Collaborative Prepositioning Network Design for Regional Disaster Response

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Abstract. We present a collaborative prepositioning strategy to strengthen the disaster preparedness of the Caribbean countries, which are frequently hit by hurricanes. Since different subsets of countries are affected in each hurricane season, significant risk pooling benefits can be achieved through horizontal collaboration, which involves joint ownership of prepositioned stocks. We worked with the inter-governmental Caribbean Disaster and Emergency Management Agency to design a collaborative prepositioning network in order to improve regional response capacity. We propose a novel insurance-based method to allocate the costs incurred to establish and operate the proposed collaborative prepositioning network among the partner countries. We present a stochastic programming model, which determines the locations and amounts of relief supplies to store, as well as the investment to be made by each country such that their premium is related to the cost associated with the expected value and the standard deviation of their demand. We develop a realistic data set for the network by processing real-world data. We conduct extensive numerical analyses and present insights that support practical implementation. We show that a significant reduction in total inventory can be achieved by applying collaborative prepositioning as opposed to a decentralized policy. Our results also demonstrate that reducing the replenishment lead time during the hurricane season and improving sea connectivity is essential to increasing the benefits resulting from the network.

Key words: prepositioning, hurricane preparedness, horizontal collaboration, risk pooling, insurance

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1. Introduction

We design a collaborative prepositioning network for disaster preparedness in the Caribbean, a region vulnerable to a variety of disasters, including storms, hurricanes, floods and earthquakes. We focus on hurricanes which have been a consistent burden on the small islands of the Caribbean, and have inflicted significant losses in the region (Kirton, 2013). For instance, in 2004, the direct losses and property damage in the Caribbean were estimated at USD two billion. The year 2017 was the second most costly in history, when three major hurricanes, Harvey, Irma and Maria, affected the United States and the Caribbean (CRED, 2018). That year, 96% of Dominica's population was affected by hurricane Maria, while the British Virgin Islands lost the equivalent of 284% of their GDP following hurricane Irma (CRED, 2018).

The Caribbean countries are often hit by multiple storms during an Atlantic hurricane season, which extends from June 1 to November 30, with a peak in September. These storms form in the warm waters of the Atlantic, which can be as far east as Africa. Each storm may follow a different track while passing through the Caribbean, and the severity of a storm may change along its track. Therefore, a storm reaching the Caribbean region may affect multiple countries simultaneously at different levels. Historical data indicate that different subsets of Caribbean countries have been affected in each season. It therefore makes sense to develop a disaster preparedness strategy based on risk pooling in order to enhance the region's response capacity.

The inter-governmental Caribbean Disaster and Emergency Management Agency (CDEMA) was established to strengthen regional integration in disaster management (Kirton, 2013). To coordinate the relief efforts, CDEMA divides the region into four subregions, each headed by a subregional focal point. However, logistical and material limitations have hindered the efficient functioning of the current system. In particular, due to the absence of dedicated storage facilities and transportation assets, ad hoc measures must be put into place after the occurrence of a disaster, which prevents a quick mobilization of the resources (Kirton, 2013). The current head of CDEMA mentioned to us that the regional prepositioning decisions (location of the warehouses and amount of inventory) have not been determined by scientific methods, and it would be useful to evaluate the current network by considering logistical infrastructure and capacity, as well as disaster risks (CDEMA, 2018). We introduce a systematic methodology that can support CDEMA's decisions for the design and management of a strongly coordinated and adequately financed regional prepositioning network to better cope with the effects of strong weather events in the Caribbean.

Prepositioning, which involves storing relief supplies at strategic locations to reach disaster-prone regions when needed, is a widely applied disaster preparedness strategy. For instance, the United Nations Humanitarian Response Depot (UNHRD) and the International Federation of Red Cross and Red Crescent Societies (IFRC) operate several facilities around the world, which keep emergency stocks to provide immediate assistance to the affected areas. However, in the humanitarian sector, the prepositioned stocks are traditionally owned and managed by a single agency, and different agencies make prepositioning decisions independently (Acimovic and Goentzel, 2016). Given the uncertainties in the timing, location and impact of disasters, prepositioning can be very expensive, and only a few agencies can cover the warehousing and inventory holding costs associated with it (Balcik and Beamon, 2008).

Our collaborative prepositioning strategy should help different countries coordinate their actions and generate risk pooling benefits. The proposed network keeps a cumulative amount of inventory of relief supplies in warehouses, which can reach the countries affected by a hurricane within a preset response time by air or by sea. We characterize the uncertainties related to hurricane occurrences and impacts by discrete scenarios. Specifically, each scenario specifies the set of countries that may be affected in a hurricane season, the timing of the hurricane, and the estimated demand for relief supplies in these countries. Moreover, we assume that warehouses may be damaged and that transportation capacity and connectivity may decrease depending on the severity of the hurricane. Hence, the decisions associated with the physical infrastructure of the proposed collaborative network involve determining the locations of the regional warehouses and the amount of inventory to store at each warehouse. Furthermore, in order for the network to be sustainable, it is essential to develop a transparent and fair cost sharing system that specifies the benefits and costs associated with this collaborative mechanism for the partner countries. In this study, we present a novel methodology to determine the amount of investment to be made by each partner country to establish and run the collaborative network. In particular, inspired by the Caribbean Catastrophic Relief Insurance Facility (CCRIF), which is a risk pooling mechanism for providing catastrophe funds to the Caribbean countries affected by disasters, we develop an insurance framework to determine the costs and benefits for each country. Accordingly, the payoff for the partners is the demand coverage and logistical service provided, while the premiums depend on the costs and risks transferred by the countries to the partnership. We develop a two-stage stochastic programming model that links network design decisions with cost allocation decisions. To test our model and obtain implementable results, we gathered real-world data from our project partners and public data sources. We illustrate the implementation of the proposed model on the Caribbean network, present numerical analyses to test the effect of different system parameters, and generate insights. While we particularly focus on the Caribbean region in this study, the proposed approach is generalizable to other settings in which regional integration can yield risk pooling benefits for the collaborating entities such as countries that are prone to similar disasters or agencies that respond to them.

The remainder of the paper is structured as follows. In §2, we position our study within the related literature. In §3, we provide an overview of the disaster management efforts in the Caribbean. In §4, we describe the collaborative prepositioning network design problem, present the mathematical model, and discuss its analytical properties. We explain the details of the data collection process and perform numerical analyses in §5. Finally, we conclude and discuss future work in §6.

2. Positioning of the Study

In this section, we position our study within the relevant streams of the literature.

2.1. Prepositioning Network Design

Problems related to designing humanitarian prepositioning networks have received considerable attention over the past decade. A growing number of studies address prepositioning problems and present mathematical models to determine the location of the warehouses and the amount of inventory to hold at each facility. We refer the reader to Anaya-Arenas et al. (2014) and Balcik et al. (2016), which review relevant prepositioning problems.

Our study shares similarities with some known relief prepositioning problems. We consider strategic prepositioning of supplies to prepare for hurricanes, as in Rawls and Turnquist (2010) and Galindo and Batta (2013). We note that Lodree et al. (2012), Davis et al. (2013) and Pacheco and Batta (2016) also consider prepositioning for hurricane preparedness; however, their studies focus on short-term prepositioning of supplies after a hurricane warning has been received. Similarly to the majority of prepositioning studies, we consider the possibility of damages to the facilities, stocks and transportation network as a result of the disaster. One of the differentiating aspects of our study is that we consider multiple events that may occur throughout a hurricane season, each of which may affect multiple countries. Furthermore, we model the replenishment of warehouses within a season, which has not been considered by studies that focus on strategic prepositioning. Since the exact location, timing and impact of disasters are not known in advance, prepositioning decisions are made under uncertainty. Two-stage stochastic programming has already been used to model the uncertainties in prepositioning problems (e.g., Salmerón and Apte, 2010). In general, prepositioning decisions are made in the first stage (before the disaster), while considering the implications of supply distribution decisions made in the second stage once uncertainty has been lifted (after the disaster). The uncertainties related to disaster occurrences are generally represented by a set of discrete scenarios, which are generated by using historical data. We refer the reader to Grass and Fischer (2016) for a review of two-stage stochastic programming applications in humanitarian logistics.

Relatively few studies are empirically grounded and performed in collaboration with humanitarian agencies. Duran et al. (2011) focus on designing a global prepositioning network for CARE International. McCoy and Brandeau (2011) develop stockpiling and shipping policies for the United Nations High Commissioner for Refugees (UNHCR) to support internally displaced people. Jahre et al. (2016) also focus on the UNHCR and present a prepositioning model that integrates short-term emergency response and longer-term development operations. Charles et al. (2016) develop a model to support IFRC's global warehouse location decisions. Toyasaki et al. (2017) consider multi-agency inventory planning within a UNHRD depot. Dufour et al. (2018) solve a network design problem for the UNHRD operations in East Africa. Arnette and Zobel (2018) model and solve a prepositioning problem encountered by the American Red Cross to locate the assets needed to open shelters for temporarily displaced people. Here we conduct a study in collaboration with an inter-governmental agency, CDEMA, which coordinates disaster preparedness and response efforts of several Caribbean countries.

2.2. Collaborative Humanitarian Supply Chains

While the benefits and needs of improving collaboration among humanitarian stakeholders have been consistently highlighted (Balcik et al., 2010; Jahre and Jensen, 2010), very few studies analytically explore collaborative humanitarian settings. Davis et al. (2013) focus on the allocation of prepositioned supplies among local agencies, which relocate the existing inventory among facilities based on short-term forecasts for an approaching hurricane. Bhattacharya et al. (2014) address the coordination of agencies running independent programs funded by earmarked donations. Coles et al. (2018) apply game theory to find compatible partners to work with during disaster response. Ergun et al. (2014) focus on using information technology tools collaboratively to manage multiple camps serving internally displaced people after an earthquake, and present a game theory framework to allocate the associated costs and benefits among the agencies. Toyasaki et al. (2017) use non-cooperative game theory to explore the horizontal cooperation of multiple agencies to manage their inventories in a UNHRD depot by exchanging stocks after a disaster. Acimovic and Goentzel (2016) introduce metrics to describe system capacity across many agents that store inventory at different locations and show that the system can be improved through coordination and inventory repositioning.

Traditionally, both in the scientific literature and in the real world, emergency relief stocks have been owned and managed by a single agency, which determines the locations of the warehouses and the amount of inventory to hold at each facility. However, such independent prepositioning decisions may result in imbalanced and ineffective distribution of stocks (Acimovic and Goentzel, 2016). Moreover, for each agency, stocking supplies in anticipation of low-probability disastrous events may lead to disproportionate investments and costs (Kunz et al., 2014). In practice, some established structures such as UNHRD, IFRC, and Logistics Cluster encourage resource sharing among humanitarian actors. De Leeuw et al. (2010) discuss the efforts of the Water Sanitation and Hygiene (WASH) cluster, which involves 17 organizations led by UNICEF, to generate shared humanitarian stockpiles, which can support up to 50,000 beneficiaries and must be positioned around the world so that materials can be delivered to the agencies within one week.

To the best of our knowledge, our study is the first to model and solve a multi-country collaborative prepositioning network design problem. While this study was conducted in collaboration with CDEMA, it can be adapted to other multi-country or multi-agency settings.

2.3. Insurance Framework

Whereas there exists abundant research on insurance theory, the ideas and methods from this field have not been widely utilized to mitigate risks in humanitarian supply chains or in commercial supply chains (Friday et al., 2018). As discussed by Lodree and Taskin (2008), an insurance framework can easily be related to quantifying the risks and benefits associated with disaster preparedness. Lodree and Taskin (2008) use such a framework to determine the amount of inventory that a single agency must preposition in order to prepare for a disaster. Some management science papers also make use of insurance-based methods to mitigate business interruptions. For example, Serpa and Krishnan (2016) study a two-firm setting in which insurance is used as a commitment mechanism to avoid free riding when coping with business interruptions. Lin et al. (2010) and Dong and Tomlin (2012) study the interactions between insurance and inventory management to mitigate supply chain disruption risks for a single firm.

Here we present an insurance framework to allocate the costs associated with the collaborative network among its members. To our knowledge, our study is the first to use insurance premium calculation principles to support collaboration among humanitarian actors.

3. Background: Caribbean Disaster Management

The Caribbean community views regional integration as an important means of improving efficiency, generating economies of scale, and promoting stable growth, because the region consists mainly of states with small and geographically isolated economies, which may not have sufficient resources to make large public investments (Bishop et al., 2011). Several institutions have been established to support regional integration in various dimensions (such as trade, environment and security). Quite importantly, the Caribbean Community and Common Market (CARICOM) is a free-trade zone that was launched in 1973 to promote regional integration and cooperation. CARICOM currently has 15 member states: Antigua and Barbuda (ATG), Bahamas (BHS), Barbados (BRB), Belize (BLZ), Dominica (DMA), Grenada (GRD), Guyana (GUY), Haiti (HTI), Jamaica (JAM), Montserrat (MST), Trinidad and Tobago (TTO), Saint Kitts and Nevis (KNA), Saint Lucia (LCA), Saint Vincent and the Grenadines (VCT), and Suriname (SUR). There are also five associate members: Anguilla (AIA), Bermuda (BMU), the British Virgin Islands (BVI), the Cayman Islands (CYM), and the Turks and Caicos Islands (TCA). These 20 CARICOM states, which constitute our region of interest, are depicted in Figure 1. Two important initiatives were established to improve regional disaster management capacity in the Caribbean, which are also unique examples for the humanitarian community; namely, the CDEMA and the Caribbean Catastrophic Relief Insurance Facility (CCRIF) support horizontal coordination in disaster management, which will be briefly described below.

3.1. The Caribbean Disaster and Emergency Management Agency (CDEMA)

CDEMA is a regional inter-governmental agency for disaster management, established in 2007 to "strengthen capacity for the mitigation, management and response to all hazards at the regional, national and community levels and to ensure coordination in all phases of disasters" (Kirton, 2013). It currently comprises 18 participating states, including all of the CARICOM members, except BMU and the CYM. It is headquartered in BRB, and the national disaster offices at each country execute CDEMA's activities (Kirton, 2013).

To manage and coordinate regional disaster relief efforts, CDEMA designated four countries as subregional focal points, each responsible for three or four countries in the region (Figure 1). The focal points were selected by considering their proximity, as well as their cultural and

Subregional focal point	Subregion
Antigua & Barbuda	AIA, ATG, BVI, MST, KNA
Barbados	BRB, DMA, LCA, VCT
Jamaica	BHS, BLZ, HTI, JAM, TCA
Trinidad & Tobago	GRD, GUY, SUR, TTO

Figure 1 **Region of interest with the current subregional focal points and the 18 countries covered by CDEMA**

economic similarities to other countries in the subregion (Kirton, 2013). To meet the operating expenses of this system, the member states contribute to an annual budget on the basis of their economic standing and risk factors (CDEMA, 2018). Specifically, each country pays a pre-agreed fixed percentage of the total prepositioning costs.

We present to CDEMA a systematic methodology for the design of a collaborative prepositioning network by incorporating important regional factors such as hurricane risks, transportation infrastructure, logistical connectivity, and costs. Furthermore, we propose a cost allocation strategy linked with the network design decisions.

3.2. The Caribbean Catastrophic Relief Insurance Facility (CCRIF)

The CCRIF is a not-for-profit structure designed to limit the financial impact of devastating hurricanes and earthquakes in the Caribbean by quickly providing financial liquidity to the affected countries in order to support the relief efforts (CCRIF, 2018). The CCRIF was established in 2004 after Hurricane Ivan, through funding from multiple donors such as Canada, the Caribbean Development Bank, the European Union, France, Japan, the United Kingdom, and the World Bank, and through membership fees from the participating governments (CCRIF, 2018). Currently, 16 of the 20 CARICOM countries are involved in CCRIF.

The CCRIF is the first “multi-country, multi-peril pooled catastrophe risk insurance facility” in the world, which allows pooling the catastrophe risks of multiple countries into a single portfolio (World Bank, 2012). Since disaster losses in the Caribbean countries can exceed multiples of their GDP, these countries cannot individually absorb the financial impact of the disasters (World Bank, 2012). Through CCRIF, the members can obtain insurance coverage at lower prices. More specifically, the price that the countries pay to CCRIF is less than half what they would pay for purchasing insurance individually through international markets (CCRIF, 2012).

Through CCRIF, the countries can receive a prompt cash payout within 14 days following a covered event, which is made possible because CCRIF pays based on parametric triggers such as predetermined wind speeds for hurricanes, but not on the actual losses, which can take months to assess on-site (CCRIF, 2018). The CCRIF policies are renewed for one year at the beginning of the hurricane season. Countries buy coverage up to USD 100 million for a given year, and there is no limit on the number of events a policy can cover (CCRIF, 2018). The payouts are based on the estimated losses calculated through a hazard loss model, and on the purchased coverage amounts. To date, CCRIF has made 22 payments to 10 countries, totaling USD 69 million (CCRIF, 2017). The country premiums are based on the coverage chosen by a country and on its risk profile, which depends on historical events. The premiums, which vary typically from USD 200,000 to USD 4,000,000, are paid by countries and donors (CCRIF, 2017).

In our study, we are motivated by CCRIF and we integrate an insurance-based framework into collaborative prepositioning, which determines country contributions by considering the needs of the partner countries and the risk they translate to the network, and also the regional logistical connectivity and costs.

4. Collaborative Prepositioning Network Design

We now define the collaborative prepositioning network design problem (§4.1) and present our mathematical model (§4.2).

4.1. Problem Definition

We focus on designing a collaborative prepositioning network in the Caribbean to support CDEMA's efforts to improve disaster preparedness and response capacity. Since extreme weather events such as hurricanes occur frequently in the Caribbean, and each event may affect a different set of states depending on its path, collaborative prepositioning could help the CDEMA countries benefit from risk pooling and resource sharing in order to cope with the immediate consequences of disasters. In the proposed collaborative prepositioning strategy, CDEMA will serve as an umbrella organization and will engage its members to become partners for keeping joint stocks for emergency relief supplies in a set of warehouses strategically located in the region. Additionally, we present an insurance-based framework to provide a sustainable financing mechanism. More specifically, the collaborative prepositioning network design problem determines i) the number and location of the warehouses to be established in the region, ii) the amount of inventory for emergency relief supplies to hold at each warehouse, iii) the investment needed to set up this collaborative network and to manage it for the first year, and iv) the premium to be paid by each partner country, while considering the uncertainties in demands for relief supplies, which may occur in multiple countries due to possible storm events throughout a hurricane season. We next describe the collaborative prepositioning network design problem in detail.

4.1.1. Network We consider a set of Caribbean countries affected by weather-related events such as hurricanes. Due to the geographical positions of these countries, a storm may hit several countries at different levels, and each country may be hit by multiple storms in the same season. Once a strong storm occurs, people may lose access to basic items and needs may arise for large amounts of emergency relief supplies. If a country's national response capacity is overwhelmed by the disaster, it is critical to quickly send relief items to the affected regions to save lives and support the survivors. We assume that all CARICOM states, which are under risk of being affected by a strong storm, can be partners of the collaborative prepositioning network. The candidate warehouse locations are also selected among these countries by evaluating their logistical infrastructure, connectivity to the region, and disaster risk. We assume that there can be multiple warehouses at each chosen location; however, the maximum number of warehouses per country is limited. Each warehouse has a fixed capacity in terms of the number of items it can store.

4.1.2. Planning Horizon and Scenarios The collaborative prepositioning network will hold sufficient inventory to cover the needs of the partners over the planning horizon, which is one hurricane season. While the Atlantic hurricane season is officially between June 1 and November 30, there may be off-season storms in some years. Based on our analysis of historical hurricane data, the planning horizon in our study extends from May 1 to December 31. These data show that multiple events have occurred in 80% of the seasons and that multiple countries have been affected simultaneously in 55% of the events. For instance, 10 events hit the Caribbean region in 2005, affecting nine countries throughout the season, four of which at least twice. To assign a time period for each event, we divide the planning horizon into two-week periods. Anytime multiple events occur in the same two-week period, we aggregate the demand of these events and work with a single event with the accumulated demand.

While making collaborative prepositioning network decisions, one should consider the uncertainties in the number, severity and timing of strong storms that may hit the region in future seasons. To this end, we use a set of discrete scenarios to represent these uncertainties. Each scenario specifies the number of storm events occurring throughout a hurricane season, the period and the severity of each event, the set of affected countries, and the estimated demand in each country. Note that because there is enough time to replenish the warehouses between two hurricane seasons (four months), the demand between two consecutive seasons is memoryless. Thus, modelling demand uncertainty using several scenarios representing a single season is equivalent to considering multiple seasons over a longer planning horizon. We assume that the availability of supplies at the warehouses and the connectivity of the transportation network are also scenario-dependent; that is, if a country with a warehouse is hit by a storm, a percentage of its supplies may not be used. Additionally, we assume that the logistical connectivity of an affected country may decrease due to effects of the hurricane on the country's logistical infrastructure.

4.1.3. Targeted Demands We consider storing family kits in the network, which contain a set of relief items such as blankets and hygiene kits necessary to support a family of five people after a hurricane. Since the proposed collaborative network works like an insurance, it must guarantee that the promised coverage amounts for the family kits can be provided to each partner country within a preset response time. We assume that the collaborative network will be designed to cover the targeted demands specified by the countries for each event category. In other words, the total capacity of the network does not aim to cover all of the needs of the affected countries in each event, but only the targeted demands. While implementing this network, each country can specify its targeted demand by evaluating relevant country-specific factors such as risk and vulnerability, national response capacity, logistical infrastructure, and capacity of handling external aid such as the maximum estimated receiving port capacity (Starr and Van Wassenhove, 2014). Since the countries' actual evaluations on their targeted demands are not currently available, in our numerical analyses, we set a country's targeted demands based on the historical percentage of the affected population and the number and strength of previous events, as detailed in Appendix A. In this way, the targeted demands and the resulting demand scenarios reflect the population exposure of the countries. Moreover, we impose that the targeted demands do not exceed a prespecified *maximum coverage limit* (MCL) in our insurance-inspired collaborative prepositioning network. In insurance theory, limits on coverage are used to help insurers deal with huge losses (Cummins and Mahul, 2004), and most insurance contracts involve a limit on coverage (Zhou et al., 2010). We set the base MCL value at 12,000 family kits in numerical experiments, which is based on IFRC Panama's weekly response capacity in the region. In our numerical analyses, we test for different levels of MCL and also show the effects of not using MCL on the network, on the costs and on the country premiums.

4.1.4. Transportation and Logistics When a disaster occurs, the supplies at the warehouses are mobilized immediately. Each warehouse can serve each country in each scenario as long as the response time requirements are met. That is, in contrast to CDEMA's current system, we do not assign a fixed service area (subregion) to the chosen warehouses. We consider two response time levels in our network: fast response (three days) and slower response (seven days). The collaborative network must be able to satisfy a preset percentage of the targeted demand of a country at the fast response level. We assume that the supplies can be shipped from the warehouses to the affected countries via air or sea, depending on the transit times and costs, and that the warehouses are located next to airports or ports, and hence do not require extensive inland transportation.

4.1.5. Replenishment of the Warehouses There could be opportunities to replenish the stocks at the warehouses throughout an eight-month hurricane season. This can be advantageous since i) it allows the system to store less inventory and operate smaller warehouses, and ii) the risk of losing supplies due to damaged warehouses can be reduced. The amount of replenishment depends on the timing of individual events and on the lead time. In Figure 2, we illustrate

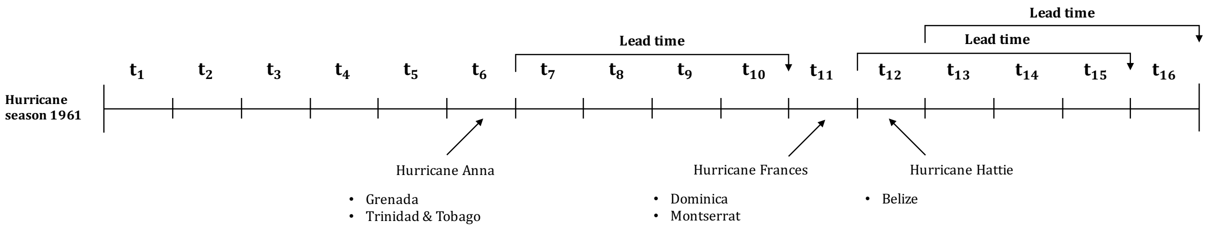

Figure 2 **Example of a hurricane season with three events. Between the first two there is time for replenishment while this is not the case between the second and the third events.**

an example focusing on the 1961 hurricane season, in which three hurricanes (Anna, Frances and Hattie) hit the Caribbean in periods 6, 11 and 12. In such a case, when the lead time is four periods, there is enough time for receiving orders made after the first event, while the third event occurs before the warehouses can be replenished after the second event. In the collaborative prepositioning network, replenishment orders are made at the end of each period. The order amount at each warehouse is equal to the sum of the items used and damaged over the past period. We assume a fixed lead time for each warehouse. The orders are received at their respective warehouses at the beginning of the period after the lead time. Note that there is enough time between the first and the second hurricanes to replenish the used supplies. However, since there is no time for replenishment between the second and third hurricanes, there must be sufficient items in the network at the beginning of time period 11 to cover the demands of both hurricanes Frances and Hattie. Since the amount of storage needed in the network is calculated by also considering the probability that some supplies may be damaged if warehouses are affected, at time period 11 there will be enough items to respond to the disasters, even if some warehouses will be hit by hurricanes Frances and Hattie. At the end of each hurricane season, once the last replenishment orders have been received, the warehouses become full. Therefore, between the end of the last season and the beginning of the next one (from January to May), the inventory at the warehouses is not utilized in our setting. However, given that the Caribbean is prone to a variety of disasters, the stocks can be used during this period to respond to other events in the region. Additionally, it would be possible to share these stocks with the humanitarian agencies operating in the region, such as the IFRC and the World Food Programme. If any supplies are used during the off-season, they need to be replaced in the warehouses before the beginning of the next hurricane season.

4.1.6. Costs and Budget The *total initial investment* required to set up the collaborative prepositioning network includes the budget necessary to cover disaster preparedness and emergency response costs for the first year. In particular, it includes the fixed cost of locating warehouses (i.e., rent, equipment, and staff), the purchase cost of supplies for building the initial cumulative inventory, the inventory holding cost, and the largest emergency response cost that may occur in a season to cover the transportation and replenishment of supplies. Note that the budget allocated to emergency response expenses can be held in the form of monetary liquidities until needed. In our network, transportation costs depend on the transportation modes used, and on the origin and destination countries. Moreover, although the inventory level at the warehouses may go down and up during a season, we charge inventory costs for the initial cumulative amount since replenishment orders for the used stocks are given immediately at the end of each period, and the warehouses are replenished up to their order-up-to level. Since the warehouses and their contents are insured, any costs resulting from possible damages are not additionally considered. Once the network is set up, at the end of each hurricane season, the countries that have used supplies will pay for the materials and logistical services they have received during the past season. Therefore, at the beginning of each season, the network will have a fixed amount of prepositioned inventory and fixed monetary reserves to cover possible emergencies.

After the first year, countries will have to pay an annual membership fee to maintain the network (i.e., to cover costs for rent, staff, equipment maintenance, etc.). That is, to be a member of the collaborative network, each country first makes a contribution to cover the total initial investment (i.e., country premiums), and then pays for annual usage and membership fees. Our collaborative prepositioning problem only focuses on optimizing the significant amount of total initial investment required to cover the first year setup and management cost, whereas the annual usage and membership fees can be calculated *a posteriori*. We next present a methodology to fairly allocate the total initial investment among the countries through an insurance-based framework.

4.1.7. Insurance Framework The proposed collaborative prepositioning network works like an insurance, which specifies a *payoff* and a *premium* for each country. The payoff is the demand coverage and logistical services provided to a country throughout a hurricane season. More specifically, the network ensures that the targeted demands can be satisfied within a week after a hurricane. In return, each partner country must pay a premium to cover the cost associated with the total initial investment. We present a methodology, inspired by premium calculation methods from actuarial science, to determine the contribution of each partner country to the total investment and set its premium by considering the costs a country transfers to the partnership.

An insurance plan sets a relatively small premium to gain protection against a potentially large future loss (Grossi et al., 2005). If an insuree is more susceptible to a specific risk, then the cost for coverage against a loss from that risk is greater. Since insurance rates are regulated and there is market competition, the premium may not fully reflect the underlying risk. Nevertheless, several actuarial models can be used to estimate the risks. Natural disasters pose a challenging set of problems for insurers compared with more frequent and non-extreme events such as car accidents and fire, partly because of the absence of data available to model the risks and losses for natural disasters, which occur infrequently and yield huge losses. For an insurance market to be profitable, it must be able to issue a large number of policies whose losses are independent. By pooling the uncorrelated risks faced by a large number of individuals, insurers can use the law of large numbers to essentially eliminate aggregate risk (Duncan and Myers, 2000). Since the losses from catastrophes can be huge, having a large number of entities spread over different regions would be beneficial, so that the insurer can collect sufficient premiums to cover large losses from a single disaster. However, this is not the case when a multi-country setting is considered. Our Caribbean network is made up of only 20 countries, which need to be insured for the losses resulting from the same disasters. Fortunately, historical data indicate that a different subset of countries is affected by the hurricanes in each season. Therefore, there may be sufficient diversity in this setting to achieve risk pooling benefits.

Calculating an insurance premium implies determining "the price of risk" for a customer or a group of customers (Deelstra and Plantin, 2014), and numerous premium calculation methods exist (Landsman and Sherris, 2001). We adopt one of the most common methods which considers the expected value and the variability of risk. Specifically, let S denote a positive real random variable, which represents future insurance claim amounts, and let $\Pi(S)$ be the premium associated to risk S. The pure premium principle states that the premium is equal to the average risk level, that is, $\Pi(S) = E(S)$. However, for catastrophic types of risk, setting premiums based solely on the expected value may not be sufficient to cover losses associated with extreme events. Therefore, insurees are often charged larger premiums than their expected losses (Froot, 2001). There exist alternative premium calculation principles that consider other characteristics of the risk distribution (Deelstra and Plantin, 2014; Kaluszka, 2001). Here, we adopt the standard deviation principle, which adds a safety margin to the pure premium proportional to the standard deviation of the risk: $\Pi(S) = E(S) + \sqrt{Var(S)}Z$, where $Z \geq 0$ is a dimensionless deviation variable to be minimized.

Denote by D_c the random variable representing total targeted demand that may occur in country $c \in C$ in a hurricane season, and by $E(D_c)$ and $Var(D_c)$ the expected value and the variance of the demand. Moreover, let Y_c denote the amount of investment allocated to partner country $c \in C$, let B denote the total investment required for setting up the network, and let b denote the estimated logistics cost per unit of supply in the network. We estimate b as the average of some benchmark solutions obtained by solving a restricted version of the collaborative prepositioning network design problem, which does not involve cost sharing aspects. The following two constraints are used to adapt the standard deviation procedure for setting premiums in our problem:

$$bE(D_c) \leq Y_c \leq bE(D_c) + b\sqrt{Var(D_c)}Z \qquad \forall c \in C \tag{1}$$

$$\sum_{c \in C} Y_c \geq B. \tag{2}$$

By minimizing Z, we will allocate costs among the countries in a fair way, so that each country pays an amount that reflects the expectation and variance of its needs. Moreover, minimizing Z implies that the network must be established by using the least investment possible.

4.2. Mathematical Model

Given a set of countries, a set of candidate countries in which to locate warehouses, and a set of scenarios that represent hurricane occurrences and demands, the collaborative prepositioning network design problem determines the number and locations of the warehouses, the inventory to hold at each warehouse, the required investment to set up and run the network, and the country premiums. We next present the notation to formulate the problem.

Sets

S: set of scenarios; $s \in S$

T: set of disaster periods in a hurricane season; $t \in T$

C: set of countries in the partnership; $c \in C$

W: set of candidate warehouse locations; $w \in W$

$\hat{C}^{st}$: set of countries affected by a hurricane in period $t \in T$ of scenario $s \in S$; $c \in \hat{C}^{st}$

M: set of transportation modes; $m \in M$

L: set of response levels; $l = 1$ for fast response and $l = 2$ for slower response; $l \in L$

$\hat{W}^{s}_{cml}$: set of candidate warehouses that can cover country $c \in C$ at response level $l \in L$ via transportation mode $m \in M$ under scenario $s \in S$; $w \in \hat{W}^{s}_{cml}$.

Parameters

d^{st}_{c}: targeted demand at country $c \in C$ in period $t \in T$ in scenario $s \in S$

p^{s}: probability associated with scenario $s \in S$

α^{st}_{w}: percentage of damaged supplies at location $w \in W$ in period $t \in T$ in scenario $s \in S$

τ: replenishment lead time

u^{st}_{wcm}: unit transportation cost for shipping a family kit to country $c \in C$ from location $w \in W^{s}_{c}$ via mode $m \in M$ in period $t \in T$ in scenario $s \in S$

κ_{w}: maximum capacity of a warehouse at candidate location $w \in W$

n_{w}: maximum number of warehouses that can be located at candidate location $w \in W$

f_{w}: fixed location and operating costs for the first year for a warehouse at location $w \in W$ (includes rent, equipment, staff and insurance for these assets)

r_{w}: unit cost of purchasing a family kit for a warehouse at location $w \in W$ (includes purchasing, insurance and inbound transportation costs)

g_{w}: r_{w} plus unit cost of holding an item in a warehouse at location $w \in W$

β^{st}_{c}: percentage of demand of country $c \in C$ to be covered at response level $l = 1$ during period $t \in T$ in scenario $s \in S$

b: estimated unit logistics cost (prepositioning and shipping one family kit in the network), obtained by averaging some benchmark solutions of a restricted model

λ: weight for the deviation objective.

First-stage decision variables

X_{w}: number of warehouses to locate at candidate location $w \in W$

I_{w}: amount of inventory to hold at candidate location $w \in W$

Y_c: premium of partner country $c \in C$

Z: maximum deviation variable

B_0: total budget required to cover disaster preparedness costs

B_1: total budget required to cover emergency response costs.

Second-stage decision variables

Q^{st}_{wcm}: amount of supplies delivered to country $c \in C$ from candidate location $w \in W^s_c$ via transportation mode $m \in M$ in period $t \in T$ in scenario $s \in S$

A^{st}_w: amount of supplies available at candidate location $w \in W$ at the beginning of period $t \in T$ in scenario $s \in S$

R^{st}_w: amount of replenishment that arrives at candidate location $w \in W$ at the beginning of period $t \in T$ in scenario $s \in S$.

We present a two-stage stochastic programming model for the collaborative prepositioning network design problem below:

$$\text{minimize} \quad \lambda Z + \sum_{w \in W} f_w X_w + \sum_{w \in W} g_w I_w + \sum_{s \in S} p^s \sum_{t \in T} \sum_{w \in W^s_{cm}} \sum_{c \in C} \sum_{m \in M} (u^{st}_{wcm} + r_w) Q^{st}_{wcm} \tag{3}$$

subject to

$$I_w \leq \kappa_w X_w \qquad \forall w \in W \tag{4}$$

$$X_w \leq n_w \qquad \forall w \in W \tag{5}$$

$$\sum_{c \in \hat{C}^{st}} \sum_{m \in M} Q^{st}_{wcm} \leq (1 - \alpha^{st}_w) A^{st}_w \qquad \forall s \in S, t \in T, w \in W \tag{6}$$

$$\sum_{m \in M} \sum_{l \in L} \sum_{w \in \hat{W}^s_{cml}} Q^{st}_{wcm} = d^{st}_c \qquad \forall s \in S, t \in T, c \in \hat{C}^{st} \tag{7}$$

$$\sum_{m \in M} \sum_{w \in \hat{W}^s_{cm1}} Q^{st}_{wcm} \geq \beta^{st}_c d^{st}_c \qquad \forall s \in S, t \in T, c \in \hat{C}^{st} \tag{8}$$

$$A^{s1}_w = I_w \qquad \forall w \in W, s \in S \tag{9}$$

$$A^{s,\ t+1}_w = (1 - \alpha^{st}_w) A^{st}_w - \sum_{c \in \hat{C}^{st}} \sum_{m \in M} Q^{st}_{wcm} + R^{s\ t+1}_w \qquad \forall w \in W, s \in S, t = 1, ..., |T| - 1 \tag{10}$$

$$R^{st}_w = \alpha^{s,\ t-\tau-1}_w A^{s,\ t-\tau-1}_w + \sum_{c \in \hat{C}^{st}} \sum_{m \in M} Q^{s,\ t-\tau-1}_{wcm} \qquad \forall w \in W, s \in S, t = \tau + 2, ..., |T| \tag{11}$$

$$R^{st}_w = 0 \qquad \forall w \in W, s \in S, t = 1, ..., \tau + 1 \tag{12}$$

$$B_0 = \sum_{w \in W} f_w X_w + \sum_{w \in W} g_w I_w \tag{13}$$

$$B_1 \geq \sum_{t \in T} \sum_{w \in W^s_{cm}} \sum_{c \in C} \sum_{m \in M} (u^{st}_{wcm} + r_w) Q^{st}_{wcm} \qquad \forall s \in S \tag{14}$$

$$\sum_{c \in C} Y_c \geq B_0 + B_1 \tag{15}$$

$$bE(D_c) \leq Y_c \leq bE(D_c) + b\sqrt{Var(D_c)} Z \qquad \forall c \in C \tag{16}$$

$$X_w,\ I_w \in \mathbb{Z}+ \qquad \forall w \in W \tag{17}$$

$$Q^{st}_{wcm} \in \mathbb{Z}+ \qquad \forall w \in W, c \in C, m \in M, s \in S, t \in T \tag{18}$$

$$R_w^{st},\, A_w^{st} \in \mathbb{Z}+ \qquad \forall w \in W, s \in S, t \in T \tag{19}$$

$$Z \geq 0 \tag{20}$$

$$Y_c \geq 0 \qquad \forall c \in C \tag{21}$$

$$B_0,\, B_1 \geq 0. \tag{22}$$

The first term of the objective function (3) minimizes the value of the maximum deviation variable, which is used to determine premiums paid by the countries. Specifically, by minimizing the maximum deviation, we minimize the amount of extra investment a country will make beyond the costs associated with its expected demand. Note that the deviation is a dimensionless variable, and is expected to take a small value. Therefore, we multiply the deviation objective by a large weight λ (see §5.2.1). The second and third terms in (3) represent the sum of the fixed costs associated with warehouses, and the cost associated with acquiring and holding inventory, respectively. The last term in (3) is the expected emergency response costs associated with transportation supplies and replenishing warehouses after a disaster occurs.

Constraints (4)–(12) are associated with the network design, while constraints (13)–(16) are related to the cost allocation decisions. Constraints (4) ensure that the amount of inventory to preposition at each opened warehouse does not exceed its capacity. Constraints (5) bound the number of warehouses to locate in each country. Constraints (6) limit the amount of supplies than can be shipped from a warehouse by the amount of available (undamaged) supplies. Constraints (7) ensure that the targeted demands are fully met. Constraints (8) are imposed to satisfy a preset proportion of the targeted demand at the first response level. Constraints (9) set the amount of inventory at the beginning of the hurricane season. Constraints (10) control the flow at each warehouse and for each period by considering the amount of undamaged supplies at a warehouse at the beginning of the previous period, the amount of shipped supplies from the warehouse during the previous period, and the replenishment amount arriving at the warehouse at the beginning of the period. Constraints (11) set the replenishment amount arriving at a warehouse in each period, which is equal to the total amount of used and damaged supplies during the lead time. Constraints (12) set the replenishment to zero for the initial periods of the hurricane season that are smaller than the lead time.

Constraints (13) and (14) determine the investment required to cover the disaster preparedness and emergency response costs. Specifically, constraint (13) sets the preparedness budget, which covers the expenses related to locating warehouses and acquiring and holding inventory. Constraints (14) determine the emergency response budget, which must be sufficient to cover the post-disaster transportation and replenishment costs for all scenarios. Constraint (15) guarantees that the country premiums cover the total initial investment. Constraints (16) bound the country premiums, as explained in Section 4.1.7. Finally, constraints (17)–(22) define the domains of the variables.

4.3. Properties of the Model

We now discuss some important properties of the proposed model.

4.3.1. Effect of λ and the Restricted Model In our model, the network design and the cost allocation decisions are linked through the deviation variable Z, which determines country premiums. Minimizing Z in (3) implies minimizing the total initial investment, which covers the disaster preparedness and the emergency response budgets (i.e., $B_0 + B_1$). Recall that the emergency response budget must be sufficiently large to cover the response expenses in each scenario (constraint (14)), while the last term of the objective function (3) minimizes the expected value of the emergency response cost. Therefore, the objective function considers both the worst-case value and the expected value of the emergency response cost, which will be affected by the network design decisions.

Since the deviation value Z is much smaller than the other cost values minimized in the objective function, we set a large value for the λ parameter. As λ increases, reducing the largest emergency response costs becomes more important than minimizing the expected response cost. In our numerical analyses, we choose a λ value that minimizes the total initial investments plus the annual costs over a fixed payback period (see §5.2.1). Note that when λ is zero, the problem ignores the cost allocation (premium setting) decisions. In other words, constraints (13)–(16) are no longer binding. The resulting model then reduces to designing a prepositioning network to minimize preparedness and expected emergency response costs, and ignores the fact that the total initial investment must be shared fairly among the partners. We use this *restricted model* to estimate an average cost associated with prepositioning and shipping one family kit in the network (i.e., to set the value of parameter b).

4.3.2. Fairness of the Country Premiums Each country's premium is set by considering the expectation and the standard deviation of its demand. Proposition 1 proves that the deviation associated with each country is the same in the optimal solution.

Proposition 1 *In any optimal solution of* (3)–(22)*, the right-hand side of constraints (16) is satisfied at equality, i.e., given the optimal value of the deviation variable Z, denoted by Z^*, each country's premium is equal to its estimated expected logistics cost, plus Z^* times the estimated standard deviation of its logistics cost.*

Proof. Assume, for the sake of contradiction, that Z^* is the minimum value that Z can take, and that one right-hand side of (16) is not satisfied at equality. Without loss of generality, let $c = 1$ be such that $Y_1^* < bE(D_1) + b\sqrt{Var(D_1)}Z^*$. Then, there exists a value $x > 0$ such that $Y_1^* + x = bE(D_1) + b\sqrt{Var(D_1)}Z^*$. Moreover, as $Y_1^* \geq bE(D_1)$ due to constraints (16), $bE(D_1) + x \leq bE(D_1) + b\sqrt{Var(D_1)}Z^*$, and therefore $x/b\sqrt{Var(D_1)} \leq Z^*$, since $b\sqrt{Var(D_1)} > 0$. Let $\Delta = x/\sum_{c\in C} b\sqrt{Var(D_c)}$, it is easy to see that $\Delta = x/\sum_{c\in C} b\sqrt{Var(D_c)} \leq x/b\sqrt{Var(D_1)} \leq Z^*$, and therefore $Z^* - \Delta \geq 0$. Define $\bar{Y}_c^*$, for $c = 1, \ldots, |C|$, as $\bar{Y}_c^* = bE(D_c) + b\sqrt{Var(D_c)}(Z^* - \Delta)$. These values of $\bar{Y}_c^*$, for $c = 1, \ldots, |C|$, satisfy the left-hand side of (16). If we show that they also satisfy constraints (15), we would find a value smaller than Z^* such that all constraints are satisfied, but this is in contradiction with the hypothesis that Z^* is minimum. Since

$$\begin{aligned}
\sum_{c\in C}\bar{Y}_c^* &= \sum_{c\in C} bE(D_c) + \sum_{c\in C} b\sqrt{Var(D_c)}(Z^*-\Delta) \\
&= \sum_{c\in C} bE(D_c) + \sum_{c\in C} b\sqrt{Var(D_c)}Z^* - \sum_{c\in C} b\sqrt{Var(D_c)}\Delta \\
&= bE(D_1) + b\sqrt{Var(D_1)}Z^* - \sum_{c\in C} b\sqrt{Var(D_c)}\Delta + \sum_{c\in C\setminus\{1\}} Y_c^* \\
&= bE(D_1) + b\sqrt{Var(D_1)}Z^* - \sum_{c\in C} b\sqrt{Var(D_c)}\frac{x}{\sum_{c\in C} b\sqrt{Var(D_c)}} + \sum_{c\in C\setminus\{1\}} Y_c^* \\
&= bE(D_1) + b\sqrt{Var(D_1)}Z^* - x + \sum_{c\in C\setminus\{1\}} Y_c^* = \sum_{c\in C} Y_c^* \geq B_0 + B_1,
\end{aligned} \tag{23}$$

there must exist a value $(Z^*-\Delta) \leq Z^*$ such that all constraints are satisfied, which contradicts our initial hypothesis that Z^* was the minimal value. ■

4.3.3. The Minimum Required Amount of Inventory In the proposed network, the total inventory on hold is sufficient to cover the full demand of a hurricane season, which is represented by a scenario, possibly involving multiple hurricanes occurring at different periods. However, the minimum inventory needed for a given scenario is not equal to the total demand of that scenario because it depends on the timing on the hurricane events over the season, on their demands, and on the lead times. We next calculate the *minimum required amount of inventory* in the network to cover the needs that will occur throughout the season. We denote by Ω_τ the minimum required amount of inventory corresponding to a fixed replenishment lead time τ. In each season, whenever a disaster occurs in a given period, we need to have enough inventory to cover the associated demand. At the end of the period, a replenishment order is given for the used supplies, and the orders arrive after the lead time. Therefore, in each period t, the network inventory must include the available inventory needed to cover the sum of the demands that occur in that period, plus the replenishment amount ordered and that will arrive after the lead time, i.e., the sum of the demands that occurred between $\max\{0, t-\tau\}$ and $\max\{0, t-1\}$. Specifically, let ω_τ^s represent the minimum amount of inventory required to meet the needs in scenario s under a lead time $\tau > 0$. Then, ω_τ^s and Ω_τ can be computed as

$$\omega_\tau^s = \max_{t\in T}\Big\{\sum_{c\in C}\Big\{d_c^{st} + \sum_{\bar{t}=\max\{0,t-\tau\}}^{\max\{0,t-1\}} d_c^{s\bar{t}}\Big\}\Big\} \quad \text{and} \quad \Omega_\tau = \max_{s\in S}\Big\{\omega_\tau^s\Big\}. \tag{24}$$

The optimal amount of inventory in the network, $I^* = \sum_{w\in W} I_w^*$, may be larger than Ω_τ due to i) the possibility of destroyed stocks at the affected warehouses, ii) the distribution of the inventory within the network driven by the logistical connectivity and costs, and iii) the coverage requirements (i.e., β_c^{st}).

4.3.4. The Benefits of Collaboration To evaluate and measure the benefits of a collaborative network, we compare the solutions obtained from our collaborative prepositioning model with a benchmark solution in which each country implements an independent prepositioning strategy by only considering its own risks. To this end, we generate a scenario set exclusive to each country and compute the minimum required amount of inventory for each country, denoted by $\widetilde{\Omega}_{c,\tau}$, by adapting (24), as follows:

$$\widetilde{\Omega}_{c,\tau} = \max_{s\in S} \left\{ \max_{t\in T} \left\{ d_c^{st} + \sum_{\bar{t}=\max\{0,t-\tau\}}^{\max\{0,t-1\}} d_c^{s\bar{t}} \right\} \right\}. \tag{25}$$

Proposition 2 *The minimum required amount of inventory needed in the collaborative network does not exceed the sum of the minimum required inventories that each country must hold independently, i.e.,*

$$\Omega_\tau \leq \sum_{c\in C} \widetilde{\Omega}_{c,\tau}. \tag{26}$$

Proof. Let $\bar{\omega}_\tau^{s,c}$ be the minimum amount of inventory needed in country c in period t in a given scenario s with lead time $\tau > 0$, which is equal to $d_c^{st} + \sum_{\bar{t}=\max\{0,t-\tau\}}^{\max\{0,t-1\}} d_c^{s\bar{t}}$. Then

$$\begin{aligned}
\Omega_\tau &= \max_{s\in S} \left\{ \omega_\tau^s \right\} = \max_{s\in S} \left\{ \max_{t\in T} \left\{ \sum_{c\in C} \left\{ d_c^{st} + \sum_{\bar{t}=\max\{0,t-\tau\}}^{\max\{0,t-1\}} d_c^{s\bar{t}} \right\} \right\}_{t\in T} \right\}_{s\in S} \\
&\leq \max_{s\in S} \left\{ \sum_{c\in C} \left\{ \max_{t\in T} \left\{ d_c^{st} + \sum_{\bar{t}=\max\{0,t-\tau\}}^{\max\{0,t-1\}} d_c^{s\bar{t}} \right\} \right\}_{t\in T} \right\}_{s\in S} \\
&= \max_{s\in S} \left\{ \sum_{c\in C} \left\{ \bar{\omega}_\tau^{s,c} \right\} \right\} \leq \sum_{c\in C} \left\{ \max_{s\in S} \left\{ \bar{\omega}_\tau^{s,c} \right\} \right\} = \sum_{c\in C} \widetilde{\Omega}_{c,\tau} \quad \blacksquare
\end{aligned} \tag{27}$$

5. Numerical Analyses

We first present test instances generated from real data related to the Caribbean network. This will be followed by the results of our numerical analyses. We calculate the benefits of collaboration and the extent of risk pooling achieved in the network.

5.1. The Caribbean Network Data Set

There appears to exist no available data set for multi-country humanitarian networks. The collaborative network considered in this study includes 20 CARICOM countries. We collected data from various publicly available sources, and also from CDEMA and IFRC. Since the available raw data were unstructured and fragmented, we applied a systematic approach to develop realistic estimates for each parameter of our model, which we now describe.

5.1.1. Hurricane Scenarios Each scenario corresponds to a season during which multiple hurricanes may occur. We developed hurricane scenarios based on historical data by validating and merging the information contained in three databases: the Emergency Events Database (EM-DAT) (EM-DAT, 2018), the National Oceanic & Atmospheric Administration (NOAA) database, known as HURDAT (NOAA, 2018), and a local database, known as the Caribbean

Hurricane Network (CHN) (CHN, 2018). We examined historical hurricane tracks from these sources focusing on a period between 1950 and 2017, and we generated a database containing the timing of each storm, the set of countries on the storm track, the strength of the storm affecting each country, and the affected population in each country. This yielded 188 events spread over 62 seasons. No two seasons are identical in terms of the number, severity and timing of events and the countries affected. For each of the 62 seasons, we generated five scenarios having the same hurricane tracks and timing, but different severities and demands. In particular, to generate scenario demands, we first assigned a severity category to the countries on each track, according to the percentage of past events affecting a country at different strengths. We classified a storm having a category less than or equal to 2 as mild (M), a storm of category 3 as strong (S), and those with larger categories as very strong (VS). Based on the assigned category of the storm and the largest percentage of affected population in that country over the years, which we obtained from historical data, we generated an estimate of the affected number of people in each country. We then divided the affected population values by five, which is the average family size, to obtain the targeted demand values. Recall that in our insurance framework a maximum coverage limit (MCL) specifies the maximum amount that can be covered for each country per hurricane event. Therefore, if the number of family kits generated by our procedure is larger than the prespecified MCL value, we accept the MCL value as the targeted demand. In our experiments, MCL is set to 5,000, 8,000 and 12,000. Finally, based on the generated demand values, we calculated the expected value and the variance of the demand for each country. As a result, we obtained 310 different and equiprobable scenarios. We provide more details about data processing and scenario generation in Appendix A.

5.1.2. The Extreme Scenarios The required initial investment for establishing the collaborative network can be quite large if a full coverage against all possible events is envisaged. It is therefore worthwhile to evaluate the implications of disregarding some of the rare and extreme scenarios on network design decisions and costs. As widely discussed in the literature, systems are not typically designed for either the average case nor for the most extreme conditions (Daskin et al., 1997). A variety of methods are used to design networks under uncertainty while addressing the effects of worst-case scenarios endogenously, including chance-constrained programming, risk-averse models, and robust models (see Snyder (2006) for a review). In this study, we use a simple approach, in which we define a restricted scenario set by removing some extreme scenarios before solving the model, where extreme scenarios are specified based on the minimum amount of inventory required to meet the needs of that scenario (i.e., ω^s_τ value). That is, we use the ω^s_τ value as a proxy for measuring the implications of including a scenario in our data set. Then, given a scenario set $\mathcal{S}$ and the ω^s_τ values for all scenarios, we remove a subset of worst scenarios with the largest ω^s_τ values and obtain the restricted scenario set $\mathcal{S}^q$. More specifically, q represents the percentage of the worst scenarios, measured in terms of the minimum amount of inventory required to meet the need of a scenario (ω^s_τ), to be removed from

$\mathcal{S}$. To illustrate, in our numerical experiments, we generate $|\mathcal{S}| = 310$ equiprobable scenarios based on historical data, and consider instances with $q = 5$, which disregards $\lfloor q|S| \rfloor = 15$ worst scenario in terms of ω_τ^s, and instances with $q = 10$, which eliminates $\lfloor q|S| \rfloor = 31$ scenarios.

We denote by Ω_τ^q the minimum required inventory in the collaborative network for a given value of q, and by $\widetilde{\Omega}_{c,\tau}^q$ the minimum required amount of inventory for a given country c if the country applies an independent prepositioning strategy based on the scenario set S^q. As expected, removing extreme scenarios decreases the required minimum amount of inventory needed. In our numerical analyses, we evaluate the benefits of collaboration for different restricted scenario sets.

Three parameters affect the demand distributions and the minimum inventory levels: MCL, q and τ. The MCL cuts some large demand values, and hence may affect the expected value and variance of the demand for some countries. The parameter q affects demand distribution since we remove some extreme scenarios from consideration. Note that changing the MCL value only affects size of demands while keeping the number of scenarios fixed, and increasing q decreases the number of scenarios in our data set. The lead time parameter τ directly affects the ω_τ^s value as shown in (24). We consider different combinations of MCL, q and τ in our analyses.

5.1.3. Relief Supplies Family kits are stored and distributed in the network. The specifications of the items in a family kit, presented in Table 8 of Appendix B, were obtained from IFRC Panama, which operates in our region of interest. A family kit costs approximately USD 147.5, weighs 41 kilograms and has a volume of 0.14 cubic meters. We assume that a pallet holds 20 kits, and a standard 20-foot container can hold 200 kits. We add insurance costs and handling costs for each family kit purchased, estimated on hourly country-specific labor cost. The cost of holding one unit of a purchased item is equal to the cost of holding items in the warehouse, plus the opportunity capital cost. The unit inventory holding cost is equal to 6% of the purchase cost.

5.1.4. Candidate Warehouses There are fundamental differences among the profiles of the CARICOM countries in terms of their population, disaster risk and logistical connectivity. We chose candidate warehouse locations among the 20 CARICOM countries based on an exploratory study. Specifically, we asked CDEMA to evaluate each country as a potential warehouse location by considering three attributes: i) risk exposure, ii) logistical infrastructure and connectivity, and iii) political stability and safety. Publicly available global indices such as the INFORM 2018 Risk Index (INFORM, 2018), the Logistics Performance Index (World Bank, 2018), and the Worldwide Governance Index (World Bank, 2017) were used by CDEMA to score the countries. Each country's performance was classified as very poor, below average, average and above average for each attribute. When a country's performance was lower than average in at least one attribute or there was no index data about the country, then that country was eliminated from the list of potential warehouse locations. In the end, 10 countries were considered as candidates. In Table 1, we present data related to the candidate warehouse locations.

We assume that a number of 10,000 square feet warehouses can be rented in these candidate locations, each capable of storing 600 pallets and hence 12,000 family kits. We set the maximum number of warehouses to locate in each location at a large value and we let the model determine the optimal number of warehouses. The fixed cost of locating a warehouse for the first year in a country was estimated by considering the annual costs of renting the facility and hiring staff, and also the purchasing cost of one forklift. The rental cost was calculated for each country based on publicly available rent indices, and considering DMA as a benchmark country, for which the warehouse rental costs were obtained from the Dominican Red Cross. We assumed the presence of one permanent worker at each warehouse. We further assumed that additional staff and equipment could be temporarily obtained; the associated costs were considered as variable costs, proportional to the amount of inventory held, and incorporated into the holding cost. We added a 1% insurance charge to the total fixed costs to cover expenses related to possible damages.

The base case fixed costs are also listed in Table 1. Additionally, in our numerical experiments, we explored solutions that could be obtained by having the same fixed cost across all candidate locations. This could be possible if the hosting governments subsidized the cost of warehousing, as was done in previous similar initiatives in the region (Balletto and Wertheimer, 2010). In this case, we assigned the average fixed cost value to each candidate warehouse. We also considered a setting in which the current subregional focal points of CDEMA have smaller fixed costs than all other locations, such as half of the network average.

Table 1 Data related to the candidate warehouse locations

Candidate location	Fixed cost (USD)	Average transit time (days)		Average unit transit cost (USD)		Number of events	Mild events (%)	Strong events (%)	Very Strong events (%)
		Air	Sea	Air	Sea				
Antigua and Barbuda	209,067	1	4.86	99.85	5.52	26	73	15	12
Bahamas	288,131	1	5.97	99.10	12.58	62	79	11	10
Belize	104,452	1	6.63	98.25	12.99	22	68	0	32
Barbados	149,741	1	4.93	77.37	6.26	22	91	9	0
Dominica	96,754	1	4.84	133.98	9.03	28	82	4	14
Grenada	110,987	1	4.89	79.19	9.11	16	81	13	6
Guyana	105,020	1	5.64	99.72	6.79	0	0	0	0
Jamaica	119,307	1	5.53	109.28	5.77	26	77	8	15
Suriname	92,899	1	5.85	99.15	6.32	0	0	0	0
Trinidad and Tobago	139,930	1	5.08	99.69	6.27	13	85	15	0

5.1.5. Sea Transportation We collected data from various publicly available sources to estimate sea transportation times and costs. The IFRC Panama uses sea transportation to serve the Caribbean region. Based on their data, it takes two to 10 days to arrange and ship items. However, both IFRC and CDEMA agree that it is possible to use sea transportation more effectively, for example by having dedicated ships. Many shipping lines carry passengers and cargo among the islands, which can be effectively used after a hurricane. To estimate sea transportation times, we first identified the major sea ports in each of the 20 CARICOM countries. We then used Internet sources (e.g., Sea Distances (2019)) to calculate the distance and travel time between each port pair by assuming a speed of 20 knots. We added a three-day allowance to the transportation times to account for handling. We conducted tests for a larger four-day allowance. Since sea transportation takes more than three days, it can only be used to serve countries during the slower response phase in our network. Furthermore, if a warehouse location is hit by a disaster, we assume that it cannot serve other countries by sea for that disaster due to possible damages and access problems. To estimate sea transportation costs, we used the container cargo prices between country pairs from World Freight Rates (2019). We also added a fixed cost per container to cover additional expenses such as port charges and documentation. This cost is assumed to be USD 80 from the IFRC data, based on its pre-agreed transportation providers in the Caribbean. We then extracted raw data from Maritime Routes in the Greater Caribbean (2019) and identified the number of shipping lines between each country pair. To reflect the connectivity of the countries, we multiplied these base costs by 1.5 whenever there was no shipping line operating between two countries, and by 0.98, 0.975, 0.97 and 0.95, if there were three, four, five or more lines, respectively. Finally, for each originating country we added cargo handling costs on the basis of local labor costs.

5.1.6. Air Transportation Air transportation costs were estimated based on cargo price data obtained from the IFRC, Caribbean Airlines and Cayman Airways. The IFRC has agreements with cargo companies, which provide IFRC a fixed cargo rate every year for shipping supplies from Panama to the Caribbean countries. Whereas several airlines operate in the region, the two airlines we considered publish their cargo rates in their webpages. Hence, we computed the average price of shipping a kilogram of cargo for each origin and destination pair. Furthermore, when two countries were not connected by any airline, we increased the price by 5% since then private planes must be used, while we reduced the unit price by 2.5% when there were multiple airlines serving the same link. Similar to sea transportation, we added handling charges per kit based on country-specific labor costs, as well as a fixed cost to account for port charges, which was estimated to be USD 0.17 per kilogram from the IFRC data. Air transportation is the only mode that can be used to meet the coverage requirements at the first response time level. However, if a warehouse location is affected by a disaster, we prevent the affected warehouse from serving other countries by air in the first three days after the disaster. Furthermore, if the amount of demand to be covered at the first response level corresponds to a partially loaded plane, we increase the amount to be covered at this level to a multiple of a plane capacity, to encourage full shipments by plane.

5.1.7. Other Parameters In the base case, the lead time τ was set at two months (four periods), which was estimated based on IFRC's average replenishment time in the Panama warehouse. In our analyses, we explored the effects of a shorter lead time period, such as one month, to understand the potential effects of a faster procurement strategy on our collaborative prepositioning network.

The percentage of damaged supplies was estimated according to the hurricane categories. We considered three settings with respect to the α_w^{st} parameter. In the base case, supplies are lost only due to destructive effects of strong hurricanes. Specifically, we assumed that 20% supplies are lost if the hurricane category is S, and 50% are lost if the category is VS. We also considered instances in which no supplies are destroyed in any event. Finally, we considered instances in which 20%, 50% and 100% of the available inventory is lost in hurricanes with M, S and VS categories, respectively. We set the minimum percentage of supplies to be satisfied within the first three days (the β_c^{st} parameter) as 10% in our base case. We explored the effects of increasing response time requirements by setting this parameter to 30%.

To summarize, we used three levels of MCL and q, and two levels of τ in the base case, which leads to 18 base case instances. For each of these instances, we conducted experiments by modifying the other parameters. Specifically, we tested for different levels of fixed costs, sea transportation times, damaged supplies percentages, and response requirements. In total, we used 126 instances to test our methodology.

5.1.8. Model Implementation We coded our model by using Java Concert Technology and we used CPLEX 12.7 to obtain solutions on a 64-bit Windows Server with two 2.0 GHz Intel Xeon CPU's and 32 GB RAM. We set a one-hour time limit for each instance. Some instances were solved within a few minutes, while others could not be solved to optimality within one hour. Therefore, to speed up the solution process for these instances, we imposed the valid inequalities $\sum_{w,c,m,s,t} Q_{wcm}^{st} \leq I_w$ to help CPLEX set the values of the Q variables. We also set the associated values of the Q variables equal to zero, when i) a country does not have a demand in a given scenario and time period, ii) a country's demand cannot be covered by a candidate warehouse by any transportation mode, or iii) a candidate warehouse is out of service due to effects of a disaster. We solved the restricted model to estimate the value of parameter b by assuming that the second-stage variables R, A and Q can be continuous. The effect of this relaxation on the b value is negligible.

5.2. Results and Discussion

Here we present and discuss the results of our numerical analyses.

5.2.1. Setting a λ Value The λ value in (3) affects the tradeoff between the amount of initial investment required to establish the collaborative network and the expected annual costs, which includes expected replenishment and transportation costs as well as fixed costs (i.e., renting, holding, staff, and insurance). Specifically, setting λ to a small value could yield a network with the lowest expected annual costs, but this choice may require large initial investments. By incurring smaller yearly total costs, the large initial investment can be recovered quickly. In contrast, by setting λ to a large value, the minimization of the initial investment needed to set up the network is prioritized, and the total yearly costs are higher. To identify the best λ value, we considered a fixed payback period for the network, and we calculated an annual equivalent value for the sum of the initial investments and the expected annual costs over this period. Specifically, we considered three alternative payback periods, of five, 10 and

15 years, and calculated annualized total investments by assuming three interest rates equal to 3%, 4% and 5%. We ran tests on our 126 instances, setting $b = 196.74$ (value obtained by solving the 126 instances on a restricted model and averaging the solution values), for seven different values of λ, ranging between 10^4 and 10^{10}. By fixing the payback period, the interest rate, and the MCL value, we calculated an average value over different q values for the sum of the annualized initial investments and expected annual costs for each value of λ. According to these results, if the desirable payback period is short, it is better to give more weight to minimizing the country investments, and as the payback period increases it becomes preferable to have a smaller value of λ and build a network that engenders smaller costs each year. While we observed these trends in individual solutions, we found $\lambda = 10^8$ to be the best choice since it yields the minimum values on most instances.

5.2.2. Collaborative Network Analysis: Identifying the Strong Candidate Locations We first analyzed the optimal solutions of our 126 instances and identified the most desirable countries where to locate warehouses. Specifically, we counted the number of times a country was selected as a warehouse location under different settings. Each setting involves 18 instances obtained by fixing a parameter and considering different combinations of MCL, q and τ values; the remaining parameters are assigned to their base case value. In each setting, if a country belongs to the top three selected locations over the 18 instances, we assigned a score of 2 to that country, while if it is among the next three locations its score is 1 (see Table 2).

Table 2 **Scores of the candidate warehouse locations (the best six locations are shown in boldface)**

	Instances							
Candidate location	**Base case**	**No damage**	**Higher damage**	**Larger sea transit time**	**Increased fast coverage**	**Smaller focal points fixed cost**	**Identical fixed cost**	**Sum of scores**
Antigua						2		2
Bahamas				1		1	2	4
Belize	2	2	1	2	2	1	2	**12**
Barbados	2	2	2	1	2	2	2	**13**
Dominica	1	2	1	2	1			**7**
Grenada	1	1		2	1		1	**6**
Guyana	2		2		2		1	**7**
Jamaica		1		1		1		3
Suriname	2	2	2	2	2			**10**
Trinidad and Tobago			1			2	1	4

The candidate warehouse location with the largest total score is BRB, which is relatively expensive in terms of fixed costs; however, it has not yet been hit by a VS event, and has the lowest air transportation costs, as well as low sea transportation costs (Table 2). The next most popular candidate is BLZ, which has been affected by VS events, but is advantageous in terms of fixed costs and air transportation costs. SUR and GUY are the third and fourth best candidates. They are never affected by hurricanes and have low fixed location costs. We also considered DMA and GRD among the strong candidates. Note that DMA and GRD have been affected by VS events, but they are good candidates due to their logistical connectivity and costs. In particular, DMA has relatively low fixed costs and high air and sea transportation costs, but a very good sea connectivity. Therefore, when other less expensive countries become less connected by sea due to higher sea transportation times, DMA becomes a preferred location. GRD is a bit more expensive in terms of fixed costs, but is cheap for air transportation. Moreover, like DMA, it has a good sea connectivity, therefore it is among the best locations when considering higher sailing times. Note that three of the CDEMA subregional focal points, ATG, JAM and TTO, do not have high scores. These locations are chosen mainly when their fixed costs are decreased (Table 2). JAM is the cheapest location for sea transportation and can serve HTI by sea. For this reason, it is among the best six locations when higher sea transportation times are considered. However, JAM has been affected by a number of VS hurricanes, which makes it a poor warehouse location. Since there are already strong candidates in the Eastern Caribbean that are geographically close to ATG and TTO, such as BRB, DMA, GUY and SUR, and BLZ in the Western Caribbean that is geographically close to JAM, we do not consider these countries among the strong candidates.

5.2.3. The Recommended Collaborative Prepositioning Network Having identified the best six candidate countries (BRB, BLZ, SUR, GUY, DMA, and GRD), we performed additional tests to design the collaborative prepositioning network. We considered different values of MCL and q and set other parameters to their base case values, and we applied our model by only considering CDEMA's current four subregional focal points, which are ATG, BRB, JAM and TTO. Note that in reality CDEMA has fixed service regions as shown in Figure 1, while in our problem we do not force single sourcing constraints, since i) we assume that warehouses can be affected by a disaster and supplies may be lost, which would prevent a warehouse from serving its assigned countries, and ii) risk pooling benefits may decrease in the region when service regions are fixed. The results for different sets of candidate locations are presented in Table 3.

Table 3 Description of the solutions obtained by solving our model (Recommended prepositioning network) and by fixing the focal points (Optimized current prepositioning network)

	Instance					
	$q = 0$		$q = 5$		$q = 10$	
	MCL = 12,000	MCL = 8,000	MCL = 12,000	MCL = 8,000	MCL = 12,000	MCL = 8,000
Recommended prepositioning network						
Warehouse locations(#)	BLZ(3), BRB(1), DMA(2), GRD(1), SUR(3)	BLZ(2), BRB(1), DMA(1), GRD(1), SUR(3)	BLZ(1), DMA(1), GRD(2), GUY(2)	BLZ(1), BRB(1), DMA(1), GUY(2)	DMA(1), GRD(1), GUY(2), SUR(2)	BLZ(1), BRB(1), GUY(2), SUR(1)
Deviation (Z)	0.167	0.161	0.150	0.139	0.135	0.123
Total inventory	116,927	89,275	69,763	51,559	61,123	46,543
Maximum Premium	6,413,974	4,236,715	5,641,772	3,621,375	4,587,978	3,010,144
Average premium	2,283,631	1,739,541	1,898,231	1,414,421	1,582,684	1,178,457
Tot required investment	41,105,350	31,311,733	34,168,161	25,459,586	28,488,312	21,212,226
Expected emergency response cost	5,737,162	4,626,316	5,296,909	4,306,228	4,980,248	4,007,110
Optimized current prepositioning network						
Warehouse locations(#)			ATG(3), BRB(1), JAM(2), TTO(1)	ATG(2), BRB(1), JAM(1), TTO(1)	ATG(1), BRB(1), TTO(4)	BRB(2), JAM(1), TTO(1)
Deviation (Z)			0.153	0.142	0.137	0.126
Total inventory	Infeasible	Infeasible	75,620	54,450	61,745	47,800
Maximum Premium			5,730,025	3,676,601	4,639,641	3,069,609
Average premium			1,929,377	1,438,435	1,601,497	1,205,019
Tot required investment			34,728,781	25,891,829	28,826,942	21,690,334
Expected emergency response cost			5,236,083	4,284,502	4,888,821	3,957,826

According to the results, when MCL = 12,000 and $q = 0$, 10 warehouses are located in five countries, which hold a total of 116,927 kits. When $q = 5$, six warehouses are needed, and the total inventory to cover all scenarios is 40% smaller, which is 69,763 units. Furthermore, a 17% decrease in average country premiums is observed, and the country premiums are equal or smaller for every country in the recommended prepositioning network. If we further eliminate scenarios with large minimum required inventory and set $q = 10$, six warehouses are located in four countries. However, the change in inventory and costs are not that dramatic in this case compared with eliminating the worst 5% from the base scenario set. We observe this trend when MCL = 8,000; that is, a large reduction of 42% in inventory is obtained if 5% of the worst scenarios are ignored when making prepositioning decisions. Given the significant saving in the amount of inventory and corresponding investments, it is reasonable to design the collaborative prepositioning network based on $q = 5$, which can cover 95% of the scenarios generated from historical data. Therefore, for the base case with MCL = 12,000, we recommend operating six warehouses in four countries.

When we ran the model by fixing CDEMA's current locations, we could not find a feasible solution in settings with $q = 0$. This is because there are some hurricane seasons in which all of the candidate warehouse locations are affected simultaneously by a hurricane. Since an affected warehouse is out of service for the first three days after a hurricane, no feasible solution exists. When $q = 5$ or 10, the current warehouse locations yield feasible solutions. However, the total amount of inventory and the required investment are larger compared with the recommended collaborative prepositioning network. Note that the solutions obtained by solving our model by fixing CDEMA's current locations do not correspond to the real current setting of CDEMA's network. Indeed, they are obtained by relaxing CDEMA's fixed subregions, which would impose that each country can be served from exactly one warehouse, making the model always infeasible. Table 3 provides the optimized solutions of the current network, for different MCL and q values.

Table 4 **Difference between the optimized current and recommended prepositioning network**

			Difference between			
	q	MCL	total investment	total inventory	maximum premium	average premium
Base case	**5**	**12,000**	560,621	5,857	88,254	31,146
		8,000	432,243	2,891	55,226	24,014
	10	**12,000**	338,630	622	51,664	18,813
		8,000	478,108	1,257	59,464	26,562
Higher damage	**5**	**12,000**	1,855,585	17,710	292,108	103,088
		8,000	1,468,251	12,320	187,593	81,570
	10	**12,000**	854,897	5,603	130,429	47,494
		8,000	888,869	4,029	110,553	49,382

Table 4 shows the differences between the solution of the optimized current and of the suggested prepositioning network, for different values of MCL and q, and for two sets of instances. For the base case instances, when $q = 5$ and MCL $= 12,000$, the optimized current network requires a total investment of UDS $560,621$ larger than the suggested network and $5,857$ more items. This leads to larger maximum and average premiums. These differences become more important when considering the set of instances with a higher damage level, i.e. those where more supplies are lost in case a warehouse is affected. When $q = 5$ and MCL $= 12,000$, the optimized current network requires the storage of $17,710$ more items than the suggested network to cover all the demand, and a total investment of almost USD 1.9 million more. Considering these numbers we believe that CDEMA could decide to keep its current focal points and use our model to optimize the inventory. However, if there is a risk of higher damages, since some of the current subregional focal points, such as JAM, are often hit and have a higher degree of exposure, we suggest some changes in the current warehouse locations.

Table 5 Investment and the usage of the network with MCL = 12,000 and when allowing a complete demand coverage, by setting MCL = ∞

							Distribution of the scenarios as a function of the average interval of used inventory (%)*							
q	**MCL**	**Tot required investment**	**# opened facilities**	**Total inventory**	**Maximum Premium**	**Average Premium**	**[0, 10]**	**]10, 20]**	**]20, 30]**	**]30, 40]**	**]40, 50]**	**]50, 80]**	**]80, 100]**	**]100, ∞[**
0	**12,000**	41,105,350	10	116,927	6,413,974	2,283,631	19.35	21.29	18.39	14.19	11.61	9.68	4.52	0.97
	∞	826,022,649	188	2,245,701	606,679,168	45,890,147	67.42	11.94	6.45	2.90	5.81	3.87	0.65	0.97
5	**12,000**	34,168,161	6	69,763	5,641,772	1,898,231	13.22	13.90	11.53	10.85	11.86	26.78	6.44	5.42
	∞	423,298,682	92	1,098,848	285,584,130	23,516,593	58.64	12.20	8.81	3.73	3.73	5.76	5.76	1.36
10	**12,000**	28,488,312	6	61,123	4,587,978	1,582,684	12.19	11.83	12.90	10.75	8.96	30.11	10.04	3.23
	∞	379,039,292	75	888,018	232,720,182	21,057,738	58.78	10.04	11.47	5.73	2.15	7.89	2.15	1.79

* For example, for $q = 0$ and MCL $= \infty$, 67.42% of all scenarios use at most 10% of the total inventory, equal to 2,245,701 family kits. For $q = 5$ and MCL = 12,000, 26.78% of all scenarios use between 50% and 80% of the total inventory, equal to 69,763 family kits.

Table 5 compares the solutions with MCL $= 12,000$ and without a maximum coverage limit (MCL $= \infty$) in terms of the total required investment, number of open warehouse facilities, total inventory, average and maximum premiums, and utilization of the inventory for different q values. As observed from this table, if MCL is unbounded, the required inventory, the number of facilities and the total investment become unaffordable. Moreover, the stock utilization drops significantly, which implies that most of the family kits would sit in the warehouse for several years before being used. Note that in more than 58% of the scenarios corresponding to potential hurricane seasons, the average percentage of used stocks is less than 10%, and this is for all q values. When designing the network with $q = 0$ and MCL $= 12,000$ units, we note that the average percentage of used stock is less than 10% for less than 20% of the scenarios, whereas this is the case for less than approximately 13% of the scenarios when $q = 5$ and $q = 10$. Thus, the utilized capacity increases significantly when imposing a maximum coverage limit. The results presented in Table 5 show that designing a prepositioning network without imposing a maximum coverage limit (MCL $= \infty$) would lead to unreasonable investments and important inefficiencies, i.e., to several mostly unused facilities, low stock utilization rate, deterioration risks, excess storage capacities and costs. They also show that using $q = 5$ and MCL $= 12,000$ units yields interesting solutions in terms of investment and inventory utilization, while providing a good coverage.

In the recommended network, the affected countries are served by warehouses located in different countries under different scenarios. Table 6 shows the average percentage of demand satisfied by each warehouse location and mode per affected country. It identifies the primary hubs and the transportation modes used to serve each affected country, when it is served from at least two different locations by sea and by air in different scenarios. For both air and sea, the demand of a country in a single event is usually served from the same warehouse. Therefore, our results do not suggest fixing service regions *a priori* as in CDEMA's current system. However, for

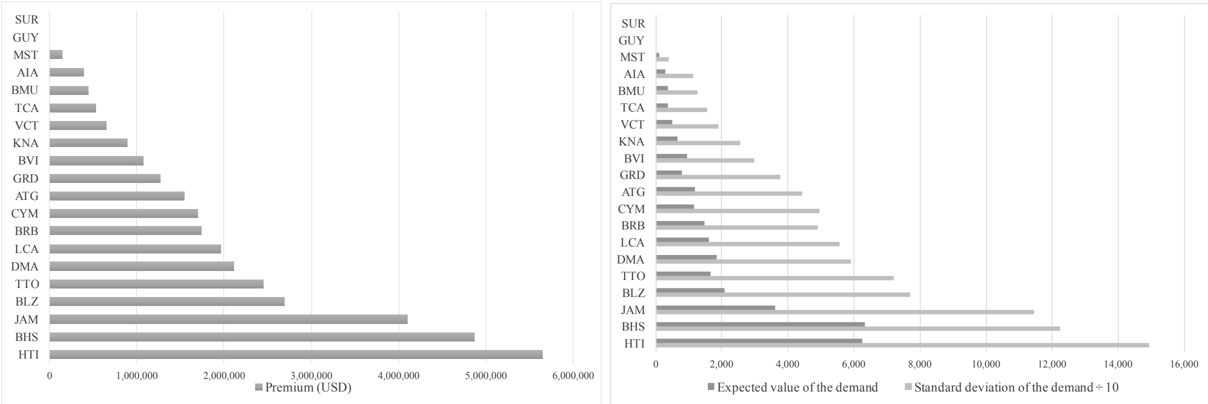

Figure 3 **Country premiums, expected demands and standard deviations of demands**

each approaching event, the affected countries can be assigned to the most logistically convenient warehouses. Moreover, air and sea connectivity can be improved on the most frequently used links in order to fully benefit from the collaborative prepositioning network.

Table 6 **Average percentage of demand served from the warehouses via air and sea**

	Belize		Dominica		Grenada		Guyana	
	Air	Sea	Air	Sea	Air	Sea	Air	Sea
AIA				3.05	50.96	41.26	1.95	2.78
ATG	0.86			33.40	21.02	24.42		20.31
BHS	0.51	69.80		9.12	12.03	8.39	0.15	
BLZ			0.82		39.89		2.38	
BMU				38.19	49.18	12.63		
BRB	3.70			49.33	12.82	23.74	2.41	8.00
BVI	0.87	0.34		48.34	21.56	17.14		11.75
CYM	0.54	4.31		56.93	17.71	18.42	2.09	
DMA	0.33				15.74	15.82	0.82	5.85
GRD	13.57			4.37			5.53	3.96
GUY								
HTI	0.41	0.09		35.55	8.14	27.04	1.48	27.29
JAM	1.52	1.27		10.55	8.84	49.88	0.45	27.48
KNA	1.38			20.53	29.62	31.79		16.67
LCA	2.80			30.62	15.65	39.64	0.38	10.90
MST				2.21	87.47	2.93	4.09	3.30
SUR								
TCA	1.10			16.18	36.69	21.14	4.37	20.52
TTO	6.01			30.82	3.37	15.56	2.70	41.54
VCT	10.08			33.13	21.93	26.78	1.98	6.10

[0,5] (5,10] (10,20] (20,30] (30,50] (50,100]

The total investment required to establish the recommended collaborative network is about USD 34.2 million. The country premiums needed to cover this investment range between USD 138,139 and USD 5,641,772. Figure 3 shows the premium of each country, as well as the expected value and the standard deviation of the demand. As indicated by these graphs, the premiums reflect the countries' average demands as well as their standard deviations. The optimal Z value is 0.15, which is the same for all countries as shown by Proposition 1. Interestingly, a similar range of premiums is reported for the CCRIF policies, as discussed in §3.2. Similarly to the CCRIF experience, highly vulnerable countries such as HTI, may not have sufficient financial resources to pay the annual premiums and may need external donors to sustain their membership.

5.2.4. Observations and Insights We present our observations related to the effects of the model parameters on the network design decisions and costs, based on the solutions of the 126 test instances, and also on some experiments performed on the proposed network.

- ***Lead time.*** In the proposed network, the lead time τ is set to two months, based on the IFRC current replenishment times. We observe that decreasing the lead time to one month could make a significant impact on the structure of the recommended solution. Specifically, for $q = 5$ and MCL $= 12,000$, although the number of warehouses to locate would be the same, the total network inventory would decrease by 8% and the total required country investment would go down by 2.9%. We observe similar trends in the solutions of the 126 test instances. Specifically, the inventory held in the network is on average 6.83% larger in instances with longer lead times, which corresponds to 1.75% larger investments. Furthermore, the location and number of facilities is affected by the lead time in 46% of the instances. These results suggest that the replenishment lead time is a critical parameter, which could help reduce the inventory held in the collaborative network. Therefore, it would be beneficial to have arrangements in place to achieve a faster replenishment during the hurricane season. This could be possible by i) making framework agreements with the suppliers to expedite shipments, and ii) having additional stocks in close hubs such as the UNHRD depot located in Panama. The cost savings achieved by the reduced lead time could be used to finance these strategies.
- ***Sea connectivity.*** In the base case, we set sea transportation times by adding a three-day delay to the pure sea transportation times to account for handling. When this delay becomes longer, some country pairs lose connectivity by sea. Since sea shipments are much cheaper than air shipments, reduced sea connectivity can have a major effect on the network and costs. In the proposed network, decreased sea connectivity primarily affects the warehouse in GUY, which is a critical location for serving HTI, JAM, TCA and TTO (see Table 6). If sea transportation times are increased by one day, GUY cannot cover three of these countries within one week. Therefore, the warehouses in GUY are shifted to other locations. However, this change could lead to significant respective increases of 7.56% and 5.04% in the expected transportation costs and in the emergency response budget. Therefore, in our recommended propositioning network, it would be useful to make arrangements to maintain and improve the sea connectivity of GUY.

We also observe the criticality of sea connectivity in the results of other test instances. Primarily, the elongated sea trips consistently lead to a larger difference between the minimum inventory required in the network (Ω_τ^q) and the optimal amount of inventory (I^*) more than any other parameter. Specifically, over all instances with $q = 5$, increased sea transportation times lead to a 2.3% larger inventory compared with the minimum required amount, which corresponds to 1,180 units on average. In many instances, the number and locations of warehouses are also affected. Because of the relative advantage of sea transportation, the model chooses to store additional inventory rather than relying on air shipments. Our discussions with CDEMA and IFRC also validated the criticality of improving sea transportation in the region. Acquiring and positioning dedicated ships for moving relief supplies among the islands is one of the options considered, which would highly enhance the network's effectiveness.

- ***Coverage requirements***. Increasing the coverage requirements in the first three days from 10% to 30% implies using more air shipments to serve the affected locations. For the proposed network, the expected transportation costs increase by 71.55%, compared with the base case. The warehouse locations are not very sensitive to faster response requirements; indeed, only the capacities of the existing locations are changed because more supplies are stored in locations that are cheaper for air transportation. Therefore, to economically improve the response times in the network, it would be beneficial to negotiate better rates with air transportation providers, especially for the most frequently used links shown in Table 6.
- ***Destroyed warehouses and supplies.*** When the risk of losing supplies in the warehouses located in hurricane-prone countries increases, more warehouses are located in GUY and SUR, which have not previously been hit by any hurricane. Whereas the total amount of inventory held in the network is not significantly affected (only 1.53% larger), since the network becomes more centralized, the expected transportation cost increases by 10.31%, and the emergency response budget goes up by 2.83%. These results highlight the importance of adequately evaluating the risks associated with losing supplies when determining the warehouse locations.

We stress that the solutions are generally more sensitive to changes in the parameters as q increases. When $q=0$, the network holds excess inventory in order to cover all scenarios, and therefore, small changes in parameter values do not considerably affect warehouse locations and the amounts of prepositioned inventory.

5.2.5. Analysis of Collaboration Benefits The collaborative prepositioning network achieves risk pooling benefits by centralizing inventory, which is shown in Proposition 2 for $q=0$. To measure this benefit for any value of q, we propose the following performance metric ϕ, which calculates the savings gained by using joint prepositioned stocks, as opposed to each country prepositioning stocks independently:

$$\phi = 1 - \frac{\Omega_\tau^q}{\sum_{c\in C} \widetilde{\Omega}_{c,\tau}^q}. \tag{28}$$

This metric can be calculated based on scenarios and without solving our optimization model. Accordingly, given a set of scenarios S_q, if the minimum inventory required in the collaborative network is close to the sum of inventories that countries would hold independently, then ϕ takes a small value, which indicates that the collaboration benefits are small. Conversely, when there is a large gap between the minimum amount of the joint stocks and the sum of the independent stocks, then ϕ becomes larger, reflecting higher benefits from collaboration.

For MCL = 12,000 and $\tau=4$, Table 7 shows the values of ϕ computed for different values of q between 0 and 50. We obtain similar values and trends for the other MCL and τ values. When $q=0$, ϕ is about 0.56, which means that the total inventory needed from all countries if each of them would store independently, is more than twice the amount that would be needed in our collaborative prepositioning network to cover all disasters. Interestingly, this ratio is aligned with what CCRIF reports for the country premiums, as discussed in §3.2. The value of ϕ tends to increase with q. The largest jump occurs when q increases from 0 to 5. This justifies our choice of designing a collaborative network with $q = 5$, which yields a large ϕ value, equal to more than 0.70 in all settings, and ensures a good service level.

Table 7 ϕ **values for different** q **values, MCL = 12,000 and** $\tau = 4$

q	**0**	**5**	**10**	**15**	**20**	**25**	**30**	**35**	**40**	**45**	**50**
ϕ	0.56	0.71	0.74	0.77	0.78	0.80	0.81	0.83	0.84	0.83	0.83

These results encourage us to develop extensions of our multi-country collaboration mechanism to other parts of the world, for example, to South-East Asia and Oceania, which are often hit by hurricanes and where risk pooling benefits may be achieved by keeping joint emergency stocks. Existing regional disaster response mechanisms in these regions may facilitate the development and implementation of a collaborative prepositioning strategy. For instance, national agencies of the IFRC, which operate worldwide, could implement collaborative prepositioning solutions to generate risk pooling benefits in their respective regions.

6. Conclusions

To close this paper, we summarize the main contributions of our study and we point to new avenues of research.

6.1. Summary of our Scientific Contributions

We have proposed a new collaborative prepositioning network design strategy to improve regional disaster management capacity in the Caribbean. We believe our study is the first ever to develop a systematic method for collaborative propositioning in a multi-country setting. Specifically, given a set of countries frequently affected by hurricanes, we determine the locations and amounts of joint stocks to be kept in the network so that the affected countries can be served quickly after a hurricane. Since different subsets of countries are affected by each event, risk pooling benefits can be achieved by keeping joint stocks. In order to sustain the proposed multi-country horizontal coordination mechanism, the required investments must be allocated fairly among the partner countries. We have developed a model inspired by insurance theory to allocate these costs among the partners in such a way that the country premiums are related to the costs associated with the expected value and the variance of their demand.

We have constructed a realistic data set to test and solve our model. We have conducted extensive numerical analyses to derive insights in order to support implementation. Our results demonstrate that important risk pooling benefits can be achieved by implementing a collaborative mechanism among the Caribbean countries affected by hurricanes. The benefits from collaboration increase significantly if the warehouse replenishment lead time during a hurricane season can be decreased and if regional logistical connectivity can be improved. The Caribbean setting constitutes an ideal example to illustrate the proposed collaborative approach since the CARICOM countries are connected to each other through economic, social and cultural ties. Furthermore, there exist established institutions such as CDEMA and CCRIF, which can support establishing and operating a collaborative prepositioning network in this region.

6.2. New Avenues of Research

Several avenues of research can be envisaged. In this study, we have concentrated on the Caribbean because it is one of the most hurricane-prone region in the world and we had a close collaboration with CDEMA and the IFRC. Extensions of the proposed multi-country horizontal collaboration mechanism to other parts of the world are possible. For instance, the proposed methodology can be adopted to South-East Asia and Oceania, which are often hit by hurricanes. Some of our methodology can also be adapted to regions that are frequently affected by earthquakes. While CDEMA, which facilitates the collaboration among the Caribbean countries, is an inter-governmental agency, the proposed methodology can be extended to other contexts, where umbrella organizations and members of the collaboration may be humanitarian agencies such as the IFRC and its national agencies.

Given that lead time has appeared as a critical parameter in our study, one could develop models that consider alternative procurement options, such as framework agreements with global suppliers and local sourcing. Recently, it was suggested by CDEMA that we look into local markets for procuring supplies. The evaluation of local market capacity would be important for that region. Moreover, potential costs that may be incurred while transitioning to the new collaborative network, such as moving the existing inventory from the current facilities to the new ones, can be explicitly considered in future models. The reallocation of supplies among the warehouses could also be incorporated in the response phase (second-stage) of the model by considering the dynamic information updates related to wind speed intensity and the path of a hurricane. Another concern of CDEMA is the state of the countries' infrastructure in the aftermath of a hurricane. While our model already considers the destruction of relief items as well as the temporary unavailability of access to infrastructure, such as port facilities, piers, warehouses and mechanical handling equipment, more accurate estimates could be obtained through the study of past data to try and predict the future absorption and onward distribution capacities of each state. In the same vein, there should be some consideration for transport modes used outside the existing commercial infrastructure, such as chartered vessels and aircraft, as well as military assets. We are currently supporting CDEMA in conducting a study on the assessment of the logistics infrastructure and post-disaster capacities in the Caribbean (e.g., local market, port and airport capacities after a strong hurricane). This will enable the development of future optimization models that incorporate disaster response operations in this region in a more explicit way.

Our work can also lead to future methodological advances in multiple directions. For instance, the model we have developed rests on the generation of scenarios based on historical data. More accurate predictions could be obtained through the use of climate change models pertaining to hurricanes, namely those that exploit the estimated influence of anthropogenic climate change (Mann and Emmanuel, 2006) and long-term trends in the frequency and intensity of tropical cyclones (Knutson et al., 2010). Considering some Latin American countries and also other types of disasters affecting the region such as earthquakes and floods may help achieve larger collaboration savings and improve regional capacity and integration. Therefore, it would be of interest to explore how to maximize risk pooling benefits in collaborative prepositioning networks and how to include other type of disasters in our demand scenarios.

In addition, the proposed insurance-based methodology can be adapted to other collaborative settings for cost and risk sharing. Furthermore, our work extends naturally to the adaptation of alternative insurance principles in order to model the risks associated with humanitarian supply chains. An interesting application of insurance theory to our collaborative prepositioning network could focus on setting country-specific upper coverage limits (i.e., MCL) by considering the demand distributions of the countries. However, the implications of country-specific MCL on total investments, country premiums and fairness of the cost allocation must be carefully evaluated. Since demand scenarios depend on MCL values, incorporating MCL as a decision variable may require devising a new methodology for cost allocation. Finally, alternative cost sharing methods can be developed to fairly allocate the costs associated with the collaborative prepositioning network among the members. One option is the use of the Shapley value (Shapley, 1953) which has been applied to apportion costs and benefits among several collaborating actors in a variety of logistics contexts, for instance in the horizontal cooperation of freight carriers (Krajewska et al., 2008). Other fair allocation methods that can be adopted to collaborative prepositioning include the alternative cost avoided method (Tijs and Driessen, 1986) and the equal profit method (Frisk et al., 2010), which were considered by Verdonck et al. (2016) in a cooperative facility location problem setting.

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Appendix A. Processing Hurricane Data and Generating Scenarios

We have examined historical hurricane tracks from three different databases focusing on a period between 1950 and 2017, but the characteristics of the events reported by different databases are sometimes different. We have therefore validated and merged the available information from these three databases. While EM-DAT involves information related to the total number of affected people, it does not report the category of the hurricane hitting a country. On the other hand, HURDAT and the CHN database report the categories, but do not contain information related to the affected population. In cases where HURDAT and the local database reported different categories for the same hurricane and the same affected country, we accepted the category provided by HURDAT. Moreover, there exist some hurricane events that are only listed in EM-DAT. To assign a category to such event, we explored the Internet to find related reports (e.g., from the NOAA, The Weather Network (2019) and ReliefWeb (2019)), and we identified the category of the storm hitting country.

EM-DAT reports the number of affected people for some of the 188 events in our data set. When we analyzed data on the number of affected people in a given country, we found the population of the country in the year of the event and we calculated the percentage of affected population. In most of the countries, the population has changed significantly over the years. For instance, MST's population decreased significantly. We recorded the *largest percentage of affected population for each country*, denoted by L_c, which is later used to develop demand scenarios associated with a hurricane of a given strength. For some countries such as BVI and MST, EM-DAT does not report any data on the number of affected people for the past hurricanes. For such countries, we considered the percentage of population affected by the same event and the same category in the close neighbouring countries, and we calculated the largest percentage of affected population accordingly.

The data on the category of the hurricanes were also used to estimate effects of a hurricane, based on their wind speed. The storms are classified into mild (M), strong (S) and very strong (VS) categories. We kept the mild storms in our data set since i) they may still cause disastrous situations due to rainfall and flooding, ii) the strength of a storm may change along its track and a country hit mildly may later be affected by a stronger event. As a result, for each country we kept the total number of events, and the percentage of events with different categories.

After processing the historical hurricane data, we developed hurricane scenarios. For each of the 62 seasons, we kept the hurricane tracks and their timing fixed, and randomly generated five scenarios differing from each other in terms of the severity of the hurricane hitting a country and of the size of the affected population. The size of the affected population was generated considering both the severity category and L_c. In total, we generated 310 different and equiprobable scenarios. We assigned a category to the countries on a track according to the percentage of the past events with M, S and VS categories. For example, JAM was hit by 26 events between 1950 and 2017, 77% of which belonged to the M category, while 8% of them were S, and 15% were

VS. Based on these percentages, we determined the number of scenarios with a specific strength for each country starting from the VS category. Specifically, for the JAM example, we generated $\lceil 5 \times 0.15 \rceil = 1$ event from the category VS, $\lceil 5 \times 0.08 \rceil = 1$ event from S, and $5 - 1 - 1 = 3$ events from M. For each scenario, we then generated an estimate for the affected number of people in the hit countries. In particular, for each country $c \in C$, we considered its population Pop_c, L_c, and the category of the hurricane. We then calculated $\Pi_c = \max\{50, L_c\} \times Pop_c$, which represents the size of the largest population that we target in our planning. An integer number chosen randomly from the interval $[0, \Pi_c \times 20/100]$ was assigned as number of affected population in country c, due to a hurricane of category M. For categories S and VS, we randomly generated the number of affected people from the intervals $(\Pi_c \times 20/100, \Pi_c \times 50/100]$ and $(\Pi_c \times 50/100, \Pi_c]$, respectively. This allowed us to take into account the exposure of the countries to the hurricanes and the impact that hurricanes of different categories can have on the number of affected people. We then divided these population values by five, which is the average family size. Finally, if the number of family kits (targeted demand) generated by this procedure was larger than the prespecified MCL value, we accepted the MCL value as the demand of a country in a scenario. We generated scenarios following this procedure because we did not have data on the countries' targeted demand. However, if such information was provided, the number of family kits could be replaced by the targeted demands and adjusted (bounded) according to the MCL value.

Appendix B. Data Used for the Computational Experiments

Table 8 Family kit contents and characteristics

Item	Quantity	Unit price (USD)	Unit weight (kg)	Unit volume (m^3)
Hygiene kit	1	24.15	7.80	0.037
Jerrycan	2	6.30	0.35	0.004
Blanket	5	25.20	3.30	0.010
Mosquito net	2	8.40	0.86	0.003
Tarpaulin	2	29.40	9.36	0.022
Shelter tool kit	1	26.25	11.30	0.035
Kitchen set	1	24.15	6.40	0.019
Plastic bucket	1	3.68	0.89	0.008
Total		**147.53**	**40.26**	**0.137**

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