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GLOBAL TRADE DYNAMICS OF SOYBEANS AND SOYBEAN FLOUR: A NETWORK ANALYSIS

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The aim of this dissertation is to obtain a doctoral (PhD) degree in the scientific field of „Management and Business"

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DECLARATION

I undersigned (name: **Henrique Friedrich de Oliveira**, date of birth: 12 Jan 1996) declare under penalty of perjury and certify with my signature that the dissertation I submitted in order to obtain doctoral (PhD) degree is entirely my own work.

Furthermore, I declare the following:

- I examined the Code of the Károly Ihrig Doctoral School of Management and Business Administration and I acknowledge the points laid down in the code as mandatory;
- I handled the technical literature sources used in my dissertation fairly and I conformed to the provisions and stipulations related to the dissertation;
- I indicated the original source of other authors' unpublished thoughts and data in the references section in a complete and correct way in consideration of the prevailing copyright protection rules;
- No dissertation which is fully or partly identical to the present dissertation was submitted to any other university or doctoral school for the purpose of obtaining a PhD degree.

Debrecen, …………………..

Henrique Friedrich de

Oliveira

signature

CONTENTS

1. INTRODUCTION

The international trade of a country has been the focus of attention to many publications and can directly affect the life of the people since a nation can benefit from selling products, and consequently, it might be a source of resources to many people (Bernard et al., 2007). Moreover, its investigation is extremely important and relevant to the academy and also to the general public.

Commerce has been present in our society since the different civilizations started being organized and decided to exchange their surpluses with other groups. Therefore, it is a very common and important topic to humans and has been very well documented over the years. The importance of this topic is such that it has been described as one of the main pillars of the world's economic structure (Lovrić et al., 2018).

Parallelly, staple food has also had an unquestionable importance in our society since the start of the agricultural era. Among this category, soybeans seem to play a prominent role in today's world, being one of the agricultural products with the biggest value of production in the year 2019 and one of the main grains (Food and Agriculture Organization of the United Nations, (FAO), 2021). Specifically in terms of the Brazilian context, it plays an even more important character since it was the main product exported in the country in 2020, with more than 28 billion USD sold in the year (UN COMTRADE, 2021). According to the same report, China is the biggest buyer of Brazilian soy, corresponding to more than 70% of the total amount exported by Brazil, followed by the Netherlands, Spain, Thailand, and Turkey, and those five countries totalize more than 85% of the country's export share (UN COMTRADE, 2021)

To deepen the understanding of the importance of this trade, one may make use of the Social Network Analysis methodology, which allows the evaluation of the structural features of a given network, pointing out the key characteristics, users, and their connections (Popp et al., 2018). The importance of network connectivity in the social sciences is not a new idea, but the widespread availability of data, as well as advances in computer science and methodology, have facilitated the use of social network analysis for one of these relatively simple systems (Cheliotis, 2010). The tools of graph theory provide a spectacular representation of network analysis results at both network and individual levels (Wasserman & Faust, 1994).

In this research, I will explore the international trade dynamics of soybeans utilizing the Social Network Analysis (SNA) methodology. This approach enables the delineation of the network hierarchy and the identification of key players within the structure. Furthermore, the analysis will be augmented by the Balassa index, offering an additional perspective on countries with comparative advantages in trading this commodity.

MAIN TOPICS AND OBJECTIVES OF THE RESEARCH

The doctoral dissertation is a substantial academic undertaking that typically involves several distinct phases. The journey commences with topic selection, where the researcher identifies a research area of interest that aligns with their academic discipline. The investigation of the trade of a given country is justified by its consequences on the development process. With the increase of the interconnection among the countries, a solid and diverse international trade structure can lead to enormous benefits, especially as a way to emerge developing countries and upgrade the quality levels of their citizens, in other words, it is an alternative to advancement (Bernard & Bradford Jensen, 1999; Mazzi et al., 2021). Additionally, the investigation of soybeans is justified since in recent years, the international soybean trade volume of soybeans has continued to grow year by year, and its related research has received increasing attention from many scholars. Likewise, the trade relationship between countries has become more complicated (Kou et al., Oct 22, 2018).

Before presenting the specific research questions and hypotheses that will guide this investigation, it is essential to acknowledge the foundational role played by the comprehensive review of relevant literature undertaken in Chapter 2. This critical review process involved a systematic examination of scholarly works, including peer-reviewed articles, books, and dissertations, that addressed the main topics of the current dissertation, mainly international trade, soybeans, and network analysis. This rigorous analysis identified key themes, concepts, and gaps in current knowledge. This in-depth exploration of the existing literature served as the facilitator for developing the following research questions and associated hypotheses that will frame this doctoral dissertation. By examining previous studies, researchers can pinpoint gaps in knowledge and formulate research questions or hypotheses that will guide their investigation.

The global soybean market is a complex ecosystem characterized by intricate relationships between producers, exporters, importers, and processors. Given its significance as a key agricultural commodity and its role in various industries (e.g., food, feed, biofuels), understanding the dynamics of this market is crucial. This study aims to comprehensively analyse the soybean trade, examining its historical trajectory, key participants, and underlying factors influencing its evolution over the past two decades. By delving into the trade's dynamics, I seek to identify prevailing patterns, trends, and challenges. Additionally, the research will undertake a comparative analysis of the soybean and soy flour trades. Given the distinct characteristics of soy flour as a processed commodity, requiring additional production steps, this comparison will illuminate the complexities and nuances of its trade relative to raw soybeans. I aim to contribute novel insights into the broader soybean value chain through this comparative lens. The first hypothesis and research question (H1 and RQ1) are more general since I will try to understand to the overall scenario in the soybean commodity trade panorama, trying to find patterns across the main nodes in the network.

RQ1 - What is the global diffusion trade pattern of soybeans among countries?

H1 - In the world international trade of soybeans, new economic countries are the exporters while developed countries are the importers of this commodity.

Hypothesis H2 delves into the power dynamics within the soybean trade network. By examining the influence of exporters and how the trade player landscape has evolved over time, this research seeks to shed light on the concentration of power within the market and its potential implications for market stability and resilience.

H2 – The exporters of soybeans have more influence within the network and less susceptible to negative impacts caused by unforeseeable outbreaks, while importers despite their significance play a relatively weaker role in the network.

H2.1. Weighted outdegree shows a strong positive correlation with closeness centrality, indicating that countries with higher export volumes are positioned closer to other countries regarding network distance, enhancing their overall connectivity.

H2.2. Weighted outdegree exhibits a significant positive correlation with betweenness centrality, suggesting that countries with high export activity play a crucial role as intermediaries or bridges between other countries in the soybean trade network.

H2.3. Weighted outdegree shows a moderate positive Spearman correlation with indegree, reflecting that countries with high export activity are also likely to be important importers, though this relationship is less pronounced than their centrality roles.

H2.4 Weighted indegree shows a significant positive correlation with closeness centrality, indicating that countries with higher import volumes are positioned closer to other countries in terms of network distance.

H2.5 Weighted indegree and weighted outdegree show significant positive correlations with betweenness centrality, reflecting that countries with high import or export activities play important intermediary roles within the network.

H2.6 There is a significant positive correlation between weighted indegree and weighted outdegree, indicating that countries with substantial import activities are also likely to engage in significant export activities.

The past two decades have witnessed transformative changes in the dynamics of global soybean trade. Geopolitical shifts, technological advancements, and evolving consumer preferences have reshaped market structures and trading patterns. Examining the historical evolution of trade dynamics offers insights into the adaptive strategies employed by market participants to navigate shifting global landscapes. Understanding these dynamics is crucial for assessing the current state and future prospects of the soybeans market. Therefore, hypothesis H3 and Research Question RQ2 focus on the overall market structure and entry barriers. Investigating the stability of the soybean market and identifying dominant players provides insights into the market's competitiveness, the potential for new entrants, and the likelihood of market disruptions.

RQ2 – How have the dynamics of trade players evolved during the last 20 years and what players have been dominating the market during the last 20 years?

H3 – The soybeans market is stable and challenging for new entrants to enter.

Additionally, this research endeavours to enhance our understanding of the soybean and soy flour trades since the latter is a more complex product, requiring additional steps after the harvesting of the grain, consequently, the product may present a different network with different nodes and connections when compared to the simple grain.

In the global agricultural trade system, soybeans and soy flour (soybean meal) represent interconnected yet distinct commodities, each with its trade dynamics and patterns. While both commodities are derived from the same crop, the trade networks for soybeans and soy flour are influenced by different factors, including production processes, demand in various markets, and the roles that countries play as exporters and importers. To explore these differences, this study hypothesizes that the international trade networks of soybeans and soy flour will exhibit distinct structural patterns. This hypothesis is further explored by analysing each network from three different perspectives reflected in the sub-hypothesis listed below.

H4 – The international trade networks of soybeans and soy flour exhibit distinct structural patterns, reflecting different dynamics for each commodity within the global agricultural trade system.

H4.1 The analysis of layer distributions reveals that the distribution of key network properties differs significantly between the soybean and soy flour trade networks.

H4.2 The comparison of individual structures demonstrates a weak correlation between the positions of countries in the soybean and soy flour networks, indicating that countries with high importance in one network do not necessarily hold significant positions in the other.

Understanding the influence and comparative advantages of exporting countries is crucial in the global soybeans market. Exporters often wield significant power due to their strategic positions and extensive networks. This hypothesis posits that certain countries will exhibit stronger network centrality and higher Balassa indices, indicating their pivotal role and superior competitive position within the global soybean trade network. By examining these factors, we aim to uncover influence and competitive advantage patterns that shape the dynamics of international soybean trade.

The dynamics of international soybean trade are multifaceted and influenced by geographical, economic, and strategic factors. This hypothesis proposes that applying network analysis alongside the Balassa index will reveal distinct clusters of countries with close trade relationships and shared comparative advantages in soybean trade. By identifying these clusters, we can gain insights into the underlying mechanisms driving trade patterns and the strategic alliances contributing to stability and growth in the global soybean market.

RQ3 –How do network analysis and the Balassa index contribute to our understanding of the international trade dynamics of soybeans?

H5 - The application of network analysis and the Balassa index in the global soybean trade network reveal certain 0-countries with stronger network centrality, and higher Balassa indices.

H5.1 Countries with high weighted outdegree exhibit a revealed comparative advantage in the Balassa index context.

H5.2. The combined use of network analysis and the Balassa index identify distinct clusters of countries that exhibit close trade relationships.

I will accept or reject the hypotheses based on the results obtained using the applied methods in chapter 4.

Once the research focus is established, the researcher meticulously constructs the research methodology. This involves selecting appropriate research methods (e.g., experiments, surveys, case studies) and developing data collection procedures to gather relevant information. The data collection phase follows, during which the researcher diligently implements the chosen methods to acquire the necessary data. Subsequently, rigorous data analysis techniques are applied to uncover patterns, trends, and relationships within the dataset.

Interpretation of these findings is a critical step, as researchers seek to understand the implications of their results. By comparing their findings to existing research, they can contribute to the broader body of knowledge in their field. The culmination of this process involves transforming the research findings, analysis, and interpretations into a well-structured dissertation. This document undergoes multiple rounds of review and revision to ensure clarity, coherence, and adherence to academic writing standards.

The final stages of the dissertation process involve formal evaluation and defence. The completed dissertation is submitted to a committee of experts for assessment. This committee scrutinizes the research's quality, originality, and overall presentation. The researcher then participates in an oral defence, where they present their findings to the committee and field questions about their research. Based on the committee's feedback, the researcher may be required to revise the dissertation before the doctoral degree is conferred.

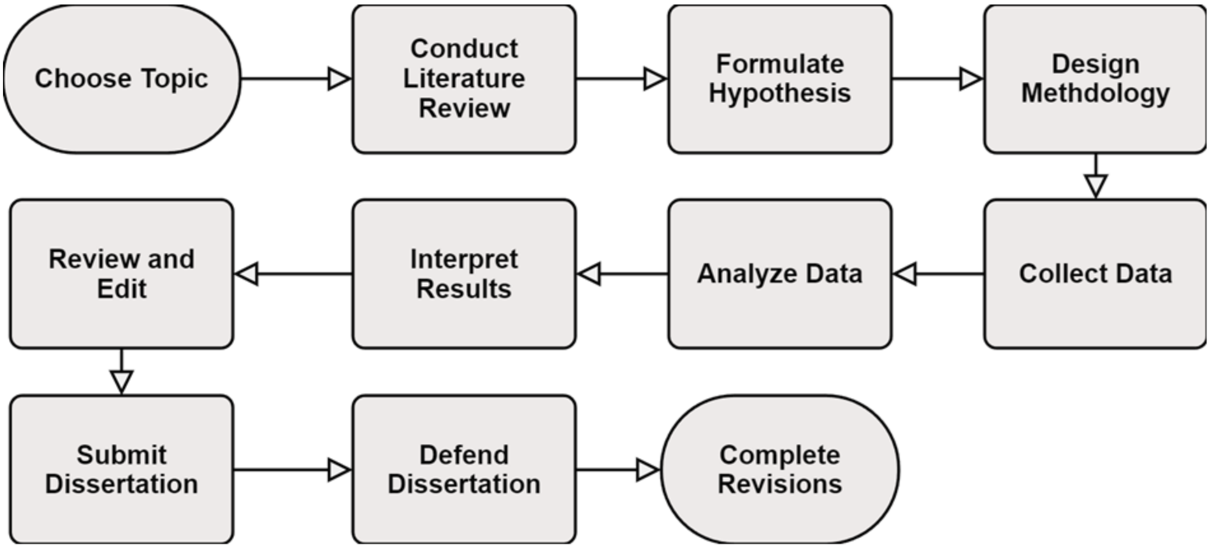

Figure 1. Research Process

Source: Own editing

2. LITERATURE REVIEW

The objective of the literature review is to map and evaluate the topic of my research, if possible identifying research gaps and exploring knowledge limitations. In this chapter, I will review the current understanding of global trading as well as its importance to the world. In the overview, I will present the development of the network analysis methodology and describe the most important research carried out with network analysis. Furthermore, I present soybeans as one of the raw materials most import when it comes to the agricultural value traded in the world, and below, I will describe the most important scientific publications on soybeans that investigate the trade and its results.

2.1. International Trade

International trade has been an important part of the global economy for centuries. The exchange of goods and services across international borders allows countries to access resources and markets that may not be available domestically. In this literature review explores some of the key reasons why countries engage in international trade. Since human communities have generated surpluses beyond self-sufficiency, they have been trading with each other. In a country where there is more than enough material to use or more to produce than the population needs, they try to sell them. If it is between different countries, we are talking about international trade.

Trade can consist of goods, such as coffee and machinery or services, an international consultation with a firm. Nevertheless, the latter has been gaining increasing importance; the trade in goods is by far the best-documented aspect of international economic relations, being present for many centuries in our civilization. Trade-in goods are by far the best-documented aspect of international economic relations. This data, therefore, provides a rich source of information on the distribution and contributes to the economic analysis of a given country consequently assessing different aspects of the nations (Balogh & Jámbor, 2017; Bojnec & Fertő, 2017).

Countries now trade with one another when the recipient country cannot produce commodities or supply the services in question or lack the resources to do so (Sherlock et al., 2004). International trade allows countries to access resources that may not be available domestically. For example, a country with an oil shortage may import oil from another country to meet its energy needs. This access to resources can help countries to maintain and improve their standard of living. International interconnectivity is a feature of the global economy, as observed in Figure 2. A country's economic fortunes are influenced by trade, foreign direct investment, and financial capital flows. Because production networks span countries and continents, a country's product supply is heavily dependent on the economic activities of numerous others (Helpman, 2011).

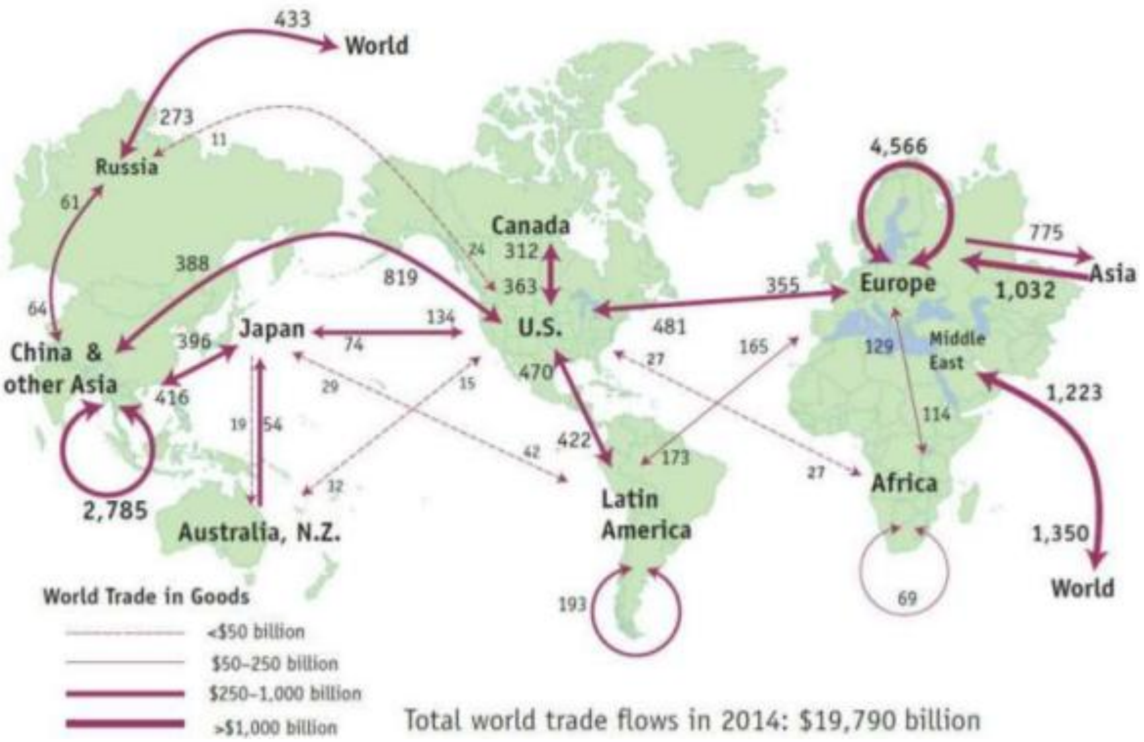

Figure 2. Amount of trade in goods ($ billions)

Source: (Taylor et al., 2008)

It is said that the difference between a country's total value of exports and the total value of imports is its trade balance (usually including both goods and services). Countries that sell more than they import, like China in recent years for example, have a trade surplus, whereas countries that import more than they export, like the United States, have a trade deficit (Taylor et al., 2008).

Thanks to globalization and the improvement of the supply chain nowadays, the whole world is commercially connected, even though some countries are more connected than others to commercializing international products. In other words, there are countries in which the movement of international goods has almost no barrier, whereas there are other countries that impose several limitations and difficulties in the entering of international goods into their territories. This difference in approach might be because of a specific strategy adopted. Some countries perceive liberalisation as an alternative to gain from trade, buying cheaper or better products from outside and also facilitating relations with other nations in order to sell them the products produced internally, such as the active market within the European Union and the strong relation between the EU and the United States, both are responsible for more than one-fourth of all the trade worldwide. Others notwithstanding prefer to protect the internal producers and rely solely on developing internally.

This debate has been done for more than a century without any definitive answer, although during different eras, different approaches prevailed, during the emergence of the nation-states, the governors were constantly worried about the flux of international goods, fearing losses for the internal producers until one of the first models presented the benefits from an international commercial cooperation.

In the last three hundred years, the subject has been investigated with more scientific rigour, Adam Smith, in his book The Wealth of Nations in 1776, introduced the concept of absolute advantage, all nations could benefit from specializing in a product that this country domain, or has an advantage, exchange it with other countries, consequently benefiting from the trade (Sills, 1968). This was a breakthrough for the time because the mainstream economic philosophy back then was mercantilism, which defended a strong policy to limit imports and an extensive focus on trying to sell products (exports) (Sills, 1968; Taylor et al., 2008).

Following Adam Smith’s work on absolute advantage, David Ricardo (1772–1823) further developed the theoretical foundations of international trade. In contrast to Smith, who emphasized absolute productivity differences, Ricardo focused on the relative costs of producing different goods across countries. He tried to investigate these different approaches and outcomes when dealing with trade, and since then, they have been studied. Researchers have been trying to understand the reasons behind the progress of some countries over others in the international trade framework and why countries specialize in producing different products (Taylor et al., 2008). Another important contribution of David Ricardo was the conceptualization behind why a country wants to trade with another. According to a Ricardian perspective, one of the main reasons for trading is the difference in technology. A country can gain trading with another one, exchanging an item whose production does not match the relative cost of buying from another one (Taylor et al., 2008). In other words, according to Ricardo (1817), one of the key reasons why countries engage in international trade is based on the principle of comparative advantage, which states that countries should specialize in the production of goods that they can produce most efficiently and trade with other countries to obtain goods that they cannot produce efficiently. This allows countries to maximize their production and consumption possibilities, leading to increased efficiency and economic welfare (Ricardo, 1817).

Another factor that influences the amount of trade of a given country is said to be its gross domestic product (GDP) size. This theory states that the more relevant the production of a nation, the more likely it will be to trade with other countries, in other words, the amount of a nation's imports and exports are strongly correlated with the size of that nation's economy (Krugman et al., 2012). This relationship is called the Gravity Equation, since it is similar to the famous Newton's law of gravity, since it resembles this law, in the sense that the trade between two countries tends to be proportional to their GDP and diminishes as the distance between the countries increases, more on this topic will be presented on the methodology. More recent explanations emphasize the importance of developing domestic capabilities and institutions to support the production and upgrading of export products since successful exporters tend to be characterized by a range of domestic capabilities, including technological capabilities, institutional capabilities, and human capital. These capabilities are essential for upgrading export products and developing new export products over time (Rodrik, 2016).

After World War II, liberalisation gained importance across many countries,; one important organization responsible for decreasing trading barriers was called the General Agreement on Tariffs and Trade (GATT). Under this agreement, countries accorded many aspects concerning the rules of trade such as tariff reduction, custom formalities, trade regulation, and similar guidelines, all aiming for an increase in commerce and a fairer exchange of products and services. Since during the 1930s, countries opted to impose higher tariffs, tighter import restrictions, foreign exchange controls, and discriminatory trade agreements all across the world in response to the Great Depression (Irwin, 2011). This organization was first negotiated in 1946 but the final agreements came about at the end of 1947, with 23 members: Australia, Belgium, Brazil, Burma, Canada, Ceylon, Chile, Republic of China, Cuba, Czechoslovak Republic, France, India, Lebanon, Luxembourg, Netherlands, New Zealand, Norway, Pakistan, Southern Rhodesia, Syria, South Africa, the United Kingdom, and the United States (Irwin et al., 2008). These settlements seemed to have the desired impact on overall international trade since the average tariff in 1947 was about 22 percent. In contrast, after many rounds of negotiations, it became around 3 percent in 1999 in the group of countries studied (Bown & Irwin, 2017). The General Agreement on Tariffs and Trade was replaced by the World Trade Organization (WTO) on 1 January 1995, which marked not only a change in the name of the agreements but also a reform in international trade (WTO, 2018).

As observed, commercialization has been present in human lives for a long time, however, conceptualization and scientific discussion were first introduced about two centuries ago. Since then, it has gained more and more attention from researchers trying to model international trade and consequently understand better the interactions, nevertheless, Ricardo's model still plays an important role on the subject, either as a mark on the discussion, but also as a reliable tool to model the trade between nations (Krugman et al., 2012; Taylor et al., 2008).

The importance of trading can be also described as a driver of growth for countries. Frankel and Romer (1999) find that increases in the share of exports to GDP are associated with increases in economic growth. This relationship holds true for both developed and developing countries (Frankel & Romer, 2017). One possible explanation for that was observed when examining the companies' differences between exporters and non-exporter industries. In their study, Bustos (2011) finds that firms that begin exporting experience significant increases in sales and productivity. These gains are particularly large for firms that begin exporting to new markets (Bustos, 2011). Consequently, it may also impact the employment market within a country, since this access to new markets and an increase in sales can lead to a larger demand for jobs and also with higher salaries compared to sectors that sell only nationally (Baldwin & Gu, 2003).

There are also bolder allegations stating that exports are a key element for the economic growth of a country, being responsible for not only the increase in the GDP, but also as a mechanism of job creation and poverty reduction by providing access to new markets, diversifying product offerings, and increasing productivity (Rodrik, 2006). However, it is important to observe the type of goods being exported, since different products impact the economy in a different way. A diverse and high-value-added export portfolio is essential for sustained economic growth and development, countries that diversify their export base and upgrade their export products are better positioned to weather external shocks and sustain economic growth over the long term, and the opposite also holds true, since countries that are heavily reliant on a narrow range of commodities or low-value-added products are vulnerable to external shocks, such as changes in global commodity prices or shifts in demand for certain products (Rodrik, 2016).

International trade today encompasses a wide range of goods, services, and resources, reflecting the interconnectedness of the global economy (Grozdanovska et al., 2017; Pigman, 2016). The exchange of these items is a key driver not only of economic growth and prosperity but also closely linked to the practice of diplomacy since the rise in international trade symbolizes the growing need for global engagement and cooperation among nations (Pigman, 2016). This interconnectedness is further underscored by the various forms of international business, including the movement of goods, contractual agreements, and establishing facilities in foreign markets (Grozdanovska, 2017).

Studies converge on the notion that exports generally act as a significant driver of economic growth, however, this relationship is stronger in some countries than in others, the benefits can be more explored, particularly in developing countries and Central and Eastern European (CEE) economies (Mudrika Thanoon Yahya et al., 2020; Popa et al., 2016). Popa (2016) highlights the time-sensitive nature of this effect, suggesting that the benefits of export-oriented policies accrue more readily in developing nations compared to established economies like the G7 (Popa et al., 2016). Another analysis strengthens this argument by emphasizing the positive impact of exports on economic growth across a broad range of developing countries (Mudrika Thanoon Yahya et al., 2020). Both studies underscore the importance of fostering an active export sector for economic prosperity.

There is also another layer of nuance in this discussion which is differentiating between the growth effects of low- versus high-quality exports (Libanio et al., 2016). While Libanio (2016) finds that lower-quality exports can initially stimulate growth, this effect tapers off over time, conversely, exports with higher technological content, though potentially slower initial growth drivers lead to more sustainable positive effects on long-term economic performance (Libanio et al., 2016). In this study, economies with a higher composition of technologically advanced exports demonstrated stronger economic growth. These combined findings suggest that while exports are a powerful tool for economic development, focusing on fostering high-quality, technologically advanced exports offers a more sustainable path to long-term economic prosperity (Libanio et al., 2016). Ram (1987) also emphasized the beneficial effects of export performance on economic growth (Ram, 1987). Therefore, the type of goods a country exports, particularly those with higher technological content, can have a greater impact on economic growth compared to the simple fact of exporting itself.

2.2. Soybeans

Soybean (*Glycine max*) is a valuable legume within the Rosaceae order, and Fabaceae family (also known as Leguminosae or Papillonaceae), This annual herbaceous plant reaches up to 1.5 metres in height and features pubescent leaves and pods along with erect, rigid stems (Fuentes et al., 2013). It has served as a dietary staple in Asian cultures for millennia and continues to be a prominent source of plant-based protein, particularly for individuals adhering to vegetarian or vegan dietary regimens. Soybeans boast a well-rounded nutritional profile, rich in protein content (Figure 3). This versatility translates into a multitude of dietary applications. The whole bean can be directly consumed, processed into milk alternatives for those with lactose intolerance, or concentrated into supplemental forms. Cultivated for its edible seeds, soybean is not only a significant source of protein but also offers a wealth of health-promoting phytochemicals. These include isoflavones and lignans, molecules that provide antioxidant and antiplatelet benefits and have been linked to potential disease prevention and management (Fuentes et al., 2013). Due to this remarkable combination of valuable protein and bioactive compounds, soybean has earned its reputation as a health-promoting food, and unsurprisingly, has been the subject of extensive scientific research (Fuentes et al., 2013).

Soybeans possess a complete amino acid profile, signifying the presence of all nine essential amino acids that the human body cannot synthesize. This characteristic elevates soybeans to a position of significance as a protein source, particularly for individuals following vegan or vegetarian dietary patterns (Metropulos & Olsen, 2023). A comprehensive nutritional analysis conducted by the United States Department of Agriculture (USDA) revealed that a 100-gram serving of cooked green soybeans, absent of added sodium, provides 141 kilocalories and the following compounds shown in figure 3 below.

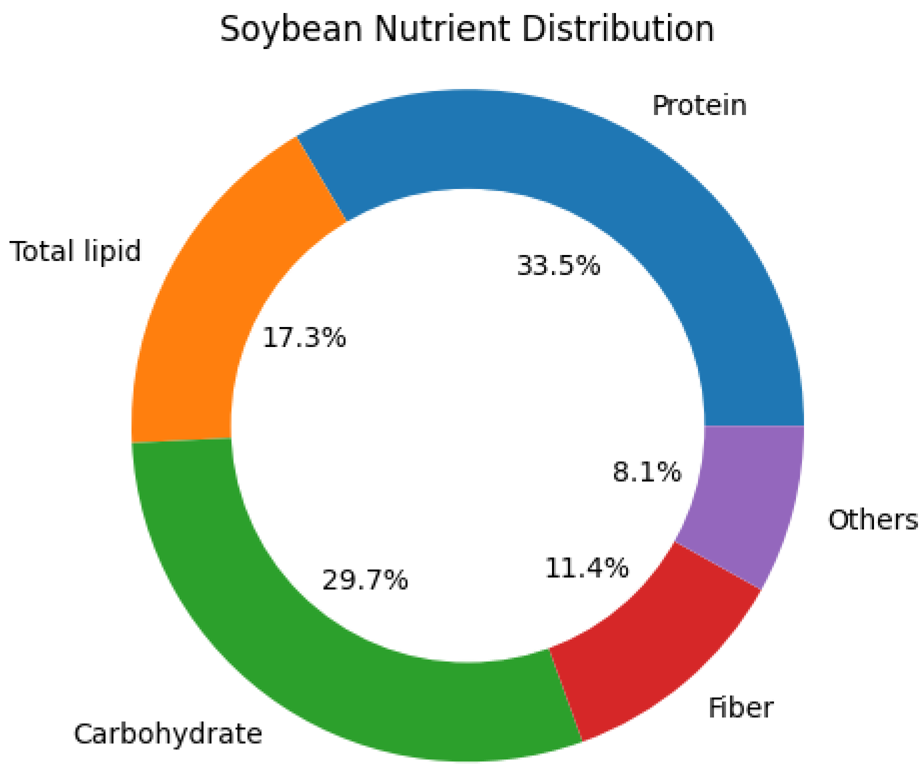

Figure 3. Soybean nutrient distribution

Source: Own editing

Furthermore, soybeans demonstrate a favourable fatty acid profile, being low in saturated fat. They are concurrently a commendable source of protein, vitamin C, and folate. Additionally, they offer a substantial amount of essential minerals including calcium, iron, magnesium, phosphorus, and potassium. Notably, soybeans also contribute thiamine, a crucial B vitamin, to the diet. Epidemiological studies indicate that consuming soybeans is linked to reduced risks of several chronic diseases like type 2 diabetes, certain cancers, and heart diseases, among others, primarily attributable to their inherent antioxidant and antiplatelet activities (Fuentes et al., 2013). It is important to acknowledge that the nutritional composition of other soy-derived products can exhibit variations based on the processing techniques employed by manufacturers and any additional ingredients incorporated during production (Metropulos & Olsen, 2023). Functional foods, like soy, are increasingly recognized as adjunctive or alternative treatments for various conditions, the FDA has acknowledged these findings, endorsing soy protein extract as a means to reduce cholesterol levels, prevent cancer and diabetes, and enhance cardiovascular health (Fuentes et al., 2013).

However, the consumption of soy products is not without contention. The advent of genetically modified soybean varieties has ignited debate regarding their potential health implications. Additionally, the extraction of soybean oil presents both opportunities and challenges. While lauded for its eco-friendly applications as a biofuel, soybean oil also finds use in the production of everyday items like candles, crayons, and even engine lubricants, raising concerns about its potential environmental footprint (Metropulos & Olsen, 2023).

2.2.1. Soybeans history

Soybean (*Glycine max*), also known as soy bean, is a very important species of plant whose seeds are used to produce a variety of food products. Vegetable soybeans are a traditional oriental food, known as "mao dou" (hairy beans) in China and "edamame" (beans on branches) in Japan, and are specialty soybeans enjoyed fresh, as snacks, or cooked. With a long history in East Asia, particularly in China and Japan, vegetable soybeans have become increasingly popular worldwide due to their health benefits and economic value (Dong et al., 2014).

The history of soybean cultivation reveals a fascinating journey across continents. This plant is believed to have been first domesticated in Asia. Some legends say it was already being used as early as 2500–2300 B.C. (Hartman et al., 2011). However, it first historical evidence points it to a later period, more specifically in the eastern half of north China approximately 1700 – 1100 BC, during this period, people consumed whole soybeans by cooking or fermenting them into pastes for various dishes (Hartman et al., 2011; Hymowitz, 2004). Later, the seeds were introduced into Europe, North America, and South and Central America, becoming a successful crop with vast production in those places (Wilcox, 2004). Despite the seeds have been known by other civilisations at least since the 13th century, the expansion of places where the seeds started being grown happened throughout the 16th century Anno Domini, primarily because of the establishment of trade routes, either by sea or roads, and the easy acceptance of the plant as a staple food in different cultures (Hymowitz, 2004). The 18th and early 19th centuries witnessed a shift, with soybeans being documented for animal feed in the Balkans (1804) and in the USA, in what today is known as the state of Georgia, around 1765 (Hartman et al., 2011).

More recently, the relevance of soybeans in the current world is unquestionable, they have been the dominant oilseed produced for the last 50 years and with an increasing trend in this period (Hymowitz, 2004). Early Western focus on soybeans centred on processing them into products like margarine and shortening, catering to the growing demand in Europe and the USA (Hartman et al., 2011). Despite this focus on vegetable oil for processed foods, some Western researchers saw soybeans as a potential solution for human food needs and explored their cultivation for direct consumption. Moreover, the soybeans, classification 702222 for standard international trade classification (SITC), were the 50th out of 768 most traded products in 2018, with Brazil figuring on the top of the biggest producers list, totalizing $33.2B of exports on the same year (OEC, 2019).

Like other cultivated crops, soybean genetic diversity has been significantly reduced through domestication and modern breeding practices, this highlights the importance of exploring and utilizing the remaining diversity within wild soybean and landrace populations for sustainable crop improvement (Li, Y. et al., 2013). Overall, a better understanding of soybean genetic diversity, including the impact of domestication and breeding, can be used to develop improved soybean cultivars to meet growing global demands for food, vegetable oil, and biofuels (Li, Y. et al., 2013).

2.3. Soybeans: A Global Staple with a Dynamic Trade Landscape

The worldwide soybean trade has witnessed a remarkable transformation in recent decades, shaped by shifting production patterns, evolving consumption trends, and geopolitical dynamics (De Maria et al., 2020). Soybeans have become one of the most important agricultural commodities traded internationally, with a global trade value exceeding that of other major agricultural products such as wheat and rice (Soybeans.com, 2023). The significance of this food commodity is illustrated in Figure 4, which presents the main grains exported in 2022 by total trade value (in billions of U.S. dollars). Soybeans lead the ranking, with export revenues approaching 100 billion USD in that year alone.

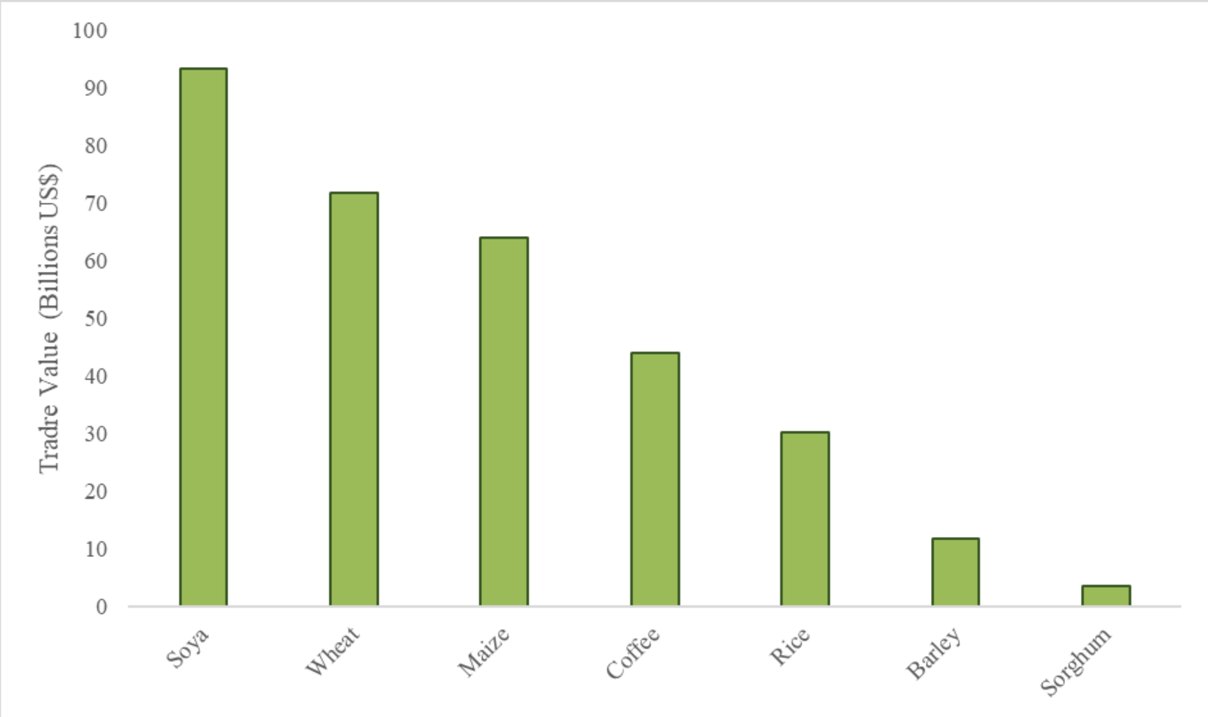

Figure 4. Global Grains export in 2022

Source: UN Comtrade data, visualised using Python (Matplotlib); figure prepared by the author

The international grain trade flow is a complex and dynamic system susceptible to a myriad of external factors, including policy decisions, diplomatic relations, trade frictions, regional conflicts, natural disasters, and others. These factors can significantly impact grain production, consumption, and trade patterns, leading to fluctuations in prices and supply chain disruptions (Wang et al., 2023).

The global soybean trade has also been influenced by geopolitical factors, with trade disputes and political tensions impacting market dynamics (De Maria et al., 2020). The ongoing trade war between the United States and China has significantly disrupted soybean trade flows, with Chinese tariffs on US soybeans leading to a decline in US exports to China (Wang et al., 2023). This has opened up opportunities for other countries to further expand their market share in China and other Asian markets, as we will see throughout this section.

In recent years, the COVID-19 pandemic and escalating trade tensions between China and the United States have emerged as prominent influencing factors, potentially altering the structure of the global soybean trade network. These disruptions are expected to have far-reaching consequences for China's soybean supply chains and the overall robustness of the trade network (Wang et al., 2023).

Understanding the interplay between these external factors and the global grain trade is crucial for anticipating and mitigating potential disruptions, ensuring food security, and promoting stability in the global food system.

2.4. Analysis of Soybeans trade between 2003 and 2023

2.4.1. Change in the export of soybeans

The evolution of the global soybean trade has been accompanied by a remarkable increase in both trade volume and value (De Maria et al., 2020). Between 2003 and 2022, global soybean trade volume increased more than eightfold, from 19 million tons to around 150 million tons. This growth was mirrored by a substantial increase in trade value, which soared from USD 10 billion to over USD 90 billion during the same period.

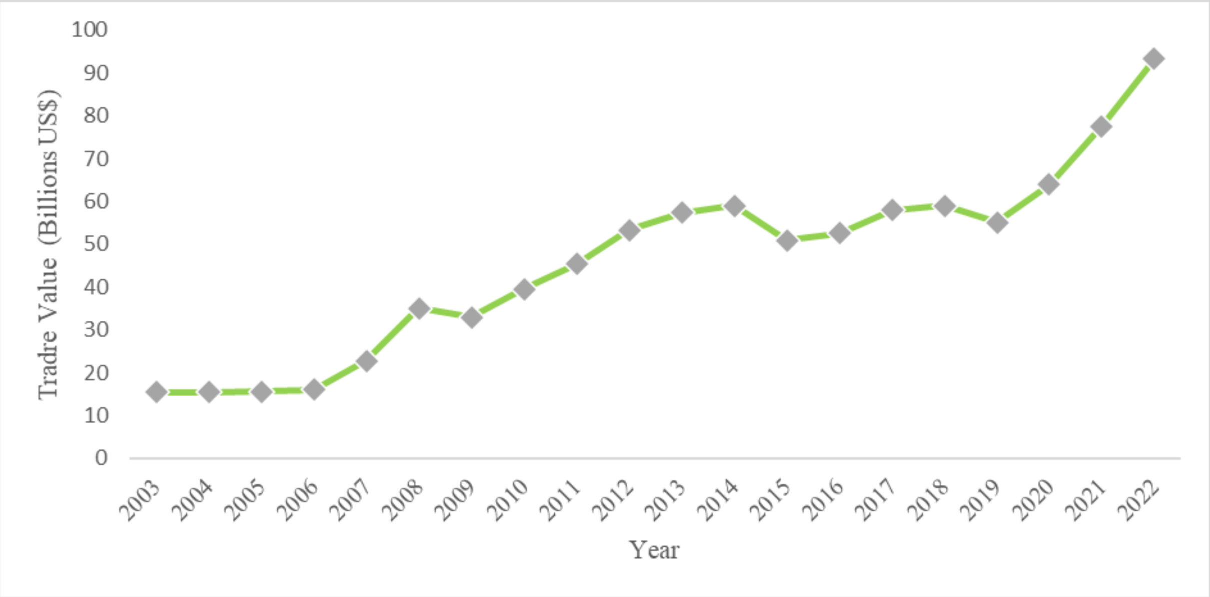

Figure 5. Change in soybeans trade export volume 2003-2022

Source: UN Comtrade data, visualised using Python (Matplotlib); figure prepared by the author

The importance of soybean trade in the context of global trade has also grown significantly (De Maria et al., 2020). This can be demonstrated by Figure 5, where the evolution of the amount traded is presented, displaying an evident increase in the total volume traded over the years. The soybean trade plays a vital role in ensuring food security and meeting the nutritional needs of a growing global population (Wang et al., 2023). It contributes therefore significantly to the economies of exporting and importing countries, generating employment and revenue (Soybeans.com, 2023).

In conclusion, the global soybean trade has witnessed a remarkable transformation in recent decades, evolving from a dominated market to a dynamic and complex network of producers, exporters, and importers (De Maria et al., 2020). The trade has grown exponentially in both volume and value, reflecting its increasing importance in the global food system and the global trade scenario (Soybeans.com, 2023). As the world grapples with food security challenges and changing dietary patterns, soybeans are poised to remain a critical component of the global food system, with their trade playing a vital role in ensuring global food security and economic stability (Wang et al., 2023).

2.4.2. Global Soybean Trade

The global soybean trade has evolved significantly over time, with key drivers including the increasing complexity of the trade network, the growing demand for animal protein and cooking oil, and the emergence of new uses for soybeans such as biofuel production (Boccaletti et al., 2014; Hart, 2017; Kou et al., Oct 22, 2018; O'Connor & McFarlane, 2014). The international soybean trade network is becoming increasingly interconnected, with some countries like the US and Brazil playing a more dominant role than others. China, a major importer, relies heavily on these key players, making its soybean trade vulnerable to external disruptions. Historically, China's Northeast region connecting with Europe and the US through successful soy trade exemplifies how economic activities intertwined with global politics in the early 20th century, shaping trade dynamics and power relations (Mizuno & Prodöhl, 2023). Furthermore, the soybean trade isn't solely driven by economics, it's also influenced by geopolitical rivalries. This concept is further underscored by the role of American journalist George Bronson Rea in highlighting the significance of the soybean in the "Manchurian problem", this historical instance emphasizes that soybeans weren't just essential for farmers, but also held geopolitical importance, influencing global politics and regional power struggles during that era (Mizuno & Prodöhl, 2023).

To ensure the sustainability of its soybean trade, China needs to both improve domestic production (self-sufficiency) and diversify its import sources (Kou et al., Oct 22, 2018; Wang et al., 2023). The trade relationship between countries has also become more reciprocal, with the trade relationship between countries becoming closer (Kou et al., Oct 22, 2018).

Soybeans, originating in China, have undergone a remarkable transformation, evolving from a modest crop to a multi-billion-dollar global industry (Hart, 2017; Kou et al., Oct 22, 2018). Since World War II, the United States has emerged as a preeminent force in both soybean production and consumption (Hart, 2017). This dominance is exemplified by data from the

2015 growing season, where US farmers cultivated over 80 million acres and yielded an impressive 4 billion bushels of soybeans (Hart, 2017). However, the trade network is vulnerable to being controlled by a few countries, which poses a risk to food security (Wang et al., 2023).

Some of the constraints that threaten soybean production include abiotic and biotic factors, abiotic constraints refer to environmental factors such as extremes in nutrients, temperatures, and moisture, which can directly reduce production. Additionally, these factors can also indirectly lead to an increase in pathogens and pests, further impacting soybean yields and quality (O'Connor & McFarlane, 2014). Biotic constraints, on the other hand, are more geographically and environmentally restricted and can pose challenges to soybean production (O'Connor & McFarlane, 2014). The limited availability of current management strategies, such as disease-resistant varieties, exacerbates these challenges. However, technological advancements, particularly genomics, offer promising avenues for improving crop resilience and quality (O'Connor & McFarlane, 2014).

A significant disease that restricts soybean production in many parts of the world is soybean rust, caused by the fungus *Phakopsora pachyrhizi*. This disease primarily targets leaves, causing small lesions typically 2 to 5 millimetres in diameter. These lesions erupt into structures called uredinia, which produce vast numbers of urediniospores, the reproductive spores that facilitate disease spread (Hartman et al., 2011). If rust is allowed to spread uncontrolled, it might result in significant losses for most soybean-producing nations worldwide. The pathogen, initially identified in Japan in 1902 on yam bean, remained confined to the Eastern Hemisphere for almost a century, however, by 1994, it reached Hawaii, and subsequently, numerous cases were reported in Africa from 1996 to 2001 in the Parana River basin of Paraguay, and by 2002, it had spread to neighbouring areas of Brazil, causing significant damage (Hartman et al., 2011).

Beyond environmental and biological challenges, socioeconomic factors also play a role. Inadequate farm credit, lack of knowledge of new production technologies, high cost of fertilizers, and labour shortages (Al-hassan & Jatoe, 2018; Jaybhay et al., 2018; Nget et al., 2021; Raghuwanshi & Sahu, 2007) Potential solutions include timely delivery of credit, improved access to high-quality seeds, and efficient dissemination of information to farmers (Al-hassan & Jatoe, 2018; Nget et al., 2021). Additionally, measures such as proper farm mechanization, water conservation, and training on improved cultivation practices can help overcome these constraints (Jaybhay et al., 2018).

When it comes to growth in the production of soybeans, the case of two countries in South America can be discussed, being them Argentina and Brazil (Kou et al., Oct 22, 2018; O'Connor & McFarlane, 2014). Although the counties are in the same region, with similar climate and soil, the reasons behind the growth are attributed to different factors.

In Argentina, the expansion of soybean production began in 1991 when the government eliminated a 41% tax rate on exports, leading to an increase in sown areas after a period of decline (O'Connor & McFarlane, 2014). Additionally, adopting zero tillage practices and the introducing genetically modified herbicide-tolerant soybeans in 1997 played a significant role in expanding soybean production in Argentina (O'Connor & McFarlane, 2014).

Fuelled by a confluence of factors, Brazil has emerged as a dominant force in global soybean production. To meet this challenge, scientists at Empresa Brasileira de Pesquisa Agropecuaria (Embrapa) developed soybean cultivars specifically adapted to the Brazilian tropical climate (Hymowitz, 2004). These new varieties boasted higher yield potential and resistance to local diseases, significantly improving production success (Hymowitz, 2004). This advancement in production technology played a crucial role in Brazil's soybean boom.

Beyond these technological advancements, economic factors further propelled production growth. The early 2000s saw a surge in international commodity prices, particularly driven by China's exponential demand. This, coupled with improvements in tradable goods prices following Brazil's 1999-2001 recession and the 2002 currency devaluation, created a perfect storm for Brazilian soybean production (O'Connor & McFarlane, 2014). Additionally, the introduction of genetically modified herbicide-tolerant varieties and a significant expansion of cultivated land further propelled production growth (O'Connor & McFarlane, 2014).

Beyond mere geographical proximity, several supranational factors significantly catalyse the expansion of global commerce. Chief among these is the negotiation of formal frameworks designed to streamline exchange and reinforce bilateral cooperation. Within the soy complex, this is best illustrated by the proliferation of Regional Trade Agreements (RTAs). Paradoxically, the prevalence of such deals is frequently criticised as a primary driver of market distortions and a structural barrier to genuine trade liberalisation. This tension was starkly evidenced during the Doha Development Round, where extended disputes regarding agricultural market access highlighted the inherent frictions between regional protectionism and global free-trade aspirations (Costa et al., 2008; World Trade Organization, 2015). In the following paragraphs, I will explore more about the evolution of this market by looking at trade agreements, prices, tariffs, and issues surrounding the product. Regional trade agreements in South America, such as the Andean (among Venezuela, Colombia, Ecuador, Bolivia, and Peru) and Mercosur (among Brazil, Argentina, Paraguay, and Uruguay) pacts, have a significant impact on global soybean trade patterns and market dynamics (Babula et al., 2005). The Andean pact is free of duty, whereas the Mercosur agreements impose a common external tariff, a study modelled the impacts of the unification of both groups into a single one. The unification could lead to trade diversion and benefit Mercosur suppliers at the expense of others, especially Bolivian and the United States, as seen in the case of the United States and Venezuela (Babula et al., 2005).

The trade picture changes also not only by directly favouring some groups of countries but also by the attack on some markets. This could be clearly demonstrated in the soybeans market by what was experienced when China attacked American agriculture in retaliation for U.S. tariffs imposed in 2018, focusing primarily on these grains, which were the main agricultural export from the United States to China prior to the trade war (Adjemian et al., 2021). Trade interruptions are very sensitive to US soybean exports, particularly from China, which is the world's largest buyer, US growers used to send around one out of every three rows they harvested to China, however after the trade battle started the market between the two countries presented a high volatility and shifted the directions for partners exploration (Adjemian et al., 2021; Chen, Z. & Yan, 2022). Trade retaliation in the form of a 25% tax caused a shift in market preferences, favouring Brazilian soybeans among Chinese purchasers (Adjemian et al., 2021; Thukral & Gu, 2018).

Beyond trade agreements, disparities in development levels among exporting countries can influence product pricing and market share. Trade and domestic policies, such as transportation costs and export taxes, further affect the competitiveness of major soybean exporters like Brazil and the United States (Costa et al., 2008) While fixed costs for U.S. soybeans were considerably higher in 2006 compared to Brazil and Argentina, the U.S. benefited from lower variable costs. Furthermore, a significant point of differentiation lies in transportation costs, with the United States demonstrating more efficient and cost-effective transportation methods, in comparison to Brazil and Argentina, particularly the former, primarily due to the considerable distance between production areas and export ports, and consequently, if a focus in improving this conditions is done, a significant gain in competitiveness can be achieved, leading to market expansion (Costa et al., 2008).

The environmental and socio-economic impacts of the global soybean trade, including deforestation and grassland conversion, are also a key consideration (Boerema, 2016). Lastly, the impact of China's soybean price support policies on price variability and welfare, both domestically and globally, is a crucial factor in understanding the dynamics of the soybean market (Wang, 2019).

Global soybean commerce is significantly impacted by geopolitical conflicts and trade policy, such as the US-China trade war. China's retaliatory tariffs against US soybean exports during the US-China trade war significantly affected soybean exports (Dhoubhadel et al., 2023). The imposition of tariffs by China on US soybeans has a direct impact on the trade dynamics between the two nations and has wider implications for the global soybean market. Furthermore, the US dollar's position as the standard currency for international soybean commerce was advantageous to US-based interests, particularly as Brazil surpassed the US to become the world's largest exporter of soybeans (Oliveira, 2016).

China, as the world's largest soybean importer, heavily relied on a few countries for its soybean imports, leading to a decline in the anti-interference ability of China's soybean trade (Wang et al., 2023). The trade policies implemented by China during periods of food crisis resulted in decreased market integration between domestic and international soybean markets, impacting the stability of the domestic soybean market (Sun et al., 2018). Moreover, the low prices of soybeans in the international market stimulated the growth of China's soybean imports, consequently influencing the expansion of soybean trade financing businesses. Furthermore, the dynamic game model applied to China's imported soybean prices in the context of economic and trade friction with the US revealed fluctuations in customs values following tax increases on imported soybeans (Lu et al., 2020)

The macroeconomic linkage of soybean trade competition between the US, Brazil, and Argentina in various import markets underscores the complexity of global soybean trade dynamics (Thraen et al., 1992). The impact of trade policies on soybean futures in China further demonstrates the intricate relationship between trade frictions and financial markets (Chen, Z. & Yan, 2022). Geopolitical risks, such as those arising from conflicts, can have asymmetric effects on agricultural commodity prices, including soybeans, affecting global food security (Rajčániová & Hudecová, 2023).

Additionally, the potential implications of a regional nuclear conflict on global food security highlight the vulnerability of food production systems, including soybeans, to geopolitical instabilities (Jägermeyr et al., 2020).

2.4.3. Impact of Soybean Trade

Soybean trading has significantly impacted the economies and societies of producing countries, particularly Brazil and Argentina. These impacts are diverse, covering environmental, socio-economic, and geopolitical aspects. The trade-in soybeans, a vital commodity in global markets, has not only influenced the economic landscapes of these nations but has also shaped social dynamics and environmental sustainability.

Brazil and Argentina, ranked as the second and third-largest soybean producers globally, have witnessed soybeans becoming a cornerstone of their economies (Pereira & Brisola, 2022). The importance of soybeans in their trade balance is evident through income generation and job creation. The expansion of the soybean industry in these countries has played a crucial role in fostering economic development and providing job opportunities for their populations. Additionally, with the enhancement of transportation infrastructures in both countries, their competitiveness in soybean exports has notably increased, leading to Brazil becoming the largest soybean exporter (Guan et al., 2019). Various factors, including export taxes and competitiveness in importing countries like China, have influenced the trade dynamics of soybeans (Valdes et al., 2023).

Geopolitical factors, such as the US-China trade war, have also influenced the global soybean trade, reshaping market dynamics. The competition between the United States and Brazil in the soybean sector has intensified, with Brazil seizing opportunities to expand its market share, especially in exports to China. The trade war has altered the structure of soybean trade, leading to implications for soybean producers in Brazil and Argentina (Dhoubhadel et al., 2023).

2.4.4. Soybeans and sustainability issues

This visible improvement in the production conditions led to a major importance of the grains in the Brazilian economic context, as can be observed in Figure 6. Transforming soybeans is one of the main players in the development of the Brazilian agricultural business and consequently, the production and trade of these products also have a geopolitical influence, giving the importance to the food in the current world (Oliveira, 2016).

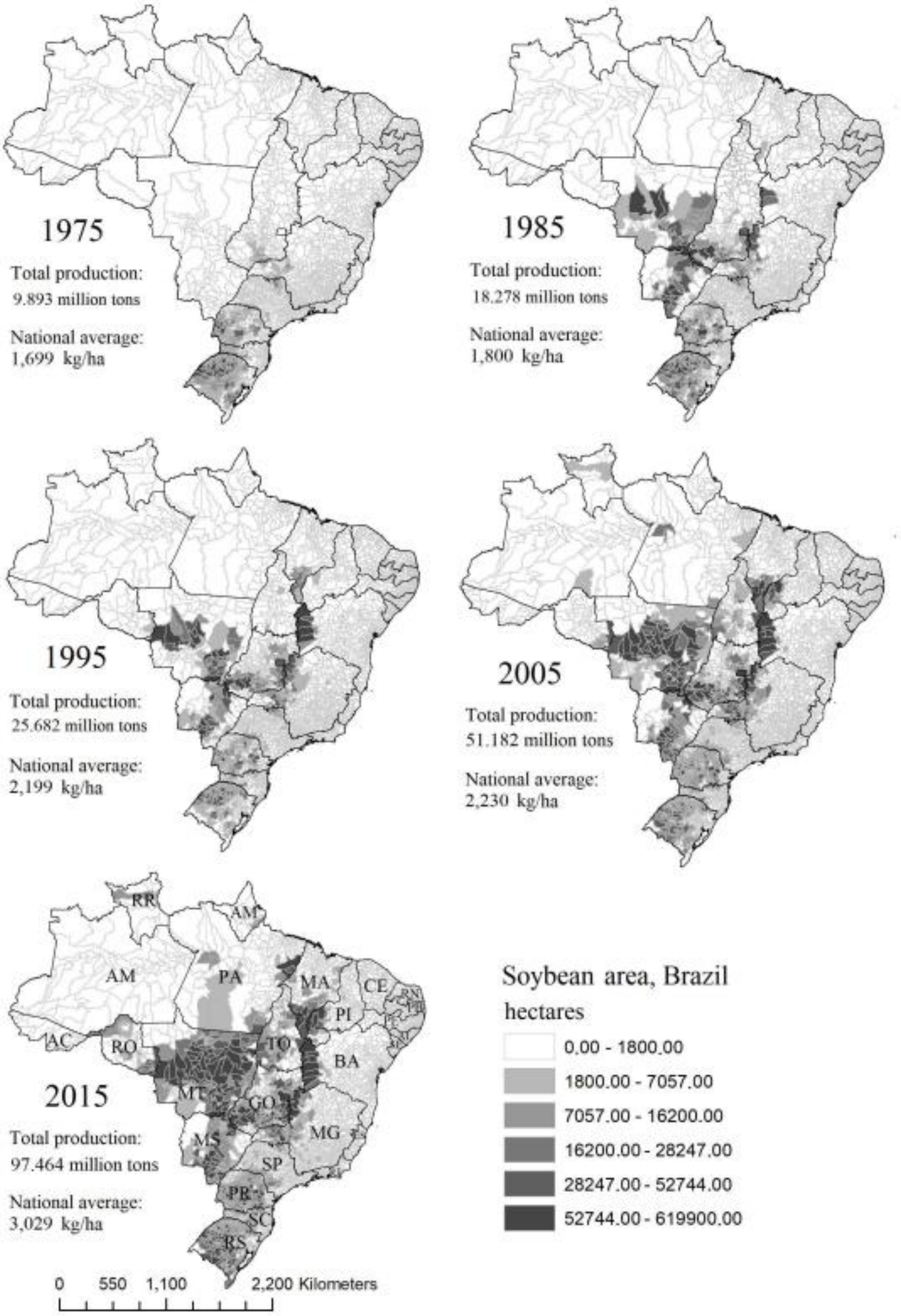

Figure 6. Soybean cultivation expansion in Brazil

Source: (Bicudo Da Silva et al., 2020)

However, there are also concerns regarding this expansion. The soybean miracle in South American countries, such as Brazil, Argentina, Bolivia, and Paraguay, has been linked to large-scale land acquisitions. This phenomenon, often called 'land grabbing,' has been associated with the expansion of agribusiness corporations in the soybean frontier (Greenpeace, 2019). The surge in soybean cultivation has led to evictions, dispossession, and land conflicts with indigenous people and local communities in these regions (Torres et al., 2017).

The environmental and socio-economic impacts of the global soybean trade are significant, highlighting the need to balance these aspects in the intercontinental market (Boerema et al., 2016). This process significantly impacts the well-being of local populations and raises concerns about environmental degradation, such as deforestation, soil erosion, and loss of natural habitats (Fearnside, 2001). The critics of environmental degradation can be illustrated by the comparative analysis of ecosystem areas in Brazil in Figure 7. The ecosystems depicted include the Atlantic Forest, Campos and Pampas Grassland, and Cerrado Savannah, with the area represented in percentage terms. The Atlantic Forest and Campos and Pampas exhibit a significant decline in area, further indicating the detrimental effects of agricultural practices on these ecosystems, particularly complemented by the increase in the Area of Cerrado Savannah, an ecosystem characterised by being more arid and less biodiversity. Overall, this analysis underscores the complex dynamics between agricultural expansion, particularly soybean cultivation, and ecosystem health in Brazil, emphasizing the urgent need for sustainable land management practices to mitigate biodiversity loss and environmental degradation.

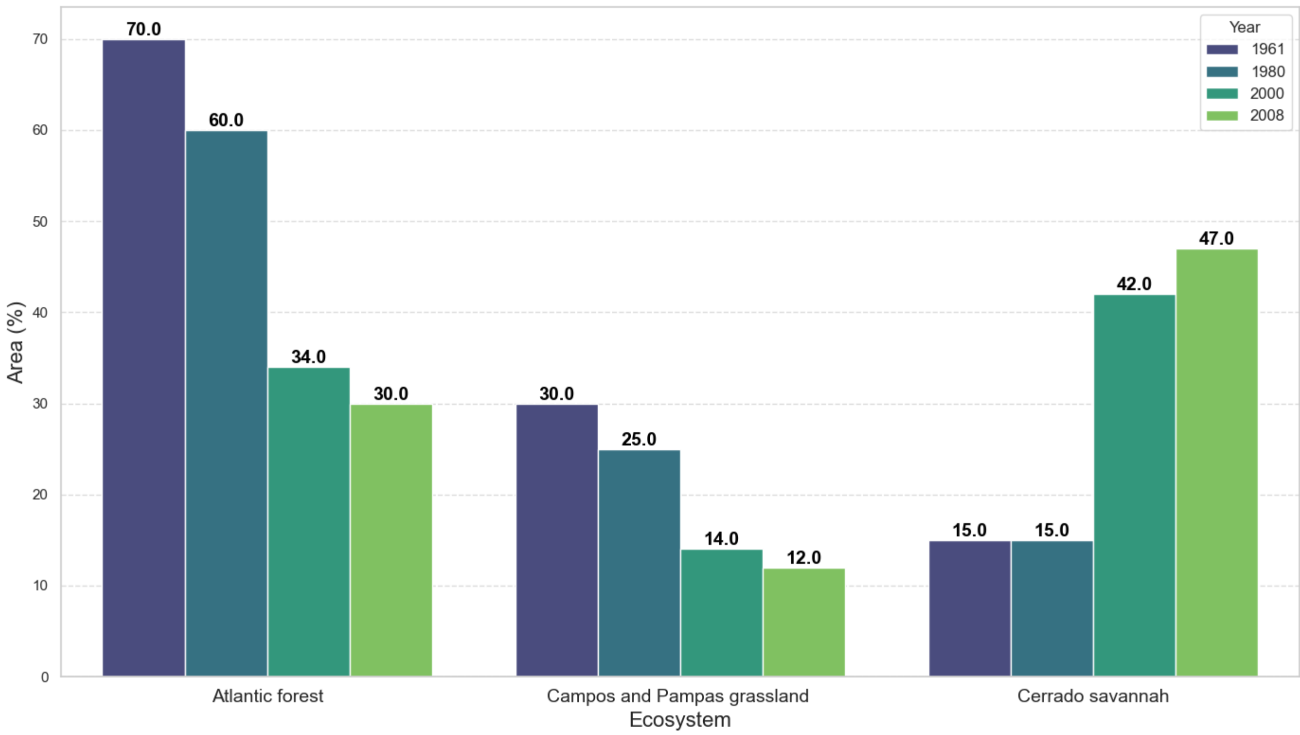

Figure 7. Comparison of Ecosystem Areas in Brazil

Source: Adapted from (Boerema et al., 2016)

The logistics performance of major soybean exporters like Argentina, Brazil, and the US also plays a crucial role in soybean exports, which are traded as grain, oil, and meal (Reis et al., 2020).

2.5. Social Network Analysis

2.5.1. Methodology of network analysis

Complex systems, such as international trade, require tools and different methods to allow better analysis and understanding of the interactions and behaviour within the system. This can be done through several methods, and among them, the application of network analysis also seems suitable (Popp et al., 2018). To most people, the term social network refers to social media websites such as Facebook and Instagram, however, when applied to the scientific fields, it refers to a completely different thing: any network in which the nodes represent individuals and the edges reflect some type of connection between them, such as friendship, is referred to as a social network (Newman, 2018).

Since the turn of the century, network analysis has been used by sociologists and psychologists to investigate social relationships between individuals and groups. Although it is hard to precisely state when the study of social networks began, this was more evidently present in the 1930s (Scott, John & Carrington, 2011). Nowadays, social network analysis is extensively used in many different fields, such as economics, marketing, social and behavioural sciences, and even engineering. The diversification of applications can be explained by the focus of the methodology, studying the relationship among the entities of a group. Thus, it can be expanded to many areas, for instance studying the economic transaction between people or companies, or the international trade among nations (Wasserman & Faust, 1994).

The evolution of this field was historically fragmented, drawing upon disparate contributions from various intellectual traditions. Among them, German scholars investigated social relations and inspected their interactions using terms such as ‘connections’, ‘points’, and ‘lines’ in their analysis. This analytical foundation was further advanced by the seminal contributions of Moreno (1934) and Lewin (1936), who conceptualised social dynamics as an integrated network. This preliminary methodology was called sociometry, and the visual representation was called sociogram (Lewin, 1936; Moreno, 1934; Scott, John & Carrington, 2011).

In 1929, Hungarian author Frigyes Karinthy proposed that everyone on the globe is divided by no more than six degrees of separation. American psychologist Stanley Milgram (1967) put this idea to the test by allowing people to send stuff to people they did not know via people they did know at first. Milgram discovered that 80 percent of the commodities supplied were received with four or fewer intermediaries. This experiment shows the connections and relationships between people that matter, not their unique features. It is also worth noting the work of Granovetter (1974), who explored job market exchanges. All these works altogether allied with the contributions of people from other scientific fields, such as physicists, mathematicians, and computer scientists, contributed to a variety of effective statistical methods for the study of network topologies that have evolved outside of the area of social sciences (Reyes, Schiavo, & Fagiolo, 2010).

But it was near the end of the millennium when the fields really dramatically changed due to its popularization, thanks mainly to two main works: the research of Watts and Strogatz (1998) about small worlds and the examination of Barabási and Albert (1999) on the distribution of degree centralities (Freeman, 2011). Since this popularization, many works on different fields have been made, impacting with new tools and the possibility of analysis, on the following part, the approach will be explained, pointing out the main points to be considered when carrying out the methodology and on the material and methods this discussion will be deepened, explaining more details and considerations about it.

The Network Analysis now has an important apparatus based mainly on graph results, although it does not require a deep use of mathematical background, it can derive conclusions also on statistics and calculations to understand the network's organization. The approach focuses on responding to the hypothesis tested from a practical point of view, therefore, because of its suitability, it has been widely used in international trade studies and the sociology field, being named Social Network Analysis (SNA) (Chaney, 2014).

The SNA applied to social relationships contains nodes and ties, other names for these two elements can appear such as junctions for the first and edges, links, or connections for the later. These other names can reinforce and facilitate the comprehension of the role of each one in the network theory. The nodes are the actors, whereas the ties represent their relationship (Popp et al., 2018). The simplest type of graph in the SNA context is binary and undirected, in other words, it means that any pair of nodes can be either connected by a link or not, and the direction of the link does not count, whereas on the undirected graph, the direction does count (Fagiolo, Reyes, & Schiavo, 2010). The product exports from a country in a given year is an example of the latter, since the amount exported from country i to j might be radically different from the exports from country j to i.

Despite the concept simplicity, the results arising from the graph-based structure can be very complex sometimes, since the flexibility of its use results in a wide range of complexity levels of results (Scott, J. & Scott, 2017). When analysing data SNA is valuable since it combines the narrative in a manner that eases the examination among the components within the network. Many different fields have applied this technique to gathering successful results, not only when used to grasp the links among the actors, but also as an alternative to find the core actors and to interpret the social connections among the nodes (McKether & Friese, 2016; Scott, 2017; Zhao & Zhao, 2016)

Different metrics, usually mathematics, are used in order to quantify the relationship on the network and grasp its main features. Those metrics are used in different fields and compound an important toolbox for anyone intending to use the methodology. The following are some main metrics that might be used when developing an SNA in any group study.

Node-level metrics

Since the beginning of the conceptualization of the Network Analysis field, one of the main notions that seeks to be understood in a group is Centrality (Wasserman & Faust, 1994). . This index tries to quantify the empirical feeling one might have observed in a group, that some nodes are more central than others (Koschützki et al., 2005). Another way to look for these metrics is as a way to answer the question: "which are the most important entities on the network?" (Newman, 2018). Among the centrality measure, there are different approaches to understanding this feature. In the Materials and Methods section some of the different types of centralities such as Degree, Betweenness, Closeness, and Eigenvector centrality will be presented.

Network-level metrics

Another important measure when studying a network compromises the definition of subgroups within the network. The role of these metrics is to identify cohesive subgroups or subsets of actors with strong, direct, and intense ties since sometimes empirically one already perceives the natural formation of groups or communities in many networks, including social and other networks: the social networks, for example, are divided into groups of friends or business partners for example, while on the Internet, one can divide it into groups of related web pages(Newman, 2018; Wasserman & Faust, 1994). A vast and fruitful topic of network theory is the definition and analysis of groups within networks (Newman, 2018). Within the group study, the definition of clique is one of the most basic ones and serves as a starting point for other more complex analyses. Basically, a clique is a collection of nodes within a network in a way that every member of the collection is also connected to every other participant (Newman, 2018).

This analysis incorporates several key metrics to characterise the network's topology. The density of the network, for instance, provides a foundational measure of connectivity by calculating the ratio of observed ties to the total number of possible relations. This is often complemented by the clustering coefficient, which gauges the transitivity of the system. Finally, the average path length serves as an indicator of the network's overall efficiency and "small-world" properties, measuring the mean geodesic distance between all pairs of nodes. Collectively, these metrics transition the analysis from individual node importance to the structural equilibrium of the entire system.

2.6. Introducing Global Trade Through Social Network Analysis

Sociologists and political scientists were the first to utilize network analysis to examine international trade connections, Snyder and Kick (1979) classified nations into a core-periphery structure using international trade statistics and network analysis, years after two more studies employed aggregated data to investigate this 'dependence hypothesis', namely Nemeth and Smith (1985) and Smith and White (1992) (Reyes et al., 2010). More recently it has widened to different areas in international trade statistics.

With these tools, several applications in different fields were largely used in the academic world, the next section will be a general summary of the main works done in the area of the present research, where topics on international trade and network analysis were connected in order to achieve particular useful insights.

3. MATERIAL AND METHODS

3.1. Bibliographic review

In the execution of my work, a comprehensive review of the vast scientific literature on the subject is a fundamental requirement. I meticulously identified the most significant contributions in the thematic area during the literature review. This was achieved by leveraging the Scopus bibliographic database, the world's largest curated database of peer-reviewed literature, and Google Scholar, a freely accessible search engine that indexes a wide range of scholarly literature across various disciplines.

The quality of these analytical pieces is as important as their quantity. To ensure this, I utilized the Scimago tool, which ranks journals based on citation, thereby aiding in refining the information. The use of high-quality data is crucial for constructing a robust outlook as it enhances the reliability of the scientific work and strengthens the academic coherence of the project.

The literature review process was bifurcated into two distinct segments. Initially, my focus was on scientific studies pertaining to network research. This was followed by an in-depth exploration of a scientific article that specifically discussed the soybean trade.

3.1.1. Bibliographic Analysis

Numerous data sources available today provide access to scientific literature metadata, such as Google Scholar, PubMed, Scopus, and Web of Science. For this analysis, I utilized the Scopus bibliographic database, which contains over 80 million records. Scopus, maintained by Elsevier, is updated daily and is widely used for scientometrics measurements and author reference exploration. Its straightforward interface supports data visualisation through software like VOS viewer (Lengyel et al., 2021).

The objective of this analysis is to uncover the role and application of network analysis in the context of international trade, as reflected in published literature. During the data collection phase, I searched for occurrences of the term's "network" and "trade," as well as "network" and "market," within the titles and keywords of relevant publications. The search was confined to the period between 1979 and 2023, using the following expression:

(TITLE (network) AND TITLE (trade) OR TITLE (market)) AND (KEY (network) AND KEY (trade) OR KEY (market)) AND PUBYEAR > 1979 AND PUBYEAR < 2023

The initial dataset consisted of 3266 documents related to the query, published up to 2023. This corpus encompasses 2087 articles, 1088 conference papers, 45 book chapters, 32 reviews, and 14 miscellaneous documents.

Figure 8 illustrates the annual fluctuation in the number of Scopus-indexed publications within the research scope from the year of 1984 until the end of 2022.

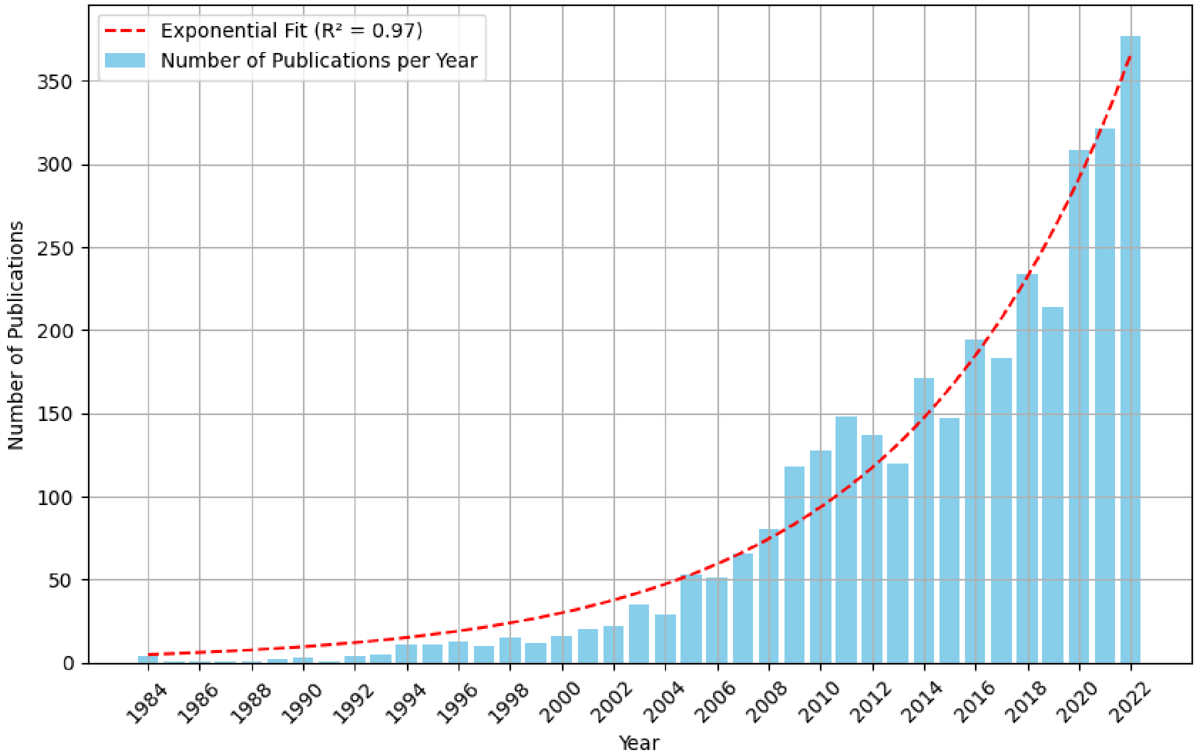

Figure 8. Number of Publications per Year between 1979 and 2004

Source: Scopus data, visualised using Python (Matplotlib); figure prepared by the author

A consistent upward trajectory in network research publications is evident. The field is experiencing a period of rapid growth, as graphically depicted. While the number of publications remained below one hundred between 1984 and 2008, a substantial increase to between two and three hundred per annum occurred subsequently. The exponential nature of this growth is confirmed by the R^2 value of 0.97 in Figure 8.

Figure 9 presents the geographical distribution of publications retrieved from our Scopus query, highlighting the countries with the highest research output in the specified topics. This visualisation offers valuable insights into the global landscape of scholarly contributions within our field of study.

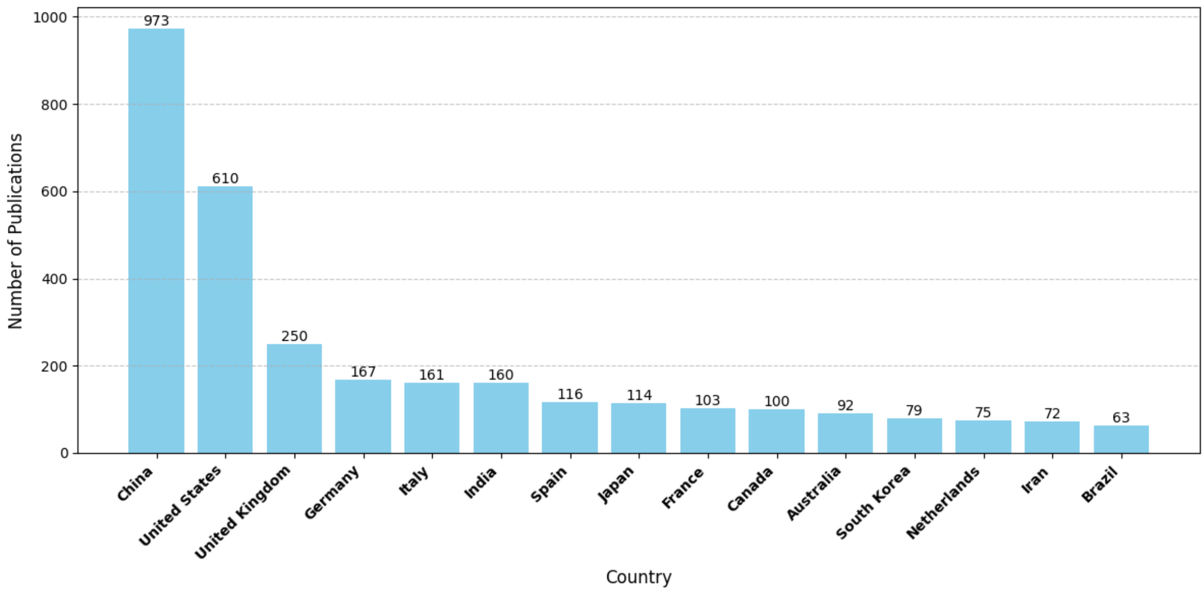

Figure 9. Countries with more publications

Source: Scopus data, visualised using Python (Matplotlib); figure prepared by the author

China emerges as the predominant contributor, with 973 publications, substantially outpacing other nations. This significant lead suggests that China is at the forefront of research in these areas, potentially due to focused investment, policy initiatives, or a robust academic infrastructure supporting these topics. The United States follows as the second most prolific country, with 610 publications, affirming its strong but comparatively lower presence in this research domain.

A considerable gap separates these two leading nations from the rest of the world. The United Kingdom, ranking third with 250 publications, produces less than half the output of the United States and approximately a quarter of China's contributions. This stark difference underscores the concentrated nature of research activities in this field. European countries demonstrate a notable presence, with Germany (167), Italy (161), Spain (116), and France (103) all featuring in the top ten. Asian representation is also prominent, with India (160) and Japan (114) showing substantial contributions.

The gradual decline in publication numbers across other countries reveals a long-tail distribution, typical in academic research output. Countries such as Canada, Australia, South Korea, the Netherlands, Iran, and Brazil, while contributing fewer publications, still play important roles in diversifying the global research landscape on these topics.

This analysis of publication distribution by country not only highlights the major players in the field but also reveals potential opportunities for international collaboration and areas where research capacity could be further developed. Future studies might explore the factors contributing to China's and the United States' dominance in these research areas, as well as strategies for fostering increased global participation and knowledge exchange.

To further explore the areas in which these two topics are implemented, I presented the number of works in the different subject areas in Figure 10. This distribution suggests a strong technological and quantitative focus in the literature, with significant contributions from social and economic disciplines, reflecting the multifaceted nature of the research topic under investigation. The chart illustrates the distribution of literature works across various subject areas retrieved from a Scopus query. Computer Science emerges as the dominant field, accounting for 20.6% of the publications. Engineering follows closely, representing 16.7% of the corpus. Mathematics and Social Sciences also have notable representations at 9.9% and 8.0% respectively. Economics, Econometrics and Finance (7.6%), Business, Management and Accounting (7.4%), and Energy (7.4%) show similar levels of contribution. Environmental Science accounts for 5.0% of the retrieved works. The "Others" category, which encompasses areas with less than 300 papers constitutes 17.3% of the results, being among then Decision Sciences, and Physics and Astronomy the most important ones, representing 4.9% and 4.6% of the total of publications.

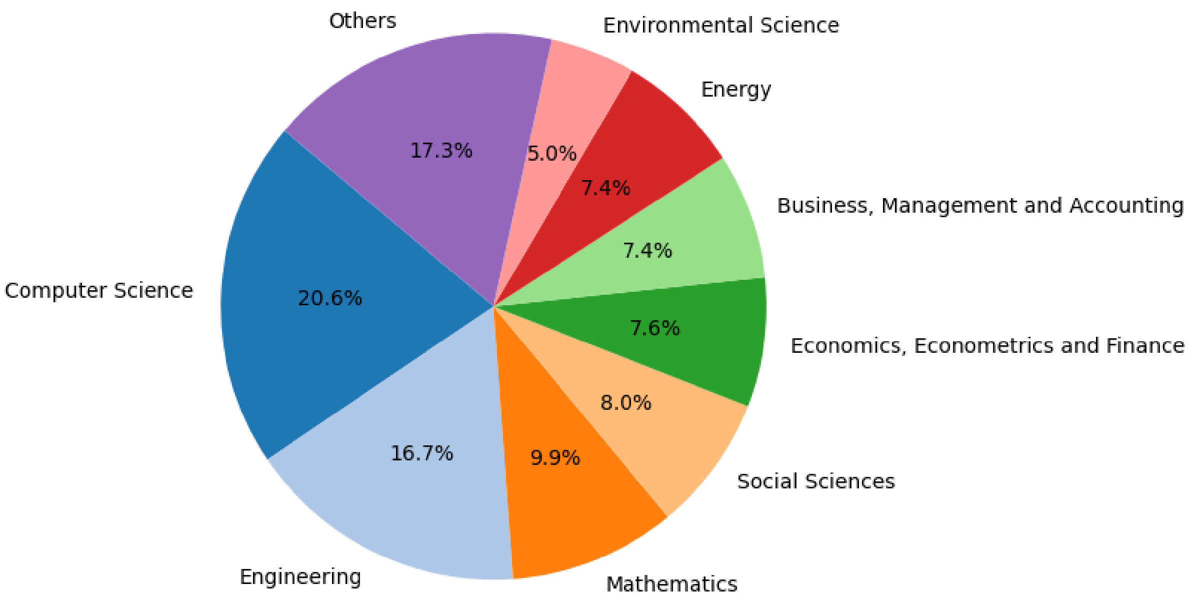

Figure 10. Distribution of Subject Areas

Source: Scopus data, visualised using Python (Matplotlib); figure prepared by the author

Among the subject areas retrieved from this first query, there are clearly areas that are not connected to the present study and consequently might not be useful for being reviewed. Therefore, I decided to narrow the query down by adding a filter related to the subject areas connected to my present work: Agricultural and Biological Sciences; Social Sciences; Economics, Econometrics, and Finance; Business, Management, and Accounting; and Environmental Science. The entirety of the new query is provided below:

(TITLE (network) AND TITLE (trade) OR TITLE (market)) AND (KEY (network) AND KEY (trade) OR KEY (market)) AND PUBYEAR > 1979 AND PUBYEAR < 2023 AND (LIMIT-TO (SUBJAREA , "ECON") OR LIMIT-TO (SUBJAREA , "BUSI") OR LIMIT-TO (SUBJAREA , "SOCI") OR LIMIT-TO (SUBJAREA , "ENVI") OR LIMIT-TO (SUBJAREA , "AGRI"))

After the additional filters were applied to the query 1358 articles were retrieved. The network of these keywords can be seen in Figure 11. In the figure, we already can see some important keywords among all the publications.

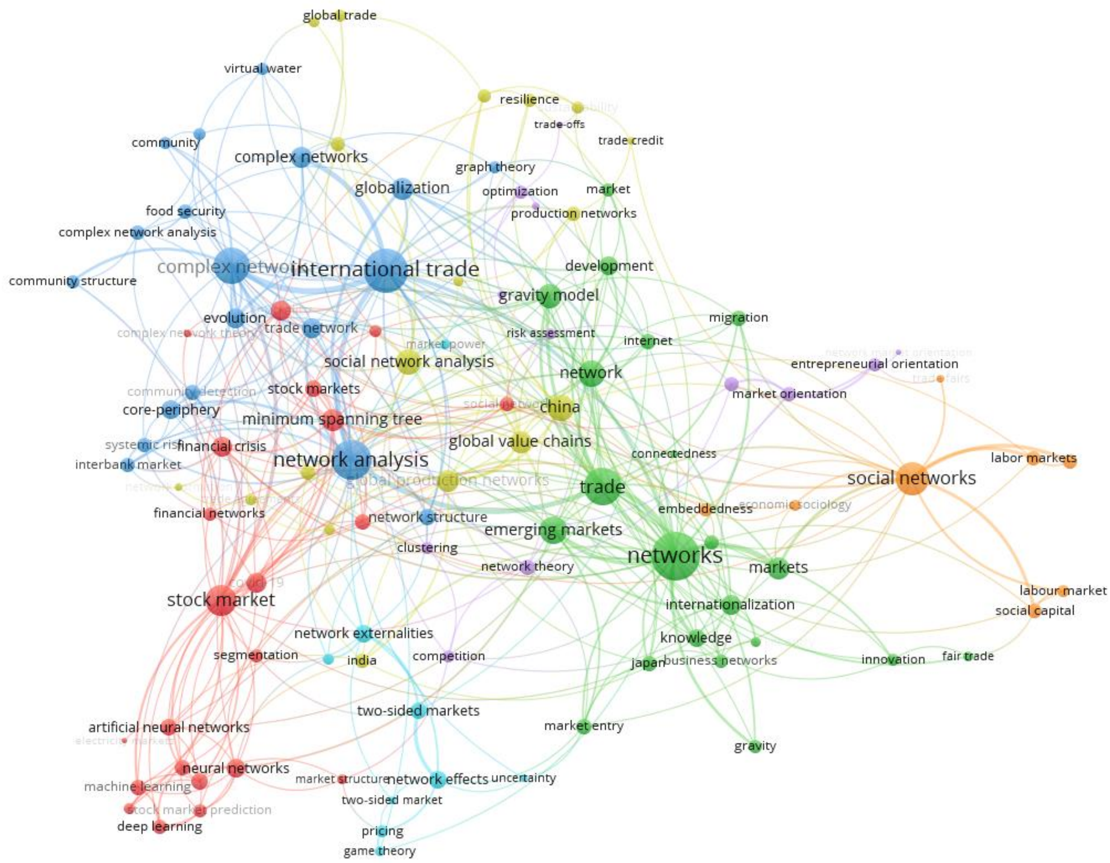

Figure 11. Network of Keywords

Source: Scopus data visualised using VOS Viewer.

To further explore the keywords, I present in Table 1 the keywords with high occurrences in the list of research papers as well as the links they have within the network.

Table 1. Number of keyword occurrences in the entire sample

Keyword	Connections	Occurrences
networks	37	95
complex network	23	75
network analysis	26	72
social networks	20	69
international trade	26	68
social network analysis	16	51
trade	21	39
stock market	22	33
emerging markets	19	28
network	20	25
network effects	6	24
China	22	22
trade network	9	21
complex networks	9	21
Artificial neural networks	10	20

Source: own research (2024)

Following a comprehensive review of key publications and an assessment of the broader landscape in the field, I refined the search criteria to establish a more focused and manageable corpus of literature. The selection process prioritized papers featuring the most frequently occurring keywords: Network Analysis, International Trade, Complex Networks, Networks, and Social Networks. To ensure relevance and currency, I restricted the search to peer-reviewed journal articles published within the last decade, exclusively in the English language. This methodical approach resulted in the following query:

(TITLE (network) AND TITLE (trade) OR TITLE (market)) AND (KEY (network) AND KEY (trade) OR KEY (market)) AND PUBYEAR > 2011 AND PUBYEAR < 2023 AND (LIMIT-TO (SUBJAREA,"ECON") OR LIMIT-TO (SUBJAREA,"BUSI") OR LIMIT-TO (SUBJAREA,"SOCI") OR LIMIT-TO (SUBJAREA,"ENVI") OR LIMIT-TO (SUBJAREA,"AGRI")) AND (LIMIT-TO (LANGUAGE, "English")) AND (LIMIT-TO (EXACTKEYWORD, "Network Analysis") OR LIMIT-TO (EXACTKEYWORD, "Networks") OR LIMIT-TO (EXACTKEYWORD, "International Trade") OR LIMIT-TO (EXACTKEYWORD, "Complex Networks") OR LIMIT-TO (EXACTKEYWORD, "Social Networks")) AND (LIMIT-TO (DOCTYPE, "ar")) AND (LIMIT-TO (SRCTYPE,"j"))

The end result of this new query retrieved 382 papers from which I extracted the abstract and selected the ones connected to the present work and I discussed some of them below.

3.1.2. Summary of Results

Despite its evident network-like nature, traditional economic models have long overlooked the network perspective in international trade (Zhou et al., 2016). Traditional trade models often fall short by treating international trade merely as exchanging goods, without acknowledging the complex web of relationships within the global trade network. This network perspective reveals that trade between two countries can influence not just those countries, but also their respective trading partners and beyond. Considering this network dynamic offers fresh insights and can challenge traditional trade model predictions, as well as deepen our understanding of the link between trade and global emissions (Aller et al., 2015).

Yu (2020) applies SNA to the international trade network of aquatic products, also called international aquatic product trade (IAPT), revealing its structure and dynamics, and comparing it to the general trade network. This analysis reveals an increasingly dense IAPT network, with key players concentrated in North America, Europe, and East and South Asia. Additionally, a core-periphery structure is identified, highlighting the central role of these regions and the less connected periphery (Yu, J. & Ma, 2020). Interestingly, the study finds some similarities between IAPT and general trade networks, suggesting broader patterns in global trade dynamics. This research provides valuable insights for understanding the interconnectedness and power dynamics within the international seafood trade.

Social Network Analysis (SNA) has been applied to international trade networks in various ways. The study made by Zhou, Wu, and Xu This study makes a significant contribution to the field of international trade network analysis by pioneering the use of top trade ties in network construction (Zhou et al., 2016). This innovative approach offers a more focused perspective on the most crucial relationships within the global trade landscape (Zhou et al., 2016). By concentrating on each country's primary import source and export destination, the constructed network effectively captures the essential structure of international trade interactions.

The network analysis was used to examine global soybean trade as well. The study done by Schaffer-Smith et al., examined 217 countries from 1986 to 2013 and quantified various aspects of the trade network, including sending and receiving systems, subnetworks, flow pathways, and changes over time (Schaffer-Smith et al., 2018). Key findings include a substantial increase in network density, which grew five-fold during the study period, indicating a more interconnected trading system, however, trade remains concentrated among a few major players, such as Brazil, China, and the USA, who hold a disproportionately large share of partnerships. The analysis also uncovered a positive feedback loop where countries with established trade relationships tended to keep and expand their networks. Furthermore, the studied highlighted a bad side of the production of soybeans, finding a notable link between soybean trade and tropical deforestation, with higher soybean exports correlating strongly with forest loss in pantropical countries (Schaffer-Smith et al., 2018).

In another study, complex network analysis was applied to China's futures market, focusing on the return and fluctuation structures of 20 different futures products from January 2013 to April 2015 (Li, H., 2017). The research revealed that the returns and fluctuations are influenced by a small number of key products, including rubber, soybean oil, and rapeseed meal, which show significant relationships with many other products. Both the revenue and fluctuation networks displayed clear community structures: the revenue network was divided into agricultural, industrial, precious metals, and metal communities, with rubber and rapeseed meals serving as key intermediaries. In contrast, the fluctuation network featured distinct, isolated communities with no inter-community connections. This analysis provides valuable insights into the structural relationships and dependencies within China's futures market, illustrating the utility of network analysis in understanding market dynamics.

3.1.3. Beyond the Bibliography analysis

After narrowing down several additional parameters to refine the query some important works were left outside the scope of the analysis. However, after reading extensively and researching different methodologies in this chapter I present some other important works that talk about the present research topic.

To start with, one of the most cited publications that used social network analysis on international trade is the work of Smith and White (1992), where they investigated the trade flows of commodities during a fifteen-year period to find the hierarchy of the international system, establish the different levels of importance on the global commerce, and the group blocks within it (Smith & White, 1992). The network analysis also can be applied to investigate more specific products, as an example the study of Raynolds (2012) can be cited, in the research it was studied the links of producers and consumers within the trade of coffee labelled as Fair Trade, and it was presented social and cultural aspects add to the economic indicators (Raynolds, 2002).

Additionally, the links among the actors can be related to another variable in other to enhance the conclusions and remarks from the country's relationships, as an example May (2009) brought the environment element to include in the business scenario, proposing a model to investigate the connection between international trade and the local pollution (May, 2009).

More recently, the introduction of weight on the web of trade relationships among world countries was proposed, allowing new insights into the economic discussion. This technique was used by Fagiolo, Reyes, and Schiavo (2010). They used the amount of trade between the pair of countries as the weight of each link on the global import and export network (Fagiolo et al., 2010). In this study, they analysed the relationship of countries between 1981 to 2000. They demonstrated that most nations have poor trade linkages, but that there is a subset of countries with many strong relationships, indicating a core-periphery structure. Furthermore, better-connected countries trade with less-connected countries while participating in highly connected trade clusters. Rich countries are also more concentrated and have more intense trade relations. Finally, they concluded that the entire network structure remained extremely stable over time (Fagiolo et al., 2010).

The application of the network analysis in the realm of international trade also revealed that the world trade network has become more interconnected over time, although integration remains incomplete and varies by region (De Benedictis & Tajoli, 2011). It highlights significant heterogeneity in countries' trade partnerships, making it difficult to pinpoint a representative country in the global trade system. By incorporating network indices into a gravity model regression, the study enhances the model's explanatory power and underscores the role of trade policies in shaping the trade network, with WTO members exhibiting closer connections than non-members.

Another important point was raised by Lovrić, Vidale, and Mavsar (2018), after making use of many tools of social network analysis on the international trade of wood and non-wood forest products, they pointed out that the employment of many SNA procedures is suitable for the international, however, great attention is needed, since not all the apparatus will be suitable to be applied on such a complex system as the global commerce (Lovrić et al., 2018).

Not only the economic indicators per se were studied, but also who has been contributing to the field and its ties to the area. Through the employment of network analysis on the publications of the domain, Wood and Khan (2015) helped the visualisation of the theoretical work done by the academic community. In the study they found that the studied international commerce co-authorship network is relatively fragmented, moreover, the main authors and institutions on the network tend also to connect to central nodes, therefore configuring a power law distribution of importance on the field (Wood & Khan, 2015).

Within the domain of social network analysis (SNA), the prevalent approach examines interactions between actors in a network established through various relationships, such as friendship, cooperation, or international trade. However, this traditional method suffers from a binary limitation, solely acknowledging the existence or absence of a connection between actors without considering the strength of that link (de Andrade & Rêgo, 2018). The study done by Andrade and Rego contends that incorporating the weight of connections, alongside the individual characteristics of actors (represented as nodes), offers a significantly more nuanced and accurate understanding of the dynamic processes at play within networks (de Andrade & Rêgo, 2018). The authors present a groundbreaking methodology that integrates both edge weights and node attributes into the analysis of the international trade network, in this network, countries are depicted as nodes, with trade transactions serving as the links. The weight of each link is determined by the cash flow associated with the trade transaction, while a country's Gross Domestic Product (GDP) serves as its corresponding node attribute. By analysing the network through four distinct lenses – unweighted, edge-weighted, and two novel methods that combine both weights and attributes – the study endeavours to achieve a more comprehensive and insightful picture of the intricate web of global trade (de Andrade & Rêgo, 2018). This innovative approach unlocks a treasure trove of valuable insights into the network's structure. The analysis not only identifies the countries that are most interconnected and possess the highest financial significance within the network, but it also pinpoints the central players who act as facilitators for the flow of wealth across the network. Furthermore, the study sheds light on the countries that reap the greatest benefits from being integrated into this network. To further illuminate the most influential factors within the network, the authors employ a principal component analysis (PCA). This analysis reveals that metrics that incorporate both the weights of connections, and the attributes of the nodes hold the most significant influence in explaining the variability observed within the network data (de Andrade & Rêgo, 2018).

The work done by Johnson and Chew (2021) highlights the potential of SNA in international development, emphasizing its ability to reveal social, political, and economic dynamics, helping researchers and practitioners understand when it comes to analysing (Johnson, 2021).

These studies collectively demonstrate the effectiveness of SNA in uncovering the underlying structures and dynamics of international trade networks, leading to a more comprehensive understanding of trade patterns and their impact on economic growth.

Network analysis has also been used to identify key players, trade patterns, and potential vulnerabilities within the global soybean trade network. Schaffer-Smith et al. (2018) and Wang, Liu, Wang, & Li (2023) both found that a few key players, such as Brazil, China, and the USA, dominate the network, with the latter highlighting China's increasing vulnerability due to its heavy reliance on a few countries. After carrying out the study, total network density surged five-fold, with a shrinking number of countries dominating trade activities, raising sustainability and food security apprehensions (Schaffer-Smith et al., 2018). As a result, when certain unpredictable events happened, including trade frictions and shifts in the importing and exporting countries' policy decisions, China's soybean trade became more and more susceptible to being closely controlled by other nations (Wang et al., 2023). Brazil significantly influenced China's management of soybean trade routes, contrasting with the United States' lesser impact. Some experts suggest for China an equilibrium between domestic production and soybean imports emerges as imperative. Essential strategies include optimizing the import system and expanding trade partnerships. Moreover, enhancing soybean self-sufficiency stands out as a core approach to alleviate heavy import reliance. These findings offer valuable perspectives for navigating international market fluctuations and enhancing the sustainability of China's soybean trade (Wang et al., 2023).

Xavier & Reis (2022) and Kou, Xian, Dong, Ye, & Zhao (2018) further explored the competitive dynamics within the network, with Xavier focusing on the competition between

Brazil and the USA, and Kou studying the increasing closeness and reciprocity of trade relationships. These studies collectively demonstrate the utility of network analysis in understanding the structure and dynamics of the global soybean trade network. Due to its extreme competitiveness, it is important to better understand the agriculture market and soybeans are no different, the SNA helps it by identifying China as a shift factor since it encompasses 67% of imports (Xavier & Reis, Feb 1, 2022). The social network analysis also revealed the trend of role within the international community, revealing deeper insights into the relationships between trading countries and potential trends in the global soybean market, since it presented the network being reciprocal but with high heterogeneity, with some countries playing important roles in the international soybean trade market while some countries have less participation (Kou et al., Oct 22, 2018).

3.2. Trade Data

In my research, I meticulously analysed soybean trade between countries spanning the years 2000 to 2022. The data for this study was sourced from the World Bank's international database, known as the World Integrated Trade Solution (WITS), with the search refined using the Harmonized System (HS) code. My investigation encompassed the entire soybeans trade, including product group HS-1201 (soya beans, whether or not broken) and product code HS-120810 (soya bean flour and meal). The evaluation of these different networks forms the foundation of the analysis. To gain insights into the evolution of the structure and interactions among the participants over time, this process will be repeated for two additional periods, thereby covering a total of 20 years of trade.

To handle the data, I utilized software from the Microsoft Office suite. Network models were created using the Gephi network analysis and visualisation software. Python software was also employed throughout the research process to create an ETL (extract, transform, load) pipeline for subsequent analysis, insight generation, and visual image production for the project.

My comprehensive database includes various critical factors, such as Product code; Export country code (ReportISO3); Name of the exporting country (ReportName); Import country code (PartneISO3); Name of the importing country (PartnerName); Year; Trade Value (in USD 1000).

3.3. Complex Network Analysis

Network Analysis methodology enables researchers to unravel the complexities of international trade, facilitating informed policy decisions and fostering a deeper understanding of economic interactions across borders (Sajedianfard et al., 2021). In the realm of understanding international trade dynamics, network analysis emerges as a powerful tool. By examining the intricate web of trade relationships between countries, researchers gain valuable insights into global commerce. This method allows us to explore the underlying structure of trade networks, revealing patterns, vulnerabilities, and opportunities.

The traditional network analysis tools are often categorized into two different groups according to their application:

Study of the network actors: these tools are meant to grasp the node's role within the network, e.g.: node-degree, node-strength, centrality-degree, and betweenness-centrality.

Study of structural properties: these tools help to analyse the network characteristics, e.g.: clustering coefficient and path length.

Thus, in this section, firstly, the single layer measures will be described, moreover, inside this section the indices measuring the node's activity will be firstly presented, followed by the structural properties' explanation. Secondly, a brief explanation of the multiplex analysis and its tools will be presented.

3.3.1. Single-layer analysis

We first conducted a traditional network analysis to examine the structural properties of the network. We calculated a range of centrality measures, including degree centrality, betweenness centrality, and eigenvector centrality, to identify the most important nodes in the network. We also examined the degree distribution, clustering coefficient, and modularity of the network to understand its overall structure and organization.

In this first part, the data of both products are analysed separately, with a single layer composing the data of ten years of countries' exports. Bellow a brief explanation about each metric is detailed.

Node-degree

Node-degree is referred to represent the number of links a given node has on the studied network, so in the international trade case, it represents the number of partners the country interacts with y (Fagiolo et al., 2010). The equation correspondent to it is given by the following:

$$d_i = \sum_j a_{ij} \quad (1)$$

Where d then represents the number of edges connected to the studied partner i, which represents the index, in the research case the partner, and finally stands for the adjacency matrix.

Node-strength

The strength as the name already indicates, tells us about the intensity of the partner connection within the network. The current research will therefore represent the amount traded between the different countries (Fagiolo et al., 2010). This can be achieved through the equation bellow, where s is the sum of all the values w a partner has with all the other nodes in the network.

$$s_i = \sum_j w_{ij} \ (2)$$

Degree Centrality

This definition encompasses the number of links incident upon a node, in other words, it is the number of ties that a node has. Since the present study uses a directed network (country A can export to country B, but the contrary is not necessarily true), then there are two possible methods to compute it varying according to the ties' direction: an outdegree is the number of edges going to other, whereas indegree counts the number of ties directed to the node studied (Freeman, 1978). Therefore, in these situations, the degree of centrality is the sum of both measures. The degree of centrality might be associated with the importance a node has among the networks since the more links a partner has the more influence and relevance it may have overall (Hanneman & Riddle, 2011)

Betweenness Centrality

Betweenness centrality is a metric, which is defined as the number of times a node i requires another node k to reach another node j through the shortest path, in other words, if let`s say a person i wants to close a deal with a person j, but this person does not have direct access to person j, consequently the integration of a third person is required in order to close this deal. Therefore, it can be understood as the control a given node has within the network, since a vast volume of links are being done through it (Borgatti, 2005; Freeman, 1978; Hanneman & Riddle, 2011).

Closeness Centrality

There are some ways to find how close a node is to any other element on the network, these different methods of measure are grouped under the closeness centrality family (Jackson, 2010). One of the main and most obvious kinds of closeness-based approach is computing the average shortest distance from a node i to each other node. The result of this computation can tell how central a node is to the network, giving a sense of the partner`s importance relative to the entire group studied.

Eigenvector Centrality

This centrality measure tries to capture the qualitative standpoint of a network, the basic premise of this measure is the assumption that having more contacts or partners related to a node is not the most important feature to have on a network, but having important ones is the main criterion to reveal the importance of a node (Hansen et al., 2011). In the Eigenvector centrality method, one assigns scores to all nodes in the network that indicate the relevance of a given node on the network's context, those scores are attributed taking into consideration a connection to a high-scoring node delivery more to the score than an equal connection to a low-scoring one (McKnight, 2014)

PageRank

Similar to the previous method explained, there is an algorithm used by Google called PageRank. This calculation is constantly associated with web search engines since it tries to evaluate the importance of a given result based on the query searched and return a high-quality match for the user input (Brin & Page, 1998). This algorithm takes into consideration the number and importance of other sites that link to a site, in other words, the quantity and relativeness of the links to node i, additionally to the tendency of those links also be connected to other partners (Hansen et al., 2011)

Clustering coefficient

The first structural measure presented is the clustering coefficient C(p), it analyses the degree to which economies tend to cluster together by measuring the chance that any two neighbours of a group S are also connected to each other, in other words, it gauges the cliquishness of a typical friendship circle by reflecting the amount to which p's friends are also friends of each other (Chen, B. et al., 2018; Watts & Strogatz, 1998).

$$C_p = \frac{E_p}{n_p \times (n_p - 1)} \quad (3)$$

The equation above can be understood with p representing a node, and the coefficient can be computed using the total number of edges (Ep) divided by all the possible connections among the neighbours (np) adjacent to this node.

Characteristic Path Length

Path length measures the typical separation between two nodes in the graph, this index is a global property, and the characteristic path length index represents the average separation between two nodes in the data studied, or in the research case, the average separation between two countries (Chen, B. et al., 2018; Watts & Strogatz, 1998).

Jeffrey's Divergence

Jeffrey's divergence *J(P‖Q)* quantifies the difference between two probability distributions *P* and *Q*. It is symmetric and based on the Kullback-Leibler divergence, adapted to be symmetric and have other useful properties (Bródka et al., 2018). The formula for Jeffrey's divergence between two probability distributions *P* and *Q* is:

$$J(P \parallel Q) = \sum_i P(i) \log\left(\frac{P(i)}{M(i)}\right) + \sum_i Q(i) \log\left(\frac{Q(i)}{M(i)}\right) \quad (4)$$

Where:

$$M(i) = \frac{P(i) + Q(i)}{2} \quad (5)$$

3.4. Kolmogorov-Smirnov test

The Kolmogorov-Smirnov test (K-S test) is a non-parametric statistical test that does not assume any particular underlying data distribution (Conover, 1999; Massey Jr, 1951). In the context of this thesis, the K-S test was applied to determine whether the distributions of key network metrics (e.g., degree and centrality measures) within the soybean trade network conformed to a normal distribution. This diagnostic step was foundational, as the resulting departure from normality necessitated the transition from parametric to non-parametric inferential statistics. Consequently, the K-S test results directly informed the selection of the Spearman rank correlation for the subsequent analysis of trade participation.

3.5. Spearman rank correlation

The Spearman rank correlation coefficient, often referred to as Spearman's rho (ρ), measures the strength and direction of monotonic associations between variables, regardless of their distribution (Hollander et al., 2013).

This method is particularly robust against the non-linearities often inherent in trade data. Specifically, this analysis was deployed to assess the relationship between a country's network position, as defined by degree and closeness centrality, and its Revealed Comparative Advantage (RCA). By correlating these metrics, the study elucidates how a nation’s structural integration within the export network relates to its competitive specialisation in the global soybean market.

3.6. Jaccard Index

The Jaccard coefficient, also known as Intersection over Union (IoU), is a similarity measure that quantifies the common elements between two sets relative to their union (Survarachakan et al., 2022). In network analysis, the Jaccard Index is a commonly used measure of similarity between two sets, which in this context are the sets of directed edges in the soybean and soy flour trade networks. The decision to use the Jaccard Index in this analysis is justified by its simplicity and interpretability. It provides a straightforward way to quantify the overlap between two networks, making it easy to understand and communicate the degree of similarity.

The Jaccard Index is particularly well-suited for comparing networks where the focus is on the presence or absence of edges rather than the intensity or weight of these connections. In this research, the index is used to measure the commonality between the sets of directed edges (trade relationships) in the soybean and soy flour networks. By focusing on the presence or absence of specific trade routes, the Jaccard Index provides critical insights into the structural differences between these two commodities. It quantifies the extent to which trade architectures remain consistent across different stages of the value chain, relative to the total number of unique trade routes identified.

It is calculated using the formula:

$$J(W_1, W_2) = \frac{|W_1 \cap W_2|}{|W_1 \cup W_2|} \quad (6)$$

Where W1 and W2 represent two sets, which, in our case, correspond to the 1-year windows of the ego networks. The Jaccard coefficient ranges from 0 to 1, with 0 indicating no overlap and 1 indicating complete overlap between the sets (Arnaboldi et al., 2015).

3.7. Balassa Index

The Balassa Index, widely known as the Revealed Comparative Advantage (RCA) Index, is a quantitative measure used to assess a country's relative advantage or specialization in the export of a particular commodity, compared to the global export average. Originally introduced by Béla Balassa (1965), the index is extensively used in international economics to analyse patterns of trade competitiveness across countries and sectors.

The Balassa Index (RCA) is calculated as the ratio between the share of a product in a country’s total exports and the share of that product in total world exports. Formally, as follows:

$$RCA_{ij} = \frac{\left(X_{ij}/X_{it}\right)}{\left(X_{nj}/X_{nt}\right)} \quad (7)$$

Where, X_{ij} is the export value of product j by country i. X_{it} is the total export value of all products by country i. X_{nj} is the total export value of product j by all countries, and X_{nt} is the total export value of all products by all countries.

An RCA value greater than 1 ($RCA > 1$) indicates that a country has a revealed comparative advantage in exporting that product, whereas $RCA < 1$ suggests a comparative disadvantage.

The Balassa Index’s methodological simplicity and alignment with observed trade flows make it a standard tool in empirical studies of trade specialization and competitiveness (Balassa, 1965; Yu, R. et al., 2009). Its application here provides valuable insights into trade dynamics, complementing network metrics and other indices used throughout the analysis.

Table 2. Summary of work done

Phase	Description
Data Collection	Conducted a comprehensive literature review using Scopus and Google Scholar, with quality assessment via Scimago. Collected soybean trade data (2000–2022) from the World Integrated Trade Solution (WITS) database for HS-1201 (soya beans) and HS-120810 (soya bean flour and meal). Data includes product code, export/import country codes and names, year, and trade value (USD 1000). Review split into network research and soybean-specific studies.
Data Processing and Visualisation Tools	Handled data using Microsoft Office suite. Created network models with Gephi. Developed an ETL pipeline and generated visualisations using Python
Single-Layer Network Analysis	Analysed structural properties of soybean and soy flour trade networks over 20 years, repeated for multiple periods. Calculated centrality measures to identify key nodes and examined network organization.
Structural Properties Analysis	Evaluated network characteristics to understand clustering and connectivity patterns.
Statistical Analysis	Quantified differences and correlations in network metrics using nonparametric tests due to non-normal data distributions.
Multiplex Network Analysis	Compared soybean and soy flour trade networks using layer-by-layer, distribution, and individual structure approaches to assess structural differences.

4. RESULTS AND DISCUSSION

This chapter presents the empirical findings of the network analysis of soybean and soy flour trade and interprets them in relation to the research questions and hypotheses formulated in Chapter 1. The section is organized around the three research questions (RQ1–RQ3), to make the decisions on the hypotheses (H1–H5) more visible and coherent.

4.1. RQ1 and H1: Global Soybean Trade Patterns

RQ1 – What is the global diffusion trade pattern of soybeans among countries?

H1 – In the world international trade of soybeans, new economic countries are the exporters while developed countries are the importers of this commodity.

To answer RQ1 and test H1, I first examine the overall topology of the soybean trade network and then analyse the economic development level of net exporters and importers.

4.1.1. Global Topology of the Soybean Trade

In this chapter, an exhaustive examination of soybeans is conducted employing a sophisticated complex network methodology. To begin, a visually compelling network representation is presented in figure 12, highlighting export trade flows. The colour scheme is dedicated to illustrating the number of soybeans exported by each country in US dollars, with the darker colour representing higher export values. Furthermore, the size of nodes corresponds to the number of trade partners associated with each node, while the thickness of edges visually represents the volume of trade between interconnected nodes.

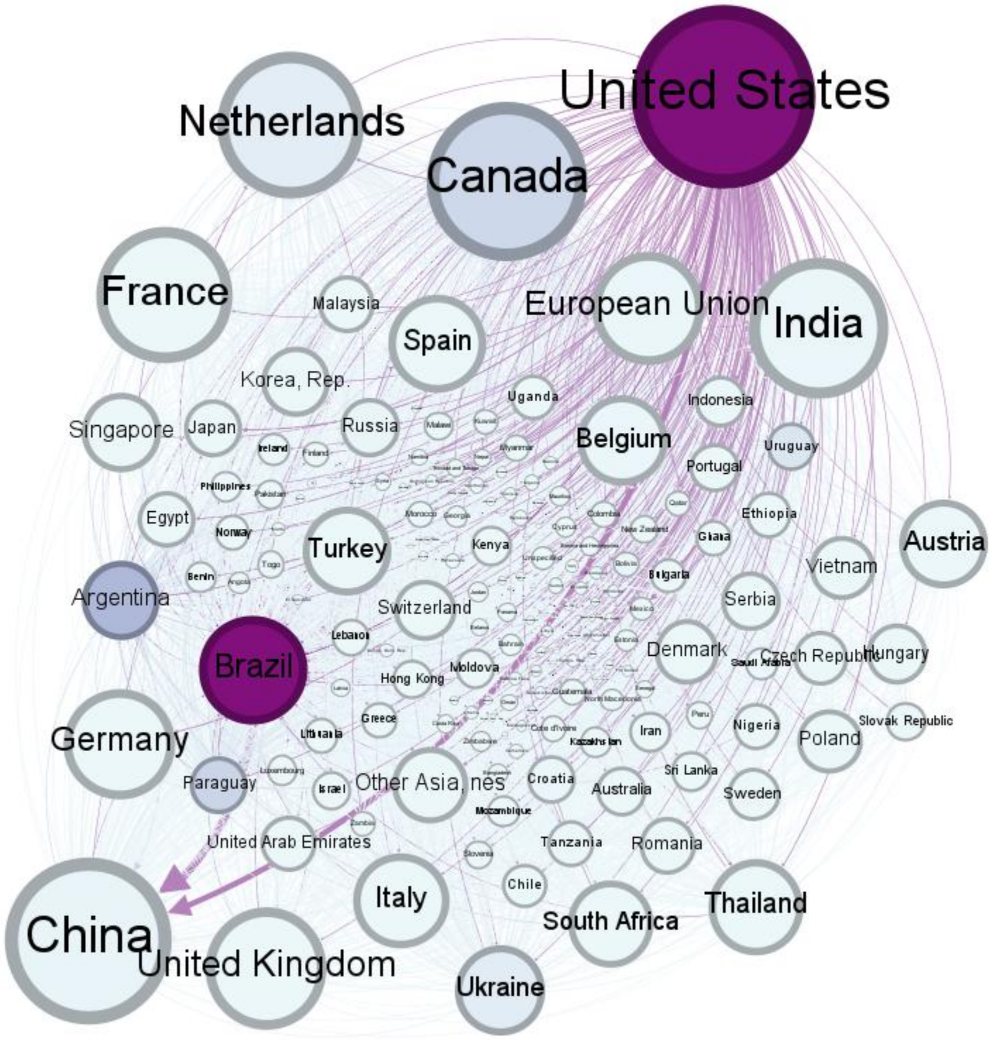

Figure 12. Soybeans export network 2003-2022

Size represents degree, colour the weighted degree, and edges the volume traded

Source: UN Comtrade database; network visualisation created using Gephi, edited by the author

This network provides us with some interesting interpretations of the global soybean supply chain during recent years. There are only a few large exporters of soybeans: Brazil, the United States, and Argentina, this consequently suggests that the global soybean supply chain is relatively centralized, with a few key players dominating the market. This could make the industry vulnerable to shocks, such as crop failures or political instability in major exporting countries.

Another interpretation of the network is that it represents the relationships between countries that are involved in the soybean trade. The thicker edges between countries represent stronger trade relationships. For example, the thick edges between the United States and China, as well as between Brazil and China suggest that the two export countries have a strong economic relationship and that soybeans are an important export for the United States and Brazil and an important import for China.

In order to illustrate the largest importers, the soybeans network in figure 13 depicts the soybean demand chain. This model visually shows very well which countries stand out in the network by purchasing the beans, since the colour of each node represents the number of soybeans imported by that country, weighted in-degree, with darker colours representing higher export values.

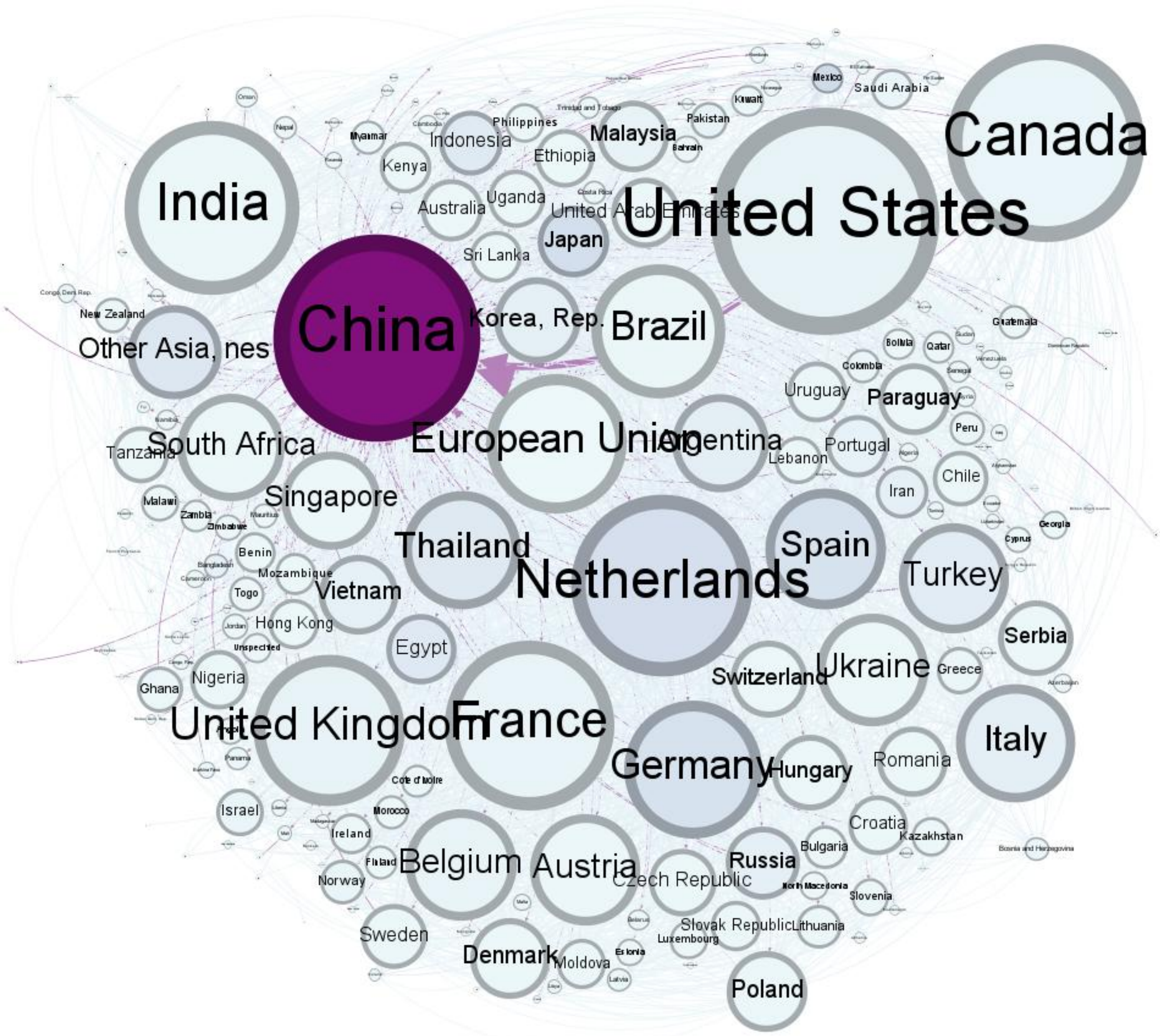

Figure 13. Soybeans import network 2003-2022

Size represents degree, colour the weighted degree, and edges the volume traded

Source: UN Comtrade database; network visualisation created using Gephi, edited by the author.

This network reveals China's dominance as the top soybean importer, followed by the European Union countries and Japan. While Brazil and the United States reign as the world's soybean exporters, their role in soybean imports remains relatively modest, underscoring the distinct dynamics of the global soybean market.

There are other ways also to visualise the importance of the nodes within the network, in other words, by observing other types of indexes and interpreting them accordingly. One example of that is the betweenness centrality measure. In the dataset of the period analysed out of the 231 node studies, 87 presented a betweenness centrality of 0, meaning that the node does not lie on any shortest paths between other pairs of nodes in the network. Thus, no shortest path between any two other nodes in the network passes through this node. Consequently, this node does not play a role in the communication or flow of information between other nodes in terms of shortest paths. Additionally, one can conclude that these nodes are peripheral and not critical for connecting different parts of the network. Removing them does not significantly impact the shortest path structure of the network because they are not pivotal for maintaining shortest path routes and consequently nodes with zero betweenness centrality have minimal influence in controlling or facilitating the flow of information across the network. They do not act as bridges or mediators between other nodes.

Taking that into account, I decided to filter out nodes with low betweenness values in order to better evaluate the network visualisation. In that regard, I selected only nodes with betweenness centrality higher than 100. The colour and size of the nodes in the network depicted in Figure 14 represent the number of this metric, with darker colours representing higher betweenness centrality values. What is easily observed is the prominence of the United States, which is the country with the highest value in this metric. What follows the previous two networks, that presented this country with a high volume exported and also with several parts, either for inflows or outflows. China comes second in the ranking, also in accordance with the previous images. It is remarkable the low importance of some producer countries, such as Argentina and Brazil, when taking this metric into account.

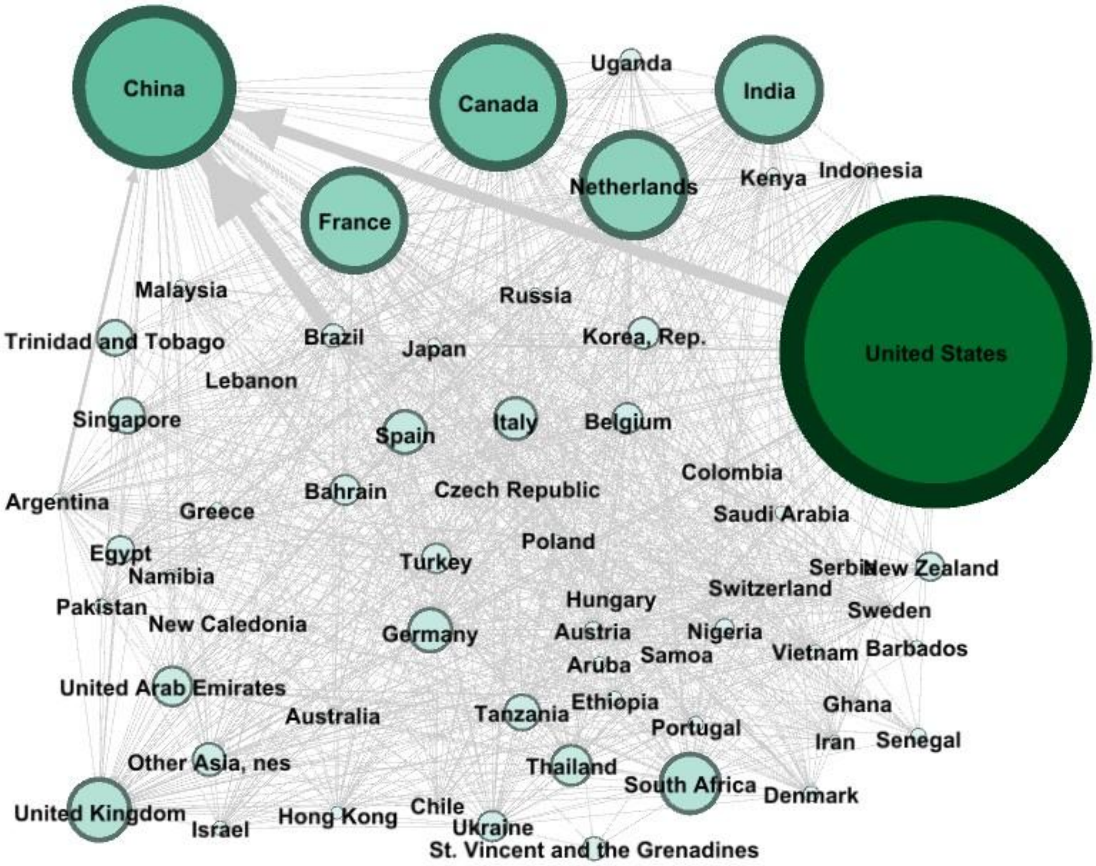

Figure 14. Soybeans betweenness centrality network 2003-2022

Source: UN Comtrade database; network visualisation created using Gephi, edited by the author.

Closeness centrality is another way to visualise the importance of nodes within the network. In the dataset of the period analysed, out of the 231 nodes studied, 83 presented a closeness centrality of 0, indicating that these nodes are completely disconnected from the rest of the network. This means these nodes cannot reach any other nodes because there are no paths leading to or from them. Consequently, these nodes are entirely isolated in terms of network connectivity. Additionally, one can conclude that these nodes are peripheral and do not participate in the overall communication or flow of information within the network. Removing them does not impact the network's efficiency in terms of information flow because they are not connected to any other nodes. Therefore, nodes with a closeness centrality of 0 have no influence on the network's structural integrity or connectivity and do not contribute to the overall cohesiveness of the network.

In contrast, nodes with high closeness centrality have shorter average path lengths than all other nodes in the network. These nodes are crucial for efficient information dissemination and are centrally located within the network. They play significant roles in maintaining the network's connectivity and can be considered important hubs or key nodes for communication pathways. Understanding the distribution of closeness centrality within a network can provide insights into the network's structure and identify critical nodes that facilitate efficient communication and information flow. This analysis is essential for understanding the robustness and efficiency of networks, whether they be social, transportation, biological, or other types of complex networks. The colour and size of the nodes in the network depicted in Figure 15 represent the number of this metric, with darker colours representing higher closeness centrality values. To be specific and have a clearer picture, I chose nodes only whose closeness centrality was more than 0.5.

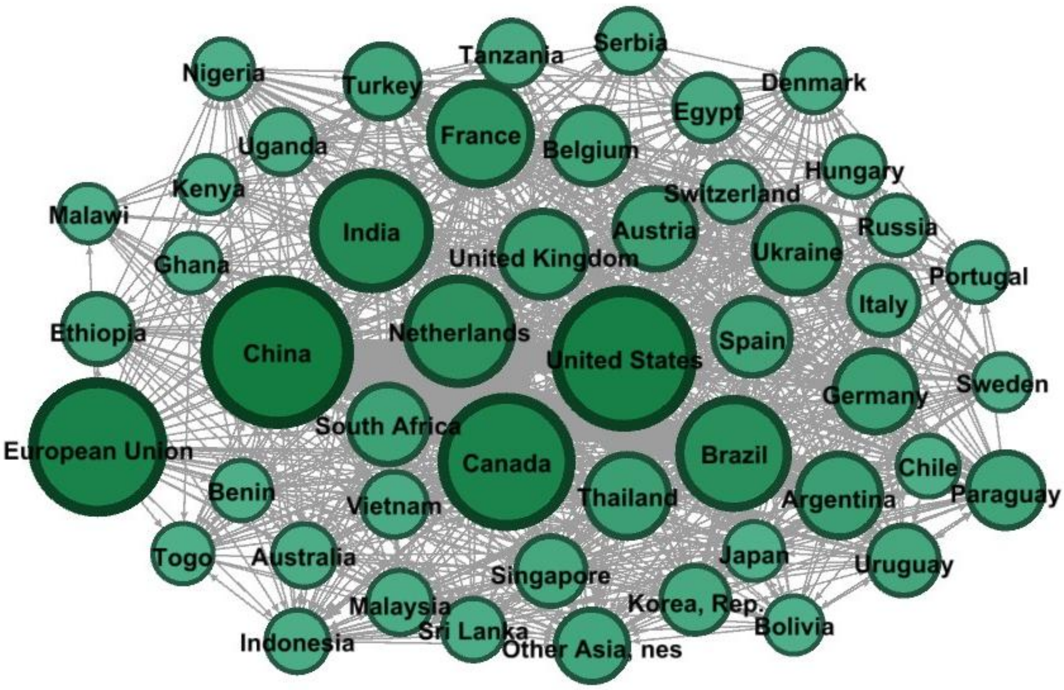

Figure 15. Soybeans closeness centrality network 2003-2022

Source: UN Comtrade database; network visualisation created using Gephi, edited by the author.

It is noticeable that this index presents a more uniform distribution of the values across the network, this pattern can be complemented by the illustration of the histogram of this network metric. In Figure 16 it is evident the high number of 0 values, but apart from that, the other values form a shape similar to what is expected from a normal distribution, with many values concentrated in the middle and just a small number of values in the high end of the tail.

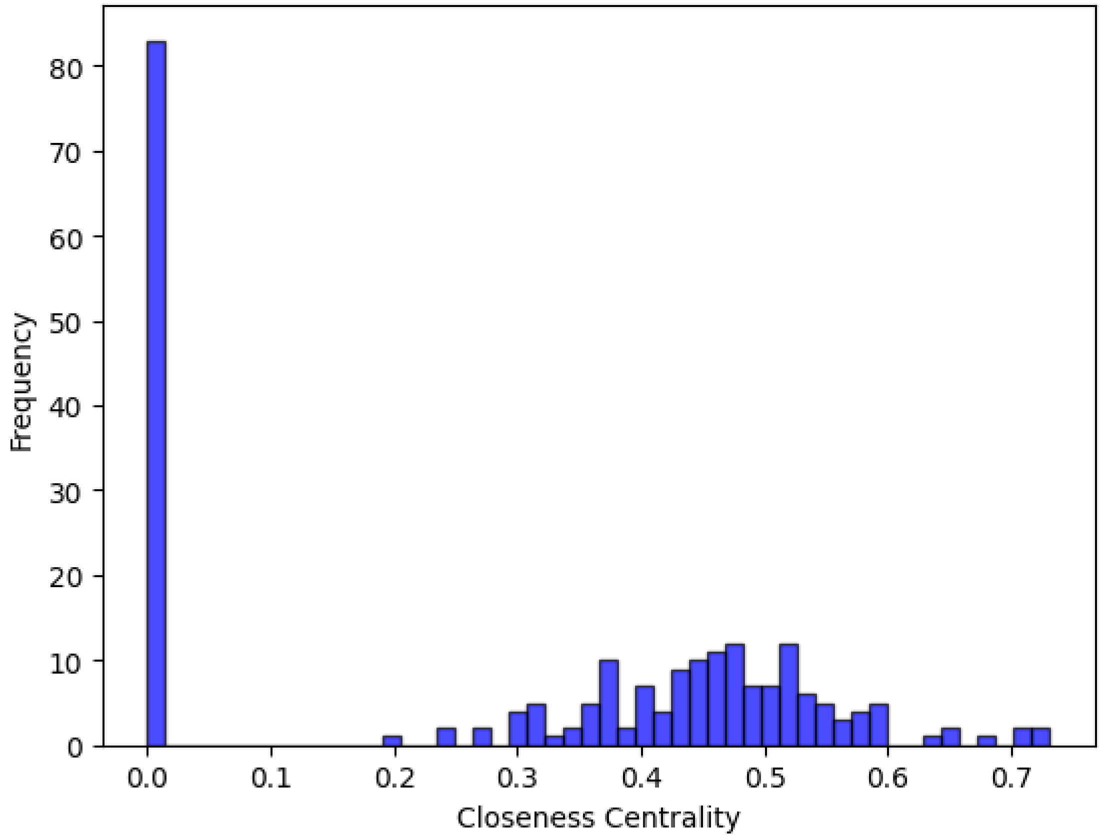

Figure 16. Soybeans closeness centrality distribution

Source: UN Comtrade data visualised using Python (Matplotlib); figure prepared by the author.

There are other ways to visualise the importance of nodes within the network such as observing different types of indexes and interpreting them accordingly. One example of this is the eigenvector centrality measure. In the dataset of the period analysed, out of the 231 nodes studied, I decided to filter out values below the threshold of 0.5 in order to give a clearer picture of the network and exclude nodes that do not have significant influence within the network because eigenvector centrality measures not only the direct connections of a node but also the centrality of its neighbours. Nodes with a low eigenvector centrality for instance are typically more isolated or connected to nodes that are themselves not central. Thus, they do not play a significant role in the network's overall connectivity or the dissemination of information. Removing these nodes would not impact the structure or dynamics of the network significantly, as they do not contribute to the network's main pathways or critical hubs. This analysis highlights the peripheral nature of these nodes and their minimal influence on the network's overall connectivity and functionality. In Figure 17 below, we observe the node size and colours representing the value of this metric, with darker colours and bigger nodes representing higher eigenvector centrality values. As the image shows, we can see the high influence and importance of the United States, as already observed in the previous networks. However, another point worth mentioning is the absence of the main producers of the commodity in the graph.

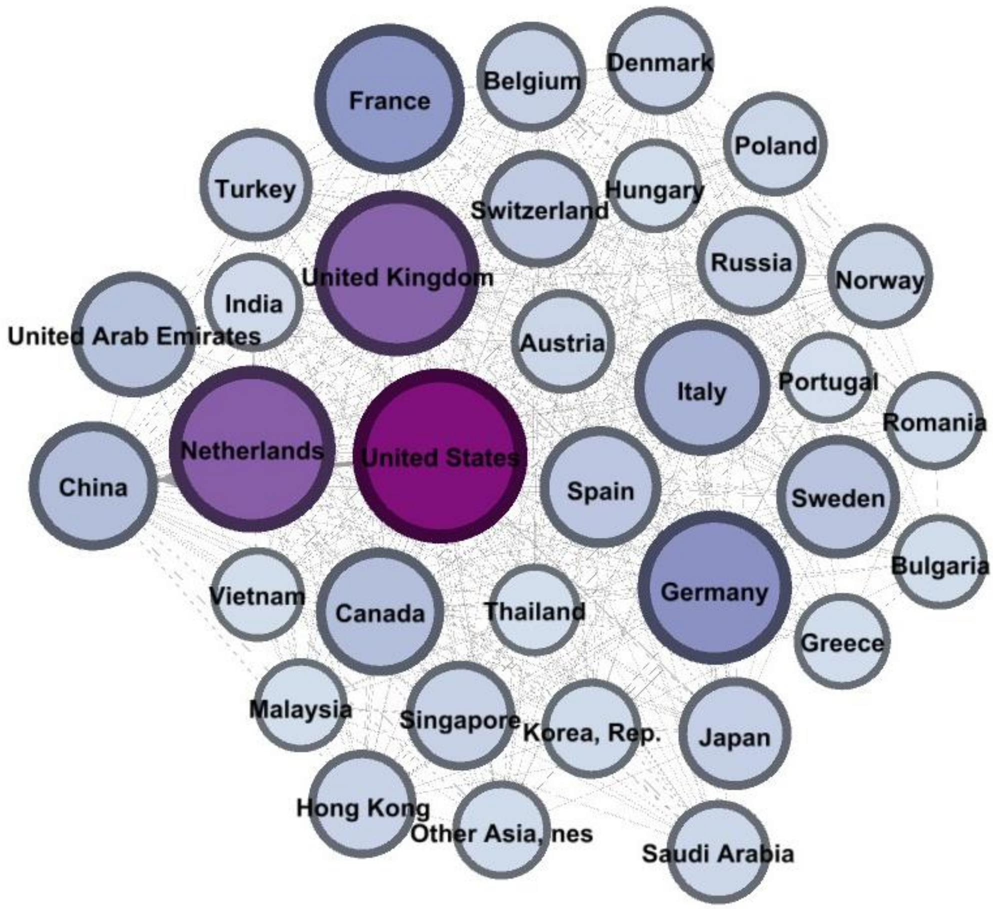

Figure 17. Soybeans eigenvector centrality distribution

Source: UN Comtrade database; network visualisation created using Gephi, edited by the author.

An additional point to complement this analysis is the distribution of the eigenvector values across the network. In Figure 18 it is possible to observe a high concentration of lower values, with just a few countries having this metric with a number higher than 0.5.

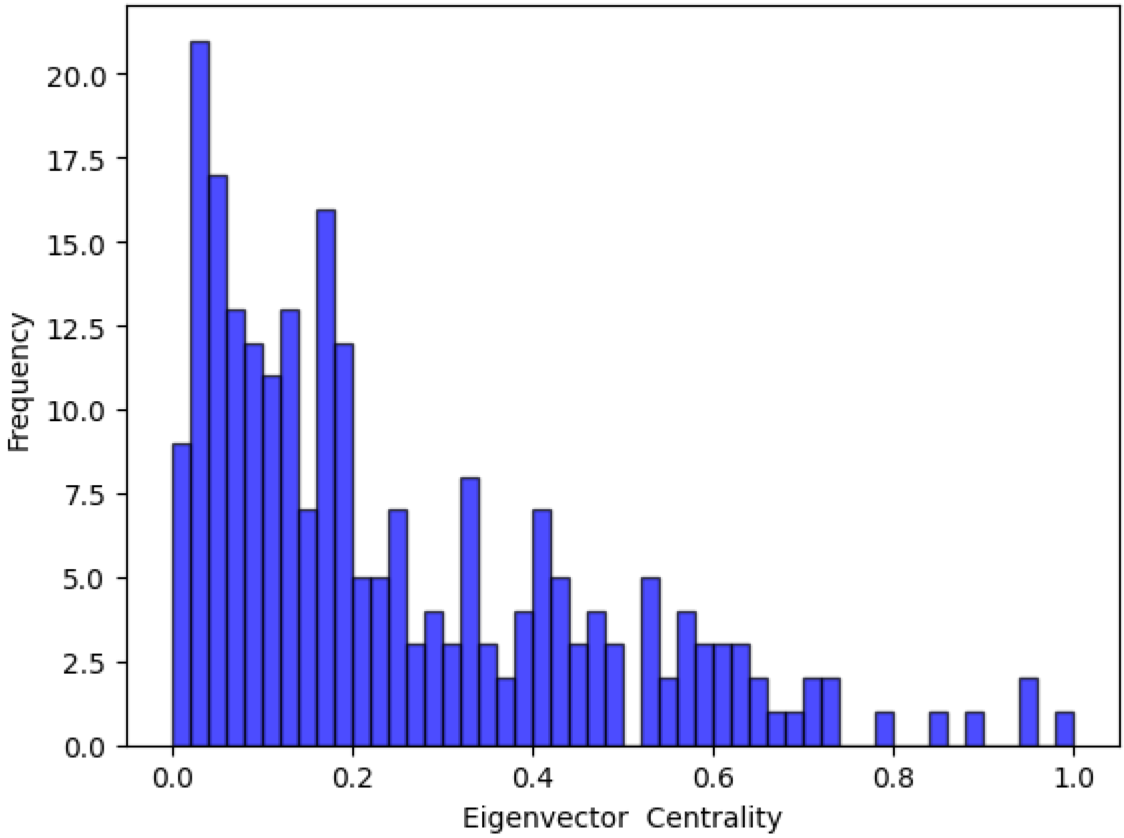

Figure 18. Soybeans eigenvector centrality distribution

Source: UN Comtrade data visualised using Python (Matplotlib); figure prepared by the author.

Progressing with the analysis, after visualising the network, it is also important to take a look at the network indicators, to capture some notions that sometimes are not be obvious by only glancing at an image. An overview of the main indicators is displayed in Table 3.

Based on the network indicators it can be said that a total of 231 countries participated in the trade network during the examined period, among which 3751 connections were established.

Table 3. Metrics of the soybean network between 2003 and 2023

Metric	Implication	Value
Nodes	Number of countries participating in trade	231
Edges	Number of trade relations	3751
Clusters	Number of clusters	4
Density	The level of trade relations between countries	0.071
Modularity	The degree to which a network's nodes can be partitioned into highly interconnected clusters or modules	0.206
Average Distance	How many connections there are on average between any two nodes	2.28

Source: Own editing (2024)

In order to visualise the different clusters in the network I provide an image displaying the nodes based on their classes, shown in Figure 19. The node's size again represents the number of edges, while the colours display the modularity class the node belongs to. Despite the presence of four clusters, the network can be effectively categorized into two primary clusters, with the remaining two clusters representing smaller groups of interconnected countries. Cluster 1, the most prominent, comprises 115 countries, including the United States, China, Brazil, and Canada. Cluster 2, the second largest, encompasses 108 countries, including Germany, Italy, Thailand, and Ukraine. Cluster 3, with only six nodes, is centred around Hong Kong and Uruguay, while Cluster 4, the smallest, consists of just two countries: Nicaragua and Honduras.

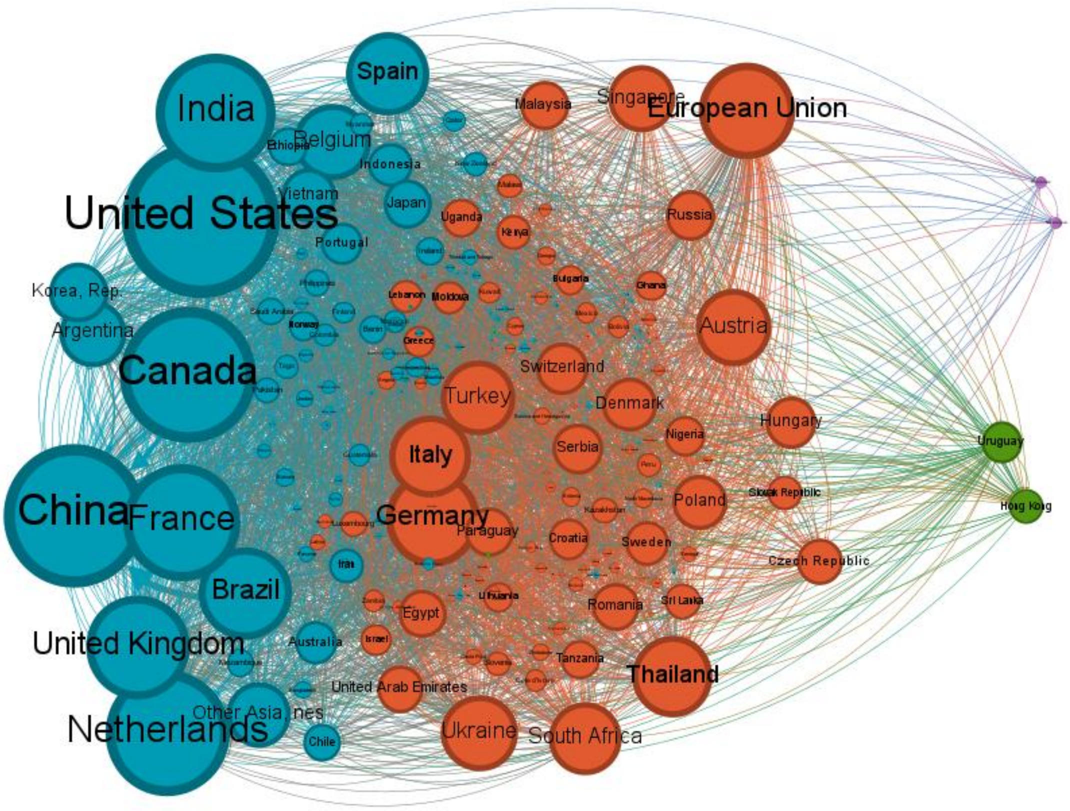

Figure 19. Soybeans clusters network 2003-2022

Source: UN Comtrade database; network visualisation created using Gephi, edited by the author.

Table 4 delves into the soybean trade network between 2003 and 2022, specifically scrutinizing incoming soybean shipments to each country. It identifies the top 10 countries based on the number of soybean trading partners and the total amount of soybeans imported during this period, represented by indegree and weighted indegree, respectively.

Examining the in-degree column, we see that the United States stands out as the country with the highest number of soybean trading partners, having established purchasing connections with 79 different nations during the analysed period. This implies that the United States is a major hub for soybean trade, serving as an important importer for a wide range of nodes. Notwithstanding the role of the United Kingdom, the Netherlands and France also are remarkable, having been supplied by more than 60 different connections.

Table 4. Import indicators of the countries in the Soybeans network, 2003 to 2023

Ranking	Country	Indegree		Ranking	Country	Weighted Indegree
1	United States	79		1	China	511.44
2	United Kingdom	68		2	Mexico	35.63
3	Netherlands	66		3	Japan	30.44
4	France	61		4	Netherlands	29.84
5	Germany	59		5	Spain	27.06
6	Canada	56		6	Germany	27.04
7	Italy	56		7	Taiwan	19.88
8	United Arab Emirates	55		8	Thailand	18.41
9	China	54		9	Egypt	17.26
10	Spain	49		10	Indonesia	16.58

Source: Own editing (based on the UN Comtrade database)

China reigns supreme in the soybean trade landscape, with a weighted indegree that far surpasses that of the second-ranked country, Mexico, by an astonishing 14 times. This dominance can be observed visually in Figure 20, which depicts the distribution of weighted indegree trade across the network's nodes. China's overwhelming position is evident, reflecting its immense influence in the global soybean trade network.

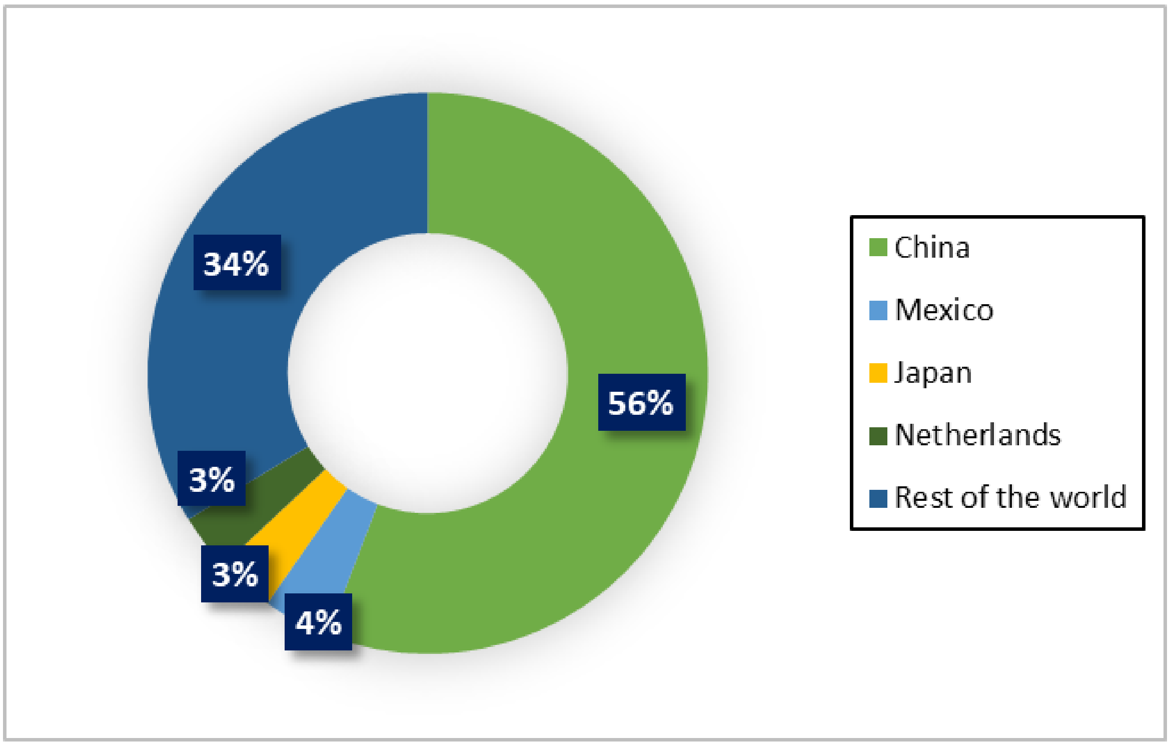

Figure 20. Soybeans Weighted Indegree share, 2003 - 2022

Source: UN Comtrade data visualised using Python (Matplotlib); figure prepared by the author.

Being consequently a major country within the network. Despite this overwhelming dominance, China's soybean imports are more concentrated, relying on a smaller number of major trading partners. This highlights the intricate dynamics of the soybean trade network, where the sheer volume of imports does not always equate to a diverse supplier base.

Table 5. Export indicators of the countries in the Soybeans network, 2003 to 2023

Ranking	Country	Outdegree		Ranking	Country	Weighted Outdegree
1	China	146		1	Brazil	379.62
2	United States	141		2	United States	363.49
3	European Union	135		3	Argentina	58.10
4	Canada	135		4	Paraguay	31.20
5	India	122		5	Canada	28.69
6	Brazil	113		6	Uruguay	16.03
7	Netherlands	109		7	Ukraine	10.19
8	France	103		8	Netherlands	9.55
9	Ukraine	80		9	China	2.97
10	United Kingdom	78		10	Russia	1.91

Source: Own editing (based on the UN Comtrade database)

Shifting our focus to the metrics related to outgoing soybean shipments, Table 5 reveals a different set of countries. However, some of them are already presented in the previous table, such as the United States, Canada, France, Netherlands, and the United Kingdom, which in turn can be interpreted as these nodes serving as a bridge between other nodes in the network. When considering the volume of soybean exports, Brazil and the United States emerged as the undisputed powerhouses, surpassing the third-ranked country by a staggering factor of six in the list during the analysed period.

A comprehensive analysis of both tables unveils a handful of pivotal nodes that command influence across both import and export flows. These include China, the United States, Canada, the Netherlands, Germany, and France. Their presence in both tables underscores their multifaceted roles as trading hubs and key players in the global soybean market. Additionally, the significant contribution of South American countries as soybean suppliers further highlights the network's diversity and interconnectedness.

Overall, the table provides valuable insights into the complex structure of the global soybean trade network, showcasing the United States, China, Mexico, Japan, the Netherlands, Spain, and Germany as key players shaping the flow of soybeans between nations from an import perspective.

4.1.2. The Economic Geography of Soy

In order to test what are the exporters' players the first step was to classify the different nodes on the network accordingly. For that a simple comparison was established, verifying the amount imported versus the amount exported, to classify if the country was an exporter or an importer. This first classification resulted in 29 exporters and 202 importers. Another important classification to consider is the definition of new economic countries or developing countries. The chosen approach was to consider the HDI (Human Development Index) mean for the studies period and then countries presenting a value lower than 0.8 would be considered developing countries.

As can already be observed in Table 5 there are some developed countries on the top exporter's indicators, such as the United States, Canada, Netherlands, France, and the UK. Among the 29 net exporters (Figure 21), 67.9% are classified as developing countries based on an HDI threshold of 0.8, confirming that exporters are predominantly new economic countries, whereas the main importers are developed. Therefore, H1 is accepted.

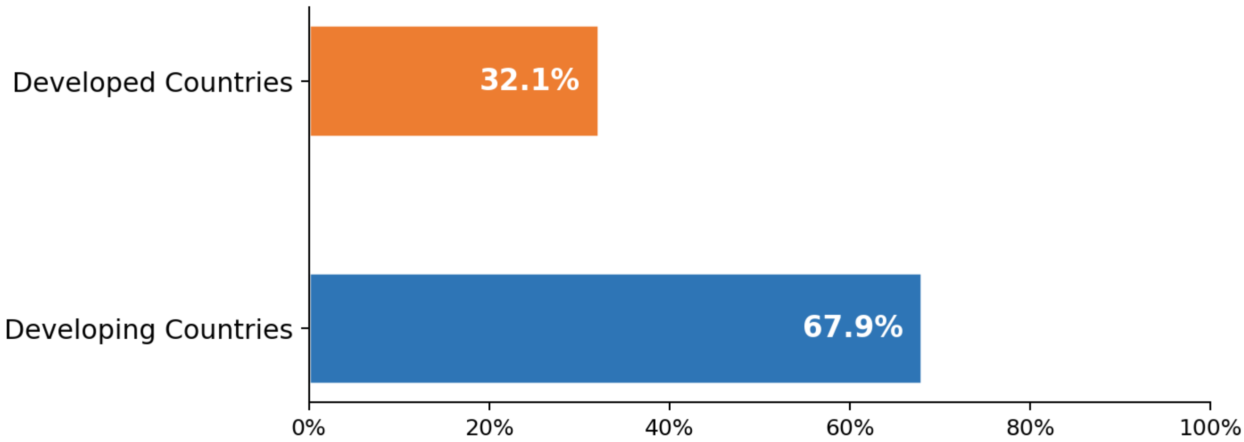

Figure 21. Soybeans Net Exporters by HDI

Source: UN Comtrade data visualised using Python (Matplotlib); figure prepared by the author.

4.2. RQ2 and H2–H3: Structural Influence and Market Stability

RQ2 – How have the dynamics of trade players evolved during the last 20 years and what players have been dominating the market during the last 20 years?

H2 – The exporters of soybeans have more influence within the network and are less susceptible to negative impacts caused by unforeseeable outbreaks, while importers, despite their significance, play a relatively weaker role.

H3 – The soybeans market is stable and challenging for new entrants to enter.

To address RQ2 and test H2 and H3, I compare the structural influence of exporter and importer nodes and analyse the temporal evolution of network indicators and key players.

In order to test whether the exporter's players are more influential in the network than the importers, the first step was to further the analysis based on the classification done before where the importers and exporter's players on the network were segregated into two groups. Another important step in the test of the hypothesis is the determination of what influential means in the network context. For that, the eigenvector centrality index was selected since it is a measure of the influence a node has in a network. It is based on the idea that the more connected a node is too high-centrality nodes, the more influential it is (Newman, 2018; Wasserman & Faust, 1994). This is because high-centrality nodes are more likely to spread information and ideas throughout the network.

Figure 22 shows the distribution of the Eigenvector along the two classes. We can observe that there are significantly more countries classified as importers than exporters, with the exporter group presenting a mean of 0.31 and the importers a mean of 0.23. To verify the difference between the two groups, the Kolmogorov-Smirnov test was applied. The test yielded a p-value of 0.010, which is less than the 0.05 threshold for statistical significance. Therefore, the null hypothesis is rejected. This means that there is a statistically significant difference in the distribution of Eigenvector centrality between exporters and importers.

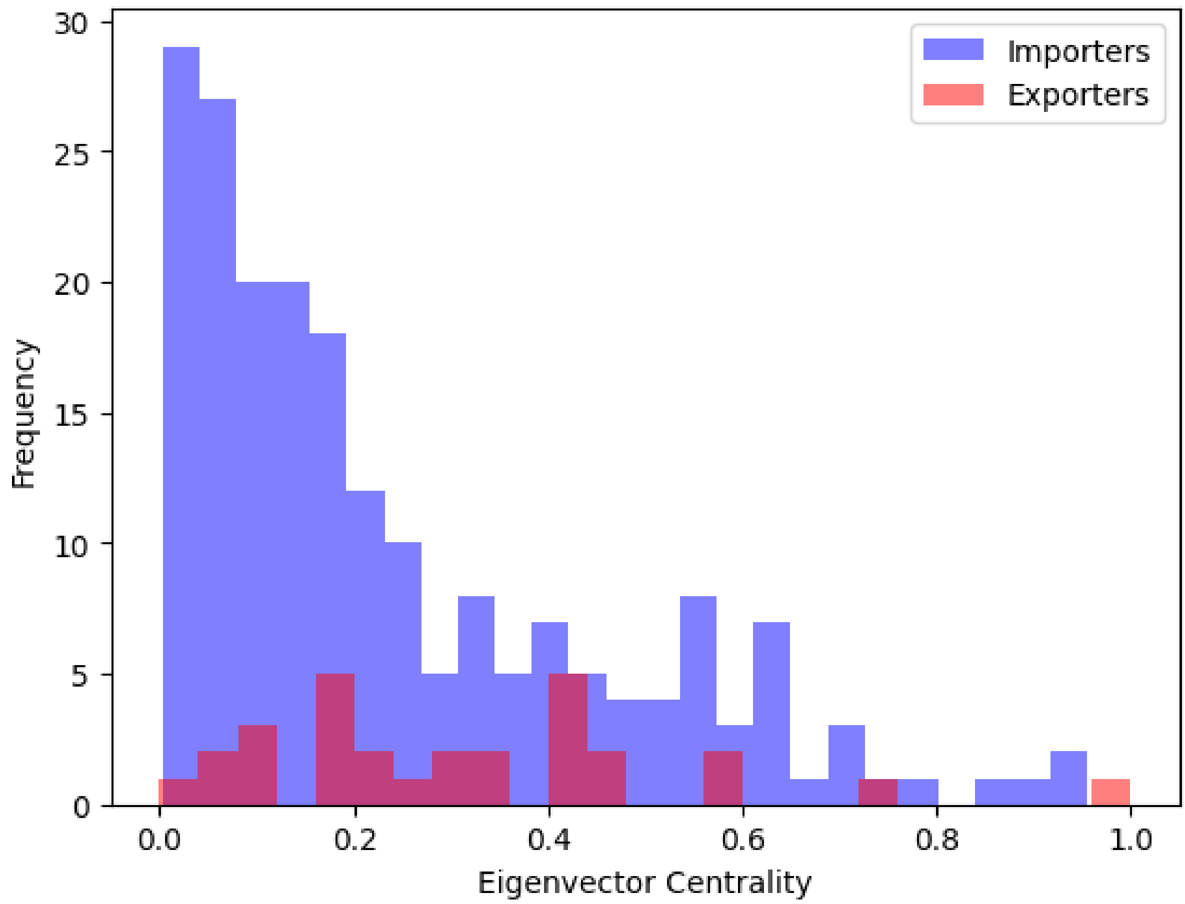

Figure 22. Eigenvector distribution for Exporters and Importers

Source: Data visualised using Python (Matplotlib); figure prepared by the author.

Another intriguing observation gleaned from the data is the relationship between the number of trading partners a node possesses and its overall importance within the network across the different groups. Figure 23 illustrates this relationship for both exporters and importers. For exporters, the relevant degree metric is their out-degree, which represents the number of countries they export to. For importers, the relevant metric is their in-degree, which denotes the number of countries they import from. The scatter plot clearly demonstrates that exporters exhibit a higher degree of dispersion compared to importers, hinting that the number of trading partners is not a reliable predictor of a country's importance as an exporter. This observation is further corroborated by examining the Spearman correlation coefficient between the relevant degree and the eigenvector centrality index for both exporters and importers (Table 6). The eigenvector centrality index quantifies a node's influence or importance within the network.

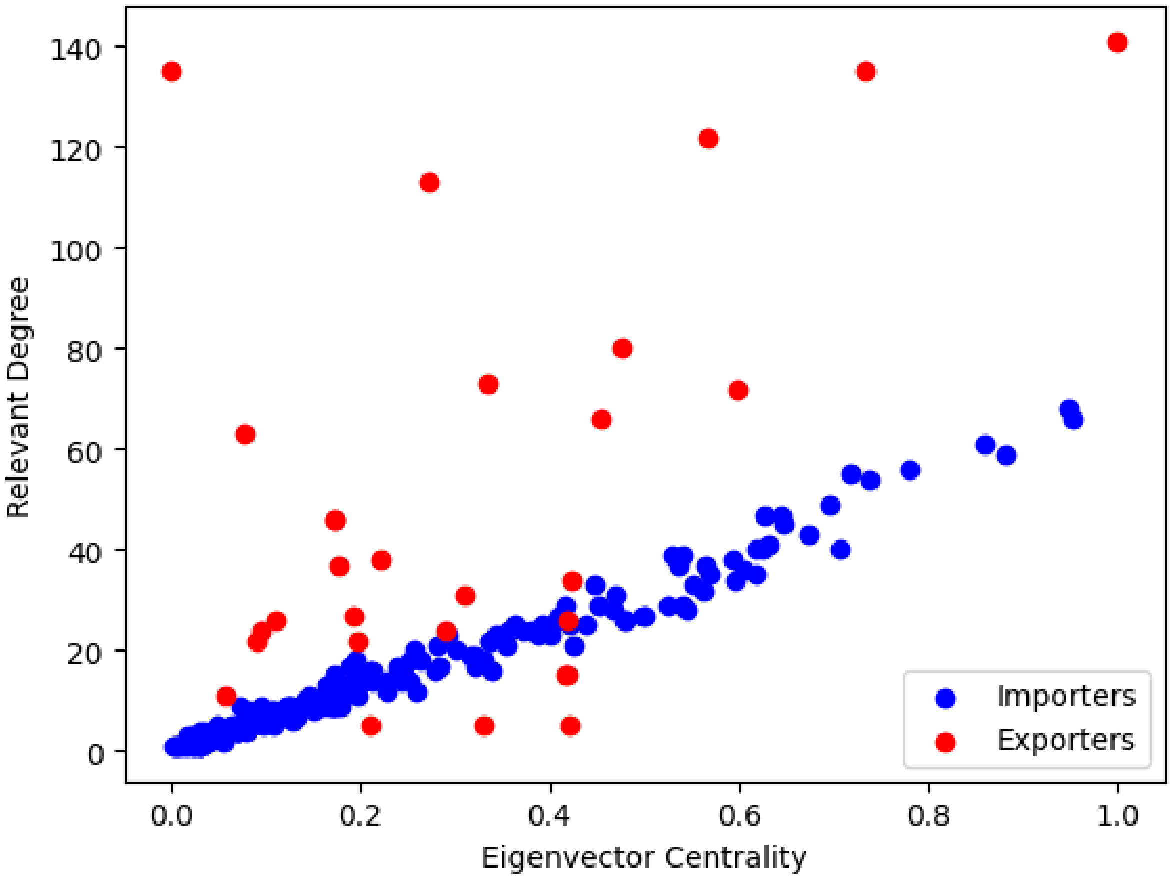

Figure 23. Correlation between Relevant Degree and Eigenvector Centrality

Source: Data visualised using Python (Matplotlib); figure prepared by the author.

The Spearman correlation coefficient for importers is a robust 0.98, implying a strong positive correlation between the number of trading partners and a country's importance as an importer. In contrast, the Spearman correlation coefficient for exporters is a relatively weak 0.28, indicating a less pronounced relationship between the number of exporter partners and a country's importance as an exporter.

Table 6.Spearman correlation Eigenvector x Relevant Degree

Importer	0.98
Exporter	0.28

Source: Own research (2024)

This finding aligns with the notion that importers tend to rely heavily on their trading partners for access to essential goods and commodities, whereas exporters may not be as reliant on their trading partners due to their ability to source raw materials and produce finished goods domestically. Consequently, I can accept the hypothesis H2 that the exporters of soybeans are more influential in the network and less susceptible to negative impacts caused by unforeseeable outbreaks.

4.2.1. Non-parametric diagnostics and correlations

To provide a more granular evaluation of the second hypothesis (H2), an additional investigation was conducted into the relationship between specific network metrics and the volume of trade participation. This exploration is formalised through three specific sub-hypotheses:

H2.1. Weighted outdegree shows a strong positive correlation with closeness centrality, indicating that countries with higher export volumes are positioned closer to other countries regarding network distance, enhancing their overall connectivity.

H2.2. Weighted outdegree exhibits a significant positive correlation with betweenness centrality, suggesting that countries with high export activity play a crucial role as intermediaries or bridges between other countries in the soybean trade network.

H2.3. Weighted outdegree shows a moderate positive Spearman correlation with indegree, reflecting that countries with high export activity are also likely to be important importers, though this relationship is less pronounced than their centrality roles.

H2.4 Weighted indegree shows a significant positive correlation with closeness centrality, indicating that countries with higher import volumes are positioned closer to other countries in terms of network distance.

H2.5 Weighted indegree and weighted outdegree show significant positive correlations with betweenness centrality, reflecting that countries with high import or export activities play important intermediary roles within the network.

H2.6 There is a significant positive correlation between weighted indegree and weighted outdegree, indicating that countries with substantial import activities are also likely to engage in significant export activities.

In order to test these relationships, it was first necessary to establish the distribution of the underlying data. The Kolmogorov-Smirnov test was utilised to evaluate normality; the results of this diagnostic determined whether a parametric or non-parametric approach was warranted. Given that trade data frequently exhibits power-law distributions or significant skewness, this step was essential to ensure the statistical validity of the subsequent correlation coefficients. Following the rejection of normality by the K-S test, the Spearman rank correlation was selected as the most robust measure for assessing the monotonic relationships between weighted out-degree and the various centrality indices.

The results for this first part can be summarized in Table 6 below. The data for the soybeans network did not display a normality distribution, so I cannot assume that the parametricity of data and consequently a proper correlation test should be selected.

Table 7. Kolmogorov-Smirnov normality test results

Metrics	D	Statistics	P-value
Weighted indegree	231	0.45	< 0.001
Weighted outdegree	231	0.48	< 0.001
Closeness centrality	231	0.24	< 0.001
Betweenness centrality	231	0.37	< 0.001
Indegree	231	0.14	< 0.001
Outdegree	231	0.28	< 0.001

Source: Own editing

The values of all six indicators significantly deviate from the normal distribution as evidenced by the Weighted Indegree, ($D(231) = 0.45$, $p < 0.001$), Weighted Outdegree ($D(231) = 0.48$, $p < 0.001$), Closeness Centrality ($D(231) = 0.24$, $p < 0.001$), Betweenness Centrality ($D(231) =0.37$, $p < 0.001$), Indegree ($D(231) = 0.14$, $p < 0.001$), and Outdegree ($D(231) = 0.28$, $p < 0.001$) statistics.

Based on the results shown above, I decided to use Spearman's correlation between two variables, which is robust to non-normally distributed data and offers a reliable approach to exploring associations between variables. This choice ensures the validity and robustness of the subsequent analyses in capturing the underlying relationships among the metrics, showing to which extend the variables are interconnected, but by no means proving causality.

4.2.2. Export-Led Connectivity

The results shown in Table 7 summarize all the outcomes from the Spearman correlation between the weighted outdegree and the network metrics analysed here, and the weighted indegree and the network metrics. I will start discussing the correlation between exports and the different metrics. The Spearman correlation coefficient (ρ) between the weighted outdegree and closeness centrality variables is 0.909, indicating a strong positive monotonic relationship between the two variables. This suggests that as the weighted outdegree of a node increases, its closeness centrality tends to increase as well, and vice versa. The associated p-value is approximately 4.37e-89, demonstrating a statistically significant correlation at a highly significant level ($p < 0.001$). Therefore, based on these results, we can conclude that there exists a robust and statistically significant positive correlation between the weighted outdegree and closeness centrality measures within the dataset. To visually represent this relationship, refer to Figure 24, where we can see the positive relationship between the two metrics. It's noteworthy that the scale for the weighted outdegree is built on a logarithmic scale in the figure, to mitigate data skewness during visualisation.

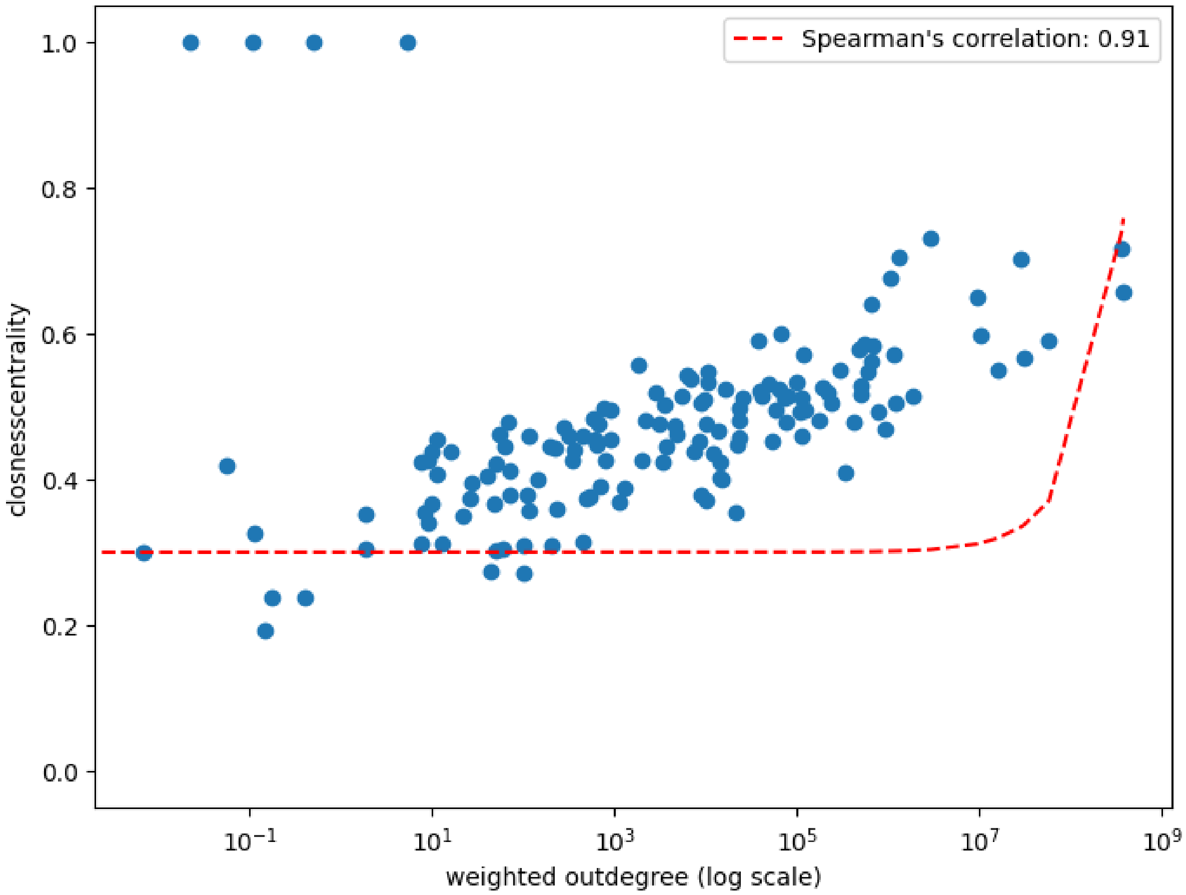

Figure 24. Correlation Weighted Outdegree x Closeness centrality

Source: Data visualised using Python (Matplotlib); figure prepared by the author.

A strong positive correlation ($\rho = 0.846$, $p < 0.001$) exists between weighted outdegree and betweenness centrality, indicating that nodes with strong outgoing influence tend to lie on many shortest paths between other nodes. This suggests these nodes play a crucial role in information flow across the network. The correlation between the variables is displayed in the Figure 25.

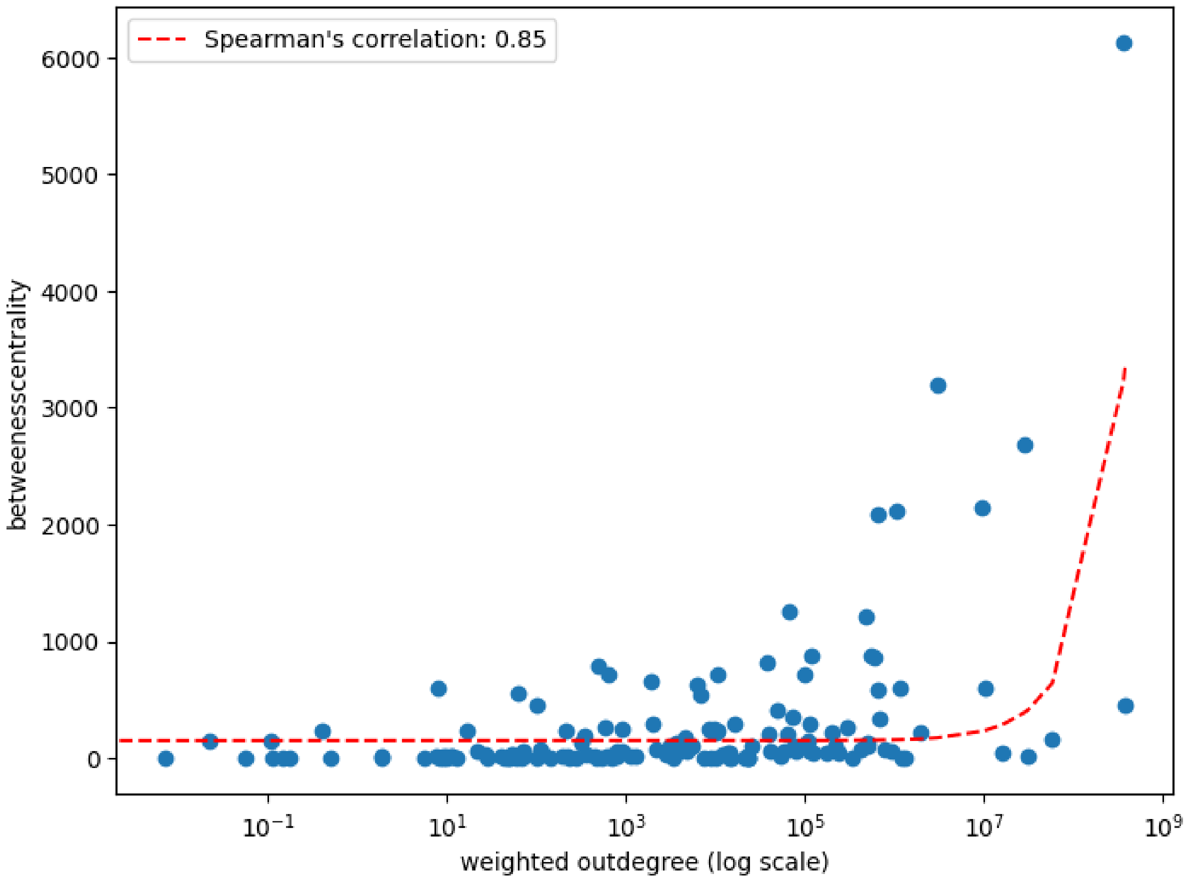

Figure 25. Correlation Weighted Outdegree x Betweenness centrality

Source: Data visualised using Python (Matplotlib); figure prepared by the author.

Similarly, a strong positive correlation ($\rho = 0.695$, $p < 0.001$) is found between weighted outdegree and indegree. This suggests that nodes with many outgoing connections also tend to receive many incoming connections, highlighting their central position within the network's communication structure.

Unsurprisingly, an exceptionally strong positive correlation ($\rho = 0.963$, $p < 0.001$) exists between weighted outdegree and outdegree, as weighted outdegree incorporates edge weights while outdegree considers only the number of outgoing edges.

The analysis of export activity (weighted out-degree) reveals a highly integrated trade architecture. As shown in Table 7, a robust positive correlation exists between weighted out-degree and closeness centrality ($\rho = 0.909$, $p < 0.001$), supporting H2.1. This suggests that as export volumes increase, a node's proximity to the rest of the network diminishes, facilitating faster exchange. Similarly, H2.2 is accepted based on the strong correlation between weighted out-degree and betweenness centrality ($\rho = 0.846$, $p < 0.001$). This confirms that nodes with high outgoing influence function as vital intermediaries within the global soybean flow.

Regarding H2.3, a moderate-to-strong correlation with in-degree ($\rho = 0.695$, $p < 0.001$) indicates that prominent exporters often occupy dual roles as significant importers, albeit with less intensity than their primary export-led influence.

Table 8. Spearman correlation weighted outdegree and network metrics

	N	Spearman coef	P-value
Closeness centrality	231	0.909	< 0.001
Betweenness centrality	231	0.846	< 0.001
Indegree	231	0.695	< 0.001
Outdegree	231	0.963	< 0.001

Source: Own editing

4.2.3. Import-Led Connectivity

When analysing the data for the imports there are some slight differences among the correlations of the metrics. The Spearman correlation coefficient (ρ) between the weighted indegree and closeness centrality variables is 0.613, with $p < 0.001$, indicating a moderate positive relationship between the two variables, contrasting the pattern displayed for the export data (Table 8).

A moderate positive correlation ($\rho = 0.673$, $p < 0.001$) exists between weighted indegree and betweenness centrality. This indicates a connection between receiving information and lying on the shortest paths, suggesting these nodes play a role in mediating information flow.

A strong positive correlation ($\rho = 0.786$, $p < 0.001$) exists between weighted indegree and indegree, similar to the outdegree case, due to the nature of the weighted indegree measure. Finally, a moderate correlation ($\rho = 0.687$, $p < 0.001$) was found between weighted indegree and outdegree.

Collectively, these results provide empirical validation for sub-hypotheses H2.4, H2.5, and H2.6. While import activities undeniably influence centrality and systemic connectivity within the global soybean complex, the magnitude of these correlations remains consistently lower than those associated with export activities. This suggests a hierarchical structure within the network, wherein structural influence is primarily driven by supply-side intensity rather than demand-side volume.

Table 9. Spearman correlation weighted indegree and network metrics

	N	Spearman coef	P-value
Closeness centrality	231	0.613	< 0.001
Betweenness centrality	231	0.673	< 0.001
Indegree	231	0.786	< 0.001
Outdegree	231	0.687	< 0.001

Source: Own editing

4.2.4. Periodical stability of the soybean trade network

Hypotheses number 3 (H3- The soybeans market is stable and challenging for new entrants to enter) speaks about the dynamism involved in the trade of these commodities. The general assumption is that those are two stable markets with lower variability over time, being a difficult area for new entries, in this case, nations. To test whether there were many changes during the twenty years studied, or if the main metrics stayed similar, the trade data was divided into four periods of five years each: Period 1 (2003–2007), Period 2 (2008–2012), Period 3 (2013–2017), and Period 4 (2018–2022). Notably, Period 2 captures the effects of the global financial crisis, while Period 4 contains the COVID-19 pandemic and the introduction of new trade tensions, such as the US-China tariff disputes and early impacts of the Russia-Ukraine conflict.

The metrics I studied are the same metrics examined before, Degree Centrality, Betweenness Centrality, Eigenvector Centrality, and Weighted Centrality. I choose to study the whole degree and weighted centrality because I want to investigate the whole dynamics of the commodities network, therefore there is no need to separate the two flows.

To achieve this, as mentioned earlier; after splitting the data I validate the distributions, checking the normality of the data using Kolmogorov-Smirnov. The results follow the same conclusions from the other calculations when the same test was applied to the entire data set. All metrics from both commodities presented a p-value lower than 0.001, consequently presenting strong evidence against the null hypothesis that the metrics values across periods exhibit significant departures from normality.

Following these tests, I tested the correlation of the main nodes presented in each calculated metric to investigate whether it showed a high volatility or stability. The idea was to test whether from one period to another the main feature of the network remained similar, and finally also the first period was compared to the last one. The results for each product can be summarized in Table 9 and Table 10. The coefficients for the soybean network (HS1201) consistently exceed 0.70, indicating a high degree of structural persistence. This suggests that the hierarchy of actors, both in terms of their connectivity (Degree) and their trade volume (Weighted Degree), remains remarkably stable across the study period. In contrast, the soy flour and meal market (HS120810) exhibits noticeably higher volatility, particularly in the earlier periods. The correlation for Weighted Degree between Periods 1 and 2 is relatively low ($\rho = 0.48$), suggesting a significant reconfiguration of trade volumes and market shares during this interval. Furthermore, the lower coefficients for Eigenvector Centrality ($\rho = 0.55$) indicate that the "influence" of nodes, based on their connectivity to other central actors, is far more fluid in the processed flour market than in the raw soybean trade. This disparity suggests that while the raw commodity market is governed by established, long-term trade architectures, the downstream flour and meal markets are more dynamic and sensitive to shifting bilateral trade agreements or processing capacities.

Table 10. Periodical Analysis of Spearman correlation network metric for HS1201 (Soybeans)

Metrics	Periods			
	1 and 2	2 and 3	3 and 4	1 and 4
Degree Centrality	0.93	0.94	0.95	0.88
Betweenness Centrality	0.85	0.87	0.90	0.81
Eigenvector Centrality	0.88	0.90	0.92	0.84
Weighted Degree	0.90	0.88	0.93	0.87

Source: Own editing

Table 11. Periodical Analysis of Spearman correlation network metric for HS120810 (Soya flour and meals)

Metrics	Periods			
	1 and 2	2 and 3	3 and 4	1 and 4
Degree Centrality	0.89	0.91	0.92	0.82
Betweenness Centrality	0.73	0.83	0.83	0.68
Eigenvector Centrality	0.85	0.87	0.92	0.80
Weighted Degree	0.76	0.87	0.85	0.76

Source: Own editing

To complement the statistical analysis of the soybean export networks, I have created visual representations of the networks for each period using Gephi (Figures 26-29). In these network visualisations, the nodes represent exporting countries, and the edges between them represent the export relationships. The size of each node is proportional to its degree centrality, indicating the number of direct connections a country has within the network. The colour of each node reflects its weighted degree, which considers both the number and the strength of connections, providing insight into the overall importance of each country in the export network. The thickness of the edges corresponds to the volume of soybean exports between countries, illustrating the intensity of trade relationships.

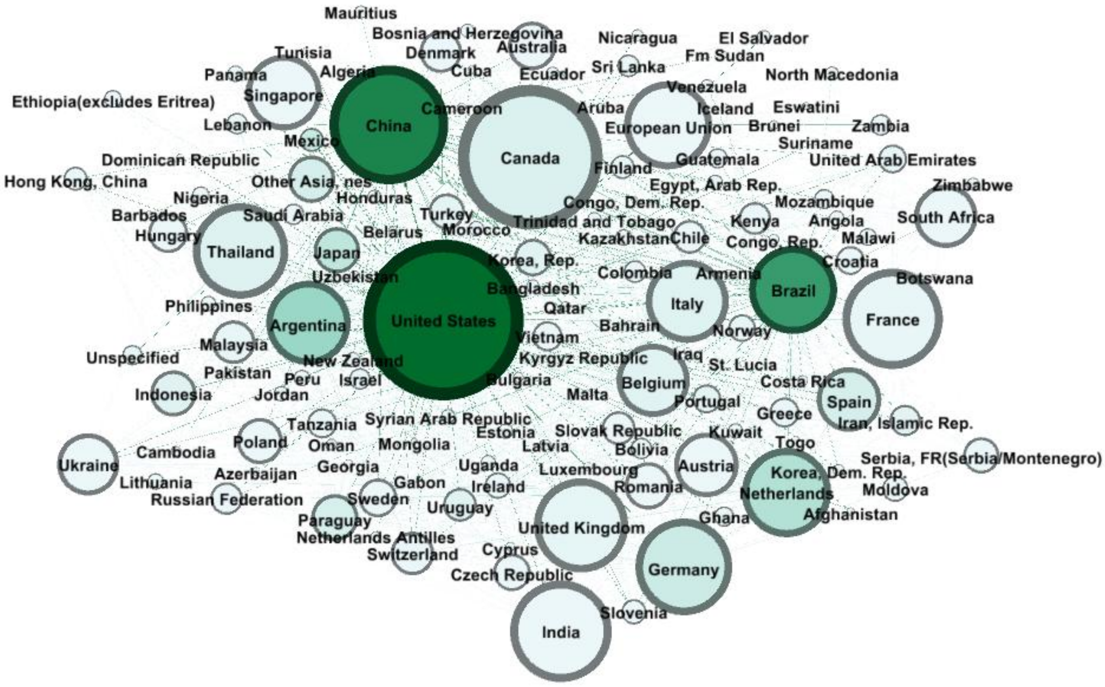

Figure 26. Soybeans export network 1st period

Size represents degree, colour the weighted degree, and edges the volume traded

Source: UN Comtrade database; network visualisation created using Gephi, edited by the author.

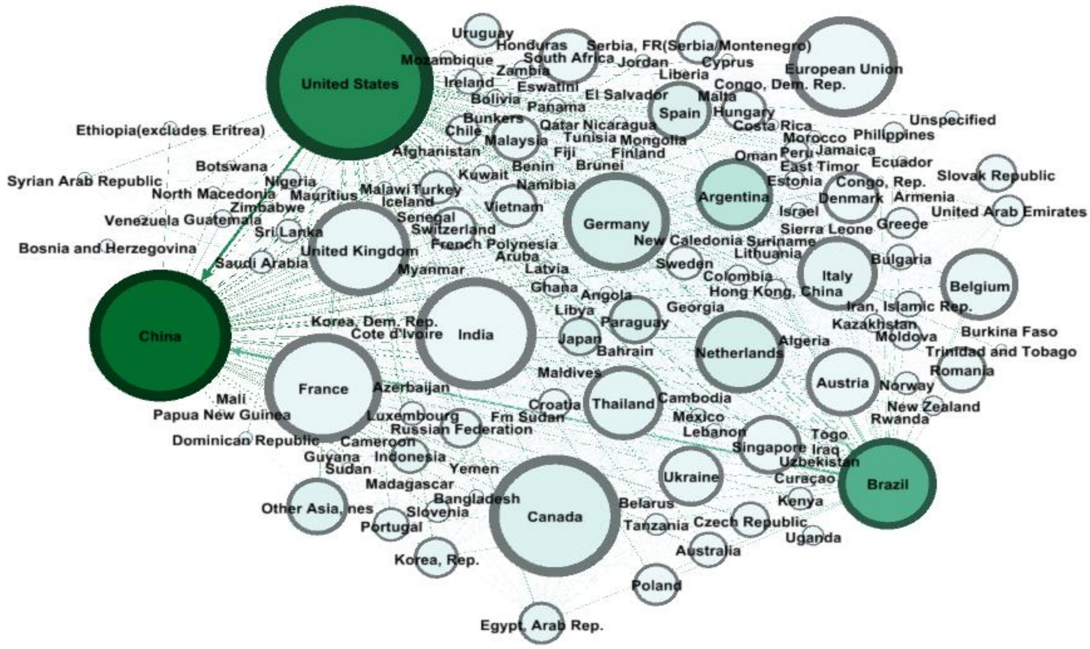

Figure 27. Soybeans export network 2nd period

Size represents degree, colour the weighted degree, and edges the volume traded.

Source: UN Comtrade database; network visualisation created using Gephi, edited by the author.

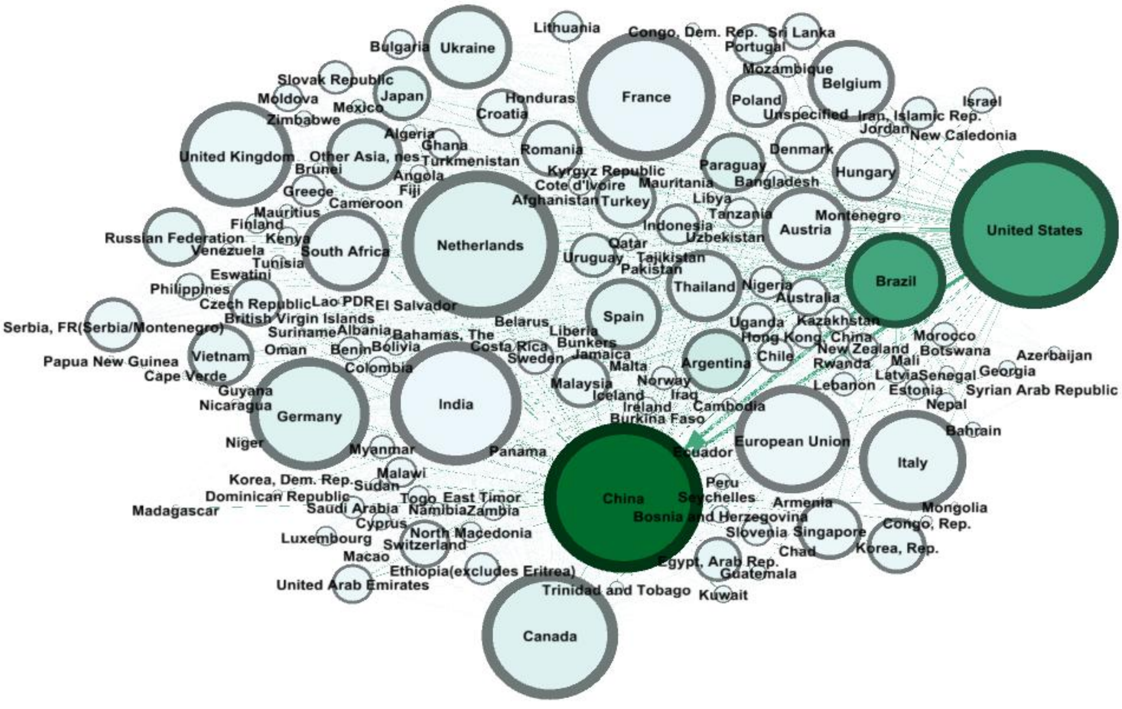

Figure 28. Soybeans export network 3rd period

Size represents degree, colour the weighted degree, and edges the volume traded.

Source: UN Comtrade database; network visualisation created using Gephi, edited by the author.

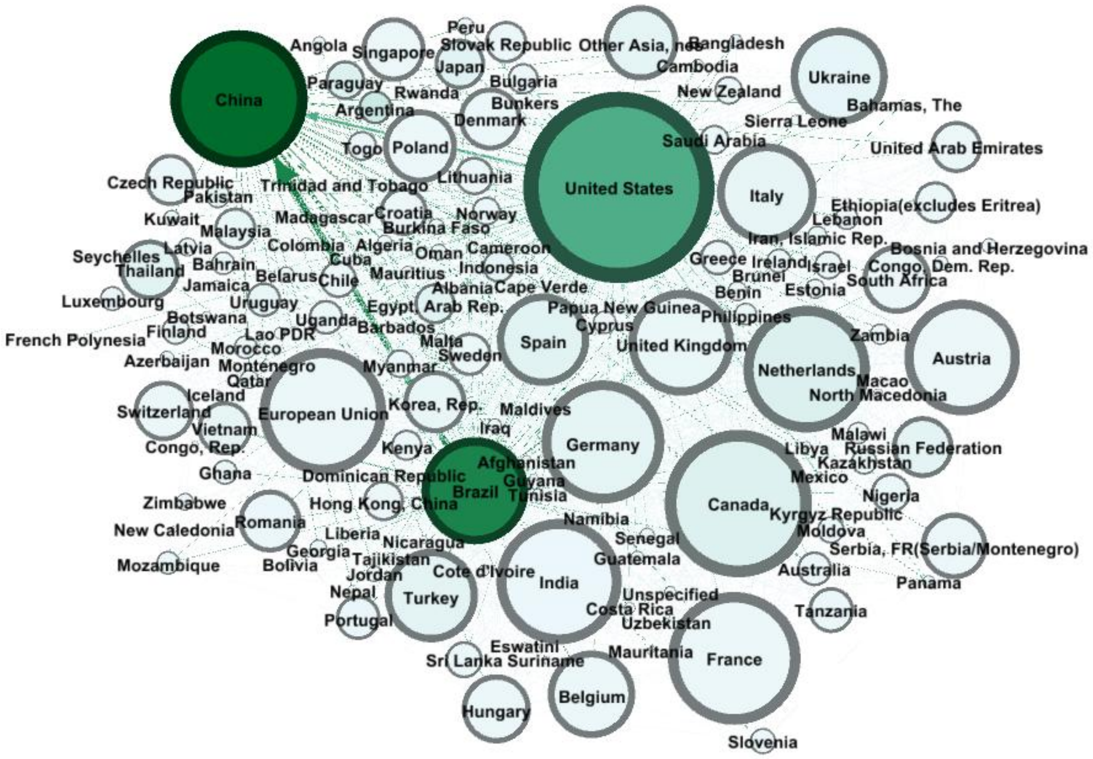

Figure 29. Soybeans export network 4th period

Size represents degree, colour the weighted degree, and edges the volume traded

Source: UN Comtrade database; network visualisation created using Gephi, edited by the author.

When examining these network visualisations, several key patterns emerge that align with the statistical findings presented in the previous section. For instance, in all periods one can see the same main characters, aligning with the high correlation of the metrics. One thing clear is the importance of the three countries United States, China, and Brazil, and the decreasing significance of Argentina over the years.

Overall, the network visualisations provide a powerful qualitative complement to the quantitative analysis, offering a clear and intuitive depiction of how the structure and dynamics of the soybean export network have evolved over the studied periods. These visual insights not only corroborate the statistical findings but also enhance our understanding of the underlying patterns and shifts within the global soybean export market. Hence after the presentation of the different networks and examining each one subsequently I can accept (H3) - The soybeans market is stable and challenging for new entrants to enter.

4.3. RQ3 and H4–H5: Soybean and Soy Flour Networks and Comparative Advantage

RQ3 – How do network analysis and the Balassa index contribute to our understanding of the international trade dynamics of soybeans?

H4 – The international trade networks of soybeans and soy flour exhibit distinct structural patterns, reflecting different dynamics for each commodity within the global agricultural trade system.

H5 – The application of network analysis and the Balassa index in the global soybean trade network reveals certain countries with stronger network centrality and higher Balassa indices, as well as distinct clusters of closely connected countries.

To address RQ3 and test H4 and H5, I first characterise the soy flour network, then directly compare the soybean and soy flour layers, and finally integrate network metrics with the Balassa index.

As done in one of the previous chapters, the presentation of the export network is introduced in Figure 30, the image depicts the global soy flour trade network during the period from 2003 to 2023. The colour scheme is dedicated to illustrating the amount in US Dollars of soybeans exported by each country, with the darker colour representing higher export values. Furthermore, the size of nodes corresponds to the number of trade partners associated with each node, while the thickness of edges visually represents the volume of trade between interconnected nodes.

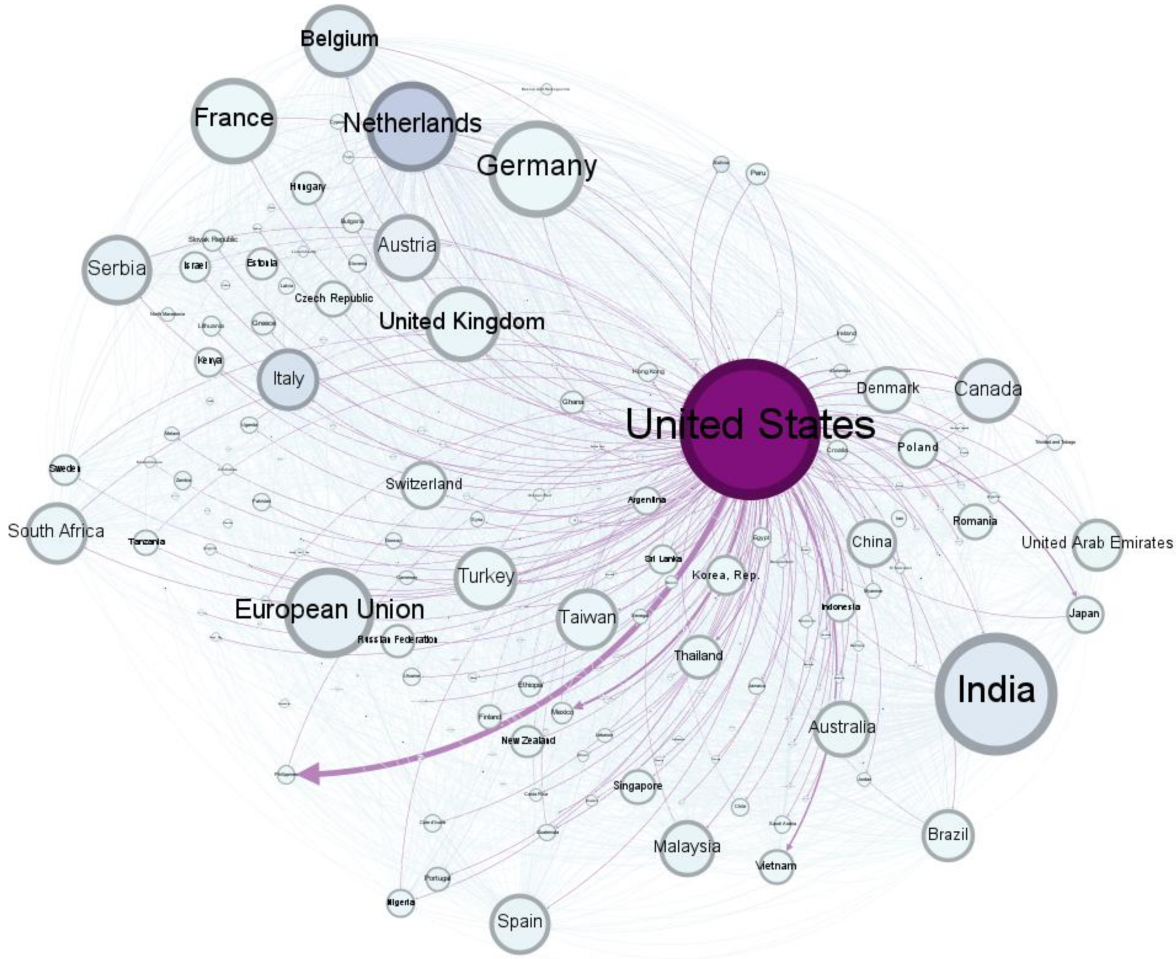

Figure 30. Soy flour export network 2003-2022

Size represents degree, colour the weighted degree, and edges the volume traded

Source: UN Comtrade database; network visualisation created using Gephi, edited by the author.

By observing the network, we can conclude some interesting points. First off, the United States stands out as the dominant node in the network, with the largest node size and the darkest colour. This indicates that the United States is the world's leading exporter of soy flour, with a vast network of trade partners and substantial export volumes.

Other notable exporters include the Netherlands, India, France, Belgium, and the European Union. These countries are represented by smaller nodes with lighter colours, but they still play an important role in the global soy flour trade.

Overall, the global soy flour trade network is a complex and dynamic system. The network is dominated by a few major exporters, but many smaller players play an important role. The network is also highly concentrated in a few regions.

As previously the soy flour demand chain is depicted in Figure 31. It is possible to notice that the volume imported is less concentrated in one country than the weighted outdegree network. It is particularly interesting to observe the main importer in this network, the Philippines, which besides being the hugest importer for the period, concentrates the purchasing in a single country, the United States. Mexico and Vietnam follow as the second and third biggest importers respectively.

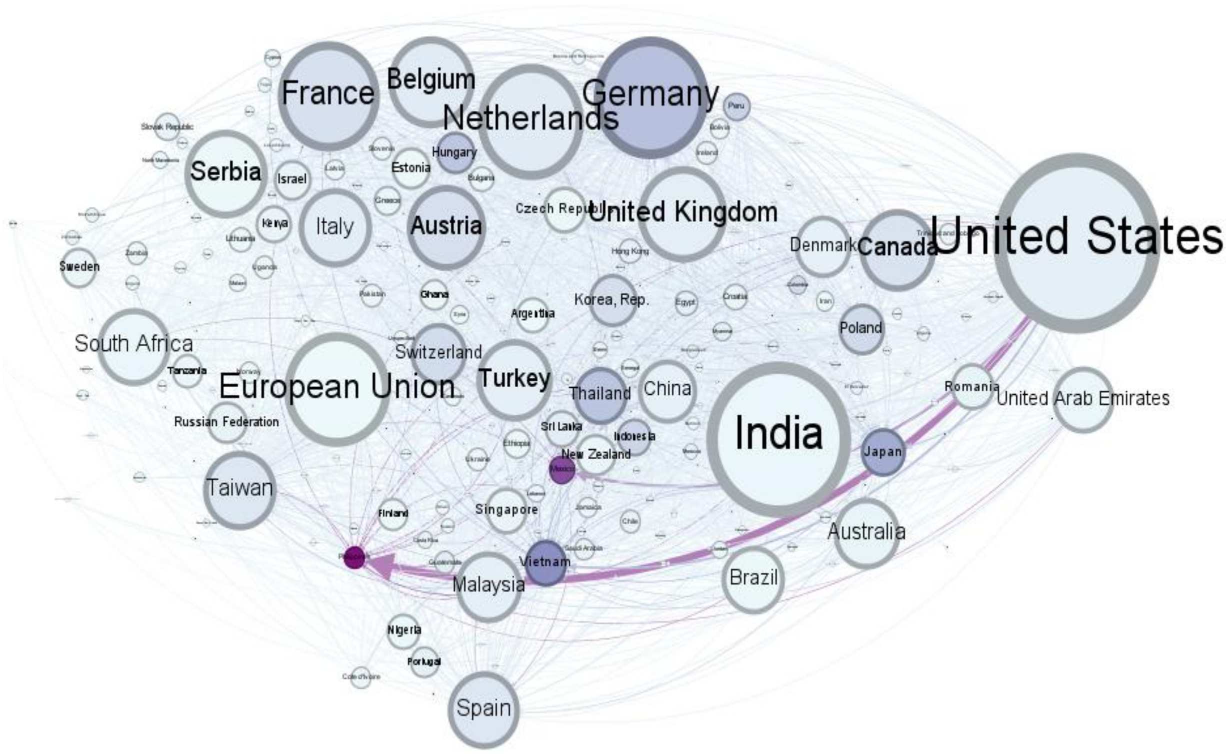

Figure 31. Soy flour import network 2003-2022

Size represents the degree, colour the weighted degree, and edges the volume traded

Source: UN Comtrade database; network visualisation created using Gephi, edited by the author.

As done previously, we can enhance the network analysis by examining different metrics, thereby visualizing a distinct network. To begin, I present the betweenness centrality network. Out of the 231 nodes, 106 have a betweenness centrality of 0, indicating that these nodes do not lie on any shortest paths between other pairs of nodes in the network. This means that no shortest paths between any two other nodes pass through these nodes. Consequently, these nodes do not contribute to the communication or flow of information in terms of shortest paths. We can infer that these nodes are peripheral and not essential for connecting different parts of the network. Their removal does not significantly impact the shortest path structure of the network since they are not crucial for maintaining shortest path routes. Thus, nodes with zero betweenness centrality have minimal influence in controlling or facilitating the flow of information across the network and do not act as bridges or mediators between other nodes.

Considering this, I decided to filter out nodes with low betweenness centrality values to improve the network visualisation. Therefore, I selected only nodes with a betweenness centrality higher than 100. In the network depicted in Figure 32, the colour and size of the nodes represent the magnitude of this metric, with darker colours indicating higher betweenness centrality values. The relevance of the United States is particularly evident when examining this metric. Additionally, it is important to highlight the roles of two Asian countries: India and the United Arab Emirates. Notably, the metrics for these two countries differ significantly. India ranks close to the USA, indicating a higher level of influence, whereas the UAE's index is closer to the next group of countries, which includes Germany, the Netherlands, and South Africa.

Figure 32. Soy flour betweenness centrality network 2003-2022

Source: UN Comtrade database; network visualisation created using Gephi, edited by the author.

Closeness centrality offers a valuable perspective for assessing the significance of nodes within a network. In the dataset corresponding to the analysed period, out of the 231 nodes examined, 99 exhibited a closeness centrality of 0. This indicates that these nodes are entirely disconnected from the remainder of the network, lacking any paths to or from other nodes. Consequently, these nodes are isolated with respect to network connectivity. It can be inferred that such nodes are peripheral and do not contribute to the overall communication or flow of information within the network. Their removal does not affect the network's efficiency in information flow, as they are not connected to any other nodes. Thus, nodes with a closeness centrality of 0 exert no influence on the network's structural integrity or connectivity and do not enhance its overall cohesiveness.

Conversely, nodes with high closeness centrality have shorter average path lengths than all other nodes in the network. These nodes are pivotal for efficient information dissemination and occupy central positions within the network. They play critical roles in maintaining network connectivity and can be regarded as essential hubs or key nodes for communication pathways. Analysing the distribution of closeness centrality within a network yields insights into the network's structure and helps identify crucial nodes that facilitate efficient communication and information flow. Such analysis is vital for comprehending the robustness and efficiency of networks, whether they pertain to social, transportation, biological, or other types of complex systems. In the network visualisation depicted in Figure 33, the colour and size of the nodes represent the values of this metric, with darker colours indicating higher closeness centrality.

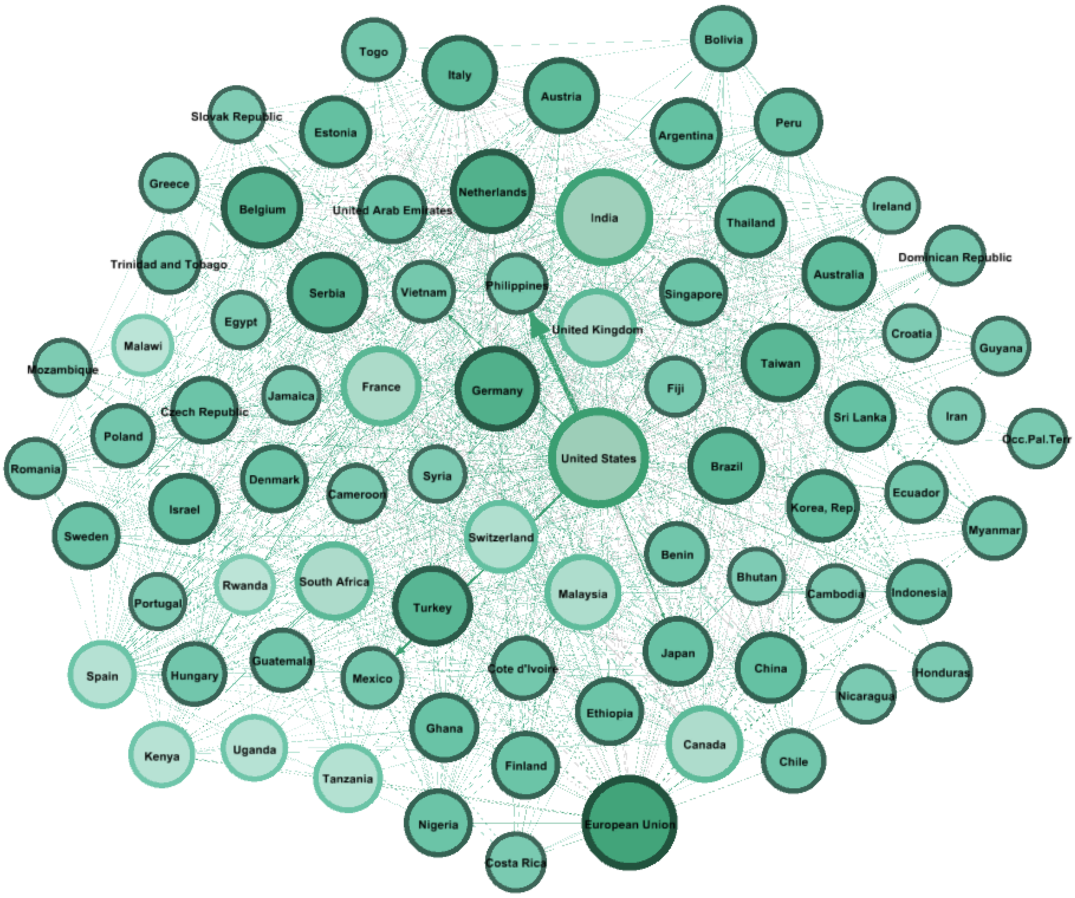

Figure 33. Soy flour closeness centrality network 2003-2022

Source: UN Comtrade database; network visualisation created using Gephi, edited by the author.

The uniformity of the data across this particular network is evident, with many nodes sharing similar ranges of the metric. This can be further explored by examining the distribution of the metric across the network, as depicted in Figure 34. As previously mentioned, the majority of the nodes are disconnected from the rest of the network. However, for those that are connected, the distribution of this metric follows a normal pattern.

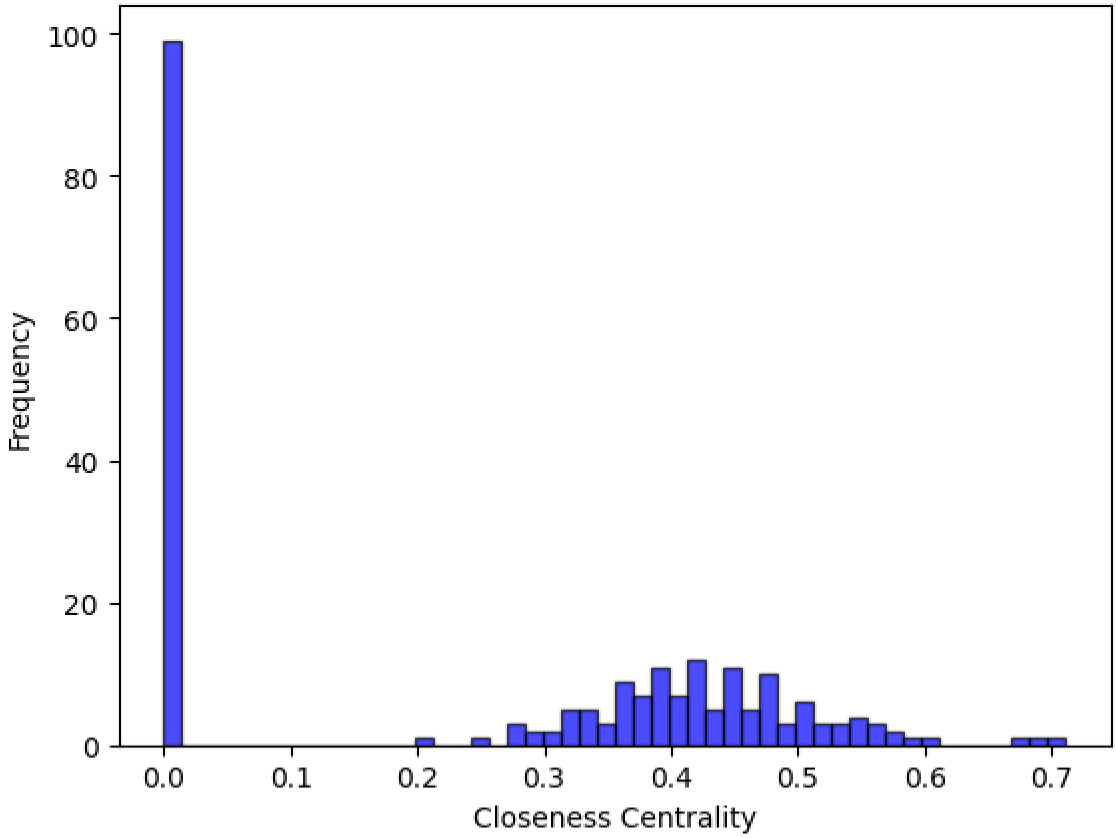

Figure 34. Soy flour closeness centrality distribution

Source: UN Comtrade data visualised using Python (Matplotlib); figure prepared by the author.

Repeating the same representation used in the analysis of the soybeans, in the dataset for the analysed period, out of the 231 nodes studied, I chose to filter out nodes with eigenvector centrality values below 0.4 to provide a clearer depiction of the network. This exclusion focuses on nodes that do not exert significant influence within the network, as eigenvector centrality evaluates not only the direct connections of a node but also the centrality of its neighbours.

Nodes with low eigenvector centrality are generally more isolated or connected to other nodes that are not central themselves. As a result, these nodes do not significantly impact the network's overall connectivity or the dissemination of information. Removing these nodes would not substantially alter the network's structure or dynamics since they do not contribute to the network's primary pathways or critical hubs. This analysis underscores the peripheral nature of these nodes and their minimal influence on the network's overall connectivity and functionality. In Figure 35, node size and colour represent the value of this metric, with darker colours and larger nodes indicating higher eigenvector centrality values.

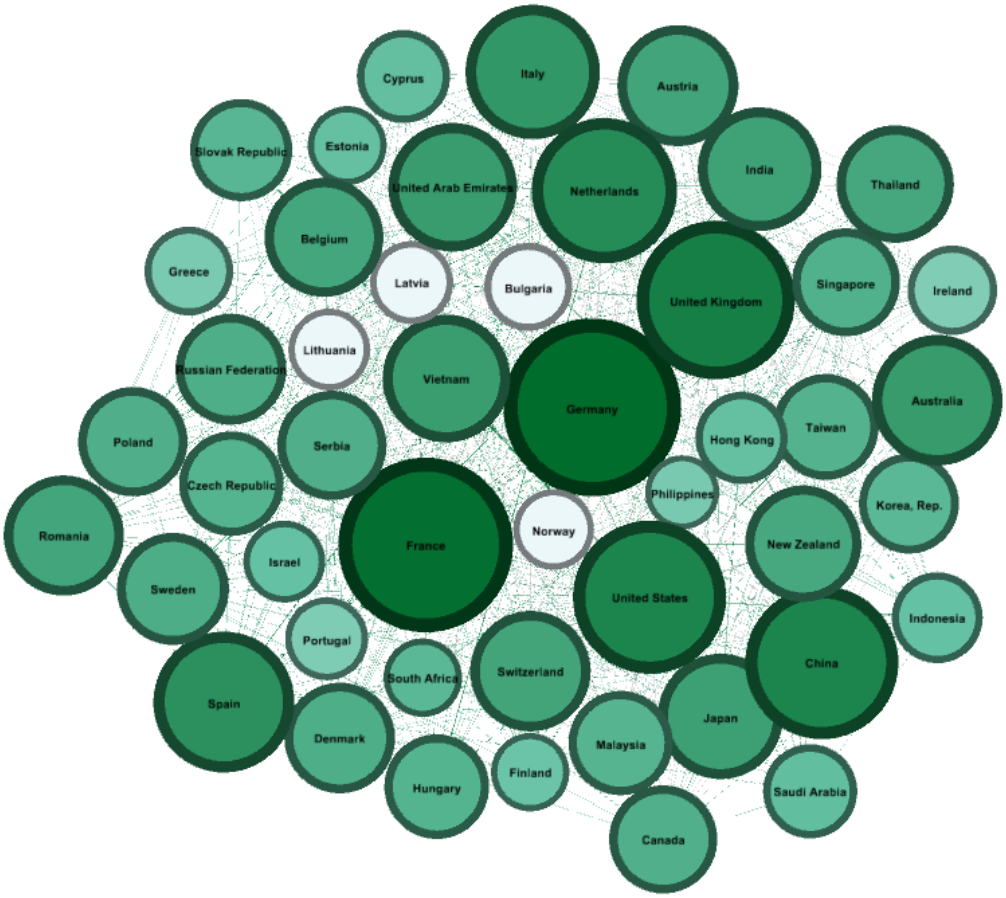

Figure 35. Soy flour eigenvector centrality network 2003-2022

Source: UN Comtrade database; network visualisation created using Gephi, edited by the author.

To further complement this analysis, we can examine the distribution of eigenvector values across the network. As shown in Figure 36, there is a high concentration of lower values, with only a few countries exhibiting eigenvector values higher than 0.5.

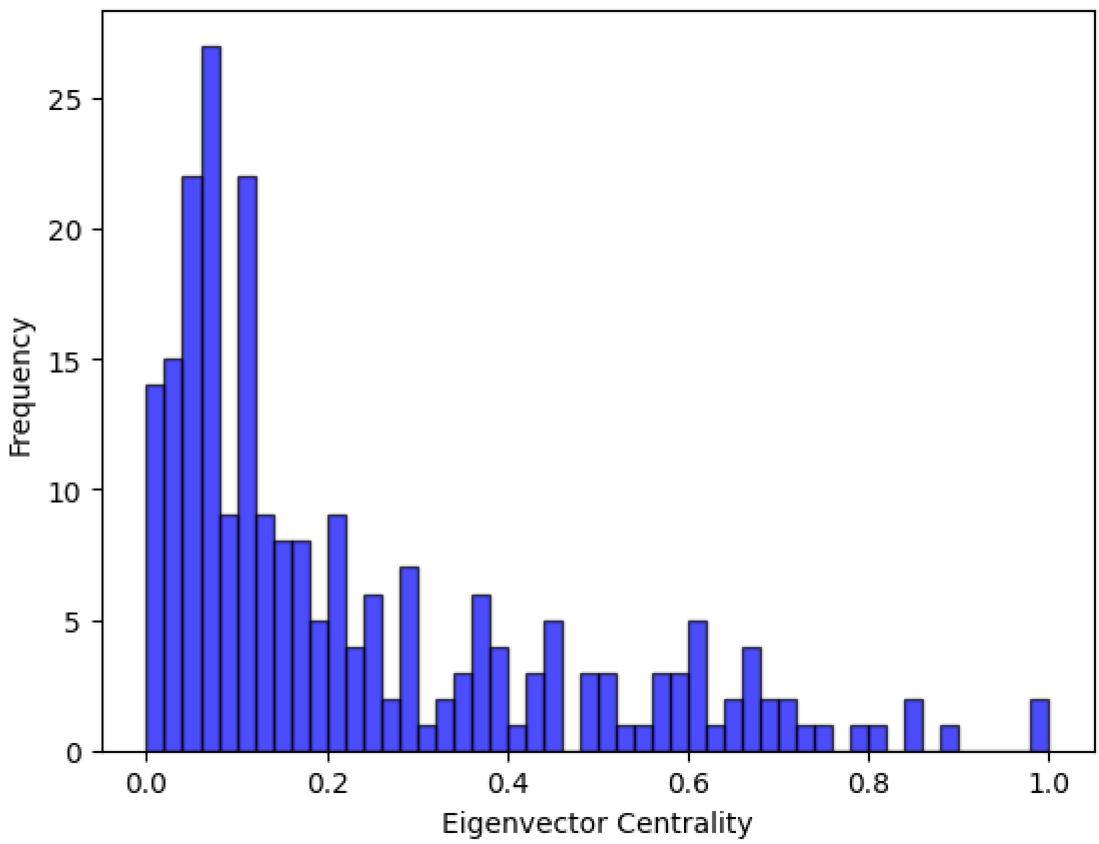

Figure 36. Soy flour eigenvector centrality distribution

Source: UN Comtrade data visualised using Python (Matplotlib); figure prepared by the author.

A summary of the soy flour network between 2003 and 2022 is shown in Tables 11-13. The network exhibited a dynamic and interconnected structure. The network comprised 231 countries engaged in soy flour trade, indicating a broad participation in the global soy flour market. Within this network, 2,483 trade relationships were established, highlighting the active exchange of soy flour between these participating countries.

The network's organization into eight distinct clusters suggested a decentralized and interconnected structure. This finding contrasts with a centralized network, which would exhibit fewer clusters and a hierarchical arrangement of trade relationships. The clustering pattern reflected the existence of regional trade blocs or groups of countries with strong trade ties, fostering closer collaboration and facilitating trade within these specific regions.

The level of trade connections within the network was quantified by the density metric, which yielded a value of 0.047. While this value may appear low, it represents the proportion of actual trade relationships relative to the total number of possible connections, emphasizing the active nature of the global soy flour trade network.

The strength of the clustering structure within the network was determined by the modularity metric, which assessed the cohesiveness of the clusters. The modularity value of 0.326 indicated a well-defined and structured trade landscape, suggesting the existence of distinct regional trade hubs and the organization of trade relationships within these hubs.

The average path length between any two nodes in the network, represented by the average distance metric, was 2.249. This low value implied that countries were more likely to be directly connected or connected through a short chain of intermediaries, facilitating efficient and streamlined trade routes within the soy flour network. Overall, the soy flour trade network between 2003 and 2022 exhibited a dynamic, interconnected, and decentralized structure, characterized by a high number of participants, active trade relationships, well-defined clusters, and efficient trade routes.

Table 12. Metrics of the soy flour network between 2003 and 2023

Metric	Implication	Value
Nodes	Number of countries participating in trade	231
Edges	Number of trade relations	2483
Clusters	Number of clusters	8
Density	The level of trade relations between countries	0.047
Modularity	The degree to which a network's nodes can be partitioned into highly interconnected clusters or modules	0.326
Average Distance	How many connections there are on average between any two nodes	2.249

Source: Own editing (based on the UN Comtrade database)

Table 13. Import indicators of the countries in the Soy flour network, 2003 to 2023

Ranking	Country	Indegree		Ranking	Country	Weighted Indegree
1	United States	52		1	Philippines	5.89
2	France	48		2	Mexico	2.17
3	Germany	47		3	Vietnam	1.46
4	United Kingdom	44		4	Japan	1.05
5	Netherlands	41		5	Germany	0.77
6	China	41		6	Thailand	0.72
7	Spain	38		7	Hungary	0.70
8	United Arab Emirates	38		8	Peru	0.52
9	India	36		9	Indonesia	0.48
10	Italy	36		10	Poland	0.42
11	Canada	35		11	Colombia	0.40
12	Vietnam	32		12	Switzerland	0.39
13	Japan	32		13	Korea, Rep.	0.36
14	Australia	32		14	Austria	0.34
15	Switzerland	31		15	France	0.33

Source: Own editing (based on the UN Comtrade database)

Table 14. Export indicators of the countries in the Soy flour network, 2003 to 2023

Ranking	Country	Outdegree		Ranking	Country	Weighted Outdegree
1	United States	135		1	United States	15.25
2	India	126		2	Netherlands	1.61
3	European Union	119		3	Italy	0.80
4	Germany	81		4	Bolivia	0.53
5	Netherlands	78		5	India	0.52
6	Turkey	68		6	Belgium	0.36
7	Belgium	68		7	European Union	0.31
8	Serbia	67		8	Serbia	0.25
9	France	66		9	Austria	0.22
10	Austria	62		10	Canada	0.19
11	South Africa	58		11	Portugal	0.16
12	Other Asia, nes	57		12	Spain	0.14
13	United Kingdom	56		13	Malaysia	0.12
14	Brazil	55		14	United Kingdom	0.10
15	Canada	50		15	China	0.10

Source: Own editing (based on the UN Comtrade database)

Another important metric concerning the trade network as a whole is the network density of a network, it measures how well-connected the nodes in the network are. It is calculated by dividing the number of actual edges in the network by the number of possible edges. A higher network density indicates that there are more connections between the nodes in the network. Figure 37 shows that the network density of both soybeans and soy flour has increased over time. This suggests that the soybean and soy flour supply chains in the world have become more interconnected in recent years.

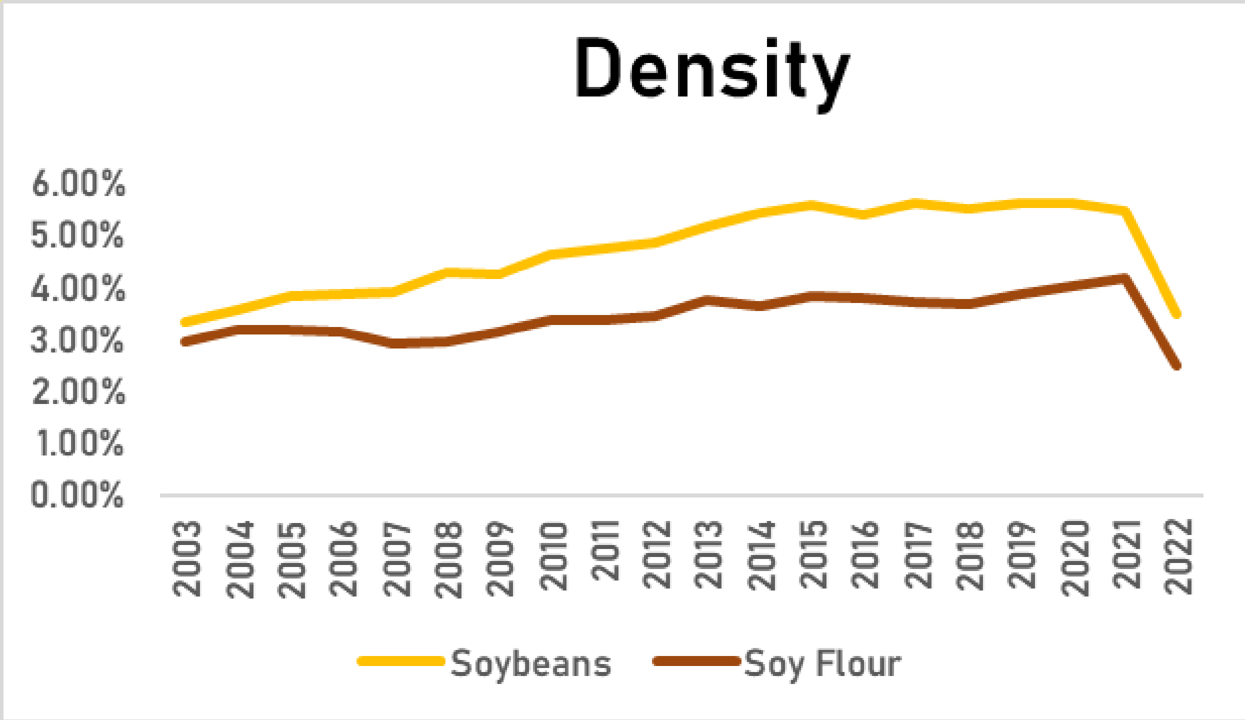

Figure 37. Network density over time 2003-2022

Source: UN Comtrade data visualised using Excel; figure prepared by the author.

This surge can be attributed to several factors: globalization and trade expansion, consolidation and vertical integration within the agricultural sector, and advancements in transportation and storage infrastructure.

The heightened network density brings about both positive and challenging aspects. On the positive side, a denser network enhances efficiency by streamlining supply chains, reducing sourcing and transportation costs, and fostering market stability. Moreover, it promotes reduced price volatility, enhances price transparency, and fosters competition and innovation. However, a denser network also increases vulnerability to disruptions, as a single event can ripple through the network more extensively.

To mitigate these risks, policymakers and industry leaders must actively monitor and address potential disruptions, promote resilience through diversification and redundancy in supply chains, and encourage investments in infrastructure and risk mitigation strategies. Additionally, researchers can continue delving into the network dynamics of the soybean and soy flour trade, exploring the impacts of various factors on network structure and its implications for global agricultural markets.

4.3.1. Multi-layer comparison of soybean and soy flour networks

Following the classification of Bródka, Chmiel, Magnani, & Ragozini (2018) the current chapter will be split into three main ways to compare layers in multiplex networks. These approaches are based on a property matrix P, in which each row represents a layer. Using an aggregation function f, each row is summarised in the first approach, and $(pl1)$ is compared to $(pl2)$, I will call it layer by layer comparison, since it calculates a function for each layer and compares with another one afterward. The second technique contrasts the value distribution between $pl1$ and $pl2$, so here I call it layer distributions since I will be comparing the different distributions of a measure across the layers. Comparing the property values of $ps,1$, and $ps,l2$ for every node s is the third technique, and here I will call individual structures. This can be illustrated by finding out if nodes with high degrees in one layer also have high degrees in another layer may be done, for instance, by computing the degree correlation. These techniques offer a thorough mechanism for examining and contrasting the structural characteristics of various multiplex network layers (Bródka et al., 2018). Based on this method in this section, I will present the three ways of comparing both networks to better understand their different nuances.

To visually illustrate the organization of the two trade networks in Figure 38, the representation includes soybean and soy flour trade relationships. In this depiction, the soybean network is depicted in orange, while the soy flour network is represented in blue. The intensity of these colours corresponds to the weighted degree of each node, emphasizing the prominence of trade relationships involving specific countries.

Additionally, dotted lines are used to connect nodes that are present in both the soybean and soy flour networks, highlighting shared trade partnerships across these commodities. In contrast, solid lines denote connections within each trade network, illustrating the direct trade flows between countries within the soybean and soy flour sectors. This visualisation method serves to elucidate both the interconnectedness and distinct trade patterns within and across the two networks, facilitating a clearer understanding of their structural relationships and implications within the global trade landscape.

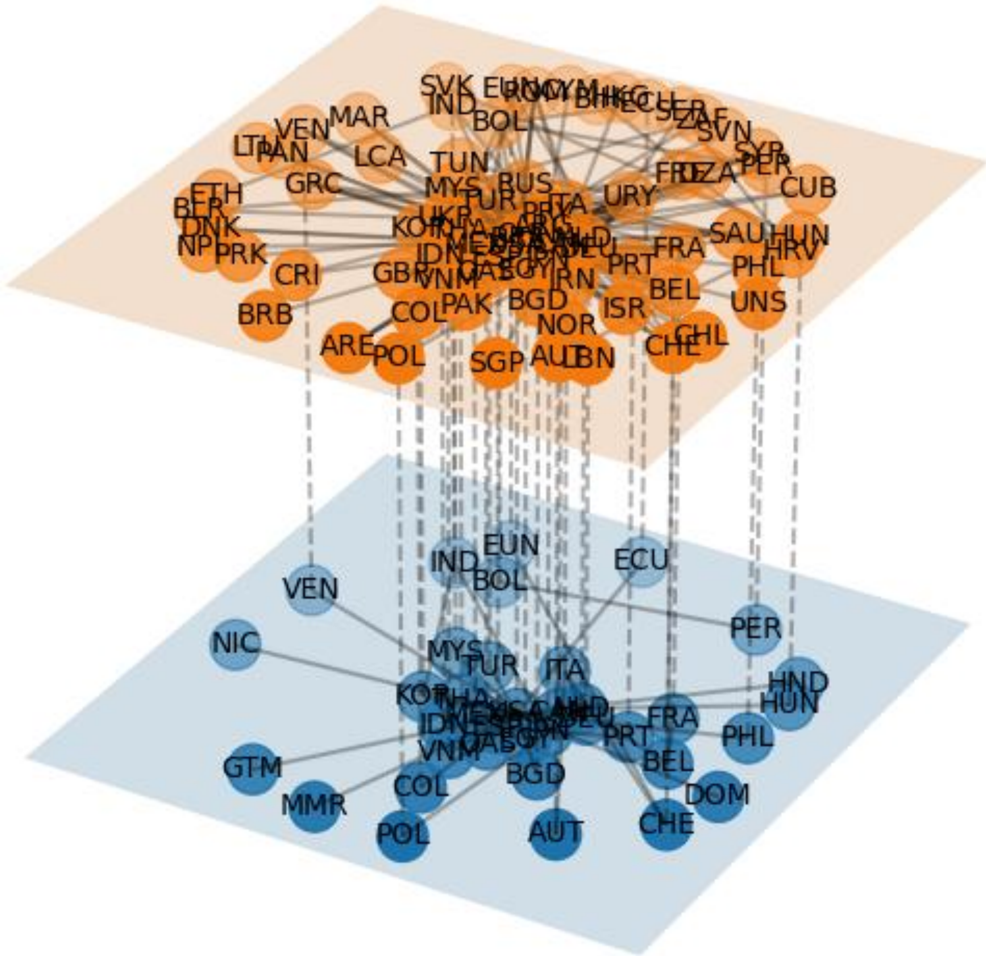

Figure 38. Multi-layered network analysis

Source: Data visualised using Python (Matplotlib); figure prepared by the author.

Layer by layer

The way this analysis is done when multiplex networks are concerned consists of examining a metric coming from different networks. This was already previously done by presenting the main network visuals and metrics from both of the datasets. However, some additional comments can be made after the presentation of both separately.

Based on the average presented by the two datasets there are some interesting points to pay attention to in each metric shown in Table 14 and 15. Starting by analysis the first table one can see that the average degree is higher for the Soybeans network (32.48) compared to the Soy Flour network (21.50), which suggests that, on average, nodes in the Soybeans network have more connections than those in the Soy Flour network, indicating a denser network structure for Soybeans. As was already expected, the weighted degree for the Soybeans network (3966759.53) is significantly higher than that for the Soy Flour network (92953.13), since there is more volume traded in this product category. The average betweenness centrality values are relatively close for both networks, with Soybeans at 182.78 and Soy Flour at 178.97. This indicates that the role of nodes in bridging or connecting different parts of the network is fairly similar in both datasets. Both networks have a similar pattern in which nodes that act as significant intermediaries or connectors are concerned.

Table 15. Average Metrics for Soybeans and Soy Flour Network

Average	Soybeans	Soy flour
Degree	32.48	21.50
Weighted Degree	3966759.53	92953.13
Betweenness	182.78	178.97
Closeness	0.31	0.26
Eigenvector	0.25	0.23

Source: Own editing

The closeness centrality is higher for the Soybeans network (0.31) compared to the Soy Flour network (0.26). Nodes in the Soybeans network, on average, can reach other nodes more quickly (in terms of the number of steps) than those in the Soy Flour network. This suggests a more compact network structure for Soybeans. The eigenvector centrality values are slightly higher for the Soybeans network (0.25) compared to the Soy Flour network (0.23). This suggests that nodes in the Soybeans network are, on average, more influential or better connected to other highly connected nodes than those in the Soy Flour network.

All in all, the Soybeans network appears to be denser and more connected, with higher average degree and closeness centrality values. This could indicate a more cohesive structure with more interactions or collaborations among nodes. However, both networks have similar patterns in terms of betweenness and eigenvector centrality, suggesting that the role of central nodes and their influence is comparable across the two datasets. However, the Soybeans network has a slight edge in terms of node influence as indicated by the higher eigenvector centrality.

Moving to the Table 15, similarly, one can observe a higher degree centrality in the Soy Flour network (135.29) compared to the Soybeans network (121.70), this indicates that there is greater variability in the number of connections per node in the Soy Flour network. The distribution of connections is more heterogeneous, suggesting the presence of both highly connected and sparsely connected nodes.

Table 16. Coefficient of Variation for Soybeans and Soy Flour Network Metrics

Average	Soybeans	Soy flour
Degree	121.70	135.29
Weighted Indegree	853.96	470.97
Weighted Outdegree	874.93	1085.05
Betweenness	309.56	301.96
Closeness	82.35	94.80
Eigenvector	87.35	97.73

The CV for weighted in-degree is significantly higher in the Soybeans network (853.96) than in the Soy Flour network (470.97). This suggests that the Soybeans network has a more varied distribution of incoming connection weights, indicating that some nodes receive significantly more interaction or flow compared to others. In contrast, the Soy Flour network has a more uniform distribution of weighted indegree. The CV for weighted outdegree is higher in the Soy Flour network (1085.05) compared to the Soybeans network (874.93). This indicates a greater disparity in the distribution of outgoing connection weights in the Soy Flour network. Some nodes in this network have a much higher outgoing interaction or flow, whereas others have very little, highlighting a more uneven distribution. The CV for betweenness centrality is slightly higher in the Soybeans network (309.56) compared to the Soy Flour network (301.96).

This implies that the distribution of betweenness values is relatively similar in both networks, with a slight tendency for the Soybeans network to have nodes with extremely high or low betweenness centrality. Similarly, the CV for closeness centrality is higher in the Soy Flour network (94.80) compared to the Soybeans network (82.35). This suggests a greater variability in the closeness centrality values in the Soy Flour network. Nodes in this network vary more in their efficiency of reaching other nodes, indicating some nodes are much more centrally located than others. The CV for eigenvector centrality is higher in the Soy Flour network (97.73) compared to the Soybeans network (87.35). This indicates a greater disparity in the influence or connectivity of nodes to other central nodes in the Soy Flour network.

Some nodes are much more influential than others, contributing to a more uneven distribution of eigenvector centrality values.

The findings presented in the preceding longitudinal and static analyses provide robust empirical support for Hypothesis 4 (H4), which posits that the international trade architectures of soybeans and soy flour exhibit distinct structural configurations. The Soybeans network is characterized by greater density and connectivity, while the Soy Flour network exhibits more variability and less centralization.

Layer distributions

Instead of relying on a single value to assess multiplex network layers, analysing the entire distribution of values across the property matrix offers a richer picture. While single values can identify denser or more clustered layers, examining the value distribution uncovers deeper connections and relationships between layers. To do that I will use Jeffrey's divergence, since this is a measure of the similarity between two probability distributions. It is symmetric and non-negative, meaning it will always yield a non-negative value and is the same regardless of the order of the distributions. In the context of network analysis, Jeffrey's divergence plays a pivotal role in comparing the degree distributions of two networks. Degree distributions capture the frequency distribution of node degrees, reflecting the connectivity patterns within each network. By computing Jeffrey's divergence between these distributions, researchers can quantitatively assess the structural differences in network connectivity.

To compute Jeffrey's divergence between two networks G_1 and G_2, several methodological steps were involved. In the first step, the network index distribution previously calculated was used as a matter of examination. This entails tabulating the frequency of nodes with each degree and centrality measure across the networks. Next, these distributions are normalized to ensure they represent probability distributions, where the sum of probabilities equals 1. This normalization step is crucial for ensuring comparability between networks of clearly different sizes and the magnitude of volume traded. Finally, Jeffrey's divergence is calculated using the normalized degree distributions using the equation presented in the methodology. This metric provides a numerical value that indicates the dissimilarity in degree distributions between the two networks, offering insights into their structural differences and potential implications for network functionality. Below I present the summary of the results after carrying out this calculation (Table 16).

Table 17. Jeffrey Dissimilarity for Soybeans and Soy Flour Network Metrics

Metric	Jeffrey's Divergence
Degree	0.862
Weighted Indegree	1.124
Weighted Outdegree	0.975
Betweenness Centrality	1.032
Closeness Centrality	0.755
Eigenvector Centrality	0.921

After calculating Jeffrey's divergence for various network metrics between the soybeans and soy flour datasets, notable differences emerge that provide insights into the structural disparities between these networks. I will comment on each metric and give some additional interpretation of the results obtained. Jeffrey's divergence of 0.862 for Degree between the soybeans and soy flour networks indicates moderate dissimilarity in the distribution of node degrees. While both networks exhibit similar overall patterns in node connectivity, there are notable differences in the prevalence of nodes with specific degrees. This suggests that the structure of connections within each network differs slightly, possibly influenced by varying factors such as network size or the nature of interactions represented. The higher Jeffrey's divergence of 1.124 for Weighted Indegree suggests a significant disparity in how nodes obtain the incoming weighted edges between the soybeans and soy flour networks. This indicates that certain nodes in one network receive considerably more weighted connections compared to their counterparts in the other network. Such divergence could reflect distinct patterns of influence or importance of specific nodes in information. Jeffrey's divergence of 0.975 for Weighted Outdegree shows a notable dissimilarity in the distribution of outgoing weighted edges from nodes between the two networks. This suggests that nodes in one network tend to exert influence through outgoing edges differently than nodes in the other network.

The Betweenness Centrality metric, with a divergence value of 1.032, indicates substantial dissimilarity in how nodes facilitate shortest paths and influence information flow across the networks. This suggests that certain nodes play pivotal roles in one network but not the other, potentially due to differences in network size or connectivity patterns. In contrast, metrics such as Degree and Eigenvector Centrality exhibit lower divergences, implying more consistent distribution patterns across both datasets. These findings underscore the importance of considering network-specific characteristics when analysing centrality metrics and highlight avenues for further research into network dynamics and functionality.

A Jeffrey's divergence of 0.755 for Closeness Centrality indicates moderate dissimilarity in how nodes are positioned in terms of their average distance to all other nodes in the networks. Nodes that are central in one network may have slightly different positions in the other network, impacting the overall network efficiency and accessibility. Finally, Jeffrey's divergence of 0.921 for Eigenvector Centrality suggests notable differences in the importance of nodes based on their connections with other highly central nodes in the soybeans and soy flour networks. Nodes identified as influential hubs in one network may not exhibit similar prominence in the other network, affecting the overall structure and stability of network communication and influence pathways.

To help visualise these different similarities across the two networks, I created a chart, displayed in Figure 39, presenting the metrics and a reference value for establishing high, moderate, and low dissimilarity. There is no consensus yet on this metric, being more of a referential line to assist the evaluation and interpretation of this metric. For reference, I present values from 0.0 to 0.5 as presenting low dissimilarity, from 0.5 to 1 presenting moderate, and above 1 displaying high dissimilarity.

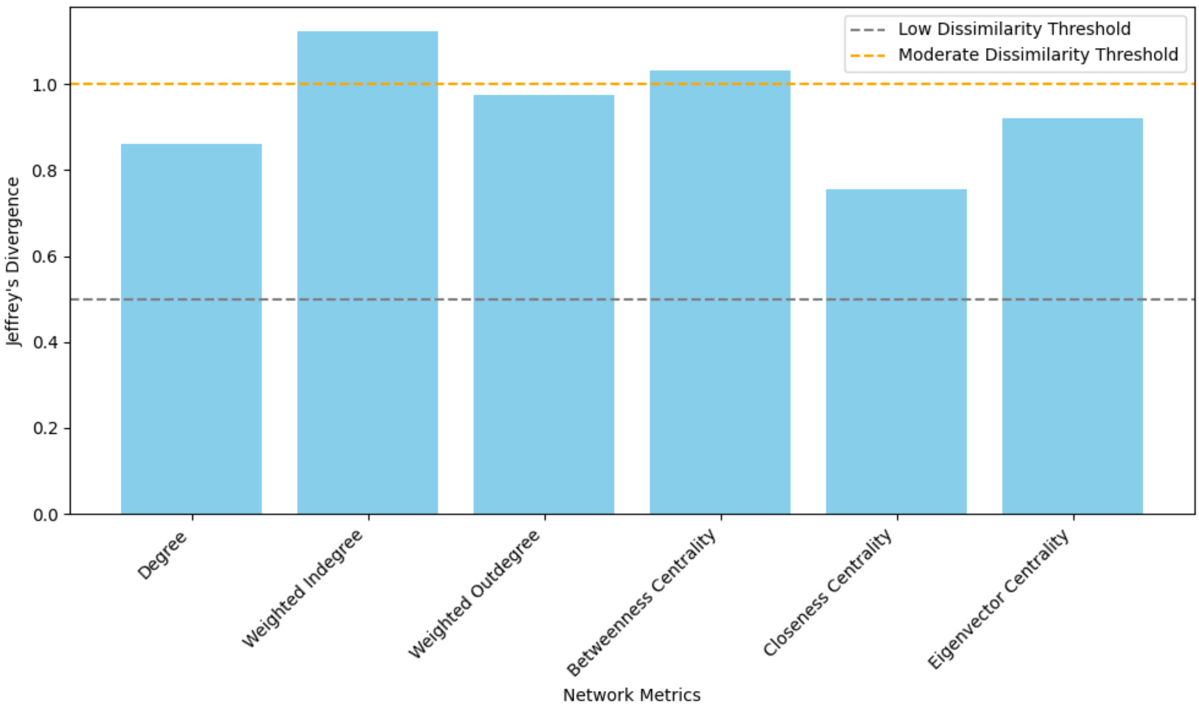

Figure 39. Comparison of Jeffrey's Divergence between Soybeans and Soy Flour Networks

Source: Data visualised using Python (Matplotlib); figure prepared by the author.

The findings in this chapter confirm hypothesis H4 and partially support hypothesis 4.1 since both trade markets present a moderate similarity overall for the metrics of both products, hence not being possible to state that these two products present a significant difference when the indexes are concerned.

Individual structures

The third and final approach to comparing two or more networks is analysing the individual structure of each network and quantifying a coefficient of similarity between the two objects of study. There are several ways to achieve this result, however, one can categorize mainly by analysing the binary properties, for instance, if the two layers are present, or numerically, computing different measures and the correlations compared (Bródka et al., 2018).

In this study, the Jaccard Index was applied to compare the two trade networks. To calculate the index, the sets of edges representing trade routes were extracted from each network. The intersection of these sets identifies the trade routes shared by both networks, while their union indicates all distinct routes present in either network. The Jaccard Index is then obtained by dividing the size of the intersection by the size of the union.

The Jaccard Index for the soybean and soy flour trade networks was found to be approximately 0.416. This value indicates that around 41.6% of the unique directed edges in the combined set of both networks are shared between the two. A Jaccard Index of 0.416 suggests a moderate level of similarity between the soybean and soy flour trade networks. This moderate overlap indicates that while there are several common trade routes between the two commodities, a significant number of trade relationships are unique to each.

Therefore, the results presented above support (H4.2) The comparison of individual structures demonstrates a weak correlation between the positions of countries in the soybean and soy flour networks, indicating that countries with high importance in one network do not necessarily hold significant positions in the other. Demonstrating that the distribution of key network properties differs significantly between the soybean and soy flour trade networks, highlighting unique patterns for each commodity.

The multi-layer analysis shows that the distribution of key network properties differs between the soybean and soy flour layers, with moderate to high Jeffreys divergences and distinct patterns in degree and strength distributions. The Jaccard index of 0.416 and the weak correlation between the positions of countries across layers indicate that countries that are central in the soybean network are not necessarily central in the soy flour network. Overall, these findings support H4 and its sub-hypotheses (H4.1 and H4.2), with H4.1 partially accepted due to heterogeneous differences across metrics and H4.2 fully accepted.

4.3.2. Network centrality and Balassa Index

To assess the comparative advantage of countries in exporting soybeans, the Revealed Comparative Advantage (RCA) index, or Balassa index, was utilized. The RCA index is a well-established measure that considers the share of a country's exports in the global market compared to the share of the product in the world's total exports. Values greater than one indicate comparative advantage, while values below one suggests comparative disadvantage.

This chapter delves into the Revealed Comparative Advantage (RCA) index for soybeans exports from 2003 to 2022. The countries with the most pronounced comparative advantage in exporting soybeans are pinpointed, and a comparative analysis with network metrics ensues, aiming to establish a correlation between the two approaches and uncover any potential connections.

To initiate the analysis, the data for soybean trade was assembled, comprising 148 countries, implying that 148 countries exported soybeans during the examined timeframe. Subsequently, the total soybeans exports during the examined period were calculated, along with the total amount exported by each country during the examined timeframe. With this data in hand, the Balassa index was calculated, representing the share of soybeans in the total amount exported by the country, divided by the share of soybeans exports in the global export trade.

To delve deeper into the analysis, Table 17 presents a summary of the top countries based on the RCA index. Notably, Paraguay emerges as the frontrunner with an RCA index of 4,191.11, followed by Uruguay (26,570.91), Brazil (19,095.80), and Argentina (7,103.78). The remaining countries in the elite top 10 are Bolivia (2,743.72), Ethiopia (2,083.80), the United States (2,038.56), Malawi (1,693.26), Ukraine (1,617.09), and Moldova (810.86).

Another noteworthy point is the geographical concentration of these top performers. All four countries with a comparative advantage in soybeans export hail from South America, raising the question of whether this regional dominance is attributable to specific factors such as soil quality, climate conditions, or any other region-specific characteristics. The fertile soils, favourable climate, and extensive agricultural infrastructure in South America might be relevant providers for a conducive environment for soybean cultivation and export.

Table 18. RCA soybeans, 2003 to 2023

Ranking	Country	Balassa Index
1	Paraguay	4419.11
2	Uruguay	2657.09
3	Brazil	1909.58
4	Argentina	710.38
5	Bolivia	274.37
6	Ethiopia	208.38
7	United States	203.86
8	Malawi	169.33
9	Ukraine	161.71
10	Moldova	81.09

Source: Own editing (based on the UN Comtrade database)

Furthermore, the dominance of South American countries in the global soybeans market is further corroborated by the network analysis previously presented and the growing demand for soybeans in the world's major soybean-consuming countries, such as China, the United States, and the European Union. These countries rely heavily on soybean imports to meet their domestic consumption needs.

The Spearman correlation coefficients between the Revealed Comparative Advantage (RCA) index and several network metrics are shown in the following Table 18.

Table 19. Correlation between Balassa Index and network metrics

Metric	Correlation	P value
Weighted outdegree	0.85	< 0.001
Closeness Centrality	0.475	< 0.001
Degree	0.465	< 0.001
Betweenness Centrality	0.24	0.003
Eigenvector centrality	0.12	0.146
PageRank	0.006	0.93

Source: Own editing

A strong positive correlation between the RCA index and weighted outdegree was found, with a p-value of 1.54E-42, indicating that countries with a higher RCA index tend to have more outgoing connections to other countries in the soybean trade network. This is consistent with the notion that countries with a comparative advantage in soybean production are more likely to be active exporters of the commodity. The strong correlation can also be visualised in Figure 40. To help visualisation before plotting the chart the natural log of both variables was calculated.

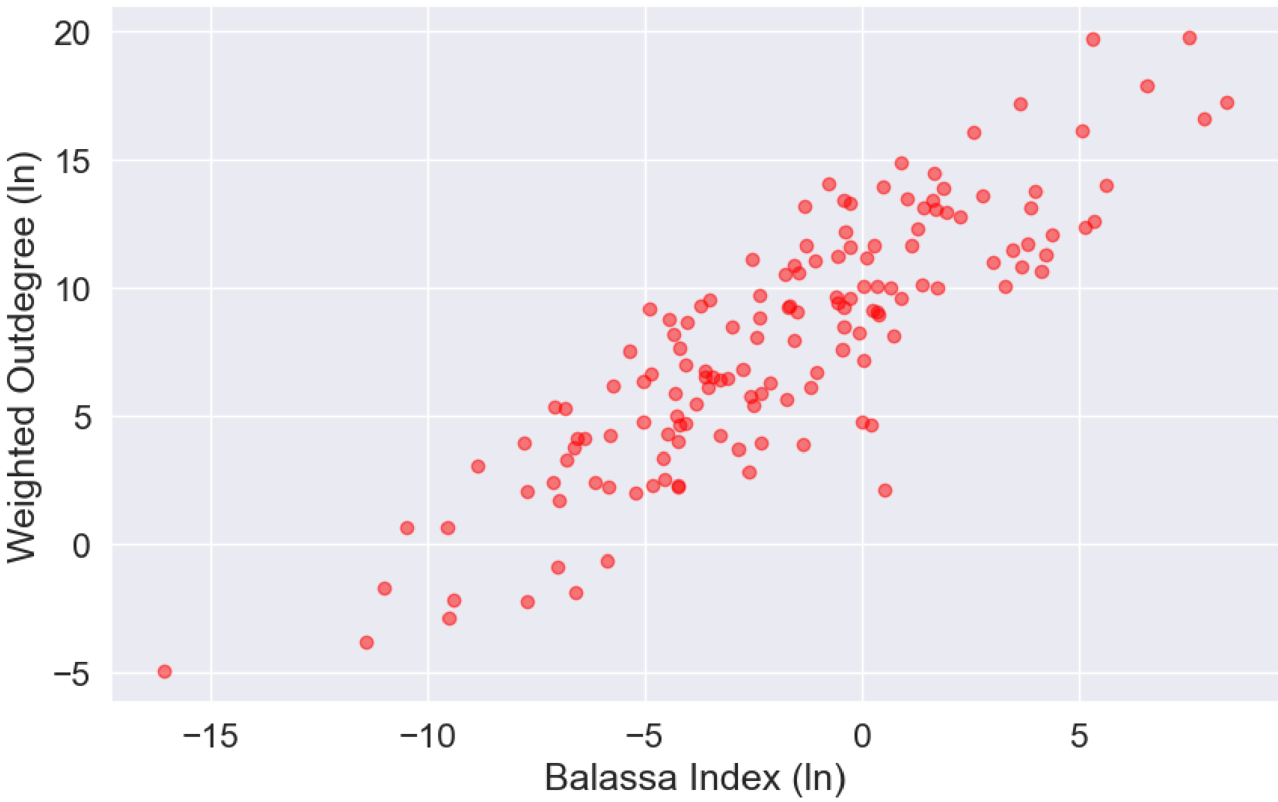

Figure 40. Balassa Index and Weighted Outdegree correlation

Source: Data visualised using Python (Matplotlib); figure prepared by the author.

A moderate positive and statistically significant correlation, with a p-value of 9.75E-10, between the RCA index and closeness centrality is observed, suggesting that countries with a higher RCA index tend to be closer to the centre of the soybean trade network. This suggests that these countries are more central players in the global soybean trade, and they may be more influential in shaping trade dynamics.

The correlation between the RCA index and betweenness centrality was weak but positive (p-value = 0.003), indicating that countries with a higher RCA index tend to play a moderate role as intermediaries in the soybean trade network. This may be due to the fact that these countries are strategically located between other soybean producers and consumers, and they may benefit from facilitating trade between these regions.

In contrast, although the correlation between the RCA index and eigenvector centrality was positive, it was not statistically significant (p-value = 0.146), suggesting that RCA cannot be considered a reliable indicator of a country's influence within highly connected clusters of the soybean trade network.

Similarly, the correlation between the RCA index and PageRank was not statistically significant (p-value = 0.93), indicating that RCA does not adequately capture a country's overall participation or prestige in the global soybean trade network as measured by PageRank.

Overall, the findings indicate that the relationship between the RCA index and network metrics in the soybean trade is not straightforward. While there is a clear connection between the RCA index and weighted outdegree—suggesting that countries with a higher RCA index are generally more active as exporters—this relationship does not extend to other network metrics. Specifically, countries with a high RCA index are not necessarily more central in the network or likely to serve as key intermediaries.

The strong correlation between RCA and weighted outdegree supports the acceptance of hypothesis H5.1, as it confirms that countries with a higher RCA index do tend to engage more actively in export activities. However, the lack of significant correlation between the RCA index and other network metrics leads to the rejection of hypothesis H5.2. Consequently, hypothesis H5 can only be partially accepted, as the connection between RCA and other aspects of network centrality is not sufficiently established. Therefore, H5.1 is accepted, while H5.2 is rejected, and H5 is partially accepted overall.

These findings provide insights into the role of comparative advantage in shaping country-specific trade patterns and the structure of the global soybean trade network, since the former analysis seems to be more limited and enlightens some areas where the network does not, therefore both analyses can be used as complementary ones. The role of producers is also important, as well as the role of intermediaries and countries with a variety of exports.

Researchers can further investigate the relationship between RCA and network metrics to better understand the dynamics of global trade. However, Network analysis presents more nuances of the importance of nodes within a network, being more and more useful in today`s world of interconnected supply chains. It is also worth noting that although the Balassa Index is important when evaluating the comparative advantage, a country has over other countries in the world, it does not capture the entire nuances within a network, for instance not only considering the intermediary role a country can play and the consequent advantage it can bring to the overall international trade.

These findings have several implications for policy and research. For policymakers, understanding the relationship between RCA and network metrics can help inform trade policy decisions. For example, countries with a high RCA index in soybean production may benefit from policies that support their export competitiveness. Additionally, the findings suggest that network analysis can be a useful tool for identifying key players and potential bottlenecks in the global soybean trade network.

5. CONCLUSION

The global trade dynamics of soybeans and soybean flour have been analysed using a comprehensive network analysis approach, yielding several key insights. Firstly, the application of advanced data analysis techniques, including network construction, visualisation, and correlation analysis, has proven effective in managing and interpreting large datasets. These tools have enabled the detailed examination of international trade networks, providing clarity on the roles different countries play within the global agricultural trade system, specifically in the soybean and soybean flour markets.

Through this analysis, the study has revealed distinct structural differences between the soybean and soybean flour trade networks, underscoring the unique dynamics of each commodity. These differences highlight the varying degrees of trade concentration, the influence of specific countries, and the robustness of trade relationships. Such insights would remain undiscovered without the application of network analysis, emphasizing the value of this method in exploring complex trade systems.

The findings from this research highlight the evolving dynamics of the global soybean and soybean meal markets, underscoring their growing significance in international trade. Over the study period, the global soybean market experienced substantial growth in both volume (tons) and value (USD) reflecting its increasing economic importance, not as a valuable product per se but as a valuable and with ever-increasing significance for the global food supply.

This growth was significantly shaped by escalating tensions between China and the USA, characterized by trade sanctions and shifting alliances that profoundly affected the global soybean trade network. The study also underscores the importance of network analysis as a more nuanced approach to understanding the role each country plays in global trade. One particular case was the role of major exporters within the soybean network, who exhibited particularly high metrics for weighted outdegree but lagged behind in other critical network metrics.

The summary of the hypothesis and respective findings are listed below in Table 20, while the overall presentation will be addressed shortly throughout the current chapter.

Table 20. Summary of research hypotheses and results

Hypothesis	Chapter	Result
H1 In the world international trade of soybeans, new economic countries are the exporters while developed countries are the importers of this commodity.	4.2.2	Accepted
H2 The exporters of soybeans have more influence within the network and less susceptible to negative impacts caused by unforeseeable outbreaks, while importers despite their significance play a relatively weaker role in the network.	4.2.2.	Accepted
H2.1 Weighted outdegree shows a strong positive Spearman correlation with closeness centrality, indicating that countries with higher export volumes are positioned closer to other countries in terms of network distance, enhancing their overall connectivity.	4.3.	Accepted
H2.2 Weighted outdegree exhibits a significant positive Spearman correlation with betweenness centrality, suggesting that countries with high export activity play a crucial role as intermediaries or bridges between other countries in the soybean trade network.	4.3.	Accepted
H2.3 Weighted outdegree has a moderate positive Spearman correlation with indegree, reflecting that countries with high export activity are also likely to be important importers, though this relationship is less pronounced compared to their centrality roles.	4.3.	Accepted
H2.4 Weighted indegree shows a significant positive Spearman correlation with closeness centrality, indicating that countries with higher import volumes are positioned closer to other countries in terms of network distance.	4.3	Accepted
H2.5 Weighted indegree and weighted outdegree will both show significant positive Spearman correlations with betweenness centrality, reflecting that countries with high import or export activities play important intermediary roles within the network.	4.3	Accepted
H2.6 There will be a significant positive Spearman correlation between weighted indegree and weighted outdegree, indicating that countries with substantial import activities are also likely to engage in significant export activities.	4.3	Accepted

Source: Own editing

Table 20. Summary of research hypotheses and results (H4-H5)

Hypothesis	Chapter	Result
H3 The soybeans market is stable and hard for new entrants.	4.5	Accepted
H4 The international trade networks of soybeans and soy flour will exhibit distinct structural patterns, reflecting different dynamics for each commodity within the global agricultural trade system.	4.6	Accepted
H4.1 The analysis of layer distributions will show that the distribution of key network properties differs significantly between the soybean and soy flour trade networks.	4.6.2	Partially accepted
H4.2 The individual structures comparison will demonstrate a weak correlation between the positions of countries in the soybean and soy flour networks, indicating that countries with high importance in one network do not necessarily hold significant positions in the other.	4.6.3	Accepted
H5 The application of network analysis and the Balassa index in the global soybean trade network will reveal certain countries with stronger network centrality, and higher Balassa indices	4.7	Partially rejected
H5.1 Countries with high weighted outdegree will also exhibit a revealed comparative advantage in the Balassa index context.	4.7	Accepted
H5.2 The combined use of network analysis and the Balassa index will identify distinct clusters of countries that exhibit close trade relationships.	4.7	Rejected

Source: Own editing

Moreover, the findings of this research offer practical implications for policymakers and stakeholders within the global agricultural sector. Understanding the structural patterns and the interconnectedness of trade networks can inform strategies to enhance trade efficiency, manage risks, and ensure the sustainability of supply chains. For instance, the research suggests that interventions targeting key countries within these networks could have significant ripple effects, either stabilizing or disrupting global trade flows.

One of the most notable trends was the increased importance of China in the soybean trade network. As China's demand for soybeans surged, its role as a key importer became more pronounced, reshaping trade patterns and influencing global market dynamics.

The study revealed distinct patterns in the soybean trade network, especially in the differentiation between exporters and importers. Exporters in the soybean market are predominantly from underdeveloped countries, such as Brazil and Argentina, which play a crucial role in supplying the global demand. In contrast, importers are generally from developed nations, including China and several European countries. This finding aligns with hypothesis H1, emphasizing the global economic disparity and the reliance of wealthier economies on agricultural imports from less developed regions. This dichotomy highlights the asymmetry in global trade, where wealthier nations rely on the agricultural output of less developed countries, reinforcing existing global inequalities.

Further analysis showed that exporters in the soybean network are strongly correlated with key network metrics, particularly with weighted outdegree, which measures the number of trade relationships and their volume. This correlation stresses the critical role that exporters play in maintaining the flow of soybeans across the globe, as found in the hypothesis H2.

The periodical analysis of the soybean trade network revealed a stable and entrenched structure, with the same key nodes consistently dominating the network over time, according to hypothesis H3. This stability indicates that the network is resistant to change, making it difficult for new entrants to penetrate and establish themselves within the market. The persistent dominance of established players suggests a mature market where competition is fierce and entry barriers are high, further reinforcing the concentration of power among a few major exporters and importers.

Given this stability of the trade network and its entry barrier, policymakers should consider targeting support for emerging exporters and diversification of supply chain for the main importers. The former are specifically applicable to developing countries with agricultural capacity, but limited market access could benefit from trade facilitation initiatives, reduced tariffs on agricultural exports, and capacity-building programs to enhance their competitiveness. Whereas the latter concerns the importing nations should strategically diversify their supplier base to reduce supply chain vulnerability and enhance resilience against geopolitical disruptions.

The identification of key nodes (major exporters and importers) with disproportionate influence suggests that targeted interventions at these critical junctures can have significant ripple effects, such as the infrastructure investment at key trade hubs. Policymakers should prioritize investment in ports, logistics, and trade infrastructure in countries that serve as network intermediaries (those with high betweenness centrality), as improvements here will enhance efficiency across the entire trade network. Secondly it is beneficial to invest on bilateral agreements with major traders, given that exporters with high weighted outdegree play crucial bridging roles, trade agreements with these key players can improve market access and price stability.

Moreover, the multilayered analysis conducted in this study highlighted the distinct structural differences and dynamics between the trade networks for soybeans and soybean meal. While both products are closely related, their trade networks exhibit different metrics and involve different key players, reflecting the unique market forces and supply chain dynamics that govern each product, relating to hypothesis H4.

The identification of distinct structural patterns in the soybean and soy flour trade networks highlights the importance of value-added strategies. Countries that primarily export raw soybeans can enhance their economic resilience and market position by developing domestic processing capacities for products like soybean flour and other derivatives. Investments in value addition not only increase export revenue but also help buffer exporters against price volatility and create jobs within the local economy. Targeted support for processing infrastructure, technical skills development, and market access can accelerate this transition, contributing to more sustainable and competitive participation in global trade.

Regarding the application of network analysis and the Balassa index (H5), the study provided mixed results. Hypothesis H5, which posited that network analysis combined with the Balassa index would reveal countries with strong network centrality and higher Balassa indices, was partially rejected. The analysis showed that while some countries with high weighted outdegree (H5.1) did exhibit a comparative advantage in the Balassa index context, this was not universally applicable across all metrics. Specifically, countries with high weighted outdegree were found to have a revealed comparative advantage, thereby confirming H5.1.

However, hypothesis H5.2, which anticipated that the combined use of network analysis and the Balassa index would identify distinct clusters of countries with close trade relationships, was rejected. The analysis did not uncover clear clusters or close trade relationships that were consistent with the Balassa index findings, indicating that network analysis and the Balassa index do not always align in identifying such patterns.

To further enhance market resilience, policymakers should develop early warning systems for trade network disruptions by leveraging real-time network analysis. Monitoring structural shifts and centrality measures enables stakeholders to anticipate supply chain vulnerabilities and design mitigation strategies before disruptions escalate. Additionally, climate and environmental considerations must be integrated into trade policy, as concentrated soybean production can drive deforestation and biodiversity loss. Coordinated interventions between trade and environmental agencies can promote sustainability while securing food supply.

While this study provides detailed insights through network analysis and trade data, several limitations should be acknowledged. First, the focus on structural network measures means the study may not fully account for other major drivers of global trade dynamics, including political relations, macroeconomic shifts, and environmental factors, which are increasingly recognized as significant in recent research. Events such as the 2008 financial crisis, the COVID-19 pandemic, shifting trade policies, and the ongoing Russia-Ukraine war have introduced substantial volatility and could alter network structure or market dominance. Furthermore, climate change impacts, most notably warming temperatures leading to production failures, as documented for the 2012 season, demonstrate the need for integrating environmental shocks and adaptation into future trade analyses (Hamed et al., 2025). Lastly, the drivers of observed structural differences between the soybean and soy flour networks, including supply chain segmentation and product specialization, merit in-depth exploration.

Future research should incorporate more diverse datasets, including policy, climate, and market fluctuation indicators, and consider causal analysis of disruptions. Studies could also investigate how synchronized shocks propagate through trade networks, the role of non-tariff measures, and strategies for increasing resilience and sustainability within global agricultural trade systems.

In conclusion, this study demonstrates that network analysis, when applied to global trade, can yield valuable insights into the functioning and structure of international markets. It provides a strong foundation for further research and policy development aimed at improving the efficiency, sustainability, and fairness of agricultural trade on a global scale.

6. NOVEL FINDINGS

Through the application of advanced network analysis techniques, this research has provided new insights into the complex and evolving dynamics of international agricultural trade. By building networks, exploring visualisation, and correlation methods, the study has illuminated previously unexplored aspects of the trade networks for soybeans trade. Additionally, by comparing soybeans and their subproducts it was possible to identify different structures and dynamics on both trades. Moreover, the present work highlights the distinctive structural features identified, the significant roles played by major exporters, and the implications of trade network stability.

1. Distinct Structural Differences Between Soybean and Soy Flour Trade Networks

This study provides the first systematic comparison of network structures between soybeans and their processed derivative (soy flour) within the same analytical framework. While both commodities originate from the same agricultural product, their trade networks exhibit fundamentally different characteristics in terms of trade concentration, hub structures, and connection patterns. This finding challenges the assumption that processed and raw agricultural commodities follow similar trade dynamics and demonstrates that value-added processing creates distinct network topologies with different vulnerabilities and opportunities for market participants.

2. Quantified Influence Patterns of Major Exporters in Soybean Networks

This research provides novel quantitative evidence of asymmetric influence patterns among major soybean exporters. Unlike previous studies that identified major players, this work demonstrates specific differences in how Brazil, the USA, and other exporters exercise network influence through different centrality measures. The findings reveal that export volume alone does not determine network influence, and that connectivity patterns create distinct strategic advantages for different exporters within the same commodity network.

3. Network Stability Despite Shifts in Major Player Roles

This research reveals an important paradox in the global soybean trade network: while the core structure of the network remains stable with consistently high barriers to entry for new participants, the relative positions and roles of established major players have shifted significantly over the study period. Notably, Brazil emerged as the dominant exporter, surpassing the United States, while China transformed from a minor exporter to the world's largest importer, fundamentally reshaping trade flow patterns. These findings demonstrate that network stability does not imply static player positions; rather, the soybean trade exhibits structural persistence at the network level combined with dynamic repositioning among existing major actors. This suggests that while breaking into the network as a new significant player remains difficult, established participants can undergo substantial transformations in their roles, influence, and market share within the stable network framework.

4. Methodological Insights on Network Analysis and Balassa Index Integration

The combined application of network analysis and the Balassa index revealed important methodological insights about the limits of integrating these analytical approaches. While high weighted outdegree was associated with revealed comparative advantage (supporting H5.1), the expected identification of distinct trade clusters through this combined approach was not achieved (rejecting H5.2). This finding contributes to methodological knowledge by demonstrating that network centrality and comparative advantage measures do not always align, suggesting these tools capture different dimensions of trade competitiveness that require separate analytical treatment.

5. Practical Implications for Policy and Strategy

The insights from this research have practical implications for policymakers and stakeholders in the global agricultural sector. Understanding the structural patterns and interconnectedness of trade networks can inform strategies to enhance trade efficiency, manage risks, and ensure supply chain sustainability. Targeting key countries within these networks for interventions could have significant impacts on global trade flows, either stabilizing or disrupting existing patterns.

SUMMARY

This dissertation investigates the global trade dynamics of soybeans and soybean flour through the lens of social network analysis, offering fresh insights into the intricate relationships and structural patterns that define these markets. The research addresses the increasing importance of soybeans in the global economy and the pivotal role they play in international trade, by means of volume or value traded in the global context. By integrating advanced network analysis techniques, the study explores the evolving trade networks of the commodity, emphasizing the role of key countries, the concentration of trade relationships, and the stability of the market over the years.

The dissertation begins with an introduction that contextualizes the global significance of soybean trade, setting the stage for a thorough literature review. The literature review covers the historical development of soybean trade, its global distribution, and the environmental and economic impacts associated with its production and export. Additionally, it introduces social network analysis as a methodology, establishing it as a powerful tool for exploring complex global trade networks. This section also discusses previous research on international trade, examining how social network analysis has been applied to different economic sectors and how it can provide deeper insights into global agricultural markets.

The methodology chapter details the data collection process and the specific network analysis techniques used in the study. The research relies on extensive trade data spanning two decades, from 2003 to 2023, to construct and analyse these networks. Techniques such as single-layer and multi-layer network models, the Kolmogorov-Smirnov test, Spearman rank correlation, and the Jaccard Index are employed to assess the structure and evolution of the trade network. These methods allow for an in-depth examination of the trade relationships, identifying major hubs, the distribution of trade partnerships, and structural changes over time. The methodological approach also includes bibliographic analysis to supplement the network-based insights, providing a broader understanding of global soybean trade dynamics.

The results and discussion chapter extensively analyse the soybean and soybean flour trade networks over the last two decades. The findings reveal key structural differences between the networks of these two commodities, with the dominance of major exporters such as Brazil, and the USA being a recurrent theme. The study finds that while certain nations consistently play central roles in the trade network, the overall market structure exhibits a high degree of stability, which can pose barriers to new entrants. The research also examines the periodical

shifts in trade patterns, exploring how external factors, such as economic policies, geopolitical tensions, and environmental concerns, have influenced global trade flows.

A significant contribution of this dissertation is its emphasis on the distinctions between different soybean-derived products, particularly through the application of a multi-layered analysis approach instead of a single-layer model. This methodology allows for a more comprehensive understanding of the differences and similarities between the trade networks of raw soybeans and processed soybean flour. The comparison reveals significant structural variations between these two layers, highlighting unique trade dynamics and characteristics associated with each product. The network model of soybean flour trade exhibits a more fragmented structure, suggesting a broader distribution of trade relationships compared to raw soybeans.

The study further delves into the correlation analysis of network metrics, investigating the interdependencies between various trade characteristics. Additionally, the research examines the comparative advantage index of soybean trade, analysing its evolution from 2003 to 2022. This analysis identifies distinct clusters within the global soybean trade network, shedding light on trade patterns that impact market access and global trade stability. By assessing these patterns, the research contributes valuable insights for policymakers and industry stakeholders aiming to enhance trade efficiency and market integration.

Another key aspect explored in this dissertation is the sustainability dimension of soybean trade. The research highlights the environmental and socio-economic challenges associated with large-scale soybean production and export, emphasizing the importance of sustainable trade practices. The dissertation discusses how major soybean-producing nations manage sustainability issues and how global trade policies influence these efforts. It also examines potential strategies to mitigate the negative environmental impacts of soybean expansion, such as deforestation and biodiversity loss.

The study's novel findings underscore the effectiveness of network analysis in understanding global trade dynamics and offer practical recommendations for policymakers and stakeholders. By focusing on the centrality and interconnectedness of key trading countries, the research provides a nuanced perspective on how global agricultural markets operate, emphasizing the critical role of both developed and developing nations in sustaining global food supplies. The analysis suggests that policymakers should consider the network structures when designing trade agreements, as the interdependencies in the trade network significantly influence market access and competition.

The dissertation concludes by reflecting on the broader implications of the study's findings and proposing directions for future research. It suggests integrating multidisciplinary approaches, including econometric modelling and machine learning techniques, to enhance the understanding of global trade systems further. Additionally, it emphasizes the need for continued monitoring of trade patterns to assess the long-term effects of global economic shifts, climate change, and policy interventions on the soybean trade network. By doing so, this research provides a solid foundation for future studies in global trade analysis and international market dynamics. Furthermore, future studies could benefit from incorporating real-time trade data and predictive analytics to offer more dynamic insights into shifting trade patterns. The integration of sustainability metrics into trade network analysis could also help policymakers address the growing environmental concerns associated with global soybean production and trade.

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