Facility location in humanitarian relief

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In this study, we consider facility location decisions for a humanitarian relief chain responding to quick-onset disasters. In particular, we develop a model that determines the number and locations of distribution centres in a relief network and the amount of relief supplies to be stocked at each distribution centre to meet the needs of people affected by the disasters. Our model, which is a variant of the maximal covering location model, integrates facility location and inventory decisions, considers multiple item types, and captures budgetary constraints and capacity restrictions. We conduct computational experiments to illustrate how the proposed model works on a realistic problem. Results show the effects of pre- and post-disaster relief funding on relief system's performance, specifically on response time and the proportion of demand satisfied. Finally, we discuss the managerial implications of the proposed model.

Keywords: Humanitarian relief chains; Emergency logistics; Facility location problem

1. Introduction

The numbers of natural disasters and the people affected by disasters have increased over recent years. The average annual number of disasters during 2000–2004 was 55% higher than during 1995–1999, and disasters affected 33% more people during 2000–2004 than during 1995–1999 (IFRC 2005). The number of people affected by disasters continued to rise in 2005; there was an 18% increase in disasters, and 157 million people – seven million more than in 2004 – required immediate assistance, were evacuated, injured or lost their livelihoods (ISDR 2006). The trends in the number and impact of disasters and the massive scale of recent global relief efforts have brought growing attention to the need for effective and efficient disaster response operations.

The objective of disaster response in the humanitarian relief chain is to rapidly provide relief (emergency food, water, medicine, shelter, and supplies) to areas affected by large-scale emergencies, so as to minimize human suffering and death (Beamon and Balcik, forthcoming). Therefore, the design and operation of the relief chain play significant roles in achieving an effective and efficient response. Although logistics is central to disaster response activities, for years, the aid sector's regard for logistics has been viewed as a necessary expense rather than an important strategic component of their work (Beamon and Kotleba 2006a). Only recently have humanitarian relief organizations begun to understand the criticality and importance of relief chain management on the success of disaster relief operations (Van Wassenhove 2006).

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Beamon (2004), Thomas and Kopczak (2005), and Van Wassenhove (2006) describe the unique characteristics of the disaster relief environment and compare and contrast humanitarian relief chains and commercial supply chains. There are fundamental differences between commercial supply chains and humanitarian relief chains in terms of their strategic goals, customer and demand characteristics, and environmental factors. The dominating characteristics that bring additional complexity and unique challenges to relief chain design and management that are most pertinent to our study are:

- unpredictability of demand, in terms of timing, location, type, and size,
- suddenly-occurring demand in very large amounts and short lead times for a wide variety of supplies,
- high stakes associated with adequate and timely delivery,
- lack of resources (supply, people, technology, transportation capacity, and money).

There are additional challenges and risks associated with post-disaster supply procurement. Acquisition and delivery of adequate relief supplies from local and/or international suppliers are typically time-consuming and expensive. Therefore, relief organizations engage in preparatory activities that enhance their logistics capabilities in responding to emergencies. Pre-positioning critical relief supplies in strategic locations around the world is a strategy recently implemented by some humanitarian relief organizations to improve their capacities in delivering sufficient relief aid within a relatively short timeframe.

Although pre-positioning increases the ability of relief organizations to mobilize relief supplies and deliver aid quickly, it can be financially prohibitive. As such, only a few relief organizations can support the expense of operating international distribution centres to store and distribute relief supplies. World Vision International (WVI) began operating a global pre-positioning system in 2000 (Beamon and Kotleba 2006a). Under the WVI system, relief supplies are pre-positioned in four locations (USA, Italy, Germany, and Dubai), and consist of pre-packaged modules, which can be immediately shipped anywhere in the world (Beamon and Kotleba 2006a). The World Food Programme (WFP) manages the United Nations Humanitarian Response Depot (UNHRD) in Italy with various partners (non-governmental organizations (NGOs), Office for the Coordination of Humanitarian Affairs, governments, etc.). UNHRD is capable of sending relief items anywhere in the world within 24–48 h to meet the needs of people affected by natural disasters and complex emergencies (UNHRD 2007).

In this study, we consider facility location and stock pre-positioning decisions in a humanitarian relief chain responding to quick-onset disasters. Facility location decisions affect the performance of relief operations, since the number and locations of the distribution centres and the amount of relief supply stocks held therein directly affect the response time and costs incurred throughout the relief chain. However, given the complexities and uncertainties of the operating environment, it is challenging for relief organizations to set up effective and efficient humanitarian relief networks. Indeed, the majority of NGOs avoids the use of stockpiles considering them to be prohibitively complicated and expensive. In these cases, NGOs tend to rely on local and international procurement, both of which may be too slow to meet emergency requirements (Adinolfi *et al.* 2005). Moreover, since quantitative methods and principles that consider the unique characteristics of the relief environment are not widely developed and practiced, relief agencies may make facility location and stocking decisions using ad-hoc methods, which may lead to an inefficient (high costs, duplication of efforts, and waste of resources) and ineffective (slow response and unsatisfied demand) response. As observed by Adinolfi *et al.* (2005), there are no global stock positioning systems in the relief system to provide information on the quantity, quality, geographical location, and ownership of stocks. Therefore, the lack of a systematic approach and supporting infrastructure for relief chain

design may prevent relief organizations from accurately assessing their response capacity and performance.

Although research on facility location problems is extensive, in terms of theory and applications, these problems have not received much attention in the domain of humanitarian relief. In this study, we take a first step in characterizing the distribution network design problem in humanitarian relief and provide an analytical approach to assist decision-makers in making effective and efficient facility location and stock pre-positioning decisions. We consider a distribution system in which a relief organization locates distribution centres in the relief network to respond to disaster scenarios whose locations and impacts are known probabilistically. We develop a mathematical model that determines the number and locations of the distribution centres in the relief network and the amount of relief supplies to be stocked at each distribution centre. Our model is a variant of the maximal covering location model; it integrates facility location and inventory decisions, considers multiple items with different criticalities and response time requirements, and captures budgetary constraints and capacity restrictions.

The rest of the paper is organized as follows: section 2 reviews the relevant literature. Section 3 describes the system and problem in detail and presents our mixed integer programming (MIP) model formulation. Section 4 describes the data set developed and reports the results of the computational experiments performed. Section 5 discusses the managerial implications of the model. Finally, we conclude in section 6 and discuss future work.

2.   Literature review

The literature in the area of humanitarian relief logistics is largely focused on handbooks developed by individual relief organizations and training documents prepared by the United Nations (Beamon and Kotleba 2006b). These handbooks explain the nature of logistics operations in a relief environment and describe the general procedures followed in various relief sectors (*e.g.* Stephenson 1993, Hale 1999, PAHO 2001). There are some recent studies in the literature that describe the disaster relief environment, compare humanitarian relief chains and commercial sector supply chains, and identify the challenges and opportunities for humanitarian logisticians in applying supply chain practices to improve relief logistics (Beamon 2004, Thomas and Kopczak 2005, Van Wassenhove 2006, Oloruntoba and Gray 2006, Thomas 2007).

Below, we first review studies that address various logistical problems in disaster relief by developing mathematical models. Then we briefly review the relevant literature on facility location, focusing primarily on the maximal covering location problem (MCLP).

2.1   *Relief logistics*

Most of the studies in disaster relief logistics focus on operational logistical activities in the relief chain with the objective of optimizing the flow of supplies through existing distribution networks. Knott (1987) considers the last mile delivery of food items from a distribution centre to a number of refugee camps, assuming a single mode of transportation that makes direct deliveries to camps. The author develops a linear programming (LP) model to determine the number of trips to each camp to satisfy demand while minimizing the transportation cost or maximizing the amount of food delivered. Knott (1988) combines operations research heuristics with artificial intelligence techniques to develop a decision support tool for the same problem.

Haghani and Oh (1996) and Oh and Haghani (1997) determine detailed routing and scheduling plans for multiple transportation modes carrying various commodities from multiple supply

points in a disaster relief operation. The authors assume that the commodity quantities are known. They formulate a multi-commodity, multi-modal network flow problem with time windows as a large-scale MIP model on a time-space network with the objective of minimizing the sum of the vehicular flow costs, commodity flow costs, supply/demand carry-over costs and transfer costs over all time periods. They develop two heuristic solution algorithms; the first utilizes a Lagrangian relaxation approach, and the second employs an iterative fix-and-run process.

Barbarosoglu *et al.* (2002) focus on tactical and operational scheduling of helicopter activities in a disaster relief operation. They decompose the problem hierarchically into two sub-problems where tactical decisions are made in the top level, and the operational routing and loading decisions are made in the second level. The authors formulate MIP models for the tactical and operational problems, and solve them using an iterative coordination heuristic. Barbarosoglu and Arda (2004) develop a scenario-based, two-stage stochastic programming model for transportation planning in disaster response. This study expands on the deterministic multi-commodity, multi-modal network flow problem of Haghani and Oh (1996) by including relief network uncertainties related to supply, route capacities, and demand requirements. The authors test their approach on real-world problem instances.

Ozdamar *et al.* (2004) address an emergency logistics problem for distributing multiple commodities from a number of supply centres to distribution centres near the affected areas. They formulate a multi-period multi-commodity network flow model to determine pick up and delivery schedules for vehicles as well as the quantities of loads delivered on these routes, with the objective of minimizing the amount of unsatisfied demand over time. The structure of the proposed formulation enables them to regenerate plans based on changing demand, supply quantities, and fleet size. They develop an iterative Lagrangian relaxation algorithm and a greedy heuristic to solve the problem.

Angelis *et al.* (2007) consider a multi-depot, multi-vehicle routing, and scheduling problem for air delivery of emergency supply deliveries for the WFP based on WFP's operations in Angola in the year 2001. Planes deliver full cargo to single clients from the warehouses in port cities. The authors set a service level for food distribution and develop a linear integer–programming (IP) model that maximizes the total satisfied demand. They provide numerical results for real problem instances.

Beamon and Kotleba (2006a) develop an inventory management strategy for a warehouse supporting a long-term emergency relief operation. Their analysis is based on a case study of a single humanitarian agency operating a warehouse in Kenya, responding to the complex humanitarian emergency in south Sudan. The authors develop a multi-supplier inventory model that optimizes the reorder quantity and reorder level based on the costs of reordering, holding, and back-orders. Beamon and Kotleba (2006b) continue this work by comparing the performance of three inventory management strategies on the same problem. The authors develop a simulation model and a relief-specific performance measurement system to identify system factors that contribute most significantly to overall performance.

There is no study in the literature that addresses strategic configuration of the relief chain. In this study, we develop a formulation that captures the critical aspects of the facility location problem in humanitarian relief.

2.2 *Maximal covering location problem*

For years, Operations Research techniques have been applied to a large variety of problems to determine the optimal geographical locations for facilities (see Owen and Daskin 1998, Hale and Moberg 2003, Klose and Drexl 2005, and Revelle and Eiselt 2005 for recent surveys

on facility location research). Facility location problems derive their importance from two factors: their direct impact on the system's operating cost and timeliness of response to the demand (Haghani 1996). While the objective of facility location models addressing private sector problems is generally to minimize cost or maximize profit, the models addressing public and emergency services instead focus on user accessibility and response time (see ReVelle *et al.* (1977) and Marianov and ReVelle (1995) for a discussion and review of emergency service facility location problems).

Models with coverage-type objectives are extensively used in facility location research and applications, especially when response time is the primary performance criterion (see Schilling *et al.* (1993) and Daskin (1995) for a detailed discussion and review of covering models). In covering-type facility location models, a source of demand is defined as covered if it is located within a specified response distance or response time from a facility. The set covering models seek to choose facilities among a finite set of candidate sites such that all demand sources are covered with a minimum number of facilities. In disaster relief, this would mean that each potential demand point must be within a specified target response time of a facility in the relief network. However, it may not be cost-efficient or even feasible to cover the entire demand of every potential disaster scenario from distribution centres. Therefore, a maximal covering-type model that chooses facility locations to maximize the amount of covered demand subject to resource limitations is more suitable for relief chain network design.

The MCLP maximizes the total number of people served within a maximal service distance, given a fixed number of facilities or budget limitations. MCLP has a broad range of applications and has been studied extensively since its introduction by Church and ReVelle (1974). Here, our intent is not to provide an extensive review of MCLP and its extensions; instead, we provide examples most relevant to our study. An assumption of the MCLP is that the facilities being sited are incapacitated. Current and Storbeck (1988), Pirkul and Schilling (1991), and Haghani (1996) extend the MCLP by introducing capacity constraints on facilities. Another assumption of the basic MCLP is binary coverage; that is, a demand point is covered completely if it is located within a critical distance/time of the facility and not covered outside of the critical distance/time. Berman and Krass (2002), Berman *et al.* (2003), Drezner *et al.* (2004), and Karasakal and Karasakal (2004) extend the MCLP by modelling coverage as a gradual decline in coverage; that is, the coverage benefit provided to a demand point decreases with increasing distance from a facility. Finally, Viswanath and Peeta (2003) formulate a multi-commodity maximal covering network design model for identifying critical routes for earthquake response. The model determines the optimal flow of multiple commodities subject to budget constraints on bridge retrofitting costs on selected routes. The authors differentiate commodities based on unit routing costs; however, the commodities are identical in terms of coverage requirements.

In this study, we develop a model that is a synthesis of various extensions developed for the maximal covering model; it considers multiple items with different coverage requirements, budgetary constraints on logistics costs, capacity restrictions on located facilities, and allows stepwise partial coverage of customers. Additionally, our model integrates facility location and inventory decisions; that is, it approximates the amount of stock to pre-position at each facility and incorporates inventory costs, while determining the number and location of facilities to locate within the relief network.

3. System and model

In this section, we describe the key aspects of the relief system affecting facility location and inventory decisions, define the facility location problem, and present the model formulation.

3.1   *System description*

In this study, we consider the relief operations of humanitarian relief organizations responding
to quick-onset global disasters. The relief system involves a large number of actors and stake-
holders (beneficiaries, host governments, local and international relief organizations, donors,
etc.) and operates in highly unpredictable, dynamic and chaotic environments. Therefore, the
disaster response activities of relief organizations vary widely and are driven by numerous
factors depending on each situation's characteristics. The uncertainties and variability in the
relief environment leads to most logistical decisions being made after disasters occur. So,
unlike commercial supply chains, in which logistic operations are relatively established and
can regularly be planned in advance of demand, most logistical decisions in the relief chain are
made within shorter time frames. However, facility location and stock pre-positioning deci-
sions in the relief chain are critical components of disaster preparedness and hence require
long-term planning to achieve a high-performance disaster response. Facility location and
stock pre-positioning decisions interact with other logistical decisions at different levels. In
this section, we briefly describe the disaster response process and the logistical operations
in the relief chain that affect and are affected by facility location and stock pre-positioning
decisions.

Once a disaster occurs, demand for large amounts of a large variety of supplies occurs
suddenly in massive amounts. The general flow of resources to the affected areas is shown in
figure 1.

This flow of resources coincides with the four main phases of disaster relief, as identified
by Thomas (2002) and Beamon (2004): (1) assessment: minimal resources are required to
identify what is needed, (2) deployment: resource requirements ramp up to meet the needs, (3)
sustainment: operations are sustained for a period of time, and (4) reconfiguration: operations
are reduced, then terminated. The length of each phase in the relief cycle varies depending on
the disaster characteristics. However, the speed of relief operations during the first days of the
disaster significantly affects the lives of many people threatened by the disaster. Hence, the
ability of a relief organization to mobilize its resources during the assessment and deployment
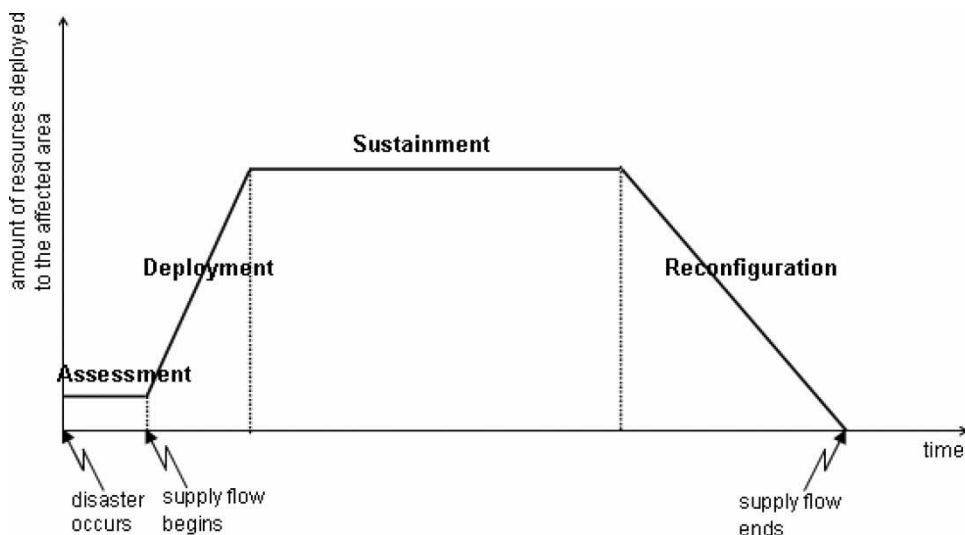phases is critical to the success of disaster response.

Figure 1.   Relief mission life cycle. *Source*: modified from Beamon (2004) and Thomas (2002).

An NGO's level of involvement in a disaster relief operation, in terms of the type and scope of logistics operations deployed may vary depending on factors such as the type, location, and impact of the disaster and resource availability. However, the flow of supplies in a typical relief distribution network is depicted in figure 2.

As illustrated in figure 2, once a disaster occurs, NGOs can acquire relief supplies from three main sources: local suppliers, international suppliers, and distribution centres (pre-positioned stocks). There are advantages and disadvantages associated with each sources.

3.1.1 Local procurement.   Acquiring supplies locally may be advantageous due to low transportation costs, prompt deliveries (no customs clearance, no delays due to congestion at the ports, etc.), and the support it provides to the local economy (PAHO 2001). Although meeting a country's emergency needs from local resources could be considered as the best procurement scenario for many reasons (including these), it may be risky to develop a response strategy that depends solely on local sources. For instance, local supplies may not always be available in the quantity and quality needed. Local procurement may also create local competition among relief organizations trying to purchase the same types of supplies, and finally may create shortages in the local market (PAHO 2001). Therefore, relief agencies procuring locally must develop contingencies for acquiring supplies from other (non-local) sources.

3.1.2 Global procurement.   Using global suppliers in post-disaster procurement increases the availability of large quantities of high-quality supplies. The potential disadvantage lies in longer delivery times and higher transportation costs (PAHO 2001). NGOs commonly acquire relief items from global suppliers through a competitive bidding process. In this process, NGOs first identify potential suppliers meeting item specifications and delivery requirements. Next, qualified suppliers are invited to bid. Finally, NGOs evaluate suppliers' offers and execute contracts with the winning suppliers, after which the delivery of supplies to the affected areas begins. As a result, supplies acquired by this process may not be delivered to affected areas during the initial critical days following a disaster. Recently, some NGOs have begun to establish pre-purchasing agreements with suppliers, specifying the quality and delivery requirements for certain critical emergency items. Under framework agreements, these suppliers may hold emergency stocks for NGOs, but an NGO's evaluation of its post-disaster procurement options still depends on the situation, and even in these cases, these suppliers are invited to bid (Salisbury 2007). Such framework agreements have the potential to streamline
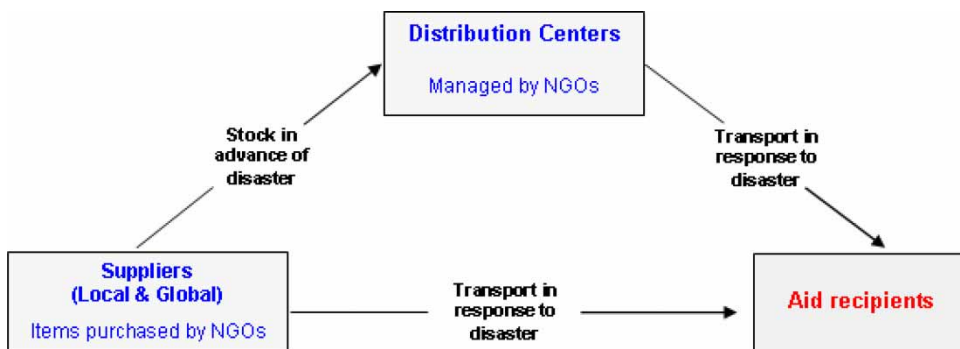

Figure 2.   Relief chain overview.

the procurement process if suppliers can be effectively integrated into the relief chain; however, such partnerships are still relatively rare in the relief sector.

3.1.3   Pre-positioned stocks.   As previously mentioned, most post-disaster procurement decisions in the relief chain are short-term decisions, since NGOs evaluate all available procurement options after needs assessments are performed. Moreover, no matter which type of post-disaster procurement sources is used, NGOs may still be unable to obtain and deliver emergency supplies to the affected areas within a critical response time period. Therefore, relief organizations stockpile ready-to-dispatch inventory in locations that have access to major disaster-prone regions to mitigate operational risks involved in the post-disaster environment.

After a disaster occurs, demand for aid supplies will likely change over time; some items are needed immediately at the earliest stages of relief operations, while other items can be safely supplied during later stages. Types of pre-positioned stocks vary, and are chosen to meet the immediate needs of those affected: food items (*e.g.* high-energy biscuits, and ready-to-eat meals), non-food items (*e.g.* jerry cans, tarps, tents, blankets, hygiene kits, and kitchen sets), medical supplies, and equipment (*e.g.* telecommunication equipment, and metal detectors). Some relief organizations store a variety of items, while some specialize in a particular sector, such as food.

In the initial days of the deployment phase, most of the critical supplies arriving to the disaster areas are sourced from relief organizations' global pre-positioned stocks. For large-scale quick-onset disasters, it is impossible to meet the entire emergency demand solely from pre-positioned stocks. Indeed, the total volume of demand satisfied from pre-positioned inventory is generally much less than the total volume of supplies sent to the disaster region over the entire relief horizon (Strash 2004).

Financial limitations and other resource restrictions limit the amount of relief supplies that can be stocked and shipped to disaster areas. For instance, for WVI, transportation capacity is one of the most limited resources in determining the capacity of their Global Pre-positioning Relief Network (GPRN) warehouses (Salisbury 2007). WVI does not have any internal transportation capacity and all transportation resources are purchased from third-party logistics contractors (3PLs) (Salisbury 2007). Therefore, supply flow through a GPRN warehouse during a disaster response is primarily limited by the transportation capacity in the region and the available budget.

To integrate a global pre-positioning system into a humanitarian relief chain, relief organizations must determine the number and location of the stocking points in the relief network and the type and amount of relief supplies to be pre-positioned in these locations, given resource restrictions. Designing a pre-positioning system that balances the costs against the risks in the relief chain and maximizes the benefits to the affected populations is vital to achieving an effective and efficient disaster response. In the next section, we present a facility location and stock pre-positioning problem for this system.

3.2   *Problem definition and model development*

We consider a distribution system in which a relief organization locates distribution centres to satisfy the immediate needs of those affected by quick-onset disasters. Given the uncertainties and resource limitations in a disaster relief environment, the problem is to determine the number and location of the distribution centres and the amount of relief inventory to stock therein to maximize the benefits provided to affected people.

Unlike commercial supply chains, it is difficult, if not impossible, to obtain reliable demand information for quick-onset disasters. However, there are ongoing initiatives to help assess

global disaster and vulnerability risks in a relief environment. For instance, Dilley *et al.* (2005) identify high-risk geographical areas, based on historical worldwide disaster frequency and mortality data, population data and economic indicators. Also, FEMA's Hazus software is an assessment tool that can estimate losses from potential hurricanes, floods, and earthquakes. Since facility locations and the amount of inventory affect relief chain costs and response times, realistic forecasts of potential demand locations and amounts will contribute to the effectiveness and efficiency of facility location and stocking decisions. In this study, we model the uncertainties of disaster locations and demand quantities by defining scenarios as disaster location-impact pairs.

We assume a relief organization that stocks and distributes multiple types of relief items. We divide relief items with respect to their response time criticalities and target response time intervals into various types. A weight, w_k, is given to each item type k to represent relative criticality. The demand for item type k can be satisfied at different coverage levels, where each coverage level, l_k, is characterized by an upper and lower response time limit ($\text{UR}_k^{l_k}$ and $\text{LR}_k^{l_k}$, respectively). The coverage benefits, $\alpha_k^{l_k}$, decrease with coverage level, and are represented by a decreasing step function. That is, for coverage levels $1 \leq 2 \leq \cdots \leq l_k \leq \cdots \leq L_k$, the associated benefits are $\alpha_k^1 = 1 > \alpha_k^2 > \cdots > \alpha_k^{l_k} > \cdots > \alpha_k^{L_k} \geq 0$. Finally, $N_s(l_k)$ represents the set of distribution centre candidates that can provide coverage level l_k for item type k demanded by disaster scenario s. The example in figure 3 illustrates different coverage levels for a single item type demanded in a single scenario. In this example, there are three candidate distribution centres and two coverage levels, where the inner circle represents the first coverage level. Distribution centre candidates at $j = 1$ and $j = 2$ are within the first and second coverage levels, respectively, whereas the distribution centre candidate at $j = 3$ is outside of both coverage levels and can therefore not provide service to the disaster location.

For presentation simplicity, we assume a particular item's characteristics (criticality, response time limits) are identical for different disaster scenarios, but the model can be readily adapted to accommodate different specifications for a single item type.

Demand for a relief item can only be satisfied from distribution centres that can cover the corresponding demand location. So, the objective is to choose a set of distribution centres in the relief network to maximize the expected benefits to affected individuals. These benefits are not only dependent on the quality of coverage (and therefore quick delivery), but also on the amount
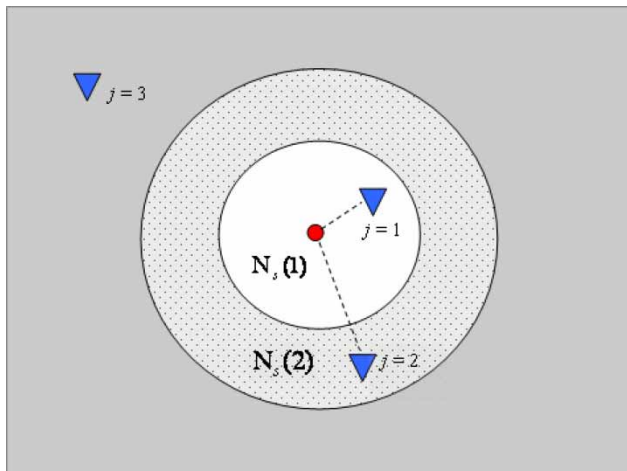

Figure 3. Coverage example.

of demand that can be delivered within that short timeframe. The latter depends strongly on the amount of stocks that can be stored and shipped from the distribution centres, both of which are limited by budgetary restrictions. Our formulation incorporates pre-disaster and post-disaster costs: we assume that the cost of establishing distribution centres and procuring and stocking relief items in the chosen distribution centres is constrained by a pre-disaster budget, which represents the relief funds allocated by relief organizations for pre-positioning. The transportation costs associated with delivering relief supplies from distribution centres to demand locations for any disaster scenario are assumed to be limited by a post-disaster budget.

The amount of stock to be pre-positioned at the distribution centres depends on the number and location of the distribution centres in the network as well as the assignment of demand locations to distribution centres, while distribution centre location and assignment decisions are affected by the amount of relief supplies to be stocked at each distribution centre. Hence, we consider these decisions in an integrated way; that is, both location and inventory decisions are made endogenously. We assume a simple stocking policy at the distribution centres. We require that the amount of inventory a distribution centre carries for each item type be no smaller than the maximum demand assigned to that distribution centre in response to a specific scenario. The implicit assumption here is that multiple scenarios will not occur simultaneously, and hence a distribution centre will never be in short supply for any scenario assigned to it.

Finally, we impose capacity restrictions on each distribution centre in the relief network, thereby limiting the amount of relief supplies to be pre-positioned. The capacity constraints may represent the space and transportation capacity restrictions in the area in which the distribution centres are located. Next, we present the mathematical model formulation of this problem.

3.3 *Model formulation*

The following notation is used to formulate the facility location and stock pre-positioning model:

Sets

S set of scenarios; $s \in S$
N set of candidate distribution centres; $j \in N$
K set of item types; $k \in K$

Parameters

p_s probability of occurrence of scenario s
d_{sk} expected demand for item type k in scenario s (units)
Cap_j capacity of distribution centre j (volume)
γ_k unit volume of item type k
B_0 emergency relief funds allocated for pre-positioning relief supplies (pre-disaster budget) (\$)
B_1 emergency relief funds allocated for post-disaster distribution (post-disaster budget) (\$)
F_j fixed cost of establishing distribution centre j (\$)
g_{jk} unit cost of acquiring and storing item type k at distribution centre j (\$/unit)

c_{sjk} unit cost of shipping item type k from distribution centre j to the disaster location of scenario s (\$/unit)

t_{sjk} time to satisfy demand for item type k in scenario s from distribution centre j (hours)

w_k criticality weight for item type k; $\sum_k w_k = 1$ and $w_k \geq 0$

l_k coverage level for item type k; $l_k = 1, \ldots, L_k$

$\alpha_k^{l_k}$ coverage level weight $\alpha_k^1 = 1 > \alpha_k^2 > \cdots > \alpha_k^{l_k} > \cdots > \alpha_k^{L_k} \geq 0$

$N_s(l_k)$ candidate distribution centre locations that can provide l_k coverage level for item type k for scenario s; $N_s(l_k) = \{j | \mathrm{LR}_k^{l_k} < t_{sjk} \leq \mathrm{UR}_k^{l_k}\}$ where

$\mathrm{LR}_k^{l_k}$ lower response time limit defining coverage level l_k, and

$\mathrm{UR}_k^{l_k}$ upper response time limit defining coverage level l_k

Decision variables

f_{sjk} proportion of item type k demand satisfied by distribution centre j in scenario s

Q_{jk} units of item type k stored at distribution centre j

$X_j = \begin{cases} 1 & \text{if distribution centre } j \text{ is located} \\ 0 & \text{otherwise} \end{cases}$

The formulation for the problem is as follows:

$$\max \quad \sum_s \sum_k \sum_{l_k} \sum_{j \in N_s(l_k)} p_s d_{sk} w_k \alpha_k^{l_k} f_{sjk} \tag{1}$$

$$\text{subject to} \quad f_{sjk} d_{sk} \leq Q_{jk} \quad \forall s \in S, j \in N, k \in K \tag{2}$$

$$\sum_{k \in K} \gamma_k Q_{jk} \leq \mathrm{Cap}_j X_j \quad \forall j \in N \tag{3}$$

$$\sum_{j \in N} \left(F_j X_j + \sum_{k \in K} Q_{jk} g_{jk} \right) \leq B_0 \tag{4}$$

$$\sum_{k \in K} \sum_{j \in N} d_{sk} c_{sjk} f_{sjk} \leq B_1 \quad \forall s \in S \tag{5}$$

$$\sum_{j \in N} f_{sjk} \leq 1 \quad \forall s \in S, k \in K \tag{6}$$

$$f_{sjk} \geq 0 \quad \forall s \in S, j \in N, k \in K \tag{7}$$

$$X_j \in \{0, 1\} \quad \forall j \in N \tag{8}$$

The objective function (1) maximizes the total expected demand covered by the established distribution centres. Constraint set (2) ensures that the inventory level at a distribution centre is no smaller than the maximum amount of demand that the distribution centre will face from a single disaster scenario. Constraint set (3) guarantees that the inventory is held only at established distribution centres, and the amount of inventory kept at any distribution centre does not exceed its capacity. Constraint (4) requires that the pre-disaster expenditures related to

establishing a distribution centre and holding inventory do not exceed the pre-disaster budget, and constraint set (5) guarantees that the transportation costs incurred between distribution centres and each disaster scenario are less than the expected post-disaster budget. Constraint set (6) ensures the amount of supplies sent to satisfy the demand of a disaster scenario does not exceed the actual demand. Finally, constraint set (7) is the nonnegativity constraint on the proportion of demand satisfied and constraint set (8) defines the binary location variable.

4. Numerical analysis

In this section, we introduce an example problem to test the proposed distribution network design model and present computational results.

4.1 *The data set*

Network-related parameters were developed by analysing historical natural hazards data from the National Geophysical Data Center (NGDC 2007). From this database, we extracted the geographical coordinates of the worldwide earthquake-caused disasters and the number of people killed by each event. We considered the 639 events that resulted in at least 10 deaths between the years of 1900 and 2006.

The geographical coordinates obtained from the NGDC corresponds to the epicentre of each earthquake. To generate disaster scenarios and estimate the demand created by these scenarios, we clustered the disasters with epicentres that were close proximity of one another and assumed that each disaster within a particular cluster is likely to affect the population located in the corresponding area. We used the following approach to create the clusters: we projected grid lines onto the earth's surface and assumed that the centroid of each grid cell represents the location of the demand when the data located a disaster in that grid cell. Since our model assumes that the disasters do not occur simultaneously, grid cells should not be too small; this would cause an underestimate of the population likely to be affected by a disaster. Also, very large grid cells may lead to an underestimate of the transportation times and costs in the network and an overestimate of the demand created by the disasters. For the purpose of our example, the grid cell dimensions were selected as 5 degrees ($5°$) of latitude and 5 degrees ($5°$) of longitude with at most 555.2 kilometres between two demand points, which occurs at the equator. So, if a grid cell contained a disaster that resulted in at least 10 deaths between the years of 1900 and 2004, we located the demand for that disaster in the centroid of that grid cell. The data and grid configuration yielded 167 grid cells. Figure 4 illustrates the demand locations as the centroid of each grid cell.

After obtaining the list of disasters associated with each grid cell, we grouped disasters based on their impact levels. We considered four disaster impact levels, which were chosen based on the number of historical deaths as shown in table 1.

Therefore, at least one and at most four disaster scenarios were associated with a single location, yielding 286 total scenarios, each of which was defined by a disaster location-impact pair. For our computational experiments, we estimated the probability of occurrence associated with each scenario based on the historical frequencies. A scenario's likelihood was assumed to be equal to the fraction of disasters in the corresponding grid cell with the same impact level.

We modelled two types of relief items, in which the first type of items represents the set of critical items that require a more rapid response time than the second type of items. The criticality weights for item types 1 and 2 were set at 0.8 and 0.2, respectively. We used two coverage levels for both types of items. For item type 1, upper response time limits were set at
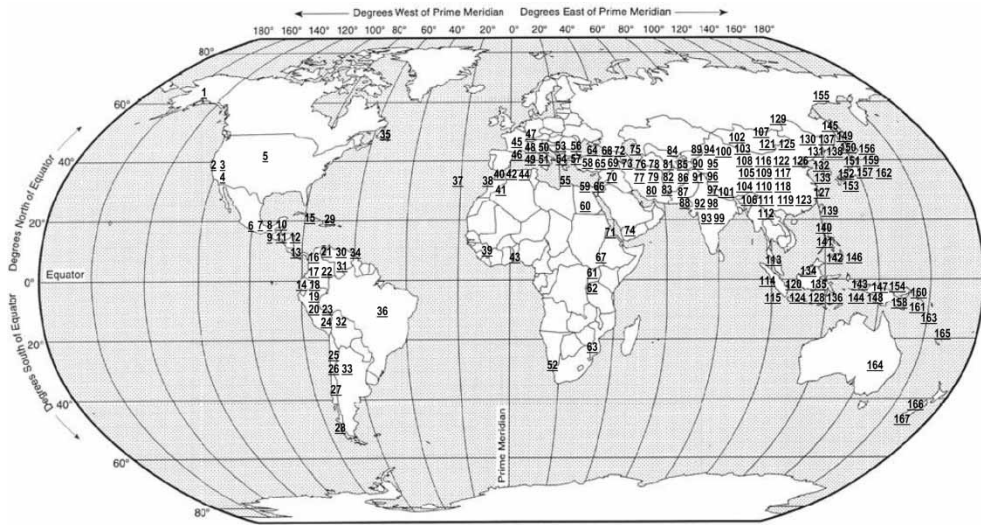
Figure 4. Potential disaster (demand) locations.

48 and 96 h for coverage levels 1 and 2, respectively. Similarly, for item type 2, upper response time limits were set at 72 and 144 h for coverage levels 1 and 2, respectively. We assumed that the coverage benefit level decreases at a higher rate for the more critical item type and so the second level coverage benefits were set to 0.4 and 0.6 for item types 1 and 2, respectively.

The expected demand for each item type for each scenario was determined based on world population data. We calculated the total population associated with each grid cell based on world population data from the SEDAC (2007). Demand for scenarios was then created randomly for both types of items based on the population in the associated grid cell and the disaster impact level.

We considered 45 candidate distribution centre locations, all located in areas with high population density (assuming that these areas would correlate to transportation accessibility) and in grid cells with zero historical disaster occurrence probability (to minimize the possibility of losing a distribution centre to a disaster itself). In our computations, we specified the distribution centre capacity constraints loosely in order to allow the model to determine the capacities (size) of the DCs simultaneously with other decisions. Other parameters required by the model were set hypothetically as shown in table 2.

4.2 *Computational results*

In this section, we present computational results and analyse the behaviour of the proposed model. The results reported below were obtained using GAMS/Cplex.

Table 1. Disaster impact levels.

Impact level	Number of deaths	The percentage of total deaths at this level (%)	Number of historical disasters at this level	Number of scenarios with this impact level
1	≤250	~1	420	145
2	≤2,000	~5	128	74
3	≤50,000	~33	82	59
4	>50,000	~61	9	8

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Table 2.   Model parameters.

Fixed cost of locating a distribution centre	$100,000 (the same for each distribution centre candidate)
Unit cost of acquiring and storing relief items	$18 per unit of item type 1; $20 per unit of item type 2 (the same for each distribution centre candidate)
Distribution centre capacity	100,000 cubic metres (the same for each distribution centre candidate)
Unit volume of relief items	1 cubic metre (the same for each item type)
Delivery time between distribution centres and demand points (hours)	40 h + (1/804.7 km/h)× (distance between grid cell centroids) (the same for each item type and distribution centre candidate)
Unit cost of shipping from distribution centres to demand points	$5× delivery time (the same for each item type and distribution centre candidate)

We ran the model under different pre- and post-disaster budget constraints, whose results are provided in tables 3 and 4. The first sets of rows in tables 3 and 4 are the results obtained by changing the pre-disaster budget while keeping the post-disaster budget constant. The second sets of rows in these tables are the results from varying post-disaster budgets while keeping the pre-disaster budget constant. Finally, the third sets of rows of tables 3 and 4 correspond to the results obtained by simultaneously changing pre- and post-disaster budgets.

Table 3 shows the solutions obtained in terms of the number of distribution centres, total amount of inventory at the distribution centres, and the minimum, average and maximum response time to satisfy demand for both types of items. Table 4 reports the percentage of scenarios in which demands were satisfied from distribution centre stocks, where each scenario belongs to one of the columns based on the proportion of demand satisfied. The last two columns of table 4 show the percentage of scenarios in which demands were satisfied at coverage level 1 for both item types; that is, these columns reflect quality of coverage for satisfied demand.

First, we observed a set of problems in which we fixed the post-disaster budget and increased the pre-disaster budget incrementally. When the pre-disaster budget was set to its minimum for our example ($200,000), the model opened one distribution centre, which was located on the Indian west coast. The single distribution centre stocked both types of items and covered a region in which the number of high-impact (in terms of frequency and population affected) disaster scenarios was large. From the results, the stocks held for item type 1 could entirely be used to satisfy only the demand of scenarios in the very close vicinity of the distribution centre, due to the limited transportation budget. As the distance between the distribution centre and the scenarios increased, the proportion of satisfied type 1 demand decreased. From table 4, type 1 demands in 16.1% of the scenarios were fully satisfied. These scenarios were those with the lowest demand, and so the inventory and transportation capacity were sufficient to satisfy those demands. Also, these cases allowed for type 2 items to be delivered with the remaining budget.

As we increased the amount of pre-disaster relief budget to $400,000, the model added a second distribution centre in Central America, which was approximately identical in capacity (for both item types) to the first distribution centre. As shown in tables 3 and 4, this increase in the pre-disaster budget led to an increase in the proportion of demand satisfied, improved coverage quality, and reduced average response time for type 1 items. For type 2 items, the proportion of satisfied demand increased; however, the number of scenarios in which demand was satisfied decreased.

As the pre-disaster budget was further increased, the model responded by locating more distribution centres (not necessarily by adding to the current set of distribution centres) with

Table 3. Results: Number of distribution centres, inventory, and response time under varying budgets.

| | | | Total inventory at the distribution centres (volume) | | Response time for satisfied demand (hours) | | | | | |
| | | | | | Minimum | | Average | | Maximum | |
Pre-budget ($)	Post-budget ($)	Number of distribution centres	Item 1	Item 2	Item 1	Item 2	Item 1	Item 2	Item 1	Item 2
200 000	1 000 000	1	4 753.98	721.42	40.69	40.69	49.05	48.82	70.31	70.31
400 000	1 000 000	2	9 534.79	1 418.69	41.07	43.09	45.85	51.65	70.31	70.31
600 000	1 000 000	3	14 663.68	1 802.69	40.69	40.98	43.85	51.63	64.93	64.93
800 000	1 000 000	4	19 499.62	2 450.34	40.69	41.54	43.40	50.38	70.31	70.31
1 000 000	1 000 000	5	24 382.29	3 055.94	40.69	40.69	43.18	49.58	70.31	70.31
1 200 000	1 000 000	6	29 390.36	3 548.67	40.69	40.69	42.97	49.23	72.90	66.30
1 400 000	1 000 000	7	34 223.62	4 198.74	40.69	40.69	42.69	49.34	55.27	70.31
1 600 000	1 000 000	8	39 195.47	4 724.28	40.69	40.69	42.55	50.51	52.67	62.35
1 800 000	1 000 000	9	44 136.00	5 277.60	40.69	40.69	42.41	49.14	52.23	68.30
2 000 000	1 000 000	10	49 004.31	5 896.12	40.69	40.69	42.33	47.62	52.23	68.24
5 000 000	1 000 000	25	122 348.08	14 854.33	40.69	40.69	41.79	46.43	47.71	68.50
1 000 000	200 000	8	7 844.16	2 940.26	40.69	41.95	42.46	48.58	49.81	69.12
1 000 000	400 000	7	13 722.23	2 649.99	40.69	41.54	42.65	47.97	55.27	66.12
1 000 000	600 000	6	17 694.77	4 074.71	40.69	41.95	42.93	48.81	72.90	63.28
1 000 000	800 000	6	20 355.56	1 680.00	40.75	40.69	43.06	50.83	72.90	66.95
1 000 000	1 000 000	5	24 382.29	3 055.94	40.69	40.69	43.18	49.58	70.31	70.31
1 000 000	1 200 000	5	25 434.44	2 109.00	40.69	42.92	43.29	50.64	72.90	66.95
1 000 000	1 400 000	4	27 486.22	5 262.40	40.69	41.95	43.40	48.97	70.31	70.31
1 000 000	1 600 000	4	30 038.77	2 927.31	40.69	41.38	43.43	51.05	70.31	70.31
1 000 000	1 800 000	4	29 424.44	3 518.00	40.69	40.69	43.67	51.36	70.31	66.12
1 000 000	2 000 000	3	29 422.71	8 519.56	40.69	40.69	43.85	48.87	64.93	64.93
1 000 000	5 000 000	2	39 846.67	4 138.00	40.69	41.54	46.19	50.80	70.31	70.31
200 000	200 000	1	983.04	714.83	40.69	43.52	49.05	52.37	70.31	70.31
400 000	400 000	3	5 555.56	0.00	40.98	–	43.88	–	64.63	–
600 000	600 000	4	10 081.11	927.00	40.79	42.45	43.63	50.87	70.31	66.12
800 000	800 000	4	15 728.68	5 844.19	40.69	41.54	43.38	48.81	70.31	70.31
1 000 000	1 000 000	5	24 382.29	3 055.94	40.69	40.69	43.18	49.58	70.31	70.31
1 200 000	1 200 000	5	30 565.48	2 491.07	40.69	41.54	43.10	51.84	72.90	70.14
1 400 000	1 400 000	6	40 304.35	3 726.09	40.69	41.54	42.99	49.72	72.9.	68.82
1 600 000	1 600 000	6	47 024.58	7 677.87	40.69	41.52	42.98	48.15	72.90	66.95
1 800 000	1 800 000	7	56 616.67	4 045.00	40.69	40.69	42.75	51.11	55.27	64.99
2 000 000	2 000 000	7	64 697.24	6 722.49	40.69	40.69	42.73	48.87	55.27	70.31
5 000 000	5 000 000	9	200 455.32	24 590.21	40.69	40.69	42.60	50.85	52.67	66.95

Table 4. Results: Amount of demand satisfied and covered under varying budgets.

| Pre-budget ($) | Post-budget ($) | Percentage of scenarios in which p% of demand is satisfied | | | | | | | | | | Percentage of scenarios in which demand is satisfied at coverage level 1 | |
| | | p = 100 | | 50 <= p < 100 | | 1 < p < 50 | | 0 < p <= 1 | | p = 0 | | | |
		Item 1	Item 2	Item 1	Item 2	Item 1	Item 2	Item 1	Item 2	Item 1	Item 2	Item 1	Item 2
200 000	1 000 000	16.1	5.9	10.1	2.1	59.8	8.4	14.0	3.5	0.0	80.1	59.8	100.0
400 000	1 000 000	17.1	8.0	10.5	3.5	58.4	5.2	14.0	0.3	0.0	82.9	78.3	100.0
600 000	1 000 000	17.5	9.1	11.2	3.1	57.0	4.9	14.3	0.3	0.0	82.5	97.2	100.0
800 000	1 000 000	17.5	10.5	11.2	2.4	57.3	4.2	14.0	0.3	0.0	82.5	97.6	100.0
1 000 000	1 000 000	18.2	11.2	10.8	1.4	57.0	5.2	14.0	0.3	0.0	81.8	97.6	100.0
1 200 000	1 000 000	18.2	11.2	10.8	2.1	57.7	4.5	13.3	0.3	0.0	81.8	98.3	100.0
1 400 000	1 000 000	18.2	11.2	10.8	1.4	57.0	5.2	14.0	0.3	0.0	81.8	99.0	100.0
1 600 000	1 000 000	18.2	11.2	10.8	1.4	57.0	5.2	14.0	0.3	0.0	81.8	99.0	100.0
1 800 000	1 000 000	18.2	11.2	10.8	1.4	57.0	5.2	14.0	0.3	0.0	81.8	99.0	100.0
2 000 000	1 000 000	18.2	11.2	11.2	2.4	56.6	4.2	14.0	0.3	0.0	81.8	99.0	100.0
5 000 000	1 000 000	18.2	11.2	11.2	2.8	57.3	3.8	13.3	0.3	0.0	81.8	100.0	100.0
1 000 000	200 000	7.7	4.9	2.4	1.0	52.1	1.4	37.8	0.3	0.0	92.3	99.0	100.0
1 000 000	400 000	10.1	6.3	5.6	1.0	54.5	2.8	29.7	0.0	0.0	89.9	99.0	100.0
1 000 000	600 000	12.9	7.7	7.0	1.7	58.7	3.5	21.3	0.0	0.0	87.1	98.6	100.0
1 000 000	800 000	15.7	8.7	8.4	2.4	59.1	3.5	16.8	1.0	0.0	84.3	98.6	100.0
1 000 000	1 000 000	18.2	11.2	10.8	1.4	57.0	5.2	14.0	0.3	0.0	81.8	97.6	100.0
1 000 000	1 200 000	19.6	10.8	10.8	3.1	59.1	5.6	10.5	0.0	0.0	80.4	98.3	100.0
1 000 000	1 400 000	22.0	14.0	11.5	1.7	58.0	6.3	8.4	0.0	0.0	78.0	97.6	100.0
1 000 000	1 600 000	24.1	12.9	11.2	4.2	58.7	6.6	5.9	0.3	0.0	75.9	97.6	100.0
1 000 000	1 800 000	25.5	14.7	12.2	3.1	57.0	7.7	5.2	0.0	0.0	74.5	97.2	100.0
1 000 000	2 000 000	28.7	17.5	11.2	1.7	55.6	9.1	4.5	0.3	0.0	71.3	97.2	100.0
1 000 000	5 000 000	42.0	18.9	11.9	7.7	44.8	15.4	1.4	0.0	0.0	58.0	78.3	100.0
200 000	200 000	7.3	4.5	1.4	1.4	51.7	1.4	39.5	0.0	0.0	92.7	59.8	100.0
400 000	400 000	9.8	0.0	5.2	0.0	54.5	0.0	30.4	0.0	0.0	100.0	97.6	0.0
600 000	600 000	12.9	5.9	6.6	2.8	59.1	4.2	21.3	0.0	0.0	87.1	97.2	100.0
800 000	800 000	15.0	9.8	9.1	1.4	59.1	2.4	16.8	1.4	0.0	85.0	97.6	100.0
1 000 000	1 000 000	18.2	11.2	10.8	1.4	57.0	5.2	14.0	0.3	0.0	81.8	97.6	100.0
1 200 000	1 200 000	19.6	11.5	10.8	2.8	59.1	5.2	10.5	0.0	0.0	80.4	98.6	100.0
1 400 000	1 400 000	22.0	12.9	11.5	2.8	58.0	6.3	8.4	0.0	0.0	75.9	98.3	100.0
1 600 000	1 600 000	24.1	15.0	11.9	2.8	58.0	5.9	5.9	0.3	0.0	75.9	98.6	100.0
1 800 000	1 800 000	26.9	15.7	12.2	2.8	55.6	8.4	5.2	0.0	0.0	73.1	99.0	100.0
2 000 000	2 000 000	29.0	17.5	11.2	2.1	55.6	9.4	4.2	0.0	0.0	71.0	99.0	100.0
5 000 000	5 000 000	43.0	30.4	10.8	5.6	45.1	7.0	1.0	0.0	0.0	57.0	99.0	100.0

approximately the same capacities, stocking more supplies of both types. The quality of coverage tended to improve as more distribution centres were established. For all instances, all distribution centres carried item type 1 in approximately equal amounts; however, the amounts of item type 2 stocks at the distribution centres varied widely as the number of distribution centres increased. Moreover, as the pre-disaster budget was gradually increased, the proportion of type 1 demand that could be satisfied for a particular scenario increased and then became steady. This was because even if the amount of inventory pre-positioned worldwide increased, a scenario's demand could only be satisfied from a set of distribution centres (due to limited post-disaster budgets). Indeed, results showed that a scenario's type 1 demand was rarely satisfied by more than one distribution centre, although type 2 demands were more commonly satisfied from multiple distribution centres. With the exception of the case containing the lowest pre-disaster budget, type 2 items were only delivered to low-demand scenario locations whose type 1 demand could be completely satisfied. It was also observed that the response time measures fluctuated for item type 2, while the average and maximum response times for type 1 items tended to improve with increases in pre-disaster funding.

The results obtained for increased pre-disaster budget amounts while fixing the post-disaster budget indicated the advantages and disadvantages of establishing a decentralized relief system. As the pre-disaster budget increased, more supplies could be stocked at many locations, the distances between facilities and disaster scenario locations decreased, and hence the system's responsiveness improved. That is, relief operations became localized, where each distribution centre served a particular local region. The practical disadvantages of excessive localization in the relief system may include the difficulties in managing many facilities and low throughput at the distribution centres (since each distribution centre is likely to respond fewer disasters) which may lead to obsolescence and hence increased inventory costs.

Next, we observed the results for the problems with a fixed pre-disaster budget and variable post-disaster budget. When the post-disaster budget is set at a minimal value, the model opened eight distribution centres, each close to areas with high population and/or high disaster risk. Each distribution centre carried an approximately equal number of item type 1, but varying numbers of item type 2. Since the transportation budget was very limited, the amount of supplies that could be delivered to meet the demands of scenarios was very low. Actually, most of the pre-disaster budget was spent on fixed cost of establishing distribution centres rather than stocking relief supplies, since there was limited funding available to deliver the supplies. However, a good coverage level and low response times were achieved for the satisfied demands. We observed that type 1 supplies were shipped from a single distribution centre, whereas type 2 demands were satisfied by multiple facilities.

As post-disaster funding increased, the number of distribution centres tended to decrease and the total amount of type 1 inventory at the distribution centres increased, while the total amount of type 2 inventory fluctuated. As observed from table 4, the percentage of scenarios whose type 1 demand was fully satisfied increased as post-disaster funding increased. Moreover, although there were fluctuations in the total amount of type 2 stocks (table 3), the percentage of scenarios receiving no type 2 supplies decreased. We observed that although a greater proportion of overall demand could be satisfied, the percentage of scenarios that could be covered at level 1 gradually decreased for type 1 items since network centralization necessitated supplies to be shipped over longer distances. As a result, average response time for the satisfied type 1 demand increased. For all instances, we observed that type 2 supplies were only delivered to locations whose type 1 demand was fully satisfied. We also observed that demands began to be satisfied from multiple distribution centres as more post-disaster funding became available. Finally, the distribution centres in the network did not have identical capacities; as the number of distribution centres decreased, the capacity differences among the distribution centres increased.

In summary, as more post-disaster relief funds became available, the distribution network tended to become more centralized. Larger demand amounts could be satisfied by fewer facilities, but at the expense of increased transportation costs and response times. As the number of distribution centres decrease and each distribution centre stocks and distributes more supplies, economies of scale may be achieved in operating relief supply inventories. However, having few stocking points would require larger transportation capacity at each distribution centre.

The results suggest that the response time for critical items was primarily affected by investments in establishing facilities and stocking supplies. However, if the post-disaster budget was limited, the amount of supplies distributed could not be increased even with increases in the number of facilities in the network. Additionally, the amount of critical supplies distributed was primarily affected by the available transportation budget; however, if pre-disaster funding is low, more demand could be satisfied only by transporting supplies very long distances.

To observe the effects of changing both types of budgets simultaneously, we solved a set of problems for various pre- and post-disaster budgets, whose results are also shown in tables 3 and 4. According to the results, as both types of budgets increased, the number of distribution centres gradually increased, additional type 1 supplies were held at and delivered from the distribution centres, and the average response time decreased. Although the amount of type 2 inventory fluctuated, there was an increasing trend in the amount of satisfied type 2 demand as well. Finally, similar to the results obtained for which one of the budgets was changed, a scenario's type 2 item demand could only be satisfied if type 1 item demand of the scenario could be fully satisfied. That is, the critical items always had priority, and if a scenario's type 1 item demand was large, type 2 item demand could not be satisfied since all resources were used to satisfy the critical demand. Therefore, system-wide inventory was comprised of mostly critical supplies; less critical supplies were stocked in minimal amounts.

We observed greater improvements in model solutions when both budgets were increased. Those improvements were observed in terms of both response time and the amount of demand satisfied, as compared to the cases in which only one of the budgets increased, while the other one was fixed. For example, suppose that both budgets were equal to $1,000,000 and an additional $400,000 would be invested for pre- and/or post-disaster relief logistics. We observed improvements in both performance measures when both budgets were increased to $1,200,000. The improvement in terms of each measure was slightly lower than what could be obtained when additional money was used completely for pre- or post-disaster investment (in this case increasing either pre- or post-disaster budget to $1,400,000). However, the system performance certainly improved by increasing both pre- and post-disaster logistics capacities if both objectives (decreasing response time and increasing amount satisfied) were important. In the next section, we discuss the managerial implications of the proposed model for relief decision-makers.

5. Management implications

The proposed model supports relief chain managers by providing an integrated global stock pre-positioning system for the relief chain. Specifically, the model determines the number and locations of distribution centres to be located in the relief network and inventory at the established facilities for various relief supplies. The model provides a systematic approach that would enable relief organizations to design an effective and efficient network and also help to assess the response capacity and performance of the designed network.

By incorporating inventory-related decisions into facility location decisions, the proposed model facilitates both tactical and strategic decisions of the relief practitioners. Since facility

location decisions (number and location of facilities) address a longer horizon and may be highly dependent on dynamic model parameters (*e.g.* unit costs, and available funding), sensitivity analysis would be recommended before finalizing these strategic decisions. On the other hand, decisions related to the amount of stocks at each facility can be updated more frequently; that is, once the facilities are located, inventory-related decision variables can be re-optimized when necessary.

Different than the traditional facility location models in the literature, the proposed model evaluates the performance of the solutions, not only based on the distance/time between the facilities and demand locations, but also a service criterion which provides information about what proportion of a scenario's demand can be satisfied from the established facilities. Moreover, the model considers multiple types of relief supplies and develops an inventory strategy for stocking different types of supplies. This inventory-related information would also help managers with other relief chain decisions, such as supplier procurement and transportation. For instance, based on the amount of stocks waiting to be delivered at each facility, sufficient transportation capacity would be established in the region. Also, managers would know the expected amounts of supplies to be procured from other sources (local and international suppliers) and could pursue appropriate pre-disaster agreements with suppliers.

Based on our computational results, pre- and post-disaster budgets significantly affect the performance of the disaster response, in terms of response time and proportion of demand satisfied for critical items. The sensitivity analysis led to important implications for relief organizations and the donor community. The results highlight the importance of pre-disaster investments and planning, which has been underrated compared to the funding of post-disaster activities. In particular, the results indicate that a rapid and efficient disaster response is not primarily achieved through post-disaster funding.

6. Conclusions and future research

In this study, our objective was to characterize the facility location problem for humanitarian relief chains and develop an analytical approach that will enable relief practitioners to make efficient and effective facility location and stock pre-positioning decisions. We developed a maximal-covering type model that determines the number and locations of the distribution centres in the relief network and the amount of relief supplies to be stocked at each distribution centre. Our computational analysis demonstrated the effects of pre- and post-disaster relief funding on relief system performance, in terms of response time and proportion of demand satisfied. The model results highlighted important implications for the decision-makers in the relief system.

A number of extensions are possible for this model. The inventory policy used in this study was based on the assumption that disasters may not occur simultaneously and that distribution centres hold enough inventory to satisfy the demand for any scenario to which it is assigned. Future research would focus on developing more sophisticated inventory policies for relief chains responding to quick-onset disasters, which would also contribute to facility location decisions. We developed the example problem based on publicly available disaster data. Due to data limitations, some parameters were estimated. For instance, we estimated relief supply demand for each disaster scenario based on mortality statistics from previous disasters and area population. Therefore, future efforts in data collection would support the implementation of this model and enhance the analysis.

Finally, many problem instances can be optimally solved using commercially available optimization software. However, for larger problems (*i.e.* if the number of scenarios, items, or

distribution centre candidates were increased) solution times and hence computational burden of model analysis would increase. Therefore, future research would include the development of heuristic approaches that find near-optimal solutions for this model.

Acknowledgements

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