ENHANCING EFFICIENCY IN HUMANITARIAN PREPOSITIONING THROUGH POSTPONEMENT AND STOCK SHARING

A Dissertation

by

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Submitted to the
Graduate School of Sciences and Engineering
in Partial Fulfillment of the Requirements for
the Degree of

Doctor of Philosophy

in the
Department of Industrial Engineering

Özyeğin University
October 2024

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To my husband and my family...

ABSTRACT

Prepositioning is a critical disaster preparedness mechanism for humanitarian organizations (HOs) but requires significant investment. Improving the efficiency of prepositioned stocks is a primary concern within the humanitarian community. This thesis, conducted in collaboration with the Emergency Supply Prepositioning Strategy (ESUPS) Working Group, examines the impact of implementing postponement and stock-sharing strategies in regional and country-level humanitarian warehouses. We focus on a setting where multiple HOs preposition supplies within the same (regional and/or country) warehouse to serve disaster-affected countries. Traditionally, these prepositioned supplies are branded with the respective HOs' logos, hindering the sharing of surplus stock during disaster response. Our proposed system defers the branding process for a portion of the stockpile in the regional warehouse until after a disaster, facilitating the sharing of unbranded stock among HOs. We limit stocks to branded form at country warehouses for faster response.

This thesis aims to achieve two primary objectives: (i) evaluate the impact of proposed collaboration strategies based on postponement and stock sharing on the post-disaster response performance of HOs, and (ii) devise effective methods for implementing these strategies. To accomplish these goals, we develop two analytical frameworks, each forming a chapter of the thesis. Together, these frameworks provide a comprehensive approach for enhancing the efficiency and effectiveness of disaster preparedness efforts in humanitarian operations management.

In Chapter 2, we focus on a setting where HOs in a single regional warehouse serve a specific region (e.g., the Caribbean), with each HO responding to disasters within its designated area in this region. To assesses the effectiveness of postponement and stock

sharing, we develop a two-phase inventory allocation model for distributing branded and unbranded stocks to disaster-affected countries and for sharing unbranded stocks among HOs. We incorporate this model into a Monte Carlo simulation algorithm that accounts for uncertainties in disaster occurrence and impact.

In Chapter 3, we consider a setting where HOs in both regional and country warehouses respond to disasters within their designated areas in a specific region. To operationalize postponement and stock sharing, we develop a two-stage stochastic optimization model that minimizes expected response time weighted by disaster severity under fixed total base stock constraints. This model optimizes the levels of branded and unbranded items for each HO across warehouses, facilitates stock sharing in the regional warehouse, and devises optimal stock mobilization strategies to affected countries.

We apply the approaches developed in this thesis to case studies on hurricane preparedness and response in the Caribbean, using data from ESUPS, its partner HOs, and the United Nations Humanitarian Response Depot (UNHRD) Panama warehouse. Our extensive numerical analyses generate practical insights and examine the sensitivity of our results to various modeling choices and parameters. The simulation study in Chapter 2 reveals a U-shaped relationship in response time as the postponement rate increases, with consistent improvements in fill rate and inventory utilization. The optimization model in Chapter 3 shows substantial key performance indicator (KPI) improvements through postponement and stock sharing and provides insights into the impact of disaster severity levels and base stock levels on network design and distribution strategies.

Overall, this thesis demonstrates significant benefits of postponement and stock-sharing strategies in improving the efficiency and effectiveness of prepositioning efforts. Our findings offer valuable insights for improving decision-making in disaster preparedness within humanitarian networks.

ÖZETÇE

Önkonumlandırma insani yardım organizasyonları (İYO) için kritik bir afet hazırlık mekanizması olmasına rağmen önemli yatırım ihtiyacı gerektirmektedir. Önkonumlandırılmış stokların verimliliğini artırmak, insani yardım topluluğu içinde önemli bir konudur. Bu tez, Emergency Supply Prepositioning Strategy (Acil Durum Tedarik Önkonumlandırma Stratejisi: ESUPS) çalışma grubu işbirliğiyle, bölgesel ve ülke düzeyindeki insani yardım depolarında erteleme ve stok paylaşım stratejilerinin uygulanmasının etkisini incelemektedir. Çalışmada birden fazla İYO'nun, afetlerden etkilenen ülkelere hizmet etmek üzere aynı (bölgesel ve/veya ülke) depo içinde malzeme önkonumlandırdığı bir durum ele alınmaktadır. Geleneksel olarak, bu önkonumlandırılmış malzemeler ilgili İYO'ların logolarıyla markalanır, bu da afet müdahalesi sırasında fazla stokun paylaşılmasını engeller. Önerilen sistemde bölgesel depodaki stokun bir kısmının markalanma süreci afet sonrasına ertelenmekte ve böylece İYO'lar arasında markasız stok paylaşımı kolaylaşmaktadır. Ülke depolarındaki stoklar ise, daha hızlı müdahale sağlamak amacıyla yalnızca markalı olarak tutulmaktadır.

Bu tezin iki ana amacı vardır: (i) erteleme ve stok paylaşımına dayalı önerilen işbirliği stratejilerinin afet sonrası müdahale performansı üzerindeki etkisini değerlendirmek ve (ii) bu stratejilerin uygulanması için etkili yöntemler geliştirmek. Bu hedeflere ulaşmak için, her biri tezin bir bölümünü oluşturan iki analitik çerçeve geliştirilmiştir. Bu çerçeveler birlikte insani yardım operasyonları yönetiminde afet hazırlık çalışmalarının verimliliğini ve etkinliğini artırmak için kapsamlı bir yaklaşım sunmaktadır.

Tezin ikinci bölümünde, tek bir bölgesel depoda bulunan İYO'ların belirli bir bölgeye (örneğin, Karayipler) hizmet verdiği ve her İYO'nun bu bölgedeki belirlenmiş

müdahale alanlarında afetlere müdahale ettiği bir durum ele alınmıştır. Erteleme ve stok paylaşımının etkinliğini değerlendirmek için, afetlerden etkilenen ülkelere markalı ve markasız stokların dağıtımı ve markasız stokların İYO'lar arasında paylaşımı için iki aşamalı bir envanter tahsis modeli geliştirilmiştir. Bu model afetlerin meydana gelmesi ve etkisi konusundaki belirsizlikleri dikkate alan bir Monte Carlo simülasyon algoritmasına dahil edilmiştir.

Üçüncü bölümde, hem bölgesel hem de ülke depolarında bulunan İYO'ların belirli bir bölgedeki (örneğin, Karayipler) belirlenmiş müdahale alanlarında afetlere müdahale ettiği bir durum ele alınmaktadır. Erteleme ve stok paylaşımını işlevsel hale getirmek için, sabit toplam başlangıç stoku kısıtları altında afetin büyüklüğü ile ağırlıklandırılmış beklenen müdahale süresini minimize eden iki aşamalı rassal eniyileme modeli geliştirilmiştir. Bu model, her İYO için depolar arasında önkonumlandırılan markalı ve markasız stok seviyelerinin en iyi seviyelerini bulurken bölgesel depodaki stok paylaşımını kolaylaştırıp etkilenen ülkelere yönelik dağıtım stratejileri geliştirmeyi sağlamaktadır.

Bu tezde geliştirilen yaklaşımlar, ESUPS, ESUPS'un birlikte çalıştığı İYO'lar ve Birleşmiş Milletler İnsani Yardım Müdahale Deposu (BİMYD) Panama deposundan alınan veriler kullanarak Karayipler'deki kasırga hazırlığı ve müdahale üzerine vaka çalışmalarına uygulanmıştır. Farklı modelleme tercihlerinin ve model parametrelerinin üstünde duyarlılık analizleri yapılıp pratikte kullanılabilecek birçok çıkarım üretilmiştir. İkinci bölümdeki simülasyon çalışması, erteleme oranı arttıkça müdahale süresinde U şeklinde bir ilişki olduğunu ortaya koyarken, doluluk oranı ve envanter kullanımında sürekli iyileşmeler sağlandığını göstermektedir. Üçüncü bölümdeki eniyileme modeli, erteleme ve stok paylaşımı yoluyla önemli temel performans göstergelerinde iyileştirmeler olduğunu göstermektedir. Ek olarak, bu model afet şiddetinin ve başlangıç stoku seviyelerinin ağ tasarımı ve dağıtım stratejilerini etkilediğini de göstermektedir.

Genel olarak, bu tez önkonumlandırma çabalarının verimliliğini ve etkinliğini artırmada erteleme ve stok paylaşım stratejilerinin önemli faydalarını göstermektedir. Bulgularımız, insani yardım ağlarında afet hazırlığını iyileştirme konusunda değerli çıkarımlar sunmaktadır.

ACKNOWLEDGEMENTS

I am deeply grateful to my academic advisor, Dr. Burcu Balçık, for her persistent support, patience, and guidance throughout my dissertation journey. It has been both an honor and a privilege to work closely with her. Her insightful feedback and unwavering encouragement have been invaluable in shaping my research and academic growth.

I extend my thanks to Florent Chanè, Sofia Minetto, and the ESUPS team for their substantial support and collaboration during this research. I am also particularly thankful to Birce Adsanver for her valuable contributions to the project discussed in Chapter 3.

I am sincerely grateful to my committee members, Dr. Enis Kayış, Dr. Bahriye Cesaret and Dr. Tuba Yılmaz Gözbaşı, for their insightful feedback and suggestions on this thesis. I also appreciate the time and effort of my committee members, Dr. Raha Akhavan-Tabatabaei and Dr. Tonguç Yavuz, in reviewing this thesis and providing constructive feedback.

I would like to express my gratitude to Dr. Mehmet Ayvacı for including me in his research project, providing continuous guidance and offering invaluable support during my time as a visiting researcher at the University of Texas at Dallas. Working with him was a true honor.

I also thank the faculty members of the Özyeğin University Industrial Engineering Department for their assistance with my research and academic development. Special thanks go to Dr. Erhun Kundakçıoğlu for his guidance and contribution to my academic progress. My sincere thanks also go to my office mates for their support.

I extend my deep gratitude to my husband Ahmet Serdar Şimşek for his unwavering encouragement and unconditional love. His support and inspiration have been essential in overcoming the challenges of the Ph.D. program. My feelings for him are difficult to put into words, but I wanted to make my love for him permanent by dedicating this thesis to him.

I also thank my family for their unconditional love and support. I am especially grateful to my parents, Nevin Kasap and Dr. Hüseyin Kasap, for their trust and significant role in my personal growth. Their sacrifices and guidance have been invaluable. I also extend my gratitude to my parents-in-law, Perihan Şimşek and Yusuf Şimşek for their unconditional encouragement and emotional support. I thank my uncles Dr. Nihat Kasap and Dr. Suat Kasap for their academic guidance and insparation, as well as my brother Caner Yavuz Kasap, Şirin Yıldızay Kasap, my uncle Nevzat İzmirli, and my in-laws Şahika Şimşek Ertorul, Düundar Ertorul, Yasin Şimşek, and Merve Şimşek for their constant support. I also dedicate this thesis to my family.

Finally, I acknowledge the financial support from the Scientific and Technological Research Council of Türkiye (TUBITAK) under the TUBITAK 1002 program [Project Number: 120M023].

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CHAPTER I

INTRODUCTION

In 2023, the UN forecasted that over 363 million individuals would need humanitarian assistance. Out of these, 245 million were targeted for aid, but only 144 million actually received it. Moreover, just over 43% of the required $56 billion in funding to meet global humanitarian needs has been secured [7]. This shortfall in funding and resources compels humanitarian organizations (HOs) to seek innovative operational strategies. Collaboration and coordination among the involved HOs are essential to optimize disaster response with limited resources. In this thesis, we explore a collaborative mechanism in prepositioning, based on postponement and loan-borrowing (i.e., stock sharing) strategies, and examine its implications for both HOs and the people in need.

Prepositioning is a widely implemented disaster preparedness strategy among humanitarian organizations (HOs), involving the storage of relief supplies in warehouses to ensure rapid response during disasters [8, 9]. However, maintaining large stockpiles in warehouses for extended periods represents dormant investments. Recent studies suggest that collaborative practices could help HOs reduce prepositioning costs while enabling timely responses [10, 11, 12, 13]. Notably, the United Nations Humanitarian Response Depot (UNHRD) network serves as a platform for collaborative prepositioning strategies [14], bringing together different HOs physically and fostering collaborative efforts, such as sharing excess stocks. Inventory in UNHRD warehouses is categorized into authorized users' (i.e., HOs') stock and suppliers' stock (i.e., white stock) [15]. Our focus is on enhancing the efficiency of HOs' stocks. While HOs may engage in stock sharing within regional warehouses, these collaborations often occur ad-hoc after disasters. We aim to present practical methods to facilitate improved collaboration among HOs for more effective and efficient prepositioning.

HOs that preposition supplies in the same regional warehouse often have distinct focus areas, selectively responding to disasters in specific countries. This offers stock sharing opportunities, allowing HOs to lend and borrow excess stocks for disaster response. However, stock sharing practices are not widely implemented for several reasons. One major hindrance is that HOs tend to keep their relief stocks branded rather than unbranded (i.e., blank, standard) for visibility and quick dispatch after disasters [16]. Sharing branded stocks, which is rarely practiced, would require a rebranding (repackaging) process, increasing resource requirements and packaging waste. Alternatively, maintaining a portion of prepositioned stocks unbranded can facilitate effective stock sharing and improved response. This thesis provides empirical evidence supporting the benefits of a collaborative approach that postpones the branding process until after a disaster and facilitates the sharing of unbranded stocks, and develops analytical frameworks to operationalize these strategies. We offer data-driven recommendations for positive transformations in the humanitarian sector.

The postponement strategy, which involves centralizing stocks in standard form and deferring product differentiation, has found widespread application in supply chains dealing with demand uncertainty [17]. While existing studies explore the benefits of postponement in commercial supply chains, its potential advantages in humanitarian supply chains, which also deal with high demand uncertainty, have not been addressed. This thesis is the first to investigate the potential benefits of implementing the postponement strategy in a humanitarian context, considering its unique challenges, such as distinct strategic goals (profit-driven versus human-suffering-reduction-driven) and complex sharing rules (involving overlapping response regions of HOs, management of branded and unbranded items, and interdependencies over time). Additionally, within the general postponement literature, this thesis is the first to explore the impact of postponing the labeling process to a country different from both the production and demand locations on key performance indicators (KPIs).

In Chapter 2 of this thesis, we introduce an analytical framework to assess the impact of keeping unbranded prepositioned stocks in a single regional warehouse and sharing them among HOs after a disaster. We specifically examine how postponement coupled with a stock sharing policy affects KPIs such as demand fulfillment, response time, and inventory utilization. Our investigation addresses whether HOs should keep unbranded stock and engage in stock sharing to enhance disaster response performance, determine the recommended proportion of unbranded stock, and explore if these strategies should vary among HOs of different sizes and response regions. To model this complex system, we develop a two-phase inventory allocation framework to share unbranded stocks in the regional warehouse after disasters. Optimization models in each phase determine the distribution of branded, unbranded, and shared stocks to affected areas. Additionally, a Monte Carlo simulation algorithm integrates this framework to evaluate the regional warehouse's performance under various disaster scenarios, considering uncertainties in disaster occurrences and impacts. Our results in this chapter demonstrate significant positive effects of postponement and stock sharing strategies on KPIs.

In Chapter 3, we examine a broader humanitarian distribution network with both regional and country-specific warehouses. Multiple HOs operate from these shared warehouses to respond to disasters in a specific region (e.g., the Caribbean). In this context, we explore the potential benefits and implementation challenges of postponing branding and stock sharing strategies. A key challenge for an HO in this network is deciding where and how much to postpone branding and how to efficiently allocate branded and unbranded stocks between regional and country warehouses. Higher inventory levels in the regional warehouse offer greater flexibility to serve multiple countries but with longer response times, whereas higher inventory levels in country warehouses ensure quicker local responses but reduce overall flexibility. We develop a two-stage stochastic optimization model to find the optimal balance between these factors. Our model determines the optimal levels of branded and unbranded items for each HO, facilitates stock sharing in the regional warehouse, and devises stock mobilization strategies to minimize expected response time weighted by disaster severity. The findings offer significant managerial insights for effectively applying these strategies.

We apply the approaches developed in Chapters 2 and 3 to case studies conducted in partnership with the Emergency Supply Prepositioning Strategy (ESUPS) Working Group, which is dedicated to enhancing prepositioning practices through improved coordination and collaboration among HOs [18]. Our case studies focus on hurricane preparedness and response in the Caribbean region, using data from ESUPS, its partner HOs, and the UNHRD Panama warehouse. We conduct extensive numerical analyses in the context of these case studies to generate practically relevant insights as well as to investigate the sensitivity of our results to relevant modeling choices and parameters. While our analyses center on specific cases, our analytical frameworks are adaptable to assess the impact of proposed strategies in diverse settings. Through our developed frameworks and findings, we aim to convince HOs, donors, and umbrella organizations like the UNHRD to implement our proposed strategies.

This thesis emerged from extensive collaborations with HOs, primarily through a long-term partnership between Özyeğin University and ESUPS. This partnership, spanning several years, provided the foundation for this thesis and ensured its practical relevance. Throughout the research conducted for this thesis, we actively engaged with numerous HOs partnered with ESUPS. These interactions allowed us to gain a deeper understanding of the operational context, collect relevant data, verify our modeling assumptions, present research findings, and gather critical feedback from practitioners. This iterative process of collaboration ensured that our research remained grounded in practical realities while adapting new theoretical concepts to humanitarian operations management.

CHAPTER II

A SIMULATION MODEL FOR ASSESSING THE BENEFITS OF POSTPONEMENT AND STOCK SHARING IN HUMANITARIAN RELIEF EFFORTS

2.1 Background and Motivation

Given the significant costs of supply chains for HOs [19], exploring strategies to enhance efficiency is crucial. In this chapter, we examine the impact of postponement and stock sharing strategies on the performance of prepositioned stocks in a regional warehouse that hosts multiple HOs, each responsible for responding to disasters in countries within their designated, and potentially overlapping, regions. Postponement involves keeping a proportion of stocks unbranded until after a disaster occurs, while stock sharing refers to the practice of lending and borrowing supplies among HOs (see Figure 1 for a comparison between the current network and the proposed network).

Collaborative strategies are generally expected to yield positive results through resource pooling, but it remains uncertain whether these enhancements are significant enough to motivate HOs to change practices. Our research in this chapter introduces an analytical framework to evaluate the effects of maintaining unbranded prepositioned stocks and sharing them among HOs after a disaster. Using this framework, we analyze how postponement combined with a stock sharing policy influences key performance indicators (KPIs) such as demand fulfillment, response time, and inventory utilization. Additionally, we demonstrate the recommended levels of uniform and HO-size-dependent postponement levels through empirical evidence. We address the following questions: (1) *Should HOs keep unbranded stock and apply stock sharing to improve disaster response performance?* (2) *If so, what should be the proportion*

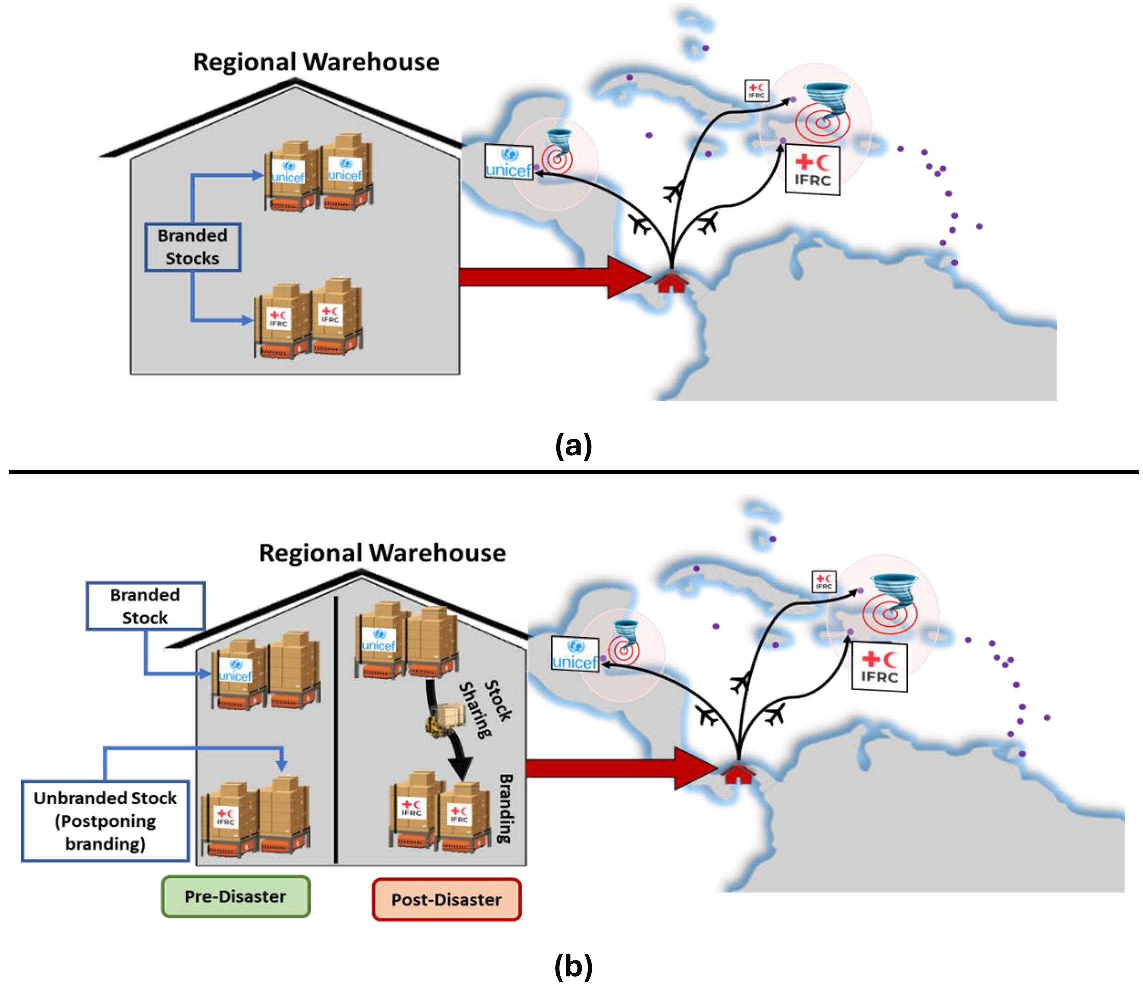

Figure 1: The illustration of the network: (a) current; (b) proposed

of unbranded stock kept by HOs? (3) *Should the decisions from questions 1 and 2 be uniformly applied across all HOs, or is there variation in decision-making among different HOs with different sizes and response regions?*

Assessing the effects of stock sharing and postponement strategies is challenging due to complexities related to modeling a realistic stock sharing system among HOs with different response regions. Specifically, we need to model the allocation of unbranded stocks in regional warehouses owned by different HOs after a disaster, accounting for simultaneous disaster impacts across multiple countries. Drawing on expert knowledge and practitioner insights, we develop a two-phase inventory allocation framework for sharing stocks in a regional warehouse. In each phase, optimization models are solved to determine the distribution of different stock types (i.e., branded, unbranded, shared) to affected areas. We also develop a Monte Carlo simulation algorithm that integrates the proposed inventory allocation framework and evaluates the expected performance of the regional warehouse under various disaster scenarios, considering uncertainties related to disaster occurrences and effects.

We implement our framework in a case study focusing on hurricane preparedness and response in the Caribbean region, using data from ESUPS, its partner HOs, and UNHRD Panama warehouse. Although our analysis is based on this specific case, our analytical framework is versatile and can be applied to evaluate the proposed strategies in various contexts. Our numerical analysis investigates: (1) *how different rates of unbranded stock and stock sharing policies influence the efficiency and effectiveness of prepositioning at both warehouse and country levels,* and (2) *factors affecting the extent of benefits from postponement in this humanitarian setting.* Our findings demonstrate that postponement and stock sharing policies substantially improve KPIs based on fill rate, response time, and inventory utilization. Specifically, as the unbranded stock rate increases, response time follows a U-shaped trend while the fill rate improves. We offer insights to explain these patterns and provide valuable managerial guidance for the effective implementation of the proposed strategies.

Our research findings in this chapter have been systematically disseminated to practitioners through multiple channels. We presented versions of our model and insights at several ESUPS Working Group meetings and at ESUPS' Humanitarian Networks and Partnerships Week in 2020 and 2022. The project's outcomes were synthesized in an executive report, published by ESUPS and presented at The Annual Global Preparedness Workshop in November 2023, jointly organized by Logistics Cluster, Welthungerhilfe, and ESUPS [20]. ESUPS publicly endorsed this report on their website, emphasizing its pioneering nature and potential to transform collaborative practices among HOs. The announcement highlighted the broader implications of our findings, urging HOs to adopt and replicate our model to refine their strategies, ultimately benefiting both the humanitarian community and those affected by crises [21]. This positive reception from ESUPS validates the practical relevance of our research and its potential to enhance humanitarian logistics operations.

We structure the remainder of the chapter as follows. In Section 2.2, we position this chapter within the existing literature. In Section 2.3, we describe current branding practices in the humanitarian landscape. In Section 2.4, we explain our proposed system and research approach. In Section 2.5, we describe the system and present our models. In Section 2.6, we describe our case study and the results of analyses. In Section 2.7, we discuss our findings and conclude the chapter.

2.2 Literature Review

While prepositioning is extensively studied in humanitarian logistics literature, existing research primarily focuses on optimizing the location and quantity of prepositioned inventory. Some studies emphasize exploring innovative strategies to enhance prepositioning practices, including collaboration, standardization, postponement, and localization [22, 12, 13, 11]. Our study, which investigates the potential impact of implementing a postponement strategy combined with stock sharing within a regional humanitarian warehouse, aligns with two key streams of literature: collaborative inventory management in humanitarian supply chains and postponement.

2.2.1 Collaborative Humanitarian Inventory Management

Collaboration in humanitarian supply chains can be categorized into vertical and horizontal types. Vertical collaboration involves interactions between an HO and other actors in the upstream or downstream supply chain, whereas horizontal collaboration occurs among different HOs at the same level [10, 23]. Our study focuses on horizontal collaboration to improve the efficiency and effectiveness of prepositioning.

While prior work has emphasized enhancing horizontal collaboration in prepositioning networks (e.g., [24, 6, 25]), our study specifically investigates stock sharing practices among HOs that preposition supplies within the same warehouse. Research on collaborative inventory planning within single warehouses, like UNHRD facilities, typically distinguishes between authorized HOs' stocks (both unbranded and branded) and suppliers' unbranded white stocks [15]. Through UNHRD's inventory portal, HOs can monitor stocks owned by others [26]. White stock, managed by suppliers under Long-Term Agreements with UNHRD, is available to member HOs. On one hand, centralized systems like white stocks can have certain advantages for HOs such as lower information costs or reduced inventory holding costs. On the other hand, white stock's post-disaster availability, especially for smaller organizations, remains uncertain [27]. Furthermore, white stock may not be present in all humanitarian warehouses. This chapter aims to enhance the efficiency of HOs' stocks through a combination of postponement and stock sharing strategies.

Existing studies on collaborative inventory planning within warehouses involving HOs' stocks or white stock typically address scenarios with two (e.g., [28, 29]) or more HOs (e.g., [30, 31]). In these systems, HOs can access additional supplies when faced with inadequate stock for disaster response. For instance, [28] investigate two HOs sharing prepositioned stocks over multiple periods, categorizing stocks based on ownership and location, including HOs' own stocks stored at UNHRD facilities, swapped stocks, and UNHRD's white stocks. They employ a multi-agent simulation model to analyze HOs' decisions on stock placement. In a different context, [29] focus on a relief network where each HO manages its own disaster region, without overlapping response areas, within a single period setting. They propose a stock sharing policy considering independent disaster risks in various regions and identify scenarios where horizontal collaboration benefits arise. Similarly, [30] examine a single-period scenario within a humanitarian network where prepositioned stocks from different warehouses can be transported directly to disaster areas or through other facilities (transshipment), incorporating stock sharing among warehouses. Lastly, [31] analyze the impact of different levels of stock sharing (partial and full-sharing) on incentivizing HOs within a single-period system. They determine membership fees for HOs maintaining stocks in shared warehouses and propose a proportional sharing policy for allocating excess stock among collaborating organizations.

While previous research has explored collaborative inventory management systems in humanitarian warehouses, our study is the first to investigate the effects of postponement in this context. Unlike previous models that focus on surplus stock sharing and overlook the branding process, our approach categorizes prepositioned stocks as either shareable (unbranded) or non-shareable (branded), enabling us to model and analyze the impact of postponement on prepositioning performance. This necessitates the development of new inventory allocation models to accurately represent current stock sharing practices in humanitarian operations.

2.2.2 Postponement in Supply Chain Management

Numerous studies have explored the application of postponement strategies in supply chains. These strategies are commonly classified into three main categories: *time*, *place*, and *form* postponement [32, 33, 34]. Time postponement involves delaying the shipment of goods until customer orders arrive. Place postponement entails delaying the shipment of goods, often focusing on storing goods centrally to facilitate inventory pooling. Form postponement refers to delaying final manufacturing or processing activities. [35] further develop this framework by considering the geographical aspect of postponement, identifying three options for postponement: the home region (i.e., the main production facility), a third-country region (i.e., a region separate from both the factory and customer locations), and the destination region (i.e., the customers' locations).

Time postponement involves delaying centralized manufacturing, impacting the positioning of finished goods within the supply chain. Finished product distribution postponement has been studied in retail (e.g., [36]), specialty retail (e.g., [37]), and electronics (e.g., [38]) industries. *Place postponement* is linked to inventory pooling strategies, where it facilitates the aggregation of demand variability across products or locations, resulting in smoother demand profiles that enhance supply chain flexibility and efficiency. Numerous studies have explored the implications of inventory pooling in supply chains, particularly in contexts with significant commercial urgency, such as spare parts management (e.g., [39, 40]), online retailing (e.g., [41, 42]), and fast fashion (e.g., [43]). The purpose of *form postponement* is to push the product's differentiation point as downstream as possible by reconfiguring the process, standardizing or modularizing the components [35]. Studies investigating form postponement include research on labeling (e.g., [44]), packaging (e.g., [45]), assembly (e.g., [46]), or manufacturing (e.g., [47]).

In our humanitarian context, we focus on a regional warehouse storing relief items of multiple HOs. In this setting, "labeling process," "finished products," and "customer order arrivals" correspond to branding process, branded items, and disaster occurrences, respectively. The current system already utilizes time and place postponement strategies. Specifically, branded items are stored in regional warehouses, separate from supplier manufacturing and disaster locations (place postponement). Additionally, these items are dispatched post-disaster (time postponement). Our proposed system adds an extra layer of postponement by delaying the branding process to a third-country until disasters occur, categorizing this chapter under third-country postponement of the labeling process, a type of form postponement.

Labelling postponement has been studied within wine (e.g., [44, 48, 49]), telecommunications (e.g., [50]), and IT (e.g., [51]) industries. Among these studies, the first four focus on home-region postponement, while the last study explores destination-region postponement. Third-country postponement has been explored for assembly postponement (e.g., [52, 53]) and finished product distribution postponement (e.g., [37]). Our study is the first to explore the impact of third-country postponement of the labeling process, addressing a gap in the literature highlighted by [35] as still underrepresented and deserving further consideration.

Investigating postponement within a humanitarian context presents unique challenges compared to its applications in supply chain settings. We outline two key distinctions. First, humanitarian supply chains prioritize alleviating human suffering, unlike profit-driven commercial chains (see, e.g., [50, 54, 47, 44]). Our models aim to reduce unsatisfied demand (weighted by the severity of disasters) rather than maximize profits. Second, the inventory allocation rules utilized in commercial contexts for distributing pooled inventory among customers do not directly apply to our humanitarian setting. Unlike typical allocation policies in commercial contexts, which are often based on fixed or randomized lists due to predictable demand structures and/or single-period considerations (e.g., [39]), our setting involves distinct sharing rules affected by the complexities of humanitarian operations, such as overlapping response regions (countries served), the management of both branded (non-shareable) and unbranded (shareable) items, interdependencies in sharing decisions over time, and highly unpredictable demands. Our inventory allocation models incorporate these aspects, significantly complicating our problem. Therefore, designing an implementable postponement and stock-sharing strategy in the humanitarian context requires the development of new models tailored to these challenges.

Lastly, in addition to its research contributions in presenting new models and insights, our study advocates for positive changes in the humanitarian sector by empirically showcasing the benefits of stock sharing and postponement strategies, ultimately leading to enhanced outcomes for disaster-affected populations.

2.3 *Current Branding Practices*

HOs commonly brand relief items with logos to enhance visibility and public relations [16]. Research underscores the correlation between brand visibility and donations [55], highlighting the significance of international media exposure for HOs. Logos also serve to credit HOs and donors' efforts [56]. They help governments in demonstrating aid origin and taxpayer money utilization, as well as improving their global image [57, 58, 59]. Branding facilitates tracking of stocks and ensures ownership during storage and distribution [3, 27]. Here we elaborate on the motivation behind branding for HOs and donors. We list the reasons as follows.

- The primary reason for branding relief items is to address the visibility and public relations concerns of HOs and donors. These concerns drive the preference for logos to be printed directly onto items/packages by suppliers, streamlining the branding process and minimizing efforts in HOs' warehouses. Additionally, HOs (especially large HOs like UNICEF) are not the only ones demanding branding; donors also have a stake in branding requirements and may request the inclusion of their logos alongside those of HOs. Academic research indicates that brand visibility correlates with donations (e.g., [55]), making it crucial for agencies to gain visibility to donor audiences through international media—especially in a highly competitive landscape where funding from donors is becoming increasingly limited. The increasing challenge of collecting donations is widely acknowledged by the humanitarian community. In a 2023 interview, the head of the Norwegian Refugee Council stated: "I think we're very far away from [not having actual donor or agency branding on the relief items]. What I predict is rather, in a more competitive climate for funding – funding is going down; 2024 will be a very tough year; 2023 is a very tough year for very good and very large agencies – there will be more pressure to really showcase to the world that we're doing well and that we need more money: 'Look at what we're doing; send more money'" [56]. This underscores the intense pressure faced by HOs to demonstrate their effectiveness and secure crucial funding through visible and impactful branding strategies.

- Logos also ensure that HOs and donors receive proper credit for their efforts. USAID's branding guide emphasizes the importance of their red, white, and blue logo in visibly acknowledging contributions from the American people [57]. Similarly, governments seek recognition for aid efforts, aiming demonstrate the origin of aid and how taxpayer money is utilized. Government branding efforts can also influence global perceptions of their countries. For example, favourable opinions of the United States in Indonesia significantly increased from 15% in 2003 to 38% following the extensive distribution of well-branded U.S. foreign aid during tsunami relief operations. As a result, 79% of Indonesians indicated a more positive view of the U.S. due to these humanitarian initiatives [58].

- In addition, branding provides benefits to recipients of the relief items by enabling them to identify where to address complaints or issues, thus facilitating accountability of the HOs [3]. Consequently, branding and logos are frequently mandated in project contracts to ensure visibility and accountability. For example, EU-funded humanitarian projects require standard visibility for the EU as a donor, which includes displaying the EU humanitarian aid field visual identity [59].

- In addition to visibility and public relations considerations, branding serves several other important purposes within humanitarian supply chains. Branding allows HOs to effectively track their stocks in warehouses and during distribution, which is essential in any supply chain network. This tracking capability is also crucial for donors, who need assurance that ownership of unbranded stock remains unchanged during storage, as highlighted by [27]. However, while branding was once deemed necessary for tracking ownership, innovative solutions have emerged to address this need without extensive branding. For example, the United Nations Humanitarian Response Depot (UNHRD) now attaches logos of HOs to shelves rather than individual packages (see Figure 2). This approach helps maintain visibility and accountability without the need for extensive item-level branding.

Figure 2: UNHRD attaches the logos of HOs to shelves [1]

- Branding also allows HOs to identify corruption in the black market [60]. It is not uncommon for the relief items ending up in local (black) market. In such cases, branding identifies the source of looting/corruption. However, visibility can also be accomplished by printing generic labels such as “For Humanitarian Use Only” or using a QR code. In the future, such technological and innovative methods can provide similar visibility provided by branding, potentially encouraging HOs to maintain unbranded (i.e., standard) stock. We anticipate that our study will contribute to discussions around enhancing supply chain visibility and efficiency, ultimately leading to incentives for adopting innovative solutions that streamline operations while maintaining accountability and donor visibility.

In the current system, HOs employ two primary methods of branding their stocks. Branding involves either printing the HO's logo directly onto the item or its packaging, or applying stickers with the HO's logo to the item or its package (see Figure 3 for visual examples of branding practices). The choice between these methods depends on the type of item and is determined by the HO.

(a) (b) (c) (d)

Figure 3: Branding examples: (a) printed logo on the item [2], (b) printed logo on the package [3], (c) sticker with HO's logo attached to the item [4], (d) sticker with HO's logo attached to the package [5]

Printing logos directly onto items or packaging is irreversible. In contrast, applying stickers, while potentially reversible, can still be time-consuming and costly to remove. Consequently, sharing branded stocks—whether permanently printed or sticker-applied—is rarely practiced due to the challenges of rebranding. Even with sticker-applied branding, the rebranding process can substantially increase expenses because it involves not only applying new brand stickers, but also the labor-intensive task of removing existing ones. As a result, this process not only generates packaging waste but also requires significantly more resources compared to branding standard items.

In current practice, HOs often utilize supplier-managed branding, either through printed logos or logo stickers, for its convenience and to streamline efforts during crises. Given the current reality and practices, branding remains essential in the humanitarian sector, and our proposed model acknowledges this reality. Instead of advocating for the elimination of branding, we propose more efficient approaches that involve minor compromises on visibility. Specifically, we investigate the performance implications of postponing branding until a disaster occurs for a portion of the stocks. This approach allows HOs to retain branding benefits while facilitating collaborative practices like stock sharing.

2.4 Research Approach

We focus on a humanitarian setting with a single regional warehouse, like UNHRD, where multiple HOs preposition stocks to respond to multiple countries. Each HO starts with a base stock (initial inventory) at the beginning of the planning horizon (e.g., a year) involving multiple periods (e.g., weeks), during which various countries may be affected by disasters. We consider seasonal disasters, such as hurricanes, which occur during a specific season each year, justifying the assumption of starting with the fully replenished base stock at the beginning of the planning horizon. However, our model can be adapted to handle occasional disasters (e.g., earthquakes) or a continuous set of disasters over a year by adjusting this base stock assumption accordingly. In our approach, HOs postpone branding process on a proportion (0% to 100%) of stocks, keeping them in an unbranded form in the regional warehouse. This facilitates HOs to quickly share these unbranded (i.e., shareable) stocks when needed. While such quick sharing after a disaster would require an effective information-sharing system, the existing UNHRD portal that provides visibility of available stocks [26] can be adapted for managing stock sharing among HOs.

We evaluate how varying unbranded stock rates (i.e., postponement rates), defined as the ratio of each HO's unbranded stocks to total stocks, impact system performance, focusing on key performance indicators (KPIs): response time, fill rate, and inventory leftover ratio. Response time is critical for saving lives and gaining visibility among donors. The fill rate measures how sharing unbranded stocks affects demand satisfaction in the network, while the inventory leftover ratio serves as a proxy for prepositioning costs.

To compute the proposed KPIs, modeling the inventory management system at a regional warehouse after a disaster is essential but challenging. The decision-making process involves determining which HOs should deploy stocks to specific countries, how to distribute branded and unbranded stocks, and how to manage shareable resources in a network with multiple HOs having overlapping response regions and countries. To facilitate comparisons across different postponement rates in this complex setting, we develop inventory allocation models that capture key trade-offs and provide an "optimal" allocation within a centralized system. While real-world decisions may differ from optimal outcomes, our approach enables objective comparisons among various strategies and sets a benchmark for HOs, guiding them in coordinating prepositioned inventory management at regional warehouses.

In our proposed inventory management system with postponement, HOs respond to disasters by mobilizing their branded, unbranded, and borrowed stocks to meet the demand. To determine the stock quantities for shipment and sharing, we formulate a two-phase inventory allocation system, which initially deploys each HO's branded and unbranded stocks and then allows sharing excess stocks if demand remains unmet. We solve two inventory allocation models in these phases: *Model 1* allocates of HOs' own stocks to disaster-affected countries, and *Model 2* addresses the allocation of shareable stocks. These models are developed based on insights from consultations with our partner organization ESUPS and its member HOs, capturing typical business objectives and constraints within this network rather than those specific to each HO. Our objective is to understand and demonstrate the effects of postponement and stock-sharing practices on KPIs on average, without prescribing specific inventory allocation decisions for individual HOs.

To compare system performance with and without the proposed strategies, we employ a Monte Carlo simulation algorithm, which calculates relevant KPIs based on numerous disaster scenarios. By integrating our inventory allocation models, we assess how different unbranded stock rates impact performance under varying disaster conditions and quantify the benefits of postponement and stock-sharing strategies.

Next, we provide a detailed system description and present our models.

2.5 System Description and Modeling

In this section, we detail the humanitarian prepositioning system components (Section 2.5.1), introduce our two-phase inventory allocation framework and models (Section 2.5.2), and present the Monte Carlo simulation algorithm (Section 2.5.4) along with KPIs (Section 2.5.5). The notation used in this chapter is summarized in Appendix C.

2.5.1 System Description

We describe the important elements of the prepositioning system and modeling framework.

2.5.1.1 Network

We consider a humanitarian relief network with multiple HOs, each maintaining prepositioned stocks in a regional warehouse serving multiple countries. Each HO has a designated disaster response region covering specific countries, where they establish disaster offices to manage and coordinate relief operations. These offices are set up before any disaster occurs, as opening new ones during the chaotic post-disaster period is impractical. Consequently, HOs do not respond to countries outside their designated response regions. Let $\mathcal{A}$ denote the set of HOs, and $\mathcal{C}$ represent the set of countries. The HOs' response regions are represented by an HO-country level response matrix (see Section 2.6.1, Table 2), which includes binary parameters $\overline{\delta}_{ac}$, where $\overline{\delta}_{ac} = 1$ if country $c \in \mathcal{C}$ is in the response region of HO $a \in \mathcal{A}$, and 0 otherwise.

2.5.1.2 Planning horizon and disaster scenarios

We focus on preparedness and response for hurricanes, which occur multiple times during a season, affecting multiple countries with varying severity levels. To address uncertainties in hurricane occurrence, we use a discrete representation of disaster scenarios based on historical data, as in [6] (see Figure 7 in Section 2.6.1). Each scenario $s \in \mathcal{S}$ represents a disaster season with periods $t \in \mathcal{T}$ (e.g., weeks). In each period, there may be zero, one, or multiple disaster events with different severity levels (λ), resulting in different severity levels and demands per affected country denoted by $\overline{\lambda}stc$ and $\overline{d}stc$. We define Γ_s and Υ_{sc} as subsets of $\mathcal{T}$ representing periods with disasters, and periods where country c is affected in scenario s, respectively. Additionally, ζ_c indicates the scenarios in which a disaster affects country c.

At the start of the planning horizon, each HO maintains an initial prepositioned inventory ($\overline{q}_a^T$), which is used and replenished throughout the horizon as the HO responds to disasters in its own region or shares stocks with other responding HOs (see Figure 5 in Section 2.5.3 for an illustration of different types of stock movements). Assumptions regarding delivery times and stock replenishment will be discussed next.

2.5.1.3 Delivery times

The response time for each disaster in each scenario depends on the *delivery times* of branded, unbranded, and shared/borrowed stocks from the regional warehouse to the disaster-affected countries, as well as the delivery time for unmet demand directly from the suppliers. We approximate shipment times without considering variations in in-land transportation, assuming they are uniform across branded, unbranded, and shared supplies.

Delivery time for branded stocks ($\overline{\tau}^b$) includes loading onto vehicles and transportation to affected countries. The delivery time of unbranded stocks ($\overline{\tau}^u$) encompass branding, loading, and transportation times. Delivery time for borrowed stocks ($\overline{\tau}^s$) adds extra time for the sharing process. If demand remains unmet, suppliers deliver directly within $\overline{\tau}^p$ units. Based on practitioner consultations, we assume $\overline{\tau}^b < \overline{\tau}^u < \overline{\tau}^s < \overline{\tau}^p$ (see Section 2.5.3 for an illustrative example).

2.5.1.4 Replenishment of the regional warehouse

Each HO's inventory decreases at the end of a period due to usage, if any, and increases at the beginning of a period upon replenishment from the supplier. While we assume a single supplier for simplicity, the model can accommodate multiple suppliers with varying delivery times. HOs place replenishment orders with the supplier at each disaster period, matching the amount used for branded, unbranded, and borrowed stocks. Replenishment orders arrive at the regional warehouse in unbranded form at the start of the first period after a replenishment lead time $\overline{\tau}^r$, which is typically longer than the supplier lead time during the response phase $\overline{\tau}^p$ (i.e., the time required for direct mobilization from the supplier to disaster-affected countries).

Upon receiving unbranded stocks at the warehouse, the responding HO (i) labels a portion of the stocks that is equal to the branded stock usage amount with its own brand to replenish its branded stock, (ii) replenishes its unbranded stock, and (iii) replenishes the unbranded borrowed stock of each sharing HO (see Section 2.5.3 for an example).

As explained before, to evaluate performance of the current and proposed systems, we simulate HOs' decisions on inventory allocation to meet demands in each disaster scenario. We define and model the inventory allocation problem with postponement and stock-sharing features in two phases, presented next.

2.5.2 Two-phase Inventory Allocation Framework

To formulate the inventory allocation problem with postponement and stock sharing, without loss of generality, we consider a single relief item prepositioned by several HOs in a regional warehouse (e.g., blankets, tarpaulins, family kits). HOs maintain a proportion (R) of the prepositioned stocks in unbranded form to facilitate sharing when needed. At the beginning of each planning horizon (e.g., hurricane season), HOs start with a total initial inventory level ($\overline{q}_a^T$). This total includes branded stocks ($\overline{q}_{sta}^b = (1-R)\overline{q}_a^T$) and unbranded stocks ($\overline{q}_{sta}^u = R\overline{q}_a^T$). Each HO owns and manages its own *branded* and *unbranded* stock. In each period, the available branded and unbranded stock of each HO depends on the usage and replenishment from the supplier over previous periods.

During each period when a disaster affects one or multiple countries, we face the critical decision of *determining how each HO will address the demand for relief supplies using branded, unbranded, and shared stocks.* This complex problem involves simultaneous relief delivery and stock sharing decisions across multiple HOs, further complicated by the need to prioritize countries. To address this challenge, we model the inventory allocation problem in two phases, as illustrated in Figure 4. This approach not only offers a practical solution for stock sharing among organizations but also ensures efficient computation in each period. By integrating this framework into our Monte Carlo simulation algorithm (Section 2.5.4), we can compute relevant KPIs for a large number of scenarios quickly, enabling comprehensive numerical analysis within reasonable times. We also developed a single optimization model that integrates both phases (see Section 2.6.2.5-a)), which yields similar results. However, we proceed with the two-phase model because the integrated model requires more computational resources and has led to out-of-memory errors during our analysis.

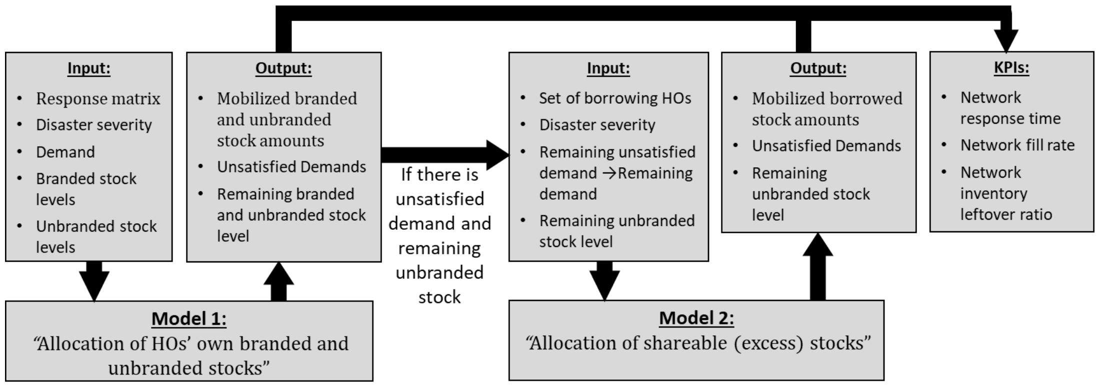

Figure 4: The illustration of the two-phase decision-making framework for inventory allocation

Figure 4 illustrates our two-phase optimization approach. We solve two optimization models sequentially in each period with a disaster throughout the planning horizon. In the first phase (Model 1), we allocate HOs' own stocks, followed by the allocation of shareable stocks in the second phase (Model 2). Next, we provide a detailed explanation of these inventory allocation problems and models.

2.5.2.1 Phase 1: Allocation of HOs' own stocks (Model 1)

In the first phase, HOs mobilize their own branded and unbranded stocks to meet the demand in disaster-affected countries within their response region. When multiple countries are affected, each HO prioritizes those affected more severely and allocates stocks accordingly. Specifically, if HOs have excess stocks after fulfilling severe demands, they respond to less severely affected countries.

Model 1 parameters include disaster demands, severities, HO response regions, and stock levels for branded and unbranded items. Key decisions involve determining the amount of unbranded (X^u_{stac}) and branded (X^b_{stac}) stocks mobilized by each HO to affected countries. Consequently, this phase identifies *responding* (i.e., $\delta_{stac} = 1$ if $X^u_{stac} + X^b_{stac} > 0$) and *non-responding* ($\delta_{stac} = 0$ if $X^u_{stac} + X^b_{stac} = 0$) HOs for disasters occurring in different countries. Additionally, U_{stc} denotes unsatisfied demand in affected countries. Furthermore, I^b_{sta} and I^u_{sta} variables keep remaining branded and unbranded stock levels, respectively.

We present Model 1, which is solved in every period $t \in \mathcal{T}$ of each scenario $s \in \mathcal{S}$ below.

$$\text{minimize} \sum_{c \in \mathcal{C}} \overline{\lambda}_{stc} U_{stc} \tag{1}$$

subject to

$$U_{stc} = \overline{d}_{stc} - \sum_{a \in \mathcal{A}} (X^b_{stac} + X^u_{stac}) \qquad \forall c \in \mathcal{C} \tag{2}$$

$$X^b_{stac} + X^u_{stac} \leq M\overline{\delta}_{ac} \qquad \forall a \in \mathcal{A}, c \in \mathcal{C} \tag{3}$$

$$\sum_{c \in \mathcal{C}} X^u_{stac} + I^u_{sta} = q^u_{sta} \qquad \forall a \in \mathcal{A} \tag{4}$$

$$\sum_{c \in \mathcal{C}} X^b_{stac} + I^b_{sta} = q^b_{sta} \qquad \forall a \in \mathcal{A} \tag{5}$$

$$I^b_{sta} \leq M(1 - Z_{sta}) \qquad \forall a \in \mathcal{A} \tag{6}$$

$$\sum_{c \in \mathcal{C}} X^u_{stac} \leq MZ_{sta} \qquad \forall a \in \mathcal{A} \tag{7}$$

$$X^b_{stac}, X^u_{stac} \geq 0 \text{ and integer} \qquad \forall a \in \mathcal{A}, c \in \mathcal{C} \tag{8}$$

$$I^b_{sta}, I^u_{sta} \geq 0 \text{ and integer} \qquad \forall a \in \mathcal{A} \tag{9}$$

$$U_{stc} \geq 0 \text{ and integer} \qquad \forall c \in \mathcal{C} \tag{10}$$

$$Z_{sta} \in \{0, 1\} \qquad \forall a \in \mathcal{A} \tag{11}$$

The objective function (1) of Model 1 minimizes the total unsatisfied demand in each country, weighted disaster severity levels. This approach, common in the literature (see, e.g., [8], [61]), aligns with our practitioner collaborators' preferences. In our case study, we explore alternative objective functions, like minimizing the maximum unsatisfied demand ratio per country weighted by disaster severity, detailed in Section 2.6.2.3-b. This analysis confirms that our primary study insights on postponement effects (Section 2.6.2.1) remain unchanged.

Constraint (2) defines the unsatisfied demand based on total mobilized stocks from HOs to an affected country and its demand. Constraint (3) restricts HOs to responding only within their designated regions. Constraints (4) and (5) limit the mobilized amounts of unbranded and branded stocks to not exceed each HO's respective stock levels, respectively. Constraints (6) and (7) ensure that HOs use unbranded stocks only after depleting their branded stocks, controlled by decision variable Z_{sta}, where $Z_{sta} = 1$ if an HO mobilizes unbranded stock, and 0 otherwise. Finally, constraints (8)-(11) define variable domains.

As shown in Figure 4, the outputs of Model 1 become inputs for Model 2 if stock sharing is necessary; otherwise, only the outputs from Phase 1 suffice to compute the relevant KPIs in our simulation algorithm.

2.5.2.2 Phase 2: Allocation of shareable stocks (Model 2)

If responding HOs' own stocks are insufficient to meet the demand in Phase 1, Model 2 is employed in Phase 2 to distribute *shareable* (i.e., excess unbranded) stocks among the responding HOs to satisfy the *remaining demand*. The outputs of the remaining demand (U_{stc}) and shareable stock ($I^{u}_{st\acute{a}}$) variables from Model 1 serve as parameters of Model 2.

In Phase 2, we establish rules for identifying HOs eligible to share and borrow shareable stocks through consultations with practitioners. Model 2 incorporates these rules to determine the amount of stocks to be shared and delivered. Accordingly, if a responding HO borrows shareable stock from either a non-responding HO or another responding HO with excess unbranded stock, the responding HO becomes a *borrowing HO*, while the lending HO becomes a *sharing HO* (see Section 2.5.3 for an illustrative example).

The rules for implementing a sharing policy in the second phase are as follows.

1. An HO that responds to a disaster-affected country in Model 1 (i.e., a responding HO) can borrow stocks for responding to that country if it has already deployed its own branded and/or unbranded stocks in Model 1. If there is no responding HO for the country in Model 1 (e.g., because all HOs that include the country within their response regions mobilized their own stocks to other countries in Model 1), then non-responding HOs that include the country within their response regions can borrow unbranded stock to respond to the country. This mechanism prioritizes HOs that already mobilized stocks (i.e., responding HOs) over those that did not (i.e., non-responding HOs) for borrowing stocks, ensuring that response resources are effectively utilized.

2. HOs responding to the same country do not exchange stocks among themselves to respond to that country.

3. A responding HO can share its excess unbranded stock with another HO after fulfilling the demands of disaster-affected countries within its response region.

4. No specific prioritization rules dictate a specific lending and borrowing sequence among multiple sharing and borrowing HOs. Allocation is determined based on the remaining demand of countries, weighted by the severity of the situation.

To formulate Model 2, we specify *candidate sharing HOs* and *candidate borrowing HOs for country c* using binary parameters $\gamma_{sta} = 1$ and $\Pi_{stac} = 1$, respectively. Specifically, $\gamma_{sta} = 1$ if $I^u_{sta} > 0$, and $\Pi_{stac} = 1$ if $\delta_{stac} = 1$ and $U_{stc} > 0$ or if $\overline{\delta}_{ac} = 1$, $\sum_{a \in \mathcal{A}} \delta_{stac} = 0$ and $U_{stc} > 0$. Furthermore, decision variables of Model 2 include the amount of stocks HO a borrows from HO $\acute{a}$ and mobilizes to the disaster-affected country c ($Y_{sta\acute{a}c}$). The unsatisfied demand of countries and the remaining unbranded stock levels of HOs are represented by V_{stc} and W^u_{sta}, respectively. We present Model 2 below.

$$\text{minimize} \quad \sum_{c \in \mathcal{C}} \overline{\lambda}_{stc} V_{stc} \tag{12}$$

subject to

$$V_{stc} = U_{stc} - \sum_{a \in \mathcal{A}} \sum_{\substack{\acute{a} \in \mathcal{A} \\ \acute{a} \neq a}} \Pi_{stac} \gamma_{st\acute{a}} Y_{sta\acute{a}c} \qquad \forall c \in \mathcal{C} \tag{13}$$

$$I^u_{st\acute{a}} - \sum_{\substack{a \in \mathcal{A} \\ a \neq \acute{a}}} \sum_{c \in \mathcal{C}} \Pi_{stac} \gamma_{st\acute{a}} Y_{sta\acute{a}c} = W^u_{st\acute{a}} \qquad \forall \acute{a} \in \mathcal{A} \tag{14}$$

$$Y_{sta\acute{a}c} \geq 0 \text{ and integer} \qquad \forall a \in \mathcal{A}, \acute{a} \in \mathcal{A}, c \in \mathcal{C} \tag{15}$$

$$V_{stc} \geq 0 \text{ and integer} \qquad \forall c \in \mathcal{C} \tag{16}$$

$$W^u_{sta} \geq 0 \text{ and integer} \qquad \forall a \in \mathcal{A} \tag{17}$$

Similar to Model 1, the objective function (12) of Model 2 minimizes the total severity-weighted unsatisfied demand. Constraints (13) ensure that the total mobilized borrowed stocks from HOs to an affected country does not exceed the demand of that country, thereby defining the unsatisfied demands. Constraints (14) guarantee that the total mobilized borrowed stocks from HOs to affected countries do not exceed the shareable amount held by HOs, while also specifying the remaining unbranded stocks of HOs after sharing. Finally, Constraints (16 and 17) define the domains of variables.

Given the solutions of Model 2, if the sum of responding HOs' branded, unbranded, and borrowed stocks is insufficient to meet the demand at the end of Phase 2, the unmet demand is satisfied by the supplier.

2.5.3 Illustrative Example for Stock Sharing with Postponement

Figure 5 (a) and (b) illustrate the core concepts in a simplified scenario, featuring a single country (C_1) and multiple countries (C_1, C_2, C_3), respectively.

In Figure 5(a), considering the predetermined response regions, only HO_1 and HO_2 respond to the disaster in C_1. HO_1 deploys two pallets of both branded and unbranded stocks, in addition to borrowing two pallets from HO_3, while HO_2 dispatches two pallets each of its own branded and unbranded stocks. Borrowing unbranded stock from HO_3 proves adequate to meet C_1's demand, which is 10 pallets. Accordingly, HO_1, HO_2, HO_3, and HO_4 can be categorized as, respectively, "responding and borrowing", "responding", "non-responding and sharing", and "non-responding". Here, HO_1 and HO_2 replenish stocks (i.e., two branded and four unbranded pallets for HO_1, and two branded and two unbranded pallets for HO_2), from the supplier. HO_1 gives back the unbranded stock amount that is borrowed (i.e., two pallets in unbranded form) to HO_3.

In Figure 5(b), HO_1 and HO_2 can respond to disaster-affected countries in C_1 and C_3, while HO_3 and HO_4 can only respond to C_2. HO_1 and HO_2 prioritize their response to C_1 due to the higher severity of the disaster there compared to C_3. However, their combined stock of eight pallets falls short of C_1's 10-pallet demand. Therefore, HO_1 borrows two excess unbranded stock pallets of HO_3 since HO_3 and HO_4 collectively possess enough stock to meet C_2's demand. Consequently, HO_3 is "responding and sharing", while HO_4 is simply "responding". Upon making the inventory allocation decisions at the warehouse, HOs deplete their entire stock, even though C_3's demand remains unmet. As a result, the supplier fulfills C_3's demand with four pallets. In addition, HO_1 mobilizes its own branded and unbranded stocks, and the borrowed stocks to arrive at C_1 at lead times $\overline{\tau}^b$, $\overline{\tau}^u$, and $\overline{\tau}^s$, respectively. After this shipment, country C_3's unmet demand is satisfied by the supplier in $\overline{\tau}^p$ lead time.

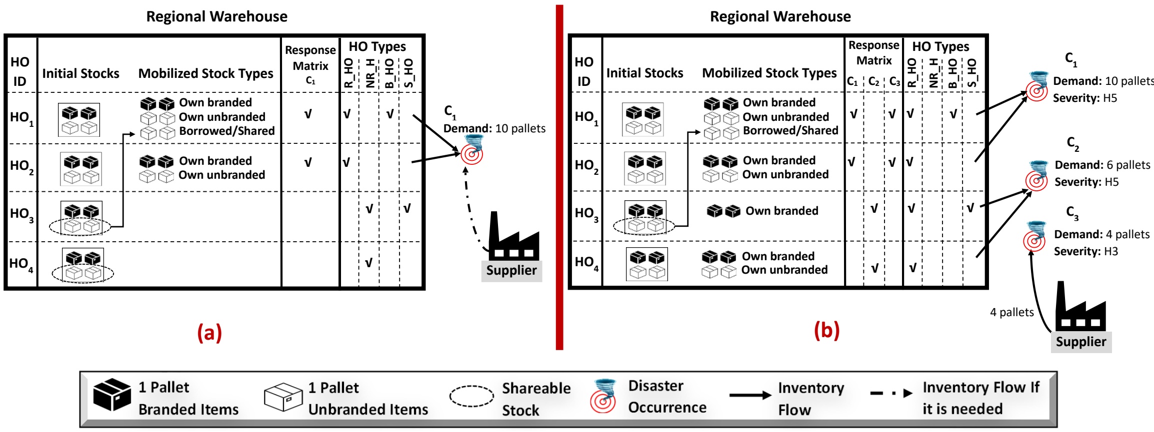

Figure 5: Inventory allocation decisions with postponement

Note: **R_HO**: responding HO, **NR_HO**: non-responding HO, **B_HO**: borrowing HO, and **S_HO**: sharing HO.

2.5.4 Monte Carlo Simulation

For a specific unbranded rate $R \in [0\%, 100\%]$, we run our simulation algorithm for each scenario and compute the relevant KPIs (Section 2.5.5). Our main goal is to compare these KPI values across different R values with a *base case*, which represents the current situation where all stocks are kept in branded form (i.e., $R = 0\%$).

We present the pseudocode of our simulation algorithm (Algorithm 1), where $s = 1, 2, \ldots, \mathcal{S}$ and $t = 1, 2, \ldots, \mathcal{T}$ represent disaster scenarios and time periods, respectively. A detailed flowchart of the simulation algorithm is available in Figure 6.

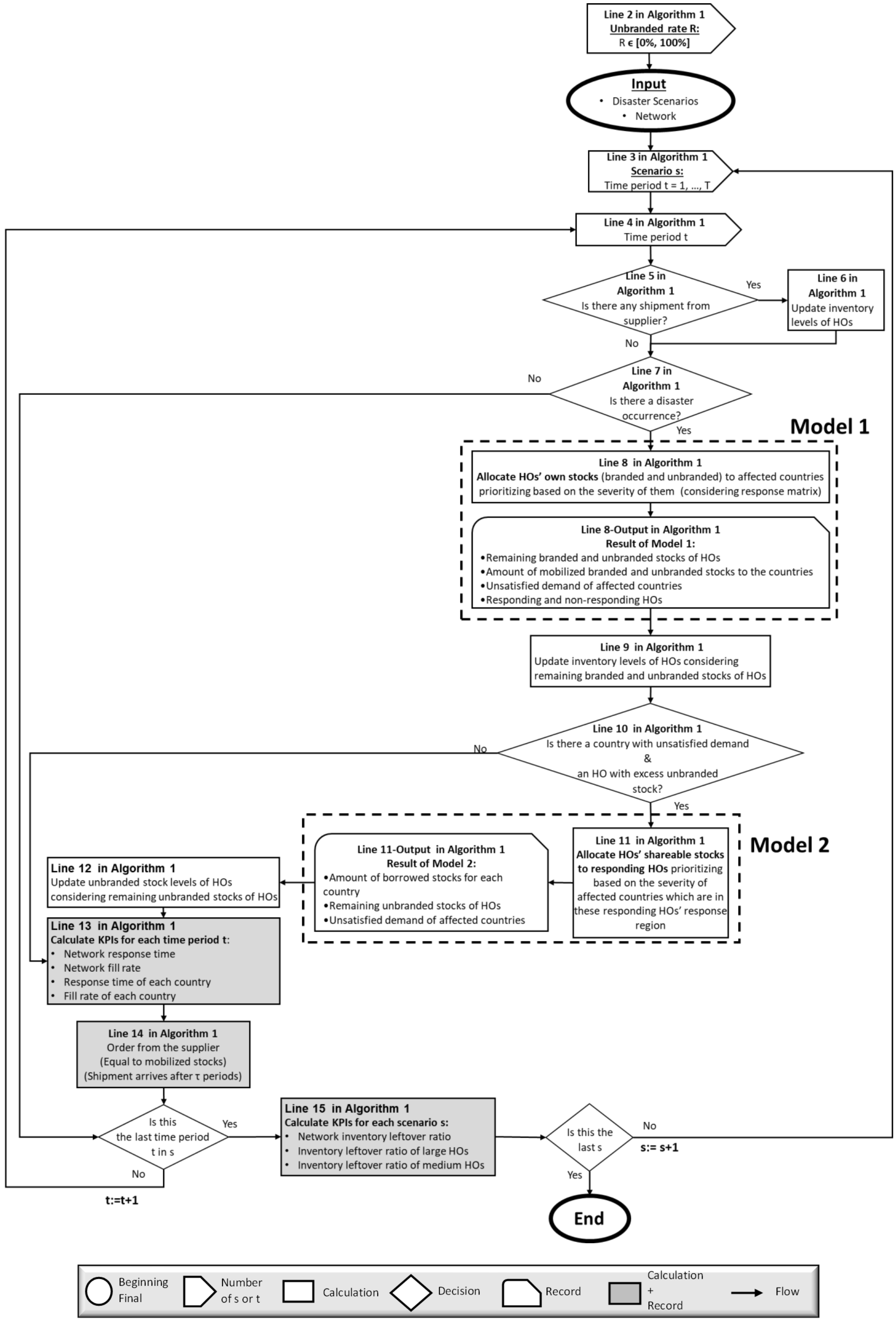

Figure 6: The flow chart of the Monte-Carlo simulation

Next, we briefly explain the algorithm's steps, referring to the lines in Algorithm 1 as needed.

Algorithm 1: Simulation Algorithm

1 Initialization;

2 **for** $R \in [0\%, 100\%]$ **do**

3   Scenario data, Network data **for** *scenario* $s = 1, 2, \ldots, S$ **do**

4   **for** *time period* $t = 1, 2, \ldots, T$ **do**

5   **if** $\exists$ *a shipment from the supplier* **then**

6   Update inventory levels based on the shipment;

7   **if** $\exists$ *a disaster in time period* t **then**

8   Solve the "Model 1–Allocation of HOs' own stocks";

                Output: X^b_{stac}, X^u_{stac}, I^b_{sta}, I^u_{sta}, U_{stc}, δ_{stac};

9   Update HOs' inventory levels depending on output;

10   **if** $\exists$ *at least one country with unsatisfied demand and at least one HO with excess unbranded stock* **then**

11   Solve the "Model 2–Allocation of shareable stocks";

                    Output: $Y_{sta\acute{a}c}$, W^u_{sta}, V_{stc};

12   Update HOs' inventory levels depending on output;

13   Calculate network response time, network fill rate, response time for each country, and fill rate for each country;

14   Open an order from the supplier, which arrives after $\overline{\tau}^r$;

15   Calculate the inventory leftover ratio at the regional warehouse (network) and for each HO ;

16   Calculate KPIs based on the aforementioned metrics in *Lines 13 and 15* for each $R > 0\%$

At the beginning of each time period in each scenario, we first update inventory levels by checking the arriving replenishments from the supplier (*Line 5*). We then initiate a response if a disaster occurs during the period (*Line 7*). If a disaster occurs, we determine the amount to allocate and ship to the affected countries by using Model

1 and Model 2 (*Lines 8-12*).

At the end of each disaster-affected time period (*Line 13*), we calculate the network response time, the network fill rate, the response time of each country, and the fill rate of each country (resp., (81) and (82), (28) and (29) to use them to calculate their corresponding KPIs (*Line 16*). Then, HOs place orders to the supplier in the amount they mobilize from branded, unbranded, and borrowed stocks (*Line 14*). Finally, at the end of each scenario (*Line 15*), we calculate the network inventory leftover ratio (see (83)) to calculate its corresponding KPI (*Line 16*). We provide the detailed formula for each KPI in the next subsection.

We use Eclipse IDE for Java Developers to run our simulation algorithm. The algorithm utilizes CPLEX libraries in Java to solve two inventory allocation models optimally within the simulation. On a standard laptop equipped with an i7-1065G7 CPU and 16.0 GB RAM, the simulation algorithm completes within a minute for each instance in our case study.

2.5.5 Key Performance Indicators (KPIs)

The impact of different unbranded rates is evaluated based on several KPIs, computed based on the outputs of the proposed two-phase inventory allocation framework. The KPIs are based on three primary concerns of the prepositioning network: *response time*, *fill rate*, and *inventory leftover ratio*, which serves as a proxy for inventory holding costs.

The response time performance of the prepositioning network in a period depends on the mix of mobilized stock types, which include branded ($\overline{X}^b_{stc} = \sum_{a\in\mathcal{A}} X^b_{stac}$), unbranded ($\overline{X}^u_{stc}$=$\sum_{a\in\mathcal{A}} X^u_{stac}$), shared/borrowed ($\overline{Y}_{stc} = \sum_{a\in\mathcal{A}} \sum_{\substack{\acute{a}\in\mathcal{A}\\ \acute{a}\neq a}} Y_{sta\acute{a}c}$), or supplier sourced ($\overline{U}_{stc} = U_{stc}$ if sharing is not needed; otherwise $\overline{U}_{stc} = V_{stc}$) items, and their delivery times ($\overline{\tau}^b$, $\overline{\tau}^u$, $\overline{\tau}^s$, and $\overline{\tau}^p$ days, respectively). The network response time, represented by ψ_{stR} for each $t \in \mathcal{T}$ in each $s \in \mathcal{S}$ and $R = [0\%, 100\%]$, is equal to the total weighted average of the response times for the four types of stocks, where weights are the ratio of the amount of each stock type to the demand ($\overline{d}_{stc}$), calculated as follows.

$$\psi_{stR} = \sum_{c \in \mathcal{C}} \left(\overline{\tau}^u \overline{X}^u_{stc} + \overline{\tau}^b \overline{X}^b_{stc} + \overline{\tau}^s \overline{Y}_{stc} + \overline{\tau}^p \overline{U}_{stc} \right) / \sum_{c \in \mathcal{C}} \overline{d}_{stc} \quad \forall R \geq 0\%, s \in \mathcal{S}, t \in \mathcal{T} \tag{18}$$

The fill rate in a disaster period is equal to the ratio of the total mobilized amount from the regional warehouse to disaster-affected countries ($\overline{X}^u_{stc} + \overline{X}^b_{stc} + \overline{Y}_{stc}$) to the total demand of these countries ($\overline{d}_{stc}$). We calculate a network-level average across all disasters, time periods, and countries. The network fill rate for each $t \in \mathcal{T}$ in each $s \in \mathcal{S}$ for each $R = [0\%, 100\%]$, which is represented by ϕ_{stR}, is calculated as follows.

$$\phi_{stR} = \sum_{c \in \mathcal{C}} \left(\overline{X}^u_{stc} + \overline{X}^b_{stc} + \overline{Y}_{stc} \right) / \sum_{c \in \mathcal{C}} \overline{d}_{stc} \qquad \forall R \geq 0\%, s \in \mathcal{S}, t \in \mathcal{T} \tag{19}$$

For each scenario, we calculate the inventory leftover ratio at the network level, ι_{sR}, by dividing the total remaining stock level in the regional warehouse at the end of the last disaster period $\bar{t}$ ($\overline{Q}_{s\bar{t}a}$) by the total beginning inventory in the regional warehouse ($\overline{q}^T_a$) as below.

$$\iota_{sR} = \sum_{a \in \mathcal{A}} \left(\overline{Q}_{s\bar{t}a} \right) / \sum_{a \in \mathcal{A}} \overline{q}^T_a \qquad \forall R \geq 0\%, s \in \mathcal{S} \tag{20}$$

While one can calculate the expected values of these three metrics at the end of Algorithm 1, our main goal is to compare these metric values with all HOs keep some proportion of unbranded stocks ($R > 0\%$) versus those obtained from the base case where all HOs keep only branded stocks ($R = 0\%$), and gain insights about the differences. Therefore, we calculate the expected relative differences for the aforementioned three metrics between each unbranded stock ratio ($R > 0\%$) and the base case ($R = 0\%$), denoted as $\mathbf{E}(\Delta\overline{\psi}_{R\to 0\%})$, $\mathbf{E}(\Delta\overline{\phi}_{R\to 0\%})$-, $\mathbf{E}(\Delta\overline{\iota}_{R\to 0\%})$, which are referred to as KPI_1, KPI_2, and KPI_3, respectively. Given the occurrence probability of each scenario ($\overline{p}_s$), we calculate KPI_1, KPI_2, and KPI_3 as follows.

$$\text{KPI}_1: \quad \mathbf{E}(\Delta\overline{\psi}_{R\to 0\%}) = \sum_{s\in\mathcal{S}} \overline{p}_s \frac{\sum_{t\in\Gamma_s} \frac{\psi_{stR}-\psi_{st0\%}}{\psi_{st0\%}}}{|\Gamma_s|} \qquad \forall R > 0\% \tag{21}$$

$$\text{KPI}_2: \quad \mathbf{E}(\Delta\overline{\phi}_{R\to 0\%}) = \sum_{s\in\mathcal{S}} \overline{p}_s \frac{\sum_{t\in\Gamma_s} \frac{\phi_{stR}-\phi_{st0\%}}{\phi_{st0\%}}}{|\Gamma_s|} \qquad \forall R > 0\% \tag{22}$$

$$\text{KPI}_3: \quad \mathbf{E}(\Delta\bar{\iota}_{R\to 0\%}) = \sum_{s\in\mathcal{S}} \overline{p}_s \frac{\iota_{sR} - \iota_{s0\%}}{\iota_{s0\%}} \qquad \forall R > 0\% \tag{23}$$

When comparing results across different R values to the base case ($R = 0$), we calculate the nominal difference for events where the metric value in the base case solution is zero, instead of computing the relative difference. This approach is essential to avoid division by zero, which could lead to undefined values and inaccurately suggest infinite savings. As a result, our approach may underestimate the observed savings in our numerical results.

2.6 Case Study

We implement the proposed approach on a case study using real data. We describe our dataset in Section 2.6.1 and present our analysis and results in Section 2.6.2.

2.6.1 Data Set

We have compiled a detailed dataset on disaster relief operations in the Caribbean by processing information from ESUPS, HO websites, and the UNHRD portal. Table 1 summarizes our data sources and main assumptions. Below, we outline the dataset's key features.

Table 1: Data set sources and assumptions

Input	Sources	Assumptions
Demand scenarios	• Adapted from [6] • ESUPS	• Caribbean hurricanes (268 scenarios, 494 events) • Hurricanes with strong (H3: 2), very strong (H4 and H5: 3) severity • Regional warehouse response target: 20% of each country's demand for each event
Relief items	ESUPS (Historical delivery data of IFRC and UNHRD)	• Tarpaulin (two tarpaulins per family in the emergency relief package)
HOs & Response regions	UNHRD & HOs' web pages	• 19 HOs working in the Caribbean region and prepositioning supplies in UNHRD Panama (seven are classified as large, and 12 are medium) • Countries served: "Where We Work" information from HO web pages
Lead times	ESUPS' network HOs	• Delivery time by air of branded, unbranded, and borrowed items = 3, 4, and 5 days, respectively • Delivery time of unmet demand from the supplier (during response) = 14 days • Order replenishment time from the supplier (after response) = 28 days
Inventory levels	• UNHRD Portal • ESUPS	• Total initial inventory level at the beginning of each season = 10,000 units (sufficient to satisfy $\sim$ 60% of the 494 events' total targeted demand) • Different initial inventory levels of large and medium HOs (based on UNHRD Daily Stock Reports extracted on April 10, 2021)

Disaster region and scenarios: We focus on hurricane preparedness in the Caribbean region, encompassing 18 vulnerable countries during the Atlantic hurricane season from June 1st to November 30th [62]: Anguilla (AIA), Antigua and Barbuda (ATG), Bahamas (BHS), Belize (BLZ), Bermuda (BMU), Barbados (BRB), British Virgin Islands (BVI), Cayman Islands (CYM), Dominica (DMA), Grenada (GRD), Haiti (HTI), Jamaica (JAM), Saint Kitts and Nevis (KNA), Saint Lucia (LCA), Montserrat (MST), Turks and Caicos Islands (TCA), Trinidad and Tobago (TTO), and Saint Vincent and the Grenadines (VCT).

We adopted hurricane scenarios from [6], representing each hurricane season divided into 16 two-week periods. An example scenario is shown in Figure 7. Furthermore, while [6] categorize hurricanes into three levels (*mild* for H2 or lower, *strong* for H3, and *very strong* for H4 and H5), our study focuses on H3, H4, and H5 hurricanes, as milder disasters often have localized relief needs.

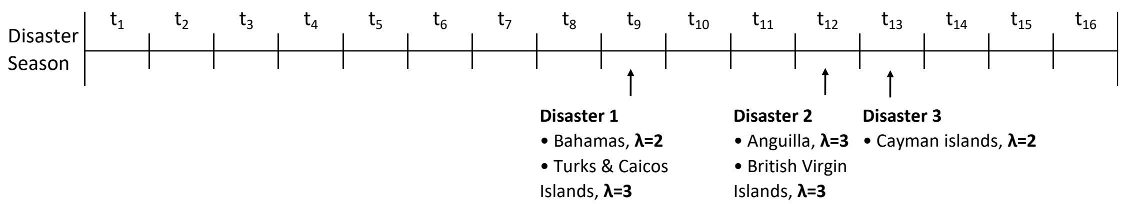

Figure 7: An example of planning horizon and scenario adapted from [6]

Note: An example scenario is shown with disasters occurring at $t = 9$, $t = 12$, and $t = 13$. For instance, at $t = 9$, a hurricane affects BHS and TCA with severity levels $\lambda = 2$ and $\lambda = 3$, respectively.

The authors in [6] utilized 62 years of historical disaster data in the Caribbean region. For each year, they generated five scenarios with identical disaster timings and locations but varying demand and severity levels, resulting in a dataset of 310 scenarios. After excluding mild disasters, our dataset comprises 268 hurricane seasons, 494 disaster periods, and 852 disaster-country combinations after excluding mild disasters. Of these, 280 were single-country events, while 214 affected two or more countries. In Figure 8, we illustrate our region of focus and the distribution of events across countries.

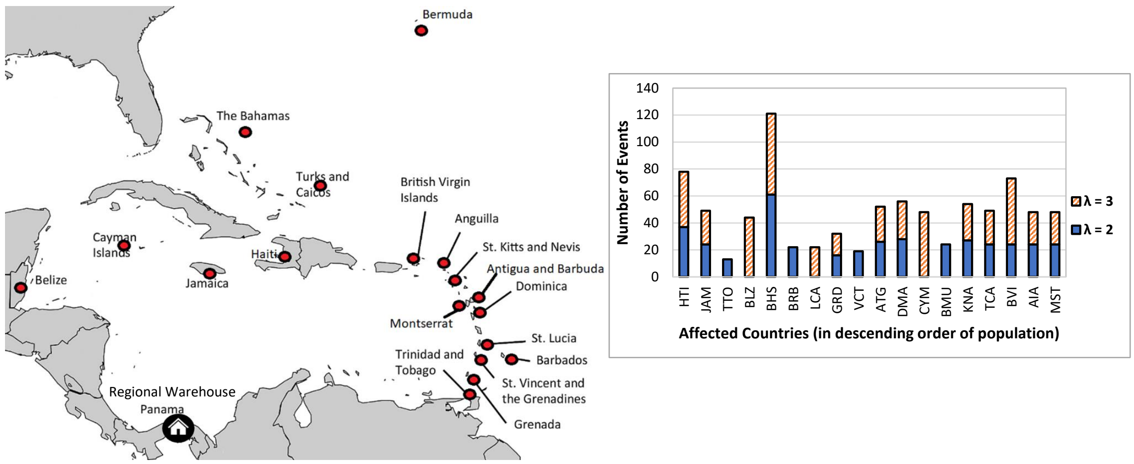

Figure 8: Region of interest and distribution of disaster events

Note: λ: disaster severity level. $\lambda = 2$ (resp., $\lambda = 3$) represents strong (resp., very strong) disasters.

Relief items. Our study focuses on tarpaulins as a representative relief item, aligning with ESUPS's guidance and historical dispatch data from HOs at UNHRD Panama and The International Federation of Red Cross and Red Crescent Societies (IFRC). Tarpaulins are among the frequently dispatched items, including hygiene kits, blankets, jerrycans, etc., which have high inventory levels. To adapt the demand values from [6] to our setting, we double the demand values for family kits because each kit contains two tarpaulins. Additionally, we adjust the demand values from the [6] dataset by assuming that 20% of the demand after a severe disaster is supplied by the regional warehouse, with the remaining sourced locally.

HOs and inventory levels. We consider 19 HOs with prepositioned stocks in a regional warehouse, such as UNHRD's regional warehouse in Panama serving the Caribbean region. The response regions of the HOs are specified based on their country office availability in the Caribbean countries obtained from ESUPS and the web pages of each HO. We categorize HOs into *large* and *medium* sizes. With the guidance of ESUPS, we assume all United Nations (UN) HOs are *large* HOs, and the non-UN ones are *medium* HOs. Although IFRC does not exactly fit this definition, we consider it in the large HO category based on the discussions with ESUPS. Our dataset includes seven large HOs and 12 medium HOs. This categorization enables us to analyze the effects of different settings, such as various unbranded stock rates, across different HO sizes. Similar-size HOs have the same initial inventory levels. The average number of countries that a large HO can respond to (about 14 countries) is significantly greater than that of a medium HO (three countries). The response matrix, along with HOs' sizes, is presented in Table 2.

Table 2: Response matrix, sizes and base stock levels of HOs

		Caribbean Countries																			
Size of HO	**HO Name**	**AIA**	**ATG**	**BHS**	**BLZ**	**BMU**	**BRB**	**BVI**	**CYM**	**DMA**	**GRD**	**HTI**	**JAM**	**KNA**	**LCA**	**MST**	**TCA**	**TTO**	**VCT**	**Total Respondent Countries**	**Base stock Level**
L	HO_1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	**18**	**904**
L	HO_2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	**18**	**904**
L	HO_3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	**18**	**904**
L	HO_4	0	1	1	1	1	1	1	0	1	1	1	1	1	1	0	0	1	1	**14**	**904**
L	HO_5	0	1	1	1	1	1	1	0	1	1	1	1	1	1	0	0	1	1	**14**	**904**
L	HO_6	0	0	0	1	1	1	1	0	0	0	1	1	0	0	0	0	1	0	**7**	**904**
L	HO_7	0	0	0	1	1	0	1	0	0	0	1	1	0	0	0	0	1	0	**6**	**904**
M	HO_8	0	1	1	1	0	0	0	0	0	0	1	1	0	0	0	0	1	1	**7**	**308**
M	HO_9	0	0	0	0	0	0	0	0	1	0	1	1	0	1	0	0	1	1	**6**	**308**
M	HO_{10}	0	0	0	1	0	1	0	0	0	0	1	1	0	0	0	0	0	0	**4**	**308**
M	HO_{11}	0	0	0	0	0	1	0	0	0	0	1	1	0	0	0	0	0	0	**3**	**308**
M	HO_{12}	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	**2**	**308**
M	HO_{13}	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	**2**	**308**
M	HO_{14}	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	**1**	**308**
M	HO_{15}	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	**1**	**308**
M	HO_{16}	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	**1**	**308**
M	HO_{17}	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	**1**	**308**
M	HO_{18}	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	**1**	**308**
M	HO_{19}	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	**1**	**308**
																				Total inventory:	**10024**

Note: The intersection of an HO's row and a country's column is 1, if that HO responds to that country (i.e., if the HO has an office in that country), and 0 otherwise. We anonymize HO names to preserve the confidentiality.

The specific inventory levels of HOs are not directly available. To determine the initial inventory level of each HO, we allocate a total initial inventory of 10,000 units for the warehouse, corresponding to the 60th quantile of demands during disaster periods in the Caribbean region. Based on UNHRD data on dispatched stocks, we computed a scale factor representing the comparative size between large and medium HOs, set at three. This results in initial inventory levels of 904 units for large HOs and 308 units for medium HOs. Additional analyses for different inventory levels are presented by modifying the base scale factor (see Section 2.6.2.3-c).

Unbranded stock rate (R). In our case analysis, we consider five unbranded stock rates: $R \in \{0\%, 25\%, 50\%, 75\%, 100\%\}$ to facilitate easy communication of the results with HOs. We also explore our setting with increased granularity in R values (increments of 5% between 0% and 100%) in Section 2.6.2.5-b), where our insights remain consistent. As explained before, $R = 0\%$ represents the base case where HOs keep all their stocks in branded form, while $R > 0\%$ represents varying degrees of postponement. For example, $R = 25\%$ implies that the HOs keep 25% of the initial inventory level in unbranded form. As suggested by ESUPS, in our *base setting*, we assume each HO keeps the same proportion of unbranded stock (R) at the beginning of each scenario, simplifying the implementation and analysis.

Delivery and replenishment lead times. Delivery time estimates are obtained from different HOs affiliated with ESUPS (see Table 1). We set delivery times of branded ($\overline{\tau}^b$), unbranded ($\overline{\tau}^u$), and shared ($\overline{\tau}^s$) stocks from the regional warehouse to countries via air to three, four (including an extra day for branding), and five (including an extra day for sharing process) days, respectively. Unsatisfied demand met by the supplier has a delivery time ($\overline{\tau}^p$) of 14 days. Replenishment lead times from suppliers ($\overline{\tau}^r$) range from four to twelve weeks in the data, so we set it as 28 days in our model (equivalent to two time periods). In our analysis, we test for the effects of varying branding times (see Section 2.6.2.3-a).

Next, we present our results illustrating the performance effects of the proposed strategies, along with in-depth analyses explaining the effects of various factors on performance.

2.6.2 Case Analysis and Results

In this section, we present the results of our numerical analysis on a case study. While our analyses demonstrate the effectiveness of the proposed approach within a single case study, we provide generalizable insights regarding the potential savings and limitations of these strategies on system performance across different scenarios and sensitivity analyses.

Our results are based on the Monte Carlo simulation algorithm explained in Section 2.5.4, which incorporates the two-phase inventory allocation models in Section 2.5.2. As outlined in Section 2.5.2, we conduct tests on the variants of our inventory allocation model, exploring different objective functions and an integrated framework as part of our preliminary analysis (see Sections 2.6.2.3-b and 2.6.2.5-a), respectively). While the results from alternatives are similar, we opted for the proposed version due to its computational efficiency. We also conduct tests with increased granularity in R values in Section 2.6.2.5-b). While the insights from this more granular analysis are similar, we opted for the proposed version to facilitate easy communication of the results with HOs.

In Section 2.6.2.1, we compare different unbranded stock rates ($R > 0\%$) with the base case ($R = 0\%$), evaluating the effects of postponement and stock sharing on network performance. In Section 2.6.2.2, we explain the observed postponement effects on KPIs and country level performance. In Section 2.6.2.3, we conduct sensitivity analyses to understand how the effects of various parameters and modeling assumptions influence our results. In Section 2.6.2.4, we compare the base setting where all HOs have identical R values with a modified setting where only medium HOs keep unbranded stocks and large HOs keep only branded stocks.

2.6.2.1 *Effects of postponement on KPIs*

In this section, we compare network-related KPIs, which are based on fill rate, response time, and inventory leftover ratio, across different unbranded rates R.

a) Response time and fill rate. Figure 9 shows the expected relative differences in network response time between four unbranded rates and the base case (KPI_1). Overall, the proposed strategy leads to lower network response times, with an exception observed at $R = 100\%$.

Figure 10 shows the impact of the proposed strategy on the expected relative differences in network fill rate between four unbranded rates and the base case (KPI_2). The network fill rate shows improvement for all R values compared to the base case, with KPI2 increasing as the R value rises. Evaluating KPI_1 and KPI_2 together, can guide the selection of a suitable R value that enhances fill rate without compromising response time. For instance, $R = 75\%$ appears favorable in our case. In Section 2.6.2.2, we provide an explanation for the behavior observed in KPI_1 and KPI_2 values with increasing R.

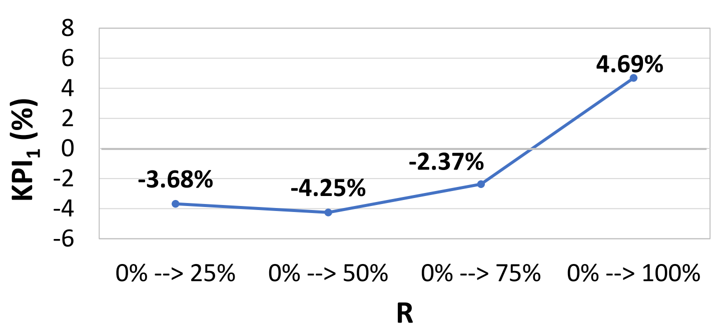

Figure 9: KPI_1 values for the base setting

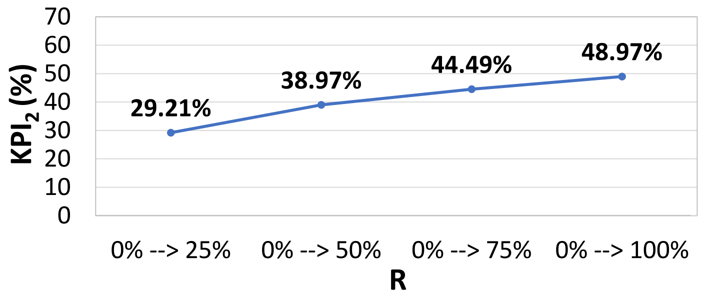

Figure 10: KPI_2 values for the base setting

b) Inventory leftover ratio. Figure 11 displays the relative differences in network inventory leftover ratio between four unbranded rates and the base case (KPI_3). Higher R values lead to improved inventory utilization for the regional warehouse. Figure 11 also shows KPI_3 values for large (KPI_3^L) and medium HOs (KPI_3^M), indicating a greater improvement in inventory utilization for medium HOs compared to large HOs with increasing R.

Figure 12 presents the expected ratios of borrowed stock to total delivered stock for large and medium HOs separately. Large HOs exhibit a significantly higher expected borrowed stock ratio than medium HOs under all R values, reflecting different borrowing/sharing behaviors. Specifically, large HOs tend to borrow more due to their larger response region, while medium HOs share their stocks more often.

Our results highlight the important impact of the R value on system performance across all KPIs. Motivated by our observations regarding response time deterioration with high R values and different sharing behaviors among organizations of different sizes, we analyze a new setting in Section 2.6.2.4 where all large HOs keep only branded stock and medium HOs keep some unbranded stock. While our practitioner collaborators advocate for equal R values across all HOs initially, they also express interest in considering varied R values among HOs in later stages.

Next, we delve into the findings to provide insights into the underlying reasons for the observed savings in fill rate and response time.

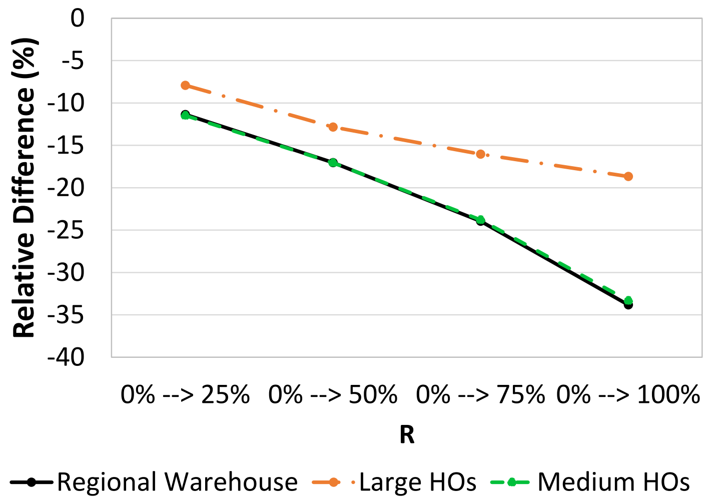

Figure 11: KPI_3 and $\text{KPI}_3^{L,M}$ values for the base setting

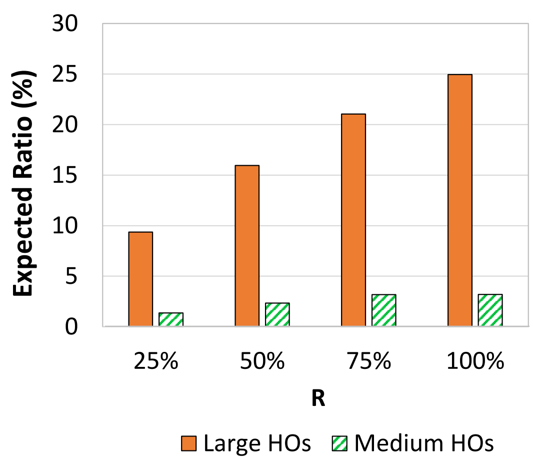

Figure 12: Expected ratio of the HOs' borrowed stock to total delivered stock for each R value

2.6.2.2 Insights on savings in fill rate and response time

Postponement and stock sharing strategies, as demonstrated in Section 2.6.2.1, consistently yield savings across all KPIs. However, specific trends and patterns emerge. While one might anticipate increased benefits with higher R values due to enhanced sharing, results show that beyond a certain threshold, KPI_1 values increase, indicating response times. Simultaneously, the rate of improvement in KPI_2 diminishes, suggesting reduced improvements in fill rate (see Figures 9 and 10). These trends are observed across different settings, including varied lead times, alternative objective functions, and diverse initial HO inventory levels (see Section 2.6.2.3).

Next, we explain the underlying reasons behind these trends under the base case and examine the conditions in which savings are positive or negative. We then investigate the effects of postponement and stock sharing strategies on another KPI based on unsatisfied demand ratio (i.e., 1-fill rate) and calculated for each disaster severity level separately, referred to as KPI_2^{λ}. Lastly, We analyze which countries benefit more from the proposed strategies in terms of fill rate and response time.

a) What are the factors affecting values of $\mathbf{KPI_1}$ and $\mathbf{KPI_2}$? We investigate why the rate of increase in KPI_2 decreases as R increases, and explore the shift in KPI_1's trend from decreasing to increasing after a certain point (the U-shaped relationship observed in Figure 9).

As discussed in Section 2.6.2.1, while KPI_2 improves with increasing R, the rate of improvement in KPI_2 diminishes (see Figure 10). To understand this effect, we categorize disaster-affected time periods into *negatively affected*, *positively affected*, and *unaffected* periods. These represent disaster-affected time periods where fill rate (i.e., KPI_2) decreases, increases, or remains unchanged when $R > 0\%$, compared to when $R = 0\%$. In Figure 13, we present the ratio of disaster-affected periods, τ^{ratio}, for different KPI_2 ranges at varying R values. Specifically, in the figure, each bar in one of the four panels (each for a different R value) represents the ratio of disaster-affected periods in which the KPI_2 value falls within the specified range for that bar. For instance, in panel (d), when $R = 100\%$, you can observe that in 4.45% of the disaster-affected time periods, the KPI_2 value lies between -100 and -75. In 0.4% of these periods, the KPI_2 falls within the range of -75 and -50, and so forth. Analyzing the impact of postponement on KPI_2 in Figure 13, we observe the following three situations: (i) disaster-affected periods with a positive postponement impact on KPI_2 value (40.49% to 42.31% occurrence under different R values), (ii)disaster-affected periods with a negative postponement impact on KPI_2 values (occurring at a rate of 5.46% to 5.87% under different R values), and (iii) disaster-affected periods with no postponement impact on KPI_2 value (52.23% to 53.64% occurrence under different R values). The frequencies of these categories average 5.61%, 41.60%, and 52.78% across $R > 0\%$ values.

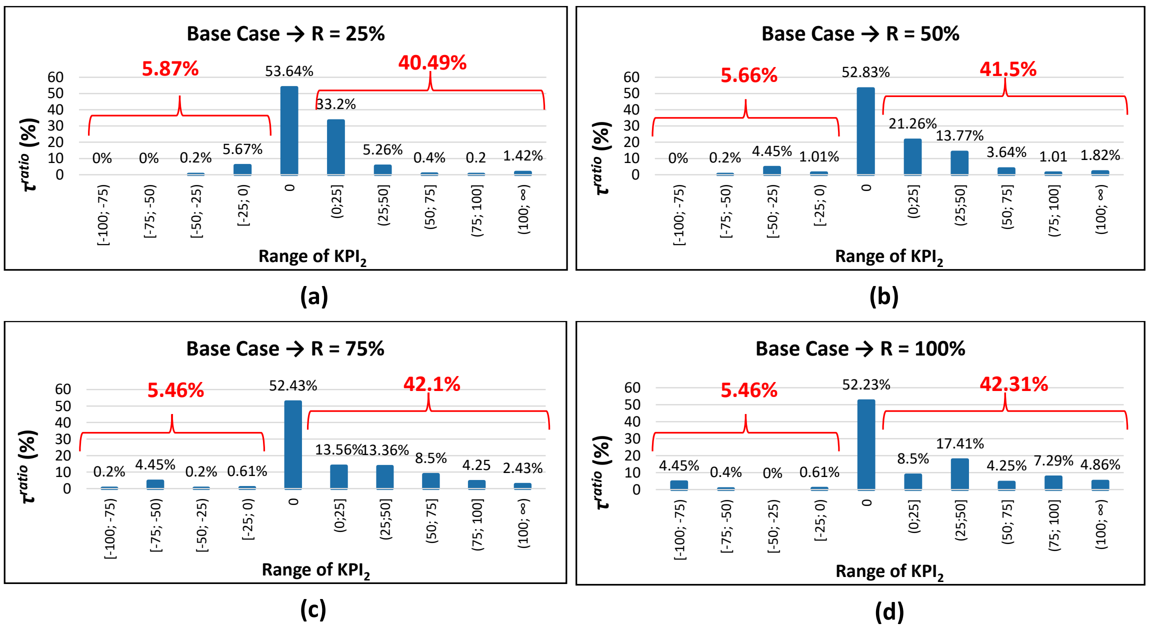

Figure 13: Percentages of disaster-affected time periods ($\tau^{ratio}\%$) for each relative difference in the network fill rate (KPI_2) range

We focus on negatively and positively affected periods separately by computing KPI_2 values, depicted in Figure 14. As R increases, the change in KPI_2 values is more pronounced for negatively affected periods compared to positively affected periods. This observation indicates diminishing returns of the R value, as a higher R is more likely to result in significantly lower KPI_2 values in certain periods.

We next explore why KPI_2 is affected adversely by increasing R in *some* periods. When total demand in a disaster period mobilizes all warehouse stocks, increased unbranded stocks prompts more extensive sharing among HOs to meet this demand.

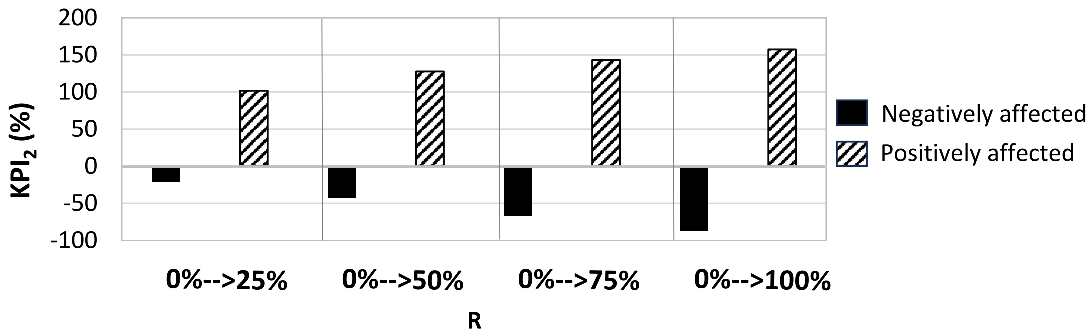

Figure 14: KPI_2 values for negatively and positively affected periods

This increased sharing can significantly improve KPI_2 for that period but may deplete inventory for subsequent periods until restocking occurs. If another disaster occurs before inventories are replenished, HOs may be unable to ship necessary amounts, resulting in significant decreases in KPI_2.

Next, we analyze the setback in KPI_1 under high R values, despite the consistent improvement in KPI_2. We observe that the effect of varying R values on KPI_1 depends on changes in KPI_2. We observe that, as R increases, (i) if KPI_2 also increases, then KPI_1 decreases; however, (ii) if KPI_2 decreases or does not change, then KPI_1 increases. Next, we elaborate on these two effects. First, in 41.60% (on average) of time periods, KPI_2 increases when R increases, resulting in less stock from the supplier, which decreases KPI_1 in these periods. This arises because the supplier's delivery time is significantly longer than that of borrowed stock. Second, in over half of the time periods, the fill rate does not change (i.e., KPI_2 is zero) because the HOs do not need sharing to meet the demand in these periods. That is, they solely mobilize their own branded and unbranded stocks. The increased R value leads to shipping more of their own unbranded stock *after branding*, which increases delivery time of unbranded stock compared to branded stock and, consequently, KPI_1 in these periods. In the remaining time periods, KPI_2 decreases when R increases. Decreasing values of KPI_2 imply larger amounts of stocks shipped from the supplier, increasing KPI_1 in these periods. However, this impact is relatively minor due to the rare occurrence of such time periods.

Combining the above two opposing effects of increasing R on KPI_1, we explain the U-shaped relationship in Figure 9 as follows. Initially, as R increases from 0 to small levels (up to 50%), the factors diminishing KPI_1 outweigh those increasing it, resulting in an overall decline in KPI_1. However, as R surpasses 50%, the factors increasing KPI_1 outweigh the opposing factors, leading to an overall increase in KPI_1.

These observations suggest that reserving some unbranded stocks or limiting stock sharing among certain HOs could be beneficial. Additionally, faster stock replenishment from suppliers may significantly improve KPI_2 performance, safeguarding against low values that can occur after severe disasters before inventories are replenished. Implementing strategies where only specific HOs retain unbranded stocks can also eliminate additional branding times associated with mobilizing unbranded stocks, potentially improving KPI_1. We explore the effects of such strategies in Section 2.6.2.4 using our framework.

b) What are the effects on unsatisfied demand for each severity level? In this section, we compare the network unsatisfied demand rate (i.e., 1- fill rate) under different R values ($R > 0\%$) with the base case ($R = 0\%$) for each severity level (i.e., $\lambda = 2$ and $\lambda = 3$) separately. To do so, we calculate the expected values of relative differences in the network unsatisfied demands between each R value and the base case, which is denoted by $\mathbf{E}(\Delta\overline{\eta}_{\lambda,R\to 0\%})$ and referred to as KPI_2^λ. The relative network unsatisfied demand for each $t \in \mathcal{T}$ in each $s \in \mathcal{S}$ for each $R = [0\%, 100\%]$ is represented by $\eta_{st\lambda R}$. Given the occurrence probability of each scenario ($\overline{p}_s$), we calculate KPI_2^λ as follows.

$$\text{KPI}_2^\lambda: \quad \mathbf{E}(\Delta\overline{\eta}_{\lambda,R\to 0\%}) = \sum_{s\in\mathcal{S}} \overline{p}_s \frac{\sum_{t\in\Gamma_s} \frac{\eta_{st\lambda R} - \eta_{st\lambda 0\%}}{\eta_{st\lambda 0\%}}}{|\Gamma_s|} \qquad \forall \lambda \in \{2, 3\}; R > 0\% \tag{24}$$

$$\eta_{st\lambda R} = \frac{\sum_{c \in \overline{C}} \overline{U}_{stc}}{\sum_{c \in \overline{C}} \overline{d}_{stc}} \qquad \forall \lambda \in \{2,3\}; R \geq 0\%; s \in \mathcal{S}; t \in \mathcal{T} \tag{25}$$

Figures (15) and (16) present KPI_λ values for each $R > 0\%$ value for severe ($\lambda = 2$) and very severe ($\lambda = 3$) disaster severity levels, respectively. Consistent with the KPI_2 (KPI based on fill rate) results, KPI_2^λ decreases as R increases for both severity levels. We note that the decline in KPI_2^λ is steeper for very severe disasters ($\lambda = 3$) compared to severe ones ($\lambda = 2$) due to the following reason. Recall, from Section 2.6.2.2, that increasing R leads to extensive sharing of stocks in response to a current disaster, leading to inventory depletion for subsequent periods until restocking takes place. As a result, when another disaster occurs before inventories are replenished, HOs may be unable to ship the necessary amounts, resulting in significant decreases in KPI_2. Therefore, as R increases, the rate of growth in KPI_2 diminishes, while KPI_2^λ exhibits significant increases under similar conditions, resulting in a reduced rate of decline as R increases. This effect is particularly pronounced for severe disasters ($\lambda = 2$), as HOs prioritize fulfilling the needs of very severe disasters ($\lambda = 3$) over those of severe ones ($\lambda = 2$). Consequently, the decrease in the decline rate is more pronounced for severe disasters ($\lambda = 2$).

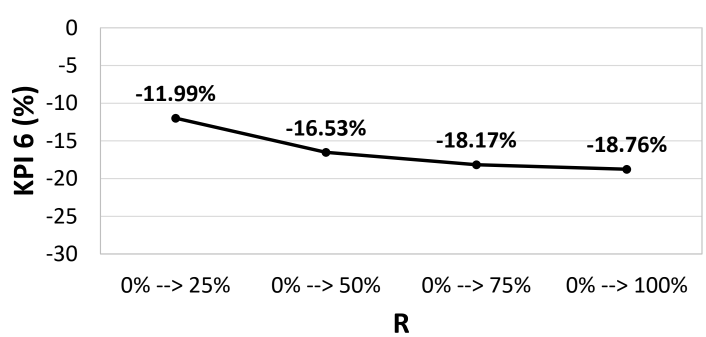

Figure 15: KPI_2^2 values for severe disaster severity level ($\lambda = 2$)

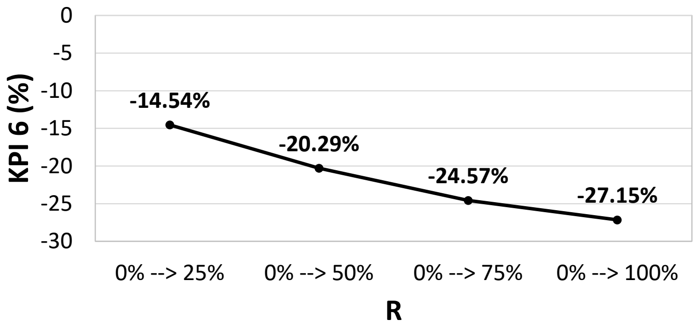

Figure 16: KPI_2^3 values for very severe disaster severity level ($\lambda = 3$)

c) Which countries benefit more? The countries in the Caribbean region exhibit varying characteristics, including the number of responding HOs, severity of disasters, and demand profiles. To understand how the benefits of proposed strategies vary across different affected countries, we calculate the expected values of response time and expected fill rate of each country denoted by $\mathbf{E}(\overline{\Omega}_{cR})$ and $\mathbf{E}(\overline{\kappa}_{cR})$, and referred to as KPI_4 and KPI_5, respectively.

The response time (resp., fill rate) of a country c for each $t \in \mathcal{T}$ in each $s \in \mathcal{S}$ for each $R = [0\%, 100\%]$ is represented by Ω_{stcR} (resp., κ_{stcR}). Given the average response time and fill rate of each country in each scenario, calculated by Equations (28) and (29), respectively, $\mathbf{E}(\overline{\Omega}_{cR})$ and $\mathbf{E}(\overline{\kappa}_{cR})$ are computed as follows.

$$\text{KPI}_4: \quad \mathbf{E}(\overline{\Omega}_{cR}) = \frac{\sum_{s \in \mathcal{S}} \overline{p}_s \frac{\sum_{t \in \mathcal{T}} \Omega_{stcR}}{|\Upsilon_{sc}|}}{\sum_{s \in \zeta_c} \overline{p}_s} \qquad \forall R \geq 0\%, c \in \mathcal{C} \tag{26}$$

$$\text{KPI}_5: \quad \mathbf{E}(\overline{\kappa}_{cR}) = \frac{\sum_{s \in \mathcal{S}} \overline{p}_s \frac{\sum_{t \in \mathcal{T}} \kappa_{stcR}}{|\Upsilon_{sc}|}}{\sum_{s \in \zeta_c} \overline{p}_s} \qquad \forall R \geq 0\%, c \in \mathcal{C} \tag{27}$$

$$\Omega_{stcR} = \left(\overline{\tau}^u \overline{X}^u_{stc} + \overline{\tau}^b \overline{X}^b_{stc} + \overline{\tau}^s \overline{Y}_{stc} + \overline{\tau}^p \overline{U}_{stc}\right) / \overline{d}_{stc} \quad \forall R \geq 0\%, s \in \mathcal{S}, t \in \mathcal{T}, c \in \mathcal{C} \tag{28}$$

$$\kappa_{stcR} = \left(\overline{X}^u_{stc} + \overline{X}^b_{stc} + \overline{Y}_{stc}\right) / \overline{d}_{stc} \qquad \forall R \geq 0\%, s \in \mathcal{S}, t \in \mathcal{T}, c \in \mathcal{C} \tag{29}$$

Figure 17 and 18 show the expected response times (KPI_4) and fill rates (KPI_5) for each country under different R values. Among the 18 countries analyzed, three consistently show improvements in KPI_4 (response time) and five in KPI_5 (fill rate) across all $R > 0\%$ values compared to the base case. Furthermore, 13 (resp., 15) countries benefit from the postponement strategy for R values up to 75%. Overall, most countries experience substantial benefits from these strategies.

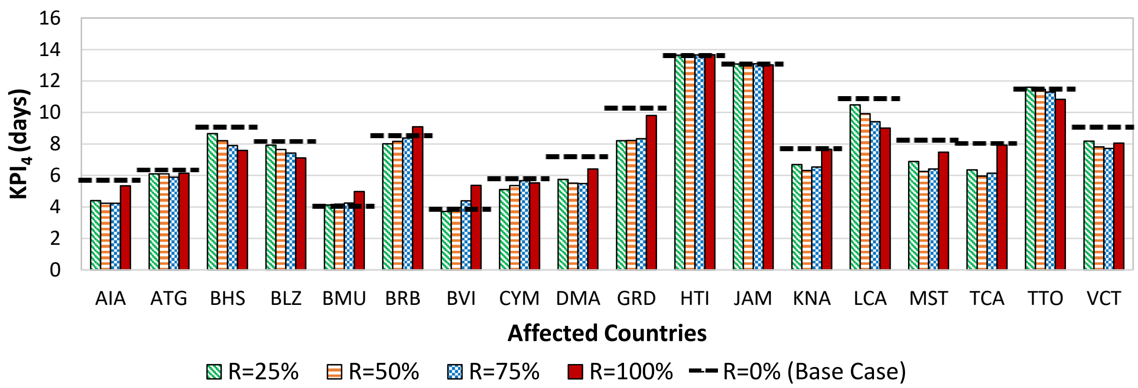

Figure 17: KPI_4 values for the base setting

Two key factors influencing the impact of postponement on KPI_4 and KPI_5 are the number of responding HOs and the severity of disasters in each country (see Table 3 for a summary of these characteristics). Specifically, countries with relatively few responding HOs and high disaster severity typically benefit from postponement due to limited ability to satisfy demand without stock sharing.

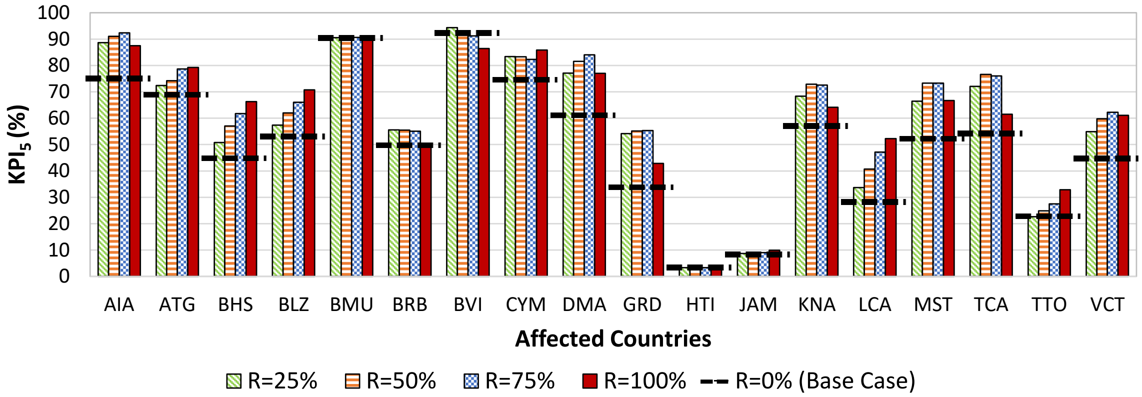

Figure 18: KPI_5 values for the base setting

Table 3: Characteristics of countries

	AIA	ATG	BHS	BLZ	BMU	BRB	BVI	CYM	DMA	GRD	HTI	JAM	KNA	LCA	MST	TCA	TTO	VCT
Expected average demand	592	2347	8581	12055	894	4446	1444	2878	3421	2898	261214	67891	1228	9510	205	827	16172	1677
Expected average severity	2.49	2.50	2.50	3	2	2	2.69	3	2.51	2.50	2.51	2.52	2.49	3	2.49	2.50	2	2
Number of responding large HOs	3	5	5	7	7	6	7	3	5	5	7	7	5	5	3	3	7	5
Number of responding medium HOs	0	1	2	2	0	2	0	0	1	0	12	5	0	1	0	0	2	2

For countries with lower disaster severity, the impact of postponement and stock sharing strategies can be mixed. If other countries' disasters consume most available stocks, there can be a negative impact. However, if some unbranded stocks remain in responding HOs from other countries, the focal country can benefit from stock sharing opportunities.

If both the number of responding HOs and the severity of disasters are relatively high in a country, that country is susceptible to the negative impacts of postponement and stock sharing. This occurs because the responding HOs in such a country may share their unbranded stock with HOs that responded to previous disasters in other countries, leading to reduced stock levels for potential disasters in the current period. Without stock sharing, a country with many responding HOs and high disaster severity has an advantage over others.

Next, we conduct a sensitivity analysis to examine how different parameters and modeling assumptions impact our results.

2.6.2.3 Sensitivity analysis

We analyze how R's effects are influenced by various parameters and modeling assumptions, testing different lead times, objective functions, and initial inventory levels of HOs.

a) Sensitivity analysis for branding time. Here, we examine the impact of varying lead times for branded stock (i.e., different branding times) on response time, by comparing the relative difference in the network response times (KPI_1) across different branding times. Our approach involves establishing constant delivery times for branded and borrowed stock at 3 days and 7 days, respectively. By maintaining the delivery time of borrowed stock, we aim to focus on the impact of an HO's own stock delivery time. Additionally, we increase the lead time of borrowed items beyond the main setting to 5 days. This adjustment allows us to explore a wider range of delivery times for unbranded stock, which we set at 3, 4, 5, and 6 days.

Figure 19 shows the progressive impact of the proposed strategy on KPI_1 through a gradual increase in the branding time of unbranded stock, while maintaining consistent delivery times for branded and borrowed items. Two key insights emerge: First, the absence of branding time yields a decreased response time across all R values, revealing the isolated influence of stock sharing. Second, increased R values worsen response time, primarily due to the extended time required for branding processes when mobilizing HOs' unbranded stocks. This, in turn, underscores the potential for improved response time outcomes for higher R values by strategically mobilizing significant branded stock levels among certain HOs categorized as borrowing HOs (i.e., large HOs), thereby shortening branded stock delivery times relative to unbranded stock delivery times.

In sum, we find that each additional day of branding time worsens KPI_1. The proposed strategy decreases the network response time, on average, up to a specific R value between $R = 75\%$ and $R = 100\%$— referred to as the *break-even* point. Our analyses show that increasing branding time reduces this break-even point. For instance, a one-day increase in branding time shifts the worsening of KPI_1 to an R value between $R = 50\%$ and $R = 75\%$.

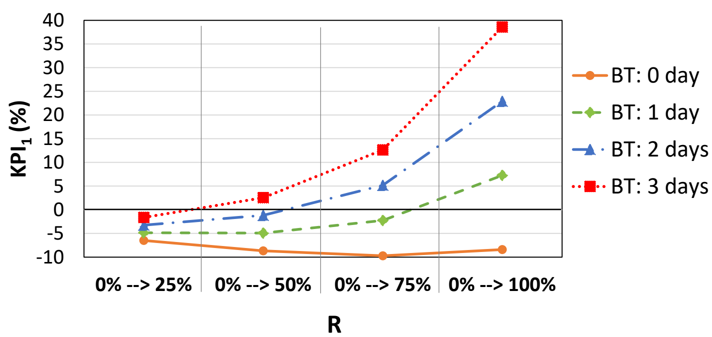

Figure 19: Effect of different unbranded delivery times on KPI_1

b) Effect of the objective function in inventory allocation. Our inventory allocation models minimize total weighted unsatisfied demand, prioritizing countries based on disaster severity. Countries with the same severity level receive equal priority, a methodology commonly used in related literature (e.g., [8], [61]). To test the sensitivity of our proposed strategies to the choice of objective function, we conduct additional tests using an alternative objective function. This alternative minimizes the maximum of each country's unsatisfied demand ratio (i.e., 1−fill rate) weighted by disaster severity, rather than minimizing the total weighted unsatisfied demand.

This objective function ensures each disaster-affected country receives a proportion of the total stock from responding HOs, promoting equitable inventory allocation among affected areas. This alternative objective function commonly used in humanitarian logistics literature (e.g., [63, 64, 65]).

Under this new objective, responding HOs allocate stock to countries based on disaster severity and demand magnitude. Note that, due to the max-min structure, this new objective may result in responding agencies not fully allocating all their mobilizable stocks to disaster-affected countries (e.g., when the minimum of the maximum proportioned value is reached). To address this, we introduce a second term to minimize the remaining total unbranded and branded stocks of HOs, ensuring that responding HOs maximize their use of available stocks to meet the demands of disaster-affected countries. We present the new objective function for Model 1 in Equation 30, and Model 2 in Equation 31.

$$\text{minimize} \quad \max_{c} \overline{\lambda}_{stc} \frac{U_{stc}}{\overline{d}_{stc}} + \sum_{a} (I^{b}_{sta} + I^{u}_{sta}) \tag{30}$$

$$\text{minimize} \quad \max_{c} \overline{\lambda}_{stc} \frac{V_{stc}}{U_{stc}} + \sum_{a} W^{u}_{sta} \tag{31}$$

We compare the results obtained by different approaches by using the main and new objective functions on KPIs based on network fill rate, network response time, and inventory leftover ratio (resp., KPI_1, KPI_2, KPI_3), as presented in Table 4. Relative savings in all KPI values under the new objective function are either lower or nearly equal to those under the main objective function. The decrease in savings observed in KPI_1 under the new objective function can be attributed to varying inventory allocation decisions involving branded, unbranded, and borrowed stocks across multiple events (the number of such extreme events varies for different R values). In summary, the main objective shows minimal differences in network-related KPIs compared to the main objective, indicating their overall similarity.

Table 4: KPI_1, KPI_2, KPI_3, and $\text{KPI}_3^{L,M}$ values under different R values and different objective functions (i.e., main and new objective functions)

	Relative Saving (%) under different objective functions									
	KPI_1		KPI_2		KPI_3		KPI_3^L		KPI_3^M	
	Main	New	Main	New	Main	New	Main	New	Main	New
0% → 25%	-3.68%	-2.87%	29.21%	28.85%	-11.35%	-11.31%	-7.91%	-7.69%	-11.48%	-11.37%
0% → 50%	-4.25%	-2.33%	38.97%	38.50%	-21.27%	-21.31%	-12.84%	-12.45%	-21.19%	-21.29%
0% → 75%	-2.37%	-0.48%	44.49%	43.86%	-29.61%	-29.67%	-16.02%	-15.34%	-29.39%	-29.67%
0% → 100%	4.69%	4.68%	48.97%	48.12%	-36.86%	-36.90%	-18.67%	-18.44%	-36.60%	-36.30%

We also analyze the effect of these two objective functions on the expected response time and fill rate of each country (resp., KPI_4 and KPI_5) in Figures 20 and 21, respectively. We compare the KPI results for various R values greater than 0% with those of the base case ($R = 0\%$) for both the main and new objectives. The consistency in savings patterns in response time and fill rate for each country under both the new and main objectives implies that the insights presented in Section 2.6.2.2 for the main objective function remain valid for the new objective function, with only slight variations observed as we increase R values.

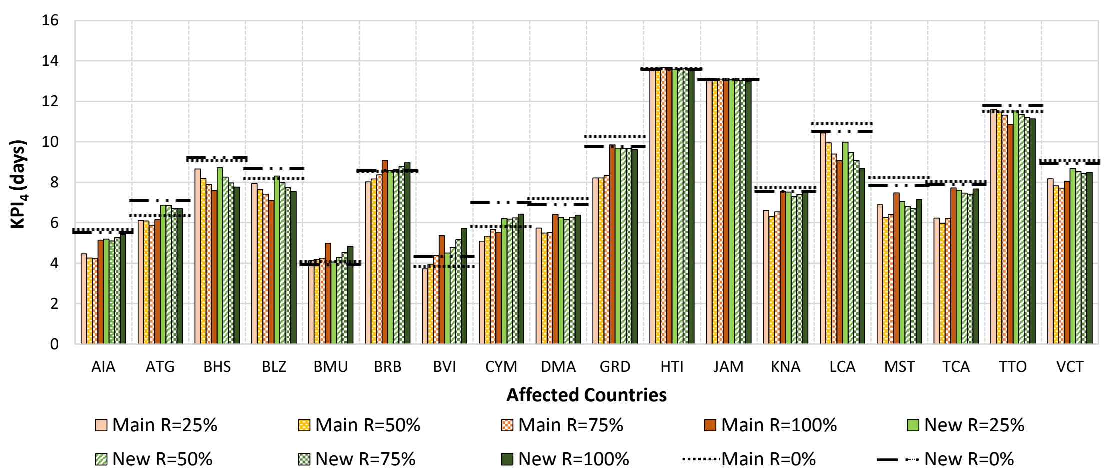

Figure 20: KPI_4 values under main and new objective functions

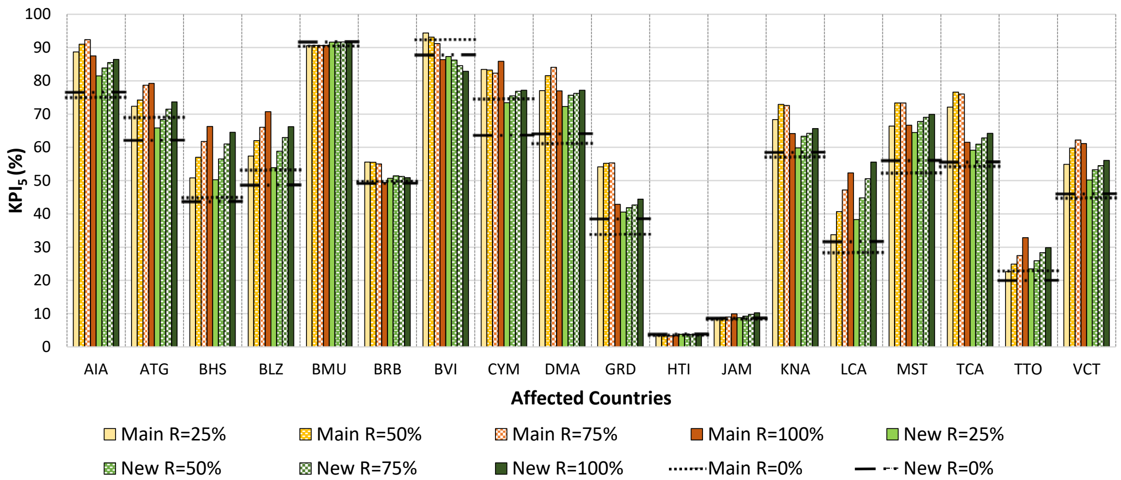

Figure 21: KPI_5 values under main and new objective functions

c) Effects of base stock levels. Here, we analyze the system's performance across varying base stock levels of HOs. Specifically, we examine cases where large HOs keep greater inventories while medium HOs keep lower amounts, yet the total inventory remains constant. This is achieved by adjusting the base setting's scale factor (3) to 3.5 and 4. The base stock levels for large and medium HOs are 904 and 308, respectively, under scale factor 3, while these values become 960 and 276, respectively under scale factor 3.5, and 1000 and 252, respectively under scale factor 4.

Table 5 presents the results of this analysis on KPIs based on network fill rates, network response times, and inventory leftover ratios (KPI_1, KPI_2, and KPI_3, respectively). A significant positive impact on these KPIs remains evident. Nonetheless, across all R values, saving on KPIs decreases with scale factors 3.5 or 4 compared to the base setting due to decreased borrowing requirements for large HOs (whose base stock levels are higher). Notably, the smaller the scale factor, the more pronounced the positive impact on KPIs due to the tendency of large HOs towards borrowing and medium HOs towards sharing (as detailed in Section 2.6.2.1). Specifically, we explore scenarios where large HOs maintain larger inventories while medium HOs retain smaller amounts, while the total inventory remains constant. Notably, this approach reduces collaboration benefits, as medium HOs, with fewer countries in their response region, tend to share more.

Regardless of inventory levels, strategies involving postponement and stock sharing consistently yield favorable impacts on all KPIs compared to the base case ($R = 0\%$). Our analysis underscores the value of increasing shareable stocks by efficiently leveraging inventories from HOs with narrower response regions.

Table 5: KPI_1, KPI_2, KPI_3, KPI_3^L and KPI_3^M values under different scale factors

		Relative difference			
KPI	Scale Factor	0% → 25%	0% → 50%	0% → 75%	0% → 100%
KPI_1	3	-3.68%	-4.25%	-2.37%	4.69%
	3.5	-2.91%	-3.20%	-1.12%	6.39%
	4	-2.56%	-2.64%	-0.43%	7.40%
KPI_2	3	29.21%	38.97%	44.49%	48.97%
	3.5	10.57%	16.17%	20.86%	24.64%
	4	8.17%	13.35%	17.68%	21.21%
KPI_3	3	-11.35%	-21.27%	-29.61%	-36.86%
	3.5	-11.04%	-20.83%	-29.09%	-36.25%
	4	-10.96%	-20.60%	-28.76%	-35.87%
KPI_3^L	3	-7.91%	-12.84%	-16.02%	-18.67%
	3.5	-3.51%	-12.84%	-16.00%	-18.10%
	4	-5.13%	-12.62%	-15.96%	-17.90%
KPI_3^M	3	-11.48%	-21.19%	-29.39%	-36.60%
	3.5	-11.34%	-20.66%	-28.69%	-35.87%
	4	-11.10%	-20.27%	-28.09%	-35.39%

Our results consistently demonstrate expected relative savings from implementing the proposed strategies, emphasizing the benefits regardless of potential variations in magnitude. These findings, along with those in Sections 2.6.2.1 and 2.6.2.2 regarding inventory utilization, motivate us to analyze a new setting where some HOs retain all stocks in branded form, preventing their complete depletion through sharing. We present this modified setting next.

2.6.2.4 Analysis of the modified setting: Different R% across HOs

Motivated by our observations on postponement effects, we consider a modified setting where only medium HOs keep unbranded stocks for sharing when needed. Here, large HOs keep only branded stocks and do not share, but can borrow unbranded stocks from medium HOs if necessary. This alternative policy is based on three observations: (i) depleting all stocks in a period can harm performance if subsequent disasters occur soon after, (ii) borrowing tendencies are more common among large HOs, while sharing tendencies are more common among medium HOs, and (iii) increasing unbranded stocks for large HOs can negatively impact network response time due to longer branding times.

We compare the relative difference in network response time (KPI_1) under the base and modified settings in Figure 22. Under the modified setting with $R = \{25\%, 50\%, 75\%, 100\%\}$, KPI_1 values are 4.08%, 6.44%, 8.22%, 9.51%, respectively. This shows an improvement in response time for all $R\%$ values compared to the base setting. We can explain this decrease with the help of Figure 24(a), which illustrates that the ratio of HOs' own unbranded delivered stocks to total delivered stocks is smaller in the modified setting, with large HOs keeping all stocks branded. Consequently, the time spent on branding decreases on average.

Recall that in the base setting where postponement applies to all HO sizes, the network fill rate (KPI_2) improves under all $R\%$. Figure 23 compares the expected relative difference in the network fill rate (KPI_2) between the base and modified settings. Although the magnitude of improvements in KPI_2 slightly decreases when only medium HOs can share stocks due to reduced total shareable stocks, Figure 24(b) demonstrates the relationship between total borrowed stock and KPI_2. Nevertheless, the benefits obtained under the modified setting justify the implementation of the postponement practice.

In the modified setting, when KPI_1 and KPI_2 are jointly considered, adopting a 100% postponement policy for medium HOs is favorable. This policy performs similarly to maintaining 75% unbranded stocks for all HOs in terms of KPI_2, but significantly surpasses the "75% postponement for all HOs" policy in improvements in KPI_1 (9.51% versus 2.37%).

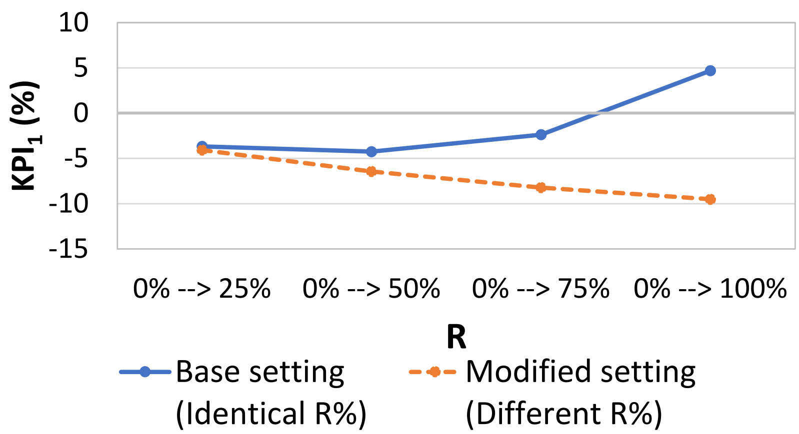

Figure 22: KPI_1 values for base and modified settings

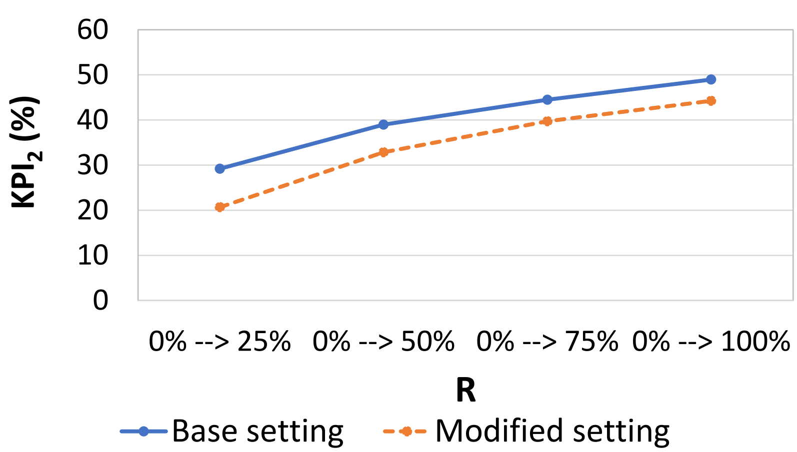

Figure 23: KPI_2 values for base and modified settings

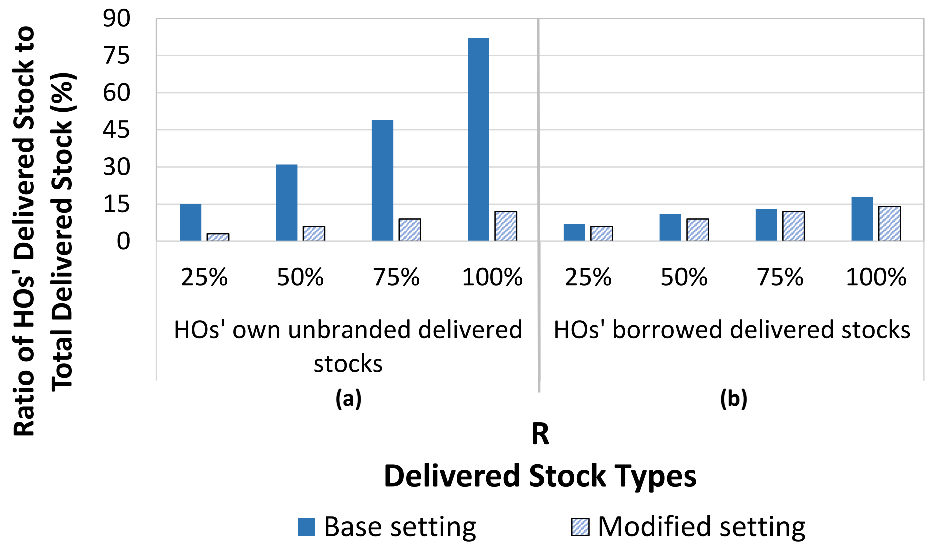

Figure 24: Ratio of HOs' (*own unbranded* in the left panel / *borrowed* in the right panel) delivered stocks to total delivered stocks for base and modified settings

Additionally, we compare the results of the base and the modified settings in terms of inventory leftover ratio (KPI_3). Figures 25 and 26 show the expected relative differences in inventory leftover ratios for the entire network, large HOs, and medium HOs (referred to as KPI_3, KPI_3^L, and KPI_3^M, respectively) for the base and the modified settings. At the network level, the inventory leftover ratio for the modified setting remains similar to that of the base setting.

Significant improvements are observed within the modified setting, particularly for medium HOs across all R values. However, these savings disappear (and the inventory leftover ratio even slightly worsens) for large HOs in all scenarios. This outcome arises due to the circumstance that two out of the seven large HOs respond to a relatively limited number of countries. This causes them to be unable to use their stock reserves effectively in most disaster-affected periods. Consequently, the inability to share these excess branded stocks leads to increased inventory leftover ratios. In sum, we find that large HOs exhibit lower inventory utilization while medium HOs show higher utilization, with overall network-level utilization remaining consistent.

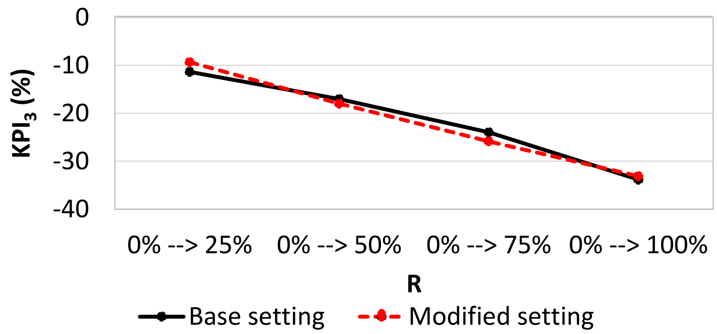

Figure 25: KPI_3 values under the base and modified settings

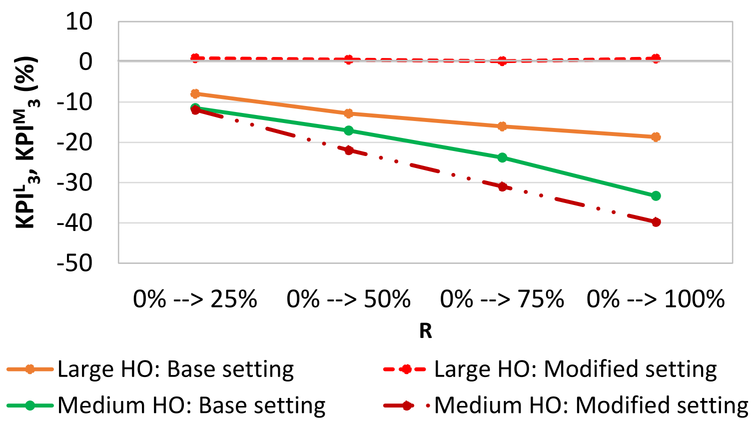

Figure 26: KPI_3^L and KPI_3^M values under the base and modified settings

We examine how the modified setting impacts the expected response time and fill rate of individual countries, denoted as KPI_4 and KPI_5 respectively. Our motivation for this analysis stems from the observation that completely consumed stocks during a disaster negatively impact savings in fill rate and response time for specific countries during the next disaster periods (as discussed in Section 2.6.2.2).

We analyze the following. Firstly, we evaluate the KPI_4 and KPI_5 values for each $R > 0\%$ against the base case ($R = 0\%$) under the modified setting. Secondly, we compare KPI_4 and KPI_5 values under the base setting (in which all HOs maintain the same $R\%$ unbranded stock) and the modified setting for every $R > 0\%$.

The first comparison reveals that in the modified setting, keeping unbranded stocks at any level (for all $R > 0\%$) improves the response time and fill rate for all countries except Haiti. Figures 27 and 28 show these improvements for KPI_4 and KPI_5 values at different R levels. Haiti's lack of improvement can be due to the fact that all large and medium HOs are already responding to Haiti, isolating from stock sharing. This emphasizes the impact of HOs' response regions on postponement and sharing strategies.

Regarding the second comparison, refer to Figures 29 and 30 for the relative differences in KPI_4 and KPI_5 under the modified and base settings at different R values. Accordingly, we present two key findings. Firstly, the number of countries experiencing improved response time steadily increases as R increases under the modified setting. This is unlike the base setting, where this number improves with R up to 75%, but worsens at $R = 100\%$ (as highlighted in Section 2.6.2.2). The improvement in response time when $R = 100\%$ under the modified setting can be attributed to the shorter branding process time resulting from large HOs keeping all stocks in branded form. Secondly, we can explain the variation in benefits for KPI_4 and KPI_5 under the base and modified settings by two country characteristics (outlined in Table 3): demand and the number of responding large HOs. The significance of the responding large HOs arises from their non-sharing behavior in the modified setting, preventing complete stock consumption. Notably, the modified setting offers greater savings in response time and fill rate for countries with high demand and a larger number of responding large HOs compared to the base setting.

We make two follow-up observations: (i) In the case of Belize, despite high demand and a significant number of responding large HOs, KPI_5 values under the base and modified settings remain largely similar. This is because the previous disaster periods have relatively lower demand that did not consume all stocks. (ii) For countries with low demand but a high number of responding large HOs, the benefits under the modified setting are noticeable mainly for higher R values ($R \geq 50\%$). This is because the demand in these countries is low enough to compensate for the negative effect of stock consumption. Overall, limiting stock sharing to medium HOs has the potential to shield the negative impacts of stock consumption on the fill rate of countries with a high number of responding HOs. In sum, our analysis indicates improved performance across most countries.

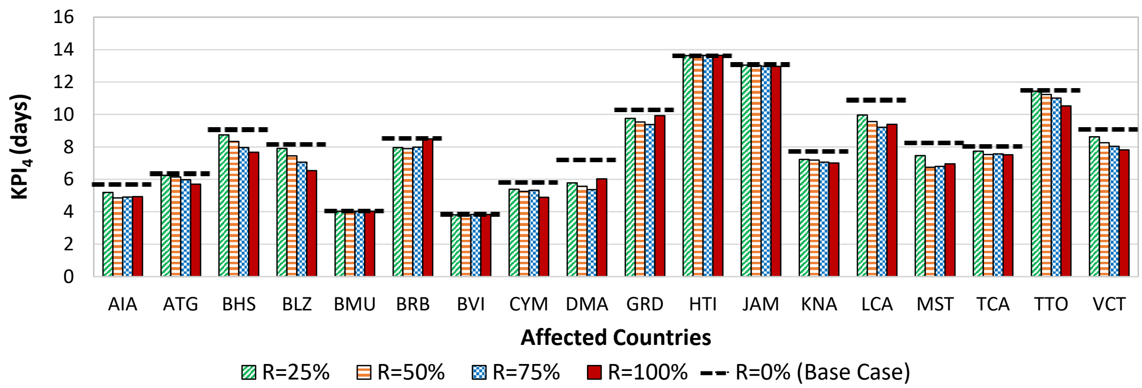

Figure 27: KPI_4 values under the modified setting

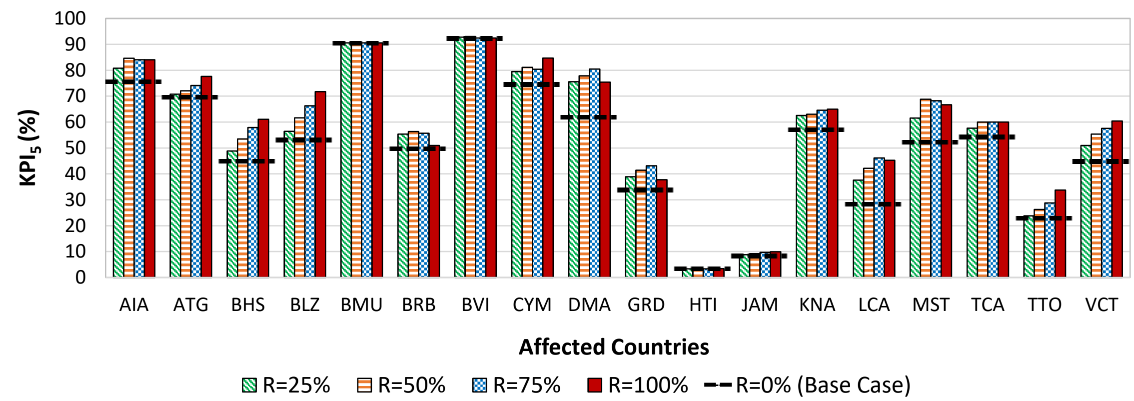

Figure 28: KPI_5 values under the modified setting

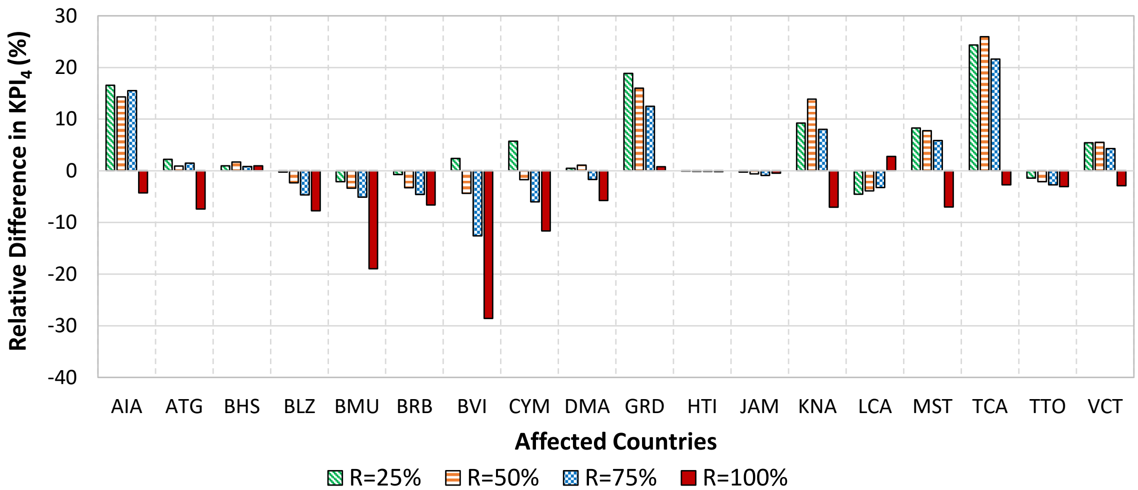

Figure 29: The relative difference in KPI_4 values of the modified setting based on one of the base settings

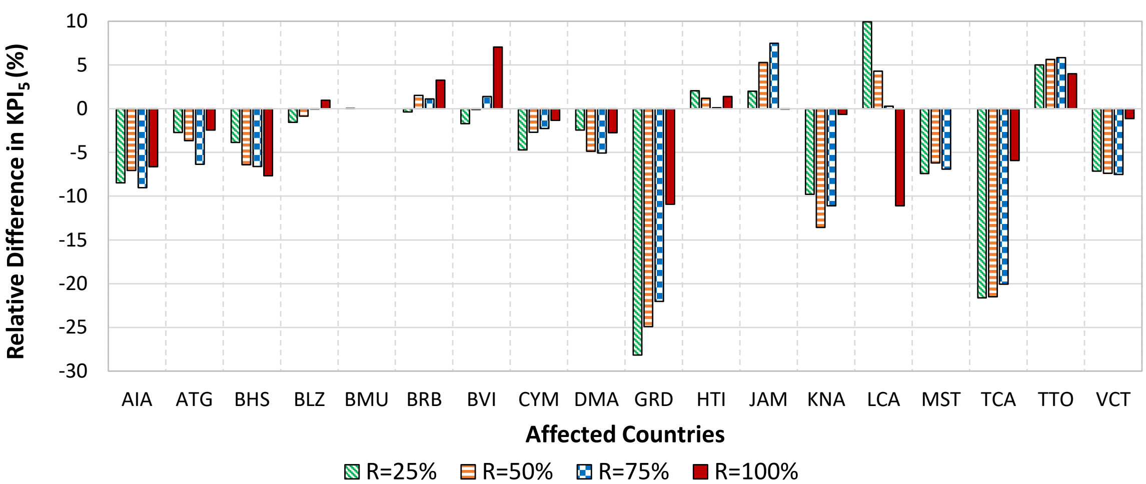

Figure 30: The relative difference in KPI_5 values of the modified setting based on one of the base settings

In summary, customizing the postponement rate for different types of HOs can enhance the impact of proposed strategies. However, our partner ESUPS prefers delaying this customized policy implementation to later stages, focusing initially on presenting postponement benefits to the humanitarian community with a simple approach. Nonetheless, our insights and results exploring different settings can guide practitioners in deploying these strategies effectively.

2.6.2.5 Additional analyses

a) Analysis of integrated inventory allocation model. In this section, we formulate the inventory allocation problem with an integrated optimization model as opposed to the two-phase model developed in Section 2.5.2. In this integrated model, the main decision variables include the amount of mobilized unbranded and branded stocks by each HO to each disaster-affected country in a period, which are denoted by X^u_{stac} and X^b_{stac}, respectively. In addition, this model also determines the amount of stocks borrowed by HO a from HO $\acute{a}$ and mobilized to each disaster-affected country c ($Y_{sta\acute{a}c}$). Auxiliary decision variables include the amount of unsatisfied demand of each disaster-affected country (U_{stc}) and remaining branded and unbranded stock levels of HOs at the end of each period (resp., I^b_{sta} and I^u_{sta}). We formulate this integrated model, which is solved in every period $t \in \mathcal{T}$ of each scenario $s \in \mathcal{S}$ as follows.

$$\text{minimize} \sum_{c} \overline{\lambda}_{stc} U_{stc} \tag{32}$$

subject to

$$U_{stc} = \overline{d}_{stc} - \sum_{a \in \mathcal{A}} (X^b_{stac} + X^u_{stac} + \sum_{\substack{\acute{a} \in \mathcal{A} \\ \acute{a} \neq a}} Y_{sta\acute{a}c}) \qquad \forall c \in \mathcal{C} \tag{33}$$

$$X^b_{stac} + X^u_{stac} + \sum_{\substack{\acute{a} \in \mathcal{A} \\ \acute{a} \neq a}} Y_{sta\acute{a}c} \leq M\overline{\delta}_{ac} \qquad \forall a \in \mathcal{A}, c \in \mathcal{C} \tag{34}$$

$$\sum_{c \in \mathcal{C}} (X^u_{stac} + \sum_{\substack{\acute{a} \in \mathcal{A} \\ \acute{a} \neq a}} Y_{st\acute{a}ac}) + I^u_{sta} = q^u_{sta} \qquad \forall a \in \mathcal{A} \tag{35}$$

$$\sum_{c \in \mathcal{C}} X^b_{stac} + I^b_{sta} = q^b_{sta} \qquad \forall a \in \mathcal{A} \tag{36}$$

$$I^b_{sta} \leq M(1 - Z_{sta}) \qquad \forall a \in \mathcal{A} \tag{37}$$

$$\sum_{c \in \mathcal{C}} X^u_{stac} \leq M Z_{sta} \qquad \forall a \in \mathcal{A} \tag{38}$$

$$\sum_{c \in \mathcal{C}} \overline{\delta}_{ac} U_{stc} \leq M(1 - \beta_{sta}) \qquad \forall a \in \mathcal{A} \tag{39}$$

$$\sum_{\substack{\acute{a} \in \mathcal{A} \\ \acute{a} \neq a}} \sum_{c \in \mathcal{C}} Y_{st\acute{a}ac} \leq M\beta_{sta} \qquad \forall a \in \mathcal{A} \tag{40}$$

$$\sum_{a \in \mathcal{A}} \overline{\delta}_{ac} (I^u_{sta} + I^b_{sta}) \leq M(1 - \Theta_{stc}) \qquad \forall c \in \mathcal{C} \tag{41}$$

$$\sum_{a \in \mathcal{A}} \sum_{\substack{\acute{a} \in \mathcal{A} \\ \acute{a} \neq a}} Y_{sta\acute{a}c} \leq M\Theta_{stc} \qquad \forall c \in \mathcal{C} \tag{42}$$

$$X^b_{stac}, X^u_{stac} \geq 0 \text{ and integer} \qquad \forall a \in \mathcal{A}, c \in \mathcal{C} \tag{43}$$

$$I^b_{sta}, I^u_{sta} \geq 0 \text{ and integer} \qquad \forall a \in \mathcal{A} \tag{44}$$

$$Y_{sta\acute{a}c} \geq 0 \text{ and integer} \qquad \forall a \in \mathcal{A}, \acute{a} \in \mathcal{A}, c \in \mathcal{C} \tag{45}$$

$$U_{stc} \geq 0 \text{ and integer} \qquad \forall c \in \mathcal{C} \tag{46}$$

$$Z_{sta}, \beta_{sta} \in \{0, 1\} \qquad \forall a \in \mathcal{A} \tag{47}$$

$$\Theta_{stc} \in \{0, 1\} \qquad \forall c \in \mathcal{C} \tag{48}$$

The objective function (32) minimizes the sum of unsatisfied demand in each country, weighted by the severity of the disasters. Constraint (33) guarantees that the mobilized total amount of stocks (branded, unbranded, and borrowed stocks) from HOs to a disaster-affected country does not exceed that country's demand, while we define the unsatisfied demand. Constraint (34) ensures that HOs only respond to countries within their response region. Constraints (35) and (36) ensure that the mobilized amount of unbranded and branded stocks from HOs to affected countries do not exceed the corresponding stock amounts held by the HO, respectively. Constraint (35) also specifies the remaining unbranded stocks of HOs after sharing. Constraints (37) and (38) together ensure that an HO cannot use its own unbranded stock before consumption of its own branded stock, controlling unbranded stock utilization with binary decision variable Z_{sta}. Specifically, if an HO mobilizes its unbranded stock, $Z_{sta} = 1$; otherwise, it takes on the value 0. Constraints (39) and (40) ensure that an HO can share its stocks only if the demands of all countries in its response region are satisfied. Specifically, if all the demand in an HO's response region is satisfied, $\beta_{sta} = 1$; otherwise, it takes on the value 0. Constraints (41) and (42) prevent HOs from borrowing stocks for each disaster-affected country if they have their own stocks, through binary decision variable Θ_{stc}. Finally, Constraints (43 and 48) define the domains of the variables. Note that if the sum of responding HOs' branded, unbranded, and borrowed stocks is still insufficient to meet the demand, the unmet demand is satisfied by the supplier.

In Table 6, we compare the results obtained by different approaches, that is, by using the main (i.e., two-phase) and new (i.e., integrated) models, on KPIs based on network fill rate, network response time, and inventory leftover ratio (resp., KPI_1, KPI_2, KPI_3). Relative savings in all KPI values under the integrated model are nearly equal to those under the two-phase model. The changes in savings under the integrated model can be attributed to varying inventory allocation decisions involving branded, unbranded, and borrowed stocks across multiple events. Specifically, this variation in inventory allocation decisions arises due to the absence of prioritization among HOs responding to countries facing disasters of the same severity level. In summary, the two-phase model demonstrates KPI values closely aligned with those under the integrated model, indicating their overall similarity. However, the integrated model is computationally more expensive than the two-phase model, which manifests itself as out-of-memory errors when we attempt to solve the problem for all R values and keep the corresponding solutions to calculate the KPI values in the simulation model. We resolved this issue by manual KPI value calculations to create Table 6.

Table 6: Network-level KPIs under different R values and models (i.e., 2-stage and integrated)

	Relative Saving (%) under different objective functions					
	KPI_1		KPI_2		KPI_3	
	2-Stage	Single	2-Stage	Single	2-Stage	Single
0% → 25%	29.19%	29.19%	-3.58%	-3.34%	-11.34%	-11.33%
0% → 50%	38.95%	38.75%	-4.03%	-3.87%	-21.23%	-21.19%
0% → 75%	44.51%	44.51%	-2.30%	-2.09%	-29.65%	-29.64%
0% → 100%	48.97%	48.97%	4.82%	4.69%	-36.86%	-36.86%

b) KPI analysis with increased granularity in R values. Here, we present the main KPIs based on response time (Figure 31), fill rate (Figure 32), and inventory left-over ratio (Figure 33) with increased granularity in R values. The KPI analysis for the refined range of R values, now including increments of 5% between 0% and 100%, demonstrates consistency with our findings in Section 2.6.2.1, reaffirming the accuracy of our insights. Furthermore, the refined analysis here allows us to further narrow down the break-even point for KPI_1 (i.e., the R value in which KPI_1 is equal to zero) and the overall recommended R value. Specifically, we now find that the break-even point for KPI_1 is between $R = 85\%$ and $R = 90\%$. Therefore, given that the KPI_2 and KPI_3 values monotonically improve (become more beneficial for HOs) for higher values of R, $R = 85\%$ becomes the most favorable point in our case.

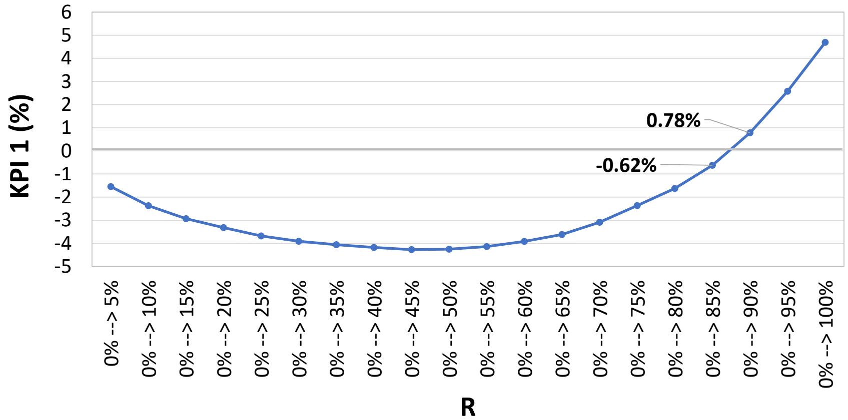

Figure 31: KPI_1 values for the base setting with increased R granularity

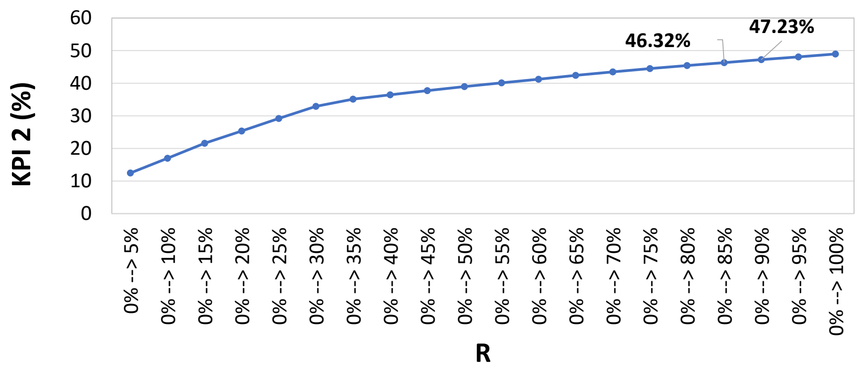

Figure 32: KPI_2 values for the base setting with increased R granularity

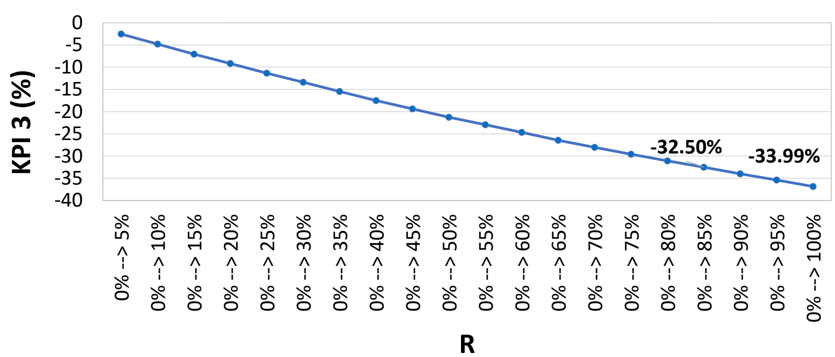

Figure 33: KPI_3 values for the base setting with increased R granularity

2.7 Discussion and Conclusion

This chapter investigates the impact of postponement and stock sharing on prepositioning efficiency in a regional humanitarian warehouse where multiple HOs keep stock for relief supplies. Although postponement is well-studied in supply chain management, its application in humanitarian operations remains underexplored. We develop an inventory management system integrating postponement and stock sharing strategies to assess improvements in important performance metrics such as fill rate, response time, and inventory utilization. Our simulation algorithm, which incorporates this inventory management system, is used to evaluate the effects of different unbranded stock levels on system performance. Through extensive numerical analysis, we develop important managerial insights for informed decision making (such as choosing the right level of unbranded stock rate based on the demonstrated implications of each level on KPIs) and effective implementation of the postponement and stock sharing strategies.

Our efficient simulation-based framework provides effective and intuitive solutions, which are shared with the humanitarian community. Results from practitioner workshops with ESUPS and partner HOs have received significant interest, highlighting the potential value of our findings for broader dissemination within the practitioner community.

Key findings and remarks from this chapter are summarized below.

- Postponement combined with stock sharing significantly enhances all relevant KPIs across various scenarios, which indicates that a shift in prepositioning practices within the humanitarian community can substantially improve the effectiveness and efficiency of prepositioning. Specifically, we propose discontinuing the practice of permanently branding items before disasters. Instead, we recommend procuring standard (unbranded) items and applying stickers after a disaster if necessary, or share them with other HOs.

- While our study focuses on a specific case study, it yields generalizable insights for implementation and policy development. For instance, we discover a U-shaped relationship between response time and unbranded stock rate, where fill rate and inventory utilization consistently improving as the unbranded stock rate increases. This pattern emerges when HOs' own unbranded stocks is sufficient to fully satisfy the demand from a disaster event, eliminating the need for stock sharing and thus increasing response time due to branding. Moreover, we show that in scenarios with consecutive disasters, maintaining high unbranded stock rates may deplete available stocks in the first disaster, making countries more vulnerable to subsequent impacts. This effect leads to diminishing fill rate improvements and increase response time. We show that a modified setting where large HOs exclusively retain branded stocks can be a remedy to this occurrence, preventing complete depletion during initial disasters and improve response time. Finally, our results highlight the importance of establishing a supplier base that can provide quick replenishment of stocks during and after response, elevating the benefits of the proposed strategies on expected response time.

- Our comprehensive analysis show that benefits of the postponement strategy may vary based on disaster scenarios (e.g., timing and demands in each country), HOs' response regions, and inventory levels. Therefore, careful analysis is crucial for each unique humanitarian setting. Our proposed algorithm facilitates efficient testing of various scenarios and parameters, allowing decision makers (e.g., HOs, umbrella organizations) to tailor unbranded stock rates to their specific context and perform relevant analyses. For example, in our case, ESUPS advocates a solution with uniform (i.e., 75%) unbranded stock rates across all HOs for ease of communication and transition to the proposed system at the UNHRD warehouse.

Implementing our proposed system requires an information-sharing infrastructure among HOs to identify members with unbranded stocks and facilitate loaning and borrowing processes. Enhancing the existing UNHRD portal, which currently provides visibility of available stocks, can support the implementation of this system. Additionally, the development of information systems to support coordination and collaboration mechanisms is a current priority within the humanitarian sector. For instance, initiatives like the STOCKHOLM platform developed by ESUPS and supported by USAID [66] demonstrate the feasibility of establishing the necessary information infrastructure.

Currently, HOs may lack strong incentives to keep unbranded stocks individually and share them when necessary, which contributes to a limited culture of stock sharing. Our discussions with ESUPS executives underscore the need for increased awareness about coordination and research demonstrating the added value of collaboration among HOs. This thesis highlights the benefits of postponing branding and engaging in collaborative unbranded stock sharing on efficiency and effectiveness of prepositioning. Through empirical evidence, we aim to influence HOs, donors, and umbrella organizations such as UNHRD to adopt these strategies. Once these stakeholders recognize the merits of our approach, they can establish incentive structures to promote broader adoption among HOs. Institutional donors (including governments), leveraging their influence through donation conditions, can encourage participation by linking funding to collaborative system involvement. Similarly, UNHRD can incentivize participation by conditioning its free warehouse storage services on joining the collaborative network. These measures can also mitigate the risk of past free-riding behavior observed in the UNHRD system (see, e.g., [31]).

CHAPTER III

COLLABORATIVE PREPOSITIONING WITH POSTPONEMENT AND STOCK SHARING IN A NETWORK WITH REGIONAL AND COUNTRY WAREHOUSES

3.1 Background and Motivation

In this chapter, we examine a humanitarian distribution network comprising multiple HOs operating from common warehouses, both regional and country-specific, to respond to disasters in a specific region (e.g., the Caribbean). The regional warehouse serves multiple countries, whereas each country warehouse serves only its respective host country. Response times from country warehouses are shorter than those from the regional warehouse, creating a flexibility-speed trade-off in inventory allocation. A higher inventory level in the regional warehouse offers greater flexibility, as supplies can be shared among HOs and dispatched to multiple disaster-affected countries, but with longer response times. Conversely, higher inventory levels in country warehouses ensure quicker response times to disasters in the host country but reduce flexibility, as these supplies can only be used locally and cannot be shared among HOs. Deciding where to preposition inventory and how much to stock at each location is a challenging problem for the HOs, even under current prepositioning practices involving only branded stocks.

In this context, we aim to explore the potential benefits and implementation challenges of postponing the branding process for a portion of supplies until after a disaster for a subset of the HOs, keeping them in unbranded form in the regional warehouse to facilitate stock sharing. Specifically, we address the following question: *In a humanitarian distribution network serving a specific region from a single regional warehouse and multiple country warehouses, how much and what type (branded and/or unbranded) of stock should each HO keep in different warehouses?*

To answer our research question, we develop a two-stage stochastic optimization model designed to allocate prepositioned branded and unbranded inventory of a single relief item across both country and regional warehouses for a rapid response. Our model reflects the reality that while HOs in country warehouses maintain branded stocks, regional warehouses may hold both branded and unbranded stocks. In other words, postponement happens in the regional warehouse, but not every HO necessarily postpones the branding process. Our model determines which HOs should postpone the branding process for what percentage of their items. Given total inventory capacities (i.e., base stocks) of each HO, which are predetermined based on available budget and overall response targets (e.g., aiming to help 10,000 families within two weeks after a disaster), the model also decides where to stock and how much to stock branded and unbranded items for each HO and how to dispatch items from warehouses to the affected countries.

As a case study to demonstrate the impact of our proposed strategies on KPIs, we examine hurricane preparedness and response in the Caribbean by utilizing data from ESUPS, its partner HOs, and the UNHRD Panama warehouse. Our numerical analyses first compare the proposed system where HOs keep branded and unbranded stocks in the regional warehouse with a base case where all HOs keep branded stock in the regional warehouse, and demonstrate the benefits of postponement and stock sharing on a broader network with both regional and country warehouses. Then, we investigate the sensitivity of the results to the weights HOs assign to disasters with different severities and initial inventory levels of each HO. Lastly, we consider country-specific KPIs and investigate supporting strategies (e.g., setting country-specific minimum inventory levels) to accomplish better response performances for all or at least a majority of countries. Overall, we characterize the relationship between different model parameters and the impact of proposed strategies on key performance metrics, such as response time, fill rate, and inventory utilization. These analyses provide significant managerial insights for the effective implementation of the proposed strategies. Through our research, we aim to influence key stakeholders, including HOs, donors, and umbrella organizations such as the UNHRD, to adopt these strategies.

We structure the remainder of the chapter as follows. In Section 3.2, we position the contribution of this chapter within the existing literature. In Section 3.3, we explain our research approach. In Section 3.4, we describe the system, present our two-stage stochastic optimization model, and describe our key performance metrics. In Section 3.5, we describe our case study and the results of analyses. In Section 3.6, we discuss our findings and conclude the chapter.

3.2 Literature Review

Our research in this chapter examines the impact of implementing a postponement strategy combined with stock sharing on the KPIs of a humanitarian distribution network with both regional and country warehouses. Building on the research in Chapter 2, this study also aligns with two key streams of literature: collaborative inventory management in humanitarian operations and postponement. Next, we describe the contributions of this chapter, different from or additional to those in Chapter 2, to these two streams.

The literature on collaborative humanitarian inventory management addresses scenarios where either each actor (e.g., HOs, governments) retains ownership of their stocks but shares excess stock when necessary or all participating actors jointly own the inventory, sharing costs and benefits according to predefined rules. In Section

2.2.1, we describe the settings and decisions of existing studies on collaborative management of agency-owned inventory. These studies typically explore stock sharing in local networks (e.g., [30, 29]) or regional networks (e.g., [28, 31]). For instance, [30] and [29] apply their models to case studies in the Gulf Coast region of the United States and Istanbul, respectively. [28] and [31] examine stock sharing among two HOs and multiple HOs, respectively, at UNHRD facilities overseeing a regional network of countries. Building on the contributions of Chapter 2, this chapter extends the literature by examining the mechanics and benefits of postponement and stock sharing among HOs in a broader distribution network that includes both regional and multiple country warehouses. This expanded network necessitates several modeling innovations, the most significant being the flexibility-speed tradeoff between regional and country warehouses, which influences the stock sharing mechanism. The presence of country warehouses, which enable quick response to local disasters, impacts the extent of stock sharing in the regional warehouse. This chapter quantifies this impact, making the insights more applicable to realistically sized networks with different types of warehouses.

Existing studies on collaborative prepositioning of jointly owned stocks typically address network design for disaster preparedness and emergency response, emphasizing the strategic prepositioning of stocks to enhance disaster resilience. For instance, [6] and [25], both conducted in collaboration with the Caribbean Disaster and Emergency Management Agency (CDEMA), explore the design of a collaborative prepositioning network among Caribbean countries. [6] presents a strategy that pools prepositioned stocks, offering significant risk pooling benefits and reducing total inventory compared to decentralized policies. The authors use a stochastic programming model to determine the optimal locations and amounts of relief supplies, emphasizing joint ownership and regional response capacity. [25] complement this by addressing equitable cost allocation methods, ensuring fair distribution of operational costs among partner countries based on disaster risk and economic capacity. [67] develop a two-stage stochastic model for a collaborative humanitarian relief chain that involves multiple HOs, focusing on the prepositioning and distribution of relief items. This model ensures efficient resource allocation and procurement, enhancing disaster response through coordinated efforts. [68] address the design of a collaborative emergency response network with uncertain demand and transportation times. The authors propose a distributionally robust optimization model to manage these uncertainties, constructing an effective network that allows inter-regional cooperation in sharing emergency facilities and resources. Our contributions to this stream of research are twofold. First, we explore the potential benefits of postponement in a collaborative network by designing a distribution network for both branded and unbranded items, proposing the postponement of labeling until after disaster occurrences, thereby maintaining unbranded items in the regional warehouse. This approach introduces flexibility and responsiveness to disaster relief efforts. Second, unlike the aforementioned papers focusing on pooled inventories and mechanisms for sharing costs and benefits, in our setting HOs retain ownership of their inventories, necessitating the modeling of stock sharing (or loan-borrowing) practices post-disaster. These stock sharing rules differ significantly from cost/benefit sharing rules, being more related to logistical operations rather than financial operations.

Finally, this chapter's contribution to the postponement literature, beyond those of the research in Chapter 2, is the expansion of the granularity of postponement decisions from an aggregate level to an HO-level. Specifically, unlike the model in Chapter 2, where either all HOs postpone branding or none do (or only HOs of a specific size postpone branding), our model determines which HOs should postpone branding in the regional warehouse and to what extent. Additionally, this chapter examines the impact of quick and local response opportunities provided by country warehouses on the benefits of postponement and stock-sharing strategies. We demonstrate that the presence of country warehouses can reduce the positive impact of these strategies on KPIs.

3.3 Research Approach

We focus on a humanitarian setting with (i) a single regional warehouse, like UNHRD, where multiple HOs preposition stocks to respond to multiple countries, and (ii) multiple country-specific warehouses where multiple HOs preposition stocks to respond to the host country only. Each HO starts with a base stock (initial inventory) at the beginning of the planning horizon (e.g., a year) involving multiple periods (e.g., weeks), during which various countries may be affected by disasters. Similar to the model in Chapter 2 (see Section 2.4), although the assumption of fully replenished base stock at the start of the planning horizon is suitable for seasonal disasters such as hurricanes, our model can also adapt to occasional disasters (e.g., earthquakes) or continuous disasters over a year by adjusting this assumption. HOs allocate this base stock between the regional and country warehouses in different (branded and unbranded) forms. In our approach, HOs postpone branding process on a proportion (0% to 100%) of stocks, keeping them in an unbranded form in the regional warehouse. This facilitates HOs to quickly share these unbranded (i.e., shareable) stocks when needed. The existing UNHRD portal that provides visibility of available stocks [26] can be adapted for building an effective information-sharing system managing stock sharing among HOs. Following ESUPS's guidance, we do not consider stock sharing between country warehouses due to the potential logistical challenges and costs, which would require different modeling considerations and significantly complicate the model. Therefore, HOs keep only branded stocks in the country warehouses, as each HO uses these stocks to serve only the host country.

We determine the optimal distribution of base stock levels for HOs between regional and country warehouses, as well as the optimal rates of unbranded stock (i.e., postponement rates). Unbranded stock rates are defined as the proportion of each HO's unbranded stocks relative to total stocks in the regional warehouse. Our goal is to minimize the expected response time, weighted by the severity of disasters, throughout the entire season. Response time is critical for saving lives and gaining visibility among donors. We also consider two other KPIs in our analyses: fill rate and inventory leftover ratio. The fill rate measures how the proposed network design affects demand satisfaction in the network, while the inventory leftover ratio serves as a proxy for prepositioning costs.

To determine the optimal distribution network design and calculate the proposed KPIs, we develop a two-stage stochastic optimization model, which is a widely adopted method to model the uncertainties in humanitarian logistics (see [69] for a comprehensive literature survey). Our model is informed by insights from consultations with our partner organization ESUPS and its member HOs, reflecting common business objectives and constraints within the network. In the first stage, we make stock prepositioning decisions when the demand is still uncertain: How many branded (respectively, branded and unbranded) stock to preposition for each country warehouse (respectively, the regional warehouse)? Recall from Section 3.1 that response times from country warehouses are shorter than those from the regional warehouse, creating a flexibility-speed trade-off. Our model identifies the optimal balance for this trade-off. In the second stage, as the actual demands for each time period are gradually revealed, we make stock allocation decisions based on each realization: How many branded (respectively, branded, unbranded, and shared) stock to allocate from the country (respectively, regional) warehouse of each affected country? We model the uncertainties associated with disaster events using a set of discrete scenarios derived from historical data.

Modeling the management of shareable resources in a network with multiple HOs having overlapping response regions and countries is essential but challenging. To determine the stock quantities for shipment and sharing, our model initially deploys each HO's branded stocks from the country warehouses, then branded and unbranded stocks from the regional warehouse, and only then allows sharing excess unbranded stocks in the regional warehouse if demand remains unmet. If there is still unmet demand after HOs mobilize all of their stocks, then this demand is fulfilled by the supplier at a higher cost (i.e., longer response time).

Next, we provide a detailed system description and present our model.

3.4 System Description and Modeling

In this section, we describe the components of the humanitarian prepositioning system under investigation and our assumptions in modeling this system (Section 3.4.1), introduce our two-stage stochastic optimization model (Section 3.4.2), and present KPIs (Section 3.4.3). The notation used in this chapter is summarized in Appendix D.

3.4.1 System Description

Our prepositioning system and modeling framework in this chapter build upon those in Chapter 2. Therefore, for brevity, we only describe the elements that are different from or additional to those in Chapter 2.

3.4.1.1 Network and inventory prepositioning

We examine a humanitarian relief network comprising multiple HOs, each potentially maintaining prepositioned stocks in both *regional* and *country-specific* warehouses. There are no capacity limits for these warehouses. Stocks in the regional warehouse can be mobilized for all countries, but country stocks are restricted for use within their respective countries, with no sharing between country warehouses. HOs can maintain both branded and unbranded stocks in the regional warehouse. Branded items are exclusive to the owning HO, while unbranded items are available for sharing among HOs. In contrast, all items in the country warehouses are branded, as HOs store stocks designated solely for the respective country, making any inter-HO sharing within the country warehouse unnecessary. Note that HOs can store their branded stocks for a specific country in a shared warehouse with other HOs or in their own country-specific warehouses. Our model accommodates both cases. In addition to the network-related notation defined in Section 2.5.1 of Chapter 2, we let N_c denote the set of HOs that can hold stocks in the country warehouse c based on the response matrix.

3.4.1.2 Planning horizon and disaster scenarios

The planning horizon and disaster scenario definitions and notations are identical to those in Section 2.5.1 of Chapter 2.

3.4.1.3 Inventory allocation

The inventory allocation structure in this chapter is considerably more complex than the model in Chapter 2, as it encompasses a broader network that includes both regional and country warehouses. We first describe how HOs make inventory allocation decisions for disasters occurring in different time periods, followed by how they allocate various types of inventory across different warehouses during simultaneous disasters (i.e., occurring within the same time period). When a disaster occurs, all HOs mobilize their available inventory to meet the demand immediately, rather than holding stock for potential future events. This behavior exemplifies the unique nature of humanitarian operations. Unlike commercial firms that might withhold inventory from current sales in anticipation of future sales at higher profits, HOs cannot withhold relief supplies from current disaster response in anticipation of a future, unpredictable event. Their primary responsibility is to alleviate human suffering to the best of their ability with the supplies at hand.

For each disaster, affected countries are assigned a severity level representing the extent of the damage. If multiple countries are affected simultaneously, the regional warehouse prioritizes these countries based on their severity levels. Specifically, HOs first respond to the most severely affected countries within their service region at the beginning of the period. HOs first respond using all available inventory in the country warehouses to satisfy demand. If the total inventory in the country warehouse is insufficient, HOs then use the inventory in the regional warehouse, considering their response regions and disaster severities. They mobilize their branded, unbranded, and borrowed stocks in that order (after branding the latter two types). If neither the regional nor the country warehouses can meet the demand, the remaining demand is fulfilled by suppliers.

3.4.1.4 Delivery times

In addition to the delivery times defined in Section 2.5.1 of Chapter 2, the delivery time for branded stocks in this chapter also depends on whether the stock is shipped from country ($\overline{\tau}^c$) or regional ($\overline{\tau}^b$) warehouses. While the regional warehouse offers advantages in stock sharing and flexibility to respond to multiple countries, its delivery time is longer than that of the country warehouses. Therefore, based on practitioner consultations, we assume $\overline{\tau}^c < \overline{\tau}^b < \overline{\tau}^u < \overline{\tau}^s < \overline{\tau}^p$.

3.4.1.5 Replenishment of the warehouses

In addition to the processes described in Section 2.5.1 of Chapter 2, replenishment orders in this chapter can be placed for both country and regional warehouses. Replenishment orders arrive at their respective warehouses in designated forms.

3.4.2 Two-stage Stochastic Modeling Framework

In this section, we formulate the network design problem including collaborative prepositioning with postponement and stock sharing strategies. In this problem, we focus on a single relief item (e.g., tarpaulins) stored by multiple HOs in a regional warehouse (in branded and unbranded forms) and multiple country warehouses (in branded form). This complex problem involves prepositioning, relief delivery, and stock sharing decisions across multiple HOs with overlapping response regions, further complicated by the need to prioritize countries based on disaster severity.

We use a two-stage stochastic programming model with full recourse to capture sequential decision-making under demand uncertainty. The first stage involves pre-disaster inventory prepositioning decisions for country and regional warehouses. In particular, each HO must decide how much of its initial prepositioned inventory ($\overline{q}_a^T$) should be stocked in branded form in each country warehouse ($\overline{Q}_{ac}^b$) and how much should be stocked in branded (Q_a^b) and unbranded (Q_a^u) forms in the regional warehouse. These decisions are made before the uncertainty in demand is revealed and, therefore, they do not depend on disaster scenario s. As the uncertainty is gradually revealed over each time period, additional decisions (i.e., recourse actions) are made to allow the system to respond to the realized demand in each period (see Figure 34 for a sample scenario). The second stage decisions are scenario-dependent and involve post-disaster operations, including the transportation of relief goods and inventory sharing. Specifically, HOs determine the amount of branded (X_{stac}^b) and unbranded (X_{stac}^u) stocks mobilized from the regional warehouse and the amount of branded stocks ($\overline{X}_{stac}^b$) mobilized from country warehouses to affected countries. The second stage decisions also include the amount of unbranded stock that is borrowed from HO a by HO $\acute{a}$ (stock flow: $a \rightarrow \acute{a}$) for country c ($Y_{sta\acute{a}c}$). After HOs mobilize their stocks, the supplier fulfills all the unsatisfied demand in affected countries (U_{stc}). This option for direct shipment from an uncapacitated supplier ensures a feasible solution, regardless of how the demand uncertainty unfolds. This feature provides our model with its full recourse characteristic.

We use the same criteria from the two-phase inventory allocation models in Section 2.5.2 of Chapter 2 to identify HOs eligible to share and borrow stocks. However, the stochastic optimization model in this chapter, which allocates both the HOs' own stocks and shareable stocks, simplifies the statement of Rule 1 from Section 2.5.2: an HO can borrow stocks to respond to a country if it lacks sufficient branded and unbranded stocks to meet the demand, and if the combined stocks of all other HOs that respond to that country are also insufficient to meet the demand. In Section 2.5.2, this rule is part of a sequential decision-making process where first, the HOs' own stocks are allocated, and then, based on which HOs are responding and which are non-responding, and which countries have unmet demand, shareable stocks are allocated. Here, the model makes all these decisions simultaneously, making the additional definitions from Section 2.5.2 unnecessary. Rules 2-4 from Section 2.5.2 remain applicable.

We also introduce the following notation before presenting our model. Let $\overline{I}^b_{stac}$ denote the amount of branded stock that HO a keeps in the country warehouse located in country c, and I^b_{sta} and I^u_{sta} denote the amounts of branded and unbranded stocks, respectively, that HO a keeps in the regional warehouse at the beginning of period t in disaster scenario s. In addition, let $\overline{L}^b_{stac}$ denote the amount of branded stock replenished for HO a in the country warehouse located in country c, and L^b_{sta} and L^u_{sta} denote the amounts of branded and unbranded stocks, respectively, replenished for HO a in the regional warehouse at the beginning of period t in disaster scenario s. Lastly, the binary variable β_{sta} indicates whether HO a satisfies the demands of all countries that are in its service region, with $\beta_{sta} = 1$, if it does and therefore it can share its extra unbranded items with other HOs, and $\beta_{sta} = 0$, otherwise.

We formulate our two-stage stochastic programming model as follows.

$$\text{minimize} \sum_{s\in\mathcal{S}} \overline{p}_s \sum_{t\in\mathcal{T}} \sum_{c\in\mathcal{C}} \overline{\lambda}_{stc} \Bigg(\overline{\tau}^c \sum_{a\in\mathcal{A}} \overline{X}^b_{stac} + \overline{\tau}^b \sum_{a\in\mathcal{A}} X^b_{stac} + \overline{\tau}^u \sum_{a\in\mathcal{A}} X^u_{stac} + \overline{\tau}^s \sum_{a\in\mathcal{A}} \sum_{\substack{\acute{a}\in\mathcal{A}\\ \acute{a}\neq a}} Y_{sta\acute{a}c} + \overline{\tau}^p U_{stc} \Bigg) \tag{49}$$

subject to

$$\sum_{c\in\mathcal{C}} \overline{Q}^b_{ac} + Q^b_a + Q^u_a = \overline{q}^T_a \qquad \forall a \in \mathcal{A} \tag{50}$$

$$\overline{I}^b_{s(t=1)ac} = \overline{Q}^b_{ac} \qquad \forall s \in \mathcal{S}, a \in \mathcal{A}, c \in \mathcal{C} \tag{51}$$

$$I^b_{s(t=1)a} = Q^b_a \qquad \forall s \in \mathcal{S}, a \in \mathcal{A} \tag{52}$$

$$I^u_{s(t=1)a} = Q^u_a \qquad \forall s \in \mathcal{S}, a \in \mathcal{A} \tag{53}$$

$$\overline{I}^b_{s(t+1)ac} = \overline{I}^b_{stac} - \overline{X}^b_{stac} + \overline{L}^b_{s(t+1)ac} \qquad \forall s \in \mathcal{S}, t = 1, \ldots, |\mathcal{T}|-1, a \in N_c, c \in \mathcal{C} \tag{54}$$

$$I^b_{s(t+1)a} = I^b_{sta} - \sum_{c\in\mathcal{C}} X^b_{stac} + L^b_{s(t+1)a} \qquad \forall s \in \mathcal{S}, t = 1, \ldots, |\mathcal{T}|-1, a \in \mathcal{A} \tag{55}$$

$$I^u_{s(t+1)a} = I^u_{sta} - \sum_{c\in\mathcal{C}} X^u_{stac} - \sum_{c\in\mathcal{C}} \sum_{\substack{\acute{a}\in\mathcal{A}\\ \acute{a}\neq a}} Y_{sta\acute{a}c} + L^u_{s(t+1)a} \qquad \forall s \in \mathcal{S}, t = 1, \ldots, |\mathcal{T}|-1, a \in \mathcal{A} \tag{56}$$

$$\overline{X}^b_{stac} \leq \overline{I}^b_{stac} \qquad \forall s \in \mathcal{S}, t \in \mathcal{T}, a \in N_c, c \in \mathcal{C} \tag{57}$$

$$\sum_{c\in\mathcal{C}} X^b_{stac} \leq I^b_{sta} \qquad \forall s \in \mathcal{S}, t \in \mathcal{T}, a \in \mathcal{A} \tag{58}$$

$$\sum_{c\in\mathcal{C}} X^u_{stac} + \sum_{c\in\mathcal{C}} \sum_{\substack{\acute{a}\in\mathcal{A}\\ \acute{a}\neq a}} Y_{sta\acute{a}c} \leq I^u_{sta} \qquad \forall s \in \mathcal{S}, t \in \mathcal{T}, a \in \mathcal{A} \tag{59}$$

$$\overline{L}^b_{stac} = \overline{X}^b_{s(t-\overline{\tau}^r-1)ac} \qquad \forall s \in \mathcal{S}, t = \overline{\tau}^r + 2, ..., |\mathcal{T}|, a \in N_c, c \in \mathcal{C} \tag{60}$$

$$L^b_{sta} = \sum_{c\in\mathcal{C}} X^b_{s(t-\overline{\tau}^r-1)ac} \qquad \forall s \in \mathcal{S}, t = \overline{\tau}^r + 2, ..., |\mathcal{T}|, a \in \mathcal{A} \tag{61}$$

$$L^u_{sta} = \sum_{c\in\mathcal{C}} X^u_{s(t-\overline{\tau}^r-1)ac} + \sum_{c\in\mathcal{C}} \sum_{\substack{\acute{a}\in\mathcal{A}\\ \acute{a}\neq a}} Y_{s(t-\overline{\tau}^r-1)a\acute{a}c} \qquad \forall s \in \mathcal{S}, t = \overline{\tau}^r + 2, ..., |\mathcal{T}|, a \in \mathcal{A} \tag{62}$$

$$\overline{L}^b_{stac} = 0 \qquad \forall s \in \mathcal{S}, t = 1, ..., \overline{\tau}^r, a \in N_c, c \in \mathcal{C} \tag{63}$$

$$L^b_{sta} = 0 \qquad \forall s \in \mathcal{S}, t = 1, ..., \overline{\tau}^r, a \in \mathcal{A} \tag{64}$$

$$L^u_{sta} = 0 \qquad \forall s \in \mathcal{S}, t = 1, ..., \overline{\tau}^r, a \in \mathcal{A} \tag{65}$$

$$U_{stc} = \overline{d}_{stc} - \sum_{a \in N_c} \overline{X}^b_{stac} - \sum_{a \in \mathcal{A}} (X^b_{stac} + X^u_{stac} + \sum_{\substack{\acute{a} \in \mathcal{A} \\ \acute{a} \neq a}} Y_{st\acute{a}ac})$$

$$\forall s \in \mathcal{S}, t \in \mathcal{T}, c \in \mathcal{C} \tag{66}$$

$$X^b_{stac} + X^u_{stac} + \sum_{\substack{\acute{a} \in \mathcal{A} \\ \acute{a} \neq a}} (1 - \delta_{\acute{a}c}) Y_{st\acute{a}ac} \leq M \overline{\delta}_{ac} \qquad \forall s \in \mathcal{S}, t \in \mathcal{T}, a \in \mathcal{A}, c \in \mathcal{C} \tag{67}$$

$$U_{stc} \leq \overline{d}_{stc} h_{stc} \qquad \forall s \in \mathcal{S}, t \in \mathcal{T}, c \in \mathcal{C} \tag{68}$$

$$\sum_{a \in A} (I^b_{s(t+1)a} - L^b_{s(t+1)a}) \delta_{ac} + I^u_{s(t+1)a} - L^u_{s(t+1)a} \leq \sum_{a \in A} \overline{q}^T_a (1 - h_{stc})$$

$$\forall s \in \mathcal{S}, t \in \mathcal{T}, c \in \mathcal{C} \tag{69}$$

$$\sum_{a \in N_c} \overline{I}^b_{s(t+1)ac} - \overline{L}^b_{s(t+1)ac} \leq \sum_{a \in A} \overline{q}^T_a (1 - h_{stc}) \qquad \forall s \in \mathcal{S}, t \in \mathcal{T}, c \in \mathcal{C} \tag{70}$$

$$\sum_{c \in \mathcal{C}} U_{stc} \overline{\delta}_{ac} \leq (\sum_{c \in \mathcal{C}} \overline{d}_{stc})(1 - \beta_{sta}) \qquad \forall s \in \mathcal{S}, t \in \mathcal{T}, a \in \mathcal{A} \tag{71}$$

$$\sum_{\substack{\acute{a} \in \mathcal{A} \\ \acute{a} \neq a}} \sum_{c \in \mathcal{C}} Y_{sta\acute{a}c} \leq M \beta_{sta} \qquad \forall s \in \mathcal{S}, t \in \mathcal{T}, a \in \mathcal{A} \tag{72}$$

$$\overline{Q}^b_{ac} \geq 0 \text{ and integer} \qquad \forall a \in \mathcal{A}, c \in \mathcal{C} \tag{73}$$

$$Q^b_a, Q^u_a \geq 0 \text{ and integer} \qquad \forall a \in \mathcal{A} \tag{74}$$

$$U_{stc} \geq 0 \text{ and integer} \qquad \forall s \in \mathcal{S}, t \in \mathcal{T}, c \in \mathcal{C} \tag{75}$$

$$\overline{I}^b_{stac}, \overline{L}^b_{stac}, \overline{X}^b_{stac}, X^b_{stac}, X^u_{stac} \geq 0 \text{ and integer} \quad \forall s \in \mathcal{S}, t \in \mathcal{T}, a \in \mathcal{A}, c \in \mathcal{C} \tag{76}$$

$$I^b_{sta}, I^u_{sta}, L^b_{sta}, L^u_{sta} \geq 0 \text{ and integer} \qquad \forall s \in \mathcal{S}, t \in \mathcal{T}, a \in \mathcal{A} \tag{77}$$

$$Y_{st\acute{a}ac} \geq 0 \text{ and integer} \qquad \forall s \in \mathcal{S}, t \in \mathcal{T}, a \in \mathcal{A}, \acute{a} \in \mathcal{A} : \acute{a} \neq a, c \in \mathcal{C} \tag{78}$$

$$Z_{sta}, \beta_{sta} \in \{0, 1\} \qquad \forall s \in \mathcal{S}, t \in \mathcal{T}, a \in \mathcal{A} \tag{79}$$

$$h_{stc} \in \{0, 1\} \qquad \forall s \in \mathcal{S}, t \in \mathcal{T}, c \in \mathcal{C} \tag{80}$$

The objective function (49) of the model aims to minimize the severity-weighted expected response time based on stock types mobilized to affected countries. Specifically, the first term within the parenthesis represents the total response time based on the branded stock from the country warehouse, whereas the second, third, fourth, and fifth terms represent the total response time for branded, unbranded, and shared stock from the regional warehouse, and stock from the supplier, respectively.

Our model has the following constraints. Constraint (50) ensures that the total inventory capacity of each HO is allocated to the country warehouses (in branded form) and the regional warehouse (in branded and unbranded forms) as initial inventory levels. For each scenario s, we set these same initial inventory levels for each country warehouse and the regional warehouse using Constraints (51)-(53). In each period, each HO's available branded and unbranded stocks in the country and regional warehouses depend on usage, sharing (for unbranded), and replenishment from the supplier over previous periods. We track these dynamics with inventory balance equations in Constraints (54)-(56). Constraints (57)-(59) ensure that HOs cannot mobilize and/or share more stocks than they have. We set replenishment amounts arriving at the country and regional warehouses based on usage and/or sharing (for unbranded) in $\overline{\tau}^r$ (replenishment lead time) periods ago using Constraints (60)-(62). Constraints (63)-(65) ensure that there are no inventory replenishments within the time frame between the initial period and replenishment lead time. Constraint (66) calculates the "unsatisfied" demand, which is fulfilled by the supplier. This constraint together with Constraint (75) ensure that HOs cannot ship more than the demand. Note that we use an equality in Constraint (66), rather than a greater/less than or equal to constraint, as this maintains tighter control over the system, despite the potential improvements in flexibility, numerical stability, and solver performance that inequalities could offer. We tested an alternative constraint where unsatisfied demand (U_{stc}) was allowed to be greater than or equal to the right-hand side of Constraint (66). However, without introducing additional constraints, this modification permitted HOs to ship more than the demand in a given period, which could artificially lower (i.e., improve) the objective value by allowing inventory to bypass lower-severity disasters in favor of later, higher-severity ones. Therefore, we retained the equality in Constraint (66) to ensure accurate results; see Appendix A for the details of this analysis. Constraint (67) ensures that HOs mobilize their branded, unbranded, and borrowed stocks from the regional warehouse to affected countries considering their response regions. Here, we ensure that HOs can only borrow stocks from only candidate sharing HOs. Constraints (68)–(70) ensure that all HOs prioritize meeting current period demand rather than reserving inventory for future periods. Specifically, Constraint (68) determines if there is any unsatisfied demand in country c. If such demand exists, Constraints (69) and (70) require HOs capable of responding to country c to fully allocate their inventory to the current demand, preventing them from carrying stock forward to the next period. Constraints (71) and (72) ensure that HOs share their excess unbranded stocks after they meet the demand in their response region. Constraints (73)-(80) define variable domains.

We utilize Eclipse for Java Developers to solve our two-stage stochastic optimization model. The model achieves a solution for our case study with zero optimality gap within nine minutes on a standard laptop.

3.4.3 Key Performance Indicators (KPIs)

We evaluate the results of the optimization model presented in Section 3.4.2 based on key performance metrics (KPIs) focusing on three main aspects of the prepositioning network: *expected response time*, *expected fill rate*, and *expected inventory leftover ratio* that serves as a proxy for inventory holding costs.

The average network response time of the prepositioning network within a given disaster period and scenario (ψ_{st}) depends on the mix of mobilized stock types. This mix includes branded stock from country warehouses, branded, unbranded, and borrowed stock from the regional warehouse, and stock from the supplier, each with its respective delivery times. We calculate the average network response time by the total weighted average of these stock types' delivery times, where the weights correspond to the ratio of each stock type's quantity to the total demand:

$$\psi_{st} = \sum_{c \in \mathcal{C}} \left(\sum_{a \in \mathcal{A}} (\overline{\tau}^c \overline{X}^b_{stac} + \overline{\tau}^u X^u_{stac} + \overline{\tau}^b X^b_{stac} + \sum_{\substack{\acute{a} \in \mathcal{A} \\ \acute{a} \neq a}} \overline{\tau}^s Y_{st\acute{a}ac}) + \overline{\tau}^p U_{stc} \right) / \sum_{c \in \mathcal{C}} \overline{d}_{stc}$$

$$\forall s \in \mathcal{S}, t \in \mathcal{T}. \quad (81)$$

The network fill rate in a disaster period and scenario (ϕ_{st}) is equal to the ratio of the total mobilized amount from the country and regional warehouses to disaster-affected countries to the total demand of these countries:

$$\phi_{st} = \sum_{c \in \mathcal{C}} \sum_{a \in \mathcal{A}} \left(\overline{X}^b_{stac} + X^u_{stac} + X^b_{stac} + \sum_{\substack{\acute{a} \in \mathcal{A} \\ \acute{a} \neq a}} Y_{st\acute{a}ac} \right) / \sum_{c \in \mathcal{C}} \overline{d}_{stc} \qquad \forall s \in \mathcal{S}, t \in \mathcal{T}. \quad (82)$$

We calculate the inventory leftover ratio at the network for each scenario (ι_s) by dividing the total remaining stock at the network at the end of the last disaster period ($\bar{t}$) by the total beginning inventory in the network:

$$\iota_s = \sum_{a \in \mathcal{A}} \left(I^b_{s\bar{t}a} + I^u_{s\bar{t}a} + \sum_{c \in \mathcal{C}} \overline{I}^b_{s\bar{t}ac} \right) / \sum_{a \in \mathcal{A}} \left(q^b_a + q^u_a + \sum_{c \in \mathcal{C}} \overline{q}^b_{ac} \right) \qquad \forall s \in \mathcal{S} \qquad (83)$$

We compute the expected values of these three metrics, denoted as $\mathbf{E}(\overline{\psi})$, $\mathbf{E}(\overline{\phi})$, and $\mathbf{E}(\bar{\iota})$, corresponding to KPI_1, KPI_2, and KPI_3, respectively. Specifically, we calculate KPI_1 and KPI_2 in two steps. First, we take the average of, respectively, ψ_{st} and ϕ_{st} across all disaster time periods. Then, using the probability of each scenario occurrence ($\overline{p}_s$), we calculate KPI$_1$ and KPI$_2$ as follows.

$$\text{KPI}_1: \quad \mathbf{E}(\overline{\psi}) = \sum_{s \in \mathcal{S}} \overline{p}_s \frac{\sum_{t \in \Gamma_s} \psi_{st}}{|\Gamma_s|} \tag{84}$$

$$\text{KPI}_2: \quad \mathbf{E}(\overline{\phi}) = \sum_{s \in \mathcal{S}} \overline{p}_s \frac{\sum_{t \in \Gamma_s} \phi_{st}}{|\Gamma_s|}. \tag{85}$$

We directly calculate KPI$_3$ using $\overline{p}_s$ as follows.

$$\text{KPI}_3: \quad \mathbf{E}(\overline{\iota}) = \sum_{s \in \mathcal{S}} \overline{p}_s \iota_s. \tag{86}$$

3.5 Case Study

We apply the proposed approach to a case study using real data. Section 3.5.1 details the dataset, and Section 3.5.2 presents our analysis and findings.

3.5.1 Data Set

The data set for the case study in this chapter is largely the same as that used in Chapter 2, with some differences. For brevity, we will only describe the elements that differ from or are additional to those in Chapter 2.

Disaster scenarios. Unlike the case study in Chapter 2, which focuses solely on the regional warehouse handling stronger disasters, this chapter's case study also includes mild disasters, as these often require localized relief from country warehouses. In particular, we categorize hurricane severity into three levels: *mild* (H2 or lower), *strong* (H3), and *very strong* (H4 and H5). In our case study, we set disaster severity levels as follows: mild at $\lambda = 0.1$, strong at $\lambda = 0.3$, and very strong at $\lambda = 0.6$. We also conduct sensitivity analyses on these weights to examine the impact of their relative magnitudes on our results and insights. Figure 34 illustrates an example of a scenario and planning horizon, during which three disasters occur at $t = 5$, $t = 9$, and $t = 11$. For instance, at $t = 5$, a hurricane affects BH, LCA and VCT with severity levels $\lambda = 0.1$, $\lambda = 0.3$, and $\lambda = 0.6$, respectively.

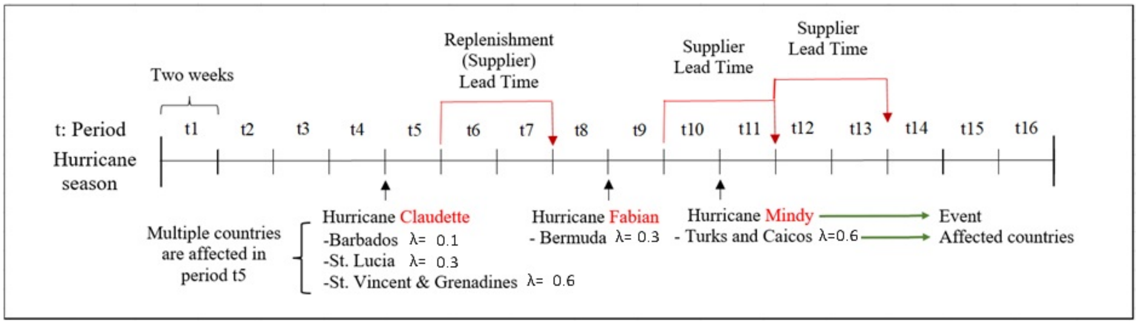

Figure 34: An illustration of planning horizon and scenario adapted from [6]

Our dataset comprises 310 scenarios with equal probability of occurrence (we investigate the impact of different occurrence probability structures in Section 3.5.2.4), 799 disaster periods, and 2,189 disaster-country combinations [6]. Among these disaster periods, 333 were single-country events, whereas 466 affected two or more countries. Additionally, there are 1,337 disaster-country combinations with mild disasters, 393 with strong disasters, and 459 with very strong disasters. In Figure 35, we illustrate our region of focus and the distribution of disaster events across countries. In Table 7, we present the percentage of scenarios featuring different combinations of disaster severity levels. In this context, demand is a function of both the severity level and the population of a country. In Figure 36, we provide the expected average demand of each country.

Relief items. We focus on tarpaulins in this case study as well. The only difference from the case study in Chapter 2, which considers only the demand satisfied by the regional warehouse, is that we do not adjust the demand values from [6]; instead, we use them as is. This is because we consider the demand satisfied by the country warehouses as well.

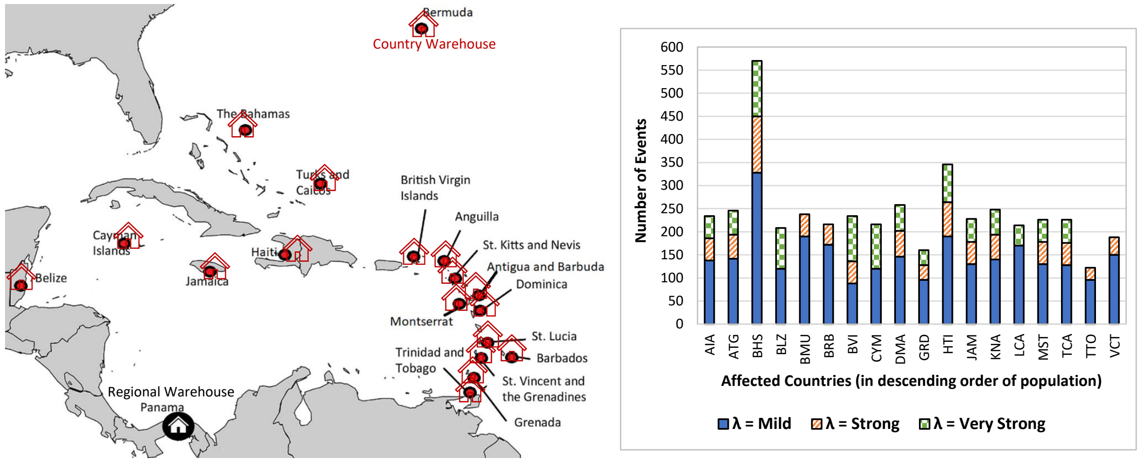

Figure 35: Region of interest and distribution of disaster events

Table 7: Proportion of scenarios by disaster severity combinations

Scenarios with:	Ratio
only mild disasters	13.55%
only strong disasters	1.61%
only very strong disasters	2.58%
mild and strong disasters	16.13%
mild and very strong disasters	20.65%
strong and very strong disasters	0.65%
mild, strong, and very strong disasters	44.84%

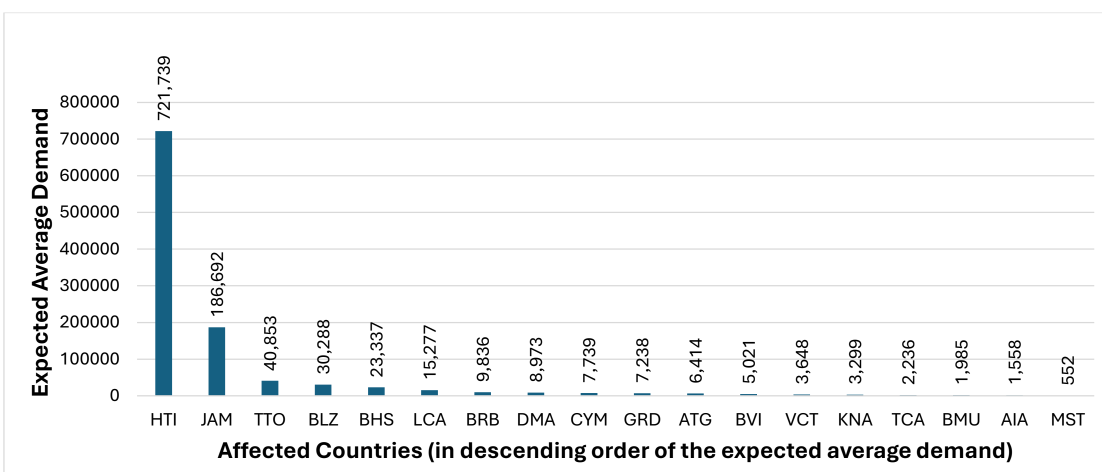

Figure 36: Expected average demand for each country

HOs and inventory levels. We modified the HOs in the case study in Chapter

2 slightly to make our model solvable and reduce solution time. In particular, we merged the same-sized HOs that have the same countries in their response regions. This resulted in four large and seven medium HOs. The modified response matrix is presented in Table 8. These merged HOs have identical features. Therefore, after solving our model and obtaining the results, we divide the assigned prepositioned inventory level of each merged HO equally across its members. We also evaluated the optimization problem using the original response matrix with 19 HOs to check whether merging the HOs affects the results. To make the problem solvable with the original response matrix, we reduced the number of disaster scenarios from 310 to 62. Our analysis confirms that the findings and insights are consistent across both response matrices; details of this analysis are provided in Appendix B.

We use the same method as in Chapter 2 to determine the initial inventory (i.e., base stock) level of each HO. In this chapter's case study, a total initial inventory of 10,024 units (allocated among all HOs) corresponds to the 30th quantile of demands during the 799 disaster periods (including mild disasters), whereas in Chapter 2, the same inventory level corresponds to the 60th quantile of demands during 494 disaster periods (excluding mild disasters). To capture a comprehensive picture, we conduct additional analyses with eight different levels for the total initial inventory: seven of these levels correspond to 30th, 45th, 60th, 75th, 90th, 95th, and 99th quantiles of demands (respectively, 10,024; 17,960; 42,380; 100,980; 650,760; 1,375,440; 2,223,820) and the eighth level corresponds to the maximum of the total demand in a scenario (i.e., 4,811,660), as detailed in Section 3.5.2.3.

Table 8: Modified response matrix, sizes and base stock levels of HOs

Number of Merged HO	Merged HOs Name	Size of HO	HO Name	AIA	ATG	BHS	BLZ	BMU	BRB	BVI	CYM	DMA	GRD	HTI	JAM	KNA	LCA	MST	TCA	TTO	VCT	Total Respondent Countries	Base Stock Level
				Caribbean Countries																			
3	HO_1, HO_2, HO_3	**L**	$\overline{HO}_1$	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	**18**	**2712**
2	HO_4, HO_5	**L**	$\overline{HO}_2$	0	1	1	1	1	1	1	0	1	1	1	1	1	1	0	0	1	1	**14**	**1808**
1	HO_6	**L**	$\overline{HO}_3$	0	0	0	1	1	1	1	0	0	0	1	1	0	0	0	0	1	0	**7**	**904**
1	HO_7	**L**	$\overline{HO}_4$	0	0	0	1	1	0	1	0	0	0	1	1	0	0	0	0	1	0	**6**	**904**
1	HO_8	**M**	$\overline{HO}_5$	0	1	1	1	0	0	0	0	0	0	1	1	0	0	0	0	1	1	**7**	**308**
1	HO_9	**M**	$\overline{HO}_6$	0	0	0	0	0	0	0	0	1	0	1	1	0	1	0	0	1	1	**6**	**308**
1	HO_{10}	**M**	$\overline{HO}_7$	0	0	0	1	0	1	0	0	0	0	1	1	0	0	0	0	0	0	**4**	**308**
1	HO_{11}	**M**	$\overline{HO}_8$	0	0	0	0	0	1	0	0	0	0	1	1	0	0	0	0	0	0	**3**	**308**
1	HO_{12}	**M**	$\overline{HO}_9$	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	**2**	**308**
1	HO_{13}	**M**	$\overline{HO}_{10}$	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	**2**	**308**
6	HO_{14}, HO_{15}, HO_{16}, HO_{17}, HO_{18}, HO_{19}	**M**	$\overline{HO}_{11}$	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	**1**	**1848**
																						Total inventory:	**10024**

Note: The intersection of an HO's row and a country's column is 1, if that HO responds to that country (i.e., if the HO has an office in that country), and 0 otherwise. We anonymize HO names to preserve confidentiality.

Delivery and replenishment lead times. Building on the delivery times of various items from the regional warehouse discussed in Chapter 2, we also consider the delivery time of branded items from a country warehouse. According to the data, the average delivery time for this scenario is one day, so we set it as one day. Replenishment lead time from the supplier is identical to that of Chapter 2 (i.e., 28 days).

3.5.2 Case Analysis and Results

In this section, we present the results of our numerical analysis. First, we compare the proposed system where HOs maintain both branded and unbranded stocks in the regional warehouse with a base (current) scenario where all HOs keep only branded stock in the regional warehouse (Section 3.5.2.1). Next, we examine the sensitivity of the results to the magnitudes of severity levels in the objective function (Section 3.5.2.2), the total initial inventory level of all HOs (Section 3.5.2.3), and disaster scenario occurrence probabilities (Section 3.5.2.4). We also explore benefits for each country in the proposed system and investigate how to accomplish better response performances for all or at least majority of countries (Section 3.5.2.5). In these analyses, we utilize the network-related KPIs based on fill rate, response time, and inventory leftover ratio, as defined in Section 3.4.3.

3.5.2.1 Benefits of postponement and stock sharing

Here, we compare a base case where HOs keep only branded stock in the regional warehouse with the proposed system, which includes postponement and stock sharing. HOs maintain different levels of branded and unbranded stocks in the regional warehouse in the proposed system. In Figures 37 and 38, we provide the resulting distributions of each HO's initial inventory level across regional-branded, regional-unbranded, and country warehouse stocks under the base case and the proposed system, respectively.

In the base case, 81.6% of the total initial inventory level of all HOs is stored in the regional warehouse, while the remaining 18.4% is stored in country warehouses. Specifically, all seven large HOs and six of the medium HOs store their stocks in the regional warehouse. The other six medium HOs, which have only HTI in their response regions, keep their stocks in HTI's country warehouse. The six medium

HOs that store their inventory in the regional warehouse, however, have broader response regions, covering additional countries alongside HTI. Specifically, one HO covers HTI and BHS, another covers HTI and JAM, and four others cover HTI, JAM, and additional countries. Thus, HOs that can respond to at least two countries prioritize flexibility by storing their inventory in the regional warehouse, while those with a single-country focus prioritize speed by storing their inventory locally in that country's warehouse.

In the proposed system, all HOs store their stocks in the regional warehouse, with 54.9% of these stocks kept in unbranded form. This approach significantly enhances flexibility and reduces expected response times more effectively than storing stocks in country warehouses as suggested in the base case. The regional warehouse not only offers greater flexibility by responding to all countries (as opposed to a single one) but also facilitates stock-sharing opportunities, which collectively provide a faster response time than what country-based storage could achieve.

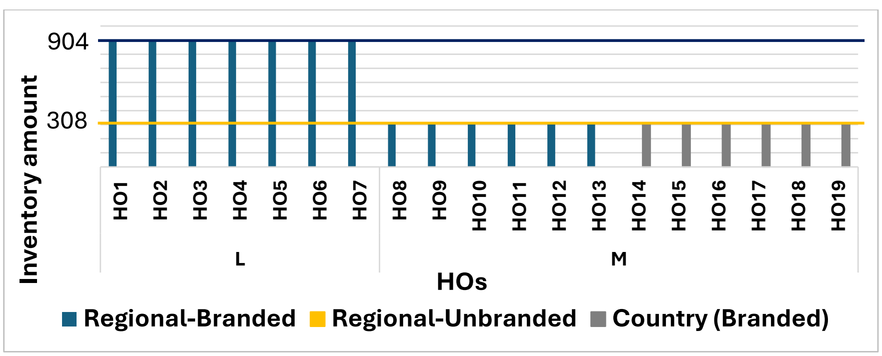

Figure 37: Distribution of each HO's initial inventory level under the base case

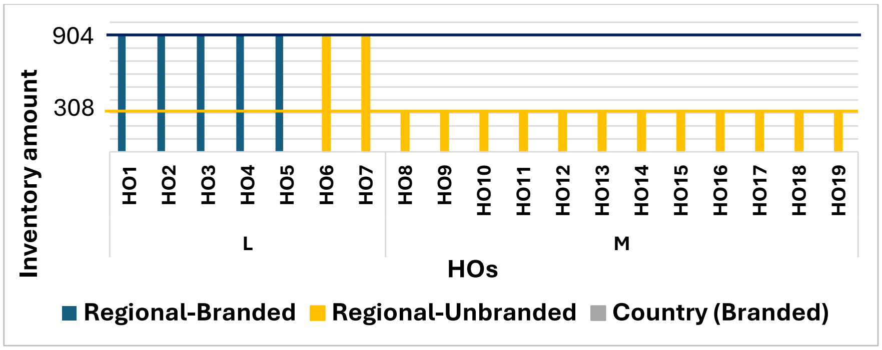

Figure 38: Distribution of each HO's initial inventory level under the proposed system

Centralizing inventory in the regional warehouse and maintaining a substantial proportion of unbranded stocks allows the proposed system to capitalize on both flexibility and collaboration, thereby enhancing the overall efficiency of the humanitarian response. Table 9 highlights the significant improvements in KPIs achieved through the proposed system.

Table 9: KPIs under the base case and the proposed system

	KPI_1	KPI_2	KPI_3
Base case	10.38 days	32.87%	35.41%
Proposed system	9.68 days	41.68%	32.57%
Expected relative difference	-6.78%	29.83%	-30.06%

The KPIs and corresponding enhancements that we report in this chapter are not directly comparable to those observed in the case study from Chapter 2, due to differences in KPI definitions and setting parameters between the chapters. To enable a meaningful comparison and draw insights on the value of the model in this chapter, we conduct the following analysis. In Chapter 2's case study (Section 2.6.2.4), a setting where large HOs keep only branded stock and medium HOs keep only unbranded stock yields the best results when considering the improvements in KPIs based on response time and fill rate. This setting, referred to as *the modified setting with 100% postponement* in Chapter 2, results in medium HOs' unbranded stocks comprising 36.87% of the regional warehouse's inventory. Therefore, we compare this rate (i.e., 36.87%) from Chapter 2 with the new unbranded stock rate in the regional warehouse (i.e., 54.9%) from this chapter. (Note that in Chapter 2 we recommended a different setting where HOs keep 75% unbranded stock in the regional warehouse for ease of communication and transition to the proposed system at the UNHRD warehouse.) To understand the source of the difference in the regional warehouse unbranded stock rates between the two chapters, we examine the various modeling aspects of Chapters 2 and 3 and analyze intermediate settings with different combinations of these aspects. We present the results of this analysis in Table 10.

In Table 10, Setting (1) corresponds to the model from Chapter 2's case study, while Setting (6) pertains to the model in Chapter 3. Settings (2)-(5) represent various combinations of factors that may contribute to the observed differences in results. These factors include: the primary consideration of the objective function (Row 2), adjustment of demand data with a multiplier (Row 3), inclusion of mild disasters (Row 4), weighting of disaster severity levels (Row 5), incorporation of country warehouses (Row 6), the total initial inventory level of all HOs (Row 7), and its corresponding quantile relative to scenario-period level demand (Row 8). To analyze these intermediate settings, we adjust the two-stage stochastic optimization model developed in this chapter accordingly and rerun it for each setting. We highlight the following observations. First, shifting the objective function's focus from unsatisfied demand to response time does not significantly impact the results (compare Settings 1 and 2). Second, permitting each HO to independently determine its unbranded stock level—rather than restricting medium HOs to unbranded stocks and large HOs to branded stocks as in Setting 1—results in a higher unbranded stock ratio in the

Table 10: Modeling aspects and resulting unbranded stock rates in the regional warehouse across the case studies of Chapters 2 and 3, including intermediate models

Setting number	(1) - Ch 2	(2)	(3)	(4)	(5)	(6) - Ch 3
objective function	unsatisfied demand	response time	response time	response time	response time	response time
demand multiplier	0.2	0.2	0.2	0.2	1	1
mild disasters	N	N	N	N	Y	Y
severity levels	2 - 3	2 - 3	2 - 3	0.3 - 0.6	0.1 - 0.3 - 0.6	0.1 - 0.3 - 0.6
country warehouses	N	N	N	N	N	Y
unbranded inventory policy	only medium	only medium	flexible	flexible	flexible	flexible
total inventory	10K	10K	10K	10K	40K	10K
quantile	60	60	60	60	60	30
Expected fill rate (%)	66.68	66.71	67.94	67.94	64.76	41.68
Expected response time (days)	6.87	6.87	6.80	6.80	7.12	9.68
Expected inventory leftover ratio (%)	34.02	39.59	38.44	38.44	38.35	32.57
Unbranded % in the regional warehouse	36.87%	36.87%	52.00%	52.00%	52.00%	54.91%

regional warehouse (52%), leading to minor KPI improvements (compare Settings 2 and 3). Third, changing the disaster severity levels from "strong: $\lambda = 2$ and very strong: $\lambda = 3$" to "strong: $\lambda = 0.3$ and very strong: $\lambda = 0.6$," does not affect the results (compare Settings 3 and 4). Fourth, incorporating country warehouses and including mild disasters, while keeping the total inventory level's quantile relative to the demand unchanged, does not alter the unbranded stock ratio but slightly worsens the KPI values. This occurs because the additional demand is mild, which is assigned low priority in our model (compare Settings 4 and 5). Finally, reducing the inventory level from the 60th to the 30th quantile worsens the KPIs and slightly increases the unbranded stock ratio (compare Settings 5 and 6), as expected because lower inventory results in poorer KPIs and a greater need for collaboration through stock sharing (this point is explored in detail in Section 3.5.2.3).

3.5.2.2 Effect of severity levels

We analyze the impact of disaster severity levels ($\overline{\lambda}_{stc}$) on KPIs by considering mild, strong, and very strong disasters separately to understand the effect of prioritizing stronger disasters. To do so, we first calculate the network response time and fill rate for each severity level, denoted by $\Psi_{st\lambda}$ and $\Phi_{st\lambda}$, respectively.

$$\Psi_{st\lambda} = \sum_{c \in \overline{C}} \left(\sum_{a \in \mathcal{A}} (\overline{\tau}^c \overline{X}^b_{stac} + \overline{\tau}^u X^u_{stac} + \overline{\tau}^b X^b_{stac} + \sum_{\substack{\acute{a} \in \mathcal{A} \\ \acute{a} \neq a}} \overline{\tau}^s Y_{st\acute{a}ac}) + \overline{\tau}^p U_{stc} \right) / \sum_{c \in \mathcal{C}} \overline{d}_{stc}$$

$$\forall \lambda \in \{\text{mild, strong, very strong}\}; s \in \mathcal{S}; t \in \mathcal{T} \qquad (87)$$

$$\Phi_{st\lambda} = \frac{\sum_{c \in \overline{C}} \sum_{a \in \mathcal{A}} \left(\overline{X}^b_{stac} + X^b_{stac} + X^u_{stac} + \sum_{\substack{\acute{a} \in \mathcal{A} \\ \acute{a} \neq a}} Y_{st\acute{a}ac} \right)}{\sum_{c \in \overline{C}} \overline{d}_{stc}}$$

$$\forall \lambda \in \{\text{mild, strong, very strong}\}; s \in \mathcal{S}; t \in \mathcal{T} \qquad (88)$$

Then, we compute the expected values of the network response time and fill rate for each severity level, denoted by $\mathbf{E}(\overline{\Psi}_\lambda)$ and $\mathbf{E}(\overline{\Phi}_\lambda)$, referred to as KPI_1^λ and KPI_2^λ, respectively. We calculate KPI_1^λ and KPI_2^λ as follows.

$$\text{KPI}_1^\lambda\text{:} \quad \mathbf{E}(\overline{\Psi}_\lambda) = \sum_{s \in \mathcal{S}} \overline{p}_s \frac{\sum_{t \in \Gamma_s} \Psi_{st\lambda}}{|\Gamma_s|} \qquad \forall \lambda \in \{\text{mild, strong, very strong}\} \tag{89}$$

$$\text{KPI}_2^\lambda\text{:} \quad \mathbf{E}(\overline{\Phi}_\lambda) = \sum_{s \in \mathcal{S}} \overline{p}_s \frac{\sum_{t \in \Gamma_s} \Phi_{st\lambda}}{|\Gamma_s|} \qquad \forall \lambda \in \{\text{mild, strong, very strong}\} \tag{90}$$

In Table 11, we present the severity-level-specific results for the expected response time (KPI_1^λ) and expected fill rate (KPI_2^λ), comparing scenarios where the severity levels are and are not factored into the model's objective function (49). As expected, prioritizing stronger disasters reduces the response time and increases the fill rate for very strong disasters, while having the opposite effect on mild disasters. The KPIs for strong disasters are comparable between scenarios with and without prioritization. Notably, the expected fill rate shows greater changes in magnitude compared to the expected response time.

Table 11: KPIs under two cases: objective with and without severity levels

KPI	objective function	mild	strong	very strong
KPI_1^λ	without severity levels	8.87 days	10.95 days	11.81 days
	with severity levels	9.95 days	10.95 days	10.89 days
KPI_2^λ	without severity levels	49.1%	29.4%	21.8%
	with severity levels	39.2%	29.2%	30.4%

3.5.2.3 Effect of total initial inventory level

We analyze the impact of total initial inventory level of all HOs (equivalently, base stock level q_a^T) on HOs' behaviors and KPIs. We examine eight different levels, ranging from the 30th quantile of the scenario-period level demands (i.e., 10,024) up to the maximum of the total demand in a scenario (i.e., 4,811,660). For each level, we distribute the total initial inventory among large and medium HOs using the same scale factor described in Chapter 2, Section 2.6.1.

Figure 39 illustrates the initial inventory prepositioning decisions of HOs across varying total initial inventory levels. Two key observations emerge. First, HOs allocate more unbranded stock to the regional warehouse when their initial inventory is limited, reflecting the need to maximize resource efficiency through stock sharing under constrained conditions. Second, as the total inventory level increases, HOs increasingly favor storing branded stocks in country warehouses rather than in the regional warehouse (in the most extreme case, 96% of the inventory is kept in the country warehouses). This shift is driven by the shorter expected response times offered by country warehouses—one day compared to three days from the regional warehouse in our case study. Essentially, when resources are abundant, the necessity for stock sharing and multi-country dispatch flexibility diminishes, allowing HOs to prioritize speed.

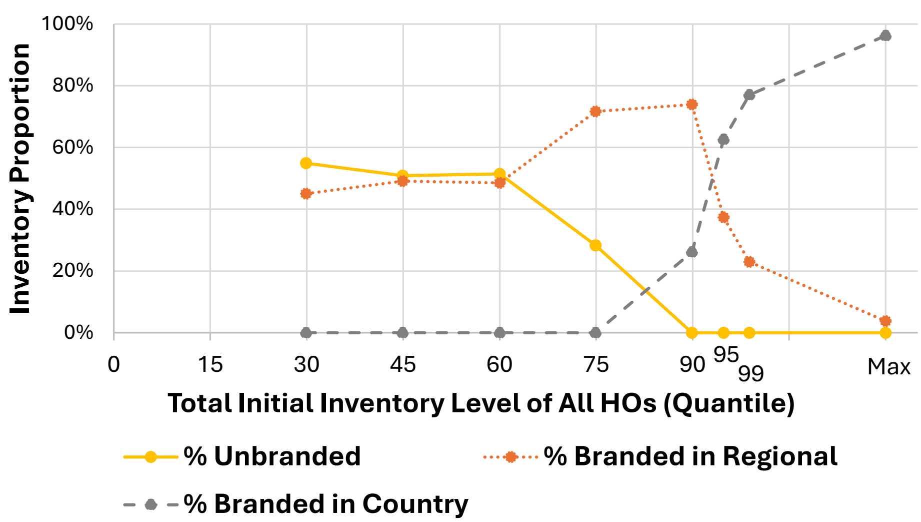

Figure 39: HOs' initial inventory prepositioning decisions across different stock and warehouse types under varying total initial inventory level

We also analyze how HOs' initial inventory location decisions—whether to store inventory in country warehouses or the regional warehouse—change as the total initial inventory level increases. Figure 40 illustrates this relationship. Initially, no HOs store branded stock in country warehouses. However, once the total initial inventory level reaches 90th quantile (i.e., 650,683), HOs begin storing stocks in country warehouses. For the 99th quantile, the number of country warehouses used increases to three, with 17 HOs storing branded stocks in these locations. At the highest initial inventory level considered, all 19 HOs store branded stocks across all 18 countries.

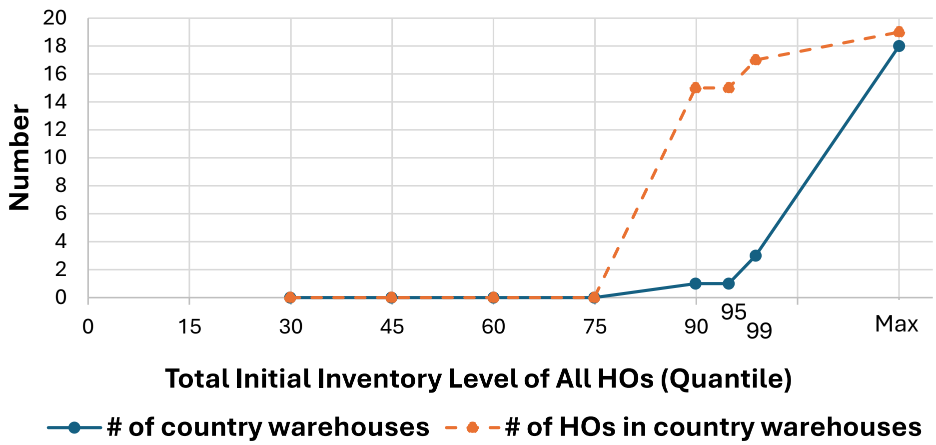

Figure 40: HOs' initial inventory location decisions under varying total initial inventory level

3.5.2.4 Effect of disaster scenario occurrence probabilities

In our main analyses, we assume that each of the 310 disaster scenarios (derived from 62 years of hurricane season data) has equal occurrence probability. In other words, we assume that hurricane patterns have remained steady over the past 62 years, meaning any of the past seasons is equally likely to represent a future season for which we are preparing and planning. However, disaster occurrences may be shifting over time, potentially driven by factors like global warming or other natural or human influences. To account for such potential shifts, we conduct an alternative analysis in two steps. In the first step, we examine the disaster data with a focus on temporal patterns. Figure 41 shows the average disaster demand across the entire Caribbean region (all 18 countries) for each year in our dataset, averaging across five randomly generated samples per year. The figure also includes a linear trend line, which reveals a clear upward trend over time.

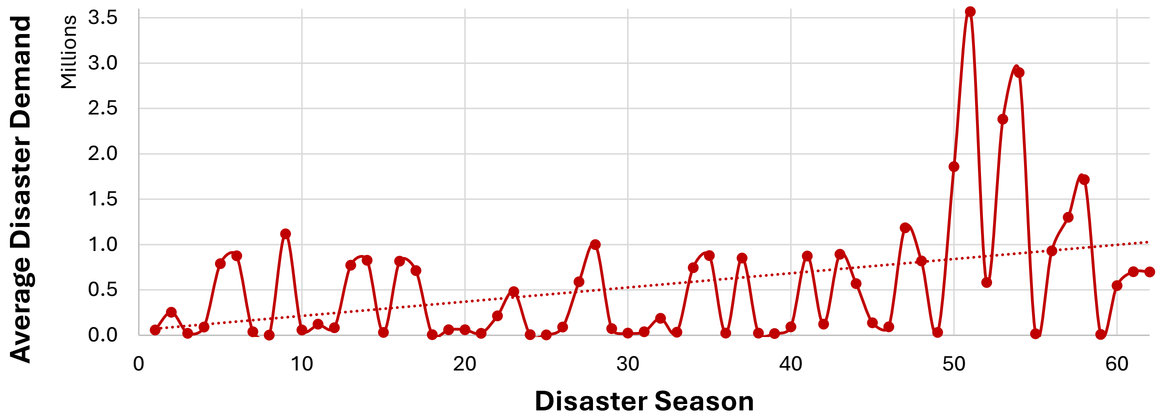

Figure 41: Evolution of the average disaster demand across all countries over time

In the second step, building on the trends observed in the first step, we run our model using varying disaster scenario probabilities. Our goal is to evaluate how HOs' prepositioning decisions would be affected if the identified trends in Figures 41-45 continue. We explore three distinct methods to capture the trends, as illustrated in Figure 42.

1. We focus on the last 13 seasons, starting from Season 50, and generate five random samples per season, resulting in 65 scenarios. Each scenario is assigned an equal probability of occurrence.

2. We use all 310 scenarios from the 62 seasons but adjust their probabilities: the 245 scenarios from the first 49 seasons are assigned lower probabilities, while the 65 scenarios from the last 13 seasons are given higher probabilities. Within each group, scenarios have equal probabilities, with the second group's probability being 3.8 times that of the first, reflecting the ratio of the average disaster demand of the second group to the first one.

3. We include all 310 scenarios from the 62 seasons and assign increasing probabilities to more recent seasons, proportional to the linear trend shown in Figure

41. Scenarios generated from the same season are assigned equal probabilities.

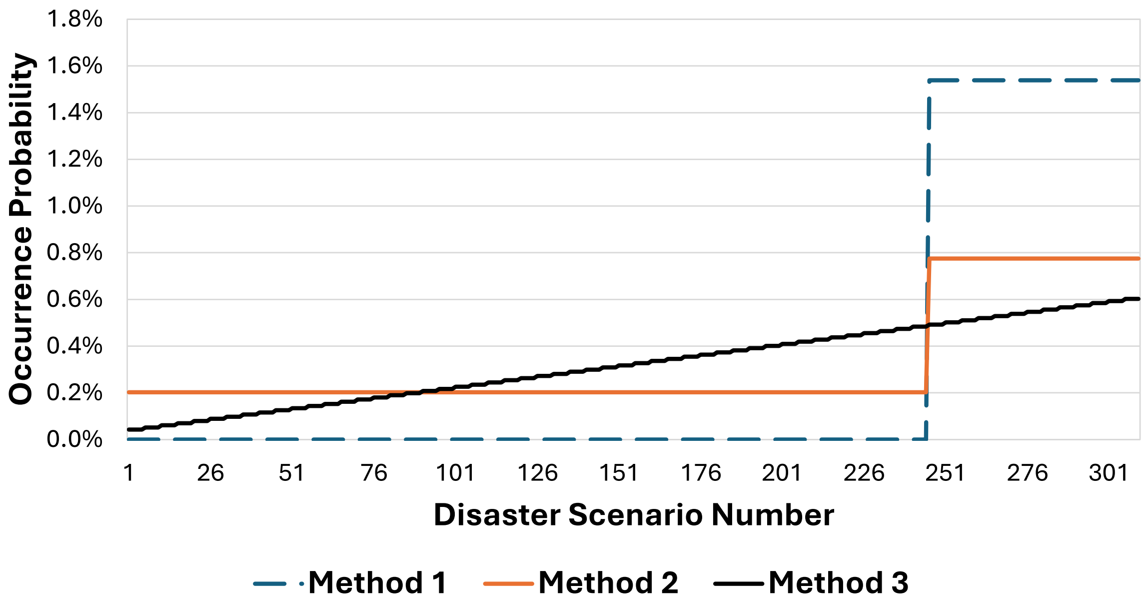

Figure 42: Three sets of scenario occurrence probabilities to capture the trends

In all methods, the "base case" solution matches our main analysis. Table 12 shows the unbranded rates of the proposed system under varying disaster occurrence probabilities, with the unbranded rates from our main analysis included in the "Method 0 (Main Analysis)" row for comparison. The unbranded rate decreases when higher occurrence probabilities are assigned to more recent disaster scenarios, especially at higher inventory levels. This trend intensifies in Method 1, where we place greater emphasis on recent scenarios.

Table 12: Unbranded rates under different scenario occurrence probabilities

	Inventory level	
Scenario Occurrence Probability	30th quantile	60th quantile
Method 0 (Main Analysis)	54.91%	51.44%
Method 1	51.84%	30.42%
Method 2	51.84%	49.34%
Method 3	51.84%	43.33%

We explain the results in Table 12 as follows. If the climate conditions that trigger hurricanes were to evolve uniformly across all Caribbean countries, we would expect country demands to change at the same rate. In such cases, the insights from our main analyses would remain unchanged. For instance, if all country demands were to double (or halve), it would be analogous to halving (or doubling) the current total initial inventory level, a scenario already addressed in Section 3.5.2.3. However, if climate conditions change at varying rates across countries, the dynamics differ. For example, in an extreme scenario where hurricanes start to occur exclusively in HTI, the model would likely recommend keeping all inventory in branded form within HTI's country warehouses. Conversely, a more balanced distribution of disasters across countries would lead to recommendations favoring higher unbranded stock rates.

To further explore this, we separately analyze the demand data for HTI, JAM, and all other countries in Figures 43, 44, and 45, respectively (motivated by the substantial demands from HTI and JAM; see Figure 36). Each figure shows an increasing trend in demand, but at different rates. Notably, HTI's demand shows a sharp increase after Season 50, and JAM's demand peaks around Season 51, which together contribute significantly to the overall demand increase observed in Figure 41 after Season 50. Therefore, our case study reveals an uneven increase in average disaster demand, with HTI experiencing the highest rate of increase, followed by JAM and other countries. Specifically, HTI's average demand over the last 13 seasons is 4.6 times that of the first 49 seasons. This ratio is 2.9 for JAM and 1.5 for the other countries, indicating that the distribution of disasters has become increasingly imbalanced over time. As more emphasis is placed on recent scenarios, this imbalance reduces the need for stock sharing across countries.

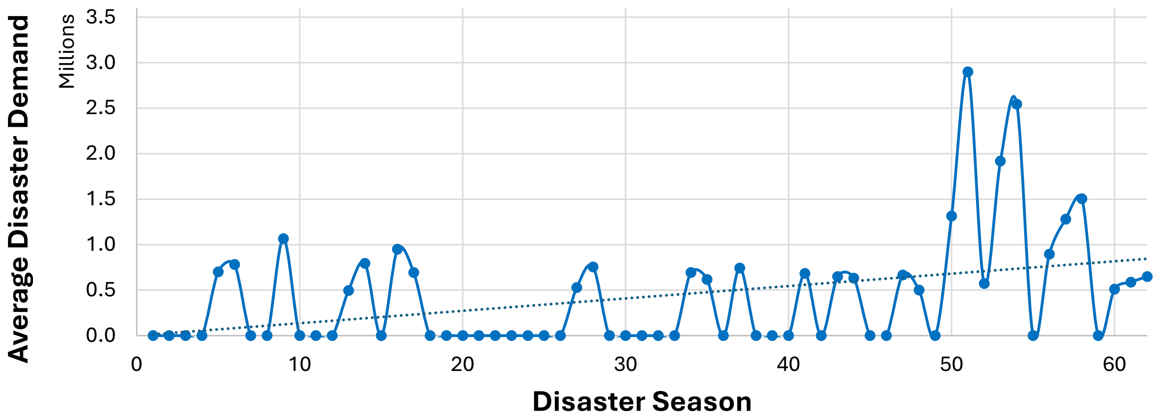

Figure 43: Evolution of HTI's average disaster demand over time

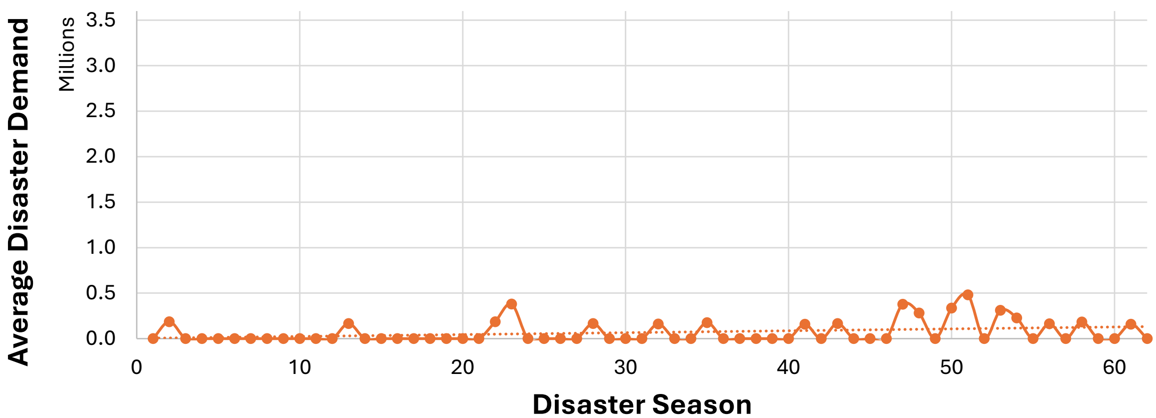

Figure 44: Evolution of JAM's average disaster demand over time

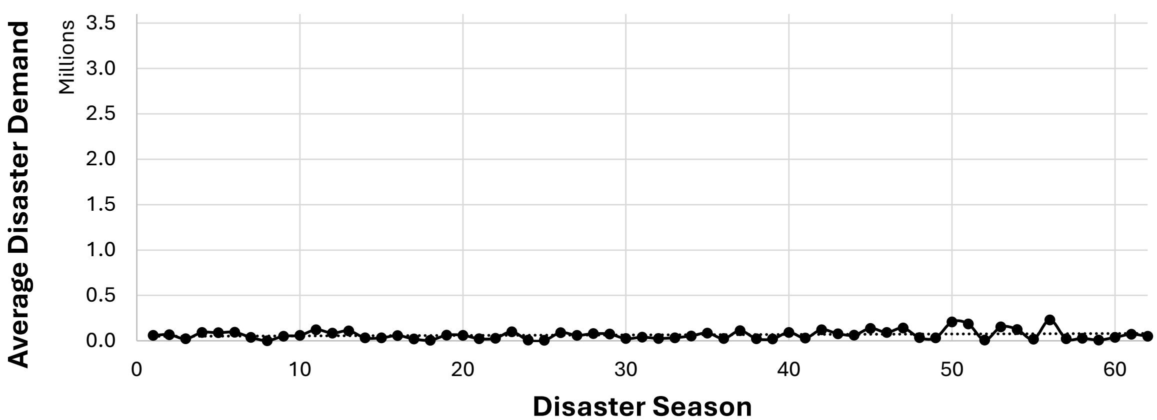

Figure 45: Evolution of other countries' average disaster demand over time

3.5.2.5 Effect of postponement and stock sharing on country related KPIs

So far, we have evaluated the proposed system based on total expected savings, adopting a *utilitarian* approach. An egalitarian approach considering the countries and identifying those most negatively impacted by the proposed system (if any) is also possible. Here we do so by analyzing how postponement and stock sharing strategies affect countries in the Caribbean region with diverse characteristics, such as the number of responding HOs, disaster severity, and demand profiles. To do so, we calculate the expected values of response time and fill rate of each country denoted by $\mathbf{E}(\overline{\Omega}_c)$ and $\mathbf{E}(\overline{\kappa}_c)$ and referred to as KPI_4 and KPI_5, respectively. To calculate these KPIs, we first define the average response time (resp., fill rate) across stock that are dispatched to a country c for time period $t \in \mathcal{T}$ in scenario $s \in \mathcal{S}$, denoted by Ω_{stc} (resp., κ_{stc}). We calculate Ω_{stc} and κ_{stc} as follows.

$$\Omega_{stc} = \left(\sum_{a \in \mathcal{A}} \left(\overline{\tau}^c \overline{X}^b_{stac} + \overline{\tau}^u X^u_{stac} + \overline{\tau}^b X^b_{stac} + \sum_{\substack{\acute{a} \in \mathcal{A} \\ \acute{a} \neq a}} \overline{\tau}^s Y_{sta\acute{a}c} \right) + \overline{\tau}^p U_{stc} \right) / \overline{d}_{stc} \quad \forall s \in \mathcal{S}, t \in \mathcal{T}, c \in \mathcal{C} \tag{91}$$

$$\kappa_{stc} = \sum_{a \in \mathcal{A}} \left(X^u_{stac} + X^b_{stac} + \sum_{\substack{\acute{a} \in \mathcal{A} \\ \acute{a} \neq a}} Y_{sta\acute{a}c} \right) / \overline{d}_{stc} \qquad \forall s \in \mathcal{S}, t \in \mathcal{T}, c \in \mathcal{C} \tag{92}$$

Not every country experiences a disaster in each scenario, therefore we calculate KPI_4 and KPI_5 as conditional expectations (i.e., conditional on experiencing a disaster). Let Υ_{sc} be the subset of periods where country c is affected in scenario s, and $|\Upsilon_{sc}|$ be the cardinality of Υ_{sc}. We calculate KPI_4 and KPI_5 as follows.

$$\mathrm{KPI}_4: \quad \mathbf{E}(\overline{\Omega}_c) = \frac{\sum_{s \in \mathcal{S}} \overline{p}_s \frac{\sum_{t \in \mathcal{T}} \Omega_{stc}}{|\Upsilon_{sc}|}}{\sum_{s \in \zeta_c} \overline{p}_s} \qquad \forall c \in \mathcal{C} \tag{93}$$

$$\mathrm{KPI}_5: \quad \mathbf{E}(\overline{\kappa}_c) = \frac{\sum_{s \in \mathcal{S}} \overline{p}_s \frac{\sum_{t \in \mathcal{T}} \kappa_{stc}}{|\Upsilon_{sc}|}}{\sum_{s \in \zeta_c} \overline{p}_s} \qquad \forall c \in \mathcal{C} \tag{94}$$

To achieve a more egalitarian outcome, we propose a four-step iterative strategy to reallocate a portion of the initial inventory among countries negatively impacted by our proposed system. The steps are as follows:

1. *Run the Model*: Execute the current model under the base case and the proposed system.

2. *Identify Negatively Impacted Countries*: Compare the results of the proposed system with the base case to identify countries that are negatively affected by the proposed system.

3. *Redistribute Initial Inventory*: Allocate a portion of the initial inventory as a lower bound to the countries identified in Step 2. (If a country warehouse already has stock under the proposed system, we set the lower bound by adding the calculated allocation to the existing stock.) The lower bound for each country's warehouse stock is calculated by multiplying the total initial inventory by two factors:

   (a) The average mild disaster demand ratio (i.e., the average demand for mild disasters divided by the sum of average demands for mild, strong, and very strong disasters).

   (b) The average demand ratio for that specific country.

4. *Iterative Re-Run and Adjustment*:

   (a) Rerun the Model: Run the model again with the newly established country warehouse stock lower bounds as additional constraints.

   (b) Check for Changes: Return to Step 2 to identify any new or persisting negatively impacted countries.

   (c) Stopping Criteria: If the number of negatively impacted countries decreases, continue this iterative process until no new countries are identified in Step 2 compared to the previous iterations, then stop.

(d) Adjust Based on Stagnation: If the number of negatively impacted countries remains the same or increases, further redistribute a portion of the initial inventory among a subset of the identified countries based on intuition or trial-and-error. Continue the iterative process until no new countries are identified compared to previous iterations, and then stop.

This iterative algorithm ensures an equitable stock distribution, as much as possible. We apply this algorithm to our case study and present the results in Table 13.

In Table 13, we report the KPI_4 and KPI_5 values for both the proposed system (PS) and the base case (BC) as defined in Section 3.5.2.1 (Step 1). The proposed system shows improvements in KPI_4 (respectively, KPI_5) for 15 (respectively, 16) out 18 countries (Step 2). In the third step, we reallocate a portion of the total initial inventory to the three countries negatively affected by the proposed system: BMU, HTI, and JAM. This allocation is set as a lower bound based on the average mild disaster demand ratio (8% in our case study) and the average demand ratios for these countries (0.18%, 67.03%, and 17.34%, respectively). These limits are listed in the "Inv. Limit – PS1" row of Table 13, and the resulting KPI values are shown in the "PS-1" row. Although BMU shows improvement, HTI and JAM still have KPI values worse than the base case, and BRB's KPIs now also fall below the base case. Thus, we proceed to Step 4(d) of our algorithm, reallocating additional stock specifically to BMU and JAM (see "Inv. Limit – PS2" row). We exclude HTI from this adjustment as its improvement would likely worsen KPIs for other countries, given that HTI's warehouse already holds 1,848 branded stocks in the base case. In this iteration, KPI_4 worsens only for HTI, and KPI_5 worsens for HTI and TTO; see "PS-2" row. Lastly, we add a lower bound for TTO and rerun the model (refer to the "Inv. Limit – PS3" and "PS-3" rows for the bounds and results, respectively). This improves the KPIs of TTO but leads to an additional country (BRB) being negatively impacted. Additionally, KPI_1 and KPI_2 values become worse under "PS-3" ($KPI_1 = 40.49\%$ and

Table 13: Country-level KPIs with equity consideration (BC: Base case, PS: Proposed system)

		AIA	ATG	BHS	BLZ	BMU	BRB	BVI	CYM	DMA	GRD	HTI	JAM	KNA	LCA	MST	TCA	TTO	VCT
KPI_4 (days)	BC	11.98	11.20	11.92	10.91	6.88	12.03	7.87	10.94	11.53	13.10	13.75	13.71	12.49	13.13	12.48	11.95	13.03	12.77
	PS	10.91	10.92	11.21	10.50	6.89	11.75	7.13	9.88	10.60	12.66	13.81	13.73	11.58	12.93	11.62	10.89	12.99	12.32
	PS-1	11.25	10.87	11.35	10.78	6.81	12.50	7.46	9.84	10.56	12.69	13.80	13.72	11.77	12.70	11.54	11.08	12.94	12.25
	PS-2	11.18	10.90	11.29	10.69	6.72	11.96	7.34	9.91	10.69	12.71	13.81	13.65	11.83	13.09	11.56	11.16	13.06	12.19
	PS-3	11.05	10.73	11.24	10.73	6.71	12.11	7.76	9.94	10.57	12.74	13.82	13.67	11.74	13.07	11.88	11.18	12.85	12.41
KPI_5 (%)	BC	18.35	25.47	18.95	28.06	64.74	17.87	55.69	27.82	22.50	8.19	2.14	2.68	13.74	7.90	13.83	18.60	8.80	11.16
	PS	31.27	30.65	27.38	33.54	66.55	22.27	67.18	40.37	33.44	12.83	1.90	2.66	23.70	10.47	23.17	30.06	9.82	16.54
	PS-1	27.66	30.90	25.88	30.76	67.18	14.78	63.41	40.42	33.60	12.70	1.89	2.65	21.67	12.76	24.25	28.07	10.25	17.19
	PS-2	28.28	30.73	26.47	31.68	67.94	20.05	65.10	39.79	32.36	12.41	1.82	3.22	21.14	8.78	24.23	27.27	9.11	17.48
	PS-3	29.82	31.89	26.86	31.09	67.89	18.65	60.34	39.53	33.35	11.81	1.74	3.09	22.05	9.12	21.01	27.04	11.03	15.37
Inv. Limit	PS-1	0	0	0	2	0	0	0	0	0	0	540	140	0	0	0	0	0	0
	PS-2	0	0	0	5	0	0	0	0	0	0	0	423	0	0	0	0	0	0
	PS-3	0	0	0	5	0	0	0	0	0	0	0	423	0	0	0	0	93	0
Average Demand		1558	6414	23337	30288	1985	9836	5021	7739	8973	7238	721739	186692	3299	15277	552	2236	40853	3648

$\text{KPI}_2 = 9.78$) compared to "PS-2" ($\text{KPI}_1 = 40.88\%$ and $\text{KPI}_2 = 9.75$). Therefore we stop at this step and propose "PS-2" as the equitable solution. We note that under "PS-2", KPI_1 and KPI_2 values are slightly lower than those in the proposed system ($\text{KPI}_1 = 41.68\%$ and $\text{KPI}_2 = 9.68$), as expected.

3.6 Discussion and Conclusion

This chapter addresses the allocation of branded and unbranded inventory in a humanitarian distribution network comprising both regional and country-specific warehouses. We explore the flexibility-speed trade-off in inventory allocation decisions, aiming to enhance disaster response efforts. The focus is on the potential benefits and implementation challenges of postponing the branding process for a portion of supplies, keeping them in unbranded form in the regional warehouse to facilitate stock sharing. To tackle this problem, we develop a two-stage stochastic optimization model that determines the optimal allocation of prepositioned branded and unbranded inventory across both country and regional warehouses for rapid response.

Through a case study on hurricane preparedness and response in the Caribbean, we demonstrate the advantages of our proposed strategies over traditional practices. Our numerical analyses show that incorporating postponement and stock sharing in the regional warehouse improves KPIs such as response time, fill rate, and inventory utilization. We also investigate the sensitivity of these results to different disaster severities and initial inventory levels, and consider supporting strategies to enhance country-specific KPIs.

Key findings and remarks from this chapter are summarized below.

- Combining postponement with stock sharing significantly improves all relevant KPIs when applied to a broader network consisting of both regional and country warehouses, and when HOs can make individual postponement decisions.

Therefore, our findings in this chapter reinforce our recommendation from Chapter 2 to discontinue the practice of permanently branding items before disasters for a portion of stocks. Instead, we advocate for procuring standard (unbranded) items for the regional warehouse, applying stickers after a disaster if necessary, or sharing them with other HOs.

- The amount of initial inventory relative to demand is a crucial factor in implementing postponement and stock sharing strategies. Specifically, lower inventory levels increase the need for sharing and enhanced resource usage efficiency in the regional warehouse. In other words, when there is limited inventory, country warehouse stocks are better used as unbranded stocks in the regional warehouse. Conversely, higher inventory levels lead to a greater proportion of stocks being stored in country warehouses.

- We develop a supporting strategy that iteratively redistributes prepositioned inventory across countries negatively impacted by our proposed strategies. This approach is recommended to enhance equity and fairness in disaster response across countries, addressing any concerns that may hinder implementation.

Our findings provide valuable managerial insights for HOs, donors, and organizations like the UNHRD, encouraging the adoption of our proposed strategies to improve disaster response efforts. The implementation requirements regarding the information-sharing infrastructure discussed in Chapter 2 remain applicable to the broader network analyzed in this chapter. The need for a robust information-sharing system among HOs to identify members with unbranded stocks and facilitate loaning and borrowing processes is still essential. Enhancing platforms like the existing UNHRD portal, which provides visibility of available stocks, continues to support the implementation of our proposed system. As previously mentioned, the development of information systems to support coordination and collaboration is a priority within the humanitarian sector, exemplified by initiatives like the STOCKHOLM platform developed by ESUPS and supported by USAID [66]. These requirements are equally relevant and critical for the broader network considerations discussed in this chapter.

CHAPTER IV

CONCLUSIONS

In this thesis, we investigate how postponement and stock-sharing strategies can enhance disaster preparedness for HOs, focusing on both regional warehouses and broader networks consisting of both regional and country-level warehouses. Conducted in collaboration with the ESUPS Working Group, the thesis proposes deferring the branding process for a portion of the stocks in regional warehouses until after a disaster to facilitate sharing among HOs.

We aim to (i) evaluate the impact of these strategies on post-disaster response performance and (ii) develop methods for their implementation. We develop two analytical frameworks to achieve these goals: a two-phase inventory allocation model incorporated in a Monte Carlo simulation approach in Chapter 2 and a two-stage stochastic optimization model in Chapter 3. These models provide a comprehensive approach to improving disaster preparedness in humanitarian operations. In particular, Chapter 2 focuses on a single regional warehouse serving a specific area, like the Caribbean, and uses a Monte Carlo simulation to assess postponement and stock-sharing effectiveness. Chapter 3 extends this to include both regional and country warehouses, optimizing branded and unbranded stock allocation and stock mobilization strategies.

We apply these models to case studies on hurricane preparedness and response in the Caribbean, using data from ESUPS, its partner HOs, and the United Nations Humanitarian Response Depot (UNHRD) Panama warehouse. Extensive numerical analyses provide practical insights and assess the sensitivity of the results to various modeling choices and parameters.

The main contributions of this thesis are:

- While previous research has explored stock sharing mechanisms in humanitarian warehouses, this thesis is the first to investigate the effects of postponement in this context. Unlike previous models that focus on surplus stock sharing and overlook the branding process, we consider the branding process, distinguish shareable (unbranded) items from non-sharable (branded) ones, and develop new inventory allocation models to accurately represent current stock sharing practices in humanitarian operations.

- This thesis investigates the impact of postponement decisions in different granularity levels ranging from unform postponement rates to HO-level postponement decisions on system KPIs. This breadth of range enables HOs to evaluate different postponement strategies and allows for a variety of applications.

- This thesis is the first to explore the impact of third-country postponement of the labeling process on KPIs, addressing a gap in the postponement literature highlighted by [35] as still underrepresented and deserving further consideration.

- This thesis is the first to investigate the potential benefits of implementing the postponement strategy in a collaborative humanitarian setting (as opposed to a commercial setting), taking into account its unique challenges including distinct strategic goals and sharing rules. Specifically, our models aim to reduce human suffering (i.e., unsatisfied demand in Chapter 2 and response time in Chapter 3), unlike profit-driven commercial chains (see, e.g., [50, 54, 47, 44]). Additionally, commercial inventory allocation policies, typically based on predictable demand and fixed lists, or cost/benefit sharing rules designed for shared usage of pooled resources (e.g., inventory), are not suitable for our humanitarian context due to its unique complexities. Our humanitarian setting involves overlapping response regions, management of branded and unbranded items, interdependencies over time, and unpredictable demands. Our models account for these factors, making the problem more complex.

- This thesis also extends the literature by examining the mechanics and benefits of postponement and stock sharing among HOs in a broader distribution network that includes both regional and multiple country warehouses. It introduces modeling innovations to address the flexibility-speed tradeoff between regional and country warehouses and quantifies the impact of this tradeoff on the stock sharing mechanism, making the insights more applicable to realistically sized networks with various types of warehouses.

In conclusion, this thesis demonstrates that postponement and stock-sharing strategies can significantly enhance the efficiency and effectiveness of prepositioning efforts, offering valuable insights for disaster preparedness decision-making in humanitarian networks. It also discusses various implementation challenges, such as the necessity of an efficient information-sharing infrastructure among HOs, and potential concerns, such as fairness and equity concerns, and provide practical solutions.

Given that postponement is an underexplored area in humanitarian systems, several future research directions exist. First, our frameworks can be adopted to examine the impact of postponement and stock sharing strategies in other humanitarian warehouses, exploring various settings with different disaster susceptibility and considering alternative inventory management systems. For example, in our case study, we generated disaster scenarios based on seasonal Atlantic hurricanes affecting the Caribbean region from June 1st to November 30th [62]. Although this seasonality enables HOs to replenish their prepositioned inventory each season, strategies and methods for non-seasonal or sudden-onset disasters like earthquakes require further exploration. Second, given the increased attention on stock sharing practices and the use of white stocks in UNHRD warehouses with growing member HOs (e.g., [27]), exploring systems and method that address managing both types of stocks would be valuable. Third, our models assume the total initial inventory level of each HO is predetermined. Developing models to optimize these initial inventory levels would provide valuable insights for the humanitarian sector. Finally, our current approach optimizes single metrics, such as expected unsatisfied demand or response time. Introducing multi-objective models that combine these metrics and/or include additional considerations can address a broader range of concerns from HOs.

APPENDIX A

AN ALTERNATIVE CONSTRAINT WITHOUT USING EQUALITY FOR THE UNSATISFIED DEMAND CALCULATION IN CHAPTER 3

In the optimization problem developed in Section 3.4.2, we use an equality in Constraint (66), rather than a greater/less than or equal to constraint, as this maintains tighter control over the system, despite the potential improvements in flexibility, numerical stability, and solver performance that inequalities could offer. We tested a modified version of this constraint:

$$U_{stc} \geq \overline{d}_{stc} - \sum_{a \in N_c} \overline{X}^{b}_{stac} - \sum_{a \in \mathcal{A}} (X^{b}_{stac} + X^{u}_{stac} + \sum_{\substack{\acute{a} \in \mathcal{A} \\ \acute{a} \neq a}} Y_{st\acute{a}ac}) \qquad \forall s \in \mathcal{S}, t \in \mathcal{T}, c \in \mathcal{C} \tag{95}$$

In the original model, Constraints (66) and (75) together ensure that HOs do not ship more than the demand. However, the modified Constraints (95) and (75) lack this safeguard, allowing the right-hand side of Constraint (95) to be negative. This can occur when shipping beyond the demand artificially decreases (i.e., improves) the objective value by, for example, bypassing a disaster with low severity to prioritize inventory for a subsequent disaster with higher severity. Constraints (68)–(70), which ensure that HOs prioritize current period demand, do not prevent such occurrences under the modified constraints.

For example, consider disasters occurring in periods 7, 9, and 10 with severities of mild, mild, and very strong, respectively, and where the first two disasters' demands are much smaller than the total initial inventory whereas the last disaster's demand exceeds the total initial inventory. In the original model, HOs must satisfy the demands in periods 7 and 9. The inventory used for the disaster in period 9 will not be replenished by period 10 (due to a two-period replenishment lead time), reducing the inventory available for the last disaster. Conversely, with Constraint (95), HOs could fully deplete inventory in the first disaster (by shipping more than the demand), skip the second disaster (because there will not be any available inventory for the disaster in period 9), and use the entire replenished stock for the last disaster, thus achieving a lower (i.e., better) objective value.

To prevent the above unrealistic allocation, we can introduce an additional constraint ensuring that dispatched amounts do not exceed the demand:

$$\sum_{a \in N_c} \overline{X}^b_{stac} + \sum_{a \in \mathcal{A}} (X^b_{stac} + X^u_{stac} + \sum_{\substack{\acute{a} \in \mathcal{A} \\ \acute{a} \neq a}} Y_{st\acute{a}ac}) \leq \overline{d}_{stc} \qquad \forall s \in \mathcal{S}, t \in \mathcal{T}, c \in \mathcal{C} \qquad (96)$$

Constraint (96) ensures that shipments do not exceed demand in any period, maintaining the integrity of the solution. Although Constraint (95) is computationally more efficient than Constraint (66), the addition of the new set of constraints (96) counterbalances this advantage, resulting in even a slight increase in computation time. Specifically, the solution time of the alternative formulation is 8.73 minutes compared to 8.72 minutes for the original formulation (solved for the proposed system with the total initial inventory of all HOs equal to 10,024).

APPENDIX B

COMPARISON OF RESULTS UNDER ORIGINAL AND MODIFIED RESPONSE MATRICES IN CHAPTER 3

In this appendix, we examine the optimization problem outlined in Section 3.4.2 using the original response matrix, which does not merge same-sized HOs with identical response regions, to assess any potential impact of merging these HOs on the results. To make the problem solvable with the original response matrix, we reduced the number of scenarios from 310 to 62. We conducted this test for two total initial inventory levels: 10,024 and 42,380, corresponding to the 32nd and 64th quantiles of the scenario-period level demand from the 62 scenarios. We present the prepositioned inventory results in Table 14. In the "11 HOs" columns, the table shows the results after dividing the prepositioned inventory levels assigned to each merged HO equally among its members. Our findings and insights remain consistent across both response matrices.

Table 14: KPIs under original and modified response matrices

	11 HOs 32th quantile			19 HOs 32th quantile			11 HOs 64th quantile			19 HOs 64th quantile		
	Q_a^b	Q_a^u	$\overline{Q}_{ac}^b$	Q_a^b	Q_a^u	$\overline{Q}_{ac}^b$	Q_a^b	Q_a^u	$\overline{Q}_{ac}^b$	Q_a^b	Q_a^u	$\overline{Q}_{ac}^b$
HO_1	904	0	0	904	0	0	3860	0	0	3860	0	0
HO_2	904	0	0	904	0	0	3860	0	0	3860	0	0
HO_3	904	0	0	904	0	0	3860	0	0	3860	0	0
HO_4	904	0	0	904	0	0	3860	0	0	3860	0	0
HO_5	904	0	0	904	0	0	3860	0	0	3860	0	0
HO_6	0	904	0	0	904	0	0	3860	0	0	3860	0
HO_7	0	904	0	0	904	0	0	3860	0	0	3860	0
HO_8	0	308	0	0	308	0	1280	0	0	1280	0	0
HO_9	0	308	0	0	308	0	0	1280	0	0	1280	0
HO_{10}	0	308	0	0	308	0	0	1280	0	0	1280	0
HO_{11}	0	308	0	0	308	0	0	1280	0	0	1280	0
HO_{12}	0	308	0	0	308	0	0	1280	0	0	1280	0
HO_{13}	0	308	0	0	308	0	0	1280	0	0	1280	0
HO_{14}	0	308	0	0	308	0	0	1280	0	0	1280	0
HO_{15}	0	308	0	0	308	0	0	1280	0	0	1280	0
HO_{16}	0	308	0	0	308	0	0	1280	0	0	1280	0
HO_{17}	0	308	0	0	308	0	0	1280	0	0	1280	0
HO_{18}	0	308	0	0	308	0	0	1280	0	0	1280	0
HO_{19}	0	308	0	0	308	0	0	1280	0	0	1280	0
Total Inventory	4520	5504	0	4520	5504	0	20580	21800	0	20580	21800	0

APPENDIX C

NOTATION SUMMARY FOR CHAPTER 2

Sets	
$\mathcal{S}$:	set of scenarios; $s \in \mathcal{S}$
$\mathcal{T}$:	set of time periods; $t \in \mathcal{T}$
$\mathcal{A}$:	set of HOs; $a \in \mathcal{A}$
$\mathcal{C}$:	set of countries; $c \in \mathcal{C}$
ζ_c:	set of scenarios in which a disaster hits country $c \in \mathcal{C}$; $s \in \zeta_c$
Γ_s:	set of disaster-affected periods in scenario s; $t \in \Gamma_s$; $\bar{t}$: the last disaster-affected period
Υ_{sc}:	set of disaster-affected periods in which a disaster hits country c in scenario s; $t \in \Upsilon_{sc}$
$\lvert \cdot \rvert$:	cardinality of a set
Parameters of the Simulation Model	
$\overline{p}_s$:	the probability of occurrence of the disaster scenario s
$\overline{\lambda}_{stc}$:	disaster severity level of each disaster-affected country c at the period t in scenario s
$\overline{d}_{stc}$:	demand of country c at the period t in the disaster scenario s
R:	proportion of unbranded stock; $R \in [0\%, 100\%]$
$\overline{q}_a^T$:	total base stock level of HO a at the beginning of each scenario
$\overline{q}_a^u$:	unbranded base stock level of HO a at the beginning of each scenario ($\overline{q}_a^u = R\overline{q}_a^T$)

$\overline{q}_a^b$:	branded base stock level of HO a at the beginning of each scenario ($\overline{q}_a^b = (1-R)\overline{q}_a^T$)
$\overline{\delta}_{ac}$:	response matrix—1 if country c is in the response region of HO a; 0 otherwise
$\overline{\tau}^b$:	delivery time of branded stocks from the regional warehouse to disaster-affected countries
$\overline{\tau}^u$:	delivery time of unbranded stocks from the regional warehouse to disaster-affected countries
$\overline{\tau}^s$:	delivery time of borrowed stocks from the regional warehouse to disaster-affected countries
$\overline{\tau}^p$:	delivery time of required amount from the supplier to disaster-affected countries
$\overline{\tau}^r$:	replenishment lead time of orders from the supplier to the regional warehouse
Variables of the Simulation Model	
$\overline{Q}_{sta}$:	the total inventory levels of HOs a at the beginning of t in the disaster scenario s (we calculate this value from remaining branded (I_{sta}^b) and unbranded (I_{sta}^u or W_{sta}^u if sharing is needed) stock levels at the end of each period $t-1$ and $t>1$ in the disaster scenario s)
$\overline{X}_{stc}^u$:	the amount of unbranded stock mobilized from the regional warehouse to country c at period t in the disaster scenario s
$\overline{X}_{stc}^b$:	the amount of branded stock mobilized from the regional warehouse to country c at period t in the disaster scenario s
$\overline{y}_{stc}$:	the amount of borrowed unbranded stock mobilized from the regional warehouse to country c at period t in the disaster scenario s
$\overline{U}_{stc}$:	the amount of mobilized stock sourced from the supplier to country c at period t in the disaster scenario s (we obtain this value from U_{stc} if sharing is not needed; otherwise we use V_{stc})

Parameters of Model 1 and Integrated Model	
q^u_{sta}:	unbranded inventory level of HO a at period t in scenario s ($q^u_{sta} = \overline{q}^u_a$ at the beginning of each scenario, then $q^u_{sta} = I^u_{s(t-1)a}$ is sharing is not needed; otherwise $q^u_{sta} = W^u_{s(t-1)a}$)
q^b_{sta}:	branded inventory level of HO a at period t in scenario s ($q^b_{sta} = \overline{q}^b_a$ at the beginning of each scenario, then $q^b_{sta} = I^b_{s(t-1)a}$)
Decision Variables of Model 1	
X^u_{stac}:	the amount of unbranded stock mobilized from the regional warehouse to country c at period t in the disaster scenario s
X^b_{stac}:	the amount of branded stock mobilized from the regional warehouse to country c at period t in the disaster scenario s
I^u_{sta}:	remaining unbranded stock level of HOs after HOs mobilize their own stocks
I^b_{sta}:	remaining branded stock level of HOs after HOs mobilize their own stocks
Auxiliary Variables of Model 1	
U_{stc}:	unsatisfied demand of country c at period t in scenario s after HOs mobilize their own stocks (we use it to find $\overline{U}_{stc}$ if sharing is not needed)
Z_{sta}:	1 if HO a responds with unbranded stock at period t in scenario s; 0 otherwise
δ_{stac}:	1 if HO a mobilizes its own stocks to the disaster-affected country c at period t in scenario s (responding HO—$\overline{X}^u_{stc} + \overline{X}^b_{stc} > 0 \Rightarrow \delta_{stac} = 1$); 0 otherwise (non-responding HO)
Parameters of Model 2	
U_{stc}:	remaining demand of country c at period t in scenario s after Model 1
I^u_{sta}:	excess unbranded stock (i.e., shareable stock) level of HO a at period t in scenario s after Model 1

Π_{stac}:	set of candidate-borrowing HOs at period t in scenario s—1 if $\delta_{stac} = 1$ and $U_{stc} > 0$ or if $\overline{\delta}_{ac} = 1$, $\sum_{a \in \mathcal{A}} \delta_{stac} = 0$, and $U_{stc} > 0$; 0 otherwise
γ_{sta}:	set of candidate-sharing HOs at period t in scenario s—1 if $I^u_{sta} > 0$; 0 otherwise
Decision Variables of Model 2	
$Y_{sta\acute{a}c}$:	the amount of unbranded stock that is borrowed from HO $\acute{a}$ by HO a (stock flow: $a' \rightarrow a$) for country c at period t in scenario s ($\overline{y}_{stc} = \sum_{a \in \mathcal{A}} \sum_{\substack{\acute{a} \in \mathcal{A} \\ \acute{a} \neq a}} Y_{sta\acute{a}c}$)
Auxiliary Variables of Model 2	
V_{stc}:	unsatisfied demand of country c at period t in scenario s after HOs mobilize their borrowed stocks (we use it to find $\overline{U}_{stc}$ if sharing is needed)
W^u_{sta}:	remaining unbranded stock level of HOs after HOs mobilize their borrowed stocks
Decision Variables of Integrated Model	
X^u_{stac}:	the amount of unbranded stock mobilized from the regional warehouse to country c at period t in the disaster scenario s
X^b_{stac}:	the amount of branded stock mobilized from the regional warehouse to country c at period t in the disaster scenario s
$Y_{sta\acute{a}c}$:	the amount of unbranded stock that is borrowed from HO $\acute{a}$ by HO a (stock flow: $a' \rightarrow a$) for country c at period t in scenario s ($\overline{y}_{stc} = \sum_{a \in \mathcal{A}} \sum_{\substack{\acute{a} \in \mathcal{A} \\ \acute{a} \neq a}} Y_{sta\acute{a}c}$)
I^u_{sta}:	remaining unbranded stock level of HOs after HOs mobilize their stocks
I^b_{sta}:	remaining branded stock level of HOs after HOs mobilize their stocks
Auxiliary Variables of Integrated Model	
U_{stc}:	unsatisfied demand of country c at period t in scenario s after HOs mobilize their branded, unbranded and borrowed stocks (we use it to find $\overline{U}_{stc}$)

Z_{sta}:	1 if HO a responds with unbranded stock at period t in scenario s; 0 otherwise
β_{sta}:	1 if all demand in HO a's response region is satisfied at period t in scenario s; 0 otherwise
Θ_{stc}:	1 if HOs do not have enough stocks to respond to country c and borrow unbranded stocks at period t in scenario s; 0 otherwise

KPI related variables

ψ_{stR}:	the network response time for time period t in scenario s for each unbranded rate R
ϕ_{stR}:	the network fill rate for time period t in scenario s for each unbranded rate R
ι_{sR}:	the network inventory leftover ratio in scenario s for each unbranded rate R
κ_{stcR}:	the fill rate of country c for time period t in scenario s for each unbranded rate R
Ω_{stcR}:	the response time of country c for time period t in scenario s for each unbranded rate R
$\eta_{st\lambda R}$:	the network unsatisfied demand for time period t in scenario s for each unbranded rate R and each disaster severity level λ
$\mathbf{E}(\Delta\overline{\psi}_{R\rightarrow 0\%})$:	the expected relative differences in the network response time between different unbranded rates ($R > 0\%$) and base case ($R = 0\%$)
$\mathbf{E}(\Delta\overline{\phi}_{R\rightarrow 0\%})$:	the expected relative differences in the network fill rate between different unbranded rates ($R > 0\%$) and base case ($R = 0\%$)

$\mathbf{E}(\Delta\bar{\iota}_{R\to 0\%})$:	the expected relative differences in the network inventory leftover ratio between different unbranded rates ($R > 0\%$) and base case ($R = 0\%$)
$\mathbf{E}(\overline{\kappa}_{cR})$:	the expected fill rate of country c under different unbranded rates ($R \geq 0\%$)
$\mathbf{E}(\overline{\Omega}_{cR})$:	the expected response time of country c under different unbranded rates ($R \geq 0\%$)
$\mathbf{E}(\Delta\overline{\eta}_{\lambda,R\to 0\%})$:	the expected relative differences in the network unsatisfied demand between different unbranded rates ($R > 0\%$) and base case ($R = 0\%$) for each disaster severity level λ
KPI_1:	the expected relative differences in the network response time ($\mathbf{E}(\Delta\overline{\psi}_{R\to 0\%})$; $\forall R > 0\%$)
KPI_2:	the expected relative differences in the network fill rate ($\mathbf{E}(\Delta\overline{\phi}_{R\to 0\%)}$; $\forall R > 0\%$)
KPI_3:	the expected relative differences in the network inventory leftover ratio ($\mathbf{E}(\Delta\bar{\iota}^{R\to 0\%}$; $\forall R > 0\%$)
KPI_4:	the expected response time of country c ($\mathbf{E}(\Omega_{cR})$; $\forall R \geq 0\%$)
KPI_5:	the expected fill rate of country c ($\mathbf{E}(\kappa_{cR})$; $\forall R \geq 0\%$)
KPI_2^{λ}:	the expected relative differences in the network unsatisfied demand ($\mathbf{E}(\Delta\overline{\eta}_{\lambda,R\to 0\%}$; $\forall R > 0\%$)
KPI_3^{L}:	the expected relative differences in the inventory leftover ratio of large HOs
KPI_3^{M}:	the expected relative differences in the inventory leftover ratio of medium HOs
τ^{ratio}:	the proportion of the disaster periods (the number of disaster-affected time periods divided by 494, which is the total of disaster periods)

APPENDIX D

NOTATION SUMMARY FOR CHAPTER 3

Sets

$\mathcal{S}$:	set of disaster scenarios; $s \in \mathcal{S}$
$\mathcal{T}$:	set of disaster periods; $t \in \mathcal{T}$
$\mathcal{A}$:	set of HOs; $a \in \mathcal{A}$
$\mathcal{C}$:	set of disaster-affected countries; $c \in \mathcal{C}$
N_c:	Set of HOs that can hold inventory in country warehouse c, $c = \{1, 2, \ldots, \lvert C \rvert\}$
Γ_s:	subset of periods in $\mathcal{T}$ with disasters in scenario s; $t \in \Gamma_s$; $\bar{t}$: the last disaster-affected period
$\lvert . \rvert$:	cardinality of .

Parameters of the 2-Stage Stochastic Model

$\overline{p}_s$:	the probability of occurrence of the disaster scenario s
$\overline{\lambda}_{stc}$:	disaster severity level of each disaster-affected country c at the period t in scenario s
$\overline{d}_{stc}$:	demand of country c at the period t in the disaster scenario s

$\overline{q}_a^T$:	total base stock level of HO a at the beginning of each scenario
$\overline{\delta}_{ac}$:	response matrix—1 if country c is in the response region of HO a; 0 otherwise
$\overline{\tau}^c$:	delivery time of branded stocks in country warehouses located in disaster-affected countries
$\overline{\tau}^b$:	delivery time of branded stocks from the regional warehouse to disaster-affected countries
$\overline{\tau}^u$:	delivery time of unbranded stocks from the regional warehouse to disaster-affected countries
$\overline{\tau}^s$:	delivery time of borrowed stocks from the regional warehouse to disaster-affected countries
$\overline{\tau}^p$:	delivery time of required amount from the supplier to disaster-affected countries
$\overline{\tau}^r$:	replenishment lead time of orders from supplier to the regional warehouse
First Stage Decision Variables	
Q_a^u:	unbranded base stock level of HO a at the beginning of each scenario
Q_a^b:	branded base stock level of HO a at the beginning of each scenario
$\overline{Q}_{ac}^b$:	branded base stock level of HO a in the country warehouse c at the beginning of each scenario
Second Stage Decision Variables	
X_{stac}^u:	the amount of unbranded stock mobilized from the regional warehouse to country c at period t in the disaster scenario s
X_{stac}^b:	the amount of branded stock mobilized from the regional warehouse to country c at period t in the disaster scenario s
$\overline{X}_{stac}^b$:	the amount of branded stock mobilized from the country warehouse located in the country c at period t in the disaster scenario s
$Y_{sta\acute{a}c}$:	the amount of unbranded stock that is borrowed from HO a by HO $\acute{a}$ (stock flow: $a \rightarrow \acute{a}$) for country c at period t in scenario s

Auxiliary Second Stage Decision Variables

$\overline{I}^{b}_{stac}$	Branded stock level of HO a that keeps stock in the country warehouse located in the country c at the beginning of period t in the disaster scenario s
I^{b}_{sta}	Branded stock level of HO a that keeps stock in the regional warehouse at the beginning of period t in the disaster scenario s
I^{u}_{sta}	Unbranded stock level of HO a that keeps stock in the regional warehouse at the beginning of period t in the disaster scenario s
$\overline{L}^{b}_{stac}$	Branded stock amount is replenished for HO a that keeps stock in the country warehouse located in the country c at the beginning of period t in the disaster scenario s
L^{b}_{sta}	Branded stock amount is replenished for HO a that keeps stock in the regional warehouse at the beginning of period t in the disaster scenario s
L^{u}_{sta}	Unbranded stock amount is replenished for HO a that keeps stock in the regional warehouse at the beginning of period t in the disaster scenario s
β_{sta}:	1 if HO a satisfies the demands of all countries that are in its service region, therefore it can share the extra unbranded items; 0 otherwise

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