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Integrating Supply Chains for Emergencies and Ongoing Operations in UNHCR

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Abstract

Humanitarian organizations (HOs) often base their warehouse locations on individuals' experience and knowledge rather than on decision-support tools. Many HOs run separate supply chains for emergency response and ongoing operations. Based on reviews of humanitarian network design literature combined with an in-depth case study of United Nations High Commissioner for Refugees (UNHCR), this paper presents a warehouse location model for joint prepositioning that incorporates political and security situation factors. Although accessibility, co-location, security, and human resources are crucial to the practice of humanitarian operations management, such contextual factors have not been included in existing network optimization models before. We found that when quantified, and modeled, such factors are important determinants of network configuration. In addition, our results suggest that joint prepositioning for emergency response and ongoing operations allows for expansion of the global warehouse network, and reducing cost and response time.

Keywords: network configuration, facility location, UNHCR, prepositioning.

1. Introduction

Improving network design to cut cost and reduce response time is critical for humanitarian logistics (Van Wassenhove, 2006; Van Wassenhove and Pedraza-Martinez, 2012). The trend among larger humanitarian organizations (HOs) such as International Federation of Red Cross and Red Crescent Societies (IFRC), United Nations High Commissioner for Refugees (UNHCR), World Food Program (WFP), Cooperative for Assistance and Relief Everywhere (CARE), and United Nations Children's Fund (UNICEF) is to preposition un-consigned relief items for emergency response in warehouses located close to disaster-prone areas (see e.g., Jahre and Heigh, 2008; Schulz, 2008; Charles, 2010; Gatignon et al., 2010; McCoy and Brandeu, 2011; Bemley et al., 2013; Komrska et al., 2013). However, stock prepositioning is expensive, and owing to funding restrictions, other alternatives have been suggested including vendor-managed inventory (Van Wassenhove and Pedraza-Martinez, 2012), framework agreements (Balcik and Ak, 2013), transfer mechanisms between programs (Bhattacharya et. al., 2014), and co-location between organizations (Acimovic and Goentzel, 2016).

Most HOs are engaged in both long- and short-term (emergency relief) operations, for which they usually operate different supply chains with separate warehouses. Recently, joint supply chains with vehicles serving both types of operations have been suggested as an alternative for saving cost (Besiou et al., 2014; Stauffer et al., 2015). In principle, one should be able to integrate the two to reduce response time and total operating cost. Long-term operations could, for instance, be serviced by using un-consigned stock to avoid long lead times from distant suppliers, while emergency relief could be serviced by using closely located stockpiles to avoid expensive express shipments over long distances. Integration of the two supply chains may allow for additional warehouses closer to demand points, but doing so would require designing and operating a joint network with different demand uncertainties, objectives, and operational procedures. In the current paper, we attempt to address those challenges. To the best of our knowledge, models that explicitly combine emergency relief and longer-term operations supply chains for prepositioning of goods have not been reported. Furthermore, factors related to political and security conditions, often mentioned in extant literature as being important for location decisions in the humanitarian context, lack empirical or quantitative justifications. The objective of this study is to develop a model that integrates factors such as hardship, security, pilferage, co-location, and accessibility in determining best joint prepositioning warehouse locations. Such a model can help quantify the impact of an expanded network on both lead time and cost. Using the developed model, we generate empirical and computational insights on the factors that significantly influence warehouse location choice.

To address the above objectives, we conducted an in-depth, exploratory case study with UNHCR, which is mandated to lead and coordinate international operations to safeguard the rights and well-being of refugees and resolve refugee problems worldwide. This case demonstrates relevant examples of the generic challenges faced by HOs in terms of reducing costs while maintaining response in a timely manner in both short- and long-term operations. As is typical for a HO, UNHCR runs two supply chains. First, in their emergency relief (ER) supply chain, speed is essential, and they have responded to this need by using fast means of transportation from large centralized global warehouses. Second, and in parallel, they support their long-term ongoing operations (OOs), for example, camp operation, with stocks transported from decentralized country warehouses or shipped directly from suppliers. Merging of the two supply chains presents an opportunity to reduce cost but also implies the need to redesign their network, particularly considering the locations of their global warehouses. One of the challenges associated with building a joint supply chain constitute the differing objectives, with ER aiming to reach the beneficiaries as fast as possible, and OOs aiming to satisfy all demand incurring minimum cost, while still being mindful of responsiveness. Hence, decisions have to consider both objectives and their trade-offs, requiring multi-objective models. In this study, we developed such a model, tested it with datasets based on the UNHCR case study, and presented an efficient frontier analysis for different budget levels. UNHCR is now working on implementing the model into their enterprise resource planning (ERP) system and as a part of their overall decision making process.

This paper answers the call for more applied, context-sensitive research in humanitarian operations (Holguín-Veras et al., 2012) with two main research contributions. First, we developed a framework and a data-driven model that integrate long-term and emergency relief supply chains, accounting for both response time and cost. Second, the study helps fill the gap in humanitarian network design literature by including security and political factors, which influence warehouse locations for prepositioned stock but have not been incorporated in decision models thus far. Through computations, we show their impact on transportation and warehousing decisions.

2. Literature review

Humanitarian research typically categorizes network design models depending on problem type, objective functions, number of levels included, and the manner in which uncertainties are treated (cf. Jia et al., 2007; Caunhye et al., 2012; Holguín-Veras et al., 2013; Ortuño et al., 2013; Rennemo et al., 2014; Özdamar and Ertem, 2015). In their overview of models, Caunhye et al. (2012) divided the literature into two main categories, namely, facility location and relief distribution. Our research falls under the former category, which can be subdivided into pure location models (e.g., Jia et al., 2007), inventory models (e.g., Campbell and Jones, 2011) and models, which, similar to our approach, combine the location problem with the amount of inventory to preposition at each location (e.g., McCoy and Brandeau, 2011).

The objective for models addressing public sector problems and humanitarian aid is often to maximize the amount of demand satisfied or to minimize lead time (e.g., Balcik and Beamon, 2008; Mete and Zabinsky, 2010; Salmerón and Apte, 2010; Duran et al., 2011; Bozorgi-Amiri et al., 2013; Barcinpour and Esmaeili, 2014; and Rennemo et al., 2014). Comprehensive reviews were presented in Caunhye et al. (2012), Holguín-Veras et al. (2013), Rennemo et al. (2014), and Özdamar and Ertem (2015) as well. To ensure maximum demand coverage, some researchers have associated a penalty cost with unmet demand and endeavored to minimize said cost (e.g., Psaraftis et al., 1986; Rawls and Turnquist, 2010). Another stream of research has focused on modeling responsiveness and has generated models that include a benefit for timely demand satisfaction in their objective function along with a penalty for unmet demand (cf. review in Holguín-Veras et al., 2013). In contrast, other studies have focused primarily on the cost aspect when solving the facility location problem (FLP) in the humanitarian aid context. For example, Iakovou et al. (1997) considered only facility and operating costs, while Barcinpour and Esmaeili (2014) and Bozorgi-Amiri et al. (2013) accounted for several cost considerations as a joint objective function. In this paper, we include both lead time and cost as objectives, along with other considerations such as security and political factors, while enforcing total demand satisfaction.

For considering multiple objectives, one common technique used is to associate weights with each objective (Doerner et al., 2009; Nolz et al., 2011) and solve the FLP as a cost minimization problem (e.g., Shen and Daskin, 2005). Because providing a single optimal solution when multiple objectives are involved remains difficult, different objective functions are often assigned weights to prioritize them, and solutions for different prioritization schemes are analyzed accordingly (Vitoriano et al. 2011). One example is Tzeng et al. (2007), wherein fuzzy logic was applied to find the optimal balance among cost, travel time, and proportion of demand met. Stauffer et al. (2015), in contrast, modeled responsiveness by including an expediting cost in the objective function. Another alternative to handle multi-objectives when the main consideration is to maximize responsiveness is including additional objectives such as cost as model constraints (e.g., Salmerón and Apte, 2010; Duran et al., 2011). We adopted this approach and modeled responsiveness by minimizing lead time as a measure of service and included a budget constraint. Our model was then used to determine (1+ε)-Pareto curves to analyze the trade-off between the cost and lead time objectives. Such methods are commonly used in multi-objective optimization (cf. Papadimitriou and Yannakakis, 2000).

Two studies are of particular interest to our research. Stauffer et al. (2015) looked at how organizations can manage short- and long-term programs together. They found that a centralized hub configuration combined with temporary hubs can reduce overall supply chain costs over a long time horizon when global vehicle supply chains for development and emergency operations are handled together. Similarly, Besiou et al. (2014) concluded that using the same vehicles for both development and emergencies affects performance ranking for service levels, suggesting that organizations "should include the operational mix in the decision-making factors when choosing the structure" (ibid, p.10). Accordingly, both aforementioned studies demonstrate the advantages of integrated network structures.

The literature on commercial FLPs (cf. Chopra and Meindl, 2010) lists several important factors from the network design viewpoint. We identified additional factors by reviewing humanitarian logistics literature and modeling papers (Appendix A). We focused on the extent to which extant research discusses, models, and quantifies factors based on real data. We found that similar to commercial models, most humanitarian models include infrastructure, demand, and cost, but there are some differences. In humanitarian research, greater weight is given to demand risk (cf. Liberatore et al., 2013; Rennemo et al., 2014). Funding issues are typically modeled as budgetary constraints (cf. Salmerón and Apte, 2010). Furthermore, political and security issues are accorded greater concern (cf. Martel et al., 2013). While various papers have discussed these factors, modeling has been limited to demand and logistics, except for one security aspect, namely, personnel availability (cf. Salmerón and Apte, 2010, Bozorgi-Amiri et al., 2013). Duran et al. (2011), for example, have provided the most extensive discussion of political and security factors, but rather than quantifying and including them in the model, they suggested ranking the locations *resulting* from the quantitative analysis, which requires decision makers to qualitatively judge each location based on how well it meets these additional factors. Accordingly, there is a big gap in prevailing research regarding (i) empirical analysis of the extent to which each factor actually impacts location decisions and (ii) quantification of any factor's potential impact using real data and its incorporation into the model. Our study contributes to filling this gap.

3. Methodology for qualitative empirical study

3.1 Case selection

An in-depth, exploratory case study was conducted with UNHCR following theory-building principles (Eisenhardt, 1989; McCutcheon and Meredith, 1993; Miles and Huberman, 1994; Yin, 2014). A single case allows one to gain more in-depth understanding of the studied phenomenon (cf. Voss et al., 2002; Yin, 2014). Accordingly, the UNHCR case provides an opportunity to acquire the rich, qualitative data required to develop a network design model useful for the humanitarian sector. The study was initiated in response to a 2012 request from UNHCR for help with developing a tool to support their warehouse location decisions. UNHCR's effort to reduce both cost and response time in long- and short-term operations is representative of the efforts of most large HOs. Many organizations including WFP and UNICEF operate in the same countries as UNHCR under comparable political and security conditions, and have similar organizational structures and human resources policies.

The case study included a field trip to UNHCR's Kenya operations (Bendz and Granlund, 2012). This operation represents a critical case (cf. Patton, 1987; Yin, 2014) considering that: i) it is among the top 20 UNHCR operations; ii) it has a global warehouse and multiple operations in different parts of the country; iii) it has a combination of local and international procurement and deliveries, and iv) in the context of external validity (Eisenhardt, 1989; McCutcheon and Meredith, 1993), UNHCR regards its Kenyan operations to be representative of other large-scale operations such those as in Syria, Pakistan, and Afghanistan.

3.2 Case description

With more than 8,600 staff and an annual budget of about USD4.3 billion, UNHCR helps approximately 34 million people each year in more than 125 countries (www.unhcr.org). The largest operations constitute assistance to refugees and internally displaced people in Asia (e.g., Afghanistan), the Middle East (e.g., the Syrian crisis), and Africa (e.g., Kenya, Democratic Republic of the Congo, and South Sudan). As a sector leader in emergency shelter and camp management, a large portion of UNHCR's work is in the form of emergency response. Moreover, UNHCR operates camps on a longer-term basis. One example is the 20-year-old refugee camp in Dadaab, Kenya (www.unhcr.org).

To support these operations, the organization depends on a three-level network structure, represented by: i) global warehouses; ii) country warehouses; and iii) supplier ship-out locations. UNHCR operates seven global warehouses, which stock core relief items (CRI) and specialized items such as information technology (IT) equipment and vehicles. The CRIs include tents, tarpaulins, mosquito nets, blankets, sleeping mats, plastic buckets, jerry cans, kitchen sets, and solar lanterns. Global stock is un-consigned, meaning that the items are not dedicated to a certain country's operations, but stored in bonded facilities or imported under duty-exempt status. In contrast, country warehouses hold consigned, customs-cleared stock as a buffer for multiple distribution points within national borders. UNHCR uses its country warehouses as merging points, combining internationally delivered items and locally purchased goods before sending them to the relevant distribution points. The organization reduced the number of country warehouses from 350 in 2013 to 192 in 2014. UNHCR procures its CRIs from a large number of suppliers. Based on 2013 statistics, the top countries for procurement of stored items include Belgium, China, Denmark, India, Jordan, Kenya, Kuwait, Lebanon, Pakistan, Turkey, Syria, and the United Arab Emirates. At present, only a small fraction of the stored items is sent directly from the suppliers to the distribution points, and one of this study's contributions is to help UNHCR determine whether more direct methods of shipment from the suppliers to the distribution points would be beneficial.

3.3 Data collection

By combining a range of qualitative and quantitative methods, and by using several data sources and investigators, we aimed to triangulate the collected information (Patton, 1987; 1999) and increase internal validity (Eisenhardt, 1989; McCutcheon and Meredith, 1993; Miles and Huberman, 1994). Data was collected in seven steps (Table 1).

Table 1
Overview of data collection.

Step	Date	Method (#/length)	Purpose	Interviewees/source	Location
1	May-Sept, 2012	Three exploratory interviews (1 hour each)	Planning and designing study, including field trip	Senior Business Analyst, Head of Logistics & Operations; Head of Supply Management Service	HQ in Budapest
2	Oct 14-16, 2012	Two semi-structured interviews (1 hour each); One group discussion (half day)	Understanding how UNHCR has set up its network of warehouses and manages operations; Collecting qualitative data for designing the model	Supply Officer, Assistant Supply Officer	Two of the four distribution points in Dadaab, Kenya
	Oct 17-19, 2012	Three semi-structured interviews (1 hour each); One group discussion (half day)		Senior Supply Officer, Assistant Supply Officer, Assistant Program Representative, Warehouse manager (Kuehne + Nagel),	One global warehouse and one country warehouse located in Nairobi, Kenya
3	Nov 18, 2012	Questionnaire (building on the list of factors in Appendix A)	Identifying contextual factors important to consider for the model	Senior Business Analyst, Head of Logistics & Operations, Senior Supply Officer	HQ in Budapest
4	Oct-Nov, 2012	ERP system data	Gathering data, including information about core relief items,	UNHCR's global ERP system, Information Management Officer	

			warehouse points, demand points, goods flow, and transportation costs		
5	Sept-Oct, 2014	Multiple structured interviews (on a weekly/daily basis)	Designing and validating the network design model for use in a humanitarian context	Senior Business Analyst, Head of Logistics & Operations, Head of Supply Logistics Management Service, Head of Inventory & Warehouse Management Unit, Chief of Emergency Coordination Unit	HQ in Budapest (via Skype and mail)
6	Nov-Dec, 2014	ERP system data, internet search on security levels, personnel, pilferage, disaster scenarios	Gathering and populating OO and ER demand, cost, and lead time data followed by cleaning, estimation, and discussion—for details, see section 4.4 and Appendix B.		
7	Jan-June, 2015	ERP system data, internet search for relevant data	Quantifying identified contextual factors and incorporating them in the developed model (cf. Section 4.4)	UNHCR's global ERP system, UNHCR supply chain management team, Brambles, ongoing consultancy project at UNHCR	HQ in Budapest (via Skype and mail)

Throughout data collection, the case study protocol was updated, including research instruments and procedures, interviewee details, interview transcriptions, field notes, case summaries, and preliminary findings (Yin, 2014). All collected data were summarized and sent back to the respondents, who then commented and confirmed the findings.

3.4 Data analysis

For data analysis, we followed the analytical abstraction process of Miles and Huberman (1994) by summarizing and categorizing data collected through interviews, group discussions, and questionnaires. First, the data were coded using a provisional list based on the factors identified in the literature review (Appendix A). Examples included budget constraints, demand risks, and infrastructure limitations. Moreover, by using open coding (cf. Ellram, 1996), additional coding categories such as hardship, security, pilferage, and co-location emerged during the analysis. The resulting coding list facilitated a logical link between the collected data and the constructed model, where each of the identified factors was, as explained in section 4.3, included in model development. In the second step, referred to herein as pattern or axial coding (Miles and Huberman, 1994; Ellram, 1996), memos from all interviews and group discussions were compared with recurring phrases and threads in the questionnaire responses to identify emerging trends and themes. One such theme was the respondents' emphasis on the difficulty of merging the two supply chains for ongoing operations and emergency response, and the different objectives of minimizing cost and minimizing response times. Additional insights from this step are discussed in section 4.1 and form an important input in model development. In the final step, all findings were discussed and confirmed with key UNHCR staff to validate the inputs used for model design and analysis.

4. Model development based on empirical findings

This section presents the empirical findings of importance for constructing the model, starting with the background to UNHCR's supply-chain strategy[1] and why they want to merge the two supply chains. Then, we present the influencing factors identified in the qualitative study (4.2), the model and how it incorporates the factors (4.3), and the data used for analysis (4.4).

4.1 Merging two supply chains

Based on an analysis of past emergency response patterns, UNHCR senior executives have, with support from major UNHCR donors, decided to install an immediate response capacity of CRIs for 600,000 beneficiaries. To enable emergency response within 72 hours, UNHCR has set up a network of global warehouses for prepositioning with fast means of transportation. However, similar to many HOs, they must consider not only time but also cost. As a critical step to lowering their total operational costs, UNHCR will merge their two supply chains.

[1]UNHCR uses the term *supply-chain strategy* to represent its setup of warehouse network, inventory control, and transportation-flow planning.

The ER-supply chain deals with highly uncertain demand occurring in sudden-onset, man-made disasters, and it is designed to minimize response time where central funds are used to buy and preposition un-consigned stock in one of the global warehouses. UNHCR reaches out centrally to a few of its big donors such as The Department for International Development in the UK (DFID) to pre-fund the central emergency stock, which can then be used to support global operations. In the case of an emergency, global stock can be "bought" by country operations and delivered by fast means of transportation as consigned stock for local consumption.

The OO supply chain deals with long-term operations characterized by continuous demand and relatively low uncertainty. It is designed to minimize cost and involves decentralized consigned stock bought under a country's budget and pushed to that country's warehouses or items shipped directly from suppliers. Once stock is shipped and clears customs in a country, it is difficult and expensive to re-export the goods to another country. The decentralized network structure of OO originates from the historical set-up of the organization, with a weaker supply chain center at its headquarters (HQ) and strong UNHCR country operations. Country operations are managed by a UNHCR Representative, appointed by the High Commissioner, based on an agreement with the host country. As such, the host country can influence these operations, but decisions pertaining to operational priorities and fund utilization reside with UNHCR. Country operations are in charge of their own budgets, in addition to reaching out to local donors. Similar to other large HOs such as WFP, local program managers decide how and when to spend their money depending on when it is made available from donors to country operations by a HQ-approved budget and spending authority. In other words, sourcing is driven by funding with limited supply chain focus, which has resulted in sub-optimization with excessively large stock in a few locations and very low stock in others. Considering that UNHCR, akin to many organizations in the public sector, operates on annual budgets, inventory has generally been regarded as a safety measure not "to lose money at year end," following the mentality that "it is always good to have stocks, we might have use for it and we do not lose the money," resulting in a high amount of dead stock.

4.2 Influencing factors identified in qualitative study

The empirical findings unearthed nine factors that can be categorized in three groups: i) demand characteristics; ii) logistics; and iii) political and security situational factors (Fig.1).

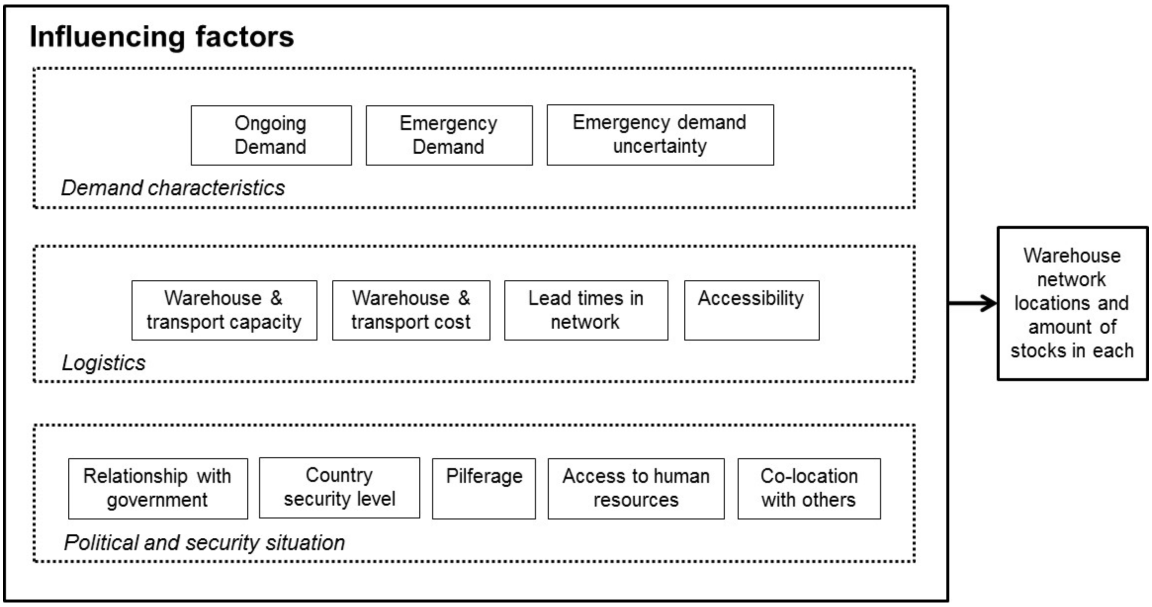

Fig.1: Framework for network design and factors to include in model development.

4.2.1 Demand characteristics

The first group of factors represents demand characteristics, and it is related to demand risk and budget constraints (cf. Appendix A). OO demand is in general continuous with low uncertainty, and it can be estimated from historic data. ER demand is encountered in sudden-onset disasters and is highly uncertain. ER demand is difficult to predict and requires scenario planning by considering the probabilities of different scenarios.

4.2.2 Logistics

Logistics-related factors (cf. Appendix A) identified in this study include capacity and cost of transportation and warehousing, lead times among suppliers, warehouses, and demand points, as well as accessibility. Transportation and warehousing capacities are typically not an issue, although the price of contracting additional transportation or warehouse space may vary. In transshipment points such as ports, humanitarian cargo may have to "compete" with fluctuating commercial transport flows. Furthermore, considering that UNHCR, similar to many other HOs, does not have its own fleet for transporting relief supplies, prices typically increases in the event of a disaster (cf. Rawls and Turnquist, 2010; Bozorgi-Amiri et al., 2013), and they may vary depending on the location and the disaster situation. Moving global warehouses closer to demand points could increase the cost of restocking said warehouses, depending on the means of transportation required and available for accessibility due to poor infrastructure. By placing the global warehouses closer to the demand points, the shipping cost, as well as lead time for this leg should be reduced. Physical accessibility aspects include available primary and secondary roads; sea freight and railway networks; and proximity to points of entry, including ports and airports. Without proper accessibility, the total operations cost of a warehouse site may increase, which brings with it the risk of jeopardizing the entire operation. Telecommunications infrastructure must also be in place to enable efficient communication and coordination within the organization and externally with the supply chain and implementing partners.

4.2.3 Political and security situation

Building on the literature review (cf. Appendix A), the following factors related to political and security situation, were identified in the current study: relationship with government, security, pilferage, access to human resources (hardship), and co-location. First, HOs depend on good relationships with host governments. By signing bilateral agreements, governments can facilitate exemptions and customs-clearance procedures when goods enter or leave the country. In some cases, goods can be cleared within a day, and in other cases, the process may take weeks or months. Moreover, governments may agree to offer land or facilities at low or no cost to the organization, thus greatly reducing certain locations' fixed costs. Second, due to its mandate, many of UNHCR's operations are set up in the midst of political instability, including military activity and civil war. Under such circumstances, running efficient, secure logistics operations can be very difficult and may require significant security arrangements. Security concerns also include pilfering and looting. Apart from the value of the goods stolen, the very risk of theft implies increased security costs in terms of insurance and guards. Lost goods could also result in ill will for the organization due to negative media publicity, damage to donors' image, and impeding future funding. Third, similar to most HOs, UNHCR employs both international and local staff. The ability to attract qualified workforce is a critical factor in deciding where to locate global warehouses. An important aspect is the rotation system for international personnel, which is based on hardship principles, implying that international staff spends only a limited time at a certain location. Hardship is often the toughest where need is the greatest, and rotation is extremely high. Following UN conditions of service, international employees at duty stations in high-risk areas also go on a five-day leave every four weeks. These contractual conditions mean that a greater number of personnel is required to run the operation. Fourth, in spite of competition among HOs for media attention and donor money, they tend to cooperate at the operational level. Co-location with other organizations in humanitarian clusters or hubs can provide benefits through complementary resources, such as shared technological resources and access to joint IT support, help with coordinating logistics and security resources, reduced operational costs, and facilitation of knowledge sharing. Copenhagen is one such example, which hosts both UNHCR and most other UN organizations, as part of the UN city established in 2013.

4.3 Model

In this section, we describe a two-stage mathematical programming model for solving a FLP. To deal with uncertainty of ER demand, we developed a scenario-based two-stage stochastic program with the aim of making robust first-stage decisions so that the second stage is feasible under all scenarios. According to Liberatore et al. (2013), such a robust programming approach is a common methodology for dealing with uncertainty when uncertain input distributions cannot be estimated reliably.

4.3.1 Problem definition

UNHCR deals with two sets of supply points: global warehouses and supplier locations. There are also two types of demand points: i) OO, where demand is stable; and ii) ER, for which locations and magnitudes are uncertain when decisions are being made. OO demand can be met through supplier locations or inventory stocked at the global warehouses, whereas ER points are supplied only by the global warehouses. We treat the historic annual ER demand volumes as scenarios with equal probability of occurring (See section 4.4. for details). Inventory at the global warehouses and in transportation is measured in twenty-foot equivalent units (TEU), a commonly used reference of volume in containerized shipping. We then convert the quantity of goods from TEU to the corresponding USD value based on estimates provided by UNHCR. Opening of each warehouse incurs a fixed cost and the inventory held at a location incurs a cost per unit stored in that warehouse.

Shipping rates and lead times differ between transportation modes. Normal shipment uses surface transportation (by road or sea) to satisfy OO demand and is generally cheaper, but the lead time is longer. UNHCR regards road and sea transport as alternatives or complementary modes with minimal cost variance and does not distinguish between them in the operational context. Express shipment employs air or road transportation (if over a short distance) to satisfy ER demand, and it is associated with higher transport costs and shorter lead times. Owing to the higher costs, express shipment via air to any particular demand point is constrained by the availability of funding and cannot exceed 10 TEUs per disaster event. Additional TEUs are sent via surface.

The goal of the proposed multi-objective model is to satisfy all ongoing and emergency demand in the fastest manner while incurring the minimal cost. To handle the dual objectives of lead time and cost, we developed three related two-stage mixed integer mathematical programs. The first program solves the FLP to minimize the expected total cost, while disregarding lead time. The analysis in the second model is based on minimizing the expected lead time of the chosen supply chain network, while disregarding cost, and in the third, the same lead time objective is used, while constraining the supply chain budget based on the optimal minimum cost value obtained from the first program plus varying mark ups. In the rest of this section we briefly describe these three models. All technical details of the models and summary of the notation used are included in Appendix B. Computational results based on UNHCR data are discussed in Section 4.4. An IBM ILOG CPLEX machine with 8 GB of RAM was used for solving each of the three mathematical models with maximum of 19,288 binary, integer, and continuous variables and 10,968 constraints. All model instances were solved within seconds.

4.3.2 *Minimum Expected Total Cost Model*

The first two-stage mixed-integer programming formulation, TC*, simultaneously determines open/close and inventory level decisions for global warehouses, along with transport and allocation decisions to satisfy demand (Fig.B2). Formulations of our models described in Appendix B, comprise three sets of variables. First, for every candidate warehouse location, we define a binary variable showing whether a global warehouse is opened. Next, nonnegative integer flows from supplier locations to global warehouses determine inventory levels at the opened warehouses. Last, we define nonnegative continuous variables going from suppliers and warehouses to demand points. These variables represent the required percentage of OO or ER demand sent from each supply location to demand points. We assume no capacity restrictions at the suppliers, warehouses, or transport arcs. The objective function in TC* minimizes the total cost associated with opening warehouses, holding necessary inventory at opened warehouses, shipping cost from suppliers to global warehouses, expected shipping cost from suppliers and global warehouses to OO points, and expected shipping cost from global warehouses to ER points. This objective is subject to several constraints: i) All OO and ER demand must be satisfied; ii) If ER demand is greater than 10 TEUs, 10 TEUs of the total demand must be sent by express air shipment and the rest by express road shipment; iii) If ER demand is less than 10 TEUs, the entire demand is sent by air. We let the model adjust OO demand allocation based on the realized ER demand under each scenario, thus hedging the risk of overstocking at the warehouses due to highly variable ER demand.

4.3.3 *Minimum Expected Lead Time Model*

The formulation LT* minimizes only the total lead time associated with all used arcs from a supply point to an OO or ER demand point (Fig.B3). Specifically, the objective function minimizes the expected lead time of shipping from suppliers to OO demand points, from global warehouses to OO demand points, and from global warehouses to ER points. We do not consider the lead times of shipments from supplier locations to global warehouses because we assume that replenishment of global warehouses is an ongoing process that does not impact supply chain responsiveness. This assumption is based on the fact that UNHCR (i) keeps a buffer stock for 600,000 beneficiaries in its global warehouses and (ii) conducts forward planning and pre-emptive timeslot-based order placement, whereby country operations do not experience any increase in lead time for deliveries from global warehouses. Analysis of the inventory ordering policies of the global warehouses are beyond the scope of this paper because we only focus on high-level planning decisions and, therefore, consider only the total annual inventory levels at the global warehouses.

4.3.4 *Budget Constrained Minimum Expected Lead Time Model*

We handle the dual objectives of lead time and cost by building a third model that minimizes the same lead time objective function as in LT* with an additional budget constraint (Fig.B4). The budget constraint requires the objective function of the minimum total cost model, TC*, to be less than or equal to the optimal value of the TC* plus a percentage, β. In our computational experiments for analyzing the trade-off between cost and lead time, we varied β such that the right-hand side of the budget constraint (Fig.B4) ranged from the optimal objective value of TC* (minimum possible cost) to the cost incurred in the optimal LT* solution. Thus, we approximated the Pareto frontier with a set of efficient solutions such that no other solution with better cost as well as better lead time exists.

4.4 Case for model testing

In this section, we present the case on which the model was tested; it is based on real data collected from or estimated in agreement with UNHCR (Appendix C). The main aspect of the analysis is to compare UNHCR’s existing warehouse network constituting 7 global warehouses with a redesigned network containing four new locations (Fig.2). The alternative locations were agreed upon in discussion with UNHCR: Subang (Malaysia) means possible co-location with UNHRD (www.unhrd.org), Algeciras (Spain) is good for transshipment (UNHRD may decide to relocate their warehouse from Las Palmas for the same reason), while Karachi (Pakistan) and Djibouti (Djibouti) both are big distribution points for OO. UNHCR has practically no operations in the Americas, and there are no plans for a global warehouse in this region.

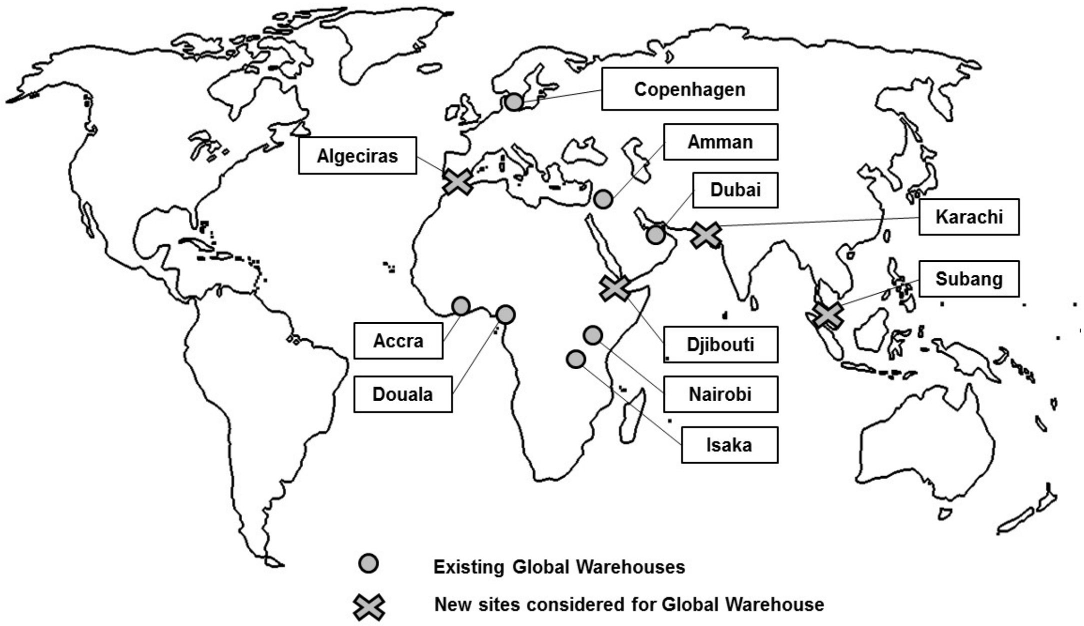

Fig.2: Warehouses in UNHCR's network (June 2015).

The resulting model includes the 11 candidate warehouse locations, 56 demand points for OO, 76 demand points for ER, and 14 supplier points. OO demand was calculated as a three-month average (in USD) per distribution point (one per country) based on historic data from the years 2011–2013. We used this data to create three emergency demand scenarios represented as three-month averages per distribution point (Fig.3), yielding representative variability and trends. Each year constitutes one scenario with an occurrence probability of 0.3333.

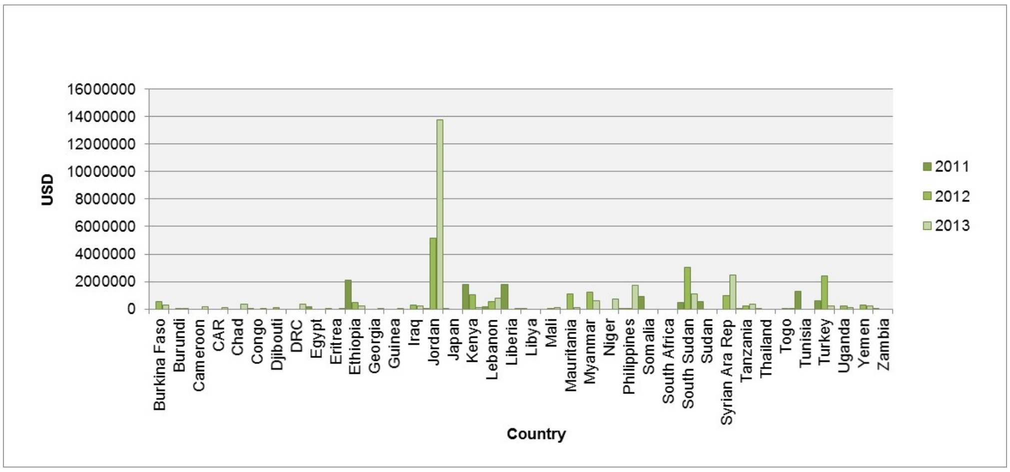

Fig.3: Variability in ER demand over 2011–2013 (three-month average) per country.

Data on transportation and warehousing were collected and used to calculate/estimate costs, capacities, and lead times (Appendix C). In agreement with UNHCR, it was decided to quantify four main influencing factors by estimating location-specific percentages and adding/subtracting from variable or fixed costs (Table 2). We see that the factors have different weights for the same location, which implies that it is important to incorporate more than one factor. In particular, hardship impacted a greater number of locations than security, and locations with high security cost such as Karachi had relatively lower accessibility cost than other locations, for example, Douala and Isaka.

Table 2
Location-specific percentages for adding to/subtracting from baseline logistics cost.

Location	% added for hardship	% added for security including pilferage	% deducted for co-location	% added for lack of accessibility
Accra (Ghana)	0 %	0 %	50 %	15.55 %
Algeciras (Spain)	0 %	0 %	0 %	0.86 %
Amman (Jordan)	0 %	0 %	0 %	12.23 %
Copenhagen (Denmark)	0 %	0 %	50 %	0.00 %
Djibouti (Djibouti)	10 %	0 %	0 %	16.00 %
Dubai (UAE)	0 %	0 %	50 %	3.28 %
Douala (Cameroon)	0 %	0 %	0 %	20.00 %
Isaka (Tanzania)	31 %	0 %	0 %	19.55 %
Karachi (Pakistan)	27 %	15 %	0 %	12.88 %
Nairobi (Kenya)	6 %	0 %	0 %	13.06 %
Subang (Malaysia)	0 %	0 %	50 %	2.59 %

The first, differentiated access to human resources, was quantified using UN's hardship classification (policy duty stations are classified from A to E, with the latter being the hardest) and payment schemes (ICSC, 2013) to calculate the additional percentage of staff's share of fixed cost and variable cost. The qualitative study suggested pilferage as an important factor, and we undertook an analysis of UNHCR insurance claim history over 2011–2014 to establish potential patterns varying with location. No such pattern was identified, and in agreement with UNHCR, we included pilferage in the differentiated security cost to account for the extra security measures taken to avoid loss (e.g. fences and guards). Security cost was quantified using the UN Security Management System Security Policy Manual with levels ranging from 1 to 6, with 6 representing the most dangerous environment (United Nations Department of Safety and Security, 2011) together with the most updated security rankings (https://trip.dss.un.org) for the locations analyzed, assuming in agreement with UNHCR, a non-linear relationship with no extra cost for levels up to 3, 15% for level 4, 45% for level 5, and a "no-go" notification for level 6 (i.e., no global warehouse in such locations). For accessibility, we used country scores from the Logistics Performance Index (http://lpi.worldbank.org/) to establish the percentages of additional variable warehousing cost. Finally, in agreement with UNHCR, co-location was accounted for by assuming 50/50 split of fixed warehousing cost with the other organization.

5. Computational results

This section presents the three key insights derived from the computational results relating to the objectives presented in section 1: i) Quantification of the impact of an expanded network on lead time and cost; ii) advantage of joint prepositioning; and iii) impact of the factors on warehouse locations, that is, network configuration.

Key insight 1: Network expansion reduces costs and shortens lead times

Fig. 4 shows the trajectories and efficient frontiers of the two different network configurations when β is varied from 0 to 0.2. The rightmost curve represents the existing network with seven candidate warehouses, and the leftmost curve represents the expanded network with an additional four warehouses. Each point on the frontiers shows the optimal lead time for the third model associated with a different β under the budget constraint that allows a cost of (1+β) times the optimal value obtained using the TC* model. That is, the minimum lead time is given on the *y* axis when spending is constrained by cost, which is represented on the *x* axis. We have highlighted one point (β = 0.015) which we will use when discussing further key insights because it represents a good trade-off between cost and lead time.

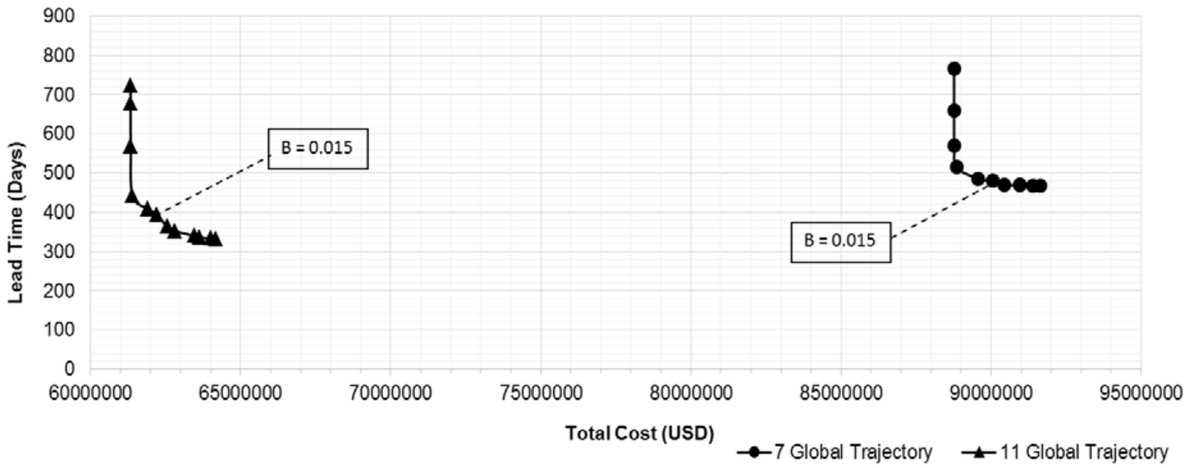

Fig.4: The total cost and associated lead time when β varies between 0 and 0.2 for networks with 7 and 11 global warehouses. β values were incremented by 0.0005 for each computation.

The results indicate that when optimizing cost and lead time, expanding the existing network by adding the four candidate locations enables a 31% cost reduction and an 18% lead time reduction when β = 0.015. When optimizing LT*, the expanded network leads to a 28% reduction in lead time. As expected, there is a trade-off between lead time and cost for both the existing and the expanded networks. It is interesting to note, however, that the increase in cost is relatively small compared to the savings in lead time. Relaxing the budget constraint by just a few percent and allowing for an expanded network of global warehouses makes it possible to achieve substantial savings in terms of lead time. In other words, based on the computational results, we see that UNHCR, as well as other HOs using prepositioning, should consider establishing additional global warehouses closer to points with high demand.

The computational experiments indicate that UNHCR should consider closing a few of the warehouses in the existing network and open new ones (Table 3). For example, when optimizing TC* ($\beta = 0$) for the expanded network, Dubai and Douala were replaced by Algeciras, Subang, and Djibouti. Copenhagen helped improving the lead time, but it increased costs; therefore, it was not viable without a further increase in budget (at $\beta = 0.035$).

Table 3
Network configurations under different budget constraints (1 = location is opened; 0 = location is closed). Table below only includes computational results from β values corresponding to different solutions as β is increased.

Location included in modeling	β = 0	β = 0.01	β = 0.015	β = 0.025	β = 0.035	β = 0.045
Accra (Ghana)	1	1	1	1	1	1
Algeciras (Spain)	1	1	1	1	1	1
Amman (Jordan)	1	1	1	1	1	1
Copenhagen (Denmark)	0	0	0	0	1	1
Djibouti (Djibouti)	1	1	1	1	1	1
Douala (Cameroon)	0	0	1	1	1	1
Dubai (UAE)	0	0	1	0	0	0
Isaka (Tanzania)	0	0	1	1	1	1
Karachi (Pakistan)	0	0	0	1	1	1
Nairobi (Kenya)	1	1	0	0	0	1
Subang (Malaysia)	1	1	1	1	1	1
Total open warehouses	6	6	8	8	9	10

A few of the open/close decisions change more than once as the budget increases. It is beneficial to open Dubai when β is large enough ($\beta = 0.015$). However, when the budget increases further and is sufficient to support Karachi, Dubai is no longer needed because Karachi is better from the lead time perspective. Having both Karachi and Dubai open at the same time is not feasible budget-wise. The above results also indicate that network configuration is sensitive to the available budget.

Key insight 2: Joint prepositioning for ER and OO demand reduces lead times and total costs

The second key insight from the model relates to the benefits of joint prepositioning for satisfying OO and ER demand. By joining the OO and ER supply chains, prepositioned stock can be used for both long- and short-term operations. To exemplify, we show what happens at β = 0.015 in Table 4, where the second column indicates whether a warehouse location is opened or closed. The third column indicates the number of TEUs shipped from each location to satisfy the total OO and ER demands, while the fourth and fifth columns show the amounts of OO and ER in USD handled through each warehouse, that is, the sum of the demands in USD provisioned from each warehouse to all ER/OO demand points in all scenarios.

Table 4
Distribution of OO and ER volumes satisfied per warehouse location at β=0.015.

Location included in modeling	Open/ Close	Total TEUs handled	Amount of OO provisioned (in USD)	Amount of ER provisioned (in USD)
Accra (Ghana)	1	51	1,237,624	3,527,735
Amman (Jordan)	1	327	29,221,081	9,020,899
Algeciras (Spain)	1	45	1,735,152	2,604,836
Copenhagen (Denmark)	0	0	-	-
Djibouti (Djibouti)	1	157	8,010,622	9,611,756
Douala (Cameroon)	1	25	1,250,275	638,785
Dubai (UAE)	1	34	3,331,454	-
Isaka (Tanzania)	1	70	3,524,451	4,461,194
Karachi (Pakistan)	0	0	-	-
Nairobi (Kenya)	0	0	-	-
Subang (Malaysia)	1	380	701,465	22,627,181

We see that eight of the warehouses satisfy OO demand and seven satisfy both OO and ER demands. In our computations, although the source of satisfying OO demand can be different, for β = 0.015, the OO demand points are served from the same global warehouses across scenarios. In comparison, the global warehouses fulfilling ER demand vary significantly with scenarios, primarily because ER demand is very volatile across the employed scenarios (cf. Fig.3). For example, there was almost no ER demand in Jordan in 2011, whereas in 2012 and 2013, the average three-month ER demand corresponded to USD5.17 million and USD13.77 m, respectively. From the computational evidence, we conclude that by introducing stable OO demand in the network, we can justify opening additional warehouses, which, in turn, leads to shorter lead times and lower total cost for both OO and ER (Fig. 4).

Key insight 3: Contextual factors matter

The third insight relates to the importance of contextual factors, in particular, political and security factors. Table 5 summarizes the computational results for β = 0.015, where each column represents a separate run of the model. The second column considers all four factors. Thereafter, we exclude only hardship, then only security, then only co-location, then only accessibility, and finally, we consider no factor (i.e., we set the factors to 0% benefit or extra cost).

Table 5
Effect of changing factors incorporated in costs at β = 0.015 (1 = opened location; 0 = closed location)

Location included in modeling	**All factors**	**Excl. Hardship**	**Excl. Security**	**Excl. Co-location**	**Excl. Accessibility**	**Excl. All factors**
Accra (Ghana)	1	1	1	1	1	1
Algeciras (Spain)	1	1	1	1	1	1
Amman (Jordan)	1	1	1	1	1	1
Copenhagen (Denmark)	0	0	0	0	0	0
Djibouti (Djibouti)	1	1	1	1	1	1
Douala (Cameroon)	1	0	0	1	1	0
Dubai (UAE)	1	0	0	0	1	0
Isaka (Tanzania)	1	1	0	0	0	1
Karachi (Pakistan)	0	1	1	0	0	0
Nairobi (Kenya)	0	0	1	1	1	0
Subang (Malaysia)	1	1	1	1	1	1
Total open	8	7	7	7	8	6

The results show that all factors influence network configuration. For example, Karachi is opened, while Douala and Dubai are closed in case either hardship or security is not accounted for. Furthermore, not accounting for the co-location factor leads to opening of Nairobi and closure of both Isaka and Dubai. Notably, Accra and Subang are kept open in spite of a 100% increase in fixed warehousing cost (because of the absence of co-location benefits), implying that they represent key locations in the network to lower costs and lead times. The exclusion of accessibility seems to have less of an effect on location selection. Finally, the exclusion of all factors implies that both Dubai and Douala are closed in contrast to the case when all factors are accounted for. It should be noted that the effect on lead time varies depending on which factor is excluded from the model. Particularly, the results show that lead time is reduced by 7.7% when the extra cost of hardship is not considered. By excluding hardship, the total cost decreases and the extra budget available can be used to open Karachi, Pakistan, which is closer to several demand points, thus helping reduce lead time. In contrast, excluding co-location increases the total cost as well as the lead time (4.7%).

To check whether the choice of β changes the impacts of the factors on network configuration, that is, to test whether our computational results related to factor analysis are robust under different budget levels, we ran the same computations with different β values. We found that all factors impact warehouse decisions at all budget levels, with the exception of settings with very low β values. This is because if the budget is very low, only a very few feasible solutions exist to begin with; for example, with β=0.001, no network that can satisfy all demand if co-location is excluded. Further, the way these factors impact network configuration might change with higher β values because higher budgets increase financial flexibility and make the decision to open/close a location less dependent on the inclusion/exclusion of extra costs, for example, those related to hardship.

6. Conclusions, implications, and future research

We introduced an optimization model for quantifying the impact of an expanded network and determining the best locations for joint prepositioning of relief items to serve both short- and long-term operations. The model was developed based on empirical evidence, and it offered data-driven insights on factors that significantly impact location choice in the humanitarian context. The results suggest that joint prepositioning allows the organization to open a greater number of global warehouses, while reducing costs and response times. Moreover, we found that factors related to security, accessibility, co-location, and human resources, when quantified and modeled, change the network configuration.

This study contributed to research on the topic at hand in two ways. First, we developed a framework and a data-driven model that integrate the long-term and the emergency relief supply chains, accounting for both response time and cost. Second, our study helps fill the gap in humanitarian network design literature by including factors that influence warehouse locations for prepositioned stock in the decision models. While our analysis is based on data from a single case study, the framework and model, as well as the process through which the factors are quantified, can be generalized and used by other HOs aiming to reduce costs, while maintaining speedy response in both short- and long-term operations. Many of these organizations such as WFP and UNICEF have similar organizational structures and HR policies, and they operate in the same countries under comparable political and security conditions as UNHCR.

The main practical contribution of this study is to provide UNHCR and other organizations with decision support in network redesign, accounting for two matters of (increasing) practical importance: improving performance through joint prepositioning and quantification of factors that should be accounted for when deciding warehouse locations. Joint prepositioning of stock can, in addition to reducing cost and lead time, enable reduction of country warehouses and inventory of consigned stock. A greater amount of un-consigned stock improves flexibility because it can be redirected toward ongoing operations in the region and/or emergencies, rather than awaiting an emergency that might not occur. Another practical implication is that stock in strategic locations can significantly cut lead times in ongoing operations. This is because budget often is made available at a late stage, with little time left to fulfill demand. Meanwhile, lead times from suppliers can be several weeks, whereas a nearby global warehouse would cut this down to a few days. The perceived response times for operations could thus be reduced by pre-ordering based on historical demand. Thereby, country operations may benefit from "guaranteed" availability within a short time frame, which reduces the perceived need for large local stocks and reduces the negative effects of delays in funding. Combining the two flows may also allow for economy of scale and better utilization of production capacity at suppliers' sites through improved planning and advance placement of non-rush orders. Finally, by allowing more time for planning and locating global warehouses closer to emergency demand points, we can increase the use of cheaper transport and reduce the use of expensive air transport.

Our model can be enhanced in several ways. One important aspect is further validation of input data such as costs of human resources, normal versus express shipment, and setting up and operating global warehouses, as well as further testing and validation of the quantification of factors. Moreover, it would be valuable to extend the model to include country warehouses, thus allowing for an analysis of the benefits of reducing consigned stock at this level and instead increasing the amount of un-consigned stock in global warehouses. Further, the model could be tested by using data from other HOs such as WFP, UNICEF, and IFRC. It could also be extended for supporting operational decision making in addition to strategic planning, which it currently supports. Finally, it is critical to consider scenario planning and development for predicting future ER demand. Scenarios could be developed for example by combining statistics provided by the Internal Displacement Monitoring Centre (IDMC) with contingency plans for specific countries and vulnerability indexes.

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Appendix A: Overview of influencing factors identified in humanitarian network design literature.

Group	Factor	Discussed	Modeled
Demand characteristics	Budget constraints	Salmerón and Apte, 2010; Mete and Zabinsky, 2010; Duran *et al.*, 2011; Martel *et al.*, 2013; Rennemo *et al.*, 2014	Salmerón and Apte, 2010; Mete and Zabinsky, 2010; Duran *et al.*, 2011; Martel *et al.*, 2013; Rennemo *et al.*, 2014
	Demand risk	Jia *et al.*, 2007; Salmerón and Apte, 2010; Mete and Zabinsky, 2010; Rawls and Turnquist, 2010; Duran *et al.*, 2011; Görmez *et al.*, 2011; Bozorgi-Amiri *et al.*, 2013; Martel *et al.*, 2013; Rennemo *et al.*, 2014	Jia *et al.*, 2007; Salmerón and Apte, 2010; Mete and Zabinsky, 2010; Rawls and Turnquist, 2010; Duran *et al.*, 2011; Bozorgi-Amiri *et al.*, 2013; Martel *et al.*, 2013; Rennemo *et al.*, 2014
Logistics	Fleet size	Salmerón and Apte, 2010; Bozorgi-Amiri *et al.*,2013; Rennemo *et al.*, 2014	Salmerón and Apte, 2010; Rennemo *et al.*, 2014
	Limitation in and/or possible damage to infrastructure including warehouses	Jia *et al.*, 2007; Salmerón and Apte, 2010; Mete and Zabinsky, 2010; Rawls and Turnquist, 2010; Duran *et al.*, 2011; Görmez *et al.*, 2011; Bozorgi-Amiri *et al.*, 2013; Galinda and Batta, 2013; Liberatore *et al.*, 2013; Martel *et al.*, 2013; Rennemo *et al.*, 2014	Jia *et al.*,2007; Rawls and Turnquist, 2010; Salmerón and Apte, 2010; Galinda and Batta, 2013; Rennemo *et al.*,2014
	Supplier proximity	Duran *et al.*, 2011; Görmez *et al.*, 2011; Martel *et al.*, 2013;	-
Political and security situation	Personnel availability	Salmerón and Apte, 2010; Bozorgi-Amiri *et al.*,2013; Rennemo *et al.*, 2014	Salmerón and Apte, 2010
	Exchange rates, tariffs, tax incentives, customs clearing	Duran *et al.*, 2011	-
	Level of unrest	Duran *et al.*, 2011	-
	Long-term agreements with governments	Martel *et al.*, 2013	-
	Price increases in the event of a disaster	Rawls and Turnquist, 2010; Bozorgi-Amiri *et al.*, 2013; Galinda and Batta, 2013; Liberatore *et al.*, 2013	-
	Sociopolitical factors	Ghanmi and Shaw, 2008; Duran *et al.*2011; Martel *et al.*, 2013	-

Appendix B: Model formulation and summary of notation

Fig.B1 summarizes the notation used in the model. Suppose there are *m* supply points and *n* demand points representing cities. Supply points include two sets of locations: global warehouses and supplier locations. Let *G* denote the set of global warehouses in the network, *S* denote the set of supplier locations, and *A* denote the set of demand points. Demand volumes are given in USD based on estimates provided by UNHCR to convert the quantity of goods in a TEU to the corresponding USD value. We treat the actual demand distribution of each year as a scenario with equal probability (See section 4.4. for details). Opening of warehouse *g* incurs a fixed cost f_g and an inventory cost v_g per unit stocked in that warehouse. OO demand is met through supplier locations or inventory stocked at the global warehouses, whereas ER points are supplied only by the global warehouses.

Shipping rates and lead times differ between transportation modes. Normal shipment uses surface transportation (by road or sea) to satisfy OO demand and is generally cheaper, but the lead time is longer. UNHCR regards road and sea transport as alternatives or complementary modes with minimal cost variance and does not distinguish between them in the operational context. Express shipment employs air or road transportation to satisfy ER demand, and it is associated with higher transport costs and shorter lead times. Owing to the higher costs, express shipment via air to any particular demand point is constrained by the availability of funding and cannot exceed 10 TEUs per disaster event. Additional TEUs are sent via surface.

Figure B1: Summary of notation – parameters and decision variables

Sets

S	*Set of suppliers*
G	*Set of potential global warehouses*
A	*Set of all demand points including ongoing and emergency*
K	*Set of emergency response scenarios*

Parameters

f_g	*Fixed cost of opening a potential global warehouses g in USD*
v_g	*Variable cost of opening a potential global warehouses g in USD*
C^{ER}_{gj}	*Transportation cost from global warehouse g to demand point j using express air shipment in USD*
CL^{ER}_{gj}	*Transportation cost from global warehouse g to demand point j using express land shipment in USD*
C^{oo}_{sj}	*Transportation cost from supplier s to demand point j using normal shipment in USD*
C^{oo}_{gj}	*Transportation cost from global warehouse g to demand point j using normal shipment in USD*
C_{sg}	*Transportation cost from supplier s to global warehouse g using normal shipment in USD*
l^{e}_{gj}	*Lead time from global warehouse g to demand point j using express air shipment in days*
lL^{e}_{gj}	*Lead time from global warehouse g to demand point j using express land shipment in days*
l^{n}_{gj}	*Lead time from global warehouse g to demand point j using normal shipment in days*
l^{n}_{sj}	*Lead time from supplier s to demand point j using normal shipment in days*
d^{oo}_{j}	*Demand for ongoing operations at location j in USD*
$d^{ER,k}_{j}$	*Demand for emergency response at location j under scenario k in USD*
lim	*Equal to 430,000 USD, the dollar value of ten TEU's*
Q_g	*A large number, or capacity of g'th global warehouse in TEU*

Decision Variables

I_g	*Required number of containers to be stocked in global warehouse g in TEU*
z_{sg}	*Number of containers to send from supplier s to global warehouse g with normal shipment in TEU*
$x^{oo,k}_{sj}$	*Percentage of ongoing demand to send from supplier s to demand point j with normal shipment in the k'th scenario*
$x^{oo,k}_{gj}$	*Percentage of ongoing demand to send from global warehouse g to demand point j with normal shipment in the k'th scenario*
$x^{ER,k}_{gj}$	*Percentage of emergency demand to send from global warehouse g to demand point j with express air shipment in the k'th scenario*
$ex^{ER,k}_{gj}$	*Excess percentage of emergency demand to send from global warehouse g to demand point j with express land shipment (after sending 10 TEU's by express air) in the k'th scenario*
y_g	1, *if global warehouse g is opened* 0, *otherwise*
bz_{sg}	1, *if containers are sent from suppliers s to global warehouse g* 0, *otherwise*
$bx^{oo,k}_{sj}$	1, *if containers are sent from supplier s to demand point j by normal shipment* 0, *otherwise*
$bx^{oo,k}_{gj}$	1, *if containers are sent from global warehouse g to demand point j by normal shipment* 0, *otherwise*
$bx^{ER,k}_{gj}$	1, *if containers are sent from global warehouse g to demand point j by express air shipment* 0, *otherwise*
$bex^{ER,k}_{gj}$	1, *if excess containers are sent from global warehouse g to demand point j by express land shipment* 0, *otherwise*

Fig.B1: Summary of notation—parameters and decision variables.

Minimum Expected Total Cost Model

Our formulation (Fig.B2) comprises of three sets of variables. First, for every node in set G, we define a binary variable y_g, where, $y_g = 1$ if the g^{th} global warehouse is opened. Next, nonnegative integer flows on arcs from supplier locations to global warehouses determine inventory levels at the opened warehouses. Last, we define nonnegative continuous variables over each arc going from suppliers and warehouses to demand points. These variables represent the required percentage of OO or ER demand sent through each of these arcs. We assume no capacity restrictions at the suppliers, warehouses, or transport arcs. The objective function (F_1) in TC* minimizes the total cost associated with opening warehouses, holding necessary inventory at opened warehouses, shipping cost from suppliers to global warehouses, expected shipping cost from suppliers and global warehouses to OO points, and expected shipping cost from global warehouses to ER points. This objective is subject to several constraints. Constraints (1) and (2) require satisfying all OO and ER demand. Constraints (3) and (4) ensure that if ER demand is greater than 10 TEUs, 10 TEUs of the total demand must be sent by express air shipment and the rest by express road shipment. If ER demand is less than 10 TEUs, the entire demand is sent by air. Constraint (5) allows only opened warehouses to have positive inventory. Constraint (6) requires the inventory stocked at any global warehouse to be equal to the sum of shipments from suppliers to said warehouse. Constraint (7) requires that the total OO and ER shipments from any given global warehouse be less than or equal to its inventory. Constraint (8) denotes $x^{oo,k}_{sj}$, $x^{oo,k}_{gj}$, $x^{ER,k}_{gj}$, and $ex^{ER,k}_{gj}$ as nonnegative continuous flow variables, (9) denotes I_g and z_{sg} as nonnegative integer variables, and (10) denotes y_g as binary variables.

Figure B2: Minimum expected total cost model (TC^*)

$$\min \quad \sum_{g\in G} f_g y_g + \sum_{g\in G}\sum_{s\in S} C_{sg} z_{sg} + \sum_{g\in G} v_g I_g + \sum_{k\in K}\sum_{j\in A} \alpha_k \Bigg((\sum_{g\in G} C^{oo}_{gj} x^{oo,k}_{gj} + \sum_{s\in S} C^{oo}_{sj} x^{oo,k}_{sj}) d^{oo}_j +$$

$$\sum_{g\in G} ((C^{ER}_{gj} x^{ER,k}_{gj})((1-\gamma^k_j) lim + d^{ER,k}_j \gamma^k_j) + (CL^{ER}_{gj} ex^{ER,k}_{gj})(1-\gamma^k_j)(d^{ER,k}_j - lim)) \Bigg) \qquad (F_1)$$

Subject to

$$\sum_{g\in G}(x^{oo,k}_{gj} d^{oo}_j) + \sum_{s\in S}(x^{oo,k}_{sj} d^{oo}_j) = d^{oo}_j, \qquad \forall j \in A \quad (1)$$

$$\sum_{g\in G}(x^{ER,k}_{gj} d^{ER,k}_j + ex^{ER,k}_{gj} d^{ER,k}_j) = d^{ER,k}_j, \qquad \forall k \in K, j \in A \quad (2)$$

$$\sum_{g\in G}(x^{ER,k}_{gj} d^{ER,k}_j) = (1-\gamma^k_j) lim + d^{ER,k}_j \gamma^k_j, \qquad \forall j \in A, k \in K \quad (3)$$

$$\sum_{g\in G}(ex^{ER,k}_{gj} d^{ER,k}_j) = (1-\gamma^k_j)(d^{ER,k}_j - lim), \qquad \forall j \in A, k \in K \quad (4)$$

$$I_g \leqslant Q_g y_g, \qquad \forall g \in G \quad (5)$$

$$\sum_{s\in S} z_{sg} = I_g, \qquad \forall g \in G \quad (6)$$

$$\sum_{j\in A}(x^{oo,k}_{gj} d^{oo}_j + x^{ER,k}_{gj} d^{ER,k}_j + ex^{ER,k}_{gj} d^{ER,k}_j) \leqslant 43000 I_g, \qquad \forall k \in K, g \in G \quad (7)$$

$$x^{oo,k}_{sj}, x^{oo,k}_{gj}, x^{ER,k}_{gj}, ex^{ER,k}_{gj} \in [0,1], \qquad \forall k \in K, s \in S, g \in G \quad (8)$$

$$z_g, I_g \quad integer, \qquad \forall g \in G \quad (9)$$

$$y_g \quad binary, \qquad \forall g \in G \quad (10)$$

Fig. B2: Minimum expected total cost model (TC*).

Minimum Expected Lead Time Model

The formulation LT* minimizes only the total lead time associated with all used arcs from a supply point to an OO or ER demand point (Fig.B3).

LT* comprises of all variables used in TC* plus the binary version of every continuous nonnegative flow variable, indicating whether each transport arc has a positive flow (constraints (11–14)). The objective function given in (F_2) minimizes the expected lead time of shipping from suppliers to OO demand points, from global warehouses to OO demand points, and from global warehouses to ER points. The entire model is not presented for the sake of brevity.

Figure B3: Objective function and additional constraints in minimum expected lead time model (LT^*)

$$\min \quad \sum_{k \in K} \sum_{j \in A} \alpha_k \left(\sum_{g \in G} l^n_{gj} bx^{oo,k}_{gj} + \sum_{s \in S} l^n_{sj} bx^{oo,k}_{sj} + \sum_{g \in G} l^e_{gj} bx^{ER,k}_{gj} + \sum_{g \in G} lL^e_{gj} bex^{ER,k}_{gj} \right) \qquad (F_2)$$

Subject to

$$bx^{oo,k}_{gj} \geqslant x^{oo,k}_{gj}, \qquad \forall g \in G, j \in A \quad (11)$$

$$bx^{oo,k}_{sj} \geqslant x^{oo,k}_{sj}, \qquad \forall s \in S, j \in A \quad (12)$$

$$bx^{oo,k}_{sj} \geqslant x^{oo,k}_{sj}, \qquad \forall s \in S, j \in A \quad (13)$$

$$bx^{oo,k}_{sj}, bx^{oo,k}_{gj}, bx^{ER,k}_{gj}, bex^{ER,k}_{gj} \quad binary, \qquad \forall g \in G \quad (14)$$

Fig. B3: Objective function and additional constraints in minimum expected lead time model (LT*).

Budget Constrained Minimum Expected Lead Time Model

Dual objectives of lead time and cost are handled by a third model, in which the same lead time objective function as in LT* is minimized subject to all previous constraints and an additional budget constraint (Fig.B4). This constraint ensures that the total cost incurred under this model is less than or equal to the optimal value of TC* plus a percentage, β. In our computational experiments for analyzing the trade-off between cost and lead time, we varied β such that the right-hand side of constraint (15) ranged from the optimal objective value of TC* (minimum possible cost) to the cost incurred in the optimal LT* solution. Thus, we approximated the Pareto frontier with a set of efficient solutions, obtained by solving the model with β values ranging from 0 to 0.2 with increments of 0.0005, such that no other solution with better cost as well as better lead time exists.

Figure B4: Budget constraint added to the minimum expected lead time model

$$\sum_{g \in G} f_g y_g + \sum_{g \in G} \sum_{s \in S} C_{sg} z_{sg} + \sum_{g \in G} v_g I_g + \sum_{k \in K} \sum_{j \in A} \alpha_k \Big((\sum_{g \in G} C^{oo}_{gj} x^{oo,k}_{gj} + \sum_{s \in S} C^{oo}_{sj} x^{oo,k}_{sj}) d^{oo}_j +$$

$$\sum_{g \in G} ((C^{ER}_{gj} x^{ER,k}_{gj})((1-\gamma^k_j) lim + d^{ER,k}_j \gamma^k_j) + (CL^{ER}_{gj} ex^{ER,k}_{gj})(1-\gamma^k_j)(d^{ER,k}_j - lim)) \Big) \leqslant TC^*(1+\beta) \qquad (15)$$

Fig.B4: Budget constraint added to the minimum expected lead time model.

Appendix C: Details of data sources, assumptions, and cost and lead time calculations*

Type	**Characteristic/ Assumptions**	**Source**
Transportation cost to satisfy ER demand by express shipment (see 4.3)	• Air transportation: 100 USD per mile * total miles + 25,000 USD (fixed cost) / (divided by) value per TEU (twenty-foot container) • Road transportation: 10 USD per mile * total miles / (divided by) value per TEU • The first 10 TEU's in each new emergency event are shipped by air. Air shipments to any particular demand point are constrained by the availability of funding and cannot exceed 10 TEUs. Additional TEUs are sent via surface	• Brambles, ongoing consultancy project at UNHCR • Triangulated via analysis of ERP data • Distances were calculated using the following link: http://www.freemaptools.com/how-far-is-it-between.htm • For value per TEU, see below
Transportation cost to satisfy OO demand by normal shipment (see 4.3)	• 10 USD per mile * total miles / (divided by) value per TEU	• Brambles, ongoing consultancy project at UNHCR • Triangulated via analysis of ERP data
Warehousing variable cost: holding cost per unit	• 20% of annual product value	• Currently UNHCR does not operate with holding cost. Even so, variable cost was, in agreement with UNHCR, set to 20% of annual product value to account for variable staff cost, and so on.
Warehousing fixed cost per site	• Staff: USD 480,000 per year: USD 360,000 (international staff) + USD 120,000 (local staff) • Rent of land/facility: USD 250,000 per year • Total: USD 730,000 per year • Assume warehouse rental so no opening or closing cost	• Average warehousing fixed costs calculated and confirmed by UNHCR
Value of goods per TEU (twenty-foot container)	• Balanced distribution of all items: USD 43,000	• UNHCR's estimate of goods value for a TEU container with a representative mix of CRI
Transportation lead time by air (for emergencies only) from confirmed order (and payment) until delivery at nearest airport	• First wave after new emergency • 3 days for all distances below 1000 miles • 4 days for all distances above 1000 miles • Set max transport by air for a new emergency to 430,000 USD (value of 10 containers) per year, the rest by sea/land	• Brambles, ongoing consultancy project at UNHCR • Triangulated by analyzing ERP data
Transportation lead time by sea/land (normal shipment for OO and for later waves of ER)	• Estimated lead time 1 day per 200 miles	• Brambles, ongoing consultancy project at UNHCR • Triangulated by analyzing ERP data

*All the above calculations, assumptions, and estimations used in the model, are based on historical data/estimations in UNHCR and have been confirmed with UNHCR's supply chain management team.