Inventory Pre-positioning for Humanitarian Operations

by

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Bachelor of Arts, Biophysics
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Submitted to the Engineering Systems Division in Partial Fulfillment of the Requirements for the Degree of

Master of Engineering in Logistics

at the

Massachusetts Institute of Technology

June 2006

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Abstract

This research examines the impact of inventory pre-positioning on humanitarian operations. The study identifies optimal locations for warehousing non-consumable inventories required for initial deployment of aid. These facility location problems are geometric optimizations using *mean annual homeless* resulting from hazards (atmospheric disruptions, floods, waves, landslides, seismic disruptions, volcanoes and wildfires) as an indirect estimation of demand for infrastructure inventory. Minimization of *per capita distance*, or the average global distance from the nearest warehouse to a forecasted homeless person, is advanced as the objective.

An array of formulations, solved using mixed-integer linear programs, predict optimal facility configurations, and corresponding per capita distances, under incremental facility constraints; thereby measuring sensitivity of mean distance to facility proliferation. The problems are devised to also gather insights into maximal covering and the effects of initial conditions. Moreover, demand patterns, along with correlated variables such as population and hazard frequency, offer views of regional vulnerability to natural disasters. The results also exhibit the absence of re-configuration, indicating that location decisions may not be impacted by the number of facilities planned.

Thesis Supervisor: Dr. Edgar E. Blanco
Title: Research Associate, MIT Center for Transportation and Logistics

Acknowledgements

Edgar – for his patient guidance, his time, and for keeping it real.
Chris and Yossi – for giving me this opportunity.
Mom, Dad, Kittie and Jerry – for being so supportive.
My MLOG cohort – for the stimulating discussions that make school so cool.
Amit – for his thoughts.

...and above all others, Andy – for being my loving wife, and tolerating the rigors of graduate school and the demands of this thesis, in our first year of wedded bliss.

Dedication

This thesis is dedicated to my father, Dr. Ramchandra G. Akkihal.

Dad, you instilled my academic curiosity, my love for family, and my inclination to do something good. More than any other reason, knowing how much it excites both you and Mom that my path led to MIT made this year so rewarding. Moreover, you have generously supported both Andy and me – we could not have afforded graduate school without your timely help.

As the patriarch of our entire extended family – having helped, in this way, nearly every person who has gone to school, both in my generation and yours – you deserve these heartfelt thanks. I kept you in my mind throughout the research and writing of this thesis. I proudly dedicate this work, my *karma yoga,* to you. Thank you Dad.

Biographical Note

Anup Akkihal is originally of Huntington, West Virginia. He was previously a consultant, specializing in techno-functional aspects of transactional and tactical systems implementation for inventory, warehouse and delivery management. He holds a Bachelor of Arts in Biophysics from The Johns Hopkins University where he researched stabilization techniques for lipid bi-layers, assisted teaching in the Electron Microscopy laboratory, and won the National Merit Scholarship. His interests include strategy, sustainability, and public goods. Akkihal and his wife, Andrea, reside in Cambridge, MA and Bangalore, India.

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1 Introduction

This research explores pre-positioning as a strategy for humanitarian logistics by measuring the impact of optimally-located facilities on delivery lead-time of the initial deployment in relief operations. Ideal positions for warehousing non-consumable items are revealed using a battery of mixed-integer linear programs. The schemas provided – location optimization formulations and algorithm, and a demand approximation model – are meant to provide a framework for thinking about positioning stock under uncertain conditions. Moreover, the study offers a perspective of regional vulnerability based on the global patterns of homelessness resulting from natural hazards.

This thesis is comprised of seven chapters. Chapter 2 provides an overview of the growing significance of disasters and the role of logistics in improving the humanitarian response. Chapter 3 reviews pre-positioning stocks in practice, providing both a scope of inventory regarded as appropriate for this strategy and reasons why it has not been widely adopted. Chapter 4 develops the theory of inventory pre-positioning, and introduces the demand and delivery chain models that adapt the general case to humanitarian logistics. It is here that the key assumptions for the model are outlined. Chapter 5 advances pre-positioning theory in the humanitarian space, detailing the methodology applied in this study. It explores the data sources, collection criteria, aggregation method, metrics, formulations, computation, and interpretation approach. Chapter 6 offers results; including maps of facility configurations, plotted distance sensitivity curves, upper bounds of a pragmatic proliferation strategy, and statistics regarding the fragility of regions. Finally, Chapter 7 draws general conclusions, noting the additional considerations for implementation of pre-positioning, and frames the analysis within the greater context of disaster preparedness.

This thesis is meant to impress upon the reader a view that strategic pre-positioning of certain inventories can potentially improve humanitarian responsiveness to disaster events; thereby mitigating the harms to public health and stimulate rebuilding and economic recovery.

2 Natural Disasters and Humanitarian Response

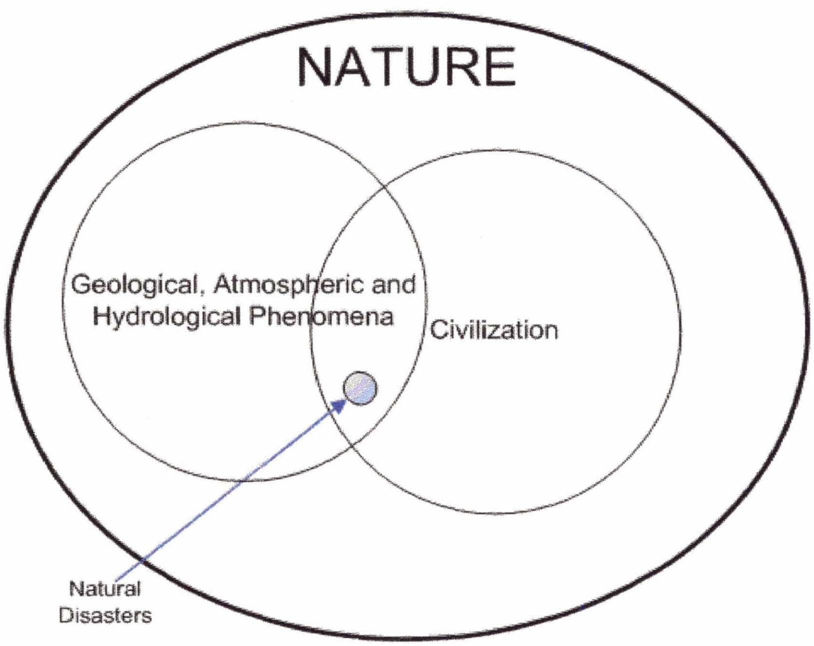
This chapter is meant to introduce the concept of natural disaster; impressing upon the reader the increasing significance of hazards, the importance of logistics in the humanitarian response, and the motivation for researching inventory pre-positioning.

2.1 Natural Disasters

Civilization is natural. We are *of* nature, not distinct from it. The earth system is comprised of a host of subsystems which dynamically impact one another, and humankind can be considered one of these subsystems. Similarly, some phenomena – earthquakes, floods, hurricanes, slides, volcanoes, waves and wildfires – can be grouped together as flows of the geological and climate subsystems. The concept of *natural disaster* inherently makes a distinction between humankind and the rest of nature, because natural disasters occur only when the set of phenomena manifested through homo-sapiens – civilization – is unable to absorb a shock stemming from natural fluctuations in the geological and climate subsystems. Civilization's failure to operate within the bounds of the rest of the earth system is generally the cause of homelessness, economic losses, and fatalities associated with natural disaster.

Figure 1 is a graphical representation of natural disasters within the context of nature's subsystems – the solid circular region shows natural disasters within the intersection of Civilization and the set of Geological, Atmospheric and Hydrological Phenomena. In parallel, one could argue that the earthly environment suffers when it fails to operate with the bounds of the earth system which includes humankind. Ecological degradation can thus be considered the same type of phenomenon as a natural disaster.

Figure 1: Natural Disasters at the Intersection of Nature's Subsystems



Nature is composed of dynamic subsystems which vie with one another. Therefore, natural disasters can be thought of as dependent upon the local relationship between two aggregated variables:

A. The magnitude and frequency of fluctuations in the geological and climate systems at a specific time and place
B. Vulnerability, or the capacity of civilization at a locality to absorb geological and climate shocks

Specifically, when A > B at the same location and time, a hazard is born.

Figure 2: Natural Fluctuations and Civilization's Threshold

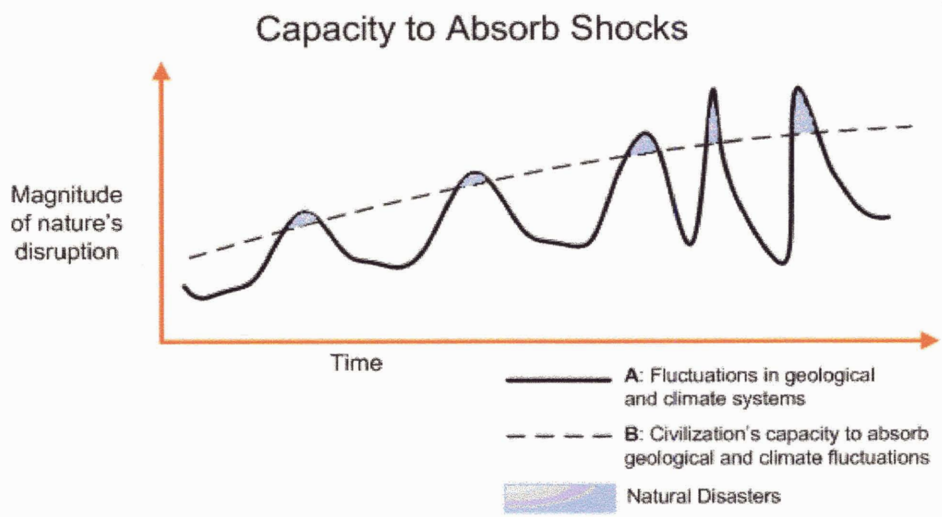
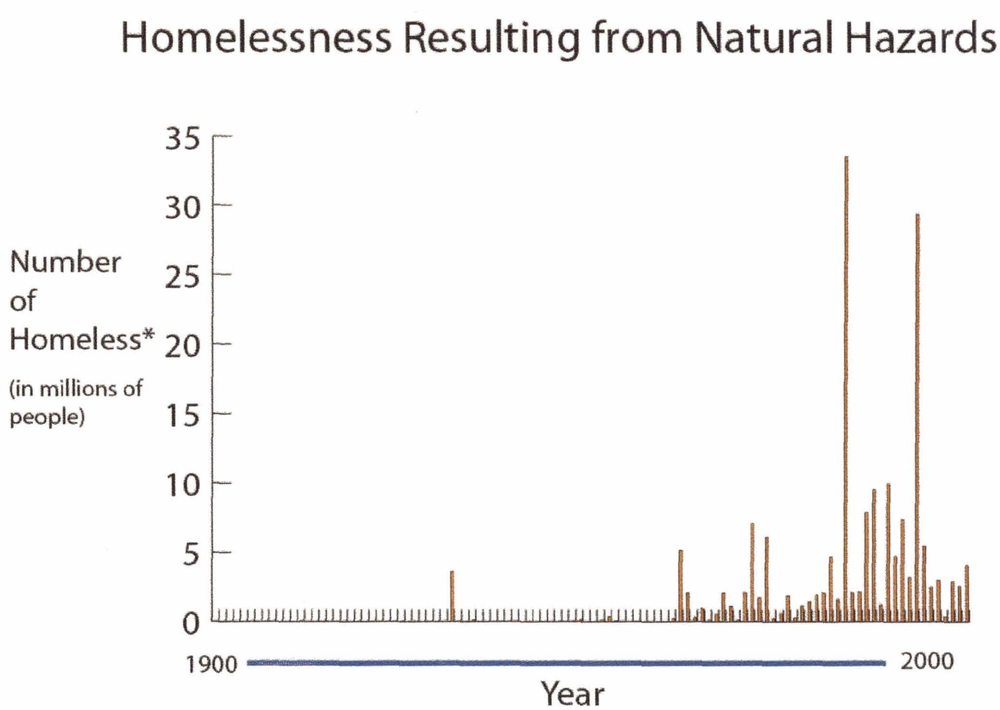


Figure 2 illustrates that, although the process of industrialization is improving civilization's ability to absorb the shocks of other systems, those systems fluctuate with sufficient magnitude that natural disasters continue to occur.

Population density and the structure of settlement points are the sources of vulnerability (Colburn, 1994 and Schiller, 2002). Although increasingly resilient infrastructure and societal experience with hazards act to increase civilization's capacity to absorb shocks, population density in coastal areas and poor access to safety in urban environments during high-magnitude geological and atmospheric fluctuations act to increase vulnerability. Moreover, asymmetrical distribution of global infrastructure renders many settlements vulnerable regardless of population density. For this reason, the dotted line in ***Figure 2*** is shown to be tapered. A report by the Center for International Earth Science Information Network (Dilley, et al., 2000) also contends that disaster losses are attributed to interactions between the hazard event and the characteristics of exposed elements, and that the frequency of disaster events is increasing.

There are additional variables contributing to hazard dynamics. On the climate-side of the equation, some scientists have demonstrated that the magnitude of atmospheric storms is increasing over time, and that this may be due to increased surface temperature of the Earth as a result of global warming (Emanuel, 2005). Using an index for total power dissipation of cyclones to measure the intensity of disruptions, Emanuel shows the index has increased nonlinearly over the past 30 years. The World Health Organization (WHO) Collaborating Center for Research on the Epidemiology of Disasters (CRED) which tracks the global hazards in an "Emergency Events Database" called EM-DAT, shows that the annual occurrence of all geological, oceanic and atmospheric disasters is increasing over time. This finding is supported by other sources (Dilley et al., 2005). ***Figure 3*** graphs this phenomenon as a function of the number of people rendered homeless as a result of hazards.

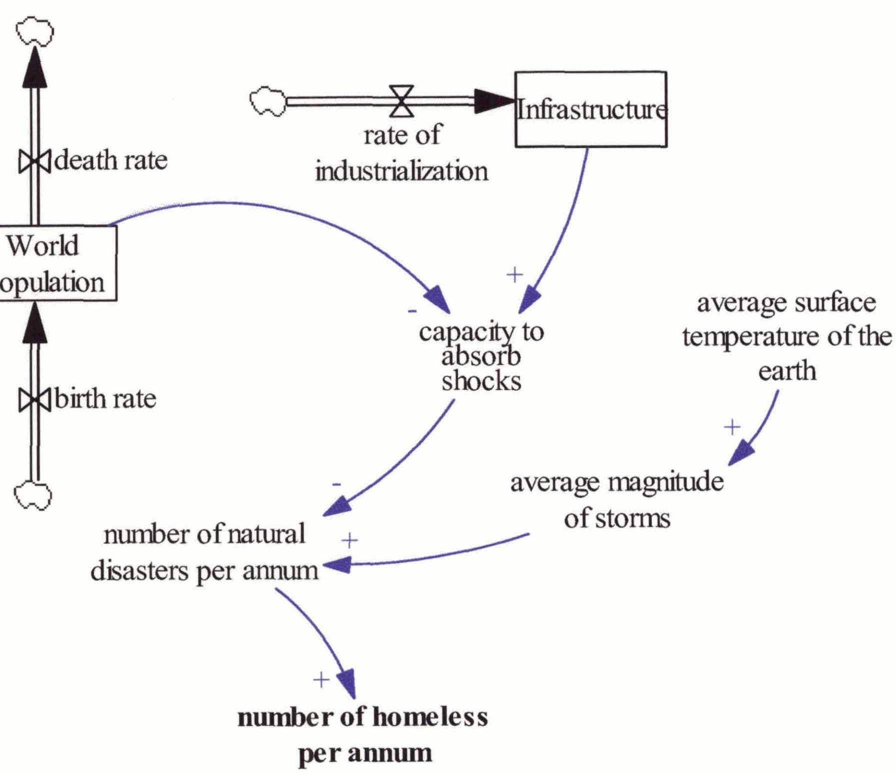
Figure 3: Increasing Displacement of Populations



* Source: EM-DAT

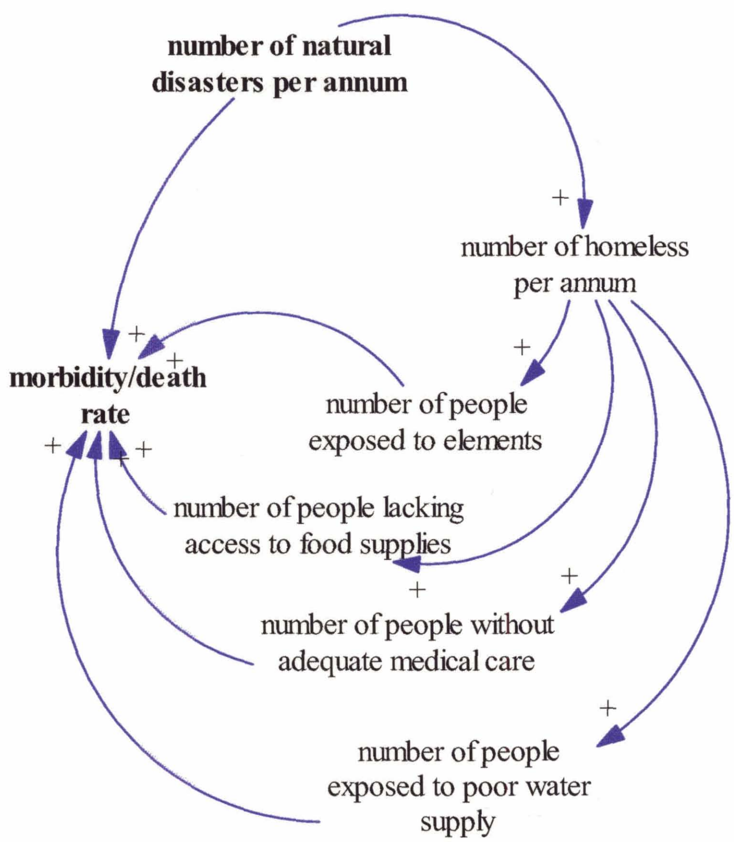
That EM-DAT was created in 1988 is noteworthy because data previous to this time have been extrapolated from secondary data sources. The causal loop diagram in ***Figure 4*** illustrates the impact of some exogenous variables on the atmospheric hazard dynamics of homelessness. Diagrams like these are commonly drawn in the System Dynamics domain, helping systems thinkers to understand the relationships between variables of complex systems. A plus (+) indicator at an arrow head indicates that a variable is positively correlated to the next, in that an increase in one variable will subsequently increase the next variable in the diagram, all other things being equal. Similarly, the minus sign (-) at an arrowhead indicates that an increase in the first variable will cause a decrease in the next.

Figure 4: Sources of Hazard-induced Homelessness



World human population is increasing exponentially while the climate and geological subsystems are becoming more volatile. As a result, there is an increased occurrence of natural hazards. When these disasters strike, those who survive may be injured or rendered homeless for some time. Homelessness triggers a number of mechanisms that result in a general decline in public health and an increase in morbidity (see ***Figure 5*** for a causal illustration).

Figure 5: Displacement and Morbidity



For example, there are indications that exposure to the elements in non-temperate climates can directly increase morbidity rates (WHO, 2001). Malnutrition occurs as a result of destroyed food stocks or food shortages caused by suboptimal distribution in the aftermath. The World Health Organization further indicates that the impact of natural disasters includes increased odds of transmission of communicable diseases, though the disaster itself does not directly cause massive outbreaks of infection (WHO, 2001). Rather, the increase in morbidity is caused by fecal contamination of food and drinking water. Finally, WHO concludes that the risk of epidemic outbreak of communicable diseases is indirectly correlated to the "density and displacement of the population".

Global economic currents are also at risk. A World Bank report (World Bank, 2006) cites that in constant dollars, the cost of disasters in the 1950's was $38 Billion, while the cost of disasters in the 1990's was $652 billion, suggesting that the costs of hazards are also rising. The globalization phenomenon represents, in part, the increasing socioeconomic connectivity among societies of the Earth. This means that each settlement, on average, is increasingly dependent on other settlement points for subsistence (Lechner and Boli, Eds. 2004). This economic connectivity means that supply disruptions at one region may impact the availability of goods in distant regions. This interconnectivity exposes areas not directly impacted by natural hazards to economic risks. Hurricane Katrina, an atmospheric disruption in the Caribbean Sea and the Gulf of Mexico in 2005, exemplifies this causation. Fuel availability decreased, and prices increased in far away locations because the Gulf region is a source of fuel supply. Supply chains, and productivity, do not rebound until those people who are affected are able to return to normalcy.

2.2 The Humanitarian Response

Hazards destroying homes and livelihoods trigger humanitarian sensibilities, so efforts are organized to rescue our fellow humans from their plight. This takes the form of humanitarian assistance in providing medical aid, nourishment, and shelter while the rebuilding process takes place. In general, the purpose of the humanitarian response is simply to mitigate the harmful impacts of the hazard on the local population.

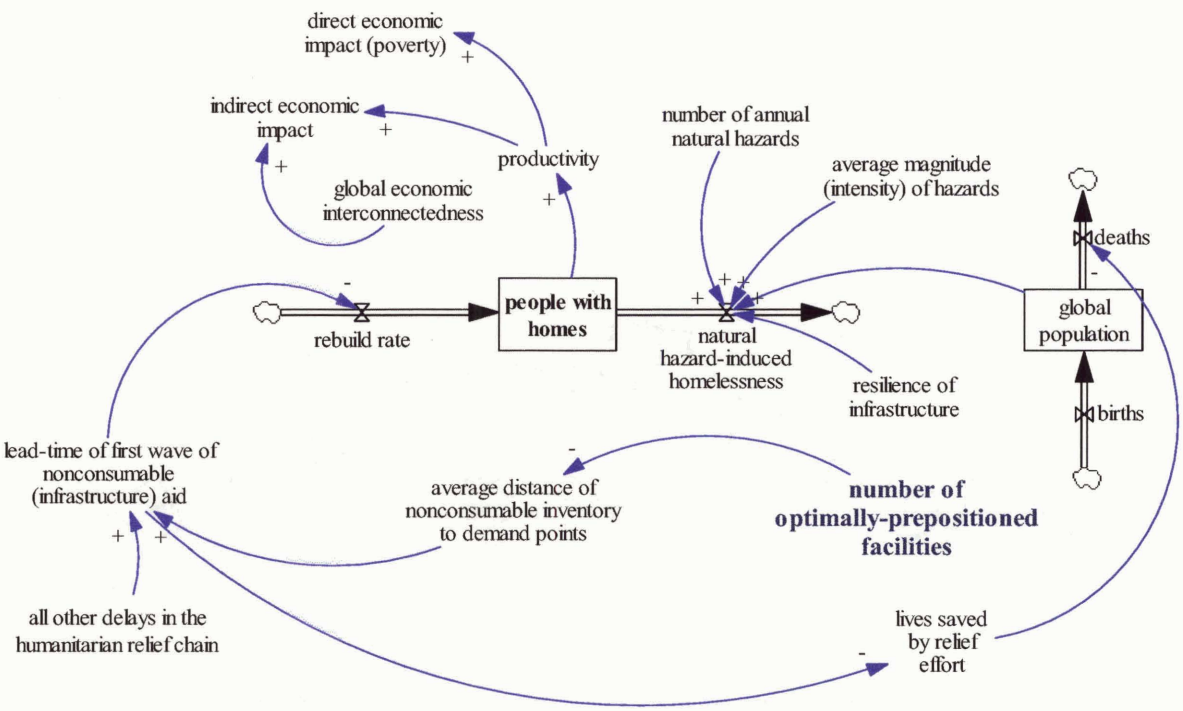
As a result of the increasing occurrence of natural disasters, and of the perception that the quality of relief is inadequate (Stoddard, 2004), the international community is calling for improvement in the process of delivering aid (Adinolfi et al., 2005). One scientist scrutinizes the reactive nature of humanitarian responses, drawing a distinction between preparedness, which is to take pre-crisis action to mitigate harms, and reactivity (Stoddard, 2004).

Specifically, logistics is regarded as an area in which improvements might yield significant benefits because coordination along the supply chain continues to challenge relief organizations (Thomas, 2003, Beamon, 2004 and Adinolfi et al., 2005); and logistics is concerned with coordinating the delivery of goods. The speed of delivery, or responsiveness, has been identified as a desired effect. Preparedness is a theme that resonates from each survey, because there is the perception that preparatory measures taken before the onset of a disaster can mitigate the hazard impact or make the response more rapid.

There is heavy debate over which strategy is appropriate for meeting these ends. Some have realized the inherent limitations of privately funded aid (Thomas, 2003), yet seek solutions within the existing frameworks; while others are critical of the regional asymmetries and supply-driven flows (Stoddard, 2004), urging a more revolutionary paradigm shift to escape the pathologies of the status quo.

Pre-positioning, or the storage of inventory at or near the location at which it will be used, has been submitted as a possible logistics strategy that would reduce delivery lead-time (WHO, 2001 and Thomas, 2003). This formal logistical strategy has been borrowed from military operations where it has been used since World War II (Lee, 1999), if not earlier. The suggestion may have been made because the requirements of humanitarian operations are similar to those of military operations, in that material demands are often unexpected and rapid response is critical to saving lives (or taking them). ***Figure 6*** illustrates how pre-positioning is expected to alleviate harms in the system.

Figure 6: Anticipated Impact of a Strategic Pre-positioning Policy



In summary, the significance of natural disasters is increasing due to variables such as population growth, climate change, and global connectivity. Although swift humanitarian response is critical to containing potential health impacts and beginning the recovery after a natural hazard occurrence, humanitarian relief deployment has not been as rapid as desired. Logistics is often-cited as an area that might improve this effort, and inventory pre-positioning has been specifically suggested as a logistical strategy towards a more rapid response. This motivates the research to predict the impacts of pre-positioning on global humanitarian operations.

3 Inventory Pre-positioning in Practice

This chapter briefly reviews the historical use of pre-positioning and identifies suitable inventories for such a policy within the humanitarian domain.

3.1 Military Applications

Modern pre-positioning has been documented by military scientists since the 1960's, when the United States positioned inventory in Europe in anticipation of the Berlin Crisis (Lee, 1999). Over time, the concept became formally known as Prepositioned Materials Configured in Unit Sets, or POMCUS. The United States Armed Forces typically uses several criteria when evaluating the appropriateness of inventory for pre-positioning. One criterion is the degree of certainty to which the materials are believed to be needed. General Zettler, USAF Director of Maintenance describes the concept as, "...taking what you know you will need, and not what you might need." speaking with respect to POMCUS-relevant materials (Lee, 1999). Furthermore, items that occupy much strategic airlift, or specifically those items that take up several pallet positions are candidates for pre-positioning (Lee, 1999). Some examples of pre-positioned materials in the military include engines, engine removal and installation trailers, munitions trailers, and "tools/toolboxes, aircraft chocks, tires, maintenance stands, light carts, aircraft jacks, tow bars, liquid oxygen carts, liquid nitrogen carts, and air conditioners." Lee's recommendation to Air Force decision makers is that the United States, with its allies, should "stockpile all kinds of supplies at strategic points near areas of potential danger in various parts of the world."

With respect to location, the U.S. Air Force categorizes land and sea pre-positioning separately. However, the United States military has the resources and capacity necessary to use large ships to position inventories prior to entering the battle theater, while humanitarian organizations cannot afford such a costly option. Humanitarian relief providers are thus limited to terrestrial positions.

3.2 Humanitarian Adaptations

The types of inventory appropriate for pre-positioning in humanitarian logistics are similar to those stocks pre-positioned by the military. Suitable items are costly, difficult to transport, or difficult to procure in hazard-stricken regions. These items are referred to in this thesis as *non-consumables*, and are generally related to building temporary infrastructure (or camp) and facilitate the operations for aid-providers. The United Nations has a facility that currently stores such items. That facility is known as the United Nations Humanitarian Response Depot (UNHRD), and it is located in Brindisi, Italy. The UNHRD website offers a list of 122 items that are stored there. The list includes:

- De-mining items
- Drugs and medical equipment
- Electricity devices
- Food items
- Individual kit
- Office and living accommodation
- Radio and telecommunication
- Safety items
- Sanitation and hygiene
- Shelter and housing
- Special items
- Tools

- Transport
- Warehousing and handling equipment
- Water supplies systems

Figure 7 and ***Figure 8*** exhibit photographs of relevant inventory considered within the scope of this research.

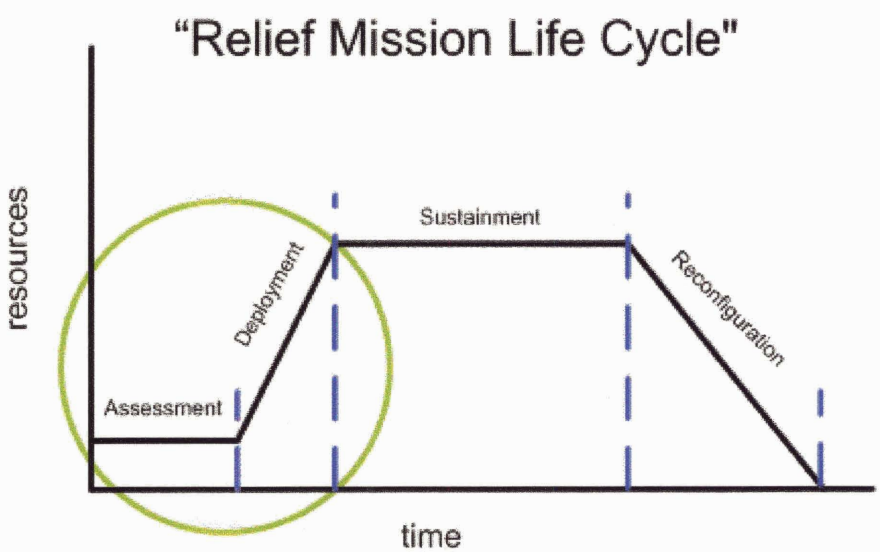
Figure 7: Photos of Humanitarian Non-consumable Goods

Figure 8: Photos of More Humanitarian Non-consumable Goods

Expedient delivery of these items to the disaster theater is critical in the initial phases of the humanitarian response, because their presence facilitates a rapid building of camp. Quickly setting up this infrastructure can improve aid-providers' abilities to assess needs on the ground, and to begin the relief provision process. The importance of the assessment period is emphasized (Russell, 2005) because the presence of relief organizations in the disaster theater is necessary to "take snapshots" of an ever-changing situation in order to generate recommendations for planning response activities. Non-consumable goods are required for camp setup, which enables an ongoing assessment, especially in remote regions. Finally, clean water supplies, shelter and medical equipment are critical to the prevention of those indirect phenomena that lead to morbidity and a general decline in public health. The more quickly these inventories reach the disaster theater, the better the chances of mitigating disaster-related harms. Beamon (Beamon,

2004) summarizes Thomas by graphing the humanitarian relief process. ***Figure 9*** is an adaptation of Beamon's illustration of the relief process cycle. The added circle indicates the phases of the process that are most time-sensitive with regard to non-consumable goods. Reducing delivery time in these initial phases is the aim of pre-positioning in this study.

Figure 9: A Generalized Relief Cycle



[Adapted from Beamon (2004), Modified from Thomas (2004)]

Thomas (Thomas, 2003) suggests that the nature of the funding process might inhibit implementation of pre-positioning, offering at least one reason why the strategy has not yet been widely adopted by humanitarian logisticians. Thomas writes, "Donor scrutiny over the usage of funds…combined with earmarking of donations for particular relief operations, drives [humanitarian response organizations] to focus on direct relief rather than investing in systems and processes that will reduce expenses or make relief more effective over the long-term."

Additionally, given the significant delays associated with coordination of human resources and inventory requirements within channels, there is a likely fear that additional positions (meaning more facilities, and thus more human resources) would compound coordination delays. The current reliance on Non-Governmental Organizations (NGOs), like the International Federation of the Red Cross and Red Crescent societies (IFRC), may also prevent the initiative.

Meanwhile, there is a growing voice from proponents of a *laissez-faire* policy regarding foreign aid. One economist (Easterly, 2006) suggests that the greater process of aid-giving from the industrialized world to the developing world might, in the long run, reinforce the dynamics of poverty. He surmises that aid as it is currently administered might encourage emergencies rather than improve the welfare of those for whom the aid is meant to help.

4 Pre-positioning Theory

Inventory pre-positioning theory can be divided into two categories. One category is the body of inventory theory that estimates item quantities required at various nodes along a supply chain, and the patterns by which the events in the supply chain are triggered. This category draws upon the decision-science of purchasing quantities, order frequency, and maintenance of safety stock levels, among other areas. The other category is the body of theory which examines the spatial aspects of operations, which is what this research is concerned with. This category explores the dynamics of geographical facility location with respect to other factors such as cost, and service.

This research aims to use facility location models to identify optimal locations for stocks. Most frameworks are formulated with specific delivery chain structures and demand models (Drezner, 2005).

This chapter reviews the basics of facility location theory, discusses the concept of using homelessness as an indirect approximation for demand for non-consumables, and outlines the delivery chain that will be used in the model. It is important to note that pre-positioning theory itself is advanced by the adaptations made in the following chapter "Methodology and Approach". Finally, this chapter lists the key assumptions of the model.

The following sections offer the basic concept of single-facility location decisions, a general discussion of multi-facility problems and geometric variants.

4.1 Basics of Facility Location

4.1.1 Facility Location Overview

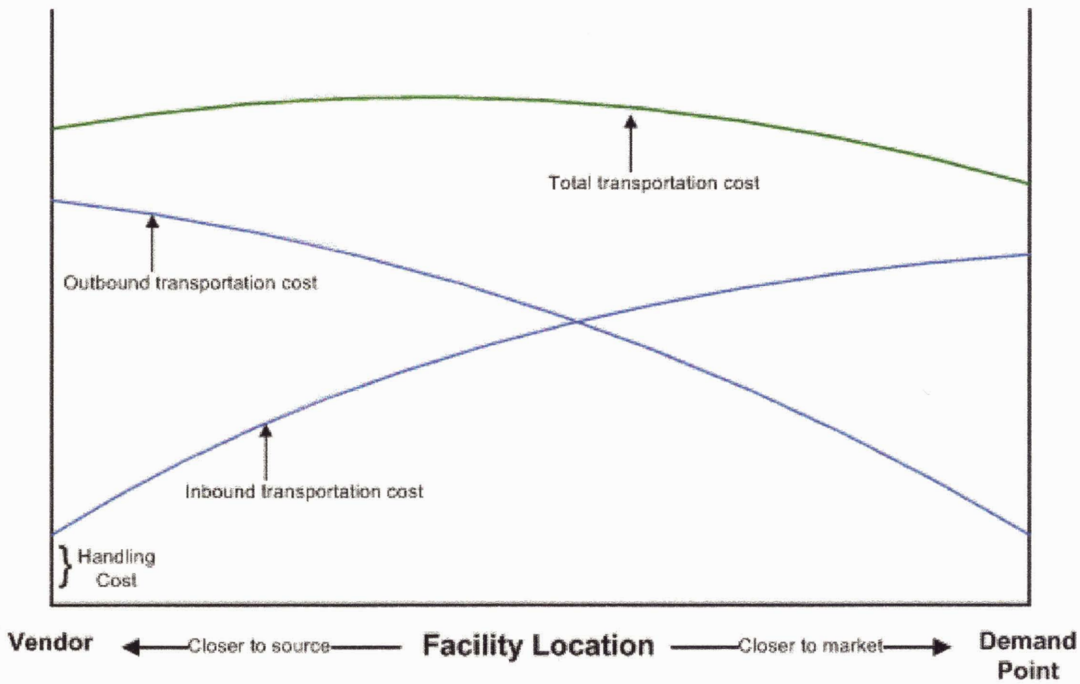
Facilities (manufacturing plants, warehouses, distribution centers, airports, train stations, seaports, etc.) – along with roads, rivers, and railways – give the supply chain structure, because they accommodate the creation, storage and transportation of goods from the source to the point of demand. Facility location decisions are made in order to meet a certain objective, such as minimizing transportation costs or capturing the largest market share (Drezner, 2005). In the humanitarian pre-positioning case, this concerns reducing the time for goods to reach those who will need it.

For over half a century, multinational corporations have employed sophisticated location techniques to determine optimal geographic settings for pipelines, terrestrial cell-phone base stations, warehouses and distribution centers. However, with regard to facilities in the global humanitarian relief chain, these techniques have not been applied. In developing the theory of pre-positioning for humanitarian logistics, the early work regarding facility location is a good starting point.

4.1.2 Single Facility Location

Edgar Hoover (Hoover, 1957) observed that transportation rates were marginally lower with greater distance traveled, and as a result, the cumulative transportation cost from source of materials to facility to market would be minimal at either the source or market locations. Hoover's model applies to a single source point and a single demand point, with a facility in the middle. The basic example is exhibited graphically in ***Figure 10.***

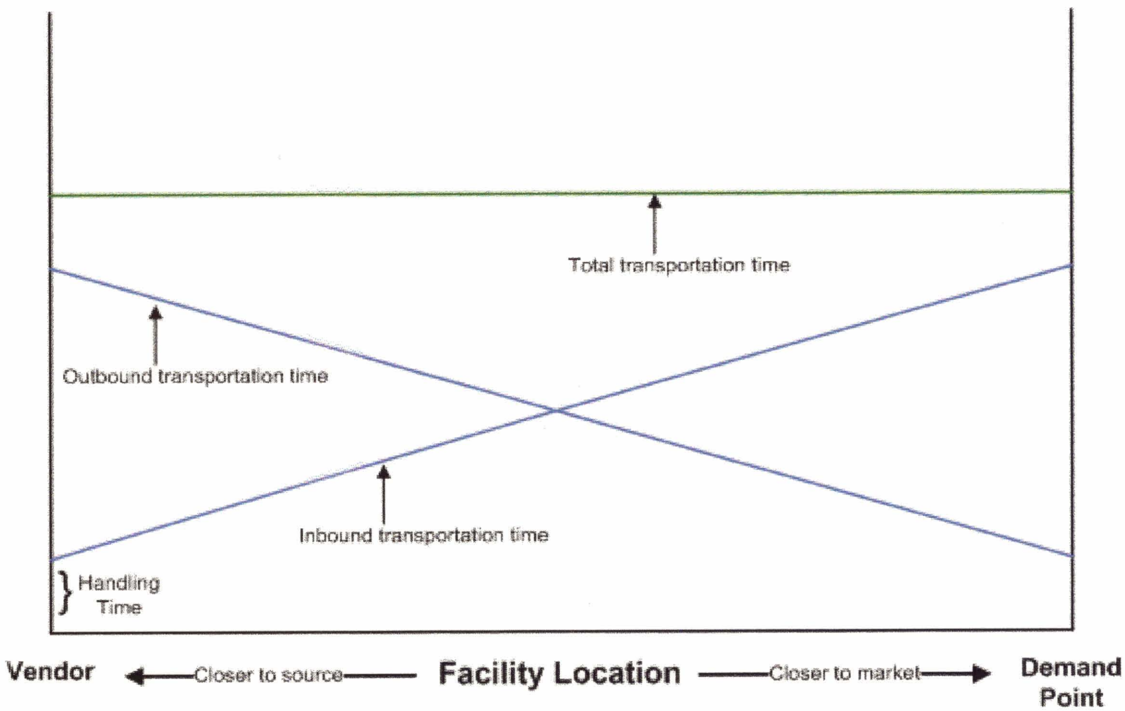
Figure 10: Facility Location and Transportation Cost



The illustration above indicates the lowest total cost for a facility located at the demand point itself. The total transportation cost is the sum of the inbound and outbound costs. This relationship is useful in the case of humanitarian non-consumables. Stocks located at either the source or at the market will minimize total transportation costs in the case of a single vendor and single market and a single product, as shown above. However, relief operations are often measured by delivery lead time (speed) rather than by cost.

For the sake of examining the impact of positioning on time, the Hoover chart above has been adapted to measure transportation times. See the ***Figure 11*** below:

Figure 11: Facility Location and Transportation Time



As one might surmise, the total transportation time remains the same regardless of facility location between source and market, because the total travel distance for the materials is ultimately the same interval. This is, again, an example for a single vendor, a single facility, and single market location. Of course, this does not account for material handling and other delays in the chain.

Pre-positioning inherently implies that the transportation time from the source to the pre-positioned facility will not be time-sensitive because this activity would presumably occur before the hazard event, or before the realization that there is a demand at any given point. Activities that take place prior to the crisis do not delay delivery lead-time because, it is assumed, these items would already reside at the facility at the time of the hazard event.

Therefore the relief timeline begins with the occurrence of the hazard. In other words the critical factor, outbound transportation time, is minimized as the stocks are positioned closer to the demand point. See ***Figure 12***.

Figure 12: Outbound Transit Time as a Function of Distance

Inventory positioned near demand points will yield lower lead times than inventory positioned nearer to the vendor because, all other things being equal, the transportation time is a linear function of distance to the demand point.

$$(rate)(time) = dist$$
$$\therefore time = dist / rate$$

Although the total transportation time is the same, the lead-time from facility to demand point is reduced with greater proximity. Positioning goods closer to market thereby reduces delivery lead time. This is the fundamental argument for pre-positioning.

4.1.3 Multifacility Location

When several facility locations must be chosen, the problem becomes more complicated. The sum of all the distances from each facility to every market which it serves must be minimized, as opposed a single path from facility to market. Moreover, a single facility may serve multiple markets. This means that the sum of each discrete arc, or path from facility to market, should be as low as possible.

Drezner discusses a broad range of optimization problems which are directed toward finding optimal facility locations under a host of constraints (Drezner, 1995). These range from location of a single facility in an environment of discrete demand points on a plane, to solving more complex multifacility problems on a sphere. Other scientists also describe approaches to multi-facility location problems on spherical surfaces using geodesic, or great circle, distances (Aykin, et al. 1987). These formulations consider the path traveled from facilities to demand point to be curved rather than straight lines. For the global humanitarian logistics domain, spherical surface calculations are appropriate, because they approximate the geometry of the Earth's surface better than planar models.

There also exist several methods of handling the demand variables. Most optimizations consider demand to exist at discrete points, though some (Fekete, et al., 2005) discuss the treatment of continuous demand as an area on a surface. This class of formulations, known as Fermat-Weber problems, is very complex; and although it might approximate global human settlements well, the computational intensity and lack of data in that form makes this approach prohibitively difficult. As a result, the models used in this research, which will be discussed in greater detail in subsequent chapters, apply methods that join discrete facility locations and discrete demand points with geodesic arcs on a spherical surface.

4.2 Demand and Delivery Chain Models

4.2.1 Demand Model

In most facility location and network flow optimization problems, demand is treated directly (i.e. if the product is toothpaste, the demand for toothpaste is measured in tubes, cases, or kilograms of toothpaste). For humanitarian supplies, ideally, demand would be measured in terms of the number of water-purification systems, the number of electrical generators, or the number of tents. However, these data are not easy to obtain, as they are not consistently recorded. Moreover, each operation uses various quantities or amounts, dependent on the population displaced, the magnitude of the hazard, and the upstream availability of non-consumable goods. To complicate matters further, operations often bring too many, or too few, of any given non-consumable due to uncertainties on the ground. In other words, there is no clear direct signal of demand, per se. Therefore, this study aims to approximate demand indirectly.

Just as the U.S. Air Force organizes pre-positioned inventory in unit sets, or item groupings, this study assumes that humanitarian logisticians can also make such a structural grouping of non-consumables. For the sake of discussion, this is called a camp. The material requirements of camps would be proportional to the size of the operation. The size of the operation is, in turn, proportional to the number of people being offered relief. From the data available, the best estimation for this demand is the number of displaced people, or the number of homeless. Therefore, the assumption is that the number of people rendered homeless as a result of a hazard is proportional to the non-consumable material requirement. The number of homeless is summated for each demand point over time, and is taken as an average per annum.

This variable is "mean annual homeless" and is measured for every region being considered in the model. The variable is represented as:

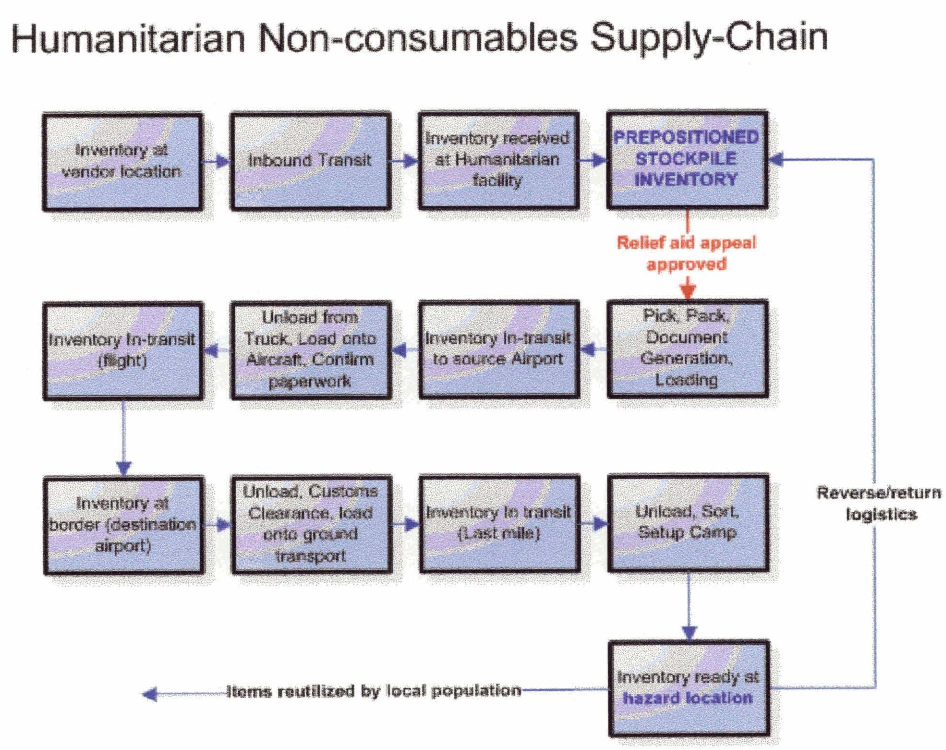
H_j = mean forecasted annual homeless for region j ***Equation 1***

For this study, the only measure of central tendency used is the mean. Standard deviation is relevant to understanding the probability density functions needed to calculate appropriate safety stock and other item and quantity decisions. For location decisions, only the average is needed.

4.2.2 Delivery Chain Models

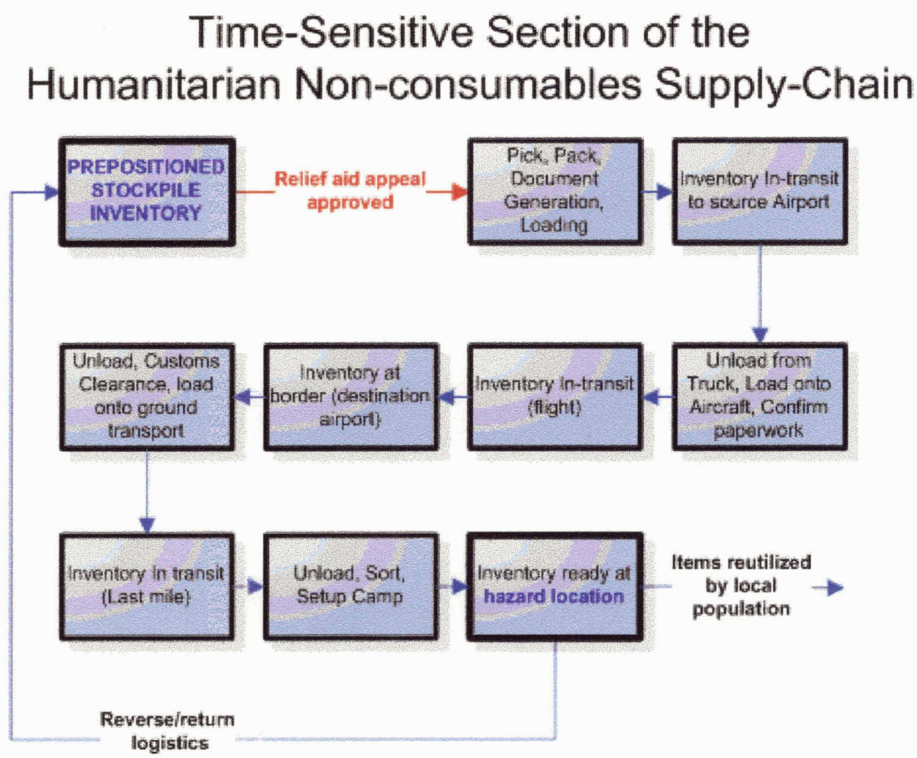
Optimizations of this nature also require a model for the delivery chain, or for the process of moving the goods from point to point. ***Figure 13*** is a representation of the humanitarian delivery chain:

Figure 13: A Humanitarian Supply Chain



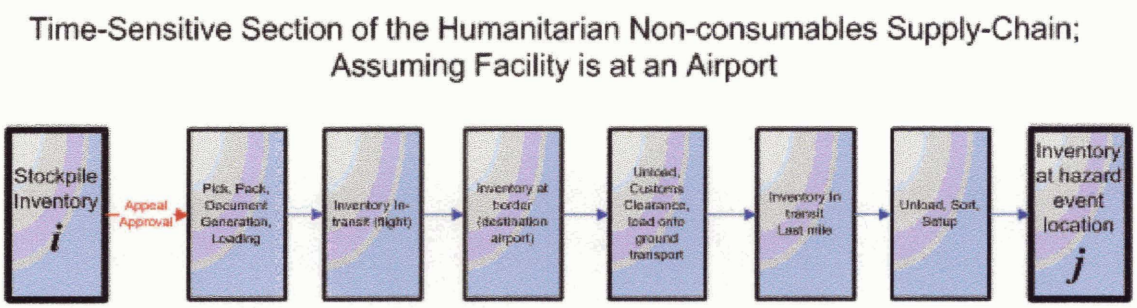
Because pre-positioning implies that stocks are already warehoused at the facility, the path from vendor to facility is not time-sensitive, and is therefore non-critical. This study focuses on only the time-sensitive section of the non-consumables supply-chain. ***Figure 14*** eliminates the path from vendor to facility from the supply chain.

Figure 14: Outbound Delivery Chain



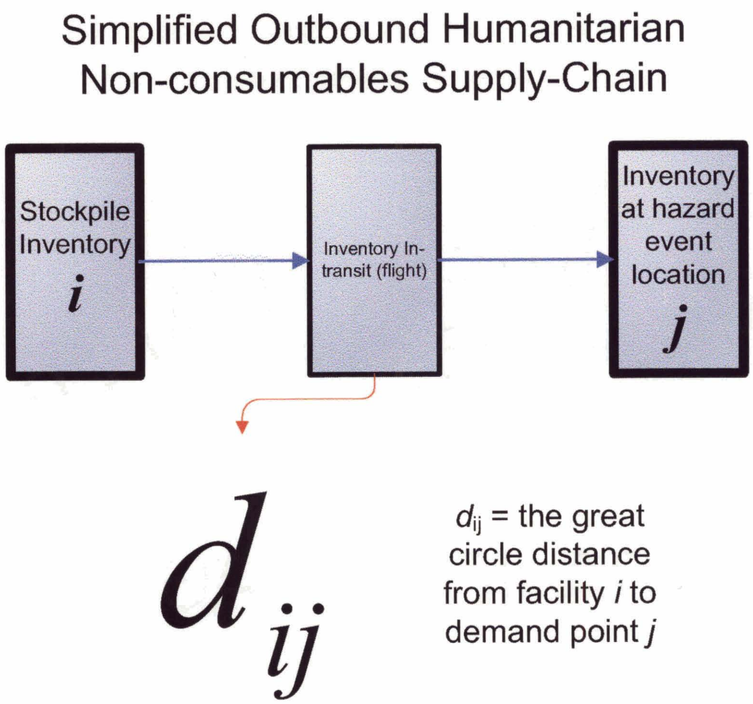
The diagram above identifies several sources of delay along the delivery chain. One of these is the approval process. Once a signal is received that a disaster has occurred, there are protocols followed by humanitarian organizations that evaluate the appeal and estimate the required material aid. This protocol requires time. After the appeal is approved, the process of choosing inventories from bins or shelves and packing these items in appropriate, transportfriendly, packaging is triggered. This is generally referred to as material handling, and it also includes the process of loading and unloading throughout the delivery chain. Furthermore, special documentation, such as bills of lading and pro-forma invoices, are required for transportation of valuable goods. When operations involve the crossing of international borders, not only must customs declarations must be generated, but also immigration documentation for those who steward the supplies. This can be a time-consuming effort, but without adequate documentation, there could be prolonged wait time at borders. Finally, there are delays associated with the transportation in the last mile, including the camp setup time. ***Figure 15*** is a representation of the delivery chain assuming that facilities are located at airports such that initial ground transportation and material handling at the source airport are removed from the chain.

Figure 15: The Time-sensitive Humanitarian Response



There currently exists no robust, sophisticated resource management system that tracks data at each node along the delivery chain detailed above; moreover, delays other than air transit time, such as handling, document generation, and camp setup, are believed to be consistent across the range of disasters and geographies. For the sake of simplicity in the optimization model, and due in part to the data available for humanitarian relief activities, this delivery chain has been simplified yet again; considering only the path from source to destination. This assumes that transaction times are constant, regardless of facility location. Therefore, the model considers only the point-to-point arc from facility to demand point. ***Figure 16*** is a graphical representation of this.

Figure 16: Overly-simplified Delivery Model for this Study



This distance is calculated using the Haversine method which is used to estimate the great circle distance between any pair of latitude (φ) and longitude (λ) coordinates on a sphere; in this case, between (φ_i, λ_i) and (φ_j, λ_j). The Haversine method assumes that the Earth is spherical and uses the formulae:

r = Earth's equatorial radius = 6377 km ***Equation 2***

$\Delta\varphi = \varphi_j - \varphi_i$

$\Delta\lambda = \lambda_j - \lambda_i$

$a = (\sin^2(\Delta\varphi/2) + \cos(\varphi_i)) * (\cos(\varphi_j)) * (\sin^2(\Delta\lambda/2))$

$c = 2 * \mathrm{atan2}(\sqrt{a}, \sqrt{(1-a)})$

$d_{ij} = r * c$

Because, in reality, large cargo aircraft carry non-consumable goods to the airport closest to the disaster theater, the model goes further to relax the constraint of maximum range for this type of aircraft. The IL 76, AN-225 and C-5 are examples of aircraft capable of carrying such loads. See ***Figure 17*** for a photo of an An-225 "Antonov", and ***Figure 18*** for a photo of a comparable C-5 "Galaxy". The people photographed in ***Figure 18*** are a good reference in estimating the size of the aircraft. Each aircraft has a maximum range proportional to its fuel supply. This range limitation is ignored for this exercise. Rather, only the aircrafts' maximum velocity and path distance are considered when calculating the delivery lead time to any given demand point.

Figure 17: The An-225 Antonov

Figure 18: A C-5 Galaxy (Image from Wikipedia Commons)

The actual network of airports, roads and river ways is de-emphasized for two reasons. First, the wide use of helicopters in remote regions (Russell, 2005) where road density or quality is low indicates that properly-funded humanitarian operations need not be constrained by the uncertainties in terrain of the last mile of delivery. Secondly, the real network is difficult to define, especially in the developing world, because new airports and roads are continually built. By examining only the aerial distance, the variances in those factors are circumvented.

4.2.3 Key Assumptions of the Model

In summary, the key assumptions of the model are:

- The hazards considered within the scope of this study include those that provide little advance notice, such as cyclones, earthquakes, and tsunamis.
- Stocks are warehoused in unit sets at facilities in advance of disaster events, and that the capacity of these facilities is infinite.
- Forecasted homelessness is roughly proportional to demand of humanitarian non-consumable unit sets.
- Facilities are located at airports, thereby eliminating the need for ground transport
- Delays other than air transit time, such as approval, picking, packing, loading and document generation, are constant or consistent across the range of disasters and geographies.
- Cargo-carrying aircraft are not restricted in range; rather, fuel capacity is infinite.
- The real network nodes and arcs are ignored; instead, aerial distance is the single criterion for calculating transit distance.

5 Methodology and Data

This chapter reviews the methodology applied in this study. It relates the metric by which pre-positioning for humanitarian preparedness will be measured. It explores the data sources, collection criteria, and aggregation methods used to give structure to the model. It then details the mathematical formulations and the algorithm procedure that predicts the optimal position configurations, and the practical upper-bounds of proliferation. This chapter also relates the computational intensity that drove data aggregation decisions. Finally, it will rationalize the approach to interpreting the results.

5.1 Approach

The question this research aims to answer is "What are the optimal locations for pre-positioning non-consumable humanitarian aid materials to minimize delivery lead-time to those people who will need it?" Implicit in this question is the candidacy of every point on earth as a facility location and every person on earth as a demand point. The computational difficulties of such a construct would prohibit solutions within the desired timeframe. Section 5.7 gives some information regarding the data sources and the structure of those data. Although one data set is granular in that the data are for every settlement point on Earth, the other set offers data regarding hazard-induced homelessness for every country. As a result, when merging those data into a single repository for manipulation, all the data had to be aggregated to represent countries. Each country became a single point (located at the geographical center of all the settlement points), with characteristics including homelessness, longitude and latitude. For computational feasibility, discussed in Section 5.5.3, these countries were again aggregated to United Nations-defined regions. These 21 regions are also represented as points on the surface of the earth, with aggregated characteristics. Furthermore, each of the 21 regional-representative points are both facility candidates and demand points. An explanation of how latitude and longitude for these points were calculated is in Section 5.7. This study uses the mean annual homeless per region, represented as H_j, for each of the 21 regions j, to represent the number of people likely to be homeless. These are the people for which delivery lead time must be minimized.

5.2 The Measure of Preparedness

The objective is to identify locations that optimize humanitarian operations; specifically, that most reduce delivery lead-time. Given a finite set of resources, where should facilities be located so that no other configuration would yield a more responsive system? Because of the simple delivery chain model being used, we are using distance as a proxy for lead-time, as these are correlated and proportional.

So the de facto objective is the minimization of distance from warehouses to people who are likely to require humanitarian aid. That means, the sum of all the paths from every facility to every person at risk of hazard-induced homelessness for which that facility is the closest facility. Each arc from inventory to likely homeless person has a length. That length is a distance measured in kilometers. In order to begin evaluating the efficacy of any logistical strategy on a system, a metric must be developed to measure the effect of any configuration. That metric is *distance per capita at risk*, or the global average length of those arcs. As a measurement of any configuration of facilities, distance per capita represents the global mean distance per person forecasted to be at risk of hazard-induced homelessness from the nearest facility, which is the measure of preparedness of the humanitarian system. Meanwhile, maximum distance represents the length of the arc from a facility to the most remote person on the earth. Maximum distance is the lower bound of responsiveness of the system. These two metrics are used to predict the average lead-time, and qualify the goodness of any given configuration of facilities.

5.3 Status Quo and Blank Page Cases

Because the aim of this exploration is the evaluation of pre-positioning as a strategic operational policy, it is important to understand complimentarity, or the compatibility of the strategy, to the status quo condition. This measurement is made relative to the strategy in the absence of the status quo. In other words, the research seeks not only optimal pre-positioning locations given the status quo conditions, but also optimal positions on an earth without humanitarian depots. The cases are referred to as the Status Quo case and the Blank Page case respectively. By doing this, we can understand the efficacy of pre-positioning in an absolute sense, as well as its impact on delivery lead-time in the real world. Moreover, the results from this approach offer insights into the impact of initial positions on the effectiveness of pre-positioning inventory.

As discussed in the chapter titled "Pre-positioning in Practice", Thomas indicates that the inherent nature of private funding is an obstacle to implementing inventory pre-positioning, and so this study includes only publicly-funded global-service facilities in the status quo. The United Nations Humanitarian Response Depot in Southern Europe is the only such facility that qualified. The Status Quo case finds optimal facilities *in addition to* the UNHRD. However, there are multiple ways of adding facilities.

5.4 Types of Pre-positioning Optimizations

The two types of facility placement considered by this study are called “freeform” and “incremental adding”. These two types can be applied to both the Status Quo and Blank Page cases discussed above, and are best described using an example.

5.4.1 Freeform versus Optimal Adding

If we aim to place 3 facilities optimally, there are two ways of doing this. On the one hand, we can place the three facilities wherever these are most optimal, by minimizing the lengths of all arcs to demand points. That method would adhere to the freeform type of placement. However, in the real world, budgeting restrictions can constrain resources such that only one facility can be built per annum, so the second and third facilities would be built if there is sufficient funding in subsequent years. Because there is sufficient uncertainty connected with the building of future facilities, the decision is made to place the first one optimally, assuming it is the only facility that will be built. In this scenario, the first facility could be placed optimally, and the other two would be placed incrementally with respect to the locations of the ones already built. This is called incremental adding because each facility is built incrementally in addition to the ones already in existence, and each one is located optimally without regard to the location of future facilities. If all three facilities were budgeted and built together, the optimal locations might be very different. The optimal location of the first facility might not be one of the two optimal locations if two facilities are placed simultaneously. This departure of a position from the set of optimal locations in the freeform type is referred to as “reconfiguration”, because the pattern of locations is reconfigured when a position within the set of optimal locations in an iteration is no longer within the set of optimal locations in a subsequent iteration where constraints on the number of facilities are relaxed.

5.4.2 Reconfiguration

The distinction between the freeform and incremental adding types of placement, namely the “reconfiguration” behavior, is illustrated in ***Figures 19 – 22***.

Figure 19: No Positions

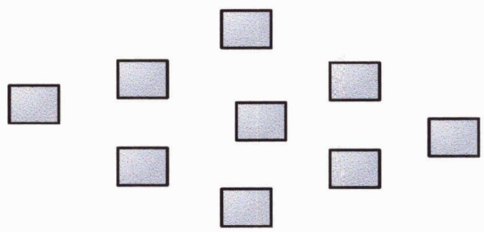


Figure 20: Single Facility

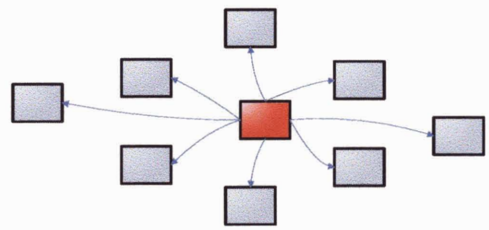


Figure 21: Two, Incrementally Added

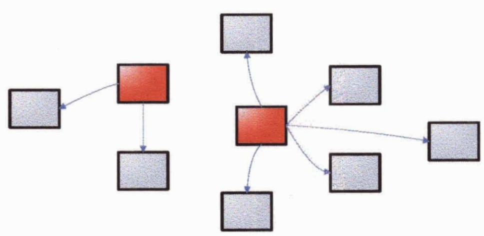


Figure 22: Two Facilities, Freeform

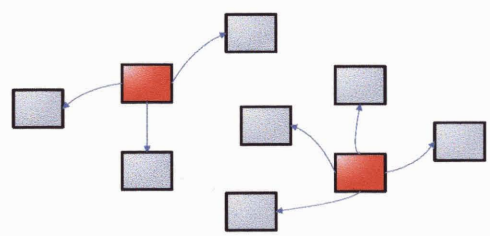


Figure 19 is a graphical representation of a Blank Page case on a plane, with 9 facility location candidates, which are also demand points. No facilities have yet been placed. In placing facilities on this plane, optimality is sought such that the sum of the length of all delivery chain paths (arcs) is minimized. ***Figure 20*** illustrates the optimal position for a single facility. Using the incremental adding method, a second facility is built at the optimal location with respect to the existence of the first facility. ***Figure 21*** illustrates the pattern of a second facility in addition to the inherited location of the first facility solution. Again, this pattern retained the

facility location determined in the previous solution because it is of the type "incremental adding". Returning to the blank page of ***Figure 19***, a different problem is posed. Instead of locating a single facility, the optimal positions of two facilities are sought. ***Figure 22*** indicates the pattern for two optimal positions. The position of a single facility (as shown in ***Figure 20***) is not within the set of optimal locations for the subsequent solution for two positions. This behavior is called reconfiguration, and it can only be exhibited in the freeform type. Incremental adding, on the other hand, cannot exhibit this behavior because subsequent solutions are inherently constrained to the positions of all previous solutions.

5.5 Identifying Positions and Measuring Sensitivity

Of course, facility location problems for global humanitarian logistics are modeled on the Earth, which is more like a sphere than a plane. However the above examples indicate the importance of formulating problems for both freeform and incremental adding. Thus, 2 cases and 2 placement types yield 4 combinations. These are the 4 different formulations (Status Quo Freeform, Status Quo Incremental Adding, Blank Page Freeform and Blank Page Incremental Adding) required to understand general sensitivity of delivery lead time to pre-positioning. This research frames 21 iterations (for optimal combinations that correspond to the number of discrete regional center points) for each of the 4 formulations. The following sections offer details of the formulations, the algorithm protocol, and some idea of the computation.

5.5.1 Formulations

There are four optimization formulations which are run iteratively that quantify the sensitivity of distance per capita to optimal facility proliferation; and there are two additional formulations that aim to quantify the minimum number of facilities required to meet a specific service level.

The objective function for the formulations aimed at determining the sensitivity of distance to facility proliferation is the minimization of average distance to forecasted homeless people. This will, from this point forward, be referred to as simply *distance per capita*. This means the sum of all the arcs from closest facilities to all the people forecasted to be homeless is minimized. The formulation uses the product $(d_{ij} \times H_j)$ as the formula for the sum of all arcs from a facility to all the people forecasted to be at risk at a given demand point. d_{ij} is the geodesic distance from facility *i* to demand point *j*. H_j is the annual mean homeless, or in other words, the forecasted number of displaced people at demand point *j*. That the product of the two variables multiplies the distance by the number of people indicates the sum of all the arcs from that facility to every person at *that* location. The distance per capita is then calculated by dividing the sum of all arcs globally, and dividing by the total number of forecasted homeless globally. Distance per capita is thus expressed as $\frac{\sum_{ij} d_{ij} H_j W_{ij}}{\sum_j H_j}$, where W_{ij} is the decision variable (with a value of 0 or 1) of the optimization because it determines if an arc (actually, the sum of *all* the arcs from a facility at point *i* to *all* the forecasted homeless people at point *j*) is 'active'.

The list below details the objective function, constraints, and variable definitions for each of the 4 formulations of the algorithm that aims to quantify distance sensitivity to pre-positioning.

5.5.1.1 Formulation A: Blank Page Freeform

The blank page case does not consider the existence of the United Nations Humanitarian Response Depot in Southern Europe that is currently operational. Instead, it simply aims to identify optimal positions of n facilities so that global distance per forecasted homeless person is minimized.

Objective function:

$$\min \sum_{ij} d_{ij} H_j W_{ij} \quad \forall\, i, j \qquad \textbf{\textit{Equation 3}}$$

$$\textit{subject to}: \quad W_{ij} \le Y_i \quad \forall i, j$$

$$\sum_i Y_i = n$$

$$\sum_j W_{ij} = 1 \quad \forall i$$

Where:

i = facility candidate locations, with latitude and longitudinal coordinates (φ,λ)

j = center points for demand regions, with latitude and longitudinal coordinates (φ,λ)

d_{ij} = Haversine distance from facility location i to demand point j

H_j = The mean annual homeless as a result of natural hazards

$Y_i \in \{0,1\} \quad \forall i$

$$Y_i = \begin{Bmatrix} 1 & \textit{if facility exists at } i \\ 0 & \textit{if} \quad \textit{otherwise} \end{Bmatrix}$$

$W_{ij} \in \{0,1\} \quad \forall i, j$

$$W_{ij} = \begin{Bmatrix} 1 & \textit{if facility } i \textit{ is assigned to region } j \\ 0 & \textit{if} \quad \textit{otherwise} \end{Bmatrix}$$

(A facility is assigned by virtue of being the closest facility in terms of great circle distance to a region)

$n =$ The total number of global positions (facilities). In the algorithm illustrated in ***Figure 23***, and for the data structure discussed in Section 5.7, n ranges from 1 to 21. It also indicates the iteration.

5.5.1.2 Formulation B: Blank Page Incremental Adding

This variant of the blank page case differs from the freeform for all iterations where n>1 because each iteration constrains the objective function such that every facility chosen as optimal in the iteration (n-1) will be carried forward to the following iteration n. The following example demonstrates this characteristic. If, in iteration n=2 $Y_{\text{Carribean}}$ and $Y_{\text{Polynesia}} = 1$, then in iteration n=3 a position will be chosen in addition to these two. So the solution could be the combination $Y_{\text{Carribean}}$ and $Y_{\text{Polynesia}}$ and $Y_{\text{Northern Europe}} = 1$, but **not** the combination $Y_{\text{Austrailia \& New Zealand}}$ and $Y_{\text{Eastern Asia}}$ and $Y_{\text{Northern Europe}}$=1. As a result of this constraint, there can be no reconfiguration phenomenon, preserving the efficacy of the initial position.

Objective function:

$$\min \sum_{ij} d_{ij} H_j W_{ij} \quad \forall\, i, j$$ ***Equation 4***

$$\textit{subject to}: \quad W_{ij} \le Y_i \quad \forall i, j$$

$$\sum_i Y_i = n$$

$$\sum_j W_{ij} = 1 \quad \forall i$$

$$^{\textit{iteration}\,(n-1)}Y_i \le {}^{\textit{iteration}\,(n)}Y_i \qquad \forall\, i$$

(The final constraint ensures that if a facility location was selected in a previous iteration, then it will remain selected)

5.5.1.3 Formulation C: Status Quo Freeform

The status quo case differs from the blank page case only in that it considers the existence of the UNHRD facility location in Southern Europe. The objective function is constrained such that this facility is always selected.

Objective function:

$$\min \sum_{ij} d_{ij} H_j W_{ij} \quad \forall\, i, j$$ ***Equation 5***

$$\textit{subject to}: \quad W_{ij} \le Y_i \quad \forall i, j$$

$$\sum_i Y_i = n$$

$$\sum_j W_{ij} = 1 \quad \forall i$$

$$Y_{\textit{Southern Europe}} = 1$$

5.5.1.4 Formulation D: Status Quo Incremental Adding

This variant of the status quo case differs from the freeform for all iterations where $n>2$ because each iteration constrains the objective function such that every facility chosen as optimal in the iteration $(n\text{-}1)$ will be carried forward to the following iteration n. As a result of this constraint, there can be no reconfiguration phenomenon, preserving the efficacy of the initial position.

Objective function:

$$\min \sum_{ij} d_{ij} H_j W_{ij} \quad \forall\, i, j$$ ***Equation 6***

$$\text{subject to}: \quad W_{ij} \le Y_i \quad \forall i,j$$

$$\sum_i Y_i = n$$

$$\sum_j W_{ij} = 1 \quad \forall i$$

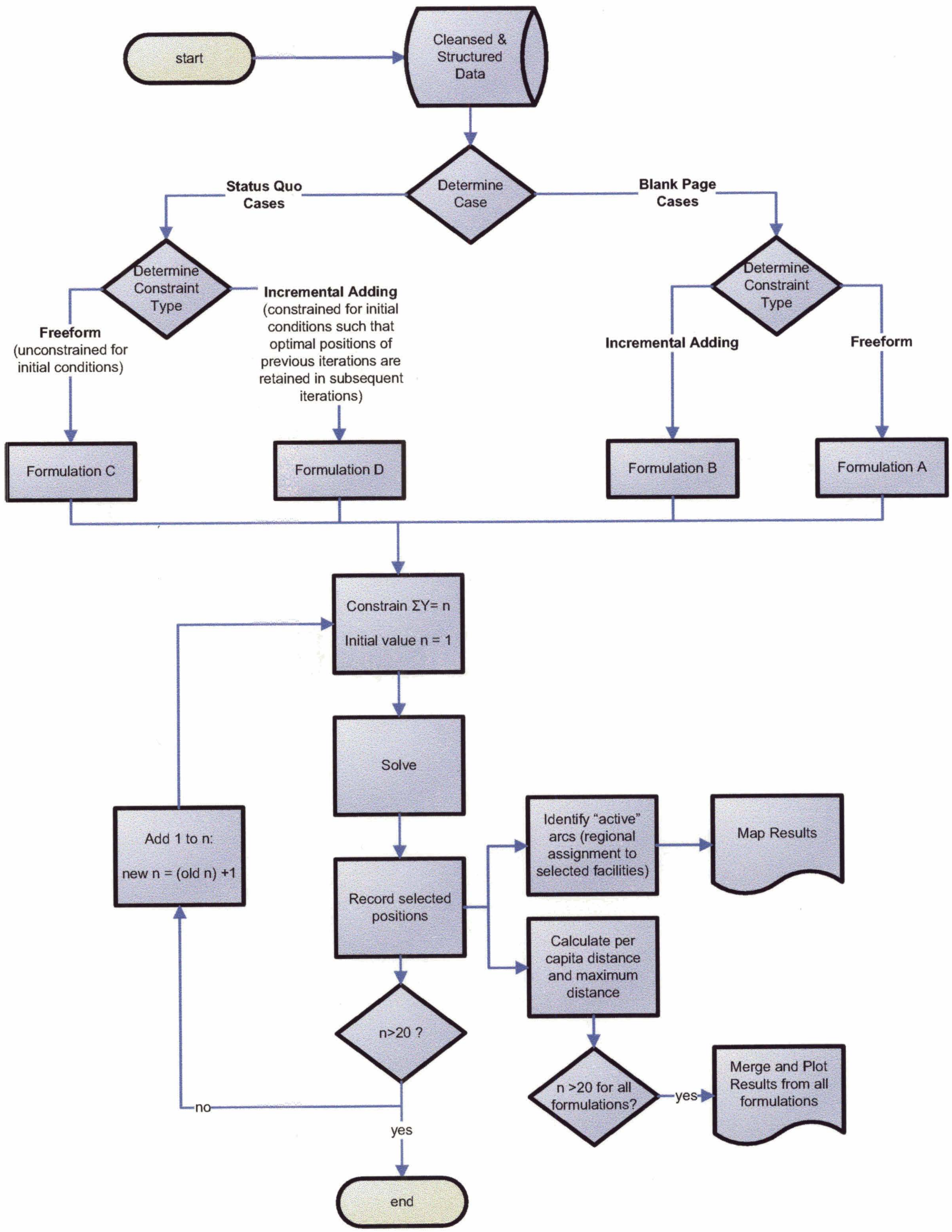
$$Y_{\text{Southern Europe}} = 1$$

$$^{\text{iteration}(n-1)}Y_i \le {}^{\text{iteration}(n)}Y_i \quad \forall i$$

5.5.2 Sensitivity-determination Algorithm

Each of the above formulations is used for 21 iterations of solutions (ranging from 1 facility to 21 facilities). Each solution yields a configuration of locations and active arcs. The locations and arcs are juxtaposed onto a map for graphical illustration. The lengths of every active arc are also used to calculate distance per capita, and maximum distance. After each formulation has completed 21 iterations, all the data are plotted in order discern distance sensitivity to each type of proliferation model. Additionally, the data are plotted such that conclusions can be drawn regarding the impact of initial positions on the metrics, as well as the relative impact of each facility. The process, or algorithm, by which these data are gathered, is illustrated in ***Figure 23***.

Figure 23: Distance Sensitivity Algorithm



5.5.3 Combinations

The number of configurations, or facility selection combinations without repetition, evaluated by the algorithm is an important consideration before deciding how to solve the problem. Each iteration of the optimization problem constrains the formulation to a specific facility number$\left(\sum_{i=1}^{21} Y_i\right)$. This value is equivalent to the total number of facilities to be located globally. In the first iteration of the free-form case, for example, we want only to select 1 facility location for the earth that would minimize the mean distance per capita. Therefore$\left(\sum_{i=1}^{21} Y_i\right)$, or the total number of facilities to be located, = 1. Similarly, $\left(\sum_{i=1}^{21} Y_i\right) = 7$ for iteration 7. Therefore, if

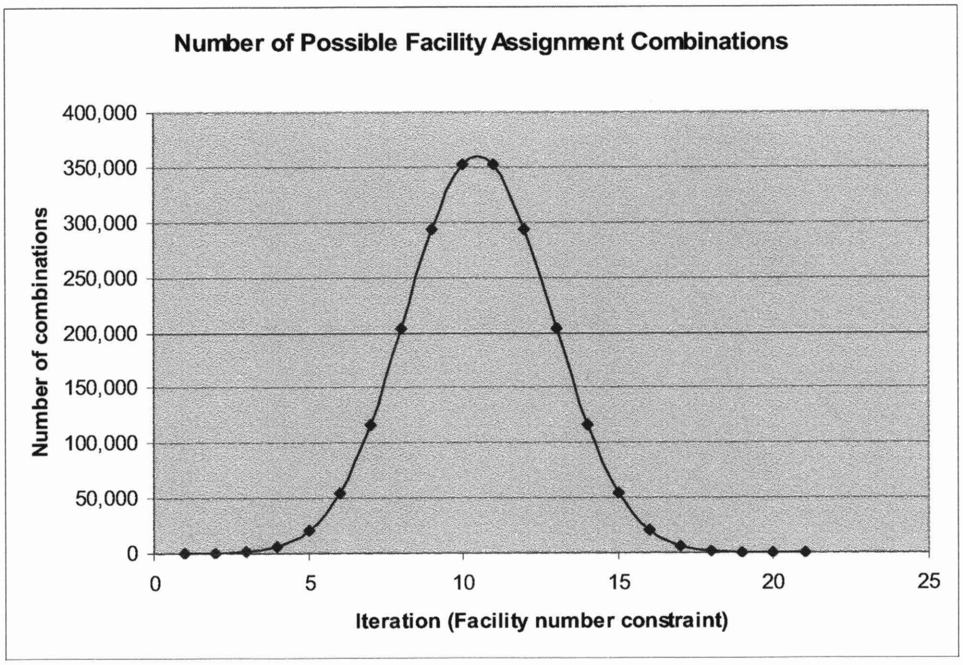
$$\left(\sum_{i=1}^{21} Y_i = N\right) \qquad \textbf{\textit{Equation 7}}$$

Then the number of feasible combinations without repetition is:

$$\binom{21}{N} = \left(\frac{21!}{(N!)\times(21-N)!}\right) \qquad \textbf{\textit{Equation 8}}$$

For the freeform case, ***Figure 24*** below captures the number of combinations without repetition for each iteration.

Figure 24: Non-repeatable Combinations by Iteration



The total number of combinations evaluated by all iterations for each formulation of the mixed-integer linear program is:

$$\sum_{N=1}^{21} \frac{21!}{(N!)\times(21-N)!} = 2^{21}-1 = 2,097,151 \qquad \textbf{\textit{Equation 9}}$$

The battery of optimization problems for the freeform case evaluates each of these combinations, and arrives at 21 solutions. There are approximately the same number of possible configurations and solutions for each of the other formulations. This is too many to be solved manually. Therefore mixed integer programming was used as a tool to quickly find the optimal solutions.

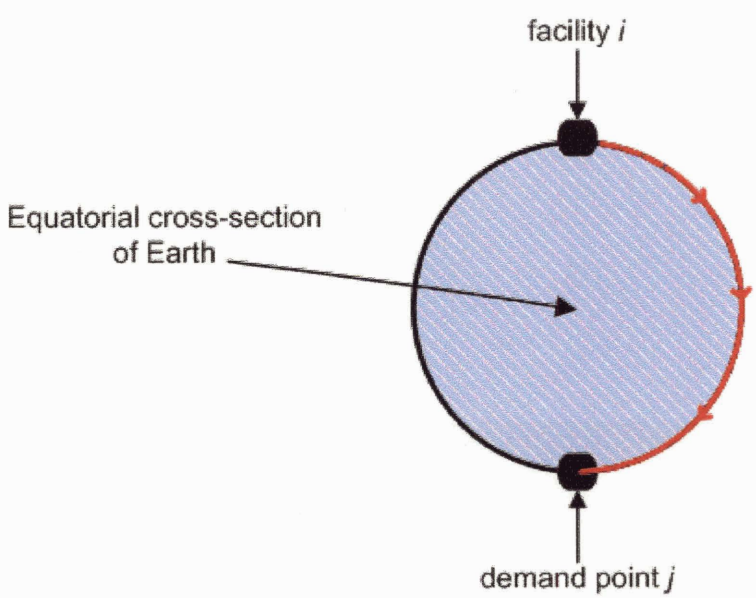
5.6 Sensible Limits to Proliferation

In addition to the set of problems framed in the algorithm, two other problems were posed to ascertain reasonable limits to facility proliferation. These problems are meant to understand the minimum number of facilities required to satisfy a service level. A service level, in this context, is a maximum distance per capita threshold, beyond which the level of service is not adequate. The greater the distance from pre-positioned inventory to a person at risk of homelessness due to natural disaster, the lower the service level.

5.6.1 Status Quo Service Levels

To anchor the concept, consider the status quo situation. The UNHRD claims "the capability of sending emergency humanitarian relief items anywhere in the world within 24/48 hours". The maximum distance between any two points on a sphere would be one half of the circumference of an equatorial cross-section (***Figure 25***).

Figure 25: Cross-section of Earth



Therefore, for the earth, this is:

$$\text{distance}_{\max} = \frac{2 \times \pi \times radius_{earth}}{2} \qquad \textbf{\textit{Equation 10}}$$

$$\text{distance}_{\max} = (\pi)(radius_{earth})$$

Using the earth's equatorial radius, and the approximation for pi:

$$r_{earth} = 6377 \text{ km}, \qquad \pi \approx 3.14159265$$

We can approximate a maximum distance from UNHRD to any point on earth to be:

$$\text{distance}_{\max} = (\pi)(radius_{earth}) \approx 20{,}034 \text{ km}$$

The average maximum speed of various cargo aircraft, the C-5 Galaxy, the An-225, the IL 76, amongst others, is approximated to be 500 km/hr. Using the standard formula:

$$\text{distance} = \text{rate} * \text{time}$$

$$\therefore \text{ time} = \text{distance} / \text{rate}$$

The transportation time, assuming only air transport with no consideration of refueling stops, for the maximum possible distance is therefore:

$$\text{time} = (20{,}034 \text{ km}) / (500 \text{ km/hr}) = 40.07 \text{ hours} \approx 40 \text{ hrs}$$

This falls within the range offered by the UNHRD. Rather than measuring the improvement for incremental facility proliferation, as was done in the previous array of problems, this problem sets targets, and meets those targets with the fewest facilities.

5.6.2 Desirable Service Levels

The arbitrarily chosen targets are captured by the following questions:

1. What are the fewest facilities required to ensure the maximum distance to any person at risk globally is less than 5000 km (10 hours transportation time)?

2. What are the fewest facilities required to ensure the maximum distance to any person at risk is less than 5000 km *and* that the global mean per capita distance is less than 500 km (approximately 1 hour transportation time)?

When all the arc distances between facility location candidates and demand points were calculated, it was clear that the Polynesian region was the most "remote", in that the distance to the nearest region (Melanesia) is greater than the distance from any other region to its nearest neighbor. Therefore, unless a facility is located in Polynesia, the maximum distance to a person at risk of homelessness is the distance from Melanesia to Polynesia, or ≈ 4314 km. It is for that reason that 5000 km was established as an appropriate maximum distance.

The question this problem aims to answer is arbitrary in that the service level criteria do not correspond to any authoritative mandate. However, it is interesting to note the solutions in Chapter 6 because it indicates a practical limit to proliferation. The framework provided may also accommodate a different service level to calculate the appropriate upper bound of a proliferation policy. Again, these two problems were solved using mixed-integer programs.

5.7 Data Construction

The two variables of the optimization problems for which data had to be collected are:

1. The mean annual homeless for every demand point (for H_j values)
2. Latitude and longitude coordinates for all facility points and demand points ((φ_i, λ_i) *and* (φ_j, λ_j) values used to calculate d_{ij})

The values of these variables were gathered from two sources known as EM-DAT (EM-DAT, 2006) and GRUMP (CIESIN, 2006). EM-DAT stores hazard data for events if at least one of the following criteria is fulfilled:

- 10 or more people reported killed
- 100 people reported affected
- declaration of a state of emergency
- call for international assistance

If an event qualifies for entry in EM-DAT, the following data are input:

1. Disaster number: A unique disaster number for each event (8 digits: 4 digits for the year and 4 digits for the disaster number - i.e.: 19950324).
2. Country: Country in which the disaster has occurred.
3. Disaster group: Three groups of disasters are distinguished in EM-DAT: natural disasters, technological disasters and complex emergencies.
4. Disaster type: Description of the disaster according to a pre-defined classification.
5. Date: When the disaster occurred, in the format Month/Day/Year.
6. Killed: Persons confirmed as dead and persons missing and presumed dead.
7. Injured: People suffering from physical injuries, trauma or an illness requiring medical treatment as a direct result of a disaster.
8. Homeless: People needing immediate assistance for shelter.
9. Affected: People requiring immediate assistance during a period of emergency; it can also include displaced or evacuated people.
10. Total affected: Sum of injured, homeless, and affected.

11. Estimated Damage: Given in US$ and/or Euro.

For the purposes of this study, this worldwide data is filtered for only those disaster types which are Earthquake, Flood, Slides, Volcano, Wave/Surge, Wildfires and Wind Storm. It is also filtered to include only those disasters which occurred within the approximately quarter-century range between the years 1980 and 2005. From these records, this examination is concerned with capturing the number of homeless, and the country. These data are married to the geographical data collected through The Global Rural-Urban Mapping Project (GRUMP).

GRUMP is an initiative of Center for International Earth Science Information Network (CIESIN) of the Earth Institute at Columbia University. GRUMP collects spatial and population data of global settlements and grids them at a resolution of 30 arc-seconds. Basically, these data are a database of human settlements, the spatial coordinates, and a population associated with each. The following is an example of what kind of data is found in the GRUMP database:

Figure 26: Sample Data from GRUMP

UNREGION	COUNTRY	SCHNM	SCHADMNM	LATITUDE	LONGITUDE	POP
Northern America	USA	CAMBRIDGE	MASSACHUSETTS	42.373746	-71.110554	101355

GRUMP was used to gather geographical coordinates, which were subsequently used to calculate geodesic arc distances using the Haversine method. This database is very granular in that it stores data for every settlement point on Earth, so GRUMP also helped to identify regional center points, which became candidate facility locations and the demand points. Every region was defined as a set of countries, and the mean longitude and latitude for all settlement points within the set of countries that comprised a U.N. region (listed in Appendix A) was accepted as the regional center point. The robust population data provided by GRUMP was used to understand regional vulnerability to disasters, and was also tested for correlation to the forecasted homeless of every region.

The two datasets, EM-DAT and GRUMP were reconciled for compatibility. This included the naming conventions for countries (for example, one database calls a nation North Korea while the other calls it the Democratic Republic of Korea) and the assignment of areas to a political entities (for example, one dataset aggregates data for Hong Kong with the People's Republic of China, while the other does not). Hazard frequency, population and homelessness were thus captured to create a local dataset which could be used by the mixed-integer program. The data looks something like this:

Figure 27: Cleansed, Aggregated and Merged Data Set

Zone Data for population, coordinates, disaster frequency						
zone(j)	**population in thousands**	**φ (latitude)**	**λ (longitude)**	**μ annual homeless**	**hazards (1980-2005)**	**annual μ hazards**
South-central Asia	1,614,798	23.7457	77.3852	2,074,333	2,114	78.30
Eastern Asia	1,535,407	33.4250	118.4129	1,641,489	1,557	57.67
South America	372,574	-14.0426	-56.0126	148,886	942	34.89
Northern Africa	193,547	30.4579	14.5658	79,478	419	15.52
South-eastern Asia	556,503	4.5415	108.4212	73,219	1,279	47.37
Western Africa	264,332	10.6444	-4.6733	59,978	785	29.07
Eastern Africa	281,304	-4.1426	40.14015	43,153	869	32.19
Eastern Europe	297,313	48.7197	28.38430	41,299	578	21.41
Western Asia	213,873	34.7790	37.6030	27,085	420	15.56
Central America	147,452	18.9037	-96.64283	26,450	521	19.30
Middle Africa	112,454	2.0183	16.74111	16,766	360	13.33
Melanesia	7,646	-11.4855	158.2433	5,804	122	4.52
Caribbean	38,803	18.3683	-69.21981	5,232	347	12.85
Southern Europe	150,647	40.9604	10.59635	4,157	398	14.74
Polynesia	621	-15.9226	-162.0629	2,942	35	1.30
Southern Africa	53,536	-27.2458	25.93949	2,705	240	8.89
North Europe	95,989	57.0505	9.093828	939	179	6.63
Australia and New Zealand	24,471	-33.9548	154.2838	718	203	7.52
Northern America	328,907	38.8143	-90.71162	462	813	30.11
Western Europe	186,289	49.6240	7.607628	10	352	13.04
Micronesia	449	9.1354	150.0030	0	19	0.70

Given the number of facility combinations that would have been evaluated for optimality, and the computational resources available, it was decided that creating regional chunks of aggregated countries would be appropriate for this study. To indicate the difference, 221 countries required evaluating (2^{221}-1), or 3.3699×10^{66} non-repetitive combinations for each formulation; whereas by adopting the 21 United Nations-defined administrative regions, the number of combinations for each formulation was bound at a little over 2 million, orders of magnitude fewer. As a result, the distance sensitivity measurements required only approximately 8 million evaluations. This was not prohibitively difficult using available computational tools.

That decision does, however, broaden the confidence interval in the model by the same measure. By accepting a lesser 'resolution', model is less adequate as a rendition of reality. Therefore, the conclusions drawn from using the 21 U.N.-defined regions must be tempered appropriately. The model's framework, however, remains intact, and the country-level data can be applied at some later date when the computation time is not a factor.

6 Results

This chapter offers the data gathered regarding geographical distinctions and demand patterns, and submits the results of both the problems framed in the algorithm and the two stand-alone optimizations.

6.1 Direct Data Analysis

This section examines the combined data sets, indicating calculations made without the use of mixed-integer programming.

6.1.1 Geographical Calculations

The 21 regions are listed below in ***Figure 28***, along with the coordinates corresponding to the geographical center of the collective human settlements within that administrative region. Additionally, the name of a large city closest to those coordinates is listed. These cities are presumed to have adequate airport facilities with the capacity to accommodate the large cargo aircraft described earlier.

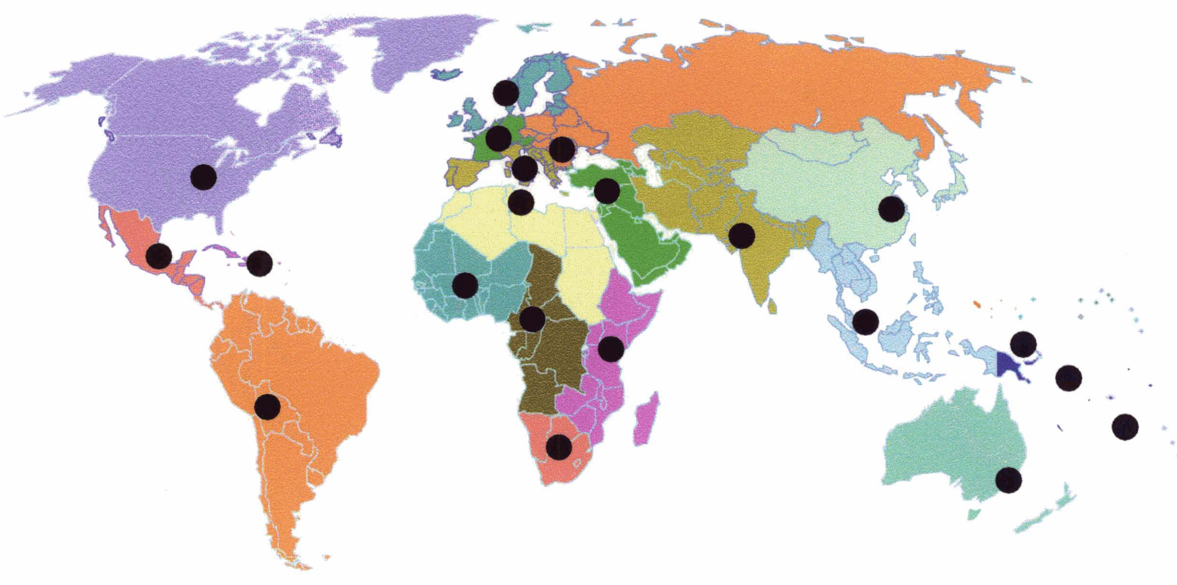
Figure 28: Regional Center Points

Region Name	φ	λ	Approximate Large City
Australia and New Zealand	-33.95486812	154.2838609	Sydney
Caribbean	18.36830096	-69.21983841	Santo Domingo or San Juan
Central America	18.9037079	-96.64289163	Veracruz or Mexico City
Eastern Africa	-4.142674102	40.14015443	Nairobi
Eastern Asia	33.42508605	118.412976	Nanjing or Shanghai
Eastern Europe	48.71979797	28.38430934	Chisinau or Bucharest
Melanesia	-11.48555051	158.2433283	Guadalcanal
Micronesia	9.135485988	150.0030065	Port Moresby
Middle Africa	2.018327487	16.74111019	Bangui
Northern Africa	30.45793557	14.56580775	Tripoli
Northern America	38.81432026	-90.71162736	St. Louis
Northern Europe	57.05053573	9.093828116	Oslo
Polynesia	-15.92260674	-162.0629369	Port Villa
South America	-14.04260802	-56.01260672	La Paz or Brasilia
South-central Asia	23.74578713	77.38529919	Ahmadabad
South-eastern Asia	4.541560897	108.4212566	Singapore or Ho Chi Minh City
Southern Africa	-27.2458155	25.93949135	Gaborone
Southern Europe	40.96047923	10.59635176	Naples
Western Africa	10.64443464	-4.673370225	Ouagadougou
Western Asia	34.7790177	37.6030836	Damascus
Western Europe	49.62406756	7.607628627	Luxembourg or Strasbourg

The total list of nations with regional assignments can be seen in Appendix A. ***Figure 29*** is a political map of the United Nations-defined regions, and ***Figure 30*** shows the regional center points which correlate to the facility candidate locations and demand points which inherit the regional homeless characteristics.

Figure 29: Map of the U.N.-defined Regions

Figure 30: Map of Regional Center Points



6.1.2 Vulnerability

The demand characteristics of each region (listed in ***Figure 27),*** are graphically shown in ***Figures 31-35. Figure 31*** simply lists the mean number of hazards recorded per annum, from left to right, in the order of descending homeless. ***Figure 32-34***, on the other hand, illustrates each region's mean annual number of homeless. These were shown on three bar graphs rather than one because the differences between regions are in the orders of magnitude. South central Asia's and Eastern Asia's homeless are so numerous compared to South America, which has the third most homeless due to hazards.

Figure 31: Mean Annual Hazards per Region Ordered by Descending Homelessness

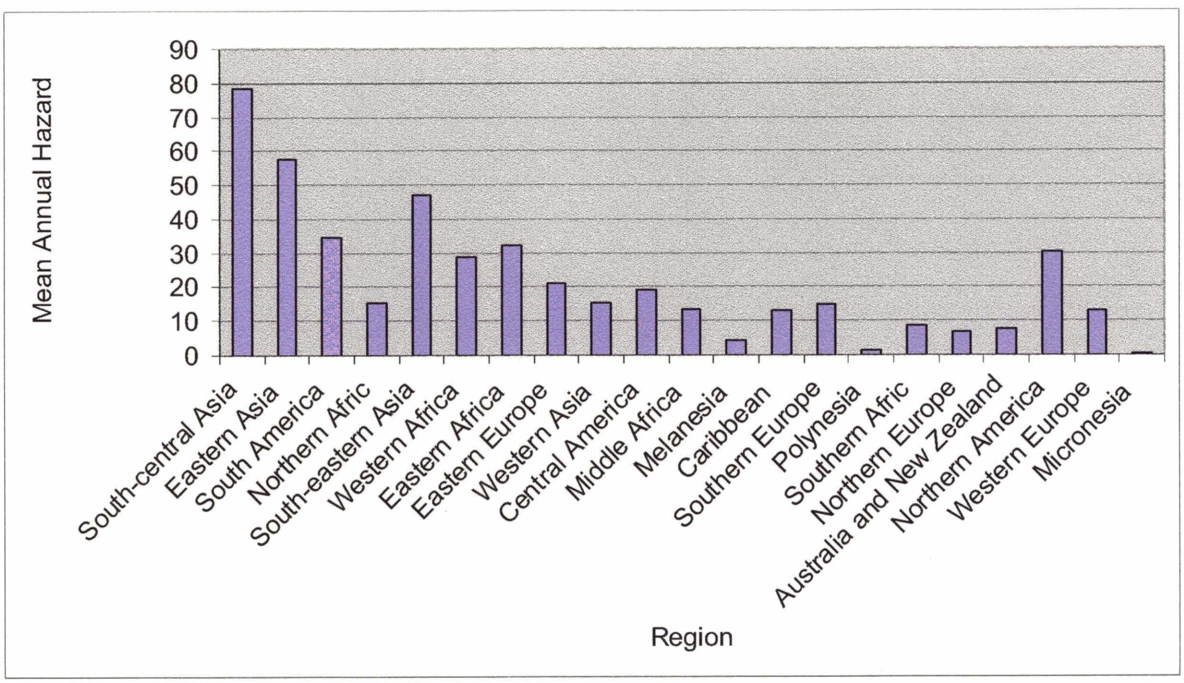


Figure 32: Regions with Heaviest Demand

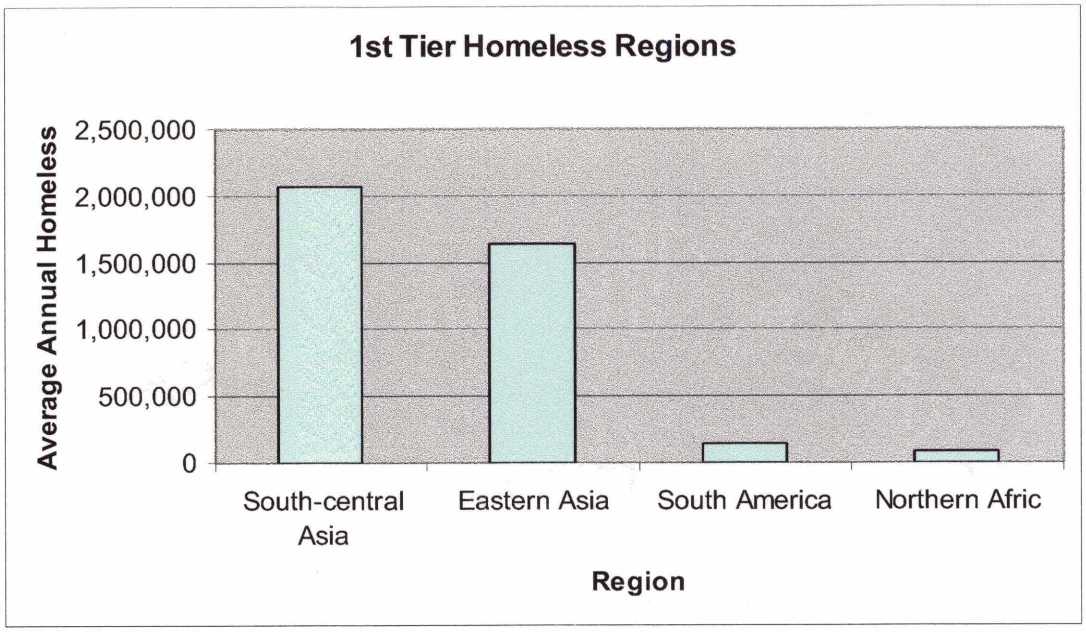


Figure 33: Regions with Demand within the Middle Tier

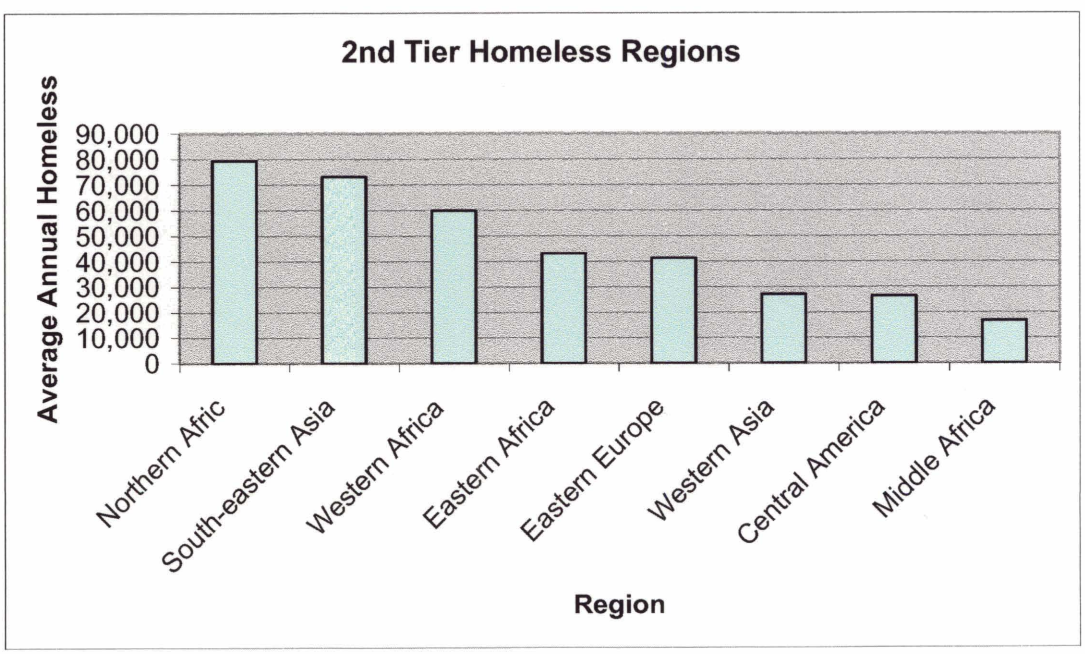
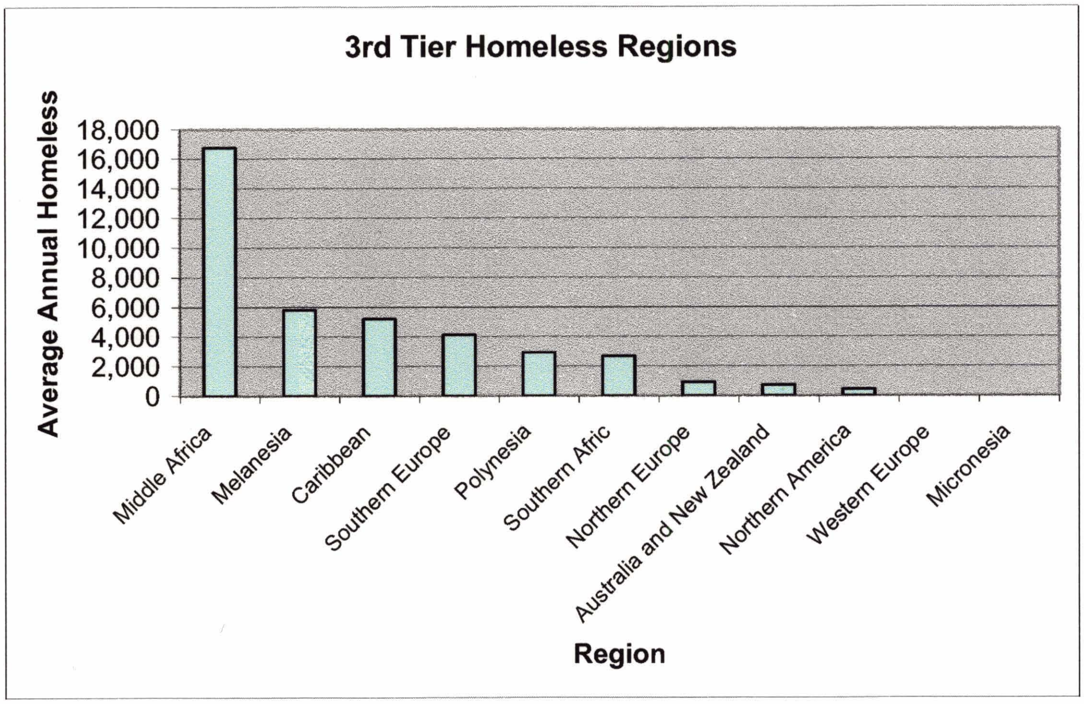
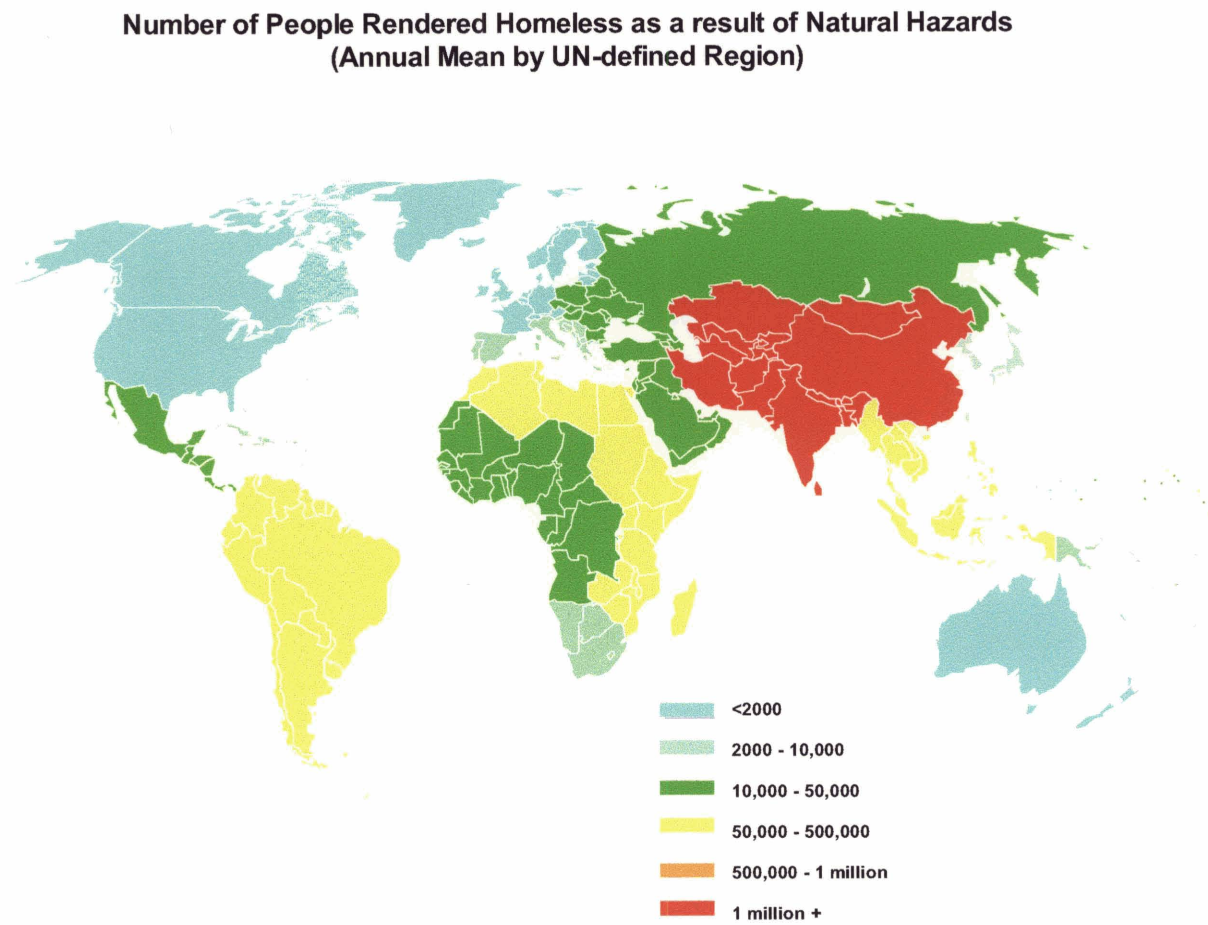


Figure 34: Regions with the Lowest Demand



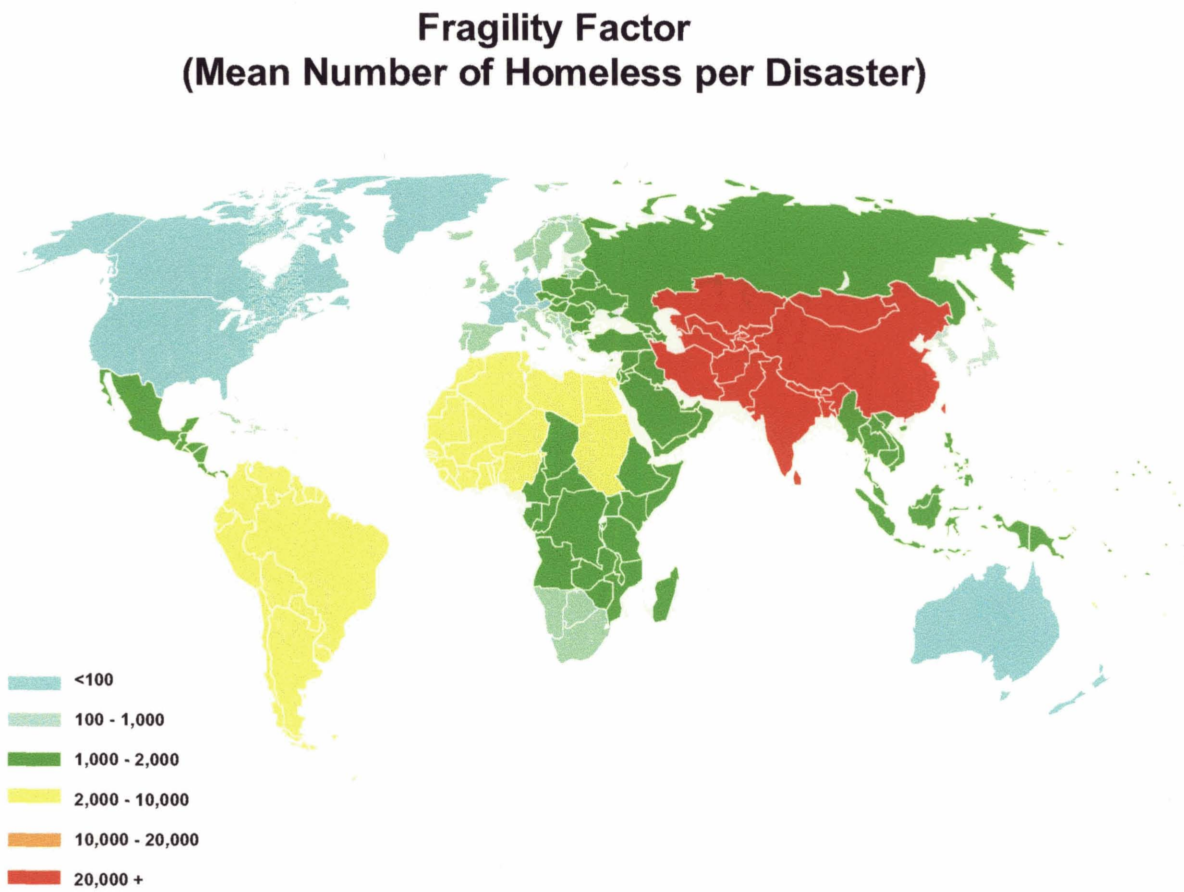
Interestingly, although the number of hazards correspond to the number of homeless (see Figure 43 for correlation) in that there is a regional correlation of 82% between annual number of hazards and annual number of homeless, the differences indicate some regions have a greater capacity to absorb shocks than other regions. The following maps will graphically develop the measurement for infrastructural vulnerability. ***Figure 35*** indicates the mean annual homeless.

Figure 35: Map of Homeless Hotspots



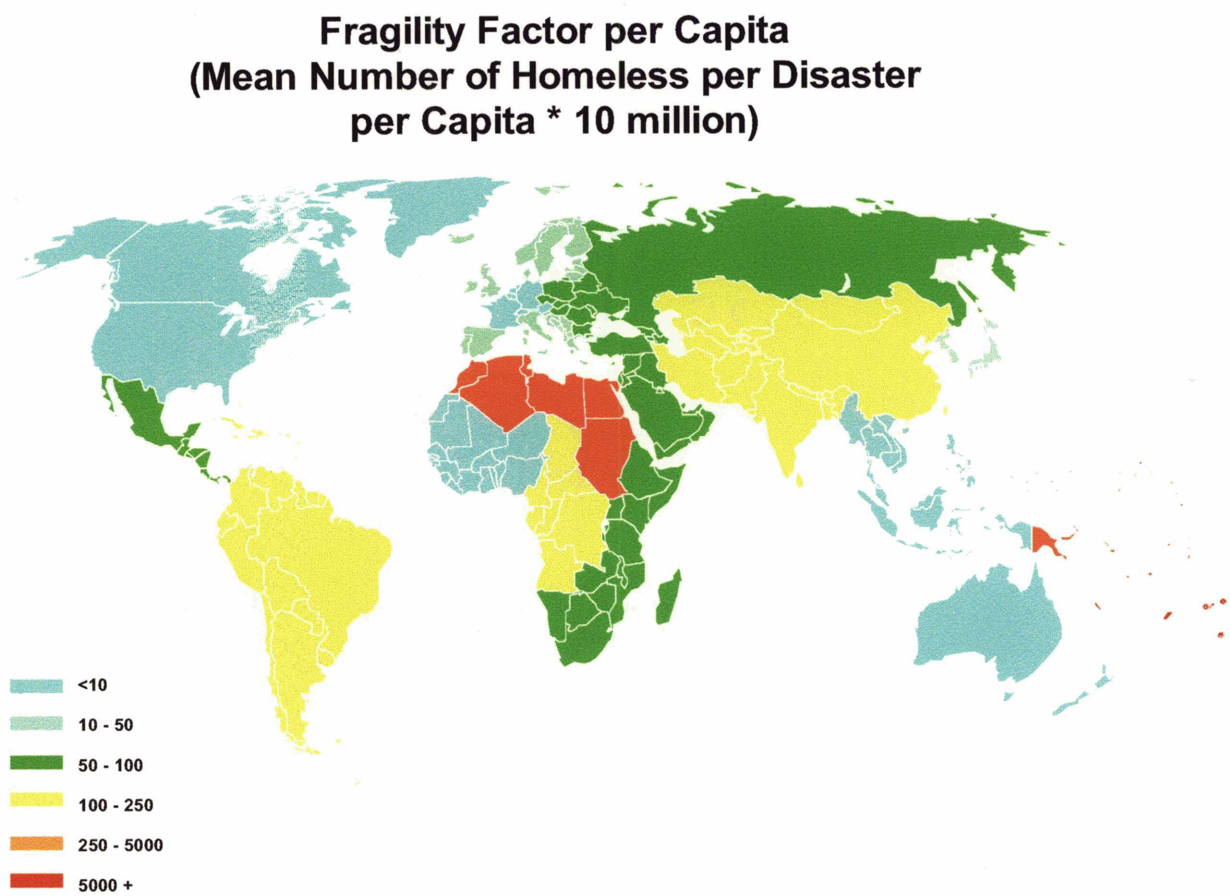
South Central Asia and Eastern Asia are the only regions which have over one million residents rendered homeless each year because of natural disasters. It is not clear that this is due to the higher frequency of disasters in these regions, though it is certainly disproportionate. So the following map was drawn to indicate the mean number of homeless per disaster. Meaning, the number of homeless are divided by the number of hazards. ***Figure 36*** displays those results.

Figure 36: Number of Homeless per Disaster



This indicates that these two regions are highly susceptible to each hazard. This might have something to do with the way EM-DAT records data, as one of the criteria is that at least 10 fatalities are reported. South Central Asia and Eastern Asia are the two most populous regions of the earth. So population was also corrected by dividing by the population of the region. The following figure illustrates the number of homeless per disaster per number of residents. All results were multiplied by 10 million because this yielded numbers greater than 1 for all regions. This is indicative of the fragility of the region, corrected for the hazard frequency and population. One might interpret that Northern Africa, Melanesia and Polynesia have the weakest infrastructure, and are thus the least resilient. These regions have little capacity to absorb shocks from the geological, oceanic and atmospheric phenomena.

Figure 37: Number of Homeless per Disaster per Residents



Graphing the Mean number of homeless per population per disaster indicates that Polynesia is, by an order of magnitude, the most fragile region on Earth.

Figure 38: Most Vulnerable Regions by Homeless per Disaster per Residents

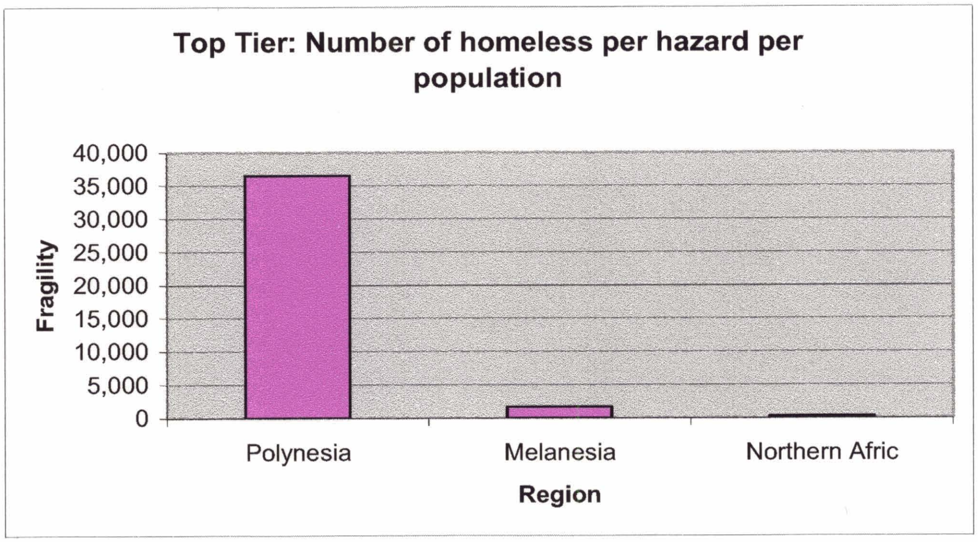


Figure 39: Regions in the Middle Tier of Vulnerability

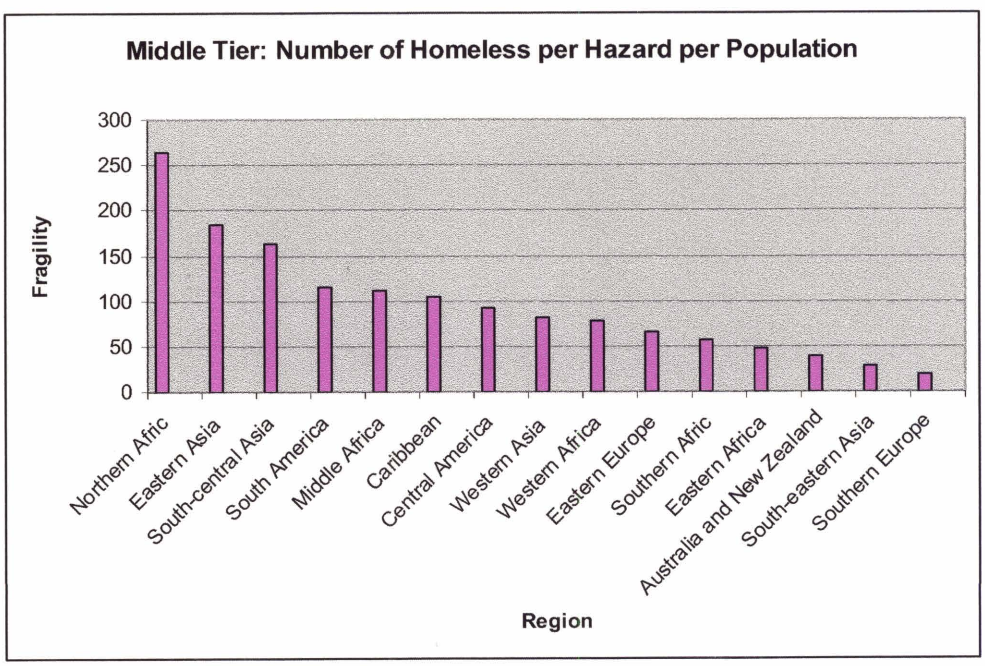
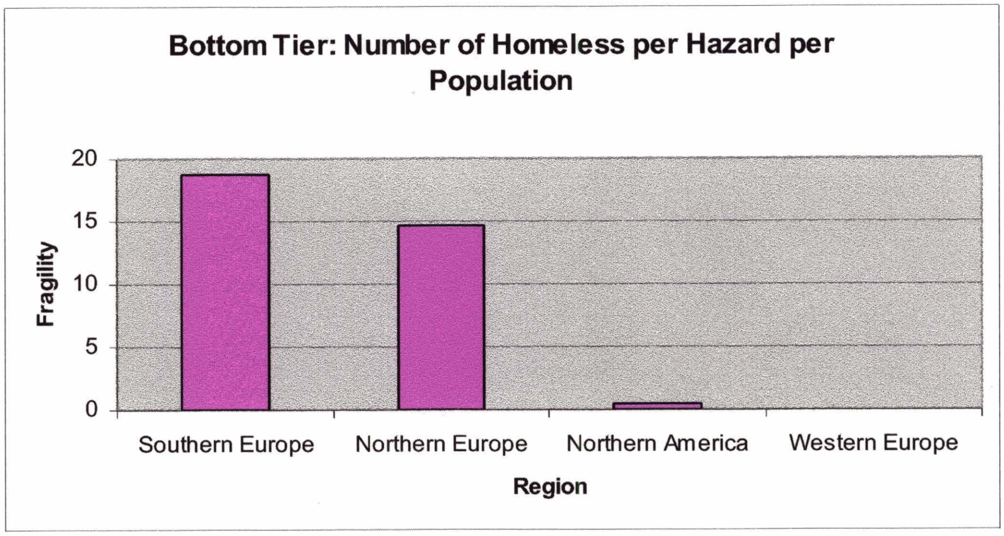


Figure 40: Least Vulnerable Regions



6.1.3 Correlation of Homelessness to Other Variables

How correlated are these variables? Correlation of mean annual homeless ($\mu_{homeless}$) to the following three variables was measured:

1. Population of region
2. Mean annual hazards ($\mu_{hazards}$) for a region
3. (Population of region) x (annual $\mu_{hazards}$) for a region

Figure 41: Regional Statistics: Population, Hazard Frequency & Homeless

zone(k)	Population in thousands	annual mean hazards	Pop*hazard (in millions)	**μ homeless**
South-central Asia	1,614,798	78.29	126,433	2,074,333
Eastern Asia	1,535,407	57.67	88,542	1,641,489
South America	372,574	34.89	12,999	148,886
Northern Africa	193,547	15.52	3,004	79,478
South-eastern Asia	556,503	47.37	26,362	73,219
Western Africa	264,332	29.07	7,685	59,978
Eastern Africa	281,304	32.19	9,054	43,153
Eastern Europe	297,313	21.41	6,365	41,299
Western Asia	213,873	15.56	3,327	27,085
Central America	147,452	19.30	2,845	26,450
Middle Africa	112,454	13.33	1,499	16,766
Melanesia	7,646	4.52	35	5,804
Caribbean	38,803	12.85	498	5,232
Southern Europe	150,647	14.74	2,221	4,157
Polynesia	621	1.30	.81	2,942
Southern Africa	53,536	8.89	475	2,705
Northern Europe	95,989	6.63	636	939
Australia and New Zealand	24,471	7.52	184	718
Northern America	328,907	30.11	9,904	462
Western Europe	186,289	13.04	2,429	10
Micronesia	449	1	.45	1

Figure 42: Correlation of Homeless to Other Regional Variables

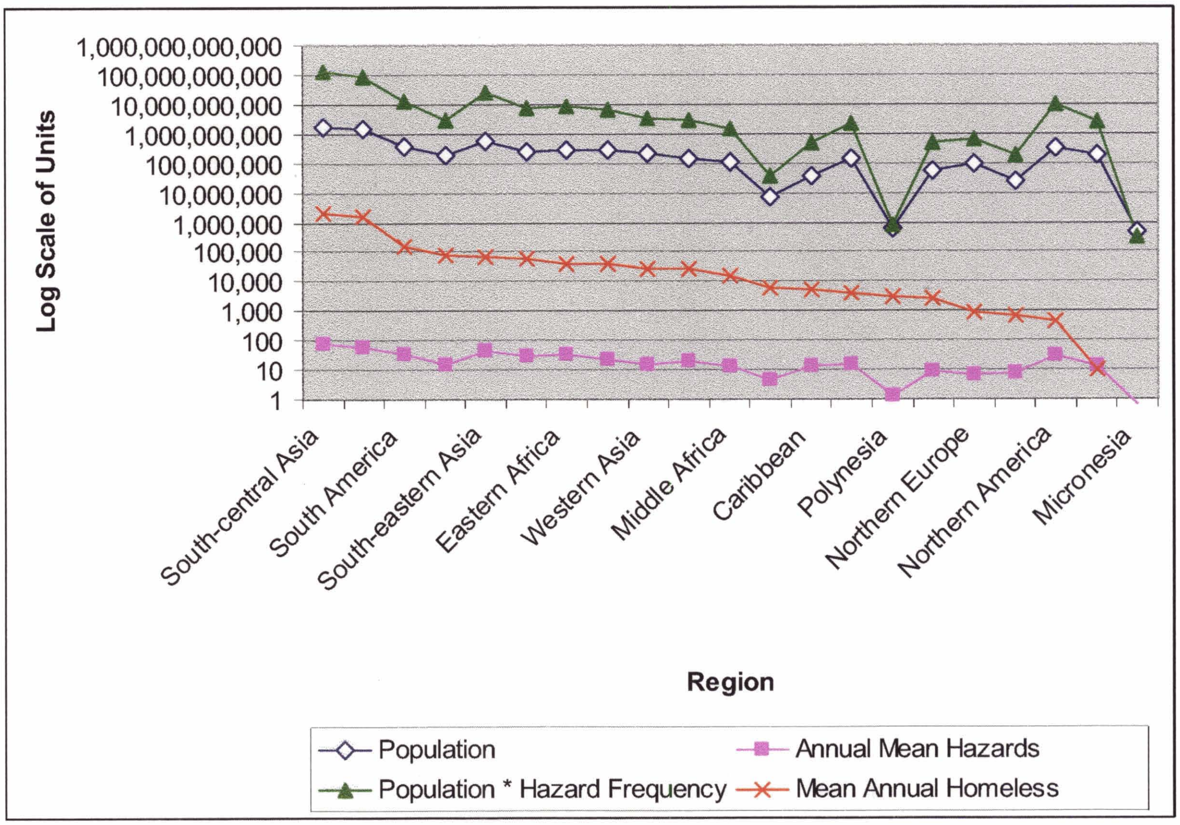


Figure 43: Correlation Percentages

Correlation of Mean Homeless to Other Regional Variables	
	annual mean homeless
annual mean hazards	81.9%
population	95.6%
(population) x (annual mean hazards)	98.5%

Figure 43 indicates that the mean number of homeless for all regions is highly correlated to the population of that region (96%). But the product of population and the mean number of hazards is even more highly correlated (99%). This means that, in the absence of homeless data, population figures and hazard frequency can also serve as the indirect estimator for demand.

6.2 Optimization Solutions

This section offers the results of the maximal covering problems, the optimal location configurations, and sensitivity analyses.

6.2.1 Sensible Limits to Proliferation

The results of the maximal covering problems are listed below. The first problem asks, "What are the fewest facilities required in order to ensure the maximum distance to any person at risk globally is less than 5000 km (approximately 10 hours transportation time)?"

For this problem, the solution was

$$\sum_i Y_i = \mathbf{5} \qquad \textbf{\textit{Equation 11}}$$

Five facilities can ensure no person is farther than 5000 km from the first wave of humanitarian relief. There were four variants of this solution, shown in ***Figure 44*** below:

Figure 44: Four configurations ensure nobody is farther than 5000km

Regions for which Y = 1	max distance = 4795 km
Caribbean	(Polynesia to Australia & New Zealand)
Eastern Asia	solution variant #1
Middle Africa	
Northern Africa	
Polynesia	

Regions for which Y = 1	max distance = 4314 km
Caribbean	(Melanesia to Polynesia)
Eastern Africa	solution variant #2
Eastern Asia	
Melanesia	
Southern Europe	

Regions for which Y = 1	max distance = 4314 km
Caribbean	(Melanesia to Polynesia)
Middle Africa	solution variant #3
Southern Europe	
Melanesia	
Southeastern Asia	

Regions for which Y = 1	max distance = 4314 km
Caribbean	(Melanesia to Polynesia)
Eastern Asia	solution variant #4
Middle Africa	
Melanesia	
Western Asia	

In other words, there are four different configurations for five facilities that ensure nobody is farther than 5000 km from a pre-positioned facility.

The second problem added a constraint with respect to the global average distance per capita. That problem asked "What are the fewest facilities required to ensure the maximum distance to any person at risk is less than 5000 km *and* that the global mean per capita distance is less than 500 km (or approximately 1 hour transportation time)?"

For this problem, the solution was:

$$\sum_i Y_i = 6$$ ***Equation 12***

Six optimally located facilities ensure no person is farther than 5000 km from the first wave of humanitarian relief, *and* that the global distance per capita is less than 500 km per person. There were three variants of this solution, shown below:

Figure 45: Three Configurations for Reasonable Service

Regions for which Y = 1	max distance = 4134 km
	(Melanesia to Polynesia)
Caribbean	mean global distance per person = 366 km
Eastern Asia	solution variant #1
Melanesia	
South Central Asia	
Southern Africa	
Southern Europe	

Regions for which Y = 1	max distance = 4134 km
	(Melanesia to Polynesia)
Caribbean	mean global distance per person = 319 km
Eastern Asia	solution variant #2
Melanesia	
South Central Asia	
Middle Africa	
Northern Africa	

Regions for which Y = 1	max distance = 4134 km
	(Melanesia to Polynesia)
Caribbean	mean global distance per person = 308 km
Eastern Asia	solution variant #3
Eastern Africa	
Melanesia	
Northern Africa	
South Central Asia	

Although these criteria are not documented to be mandated by an international authority, it is useful to understand that only 6 positions would ensure a reasonable service level. Facility proliferation, without regard to border-related delays, need not exceed the number of U.N.-defined regions. Interestingly, Southern Europe is within the set of locations chosen in solution variant #1. Of course, this calculation is within the 21-region structure used in this study.

Conclusions like this are highly dependent on this structure and may change when more granular data is used.

6.2.2 Optimal Facility Locations

The solutions of the algorithm-framed problems are interesting because the facility location solutions for freeform and incremental adding types did not differ from one another. The optimal positions were identical for each type in every iteration. A discussion of this can be seen in Section 7.2. Therefore, ***Figures 47-66*** simply display the results listed by Case (Blank Page or Status Quo) and iteration (number of facilities). ***Figure 46*** in Appendix B is a list of figures (maps) with corresponding iterations of the algorithm. Only three maps for each case are shown in this chapter, while the remaining maps are available in Appendix B. Even in the Appendix, maps for only the first ten iterations are shown because, as the maximal covering solutions demonstrate, the benefit (change in distance per capita) is nominal after this point.

Figure 47: Map of a Single Optimally-located Position on the Blank Page

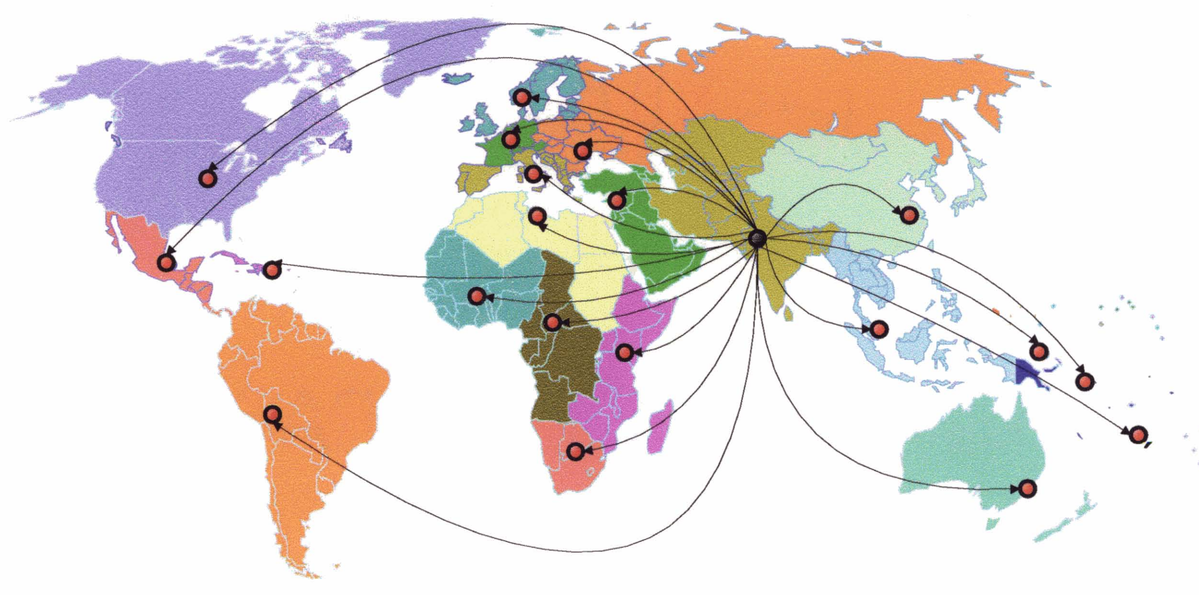


Figure 48: Map of Two Optimally-located Positions on the Blank Page

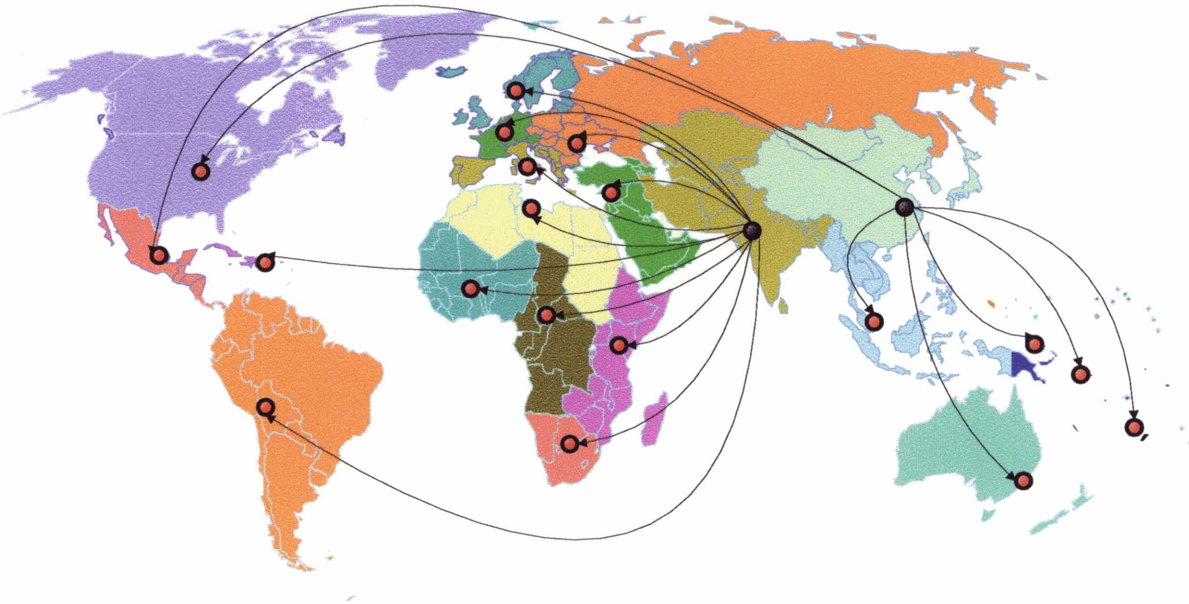


Figure 49: Map of Three Optimally-located Positions on the Blank Page

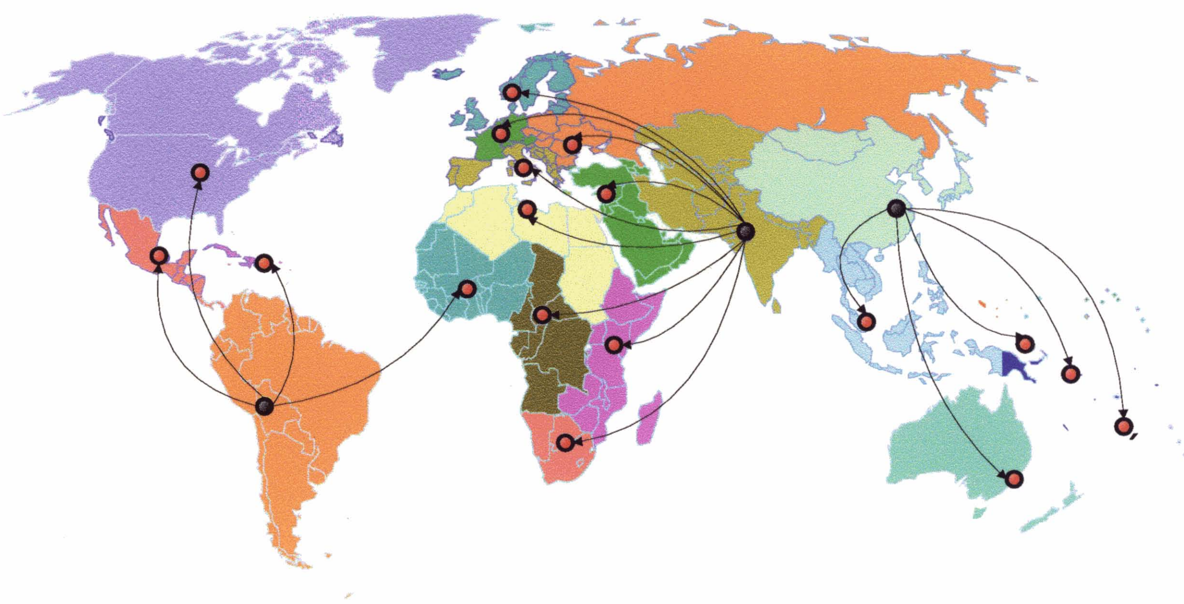


Figure 57: Map of the Status Quo (One Facility is the UNHRD)

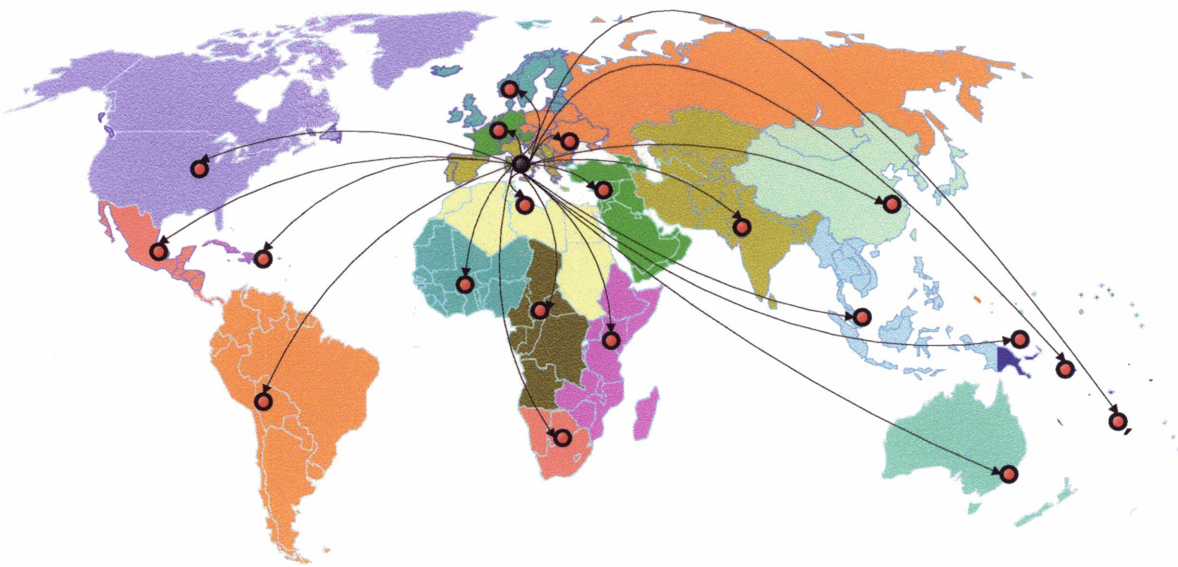


Figure 58: Map of Two Optimally-located Positions on the Status Quo

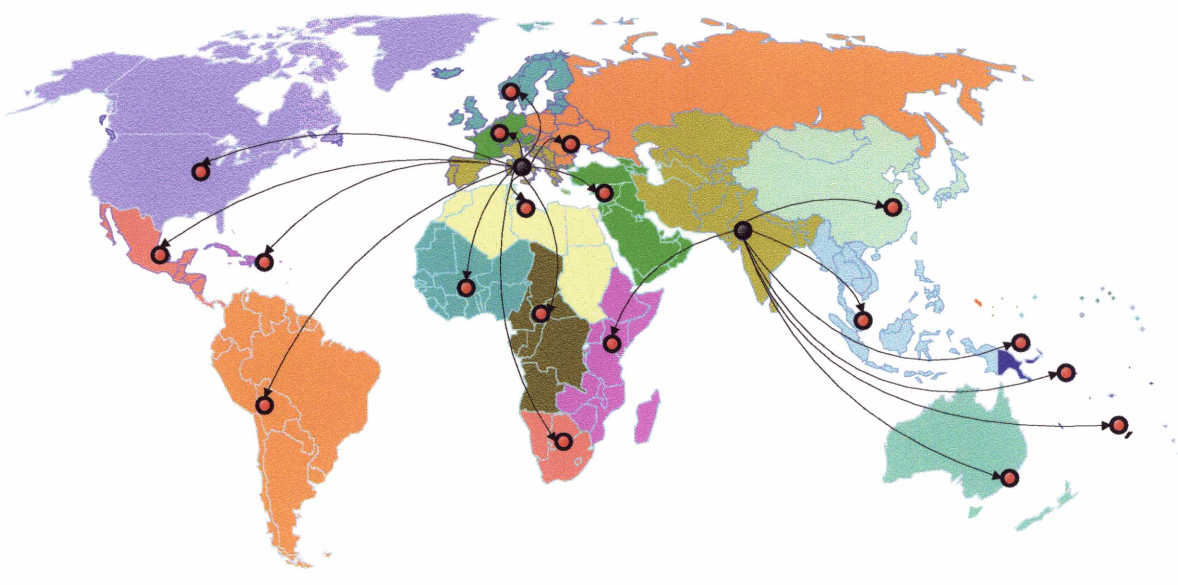
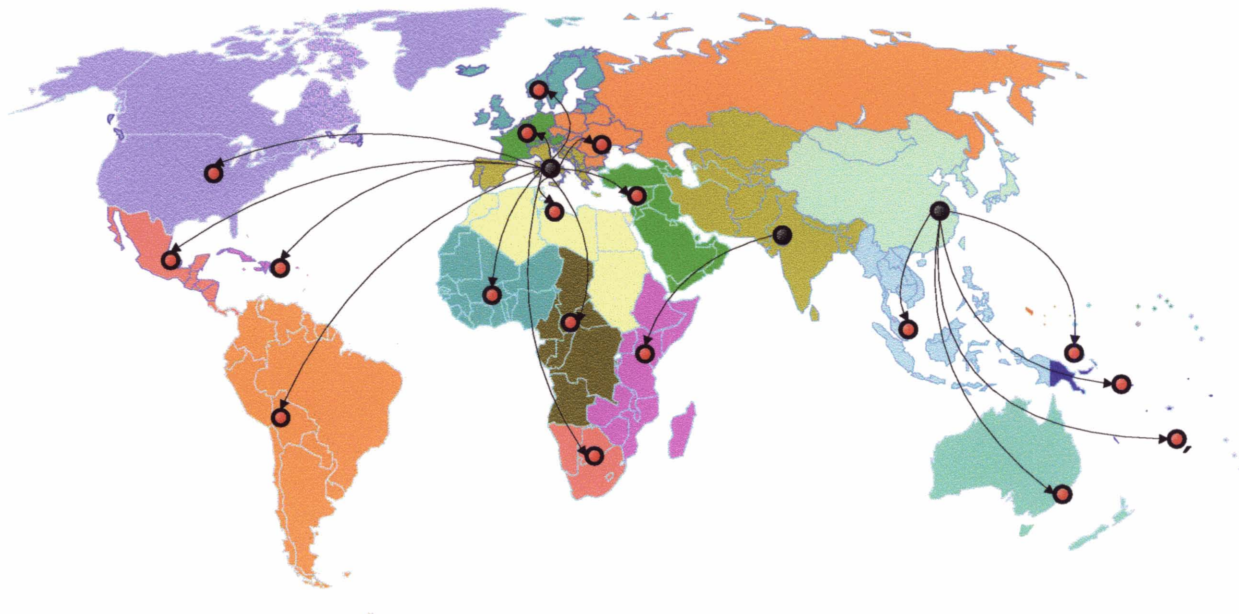


Figure 59: Map of Three Optimally-located Positions on the Status Quo



6.2.3 Distance Sensitivity

The plotted distance per capita for each case is illustrated in the following figures. The data are plotted such that Status Quo and Blank Page cases can be compared. Because the Blank Page solutions are optimized without constraints on the initial position of the UNHRD, these distance per capita values are lower than the corresponding Status Quo values.

The distance per capita, which means the average global distance per likely homeless person to the nearest inventory depot, is calculated using a simple routine. First, the objective value $\left(\sum_{ij} d_{ij} H_j W_{ij}\right)$ is calculated by the program. This value represents the sum of all arcs (distance from facility to forecasted homeless person) globally where the facility i is the nearest to the demand point j; meaning, the total distance to every forecasted homeless person. The distance per capita then, is simply that value divided by the total number of forecasted homeless globally, or:

$$\frac{\sum_{ij} d_{ij} H_j W_{ij}}{\sum_j H_j} \quad \forall\, i, j \qquad \textbf{\textit{Equation 13}}$$

Figure 67 (on page 83) lists the per capita distance all iterations, and for both cases. This table does not indicate if the type is freeform or optimal adding, because, as will be discussed in Chapter 7, the system exhibits no reconfiguration, so these configurations are identical. The maximum distance is also captured. ***Figure 68*** plots these data.

Figure 68: Distance per Capita Sensitivity to Facility Proliferation

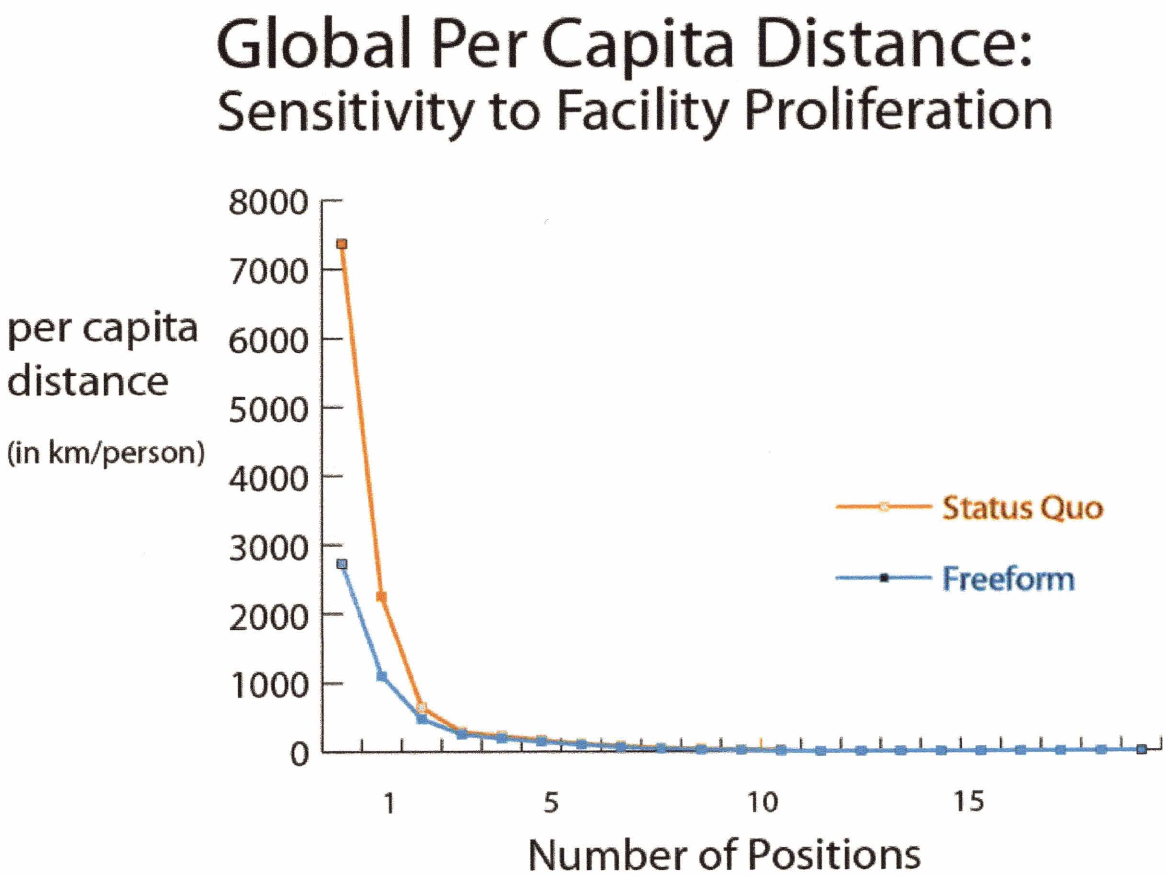
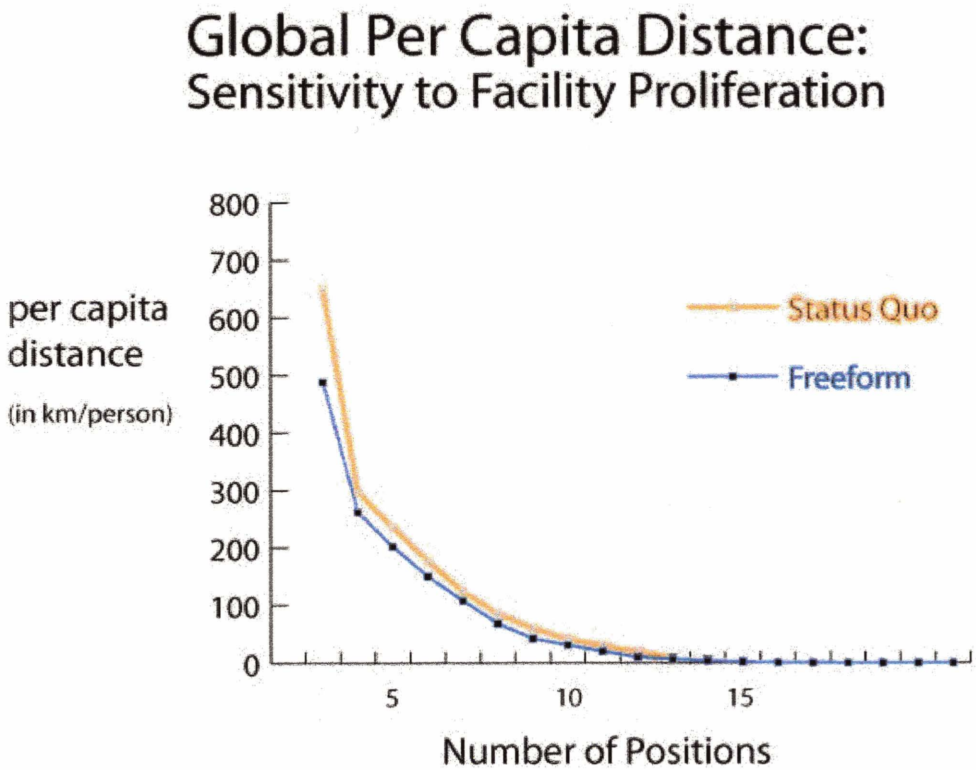


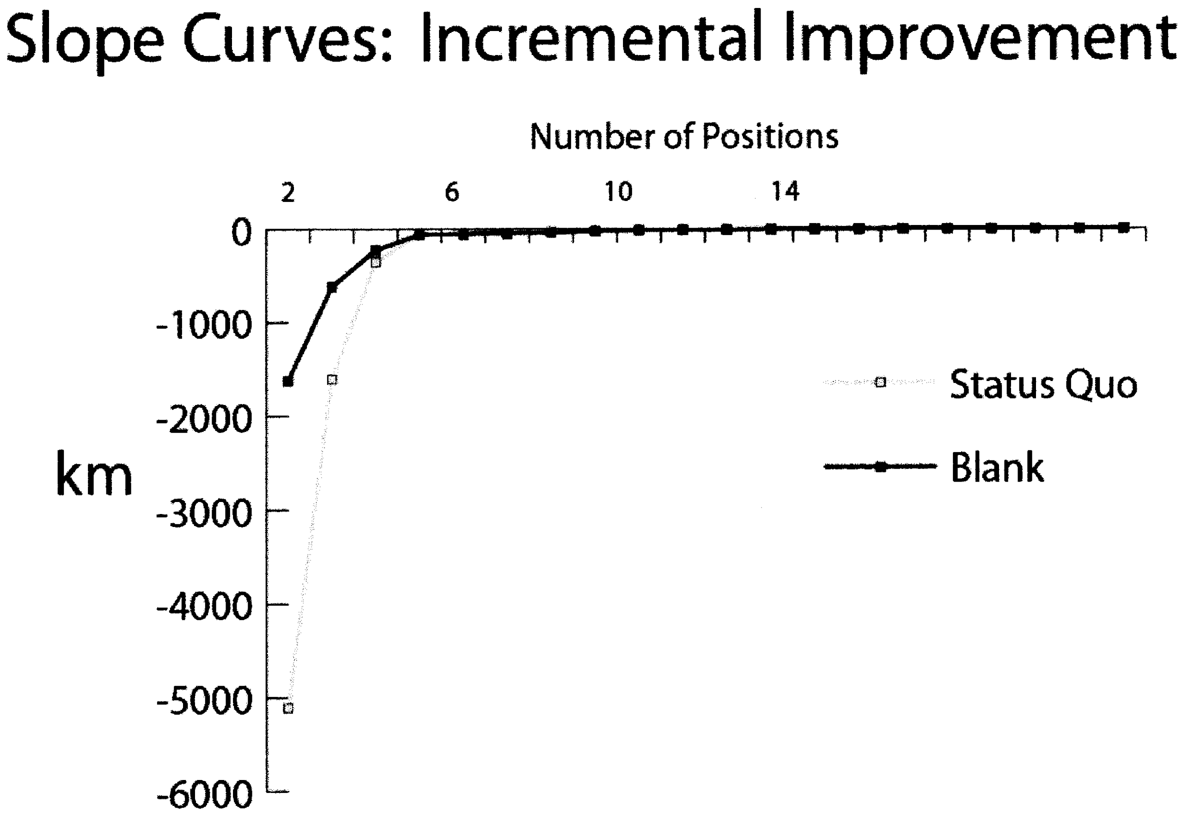
Figure 69 shows the same data, but does not draw the first two iterations because it helps to visualize the gap between the two cases.

***Figure 69**: Distance per Capita Sensitivity to Facility Proliferation; from Iteration 3*



The improvement (reduction) in distance gained by a adding single facility to the system is calculated as the distance per capita (of the iteration which adds the facility whose impact is being measured) minus the distance per capita from the previous iteration. This is essentially the slope of the sensitivity curve drawn in ***Figure 68***, and is plotted in ***Figure 70***. A steeper slope indicates a more significant impact in the reduction of global per capita distance. The graph suggests that each additional facility makes a lesser impact on the distance. This can be thought of as diminishing returns on positions. Therefore slope indicates the marginal impact of each additional position to the system.

Figure 70: Incremental Benefit of Additional Facilities Diminished with Proliferation



The incremental improvement purported by the title of ***Figure 70*** should be understood as incremental improvement at a diminishing rate. When facility proliferation is pursued, each position reduced the per capita distance, but by less than the previous facility. ***Figure 71*** is a 'close-up' of the same graph as it plots only those points from iteration six onwards.

Figure 71: Incremental Benefit of Additional Facilities from Iteration 6

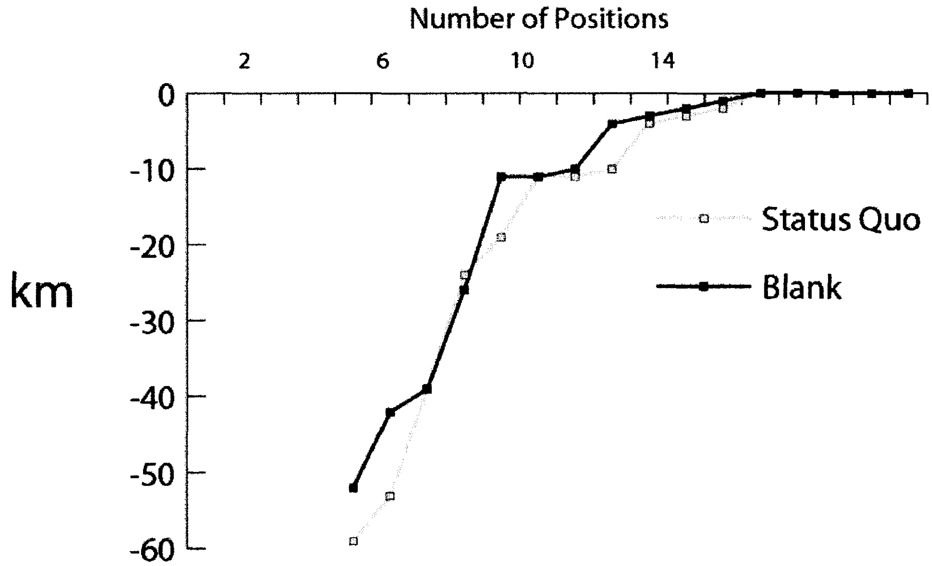


Figure 67: Distance per Capita, Maximum Distance and Slope for all Iterations

	Blank Page (km)			Status Quo (km)		
facilities	per capita distance	Max distance	slope	per capita distance	max distance	slope
1	2,728.21	15,243		7,367.35	17,159	
2	1,107.11	15,032	-1,621.10	2,257.62	13,791	-5,109.73
3	487.93	10,050	-619.18	649.87	10,050	-1,607.75
4	261.79	10,050	-226.13	297.48	10,050	-352.38
5	202.33	10,050	-59.46	236.15	10,050	-61.33
6	150.36	10,050	-51.97	176.69	10,050	-59.46
7	107.95	10,050	-42.40	124.11	10,050	-52.58
8	69.04	8,144	-38.90	85.20	8,144	-38.90
9	42.92	8,144	-26.12	60.77	8,144	-24.43
10	31.71	4,314	-11.21	41.72	8,144	-19.04
11	20.71	4,314	-10.99	30.51	4,314	-11.21
12	10.65	4,314	-10.06	19.52	4,314	-10.99
13	7.10	4,314	-3.55	9.45	4,314	-10.06
14	4.11	2,981	-2.98	5.90	4,314	-3.55
15	2.22	2,533	-1.89	2.92	2,981	-2.98
16	1.02	2,533	-1.19	1.02	2,533	-1.89
17	0.600	2,470	-0.42	0.60	2,470	-0.427
18	0.250	2,470	-0.34	0.25	2,470	-0.349
19	0.002	2,470	-0.24	0.002	2,470	-0.248
20	0.000000001	2,470	-0.002	0.000000001	2,470	-0.0020
21	0	0	-0.000000001	0	0	-0.000000001

6.2.4 Impact of the Initial Position

The study set out to also understand the impact of initial conditions of optimal facility location. This is done by comparing the difference between the Status Quo and Blank results. ***Figure** 72* illustrates that this is done by calculating the difference between distance per capita for each case and corresponding iteration.

Figure 72: Illustration of How the Differential is Calculated

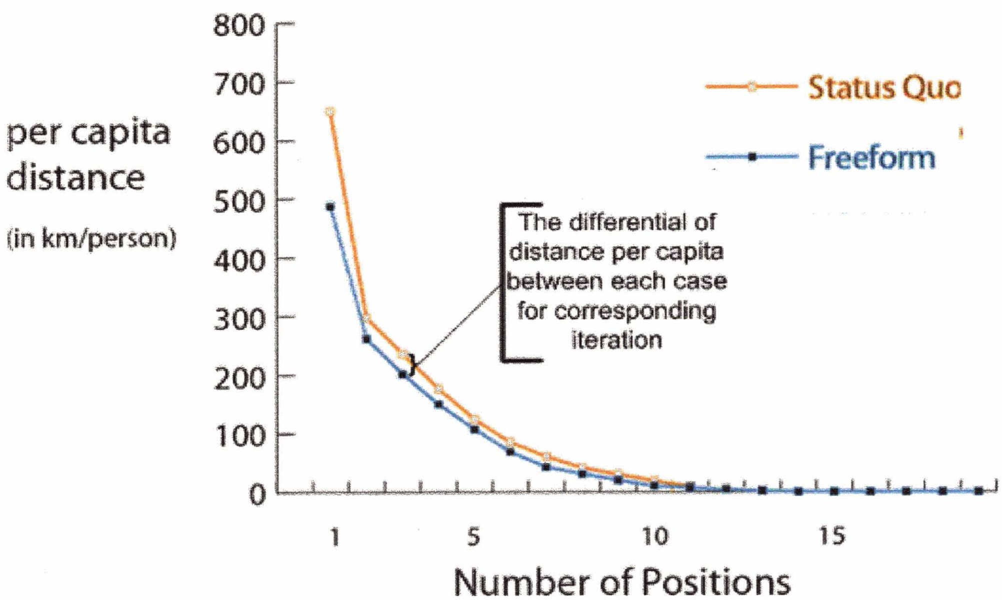


Figure 73: Values of the Differential by Iteration

	Blank Page (km)	Status Quo (km)	
facilities	per capita distance	per capita distance	difference in distance
1	2,728	7,367	4,639
2	1,107	2,258	1,151
3	488	650	162
4	262	297	36
5	202	236	34
6	150	177	26
7	108	124	16
8	69	85	16
9	43	61	18
10	32	42	10
11	21	31	10
12	11	20	9
13	7	9	2
14	4	6	2
15	2	3	0.7
16	1	1	0
17	0.60	0.60	0
18	0.25	0.25	0
19	0.002	0.002	0
20	0.000000001	0.000000001	0
21	0	0	0

Figure 73 is a tabulation of the difference between the Status Quo and Blank Page distance per capita for all iterations. Although the difference between the status quo condition and bank ideal is vast for the first two iterations, by the third iteration, global distance per capita is only different by 161 km, which is less than half an hour flight time. So it can be argued that the initial position in Southern Europe does not diminish the responsiveness of operations when two other facilities are added in Eastern Asia and South Central Asia. ***Figure 74*** is the plotted difference, and ***Figure 75*** is a close-up of the same graph, beginning at iteration 3. It is clear that by the fourth iteration the difference is less than 50 km which is nominal.

Figure 74: Impact of the Initial Position on Minimizing Distance Per Capita

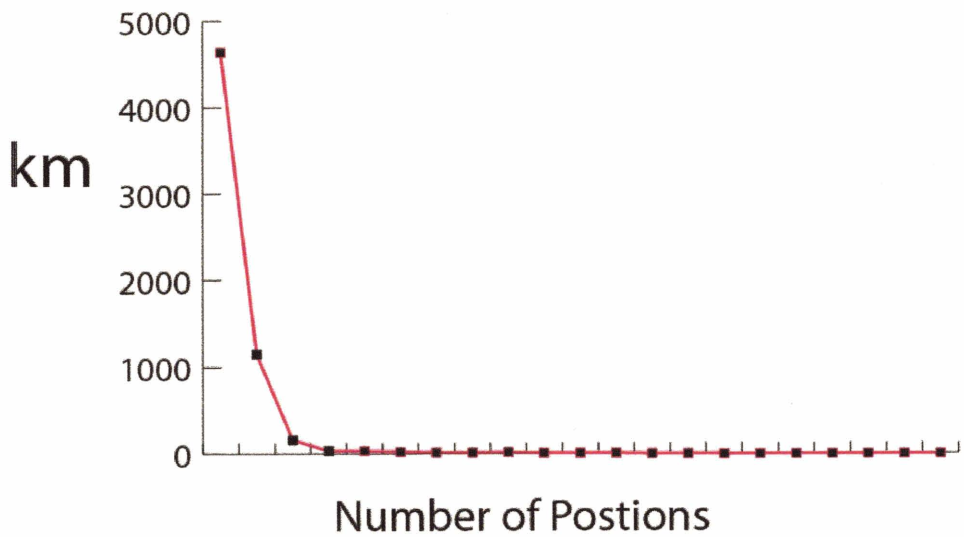


Figure 75: Impact of the Initial Position from Iteration 3

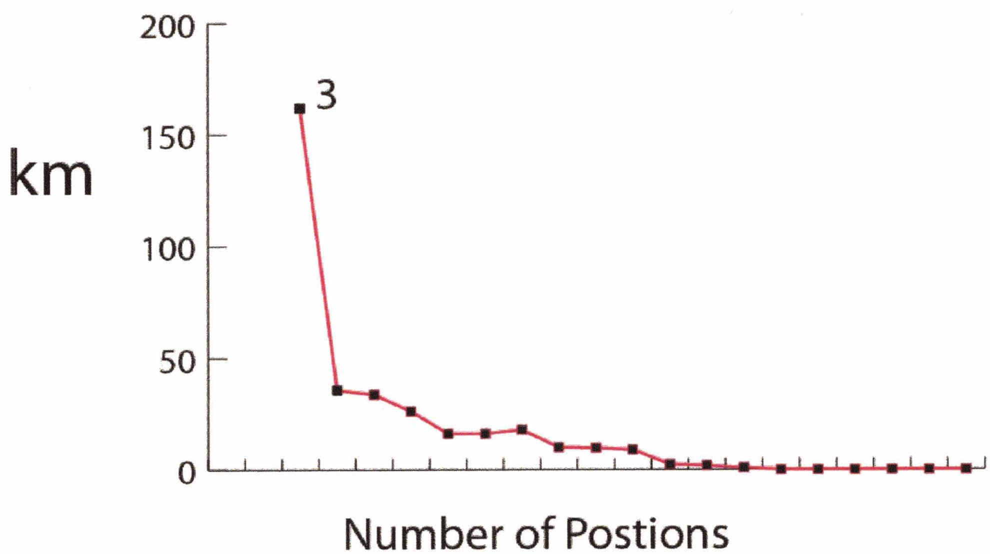


Figure 76: Impact of the Initial Position from Iteration 5

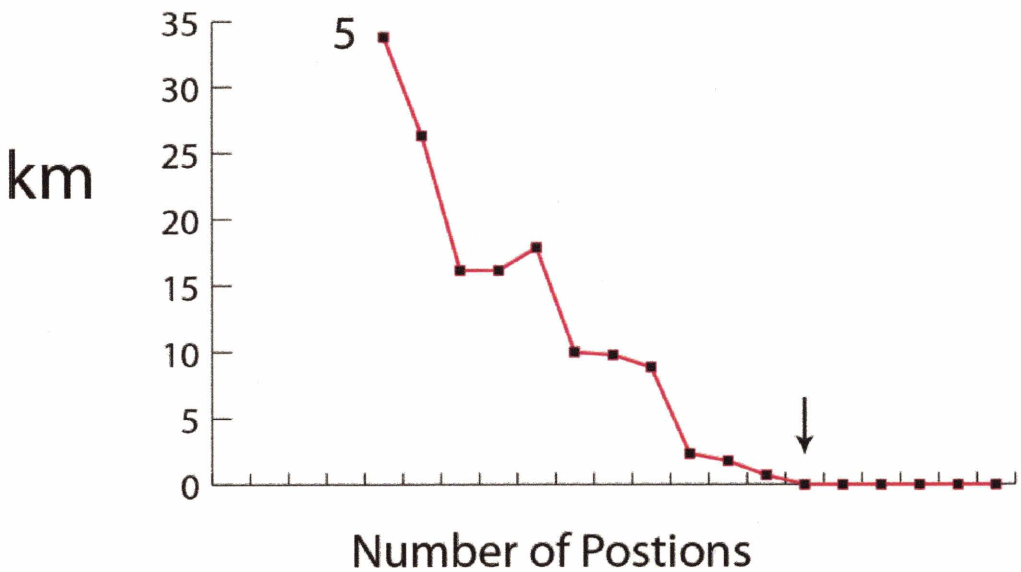


Figure 76 is yet another close-up, starting with iteration 5. The arrow in this figure (at iteration 16) shows where the difference becomes zero. This is because in iteration 16, Southern Italy joins the set of optimal positions. The values beyond iteration 15 are all zero because the configurations of facilities from this iteration forward are identical.

7 Analysis and Conclusions

This chapter offers analysis of the results and commentary. Section 1 draws insights from the data regarding vulnerability. Section 2 analyzes the optimal configurations shown on the maps, and reasons the absence of reconfiguration in the freeform type. Section 3 discusses the impacts of pre-positioning on distance and practical upper-bounds of proliferation. This section also addresses the impact of the initial position on subsequent iterations. Section 4 indicates the areas in which this research can be further improved, while Section 5 places this research within the context of other implementation considerations. Finally, Section 6 discusses potential externalities of a pre-positioning strategy in humanitarian logistics, and forecasts the future of implementation, preparedness and prevention.

7.1 Demand and Vulnerability

The data suggest that the overwhelming majority, approximately 90% of homelessness due to natural hazards occurs in Asia, most of which can be considered the developing world (though Asia only accounts for 44% of hazards). On the other end of the spectrum, the rich countries of Northern America, Australia and New Zealand, Northern, Western and Southern Europe, together account for less than 2% of homelessness worldwide. This underscores the correlation between homelessness and infrastructure. It is also important to note that transportation networks in the developing world are changing so rapidly that it encourages the aerial distance approach taken in the simplified delivery chain.

The definition of hazards as the relationship between geological, hydrological and atmospheric phenomena and civilization's capacity to absorb shocks is supported by the demonstrated correlation of population and hazard frequency to homelessness. Upon correction for the correlated variables (population and hazard frequency), the *number of homeless per disaster per residents* expose those regions most vulnerable to hazards, perhaps indicating weakness of infrastructure. Polynesia is, by orders of magnitude, the most fragile of all regions with respect to hazard vulnerability. Interestingly, Polynesia is also the most remote region of the Earth. Melanesia and Northern Africa are the second and third most fragile respectively.

7.2 Optimal Positions and Reconfiguration

The optimization that regards the mean global distance from facility to forecasted homeless person, or distance per capita, clearly demands facilities in Asia. In the Status Quo case, the solutions for first two positions in addition to Southern Europe are South Central Asia and East Asia respectively, followed by South America, Eastern Africa, and Southeastern Asia. Half, of the first six positions are in Asia. Beyond these six facilities, the marginal benefit seen from added positions is small, an improvement of less than 50 km per capita distance. Six facilities are, perhaps, an appropriate upper-bound for facility proliferation.

The difference between per capita distance in the Status Quo and Blank Page cases indicate that, although there is a significant disparity when the number of facilities are low, by the time the fourth facility is placed in the Status Quo case, the difference in service level is less than 50 km. So it can be said that the impact of the initial position is low when at least 4 facilities are introduced to the system.

The research indicated that there is no difference between the solutions of freeform and optimal adding formulations. That the system exhibits the absence of re-configuration has practical implications for decision-makers in that by placing a single facility optimally, in lieu of placing many facilities optimally, the service level of the system will not be less than it otherwise would have been if all facilities were placed together. There is, practically, no reservation cost. Under severe resource constraints, the humanitarian response system may not easily afford to build several facilities at once. This study indicates that optimal incremental addition will not alter the configuration of subsequent iterations.

However, the conclusion regarding reservation costs must be tempered in light of the feasible reasons for this behavior. The absence of reconfiguration is attributable to two sources. A system with the combination of few regional points (meaning large, "chunky" regions) and a steep homelessness curve (meaning the plot of mean annual number of regional homeless in descending order), is unlikely to reconfigure. Given the discrete point-characteristic of the demand entities, when a facility is located at a point, the product of $d_{ij}H_j$ is zero. The optimization is seeking a minimum value, thus encouraging facility location at the very largest demand sources in order to reduce the objective value to zero, and so the regions with the most significant homelessness will attract a facility when the homelessness curve is sufficiently steep. Moreover, the geometric disparities do not overcome the importance of homelessness in the objective function when the differences are in orders of magnitude.

Re-configuration may have been exhibited had the regional distinctions been finer (greater resolution). For example, if South Central Asia were split into Bangladesh, Nepal, South India, North India, Sri Lanka, and so on, there may have been shifting of optimal positions within the subcontinent as the algorithm ran through the iterations of the freeform type. Because this particular study used large "chunks" (South Central Asia, Eastern Asia, etc.) this may have yielded the results seen. The framework of the model, however, is capable of accepting finer data.

7.3 Research Improvement

The research can be improved in many ways. Foremost is with access to supply chain transactional data, especially point-of-use informations, because a direct demand signal is better than an indirect one. Homelessness is an indirect estimation for demand because it is assumed to be proportional to the demand for non-consumable unit sets. However, the research would be improved were the correlation established beyond syllogism. If this relationship is properly substantiated, the implications to demand forecasting and humanitarian planning would be more significant. A unique combination of hazard type, magnitude, and regional characteristics such as population and infrastructure, could yield a disaster "footprint" with specific material and process requirements. This type of benchmarking can help to predict inventory requirements at the disaster theater, thereby improving operational efficiencies within the relief system.

As discussed in section 2, using data with greater spatial resolution would improve the output results, therefore improving the analysis. Regional groupings could be disaggregated to country-level, and again to a level that ignores administrative boundaries, using geometrically equivalent units. This would deemphasize the inequities of political boundaries; instead equating demand points by either population or surface area. Moreover, using data gathered over longer periods of time would improve the understanding of the patterns of natural hazards.

7.4 Model Expansion

There are several ways this study could be expanded to improve the appropriateness of the model for real-world decisions. First, minimizing the distance not only from the closest facility, but also from the second-closest, would provision service when the closest facility is eliminated by the hazard itself. Secondary, even tertiary, arcs can be optimized for such situations. Additionally, consideration of realistic aircraft range, requiring the inclusion of re-fueling stops along the network, would make the model more realistic, but also add significant complexity. Yet another realistic inclusion would be that of models of the last-mile transit. Variables such as road density, road quality and terrain type in various regions would help to estimate the delays on this last leg of the delivery chain. Other components of the delivery chain (border delays, appeal approval, picking, etc) may also be modeled with the inclusion of transactional data.

7.5 Pre-positioning Implementation Decisions

The argument for pre-positioning is a compelling one when evaluated on performance alone. There are, however, several other factors which would also be given consideration. Adding facilities of this kind to the system would increase operating costs. Facility construction, or rental, is one type of cost; and if these are located at airports then tariffs are another source. Fixed overhead, staffing, and stocking these warehouses are a significant cost. From a supply chain perspective, when the number of distribution centers is increased, the necessary safety stock increases by $\sqrt{M/N}$ where N is the initial number of facilities and M is the new number of facilities; the incremental inventory holding costs increase proportionally, though outbound transportation costs would diminish with proliferation. Depending on the location of vendors, inbound transit, purchasing, and coordination may even increase overall costs.

7.6 Additional Technology and Process Measures

Implementing a pre-positioning strategy may improve global service levels, but there are also other technologies and processes which augment preparedness. Enterprise information technologies which record transactional data across numerous disciplines in the organization, such as those used by large corporations, are largely absent in the humanitarian space. This type of technology would provide the visibility necessary for making logistics decisions that optimize the supply chain. Moreover, terrain walks and scenario planning are tactics used in military operations (Fletcher, 2006) and can be adapted for humanitarian operations, improving predictability along the delivery chain.

7.7 Conclusion

Experts have argued that the amount of private funding before the onset of disasters is typically inadequate for long-term investments in preparation. This is perhaps the greatest obstacle to implementation of inventory pre-positioning. A paradigmatic shift is likely required to create an environment where humanitarian organizations (perhaps publicly-provisioned international bodies such as the U.N. venue) are endowed with adequate resources to pursue intelligent strategies towards operational excellence. The recent World Bank-commissioned report (World Bank, 2006) has quantified the vast economic losses that result from natural hazards, underscoring the increasing volume of dialogue with respect to hazards (Altay & Green, 2005). Moreover, it indicates that the economic losses, along with increasing global interconnectivity, make it likely that future infrastructures – especially in the developing world –

will be built to prevent damages or be located away from hotspots. Perhaps the time has come that the economic welfare of the developed world, via global supply chain interconnectivity, is sufficiently impacted by natural hazards, encouraging the types of investments that promote preparedness.

Ultimately, however, preservation of civilization might depend more upon preventative measures than preparatory ones. Preparing for hazard response may be less necessary if disasters are prevented altogether. The causal relationship between rapid industrial growth, global warming, and the destructiveness of hazards has not been adequately established in public perception. As a result, disaster prevention more often means increasing civilization's capacity to absorb shocks by constructing more resilient infrastructure, rather than focusing on discouraging the destructiveness of storms by mitigating the global warming phenomenon. Moreover, another pragmatic strategy is settling in places away from disaster hotspots, where the Earth system nurtures humanity rather than threatening it. These can be considered preventative measures that reinforce sustainable growth and treading lightly upon the Earth.

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A Appendix A

Figure 77: Nations with Regional Assignment

Country name	Region (j)
Afghanistan	South-central Asia
Albania	Southern Europe
Algeria	Northern Africa
American Samoa	Polynesia
Andorra	Southern Europe
Angola	Middle Africa
Anguilla	Caribbean
Antigua and Barbuda	Caribbean
Argentina	South America
Armenia	Western Asia
Aruba	Caribbean
Australia	Australia and New Zealand
Austria	Western Europe
Azerbaijan	Western Asia
Bahamas	Caribbean
Bahrain	Western Asia
Bangladesh	South-central Asia
Barbados	Caribbean
Belarus	Eastern Europe
Belgium	Western Europe
Belize	Central America
Benin	Western Africa
Bermuda	Northern America
Bhutan	South-central Asia
Bolivia	South America
Bosnia-Herzegovina	Southern Europe
Botswana	Southern Africa
Brazil	South America
British Virgin Islands	Caribbean
Brunei	South-eastern Asia
Bulgaria	Eastern Europe
Burkina Faso	Western Africa
Burundi	Eastern Africa
Cambodia	South-eastern Asia
Cameroon	Middle Africa
Canada	Northern America
Cape Verde	Western Africa
Cayman Islands	Caribbean
Central African Republic	Middle Africa

Country name	Region (j)
Chad	Middle Africa
Chile	South America
China	Eastern Asia
Colombia	South America
Comoros	Eastern Africa
Congo	Middle Africa
Cook Islands	Polynesia
Costa Rica	Central America
Cote d'Ivoire	Western Africa
Croatia	Southern Europe
Cuba	Caribbean
Cyprus	Western Asia
Czech Republic	Eastern Europe
Democratic Republic of the Congo	Middle Africa
Denmark	Northern Europe
Djibouti	Eastern Africa
Dominica	Caribbean
Dominican Republic	Caribbean
East Timor	South-eastern Asia
Ecuador	South America
Egypt	Northern Africa
El Salvador	Central America
Equatorial Guinea	Middle Africa
Eritrea	Eastern Africa
Estonia	Northern Europe
Ethiopia	Eastern Africa
Falkland Islands	South America
Faroes Islands	Northern Europe
Fiji	Melanesia
Finland	Northern Europe
France	Western Europe
French Guiana	South America
French Polynesia	Polynesia
Gabon	Middle Africa
Gambia	Western Africa
Georgia	Western Asia
Germany	Western Europe
Ghana	Western Africa
Gibraltar	Southern Europe
Greece	Southern Europe
Greenland	Northern America
Grenada	Caribbean
Guadeloupe	Caribbean
Guam	Micronesia
Guatemala	Central America
Guinea	Western Africa
Guinea-Bissau	Western Africa

Country name	Region (j)
Guyana	South America
Haiti	Caribbean
Honduras	Central America
Hungary	Eastern Europe
Iceland	Northern Europe
India	South-central Asia
Indonesia	South-eastern Asia
Iran (Islamic Republic of)	South-central Asia
Iraq	Western Asia
Ireland	Northern Europe
Israel	Western Asia
Italy	Southern Europe
Jamaica	Caribbean
Japan	Eastern Asia
Jordan	Western Asia
Kazakhstan	South-central Asia
Kenya	Eastern Africa
Kiribati	Micronesia
Korea, North	Eastern Asia
Korea, South	Eastern Asia
Kuwait	Western Asia
Kyrgyzstan	South-central Asia
Laos	South-eastern Asia
Latvia	Northern Europe
Lebanon	Western Asia
Lesotho	Southern Africa
Liberia	Western Africa
Libyan Arab Jamahiriya	Northern Africa
Lithuania	Northern Europe
Luxembourg	Western Europe
Macedonia	Southern Europe
Madagascar	Eastern Africa
Malawi	Eastern Africa
Malaysia	South-eastern Asia
Maldives	South-central Asia
Mali	Western Africa
Malta	Southern Europe
Marshall Islands	Micronesia
Martinique	Caribbean
Mauritania	Western Africa
Mauritius	Eastern Africa
Mexico	Central America
Micronesia	Micronesia
Moldova	Eastern Europe
Mongolia	Eastern Asia
Montserrat	Caribbean
Morocco	Northern Africa

Country name	Region (j)
Mozambique	Eastern Africa
Myanmar	South-eastern Asia
Namibia	Southern Africa
Nepal	South-central Asia
Netherlands	Western Europe
Netherlands Antilles	Caribbean
New Caledonia	Melanesia
New Zealand	Australia and New Zealand
Nicaragua	Central America
Niger	Western Africa
Nigeria	Western Africa
Norway	Northern Europe
Oman	Western Asia
Pakistan	South-central Asia
Palau	Micronesia
Palestinian Territory	Western Asia
Panama	Central America
Papua New Guinea	Melanesia
Paraguay	South America
Peru	South America
Philippines	South-eastern Asia
Poland	Eastern Europe
Portugal	Southern Europe
Puerto Rico	Caribbean
Qatar	Western Asia
Reunion	Eastern Africa
Romania	Eastern Europe
Russian Federation	Eastern Europe
Rwanda	Eastern Africa
Samoa	Polynesia
Sao Tome and Principe	Middle Africa
Saudi Arabia	Western Asia
Senegal	Western Africa
Serbia and Montenegro	Southern Europe
Seychelles	Eastern Africa
Sierra Leone	Western Africa
Singapore	South-eastern Asia
Slovakia	Eastern Europe
Slovenia	Southern Europe
Solomon Islands	Melanesia
Somalia	Eastern Africa
South Africa	Southern Africa
Spain	Southern Europe
Sri Lanka	South-central Asia
St. Kitts-Nevis	Caribbean
St. Lucia	Caribbean
St. Vincent & Grenadines	Caribbean

Country name	Region (j)
Sudan	Northern Africa
Suriname	South America
Swaziland	Southern Africa
Sweden	Northern Europe
Switzerland	Western Europe
Syrian Arab Republic	Western Asia
Taiwan	Eastern Asia
Tajikistan	South-central Asia
Tanzania	Eastern Africa
Thailand	South-eastern Asia
Togo	Western Africa
Tonga	Polynesia
Trinidad and Tobago	Caribbean
Tunisia	Northern Africa
Turkey	Western Asia
Turkmenistan	South-central Asia
Turks and Caicos Islands	Caribbean
U.S. Virgin Islands	Caribbean
Uganda	Eastern Africa
Ukraine	Eastern Europe
United Arab Emirates	Western Asia
United Kingdom	Northern Europe
United States of America	Northern America
Uruguay	South America
Uzbekistan	South-central Asia
Vanuatu	Melanesia
Venezuela	South America
Vietnam	South-eastern Asia
Yemen	Western Asia
Zambia	Eastern Africa
Zimbabwe	Eastern Africa

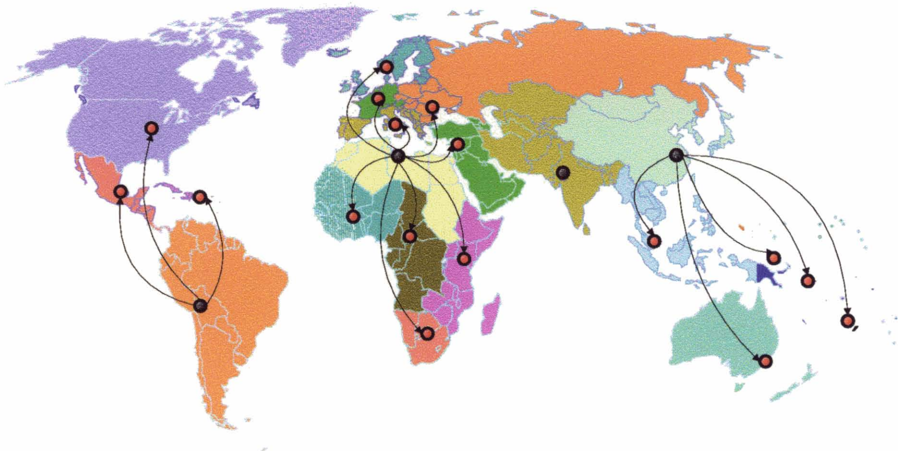
B Appendix B

The following table navigates the set of maps representing solutions for the algorithm-framed problems:

Figure 46: Table to Navigate Maps

Figure	Case	Iteration
47	Blank Page	1
48	Blank Page	2
49	Blank Page	3
50	Blank Page	4
51	Blank Page	5
52	Blank Page	6
53	Blank Page	7
54	Blank Page	8
55	Blank Page	9
56	Blank Page	10
57	Status Quo	1
58	Status Quo	2
59	Status Quo	3
60	Status Quo	4
61	Status Quo	5
62	Status Quo	6
63	Status Quo	7
64	Status Quo	8
65	Status Quo	9
66	Status Quo	10

Figure 50:



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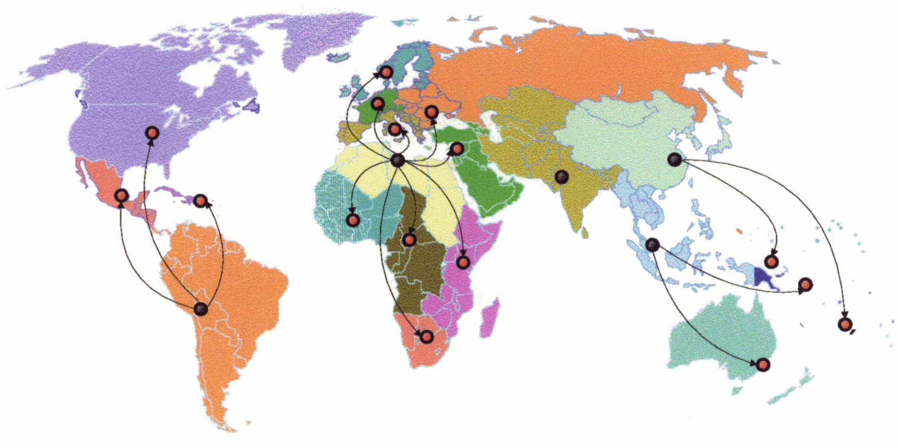
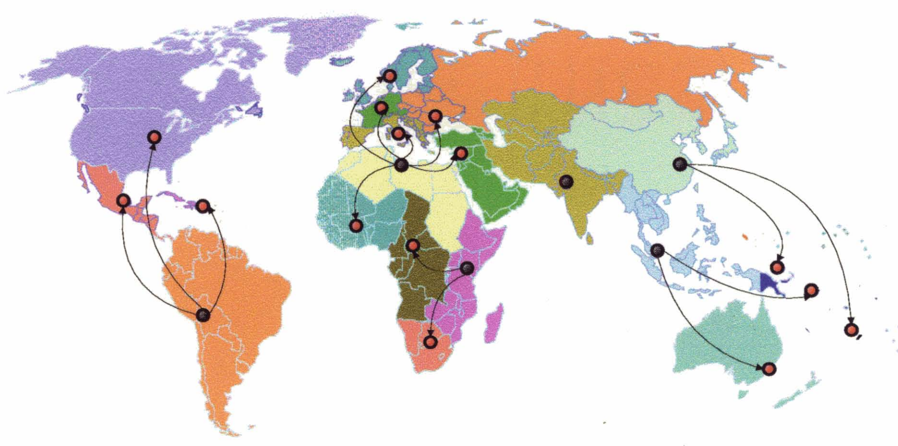


Figure 52:



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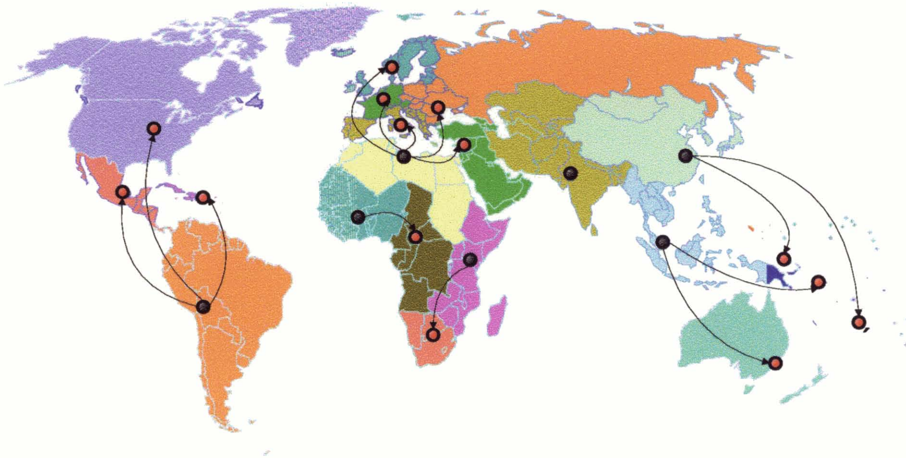

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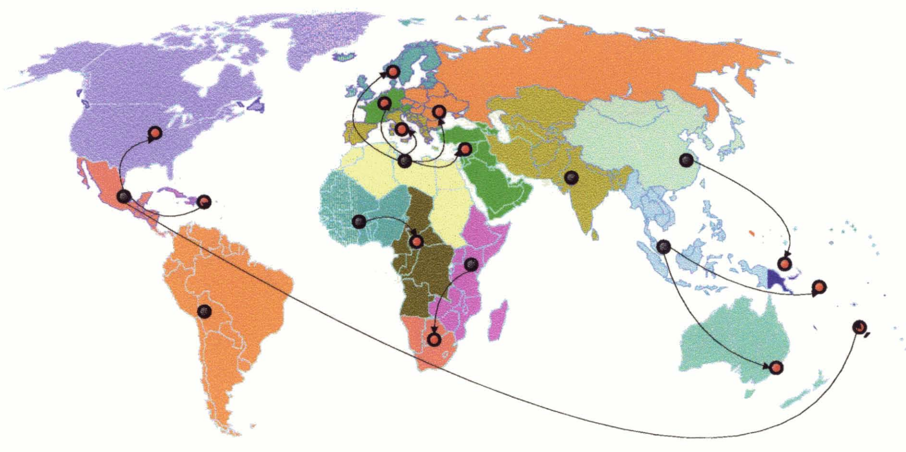

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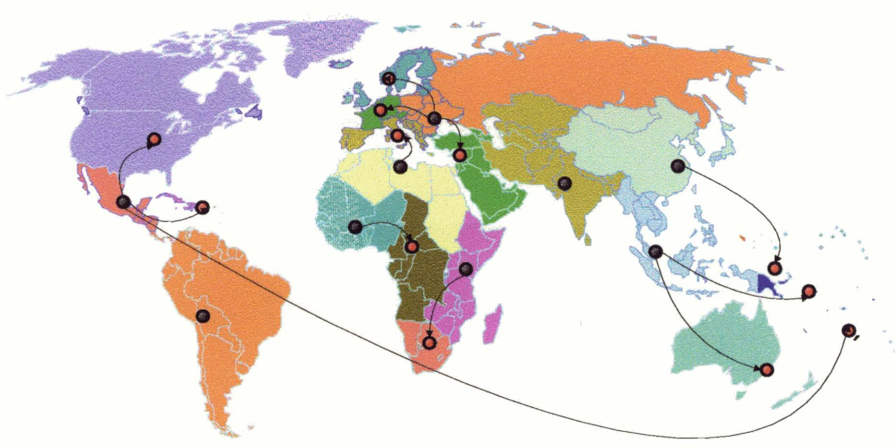

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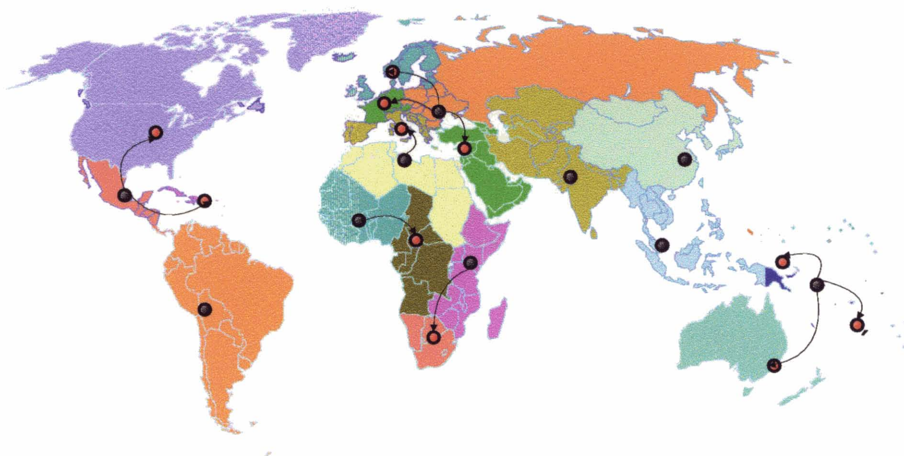


Figure 60:

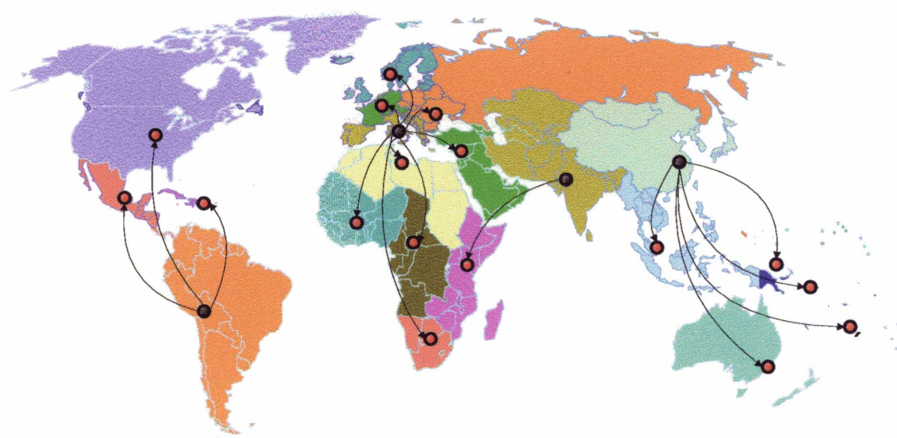


Figure 61:

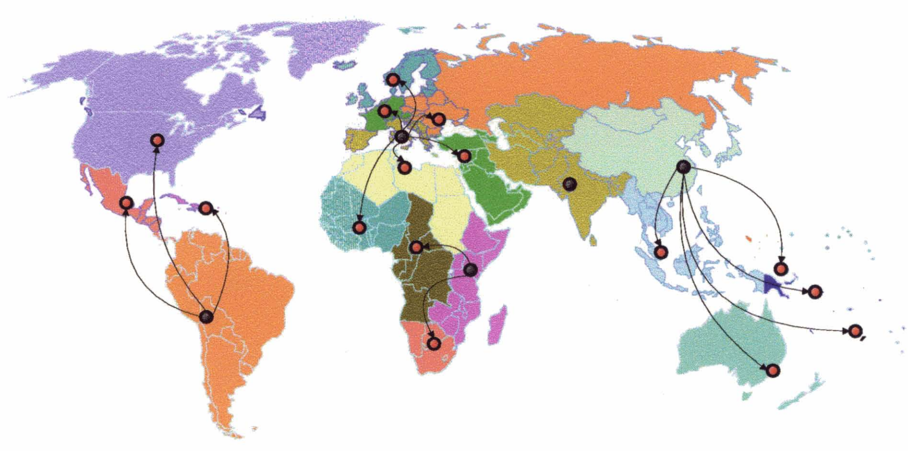


Figure 62:

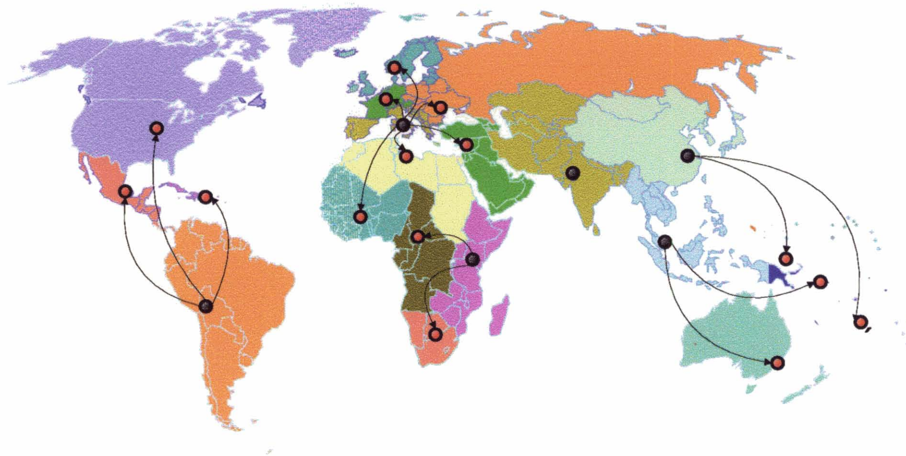
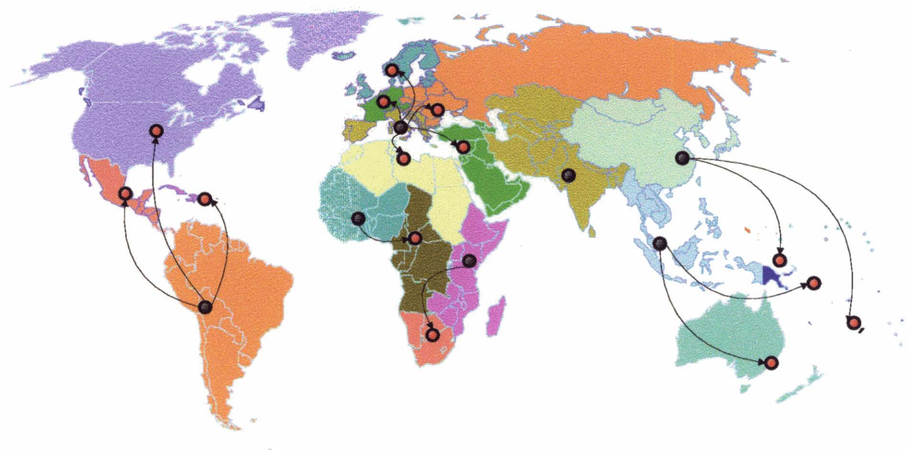


Figure 63:



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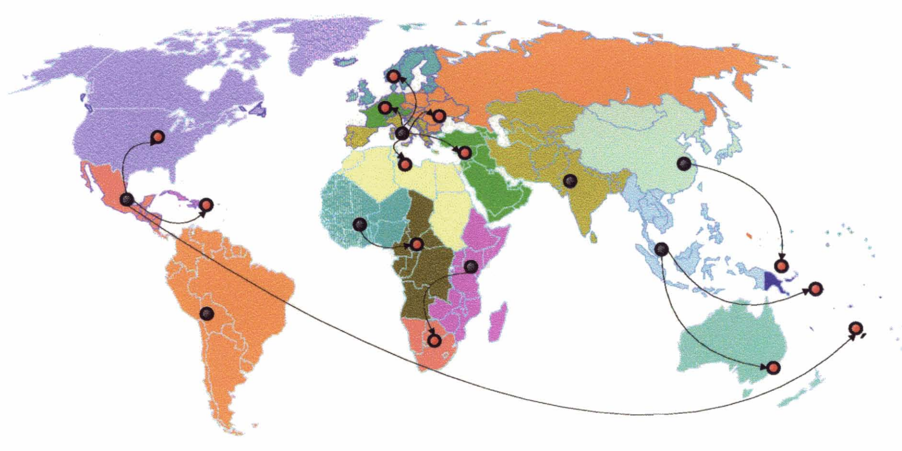

Figure 65:

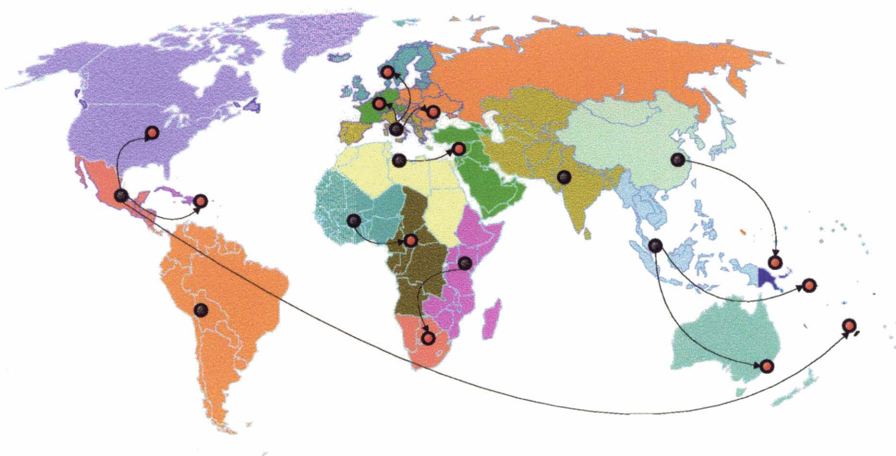

Figure 66: