Resilience in Food-Trade Network of Bangladesh under Changing Climate

by

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DECLARATION

I hereby declare that this thesis/project is my own work and to the best of my knowledge it contains no materials previously published or written by another person or has been accepted for the award of any other degree or diploma at Bangladesh University of Engineering and Technology (BUET) or any other educational institution, except where due acknowledgment is made. I also declare that the intellectual content of this thesis is the product of my own work and any contribution made to the research by others, with whom I have worked at BUET or elsewhere, is explicitly acknowledged.

Jerin Tasnim

Jerin Tasnim

Dedicated

to

“Ammu”

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ABSTRACT

Rising temperature and unstable precipitation pattern due to climate change along with a variety of natural disasters affect the agricultural production around the world. Any changes in crop production scenarios would lead to a change in patterns and intensities of crop trade (import and export), worldwide. Crop trade scenarios in Bangladesh, which depends significantly on imports, would also affect due to the global change. As Bangladesh is particularly vulnerable to the effects of climate change, change in any crop trade scenario might have a significant impact on country's food supply. It is critical to characterize and study the topology of the dynamics of food-trade network, as well as its resilience and ability to withstand disruptions, both, on a global and local (Bangladesh perspective) scale.

This study proposes an approach to assess the global and Bangladesh's resilience and efficiency in food trade in changing climate. Here, the global trade data for rice, maize, and wheat for 31 years is used to build the trade network. These networks are analyzed by applying the network science algorithm to understand the existing topology, resilience, and efficiency, the centrality of Bangladesh compared to its neighbors, and Bangladesh's shock-withstanding capacity.

The major findings of the research are that the global cereal grain network has been identified as disassortative and the connections between countries are increasing over time. Looking at the Eigenvector Centrality evolution and the clustering coefficient evolution it was found that Bangladesh is gradually connecting to the more important trading partner. The assessment of the shock propagation finds that the resilience of Bangladesh appears zero if its important neighbors are removed considering its present capacity. Bangladesh's maize import has been found to be most vulnerable, the country's system cost needs to be increased by 15.4% to withstand the shock due to climate-change-related grain reduction vulnerability. Increasing the trade diversity and number of neighbors also can be an option to encounter the impact.

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LIST OF ABBREVIATIONS

Name	Abbreviations
ACC	Average Clustering Coefficient
APL	Average Path Length
BC	Betweenness Centrality
CC	Closeness Centrality
CCo	Clustering Coefficient
d	Density
DC	Degree Centrality
EC	Eigenvector Centrality
ExpMaize	Export of Maize
ExpRice	Export of Rice
ExpWheat	Export of Wheat
ImpMaize	Import of Maize
ImpRice	Import of Rice
ImpWheat	Import of Wheat
WITS	World Integrated Trade Solutions

CHAPTER 1

INTRODUCTION

1.1 Background and Motivations

Climate impacts all life on Earth, because variability in temperature, precipitation and water availability affect primary productivity and thus food availability at all trophic levels (Dolfing et al., 2019). It is already established by previous studies that climate change affects mean yield of crop production and is responsible for crop yield variability (McCarl et al., 2008; Rayid et al., 2019). To encounter the local food production variability, regions import when they face deficit and export when they have surplus. This redistribution of resources from regions with surplus to regions with deficit increases the carrying capacity of the network (Dolfing et al., 2019). However, the interdependency of food supply via trade means that changes in one part of a trade network may have implications for food supply in another part of the network. A study of virtual water trade in the ancient world demonstrated that trade could save resources on average (Dermody et al., 2014), but other studies show that increased reliance on trade increases vulnerability to food shortages in the real-world trading network (Marchand et al., 2016; Puma et al., 2015). The challenge of food supply will be complicated even further by anthropogenic climate change, which alters the frequency and amplitude of climate variables such as rainfall and temperature patterns (Gregory et al., 2005).

Network analysis has been increasingly used to disentangle and uncover patterns in a wide variety of complex systems, ranging from molecular e.g., signal transduction pathways (Milo et al., 2004) to individual e.g., social networks (MacRae, 1960; Van Duijn et al., 2003); to global e.g., world city networks (Brown et al., 2010; Derudder and Taylor, 2005) scales (Shutters and Muneepeerakul, 2012). As nations become more interconnected in the era of globalization, trade networks play an increasingly significant role in the well-being of nation states (Fair et al., 2017a). The ways in which countries select trading partners; the global impact of local economic crises due to globalization; and how country-level characteristics are affected by network metrics can be explored by analyzing these trade networks (Lee et al., 2011). Characterizing and analyzing the topology of global food-trade network, its trade efficiency in dynamic temporal domain and resilience against perturbations has been proven to be vital. Global food exports began increasing exponentially after the 1960s and are growing more rapidly than food production (Ercsey-Ravasz et al., 2012). This upswing in exports, along with the 50% increase in food demand predicted to occur by 2030, indicates that food trade will only increase in political and economic importance (Tamea et al., 2016). Climate change in Bangladesh is a critical issue as the country is one of the most vulnerable to the effects of climate change (Kulp and Strauss, 2019). Bangladesh experienced an annual mean temperature increase of around 0.5 ∘C along with increasing average rainfall (Fahad et al., 2018). The vitality of temperature and precipitation for agricultural production has already been stated, so it is obvious that Bangladesh is also going to encounter impacts of global food-trade due to climate change. As Bangladesh has just emerged as a developing country, the economic condition can be pivotal, if necessary, steps are not taken from policy level.

1.2 Existing Research Limitations and Scopes

Because of the lack of open-source data, most of the studies assessed the cascading failure scenarios by simulating model networks that have characteristics similar to the real-world agricultural network. Burkholz and Schweitzer (2019); Li et al. (2022) performed their study on real data, but more studies are necessary to understand the topological properties. Also, they mostly simulated shock propagation by removing nodes or links only, the most used conventional cascading failure model has not been used in much research. Given the fact that real networks are growing and gaining more complexity, analysis of the resilience and vulnerability of networks using cascading failure can provide much insight about the fragmented networks.

Considering the gradual growth of the number of countries participating in global crop trade, a country specific network science parametric study is necessary to understand the historical evolution, how the country is coping up with the complex network dynamics. These assessments are crucial for policymakers to understand if the country should increase its intrinsic capacity, or the country can safely continue its crop import. Also, as resources are constrained, how much capacity should be increased to tackle the trade bans imposed due to climate adversity-based crop production reduction, which needs to be measured, to get an idea. Bangladesh, being vulnerable to climate change, this research is crucial to understand the present resilience and vulnerability against failure propagation.

In this study, the evolutionary dynamics of global rice, wheat, and maize trade networks had been conducted. The networks are formed as per figure 1-1 where the structural characteristics of the network will be assessed. Also, their results are compared with Bangladesh in terms of the centrality measures. An assessment of the efficiency and resilience of the global crop-trade network to understand the heterogeneity of the networks because of the trade weight. Finally, cascading failure was generated in each network to estimate how much capacity should be increased to withstand shock and the result is compared with the crop production reduction due to future climate change.

1.3 Objectives of the Research

The main objective of the research is to evaluate Bangladesh's food-trade network's resilience to climate-related fluctuation and shock. The following specific goals are set forth:

i) Identification of the global food trade, i.e., rice, maize and wheat trade network's topology and their temporal evolution.

ii) Evaluation of Bangladesh's crop trade pattern's resilience and how it has changed through time

iii) An assessment of Bangladesh's crop-trade network's capacity to withstand shocks and variations brought on by climate change in scenarios including international trade.

1.4 Outline of Methodology

To complete this research work and to achieve all the mentioned objectives, the following activities will be undertaken.

i. The network has been built using annual food trade statistics for all nations from 1991 to 2021 that were collected from the World Integrated Trade Solution website (WITS - COMTRADE By Product). The networks created will be multidirected weighted networks since the nations will be treated as nodes and the export volume in US dollars as edge weight.

ii. The analysis of the network topology time series has been concentrated on how the topology changed over time utilizing different node properties. Analysis is thought to be based on the Albert-Barabasi model.

iii. The visual representation of Bangladesh's contribution to the global trade network based on various local centrality parameters.

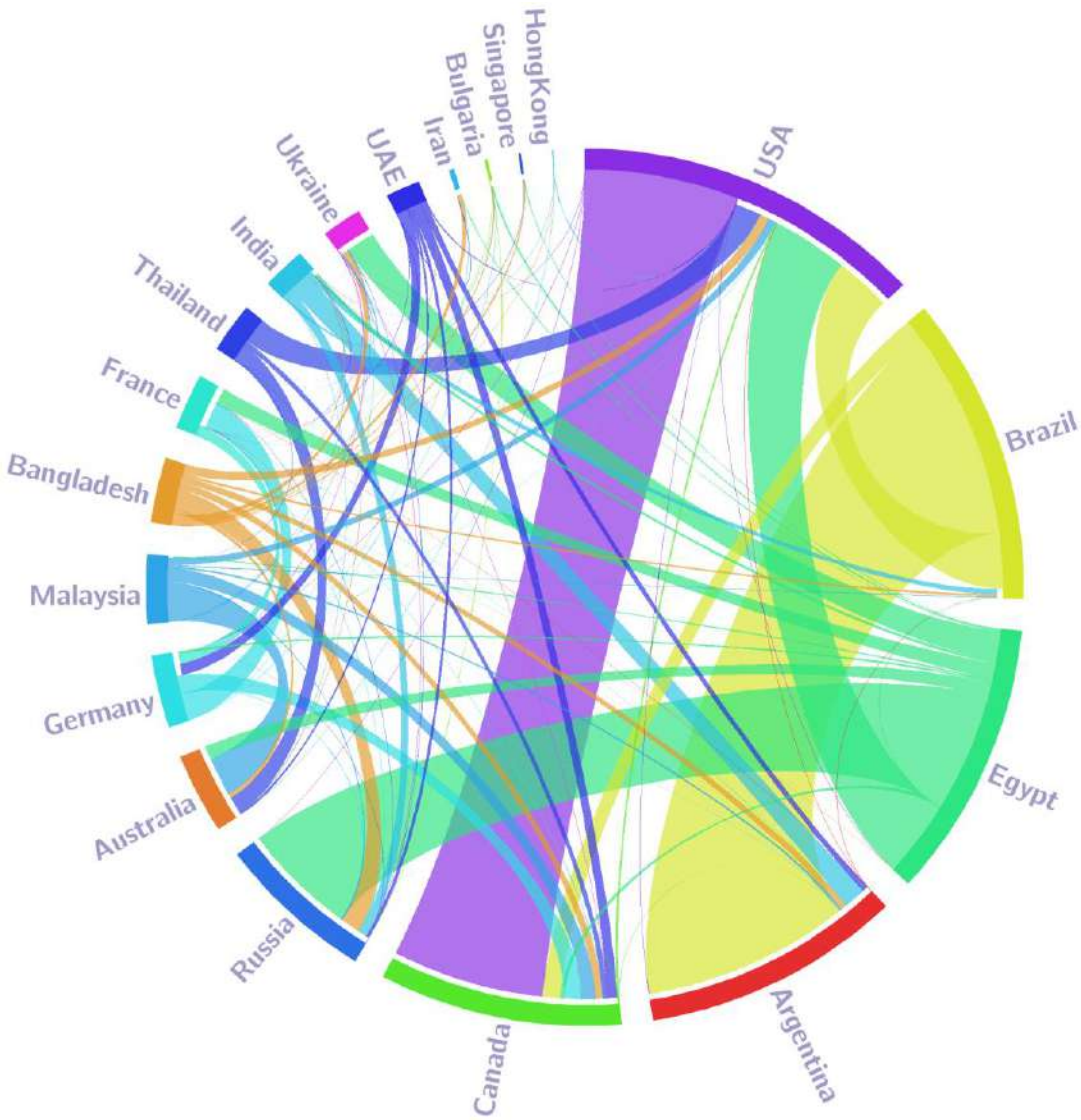


Figure 1-1 A sample maize trade network for the year 2008 for Bangladesh with its neighbors for the year 2008

iv. Trade shock scenario analysis, which includes node removal and the assessment of the network's effectiveness and resilience. Nodes that have been removed will no longer export food but will instead import it. When generating trade shocks, climate variability will be considered. It has been looked at how shock-sensitive the current architecture is and how resilient it is. After the initial shock wears off, the effectiveness of the nodes—i.e., how well the nation begins exporting—will also be examined, with a focus on Bangladesh's involvement as a trade entity in the global network topology.

1.5 Organization of the thesis

This thesis consists of six main chapters which are as follows:

Chapter 1: Introduction and Objective. This chapter provides the background and motivations of the research. The overall objectives and expected outcomes are also described in this chapter.

Chapter 2: Literature Review. This chapter reviews the related works in the and limitations related to crop trade network analysis literatures and shock propagations and provides necessary fundamentals for the thesis.

Chapter 3: Methodology. This chapter describes the methodology adopted to carry out the research.

Chapter 4: Analysis of Crop Trade Network. This chapter describes the results of topological evolution of global and Bangladesh crop trade networks.

Chapter 5: Resilience and Efficiency of Trade Network under Changing Climate. This chapter presents the assessment in efficiency and resilience measures for both weighted and unweighted network. Then the shock propagation is simulated in the network considering cascading failure simulation. Finally, the resilience against shock is compared with the climate change impacted crop production.

Chapter 6: Conclusion and Recommendation for Future Study. This chapter summarizes the conclusions and major contributions of this study and provides recommendations for future studies.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter gives an overview on the relevant research and existing research gaps, as well as the fundamentals of the network theory and the metrics that later will be used to assess the topological characteristics of the real-world crop trade networks. The weighted and unweighted efficiency and resilience parameters will also be discussed. The objective of the thesis is to assess the robustness and invulnerability of the networks due to trade shocks induced by cascading failure. So, the mathematical model of the cascading failure simulation will be discussed in detail.

2.2 Significances of Global Crop Trade

The global crop trade network has a long and complex history, shaped by a variety of economic, political, and cultural factors. In the early days of international trade, there was little involvement from outside players (Delaquis et al., 2018). However, as transportation and communication technologies improved, and global demand for these staple crops increased, the trade network expanded and became more complex (Brugnoli et al., 2018). Today, the global trade in rice, maize, and wheat is dominated by a handful of powerful countries and multinational corporations, with significant implications for global food security and economic development (Fair et al., 2017b). For example, in recent years, China has become a major player in the global rice trade, importing large quantities of rice from countries like Vietnam and Thailand to meet domestic demand, which has led to concerns about the impact of Chinese demand on global prices and the availability of rice, particularly for smaller, less developed countries that rely heavily on rice as a staple food (Qiang et al., 2020). Additionally, multinational corporations like Cargill and ADM have significant control over the global maize and wheat trade, these corporations have been accused of using their market power to manipulate prices and exploit small farmers in developing countries (Murphy, 2006). Despite these challenges, the global trade network for rice, maize, and wheat continues to be a vital component of the global food system, providing essential food security and economic opportunities for millions of people around the world (Scott et al., 2000).

Global trade patterns for rice, maize, and wheat currently show a move toward growing demand from developing nations, especially in Asia and Africa (Shiferaw et al., 2011). Due to increased investment in infrastructure and technology to support the expansion of the agricultural sector, production has expanded in these areas (Shiferaw et al., 2011). However, worries about the influence of climate change on food yields and the possibility of trade disruptions because of political unrest or conflict persist (Scheffran and Battaglini, 2011). Additionally, concerns about the fairness and transparency of the system as well as the possibility of the exploitation of weaker, smaller nations are raised by the dominance of multinational firms in the global trade network (Scheffran and Battaglini, 2011).

2.3 Climate Change Impact

Climate change is one of the most pressing issues of our time, and it is having a significant impact on global crop production. Rising temperatures, changes in precipitation patterns, and more extreme weather events are all taking a toll on crop yields. One of the most immediate impacts of climate change on crop production is the shortening of growing seasons. In many parts of the world, temperatures are rising at a rate that is making it difficult for crops to mature before the end of the growing season. This is particularly problematic for crops that are already sensitive to heat, such as corn and soybeans. In addition to shortening growing seasons, climate change is also leading to more extreme weather events, such as droughts, floods, and heat waves. These events can damage crops directly, or they can make it difficult for farmers to access their fields or to apply water and fertilizer. Climate change is also impacting crop yields through changes in precipitation patterns. In some areas, precipitation is becoming more erratic, with more frequent droughts and floods. This can make it difficult for farmers to know when to plant and irrigate their crops, and it can also lead to soil erosion and waterlogging. In other areas, precipitation is becoming more concentrated, with heavier rains falling in shorter periods of time. This can lead to flooding and runoff, which can wash away crops and nutrients from the soil.

The impacts of climate change on crop production are already being felt around the world, and they are expected to become more severe in the future. According to the Intergovernmental Panel on Climate Change (IPCC), global crop yields could decline by up to 25% by 2050 if no action is taken to mitigate climate change. This decline in crop yields could have a significant impact on global food security. The world's population is expected to reach 9.7 billion by 2050, and we will need to produce more food to feed this growing population. However, if climate change continues to disrupt crop production, it will be difficult to meet this demand.

2.4 Climate Change Impact on Crop Production

Climate change refers to the long-term changes in the Earth's climate, particularly the increase in global temperatures due to human activities such as the burning of fossil fuels. This phenomenon has had a significant impact on agriculture, particularly crop production. As the climate continues to warm, crop yields are expected to decline due to changes in precipitation patterns, increased pest and disease pressure, and heat stress. Various researchers explore the effects of climate change on crop production and discuss potential solutions to mitigate these impacts (Doney et al., 2014). Several publications have found out that whereas synchronous shocks in maize yield are currently unusual, they will become considerably more common if the climate warms further. Researchers contend that in order to prevent a low-yield, high-volatility future while maintaining maize systems, breeding for heat tolerance is a high-priority but as-yet unachieved goal in maize development (Tigchelaar et al., 2018). Another paper examined the drivers of uncertainty surrounding climate models, crop models, and CO_2 responses while presenting the most recent ensemble projections for the productivity of major crops for the twenty-first century. It also evaluated the risks associated with crop yield impacts of climate change. The average end-of-century global productivity response is 10% lower for maize, the most significant crop in terms of total production and food security in many places. While maize, soybean, and rice outcomes are noticeably more negative, wheat results are more positive (Jägermeyr et al., 2021). The relevant crop production reduction in future is shown in figure 2-1. This literature depicts that climate change is going to impart significant impacts on global crop production.

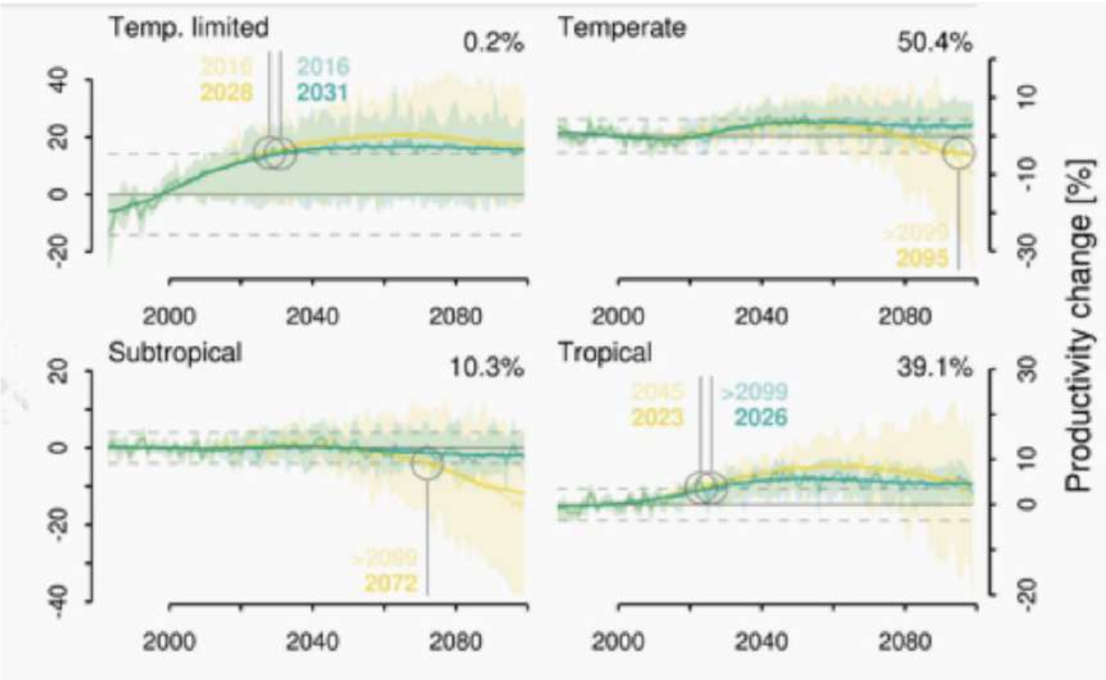


Figure 2-1 Global rice productivity change for the four Koeppen-Geiger zones (Jägermeyr et al., 2021)

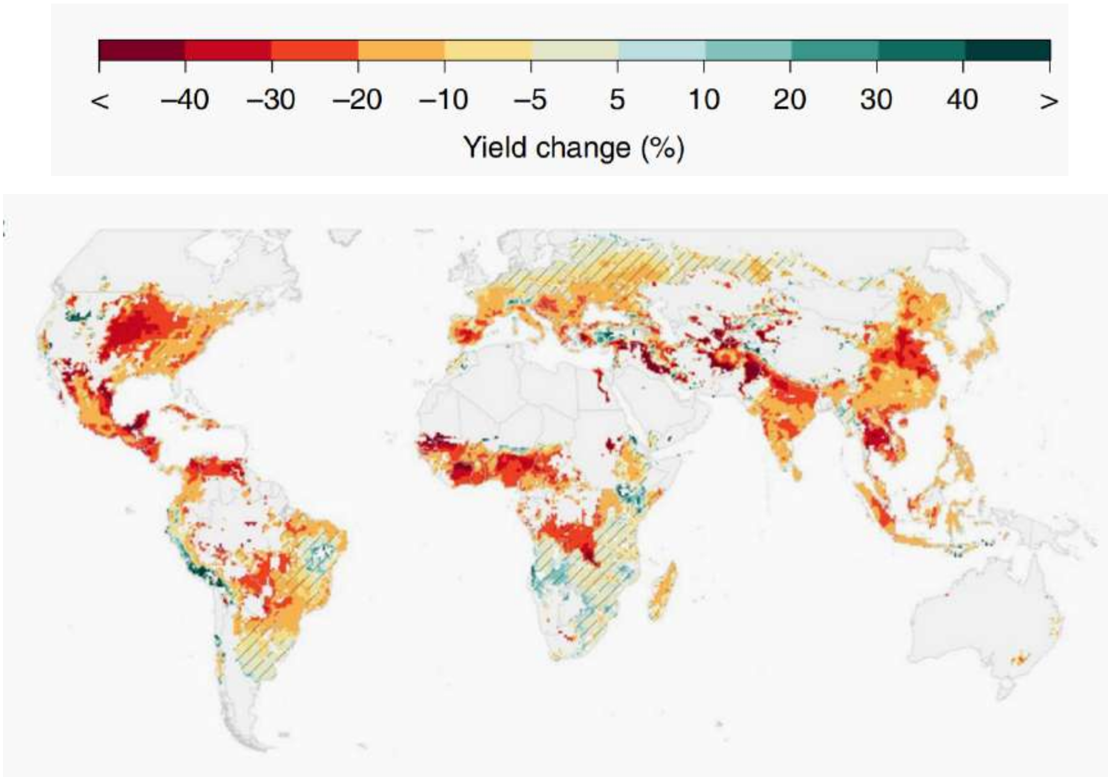


Figure 2-2 Impacted global maize production due to changing climate (Jägermeyr et al., 2021)

2.5 Dynamics of Trade Evolution and Shock Propagation

In the age of globalization, as nations are more interconnected, trade networks are becoming more important to nations' development. By examining these trade networks, it is possible to get insight into how nations choose their trading partners, the effects of local economic crises on the global economy, and how network measures affect country-level features. Numerous studies have described trade networks' characteristics and their cyclical evolution. The property and characteristics of evolution dynamics have been previously studied in many types of networks. The very first research of this kind had been carried out by Barabasi et al. (2002). The goal of this research is to comprehend the dynamic and structural factors that control the evolution and topology of this complex system during an eight-year period (1991–1998) by examining the co-authorship network of mathematicians and neuroscientists. The findings show that the network is scale-free and that preferential attachment, which influences both internal and external links, controls the network's growth (Barabási et al., 2002). In complex artificial metabolic networks that encode a growing quantity of environmental information while adopting pervasive characteristics of biological, social, and engineering networks, Hintze and Adami, (2008) studied the evolution of modularity and robustness. Monge et al., (2017) investigated the organizational network evolution by providing conceptual tools for comprehending how communication and other network linkages inside an organizational network form, develop, are maintained, and ultimately fall apart. Using network analysis techniques, J. Wang et al., (2014) tracked the development of China's air transport system since 1930, finding a considerable increase in connectedness. However, studies focusing on the agri-food trade evolution dynamic assessment exist but the research in this sector is not as vast as the social, transportation, communication, or biological networks as mentioned before. Recently researchers are showing interest in the formation of global agri-food trade networks and their historical evolution.

Gephart and Pace (2015) discuss the structuring and evolution of the global seafood trade network, as well as criteria for measuring the globalization of the seafood industry, changes in the bilateral trade flows, changes in centrality, and parallels of the seafood trade network to the networks for agriculture and industry. They demonstrated how, in terms of the number of trading partners and overall trade flows, the global seafood trade network expanded quickly from 1994 to 2012. Globalization, changes in bilateral trade flows, and transformations in the most important players are the main forces behind this evolution. The study conducted by J. Wang and Dai, (2021) used complex network analysis to examine the global agricultural trade network and its development from 1992 to 2018. The findings indicate that there has been a rise in the complexity, effectiveness, and tightness of food trade connections. Communities involved in the global food trade have grown more stable, and the trade network has changed from "unipolar" to "multipolar." The core exporting countries have been consistent and concentrated during the past almost 30-year period, but the core importing countries are somewhat spread.Y. T. Zhang and Zhou (2022) also conducted similar research considering the four crops which are rice, maize, wheat, and soybean and they found the network outcomes similar to those in terms of the networks' growth, complexity, efficiency, and tightness. They also discovered that the degree assortative coefficients are affected by crop types and degree orientations. According to the analysis of assortativity, economies with high out-degree connections tend to connect with economies with low in-degree and low out-degree connections. Even though the broad evolutionary patterns of all crop trade networks are comparable, some crops demonstrate distinctive trade patterns.

Studying failures in networks is crucial because they expose risks, vulnerabilities, and interdependencies in complex systems, allowing for the creation of methods to improve resilience and lessen effects. Planning infrastructure, determining risks, formulating policies, and managing crises are all made easier by understanding how failures spread through a network. This improves the reliability, security, and effectiveness of essential systems. Failure phenomena have been simulated in power distribution networks, communication networks, transportation networks, and social networks. The application of failure propagation in crop-trade networks is comparatively a growing interest to researchers because of the concerns of anomalous crop production due to climate change. The dynamics of the world wheat trade network and its resistance to shocks are covered in the study by Fair et al. (2017). By incorporating shocks that cause nodes to lose their outgoing (export) edges, the shock simulation is carried out. Errors and attacks are thought of as two different kinds of shocks. To evaluate the network's error tolerance, the outgoing edges of a random subset of nodes are eliminated. Since these are thought to be the most crucial nodes in the network, nodes with the highest connectivity are the ones that are targeted in attacks. Another study by Li et al. (2022) shows disruption propagation in the agri-food supply chain network. In this study, they explore how public health crises and severe weather might disrupt China's agri-food supply chain networks. The authors build weak tie networks and examine the effects of fortifying current business ties and forming new ones on the spread of disruption in agri-food supply chain networks. Weak ties are links between network nodes that are not recurring, continuous, or fixed. Weak linkages in the supply chain network suggest that nodes without a direct supply-demand relationship at the moment might do so later. When a node in an agri-food supply chain breaks, it is said that the nearby nodes may create new edges using weakly linked nodes rather than all nodes. Cascading failure generation in crop-trade network is first reported by Burkholz and Schweitzer (2019). According to this study, as the global trade in maize, rice, soy, and wheat has grown more complicated over time, trade networks have become more vulnerable to failure cascades brought on by exogenous shocks. In this study, the cascading failure was produced by putting export limits on nations that make up for demand imbalances brought on by external shocks. For the various crops and years, the authors build higher-order trade dependency networks to represent the cascading consequences of these export limitations. These networks expose unspoken interdependencies between nations and estimate the stock reserves required to shield nations from cascading export bans. The authors discover that export restrictions on rice commerce are most likely to cascade.

2.6 Fundamentals of Network Science Theory

Figure 2-3 shows a schematic network which is unweighted and undirected. This figure will be used to understand how the parameters are calculated in the simplest form. To understand the topological evolution of the trade network and how the node of interest evolved and participated in the context of global trade both topology-based and node-based metrics had been chosen. The following metrics discussed had been used to unveil the inherent characteristics of network topology, and its evolution for each crop considering both export and import. Also, network robustness and trade efficiency can be understood well using these metrics.

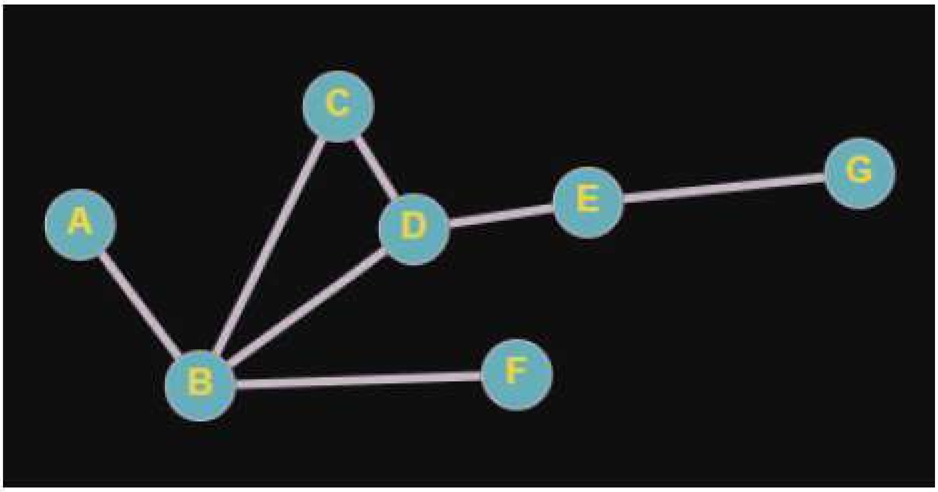


Figure 2-3 A schematic unweighted undirected network with seven nodes and seven edges

2.6.1 Degree

The degree of a node refers to the number of neighbors it has direct trade relations with (Diestel, 2017). Neighbors refer to the other nodes that the one node is connected to. It is defined as k_i for node *i* and the mathematical equation is below cited by J. Wang and Dai (2021)

$$k_i = \sum_{j=1}^{N} a_{ij} \tag{1}$$

For bilateral network, the degree of a node can be divided into out-degree and in-degree. For node i, if the outflow is represented as a_{ij} and the inflow as a_{ji}, the corresponding out-degree equation is

$$k_i^{out} = \sum_{j=1}^{N} a_{ij} \tag{2}$$

and in-degree equation is

$$k_i^{in} = \sum_{j=1}^{N} a_{ji} \tag{3}$$

From figure 2-3 the degree of node D is 3 as it is connected to 3 other nodes. The higher the degree of a node, the country has trading relations with a greater number of countries. A node will be called isolated when its degree is zero. The global average degree of a network *G* can also be estimated by $\langle k \rangle = {|E|}/{N}$, where $|E|$ = total edges in the network. The average degree can also be grouped as average out-degree and average in-degree of network *G* based on the trade flow direction. The equation for average out-degree is $\langle k^{out} \rangle = {|E^{out}|}/{N}$, where $|E^{out}|$ means outflow edges or export. For average in-degree estimation the equation is $\langle k^{in} \rangle = {|E^{in}|}/{N}$, where $|E^{in}|$ means inflow edges or import. Here, total number of edges $|E|$ is half of the sum of degrees of all nodes, i.e., $|E| = \frac{1}{2}\sum_{i=1}^{N} k_i$, as every edge is counted twice (Diestel, 2017).

2.6.2 Degree Distribution

The probability of degrees of nodes over the whole network G is called degree distribution of a network. The degree distribution is a probability value ranging from 0 to 1 and it represents that what is the probability of a randomly chosen node having k degree (A.-L. Barabási, 2015). For a network G with *N* nodes the degree distribution is given by $p_k = {N_k}/{N}$, where N_k = number of nodes having k degree. It returns a histogram, and the type of distribution depends on the characteristic of the network. For random network of *N* nodes, the probability that a node has exactly k edges is given by the binomial distribution:

$$p_k = \binom{N-1}{k} p^k \, (1-p)^{N-1-k} \tag{4}$$

If a network is sparse for which $\langle k \rangle \ll N$, the probability of finding a node with k neighbors is given by the Poisson distribution:

$$p_k = e^{-\langle k \rangle} \frac{\langle k \rangle^k}{k!} \tag{5}$$

Networks whose distribution follows a Power Law are referred to as Scale-Free network. The power law degree distribution can be defined in both discrete and continuous formalism. The distribution can be stated as:

$$p_k = Ck^{-\gamma} \tag{6}$$

A network can be categorized into a random network, scale free network or a sparse network depending on the degree distribution of the nodes. These are explained following:

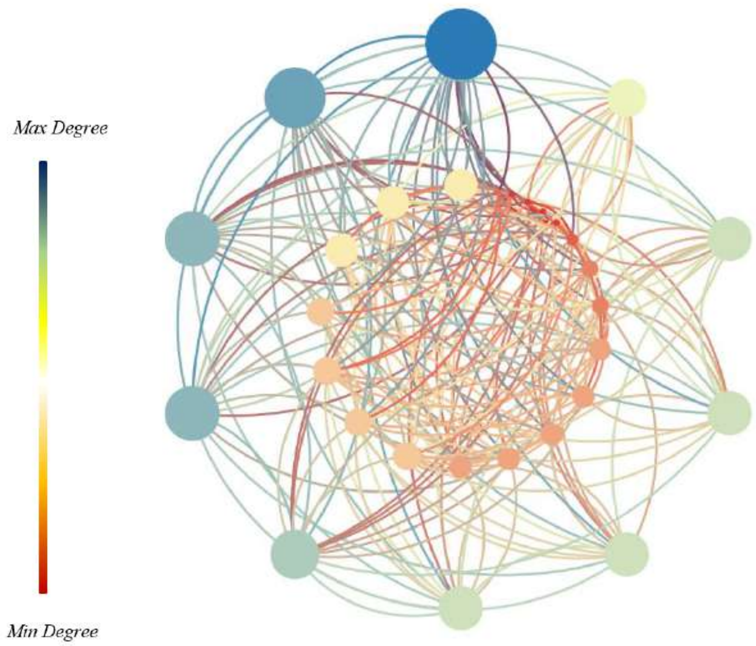


Figure 2-4 A schematic graph following Erdős-Rényi with 30 nodes and probability of 0.5.

2.6.2.1 *Erdős-Rényi Random Network*

The Erdős -Rényi (ER) random network is a particular kind of random graph that is produced using a probabilistic model. In an ER network, all pairs of nodes have the same chance of being connected by an edge. As a result, the network's nodes have roughly equal degrees (number of connections), and the distribution of degrees is Poissonian. ER networks are frequently used as a standard against which to measure other network configurations.

2.6.2.2 *Albert-Barabási Scale-Free Network*

The Albert-Barabási (AB) scale-free network is a particular kind of network in which the degree distribution resembles a power law. New nodes are introduced to an AB network, and they attach to existing nodes with a high degree of preference. As a result, only a small number of nodes in the network have very high degrees, while the majority have low degrees. This kind of network is frequently seen in real-world networks, such the internet and social networks, where a small number of highly linked nodes (hubs) have a significant impact on the network's overall structure and functionality.

2.6.2.3 *Sparse Network*

A sparse network is one in which the number of edges is significantly less than the total number of edges that could be present in the network. Most nodes in a sparse network have low degrees, and the network may be densely clustered (with many triangles). Many systems in the real world, such as social, ecological, and transportation networks, frequently contain sparse networks. The ratio between the actual number of edges and the network's maximum number of edges, or sparsity, can be used to define sparse networks.

2.6.3 Shortest Path Length/Distance

In general, path means the number of edges or links required to go from node i to node j. The shortest path between nodes i and j is the path with the ewest number of edges (Barabási, 2015). The shortest path is also called distance and is denoted by d_{ij}. The average path length (APL) is defined by the average value of the shortest path between all node pairs in the network. It can be represented as follows:

$$\langle d \rangle = \frac{1}{N(N-1)} \sum_i \sum_j d_{ij} \tag{7}$$

The APL represents how efficiently products can be traded throughout the network. If APL is larger, then a country must encounter more steps to build a trade relation with another country, reducing the overall trade efficiency. On the other hand, lower value of APL means greater trade transmission efficiency within the network.

2.6.4 Centrality

The centrality of a node identifies its importance in a network. Node with high centrality score indicates its influence and control over the network. A range of centrality measures are presented to identify the most influential node of a network. As the aim of this study is to unveil a node or country's resourcefulness, control, transmission efficiency and influence over other countries, four centrality measures will be discussed and used for network characterization.

2.6.4.1 *Degree Centrality*

The degree centrality (DC) metric identifies the network nodes with the greatest number of connections to other nodes. It provides an answer to queries like which node in the network is the most or least popular and who has the most access to resources by providing the most basic measurement of a node's connectivity. It is measured as following:

$$C_d(i) = \frac{\sum_{j=1}^{N} a_{ij}}{N-1} \tag{8}$$

Here from figure 2-3 the degree centrality for node D can be calculated as, degree of node D divided by $N-1$, which is: $DC_D = {}^{3}/_{(7-1)} = 0.5$. For bilateral graph degree centrality can be divided into indegree centrality and outdegree centrality. For trade relationships, a higher indegree centrality can be an indication of more dependence on other countries or less internal production of that crop. A higher value of out-degree centrality can mean that the country is more self-sufficient and more inclined to export the surplus to other trade entities.

2.6.4.2 *Betweenness Centrality*

The sum of the fraction of all-pairs shortest paths that pass through a node makes up its betweenness centrality (BC). The nodes that serve as "bridges" between other nodes most commonly have high betweenness centrality scores. The BC of a node i can be measured as following proposed by (Brandes, 2008):

$$c_B(i) = \sum_{s,t \in V} \frac{\sigma(s,t|i)}{\sigma(s,t)} \tag{9}$$

Where V is the set of nodes, $\sigma(s,t)$ is the number of shortest paths and $\sigma(s,t|i)$ is the number of those paths passing through some node i other than s,t.

For node D, possible shortest paths are:

A-B, A-B-C, A-B-F, A-B-D-E, A-B-D-E-G; B-F, B-C, B-D-E, B-D-E-G; C-B-F, C-D-E, C-D-E-G; E-G, E-D-B-F = 14. D in them = 7; so, BC of node D is ${}^{7}/_{14} = 0.5$. BC answers to issues like who or what can most powerfully regulate information flow throughout the network and who or what would cause the most disruption to flow if they/it were removed. They also construct the shortest communication paths inside the network.

2.6.4.3 *Closeness Centrality*

Closeness centrality (CC) is intended to quantify one node to the other nodes' sum distances (Zhang and Luo, 2017). If the length of node N's shortest pathways with other nodes in the network is small, then the node has a high CC. An updated formula is put out by Wasserman and Faust for graphs with several connected components and it is the ratio between the average distance from the reachable players and the fraction of the group's actors who can be reached is the outcome (Galaskiewicz and Wasserman, 1993). For a network, the CC for node i can be formulated as

$$c_c(i) = \frac{n-1}{N-1}\frac{n-1}{\sum_{j=1}^{n-1} d_{ji}} \tag{10}$$

Where, d_{ji} is the shortest path distance between node j and i and $(n-1)$ is the number of nodes reachable from the node i.

For node D the shortest distances: A-D = 2, B-D = 1, C-D = 1, E-D = 1, F-D = 2 and G-D = 2. Sum = 9. So, the CC for node D is $\frac{6}{9} = 0.67$. CC provides answers to issues like who can learn about other network nodes the fastest and who can spread information the fastest in a network. It provides the most useful information when a network is sparsely linked. In a network with plenty of connections, every node might have a comparable rating.

2.6.4.4 *Eigenvector Centrality*

Based on the centrality of its neighbors, eigenvector centrality (EC) calculates a node's centrality. The EC for node i is the i-th element of the vector x defined by the equation:

$$A_{ij}x = \lambda x \tag{11}$$

Where A_{ij} is the adjacency matrix of the corresponding network with eigenvalue λ. By virtue of the Perron–Frobenius theorem, there is a unique solution x, all whose entries are positive, if λ is the largest eigenvalue of the adjacency matrix A_{ij} (Newman, 2010). EC is helpful because it shows influence over nodes more than one hop away as well as direct influence over neighbors. A node may have many connections, or a high degree score, but a low Eigen Centrality score if many of those connections are with other nodes with comparable low scores, and vice versa. It provides answers to questions like "Who or what has broad impact in my network?" and "Who or what is significant in my network on a macro scale?"

2.6.5 Clustering Coefficient

The clustering coefficient refers to the likelihood that a country has business ties with its trading partners. In essence, it counts the number of triangles present in the networks. There are a few different approaches to define clustering for weighted graphs; the one used here is defined as the geometric average of the subgraph edge weights (Onnela et al., 2005). For node i, the clustering coefficient can be stated as for the triangle neighbor j and k

$$c_u = \frac{\sum_{jk} (\widehat{w_{ij}}\widehat{w_{ik}}\widehat{w_{jk}})^{1/3}}{k_i(k_i-1)} \tag{12}$$

Here, edge weight $\widehat{w_{ij}}$ is normalized by the maximum edge weight of the network, i.e.,

$$\widehat{w_{ij}} = \frac{w_{ij}}{\max(w)} \tag{13}$$

Here for figure 2-3, considering node D the number of triangles possible among the neighbors are 3 and number of triangle present is 1. So, the CCo for node D is 1/3. The overall network's average degree of clustering is reflected in the average clustering coefficient (ACC). The equation can be given by

$$\mathrm{ACC} = \frac{1}{N}\sum_{i=1}^{N} c_u \tag{14}$$

2.6.6 Assortativity

Assortativity gauges how similarly connected nodes are to one another in a graph. Disassortativity refers to a node's propensity to connect to other nodes in a network that have different characteristics. The assortativity coefficient is measured as following:

$$r = \frac{\sum_{(i,j)\in E} (k_i - \overline{k_1})(k_j - \overline{k_2})}{\left(\sum_{(i,j)\in E}(k_j - \overline{k_2})\right)\left(\sum_{(i,j)\in E} (k_j - \overline{k_2})\right)^2} \tag{15}$$

Where, E is the set of edges of the network and

$$\overline{k_1} = \frac{\sum_{(i,j)\in E} Ek_i}{|E|} \tag{16}$$

and

$$\overline{k_2} = \frac{\sum_{(i,j)\in E} Ek_j}{|E|} \tag{17}$$

The assortativity coefficient measures the Pearson correlation of a particular node property (here, the degree of nodes) between connected node pairs (LibreTexts, 2020). While negative coefficients suggest disassortativity, positive values suggest assortativity. Because of inherent structural restrictions known as structural cutoffs, scale-free networks with finite sizes naturally exhibit negative disassortativity. The reason for this disassortativity is because there aren't enough hub nodes accessible for them to link to preserve assortativity.

2.6.7 Density

The ratio of real trade ties to all potential trade links is referred to as the network's density. The value's range is [0, 1]. The equation for density is given by for directed network:

$$d = \frac{E}{N(N-1)} \tag{18}$$

For the schematic network of figure 2-3, *Density = #edges in network / #all possible connections*

Here for the network, #edges = 7; possible conn = 0.5X7X6 = 21, density = 1/3.

It is used to gauge how closely together all the countries that engage in international trade are. A tight network results from high density.

The table 2-1 shows the topological parametric values for node D in the figure 2-3 is stated.

Table 2-1 Topological parametric value for node D of figure 2-3

Node D's Topological Parameters Names	Values Calculated
Degree	3
Degree Centrality	0.5
Betweenness Centrality	0.5
Closeness Centrality	0.67
Clustering Coefficient	0.33

2.7 Network Efficiency and Resilience Measures

The goal of the study is to understand the efficiency and resilience evolution of the three crop trade networks. To do so, the study analyses using the topological and weighted efficiency and resilience metrics. (Bellingeri et al., 2019) showed in their research that if link weights are introduced in the network, the link weight asymmetry can alter the robustness behavior using seven real-world complex weighted networks. In this study, an approach is made to assess the trade efficiency and resilience behavior of the food-trade network using metrics for both the topological or unweighted scenario and the weighted scenario.

2.7.1 Topological Efficiency and Resilience Metrics

2.7.1.1 *Topological Efficiency*

Karakoc and Konar (2021) used the average shortest path length parameter, denoted as $\hat{d}$ as the topological efficiency measuring metric. From the formula as shown in table 3.1, N refers to the number of nodes in the network and d_{ij} is the number of hops required between i and j which is computed by the Dijkstra's algorithm (Golden, 1976).

As discussed before, if $\hat{d}$ is larger, more hops are required to reach from one node to another, diminishing the efficiency of the network. More jumps between any two nodes in the network are represented by larger $\hat{d}$ values. Since each node is directly linked to every other node, the closer d is to 1, the more efficient the network will be (Karakoc and Konar, 2021). Lower $\hat{d}$ indicates fewer intermediate pauses in the flow of commodities between any producer and the end user from the standpoint of the supply chain (Hearnshaw and Wilson, 2013).

2.7.1.2 *Topological Resilience*

The topological resilience metrics, denoted as $\bar{\lambda}$, represented by the percentage change in the dominant eigenvalue of the unweighted network's adjacency matrix when the node with the highest export connection, meaning the highest out-degree node is removed from the network. The targeted node attack, meaning the removal of the highest degree node is a widely used approach to understand the robustness of the network (Bellingeri et al., 2019; Fair et al., 2017b). $\bar{\lambda}$ is a novel metric proposed by Karakoc and Konar (2021) to visualize the resilience of the unweighted network on the highest node degree.The dominant eigenvalue of the adjacency matrix of unweighted network, represented by λ_1, is the spectral radius. Variations in node degree are associated with the spectral radius. Higher degree differences in network topologies result in larger dominant eigenvalues, whereas lower degree variations in topologies result in lower dominant eigenvalues (Meghanathan, 2015). Table 2-3. shows the pseudocode for the estimation of the dominant eigenvalue of an adjacency matrix using the power iteration method (Booth, 2017).

The topological resilience matrix, $\bar{\lambda}$, gets lower if the network is largely dependent on the most exporter node, representing the network's vulnerability to the most exporting entity. On the other hand, if $\bar{\lambda}$ value is high, it means that the network is less dependent on the most exporting node, representing the robustness of the network topology.

Table 2-2. Complex network framework for both unweighted (topological) and weighted efficiency and resilience

Measure	Symbol	Equation	Definition	Remarks
Topological Efficiency and Resilience				
Topological Efficiency: Average Shortest path length of network	$\hat{d}$	$\hat{d} = \frac{1}{N(N-1)} \sum_{(i,j):i \neq j} d_{ij}$	Efficiency as the number of intermediate steps between any two trade patterns	Lower value of $\hat{d}$ indicates more efficiency as a smaller number of intermediate steps are required for trade flow
Topological Resilience: Change in spectral radius of network	$\bar{\lambda}$	$\bar{\lambda} = \frac{\lambda_1 - \acute{\lambda}_1}{\lambda_1}$	Resilience to targeted attack on the exporter with most trade partners	A higher value indicates more dependence on the removed node, meaning less resilient network structure. Lower value means trade flow is less affected from node removal
Epidemic Threshold	τ	$\tau = \frac{1}{\lambda_1}$	Resilience against a food-borne disease contamination among commodities	If the epidemic threshold value is higher, the probability of disease contamination is lower
Weighted Efficiency and Resilience				
Weighted Efficiency: Average shortest path length per transported mass	$E(\mathrm{r})$	$E(\mathrm{r}) = \frac{1}{N(N-1)} \sum_{(i,j):i \neq j} \frac{d_{ij}}{w_{ij}}$	Efficiency as the transportation of larger masses through shorter paths	$E(\mathrm{r})$ decrease means the increase in network efficiency as more mass is transported
Weighted Resilience: Change in mass supply of the trade network	$R(\mathrm{r})$	$R(\mathrm{r}) = \frac{\sum_i W_{out}^i - \max(W_{out})}{\sum_i W_{out}^i}$	Resilience to targeted attack on the major exporter with most mass supply	Smaller $R(\mathrm{r})$ indicates greater resilience against the major mass trader

$\boldsymbol{d_{ij}}$: Minimum number of hops (i.e., shortest path length) between nodes $\boldsymbol{i}$ and $\boldsymbol{j}$ in the unweighted trade network

$\boldsymbol{N}$: Number of nodes in the trade network

$\boldsymbol{\lambda_1}$: Dominant Eigenvalue of the original unweighted trade network adjacency matrix

$\boldsymbol{\acute{\lambda}_1}$: Dominant Eigenvalue of the unweighted trade network adjacency matrix after the removal of most trade connections exporter

$\boldsymbol{W_{out}^{i}}$: Supply amount (in 1000 USD) of node $\boldsymbol{i}$ in weighted trade network

max $(\boldsymbol{W_{out}})$: largest supply amount (in 1000 USD) in the weighted trade network by a single node

$\boldsymbol{w_{ij}}$: flow amount (in 1000 USD) on the edge between node $\boldsymbol{i}$ and $\boldsymbol{j}$ in the weighted trade network

2.7.1.3 *Epidemic Threshold*

The inverse of the dominant eigenvalue of the adjacency matrix of the unweighted network is known as the epidemic threshold, represented as τ (Karakoc and Konar, 2021). It is used as a threshold value to measure the spreading of risk in the network (Boguñá et al., 2003). When the λ_1 is higher, there is more connectivity within the network, and τ will be lower, means that the threshold value for the epidemic or risk spreading in the network is low, so the spread of the risk will be faster. On the contrary, if λ_1 is lower, the threshold value will be high, so the probability that the risk to transmit throughout the network is diminished.

2.7.2 Weighted Efficiency and Resilience Metrics

2.7.2.1 *Weighted Efficiency*

The number of average hops required to transport per unit weight from one node to another is called the weighted efficiency, which is denoted by $E(\Gamma)$ (Karakoc and Konar, 2021). Here, the weight used in the study is the total cost of product in US dollars. The weighted network can be called efficient when $E(\Gamma)$ is smaller, as from the formula it means that the node would need to cross less path and more weight can be transported. On the other hand, the network will be less efficient if $E(\Gamma)$ is higher, as the country must overcome more hops or less mass can be transported.

2.7.2.2 *Weighted Resilience*

$R(\Gamma)$, or weighted resilience, measures how much the network depends on the biggest mass supply country. $R(\Gamma)$ specifically determines the mass that is still there in the commerce system after the biggest mass exporter is taken out (Karakoc and Konar, 2021). The weighted resilience of the network is higher because larger values of $R(\Gamma)$ show that the network's mass is less dependent on the main mass exporter. Lower values of $R(\Gamma)$ suggest that the food trade network is more vulnerable to the targeted removal of this node or that the network is more dependent on the big mass exporter for the mass accessible to the trade system.

2.8 Summary

In this chapter, an overview of the crop trade network’s significance, relevant research on the evolution dynamics, and shock propagation had been discussed. The limitations of this research were found followed by the scope of the study. Later, the fundamentals of the network parameters were discussed based on which the results will be derived. Finally, an overview of the topological and weighted efficiency and resilience parameters were provided.

CHAPTER 3

METHODOLOGY

3.1 Introduction

This chapter will discuss the methodology of the research work. The methodology chapter includes the data sources, data processing, and analysis method. In this chapter, necessary steps that had been adopted for network formation will be discussed to aid in the future replication of similar research. The cascading failure will be discussed in an algorithmic manner. Finally, how the climate change scenario will be incorporated will be discussed in the chapter.

3.2 Methodology Overview

The overall methodology of this study can be shown by the flowchart shown in Figure 3-1. The final result that we want to achieve from the study is (i) an assessment of the crop trade topological dynamics in terms of generalized network parameters and the efficiency and resilience parameters and (ii) an understanding of the shock propagation in the network to understand the resilience and comparing the result with the future crop production change due to climate change impact. To do so, the first data will be collected. Then the data will be processed. Using them empirical networks will be formed. After the formation of these networks, their topological properties will be assessed using the parameters discussed previously in chapter 2. The processes mentioned in Figure 3-1 are mentioned following in this chapter in detail.

3.3 Data Source

The global rice, maize, and wheat trade data, both export and import, were downloaded from the World Integrated Trade Solutions (WITS) database (World Bank, 2020). The gross export and import data from the year 1991 to 2021 were used in this research. Trade data were grouped as Standard International Trade Classification (SITC), and for this research 3rd revision data were used. The dataset contains bilateral trade relations, meaning trade value from country A to country B. The trade value was represented in per thousand US dollars. To construct a food trade network, this dataset is more useful than the commonly used Food and Agricultural Organizations (FAO) crops database, which provides only the yearly total import and export value, it does not provide any information about the corresponding trading partners. Moreover, (Gephart and Pace, 2015) carried out a linear regression against the total imports and exports of FAO and WITS data and found that WITS data is strongly correlated with FAO's estimates for both total imports and exports across the year. As WITS data agree well with FAO's crops database, the former was used for this research.

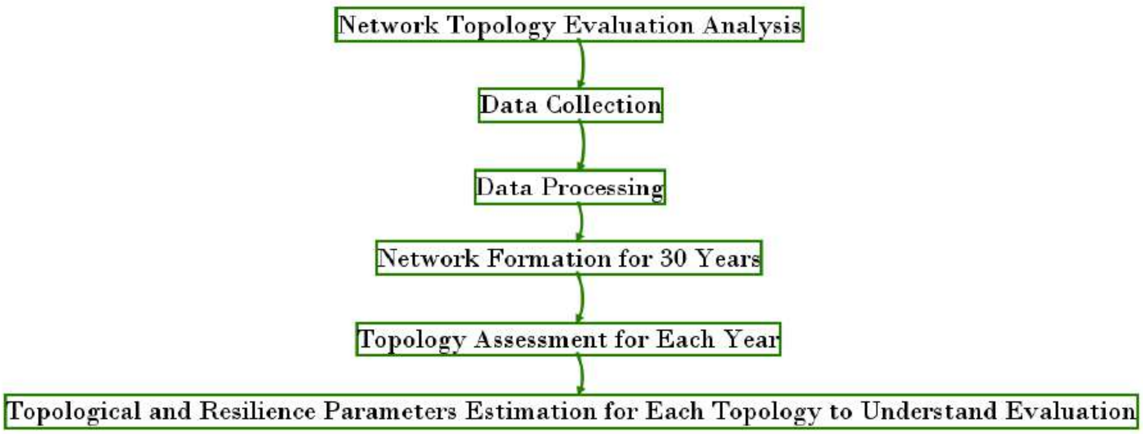


Figure 3-1 Flow diagram on the methodology step for network topology evaluation assessment.

3.4 Data Processing

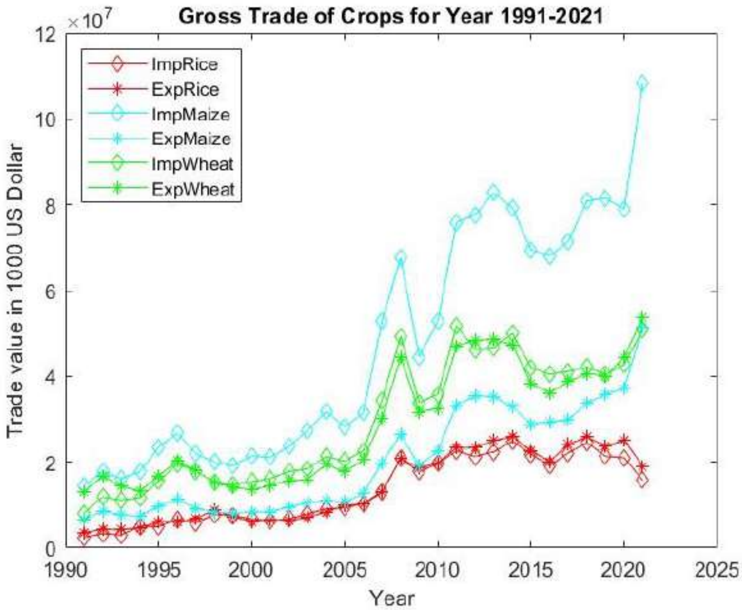
The dataset downloaded contains both independent countries and territories. Territories refer to the trading entity that independently operates and report their corresponding trade flow with their ISO3 country codes, although they are not independent countries (e.g., Hong Kong). Their trade values were used individually and not dissolved with the corresponding countries they belong to, and (Gephart and Pace, 2015) also followed a similar approach. The WITS database also contained country names that were reported with their ISO3 codes, but their geographical existence like latitudes and longitudes was uncertain, so these territories were excluded. The list also contains "World" and aggregated communities like "European Union". As their corresponding country trade flows were already reported, they were also removed from the dataset used.

3.5 Global Crop Trade Network and Statistics

The time series representation of figure 3-2(a) states the yearly variation of crop trade. The distribution of data is seen from figure 3-2(b). The crop trade is supposed to increase each year because of increased regional production and per capita demand due to increased population (D'Odorico et al., 2014). However, figure 3-2(a) shows the global gross trade faces some decrease in trade value from the previous year and some abrupt increase. Among the three crops, maize is the most imported crop and wheat is the most exported one. The average import of maize is more than 3.5 times higher than the average import of rice, and more than 1.6 times higher than the average import of wheat. Similarly, the average export of wheat is 2 times higher than the average export of rice and 1.4 times higher than the average export of maize. Here, in 2008 a peak is visible for the three crops, their trade value rises by double from the year 2005. Again in 2009, the import and export of crops dropped by 15% to 35% compared to the previous year. Another peak can be seen for the maize and wheat trade for the year 2021, the trade of maize increased by approximately 37%, and for wheat, it was approximately 20% from the previous year. For the rice trade, during 2014 the most import and export occurred, but in 2021, the trade value of rice dropped by around 25%.

Here, for rice, the gross export worldwide and the gross import are almost identical, meaning the total export of rice is almost equal to the total import of rice. A similar scenario can be stated for wheat also. For the maize trade, a significant difference between the gross import and gross export can be seen, the import of maize is on average more than double the average export of maize.

In order to understand the central tendency, variability, and skewness of the global gross crop trade a boxplot for the three crops was shown in figure 3-2(b). First, the interquartile range (IQR) for each crop is discussed, as the significance of the IQR lies in its ability to provide information about the spread of the data while being robust to outliers. The IQR focuses on the middle 50% of the data and is therefore less sensitive to outliers and extreme values. The spread of the middle 50% of the data signifies the range of values that encompasses the majority of the data in a set. Here, from figure 3-2(b) it can be stated that for rice trade, the IQR, meaning, the global majority of trade occurred with a value of 6 billion US dollars to 20 billion US dollars for the years 1991 to 2021.



(a)

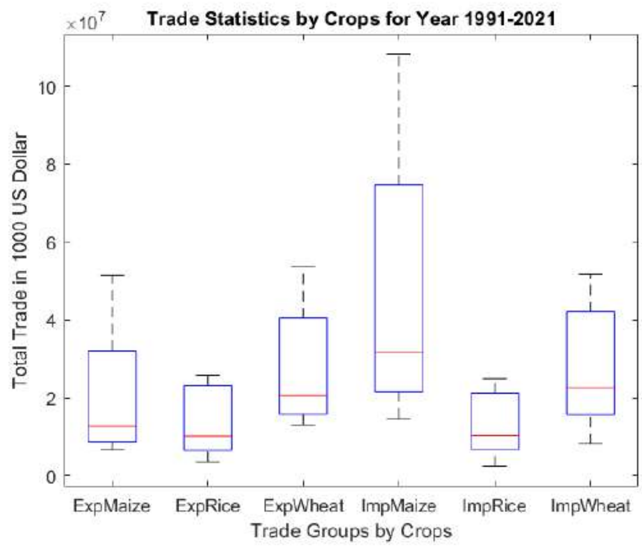


Figure 3-2 (a) Global gross crop trade for the timeframe 1991-2021. (b) Boxplot for global gross crop trade for 1991-2021 for rice, maize and wheat

(b)

For wheat, the most occurred gross trade value lies between 15 billion US dollars to 40 billion US dollars. As the import of maize is approximately two times the export of maize, their interquartile range is also different. For maize, most imports occurred between 20 billion US dollars to 70 billion US dollars, and most exports occurred between 8 billion US dollars to 30 billion US dollars. From figure 3-2(b) it is clear that the median is closer to Q1 than Q3, which indicates that the mean is greater than the median. This means that for all three crops, the gross trade for each year follows a positively skewed or right-skewed distribution. If the median is less than the mean, it means that the distribution of the data is positively skewed, which means that there are more values on the right side of the distribution than on the left side. In this case, the mean is pulled to the right of the median by the presence of these larger values. For figure 3-2(b), all three crops throughout the year mostly traded crops with lower values, and a high amount of trade occurred only a few times, attributed to the proximity of the median to Q1.

The boxplots for maize and wheat have longer upper whiskers, which means that the trade distribution data for maize and wheat are positively skewed. A distribution is considered "Positively Skewed" when the mean is greater than the median. It means the data constitutes a higher frequency of high-valued scores. For maize, higher-value imports occurred throughout the year than for the rest of the crops.

Alternatively, compared to the maize and wheat trade, the boxplots for the rice trade appear shorter than the rest of the two crops, also consisting of equal-length short tails on both sides. If the box is short and the whiskers are also short, it means that the data is tightly clustered around the median, with few outliers. In this case, the distance between the median and Q1 is relatively small, which indicates that the data is skewed to the right. Compared to maize and wheat, rice exported and imported throughout the years had a less standard deviation, also, the rice trade didn’t face any extreme peak unlike the maize and wheat trade, which justifies the short shape of their boxplot.

3.6 Bangladesh Crop Trade Scenario

Although globally maize is the most traded crop which accounts for more than 52% of imports, for Bangladesh the trade of rice is prioritized. Due to the large per capita intake of rice in this nation, rice serves as the primary source of nutrition for the majority of the population (Shelley et al., 2016), for which the trade of rice is emphasized over maize and wheat. From the gross temporal trade graph for Bangladesh, as shown in figure 3-3(a), it can be seen that wheat is more imported than rice and maize. The higher import value of wheat can be attributed to, to meet up the surging demand, the country has to rely on wheat import mostly (Barma et al., 2019). Since 1991 the import of rice has been increasing, during 2010 the rice import increased by 39 times. For wheat, during 1991 the import of wheat is 22 times higher than that of rice, so the rise in wheat import in 2010 might not be as high as rice, it was 4 times higher than the wheat import in 1991. In 2021 the rice import was 3 times higher than in 2010. The overall rice trade temporal graph continually rises and falls. Bangladesh also is seeming increasing rice export throughout the years. Whereas in 1991 the rice export value was barely 1000 US dollars, in 2010 the export value rises to 5 million US dollars. In 2021, the rice export increases by 2.2 times higher than in 2010. Similarly, for wheat, the imports after 2010 faced continuous rise and fall. The first peak import value was recorded in 2011, which is 1.2 times higher than in 2010. In 2021, Bangladesh imported highest amount of wheat so far, of more than 191 million US dollars, which is 2.5 times higher than in 2010. For maize, although not as much important in trade value as for rice and wheat, Bangladesh started to import maize in 1992. While import of maize was barely 12 thousand US dollars in 1992, in 2010, the import value of maize becomes 15.6 million US dollars. Bangladesh also exported wheat and maize, but these are pretty negligible than to import values. Overall, from 1991 to 2021, Bangladesh exported maize of 2.28 million Dollars. Whereas total rice export is 16 million US Dollars and wheat export is 0.02 million US Dollars.

The boxplot in figure 3-3(b) shows the variability, centrality, and skewness of crop trade in Bangladesh from 1991 to 2021. Bangladesh merely exports crops to other countries so the boxplots for crop exports are showing either a single line or three very close lines, as the difference is quite negligible comparing to the export value. The boxplots for the import of crops show longer upper whiskers with median values closer to Q1, which indicates that the boxplots are positively skewed. It means that the data have a higher frequency of higher import values. The phenomenon signifies that Bangladesh mostly imported crops with a pretty high value. This also signifies that Bangladesh is not

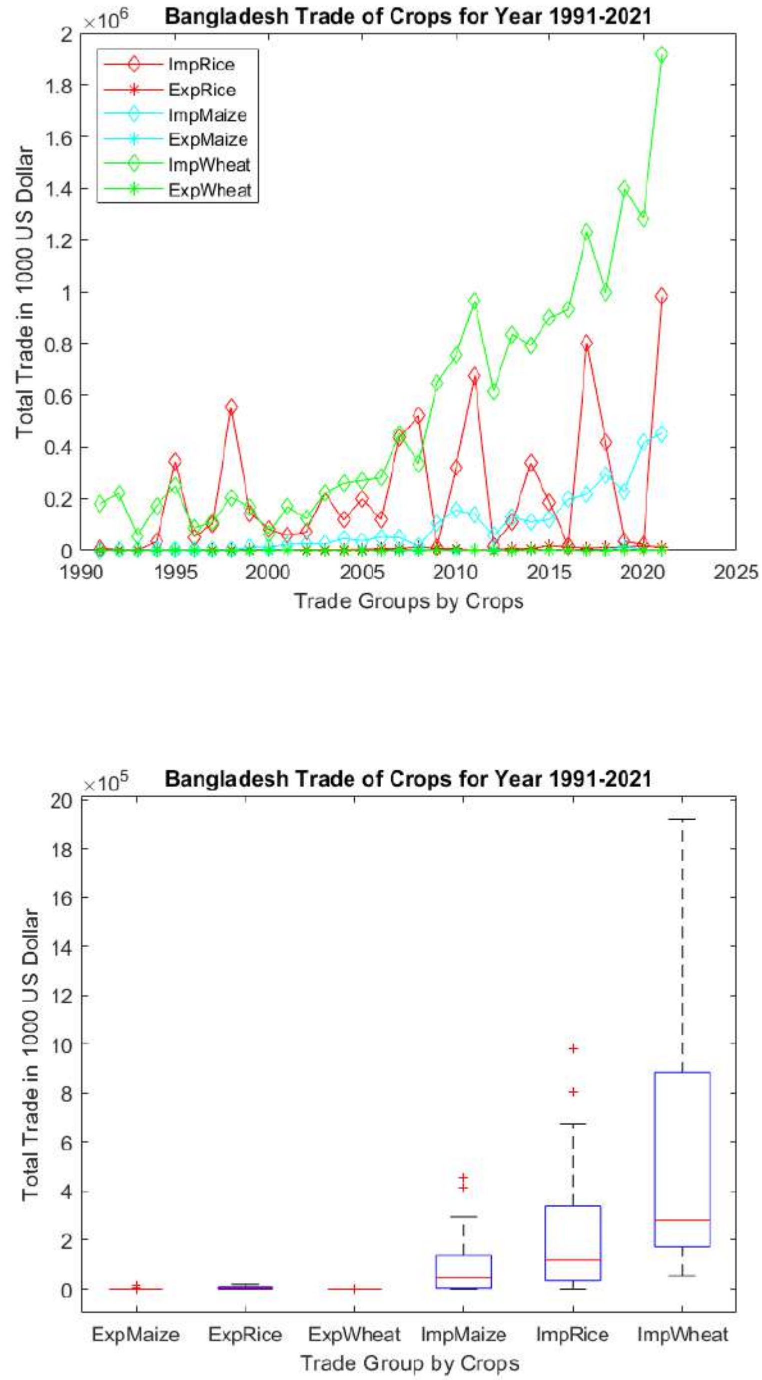


Figure 3-3 (a) Bangladesh gross crops trade evolution for 1991-2021 (b) Boxplot of Bangladesh crop trade for 1991-2021

self-sufficient in domestic production, and the demand for crops is surging due to higher per capita demand. Globally for maize, higher value imports occurred throughout the year than for the rest of the crops but in the case of the Bangladesh trade scenario, the import of wheat is emphasized.

Figure 3-3. (b) is different from figure 3-2.(b) with the absence of the down whisker. Here, Bangladesh did not export for several years, for which the minimum and Q1 appeared zero for maize and wheat. The import of maize varies from 0.12 million US dollars to 14 million US dollars, the import of rice varies from 3.3 million US dollars to 34.2 million US dollars and the import of wheat varies from 17 million US dollars to 90 million US dollars. The mean import of wheat is more than 2 times higher than the mean rice import and 5.8 times higher than the mean maize import.

3.7 Network Formation

It is already established that a complex network model can be a significant tool for visualizing the overall structural characteristics of the network, the interaction between nodes (J. Wang and Dai, 2021), and each node's position in the global network. The global rice, wheat, and maize trade network is a complex network containing nodes as trading countries or territories, edges as trading links, and weights as trade values, which show the characteristics of a complex network.

In this study, the trade flow relationship between countries for rice, wheat, and maize had been visualized by constructing the network model for each year. The complex crop trade network can be modeled as $G = (N, E, W)$. Here, N is the set of nodes comprising food trading countries, E is the edge set of food trading relations (export or import) between countries for specific crops and W is the set of functions of the trade quantity relationship between two countries and $w_{ij}(t)$ denotes the trade quantity in terms of 1000 US dollar between node i and j, i.e., the weight of edges. As we took trade data for the crops from the year 1991 to 2021, 30 time-stepped bilateral graph networks had been constructed for both imports and exports for each crop. When $w_{ij}(t) > 0$, it means that there exists a trade relationship between node i and node j. The absence of a trade relationship is represented as $w_{ij}(t) = 0$. The constructed graph network for each year can be expressed by a topological adjacency matrix, $A = (a_{ij})$, where,

$$aij(t) = \begin{cases} 1 \; if \; w_{ij}(t) > 0 \\ 0 \; if \; w_{ij}(t) = 0 \end{cases} \tag{19}$$

Python network library had been used to build the network. For network visualization, Gephi had been used. Different parameters had been estimated either from the default network function or by creating local functions. To understand the status of Bangladesh in the topology, the centrality measures of Bangladesh along with its important neighbors had been estimated. They were compared with the global average centrality values of the network.

3.8 Impact Assessment of Climate Change on Global Food Production

Global food output is being impacted by altered agricultural ecosystems brought on by warming temperatures, shifting precipitation patterns, and extreme weather events linked to climate change. According to Lobell et al (2001), the yields of maize and wheat have decreased globally because of temperature rises brought on by climate change, with losses estimated at 3.8% and 5.5%, respectively, from 1981 to 2002 (Lobell et al., 2011). Schlenker and Roberts showed that over the past 30 years, climate change has had a negative impact on worldwide rice production, with projected yield losses of 10% (Schlenker and Roberts, 2009).

This study used the results from Jägermeyr et al (2021) which estimated the global crop production projection using the ensembles of latest-generation crop and climate models (Jägermeyr et al., 2021). This paper presents the latest-generation ensemble projections for the productivity of major crops for the twenty-first century and assesses climate change impacts on crop yields from a risk perspective. It uses a protocol like the one used by the Coupled Model Intercomparison Project (CMIP) for climate models to develop benchmarked multi-model ensemble simulations driven by harmonized simulation protocols. Globally the regions had been stratified into four major Koeppen–Geiger climate zones, which are temperature limited, temperate, tropical, and subtropical. The study defines the Time of Emergence (TOE) metric to identify the year in which the smoothed climate change signal exceeds the underlying internal variability and model uncertainty. The signal is the multi-model ensemble mean crop productivity change against the 1983-2013 reference period, and noise is defined as the standard deviation of simulated historical variability of crop productivity across all individual GCM × GGCM combinations (1983-2013). According to the study, the effects of climate change on crop production are probably more severe than previously thought.

Here, the percent change in production of rice, maize, and wheat results had been derived from the study for the country of interests, during the TOE. This is shown from figure 3-4. For example, let's consider that Bangladesh imported a significant amount of maize in 2019, and most of its land area is situated in tropical region. The maize productivity change due to climate change appears to be -8%, so the productivity decrease will be 8% for India. The values are presented in table 3-1 for all the neighbors. Then the cascading failure had been simulated using the assumption of complete node removal. In this case, the country will be removed completely from the network, and the cascading failure had been generated accordingly. The important neighbors will be chosen to stimulate the cascading. Later, the neighboring countries' Koeppen-Geiger Climate zone will be identified, the percent change in production will be derived from the study and a comparative analysis will be conducted between the percent global change vs the capacity needs to be increased to be resilient against cascading. The capacity increase refers to the global capacity increase. So, this also will imply that how much capacity of Bangladesh needs to be increased to withstand the cascading due to the removal of the country of interest.

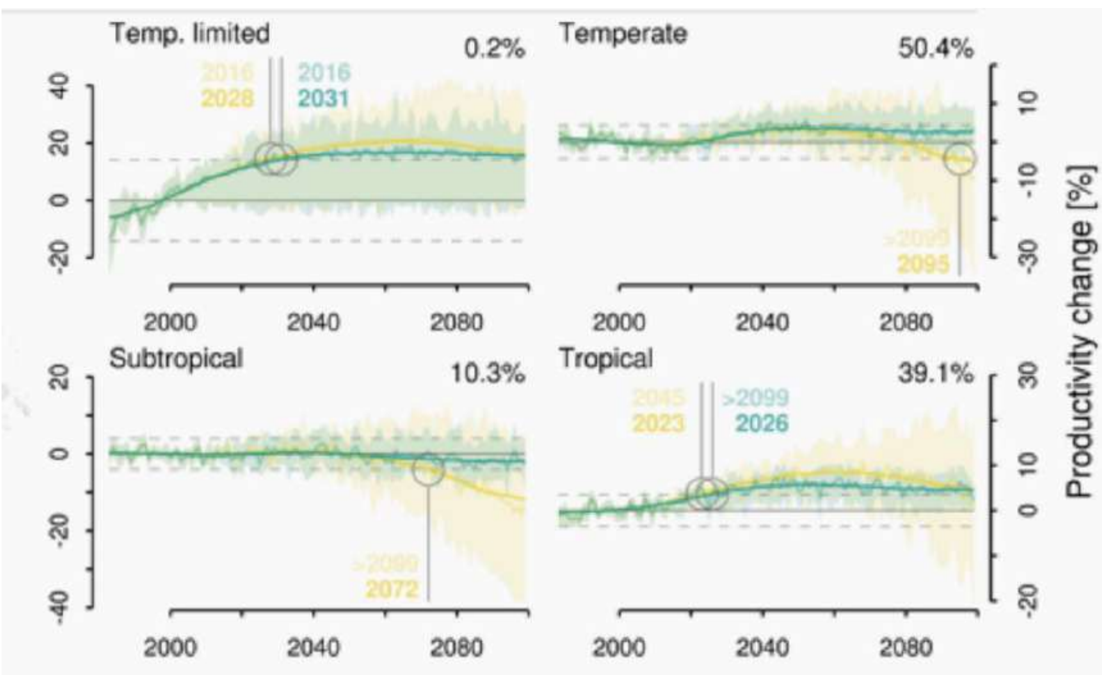


Figure 3-4 Maize productivity change due to climate change impacts (Jägermeyr et al., 2021)**.**

It is to be noted that for the simplicity of the analysis, the assumption of trade reduction proportional to crop production reduction is made. As the study had been considering the extreme case scenario, it will give an idea how much the networks' structure would be affected for any proportion of reduction of crop export.

Table 3-1 Crop yield productivity change due to climate change impact for the Bangladesh neighbors

Crop Names	Name of the Bangladesh Neighbors	Koeppen -Geiger Climate Zone	Climate Change Impacted Yield Change (%)
Rice	India	Tropical	+4
	China	Subtropical	-3
Maize	Brazil	Tropical	-8
	Argentina	Subtropical	-6
	India	Tropical	-8
Wheat	Russia	Temperature Limited	+10
	Ukraine	Temperate	+7
	Canada	Temperature Limited	+10
	Argentina	Subtropical	+6
	USA	Temperate	+7

3.9 Shock Propagation by Cascading Failure Simulation

In this study the trade shock had been analyzed by simulating cascading failure. The overall algorithmic process of cascading failure can be understood from figure 3-5. Cascading failure had been simulated in this study for the network of the year 2019, as at this year the network provides the most recent information about the topology and unaffected by shocks due to COVID-19 or another catastrophe.

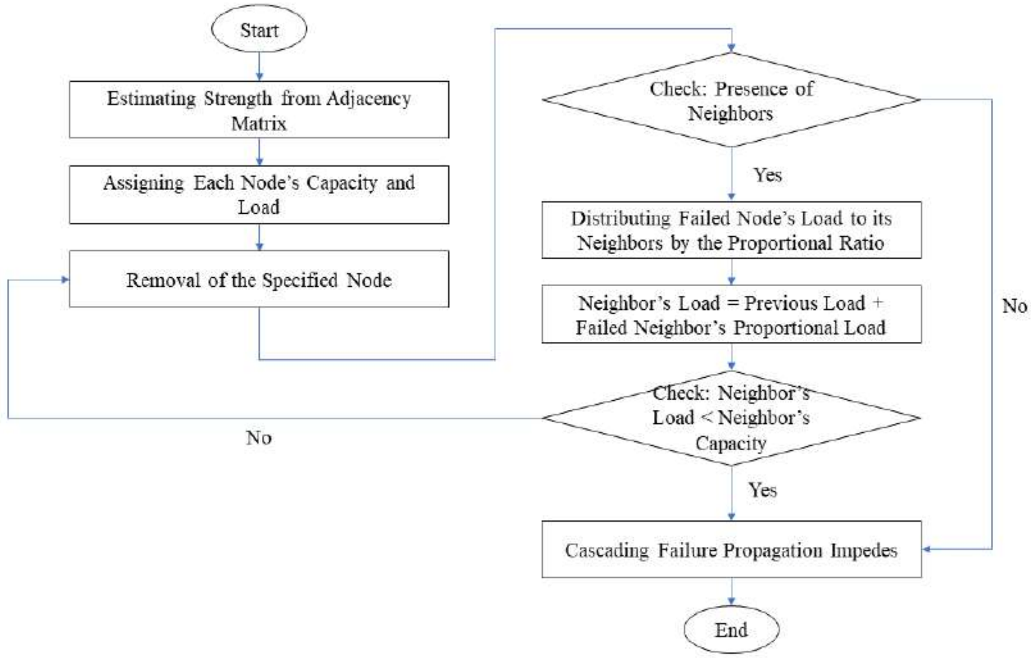


Figure 3-5 Algorithm on the cascading failure simulation of the network

As discussed before, the adjacency matrix of a network, denoted as A, is used to estimate the intensity of node's weight. The correlation degree of nodes is represented by intensity denoted as S_i, which is the total of the weights of the connected edges that are directly related to node i. In the actual crop trade network, the nodes with higher intensities correlate to the nodes with bigger crop export volumes, more trade capacity, and centralized transfer. S_i can be formulated as

$$S_i = \sum_{j \in \Gamma_i} w_{ij} \tag{20}$$

Where Γ_i is the neighbors of node i; w_{ij} is the weights of connected edge between node i and j , found from the adjacency matrix. In this study, cascading failure of a weighted crop trade network occurs when a single node, or country i, fails due to intentional attacks, causing its initial load to be distributed to nearby neighboring countries. If the updated load of node j exceeds its own capacity limit, node j will fail, causing failure to spread gradually and leading to failure of a sizable portion of the crop trade network, and even the entire network. Here, the initial load L_i is defined by the following equation:

$$L_i = S_i^{\beta} \tag{21}$$

where β is the load distribution control parameter, assuming $\beta \geq 1$. The larger the β value is, the more uneven the load distribution will be, i.e., the heterogeneity of the network is more significant. From the initial load parameter, the capacity of node i can be estimated from the following equation:

$$C_i = (1 + \alpha)L_i \tag{22}$$

where α is the load tolerance parameter.

When the node i is failed, load L_i is allocated the neighbor j in accordance with the ratio δ_j, which is the capacity proportion of station j in neighbors, which can be formulated as

$$\delta_j = \frac{C_j}{\sum_{n \in \Gamma} C_n} = \frac{(1 + \alpha)L_j}{\sum_{n \in \Gamma}(1 + \alpha)L_n} \tag{23}$$

Thus, the redistributed load $\Delta L_{i \to j}$ that is distributed to node i from node j can be formulated by the equation:

$$\Delta L_{i \to j} = \delta_j L_i \tag{24}$$

When the updated load L_j is greater than capacity C_j, the station j is paralyzed. If the station j has neighbors, then the cascading failure occurs.

$$L_j + \Delta L_{i \to j} > C_j \tag{25}$$

For any node j, if the above condition is met but the node has no neighbor, then the node j is paralyzed and the cascading failure is terminated. Again, if the updated load L_j is less than or equal to the capacity C_j, the node is normal or is not paralyzed and thus the cascading failure is terminated.

$$L_j + \Delta L_{i \to j} \leq C_j \tag{26}$$

Assuming the initial weighted network has h failure nodes, and their load is redistributed to the adjacent nodes, the h' failure nodes that are caused by cascading failure are present when the network is in its stable state. The nodes cascading failure ratio, or CF for short, is a normalization indicator that can be expressed as the following equation:

$$CF = \frac{h'}{h(N-h)} \tag{27}$$

Where N is the total number of nodes in the trade network. Here, cascading failure caused by a single node is considered, so the CF can be rewritten as:

$$CF = \frac{h'}{N-1} \tag{28}$$

3.10 Summary

This chapter provides an overview of the methodology adopted in this study in detail. The data source and network formation had been discussed, followed by the cascading failure algorithm. Finally, how the results will be compared complying with the climate change scenario had been stated.

CHAPTER 4

ANALYSIS OF CROP TRADE NETWORK

4.1 Introduction

This chapter gives an overview of the structural dynamics and characteristics of the global crop trade network. The chapter discusses the crop trade status for both the global context and Bangladesh, followed by how the global crop trade network evolved for the timeframe 1991-2021. Then different network science parameters had been used for the assessment of the network structure. The centrality assessment had been estimated to understand the importance of the neighbors of Bangladesh in the global trade context.

4.2 Degree connectivity evolution of global crop trade network

Figure 4-1 shows the schematic crop trade network for the rice trade. The layout is dual circular layout where the top fifteen highest degree nodes are arranged in anticlockwise order at the outer periphery. In the inner periphery the nodes are also arranged in the order of their degree value in anti-clockwise order. The colors of the edges are similar to their corresponding parent node. The frequency distribution of the number of trade partners (or degree) that each node (or country) has in the crop-trade network is referred to as the degree distribution. A food-trade network's degree distribution evolution over time provides insight into the network's morphology and rate of expansion. With a few highly linked countries dominating the crop-trade network, if the degree distribution of the network evolves over time to a more skewed distribution, this may be an indication that these nations are playing a larger role as significant food importers or exporters. On the other side, if the degree distribution evens out over time, this can mean that the network is growing more diversified and interconnected. The difference in global rice trade network is presented by the graph shown in figure 4-2. The graphs show that in 1991 only the USA was the node with the highest degree whereas clearly in 2019 the countries with maximum degree increased, indicating the increase in connectivity. The export and import degree distribution of the discussed three crops is shown in figure 4-4.

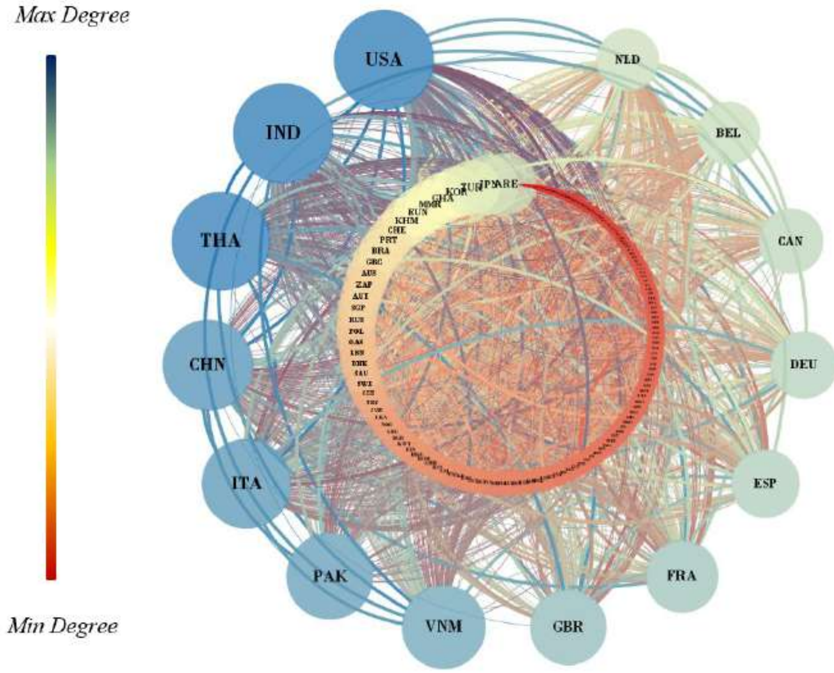


Figure 4-1 Global rice crop trade network for the year 2019.

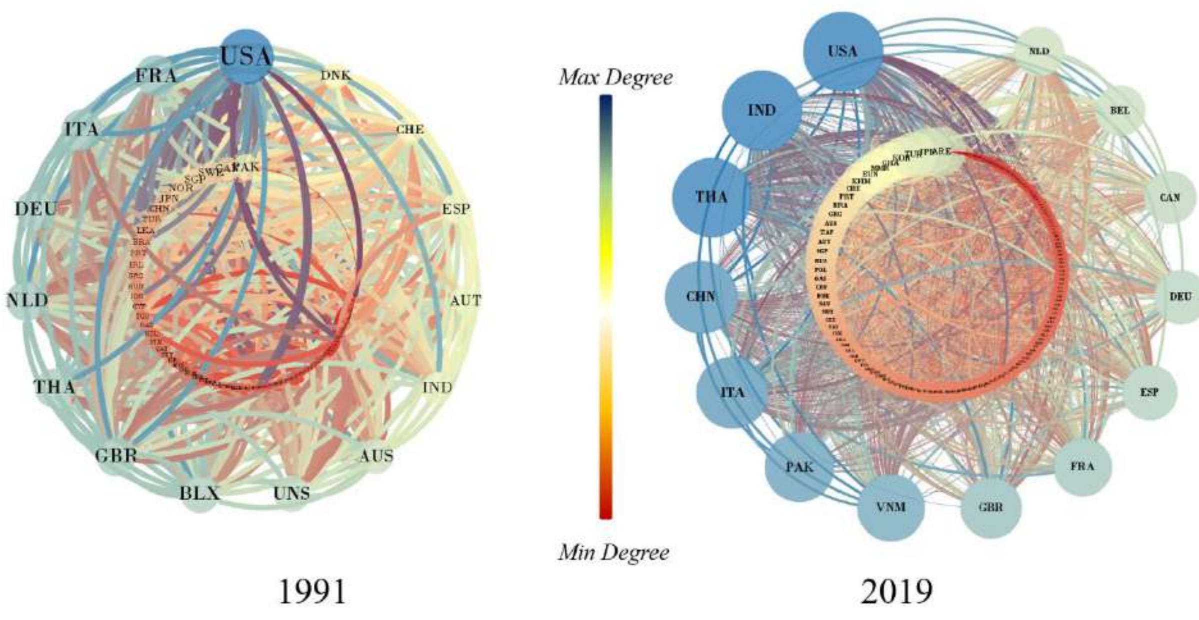
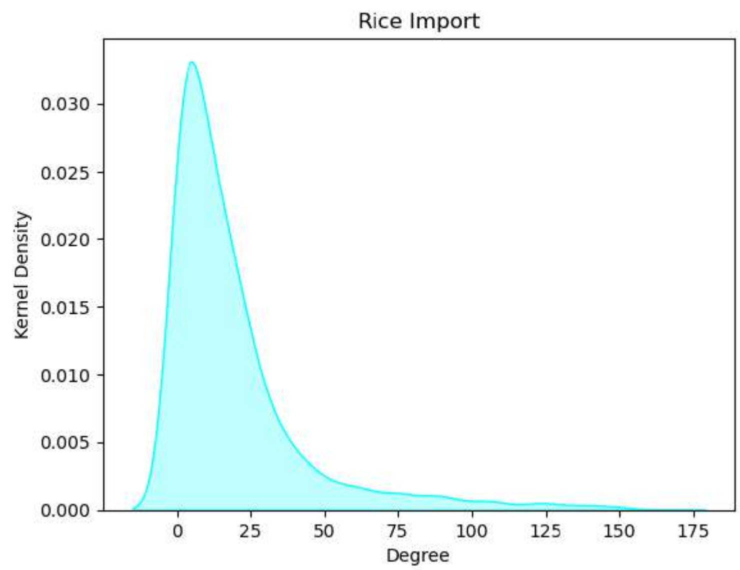


Figure 4-2 Difference in rice trade network between the years 1991 and 2019.

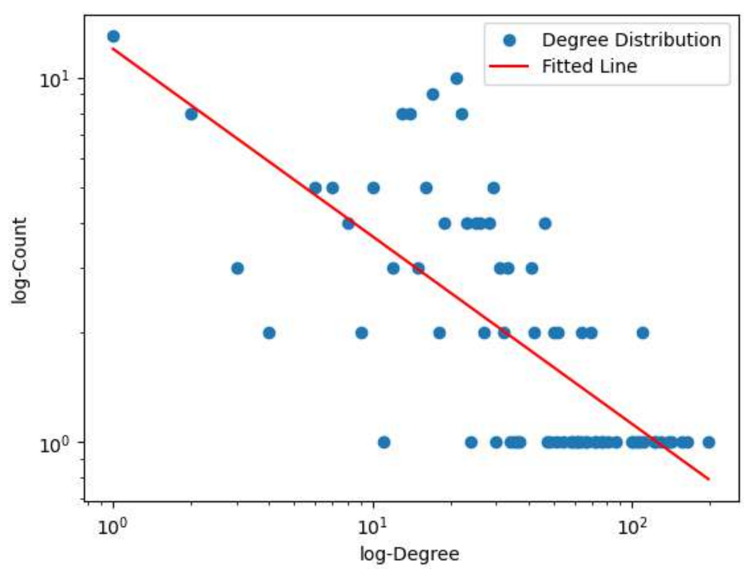
From the figure, the very first observation of the violin plots is that they are showing kernel distribution for negative values of degrees, although the data does not contain any negative value. The reason is explained in the 4-3(a) and (b). Figure 4-4(a), (b), and (c) shows the degree distribution evolution. Here for all three crops, it is observed that both import and degree distribution increase over time. The violin plot shows the distribution shape, and for most cases, the import and export distribution are not symmetric. For all three crop trade networks, hubs are significant which can be attributed to the right skewness of the violin plots and their corresponding mean values are greater than the medians. Most of the countries' degrees vary from 2 to 35, and the degree value of the most central node can be as high as 150. This phenomenon indicates that the networks follow either the Power Law distribution or the sparse distribution, meaning most of the nodes have few degrees while few nodes with exceptionally higher degrees. In order to follow the power law, the degree distribution must form a straight line when plotted on a log-log scale. From figure A-2 it is evident that the degree distribution does not form a straight line as plotted in the log-log scale. This indicates that the networks are indeed sparse networks, with heterogenous degree distribution.

Although rice, wheat, and maize show similar complex network evolution characteristics, their numerical rates of evolution differ. Whereas the highest degree for rice and maize trade appears higher than 150 after 2010 most frequently, the highest degree value for wheat trade appears at 119. This indicates that although globally wheat is traded more than rice in terms of quantity, most of the countries perform rice and maize trade. For wheat trade, 75% of the country's trade the crop from less than 28 countries or below, and for rice and wheat, the 75th percentile value is 35.

As mentioned before, the export and import are not symmetric for all three crops. The export degree is higher than the import degree. Although for maize and wheat, the highest node degree appears in 2016, for rice export the highest node degree is in 2021. But the rice imports in 2021 is less than in 2016.

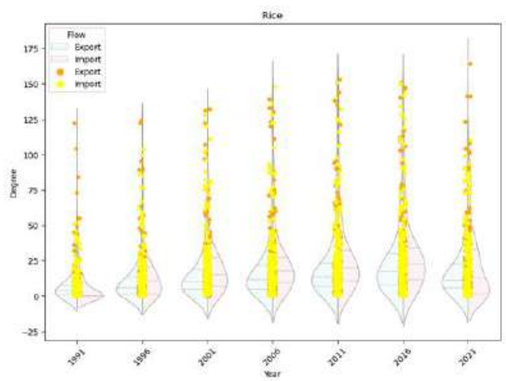


(a)

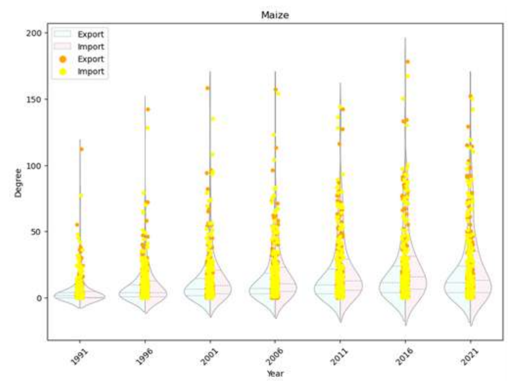


(b)

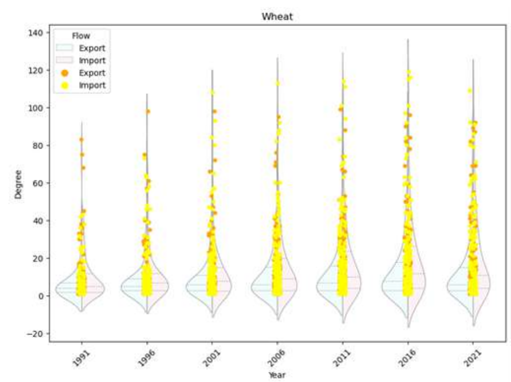
Figure 4-3 (a) Kernel distribution for rice import degree distribution (b) Check for scale free property



(a)



(b)



(c)

Figure 4-4 Global import and export degree distribution violin plot for seven years (a) rice (b) maize (c) wheat

From fig 4-3(a) it is seen that the reason behind the negative kernel value is that the number of countries is considered fixed for all seven years. There are many countries in the data where their degree value is zero. So, in terms of probability distribution, the probability that a country's degree becomes zero gives a positive value. So, while kernel smoothing the seaborn library of Python shows that zero probability value starts at a negative degree value. The figure shows the corresponding kernel distribution for rice, which explains the above scenario. Figure 4-3(b) Check for power law distribution for a given network. Here, the rice import network for the year 2011 is considered. The threshold considered for the graph to follow power law distribution is R2 $\geqslant$ 0.8 and slope.

4.3 Assessment of Centralities of global crop trade network

A network's average centrality measures, which consider the centrality measures of all of the nodes in the network, are used to give an overall idea of the significance of each node in the network. They give a basic idea of the network's structure, point out significant nodes, contrast various networks, and can help with network improvement. The following section discusses the global average centrality measures in terms of average degree centrality, average betweenness centrality, average closeness centrality, and average eigenvector centrality to understand the network growth, bridging between nodes, efficiency, and resilience.

4.3.1 Degree Centrality

The average number of connections for each node in the network has been known as the average degree centrality (DC). This metric provides a general understanding of the network's density and the degree of node connectivity. Whether a network is expanding over time or not can be determined by tracking the change of average degree centrality. If a network's average degree of centrality rises with time, it indicates that the network is expanding, and nodes are connecting to one another more frequently.

Figure 4-4 shows the average degree centrality evolution from 1991 to 2021 for the three crop trades. The export degree centrality for the three crops shows steady growth. DC value for rice export is higher than that for maize and wheat, although a significant drop in rice export degree centrality is visible for the year 2021.

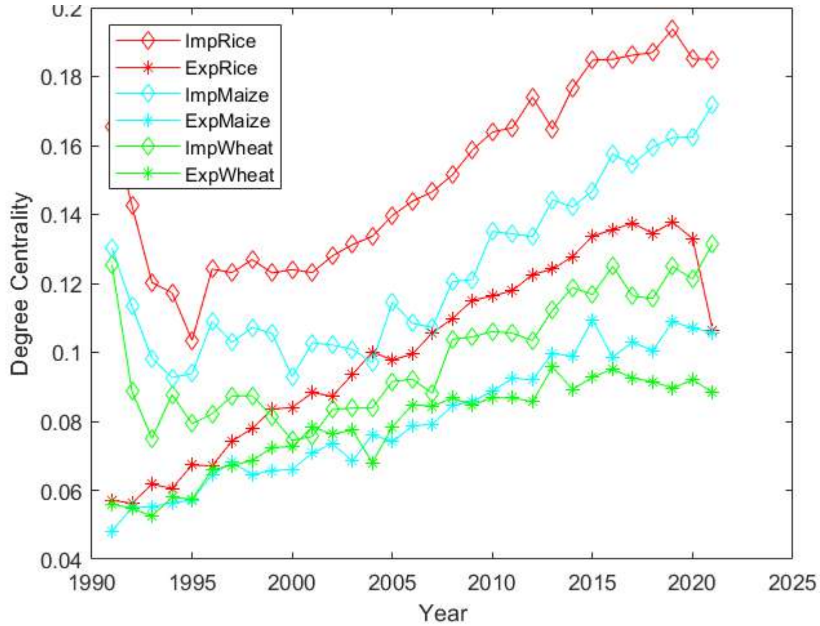


Figure 4-5 Average degree centrality of rice, maize and wheat export and import for 1991-2021

This implies that the rice export network is growing, although for the year 2021, the decreased value in DC can be attributed to the limited export due to the COVID-19 outbreak and border closure (Koppenberg et al., 2021). for maize. But after 2004 average DC for maize becomes higher. No major peak values are visible for the export average DC of the three crops.

On the contrary, the average DC value for the three crop imports face a major decrease in 1995. Their corresponding DC values drop by approximately 40% in 1995 than they were in 1991. Although figure 4-3(a) shows that the gross global crops trade increased in 1995, the import degree centrality value shows a significant drop. 1995 saw a long-lasting drought with severe outbursts and a scorching summer heat wave over Europe. It resulted in significant crop damage and decreased wheat and maize production in various nations (Wreford and Neil Adger, 2011).

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Table 4-1 Top 10 countries with the highest DC for rice, maize, and wheat import and export network for the years 1991 and 2021.

Import												
	Rice				**Maize**				**Wheat**			
	1991		**2021**		**1991**		**2021**		**1991**		**2021**	
Rank	**Country**	**DC**	**Country**	**DC**	**Country**	**DC**	**Country**	**Dc**	**Country**	**`DC**	**Country**	**DC**
1	USA	0.77	USA	0.91	USA	0.85	France	0.91	USA	0.61	France	0.71
2	France	0.59	Italy	0.75	France	0.53	USA	0.86	France	0.57	Netherland	0.60
3	Italy	0.58	Netherland	0.75	Netherland	0.49	South Africa	0.72	Germany	0.55	Germany	0.59
4	Netherland	0.57	France	0.74	Germany	0.46	Argentina	0.68	Canada	0.47	USA	0.59
5	UK	0.57	India	0.71	Italy	0.40	Netherland	0.67	UK	0.42	Canada	0.55
6	Thailand	0.54	UK	0.69	Belgium	0.35	Turkey	0.61	Turkey	0.34	Russia	0.54
7	Germany	0.54	Spain	0.66	Canada	0.35	Germany	0.59	Italy	0.34	Italy	0.52
8	Belgium	0.52	Germany	0.63	UK	0.33	Hungary	0.54	Belgium	0.33	UK	0.50
9	Australia	0.48	Belgium	0.61	Spain	0.32	Italy	0.53	Denmark	0.32	Ukraine	0.46
10	India	0.45	Canada	0.61	Austria	0.31	UK	0.53	Netherland	0.30	Romania	0.42

Export												
	Rice				**Maize**				**Wheat**			
	1991		**2021**		**1991**		**2021**		**1991**		**2021**	
Rank	**Country**	**DC**	**Country**	**DC**	**Country**	**DC**	**Country**	**Dc**	**Country**	**DC**	**Country**	**DC**
1	USA	0.74	India	0.84	USA	0.77	USA	0.74	France	0.60	France	0.63
2	Thailand	0.57	USA	0.83	France	0.38	France	0.63	USA	0.58	Russia	0.56
3	Italy	0.52	Turkey	0.66	Netherland	0.26	Turkey	0.56	Canada	0.47	USA	0.52
4	Pakistan	0.44	Italy	0.62	Germany	0.25	South Africa	0.55	Germany	0.38	Canada	0.50
5	France	0.36	Spain	0.62	Canada	0.24	Brazil	0.50	Belgium	0.31	Germany	0.49
6	India	0.34	France	0.59	Thailand	0.21	Netherland	0.45	UK	0.31	Ukraine	0.42
7	Spain	0.32	Germany	0.57	Belgium	0.21	Spain	0.45	Australia	0.26	Italy	0.40
8	Belgium	0.31	Pakistan	0.56	Italy	0.20	Germany	0.44	Denmark	0.26	Netherland	0.38
9	Netherland	0.29	UAE	0.54	Spain	0.20	UAE	0.43	Turkey	0.24	India	0.37
10	UK	0.29	Netherland	0.52	Zimbabwe	0.19	Ukraine	0.42	Italy	0.21	Turkey	0.37

Therefore, even though there were fewer nations from which crops could be imported, the total amount of imports was larger than the previous year because the impacted nations imported more items to meet the demand. After 1995, the average DC for the three-crop import shows a steady increase, meaning growth of the import network. The country-specific DC values can be useful to understand the connectivity of the networks. Table 4-1. shows the top 10 countries with the highest DC that import and export rice, maize, and wheat for the year 1991 and 2021. The table shows that the DC values increase from 1991 to 2021, which indicates the growth of trade network or that more countries participated in trade. Among the top 10 countries, the USA is mostly occupying the top position both in 1991 and 2021 for the trade of all three crops. The table is mostly occupied by European countries, and among the Asian countries India and Thailand are noteworthy. In 2021, UAE is also emerging as an important mostly connected country for both import and export. In terms of DC values, the import of maize has the highest DC values.

4.3.2 Betweenness Centrality

Based on how frequently a node functions as a bridge along the shortest path connecting other nodes in a network, betweenness centrality assesses a node's significance in the system. A measure of how the centrality of nodes in a network varies over time is the average betweenness centrality development. The average betweenness centrality evolution can provide light on how the network's structure is evolving over time and can be used to pinpoint important nodes or clusters of nodes that are essential to the network's operation. Changes in the average betweenness centrality, for instance, may show that specific nodes are playing a greater role as connectors or mediators between various network segments. The network's general structure may also alter as a result of changes in the average betweenness centrality, such as the formation of new clusters or the dissolution of old ones.

The global average betweenness centrality for all three crops shows a diminishing or steady evolution. Figure 4-5 shows that for the maize and rice import and export, the global average BC shows a decreasing trend. On the contrary, the wheat trade is showing an increasing trend. Decrease in BC happens when there are many nodes participating in trade and they may disrupt the existing shortest path, reducing the BC values. For crop trade the nations directly rely on the crop trade between two nodes, here there is no contribution of the third countries. So, the shortest path here does not play a key role, as the trade relationship between two nodes is direct. Table A-3. shows that from 1991 there is a significant drop in the countries' corresponding BC value in 2021 for both maize and rice, and an increase is seen for wheat trade. Among the top 10 countries USA is taking the top position mostly, and the country is always in top 10 for both export and import.

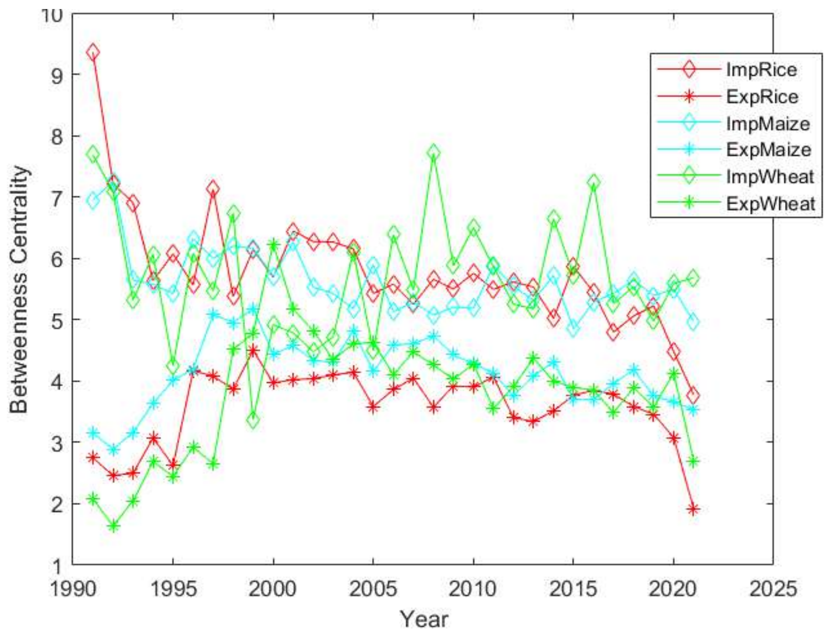


Figure 4-6. Average betweenness centrality of rice, maize, and wheat export and import for 1991-2021

4.3.3 Closeness Centrality

A network's average closeness centrality evolution is a gauge of its connectivity and the ease with which information can move around the network. Closeness centrality measures the distance of a node to all other nodes in the network, with a higher value indicating a shorter distance and hence a more central position. The evolution of average closeness centrality over time can provide useful insights into the dynamics of a network. For instance, it might be a sign of increasing network connectivity if the average closeness centrality rises over time.

With the growth of the degree centrality of the global crop trade network, the CC is also increasing as seen from the figure 4-6. Here, the CC metric is capturing the global trade disruption in 1995 due to the European drought and in 2019-2021 trade ban due to COVID-19. The CC of rice export and import is higher than that for the CC for maize and wheat. In 2020 and 2021, there is a significant drop in the CC for rice export and import, more than the maize and wheat export and import.

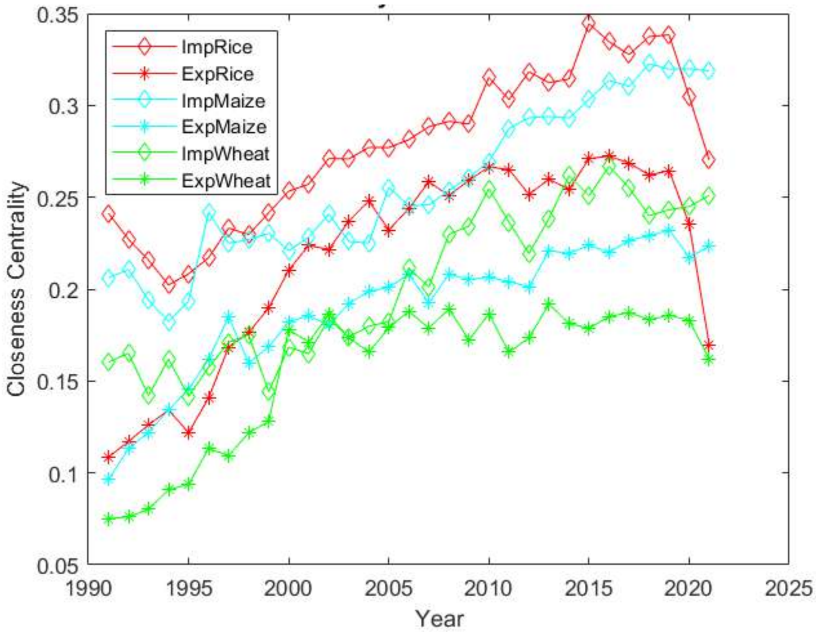


Figure 4-7. Average closeness centrality of rice, maize, and wheat export and import for 1991-2021

Whereas the rice and maize export and import CC are showing steady increase, for wheat there is some significant drop in CC for some years. The increase in CC values means that the decrease in the shortest path, and as countries are directly building trade relationship with each other without the presence of any middle country, this results in the increased CC value.

The higher CC value nodes can be important to serve as a bottleneck of the overall network. Here in table A-4, a list of the top 10 countries with the highest CC is provided. Interestingly, the export CC values are much lower than their corresponding import CC values. Also, the export CC values of the top 10 countries do not vary significantly.

4.3.4 Eigenvector Centrality

When a network's average eigenvector centrality importance varies over time or as the network matures, it means that the nodes' relative importance as indicated by their eigenvector centrality values has changed. A node's value in a network is determined by the importance of its nearby nodes using the Eigenvector centrality metric. Due to their connections to other nodes with high eigenvector centrality, nodes with high eigenvector centrality are more significant in the network. An understanding of how a network's average eigenvector centrality importance changes over time can help determine how the network's topology and structure are evolving as well as how individual nodes' relative importance is changing. An indication that specific nodes are growing more significant and influential in the network, perhaps as a result of changes in their connections or relationships with other nodes, is, for instance, the average eigenvector centrality importance rising with time. On the other hand, if the average eigenvector centrality importance is dropping, it can mean that some nodes in the network are losing their significance or their links to other significant nodes.

The eigenvector centrality evolution for rice, wheat, and maize from 1991 to 2021 is shown in figure 4-7. The figure shows a steady decrease in the average EC from 1991 to 2021 for the import relationship of all three crops. On the other hand, for the export of the three crops, the EC evolution graph shows a flat line, meaning there is hardly any change in the global EC average value.

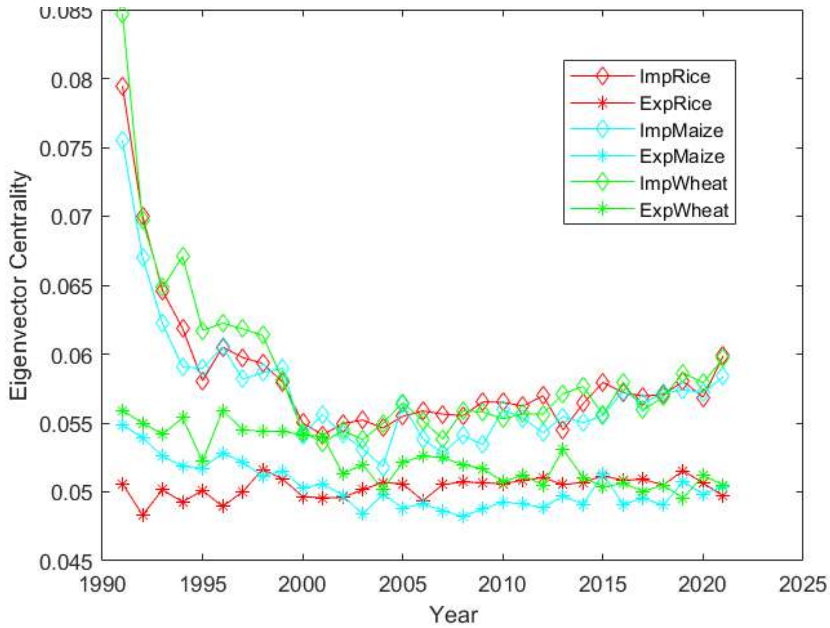


Figure 4-8. Average eigenvector centrality of rice, maize, and wheat export and import for 1991-2021

However, the average EC for imports is higher than the average EC for export relationships. The graph indicates that for crop import, although there is an increase in degree meaning an increase in trade connection, which suggests that the network is becoming more decentralized and less hierarchical over time. If new nodes with relatively low eigenvector centrality are introduced to the network and connected to existing nodes with high degree centrality but low eigenvector centrality, a network may have grown with average degree centrality but decreasing average eigenvector centrality. Because the new nodes are contributing more edges to the network, this can result in a gain in average degree centrality, but a fall in average eigenvector centrality because the new nodes are not strongly connected to other well-connected nodes with high eigenvector centrality. Table A-5 shows the change in EC values of the top 10 highest EC-valued countries in 1991 and 2021. Most of the countries have lower values compared to 1991. However, India is having higher EC value for rice export, meaning India is now becoming connected to more important nodes of the network. On the other hand, as the EC of most of the countries is declining, their hierarchical property is diminishing, although the rate is very low compared to the increase in their degree centrality value.

4.3.5 Comparison of the 4 centrality measures and their correlation

The correlation between the above four average centrality measures can be shown in Figure 4-8. Table 4-2. also discusses the interrelationship between these average centrality measures.

Table 4-2 Relationship between the four centrality measures

Centrality Measures	Low DC	Low BC	Low CC	Low EC
High DC	N/A	Redundant connection	Embedded in the cluster that is away from the rest of the network	sparse or random network, neighbors having a comparable degree (random network) or redundant
High BC	Individuals' few ties are crucial for network flow	N/A	Individual monopolizes the ties from a few people to many other (Rare)	acts as a bridge to many paths but the neighbors are not central, radial network and disassortative
High CC	Connected to active/important actors (shortest path)	Maybe the network exists with many paths, the individual is near to many actors but so are many others (Multiple Hub)	N/A	In between many paths but the neighbors are not central, radial network and disassortative
High EC	Connected to powerful actors	Maybe have few neighbors with high centrality	The network is highly centralized around a few highly central nodes	N/A

To understand the correlation between the four discussed average centrality measures, the data on average centrality for 31 years for all six trade relationships is considered, so there are 186 data points in total for each average centrality measure. Figure 4-8 shows that there lies a strong positive correlation between the average DC and the average CC, and both measures are in a weak positive correlation with the average BC and the average EC measures. On the other hand, the average EC and the average BC are in a moderately strong positive correlation. The distribution plots in figure 4-8 also imply significant characteristics. Here, average CC follows a normal distribution curve.

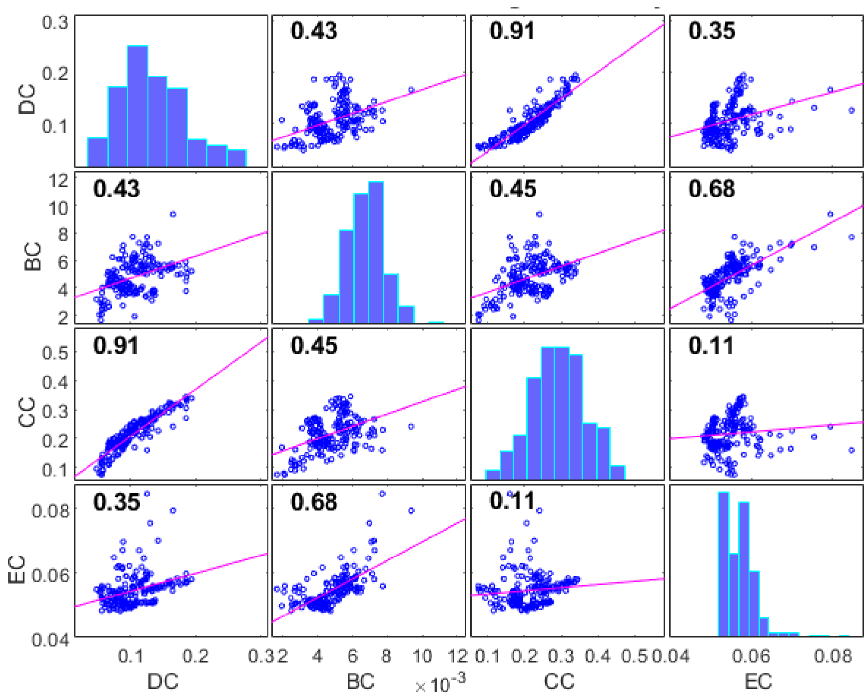


Figure 4-9 Correlation and distribution plots of the four average centrality metrics for global crop trade

Whereas the rest of the three centrality measures follow a left-skewed distribution. The implications of these correlations can be explained from table 4-8. As average degree centrality and average closeness centrality have a significant correlation, it follows that nodes with high degree centrality are more likely to have strong connections to other nodes in the network, which also means they are more likely to have high closeness centrality. This may indicate that there is a high level of connectivity and information or resource flow efficiency inside the network. The limited association between degree/closeness centrality and betweenness centrality raises the possibility that there may not be a substantial correlation between a node's degree of connectivity and the frequency with which it is connected to other nodes in the network via the shortest path. This might be because there are more paths or hubs that can go around specific nodes. It is possible that nodes with high degree/closeness centrality do not necessarily have profound influence or centrality in the network, as shown by eigenvector centrality, given the weak association between degree/closeness centrality and eigenvector centrality. Although the tendency is waning over time, as can be seen from the temporal evolution graphs, the moderately strong correlation between eigenvector centrality and betweenness centrality suggests that nodes that are located on numerous shortest paths between other nodes tend to be well connected to other highly influential nodes in the network.

4.4 Evolution of Global Crop Trade Network Structures

When nations develop new trade ties and increase their agricultural output, the structure of a crop trading network may change over time. In order to comprehend this progression, a number of network indicators are helpful. An increasing average degree can indicate a growing number of trade linkages between nations. Average degree is a measure of the connections each node in the network has. The average clustering coefficient is a measurement of how closely nodes in a network tend to cluster together, demonstrating how localized trade links are within specific geographic areas or groups of nations. A decreasing average path length can indicate that trade links are getting more efficient. Average path length quantifies the typical distance between two nodes in the network. Assortativity examines how often nodes with comparable properties (like degree) connect to one another and can show whether a country prefers to trade with other nations that have a similar level of economic or agricultural productivity. The fraction of potential trade linkages that actually exist in the network is measured by density, and an increase in density can indicate a more integrated and connected global agricultural trading system. Knowing how these measures vary over time can help us better understand how crop trading networks' structure and dynamics are changing.

4.4.1 Average Degree

A key indicator of a network's connection is its average degree (AD), which is the average number of edges each node possesses. A network's expansion and development can be understood by looking at how the AD changes over time. The development of new connections or the addition of new nodes to the network, for instance, may be indicated by a sudden spike in AD.

Figure 4-10 shows that the ADs of the three crops are increasing since 1990. Rice imports have the highest AD increase, whereas wheat exports have the lowest AD increase. During 2021, there is a significant drop in both rice export and import due to the trade restriction for COVID-19. Interestingly, there is no decrease in ADs in the wheat and maize trade. This scenario implies that rice trade, especially the import of rice, is becoming more centralized and prone to cascading failure.

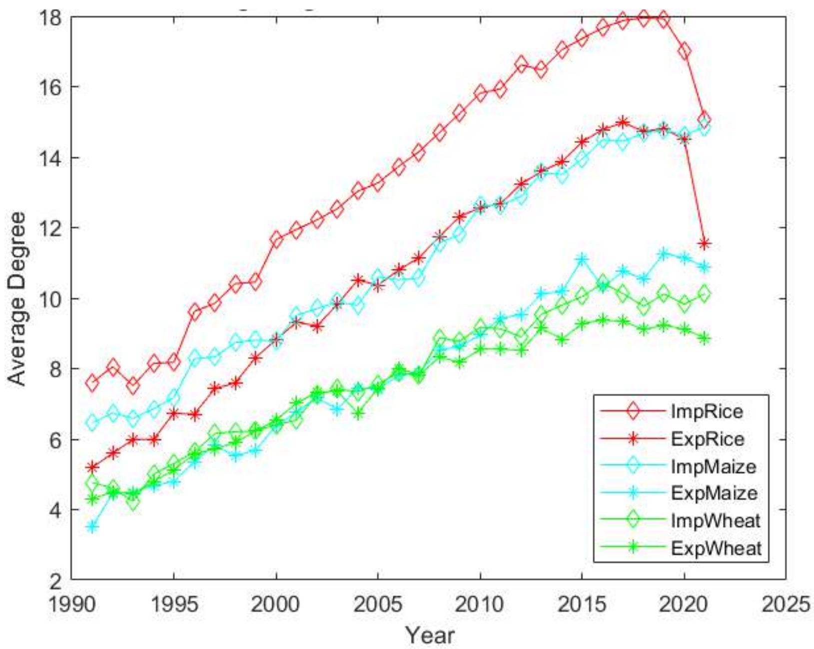


figure 4-10 average degree evolution for crop trade network for the year 1991-2021

The import AD is higher than the export AD for rice and maize. For wheat the increase rate for the import and export are almost equal, most of the years the ADs for import and export of wheat overlap. The increase suggests that the trade network is growing. Also, more countries are participating in crop trade, diminishing the sparseness of the network.

4.4.2 Average Path Length

An essential measure of a network's information transfer efficiency is the evolution of the average path length (APL). The density and connectedness of the network have an impact on APL, which is the average number of steps needed to get from one node to another in the network. The addition of new nodes and edges may alter the APL of a network as it develops. The average path length may decrease over time as the network becomes increasingly centered on a few highly linked hubs if new nodes are introduced with preferred attachments, where they connect to highly connected nodes.

The APL of the global crop trade network is decreasing since 1991 as seen in figure 4-11. Here, the import of maize is showing the lowest APL and the export of maize is showing the highest APL. This observation is interesting because for the same crop, maize can be imported more efficiently than its export. In a sparse network, a declining average path length may indicate that the network is getting more linked and effective at communicating information or other sorts of data. The network can function more effectively, and nodes can reach each other more easily when the average path length declines.

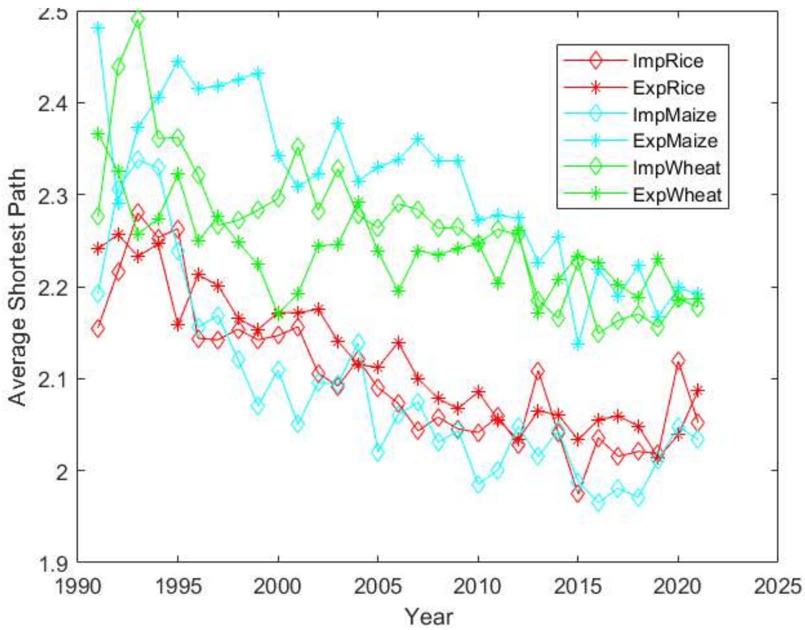


Figure 4-11 Average path length evolution for crop trade network for the year 1991-2021

4.4.3 Average Clustering Coefficient

An indicator of how closely interconnected a network's nodes is its average clustering coefficient (ACC). It evaluates a node's propensity to cluster or group together and is a crucial indicator of how well a network's local structure is understood. Understanding the dynamics of the network can be gained from looking at how the ACC changes over time. For instance, if a network's ACC rises with time, it might mean that nodes are getting more grouped together, which might point to the creation of communities or functional modules inside the network. However, if the ACC is dropping over time, it can be a sign that the network is destabilizing or becoming less organized.

Figure 4-12 shows that there is a slow increase in ACC for the three crops for both export and import. Interestingly the ACCs for the global export of crops are higher than the import of crops. The rice export shows the highest ACC, and the wheat import has the lowest ACC.

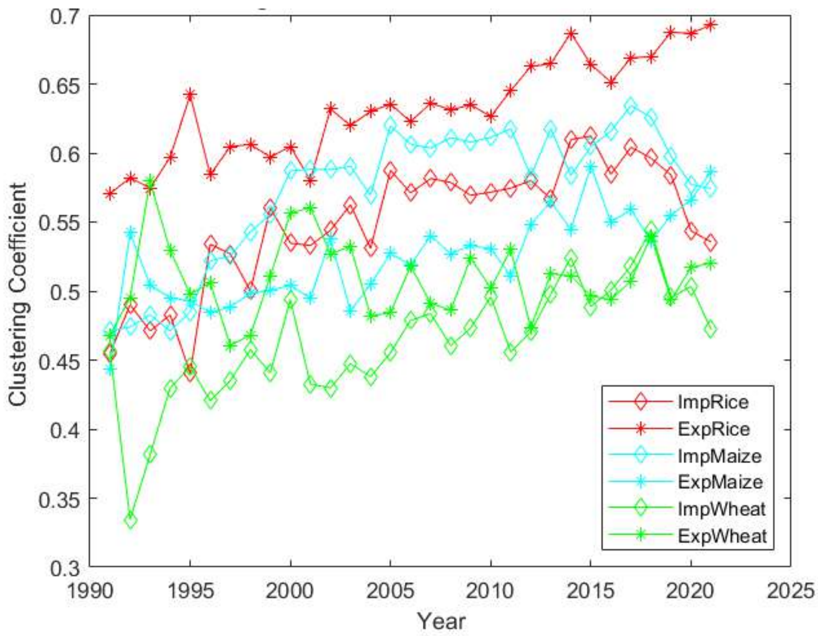


Figure 4-12. Average clustering coefficient evolution for crop trade network for the year 1991-2021

As it is proven from the centrality study that the global crop network is a sparse network, and there is a slow increase in ACC, this phenomenon indicates that the network may have a small-world structure, where nodes tend to connect to both nearby and distant nodes, the average clustering coefficient may increase over time as more local clusters form.

4.4.4 Assortativity

The tendency of nodes in a network to link with other nodes who have a similar degree is measured by assortativity. In other words, it assesses how often low-degree nodes connect to high-degree nodes and high-degree nodes connect to low-degree nodes. Targeted assaults on high-degree nodes are more likely in assortative networks because high-degree nodes frequently connect to other high-degree nodes and low-degree nodes frequently connect to other low-degree nodes. This is because the network may become fragmented into smaller parts if a few high-degree nodes are removed.

Disassortative networks, on the other hand, can be more resistant to targeted attacks on high-degree nodes because high-degree nodes tend to be connected to low-degree nodes in these networks. In these networks, the network is less likely to fracture because of the removal of a few high-degree nodes.

The global crop trade network is disassortative, as seen from figure 4-13. Here the assortativity coefficient value is negative, representing the networks are disassortative in manner. The figure shows that there is no steady increase or decrease in the assortativity coefficient. For rice import, the assortativity decreases up to 1999, then stays steady and after 2015 the assortativity starts to increase. On the contrary, the assortativity coefficient of the export of rice is showing the reverse characteristics. This means that initially the rice trade network was used to be disassortative, meaning the low-degree nodes imported rice from high-degree nodes. After 2015 the tendency starts to diminish a little, although not very rapidly, as the assortativity coefficient is still negative. On the other hand for rice export the low-degree countries tried to form clusters within them, similar is applicable for high degree countries. But this tendency is waning after 2015 for rice export.

For wheat and maize import and export, with time they are becoming more disassortative, meaning the emerging low-degree nodes are connecting more to the high-degree nodes, and this characteristic is showing mostly after 2010. Before that time the assortativity coefficient was increasing. This scenario can infer that the high-degree countries are possibly cutting trade relationship with each other and focused on trading with low degree countries, or vice versa, although the number could be very low.

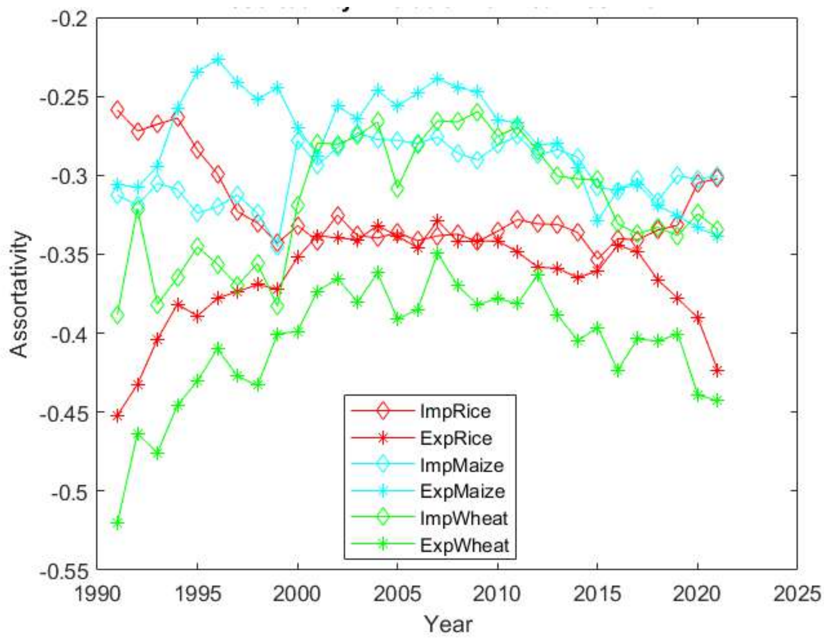


Figure 4-13 Assortativity evolution for crop trade network for the year 1991-2021

4.4.5 Density

The ratio of the number of edges in a network to the total number of edges that might connect all pairs of nodes is known as the network's density. It displays the percentage of network nodes that are genuinely linked to one another.

Figure 4-14. shows that the density of the global crop trade network is increasing. The plot is similar to the average degree centrality evolution, where the rice import density is increasing the most. The increase signifies that the number of edges in the network is increasing relative to the number of possible edges. This could mean that new nodes are being added to the network or that existing nodes are forming more connections. As the trade networks are sparse in nature, the density of a network increases, the likelihood of direct trade connections between any two countries in the network also increases. This can indicate an increase in the overall level of trade cooperation or integration between countries in the network.

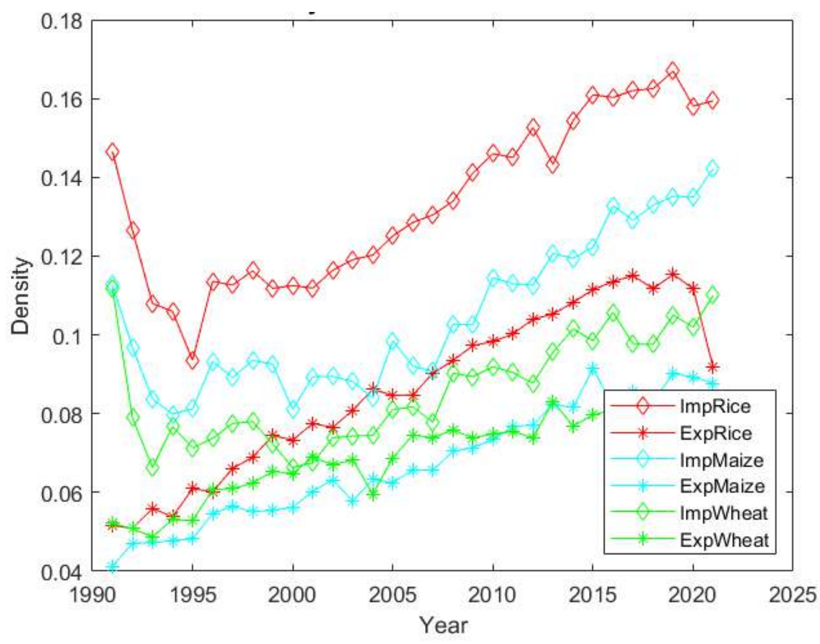
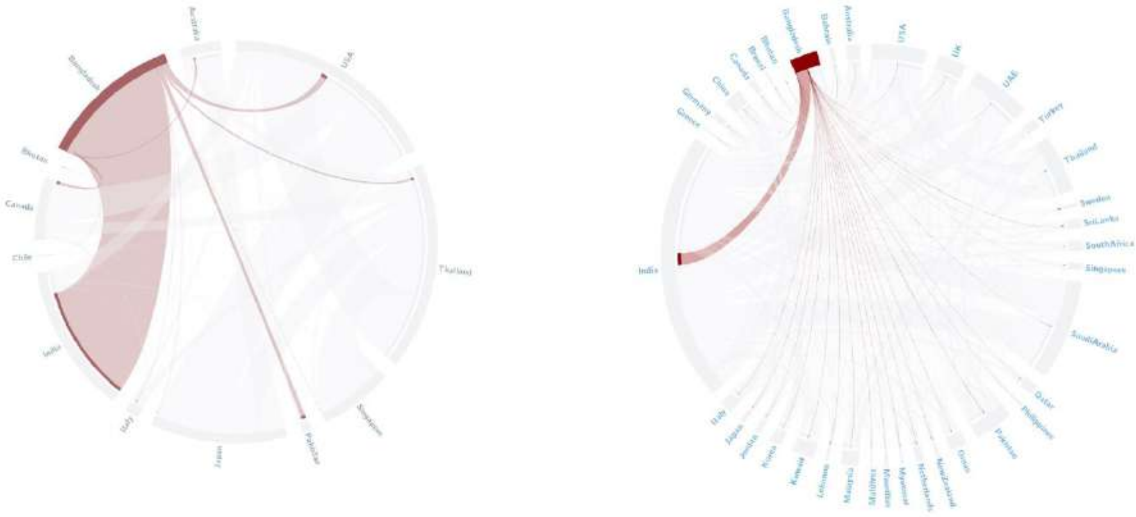


Figure 4-14 Density evolution for crop trade network for the year 1991-2021

4.5 Bangladesh Crop Trade Statistics with Neighbors

Figure 4-14 shows the chord diagram which shows the trade flow between Bangladesh and other neighboring countries. Here in 1991 the quantity imported was small comparing to its neighbors, but at that time Bangladesh was solely dependent on India. In 2014, the quantity increased but it is not significant comparing the trade weight of other countries, that's why the thickness is appearing trivial. Once the significance of cereal import for Bangladesh is established, it is now important to visualize which countries Bangladesh historically relied on more for cereal import, and which countries so far received most of the crops from Bangladesh. To assess this scenario, network science-based parameters can be vital. Here, a comparative analysis between the frequency and quantity is conducted.



1991 2014

Figure 4-15 Rice import between Bangladesh and its other neighbors in 1991 and 2014.

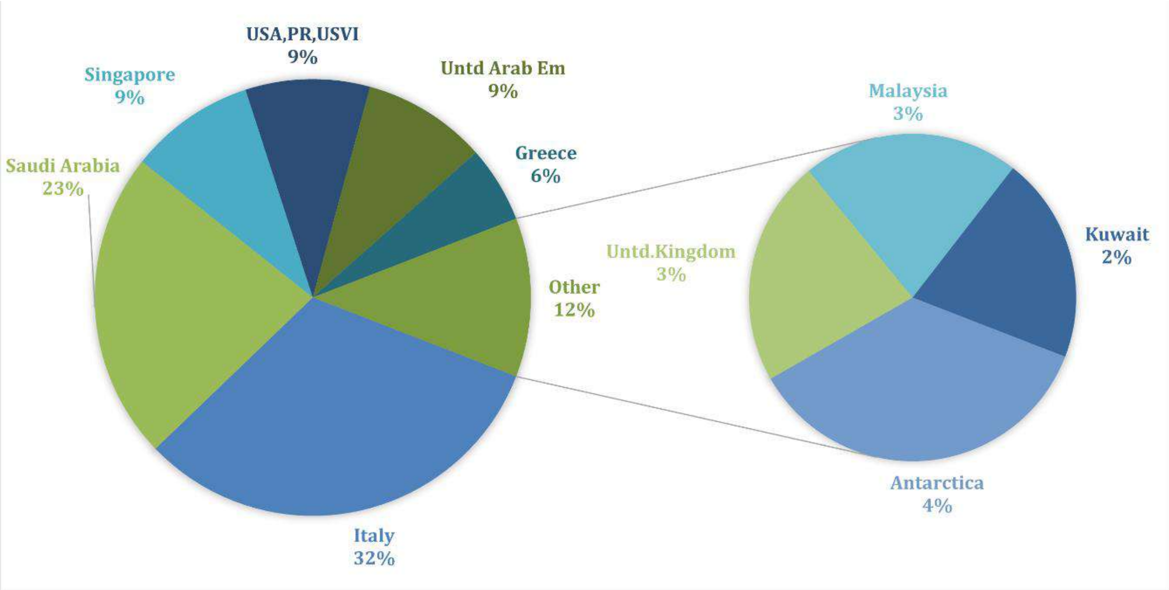
The frequency refers that how many times within 1991-2021 Bangladesh made a trade relationship with a specific country. Quantity is specified by the total amount of crops Bangladesh traded with that specific country expressed in US dollars. As for the trade relationship, here only the export of rice is discussed here, as the quantity and frequency of maize and wheat import are trivial, as discussed in the previous section. The import scenario of all three crops is discussed here.

Here, table 4-3 shows the top ten countries with the highest rice export quantity and the highest export frequency for Bangladesh. From the table, it is seen that Bangladesh exported the most rice to Italy within 1991-2021, which is more than 18 million US dollars. In terms of trade frequency, between 1991-2921 Bangladesh exported to USA and UAE for 15 years. The top countries where Bangladesh exports rice can be attributed to the countries listed in table A-6, which shows the top ten countries where most migrated Bangladeshi dwell (United Nations Population Division, 2021). The countries in table A-6 are the neighbors where Bangladesh exported the most rice, so this can be concluded that Bangladesh mainly exports rice to neighbors to meet up the demand of the migrated Bangladeshis.

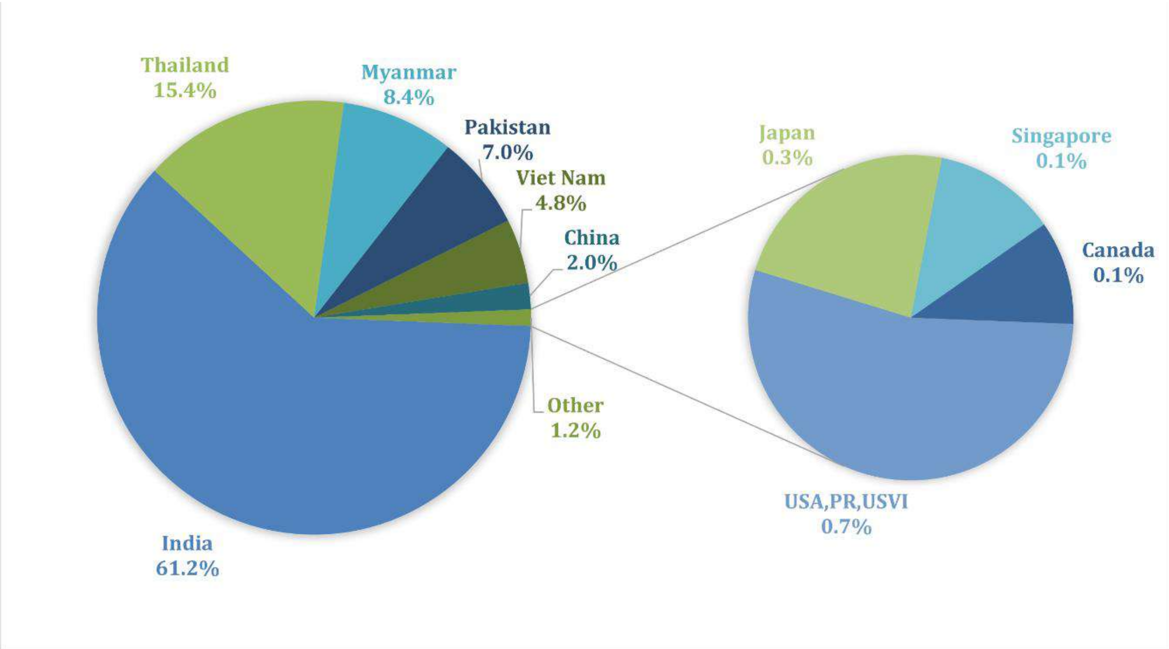
One exception in rice export quantity can be seen as Antarctica is one of Bangladesh's top ten exporting countries. Figure 4-15(i) shows that Bangladesh exported 4% of rice to Antarctica. Although USA and UAE are the most frequent countries where Bangladesh exported rice, the quantity is only 9% for both.

The import of three crops is important as discussed in section 4.6 in terms of quantity. Whereas the highest export frequency value for rice is 15, the highest import frequency value is 22 for rice and wheat, and 20 for maize, as seen in table 4-4. The highest rice importer to Bangladesh from the 31 years period is India, so far Bangladesh imported rice of 2.5 billion US dollars value. The highest gross rice import value is almost 139 times higher than Bangladesh's highest export of rice to Italy. Again, Bangladesh mostly imported rice from Pakistan, but the quantity is 287 million US dollars, which is approximately one-tenth of the total rice imported from India. India also contributes to 61% of Bangladesh's rice imports for Bangladesh as seen in figure 4-15(ii). Whereas the second most importer, i.e., Thailand, contributes to 15% import of rice. Bangladesh significantly exported rice to the USA, it exported rice of 5.2 million US dollars. But Bangladesh also imported rice from the USA 17 times with a gross trade value of 27.7 million US dollars, almost 5 times higher than the export value. Another significant observation is that, among Bangladesh's top ten rice importers, 8 of them are Asian and 2 of them are North American. Similarly, Middle Eastern countries are top rice exporters to Bangladesh. So, it can be said that for rice import these geographical regions' climate change can alter the rice trade behavior to Bangladesh.

Since the beginning, Bangladesh is entirely an import-dependent country for wheat, and its trade value is higher than that of rice and maize. Whereas Bangladesh relies mostly on the south-Asian, eastern-Asian, and north American regions for rice import, the Maize and wheat import is geographically diverse, as seen in figure 4-15, 4-16 and table 4-5.

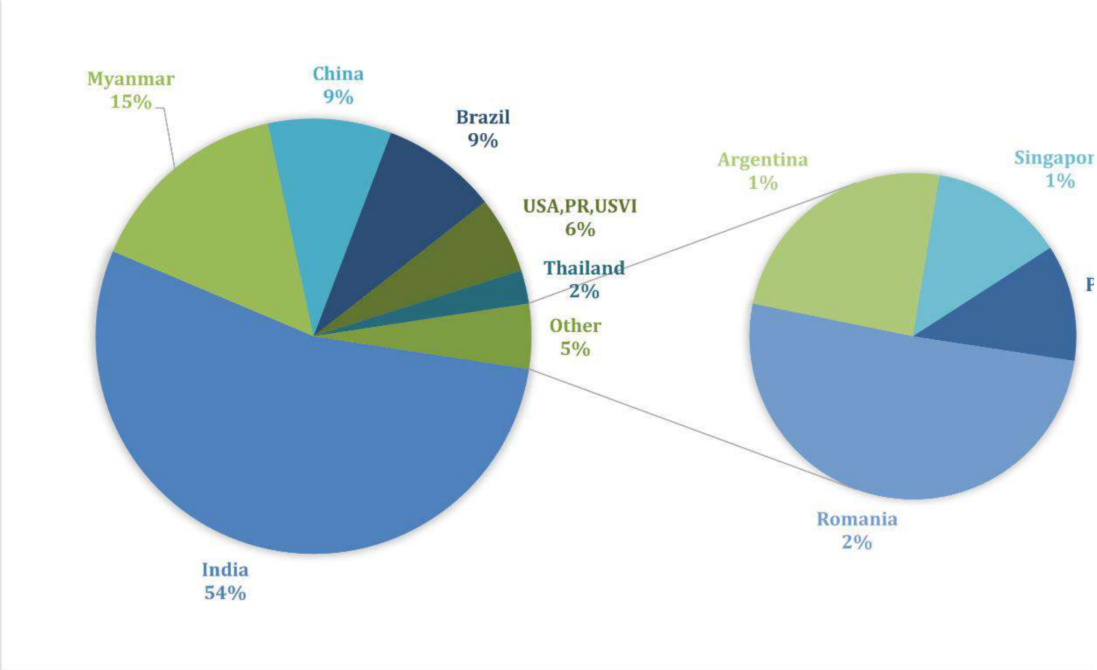


(a)

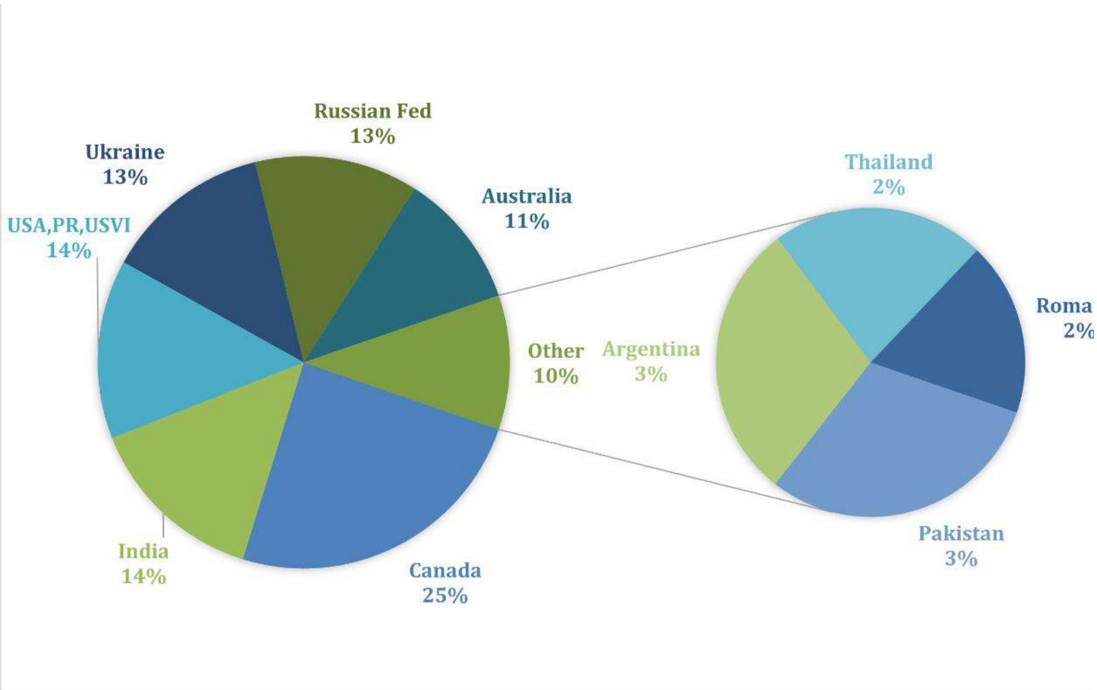


(b)

Figure 4-16 (a) Bangladesh's top 10 rice export neighbors and percentage of export quantity from 1991-2021 (b) Bangladesh's top 10 rice import neighbors and percentage of import quantity from 1991-2021



(a)



(b)

Figure 4-17 (a) Bangladesh's top 10 rice export neighbors and percentage of export quantity from 1991-2021 (b) Bangladesh's top 10 rice import neighbors and percentage of import quantity from 1991-2021

Table 4-3 Top ten countries with the highest rice export quantity and frequency for Bangladesh from 1991-2021

Rank	Rice Export from 1991 to 2021			
	Quantity		Frequency	
	Neighbors	Trade Value in Million US Dollars	Neighbors	Trade Frequency
1	Italy	18.04	USA	15
2	Saudi Arabia	12.92	UAE	15
3	Singapore	5.26	Malaysia	14
4	USA	5.21	Saudi Arabia	14
5	UAE	5.21	Australia	14
6	Greece	3.20	Singapore	14
7	Antarctica	2.38	UK	13
8	UK	1.48	Oman	13
9	Malaysia	1.43	Italy	13
10	Kuwait	1.35	Kuwait	12

Bangladesh is still mostly relying on India for maize and wheat imports, India contributes to Bangladesh's 54% of maize imports and 14% of wheat imports. An interesting observation is that Canada is the top importer of wheat, but the percentage value is only 25%. The variation of wheat import quantity from Canada, India, USA, and Ukraine is minimal, with an exception from maize and rice import. Although the import of wheat from Canada is approximately 8 times higher than the import of maize from India, diversification of crop dependency can impart less impact in case of shock or epidemic transmission because of climate change. Inherently Bangladesh relies on Thailand, USA, India, and Pakistan for all three crops import, and India is a major rice, wheat, and maize import country for Bangladesh.

Rice				Maize				Wheat			
Quantity		Frequency		Quantity		Frequency		Quantity		Frequency	
Neighbors	**Trade Value in Million US Dollars**	**Neighbors**	**Import Frequency**	**Neighbors**	**Trade Value in Million US Dollars**	**Neighbors**	**Import Frequency**	**Neighbors**	**Trade Value in Million US Dollars**	**Neighbors**	**Import Frequency**
India	2506.33	Pakistan	22	India	235.84	India	20	Canada	1873.70	Australia	22
Thailand	628.74	Thailand	19	Myanmar	66.64	Thailand	19	India	1087.16	Canada	22
Myanmar	343.12	Japan	19	China	40.04	Australia	17	USA	1075.00	USA	22
Pakistan	287.41	India	19	Brazil	37.65	China	13	Ukraine	1001.85	India	15
Viet Nam	197.01	USA	17	USA	24.92	USA	13	Russia	982.84	Malaysia	13
China	80.30	Myanmar	16	Thailand	10.84	Myanmar	12	Australia	816.06	France	12
USA	27.17	S. Korea	16	Romania	10.69	Vietnam	8	Pakistan	243.96	Ukraine	11
Japan	11.71	Singapore	16	Argentina	5.14	Singapore	7	Argentina	234.61	Russia	11
Singapore	6.13	Australia	16	Singapore	2.79	Malaysia	7	Thailand	179.73	Argentina	10
Canada	5.18	China	16	Pakistan	2.43	Pakistan	6	Romania	146.22	Nepal	9

Table 4-4. Top 10 Countries with the most trade frequency and quantity for Bangladesh between 1991-2021

4.6 Bangladesh Crop Trade Centrality Measures

To determine the significance of nodes within a network, the idea of centrality is employed in network analysis. It gauges a node's influence inside a network based on the connections it has with other nodes. In this research the centrality assessment is performed for important Bangladesh neighboring countries, and how they evolve with time. Section 4.7 discusses the neighboring countries of Bangladesh and their contribution to crop import in terms of quantity and frequency for the timeframe 1991-2021. Based on table 4-4 several countries were chosen, and their temporal centrality evolution had been determined to compare with the centrality measures of Bangladesh. This comparison is expected to identify the status of Bangladesh in crop import in terms of centrality measures, and its importance in the network, and understand its evolution trend. It is to be noted that the centrality metrics were measured considering the networks are undirected, to get an idea of the importance of the node.

4.6.1 Centrality for Rice Import

The neighbors of Bangladesh chosen to compare with Bangladesh's centrality metrics for rice import network are India, Thailand, Myanmar, Pakistan, USA, and Japan and the average global centrality metrics had been used for comparison.

Figure 4-16 shows the centrality evolution of the seven countries for 1991-2021 for rice import. Here, the USA is consistently maintaining the highest DC, BC, CC, and EC values over the period, followed by Thailand, India, and Pakistan. Bangladesh and Myanmar are showing the lowest centrality values for rice imports. Since the beginning, the USA is connected to more than 80% of the total countries for rice import, as derived from its DC evolution graph. India, Thailand, Japan, and Pakistan are also showing increasing DC. A similar scenario can be seen for the CC evolution of the countries also. Although, after 2015 the CC for India and Thailand exceed the CC for USA. Myanmar faces a continual shrinking and growth in DC, its DC was below the average DC of the network for 17 years. The DC of Bangladesh started to grow more than the average DC after 1994, but the growth in the network is not significant. In contrast, the CC plot shows that the CC of Bangladesh and Myanmar are 1.2 times more than the average CC of the network, and there is a consistent increase in their CC.

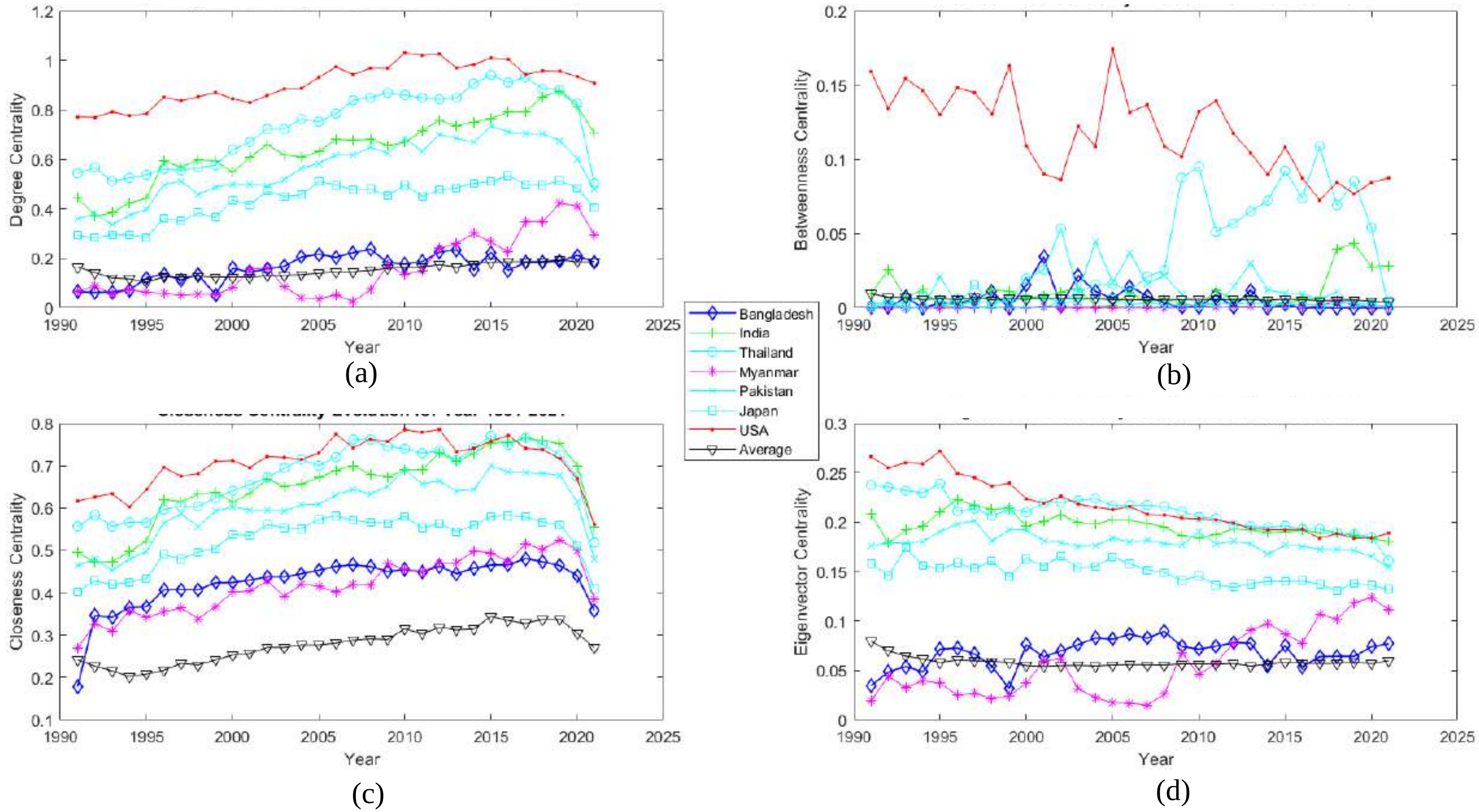


Figure 4-18 Centrality evolution for rice import for the timeframe 1991-20 (a) Degree centrality (b) Betweenness centrality (c) Closeness centrality (d)Eigenvector centrality

This indicates that although Bangladesh has lower centrality value in terms of the number of connections, its connections to other nodes are closer in terms of shortest path distance. Bangladesh may not trade with many other countries directly, but it is located in a central geographical location that makes it a key transit point for trade between other countries.

For BC evolution plot only, USA is having the highest BC value. Until 2005, the rest of the countries have almost similar BC values. After 2005, only Thailand 's BC starts to increase, and it supersedes the BC of USA in 2016, although its BC drops in 2020 potentially for COVID-19 outbreak. The node with high BC value can be identified as a key player in the network, and for the rice trade among the neighbors of Bangladesh only USA and Thailand are so far identified as the key nodes in terms of bridging the connection with the other nodes.

The EC evolution plot shows that the countries whose connections were growing in terms of DC are showing a decreasing trend. In contrast, while Myanmar faced shrinking and growth in EC, Bangladesh's EC is increasing. This means that Bangladesh is trying to connect to more central nodes with time, indicating that Bangladesh has more potential to connect to influential neighbors. Although the rate is comparatively slow.

4.6.2 Centrality for Maize Import

The neighbors chosen to compare the centrality are India, Thailand, Pakistan, USA, Myanmar, and China. They are chosen based on the frequency and quantity of maize imported to Bangladesh. Figure 4-19 shows the centrality evolutions for the maize trade of these countries compared to the global average maize centrality value.

The DC, BC, CC and EC evolution show that the USA has maintained the highest centrality throughout the years. The DC of the rest of the neighbors is much lower than that of USA. As the rest of the countries are Asian, this means that globally Asian countries are lagging in terms of connecting with other countries for maize trade networks. The next highest DC value belongs to China, but it's still one-fourth of the number of connections USA belongs. Thailand, India, and Pakistan then follow China. While the DC of Thailand is always above the global average DC, the DC of Pakistan barely makes it past the average DC. The DCs of Bangladesh and Myanmar are almost similar in manner, the number of connections is very low compared to Bangladesh's neighbors.

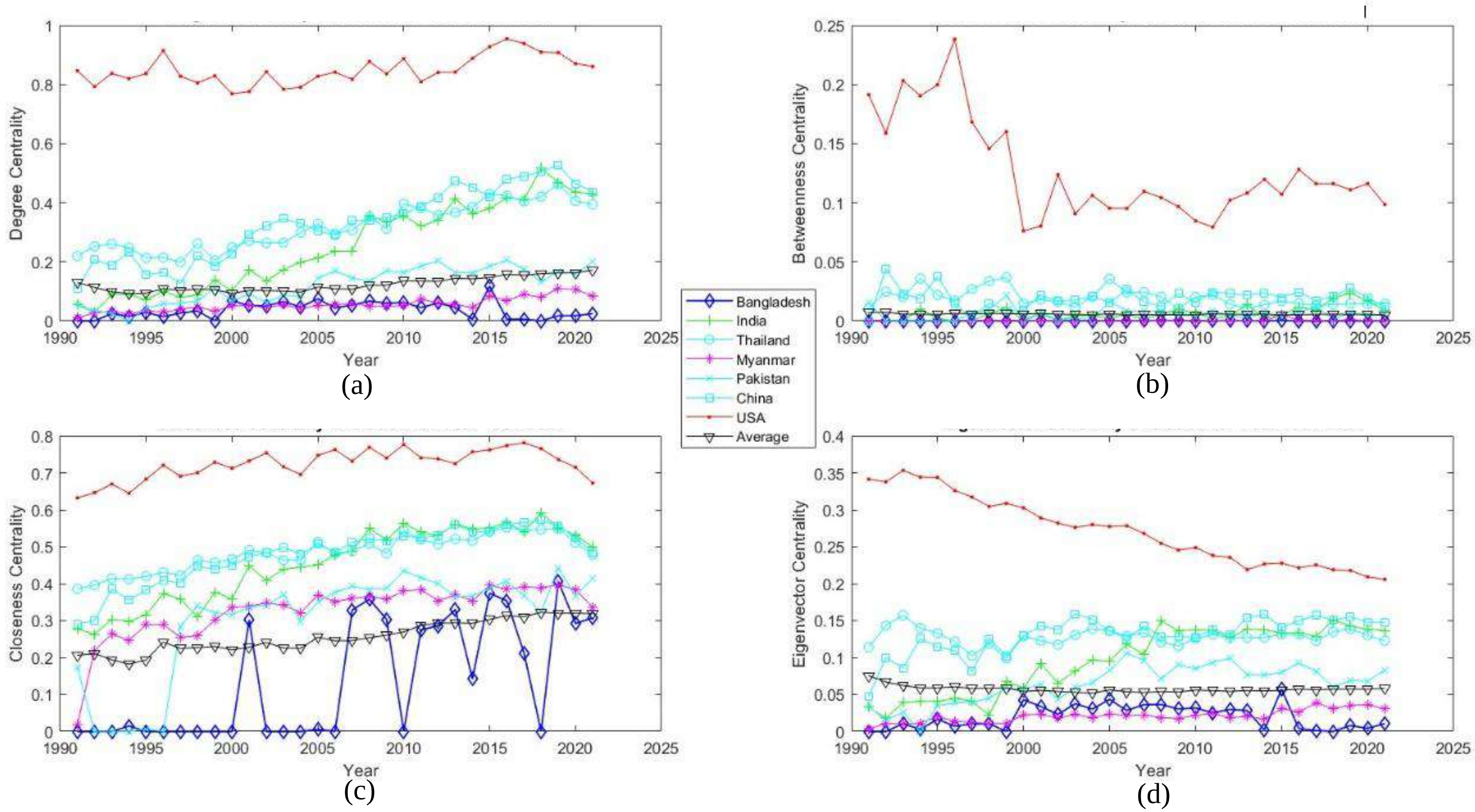


Figure 4-19 Centrality Evolution for Bangladesh and its neighbors for maize trade for the timeframe 1991-2021 (a) Degree centrality (b) Betweenness centrality(c) Closeness centrality (d)Eigenvector centrality

Bangladesh reached the average DC only in two years, one in 200 and the other time is in 2015. It is noteworthy that from figure 4-16(a), Bangladesh had the highest maize import during both these years. So, this can be stated that there is a good correlation with the number of connections or DC and the gross trade import.

The CC graph shows that China, Thailand, and India are having better CC evolution compared to their DC values, which indicates that they are closer to most countries, despite having fewer direct connections to other countries. Even, Myanmar, whose DC is as close as Bangladesh, has CC values higher than the global average CC. In contrast, the CC of Bangladesh is most of the time close to zero. This means that although both Myanmar and Bangladesh have the same number of connections, Bangladesh is less connected to other nodes in the network and is more isolated as its closeness centrality is near to zero. Bangladesh may have connections that are less direct or may be more isolated than Myanmar, which may be situated in a central location with many direct connections to neighboring nodes. Bangladesh’s CC exceeds the average CC when the country imports maize from USA. So, the centrality of country from which Bangladesh is building the trade relationship plays a vital role in the resilience of Bangladesh against failure.

The BC evolution shows that other than USA, rest of the countries are having BC very low. This refers to the fact that only the USA acts as a key node in the overall maize trade network. The phenomenon may indicate that these nodes only engage in limited trade with a small number of other nodes, as opposed to engaging in more varied trade with a larger number of nodes in the network. Also, it can suggest that the nodes are not situated in a beneficial area of the network, which might affect its capacity to obtain resources from other nodes.

The EC evolution shows that the USA has the highest EC, its EC is declining gradually. China and Thailand are maintaining a static EC, whereas for India its EC is rising after 2000. The EC of Bangladesh starts to rise more than that of Myanmar from 2000. This indicates that although Myanmar is closer to more central nodes, Bangladesh is connected to more influential nodes, even though Bangladesh has more possibility to face isolation during shock propagation.

4.6.3 Centrality for Wheat Import

The neighbors chosen for wheat trade centrality comparison are India, Thailand, Canada, Australia, Ukraine, Russia, and the USA. While Bangladesh mostly relied on Asian countries for most of the time, for wheat import the European, North American, and Australian countries have a dominant contribution.

Figure 4-20 shows the evolution of the degree centrality, betweenness centrality, closeness centrality and the eigenvector centrality for the eight countries, and also the average of all centrality values. Here, the USA has the highest degree centrality over the years, followed by Canada, Australia, Russia, Ukraine, and India. Canada exceeded the DC of USA in 2018, and Russia is showing the greatest increase in DC since 1991, exceeding Australia's DC. India and Ukraine's wheat trade connections are also rapidly growing, they exceeded Australia in 2020. The decrease in Australia's DC in the last three years can be attributed by the occurrence of the bushfire and drought in 2017-20, which impacted to vegetation, affecting the crop trade globally (Kumar et al., 2021; Wittwer and Waschik, 2021). Thailand, its DC is comparable with the average DC throughout the years. Bangladesh 's DC faces continual growth and shrink, the country is actively connected to countries from 2001 to 2013, and its DC shows the minimum value from 2016 to 2020 at stretch.

For CC evolution, the USA, Canada, Australia, Russia, and Ukraine show similar behavior as for their DC evolution. India shows a great increase in CC from 2000 to 2021. Thailand's CC is also higher than the average CC, showing the potential of the country to be in trade relationships with many countries as the intermediate path length is small. Interestingly, the CC of Bangladesh is showing interesting behavior. The country, despite having very low connectivity shown in DC evolution, its CC is higher than the average from 2016 to 2021, except for 2020. The reason is that despite Bangladesh trading wheat from a very low number of countries at that time resulting in lower DC value, it imported wheat from countries that have high DC and CC. If a country has a low DC but a high CC value, it suggests that even though it lacks direct connections to other nodes in the network, it can still connect to other nodes via a few middlemen. In other words, even if the nation isn't directly engaged in the trade of the particular good being examined, it still has strong connections to other nodes in the network.

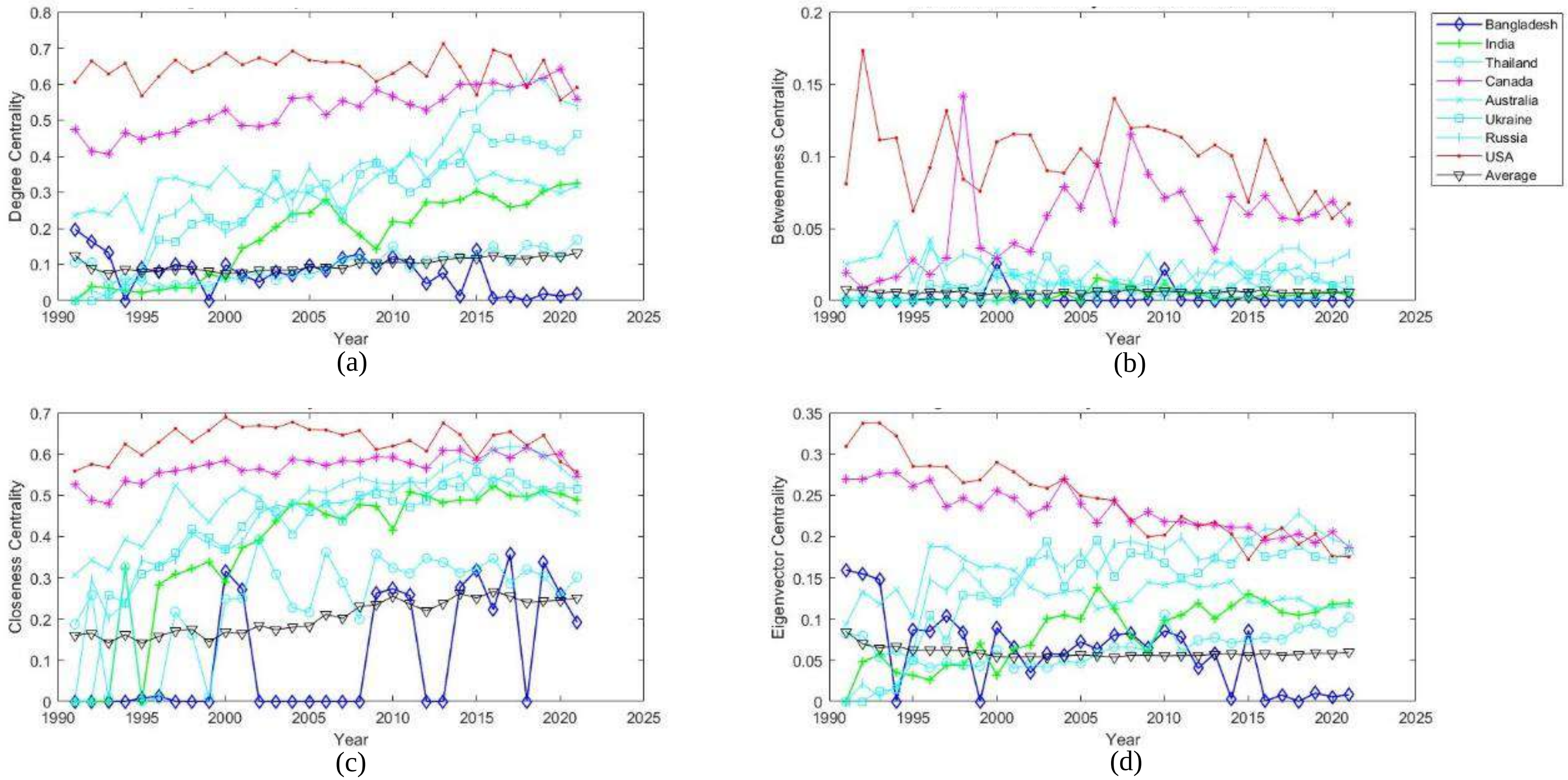


Figure 4-20 Centrality evolution for wheat trade for the timeframe 1991-2021 a) Degree centrality (b) Betweenness centrality(c) Closeness centrality (d)Eigenvector centrality

This may be due to the nation's solid trading relationships with other developed nations or its advantageous location in a region with several trade routes. Although having low DC, the country's high CC score suggests that it is situated in the center of the network.

The BC evolution graph shows that both USA and Canada show the highest BC value since 2000. Before 2000, the BC of Canada was below 0.05, except for 1998 when a sudden rise in BC is seen, although in 1998 there is no sudden change in DC. The possible reason is that although the DC did not increase that much in 1998, the connectivity of the neighbors in Canada might increase in 1998, for which Canada might acquire many indirect connections, resulting in high BC values.

Despite being higher than average, the BCs of Russia, Australia, and Ukraine are comparable to and significantly lower than those of the USA or Canada.4.8.6. Comparison between Bangladesh and Global Trade Centrality. The BCs of India and Thailand are mostly equal to or below the average DC. The BC of Bangladesh for wheat trade is mostly zero, except for the years 2000 and 2010. This means that Bangladesh is mostly dependent only on some countries for wheat import. A country is not a bridge between distinct regions of the network if it has non-zero DC but zero BC. The nation may have several links with other nations, but these connections do not act as significant channels for the movement of data or resources around the network. The country may find itself in this predicament if the majority of trade takes place within a cluster of nodes that is tightly connected. As a result, the node may have little effect on the network's general behavior and its removal may not significantly affect the network's functionality.

The EC evolution graph shows that USA and Canada have the highest EC, and after 2015 the EC of Ukraine and Russia supersede them. The EC of Australia starts to decrease after 1997, and the EC of India increases after 2000. Interestingly the curve shape of EC evolution for Bangladesh is like the curve shape for DC evolution. This proves the fact that Bangladesh mostly imported crops from countries that have high centrality value in the network.

4.7 Clustering Coefficient Evolution

The degree of connectivity between a node's neighbors is gauged by the clustering coefficient (CCo) of that node in a network. It offers details on the area of that node's local network structure, including how cohesive or dispersed it is. When a node's CCo varies over time as the network changes or evolves, this is referred to as the node's evolution of the CCo over time. Insights into the dynamics of the network and how it is evolving, as well as the evolution of the local structure near a specific node, can be gained from this. For instance, when a node's neighbors grow more interconnected over time, an increased CCo for that node may indicate that the node is becoming more influential or significant within its local neighborhood. Another possibility is that a node's neighborhood is getting more dispersed or less cohesive over time, which could have an impact on the node's function within the network. This is indicated by a declining CCo over time.

Whereas from the centrality it is evident that the USA, Canada, Russia, Australia, and Thailand are the most central nodes over the year for the rice, maize, and wheat trade, the scenario is otherwise for their corresponding CCo evolution. Figure 4-17. shows the CCo of these countries are stacked at the bottom of the evolution plots, and the CCo of the least central nodes, i.e., Bangladesh and Myanmar are showing high CCo for most of the years. Due to their propensity for having several connections to other nodes, high central nodes may be linked to nodes that are not physically related to one another. Because there are fewer connections between the neighbors of the node, the CCo may be reduced as a result. On the other hand, neighbors of low central nodes are more likely to be directly connected to one another because they often have fewer connections to other nodes. Because there are more connections between the neighbors of the node, the CCo may increase as a result. However, the CCo of the USA, Canada, Pakistan, and Australia are showing a steady trend throughout the years, and the CCo of Bangladesh and Myanmar shows a drastic change, they follow neither an increasing nor a shrinking trend. This proves the disassortativity of the network, as the low degree nodes are connecting with the high centrality nodes.

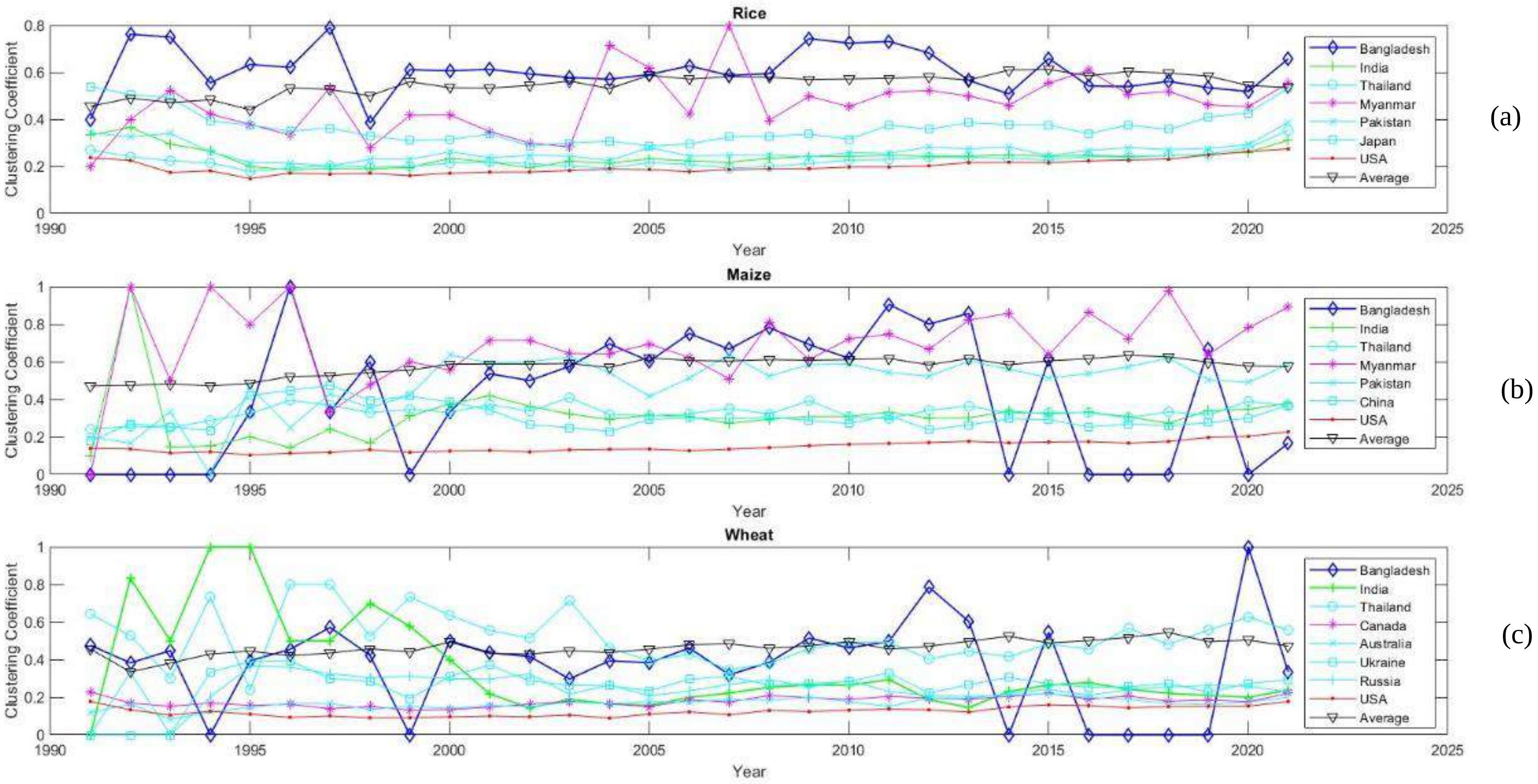


Figure 4-21 Clustering coefficient evolution for Bangladesh and its neighbors for (a)Rice (b)Maize, and (c)Wheat trade evolution for 1991-2021

4.8 Summary

This chapter discusses the global crop trade statistics. It gives an overview on historical topological properties of rice, maize, and wheat trade network, and how they evolve with time in detail. Finally, the centrality measures of Bangladesh had been assessed and compared with its neighboring countries to understand the nodal importance of Bangladesh.

CHAPTER 5

RESILIENCE OF NETWORK UNDER CHANGING CLIMATE

5.1 Introduction

This chapter presents the assessment in efficiency and resilience measures for both weighted and unweighted network. Then the shock propagation is simulated in the network considering cascading failure simulation. Finally, the resilience against shock is compared with the climate change impacted crop production.

5.2 Evolution of Resilience of Efficiency for Unweighted Network

Figure 5-1 shows the evolution of topological efficiency and resiliency metrics, denoted by d, $\bar{\lambda}$, and τ. Here, Sradius means the percentage change in spectral radius or dominant eigenvalue of the adjacency matrix, represented in the study as $\boldsymbol{\bar{\lambda}}$, which is the discussed topological resilience metric of the unweighted network. Epithreshold means the epidemic threshold, denoted by $\boldsymbol{\tau}$. d_effun means the average shortest path length, or the efficiency of the unweighted network, denoted by $\boldsymbol{d}$. Here, the evolution studies are conducted for rice, maize, and wheat trade for the timeframe 1991-2021. The topological efficiency evolution characteristics are already discussed previously in section 4.4. Here, the $\bar{\lambda}$ evolution graph exhibits the resilience characteristics of the networks throughout the year. For the rice trade, $\bar{\lambda}$ for rice import network is more resilient against the removal of the largest degree node than for the export network. Specifically, in 2021, the resilience of the export network against the highest degree node removal is the least, attributed by the higher percentage change in the dominant eigenvalue. Similar values are also observed in the 1995, 2002, and 2003 rice export networks. Overall, during these years the dominant eigenvalue or spectral radius changes by around 8%. The evolution graph also shows that from 1991 to 1995, there had been an increase in $\bar{\lambda}$, and after 1995, except for some years there is a decreasing trend in $\bar{\lambda}$. This can be attributed by the increase in connectivity of the rice trade network, for which the networks are getting more resilient against the removal of the giant degree nodes.

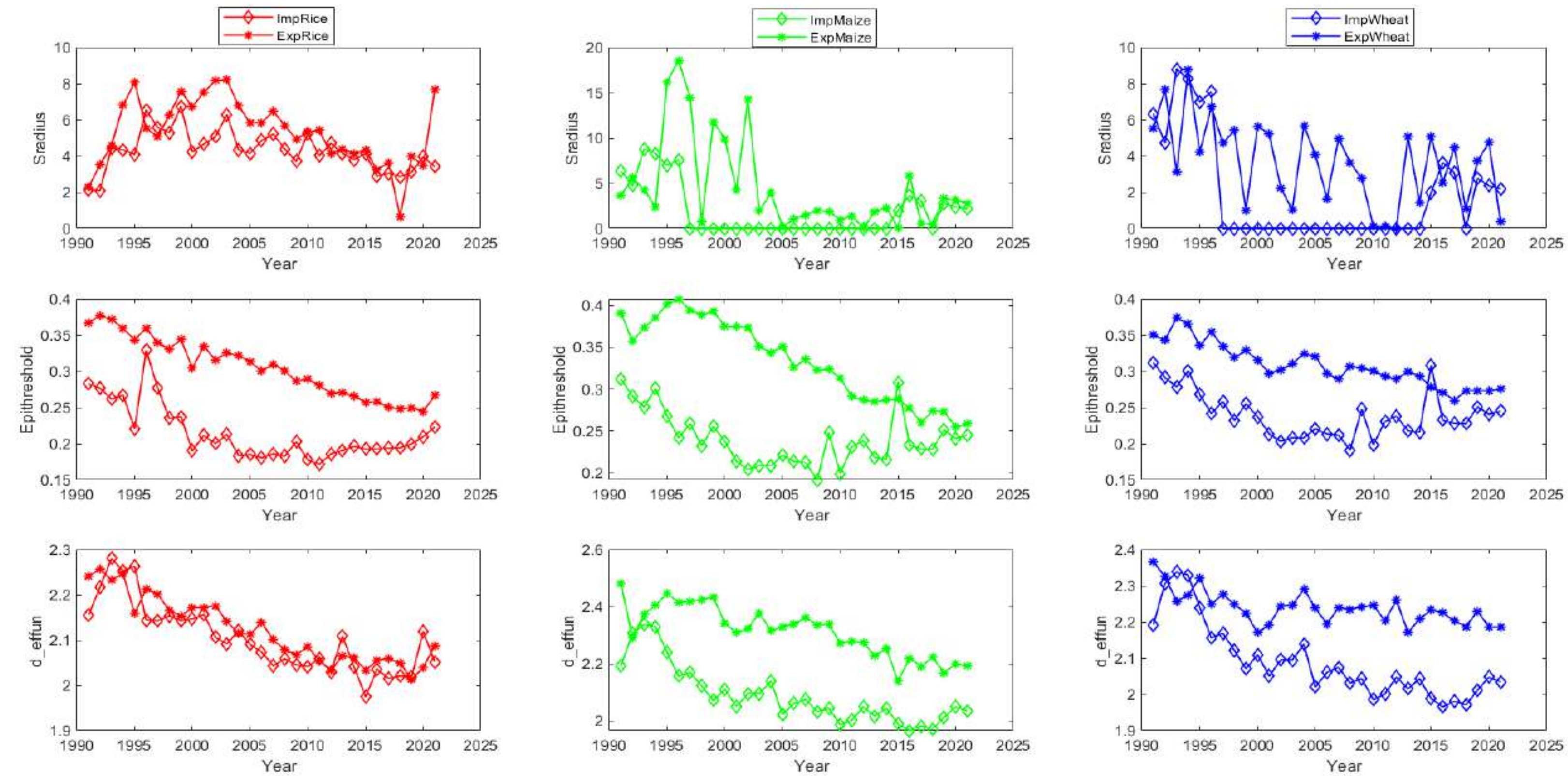


Figure 5-1 Topological efficiency and resilience evolution of rice, wheat, and maize import and export networks for the timeframe 1991-2021.

For the maize trade network, the $\bar{\lambda}$ is zero for the maize import network from 1997 to 2014 at stretch and in 2018. This phenomenon indicates that in the maize import network topology, the countries are well connected, and there could be many countries found to be the highest importer in terms of node degree. So, in these years, the import trade network was the most resilient one. On the contrary, for the maize export, from 1994 to 2004 the network faced many up and down, especially in 1995-1997 the maize export network faced the least topological resilience. The greater European crop scarcity due to the extreme drought and heat wave is captured well. This means that during those times, there is fewer exporting countries due to lower production specifically in the European regions. How the trade weight resiliency was affected during those times will be discussed in the later section. After 2005 the maize export network starts to get more resilient.

The wheat trade network shows a similar pattern as that of the maize trade, except for the fact that the maize export network starts to get more resilient after 2005, mostly showing 2% increase in spectral radius change, and the wheat export network 's $\bar{\lambda}$ ranges mostly 2% to 6% after 1995. From previous study it is seen that for the real-world food-trade network, the $\bar{\lambda}$ does not exceed 25% (Karakoc and Konar, 2021). The results from the study also show the similar value.

The epidemic threshold evolution of the three crops shows that, the import trade network of all three crops have lower threshold values than their corresponding export network. This can be attributed by the increase in connectivity raises the import efficiency, and for this reason if there is a diseases outbreak then the import network must overcome less threshold value to spread to the network than that of the export network. (Karakoc and Konar, 2021) estimated the τ for the empirical food network and the range of the values are similar to this study.

5.3 Evolution of Resilience and Efficiency for Weighted Network

Figure 5-2 shows the efficiency and resilience evolution for rice, wheat, and maize weighted trade network for the timeframe 1991-2021. As discussed before, lower value of $E(\Gamma)$ and higher value of $R(\Gamma)$ is expected to make the network more efficient and resilient accordingly. Here, the $E(\Gamma)$ for all three crops are showing an increasing trend, meaning a gradual decrease in weighted efficiency. The import efficiency is less than that of the export efficiency. Although globally the average path is decreasing, and the mass transport is increasing as shown by figure 4.1(a) and figure 4.4.2. respectively, the weighted efficiency is decreasing, whereas it should show an increasing trend from figure 5-2. It is to be observed that the variation in $E(\Gamma)$ throughout the year is between 0.45 to 0.56. So, there is hardly any change in the overall weighted efficiency of the network.

From the weighted resilience graph, the values of $R(\Gamma)$ are mostly more than 80%. This means that the crop network is mostly resilient throughout the years against the removal of the major flux transporting node. The resilience is showing an increasing trend, which indicates that the reliance on the major exporting node is gradually diminishing if the weighted resilience is considered.

5.4 Comparison between unweighted and weighted network

In terms of resilience, both the weighted and the weighted metrics result to prove that the food trade network is resilient against the single major exporting node. The $\bar{\lambda}$ value will be lower if the unweighted network is resilient against the highest export degree node and $R(\Gamma)$ will be higher if the network is resilient against the highest weight exporting node. The evolution graphs show that the network is resilient against the trade shock, i.e., the removal of the highest influential node. This indicates that there are multiple top exporting countries in the network, so if a country fails then there are other nations on whom the rest of the nodes can rely on to sustain the global trade flow.

The efficiency for both the unweighted and the weighted networks, however, show different characteristics. While d evolution graph shows that the overall efficiency is increasing by the decrease of shortest path among the countries, $E(\Gamma)$ evolution graph shows that the weighted efficiency is static. A possible reason can be, there are the occurrences of trade with fractional amount of weight. From the formula, if the denominator value is fractional then $E(\Gamma)$ will increase. For the suggested network, although the overall shortest path length is decreasing, there are still lots of fractional weight trade occurring. This represents that despite establishing shortest path with countries, there is still not that much efficient flux flow throughout the network, and the weight flow performance is slowly decreasing over time. The discrepancy in weight demand can be a possible reason. A small number of countries may need to trade a high quantity of crops, while the rest of the country's trade crops of fractional quantity.

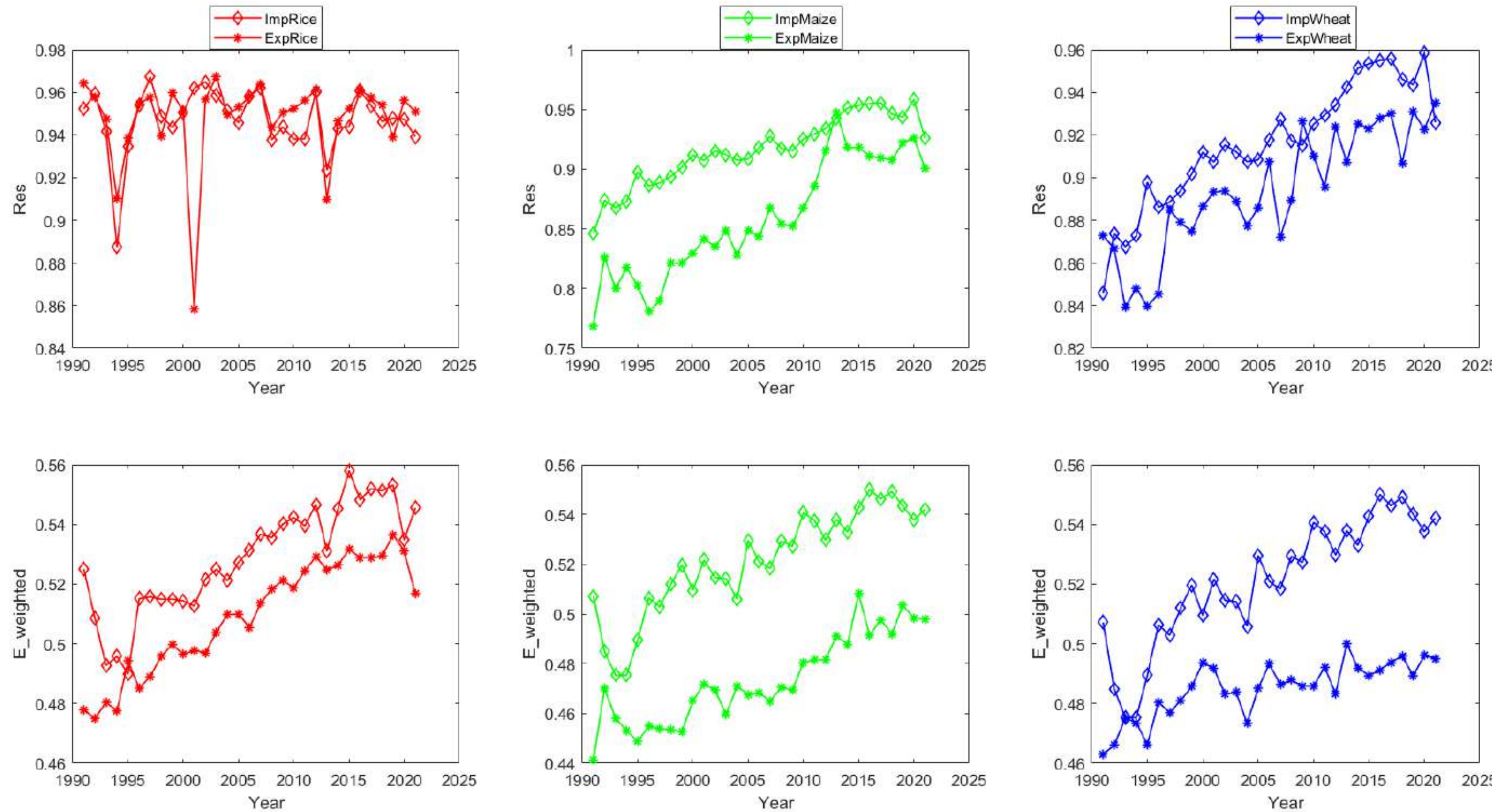


Figure 5-2 Efficiency and resilience evolution for rice, wheat, and maize weighted trade network for the timeframe 1991-2021. here, e_weighted means the e(г) or the weighted efficiency and res means r(г) or weighted resilience of the network.

The implication is that due to climate change scenarios, in case of the import bans then the under-represented countries may face obstacles to trade with countries as there is still not an efficient flux transport is established. Although, their high resilience value shows that the network structure will not collapse because of the presence of several influential exporters.

5.5 Cascading Failure of the Network

In this study, the impact of cascading failure on the global crop trade network has been explored using the nonlinear cascading failure algorithm as discussed in the methodology section. Here, for the analysis, the most recent trade network, i.e., the crop trade network for the year 2019 had been used to simulate cascading. This year had been chosen as later the global trade network faced many exports ban from countries due to COVID-19 situation.

Different researchers chose different methods to choose the nodes that would be removed to generate cascading. For example, Wang et al., used four types of attack strategies: removing random nodes, removing nodes of lowest and highest degree and removal of the average degree node among the neighbors (J.-W. Wang et al., 2009). Again, Bellingeri et al., additionally applied weighted node removal strategy: the node with the highest strength, i.e., weight is removed from the network to analyze cascading failure (Bellingeri et al., 2019). In this study, the countries from which Bangladesh exported most crops had been chosen for removal. The list of the countries for the rice, maize and wheat is provided in table 5.1.

Table 5-1 List of countries with the most export to Bangladesh for the year 2019.

Rice		Maize		Wheat	
Country Name	Quantity (Million US dollars)	Country Name	Quantity (Million US dollars)	Country Name	Quantity (Million US dollars)
India	26	Argentina	17	Argentina	72
China	3	Brazil	193	Canada	306
		India	14	Russia	525
				Ukraine	418
				USA	51

Cascading had been simulated using four load distribution control parameter values, i.e., β. The β values considered are $\beta = 1,2,4 \ and \ 6$. Here, $\beta \geq 1$, as the crop weights are supposed to increase with time. Also, as the neighbors chosen to have high degree, scale-free network becomes the most vulnerable if $\beta \geq 1$ is considered (J.-W. Wang et al., 2009). The load tolerance parameter, i.e. α is considered from 0 to 0.18 with an increment of 0.001. This represents the % of capacity needs to be increased. For example, if $\alpha = 0.01$, this refers the capacity of all the nodes of the network is increased by 1%. Cascading had been simulated for all the countries of table 5.1 individually, meaning the properties of the networks had been explored for a single country. The objective is to find the optimum or minimum value of α, so that maximum number of countries can withstand cascading. This minimum threshold capacity value is considered as $T_{c,\beta}$, meaning the threshold capacity at β. The significance of $T_{c,\beta}$ is that this measure will give an estimation of the least amount of cost or capacity that needs to be increased at the node distribution parameter, β.

For each country removal, five types of measurements were assessed. The first one is the cascading failure ratio (CF) vs α, which represents the percentage of nodes in the network failed due to that specific country removal. CF will be high if most of the countries fail, and CF will be zero if no country fails. Then to understand the topology and the efficiency and resilience of the network the average degree centrality (DC), density, weighted efficiency and weighted resilience metrics were explored. Here, increased DC and density means the average connectivity between the nodes is increasing. If $E(\Gamma)$ increases it means the weighted efficiency is decreasing, as least weight is transported or to transport crops from one node to another the country must follow longer paths. $R(\Gamma)$ increase means the increase in robustness against the largest weighted exporter, meaning that there is more than one country exist in the network who have maximum weight.

5.5.1 Rice Trade Network Cascading Simulation

In 2019 Bangladesh imported a major portion of rice from India, and then the next highest import was from China. So, the cascading failure of rice export for India and

China had been simulated. Figure 5-3 and 5-4 depicts the cascading failure result for India and China respectively.

According to the analysis in Figure 5-3(a) and A-6(a), the system has the lowest damage resistance when α is disregarded i.e., $\alpha = 0$, but with an increase in α in a small range, the system's damage resistance can be significantly enhanced. For both China and India, 60% of the nodes fail if the present capacity of the system prevails. A higher cost incurs for ensuring system invulnerability if the load distribution parameter or β is lower. If $\beta = 6$, the system attains invulnerability at the lowest cost increase for both the countries. Here, only increasing the α by 0.1% there is a drastic change in CF, meaning only increasing the system cost by 0.1% the invulnerability of the whole system can be ensured for a specific load distribution. However, after reaching $T_{c,\beta}$, even after increasing the cost the damage resistance of the system doesn't change. For China the network is the least robust if $\beta = 1$ but for India the least robustness is seen for $\beta = 2$, however for both the cases the highest cost is incurred to achieve the least damage resistance.

The average DC and density for the fragmented network shows an increase for higher cost, but after $T_{c,\beta}$ the DC and density doesn't change even after an increase in system capacity. However, while at $T_{c,\beta}$ the CF changes drastically, for DC and density this occurs when $\alpha = 0.001$. Although at that point DC and density are close to zero. Another observation is that the average DC and the density of the fragmented network are equal. This may occur if the cascade failures produce a core subgraph with many isolated nodes or small subgraphs surrounding it, which is highly connected. Due to its numerous connections, the core subgraph in this scenario would have a high degree of centrality, whereas the overall density of the fragmented graph would be low due to the numerous isolated nodes or small subgraphs.

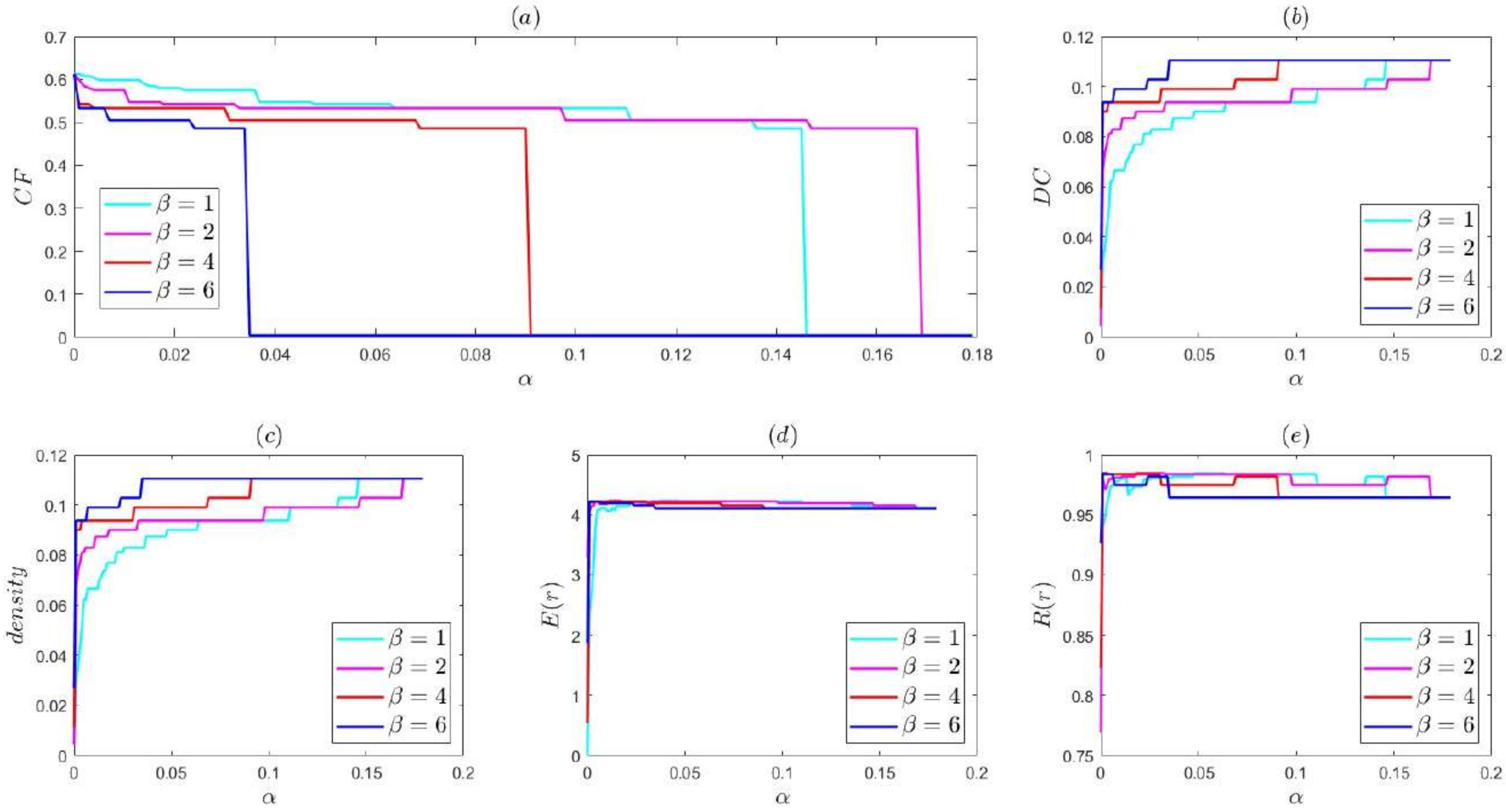


Figure 5-3 Cascading failure for India removal of the rice trade network for the year 2019. (a) Cascading failure ratio vs α. (b) Degree centrality vs α. (c) Density vs α. (d) Weighted efficiency vs α. (e) Weighted resilience vs α.

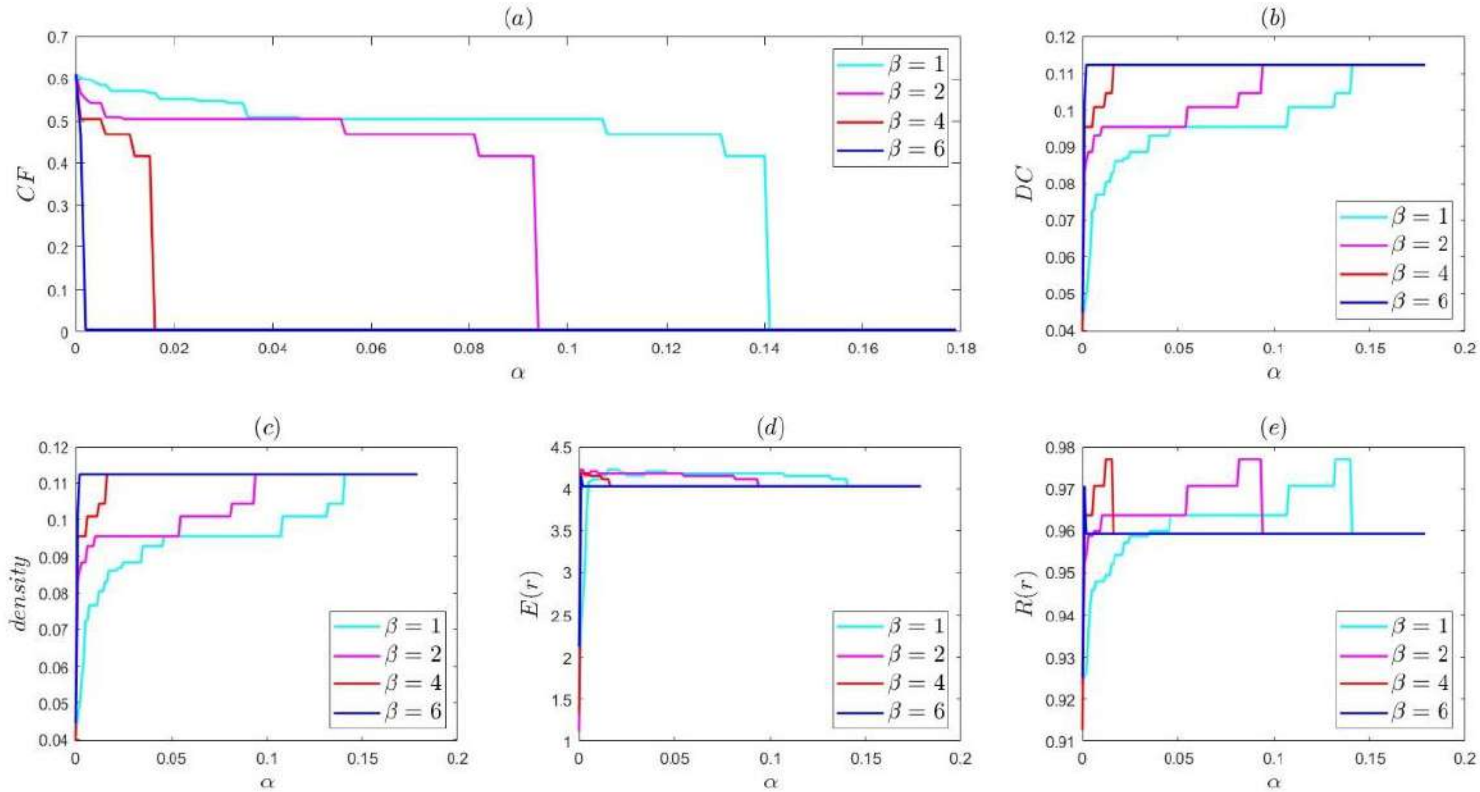


Figure 5-4 Cascading failure for China removal of the rice trade network for the year 2019. (a) Cascading failure ratio vs α. (b) Degree centrality vs α. (c) Density vs α. (d) Weighted efficiency vs α. (e) Weighted resilience vs α.

The weighted efficiency of the fragmented network decreases to a great extent after cascading, implying that less weights are transported from one node to another, or the average path is increased when India and China are removed. From the figure 5-3(d) and A-6(d) it is found that the system efficiency of the fragmented network is declined to almost 1/4th times its actual capacity before cascading and even after the system cost increase the efficiency is not restored close to the previous state. On the other hand, the weighted resilience is increased if the system pays higher cost up to $T_{c,\beta}$. After increasing the cost more than $T_{c,\beta}$ the weighted resilience starts to decrease, but the value remains static after some cost increase. This represents the overall increase in robustness of the system even after the removing the nodes with the system cost increase. So, this implies that by cost increase even if the system's robustness can be increased and the number of decapacitated nodes can be decreased as represented by the increase in the number of functional nodes, average DC, density, and weighted resilience, the weighted efficiency faces a huge decrease due to cascading for India or China removal from the rice export network.

5.5.2 Maize Trade Network Cascading Simulation

Bangladesh imported most of the maize from Brazil, followed by Argentina and India in 2019. Figure 5-5 shows the cascading failure result for Brazil removal and for Argentina and India removal the results are shown in figure 5-6 and 5-7. From figure 5-4(a), A-7(a), and A-8(a) it is seen that for Brazil removal the complete invulnerability is achieved by increasing system cost, but for India and Argentina the complete invulnerability is not achieved even after increasing the system cost to 18%, i.e., $CF > 0$. This depicts that removal of Argentina and India imparts more vulnerability in the network topology by cascading than for Brazil removal. Here, $T_{c,\beta}$ is achieved at $\beta = 6$, proving the fact that increase in load distribution increases faster invulnerability at lower cost increase. For the average DC and density their resulting values are close to zero. They show that even by the cost increase of the system by 18%, more than 90% of the nodes are staying disconnected because of their removal from the network. The weighted efficiency and resilience provide the similar result as for rice trade cascading, although for India removal there is a small change in the overall weighted resilience

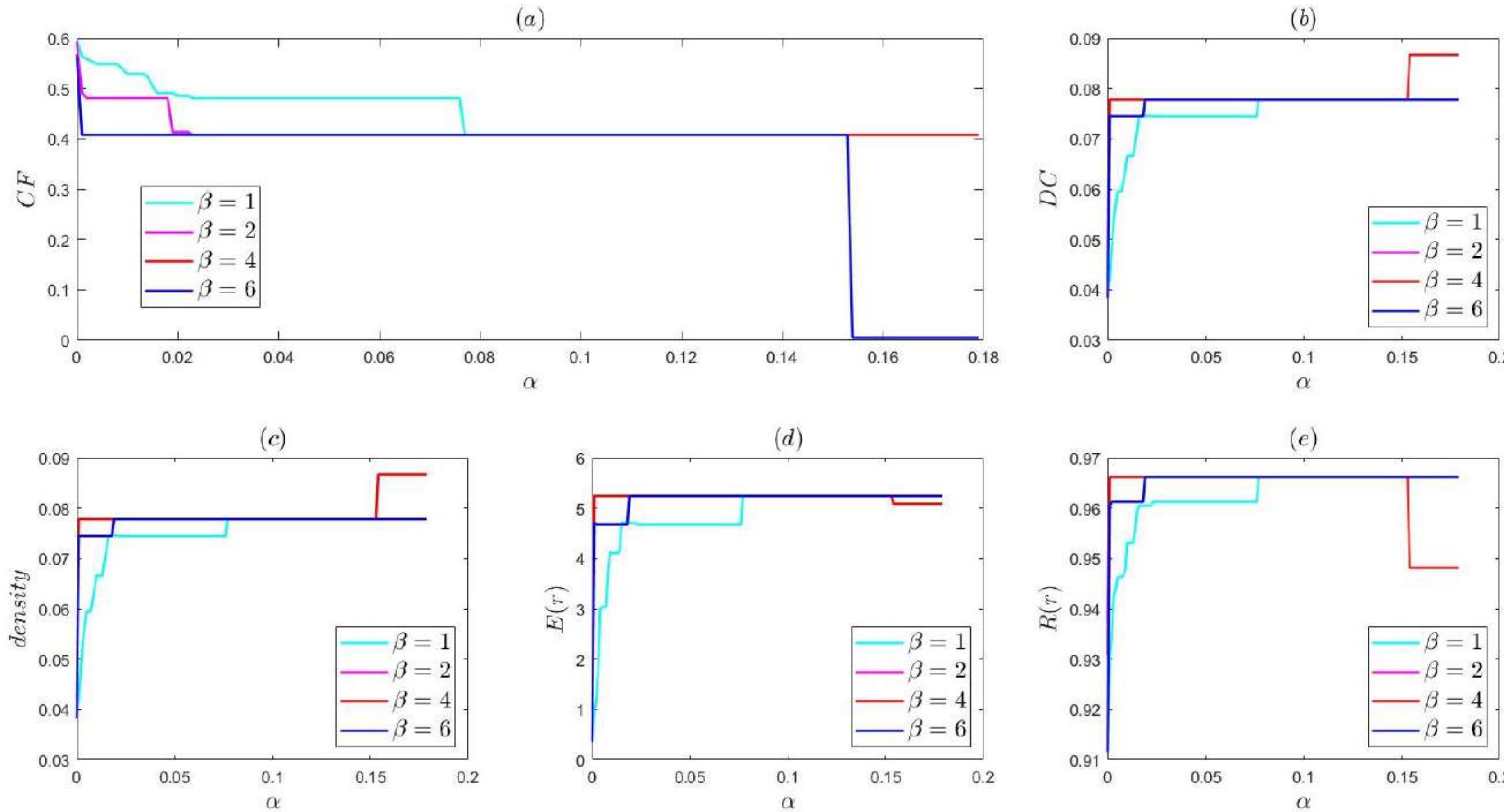


Figure 5-5 Cascading failure for Brazil removal of the maize trade network for the year 2019. (a) Cascading failure ratio vs α. (b) Degree centrality vs α. (c) Density vs α. (d) Weighted efficiency vs α. (e) Weighted resilience vs α.

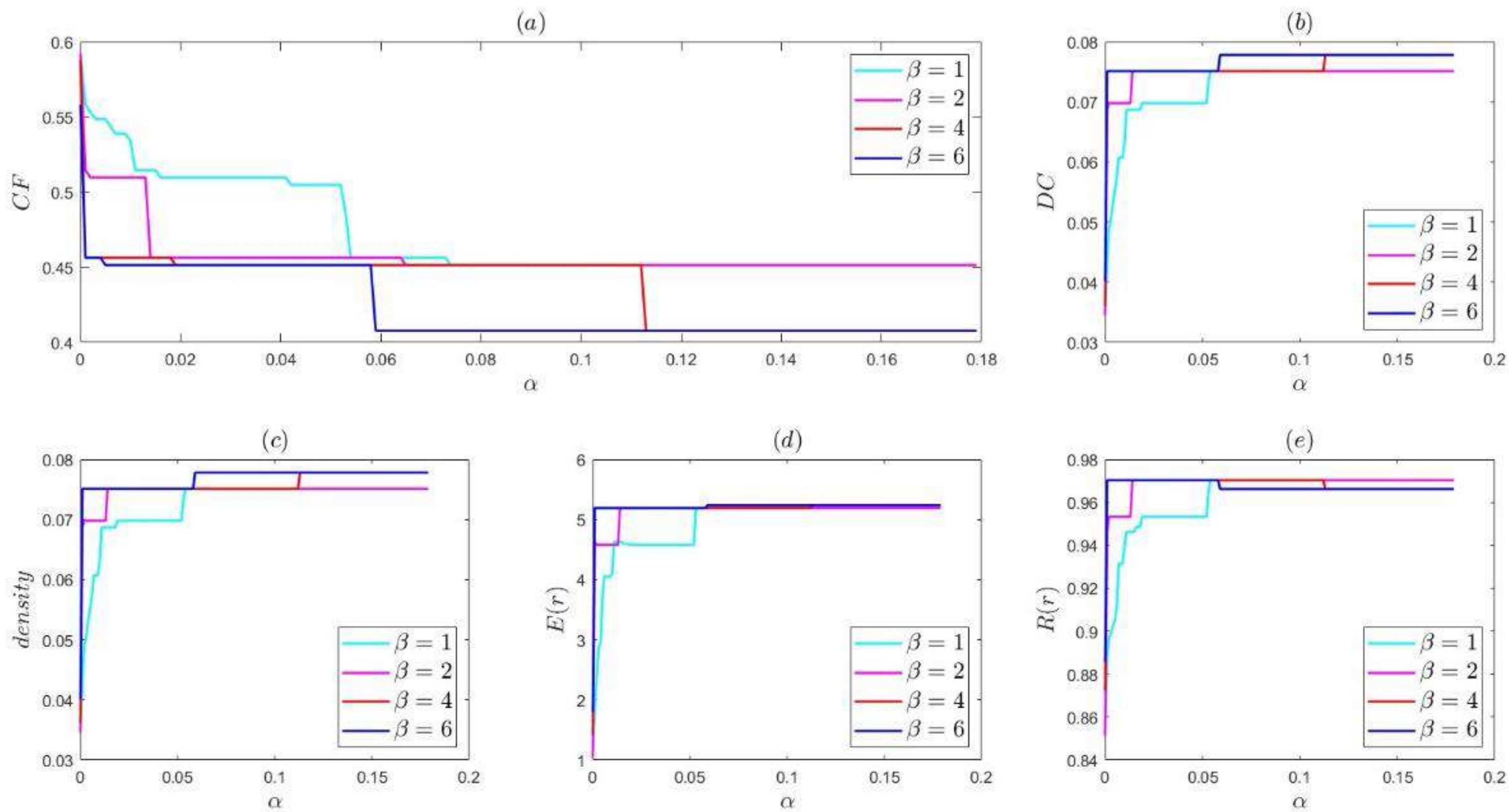


Figure 5-6 Cascading failure for Argentina removal of the maize trade network for the year 2019. (a) Cascading failure ratio vs α. (b) Degree centrality vs α. (c) Density vs α. (d) Weighted efficiency vs α. (e) Weighted resilience vs α.

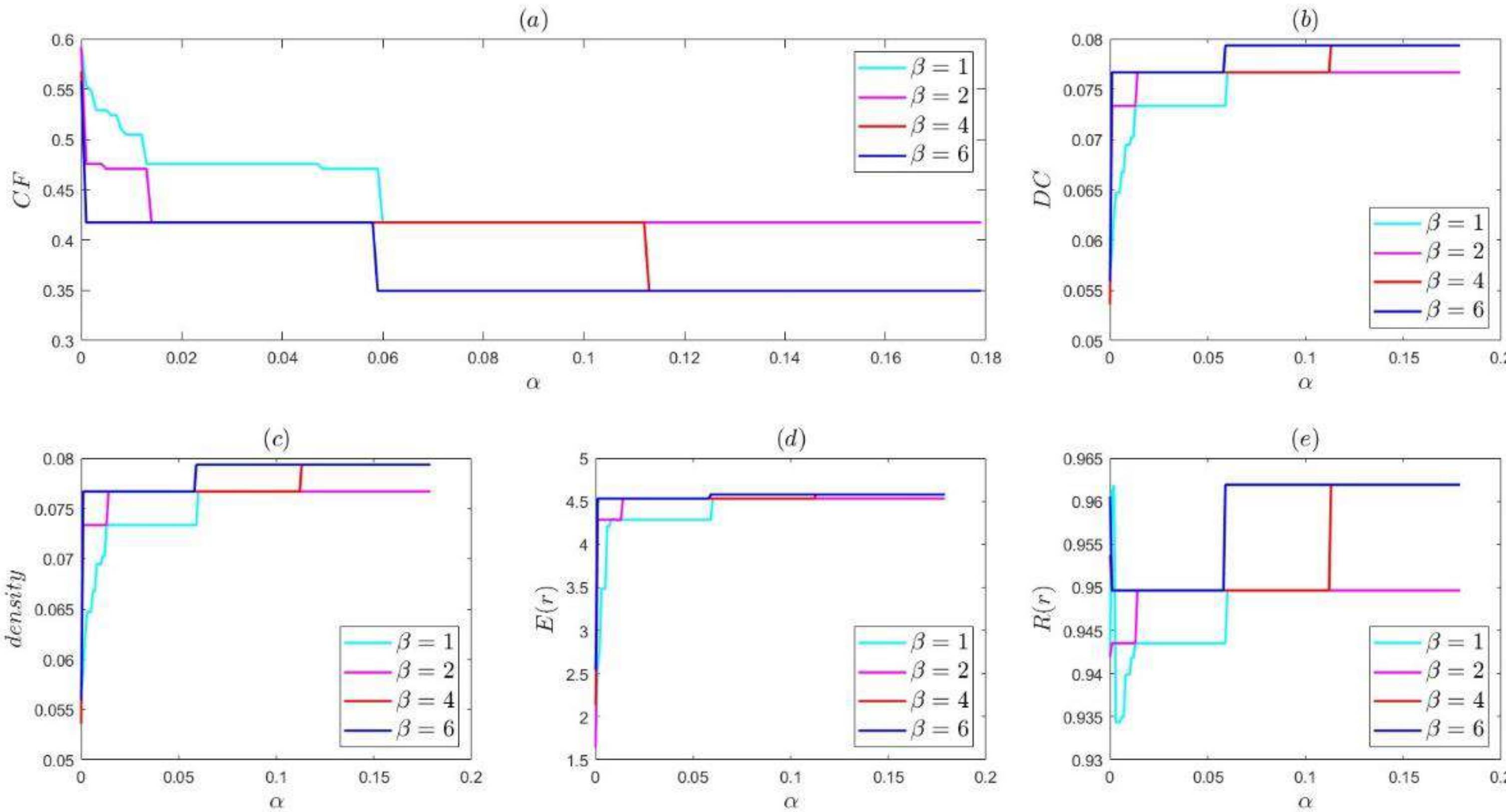


Figure 5-7 Cascading failure for India removal of the maize trade network for the year 2019. (a) Cascading failure ratio vs α. (b) Degree centrality vs α. (c) Density vs α. (d) Weighted efficiency vs α. (e) Weighted resilience vs α.

5.5.3 Wheat Trade Network Cascading Simulation

As Bangladesh relies mostly on wheat import, the number of neighbors is higher than for the rice and maize import. The neighbors of interest for cascading failure simulation are Argentina, Canada, Russia, Ukraine, and USA. Among them Bangladesh imported the most amount of wheat from Russia, followed by Ukraine, Canada, Argentina, and USA in 2019. The results are shown in figure 5-8,5-9, 5-10, 5-11 , and 5-12.

From the figures it is depicted that Russia, Ukraine, Canada attains almost complete invulnerability due to the system cost increase, and Argentina and USA do not attain the complete invulnerability even by increasing the system cost by 18% for all the load distribution scenarios. Ukraine and Russia have the fastest system invulnerability. For Argentina and USA, the density and average DC has the least increase than for the rest three, which infers that for USA and Argentina removal the network topology is more vulnerable. The decrease in weighted efficiency and resilience is lower than for the rice and maize trade network, as them exist many major wheats exported countries in the network, and it is possible to attain system resilience and invulnerability by increasing system cost.

5.6 Climate Change Impact on Cascading Failure of Network

To conduct a comparative analysis between the impact due to cascading failure and projected crop production change due to climate change, the global production change at the Koeppen-Geiger climate zones had been derived at first during TOE. Although due to the vastness, a country is subjected to exhibit more than one type of Koeppen-Geiger climate zone, to simplify the variability by considering that the country is identified as a single Koeppen-Geiger climate zone. This singularity is considered by assuming most of the cropland of the country that falls into that zone. For example, India has a wide variety of climate zones, but as most of the croplands fall into the tropical climate zone, we identified India's Koeppen-Geiger's classification as "tropical". Table 5-2 shows the system cost increase for impeding cascading and the projected crop production change at TOE.

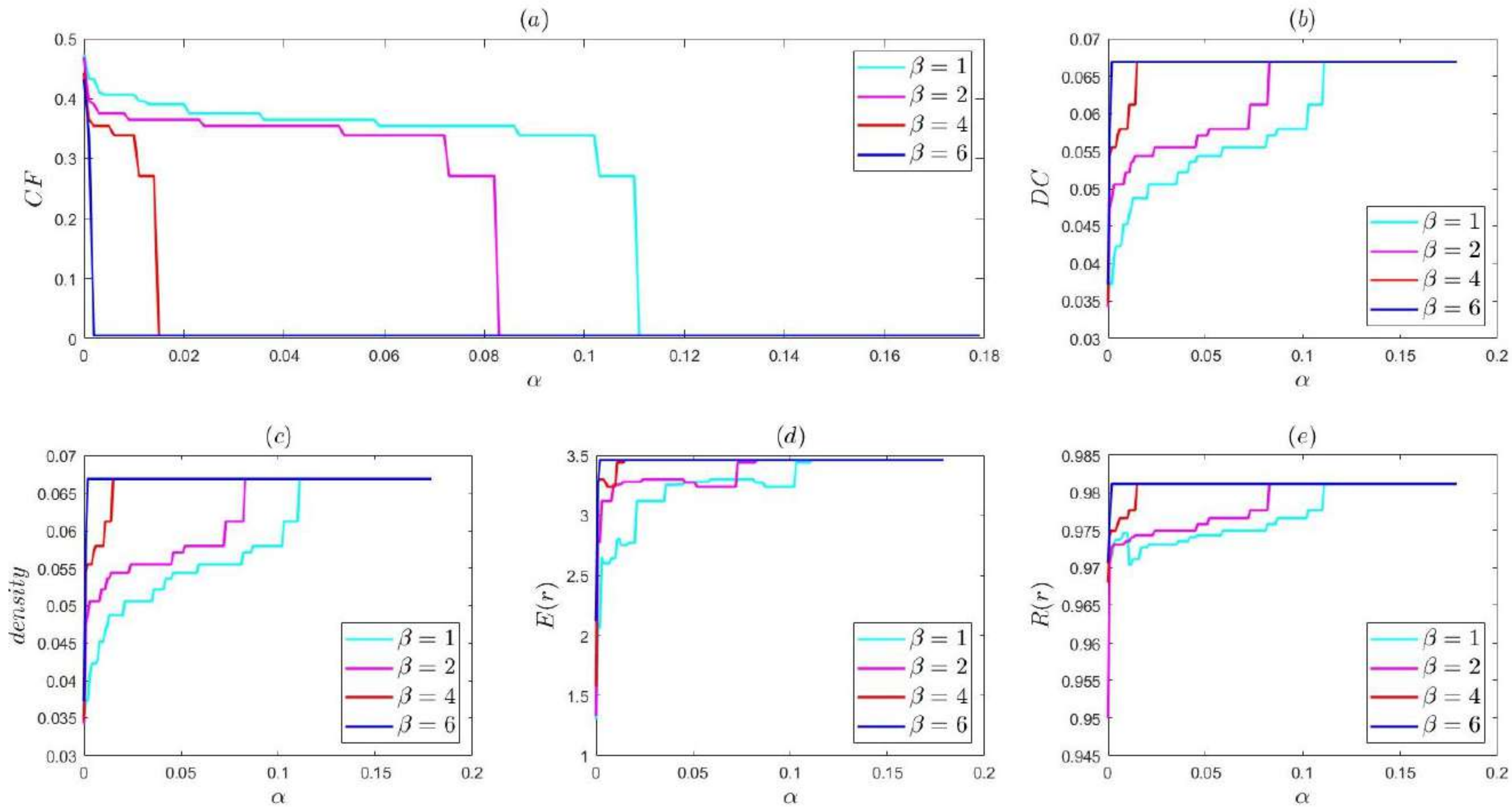


Figure 5-8. Cascading failure for Russia removal of the wheat trade network for the year 2019. (a) Cascading failure ratio vs α. (b) Degree centrality vs α. (c) Density vs α. (d) Weighted efficiency vs α. (e) Weighted resilience vs α.

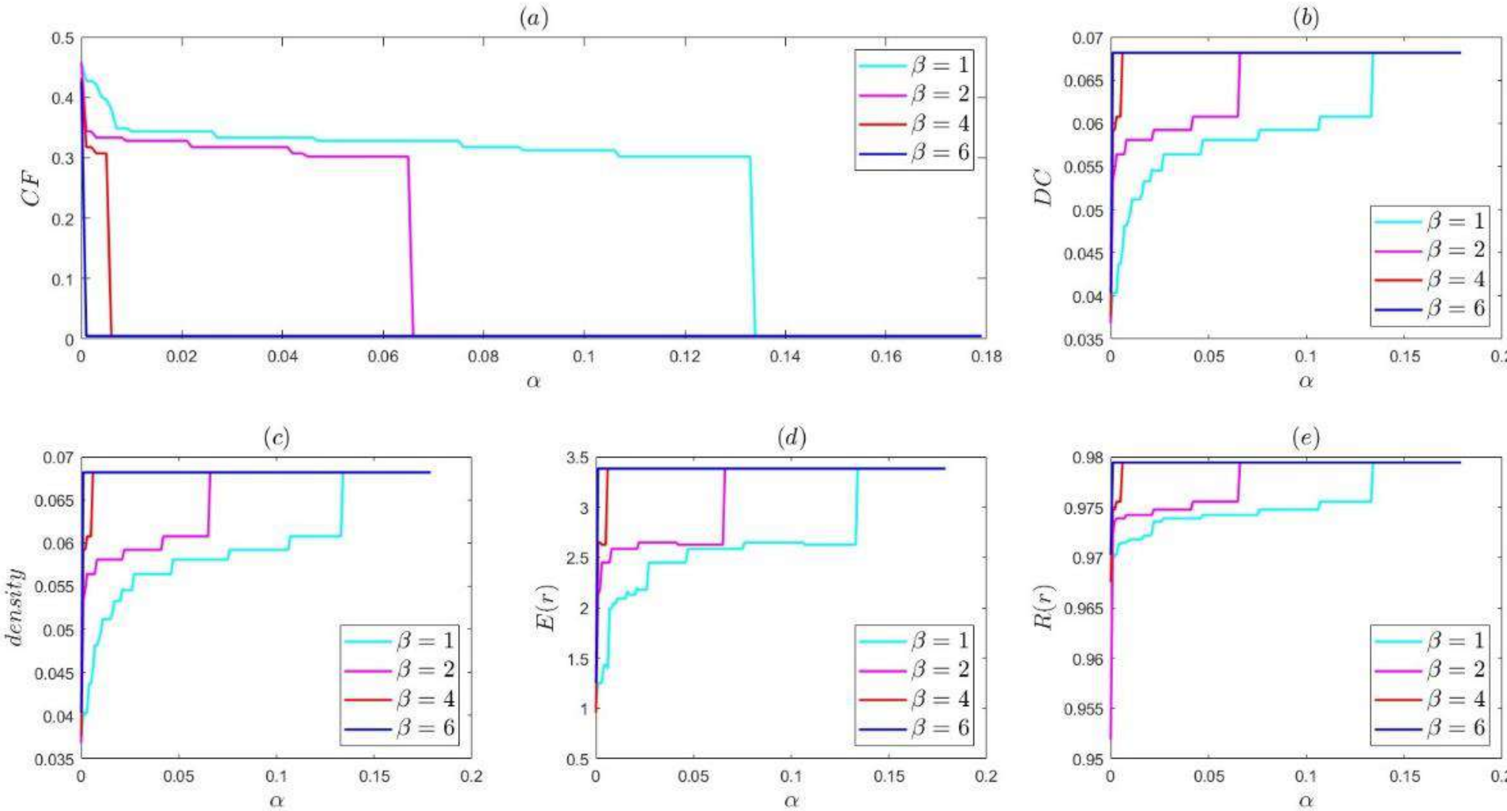


Figure 5-9 Cascading failure for Ukraine removal of the wheat trade network for the year 2019. (a) Cascading failure ratio vs α. (b) Degree centrality vs α. (c) Density vs α. (d) Weighted efficiency vs α. (e) Weighted resilience vs α.

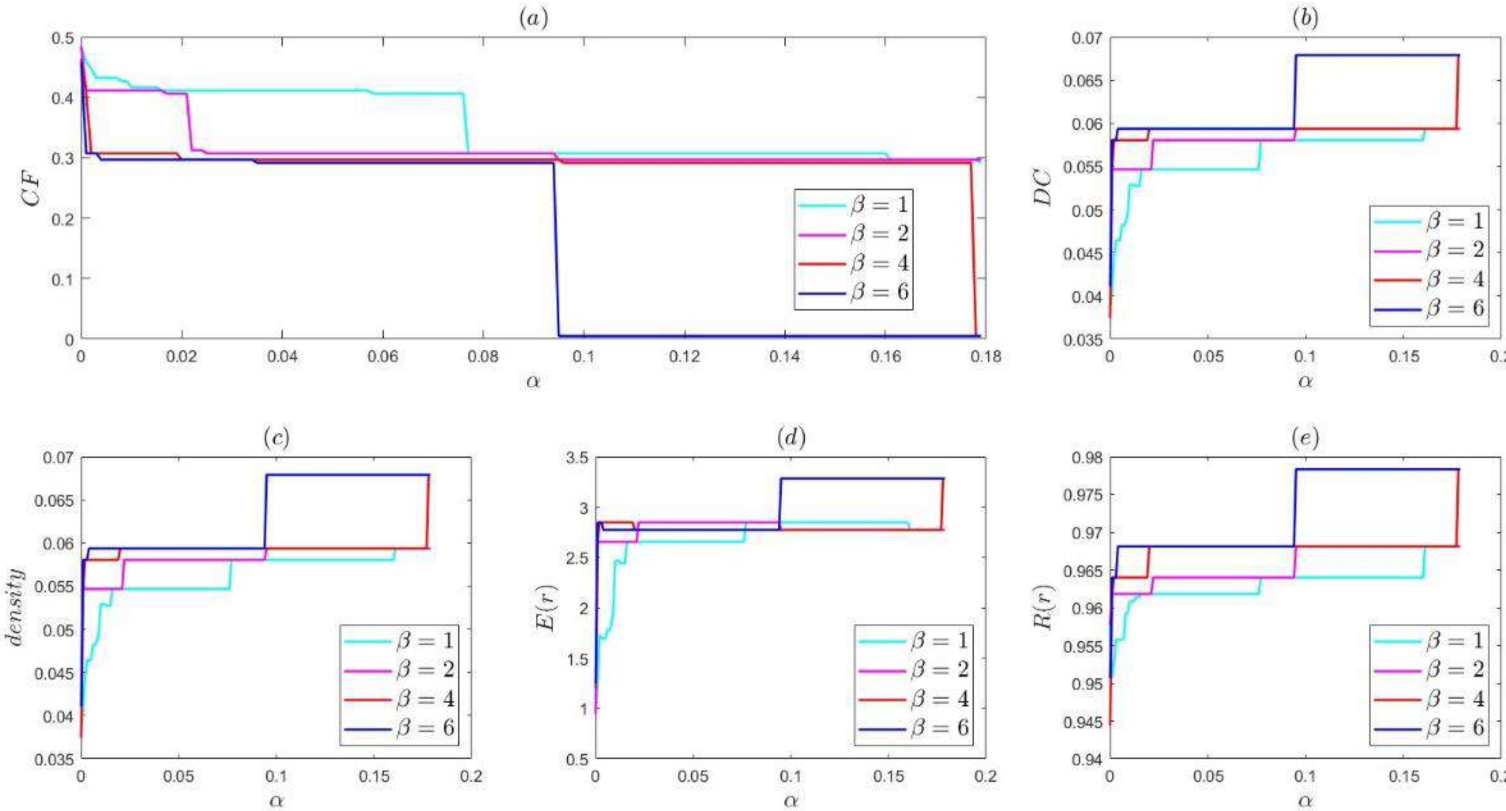


Figure 5-10 cascading failure for Canada removal of the wheat trade network for the year 2019. (a) Cascading failure ratio vs α. (b) Degree centrality vs α. (c) Density vs α. (d) Weighted efficiency vs α. (e) Weighted resilience vs α.

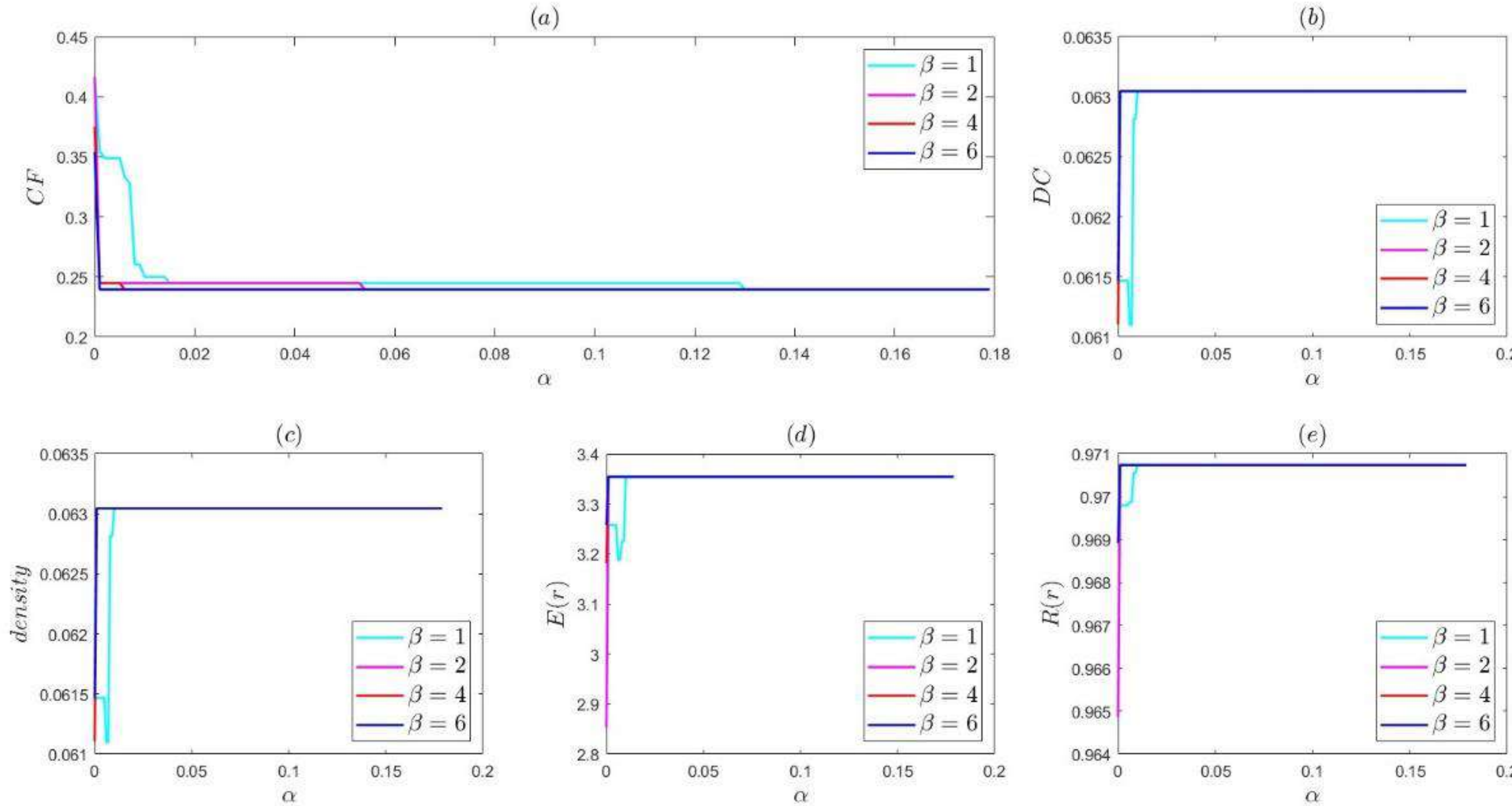


Figure 5-11 Cascading failure for Argentina removal of the wheat trade network for the year 2019. (a) Cascading failure ratio vs α. (b) Degree centrality vs α. (c) Density vs α. (d) Weighted efficiency vs α. (e) Weighted resilience vs α.

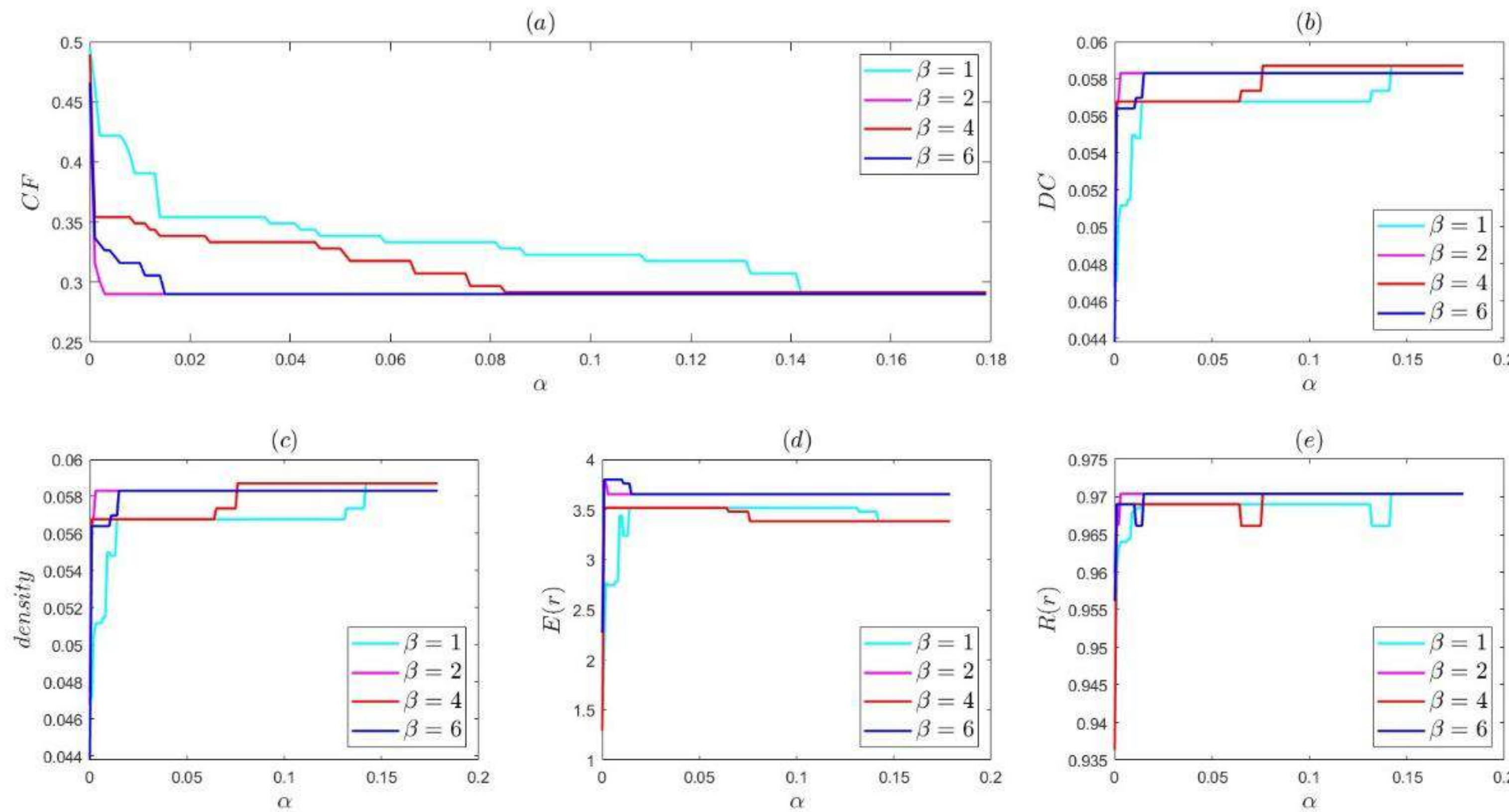


Figure 5-12 Cascading failure for USA removal of the wheat trade network for the year 2019. (a) Cascading failure ratio vs α. (b) Degree centrality vs α. (c) Density vs α. (d) Weighted efficiency vs α. (e) Weighted resilience vs α.

Table 5-2 Global threshold system cost increase ($T_{c,\beta}$) and projected crop production changes for the neighbors of Bangladesh considered for cascading for rice, maize, and wheat. Here bold numbers of $T_{c,\beta}$ rows indicate that the cascading failure is not eliminated.

Crop	Country	Load Distribution (β) at $T_{c,\beta}$	$T_{c,\beta}$ (% increase)	Koeppen-Geiger Climate Zone	Crop Production Change (%)
Rice	India	6	0.35	Tropical	+4
	China	6	0.2	Subtropical	-3
Maize	Brazil	6	15.4	Tropical	-8
	Argentina	6	**5.9**	Subtropical	-6
	India	6	**5.9**	Tropical	-8
Wheat	Russia	6	0.2	Temperature Limited	+10
	Ukraine	6	0.1	Temperate	+7
	Canada	6	9.5	Temperature Limited	+10
	Argentina	6	**13**	Subtropical	+6
	USA	6	**1.8**	Temperate	+7

From table 5-2 it is seen that for maize trade the maximum system cost needs to be increased to ensure complete resistance against cascading, and the countries considered for removal also face the worst impact due to projected climate change. For Brazil the global cost increase is the most, meaning if Brazil is removed from the network the capacity of all the nodes of the networks needs to be increased by 15.4% if the load distribution, $\beta = 6$. On the other hand, from the projection it is seen that the country has the most percentage decrease in maize production. Argentina and India are also going to face negative production in upcoming years, and their impact of cascading is not completely removed.

5.7 Impact on Bangladesh's Resilience to Withstand Shock due to Climate Change

The focus of the research was to understand and assess that how much Bangladesh can withstand the shock because of the climate change. Here, from table 5-2 it is seen that maize trade is supposed to be impacted the most and Bangladesh is vulnerable as the country imports a major portion of crops from these countries. So, Bangladesh needs to focus more on the internal capacity increase for maize production to keep up with the growing demand.

For the rice trade, India's production is increased for the projected climate change, but China's production is shown negative in coming years. Bangladesh is self-sufficient i.e., less import-dependent in rice production, although the country imports some amount of rice during some seasons mostly from India. The temperate climate zones mostly contribute to the global rice production, followed by the tropical climate zones. The literature shows that global rice projected production may have positive increase for climate change scenarios. So, Bangladesh can look for other countries that are in either temperate or tropical Koeppen-Geiger climate zone. Also, the impact on cascading although visible, but not prominent. So, the present capacity is enough to encounter the climate change impacts.

Wheat production mostly faces a positive increase because of the projected climate change. The wheat trade network is mostly robust, except for Argentina and its neighbors, but as other entities have a greater positive production, Bangladesh can switch to other countries for wheat import. Overall, Bangladesh can rely on import to meet up the wheat's internal demand.

5.8 Summary

In this chapter, an overview on the topological evolution of efficiency and resilience metrics for both weighted and unweighted network had been discussed. The cascading failure propagation had been conducted by removing important neighbors of Bangladesh to understand the shock withstanding capacity. Finally, the results had been compared with the climate change related production change to understand the future resilience.

CHAPTER 6

Conclusions

6.1 Introduction

The study aims at applying network science algorithm to understand and assess the crop trade evolution throughout the years for both global context and the context of Bangladesh. The study also focused to understand shock propagation and resilience of Bangladesh under changing climate. The corresponding results had been described in chapter 4 and chapter 5 respectively. This chapter summarizes the key findings and discusses the relevant limitations for future research direction of the study.

6.2 Conclusions

This research used the global crop trade data, i.e., the trade data for rice, maize, and wheat for 31 years, and formed the corresponding networks. Then their topological evolution had been assessed by applying network science algorithms. The average degree, centrality, clustering coefficients, average path lengths, and density evolution had been determined for global context. For Bangladesh and its neighboring countries their local centrality evolution had been assessed to understand Bangladesh's trade history and current situation. Finally, Bangladesh's resilience against shock propagation had been estimated due to changing climate by simulating the cascading failure scenario.

The major findings of the results are described as follows:

1) Maize is imported with the greatest efficiency, according to the average path length evolution. The evolution of the clustering coefficient reveals that the rice export has the largest value, which indicates that the neighbors are more likely to connect via rice imports. While the average degree of rice commerce declines in 2021, that of wheat and maize increases steadily. The disassortative nature of the trade networks indicates that more higher degree nodes are linking to more lower degree nodes. The degree centrality evolution for the rice trade is the highest, with the United States and European countries possessing the highest degree centrality values, indicating that the United States has trading links with the most nations. The drop in

trade inclination in 1995 as a result of the mid-European draught was clearly shown by the degree centrality progression.

2) India was the source of all three of Bangladesh's imports of these crops. According to the centrality evolution of Bangladesh's agricultural commerce, Bangladesh can be a significant transit country for imported rice, and its eigenvector centrality is rising. In comparison to its neighbors, maize and wheat's centrality scores are not so high. The neighbors are more likely to develop trade among themselves since the clustering coefficient is higher than usual.

3) From the efficiency and resilience analysis for both weighted and unweighted network it is found that both the weighted and the unweighted network showed resilience, but the weighted efficiency showed a decrease whereas the unweighted efficiency evolution showed an increase over time.

4) The cascading simulation results show that from climate change perspective, the rice and wheat trade network is resilient, but the maize trade network is more susceptible to vulnerabilities due to climate change. Bangladesh is vulnerable in maize import under the simulated climate change scenario, as reduction in global maize production would lead to non-resilient trade relationships with current partners. Bangladesh needs to increase its intrinsic production capacity or diversify its trade partners for maize import.

6.3 Recommendations for Further Studies

Recommendations for further studies are stated below.

1) In this study only the overall trade data was analyzed. But for any trade analysis the intrinsic demand analysis plays an important role. With time the country-based demand for crops is susceptible to deviating, so in future research the data including country demand projection can be included to get better analysis results.
2) Here the climate change induced future crop production data had been used from previous literatures. The availability of country-specific crop production data can project the impacts of crop production and the trade status in a more precise manner.
3) A country can have multiple Koeppen-Geiger climate zones, but for the simplicity of analysis each country has been identified to be in a single climate zone. The aggregated

total production change for each country should be considered to get a better forecast of the future climate-change impacted production.

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APPENDIX A

Table A-1 Appendix Trade Statistics for Gross Global Crop Import and Export for the Year 1991-2021

Trade and Crops Statistics	Trade Value in Billion US Dollars					
	Import Rice	**Export Rice**	**Import Maize**	**Export Maize**	**Import Wheat**	**Export Wheat**
min	2.45	3.57	14.52	6.58	8.13	13.08
mean	13.26	14.08	46.91	19.96	29.21	28.43
std	7.65	8.28	27.77	12.57	14.61	13.82
25%	6.73	6.46	21.69	8.84	15.83	15.80
50%	10.34	10.22	31.76	12.68	22.64	20.52
75%	21.15	22.94	73.64	31.32	42.08	40.36
max	24.86	25.86	108.26	51.45	51.73	53.61

Table A-2 Trade Statistics for Gross Bangladesh Crop Import and Export for the Year 1991-2021

Trade and Crops Statistics	Trade Value in Million US Dollars					
	Export Rice	**Import Rice**	**Export Maize**	**Import Maize**	**Export Wheat**	**Import Wheat**
min	0.00	0.05	0.00	0.00	0.00	5.57
mean	0.53	22.56	0.07	9.40	0.00	54.48
std	0.54	25.26	0.28	11.90	0.00	46.83
25%	0.03	3.30	0.00	0.12	0.00	17.09
50%	0.41	11.71	0.00	4.50	0.00	28.08
75%	0.92	34.20	0.01	13.90	0.00	90.05
max	1.86	98.31	1.58	45.29	0.01	191.92

Table A-3 Top 10 countries with the highest BC for rice, maize, and wheat import and export for the years 1991 and 2021.

Import												
Rank	**Rice**				**Maize**				**Wheat**			
	1991		**2021**		**1991**		**2021**		**1991**		**2021**	
	Country	**BC**	**Country**	**BC**	**Country**	**BC**	**Country**	**BC**	**Country**	**BC**	**Country**	**BC**
1	USA	0.16	USA	0.09	USA	0.19	France	0.12	Germany	0.10	Netherlands	0.10
2	UK	0.08	France	0.05	France	0.07	USA	0.10	USA	0.08	France	0.09
3	France	0.07	Netherland	0.04	Netherland	0.06	South Africa	0.09	Turkey	0.08	USA	0.07
4	Netherland	0.07	Canada	0.04	UK	0.05	Netherland	0.05	France	0.07	Canada	0.05
5	Germany	0.07	UAE	0.04	Japan	0.03	Canada	0.04	Spain	0.06	South Africa	0.04
6	Italy	0.06	Italy	0.03	Ireland	0.03	UAE	0.04	Italy	0.03	UK	0.04
7	Australia	0.04	Spain	0.03	Germany	0.03	UK	0.03	Australia	0.03	UAE	0.04
8	UK	0.04	India	0.03	Italy	0.02	Turkey	0.03	UK	0.02	Russia	0.03
9	Spain	0.04	UK	0.03	UK	0.02	Germany	0.02	Indonesia	0.02	Turkey	0.03
10	Turkey	0.04	UK	0.02	Brazil	0.02	Argentina	0.02	Sweden	0.02	Germany	0.03
Export												
Rank	**Rice**				**Maize**				**Wheat**			
	1991		**2021**		**1991**		**2021**		**1991**		**2021**	
	Country	**BC**	**Country**	**BC**	**Country**	**BC**	**Country**	**BC**	**Country**	**BC**	**Country**	**BC**
1	USA	0.10	USA	0.08	USA	0.12	USA	0.12	France	0.05	USA	0.09
2	Italy	0.04	India	0.03	Thailand	0.04	France	0.06	UK	0.04	France	0.06
3	Pakistan	0.03	UAE	0.02	Zimbabwe	0.03	UAE	0.06	Italy	0.03	Russia	0.04
4	France	0.03	Germany	0.02	France	0.03	South Africa	0.05	Germany	0.03	Canada	0.02
5	UK	0.02	New Zealand	0.02	UK	0.02	Turkey	0.03	USA	0.03	Germany	0.02
6	Singapore	0.02	Spain	0.02	Netherland	0.02	Germany	0.02	Singapore	0.02	Italy	0.02
7	UK	0.02	Italy	0.02	Canada	0.02	Brazil	0.02	Australia	0.02	UK	0.02
8	India	0.02	Turkey	0.02	Singapore	0.02	Netherland	0.02	Canada	0.02	Brazil	0.02
9	Netherland	0.02	France	0.02	Australia	0.02	Russia	0.02	Saudi Arabia	0.02	Turkey	0.02
10	Thailand	0.02	Netherland	0.02	Spain	0.02	New Zealand	0.02	Thailand	0.02	South Africa	0.02

Table A-4. Top 10 countries with the highest CC for rice, maize, and wheat import and export for the years 1991 and 2021.

Import												
Rank	**Rice**				**Maize**				**Wheat**			
	1991		**2021**		**1991**		**2021**		**1991**		**2021**	
	Country	**CC**	**Country**	**CC**	**Country**	**CC**	**Country**	**CC**	**Country**	**CC**	**Country**	**CC**
1	USA	0.62	USA	0.56	USA	0.63	USA	0.67	USA	0.56	USA	0.56
2	Thailand	0.56	India	0.56	Argentina	0.43	Argentina	0.63	Canada	0.53	Canada	0.55
3	India	0.50	Thailand	0.52	Canada	0.43	France	0.57	Turkey	0.45	France	0.54
4	Italy	0.47	Italy	0.50	France	0.41	South Africa	0.54	France	0.44	Russia	0.53
5	Pakistan	0.46	China	0.50	Netherland	0.41	Turkey	0.52	Germany	0.44	Germany	0.53
6	UK	0.41	Vietnam	0.48	Italy	0.39	Brazil	0.52	UK	0.41	Ukraine	0.52
7	Australia	0.41	Pakistan	0.48	Thailand	0.39	Germany	0.50	Belgium	0.38	Italy	0.51
8	Japan	0.40	Spain	0.45	Chile	0.38	India	0.50	Saudi Arabia	0.38	India	0.49
9	Spain	0.40	France	0.42	Spain	0.38	Mexico	0.50	Italy	0.37	UK	0.49
10	Singapore	0.39	Cambodia	0.41	Turkey	0.37	Hungary	0.49	China	0.36	Argentina	0.47
Export												
Rank	**Rice**				**Maize**				**Wheat**			
	1991		**2021**		**1991**		**2021**		**1991**		**2021**	
	Country	**CC**	**Country**	**CC**	**Country**	**CC**	**Country**	**CC**	**Country**	**CC**	**Country**	**CC**
1	Russia	0.15	USA	0.25	Japan	0.14	USA	0.31	UK	0.12	France	0.22
2	UK	0.15	UK	0.24	UK	0.14	France	0.31	Russia	0.12	Italy	0.22
3	Germany	0.15	Germany	0.24	Russia	0.14	UK	0.30	Germany	0.11	USA	0.22
4	Belgium	0.14	Netherland	0.22	Belgium	0.14	Italy	0.30	Pakistan	0.11	UK	0.21
5	France	0.14	France	0.22	Netherland	0.13	Germany	0.29	Bangladesh	0.11	Netherland	0.21
6	Denmark	0.14	Canada	0.21	France	0.13	Netherland	0.29	Indonesia	0.10	Belgium	0.20
7	Italy	0.14	Spain	0.21	Germany	0.13	UAE	0.29	Italy	0.10	Germany	0.20
8	Sweden	0.14	Italy	0.21	Spain	0.13	Japan	0.28	France	0.10	Saudi Arabia	0.20
9	Netherland	0.14	Sweden	0.21	Saudi Arabia	0.13	Belgium	0.28	South Korea	0.10	Morocco	0.20
10	Poland	0.14	Denmark	0.21	USA	0.13	Spain	0.28	Egypt	0.10	Portugal	0.20

Table A-5 Top 10 countries with the highest EC for rice, maize, and wheat import and export for the years 1991 and 2021.

Import												
Rank	**Rice**				**Maize**				**Wheat**			
	1991		**2021**		**1991**		**2021**		**1991**		**2021**	
	Country	**EC**	**Country**	**EC**	**Country**	**EC**	**Country**	**EC**	**Country**	**EC**	**Country**	**EC**
1	USA	0.27	USA	0.19	USA	0.34	USA	0.21	USA	0.31	France	0.22
2	Thailand	0.24	Italy	0.18	Netherland	0.26	Argentina	0.20	France	0.28	Netherland	0.20
3	Italy	0.23	India	0.18	Germany	0.25	France	0.20	Canada	0.27	Germany	0.20
4	UK	0.21	UK	0.17	France	0.24	Netherland	0.17	Germany	0.26	Russia	0.19
5	France	0.21	Netherland	0.17	Belgium	0.23	SouthAfrica	0.17	UK	0.24	UK	0.19
6	India	0.21	France	0.17	Canada	0.22	Turkey	0.17	Turkey	0.22	Italy	0.19
7	Germany	0.21	Spain	0.16	Argentina	0.21	Germany	0.16	Italy	0.22	Canada	0.18
8	Netherland	0.21	China	0.16	Italy	0.21	UK	0.16	Belgium	0.21	Ukraine	0.18
9	Belgium	0.21	Thailand	0.16	UK	0.20	Canada	0.15	Denmark	0.21	USA	0.18
10	Australia	0.20	Belgium	0.16	Spain	0.19	Italy	0.15	Netherland	0.20	Turkey	0.17

Export												
Rank	**Rice**				**Maize**				**Wheat**			
	1991		**2021**		**1991**		**2021**		**1991**		**2021**	
	Country	**EC**	**Country**	**EC**	**Country**	**EC**	**Country**	**EC**	**Country**	**EC**	**Country**	**EC**
1	USA	0.30	India	0.23	USA	0.43	USA	0.21	France	0.31	France	0.24
2	Thailand	0.29	USA	0.20	France	0.29	France	0.20	USA	0.30	Canada	0.22
3	Italy	0.26	Turkey	0.20	Netherland	0.24	Turkey	0.20	Canada	0.29	Russia	0.21
4	Pakistan	0.22	Italy	0.20	Germany	0.23	Spain	0.18	Germany	0.26	Germany	0.21
5	France	0.21	Spain	0.19	Belgium	0.21	Ukraine	0.17	Belgium	0.23	Ukraine	0.19
6	India	0.21	Pakistan	0.19	Canada	0.20	Brazil	0.17	UK	0.23	USA	0.18
7	Belgium	0.19	France	0.18	Austria	0.19	Netherland	0.17	Turkey	0.20	Romania	0.18

8	Spain	0.19	Germany	0.18	Spain	0.18	SouthAfrica	0.17	Denmark	0.18	Netherland	0.18
9	Netherland	0.19	Netherland	0.17	Italy	0.17	Germany	0.16	Italy	0.17	Italy	0.18
10	Germany	0.19	UAE	0.16	UK	0.16	Italy	0.16	Netherland	0.15	Turkey	0.18

Table A-6. Top ten countries with the highest migrated Bangladesh descendants **(United Nations Population Division, 2021)**

Rank	Neighbors	Migrated Bangladeshis in million
1	Saudi Arabia	2.50
2	Malaysia	1.00
3	UAE	0.71
4	Oman	0.68
5	UK	0.58
6	Italy	0.40
7	Qatar	0.40
8	Kuwait	0.35
9	South Africa	0.30
10	USA	0.21