Global Home Care Supply Network Design Optimization

by

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Submitted to the Program in Supply Chain Management
on May 6, 2022 in Partial Fulfillment of the
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ABSTRACT

Companies can expect to lose almost 42% of one year's profit every decade because of supply chain disruptions. Working to have better supply chain resilience and robustness is now a necessity to stay competitive and profitable. This capstone addresses the creation of a comprehensive and scalable vulnerability assessment framework for an FMCG company to help assess risks in supply chains and take the right resilience measures. Currently, the sponsoring company is facilitating this process by event simulations, but results are not consistent, as the input variables to its simulation model are not based on empirical data. To address this problem, this research project developed a step-by-step methodology for creating a vulnerability map for the supply chain in scope. Questions to answer were: what can go wrong, what is the likelihood of it occurring, what is the consequence from it, and what are recommended resilience strategies? The approach taken was threefold. First, we mapped the supply chain by location and gathered data of natural disruptions and their consequences to establish statistical database. Second, we developed a model that simulated the natural disruptions for each country in scope by using Monte-Carlo technique. Third, we translated the results of natural disruptions into operations shutdown days. Our results were fairly high and showed that our sponsoring company's supply chain in scope could expect to have 227 days of total operations shutdown in the next 10 years. Results were visualized on a vulnerability map with the countries as nodes together with a breakdown of where most of the risks come from. In closing, our sponsoring company now has a model to better assess vulnerability on its supply chain and can therefore focus on resilience strategies to mitigate the risks by more accurate simulations of events.

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1. INTRODUCTION

1.1. Motivation and Relevance

Contemporary supply chains involve a large number of actors, such as suppliers, contract manufacturers, distributors, logistics providers, wholesalers, and retailers. As supply chain networks expand globally, this creates more complexities, interdependencies, and exposure to global vulnerabilities, risks, and disruptions (Sheffi, 2005). The recent COVID-19 pandemic has fueled the debate over the vulnerabilities of an interconnected world where the goods have to pass through a very complex and multi-layered supply chain to reach an end customer (Korbin, 2020). In this context, supply chain risk management (SCRM) is receiving increasing attention. Multinational companies are seeking to gain better understanding of the vulnerabilities in their global supply chain and are rethinking their resilience measures.

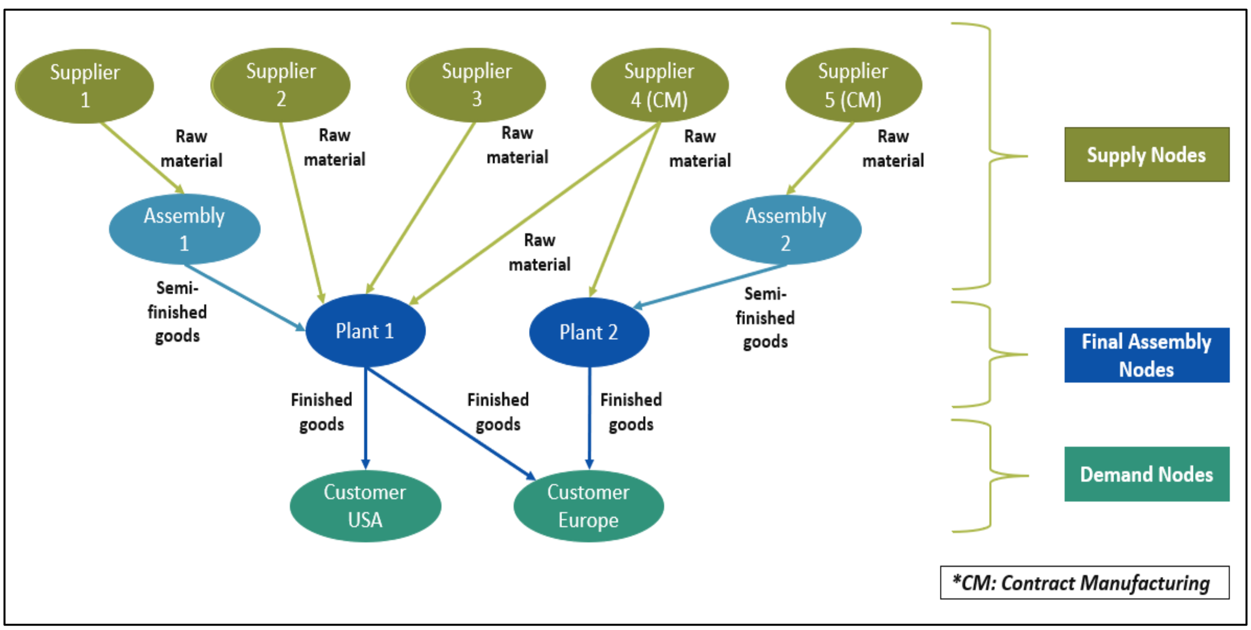
Recently several studies have been conducted on market leaders of different industry domains to evaluate the impact of major catastrophic events on their supply chain networks. The studies reveal that different key areas of supply chain, such as supply, production-distribution capacity, and demand, can be severely affected due to these adversities (Martel & Klibi, 2016). Taylor (2013) found that more than 63% of the companies in Europe, Africa, and Middle East have experienced disruptions in their supply chain networks due to numerous unexpected events arising from natural calamities, supplier difficulties, economic situation, political unrest, and extremism. According to the same study, it also takes an average of 63 days for a company to regain its usual business form.

In addition, the COVID-19 pandemic has added new dimensions in the disruptions of supply chain networks that the companies have never faced before. Drastic failure in product supply due to sudden shutdown of manufacturing plants across the world, shipping and transportation delays or halt due to port closure and container shortages, unprecedented disruption in ocean freight, and unavailability of manpower due to lockdown have compelled supply chain managers to think differently. These factors have also made clear the necessity of an appropriate risk analysis model that can anticipate future risks and provide recommendations regarding choice of suitable resilience strategies.

Our sponsor is a globally prominent fast-moving consumer goods (FMCG) company with a wide portfolio. The product chosen for the capstone project is one of their high-demand home care products. As shown in Figure 1.1, the product relies on a complex global supply chain. It is manufactured, assembled, and distributed through contract manufacturing business model from two primary locations (denoted as “assembly” and “plant”). These locations primarily serve the customer distribution networks (denoted as “customer”) located in the US East Cost and greater Europe. To support the final assembly, different components of the product are manufactured, transported, and distributed from different suppliers (denoted as “supplier”) located in North America, Europe, and Asia.

Figure 1.1

Current State of Global Supply Chain of the Selected Home Care Product



Long-distance relationships with suppliers and the contract manufacturing model result in exposure to disruptions with different magnitudes of probabilities and consequences. During the COVID-19 pandemic, the supply chain of this product has faced significant disruptions due to ocean transportation delays or halts, container shortages, and supply inaccessibility. This resulted in supply disruptions and unavailability of the product in the primary markets. Even though its current global supply chain model gives greater control of the overall supply chain processes and offers cost reduction opportunities, it also poses bigger risks for business continuity at the time of unexpected disruptions, such as the COVID-19 outbreak.

In this context, our sponsoring company wishes to assess the risks and vulnerabilities associated with their complex global supply chains. To perform this assessment, they can leverage various tools that allow them to simulate the impacts of various disruptions and perform network optimization studies. While they already have these analytical tools available, they are unable to incorporate vulnerabilities in different supply chain nodes due to the lack of structured definition and data of relevant disruptions. In particular, they are not able to quantify the impact of such disruptive events. The company is in a need of a vulnerability assessment framework and risk analysis model that can be incorporated in their supply chain network design simulation tool, for more realistic supply chain resilience insights and investment decision-making.

1.2. Problem Statement

Our primary objective in this capstone project is to develop a comprehensive and scalable vulnerability assessment framework for the analysis of risks and vulnerabilities of global supply chains. In line with extant contributions in the area of risk assessment for supply chain management, such as Sheffi and Rice Jr. (2005), our vulnerability assessment framework will address the following research questions:

- RQ1: What can go wrong, i.e., which are the disruptions that could potentially be detrimental for business continuity?
- RQ2: What is the likelihood of the event, i.e., what is the probability of the identified disruptions?
- RQ3: What are consequences resulting from the event, i.e., what is the magnitude of the potential consequences or impacts resulting from the identified disruptions?
- RQ4: What risk mitigation and resilience strategies can be put forward to minimize the impact of the identified disruptions?

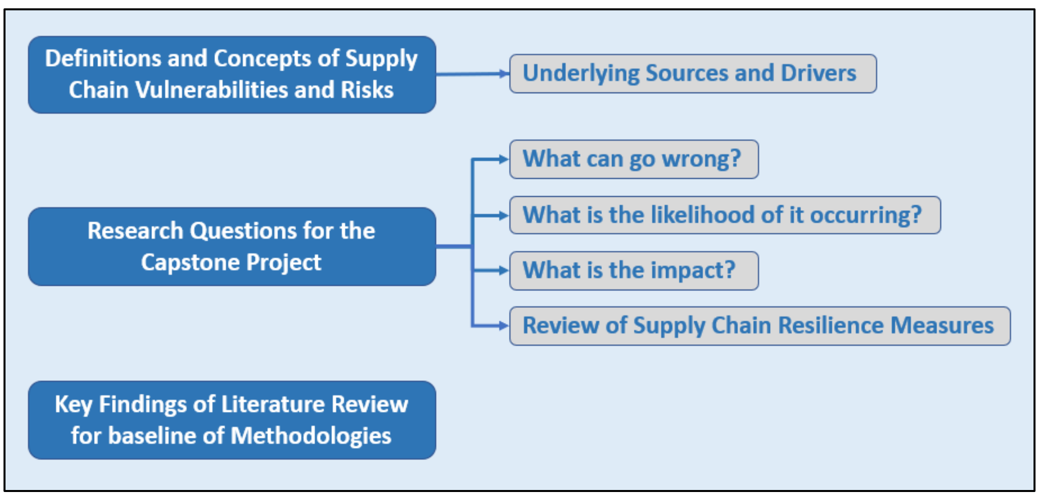
Further, our objective is to apply the vulnerability assessment framework to a specific pilot product of a company, allowing us to validate our approach and assumptions as well as derive specific recommendations. The vulnerability assessment framework will be designed in a scalable way in order to allow for its application to other supply chains within the organization, beyond the scope of this capstone project.

2. LITERATURE REVIEW

There is a vast literature on vulnerability, risk, and supply chain disruptions. To present our literature review, we started by reviewing some main concepts and the guiding vulnerability framework that we used in the capstone project (*Section 2.1*). In the second part of our literature review, we addressed four research questions: what can go wrong *(Section 2.2)*, methods to quantify the probability of the disruptions *(Section 2.3)*, methods to measure the impact of the disruptions *(Section 2.4)*, and supply chain resilience measures in contemporary research and studies to enhance the robustness of global supply chain against the exposed risks *(Section 2.5)*. We concluded our literature review by connecting the key findings as the baseline for methodologies *(Section 2.6)*. The structure of literature review is illustrated in Figure 2.1.

Figure 2.1

Structure of the Literature Review



2.1. Key Concepts and Frameworks for Supply Chain Resilience

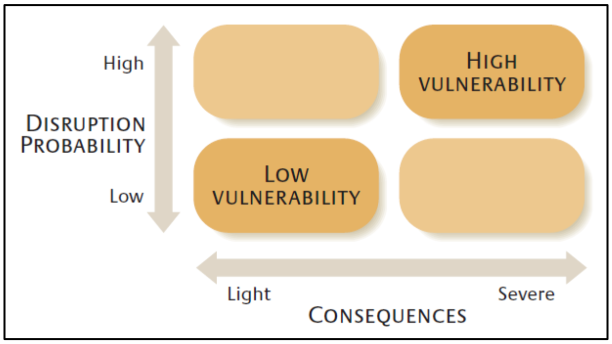
Sheffi (2005) defines the vulnerability of a firm toward a disruptive event as a combination of the likelihood of the disruption and the potential consequence of the disruption. Husdal (2015), echoing Sheffi, also defines vulnerability as the degree of the inability of a system in managing effects of internal or external events that the system is exposed to. According to a report from

Cranfield University School of Management (2003), vulnerability of the global supply chain is a measure of exposure to serious disturbance. Pettit et al. (2010) further elaborate the definition of vulnerability with a comprehensive list of seven different types of supply chain vulnerabilities: turbulence, deliberate threats, external pressures, resource limits, sensitivity, connectivity, and supplier/customer disruptions. According to the literature review, supply chain vulnerabilities and risks can be defined as the state of exposure to any unexpected event in supply or demand.

Vulnerabilities are different for enterprises depending on the likelihood and impact of nature of disruptions. From literature review, similarities are observed between different vulnerability frameworks suggested by scholars and researchers in supply chain resilience. Sheffi and Rice Jr. (2005) suggest a vulnerability assessment framework with two dimensions: probability of disruptions and consequence of disruptions (see Figure 2.2). The risk exposure matrix proposed by Norrman and Jansson (2004), illustrated in the Figure 2.3, is also summarized with the two dimensions of basic risk assessment approaches: probability (likelihood) and impact (consequence). In both cases, the frameworks are further split into a 2x2 matrix to categorize different levels of vulnerabilities. Because of the widespread practice of probability and impact as the two most common matrices in the studies of vulnerability assessments, our literature review was further extended based on the form of risk matrix shown in Figure 2.2 and 2.3.

Figure 2.2

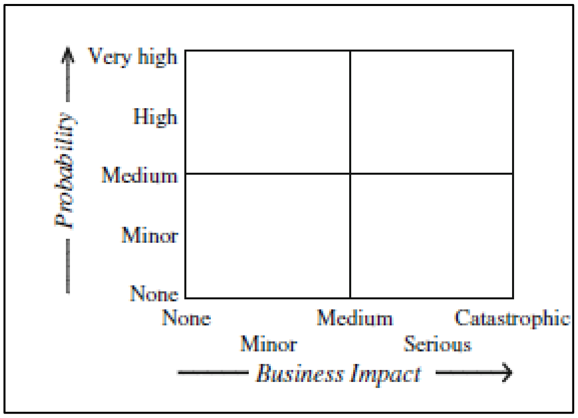
Dimensions of Vulnerability Assessment Framework



Note. Adapted from Sheffi, Y., & Rice Jr., J. B. (2005). A supply chain view of the resilient enterprise. *MIT Sloan Management Review*, *47*(1), 41–48.

Figure 2.3

Risk Exposure Matrices



Note. Adapted from Martel, A., & Klibi, W. (2016). *Designing Value-Creating supply chain networks*. Springer Publishing.

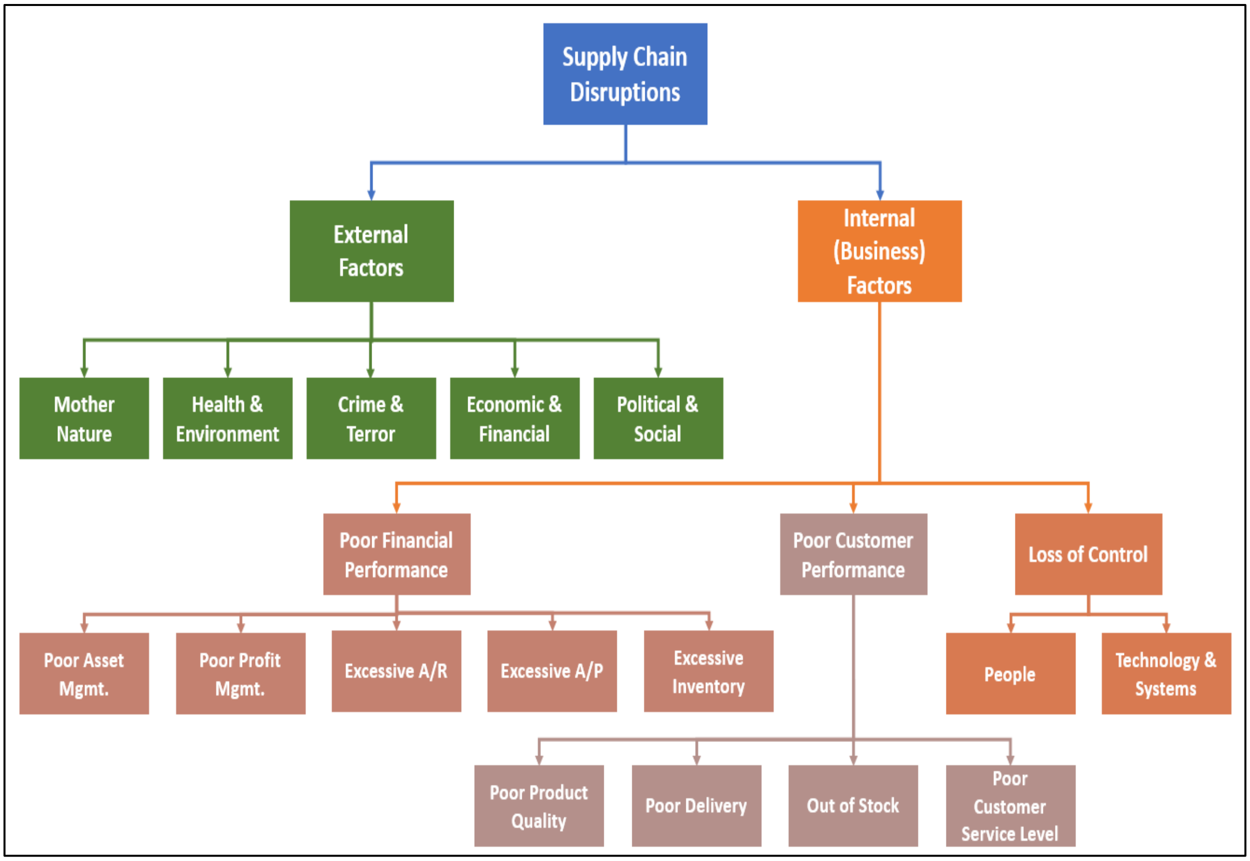
2.2. Defining Disruptions in Global Supply Chain (What Can Go Wrong?)

To answer the question "what can go wrong?" definitions and classifications of disruptions in different literature can be summarized in three broad categories: disruptions according to source of uncertainty, disruptions based on randomness of uncertainty, and disruptions based on frequency-impact combination.

In the literature, sources and factors of supply chain risks and vulnerabilities are broadly classified into two categories: internal and external. A report by MIT Center for Transportation & Logistics (2009) classifies supply chain risks, as shown in Figure 2.4, into two categories: internal risks (related to a company's internal business practices), and external risks (related to a company's external affairs). Martel and Klibi (2016) identify three key sources of supply chain vulnerability: supply chain network assets (internal), supply chain network partners (internal and external), and public infrastructure (external). Agrawal and Pingle (2020) explain supply chain vulnerability sources in a 2x2 matrix with two dimensions: risk class (namely internal and external), and risk controllability (namely controllable and uncontrollable). While there are different factors can be involved to different extents behind supply chain disruptions, literature review indicates that external factors, which are difficult to predict or anticipate for any organization, play a crucial rule in supply chain vulnerabilities.

Figure 2.4

External and Internal Risk Factors of Supply Chain Disruptions



Note. Adapted from MIT Center for Transportation & Logistics. (2009). *Global supply chain risk management part 2: Differences in frequencies and priorities*. https://ctl.mit.edu/research/current-projects/global-scale-risk-initiative

For our capstone project, we found the classification stated by Sheffi (2005) most appropriate due to its simplicity and comprehensiveness. In this classification, disruptions can be segmented into three categories: natural disasters (e.g., earthquakes), accidents (e.g., transport accidents), and intentional disruptions (e.g., acts of terrorism or sabotage). Data on historical disruptive events from the Centre for Research on the Epidemiology of Disasters (CRED, www.emdat.be) can be useful in developing a classification model like that prescribed by Sheffi (2005).

- A recent survey by the World Economic Forum (WEF) states that natural disasters are the most threatening and extreme disruptions to supply chain network (Martel & Klibi, 2016). CRED (2020) report shows that natural hazards events have increased worldwide by 74% from 1980-1999 (4,212) to 2000-2019 (7,248) resulting in approximately 4 million deaths, 780 million people affected and 1.34 billion USD economic losses. According to the same report, it can justifiably be said that the trend toward more natural disasters is causing massive human and economic losses.
- Accidental disasters also follow Pareto's law similar to natural disasters, i.e., a small proportion of the disruption causes a large part of the damage (Sheffi, 2005).
- Attacks against a company's assets or processes with the intent of interrupting its operations are considered as intentional disruptions. Intentional disruption can be classified as terrorism, strikes, economic recession, political unrest, cyber-attacks, cargo piracy, theft, kidnapping, sabotage, and corporate espionage. Innovations of one company may also be disruptive to the existing business of other companies. The introduction of Apple's iPhone in 2007, Toyota's lean manufacturing strategy in the 1970s, and LCD TV innovations have posed strong existential challenges to the businesses of other companies (Sheffi, 2015).

After defining all the disruptions categories, we had the foundation to quantify the likelihood of these disruptions, which is elaborated in the next section.

2.3. Quantifying Likelihood of Disruptions (What is the Likelihood of It Occurring?)

In this section, we extended our literature review to methods applied to quantify the probability of three types of disruptions identified in Section 2.2. We identified two primary methods of quantifying probability of disruptions: the mathematical modeling approach (e.g., probability models), and the subjective evaluation approach (e.g., Delphi method). The applicability of the methods varies depending on the nature of the disruptive events, which is illustrated in following subsections.

2.3.1. Mathematical Modeling Approach

Researchers have applied a variety of mathematical modeling approaches to convert risks into numerical values that could then be incorporated into decision-making models. Approaches include but are not limited to: analytic approaches (to assess risk as a function of occurrence and impact), probability models (in developing advanced catastrophe models, e.g., “CAT” by Applied Insurance Research), and power law distribution (also known as Pareto’s law or 80/20 law that postulates 80 percent of events will be frequent and minor events in the context of disruptions) (Amendola et al., 2012; Ravindran et al., 2009; Sheffi, 2015).

2.3.1.1. Assessing and Modeling Natural Disasters (Random Events)

Statistical models are widely used in assessing the likelihood and magnitude of natural disasters. Diverse data sources are available for the occurrences of such natural disasters in various parts of the world, such as models developed by insurance companies for the likelihood of earthquakes, floods, or lightning strikes; the U.S. Geological Survey (USGS) data for the susceptibility of areas to earthquake events; and the U.S. National Oceanic and Atmospheric Administration (NOAA) data for severe weather and climate conditions. The frequency and size of near-misses or small disruptions can assist in anticipating the possibility of a larger low probability-high impact natural catastrophe. Although such correlations are not exact in predicting the timing or magnitude of future disruptions, they can be used to evaluate the relative likelihood of future occurrences in comparison to other possible disruptions (Sheffi, 2005).

2.3.1.2. Assessing and Modeling Accidental Events

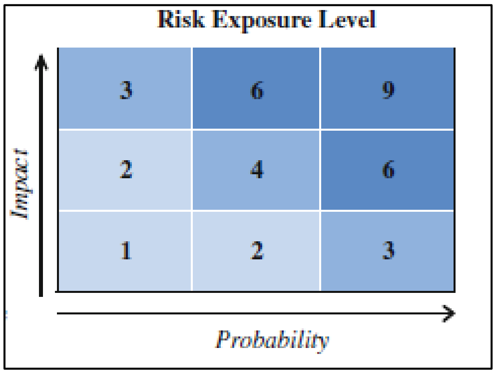
Despite efforts to prevent accidents and hazards, many accidents affecting supply chains still occur, and that is why, determining the likelihood of accidental events is the first and important step in risk assessment approach. The majority of analyses aiming at determining such likelihood rely on one of the two methods: statistical models based on historical data or the near-miss framework (Sheffi, 2005). Martel and Klibi (2016) propose an alternative type of multi-hazard (i.e., meta-events having generic impacts on supply chain network resources, partners, and markets) modeling, which requires characterizing the occurrence, intensity, and duration of multi-hazards by zones or exposure levels. A compound stochastic process uses two random and highly correlated variables to explain how multi-hazards occur in space and time: the impact intensity and the incident duration. Intensity is typically determined by loss level or fatality level on a normalized scale, and duration is determined by impact-duration function. In practice, Poisson distributions are commonly used in catastrophe models to estimate the likelihood of accidental events for a given period (Banks, 2005).

2.3.2. Subjective Evaluation Approach

Subjective scoring methods are often utilized in the absence of adequate data and precise evaluations of impact and likelihood. Subjective methods include but are not limited to: game theory (Major, 2002), qualitative assessment by risk rating (Portillo, 2009), risk prioritization and mapping using Risk Priority Number (Ravindran & Jr., 2012), simulation (Vilko & Hallikas, 2012), and stochastic model (Goh et al., 2007). The narrative for subjective evaluation is that it is comparatively easier for an organization to assess “what happens if supplier A fails to deliver for two months?" instead of "the probability or likelihood that supplier A would fail to deliver” (Sheffi, 2015). It is common to have an accumulating succession of failures that culminate in a disaster. Matrices, depicted on the Figure 2.5, are primarily used to assign a subjective exposure level to possible risks (Martel & Klibi, 2016). Many industries have established a management reporting and analysis system based on near-miss framework (see Figure 2.6) to minimize the possibility of future high-impact disruptions (Sheffi, 2005).

Figure 2.5

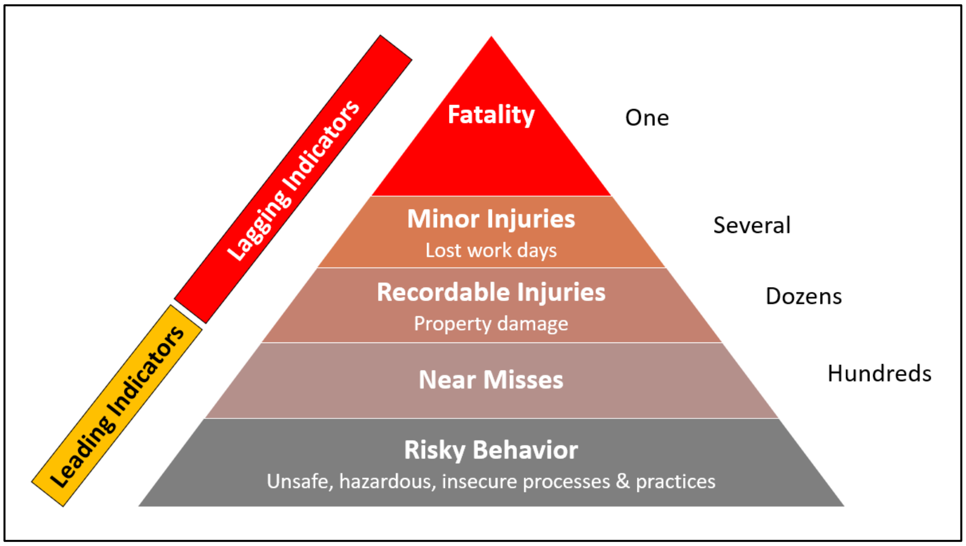
Risk Exposure Matrices with Subjective Evaluation or Scoring



Note. Adapted from Martel, A., & Klibi, W. (2016). *Designing Value-Creating supply chain networks*. Springer Publishing.

Figure 2.6

The Near-Miss Pyramid



Note. Adapted from MIT MicroMasters. (2020). *Supply chain dynamics.* [Slides]. MITx MicroMasters SC3x course. https://www.edx.org/course/supply-chain-dynamics

2.3.2.1. Assessing and Modeling Intentional Events

Unlike natural disasters and accidents that follow power law distribution and can be inferred from small disruptions or near-miss frameworks, intentional disruptions are completely different. Intentional disruptions, according to Sheffi (2005), are adaptable threats in which attackers strive to assure the effectiveness of the attack while also maximizing the damages at the most unprotected and vulnerable state of the organizations. When assessing the nature of a new intentional threat, historical data are of limited use because of the adaptive nature of intentional disruptions.

2.4. Quantifying Consequences of Disruptions (What is the Impact?)

In this section, we extended our literature review to methods applied to quantify the impact of three types of disruptions identified in Section 2.2. Our literature review revealed that value-at-risk (VaR), time-to-recovery (TTR) and time-to-survive (TTS) models are widely used to quantify the impacts of disruptive events. The applicability of the methods varies depending on the nature of the disruptive events and the segment of supply chain impacted. Sheffi et al. (2003) identify six different types of failure modes and their varying level of potential impacts on the global supply chain: supply, transportation, facilities, freight breaches, communications, and human resource capacity.

2.4.1. Value-at-Risk (VaR) Model

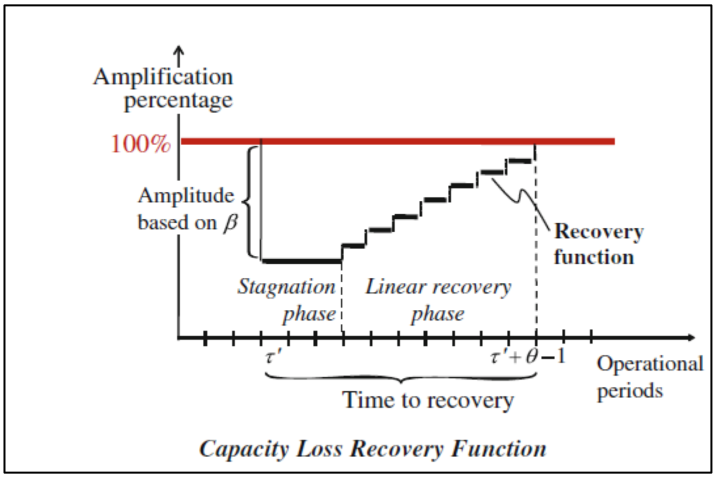
The value-at-risk (VaR) model is one of the most widely used models in supply chain risk management. While VaR model was originally developed by JP Morgan for the banking sector to manage and reduce the risk of trade losses, it can also be adapted to the supply chain context for assessing the consequences of any disruptive events. This model is based on probability and statistics and can be calculated in several ways, including historical, variance-covariance, and Monte-Carlo methods (Olson & Wu, 2020). VaR model has primarily three components: the amount of potential loss due to disruption, the probability of a disruptive event occurring, and the duration of the event’s occurrence (Lim et al., 2013).

2.4.2. Time-to-Recovery (TTR) and Time-to-Survive (TTS) Models

Time-to-recovery (TTR) and time-to-survive (TTS) are two methods for calculating the impacts of supply chain disruptions. TTR is the length of time it takes for a supply chain node to restore to full capacity following a disruption, whereas TTS is the maximum amount of time a supply chain node can continue operations while a disruption is underway. An adequate backup plan is required if a supply chain’s TTR is longer than its TTS. Disruptive events with low probability-high impact are relatively challenging to be quantified. Simchi-Levi et al. (2015) construct a mathematical model based on TTR as input to quantify the economic and operational impact of supply chain node failure instigated by varied severity of disruptive events. TTR can be estimated under various scenarios from suppliers’ data, such as location, products, lead-time, and cost of loss. The model identifies and calculates enterprises' risk areas in depth by combining TTR information, bill-of-material data, operational and financial measures, inventory levels, and demand projections. Martel and Klibi (2016) demonstrate capacity-loss recovery function using TTR method, as shown in Figure 2.7, which implies the capacity recovery profile for manufacturing supply chain node at the course of disruption-hit.

Figure 2.7

Capacity-Loss Recovery Function



Note. Adapted from Martel, A., & Klibi, W. (2016). *Designing Value-Creating supply chain networks*. Springer Publishing.

2.5. Supply Chain Resilience Measures against Disruptions

Supply chain resilience can be defined as the ability to bend and bounce back from adversity (Coutu, 2002). According to Mitroff and Alpaslan (2003), organizations that are proactive and crisis-prepared endure fewer disasters and recover more quickly from adversity. Experts suggest different resilience measures (illustrated in Table 2.1) to support and reinforce an organization's resilience and robustness of supply chain network in times of disruptions. Sheffi (2005) provides a strategic evaluation of different resilience measures in supply chain, such as redundancy, flexibility, product and process standardization, postponement, comprehensive tracking and monitoring, and total supply network visibility. Sheffi (2015) also emphasizes developing and improving detectability in assessing supply chain vulnerabilities and risks.

Table 2.1

Indicators of Supply Chain Resilience

Indicator	Author's Name
Agility	Kamalahmadi and Parast (2016)
Flexibility	Sheffi and Rice Jr. (2005), Pettit et al. (2013)
Robustness	Ehrenhuber et al. (2015), Sheffi and Rice Jr. (2005)
Redundancy	Rice and Caniato (2003), Ali et al. (2017)
Visibility	Christopher and Peck (2004)
IT capability/ information sharing	Jain et al. (2017)
Collaboration	Papadopoulos et al. (2017)
Sustainability	Jain et al. (2017)
Adaptability	Chowdhury and Quaddus (2016)
Supply chain network design	Christopher and Peck (2004)
Security	Rice and Caniato (2003)

Note. Adapted from Singh, C. S., Soni, G., & Badhotiya, G. K. (2019). Performance indicators for supply chain resilience: Review and conceptual framework. *Journal of Industrial Engineering International*, *15*(S1), 105–117. https://doi.org/10.1007/s40092-019-00322-2

2.6. Conclusions of Literature Review

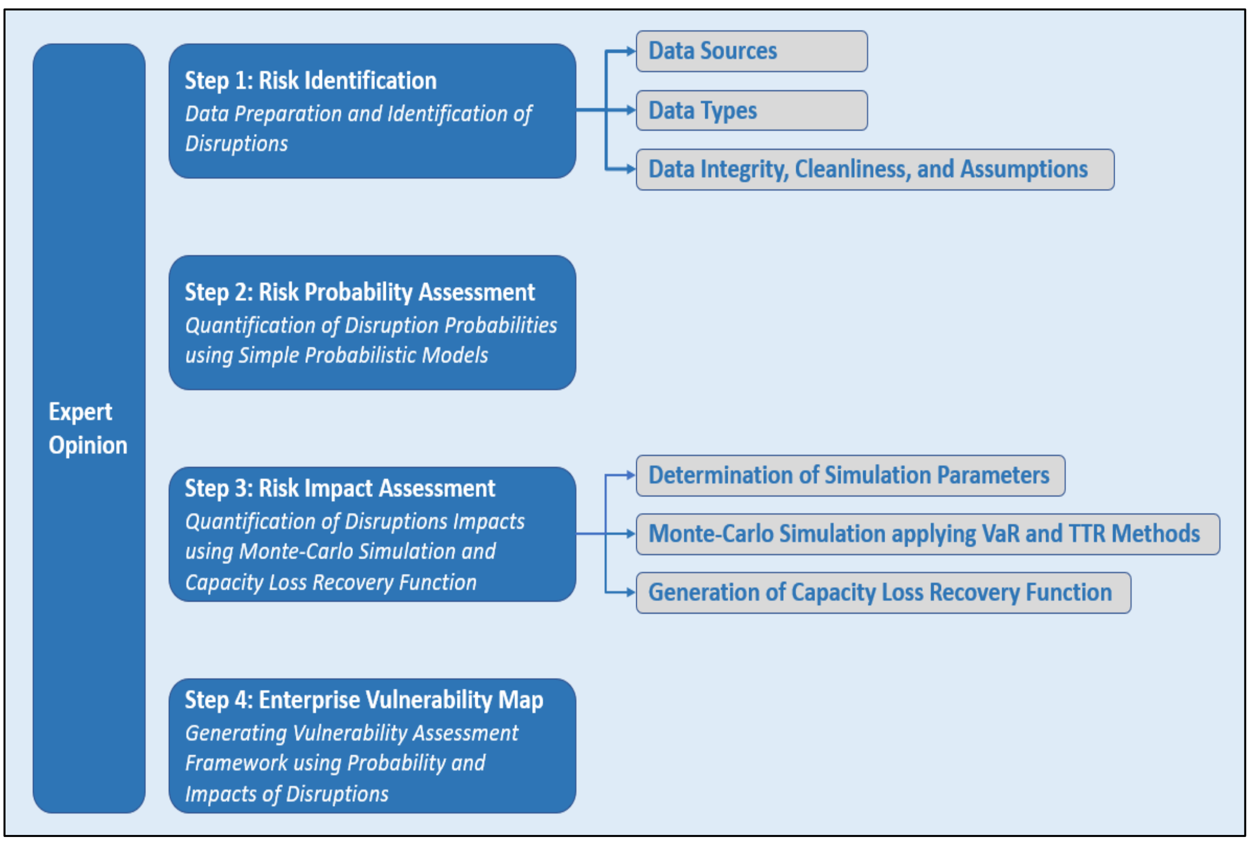
This literature review explored different contemporary research and studies regarding supply chain risk management to find the best-fit methods for assessing the current risk exposure to the sponsoring company's existing global supply chain. From our literature review, we observed that probabilities and impacts were the two most primary matrices of vulnerability and probability-impact methods were used as a framework for vulnerability assessment (Norrman & Jansson, 2004; Sheffi & Rice Jr., 2005). Different scholars identified risks from different points of view, such as external and internal to the business and supply chain, and nature of hazards. The common and widely accepted classification was found to be: natural disasters, accidental disasters, and intentional (man-made) disasters (Sheffi, 2005). For quantification of risk probabilities, both mathematical modelling and subjective evaluation approaches were adopted in different fields of research (Martel & Klibi, 2016; Sheffi, 2005; Sheffi, 2015). Mathematical modelling was primarily based on statistical and probabilistic models and appropriate in availability of data. Subjective evaluations were effective when availability of data was in question. For quantification of risk impacts, our literature review mainly focused on value-at-risk (VaR), time-to-recovery (TTR) and time-to-survive (TTS) models, and observed that these models had relevancies in supply chain vulnerabilities (Simchi-Levi et al., 2015). Monte-Carlo simulation was found effective in determining and applying these models (Martel & Klibi, 2016). We will next move to the methodology chapter to build a vulnerability assessment framework specific to the sponsoring company's supply chain network using the approaches and methods identified from our literature review.

3. METHODOLOGY

The primary need for our sponsoring company is a vulnerability assessment framework and risk analysis model that successfully incorporates relevant disruptions in all the nodes of the global supply chain of the pilot product. After a careful analysis of the literature review and expert reviews, we decided that developing an "enterprise vulnerability map" (a vulnerability assessment map) from Sheffi and Rice Jr. (2005) would be best-fit for our sponsor because the model is widely used and comprehensive; and was aligned with the requirement from the sponsoring company that being able to be used as an input to their simulation (*Step 4, Section 3.2.4*). A general framework of our methodology is explained in Figure 3.1.

Figure 3.1

Structure of the Methodology



To develop such a vulnerability assessment map, we kept in mind that how the vulnerability assessment framework could be relevant for the sponsor's global supply chain, simple yet effective, and easy-to-use for the users. Risk classifications were adopted from Sheffi (2005) because of the suitability with the scope (*Step 1, Section 3.2.1*). The disruptions were identified based on the relevancy of the geographical location of the node, but all the disruptions were restricted to natural disasters for two reasons:

1. primary contributors to supply chain disruptions (represented more than 50% contributions)
2. availability and reliability of data (compared to accidental and intentional disasters)

We mainly used simple probabilistic models from Martel and Klibi (2016) to quantify the probabilities of disruptions (*Step 2, Section 3.2.2*). We found it impractical to separately analyze the probability distribution for each disruption and not viable from a risk management approach. Frequencies, trends, and types of disruptions were analyzed and validated for quantifying disruption probabilities in different nodes. To quantify the impacts of disruptions, we adopted an approach from Martel and Klibi (2016) where we implied both value-at-risk (VaR) and time-to-recovery (TTR) models using Monte-Carlo simulations and generated a capacity-loss recovery function (*Step 3, Section 3.2.3*). Monte-Carlo simulation method was used because it is a model to effectively predict the probability of different outcomes when randomness is present within the variables. We also introduced the concept of "operations shutdown days" in the basis of capacity-loss recovery function, as we found it as an important supply chain resilience measure from a management perspective.

3.1. Expert Interviews and Opinions

According to our literature review (see Section 2.3.2), subjective evaluations are also extensively used in risk management studies along with mathematical models in the absence of adequate data and precise risk assessments. Although our aim in the capstone was to build a vulnerability assessment framework based on facts and mathematical modeling, we also decided to incorporate expert opinions in shaping the entire model. To know the industry-wide best practices in terms of risk management, we conducted expert interviews with supply chain industry leaders. The core objective of such expert interviews was to get insights about how similar industries were dealing with disruptions and quantifying risks in their supply chains, as well as how impacts were assessed and what performance metrics were used to adopt appropriate resilience measures.

We also conducted feedback sessions with the representatives from our sponsoring company to get their opinions of disruptions and impacts in their entire global supply chain. We used their feedback to validate the relevance of our initial findings from data research and to calibrate the capstone project scope.

3.2. Methodology of Developing Vulnerability Assessment Framework

From our literature review of Sheffi and Rice Jr. (2005), we identified that developing an enterprise vulnerability map as vulnerability assessment framework would enable the sponsor to accomplish their requirement of supply chain risk assessment. Figure 2.2 and 2.3 can be expressed as a simplified relationship of probability and impact for our vulnerability assessment framework:

$$\text{Risk} = \text{Probability} \times \text{Impact}$$

There two attributes- probability and impact- were keys throughout our research. The probability was defined as the measure of likelihood of any potential disruption or group of disruptions in a specific supply chain node. The impact was defined as the potential value-at-risk and time-to-recovery in a specific supply chain node as a consequence of the disruption or group of disruptions.

We divided the development of our model into four key segments: risk identification, risk probability assessment, risk impact assessment, and development of an enterprise vulnerability map.

3.2.1. Risk Identification

For global supply chain networks in which entities are in different geographical regions and goods are moved through various transportation links, each entity and transportation link has its own risk and vulnerability conditions that may lead to the disruption of the entire supply chain network. To answer the question “what can go wrong?” we used the classification stated by Sheffi (2005) and segmented disruptions into three categories: natural disasters, accidental disasters, and intentional disasters. We identified potential disruptions of a particular supply chain node by analyzing the location-related disruption databases and grouped them in the three mentioned categories. We then restricted our analysis to natural disasters only, as explained in Section 3. We used the databases from the data sources mentioned in Section 3.2.1.1. We also validated the data from the representatives of the sponsoring company with their past experiences.

3.2.1.1. Data Sources

To begin with the development of the vulnerability assessment framework, we analyzed data for each node (location) of the global supply chain of the pilot product. For our analysis, we mainly used external data sources. External data was demarcated as the data from authentic external databases of globally recognized research and survey centers, which included the following:

- Centre for Research on the Epidemiology of Disasters (CRED, 2020)
- “Statista” (Statista, 2021)
- World Risk Index Report published by Bündnis Entwicklung Hilft, an alliance of nine German development and relief organizations including Oxfam (Bündnis Entwicklung Hilft, 2021)

For our capstone project, we significantly relied on those external sources of databases and leveraged the network of MIT affiliation with those external parties.

3.2.1.2. Data Types

For location-wise disruption and disaster information, we used databases from Centre for Research on the Epidemiology of Disasters (CRED, 2020). For countries as supply chain nodes, we used data from the World Risk Index Report to assign exposure level and impact level to each country (Bündnis Entwicklung Hilft, 2021).

3.2.1.3. Data Integrity, Cleanliness, Assumptions and Limitations

Although the external databases that we primarily relied on are widely used for research work, we made initial integrity checks and cleaned of the data (e.g., removing null values and outliers). We collected 60 years of data but sometimes restricted our horizon to 20 years in the analysis on the assumption that the latest 20 years had the more accurate data. We collected data for the supply chain node countries from global databases. For accidental and intentional disasters, e.g., transport accidents, terrorism, and malware attacks, the sources of reliable statistics are still very limited and not used in our analysis.

3.2.2. Risk Probability Assessment: Quantification of Disruption Probability

After identifying the list of disruptions for a supply chain node, we started assessing the probabilities of the listed disruptions. Since disruptions may vary from location to location, and the same type of disruption can occur in different patterns in different locations, we applied and structured our analysis in the following steps to quantify the disruption probability:

1. Country was considered to be the lowest node point instead of specific location (e.g., state or city). The reasons behind that approach were uneven availability of disruption data for specific locations and to maintain parity of analysis.

2. We analyzed and validated the trends and types of disruptions in a specific country (i.e., node) from the data sources mentioned in Section 3.2.1.1.
3. We calculated "yearly disaster frequency," f, which indicated the average number of disasters for a specific country. While calculating, we considered all disruptions within our restrictions and specified time range. If the total number of disruptions in a specific time period is n and the time range (in years) is t, then f can be expressed as shown in the Equation 3.1. We also calculated "mean inter-arrival time," μ_i, which indicated the average number of days between two disruptions. If the arrival times (days of year) for the *nth* and *(n-1)th* disruption events are denoted as d_n and d_{n-1}, then μ_i can be expressed as shown in Equation 3.2. Yearly disaster frequency and mean inter-arrival time served in combination as a good proxy of disruption probability as a whole. They indicated how frequently the country was expected to face disruption. For example, if yearly disaster frequency and mean inter-arrival time are 15.7 and 23 for a country, it indicates that roughly 15.7 disasters strike in that country every year and each disruption is likely to occur in 23 days apart. In reality, it is not practical for a company to analyze and deploy different risk management approaches for different disruptions; rather a combined and simplified risk management approach is more feasible for management. Hence, we discarded the individual disruption probability from our model, and used yearly disaster frequency and mean inter-arrival time.

$$f = \frac{n}{t} \tag{3.1}$$

$$\mu_i = \frac{\sum_{n=2}^{n=n}(d_n - d_{n-1})}{n-1} \tag{3.2}$$

4. When a country is affected by any disruption, neither the entire country is affected at the same time nor are disrupted areas affected equally. We used the "attenuation probability" concept, which served as the proxy of average disruption probability for any specific

location within a country. Attenuation probability, *a*, helped us to establish our analysis from country level to specific location level, *l*. For example, if an attenuation probability of a country is 0.02, it indicates that if the country is hit by any disruption, the average probability of any location within the country getting hit will be 0.02 (~2%). We assigned attenuation probability of each country from Bündnis Entwicklung Hilft (2021) on a scale of 0 to 1 based on the area of the country. The larger the area of the country, the lower the attenuation probability was (because the lower the chance that any location would get disrupted), and vice-versa. Let X be the set of countries considered in our analysis. If, a country has *l* locations, probability of location *l* being hit by any disruption when the country being hit by the same disruption is *P(l)*, and areas of location and country are A_l and A_x, then *a* can be expressed as shown in Equation 3.3.

$$a = P(l) = \frac{\sum_{l=1}^{l=l}(\frac{A_l}{A_x})}{l} = \frac{1}{l} \quad \forall x \in X \tag{3.3}$$

Although such correlations and assumptions might not be exact in predicting the timing or magnitude of future disruptions, they could be used to evaluate the relative likelihood (probability) of future occurrences in comparison to other possible disruptions (Sheffi, 2005).

After determining the yearly disaster frequency of a supply chain node, we considered higher probability of disruption if the yearly disaster frequency was high, and similarly, lower probability of disruption if the yearly disaster frequency was low.

3.2.3. Risk Impact Assessment: Quantification of Disruption Impact

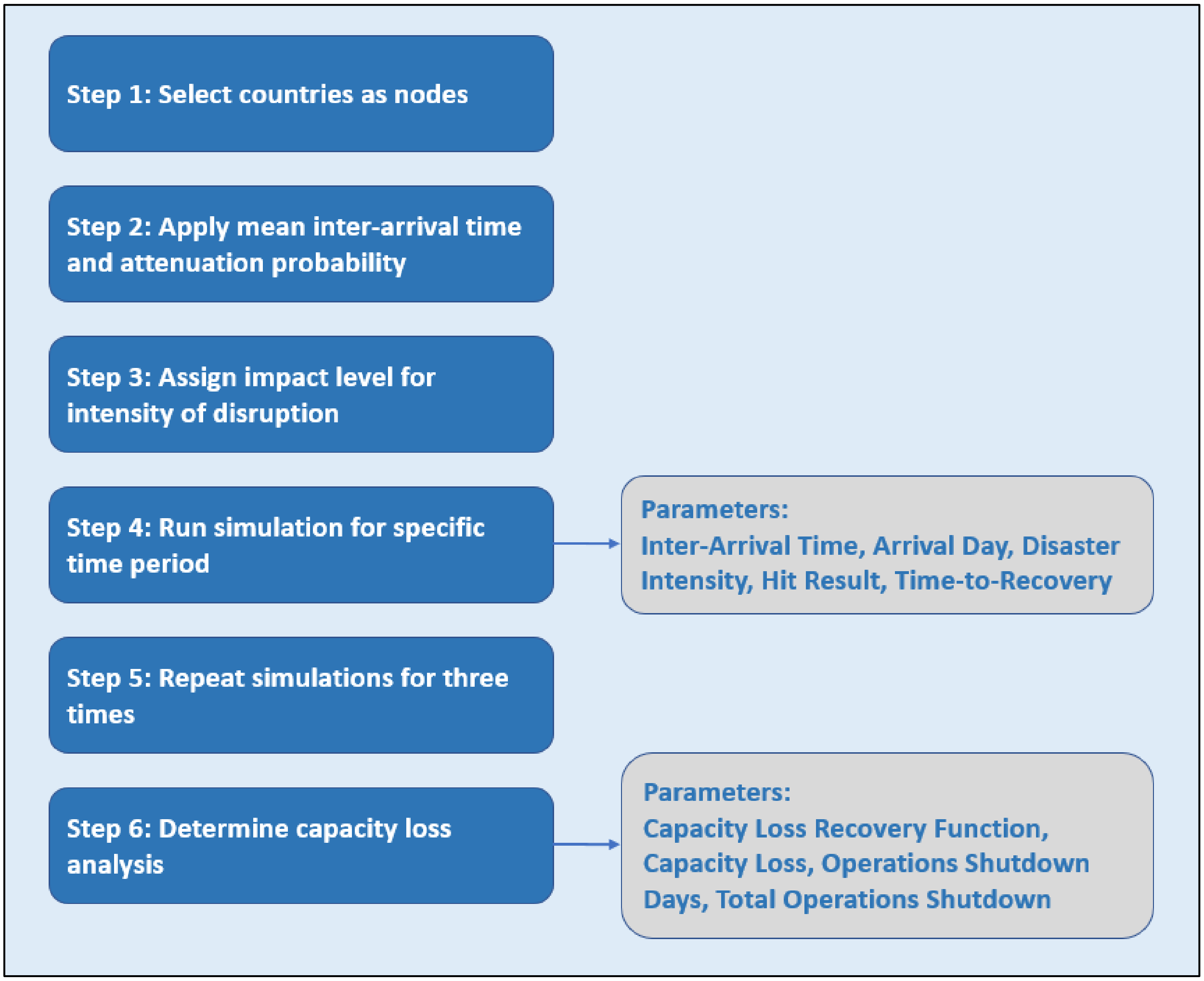
After identifying the list of disruptions and determining their probabilities for a supply chain node, we started assessing the impacts of the listed disruptions. We applied and structured our analysis in the following steps to quantify the disruption impact:

1. Shutdown or halt of production for a certain period caused by disruptions was defined as the production stoppage time, and interruptions in supply of raw materials for a certain period caused by disruptions was defined as the transportation stoppage time. The production stoppage time and transportation stoppage time were together defined as "operations shutdown days" for a node and expressed in days. According to McKinsey and Company (2020), operations shutdown days are represented with approximately 30-50% of one year's EBITDA loss for a company every decade, and hence, were considered in our model as a basis of quantifying impacts in different nodes.
2. We used Monte-Carlo simulation for a specific time period (typically 5 years and 10 years) to determine operations shutdown days for a node.
3. Operations shutdown days usually follow step function (see Figure 2.7). For example, if a plant is impacted by any disruption and caused operational shutdown, the impact is high at the initial phase and causes a quick drop of production capacity. Then there might be a stagnation phase for getting the recovery measures organized, and then the system gradually recovers to its original state. To capture the effect, we also generated capacity-loss recovery function using Monte-Carlo simulation and translated operations shutdown into performance metrics, such as production capacity loss.

Monte-Carlo simulation relied on repeated sampling and the steps of Monte-Carlo simulation are illustrated in Figure 3.2.

Figure 3.2

Steps of Monte-Carlo Simulation



The steps and calculations of Monte-Carlo simulation are explained in the following:

- <u>Step 1: Select countries as nodes</u>

Country or multiple countries were selected as the first parameter in the Monte-Carlo simulation.

- <u>Step 2: Apply mean inter-arrival time and attenuation probability</u>

Mean inter-arrival time for each selected country, $\mu_{i,\,x}$, was calculated from the database using the formula shown in Equation 3.2, and is expressed in Equation 3.4.

$$\mu_{i,\ x} = \frac{\sum_{n=2}^{n=n}(d_n - d_{n-1})}{n-1} \qquad \forall x \in X \tag{3.4}$$

Attenuation probability was assigned to each selected country as explained in Section 3.2.2.

- Step 3: Assign impact level for intensity of disruption

We determined exposure level and impact level of each country from Bündnis Entwicklung Hilft (2021). Impact level was required to determine "intensity of disruption," which was a key parameter in Monte-Carlo simulation. From our literature review of Martel and Klibi (2016), we observed that impact level was considered as a uniform distribution function. Lower impact level and upper impact level served as the lower limit and upper limit of a uniform distribution function, respectively (see Equation 3.5).

$$Uniform\ distribution\ function, P(x) = U\sim(p,q)\ where\ p \leq x \leq q \tag{3.5}$$

Due to the lack of data to support a proper mathematical method, we decided to go with subjective evaluation for determining exposure level. We assigned exposure level and impact level using criteria explained in Table 3.1.

Table 3.1

Criteria for Assigning Exposure Level and Impact Level

Ranking of country (higher ranking indicates more risk exposure)	Exposure level	Lower impact level, p	Higher impact level, q	Uniform distribution for impact level, U~(p,q)
1-30	Very high	9	10	U~(9,10)
31-70	High	7	8	U~(7,8)
71-110	Medium	5	6	U~(5,6)
111-150	Low	3	4	U~(3,4)
> 150	Very low	1	2	U~(1,2)

- Step 4: Run simulation for specific time period

In the next step, we ran Monte-Carlo simulation for 5 years and 10 years period for each selected country using the following parameters:

Inter-arrival time (unit in days):

Inter-arrival time between two events and random function are denoted as i_x and *RAND*, and the relationship is expressed in Equation 3.6.

$$i_x = \{-\ln(1 - RAND)\} \times \mu_{i,\ x} \quad \forall x \in X \tag{3.6}$$

Arrival day (unit in days):

Arrival day for new event and arrival day for previous event within the simulation are denoted as $d_{n,\ x}$ and $d_{n-1,\ x}$, and the relationship is expressed in Equation 3.7.

$$d_{n,\ x} = d_{n-1,\ x} + i_x \quad \forall x \in X \tag{3.7}$$

Disaster intensity:

Disaster intensity is denoted as β, and the relationship with lower impact level (p) and higher impact level (q) from Table 3.1 is expressed in Equation 3.8.

$$\beta = 1 + RAND \times (p - q) \tag{3.8}$$

Hit result:

Hit result, h, was 1 when the disruption affected the specific location of the node within the country, and 0 otherwise. The relationship with attenuation probability, a_x, can be expressed mathematically as shown in Equation 3.9.

$$h = \begin{cases} 1\ if\ RAND < a_x \\ 0\ if\ RAND\ \geq a_x \end{cases} \quad \forall x \in X \tag{3.9}$$

Time-to-recovery (unit in days):

Time-to-recovery, θ and θ_{actual}, indicated the gradual recovery from the time any disruption occurred until the system reached the original state for each successful hit. From the literature review of Martel and Klibi (2016), time-to-recovery was directly related to the disaster intensity

(β). The associated error band, ε, allowed the encapsulation of ±15% deviations or randomness in the analysis and was added with actual time-to-recovery (θ_{actual}). The relationships are expressed in Equation 3.10, 3.11 and 3.12.

$$\theta = \theta_{actual}(\beta) + \varepsilon \tag{3.10}$$

$$\theta_{actual}(\beta) = 0.8\beta^2 + 4\beta \tag{3.11}$$

$$\varepsilon \sim U(-0.15\theta_{actual}(\beta), +0.15\theta_{actual}(\beta)) \tag{3.12}$$

- Step 5: Repeat simulations

We repeated the simulations three times and considered average value from the aggregated results to avoid sampling errors and get more plausible outcomes.

- Step 6: Determine capacity loss analysis

Capacity-loss recovery function per recovery period, r_τ, and capacity loss per recovery period, *c*, were determined for each successful hit and recovery period, τ, in the simulations from step 5, and are expressed in Equation 3.13 and 3.14, respectively. Operations shutdown days per event, *s*, were calculated as the sum of capacity loss per recovery period (*c*) for the entire disruption event (see Equation 3.15). Total operations shutdown, $T_{s,\,x}$, for each selected country was derived from the summation of operations shutdown days for all discrete disruptions during the simulation period (see Equation 3.16).

$$r_\tau(\beta,\theta) = \begin{cases} 1 - 0.1\beta \; if \; 1 \le \tau \le 0.25\theta \\ 1 - 0.1\beta\left\{\frac{(\theta+1-\tau)}{(\theta+1-0.25\theta)}\right\} \; if \; (0.25\theta + 1) < \tau \le \theta \end{cases} \tag{3.13}$$

$$c = 1 - r_\tau \tag{3.14}$$

$$s = \sum_{\tau=1}^{\tau=\theta} c \tag{3.15}$$

$$T_{s,\;x} = \sum_{x \in X} s \tag{3.16}$$

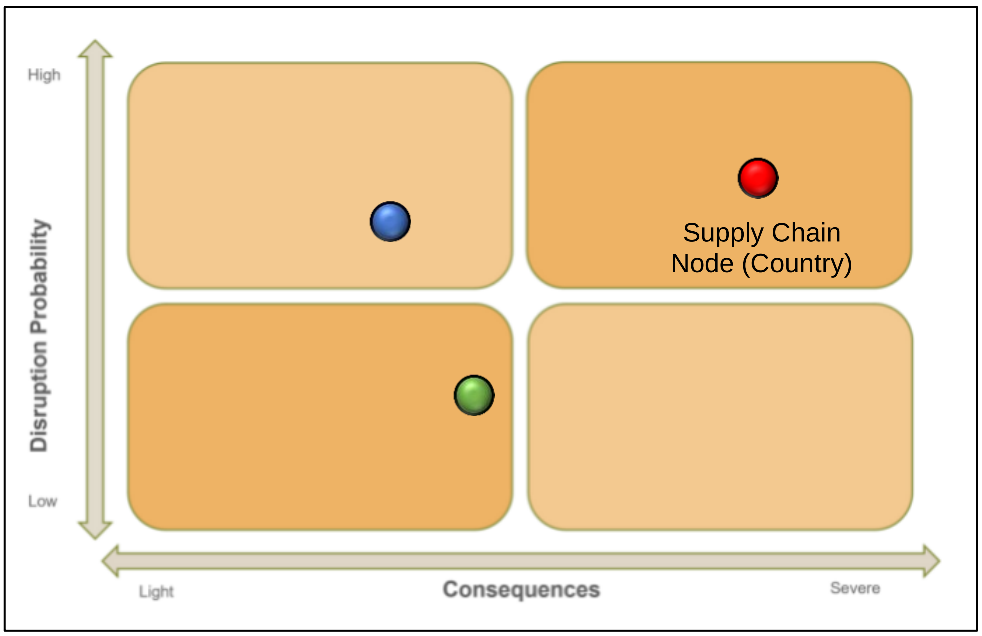
After determining the total operations shutdown of a supply chain node, we considered higher impact of disruption if the total operations shutdown was high, and similarly, lower impact of disruption if the total operations shutdown was low.

3.2.4. Enterprise Vulnerability Map Development

Once both probabilities and impacts of disruptions were determined for a supply chain node, the last step was to build and visualize an enterprise vulnerability map to understand the vulnerability condition of the node. We plotted a XY scatter chart for the supply chain node with disruption probability (as explained in Section 3.2.2) in the x-axis and disruption impact (as explained in Section 3.2.3) in the y-axis. The output of the model was a visual report of the vulnerability assessment map with breakdown of details, as shown in Figure 3.3.

Figure 3.3

Enterprise Vulnerability Map for a Particular Supply Chain Node (Country)



4. RESULTS AND ANALYSIS

In this chapter, we have presented and analyzed the results obtained from our outlined methodology and data preparation explained in Chapter 3, and discussed about limitations and future recommendations. We have started with explaining the tools we used to derive results and insights. In order to maintain confidentiality of the sponsoring company, we have presented hypothetical data to illustrate our results. The supply chain demonstrated was carefully selected so that it shared very similar characteristics with the actual one, and could serve as a representative and realistic exhibition of the analysis of results. We have presented and analyzed the current state of the supply chain for the pilot product in our vulnerability assessment framework and explained sensitivity analysis by altering the locations and comparing the results with the current supply chain. In our model, we mapped all supply chain nodes considering supply and manufacturing locations and excluded demand locations. Demand is generally associated with other organizational and market factors and can be handled within the simulation tool used by the company. The discussions and pilot recommendations are also based on the same hypothetical data.

<u>Tools for analysis and visualization</u>

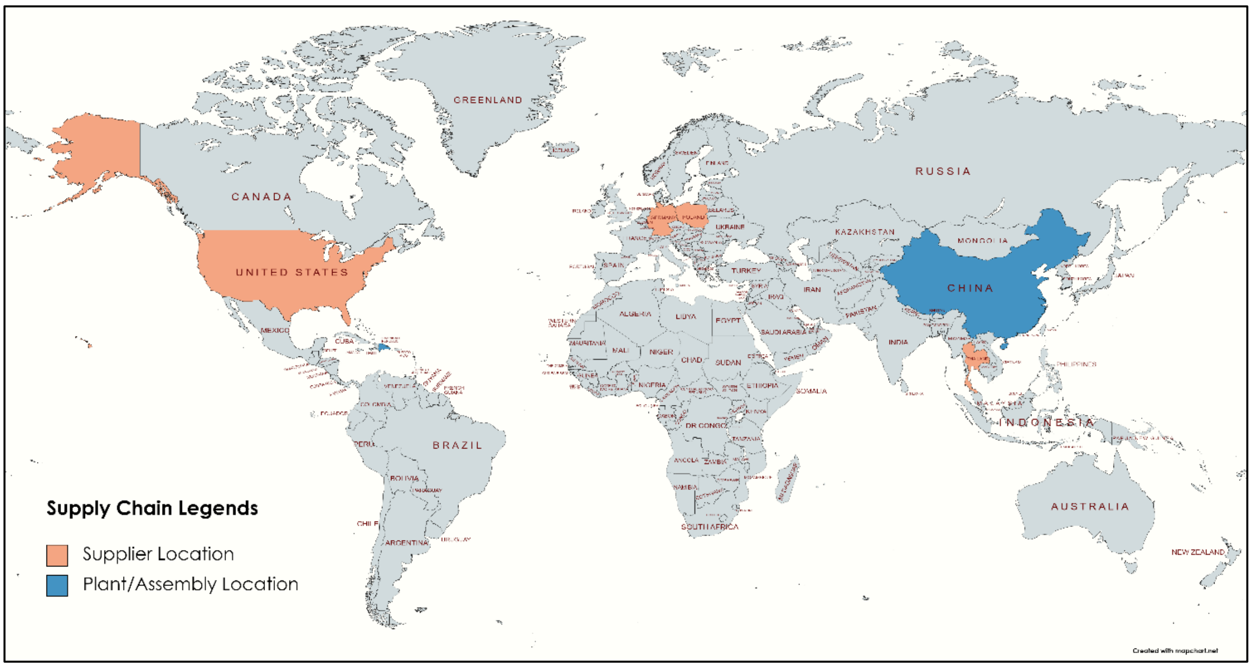
We used Python program as a primary tool to analyze data sources from different external databases and formulate Monte-Carlo simulation with required parameters explained in Section 3.2.3. The external databases were imported into Python and the simulation period was defined. According to the databases and set parameters, simulation data for all countries were generated and extracted as outputs from Python. We used Microsoft PowerBI software as a visualization tool to develop a dashboard for the sponsoring company. In the visualization tool, both external databases and the outputs of simulation data from Python were imported as inputs to visualize disaster probability (frequency) and trends, capacity-loss recovery function, country-wise heat-map, and an enterprise vulnerability map.

<u>Mapping and visualization of supply chain</u>

We started with six countries as the most representative examples for our global supply chain. The countries selected are shown in Figure 4.1. As depicted in Figure 1.1, selected countries represented the supplier, assembly, and plant locations of the supply chain. Among the selected countries, USA and Dominican Republic are from North America, China and Thailand are from Asia, and Germany and Poland are from Europe.

Figure 4.1

Selected Countries for Analysis of Vulnerability Assessment Framework



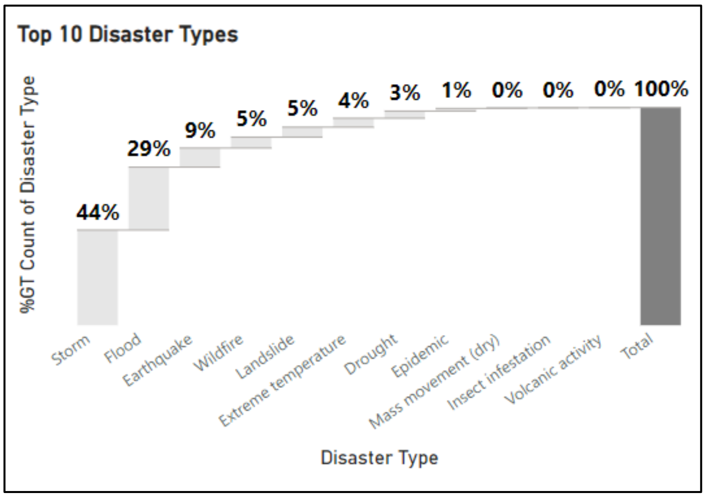
Note. Own elaboration.

4.1. Risk Identification

As formulated in our methodology for RQ1 (risk identification), we identified the top contributing natural disasters from 2001 to 2020 for the selected baseline countries. The results determined using Python and visualization tool are illustrated in Figure 4.2 and 4.3. From Figure 4.2, it is clear that both storms and floods were mostly responsible (~73%) for disruptions caused by natural disasters in the selected supply chain. When only USA was considered, we observed that USA was also exposed to storms and floods (~80%) as the major threats of natural catastrophes (see Figure 4.3). Among the other contributing natural disasters, USA was more exposed to wildfires, whereas the selected supply chain was more prone to earthquakes.

Figure 4.2

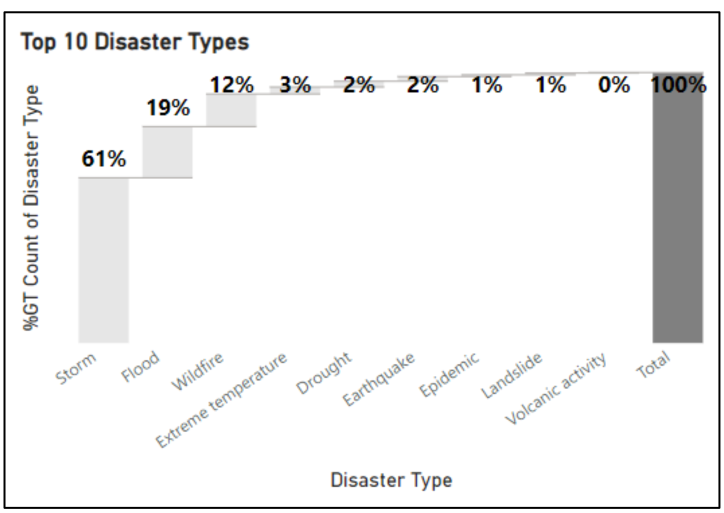
Types of Natural Disasters in the Selected Supply Chain Nodes during 2001-2020



Note. Own elaboration.

Figure 4.3

Types of Natural Disasters in USA during 2001-2020



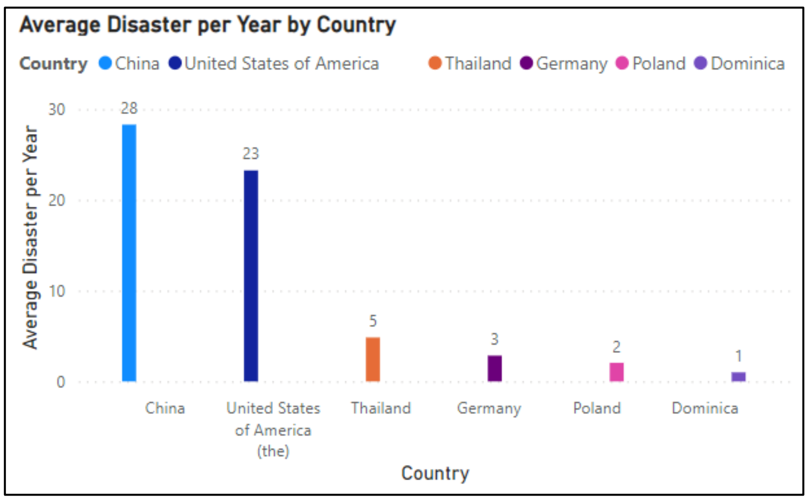
Note. Own elaboration.

4.2. Risk Probability Analysis

Once the major risks were identified from the database, we calculated the yearly disaster frequencies for the listed countries as formulated in our methodology for RQ2 (quantification of risk probability) and illustrated in Figure 4.4. From Figure 4.4, it is clear that both China and USA were the leading countries in terms of yearly disaster frequency, with 28 and 23 disasters on average per year, respectively. It also indicated that China and USA were responsible for ~82% of the total natural disasters happened within the selected supply chain with yearly 51 natural disasters on average.

Figure 4.4

Yearly Disaster Frequencies in the Selected Supply Chain Nodes during 2001-2020

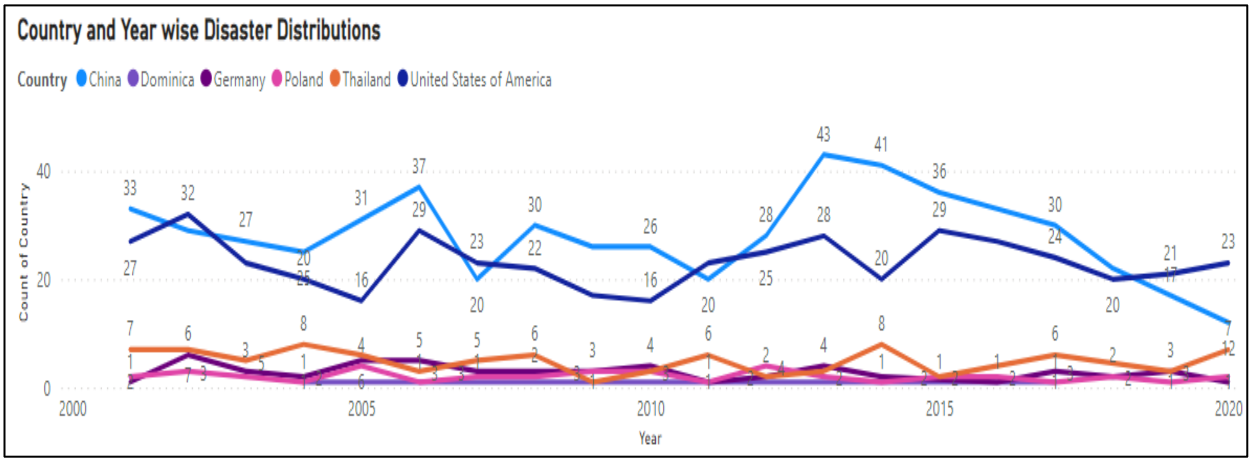


Note. Own elaboration.

We also identified and plotted the trends of natural disasters in the listed countries for the last 20 years (from 2001 to 2020) to understand the future exposure to threats of natural calamities. From Figure 4.5, we observed that the numbers of natural disasters were consistently low in the European and South-East Asian countries. While there were no major fluctuations in the trends of China and USA, these two countries had historically been highly vulnerable to natural disasters. Although a slight decrease was observed in the trend for China for last 5 years, this short time span could be ambiguous to draw any conclusion that China would be facing fewer natural disasters in the future.

Figure 4.5

Trends of Total Natural Disasters in the Selected Supply Chain Nodes during 2001-2020



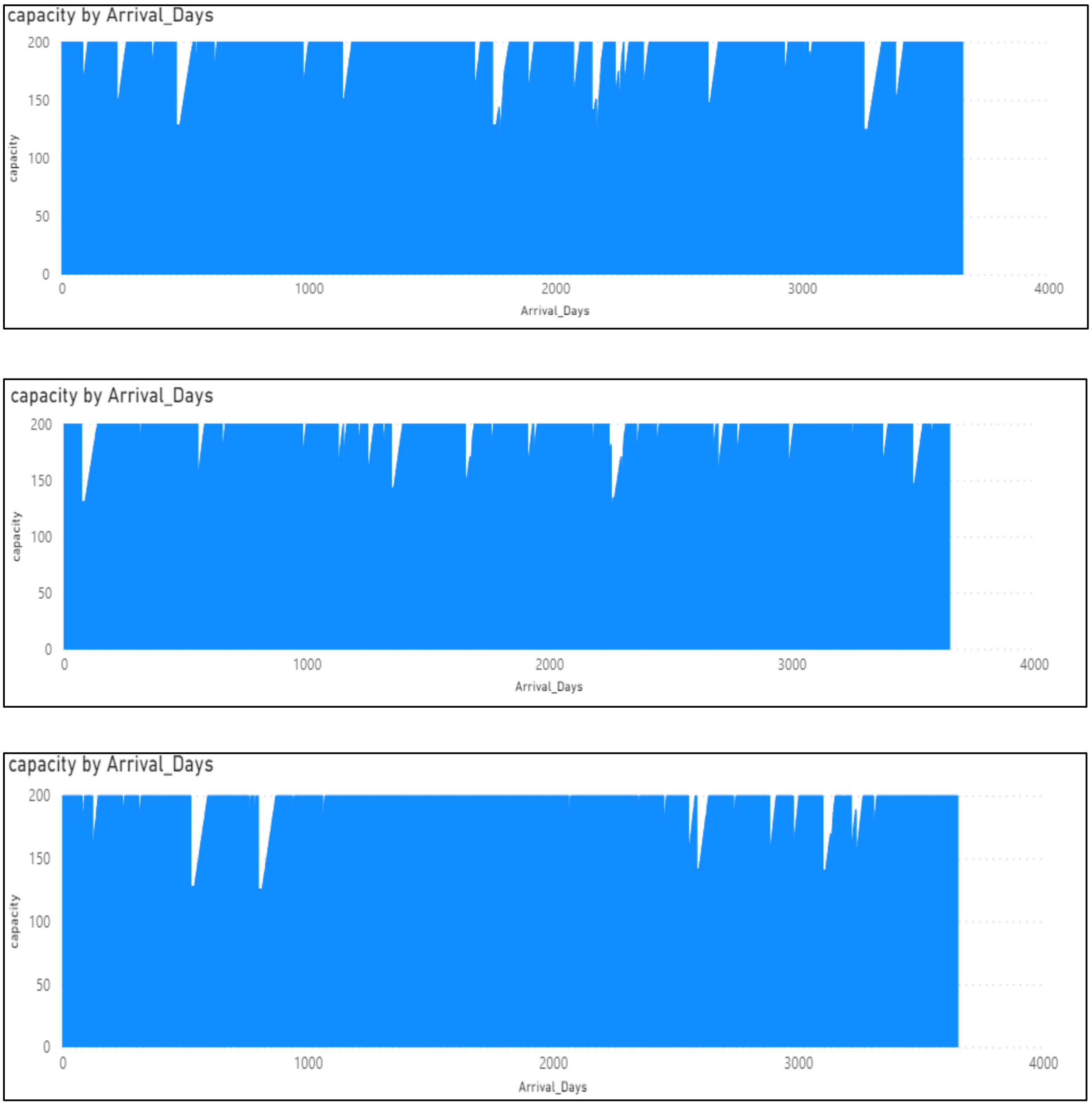
Note. Own elaboration.

4.3. Risk Impact Analysis

After identifying the risks and determining the probabilities and trends of risks, we calculated the total operations shutdowns for the listed countries as formulated in our methodology for RQ3 (quantification of risk impact). It was calculated using Monte-Carlo simulation using the methodology and parameters explained in Section 3.2.3. The parameters were calculated within the simulation using the data imported to Python. Since Monte-Carlo simulation generates future plausible scenarios based on the randomness and historical data, this plausible future generation process involves the construction of representative sample scenarios from different subsets. Similarly, we also conducted the simulation three times to comply with the statistical sampling before aggregating the final results in our model. We assumed that these subsets of simulations reduced the sampling errors of the aggregated simulation. For each instance, simulation was run for 10 years. The aggregated simulation was then calculated based on the average of three-run simulations. The subset simulations are illustrated in Figure 4.6.

Figure 4.6

Results of Sampling Simulation Runs for 10 years for the Final Aggregated Simulation

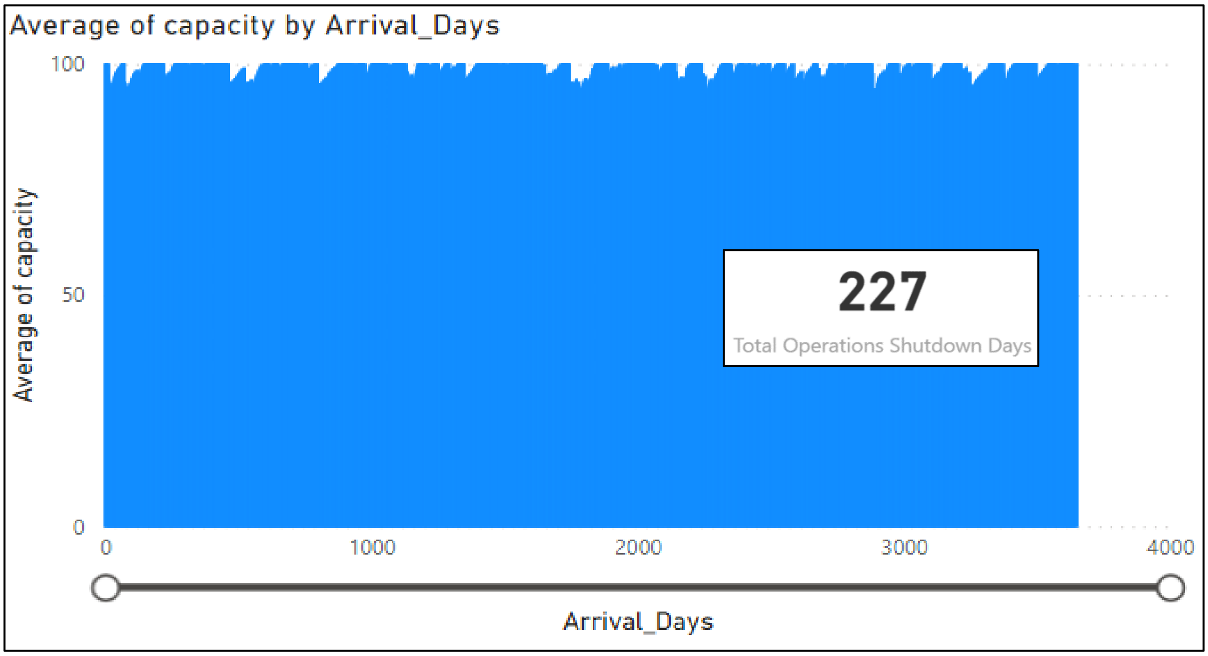


Note. Own elaboration.

The aggregated simulation results are illustrated in Figure 4.7. The y-axis represents the capacity-per-day of the selected supply chain and the x-axis represents the days of simulation. The value of capacity-per-day was denoted as the percentage of capacity. The total capacity available per day for the selected supply chain was considered to be 100%. From the simulation, disruptions happened in different times and supply chain locations. When a disruption happened in any location, it followed the capacity-loss recovery function explained in Section 3.2.3. The capacity dropped from 100% and slowly recovered to 100% during the disruptive period (i.e., time-to-recovery, or TTR). An example of capacity-loss recovery function is explained in Table 4.1 and Figure 4.8. In our analysis, we simulated each country separately for the defined simulation period (i.e., 10 years) and calculated total operations shutdown for the country. When multiple countries were selected in the supply chain, individual country-wise simulation results of total operations shutdown were added to determine the results of total operations shutdown for the entire supply chain. The combined results were not likely to behave the same as the capacity-loss recovery function. The same concept applied when multiple simulations were aggregated based on average, i.e., the aggregated simulation was not likely to behave the same as the capacity-loss recovery function.

Figure 4.7

Results of Final Aggregated Simulation for 10 Years



Note. Own elaboration.

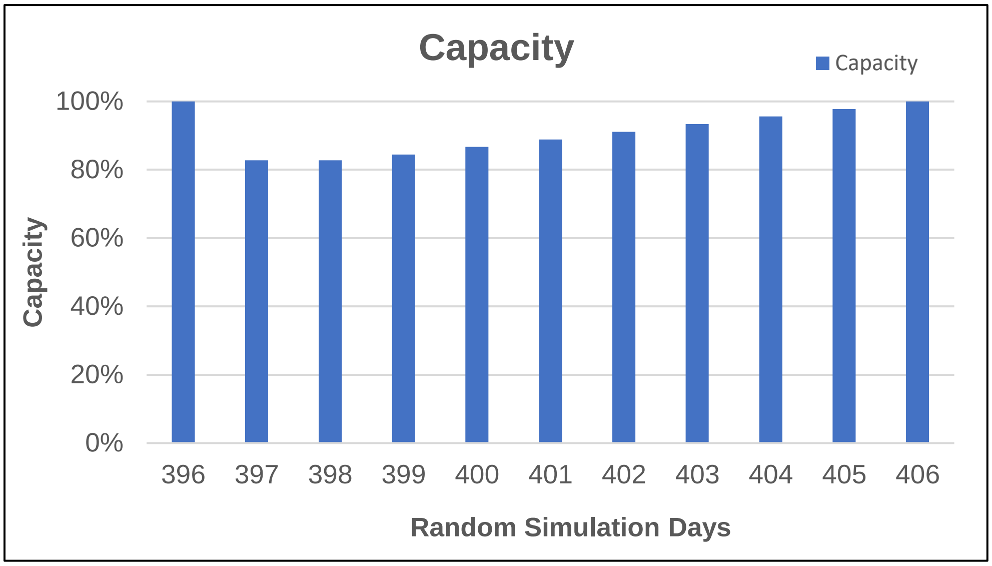
Table 4.1

Demonstration of Capacity-Loss Recovery Function for a Disruptive Event

Random simulation days	Recovery days (time-to-recovery period)	Capacity-loss recovery function (%)	Capacity loss (%)	Remarks
396		100.0	0.0	
397	1	82.8	17.2	Disruption hit
398	2	82.8	17.2	
399	3	84.5	15.5	
400	4	86.7	13.3	
401	5	88.9	11.1	
402	6	91.1	8.9	
403	7	93.3	6.7	
404	8	95.6	4.4	
405	9	97.8	2.2	
406		100.0	0.0	Fully recovered

Figure 4.8

Demonstration of Capacity-Loss Recovery Function for a Disruptive Event

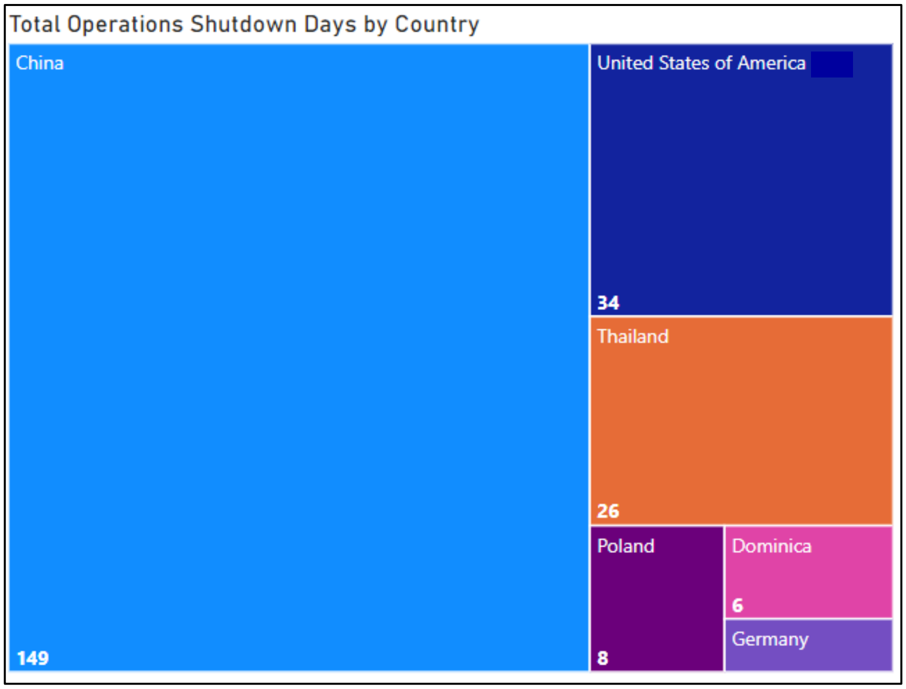


Note. Own elaboration.

From our analysis, total operations shutdown for the aggregated simulation period of 10 years was observed as 227 days, which was on average 23 days per year. The individual country-wise contributions are shown in the heat-map in Figure 4.9. From Figure 4.9, it is observed that China had the most total operations shutdown: 149 days (~64%), with a yearly average of 15 days. Although we observed that both China and USA were highly exposed and vulnerable to supply chain disruptions, total operations shutdown of China was almost 5 times higher than USA in a simulated environment. The reason was the risk indexes of countries, which were incorporated in the model to determine the capabilities of countries to withstand natural disasters in different criteria. It was observed that the incorporation of risk indexes allowed us to get realistic insights about the preparedness of any country. Even if any country might face frequent natural disasters, it could reduce the long-term impacts by making better infrastructure and strategic policies, and improve its scores to be a viable choice in supply chain in terms of sourcing and manufacturing.

Figure 4.9

Country-wise Total Operations Shutdown for 10 Years Simulation



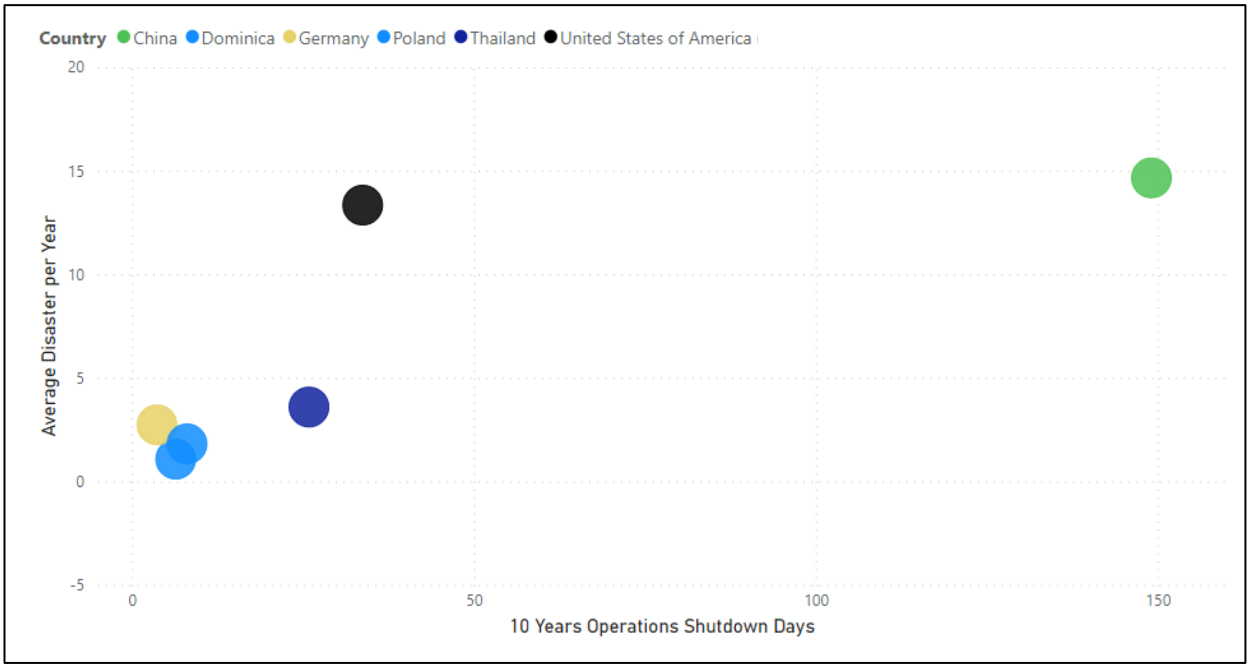
Note. Own elaboration.

4.4. Generation of Enterprise Vulnerability Map

As the last step of our methodology shown in Figure 3.1, we created an enterprise vulnerability map using the visualization tool and by combining the risk probability and risk impact for the listed countries. The final output for the enterprise vulnerability map is shown in Figure 4.10. From Figure 4.10, we observed that China, with higher risk probabilities and risk impacts, was the most vulnerable country in terms of supply chain disruptions. Even though USA had higher risk probabilities of natural disasters, its capability to minimize the impact to a significant extent and better score in the World Risk Index Report placed it in a moderately vulnerable zone for supply chain disruptions. European and South-East Asian countries also showed much lower risk probabilities and risk impacts compared to China and USA, making them favorable for supply chain operations.

Figure 4.10

Enterprise Vulnerability Map for the Selected Supply Chain Nodes for 10 Years Simulation



Note. Own elaboration.

5. DISCUSSION

In this chapter, we have discussed our findings and insights from the analysis of results and demonstrated the mitigation and resilience strategies in view of the Table 2.1. We have also analyzed limitations of the model and provided future recommendations to improve model outputs.

5.1. Insights and Recommendations from Model Results

- After assessing and analyzing the supply chain nodes through the enterprise vulnerability map, the sponsoring company can perform comparative analysis regarding the relative risks of supply chain nodes and conduct trade-off analysis with long term costs and impacts. Extending the majority of suppliers, contract manufacturers, or own manufacturing establishments to highly vulnerable countries needs careful analysis before execution and considering short-term cost benefits. In our analysis, we observed that reducing high dependency on China could reduce the chances of total operations shutdown by 60% in the supply chain. We also observed that moving to USA as part of the localization strategy could partially improve the overall vulnerability score but would still comprise a significant exposure to disruptions. Alternatively, sourcing from or manufacturing in European countries could improve the overall vulnerability score in the supply chain by reducing the chances of total operations shutdown.
- The vulnerability assessment framework is scalable to any supply chain network design irrespective of the number of nodes. The Python program behind the model performs all the location-specific calculations and simulations based on the imported databases and makes the model easy to scale.
- In our analysis, three simulations with 10 years of each simulation period were used to derive the final aggregated simulation result. The company can adjust the numbers of

simulations and duration of simulation period according to the required “confidence interval” (a statistical feature that indicates the accuracy of the sampling data).

- Because of the scalability, users can select different countries as supply chain nodes to understand and compare risks and vulnerability conditions among different supply chain design choices.
- The outputs of the model, such as overall vulnerability scores, location-specific risk probabilities and impacts can be used as inputs in the analysis of supply chain network design and optimization tool. The results from the model allow and support to perform network design taking resilience factors into consideration.
- The outputs of the model can be used to determine different supply chain performance metrics (e.g., lost sales), assess the comparative risks, and suggest resilience recommendations. It should be noted that incorporating complex features in the model requires thorough analysis of complexity, feasibility, applicability, and cost-benefit impacts.

5.2. Analysis of Supply Chain Risk Mitigation and Resilience Strategies

There is a wide variety of supply chain risks in real operations. Unfortunately, there is no royal road to mitigating supply chains’ risks. Not long before the COVID-19 pandemic, supply chain resilience measures were part of organizations’ core supply chain principles. Now the importance of resilient supply chain is getting more attention and priority. In our vulnerability assessment framework, we analyzed risks in supply chain and focused on three resilience strategies relevant for the sponsoring company’s global supply chain: redundancy, flexibility, and supply chain network design.

5.2.1. Redundancy

In general, redundancy means having backup of resources, e.g., supplier and stock. In our case, redundancy is more relevant to the backup or alternative suppliers and the amount of time it takes for an organization to switch between suppliers following a disruption. Our model showed that the organization could face enormous risks with a primary supplier situated somewhere with high disruption risk probability. From the results, we observed that China was posing a bigger disruption risk in the supply chain and European countries were deemed to have low vulnerability for the supply chain and business continuity. From our analysis, it can be suggested that forming single-sourcing, strategic supplier partnerships, or contract manufacturing from China can be vulnerable for the entire supply chain. Our sponsoring company should incorporate supply chain disruption scores in evaluating suppliers and segment the majority or strategic supplier bases in regions of low to moderate vulnerability. When this option is strategically not feasible for the company, they must partially arrange alternative or backup sourcing from suppliers in less to moderately vulnerable countries.

5.2.2. Flexibility

Supply chain flexibility means the ability to easily adjust production levels, raw-material procurement, and transport capacity. It has enormous benefits compared to traditional supply chain management. A traditional approach to supply chain management is rigid and does not allow for fast changes as needed. This creates a scope to cause disruptions to the entire supply chain in times of demand spikes, drops, or holdup in the supply chain. Our sponsoring company can adopt flexibility in countries where supply chains are less vulnerable. The advantages of flexibility will not be effective unless processes and products are standardized.

5.2.3. Supply Chain Network Design

Optimization of supply chain network design is a costly solution. But whenever the company needs to perform optimization, they should incorporate vulnerability scores while determining potential supply chain nodes for sourcing or setting up manufacturing units.

5.3. Model Limitations and Areas for Improvement

The objective of the vulnerability assessment framework was to provide a comprehensive risk analysis model to the sponsoring company, which would be based on facts and easy to incorporate in any supply chain network design simulation tool. Like any risk management modeling approach, this approach was also not exact, and had a few limitations and areas for improvement.

The limitations of the vulnerability assessment framework were:

- As country was considered the lowest point of supply chain node, the number of plants in any country had no impact in our model. The insights about the disruption profile of the country would be the same regardless of the existence of multiple plants in the same country.
- The model was limited to specific risk category only, i.e., natural disasters. Although this broad category could cover most external factors of disruptions, accidental and intentional disasters could also be incorporated if reliable data and proper quantitative approach were available.
- The impact analysis was node-centric. Synchronous impacts were not considered, i.e., the impact of disruptions in one particular node for the impact of disruptions in other connected nodes were not taken into considerations, as it would make the model more complicated.

- Internal and other exogenous factors than natural disasters were not considered. In reality, there are many factors that can lead to disruptions for a supply chain node. It was practically not feasible to include and quantify all the factors, such as financial and economic, in a single model.

The future improvement areas of the risk model are:

- The model is built upon a framework which is able to provide more accurate results with the availability of more volume and granularity of data. If there is a requirement for more granular level analysis, such as city or location-specific disruption profile, the sponsoring company can source and arrange empirical data based on expert opinions.
- The input data can be queried from the relevant sources using application programming interface (API) technology and automatically fed to the model. This will reduce the manual intervention of users regarding data and automate the data-import process for the model.

6. CONCLUSION

Supply chains are becoming more global and exposed to different types of disruptions more than ever. As a result, there is growing interest in supply chain risk management. Organizations are focusing more on assessing and improving their supply chain resilience, specifically after the COVID-19 pandemic. To take the right resilience measures, it is important for the companies to know, assess, and visualize the current state of risk exposures in the supply chain. In our capstone project, we developed a vulnerability assessment framework for our sponsoring company that would help assess the risks and vulnerabilities in its current global supply chains and could be used as an input to its supply chain network design and optimization tool.

We applied the vulnerability assessment framework to a specific pilot product of the sponsoring company, validated our approach and assumptions, and derived specific recommendations. Different organizations have different pain-points and perspectives in regard to resilience. With that in mind, one of the major decisions was to decide and identify the risks to be incorporated. While there can be several factors that cause disruptions in supply chains, we restricted our analysis to natural disasters because we observed their consistency in terms of impacts. Insights provided from our model will not be changed much by adding more different disruptions, but there will always be room for improvement in the model to incorporate other disaster categories provided that appropriate method and right data are available. Perceiving and incorporating important feedback from the sponsoring company at different phases of the project also helped to understand the requirement from the beginning and make the model suitable for industry-scale.

In closing, the objective of the research was to develop a vulnerability assessment framework that would help our sponsoring company in building resilient supply chain and sustainable ecosystem for all stakeholders. Our sponsoring company now has a model to better assess vulnerability on its supply chain and can therefore focus on resilience strategies to mitigate the risks by more accurate simulations of events. We recommend that the sponsoring company examine our framework for risk identification and risk quantification (probabilities and impacts) in its supply chain, and use the insights from the model in taking decisions of supply chain resilience, such as redundancy, flexibility, and optimized supply chain network design.

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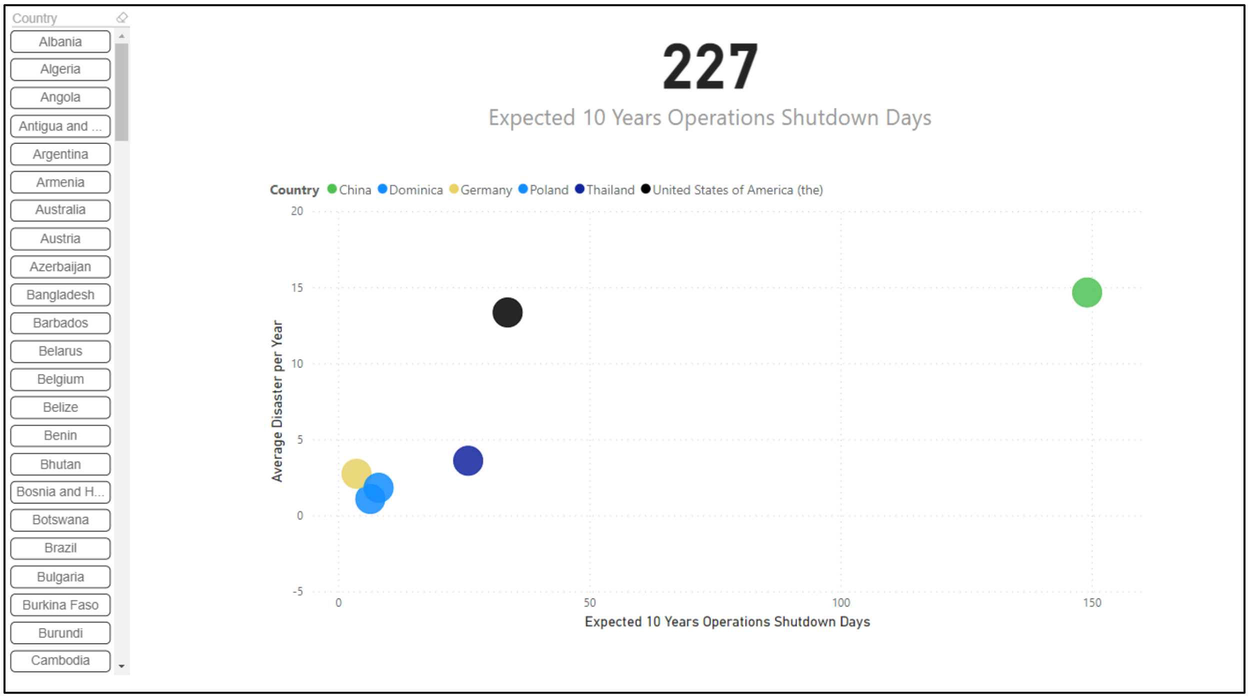
8. APPENDICES

8.1. Appendix A: List of Parameters Used from External Databases

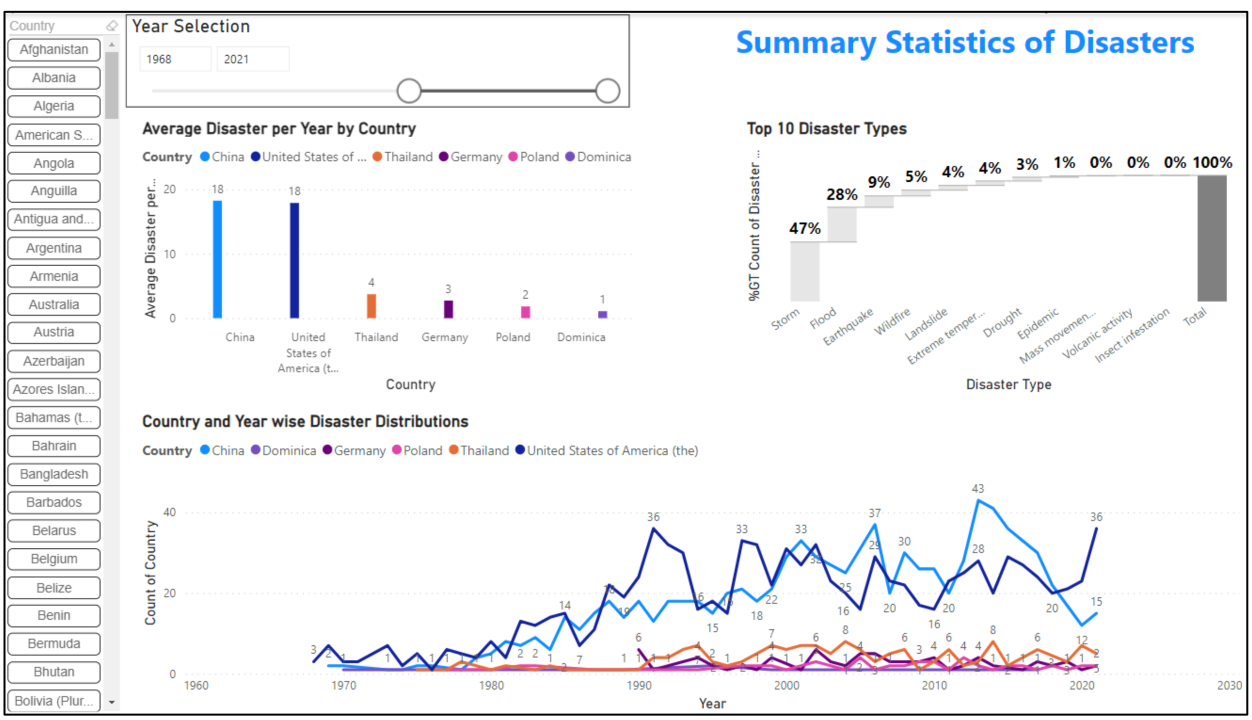
Source	Parameters	Parameters Remarks
Centre for Research on the Epidemiology of Disasters (CRED)	Disaster code/No.	Indexing of the disasters
	Disaster group	Specified as natural disaster
	Disaster subgroup	Further classified the disaster group as, e.g., biological, climatological, extra-terrestrial, geophysical, hydrological, meteorological
	Disaster type	Specified as, e.g., flood, storm, earthquake, epidemic
	Disaster subtype	Further classified the disaster type as, e.g., coastal flood, flash flood, riverine flood
	Country	Country of disaster origin
	Continent	Continent of disaster origin
	Latitude	
	Longitude	
	Start year	Recorded start time of the disaster
	Start month	
	Start day	
	End year	Recorded end time of the disaster
	End month	
	End day	
World Risk Index Report published by Bündnis Entwicklung Hilft	Ranking	higher ranking indicated more risk exposure
	Exposure factor	
	Vulnerability factor	
	Susceptibility factor	
	Lack of coping capacities	
	Lack of adaptive capabilities	

8.2. Appendix B: PowerBI Visualization

<u>Executive Dashboard:</u>



<u>Summary Statistics for Quantification of Risk Probabilities:</u>



Simulation Results: