Criticality of U.S. Food Supply Chains from Latin America

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Abstract

Food imports from overseas via ocean transport are important for the U.S. food supply and economic growth. Latin America and the Caribbean is a growing exporting region of agri-food products, which typically arrive in the U.S. via ports. The resilience of the U.S. port network is fundamental in maintaining this supply. A disruption in one or more ports could compromise the network's capacity to keep a smooth flow of perishable goods before expiration. This study considers seven critical perishable goods, including dry, cold, and frozen containerized cargo. It first develops a network analysis for each node and path, identifying the centrality and criticality of primary ports and maritime routes within the U.S. Furthermore, it explores the potential consequences of disruption in these primary ports through discrete-event simulation and proposes contingency strategies. The results rank the most critical ports by node degree, in-betweenness and closeness centralities, and volume of goods received. This ranking shows that the ports of Philadelphia and Wilmington are the most critical ports in the vessel routes carrying bananas. The discrete event simulation also displays the network's performance when transporting and receiving products into specific ports. To illustrate our approach, we show how banana supply chains would work if the Port of Wilmington in Delaware suffered a complete shutdown of its operations. Such an analysis offers alternative solutions within the U.S. port network for vessels whose original destinations experience disruptions.

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Table of Contents

1. Introduction

According to the United States Department of Agriculture (USDA), the import of food and beverages to the U.S. grew 14.8% in 2022, after having a substantial 18% growth in 2021, setting a record by importing up to $199 billion worth of these goods (USDA, 2022). A growing share of commodities from diverse food categories, such as cereals, fruits, meats, and vegetables, reflects the ethnic diversity, economic progress, and immigration influence in the U.S. In addition, $85 billion of U.S. imports can be attributed to intra-industry trade. This trend echoes the importance of the food and beverage import supply chain in the nation's stability, growth, and progress (Miller & Hyodo, 2022). Food and beverage transportation includes dry, cold, and frozen multimodal cargo with added complexity due to the related operations volatility, and short product life cycles, among other factors.

An essential element of this transportation component is the ocean transportation system, sustained by ports handling the movement of imports and exports (USDA, 2017). According to the United States Department of Transportation (USDOT), maritime transportation constitutes 40% of the total value of U.S. imports and 60% of its total weight in 2021, surpassing any other mode of transportation. This percentage increases globally, with 80% of international trade volume transported by sea (UNCTAD, 2021). Furthermore, when focusing specifically on food movements, nearly 60% of food miles (ton-kilometers) are attributed to water transport (Ritchie, 2020). Since approximately 90% of non-bulk manufactured goods in international trade are currently shipped in containers (USDOT, 2023), this capstone only considers containerized cargo volume measured in 20-foot equivalent units (TEU).

A situation that has influenced the volume and sources of current U.S. imports, primarily after COVID-19, has been companies' investment in risk mitigation and supply chain resilience to face any possible agri-food disruption. Companies can reduce the likelihood and magnitude of disruptions, transportation costs, and greenhouse emissions by applying such strategies as regionalization, nearshoring and friendshoring, meaning the relocation of suppliers and/or factories to a location closer to the main markets (Robertson, 2023). As part of this phenomenon, many U.S.-based companies have already moved their manufacturing sources to Latin American countries due to their proximity (Doheny, 2022).

Considering the relevance of food and beverage imports for the U.S. economy, as well as the ongoing trend of regionalization with Latin America as a key player, the MIT Food and Retail Operations Lab, one of the research laboratories of the MIT Center for Transportation and Logistics, is interested in developing strategic visibility and data- and model-driven analyses of food and beverage maritime flows from Latin America to the United States. The lab aims to identify the primary ports and routes within the port network of this region, understand the potential consequences of disruptions in these ports, and determine the factors that could help mitigate those consequences to maintain a log-term sustainable food flow for the U.S.

Seven critical goods from the American basic food basket were selected for this project as the objects of study: bananas, tomatoes, potatoes, poultry, cocoa, corn, and rice. Together, they account for 4.7% of total 2022 U.S. food imports, amounting to $9.3 billion. These selections were made due to their diverse nutritional profiles and significance in the American diet. Additionally, they encompass a range of dry, cold, and frozen containerized cargo types, making them representative of various transportation and storage conditions. The analysis considers imports of these goods from 2010 to 2023. The chosen exporting countries for this investigation include all the countries in Latin America and the Caribbean. Combined, they represent 62% of the total value of U.S. imports of the specified agricultural products.

1.1 Problem Statement and Research Questions

The objective of preventing disruptions in the flows of food from Latin America to the U.S. relates to the uncertainty drivers behind the goods imports, the role that logistics facilities such as ports play in these flows, and the effect regionalization can have on this port system.

Studying, analyzing, and understanding the reasons behind these uncertainties is crucial for providing data- and model-driven recommendations to keep the agri-food systems working effectively in their current supply chain context.

Therefore, the main research questions to be answered through this project are:

- What is the criticality of ports connecting Latin American countries to the U.S.?
- How does logistics infrastructure dependency affect port adaptability and agility in case of a disruption?
- How resilient is the current port network in mantaining food imports if a specific port suffers a reduction in operations?

1.2 Main hypothesis

We hypothesize that it will be possible to identify their criticality for the U.S. network by analyzing goods import data and employing network analysis on the involved logistics facilities and ports (i.e., treating them as nodes). Additionally, what-if scenarios can be built to simulate a disruption in a critical port. By concluding those scenarios, it would be possible to provide strategic data- and model-driven recommendations preventing supply chain disruptions in this sector, considering vulnerability, perishability, infrastructure, and pre-determined maritime routes.

1.3 Project Goals and Expectations

The main expected contribution is to provide a list of strategic, data- and model-driven recommendations on gaining agility and adaptability to prevent supply chain disruptions in the food sector. The baseline for this analysis will be U.S. port imports from Latin America, and the recommendations will address the primary drivers that underlie the current flows, volumes, and frequencies between the ports.

In that context, the deliverables include:

1. Interactive dashboards displaying the results of:
    a. The exploratory analysis, which provides strategic visibility for a seven-item list of commodities with volumes, frequencies, and variability visualizations.
    b. The network analysis of U.S. ports, which shows the assessment of the criticality and centrality of the ports handling the seven-item list, and the dependence on logistics infrastructure and stakeholders to receive and ship the items on time.
2. Python built simulation with scenarios that account for disruptions of U.S. critical ports.
3. A list of strategic data-driven recommendations based on the mentioned analysis to gain adaptability capabilities in segmented supply chains by continent for the selected products, with the Latin America case as a reference.

2. State of the Practice

This study aims to assess the criticality of specific U.S. seaport suggesting alternative ports or routes for vessels in the event of a crisis to ensure products' freshness. Thus, to understand potential risks and provide strategic recommendations, literature was reviewed across various domains regarding US ports and their role in food imports. Subsection 2.1 delineates the characteristics that define a port's capacity to handle diverse cargo types, and the difference between nearshoring and offshoring strategies. Subsequently, subsection 2.2 presents research done around port network analysis. Finally, subsection 2.3 explores discrete event simulation concepts and examples pertinent to port operations and food supply chains.

2.1 Ports Overview

2.1.1 Ports Infrastructure, Specialization, and Flexibility

A large port typically has multiple terminals that together can handle many cargo types; however, individual terminals are usually designed to move a single cargo type. The requirements of loading, unloading, and storing different cargo types lead to significant differences in terminal design and overall port infrastructure (USDOT, 2023). A strategic decision in a port infrastructure design is to choose between specialization and flexibility.

Specialization is necessary to handle certain types of cargo, with mandatory services, processes, equipment, infrastructure, and conditions to protect the goods' quality and freshness (and other features). Some examples related to food supply chains are temperature-controlled storage facilities, fumigation, weighing, testing, sacking, and humidification systems. These unique requirements play an important role in determining whether a port can serve as a viable alternative for cargo reception during a disruption at a nearby port.

Flexibility is a vital representation of a port's agility and adaptability. Agile flexibility enables port operators, ocean carriers, and logistics service providers (LSPs) to rapidly interact and adapt their assets and operations to different service types and volumes. By becoming more adaptable, ports can evolve from logistics distribution centers into transport solution providers and support structural changes in port ecosystems. The development of flexibility in a port environment is supported by four dimensions: a) making customers more profitable, b) cooperating to enhance competitiveness, c) mastering change so the business improves its adaptability in the long term, and d) leveraging the impact of people and information (Paixao et al. 2003). The need for flexibility to combat uncertainty, avoid port congestions, and keep freight moving is high (Russell et al., 2022).

These characteristics are generally intrinsic to any port's operational strategy and vary according to its purpose in the maritime supply chain network.

2.1.2 U.S. Ports Capacity Metrics

Port performance is impacted by the trade-off between highly specialized strategies restricted to specific cargo types, and open strategies designed for everyday use. The measurement of this performance involves prosecutorial performance indicators (PPIs) that reflect regional competitiveness and optimum throughput. When comparing equal cargo, the higher the specialization, the better PPIs are. Capacity is among the essential PPIs, and it considers berthing, storing, loading/unloading equipment, port area, and number of gate lanes (Metalla et al., 2016). At a national level, capacity is measured by evaluating i) container cranes, ii) multimodal transportation (e.g., rail), iii) terminal dimensions (i.e., acreage), and iv) the spatial measurements, air draft distance, berth length, and channel depth (USDOT, 2023).

Port operations strategy (specialized or flexible) and the port's capacity are defined during the port planning stage. They focus on having a feasible cost tariff structure and consider global and specific economies of scale.

Capacity availability propels port growth and contributes to the overall network resilience in the face of disruptions. National security needs to have a robust port ecosystem, and for this purpose the U.S. government created the Council of Supply Chain Resilience (The White House, 2023). The Council has a long-term, government-wide strategy to increase supply chain resilience, involving Senior officials from various agencies, including the National Security Advisor, National Economic Advisor, Secretaries of Agriculture, Commerce, Defense, Energy, Health and Human Services, Homeland Security, Housing and Urban Development, Interior, Labor, State, Transportation, Treasury, and Veterans Affairs, among others.

Table 1 shows the top 25 US container ports in 2020, according to the number of twenty-foot equivalent units (TEU) handled. The list considers both imports and exports. The table also displays the number of container cranes and total containerized imports (TCI) in thousands of TEUs (USDOT, 2020).

Table 1

Top 25 Container Ports Capacity Characteristics. Year 2020

Port Ranking	State(s)	Port	Container Cranes			TCI
			Other	Super Post-Panamax	Total	
20	Alabama	Mobile	0	4	4	221
19	Alaska	Alaska (Anchorage)	3	0	3	0
2	California	Long Beach	18	54	72	4,228
1	California	Los Angeles	33	34	67	5,028
7	California	Oakland	13	13	26	1,015
22	Delaware	Wilmington	2	0	2	196
12	Florida	Jacksonville	16	3	19	225
13	Florida	Miami	7	6	13	504
16	Florida	Port Everglades	9	6	15	302
4	Georgia	Savannah	8	30	38	2,365
14	Hawaii	Honolulu	8	0	8	19
18	Louisiana	New Orleans	5	4	9	143
15	Maryland	Baltimore	11	12	23	524
23	Massachusetts	Boston	6	6	12	144
25	Mississippi	Gulfport	3	0	3	58
24	New Jersey	South Jersey	2	0	2	63
3	New York-New Jersey	NY-NJ	35	24	59	4,186
21	North Carolina	Wilmington	7	0	7	127
17	Pennsylvania	Philadelphia	6	5	11	435
11	Puerto Rico	San Juan	11	0	11	206
8	South Carolina	Charleston	3	24	27	1,084
5	Texas	Houston	14	14	28	1,343
6	Virginia	Virginia	0	28	28	1,320
10	Washington	Seattle	6	10	16	618
9	Washington	Tacoma	8	17	25	710

Note: TCI = Total Containerized Imports, in thousands.

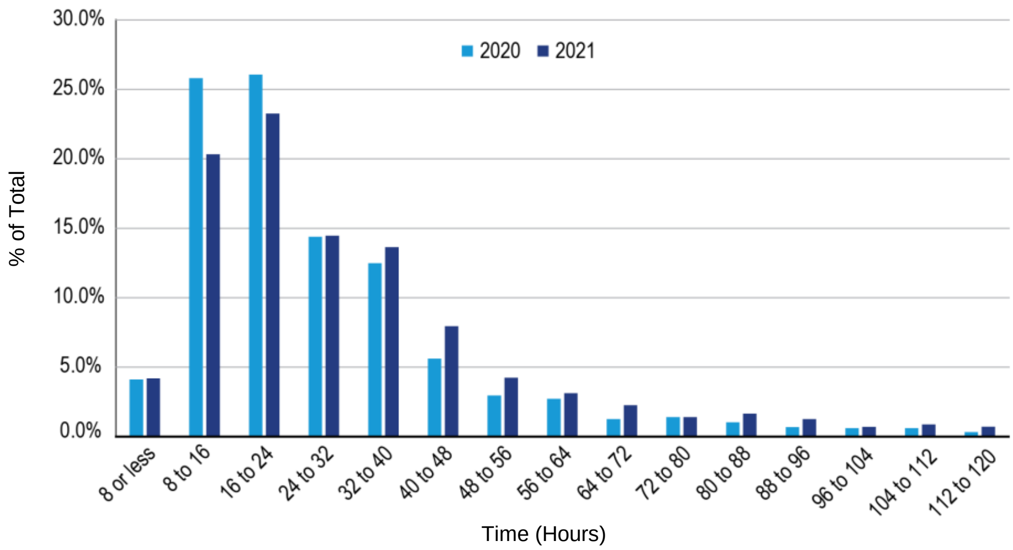
2.1.3 U.S. Port Performance Metrics

Port performance and trade facilitation are integral to ensuring the efficiency of maritime transport (UNCTAD, 2023). Therefore, according to the Fixing America's Surface Transportation (FAST) Act, the Bureau of Transportation Statistics measures the U.S. top 25 ports' (by tonnage, TEUs, and dry bulk) throughput and capacity. However, developing nationally consistent port performance assessments is challenging, given the diversity of port ownership arrangements, operating methods, and cargo handling (USDOT, 2023).

The time vessels wait in ports is a significant factor in port performance. "Vessel dwell time" refers to the time a vessel spends in port actively loading or unloading cargo, which, in turn, contributes to both port capacity and throughput performance. Port terminals focus on minimizing vessels' call duration to provide sufficient capacity to discharge and load containers within the shortest amount of time. The Bureau of Transportation Statistics (BTS) uses the U.S. Coast Guard's (USCG) Automatic Identification System (AIS) data to calculate ships' dwell times at berth, including for container vessels (USDOT, 2023). Figure 1 shows the distribution of observed container vessel dwell times between 2020 and 2021 (USDOT, 2023).

Figure 1

Distribution of Observed Container Vessel Dwell Times: 2020 and 2021



A PPI that connects capacity, infrastructure, and performance (operative and financial) is the berth throughput, which is the total tonnage of cargo handled across a berth. This indicator is primarily influenced by the class of cargo handled. It affects the financial performance of the port, due to the relationship between its income generation operating surpluses, and expenditures, to total Gross Registered Tons (The World Bank, 1993).

A port's capacity to handle containers for export, import, and trans-shipment is reflected by the Container Port Performance Index (CPPI). According to this index, the top-performing regions are Asia, Latin America, and the Caribbean, while the U.S. and Canada are the bottom performers. A port specialization degree can explain some differences in the CPPI rankings. For example, bottom performers like the U.S. focus mainly on imports. Considering the average minutes per container moved, one metric of the CPPI metrics, the

U.S. ports require 68% more time than the average of the top 25 countries (Review of Maritime Transport 2023, 2023). The U.S. government launched the office of Multimodal Freight Infrastructure and Policy to improve their performance, which is "responsible for maintaining and improving the condition and performance of the nation's multimodal freight network…" (The White House, 2023).

2.2 Nearshoring vs. Offshoring

Offshoring, popular during the globalization process, means an expansion of global production networks. On the contrary, nearshoring can be described as a shift from global supply network to a smaller geographical scope, implying a regionalization of value chains (Pietrobelli & Seri, 2023). Nearshoring permits supply chains to be sourced closer to domestic markets, allowing quicker responses, shorter lead times, sourcing stability, and disruption-mitigation support. Other advantages of nearshoring are time-zone alignment, which makes collaboration more accessible and efficient, fuel savings, improved carbon footprint, and environmental, social, and governance sustainability (Fernandez-Miguel et al. 2022).

Since the end of 2022, there has been a notable increase in nearshoring, indicating a reorientation of the international flow of goods, primarily influenced by political affinity. Sustainable practices, technology advancements, and developed economies seeking to reduce their dependence on China are expected to fuel this trend in the upcoming years (UNCTAD, 2023). In the context of the global food and beverage system, weather and supply-related events have generated historical disruption scenarios almost totally. However, the Russia-Ukraine war that began in 2022 exposed vulnerabilities in supply chain hubs, resulting in secondary effects on other key breadbaskets (Aminetzah & Denis, 2022). Moreover, before the conflict, COVID-19 had already intensified supply chain uncertainties, reaching levels not seen since the container revolution began in the late 1970s (Russell et al. 2022).

An example of a U.S. nearshoring strategy related to Latin America and the Caribbean (LAC) is the Panama Canal Expansion (PCE). It is an intervention that sought to increase maritime activities between these regions. Significant port growth was recorded after the expansion was concluded in 2016, except for five regional ports in Central America and the Caribbean. The challenges for the LAC ports to be sustainable and competitive are, among others, investments in infrastructure and equipment to receive neo-Panamax vessels, logistics infrastructure, and value-added services (Miller & Hyodo, 2022). Similar approaches have been observed in neighboring countries like Mexico and Canada via the new U.S., Canada, and Mexico agreement sign.

2.3 Network Analysis

Part of the hypothesis of this work is that specific ports are more critical than others, and that by employing network analysis techniques, this hypothesis can be tested. The fundamental concepts in the study of networks are nodes, links, and criticality. Nodes, representing entities such as organizations, people, countries (Opsahl, et al., 2010), or airports, establish connections between themselves through links. For example, in airports serving as nodes, the routes between origins and destinations represent the links (Park et al., 2023). Finally, critical nodes and edges (an alternative term for links) are defined as those whose failure could significantly alter the characteristics of the entire network (Gaur et al., 2020).

Another key network analysis concept related to criticality is centrality, which can be calculated through various methods. The most common measurements are degree centrality, betweenness centrality, and closeness centrality. Degree refers to the total number of links a node has. Generally, the more links a node has, the more critical it is in the network. Betweenness (also known as in-betweenness) represents the capability of a node to control the flows between other nodes that are not directly connected to each other. And closeness refers to how close a node is to the other ones in the network (Park et al., 2023).

Ducruet and Itoh (2022) studied the drivers behind vessels' turnaround times at approximately 2,300 ports between 1977 and 2016. As part of their research, they performed a network analysis where ports were the nodes and inter-port trips were the links. They measured the centrality of the nodes with four methods, two of which were degree and betweenness centrality. They found that ports with elevated betweenness had higher average turnaround times, concluding that accessibility is not determinant to decrease turnaround time.

A different study was conducted to analyze the network of Caribbean cruise ports using ports and network analysis techniques. In this case, a social network analysis was carried out, measuring degree centrality, betweenness centrality and out-degree centrality, defined as the number of nodes connected externally from a port. The authors interpreted the centrality of the 89 ports forming Caribbean's cruise network. Their results include a list of ports that can significantly impact in the entire region by optimizing their interaction with the Caribbean cruise network, as well as a suggestion of five ports to establish new route links and maximize the flow of passengers (Lopez Rodriguez et al., 2021).

The concept of traditional network centrality was expanded in a network study (Park et al., 2023) of 100 airports, which studied network centrality for cold chain products under COVID-19. This research was based on a weighted network approach, measuring weighted degree, weighted closeness, and weighted betweenness centralities. The authors used air cargo traffic as the weight, stating that weights permit a more precise analysis. The research results highlight the top five airports with the most connections for cold chain products, and the top five airports that serve as transfer hubs, playing an intermediary role. Park et al. (2023) also uncover which airports suffered a ranking increase or decrease after COVID-19.

Ducruet and Itoh (2022), Lopez Rodriguez et al. (2021), and Park et al. (2023) utilize network analysis as their primary technique to draw the study's conclusions. Ducruet and Itoh's work is relevant because their findings explain how logistics factors can impact the flows within a port. However, while they considered worldwide ports, this capstone project focuses exclusively on Latin America and U.S. ports. The Caribbean cruise port network study is also informative in the current context since it explains the convenience of employing the specific social network analysis approach. Lastly, even though Gaur et al. (2020) centers on airports, the concepts of nodes and arcs apply similarly to ports. Furthermore, that paper suggests employing weighted metrics, an approach that can increase the result’s precision.

2.4 Discrete Event Simulation

This type of simulation traces the operational status of entities such as customers, operators, ports, and facilities within a sequential process over time. It involves entities arriving at facilities, with input details such as entity arrival rate, facility processing time and capacity, and output details such as costs, defects, total processing time and entities served. Discrete event simulations have the advantage that they can be rerun *n* number of times to obtain behavioral distributions (Olson, 2003).

Simulation has long been used to analyze supply chain, logistics or manufacturing challenges. However, simulating supply chain disruptions involves a different and unique set of problems. Dealing with supply chain disruptions means that the simulation model should focus on one specific node, which will suffer the consequences of the disruption. In most cases the simulation results will answer questions such as: Has the system performance been significantly altered? Is the system's state before the disruption significantly different from its state after the disruption? (Melnyk, et al., 2009)

Zhou et al. (2022) study the impact of a Suez Canal blockage on the Port of Singapore (PSA) in 2021 and presents an example of how discrete event simulation can be leveraged to assess and predict disruptions' repercussions. The latter is especially true after the COVID-19 pandemic generated unprecedented congestion in ports, which, in turn, affected businesses and provoked financial stress. The model Zhou et al (2022) created considers container vessels from the Suez Canal and other ports travelling to the PSA, where three terminals serve them, and then leave the port. The simulation results concluded that the blockage of the Suez Canal would not cause significant congestion at the PSA, given the throughput of the canal, the port's operational efficiency, and the imminent rerouting of some vessels.

Parola and Sciomachen (2005) conducted a study involving diverse simulation scenarios for the entire logistics chain within the two ports of Genoa and the port of La Spezia, all situated in Italy. They developed a discrete event simulation model, assuming a constant growth in sea traffic over 10 years. The study involved varying the level of modernization and expansion of the adjacent railway lines. In the most favorable scenario, which involved constructing a new railway line and doubling the capacity of the existing one, the rail traffic successfully coped with the additional sea volume. On the contrary, road traffic congestion resulted in the least favorable scenario, where only the restructuring of the existing lines was considered.

Van der Vorst et al. (2000) focus on discrete event simulation for food supply chains. Their study examines chilled salads flowing from a producer to a distribution center, and ultimately to a retailer. The simulation's objective was to assess the impact of various process designs on indicators such as holding costs, logistical costs, number of stock-outs, delivery reliability, remaining food freshness and utilization percentage of carriers. The authors ran multiple scenarios using data from eight representative products, to extrapolate the findings to the entire range of comparable products. The outcomes of these simulations underscore the advantages of employing discrete event simulation as a decision-making tool in supply chains. Specifically, the study reveals that diminishing the producer lead time, increasing delivery and ordering frequency, and integrating new information systems enhanced this supply chain.

Studies by Olson (2003) and Melnyk et al. (2009) show how discrete event simulation can be employed to understand variables contributing to vessel congestion at the ports. Given the perishable nature of food and its potential complete devaluation if not timely unloaded and distributed, avoiding port congestion is a critical factor for this study. However, Zhou, et al. (2022) and Parola and Sciomachen (2005) centered on a particular port district, and a specific port, respectively. In contrast, this study aims to understand disruption repercussions for a whole network of ports. Van der Vorst, et al. (2000) do not explore simulation scenarios for maritime transportation, but they exemplify how to consider and monitor food freshness within a discrete event simulation.

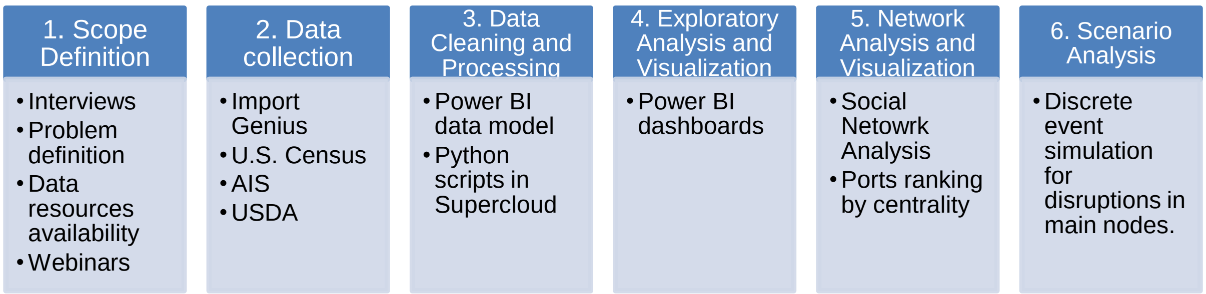
This capstone project combines the state of the practice related to port infrastructure, port capacity, and network analysis to generate a series of parameters to be used as input for a discrete event simulation. The complete description of the methodology is described in depth in Section 3.

3. Methodology

Considering the research questions and the state of the practice, the methodology of this project transitioned from a broad perspective to a more specific focus. It began by examining global food imports to U.S. ports by continent. It narrowed down to individual container ships from Latin America, culminating with scenario analysis in case of a specific port shutdown. The main tools or methods employed for this purpose were social network analysis and discrete event simulation, and the cargo of interest was the seven-item list of food defined in Section 1. This methodology has been organized into six steps, as illustrated in Figure 2.

Figure 2

Methodology Steps



3.1 Data Collection

The first step of the methodology consisted of collecting the necessary data and attending webinars with subject matter experts. Additionally, to contrast the qualitative and quantitative collected data with the state of the practice in the field, three port terminals were visited in person: Terminal DP World in Port of Callao, Peru; Conley Terminal in Massport, United States; and Terminal 3 in Port of Mar del Plata, Argentina.

The data sources were the U.S. Census, USDA, Import Genius, and Marine Cadastre. The U.S. Census, a public database, provided imports data on how much volume (measured in weight and dollars) of each commodity had been imported monthly to each port, specifying the continent and country of origin. Import Genius, a private online platform, provided more detailed data showing imports at a shipment level, the description of the cargo being transported, the name of the vessel transporting it, and the exact date of arrival to the port of destination. Finally, Marine Cadastre, a restricted governmental database, provided AIS data that presented the latitude and longitude of each vessel close to the U.S. on average every two minutes.

3.2 Data Cleaning and Processing

Import Genius was a bridge between the Marine Cadastre AIS data and the data structure required to perform a network analysis, see Figure 3. Import Genius included the cargo description of vessel being transported, while the AIS data did not. This field was necessary to filter the AIS data and only keep the vessels that transported the seven-item food list, which was defined in Section 1. Therefore, several slices of data were exported using the Import Genius platform, containing only information for the seven items and the Latin America countries of interest. Afterward, the vessel names in these files were used to filter the AIS data.

However, the Marine Cadastre AIS data represented a computational challenge because a CSV file with approximately eight million rows existed for each day of the year. This means that one semester of data included almost 1.5 billion rows, which requires significant computing resources to be manipulated. Therefore, the data was processed using MIT SuperCloud, a high-performance computer designed to support many concurrent users and application codes. Within SuperCloud, a Python script combined the Import Genius and AIS data. First, the script filtered all the daily files to include only data from the vessels found in the Import Genius data. Second, all the files were combined into a single table. Lastly, the data was grouped at a two-hour level, instead of a two-minute level. In this way, the level of data granularity remained sufficient to provide valuable insights into a given vessel's whereabouts, the ports it visited, and its route. Simultaneously, data management complexity was reduced, requiring less computational power.

Additionally, a field was added to the data containing the names of the ports corresponding to each latitude and longitude. A separate catalog table with defined latitude and longitude quadrants per port was created to do this. If a particular pair of the AIS latitude and longitude data was inside one of the quadrants, then the port name in the catalog was added to the port name field in the AIS table. Additionally, the coordinates of the geographic boundaries of the U.S. coast were added, to eliminate incorrect links in the vessel's routes.

Besides the AIS data processing, a data model was created in Power BI to allow a smooth exploratory analysis of the U.S. Census imports and the Marine Cadastre AIS data. Some minor data cleaning steps, such as renaming certain fields, were taken to achieve this. The relationship and its cardinality and direction can be seen in Figure B-1 in Appendix B.

3.3 Exploratory Analysis

During the third step of the methodology, Power BI was used to create dashboards that visually displayed important properties of the seven items' port network. A helpful feature of this tool was the capability to create a dashboard for a specific purpose, and by using a commodity filter, display information just for a specific commodity, without creating separate dashboards for each. Considering this feature, the purposes of the dashboards were to:

1. Identify the ports that handled the biggest volumes of cargo, measured in weight and dollars.
2. Analyze the import volume trends over months and years and discover seasonal patterns.
3. Understand which ports handled which commodities and if a specific port specialized in a particular commodity type.
4. Analyze how relevant Latin America was compared to other parts of the world regarding the volume exported to the U.S.
5. Understand which countries from Latin America were the most important ones in terms of the volume they exported to the U.S.
6. See each vessel's routes, generate an overview of the port network, and validate the AIS data processing described in Section 3.2.

3.4 Network Analysis

The exploratory data analysis provided a general understanding of which were the most important ports to consider when importing any of the seven commodities of interest. However, that analysis did not consider other ports that might have not received this type of cargo but had been part of the routes followed by the ships transporting this cargo. Therefore, a network analysis was performed to evaluate the criticality of the whole port's network of these seven commodities.

First, it was necessary to arrange the preprocessed data in Python into a specific structure of two tables: edges and nodes (See Figure 3). The edges table denotes all the possible combinations of origin and destination pairs of nodes in the network and must have at least two columns: origin node and destination node. The nodes table is a list of all the nodes that appear in the edges table, and it must have at least one column: nodes.

Figure 3

Example of Data Structure for Network Analysis

Edges Table

Origin	Destination
A	B
B	C
A	D
C	D

Nodes Table

Nodes
A
B
C
D

Once this data structure was created, the Python library *NetworkX* was used to calculate the degree centrality, betweenness centrality, and closeness centrality of all the ports involved in the network routes as described in Section 2.3.

Degree centrality in a network measures the degree to which a node is connected to another node within the network. Betweenness centrality is used as an indicator to evaluate the probability of control or brokerage between two nodes in a network. It is recognized as a good representation of the function of transshipment ports in a port network. Closeness centrality is used to see how close one node is to the other nodes, measured based on the shortest distance between the two nodes.

Degree Centrality notation:

Cd (i): weighted degree centrality for port i.

x_{ij}: a binary variable, if nodes i and j are connected, x_{ij} is assigned a value of 1; otherwise, x_{ij} takes a value of 0.

i : focal port.

j : other ports.

n: total number of ports.

$\sum_{j}^{n} x_{ij}$: number of trades between port i and all other ports.

Degree Centrality function:

$$C_d(i) = \sum_{j}^{n} x_{ij}, i \neq j ,$$

Betweenness Centrality notation:

Cb (i): weighted betweenness centrality for port i.

g_{jk}: where g_{jk} is the number of binary shortest routes between ports, and $g_{jk}(i)$ is the number of those routes that go through port i.

i : focal port.

j : other ports.

Betweenness Centrality function:

$$C_b(i) = \frac{g_{jk}(i)}{g_{jk}}, i \neq j \neq k$$

Closeness Centrality notation:

C_c (i): weighted closeness centrality for port i.

i : focal port.

j : other ports.

n: total number of ports.

$\sum_{j}^{n} d(i,j)$: sum of binary shortest ports distances between two ports.

Closeness Centrality function:

$$C_c(i) = \left[\sum_{j}^{n} d(i,j)\right]^{-1}, i \neq j$$

The three centrality measures were calculated seven times, one per commodity. In this way each network can be analyzed separately.

3.5 Discrete Event Simulation

Once the network analysis provided an understanding of the centrality of the ports in the network aside from the import volumes they handle, a discrete event simulation was developed to test the network's resiliency. It was decided only to consider bananas and simulate a disruption in the Port of Wilmington as proof of concept for illustrating the technique. A similar simulation may be performed for the network of the other six commodities, and the disruption of other critical ports may be performed.

Bananas were selected because from the U.S. imports studied, they represent the greatest volume in terms of weight and value (see Figure 9). Wilmington was selected for two reasons. First, even though it is not a central port in the network (see Table 6), it is the main entry point of bananas to the U.S. from Latin America (see Figure 9); second, because it is just a few miles from the Port of Philadelphia, which is the most central port in the network according to the degree and closeness centralities rankings (see Table 6). Additionally, an overall criticality ranking was created after analyzing the combined results of the exploratory analysis and network analysis. Table 23 in Section 5.1 displays this ranking, ranking Philadelphia as the most critical port and Wilmington as the second.

The simulation was constructed using the Python library SimPy. The code simulates vessels initially heading to Wilmington which must seek another port to unload their cargo. The vessels carry varying numbers of refrigerated containers (commonly referred to as "reefers") with bananas and travel a specific route until port serves them with enough capacity. Two routes (northbound or southbound) are available for the vessel. These routes were built according to the network analysis for bananas and the top six most critical ports, which is shown in Table 25. The northbound route encompasses the ports of Philadelphia and New York. The southbound route encompasses the ports of Baltimore, Norfolk-Newport News, and Wilmington, NC, located between Wilmington, DE, and Charleston. A detailed explanation of the steps that the simulation follows can be found in Table 2.

Table 2

Events Generated by the Simulation

No.	Event	Description
1	Generate vessel	A vessel containing bananas as part of its cargo arrives at the Port of Wilmington and then leaves.
2	Vessel arrives at other ports	The port capacity to serve an incoming vessel is calculated.
3	Port serves the vessel	If it has enough capacity, the port serves the vessel.
4	The vessel decides to wait or leave	If the port doesn't have enough capacity, an expected waiting time is calculated and compared against an expected travel plus waiting time at the next port. The vessel decides to either go away or trigger Event 2 in the next port or stay and trigger Event 3 when the port becomes available.
5	Port frees up reefers	Every day all the ports dispatch a certain number of reefers that are plugged in, freeing capacity to serve new vessels.

Table 3 presents five different simulation scenarios (including the baseline run), which are considered to evaluate the different alternatives for vessels under different operative circumstances.

Table 3

Simulation Scenarios Considering a Disruption in the Port of Wilmington, DE

Scenario	Description
Baseline	Built considering historical data.
1	Only small vessels arrive at the Port of Wilmington, DE.
2	20% of the vessels generated are small, 30% medium, and 50% large.
3	Ports’ capacity increases by 20% (measured in number of reefer plugs).
4	Ports’ capacity decreases by 20% (measured in number of reefer plugs).

Table 4 displays the complete list of parameters that exist within the simulation and can be changed to generate the proposed scenarios.

Table 4

Description of the Parameters used in the Simulation

No.	Parameter	Description	Baseline value
1	Ports, Routes, and Travel Time	List of U.S. ports capable of handling refrigerated cargo ordered by proximity. The number of days it takes to travel to that port from the previous port is shown in parentheses.	North: Philadelphia (0.5) – New York (2) South: Baltimore (1) – Norfolk-Newport (0.5) – Wilmington, NC (1) – Charleston (1)
2	Vessel Size	A random number of banana containers are carried by a vessel and divided into small, medium, and large categories.	Small: [1,40] reefers Medium: [41, 449] reefers Large: [450, 850] reefers
3	Vessel Generation	Number of days between the generation of vessels carrying bananas.	Small: 2 days Medium: 3 days Large: 3.5 days
4	Port Serving Time	Number of days it takes a port to completely serve a vessel.	Small: 1 day Medium: 2 days Large: 2 days
5	Port Capacity	The capacity of each port, is measured by the number of reefer plugs used to handle refrigerated cargo.	Philadelphia: 1,500 New York: 5,000 Baltimore: 350 Norfolk-Newport: 800 Wilmington, NC: 1,500 Charleston: 2,274
6	Dedicated Capacity	The percentage of the total capacity that can be dedicated to bananas.	50%
7	Reefer Throughput	The rate indicates the number of reefers moved inland via truck per day.	50% of dedicated capacity
8	Simulation Duration	The number of days that the simulation runs for.	180 days

Finally, Table 5 presents the assumptions under which this simulation operates.

Table 5

Assumptions Considered when Building the Discrete Event Simulation.

No.	Description
1	The port that suffers the disruption (Port of Wilmington) suffers a 100% reduction of its capacity.
2	Any vessel travels to the nearest port, regardless of the port's capacity. It cannot travel directly to the farthest port with available capacity.
3	A vessel carries other commodities besides the commodity of interest (bananas).
4	A vessel traveling north would prefer to continue going north than going back south, and vice versa.
5	The parameters of the baseline scenario were established using data sourced from Marine Cadaster (AIS Data), Import Genius, each US port official website, and interviews with senior management from Massport (Boston, MA, US) and Port of Callao (Lima, Peru).
6	The destination ports' infrastructure appropriately serves the different simulated vessel sizes.

The results of each step in the methodology are shown in section 4. The insights obtained from the network analysis are used to evaluate and complement the results from the network analysis. In the same way, the results from the network analysis are used to decide which port region to simulate in the final step.

4. Results

This section presents the results obtained after concluding the development of the six-step methodology illustrated in Figure 2. The results focus on the dashboards created as part of the exploratory data analysis, the port rankings by centrality resulting from the network analysis, and the ports performance metrics generated through the discrete event simulation.

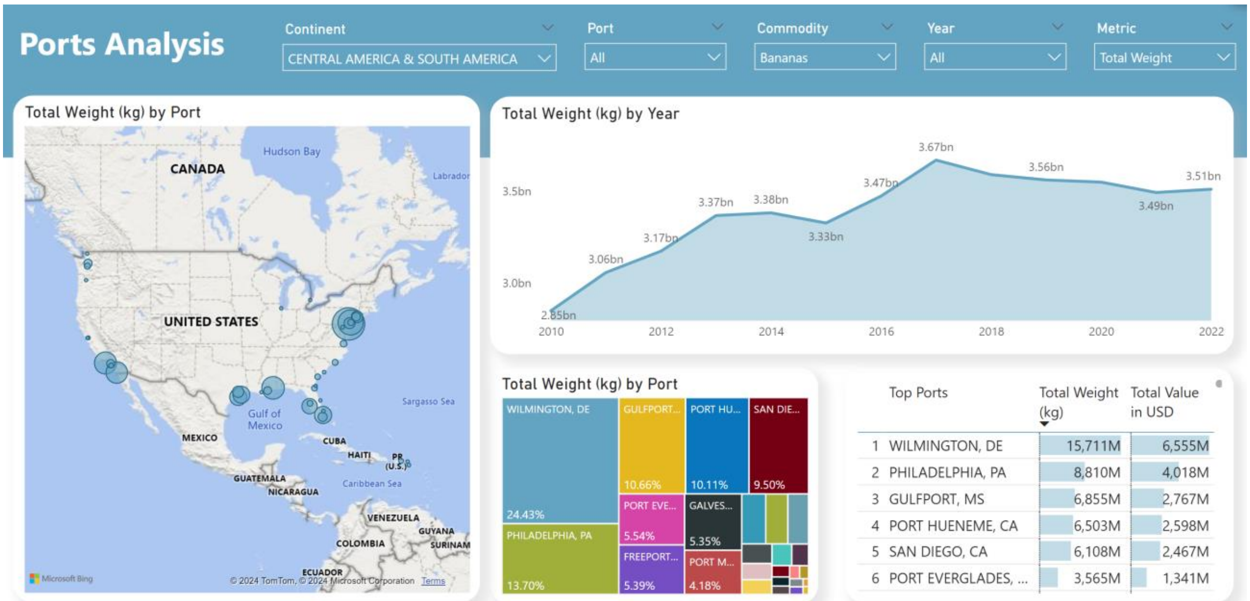
4.1 Exploratory Analysis Insights

This section presents three interactive dashboards created with Power BI for exploratory analysis. They display data related to the U.S. maritime imports from Latin America of the seven-item list in Section 1. Power BI was chosen to create the dashboards given that it is a user-friendly low-code interface which specializes in business analytics and reports generation. More examples of dashboards can be found in Appendix A.

The dashboard shown in Figure 4 shows the distribution of U.S. imports by port. Considering only bananas, Wilmington and Philadelphia are the ports that receive the most significant amount of cargo measured by weight and value.

Figure 4

Bananas U.S. Imports by Port



Focusing now on origin countries, Figure 5 displays which countries are the main contributors to U.S. food imports. In this case, it can be seen that Guatemala is the biggest exporter of Cavendish bananas, the most consumed type of banana in the U.S., considering both import weight and value in USD.

Figure 5

Latin America Bananas Maritime Exports to the U.S.

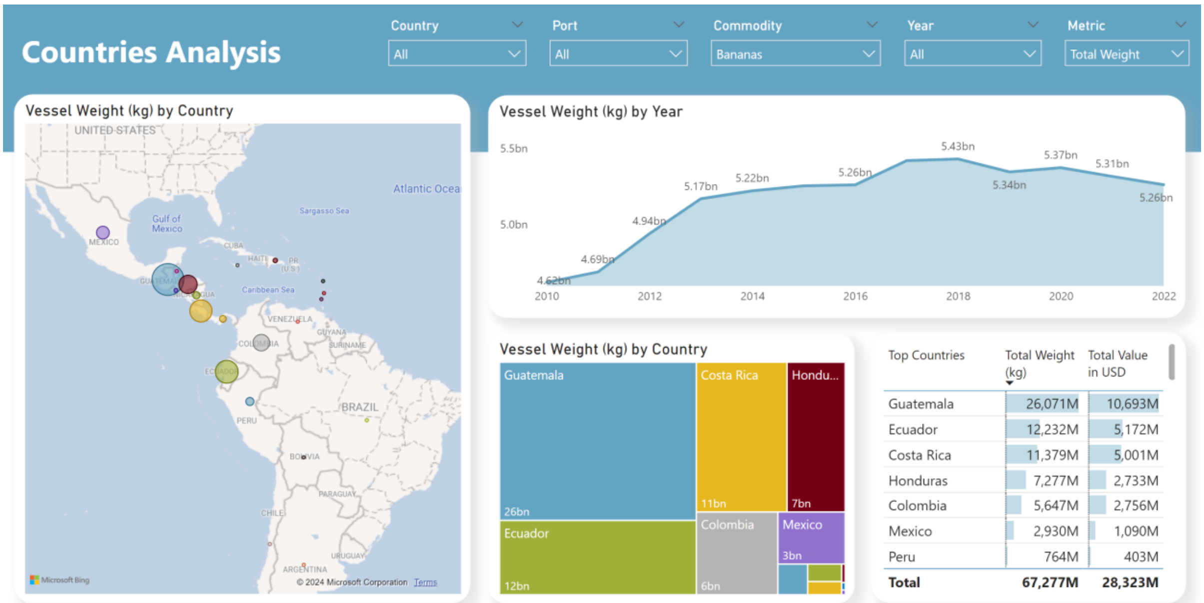
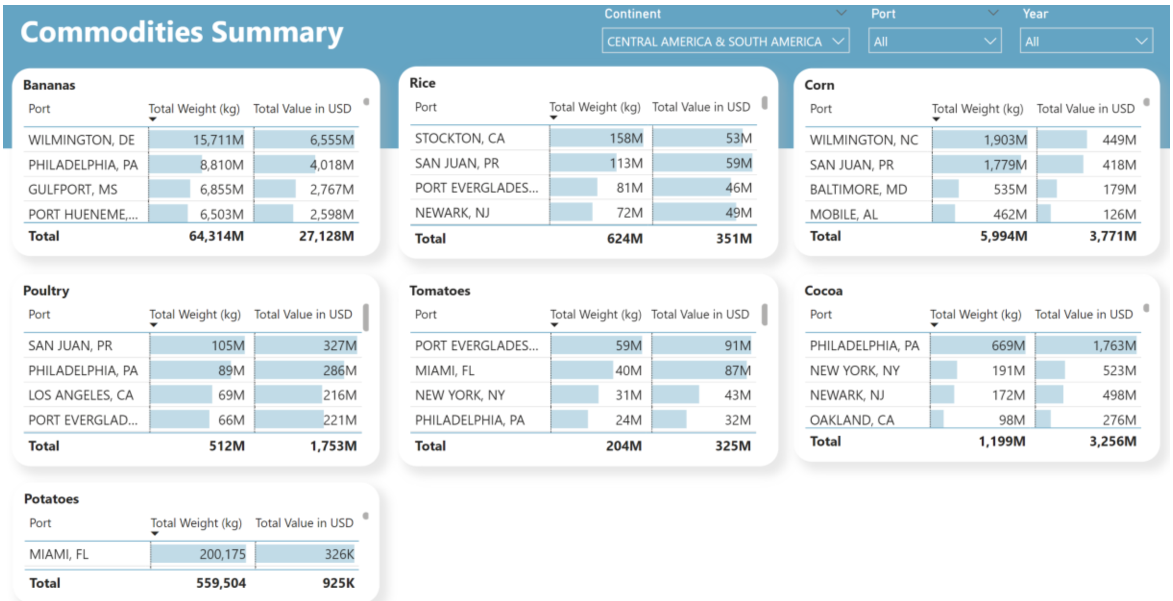


Figure 6 summarizes of all seven items, listing the top four ports for each commodity ranked by weight and value. Here it can be appreciated that bananas are the item with the largest imports volume and that Wilmington is the principal port for bananas. The dashboard also shows that Philadelphia is the top port for both poultry and cocoa.

Figure 6

Commodities - Top 4 Import Ports by Weight and Value



Looking at the imports at a continent level, Figure A-1 Iin Appendix A displays the importance of South America for the U.S. corn supply. Europe is another big player compared to other continents, but it only accounts for 21% of total corn imports.

Figure A-2 presents a trend analysis dashboard that compares the imports of the main ports throughout the years. For example, filtering by poultry, Philadelphia did not become the biggest port in weight processed until 2022.

Figure A-3 displays a summary by port, listing the items they receive and how much percentage they represent. For example, Port Everglades is a port that owns the necessary equipment to receive and process a broader portfolio of different goods. On the contrary, Gulfport only processes bananas out of the seven items.

Finally, Figure A-4 presents a first approach to the automated identification system (AIS) data. In this dashboard the graph on the right shows the route and arrival of a specific vessel on a specific date to the Port of Philadelphia. The details of its position, speed over ground, course over ground, heading and exact time when the data was transmitted are shown on the left.

4.2 Network Analysis Results

This section presents the network analysis results for the seven items studied in this project. The period of study for this analysis was from January to September 2023, given that it was the only available period of data. Each subsection includes a map displaying the flows of vessels carrying a specific item between the network of ports. The darker and denser the lines connecting the ports are, the higher the number of ships that navigated that route. The maps are only a visual representation of the networks. For a detailed analysis a table is presented for each item, ranking the ports in that specific network by their degree, closeness, and betweenness centralities.

4.2.1 Bananas

Table 6 denotes the importance of Philadelphia for the whole network of banana transportation. It is ranked in 1st place in both degree centrality and closeness centrality, and 3rd in the betweenness centrality ranking, serving as a node for an average of 18 vessels containing bananas per month. This means that this port is extensively linked to other ports, it could function as a transshipment port in the network, and it has relatively short distances to the other ports in the network. In relation to the volume of bananas handled, the Port of Philadelphia is ranked 2nd, behind Wilmington, DE. The connection between the ports involved in bananas transportation is shown in Figure 7.

Table 6

Centrality Metrics for each Port in the Vessel Routes Carrying Bananas

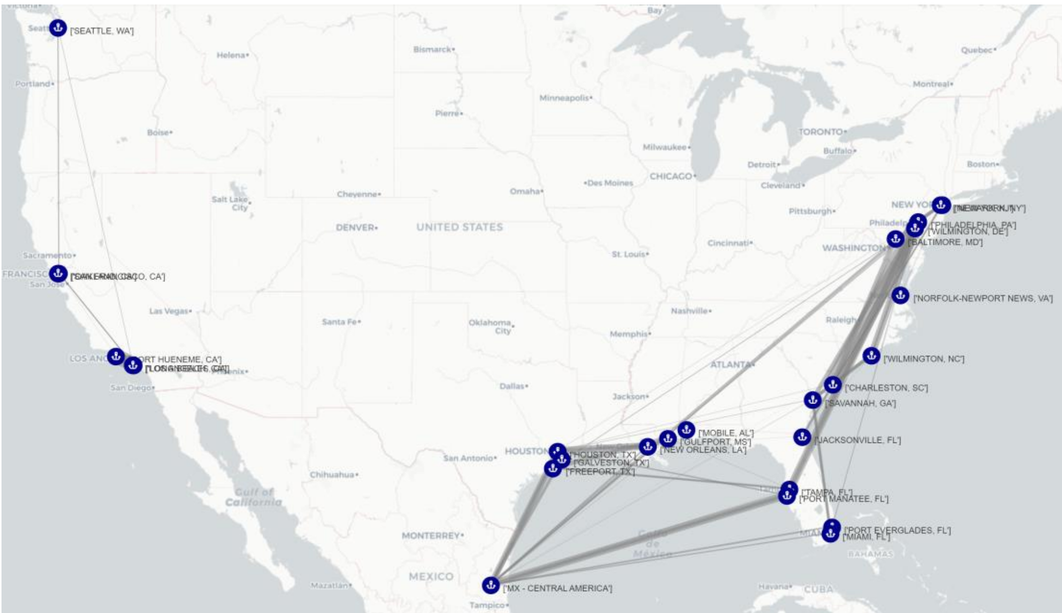
Degree Centrality		
Port	Rank	Centrality
PHILADELPHIA, PA	1	0.38
CHARLESTON, SC	2	0.35
SAVANNAH, GA	2	0.35
HOUSTON, TX	4	0.31
NEW YORK, NY	5	0.27
NEWARK, NJ	5	0.27
WILMINGTON, DE	7	0.23
LOS ANGELES, CA	8	0.19
MIAMI, FL	8	0.19
OAKLAND, CA	8	0.19
FREEPORT, TX	11	0.15
NORFOLK-NEWPORT NE…	11	0.15
PORT HUENEME, CA	11	0.15
WILMINGTON, NC	11	0.15
BALTIMORE, MD	15	0.12
GULFPORT, MS	15	0.12
JACKSONVILLE, FL	15	0.12
LONG BEACH, CA	15	0.12
PORT EVERGLADES, FL	15	0.12
PORT MANATEE, FL	15	0.12
SAN FRANCISCO, CA	15	0.12
TAMPA, FL	15	0.12
GALVESTON, TX	23	0.08
MOBILE, AL	23	0.08
NEW ORLEANS, LA	23	0.08
SEATTLE, WA	23	0.08

Closeness Centrality		
Port	Rank	Centrality
PHILADELPHIA, PA	1	0.51
SAVANNAH, GA	2	0.50
HOUSTON, TX	3	0.48
NEWARK, NJ	4	0.47
CHARLESTON, SC	5	0.45
WILMINGTON, DE	6	0.44
MIAMI, FL	7	0.42
NEW YORK, NY	7	0.42
PORT EVERGLADES, FL	7	0.42
WILMINGTON, NC	10	0.40
FREEPORT, TX	11	0.39
PORT MANATEE, FL	11	0.39
GALVESTON, TX	13	0.38
MOBILE, AL	13	0.38
NEW ORLEANS, LA	13	0.38
GULFPORT, MS	16	0.37
TAMPA, FL	16	0.37
JACKSONVILLE, FL	18	0.36
NORFOLK-NEWPORT NE…	18	0.36
BALTIMORE, MD	20	0.33
LOS ANGELES, CA	21	0.19
OAKLAND, CA	21	0.19
PORT HUENEME, CA	23	0.16
LONG BEACH, CA	24	0.14
SAN FRANCISCO, CA	24	0.14
SEATTLE, WA	26	0.12

Betweeness Centrality		
Port	Rank	Centrality
CHARLESTON, SC	1	0.06
HOUSTON, TX	2	0.05
PHILADELPHIA, PA	3	0.04
SAVANNAH, GA	4	0.04
NEWARK, NJ	5	0.04
WILMINGTON, DE	6	0.03
NEW YORK, NY	7	0.02
WILMINGTON, NC	8	0.01
FREEPORT, TX	9	0.01
LOS ANGELES, CA	10	0.01
OAKLAND, CA	10	0.01
MIAMI, FL	12	0.00
PORT EVERGLADES, FL	13	0.00
NORFOLK-NEWPORT NE…	14	0.00
JACKSONVILLE, FL	15	0.00
PORT HUENEME, CA	16	0.00
BALTIMORE, MD	17	0.00
GALVESTON, TX	17	0.00
GULFPORT, MS	17	0.00
LONG BEACH, CA	17	0.00
MOBILE, AL	17	0.00
NEW ORLEANS, LA	17	0.00
PORT MANATEE, FL	17	0.00
SAN FRANCISCO, CA	17	0.00
SEATTLE, WA	17	0.00
TAMPA, FL	17	0.00

Figure 7

Port Network Serving Vessels Carrying Bananas



4.2.2 Potatoes

New York is ranked 1st in all three centralities as can be seen in Table 7. It serves as node for an average of five vessels carrying potatoes per month. Miami also plays a central role in this network. It is ranked 2nd in closeness and betweenness centralities, serving as node for an average of nine vessels carrying potatoes per month. Although Miami is not directly connected to as many ports as New York, it is part of the shortest routes between other ports. From the ports in Table 7, Miami and Newark are the top two importing ports of potatoes by volume. Figure 8 provides a visual representation of this network.

Table 7

Centrality Metrics for each Port in the Vessel Routes Carrying Potatoes

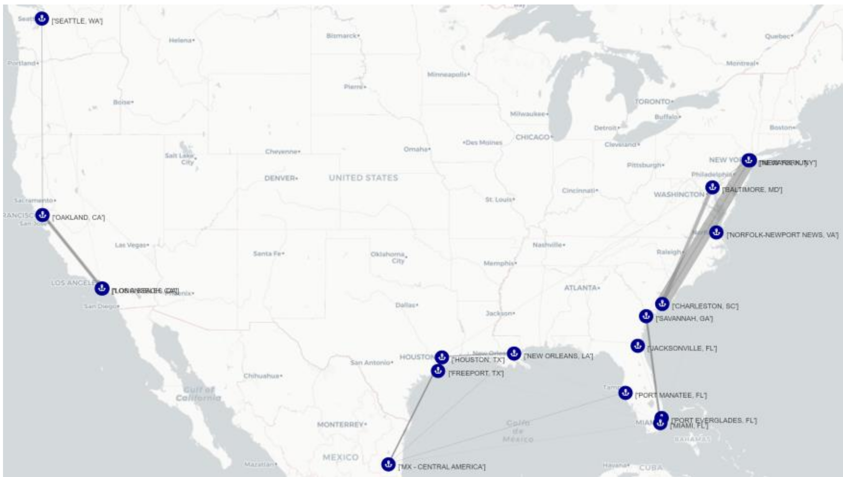
Degree Centrality		
Port	Rank	Centrality
NEW YORK, NY	1	0.41
BALTIMORE, MD	2	0.35
CHARLESTON, SC	3	0.29
MIAMI, FL	3	0.29
HOUSTON, TX	5	0.24
SAVANNAH, GA	5	0.24
LOS ANGELES, CA	7	0.18
NEW ORLEANS, LA	7	0.18
NEWARK, NJ	7	0.18
JACKSONVILLE, FL	10	0.12
NORFOLK-NEWPORT NE…	10	0.12
OAKLAND, CA	10	0.12
PORT EVERGLADES, FL	10	0.12
PORT MANATEE, FL	10	0.12
SEATTLE, WA	10	0.12
FREEPORT, TX	16	0.06
LONG BEACH, CA	16	0.06

Closeness Centrality		
Port	Rank	Centrality
NEW YORK, NY	1	0.52
MIAMI, FL	2	0.43
SAVANNAH, GA	2	0.43
BALTIMORE, MD	4	0.41
CHARLESTON, SC	5	0.40
HOUSTON, TX	5	0.40
NEWARK, NJ	7	0.37
NORFOLK-NEWPORT NE…	8	0.34
NEW ORLEANS, LA	9	0.32
JACKSONVILLE, FL	10	0.29
PORT MANATEE, FL	10	0.29
FREEPORT, TX	12	0.28
PORT EVERGLADES, FL	12	0.28
LOS ANGELES, CA	14	0.18
OAKLAND, CA	15	0.13
SEATTLE, WA	15	0.13
LONG BEACH, CA	17	0.11

Betweeness Centrality		
Port	Rank	Centrality
NEW YORK, NY	1	0.25
MIAMI, FL	2	0.17
HOUSTON, TX	3	0.10
BALTIMORE, MD	4	0.10
CHARLESTON, SC	5	0.08
SAVANNAH, GA	6	0.05
LOS ANGELES, CA	7	0.01
JACKSONVILLE, FL	8	0.01
NEW ORLEANS, LA	9	0.00
PORT EVERGLADES, FL	10	0.00
FREEPORT, TX	11	0.00
LONG BEACH, CA	11	0.00
NEWARK, NJ	11	0.00
NORFOLK-NEWPORT NE…	11	0.00
OAKLAND, CA	11	0.00
PORT MANATEE, FL	11	0.00
SEATTLE, WA	11	0.00

Figure 8

Port Network Serving Vessels Carrying Potatoes



4.2.3 Tomatoes

Table 8 displays a port centrality ranking for the tomatoes network. Philadelphia, Charleston, Houston, Savannah, New York, and Port Everglades are ranked in the same order, from one to six, in the three metrics. Philadelphia serves as a node for an average of 16 vessels containing tomatoes per month, followed by Charleston with nine vessels. Similar to the banana network, Philadelphia is the most central port. In relation to the volume of tomatoes handled, Miami, Port Everglades, New York, and Philadelphia share the first four positions. Additionally, Figure 9 displays the network transporting this commodity.

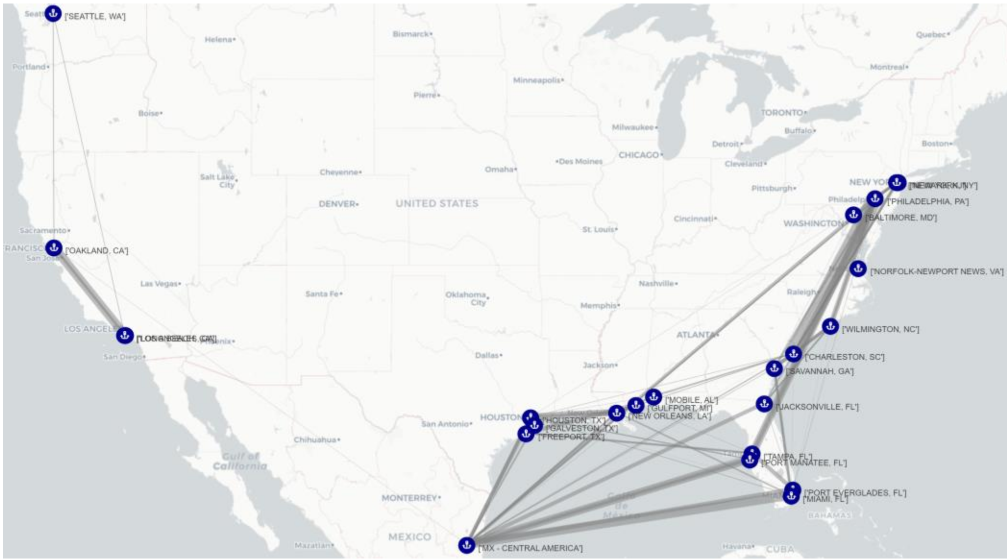
Table 8

Centrality Metrics for each Port in the Vessel Routes Carrying Tomatoes

Degree Centrality			Closeness Centrality			Betweeneess Centrality		
Port	Rank	Centrality	Port	Rank	Centrality	Port	Rank	Centrality
PHILADELPHIA, PA	1	0.50	PHILADELPHIA, PA	1	0.58	PHILADELPHIA, PA	1	0.09
CHARLESTON, SC	2	0.42	CHARLESTON, SC	2	0.54	CHARLESTON, SC	2	0.04
HOUSTON, TX	3	0.38	HOUSTON, TX	3	0.52	HOUSTON, TX	3	0.03
SAVANNAH, GA	4	0.33	SAVANNAH, GA	4	0.50	SAVANNAH, GA	4	0.02
NEW YORK, NY	5	0.29	NEW YORK, NY	5	0.49	NEW YORK, NY	5	0.02
PORT EVERGLADES, FL	5	0.29	PORT EVERGLADES, FL	5	0.49	PORT EVERGLADES, FL	6	0.02
JACKSONVILLE, FL	7	0.25	JACKSONVILLE, FL	7	0.47	OAKLAND, CA	7	0.01
MIAMI, FL	7	0.25	MIAMI, FL	7	0.47	JACKSONVILLE, FL	8	0.01
NEWARK, NJ	7	0.25	NEWARK, NJ	7	0.47	MIAMI, FL	9	0.00
MOBILE, AL	10	0.21	WILMINGTON, NC	10	0.46	TAMPA, FL	10	0.00
NEW ORLEANS, LA	10	0.21	MOBILE, AL	11	0.44	WILMINGTON, NC	11	0.00
WILMINGTON, NC	10	0.21	NEW ORLEANS, LA	11	0.44	MOBILE, AL	12	0.00
OAKLAND, CA	13	0.17	PORT MANATEE, FL	11	0.44	NEWARK, NJ	13	0.00
PORT MANATEE, FL	13	0.17	TAMPA, FL	14	0.42	LOS ANGELES, CA	14	0.00
TAMPA, FL	13	0.17	FREEPORT, TX	15	0.41	NEW ORLEANS, LA	15	0.00
BALTIMORE, MD	16	0.13	GULFPORT, MS	15	0.41	BALTIMORE, MD	16	0.00
FREEPORT, TX	16	0.13	GALVESTON, TX	17	0.40	FREEPORT, TX	17	0.00
GULFPORT, MS	16	0.13	BALTIMORE, MD	18	0.39	GALVESTON, TX	17	0.00
LOS ANGELES, CA	16	0.13	NORFOLK-NEWPORT NE…	19	0.36	GULFPORT, MS	17	0.00
GALVESTON, TX	20	0.08	OAKLAND, CA	20	0.17	LONG BEACH, CA	17	0.00
LONG BEACH, CA	20	0.08	LOS ANGELES, CA	21	0.13	NORFOLK-NEWPORT NE…	17	0.00
NORFOLK-NEWPORT NE…	20	0.08	LONG BEACH, CA	22	0.11	PORT MANATEE, FL	17	0.00
SEATTLE, WA	20	0.08	SEATTLE, WA	22	0.11	SAN FRANCISCO, CA	17	0.00
SAN FRANCISCO, CA	24	0.04	SAN FRANCISCO, CA	24	0.10	SEATTLE, WA	17	0.00

Figure 9

Port Network Serving Vessels Carrying Tomato



4.2.4 Corn

Regarding corn, Table 9 shows that Houston occupies the top spot in the three rankings, making it the best-connected port in the network, and serving as a node for an average of 40 vessels containing potatoes per month. Charleston is also a central port, occupying the 2nd place in the degree and closeness centrality rank, and the 3rd place in the betweenness rank. Additionally, New Yok is in 3rd place in the degree and closeness centrality. This represents a wide coverage of the South, Southeast and Northeast regions. There is no significant volume of corn handled by the ports of Houston and Charleston. Baltimore accounts for more than 25% of the total US imports. Figure 10 shows a visual representation of this network.

Table 9

Centrality Metrics for each Port in the Vessel Routes Carrying Corn

Degree Centrality

Port	Rank	Centrality
HOUSTON, TX	1	0.74
CHARLESTON, SC	2	0.61
NEW YORK, NY	3	0.52
JACKSONVILLE, FL	4	0.48
NEWARK, NJ	4	0.48
SAVANNAH, GA	4	0.48
SAN JUAN, PR	7	0.43
BALTIMORE, MD	8	0.39
MIAMI, FL	8	0.39
PORT EVERGLADES, FL	8	0.39
NEW ORLEANS, LA	11	0.35
NORFOLK-NEWPORT NE…	12	0.30
MOBILE, AL	13	0.26
FREEPORT, TX	14	0.22
TAMPA, FL	14	0.22
WILMINGTON, NC	14	0.22
LOS ANGELES, CA	17	0.17
OAKLAND, CA	17	0.17
GALVESTON, TX	19	0.13
GULFPORT, MS	19	0.13
PORT MANATEE, FL	19	0.13
LONG BEACH, CA	22	0.09
SAN FRANCISCO, CA	22	0.09
SEATTLE, WA	22	0.09

Closeness Centrality

Port	Rank	Centrality
HOUSTON, TX	1	0.74
CHARLESTON, SC	2	0.64
NEW YORK, NY	3	0.59
JACKSONVILLE, FL	4	0.56
NEWARK, NJ	5	0.54
SAVANNAH, GA	5	0.54
BALTIMORE, MD	7	0.52
MIAMI, FL	7	0.52
PORT EVERGLADES, FL	7	0.52
SAN JUAN, PR	7	0.52
NEW ORLEANS, LA	11	0.49
NORFOLK-NEWPORT NE…	12	0.47
FREEPORT, TX	13	0.45
MOBILE, AL	13	0.45
TAMPA, FL	13	0.45
WILMINGTON, NC	13	0.45
PORT MANATEE, FL	17	0.43
GALVESTON, TX	18	0.41
GULFPORT, MS	19	0.35
LOS ANGELES, CA	20	0.17
OAKLAND, CA	20	0.17
LONG BEACH, CA	22	0.12
SAN FRANCISCO, CA	22	0.12
SEATTLE, WA	22	0.12

Betweeness Centrality

Port	Rank	Centrality
HOUSTON, TX	1	0.13
CHARLESTON, SC	2	0.05
PORT EVERGLADES, FL	3	0.05
JACKSONVILLE, FL	4	0.03
NEW YORK, NY	5	0.03
FREEPORT, TX	6	0.02
SAVANNAH, GA	7	0.02
MIAMI, FL	8	0.01
BALTIMORE, MD	9	0.01
TAMPA, FL	10	0.01
NEWARK, NJ	11	0.01
LOS ANGELES, CA	12	0.01
OAKLAND, CA	12	0.01
SAN JUAN, PR	14	0.01
NEW ORLEANS, LA	15	0.00
WILMINGTON, NC	16	0.00
GULFPORT, MS	17	0.00
NORFOLK-NEWPORT NE…	18	0.00
GALVESTON, TX	19	0.00
LONG BEACH, CA	19	0.00
MOBILE, AL	19	0.00
PORT MANATEE, FL	19	0.00
SAN FRANCISCO, CA	19	0.00
SEATTLE, WA	19	0.00

Figure 10

Port Network Serving Vessels Carrying Corn

4.2.5 Cocoa

In the case of cocoa, Table 10 shows that Charleston and Savannah are the most linked and with the least distance to other ports. These ports serve as a node for an average of 19 and 17 vessels containing cocoa per month respectively. Houston, on the other hand, holds the 1st position in betweenness centrality and low positions in the others, suggesting that it plays the role of a hub in this network. In terms of the volume imported, Philadelphia handled 70% of the total cocoa imported. The port connections can be seen in Figure 11.

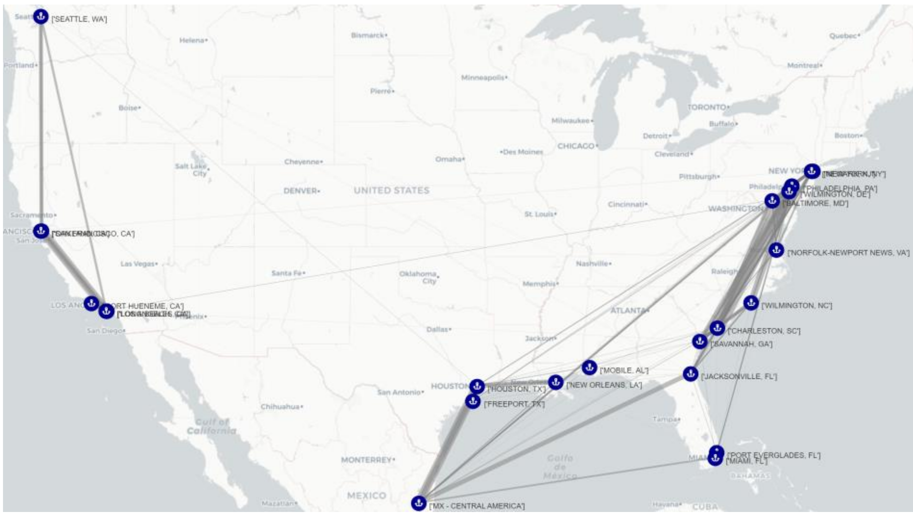
Table 10

Centrality Metrics for each Port in the Vessel Routes Carrying Cocoa

Degree Centrality			Closeness Centrality			Betweeneess Centrality		
Port	Rank	Centrality	Port	Rank	Centrality	Port	Rank	Centrality
CHARLESTON, SC	1	0.78	CHARLESTON, SC	1	0.818	HOUSTON, TX	1	0.125
SAVANNAH, GA	1	0.78	SAVANNAH, GA	1	0.818	MOBILE, AL	2	0.123
PHILADELPHIA, PA	3	0.72	PHILADELPHIA, PA	3	0.750	CHARLESTON, SC	3	0.092
JACKSONVILLE, FL	4	0.67	JACKSONVILLE, FL	4	0.720	SAVANNAH, GA	4	0.068
NEWARK, NJ	5	0.61	NEWARK, NJ	5	0.692	PHILADELPHIA, PA	5	0.052
BALTIMORE, MD	6	0.56	HOUSTON, TX	6	0.667	JACKSONVILLE, FL	6	0.046
NEW YORK, NY	6	0.56	NORFOLK-NEWPORT NE…	6	0.667	NEWARK, NJ	7	0.029
NORFOLK-NEWPORT NE…	6	0.56	BALTIMORE, MD	8	0.643	WILMINGTON, NC	8	0.016
HOUSTON, TX	9	0.50	MOBILE, AL	8	0.643	NORFOLK-NEWPORT NE…	9	0.010
WILMINGTON, DE	9	0.50	NEW YORK, NY	8	0.643	WILMINGTON, DE	10	0.009
MOBILE, AL	11	0.44	WILMINGTON, DE	11	0.621	MIAMI, FL	11	0.007
MIAMI, FL	12	0.39	WILMINGTON, NC	12	0.600	NEW YORK, NY	12	0.006
WILMINGTON, NC	12	0.39	MIAMI, FL	13	0.581	BALTIMORE, MD	13	0.006
FREEPORT, TX	14	0.33	NEW ORLEANS, LA	13	0.581	NEW ORLEANS, LA	14	0.006
NEW ORLEANS, LA	15	0.28	FREEPORT, TX	15	0.563	FREEPORT, TX	15	0.002
PORT EVERGLADES, FL	16	0.22	PORT EVERGLADES, FL	16	0.529	PORT EVERGLADES, FL	16	0.001
GALVESTON, TX	17	0.06	GALVESTON, TX	17	0.409	GALVESTON, TX	17	0.000
TAMPA, FL	17	0.06	TAMPA, FL	18	0.400	TAMPA, FL	17	0.000

Figure 11

Port Network of vessels Carrying Cocoa



4.2.6 Rice

Charleston and Savannah are the key players in the port network transporting rice. As Table 11 denotes, both ports serve as a node for an average of twelve and eight vessels per month, respectively. They share 1st place in the degree and closeness centralities rankings and are 1st and 2nd place in terms of betweenness centrality. They are extensively linked to other ports and can function as a transshipment point in the network. However, the volume of rice that Charleston and Savannah handled was about 2% and 1% of the total imported in the U.S, respectively. Figure 12 displays the connection between the ports in the network.

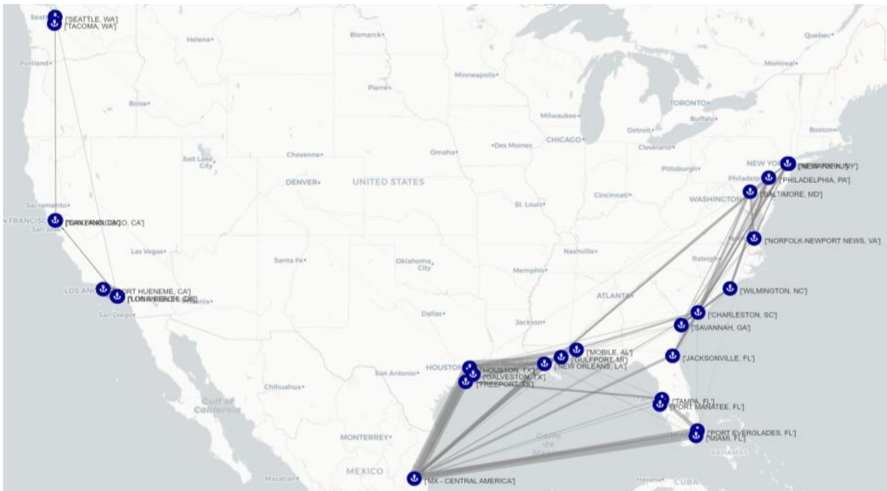
Table 11

Centrality Metrics for each Port in the Vessel Routes Carrying Rice

Degree Centrality			Closeness Centrality			Betweeness Centrality		
Port	Rank	Centrality	Port	Rank	Centrality	Port	Rank	Centrality
CHARLESTON, SC	1	0.63	CHARLESTON, SC	1	0.73	SAVANNAH, GA	1	0.06
SAVANNAH, GA	1	0.63	SAVANNAH, GA	1	0.73	CHARLESTON, SC	2	0.05
PHILADELPHIA, PA	3	0.58	PHILADELPHIA, PA	3	0.70	HOUSTON, TX	3	0.04
HOUSTON, TX	4	0.47	HOUSTON, TX	4	0.66	PHILADELPHIA, PA	4	0.03
NEWARK, NJ	4	0.47	NEWARK, NJ	4	0.66	MIAMI, FL	5	0.02
MIAMI, FL	6	0.42	MIAMI, FL	6	0.63	NEWARK, NJ	6	0.02
NEW YORK, NY	6	0.42	NEW YORK, NY	6	0.63	NEW YORK, NY	7	0.01
NEW ORLEANS, LA	8	0.37	NEW ORLEANS, LA	8	0.61	NORFOLK-NEWPORT NE…	8	0.01
NORFOLK-NEWPORT NE…	8	0.37	NORFOLK-NEWPORT NE…	8	0.61	FREEPORT, TX	9	0.01
JACKSONVILLE, FL	10	0.32	JACKSONVILLE, FL	10	0.59	JACKSONVILLE, FL	10	0.00
BALTIMORE, MD	11	0.26	MOBILE, AL	11	0.58	NEW ORLEANS, LA	11	0.00
MOBILE, AL	11	0.26	WILMINGTON, NC	12	0.56	GULFPORT, MS	12	0.00
FREEPORT, TX	13	0.21	FREEPORT, TX	13	0.54	TAMPA, FL	12	0.00
GULFPORT, MS	13	0.21	GULFPORT, MS	13	0.54	WILMINGTON, NC	14	0.00
TAMPA, FL	13	0.21	TAMPA, FL	13	0.54	BALTIMORE, MD	15	0.00
WILMINGTON, NC	13	0.21	PORT EVERGLADES, FL	16	0.53	GALVESTON, TX	15	0.00
PORT EVERGLADES, FL	17	0.16	GALVESTON, TX	17	0.51	MOBILE, AL	15	0.00
GALVESTON, TX	18	0.11	PORT MANATEE, FL	17	0.51	PORT EVERGLADES, FL	15	0.00
PORT MANATEE, FL	18	0.11	BALTIMORE, MD	19	0.49	PORT MANATEE, FL	15	0.00

Figure 12

Port Network of Vessels Carrying Rice



4.2.7 Poultry

Finally, regarding Poultry, Newark is the most central port in the network. It is ranked 1st in all the metrics, and it serves an average of five vessels carrying bananas per month. Jacksonville also plays an important role, being extensively linked to other ports. This ranking is shown in Table 12. In terms of volume, Newark and Jacksonville only handled 3% and 1% of the total imports, respectively. A visual representation of the network is shown in Figure 13.

Table 12

Centrality Metrics for each Port in the Vessel Routes Carrying Poultry

Degree Centrality			Closeness Centrality			Betweeness Centrality		
Port	Rank	Centrality	Port	Rank	Centrality	Port	Rank	Centrality
NEWARK, NJ	1	0.42	NEWARK, NJ	1	0.49	NEWARK, NJ	1	0.07
JACKSONVILLE, FL	2	0.37	JACKSONVILLE, FL	2	0.47	HOUSTON, TX	2	0.04
NORFOLK-NEWPORT NE…	2	0.37	HOUSTON, TX	3	0.43	JACKSONVILLE, FL	3	0.04
CHARLESTON, SC	4	0.32	NEW YORK, NY	3	0.43	FREEPORT, TX	4	0.04
SAVANNAH, GA	4	0.32	SAVANNAH, GA	6	0.40	TAMPA, FL	4	0.04
HOUSTON, TX	6	0.26	NORFOLK-NEWPORT NE…	7	0.38	SAVANNAH, GA	6	0.03
NEW YORK, NY	6	0.26	CHARLESTON, SC	8	0.37	NEW YORK, NY	8	0.02
BALTIMORE, MD	9	0.21	FREEPORT, TX	9	0.36	NORFOLK-NEWPORT NE…	9	0.01
LOS ANGELES, CA	9	0.21	TAMPA, FL	9	0.36	CHARLESTON, SC	10	0.01
OAKLAND, CA	9	0.21	BALTIMORE, MD	11	0.34	LOS ANGELES, CA	11	0.01
FREEPORT, TX	12	0.16	MOBILE, AL	11	0.34	OAKLAND, CA	11	0.01
LONG BEACH, CA	12	0.16	NEW ORLEANS, LA	11	0.34	BALTIMORE, MD	13	0.00
TAMPA, FL	12	0.16	LOS ANGELES, CA	15	0.21	LONG BEACH, CA	13	0.00
MOBILE, AL	16	0.11	OAKLAND, CA	15	0.21	MOBILE, AL	13	0.00
NEW ORLEANS, LA	16	0.11	LONG BEACH, CA	17	0.17	NEW ORLEANS, LA	13	0.00
SEATTLE, WA	16	0.11	SEATTLE, WA	19	0.14	SEATTLE, WA	13	0.00

Figure 13

Port Network of Vessels Carrying Poultry

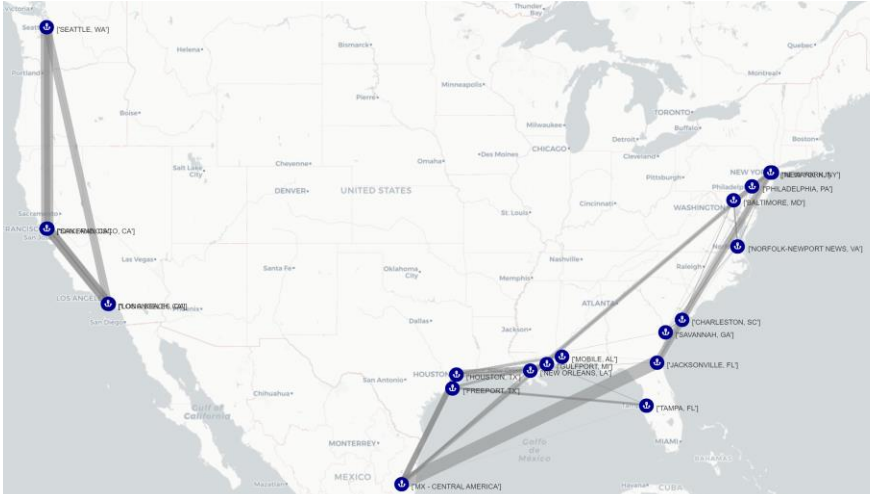


Table 13 presents a summary of all the seven network analysis results. It displays the 1st place ports by each of the centrality rankings and commodities.

Table 13

Top One Ports by Centrality Metric and Commodity

	Commodities						
Centrality	Banana	Poultry	Tomato	Cocoa	Corn	Potatoes	Rice
Degree	Philadelphia	Newark	Philadelphia	Charleston	Houston	New York	Charleston
Closeness	Philadelphia	Newark	Philadelphia	Charleston	Houston	New York	Charleston
Betweenness	Charleston	Newark	Philadelphia	Houston	Houston	New York	Savannah

4.3 Discrete Event Simulation Results

The simulation described in Section 3.5 was run for each scenario presented in Table 3. Eight metrics were monitored to understand the performance of the port network in each scenario, for both southbound and northbound routes. Table 14 describes each of these metrics in depth, and Sections 4.3.1 through 4.3.5 display the specific results per scenario. Section 5.1 discusses the insights generated after running the scenarios.

Table 14

Metrics Monitored in each Simulation Run

	Metric	Description
1	% of vessels served by the port.	The number of vessels each port serves is divided by the total number of vessels in the system.
2	% of small vessels served by the port.	The number of small vessels each port serves is divided by the system's total number of small vessels.
3	% of large vessels served by the port.	The number of large vessels each port serves is divided by the system's total number of large vessels.
4	Average number of vessels in the queue of each port.	The average quantity of vessels waiting to be served in each port.
5	Average vessel waiting time to be served by port.	The average time that a vessel waits to be served at a particular port.
6	Average % of capacity utilization by port.	Considering the constraints in each scenario, the average number of reefer plugs occupied at a given time is divided by the total number of plugs reserved for banana reefers.
7	Average total days of delay.	The total number of days a vessel spends in the queues, traveling (in case of being diverted to another port/s), and being served by a specific port.
8	% of unserved vessels.	The total number of vessels that could not be served at any port is divided by the total number of vessels generated by the simulation.

4.3.1 Model Baseline

A baseline model was defined before running the scenarios. This model already considers the disruption in the Port of Wilmington and is set with the parameters described in Table 4. The results of the route simulation are presented in Table 15 and Table 16, for the northbound and southbound routes, respectively.

In both routes there is one port serving the 100% of small vessels. This accounts for the small percentage of capacity utilization of New York and Charleston. They are only receiving large vessels arriving every 3.5 days, giving those ports enough time to free up the occupied reefer plugs.

Table 15

Performance of Ports and Vessels in the North Network under the Model Baseline

		Port	
	Metric	Philadelphia	New York
1	% of vessels served	91.3	8.7
2	% of small vessels served	100	0
3	% of large vessels served	77	23
4	Average number of vessels in the queue	2	1
5	Average vessel waiting time to be served (days)	2.0	2.0
6	Average % of capacity utilization	23	0.4
7	Average total days of delay	2.5	4.5
8	% of unserved vessels (all ports)	0	

Table 16

Performance of Ports and Vessels in the South Network under the Model Baseline

		Port			
	Metric	Baltimore	Norfolk-Newport News	Wilmington, NC	Charleston
1	% of vessels served	64	0	0	36
2	% of small vessels served	100	0	0	0
3	% of large vessels served	0	0	0	100
4	Average number of vessels in the queue	1	0	0	1
5	Average vessel waiting time to be served (days)	2	0	0	2
6	Average % of capacity utilization	1	0	0	9.8
7	Average total days of delay	3.0	0	0	5.5
8	% of unserved vessels (all ports)	0			

4.3.2 Scenario 1

This scenario consists of modifying the size of the vessels generated so that only small vessels carrying a random number between 1 and 40 containers are generated. Table 17 and Table 18 display the results of this simulation.

Table 17

Performance of Ports and Vessels in the North Network under Scenario 1

	Metric	Port	
		Philadelphia	New York
1	% of vessels served	100	0
2	% of small vessels served	100	0
3	% of large vessels served	0	0
4	Average number of vessels in the queue	2	0
5	Average vessel waiting time to be served (days)	2	0
6	Average % of capacity utilization	0.2	0
7	Average total days of delay	2.5	0
8	% of unserved vessels (all ports)	0	

Table 17 shows that in Scenario 1 all the vessels were served by the 1st port, Philadelphia, regardless of the vessel size.

Table 18

Performance of Ports and Vessels in the South Network under Scenario 1

	Metric	Port			
		Baltimore	Norfolk-Newport News	Wilmington, NC	Charleston
1	% of vessels served	100	0	0	0
2	% of small vessels served	100	0	0	0
3	% of large vessels served	0	0	0	0
4	Average number of vessels in the queue	2	0	0	0
5	Average vessel waiting time to be served (days)	2	0	0	0
6	Average % of capacity utilization	4	0	0	0
7	Average total days of delay	3	0	0	0
8	% of unserved vessels (all ports)	0			

Similar to the northbound route, Table 18 shows that in Scenario 1 for the southbound route, all the vessels were served by the 1st port in the route, Baltimore**.**

4.3.3 Scenario 2

Scenario 2 varies the size of the vessels generated according to the number of bananas they carry. It considers that 20% of the total vessels generated are small (carrying 2 to 40 containers), 30% medium (carrying 41 to 450 containers), and 50% large (carrying 451 to 850 containers). The results are displayed in Table 19 and Table 20.

Table 19

Performance of Ports and Vessels in the North Network under Scenario 2

		Port	
	Metric	Philadelphia	New York
1	% of vessels served	55	45
2	% of small vessels served	100	0
3	% of large vessels served	50	50
4	Average number of vessels in the queue	2	1
5	Average vessel waiting time to be served (days)	2	2
6	Average % of capacity utilization	21	3.5
7	Average total days of delay	2.5	4.5
8	% of unserved vessels (all ports)	0	

Table 19 shows that in Scenario 2, New York focuses on serving all large vessels at 100%.

Table 20

Performance of Ports and Vessels in the South Network under Scenario 2

		Port			
	Metric	Baltimore	Norfolk-Newport News	Wilmington, NC	Charleston
1	% of vessels served	28	0	0	72
2	% of small vessels served	100	0	0	0
3	% of large vessels served	0	0	0	100
4	Average number of vessels in the queue	1	0	0	1
5	Average vessel waiting time to be served (days)	2	0	0	2
6	Average % of capacity utilization	2	0	0	22
7	Average total days of delay	3	0	0	5.5
8	% of unserved vessels (all ports)	0			

In the case of the southbound route shown in Table 20, Charleston resembles New York as the other port serving large vessels at 100%. Norfolk-Newport News and Wilmington, NC, do not participate, as they do not have enough capacity to serve the large vessels.

4.3.4 Scenario 3

This scenario portrays a situation in which the available capacity of all ports increases by 20%, measured in the number of reefer plugs. Table 21 and Table 22 present the results.

Table 21

Performance of Ports and Vessels in the North Network under Scenario 3

		Port	
	Metric	Philadelphia	New York
1	% of vessels served	100	0
2	% of small vessels served	100	0
3	% of large vessels served	100	0
4	Average number of vessels in the queue	2	0
5	Average vessel waiting time to be served (days)	2	0
6	Average % of capacity utilization	10	0
7	Average total days of delay	2.5	0
8	% of unserved vessels (all ports)	0	

As expected, Table 21 shows that in Scenario 3, Philadelphia has the capacity to serve 100% of the vessels. Philadelphia had enough capacity to serve all the vessels.

Table 22

Performance of Ports and Vessels in the South Network under Scenario 3

		Port			
	Metric	Baltimore	Norfolk-Newport News	Wilmington, NC	Charleston
1	% of vessels served	64	0	29	7
2	% of small vessels served	100	0	0	0
3	% of large vessels served	0	0	80	20
4	Average number of vessels in the queue	1	0	1	1
5	Average vessel waiting time to be served (days)	2	0	2	2
6	Average % of capacity utilization	0	0	19	4
7	Average total days of delay	3	0	4.5	5.5
8	% of unserved vessels (all ports)	0			

Scenario 3 serves differently the vessels generated for the southbound route. Baltimore focuses on serving 100% of small vessels, while Wilmington, NC, and Charleston serve large vessels. The former serves 80% of large vessels to release extra capacity for Charleston.

4.3.5 Scenario 4

Scenario 4 portrays a situation in which the available capacity of all ports decreases by 20%, measured in the number of reefer plugs. The results of this scenario are described in Table 23 and Table 24.

Table 23

Performance of Ports and Vessels in the North Network under Scenario 4

		Port	
	Metric	Philadelphia	New York
1	% of vessels served	95	5
2	% of small vessels served	100	0
3	% of large vessels served	0	10
4	Average number of vessels in the queue	1	0.5
5	Average vessel waiting time to be served (days)	2	2
6	Average % of capacity utilization	0	3
7	Average total days of delay	2.5	4.5
8	% of unserved vessels (all ports)	31	

In Table 23, 90% of large vessels were not served, representing 31% of the total vessels. All these vessels traveled up to New York, but they could not be accommodated due to a shortage of reefer plug capacity.

Table 24

Performance of Ports and Vessels in the South Network under Scenario 4

		Port			
	Metric	Baltimore	Norfolk-Newport News	Wilmington, NC	Charleston
1	% of vessels served	85	15	0	0
2	% of small vessels served	85	15	0	0
3	% of large vessels served	0	0	0	0
4	Average number of vessels in the queue	4	1	0	0
5	Average vessel waiting time to be served (days)	3	2	0	0
6	Average % of capacity utilization	20	1.5	0	0
7	Average total days of delay	4	4.5	0	0
8	% of unserved vessels (all ports)	33			

In Table 24, 100% of the large vessels could not be served, representing 33% of the total vessels. They could not be accommodated in any given port due to a shortage of reefer plug capacity.

5. Managerial insights

This section presents the insights from the exploratory analysis, the network analysis, and the discrete event simulation. It also describes how the results of each step were used as input for the next step, and responds to the research questions established in Section 1.1. Finally, it provides a list of three strategic recommendations for how to gain adaptability to prevent supply chain disruptions in the food sector, specifically for importing bananas.

5.1 Discussion

As a first step, the results of the exploratory analysis depicted a complete image of the U.S. food imports, highlighting the main destination ports, the ports' level of specialization in specific commodities, and the routes of the vessels transporting the seven items studied. One relevant insight gathered from this analysis was that from the seven commodities studied, bananas represent the most significant volume of U.S. imports in terms of weight and value (see Figure 6). Other relevant insights obtained in this step were the ports in which the banana imports are concentrated by region: Hueneme, CA, and San Diego, CA, in the Southwest; Houston, TX, and Gulfport, MS, in the South; Manatee, FL, and Everglades, FL, in the Southeast; and Wilmington, DE, and Philadelphia, PA, in the Northeast (see Figure 4).

Afterward, the network analysis was useful to identify how well connected these ports are to the rest of the ports in the network. The rankings by degree, closeness, and betweenness centralities for bananas indicate that Philadelphia is the most central port, followed by Charleston and Savannah; these two ports are not identified as relevant in the exploratory analysis but are capable of receiving bananas. Wilmington, DE, does not appear in the top-ranked ports, even though it is the port that receives the most considerable number of bananas.

To account for these differences, it is possible to combine the results of both the exploratory analysis and the network analysis, and then generate an overall criticality ranking, assigning an equal weight to the ranking of the four metrics: ranking by degree centrality, by closeness centrality, by betweenness centrality, and by total weight imported. The ranking is displayed in Table 25.

Table 25

Top Six Ports Ordered by Criticality Ranking

Port	Criticality Rank	Degree Centrality	Rank	Closeness Centrality	Rank	Betweeneess Centrality	Rank	Total Weight	Rank
PHILADELPHIA, PA	1	0.38	1	0.51	1	0.04	3	13.7%	2
WILMINGTON, DE	2	0.23	7	0.44	6	0.03	6	24.4%	1
HOUSTON, TX	3	0.31	4	0.48	3	0.05	2	1.8%	11
NEWARK, NJ	4	0.27	5	0.47	4	0.04	5	0.8%	14
NEW YORK, NY	5	0.27	5	0.42	7	0.02	7	2.0%	10
SAVANNAH, GA	6	0.35	2	0.50	2	0.04	4	0.2%	24

The discrete event simulation focuses on the Northeast region, where four of these critical ports are located. The analysis of the different scenarios raised the following insights:

- In both northbound and southbound routes, the closest ports to Wilmington receive the small vessels. Philadelphia can also receive some of the large vessels, but in general, large ships are attended by the ports far away from both routes, New York and Charleston. In the southbound route, the ports in the middle do not have enough reefer plugs to receive those vessels.
- All vessels are served at some point unless the number of reefer plugs of the ports dedicated to bananas is reduced. The vessel generation intervals and the size of the vessels are not critical factors.
- The only scenario where not all vessels can be served is Scenario 4, where the capacity dedicated to bananas is decreased by 20%. Not even New York or Charleston had enough reefer plugs to serve all the large vessels.
- Even though all the vessels are served in all but one scenario, the capacity utilization percentage is low. This happens because ports can unload reefers from an inbound vessel, connect them to their plugs, and dispatch them out of the port within the same day, or up to 72 hours. As a result, the number of reefers plugged in at the end of a day is less than the number of containers the served vessel was carrying.
- Philadelphia could serve as the main point of contingency if it dedicates 50% of its reefer plugs to serve the vessels headed initially to Wilmington.

These insights suggest that the current port network is resilient enough to maintain banana imports if the Port of Wilmington were completely shut down. It has extra capacity to sustain even higher demand. However, as Scenario 4 pointed out, the network could not serve all demand if the other ports' capacity was also reduced. Therefore, it is recommended that the list of strategic recommendations presented in Section 5.2 be considered.

5.2 Strategic Recommendations

In case of a disruption in the Port of Wilmington for the case study of bananas:

1. If the vessel's direction is North, a small vessel should travel to the Port of Philadelphia to be served there and a large vessel should travel to the Port of New York. If the vessel's direction is South, a small vessel should travel to the Port of Baltimore to be served there and a large vessel should travel to the Port of Charleston.
2. If a vessel is willing to choose any direction to be served, it should choose to go North. Specifically, Philadelphia is the best destination option given its closeness to Wilmington and the number of reefer plugs it could assign to address the disruption.
3. In the northbound route, Philadelphia and New York ports should not operate with less than 17% of reefer plugs dedicated to bananas. In the southbound route, Baltimore, Wilmington, NC, and Charleston ports should not operate with less than 28% of reefer plugs dedicated to bananas.

In case of a disruption in any port:

4. The reefer plugs are the principal logistics infrastructure influencing the adaptability of ports in case of a disruption. To increase its adaptability, a port should focus on improving the rate at which it frees up the plugs. This will allow the port to serve more vessels carrying refrigerated cargo in a shorter period.
5. Two ports must be considered as alternative destinations in case of a disruption. This will help prevent longer queues of vessels and impacts on food shelf life. One port should serve the small vessels and the other the large ones. In this way both ports can continue their everyday operations. An exception would be if the closest port shifts its operations and dedicates its refrigerated capacity only to serve the diverted vessels.
6. Alternative destination ports must have a minimum number of available plugs to accommodate banana vessels efficiently. Failure to meet this requirement could lead to longer wait times and dependency on land transportation. The required plugs are 40 for small and 850 for large vessels.

6. Conclusion

This capstone project offers a comprehensive view of the maritime U.S. imports from Latin America of seven items belonging to the basic food basket and the potential consequences of a supply chain disruption in one of the U.S. ports handling those products. Import volumes are shown at different granularities for continents, countries, ports, and commodities. Furthermore, rankings show how central each port is within the U.S. port network transporting each of the seven items. A port criticality ranking is proposed as a structured way of considering both the volume of the imports and the centrality of each port. This criticality ranking answers the research question of *the criticality of ports connecting Latin American countries to the U.S.* The most critical ports in the port network transporting bananas are Philadelphia, Wilmington, Houston, Newark, New York, and Savannah; accounting for 44% of the total U.S. banana imports from Latin America.

Focusing on the banana criticality ranking, a discrete event simulation was built to simulate a complete shutdown of the Port of Wilmington, DE. By running five different what-if scenarios it was possible to assess the ports' logistics infrastructure dependency. *Ports are dependent on their available capacity (e.g., reefer plugs) to store containers to be able to adapt in case of a disruption.* The simulation results also made it possible to assess the resiliency of the port network. *The current port network is resilient enough in maintaining banana imports if the Port of Wilmington, DE, suffers a reduction of operations up to a 17% threshold.* All the vessels are attended in the scenario analyses except for the case when the number of reefer plugs is reduced by 20%.

Potential research venues include assessing the resiliency of the networks of the six other commodities studied in this capstone, including dry and frozen cargo, in addition to refrigerated cargo. Also, the model could be extended to acknowledge seasonal demand inherent to seasonal goods and consider the impact on ground transportation cost for each solution. Despite these potential research venues, the proposed methodology can be used to address disruptions in any given network port from the seven items studied. Accordingly, this project offers a list of strategic recommendations for preventing supply chain disruptions in the maritime transportation of food sector.

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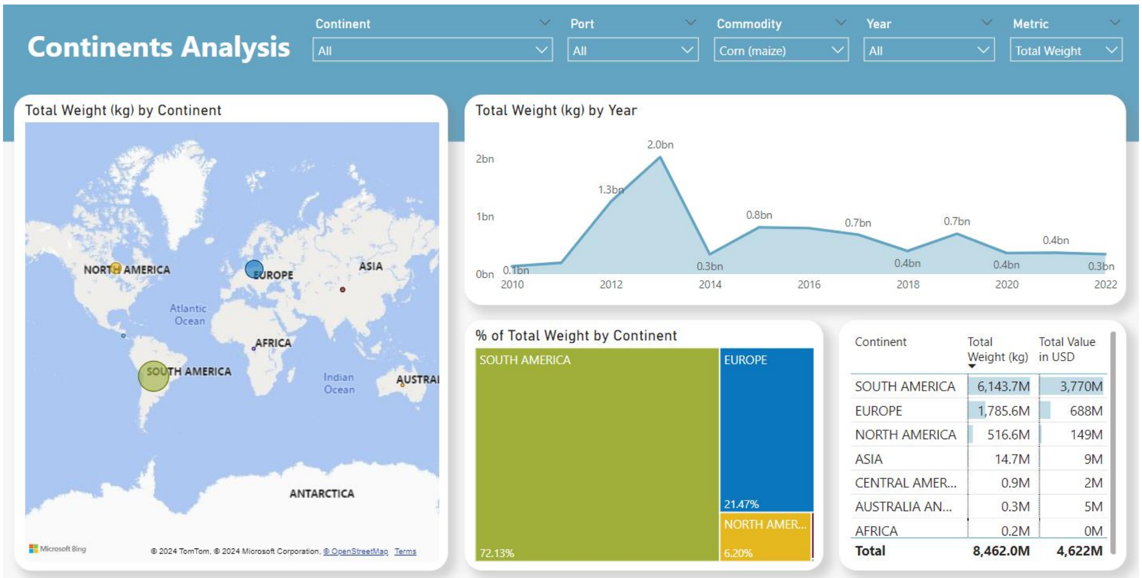
Appendix A

Figure A-1

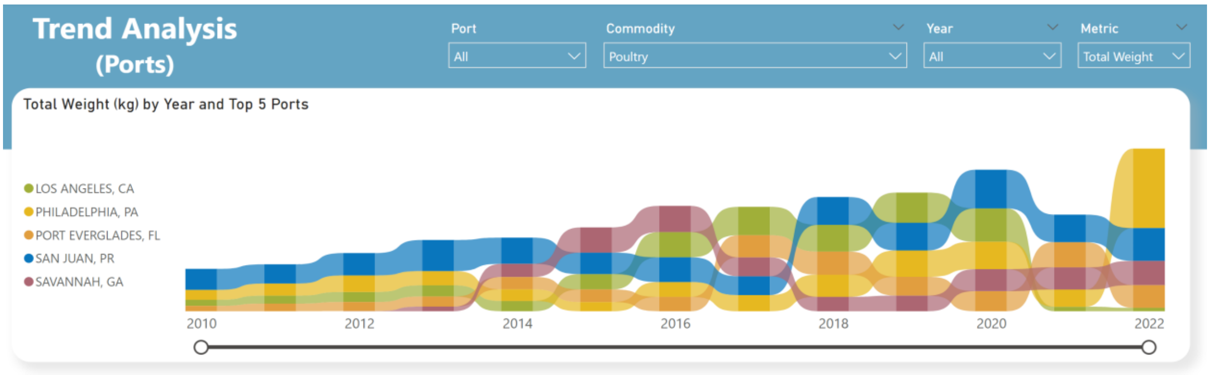
Corn U.S. Imports by Continent of Origin



Continent	Total Weight (kg)	Total Value in USD
SOUTH AMERICA	6,143.7M	3,770M
EUROPE	1,785.6M	688M
NORTH AMERICA	516.6M	149M
ASIA	14.7M	9M
CENTRAL AMER...	0.9M	2M
AUSTRALIA AN...	0.3M	5M
AFRICA	0.2M	0M
Total	**8,462.0M**	**4,622M**

Figure A-2

Primary U.S. import ports trend by commodity



Port	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
SAN JUAN, PR	6,766K	6,180K	7,204K	10,020K	8,434K	6,909K	7,967K	6,056K	8,978K	8,921K	12,462K	8,860K	10,589K
PHILADELPHIA, PA	3,206K	3,905K	5,337K	4,582K	3,774K	2,962K	4,778K	5,202K	7,134K	8,497K	8,837K	5,537K	25,617K
LOS ANGELES, CA	1,956K	2,576K	3,231K	3,600K	3,298K	4,948K	8,139K	9,155K	8,621K	9,723K	10,748K	1,449K	1,094K
PORT EVERGLADES, FL	1,731K	2,457K	2,925K	3,264K	3,983K	4,065K	4,633K	7,138K	7,441K	6,074K	6,476K	8,126K	7,341K
SAVANNAH, GA			48K	1,496K	4,226K	8,132K	8,434K	6,097K	4,638K	5,020K	7,083K	7,153K	7,779K
Total	**13,660K**	**15,118K**	**18,744K**	**22,961K**	**23,715K**	**27,016K**	**33,950K**	**33,648K**	**36,812K**	**38,234K**	**45,606K**	**31,125K**	**52,420K**

Figure A-3

Commodity Portfolio by port

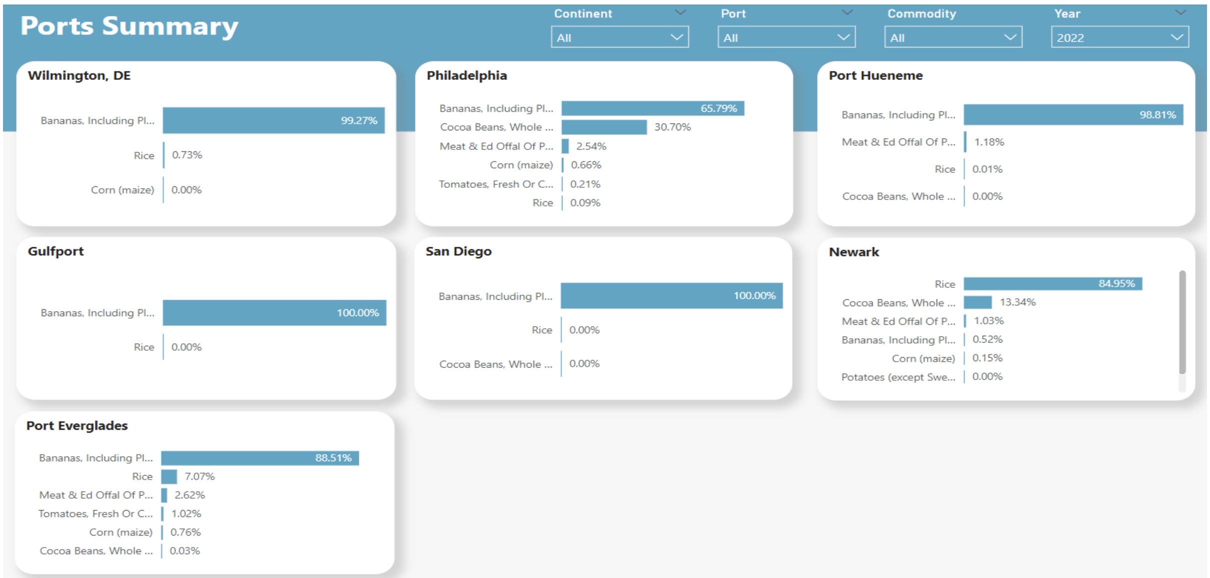
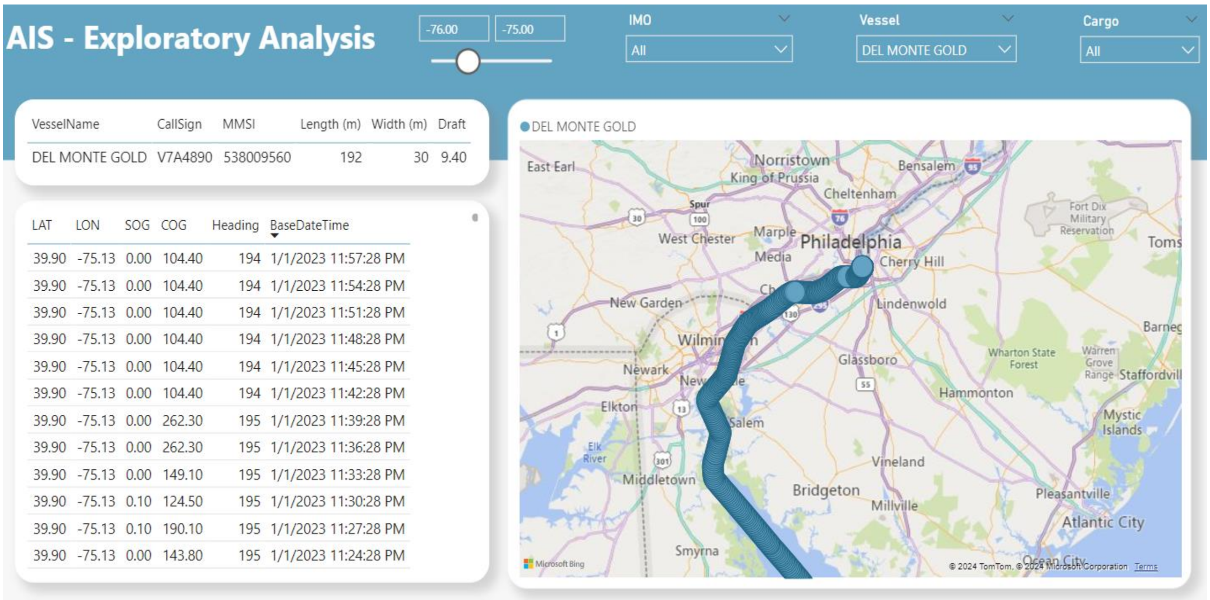


Figure A-4

AIS data visualization by individual vessel



Appendix B

Figure B-1

Power BI Data Model