Sharifyazdi, M., Navangul, K. A., Gharehgozli, A., & Jahre, M. (2018). On- and offshore prepositioning and delivery mechanism for humanitarian relief operations. *International Journal of Production Research, 56*(18), 6164-6182. doi:10.1080/00207543.2018.1477260

On- and Off-Shore Prepositioning and Delivery Mechanism for Humanitarian Relief Operations

Mehdi Sharifyazdi[1], Kaustubh Anil Navangul[2], Amir Gharehgozli[*,3], Marianne Jahre[1]

[1] Department of Accounting, Auditing, and Business Analytics, BI Norwegian Business School, Oslo, Norway
[2] Norwegian Refugee Council, Oslo, Norway
[3] Department of Maritime Administration, Texas A&M University, Galveston, TX, the USA
mehdi.sharifyazdi@bi.no, kaustubh.navangul@nrc.no, gharehga@tamug.edu, marianne.jahre@bi.no

Traditionally, international humanitarian organizations have used on-demand dispatch of disaster relief goods from regional logistics units for sudden onset disaster response. This paper investigates the improvements in efficiency and resilience of disaster relief operations by combining the existing method of on-shore prepositioning of relief items in regional logistics units with off-shore prepositioning of relief items on-board vessels and at seaport terminals. The model operationalizes certain resilience dimensions, thus contributing to organization theory. The problem is formulated as a linear programming model that incorporates different logistical costs, including inventory cost, replenishment cost, and transportation cost, to find the best combination of disaster relief methods. At the tactical level, the model determines how much and where disaster relief items need to be prepositioned. At the operational level, the model addresses how much and by which mode of transport the disaster relief items need to be transported to disaster points. The model is tested on 16 major disasters in Southeast Asia. The main finding is that off-shore prepositioning can contribute to cost reduction and resilience without compromising on the speed or the scale of the response. The results also suggest that the benefits depend on the duration of the disaster emergency period and the ratio of off-shore storage cost to on-shore storage cost.

Keywords: Humanitarian logistics; Off-shore prepositioning; Shipping and port operations; Resilience in humanitarian operations; Mathematical modeling

[*] *Corresponding author*: PO Box 1675, Galveston, Texas 77553, USA. Tel: +1 (409) 740-4854, Fax: +1 (409) 741-4014, Email: GharehgA@TAMUG.edu.

1. Introduction

Improvements in logistics preparedness are very important for increasing the effectiveness and efficiency of disaster relief operations. Both theory and practice suggest prepositioning as a key strategy (Van Wassenhove, 2006; Duran et al., 2011; Jahre et al., 2016b; Manopiniwes and Irohara, 2017). However, prepositioning can be costly, so it is important to find more cost-effective ways of delivering aid without compromising on the speed of the response (Ransikarbum and Mason, 2016). To this end, various alternatives to prepositioning have been suggested, including vendor-managed inventory (Van Wassenhove and Pedraza-Martinez, 2012), framework agreements (Balcik and Ak, 2014), transfer mechanisms between programs (Bhattacharya et. al., 2014), and co-location of stocks between organizations (Acimovic and Goentzel, 2016).

The current practice in prepositioning is on-shore stockpiling in warehouses close to disaster-prone areas (e.g. Duran et al., 2011; Jahre et al., 2016a). During the operations, airfreight is commonly used as a means of transportation to the affected populations. While transporting relief items by air is quick, it is also expensive. Therefore, there is a definite need for finding more cost-effective ways of delivering aid without compromising on the speed of the response (Sarkis et al., 2012) and prepositioning on-board ships and at seaport terminals has been suggested as a possibly less costly solution, either by itself or in combination with prepositioning on-shore. Moreover, access to seaports creates extra capacity after disasters, when airports may have insufficient capacity. This approach is commonly used in the military context, where it is called sea-basing (Clark, 2002). While on-shore prepositioning has received considerable research attention (Caunhye et al., 2012), off-shore studies in the HL context are scarce (Tatham et al. 2016). Similarly, the comprehensive literature on seaport terminal operations (Gorman et al., 2014; Gharehgozli et al., 2016, 2017) and shipping operations (Lee and Song, 2017; Fransoo and Lee, 2013; Christiansen et al., 2013) do not seem to offer much in terms of how vessels and terminals can be utilized for humanitarian purposes.

The present study aims to fill this gap. By testing various combinations of on- and off-shore prepositioning using commercial vessel capacity for transportation and warehousing, we address the following research question: *To what extent, under what conditions, and in which combinations can off-shore prepositioning offer a good alternative to on-shore solutions?* This question is answered by developing and testing an optimization model for location, prepositioning, and distribution (Caunhuye et al. 2012). The combined on- and offshore solution with moving warehouses and multiple transport alternatives can be seen as a more resilient prepositioning option than the classical options. Accordingly, we discuss the analytical approach and our results in relation to the resilience concept, providing avenues for further research. While HL studies concerned with resilience are increasingly popular (Day, 2014), our review did not identify such studies connected to prepositioning.

Our study was initiated in a collaborative research project with International Federation Red Cross Red Crescent (IFRC) and Wilh. Wilhelmsen, a large Norwegian shipping company, between 2010 and 2013. The genesis of the model is rooted in extensive consultations between practitioners from the humanitarian and commercial sector. The idea was to analyze cost and response time effects of using liner vessels as resources in disaster response. We formulate the prepositioning problem as an optimization model with the objective function of minimizing total cost, with the goal of finding the best combination of on- and off-shore prepositioning. The model was tested using real-world data regarding demand and cost.

The results show that using on-shore and off-shore prepositioning simultaneously can reduce the total cost, while responding to demand for disaster relief items within comparable lead times. The key contribution of our study is the analytical approach for testing combinations of on- and off-shore prepositioning solutions with use of real-world data. We tested a new prepositioning model and operationalized certain dimensions of resilience, showing that off-shore prepositioning can provide solutions that are resilient, fast, and cost-efficient. To our knowledge, this is the first study to formulate an off-shore prepositioning model that operationalizes resilience dimensions, thus contributing to organization theory.

The remainder of this paper is organized as follows. Section 2 reviews the literature on off-shore prepositioning as well as on resilience in humanitarian operations. In Section 3, the problem and the assumptions are discussed and the model is formulated. Section 4 describes the case study and the data used to evaluate the model. Section 5 is dedicated to the numerical experiments. Section 6 concludes the paper.

2. Literature Review

This section begins with a brief literature review of mathematical and analytical models for off-shore prepositioning. It continues with a review of the literature on connections between resilience and prepositioning. The section concludes with the contributions of the paper in comparison with the literature.

2.1 Off-shore prepositioning

When it comes to analytical and mathematical modelling, there is a quite large body of literature about on-shore prepositioning in the context of disaster relief and humanitarian logistics (Ukkusuri and Yushimito, 2008; Caunhye et al., 2012; Duran et al., 2013; Manopiniwes and Irohara, 2017), but the research on off-shore prepositioning is still in its embryonic stages. The present study seeks to fill this gap.

The concept has been studied in the military context. An important aspect of militaries' logistical strategies since the 1960s has off-shore based prepositioning, known in military parlance as sea-basing (Lee, 1999; Clark, 2002; Beach, 2010). The issue of humanitarian assistance has also found mention (e.g. Beach, 2010; Apte et al., 2012). According to Martinez (2008), the US army regularly engages in relief operations in response to natural or man-made disasters. Some notable recent examples include Operation Unified Assistance in response to 2004 Indian Ocean tsunami and Operation Lifeline in response to the 2005 Kashmir earthquake.

When it comes to the humanitarian logistics literature, Akkihal's (2006) discussion of the facility location problem explicitly acknowledged that sea-basing is not uncommon in the realm of military logistics preparedness. However, that study considered only terrestrial positions while solving the facility location problem, asserting that sea-based prepositioning would be unaffordable for humanitarian organizations. Tatham and Kovacs (2007) worked on a concept that envisaged a 'floating warehouse' located close to a primary risk area. An appropriately sized ship is held at very short notice to transit to the relevant country with a cargo containing sufficient supplies of relief items to meet the immediate needs of a significant number of beneficiaries. Tatham and Kovacs concluded that if the sea-basing concept had been implemented during the relief operations for the 2005 Pakistan earthquake, this would have resulted in a significant cost savings for the humanitarian aid community, at the same time as maintaining or even improving upon the quality of logistical services delivered. Bemley et al. (2013) proposed a stochastic facility location model for prepositioning of goods and staff to recover aids to navigation (ATONs) on waterways after a disaster. The model maximizes the number of ATONs repaired through bi-level optimization. The first- and second-level models make the location and distribution decisions, respectively. They run the model for a number of demand scenarios and do a sensitivity analysis on the cost. Finally, Ozkapici et al. (2016) proposed a mixed integer programming model for a similar problem. The proposed mathematical model utilizes the seaports of Istanbul for maritime transportation and allows for the transportation of relief items between Istanbul's European and Anatolian sides. Their model used one land-based warehouse and two ships as floating warehouses for prepositioning of relief items. The model minimizes the total transportation time of relief items, while also satisfying demand and complying with limitations on transshipment capacity, number of daily trips, and supply capacity of sources.

2.2 Resilience and prepositioning

Resilience has become a highly important concept in operations management (Ponomarov and Holcomb, 2009, Bhamra et al. 2011, Datta and Datta, 2017). The term is often linked with agility (e.g. Scholten et al. 2014, Dubey et al. 2014, Dubey and Gunasekaran, 2016) and concerned with the development of supply chain strategies to become more resilient (e.g. Gunasekaran et al. 2015). Resilience has received increasing attention in HL research, from the supply network perspective – that is, those preparing for and responding to disasters (e.g. Day, 2014) – and also from the perspective of the local community (e.g. Matopoulos et al., 2014), the infrastructures and supply chains that are disrupted by the disaster (e.g. Zobel and Khansa. 2014), as well as how they impact each other (Papadopoulos et al. 2017). The term resilience has been mentioned in recent prepositioning papers such as Manopiniwes and Irohara, (2017), Tofighi et al. (2016) and Ransikarbum and Mason (2016), but not modeled. However, Duhamel et al. (2016) conclude that while resilience as a whole may be hard to express mathematically, optimization plays a key role through its potential impact on robustness, resourcefulness, and rapidity. They suggested that redundancy, which normally contributes to resilience, often contrasts the efficiency criterion in optimization models. Similarly, Ivanov et al. (2014) suggested there are trade-offs between efficiency, flexibility, and resilience. Day (2014) developed propositions on disaster relief network characteristics that can enhance resilience; three of these are particularly interesting to us. The first is *adaptive entity capacity*, which means that entities can quickly alter their focus or increase throughput capacity. The second is *redundancy and path length*, because multiple ways and more direct ways of distribution enhance resilience. The third characteristic is *supply base flexibility*. Singh et al. (2018) have employed ISM and fuzzy MICMAC to specify critical factors for a humanitarian supply chain to be resilient. They have listed twelve factors on the basis of literature and suggested that three of them are critical, among which *strategy and capacity planning* is relevant to our work.

Resilience research from the perspective of how companies should develop resilient networks to cope with disruptions has come further in terms of modeling; three papers are of particular interest to us in this regard. Firstly, Miller-Hooks et al. (2012) proposed a method for assessing and maximizing the resilience of an intermodal freight transport network, conceptualizing resilience both in terms of the network's inherent coping capacity and the potential impact of immediate recovery action. Secondly, Sokolov et al. (2016) combined a static and a dynamic model to quantify supply chain ripple effects, modeling resilience (that is, the ability to continue execution despite disruptions) by node and arc connectivity. Thirdly, Liu et al. (2016) showed how supply chain resilience can be built through virtual stockpile pooling, where stockpiles are dynamically reallocated in accordance with demand.

In conclusion, considering the opportunities offered by off-shore prepositioning, the number of studies focusing on this stream is surprisingly small compared with on-shore prepositioning, let alone simultaneous on-shore and off-shore prepositioning. Such studies are even more scarce when it comes to analytical/mathematical decision-making models. The present study will contribute to filling this gap in the literature, by developing and solving a mathematical model that incorporates off-shore prepositioning and on-demand sea transport for disaster relief operations, in addition to other common existing methods such as on-demand air transport and on-shore prepositioning, while not sacrificing the speed of the response. Moreover, the model formulates off-shore prepositioning on-board moving commercial vessels, while the comparable existing models consider off-shore prepositioning only on fixed vessels or locations. Finally, from the perspective of organizational theory, as the literature lacks analytical models for resilient disaster relief networks (Day, 2014) our study aims to contribute to the literature by employing off-shore prepositioning besides other aforementioned methods in disaster relief operations. In addition, as Singh et al. (2018) suggest, planning for locations and levels of prepositioned relief items has a significant impact on resilience of disaster relief supply chains.

3. The Mathematical model

This section includes details of the problem description and formulates the problem as a linear programming model. Compared with the simulation models that evaluate only specific solutions, our proposed model can consider all options for prepositioning of relief items at the same time and find the optimal solution in a relatively short time.

3.1 Problem description

In response to improving their logistics preparedness to deal with emergencies, a number of IHOs have established prepositioning facilities in different parts of the world of varying capacities. For example, one of the largest IHOs has established prepositioning facilities, based on its own assessment of needs, in strategic locations across the world such as Dubai, Kuala Lumpur, and Panama. These prepositioning facilities are designated as regional logistics units (RLUs) and store emergency relief items to meet the needs of 300,000 people for one month.[2] These emergency supplies include both food items and non-food items and they are usually used to meet initial needs in the immediate aftermath of a disaster.

In the event of a sudden onset disaster, the prepositioned items are typically airfreighted during the emergency phase of the disaster relief operations. This is followed by regular follow-up replenishments that are shipped via more traditional means of transportation, such as by sea freight, as needed (Gatignon et al., 2010). In this context, the cost of air-freighting has been shown to be significantly higher than the cost of sea freight (Tatham and Kovacs, 2007). Despite its higher cost, this method is still a vast improvement over the earlier more centralized system, in the days prior to the establishment of the RLUs, when the disaster relief items were transported in large quantities by air through trans-continental flights. Such a system was even more expensive and it took longer to deliver the relief items to the disaster-affected areas.

However, even if the use of air freight is limited to the emergency phase, it means that a vast amount of funds is spent in transportation, which leaves less money for provision of actual aid and relief to the affected population. IHOs are constantly being pressured to find more cost-effective ways of delivering the relief items to the affected populations without compromising on the speed of the response (Majewski et al., 2010). In summary, a key question is whether there can be any alternative mechanism of delivering relief items that is not significantly slower than airfreight and is also cost-effective? For example, is it possible to use sea freight during the emergency phase, not just as a mode of transport but also for offshore prepositioning? This question will be discussed in greater detail in the next section.

[2] http://www.ifrc.org/en/what-we-do/disaster-management/preparing-for-disaster/disaster-preparedness-tools/logistics-preparedness/

3.2 Problem statement and assumptions

In order to address the problem described in the previous section, we developed a linear programming model; some key characteristics and assumptions related to the model are described below.

3.2.1. Prepositioning facilities

As per the model presented in this paper, the relief items are considered for prepositioning in the following four types of facilities (see Figure 1):

- **The Regional Logistics Unit (RLU)**, which is, as explained earlier, normally used by IHOs for prepositioning emergency relief items for responding to disasters in a particular region of the world. It is assumed that once the relief items are shipped from the RLU, the facility is replenished within a certain lead time.
- **The regional port terminal** is operated only by the shipping company and replenishes the items that are shipped from the port terminals as well as the inventory on-board the vessels. Like the RLU, the regional port terminal is also assumed to be replenished with items received directly from the suppliers of relief items within a given amount of lead-time.
- **Port terminals** are used for prepositioning limited amount of relief items. They are replenished as required with items from the regional port terminal .
- **Vessels** can also continuously carry a limited amount of relief items on-board. These vessels can deliver the prepositioned items to the ports in case a disaster occurs. The inventory on-board each vessel is replenished whenever the vessel visits the regional port terminal.

3.2.2. Distribution points

In order to deliver the items to the disaster location, items must first be transferred to the nearest distribution point. Each disaster location may have a number of dedicated distribution points. It is assumed that the distribution points have no limits when it comes to receiving and storing the disaster relief items. This is reasonable since they have a high turnover during the disaster relief operations.

3.2.3. Distribution methods

Overall, there are four different distribution methods (referred to as channels hereafter) via which disaster relief items can be delivered to the disaster locations. They are as follows (see Figure 1):

i. **Channel 1 (by air from the RLU):** Items are stored at the RLU, sent on demand by air to the closest airport to the disaster location, and delivered to a distribution point that corresponds to the disaster location by land.

ii. **Channel 2 (by sea from the RLU)**: Items are stored at the RLU, sent on demand by sea to a port close to the disaster location, and delivered to a distribution point corresponding to the disaster location by land.

iii. **Channel 3 (storage on-shore):** Items are prepositioned at port terminals and are sent on demand by land to a distribution point corresponding to the disaster locations. Inventory at port terminals will be replenished by sea from the regional port terminal.

iv. **Channel 4 (storage off-shore):** Items are prepositioned on-board vessels, delivered to port terminals close to the disaster location and sent further by land to a distribution point corresponding to the disaster location. Inventory on-board vessels will be replenished whenever the vessels visit the port where the regional port terminal of the shipping company is located.

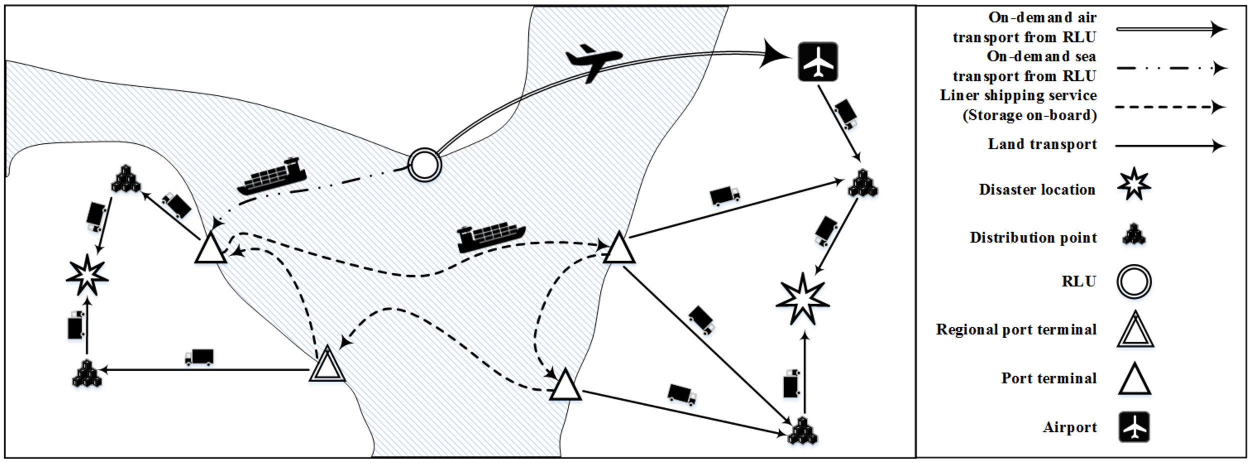


Figure 1. An illustration of the distribution network of disaster relief items

3.2.4. The goals of the model

In the mathematical model, the goal is to satisfy demand for relief items during the emergency period by means of on-shore and off-shore prepositioning without compromising on the speed of the response. This is ensured through the constraints of the model. The objective function of the model is to minimize the total logistical cost, including inventory-holding costs and loading/unloading costs (which are part of replenishment costs) on-board the vessels, at the port terminals, and at the RLU, in addition to transport costs. Key inputs needed for the model are transportation costs and times for different modes of transport between the nodes of the network, including the RLU, regional terminal, port terminals, and distribution points. Transportation times can be calculated given the distance between nodes, average speed, and loading/unloading times. Inventory-holding rates must be given; these can be calculated based on the value of disaster relief items and interest rates. Another important piece of information is the schedule and sequence of the ports on liner shipping routes. Specifically, the replenishment lead-time of the inventory on-board the vessels and at the port terminals can be calculated based on the average speed of the vessels, stop times at the ports, and their distance to the regional terminals. As for each disaster, the location of the vessels must be known when the disaster occurs. Last but not least, the estimated demand for the disaster relief items needed during the emergency phase of the disaster relief operations is known and uniformly distributed throughout the period.

It is assumed that the disaster relief items delivered by the vessels on the liner shipping routes to the ports will be dispatched to the corresponding distribution points immediately and will not be stored at the terminals. There is no limit for such deliveries at the ports. Replenishment costs at the RLU, regional terminal, and distribution points are not considered in the model since they are not dependent on the decisions made by the model and have to be paid regardless of what source is chosen to send disaster relief items to disaster locations. Disaster relief items are either directly or indirectly provided from the RLU and regional port terminal. Moreover, the port terminals and the RLU will issue a replenishment order as soon as they have dispatched items to the distribution points. Finally, transport, replenishment and inventory holding costs and cost of the relief items themselves are assumed to remain fixed during the planning period. All input data, including costs, demand, and transport times, are given and deterministic.

3.3 Formulation of the model

In this section, we formulate the problem as a linear programming model. In general, the model comprises three sets of decision variables: the maximum inventory to be held on-board vessels, at seaport terminals, and in RLUs ($\boldsymbol{x}$ variables); the inventory level on-board vessels, at seaport terminals, and in RLUs at the end of each period ($\boldsymbol{I}$ variables); and the quantity of each disaster relief item to be sent to the disaster locations ($\boldsymbol{y}$ variables). Appendix C provides more details with respect to the indices and sets, parameters, and decision variables.

The objective is to minimize the total cost, including transport cost, inventory holding cost and replenishment (loading/unloading) cost. Constraints (2)–(5) are the demand and inventory constraints at disaster locations. While some models, as in Hu et al. (2016), safeguard the equity of service among disaster points, by formulating equity as an objective function beside other objective functions as cost efficiency, the latter constraints in our model guarantee equity of service as well. These constraints also ensure a 100 percent service level. In other words, all of the requirements of a distribution point (disaster) at each period must be delivered without any delay. In addition, these constraints (Constraints (6)–(8), (9)–(11), (12)–(14), and (15)–(17)) represent the inventory constraints at the port terminals, on-board the vessels, at the RLUs, and at the regional port terminals, respectively. Constraints (18) ensure that delivery is possible only when a vessel visits a port. In these constraints M is a very big number. Constrains (19), (20), (21), and (22) denote the capacity constraints on vessels, at the port terminals, regional port terminals, and RLUs, respectively. Constraints (23) are the constraints to ensure no item is dispatched towards a disaster location, before the disaster happens. Finally, constraints (24) are the sign constraints.

$$\begin{aligned}\text{Min } & \sum_{d\in D}\sum_{t\in T}\sum_{j\in S}\Big[\sum_{p\in P}\big(k^P_{pj}.y^P_{pdjt}+\sum_{i\in V}k^V_{ij}.y^V_{ipdjt}\big)+\sum_{g\in G}\Big(k^G_{gj}\big(\sum_{p\in P}y^{GS}_{gpdjt}+\\ & y^{GF}_{gdjt}\big)\Big)+\sum_{r\in R}\Big(k^R_{rj}\big(y^{RS}_{rdjt}+y^{RF}_{rdjt}\big)\Big)\Big]+\\ & \sum_{j\in S}\sum_{t\in T}\big(\sum_{p\in P}h^P_{pj}.I^P_{pjt}+\sum_{i\in V}h^V_{ij}.I^V_{ijt}+\sum_{g\in G}h^G_{gj}.I^G_{gjt}+\sum_{r\in R}h^R_{rj}.I^R_{rjt}\big)+\\ & \sum_{d\in D}\sum_{t\in T}\sum_{j\in S}\big(\sum_{p\in P}\big[c^P_{pdj}.\big(y^P_{pdjt}+\sum_{i\in V}y^V_{ipdjt}\big)+\sum_{g\in G}\big(c^{GS}_{gpj}+c^P_{pdj}\big).y^{GS}_{gpdjt}\big]+\\ & \sum_{r\in R}\big(c^{RF}_{rdj}.y^{RF}_{rdjt}+c^{RS}_{rdj}.y^{RS}_{rdjt}\big)+\sum_{g\in G}c^{GF}_{gpj}.y^{GF}_{gdjt}\big)\end{aligned} \tag{1}$$

Subject to

$$\begin{aligned}I^D_{djt} &= I^D_{dj(t-1)}-q_{djt}+\sum_{p\in P}\Big(y^P_{pdjt\left(t-\tau^P_{pd}\right)}+\sum_{i\in V}y^V_{ipdj\left(t-\tau^P_{pd}\right)}+\\ & \sum_{g\in G}y^{GS}_{gpdjt\left(t-\tau^P_{pd}-\tau^{GS}_{gp}\right)}\Big)+\sum_{g\in G}y^{GF}_{gdjt(t-\tau^{GF}_{gp})}+\sum_{r\in R}\Big(y^{RF}_{rdj(t-\tau^{RF}_{rd})}+\\ & y^{RS}_{rdj(t-\tau^{RS}_{rd})}\Big),\quad \forall d\in D, j\in S, t\in T, t>0\end{aligned} \tag{2}$$

$$I^D_{djt}\geq 0,\quad \forall d\in D, j\in S, t\in T, t>0 \tag{3}$$

$$I^D_{dj0}=0,\quad \forall d\in D, j\in S \tag{4}$$

$$y_{gdjt}^{GF}, y_{gpdjt}^{GS}, y_{gdjt}^{RF}, y_{gpdjt}^{RS}, y_{pdjt}^{P}\ \ y_{ipjt}^{V} = 0, \ \ \forall j, i, p, g, r, d, t \leq 0 \tag{5}$$

$$I_{pjt}^{P} = I_{pj(t-1)}^{P} - \sum_{d \in D} y_{pdjt}^{P} + \sum_{d \in D} y_{pdj(t-\rho_p)}^{P}, \ \ \forall p \in P, j \in S, t \in T, t > 0 \tag{6}$$

$$I_{pjt}^{P} \geq 0, \ \ \forall p \in P, j \in S, t \in T, t > 0 \tag{7}$$

$$I_{pj0}^{P} = x_{pj}^{P}, \ \ \forall p \in P, j \in S \tag{8}$$

$$I_{ijt}^{V} = I_{ij(t-1)}^{V} - \sum_{d \in D} \sum_{p \in P} y_{ipdjt}^{V} + a_{igt}^{G}.\left(x_{ij}^{V} - I_{ij(t-1)}^{V}\right), \ \forall i \in V, j \in S, t \in T, t > 0 \tag{9}$$

$$I_{ijt}^{V} \geq 0, \ \ \forall i \in V, j \in S, t \in T, t > 0 \tag{10}$$

$$I_{ij0}^{V} = x_{ij}^{V}, \ \ \forall i \in V, j \in S \tag{11}$$

$$I_{rjt}^{R} = I_{rj(t-1)}^{R} - \sum_{d \in D}\left(y_{rdjt}^{RF} + y_{rdjt}^{RS}\right) + \sum_{d \in D}\left(y_{rdj(t-\rho_r^R)}^{RF} + y_{rdj(t-\rho_r^R)}^{RS}\right), \ \ \forall r \in R, j \in S, t \in T, t > 0 \tag{12}$$

$$I_{rjt}^{R} \geq 0, \ \ \forall r \in R, j \in S, t \in T, t > 0 \tag{13}$$

$$I_{rj0}^{R} = x_{rj}^{R}, \ \ \forall r \in R, j \in S \tag{14}$$

$$I_{gjt}^{G} = I_{gj(t-1)}^{G} - \sum_{d \in D}\left(y_{gdjt}^{GF} + \sum_{p \in P} y_{gpdjt}^{GS}\right) + \sum_{d \in D}\left(y_{gdj(t-\rho_g^G)}^{GF} + \sum_{p \in P} y_{gpdj(t-\rho_g^G)}^{GS}\right), \ \forall g \in G, j \in S, t \in T, t > 0 \tag{15}$$

$$I_{gjt}^{G} \geq 0, \ \ \forall g \in G, j \in S, t \in T, t > 0 \tag{16}$$

$$I_{gj0}^{G} = x_{gj}^{G}, \ \ \forall g \in G, j \in S \tag{17}$$

$$\sum_{d \in D} \sum_{j \in S} y_{ipdjt}^{V} \leq M. a_{ipt}^{P}, \ \ \forall i \in V, p \in P, t \in T \tag{18}$$

$$0 \leq \sum_{j \in S} m_j. x_{ij}^{V} \leq b_i^{V}, \ \ \forall i \in V \tag{19}$$

$$0 \leq \sum_{j \in S} m_j. x_{pj}^{P} \leq b_p^{P}, \ \ \forall p \in P \tag{20}$$

$$0 \leq \sum_{j \in S} m_j. x_{gj}^{G} \leq b_g^{G}, \ \ \forall g \in G \tag{21}$$

$$0 \leq \sum_{j \in S} m_j. x_{rj}^{R} \leq b_r^{R}, \ \ r \in R \tag{22}$$

$$y_{ipdjt}^{V} = y_{pdjt}^{P} = y_{gdjt}^{GF} = \ y_{gpdjt}^{GS} \ = \ y_{gdjt}^{RS} \ = 0, \tag{23}$$

$$\forall i \in V, p \in P, j \in S, g \in G, r \in R, d \in D, t \in T, t < \theta_d$$

$$y^{V}_{ipdjt}, y^{P}_{pdjt}, y^{GF}_{gdjt}, y^{GS}_{gpdjt}, y^{RF}_{gdjt}, y^{RS}_{gdjt}, x^{V}_{ij}, x^{P}_{pj}, x^{R}_{rj}, x^{G}_{gj} \geq 0, \tag{24}$$
$$\forall i \in V, p \in P, j \in S, g \in G, r \in R, d \in D, t \in T$$

For the sake of readability and to avoid repeating one group of constraints several times for specific cases, the inventory constraints at the distribution points, port terminals, RLUs and vessels are written such that transport variables – that is, $y^{V}_{ipdjt}, y^{P}_{pdjt}, y^{GF}_{gdjt}, y^{GS}_{gpdjt}, y^{RF}_{rdjt}$ and y^{RS}_{rdjt}, – might sometimes take a negative time index that is meaningless. Therefore, in the aforementioned constraints, let $y^{V}_{ipdjt}, y^{P}_{pdjt}, y^{GF}_{gdjt}, y^{GS}_{gpdjt}, y^{RF}_{rdjt}$ and y^{RS}_{rdjt} be zero, wherever $t < 0$.

Although he number of variables and constraints grows at a fast rate when the number of prepositioning facilities increases, since the model is linear programming, solution time for real-world cases will not be a major issue if a powerful solver like CPLEX is used. Another dimension of the model's complexity is that it encompasses two decision-making problems: inventory/distribution management (operational) and prepositioning management (tactical). On the other hand, the time horizons for tactical and operational uses of the model are years and weeks, respectively. Accordingly, obtaining an optimal solution within minutes is not essential for these decisions. Thus, CPLEX is used to solve the problem as it can obtain an optimal solution for realistically sized instances in a few minutes. Moreover, if the model is used only for operational decision making – that is, if prepositioning levels are given – there will be far fewer variables and constraints. Therefore, solution time will be much shorter than what we will see in the results.

4 Case study

Historical data for 16 disasters that occurred in Southeast Asia between 2005 and 2010 were collected from secondary sources. These data include information about the type of disaster, its date of occurrence, and the demand for relief items. Other data, such as cost of logistical activities, shipping routes, and transit times, were also collected.

4.1. Demand data: disasters, locations and response

An estimated 1 billion persons were affected by 4067 disasters occurring globally from 2005 to 2010 (Jahre et al., 2011). Of these 4067 disasters, 605 had an international response, from which actual response data for a statistically significant sample of 63 disasters was collected (Jahre et al., 2011; Wilberg and Olafsen, 2012). The model formulated in this paper uses the data related to 16 of the aforementioned disasters in Asia that were of large scale and required international assistance. For each of these disasters, the following information was sourced from Emdat:[3] location, date of occurrence, and type. For ease of understanding, the geographical locations of these disasters have been depicted on a map in Figure 4-a in Appendix B. Further, relevant data concerning the actual response provided by the key stakeholders in each disaster was sourced from Jahre et al. (2011). The key data fields included relief items delivered and their respective cost and quantities in terms of the number of pallets. This data was used as 'demand' data. More data is collected from a global shipping firm in Norway. Table 6 in Appendix A presents more details with respect to each disaster.

4.2. Supply data

Real-world data about shipping routes in the South East Asian region, the number of vessels operating on these routes, transit times, and frequencies of sailing were obtained from the same shipping firm.

[3] www.emdat.be

Based on the locations of the disasters (Table 6 in Appendix A and Figure 4-a in Appendix B), the shipping company identified two commercial shipping routes: the Intra Asia NE–SE and the SE Asia Express (Figure 4-c and Figure ***4***-d in Appendix B). Only those vessels that serve the routes on a regular basis were included in the study. One vessel serves the Intra Asia NE–SE route, while four vessels serve the SE Asia Express route. Along with the shipping routes, the key ports in terms of their nearness to the disaster locations (Table 6) along these routes were also identified.

The shipping company has access to a large number of port terminals throughout Asia where relief items could be prepositioned. Based on geographical locations of the 16 disasters, six port terminals were identified where relief items would be prepositioned: Tianjin (China), Shanghai (China), Laem Chabang (Thailand), Singapore (Singapore), Jakarta (Indonesia), and Chennai (India) (Figure 4-b in Appendix B). Of these, the Singapore port terminal also served as a transshipment terminal used for reloading the vessels. Table 1 summarizes the prepositioning facilities in this case study.

Table 1. Prepositioning facilities

No	Type of facility	Location	Source of replenishment	Operator
1	Regional Logistics Unit	Kuala Lumpur	Directly from the suppliers of relief items	Typically, IHOs (for example, IFRC)
2	Regional port terminal	Singapore	Directly from the suppliers of relief items	Shipping company
3	Port terminals	Tianjin, Shanghai, Laem Chabang, Singapore, Jakarta and Chennai	Regional port terminal, Singapore	Shipping company
4	On-board vessels	1 vessel operating on the Intra Asia NE – SE route and 4 vessels operating on the SE Asia Express route	Regional port terminal, Singapore	Shipping company

Commercial prices and, where relevant, the lead times of relevant logistical services were also obtained from the same shipping firm. Data concerning the costs and transit times for air freight were obtained from World Freight Rates.[4]

5 Numerical experiments

In this section, we perform extensive numerical experiments to evaluate the prepositioning methods and transportation channels. In order to observe the contribution of each of the aforementioned delivery channels on the total logistical cost, five settings are compared.

- In setting 1, which represents today's situation, the only available channel during emergency period is on-demand delivery from the RLU by air; that is, channel 1.
- In setting 2, in addition to channel 1, on-demand dispatch of disaster relief items from the RLU by sea to ports and then by land to distribution points (that is, channel 2) is allowed as well.
- In setting 3, channels 1 and 3 (that is, prepositioning at port terminals) are allowed.
- In setting 4, in addition to channels 1 and 3, channel 4 (prepositioning on-board vessels) is also allowed.
- Finally, in setting 5, which represents a somehow ideal situation, all of the channels are allowed.

The model is programmed in the AIMMS® environment and solved using the CPLEX® 12.6.1 solver. The solution time for setting 5, which is the largest setting in terms of the number of variables and constraints, is 8 minutes and 38 seconds on a computer with an Intel® Core™ i5-3320M processor and a Microsoft Windows® 7 Enterprise 64-bit operating system. That is

[4] http://worldfreightrates.com/

acceptable considering the size of the problem (168,106 variables and 20,253 linear constraints) and the frequency of usage. Furthermore, this solution time was achieved without any initial solution.

5.1 Performance of the prepositioning method in different settings

Table 2 shows the (maximum) number of pallets to be prepositioned at the RLU, the regional port terminal (Singapore), the port terminals, and on-board the vessels. Table 3 shows the logistical costs per pallet per week in the optimal solution for different settings. It is interesting that in the settings where storage on-board vessels is allowed (settings 4 and 5), there is an inventory on board in the optimal solution. Similarly, wherever storage in the terminals of the affiliate shipping company is allowed (settings 3, 4 and 5), there is a stock of disaster relief items at both the smaller port terminals and the regional port terminal (Singapore). This shows that prepositioning can contribute to cost reduction. In addition, the difference between prepositioned inventory at the Singapore terminal in settings 4 and 5 shows that if on-demand sea transport from the RLU is not possible (setting 4), quite a large amount of inventory must be prepositioned at the regional port terminal in order to feed the vessels and avoid high air transport costs.

Table 2. Number of pallets to be prepositioned at prepositioning facilities

Setting	Prepositioned inventory (pallets)			
	RLU	***Terminals***	***Singapore***	***Vessels***
1	2694	0	0	0
2	4041	0	0	0
3	2419	2990	526	0
4	2694	58	2694	330
5	3882	832	275	552

A look at the costs shows that, as expected, whenever all of the channels are available (setting 5), the total cost will be the lowest. However, among the other settings, it is setting 2 that has a significantly lower cost (even close to setting 5). Therefore, in the given example, it is the on-demand sea transport option that has the greatest effect on cost reduction, even greater than the effect of prepositioning.

Table 3. Optimal logistical costs per pallet per week for different settings

Planning period (weeks)		**1760**		**Total demand (pallets)**		**89667**	
Per pallet per week costs (US dollars)							
Setting	***Total***	***Holding***	***Replenishment***	***Transport***	***Air transport from the RLU***	***Sea transport from the RLU***	***Land transport***
1	0.812	0.091	0.000	0.721	0.721	0.000	0.000
2	0.498	0.136	0.000	0.362	0.288	0.075	0.000
3	0.708	0.171	0.010	0.527	0.500	0.000	0.027
4	0.811	0.097	0.000	0.715	0.713	0.000	0.002
5	0.483	0.160	0.004	0.318	0.238	0.064	0.016

5.2 Sensitivity analysis

In order to reach some general conclusions and to cope with the latent uncertainty in the parameters, we conducted a sensitivity analysis on some of the important parameters. The sensitivity analysis was conducted on setting 5 where all of the channels are available.

5.2.1. Sensitivity analysis on the length of the emergency period

When a disaster occurs, the demand for disaster relief items for the whole emergency period is estimated. This demand is then distributed evenly over the emergency period. Therefore, the length of the emergency period goes hand in hand with how quickly disaster relief items are required at disaster locations. Specifically, we are interested in the effects of the length of the emergency period on the use of different channels. The results are presented in Table 4.

Table 4. Sensitivity analysis of the length of the emergency period

Emergency period (weeks)	**Setting**	**Total cost per week per pallet**	**Prepositioned inventory (pallets)**				
			RLU	***Singapore***	***Terminals***	***Vessels***	***Total***
6	5	0.74	6132	338	1227	0	7696
7	5	0.73	6310	275	1025	275	7885
8	5	0.67	5823	275	835	283	7216
9	5	0.61	5176	275	834	282	6567
10	5	0.56	4658	275	833	282	6048
11	5	0.52	4235	275	832	281	5623
12	5	0.48	3882	275	832	552	5540
13	5	0.45	3583	275	831	587	5277
14	5	0.43	3327	275	831	593	5027
15	5	0.41	3105	275	831	585	4796
16	5	0.39	2910	275	831	591	4608
17	5	0.37	2738	275	832	590	4435
18	5	0.36	2585	275	832	589	4282

The total cost decreases as the length of the emergency period increases because longer periods provide greater opportunities to use less costly (but slower) channels. It is also interesting that the total prepositioned inventory, including that of the RLU, declines as the emergency period becomes longer. This could be due to lower need to keep inventory at storage points when the emergency period is longer and, consequently, the lower demand per period. This makes it possible to order what is needed instead of keeping it in stock. The only type of prepositioned inventory whose level increases as the emergency period is prolonged is the inventory on-board vessels; this is because this inventory can serve disasters in multiple locations. Therefore, it can aggregate the demand at one place and, consequently, contributes to cost reduction. However, this channel is comparatively slow, since it may take some time to receive the pallet at the ports from which they are going to be forwarded to the disaster locations. Therefore, the emergency period must be long enough to justify the use of this channel. Furthermore, the level of prepositioned inventory at the terminals of the affiliate shipping company (both the Singapore regional port terminal and the port terminals) does not change much, partly due to the minimum requirements of prepositioning in the proximity of the disaster locations, specifically during the early weeks after disasters. Figure 2 summarizes the results in one chart, where the total cost and storage levels are normalized; that is, divided by the maximum observed value.

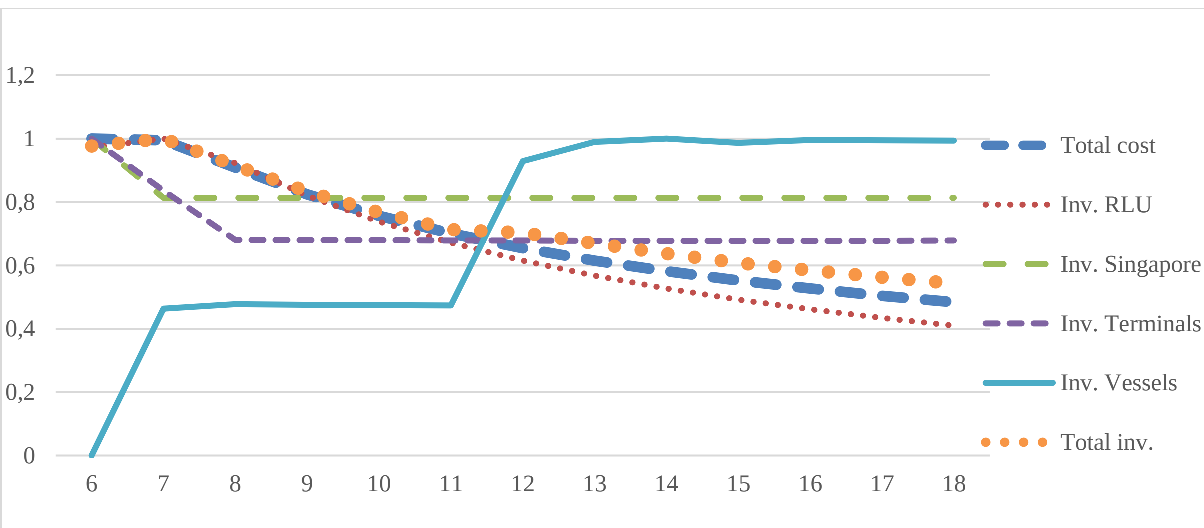


Figure 2. Sensitivity analysis of the length of the emergency period

5.2.2. Sensitivity analysis on the storage costs

In order to study the effects of storage costs on the preference of different channels, we conducted a sensitivity analysis on a parameter; namely, the *storage cost ratio*. This parameter shows the ratio of offshore (on-board the vessels) storage cost to on-shore (port terminals, regional port terminal, and the RLU) storage cost per pallet per time unit. Therefore, the greater the storage cost ratio, the costlier offshore prepositioning will be compared to on-shore prepositioning. In the case presented in the paper, all of the on-shore storage costs (per pallet per time unit) are equal. Also, offshore storage cost is the same for all of the vessels. To calculate offshore storage cost based on storage cost ratio, we use the following formulas:

$$h_{ij}^{V} = v + w = \omega . s + w, \quad \forall i, j \tag{25}$$

$$h_{pj}^{P} = h_{gj}^{G} = h_{rj}^{R} = s + w, \quad \forall p, g, r, j \tag{26}$$

where ω, s, v and w denote storage cost ratio, on-shore storage cost, offshore storage cost, and inventory holding cost, respectively (all per pallet per time unit).

The results are shown in Table 5. Figure 3 shows the optimal prepositioned inventory plotted versus storage cost ratio.

Table 5. Sensitivity analysis of the storage costs

Storage cost factor	**Total cost per week per pallet**	**Prepositioned inventory (pallets)**			
		RLU	Terminals	Singapore	Vessels
0	0.467	3882	832	275	1400
0.1	0.470	3882	832	275	1337
0.2	0.472	3882	832	275	1337
0.3	0.474	3882	832	275	1273
0.4	0.476	3882	832	275	1207
0.5	0.477	3882	832	275	1025
0.6	0.479	3882	832	275	998
0.7	0.480	3882	832	275	998
0.8	0.481	3882	832	275	998
0.9	0.482	3882	832	275	668
1	0.483	3882	832	275	552
1.1	0.483	3882	832	275	275
1.2	0.484	3882	832	275	275

1.3	0.484	3882	832	275	275
1.4	0.484	3882	832	275	275
1.5	0.484	3882	832	275	275
1,6	0,484	3882	832	275	275
1,7	0,485	3870	844	275	0
1,8	0,485	3870	844	275	0
1,9	0,485	3870	844	275	0
2	0,485	3870	844	275	0

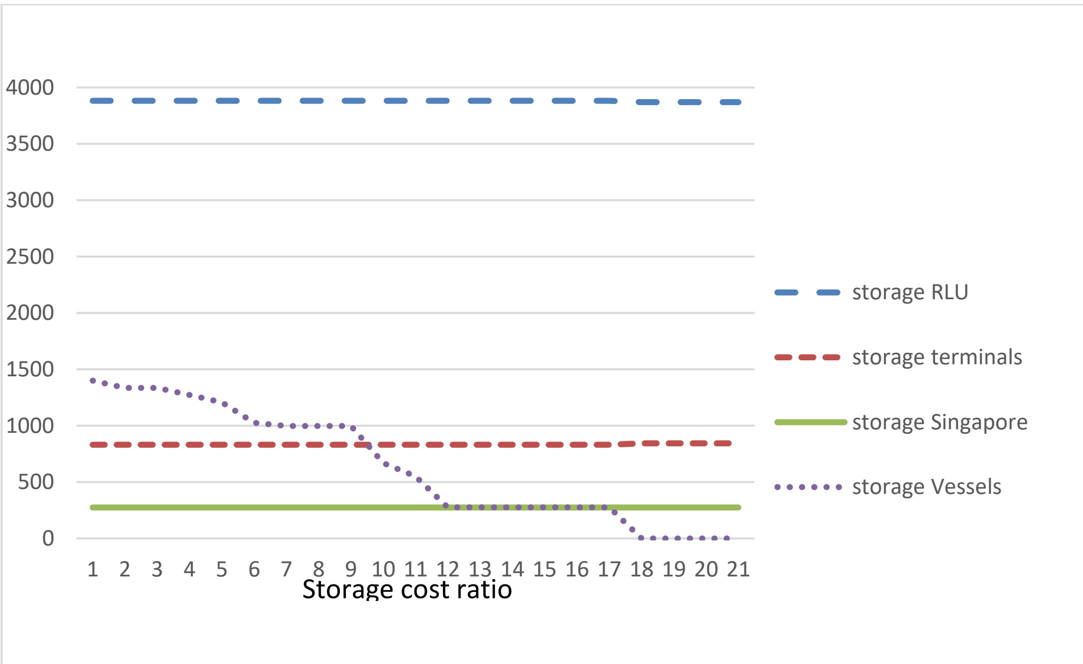


Figure 3. Sensitivity analysis of the prepositioned inventories versus storage cost ratio

It is interesting that the storage level at all of the nodes of the network remains almost unchanged as the storage cost ratio (hence storage cost on-board) increases. Only the offshore prepositioned inventory is affected by storage cost on-board. If storage cost on-board increases, the prepositioned inventory on-board decreases, but it is not stored elsewhere in the network. In fact, when storage cost on-board increases, prepositioned inventory on-board is replaced with on-demand dispatch from on-shore facilities. Note that the level of inventory in on-shore facilities does not increase, since the relief items are replenished if necessary. Therefore, within the given example, prepositioning offshore and on-shore are complementary rather than competing methods.

Finally, the sensitivity analysis shows that if the storage cost on-board is more than 1.7 times the storage cost on-shore, prepositioning of inventory on the vessels is no longer reasonable, regardless of how much flexibility it adds to the network.

6 Discussion, conclusions, and further research

Relief items are essentially one of the core elements in humanitarian relief operations and, depending on where they are prepositioned, can determine the cost and speed of the operations. This paper presents a linear programming model for simultaneous on-shore and off-shore prepositioning of relief items for efficient disaster relief operations. The model can determine the optimal level of prepositioned inventory of disaster relief items at given on-shore storage facilities as well as on-board vessels, which travel through given commercial liner shipping routes. The model can be also used to plan period-to-period flows of disaster relief items between supply, storage, and demand points, which are operational decisions. The objective function of the model is to minimize costs, including the inventory holding cost, transportation cost, and the part of replenishment costs, without compromising on the speed of the response. The model provides disaster relief networks with a solution, which, in addition to being effective and effiecient, is resilient. Referring to the three characteristics mentioned earlier in the literature review section, which enhance resilience in disaster relief networks (Day, 2014), the resilience goal is achieved by satisfying demand for relief items by using parallel sources, links and modes of transport that contribute to redundancy, flexibility and adaptability.

Using a real-world case, the results obtained from the model show that prepositioning of disaster relief items at land (port) terminals, in combination with prepositioning on-board vessels, does contribute to the reduction of logistical costs while providing disaster locations with the required relief items during emergency period. Furthermore, the sensitivity analysis signifies that if the emergency period becomes longer but total demand remains the same (that is, if emergency demand is distributed over a longer period of time), prepositioning on-board vessels can partly replace other channels of delivering disaster relief items such as prepositioning at terminals and on demand air transport. Moreover, sensitivity analysis indicates that as inventory holding cost on-board vessels increases, it mainly affects only the prepositioned inventory on-board vessels (to be reduced). Inventory prepositioned in other places will not increase to compensate that; other delivery channels will replace it.

The model is formulated from a very general perspective. That is, it can be used to plan disaster relief networks with multiple relief items, multiple RLUs, multiple regional port terminals, and multiple port terminals, while storage points can be linked to multiple ports, distribution points, and disaster locations. However, the topology of the distribution network in the given case is quite specific. For further research, it would be interesting to test the model on cases with a higher number of disasters and more complex network topologies. The aspect of environmental impact of the disaster relief operations when using on-board prepositioning could also be an interesting area of research. Furthermore, in the problem studied in this paper, all parameters are given and deterministic. The same sensitivity analysis approach can be used to deal with uncertainty in parameters by creating several scenarios or changing values of the parameters. Nonetheless, it would be interesting to develop a model for a stochastic scenario in which some of the parameters, such as the travel times, costs, or demands, are not deterministic. Last but not least, to enhance the advantage of the concept of simultaneous on-shore and off-shore prepositioning, there is a need to study the implications for ‘softer issues’ such as information diffusion, culture, responsibility, and collaboration.

Acknowledgment

The authors would like to thank the guest editor and anonymous reviewers whose constructive comments and suggestions helped us to improve the quality of this paper.

References

Acimovic, J., & Goentzel, J. 2016. Models and metrics to assess humanitarian response capacity. Journal of Operations Management, 45:11–29.

Akkihal, A. R. 2006. Inventory pre-positioning for humanitarian operations. Massachusetts Institute of Technology.

Apte, A., Yoho, K., Greenfield, C., & Ingram, C. 2012. An analysis of United States Navy disaster relief operations. In Proceedings of the 41st Annual Meeting of Western Decision Sciences Institute.

Balcik, B., & Ak, D. 2014. Supplier selection for framework agreements in humanitarian relief. Production and Operations Management, 23(6): 1028–1041.

Beach, N. V. 2010. Systems architecture of a sea base surface connector system in a 2020 humanitarian assistance/disaster relief joint operational environment. DTIC Document.

Bemley, J. L., Davis, L. B., & Brock III, L. G. 2013. Pre-positioning commodities to repair maritime navigational aids. Journal of Humanitarian Logistics and Supply Chain Management, 3(1): 65–89.

Bhamra, R., Dani, S., & Burnard, K. 2011. Resilience: the concept, a literature review and future directions. International Journal of Production Research, 49(18): 5375–5393.

Caunhye, A. M., Nie, X., & Pokharel, S. 2012. Optimization models in emergency logistics: A literature review. Socio-Economic Planning Sciences, 46: 4–13.

Clark, V. 2002. Sea Power 21: Projecting decisive joint capabilities. DTIC Document.

Datta, P., & Datta, P. 2017. Supply network resilience: a systematic literature review and future research. The International Journal of Logistics Management, 28(4): 1387–1424.

Day, J. M. 2014. Fostering emergent resilience: the complex adaptive supply network of disaster relief. International Journal of Production Research, 52(7): 1970–1988.

Dubey, R., Ali, S. S., Aital, P., & Venkatesh, V. G. 2014. Mechanics of humanitarian supply chain agility and resilience and its empirical validation. International Journal of Services and Operations Management, 17(4): 367–384.

Dubey, R., & Gunasekaran, A. 2016. The sustainable humanitarian supply chain design: agility, adaptability and alignment. International Journal of Logistics Research and Applications, 19(1): 62–82.

Duhamel, C., Santos, A. C., Brasil, D., Châtelet, E., & Birregah, B. 2016. Connecting a population dynamic model with a multi-period location-allocation problem for post-disaster relief operations. Annals of Operations Research, 247(2): 693–713.

Duran, S., Gutierrez, M. A., & Keskinocak, P. 2011. Pre-positioning of emergency items for care international. Interfaces, 41: 223–237.

Duran, S., Ergun, Ö., Keskinocak, P., & Swann, J. L. 2013. Humanitarian logistics: advanced purchasing and pre-positioning of relief items. In Handbook of global logistics (pp. 447-462). Springer New York.

Fransoo, J. C., & Lee, C. Y. 2013. The critical role of ocean container transport in global supply chain performance. Production and Operations Management 22(2): 253–268.

Gatignon, A., Van Wassenhove, L. N., & Charles, A. 2010. The Yogyakarta earthquake: Humanitarian relief through IFRC's decentralized supply chain. International Journal of Production Economics, 126: 102–110.

Gharehgozli, A. H., Roy, D., & de Koster, R. 2016. Sea Container Terminals: Recent Developments and OR Models. Maritime Economics and Logistics, 18(2): 103–140.

Gharehgozli, A. H., Mileski, J., Adams, A. & von Zharen, W. 2017. Evaluating a "Wicked Problem": A Conceptual Framework on Seaport Resiliency in the Event of Weather Disruptions. Technological Forecasting & Social Change. Forthcoming.

Gorman M., Clarke, J. P., Gharehgozli, A. H., Hewitt, M. de Koster, R., & Roy, D. 2014. State of the Practice: Application of OR/MS in Freight Transportation. Interfaces 44(6): 535–554.

Gunasekaran, A., Subramanian, N., & Rahman, S. 2015. Supply chain resilience: role of complexities and strategies, International Journal of Production Research, 53(22): 6809–6819.

Hu, C.L., Liu, X., & Hua, Y.K. 2016. A bi-objective robust model for emergency resource allocation under uncertainty, International Journal of Production Research, 54(24): 7421-7438.

Ivanov, D., Sokolov, B., & Dolgui, A. 2014. The Ripple effect in supply chains: trade-off 'efficiency-flexibility-resilience' in disruption management. International Journal of Production Research, 52(7): 2154–2172.

Jahre, M., Kembro, J., Rezvanian, T., Ergun, O., Håpnes, S. J., & Berling, P. 2016a. Integrating supply chains for emergencies and ongoing operations in UNHCR. Journal of Operations Management, 45: 57–72.

Jahre, M., Pazirandeh, A., & Van Wassenhove, L. N. 2016b. Defining logistics preparedness: a framework and research agenda. Journal of Humanitarian Logistics and Supply Chain Management, 6(3): 372–398.

Jahre, M., Navangul, A. K., Dieckhaus, D., Heigh, I., & Gomez-Tagle Leonard, N. 2011. Predicting the unpredictable – demand forecasting in international humanitarian response. In Proceedings of the 23rd Annual NOFOMA Conference. Harstad, Norway (pp. 265–281).

Lee, J. R. 1999. Prepositioning: A Logistics Concept for the AEF. Air Command and Staff College, USAF.

Lee, C. Y., & Song, D. P. 2017. Ocean container transport in global supply chains: Overview and research opportunities. Transportation Research Part B: Methodological, 95: 442–474.

Liu, F., Song, J. S., & Tong, J. D. 2016. Building supply chain resilience through virtual stockpile pooling. Production and Operations Management, 25(10): 1745–1762.

Majewski, B., Navangul, K. A., & Heigh, I. 2010. A Peek into the Future of Humanitarian Logistics: Forewarned is Forearmed. Supply Chain Forum: an International Journal, 11: 4–19.

Manopiniwes, W., & Irohara, T. 2017. Stochastic optimisation model for integrated decisions on relief supply chains: preparedness for disaster response. International Journal of Production Research, 55(4): 979–996.

Martinez, M. R. 2008. Lessons from Significant Foreign Disaster Relief Operations Applied to AFRICOM. DTIC Document.

Matopoulos, A., Kovács, G., & Hayes, O. 2014. Local resources and procurement practices in humanitarian supply chains: An empirical examination of large ‐ scale house reconstruction projects. Decision Sciences, 45(4), 621–646.

Miller-Hooks, E., Zhang, X., & Faturechi, R. 2012. Measuring and maximizing resilience of freight transportation networks. Computers & Operations Research, 39(7): 1633–1643.

Ozkapici, D. B., Ertem, M. A., & Aygunes, H. 2016. Intermodal humanitarian logistics model based on maritime transportation in Istanbul. Natural Hazards, 83: 345–364.

Papadopoulos, T., Gunasekaran, A., Dubey, R., Altay, N., Childe, S. J., & Fosso-Wamba, S. 2017. The role of Big Data in explaining disaster resilience in supply chains for sustainability. Journal of Cleaner Production, 142: 1108–1118.

Ponomarov, S. Y., & Holcomb, M. C. 2009. Understanding the concept of supply chain resilience. The International Journal of Logistics Management, 20(1): 124–143.

Ransikarbum, K., & Mason, S. J. 2016. Multiple-objective analysis of integrated relief supply and network restoration in humanitarian logistics operations. International Journal of Production Research, 54(1): 49–68.

Sarkis, J., Spens, K. M, & Kovács, G. 2012. A study of barriers to greening the relief supply chain. Relief Supply Chain Management for Disasters: Humanitarian, Aid and Emergency Logistics, IGI Global: 196–207.

Scholten, K., Sharkey Scott, P., & Fynes, B. 2014. Mitigation processes–antecedents for building supply chain resilience. Supply Chain Management: An International Journal, 19(2): 211–228.

Singh, R. K., Gupta, A., & Gunasekaran, A. 2018. Analysing the interaction of factors for resilient humanitarian supply chain. International Journal of Production Research, DOI: 10.1080/00207543.2018.1424373.

Sokolov, B., Ivanov, D., Dolgui, A., & Pavlov, A. 2016. Structural quantification of the ripple effect in the supply chain. International Journal of Production Research, 54(1): 152–169.

Tatham, P. & Kovacs, G. 2007. An initial investigation into the application of the military sea-basing concept to the provision immediate relief in a rapid onset disaster. POMS 18th Annual Conference, Texas, USA: 4–7.

Tofighi, S., Torabi, S. A., & Mansouri, S. A. 2016. Humanitarian logistics network design under mixed uncertainty. European Journal of Operational Research, 250(1): 239–250.

Ukkusuri, S. V., & Yushimito, W. F. 2008. Location routing approach for the humanitarian prepositioning problem. Transportation Research Record: Journal of the Transportation Research Board, 2089, 18–25.

Van Wassenhove, L. 2006. Humanitarian aid logistics: supply chain management in high gear. Journal of the Operational Research Society, 57: 475–489.

Van Wassenhove, L., & Pedraza-Martinez, A.J., 2012. Using OR to adapt supply chain management best practices to humanitarian logistics. International Transactions in Operations Research, 19 (1–2): 307–322.

Wilberg, K. H., & Olafsen, A. L. 2012. Improving humanitarian response through an innovative pre-positioning concept: an investigation of how commercial vessels can be used to store and transport relief items. Unpublished MSc thesis, BI Norwegian Business School, Oslo

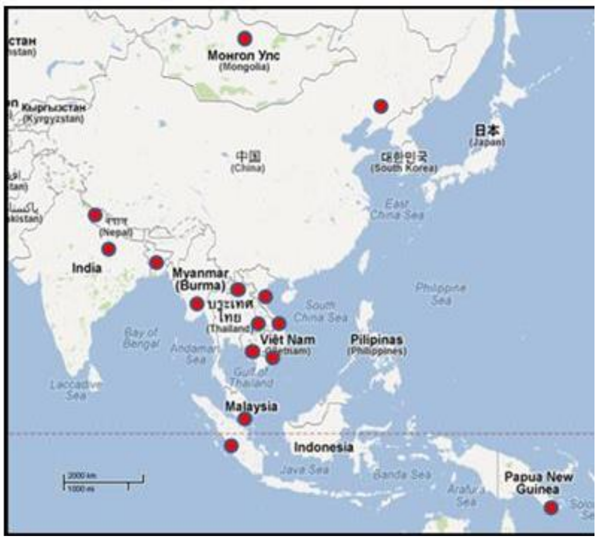
Zobel, C. W., & Khansa, L. 2014. Characterizing multi-event disaster resilience. Computers & Operations Research, 42: 83–94.

Appendix A. Case study data

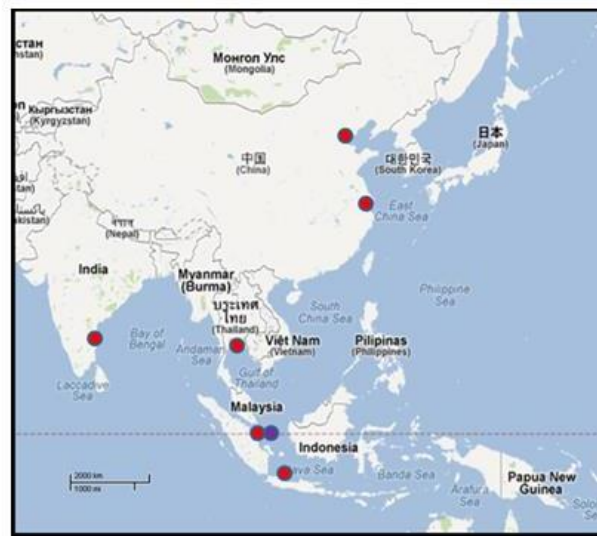
Table 6. Key data related to disasters (source: www.emdat.be; Jahre et al., 2011; Wilberg and Olafsen, 2012)

Disaster code	*Country*	*Disaster Type*	*Date of occurrence*	*Demand for relief items (Pallets)*
2007-0311	Bangladesh	Flood/Hurricane	21.07.2007	8613
2009-0414	Cambodia	Flood/Hurricane	29.09.2009	12569
2007-0274	Cambodia	Flood/Hurricane	01.07.2007	155
2005-0475	China	Flood/Hurricane	13.08.2005	3926
2007-0320	India	Flood/Hurricane	07.03.2007	32327
2009-0421	Indonesia	Flood/Hurricane	30.09.2009	10763
2008-0452	Laos	Flood/Hurricane	18.08.2008	3014
2007-0021	Malaysia	Flood/Hurricane	01.11.2007	699
2009-0632	Mongolia	Flood/Hurricane	01.12.2009	1869
2006-0241	Myanmar	Flood/Hurricane	03.08.2006	40
2009-0434	Nepal	Flood/Hurricane	10.04.2009	8615
2007-0557	Papua N.G	Flood/Hurricane	11.12.2007	1092
2010-0120	Solomon Is	Flood/Hurricane	15.03.2010	6
2006-0648	Vietnam	Flood/Hurricane	30.11.2006	113
2009-0611	Vietnam	Flood/Hurricane	25.09.2009	5241
2008-0329	Vietnam	Flood/Hurricane	08.08.2008	625

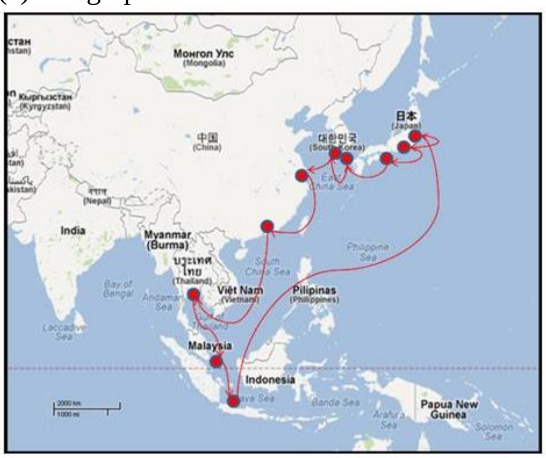
Appendix B. Geographical locations of the disasters and the trade routes in the case study



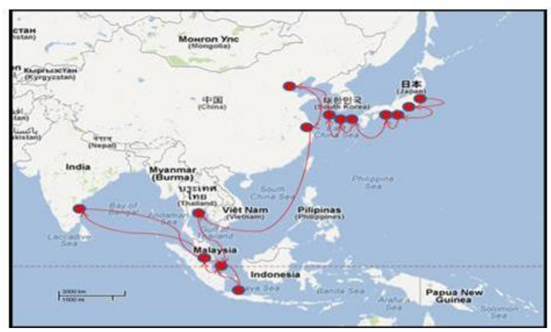
(a) Geographical location of the disasters



(b) Geographical locations of the 6 port terminals



(c) Intra Asia NE – SE trade route



(d) SE – Asia trade route

Figure 4. Geographical representation of the case study (Wilberg and Olafsen, 2012)

Appendix C. indices, parameters and decisions variables of the model

Sets of indices
R: Set of RLUs
G: Set of regional port terminals
P: Set of port terminals
V: Set of vessels on liner shipping routes
D: Set of disasters; if multiple disasters occur in (almost) the same location, each one must be given a different index in the set.
T: Set of time periods
S: Set of disaster relief items

Parameters
c_{pdj}^{P} : Cost of transporting 1 unit of disaster relief item j from port terminal p to disaster location (corresponding distribution point) d on road
c_{rdj}^{RF} : Cost of transporting 1 unit of disaster relief item j from RLU r to disaster location (or the corresponding distribution point) d by air (the faster and more expensive mode of transport). This includes eventual road transport costs between the RLU and airport, as well as between the airport and distribution point.
c_{rdj}^{RS} : Cost of (on-demand) transportation of 1 unit of disaster relief item j from RLU r to disaster location (or the corresponding distribution point) d by sea and road (the slower and cheaper mode of transport)
c_{gpj}^{GS} : Cost of on-demand shipping directly (not to be mistaken for the stock held on-board vessels on liner shipping routes) 1 unit of disaster relief item j from regional port terminal g to port p
c_{gdj}^{GF} : Cost of transporting 1 unit of disaster relief item j from regional port terminal g to disaster location (corresponding distribution point) d by air; note that cost of land transport from the destination airport to the corresponding distribution point is also included in the above "air transport cost".
τ_{pd}^{P} : Transport time of disaster relief items from port terminal p to disaster location (corresponding distribution point) d on road. All transport times are given in terms of the number of periods.
τ_{rd}^{RF} : Transport time of disaster relief items from RLU r to disaster location (corresponding distribution point) d by air (the faster and more expensive mode of transport)
τ_{rd}^{RS} : Transport time of disaster relief items from RLU r to disaster location (corresponding distribution point) d by sea and road (the slower and cheaper mode of transport)
τ_{gp}^{GS} : Direct shipping time of disaster relief items from regional port terminal g to port terminal p
τ_{gp}^{GF}: Transport time of disaster relief items from regional port terminal g to disaster location (corresponding distribution point) d by air
b_{i}^{V} : Maximum capacity (volume) of vessel i that can be assigned to store disaster relief items on board
b_{p}^{P} : Maximum capacity (volume) of port terminal p that can be assigned to store disaster relief items
b_{r}^{R} : Maximum capacity (volume) of RLU r that can be assigned to store disaster relief items
b_{g}^{G} : Maximum capacity (volume) of regional port terminal g that can be assigned to store disaster relief items

h_{ij}^{V} : Cost of holding one unit of disaster relief item j on board vessel i for one time period h_{pj}^{P} : Cost of holding one unit of disaster relief item j at port terminal p for one time period h_{gj}^{G} : Cost of holding one unit of disaster relief item j at regional port terminal g for one time period h_{rj}^{R} : Cost of holding one unit of disaster relief item j at RLU r for one time period k_{ij}^{V} : Cost of replenishing one unit of disaster relief item j on vessel i k_{pj}^{P} : Cost of replenishing one unit of disaster relief item j at port terminal p k_{gj}^{G} : Cost of replenishing one unit of disaster relief item j at regional port terminal g k_{rj}^{R} : Cost of replenishing one unit of disaster relief item j at RLU r q_{djt}: Quantity of disaster relief item j needed at disaster location d at period t Including index d in the above parameter as well as some other parameters and variables, ensures that no emergency action (such as dispatching of disaster relief items to disaster locations) will be taken before the corresponding disaster happens. However, that is only possible if no two disasters overlap. Another parameter, θ_d, will be introduced to denote when a disaster happens. Then, constraints are added to the model to ensure nothing is done for a disaster before it happens. a_{ipt}^{P}: It is 1 if vessel i visits port terminal p at period t, and 0 otherwise. a_{igt}^{G}: It is 1 if vessel i visits regional terminal (port) g at period t, and 0 otherwise. ρ_p^P: Replenishment lead time for port terminal p ρ_g^G: Replenishment lead time for regional port terminal g ρ_r^R: Replenishment lead time for RLU r θ_d: Time period when disaster d occurs m_j: Volume of one unit of disaster relief item j

Decision variables
x_{ij}^{V}: [Maximum] inventory of disaster relief item j to be held on board vessel i x_{pj}^{P}: [Maximum] inventory of disaster relief item j to be held at port terminal p x_{gj}^{G}: [Maximum] inventory of disaster relief item j to be held at regional port terminal g x_{rj}^{R}: [Maximum] inventory of disaster relief item j to be held at RLU r I_{ijt}^{V}: Inventory level of disaster relief item j on board vessel i at the end of period t I_{pjt}^{P}: Inventory level of disaster relief item j at port terminal p at the end of period t I_{gjt}^{G}: Inventory level of disaster relief item j at regional port terminal g at the end of period t I_{rjt}^{R}: Inventory level of disaster relief item j at RLU r at the end of period t I_{djt}^{D}: Total inventory level of disaster relief item j at the distribution points of disaster location d at the end of period t y_{ipdjt}^{V}: Quantity of disaster relief item j delivered from vessel i to port terminal p at period t to be immediately dispatched towards the disaster location d Replenishment costs of the vessels can include the cost of unloading items from vessels, loading on trucks and other necessary operations done at ports.

y_{pdjt}^{P}: Quantity of disaster relief item j dispatched from the inventory held at port terminal p to disaster location d at period t

y_{rdjt}^{RF}: Quantity of disaster relief item j dispatched from RLU r by air (the faster and more expensive mode of transport) to disaster location d at period t

y_{rdjt}^{RS}: Quantity of disaster relief item j dispatched from RLU r by sea and land (the slower and cheaper mode of transport) to disaster location d at period t

y_{gpdjt}^{GS}: Quantity of disaster relief item j sent by sea from regional port terminal g to port p at period t to be immediately transferred from the port towards the disaster location d

y_{gdjt}^{GF}: Quantity of disaster relief item j sent by air from regional port terminal g to disaster location d at period t