However, adjacent countries' trade connectivity showed a more large downward trend in low and high-income countries, suggesting that low-income countries have more difficulty in adapting to changes due to poor trade infrastructure and more homogeneous trade routes, while high-income countries might be affected by epidemic policies and export controls (Derindag et al., 2024; Barbero et al., 2021). These results collectively underscore the uneven impacts of the COVID-19 pandemic on global food trade resilience, with lower income countries facing more pronounced challenges. The findings highlight the critical need for targeted interventions to enhance resilience, particularly in the most vulnerable regions. Enhanced trade diversification, strengthened domestic production, and improved political stability are essential for building resilient food trade systems capable of withstanding future global disruptions.

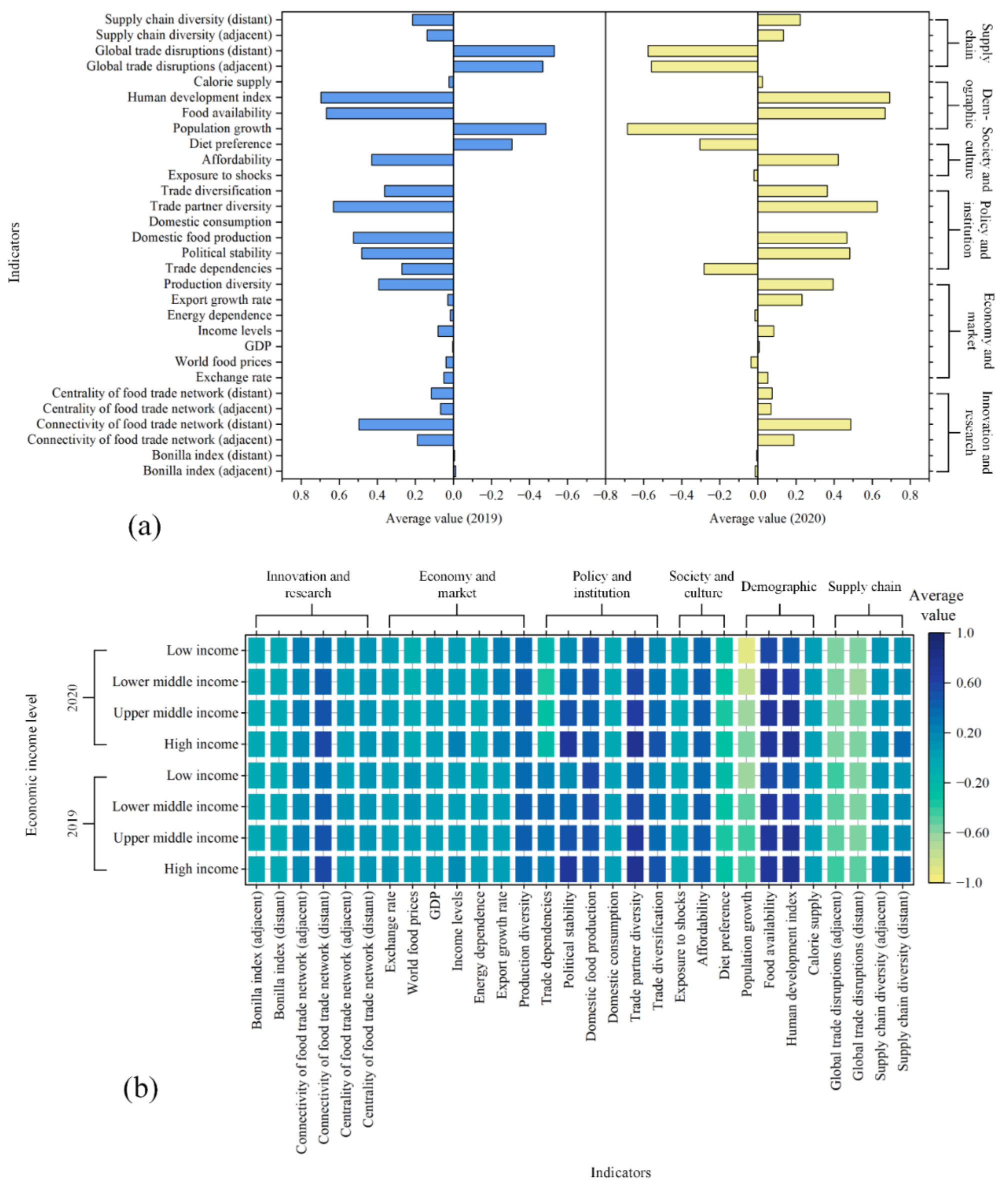


Figure 3. 3 Comparative results of food trade resilience indicators across income levels in 2019 and 2020. (a) is the average value of each indicator of 2019 and 2020; (b) is a comparison of the 2019 and 2020 indicators' average value through different income levels.

Figure 3.4 illustrates the contribution of various indicators to the overall food trade resilience difference, highlighting the impact of different drivers on resilience outcomes during the COVID-19 pandemic. The Sankey diagram categorizes the indicators into six key drivers: “Policy and Institutional”, “Demographic”, “Economy and Market”, “Innovation and Research”, “Supply Chain”, and “Socio-culture”. The “Policy and Institution” shows a large positive contribution to food trade resilience, indicating that countries with strong political stability, effective governance, and robust institutional frameworks were better able to manage trade disruptions and maintain resilience. Effective policies likely facilitated smoother trade operations and quicker adaptation to new trade regulations imposed during the pandemic. Similarly, the “Demographic” driver contributes positively, suggesting that countries with better social development and higher human capital could adapt more efficiently to the disruptions, possibly managing labor shortages and ensuring food availability during the pandemic. In contrast, the “Economy and Market” drivers exhibit a negative contribution, indicating that economic factors such as GDP growth, trade dependencies, and energy dependence largely affected resilience negatively. Countries heavily reliant on specific trade partners or with less diversified economies struggled more during the pandemic, as economic crises and fluctuating global markets directly impacted their trade stability. “Innovation and Research” contribute positively, reflecting those countries with high levels of research and development, innovation in food production, and technological advancements could better mitigate the adverse effects of the pandemic on food trade. Innovative practices in agriculture and supply chain management played a crucial role in sustaining food trade resilience. The “Supply Chain” driver also shows a positive contribution, emphasizing the importance of supply chain diversity and connectivity. Countries with well-established and diversified supply chains could more effectively handle disruptions, reroute trade flows, and maintain steady food supplies despite global interruptions. Lastly, the “Socio-culture” positively impacts resilience, suggesting that social factors such as diet preferences, food culture, and community support mechanisms helped countries maintain resilience. Socio-cultural adaptability may have enabled quicker shifts in consumption patterns and national production practices, thereby sustaining food trade stability. Overall, Figure 3.4 highlights the multifaceted nature of food trade resilience, where different types of indicators contribute to varying extents. The positive impact of strong institutional frameworks, demographic factors, innovation, supply chain diversity, and socio-cultural adaptability underscores the importance of these drivers in building robust and resilient food trade systems. Conversely, economic vulnerabilities highlight areas where targeted interventions are needed to enhance resilience against future disruptions.

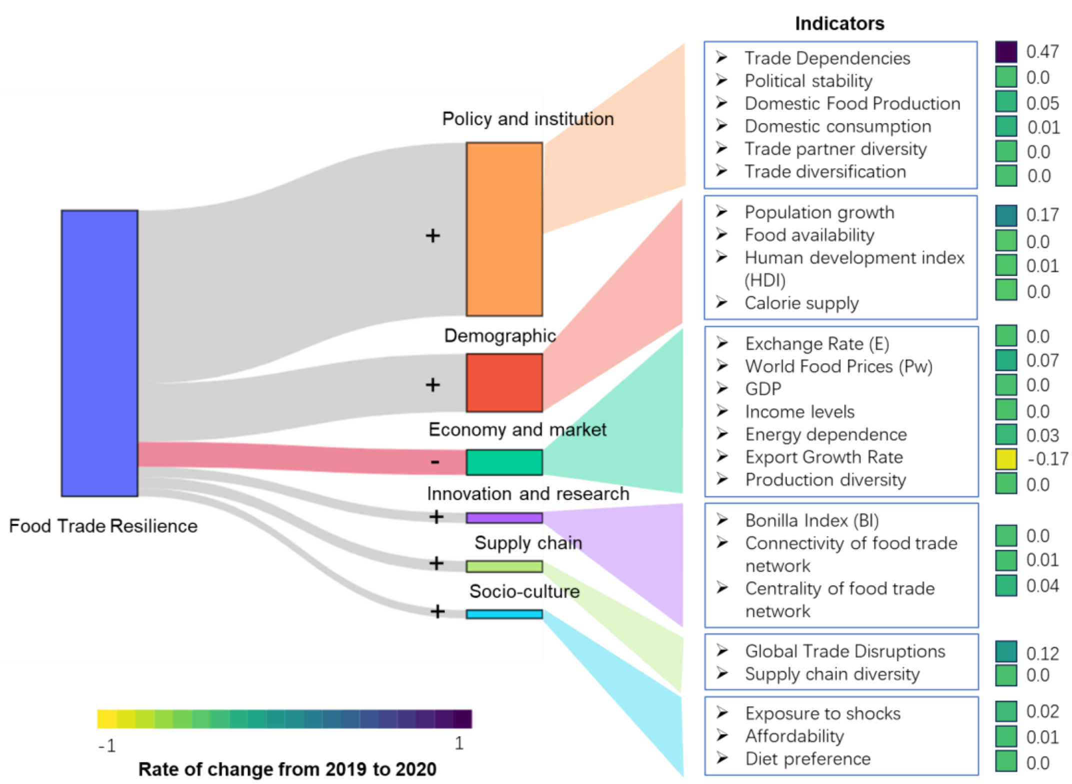


Figure 3. 4 Contribution of key drivers to food trade resilience difference during COVID-19. It illustrates the contributions of six major drivers—policy and institution, demography, economy and market, innovation and research, supply chain, and socio-cultural factors—to the variations in food trade resilience during the COVID-19 pandemic. The Sankey diagram highlights the positive (+) and negative (-) contributions of each driver, with their relative magnitudes represented by the width of the connecting flows. The right-hand side visualizes the distribution of individual sub-indicators within each driver category, offering a detailed breakdown of their respective impacts on resilience changes. The color gradient at the bottom represents the intensity of the contribution, ranging from negative (yellow) to highly positive (purple), emphasizing the multidimensional and interconnected nature of factors influencing food trade resilience during global disruptions.

3.5.3 Resilience of Food Trading Systems in Different Income Countries Affected by COVID-19

The pandemic-induced disruptions have distinctly impacted food trade resilience across different economic brackets, highlighting the interplay between a country's economic status and its capacity to manage crises. The resilience maps overlaid with income levels for 2019 and 2020 provide a compelling visual narrative of these impacts.

There is a clear trend of higher food trade resilience scores associated with higher income levels in both 2019 and 2020 (Figure 3.5). High-income countries, on average, displayed the highest resilience scores, followed by upper-middle-income, lower-middle-income, and low-income countries. This pattern emphasizes that economic capacity strongly correlates with food trade resilience, as countries with more resources generally have better infrastructure, governance, and adaptive capacity to handle global disruptions. However, compared to 2019, resilience scores across all income groups declined in 2020, reflecting the universal impact of the COVID-19 pandemic. The pandemic introduced widespread disruptions in food trade, affecting even the most resilient systems. The consistent decline across income levels highlights the strain that the pandemic placed on food security worldwide, though the degree of resilience loss varied among countries within each income bracket.

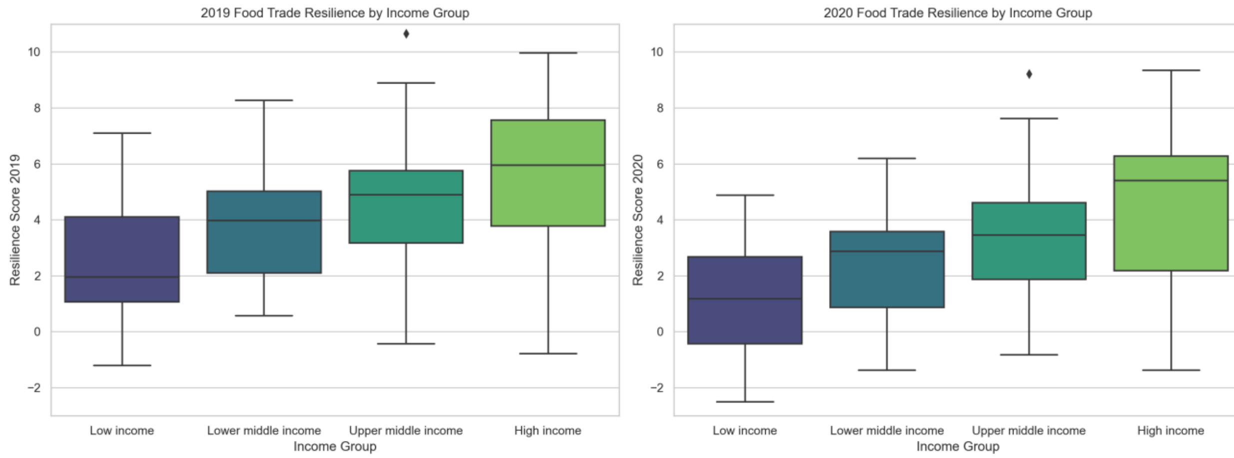


Figure 3. 5 Food trade resilience by income group comparison. The figure presents the distribution of normalized food trade resilience scores across income groups in 2019 (left panel) and 2020 (right panel). The box plots illustrate the variations in resilience among low-income, lower-middle-income, upper-middle-income, and high-income countries. The black line in the figure means the median value of this income level.

The differential impacts of the pandemic are shown in Fig. 6, with certain regions experiencing greater shifts in resilience. High-income countries such as Canada, Australia, and the United Kingdom exhibited substantial resilience changes between 2019 and 2020. Despite their strong economic positions, these countries experienced large disruptions, indicating their reliance on global supply chains. In contrast, countries like Germany and Japan displayed relatively stable resilience, suggesting their diversified trade networks and robust infrastructure mitigated the pandemic's impact. France and the United States also showed moderate resilience changes, reflecting partial vulnerability within their food trade systems. Upper-middle-income countries displayed mixed resilience changes. China demonstrated minimal change in resilience, highlighting effective policy responses and infrastructure that helped stabilize its food trade system. Similarly, Russia showed limited resilience change, benefiting from domestic production and self-sufficiency in certain food sectors. However, Brazil and Turkey experienced more substantial declines, indicating greater susceptibility to pandemic disruptions. South Africa also showed notable resilience loss, reflecting the challenges it faced in maintaining stable trade amid economic pressures.

Lower-middle-income countries experience greater resilience declines overall. Countries such as India, Vietnam, and the Philippines exhibited noticeable resilience decreases, showing vulnerability to supply chain interruptions and export restrictions. Egypt and Indonesia also reveal resilience declines, which highlight the challenges posed by import dependencies and limited resources to buffer against external crises. Other countries, like Pakistan and Bangladesh, showed resilience losses, reflecting the broader challenges lower-middle-income nations face in sustaining food trade stability. Low-income countries, especially in Africa, faced the most large declines in resilience. Chad, Sudan, and the Democratic Republic of the Congo demonstrated marked resilience losses, underscoring the severe impact on countries with limited infrastructure, high import dependencies, and economic constraints. Ethiopia and Mali also showed substantial resilience declines, highlighting the strain on food security systems in low-income regions. In contrast, some low-income countries like Nepal showed relatively smaller resilience changes, likely due to their lower integration in global food trade, which may have insulated them from some pandemic-related disruptions.

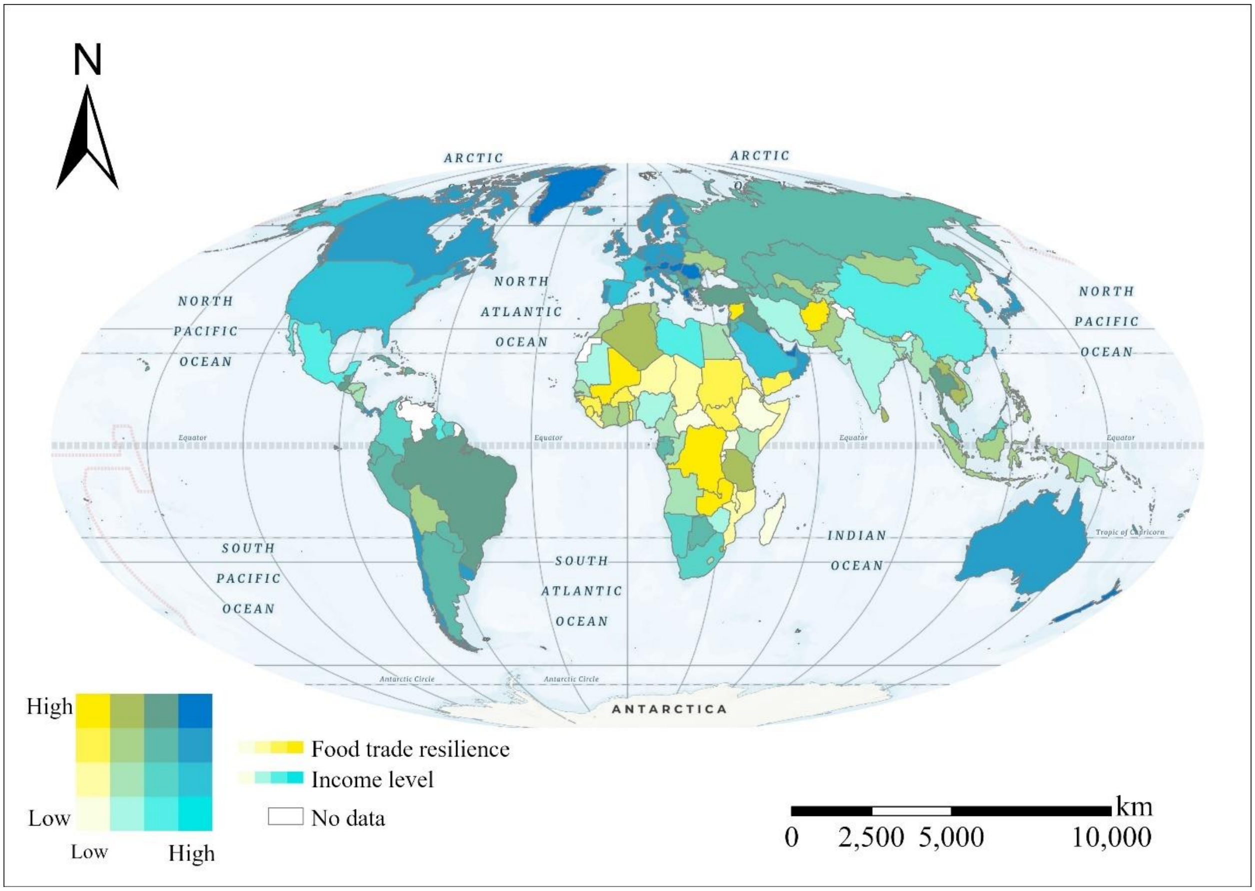


Figure 3. 6 Spatial distribution of differences (from 2019 to 2020) in income levels and food trade resilience. This map illustrates the global spatial distribution of food trade resilience in conjunction with income levels. High-income countries, primarily located in North America, Europe, and parts of Oceania, exhibit high food trade resilience, represented in darker yellow tones. Conversely, low-income nations, predominantly in Sub-Saharan Africa and South Asia, show lower resilience, highlighted in lighter yellow and cyan shades. Regions lacking data are depicted in white.

3.5.4 Trade Indicators Dynamics across Spatial Scales

The separation of these five indicators—Bonilla index, centrality, connectivity, global trade disruptions, and supply chain diversity—into adjacent and distant trade components enables a nuanced view of trade resilience across spatial scales. This approach highlights the importance of the coexistence of regional assessments and global trading networks, as it reveals how dependence based on adjacent and distant trading interconnectedness responds differently to global crises.

The Bonilla index (Figure 3.7) reveals concentrated resilience impacts in adjacent regions, particularly in North African countries like Libya and Egypt. In 2019 for adjacent trade (Figure 3.7(a)), resilience values were moderately low, between -0.20 and -0.80. By 2020 (Figure 3.7(b)), these values declined further to -1.00, indicating a heightened vulnerability in these regions. In contrast, the distant trade network (Figure 3.7(c) and (d)) remained stable over this period, suggesting that resilience challenges were more acute in nearby trade relationships as countries prioritized regional trade networks (trade with adjacent countries) during the pandemic.

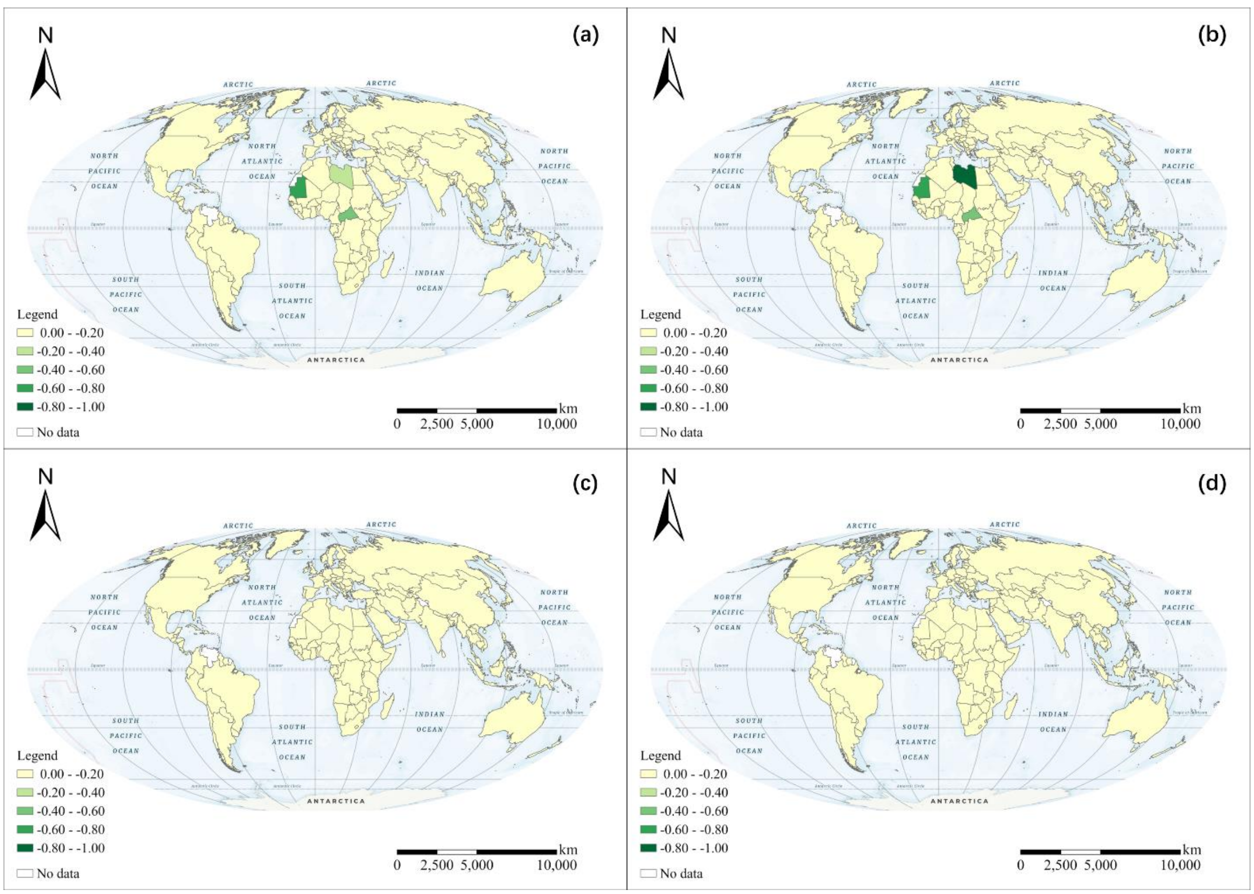


Figure 3. 7 Bonilla index of trade resilience in adjacent and distant trade networks for 2019 and 2020. This figure shows the spatial distribution of the Bonilla index, measuring resilience in adjacent and distant trade networks across 2019 and 2020.

The centrality index (Figure 3.8) reflects changes in the importance of countries within their trade networks, capturing how some regions became more influential in adjacent trade due to pandemic-induced shifts. In 2019 for adjacent trade (Figure 3.8(a)), high centrality was observed across North African and Middle Eastern countries, indicating their critical role in regional trade. By 2020 (Figure 3.8(b)), centrality increased across Eastern Europe and Central Asia, reflecting a shift towards regional interdependence, likely as a response to disrupted global trade routes. However, this increase in centrality does not imply that these Eastern European and Central Asian countries expanded their total trade connections but rather that their influence within the regional trade network grew due to temporary reorientation.

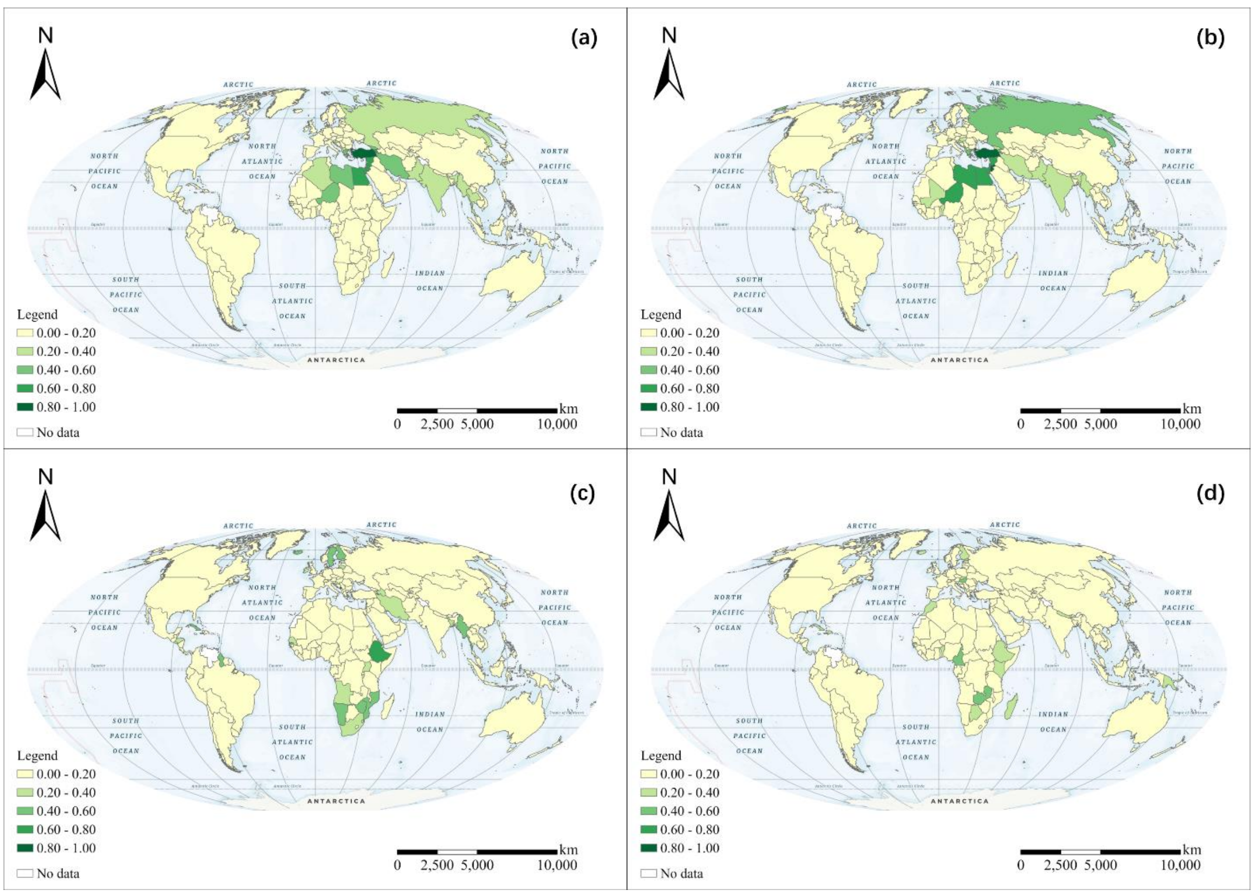


Figure 3. 8 Centrality of trade networks in adjacent and distant trade for 2019 and 2020. Centrality scores highlight the prominence of countries within their respective trade networks.

In contrast, the connectivity index (Figure 3.9) remained robust across African, South American, and Asian countries in both adjacent and distant trade networks, despite the pandemic. For adjacent trade in 2019 (Figure S3.10(a)), regions such as Brazil and Nigeria showed strong connectivity, with values between 0.60 and 1.00, indicating a high volume of trade links. By 2020 (Figure 3.9(b)), this connectivity was largely retained, signaling resilience in the number of trade connections. For distant trade (Figure 3.9(c) and (d)), connectivity also remained stable, showing that while trade dynamics shifted regionally (as seen in centrality), countries maintained broad trade relationships. The differing patterns between centrality and connectivity highlight that while some regions increased their influence (centrality), many countries maintained extensive trade links (connectivity) without necessarily becoming more central hubs.

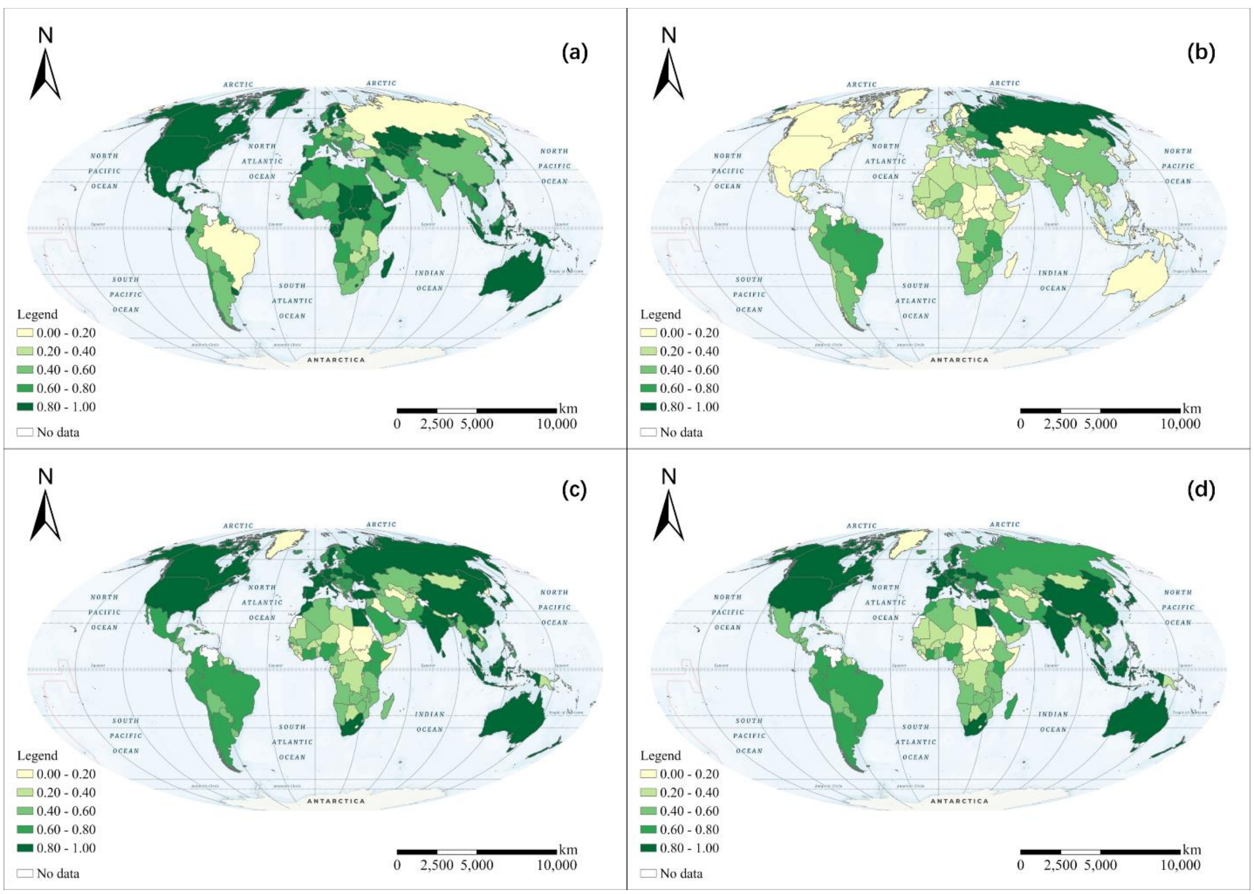


Figure 3. 9 Connectivity of trade networks in adjacent and distant trade for 2019 and 2020. Connectivity levels illustrate the resilience of trade links in both adjacent and distant networks.

The global trade disruptions index (Figure 3.10) underscores the heightened vulnerability of low-income and developing regions, particularly in Africa. In 2019 for adjacent trade (Figure 3.10(a)), countries in Southern Africa exhibited moderate to high disruption levels, with values ranging from 0.40 to 0.80. By 2020 (Figure 3.10), disruptions intensified across Central and Southern Africa. For distant trade networks (Figure 33.10(c) and (d)), disruptions were also large in parts of Africa and South America, indicating that both adjacent and distant trade were adversely affected, although connectivity remained stable. This contrast suggests that while many trade links were preserved, their functionality or stability was compromised, especially in vulnerable regions (as low-income and developing regions).

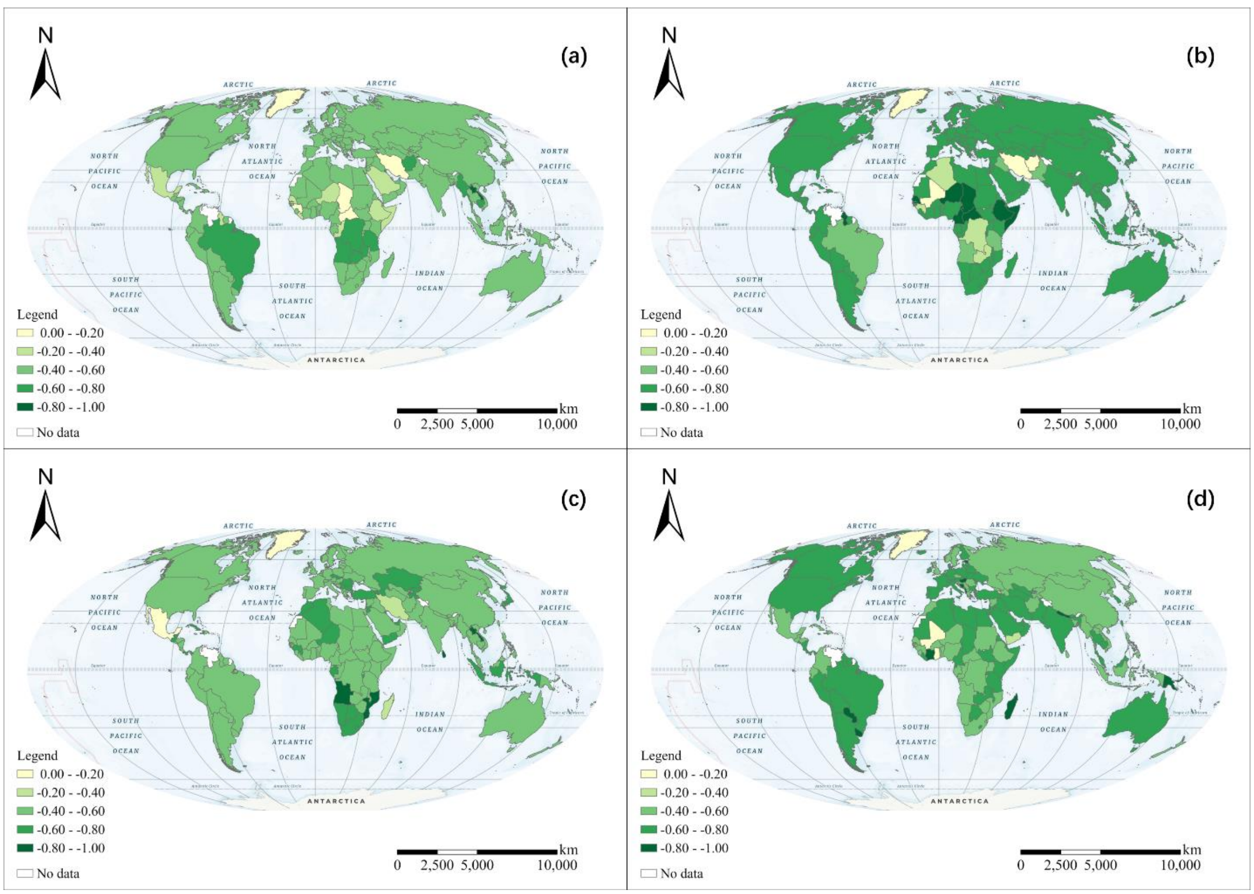


Figure 3. 10 Global trade disruptions in adjacent and distant trade networks for 2019 and 2020. This figure depicts trade disruptions, which reflect instability in trade systems across adjacent and distant networks.

Finally, the supply chain diversity index (Figure 3.11) highlights the adaptive capacity of high-income countries in comparison to lower-income regions. In 2019 for adjacent trade (Figure 3.11), high-income countries, especially in Europe and North America, exhibited high supply chain diversity, with values approaching 1.00. By 2020 (Figure 3.11), diversity remained stable in these regions, indicating resilience in maintaining diverse supply chain partners. In contrast, the distant trade network (Figure 3.11(c) and (d)) also saw high diversity levels in Europe and North America across both years, underscoring their ability to withstand disruptions through a variety of trade partnerships.

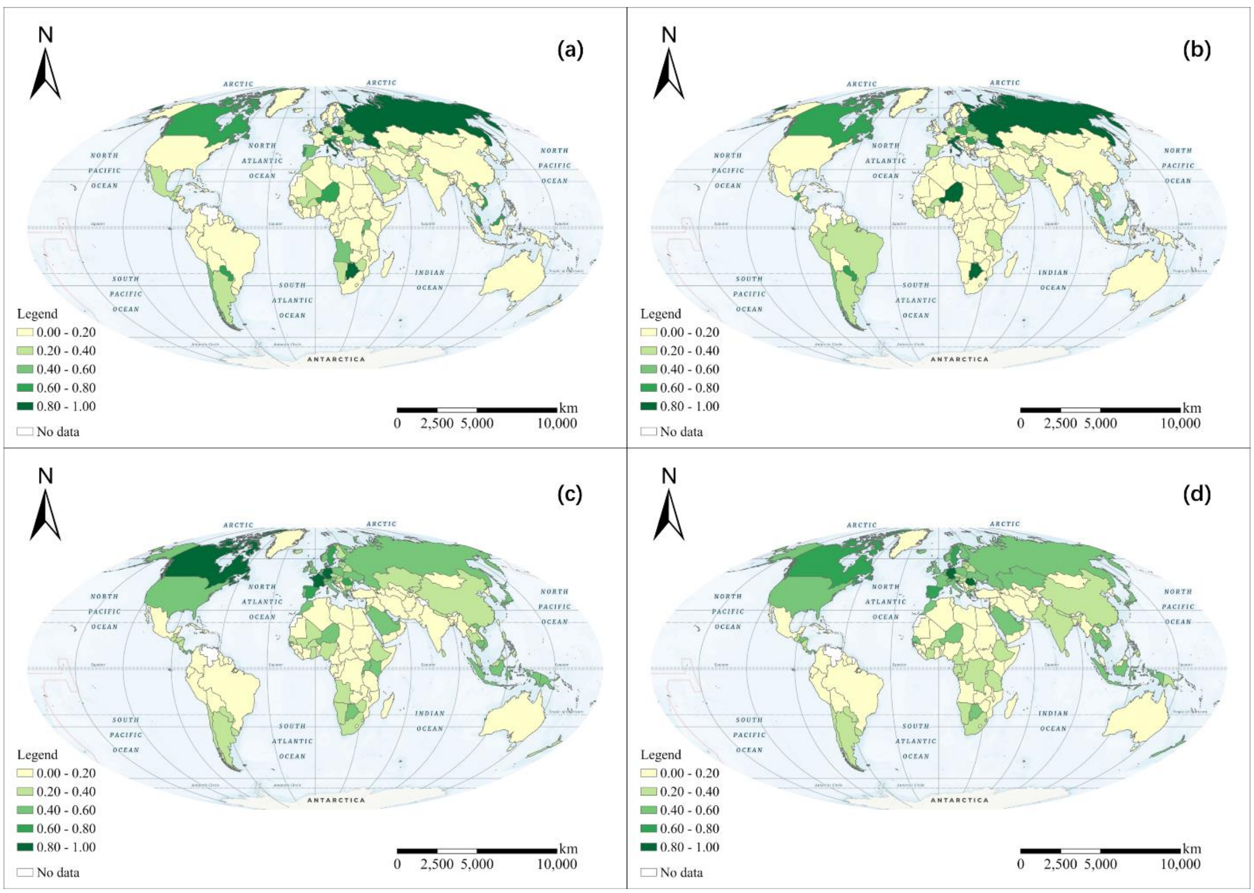


Figure 3. 11 Supply chain diversity in adjacent and distant trade networks for 2019 and 2020. Supply chain diversity reflects the adaptive capacity of countries through varied trade partnerships.

Together, these indicators present a multi-faceted view of trade resilience. The stability in connectivity highlights the preservation of trade links, while shifts in centrality reflect temporary adaptations to regional reliance. Meanwhile, global trade disruptions and Bonilla index changes show where trade vulnerabilities were most pronounced, especially in low-income regions. The supply chain diversity observed in high-income countries underscores their adaptive advantage, suggesting that countries with more diversified trade are better equipped to absorb crises.

3.6 Discussion and Conclusion

This study has illuminated stark disparities in food trade resilience across different income levels, notably underscoring the acute vulnerabilities of low-income countries. Our findings align with existing literature portraying economic constraints as large amplifiers of global crisis impacts, such as those seen with the COVID-19 pandemic (Hallegatte, 2019; Nébié et al., 2021). Regions with limited economic resources exhibited pronounced susceptibility due to their inadequate infrastructural and institutional supports. In contrast, high-income countries, equipped with more robust mechanisms, demonstrated greater capacity to swiftly adapt and mitigate such disruptions. These differences highlight the urgent need for more intense international support and strategic policy interventions to strengthen food trade resilience in low-income regions.

Beyond income disparities, the segmentation of resilience indicators into adjacent and distant trade components provided deeper insights into how spatial proximity influences trade vulnerability. Our analysis revealed that adjacent trade networks, particularly in low-income countries, were more prone to disruptions, largely due to reliance on a smaller number of neighboring partners. For instance, the Bonilla Index results showed that adjacent networks in North Africa, such as those involving Libya and Egypt, experienced marked declines in resilience, indicating heightened sensitivity to localized crises. In contrast, distant trade networks, benefiting from diversified partnerships, exhibited relatively stable resilience during the pandemic, suggesting that geographical diversification can act as a buffer against global shocks.

Changes in network centrality further reflected how some regions adapted during the crisis. In adjacent trade networks, Eastern Europe and Central Asia displayed increased centrality in 2020, suggesting a regional shift as countries turned more heavily toward nearby partners. However, this rise in centrality did not always correspond to an increase in connectivity, as the number of trade links remained largely stable across both adjacent and distant networks. This finding indicates that while the importance of certain countries within their regions may shift during crises, the overall trade structure remains resilient enough to sustain essential flows.

The results for global trade disruptions and supply chain diversity deepen the understanding of compounded vulnerabilities, particularly among low-income regions. Adjacent trade disruptions were especially severe in Central and Southern Africa, where strong regional dependencies intensified the impacts of global trade instability. Conversely, high-income countries, supported by diverse trade networks, showed greater adaptability, maintaining stable supply chain diversity across both adjacent and distant networks. The role of supply chain diversity in buffering against crises became evident, particularly in countries with developed political systems and industrial infrastructures, such as China. However, it is important to note that some highly globalized high-income countries, including Canada, Australia, and the United Kingdom, experienced noticeable declines in resilience, demonstrating that deep integration into international markets can also carry risks during major disruptions.

The approach introduced in this study offers an integrated framework that aggregates diverse evaluative perspectives from the extant literature, providing a more comprehensive analysis of food trade resilience. Unlike many prior studies that focus on isolated aspects, our framework embeds economic, political, socio-cultural, and logistical dimensions into a unified system. This holistic method is pivotal for crafting nuanced insights that can better inform resilience-enhancing strategies. By integrating multiple data sources and metrics, and utilizing datasets from reputable international organizations such as the FAO, World Bank, and UN Comtrade, we traced year-to-year fluctuations in resilience and highlighted the critical roles of economic stability and diversified trade networks. These results contribute valuable empirical evidence to ongoing discussions of global food security and provide practical guidance for policymakers and stakeholders aiming to strengthen food trade systems.

It is important to acknowledge that the method used to assign weights to indicators—based on their frequency of appearance in previous literature—may introduce bias. This approach, while grounded in academic precedent, could overemphasize commonly studied dimensions at the expense of underexplored but equally critical aspects. Previous studies have also highlighted this limitation. For example, Gu et al. (2018) pointed out that indicator weightings based solely on literature frequency may reinforce entrenched priorities rather than respond to current or emerging vulnerabilities. While our strategy enables comparability across multiple resilience categories, future work could integrate more participatory or adaptive weighting mechanisms, such as expert elicitation, analytic hierarchy process (AHP), or entropy-based methods, to improve robustness and mitigate potential bias.

Although this study provides an extensive analysis, it also opens important avenues for future research. Long-term assessments of the cumulative impacts of recurring global disruptions on food trade resilience, particularly in economically marginalized regions, remain needed. Developing dynamic predictive models to anticipate changes in resilience under future economic and environmental shifts could enhance strategic planning efforts. One limitation of the current study lies in its reliance on secondary data sources, which may not fully capture the immediacy and finer dynamics of real-time trade patterns. Future research could benefit from primary data collection and more frequent updates to offer a more detailed and timely understanding of food trade resilience.

In sum, this research highlights persistent disparities in food trade resilience across economies, emphasizing the urgent need for targeted efforts to bolster the resilience of low-income countries against future crises. The integrated framework proposed here offers a strong foundation for more informed research and policymaking, supporting the development of resilient and adaptable global food trade systems in an era of mounting uncertainty.

CHAPTER 4: THE RUSSIA-UKRAINE WAR REDUCED WINTER CEREAL YIELDS AND EXPORTS WITH A DISPARATE GEOGRAPHICAL IMPACT

4.1 Abstract

The transboundary impacts of regional war on global food trade remain underexplored, particularly regarding disruptions to production and trade networks. Here we address this gap by developing a rapid assessment framework that integrates remote sensing, policy monitoring, and network analysis to evaluate the effects of the Russia-Ukraine war on global winter cereal production and trade. Using satellite data, we estimated yield reductions for wheat, barley, and oats and analyzed the effects of export-ban policies enacted since February 24, 2022. Our findings indicate that lower- and middle-income countries were disproportionately impacted, as trade networks became fragmented, forming isolated clusters that threatened food accessibility. Geographically distant countries experienced greater disruptions than those near the conflict. This framework provides insights into the cascading effects of conflict on global food systems and offers a predictive tool for policymakers to address food availability challenges during future crises.

4.2 Introduction

As major producers and exporters of agricultural commodities, Russia and Ukraine play critical roles in the global staple food supply. They export more than 54% of globally traded wheat, barley, and oats (USDA, 2018). A number of countries, including some with vulnerable food availability, heavily rely on imports from these two countries. For instance, the shares of wheat imported from Ukraine by Egypt and Lebanon are 85% and 81% of their total wheat imports (Behnassi & El Haiba, 2022). The war between Russia and Ukraine, which began on February 24, 2022, has raised serious concerns about Ukraine's crop production and global food shortages

(Osendarp et al., 2022). A series of cascading effects of the war, such as loss of agricultural labor, destruction of infrastructure, and limited access to agricultural inputs, have threatened food production in Ukraine (Deininger et al., 2023; Abay et al., 2023; Shumilova et al., 2023). Alongside high energy costs and supply-chain disruptions, the war has further exacerbated the global rise in food prices (Carriquiry et al., 2022). International cereals' prices increased by 20% within the first three months after the start of the Russia-Ukraine war (FAO, 2022). The soaring prices have reduced the purchasing power of food importers and caused hunger, especially in low-income countries in Africa, the Middle East, and South America (Pereira et al., 2022). The Food and Agriculture Organization (FAO) models suggested that 13 million more people would be undernourished in 2022 due to the Russia-Ukraine war (IPES-Food, 2022). Furthermore, over 20 nations, including India and Kazakhstan, have declared stringent prohibitions and restrictions on grain exports after the Russia-Ukraine war, worsening the global grain supply and food availability (The Economist, 2022). Quantifying such cross-border impacts is therefore necessary for assessing food availability and making timely responses.

Recent studies have aimed to explore the quantitative impact of the Russia-Ukraine war on global food trade and food availability. Established studies have assessed the direct, indirect, and cascading effects of the Russia-Ukraine war by measuring the resilience, dependence, availability, and stability of other countries (Ben Hassen & El Bilali et al., 2022). Steinbach used product-level empirical modeling to identify reductions in Ukrainian exports and substantial trade diversions in Russia's favor (Steinbach, 2023). Some studies similarly emphasize the increase in global agricultural import prices, quantifying the impact of the war on food prices, trade volumes, and security (Feng et al., 2023; Lin et al., 2023). Some studies have examined the impact of war on trade and supply chains. For example, Arndt et al. used a global trade model to assess the impact of the Russia-Ukraine war on developing food supply chains (Arndt et al., 2023). The study emphasized the importance of diversifying sources of food supply. The study by Zhou et al. examined the economic impact of the war on agricultural markets, highlighting trade disruptions and food price increases (Zhou et al., 2023). Structural general equilibrium trade models have been used to illustrate how a reduction in Ukraine's wheat production would affect global food security (Lin et al., 2023). Van Meijl et al. (2024) assessed the impacts of the conflict on global grain markets and food security. The study reveals severe supply disruptions and price increases and argues for policy interventions to stabilize markets. However, these studies still fail to integrate rapid export ban policy data into exploring the impact of the war on countries with different income levels, and it is not clear whether the impacts vary among countries at different spatial distances. This knowledge gap may result in some of the most affected countries being overlooked.

Also, some studies attempted to examine changes in food production in Ukraine and the war's transboundary effects but are based on qualitative analysis or untested quantitative analyses (Abay et al., 2023; Carriquiry et al., 2022; Jagtap et al., 2022). While existing studies provide valuable insights into the economic impacts of the Russia-Ukraine war on grain-importing countries, a complementary approach is needed to conceptualize the trading system as a dynamic, interconnected network (Figure 4.1). This allows us to assess the structural changes within global trade relationships and explore the resilience of the global trade network in response to external crises. Collecting ground data in conflict zones is dangerous and challenging. Previous studies have demonstrated the efficacy of remote sensing in assessing the socioeconomic and environmental impacts of war in countries such as Uganda, Iraq, Syria, South Sudan, and Yemen (Berrang Ford, 2007; Li & Li, 2014; Jiang et al., 2017; Abdo, 2018; Hanna et al., 2021; Jumaah et al., 2021; Li et al., 2022). While a few studies have applied remote sensing to monitor agricultural production in Ukraine, they lack systematicity and often focus on specific aspects such as changes in land cover or yields of a single crop (Lin et al., 2023; Ma et al., 2022). Furthermore, the impact of the Russia-Ukraine war on food availability in countries at different distances remains underexplored. To summarize, the impact of the Russia-Ukraine war on adjacent and distant national food systems in different income levels is not well understood in a metacoupled world (e.g., socioeconomic-environmental interactions within and across national borders) (Liu, 2023; Vina & Liu., 2023).

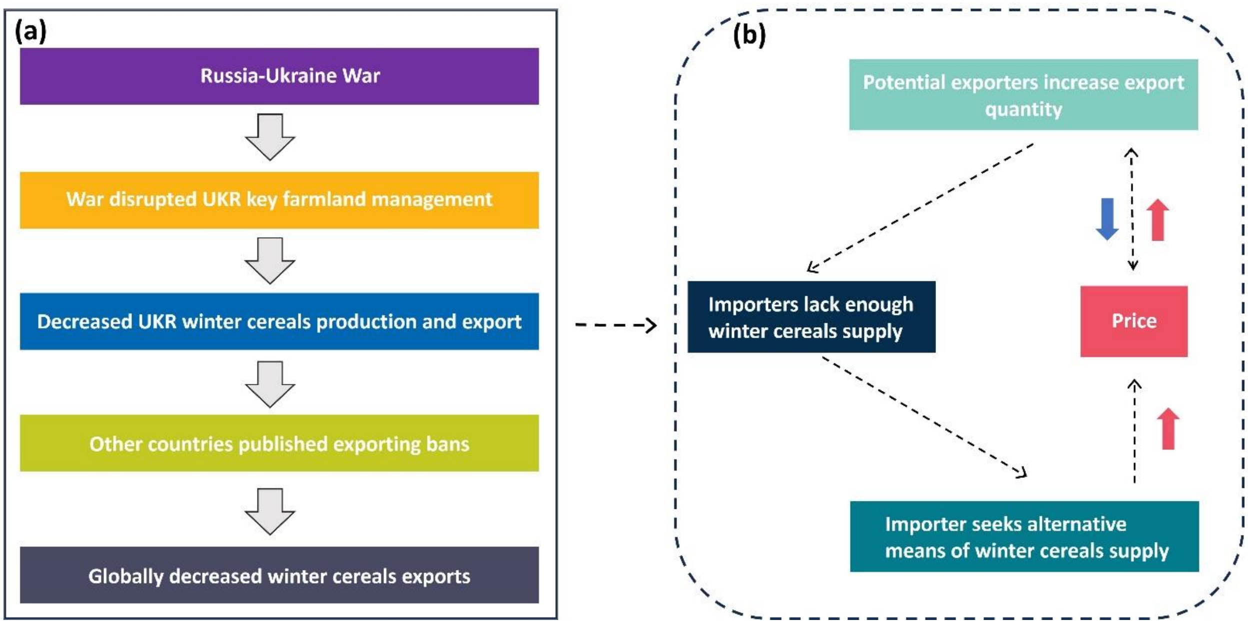


Figure 4. 1 Cascading mechanism by which war affects the global winter cereal network by decreasing production and prompting other exporting countries to publish export policies. (a) is the crisis of the Russia-Ukraine war on the volume of food trade exports, while (b) shows the resilience of the trading system, mitigating the crisis through price changes. The gray arrows refer to the quantified impacts covered in this paper. The black dashed arrows are the potential impacts discussed in the qualitative aspects of this paper. The blue arrows in (b) refer to negative impacts on price, i.e., when potential exporters export in large quantities, which reduces cereal prices; the red arrows refer to positive impacts on price, i.e., when import demand increases or there is a shortfall in export volumes, which raises cereal prices.

Considering the above gaps, we developed a rapid quantitative predicting framework integrating remote sensing and export ban policies with network analysis to build a trade network simulation. The simulation aims to assess the impact of the Russia-Ukraine war on food production in Ukraine. Since winter crops in Ukraine are dominated by canola and cereal, we used climatic algorithms to differentiate the acreage of winter cereals (wheat, barley, and oats) by analyzing seasonal growth differences using the widely used radar satellite images, Sentinel-1 (Marchetti et al., 2023). The method is still limited by some of the inherent shortcomings of remotely sensed imagery. For example, the spatial and temporal resolutions of the Sentinel-1 data are not suitable enough for accurately distinguishing morphological changes in crop plots at small scales over short periods of time (Marchetti et al., 2023). While other satellite-based sensors with higher spatial resolution ground sampling distances and/or daily revisits may be better suited to detecting such changes, these options currently require the use of commercial solutions, which can increase survey costs. Considering several advantages, such as not being limited by weather, and timing of visits (which may be obscured by cloud cover in fall and winter), low cost (compared to commercial solutions) and secure access (despite the ongoing war in the study area), the Sentinel-1 is a useful source of data for the monitoring effort. Subsequently, we generated a 10-m resolution map of annual winter cereal farmland extents at the state level within Ukraine. After obtaining a spatial distribution map of annual winter cereals, we estimated the winter cereal yield using a random forest regression model, with model inputs such as the normalized difference vegetation index (NDVI), climate variables, and reference crop yield statistics. Given that staple crops affect food availability, we focused on three major staple crops in Ukraine—wheat, barley, and oats—to assess changes in food production. The planting area and yields of the three cereals account for more than 80% of all cereals (SSSU, 2022).

The complex and interdependent nature of the global food system underscores the imperative for a rigorous and comprehensive approach to quantifying the effects of the armed conflict (Ben Hassen & El Bilali, 2022). Network analysis is a method of studying the relationships between the nodes in a network and understanding how the network functions as a whole. It has been widely used for systematic analysis in sociology, medicine, sustainable development, and ecosystems (Wasserman & Faust, 1994; Zhao & Frank, 2003; Pósfai et al., 2011; Felipe-Lucia et al., 2020; Chung et al., 2021; Wu et al., 2022). Network analysis allows us to understand how changes in one part of the system can ripple through the entire network, affecting everything from production to distribution to consumption. Additionally, network analysis enables us to identify which countries and regions are most vulnerable to global food-system disruptions and target interventions in those areas (Gutiérrez-Moya et al., 2021). Overall, network analysis is a valuable tool for understanding the complex dynamics of the global food system (Schaffer-Smith et al., 2018) and developing effective strategies to enhance its resilience and sustainability. Here we constructed a correlation network in which a network node is a country in the global trade systems of wheat, barley, and oats, and the strength of each link is the trade quantity between countries. Thus, we built export networks for the three crop trade systems.

Here, we utilized rapid policy data and remotely sensed data in conjunction with trade network analysis and used simulations to gain a comprehensive understanding of global winter cereal trade dynamics affected by the Russia-Ukraine war. Specifically, we aimed to address the following questions:

(1) What is the status of reductions in the production of winter cereal (wheat, barley, and oats) in Ukraine?

(2) How have the structures and interdependencies of the global trade networks of winter cereals changed in the simulated 2022 trade network compared to 2021, taking into account the reduction in winter cereal production in Ukraine as well as the export bans on wheat, barley, and oats in other countries?

(3) How does the war affect countries at different income levels and across distances? Are countries farther from the exporting countries affected differently compared to those near the exporting countries?

4.3 Materials and Methods

4.3.1 War-affected Areas in Ukraine

There is an ongoing geopolitical dispute between Russia and Ukraine (O'Loughlin et al., 2020). The main battleground of the armed conflict is primarily located in the eastern part of Ukraine, and the conflict has spread to multiple states including Kherson, Luhansk, Zaporizhzhya, Mykolayiv, Donetsk, Kharkiv, Crimea, and Sevastopol (Mazepus et al., 2023). These states have all been impacted to varying degrees by the war, which has directly affected agricultural production by causing crop losses and damage to agricultural infrastructure (Deininger et al., 2023; Shumilova et al., 2023). These regions directly affected by the war are the main agricultural states of Ukraine. Their winter production of wheat, barley, and oats accounts for 30% of the total production of these three crops of winter wheat in Ukraine in 2021. Among them, the production of winter wheat is 42.08% of the total production in Ukraine, and the production of barley is 41.32% of the total winter wheat production. When these major agricultural states are hit by the war, their reduced production may have a ripple effect. In addition to the yield losses caused by these war-affected regions, in other regions of Ukraine, panic may also cause yield reductions due to untimely management of farmland.

4.3.2 Materials

4.3.2.1. Satellite data and processing

We collected Sentinel-2 and Sentinel-1 images from 2019 to 2022 as the main model input. These data were produced by the European Space Agency (ESA) and freely available on the Google Earth Engine (GEE) platform. Sentinel-1 images were acquired in Interferometric Wideswath (IW) mode, which provides a dual polarization (VH and VV) at 10 m spatial resolution. The Sentinel-1 images on the GEE platform have been processed using the Sentinel-1 SNAP7 Toolbox to generate Ground Range Detected (GRD) images (Markert et al., 2020). Sentinel-2 satellites provide optical images in 13 spectral bands at 10, 20, and 60 m spatial resolution. We used the atmospherically corrected Sentinel-2 surface reflectance (SR) product and eliminated the cloud-covered pixels via the Sentinel-2 cloud probability dataset (https://developers.google.com/earth-engine/datasets/catalog/COPERNICUS_S2_CLOUD_PROBABILITY). Then, the red and NIR bands from Sentinel-2 images were used to derive the NDVI time series characterizing crop phenology.

4.3.2.2. Agricultural map and official statistical data

The cropland distribution data were derived from the 10-m global land-cover map produced by ESA (Van De Kerchove et al., 2021). In addition, the RapeseedMap10 dataset with a spatial resolution of 10 m was used to assist in the extraction of the annual spatial distribution of rapeseed planting areas in Ukraine (Han et al., 2021). However, the dataset lacks spatial information on winter rapeseed after 2019. We obtained data on planted areas and yield statistics for winter crops (wheat, barley, rye, and rapeseed) at the state level between 2019 and 2021 from the State Statistics Committee of Ukraine. These data were used to train yield models and to validate the derived winter cereal maps and yield forecasts.

4.3.2.3 Meteorological data

Temperature and precipitation data were utilized as important inputs to the yield model to explore the relationship between climate and yield (Johnson, 2014). The temperature data were derived from the remotely sensed thermal product (MYD11A2.006) from the Aqua MODIS sensor at 1-km resolution. The precipitation data were acquired from CHIRPS dataset, corresponding to a resolution of 0.05×0.05 degrees (Funk et al., 2015).

4.3.2.4. Trade data

The overall global trade data were collected from United Nations Commodity Trade Statistics Database (UN Comtrade database, see Data availability section), which is the original and probably the most widely used data source to support physical trade analysis from 2020 to 2021. Comtrade has been considered a reliable source of data by previous studies for purposes such as establishing trade networks, building trade-related databases, and conducting logistics analysis. Since the primary source of Comtrade data is the country itself as a reporter, there may be political motivations to keep information confidential and cause errors. Previous studies have indicated that UN Comtrade data have three main quality issues: outliers, missing values, and bilateral asymmetries. We compared imports and exports for the crops we used and found that both were missing data, with imports missing 15.27% more than exports. Thus, we believe the export volume data can better reflect the country's agricultural trade (Jones & Olken, 2010). Global wheat, barley, and oats trade data were collected for 2020–2021. We also fitted the export and import data (as shown in Figure S4.6 and Figure S4.3) and found that they are similar, and all of their P values are less than 0.05, which indicates the results obtained by using the export data are reliable.

We planned to introduce some pre-hints to predict the impacts of war on global food trade, thus we collected export restriction acts through tracking websites that had monitored relevant news and policies since the beginning of the war to assess the change in the volatility of exports of 218 countries and regions. Since Ukraine has many battlefields, there is a reduction in production due to negative effects such as a lack of agricultural management and unavailability of harvest. After using NDVI to estimate the yield, we set 30% as the unavailability of harvest based on the FAO report (FAO, 2022). We used the pixel- and phenology-based model to estimate the yield reduction of winter crops in Ukraine. Second, considering that Ukraine will not export all its winter crops, we calculated the proportion of exports by total production in 2021 and exports in 2021 and used the proportion of grain exports in 2021 as the proportional distribution of exports to countries in 2022. From these calculations, we constructed the trade networks for 2022.

4.3.2.5. Trade ban data

The trade policy ban data are mainly from the food availability portal - food and fertilizer export restrictions tracker - collected in the press and provided by the International Food Policy Research Institute (IFPRI), which the European Commission financially supports. The rest of the ban data is mainly from government websites and news. We have collected a total of 20 countries that have issued export bans related to winter grains and their products, and the specific data can be viewed in Appendix B.

4.3.3 Assessment of Total Reductions

The whole predicting framework consists of two main parts: the assessment of reduction in Ukraine, and the simulation of the next year's trade networks through tracking export bans. The summary and workflow of the remote sensing part are shown in Figure 4.2 with more details reported in the text. The workflow consists of the following steps: (1) Winter Crop Extraction, (2) Winter Cereal Extraction, and (3) Winter Cereal Yield Assessment.

4.3.3.1 Winter crop extraction

To obtain maps of three annual winter cereals (wheat, barley, and oats), we implemented an automatic winter crop extraction approach proposed by Skakun et al., which was previously applied to map winter crops in Ukraine for 2016–2018 (Skakun et al., 2017). The approach uses a phenological metric known as the maximum NDVI during the green-up stage of winter crop development to differentiate winter crops from summer crops. A cropland map was used as input data to generate a binary cropland mask to eliminate the non-cropland area. For the remaining areas, we extracted the maximum NDVI from March 1 to April 6, which is considered the best informative period for early differentiation between summer and winter crops (Skakun et al., 2017; Skakun et al., 2019). Since the NDVI was higher for winter crops and lower for summer crops during this period, we applied the maximum between-class variance method (OTSU thresholding) to automatically select appropriate thresholds for differentiating winter and summer crops (Wang et al., 2022). Taking into account the effect of regional differences, we chose a threshold that best fit each state. Finally, the binary mathematical morphological operations of erosion and dilation with a radius of 6 pixels were applied to the winter crop maps to reduce the salt-and-pepper noise presented as image speckles.

4.3.3.2 Winter cereal extraction

In the previous step, we extracted winter crop distributions. To obtain the distribution of winter cereal, it is also necessary to remove the disturbance of winter rapeseed, which has a similar crop calendar to winter cereal. According to previous studies, the VH backscatter of winter rapeseed has large differences from winter cereal in terms of its taller plants and randomly oriented branches at late growth stages in May (Veloso et al., 2017). Thus, the maximum VH backscatter in May was employed as a specific characteristic to distinguish winter rapeseed from winter cereal (Huang et al., 2022). After that, a mean filter with a kernel radius of 1 pixel was applied to reduce speckle noise in VH-intensity images (Mullissa et al., 2021). Once again, we used OTSU thresholding and winter crops mask to select thresholds for each state that would more accurately identify winter rapeseed and winter cereal. For most of the Ukrainian states, the area of winter rapeseed is much smaller than that of winter cereal. In this case, the VH-VH-intensity image histogram was dominated by winter cereal. It no longer exhibited bimodality, which results in the OTSU thresholding method selecting an inappropriate threshold value. To address this issue, we collected winter rapeseed samples from the RapeseedMap10 dataset and the same number of winter cereal samples from winter crop maps after excluding winter rapeseed. We used these samples as input to the OTSU thresholding method and mapped winter cereal from 2019 to 2021 with the output threshold. As before, we implemented binary mathematical morphology operations to reduce the salt-and-pepper noise resulting from the classification. Considering the general decline in crop NDVI due to the war, we anticipated that our method might not perform well in extracting winter cereals for 2022. Therefore, for the 2022 winter cereal distribution, we used the 2021 winter cereal data to represent it. Moreover, at the time of planting the winter crop in 2021, farmers did not anticipate the war and therefore would not have reduced the planted area. This estimation method was validated as feasible in previous studies due to the low inter-annual fluctuations in crops (Lin et al., 2023). There was a negligible difference in the winter cereal distribution between 2021 and 2022.

4.3.4 Winter Cereal Yield Assessment

Winter cereal yield assessment was done by developing a random forest regression model combining NDVI, climate records, and reference crop yield statistics (Figure 4.2). With the winter cereal mask, we extracted the maximum NDVI, cumulative precipitation, and average temperature during the growing season at the state level as input. These variables were considered to be associated with crop yields (Lin et al., 2023; Johnson, 2014)[15,64]. We randomly selected 80% of the samples for training and reserved the remaining 20% for evaluating model accuracy.

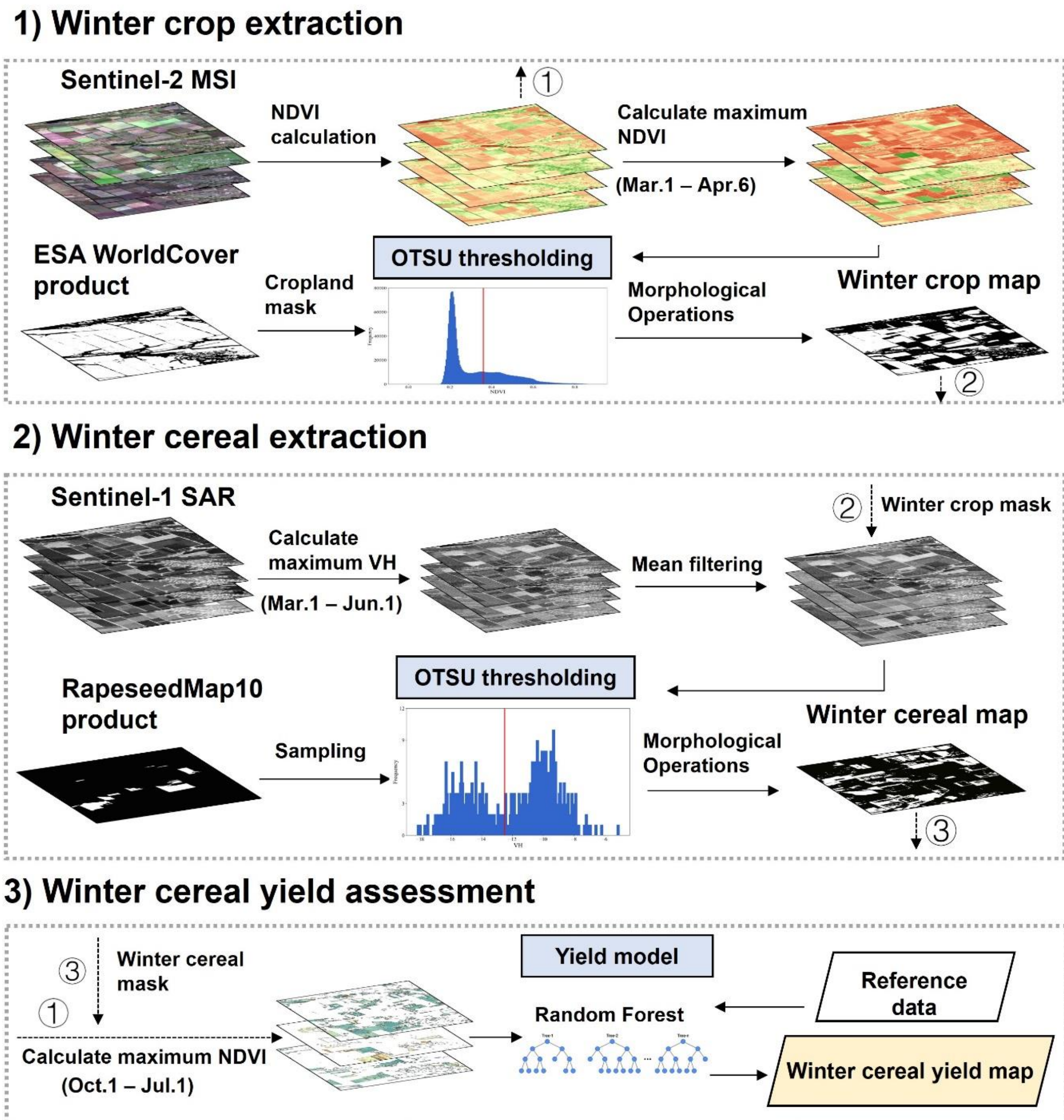


Figure 4. 2 Winter cereal yield map generation flow. (1) Extraction of winter full crop maps was based on Sentinel-2 MSI data and ESA WorldCover products to determine NDVI thresholding values through OTSU. (2) Maximum VH data were calculated based on Sentinel-1 SAR data, and after the mean filtering process, the winter cereal map was obtained by OTSU thresholding based on the winter crop mask and RapeseedMap 10 product. (3) Yield estimation was based on NDVI and real yield data of previous years combined with winter cereal map.

4.3.5 Confidence Intervals Calculation for the Prediction

To compensate for the fact that the prediction results may include uncertainties such as randomness and assumptions based on historical data, we calculated 95% confidence intervals for the predicted data to improve the robustness of the data. These assumptions, including changing environmental factors, such as soil conditions and climatic factors, are considered consistent across the dataset. The steps for calculating the confidence intervals were as follows.

First, the mean of the data set was calculated:

$$\mu = \frac{\sum x_i}{n} \quad \text{Formula (1)}$$

where μ is the number of data points, x_i represents each data point, and n represents the total number.

Second, we calculated the standard deviation (s):

$$s = \sqrt{\frac{\sum(x_i - \mu)^2}{n-1}} \quad \text{Formula (2)}$$

Third, we calculated the standard error (*SE*). This step was used to calculate the margin of the error:

$$SE = \frac{s}{\sqrt{n}} \quad \text{Formula (3)}$$

Fourth, we calculated the confidence interval (*CI*):

$$CI = \mu \pm (\mathrm{Z} \times SE) \quad \text{Formula (4)}$$

where Z =1.96 for a 95% confidence level.

Finally, the sum range based on the confidence interval was calculated by multiplying the bounds of the confidence interval by the number of data points:

$$Sum\ Range = CI \times n \quad \text{Formula (5)}$$

4.3.6 Network Analyses

Network analysis is a widely accepted approach. It has been used to examine the relationships within and between networks of nodes and the connections, or edges, that link them. The nodes of network analysis are usually entities (including individuals, organizations, and countries), while the edges represent the relationships or interactions between these entities. Network analysis has been extensively applied in multidisciplinary studies to reveal the underlying patterns and dynamics of complex systems. It has been essential to sociology's understanding of social interactions and community structures, illuminating the connections between people and groups (Granovetter, 1973). Network analysis has also contributed to the field of biology, where it has been used to study gene interactions and protein function, thus contributing to the development of genomics and systems biology (Pósfaiet al., 2011). Previous work also demonstrates a solid foundation for examining the complexities of global trade systems by network analysis. Kim and Shin applied a social network approach to examine how regionalization and globalization impact international trade patterns. They provided a longitudinal view of the evolution of trade networks toward denser and more decentralized forms, which validates the use of network analysis to comprehend global economic integration (Kim & Shin, 2002). Mahutga explored how globalization and the "new international division of labor" affect structural inequality in the world economy through a network analysis (Mahutga, 2006). Notably, other research further discussed the trade structure. For instance, Fagiolo et al. provided a detailed examination of the World Trade Web using a weighted network analysis, highlighting the structural properties of trade relationships and their evolutions over time, which revealed insights into trade interdependencies and clustering behaviors of nations based on trade intensity (Fagiolo, 2008). In addition, Smith and White explored how countries interacted in the global trading system and the changing nature of their economic exchanges, thereby revealing structural changes in trade networks (Smith & White, 1992). The analysis of specific food trade networks has also been conducted, with Chung et al. discussing the dynamics of trade networks in space and exploring food trade networks in the context of human health, which are influenced by a variety of factors in health, agricultural, and trade policies (Chung et al., 2020; Chung et al., 2021). Previous studies have also examined global seafood trade networks from 1994 to 2012, highlighting the trend of increasing globalization of seafood trade. Through network analysis, the authors identified changes in trade patterns, centrality, and partnerships, indicating increased regionalization (Chung et al., 2020; Herzberger et al., 2019; Gephart & Pace, 2015). The studies also discussed the implications of these changes for food availability and environmental impacts. Useful attempts have also taken place in the trading system of crops. For example, a complex network analysis was used to study the international wheat trade network from 2009 to 2013. The authors assessed the network's resilience and vulnerability to supply crises, noting that while the network's resilience has improved slightly, some developing countries have become more vulnerable. The study simulated the impact of supply disruptions on food availability and analyzed how COVID-19 might affect global wheat trade dynamics. These foundational studies underscore the suitability of network analysis for exploring the complex dynamics of interactions and dependencies among countries that characterize global trade (Gutiérrez-Moya et al., 2021). Thus, in this study, we used network analysis to build a real-world crop trade network and simulated crop trade networks affected by war production cuts and trade ban policies enacted by global exporters. We focused on the dynamics of three key network metrics: connectance, evenness, and modularity, which reflect the impacts of war on the food trade system. We used the 2021 UN Commodity Trade Statistics Database (Comtrade) to build the 2021 real-world trade network. Comtrade provides information on the year of trade, commodity type, volume of goods, amount of trade, exporting country, and importing country, and has been verified as a reliable source of data for constructing trade networks for commodities (Chen et al., 2022). The network data for 2022 were constructed as a simulation combining the results of remote sensing forecasts—production data after the Ukraine production cuts—and policy data. First, the ratio between total Ukraine exports and production in 2021 was obtained, and the total amount of exports in 2022 was projected. Second, keeping the ratio between Ukraine's exports to other countries in 2021, data on Ukraine's exports to other countries in 2022 were allocated using the total amount of predicted exports. The countries that had enacted export bans were considered "no trade" in 2022. Then, we constructed simulated trade networks for 2022. To validate the accuracy of the simulated 2022 trade network, we compared the predicted trade quantities for wheat, barley, oats, and total winter cereals against actual trade data obtained from the 2022 Comtrade dataset. We conducted a comparative analysis by plotting the predicted and actual trade quantities across income groups (high, upper-middle-, lower-middle-, and low-income) to assess how well the simulation aligned with real-world outcomes. We further conducted linear regression analyses between the predicted and actual trade values, calculating R^2 values to measure the strength of the correlation.

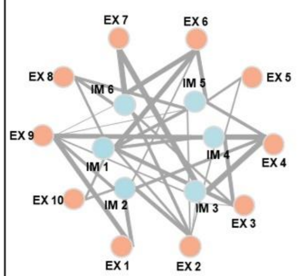
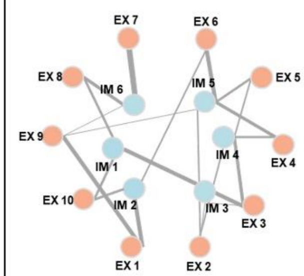
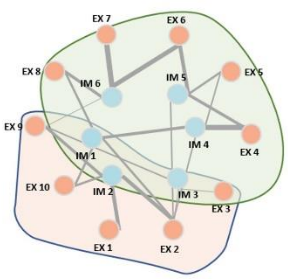
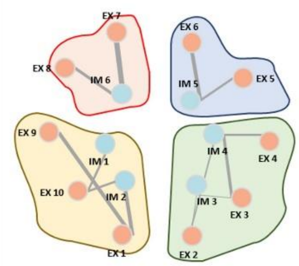
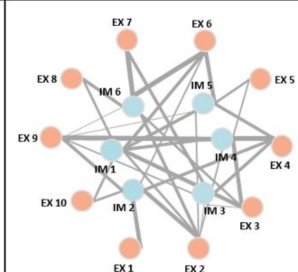
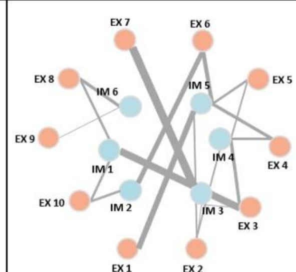
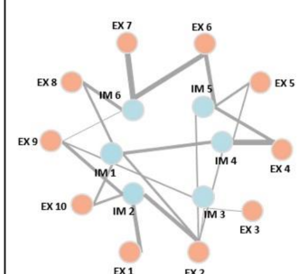
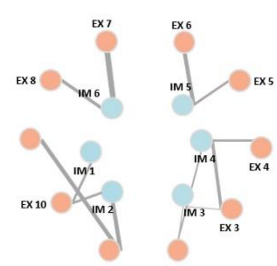
Network metric	Predicted changes with time and war	Potential effect of war on winter cereal trade network metrics	
		Before war	After war
Connectance	Decline if wars happened or affected trade supply chain. It represents the trade intensity of importer and exporter, and we normalize the annual trade volume as an indicator of connetance. When before the war, thanks to the trend of trade globalization, the network had a high connectance value, representing a trade boom between countries. After the war, the connectedance value is lower due to reduced production and reduced exports due to shocks to the supply chain of trade caused by wars, extreme weather events, etc., or due to trade ban policies.		
Module	A module represents a group of nodes that are highly connected among them and loosely connected to others. More decentralized modules from countries are more likely to emerge when war occurs.		
Evenness	The diversity of both exporting and importing countries representing cereals is relatively rich and importers have a low dependence on the choice of importers. However, when war occurs, the selection becomes less, making these importers more dependent on a fixed number of exporters, causing the nodes to change from being even connected to having strong links.		
Modularity	Modularity represents the strength of the partition of a network into modules. In highly modular networks, grain trade links between countries are divided into isolated groups, while in less modular networks, the interconnection of trade networks between countries is higher.		

Figure 4. 3 Network metrics in global winter cereal trade network analysis**.** Connectance, modularity, evenness, and modularity from top to bottom.

For each network, we calculated the connectance, evenness, and modularity indices of the global trade networks for wheat, barley, and oats by year for 2021 and 2022 through R package igraph. Connectance was calculated as the proportion of present links to all possible links in the network, weighted by the absolute value of the correlation coefficient in previous studies (Csardi et al., 2006). Here, we adapted the traditional concept of connectance by using trade volumes as proxies. This approach allowed us to quantify not only the existence of trade relationships between countries but also the intensity and economic significance of these connections. As a result, the connectance values reported reflect the absolute magnitudes of trades, rather than a normalized proportion of possible connections, which is particularly valuable for analyzing the resilience and vulnerabilities of global trade networks in the context of disruptions like the Russia-Ukraine war. Evenness was referred to as the homogeneity of the link strengths in the network. In the context of this research, where understanding the complex interdependencies of international trade networks is essential, igraph offers a range of community detection algorithms (Csardi et al., 2006). However, many of these algorithms have limitations for this specific application. The edge betweenness algorithm, which identifies clusters by removing high betweenness edges, can be too computationally intensive for large trade networks. The fast greedy algorithm, while efficient in modularity optimization, may struggle with the complex, overlapping relationships of global crop trade. The InfoMap method, which relies on information theory to reveal communities, may not accurately capture the nuanced trade flows. The louvain algorithm is efficient for large networks but might miss subtler community structures. The optimal algorithm offers the best modularity but is computationally impractical for such vast datasets. Spinglass uses simulated annealing for modular networks but can be sensitive to parameter selection, and the leiden algorithm improves on louvain but still might not capture the trade networks' intricate patterns as effectively. In contrast, the walktrap algorithm is best suited for capturing the nuanced and overlapping communities within global crop trade networks, providing more meaningful insights into complex trade relationships. Thus, modularity was calculated by using walktrap in igraph, which separates densely connected subgraphs via random walks using correlation coefficients as weights.

First, the volume of food trade is one of the hallmarks of globalization. As globalization becomes more advanced, developed supply chains facilitate food trade between countries, providing food availability to more people in food crises and increasing internal connectance. Conversely, counterglobalization trends can reduce the volume of trade and cause decoupling between countries. Moreover, reduced production caused by, for example, natural disasters and wars, can increase demand in food-importing countries yet weaken the exports and capacities of food-exporting countries. Second, suppose the evenness of food trade networks among countries decreases by restricting or banning certain food exports through export policies. In that case, the dependence of food-importing countries increases globally for a few major exporting countries and reduces the resilience of the network. A reduction in production in the remaining exporting countries, for any reason, could trigger a dramatic food availability risk. Third, a decrease in modularity (i.e., the emergence of an oligarchy of food exporters) may breed new hegemonies. The pricing power for food would be in the hands of a few countries, and the number of people who cannot afford to buy food will increase. Therefore, determining how diverse crises alter these different network metrics can provide a more integrated view of war impacts on global food availability.

The trade volume between countries was converted to a network graph object and analyzed by the R package igraph (Csardi et al., 2006). In the network, the nodes represent the individual countries that interact, and the trade quantity between the nodes represents the directed food flows and their weights. Specifically, in 2021, we used the export data reported by countries with their partners to construct a directed trade network, using the absolute trade quantity, or trade quantity, as the connection weight between nodes. For 2022, we assumed that the trade network of countries would have remained unchanged, except for the decline in exports due to reduced production in Ukraine and the bans on exports by other countries to protect their domestic food availability. Thus, the network for 2022 was calculated based on 2021, and the trade volumes of countries that had enacted export bans were zeroed based on 2021, meaning that these countries would not export wheat, barley, or oats to any country in 2022. In contrast, 2022 imports from Ukraine were recalculated for importing countries based on remotely estimated production. First, we calculated the ratio between total exports and total production of wheat, barley, and oats in 2021, which was used to calculate the ratio of exports of these three winter cereals in 2022. Then, this ratio was applied to the production estimated by remote sensing for 2022 to obtain the total exports of the three cereals in 2022. Next, by calculating the ratio of exports to each country to total exports, we simulated the exports from Ukraine to other countries in 2022 and used these export volumes as weights for the network. Besides the network metrics, we used the weighted node degree (the average strength of connection to other nodes, calculated as the product of the degree of a node and the mean of the absolute correlation coefficients of all connections) to calculate the connectance of countries in the interaction networks. We calculated this value for each node in the networks to identify the most connected node and the change in connectance of each node along the winter crop trade network. We compared the composition of the network modules from 2021 to 2022. Note that the existence and composition of the modules in a network are independent of the network's modularity value, which means that modules can be identified even if the modularity value is low.

4.4 Results

4.4.1 Winter Crop Production Reduction Observed from Satellite

Based on the state-level official statistical data, we evaluated the performance of our method at the state level for identifying winter cereals. Appendix B Figure 1 shows the mapping results of the validation for 2019 to 2021. The R^2 values between the satellite-derived area and the official statistical data ranged from 0.80 to 0.94 for 26 states. Meanwhile, the root mean square error (RMSE) ranged from 55.94 km^2 to 116.11 km^2. Overall, there is good correspondence between official statistical data and identified planted areas. In addition, our state-level yield estimation results compared well against official statistics, with an RMSE of 346 kg/ha and an R^2 of 0.70 (Povey & Grainger, 2015; Wasserman, 2013). The prediction errors can arise due to the inherent noise in historical data, inaccuracies in model assumptions, or the unpredictability of future conditions not captured in historical observations (Agrawal & Patel, 2020; Chatfield & Xing, 2019; Smith & White, 1992). To account for these uncertainties, we have calculated a 95% confidence interval, depicted in Figure S4.1. This interval reflects our best estimate of the expected range of predicted values, accounting for possible variations inherent in our modeling framework.

The monitoring results of remote sensing satellites and official statistical data show that the winter crop was mainly distributed in the central and southern parts of Ukraine in 2022 (Figure 4.4). After the war's outbreak, winter crops' main production areas shifted from Odessa, Zaporizhzhya, and Mykolayiv states to Zaporizhzhya, Dnipropetrovs'k, and Kherson states. Meanwhile, war in the eastern region threatened the crops in the war-affected areas and affected the growth and development of winter crops in the entire region (NDVI<0). From the NDVI changes in the longitude (Figure 4.4 (a)) and latitude (Figure 4.4 (c)) directions, the NDVI values in the central part of the study area were higher than those in the surrounding areas, and the winter crops yield was higher. The yield estimation results (Figure 4.4 (d)–(g)) show that the war threatened agricultural production and food availability in Ukraine. If war losses are not considered, compared to 2021, winter crop yield reduced by 5.42 million tons (95% *CI* range: (-0.05, 10.88)) in Ukraine, including 4.72 million tons (95% *CI* range: (-0.22, 9.67)) of winter wheat and 0.86 million tons (95% *CI* range: (-0.43,2.15)) of winter barley. But, if we consider 30% of war losses, compared to 2021, winter crop yield would be reduced by 15.04 million tons (95% *CI* range: (8.68, 21.40)), including 12.89 million tons (95% *CI* range: (7.72, 18.05)) of winter wheat, 2.09 million tons (95% *CI* range: (0.29, 3.89)) of winter barley, and 0.07 million tons (95% *CI* range: (0.02, 0.12)) of winter oats (Lin et al., 2023). As the main battlefields of the war, the food-producing croplands of the states near the eastern and southern parts of Ukraine have been affected. The total yield of winter cereal in Odessa, Donets'k, Kharkiv, Zaporizhzhya, and Mykolayiv states decreased by over 7.68 million tons. This decline was also observed in the total yield of winter wheat within these states, with a decrease exceeding 6.29 million tons. Similarly, the total yield of winter barley exhibited a reduction, surpassing 1.38 million tons, particularly in Odessa, Zaporizhzhya, Mykolayiv, and Kherson states. In addition, the yield of winter oats also decreased. The observed decline in NDVI across Ukraine's major winter cereal production zones reflects more than just a decrease in output. These patterns likely signal environmental degradation caused by direct and indirect consequences of war. Active conflict zones have experienced destruction of agricultural infrastructure, abandonment of cropland, and limitations on irrigation access, all of which contribute to reduced vegetation productivity.

Beyond short-term yield losses, prolonged exposure to these stressors could degrade soil structure, reduce organic content, and increase the risk of erosion or salinization — especially in semi-arid regions of eastern Ukraine. These environmental consequences may persist long after hostilities cease, underscoring the long-tail effects of war on agroecosystems. While our analysis focuses on NDVI as a proxy for vegetation condition, future studies could incorporate field validation or finer-scale indices (e.g., NPP, land surface temperature, or evapotranspiration) to quantify the cascading environmental damages more precisely.

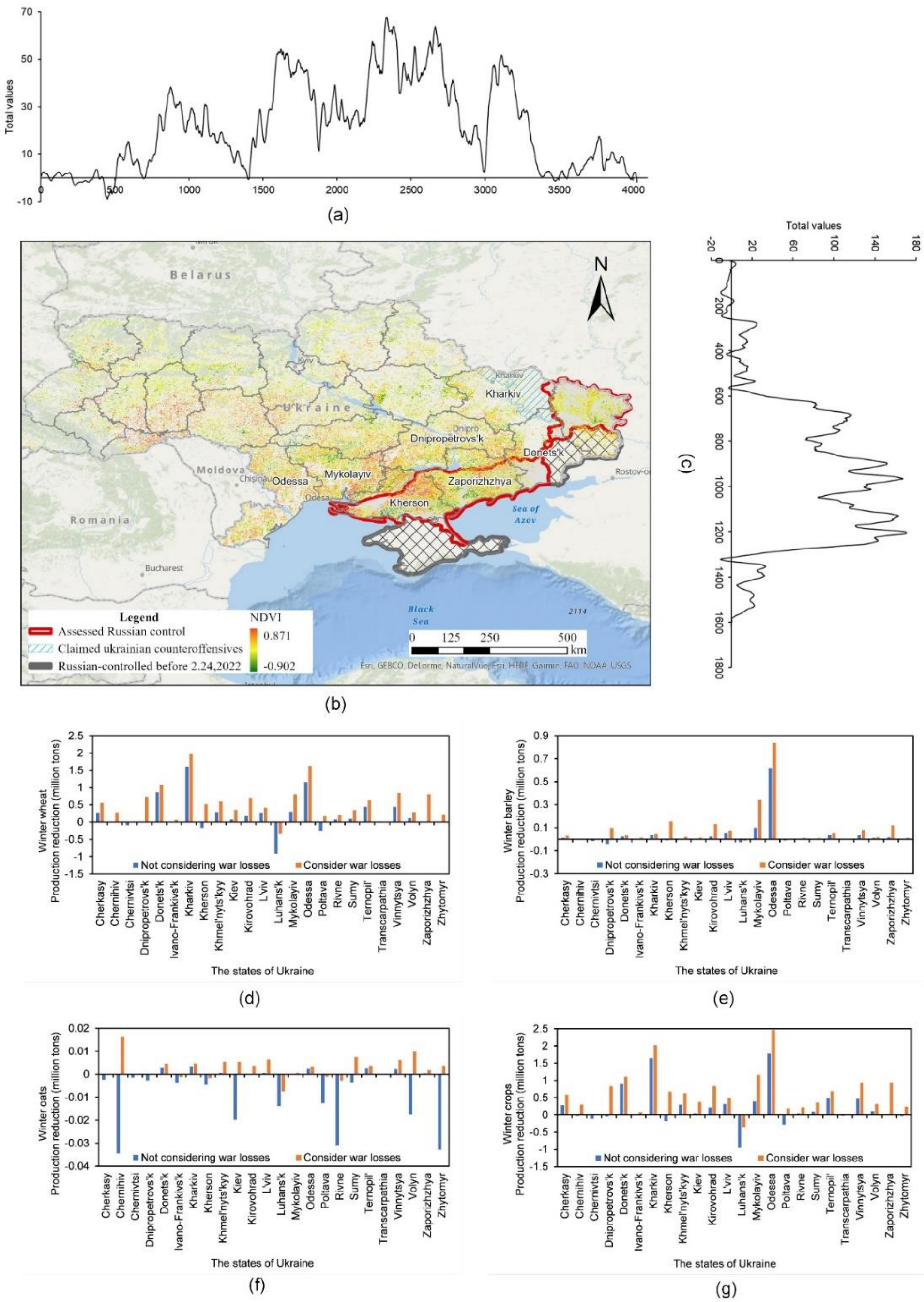


Figure 4. 4 Satellite observations reveal that winter crop yield in Ukraine decreased in 2022. (a) NDVI change in longitude direction; the x-axis is the pixel number while the y-axis is the sum of total NDVI change value. (b) Schematic diagram of NDVI and war areas. (c) NDVI change in latitude direction. (d) The reduction in winter wheat yield in each state. (e) The reduction of winter barley yield in each state. (f) The reduction of winter oats yield in each state. (g) The reduction of winter crop yields in each state. Due to Russia's control, crop yields in the Crimea and Sevastopol regions were not considered in this study; the y-axis is the pixel number while the x-axis is the sum of the total NDVI change value.

4.4.2 Winter Cereal Trade Networks in 2021

We visualized the global trade networks for wheat, barley, and oats in 2021 (Figure 4.5 (a)–(c), three letters represent abbreviations of country names; for specific names of countries, see Appendix B Table S1). Ukraine is one of the major exporters in the world's network of wheat, along with the USA, Russia, Canada, Australia, and France. These major exporting countries have very different structures of cooperation partners. For example, the United States, Russia, and Canada export mainly to countries with upper-middle-income levels. The United States exports mainly to Mexico, Philippines, China, Japan, Korea, Colombia, and Thailand. Russia exports mainly to Turkey, Egypt, Azerbaijan, Kazakhstan, Nigeria, Bangladesh, and Thailand. In contrast, Canada exports mainly to China, Japan, Indonesia, Peru, Colombia, and France's main partners are mostly high-income countries. Australia and Ukraine are the main exporters to lower-middle-income countries. Among them, Ukraine is the only one of these major exporters in the lower-income (lower-middle-income and low-income) level category. It mainly exports to countries with lower-middle-income levels, such as Egypt, Indonesia, Pakistan, Morocco, Bangladesh, and the Philippines, and low-income countries, such as Ethiopia, Yemen, Mozambique, Madagascar, and Indonesia. A number of countries with upper-middle-income or high-income are the major wheat-importing countries in this trade network: China, Turkey, Italy, and Brazil. The reasons for this are closely related to these countries' population sizes, cultivated patterns, and dietary habits.

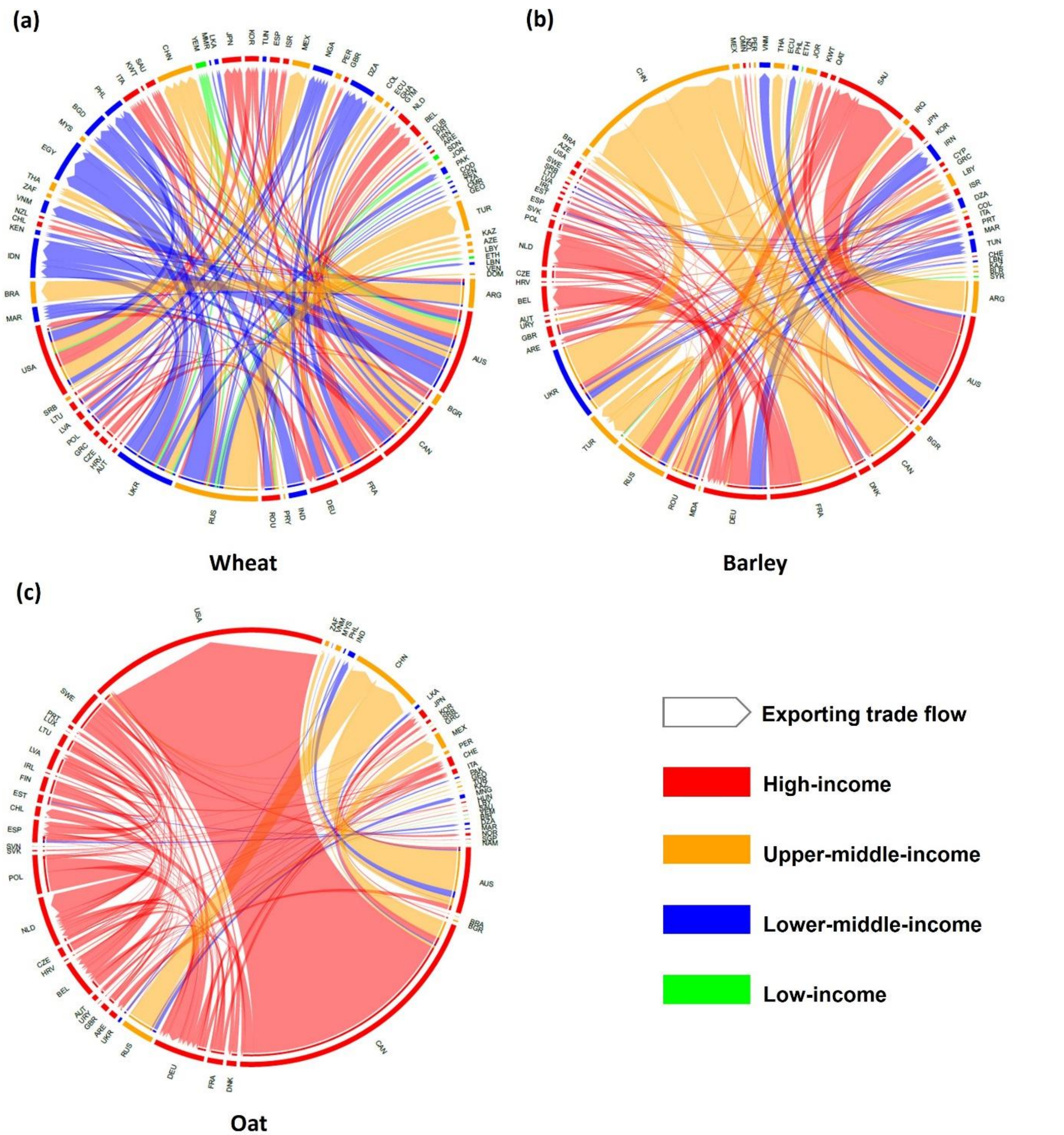


Figure 4. 5 Global trade flows (top 25%) of winter cereals among income groups in 2021 (for trade flows among all countries, see Appendix B Figure S4.2). Networks for winter cereals—wheat (a), barley (b), and oats (c)—classified by income levels. Trade flows are depicted using chord diagrams, with the direction and volume of trade represented by the connecting bands between countries. The color coding distinguishes the income levels of countries, with high-income countries in red, upper-middle-income countries in yellow, lower-middle-income countries in blue, and low-income countries in green. Thicker bands indicate higher volumes of trade between the respective countries.

In the global trade network for barley, the top exporters are very similar to those for wheat and include Australia, Ukraine, Russia, France, Canada, Argentina, and Germany. Ukraine remains the main exporting country with the lowest overall income level among them, and it exports large quantities of barley to China, Turkey, Saudi Arabia, Libya, Tunisia, and other countries. In this trade network China, Saudi Arabia, Netherlands, Turkey, and Belgium are the most important importers of barley. In the global trade network of oats, Canada's export to the United States is the largest trade flow, making Canada and the United States the largest oats exporters and importers in the world, respectively. Australia, Poland, Russia, and Sweden are also major exporters, while USA, Germany, China, Netherlands, Belgium, and Spain are the main importers of oats.

In summary, Ukraine is one of the leading exporters of winter grains, with the highest total exports of wheat and barley, and trades mainly with lower- and upper-middle-income. As the only lower-middle-income exporting country, Ukrainian population may be having difficulty affording its own grain production investments during the war, and its reduced production may impact food availability for populations in more vulnerable middle-income countries.

4.4.3 Affected Winter Cereal Trade Networks

The winter cereals (wheat, barley, and oats) for 2021–2022 are used as an example to visualize the predicted dynamics in each country in the trade networks under war effects. We simulated and analyzed it based on the fact that Ukraine's reduced production led to a drop in exports to other countries and a ban on exports by other countries.

The validation results, shown in Figure S4.3, demonstrate a strong correlation between the simulated 2022 trade networks and actual trade data for wheat, barley, oats, and total winter cereals. Although some variations exist, particularly for lower-middle- and low-income countries, where greater deviations in trade quantities are observed due to higher vulnerability to market crises, the overall distribution patterns remain consistent across income levels. The regression analysis further supports the reliability of the simulation, with the R^2 value of total winter cereals is 0.72, the R^2 value of wheat is 0.76, the R^2 value of barley is 0.73 while the R^2 value of oat is 0.59. The validation results indicate that our simulation effectively captures the general trends in global trade volumes.

Based on the simulation result, we analyzed the percentage impact of each country in the three winter cereal trade networks for the 2021–2022 season. The visualizations (Figure 4.6; for specific decreasing rates, see Appendix B) reveal that countries in Africa and Asia were the most affected, with reductions in imports ranging from 75% to 100%. Specifically, countries such as Guinea-Bissau, Sierra Leone, the Democratic Republic of Congo, Somalia, and Eritrea in Africa, as well as Montenegro, Albania, the former Yugoslav Republic of Macedonia, and Belarus in Europe, were among the most heavily impacted. Additionally, the European countries Macedonia, and Belarus were expected to experience reductions in imports, while in Asia affected countries included Turkey, the Syrian Arab Republic, Georgia, Armenia, Azerbaijan, Kazakhstan, Uzbekistan, Kyrgyzstan, Mongolia, Nepal, and Bhutan. A noteworthy observation is that among the countries most heavily impacted by the reductions in winter cereal exports, only Antigua and Barbuda belong to the high-income group. Six affected countries are classified as low-income, seven as low to middle-income, and eight as middle-to high-income. The disparities in the impacts of the export reductions between high-income and low-income countries underline the importance of targeted policies and programs to support vulnerable populations during times of conflict. By recognizing and addressing different groups' unique needs and challenges, we can work toward building more resilient and equitable societies.

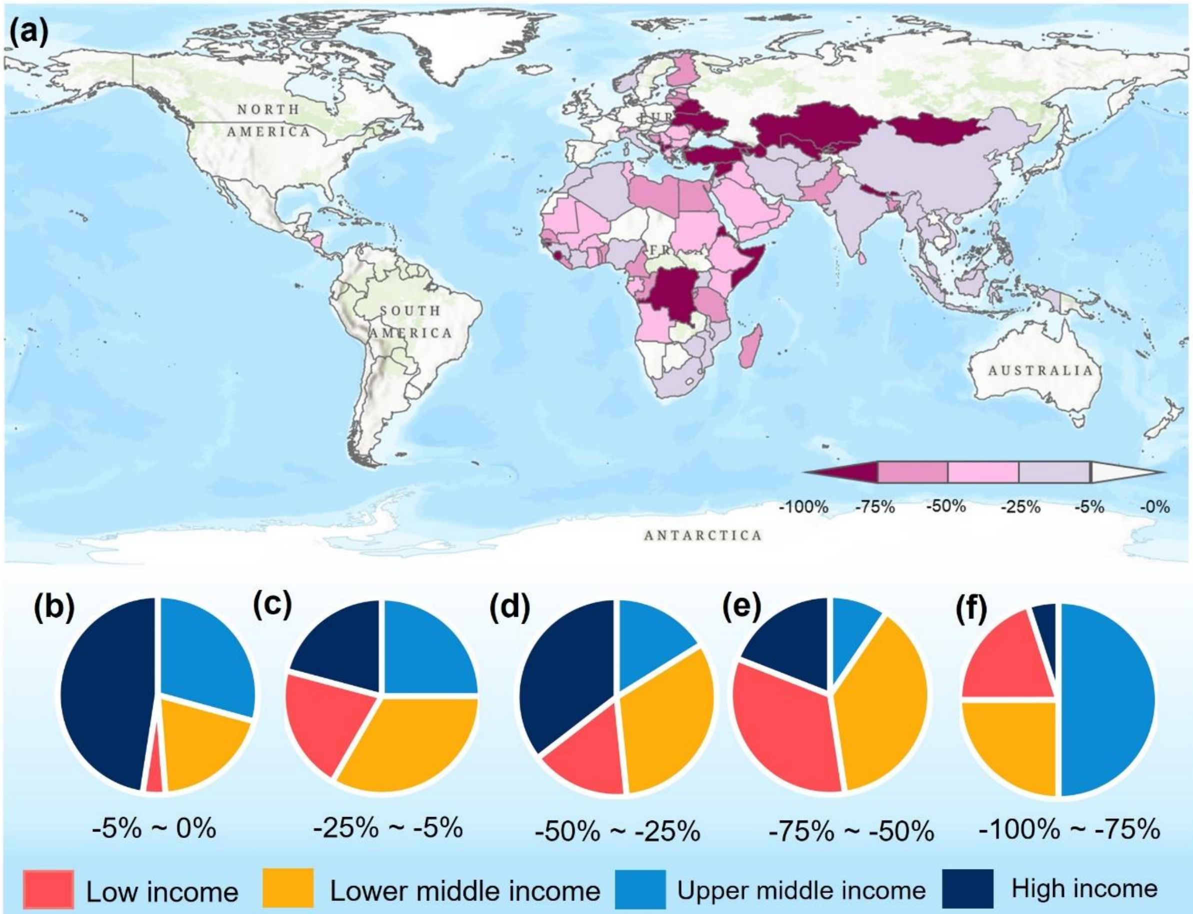


Figure 4. 6 Percentage reductions in projected imports in 2022 for each country. (a) Absolute value and rate of change of total import volume by country from 2021 to 2022; contents of (b)–(f) are the shares of countries with different income levels in different affected percentage intervals.

Nine countries in the highly impacted category (more than 50%), are classified as lower-middle-income: Egypt, Bangladesh, Senegal, Pakistan, Lebanon, Congo, Cameroon, Benin, and the United Republic of Tanzania. Five countries at the low-income level and nine lower-middle-income countries were highly impacted, along with four upper-middle-income level countries and five high-income countries. In the countries less impacted (25%–50% reduction in imports), most are in the high-income category which indicates that high-income countries are more resilient and have a greater diversity of import providers.

Based on remotely sensed yield estimates and information on export ban policies, we simulated the winter cereals trade networks of 2022 to reflect the effects of these conditions (Figure 4.7). We considered the global trade networks to remain consistent with 2021 in terms of export volumes and trade parties, except for the impacts of reduced production and policy measures. To analyze these changes, we employed network analysis to model the trade network dynamics, focusing on key metrics—connectance, evenness, and modularity—to capture the war's impact on the global food trade system. The 2021 network was built using data from the UN Comtrade database, which provides detailed trade statistics. For 2022, we simulated the network by integrating remote sensing–based yield forecasts and export policy data. We maintained the 2021 ratio of Ukraine's exports to its production, projecting the total exports for 2022, and allocated exports proportionally to countries. For those countries with export bans, trade was assumed to cease, allowing us to construct simulated 2022 trade networks reflecting the expected shifts. According to the simulated results, the most affected importers in the wheat trade network were mainly Turkey at the upper-middle-income level, Egypt, Bangladesh, Indonesia, and Nigeria at the lower-middle-income level, and Yemen at the low-income level. Overall, the most affected group of countries was the upper-middle-income countries, which were expected to lose more than 46.58 million tons of wheat imports, followed by the lower-middle-income countries, which would see a reduction of 38.92 million tons of imports compared to 2021 imports. The low-income countries were estimated to face a shortfall of 25.59 million tons of grain imports, while high-income countries were the least affected, facing only 20 million tons of import reduction.

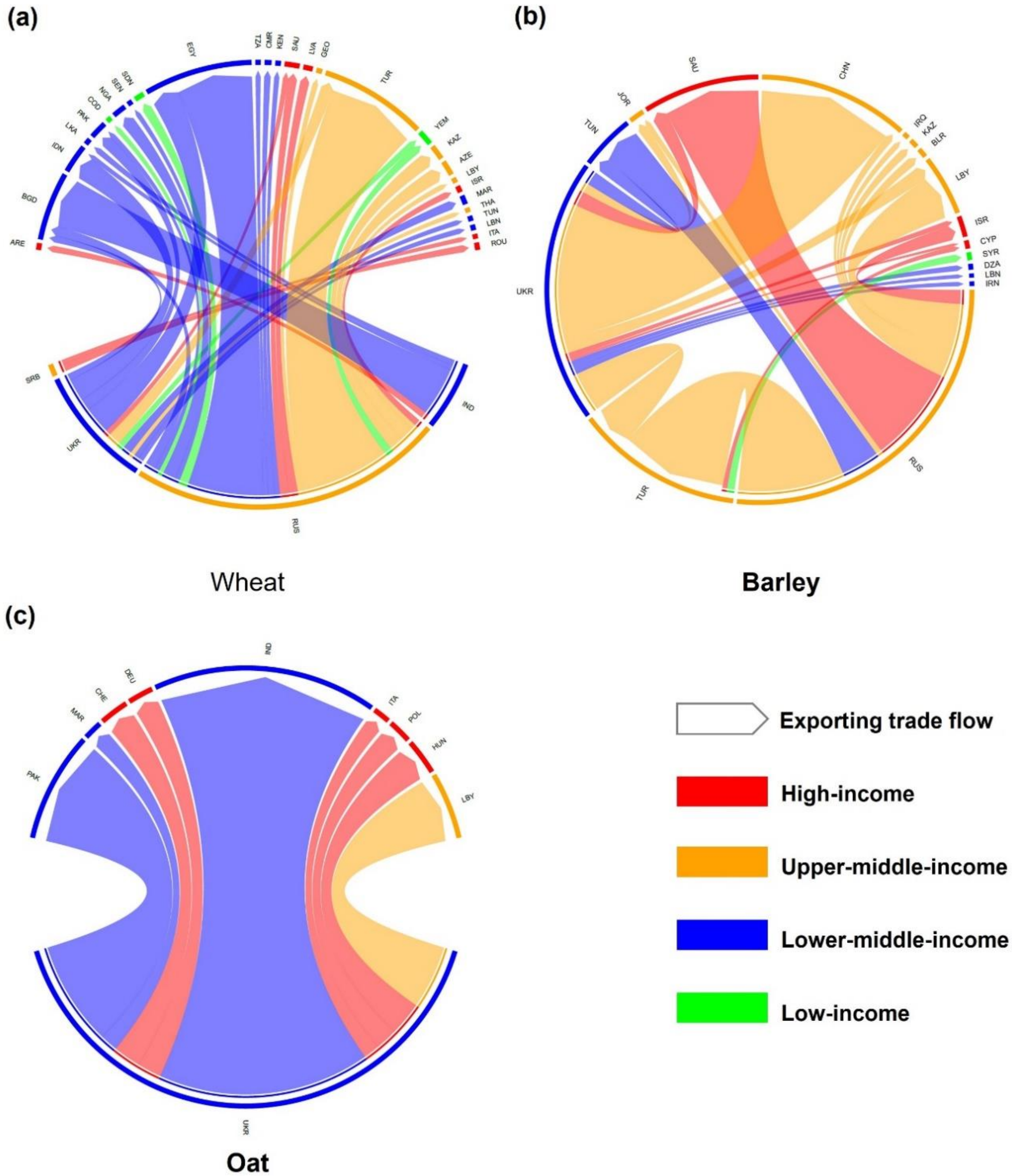
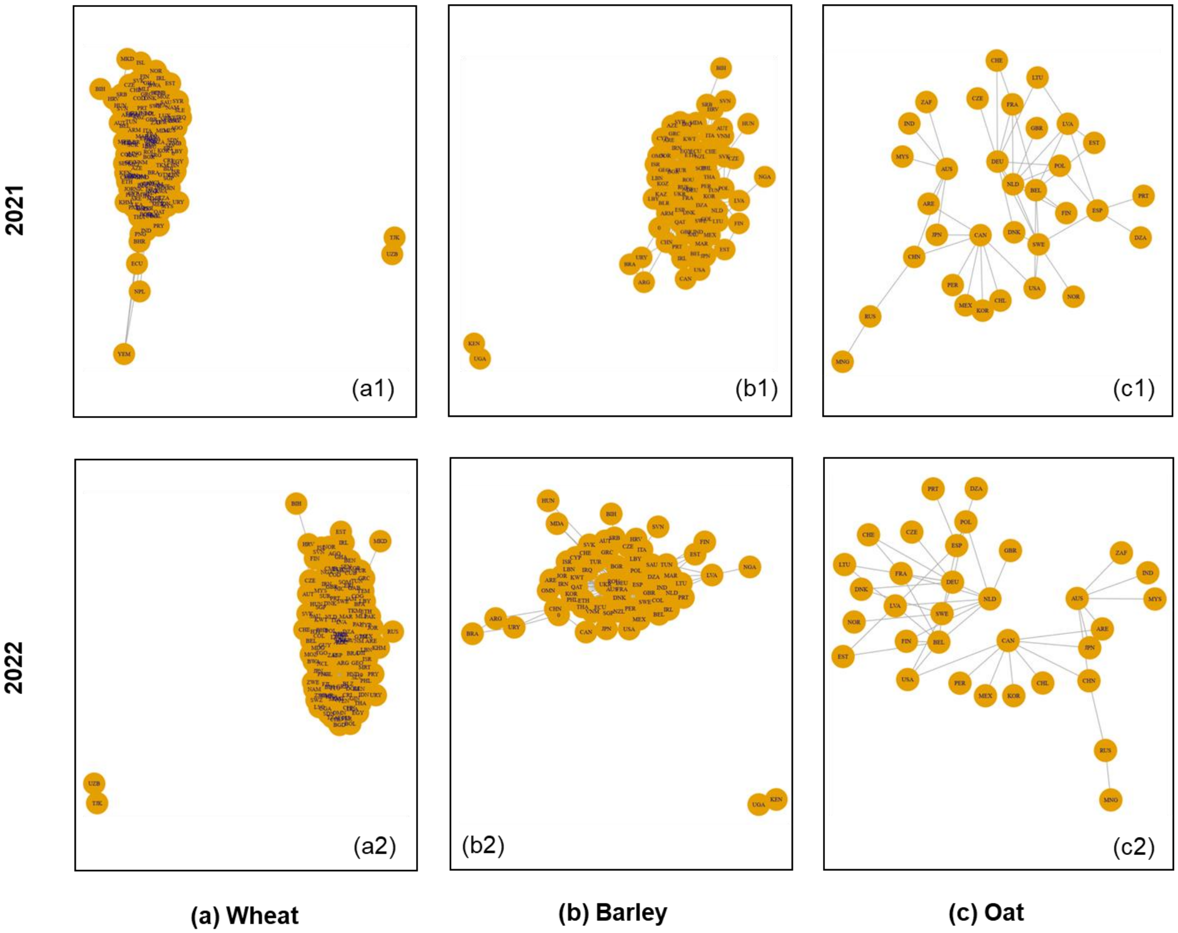


Figure 4. 7 Trade networks affected by production cuts in Ukraine and external cereals export bans in 2022 (top 25%) (for trade flows among all countries, see Appendix B Figure S4.4). Global trade networks for winter cereals—wheat (a), barley (b), and oats (c)—across various countries classified by income levels. Trade flows are depicted using chord diagrams, with the direction and volume of trade represented by the connecting bands between countries. The color coding distinguishes the income levels of countries, with high-income countries in red, upper-middle-income countries in yellow, lower-middle-income countries in blue, and low-income countries in green. Thicker bands indicate higher volumes of trade between the respective countries.

For the worldwide barley trade network, reducing production in Ukraine and national trade protectionism in Russia were the most influencing factors. Turkey, China, and Libya at the upper-middle-income level, Tunisia at the lower-middle-income level, and Saudi Arabia at the high-income level are the most affected countries. In the oats trade network, despite the ban on oats exports published by Hungary, Kyrgyzstan, Kuwait, and Turkey, the reduction in production in Ukraine still had the most impactful role due to the volume of trade. The most affected countries were India and Pakistan at the lower-middle-income level, Libya, Serbia, Bosnia Herzegovina at the upper-middle-income level, and Hungary, Switzerland, and Germany at the high-income level.

Production reduction in Ukraine and the introduction of protectionist bans on the trade of winter cereals in various countries as a result of the Russia-Ukraine war have reduced the connectance of the global trade networks for the three grains, with the wheat trade network being the most affected (Figure 4.8). The modularity of the three networks has also increased, which illustrates the impact of the war on the network, causing elevated national protectionism and reduced trade between countries. Specifically, in 2021, wheat, barley, and oats trade networks displayed high connectance and global integration, signifying well-established supply chains. In 2022, the geopolitical disruptions due to the Russia-Ukraine war caused disruptions manifested as a pronounced fragmentation in the trade networks of all three grains, leading to smaller, regionally concentrated clusters.



		Wheat	Barley	Oat
Modularity	2021	0.4047	0.4988	0.5477
	2022	0.4119	0.5160	0.5481
Connectance	2021	13724029.0830	8345134.0850	1225087.8494
	2022	12486018.4511	8115596.3616	1223601.2806
Evenness	2021	0.8088	0.7174	0.8159
	2022	0.8044	0.7085	0.8166

Figure 4. 8 Effect of war on the network structure of winter cereals. For 2021 and 2022, respectively, (a1) and (a2) indicate the wheat network, (b1) and (b2) indicate the barley network, and (c1) and (c2) indicate the oats network. These figures show the effects of the Russia-Ukraine war on (i) connectance, (ii) modularity, and (iii) evenness in different years. Each colored connecting piece in the figure represents a small trade group with strong trade links. The connectance values exceed the typical [0,1] interval because they are derived from trade volumes, which measure the strength and economic impact of trade connections. This method allows us to capture the intensity of trade flows, offering a more detailed understanding of the network's structure and the potential impact of disruptions on global food security.

For wheat, the trade network's fragmentation was particularly evident (Figure 4.8 (a1), (a2)). In 2021, the dense connections between countries reflected a high level of global trade, corroborating findings by the FAO that highlight the importance of Ukraine and Russia as wheat exporters (FAO, 2023a). However, the 2022 data indicate a decline in connectivity, signaling the urgent search for alternative suppliers due to Ukraine's diminished production and export restrictions by other nations. This shift resulted in isolated regional clusters, showing a decline in global trade interconnectedness.

Similarly, the barley network faced reorganization (Figure 4. (b1), (b2)). As per the International Grains Council (2022), Ukraine was one of the world's leading barley exporters, and the decrease in its production due to conflict had cascading effects. The 2022 network reflects fewer trade connections, and regional clusters emphasize countries' relying more on local or nearby suppliers.

The oats network, comparatively smaller and less globally connected, also underwent a noticeable shift (Figure 4. (c1), (c2)). While its 2021 network showed less connectivity than wheat or barley, the 2022 data further highlight fragmentation, emphasizing regional clusters more pronouncedly. The shift to localized trade reflects broader trends observed in supply chain research during crises (Gereffi, 2020).

Our results indicate that war reduces the homogeneity of wheat and barley trade networks, suggesting that trade between countries was more isolated than before. Interestingly, the conflict causes a slight increase in the evenness of the oats network, which may be because the decrease in trade in the oats network is mainly driven by a single country, Ukraine, thus making the overall network more even as Ukraine's importing countries chose other import channels.

These observations underscore the global grain trade's vulnerability to geopolitical events and the imperative need to diversify supply sources to bolster resilience. As witnessed during the COVID-19 pandemic (Gereffi, 2020), this fragmentation and regionalization of trade networks, driven by geopolitical factors, necessitate a rethink in supply chain strategies to ensure global food security.

4.4.4 War Affects Adjacent and Distant Countries Differently

Generally speaking, in a metacoupled world, war or other crises can have internal, peripheral, and distant effects. The impact on adjacent countries due to local wars is often referred to as a pericoupling effect, while the impact on distant countries is a telecoupling effect (Liu, 2023). To quantify how the Russia-Ukraine war has differentially affected adjacent and distant countries in the winter cereals network, we accounted for all affected exporters and their neighboring and distant importers. We found that to the extent that wheat, barley, and oats were affected, the war had a much greater impact on distant countries than on adjacent countries, which means a larger trade difference (see Table 4.1).

Table 4. 1 Trade quantity differences between adjacent and distant countries of Ukraine and other countries (Unit: ton) from 2021 to 2022

Country	Type	Wheat	Barley	Oats
Ukraine	Distant	7828.89	2252.23	1.75
	Adjacent	41.82	0.19	0.19
Other countries	Distant	181,829.83	3748.59	0.16
	Adjacent	50,292.37	431.02	0.17

Note: The values in the table are the sums of differences of the countries' trade with adjacent and distant countries.

Wheat exports to distant countries curtailed a total of 189,658.72 tons in 2022, while exports to adjacent countries shrank by only 50,334.19 tons. A similar phenomenon was observed for barley, where imports in distant countries shrank by 6000.82 tons, while imports in adjacent countries shrank by only 431.21 tons. In the least affected oats trade network, the distant importing countries experienced a total reduction of 1.91 tons, while the adjacent countries had a total reduction of 0.36 tons.

Ukraine and other exporting countries had different levels of impact on distant and adjacent places (Figure 4.9). Ukraine showed a clear tendency to have a higher degree of influence on distant places in all trade networks of wheat, barley, and oats, while other exporters showed a tendency to have a higher degree of influence on distant places in wheat and barley networks. In the trade networks of other countries' exports of oats, there is no large difference in the degree of influence between distant and adjacent partners.

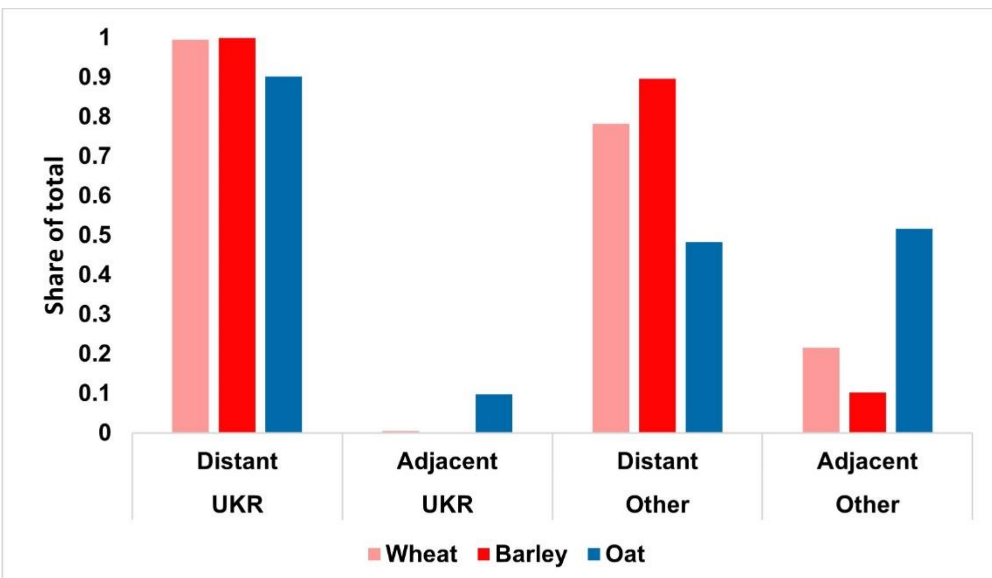


Figure 4. 9 Comparison of the degree of impact of Ukraine and other exporting countries on distant and adjacent importing countries. Share of total wheat, barley, and oats exports by geographic proximity and exporter type. The bars represent the proportion of winter cereal exports (wheat in light red, barley in red, and oats in blue) to distant and adjacent countries relative to Ukraine (UKR) and other major exporters in 2022. "Distant UKR" represents countries geographically distant from Ukraine, while "Adjacent UKR" refers to neighboring countries. Similarly, "Distant Other" and "Adjacent Other" indicate non-Ukraine exporters, categorized by their proximity to major importing regions.

The greater impact on distant countries can be attributed to both logistical and strategic trade dependencies. Distant nations, particularly those in Africa, the Middle East, and parts of Asia, rely heavily on Black Sea exporters like Ukraine and Russia for their cereal imports due to established long-distance trade agreements, price competitiveness, and historical supply patterns. These countries often lack regional alternatives with comparable export capacity, making them more vulnerable to sudden supply chain disruptions. In contrast, adjacent countries, despite geographic proximity, typically maintain more diversified import portfolios within their regional blocs or have greater overland transport and contingency options available.

Furthermore, maritime shipping routes to distant countries were disproportionately affected due to disruptions in port operations, heightened insurance costs, and geopolitical risks in the Black Sea region. Many distant importers lack domestic cereal production to buffer shortfalls, increasing their exposure to international shocks. Adjacent countries, such as those in Eastern Europe, benefited from overland logistical flexibility and often received prioritized grain flows through humanitarian corridors or bilateral agreements. As a result, the relative shock magnitude observed in distant importers reflects both structural trade dependencies and the compounded risks of distance, limited substitution, and reduced logistical resilience.

4.5 Discussion

To quantify the impact of war on winter crop production in Ukraine, we used remote sensing algorithms to map the distribution of winter cereal and predict the production of winter cereals (Otsu, 1975)[49]. Considering 30% of war losses, results indicate that compared to 2021, winter crop production in Ukraine decreased by 15.04 million tons (95% CI range: (8.68, 21.40)), with the main war zones in the eastern and southern regions severely affected, which shows production distribution trends similar to the research findings of Jagtap et al., Deininger et al., and Lin et al. However, the resolution in our study is 30-m which is much higher than in other studies (Deininger et al., 2023; Lin et al., 2023; Jagtap et al., 2022). It indicates that our results will have a more accurate estimation of the specific amount of production decrease. As a net exporter of grain, Ukraine has always been an important granary for Europe and even the world (Hellegers, 2022; Mottaleb et al., 2022). The ongoing war has directly damaged arable land and agricultural infrastructure, leading to direct losses of crops in the war zones and difficulties in cultivating some arable land (Behnassi & El Haiba, 2022; Shumilova et al., 2023; Levy & Leaning, 2022). Ukraine's lost production of three winter cereals in 2021 could have met the caloric needs of 76 million adults for a year (FAO, 2001; FAO, 2023b). At the same time, the war brought huge labor losses, with at least 6.5 million refugees from Ukraine recorded globally, leading to a shortage of agricultural labor and the abandonment of arable land (Ben Hassen & El Bilali, 2022; USA for UNHCR, 2023). The ongoing Russia-Ukraine war has impacted Ukraine's winter crop production, as the war disrupted key stages of farmland management such as fertilization and irrigation, leading to a large reduction in grain production (Deininger et al., 2023; Lin et al., 2023). This reduction could exacerbate an already precarious global food supply, particularly given the potential for further disruption caused by extended heatwaves in the northern hemisphere in 2022 and the sanctions imposed on Russia. The war has also led to a surge in global fertilizer and energy prices, which has created disruptions in the fertilizer market and reduced farmers' willingness to use energy and fertilizers, potentially leading to worldwide crop reduction and food crisis (Abay et al., 2023; Pörtner et al., 2022). The complex interplay between geopolitical war and global food availability underscores the need for proactive measures to address the vulnerabilities of global food supply chains, particularly in regions that are prone to instability or war.

Fortunately, potential remains for mitigating an impending food crisis that could be triggered by the simulated results in this study. Notably, some major grain-exporting countries boosted their exports to compensate for the absence of Ukraine and other countries that have enacted trade bans from the market (Glauben et al., 2022). The results of a 2023 network analysis reveal important shifts in the global trade dynamics for wheat, barley, and oats following the disruptions caused by the Russia-Ukraine war and export bans in 2022 (Figure S4.5). Several major grain-exporting countries have stepped in to mitigate the decline in Ukrainian exports, ensuring a relatively stable global supply. Notably, the United States, Australia, Canada, and Argentina have increased their wheat exports, helping to balance the shortfall. As the 2023 wheat network analysis indicates, the connectance value has increased (14871835.6793), and the evenness metric (0.8283) suggests a more balanced distribution of trade flows, reflecting the successful redistribution of supply routes among key exporters. In the barley trade network, countries such as Australia, France, and Germany have emerged as crucial exporters, alongside Argentina and Canada, filling the void left by the disrupted Ukrainian supply chains. The 2023 analysis shows a connectance value of 14549313.9751 and the evenness of 0.7727, indicating that the barley trade system has also adapted to the disruptions, with more countries sharing the export burden. The oats trade network has seen similar adjustments, with Poland, Australia, and Brazil playing pivotal roles in stabilizing the global supply chain. The 2023 network analysis highlights a connectance of 3071156.198 and the evenness of 0.888, signifying a relatively equal distribution of trade volumes among key exporters.

However, it is also important to note that many of the exporters stepping in to fill these gaps are from high-income or upper-middle-income countries. These countries are typically better equipped to respond to sudden increases in global demand due to their established infrastructure, robust agricultural sectors, and the ability to quickly scale production and have a strong motivation to increase their export quantity with a rapidly increasing price. Although these countries can bridge the gap caused by Ukraine's absence in terms of total exports, several challenges need to be addressed. Negative factors, such as panic surrounding food availability and port blockades resulting from the Russia-Ukraine war, have rapidly increased agricultural commodity prices in a short period. Ukraine's primary trading partners include lower-middle-income and upper-middle-income countries, with fewer high-income and low-income countries. Regions such as low-income European and African countries that rely on food imports from Ukraine to meet domestic needs face a huge challenge because their populations cannot afford the rapidly rising food prices. Consequently, while major exporting countries may close the export gap, reduced affordability continues to pose a threat to global food availability. Some countries have tried to create new cropland from forests or other lands to increase food production, but this may further affect environmental sustainability. Using the metacoupling framework, we quantitatively estimated the negative impact of the Russia-Ukraine war on the winter grain trade there and in interlinked countries worldwide (Liu, 2023). While reducing imports from countries adjacent to the focal system, the war also has a much larger impact on distant importers (Chai et al., 2024). This finding reveals the urgency and need for attention to potentially vulnerable countries. In the face of these challenges, the international community needs to improve its overall understanding of the countries affected. The regions where imports will be most affected may not be those bordering these countries, but rather the distant regions. Policies and subsidies for these countries, which may be underrecognized, will be essential for achieving sustainable development goals.

The current food crisis resulting from the Russia-Ukraine war poses many challenges, including rapidly escalating global commodity prices, declining affordability in less developed countries, and geopolitical tensions. In order to achieve food availability, the international community must focus on the seemingly localized impacts that transcend regions. We recommend calling for a highly resilient agenda, led by international organizations such as the FAO, that focuses on distant places of high vulnerability and fosters intercountry cooperation. This agenda should prioritize countries with low levels of development and high dependence on food imports in order to guarantee food availability for vulnerable groups. By working together under a harmonized and resilient framework, the international community could take decisive steps toward achieving Sustainable Development Goal 2 and ensuring a world free from hunger for all. It is important to note that inherent uncertainties in trade dynamics data and satellite imagery may influence the reliability of our results. Nationally reported export data might contain inaccuracies due to reporting errors or political and economic motives. Some exporters with large winter cereals storage capacity might have increased their exports driven by increasing prices, creating differences between the true trade network and the simulated results (Figure S4.5). Similarly, satellite imagery, while effective in monitoring large-scale agricultural changes, has limitations in spatial and temporal resolution that might affect the accuracy of yield estimates. The Sentinel-1 data, while offering advantages like cost-effectiveness and all-weather imaging, still pose challenges in distinguishing crop changes at small scales over short periods. These factors, along with model assumptions and unpredictable future conditions, necessitate caution when interpreting our findings. To address these uncertainties, we calculated confidence intervals for our yield predictions, reflecting possible variations in our modeling framework. In addition, because the simulation setup considers changes based on the 2021 trade system and may ignore the elasticity of the markets, i.e., changing prices, some exporters may increase their exports to compensate for deficiencies. Our simulation setup may result in simulated network exports that differ from the real market situation. While the trade analysis emphasized disrupted flows and emerging trade routes, our satellite-based assessment reveals that environmental degradation was a simultaneous and compounding outcome of the war. The reduction in winter cereal productivity, as indicated by NDVI, should be interpreted not only as an economic loss but also as a signal of biophysical stress. These findings point to the dual role of war in both disrupting trade structures and impairing ecological conditions, thereby reducing the long-term resilience of regional food systems.

4.6 Conclusion

In this study, we developed a comprehensive and rapid assessment framework that integrates remote sensing, policy monitoring, and network analysis to quantify the impact of the Russia-Ukraine war on global food systems. Our methodology involved using remote sensing–based algorithms to extract and map winter cereal crop areas and a random forest regression model to estimate yield reductions in Ukraine. We also collected global trade and policy data to model the impacts on the global trade networks of wheat, barley, and oats.

Our findings reveal that winter cereal production in Ukraine decreased due to the conflict, with yield reductions primarily affecting regions such as Odessa, Donetsk, Kharkiv, Zaporizhzhya, and Mykolayiv. These reductions, coupled with protectionist policies enacted by a number of exporting nations, impacted the global trade network. The study shows that countries with lower- and middle-income levels were more affected than high-income nations. Furthermore, countries that are geographically distant from exporting regions experienced greater disruptions than neighboring nations. Our analysis suggests that these changes in the trade network structure can exacerbate food shortages in vulnerable countries.

The holistic framework developed in this study allows for a nuanced understanding of the intricate dynamics of the global food system in times of conflict, offering valuable insights into which countries are most vulnerable to disruptions in trade. The research highlights the cascading effects of regional conflicts on the global food system (Fig. 1), emphasizing the need for international cooperation and targeted policies to safeguard food availability.

CHAPTER 5: GLOBAL WHEAT TRADE UNDER MULTIPLE CRISES AND THE EVOLVING DISPARITIES IN TRADE NETWORKS OVER THREE DECADES

5.1 Abstract

The global wheat trade network has been shaped by the combined effects of multiple global crises over the past three decades, including the 2008 financial crisis, the 2010 Russian wheat export ban, and the 2020 COVID-19 pandemic. This study examines how these crises influenced wheat trade patterns using network analysis, scenario simulation, the synthetic control method, and generalized additive models. The results show that each crisis produced distinct effects, but their combined effects created long-term shifts in trade structure, connectivity, and performance across regions and income levels. The financial crisis reduced liquidity and slowed recovery. The export ban led to supplier diversification. The COVID-19 pandemic disrupted logistics but also triggered broader trade expansion in some regions. High-income countries initially maintained stability but experienced increasing trade deviation during the pandemic. Upper-middle-income countries showed delayed recovery and missed growth potential. In contrast, lower-middle-income countries exceeded projected export levels under all crisis scenarios, suggesting emerging resilience. Low-income countries faced persistent trade shortfalls and limited recovery. Key exporters such as Russia, the United States, Canada, and Ukraine demonstrated different trade roles over time, shaped by policy and geography. Adjacent trade remained more stable under crisis conditions, while distant trade was more sensitive to disruption. This study introduces a method to quantify the combined effects of multiple crises on trade. The results underscore the unequal distribution of resilience across income levels and space. They also point to the need for inclusive and adaptive trade policies that can address structural disparities and support long-term stability in the global food system.

5.2 Introduction

Food is the cornerstone of maintaining human survival and social development (Friel & Ford, 2015). However, due to differences in climate, soil, water resources, and technological levels, there are large differences in food production types, quantities, and quality among different countries and regions (Rask & Rask, 2011; Chen et al., 2023). These differences have led to the emergence of global food trade, which plays a crucial role in optimizing resource allocation, increasing dietary diversity, and balancing regional disparities in food production capacity and demand (Brown et al., 2017; Davis et al., 2021). As one of the world's most essential staple crops, wheat serves as a fundamental component of global food security and economic stability (Brown et al., 2017). Despite its widespread cultivation, wheat trade remains highly sensitive to crises because production and demand are unevenly distributed across regions (Baines Joseph, 2017; Clapp J & Moseley, W, 2020). Many countries rely on imports to meet their food security needs, making the global wheat trade network vulnerable to supply chain disruptions during crises (Gutiérrez-Moya et al., 2021; Bertassello et al., 2023).

The global food trade system is considered to play a key role in achieving multiple Sustainable Development Goals (SDGs) (e.g., biodiversity (SDG14 and SDG15), decent work and economic growth (SDG8), and reduced inequalities (SDG10)) simultaneously, in addition to achieving SDG 2 (zero hunger) (Tanumihardjo et al., 2020; Chen et al., 2023). However, in recent years, this complex system has faced numerous challenges, such as climate change, the pandemics, financial crises, natural disasters, and geopolitical conflicts (Behnassi & El Haiba, 2022; Fan et al., 2021; Li et al., 2022; Lin et al., 2023; Olsen et al., 2021; Reed et al., 2022; Artiushyn et al, 2011). Among these, three major crises—the 2008 global financial crisis, the 2010 Russian wheat export ban, and the 2020 COVID-19 pandemic—have had profound and distinct impacts on wheat trade networks. Unlike previous studies that have treated these crises as general disruptions, we seek to differentiate their individual and interacting effects to trade fluctuations. A large challenge in existing research is the difficulty in isolating the impact of specific crises on trade patterns, as their effects often overlap. To address this, we employ the synthetic control method (SCM) to construct counterfactual scenarios that estimate what wheat trade patterns would have been in the absence of each crisis. This approach allows us to quantify the individual impact of the 2008-2009 financial crisis, the 2010-2011 Russian wheat export ban, and the 2020-2021 COVID-19 pandemic, thereby improving our understanding of their respective roles in reshaping wheat trade networks (Headey Derek, 2011; Welton George, 2011; Svanidze et al., 2022; Arita, et al., 2022).

Using systems integration and long-term analysis to evaluate complex trade systems has been widely accepted as a feasible quantitative method (Dalin et al., 2012; Distefano et al., 2018; Wang & Dai, 2021). Multiple studies have assessed the resilience, vulnerability, complexity, structure, and evolution of food trade networks, aimed to provide qualitative and quantitative descriptions of the nature and temporal dynamics of food trade networks, while in recent years some studies have focused on revealing multiple crises and impacts on trade networks based on the basic properties of the networks (Burkholz & Schweitzer, 2019; Dalin et al., 2012; De Benedictis et al., 2014; Distefano et al., 2018; Dolfing et al., 2019; Ercsey-Ravasz et al., 2012; Fair et al., 2017; Gephart et al., 2016; Gephart & Pace, 2015; Grassia et al., 2022; Wang & Dai, 2021). Network analysis as a holistic approach with the ability to describe and visualize complex systems in a highly coupled world can be used as a way to explore the dynamics of long time series of complex international food trade networks, revealing how crises within countries, between neighboring countries and distant countries are transmitted and affect each other, ultimately affecting the entire network (De Benedictis et al., 2014; Gutiérrez-Moya et al., 2021). Network analysis can be used to explore the dynamics of international food trade networks through a series of network metrics (e.g., Betweenness (Robustness) centrality, Eigenvector centrality, evenness, modularity, connectance, clustering coefficient, assortativity, rich-club coefficient). These indicators measure the impact of various crises on food trade networks and provide a clear visual perspective and quantitative description of the interactions between these variables to elucidate these interactions (Felipe-Lucia et al., 2020; Tamea et al., 2016; Wu et al., 2022; Xie et al., 2022). Although previous studies have advanced understanding of the complexity and systemic nature of the impact of multiple crises on food trade networks separately, there is limited research on the dynamics of multiple crises overlapping each other, i.e., how the interaction of the two changes with progress. Revealing the dynamics of multiple crises and food trade system interactions over a long time series allows us to estimate the impact of different crisis types. This helps identify obstacles and opportunities for countries at different income levels as they face crises in a highly interconnected and interacting world, and to find specific priorities for action for countries at different income levels based on specific levels of impact. To fill this knowledge gap, this study employs network analysis methods to examine the spatio-temporal dynamics of 218 countries and regions from 1993 to 2022 and investigates whether wheat trade networks are becoming less interconnected in the face of these challenges. To complement the network analysis, we also developed a scenario simulation framework to quantify the combined effects of the three major crises. This approach compares actual trade outcomes with baseline projections under no-crisis and single-crisis scenarios, allowing us to evaluate both individual and cumulative crisis effects on global and income-group-specific wheat exports. By focusing on this key crop trade network, the research aims to provide valuable insights into the functioning and resilience of the global food trade system in the context of multiple crises. I constructed the wheat trade networks over the last three decades using absolute and relative trade volumes between countries, respectively, and evaluated connectance, modularity, evenness, weighted degree, betweenness (robustness) centrality, eigenvector centrality, clustering coefficient, assortativity, and rich-club coefficient. These indicators can reflect how different crises affect trade networks and are transmitted through time and space. To understand the long-term trends of these indicators, I also used a synthetic control method (SCM) fitted 1993 to 2022 trend pairs, which was used to analyze their trends and long-term dynamics.

To sum up, I aim to answer the following scientific questions:

(1) What are the patterns of spatio-temporal dynamics in global wheat trade networks over the three decades? How have multiple crises, including the financial crisis, export ban, and the COVID-19 pandemic, affected the global wheat trade system from 1993 to 2022?

(2) How did the different crises interact with each other and ultimately reshape the global wheat trading network??

(3) How are countries with different income levels affected differently?

5.3 Data and Methods

5.3.1 Trade Data Collection

The global wheat trade data from 1993 to 2022 for this study were obtained from the Food and Agriculture Organization (FAO, http://www.fao.org/statistics/en/). FAO provides comprehensive and widely used agricultural trade data, frequently utilized in international trade analysis.

Previous studies have relied on this dataset to construct trade networks, develop trade-related databases, and analyze global food logistics.

Since FAO data aggregate information from multiple national and international sources, some discrepancies may exist due to variations in reporting standards and data harmonization processes. Research suggests that import-reported data are generally more reliable than export-reported data (Escaith, H), as importing countries have stronger incentives to maintain accurate records for taxation and regulatory purposes. To reduce potential inconsistencies, this study primarily uses import data and supplements them with export data where necessary. This study constructs two types of wheat trade networks based on absolute and relative trade volumes. The absolute weight network represents trade connections using the total wheat trade volume (in metric tons) exchanged between countries, capturing major trade flows and high-volume transactions. The relative weight network reflects the share of a country's total wheat exports directed to each trading partner, ensuring that smaller wheat-exporting countries are not overlooked in the network analysis.

5.3.2 Multiple Crises Cases Selection

The selection of 2008, 2010, and 2020 as key years for analysis in this study is based on their widely recognized significance as crises that had substantial and lasting effects on the global wheat trade network (Götz et al., 2010; Gutiérrez-Moya et al., 2021). While fluctuations in network properties occur throughout the study period, these three years represent distinct events that triggered systemic disruptions with long-term consequences for trade connectivity, structure, and resilience. The 2008 global financial crisis marked a turning point for international trade, including wheat markets, as financial instability led to declining trade liquidity, increased volatility in commodity prices, and export restrictions from major producers (Acharya et al., 2012; Götz et al., 2013; Fair et al., 2017). Although the immediate changes in wheat trade network metrics were not extreme, the crisis set off a series of cascading effects, including heightened concerns over food security and policy interventions that reshaped trade patterns in subsequent years. The persistence of trade restrictions and shifts in supply chain strategies following 2008 make it a critical moment for understanding the long-term structural evolution of the wheat trade network.

The 2010 Russian wheat export ban was a direct intervention in global wheat markets that had pronounced regional and international effects (Welton et al., 2011; Götz et al., 2015; Svanidze et al., 2022). While some trade network properties, such as connectance and modularity, may not exhibit abrupt changes in that specific year, the ban redefined the role of alternative suppliers and contributed to long-term trade realignments. European and Black Sea exporters gained prominence, while import-dependent nations diversified their sources, leading to enduring modifications in trade routes. The implications of this policy decision extended beyond the immediate supply constraints, reinforcing the role of government intervention in shaping food trade networks.

The 2020 COVID-19 pandemic caused unprecedented disruptions to global supply chains, yet its impact on wheat trade differed from other economic crises (Kiselev et al., 2020; Gutiérrez-Moya et al., 2020; Özden 2022). Unlike previous crises that led to fragmentation, 2020 saw an increase in trade connectivity as countries sought to secure food supplies through expanded partnerships and diversified trade routes. While the immediate structural shifts were not as pronounced as might be expected for such a large-scale disruption, the pandemic accelerated ongoing trends toward resilience and adaptation in the wheat trade network. The reorganization of supply chains and trade dependencies during this period had lasting implications for global food security.

Although the magnitude of changes in network metrics for these three years varies, their selection is justified by their recognized significance in economic and food trade research. Each crisis introduced distinct challenges that reshaped trade strategies and policies, leaving lasting imprints on the wheat trade network. By focusing on these years, this study captures not just short-term fluctuations but the broader evolution of the trade system in response to global crises.

5.3.3 Network Analysis

Network analysis offers a powerful tool for examining the structure and dynamics of complex systems, such as the global food trade. In this study, I apply network analysis methods to analyze the spatio-temporal dynamics of wheat trade on both network common metrics and compare the differences between various income levels (Figure 5.1). This approach allows for identifying crucial nodes, connections, and vulnerabilities within the system, as well as assessing how the system's structure has evolved in response to crises.

The trade volume between countries is converted to a network graph object and analyzed by the R packages 'igraph', and 'tnet', along with Python package 'cpnet' (G. Csardi, and T. Nepusz, 2006; Opsahl T, 2009; Rossa F., Dercole F., Piccardi C., 2013).

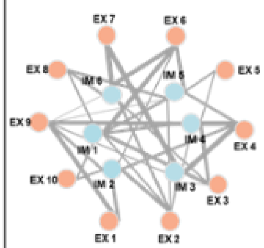
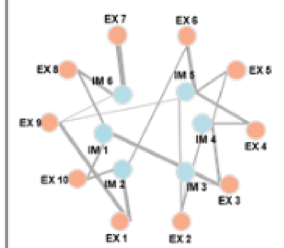
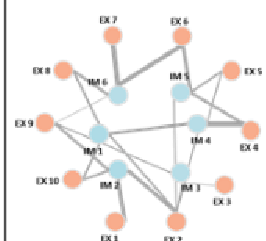
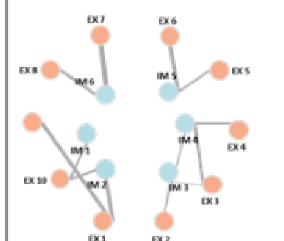
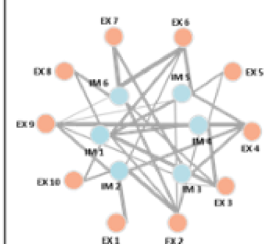
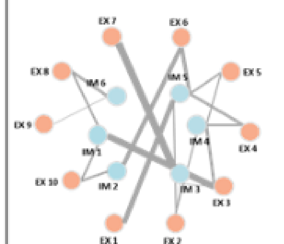
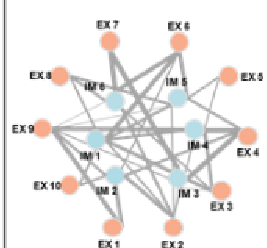
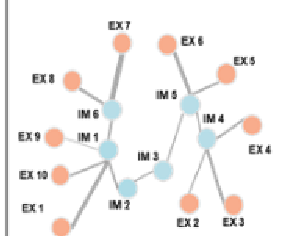
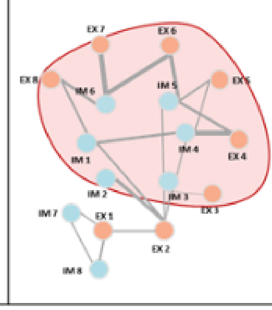
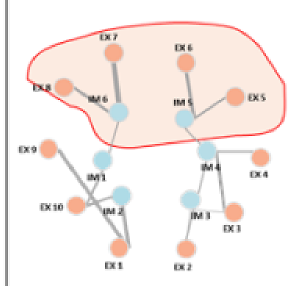
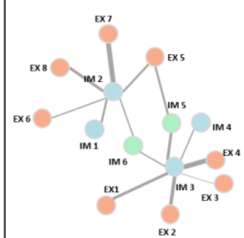
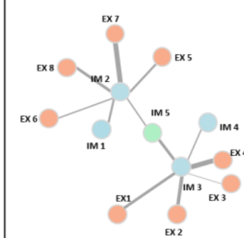
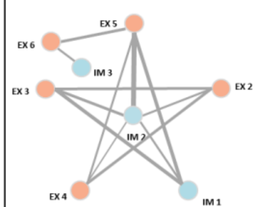
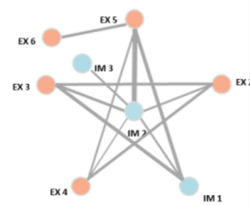
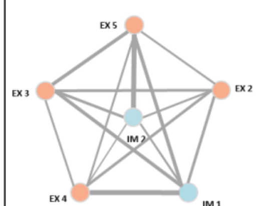
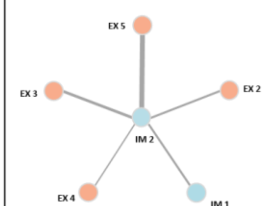
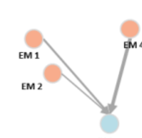
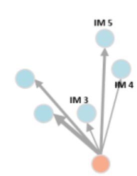
Network metric	Predicted changes with time and multiple crises	Potential effect of multiple crises on winter cereal trade network metrics	
		Before crises	After crises
Connectance	Decline if crises happened or affected trade supply chain. It represents the trade intensity of importer and exporter, and we normalize the annual trade volume as an indicator of connetance. When before the crisis, thanks to the trend of trade globalization, the network had a high connectance value, representing a trade boom between countries. After the crisis, the connectedance value is lower due to reduced production and reduced exports due to crises to the supply chain of trade caused by wars, extreme weather events, etc., or due to trade ban policies.		
Modularity	Modularity represents the strength of the partition of a network into modules. In highly modular networks, grain trade links between countries are divided into isolated groups, while in less modular networks, the interconnection of trade networks between countries is higher.		
Evenness	The diversity of both exporting and importing countries representing cereals is relatively rich and importers have a low dependence on the choice of importers. However, when polycrisis occurs, the selection becomes less, making these importers more dependent on a fixed number of exporters, causing the nodes to change from being evened connected to having strong link.		
Assortativity	Measures the tendency of nodes with similar properties or attributes to connect with each other. It reflects the level of homophily within a network. In times of crisis, assortativity may change as nodes (countries) with specific attributes face disruptions, leading to alterations in the network structure.		
Rich-club coefficient	It measures the level of connectivity between high-degree nodes relative to their maximum possible connections. A high rich-club coefficient indicates that well-connected nodes tend to connect with each other, creating a dense and influential core within the network.		

Figure 5. 1 Network metrics in global wheat trade network analysis. Nodes represent countries, with blue indicating importers and red indicating exporters, while edges represent trade relationships. Each row visualizes a different metric, including five network-level metrics—connectance, modularity, evenness, assortativity, and clustering coefficient—and five node-level

Figure 5.1 (cont'd)

metrics—rich-club coefficient, core–periphery structure, average degree, density, and modularity-based community clustering—demonstrating their structural characteristics within the trade network.

Network metric	Predicted changes with time and multiple crises	Potential effect of multiple crises on winter cereal trade network metrics	
		Before crises	After crises
Betweenness (Robustness) centrality	**The degree to which a node (a country) serves as a bridge or intermediary connecting other nodes in the system. A high betweenness centrality score indicates that a node plays a critical role in maintaining the connectivity and flow of goods within the global food system, while a low score suggests a more peripheral role. It refers to the resilience of the food system to crises or disruptions. If a node with a high betweenness centrality score were to be removed or significantly impacted (due to natural disasters, political instability, or other factors), the overall food system could become less resilient and more susceptible to disruptions.**		
Core-periphery	Core–periphery analysis distinguishes central countries with dense connections from peripheral ones with sparse links, revealing structural cohesion in trade networks.		
Clustering coefficient	Measures a node's influence by considering its connections and the importance of connected nodes. High scores indicate significant impact on food trade stability and flow. In times of crisis, eigenvector centrality could change, as key players' connections and influence may be disrupted, affecting the global food system's resilience and potentially leading to imbalances in food trade and distribution.		
Degree in	The number of trade connections a country receives, representing the number of exporters supplying food to the country.		
Degree out	The number of trade connections a country initiates, representing the number of importers that a country exports food to.		

In the wheat trade network, nodes represent individual countries, while edges (connections) represent directed wheat trade flows between them. The edge weights correspond to the volume of wheat traded between countries. This study constructs the global wheat trade network from 1993 to 2022, capturing bilateral trade relationships over time. The network structure enables an assessment of trade resilience, connectivity, and disruptions caused by crises.

This study evaluates ten key network metrics to assess the impact of crises on the global wheat trade system. These metrics include connectance, modularity, evenness, assortativity, and the rich-club coefficient of the whole trade network. And betweenness centrality, core–periphery structure, clustering coefficient, degree in, and degree out of each node properties. Each metric captures different aspects of trade structure, resilience, and vulnerability under crises. The volume of wheat trade is a fundamental indicator of globalization. Well-developed supply chains facilitate trade between countries, improving wheat accessibility, especially during crises. Conversely, counter-globalization trends, such as trade restrictions or geopolitical tensions, can reduce trade volumes and weaken network connectivity. External crises, including natural disasters, economic downturns, and conflicts, can also disrupt wheat production. This may increase demand in wheat-importing countries while reducing the export capacity of major wheat suppliers.

Changes in evenness reflect shifts in trade dependency. If wheat trade becomes concentrated among fewer exporters due to trade restrictions, importing countries face higher risks during supply crises. A decrease in modularity suggests the emergence of dominant wheat-exporting nations. This shift may lead to pricing power imbalances, increasing global food insecurity by limiting access for lower-income countries. For network analysis, we calculate weighted degree using the weighted_degree_table function. Betweenness centrality, which measures the influence of key transit countries, is computed using the betweenness function in the R ‘igraph’ package. Additional metrics, including core–periphery structure, clustering coefficient, and assortativity, are derived using functions from the same package. The core–periphery metric is calculated using the Python package cpnet, based on the Borgatti–Everett model (Borgatti & Everett, 2000; Rossa, F. D., Dercole, F., & Piccardi, C., 2013), which identifies hierarchical structures in trade networks by distinguishing densely connected “core” countries from sparsely linked “periphery” countries. This method has been applied in global food trade studies such as Chen et al. (2021). The rich-club coefficient, which identifies highly interconnected wheat-exporting hubs, is estimated using as_tnet and rich_club_coefficient_w from the ‘tnet’ package. These analyses provide a quantitative assessment of how major crises have reshaped the global wheat trade network over time.

5.3.4 Generalized Additive Model (GAM)

The GAM is a flexible statistical approach used to capture nonlinear relationships between variables. Unlike traditional linear regression models, which assume a constant effect of explanatory variables, GAM allows for smooth, data-driven relationships by using nonparametric smoothing functions. This feature makes GAM particularly useful for analyzing long-term trends and fluctuations in complex time series data, such as global trade flows.

In this study, we employ GAM to model the temporal dynamics of wheat trade for key countries, including the United States, Brazil, Russia, and Egypt, from 1993 to 2022. GAM is used to estimate the trends in wheat export and import volumes, providing a continuous and smoothed representation of trade patterns over time. This approach enables us to identify key periods of growth, decline, and stabilization in wheat trade, which would be difficult to capture using simple linear trends.

The GAM model is specified as follows:

$$Y_t = \beta_0 + f(t) + \epsilon_t$$

where Y_t represents wheat trade volume at time ttt, β_0 is an intercept, $f(t)$ is a smooth function of time that captures nonlinear trends, and $\epsilon\epsilon_t$ is the error term.

5.3.5 Synthetic Control Method

The Synthetic Control Method (SCM) is a data-driven approach designed to estimate causal effects by constructing a counterfactual scenario for a treatment unit that has experienced an intervention or crisis (Abadie & Gardeazabal, 2003; Abadie et al., 2010). Unlike traditional difference-in-differences (DID) methods, SCM does not assume parallel trends but instead constructs a synthetic control unit—a weighted combination of untreated units that best approximates the characteristics of the treated unit before the intervention (Goodman-Bacon, A, 2021; Callaway& Sant'Anna, 2021, Suh et al., 2024). This enables a more accurate estimation of the impact of a particular crisis by comparing observed outcomes with an estimated counterfactual trajectory (Kaul et al., 2015; Billmeier & Nannicini, 2013).

The SCM has been widely applied in economic and trade studies to assess the impact of interventions on market dynamics. Previous research has used SCM to evaluate the consequences of trade agreements (Billmeier & Nannicini, 2013) and economic sanctions (Hinrichs, 2012), providing insights into how policy changes alter international trade flows. In commodity markets, SCM has been employed to measure the effects of oil price fluctuations (Becker, 2021) and agricultural trade restrictions (Abadie, 2019), demonstrating its capability to isolate interventions in supply chains. Similarly, it has been used to analyze macroeconomic policy interventions, such as the economic consequences of Brexit (Campos et al., 2019) and the effects of monetary policy on food security (Arndt et al., 2016). More recently, SCM has been applied to quantify the trade disruptions caused by COVID-19 and its impact on global supply chains (Kichurchak et al., 2024), highlighting its relevance in crisis assessment. Given these applications, SCM is particularly well-suited for this study, as it enables the construction of a counterfactual wheat trade network that estimates what trade patterns would have been in the absence of major crises. By applying SCM, this study can disentangle the specific impacts of the crises distinguished by financial crisis, export ban, and the COVID-19 pandemic on wheat trade network, distinguishing their individual effects on the structure, resilience, and connectivity of the global wheat trade network. This approach provides a robust scenario simulation framework, allowing for a precise decomposition of crisis-driven disruptions and offering deeper insights into the mechanisms by which these crises have reshaped international wheat trade.

This study applies the SCM to estimate the impact of three major crises distinguished by financial crisis, export ban, and the COVID-19 pandemic on global wheat trade. The analysis incorporates economic, infrastructural, and production-related factors that influence wheat trade resilience. Key predictors include labor force participation rates, GDP per capita, government borrowing capacity, income inequality, trade infrastructure, and wheat production indicators, all sourced from the World Bank (Van Der Mensbrugghe, D., 2016). These covariates capture structural conditions that shape trade performance and are averaged over a pre-crisis period to ensure that the synthetic control unit closely matches the characteristics of affected countries before the intervention.

The SCM model estimates the difference between actual wheat trade volumes and the counterfactual projection, expressed as:

$$Y_{it} = Y_{it}^{N} + D_{it}\tau_{it}$$

where Y_{it} represents observed wheat trade for country i at time t, Y_{it}^N denotes the estimated counterfactual trade volume, D_{it} is a binary indicator for crisis exposure, and τ_{it} captures the crisis-induced deviation in wheat trade.

Since SCM constructs country-specific counterfactuals based on tailored covariates, the results are not directly aggregable across countries or income groups. This limitation prevents us from generating group-level estimates or figures that show the simultaneous effect of all three crises. Control variables such as labor force participation and logistics performance indices vary in form and availability across countries, making cross-country synthesis infeasible.

To construct the synthetic control unit, weights are assigned to donor countries so that the weighted sum of their wheat trade patterns minimizes the difference from the treated country's pre-crisis trajectory. The counterfactual estimate is given by:

$$\hat{Y}_{1t}^N = \sum_{j=2}^{J+1} w_j Y_{jt}$$

where w_j represents the optimal weights assigned to each donor country, constrained to sum to one.

The estimated impact of the crisis is then computed as the difference between observed and counterfactual trade:

$$\tau_{1t} = Y_{1t} - \hat{Y}_{1t}^N$$

A large deviation in τ_{1t} indicates that the crisis altered wheat trade beyond expected market fluctuations.

Implementation is conducted in **R using the tidysynth package**, with wheat trade data from 1993 to 2022 (Eric Dunfor, 2020; Lamba et al., 2023). The model assigns donor weights based on **pre-crisis economic and trade conditions**, optimizes them for best fit, and estimates synthetic wheat trade trajectories. By comparing observed and counterfactual values, this approach quantifies how different crises have reshaped global wheat trade networks and assesses their impact on trade resilience across countries.

5.3.6 Scenario Simulation Framework

To assess the combined and individual effects of multiple global crises on wheat trade, we developed a scenario simulation framework based on pre-crisis export trends. This method estimates how trade would have evolved under different crisis conditions and helps isolate the contribution of each event. Four scenarios were constructed: (1) a baseline assuming no crisis occurred, (2) a scenario incorporating only the 2008 financial crisis, (3) a scenario including both the 2008 financial crisis and the 2010 Russian wheat export ban, and (4) the actual observed exports, which reflect the combined effects of all three crises, including the 2020 COVID-19 pandemic.

Each scenario was simulated using linear extrapolation based on data before the first structural break. By comparing simulated export trajectories with actual values, we estimated the effects of each crisis and their cumulative influence on wheat trade over time. The stepwise structure of the scenarios allowed us to identify how each additional crisis shaped deviations from the no-crisis baseline. This simulation was applied globally and to four income-level country groups to evaluate spatial disparities in exposure, adaptation, and resilience. The approach complements the network and SCM analyses by quantifying long-term crisis effects on trade performance across diverse economic contexts.

5.4 Results

5.4.1 Dynamics of the Global Wheat Trade Network

The global wheat trade network exhibited substantial structural shifts over the past three decades, with major disruptions occurring in 2008–2009, 2010–2011, and 2020–2021 (Figure 5.2). These crises triggered noticeable changes in network connectivity, trade modularity, evenness, assortativity, and the dominance of key exporters. The 2008 financial crisis led to a sharp contraction in trade connectivity, reflected in a lower connectance value, as countries imposed export restrictions and reduced the number of trading partners. Despite this fragmentation, modularity remained high, suggesting that while global trade diminished, regional trade communities persisted. Evenness declined slightly, indicating a stronger concentration of wheat trade among a few dominant exporters. The assortativity value stayed negative, reinforcing the trend of trade between structurally different nations rather than within homogeneous economic blocs. The rich-club coefficient remained stable, indicating that the core group of major exporters continued to maintain strong internal connectivity despite overall trade reductions. By 2009, trade connectivity showed partial recovery, but the increased modularity suggested that trade expansions occurred primarily within established regional trade blocs rather than through broader global reintegration.

The 2010–2011 Russian wheat export ban marked another large disruption, influencing global wheat trade patterns. Following the ban, connectance rebounded as nations sought alternative suppliers, mitigating the immediate trade crisis. However, modularity remained elevated, emphasizing that trade restructuring occurred within distinct regional clusters rather than through full globalization. Evenness increased, reflecting a more balanced distribution of trade, as importers diversified their sources to ensure food security. Meanwhile, the assortativity value remained relatively stable, highlighting continued trade between different economic groups rather than within homogenous trade zones. The rich-club coefficient declined slightly, suggesting a temporary weakening of interconnections among dominant exporters as new trade routes emerged.

The COVID-19 pandemic in 2020–2021 introduced another major structural transformation in the wheat trade network. Contrary to initial expectations of market contraction, connectance surged, surpassing pre-pandemic levels and indicating that global wheat trade became more interconnected. This rise in connectivity was accompanied by a decline in modularity, reflecting enhanced market integration and reduced fragmentation compared to previous crises. Evenness peaked at its highest level in three decades, demonstrating a broader distribution of wheat trade across countries. Notably, assortativity moved closer to zero, signaling a weakening of prior trade preferences and a shift toward a more adaptive and flexible global trade system. The rich-club coefficient rebounded, suggesting the reinforced connectivity of major wheat-exporting nations, ensuring trade stability amid pandemic-induced supply chain disruptions. The evolution of these network properties underscores the adaptive nature of the global wheat trade system in response to economic and geopolitical crises. While each crisis introduced periods of fragmentation and consolidation, the long-term trend suggests increasing connectivity, diversification of trade flows, and resilience among major exporters.

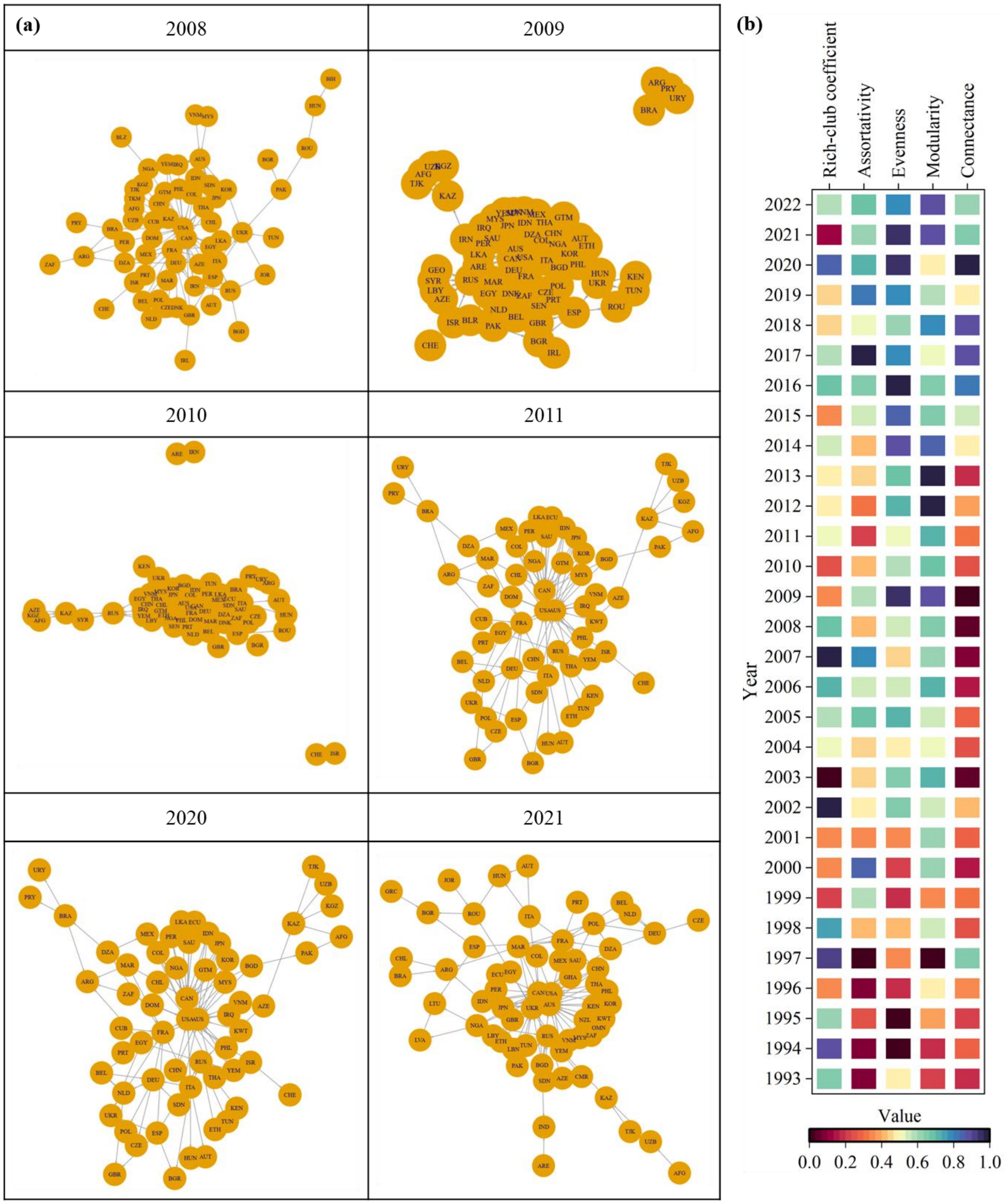


Figure 5. 2 Evolution of the global wheat trade network and network metrics over time. Visualization of the global wheat trade network structure in selected years (1993, 2008, 2010, and 2020), illustrating the evolution of trade communities and connectivity patterns. Nodes represent countries, with edges indicating trade relationships. The colored regions highlight modular structures within the network. (b) Temporal trends of key network metrics, including connectance, modularity, evenness, rich-club coefficient, and assortativity value, from 1993 to 2022, capturing the long-term dynamics of global wheat trade.

5.4.2 Wheat with Multiple Crises

The role of individual countries in the wheat trade network evolved considerably over time, particularly in response to crises in 2008, 2010, and 2020 (Figure 5.3). The financial crisis of 2008 led to a decline in betweenness centrality, reflecting disruptions in trade intermediaries and reduced global trade coordination. The average betweenness centrality value was lower than in subsequent years, indicating that fewer countries acted as key transit hubs for wheat trade. The disruption in intermediary roles coincided with a decline in wheat availability in several import-dependent regions, prompting governments to impose trade restrictions to safeguard domestic supplies. At the same time, eigenvector centrality remained relatively low, suggesting a concentration of trade power among a few dominant exporters. The clustering coefficient dropped to its lowest level, highlighting the fragmentation of regional trade networks as economic instability disrupted established trade relationships.

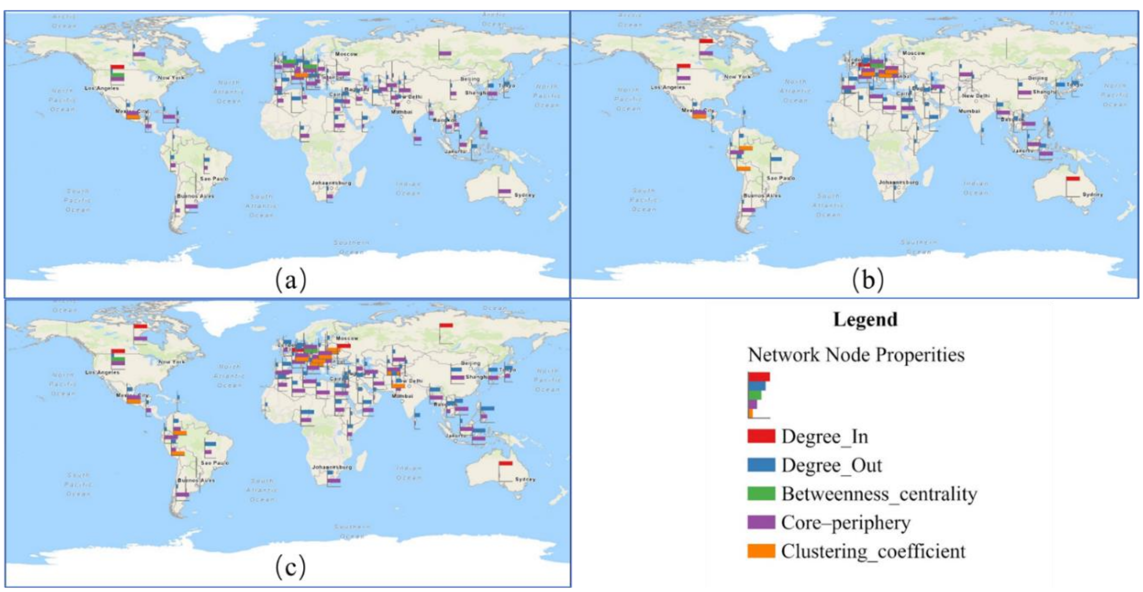


Figure 5. 3 Global wheat trade network: node centrality and connectivity analysis. Global wheat trade network's structural properties, highlighting key network metrics for different countries. Panels (a), (b), and (c) illustrate the spatial distribution of network node properties of 2008, 2010, and 2020, including degree in (red), degree out (green), betweenness centrality (blue), core-periphery (purple), and clustering coefficient (orange).

By 2010, the network showed signs of reorganization. The Russian wheat export ban altered trade routes, increasing the betweenness centrality of several European and Black Sea countries as new suppliers emerged. The mean betweenness centrality value rose, indicating that more countries played intermediary roles in the global wheat supply chain. Countries that had previously relied on Russia as a major supplier diversified their imports, strengthening connections with alternative exporters such as Kazakhstan, Ukraine, and EU nations. The core–periphery scores of several Eastern European countries increased, reflecting their transition from peripheral to more central positions within the global trade network. The clustering coefficient nearly doubled compared to 2008, signaling a re-establishment of regional trade connections and the formation of new supplier-importer relationships. Despite the trade reconfiguration, lingering concerns over price volatility and supply security prompted some governments to pursue longer-term trade agreements to mitigate future crises.

In 2020, the COVID-19 pandemic introduced another major crisis, but its impact on node-level properties differed from previous crises. Betweenness centrality dropped largely to its lowest observed value, indicating a shift toward more direct trade relationships and reduced reliance on intermediary nations. This suggests that countries sought to secure supply chains through more direct agreements rather than relying on traditional trade hubs. Governments prioritized national food security by minimizing dependence on intermediaries and reinforcing bilateral trade relationships, reducing logistical uncertainties. Core–periphery values declined for many top exporters, reflecting a weakening of structural hierarchy and a flattening of trade importance between core and peripheral countries. However, the clustering coefficient remained stable, suggesting that despite initial disruptions, regional wheat trade networks maintained their cohesion, preventing widespread breakdowns in supply. The resilience of regional trade clusters highlights the increasing reliance on geographically closer partners, a trend that could persist as nations seek to buffer future supply chain crises.

These changes highlight the adaptability of global wheat trade networks in response to interventions. While 2008 and 2010 saw shifts in trade influence and restructuring of intermediary roles, 2020 marked a transition toward a more decentralized and regionally stable trade system. The decline in betweenness centrality and core–periphery structure, alongside the resilience of clustering patterns, suggest that nations have increasingly diversified their trade strategies, reducing vulnerability to interventions and strengthening regional partnerships in global wheat trade. The shifts in node-level properties underscore the evolving dynamics of global wheat markets, with an increasing emphasis on resilience, redundancy, and adaptive trade strategies to ensure food security amid global uncertainties.

5.4.3 Key players of global wheat trade

To comprehensively analyze the structural dynamics of the global wheat trade network, we select four representative countries—the United States (USA), Russia, Brazil, and Egypt—based on their economic classifications and strategic roles in the trade system. These countries are chosen from distinct income groups: high-income (USA), upper-middle-income (Russia), lower-middle-income (Brazil), and low-income (Egypt). The USA serves as a dominant wheat exporter, shaping global supply chains and influencing market stability. Russia, an emerging powerhouse in wheat production, has largely impacted global trade flows, particularly in recent decades. Brazil, traditionally an importer, plays a crucial role in the South American market, reflecting the trade dependencies of developing economies. Egypt, one of the world’s largest wheat importers, represents food security challenges faced by low-income nations reliant on international trade.

Together, these four countries capture key trade dynamics across income levels, making them essential focal points for studying the resilience and evolution of the global wheat trade network.

USA:

From 1993 to the early 2000s, the GAM fit indicates a steady increase in U.S. wheat exports, reflecting strong global demand, trade liberalization, and favorable agricultural policies. The trade chord analysis from 1993 shows a broad network of trading partners, with a concentration of high-income (red) and upper-middle-income (orange) importers. The U.S. maintained strong wheat trade relationships with North America, Western Europe, and developed Asian economies such as Japan and South Korea. While lower-middle-income (blue) and low-income (green) countries participated in trade, their share remained limited. This period marked the height of U.S. wheat dominance before competition from emerging exporters reshaped the global market.

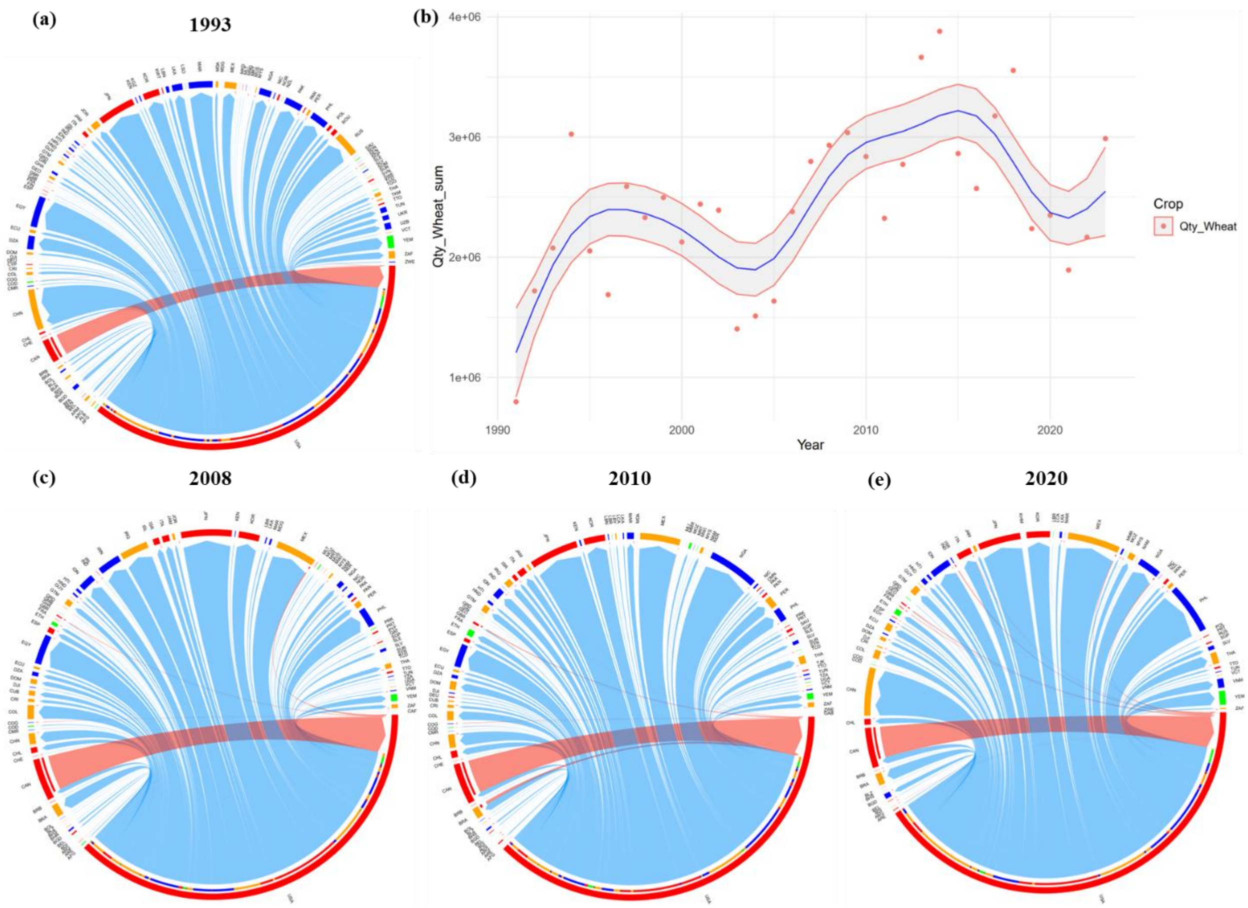


Figure 5. 4 Evolution of U.S. wheat trade networks and export dynamics from 1993 to 2020. The figure presents the structural evolution of U.S. wheat trade networks alongside export dynamics over three decades. The (a) displays the 1993 wheat trade chord diagram, illustrating the trade relationships between the U.S. and its trading partners. The (b) shows the generalized additive model (GAM) fit of U.S. wheat export volumes over time, with the red points representing observed trade values, the blue line indicating the fitted trend, and the shaded area representing confidence intervals. The bottom panels depict wheat trade chord diagrams for 2008 (c), 2010 (d), and 2020 (e), highlighting shifts in trade relationships before and after major crises. The chord diagrams use color-coded arcs to represent different income-level groups among trade partners, with blue indicating lower-middle-income countries, orange representing upper-middle-income countries, red for high-income countries, and green for low-income countries. The width of the connecting bands indicates the trade volume between the U.S. and its respective trade partners in each given year.

The 2008 financial crisis triggered a downturn in U.S. wheat exports, as reflected in the GAM trend, which shows a sharp decline during this period. Economic instability reduced trade liquidity and increased price volatility, leading to a contraction in export volumes. However, the chord diagram for 2008 does not show a dramatic reduction in the number of trading partners, suggesting that while trade volume declined, the structural composition of wheat importers remained relatively stable. High-income countries remained key importers, though their dominance slightly weakened as economic pressures led to import reductions. The share of upper-middle-income and lower-middle-income countries increased slightly, indicating that U.S. wheat was still reaching developing markets that were less affected by the financial crisis.

In 2010, the Russian wheat export ban led to a temporary surge in U.S. wheat exports, as observed in the GAM results. Export volumes rebounded quickly as countries that had relied on Russian wheat sought alternative suppliers. The chord diagram for 2010 highlights an expansion in the number of trade connections with lower-middle-income and upper-middle-income countries, particularly in Africa, the Middle East, and Southeast Asia. This shift underscores the adaptability of U.S. wheat trade, as it gained access to new markets during a period of supply disruption. While high-income countries continued to be major buyers, the trade network had become more diversified, with developing nations playing an increasingly important role.

The 2020 COVID-19 pandemic introduced another large disruption, but unlike previous crises, its impact on U.S. wheat exports followed a different pattern. The GAM fit indicates an initial decline in exports, likely due to logistical constraints and temporary restrictions, followed by a rapid recovery as supply chains adapted. The trade chord diagram for 2020 shows a relatively stable set of trading partners, suggesting that despite pandemic-related challenges, U.S. wheat trade networks remained intact. High-income countries continued to be key buyers, but lower-middle-income and low-income countries exhibited greater volatility, likely due to economic uncertainties and supply chain constraints. Upper-middle-income countries emerged as particularly stable trade partners, reinforcing the importance of economic resilience in shaping trade flows during global disruptions.

By 2022, the GAM fit suggests a stabilization in U.S. wheat exports, though volumes remained below historical peaks. The long-term trajectory points to an increasingly competitive global wheat market, where the U.S. must contend with shifting demand patterns and growing competition from other major exporters. The income structure of trade partners, as shown in the chord analysis over the decades, highlights a gradual diversification of U.S. wheat markets. While high-income countries continue to be core buyers, the increasing role of developing economies underscores the need for flexible trade policies and strategic market adaptation.

Brazil:

The wheat trade dynamics of Brazil, a lower-middle-income country, from 1993 to 2022 reflect its evolving role in the global market as both an importer and, more recently, an emerging exporter. The generalized additive model (GAM) fit captures fluctuations in Brazil's wheat trade volumes, while trade chord diagrams for 1993, 2008, 2010, and 2020 illustrate structural shifts in its trade partnerships and income-level composition of trade partners.

The GAM fit reveals a steady increase in Brazil's wheat imports from 1993 to the early 2000s, reflecting the country's reliance on external suppliers due to domestic production constraints. The 1993 trade chord diagram highlights a high concentration of trade with high-income countries, particularly the United States, Canada, France, and Switzerland, as well as Argentina and Uruguay. Argentina, as a key regional supplier, dominated Brazil's wheat imports due to geographic proximity and trade agreements within Mercosur. The composition of trade partners at this stage reflects Brazil's strong dependence on a few high-income and upper-middle-income wheat-exporting nations, with minimal engagement with lower-middle-income or low-income suppliers.

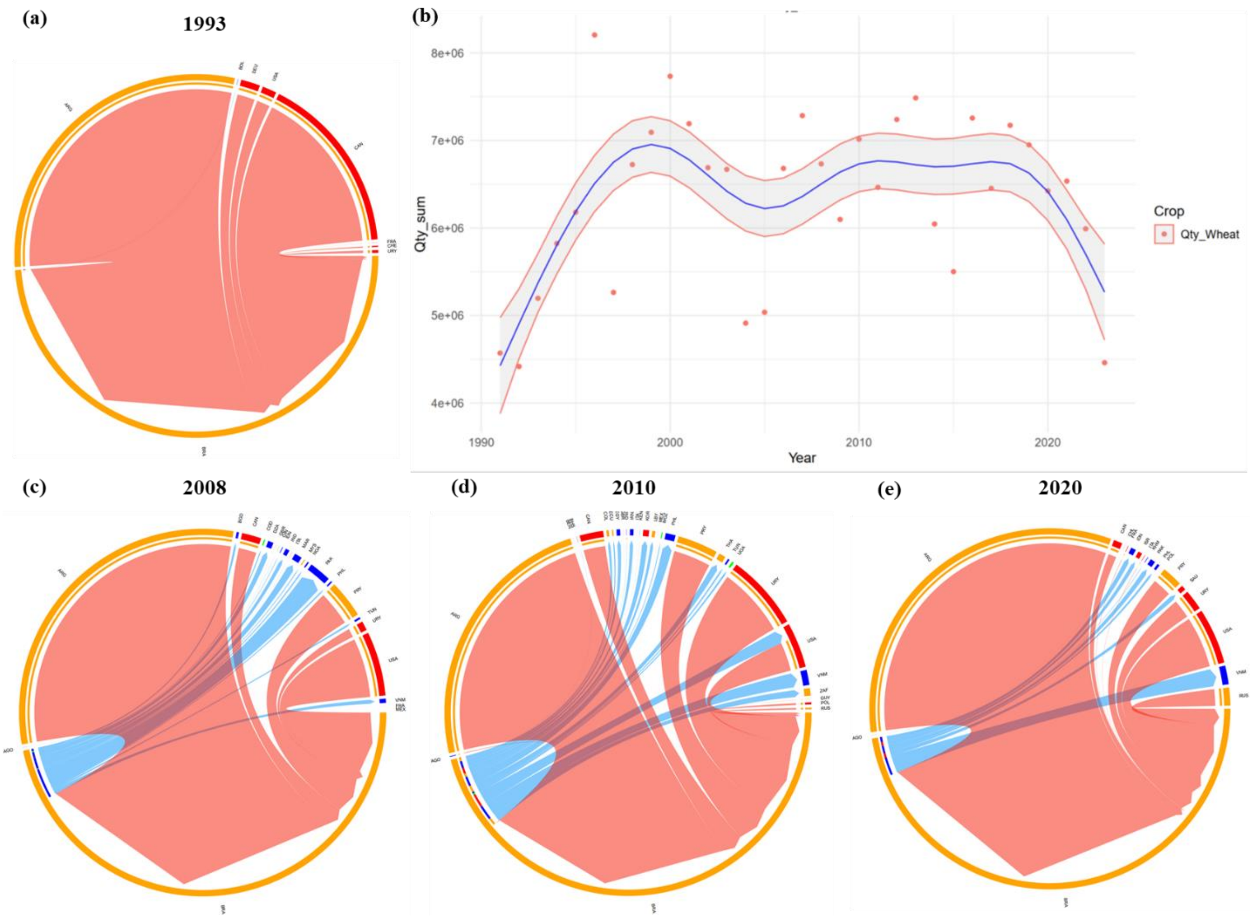


Figure 5. 5 Evolution of Brazil's wheat trade networks and import dynamics from 1993 to 2020. The figure presents the structural evolution of Brazil's wheat trade networks alongside import dynamics over three decades. The (a) the 1993 wheat trade chord diagram, illustrating Brazil's primary wheat suppliers and trade relationships. The (b) shows the generalized additive model (GAM) fit of Brazil's wheat import volumes over time, with red points representing observed trade values, the blue line indicating the fitted trend, and the shaded area representing confidence intervals. The bottom panels depict wheat trade chord diagrams for 2008 (c), 2010 (d), and 2020 (e), highlighting shifts in trade relationships before and after major crises. The chord diagrams use color-coded arcs to represent different income-level groups among trade partners, with blue indicating lower-middle-income countries, orange representing upper-middle-income countries, red for high-income countries, and green for low-income countries. The width of the connecting bands represents the trade volume between Brazil and its respective wheat suppliers in each given year.

By 2008, the financial crisis introduced economic volatility, but Brazil's wheat trade remained relatively stable, as seen in the GAM trends. The trade chord diagram for 2008 shows an increase in the number of lower-middle-income partners (blue), including Indonesia, India, and Nigeria, suggesting a diversification of wheat suppliers beyond traditional sources. However, Argentina and the United States remained dominant. This diversification likely reflects Brazil's strategic efforts to hedge against supply risks, particularly during economic uncertainty, while still maintaining strong ties with historical trade partners.

The 2010 Russian wheat export ban had a more pronounced effect on Brazil's trade composition, as seen in both the GAM fit and the 2010 chord diagram. The GAM results show an initial dip followed by a recovery, indicating that while trade volumes briefly declined, Brazil quickly adapted by expanding partnerships with alternative suppliers. The trade chord diagram reveals a further increase in lower-middle-income country trade, including Kenya, Mozambique, and Vietnam, alongside new high-income suppliers such as South Korea and Poland. Argentina and the United States continued to be major sources, but Brazil's trade network had become more diverse compared to earlier years. This period highlights the increasing role of developing economies in Brazil's wheat trade, driven by shifts in global supply availability.

The COVID-19 pandemic in 2020 brought new challenges, but Brazil's wheat trade remained resilient, as reflected in the GAM trends. The initial disruption in trade logistics led to a temporary drop in imports, but a swift recovery followed as global markets adjusted. The 2020 trade chord diagram shows a stable core network, with Argentina, the United States, and Uruguay remaining primary suppliers. Notably, Russia emerged as a new trade partner, marking a shift toward greater diversification in global wheat sourcing. Additionally, Saudi Arabia and

Pakistan appeared as importers, indicating that Brazil was increasingly engaging in wheat trade beyond just imports, possibly laying the groundwork for its role as a wheat exporter.

By 2022, the GAM fit suggests stabilization in trade volumes, with Brazil maintaining a diversified supplier base while exploring export opportunities. The long-term trajectory indicates a transition from heavy dependence on high-income suppliers to a more balanced trade network, incorporating lower-middle-income and upper-middle-income partners. The chord diagrams demonstrate Brazil's shift from a trade structure dominated by a few high-income suppliers to a more resilient and adaptable network, better positioned to navigate global economic and supply chain disruptions.

Russia:

It shows a consistent decline in wheat imports from the 1990s to the early 2000s, followed by a gradual stabilization at low levels, reflecting the country's shift toward self-sufficiency and eventual dominance as an exporter. The trade chord diagrams for 1993, 2008, 2010, and 2020 further illustrate the structural evolution of Russia's wheat trade relationships, highlighting the expansion of its export network, the diversification of trading partners, and shifts in trade flows due to crises. In 1993, Russia's wheat trade network was characterized by heavy dependence on imports, primarily from high-income and upper-middle-income countries. The chord diagram for this period shows a dominant share of imports coming from the United States, Canada, and European suppliers, reflecting Russia's reliance on external sources to meet domestic demand in the post-Soviet economic transition. The GAM fit indicates a declining trend in wheat imports, suggesting that domestic production was gradually increasing, reducing the need for foreign wheat supplies.

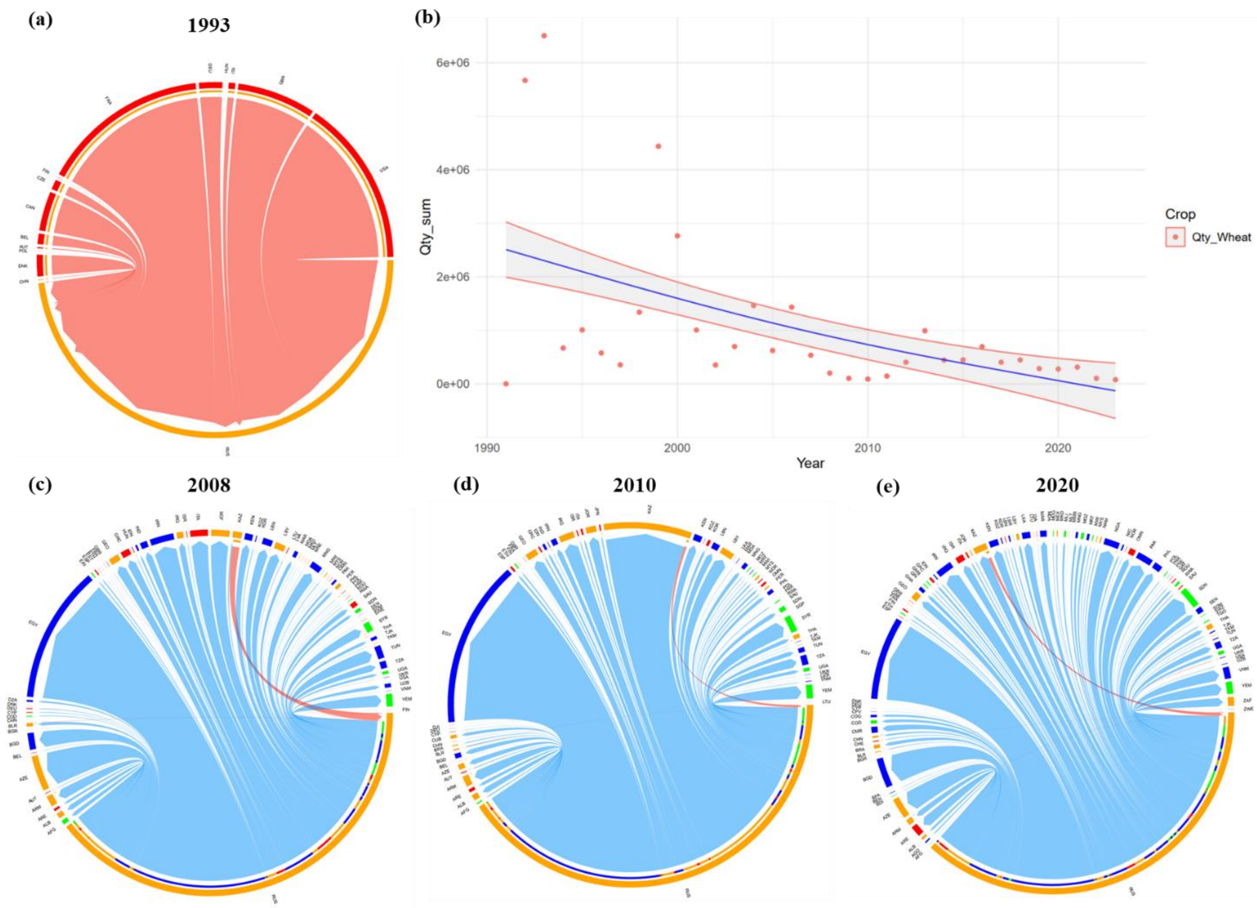


Figure 5. 6 Evolution of Russia's wheat trade from import dependence to export dominance (1993–2020). The figure illustrates the evolution of Russia's wheat trade network and import-export dynamics over three decades. The (a) displays the 1993 wheat trade chord diagram, showing Russia's reliance on wheat imports, primarily from high-income and upper-middle-income countries. The (b) presents the generalized additive model (GAM) fit of Russia's wheat trade volumes over time, with red points representing observed trade values, the blue line showing the fitted trend, and the shaded area representing confidence intervals. The bottom panels depict wheat trade chord diagrams for 2008 (c), 2010 (d), and 2020 (e), illustrating Russia's transition from an importer to a major global wheat exporter. The chord diagrams use color-coded arcs to represent different income-level groups among trade partners: blue for lower-middle-income countries, orange for upper-middle-income countries, red for high-income countries, and green for low-income countries. The width of the connecting bands represents the volume of wheat traded between Russia and its partners in each given year.

By 2008, Russia had made large progress in expanding its wheat production and export capacity. The trade chord diagram for this year reflects the country's emergence as a regional wheat supplier, with exports primarily directed to lower-middle-income and upper-middle-income countries. Notably, Russia's role as an importer had diminished considerably, aligning with its growing presence in global wheat markets. However, the financial crisis of 2008 introduced economic instability that influenced trade relationships. While high-income trade partners remained important, Russia's growing ties with Middle Eastern, African, and Asian markets suggest that trade diversification strategies were already taking shape before the major supply disruptions of 2010. The 2010 Russian wheat export ban marked a critical turning point in Russia's wheat trade. The GAM fit does not show a major deviation in import volumes, but the trade chord diagram illustrates the immediate impact on Russia's export network. Wheat exports were temporarily halted, forcing key trade partners, including Egypt and Turkey, to seek alternative suppliers. The sudden restriction of exports underscores Russia's growing influence in global wheat markets, as the absence of Russian wheat created large disruptions in international trade flows. This period also led to long-term shifts in Russia's trade strategy, reinforcing its commitment to expanding domestic production and securing stable trade agreements to prevent future supply crises.

By 2020, Russia had established itself as a dominant wheat exporter, with a trade network spanning lower-middle-income and upper-middle-income countries across Africa, the Middle East, and Asia. The COVID-19 pandemic posed logistical challenges, but the GAM fit suggests that Russia's wheat trade remained relatively stable, with exports continuing despite global disruptions. The chord diagram for 2020 highlights Russia's strong ties with key importers, particularly Egypt, Turkey, and countries in Sub-Saharan Africa, demonstrating the resilience of its wheat export network. Unlike previous crises, where trade was largely disrupted, Russia's wheat trade in 2020 exhibited greater stability, reflecting a more mature, diversified export market that had adapted to crises.

Egypt:

In 1993, Egypt's wheat imports were primarily sourced from high-income countries, with the United States, Canada, France, Germany, Italy, and Sweden among its main suppliers. The trade chord diagram shows a strong reliance on Western exporters, reflecting long-established trade relationships and the dominance of traditional grain-exporting nations in global markets. The GAM fit suggests a steady increase in wheat imports during this period, aligning with population growth and rising domestic demand. The reliance on high-income suppliers was consistent with Egypt's trade preferences in the early 1990s when government policies prioritized stable, established sources for securing wheat supplies. By 2008, Egypt's wheat trade network had begun to diversify. The trade chord diagram shows an expansion of suppliers, with Ukraine and Russia emerging as key exporters alongside Argentina and Australia. While high-income countries like the United States and France remained important, the increased presence of Eastern European and South American suppliers reflects a shift in Egypt's sourcing strategy, likely driven by cost considerations and growing competition in the global wheat market. The GAM fit reveals no sharp decline in trade volume, suggesting that despite financial instability worldwide, Egypt was able to sustain its wheat imports by broadening its supplier base. This diversification likely helped mitigate potential disruptions caused by the global economic downturn.

Figure 5. 7 Evolution of Egypt's wheat trade network and import patterns from 1993 to 2020. The figure illustrates the evolution of Egypt's wheat trade network and import trends over three decades. The (a) displays the 1993 wheat trade chord diagram, showing Egypt's reliance on wheat imports, primarily from high-income countries. The (b) presents the generalized additive model (GAM) fit of Egypt's wheat import volumes over time, with red points representing observed trade values, the blue line showing the fitted trend, and the shaded area representing confidence intervals. The bottom panels depict wheat trade chord diagrams for 2008 (c), 2010 (d), and 2020 (e), illustrating Egypt's shifting trade partnerships and supplier diversification over time. The chord diagrams use color-coded arcs to represent different income-level groups among trade partners: blue for lower-middle-income countries, orange for upper-middle-income countries, red for high-income countries, and green for low-income countries. The width of the connecting bands represents the volume of wheat traded between Egypt and its partners in each given year.

In 2010, the Russian wheat export ban disrupted trade flows, forcing Egypt to adjust its import strategy. The chord diagram shows an increased reliance on alternative suppliers, particularly Ukraine, Argentina, and Canada, as Russia temporarily withdrew from the market. Egypt's trade relationships with European and North American exporters remained intact, but the shift toward Eastern European and Latin American suppliers highlights the adaptability of its trade network. The GAM fit captures a brief decline followed by a recovery, consistent with Egypt's ability to navigate supply crises through trade diversification. Notably, wheat imports from Middle Eastern and North African countries, such as Jordan and Lebanon, also appeared in the 2010 network, indicating an effort to secure supplies from regional partners during periods of uncertainty. The COVID-19 pandemic in 2020 introduced another phase of adaptation in Egypt's wheat trade. Unlike the disruptions caused by the financial crisis and the Russian export ban, the pandemic prompted logistical challenges rather than a direct supply shortage. The chord diagram for 2020 shows a continued reliance on Russia and Ukraine, alongside high-income suppliers like the United States, France, and Italy. However, a notable increase in wheat imports from lower-middle-income and low-income countries, including Sudan, Ethiopia, and Somalia, reflects a shift toward regional trade partnerships, possibly as part of broader food security strategies in response to supply chain uncertainties. The GAM fit indicates a temporary decline at the onset of the pandemic, followed by a rapid recovery, suggesting that Egypt's wheat trade network had become more resilient compared to previous crises.

By 2022, Egypt's wheat trade appeared to stabilize, with Russia and Ukraine playing dominant roles, alongside long-standing suppliers from North America and Europe. The long-term trajectory of Egypt's wheat trade suggests a progressive shift from reliance on high-income Western suppliers toward a more diversified network incorporating Eastern European, Latin American, and regional partners. The interplay between GAM trends and trade chord analysis highlights Egypt's increasing capacity to adapt to crises, ensuring food security despite economic fluctuations and geopolitical disruptions.

5.4.4 Crisis-Induced Trade Adjustments and Structural Shifts in Global Wheat Markets

Egypt is selected as the focus of this analysis due to its status as one of the world's largest wheat importers, making it highly sensitive to crises. Unlike major exporters such as the U.S. and Brazil, whose trade dynamics are influenced by global demand, Egypt's wheat trade fluctuations are largely supply-driven. This makes Egypt an ideal case for examining how different crises reshape import-dependent economies and, by extension, the global wheat trade network. The SCM results for Egypt in 2008, 2010, and 2020 reveal substantial deviations between actual and predicted trade, highlighting how crises force rapid adjustments in import strategies, trade relationships, and market resilience.

In 2008, the financial crisis disrupted global credit markets, increasing volatility in commodity prices and trade financing. The SCM results show that Egypt's actual wheat imports closely tracked synthetic estimates, suggesting that while the financial crisis created economic uncertainty, it did not immediately translate into a severe trade contraction. However, Egypt's observed trade fluctuated more than the synthetic model predicted, reflecting short-term adjustments to changing price dynamics and supplier reliability. The ability to maintain relatively stable wheat imports during a financial downturn underscores the role of government policies and strategic trade partnerships in mitigating demand-side crises. The 2010 Russian wheat export ban had a much more pronounced impact, creating the largest observed deviation from synthetic trade estimates. Under normal conditions, Egypt's wheat trade would have followed a stable trajectory, as projected by the synthetic model. Instead, actual imports spiked sharply beyond predicted levels, reflecting Egypt's aggressive response to a major supply crisis. The SCM results indicate that Egypt's wheat imports diverged from previous patterns, reinforcing evidence from the trade chord analysis that Egypt rapidly diversified its supplier base. The surge in actual imports, particularly from Ukraine, Argentina, and Canada, suggests that Egypt anticipated prolonged disruptions and acted preemptively to secure alternative sources and stabilize domestic food security. The magnitude of this deviation highlights how supply crises lead to immediate and large-scale trade restructuring, in contrast to financial crises, which tend to produce more gradual adjustments.

By 2020, the COVID-19 pandemic introduced a different kind of disruption, primarily affecting logistics, supply chain continuity, and government trade restrictions. The SCM results for this period reveal an initial decline in actual trade compared to synthetic estimates, reflecting early-stage logistical constraints and trade policy uncertainties. However, this gap closed rapidly, and actual trade even exceeded synthetic predictions later in the year. Unlike 2010, where Egypt's response was characterized by supplier diversification, the 2020 crisis led to greater reliance on regional trade, as seen in increased wheat imports from Sudan, Ethiopia, and Somalia. The SCM results suggest that Egypt had adapted to global supply chain risks by integrating shorter-distance suppliers into its network, ensuring continued wheat availability despite international shipping disruptions.

The SCM results across these three crises reveal a clear pattern: economic, supply, and logistical crises produce different types of trade disruptions, but their cumulative effect reshapes the structure of global wheat trade over time. The 2008 crisis tested Egypt's financial capacity to sustain wheat imports under economic pressure, while the 2010 supply crisis forced a structural shift toward diversification. In 2020, the pandemic reinforced the importance of flexible trade networks, accelerating Egypt's regional trade integration as a risk-management strategy. The SCM deviations show that crisis responses are not temporary fluctuations but contribute to long-term market transformations, reinforcing the idea that trade networks evolve in response to repeated crises.

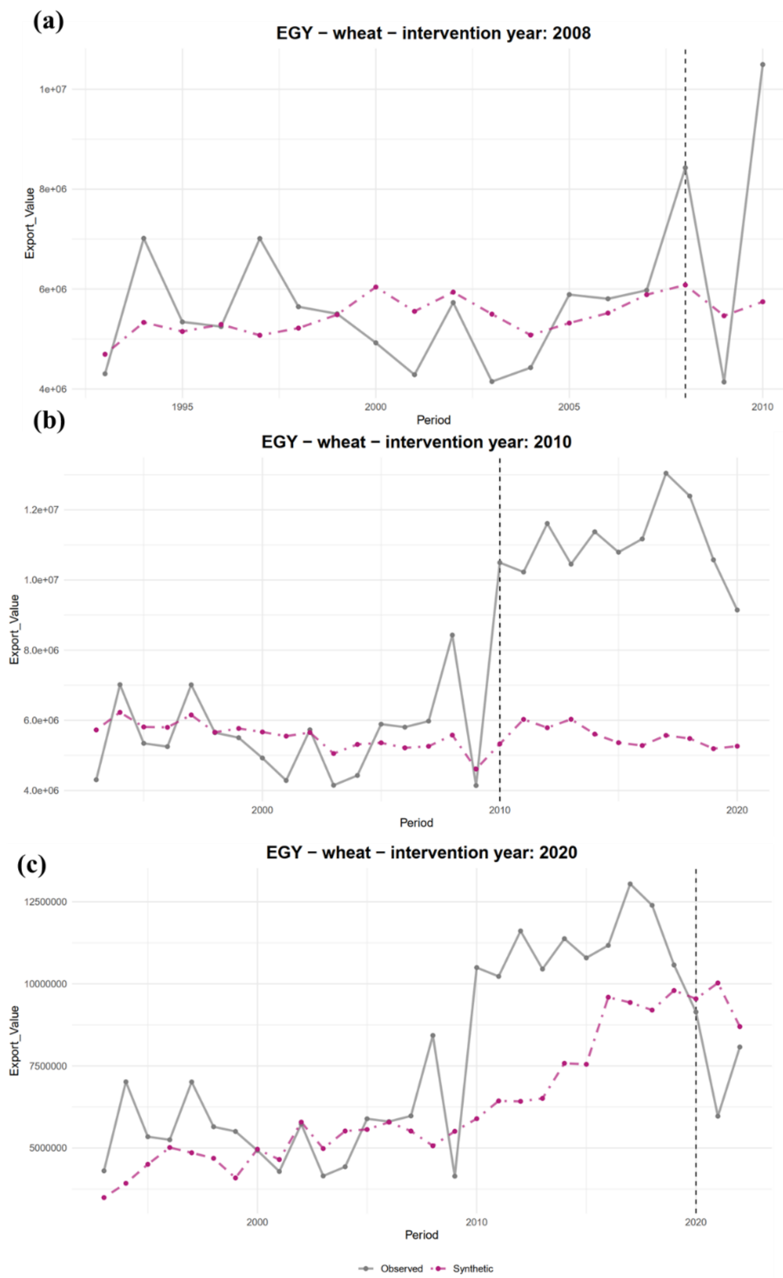


Figure 5. 8 SCM-based analysis of Egypt's wheat trade response to global crises in 2008, 2010, and 2020. Observed and synthetic wheat trade values for Egypt under the synthetic control method (SCM) for intervention years (a) 2008, (b) 2010, and (c) 2020. The solid gray line represents actual observed wheat trade, while the dashed magenta line represents the counterfactual synthetic trade value, which estimates expected trade had the crisis not occurred. The vertical dashed line indicates the intervention year for each crisis.

Beyond Egypt, these findings reflect broader systemic changes in the global wheat trade network. The SCM results suggest that predicting trade flows based solely on pre-crisis trends is increasingly unreliable, as trade structures are continuously reshaped by crises. The sharp deviations between synthetic and actual trade during crises highlight the need for more dynamic trade models that incorporate real-time policy responses, supplier shifts, and geopolitical considerations rather than assuming stability in trade relationships. The long-term trajectory of Egypt's wheat imports demonstrates that crises are not isolated events but interwoven disruptions that cumulatively shape market behavior.

5.4.5 Shifting Wheat Trade Patterns with Adjacent and Distant Partners under Global Crises

We compared the wheat trade dynamics of the USA, Russia, Brazil, and Egypt over three decades, focusing on the trade balance changes with neighboring countries (adjacent trade) versus those with geographically distant partners (distant trade) under the metacoupling framework (Liu J, 2023). For the United States, trade dynamics with distant partners exhibited high volatility, with notable contractions during 1994-1996 and 2008-2009, aligning with the North American market restructuring and the 2008 financial crisis. While distant trade showed signs of recovery post-2010, adjacent trade remained relatively stable but experienced minor fluctuations. A decline in adjacent trade after 2015 suggests a shifting reliance toward more geographically diverse trade partners, rather than maintaining strong regional trade relationships. Russia's wheat trade demonstrated a fundamental shift from an import-dependent to an export-driven network. In the late 1990s and early 2000s, distant trade remained negative, reflecting a reliance on foreign imports. However, by the mid-2000s, Russia's trade balance with distant partners improved largely, particularly post-2010 following the Russian wheat export ban. Meanwhile, adjacent trade remained volatile, with sharp increases in 2011-2012 and 2016-2017, indicating stronger trade connections with neighboring markets, particularly in the Commonwealth of Independent States (CIS) region. The sharp decline in adjacent trade in 2020-2021 suggests potential disruptions due to logistics and trade restrictions during the COVID-19 pandemic. Brazil, primarily an importer of wheat, shows a consistently negative trade balance with distant and adjacent partners, with fluctuations reflecting import dependency. Adjacent trade with Argentina and Paraguay dominates Brazil's wheat supply, evident in the recurring negative balance. However, an increasing volume of wheat imports from distant suppliers post-2010, particularly from North America and Eastern Europe, suggests diversification in sourcing strategies. The 2014-2015 period saw a marked contraction in adjacent trade, potentially linked to regional production shortfalls and currency fluctuations affecting wheat prices.

Egypt's trade balance highlights its reliance on distant wheat suppliers, particularly from the Black Sea region, North America, and Europe. Throughout the early 2000s, Egypt's distant trade balance remained largely positive, peaking in 2010-2011 following the Russian wheat export ban, which led to a surge in imports from alternative suppliers. However, post-2020, Egypt's trade dynamics shifted, showing a contraction in distant trade, potentially due to supply chain disruptions during COVID-19 and shifts in global wheat availability. Meanwhile, adjacent trade remained relatively low and unstable, reflecting Egypt's limited reliance on regional wheat suppliers. These findings underscore how wheat trade networks adapt differently across nations based on their economic positioning and strategic trade preferences. Exporting countries like Russia and the U.S. have expanded their reach toward distant partners, while importers like Egypt and Brazil continue to navigate supplier diversification. The impact of crises, including financial downturns, export bans, and the COVID-19 pandemic, has shaped these patterns, reinforcing the importance of resilience in global food trade strategies.

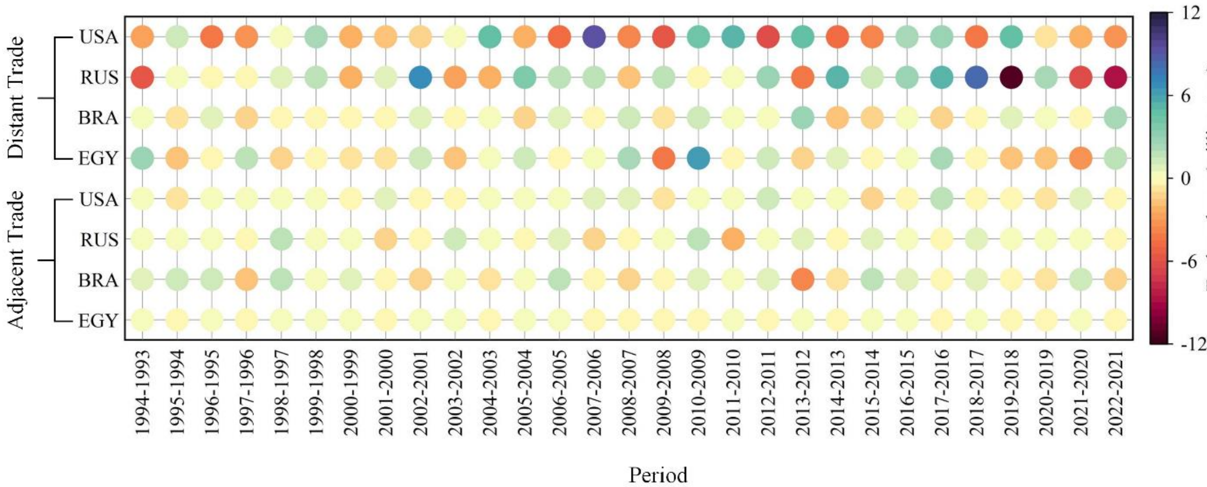


Figure 5. 9 Comparison of wheat trade dynamics with adjacent and distant partners for the United States, Russia, Brazil, and Egypt (1993–2022). The annual changes in wheat trade volume between distant and adjacent trade partners for the United States (USA), Russia (RUS), Brazil (BRA), and Egypt (EGY) from 1993 to 2022. The top section represents distant trade, while the bottom section represents adjacent trade. The color gradient indicates trade volume, with green shades representing trade surpluses (positive values) and brown shades indicating trade deficits (negative values). Each row corresponds to a yearly trade period, showing the shifts in wheat trade balances for each country over time.

5.4.6 Scenario-based Simulation of Global Wheat Exports under Crises

To assess the impacts of multiple global crises on wheat exports, we conducted a series of scenario simulations based on pre-crisis trends. The model estimates export levels in the absence of the 2008 financial crisis, the 2010 Russian export ban, and the 2020 COVID-19 pandemic. By comparing these simulation results with actual export data, we evaluated how global and income-level trade patterns responded to each crisis.

Figure 5.10 presents the global scenario simulation results. The no-crisis simulation shows the highest export level, followed by the simulations that remove only the 2010 export ban or the 2020 pandemic. In all three cases, actual export volumes fall below the simulated levels, confirming that the combined effect of these crises suppressed global wheat trade. The gap between the no-crisis scenario and actual data reflects the long-term impact of repeated disruptions. The simulation without the 2010 export ban diverges from actual trade starting around 2011, while the simulation without the 2020 pandemic shows a more abrupt drop after 2020. These results show that each crisis affected trade differently, both in timing and in mechanism.

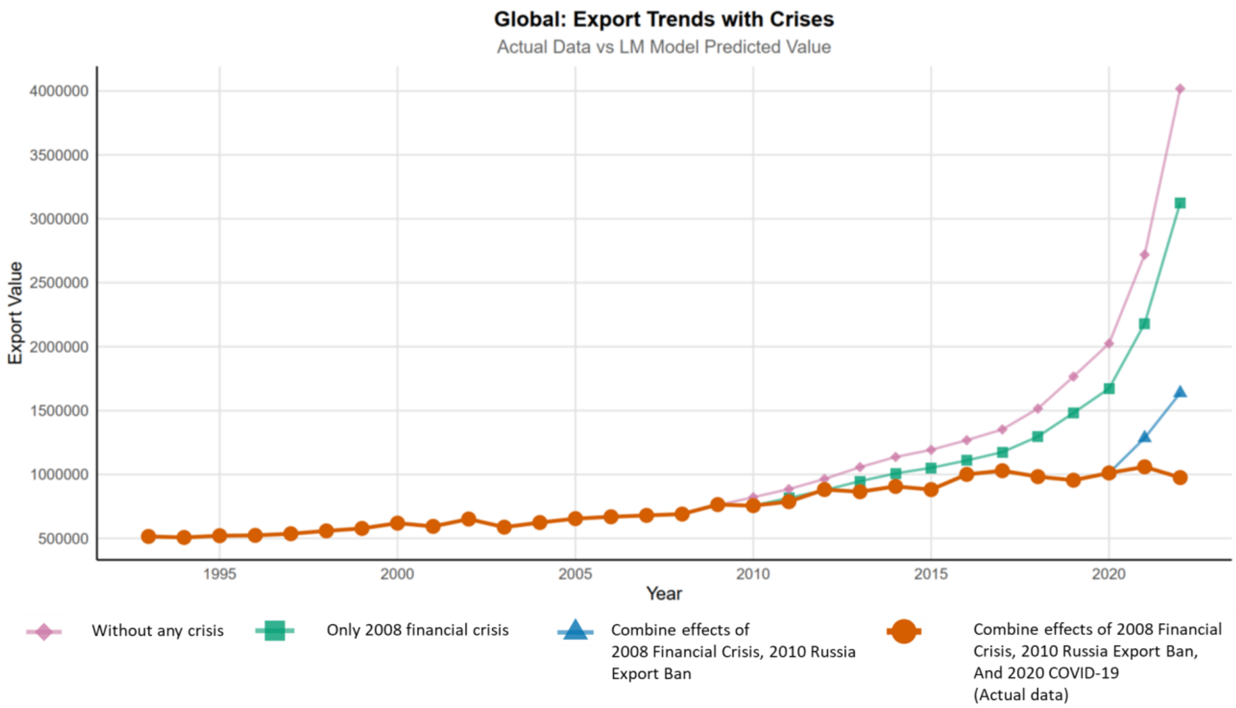


Figure 5. 10 Global wheat export volumes under simulated crisis scenarios and observed data, 2000–2022. This figure compares actual global wheat export volumes with simulated export values under three crisis scenarios using a linear model. The orange solid circle (●) represents actual observed export data, which also represents the combined effects of the three crises. The pink diamond (◆) represents the simulated scenario without the 2008 financial crisis. The green square (■) represents the simulated scenario without the 2010 Russian wheat export ban. The blue triangle (▲) represents the simulated scenario without the 2020 COVID-19 pandemic. The x-axis shows the year (1990–2022), and the y-axis displays export values.

When separated by income group, the results reveal more specific and contrasting patterns (Figure 5.11). In low-income countries, actual export volumes were higher than simulated values following the financial crisis. This suggests that the crisis created trade opportunities, possibly by shifting demand toward new suppliers. However, after the 2010 Russian export ban, actual exports fell below the simulated scenario, showing a negative impact. The COVID-19 pandemic deepened this gap, with actual exports consistently below predicted levels. These shifts imply that early gains were later offset by structural and logistical limitations.

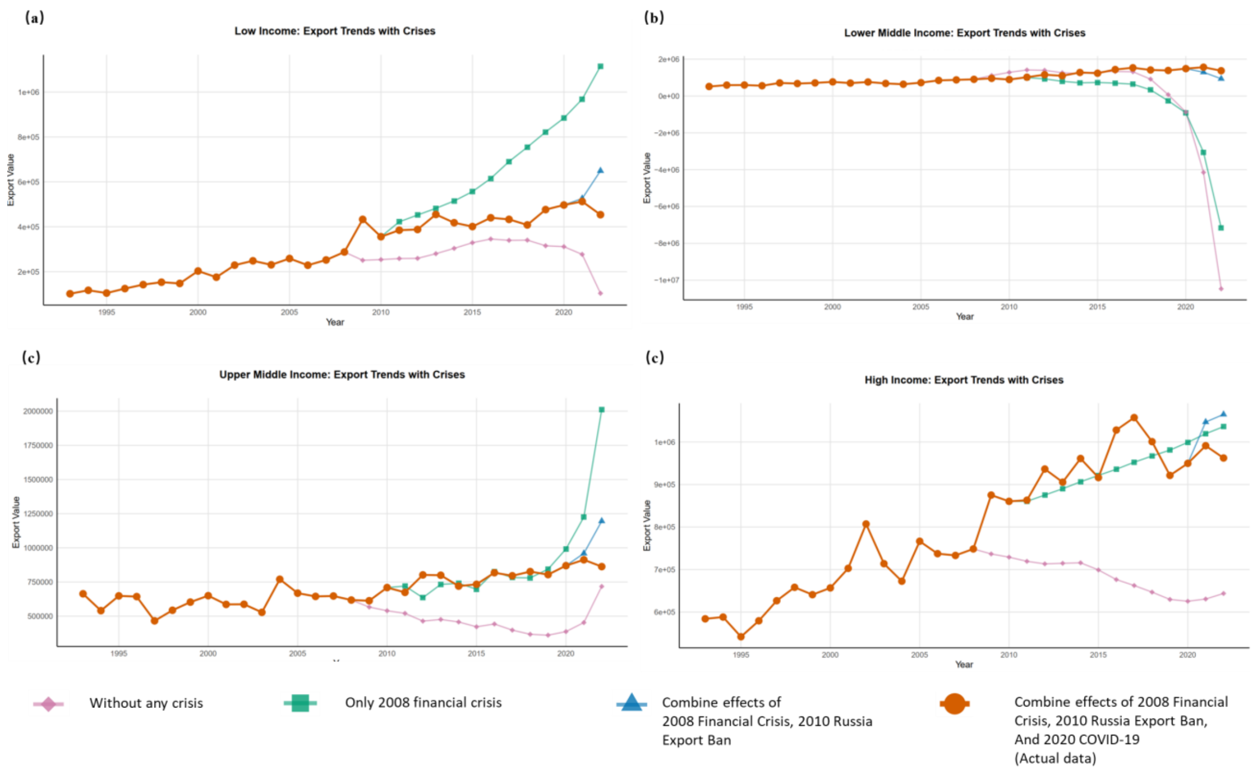


Figure 5. 11 Wheat export volumes under simulated crisis scenarios and observed data by income group, 1990–2022. This figure shows the comparison between actual wheat export volumes and simulated counterfactual values under three crisis scenarios for four income groups: (a) low-income, (b) lower-middle-income, (c) upper-middle-income, and (d) high-income countries. The orange solid circle (●) represents actual observed export data. The pink diamond (◆) represents the simulated scenario without the 2008 financial crisis. The green square (■) represents the simulated scenario without the 2010 Russian wheat export ban. The blue triangle (▲) represents the simulated scenario without the 2020 COVID-19 pandemic. The x-axis indicates the year (1990–2022), and the y-axis shows export values.

For lower-middle-income countries, actual exports remained above all three simulated crisis scenarios. These countries consistently exceeded expected performance during each disruption period. The difference is most pronounced during the COVID-19 pandemic, when actual exports grew well above simulated values. This may reflect growing competitiveness, expanded trade networks, or improvements in export infrastructure. In upper-middle-income countries, the simulation results for the export ban and the pandemic were both higher than the actual export values, especially after 2015. This suggests that these crises constrained export growth, even though pre-crisis trends indicated greater potential. The scenario without the financial crisis remained closer to actual values, indicating that its impact was more limited. High-income countries showed a delayed but increasing gap between simulated and actual exports. The scenario without the pandemic in particular shows that exports could have grown further if disruptions had not occurred. The growing difference after 2015 suggests that export performance in this group was increasingly affected by supply chain issues, changing market conditions, or trade policy responses.

These simulation results show that the effects of crises vary across income groups. While the overall suppressive effect is most visible at the global level, some countries, particularly in the lower-middle-income group, adapted well and even strengthened their trade positions. Others, especially low- and upper-middle-income exporters, experienced more limited recovery. These differences highlight not only the need for targeted trade support and context-specific policy interventions, but also the importance of addressing spatial disparities in resilience. Countries across different regions and income groups experienced distinct trade impacts, indicating that global crises interact with local vulnerabilities and regional trade dynamics in uneven ways.

5.5 Discussion

This study demonstrates how multiple global crises—economic, supply-driven, and logistical—have collectively shaped the structure and function of the global wheat trade over the past three decades. Through the combination of scenario simulation and network analysis, we show that the effects of the 2008 financial crisis, the 2010 Russian wheat export ban, and the 2020 COVID-19 pandemic were not isolated events. Instead, their impacts accumulated over time, influencing trade performance across different income levels and geographic regions.

Each crisis contributed differently to changes in trade patterns. The financial crisis primarily reduced global liquidity and altered trade financing conditions. Although it did not immediately disrupt the network structure, it contributed to long-term shifts in trade behavior, such as stockpiling and supplier diversification among middle-income countries. These findings are consistent with previous studies that recognized financial crises as indirect yet influential stressors on trade dynamics (Belke, 2010; Davis et al., 2021; Gephart et al., 2016). In contrast, the 2010 Russian wheat export ban had a more direct impact. Many import-dependent countries were forced to diversify their supply sources, leading to structural shifts in global wheat flows. This outcome aligns with earlier research indicating that supply-side disruptions often accelerate trade network reconfiguration (Devadoss & Ridley, 2024; Svanidze et al., 2022; Arita et al., 2022). The COVID-19 pandemic introduced a distinct set of constraints by disrupting logistics, labor availability, and trade regulation. While some countries adapted by strengthening existing partnerships or establishing new channels, others—particularly low-income regions—experienced prolonged setbacks. Previous studies have similarly emphasized how the pandemic triggered both fragmentation and reconnection within global food supply chains (Mahajan & Tomar, 2021; Li et al., 2022; Lin et al., 2023).

Importantly, our results reinforce the notion that the global wheat trade system is path-dependent. Responses to one crisis often shaped outcomes in the next. For example, the diversification strategies initiated after the export ban helped some countries cushion the impacts of COVID-19-related disruptions. However, the capacity to adopt such strategies was uneven. High-income and upper-middle-income countries generally absorbed and adapted to multiple crises more effectively. In contrast, lower-middle- and low-income countries faced greater trade suppression and slower recovery, echoing spatial and economic disparities noted in earlier studies (Gephart et al., 2016; Behnassi & El Haiba, 2022).

Scenario simulations further revealed the heterogeneity in exposure and recovery across income groups. Some lower-middle-income countries exceeded their predicted export levels under all crisis scenarios, demonstrating resilience and adaptability. Others remained persistently below projections, reflecting deeper structural constraints that limited their recovery capacity. Beyond these income-based patterns, the analysis of major exporters provides additional insights. Russia, the United States, Canada, and Ukraine showed distinct trade responses across crisis periods. Russia's policy decisions and trade disruptions had broad effects across the network, while the United States and Canada maintained relatively stable roles. Ukraine, which had been gaining importance before 2020, faced setbacks due to conflict and crisis spillovers. These national-level trajectories illustrate how political conditions and geographic positioning mediate trade adjustments under stress.

Differences between adjacent and distant trade flows further highlight the spatial dynamics of resilience. Adjacent trade proved more resilient under crisis conditions, likely benefiting from geographic proximity, shared infrastructure, and lower transaction costs. In contrast, distant trade relationships were more sensitive to disruption, particularly during the COVID-19 pandemic. This divergence suggests that regional integration may offer advantages for maintaining trade continuity during global crises, and highlights the role of proximity in buffering against widespread shocks.

Beyond empirical findings, this study also offers a methodological contribution by providing a quantitative approach to evaluate the combined effects of multiple crises on global trade flows.

By linking scenario simulations with network analysis, we developed a framework to better understand how sequential disruptions reshape trade across both space and income groups. Through this approach, we addressed three central questions: how the global wheat trade responds to different types of crises; how these impacts vary across country groups and regions; and how structural disparities influence resilience and recovery trajectories.

The findings have clear implications for trade governance and crisis management. Increasing the resilience of the global wheat trade will require inclusive policy frameworks that account for uneven adaptive capacities, stronger regional cooperation to support adjacent trade resilience, and targeted investments in transport, storage, and market access. Without addressing the structural disparities that shape trade vulnerability, future crises may continue to widen the global divide in food security.

CHAPTER 6: SYNTHESIS

This dissertation advances the application of the metacoupling framework to evaluate the resilience and transformation of food trade systems in a crisis-prone world. By combining systematic literature review, remote sensing, trade data analysis, and statistical modeling, this research offers a cross-scale, multi-method understanding of how global wheat trade systems respond to both short-term disruptions and long-term pressures. Each chapter builds on the concept of intra-, peri-, and telecoupling to reveal how sending, receiving, and spillover systems are reshaped across time and space.

Chapter 2 presents a systematic review of 455 peer-reviewed articles and identifies major gaps in existing food trade resilience research. While many studies emphasize national-scale dynamics, few consider spillover systems or cross-scale trade linkages. This chapter synthesizes fragmented indicators into a unified framework structured around human- and nature-related drivers. It highlights the urgent need to incorporate underexplored metacoupling dimensions in resilience evaluations.

Chapter 3 develops an evaluation framework to assess how the COVID-19 pandemic disrupted global food trade. By disaggregating Bonilla index, centrality, connectivity, trade disruption, and supply chain diversity into adjacent and distant trade components, this chapter reveals spatial inequalities in resilience. Low-income countries experienced more severe adjacent trade disruptions, while high-income countries maintained stability through diversified distant connections. These findings emphasize the importance of spatial structure and trade diversity for navigating global crises.

Chapter 4 introduces a rapid assessment approach to quantify the 2022 Russia–Ukraine war’s impact on winter wheat trade. Using remote sensing-based cropland data combined with trade network metrics, the chapter identifies reduced connectivity and the emergence of new peripheral trade routes. The war's disruption to a critical supply region revealed the vulnerability of over-concentrated trade networks and emphasized the role of near-real-time data in monitoring supply chain risks.

Chapter 5 extends the analysis across three decades (1991–2022) to examine long-term structural changes in the global wheat trade network. Using network analysis, structural change modeling (SCM), and generalized additive models (GAM), the chapter detects critical turning points associated with three major global events: the 2008 financial crisis, the 2010 Russian wheat export ban, and the 2020 COVID-19 pandemic. The results show growing dominance of distant trade, persistent income-based inequalities in centrality and connectivity, and increased trade concentration in high-income countries. These findings reveal how recurring crises can reinforce long-term disparities and reshape the structure of global wheat trade networks.

In summary, this dissertation contributes both conceptually and methodologically to the study of food trade resilience under the metacoupling framework. It introduces a new classification system for resilience indicators, demonstrates empirical methods for assessing crises at multiple scales, and links structural changes in trade to crises. Future research should explore how cascading crises interact across systems and scales and incorporate subnational and firm-level data to improve resolution. Integrated modeling approaches and scenario-based simulations are also needed to anticipate nonlinear system behaviors and feedbacks.

By providing an integrated framework to evaluate food trade system resilience, this research supports the design of more adaptive and equitable trade policies. The findings contribute to a deeper understanding of how global food systems evolve under pressure and offer practical insights for strengthening resilience in pursuit of the Sustainable Development Goals.

REFERENCES:

Abadie, A., Gardeazabal, J., 2003. The economic costs of conflict: A case study of the Basque Country. American Economic Review 93(1), 113–132. https://doi.org/10.1257/000282803321455188

Abadie, A., Diamond, A., Hainmueller, J., 2010. Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program. Journal of the American statistical Association 105(490), 493–505. https://doi.org/10.1198/jasa.2009.ap08746

Abay, K.A., Breisinger, C., Glauber, J., Kurdi, S., Laborde, D., Siddig, K., 2023. The Russia-Ukraine war: Implications for global and regional food security and potential policy responses. Global Food Security 36, 100675. https://doi.org/10.1016/j.gfs.2023.100675

Abdo, H.G., 2018. Impacts of war in Syria on vegetation dynamics and erosion risks in Safita area, Tartous, Syria. Regional Environmental Change 18, 1707–1719. https://doi.org/10.1007/s10113-018-1280-3

Acharya, S.S., Chand, R., Birthal, P.S., Kumar, S., Negi, D.S., 2012. Market integration and price transmission in India: A case of rice and wheat with special reference to the world food crisis of 2007/08. Rome: Food and Agriculture Organization 447-456.

Aday, S., Aday, M.S., 2020. Impact of COVID-19 on the food supply chain. Food Quality and Safety 4(4), 167–180. https://doi.org/10.1093/fqsafe/fyaa024

Adger, W.N., Brown, K., Nelson, D.R., Berkes, F., Eakin, H., Folke, C., Galvin, K., Gunderson, L., Goulden, M., O'Brien, K., Ruitenbeek, J., Tompkins, E.L., 2011. Resilience implications of policy responses to climate change. Wiley Interdisciplinary Reviews: Climate Change 2(5), 757–766. https://doi.org/10.1002/wcc.133

Adiga, A., Palmer, N., Sinha, S., Waghalter, P., Dave, A., Lazarte, D.P., Brévault, T., Apolloni, A., Mortveit, H., Baek, Y.Y., Marathe, M., 2022. Realistic Commodity Flow Networks to Assess Vulnerability of Food Systems. Complex Networks & Their Applications X 1072, 168–179. https://doi.org/10.1007/978-3-030-93409-5_15

Agrawal, S., Patel, A., 2020. Clustering algorithm for community detection in complex network: A comprehensive review. Recent Advances in Computer Science and Communications (Formerly: Recent Patents on Computer Science) 13, 542–549. https://doi.org/10.2174/2213275912666190710183635

Arita, S., Grant, J., Sydow, S., Beckman, J., 2022. Has global agricultural trade been resilient under coronavirus (COVID-19)? Findings from an econometric assessment of 2020. Food Policy 107, 102204. https://doi.org/10.1016/j.foodpol.2021.102204

Arndt, C., Davies, R., Gabriel, S., Harris, L., Makrelov, K., Robinson, S., Levy, S., Simbanegavi, W., van Seventer, D., Anderson, L., 2020. COVID-19 lockdowns, income distribution, and food security: An analysis for South Africa. Global Food Security 26, 100410. https://doi.org/10.1016/j.gfs.2020.100410

Arndt, C., Davies, R., Makrelov, K., Thurlow, J., 2013. Measuring the carbon intensity of the South African economy. South African Journal of Economics 81(3), 393–415. https://doi.org/10.1111/j.1813-6982.2012.01324.x

Arndt, C., Diao, X., Dorosh, P., Pauw, K., Thurlow, J., 2023. The Ukraine war and rising commodity prices: Implications for developing countries. Global Food Security 36, 100680. https://doi.org/10.1016/j.gfs.2023.100680

Arouri, M.E.H., Jouini, J., Nguyen, D.K., 2012. On the impacts of oil price fluctuations on European equity markets: Volatility spillover and hedging effectiveness. Energy Economics 34(2), 611–617. https://doi.org/10.1016/j.eneco.2011.08.009

Atashgar, K., 2013. Identification of the change point: an overview. The International Journal of Advanced Manufacturing Technology 64, 1663–1683. https://doi.org/10.1007/s00170-012-4131-2

Balike Dieudonné, Z., 2021. Mathematical model for the mitigation of the economic effects of the COVID-19 in the Democratic Republic of the Congo. PLoS one 16(5), e0250775. https://doi.org/10.1371/journal.pone.0250775

Barabási, A.L., Gulbahce, N., Loscalzo, J., 2011. Network medicine: a network-based approach to human disease. Nature Reviews Genetics 12, 56–68. https://doi.org/10.1038/nrg2918

Pósfai, M., Barabási, A.L., 2016. Network science. Cambridge, UK: Cambridge University Press.

Barbero, J., de Lucio, J.J., Rodríguez-Crespo, E., 2021. Effects of COVID-19 on trade flows: Measuring their impact through government policy responses. PloS one 16(10), e0258356. https://doi.org/10.1371/journal.pone.0258356

Bassett, H.R., Lau, J., Giordano, C., Suri, S.K., Advani, S., Sharan, S., 2021. Preliminary lessons from COVID-19 disruptions of small-scale fishery supply chains. World Development 143, 105473. https://doi.org/10.1016/j.worlddev.2021.105473

Becker, M., Pfeifer, G., Schweikert, K., 2021. Price effects of the Austrian fuel price fixing act: a synthetic control study. Energy Economics 97, 105207. https://doi.org/10.1016/j.eneco.2021.105207

Behnassi, M., El Haiba, M., 2022. Implications of the Russia–Ukraine war for global food security. Nature Human Behaviour 6(6), 754–755. https://doi.org/10.1038/s41562-022-01391-x

Belke, A., 2010. Financial crisis, global liquidity and monetary exit strategies. ROME Discussion Paper Series.

Ben Hassen, T., El Bilali, H., 2022. Impacts of the Russia-Ukraine war on global food security: towards more sustainable and resilient food systems?. Foods 11, 2301. https://doi.org/10.3390/foods11152301

Béné, C., 2020. The resilience of local food systems and links to food security–A review of some important concepts in the context of COVID-19 and other shocks. Food Security 12, 805–822. https://doi.org/10.1007/s12571-020-01076-1

Berkhout, E., Sovová, L., Sonneveld, A., 2023. The Role of Urban–Rural Connections in Building Food System Resilience. Sustainability 15(3), 1818. https://doi.org/10.3390/su15031818

Bernal-Verdugo, L.E., Furceri, D., Guillaume, D., 2012. Labor market flexibility and unemployment: new empirical evidence of static and dynamic effects. Comparative Economic Studies 54, 251–273. https://doi.org/10.1057/ces.2012.3

Berrang Ford, L., 2007. Civil conflict and sleeping sickness in Africa in general and Uganda in particular. Conflict and Health 1, 6. https://doi.org/10.1186/1752-1505-1-6

Billmeier, A., Nannicini, T., 2013. Assessing economic liberalization episodes: A synthetic control approach. Review of Economics and Statistics 95(3), 983–1001. https://doi.org/10.1162/REST_a_00324

Borgatti, S. P., & Everett, M. G. 2000. Models of core/periphery structures. Social Networks, *21*(4), 375-395.

Brown, M.E., Carr, E.R., Grace, K.L., Wiebe, K., Funk, C.C., Attavanich, W., Backlund, P., Buja, L., 2017. Do markets and trade help or hurt the global food system adapt to climate change?. Food Policy 68, 154–159. https://doi.org/10.1016/j.foodpol.2017.02.004

Burkholz, R., Schweitzer, F., 2019. International crop trade networks: The impact of shocks and cascades. Environmental Research Letters 14(11), 114013. https://doi.org/10.1088/1748-9326/ab4864

Callaway, B., Sant'Anna, P.H., 2021. Difference-in-differences with multiple time periods. Journal of Econometrics 225(2), 200–230. https://doi.org/10.1016/j.jeconom.2020.12.001

Campos, N.F., Coricelli, F., Moretti, L., 2019. Institutional integration and economic growth in Europe. Journal of Monetary Economics 103, 88–104. https://doi.org/10.1016/j.jmoneco.2018.08.001

Carlson, A.K., Young, T., Centeno, M.A., Levin, S.A., Rubenstein, D.I., 2021. Boat to bowl: Resilience through network rewiring of a community-supported fishery amid the COVID-19 pandemic. Environmental Research Letters 16(3), 034054. https://doi.org/10.1088/1748-9326/abe4f6

Carriquiry, M., Dumortier, J. Elobeid, A., 2022. Trade scenarios compensating for halted wheat and maize exports from Russia and Ukraine increase carbon emissions without easing food insecurity. Nature Food 3, 847–850. https://doi.org/10.1038/s43016-022-00600-0

Chai, L., Liu, A., Li, X., Guo, Z., He, W., Huang, J., Bai, T., Liu, J., 2024. Telecoupled impacts of the Russia–Ukraine war on global cropland expansion and biodiversity. Nature Sustainability 7(4), 432–441. https://doi.org/10.1038/s41893-024-01292-z

Chang, T.C., Gan, F.F., 1995. A cumulative sum control chart for monitoring process variance. Journal of Quality Technology 27(2), 109–119. https://doi.org/10.1080/00224065.1995.11979574

Chatfield, C., Xing, H., 2019. The Analysis of Time Series: An Introduction with R. Chapman and Hall/CRC.

Chatzopoulos, T., Pérez Domínguez, I., Toreti, A., Adenäuer, M., Zampieri, M., 2021. Potential impacts of concurrent and recurrent climate extremes on the global food system by 2030. Environmental Research Letters 16(12), 124021. https://doi.org/10.1088/1748-9326/ac343b

Chen, C., Frank, K. A., Wang, T., & Wu, F. 2021. Global wheat trade and Codex Alimentarius guidelines for deoxynivalenol: A mycotoxin common in wheat. Global Food Security 29, 100538.

Chen, C., Jiang, Z., Li, N., Wang, H., Wang, P., Zhang, Z., Zhang, C., Ma, F., Huang, Y., Lu, X., Wei, J., Qi, J., Chen, W.Q., 2022. Advancing UN Comtrade for physical trade flow analysis: review of data quality issues and solutions. Resources, Conservation and Recycling 186, 106526. https://doi.org/10.1016/j.resconrec.2022.106526

Chen, W., Wang, G., Cai, W., Che, X., Zhou, W., Zhang, C., Zeng, J., 2023. Spatiotemporal mismatch of global grain production and farmland and its influencing factors. Resources, Conservation and Recycling 194, 107008. https://doi.org/10.1016/j.resconrec.2023.107008

Chen, X., Shuai, C., Wu, Y., 2023. Global food stability and its socio-economic determinants towards sustainable development goal 2 (Zero Hunger). Sustainable Development, 31(3), 1768–1780. https://doi.org/10.1002/sd.2482

Chepeliev, M., Maliszewska, M., Pereira, M.F.S.E., 2023. The war in Ukraine, food security and the role for Europe. EuroChoices 22(1), 4–13. https://doi.org/10.1111/1746-692X.12389

Chung, M.G., Frank, K.A., Pokhrel, Y., Dietz, T. Liu, J., 2021. Natural infrastructure in sustaining global urban freshwater ecosystem services. Nature Sustainability 4, 1068–1075. https://doi.org/10.1038/s41893-021-00786-4

Chung, M.G., Kapsar, K., Frank, K.A., Liu, J., 2020. The spatial and temporal dynamics of global meat trade networks. Scientific Reports 10, 16657. https://doi.org/10.1038/s41598-020-73591-2

Chung, M.G., Li, Y., Liu, J., 2021. Global red and processed meat trade and non-communicable diseases. BMJ Glob Health. 6, e006394. https://doi.org/10.1136/ bmjgh-2021-006394

Coopmans, I., Bijttebier, J., Marchand, F., Mathijs, E., Messely, L., Rogge, E., Sanders, A., Wauters, E., 2021. COVID-19 impacts on Flemish food supply chains and lessons for agri-food system resilience. Agricultural Systems 190, 103136. https://doi.org/10.1016/j.agsy.2021.103136

Crippa, M., Guizzardi, D., Muntean, M., Schaaf, E., Dentener, F., Solazzo, E., & Vignati, E. (2022). *EDGAR v7.0: Emissions Database for Global Atmospheric Research* [Data set]. European Commission, Joint Research Centre (JRC). https://edgar.jrc.ec.europa.eu/report_2022#data_download

Csardi, G. Nepusz, T., 2006. The igraph software package for complex network research. InterJournal, Complex Systems, 1695 (5): 1–9.

Dalin, C., Konar, M., Hanasaki, N., Rinaldo, A., Rodriguez-Iturbe, I., 2012. Evolution of the global virtual water trade network. Proceedings of the National Academy of Sciences 109(16), 5989–5994. https://doi.org/10.1073/pnas.1203176109

Davis, K.F., Downs, S., Gephart, J.A., 2021. Towards food supply chain resilience to environmental shocks. Nature Food 2(1), 54–65. https://doi.org/10.1038/s43016-020-00196-3

De Benedictis, L., Nenci, S., Santoni, G., Tajoli, L., Vicarelli, C., 2014. Network Analysis of World Trade using the BACI-CEPII Dataset. Global Economy Journal 14, 287–343. https://doi.org/10.1515/gej-2014-0032

Deininger, K., Ali, D.A., Kussul, N., Shelestov, A., Lemoine, G., Yailimova, H., 2023. Quantifying war-induced crop losses in Ukraine in near real time to strengthen local and global food security. Food Policy 115, 102418. https://doi.org/10.1016/j.foodpol.2023.102418

Demeke, A.B., Keil, A., Zeller, M., 2011. Using panel data to estimate the effect of rainfall shocks on smallholders' food security and vulnerability in rural Ethiopia. Climatic Change 108, 185–206. https://doi.org/10.1007/s10584-010-9994-3

Derindag, O.F., Yasar, Z.R., Aslan, C., Parmaksiz, S., 2024. Analyzing the differential effects of COVID-19 on export flows: a focus on customs procedures. Empirica 51(4), 977–1000. https://doi.org/10.1007/s10663-024-09634-y

Devadoss, S., Ridley, W., 2024. Impacts of the Russian invasion of Ukraine on the global wheat market. World Development 173, 106396. https://doi.org/10.1016/j.worlddev.2023.106396

Diaz-Bonilla, E., Ron, J.F., 2010. Food security, price volatility and trade: Some reflections for developing countries.

Dong, B., Ma, X., Zhang, Z., Zhang, H., Chen, R., Song, Y., ... & Xiang, R. (2020). Carbon emissions, the industrial structure and economic growth: Evidence from heterogeneous industries in China. Environmental Pollution*, 262,* 114322.

International Centre for Trade and Sustainable Development (ICTSD) 28. https://doi.org/10.22004/ag.econ.320195

Diserens, F., Choptiany, J., Barjolle, D., Graeub, B., Durand, C., Six, J., 2018. Resilience Assessment of Swiss Farming Systems: Piloting the SHARP-Tool in Vaud. Sustainability 10(12), 4435. https://doi.org/10.3390/su10124435

Distefano, T., Laio, F., Ridolfi, L., Schiavo, S., 2018. Shock transmission in the International Food Trade Network. PLoS one 13(8), e0200639. https://doi.org/10.1371/journal.pone.0200639

Dolfing, A.G., Leuven, J.R.F.W., Dermody, B.J., 2019. The effects of network topology, climate variability and shocks on the evolution and resilience of a food trade network. PLoS one, 14(3), e0213378. https://doi.org/10.1371/journal.pone.0213378

Elsig, M., 2011. Principal–agent theory and the World Trade Organization: Complex agency and 'missing delegation. European Journal of International Relations 17(3), 495–517. https://doi.org/10.1177/1354066109351078

Engemann, H., Jafari, Y., 2022. COVID-19 and changes in global agri-food trade. Q Open 2(1), qoac013. https://doi.org/10.1093/qopen/qoac013

Ercsey-Ravasz, M., Toroczkai, Z., Lakner, Z., Baranyi, J., 2012. Complexity of the international agro-food trade network and its impact on food safety. PLoS one 7(5), e37810. https://doi.org/10.1371/journal.pone.0037810

Eric, D., Etienne, B., 2020. tidysynth. https://github.com/edunford/tidysynth

Escaith, H., 2012. Understanding international trade statistics. World Trade Organization International Trade Statistics, Geneva. https://doi.org/10.30875/48d5b7a1-en

Fagiolo, G., Reyes, J., Schiavo, S., 2008. On the topological properties of the world trade web: A weighted network analysis. Physica A: Statistical Mechanics and its Applications, 387(15), 3868–3873. https://doi.org/10.1016/j.physa.2008.01.050

Fair, K.R., Bauch, C.T., Anand, M., 2017. Dynamics of the global wheat trade network and resilience to shocks. Scientific Reports 7(1), 7177. https://doi.org/10.1038/s41598-017-07202-y

Fan, S., Teng, P., Chew, P., Smith, G., Copeland, L., 2021. Food system resilience and COVID-19 – Lessons from the Asian experience. Global Food Security 28, 100501. https://doi.org/10.1016/j.gfs.2021.100501

FAO (Food and Agriculture Organization of the United Nations), 2001. Food Balance Sheets: A handbook. https://www.fao.org/3/X9892E/X9892E00.htm#TopOfPage

FAO (Food and Agriculture Organization of the United Nations), 2023a. Hunger and food insecurity. https://www.fao.org/hunger/en/#jfmulticontent_c130584-2

FAO (Food and Agriculture Organization of the United Nations), 2022. Impact of the Ukraine-Russia Conflict on Global Food Security and Related Matters under the Mandate of the Food and Agriculture Organization of the United Nations (FAO). https://www.fao.org/3/ni734en/ni734en.pdf

FAO (Food and Agriculture Organization of the United Nations), 2023b. The importance of Ukraine and the Russian federation for global agricultural markets and the risks associated with the war in Ukraine. https://openknowledge.fao.org/server/api/core/bitstreams/4fce6098-a3ba-4742-b8f4-685454a5d409/content

FAO (Food and Agriculture Organization of the United Nations), 2023c. World food situation: FAO food price index. https://www.fao.org/worldfoodsituation/foodpricesindex/en/

Felipe-Lucia, M.R., Soliveres, S., Penone, C., Fischer, M., Ammer, C., Boch, S., Boeddinghaus, R.S., Bonkowski, M., Buscot, F., Fiore-Donno, A.M., Frank, K., Goldmann, K., Gossner, M.M., Hölzel, N., Jochum, M., Kandeler, E., Klaus, V.H., Kleinebecker, T., Leimer, S., Manning, P., Oelmann, Y., Saiz, H., Schall, P., Schloter, M., Schöning, I., Schrumpf, M., Solly, E.F., Stempfhuber, B., Weisser, W.W., Wilcke, W., Wubet, T., Allan, E., 2020. Land-use intensity alters networks between biodiversity, ecosystem functions, and services. Proceedings of the National Academy of Sciences 117(45), 28140–28149. https://doi.org/10.1073/pnas.2016210117

Feng, F., Jia, N., Lin, F., 2023. Quantifying the impact of Russia–Ukraine crisis on food security and trade pattern: Evidence from a structural general equilibrium trade model. China Agricultural Economic Review 15, 241–258. https://doi.org/10.1108/CAER-07-2022-0156

Foong, A., Pradhan, P. Frör, O., 2023. Supply chain disruptions would increase agricultural greenhouse gas emissions. Regional Environmental Change 23, 94. https://doi.org/10.1007/s10113-023-02095-2

Freeman, L.C., 1977. A set of measures of centrality based on betweenness. Sociometry 40(1), 35–41. https://doi.org/10.2307/3033543

Fridman, D., Koellner, T., Kissinger, M., 2021. Exploring global interregional food system's sustainability using the functional regions typology. Global Environmental Change 68, 102276. https://doi.org/10.1016/j.gloenvcha.2021.102276

Friel, S., Ford, L., 2015. Systems, food security and human health. Food Security 7, 437–451. https://doi.org/10.1007/s12571-015-0433-1

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A., Michaelsen, J., 2015. The climate hazards infrared precipitation with stations—A new environmental record for monitoring extremes. Scientific Data 2, 150066. https://doi.org/10.1038/sdata.2015.66

Gephart, J.A., Pace, M.L., 2015. Structure and evolution of the global seafood trade network. Environmental Research Letters 10(12), 125014. https://doi.org/10.1088/1748-9326/10/12/125014

Gephart, J.A., Rovenskaya, E., Dieckmann, U., Pace, M.L., Brännström, Å., 2016. Vulnerability to shocks in the global seafood trade network. Environmental Research Letters 11(3), 035008. https://doi.org/10.1088/1748-9326/11/3/035008

Gereffi, G., 2020. What does the COVID-19 pandemic teach us about global value chains? The case of medical supplies. Journal of International Business Policy 3(3), 287. https://doi.org/10.1057/s42214-020-00062-w

Glauben, T., Svanidze, M., Götz, L., Prehn, S., Jamali Jaghdani, T., Đurić, I., Kuhn, L., 2022. The war in Ukraine, agricultural trade and risks to global food security. Intereconomics 57(3), 157–163. https://doi.org/10.1007/s10272-022-1052-7

González-Mon, B., Bodin, Ö., Schlüter, M., 2023. Small-scale fisheries and agricultural trade networks are socially embedded: Emerging hypotheses about responses to environmental changes. Ecology and Society 28(3), art9. https://doi.org/10.5751/ES-14265-280309

Goodman-Bacon, A., 2021. Difference-in-differences with variation in treatment timing. Journal of Econometrics 225(2), 254–277. https://doi.org/10.1016/j.jeconom.2021.03.014

Götz, L., Djuric, I., Glauben, T., 2015. Wheat export restrictions in Kazakhstan, Russia and Ukraine: impact on prices along the wheat-to-bread supply chain. Transition to agricultural market economies: the future of Kazakhstan, Russia and Ukraine 191-203. https://doi.org/10.1079/9781780645353.0191

Götz, L., Glauben, T., Brümmer, B., 2013. Wheat export restrictions and domestic market effects in Russia and Ukraine during the food crisis. Food Policy 38, 214–226. https://doi.org/10.1016/j.foodpol.2012.12.001

Götz, L., Glauben, T., Brümmer, B., 2010. Impacts of export controls on wheat markets during the food crisis 2007/2008 in Russia and Ukraine. https://doi.org/10.22004/ag.econ.61626

Granovetter, M.S., 1973. The strength of weak ties. American Journal of Sociology 78, 1360–1380. https://doi.org/10.1086/225469

Grassia, M., Mangioni, G., Schiavo, S., Traverso, S., 2022. Insights into countries' exposure and vulnerability to food trade shocks from network-based simulations. Scientific Reports 12(1), 4644. https://doi.org/10.1038/s41598-022-08419-2

Gren, I.M., Jonasson, L., Andersson, H., Knutsson, R., 2024. Economic impact and food security effects of trade disruptions in agricultural products for Sweden. Agriculture & Food Security 13(1), 28. https://doi.org/10.1186/s40066-024-00483-3

Groundstroem, F., Juhola, S., 2021. Using systems thinking and causal loop diagrams to identify cascading climate change impacts on bioenergy supply systems. Mitigation and Adaptation Strategies for Global Change 26(7), 29. https://doi.org/10.1007/s11027-021-09967-0

Gu, H., Du, S., Liao, B., Wen, J., Wang, C., Chen, R., & Chen, B. (2018). A hierarchical pattern of urban social vulnerability in Shanghai, China and its implications for risk management. Sustainable Cities and Society, 41, 170-179.

Gutiérrez-Moya, E., Lozano, S., Adenso-Díaz, B., 2020. Analysing the structure of the global wheat trade network: an ERGM approach. Agronomy 10(12), 1967. https://doi.org/10.3390/agronomy10121967

Gutiérrez-Moya, E., Adenso-Díaz, B. Lozano, S., 2021. Analysis and vulnerability of the international wheat trade network. Food Security 13, 113–128. https://doi.org/10.1007/s12571-020-01117-9

Gyuris, F., 2022. Diversifying Dependencies? Hungary, the EU, and the Multifaceted Geopolitics of Chinese Infrastructure Investments. The Rise of the Infrastructure State. Bristol University Press. 254-266. https://doi.org/10.51952/9781529220803.ch018

Hadida, G., Ali, Z., Kastner, T., Carr, T.W., Prentice, A.M., Green, R., Scheelbeek, P., 2022. Changes in climate vulnerability and projected water stress of the Gambia's food supply between 1988 and 2018: Trading with trade-offs. Frontiers in Public Health 10, 786071. https://doi.org/10.3389/fpubh.2022.786071

Hallegatte, S., 2019. Disasters' impacts on supply chains. Nature Sustainability 2, 791–792. https://doi.org/10.1038/s41893-019-0380-5

Han, J., Zhang, Z., Luo, Y., Cao, J., Zhang, L., Zhang, J., Li, Z., 2021. The RapeseedMap10 database: Annual maps of rapeseed at a spatial resolution of 10 m based on multi-source data. Earth System Science Data 13(6), 2857–2874. https://doi.org/10.5194/essd-13-2857-2021

Hanna, T., Bohl, D.K. Moyer, J.D., 2021. Assessing the impact of war in Yemen: pathways for recovery. Unted Nations Development Programme (UNDP). https://www.undp.org/publications/assessing-impact-war-yemen-pathways-recovery

Harris, F., Amarnath, G., Joy, E.J., Dangour, A.D., Green, R.F., 2022. Climate-related hazards and Indian food supply: Assessing the risk using recent historical data. Global Food Security 33, 100625. https://doi.org/10.1016/j.gfs.2022.100625

Headey, D., 2011. Rethinking the global food crisis: The role of trade shocks. Food Policy 36(2), 136–146. https://doi.org/10.1016/j.foodpol.2010.10.003

Hellegers, P., 2022. Food security vulnerability due to trade dependencies on Russia and Ukraine. Food Security 14(6), 1503–1510. https://doi.org/10.1007/s12571-022-01306-8

Hellegers, P., 2022. Food security vulnerability due to trade dependencies on Russia and Ukraine. Food Security 14, 1503–1510. https://doi.org/10.1007/s12571-022-01306-8

Hertel, B.T.W., Baldos, U.L.C., Fuglie, K.O., 2020. Trade in technology: A potential solution to the food security challenges of the 21st century. European Economic Review 127, 103479. https://doi.org/10.1016/j.euroecorev.2020.103479

Herzberger, A., Chung, M.G., Kapsar, K., Frank, K.A., Liu, J., 2019. Telecoupled food trade affects pericoupled trade and intracoupled production. Sustainability 11(10), 2908. https://doi.org/10.3390/su11102908

Hinrichs, P., 2012. The effects of affirmative action bans on college enrollment, educational attainment, and the demographic composition of universities. Review of Economics and Statistics 94(3), 712–722. https://doi.org/10.1162/REST_a_00170

Homann-Kee Tui, S., Valdivia, R.O., Descheemaeker, K., Sisito, G., Moyo, E.N., Mapanda, F., 2023. Balancing co-benefits and trade-offs between climate change mitigation and adaptation innovations under mixed crop-livestock systems in semi-arid Zimbabwe. CABI Agriculture and Bioscience 4(1), 24. https://doi.org/10.1186/s43170-023-00165-3

Horn, B., Ferreira, C., Kalantari, Z., 2022. Links between food trade, climate change and food security in developed countries: A case study of Sweden. Ambio 51(4), 943–954. https://doi.org/10.1007/s13280-021-01623-w

Hou, H., Zhu, Y., 2022. Analysis of spillover effects of regional environmental pollution: An interprovincial study in China based on spatiotemporal lag model. Environmental Science and Pollution Research 29(1), 836–853. https://doi.org/10.1007/s11356-021-15739-9

Hu, Q., Guo, M., Wang, F., Shao, L., Wei, X., 2023. External supply risk of agricultural products trade along the Belt and Road under the background of COVID-19. Frontiers in Public Health 11, 1122081. https://doi.org/10.3389/fpubh.2023.1122081

Huang, X., Fu, Y., Wang, J., Dong, J., Zheng, Y., Pan, B., Skakun, S., Yuan, W., 2022. High-resolution mapping of winter cereals in Europe by time series Landsat and Sentinel images for 2016–2020. Remote Sensing 14(9), 2120. https://doi.org/10.3390/rs14092120

Ihle, R., Rubin, O.D., Bar-Nahum, Z., Jongeneel, R., 2020. Imperfect food markets in times of crisis: economic consequences of supply chain disruptions and fragmentation for local market power and urban vulnerability. Food Security 12(4), 727–734. https://doi.org/10.1007/s12571-020-01084-1

Ingram, J., 2011. A food systems approach to researching food security and its interactions with global environmental change. Food Security 3(4), 417–431. https://doi.org/10.1007/s12571-011-0149-9

International Grains Council, 2022. Grain Market Report, GMR538 – 17 November 2022. https://www.igc.int/en/gmr_summary.aspx

IPES-Food, 2022. Breaking the cycle of unsustainable food systems, hunger, and debt. Brussels.

Jagtap, S., Trollman, H., Trollman, F., Garcia-Garcia, G., Parra-López, C., Duong, L., Martindale, W., Munekata, P.E.S., Lorenzo, J.M., Hdaifeh, A., Hassoun, A., Salonitis, K., Afy-Shararah, M., 2022. The Russia-Ukraine conflict: Its implications for the global food supply chains. Foods 11(14), 2098. https://doi.org/10.3390/foods11142098

Jiang, W., He, G., Long, T. Liu, H., 2017. Ongoing conflict makes Yemen dark: From the perspective of nighttime light. Remote Sensing 9, 798. https://doi.org/10.3390/rs9080798

Johnson, D.M., 2014. An assessment of pre-and within-season remotely sensed variables for forecasting corn and soybean yields in the United States. Remote Sensing of Environment 141, 116–128. https://doi.org/10.1016/j.rse.2013.10.027

Jones, B.F., Olken, B.A., 2010. Climate shocks and exports. American Economic Review 100, 454–459. https://doi.org/10.1257/aer.100.2.454

Jumaah, H.J., Kalantar, B., Ueda, N., Sani, O.S., Ajaj, Q.M., Jumaah, S.J., 2021. The effect of war on land use dynamics in Mosul Iraq using remote sensing and GIS techniques. In 2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS 6476-6479. https://doi.org/10.1109/IGARSS47720.2021.9553165

Kafi, A., Zainuddin, N., Saifudin, A.M., Shahron, S.A., Razalli, M.R., Musa, S., Ahmi, A., 2023. Meta-analysis of food supply chain: pre, during and post COVID-19 pandemic. Agriculture & Food Security 12(1), 27. https://doi.org/10.1186/s40066-023-00425-5

Kahiluoto, H., 2020. Food systems for resilient futures. Food Security 12(4), 853–857. https://doi.org/10.1007/s12571-020-01070-7

Kahiluoto, H., Rimhanen, K., Rötter, R., Tseganeh, B., 2012. Mitigation of climate change to enhance food security: An analytical framework. Forum for Development Studies 39(1), 51–73. https://doi.org/10.1080/08039410.2011.635381

Karakoc, D.B., Konar, M., 2021. A complex network framework for the efficiency and resilience trade-off in global food trade. Environmental Research Letters 16(10), 105003. https://doi.org/10.1088/1748-9326/ac1a9b

Kaul, A., Klößner, S., Pfeifer, G., Schieler, M., 2015. Synthetic control methods: Never use all pre-intervention outcomes together with covariates.

Kichurchak, M., Paslavska, I., Hrynkevych, O., Mishchuk, H., Bilan, Y., 2024. Examining tertiary education amid the war in Ukraine: A synthetic control approach. European Journal of Interdisciplinary Studies 16(2), 95–115. https://doi.org/10.24818/ejis.2024.13

Kim, S., Shin, E.H., 2002. A Longitudinal analysis of globalization and regionalization in international trade: A social network approach. Social Forces, 81(2), 445–468. https://doi.org/10.1353/sof.2003.0014

Kiselev, S., Seitov, S., 2020. Regulating the Russian wheat export trade during the COVID-19 pandemic. Food Security in Eurasia. 83–102.

Kubatko, O., Merritt, R., Duane, S., Piven, V., 2023. The impact of the COVID-19 pandemic on global food system resilience. Mechanism of an Economic Regulation, 1 (99), 144–148. https://doi.org/10.32782/mer.2023.99.22

Kummu, M., Kinnunen, P., Lehikoinen, E., Porkka, M., Queiroz, C., Röös, E., Troell, M., Weil, C., 2020. Interplay of trade and food system resilience: Gains on supply diversity over time at the cost of trade independency. Global Food Security 24, 100360. https://doi.org/10.1016/j.gfs.2020.100360

Lamba, A., Teo, H.C., Sreekar, R., Zeng, Y., Carrasco, L.R., Koh, L.P., 2023. Climate co-benefits of tiger conservation. Nature Ecology & Evolution 7(7), 1104–1113. https://doi.org/10.1038/s41559-023-02069-x

Larochez-Dupraz, C., Huchet-Bourdon, M., 2016. Agricultural support and vulnerability of food security to trade in developing countries. Food Security 8(6), 1191–1206. https://doi.org/10.1007/s12571-016-0623-5

Le Mouël, C., Forslund, A., Marty, P., Manceron, S., Marajo-Petitzon, E., Caillaud, M.A., Dumas, P., Schmitt, B., 2023. Can the Middle East-North Africa region mitigate the rise of its food import dependency under climate change? Regional Environmental Change 23(2), 52. https://doi.org/10.1007/s10113-023-02045-y

Lehikoinen, E., Kinnunen, P., Piipponen, J., Heslin, A., Puma, M.J., Kummu, M., 2021. Importance of trade dependencies for agricultural inputs: A case study of Finland. Environmental Research Communications 3(6), 061003. https://doi.org/10.1088/2515-7620/ac02d0

Lehikoinen, E., Kinnunen, P., Piipponen, J., Heslin, A., Puma, M.J., Kummu, M., 2021. Importance of trade dependencies for agricultural inputs: A case study of Finland. Environmental Research Communications 3(6), 061003. https://doi.org/10.1088/2515-7620/ac02d0

Levy, B.S. Leaning, J., 2022. Russia's war in Ukraine—the devastation of health and human rights. New England Journal of Medicine 387(2), 102–105. https://doi.org/10.1056/NEJMp2207415

Li, X. Li, D., 2014. Can night-time light images play a role in evaluating the Syrian Crisis?. International Journal of Remote Sensing 35, 6648–6661. https://doi.org/10.1080/01431161.2014.971469

Li, X.Y., Li, X., Fan, Z., Mi, L., Kandakji, T., Song, Z., Li, D., Song, X.P., 2022. Civil war hinders crop production and threatens food security in Syria. Nature Food 3(1), 38–46. https://doi.org/10.1038/s43016-021-00432-4

Lin, F., Li, X., Jia, N., Feng, F., Huang, H., Huang, J., Fan, S., Ciais, P., Song, X.P., 2023. The impact of Russia-Ukraine conflict on global food security. Global Food Security 36, 100661. https://doi.org/10.1016/j.gfs.2022.100661

Liu, J., 2017. Integration across a metacoupled world. Ecology and Society 22(4), art29. https://doi.org/10.5751/ES-09830-220429

Liu, J., 2023. Leveraging the metacoupling framework for sustainability science and global sustainable development. National Science Review 10(7), nwad090. https://doi.org/10.1093/nsr/nwad090

Liu, J., Dietz, T., Carpenter, S.R., Taylor, W.W., Alberti, M., Deadman, P., Redman, C., Pell, A., Folke, C., Ouyang, Z., Lubchenco, J., 2021. Coupled human and natural systems: The evolution and applications of an integrated framework. AMBIO 50(10), 1778–1783. https://doi.org/10.1007/s13280-020-01488-5

Liu, J., Hull, V., Batistella, M., DeFries, R., Dietz, T., Fu, F., Hertel, T.W., Izaurralde, R.C., Lambin, E.F., Li, S., Martinelli, L.A., McConnell, W.J., Moran, E.F., Naylor, R., Ouyang, Z., Polenske, K.R., Reenberg, A., de Miranda Rocha, G., Simmons, C.S., Verburg, P.H., Vitousek, P.M., Zhang, F., Zhu, C., 2013. Framing sustainability in a telecoupled world. Ecology and Society 18(2), art26. https://doi.org/10.5751/ES-05873-180226

Ma, Y., Lyu, D., Sun, K., Li, S., Zhu, B., Zhao, R., Zheng, M., Song, K., 2022. Spatiotemporal analysis and war impact assessment of agricultural land in Ukraine using RS and GIS technology. Land 11(10), 1810. https://doi.org/10.3390/land11101810

Maggio, A., Van Criekinge, T., Malingreau, J.P., 2016. Global food security: Assessing trends in view of guiding future EU policies. Foresight 18(5), 551–560. https://doi.org/10.1108/FS-07-2015-0040

Mahajan, K., Tomar, S., 2021. COVID-19 and supply chain disruption: Evidence from food markets in India. American Journal of Agricultural Economics 103(1), 35–52. https://doi.org/10.1111/ajae.12158

Mahutga, M.C., 2006. The persistence of structural inequality? A network analysis of international trade, 1965-2000. Social Forces 84(4), 1863–1889. https://doi.org/10.1353/sof.2006.0098

Marchand, P., Carr, J.A., Dell'Angelo, J., Fader, M., Gephart, J.A., Kummu, M., Magliocca, N.R., Porkka, M., Puma, M.J., Ratajczak, Z., Rulli, M.C., Seekell, D.A., Suweis, S., Tavoni, A., D'Odorico, P., 2016. Reserves and trade jointly determine exposure to food supply shocks. Environmental Research Letters 11(9), 095009. https://doi.org/10.1088/1748-9326/11/9/095009

Marchetti, G., Manconi, A., Comiti, F., 2023. Limitations in the use of Sentinel-1 data for morphological change detection in rivers. International Journal of Remote Sensing 44(21), 6642–6669. https://doi.org/10.1080/01431161.2023.2274317

Markert, K.N., Markert, A.M., Mayer, T., Nauman, C., Haag, A., Poortinga, A., Bhandari, B., Thwal, N.S., Kunlamai, T., Chishtie, F., Kwant, M., Phongsapan, K., Clinton, N., Towashiraporn, P., Saah, D., 2020. Comparing sentinel-1 surface water mapping algorithms and radiometric terrain correction processing in southeast asia utilizing google earth engine. Remote Sensing 12(15), 2469. https://doi.org/10.3390/rs12152469

Mastronardi, L., Cavallo, A., Romagnoli, L., 2022. How did Italian diversified farms tackle Covid-19 pandemic first wave challenges? Socio-Economic Planning Sciences 82, 101096. https://doi.org/10.1016/j.seps.2021.101096

Mazepus, H., Osmudsen, M., Bang-Petersen, M., Toshkov, D., Dimitrova, A., 2023. Information battleground: Conflict perceptions motivate the belief in and sharing of misinformation about the adversary. PLoS one 18, e0282308. https://doi.org/10.1371/journal.pone.0282308

Miralles, I., Dentoni, D., Pascucci, S., 2017. Understanding the organization of sharing economy in agri-food systems: Evidence from alternative food networks in Valencia. Agriculture and Human Values 34(4), 833–854. https://doi.org/10.1007/s10460-017-9778-8

Moher, D., Liberati, A., Tetzlaff, J., Altman, D.J., Group, P., 2010. Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. International Journal of Surgery 8(5), 336-341. https://doi.org/10.1016/j.ijsu.2010.02.007

Mottaleb, K.A., Kruseman, G., Snapp, S., 2022. Potential impacts of Ukraine-Russia armed conflict on global wheat food security: A quantitative exploration. Global Food Security 35, 100659. https://doi.org/10.1016/j.gfs.2022.100659

Mullissa, A., Vollrath, A., Odongo-Braun, C., Slagter, B., Balling, J., Gou, Y., Gorelick, N., Reiche, J., 2021. Sentinel-1 SAR backscatter analysis ready data preparation in google earth engine. Remote Sensing 13(10), 1954. https://doi.org/10.3390/rs13101954

Nava, N.J., Ridley, W., Dall'erba, S., 2023. A model of the U.S. food system: What are the determinants of the state vulnerabilities to production shocks and supply chain disruptions? Agricultural Economics 54(1), 95–109. https://doi.org/10.1111/agec.12750

Nébié, E.K.I., Ba, D., Giannini, A., 2021. Food security and climate shocks in Senegal: Who and where are the most vulnerable households?. Global Food Security 29, 100513. https://doi.org/10.1016/j.gfs.2021.100513

Nicholson, C.C., Emery, B.F., Niles, M.T., 2021. Global relationships between crop diversity and nutritional stability. Nature Communications 12(1), 5310. https://doi.org/10.1038/s41467-021-25615-2

Nisar, U., Zhang, Z., Cui, Z., Mu, Y., Zhang, H., 2023. Impact of COVID-19 on fish and crustacean export from China with building resilient food system through China’s lens.

Frontiers in Sustainable Food Systems 7, 1189526. https://doi.org/10.3389/fsufs.2023.1189526

Nordin, S.K.S., Sek, S.K., 2019. Modeling the spatial spillover effects of energy consumption, environmental degradation and economic growth in high and middle-income countries. AIP Conference Proceedings 2184, 050009. https://doi.org/10.1063/1.5136397

O'Loughlin, J., Toal, G. Kolosov, V., 2020. Who identifies with the "Russian World"? Geopolitical attitudes in southeastern Ukraine, Crimea, Abkhazia, South Ossetia, and Transnistria. Political Geographies of the Post-Soviet Union Routledge. 6-39.

Olsen, V.M., Fensholt, R., Olofsson, P., Bonifacio, R., Butsic, V., Druce, D., Ray, D., Prishchepov, A.V., 2021. The impact of conflict-driven cropland abandonment on food insecurity in South Sudan revealed using satellite remote sensing. Nature Food 2(12), 990–996. https://doi.org/10.1038/s43016-021-00417-3

Opsahl, T., 2009. Structure and Evolution of Weighted Networks. University of London (Queen Mary College), London, UK. http://toreopsahl.com/publications/thesis/

Osendarp, S., Verburg, G., Bhutta, Z., Black, R.E., de Pee, S., Fabrizio, C., Headey, D., Heidkamp, R., Laborde, D., Ruel, M.T., 2022. Act now before Ukraine war plunges millions into malnutrition. Nature 604(7907), 620–624. https://doi.org/10.1038/d41586-022-01076-5

Otsu, N., 1975. A threshold selection method from gray-level histograms. Automatica 11(285-296), 23–27.

Özden, C., Bulut, M., Şen, B., 2022. COVID-19 and food security: impact on wheat. Turkish Journal of Agriculture-Food Science and Technology 10(4), 549–554. https://doi.org/10.24925/turjaf.v10i4.549-554.4581

Pereira, P., Zhao, W., Symochko, L., Inacio, M., Bogunovic, I., Barcelo, D., 2022. The Russian-Ukrainian armed conflict will push back the sustainable development goals. Geography and Sustainability 3(3), 277–287. https://doi.org/10.1016/j.geosus.2022.09.003

Pimentel, D., 2018. World food, pest losses, and the environment. Routledge. https://doi.org/10.1201/9780429268076

Pörtner, L.M., Lambrecht, N., Springmann, M., Bodirsky, B.L., Gaupp, F., Freund, F., Lotze-Campen, H., Gabrysch, S., 2022. We need a food system transformation—In the face of the Russia-Ukraine war, now more than ever. One Earth 5(5), 470–472. https://doi.org/10.1016/j.oneear.2022.04.004

Povey, A.C., Grainger, R.G., 2015. Known and unknown unknowns: Uncertainty estimation in satellite remote sensing. Atmospheric Measurement Techniques 8(11), 4699–4718. https://doi.org/10.5194/amt-8-4699-2015

Prasetyo, A.P., McDevitt, A.D., Murray, J.M., Barry, J., Agung, F., Muttaqin, E., Mariani, S., 2021. Shark and ray trade in and out of Indonesia: Addressing knowledge gaps on the path to sustainability. Marine Policy 133, 104714. https://doi.org/10.1016/j.marpol.2021.104714

Priyadarshini, P., Abhilash, P.C., 2021. Agri-food systems in India: Concerns and policy recommendations for building resilience in post COVID-19 pandemic times. Global Food Security 29, 100537. https://doi.org/10.1016/j.gfs.2021.100537

Mao, Q., Xu, L., Sun, Q., Guo, M., 2023. Stochastic evolutionary game analysis of food cooperation among countries along the Belt and Road from the perspective of food security. Frontiers in Sustainable Food Systems 7, 1238080. https://doi.org/10.3389/fsufs.2023.1238080

Rabbi, M.F., Ben Hassen, T., El Bilali, H., Raheem, D., Raposo, A., 2023. Food security challenges in Europe in the context of the prolonged Russian–Ukrainian conflict. Sustainability 15(6), 4745. https://doi.org/10.3390/su15064745

Rask, K.J., Rask, N., 2011. Economic development and food production–consumption balance: a growing global challenge. Food Policy 36(2), 186–196. https://doi.org/10.1016/j.foodpol.2010.11.015

Ray, D.K., West, P.C., Clark, M., Gerber, J.S., Prishchepov, A.V., Chatterjee, S., 2019. Climate change has likely already affected global food production. PLoS one 14(5), e0217148. https://doi.org/10.1371/journal.pone.0217148

Reed, C., Anderson, W., Kruczkiewicz, A., Nakamura, J., Gallo, D., Seager, R., McDermid, S.S., 2022. The impact of flooding on food security across Africa. Proceedings of the National Academy of Sciences 119(43), e2119399119. https://doi.org/10.1073/pnas.2119399119

Rizou, M., Galanakis, I.M., Aldawoud, T.M., Galanakis, C.M., 2020. Safety of foods, food supply chain and environment within the COVID-19 pandemic. Trends in Food Science & Technology 102, 293–299. https://doi.org/10.1016/j.tifs.2020.06.008

Rothwell, A., Ridoutt, B., Page, G., Bellotti, W., 2016. Environmental performance of local food: Trade-offs and implications for climate resilience in a developed city. Journal of Cleaner Production 114, 420–430. https://doi.org/10.1016/j.jclepro.2015.04.096

Rossa, F. D., Dercole, F., & Piccardi, C., 2013. Profiling core-periphery network structure by random walkers. Scientific Reports, 3(1), 1467.

Saman, C., Alexandri, C., 2018. The impact of the world food price index on some East-European economies. Journal of Business Economics and Management 19(2), 268–287. https://doi.org/10.3846/jbem.2018.5208

Schaffer-Smith, D., Tomscha, S.A., Jarvis, K.J., Maguire, D.Y., Treglia, M.L., Liu, J., 2018. Network analysis as a tool for quantifying the dynamics of metacoupled systems. Ecology and Society 23(4), 3. https://doi.org/10.5751/ES-10460-230403

Seekell, D., Carr, J., Dell'Angelo, J., D'Odorico, P., Fader, M., Gephart, J., Kummu, M., Magliocca, N., Porkka, M., Puma, M., Ratajczak, Z., Rulli, M.C., Suweis, S., Tavoni, A., 2017. Resilience in the global food system. Environmental Research Letters 12(2), 025010. https://doi.org/10.1088/1748-9326/aa5730

Short, K.R., Kedzierska, K., Van de Sandt, C.E., 2018. Back to the future: Lessons learned from the 1918 influenza pandemic. Frontiers in Cellular and Infection Microbiology 8, 343. https://doi.org/10.3389/fcimb.2018.00343

Shumilova, O., Tockner, K., Sukhodolov, A., Khilchevskyi, V., De Meester, L., Stepanenko, S., Trokhymenko, G., Hernández-Agüero, J.A., Gleick, P., 2023. Impact of the Russia–Ukraine armed conflict on water resources and water infrastructure. Nature Sustainability 6(5), 578–586. https://doi.org/10.1038/s41893-023-01068-x

Skakun, S., Franch, B., Vermote, E., Roger, J.C., Becker-Reshef, I., Justice, C., Kussul, N., 2017. Early season large-area winter crop mapping using MODIS NDVI data, growing degree days information and a Gaussian mixture model. Remote Sensing of Environment 195, 244–258. https://doi.org/10.1016/j.rse.2017.04.026

Skakun, S., Vermote, E., Franch, B., Roger, J.C., Kussul, N., Ju, J., Masek, J., 2019. Winter wheat yield assessment from Landsat 8 and Sentinel-2 data: Incorporating surface reflectance, through phenological fitting, into regression yield models. Remote Sensing 11(15), 1768. https://doi.org/10.3390/rs11151768

Smith, D.A., White, D.R., 1992. Structure and dynamics of the global economy: network analysis of international trade 1965–1980. Social Forces 70(4), 857–893. https://doi.org/10.1093/sf/70.4.857

Smith, V.H., Glauber, J.W., 2020. Trade, policy, and food security. Agricultural Economics 51(1), 159–171. https://doi.org/10.1111/agec.12547

SSSU, 2022. Agricultural production by region statistics of Ukraine. State Stat Serv Ukr. (2022).

Steinbach, S., 2023. The Russia–Ukraine war and global trade reallocations. Economics Letters 226, 111075. https://doi.org/10.1016/j.econlet.2023.111075

Suh, J., Chung, H., Cho, C., Kim, J., 2024. A comparative study of Difference-in-Differences (DID), Synthetic Control Method (SCM), Synthetic Difference-in-Differences (SDID): Effects of early-morning delivery. Journal of Channel and Retailing 29(4), 121–148. https://doi.org/10.17657/jcr.2024.10.31.6

Sun, J., Mooney, H., Wu, W., Tang, H., Tong, Y., Xu, Z., Huang, B., Cheng, Y., Yang, X., Wei, D., Zhang, F., Liu, J., 2018. Importing food damages domestic environment: Evidence from global soybean trade. Proceedings of the National Academy of Sciences 115(21), 5415–5419. https://doi.org/10.1073/pnas.1718153115

Suweis, S., Carr, J.A., Maritan, A., Rinaldo, A., D'Odorico, P., 2015. Resilience and reactivity of global food security. Proceedings of the National Academy of Sciences 112(22), 6902–6907. https://doi.org/10.1073/pnas.1507366112

Svanidze, M., Götz, L., Serebrennikov, D., 2022. The influence of Russia's 2010/2011 wheat export ban on spatial market integration and transaction costs of grain markets. Applied Economic Perspectives and Policy 44(2), 1083–1099. https://doi.org/10.1002/aepp.13168

Syfongxay, C., Kongmanila, D., Sinavong, P., Sacklokham, S., Alexander, K.S., 2022. Disruption to vegetable food systems during the COVID-19 pandemic in the Lao People's Democratic Republic. Singapore Journal of Tropical Geography 43(3), 363–382. https://doi.org/10.1111/sjtg.12447

Szymczak, L.S., de Faccio Carvalho, P.C., Lurette, A., De Moraes, A., de Albuquerque Nunes, P.A., Martins, A.P., Moulin, C.H., 2020. System diversification and grazing management as resilience-enhancing agricultural practices: The case of crop-livestock integration. Agricultural Systems 184, 102904. https://doi.org/10.1016/j.agsy.2020.102904

Tamea, S., Laio, F., Ridolfi, L., 2016. Global effects of local food-production crises: A virtual water perspective. Scientific Reports 6(1), 18803. https://doi.org/10.1038/srep18803

Tanumihardjo, S.A., McCulley, L., Roh, R., Lopez-Ridaura, S., Palacios-Rojas, N., Gunaratna, N.S., 2020. Maize agro-food systems to ensure food and nutrition security in reference to the Sustainable Development Goals. Global Food Security 25, 100327. https://doi.org/10.1016/j.gfs.2019.100327

Thanichanon, P., Schmidt-Vogt, D., Epprecht, M., Heinimann, A., Wiesmann, U., 2018. Balancing cash and food: The impacts of agrarian change on rural land use and wellbeing in Northern Laos. PLoS one 13(12), e0209166. https://doi.org/10.1371/journal.pone.0209166

The Economist, 2022. The coming food catastrophe. https://www.economist.com/leaders/2022/05/19/the-coming-food-catastrophe

Thow, A.M., 2009. Trade liberalisation and the nutrition transition: Mapping the pathways for public health nutritionists. Public Health Nutrition 12(11), 2150–2158. https://doi.org/10.1017/S1368980009005680

Thow, A.M., Hawkes, C., 2009. The implications of trade liberalization for diet and health: A case study from Central America. Globalization and Health 5(1), 5. https://doi.org/10.1186/1744-8603-5-5

Toth, A., Rendall, S., Reitsma, F., 2016. Resilient food systems: a qualitative tool for measuring food resilience. Urban Ecosystems 19, 19–43. https://doi.org/10.1007/s11252-015-0489-x

Travnikar, T., Bele, S., 2022. Vulnerability of the Slovenian food system in connection with the war in Ukraine. Journal of Central European Agriculture 23(4), 921–934. https://doi.org/10.5513/JCEA01/23.4.3775

USA for UNHCR, 2023. Ukraine emergency. https://www.unrefugees.org/emergencies/ukraine/

USDA (United States Department of Agriculture), 2018. USDA Foreign Agricultural Service Production, Supply, and Distribution Database. Foreign Agricultural Service, Department of Agriculture. https://data.nal.usda.gov/dataset/usda-foreign-agricultural-service-production-supply-and-distribution-database

Van De Kerchove, R., Zanaga, D., Keersmaecker, W., Souverijns, N., Wevers, J., Brockmann, C., Grosu, A., Paccini, A., Cartus, O., Santoro, M., Lesiv, M., Georgieva, I., Fritz, S., Carter, S., Tsendbazar, N.E., Li, L., Herold, M., Arino, O., 2021. ESA WorldCover: Global land cover mapping at 10 m resolution for 2020 based on Sentinel-1 and 2 data. AGU Fall Meeting Abstracts 2021, GC45I-0915.

Van Der Mensbrugghe, D., 2016. Using R to extract data from the World Bank's world development indicators. Journal of Global Economic Analysis 1(1), 251–283. https://doi.org/10.21642/JGEA.010105AF

van Meijl, H., Bartelings, H., van Berkum, S., Cui, H.D., Kristkova, Z.S., van Zeist, W.J., 2024. The Russia-Ukraine war decreases food affordability but could reduce global greenhouse gas emissions. Communications Earth & Environment 5(1), 59. https://doi.org/10.1038/s43247-024-01208-x

Veloso, A., Mermoz, S., Bouvet, A., Le Toan, T., Planells, M., Dejoux, J.F., Ceschia, E., 2017. Understanding the temporal behavior of crops using Sentinel-1 and Sentinel-2-like data for agricultural applications. Remote Sensing of Environment 199, 415–426. https://doi.org/10.1016/j.rse.2017.07.015

Vina, A. Liu, J., 2023. Effects of global shocks on the evolution of an interconnected world. AMBIO 52, 95–106. https://doi.org/10.1007/s13280-022-01778-0

Wang, J., Dai, C., 2021. Evolution of global food trade patterns and its implications for food security based on complex network analysis. Foods 10(11), 2657. https://doi.org/10.3390/foods10112657

Wang, L., Jin, G., Xiong, X., Zhang, H. Wu, K., 2022. Object-based automatic mapping of winter wheat based on temporal phenology patterns derived from multitemporal Sentinel-1 and Sentinel-2 imagery. ISPRS International Journal of Geo-Information 11(8), 424. https://doi.org/10.3390/ijgi11080424

Wasserman, L., 2013. All of Statistics: A Concise Course in Statistical Inference. Springer Science & Business Media.

Wasserman, S., Faust, K., 1994. Social network analysis: Methods and applications. USA: Cambridge University Press.

Welton, G., 2011. The impact of Russia's 2010 grain export ban. Oxfam Policy and Practice: Agriculture, Food and Land 11(5), 76–107.

Willer, D.F., Aldridge, D.C., 2023. Enhancing domestic consumption to deliver food security in a volatile world. Global Sustainability 6, e18. https://doi.org/10.1017/sus.2023.17

Wirsenius, S., Azar, C., Berndes, G., 2010. How much land is needed for global food production under scenarios of dietary changes and livestock productivity increases in 2030? Agricultural Systems 103(9), 621–638. https://doi.org/10.1016/j.agsy.2010.07.005

World Bank. (2023, July 1). *World Bank country classifications by income level for 2024–2025*. https://blogs.worldbank.org/en/opendata/world-bank-country-classifications-by-income-level-for-2024-2025

Wood, A., Queiroz, C., Deutsch, L., González-Mon, B., Jonell, M., Pereira, L., Sinare, H., Svedin, U., Wassénius, E., 2023. Reframing the local–global food systems debate through a resilience lens. Nature Food 4(1), 22–29. https://doi.org/10.1038/s43016-022-00662-0

Wu, X., Fu, B., Wang, S., Song, S., Li, Y., Xu, Z., Wei, Y., Liu, J., 2022. Decoupling of SDGs followed by re-coupling as sustainable development progresses. Nature Sustainability 5(5), 452–459. https://doi.org/10.1038/s41893-022-00868-x

Xie, W.J., Li, J.A., Wei, N., Wang, L., Zhou, W.X., 2022. Robustness and efficiency of international pesticide trade networks subject to link removal strategies. Scientific Reports 12(1), 19641. https://doi.org/10.1038/s41598-022-21777-1

Yu, A., She, H., Cao, J., 2023. Evolution of the Spatial Patterns of Global Egg Trading Networks in the 21 Century. Sustainability 15(15), 11895. https://doi.org/10.3390/su151511895

Zhang, Y.J., Fan, Y., Tsai, H.T., Wei, Y.M., 2008. Spillover effect of US dollar exchange rate on oil prices. Journal of Policy Modeling 30(6), 973–991. https://doi.org/10.1016/j.jpolmod.2008.02.002

Zhang, Z., Abdullah, M.J., Xu, G., Matsubae, K., Zeng, X., 2023. Countries' vulnerability to food supply disruptions caused by the Russia–Ukraine war from a trade dependency perspective. Scientific Reports 13(1), 16591. https://doi.org/10.1038/s41598-023-43883-4

Zhao, Y., Frank, K.A., 2003. Factors affecting technology uses in schools: An ecological perspective. American Educational Research Journal 40(4), 807–840. https://doi.org/10.3102/00028312040004807

Zhou, X.Y., Lu, G., Xu, Z., Yan, X., Khu, S.T., Yang, J., Zhao, J., 2023. Influence of Russia-Ukraine war on the global energy and food security. Resources, Conservation and Recycling 188, 106657. https://doi.org/10.1016/j.resconrec.2022.106657

APPENDIX A SUPPORTING INFORMATION FOR CHAPTER 3

Table S3. 1 Data sources

Broad category	Variables	Impacts on food trade resilience	Reference study
Innovation and research	Bonilla Index (BI)	-	https://www.fao.org/faostat/en/#data
	Connectivity of trade network	+	https://comtradeplus.un.org/
	Centrality of trade network	+	https://comtradeplus.un.org/
Economy and market	Exchange Rate (E)	+	https://www.xe.com/zh-CN/currencyconverter/convert/?Amount=1&From=SPL&To=CNY (173 countreis avaliable)
	World Food Prices (Pw)	-	https://www.fao.org/faostat/en/#data
	GDP	+	https://data.worldbank.org/indicator/NY.GDP.MKTP.CD
	Income levels	+	https://data.worldbank.org.cn/indicator/NY.GNP.PCAP.CD
	Energy dependence	-	https://yearbook.enerdata.net/total-energy/world-consumption-statistics.html
	Export Growth Rate	+	https://data.worldbank.org/indicator/NE.EXP.GNFS.KD.ZG
	Production diversity	+	https://www.fao.org/faostat/en/#data/MDDW
Policy and institution	Trade Dependencies	-	https://data.worldbank.org/indicator/TM.VAL.FOOD.ZS.UN
	Political stability	+	https://databank.worldbank.org/source/worldwide-governance-indicators/preview/on
	Domestic Food Production	+	https://www.fao.org/faostat/en/#data/MDDW
	Domestic consumption	-	https://www.fao.org/faostat/en/#data/CP
	Trade partner diversity	+	https://kof.ethz.ch/en/forecasts-and-indicators/indicators/kof-globalisation-index.html
	Trade diversification	+	https://economicdiversification.com/the-index/
Society and culture	Exposure to crises	-	https://github.com/owid/covid-19-data
	Affordability	+	https://ourworldindata.org/food-prices
	Diet preference	-	https://globaldietarydatabase.org/our-data/data-visualizations/dietary-data-country
Demographic	Population growth	-	https://www.worldpop.org/
	Food availability	+	https://www.fao.org/faostat/en/#data/SUA
	Human development index (HDI)	+	https://hdr.undp.org/data-center/human-development-index#/indicies/HDI
	Calorie supply	+	https://www.fao.org/faostat/en/#data/SCL
Supply chain	Global Trade Disruptions	-	https://www.fao.org/faostat/en/#data
	Supply chain diversity	+	comtradeplus.un.org

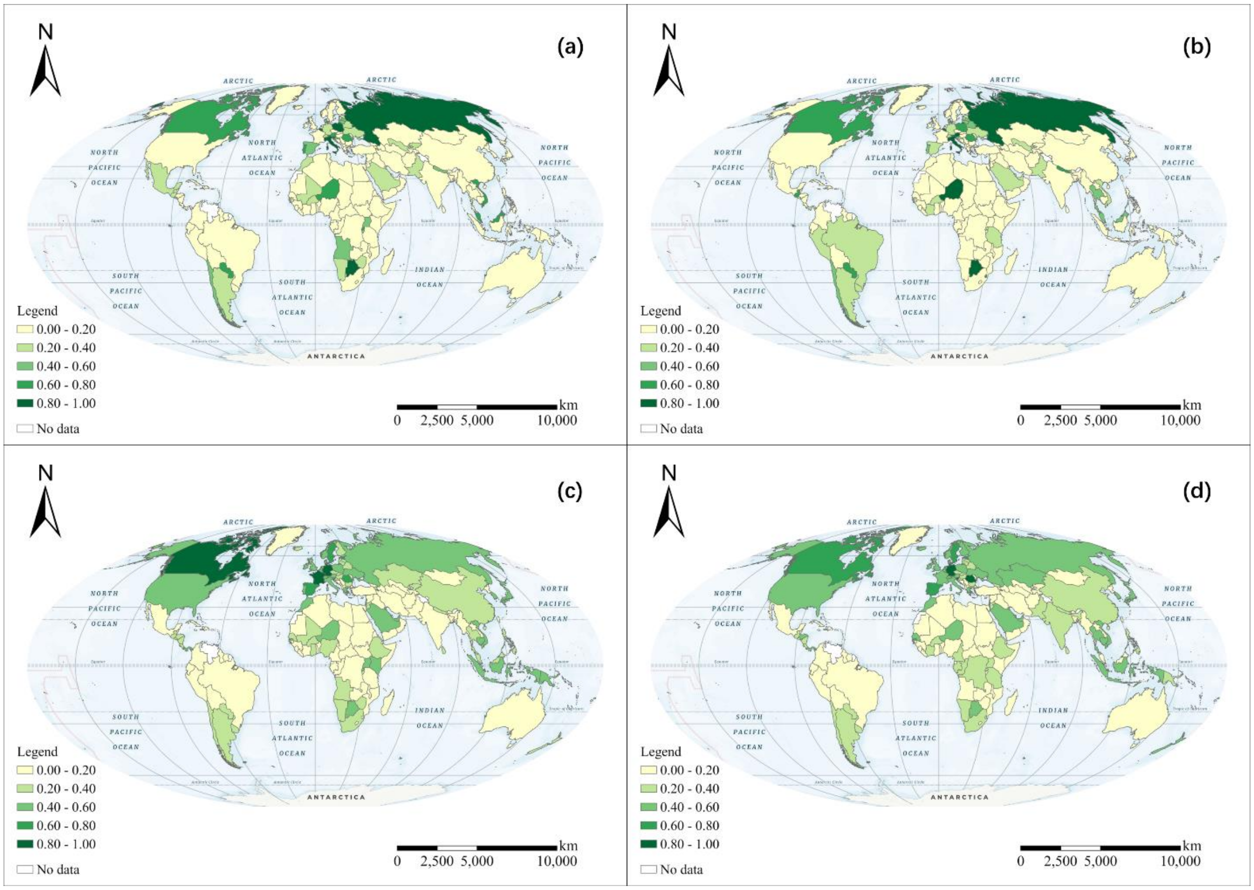


Figure S3. 1 Supply chain diversity in adjacent and distant trade networks for 2019 and 2020. Supply chain diversity reflects the adaptive capacity of countries through varied trade partnerships.

Supplementary Results

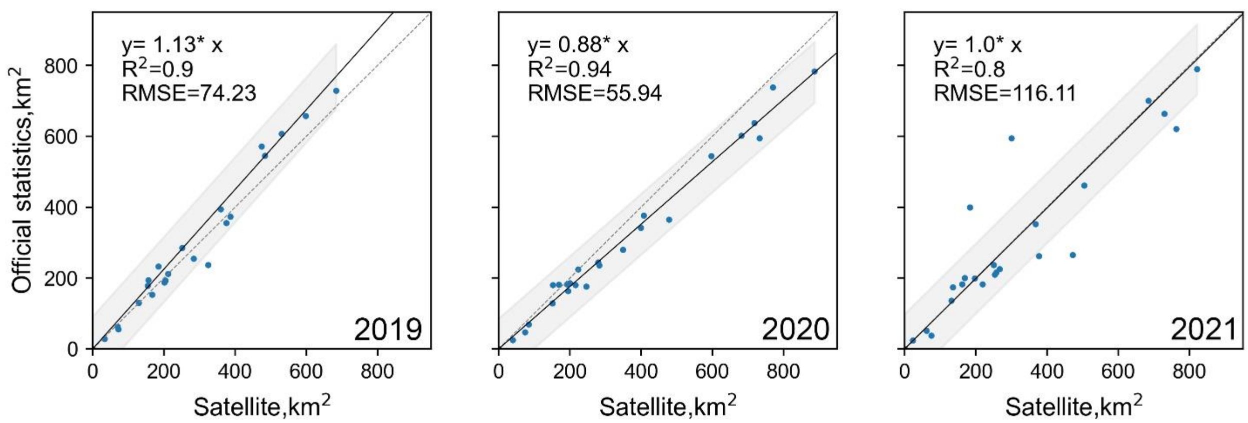


Figure S4. 1 Comparison of official statistics and satellite-derived winter cereal planting area at the state level for 2019–2021. Comparison between satellite-derived winter cereal yield estimates and official statistics from 2019 to 2021. Each panel represents the regression results for a different year, with satellite data on the x-axis and official statistics on the y-axis. The solid line in each panel represents the linear regression fit, while the shaded area indicates the confidence interval of the regression. The equation of the regression line, R^2, and RMSE (root mean square error) in each panel show the strong correlation between the satellite estimate and official statistic. The high R^2 values (ranging from 0.80 to 0.94) and low RMSE values across all years suggest the reliability of satellite data in estimating winter cereal yields, thus supporting its use in assessing production reductions due to the Russia-Ukraine war.

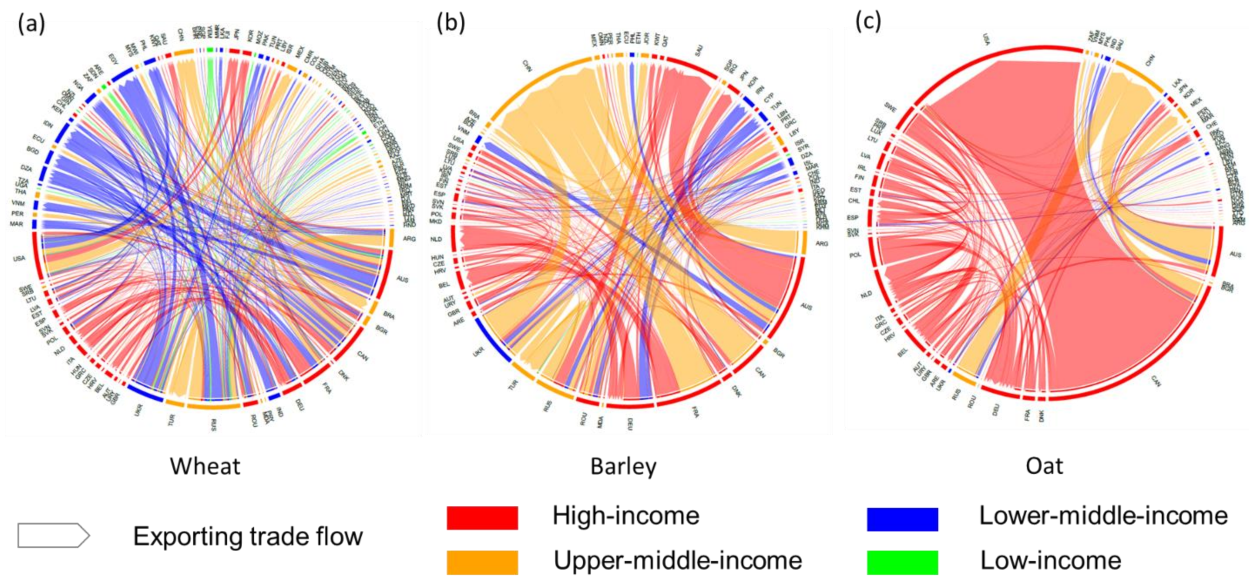


Figure S4. 2 Global trade flows of winter cereals among income groups in 2021 (100%). Global trade networks for winter cereals—wheat (a), barley (b), and oats (c)—across various countries, classified by income levels. Trade flows are depicted using chord diagrams, with the direction and volume of trade represented by the connecting bands between countries. Color coding distinguishes the income levels of countries, and thicker bands indicate higher volumes of trade between the respective countries.

Panel (a) shows the global wheat trade network, with high-income countries (red) playing a dominant role in both exporting and importing activities. Key wheat exporters such as the United States and countries within the European Union are interconnected with major wheat importers. Upper-middle-income countries (yellow), including China and Turkey, are also largely integrated into the global wheat trade, although their connections are less dense compared to high-income countries. Panel (b) depicts the barley trade network, where high-income countries are again the primary actors in the exchange of barley. Major exporters such as Australia and European countries form robust trade links with importing countries. Notably, upper-middle-income countries like Argentina and Brazil are also important players in the barley market. The presence of lower-middle-income countries (blue) is relatively limited in this network, suggesting that barley trade is more concentrated among wealthier nations. Panel (c) illustrates the oats trade network, where high-income countries dominate trade relations. The network for oats is characterized by fewer, but still substantial, connections between key exporters such as Canada and Australia and their primary importing partners, mostly in Europe. The overall volume of oats trade is smaller compared to wheat and barley, but it remains largely concentrated among a select group of high-income countries.

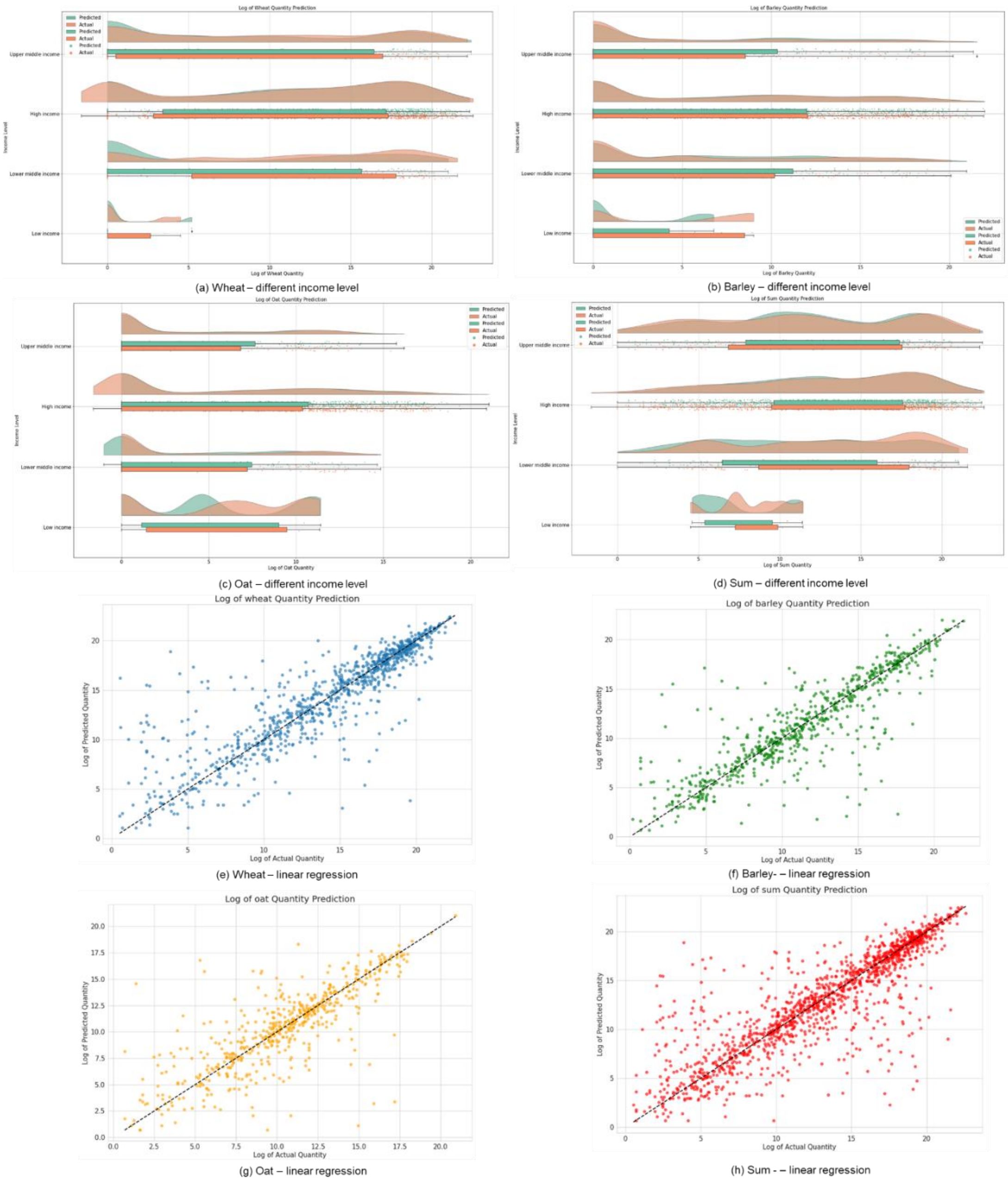


Figure S4. 3 Uncertainty analysis of simulated 2022 trade networks for wheat, barley, oats, and total cereal quantities compared to real 2022 trade data. (a) to (d) show the distribution of predicted trade quantities for wheat, barley, oats, and the sum of all winter cereals, respectively, for 2022, comparing simulated data to real trade values across different income levels (high-, upper-middle-, lower-middle-, and low-income). (e) to (h) present the linear regression analysis between the predicted (simulated) and actual trade quantities for wheat, barley, oats, and the sum total, respectively. The scatter plots visualize the relationship between the logarithms of predicted and actual trade quantities. The dashed diagonal lines represent perfect predictions (i.e., where predicted equals actual). The strength of the fit is indicated by how closely the points align with this line, and the correlation coefficients are reflected in the regression slopes.

The validation presented in Figure S4.3 highlights the comparison between the simulated 2022 trade networks and the actual trade data for wheat, barley, oats, and total winter cereal quantities. Panels (a) to (d) reveal that, although there are variations between the predicted and real data, the overall distribution patterns are generally consistent across income levels. High-income countries exhibit relatively minimal deviation, whereas lower-middle and low-income countries show more noticeable divergence in trade quantities, which could be attributed to their higher vulnerability to market crises and supply chain disruptions. This is particularly evident in oats and barley trades.

In the regression analysis (panels e to h), the linear regression between simulated and actual trade quantities demonstrates strong correlation across all crops. The scatter plots for wheat, barley, oats, and the total cereals indicate high R^2 values, suggesting that the simulation accurately captures the overall trend in trade volumes. While some deviations are observed, particularly in lower-income regions and for oats, the error remains within an understandable range given the complexity of global trade networks and the uncertainties inherent in predictive modeling.

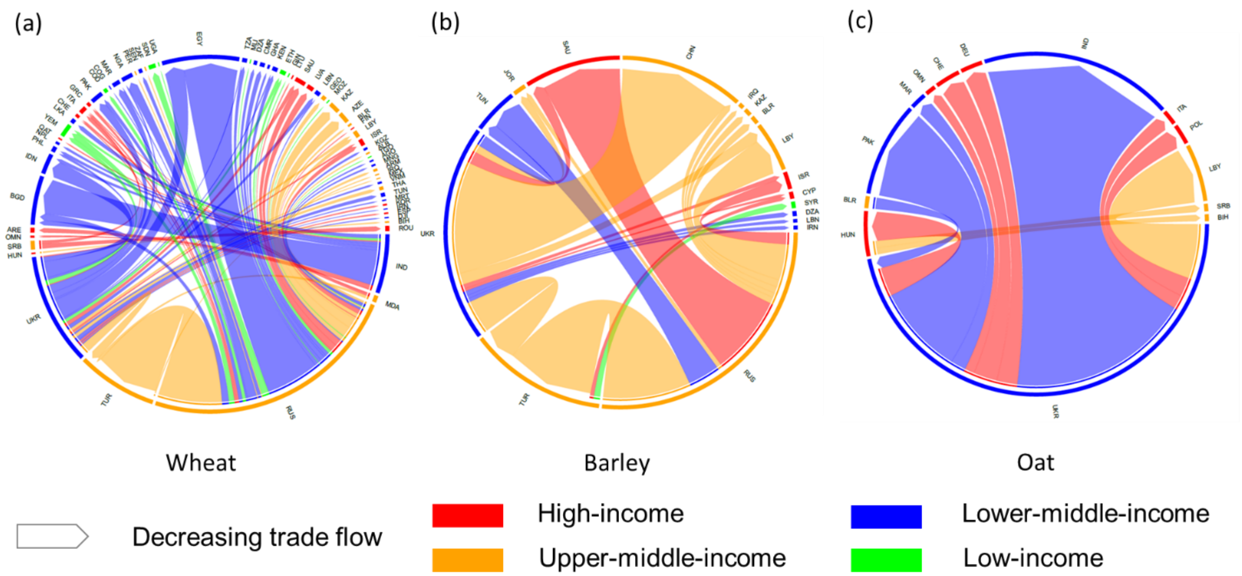


Figure S4. 4 Trade networks affected by production cuts in Ukraine and cereal export bans in importing countries. Global trade networks for winter cereals—wheat (a), barley (b), and oats (c)—across various countries, classified by income levels. Trade flows are depicted using chord diagrams, with the direction and volume of trade represented by the connecting bands between countries. Color coding distinguishes the income levels of countries, and thicker bands indicate higher volumes of trade between the respective countries.

The figure highlights the decrease in global trade volumes and the fragmentation of trade networks due to the combined effects of the Russia-Ukraine war and export bans. In the wheat network (panel a), there is a noticeable contraction in the trade flows, especially between high-income and upper-middle-income countries, with fewer connections to low-, and lower-middle-income nations. The barley trade network (panel b) shows a similar pattern, with high-income countries continuing to dominate the trade, though the overall volume has decreased. Oats trade (panel c) also exhibits a reduction in export flows, with the impact being more pronounced among lower-middle-income countries, as seen by the thinner and more fragmented connections. The overall reduction in connectivity and trade volume across these three cereal types demonstrates the large disruption to global food systems in 2022, disproportionately affecting lower-income and geographically distant countries.

Table S4. 1 Country names with ISO abbreviations

Country (from ISO list)	Alpha-2 code	Alpha-3 code	Numeric
Afghanistan	AF	AFG	4
Albania	AL	ALB	8
Algeria	DZ	DZA	12
American Samoa	AS	ASM	16
Andorra	AD	AND	20
Angola	AO	AGO	24
Anguilla	AI	AIA	660
Antarctica	AQ	ATA	10
Antigua and Barbuda	AG	ATG	28
Argentina	AR	ARG	32
Armenia	AM	ARM	51
Aruba	AW	ABW	533
Australia	AU	AUS	36
Austria	AT	AUT	40
Azerbaijan	AZ	AZE	31
Bahamas (the)	BS	BHS	44
Bahrain	BH	BHR	48
Bangladesh	BD	BGD	50
Barbados	BB	BRB	52
Belarus	BY	BLR	112
Belgium	BE	BEL	56
Belize	BZ	BLZ	84
Benin	BJ	BEN	204
Bermuda	BM	BMU	60
Bhutan	BT	BTN	64
Bolivia (Plurinational State of)	BO	BOL	68
Bonaire, Sint Eustatius and Saba	BQ	BES	535
Bosnia and Herzegovina	BA	BIH	70
Botswana	BW	BWA	72
Bouvet Island	BV	BVT	74
Brazil	BR	BRA	76
British Indian Ocean Territory (the)	IO	IOT	86
Brunei Darussalam	BN	BRN	96
Bulgaria	BG	BGR	100
Burkina Faso	BF	BFA	854
Burundi	BI	BDI	108
Cabo Verde	CV	CPV	132
Cambodia	KH	KHM	116
Cameroon	CM	CMR	120
Canada	CA	CAN	124
Cayman Islands (the)	KY	CYM	136
Central African Republic (the)	CF	CAF	140

Table S4. 1 (cont'd)

Chad	TD	TCD	148
Chile	CL	CHL	152
China	CN	CHN	156
Christmas Island	CX	CXR	162
Cocos (Keeling) Islands (the)	CC	CCK	166
Colombia	CO	COL	170
Comoros (The)	KM	COM	174
Congo (The Democratic Republic of the)	CD	COD	180
Congo (The)	CG	COG	178
Cook Islands (The)	CK	COK	184
Costa Rica	CR	CRI	188
Croatia	HR	HRV	191
Cuba	CU	CUB	192
Curaçao	CW	CUW	531
Cyprus	CY	CYP	196
Czechia	CZ	CZE	203
Côte d'Ivoire	CI	CIV	384
Denmark	DK	DNK	208
Djibouti	DJ	DJI	262
Dominica	DM	DMA	212
Dominican Republic (The)	DO	DOM	214
Ecuador	EC	ECU	218
Egypt	EG	EGY	818
El Salvador	SV	SLV	222
Equatorial Guinea	GQ	GNQ	226
Eritrea	ER	ERI	232
Estonia	EE	EST	233
Eswatini	SZ	SWZ	748
Ethiopia	ET	ETH	231
Falkland Islands [Malvinas]	FK	FLK	238
Faroe Islands (the)	FO	FRO	234
Fiji	FJ	FJI	242
Finland	FI	FIN	246
France	FR	FRA	250
French Guiana	GF	GUF	254
French Polynesia	PF	PYF	258
French Southern Territories (the)	TF	ATF	260
Gabon	GA	GAB	266
Gambia (the)	GM	GMB	270
Georgia	GE	GEO	268
Germany	DE	DEU	276
Ghana	GH	GHA	288
Gibraltar	GI	GIB	292
Greece	GR	GRC	300

Table S4. 1 (cont'd)

Greenland	GL	GRL	304
Grenada	GD	GRD	308
Guadeloupe	GP	GLP	312
Guam	GU	GUM	316
Guatemala	GT	GTM	320
Guernsey	GG	GGY	831
Guinea	GN	GIN	324
Guinea-Bissau	GW	GNB	624
Guyana	GY	GUY	328
Haiti	HT	HTI	332
Heard Island and McDonald Islands	HM	HMD	334
Holy See (the)	VA	VAT	336
Honduras	HN	HND	340
Hong Kong	HK	HKG	344
Hungary	HU	HUN	348
Iceland	IS	ISL	352
India	IN	IND	356
Indonesia	ID	IDN	360
Iran (Islamic Republic of)	IR	IRN	364
Iraq	IQ	IRQ	368
Ireland	IE	IRL	372
Isle of Man	IM	IMN	833
Israel	IL	ISR	376
Italy	IT	ITA	380
Jamaica	JM	JAM	388
Japan	JP	JPN	392
Jersey	JE	JEY	832
Jordan	JO	JOR	400
Kazakhstan	KZ	KAZ	398
Kenya	KE	KEN	404
Kiribati	KI	KIR	296
Korea (the Democratic People's Republic of)	KP	PRK	408
Korea (the Republic of)	KR	KOR	410
Kuwait	KW	KWT	414
Kyrgyzstan	KG	KGZ	417
Lao People's Democratic Republic (the)	LA	LAO	418
Latvia	LV	LVA	428
Lebanon	LB	LBN	422
Lesotho	LS	LSO	426
Liberia	LR	LBR	430
Libya	LY	LBY	434
Liechtenstein	LI	LIE	438
Lithuania	LT	LTU	440
Luxembourg	LU	LUX	442

Table S4. 1 (cont'd)

Macao	MO	MAC	446
Madagascar	MG	MDG	450
Malawi	MW	MWI	454
Malaysia	MY	MYS	458
Maldives	MV	MDV	462
Mali	ML	MLI	466
Malta	MT	MLT	470
Marshall Islands (the)	MH	MHL	584
Martinique	MQ	MTQ	474
Mauritania	MR	MRT	478
Mauritius	MU	MUS	480
Mayotte	YT	MYT	175
Mexico	MX	MEX	484
Micronesia (Federated States of)	FM	FSM	583
Moldova (the Republic of)	MD	MDA	498
Monaco	MC	MCO	492
Mongolia	MN	MNG	496
Montenegro	ME	MNE	499
Montserrat	MS	MSR	500
Morocco	MA	MAR	504
Mozambique	MZ	MOZ	508
Myanmar	MM	MMR	104
Namibia	NA	NAM	516
Nauru	NR	NRU	520
Nepal	NP	NPL	524
Netherlands (the)	NL	NLD	528
New Caledonia	NC	NCL	540
New Zealand	NZ	NZL	554
Nicaragua	NI	NIC	558
Niger (the)	NE	NER	562
Nigeria	NG	NGA	566
Niue	NU	NIU	570
Norfolk Island	NF	NFK	574
Northern Mariana Islands (the)	MP	MNP	580
Norway	NO	NOR	578
Oman	OM	OMN	512
Pakistan	PK	PAK	586
Palau	PW	PLW	585
Palestine, State of	PS	PSE	275
Panama	PA	PAN	591
Papua New Guinea	PG	PNG	598
Paraguay	PY	PRY	600
Peru	PE	PER	604
Philippines (the)	PH	PHL	608

Table S4. 1 (cont'd)

Pitcairn	PN	PCN	612
Poland	PL	POL	616
Portugal	PT	PRT	620
Puerto Rico	PR	PRI	630
Qatar	QA	QAT	634
Republic of North Macedonia	MK	MKD	807
Romania	RO	ROU	642
Russian Federation (the)	RU	RUS	643
Rwanda	RW	RWA	646
Réunion	RE	REU	638
Saint Barthélemy	BL	BLM	652
Saint Helena, Ascension and Tristan da Cunha	SH	SHN	654
Saint Kitts and Nevis	KN	KNA	659
Saint Lucia	LC	LCA	662
Saint Martin (French part)	MF	MAF	663
Saint Pierre and Miquelon	PM	SPM	666
Saint Vincent and the Grenadines	VC	VCT	670
Samoa	WS	WSM	882
San Marino	SM	SMR	674
Sao Tome and Principe	ST	STP	678
Saudi Arabia	SA	SAU	682
Senegal	SN	SEN	686
Serbia	RS	SRB	688
Seychelles	SC	SYC	690
Sierra Leone	SL	SLE	694
Singapore	SG	SGP	702
Sint Maarten (Dutch part)	SX	SXM	534
Slovakia	SK	SVK	703
Slovenia	SI	SVN	705
Solomon Islands	SB	SLB	90
Somalia	SO	SOM	706
South Africa	ZA	ZAF	710
South Georgia and the South Sandwich Islands	GS	SGS	239
South Sudan	SS	SSD	728
Spain	ES	ESP	724
Sri Lanka	LK	LKA	144
Sudan (the)	SD	SDN	729
Suriname	SR	SUR	740
Svalbard and Jan Mayen	SJ	SJM	744
Sweden	SE	SWE	752
Switzerland	CH	CHE	756
Syrian Arab Republic	SY	SYR	760
Taiwan (Province of China)	TW	TWN	158
Tajikistan	TJ	TJK	762

Table S4. 1 (cont'd)

Tanzania, United Republic of	TZ	TZA	834
Thailand	TH	THA	764
Timor-Leste	TL	TLS	626
Togo	TG	TGO	768
Tokelau	TK	TKL	772
Tonga	TO	TON	776
Trinidad and Tobago	TT	TTO	780
Tunisia	TN	TUN	788
Turkey	TR	TUR	792
Turkmenistan	TM	TKM	795
Turks and Caicos Islands (the)	TC	TCA	796
Tuvalu	TV	TUV	798
Uganda	UG	UGA	800
Ukraine	UA	UKR	804
United Arab Emirates (the)	AE	ARE	784
United Kingdom of Great Britain and Northern Ireland (the)	GB	GBR	826
United States Minor Outlying Islands (the)	UM	UMI	581
United States of America (the)	US	USA	840
Uruguay	UY	URY	858
Uzbekistan	UZ	UZB	860
Vanuatu	VU	VUT	548
Venezuela (Bolivarian Republic of)	VE	VEN	862
Viet Nam	VN	VNM	704
Virgin Islands (British)	VG	VGB	92
Virgin Islands (U.S.)	VI	VIR	850
Wallis and Futuna	WF	WLF	876
Western Sahara	EH	ESH	732
Yemen	YE	YEM	887
Zambia	ZM	ZMB	894
Zimbabwe	ZW	ZWE	716
Åland Islands	AX	ALA	248

Table S4. 2 Decreasing rate range statistics

ISO code	Partner	Rate Range	2021_Qty	2022_Qty	Income level
GUM	Guam	-5%-0%	48	48	High-income
ABW	Aruba	-5%-0%	2836	2836	High-income
AND	Andorra	-5%-0%	176531	176531	High-income
BMU	Bermuda	-5%-0%	195000	195000	High-income
GRL	Greenland	-5%-0%	274131	274131	High-income
PYF	French Polynesia	-5%-0%	629232	629232	High-income
URY	Uruguay	-5%-0%	1046138	1046138	High-income
BRB	Barbados	-5%-0%	8935886	8935886	High-income
NCL	New Caledonia	-5%-0%	33829904	33829904	High-income
LUX	Luxembourg	-5%-0%	1.14E+08	1.14E+08	High-income
TTO	Trinidad and Tobago	-5%-0%	1.23E+08	1.23E+08	High-income
IRL	Ireland	-5%-0%	5.36E+08	5.36E+08	High-income
CHL	Chile	-5%-0%	1.45E+09	1.45E+09	High-income
NZL	New Zealand	-5%-0%	6.07E+08	6.07E+08	High-income
PRT	Portugal	-5%-0%	1.35E+09	1.35E+09	High-income
PAN	Panama	-5%-0%	1.42E+08	1.42E+08	High-income
ISL	Iceland	-5%-0%	47611487	47611426	High-income
JPN	Japan	-5%-0%	6.5E+09	6.5E+09	High-income
SWE	Sweden	-5%-0%	1.26E+08	1.26E+08	High-income
USA	USA	-5%-0%	3.08E+09	3.08E+09	High-income
CAN	Canada	-5%-0%	5.21E+08	5.21E+08	High-income
SGP	Singapore	-5%-0%	2.14E+08	2.14E+08	High-income
DEU	Germany	-5%-0%	5.67E+09	5.67E+09	High-income
KWT	Kuwait	-5%-0%	1E+09	1E+09	High-income
AUS	Australia	-5%-0%	943943	943019	High-income
FRA	France	-5%-0%	5.52E+08	5.51E+08	High-income
CZE	Czechia	-5%-0%	1.22E+08	1.22E+08	High-income
HUN	Hungary	-5%-0%	2.18E+08	2.18E+08	High-income
BEL	Belgium	-5%-0%	5.63E+09	5.62E+09	High-income
POL	Poland	-5%-0%	7.8E+08	7.78E+08	High-income
NLD	Netherlands	-5%-0%	7.37E+09	7.34E+09	High-income
BHR	Bahrain	-5%-0%	94446353	93857218	High-income
SVN	Slovenia	-5%-0%	63215134	62695474	High-income
AUT	Austria	-5%-0%	8.07E+08	7.99E+08	High-income
GBR	United Kingdom	-5%-0%	1.66E+09	1.63E+09	High-income
BRN	Brunei Darussalam	-5%-0%	17609	17219	High-income
ESP	Spain	-5%-0%	4.45E+09	4.29E+09	High-income
GIB	Gibraltar	-5%-0%	104	100	High-income
DNK	Denmark	-5%-0%	1.77E+08	1.69E+08	High-income
CAF	Central African Rep.	-5%-0%	120	120	Low-income
NER	Niger	-5%-0%	700	700	Low-income
ZMB	Zambia	-5%-0%	47027822	47027822	Low-income
WSM	Samoa	-5%-0%	60	60	Lower-middle-income
VUT	Vanuatu	-5%-0%	632	632	Lower-middle-income

Table S4. 2 (cont'd)

TLS	Timor-Leste	-5%-0%	1067	1067	Lower-middle-income
COM	Comoros	-5%-0%	4864	4864	Lower-middle-income
LAO	Lao People's Dem. Rep.	-5%-0%	4023568	4023568	Lower-middle-income
CPV	Cabo Verde	-5%-0%	4594149	4594149	Lower-middle-income
LSO	Lesotho	-5%-0%	33619423	33619423	Lower-middle-income
SWZ	Eswatini	-5%-0%	45641015	45641015	Lower-middle-income
PNG	Papua New Guinea	-5%-0%	2.53E+08	2.53E+08	Lower-middle-income
HND	Honduras	-5%-0%	2.98E+08	2.98E+08	Lower-middle-income
SLV	El Salvador	-5%-0%	3.14E+08	3.14E+08	Lower-middle-income
KHM	Cambodia	-5%-0%	55184533	54809533	Lower-middle-income
IND	India	-5%-0%	58235410	57516547	Lower-middle-income
TJK	Tajikistan	-5%-0%	21984809	21520170	Lower-middle-income
VNM	Viet Nam	-5%-0%	5.31E+09	5.11E+09	Lower-middle-income
MMR	Myanmar	-5%-0%	4.81E+08	4.6E+08	Lower-middle-income
TON	Tonga	-5%-0%	2768	2768	Upper-middle-income
ARG	Argentina	-5%-0%	13597399	13597399	Upper-middle-income
GRD	Grenada	-5%-0%	13755658	13755658	Upper-middle-income
BLZ	Belize	-5%-0%	13782010	13782010	Upper-middle-income
SUR	Suriname	-5%-0%	32347242	32347242	Upper-middle-income
GUY	Guyana	-5%-0%	47348036	47348036	Upper-middle-income
NAM	Namibia	-5%-0%	50434752	50434752	Upper-middle-income
BWA	Botswana	-5%-0%	60040080	60040080	Upper-middle-income
MUS	Mauritius	-5%-0%	1.31E+08	1.31E+08	Upper-middle-income
FJI	Fiji	-5%-0%	1.7E+08	1.7E+08	Upper-middle-income
JAM	Jamaica	-5%-0%	1.91E+08	1.91E+08	Upper-middle-income
CRI	Costa Rica	-5%-0%	2.52E+08	2.52E+08	Upper-middle-income
CUB	Cuba	-5%-0%	5.02E+08	5.02E+08	Upper-middle-income
GTM	Guatemala	-5%-0%	5.66E+08	5.66E+08	Upper-middle-income
ECU	Ecuador	-5%-0%	1.56E+09	1.56E+09	Upper-middle-income
PRY	Paraguay	-5%-0%	161361	161025	Upper-middle-income
BRA	Brazil	-5%-0%	6.7E+09	6.67E+09	Upper-middle-income
MDV	Maldives	-5%-0%	52414	52144	Upper-middle-income
DOM	Dominican Rep.	-5%-0%	5.9E+08	5.87E+08	Upper-middle-income
COL	Colombia	-5%-0%	2.16E+09	2.13E+09	Upper-middle-income
MEX	Mexico	-5%-0%	5.63E+09	5.54E+09	Upper-middle-income
GNQ	Equatorial Guinea	-5%-0%	116963	113558	Upper-middle-income
RUS	Russian Federation	-5%-0%	1.04E+08	1E+08	Upper-middle-income
PER	Peru	-5%-0%	2.08E+09	1.98E+09	Upper-middle-income
KOR	Rep. of Korea	-25%--5%	4.52E+09	4.27E+09	High-income
HRV	Croatia	-25%--5%	72028774	64657769	High-income
ITA	Italy	-25%--5%	6.3E+09	5.6E+09	High-income
NOR	Norway	-25%--5%	3.23E+08	2.87E+08	High-income
SVK	Slovakia	-25%--5%	75536662	63464766	High-income
MOZ	Mozambique	-25%--5%	6.75E+08	5.61E+08	Low-income
AFG	Afghanistan	-25%--5%	7196829	5896119	Low-income

Table S4. 2 (cont'd)

UGA	Uganda	-25%--5%	4.06E+08	3.22E+08	Low-income
GIN	Guinea	-25%--5%	3.86E+08	2.98E+08	Low-income
MWI	Malawi	-25%--5%	1.63E+08	1.24E+08	Low-income
DZA	Algeria	-25%--5%	8.5E+09	8.06E+09	Lower-middle-income
IRN	Iran	-25%--5%	1.81E+09	1.72E+09	Lower-middle-income
PHL	Philippines	-25%--5%	6.4E+09	5.94E+09	Lower-middle-income
MAR	Morocco	-25%--5%	5.06E+09	4.48E+09	Lower-middle-income
HTI	Haiti	-25%--5%	2.67E+08	2.36E+08	Lower-middle-income
IDN	Indonesia	-25%--5%	1.12E+10	9.68E+09	Lower-middle-income
NGA	Nigeria	-25%--5%	6.3E+09	5.22E+09	Lower-middle-income
ZWE	Zimbabwe	-25%--5%	58895612	46995612	Lower-middle-income
MYS	Malaysia	-25%--5%	1.76E+09	1.67E+09	Upper-middle-income
ZAF	South Africa	-25%--5%	1.68E+09	1.58E+09	Upper-middle-income
CHN	China	-25%--5%	2.2E+10	2.07E+10	Upper-middle-income
THA	Thailand	-25%--5%	3.54E+09	3.31E+09	Upper-middle-income
TKM	Turkmenistan	-25%--5%	12185420	11042020	Upper-middle-income
JOR	Jordan	-25%--5%	1.61E+09	1.39E+09	Upper-middle-income
GRC	Greece	-50%--25%	1.38E+09	1.03E+09	High-income
SAU	Saudi Arabia	-50%--25%	8.28E+09	6.14E+09	High-income
QAT	Qatar	-50%--25%	5.65E+08	4.14E+08	High-income
ARE	United Arab Emirates	-50%--25%	1.7E+09	1.15E+09	High-income
OMN	Oman	-50%--25%	6.75E+08	4.41E+08	High-income
EST	Estonia	-50%--25%	20156801	13094973	High-income
CHE	Switzerland	-50%--25%	8.36E+08	5.21E+08	High-income
CYP	Cyprus	-50%--25%	3.83E+08	2.37E+08	High-income
ISR	Israel	-50%--25%	2.03E+09	1.21E+09	High-income
ROU	Romania	-50%--25%	1.28E+09	7.22E+08	High-income
LTU	Lithuania	-50%--25%	2.62E+08	1.44E+08	High-income
MLI	Mali	-50%--25%	2.79E+08	1.97E+08	Low-income
ETH	Ethiopia	-50%--25%	1.4E+09	9.3E+08	Low-income
BFA	Burkina Faso	-50%--25%	1.71E+08	1.09E+08	Low-income
YEM	Yemen	-50%--25%	3.07E+09	1.93E+09	Low-income
SDN	Sudan	-50%--25%	1.86E+09	1.16E+09	Low-income
KEN	Kenya	-50%--25%	1.78E+09	1.31E+09	Lower-middle-income
DJI	Djibouti	-50%--25%	3.26E+08	2.37E+08	Lower-middle-income
AGO	Angola	-50%--25%	5.81E+08	4.2E+08	Lower-middle-income
GHA	Ghana	-50%--25%	8.17E+08	5.85E+08	Lower-middle-income
MRT	Mauritania	-50%--25%	4.05E+08	2.89E+08	Lower-middle-income
TUN	Tunisia	-50%--25%	2.78E+09	1.9E+09	Lower-middle-income
LKA	Sri Lanka	-50%--25%	1.51E+09	9.93E+08	Lower-middle-income
PAK	Pakistan	-50%--25%	2.32E+09	1.37E+09	Lower-middle-income
LBN	Lebanon	-50%--25%	1.13E+09	6.38E+08	Lower-middle-income
NIC	Nicaragua	-50%--25%	1.42E+08	76746200	Lower-middle-income
GAB	Gabon	-50%--25%	1.24E+08	92090338	Upper-middle-income
SRB	Serbia	-50%--25%	19296601	13488188	Upper-middle-income

Table S4. 2 (cont'd)

MDA	Rep. of Moldova	-50%--25%	3905887	2406351	Upper-middle-income
IRQ	Iraq	-50%--25%	4.86E+08	2.67E+08	Upper-middle-income
BGR	Bulgaria	-50%--25%	20313717	10666224	Upper-middle-income
MLT	Malta	-75%--50%	33361062	14516780	High-income
LVA	Latvia	-75%--50%	1.15E+09	4.79E+08	High-income
SYC	Seychelles	-75%--50%	371985	154971.6	High-income
FIN	Finland	-75%--50%	1.26E+08	37727126	High-income
TGO	Togo	-75%--50%	1.55E+08	75354200	Low-income
BDI	Burundi	-75%--50%	56362963	25042963	Low-income
MDG	Madagascar	-75%--50%	1.31E+08	51828810	Low-income
RWA	Rwanda	-75%--50%	1.21E+08	47488651	Low-income
LBR	Liberia	-75%--50%	16551191	6050208	Low-income
ERI	Eritrea	-75%--50%	60231577	16758185	Low-income
SOM	Somalia	-75%--50%	73266524	18573346	Low-income
BEN	Benin	-75%--50%	24690734	12092050	Lower-middle-income
TZA	United Rep. of Tanzania	-75%--50%	8.32E+08	3.91E+08	Lower-middle-income
CMR	Cameroon	-75%--50%	8.95E+08	4.02E+08	Lower-middle-income
UKR	Ukraine	-75%--50%	58774144	24796593	Lower-middle-income
SEN	Senegal	-75%--50%	5.95E+08	2.43E+08	Lower-middle-income
EGY	Egypt	-75%--50%	1.19E+10	4.82E+09	Lower-middle-income
COG	Congo	-75%--50%	1.34E+08	47870475	Lower-middle-income
BGD	Bangladesh	-75%--50%	6.98E+09	2.25E+09	Lower-middle-income
LBY	Libya	-75%--50%	2.22E+09	1.01E+09	Upper-middle-income
BIH	Bosnia Herzegovina	-75%--50%	3.01E+08	84117423	Upper-middle-income
ATG	Antigua and Barbuda	-100%--75%	18	3	High-income
SYR	Syria	-100%--75%	1.34E+08	17725351	Low-income
COD	Dem. Rep. of the Congo	-100%--75%	4.05E+08	49722114	Low-income
GNB	Guinea-Bissau	-100%--75%	547	47	Low-income
SLE	Sierra Leone	-100%--75%	10321600	272990	Low-income
MNG	Mongolia	-100%--75%	2.04E+08	21489320	Lower-middle-income
UZB	Uzbekistan	-100%--75%	5694515	135000	Lower-middle-income
KGZ	Kyrgyzstan	-100%--75%	2.49E+08	1119639	Lower-middle-income
NPL	Nepal	-100%--75%	2.38E+08	569179	Lower-middle-income
BTN	Bhutan	-100%--75%	1912202	1902	Lower-middle-income
TUR	Turkey	-100%--75%	1.17E+10	2.51E+09	Upper-middle-income
MNE	Montenegro	-100%--75%	11670080	2413482	Upper-middle-income
ALB	Albania	-100%--75%	2.27E+08	29207100	Upper-middle-income
MKD	North Macedonia	-100%--75%	78658670	8565198	Upper-middle-income
GEO	Georgia	-100%--75%	4.67E+08	47700835	Upper-middle-income
BLR	Belarus	-100%--75%	2.95E+08	4381420	Upper-middle-income
ARM	Armenia	-100%--75%	2.58E+08	1852957	Upper-middle-income
KAZ	Kazakhstan	-100%--75%	1.14E+09	2191143	Upper-middle-income
AZE	Azerbaijan	-100%--75%	1.07E+09	270194.2	Upper-middle-income
PLW	Palau	-100%--75%	10	0	Upper-middle-income

- **ISO code:** The official two- or three-letter country or region code according to the International Organization for Standardization (ISO) standard.
- **Partner:** The name of the country or region (identified by the ISO code) involved in the trade or study.
- **Rate Range:** The percentage range indicating the rate of decrease in trade quantity or production between 2021 and 2022.
- **2021_Qty:** The quantity of cereals (likely wheat, barley, and oats in this manuscript) recorded in 2021 for the respective country or region.
- **2022_Qty:** The corresponding quantity of cereals recorded in 2022 for the respective country or region.
- **Income level:** The income classification of the country or region, indicating whether it is categorized as high-income, upper-middle-income, lower-middle-income, or low-income based on global income classifications.

Supplementary Discussion

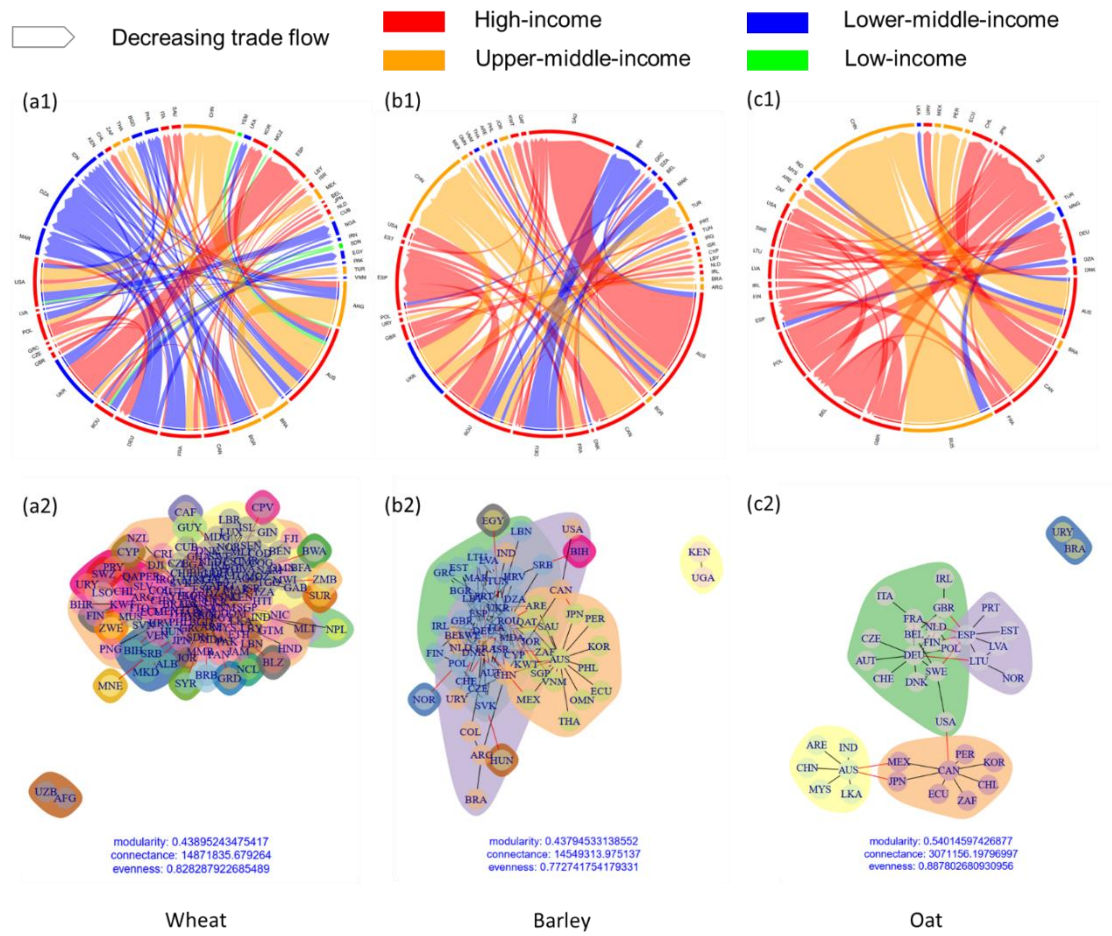


Figure S4. 5 Global trade flows decrease in winter cereals among income groups from 2022 to 2023 and the trade networks of winter cereals. (a1), (b1), and (c1) show the decrease in trade flows for wheat, barley, and oats, respectively, from 2022 to 2023 among countries categorized by income group. High-income countries (red) maintain the largest volume of trade, as evidenced by the thick connecting bands, though a decline in their interactions with lower-middle-income and low-income countries (blue and green, respectively) is apparent. Upper-middle-income countries (yellow) show a moderate level of trade decline, mostly with lower-income-countries, reflecting the uneven impact of disruptions in global cereal trade. (a2), (b2), and (c2) represent the structural changes in the global trade networks for wheat, barley, and oats, respectively. The modularity, connectance, and evenness metrics shown at the bottom of each panel reflect the fragmentation and concentration within the networks. Higher modularity indicates greater clustering among specific groups of countries, while reduced connectance signifies decreased trade relationships overall. Evenness values reflect the balance of trade volumes across countries, with lower evenness in the barley network (b2) showing a more uneven distribution of trade flows. In contrast, the oats trade network (c2) shows a relatively higher evenness, suggesting a more balanced trade system among participating countries, even though the overall volume is lower.

Supplementary Methods and Materials

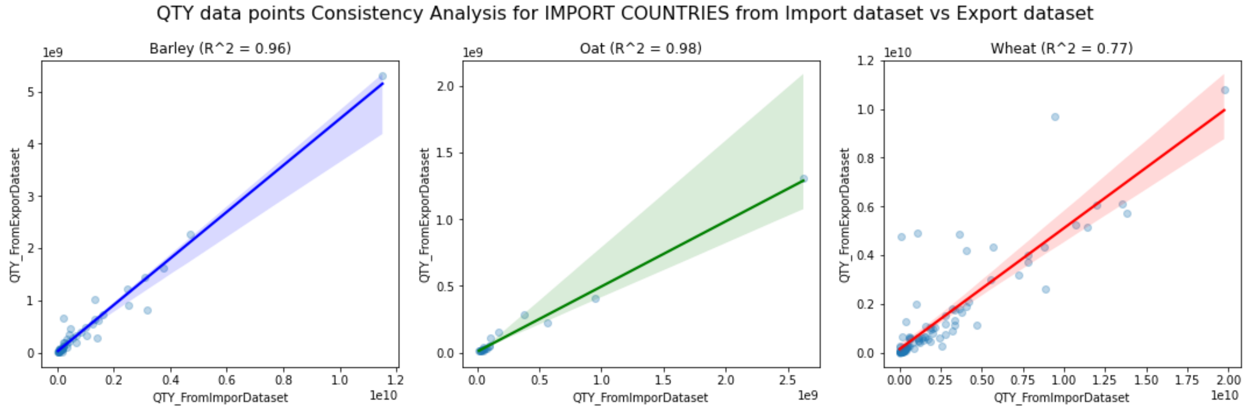


Figure S4. 6 Trade quantity data linear regression. Regression analysis results, highlighting the strong correlation between export and import data. The three panels represent different income groups: lower-middle-income (left, blue), upper-middle-income (center, green), and high-income (right, red) countries. Each plot shows the linear relationship between export and import volumes for the respective income group, with the shaded area representing the confidence interval of the regression line. This analysis is the consistency of trends between exports and imports across income groups, as indicated by the strong linear relationships in all three panels, which suggest that export data can be reliably used to infer trade flow dynamics, as it mirrors the trends observed in imports. Hence, focusing on export data provides a representative view of global trade flows, supporting the decision to prioritize export over import data in this study's analysis of trade disruptions.

Table S4. 3 Statistics of 2021 wheat, barley, and oats imports and exports in ComTrade

Winter Cereal Type	Data Type	Import Dataset	Export Dataset
Wheat	Import countries	114	149
	Export Countries	38	37
Barley	Import countries	51	66
	Export Countries	17	20
Oats	Import countries	25	24
	Export Countries	7	6
Total	Import countries	200	239
	Export Countries	62	63
Sum		262	302

The data show that while the number of countries exporting these cereals is relatively consistent across wheat, barley, and oats, the number of importing countries varies largely, with fewer countries providing comprehensive import data. For example, wheat has 149 export countries but only 114 import countries listed. This discrepancy in the number of reporting countries introduces uncertainty when relying on import data to analyze global trade flows.

Given this lack of comprehensive import data, the decision to use export data as a proxy for understanding global trade dynamics is justified. The higher availability and consistency of export data provide a more reliable basis for assessing the trade flows of winter cereals and allow for a more accurate depiction of the global cereal trade network, minimizing the uncertainties introduced by incomplete import datasets.