THE EFFECTS OF NATURAL DISASTER TRENDS ON THE PRE-POSITIONING IMPLEMENTATION IN HUMANITARIAN LOGISTICS NETWORKS

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THE EFFECTS OF NATURAL DISASTER TRENDS ON THE PRE-POSITIONING IMPLEMENTATION IN HUMANITARIAN LOGISTICS NETWORKS

Submitted by **MELDA BOZKURT** in partial fulfillment of the requirements for the degree of **Master of Science in Industrial Engineering Department, Middle East Technical University** by,

Prof. Dr. Canan Özgen
Dean, Graduate School of **Natural and Applied Sciences** _____________________

Prof. Dr. Sinan Kayalıgil
Head of Department**, Industrial Engineering** _____________________

Assist. Prof. Dr. Serhan Duran
Supervisor, **Industrial Engineering Dept., METU** _____________________

Examining Committee Members:

Assist. Prof. Dr. İsmail Serdar Bakal
Industrial Engineering Dept., METU _____________________

Assist. Prof. Dr. Serhan Duran
Industrial Engineering Dept., METU _____________________

Assist. Prof. Dr. Cem İyigün
Industrial Engineering Dept., METU _____________________

Assist. Prof. Dr. Sinan Gürel
Industrial Engineering Dept., METU _____________________

Navy Lt. Ertan Yakıcı (M.Sc.)
Turkish Naval Forces Command, TAF _____________________

Date: _____________________

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

Name, Last Name: Melda BOZKURT

Signature :

ABSTRACT

THE EFFECTS OF NATURAL DISASTER TRENDS ON THE PRE-POSITIONING IMPLEMENTATION IN HUMANITARIAN LOGISTICS NETWORKS

Bozkurt, Melda
M.Sc., Department of Industrial Engineering
Supervisor: Assist. Prof. Dr. Serhan Duran

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The most important aim of pre-positioning is to reduce the delivery lead time with eliminating the procurement stage by positioning items closer to the disaster area. The last 30 years' data is used to designate the disaster trends; EM-DAT database is used to acquire the necessary data which includes the disaster locations, type of disasters and number of people affected. Also the most recent four years' data is used for verification of the results.

Locations of the optimal warehouses for pre-positioning are determined considering the generated emergency response scenarios. When we pursue this exploration, besides determining the optimal pre-positioning locations given by CARE International, we also determined where the natural disaster trend drifts towards. Therefore, this research tries to find an answer whether the disaster trends should be considered to determine the location of the pre-positioned items or not.

Key words: Pre-positioning; Natural Disaster Trends; Disaster Response

ÖZ

DOĞAL AFET TRENDLERİNİN İNSANİ LOJİSTİK AĞLARINDA UYGULANAN ÖN-KONUMLAMA STRATEJİSİNE ETKİSİ

Bozkurt, Melda
Yüksek Lisans, Endüstri Mühendisliği Bölümü
Tez Yöneticisi: Yard. Doç. Dr. Serhan Duran

Mayıs 2011, 68 Sayfa

Anahtar Kelimeler: Ön-konumlama; Doğal Afet Trendleri; Acil Durum ve Afet Yönetimi

Ön konumlamanın en önemli amacı malzemeleri afet bölgesine daha yakın olan alanlarda konumlandırıp, tedarik aşamasını ortadan kaldırarak teslimat süresini azaltmaktır. Doğal afet trendlerini belirlemek için son 30 yılın EM-DAT veritabanından elde edilen verileri kullanıldı. Bu veriler doğal afet yerlerini, doğal afet türlerini ve etkilenen insan sayısını içermektedir. Son dört yılın verileri de bu sonuçları doğrulamak için kullanılmıştır.

Ön konumlandırma için optimal depo yerleri, oluşturulan acil müdahale senaryoları göz önünde bulundurularak belirlenir. Bu çalışma sonucunda, sadece CARE International tarafından sağlanan ön konumlama yerlerinin değil doğal afet trendlerinin ne yöne gittiğinin de belirlenmiştir. Bu sebeple, yapılan araştırma ön

konumlama yapılırken doğal afet trendlerinin dikkate alınmasının gerekip gerekmediği sorusunun cevabını bulmaya çalışmaktadır.

To my family

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ABBREVIATIONS

CRED: Centre for Research on the Epidemiology of Disasters
EM- DAT: Emergency Events Database
IFRC: International Federation of Red Cross and Red Crescent Societies
MIP: Mixed Integer Programming
MRE: Meal Ready to Eat
UNICEF: The United Nations Children's Fund
UNHRD: The United Nations Humanitarian Response Depot
WHO: World Health Organization

CHAPTER 1

INTRODUCTION

In this thesis we analyze the effects of natural disaster trends on pre-positioning warehouse implementations in humanitarian logistic networks. This research utilizes a facility location model to identify optimal locations for relief items to be stored considering the natural disaster trends observed. Fundamental argument for pre-positioning is to reduce the delivery lead time by positioning items closer to the disaster area and eliminating the procurement stage partially or totally. Candidate warehouse locations used in this thesis are provided by CARE International. Demand data is obtained from EM-DAT database and last 30 years' data is used to assess the disaster trends. This three decade period is chosen considering the data quality and consistency. Also the most recent four years' data is used to verify the results. The data includes the locations where the disasters occur globally and the number of people that are affected by different types of disasters in various regions.

Emergency response scenarios are generated and these scenarios were used as inputs to a Mixed Integer Programming (MIP) Model to determine the location of the warehouses for a number of parameters. These parameters are the number of warehouses to open which changes in a range of 1-12 and the inventory level to be rationed between those warehouses; high, medium and low. This exploration is an evaluation of pre-positioning as a strategic policy; this research inquires not only optimal pre-positioning locations suggested by CARE International, but also takes into account the direction where the probability of disaster occurrence drifts towards. Therefore, this work will help to answer whether the disaster trends should be considered to determine the location of the pre-positioned items or not.

CHAPTER 2

LITERATURE STUDY

In this chapter, an overview of the relevant literature is provided. In Section 2.1, humanitarian logistic and other supply chains are compared to each other and their differences are illustrated with examples. In Section 2.2, the related academic studies on pre-positioning relief items in humanitarian supply chains are presented. This section also includes a review on advantages and disadvantages of the pre-positioning strategy. In Section 2.3, natural disasters data between the years 1977-2006 are analyzed to exemplify the disaster trends.

2.1 Humanitarian Logistics and Its Unique Characteristics

Humanitarian logistics is defined as "the process of planning, implementing and controlling the efficient, cost-effective flow and storage of goods and materials as well as related information, from point of origin to point of consumption for the purpose of meeting the end beneficiary's requirements of vulnerable people who are affected by disasters" (Thomas and Mizushima, 2005). Disaster can be defined as a natural or man-made deterioration which affects a whole system by threatening its objectives and priorities. Humanitarian logistics involves delivering the right supplies to the right people, at the right place, at the right time, and in the right quantities (Cottam, Roe, & Challacombe, 2004; WFP, 2005). It includes a series of activities such as tracking and tracing inventory, customs clearance, local transportation, storage, distribution, supply and transportation. Actually, all logistic operations include planning and preparation, design, supply, transportation, inventory, warehousing, distribution, and supplemental ones such as appeal and mobilization. However for humanitarian logistics these operations are vital since any kind of interruption costs human life.

Logistics is very important for disaster relief since it provides the connection between procurement and response. Major humanitarian needs like food, shelter, water and hygiene should arrive to affected area soon after the disaster. Therefore, increasing the speed of response and effectiveness of distribution are the most expensive and vital parts of a relief response. Humanitarian logistics can be used to reduce disaster effects and contribute to improve the areas as knowledge management, technology, measurement, and positioning.

It is important to note two factors in assessing the unique characteristics of the humanitarian supply chain. First, the supply chain must be planned at the beginning of an urgent situation. Beamon (2004) develops the relief mission life cycle model by considering assessment and deployment periods before sustainment and reconfiguration of resources. Relief mission life cycle is illustrated in Figure 2.1. From response phase of relief activities to recovery and development, the supply chain moves in between push and pull strategies, depending on the quantity of aid. If aid is supplied independently from the demand quantity, supply chain moves away from the push strategy (Russel, 2005).

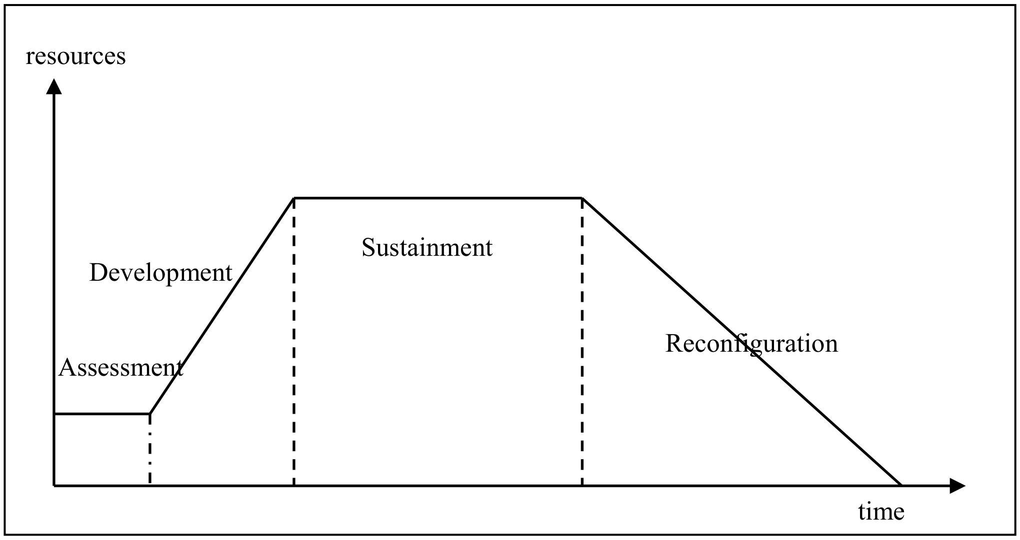


Figure 2.1: Relief Mission Life Cycle (Beamon, 2004)

Most of the current literature on humanitarian logistics focuses on the comparison of humanitarian and private sector supply chains. Thomas and Mizushima (2005) state that it is hard to manage the humanitarian supply chains since it is impossible to know when and where a disaster is going to happen and how many people are going to be affected. Also Gustavsson (2004) emphasized that there is a challenging difference between private sector and humanitarian logistics. Private sector supply chains are based on long term predictability while a humanitarian logistics supply chains need an investment for a short-term emergency response. Wassenhove (2006) indicates that both of them can learn from each other by adapting the models to their specific situations as algorithmic planning can be used for the applications of all supply chains. Humanitarian supply chains had to respond to uncertain trends more than business supply chains.

Inventory control policy in humanitarian context is a subject that has not been studied extensively yet. Beamon and Kotleba (2006) introduce an inventory model which has normal and emergency options for re-supply. According to the model if the inventory level decreases below the normal re-order point an emergency occurs. The inventory model figures out the optimal inventory level and re-order points for both normal and emergency cases. Humanitarian supply chain's objectives and performance measurements are different from other supply chains. In case of a disaster, most of the supplies come from donations while regular supply chains follow a standardized order process. Unlike other supply chains profit cannot be used for a success metric for humanitarian supply chains since cash flow data may not explain the benefits. On the other hand it is possible to apply many models based on cost minimization to the humanitarian supply chains directly or with modifications (Ergun, 2008). As an example for such a modification; Lodree and Taskin (2006) work on inventory control models for recovery planning to optimize the trade-off between logistics forecast accuracy and cost.

Larson (2006) states that Operations Research (OR) can help decision makers to plan and respond to emergencies by considering what supplies and equipment they need. The location has to be taken into account since it affects the respond time. He also indicates that possible destruction of located facilities, possible inaccessibility of transportation pathways and the nearness of facilities to others should be analyzed to plan an emergency response. Donors and vendors can also affect the supply availability as the shortage or overage of supplies may cause emergency response to be ineffective and result in increased human suffering (Knott, 1987). Developing strategies is important to minimize the response time and to cope with unpredictability of demand. Pre-positioning is a strategic attempt that allows both faster response and better procurement planning and an improvement on distribution costs (Ergun, 2008). However, an additional investment before the disaster is required and the funds are more difficult to obtain in that pre-disaster period.

2.2 The Advantages and Disadvantages of Pre-positioning

Wassenhove (2006) defines pre-positioning as a tool enabling to respond faster as items like medical supplies and food are pre-positioned in warehouses close to the disaster-prone regions. UNICEF reports that pre-positioning of relief supplies near the affected area has proven to be an effective strategy for responding to sudden-onset emergencies (UNICEF, 2005). WHO (2001) and Thomas (2003) indicate that pre-positioning, or the storage of inventory at or near the location at which it will be used, has been emerged as a possible logistics strategy that would reduce delivery lead-time. World Vision International implements a pre-positioning system which is based on pre-positioning units (GPUs). The GPU system was launched with three warehouse locations in 2000; Denver, Colorado; Brindisi, Italy and Hanover, Germany. Although the benefit of a GPU system is rapid response, integrating GPU system into a long-term humanitarian relief response brings high transportation expenses.

Literature on pre-positioning in supply chains mostly aims to minimize emergency response time of relief items. Duran et. al. (2010) constructed a model to determine the effects of pre-positioning relief items on the average response time. Balcik and Beamon (2008) constructed a model to determine the locations and the number of pre-positioning warehouses to minimize the emergency response time. The model in Balcik and Beamon (2008) gives inventory decisions by considering a budget and cost, whereas the one in Duran et. al. (2010) gives inventory decisions without a budget constraint since the locations suggested by the non-profit organization they collaborate (CARE International), are no- and low-cost warehouse locations.

Humanitarian supply chains have many players such as donors, NGOs, government, suppliers and military. Hence coordination and management of disaster supply chains are much harder. Most of the NGOs are not specialized in management and operating a warehouse is a challenging task since pre-positioning of stocks is considered as overhead for most of them. Strategically located warehouses are used to respond quickly to disasters; on the other hand supporting the expenses of operating a warehouse is high for most of the NGOs. Transportation is not only dependent on the location, but also on changing conditions since the onset of a disaster can disrupt airports, seaports and highways or communication infrastructure. Choice of an improper transportation mode causes incompetent planning and high expediting costs. Kapucu (2006) states that the strategies such as use of staging areas for pre-positioning help cutting through the difficulties in getting the right supplies to the right people, at the right time, at the right place.

Beamon and Kotleba (2006) evaluated a survey to find out if prepositioned stocks meet the needs by assigning answers to the following question.

Did the pre-positioned stock meet your needs?

Scale

5: *Yes, exceeded needs.*

4: *Yes, met all needs.*

3: *Yes, adequately met needs.*

2: *Yes, met some needs.*

1: *Yes, but did not meet needs*

0: *No pre-positioned stock*

According to the survey result provided in Table 2.1, it is seen that pre-positioning is not common in regional and national area. There could be difficulties such as the need of extra paper work, and additional delays due to specific policies of the region.

Table 2.1: Pre-positioned Stock’s Survey Result

	Average	**Individual Responses**																	
International	**2.09**	**0**	**0**	**0**	**0**	**0**	**1**	**1**	**2**	**2**	**2**	**3**	**4**	**4**	**5**	**5**	**5**		
Regional	**0.15**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**2**					
National	**0.8**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**1**	**1**	**1**	**2**	**2**	**2**	**3**			
Area	**0.31**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**2**	**2**					

Akkihal (2006) compares the humanitarian and military operations and comes to the conclusion that the requirements of both of them are similar as material demands are often unexpected and rapid response is critical to saving lives. He divided inventory pre-positioning into two categories. The first category is the estimation of item

amounts required along a supply chain and the second one is the patterns which are triggered by events in the supply chain. He indicates that the response time from the source to the prepositioned warehouse will not be time-sensitive since this activity may occur before the hazard event. Items are stocked at the warehouse to decrease the delivery lead-time. Therefore, the response time is minimized as the stocks are pre-positioned closer to the demand point. The lead time of the inventory positioned near demand points would be less than inventory positioned nearer to the vendor as the transportation time is a linear function of distance to the demand point. Facility locations’ effects on lead time are illustrated in Figure 2.2.

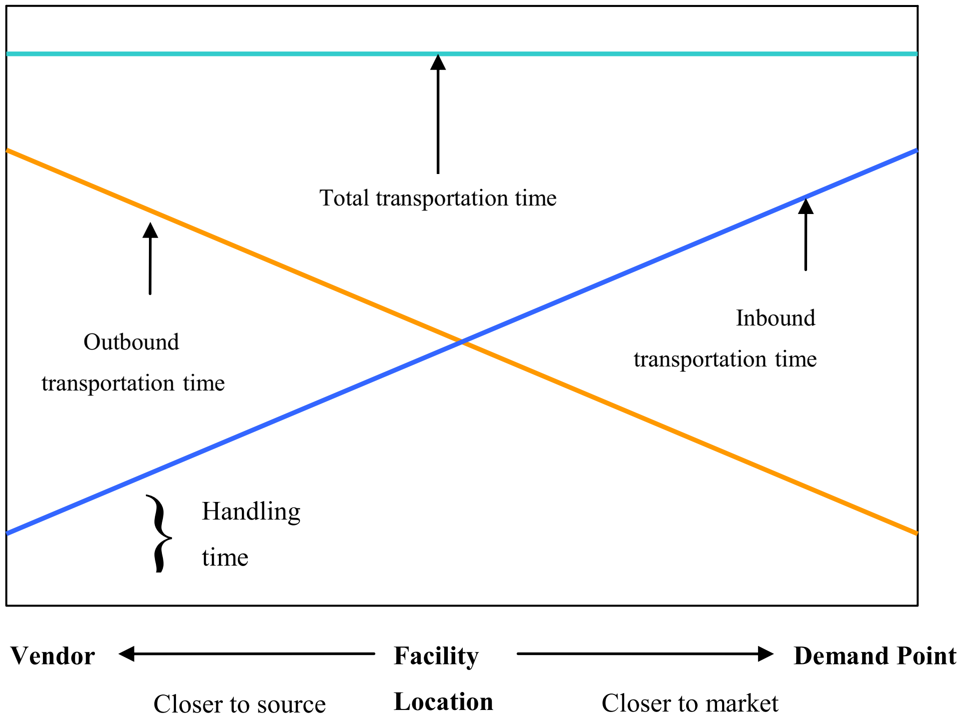


Figure 2.2: Facility Locations' Effects on Lead Time (Akkihal, 2006)

2.3 The Need of Trend Analysis for Pre-Positioning

Increasing number of natural disasters necessitates the increase in capacity for delivering humanitarian relief. Accordingly, it becomes crucial to develop an inventory management strategy for a warehouse supporting relief operations.

The trend in number of affected people is influenced by single major events that have high impact. Therefore, the number of affected people and natural disaster occurrences change from year to year. It is hard to generalize the trend as increasing or decreasing by considering short period data, such as annual, as it fluctuates considerably. According to the Annual Disaster Statistical Review (Vos et al., 2006) the year 2006 had less human impacts compare to the recent years, the number of deaths by natural disasters was 16,940 people while the number is increased to 235,272 in 2008. Although the number of natural disasters had an annual average of 392 during the period 2000-2008, 350 natural disasters occurred in 2008 and also the number dropped to 335 in 2006. The average share of flood and storm were 76.8% during the period 2000-2008. The share was 79% in 2006 and 82.6% in 2008. The average of economic damages was US$ 102.6 billion for the period 2000-2008, while the damage was higher in 2008 (US$ 189.2 billion) and less than half of the average in 2006 (US$ 41.3 billion). Thus, we use decade aggregation level to analyze the disaster trend to overcome annual fluctuations. Detailed information and comparison of disaster data for previous three decades are given in Section 3.

Trend analysis may be crucial to determine the optimal locations for pre-positioning. Once the pre-positioning warehouse locations are established, they will be used for a long time. Therefore, the chosen locations should be robust enough to enable extensions, and cope with changing disaster trends in disaster types, locations and magnitudes.

CHAPTER 3

NATURAL DISASTER TRENDS

We utilized Emergency Events Database (EM-DAT) to obtain the disaster data and to create disaster scenarios. The disaster scenarios served as input to our mathematical model which in return determines the optimal pre-positioning warehouse locations.

EM-DAT was created by WHO Collaborating Centre for Research on the Epidemiology of Disasters (CRED) and initial support of the Belgian Government in 1988. It aims to serve the intents of humanitarian action at local and global levels. The main objective is to facilitate decision making for disaster preparedness. The database is compiled from non-governmental organizations, insurance companies, UN agencies, research institutes and press agencies. EM-DAT provides data for not only natural disasters but also man-made disasters such as biological and technological disasters. In this thesis we did not consider man-made disasters since it is hard to determine a trend for them; therefore, we based our findings on the natural disasters only.

EM-DAT includes data on the effects of disasters all around the world from 1900 to present. The data contains the locations, dates, number of affected people, duration of each disaster and disaster-related economic damage estimates. We used the data between the years 1977 and 2006 to analyze the natural disaster trends. We divide the considered 30 years into three periods to observe whether

there is a detectable trend in disaster locations and number of affected people. In the database, “affected” is defined as “requiring basic survival needs such as food, water, shelter, sanitation e.t.c...” We also used the data of the years 2007, 2008, 2009 and first six months of 2010 to verify our results.
We collected the data with respect to countries first, and then we assign each country to one of the United Nations’ (UN) 22 sub-regions, and, the centers of mass of those sub-regions are regarded as demand points. This level of aggregation facilitates analysis of the trends of natural disasters in terms of location and disaster types.

3.1 Natural Disasters between 1977-2006

4,326 natural disasters occurred between the years 1977-2006 and 3,458,419,465 people had been affected by them in that thirty years period. When we scrutinize the data given in Table 3.1., it is easily seen that highest number of disasters occurred in South Eastern Asia, Southern Asia and Eastern Asia regions in descending orders. On the other hand, the number of affected people listed in the reverse order which can be explained by the density of population and destruction level of the natural disasters. In the rest of this section we will analyze the data from 30 years when we evaluated the data by dividing it to three periods.

846 natural disasters occurred between 1977 and 1986; 402,578,682 people affected are affected. The highest number of disasters occurred in order of South Eastern Asia, Southern Asia and Eastern Asia regions. The highest number of affected people can be listed in order of Southern Asia, South Eastern and Eastern Asia. When we compare the data of years between 1987 and 1996 with the first 10 years’ period; we observe that the number of natural disasters occurred increased to 1,179 while the number of affected people increased more than triple times and became 1,495,864,468. The highest number of disasters occurred in the same regions while, number of affected people dispersed mostly in Eastern Asia,

Southern and South Eastern Asia followed by Eastern Asia. The number of disasters occurred had an increasing trend and the data from the third decade indicates 2,301 disasters. The number of affected people also followed an increasing trend and reached 1,558,976,315.

When we analyzed the data of thirty years it can be seen that the trend of number of natural disasters occurred and number of affected people is increasing decade by decade. In the first period Eastern Asia ranked third place for both categories, on the other hand in the second and third period the highest number of affected people belonged Eastern Asia. Caribbean, Central Asia, Eastern Africa, Eastern Europe, Micronesia, Middle Africa, Northern Africa, Western Asia and Western Europe have an increasing trend in number of natural disasters occurred and number of affected people, however Melanesia and South America have a decreasing trend which means those locations may not be appropriate to pre-position the items.

As we consider pre-position relief items for different types of natural disasters such as earthquakes, floods and wind storms, we need to determine which type of disaster tends to be occurred in which region. This information will be used to calculate the number of pre-positioned items required as each type of natural disasters requires different kind of items.

Table 3.1: Natural Disasters and Affected People by Regions (1977-2006)

Number of Disasters Occurred			**Number of Affected People**			**Region**
1977-1986	**1987-1996**	**1997-2006**	**1977-1986**	**1987-1996**	**1997-2006**	
19	34	49	28,402	3,986,725	53,679	**Australia and New Zealand**
32	69	90	3,590,680	6,847,385	11,807,417	**Caribbean**
46	74	124	9,484,275	2,866,447	11,909,294	**Central America**
0	10	29	-	542,414	604,004	**Central Asia**
40	51	172	4,040,294	6,516,999	19,498,878	**Eastern Africa**
111	171	313	22,938,574	906,987,392	1,004,086,931	**Eastern Asia**
10	27	115	416,399	3,262,711	5,099,714	**Eastern Europe**
19	18	31	948,146	536,479	210,632	**Melanesia**
0	5	8	-	12,318	30,695	**Micronesia**
3	14	44	2,450	396,363	1,279,755	**Middle Africa**
16	26	49	1,337,983	3,207,891	4,383,401	**Northern Africa**
34	61	164	1,248,151	1,199,263	10,185,405	**Northern America**
2	8	23	18	1,001,080	286,281	**Northern Europe**
7	10	11	172,574	291,005	49,114	**Polynesia**
97	101	174	19,654,312	11,668,911	9,078,576	**South America**
174	201	276	54,937,829	72,234,216	71,901,737	**South Eastern Asia**
6	15	36	1,213,885	223,131	661,494	**Southern Africa**
145	184	295	276,135,472	467,522,586	393,341,107	**Southern Asia**
41	26	79	2,621,127	111,862	1,369,287	**Southern Europe**
14	28	84	1,116,030	2,571,369	2,918,931	**Western Africa**
19	27	76	2,660,387	3,468,531	6,138,633	**Western Asia**
11	19	59	31,694	409,390	4,081,350	**Western Europe**
846	1,179	2,301	402,578,682	1,495,864,468	1,558,976,315	**TOTAL**

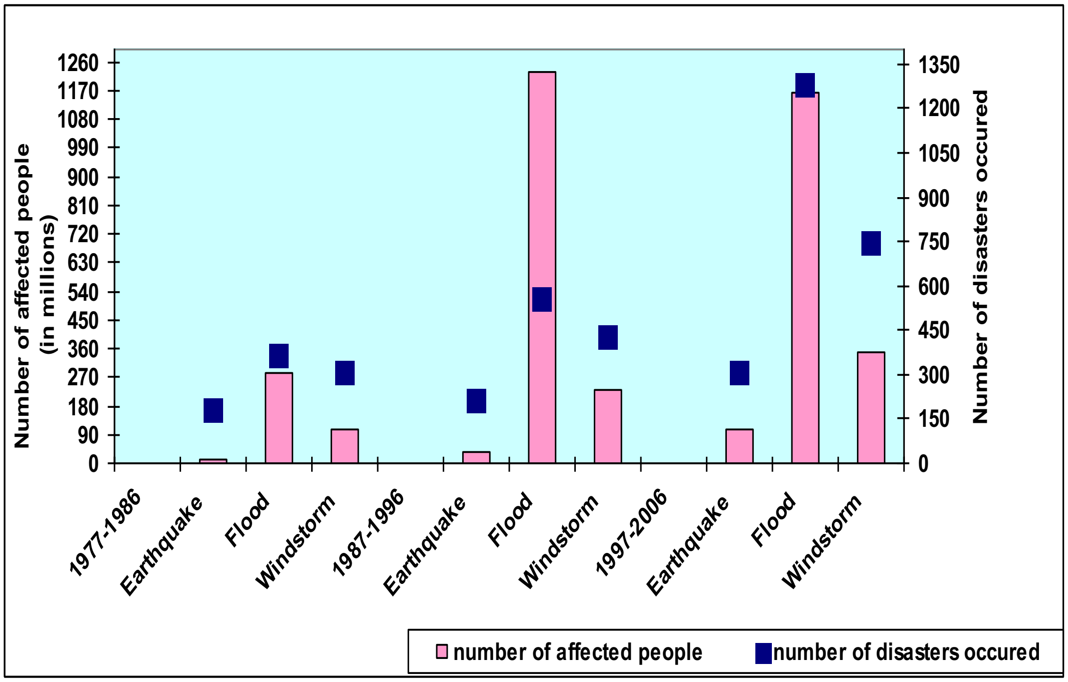


Figure 3.1: Trends of Three Natural Disaster Types in Occurrence and Number of Affected for Three Decades

As in Duran et. al. (2010), the items we considered to pre-position are cold tent, hot tent, household kit, MREs, hygiene kit, sanitation and water, and each item has a need probability according to the type of the disaster. The probabilities are decided utilizing operational guidelines from the International Federation of Red Cross and Red Crescent Societies (IFRC 2000, see also APPENDIX A). The likelihoods are expressed as “high”, “medium” and “low” potential need. The probabilities of 0.75, 0.50 and 0.25 are used for “high”, “medium” and “low”, respectively.

Table 3.2: Probabilities of Need for Pre-positioned Items upon Type of Natural Disasters

Disaster Type	Cold Tent	Hot Tent	Household	MREs	Hygiene	Sanitation	Water
Earthquake	0.125	0.125	0.25	0.75	0.75	0.75	0.75
Flood	0.125	0.125	0.25	0.50	0.50	0.50	0.50
Wind Storm	0.125	0.125	0.25	0.50	0.50	0.50	0.50

3.1.1 Earthquakes Occurred between 1977-2006

652 earthquakes occurred in thirty years period and 91,980,152 people are affected due to those. Southern Asia, Eastern Asia and South Eastern Asia are the regions that earthquakes mostly hit. Also number of affected people is high in those regions. Other than the continent of Asia, Central America has a significant number of affected people by earthquakes.

According to the data of the three decades, it is seen that Southern Europe's number of earthquakes trend is decreasing while Eastern Asia's is increasing, South and South Eastern Asia regions have active fault lines and as a result they also have an increasing trend for number of earthquakes occurred. The number of affected people is high in those regions as the population density is high, which can be a determining property to pre-position the items needed after an earthquake nearby. Micronesia, Northern Europe and Southern Africa are the regions that had been less exposed to earthquakes.

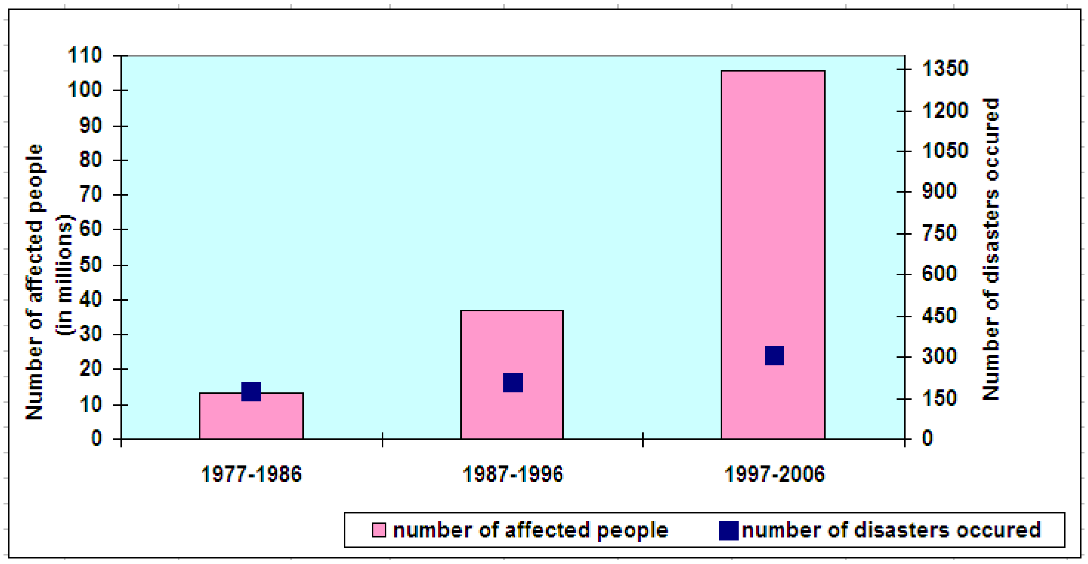


Figure 3.2: Trends in Occurrence and Number of Affected People for Earthquakes

3.1.2 Floods Occurred between 1977-2006

Among 4,326 natural disasters occurred between the years 1977 and 2006; 2,199 of them were floods. 2,678,127,091 people were affected by floods in the thirty year time period. The highest number of floods occurred in South America, Southern Asia and South Eastern Asia; the number of affected people is high in Eastern, Southern and South Eastern Asia.

Most of the regions as Central and Northern America; Central, Eastern and South Eastern Asia; Middle, Eastern, Northern, Southern and Western Africa and Western Europe have an increasing trend both for number of floods occurred and number of affected people. On the other hand Melanesia has a decreasing trend for both of those two categories. Southern Asia and South America have an increasing trend on number of floods occurred but number of affected people in South Asia has a decreasing trend despite the increasing number of floods trend. There were no flood data for Micronesia and the remaining regions did not have a specific trend as an increase or a decrease for number of disasters occurred and number of people affected.

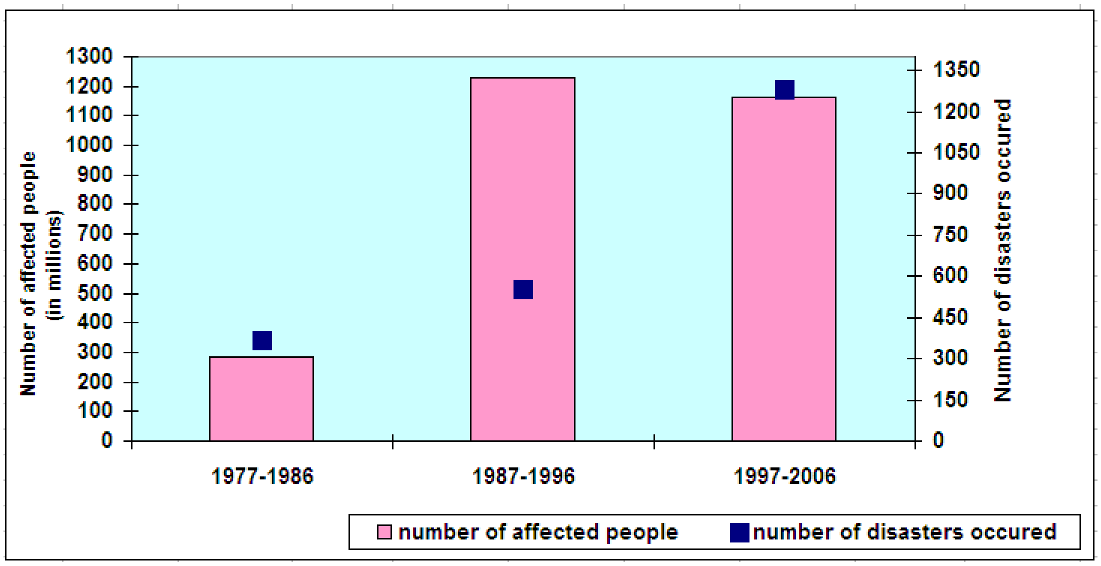


Figure 3.3: Trends in Occurrence and Number of Affected People for Floods

3.1.3 Wind Storms Occurred between 1977-2006

The last type of natural disaster that we considered is Wind Storms (hurricanes, cyclones, storms, tornadoes, tropical storms, and typhoons). 687,312, 222 people were affected by 1,475 wind storms in thirty year time period. Wind storm is the second most destructive disaster after floods when the data is analyzed according to number of disasters occurred and number of people affected categories. Caribbean, Central Asia, Melanesia, Micronesia, Polynesia and Northern America are the regions that suffered most from wind storms comparatively to other natural disasters.

When we analyze the trends of thirty years; we came to the following a conclusions. The number of wind storms occurred between the years 1997-2006 is more than double of the number between the years 1977-1986; also the number of affected people is more than quadruple. The number of wind storms occurred in Northern America between the years 1997-2006 is more than five times of the number between 1977-1986, which means Northern America became a region to consider and the disaster trend shifts to Northern America from the continent of Asia.

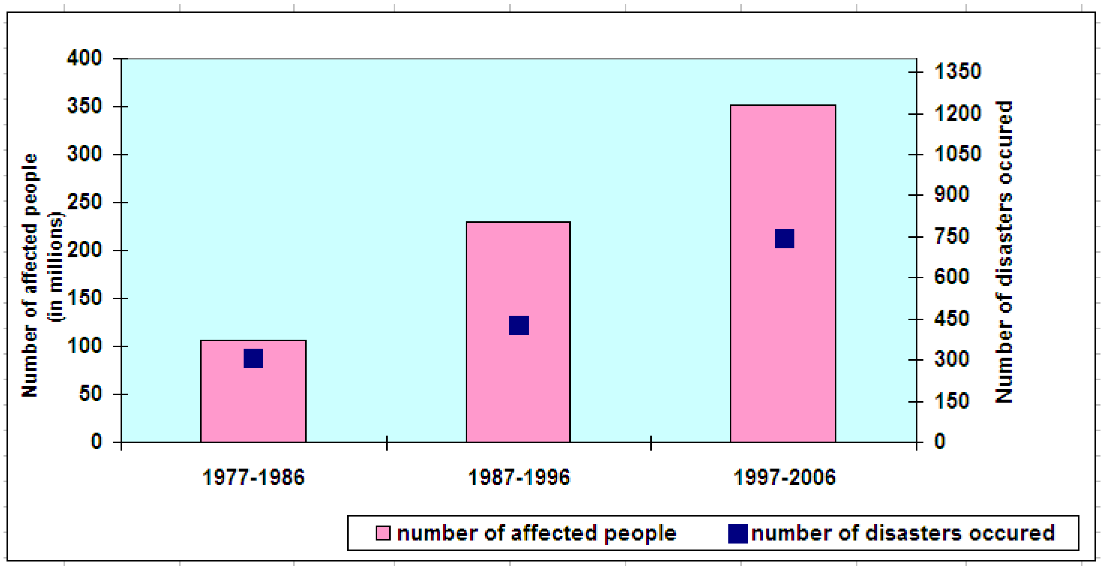


Figure 3.4: Trends in Occurrence and Number of Affected People for Wind Storms

3.2 Total Items Needed between 1977-2006

We calculated the total number of relief items in scenarios by consider three different disaster types which of each requires different kind of relief items. In each scenario the inputs are the type of the disaster, the relief items and their probabilities for each type of disaster, demand locations and number of affected people. The likelihood of need for each item by different kind of disasters is illustrated in Table 3.2. These probabilities are used to estimate the probability of relief items being required at regional demand locations by a person affected by a disaster.

CHAPTER 4

MODEL

Total inventory level and the number of warehouses to open are the main parameters for the configuration of the pre-positioning network. Warehouse opening and operating costs are not considered since the performance measurements in humanitarian logistics are usually non-profit and the locations considered are no- or low-cost locations. The model is developed by Duran et. al. (2010), with the collaboration of CARE International. CARE International is a non-profit humanitarian organization and it is assumed that the warehouse operating cost would low due to supports from governments and other organizations such as The United Nations Humanitarian Response Depot (UNHRD). That is why our candidate locations are composed of the warehouses that CARE International considers and UNHRD locations.

A mixed-integer programming (MIP) inventory location model was developed by Duran et. al. (2010) to minimize the average response time which finds a network configuration for a given initial investment. The model finds the configuration of the pre-positioning network by considering demand instances, inventory level and maximum number of warehouses to open. It finds out the best possible locations to pre-position the inventory by minimizing the average response time over all the demand instances. The model gives the best possible locations among candidate warehouse locations. The quantity and type of items that would be held in inventory in each warehouse is also obtained from the model.

The model was executed for only ten years time period (1997-2006) in Duran et. al. (2010). In this thesis, we enhance the findings by executing the model for the past thirty years to analyze the effects of natural disaster trends on the pre-positioning network implementation and expansion. We also verify our results using the natural disaster data for the years 2007, 2008, 2009 and 2010.

4.1 Demand

The model considers demand for relief supplies caused by sudden-onset natural disasters; earthquakes, windstorms (hurricanes, cyclones, storms, tornadoes, tropical storms, and typhoons) and floods and number of people affected by them. Slow-onset disasters such as famine are not included in this study since pre-positioning does not have a distinct benefit to minimize the response time in slow-onset cases.

We mentioned our data source, categories of data we used and the procedure followed to create the demand instances in Chapter 4.3. We used historical data to measure past demand for relief supplies and create demand scenarios. Demand is usually estimated by using sales data in supply chain problems. In this thesis, we calculated demand by taking the indirect approach of first measuring the number of affected people and then supporting the demand estimate by this statistic to determine the number of items needed for each demand scenario. We used past 30 years' data to calculate the demand using the probability of need for different relief items and the number of items required by an affected person.

We used United Nations' 22 sub-regions to model the demand locations. We suppose that when a disaster occurs in a region, the demand occurs at that region's center of population. The database of Global Rural-Urban Mapping Project (GRUMP 2006) is used to calculate the centers of population.

4.2 Supply

In the model, it is assumed that the demand can be met and replenished by the suppliers. The average lead time and performances of different suppliers are neglected since most of the humanitarian non-profit organizations do not track the suppliers' history.

We set the supply time of any item from suppliers directly to a region as 14 days. 14 days estimation is based on the experience of CARE International with its suppliers. Most of global suppliers were reported to send the relief items within 2 weeks. (Duran et. al., 2010, pg 8.). The 12 candidate warehouse locations are illustrated in Table 4.1 and Figure 4.1.

Table 4.1: Candidate Warehouses for Pre-positioning

Sequence Number	Location
1	Cambodia (UNHRD)
2	China, Hong Kong (CARE Int.)
3	Denmark (CARE Int.)
4	Germany (CARE Int.)
5	Honduras (CARE Int.)
6	India (CARE Int.)
7	Italy (UNHRD)
8	Kenya (CARE Int.)
9	Panama (UNHRD and CARE Int.)
10	South Africa (CARE Int.)
11	UAE, Dubai (UNHRD and CARE Int.)
12	USA, Miami (CARE Int.)

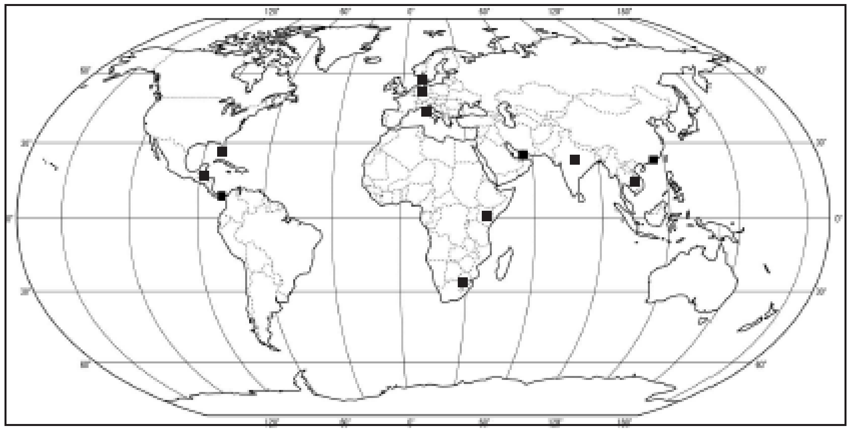


Figure 4.1: Candidate Locations for Pre-positioning Warehouses

4.3 Demand Instance Generation

The data we analyzed so far was used to generate scenarios at regional aggregation level. It is assumed that a global supplier can ship relief items to any demand location within two weeks. This two week lead is determined according to the experiences of CARE International. Therefore during the two-week period more than one disaster could occur and pre-positioning network may have to respond those multiple disasters from the inventory available without replenishment. The disaster data is sorted considering each disaster's start dates and end dates. The time between two disaster occurrences is calculated by using start and end date of each disaster. Finally, the disaster data is grouped into instances which includes disasters occurred in two-week time periods. Each demand instance consists of demand quantities for different relief items at one or more demand points. The generation of demand instances is illustrated in Figure 4.2.

We used the number of total disasters, number of affected people, start dates and end dates of each disaster, the day difference between the next disaster and type of the disaster as an input for a C++ code. The code evaluated the number of items required by also considering the probability of the need of each item upon type of the disaster occurred. Number of total items needed for each scenario is found for each disaster type for ten year time periods separately. We used 22 regions as demand points and looked for demand instances for those 22 regions. Demand instances are prepared to model the possibility of acquiring emergency response to concurrent events in different locations since during the warehouse replenishment time, demand should be satisfied only from the on-hand inventory among warehouses.

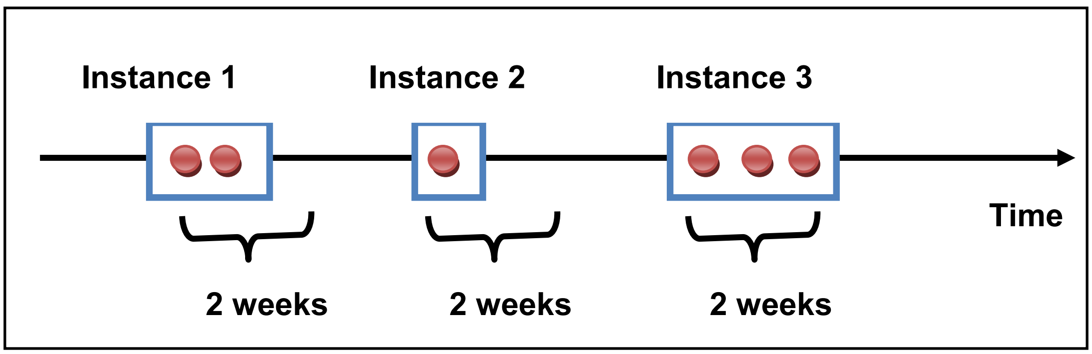


Figure 4.2: Generation of Demand Instances

4.4 Response Time

The MIP model's objective function minimizes the average of weighted response times over the demand instances. Demand instances include information on the locations demand for the relief items. There are 198 demand instances for the 1977-1986 time period, 210 demand instances for the 1987-1996 time period and 240 demand instances for the 1997-2006 time period.

The response time is calculated by considering the distance between the warehouse and the demand location. The distances are found by taking the great arc distance between the points. The response time is regarded as the time that a common cargo plane takes to fly that distance plus 24 hours for set up and material handling. The common cargo plane used in relief operations is C-130, so the flight time is calculated according to average speed of a C-130. The external factors such as road damage and socio-political factors are neglected concerning their low affects to pre-positioning network configuration. The flight times between the candidate warehouses and demand locations (regions) is provided in APPENDIX B in Table B.1.

4.5 The Mixed Integer Programming (MIP) Formulation

Definitions of Index sets, variables and parameters are given below;

Index Sets:

$\boldsymbol{J}$ set of possible pre-positioning warehouses,
$\boldsymbol{H}$ set of disaster types,
$\boldsymbol{I}$ set of regional demand locations,
$\boldsymbol{L}$ set of supply items,
$\boldsymbol{K}$ set of demand instances need to be responded by the pre-positioning warehouses,

Variables:

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

$q_{j\ell}$ quantity of supply ℓ held at warehouse j,
$x_{ijk\ell}$ quantity of supply ℓ sent to regional demand location i from warehouse j in demand instance k,

$\bar{x}_{ik\ell}$ 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,
$\bar{t}_{ij}$ response time from warehouse j to regional demand location i (flight time),
$\bar{t}_{i\ell}$ 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,
$p_{hi\ell}$ probability of supply ℓ being required at regional demand location i by a person affected by disaster type h,
$a_{hi\ell}$ quantity of supply ℓ required by a person affected by disaster type h in demand location i,
$\bar{d}_{ik\ell}$ expected demand for supply ℓ at regional demand location i in demand instance k,

Based on the above definitions, Duran et.al. (2010) developed the following MIP formulation:

$$z = \min \text{pk} \sum_{k \in K} \left[\frac{\sum_{i \in I} \sum_{\ell \in L} \bar{x}_{ik\ell} \bar{t}_{i\ell} + \sum_{i \in I} \sum_{j \in J} \sum_{\ell \in L} x_{ijk\ell}\, t_{ij}}{\sum_{i \in I} \sum_{\ell \in L} \bar{d}_{ik\ell}} \right] \qquad (1)$$

s.t.

$$\bar{d}_{ik\ell} = \sum_{h \in H} a_{hi\ell}\, p_{hi\ell}\, d_{hik} \qquad i \in I, k \in K, \ell \in L, \qquad (2)$$

$$\sum_{j \in J} x_{ijk\ell} + \bar{x}_{ik\ell} \geq \bar{d}_{ik\ell} \qquad i \in I, k \in K, \ell \in L, \qquad (3)$$

$$\sum_{i \in I} x_{ijk\ell} \leq q_{j\ell} \qquad j \in J, k \in K, \ell \in L, \qquad \textbf{(4)}$$

$$q_{j\ell} \leq Q\, y_j \qquad j \in J, \ell \in L, \qquad \textbf{(5)}$$

$$\sum_{j \in J} \sum_{\ell \in L} q_{j\ell} \leq Q, \qquad \textbf{(6)}$$

$$\sum_{j \in J} y_j \leq N, \qquad \textbf{(7)}$$

$$x_{ijk\ell},\ \bar{x}_{ik\ell},\ q_{j\ell} \geq 0 \qquad y_j \in \{0,1\}, \qquad \textbf{(8)}$$

(1) The objective function z: It minimizes the expected average relief response time over all demand instances.

(2) Constraint 1: It calculates the expected demand of different supply items at different regional demand location in a demand instance with respect to the number of affected people by different natural disaster types in a scenario.

(3) Constraint 2: It ensures the quantity of supply at each regional demand location is totally satisfied from the warehouses and/or the suppliers in each demand instance.

(4) Constraint 3: It ensures the quantity of supply items sent to a regional demand location shipped from a warehouse in a certain demand instance should be less than or equal to the inventory held at that warehouse.

(5) Constraint 4: It assures that inventory is held only in opened warehouses

(6) Constraint 5: It ensures that the sum of the inventories that are assigned to the different warehouses is less than or equal to the total inventory level (*Q)*.

(7) Constraint 6: It ensures that the number of warehouses opened is less than or equal to maximum number of opened warehouse.

(8) Constraint 7: It assures that the quantity of supply is non-negative. The variable *y* indicating whether a warehouse is open or not and it is binary.

Our objective function minimizes the average response time of the relief items send throughout a scenario. Therefore, the dispatching times could be varied for each item significantly, and this may result in inefficient relief response. The model objective could be modified to minimize maximum response times among items with the aim of obtaining closer dispatching times for the relief items. But in this case you should not have any items send from global suppliers, otherwise the objective value will always be 336 hours and the model will not provide meaningful results. With the inventory levels (25%-100% of average demand in a scenario) that we consider in this thesis, this modification is not possible.

CHAPTER 5

RESULTS

The main parameters of our problem are the number of warehouses to open and the inventory amount. The model makes a decision on which warehouses should be opened to minimize the emergency response time by assuming that it is faster to satisfy the demand from the pre-positioning warehouses than direct shipments.

We run the model for 1-9 warehouses to open and for high, medium and low levels of inventory, corresponding 100%, 50% and 25% of the average demand per demand instance. Since inventory holding cost is high, low inventory level is preferred while determining the best possible locations for pre-positioning relief items. We executed our model for the data of 1977-1986; 1987-1996 and 1997-2006 time periods for high, medium and low inventory levels. The model gives 27 different solutions for each decade as we try all the combinations for 9 candidate warehouses to open and 3 inventory levels.

We performed the computations for each ten-year period using GAMS with the MIP solver. The model includes 22 demand points, 12 candidate warehouse locations, 7 relief items and different number of demand instances for each period are created from historical data of that ten-year period. The average response time decreases for a specified level of inventory at a diminishing rate and later, the marginal benefit from opening an additional warehouse reaches a minimum.

Therefore, number of warehouses to open fluctuates between 3 and 4 according to the inventory level.

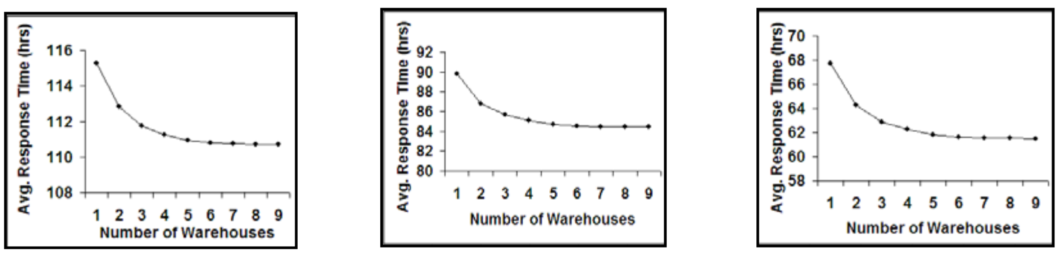
Currently, CARE International can afford three warehouses to operate in total due to financial restrictions. On the other hand there are 12 candidate warehouses and the number of opened warehouses can easily be increased to four, five or more if the necessary financial support is provided.

5.1 Optimal Locations and Response Times for the Time Period of 1977-1986

We executed our model for the data from 1977-1986 time period for high, medium and low inventory levels. Our parameters were number of warehouses to open and the inventory level to find the average response time.

The total number of items needed for disasters is calculated as 966,799,126 for the 1977-1986 time period. We obtained 198 demand instances for this time period. We set the high inventory level as the average inventory level for a demand instance, which are approximately 4,800,000. The medium inventory level is assumed to be the half of that value which is 2,400,000 and the low inventory level is assumed to be the quarter of the average inventory level which is 1,200,000.

On the other hand, average response times are approximately 67, 90 and 115 hours for high, medium and low inventory levels on the condition of one opened warehouse. The average response time decreases with respect to the number of opened warehouses and the amount of inventory. The results argue that there is a significant improvement in response times for demand instances compared to no pre-positioning case, since the average response time of direct shipment is taken as 336 hours. Average response time for high inventory level is considerably lower than others; on the other hand monetary constraints restrict to spend more for inventory. That is the reason why we focus on the results for low inventory level in determining optimal warehouse locations. The average response time for low inventory level is varied between 115 and 110 hours according to the number of opened warehouses. When we choose three warehouses to open the resulting response time is 112. The average response times for number of opened warehouses according to inventory level is illustrated in Figure 5.1.



(a) Low Inventory Level (b) Medium Inventory Level (c) High Inventory Level

Figure 5.1: Average Response Time under Low, Medium, and High Inventory Levels for 1977-1986 Time Period

For the low inventory level the best possible locations for pre-positioning is listed as -Cambodia, Italy and Panama. The optimal three warehouse locations and their inventory shares for low inventory level are illustrated in Figure 5.2.

Half of the pre-positioned items are located in Cambodia since number of affected people by natural disasters is mostly located in Southern and South Eastern Asia. When we analyze the share of the items in the warehouses it is seen that hygiene, sanitation, MREs and water have the highest proportions and the share of seven items within each warehouse is approximately the same. The proportions of the relief items in warehouses are given in Table 5.1.

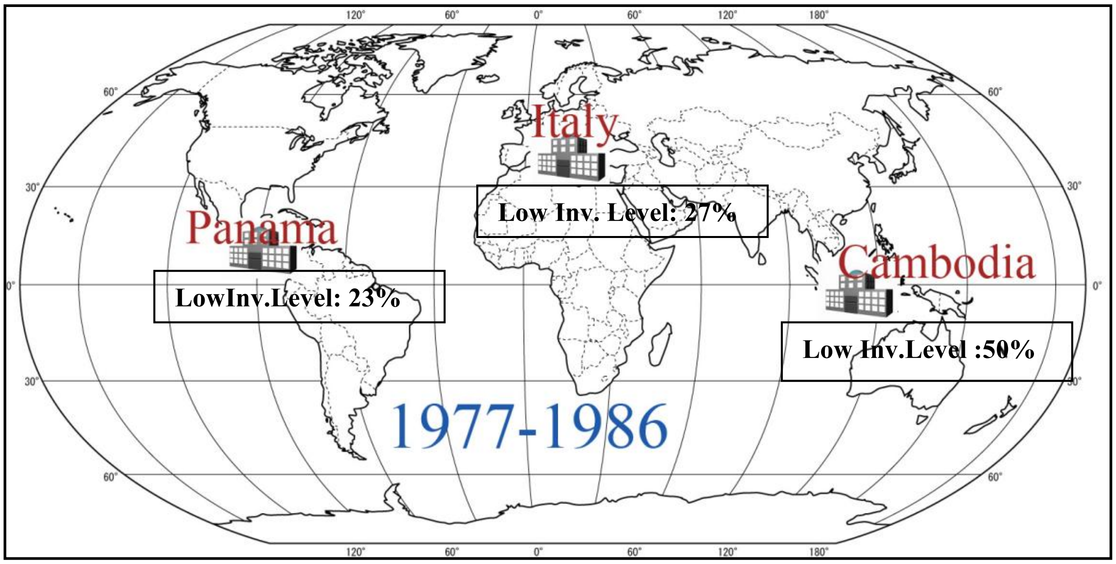


Figure 5.2: Optimal Locations for Pre-positioning Warehouses considering the 1977-1986 Time Period

Table 5.1: The Proportions of the Relief Items in Optimally Selected Warehouses (1977-1986)

Warehouse	**Items**						
	Cold Tent	Hot Tent	Household	MREs	Hygiene	Sanitation	Water
Panama	4%	4%	8%	21%	21%	21%	21%
Italy	4%	4%	8%	21%	21%	21%	21%
Cambodia	5%	5%	9%	20%	21%	20%	20%

As inventory level changes the optimal warehouse locations do not change considerably excluding the eight warehouses to open case. When we run the model for eight warehouses to open, Germany replaces Dubai. The complete list of optimal warehouse locations is given in Table 5.2.

Table 5.2: Optimal Warehouse Locations with Respect to Inventory Level (1977-1986)

	Low Inventory									Medium Inventory									High Inventory								
Warehouses	1	2	3	4	5	6	7	8	9	1	2	3	4	5	6	7	8	9	1	2	3	4	5	6	7	8	9
Cambodia		X	X	X	X	X	X	X	X			X	X	X	X	X	X	X			X	X	X	X	X	X	X
USA, Miami							X	X	X																		
Denmark																											
Germany																	X	X									X
Honduras								X	X							X	X	X							X	X	X
Hong Kong					X	X	X	X	X						X	X	X	X						X	X	X	X
India	X		X	X	X	X	X	X	X	X	X		X	X	X	X	X	X	X	X		X	X	X	X	X	X
Italy						X	X	X	X				X	X	X	X	X	X				X	X	X	X	X	X
Kenya				X	X	X	X	X	X					X	X	X	X	X					X	X	X	X	X
Panama		X	X	X	X	X	X	X	X		X	X	X	X	X	X	X	X		X	X	X	X	X	X	X	X
South Africa																											
UAE, Dubai									X			X						X			X					X	X

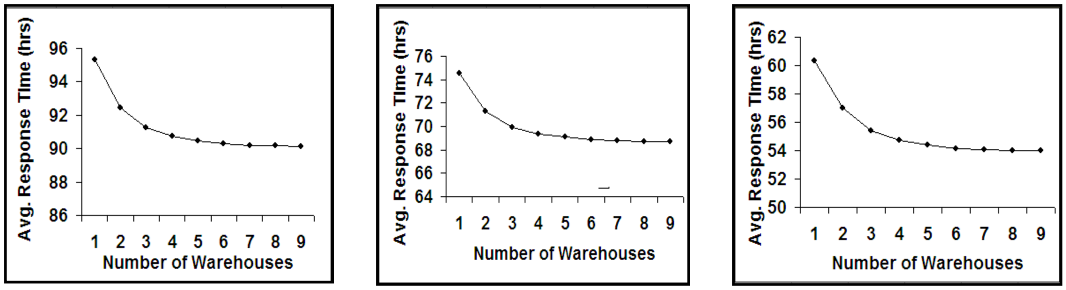
5.2 Optimal Locations and Response Times for the Time Period of 1987-1996

We also executed our model for the data from the 1987-1996 time period for high, medium and low inventory levels. Our parameters were again the number of warehouses to open and the inventory level to find the response time.

The total number of items needed for disasters is calculated as 3,774,349,568 for the 1987-1996 time period. The amount is approximately quadruple of the amount that belongs to the 1977-1986 time period and the number of demand instances increase to 210 for this time period. We set the high inventory level as the average inventory level for a demand instance, which are approximately 18,000,000. The medium inventory level is assumed to be the half of that value which is 9,000,000 and the low inventory level is assumed to be the quarter of the average inventory level which is 4,500,000.

Average response times are found as 60, 74 and 95 hours for high, medium and low inventory levels, respectively, for a single warehouse network which means the pre-positioning network brings more benefit compared to the previous time period. The response times for the second decade also supports that the pre-positioning provides lower emergency response time compared to direct shipment and the average response time for low inventory level fluctuate between 96 hours and 90 hours, which is lower compared to the first decade results. Specifically, the response time is 91 hours for three warehouses to open condition which is 21 hours less with respect to last ten years' results. The data of this decade is more accurate and reliable than the first one as it was hard to keep record of every natural disaster and detect the accurate number of people affected in 70s. The average response times according to inventory level is illustrated in Figure 5.3.

At the low inventory, the best possible locations for pre-positioning are listed as Cambodia, India and Panama. Italy is replaced by India for the second ten-year period which is indicating a trend shifting from Europe to South-East Asia. The optimal warehouse locations and distribution of inventories for the second ten-year period that is determined according to low inventory level are illustrated in Figure 5.4.



(a) Low Inventory Level (b) Medium Inventory Level (c) High Inventory Level

Figure 5.3: Average Response Times under Low, Medium, and High Inventory Levels for 1987-1996 Time Period

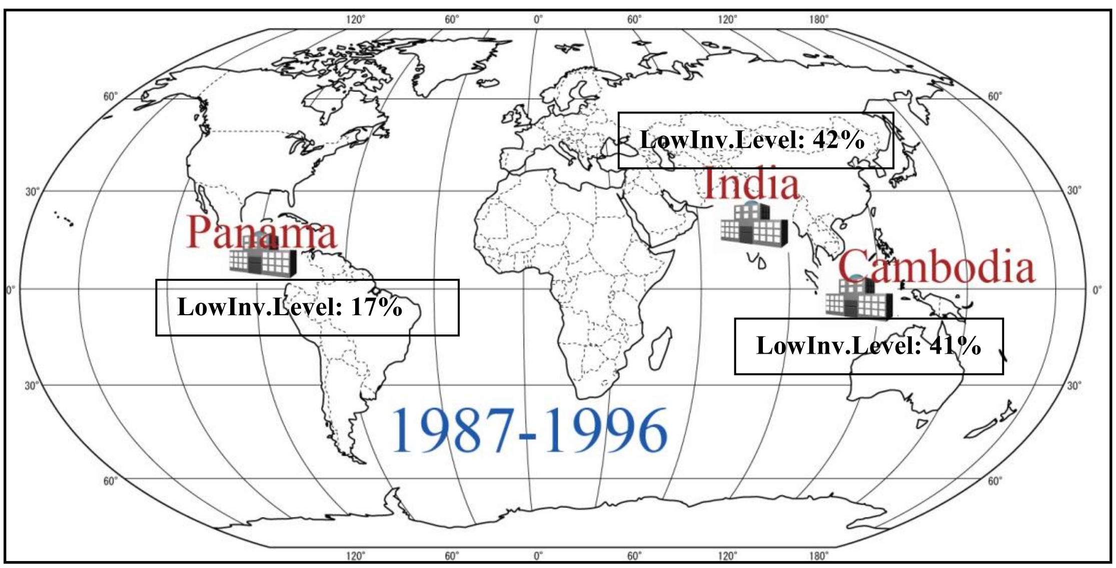


Figure 5.4: Optimal Locations for Pre-positioning Warehouses considering the 1987-1996 Time Period

When we analysis the inventory dispersal, it is seen that Cambodia and Panama's shares decreased while third location's share increased, also the share of Cold and Hot Tents decreased with respect to the results of the previous decade. 83 % of the items are stored within Asia region. The distribution of items in warehouses is given in Table 5.3.

Table 5.3: The Proportions of the Relief Items in Optimally Selected Warehouses (1987-1996)

Warehouse	**Items**						
	Cold Tent	Hot Tent	Household	MREs	Hygiene	Sanitation	Water
Panama	1%	1%	2%	24%	24%	24%	24%
India	1%	1%	10%	22%	22%	22%	22%
Cambodia	1%	1%	10%	22%	22%	22%	22%

As the inventory level increases, the optimal warehouse locations do not differ significantly. When we run the model for different number of warehouses to open, locations of the warehouses are seen to be exactly the same for low and medium inventory levels, on the other hand for high inventory level; there is a significant shift of inventory from Honduras to Dubai when the number of warehouses to open is set to eight. The results for 1987-1996 time period denote that the trend of number of affected people shifts from Europe to Africa and Central America. The complete list of optimal warehouse locations is given in Table 5.4.

Table 5.4: Optimal Warehouse Locations with Respect to Inventory Level (1987-1996)

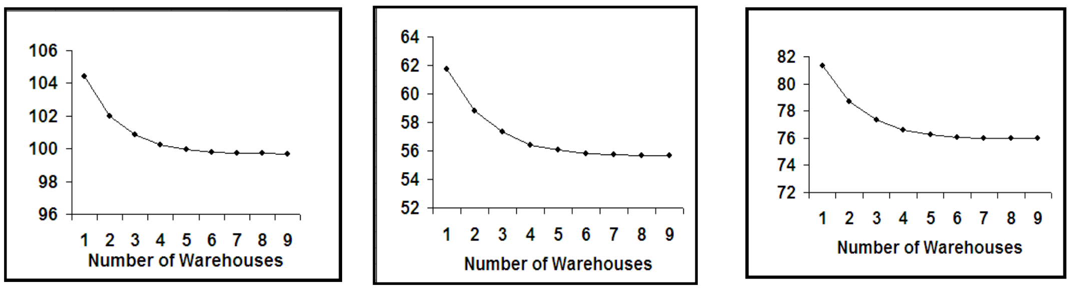
	Low / Medium Inventory									High Inventory								
Warehouses	1	2	3	4	5	6	7	8	9	1	2	3	4	5	6	7	8	9
Cambodia		X	X	X	X	X	X	X	X			X	X	X	X	X	X	X
USA, Miami							X	X	X									
Denmark																		
Germany																	X	X
Honduras								X	X							X	X	X
Hong Kong					X	X	X	X	X						X	X	X	X
India	X		X	X	X	X	X	X	X	X	X		X	X	X	X	X	X
Italy						X	X	X	X				X	X	X	X	X	X
Kenya				X	X	X	X	X	X					X	X	X	X	X
Panama		X	X	X	X	X	X	X	X		X	X	X	X	X	X	X	X
South Africa																		
UAE, Dubai									X			X						X

5.3 Optimal Locations and Response Times for the time period of 1997-2006

We also executed our model for the data from the 1997-2006 time period for high, medium and low inventory levels. The number of demand instances increase to 240 when we execute the scenario generation procedure. The results from this decade we can also be found in Duran et.al. (2010).

Average response times are 62, 82 and 105 hours for high, medium and low inventory. It is obvious that again pre-positioning provides lower emergency response times compared to direct shipment. On the other hand, the average response times are more than the second decade, which can be explained by the fact that the disasters occurred expand to wider areas so the location of warehouses become insufficient to intervene in case of emergency. Increasing average response times create a need for more warehouses to pre-position the relief items.

The emergency response times vary between 105 hours and 99 hours for low inventory level, and it is 101 hours for three warehouses network. The average response times according to inventory levels are illustrated in Figure 5.5.



(a) Low Inventory Level (b) Medium Inventory Level (c) High Inventory Level

Figure 5.5: Average Response Time under Low, Medium, and High Inventory Levels for 1997-2006 Time Period

At the low inventory level the best possible locations for pre-positioning is listed as Panama, Dubai and Hong Kong. India is replaced by Dubai and Cambodia is replaced by Hong Kong, China considering the previous decade's results. The optimal warehouse locations for low inventory level and their inventory shares are illustrated in Figure 5.6.

Share of tents and households is lower in Hong Kong warehouse compared to other two warehouses. The distribution of items in optimally located warehouses is given in Table 5.5.

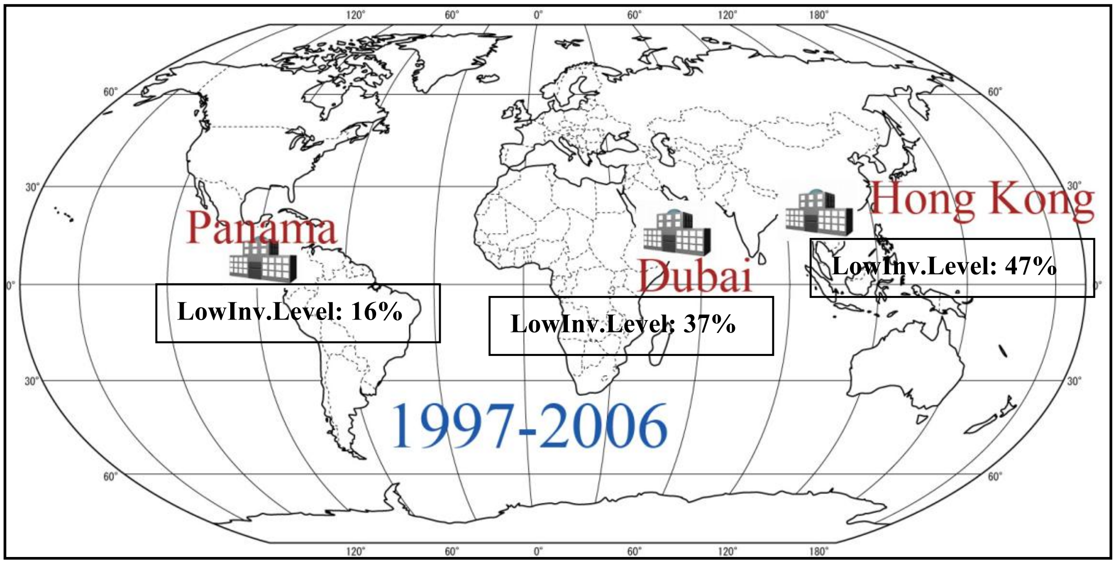


Figure 5.6: Optimal Locations for Pre-positioning Warehouses considering the 1997-2006 Time Period

Although the dispersal of inventories through world is close to the previous decade, we observe a further shift of inventory to east, thus the share of South Eastern Asia increased. Again 84 % of inventory is located in the Asia regions.

The only difference between low and medium inventory levels with high inventory level is seen in three warehouses to open condition; it is listed as Panama, Kenya and Hong Kong for high level inventory. Panama stays stable for all three decades while the other candidate locations change. Cambodia and India pair is closer to each other compared to Hong Kong and Dubai pair, which indicates that the distribution of the disasters expands to a wider area. The complete list of optimal warehouse locations is given in Table 5.6.

Table 5.5: The Proportions of the Relief Items in Optimally Selected Warehouses (1997-2006)

Warehouse	**Items**						
	Cold Tent	Hot Tent	Household	MREs	Hygiene	Sanitation	Water
Panama	5%	5%	10%	20%	20%	20%	20%
Dubai	5%	5%	10%	20%	20%	20%	20%
Hong Kong	1%	1%	1%	24%	24%	24%	25%

For the third decade, we calculated standard deviation of items needed by disasters. To eliminate the effect of mega disasters that happen very infrequently, we set the maximum amount of items that can be needed from any disasters to average number of items plus the three times standard deviation value which is 16,281,392. When we executed the model for low inventory option, we found the optimal warehouse locations as India, Panama and Kenya on the other hand average response time became 173 hours as inventory level decreased by ignoring the disasters that have an extreme magnitude. In new locations Hong Kong is replaced by India, while UAE, Dubai replaced by Kenya. Reason for shifting from Dubai to Kenya can be associated with ignoring the large populations in the Eastern Asia regions including China and India by ignoring the disaster magnitude.

It is seen that the trend of natural disasters is increasing decade by decade as we mentioned before. Since the emergency response times become higher and the distance between the warehouses to open become far away, the results make us investigate whether three warehouses are enough to pre-position the relief items, or not. We also applied this model for the most recent data available between the years 2007 and 2010 for verification purposes.

Table 5.6: Optimal Warehouse Locations with Respect to Inventory Level (1997-2006)

	Low Inventory										Medium / High Inventory								
Warehouses	1	2	3	4	5	6	7	8	9		1	2	3	4	5	6	7	8	9
Cambodia			X	X	X	X	X	X	X				X		X	X	X	X	X
USA, Miami								X	X									X	X
Denmark																			
Germany																			
Honduras						X		X	X								X	X	X
Hong Kong					X	X	X	X	X					X	X	X	X	X	X
India	X	X		X	X	X	X	X	X		X	X		X	X	X	X	X	X
Italy						X	X	X	X							X	X	X	X
Kenya			X	X	X	X	X	X	X				X	X	X	X	X	X	X
Panama		X	X	X	X	X	X	X	X			X	X	X	X	X	X	X	X
South Africa																			X
UAE, Dubai									X										

CHAPTER 6

VERIFICATION OF RESULTS CONSIDERING RECENT YEARS

When we investigate recent years' data to verify the results, it is obviously seen that natural disaster trends shift to Central America from South and North America. On the other hand number of affected people becomes higher in North America which is an effect of Hurricane Katrina.

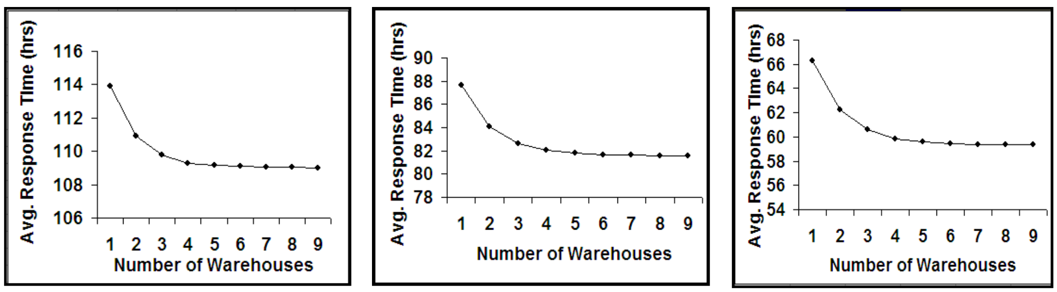
Eastern Africa is exposed to more natural disasters and the number of affected people for four recent years is more that the past thirty years' data in Middle Africa. This condition should be considered while choosing the right locations to pre-position the relief items. The total number of affected people and disasters occurred is given in Table 6.1.

When we execute our model for the data between the years 2007 and 2010, we find the average emergency response times as 66 for high, 87 for medium and 113 for low inventory levels for the condition of one opened warehouse. The average response time for three warehouses to open condition is 110, which is 9 hours more than the last decade results.

Table 6.1: Percentage of Natural Disasters and Number of Affected People by Regions for the Time Period of 1977-2010

Number of Disasters Occurred		Number of Affected People		Region
1977-2006	2007-2010	1977-2006	2007-2010	
2,36%	1,33%	0,12%	0,01%	Australia and New Zealand
4,42%	5,43%	0,64%	0,87%	Caribbean
5,64%	7,44%	0,70%	1,01%	Central America
0,90%	1,24%	0,03%	0,02%	Central Asia
6,08%	8,29%	0,87%	0,93%	Eastern Africa
13,75%	9,91%	55,94%	64,39%	Eastern Asia
3,51%	3,62%	0,25%	0,08%	Eastern Europe
1,57%	1,62%	0,05%	0,09%	Melanesia
0,30%	0,10%	0,00%	0,00%	Micronesia
1,41%	3,15%	0,05%	0,74%	Middle Africa
2,10%	2,10%	0,26%	0,14%	Northern Africa
5,99%	7,05%	0,37%	2,26%	Northern America
0,76%	0,19%	0,04%	0,00%	Northern Europe
0,65%	0,48%	0,01%	0,00%	Polynesia
8,60%	6,58%	1,17%	2,31%	South America
15,05%	14,49%	5,76%	6,68%	South Eastern Asia
1,32%	1,53%	0,06%	0,08%	Southern Africa
14,42%	11,44%	32,89%	19,46%	Southern Asia
3,37%	2,86%	0,12%	0,00%	Southern Europe
2,91%	6,48%	0,19%	0,78%	Western Africa
2,82%	1,91%	0,35%	0,03%	Western Asia
2,06%	2,76%	0,13%	0,08%	Western Europe
100,00%	100,00%	100,00%	100,00%	TOTAL

We can conclude that the average response times become higher as a result of wider disperse of disasters and increased number of disasters can be a secondary reason. Average response times with respect to number of opened warehouses are illustrated in Figure 6.1.



(a) Low Inventory Level (b) Medium Inventory Level (c) High Inventory Level

Figure 6.1: Average Response Time under Low, Medium, and High Inventory Levels for 2007-2010

The optimal locations to pre-position are listed as Cambodia, Kenya and Panama for all inventory levels. The warehouse locations are eventuated all same for all inventory levels excluding nine warehouses to open condition. South Africa becomes an option if the number of warehouse to open increases for high inventory level. Optimal warehouse locations are illustrated in Table 6.2.

The locations for low inventory level are illustrated on World Map in Figure 6.2. It is observed that 25% percent of the inventory is pre-positioned to be used in America, 15% percent in Afica and 60% in Asia.

Table 6.2: Optimal Warehouse Locations with Respect to Inventory Level (2007-2010)

	Low Inventory									Medium / High Inventory								
Warehouses	1	2	3	4	5	6	7	8	9	1	2	3	4	5	6	7	8	9
Cambodia			X	X	X	X	X	X	X			X		X	X	X	X	X
USA, Miami								X	X								X	X
Denmark																		
Germany																		
Honduras							X	X	X							X	X	X
Hong Kong					X	X	X	X	X				X	X	X	X	X	X
India	X	X		X	X	X	X	X	X	X	X		X	X	X	X	X	X
Italy						X	X	X	X						X	X	X	X
Kenya			X	X	X	X	X	X	X			X	X	X	X	X	X	X
Panama		X	X	X	X	X	X	X	X		X	X	X	X	X	X	X	X
South Africa																		X
UAE, Dubai									X									

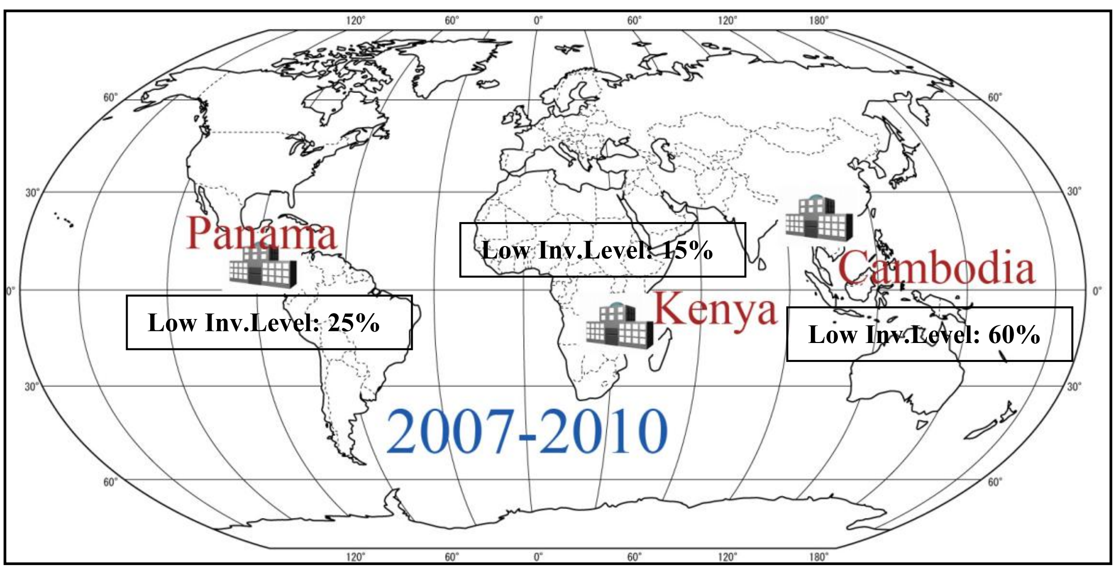


Figure 6.2: Optimal Locations for Pre-positioning Warehouses considering the Time Period of 2007-2010

When we compare the dispersal of the inventories it is easily seen that the trend shifts through South Eastern Asia, so the number of inventories pre-positioned as well. We can conclude that Africa rises as a new demand location for relief items. The distribution of inventory in warehouses is listed in Table 6.3.

Table 6.3: The Proportions of the Relief Items in Optimal Warehouses (2007 - 2010)

Warehouse	**Items**						
	Cold Tent	Hot Tent	Household	MREs	Hygiene	Sanitation	Water
Panama	1%	1%	11%	22%	22%	22%	21%
Kenya	1%	1%	1%	23%	23%	23%	28%
Cambodia	5%	5%	10%	20%	20%	20%	20%

We also execute the model by ignoring the big disasters to observe if optimal locations change. We calculated average number of relief items and the standard deviation of number of total relief items by disasters. We set the upper bound as average number of relief items plus triplicate of standard deviation to include approximately 99% of the data. The average number of relief items is calculated as 60039, 96. The standard deviation is calculated as 486989, and we set the upper bound for relief items needed as 1,521,006 and compensate the data that are more than that value. The average response time is decreased to 108 hours for low inventory case. With this limitation, the optimal locations of warehouses do not change, which indicates that the locations are optimal even in the presence of some outlier data of relief items needed by mega disasters.

When the results obtained concerning those 33 years are considered;
Cambodia, Italy, Panama are the optimal locations for 1977-1986, also Italy is replaced with UAE, Dubai with respect to higher inventory level. The optimal locations become Cambodia, India and Panama for 1987-1996; India is also replaced with UAE, Dubai for high inventory level. Panama stays stable for three decades on the other hand Cambodia is replaced by Hong Kong and India is replaced by Dubai for 1997-2006. We find the three candidate warehouses as Panama, Kenya and Cambodia for 2007-2010. While Panama and Cambodia appear in almost every result, the location of the third warehouse indicates a clear shift. The change in locations of third warehouse is illustrated in Figure 6.3.

It is seen that the natural disaster trend is shifting through south from Europe to Africa, which is an indicator for decision makers to plan emergency response.

The average response times becoming higher and the distances between the warehouses getting far away and also increasing trend of natural disasters occurred (mentioned in Chapter 3), motivate us to attempt to improve the average response time. There are two possible approaches to decrease the response time, which are directly concerned with financial support nature of non-profit organizations. One of them is increasing the inventory level to pre-position, and the other is opening a new warehouse. It is not feasible to hold too many inventories on hand as relief items. We consider low inventory level while determining best possible warehouse locations since the warehouses have capacity limits and minimum high inventory level that we calculated for demand scenarios is approximately 5 million. Consequently, increasing the level of inventory to hold in a warehouse is not practical to reduce the average response time. Therefore, we proceed with expansion of the number of opened warehouses in Chapter 7.

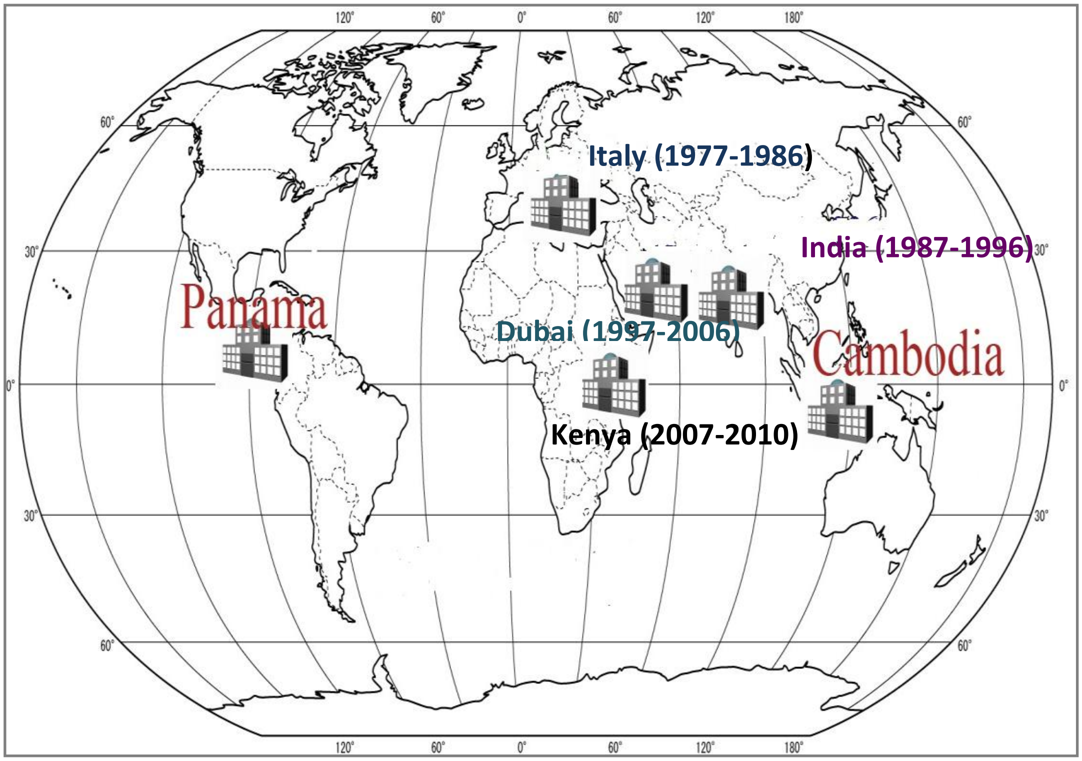


Figure 6.3: Optimal Location Shift of the Third Warehouse Considering the Data from 1977-2010

CHAPTER 7

EXPANSION OF THE NUMBER OF OPENED WAREHOUSES

In Chapter 3, it is seen that the number of affected people and number of disaster occurrence have an increasing trend. In Chapter 5, we find the best possible locations to pre-position relief items by considering average emergency response time for each candidate location. The locations differ from decade to decade as results of wider disperse of disasters through time. If only the number of affected people and number of disasters occurred were increasing free from the locations that the disasters took place, the best possible warehouse locations are expected to be same or to change inconsiderably, since our inventory levels are determined from that decade's average demand requirements. However in Chapter 6, it is verified that two locations stay almost stable for all decades and the place of the third warehouse location shifts from South Europe to Eastern Africa within 33 years. As a result of that shift average emergency response time has an increasing trend for three warehouses to open option decade by decade (1987-1996, 1997-2006, 2007-2010). The change in average emergency response time is illustrated in Figure 7.1.

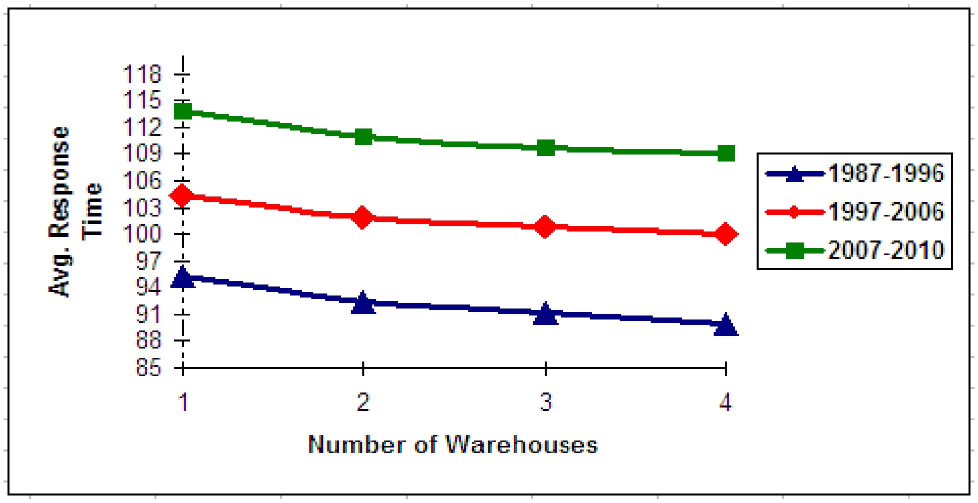


Figure 7.1: Change in Average Emergency Response Time between the Years 1987-2010

The existing locations that are found for 1997-2006 (Panama, Hong Kong and Dubai) do not meet the requirements as the disaster trend is shifting through Eastern Africa, and also the increasing emergency response time values make us to reconsider the expansion options. There are two options: increasing the inventory level and increasing the number of warehouses. As we have 12 candidate locations to pre-position the relief items and increasing inventory level will be costly, we should think of expanding the number of opened warehouses. More warehouses can be opened with lower levels of financial support, since the locations are low- or at-cost locations provided by government and UNHRD.

When we evaluated the average emergency response times for four warehouses to open, it is seen that the average response time decreases. We run the model for three decades and the most recent four years data by considering low inventory level and four warehouses to open condition. We try to find out the location for an additional warehouse for each decade and the decrease in average emergency response time by comparing three and four warehouses to open cases. We also analyze the trends by evaluating the shifts between warehouse locations and come to a conclusion on the optimal locations of the fourth warehouse to pre-position the relief items.

For the first decade (1977-1986), low inventory level is 1,200,000 items. As a result of running the model for four warehouses to open, India becomes the fourth warehouse location. The average emergency response time is evaluated as 111.8 hours for three warehouses and the time decreases to 111.2 hours for four warehouses. In first decade we get an improvement of 36 minutes in average emergency response time. The locations of four warehouses and their inventory shares can be seen in Figure 7.2.

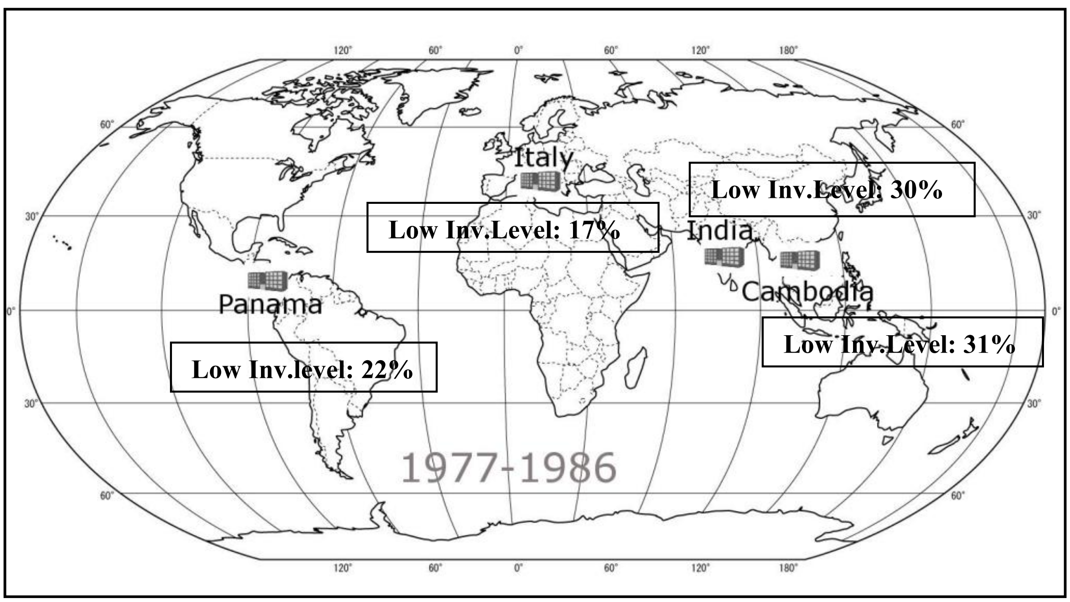


Figure 7.2: Optimal Locations of Four Warehouses for 1977-1986

When we compare the dispersion of the number of items needed to the result for three warehouses to open condition, it is seen that a significant part of the inventories shifted to India from Italy and Cambodia. However, the share of the relief items did not vary within the warehouses considerably. The distribution of the items is given in Table 7.1.

Table 7.1: The Proportion of Relief Items in Optimal Warehouses (1977-1986)

Warehouse	Items						
	Cold Tent	Hot Tent	Household	MREs	Hygiene	Sanitation	Water
Panama	4%	4%	8%	21%	21%	21%	21%
Italy	4%	4%	8%	21%	21%	21%	21%
India	5%	5%	10%	20%	20%	20%	20%
Cambodia	5%	5%	10%	20%	20%	20%	20%

For the second decade (1987-1996), low inventory level is 4,500,000 items which is more than triple of the first decade. When the capacity is considered, opening an additional warehouse is required. The fourth warehouse location is determined as Kenya for the second decade. India was found as the fourth place to open an additional warehouse in the previous decade, on the other hand Panama, Cambodia and India are found in primary solution. The result verifies that the natural disaster trend shifts through South Asia. When we compare the results for two decades; it is seen that Italy is not an optimal location for pre-positioning anymore and Kenya is more appropriate for pre-positioning relief items for the purpose of proximity to disaster area. Average emergency response time is evaluated as 91.24 hours for three warehouses to open and the response time decreases to 90.7 hours by adding a warehouse. The decrease in average emergency response time is approximately 33 minutes, close to the first decade's result. The locations of four warehouses are illustrated in Figure 7.3.

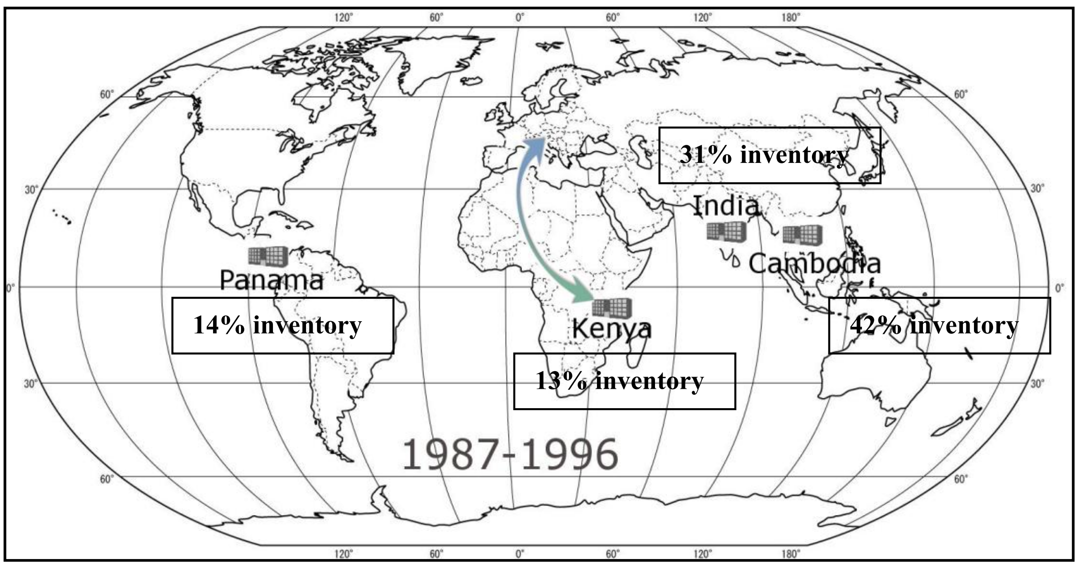


Figure 7.3: Optimal Locations of Four Warehouses for 1987-1996 Time Period

When we compare the dispersion of the number of items needed to the result for three warehouses to open condition, it is seen that a significant part of the inventories shifted from India to Kenya. However, the share of the items within warehouses did not change. If we compare the results with the previous decade, Panama's share decreased while Cambodia's share increased, also the share of Tents and Households decreased as well. The proportion of the relief items is given in Table 7.2.

Table 7.2: The Proportion of Relief Items in Optimal Warehouses (1987-1996)

Warehouse	Items						
	Cold Tent	Hot Tent	Household	MREs	Hygiene	Sanitation	Water
Panama	1%	1%	1%	24%	24%	24%	25%
Kenya	1%	1%	1%	25%	22%	25%	25%
India	1%	1%	10%	22%	22%	22%	22%
Cambodia	1%	1%	9%	22%	23%	22%	22%

The last decade (1997-2006), also refers the current situation for three warehouse network used. Panama, Dubai and Hong Kong are the current optimal locations for prepositioning. On the other hand when we run the model for four warehouses; we get Panama, Kenya, India and Hong Kong. India and Kenya are the fourth warehouse locations by order of the first and second decades and Dubai is replaced by these locations which verifies the shift of the trend through South Asia and East Africa. Cambodia is replaced by Hong Kong; despite Hong Kong is located on the North-East of Cambodia, two locations are close to each other and the difference is negligible. Average emergency response time is 100.85 for three warehouses and 100.2 for four warehouses. The improvement in average response time is 39 minutes for the current situation. The locations of four warehouses and low inventory levels in percentage are illustrated in Figure 7.4.

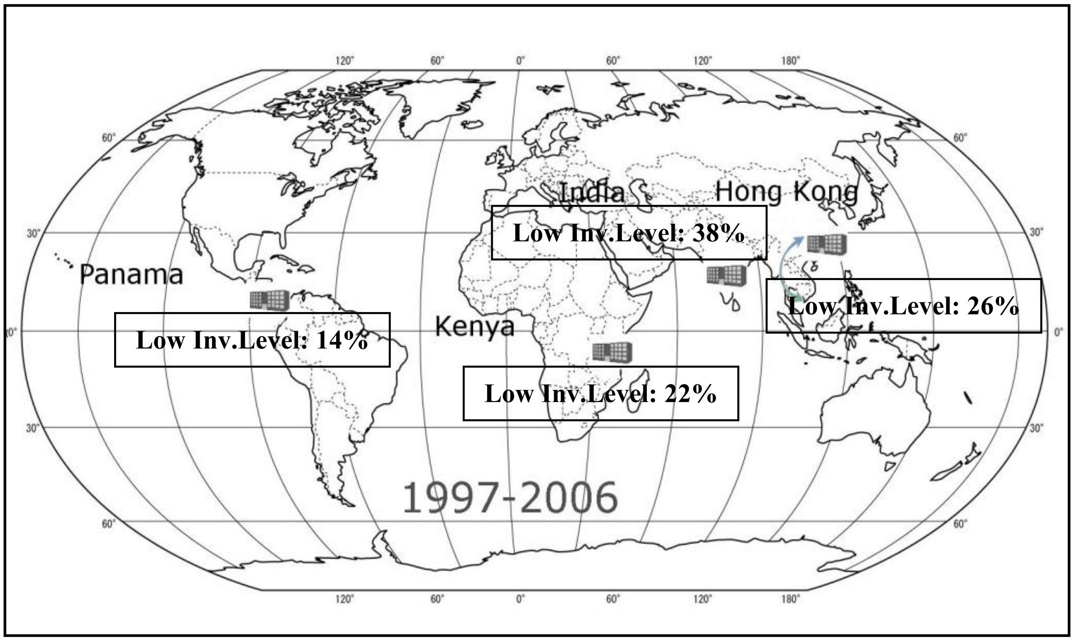


Figure 7.4: Optimal Locations of Four Warehouses for 1997-2006 Time Period

64 % of the inventories are located in Asia regions while 22% of the inventories are located in Africa. The distribution of inventories in Asia regions were approximately about 80% for three warehouses opened case. On the other hand 25% of the inventories that are located in Asia are shifted to Africa. When we analyze the proportion of relief items within warehouses in Table 7.3., it is seen that they are distributed in balance which also proves that the wider disperse of natural disasters.

When we apply the model for the recent four years' data, the three warehouse locations were found as Cambodia, Kenya and Panama. India becomes the additional warehouse for four warehouses to open condition. The locations of optimal warehouses and low inventory levels for 2007-2010 data are illustrated in Figure 7.5.

Table 7.3: The Proportion of Relief Items in Optimal Warehouses (1997-2006)

Warehouse	**Items**						
	Cold Tent	Hot Tent	Household	MREs	Hygiene	Sanitation	Water
Panama	5%	5%	10%	11%	23%	23%	23%
Kenya	5%	5%	10%	20%	20%	20%	20%
India	5%	5%	10%	11%	23%	23%	23%
Hong Kong	5%	5%	10%	20%	20%	20%	20%

Since the distance between Cambodia and Hong Kong is negligible, the result is almost the same with the last decades'. The average emergency response time is calculated as 109.76 for three warehouses and 109.29 for four warehouses. The improvement is 28 minutes, which is less than the other decades. We also execute the model by ignoring the big disasters to observe if optimal locations change. The average response time is calculated as 172.7 hours for four warehouse is opened condition which is approximately 63 hours worse, on the other hand the optimal locations are found as Cambodia, India, Panama and Kenya which is nearly same as the distance between Cambodia and Hong Kong is negligible.

The current warehouse locations in operation are Panama, Dubai and Hong Kong and we observed a clear shift to Kenya. Therefore, when the results are considered opening the fourth warehouse at Kenya would be logical considering that the disasters are dispersed to wider area through the last 33 years.

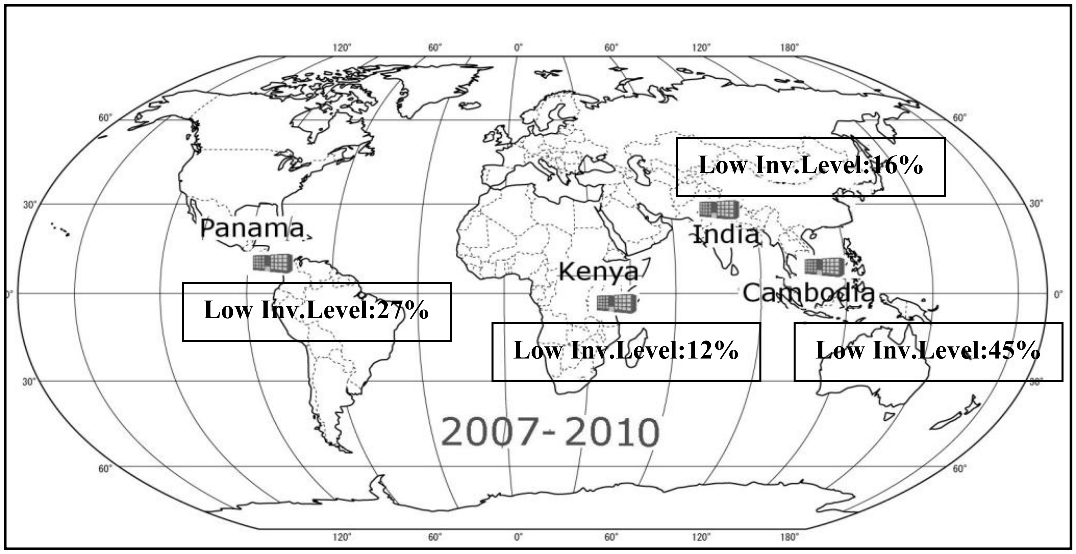


Figure 7.5: Optimal Locations of Four Warehouses for 2007-2010 Time Period

When we evaluate the inventory shares according to recent years' data, it is seen that the percentage of inventories located in Asia regions shifted through other regions. The percentage becomes 61% by decreasing %3 more according to the last decade's results which proves the disasters have a trend of wider dispersal. Please see Table 7.4. for the proportion of relief items within warehouses.

We calculate the average response times' variations among scenarios for three warehouses and four warehouses configurations, and illustrates the values shown in Figure 7.6 and 7.7. respectively.

Table 7.4: The Proportion of Relief Items in Optimal Warehouses (2007-2010)

Warehouse	**Items**						
	Cold Tent	Hot Tent	Household	MREs	Hygiene	Sanitation	Water
Panama	1%	1%	10%	22%	22%	22%	22%
Kenya	1%	1%	1%	25%	24%	24%	24%
India	1%	1%	1%	24%	25%	24%	24%
Cambodia	1%	1%	10%	22%	21%	22%	23%

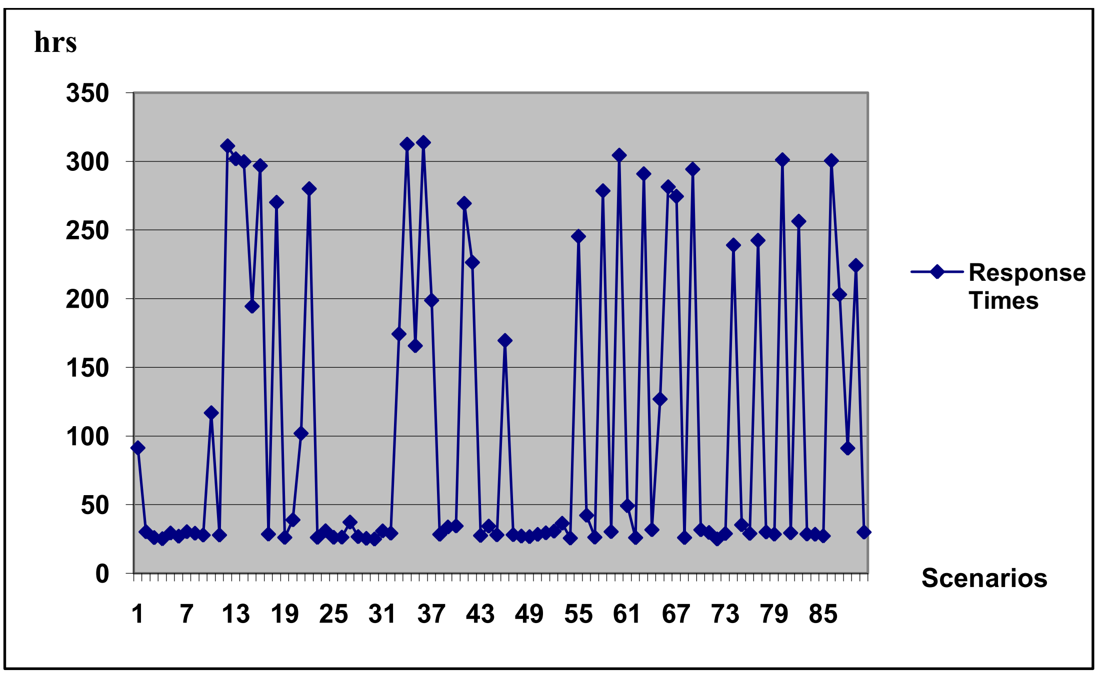


Figure 7.6: Average Response Time Variations among Scenarios for Three Warehouses for 2007-2010

We also calculated the standard deviation values of the response times among scenarios for all warehouse configurations under low inventory level. The response time is given as 336 hours without pre-positioning and according to Chebyshev's Rule, at least 3/4 of the scores fall within 2 standard deviations of the mean (within the interval [$\mu-2\sigma$, $\mu+2\sigma$]) $\mu+2\sigma$ values of all configurations are less than 336 hours.

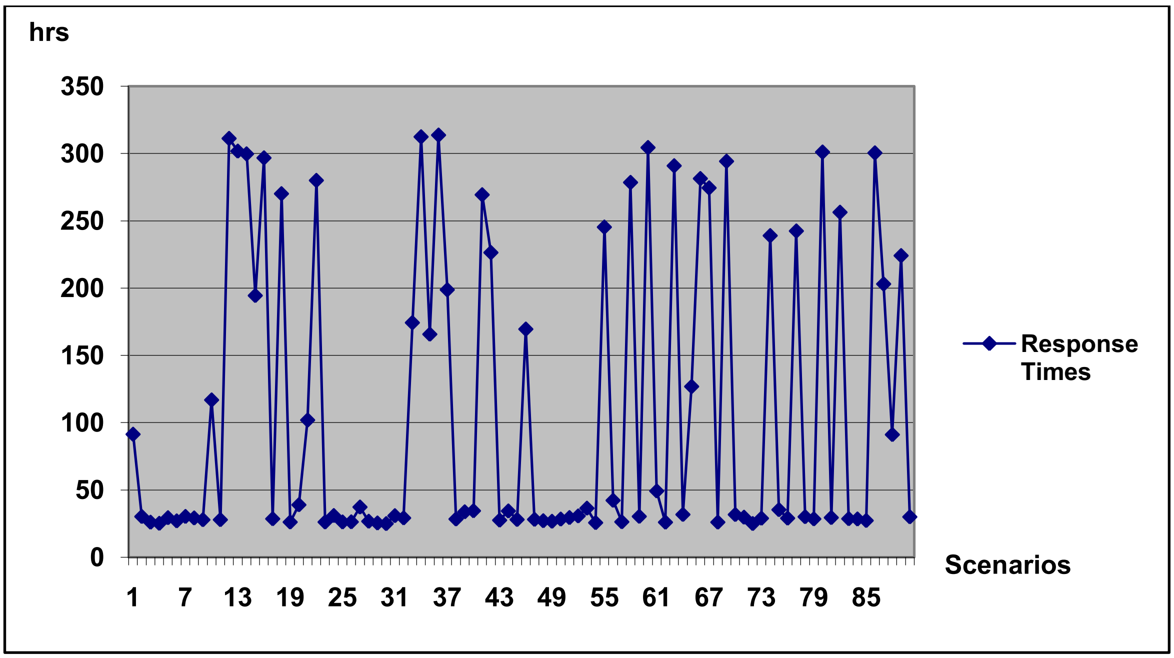


Figure 7.7: Average Response Time Variations among Scenarios for Four Warehouses for 2007-2010

Thus, we can conclude that pre-positioning strategy decreases the average response time. The mean and standard deviations of response times can be seen in Figure 7.8. $\mu + 2\sigma$ values of all configurations can be seen in Figure 7.9.

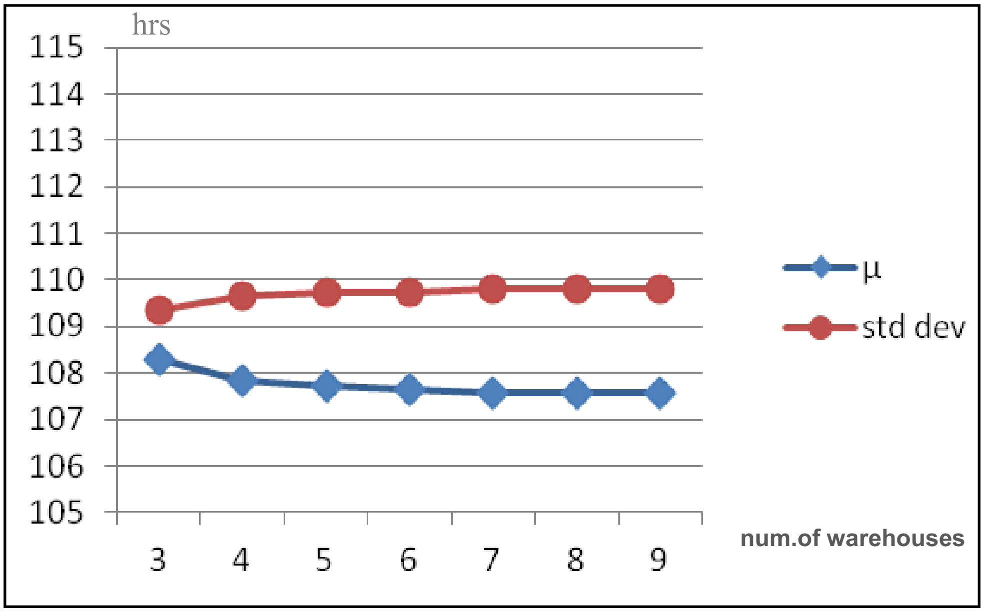


Figure 7.8: Average and Standard Deviation of Response Time

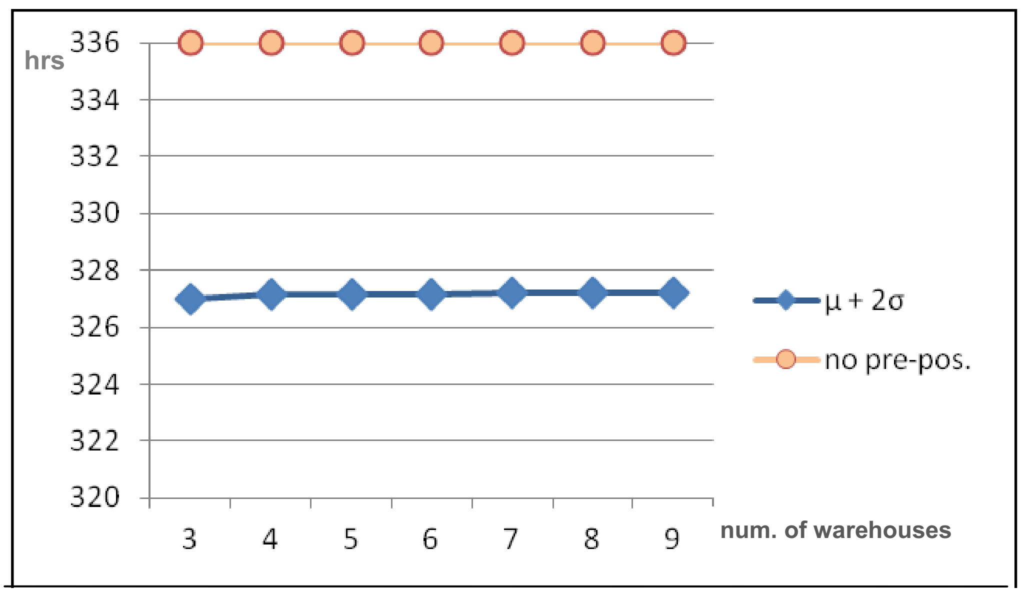


Figure 7.9: μ+2σ Values for 3 to 9 Warehouses Configurations

CHAPTER 8

CONCLUSIONS

In this study we focused on the change in natural disaster trends throughout decades. First we collected the relevant data and grouped them in regions and decades terms. We considered 30 years data and analyzed it by separating it into three decades. Next step was representing the model that was developed by Duran et al. (2010) and executing the model upon number of warehouses to open (1-9) and inventory levels (low, medium and high), for each decade. We analyzed the results by mostly focusing on low inventory level and current number of opened warehouses. First, we considered three warehouses to open for low inventory level to observe the change in warehouse locations for pre-positioning relief items. It is seen that while Panama and Cambodia were stable locations for all decades the location of the third warehouse has changed in each decade. In first decade the location was found as Italy, it was replaced by India in the second decade and Dubai in the last decade. These findings make us to re-think about the current situation and future as the natural disaster trends were shifting through South Africa. We used the data of the years 2007, 2008, 2009 and 2010 to verify the shift of the natural disaster trends. The result for recent years verified the natural disasters trend shifting through South Africa as the third warehouse location was found as Kenya. This observation suggests that the current locations may not be optimal anymore. On the other hand average emergency response time increased decade by decade as a result of natural disasters' expansion to a wider area. This motivated us to think about decreasing response time by opening an additional warehouse as the average emergency response time decreases with the number of warehouses. We run the model for four warehouses to open condition and evaluated the results in terms of warehouse locations and average emergency response times for each decade. The results showed us that the fourth location of each decade became the third location for the next decade which also verified that the natural disaster trends traced a path. We also run the model for recent years and came to a conclusion that if the fourth warehouse is opened in Kenya the average emergency response time would be decreased. Natural disasters have an increasing trend and also disperse to a wider area decade by decade and that is the reason why an additional location provides improvement in response time.

Apparently, Kenya appears as a good candidate for the fourth warehouse location since we see that location to be optimal for the best three warehouse configuration (2006-2010) and four warehouse configuration for all periods. When we consider the current three warehouse configuration situation; 16% of the inventories are located in Panama, 47% of the inventories are located in Hong Kong and 37% of inventories are located in Dubai. Our findings make us to suggest a new distribution for pre-positioning system. The suggestion consists of opening a new warehouse at Kenya, and moving the half of the inventories in Dubai warehouse to Kenya.

For future studies production capacity reserve can be considered as a new option to integrate location, inventory, production and delivery decisions. A pre-production agreement could be made with suppliers for reserving capacity at their production facilities in case of emergency. Pre-purchasing and holding costs could be included to pre-disaster budget as establishing partnership with relief supplies.

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APPENDIX A

This operational guideline is prepared by International Federation of Red Cross and Red Crescent Societies (IFRC) and we use it to estimate $p_{hi\ell}$ in our model, which is the probability of supply ℓ being required at regional demand location i by a person affected by disaster type h.

Table A.1: IFRC's Operational Guideline

	Earthquakes	**Floods**
Water and Sanitation		
Storage, processing, distribution	**H**	**H**
Rodent and insect control	**M**	**H**
Personal Hygiene	**H**	**M**
Food and Nutrition		
Agriculture	**L**	**M**
Short term distribution	**H**	**M**
Supplementary curative feeding	**L**	**M**
Shelter and Household Stock		
Fuel for dwellings	**L**	**M**
Kitchen utensils	**H**	**M**
Emergency shelter	**L***	**L**

*** Depends on the climate**

H:High **M:**Medium **L:** Low

APPENDIX B

Table B.1: The Flight Times (in hrs) between the Candidate Warehouses and Demand Locations (Regions)

	Cambodia	Hong Kong	Denmark	Germany	Honduras	India	Italy	Panama	Kenya	South Africa	Dubai, UAE	Miami, USA
Australia and New Zealand	**36.96**	**52.11**	**53.75**	**54.23**	**49.81**	**37.56**	**41.97**	**54.05**	**46.20**	**50.35**	**43.99**	**46.08**
Caribbean	**54.60**	**25.83**	**38.62**	**38.54**	**26.92**	**52.33**	**50.97**	**39.22**	**46.59**	**26.56**	**46.23**	**47.29**
Central America	**52.98**	**27.65**	**41.26**	**41.53**	**25.43**	**50.14**	**52.49**	**42.68**	**51.31**	**28.32**	**50.77**	**50.35**
Central Asia	**32.98**	**45.78**	**31.96**	**32.31**	**48.40**	**32.75**	**28.72**	**32.42**	**34.87**	**48.95**	**40.74**	**38.31**
Eastern Africa	**38.28**	**48.23**	**37.61**	**36.85**	**49.80**	**40.57**	**34.19**	**35.17**	**40.811**	**48.33**	**28.96**	**31.48**
Eastern Asia	**29.55**	**48.07**	**39.02**	**39.78**	**49.54**	**26.74**	**32.18**	**40.51**	**41.82**	**51.29**	**46.50**	**35.87**
Eastern Europe	**37.42**	**41.80**	**27.57**	**27.87**	**44.47**	**36.99**	**32.79**	**28.23**	**34.91**	**44.73**	**40.68**	**29.96**
Melanesia	**36.42**	**49.14**	**50.90**	**51.77**	**47.61**	**35.74**	**41.84**	**52.64**	**49.10**	**48.88**	**48.47**	**46.36**
Micronesia	**33.53**	**48.42**	**46.05**	**46.93**	**48.03**	**31.86**	**38.54**	**47.91**	**47.59**	**49.81**	**49.71**	**42.87**
Middle Africa	**42.17**	**44.02**	**35.94**	**34.99**	**45.48**	**44.09**	**37.38**	**33.23**	**28.15**	**44.02**	**29.81**	**33.50**
Northern Africa	**40.74**	**41.37**	**29.59**	**28.70**	**43.74**	**41.37**	**35.32**	**26.95**	**31.29**	**43.11**	**36.00**	**30.84**
Northern America	**50.15**	**27.43**	**37.56**	**37.96**	**28.99**	**47.49**	**48.61**	**39.30**	**48.94**	**30.55**	**50.73**	**46.59**
Northern Europe	**41.59**	**37.74**	**24.68**	**24.95**	**40.40**	**40.87**	**37.00**	**26.69**	**36.75**	**40.53**	**41.61**	**33.65**
Polynesia	**44.13**	**42.34**	**52.90**	**53.82**	**40.25**	**42.92**	**49.48**	**55.58**	**55.91**	**41.24**	**51.64**	**53.93**
South America	**57.23**	**33.58**	**42.53**	**41.90**	**32.73**	**58.64**	**52.24**	**41.50**	**43.15**	**30.83**	**39.94**	**47.80**
South Eastern Asia	**25.88**	**54.70**	**42.78**	**43.14**	**55.99**	**27.94**	**31.02**	**42.99**	**38.85**	**57.86**	**41.47**	**35.46**
Southern Africa	**41.55**	**47.87**	**41.53**	**40.62**	**48.30**	**44.24**	**38.57**	**38.86**	**29.91**	**46.45**	**24.00**	**36.39**
Southern Asia	**30.13**	**49.82**	**36.64**	**35.76**	**52.47**	**31.23**	**24.73**	**35.35**	**33.34**	**52.81**	**38.51**	**27.87**
Southern Europe	**41.99**	**38.77**	**27.00**	**26.00**	**41.30**	**41.93**	**36.82**	**24.79**	**34.34**	**40.98**	**38.84**	**32.73**
Western Africa	**45.22**	**39.74**	**33.81**	**32.80**	**41.37**	**46.47**	**39.91**	**31.30**	**32.07**	**40.08**	**33.53**	**35.47**
Western Asia	**37.03**	**43.97**	**30.00**	**29.63**	**46.55**	**37.59**	**31.67**	**28.64**	**31.24**	**46.28**	**37.05**	**27.43**
Western Europe	**41.72**	**38.13**	**25.39**	**24.47**	**40.75**	**41.25**	**36.87**	**25.65**	**35.79**	**40.70**	**40.53**	**33.20**