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Pre-Positioning of Emergency Items for CARE International

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Each year, about 500 natural disasters kill approximately 70,000 people and affect more than 200 million people worldwide. In the aftermath of such events, large quantities of supplies are needed to provide relief aid to the affected. CARE International is one of the largest humanitarian organizations that provide relief aid to disaster survivors. The most vital issues in disaster response are agility in mobilizing supplies and effectiveness in distributing them. To improve disaster response, a research group from Georgia Institute of Technology collaborated with CARE to develop a model to evaluate the effect that pre-positioning relief items would have on CARE's average relief-aid emergency response time. The model's results helped CARE managers to determine a desired configuration for the organization's pre-positioning network. Based on the results of our study and other factors, CARE has pre-positioned relief supplies in three facilities around the world.

Key words: pre-positioning; stockpiling; humanitarian logistics; preparedness; disaster response.
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When a disaster strikes, unavailability of supplies or slowness in mobilizing them may cause emergency responses to be ineffective, resulting in increased human suffering and loss of life. One way that humanitarian organizations can enhance their emergency-response capacity and preparedness for natural disasters and ensure higher availability of relief supplies is by pre-positioning (i.e., stockpiling) inventory. An established pre-positioning network would be most beneficial to these organizations in responding to sudden-onset natural disasters such as earthquakes, which occur without a transitional phase; such a network would eliminate the procurement phase of the response. Nevertheless, structuring a pre-positioning network to support emergency response for sudden-onset disasters is challenging because the magnitude, timing, and location of disasters can be highly unpredictable.

CARE International, with programs in more than 65 countries, is one of the largest international relief and humanitarian organizations that provide relief aid to survivors of natural and man-made disasters. It was founded in 1945 when 22 American organizations worked together to provide "care packages" to the survivors of World War II. Today CARE provides emergency relief both during and after disasters and conducts development programs addressing underlying causes of poverty. Although CARE's main focus is long-term development, emergency relief plays a vital role in its work of developing lasting solutions to poverty, because many communities in the developing world lack the basic resources to cope with the struggles of everyday life. When a disaster strikes, these struggles become impossible without assistance. Moreover, disasters can drive otherwise self-sustaining communities into poverty and erase years of development.

CARE's Approach to Disaster Response

Until recently, CARE conducted most of its activities to set up a supply chain to support an emergency response after the disaster's onset. Some of its major activities include identifying possible suppliers (both local and international), conducting the procurement process, identifying potential warehouse sites, and renting and setting up warehouses. It outsources most of the transportation. International suppliers, for example, usually ship the items to an entry port of the affected country by air because of the time sensitivity of demand for relief supplies, and then ship the supplies by road from the port to a CARE warehouse or distribution point. Although the distribution network may take many different forms, CARE relies mostly on third parties for warehousing and transportation. The lack of a reliable transportation network and the relatively low level of preparedness are common challenges that organizations such as CARE face because of the nature of the funding that they receive. Funding is relatively easy to obtain after a disaster has struck and received press coverage; however, obtaining funding for preparedness and for developing the infrastructure is considerably more difficult (Murray 2005).

The source of relief supplies plays an important role in emergency-response performance. CARE's traditional approach has been to use direct shipments from local and international suppliers. Because organizations such as CARE work toward the dual goals of socioeconomic development and relief aid, they often prefer local suppliers. Local procurement has the advantages of fast delivery of culturally acceptable products and stimulation of the local economy; therefore, it usually results in a faster recovery of the affected community. However, in a disaster's wake, local procurement may result in uncertainties about product quality, availability, production capacity, and the risk of inflated prices because of scarcity. When supplies are not available locally, organizations procure them internationally. Procuring items from large, reputable international suppliers can increase the availability of higher-quality supplies. In addition, by buying larger volumes from fewer international suppliers, relief organizations can leverage their purchasing power and receive lower prices because of quantity discounts. The disadvantages are higher transportation costs and longer response times because of the long distances that must be traveled from unanticipated sources using unanticipated transportation channels.

CARE and Georgia Institute of Technology collaborated on a project in which we explored the option of pre-positioning relief items to improve CARE's emergency response times. Relief items would be stored in warehouses in strategic locations worldwide and deployed following a disaster. Currently, the United Nations Humanitarian Response Depot (UNHRD, http://www.unhrd.org) and some national governments are offering free or at-cost warehouse storage space and logistics support to international humanitarian organizations, making the implementation of such a pre-positioning network financially and logistically feasible. By serving as a complement to the current practice of shipping relief supplies directly from suppliers, a pre-positioning strategy could eliminate the procurement phase in some response situations and reduce the time pressure on suppliers in others. In addition, relief supplies can be located closer to potential demand locations, and transportation arrangements can be made in advance, resulting in faster response times and reduced human suffering.

Literature Review

The pre-positioning problem falls into the area of humanitarian logistics, which an advisory committee at the Fritz Institute has formally defined as

> the process of planning, implementing and controlling the efficient, cost-effective flow of and storage of goods and materials as well as related information, from point of origin to point of consumption for the purpose of alleviating the suffering of vulnerable people. (Thomas and Mizushima 2005, p. 2)

Humanitarian logistics is essential to the timely and effective mobilization of resources to aid people made vulnerable by natural disasters and crises. The unpredictable nature of such events, in addition to the large casualties that are often at stake, makes humanitarian logistics a critical aspect of any relief-aid operation.

Despite humanitarian logistics' importance, the literature in this area is limited (Van Wassenhove 2006). Recent disasters, such as the 2004 Indian Ocean tsunami, have exposed the challenges and complexities associated with relief-aid efforts and have prompted a significant response for the improvement of operations from academics and humanitarian logistics practitioners.

Many articles, including Ergun et al. (2008), provide overviews of humanitarian logistics. Alexander (2006) conducts a critical survey of the logistical and organizational components of humanitarian relief. Katoch (2006) examines the conditions that create the distinct, tumultuous atmosphere at a disaster site; the specific characteristics of disasters that make coordination and response difficult; the instruments used to respond to disasters; and the barriers to effective communication that have developed recently. The Fritz Institute has also released white papers (see Thomas and Kopczak 2005) that outline the nature of disasters and how this nature adversely affects logistical operations. Larson et al. (2006) focus on five recent major emergencies; they point out the problems faced in responding to these high-consequence, low-probability events.

Several papers, including Long (1997) and Van Wassenhove (2006), discuss the differences between logistics in the industrial (private) and humanitarian sectors, highlighting the similarities and differences, the "cross-learning" potential between them, and the need for greater collaboration among industry, academia, and humanitarian organizations for more effective supply chains across the board. Rodman (2004) explores the ways in which an interdisciplinary approach to supply chain coordination—using principles from supply chains in the private, nonprofit, and military sectors—can improve humanitarian operations.

Academic literature relevant to our work falls into three streams: facility location, inventory management, and network flows. Research on facility location focuses on the spatial aspects of operations and explores the effects of facility location on factors such as cost, service, and response time within the humanitarian relief context. Akkihal (2006) identifies optimal locations for warehousing nonconsumable inventories required for the initial deployment of aid. This study solves a p-median problem by using historical information on mean annual numbers of homeless people that result from natural disasters, as the weights for the different demand locations. As such, the model minimizes the average distance from a homeless person to the nearest warehouse. The most important underlying assumptions are (1) every disaster requires a response from a warehouse (its closest warehouse), and (2) warehouses always have enough inventory to satisfy the demand. Balcik and Beamon (2008) address the issue of pre-positioning relief supplies. They find the optimal warehouse locations and capacities when demand for relief supplies can be met from suppliers and warehouses. Based on historical information, they create scenarios for disaster location and impact (demand) for a single event and minimize the expected response time over all scenarios. Because the set of (location, demand) scenarios considers only single events, their underlying assumption is that warehouse replenishment lead time is zero. However, as the actual replenishment time increases, this assumption becomes less likely to hold.

Inventory-management research focuses on estimating item quantities required at various nodes along a supply chain, purchasing quantities, order frequency, and maintenance of safety-stock levels. The most recent and relevant works in this category are Beamon and Kotleba (2006a, b). Beamon and Kotleba (2006b) develop a stochastic inventory control model, in the form of (Q_1, Q_2, r_1, r_2), that determines optimal order quantities and reorder points for a pre-positioned warehouse responding to a complex humanitarian emergency. In their model, the warehouse supplies items for highly variable demand. They allow for two types of lot sizes for ordering: Q_1 for a regular order (when the inventory reaches level r_1) and Q_2 for an urgent order (if the inventory level reaches r_2, where $r_1 > r_2$). Beamon and Kotleba (2006a) use simulation to compare the performance of the (Q_1, Q_2, r_1, r_2) model with two heuristics.

Given the decisions regarding location and replenishment, the next step is the delivery of goods, which can be modeled as a network flow. Haghani and Oh (1996) analyze the transportation of multiple commodities on a network with time windows to minimize loss of life. They formulate a multicommodity, multimodal network flow with time windows, and they present two solution methods. Barbarosoglu and Arda (2004) formulate a similar model but introduce uncertainty. Their model is a two-stage stochastic program over a multicommodity, multimodal network with uncertainty in demand, in vulnerability of commodity sources, and in survivability of arcs. Barbarosoglu et al. (2002) develop a mathematical model for planning helicopter operations for disaster relief. The model uses operational information to improve tactical decisions in an iterative process. Ozdamar et al. (2004) examine logistics planning in emergency situations that involve dispatching commodities to distribution centers of affected areas. Their multicommodity network-flow model addresses a dynamic time-dependent transportation problem, and repetitively derives a solution at given time intervals to represent ongoing aid delivery. The model regenerates plans by incorporating new requests for aid material, new supplies, and new transportation means that become available during the current planning time horizon. The research of Tean (2006) differs from other research in this literature stream in that it allows the capacity expansion of located physical facilities and health personnel under a budget constraint. A two-stage, linear, mixed-integer program (MIP) is used to maximize the number of rescued survivors and the amount of delivered relief items via land, sea, and air transportation.

Our work relates closely to that of Balcik and Beamon (2008). Specifically, we find the optimal number and location of pre-positioning warehouses given that demand for relief supplies can be met from both pre-positioned warehouses and suppliers. However, a major difference is that we allow multiple events to occur within a replenishment period, thus capturing the adverse effect of warehouse replenishment lead time. Another important difference is that we allow the probability of need for each item to depend on both local conditions and the natural-hazard type. For example, the probability that a community affected by an earthquake needs hygiene kits is higher than that of a community affected by a flood.

Model

The following factors influence the choice of configuration for a pre-positioning network:

1. up-front investment (initial inventory stocking and warehouse setup);
2. operating costs (relief-item purchasing, transportation, and warehousing cost);
3. average response time.

We focus on the up-front investment and average response time and ignore operating costs for now because obtaining information and data about operating costs (i.e., costs of supplies and transportation) based on CARE's past responses was not possible. We expect that the warehouse operating cost will not be very significant because of government subsidies and collaboration with the UNHRD and other humanitarian organizations. Hence, we try to answer the question, Given an initial investment, which network configuration minimizes the average response time?

To find the optimal configuration, we develop a mixed-integer programming (MIP) inventory-location model (see Appendix A). The model considers a set of typical demand instances and, given a specified up-front investment (in terms of the maximum number of warehouses to open and the total inventory available to allocate), finds the configuration of the supply network that minimizes the average response time over all the demand instances. We obtain the typical demand instances from historical data; the supply network consists of the number and the location of warehouses and the quantity and type of items held in inventory in each warehouse.

Demand

Because the objective of the pre-positioning network is to enhance CARE's capacity to respond to sudden-onset disasters, the model considers the worldwide demand for relief supplies caused by sudden-onset natural disasters. Specifically, we consider the number of people affected by earthquakes, windstorms (e.g., hurricanes, cyclones, storms, tornadoes, tropical storms, and typhoons), wave surges (e.g., tsunamis and tidal waves), and floods. We disregard slow-onset disasters such as famine because relief-aid providers can prepare in advance to respond to such disasters and provide an effective response without using the pre-positioning network.

To measure past demand for relief supplies, we use historical data from the International Disaster Database (Centre for Research on the Epidemiology of Disasters 2007) on the number of people affected by natural disasters during the last 10 years. In the database, "affected" is defined as "...[a person] requiring basic survival needs such as food, water, shelter, sanitation...." Whereas demand can usually be measured (or estimated) directly, such as sales per month in a common facility-location problem, we take the indirect approach of first measuring the number of affected people and then basing the demand estimate on this statistic for several reasons. First, CARE does not have accurate records of past responses in terms of quantity and type of items supplied. Second, CARE often collaborates with other organizations and only provides aid to some of the affected communities. Hence, even if CARE had accurate records, we would have to consolidate data from numerous organizations. Third, in past responses, relief items might have been over- or undersupplied to assisted communities. Hence, using the indirect approach is more convenient and accurate in estimating the total global demand for an organization, such as CARE, that wants to offer disaster relief aid worldwide.

After collecting data for the number of people affected by different disasters over the last 10 years, we estimate the demand quantities by using the probability of need for different relief items and the number of items an affected person requires. For the probability of need, we rely on operational guidelines (International Federation of the Red Cross and Red Crescent Societies (IFRC) 2000), as described in Appendix B. The guidelines, based on field experience, provide the likelihood of different needs of people affected by different disasters. The likelihoods are expressed as high, medium, and low potential need. For our calculation, we assign the probabilities of 0.75, 0.50, and 0.25 to high, medium, and low potential need, respectively. To determine the number of items an affected person requires, we use CARE's specifications. To illustrate the procedure, consider a hurricane that affects 10,000 people in a hot region of Central America. The IFRC guidelines state that the potential need for emergency shelter in hot weather after a hurricane is high, and CARE's specifications state that one emergency shelter should be provided for five people. Therefore, our estimate of the number of emergency shelters required for this response is 1,500.

To model the demand locations, we aggregate data by geographical regions and use the 22 subregions of the United Nations as demand points. We assume that when a disaster hits one of the countries in a subregion, the demand associated with the event occurs at the subregion's center of population (center of mass). To calculate the centers of population of the subregions, we use the data from the global rural-urban mapping project database (Socioeconomic Data and Applications Center 2007), which contains the geographic locations of different human settlements around the world and their sizes. As a result, the model contains 22 demand points, each corresponding to a subregion in the world. (To verify the level of aggregation on demand locations, we solved the model with 100 demand locations for the cases of three and four warehouses and obtained the same results.)

The final step in preparing the demand instances is to model the possibility of providing emergency response to simultaneous events in different locations. This is important because disasters that happen within the warehouse replenishment time share the inventory on hand in warehouses. Assuming that the replenishment lead time for the pre-positioning warehouses is two weeks, based on CARE's expectation of the potential suppliers' lead time, we group historical events that occurred within the lead time and obtain 240 demand instances from the data of the last 10 years (1997–2006). Each demand instance consists of demand quantities for the different relief items at one or more demand points.

Supply

In the model, demand can be met from the suppliers and (or) pre-positioned warehouses. Global suppliers can provide direct shipments for emergency response and also replenish the pre-positioning warehouses. Humanitarian organizations often do not track the performance of the suppliers; hence, information about the geographic location and average lead time of different suppliers was unavailable for our study. To overcome this problem, the model assumes that suppliers are available to ship all relief items to any demand point within an average time of two weeks, considering the time required for the procurement phase and transportation to the affected country. The estimate is based on recent experiences of CARE; global suppliers were usually able to send relief items to any affected location within two weeks (D. Gazashvili, personal communication). As part of our sensitivity analysis, we also tested the models with one week of shipping lead time.

CARE provided 12 sites to consider as candidate warehouse locations (see Figure 1). As Table 1 illustrates, these include both UNHRD locations and other

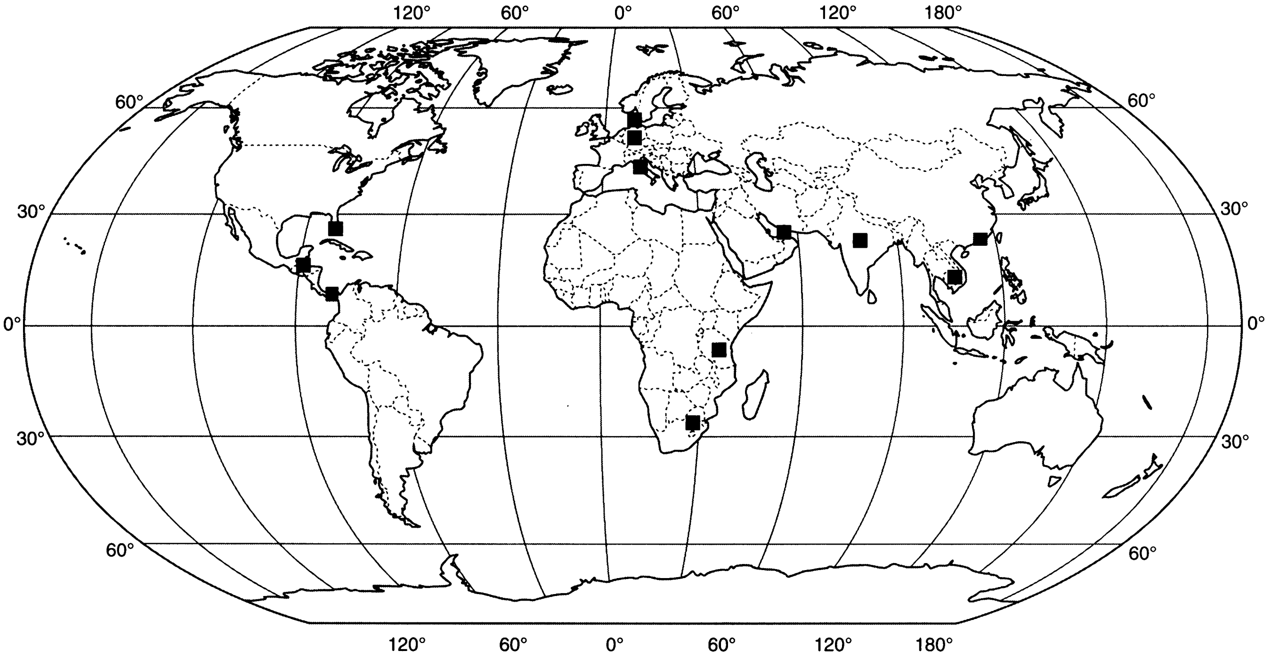

Figure 1: The map shows candidate locations for pre-positioning warehouses.

locations CARE was considering for opening a warehouse, possibly in collaboration with other humanitarian organizations. Therefore, these 12 locations are no- or low-cost opportunities for CARE in terms of initial warehouse opening costs.

CARE identified seven relief items to be stored in the pre-positioning warehouses: food, water, sanitation kits, hot-weather tents, cold-weather tents, household kits, and hygiene kits. We consider a preset inventory level at each warehouse and assume that inventory is replenished after each response. The warehouses are replenished by global suppliers, and no transshipment activity occurs between warehouses.

Country	UNHRD	CARE
Cambodia	×	
China, Hong Kong		×
Denmark		×
Germany		×
Honduras		×
India		×
Italy	×	
Kenya		×
Panama	×	×
South Africa		×
UAE, Dubai	×	×
USA, Miami		×

Table 1: The table shows potential warehouse locations considered by CARE.

Response Time

The objective function of the MIP model (see Appendix A) minimizes the average of the weighted response times over the 240 demand instances. (The weights correspond to the proportions of demand met from the global suppliers and warehouses, respectively.) The response time is the time required for the initial shipment to arrive at an entry port of the affected country after the disaster's onset. Hence, the response time is two weeks for direct shipments from suppliers; however, it depends on the distance between the warehouse and the demand location for the pre-positioning warehouses. Specifically, we consider the time required to fly the great arc distance between the points at the speed of a common cargo airplane used in humanitarian relief—the C-130—plus one day for setup and material handling at the warehouse.

Other factors, such as customs clearing, level of unrest, road damage, sociopolitical factors, and last-mile distribution, could impact the response time. However, we focus on international transportation and ignore these factors because their effect would be the same regardless of the pre-positioning network configuration.

Results

We consider two types of capacity (or budget) constraints: the number of warehouses to open and the inventory amount to keep throughout the pre-positioning network. Both Constraint (6) and Constraint (7) (see Appendix A) are always binding because the model assumes that demand can be satisfied faster from the pre-positioning warehouses than from direct shipments from the suppliers. We run the model for opening one to nine warehouses and for three levels of inventory (high, medium, and low, which correspond to 100, 50, and 25 percent of the average demand per demand instance, respectively). The model decides which warehouses to open and how to allocate the inventory among them.

We use the number of warehouses and maximum inventory as test parameters because CARE often receives in-kind donations in the form of relief supplies and services. A donor might be interested in donating water sanitation kits, or an organization or government might be willing to donate a warehouse and manage it for CARE. For example, the UNHRD is willing to provide warehouse space for CARE and other organizations in locations around the world and services, such as material handling, on a cost-recovery basis. Therefore, estimating a warehouse setup cost and prices for the initial stocking of supplies was not critical in this context.

We performed all the computations on a 4 × 900 MHz processor using ILOG OPL Studio with the CPLEX solver. The model includes 22 demand points, 12 candidate warehouse locations, seven relief items, and 240 demand instances. As a result, the MIP model includes about 470,000 variables, 12 of which are binary, and approximately 56,000 constraints. All computation runs reached the optimal solution within four hours. Figure 2 illustrates the results for one to nine warehouses and three levels of inventory.

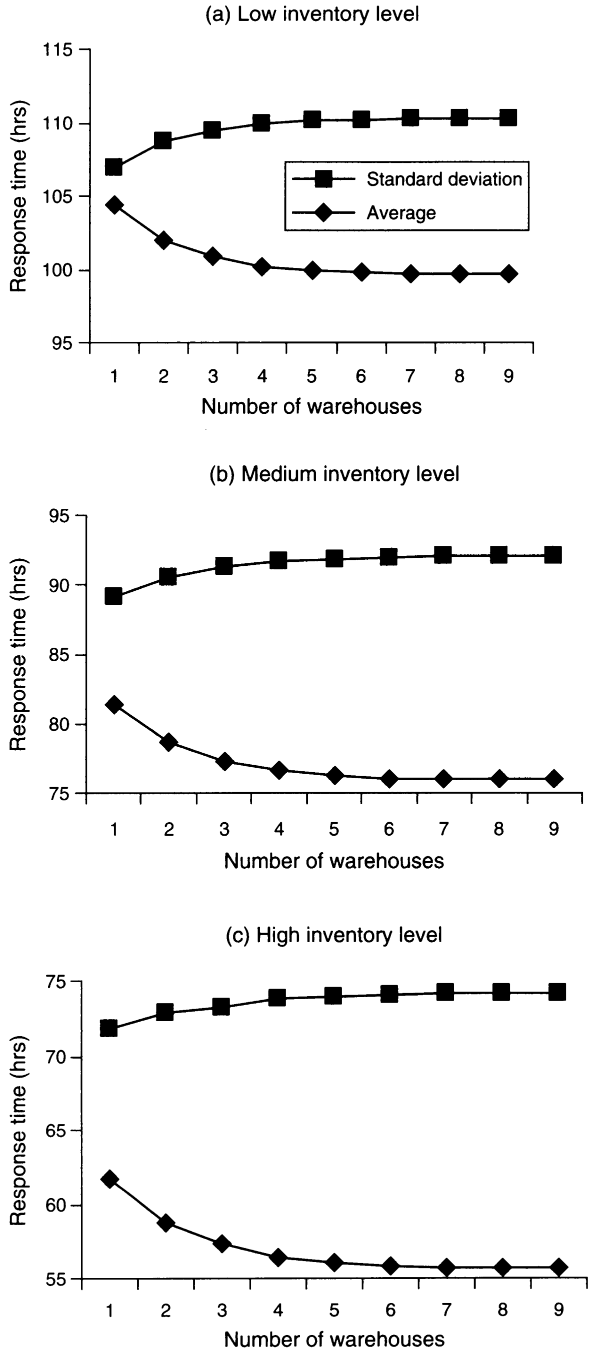

Figure 2: The three graphs show average and standard deviations of response time under low, medium, and high inventory levels as the number of open warehouses increases.

As we expected, for a given level of inventory, the average response time decreases at a diminishing rate as the number of warehouses increases; it reaches a minimal marginal benefit after three to four warehouses, indicating the desired final size of the pre-positioning network. For all inventory levels and warehouse configurations, the standard deviations of the response times are larger than the average response time, indicating significant variations. However, the two-standard deviation level from the average response time is approximately 200, 260, and 320 hours for high, medium, and low inventory levels, respectively, for all warehouse configurations. This indicates that using pre-positioning leads to a significant improvement in response times for most demand instances, when compared to instances in which we do not use pre-positioning; such instances show an average response time of 336 hours.

Figure 3 illustrates the optimal locations of three warehouses and their relative allocations of inventory. At the low inventory level, approximately 50 percent of the inventory is held in Southeast Asia (Hong Kong), 35 percent in the Middle East (Dubai), and 15 percent in Central America (Panama). As the inventory level increases, a relative shift of inventory to Southeast Asia also increases until it is so high (69 percent of inventory held at Hong Kong when inventory level is high) that it can be used to satisfactorily cover demand in South and Central Asia and part of the Middle East; although opening a warehouse in the Middle East (Dubai) is no longer optimal, opening one in Africa (i.e., in Kenya, which has 20 percent of the inventory) is. For the case of four or more warehouses, the optimal warehouse locations do not change with increasing inventory levels. The optimal solution for four warehouses includes all the locations of the optimal solution for three warehouses, except for Dubai, which is replaced by India. Table 2 shows the complete list of optimal warehouse locations.

CARE expects to receive gradual funding from donors for the pre-positioning network; that is, it does not have the resources to set up four or five warehouses from the beginning and stockpile millions of dollars worth of relief supplies. As such, considering the optimal solutions for different numbers of warehouses and inventory levels (see Figure 2) is important. At the time of this study, CARE expected to receive a small amount of funding to start pre-positioning at a single warehouse and then gradually

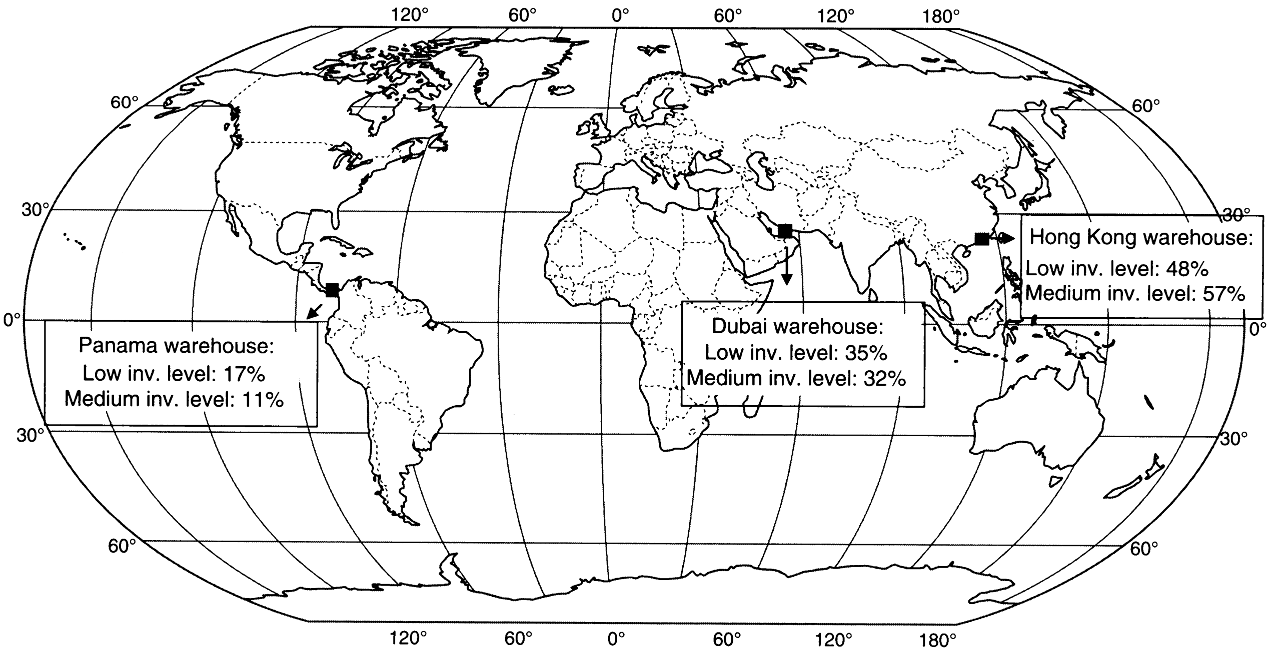

Figure 3: The map shows optimal locations and inventory allocations for three pre-positioning warehouses with low or medium inventory.

	Number of warehouses								
Locations	1	2	3	4	5	6	7	8	9
Cambodia						×	×	×	×
China, Hong Kong			×	×	×	×	×	×	×
Denmark									
Germany									
Honduras									×
India	×	×		×	×	×	×	×	×
Italy					×	×	×	×	×
Kenya				×	×	×	×	×	×
Panama		×	×	×	×	×	×	×	×
South Africa									
UAE, Dubai			×					×	×
USA, Miami							×	×	×

Table 2: The table shows optimal locations for a given number of warehouses for low and medium inventory levels. For high inventory levels, the only location change is Kenya, instead of Dubai, when the number of warehouses to open is three.

build up the inventory and expand to three locations. In such a situation, in which a gradual expansion plan will be implemented, deciding where to locate the first warehouse is critical; this plan will initially include only a single warehouse and will expand to a three-warehouse configuration, which CARE is expected to use for a considerable period because of its funding deficiency.

In our meetings with CARE staff members, we realized that they strongly prefer the Dubai location for both political and bureaucratic reasons. Warehouse space is already available on a cost-recovery basis through UNHRD in the international humanitarian city of Dubai (IHC, http://www.ihc.ae); IHC provides excellent airport and seaport infrastructure with free-zone benefits. Therefore, our final recommendations to CARE were to open the first warehouse in the Middle East, expand to Central America, and then to Southeast Asia; it should aim to allocate approximately 35, 15, and 50 percent of the inventory, respectively, among the warehouses when all three are operating. Following this gradual-expansion plan, the pre-positioning network would be very close to the optimal configuration at each step, as Figure 3 shows—especially for the low and medium inventory levels, which are more realistic than the high inventory level. If CARE continues expanding its pre-positioning network and opens a fourth warehouse in Africa and even a fifth in Europe, our sensitivity analysis results indicate that the performance would be close to the optimal.

Sensitivity Analysis

In our computational study, we used 240 demand instances from the last 10 years of disaster history, in which CARE needed to respond to a disaster or a group of disasters without any replenishment. To test whether the results we obtained are robust, we also generated demand scenarios using probability distributions from historical data. First, based on the historical data, we calculated frequencies of the disaster types that took place at various locations; we then used them as the probabilities of different disaster types striking these locations. Similarly, we determined the discrete probability distribution of the number of affected people at each demand location by disaster type. Then, using simulation techniques (see Appendix C), we again created 240 demand instances representing alternative 10-year scenarios. We did not observe significant differences in the results when we used the historical scenarios or the simulation-generated scenarios. The locations of the warehouses and the allocation of inventory are very similar across the scenarios we tested (see Appendix C).

As Table 2 shows, the India location is suboptimal only in the case of operating exactly three warehouses; in that case, the Dubai location replaces India. To analyze the trade-off between opening a warehouse in Dubai versus India in the initial steps of developing the pre-positioning network and to provide a robust expansion plan to CARE, we performed additional computations. We observe that in the three-warehouse configuration, the selection of the India warehouse creates 0.45 and 0.35 percent deviations from the optimal solution (where the Dubai location is optimum for medium and low inventory levels); these deviations correspond to a delay of approximately 20 minutes. For four or more warehouses, the selection of the Dubai warehouse creates at most a 0.24 percent deviation from the optimal solution (where the India location is optimum for medium and low inventory levels); this deviation corresponds to approximately a 10-minute delay at most (see Table C.1). Therefore, we conclude that opening a warehouse in Dubai instead of India has a relatively small effect on the response times if CARE decides to expand its network beyond three warehouses.

Similar to the Dubai versus India location comparison, our model can also be used for "what-if" analysis in the future phases of the network expansion (e.g., what if we require the model to open certain warehouses?). The model solution with that restriction can be compared to the optimal solution to weigh the pros and cons of opening specific locations because of reasons that we cannot include in the model, such as political concerns, taxes, and customs regulations.

To evaluate the sensitivity of the results to the response time from global suppliers, we solve the model again for the case in which the response time from global suppliers is one week. Figure 4 shows that our observation about diminishing returns from adding more warehouses to the pre-positioning network and the minimal marginal benefit being reached after three to four warehouses continues to hold in the case of one-week response time from global suppliers.

Conclusion

Emergency-supply pre-positioning, as a complement to the current strategy of direct shipments, can have several benefits, including more efficient procurement of goods and improvement of response times. The benefits, in particular the reduction in response time, depend greatly on the configuration of the prepositioning network. The results of our study illustrate how to best use up-front investment to achieve the largest possible response-time benefit and also support the implementation of a gradual network-expansion strategy. The model estimates the frequency, location, and magnitude of potential demand based on historical data; it also optimizes the location of warehouses and inventory allocation, given an up-front investment in the number of warehouses to open and the amount of inventory to hold in each location.

The model helped CARE to determine the desired configuration of its network and provided a roadmap of how to achieve that configuration as funds become available. By understanding the potential performance benefits and the trade-offs in the overall network configuration, CARE was able to narrow its initial options. Within each proposed region, it then considered other criteria, such as the political stability of the candidate location, customs regulations, warehouse maintenance, labor skill level, labor costs, logistics accessibility, and the possibility of collaboration with other organizations. CARE then made its final decision.

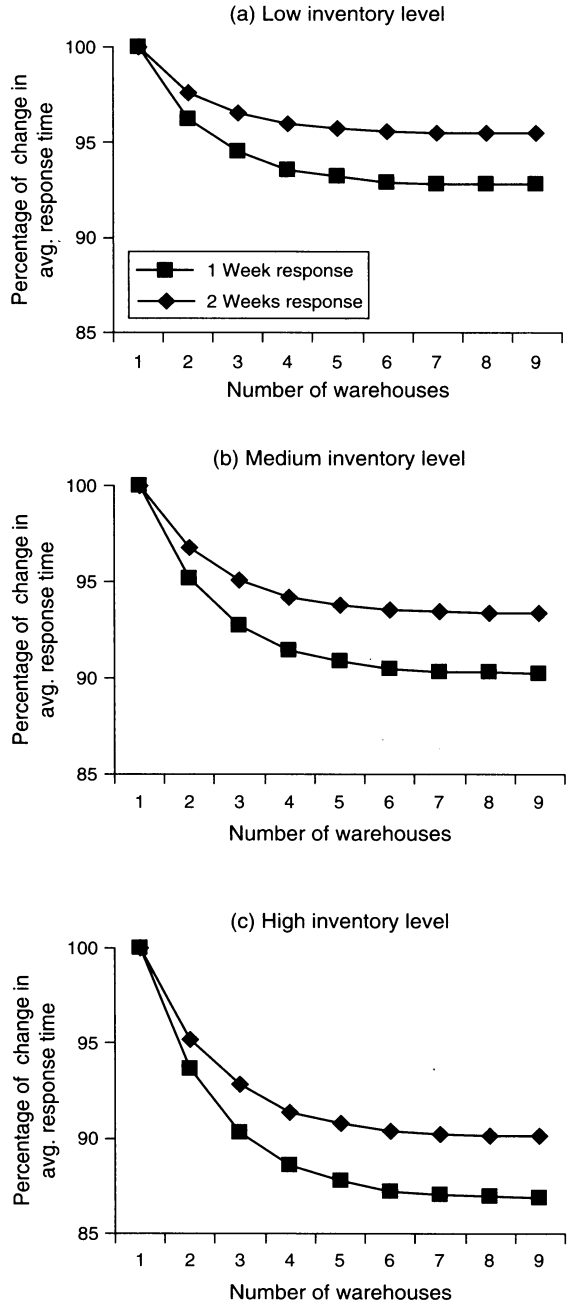

Figure 4: The three graphs show the percentage decrease in average response time as the number of open warehouses increases under low, medium, and high inventory levels; we assume one- and two-week supplier response time.

Based on our recommendations, and in collaboration with other humanitarian organizations, CARE decided to establish its first pre-positioning facility in Dubai in 2008, and its second and third in Panama and Cambodia, respectively, in 2009. Thus far, CARE has pre-positioned more than one million sachets of water purification kits in each facility. Most recently, water purification tablets in its Panama warehouse were used during the response to the 2010 Haiti earthquake (Esterl and McKay 2010). In addition, our study is serving as a basis for funding proposals for CARE's pre-positioning network. CARE is soliciting financial support from several donors using our project as a justification for its funding requests; it intends to use future funding to purchase additional relief supplies, such as plastic sheeting, tents, blankets, and jerry cans.

Appendix A. The Mixed-Integer Programming (MIP) Formulation

Index Sets

J set of possible pre-positioning warehouses.
H set of disaster types.
I set of regional demand locations.
L set of supply items.
K set of demand instances need to be responded to by the pre-positioning warehouses.

Variables

$$y_j \begin{cases} 1 & \text{if warehouse } j \text{ is opened,} \\ 0 & \text{otherwise.} \end{cases}$$

q_{jl} quantity of supply l held at warehouse j.
x_{ijkl} quantity of supply l sent to regional demand location i from warehouse j in demand instance k.
$\bar{x}_{ikl}$ quantity of supply l sent to regional demand location i from suppliers in demand instance k.

Parameters

N maximum number of warehouses to open.
Q total inventory allowed.
p_k probability of demand instance k.
t_{ij} response time from warehouse j to regional demand location i (flight time).
$\bar{t}_{il}$ response time from suppliers to regional demand location i for supply l.
d_{hik} number of affected people at regional demand location i by disaster type h in demand instance k.
p_{hil} probability of supply l being required at regional demand location i by a person affected by disaster type h.
a_{hil} quantity of supply l required by a person affected by disaster type h in demand location i.
$\bar{d}_{ikl}$ expected demand for supply l at regional demand location i in demand instance k.

Based on the above definitions, we developed the following MIP formulation:

$$\min \sum_{k\in K} p_k \left[\frac{\sum_{i\in I}\sum_{l\in L}\bar{x}_{ikl}\bar{t}_{il} + \sum_{i\in I}\sum_{j\in J}\sum_{l\in L} x_{ijkl}t_{ij}}{\sum_{i\in I}\sum_{l\in L}\bar{d}_{ikl}} \right] \quad (1)$$

$$\text{s.t.} \quad \bar{d}_{ikl} = \sum_{h\in H} a_{hil}p_{hil}d_{hik} \quad i\in I,\ k\in K,\ l\in L, \quad (2)$$

$$\sum_{j\in J} x_{ijkl} + \bar{x}_{ikl} \ge \bar{d}_{ikl} \quad i\in I,\ k\in K,\ l\in L, \quad (3)$$

$$\sum_{i\in I} x_{ijkl} \le q_{jl} \quad j\in J,\ k\in K,\ l\in L, \quad (4)$$

$$q_{jl} \le Qy_j \quad j\in J,\ l\in L, \quad (5)$$

$$\sum_{j\in J}\sum_{l\in L} q_{jl} \le Q, \quad (6)$$

$$\sum_{j\in J} y_j \le N, \quad (7)$$

$$x_{ijkl}, \bar{x}_{ikl}, q_{jl} \ge 0, \quad y_j \in \{0,1\}. \quad (8)$$

Constraints (2) calculate the expected demand of different supply items given that a number of people are affected by a specific disaster type. Constraints (3) ensure that demand at each regional demand location is completely satisfied from the warehouses and (or) the suppliers in each demand instance. Constraints (4) ensure that for each demand instance the number of supply items shipped from a warehouse is less than or equal to the inventory held at that warehouse. Constraints (5) allow only opened warehouses to hold inventory. Constraint (6) ensures that the sum of the inventories allocated to the different warehouses is less than or equal to the total inventory (Q) allowed. Constraint (7) ensures that the number of warehouses opened is less than or equal to N. The objective function (1) of this model is to minimize the expected average response time over all the demand instances.

As we discussed in the *Model* section, the computational results are obtained by considering

12 warehouse candidate locations and four disaster types. The warehouses are replenished by global suppliers, and a two-week replenishment lead time is assumed (thus, $\bar{t}_{il} = 336$ hrs). Using a two-week time window in which disasters must be responded to without replenishment, we use the last 10 years of historical data to create 240 demand instances. Each demand instance contains the amount of seven supply items needed at the 22 regional demand locations worldwide. Therefore, we assume that the probability of any such demand instance is the same, that is, $p_k = 1/240$; thus, it can be omitted from the formulation.

In the objective function, we choose the minimization of average response time rather than maximum travel time because of the existence of extremely high-demand events (such as 2004 Indian Ocean tsunami, which definitely requires a global supplier delivery) in the demand instances considered. Average response time is calculated using the weighted time average of the supply items sent from warehouse locations or global supplier locations. The numerator of objective function (1) is composed of two parts for a demand instance; the first sum is the total time (times × items) needed to respond from global suppliers to all demand locations for all types of supply items needed; the second part is the total time (times × items) needed to respond from all pre-positioning warehouses to all demand locations for all types of supply items needed. The denominator of objective function (1) is the total amount of relief supplies sent to all demand locations. Therefore, the objective function of the model gives us an overall performance of the selected pre-positioning network based on its expected weighted average response time. The time to respond from a warehouse location to any regional demand location is calculated as the flight time of the "great arc distance" over the earth between these locations by a C-130 cargo plane, plus an additional day for material-handling operations at the warehouse.

Appendix B. Operational Guidelines Adapted from the International Federation of Red Cross and Red Crescent Societies (IFRC)

To calculate the demand for the actual items, we translate the data that show the number of affected people by different disasters into numbers of items required. Table B.1 shows potential emergency needs. For example, consider emergency shelter (tents). The likelihood of need after earthquakes is generally low, but also depends on the climate. The likelihood of this need increases in cold weather. For floods, the likelihood of need is lower because the population affected by a flood is usually not displaced from their homes for a long period of time (there are obvious exceptions, such as the case of Hurricane Katrina). This qualitative information and the climate conditions of the demand locations are used to estimate p_{hil}; probability of supply item l being required at regional demand location i by a person affected by a disaster type h.

	Earthquakes	Floods
Water and sanitation		
Distribution, storage, processing	H	H
Personal hygiene	H	M
Insect and rodent control	M	H
Food and nutrition		
Short-term distribution	H	M
Supplementary/curative feeding	L	M
Agriculture	L	M
Shelter and household stock		
Emergency shelter	L, C	L
Fuel for dwellings	L	M
Kitchen utensils	H	M

Table B.1: We adapted these data from IFRC (2000). They illustrate the likelihood (low, medium, high) of need for each item by people affected by different hazards.

Appendix C. Results of the Sensitivity Analysis

To create a demand instance, we simply generate a sequence of uniform random numbers; $u_1, \ldots, u_{88}$. We use each random number to determine if one of the four disaster types takes place at one of the 22 demand locations by comparing it to the frequency obtained from historical data. If a disaster strikes a location, we use an additional uniform random number to determine the number of people affected from the corresponding discrete probability distributions. We then repeat this process to obtain 240 randomly generated demand instances.

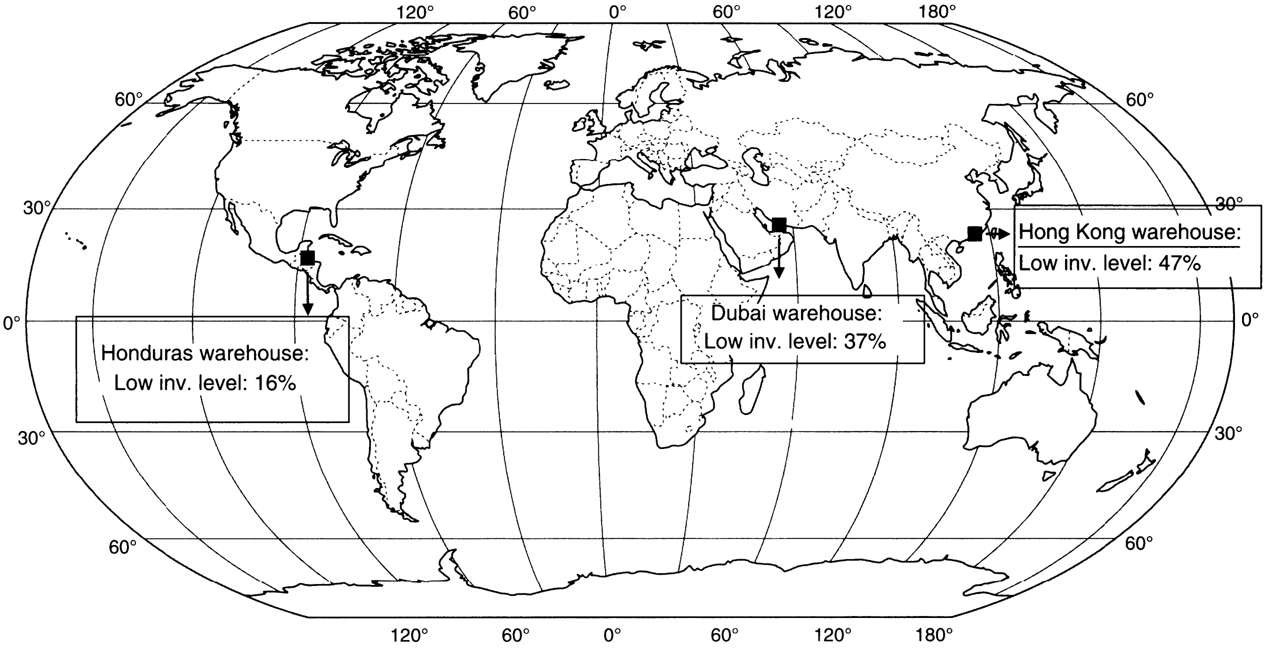

Figure C.1: The map shows optimal locations and inventory allocations for three pre-positioning warehouses that have low inventory for randomly generated scenarios.

Figure C.1 illustrates the optimal location and inventory allocations while responding to 10 randomly generated scenarios when the inventory level is low. If we compare them with the corresponding results of the demand instances generated from the historical data in Figure 3, we see that the inventory allocations are very similar; the only difference is the location of the Central America warehouse from Panama to a close proximity location, Honduras.

To clarify the trade-off of choosing the Dubai location instead of India, we also solved the model separately for the case in which the Dubai location is always selected. We compared the average response times to the optimal results given in Figure C.1 and provided the "percentage deviation from optimal average response times" in Table C.1.

To further evaluate the appropriateness of the Dubai location, we compared the standard deviation of response times to the optimal solution when we always include the Dubai warehouse in the pre-positioning network (see Table C.2). The standard deviation change is less than 1 percent for up to three warehouse configurations and less than 0.1 percent (roughly corresponding to six minutes) for four or more warehouse configurations. Therefore, we conclude that the selection of the Dubai location has no significant effect on increasing or decreasing the variation in response times among demand instances.

Inventory levels	Number of warehouses								
	1	2	3	4	5	6	7	8	9
High	1.30	2.31	0.16	0.39	0.32	0.32	0.10	0	0
Medium	0.76	1.50	0	0.24	0.19	0.19	0.05	0	0
Low	0.39	0.94	0	0.16	0.11	0.11	0.03	0	0

Table C.1: The table shows the percentage deviation from optimal average response times with the selection of the Dubai warehouse.

Inventory levels	Number of warehouses								
	1	2	3	4	5	6	7	8	9
High	0.08	−0.65	0.00	−0.05	−0.10	−0.10	−0.02	0.00	0.01
Medium	0.01	−0.59	0.00	−0.08	−0.09	−0.08	−0.07	0.00	0.00
Low	0.08	−0.55	0.38	−0.07	−0.09	−0.09	−0.02	0.00	0.00

Table C.2: The table shows the percentage change in the standard deviation of response times with the inclusion of the Dubai warehouse in the pre-positioning network.

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Rigoberto Giron, Director, Emergency and Humanitarian Assistance Unit, CARE USA, 151 Ellis Street, NE, Atlanta, Georgia 30303-2440, writes: "I am writing this letter to comment on the paper titled 'Pre-Positioning of Emergency Items for CARE International' submitted to *Interfaces* by Serhan Duran, Marco A. Gutierrez, and Pinar Keskinocak based on a project conducted jointly between CARE and Georgia Tech.

"I am the Director of the Emergency and Humanitarian Assistance Unit at CARE, one of the world's largest private international humanitarian aid organizations with the mission of serving individuals and families in the poorest communities of the world. I have been in my current position for over three years and have been with CARE for eight years. I am responsible for global emergency preparedness and emergency response capacity building efforts and provide support to emergency operations within an organization that has operations in 69 countries. One of my primary goals has been to develop strategic relationships with partners that can enhance our ability to reach those in need in a more timely and effective manner.

"The CARE-Georgia Tech collaboration began in the summer of 2005, and the project described in the paper actively started in January 2007. The team analyzed potential locations for pre-positioning inventory, which becomes increasingly important for shortening disaster response times. Following the team's recommendations based on their analysis along with other considerations, we decided to establish our first pre-positioning facility in Dubai in 2008, a second one in Panama in 2009, and a third one in Cambodia also in 2009 in collaboration with other humanitarian organizations. So far, we have prepositioned more than one million sachets of water purification kits in each of these facilities. The team's work not only gave us excellent recommendations regarding locations, inventory levels, and an expansion strategy for the network, but is also serving as the basis for funding proposals for the network. In June, 2009, for example, we will request additional funding for the network from a consortium of various Atlanta-based companies using the team's project as the main justification. We intend to use this funding to purchase additional relief items such as plastic sheeting, blankets, jerry cans, etc.

"By pre-positioning we expect to reduce response time from weeks to 48–72 hours, reduce procurement costs by buying in larger quantities, reduce freight costs by using transportation resources more efficiently and improve coordination with other responding organizations. We plan to continue working with Georgia Tech on the further implementation steps of the pre-positioning network as well as with other supply chain improvement initiatives."