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Global Soybean Trade: A Complex Network Analysis of Key Exporters and Importers (2003-2023)

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Abstract: The article provides a comprehensive analysis of the global soybean trade, emphasizing its evolution and significance in the context of food security and nutrition. Originating in East Asia, soybeans have transformed into a crucial commodity, particularly influenced by geopolitical dynamics and trade relations, especially between the United States and China. Recent disruptions, including tariffs and the COVID-19 pandemic, have reshaped trade flows, presenting both challenges and opportunities for various countries. Utilizing Social Network Analysis (SNA), the study elucidates the complex interconnections among producers, exporters, and importers, highlighting key players like the U.S. and Brazil as dominant exporters while China stands out as the largest importer. The research underscores the environmental implications of soybean cultivation, particularly in Brazil, where expansion has led to deforestation. By analyzing trade patterns from 2003 to 2023, the article aims to inform policymakers and stakeholders about the intricate dynamics of soybean trade, ensuring strategies that promote food security and sustainable practices amid ongoing global challenges.

Keywords: International Trade, Network Analysis, Soybeans,

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INTRODUCTION

Soybeans, a versatile legume native to East Asia, have emerged as a global agricultural powerhouse, playing a pivotal role in food security, nutrition, and animal feed. Their cultivation dates back millennia, and over the past century, soybeans have become an essential component of the global food system. 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).

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, Liu, Wang, & Li, 2023).

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, Liu, Wang, & Li, 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, Liu, Wang, & Li, 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.

Using the Social Network Analysis methodology can help one gain a deeper understanding of the significance of this trade by evaluating the structural elements of a particular network and highlighting its important users and connections (Popp et al., 2018). Although the significance of network connectedness in the social sciences is not new, social network analysis has become easier to use for one of these comparatively basic systems due to the increasing availability of data and advancements in computer science and technique (Cheliotis, 2010). And since the trade relationship between countries has become more complicated Graph theory tools offer an impressive way to visualize the results of network analysis at the individual and network levels (Kou, Xian, Dong, Ye, & Zhao, 2018; Wasserman & Faust, 1994).

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 as can be seen this importance in figures 1 and 2. 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, Liu, Wang, & Li, 2023).

This study is essential as it provides a comprehensive analysis of the evolving global soybean trade network, a critical component of the global food system. The past two decades have been marked by significant shifts in trade patterns due to technological advancements, trade disputes, and emerging global risks, such as the COVID-19 pandemic. By examining the changes in key exporters and importers from 2003 to 2023, this research offers insights into how geopolitical tensions, environmental concerns, and market disruptions influence global trade. Such analysis is crucial for policymakers, economists, and industry stakeholders who need to understand the complexity of the soybean trade in order to develop strategies that ensure food security, stabilize markets, and promote sustainable agricultural practices. Furthermore, studying these dynamics provides valuable lessons on how interconnected global trade networks respond to external shocks, with implications beyond the soybean industry.

LITERATURE REVIEW

The evolution of soybean trade has been a subject of extensive research, reflecting its significance in global agriculture and economy. This review synthesizes findings from multiple studies to provide a comprehensive understanding of the historical and structural changes in the soybean trade network.

Soybeans were initially cultivated in China and later became a global commodity through complex geopolitical interactions. The Japanese trading company Mitsui Bussan played a crucial role in the early 20th century by navigating the geopolitical tensions between China, Japan, and Russia, thereby facilitating the global commodification of soybeans. This period marked the beginning of soybeans' transformation from a regional crop to a significant player in international trade (Mizuno & Prodöhl, 2023).

In the early 20th century, soybeans underwent a pivotal transformation from a regional cash crop in Northeast China to a globally significant commodity, driven by geopolitical forces and economic demands. Initially a key export for China, soybeans gained traction in Western markets, especially Japan and Europe, as industrialization increased the demand for versatile products like soy oil. Japan's expansion into Manchuria further boosted production and exports (Prodöhl, 2013). However, it was during the Great Depression and World War II that soy's true potential was unlocked in the United States, faced with agricultural challenges, American farmers turned to soybeans for their versatility in producing oil, livestock feed, and industrial products. By the end of World War II, the U.S. had surpassed China as the world's largest soybean producer, making soy a cornerstone of American agriculture and global trade (Prodöhl, 2013). The importance of soybean trade in the global trade scenario has also grown significantly and consequently it plays a vital role in ensuring food security and meeting the nutritional needs of a growing global population (Wang, Liu, Wang, & Li, 2023).

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.

The global soybean trade network (GSTN) has undergone significant structural changes from 2000 to 2020. Studies using complex network analysis have shown that the GSTN has become increasingly complex, exhibiting properties of small-world and scale-free networks, and additionally major soybean-producing countries in the Americas, particularly the US and Brazil, dominate the export market (Ma, Zhao, Li, & Niu, 2024). China, as the largest importer, faces vulnerabilities due to its heavy reliance on a few exporting countries, making its soybean trade susceptible to international market fluctuations and geopolitical tensions (Kou, Xian, Dong, Ye, & Zhao, 2018; Wang, Liu, Wang, & Li, 2023).

Another point that has been analysed given the growth of soybeans relevance in the international trade realm are the environmental impacts of its cultivation. The relationship between soybean trade and environmental impacts is complex. Studies have shown that the expansion of soybean cultivation, particularly in Brazil, has led to significant deforestation and loss of biodiversity, as land previously used for natural ecosystems is converted for agricultural use (Boerema et al., 2016; da Silva, Moran, Millington, Viña, & Liu, 2023). This phenomenon is exacerbated by the demand from international markets, particularly from Europe and China, where soybean is primarily used as livestock feed (Rezende, Ali, Bonaudo, & Gameiro, 2023; Sun et al., 2018). The environmental consequences of this trade are profound, with increased nitrogen pollution observed in importing countries due to the conversion of soybean lands to other crops that require higher nitrogen inputs (Sun et al., 2018). Possible solutions to mitigate the negative impacts of soybean cultivation include reducing soybean import by promoting alternatives for soybean feed, increasing food chain efficiency to reduce food waste, stimulating European protein crop production, implementing sustainable agricultural practices like agroforestry and crop rotation, importing soybeans from various regions to spread the pressure, and establishing certification systems for sustainable soybean production (Boerema et al., 2016).

METHODOLOGY

Data Sources and Tools

The data for this study was obtained from the United Nations Comtrade database, a comprehensive international trade database. The analysis focused on the entire global soybean trade, specifically product group HS-1201 (soya beans, whether or not broken). This dataset encompasses key trade attributes, including product codes, export and import country codes (ISO3), country names, trade year, and trade value (in USD).

Data processing and preliminary analysis were conducted using Microsoft Office tools, while network models were constructed and visualized using Gephi, a powerful software for network analysis and visualization. This combination of tools allowed for efficient data handling and the creation of complex trade networks that serve as the foundation of this study.

Network Analysis Approach
Network analysis is an invaluable tool for examining the intricate relationships within international trade (Sajedianfard et al., 2021). By modeling the global soybean trade as a network of exporting and importing countries, this study aims to reveal structural patterns and key actors within the trade system. This approach provides deeper insights into trade dynamics, offering a framework for understanding the flow of commodities and identifying potential vulnerabilities in the global supply chain.
To organize the analysis, traditional network analysis techniques are classified into two categories:
Actor-based analysis: This includes tools such as node-degree, node-strength, degree centrality, and betweenness centrality, which are used to evaluate the roles of individual countries within the trade network.
Structural analysis: This examines the overall network characteristics, using measures such as clustering coefficients and path lengths. However, this study primarily focuses on actor-based analysis.

Node-degree
Node-degree represents the number of direct connections (edges) a given node (country) has within the network. In the context of international trade, it reflects the number of trading partners a country interacts with (Fagiolo, Reyes, & Schiavo, 2010). The node-degree d_i is calculated as:

$$d_i = \sum_j a_{ij}$$

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 a stand for the adjacency matrix.

Node-strength
Node-strength measures the intensity of connections, representing the total trade volume between a country and its partners. It provides insight into the economic significance of a country's trade relations. The s_i node-strength is computed as:

$$s_i = \sum_j w_{ij}$$

Degree Centrality
Degree centrality captures the number of ties a node has, signifying the country's influence within the network. In this study, the trade network is directed, allowing for the distinction between indegree (number of imports) and outdegree (number of exports). Degree centrality is particularly relevant for assessing a country's importance in global trade, as it indicates the extent of its connections to other countries (Hanneman & Riddle, 2011).

Betweenness Centrality
Betweenness centrality quantifies how often a node acts as a bridge along the shortest path between two other nodes. In trade networks, these metric highlights countries that play intermediary roles in trade flows. A country with high betweenness centrality is critical to the network's connectivity, as it facilitates trade between otherwise unconnected countries (Borgatti, 2005; Freeman, 1978; Hanneman & Riddle, 2011).

Closeness Centrality
Closeness centrality reflects how close a node is to all other nodes in the network, based on the average shortest path from the node to all others. A country with high closeness centrality can quickly interact with other countries, indicating its central position within the trade network, and consequently the measure is particularly useful for assessing the efficiency of trade relations (Jackson, 2010).

Eigenvector Centrality
Eigenvector centrality takes into account not only the number of a node's connections but also the quality of those connections (Hansen, Shneiderman, Smith, & Himelboim, 2020). In this study, it assesses the importance of a country's trading partners in determining its own importance within the network. Countries that are connected to influential partners will score higher in this metric, indicating a more dominant position in global trade.

Network Density
Density measures the proportion of actual connections between countries relative to all possible connections. A low-density value indicates that only a small fraction of the potential trade relations are realized, suggesting that the global soybean trade network is relatively sparse.

Average Distance
Average distance refers to the average number of steps or connections it takes for a country to reach any other country in the network. It provides a measure of how efficiently trade can occur across the network.

RESULTS AND DISCUSSION

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 3, highlighting export trade flows. The colour scheme is dedicated to illustrating the amount in US Dollars of soybeans exported by each country, 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.

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, and 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 be able to illustrate also the largest importers, the soybeans network in Figure 4 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.

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, its role in soybean imports remains relatively modest, underscoring the distinct dynamics of the global soybean market.

There are other ways also to visualize 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 nodes 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 visualization. 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 5 represents the number of this metric, with darker colours representing higher betweenness centrality values. What is easily observed is the prominence of the United States, being the country with higher value in this metric. What follows the previous two networks, that presented this country with a high volume exported and also with several partes, 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.

There are other ways to visualize the importance of nodes within the network by 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 excluding 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 in 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 the Figure 6 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 a high influence and importance of the United States, as already observed in the previous networks, however another point worth mentioning is the low role represented by the main producers of the commodity.

An additional point to complement this analysis is the distribution of the eigenvector values across the network. In the Figure 7 it is possible to observe a high concentration on lower values, with just a few countries having this metric with a number higher than 0.5.

Network Structural analysis

Progressing with the analysis, after visualising the network, it is also important take a look at the network indicators, to capture some notions that sometimes but not be obvious by only glancing an image. An overview of the main indicators is displayed on table 01.

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.

The network exhibits a density of 0.071, indicating a relatively sparse connection between countries. Notably, four clusters were identified within the network, suggesting a degree of modularity (0.206) that highlights interconnectedness among certain groups while maintaining distinct separations.

Import Dynamics

The table 02 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, Netherlands and France also is remarkable, having been supplied by more than 60 different connections.

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, reflecting its immense influence in the global soybean trade network.

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.

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.

Export Dynamics

Shifting our focus to the metrics related to outgoing soybean shipments, the Table 3 reveals a different set of countries. However, some of them are already presented in the previous table, as the United States, Canada, France, Netherladas, 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.

The findings indicate a centralized structure in soybean exports dominated by Brazil and the United States, which raises concerns about vulnerability to shocks such as crop failures or political instability. Conversely, China's concentrated import strategy suggests potential risks associated with relying on fewer trading partners.

Figures illustrating various centrality measures reveal that while some countries like the United States maintain high betweenness centrality—indicating their role as bridges within the network—others like Argentina show lower influence despite being major producers.

CONCLUSIONS

The global soybean trade network has transformed into a complex system characterized by significant interdependencies among key players such as China, Brazil, and the United States. This concentration poses potential risks, as disruptions in these key exporters—due to factors like crop failures or political instability—could significantly affect global supply chains. On the import side, China's reliance on a few major trading partners underscores its vulnerability to shifts in the global market. Understanding these dynamics is crucial for anticipating disruptions and ensuring food security amid changing global conditions.

Moreover, the analysis of network centrality measures provides further insights into the structure of trade relationships. Countries like the United States hold high betweenness centrality, acting as crucial intermediaries and bridging different regions of the network. In contrast, Argentina, despite being a major soybean producer, plays a less influential role, as indicated by its lower centrality. This suggests that a country's production volume does not always correlate with its strategic importance in the global trade network.

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Table 01
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

Table 02
Import indicators of the countries in the Soybeans network, 2003 to 2023

	Country	Indegree		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

Table 03
Export indicators of the countries in the Soybeans network, 2003 to 2023

	Country	Outdegree		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

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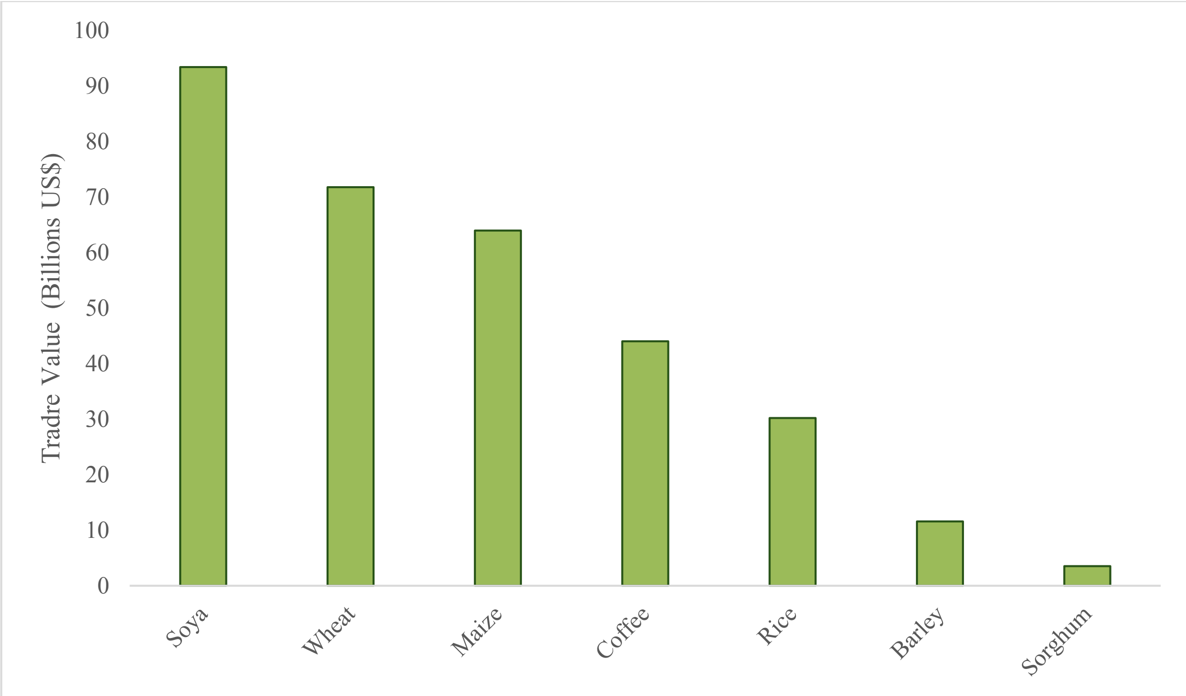

Figure 1.
Grains export in 2022
Source: UN Comtrade database

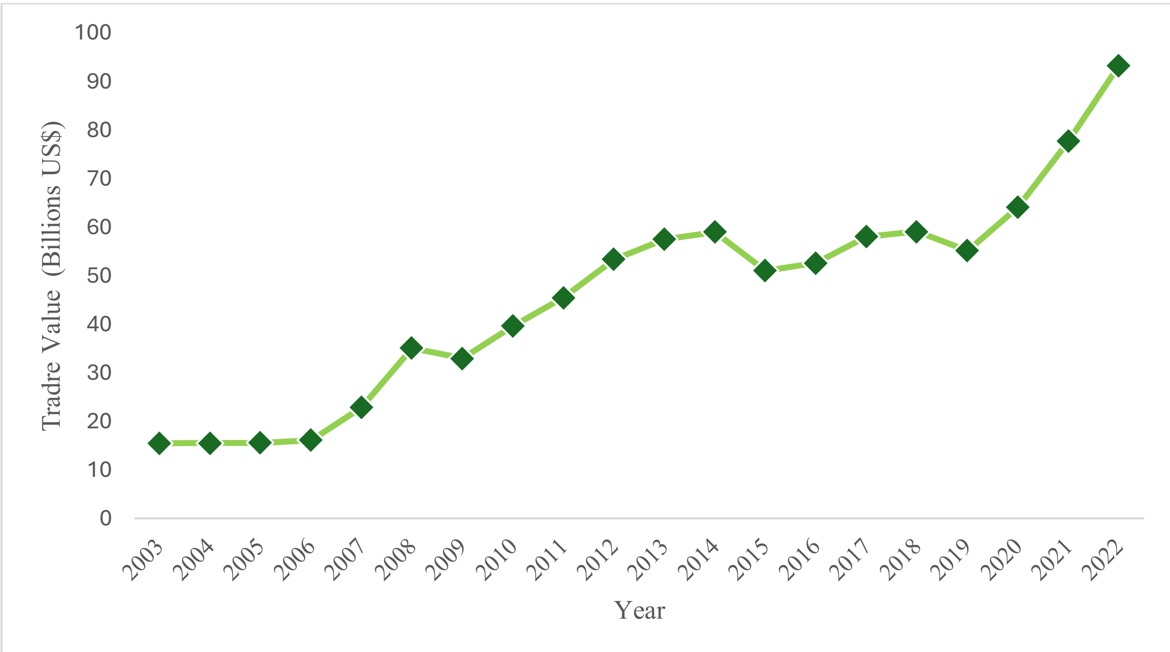

Figure 2.
Change in soybeans trade export volume 2003-2022
Source: UN Comtrade database

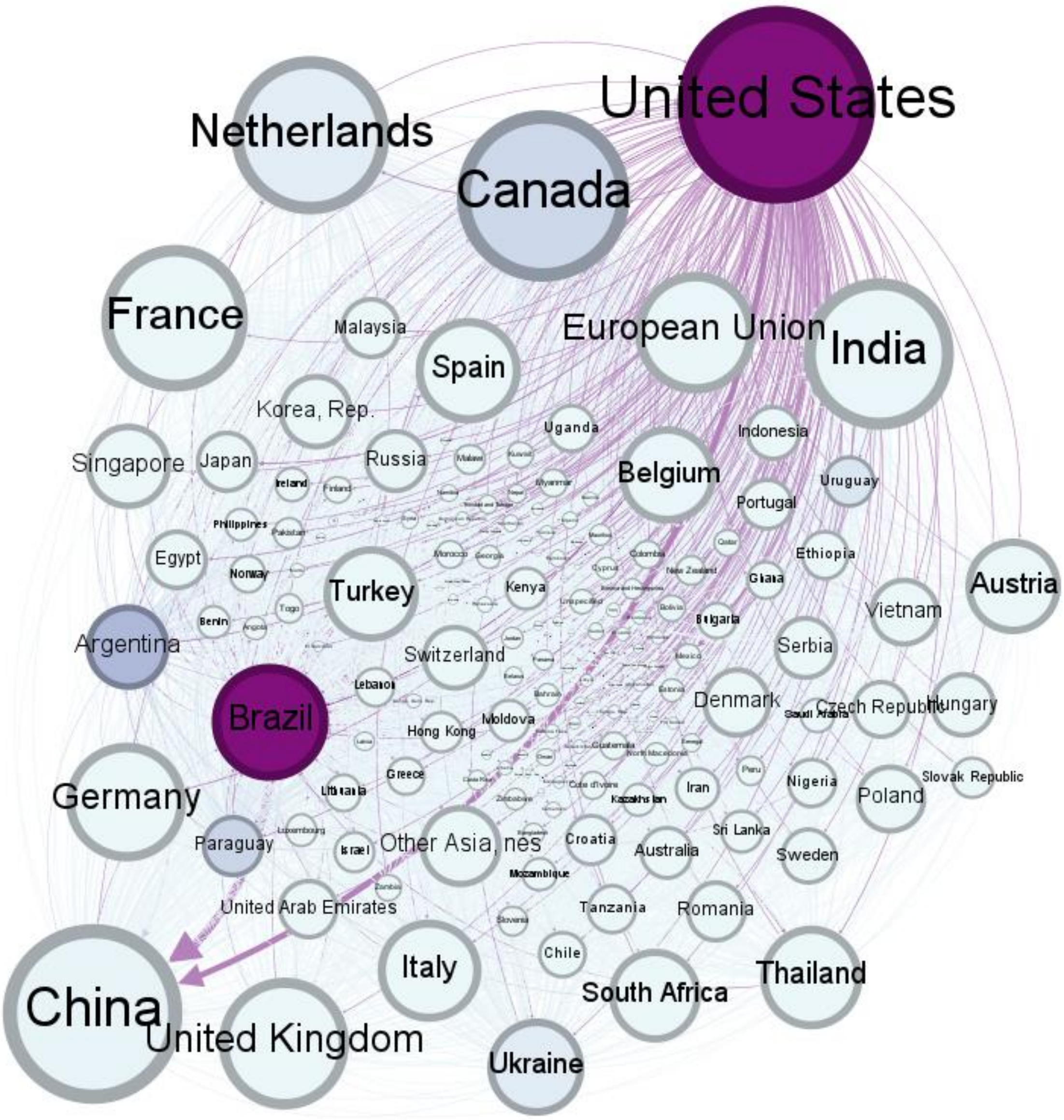

Figure 3.
Soybeans export network 2003-2022, size represents degree, color the weighted degree and edges the volume traded.
Source: Authors

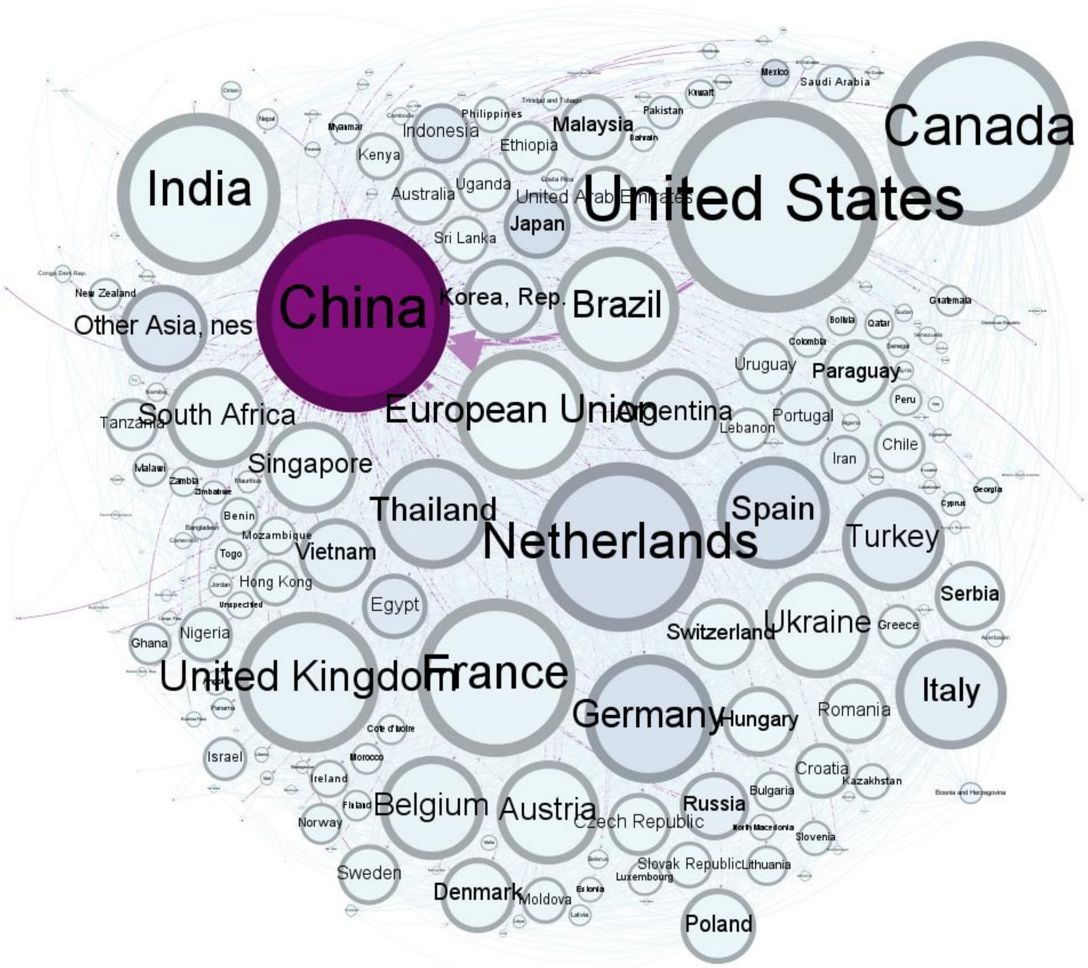

Figure 4.
Soybeans import network 2003-2022, size represents degree, colour the weighted degree and edges the volume traded.
Source: Authors

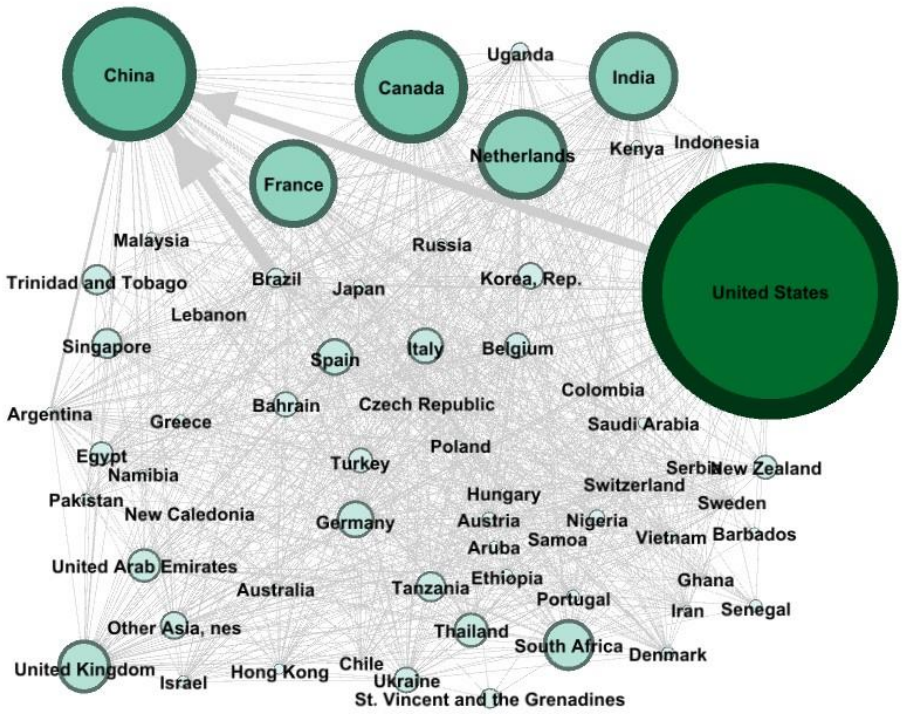

Figure 5.
Soybeans betweenness centrality network 2003-2022
Source: Authors

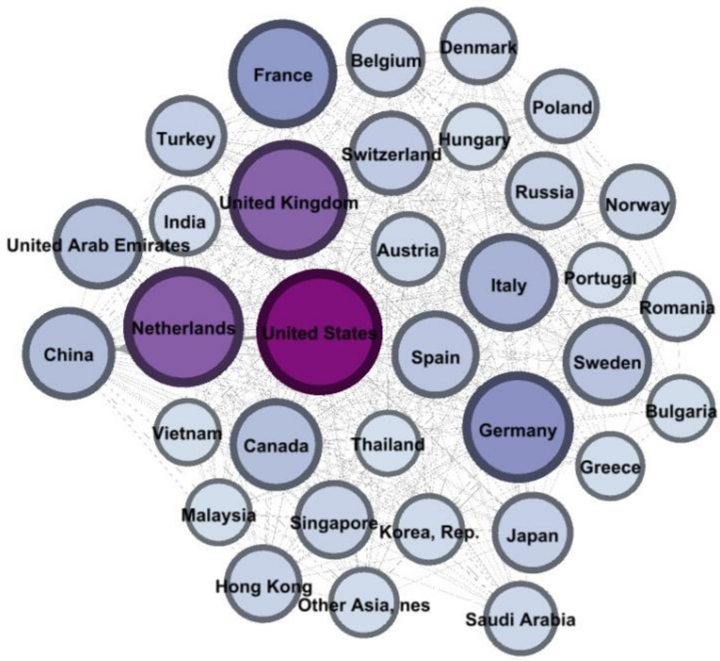

Figure 6.
Soybeans eigenvector centrality distribution
Source: Authors

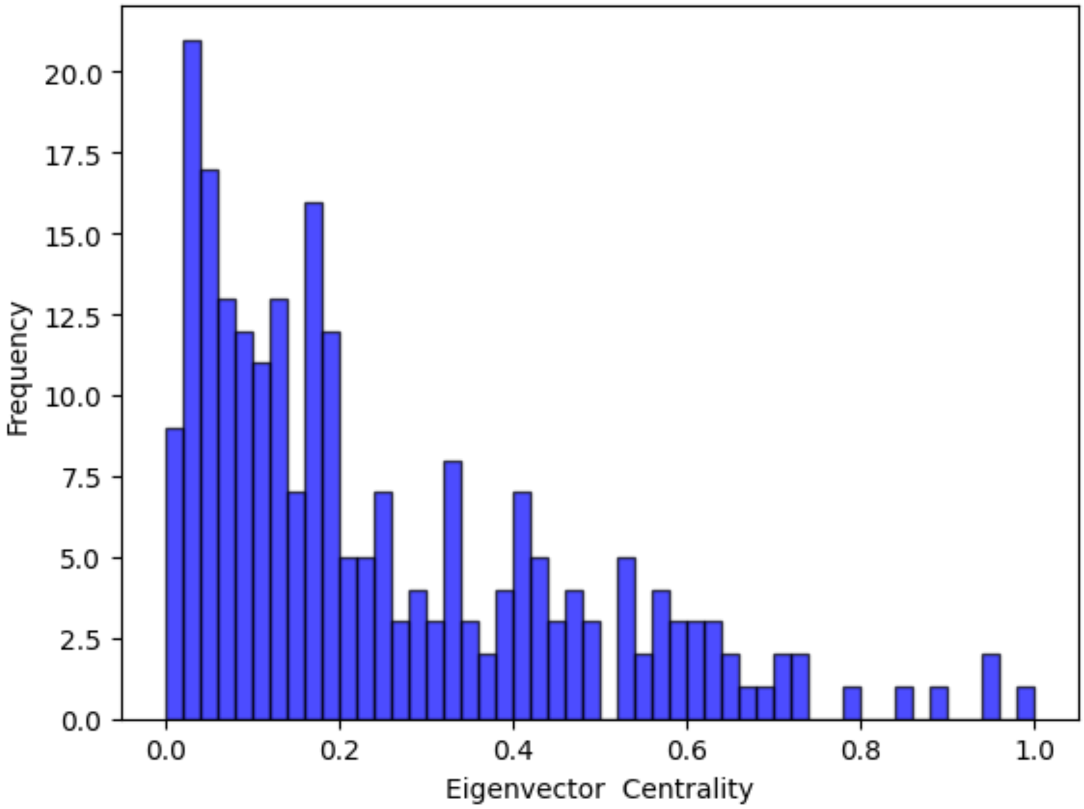

Figure 7.
Soybeans eigenvector centrality distribution
Source: Authors