IMPACT OF DECENTRALIZED DECISION MAKING ON ACCESS TO CHOLERA TREATMENT IN HAITI

by

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B.S., Kansas State University, 2012

A THESIS

submitted in partial fulfillment of the requirements for the degree

MASTER OF SCIENCE

Department of Industrial and Manufacturing Systems Engineering
College of Engineering

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2012

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Abstract

In many humanitarian and public health settings, multiple organizations act independently to locate facilities to serve an affected population. As a result of this decentralized decision-making environment, individuals' access to facility resources may suffer in comparison to a hypothetical system in which a single planner locates the facilities to optimize access for all. Furthermore, due to the unanticipated nature of humanitarian events and the urgency of the need, responders often must cope with a high level of uncertainty regarding the future supply of resources and demand for relief.

The contributions of this thesis address the challenges that arise due to the decentralized and dynamic nature of humanitarian response. The first goal of this research is to quantify the difference between decentralized system performance and that possible with a centralized planner. The second goal is to demonstrate the value and feasibility of using a dynamic, rolling-horizon framework to optimize facility location decisions over time.

This work compares individuals' access to health facilities resulting from location decisions made by decentralized decision-makers to the access achieved by a centralized model that optimizes access for all. Access is measured using a special case of the gravity model, the Enhanced Two-Step Floating Catchment Area (E2SFCA) method, which is a distance-weighted ratio of capacity to demand. The E2SFCA method is integrated with integer programming to optimize public access to health facilities. This method is applied to the location of cholera treatment facilities in Haiti, which has been afflicted with a cholera epidemic since October 2010.

This research finds that access varied significantly across Haiti, and in the month of February 2011, thirty-seven of the 570 sections, representing 474,286 persons (4.8 percent of the population), did not have adequate access to cholera treatment facilities. Using centralized models to optimize accessibility, performance can be improved but no single model is dominant. This paper recommends use of an efficiency-oriented model in conjunction with an equity constraint to make facility location decisions in future responses. Finally, this work successfully integrates measures of access and equity into a rolling-horizon facility location model and demonstrates that these measures can be incorporated in a full-scale implementation to provide dynamic decision support to planners. This paper advocates for greater awareness of the impact of decentralization in humanitarian response and recommends that future work be undertaken to discover incentives and strategies to mitigate the impact of decentralization in future responses.

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Acknowledgements

For her skillful guidance and immeasurable patience, I would like to thank Dr. Jessica Heier Stamm, who has pushed me to achieve more than I ever thought possible. This work would not exist today without her help and encouragement. I would also like to acknowledge the contributions of Dr. Todd Easton and Dr. Marcelus Caldas on my review committee. Dr. Easton can be credited with persuading me to join the Industrial and Manufacturing Systems Engineering Department at Kansas State University, to pursue a Master's degree, and for connecting me with Dr. Heier Stamm. Lastly, I would like to thank the faculty, staff, and students of the IMSE department, who have encouraged, challenged, shaped and molded me over the course of my college education.

Dedication

This work is dedicated to my family for their lifelong support of my education, and to my friends, for their understanding and encouragement.

1 INTRODUCTION

In response to epidemics and natural disasters, a large number of governmental, non-governmental and private organizations react quickly to minimize human loss and suffering. Centralized decision-making, where a single person or organization makes decisions for all, is often unrealistic due to the urgency of the situation and the number of actors. Decentralized responses, however, may lead to inefficient use of resources and inequity in access to relief resources. This thesis examines the impact of decentralization on humanitarian response with a focus on the 2010 cholera epidemic in Haiti.

This paper studies the facility location decisions made by decentralized agencies. The goal is to quantify the difference between actual, decentralized location decisions and a hypothetical response in which location decisions are made by a centralized planner. Measuring access is important in public health settings to identify gaps in coverage and ensure that no persons are unable to reach medical services. To accomplish this, a method is selected to measure accessibility. Next, facility locations are optimized in the centralized setting using several integer programming models and the resultant access is compared with that of the decentralized system. Multiple models are considered to study the tradeoffs that exist between efficiency and equity. This work demonstrates that it is possible to improve access and equity by locating facility resources more strategically.

Humanitarian events often pose a number of challenges for responders due to the unanticipated nature of the event and the urgency of the need. As a result, responders must cope with large fluctuations in the supply of resources and demand for relief. There is a need for decision support tools to guide decision-makers in such a dynamic environment. This paper provides a rolling-horizon model that can be recomputed periodically, helping responders deal with the high level of uncertainty.

This thesis begins with a discussion on the background, research questions and contributions in Chapter 1. Chapter 2 reviews literature relevant to accessibility, equity, decentralized systems, facility location and rolling-horizon models. Chapter 3 introduces a static approach that quantifies the difference between access in centralized and decentralized systems. Chapter 4 investigates the impact of dynamic supply and demand on location decisions and proposes a rolling-horizon model to aid decision-makers in location planning decisions. Finally, Chapter 5 summarizes the findings of this paper and indicates areas of future research.

1.1 BACKGROUND

This research is motivated by three main factors: the overwhelming burden of the cholera epidemic on Haiti, the need to scientifically study the impact of decentralization on humanitarian responses, and the need for a practical tool to help decision-makers cope with the uncertainties inherent in disaster relief.

1.1.1 CHOLERA BURDEN

Cholera (*Vibrio cholerae* bacterium) is an acute diarrheal disease caused by infection of the intestines. An estimated three to five million cases and 100,000 deaths occur annually because of cholera worldwide. The infection is often mild and symptomless, but approximately five percent of infected persons suffer a severe response of watery diarrhea, vomiting and leg cramps. Cholera can kill within just a few hours if untreated due to rapid dehydration of the body [1]. For people that show symptoms of cholera, 80 percent of cases can be treated successfully with oral rehydration salts, fluids designed to replace sugar and electrolytes lost in dehydration. The most severe cases are treated with intravenous fluids and antibiotics. With proper treatment, the fatality rate of cholera can be reduced to less than one percent [2].

Cholera is usually spread through the consumption of food or water contaminated with the bacteria. In an epidemic, the source of contamination is usually feces from an infected person that contaminates a water or food supply. The disease is typically not transferred directly between two persons [2]. Providing access to safe drinking water and sanitation is the most common, and arguably the most effective, way to prevent cholera. Vaccines that prevent cholera exist, but cannot replace prevention and control measures because they are not available in quantities adequate to vaccinate an entire population [2].

Due in part to preexisting living conditions in Haiti, and exacerbated by the 7.0 magnitude earthquake in January 2010, a cholera outbreak occurred in October 2010. Prior to the outbreak, cholera had not been documented in Haiti or anywhere in the Caribbean since the mid-nineteenth century [3]. The U.S. Centers for Disease Control and Prevention (CDC) confirmed the first case of cholera near the Artibonite River on October 21, 2010 [3], and cholera quickly spread to all ten of the country's departments by the end of the year.

The United Nations originally forecasted that Haiti would see up to 200,000 cases within one year of the onset of the outbreak in October of 2010 [4]. By December 2010 the forecast was increased to 400,000 cases [5], which was still below the 481,339 cases actually documented by the end of the year [6]. As of April 8, 2012, Haiti has documented 532,925 cases (five percent of the population) and 7,095 deaths with some departments still experiencing fatality rates as high as 4.3 percent [7]. Especially in the early weeks of the response, these figures probably suffered from underreporting. Although the true extent of underreporting in Haiti is currently unknown, the World Health Organization (WHO) believes officially reported cases represent just five to ten percent of actual cholera cases worldwide [8].

Although cholera is a serious and potentially life-threating disease, cholera is easily treated if individuals have access to treatment facilities. Therefore, locating facilities to ensure access to treatment is an important problem.

1.1.2 Decentralized Response

In response to this crisis, hundreds of governmental and non-governmental organizations (NGOs) from all over the world opened and operated cholera treatment facilities across Haiti. The medical response to the epidemic was led by the Global Health Cluster, a group of 39 humanitarian relief organizations led by the WHO [9], but there was no oversight of the location of medical facilities. Governmental organizations and NGOs opened three types of facilities:

1. Oral Rehydration Points (ORP) typically contain less than 20 beds, treat only mild cases, are staffed community health workers 12 hours per day, and are intended to be located in every community. ORPs refer all symptomatic patients to a CTU or CTC after stabilization.
2. Cholera Treatment Units (CTU) contain 20 to 30 beds, treat mild to moderate cases, operate 12 to 24 hours per day, and are staffed by two to three nurses, two to three nurse auxiliaries and some support staff.
3. Cholera Treatment Centers (CTC) support 30 to 500 beds, treat mild to severe cases, operate 24 hours per day, and have trained physicians on site.

The Health Cluster did not have authority to make location decisions, and each responding organization made locations decisions independently. According to the CDC cholera training manual, “There are no rigid rules to follow in deciding when to set up a CTC and what the ideal location for such a center would be” [10]. Data compiled by the Pan

American Health Organization (PAHO) identifies more than 110 different organizations that operated CTCs and CTUs throughout the response [11].

Systems like this in which decisions are made by many decentralized agents are often less efficient and less equitable than those where a centralized planner makes decisions for all. To improve the effectiveness of humanitarian relief, it is important to quantify the differences in centralized and decentralized responses and to better understand the tradeoffs between equity and efficiency. These problems are not well understood in literature.

1.1.3 DYNAMIC SYSTEM

Humanitarian relief efforts pose a number of significant challenges for responders, such as a complex operating environment, large number of stakeholders, politically volatile climate, time pressure and high rate of staff turnover. Perhaps the most pertinent to planners though is the high level of uncertainty surrounding the availability of future supplies and demand. Volunteering organizations can respond very quickly to an emerging need, but can disappear nearly as quickly to respond to another disaster or due to a lack of funds. Perfect information is rarely available during relief efforts, but even if it was, the wide fluctuations in supply and demand would be challenging to manage alone [12].

The volatile nature of the supply and demand during the cholera epidemic proves that Haiti is no exception. Cholera prevalence is very seasonal, and because cholera is most often spread through contaminated water sources, cholera prevalence increases dramatically during rainy seasons. Figure 1-1 below demonstrates the dynamic nature of the demand placed on cholera treatment personnel. It shows the daily number of documented cholera cases between January 1, 2011, and April 4, 2012 [6].

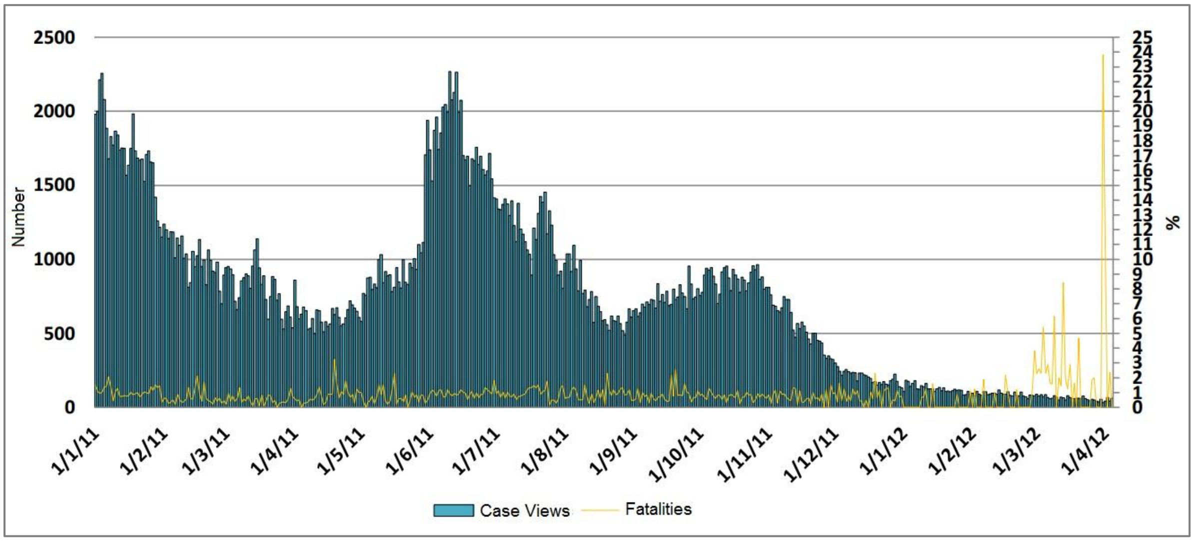

FIGURE 1-1: DAILY CHOLERA CASE VIEWS OVER TIME [6]

To compound matters, health officials must not only plan for variability in the demand overall, but also account for the rate and direction of the disease's spread (called the demand vector). Figure 1-2 below shows cumulative case count for each department in Haiti [6] and shows how the prevalence rate changes across departments over time. Although cholera was originally most prevalent in the Artibonite department, it was overtaken by the Port-au-Port-au-Prince department in March, 2011.

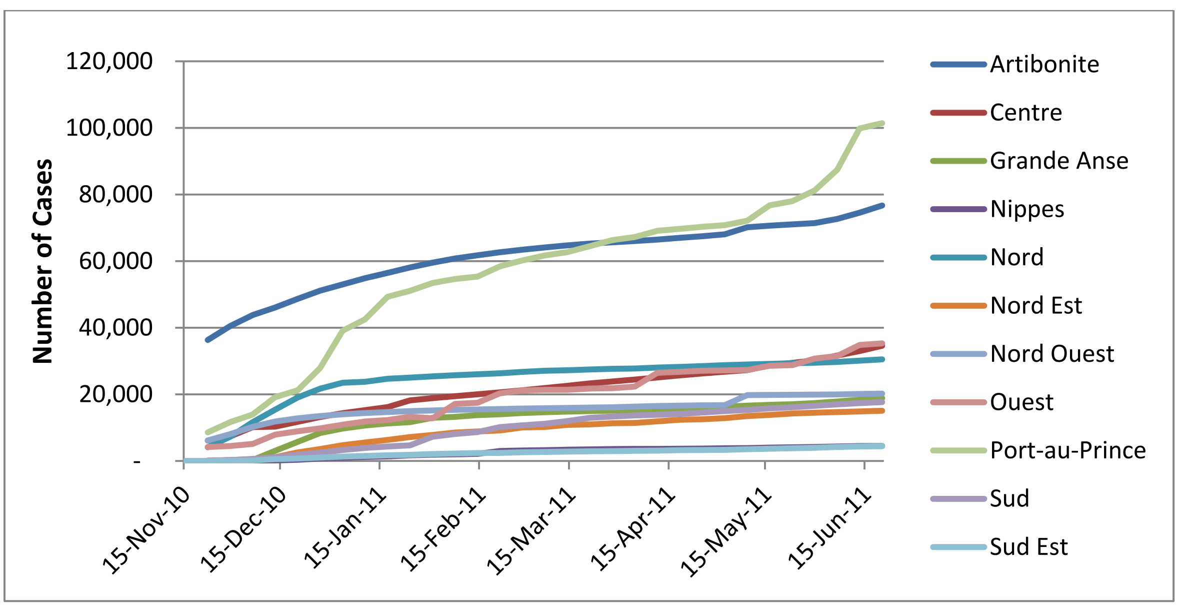

FIGURE 1-2: CUMULATIVE NUMBER OF CASES OVER TIME BY DEPARTMENT [6]

Finally, the supply of resources is also unpredictable. Responders are often at the mercy of public interest to maintain operating funds and many are forced to close their doors early due to insufficient donations. Figure 1-3 below shows the number of CTCs and CTUs operating in Haiti between November, 2010, and October, 2011. The figure shows a large spike in the number of treatment facilities in early 2011 and a decline as public interest began to wane in mid-2011. Uncertainties in the availability of future resources can be problematic for decision-makers.

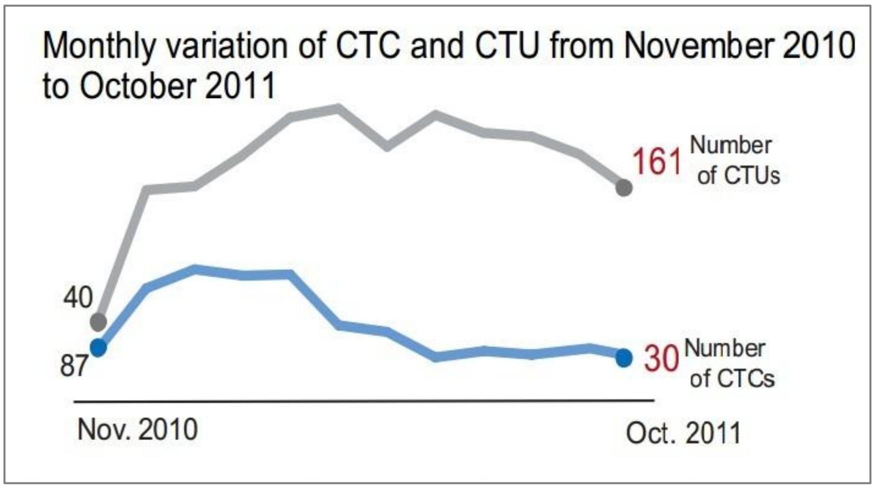

FIGURE 1-3: DYNAMIC SUPPLY OF CHOLERA TREATMENT FACILITIES [7]

Managing systems with dynamic supply and demand is challenging. The need exists for decision support tools that will guide decision-makers in such a dynamic environment.

1.2 RESEARCH GOALS

The aim of this thesis is to study the impact of decentralization on humanitarian response. The author hypothesizes that decentralization in facility location decisions adversely affects the efficacy of response efforts. The first goal of this work is to quantify the difference between the actual, decentralized response in Haiti and a theoretical response possible if location decisions were centralized. The second goal of this work is to explore the feasibility of using a rolling-horizon model framework to optimize facility location decisions over time and investigate potential benefits of using such an approach.

1.3 RESEARCH CONTRIBUTIONS

This research is related to existing literature in accessibility, equity, decentralized systems, facility location and rolling-horizon models. It make the following contributions:

1. Quantify the population's access to cholera treatment during the 2010-2011 epidemic in Haiti. To the author's knowledge, this work is the first to methodically evaluate effectiveness of treatment facility locations.
2. Evaluate the impact of decentralization on accessibility. Many have studied the impact of decentralization in commercial supply chains and developed ways to overcome it, but the need exists to quantify the impact of non-coordination on humanitarian logistics operations. This paper finds that decentralization significantly hampers the accessibility and equity of a humanitarian response.
3. Provide five optimization models that can be solved to improve efficiency and/or equity, and discuss the tradeoffs between these measures. Existing measures of access and equity are borrowed from other disciplines, but this paper's contribution is to highlight the tradeoffs inherent by choosing one model over another. It finds that the models produce very different results, and each identifies opportunities for improvement in comparison to the decentralized system.
4. Demonstrate the plausibility of implementing a rolling-horizon framework to model the complex interaction of supply and demand over time. Partly due to their computational complexity, access and equity measures have historically been applied statically. This thesis shows that access and equity measures can be successfully integrated in a large-scale, dynamic optimization model to provide decision support to planners.
5. Apply the E2SFCA method, an approach for measuring accessibility, using actual demand data and propose techniques to address model infeasibility when demand approaches zero. The method has previously been used where demand is much greater than supply. By applying method with actual cholera case rates from the epidemic, shortcomings of using the method are discovered and mitigated.

While these research contributions are presented within the context of their application to the cholera response in Haiti, they have broad implications for the analysis and management of general decentralized, dynamic systems. The work also leads to interesting questions for future research.

2 LITERATURE REVIEW

This chapter introduces definitions, reviews relevant literature, and highlights how the contributions of this paper differ from existing studies. It begins with a review of the concepts of access and equity. Next it discusses decentralized systems with a focus on public health. Finally, Chapter 2 looks at facility location and rolling-horizon models which serve as the foundation for work in Chapters 3 and 4, respectively.

2.1 ACCESSIBILITY

Access refers to the ease with which goods or services can be reached from a given location [13]. This paper focuses on access to healthcare. Access to healthcare varies across space because it is influenced by a number of factors including supply (number of providers), demand (population), socio-economic factors, public knowledge about health services, and distance or difficulty of travel - none of which are uniformly distributed across space [14]. Therefore, access refers to more than just the **availability,** or the number of providers from which a person may choose [15].

Typically, healthcare access can be divided into either potential or realized access, and spatial or aspatial access [15]. **Potential access** refers to the availability of and feasible access to health services, and **realized access** refers to how the services are actually consumed. **Spatial access** stresses the importance of geographical distance, while **aspatial access** stresses non-spatial variables like income, age, race and gender [15, 16].

During the cholera epidemic in Haiti, the Health Cluster used potential regional availability (capacity-to-population ratio) to identify departments with an insufficient number of cholera treatment facilities. This method, although quick and easy to calculate, ignores spatial variations within each region. In reality, not all persons in a given region (e.g. state, county, city, census tract) have equal access to available resources. Additionally, this method assumes that region borders are impermeable. Typically, region borders are artificial and do not inhibit citizens from using services in other regions [16].

One other measure of access seen in public health is potential spatial accessibility. This measure treats a population's willingness to travel as binary, such that all populations within a threshold travel distance have access, and those beyond do not. This formulation is essentially a "covering" model, which is described in Section 2.4. For example, as shown in Figure 2-1, the Pan American Health Organization (PAHO) uses a five-kilometer (one walking hour) buffer around CTCs and CTUs to identify gaps in coverage. This method ignores any non-spatial factors, as well as the interaction between supply and demand.

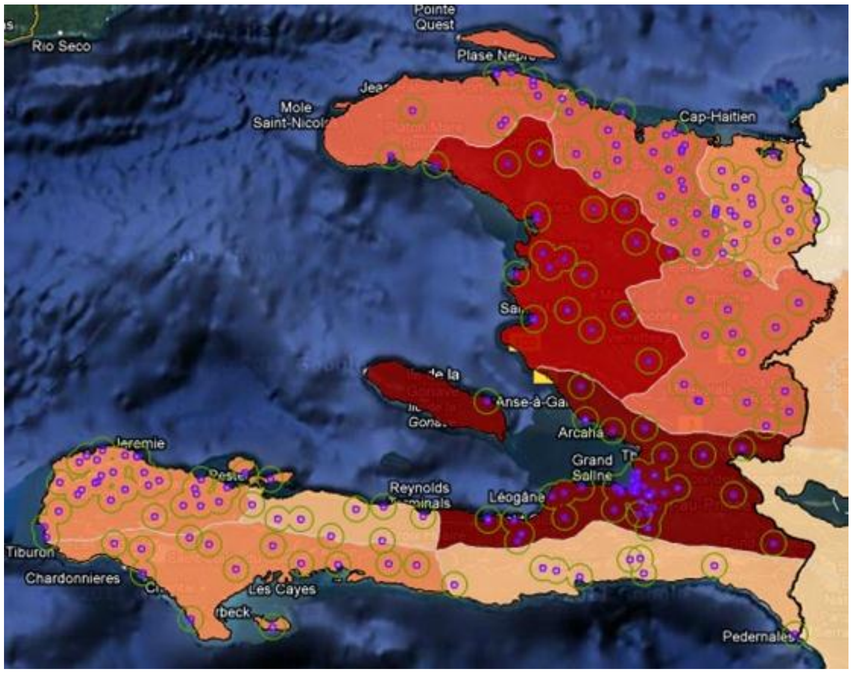

FIGURE 2-1: PAHO 5KM RADIUS FOR ACCESSIBILITY [17]

The problems of availability and accessibility are still not well resolved in literature, partly due to the complexity of the problem [13]. More sophisticated measures attempt to incorporate both availability (do resources exist) and accessibility (can they be accessed). One such measure, the gravity model, attempts to mimic Newton's Law of Gravitation, where the attraction between two objects is determined by both the objects' mass and distance apart. It accounts for distance via a "friction of space" coefficient, and supply/demand as attracting masses. The method is criticized because the results are unintuitive to interpret and because the friction coefficient can be difficult to determine [13].

Radke and Mu proposed the two-step floating catchment area method (2SFCA) in 2000, later modified by Luo and Wang in 2003 [16], which is a special, discrete case of the gravity model. It works by assuming a "catchment" around each resource location and each population (demand) location. Locations within the catchment are considered accessible and those outside the catchment are not. Step one of the two-step process is to calculate the physician-to-population ratio within the catchment of every physician location. Step two searches all physician locations and sums the ratios within each population location's catchment.

Luo and Qi (2009) proposed the enhanced two-step floating catchment area (E2SFCA) method, which relaxes the assumption of uniform inter-catchment access by dividing the catchment into travel time zones with discrete distance-decay ("friction of space") weights. The method explicitly accounts for decreasing willingness to travel with increasing distance and the interaction between supply and demand, yet still has an intuitive interpretation [13]. For these reasons, the E2SFCA method is selected to measure access to cholera treatment facilities in Haiti.

The 2SFCA and the E2SFCA methods have been applied in a number of public health settings to quantify access, but the use of these methods to optimize access has been limited [15, 18, 19]. Gu, Wang and McGregor (2010) apply the 2SFCA method in a bi-objective, integer programming model to locate preventative care facilities so as to maximize participation [19]. To the author's knowledge, the E2SFCA has not yet been applied in an integer programming model and neither method has been applied in a rolling-horizon framework. Therefore, this research provides two unique applications of the E2SFCA, a static facility location model and a dynamic, rolling-horizon location model.

2.2 Equity

Equity is an important concept in many applications, particularly in public health, and refers to the "absence of systematic disparities in access between different groups of people, identified by location or underlying socioeconomic variables" [20]. Conventional facility location problems are primarily concerned with **efficiency** [21, 22], where an efficient solution is one that achieves the maximum or minimum sum over an entire population of a specified measure (for example, maximum sum of E2SFCA access measures or minimum sum of travel distances) but have no regard for how this measure differs between individuals. In the public service sector, where facility locations must be accepted by the general public, pure efficiency-oriented location models may not be acceptable.

The equitable distribution of resources can be divided into four categories:

1. Equally (regardless of need or other factors)
2. According to need (perceived)
3. According to demand
4. According to market criteria (e.g. willingness to pay) [23, 24]

It is important to note the distinction between equity and equality. Equity is a broader concept than just equality. **Equality** is a mathematical notion describing when two or more measurements have the same value. Equity, however, is a societal construct and implies whether something is "fair" or "just." The two terms are not interchangeable, but many use equality as a means to model equity [21].

Many different measures of equity exist and there is currently no consensus in literature about which measure is best [23, 25]. For example, one group may believe that a solution is only equitable if everyone receives the same benefit; others may feel that those with the greatest need should receive the most benefit. Marsh and Shilling (1994) discuss twenty existing measures from literature and provides some approaches for selecting an appropriate equity measure [24]. Erkut (1993) presents several axioms for the evaluation of equality measures (i.e. satisfies principle of transfers, scale invariant), and assesses seven popular measures [21]. Erkut recommends the Gini coefficient (a popular inequality measure in economics) and coefficient of variance (CV) as two measures appropriate for measuring equity. They acknowledge, however, that the nonlinearity of the CV measure may be problematic for optimization, and that there is still no agreement about the best method. For a comprehensive look at existing equity measures, the reader refer is referred to [24]. This research integrates equity measures with the E2SFCA accessibility measure to study the tradeoffs that occur between efficiency, access, and equity.

2.3 Decentralized Systems

Decentralized systems, where decisions are made by many independent decision-makers, often perform worse than **centralized systems** that have a single agency making decisions for all [26, 27]. Decentralized systems are common in humanitarian logistics because most relief efforts involve a large number of organizations with varying interests, capacities and experience, and no single organization has complete authority over the response [28, 29, 30]. Many recognize the importance of promoting cooperation and coordination between relief agencies, but this remains an area for continued improvement in future responses [26, 31, 32].

Previous studies have examined the loss of efficiency due to decentralization theoretically using game theory [26]. Most commonly applied in disciplines such as economics and political science, game theory has also become a powerful tool in supply chain management [33]. While many have studied the impact of decentralization and identified ways to overcome it in commercial supply chains [34, 35], the need exists to quantify the impact of non-coordination on humanitarian logistics operations. To the author's knowledge, this study is the first to consider impact in a public health environment where different organizations make facility location decisions. This research quantifies the disparity between the actual, decentralized response to the cholera epidemic in Haiti and the potential gains that could be realized if better coordination were achieved.

2.4 FACILITY LOCATION

The majority of facility location literature centers on three basic location models: the *p*-median, *p*-center, and covering formulations. The ***p*-median** model is a pure efficiency-oriented model that minimizes the total demand-weighted travel distance between demands and facilities [36]. The drawback to the median model is that it does not incorporate equity and is therefore not appropriate for use in many public service areas. The ***p*-center** model seeks to minimize the maximum distance between any demand and the nearest facility. It improves the access of those who are worst-off (farthest from a facility), decreasing the disparity between the best and worst-off. The center model is the only model of the three to consider equity directly [24]. The drawback of the center model is that it focuses entirely on reducing the maximum distance and the overall efficiency of the solution is not considered. The third model, the **covering model**, locates a facility within a threshold distance of every recipient [21]. The covering model is typically used in instances where a certain level of coverage must be guaranteed to all customers (e.g. emergency medical service must be able to reach all beneficiaries within a given period of time). The drawback to this formulation is that it makes no distinction about the size of the demand at each node, so whether the node represents a single customer or the majority of the total demand, the node must be covered regardless of cost. All three models belong to the *NP*-hard complexity class [36, 37], which means that there are no known exact efficient solution methods [38]. This means that the effort required to solve these problems may increase exponentially with the size of the problem, and finding a solution may exceed available time or computer memory. For a comprehensive review of facility location literature, the reader is referred to [25] and [36].

Equitable solutions often differ greatly from efficient solutions. Take for example three points on a line as shown in Figure 2-2. The dots represent populations (demand) and a planner seeks to locate one facility to serve the three populations. An efficient solution would attempt to locate the facility at B to minimize the overall travel distance without regard for individuals' travel distance. An equitable solution, however, would seek to locate the facility an infinite distance away so that the travel distance for each population is equal (infinity). Clearly such a solution is impractical because no population would have access to the facility at all [21].

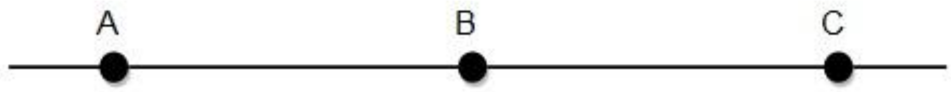

FIGURE 2-2: EFFICIENCY VS. EQUITY [21]

Many other location models exist, but this review focuses on those that relate to humanitarian logistics or consider access/equity. Prior work has considered the equity of ambulance service coverage between rural and urban areas through a bi-objective covering model and *p*-center model [39, 40]. Multi-objective models have been used to find a compromise between efficient and equitable solutions [22, 41]. Previous studies have examined algorithmic issues related to solving location problems with equity measures and have found ways to reduce the complexity of several equity measures [42]. Related to humanitarian logistics, previous studies have located distribution centers in a relief supply chain using a maximal covering model, finding that it could be a useful tool in pre-positioning relief supplies [43]. Gu et al. (2010) apply the 2SFCA method in a bi-objective model to locate preventative care facilities so as to maximize participation [19].

Although many have applied concepts of equity to facility location, few have studied the simultaneous consideration of access and equity. Fewer still apply the concepts to improve public health. This research provides five models that can be solved to improve access, equity or both, and applies them to the cholera epidemic response in Haiti.

2.5 Rolling-Horizon Models

In static optimization models, inputs are assumed to be fixed and unchanging over time. In reality, however, supply, demand and other parameters vary with time, and dynamic models can be used to account for future changes by periodically or continuously updating information [44, 45]. Rolling-horizon models, commonly used in scheduling and forecasting, are also becoming increasingly common in the field of location science [36].

Rolling-horizon models are especially useful in public health, where future conditions can be difficult to forecast, because they allow solutions to be generated periodically as new information becomes available. This is desirable because an optimal strategic plan is only "optimal" so long as the assumptions under which the plan was developed remain true. If population location, disease prevalence, resource availability, or other factors change, a rolling-horizon model can be solved to create a new best response strategy based on the updated information. According to [46], the main difficulty in solving the dynamic facility location problem arises from uncertainty about future events, and the authors argue that the best way of dealing with it is to postpone decision-making as long as possible.

Previous work with rolling-horizon models has considered optimizing the use of logistics resources when future supplies and demands are uncertain [44, 47]. Ndiaye and Alfares (2008) study the location of public health facilities for a nomadic population group where demand is seasonal and extremely dynamic [45]. Several studies provide methods for formulating and solving dynamic facility location problems [37, 48]. Many of the static location problems from which dynamic location problems are derived are extremely difficult to solve, and therefore solving dynamic location problems is not trivial, either. A good portion of literature deals with heuristics for finding near-optimal solutions [36]. For a comprehensive review of facility location and dynamic facility location, the reader is referred to [36].

To the author's knowledge, this study is the first to apply measures of accessibility and equity in any type of forward-looking, dynamic facility location framework. Demand is represented using actual case counts and not population estimates, and in so doing have uncovered challenges in using the E2SFCA when demand (case count) is very close to zero. This work provides one method for addressing these issues and is the first point to the need for future research on this problem (see Section 4.2.1). Although static point forecasts are used in this study, a real application of this research could be implemented with dynamic point forecasts. Finally, the method in this paper is successfully applied to the cholera epidemic in Haiti, demonstrating the potential benefit of rolling-horizon models in improving facility location in future humanitarian responses. The authors in [36] look forward to the "development of tractable models which consider both the stochastic and dynamic aspects of facility location" in "larger, more complex and more realistic problems," and this work demonstrates the feasibility of modeling these realistic, complex problems.

3 QUANTIFYING ACCESS TO CHOLERA TREATMENT

This chapter quantifies the actual access to cholera treatment in Haiti and calculates the difference between the actual access and hypothetical access in centralized models. It begins with a description of the method by which access to cholera treatment is measured. Next it applies the method to the Haiti cholera epidemic response during the month of February, 2011. Optimization models are developed with the goal of quantifying the possible improvement in access and then comparing the access in the centralized and decentralized models. Chapter 3 concludes with sensitivity analysis on parameter assumptions.

3.1 MEASURING ACCESSIBILITY

This section describes the way by which access to cholera health services is quantified. Although the E2SFCA method as proposed by [13] measures access to physicians, this study frames the method around access to bed capacity because physician data is unavailable at the local level in Haiti. The E2SFCA is essentially a weighted bed capacity-to-population ratio and works by first assigning "catchments" around every population location and facility. A catchment is the maximum distance a population is willing to travel for health services and is divided into catchment zones indexed by *r*. Locations within zone *r* of a catchment are denoted by the parameter I_{irj} , which is 1 if facility *j* is within zone *r* of population *i*. Because the catchment size of facilities is the same as that of populations, if facility *j* is within zone *r* of population *i,* then the converse is also true that population *i* is within zone *r* of facility *j.*

Step one of the two-step method calculates the bed capacity-to-population ratio R_j by dividing the supply S_j (bed capacity) by the weighted demand P_i (population) within the catchment of each facility *j*. The demand is multiplied by a catchment zone weight W_r to account for decreasing willingness to travel as the distance to the facility increases. Step two calculates the accessibility A_i for every population location *i* by summing the bed capacity-to-population ratios R_j within the population's catchment and weighting them according to their zone again using weights W_r. The method is summarized below using a case with three catchment zones.

Notation and Parameters:

i	=	index of population locations
j	=	index of facility locations
r	=	index of catchment zones
L	=	set of population locations

F = set of facility locations
I_{irj} = 1 if facility j is within zone r of population i, 0 if not
W_r = willingness-to-travel weight for zone r
R_j = weighted bed capacity-to-population ratio at j
P_i = population of location i
S_j = bed capacity at facility j

Method:

Step 1: For each facility location j, calculate the weighted bed capacity-to-population ratio R_j by dividing the bed capacity S_j by the weighted population in j's catchment.

$$R_j = \frac{S_j}{\sum_{r=1}^{3}\sum_{i\in L} I_{irj}P_iW_r} = \frac{S_j}{\sum_{i\in L} I_{i1j}P_iW_1 + \sum_{i\in L} I_{i2j}P_iW_2 + \sum_{i\in L} I_{i3j}P_iW_3} \quad \forall\ j \quad (1)$$

Step 2: For each population location i, calculate the accessibility A_i by summing the bed capacity-to-population ratios R_j within each catchment zone centered at i and multiply them by the zone weight, W_r.

$$A_i = \sum_{r=1}^{3}\sum_{j\in F} I_{irj}R_jW_r = \sum_{j\in F} I_{i1j}R_jW_1 + \sum_{j\in F} I_{i2j}R_jW_2 + \sum_{j\in F} I_{i3j}R_jW_3 \quad \forall\ i \quad (2)$$

Consider the following example. Figure 3-1 shows one facility location j_1 represented by a square and four population locations (1, 2, 3, 4) represented by dots. The region within the largest circle is the catchment for facility j_1 and each of the three circles represents a catchment zone. Step one divides the bed capacity of facility j_1 by the weighted sum of the populations within catchment j_1. As such, P_1 is multiplied by distance weight W_1, P_2 and P_4 are multiplied by W_2, and P_3 is multiplied by W_3. If there are any other populations outside the catchment, they are ignored. This process is repeated to find the weighted bed capacity-to-population ratios R_j for all facilities j.

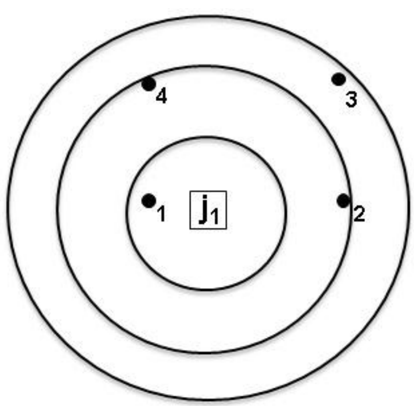

FIGURE 3-1: STEP 1 OF E2SFCA METHOD – CALCULATING R_j

Step two searches all facility locations j within the catchment of population i and sum the weighted bed capacity-to-population ratios. Figure 3-2 below illustrates the process for location 1, where R_1 is multiplied by weight W_1, R_2 and R_3 by W_2. There are no facilities in zone 3. This process is repeated for all populations.

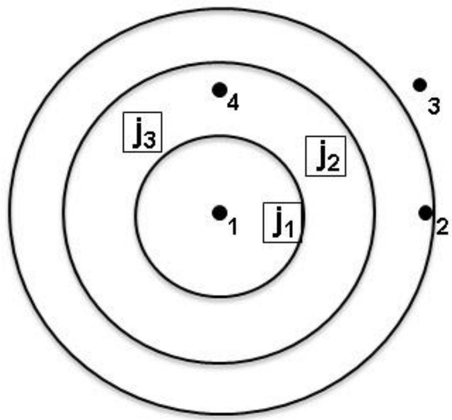

FIGURE 3-2: STEP 2 OF E2SFCA METHOD – CALCULATING A_i

The result of the E2SFCA method is an accessibility measure A_i for every population that includes the effects of distance, supply, demand, and willingness to travel. To aid intuition, the E2SCFA may be thought of as a *weighted capacity-to-demand ratio*. In the most basic case where one facility provides access to exactly one population location and all weights equal 1, A_i is simply a capacity-to-demand ratio, where $A_i = 0$ implies that there is no supply and $A_i = 1$ implies that supply equals demand. Now consider the case shown below in Figure 3-3 where a population location i_1 has access to two facilities, but facility j_1 also serves another population location i_2.

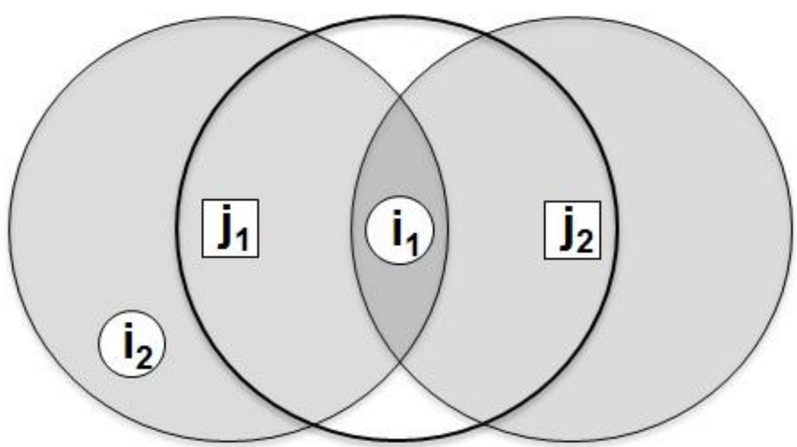

FIGURE 3-3: EXAMPLE OF HOW CHANGE IN SUPPLY AFFECTS A_i

For this example, assume that each facility has a bed capacity $S_1 = S_2 = 50$, and that each population is given by $P_1 = P_2 = 1000$. Here, $\mathrm{R}_1 = \frac{50}{1(1000+1000)} = 0.025$, $\mathrm{R}_2 = \frac{50}{1(1000)} = 0.05$, and the resulting access $A_1 = 1(0.025) + 1(0.05) = 0.075$. To increase A_1 by 10 percent, for example, would require either a 30 percent increase in S_1, a 15 percent increase in S_2, or some combination of the two. Clearly, the addition of more catchment zones, different catchment weights, and more overlap of supply and demand will increases the number of interacting factors that affect access scores. The point is to illustrate that the access score A_i may be considered a weighted capacity-to-demand ratio, and that any improvement in A_i corresponds to *at least* as significant of an increase in available supply relative to demand.

3.2 DATA

The E2SFCA method is applied to quantify access to cholera treatment centers (CTCs) and units (CTUs) in Haiti, beginning with the actual decentralized cholera response. This study requires three types of data: population estimates, cholera treatment facility data, and travel distance estimates.

3.2.1 POPULATION ESTIMATES

Demand for cholera treatment is represented with the population. This is appropriate because cholera was confirmed in all ten departments in Haiti. Also, the Health Cluster used population to identify CTC and CTU shortages via facility-to-population ratios [11]. Since disease spread is uncertain, planners are concerned about access for all.

Haiti is divided into four levels of government: 10 departments (first level), which are divided into 41 arrondissements (second level), 133 communes (third level), and 570 sections (fourth level). Population at the section level is used because it allows us to see the impact of national decisions on a local level. The section population is assumed to be located at the centroid, the geographic center of each section. Of Haiti's 570 sections, 12 (2.1 percent) of the centroid latitude and longitude coordinates contained errors. The centroid coordinates were manually corrected for these points. The source of the population data is the Haitian Institute of Statistics and Information [49, 50], which is the same data used by PAHO and other major response partners [17].

3.2.2 Facility Locations and Capacity

This study uses existing facility locations and bed capacities to evaluate the performance of the decentralized system. Treatment facility data is obtained from the Health Cluster and PAHO [11]. The Health Cluster published CTC and CTU data monthly starting in November 2010. Data from a February 13, 2011 report is selected because the reporting system had matured by February, making the data more reliable than in initial reports. Additionally, by February 13, the number of open CTCs and CTUs had reached a maximum and began to decline in the subsequent months.

Eight of the 96 CTC records (8.3 percent) and 72 of the 188 CTU records (22.3 percent) in the Health Cluster/PAHO dataset do not have bed capacities. Mean bed capacities are substituted where capacity data is missing: 89 beds for CTCs and 25 beds for CTUs. Latitude and longitude coordinates are available for all locations except one CTC (1.0 percent) and three CTUs (1.6 percent). Facilities without coordinate information are not included in the analysis.

3.2.3 Travel Distance and Willingness-to-Travel Estimates

Latitude and longitude coordinates are employed to calculate travel distances between every population and facility, and Great Circle distances are used because of insufficient road network data. A catchment size of 15 kilometers is used because severe cholera cases can be fatal if treatment is not administered within a few hours [1, 2]. Each catchment is divided into three five-kilometer zones, [0, 5], (5, 10], and (10, 15] kilometers for catchment zones $1-3$, respectively. Five kilometers is approximately one walking hour [17]. In Haiti, 80 percent of the population lives below the poverty line and only 3.6 percent own a vehicle [51]. Therefore this study assumes infected persons traveling by foot are unwilling or unable to travel long distances and uses distance weights with a quick decay. Specifically, distance decay weights W_r of 1.0, 0.5, and 0.1 for catchment zones 1 – 3, respectively. Section 3.7 tests the sensitivity of the results to these parameter assumptions.

3.3 Decentralized Access

This section evaluates the accessibility of cholera treatment facilities to section populations during the decentralized cholera response as of February 13, 2011. At this time, a total of 96 cholera treatment centers and 188 cholera treatment units were open throughout Haiti [11]. Using the E2SFCA method, this study finds that the mean access in the 570 sections of Haiti is 0.001030 and maximum access is 0.006091. Thirty-seven the 570 sections, representing 474,286 persons and 4.8 percent of the population, have no access at all according to the chosen measure. The coefficient of variation (CV), a ratio of the standard deviation to the mean, is 94 percent, indicating high variability in access across the sections. Table 3-1 summarizes the decentralized system performance. Figure 3-4 displays a map of access in Haiti and the location of CTCs (denoted by circles) and CTUs (triangles). Sections colored in red, corresponding to low numerical access scores, have little or no access to cholera treatment, and sections in green represent those with the best access and higher numerical access scores. The color scale uses the Jenks natural breaks classification which minimizes the variance within classes (each color represents a class) while maximizing the variance between classes.

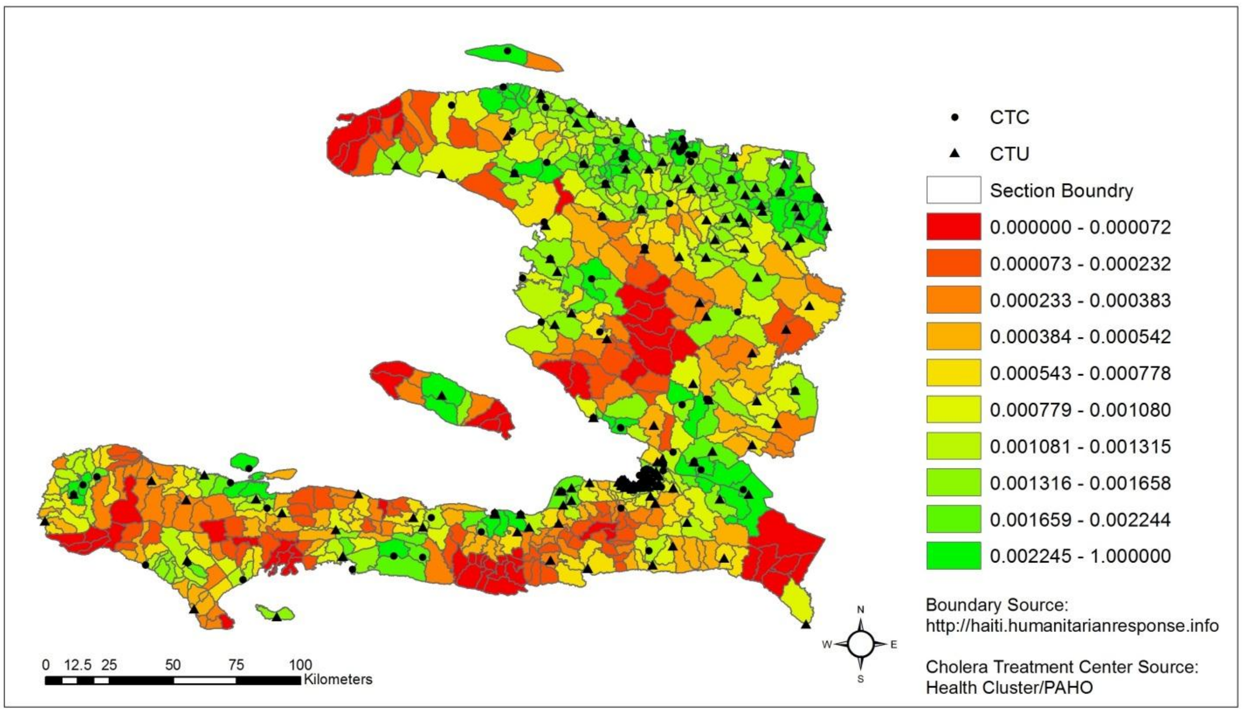

FIGURE 3-4: ACCESS IN DECENTRALIZED SYSTEM

TABLE 3-1: ACCESS STATISTICS FOR DECENTRALIZED SYSTEM

Maximum	0.006091
Minimum	0.000000
Range	0.006091
Mean	0.001030
Median	0.000779
St. Dev.	0.000968
CV	94%
# Facilities	279
Bed Capacity	12,959

Next, this study proceeds to optimize access using a centralized model for location decisions. Centralized results are compared with decentralized system to gauge the relative improvement in accessibility.

3.4 OPTIMIZING ACCESS

Having seen in the previous section that decentralized decision-making can lead to spatial differences in accessibility, here methods for optimizing accessibility are selected and applied to Haiti. Centralized models are hypothetical, intended to represent the accessibility that might be possible if a single planner were directing the response. To select an appropriate method for optimizing cholera treatment facility locations, this section first identifies precisely which factors constitute "good" access. Then it selects additional, candidate facility sites to allow facility locations to be optimized by the integer program.

As mentioned in Section 2.4, efficient and equitable solutions conflict, and sometimes tradeoffs are necessary to achieve a practical solution. In such cases, the "optimal" solution to one planner may not be the "optimal" solution to another. This study identifies five criteria to use as a basis for developing optimization models based on factors that are important in the context of the Haiti cholera response, although similar criteria are broadly applicable to other systems.

- **Adequate**: All populations must have adequate access to cholera treatment. 'Adequate' access is admittedly subjective; however, access for all populations must be (as a minimum) greater than zero.
- **Equitable**: Prefer an absence of systematic disparities in access to treatment facilities [25, 52].
- **Efficient**: Optimal solutions shall make good use of existing resources and not require unnecessary travel.

- **Feasible**: The solution shall use no more resources than the decentralized system.
- **Intuitive**: Methods should be intuitive and explainable to the general public.

Additional facility locations beyond those actually opened in the response are necessary to optimize the location of facilities. First, a discrete set of locations is generated using a grid. The intent is not to locate a facility directly on the candidate latitude and longitude location, but to highlight approximately where one should situate a new facility. Because a tradeoff exists between the accuracy of the location and the solution time, the grid resolution should be small enough to be useful while still computationally feasible. This study uses a 15 kilometer grid that generates 126 candidate facility sites. The candidate sites could be either a CTC or CTU. This doubles the number potential sites, one set for potential CTCs and another for potential CTUs, resulting in 252 candidate sites. The bed capacity at each candidate facility is equal to the mean capacity at a facility of its type in the actual decentralized system, namely 89 beds for CTCs and 25 beds for CTUs. Original facility locations are still possible, so the total number of feasible locations is 532.

3.4.1 Definitions and Methods

Five location models, each with a unique objective function, are presented to examine the tradeoffs between the criteria described previously. This section describes the methods which are common across all models and presents one of the five models. Section 3.4.2 discusses the four other models. The notation, parameters, decision variables and model are summarized below.

Notation and Parameters:

i	=	index of population locations
j,k	=	index of facility locations
r	=	index of catchment zones
L	=	set of population locations
CTC	=	set of CTCs in decentralized response
CTU	=	set of CTUs in decentralized response
$CCTC$	=	set of new candidate CTC locations
$CCTU$	=	set of new candidate CTU locations
F	=	set of all facility locations (*CTC, CTU, CCTC, CCTU*)
C	=	number of CTCs in decentralized response
U	=	number of CTUs in decentralized response
B	=	bed capacity of decentralized response
P_i	=	population of location *i*
R_j	=	weighted bed capacity-to-population ratio at *j*
I_{irj}	=	1 if facility *j* is within zone *r* of population *i*, 0 if not
W_r	=	willingness-to-travel weight for zone *r*
S_j	=	bed capacity at facility *j*

Decision Variables:

A_i = access of population *i*

x_j = 1 if facility *j* is open, 0 if not

Model:

The centralized planner's problem is given by:

$$maximize \quad \sum_{i \in L} P_i A_i \tag{3}$$

$$subject\ to \quad \sum_{r=1}^{3} \sum_{j \in F} x_j I_{irj} R_j W_r = A_i \quad \forall\ i \tag{4}$$

$$\sum_{j \in CTC} x_j + \sum_{k \in CCTC} x_k \leq C \tag{5}$$

$$\sum_{j \in CTU} x_j + \sum_{k \in CCTU} x_k \leq U \tag{6}$$

$$\sum_{j \in F} x_j S_j \leq B \tag{7}$$

$$x_j + x_k \leq 1\ \forall\ \{j = k | j \in CCTC, k \in CCTU\} \tag{8}$$

$$x_j \in \{0,1\}\ \forall\ j \tag{9}$$

Each treatment facility *j* has a Boolean variable x_j that is 1 if the facility is open and 0 if closed. The centralized planner seeks to maximize the population-weighted sum of access in the system as shown in expression (3). This model is referred to as "Max PA." I_{irj} is a parameter that is 1 if facility j is within zone r of population i's catchment, and 0 if not. Constraint (4) calculates the access score, A_i, as defined by Step 2 of the E2SFCA method. Here, access A_i for every population is equal to the product of the bed capacity-to-population ratio R_j, I_{irj}, the distance weight W_r, and the decision variable x_j. Constraints (5) and (6) require that the total numbers of CTCs and CTUs opened in the centralized solution be less than or equal the numbers used in the decentralized system, denoted by C and U, respectively.

Constraint (7) requires the total bed capacity be less than or equal to the bed capacity in the decentralized system B. Constraint (8) stipulates that a maximum of one CTC or CTU can be opened at any candidate site.

3.4.2 Objective Functions

Now four additional objective functions are presented that consider other desirable criteria described in Section 3.4. Each objective is described below. Note that expressions denoted by '*' only apply to the Max PY objective (14).

Max Mean	*maximize*	$\sum_i A_i /\text{n};$	(11)
Min MAD	*minimize*	$\sum_i \lvert A_i - \sum_i A_i/\text{n} \rvert ;$	(12)
Max Min	*maximize*	$min\ A_i ;$	(13)
Max PY	*maximize*	$\sum_i P_i y_i ;$	(14)
	subject to	$A_i - z \leq M y_i;\ \ \forall\ \text{i};$	(15)*
		$A_i - z \geq -M(1 - y_i);\ \ \forall\ i;$	(16)*
		$\text{y}_\text{i} \in \{0,1\} \quad \forall \quad i;$	(17)*

Maximizing the mean access (11) and maximizing the population-weighted sum (3) seek to maximize efficiency. Minimizing the mean absolute deviation (MAD) (12) improves equity. Maximizing the minimum access (13) and maximizing the sum of $P_i y_i$, the population with accessibility greater than some threshold z (14), represent adequacy. Constraints (15-17) only apply Max PY (14) and define the decision variable y_i, which is 1 if A_i is greater than or equal to threshold z, and 0 if not. M is a sufficiently large constant. Each of the five objectives is treated as a unique model of the centralized planner's problem, and thus there are five centralized models.

3.5 Centralized Access Results

Using the methods and models described previously, the theoretical accessibility in a centralized system in determined. This section reports the facility locations and the accessibility achieved by the centralized models. Because the accessibility score of each population is a function of location decisions, step one of the E2SFCA method is completed in advance as a model parameter and step two as a constraint in the model. Models are solved via ILOG OPL version 4.2 using a 2.67 GHz MS-7593 computer with 6.00 GB of RAM. All solutions are optimal except the Min MAD; the optimality gap of the partial solution is 25.33 percent. The Max PY model is run with a *y*-value of 0.0065. Table 3-2 below presents a summary of the centralized results. The next section discusses the differences in the access between the five centralized models and compares them to the access present in the decentralized system.

TABLE 3-2: CENTRALIZED ACCESS RESULTS

STATS	Max Mean	Max Min	Min MAD*	Max PA	Max PY
Max	0.013242	0.005648	0.002711	0.012180	0.004777
Min	0.000009	0.000158	0.000063	0.000000	0.000139
Range	0.013233	0.005490	0.002648	0.012180	0.004638
Mean	0.002067	0.001204	0.001083	0.001346	0.001386
Median	0.001865	0.001060	0.001088	0.001052	0.001287
St. Dev.	0.001603	0.000756	0.000321	0.001279	0.000591
CV	78%	63%	30%	95%	43%
# Facilities	276	138	279	256	241
Bed Capacity	12,954	10,081	11,172	12,959	12,946
Run Time (sec)	2.46	4.46	308,859*	2.23	3.31

** Partial solution*

3.6 Comparison of Centralized and Decentralized Results

The five centralized models result in different distributions of access across Haiti. Figure 3-5 contains a box-and-whisker plot to illustrate the impact of the choice of objective function on the minimum, median, maximum, and first and third quartile values of the access scores. Note that outliers have been excluded from Figure 3-5. See Appendix A for a box-and-whisker plot with outliers included. As expected, the spread of access scores is smaller for the equity-oriented model (Min MAD) than for the efficiency-oriented models (Max Mean, Max PA). Min MAD and the two models emphasizing adequate access, Max Min and Max PY, have significantly lower maximum access scores than do the Max Mean and Max PA models. All models, however, achieve an improved median access score in comparison to the actual decentralized system.

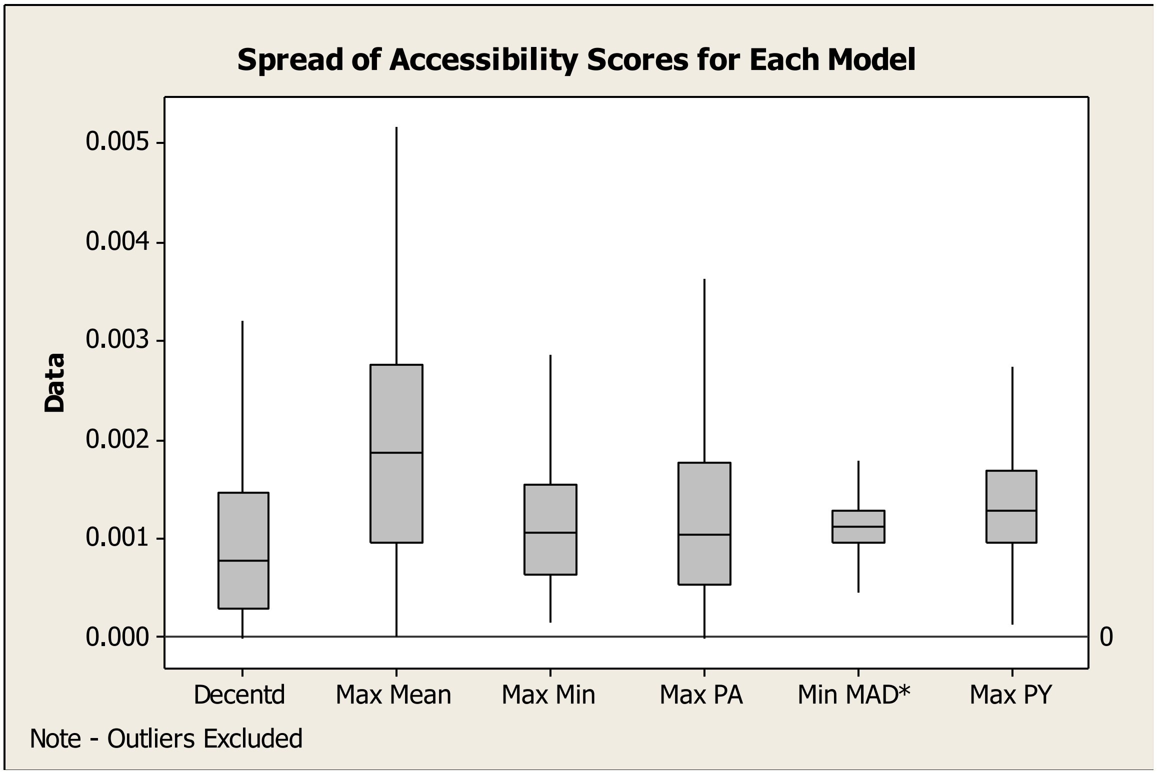

FIGURE 3-5: OBJECTIVE FUNCTION COMPARISON

The impact of the choice of the centralized model on access is most clearly seen in the maps below. Figure 3-6 displays a map of access for each model, again where sections in red have relatively poor access, and sections in green have the best access. Observe that in comparison to the decentralized access map, centralized maps have fewer regions that are red and orange, indicating general improvements in access overall in the centralized systems.

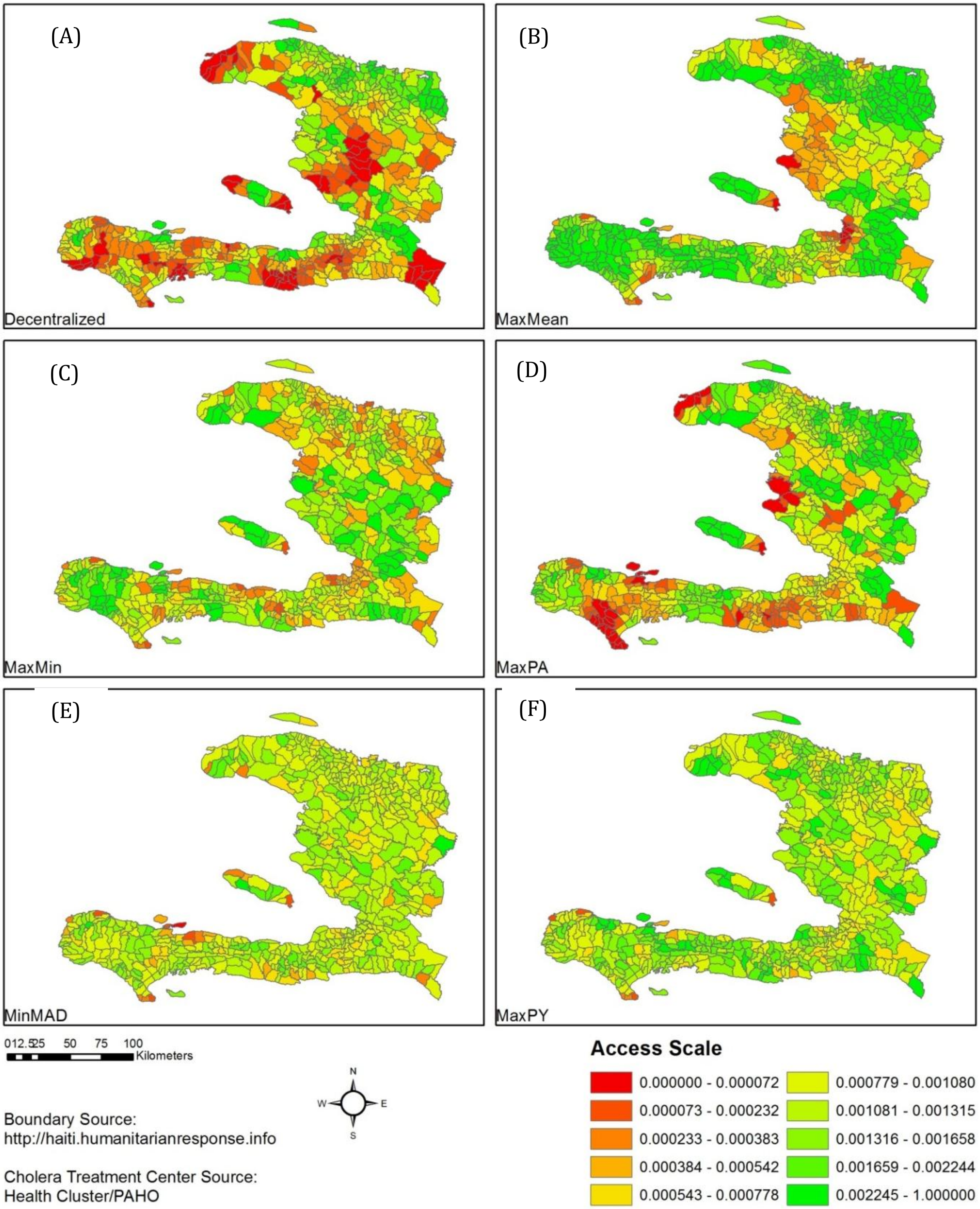

FIGURE 3-6: MAPS OF ACCESS IN THE DECENTRALIZED MODEL (A), AND MAX MEAN (B), MAX MIN (C), MAX PA (D), MIN MAD (E), MAX PY (F) CENTRALIZED MODELS

Table 3-3 presents the difference in access scores between each centralized model and the decentralized model, and Table 3-4 shows the percent change.

TABLE 3-3: CENTRALIZED - DECENTRALIZED RESULTS

	Max Mean	**Max Min**	**Min MAD***	**Max PA**	**PY**
Max	0.007151	-0.000443	-0.003380	0.006089	-0.001314
Min	0.000009	0.000158	0.000063	0.000000	0.000139
Range	0.007142	-0.000601	-0.003443	0.006089	-0.001453
Mean	0.001037	0.000174	0.000053	0.000316	0.000356
Median	0.001086	0.000281	0.000309	0.000273	0.000507
St. Dev.	0.000635	-0.000213	-0.000647	0.000311	-0.000377
CV	-16%	-31%	-64%	1%	-51%
Facilities	-3	-141	0	-23	-38
Bed Cap	-5	-2878	-1787	0	-13

TABLE 3-4: PERCENT CHANGE FROM DECENTRALIZED SYSTEM

	Max Mean	**Max Min**	**Min MAD***	**Max PA**	**PY**
Max	117	-7	-55	100	-22
Min	-	-	-	-	-
Range	117	-10	-57	100	-24
Mean	101	17	5	31	35
Median	139	36	40	35	65
St. Dev.	66	-22	-67	32	-39
CV	-18	-33	-68	1	-55
Facilities	-1	-51	0	-8	-14
Bed Cap	0	-22	-14	0	0

Percentage change in the minimum value is excluded because it divides by zero.

Comparison of the centralized model access to the decentralized access leads us to the following observations:

- The Max Mean model produces the highest maximum, mean, median, range, and standard deviation of access scores.
- The Max Mean solution may not be feasible in practice because it treats all sections equally in calculating the average access score rather than accounting for their respective populations. This results in poor access in areas of highest demand, such as the capital, Port-au-Prince.
- The (partial) Min MAD solution performs well on measures of equity, achieving the smallest range, standard deviation, and coefficient of variation.
- Minimum accessibility is greater than zero in all centralized models except Max PA.

- The Max Min model achieves the best 'worst case' performance with a minimum accessibility of 0.000158 using less than half as many facilities and 22 percent less bed capacity than the decentralized system.
- All centralized models improved the mean and median in comparison to the decentralized model.

Comparing the accessibility of the five centralized models, this study finds that a substantial tradeoff exists between the efficiency and equity of the solutions. For example, the maximum accessibility of the Max Mean model, which emphasizes efficiency, is 388 percent higher than the Min MAD model emphasizing equity. The standard deviation, however, is nearly 400 percent larger, indicating increased disparity in access across the country. Some of the models ensure than everyone has some access (adequacy), while others such as Max PA (efficiency) leave more than 228,000 people (2.3 percent of the population) without any access at all.

3.7 SENSITIVITY ANALYSIS

Due to the uncertainty inherent in the selection of appropriate input parameters, sensitivity analysis is conducted on three key parameters. First, this study examines the impact of greater willingness to travel to receive treatment by replacing the previous distance weights, $W_r = \{1.0, 0.5, 0.1\}$, with $W_r = \{1.0, 0.7, 0.2\}$ for catchment zones 1, 2, and 3, respectively. Second, the impact of larger catchment zones is examined. The default parameter settings included three catchment zones of five kilometers each; now three catchment zones of 10 kilometers each are used. Finally, this section tests the sensitivity of model results to candidate facility bed capacity assumptions by solving the models with optimistic {140, 30} and pessimistic {50, 20} bed capacities for candidate CTCs and CTUs, respectively.

3.7.1 WILLINGNESS TO TRAVEL

The default parameters assume willingness-to-travel weights similar to those used in [13], where $W_r = \{1.0, 0.5, \text{and } 0.1\}$ for catchment zones 1, 2, and 3, respectively. This section looks at the effect on location decisions if the population were less averse to travel. This test uses distance weights $W_r = \{1.0, 0.7, 0.2\}$ and compares the resultant facility location decisions and access scores to the default.

Table 3-5 summarizes the fraction of location decisions in common between the default and new parameter settings for each of the five centralized models. Location decisions are said to be in common if a facility is opened at the location under both the default and new parameter settings or closed under both settings. This measure does not distinguish between the type of facility opened (CTC or CTU) at a candidate site, but rather seeks to quantify the degree to which the models are identifying the same locations at which to open some type of facility.

TABLE 3-5: PERCENT OF FACILITY LOCATION DECISIONS IN COMMON BETWEEN MODEL WITH DEFAULT PARAMETERS AND MODEL WITH ALTERNATIVE PARAMETERS

Alternative Parameters	Max Mean	Max Min	Min MAD*	Max PA	Max PY
Increased Willingness to Travel	96%	77%	83%	61%	71%
Larger Catchment Size	91%	69%	71%	57%	62%
Increased Willingness to Travel and Larger Catchment Size	90%	65%	69%	55%	63%
Optimistic Bed Capacities	73%	69%	81%	78%	60%
Pessimistic Bed Capacities	90%	71%	78%	77%	68%

Comparing the location decisions of the two weight sets finds that location decisions within the Max Mean model are most robust to changes in W_r, where 96 percent of the decisions are consistent with default. The other model solutions are also robust, albeit slightly less robust than Max Mean, having 61 to 83 percent of locations in common with those solved under default parameters.

To analyze the effect that the parameter change has on the accessibility achieved by each model, the discussion is centered on the model goals of efficiency, equity, and adequacy. Table 3-6 summarizes the percent change in access resulting from the increase in distance weights. In the Max Mean model, which emphasizes efficiency, the mean decreases by one percent, and the median increases by one percent. Max PA, another efficiency-oriented model, sees a nine and 11 percent increase in the mean and median, respectively. The minimum of the Max Min model, a measure of adequacy, improves by 47 percent. The minimum accessibility achieved by Max PY, which emphasizes adequacy, improves by 67 percent. Finally, the Min MAD model, which emphasizes equity between locations, experiences a 19 percent decrease in the standard deviation and 17 percent decrease in the coefficient of variance. See Appendix B for complete access results.

TABLE 3-6: PERCENT CHANGE (NEW – DEFAULT) WILLINGNESS TO TRAVEL RESULTS

	Max Mean	***Max Min***	***Min MAD****	***Max PA***	***Max PY***
Max	-2%	91%	-17%	-28%	-11%
Min	-100%	47%	46%	-	67%
Range	-2%	92%	-19%	-28%	-14%
Mean	-1%	-8%	-3%	9%	0%
Median	1%	-10%	-3%	11%	-4%
St. Dev.	-9%	12%	-19%	-10%	0%
CV	-7%	21%	-17%	-17%	0%
# Facilities	-4%	-24%	0%	-4%	-13%
Bed Capacity	0%	-12%	0%	0%	-2%

** Partial solution solved to 30.5% of optimal*

Overall, it appears that the access scores are somewhat sensitive to changes in the distance decay weights, but that the higher weights push each model closer toward its goal. Intuitively, this is to be expected because a population that is more willing to travel should have more access to services. The majority of location decisions are unchanged in all models. As noted in [13], more study should be conducted on how to correctly estimate willingness-to-travel parameters.

3.7.2 CATCHMENT RADII

Default model parameters assume a catchment size of 15 kilometers (approximately three walking hours), divided into three five-kilometer zones. This section studies the effect on model results if the catchment radius is increased to 30 kilometers. The catchment is now divided into three 10-kilometer zones given by [0,10], (10,20], and (20,30] kilometers for zones 1-3, respectively.

Table 3-5 summarizes the fraction of location decisions in common between the default and the larger catchment setting for each of the five centralized models. Comparing the location decisions found with different catchment sizes, the Max Mean model finds the most robust location decisions, with 91 percent of locations in common between the default and new parameter settings. The four other models have between 57 and 71 percent of locations in common with the default. The Max Mean locations, although very similar to the default locations, tend to be further from high population areas like Port-au-Prince because the marginal access can be increased most dramatically in sparsely-populated sections. The Max Min model here tends to locate fewer facilities in central Haiti and covers more area with less, using 15 percent fewer facilities than in the default model. Both the Min MAD and Max PY models tend to locate facilities more peripherally, towards the coasts and away from inland Haiti. Finally, the Max PA model now tends to have larger areas without facilities, likely because it can boost the accessibility score by locating nearer to high-population areas while still covering rural areas under the larger catchment.

Moving on to accessibility, Table 3-7 shows the percent change in access between new and default catchment sizes, and the access results are included in Appendix B. The larger catchment results in a 10 to 58 percent decrease in the CV of every model. The decrease can be attributed to the substantial increase in minimum access scores, which improve by 254 to 703 percent for all models except Max PA. For Max PA, the decrease in CV can be attributed to a 58 percent decrease in the maximum access score. Evaluating the results according to the effect on each model's goal finds that the mean access in the Max Mean model decreases by seven percent, the minimum access of Max Min increases by 254 percent, the CV decreases by 58 percent in Min MAD, the mean of the Max PA decreases by one percent, and the minimum access in Max PY model increases by 302 percent.

TABLE 3-7: PERCENT CHANGE (NEW – DEFAULT) CATCHMENT SIZE RESULTS

Test 2	***Max Mean***	***Max Min***	***Min MAD****	***Max PA***	***Max PY***
Max	-25%	12%	-43%	-58%	47%
Min	400%	254%	703%	-	302%
Range	-25%	5%	-61%	-59%	39%
Mean	-7%	-3%	-1%	-1%	-6%
Median	6%	2%	-1%	8%	-7%
St. Dev.	-22%	-36%	-58%	-41%	-15%
CV	-16%	-34%	-58%	-41%	-10%
# Facilities	-5%	-15%	0%	-3%	0%
Bed Capacity	0%	3%	-3%	0%	-7%

** Partial solution solved to 12.1% of optimal*

This table reveals that increasing the catchment size typically raises the minimum and reduces the variance among access scores. For the values tested, it appears that the access scores are slightly more sensitive to the catchment size than in catchment weights. A 100 percent change can affect the minimum access score by as much as 700 percent. Therefore if the catchment size is overestimated, accessibility in the system can be severely overstated. Catchment sizes should be carefully selected and further research may be necessary to determine appropriate catchment radii. Perhaps a distinction needs to be made between catchment sizes in rural and urban areas.

3.7.3 Combination of Catchment Size and Weight

Next, the sensitivity to both the slower distance decay and larger catchment radius is considered. Refer again to Table 3-5 for the fraction of location decisions in common between the default and the new parameter settings. This test finds that the Max Mean is still the most robust against parameter changes, with 90 percent of locations unchanged from the solution under default settings. For the other models, the majority of location decisions are unchanged, ranging from 55 to 69 percent.

The effect of combined parameter changes is to narrow the spread of access scores: the maximum access decreases, the minimum increases (for all models except Max PA, which has no change), and the standard deviation decreases for every model. Note that access results of the combined parameters change are not much different from the access resulting from change in catchment size only. The implication to decision-makers is that access results are much more sensitive to catchment size than distance weights, although it is important to note that a change in catchment size also implies a change in willingness to travel. For example, doubling the catchment size implies that people are much more willing to travel, even if the willingness-to-travel weight remains unchanged. Perhaps future work should be undertaken to better understand the link between the two. Table 3-8, below, shows the percent change in accessibility between the new and default parameters, and the access results are included in Appendix B.

TABLE 3-8: PERCENT CHANGE (NEW – DEFAULT) FROM DEFAULT CATCHMENT SIZE, WEIGHTS

	Max Mean	***Max Min***	***Min MAD****	***Max PA***	***Max PY***
Max	-33%	-46%	-36%	-68%	-49%
Min	167%	304%	784%	-	360%
Range	-33%	-56%	-55%	-68%	-61%
Mean	-7%	-6%	-1%	-4%	-15%
Median	5%	2%	-1%	17%	-11%
St. Dev.	-24%	-56%	-63%	-56%	-50%
CV	-18%	-54%	-63%	-54%	-41%
# Facilities	-6%	-12%	0%	-2%	-2%
Bed Capacity	0%	2%	-5%	0%	-15%

** Partial solution solved to 6.7% of optimal*

3.7.4 BED CAPACITY AT CANDIDATE SITES

This section proposes two scenarios, optimistic and pessimistic, to test the models' sensitivity to bed capacity assumptions. The default setting uses the mean bed capacities, 89 beds for CTCs and 25 beds for CTUs, as the capacity for candidate CTCs and CTUs. The Health Cluster/PAHO records [11] from which facility data is acquired actually lists two bed capacities for each facility: bed capacity under normal operating conditions, and maximum possible bed capacity. Default settings use the normal bed capacity, but the optimistic test uses the average of the maximum capacities: 140 and 30 beds for CTCs and CTUs, respectively. The pessimistic test uses CTC and CTU capacities of 50 and 20 beds, respectively, corresponding to the first quartile of bed capacities under normal operating conditions. The optimistic setting is a 57 and 20 percent increase in CTC and CTU capacity, respectively. The pessimistic settings represent a capacity decrease of 44 and 20 percent for CTCs and CTUs, respectively. Table 3-9 compares these results with models solved under default parameters, and the access results are provided in Appendix B.

TABLE 3-9: PERCENT CHANGE (OPTIMISTIC – DEFAULT) BED CAPACITY

	Max Mean	*Max Min*	*Min MAD**	*Max PA*	*Max PY*
Max	56%	152%	42%	-52%	37%
Min	-100%	38%	-100%	-	18%
Range	56%	156%	45%	-52%	38%
Mean	25%	38%	1%	-1%	20%
Median	25%	27%	-2%	6%	11%
St. Dev.	53%	89%	43%	-21%	53%
CV	22%	38%	42%	-20%	28%
# Facilities	-36%	-6%	0%	-7%	-20%
Bed Capacity	4%	28%	14%	4%	4%

**Partial solution solved to 34.4% of optimal*

Evaluating these models according to their goals, finds that the average accessibility increases by 25 percent for the Max Mean model, which is to be expected from an increase in capacity. Later the pessimistic setting will result in a 26 percent decrease in the average access for the Max Mean. The average access decreases by one percent for the Max PA model (efficiency). The minimum access score improves by 38 percent for the Max Min model and 18 percent for Max PY. Min MAD and Max PA are the only models that perform worse according to their objectives. For the Min MAD, this is likely due to an increase in *bed capacity* variation, where increasing the capacity of candidate sites increases the variance from the average bed capacity. In fact, four of the five models show significant increases in the CV and standard deviation of access. As will be shown in the following paragraphs, decreasing the variance in bed capacities (pessimistic capacity settings) results in a lower standard deviation in access.

TABLE 3-10: PERCENT CHANGE (PESSIMISTIC – DEFAULT) BED CAPACITY

	Max Mean	***Max Min***	***Min MAD****	***Max PA***	***Max PY***
Max	-43%	20%	-20%	-51%	-27%
Min	378%	-32%	-3%	-	-69%
Range	-43%	21%	-20%	-51%	-26%
Mean	-26%	-35%	-25%	-10%	-22%
Median	-27%	-44%	-25%	-5%	-23%
St. Dev.	-30%	-12%	-25%	-27%	-25%
CV	-5%	36%	0%	-19%	-4%
# Facilities	1%	-9%	0%	9%	15%
Bed Capacity	-11%	-33%	-24%	-3%	-16%
Run Time (sec)	23%	-7%	-	1%	-19%

**Partial solution solved to 27.2% of optimal*

Table 3-10 shows the percent change in access between the pessimistic and default parameter settings, and the access results are included in Appendix B. The pessimistic bed capacities of {50, 20} beds for CTCs and CTUs, respectively, generally have an adverse impact on access scores. The mean and median are lower in all five models. The average accessibility of the Max Mean and Max PA models decrease by 26 and 22 percent, respectively, which is not surprising given that the overall capacity is lower, reducing capacity-to-demand ratios. The minimum access in the Max Min and Max PY models decline by 32 and 69 percent, respectively. The only model that moves closer toward its goal is the Min MAD, whose standard deviation decreases by 25 percent.

Finally, the location decisions of both models are compared to the default. Comparison reveals that the Max Mean is most robust against a decrease in bed capacity, and the Min MAD is most robust against an increase in bed capacity. The number of locations in common with the default range from 60 percent to 90 percent. The optimistic capacity in the Max Mean model results in locations away from high-population areas. In fact, the model does not open a single facility in Port-au-Prince! Pessimistic capacity does produce a more even distribution of facilities, however. One possible explanation is that the model cannot increase the average access by raising the maximum when capacities are small, so it must compensate by increasing minimum – hence, locating facilities in a more even distribution.

The lesson that decision-makers can take away from these tests is that the access results of the models are moderately to highly sensitive to changes in capacity, but the location decisions are fairly robust to parameter changes. The Max Mean model is the most robust against parameter changes, with 73 percent or more locations in common with the locations of the default model.

3.7.5 Insights From Sensitivity Analysis

These sensitivity tests reveal that the location decisions of the centralized optimization models are moderately to highly robust to changes in the values of distance weights, catchment size, and bed capacity. Between 55 and 96 percent of location decisions remain the same when model parameters are changed.

Access scores, on the other hand, are found to vary as a result of different input parameter values. This is to be expected because access depends directly on both demand (arising from willingness to travel and catchment zone sizes) and on supply (bed capacity). When willingness to travel increases, the maximum and minimum access scores change, but the mean, median, standard deviation, and coefficient of variation of access scores are moderately to highly robust. When the catchment zones are larger, minimum access scores increase significantly across all models. This leads to a decrease in standard deviation and coefficient of variation in access scores. Treatment accessibility is more sensitive to the changes in catchment zone size than changes in willingness to travel, but the two are interrelated. This highlights the importance of understanding the maximum distances individuals may be willing to travel for treatment. Access scores are also moderately sensitive to changes in assumptions about bed capacity. As expected, access scores decrease when candidate sites have smaller bed capacities and increase when this parameter value is larger. The regions of the country in which this assumption is most important are those in which few facilities were actually opened in the decentralized response, because access to treatment in these areas is dependent upon access to the candidate facility sites opened by the centralized optimization models.

3.8 Insights From Chapter 3

This chapter demonstrates that there is a quantifiable difference between the decentralized response in Haiti and a theoretical centralized response. Different models perform better in different areas, but no single centralized model dominates. Coordinated facility location decision-making should account for the tradeoffs between efficiency and equity. These lessons apply more broadly as well, and this research provides one documented case where significant gains in both efficiency and equity could have been possible with the help of a centralized planner.

Of the five models tested, the Max PA model seems most appropriate for use by a centralized planner in an epidemic because it efficiently locates facilities according to demand. The Max PA can overlook low population (low demand) areas, which calls for the design of hybrid models that explicitly integrate the different goals. Chapter 4 presents such a model which is based loosely on the Max PA model but includes an equity constraint that raises the minimum access in the system. A close second, in the author's opinion, is the Max PY model which seeks to maximize the number of persons with access greater than some threshold value. Although less efficient overall than the Max PA model, it ensures that all populations have non-zero access. Care should be exercised when selecting the threshold value, which affects both the location decisions and difficulty of solving the model, and this calls for future research. The Max Mean model, which does not open a *single* facility in high population areas like Port-au-Prince, is not appropriate for use as a humanitarian response model alone. Finally, the Max Min and Min MAD models produce more equitable results but may not constitute the most efficient or effective use of resources. Pure equity-oriented models such as these may be appropriate for situations where fairness is the primary concern, but in the author's opinion, is not suitable for planners' use in a humanitarian response alone. The author advocates for the integration of efficiency- and equity-oriented models.

In many humanitarian responses, centralized decision-making about facility locations may not be feasible. In fact, it may be unrealistic to expect responding organizations to concede complete control over their resources to a centralized planner. Research should be conducted to identify incentives and strategies that encourage cooperation between decentralized organizations and thereby mitigate the effect of decentralization. For example, the Health Cluster could use one of the models presented here to determine shortage areas and provide financial or other incentives for organizations to open facilities in needy areas. Similar incentives are already used in the United States to encourage physicians to locate practices in rural areas [53]. The author advocates for greater awareness about the impact of decentralization on humanitarian response.

4 FACILITY LOCATION IN A DYNAMIC ENVIRONMENT

"The recent surge in new cholera cases reported in the commune of Thiotte (Southeast department) highlights the need for more vigilance in that area, particularly given the fact that the fatality rates in that department are still the highest, nationwide. With the effective or planned withdrawal of most international NGOs, the local health structures still do not have enough capacity to face the challenges of a sudden outbreak of new cholera cases, anticipated especially with the upcoming rainy season" [54].

In Chapter 3, a single point in the history of the cholera response was selected as the basis for study of the population's access to cholera treatment facilities. As the quote above indicates, the operating environment of humanitarian relief situations continuously changing, and in such an environment, static optimization models can only be of limited value. The need exists for a tool that can help decision-makers manage the changing conditions over time.

This chapter presents a rolling-horizon model that can be used to guide location decisions throughout the epidemic response. This model allows decision-makers to account for the extremely dynamic conditions present during humanitarian events, including changes in both supply and demand. Rolling-horizon frameworks allow users simultaneously make optimal or near-optimal decisions at the present time, and generate plans for future months. The model is re-run at fixed time intervals to create a new plan that accounts for the most current information.

The model presented here is intended to be used as a tool to aid decision-makers in making facility location and capacity planning decisions in humanitarian settings. Although applied specifically to the 2010 cholera epidemic in Haiti, the model is presented in the general case so that it can be adapted to future events. Because the formulation is based on accessibility as measured by [13], its primary aim is to improve the efficiency and equity of facility locations amongst the affected population.

Chapter 4 is organized as follows. First, a rolling-horizon facility location model is developed that incorporates the E2SFCA method. Next, access to cholera treatment is optimized using the model and the results are compared with the actual access over the course of the cholera response. Finally, the chapter draws observations from the relative performance of the centralized and decentralized systems.

4.1 ROLLING-HORIZON FACILITY LOCATION MODEL

This section describes the method used to model the response to the cholera epidemic using a rolling-horizon model. It begins with a basic explanation of the approach, summarizes the indices, sets and parameters, and then introduces the model.

Chapter 3 provides five optimization models that have various performance objectives, such as maximizing the efficient utilization of resources or improving the equity in healthcare accessibility amongst all populations. Now one model, the Max PA model, is selected as the basis for further study. The choice of a model is ultimately subjective and any function could be substituted for the Max PA function. This model is chosen, however, because it efficiently locates facilities according to demand. The main drawback to the Max PA was that it had little regard for the equity of access, resulting in a minimum access score of zero in the static model. To compensate for this, an equity constraint is added to raise the minimum access. Thus, this section uses a model that seeks a middle-ground between efficiency and equity, is intuitive, and can be solved quickly.

Demand in Chapter 3 was static and was represented by the section population. Now the demand parameter θ_i^t is substituted for the population parameter P_i to allow for dynamic demand to be incorporated into model. The model considers the optimization of access at the current time, plus a discrete number of periods in the future (known as the *planning horizon*). The objective function is multiplied by a coefficient that decreases with time, giving the greatest significance to nearest time periods. Finally, the model includes several constraints that incorporate some sense of "memory" into the model so that previous period's plans are taken into consideration when creating a new one. The model is summarized below.

Indices:

t = index of time periods for facility decisions, $t = 0, \dots, T$
l = index of time periods for historical facility decisions, $l = 0, \dots, t^0 - 1$
i = index of population locations
j, k = index of facility locations

Sets:

CTC^t = set of CTCs in decentralized response at period t
CTU^t = set of CTUs in decentralized response at period t
$CCTC$ = set of new candidate CTC locations
$CCTU$ = set of new candidate CTU locations
F^t = set of all decentralized and candidate locations at period t (CTC^t, CTU^t, $CCTC$, $CCTU$)
L = set of all population locations

Parameters:

t_0 = current time period, start of planning horizon

T = last time period for facility decisions
τ = planning horizon length (number of periods)
α^t = objective function coefficient for period t
θ_i^t = demand of population i in period t
W_r = willingness-to-travel weight for zone r
R_j^t = weighted bed capacity-to-demand ratio for j in t $(= S_j^t / \sum_{r=1}^{3} \sum_{i \in L} I_{irj} \theta_i^t W_r \;\; \forall \; j, t)$
I_{irj} = 1 if facility j is within zone r of population i, 0 if not
C^t = number of CTCs in decentralized response in period t
U^t = number of CTUs in decentralized response in period t
B^t = bed capacity of decentralized response in period t
N^t = total original facilities in period t $(= C^t + U^t)$
S_j^t = bed capacity of facility j in period t
P_j^t = last period's plan for opening or closing facility j in period t
δ = plan flexibility (percentage)
H_j^l = 1 if facility j was open in period l, 0 if not
h_j = 1 if facility j has been opened before t_0, 0 if not
m = minimum allowable facility life (periods)
f_j^t = relaxation for facilities to be open beyond τ, $(= \max\{0,\; \mathrm{t} - (\tau + \mathrm{t}_0) + (\mathrm{m} - 1)\})$
φ = minimum acceptable accessibility score

Decision Variables:
A_i^t = access of population i in period t
x_j^t = 1 if facility j is open in period t, 0 if not
${}^{+}y_j^t$ = 1 if facility j is closed when planned to be open in period t, 0 if not
${}^{-}y_j^t$ = 1 if facility j is open when planned to be closed in period t, 0 if not
z_j^t = 1 if t is the period in which facility j was first opened, 0 if not

Model:
The centralized planner's problem is given by:

$$\textit{maximize} \qquad \sum_{t=t_0}^{t_0+\tau} \sum_{i \in L} \alpha^t \theta_i^t A_i^t \tag{18}$$

$$\textit{subject to} \qquad \sum_{j \in F^t} \sum_{r=1}^{3} R_j^t I_{irj} W_r x_j^t \; = \; A_i^t \quad \forall \; i, t = t^0 \dots \tau \tag{19}$$

$$\sum_{j \in CTC^t} x_j^t \; + \sum_{k \in CCTC} x_k^t \; \leq \; C^t \quad \forall \; t = t^0 \dots \tau \tag{20}$$

$$\sum_{j \in CTU^t} x_j^t \; + \sum_{k \in CCTU} x_k^t \; \leq \; U^t \quad \forall \; t = t^0 \dots \tau \tag{21}$$

$$\sum_{j \in F^t} x_j^t S_j^t \; \leq \; B^t \quad \forall \; t = t^0 \dots \tau \tag{22}$$

$$x_j^t + \ x_k^t \leq 1 \ \forall \ t = t^0 \ldots \tau, j = k \quad s.t. \ j \in CCTC, k \in CCTU \tag{23}$$

$$P_j^t - \ x_j^t \ \leq \ {}^{+}y_j^t \quad \forall \ j, t = t^0, \ldots, \tau \tag{24}$$

$$x_j^t - P_j^t \ \leq \ {}^{-}y_j^t \quad \forall \ j, t = t^0, \ldots, \tau \tag{25}$$

$${}^{+}y_j^t + {}^{-}y_j^t \leq 1 \quad \forall \ j, t = t^0, \ldots, \tau \tag{26}$$

$$\sum_{j \in F^t} \left({}^{+}y_j^t + {}^{-}y_j^t \right) \ \leq \ \delta N^t \quad \forall \ t = t^0, \ldots, \tau \ \ s.t. \ \ t > 1 \tag{27}$$

$$x_j^t - \ x_j^{t-1} \ \leq \ z_j^t \quad \forall \ j, t = t_0 + 1, \ldots, t_0 + \tau \tag{28}$$

$$x_j^{t_0} - \ H_j^{t_0 - 1} \leq \ z_j^{t_0} \quad \forall \ j \tag{29}$$

$$\sum_{t=t_0}^{t_0+\tau} z_j^t + \ h_j \leq \ 1 \quad \forall \ j \tag{30}$$

$$\sum_{l=0}^{t_0-1} H_j^l + \sum_{t=t_0}^{t_0+\tau} \left(x_j^t + z_j^t \ f_j^t \right) \geq \ m \left(\sum_{t=t_0}^{t_0+\tau} z_j^t + h_j \right) \quad \forall \ j \tag{31}$$

$$x_j^t, {}^{+}y_j^t, {}^{-}y_j^t, z_j^t \in \{0,1\} \ \forall \ j, t = t^0, \ldots, \tau \tag{32}$$

$$A_i^t \geq \varphi \quad \forall \ i, t = t^0, \ldots, \tau \tag{33}$$

The centralized planner seeks to maximize the demand-weighted sum of access in the system as shown in expression (18). The objective function coefficient α^t, which uses larger values of α^t for t early in the planning horizon, causes the model to prioritize access in the earlier periods but still account for access in later periods of the horizon. Each treatment facility *j* has a Boolean decision variable x_j^t that is 1 if the facility is open and 0 if closed in period *t*. I_{irj} is a parameter that is 1 if facility *j* is within zone *r* of population *i*'s catchment and 0 if not. Constraint (19) calculates the access score A_i^t according to Step 2 of the E2SFCA method. Here, access A_i^t for every population and period is equal to the product of the bed capacity-to-demand ratio R_j^t, I_{irj}, the willingness-to-travel weight W_r, and the decision variable x_j^t. Constraints (20) and (21) require that the total number of CTCs and CTUs opened in the centralized solution be less than or equal to the number used in the decentralized system for a given period *t*, denoted by C^t and U^t, respectively. Constraint (22) dictates that the total bed capacity be less than or equal to the bed capacity in the decentralized system B^t. Constraint (23) allows either a CTC or a CTU, but not both, to be opened at any candidate site in any period.

The next set of constraints is new and specific to the rolling-horizon model. Constraints (24) – (27) limit the number of deviations between the plan and the actual action to a percentage δ of the total number of location decisions N^t. This feature is important so that the model produces robust decisions that do not deviate greatly from the plan produced in prior periods. A large δ-value implies that decision-makers are relatively inflexible to changes after a facility location plan is produced, and a low δ implies that decision-makers do not mind altering plans. Constraints (24) and (25) define the decision variables ${}^{+}y_j^t$ and ${}^{-}y_j^t$ such that ${}^{+}y_j^t$ is 1 when a facility is closed that was previously planned to be open, and ${}^{-}y_j^t$ is 1 when a facility is opened when planned to be closed. Constraint (26) prevents the values of ${}^{+}y_j^t$ and ${}^{-}y_j^t$ from both equaling 1, which if true, would mean that a facility was simultaneously planned to be both open and closed. Constraint (27) says that the summation of all plan deviations must be less than or equal to given percentage δ of the total number of facilities for all periods in the horizon.

The next set of constraints requires that if a facility is opened, it must stay open at least *m* periods. Without this feature, facilities could be opened and closed any time with no consequences. In reality, there are costs associated with opening and closing facilities, such as the transportation expenses for moving staff, patients, and medical supplies, or costs that are more difficult to quantify such as human lives lost while the facility was inoperable. As a result, this work does not attempt to estimate the cost, but models the situation by assuming that a planner has a limited number of (facility) resources and must choose if and when to open a given facility at most one time.

Constraints (28-29) calculate z_j^t, which is 1 for facility *j* at period *t* when the facility is open at *t* but was closed previously in *t*-1. Constraint (28) applies to all future periods in the planning horizon, and Constraint (29) applies to period t_0 and the case where facility j was open prior to period t_0. Constraint (30) dictates that a facility can only be opened one time, and if it was opened previously ($h_j = 1$) then it cannot be reopened in the current horizon. Constraint (31) requires that if a facility is opened, it must stay open for at least *m* periods. (Since (30) prevents a closed facility from being reopened, the combination of (29) and (30) forces the facility to stay open *m consecutive* periods). The sum of open facilities in model history H_j^l plus the sum of open facilities must be greater than or equal to *m* times whether or not the facility has ever been opened. The expression $z_j^t f_j^t$ is added to the sum of x_j^t's in (31) because without it the model would never open a facility within *m* periods of the end of the horizon. The value of parameter $f_{\mathrm{j}}^{\mathrm{t}}$ is calculated outside the model and is given by $f_j^t = max\{0,\ t - (\tau + t_0) + (m-1)\}$. Choose the maximum of the two terms ensures that f is never zero. Constraint (32) requires the values of x_j^t, z_j^t, ${}^{+}y_j^t$ and ${}^{-}y_j^t$ to be Boolean.

Finally, Constraint (33) stipulates that every population's accessibility must be greater than or equal to some constant φ in every period. Because the Max $D_i^t A_i^t$ objective is primarily focused on efficiency, it can overlook sections with low demand. Constraint (33) improves the worst-case performance of the system and results in more equitable solutions.

Consider the following example as shown in Figure 4-1 where the current period $\mathrm{t}_0 = 4$ and the planning horizon $\tau = 3$ periods. For simplicity, consider just one facility j. If opened, the facility must stay open at least $m = 4$ periods. The facility has never before been opened ($h_\mathrm{j} = 0$ and $\sum_{\mathrm{l=o}}^{\mathrm{t_0}-1} H_\mathrm{j}^\mathrm{l} = 0$). The value of parameter f_j^t, calculated outside the model, is found by $f_j^t = max\{0, t - (\tau + t_0) + (m-1)\}$.

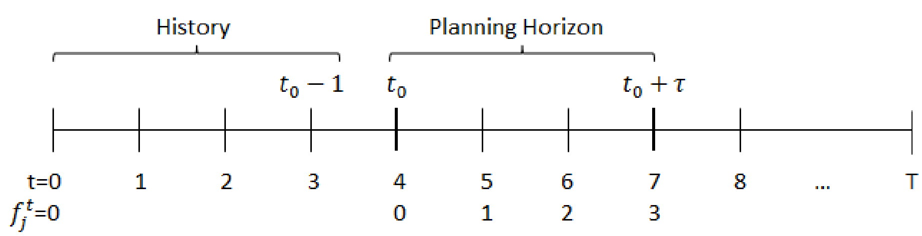

FIGURE 4-1: ROLLING-HORIZON MODEL EXAMPLE

Constraint (31) in this example then reduces to:

$$0 + \left(\mathrm{x_j^4} + \mathrm{z_j^4}(0)\right) + \left(\mathrm{x_j^5} + \mathrm{z_j^5}(1)\right) + \left(\mathrm{x_j^6} + \mathrm{z_j^6}(2)\right) + \left(\mathrm{x_j^7} + \mathrm{z_j^7}(3)\right) \geq\ 4\left(\sum_{\mathrm{t=t_0}}^{\mathrm{t_0+\tau}} \mathrm{z_j^t} + 0\right) \quad (34)$$

The program can now choose to open the facility in any, all, or none of the time periods in the planning horizon. Constraint (30) prohibits a site from being opened more than once by requiring that the sum of all z_j^t variables within the horizon to equal no more than one. The model cannot choose $\{x_j^4, x_j^5, x_j^6, x_j^7\} = \{1,0,0,1\}$, for example, because both z_j^4 and z_j^7 would equal 1, violating constraint (30). Therefore, if the model chooses to open a facility, it must stay open at least four consecutive periods. Consider the case if facility j is opened in period 6. Expression (34) then becomes:

$$0 + (0 + 0) + (0 + 0) + \left(1 + (1)(2)\right) + (1 + 0) \geq\ 4(1 + 0)$$

This means that $x_j^6 = 1$ and $z_j^6 = 1$. Thus, the right-hand side must be 4, and to satisfy this, expression (34) requires that x_j^7 also equal 1. If the sum of the right-hand side could not equal one, then the solutions {1,0,0,1} would be infeasible. Now consider the case if the model chooses to open no facilities, in which case (34) is:

$$0 + (0 + 0) + (0 + 0) + (0 + 0) + (0 + 0) \geq 4(0 + 0)$$

Here, since the facility has never been opened nor is opened in the current planning horizon, both sides of the equation equal zero and {0,0,0,0} is a feasible solution. Alternatively, consider the situation in which facility *j has* been opened previously. Then $h_j = 1$ and $\sum_{l=o}^{t_o-1} H_j^l \geq 0$. In this case, Constraint (30) prevents the value of z_j^t from being greater than 0 in any time period. If *j* was open in period $t_0 - 1$, then it would be forced to stay open until the sum of open periods was at least *m*. If $h_j = 1$ but *j* was *not* open in period $t_0 - 1$, then $\{x_j^4, x_j^5, x_j^6, x_j^7\}$ would equal {0,0,0,0} because facility *j* would have been opened and closed prior to the planning horizon, and could not be reopened.

4.2 DATA

This method is applied to the location of CTCs and CTUs in the Haiti cholera response between February and August, 2011. The data sources in this chapter are the same as in Chapter 3 plus the addition of cholera case count data for demand. The number of cholera cases per department per month is acquired from the Ministry of Public Health and Population (MSPP) in Haiti [6], a Health Cluster partner. Population estimates are obtained from the Haitian Institute of Statistics and Information [49, 50] to disseminate the estimates to the section-level.

Cholera treatment facility data comes from the Health Cluster/PAHO. Chapter 3 uses data from a February 13, 2011 report. Chapter 4 uses facility location and capacity data compiled from reports dated February 13 through August 1, 2011 [11]. Candidate facility locations are modeled as in Chapter 3, but now use bed capacity averaged over the seven months between February and August, 80 beds and 30 beds for CTCs and CTUs, respectively.

The catchment size and weights are the same as the default settings in Chapter 3: a 15-kilometer catchment divided into three five-kilometer zones and willingness-to-travel weights W_r given by {1.0, 0.5, 0.1} for zones 1-3, respectively. The objective function coefficients α^t equal {0.535, 0.268, 0.130, 0.067}, where each time period is weighted by half the preceding period's weight, similar to the method used in [36]. The minimum accessibility parameter $\varphi = 0.02$, which is as high as possible without causing the problem to be infeasible. This study limits the number of allowable changes in any given period δ to 25 percent of all location decisions. The planning horizon length τ is three periods into the future. Admittedly this value is arbitrary, but the author argues that $\tau = 3$ is reasonable because the uncertainty inherent in estimating conditions more than three months in advance makes such attempts futile. Finally, this study considers scenarios where the minimum allowable facility life m is equal to two or three periods, respectively. Thus, Chapter 4 presents three models: decentralized (D), centralized where $m = 2$ (M2), and centralized where $m = 3$ (M3).

It is important to note that the demand used in Chapter 4 is the number of cholera cases per month and therefore accessibility results cannot be compared with Chapter 3 which uses population as demand. Previously, demand (population) was much greater than supply, resulting in access values of less than one. Now, supply is often greater than demand, which can be zero or close to zero. This is problematic for the bed capacity-to-demand ratio used in the calculation of the E2SFCA and R_j^t approaches infinity as demand approaches zero. The high ratio values interfere with the model performance when R_j^t is abnormally large for areas with low demand, it actually locates facilities opposite of the way it was intended, towards populations with very little demand.

To address this problem, R_j^t is set to zero when demand is zero. This discourages the model from locating facilities in areas that have no cholera cases. When demand is greater than zero but less than the average CTU bed capacity, the demand is modified to equal 30, the average CTU capacity. Rounding up ensures that no infected populations are overlooked, and setting the demand to the CTU capacity reduces the maximum value of R_j^t to values that do not cause significant interference. This method, as opposed to setting the maximum value of $R_j^t = 1$, for example, is chosen because the model should reflect the reality of the access in system, which may in fact have bed capacity-to-demand ratios greater than 1. Any interference with the bed capacity ratios should *overstate* demand, ultimately resulting in too much coverage, not too little.

4.2.1 Limitations

The research in Chapter 4 is limited by the quality of treatment facility data available. In humanitarian responses where the event is unexpected and the need is urgent, databases are often implemented after the fact in an ad hoc fashion, resulting in poor design and performance. Analysis of monthly facility location reports reveals a significant number of duplicate entries, as well as discrepancies in longitude and latitude coordinates over time and bed capacities over time. Although reports from November 2010 through January 2011 exist, they cannot be used in this analysis because the facilities do not have unique identifiers that allow the location to be traced over time. For the months between February and August, which do have unique facility identifies, 448 unique locations are identified. Of these facility records, 52 percent have at least one change in coordinate values, and 50 percent have at least one change in capacity. The mode is used for conflicting locations or capacities, and in the case of a tie, the first value is selected.

Although not perfect, the Health Cluster/PAHO data is, to the author's knowledge, the best available and the only comprehensive source for treatment facility data. This issue points to the continued need for the development of robust and practical record keeping practices that work well in humanitarian responses. Part of the value of this work is to reveal the benefit of capturing higher quality data. This paper proceeds to show the feasibility and potential benefit of using a rolling-horizon model to improve the accessibility and equity of clinic locations during humanitarian response.

4.3 ACCESS RESULTS AND COMPARISON

Using the methods and models described previously, this section reports the access which section populations had to cholera treatment facilities during the seven-month span between February 13 and August 1, 2011. This section reports on the accessibility and the facility locations found by the three models D, M2 and M3. Models are solved via ILOG OPL version 4.2 using a 2.67 GHz MS-7593 computer with 6.00 GB of RAM. All models in all periods are solved to an optimality gap of 0.08 percent with the exception of the first period of M3, which is solved to within 9.1 percent of optimal.

Table 4-1 presents each model's objective value from every period. Comparing the performance of the three models finds that the centralized models significantly outperform the decentralized system in every period. The total objective value of M2 is 33 percent higher than D, and M3 is 25 percent higher. These differences demonstrate the capability of the rolling-horizon method to make a substantial improvement to the overall performance of the response effort.

TABLE 4-1: OBJECTIVE VALUES OF THE DYNAMIC MODELS

Period	*Dec*	*M2*	*M3*
1	10,373.3	12,360.2	10,598.4
2	9,250.5	11,756.2	10,203.8
3	7,672.0	10,264.5	10,055.9
4	7,190.6	9,917.7	9,918.0
5	6,276.8	8,835.8	8,663.6
6	4,951.7	7,034.5	6,945.7
7	2,911.1	4,583.7	4,459.4
Total	*48,626.0*	*64,752.6*	*60,844.8*

Figure 4-2 shows a histogram of the objective values over time. During the first and second periods M2 significantly outperforms M3, but over time the objective values converge. This could be due to the fact that M3 may be as far as 9.1 percent from optimal in period one. Over all periods, however, the two centralized models surprisingly perform nearly identically. This study finds that increasing the number of periods an open facility must remain open has very little effect on the overall performance. Also note in Figure 4-2 that the objective values of ALL models decline over time, a result of the closure of many CTCs and CTUs between April and August, 2011 (see Figure 1-3). This decrease in treatment capacity adversely affects the access achieved by all models.

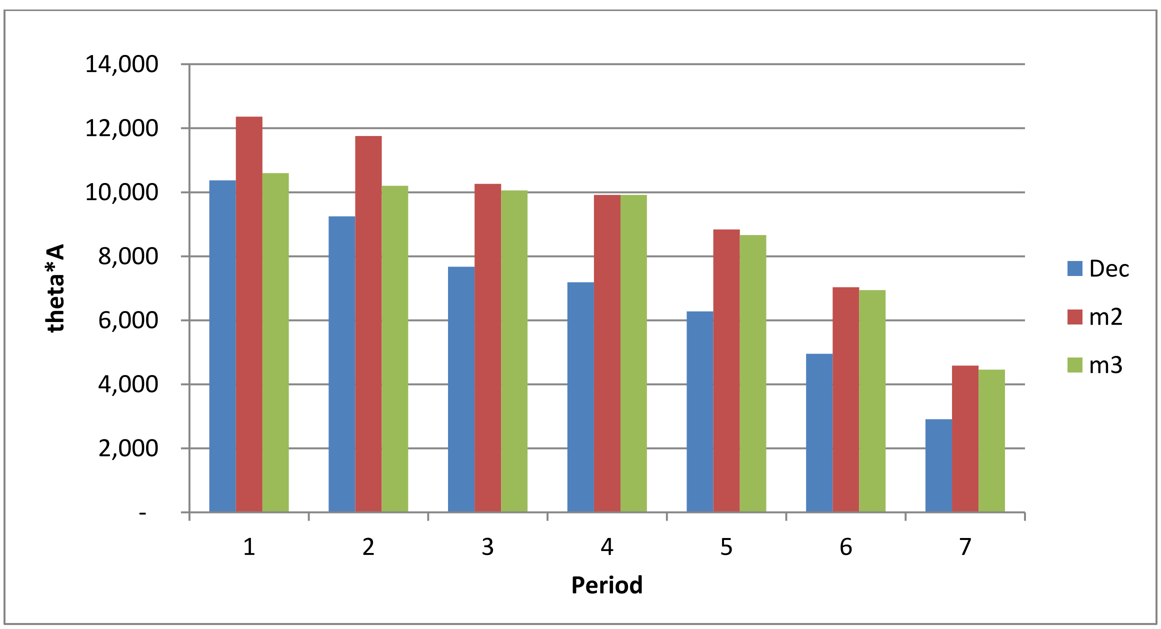

FIGURE 4-2: OBJECTIVE VALUES FOR EACH TIME PERIOD

Finally, this work finds that there is a cumulative effect of the models and the relative improvement of the centralized models increases over time. Figure 4-3 illustrates the increasing percent change for M2 and M3. The impact centralized rolling-horizon model is greatest in periods where resources are most scarce.

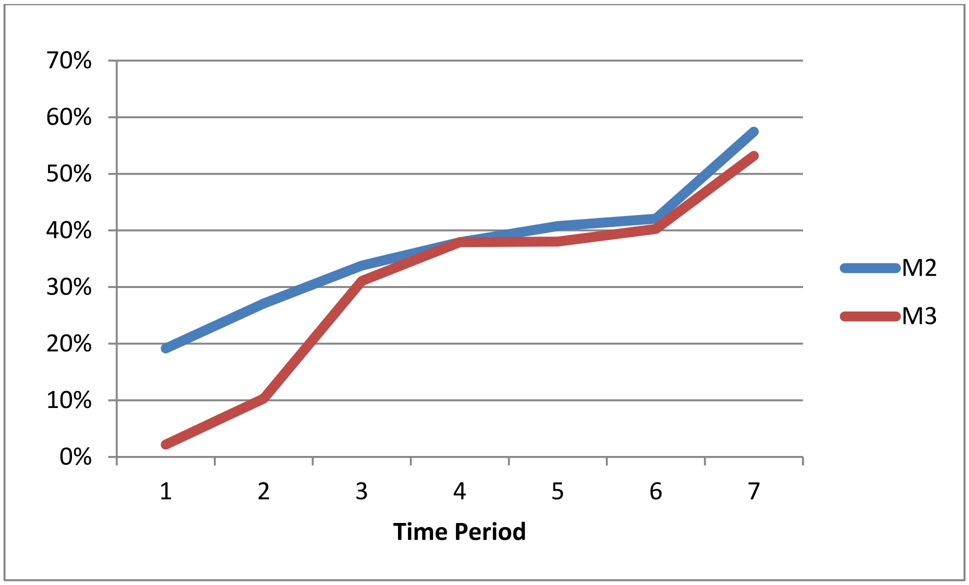

FIGURE 4-3: PERCENT CHANGE FROM THE DECENTRALIZED MODEL OVER TIME

Now the focus is turned from the aggregate, nation-wide results to the implications at the local, section-level. Table 4-2 presents the accessibility results of the three models, and Table 4-3 shows the percent change between the centralized and decentralized models.

TABLE 4-2: ACCESS RESULTS FROM ROLLING-HORIZON MODELS

	Mean	St Dev	CV	Min	Q1	Median	Q3	Max	Range	IQR
Dec	0.29	0.41	141.98	0.00	0.07	0.18	0.36	5.68	5.68	0.29
m=2	0.25	0.38	154.36	0.02	0.07	0.13	0.28	6.87	6.85	0.21
m=3	0.24	0.40	165.02	0.02	0.08	0.14	0.26	9.41	9.39	0.19

TABLE 4-3: PERCENT CHANGE FROM DECENTRALIZED MODEL

	Mean	St Dev	CV	Min	Q1	Median	Q3	Max	Range	IQR
m=2	-14.9%	-7.5%	8.7%	-	-3.9%	-25.6%	-24.6%	20.9%	20.6%	-29.6%
m=3	-16.6%	-3.1%	16.2%	-	6.6%	-23.9%	-28.0%	65.6%	65.3%	-36.3%

The first notable observation is that the minimum access in both centralized models is 0.02 greater than the decentralized model. In the D model an average of 44 sections per period, or total of 309 sections over the seven periods, have no access to treatment facilities at all. Thus the centralized models provide some level of access to 12,260 persons with cholera that did not have access in the actual response.

Secondly, this study finds that the maximum accessibility is 20 to 65 percent higher in the centralized settings, and although this increases the range, the interquartile range (IQR) decreases from 29 to 36 percent. The mean access is 14.9-16.6 percent lower and median access is 23.9-25.6 percent lower in the centralized models than D. Therefore the overall effect of running the Max $\theta_i^t A_i^t$ objective is to improve the minimum access and decrease the disparity in access for the majority of sections in exchange for a moderately lower mean and median (efficiency). Recall from Chapter 3 that the Max PA model was a pure efficiency-focused model, but Chapter 4 trades some efficiency for greater equity. Figure 4-4 below combines the access scores from every time period and shows the spread for each model. Note that the outliers have been excluded; see Appendix A for boxplots with outliers.

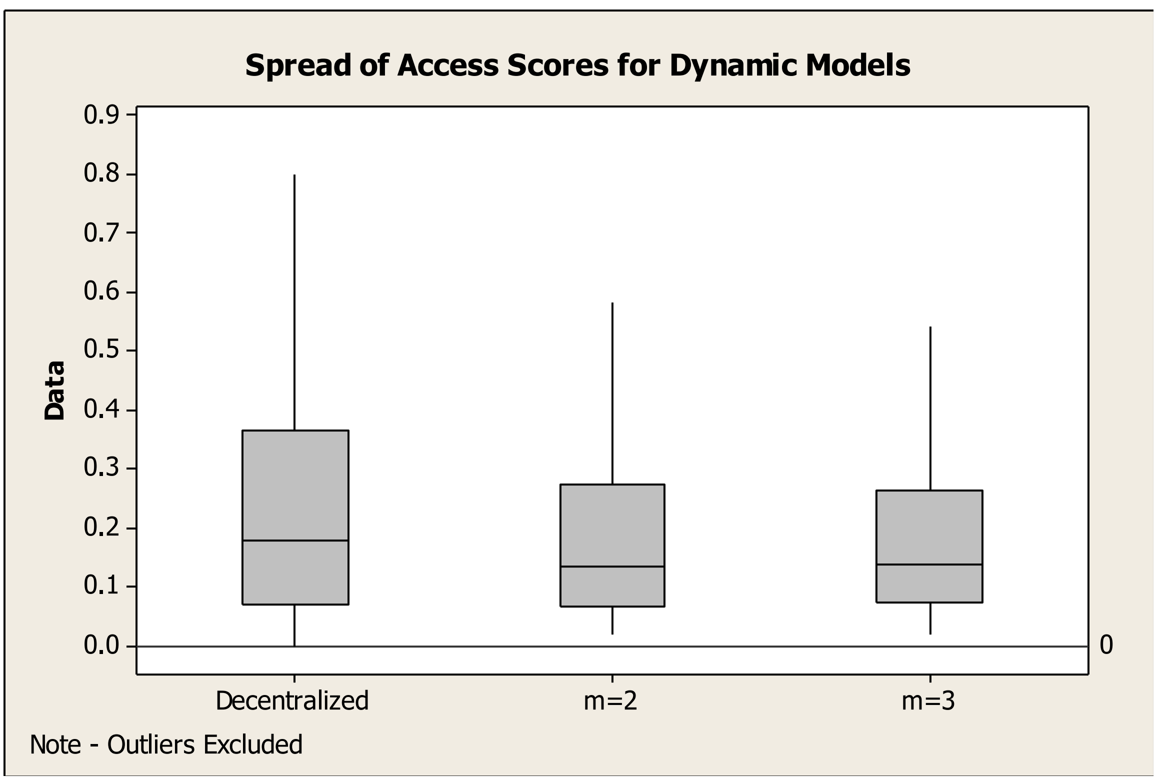

FIGURE 4-4: SPREAD OF ACCESS SCORES FOR DYNAMIC MODELS

The impact of the centralized models on access is clearly illustrated in the maps on the following page. Figures 4-5 and 4-6 display access maps for each model over time, where sections in red have relatively poor access, and sections in green have the best access. Open facilities are denoted by black dots. Observe that, in comparison to the decentralized access map on the left, there are fewer regions that are red and orange, indicating general improvements in access overall in the centralized systems. Additionally, centralized models open more facilities in central Haiti which have the highest number of cholera cases. The areas in green with relatively good access in the centralized models tend to better align with areas of high demand than in the decentralized model. See Appendix C for maps of demand over time.

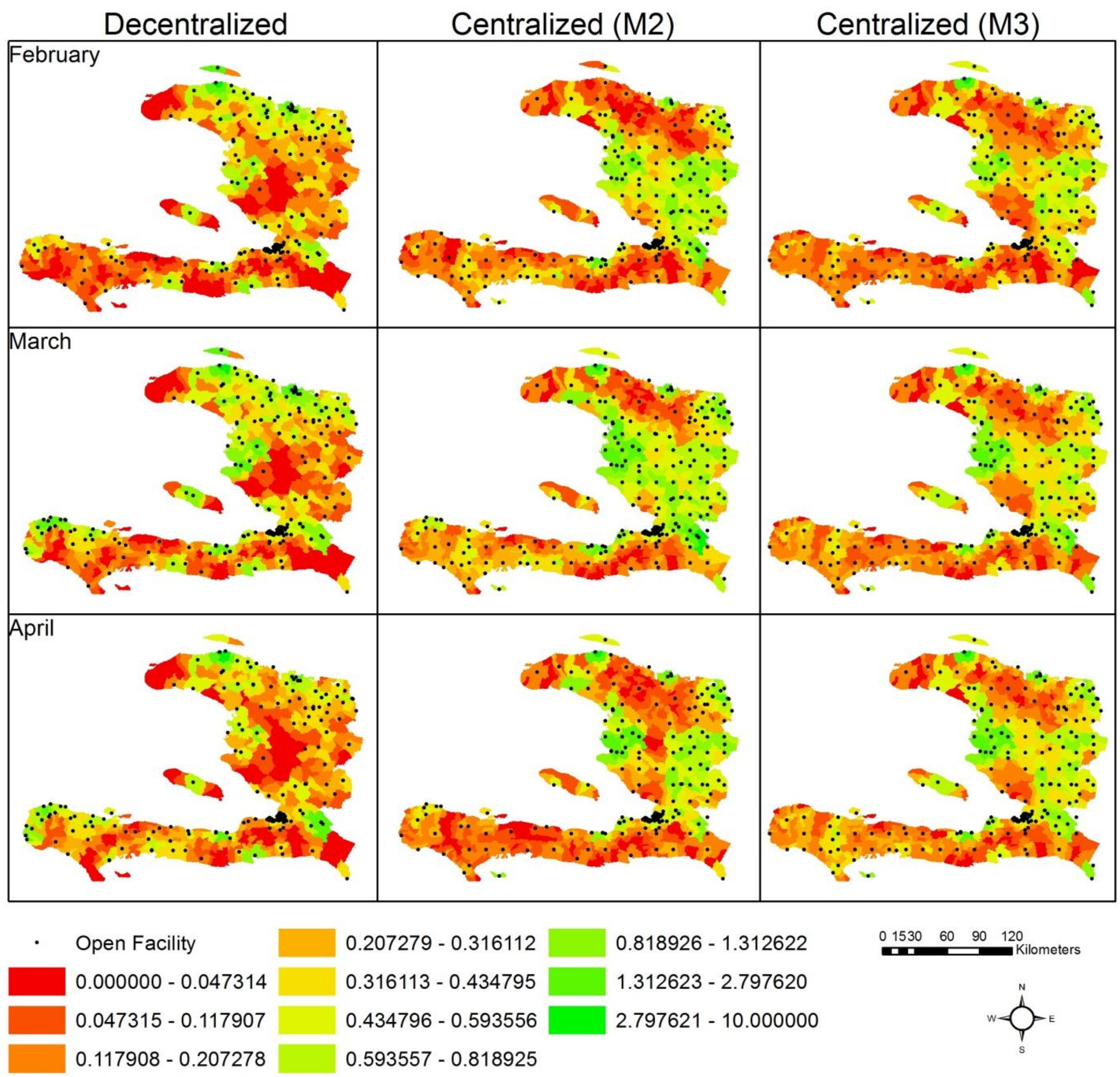

FIGURE 4-5: ACCESS MAPS OF DYNAMIC MODELS (1 OF 2)

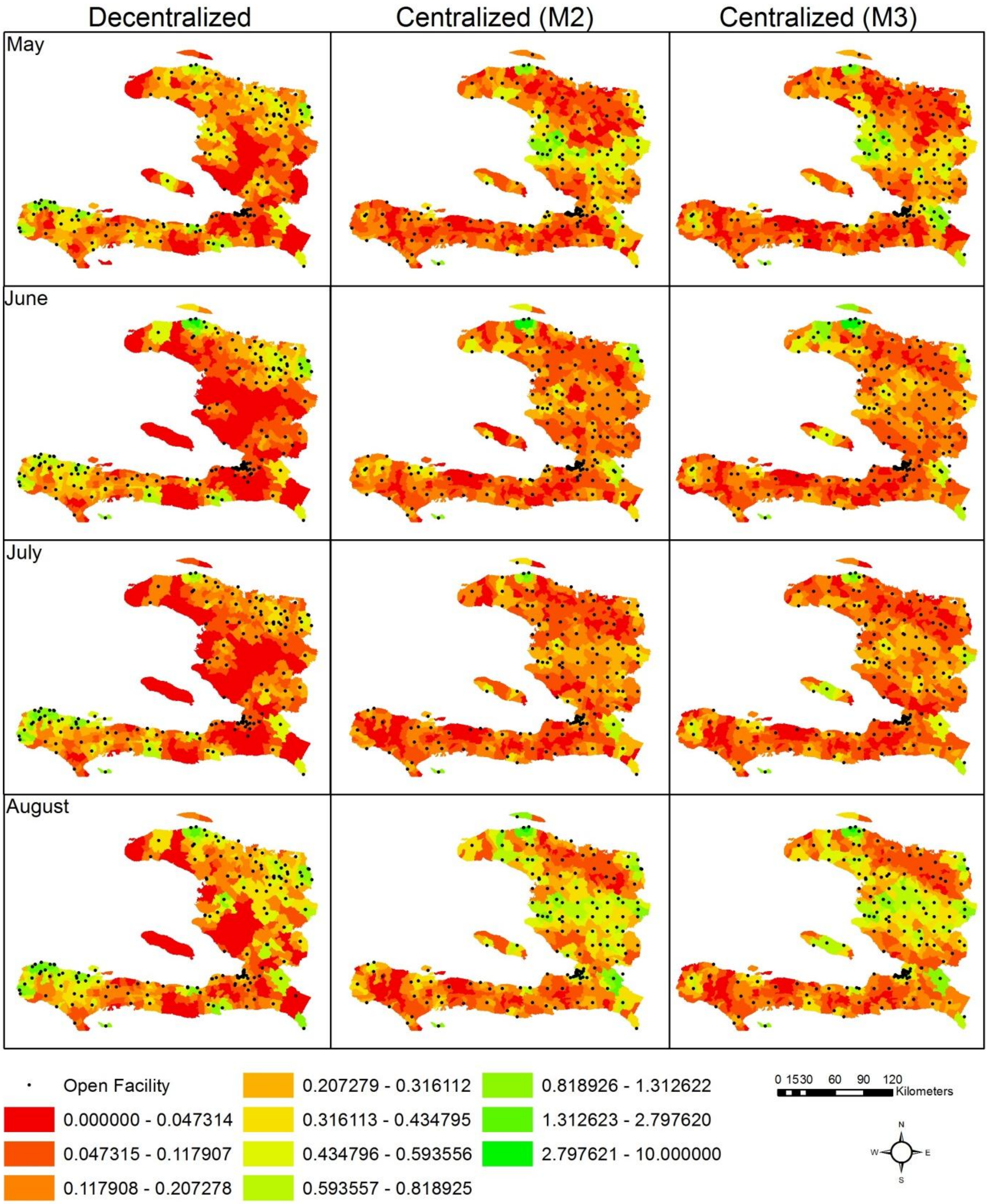

FIGURE 4-6: ACCESS MAPS OF DYNAMIC MODELS (2 OF 2)

4.4 INSIGHTS FROM CHAPTER 4

Chapter 4 introduces two rolling-horizon facility location models that maximize the sum of demand-weighted access as measured by the E2SFCA method. While many have identified that a tradeoff exists between efficiency and equity, few have studied the tradeoffs in the context a real, full-scale humanitarian logistics problem. Here an efficiency-oriented objective, Max $\theta_i^t A_i^t$, is applied with an equity constraint and find a tradeoff solution that considers both efficiency and equity in access. This research finds that decentralization substantially hinders the access and equity of the response in comparison to centralized approaches that are forward-looking in their location decisions. In this study of the cholera response in Haiti, the effect of the centralized rolling-horizon models was cumulative over time and was shown to improve the demand-weighted access by as much as 25-33 percent over the seven month study horizon. In future epidemics, the author recommends dynamic location models over static models to account for the changing conditions that can quickly render static optimization solutions obsolete.

The models presented in the chapter provide a unique application of the E2SFCA that uses actual or forecasted demand rather than population to estimate demand. Doing so uncovers challenges that arise when demand is less than supply – specifically, that bed capacity-to-demand ratios approach infinity when demand approaches zero. This work provides one method to resolve the issue and finds that it successfully mitigates the problem.

Finally, this study is limited by the quality of publicly available data, so the results are presented only to demonstrate the feasibility and potential value of using a rolling-horizon facility location model to improve access in humanitarian response. The author advocates for development of standardized record-keeping practices that work well in chaotic relief environments. Although decision-making in humanitarian response is decentralized, record-keeping practices need not be. Although the Health Cluster already tries to foster cooperation in data collection, further improvements are necessary to realize the full benefits of quantitative location models such as those presented in Chapter 4.

5 CONCLUSIONS AND FUTURE WORK

Since it began in late 2010, the cholera epidemic in Haiti has affected more than half a million people and caused more than 7,000 deaths. Cholera is easily treated if individuals have access to treatment facilities. Due to the large number of actors, urgency of the response, and many other factors, centralization of decision-making power is not realistic in many humanitarian responses. This thesis quantifies the difference between access in the actual, decentralized cholera response in Haiti and a hypothetical centralized one for the purpose of demonstrating the potential value in achieving better coordination in the location decisions of future responses. It demonstrates that operations research techniques can help decision-makers deal with the challenge of making location decisions in such a rapidly changing environment.

This study finds that access varied significantly across Haiti, and in the month of February 2011, thirty-seven the 570 sections, more than 470,000 persons, did not have access to cholera treatment facilities. Using integer programming models to optimize accessibility, this work shows a quantifiable difference between the decentralized response in Haiti and a theoretical centralized response. Five optimization models are presented to illustrate various tradeoffs between efficiency and equity, and no single model dominates. Some models, such as the Max Mean and Min MAD models, are not appropriate for use in a planning function in humanitarian response if applied alone without incorporating other concepts. The author recommends that facility location models in public health include concepts of both efficiency and equity, and therefore find a compromise between the two. Sensitivity analysis shows that location decisions in the models are robust against changes in parameters, but the access scores are less robust, especially to changes in the size of the catchment.

This paper also demonstrates the value and feasibility of using a dynamic facility location model to account for the uncertainties so prevalent in public health. It presents a rolling-horizon facility location model that integrates concepts of both access and equity. The centralized model improves the overall performance of the system by as much as 25-33 percent over the seven month study horizon, and the impact was greatest during periods of greatest resource limitation. This work demonstrates that such dynamic location models can provide useful decision-support to planners. Together, these contributions represent important advances that have the potential to improve humanitarian response.

This work leads to several areas of future research. First, it points to the need for coordination mechanisms in humanitarian response. Many have studied coordination mechanisms in commercial supply chains, but more work should be undertaken in the humanitarian and public health fields. Second, the uncertainty surrounding both modeling parameters and the response itself highlights the need for further study in developing robust optimization approaches. Such models could also incorporate both stochastic and dynamic inputs. Third, Chapter 4 was limited due to the quality of data available. For the full benefits of quantitative location models to be realized, this is an area that must see improvement. The author advocates for development of standardized record-keeping practices that work well in chaotic relief environments. Finally, this work highlights the need for further study of E2SFCA method parameters including catchment size and willingness-to-travel weights. Perhaps a distinction should be made between rural and urban applications.

In conclusion, this research supports the following recommendations:

1. Use an access model that measures access at an individual level of aggregation rather than higher levels, such as a department-wide supply-to-demand ratio.
2. Use an efficiency-oriented location model with an equity constraint, similar to that provided in Chapter 4, to locate facilities in future epidemic responses.
3. Develop new location models that integrate both efficiency and equity concepts to find locations that compromise between the two extremes, each of which is undesirable.
4. Identify incentives and strategies that encourage cooperation between decentralized agencies and mitigate the effect of decentralization.
5. Advocate for greater public awareness about the impact of decentralization on humanitarian response.
6. Use dynamic location models rather than static models to account for changing supply and demand conditions.
7. Standardize data collection and record-keeping practices that work well in the relief environments.

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APPENDIX A: ACCESS BOXPLOTS WITH OUTLIERS

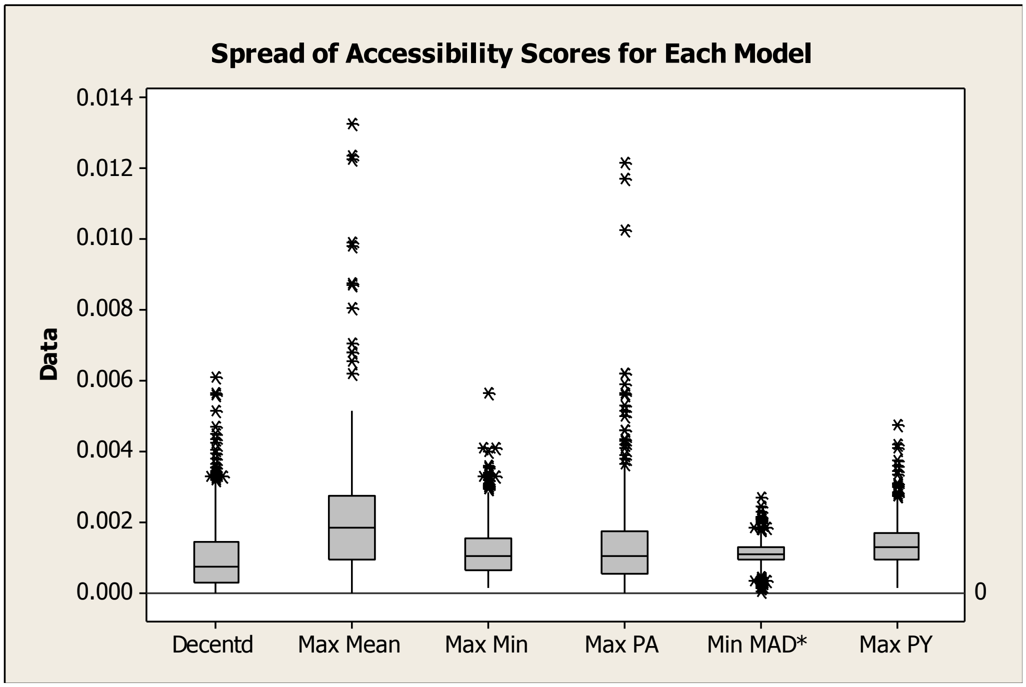

FIGURE A-1: SPREAD OF ACCESS SCORES FOR STATIC MODELS, OUTLIERS INCLUDED

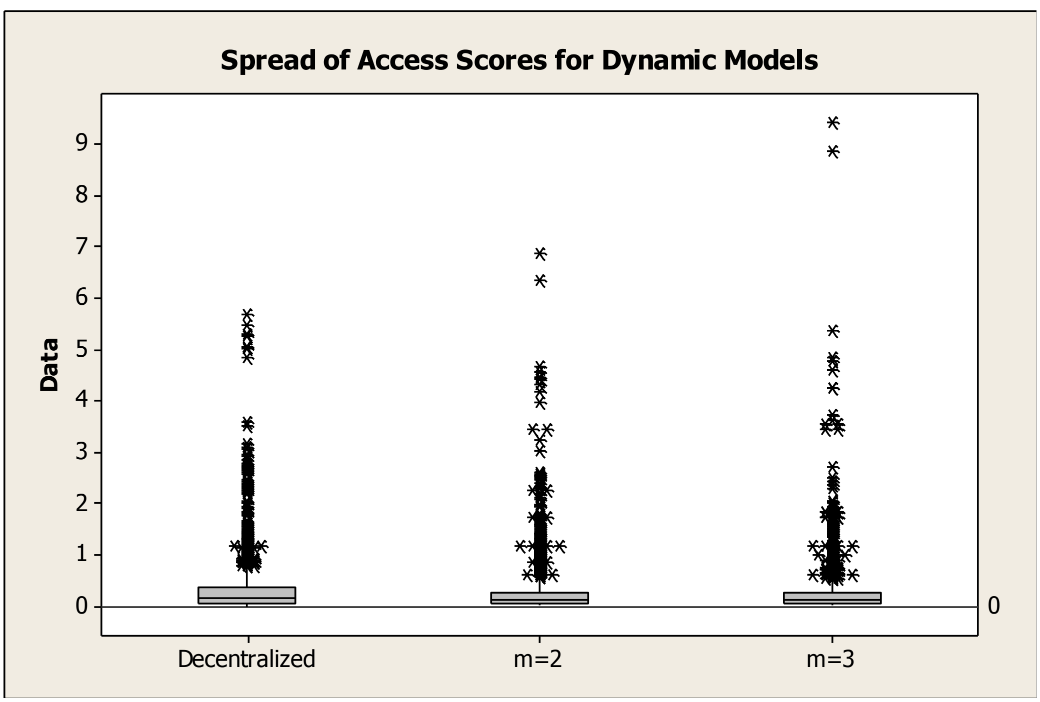

FIGURE A-2: SPREAD OF ACCESS SCORES FOR DYNAMIC MODELS, OUTLIERS INCLUDED

APPENDIX B: SENSITIVITY ANALYSIS RESULTS

TABLE B-1: ACCESSIBILITY RESULTS WITH HIGHER WILLINGNESS-TO-TRAVEL WEIGHTS

	Max Mean	***Max Min***	***Min MAD****	***Max PA***	***Max PY***
Max	0.013019	0.010785	0.002244	0.008732	0.004240
Min	0.000000	0.000232	0.000092	0.000000	0.000232
Range	0.013019	0.010553	0.002152	0.008732	0.004008
Mean	0.002037	0.001106	0.001050	0.001461	0.001403
Median	0.001881	0.000959	0.001056	0.001167	0.001249
St. Dev.	0.001465	0.000843	0.000259	0.001151	0.000610
CV	0.719	0.762	0.246	0.788	0.435
# Facilities	265	105	279	247	209
Bed Capacity	12,959	8,856	11,210	12,959	12,660
Run Time (sec)	2.45	3.04	171,304*	1.82	1.82

TABLE B-2: ACCESSIBILITY RESULTS WITH LARGER CATCHMENT RADII

Test 2	***Max Mean***	***Max Min***	***Min MAD****	***Max PA***	***Max PY***
Max	0.009934	0.006304	0.001538	0.005060	0.007004
Min	0.000045	0.000559	0.000506	0.000108	0.000559
Range	0.009889	0.005745	0.001032	0.004952	0.006445
Mean	0.001920	0.001167	0.001074	0.001333	0.001324
Median	0.001970	0.001081	0.001076	0.001135	0.001217
St. Dev.	0.001243	0.000484	0.000135	0.000754	0.000520
CV	0.647	0.415	0.126	0.566	0.393
# Facilities	263	117	279	248	240
Bed Capacity	12,958	10,404	10,865	12,959	11,995
Run Time (sec)	1.23	3.04	175,588*	1.82	2.43

TABLE B-3: ACCESSIBILITY RESULTS WITH LARGER CATCHMENT SIZE, WEIGHTS

Test 3	***Max Mean***	***Max Min***	***Min MAD****	***Max PA***	***Max PY***
Max	0.008934	0.003046	0.001743	0.003896	0.002444
Min	0.000024	0.000639	0.000557	0.000034	0.000639
Range	0.008910	0.002407	0.001186	0.003862	0.001805
Mean	0.001916	0.001136	0.001069	0.001296	0.001199
Median	0.001959	0.001079	0.001075	0.001231	0.001156
St. Dev.	0.001223	0.000330	0.000119	0.000564	0.000308
CV	0.639	0.291	0.111	0.436	0.257
# Facilities	259	121	279	251	237
Bed Capacity	12,954	10,329	10,580	12,959	10,986
Run Time (sec)	1.62	3.04	175,838*	1.62	1.82

TABLE B-4: ACCESSIBILITY RESULTS WITH OPTIMISTIC CAPACITY

	Max Mean	***Max Min***	***Min MAD****	***Max PA***	***Max PY***
Max	0.020644	0.014250	0.003842	0.005884	0.006545
Min	0.000000	0.000218	0.000000	0.000000	0.000164
Range	0.020644	0.014032	0.003842	0.005884	0.006381
Mean	0.002590	0.001656	0.001093	0.001337	0.001681
Median	0.002339	0.001344	0.001062	0.001111	0.001450
St. Dev.	0.002449	0.001431	0.000459	0.001018	0.000939
CV	0.945	0.864	0.420	0.761	0.559
# Facilities	178	130	279	239	194
Bed Capacity	13,464	12,897	12,717	13,471	13,439
Run Time (sec)	1.03	2.64	170,396*	1.00	1.20

**Partial solution solved to 34.41% of optimal*

TABLE B-5: ACCESSIBILITY RESULTS WITH PESSIMISTIC CAPACITY

	Max Mean	***Max Min***	***Min MAD****	***Max PA***	***Max PY***
Max	0.007585	0.006754	0.002169	0.005952	0.0035
Min	0.000043	0.000107	0.000061	0.000000	0.0000
Range	0.007542	0.006647	0.002108	0.005952	0.0035
Mean	0.001528	0.000784	0.000808	0.001205	0.0011
Median	0.001366	0.000598	0.000821	0.000996	0.0010
St. Dev.	0.001127	0.000668	0.000239	0.000931	0.0005
CV	0.739	0.852	0.296	0.773	0.418
# Facilities	279	126	279	279	278
Bed Capacity	11,491	6,774	8,543	12,529	10,900
Run Time (sec)	2.24	2.63	170,665*	1.63	1.81

**Partial solution solved to 27.19% of optimal*

APPENDIX C: DYNAMIC DEMAND IN HAITI

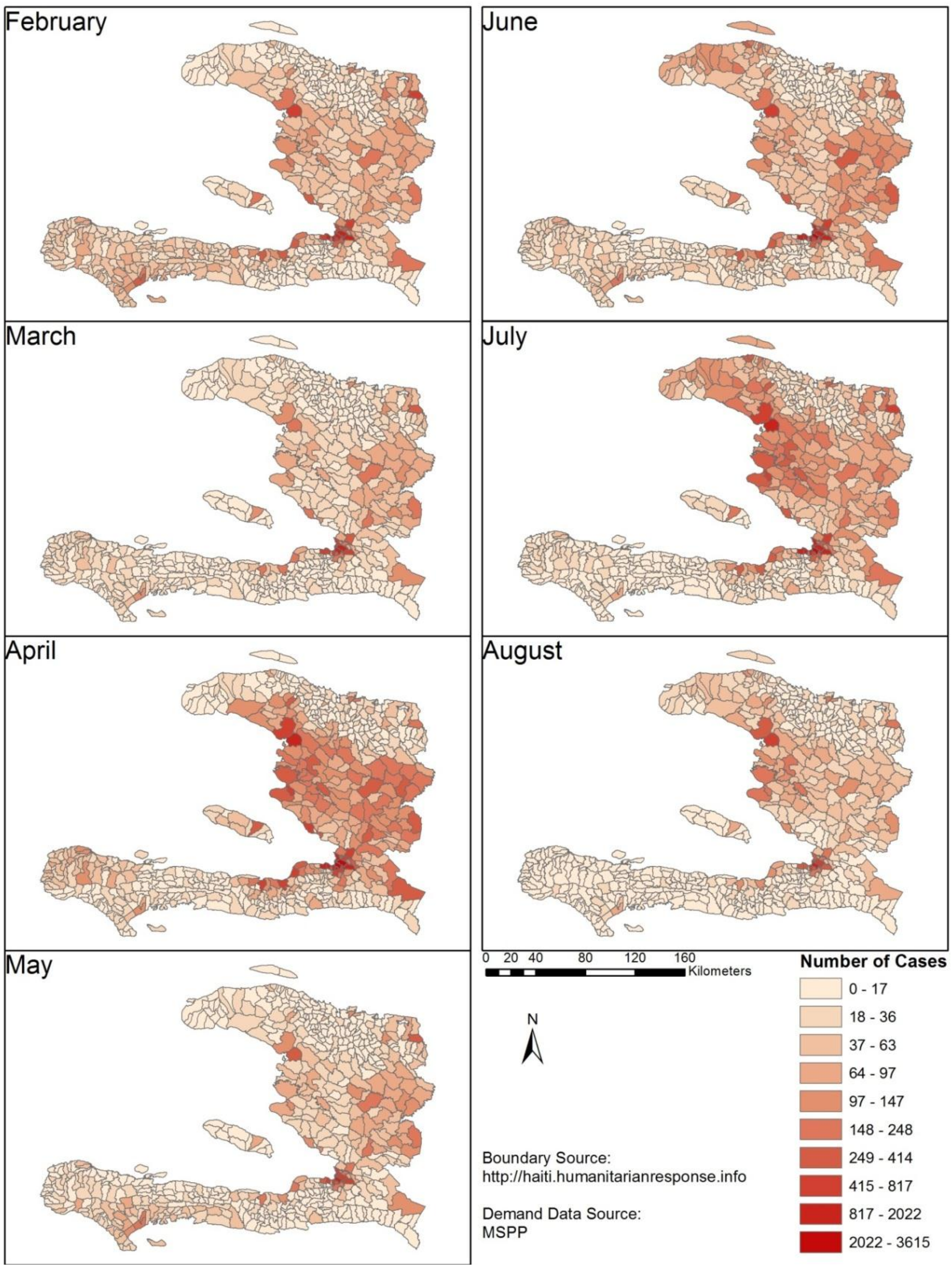

FIGURE C-1: NUMBER OF CHOLERA CASES PER SECTION FEB - AUG, 2011