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Cost Sharing Mechanisms for Multi-Country Partnerships in Disaster Preparedness

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Abstract. We analyze a multi-country disaster preparedness partnership involving the joint prepositioning of emergency relief items. Our focus in the Caribbean region, which faces increasing disaster threats due to weather-related events and has already committed to share its resources for regional integration. We collaborate with the inter-governmental Caribbean Disaster and Emergency Management Agency (CDEMA), which is interested in creating a methodology to equitably allocate the costs necessary to operationalize this commitment. We present alternative cost allocation methods among the partner countries by considering their risk level and their ability to pay. Specifically, we adapt some techniques borrowed from the cooperative game theory literature such as the Shapley value, the equal profit method, and the alternative cost avoided method, and we also propose a new insurance-based allocation scheme to determine the country contributions. The proposed mechanism, which is formulated as a linear programming model, sets country premiums by considering the expected value and the standard deviation of country demands and their gross national income. We discuss the structural properties of these methods and numerically evaluate their performance in achieving an equitable allocation scheme based on several key performance indicators (KPIs). Our proposed cost sharing mechanism not only achieves superior solutions compared with other methodologies with respect to the proposed KPIs, but is also computationally efficient. We also show that although some high-risk and impoverished countries bring additional burden to the partnership, all CDEMA members benefit from being a partner in the collaborative prepositioning network.

Keywords: Multi-country partnerships, cost sharing, disaster preparedness, prepositioning, insurance.

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1. Introduction

Every year millions of people are affected by natural disasters such as earthquakes, floods, storms and pandemics, and by human-made disasters such as armed conflicts and nuclear accidents. In recent years, the world has witnessed several major disastrous events, including the South Asian tsunami in 2004, Hurricane Katrina in the United States (US) in 2005, the Haiti earthquake in 2010, the earthquake and tsunami in Japan in 2011, Typhoon Haiyan in the Philippines in 2013, the Nepal earthquake in 2015, Hurricanes Maria and Irma in the US and the Caribbean in 2017, the wildfires in Australia in 2019, and the COVID-19 pandemic in 2020. Moreover, the Syrian war, which started in 2011 has caused the largest refugee crisis since World War II and has created massive immediate and long-term humanitarian needs (The International Rescue Committee, 2020). The damages on human life, property and the environment caused by such disasters are beyond the coping capacity of the respective local communities, and substantial international funding and aid are typically required to alleviate the losses. Moreover, the projected humanitarian needs for the coming years are increasing, with no reduction in sight, and the major drivers are political conflicts, climate change and pandemics (The United Nations, 2020). Although the humanitarian system is more effective and innovative than ever (OCHA, 2020), transformative practices are needed to use the limited available resources in the best possible way to respond to the growing humanitarian needs. In this regard, collaborative approaches that allow pooling resources among different actors to achieve the greatest efficiency and impact are gaining in popularity in the humanitarian sector (Lacourt and Radosta, 2018).

The United Nations (UN) has also made it a priority for all actors to collaborate more closely by working towards collective outcomes aimed at reducing risk, vulnerability and need (OCHA, 2020). The 2030 Agenda for Sustainable Development, adopted by the 193 UN member states at the General Assembly in September 2015, approved a global program consisting of a series of 17 goals, which are an urgent call to improve lives and transform the world (UN, 2020b). In particular, the Sustainable Development Goal (SDG) 17, called "Partnerships for the Goals", seeks to strengthen the global partnerships by bringing together national governments, the international community, civil society, the private sector and other actors in tackling problems in order to achieve sustainable impact (UN, 2020a). It is stressed that the ambitious targets of the 2030 Agenda can only be met with strong partnerships and cooperation, and hence significant progress must be made on SDG 17 (Pierce, 2020; UNDP, 2020).

Although the importance of partnerships is frequently stated, these are not easy to develop and implement successfully. Indeed, while a multitude of collaborative approaches and initiatives (from global down to local levels; from international networks to bilateral arrangements; from multi-sector, multi-issue platforms, to single-sector, single-issue interest groups) have been proposed and implemented in the realm of sustainable development, the partnerships that generate sufficient impact and reach their intended potential are relatively few (Stibbe et al., 2020). The general challenges associated with establishing cross-sectoral and cross-country partnerships include: i) the difficulties of finding the right approach for a particular context (Stibbe et al., 2020), ii) the need for strong commitment and significant investment of both time and resources from all partners involved (Lacourt and Radosta, 2018), and iii) the difficulties associated with quantifying and allocating the benefits, risks and costs of the partnership among the actors involved (Stibbe et al., 2020).

In this paper, we focus on SDG 17 from the perspective of developing multi-country partnerships to improve the effectiveness of disaster preparedness and emergency response through a collaborative prepositioning network. Cross-country partnerships have a high potential to transform the current individualistic efforts as the most severe humanitarian crises from today involve multiple regions or countries. For instance, the political crises often cause immense population displacements and may affect many countries in a region, such as the ongoing Syria war and the ensuing refugee crisis. Moreover, many countries in close geographic areas are affected by the same climatic patterns and hence tend to face similar natural disaster threats such as earthquakes, hurricanes, floods, droughts, forest fires and heat waves. Given that many countries face similar risks, collaborative preparedness practices can help countries improve the cost effectiveness and impact of disaster response by pooling their resources.

There exist some financial instruments built upon multi-country partnerships to jointly deal with disaster risks. For instance, the European Union Solidarity Fund (EUSF), which was established in 2002 as a reaction to the severe floods in central Europe, assists disaster-stricken areas within Europe by providing financial assistance to the member countries from its annual 500 million euro budget (European Commission, 2020). The Caribbean Catastrophic Relief Insurance Facility (CCRIF), a pooled catastrophe risk insurance institution, was established to provide financial liquidity quickly to the affected member countries in order to support disaster relief efforts (CCRIF, 2018). Similarly, the Pacific Catastrophe Risk Assessment and Financing Initiative (PCRAFI) was created to increase the financial resilience of the Pacific Island Countries against climate- and disaster-related risks (PCRAFI, 2020; Nishizawa et al., 2020). Finally, the African Risk Capacity (ARC) is another insurance scheme that capitalizes on the natural diversification of weather risk across Africa, allowing countries to manage their drought risk as a group in a financially efficient manner (ARC, 2020). As exemplified by these practices, insurance can serve as a key economic instrument to pool disaster risks. The associated financial capital comes from donors, the participating countries' premiums as well as from one-time partner contributions.

While the existing insurance-based partnerships supports the partner countries by providing immediate cash to assist disaster response and recovery efforts, it is also important to enhance the regional disaster preparedness capacity through collaboration, which helps countries pool their material and logistical resources, such as warehouses, stocks, transportation facilities, and infrastructure. One example of such a partnership arises in the Caribbean region, which is under permanent and increasing threat of natural disasters, in part as a result of climate change (The World Bank, 2020b). Over each of the past 20 years, natural disasters have directly affected an average of 1.2 million people in the Caribbean, and direct damages due to natural disasters have averaged almost US$1.6 billion per year (The World Bank, 2020a). In particular, the Caribbean countries are under permanent threat throughout the Atlantic hurricane season, which extends from June to November. In many seasons, several strong hurricanes occur, some of which severely affect multiple Caribbean countries simultaneously. For instance, the 2017 Atlantic hurricane season was categorized as extremely active, which included multiple successive strong hurricanes (e.g., Jose, Irma, Maria, Harvey), causing an unprecedented level of destruction across the region. Given the existing and future threats, disaster preparedness in the Caribbean has always been a high priority for both the national governments and the international community. Developing transparent, coordinated and integrated partnerships has continuously been promoted to enhance regional capacity to tackle the challenges faced by the Caribbean states (ECLAC, 2018b,a). Consequently, several collaborative regional platforms and initiatives for disaster risk reduction, preparedness and response have been launched over the years (The World Bank, 2020a; ECLAC, 2018b). In particular, the inter-governmental Caribbean Disaster and Emergency Management Agency (CDEMA) is responsible for coordinating the disaster management activities of the 18 participating states (CDEMA, 2020b). To ensure fast and effective regional response, CDEMA operates a prepositioning network in the region, where emergency relief supplies are stored in strategically located warehouses in four subfocal countries (Kirton, 2013). Once a disaster hits the region, the prepositioned supplies are immediately dispatched to help the affected countries. Recently, the World Food Programme (WFP) has decided to back up the regional response system implemented by CDEMA to strengthen its local emergency response capacity and contribute to the SDG 17 (WFP, 2020).

The budget required to operate the collaborative prepositioning network is allocated by CDEMA among the partner countries. The cost allocation scheme currently implemented by CDEMA relies on a simple formula that uses population as a proxy for risk, as well as the economic welfare level of each country (CDEMA, 2019). However, CDEMA is interested in determining the country shares by using scientific methods in order to operate an effective and transparent partnership network with sufficient clarity on the benefit and cost allocation mechanisms. Moreover, it wants to show to the partner countries and donors the positive impact of operating a collaborative disaster preparedness network in the region. Our study aims to support CDEMA's goal by presenting methodologies for assessing the net value of the proposed collaborative prepositioning network for each partner. It seeks an equitable (fair) allocation of the required disaster preparedness budget among the partner countries by considering their risk exposures and their economic profiles.

Balcik et al. (2019) addressed the regional disaster management system of CDEMA and presented a mathematical model for the design of a collaborative prepositioning network, which allocates the costs associated with establishing and managing the network among the partner countries based on an insurance framework. Specifically, these authors allocate the required budget among the partners in such a way that the country premiums are allocated proportionally to the costs associated with the expected value and the standard deviation of their demand. In this study, we take a deeper look at this multi-country collaborative prepositioning network to investigate its network-wide and country-specific benefits, and we also devise an insurance-scheme to determine country contributions by additionally accounting for the economic status of the countries (i.e., gross national income, GNI), which is an important factor for the success of multi-country partnerships. For instance, it is important for CDEMA to support highly fragile countries like Haiti, which is one of the poorest and most disaster-prone countries in the world, via such a regional partnership to ensure the long-term viability of the partnership. This partnership should be developed without creating a significant additional burden for the other partner countries, and by proposing a cost allocation scheme that is acceptable to every partner. Since SDG 17 invites the countries to form effective global partnerships, it is of value to develop methods that account for the differences in their capacity to cover the partnership costs.

To evaluate the effectiveness of the proposed cost sharing method, we adapt and compare several methodologies pertaining to the cooperative game theory literature which are widely used to distribute gains and costs to several actors working in a coalition, such as the Shapley value (Shapley, 1953), the equal profit method (EPM) (Frisk et al., 2010), and the alternative cost avoided method (ACAM) (Tijs and Driessen, 1986). We also develop key performance indicators (KPIs) to assess the quality of the proposed partnership scheme and we conduct an extensive computational study to evaluate and compare the performance of alternative cost sharing approaches with respect to several KPIs. Our results show that the proposed insurance-based approach is not only beneficial in terms of the proposed KPIs, but also in terms of computational efficiency, which depends on the number of countries in the partnership. Moreover, we also show that all current CDEMA countries, irrespective of their significantly different risk and economical profiles, can benefit from being a member of this partnership compared with acting alone. We evaluate the effects of incorporating economic profiles in setting country contributions. Finally, we compare the country contributions obtained by our methodology with those implemented by our collaborator CDEMA, and we discuss the implications.

The Caribbean region constitutes an ideal setting to implement multi-country partnerships for disaster preparedness since i) the Caribbean countries are under similar and increasing risks associated with natural hazards, ii) an umbrella organization (CDEMA) exists to manage the partnership and coordinate emergency response activities, and iii) the partner countries are connected with each other through economic, social and cultural ties, and a strong sense of solidarity, which leads to a high level of commitment for regional integration. Moreover, SDG 17 is among the prioritized goals for addressing the region's sustainable development needs (Mead, 2020; ECLAC, 2018c). By assessing methodologies that support multi-country partnerships in disaster preparedness, our study supports the SDG 17 targets related to i) strengthening cooperation between nation states in disaster preparedness and supporting capacity building in developing countries (Target 17.9), and ii) enhancing multi-stakeholder partnerships that mobilize and share knowledge, expertise, technology and financial resources to support the achievement of the SDGs in all countries, in particular the developing countries (Target 17.16, UN (2020a)). Similar partnerships can be adapted to other regions of the world among countries, as well as among their respective national agencies, in order to derive a benefit from pooling their disaster risks and logistical resources. Our study presents a general methodological framework that links prepositioning decisions with cost allocation schemes by considering actors with highly different risk and economical profiles, as well as assessing the effectiveness of a partnership. Given that building multi-stakeholder partnerships is by no means easy and that there can be different ways to achieve the challenging SDG 17 (GUNI, 2020), our study can be used as a benchmark in future efforts for establishing multi-country partnerships for disaster preparedness and support their implementation.

The remainder of the paper is structured as follows. In §2, we review the related literature. In §3, we present the problem and the model for collaborative prepositioning network design, and we explain the alternative cost allocation methods to determine the country contributions. We present our numerical analysis and results in §4. Finally, we conclude and discuss future work in §5.

2. Literature Review

We now review the relevant literature in humanitarian partnerships and cost allocation methods.

2.1. Humanitarian Partnerships

Partnerships are defined as non-hierarchical alliances in which several actors from one or multiple levels of government, the business domain or civil society pursue common goals by sharing resources, information skills and risks to generate benefits that they cannot generate individually (Van Huijstee et al., 2007; Audy et al., 2012; Bauer and Steurer, 2014). In humanitarian supply chains, establishing partnerships with different actors (e.g., private sector companies, local relief agencies, governments) can help reduce costs and increase the speed of operations through different stages of a disaster (Tomasini and Van Wassenhove, 2009). The collaborations can be in the front-office (response) or in the back-office (preparedness) depending on the core competencies and assets exchanged (Tomasini and Van Wassenhove, 2009). Both vertical (with other organizations in upstream or downstream supply chain) and horizontal (with other organizations at the same level within the chain) partnership opportunities are pursued over information sharing, needs assessment, resource mobilization, joint procurement, transportation, warehousing, or last-mile delivery (Moshtari, 2016).

The literature on partnerships in the humanitarian operations and disaster management (HODM) field is rich in the sense that the necessities, benefits and challenges associated with coordination or collaboration among different actors have been well studied (e.g., Balcik et al., 2010; Tatham et al., 2010; Bealt et al., 2016; Wagner and Thakur-Weigold, 2018; Nurmala et al., 2018; Wankmüller and Reiner, 2020). While most of the existing papers conceptually discuss the collaborative approaches from different perspectives, in recent years, there has also been an increase in the number of analytical studies on collaborative approaches implemented over a variety of tasks during different stages of a disaster. Most of the existing work focuses on showing the benefits of collaboration and presenting methodologies for cost sharing and decision making under collaboration.

Game theory, which is a powerful tool for modeling the interactions of independent decision makers, has been used to analyze various types of horizontal partnerships among humanitarian agencies (Muggy and Stamm, 2014). Game theory comprises two branches. Non-cooperative game theory models how players should rationally make decisions in a setting where they cannot make binding agreements, whereas cooperative game theory models how agents cooperate as coalitions to create value and possibly make agreements (Chatain, 2016). The number of studies on humanitarian partnerships via both game theoretical frameworks has been increasing in recent years (see reviews by Coles and Zhuang, 2011; Muggy and Stamm, 2014; Seaberg et al., 2017). For instance, Ergun et al. (2014) present a cooperative model to allocate the costs and benefits of using information technology tools to improve last-mile supply distribution and data management in the camps for internally displaced persons. The camps that collaborate and form a coalition adopt the same registration system and share information with each other. The proposed cooperative game theory model for the allocation of joint investment costs among different camps is illustrated on an example based on eight camps established during the 2010 Haiti earthquake response. Nagurney et al. (2016) present a generalized Nash equilibrium network model for post-disaster relief distribution conducted by non-governmental organizations, which gain utility by providing relief supplies to victims of the disaster while competing with each other for donations. The authors illustrate their model on a case study based on Hurricane Katrina. Toyasaki et al. (2017) use non-cooperative game theory to explore the horizontal cooperation of multiple agencies to manage their inventories in a joint United Nations Humanitarian Response Depot (UNHRD) by exchanging stocks after a disaster. The authors analyze member humanitarian organizations' incentives for joining the network. Coskun et al. (2019) also focus on two agencies sharing stocks in a joint depot and present a non-cooperative game theory model in which agencies make stocking decisions independently. The authors optimize the stock quantity for each agency in response to the other's quantity and compute a Nash equilibrium solution numerically. The proposed approach is applied to the case of earthquake preparedness in Istanbul to optimize the stocking decisions of an agency for shelter units in cooperation with another agency.

There is an increased awareness in the humanitarian community of the benefits of collaborative practices. Indeed, donors such as the European Commission Humanitarian Aid (ECHO) are not only promoting and investing in emergency preparedness, but are explicitly expecting their partners to work together on joint logistics efforts to improve impact and efficiency (Lawry-White et al., 2018). Despite their high potential to improve supply chain efficiency and increase operations' impact for beneficiaries (reactivity, quality, and coverage) (Lacourt and Radosta, 2018), collaborative prepositioning networks have not yet received much attention. There are few studies that explore stock sharing practices among agencies. Toyasaki et al. (2017) and Coskun et al. (2019) focus on stock sharing among multiple agencies in one depot. Acimovic and Goentzel (2016) consider a prepositioning network in which several agencies preposition inventory at different locations and show that the system can be improved through coordination of inventory repositioning.

In contrast to the existing studies, we focus on cost sharing in a collaborative prepositioning network in which multiple Caribbean countries horizontally partner for disaster preparedness, and the partnership is coordinated by a central agency. This was the setting considered in Balcik et al. (2019), who presented a mathematical model for this problem and showed that significant savings can be achieved by reducing the amount of inventory and corresponding investments through collaborative prepositioning. Here we address the question of sharing the costs associated with establishing and operating this multi-country partnership network among the partners by now considering the risks and economic welfare of the countries and comparing the results obtained by this approach with classic cost sharing mechanisms proposed in the literature.

Global partnerships involving multiple countries are observed in other areas than disaster preparedness and response. Indeed, managing complex social, economic and environmental problems through partnership-based arrangements has become increasingly popular in the last 20 years (Harman et al., 2015). For example, partnerships among different stakeholders in global health are increasing as no single country or organization can fight complex epidemics alone (Johnson et al., 2018). Moreover, there exist multilateral organizations, funded by multiple governments, that support projects in various developing countries to fight diseases such as AIDS, tuberculosis, and malaria (Johnson et al., 2018). Moreover, some multi-governmental collaboration initiatives are being pursued to cover the heavy investment in the research, development, production and distribution of vaccines, for instance in Africa (Songane, 2018). Furthermore, a fair allocation of the multilateral climate change adaptation funding among the most vulnerable countries, such as the small island states in the Caribbean and several African countries, to cover costs such as infrastructure investments, is important given the scarcity of resources and uncertainties regarding future potential impacts (Robinson and Dornan, 2017). In such global partnerships, it is important to evaluate costs and benefits, and distribute funds by implementing effective and transparent cost sharing mechanisms that account for all relevant factors of the countries, such as population, per capita income, and vulnerability. Our study presents an alternative analytical framework for making collaborative decisions in a multi-country partnership. In particular, our analysis shows how insurance schemes may be adapted to support long-term stability of other global partnerships.

2.2. Cost allocation methods in collaborative logistics

Analytical approaches that support horizontal collaboration in various supply chain and logistics activities, such as warehousing, transportation, and distribution, have been widely implemented and studied. It has been shown that collaborative practices can decrease costs, increase service level and market share, and reduce the consequences of the bullwhip effect (Audy et al. 2012). The literature on measuring the benefits created by collaborative activities and sharing the benefits and costs created by collaboration is rich. Cruijssen et al. (2007), Guajardo and Rönnqvist (2016) and Gansterer and Hartl (2018) review the related literature on cooperation in transport and logistics.

Cost allocation is one of the main challenges faced when implementing a collaboration, and it is vital to fairly distribute costs and benefits among the partners to sustain a partnership. Cost sharing problems are prevalent in the public sector, such as public transport (Ralf and Hoang, 2015) and health services (Martin and James, 2002), as within private enterprises, e.g., sharing the overhead cost in a multi-divisional firm (Maurice, 2002). In fact, sharing occurs in several collaborative contexts and can be based on a variety of methodologies. For instance, Guajardo and Rönnqvist (2016) identify over 40 different cost allocation schemes applied to collaborative transportation problems. There is widespread agreement that no single cost allocation method works best to achieve a fair cost allocation in all situations. As pointed in Audy et al. (2012), in order to choose or develop a cost allocation method, it is necessary to seek one that satisfies specific characteristics considered essential in the context of the collaboration. Most available cost allocation methods for a particular context are modified versions of the traditional allocation methods obtained by adding new additional desirable properties. Since the concept of a fair distribution depends on the nature of each problem, methods developed to address a specific feature of the problem usually outperform alternative methods that may not directly account for its critical characteristics.

Proportional allocation methods are commonly used since they can be easily understood, computed and implemented (Özener and Ergun, 2008; Liu et al., 2010). In these methods, each partner is assigned a share of the total cost, based on a weight defined according to a specific criterion, such as demand volume or travelled distance. However, most studies use concepts and sharing methods based on cooperative game theory such as the Shapley value and the nucleolus (Audy et al., 2012; Guajardo and Rönnqvist, 2016; Gansterer and Hartl, 2018). According to Guajardo and Rönnqvist (2016), the most traditional method being the Shapley value which provides an allocation that satisfies certain axioms by which equal players obtain equal consideration. The nucleolus procedure lexicographically maximizes the minimal excess and yields a unique cost allocation that belongs to the core if it is not empty. The excess is understood as a degree of satisfaction of the coalition with the allocation and can be measured as the difference between the stand-alone cost and the cost allocated to the participant. A frequent approach is to use allocation techniques with additional specific properties that are inherent to game theory. For instance, some authors propose methods based on separable and non-separable costs, where the separable cost of a partner captures the increase of the total cost allocated to a partner who joins the coalition, whereas the non-separable costs are allocated among all partners. Tijs and Driessen (1986) propose three ways of allocating the non-separable cost: the equal charge method (ECM) where the non-separable costs are divided between all partner equally, the cost gap method (CGM) where the weights to allocate the non-separable cost are computed proportional to the non-separable cost of the best coalition in which each partner can be, and the alternative cost avoid method (ACAM) where the weights are based on the saving that each partner makes by joining the partnership. Some allocation methods focus on ensuring similar benefits among all participants. For instance, Frisk et al. (2010) and Liu et al. (2010) propose cost allocation methods where the maximum difference in pairwise relative savings is minimized.

A difficulty to overcome in cost allocation is the computational effort required to implement most of the methods in cases with several partners (i.e the Shapley value, the nucleolus, or the EPM), which may hinder their applicability. Only a limited number of papers deal with partnerships having more than 15 participants. Göthe-Lundgren et al. (1996) and Engevall et al. (2004) propose computational approaches to compute the nucleolus in a vehicle routing problem with 25 and 21 partners, respectively. Flisberg et al. (2015) also adapt the nucleolus for cost sharing among 29 partners in a transportation planning setting. Dahl and Derigs (2011) and Özener (2014) present new proportional methods based on real cases where up to 50 partners are involved. Özener et al. (2013) consider a vendor managed inventory problem and develop methods to compute cost-to-serve values among 25–80 partners by using a Shapley approximation. Altan and Özener (2019) propose four cost allocation mechanisms in a peer-to-peer network, namely dual linear programming, an approximation of the Shapley value, a partition-based mechanism, and an approximation to the nucleolus in order to allocate costs in instances that include up to 40 partners.

Among the problems that apply cost allocation methods in collaborative supply chain settings, the one that is most related to our study is the cooperative facility location problem, in which partners share their distribution centers, and out of a given set of potential locations, an optimal set of facility locations must first be selected and then the total cost is allocated among customers or carriers in a fair manner (e.g., Tamir, 1993; Goemans and Skutella, 2004; Verdonck et al., 2016). Specifically, the goal is to allocate the optimized location costs to the customers so that no coalition of customers has the incentive to build its own facilities or to ask a competitor to service them (Goemans and Skutella, 2004). A variety of traditional or problem-based cost allocation methods are implemented to solve this allocation problem. Another related problem where cooperative game theory cost allocation methods are used in horizontal collaborative settings arises in spare part inventory sharing (e.g., Wong et al., 2007; Karsten and Basten, 2014; Guajardo and Rönnqvist, 2015), in which several locations cooperate by pooling their inventories and lateral transshipments are used to satisfy demands. Several game-theoretical allocation methods are used to share the pooling benefits in numerous inventory planning settings. For instance, Kemahlıoğlu-Ziya and Bartholdi (2011) use the Shapley value to allocate expected excess profit because of pooling. In contrast with these streams of literature that specifically focus on facility location and inventory planning, our study focuses on a network design problem that involves location, inventory and transportation decision and costs, and demand results from uncertain disaster event occurrences. Each partner is randomly affected by possible disasters, and the associated demand must be fully satisfied from the joint stocks. Moreover, an equitable cost allocation solution in our case must incorporate disaster risks along with the economic welfare of the actors, which are not considered in the usual cost allocation problems and methodologies.

In summary, this study contributes to the related literature by introducing a new cost sharing problem that arises in a multi-country partnership setting where both disaster risks and economic welfare of the partner countries must be considered in determining country shares. We develop an effective and easy-to-compute insurance-based method for cost sharing in a collaborative prepositioning network involving several actors. We also present a methodology for adapting and implementing the traditional cost allocation methods for the problem. We compare the structural properties and performance of the alternative methods in terms of achieving equitable allocation, and we present a numerical study to analyze the behavior of the proposed method and the partnership benefits in the Caribbean network.

3. Cost Allocation in Collaborative Prepositioning Network Design

Here we first describe the characteristics of the logistics system studied in the context of our problem and the current cost allocation practices of CDEMA (§3.1). We then define the collaborative prepositioning network design problem based on Balcik et al. (2019) and we describe our methodology (§3.2). Finally, we present several cost allocation mechanisms to determine country contributions associated with the collaborative network and we discuss their structural properties (§3.3).

3.1. System's Description

To deal with the negative consequences of the severe weather events in the Atlantic, predicted to increase in the coming years as a result of climate change, the Caribbean Community has been developing strategies to strengthen regional integration for effective disaster preparedness. We consider the regional collaborative prepositioning network operated by the inter-governmental organization CDEMA, in which emergency relief supplies are currently stored in four sub-focal countries (Antigua and Barbuda, Barbados, Jamaica, and Trinidad and Tobago) and used to serve the countries affected by disasters. The costs associated with this network are covered from CDEMA's disaster preparedness and emergency response budgets. The 18 participating states, depicted in Figure 1 of Appendix A, have signed a set of agreement terms for regional cooperation, which involve contributing to the total disaster management budget of CDEMA. In order to develop a viable regional partnership, it is important for CDEMA to apply a transparent and equitable cost allocation mechanism acceptable to all partner countries.

Under the current system, in order to allocate the required budget among the member countries, CDEMA follows a contribution scheme based on a simple method, which involves first grouping countries by considering their demographical (i.e., population) and economical data (e.g., gross domestic product (GDP) or gross national income (GNI)), and then setting a contribution percentage for each group of countries. In CDEMA's current contribution scheme, there are three groups of countries. Groups #1, #2 and #3 include five, nine and four countries, respectively. The contribution percentages by country are identical for all countries of the same group, and are set to 8.1%, 5.4% and 2.7% for Groups #1, #2 and #3, respectively. Specifically, CDEMA applies a so-called 3:2:1 weighted policy, in which each unit of contribution is worth 2.7%, which is then weighted by a factor of 3, 2 or 1. That is, every country in Group #3 pays a single unit of contribution, while every country in Group #2 pays twice that amount, and every country in Group #3 pays three times. As a result, the total percentage budget paid by the countries in Group #1, #2 and #3 are about 40%, 49% and 11%.

We focus on the budget allocation problem of CDEMA and apply and compare more sophisticated methodologies in order to determine the country contributions for sharing the costs associated with the design and operations of a collaborative regional prepositioning network for hurricane preparedness. In our approach, in addition to the demographical and economic characteristics of the countries, we also consider the risk exposure of the countries to hurricanes, which is not incorporated explicitly in the current budget allocation scheme of CDEMA.

In general, for any collaborative disaster preparedness framework with multiple partners to be viable, i) the outcomes and impact of the partnership must be greater than the sum of what each actor can achieve alone (Stibbe et al., 2020), ii) each individual partner must achieve a net benefit from the partnership (Stibbe et al., 2020), and iii) there must be an adequate and transparent financing mechanism, in which the benefits and costs are shared equitably between the countries, where equity (fairness) may need to be defined depending on the specific context. In particular, given the significant differences among the profiles of these Caribbean countries both in terms of demographics, risk exposure and economic welfare, equity here needs a unique interpretation compared with its traditional use in cooperative game theory. Specifically, in the cooperative game theory literature, while there exists no consensus on the definition of equity, the concept of "core" is accepted to represent the highest form of fairness, which implies that no subset of the partners should have an incentive to leave the coalition and form another one. Moreover, if the core does not exist (or may not be easily computed), an approximate allocation is sought, and it is assumed that the closer is the approximation to the core, the fairer is the allocation (Altan and Özener, 2019). In the Caribbean collaborative prepositioning network, it may not be reasonable to aim for a fair solution in the traditional sense in terms of the core for two reasons. First, even before making any computations, one can easily observe that extremely risky and highly populated counties like Haiti may not be desirable partners due to the cost they will add to the partnership. That is, a core solution may not exist for such network. However, even if some countries may bring an extra burden, they should be kept in the partnership for better regional integration and local capacity strengthening; so we may be looking for a "fair" solution beyond what the core would usually imply. Second, even if there may be a setting in which a core allocation existed in terms of disaster risks, we also want to account for the ability to pay; that is, we must consider economic welfare of the countries, which may lead to a solution that is even farther from the core. Nevertheless, while the wealthier but still risky CDEMA countries such as Barbados, Bahamas and Trinidad and Tobago may be willing to financially support the most vulnerable countries like Haiti and the small island states, the additional financial burden for these wealthier countries must not make the partnership more costly for them than acting alone. Therefore, determining country contributions to cover the budget required for establishing a collaborative prepositioning network is not straightforward in this setting, but important for achieving effective regional integration. In §3.2, we describe a mathematical model and alternative cost sharing methods that can be used to determine country contributions in a multi-country collaborative prepositioning network to sustain a regional partnership for disaster preparedness.

3.2. Problem Definition and Modelling Approach

The collaborative prepositioning network design problem, introduced in Balcik et al. (2019), involves determining i) the locations and the amount of relief stocks to hold in the network so that the emergency needs of the affected member states can be met quickly throughout a hurricane season, ii) the total initial investment needed to establish the network, which involves disaster preparedness and emergency response budgets, and iii) the allocation of the total initial investment among the partners (state members) and determining their cost contributions. Since each hurricane season may involve multiple events occurring at different times, and each event may affect multiple countries, risk pooling benefits occur as a result of collaborative prepositioning. The objective of the decision-maker (CDEMA) is to establish a prepositioning network that holds enough inventory of relief items so that the demands of the affected countries can be satisfied within a desired response time via air or sea shipments, while minimizing the sum of the annualized disaster preparedness costs generated by the initial network design (i.e., fixed warehouse costs, material purchasing and holding costs) and the emergency response costs equal to the expected costs that may occur over a hurricane season (i.e., transportation and stock replenishment costs). Note that for CDEMA to be prepared to respond to any possible event, it needs to hold sufficient financial resources to cover the emergency response costs to satisfy the demands associated with the "worst" possible event. That is, the total expected annualized costs, which are minimized when designing the network, are different from the total initial investment required to create disaster preparedness (B_0) and from the emergency response budgets (B_1), which are shared among all the member countries to sustain the network.

Balcik et al. (2019) formulated the collaborative prepositioning network design problem in which the prepositioning network design decisions are linked with the cost allocation decisions via an insurance-inspired framework. Accordingly, the total initial investment required to design and manage the prepositioning network is endogenously allocated among the countries and the country cost shares (premiums) are based on the expected value and on the standard deviation of the demand. In this paper, we extend the problem setting of Balcik et al. (2019) by including the concerns of CDEMA to consider the economic profiles of the countries in the cost allocation schemes. Furthermore, in order to implement alternative cost allocation methods and compare their performance, we present an alternative modelling approach, which involves first identifying the minimum cost prepositioning network design solution by solving a centralized prepositioning network design problem (CenPNDP), and then allocating the total initial investment required to establish and manage this network among the partner countries by solving a cost allocation problem (CAP). To decompose the integrated model proposed by Balcik et al. (2019) into network design and cost allocation subproblems, we also present a new objective function. This allows to compare different cost allocation methods.

In the CenPNDP, we consider a set of demand locations (countries), which may be affected by multiple disasters that may occur throughout a hurricane season. There exists a set of warehouse locations (countries) where the relief supplies (family kits) will be prepositioned. Each warehouse has a maximum capacity, and multiple warehouses can be opened in each selected country. When a disaster occurs, the affected countries are served from a warehouse via sea or air shipments. The transportation costs and times differ across the modes and the transportation costs depend on the number of fully-loaded vehicles (e.g., airplanes) used, as well as on the total number of kits that are shipped. If a warehouse is located in a country affected by a disaster, the stock in that warehouse may not be available since it can be damaged, and transportation from an affected country may not be arranged during the initial chaotic days after the disaster. Replenishment orders are immediately given for the used or damaged supplies, which arrive after a fixed lead time. The CenPNDP determines the number and locations of warehouses to place in the network as well as the amount of supplies to preposition in each warehouse by minimizing the annual equivalent of the total initial investment (i.e., the fixed cost for locating warehouses, the purchasing and holding costs for family kits, the investment required to cover the transportation and replenishment costs associated with the worst-case scenario), and the expected emergency response cost.

To model the CenPNDP, the uncertainty associated with the storm events that may occur in a hurricane season is modelled by means of a set of discrete scenarios. We use a two-stage stochastic programming framework (Birge and Louveaux, 2011), in which the first-stage decisions (i.e., the locations of warehouses and inventory levels) are determined by considering the expected costs associated with recourse decisions (i.e., the transportation of relief supplies to meet demands) made under each hurricane scenario. In Appendix B, we present the CenPNDP mathematical model, which is modified from Balcik et al. (2019) by formulating a new objective function and piecewise linear transportation costs. More specifically, the objective function of the CenPNDP does not involve any cost allocation component. Instead, it assumes a return on investment rate over a fixed payback period and accordingly minimizes the annual equivalent of the total investment cost in addition to the expected response cost. Moreover, in contrast to Balcik et al. (2019), who only use flow variables to model the second stage transportation decisions and charge per unit transportation cost, we additionally consider a fixed shipment cost in the second stage associated with the number of different types of capacitated airplanes hired to carry supplies between countries. That is, air transportation costs do not linearly increase in the CenPNDP.

The resulting total initial investment of a CenPNDP solution involving a set C of countries, which is denoted by $\zeta(C) = B_0 + B_1$, must be shared among the countries by considering country risks and economic welfare levels. We apply four alternative cost allocation methods adapted from existing techniques to solve the CAP and set country premiums. The cost allocation methods used to determine country shares are presented in §3.3.

3.3. Cost Allocation Methods

In this section, we present four cost allocation methods used to solve the CAP. First, we present our new insurance-based scheme, which extends the cost sharing method presented in Balcik et al. (2019). We then explain the cost allocation methods to solve the CAP adapted from the literature, i.e., the Shapley value (Shapley, 1953), the equal profit method (EPM) (Frisk et al., 2010), and the alternative cost avoided method (ACAM) (Tijs and Driessen, 1986). While there exist numerous other ways to implement cost allocations in a collaborative contexts (e.g., see Guajardo and Rönnqvist, 2016), we chose these three traditional methods because they can be readily adapted, they are intuitively appealing, and they do not require extensive data (Verdonck et al., 2016).

Let C be the set of all countries and let Ω be the set of all the subsets of C (subcoalitions). Then, the cost of a subcoalition $\Lambda \in \Omega$ is defined by the characteristic function $\zeta : \Omega \rightarrow \mathbb{R}$, which is calculated by solving the CenPNDP for the partners involved in coalition Λ. As mentioned previously, the total budget to be allocated among the countries corresponds to the total initial investment (i.e., the budget required to cover disaster preparedness network cost, plus the worst-case emergency response cost). The objective of the CAP is to divide $\zeta(C)$ among the partner countries by considering their expected value and the standard deviation of their demands, denoted by $E(D_c)$ and $\sigma(D_c)$, respectively, and an economic indicator, which is represented by their gross national income, denoted by GNI. Additionally, the premium paid by country $c \in C$ is denoted by Y_c, and the total premiums from the partner countries must cover $\zeta(C)$, i.e., $\sum_c Y_c = \zeta(C)$.

3.3.1. Insurance-based Method. We propose a cost allocation method inspired by the catastrophic insurance theory, which differs from the standard insurance plans (such as those for health care and car accidents) in that the premiums computed solely based on the expected losses cannot usually cover the massive catastrophic losses. Moreover, in catastrophic insurance, since the number of insurees is typically smaller and their losses are correlated, diversifying risks to achieve risk pooling benefits is more difficult for the insurers (Duncan and Myers, 2000). Therefore, the premiums are high relative to the expected losses (Froot, 2001). It is common to add a safety margin to the pure premiums based on expected risk, which are proportional to the standard deviation of the risk (Deelstra and Plantin, 2014). In the proposed insurance-based cost allocation method, each country's premium also covers the costs associated with its expected demand, similar to what was done in Balcik et al. (2019). However, since premiums based on expected costs may not cover the required budget for disaster preparedness and emergency response, we add a safety margin proportional to the standard deviation of the risk and GNI of the country. Our approach is similar to the one used in the integrated prepositioning model of Balcik et al. (2019); however, we additionally include the GNI of the countries in the cost allocation, which leads to a multi-objective cost allocation model.

We present a linear programming (LP) model that allocates $\zeta(C) = B_0 + B_1$ among the countries and sets the Y_c values by minimizing a maximum deviation variable Z. Specifically, by minimizing Z, we minimize the amount of extra investment a country will make beyond the costs associated with its expected demand. The dimensionless variable Z represents the extra investment that each country $c \in C$ will pay proportionally to its normalized standard deviation, denoted by $\widetilde{\sigma(D_c)}$, which is a measure of risk representing the volatility of its demands across different hurricane seasons, and its normalized GNI, represented by $\widetilde{GNI}$, which represents the country's economic welfare level. In our model, for each $c \in C$, we scale the standard deviation and GNI parameters by using an unity-based normalization; i.e., the normalized standard deviation of demand and GNI are calculated as: $\widetilde{GNI_c} = (GNI_c - \min_{c\in C}(GNI_c))/(\max_{c\in C}(GNI_c) - \min_{c\in C}(GNI_c))$, and $\widetilde{\sigma(D_c)} = (\sigma(D_c) - \min_{c\in C}(\sigma(D_c))/(\max_{c\in C}(\sigma(D_c) - \min_{c\in C}(\sigma(D_c))$. To control how much weight to give to the risk and economical factors, we also define two weights for the standard deviation and the GNI parameters, which are denoted by $\theta_{risk} \in [0, 1]$ and $\theta_{GNI} \in [0, 1]$ respectively, where $\theta_{risk} + \theta_{GNI} = 1$. Finally, we define an estimated average per unit logistics cost parameter b (covering prepositioning and shipping costs of one family kit in the network), which is computed based on the solution of the CenPNDP. The insurance-based cost allocation model (InsBased) is presented below:

$$\text{minimize} \quad Z \tag{1}$$

subject to

$$\sum_{c\in C} Y_c \geq \zeta(C) \tag{2}$$

$$bE(D_c) \leq Y_c \leq bE(D_c) + b(\theta_{risk}\widetilde{\sigma(D_c)} + \theta_{GNI}\widetilde{GNI_c})Z \qquad c \in C \tag{3}$$

$$Z \geq 0 \tag{4}$$

$$Y_c \geq 0 \qquad c \in C. \tag{5}$$

Constraint (2) guarantees that the country premiums cover the total initial investment. Constraints (3) bound the country premiums. They also ensure that each country premium covers at least the estimated cost of its expected demand. In addition, each country premium is bounded by the sum of the cost of its expected demand and a cost proportional to a trade-off between the standard deviation of its demand and its GNI. Finally, constraints (4)–(5) define the variable domains. Solving the InsBased is computationally easy, which makes this method attractive compared with classic cost allocation methods. Moreover, some desirable allocation properties such as efficiency and symmetry are satisfied by this insurance-based cost allocation method (see Appendix C).

3.3.2. Alternative Cost Avoided Method (ACAM). The ACAM proposed by Tijs and Driessen (1986) is based on the distinction between separable and non-separable costs. Each partner contributes to its separable cost, and the non-separable cost is distributed between all the participants according to given weights. The separable cost of a participant c, denoted by m_c, corresponds to its marginal cost with respect to the grand coalition and is computed as $\zeta(C) - \zeta(C \setminus \{c\})$. If the sum of the separable costs of all the participants do not cover the cost of the grand coalition, the remaining cost is considered to be non-separable and is shared among the participants proportionally to their savings made by joining the grand coalition with respect to their stand-alone cost. According to the ACAM, the country premiums can be computed as

$$Y_c = m_c + \frac{\zeta(c) - m_c}{\sum_{c'=1}^{|C|}(\zeta(c') - m_{c'})}\big(\zeta(C) - \sum_{c'=1}^{|C|} m_{c'}\big) \qquad c \in C. \tag{6}$$

Implementing ACAM requires computing $2|C|+1$ subcoalition costs. Therefore, dividing $\zeta(C)$ among the countries requires a reasonable computational effort. Moreover, the cost allocation scheme provided by the traditional ACAM satisfies the properties of efficiency and symmetry, but does not ensure stability since the method does not take into account other coalitions that include one or $|C|-1$ participants (see Appendix C).

3.3.3. Shapley Method. The Shapley value is a well-known cost allocation method from cooperative game theory. The allocation is based on the average marginal contribution of the partners to a coalition. Hence, each partner contributes according to the average of its contributions to all possible joining orders to form the grand coalition, assuming it is formed by adding the participants one by one. The country premiums are computed as

$$Y_c = \sum_{\Lambda \subseteq C \setminus \{c\}} \frac{(|\Lambda|-1)!(|C|-|\Lambda|)!}{|C|!}[\zeta(\Lambda \cup \{c\}) - \zeta(\Lambda)] \qquad c \in C. \tag{7}$$

The Shapley value is generally considered one of the best methods for determining a fair distribution because it satisfies four properties: efficiency, symmetry, dummy, and additivity. Furthermore, it provides a unique cost allocation of the country contributions. Despite some desirable properties of the Shapley value (see Appendix C), the time required to compute it when there are several partners is significant due to the exponential effort needed to calculate the marginal contributions. Therefore, it may not be possible to find a solution when there are many partners, as is the case for the Caribbean.

3.3.4. Equal Profit Method (EPM). The EPM aims to allocate costs by minimizing the maximum difference in pairwise relative cost savings. This allocation requires to solve the following problem:

$$\text{minimize } f \tag{8}$$

subject to

$$f \geq \frac{Y_c}{\zeta(c)} - \frac{Y_c'}{\zeta(c')} \qquad c, c' \in C \tag{9}$$

$$\sum_{c \in \Lambda} Y_c \leq \zeta(\Lambda) \qquad \Lambda \in \Omega \tag{10}$$

$$\sum_{c \in C} Y_c = \zeta(C). \tag{11}$$

Constraints (9) measure the largest profit difference between pairs of participants to be minimized. Inequalities (10) ensure that the cost allocation is such that no subcoalition Λ exists in which a set of partners would be better off, and no single partner or subcoalition of partners would benefit from leaving the grand coalition. Hence these constraints ensure stability. Constraint (11) guarantees that the total cost is shared between all the partners in the grand coalition, which ensures efficiency. Another important characteristic of the EPM is that it provides a solution only if the core is non-empty, and if so, a stable solution is guaranteed. Despite the properties of EPM (see Appendix C), computing the solution involves significant computational challenges, similarly to Shapley.

As discussed above, significant differences exist between the computational efficiency of the different cost allocation methods. Specifically, while it is relatively easy to compute premiums via the insurance-based method and the ACAM, it is not computationally feasible to directly solve the CAP by using the Shapley value or the EPM for all CDEMA partners, which cover 18 countries. Therefore, we present a clustering-based approximation heuristic to evaluate the Shapley value and the EPM in order to solve the CAP. Another important issue is that only the insurance-based method can be directly applied to determine country premiums by considering the risk and economic factors; the other cost allocation methods need to be adapted to incorporate these important factors. That is, the standard implementation of ACAM, EPM and Shapley presented above would not consider the differences in the ability of countries to pay the premiums. In §3.3.5, we present a clustering-based method to adapt the Shapley value, the ACAM, and the EPM to solve the CAP and incorporate the economical factors in setting country premiums.

3.3.5. Cluster-First-Divide-Second Heuristic for ACAM, Shapley and EPM. Given the 18 participating states of CDEMA, determining country premiums based on the Shapley value and on EPM requires solving the CenPNDP for each of the 2^{18} possible subcoalitions $\Lambda \in \Omega$, in order to obtain all the required costs $\zeta(\Lambda)$. That is, since the computational complexity increases exponentially with the number of actors in the coalition, these allocation methods cannot be directly applied to realistic-size instances. It is common to implement approximate methods to ease the computation burden (e.g., Fatima et al., 2008; Castro et al., 2009; Altan and Özener, 2019). While implementing the ACAM within a reasonable computational effort is possible, in its pure form, it does not account for the differences in the GNI levels of the partner countries.

Inspired by the simple method applied by CDEMA to assign country premiums, as explained in §3.1, we develop a cluster-first-divide-second heuristic to solve the CAP. This method first clusters the countries based on their risk (i.e., expected value and standard deviation of demand) and economic levels (i.e., GNI) by using a K-means algorithm (see Appendix D) and solves the CAP on the clusters as opposed to the individual countries. It then applies seven policies to divide the total cluster premium among the cluster's countries. Let K be the set of countries in a given cluster, and let $\hat{Y}_K$ represent the total cluster premium. Similarly, $E(D_K)$ and $\sigma(D_K)$ correspond to the expected value and the standard deviation of the demand for cluster K, which have also been normalized across the clusters. Table 1 presents the policies we have implemented to distribute $\hat{Y}_K$ among the clustered countries and then set the country premiums Y_k. As described in Table 1, Policy #1 simply divides the premiums equally among the cluster countries, while the other policies consider one or several of the relevant allocation factors (expected demand, standard deviation of the demand, and the GNI). The fairness of the premiums is based on whether they reflect the country profiles in terms of risk exposure and economic welfare. Thus, in order to better capture the country profiles, we propose several policies based on these factors.

4. Computational Study

In this section, we present the result of the computational study we have performed to assess the behavior of the different cost allocation methods. In §4.1, we describe our data set and explain the implementation details of our approach. In §4.2, we present our numerical results and analysis. In §4.3, we discuss the managerial implications of the results.

4.1. Data Set and Implementation Details

We have tested different cost allocation methods on a data set that includes the 18 members of CDEMA (Appendix A). The instance used in the computational study was adapted from Balcik et al. (2019), who gathered and processed historical hurricane data for this region. The resulting data set involves 310 equiprobable scenarios, where each scenario corresponds to a possible hurricane season including information related to the countries affected by each event,

Table 1 Policies applied to divide the cluster premium into country premiums.

#	Policy name	Premium allocation rule	Allocation policy description
1	PEqu	$Y_k = \hat{Y}_K/\lvert K\rvert$	Allocate equally among the countries in the cluster.
2	PE	$Y_k = \hat{Y}_K \frac{E(D_k)}{E(D_K)}$	Allocate proportionally to the expected demand of each country.
3	Pσ	$Y_k = \hat{Y}_K \frac{\sigma(D_k)}{\sigma(D_k)}$	Allocate proportionally to the standard deviation of the demand of each country.
4	PGNI	$Y_k = \hat{Y}_K \frac{GNI_k}{GNI_K}$	Allocate proportionally to the GNI of each country.
5	PEσ	$Y_k = \hat{Y}_K \frac{E(D_k)+\sigma(D_k)}{E(D_K)+\sigma(D_K)}$	Allocate proportionally to the expected demand and the standard deviation of the demand of each country.
6	PEGNI	$Y_k = \hat{Y}_K \frac{\widetilde{E(D_k)}+\widetilde{GNI_k}}{\widetilde{E(D_K)}+\widetilde{GNI_K}}$	Allocate proportionally to the expected demand and the GNI of each country.
7	PEσGNI	$Y_k = \hat{Y}_K \frac{\widetilde{E(D_k)}+\widetilde{\sigma(D_k)}+\widetilde{GNI_k}}{\widetilde{E(D_K)}+\widetilde{\sigma(D_K)}+\widetilde{GNI_K}}$	Allocate proportionally to the expected demand, the standard deviation of the demand and the GNI of each country.

the impact of the event, and the targeted demand values per country which are generated based on country's population and the impact of the event. To prevent the model from prepositioning an excessive amount of supplies, the demand per event per country is limited by 12,000 family kits for each country, which is aligned with the coverage targets of the IFRC Panama that operates in the region. Furthermore, to avoid large investments due to extreme scenarios, which results in an excess of infrequently used stock and in increased damage or spoilage risks, 5% of the worst-case scenarios are removed.

The logistical data for the CDEMA network, which includes material costs, warehouse location and operating costs, travel times and costs in the networks, are also obtained from Balcik et al. (2019). Differently, we consider two types of capacitated airplanes (i.e., midsize aircraft and charter), and air transportation costs are modified by considering fixed and variable costs separately to encourage using the full airplane capacity. The minimum demand to be satisfied over the first three days is 10%, we assume a replenishment lead time of two weeks. Finally, if a country with a warehouse is hit by a hurricane, the percentages of damaged supplies are assumed to be 0%, 20%, and 50% for the categories corresponding to moderate, strong, and highly strong events, respectively. In this study, we represent the economic welfare of the countries based on their GNIs. The GNI data for the CDEMA countries were obtained from United Nations Statistics Division (2017). We present the data related to risk and GNI profiles of each country in Table 4 (Appendix A).

Given the Caribbean network data and disaster scenarios, the optimal prepositioning network design solution obtained by solving the CenPNDP model (Appendix A) involves six warehouses, which are located in Dominica (two warehouses), Grenada (one warehouse), Guyana (two warehouses) and Jamaica (one warehouse). A total of 69,826 kits are prepositioned in the network when the yearly interest rate is $\gamma = 4\%$ and the payback period is $n = 7$ years. The required total initial investment associated with this network is 33,398,719 USD, which decomposes into 11,664,135 USD for the disaster preparedness budget (B_0) and 21,734,584 USD for the emergency response budget (B_1). The resulting average logistics cost per family kit is $b = 183.53$ USD.

We next implement the proposed cost sharing methods to allocate the total initial investment associated with this CenPNDP solution among countries and set premiums. Implementing the insurance-based method is straightforward as it requires solving an LP (§3.3.1). However, as discussed in §3.3.5, the alternative cost sharing methods EPM, Shapley value and ACAM are implemented by using a cluster-first-divide-second heuristic to deal with computational difficulties and account for countries' wealth considerations. Therefore, we first cluster the countries based on their risk and GNI profiles by using a K-means algorithm (see Appendix D) and then apply different premium allocation methods within each cluster (Table 1). The clusters of each CDEMA country obtained by our algorithm are presented in the last column of Table 4 (Appendix A) and depicted in Figure 9 (Appendix D).

The CenPNDP model, the insurance-based method, and the EPM were implemented in Java Concert Technology. We used IBM CPLEX 12.7 with a one-hour time limit for each instance with default parameter settings. All instances were solved to optimality within less than one hour. The Shapley value and the ACAM computations were made in Octave 4.4.1. All experiments were run on a 2.80 GH Intel Core i7 machine with 16 GB of memory.

4.2. Results and Analyses

In this section, we first present the key performance indicators (KPIs) used for analyzing the equity of the cost allocation solutions. We then present results that focus on evaluating the benefits of the partnership, analyzing the proposed insurance-based method, and comparing alternative methods.

4.2.1. Performance indicators for solution comparison. In order to compare the quality of the different cost allocation methods and policies, we propose and use a series of KPIs to evaluate the equity of the cost distribution among the participants. The KPIs are defined based on the average, the standard deviation and the Gini coefficient of eight attributes, denoted by $\mathcal{A}$ and summarized in Table 2. The function used to determine the KPI value of country c, denoted by $\mathcal{A}_c$, are also presented in Table 2.

As discussed in Schilling (1994), there are numerous ways of measuring equity. In our context, considering a fair cost allocation among countries, their premiums should reflect their profiles in terms of risk exposure and economic welfare. Thus, we define each attribute as a function that represents a proportion of a country's premium relative to the factors defining its profile, i.e., the expected value and standard deviation of its demand, its GNI, and combinations of these. Let

Y_c be the premium of country c, then $Y_c(\%)$ corresponds to the percentage of $\zeta(C) = \sum_{c' \in C} Y_{c'}$ paid by country c. Similarly, the percentage of a factor corresponds to the percentage of the total factor associated with country c, e.g, $E_c(\%) = 100 \frac{E(D_c)}{\sum_{c' \in C} E(D_{c'})}$, $\sigma_c(\%) = 100 \frac{\sigma(D_c)}{\sum_{c' \in C} \sigma(D_{c'})}$, and $GNI_c(\%) = 100 \frac{GNI_c}{\sum_{c' \in C} GNI_{c'}}$. Y_c^{alone} corresponds to the premium of country c if it would have to respond alone to its own disasters ($Y_c^{alone} = \zeta(c)$).

Table 2 Attributes used for defining the KPIs.

#	$\mathcal{A}$	Attribute function $\mathcal{A}_c$	Description
1	AZ	$Z_c = \frac{Y_c - bE(D_c)}{b\sigma(D_c)}$	Value of the dimensionless deviation variable for each country.
2	Alone	$Alone_c = 100 \frac{Y_c^{alone} - Y_c}{Y_c^{alone}}$	Percentage of premium reduction in comparison with stand-alone costs.
3	AE	$AE_c = \frac{Y_c(\%)}{E_c(\%)}$	Proportion of the percentage of the premium relative to the percentage of the expected demand.
4	Aσ	$A\sigma_c = \frac{Y_c(\%)}{\sigma_c(\%)}$	Proportion of the percentage of the premium paid relative to the percentage of the GNI.
5	AGNI	$AGNI_c = \frac{Y_c(\%)}{GNI_c(\%)}$	Proportion of the percentage of the premium relative to the percentage of the standard deviation of the demand.
6	AEσ	$AE\sigma_c = \frac{Y_c(\%)}{(E+\sigma)_c(\%)}$ [1]	Proportion of the percentage of the premium paid relative to the percentage of the expected demand plus the standard deviation of the demand.
7	AEGNI	$AEGNI_c = \frac{Y_c(\%)}{(\widetilde{E} + \widetilde{GNI})_c(\%)}$ [2]	Proportion of the percentage of the premium paid relative to the percentage of the expected demand plus the GNI.
8	AEσGNI	$AE\sigma GNI_c = \frac{Y_c(\%)}{(\widetilde{E} + \widetilde{\sigma} + \widetilde{GNI})_c(\%)}$ [3]	Proportion of the percentage of the premium paid relevant to the percentage of the expected demand plus the standard deviation of the demand plus the GNI.

[1] $(E+\sigma)_c(\%) = 100 \frac{E(D_c) + \sigma(D_c)}{\sum_{c' \in C}[E(D_{c'}) + \sigma(D_{c'})]}$

[2] $(\widetilde{E} + \widetilde{GNI})_c(\%) = 100 \frac{\widetilde{E(D_c)} + \widetilde{GNI_c}}{\sum_{c' \in C}[\widetilde{E(D_{c'})} + \widetilde{GNI_{c'}}]}$

[3] $(\widetilde{E} + \widetilde{\sigma} + \widetilde{GNI})_c(\%) = 100 \frac{\widetilde{E(D_c)} + \widetilde{\sigma(D_c)} + \widetilde{GNI_c}}{\sum_{c' \in C}[\widetilde{E(D_{c'})} + \widetilde{\sigma(D_{c'})} + \widetilde{GNI_{c'}}]}$

The average is a well-known measure of central tendency. It allows us to know the central tendency of each of the eight attributes and check whether the tendency aligns with the aim of the analyzed attribute. Average-based KPIs are represented by Average[$\mathcal{A}$] (e.g., see Table 3). The standard deviation measures the dispersion of the set of values of the attributes. It can be used to measure fairness between participants, considering that when it is low, all partners have a similar value of the analyzed attribute. Standard deviation-based KPIs are represented by StDev[$\mathcal{A}$]. The Gini coefficient (Gini, 1936) measures the inequality among values of a frequency distribution. Let $\bar{A}$ denote the mean of $\mathcal{A}_c$ across countries $c \in C$. We have computed the Gini coefficient of an attribute $\mathcal{A}$ and defined the Gini-based KPIs as follows: Gini[$\mathcal{A}$]=

$\dfrac{1}{2|C|^2\bar{A}}\sum_{c\in C}\sum_{c'\in C}|\mathcal{A}_c - \mathcal{A}_{c'}|$. A Gini value of one represents absolute inequity and a value of zero corresponds to perfect equity.

Note that while for all attributes the desirable standard deviation and the desirable Gini coefficient are the smallest values, the desirable central tendency depends on the attribute. For the Z_c attribute it would be desirable to be close to zero, so that the safety margin of the premiums is small, ensuring that each country contributes for about its expected demand. For the $Alone_c$ attribute, we aim to reduce as much as possible the premium of a country compared with what it should pay if it was stand-alone. Therefore, the larger this value is, the better it is. For the remaining attributes, the desirable central tendency to ensure a fair distribution among the countries corresponds to an average value close to one, since this means that premiums are distributed proportionally to the measure considered by each attribute.

4.2.2. Impact of giving more weight on GNI. The graph presented in Figure 1 depicts the impact on countries' premiums when the weight given to GNI increases. This graph presents the percentage of the total premium paid by each country as a function of the weights given to risk and GNI (θ_{risk}; θ_{GNI}) when using our insurance-based method. Dark lines are associated with the countries that are relatively wealthier than risky since their premiums increase when more weight is given to GNI than to risk, whereas grey lines are associated with the countries that are relatively riskier than wealthy since their premiums decrease when more weigth is given to GNI than to risk. This order of importance is highlighted by the size of the dotted lines. Solid lines are used for the countries with the largest difference between risk and GNI, and the smallest dots are used for the countries that have a smaller difference between risk and GNI (see Table 4). We can observe that the premiums of Trinidad and Tobago (TTO), Jamaica (JAM), Suriname (SUR), and Guyana (GUY) increase considerably when more weight is given to GNI than to risk, whereas the premiums of Belize (BLZ), Dominica (DMA), and Haiti (HTI) decrease considerably when more weight is given to GNI than to risk. These countries are therefore supported by wealthier countries when more weight is given to GNI. In the following, we analyze in more detail the impacts of the weights given to risk and GNI on different KPIs.

4.2.3. Analysis of the weights given to risk and GNI. The values given to θ_{risk} and θ_{GNI} influence how costs are shared between partners (country premiums) according to the risk they bring to the collaborative prepositioning network and according to their wealth. How to set these weights depends on the preferences of the decision makers, and these should be determined through an agreement between partners after carefully analyzing the impacts of these weights on the solution. While setting the weights for different factors, the decision maker may be interested in maximizing the total saving created by including the countries in the partnership. There may be alternative ways to calculate the total saving, but we have computed a measure that evaluates the sum of the countries' savings generated by including each country in the partnership. In Figure 2, we present the graph of the sum of the countries' savings obtained by

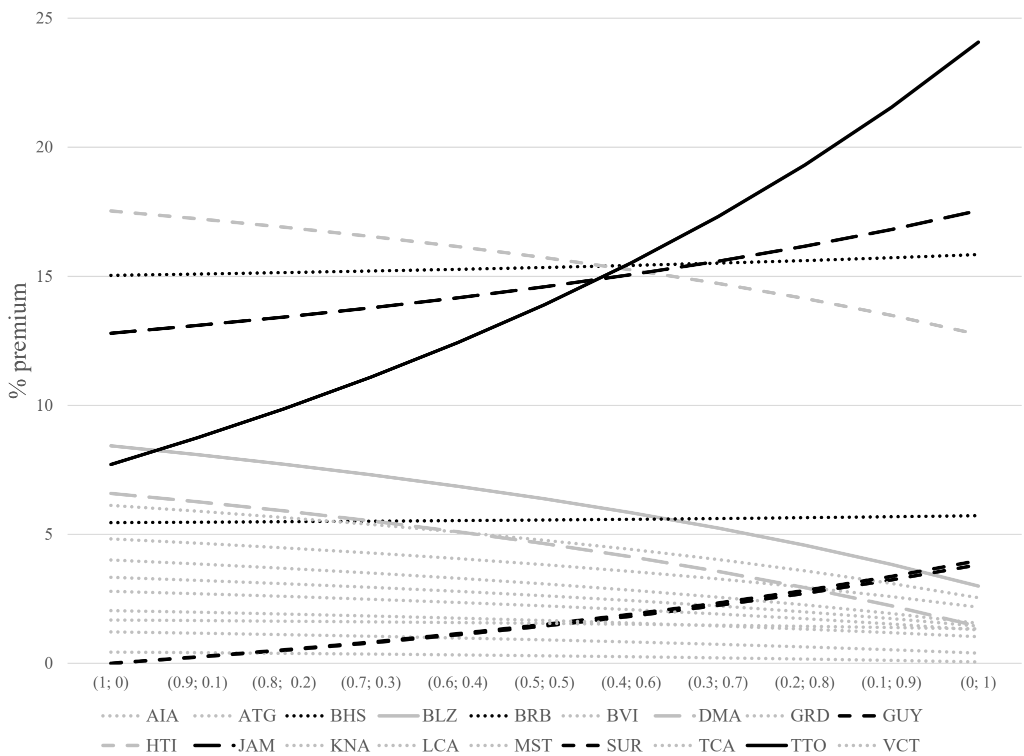

Figure 1 **Country premium percentages as a function of the weights given to risk and GNI (θ_{risk}; θ_{GNI}).**

adding every country separately to the partnership as a function of the weights given to risk and GNI. Let $Y_c^{c'}$ be the premium of country c obtained by solving the model when country c' is not in the partnership (allocating $\zeta(C \setminus \{c'\})$), whereas Y_c is the premium of country c when all countries are in the partnership (allocating $\zeta(C)$). The sum of the countries' savings obtained by adding each country separately to the partnership corresponds to $\sum_{c' \in C}[\sum_{c \in C \setminus \{c'\}}(Y_c - Y_c^{c'})]$. The sum of the savings across all countries is plotted in Figure 2. As can be seen, the largest total savings occur when $\theta_{risk} = 0.7$ and $\theta_{GNI} = 0.3$. The second and the third largest savings occur when $(\theta_{risk}; \theta_{GNI})$ are equal to (0.3; 0.7) and (0.5, 0.5), respectively.

While setting the model weights based on the generated cumulative savings as above could be an option, the associated premiums may not lead to an equitable cost allocation among the partner countries. Therefore, it is of prime importance to also analyze the impacts of the θ_{risk} and θ_{GNI} values on different KPIs that assess the equity of the cost-allocation distribution among the partners. Figure 3 plots the graphs of KPIs as a function of risk and GNI between countries. These are obtained by computing the average, the standard deviation and the Gini coefficient of the eight attributes presented in Table 2, as a function of the weights given to risk and GNI. In each graph of Figure 3, the best value achieved for each KPI is represented by a diamond (◆). We can observe that for the KPIs defined on a single factor (i.e., risk or GNI), the best values are mostly obtained with $(\theta_{risk}; \theta_{GNI})$ equal to $(1; 0)$ and $(0; 1)$, which is consistent. For the KPIs that consider a combination of risk and GNI factors, the best values are obtained when θ_{risk} is between 0.3 and 0.5, and θ_{GNI} is between 0.5 and 0.7. From these results, we can conclude that ($\theta_{risk} = 0.5$; $\theta_{GNI} = 0.5$) provides a good compromise if the decision maker

Figure 2 **Sum of the countries' savings obtained by adding every country separately to the partnership as a function of the weights given to risk and GNI (θ_{risk}; θ_{GNI}).**

(CDEMA in this case) aims to share costs among the countries according to their risk and wealth, as no other weight combination provides a superior solution over all KPIs. Therefore, while evaluating the performance of alternative methods in §4.2.6 (Table 3), we implement the proposed insurance-based method $\theta_{risk} = 0.5$ and $\theta_{GNI} = 0.5$ to assess its overall performance.

4.2.4. Benefits of belonging to the partnership. To assess the benefit for each country c of belonging to this disaster preparedness partnership, we compare the difference in cost for each country c between responding alone or in partnership to sustain relief efforts ($Alone_c$). The attribute used to make this comparison relates to the individual rationality property (Appendix C). The bar chart presented in Figure 4 presents the percentages (Y_c^{alone}) obtained when the insurance-based model is solved by using different weights (θ_{risk}; θ_{GNI}): $(1;0)$, $(0.5;0.5)$, and $(0;1)$.

We note that every country, except Guyana (GUY) and Suriname (SUR), benefits considerably from being in the partnership. Guyana and Suriname do not benefit from the partnership when θ_{GNI} is positive since they have not been hit by hurricanes in the past (i.e., their demand is null in every scenario), and they contribute to the partnership only because they are relatively wealthier countries. Therefore, their risks are considered to be equal to zero in our model, which explains why their benefits of being part of the partnership are negative when the cost allocation is made by assigning a positive weight on GNI, as this is the case in CDEMA's current cost allocation policy. Moreover, the benefit derived by Trinidad and Tobago (TTO) from belonging to the partnership is negative when the costs are allocated by considering only the GNI because

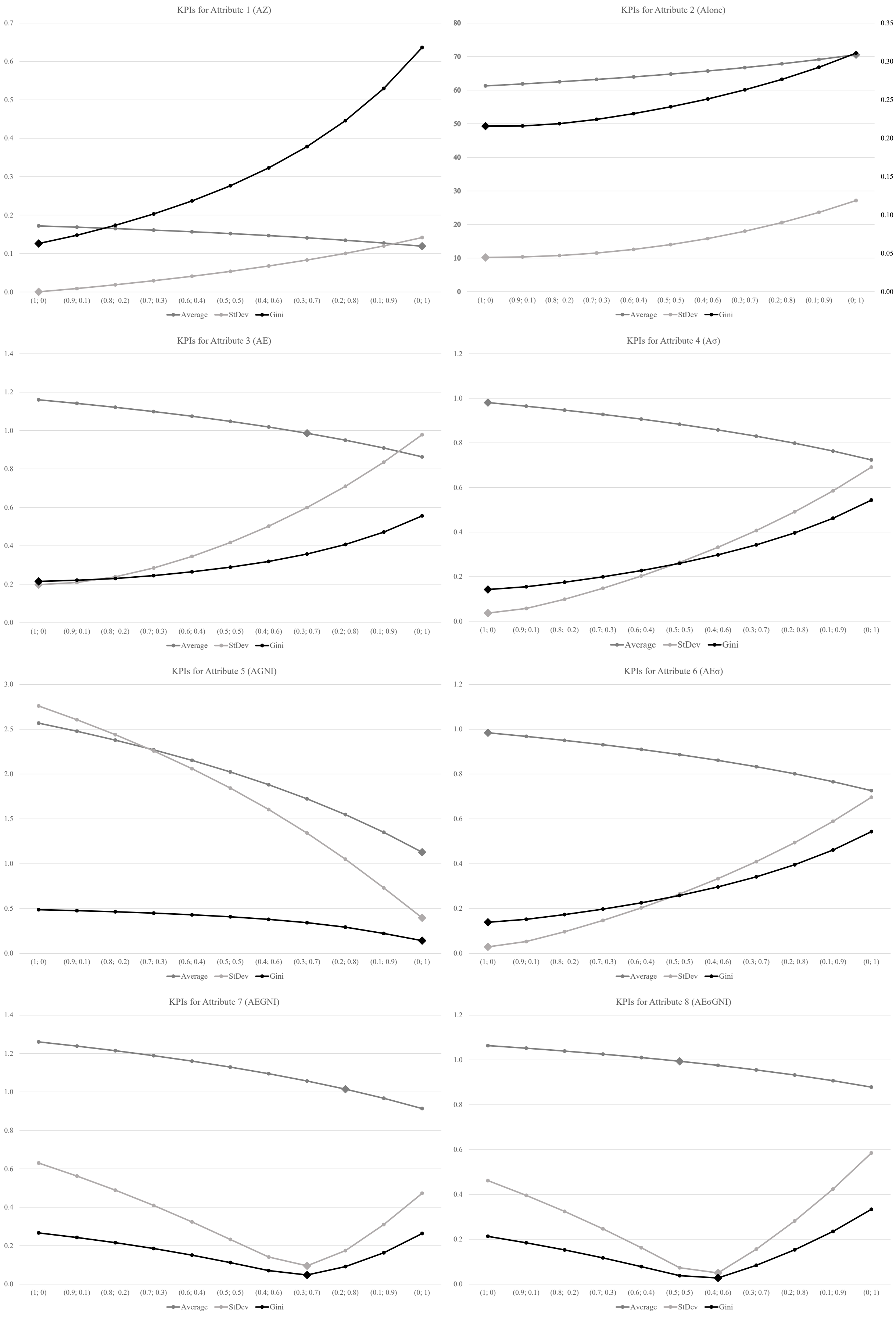

Figure 3 **KPIs as a function of the weights given to risk and GNI ($\theta_{risk}; \theta_{GNI}$).**

this country is wealthier and less risky. Beside these special cases, our results show that the collaborative prepositioning network is beneficial for all other countries since their costs are reduced considerably when they pool their resources through the partnership.

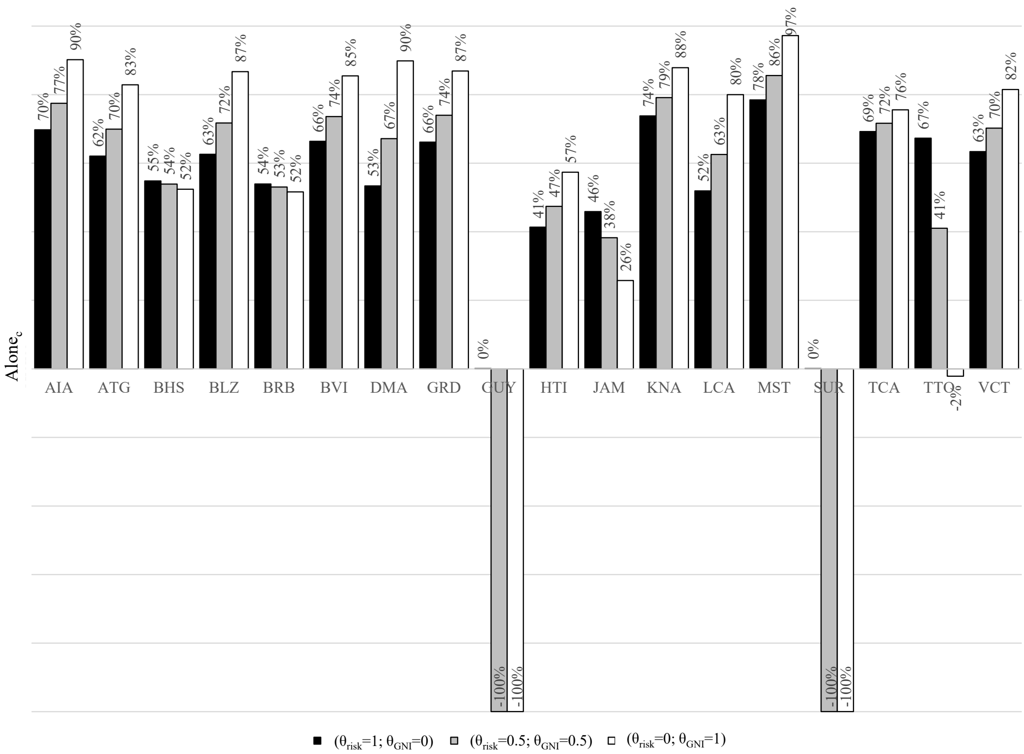

Figure 4 **Bar chart of the percentage cost benefits derived from belonging to the partnership.**

4.2.5. Impacts of including a country to the partnership. To evaluate the impact of including every country to the partnership, we have computed the average percentage increase in the country contributions. Given $Y_c^{c'}$, the premium of country c when country c' is not in the partnership, and Y_c, the premium of country c under the grand coalition, the percentage increase in a country contributions is $100(Y_c - Y_c^{c'})/Y_c$. The bar chart of Figure 5 presents the average of these percentages for $(\theta_{risk} = 1; \theta_{GNI} = 0)$, $(\theta_{risk} = 0.5; \theta_{GNI} = 0.5)$, and $(\theta_{risk} = 0;\ \theta_{GNI} = 1)$. If the average percentage increase is positive, this implies that the other countries $(C \setminus \{c\})$ have to pay more on average when country c is included in the partnership. When the cost allocation is determined by considering risk only, i.e., with $\theta_{risk} = 1$ and $\theta_{GNI} = 0$, the country premiums increase only when Haiti (HTI) and Jamaica (JAM) are included in the partnership, since these countries are extremely prone to hurricanes compared with others. When more weight is given to the GNI, including some countries (Belize (BLZ); Grenada (GRD); Haiti (HTI); and Saint Vincent and the Grenadines (VCT)) makes other countries' premiums increase on average since they are relatively more risky and poorer compared with the others. These results show that some countries individually add some burden to the partnership although, as shown previously, it is beneficial for all countries to be part of the grand coalition when $\theta_{GNI} = 0$

(i.e., the individual rationality property is satisfied). This analysis implies that the coalition of all countries does not satisfy the stability property. However, in this humanitarian context, where partners have a strong sense of solidarity and have signed agreements with CDEMA on cost sharing, some countries will support the more vulnerable countries to strengthen regional integration and build local capacity.

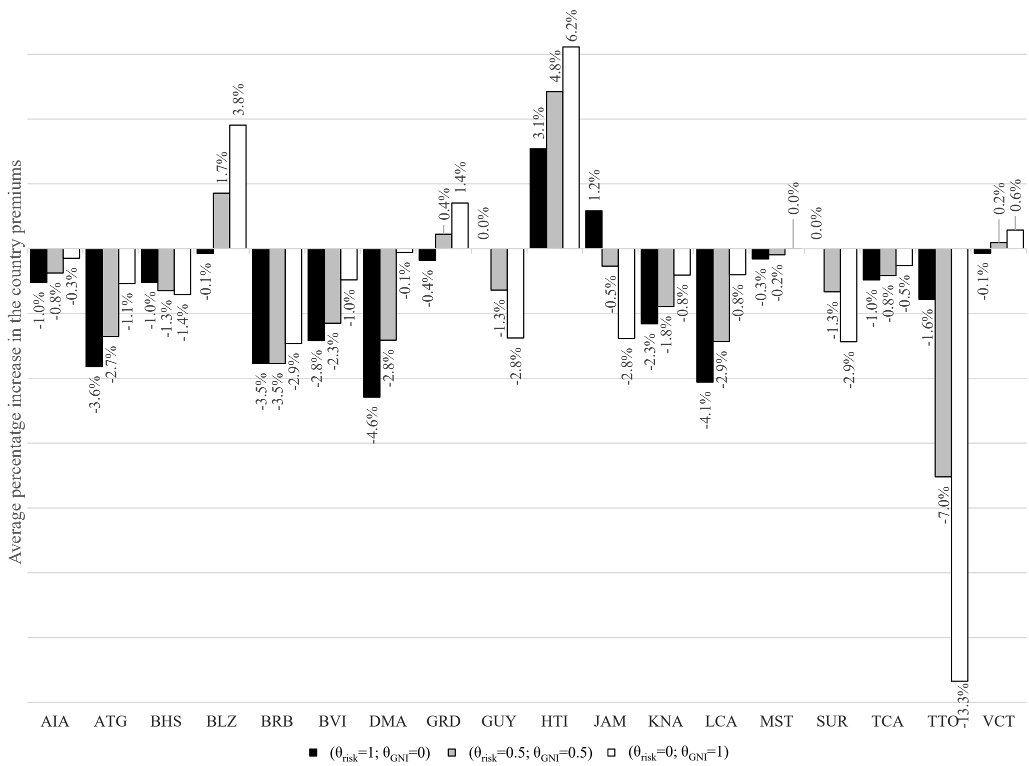

Figure 5 **Bar chart of the average percentage increase in countries' contributions when adding a country to the partnership.**

4.2.6. Analysis of different cost allocation mechanisms. Table 3 summarizes the results obtained under the four cost allocation methods. The KPIs values obtained by using our insurance-based method (InsBased) with the recommended θ_{risk} and θ_{GNI} weights, i.e., $(0.5; 0.5)$, are presented in the first column. The last three sets of columns present the values of the KPIs obtained by means of the ACAM, EPM, and Shapley and by allocating the cluster premiums among countries using the policies presented in Table 1. In Table 3, the best KPI values among all methods are highlighted in dark grey cells. We also highlight in light grey the cells with values that are close to the best one (i.e., ± 1.0 of the best KPI value for Average[Alone] and StDev[Alone], and ± 0.1 of the best KPI value for all the other KPIs). Finally, the best value obtained by different policies used to divide the cluster premiums are highlighted in bold italic font.

We observe that our insurance-based method performs the best for most of the KPIs (dark grey cells), whereas the Shapley value and EPM perform the best for some KPIs. We believe that the indicators that combine risk and GNI are more appropriate in our case due to the motivations of this study, and that the KPIs obtained with Attributes 5, 7, and 8 are more in line with CDEMA's practice. The other cost sharing methods (ACAM, EPM, and Shapley value) perform relatively better for the KPIs related to the average of the eight attributes, but not for those related to the standard deviation. This implies that sharing costs according to these methods yields country premiums that are smaller on average, but that vary more between countries (i.e., some countries pay differently relative to their risk or GNI), therefore leading to less equity. However, the Gini index computed for the difference between the premiums that the countries would pay if they had to bear the full cost of their own disasters (Gini[Alone]) is similar to the best obtained value (light grey cells), which implies that all the cost sharing approaches tend to be equitable regarding Attribute 2 (Alone). We can also observe that the Shapley value and the ACAM provide better results than EPM. Nevertheless, we note that the results obtained with the insurance-based method generally outperform those obtained by all the other methods.

Regarding the policies applied to divide the cluster premiums among countries in order to determine the country premiums (see descriptions in Table 1) for the classical cost sharing approaches, allocating costs according to the same factors evaluated by the KPI for Attributes 3–6 (i.e., expected demand, standard deviation of demand, GNI or a combination of these factors) may not necessarily lead to the best KPI values among those obtained for the same attribute and method (the KPI values highlighted using bold italic fonts in Table 3), except for Attribute 5 (AGNI). This is more obvious for Attribute 4 (Aσ) and Attribute 7 (AEGNI). For the other attributes (AE, AEσ, AEσGNI), there is more consistency between the attribute and the factor emphasized by the division policy when the KPIs to assess equity between countries, i.e., when they evaluate the standard deviation and the Gini index. When the KPIs assess the attribute average, there is no clear pattern regarding which policy leads to the best KPI values. For the two first attributes (AZ and Alone), the best policy for obtaining a better equity between countries is PEσ, whereas the GNI has to be factored in for obtaining better results for the average. However, even if some division policies performed better depending on the KPI evaluated, the best method to obtain fairer solutions overall remains our insurance-based method with equal weights on risk and GNI.

4.3. Discussion and managerial insights

The results of our computational study show that our proposed insurance-based cost sharing method is the most effective for two main reasons. The first reason is that is easy to implement because solving the insurance-based cost allocation problem is straightforward. It is also flexible since one can decide to use it to share costs without optimizing the prepositioning network first and directly use the costs associated with the current design and managerial practices. This is an advantage of being able to solve the network design and cost sharing problems separately, since our cost-sharing method can be used independently of the network design optimization problem. The insurance-based cost sharing method can also be used to share costs or benefits in different contexts, where there is variability among the partners with respect to the factors that are relevant to consider for the allocation. Moreover, other factors than statistics on demand and GNI can easily be considered and incorporated in the CAP.

The second reason for the superiority of our cost sharing scheme is that when evaluating different KPIs to assess equity (see the results of Table 3), the best solutions are obtained by using our methodology compared with those yielded by the classical cost sharing schemes, which are more computationally demanding and difficult to implement when there are several stakeholders involved. Therefore, our approach has the advantages of being more flexible and effective.

For CDEMA, we suggest to better incorporate risk for managing their prepositioning network as well as for sharing its associate costs among the participating countries. To this end, we have processed historical data about past hurricanes in the Caribbean in order to create demand scenarios used in the network design problem. We have computed statistics on the expected value and the standard deviation of the demand of each country, and we have incorporated these statistics in the cost sharing optimization problems. CDEMA did not have the resources required to assess country risk, and they only relied on demographical and economical data to consider vulnerability. Our methodology allows them to better assess risk and incorporate it in their decision making processes.

Table 3 KPI values obtained under different cost sharing methods.

No $\mathcal{A}$	KPIs	InsBased	ACAM							Shapley value							EPM						
		(0.5;0.5)	PEqu	PE	Pσ	PGNI	PEσ	PEGNI	PEσGNI	PEqu	PE	Pσ	PGNI	PEσ	PEGNI	PEσGNI	PEqu	PE	Pσ	PGNI	PEσ	PEGNI	PEσGNI
	Average[AZ]	***0.15***	0.15	0.14	0.14	***0.13***	0.14	0.13	0.13	0.14	0.13	0.14	0.13	0.14	***0.13***	0.13	0.13	0.13	0.13	0.12	0.13	***0.12***	0.12
1	StDev[AZ]	***0.05***	0.10	0.06	0.06	0.15	***0.06***	0.09	0.09	0.09	0.06	0.06	0.15	***0.06***	0.09	0.09	0.12	0.11	0.11	0.17	***0.11***	0.13	0.13
	Gini[AZ]	***0.28***	0.46	0.35	0.34	0.70	***0.34***	0.50	0.48	0.45	0.34	0.33	0.71	***0.33***	0.51	0.49	0.56	0.50	0.49	0.78	***0.49***	0.63	0.62
	Average[Alone]	***64.79***	66.61	66.57	66.13	***69.37***	66.15	68.97	68.25	67.07	67.27	66.81	***69.03***	66.82	68.96	68.35	68.12	68.43	68.02	69.24	68.04	***69.43***	68.98
2	StDev[Alone]	***14.02***	18.47	18.32	17.26	28.28	***17.24***	19.80	20.05	18.78	18.73	17.69	29.09	***17.68***	20.11	20.44	24.77	24.82	24.21	32.54	***24.20***	25.77	25.90
	Gini[Alone]	***0.24***	0.27	0.26	0.26	0.34	***0.26***	0.28	0.28	0.27	0.26	0.26	0.34	***0.26***	0.28	0.29	0.31	0.30	0.30	0.36	***0.30***	0.32	0.32
	Average[AE]	***1.05***	1.02	0.94	***0.98***	0.92	0.98	0.88	0.92	***0.98***	0.90	0.94	0.92	0.94	0.87	0.91	***0.93***	0.85	0.89	0.90	0.89	0.85	0.88
3	StDev[AE]	***0.42***	0.65	***0.29***	0.37	1.04	0.36	0.59	0.64	0.62	***0.22***	0.33	1.05	0.33	0.59	0.64	0.79	***0.64***	0.67	1.11	0.67	0.80	0.82
	Gini[AE]	***0.29***	0.43	***0.26***	0.31	0.63	0.31	0.43	0.43	0.42	***0.24***	0.29	0.63	0.29	0.44	0.44	0.50	***0.39***	0.42	0.69	0.42	0.54	0.54
	Average[Aσ]	***0.88***	***0.86***	0.83	0.84	0.76	0.84	0.76	0.78	***0.84***	0.80	0.81	0.76	0.81	0.75	0.77	***0.79***	0.76	0.77	0.75	0.77	0.74	0.75
4	StDev[Aσ]	***0.26***	0.47	0.34	0.31	0.73	***0.31***	0.45	0.46	0.44	0.33	0.30	0.75	***0.30***	0.46	0.47	0.60	0.56	0.55	0.83	***0.55***	0.63	0.63
	Gini[Aσ]	***0.26***	0.41	0.32	***0.31***	0.59	0.31	0.44	0.42	0.40	0.32	***0.30***	0.60	0.30	0.45	0.43	0.49	0.45	***0.44***	0.66	0.44	0.54	0.53
	Average[AGNI]	***2.02***	2.10	2.00	1.96	***1.22***	1.97	1.59	1.64	1.98	1.92	1.88	***1.19***	1.88	1.56	1.60	2.00	1.98	1.95	***1.31***	1.95	1.68	1.71
5	StDev[AGNI]	***1.84***	2.40	1.92	1.85	***1.25***	1.86	1.54	1.55	2.14	1.93	1.85	***1.08***	1.86	1.54	1.56	2.73	2.77	2.71	***2.17***	2.71	2.51	2.52
	Gini[AGNI]	***0.41***	0.52	0.47	0.46	***0.43***	0.46	0.44	***0.43***	0.51	0.47	0.46	***0.42***	0.46	0.45	0.44	0.59	0.57	0.57	***0.56***	0.57	0.58	0.57
	Average[AEσ]	***0.89***	***0.87***	0.83	0.85	0.76	0.85	0.76	0.79	***0.84***	0.80	0.82	0.77	0.81	0.76	0.78	***0.80***	0.76	0.78	0.75	0.77	0.74	0.75
6	StDev[AEσ]	***0.27***	0.47	0.33	0.31	0.74	***0.31***	0.45	0.47	0.45	0.32	0.30	0.76	***0.29***	0.46	0.47	0.61	0.56	0.55	0.83	***0.55***	0.63	0.64
	Gini[AEσ]	***0.26***	0.41	0.32	0.31	0.59	***0.31***	0.44	0.42	0.40	0.32	0.30	0.60	***0.30***	0.45	0.43	0.49	0.45	0.43	0.66	***0.43***	0.54	0.53
	Average[AEGNI]	***1.13***	1.09	***1.02***	1.03	0.86	1.03	0.91	0.94	***1.02***	0.97	0.97	0.84	0.97	0.88	0.90	***0.98***	0.94	0.94	0.84	0.94	0.88	0.89
7	StDev[AEGNI]	***0.23***	0.79	0.60	0.58	0.62	0.58	0.48	***0.48***	0.63	0.51	0.49	0.58	0.49	0.44	***0.43***	0.97	0.96	0.95	1.01	0.95	0.95	***0.94***
	Gini[AEGNI]	***0.11***	0.32	0.30	0.28	0.37	0.28	0.22	***0.22***	0.30	0.27	0.25	0.37	0.25	***0.24***	0.24	0.40	0.39	***0.38***	0.50	0.38	0.38	0.39
	Average[AEσGNI]	***0.99***	***0.94***	0.89	0.88	0.79	0.88	0.82	0.83	***0.89***	0.85	0.84	0.76	0.84	0.79	0.80	***0.84***	0.82	0.81	0.75	0.81	0.78	0.78
8	StDev[AEσGNI]	***0.07***	0.55	0.51	0.47	0.52	0.47	0.40	***0.38***	0.45	0.47	0.41	0.50	0.41	0.38	***0.36***	0.76	0.78	0.76	0.82	0.76	0.76	***0.75***
	Gini[AEσGNI]	***0.04***	0.28	0.30	0.26	0.35	0.26	0.24	***0.21***	0.27	0.29	0.25	0.36	0.25	0.25	***0.23***	0.38	0.41	0.38	0.48	0.38	0.39	***0.37***

Figure 6 presents the percentages of increase (dark grey) or decrease (light grey) in country premiums compared to CDEMA's current premiums, obtained for five different weight combinations. Our cost allocation framework suggests increasing the premiums for three countries with a high risk profile (Bahamas (BHS); Haiti (HTI); and Jamaica (JAM)) regardless of the weights given to risk and GNI. It also suggests increasing the premiums of Belize (BLZ), the British Virgin Islands (BVI), Dominica (DMA) and Saint Lucia (LCA) when more weight is given to risk, and to decrease them when more weight is given to GNI, whereas this is the opposite for the premiums of Trinidad and Tobago (TTO). Our methodology suggests decreasing the premiums of all other countries. This can be explained by the fact that CDEMA currently apportions costs according to population and GDP, which does not take into account the country hurricane risk profiles. Our solutions have been provided to CDEMA to support future discussions with its partner countries. The director of CDEMA indicated a preference for the solutions with more weight given to GNI than to risk, since they are obtained following a policy similar to that currently implemented while they still consider risk, due to the lower bound of the country premiums imposed by constraints 3. The proposed solutions with their consequent impacts on the KPIs and the difference between the current country premiums can be presented to the partners to facilitate discussions and reach an agreement on how to share cost based on a more scientific basis.

Country		Percentage increase or decrease in countries' premiums obtained with different (θ_{risk}; θ_{GNI}) combinations compared to CDEMA's current premiums				
		(1; 0)	(0.7; 0.3)	(0.5; 0.5)	(0.3; 0.7)	(0; 1)
Anguilla	AIA	-1.48	-1.65	-1.79	-1.96	-2.30
Antigua & Barbuda	ATG	-0.59	-1.13	-1.59	-2.14	-3.23
Bahamas	BHS	6.93	7.10	7.24	7.41	7.74
Belize	BLZ	3.02	1.90	0.96	-0.17	-2.41
Barbados	BRB	-2.65	-2.59	-2.55	-2.49	-2.38
British Virgin Islands	BVI	0.64	0.24	-0.08	-0.48	-1.26
Dominica	DMA	1.18	0.11	-0.77	-1.85	-3.97
Grenada	GRD	-1.40	-1.91	-2.33	-2.84	-3.86
Guyana	GUY	-5.41	-4.62	-3.96	-3.17	-1.59
Haiti	HTI	9.43	8.44	7.62	6.62	4.64
Jamaica	JAM	4.69	5.68	6.49	7.48	9.44
St Kitts & Nevis	KNA	-2.62	-2.93	-3.18	-3.50	-4.12
Saint Lucia	LCA	0.71	-0.03	-0.64	-1.39	-2.86
Montserrat	MST	-2.26	-2.34	-2.41	-2.49	-2.64
Suriname	SUR	-5.41	-4.59	-3.90	-3.07	-1.43
Turks & Caicos Islands	TCA	-1.02	-1.09	-1.15	-1.22	-1.37
Trinidad & Tobago	TTO	-0.39	2.99	5.80	9.21	15.97
St Vincent & the Grenadines	VCT	-3.37	-3.58	-3.75	-3.96	-4.38
Average % increase		3.80	3.78	5.62	7.68	9.45
Average % decrease		-2.62	-2.41	-2.16	-2.19	-2.70

Figure 6 **Percentages of increase (dark grey) or decrease (light grey) in country premiums compared with CDEMA's current premiums.**

5. Conclusions

Given the increasing frequency and intensity of disasters, collaborative disaster management practices could provide an efficient and equitable way of pooling risks and resources. To reach this goal, any collaborative partnership must provide benefits to each participating member, and the benefits and costs of the partnership must also be shared equitably among the partners. Inspired by the regional integration efforts for disaster management in the Caribbean, which includes several highly vulnerable developing countries with diverse profiles in terms of risk and economic status, this study focuses on establishing a multi-country disaster preparedness partnership through joint prepositioning of emergency supplies. We have presented and compared several methods to fairly allocate the total budget required to establish and manage a collaborative prepositioning network among the partner countries. In contrast to the traditional definition of equity used in cooperative game theory, an equitable cost allocation in this regional partnership context must account for both the disaster risks and also for the economic ability of the partners to pay their share. We have developed an insurance-inspired practical cost allocation method that captures the unique characteristics of the Caribbean such as disparities in economic welfare levels of the member countries and hence could support developing a partnership in the region that allows partner countries to pool financial and logistical resources while enhancing their disaster preparedness and response capacities. We have also adapted available cost allocation methods to assess the performance of the proposed method in terms of several key performance indicators.

The road map provided by the UN SDGs is perceived as an important historic opportunity for the Caribbean, since it addresses some of the region's most urgent priorities. This study particularly supports SDG 17, which focuses on establishing global partnerships among several stakeholders to deal with the problems of the developing countries. In this respect, our results first support the efforts of CDEMA by analytically showing that despite the huge differences in country profiles, all countries can benefit from a collaborative prepositioning network. Moreover, they yield a practical and flexible tool, which helps the decision makers to analyze the effects of weights assigned to risk and economic factors and develop an equitable and transparent financial plan to support the partnership. Second, our collaboration with CDEMA serves the organization's mandate in establishing partnerships with various stakeholders including academia to ensure that limited resources are used efficiently but also in harmony across the area of interest, as well as in the planning and implementation processes (CDEMA, 2020a).

There has been an increase in the global funding and insurance schemes that aim to support the most vulnerable countries in disaster preparedness and response efforts (e.g., see World Health Organization, 2020). While insurance can be an effective disaster risk management method, it is challenging to develop effective catastrophic insurance policies (World Bank, 2017). Research on the development of insurance frameworks to support humanitarian operations currently lags behind. However, we can identify several future research directions. First, in this study, the proposed insurance scheme applied to develop a collaborative prepositioning network assumes that a maximum coverage limit for each country is specified. However, country coverage limits can be set endogenously in designing an insurance policy. Future research can explore methods for designing more elaborate insurance policies to support multi-country disaster preparedness partnerships. Second, in the CDEMA network considered in this study, all countries must be included in the partnership due to the existing bonds and agreements. In a different problem setting, it may be important to determine which subset of countries can establish the best partnership, that is, the largest coalition that brings the most benefits. The proposed cost allocation approaches can be adapted to such settings which may be relevant to other disaster-prone areas, in which the countries are reluctant to share the additional burden brought by riskier or poorer countries.

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Appendix A. CDEMA Member Countries

Figure 7 shows a map of the 18 CDEMA members in the Caribbean. The countries in bold letters represent the current CDEMA subfocal points. Table 4 presents for each country the data related to risk and GNI profiles, and the cluster they belong according to the K-means algorithm applied.

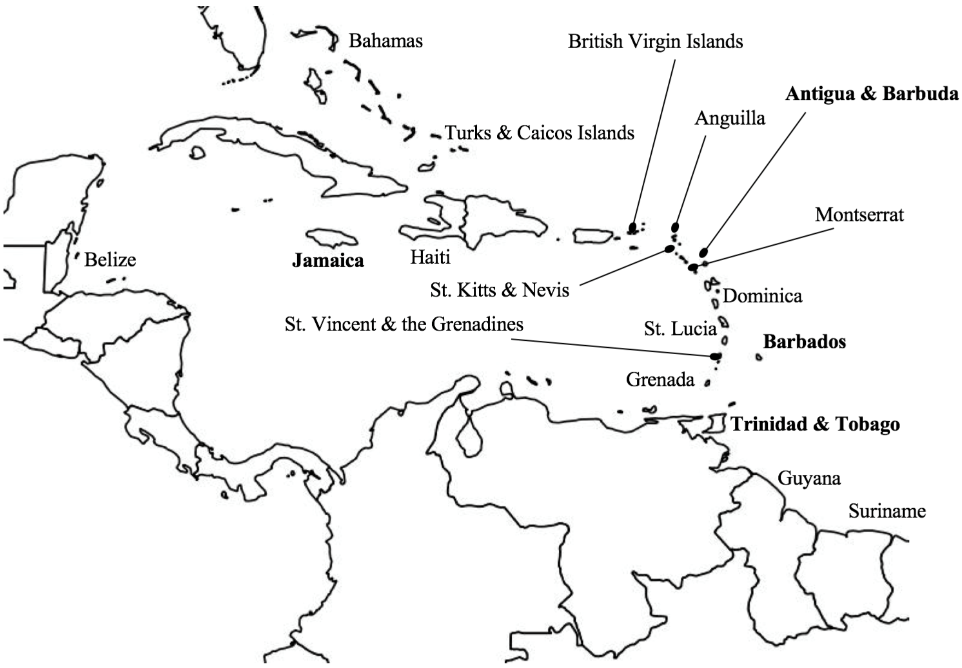

Figure 7 Map of the 18 CDEMA member countries.

Table 4 List of the 18 CDEMA member countries and their profiles

ID	Country	$E(D_c)$	$\sigma(D_c)$	GNI (USD M)	Cluster
AIA	Anguilla	299	11,230	281	5
ATG	Antigua & Barbuda	1,182	44,197	1,474	4
BHS	Bahamas	6,322	122,470	11,435	1
BLZ	Belize	2,078	77,133	1,773	2
BRB	Barbados	1,479	49,083	4,575	3
BVI	British Virgin Islands	938	29,886	908	4
DMA	Dominica	1,853	58,957	432	3
GRD	Grenada	799	37,742	1,088	4
GUY	Guyana	0	0	3,564	5
HTI	Haiti	6,249	149,315	8,622	1
JAM	Jamaica	3,603	114,546	14,378	1
KNA	St Kitts & Nevis	669	25,691	904	4
LCA	Saint Lucia	1,596	55,617	1,598	3
MST	Montserrat	101	3,997	58	5
SUR	Suriname	0	0	3,716	5
TCA	Turks & Caicos Islands	362	15,628	1,112	5
TTO	Trinidad & Tobago	1,658	71,961	21,365	1
VCT	St Vincent & the Grenadines	486	18,842	764	5

Appendix B. Mathematical Model: Centralized Prepositioning Network Design Problem (CenPNDP)

We present the notation and the formulation for the CenPNDP below.

Sets

C: set of countries in the coalition, $c \in C$;

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

T: set of disaster periods in the planning horizon, $t \in T$;

$\hat{C}^{st}$: set of countries that are simultaneously affected by the disaster that occurs in period $t \in T$ of scenario $s \in S$;

W: set of potential warehouse locations, $w \in W$;

M: set of transportation modes (sea and air), $m \in M$;

L: set of response time levels, $l \in L$ where $l = 1$ indicates fast response and $l = 2$ for a slower response;

$\hat{W}^s_{cml}$: 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 $s \in S$.

Parameters

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

β^{st}_c: percentage of country's demand $c \in C$ to be covered at first level, $l = 1$, during period $t \in T$ under scenario $s \in S$;

τ: replenishment lead time;

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

κ_w: maximum capacity of a warehouse at location $w \in W$;

n_w: maximum number of warehouses that can be opened at location $w \in W$;

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

ϑ^{st}_{wm}: total capacity of transportation mode $m \in M$ at location $w \in W$ in period $t \in T$ under scenario $s \in S$;

f_w: annualized fixed location and operation costs for a warehouse at location $w \in W$;

r_w: unit cost of purchasing a family kit for a warehouse at location $w \in W$;

g_w: unit cost of purchasing and holding an item in a warehouse at location $w \in W$;

o^{st}_{wcm}, u^{st}_{wcm}: fixed and unit transportation costs to serve country $c \in C$ from warehouse $w \in W^s_c$ via transportation mode $m \in M$ to meet the demand in period $t \in T$ under scenario $s \in S$;

γ: interest rate per year;

n: length of the payback period (years).

First-stage decision variables

X_w: number of warehouses to open at candidate location $w \in W$;

I_w: inventory allocated to warehouse $w \in W$;

Z: maximum deviation variable;

B_0: total budget required to cover disaster preparedness costs;

B_1: total budget required to cover emergency response costs;

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

Second-stage decision variables

Q^{st}_{wcm}: amount of supplies delivered to country $c \in C$ from warehouse $w \in W^s_c$ via transportation mode $m \in M$ to meet the demand that occur in period $t \in T$ under scenario $s \in S$;

V^{st}_{wcm}: number of shipments made to serve country $c \in C$ from warehouse $w \in W^s_c$ via transportation mode $m \in M$ to meet the demand that occur in period $t \in T$ under scenario $s \in S$;

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

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

Formulation

$$\text{minimize} \quad \frac{\gamma[\sum_{w\in W} r_w I_w + B1]}{1-(1+\gamma)^{-n}} + \sum_{w\in W} f_w X_w + \sum_{w\in W}(g_w - r[w])I_w +$$
$$\sum_{s\in S} p^s \left[\sum_{t\in T}\sum_{w\in W^s_{cm}}\sum_{c\in C}\sum_{m\in M} o^{st}_{wcm}V^{st}_{wcm} + (u^{st}_{wcm}+r_w)Q^{st}_{wcm}\right] \tag{12}$$

subject to

$$X_w \le n_w \qquad w \in W \tag{13}$$

$$I_w \le \kappa_w X_w \qquad w \in W \tag{14}$$

$$A^{s1}_w = I_w \qquad w \in W, s \in S \tag{15}$$

$$A^{s\ t+1}_w = (1-\alpha^{st}_w)A^{st}_w - \sum_{c\in \hat{C}^{st}}\sum_{m\in M} Q^{st}_{wcm} + R^{s\ t+1}_w \qquad w \in W, s \in S, t = 2,\ldots,|T-1| \tag{16}$$

$$R^{st}_w = 0 \qquad w \in W, s \in S, t = 1,\ldots,l^s_w + 1 \tag{17}$$

$$R^{st}_w = \alpha^{s\ t-l^s_w-1}_w A^{s\ t-l^s_w-1}_w + \sum_{c\in \hat{C}^{st}}\sum_{m\in M} Q^{s\ t-l^s_w-1}_{wcm} \qquad w \in W, s \in S, t = l^s_w+2,\ldots,|T| \tag{18}$$

$$\sum_{m\in M}\sum_{w\in \hat{W}^s_{cm1}} Q^{st}_{wcm} \ge \beta^{st}_c d^{st}_c \qquad s \in S, t \in T, c \in \hat{C}^{st} \tag{19}$$

$$\sum_{m\in M}\sum_{l\in L}\sum_{w\in \hat{W}^s_{cml}} Q^{st}_{wcm} \ge d^{st}_c \qquad s \in S, t \in T, c \in \hat{C}^{st} \tag{20}$$

$$Q^{st}_{wcm} \le \vartheta^{st}_{wm} V^{st}_{wcm} \qquad w \in W, s \in S, t \in T, c \in C, m \in M \tag{21}$$

$$\sum_{c\in \hat{C}^{st}}\sum_{m\in M} Q^{st}_{wcm} \le (1-\alpha^{st}_w)A^{st}_w \qquad s \in S, t \in T, w \in W \tag{22}$$

$$B_0 = \sum_{w\in W} f_w X_w + \sum_{w\in W} g_w I_w \tag{23}$$

$$B_1 \geq \sum_{t\in T} \sum_{w\in W_{cm}^s} \sum_{c\in C} \sum_{m\in M} o_{wcm}^{st} V_{wcm}^{st} + (u_{wcm}^{st} + r_w) Q_{wcm}^{st} \qquad s \in S \tag{24}$$

$$X_w \geq 0 \qquad w \in W \tag{25}$$

$$I_w \geq 0 \qquad w \in W \tag{26}$$

$$Q_{wcm}^{st} \geq 0 \qquad w \in W, c \in C, m \in M, s \in S, t \in T \tag{27}$$

$$V_{wcm}^{st} \geq 0 \qquad w \in W, c \in C, m \in M, s \in S, t \in T \tag{28}$$

$$A_w^{st} \geq 0 \qquad w \in W, s \in S, t \in T \tag{29}$$

$$R_w^{st} \geq 0 \qquad w \in W, s \in S, t \in T \tag{30}$$

$$B_0 \geq 0 \tag{31}$$

$$B_1 \geq 0. \tag{32}$$

The first term of the objective function (12) minimizes the annualized value of purchasing the inventory, plus the total budget required to cover the worst case. The second and third terms represent the sum of the fixed costs associated with warehouses, and the cost associated with holding inventory, respectively. The last term is the expected emergency response cost associated with the transportation supplies and replenishing warehouses after a disaster occurs.

Constraints (13) bound the number of warehouses to locate in each country. Constraints (14) ensure that the amount of inventory prepositioned in each opened warehouse does not exceed its capacity. Constraints (15) set the amount of inventory at the beginning of the hurricane season. Constraints (16) control the flow at each warehouse 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 (17) set the replenishment to zero for the initial periods of the hurricane season that are shorter than the lead time. Constraints (18) 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 (19) are imposed to satisfy a preset proportion of the targeted demand at the first response level. Constraints (20) ensure that the targeted demands are fully met. Constraints (21) limit the amount of supplies than can be delivered to a country from a warehouse via a transportation mode in each period under each scenario, considering the total capacity of the transportation mode. Constraints (22) limit the amount of supplies than can be shipped from a warehouse by the amount of available (undamaged) supplies. Constraints (23) and (24) determine the budget required. In particular, constraint (23) sets the preparedness budget which covers the the network and inventory expenses. Constraints (24) determine the emergency response budget, which must be sufficient to cover the post-disaster transportation and replenishment costs for all scenarios. Finally, constraints (25)–(32) define domains of the variables.

Appendix C. Properties of the Allocation Methods

One of the most challenging issues arising in cost allocation is to ensure a fair division among the participants in the coalition. In this sense, a variety of desirable properties in the context of a horizontal collaboration have been proposed (Verdonck et al., 2016), which are briefly explained below.

Efficiency The total cooperative cost is shared between all the partners in the grand coalition.

Individual rationality No partner pays more than its stand-alone cost.

Symmetry The solution is independent of the partners' names. That is, when several partners are indistinguishable (generating the same marginal contributions), they should be charged equally.

Stability No single partner or subcoalition of partners would benefit from leaving the grand coalition. Partners have an incentive to form the grand coalition if there is no smaller coalition in which they could get smaller premiums, i.e., the solution lies in the core.

Cross-monotonicity When a new partner joins the coalition, the allocated benefit of the current partners should not decrease.

Dummy Partners that do not bring anything in the coalition do not get any value.

Additivity If a game is decomposed into the sum of two cost sharing games, then the premium allocation for the original game should be equal to the sum of premiums they would have achieved under the two separate games.

Verdonck et al. (2016) provide an outline of the desirable well-known properties satisfied by the standard Shapley value, the ACAM, and the EPM. Table 5 presents the properties satisfied by the different cost allocation methods implemented to solve the CAP in this study, including the proposed insurance based method.

Table 5 Properties satisfied by the allocation methods (adapted from Verdonck et al. (2016)).

Property	Shapley	EPM	ACAM	InsBased($\theta_{GNI} = 0$)	InsBased($\theta_{GNI} > 0$)
Efficiency	✓	✓	✓	✓	✓
Individual rationality	✓	✓		* [1]	
Symmetry	✓	✓	✓	✓	✓
Stability		✓			
Cross-monotonicity		✓			
Dummy	✓			✓	
Additivity	✓				

[1] * This was shown experimentally.

In the case of the insurance-based method (InsBased), efficiency is ensured by (2). Although the contributions of the partners are given by constraints (3) based on their expected demand and standard deviation, symmetry is guaranteed by the fact that the inequalities (3) are bounded at optimality, which implies that partners with the same profile pay equal premiums. In order to evaluate the dummy property, we understand that a country does not bring anything in the coalition when its risk profile is null. In this sense, the dummy property only holds for $\theta_{GNI} = 0$, where due to (2) if the expected demand and the standard deviation of the demand are zero, then the premium is zero. Individual rationality does not necessary hold for the insurance-based method. By itself, a partner has to pay for its demand plus its network cost. In the insurance-based method, each partner has to pay at least for its expected demand (left-hand side of (3)) and, if necessary each partner pays an extra premium given by the weighted standard deviation and GNI. Since the networks and its associated cost are different based on the partners involved (grand coalition versus stand-alone), the total premium a partner has to pay in the coalition can be higher than in the stand-alone case. However, we are able to show experimentally that this property holds when $\theta_{GNI} = 0$, which is indicated by an asterisk in Table 5.

It is important to observe that when we apply the cluster-first-divide-second heuristic, some properties of Shapley, EPM and ACAM may no longer hold. We report in Table 6 the properties that hold when applying the policy to divide the premiums among countries in clusters.

Table 6 Properties satisfied by the policies.

Property	PEqu	PE	Pσ	PGNI	PEσ	PEGNI	PEσGNI
Efficiency	✓	✓	✓	✓	✓	✓	✓
Individual rationality							
Symmetry		✓	✓	✓	✓	✓	✓
Stability							
Cross-monotonicity							
Dummy		✓	✓		✓		
Additivity	✓	✓	✓	✓	✓		

Appendix D. K-means Algorithm for Clustering Countries

As mentioned in Section 3.3.5, in order to deal with the high computational effort, we have used a clustering-based approximation for the Shapley value and the EPM. Moreover, even though small instances of Shapley and EPM and any instance of ACAM can be easily computed, we need a way to incorporate GNI into cost allocation for these three methods. Therefore, we first cluster the countries based on their risk and GNI profiles by using a K-means algorithm and then apply different premium allocation methods within each cluster.

We implement a K-means algorithm to cluster the countries based on their risk and economic profiles. The data required for the algorithm include the normalized values of the expected value and of the standard deviation of the demand, and the GNI for each country (Table 4). The steps of the clustering algorithm are provided below (Algorithm 1).

The maximum number of iteration for the stopping criteria has been set to 50. Furthermore, to avoid possible effects of the selection of the initial centroids on the solution, the algorithm has been applied 50 times with different randomly selected centroids. Note that the number of clusters is an input to the algorithm. Therefore, it is relevant to choose adequately the desired number of clusters. Here we use the elbow method (Bholowalia and Kumar, 2014). The idea is to run the K-means algorithm for a range of values of K, in our case $|K| = \{2, ..., C-1\}$, and for each value of K calculate the distortion. The distortion graph (see Figure 8) looks like and

Algorithm 1 Pseudocode of K-Means Algorithm.

Require: C set of data points (countries) and number of desired clusters $|K| \geq 2$
Ensure: K set of clusters
  Select randomly $|K|$ points as cluster centers $k_1, k_2, ..., k_{|K|}$
  iter $= 0$
  repeat
    for all data points $c \in C$ **do**
      Assign c to the closest k_j $\quad 1 \leq j \leq |K|$
    end for
    Recompute the cluster centers according to the assigned data points
    iter++
  until iter $= iter_{max}$

arm, and the "elbow" on the arm, point after which the distortion starts decreasing in a linear fashion, is the best value of K. Thus for the given data, we conclude that the optimal number of clusters for the data is $|K| = 5$. Figure 9 depicts the resulting country clusters by showing the position of each country c in terms of risk ($\sigma(D_c)$) and wealth (GNI_c).

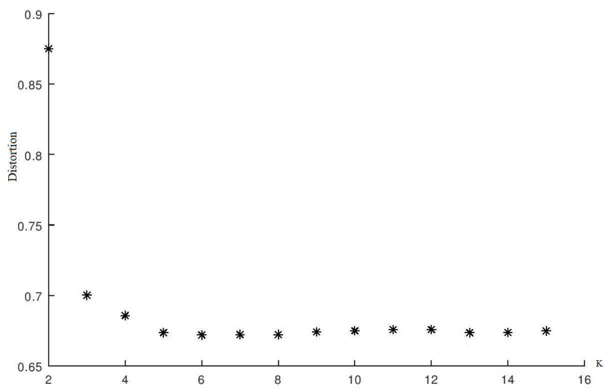

Figure 8 **Cost function graph of the K-means algorithm.**

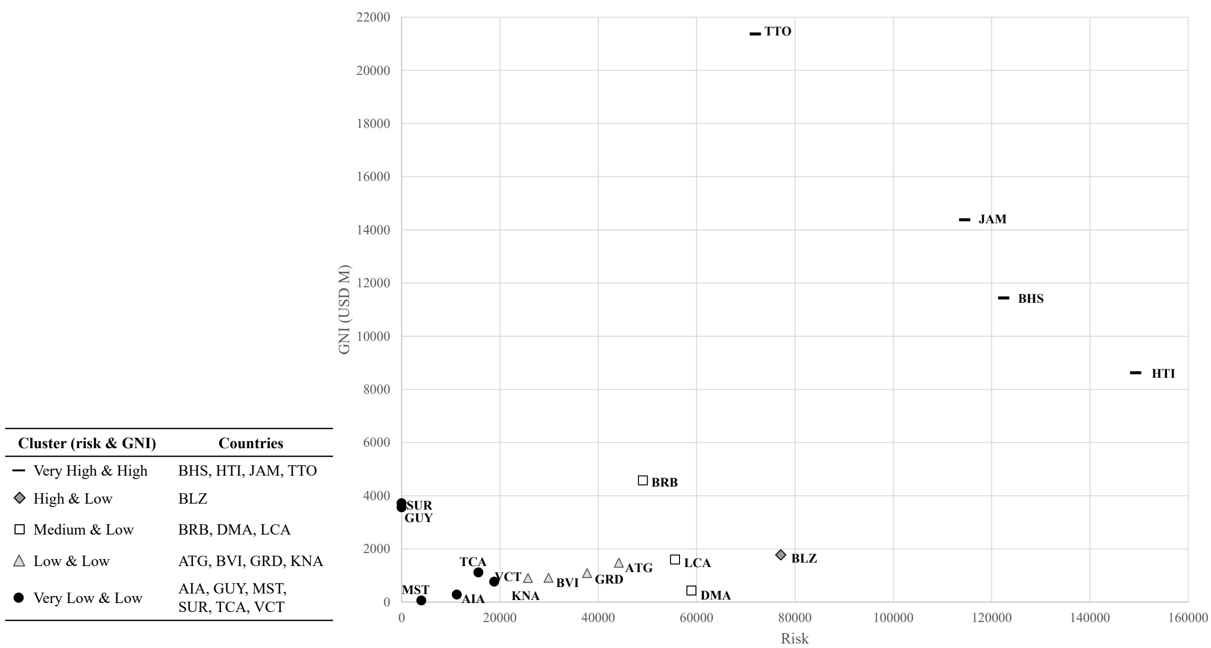

Figure 9 **Graph of the country clusters depicting their risk and wealth profiles.**

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