MITIGATING THE IMPACT OF GIFTS-IN-KIND: AN APPROACH TO STRATEGIC HUMANITARIAN RESPONSE PLANNING USING ROBUST FACILITY LOCATION

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Abstract

Gifts-in-kind (GIK) donations negatively affect the humanitarian supply chain at the point of receipt near the disaster site. In any disaster, as much as 50 percent of GIK donations are irrelevant to the relief efforts. This proves to be a significant issue to humanitarian organizations because the quantity and type of future GIK are uncertain, making it difficult to account for GIK donations at the strategic planning level. The result is GIK consuming critical warehouse space and manpower. Additionally, improper treatment of GIK can result in ill-favor of donors and loss of donations (both cash and GIK) and support for the humanitarian organization.

This thesis proposes a robust facility location approach that mitigates the impact of GIK by providing storage space for GIK and pre-positions supplies to meet initial demand. The setting of the problem is strategic planning for hurricane relief along the Gulf and Atlantic Coasts of the United States. The approach uses a robust scenario-based method to account for uncertainty in both demand and GIK donations. The model determines the location and number of warehouses in the network, the amount of pre-positioned supplies to meet demand, and the amount of space in each warehouse to alleviate the impact of GIK. The basis of the model is a variant of the covering facility location model that must satisfy all demand and GIK space requirements. A computational study with multiple cost minimizing objective functions illustrates how the model performs with realistic data. The results show that strategic planning in the preparedness phases of the disaster management cycle will significantly mitigate the impact of GIK.

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Dedication

This thesis is dedicated to my loving wife, Jackie, for her endless support and patience throughout this endeavor.

Chapter 1 - Introduction

Many governmental, non-governmental, and private humanitarian organizations provide immense support during humanitarian disasters, especially in regards to immediate disaster response. Uncertainty associated with humanitarian disasters plays a substantial role in planning and executing disaster response. Timing (when disasters strike), location, and demand (amount of people affected) are typical areas of uncertainty. However, a new uncertainty, gifts-in-kind (GIK), has become increasingly prevalent in recent disasters as people around the world are inspired to donate to help relief efforts. All donations are well-intentioned, but GIK donations can disrupt the humanitarian supply chain. A major concern with GIK is items are ineffective for the specific relief effort. Another significant concern for humanitarian organizations is improper treatment of GIK that may result in ill-favor with donors and a decrease in future donations. An example of this comes from Alanna Shaikh’s blog (in reaction to an incident in 2008 involving World Vision distributing Super Bowl t-shirts to developing countries) in which she explains that non-governmental organizations (NGO) feel pressure to accept GIK from partnered companies in order to maintain a respectable relationship in hopes of receiving a generous cash donation or specific items required for disaster relief (Shaikh 2011). Therefore, humanitarian organizations must store, handle properly, and account for GIK (no matter how counterproductive) in relief assets (warehouse or staging areas). Despite all uncertainty, these organizations still need to respond quickly and effectively to humanitarian disasters. The focus of this thesis is pre-positioning strategies, under uncertainty, to mitigate the impact of GIK with respect to a hurricane disaster along the Gulf and Atlantic Coasts of the United States.

Humanitarian organizations focus on providing support after a disaster event. The prevalence of major global disasters, both natural and man-made, from 2004-2012 has forced humanitarian organizations to rethink their focus and invest in strategic pre-positioning of supplies in order to reduce response effort burdens and hedge against uncertainty in humanitarian disasters. Decisions must be made as to the location of facilities to house pre-positioned supplies, what supplies to store, and how much of each type of supply to store. Previous pre-positioning approaches focus on improving the response to demand uncertainty; the approach in this paper adds the uncertainty of GIK to the strategic planning process.

The goal of this thesis is to introduce a strategic pre-positioning approach that simultaneously accounts for uncertainty in both demand and GIK to improve humanitarian response operations and mitigate the impact of GIK. GIK requires significant attention because it adds complexity to disaster response. The approach uses a robust optimization method to account for the general uncertainty that is typical with humanitarian crises, specifically amount of demand and GIK. This paper focuses on hurricane strikes along the Atlantic and Gulf Coasts of the United States. The model introduces GIK as an uncertain parameter along with demand. The approach creates a robust model that bounds the uncertainty in the parameters to a certain level. A robust facility location model establishes a method of strategically locating warehouses with pre-positioned aid supplies while maintaining adequate space for GIK when a disaster strikes. A computational study of hurricanes demonstrates the usefulness of this approach.

The five chapters of this thesis explain the effect of GIK in the strategic planning of humanitarian response. The background, research question, and contribution complete Chapter 1. Chapter 2 is the literature review of robust optimization, facility location models, and GIK. Chapter 3 presents three discrete pre-positioning robust facility location models with uncertain demand and GIK. Chapter 4 provides the results of the computational study. Chapter 5 concludes the thesis by summarizing the findings and presenting areas of future research.

1.1 Background and Motivation

The motivation behind this research is the lack of robust optimization models pre-positioning aid for humanitarian disasters that also include the uncertainty of GIK. Additionally, there are no quantitative studies mitigating the impact of GIK on humanitarian logistics, both in pre-positioning and disaster response. This section describes the classification of humanitarian disasters, humanitarian logistics, and GIK donations.

1.1.1 Disaster Classification and Phases

Van Wassenhove (2006) classifies disasters as sudden-onset or slow-onset and man-made or natural, as depicted in Figure 1.1, thus establishing basic design and frame of reference for humanitarian disasters. Sudden-onset disasters, like hurricanes, offer little or no warning before striking. Even with warning systems that track storm development and movement, the size, volatility, and path uncertainty of hurricanes place them in the category of sudden-onset.

	Natural	Man-made
Sudden-onset	Earthquake Hurricane Tornadoes	Terrorist Attack Coup d'Etat Chemical leak
Slow-onset	Famine Drought Poverty	Political Crisis Refugee Crisis

Figure 1.1: Disaster Chart (Van Wassenhove 2006)

Apte (2009) expands on Van Wassenhove's (2006) research idea to include location of disasters and difficulty of logistical support, as shown in Figure 1.2. Two types of locations exist for both sudden-onset and slow-onset disasters: dispersed and localized. Localized locations are defined as a single region or country, and dispersed locations are defined as multiple regions or countries. This creates four quadrants for disaster classification with difficulty level increasing by the quadrant number. Quadrant I represents localized and slow-onset disasters, such as a political crisis or drought, where the disaster is isolated in a specific region. Logistically, this type of disaster is the least difficult of the four quadrants. The second quadrant is a dispersed slow-onset disaster, like a refugee crisis affecting multiple neighboring regions. The third quadrant is a localized sudden-onset disaster, such as hurricanes, tornadoes, earthquakes, and flash flooding. An example of the fourth quadrant, dispersed sudden-onset disaster, is the 2004 tsunami that not only affected the eastern coast of India, but also severely affected Indonesia, Malaysia, and Thailand.

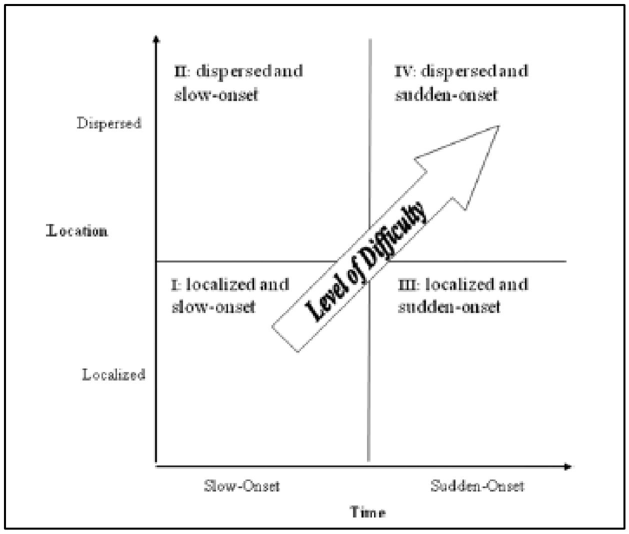


Figure 1.2: Disaster Chart (Apte 2009)

As previously described, the emphasis of this research is the Atlantic and Gulf Coasts of the United States. The disaster classification utilizes the Apte (2009) model with localized and sudden-onset hurricanes.

Many humanitarian organizations and researchers follow various designs of disaster life cycle or disaster management cycle. The most common design utilizes four phases: mitigation, preparedness, response, and recovery (Altay and Green 2006). Figure 1.3 shows an example of typical activities during each phase of the disaster management cycle. Mitigation prevents or reduces the impact of disasters through governmental policies and risk assessments. The preparedness phase arranges for a region or community to respond to disasters and includes the training of emergency personnel and pre-positioning of supplies. The response phase begins immediately after the disaster and can encompass search and rescue, providing emergency supplies and medical care, and opening emergency shelters. The recovery phase is the long-term stabilization of the affected area after the initial effects of the disaster (Altay and Green 2006). Most disaster management cycles demonstrate some form of the characteristics mentioned, whether in three phases or five. The research of this paper focuses on the preparedness phase and the response phase when there is realization of uncertain data.

Mitigation

- Zoning and land use controls to prevent occupation of high hazard areas
- Barrier construction to deflect disaster forces
- Active preventive measures to control developing situations
- Building codes to improve disaster resistance of structures
- Tax incentives or disincentives
- Controls on rebuilding after events
- Risk analysis to measure the potential for extreme hazards
- Insurance to reduce the financial impact of disasters

Preparedness

- Recruiting personnel for the emergency services and for community volunteer groups
- Emergency planning
- Development of mutual aid agreements and memorandums of understanding
- Training for both response personnel and concerned citizens
- Threat based public education
- Budgeting for and acquiring vehicles and equipment
- Maintaining emergency supplies
- Construction of an emergency operations center
- Development of communications systems
- Conducting disaster exercises to train personnel and test capabilities

Response

- Activating the emergency operations plan
- Activating the emergency operations center
- Evacuation of threatened populations
- Opening of shelters and provision of mass care
- Emergency rescue and medical care
- Fire fighting
- Urban search and rescue
- Emergency infrastructure protection and recovery of lifeline services
- Fatality management

Recovery

- Disaster debris cleanup
- Financial assistance to individuals and governments
- Rebuilding of roads and bridges and key facilities
- Sustained mass care for displaced human and animal populations
- Reburial of displaced human remains
- Full restoration of lifeline services
- Mental health and pastoral care

Figure 1.3: Four Phase Disaster Cycle Activities (Altay and Green 2006)

1.1.2 Humanitarian Logistics

"There is a need during humanitarian crisis to reduce [reducing] the human suffering by proactively preparing by establishing pre-positioned stocks in the best possible locations before a disaster; this is very strategic in nature," (Apte 2009).

The definition of humanitarian logistics is "the process of planning, implementing, and controlling the efficient, cost-effective, flow and storage of goods and materials, as well as related information, from point of origin to point of consumption for the purpose of meeting the end beneficiary's requirements" (Apte 2009). As with military and commercial logistics, humanitarian logistics shares the goal of ensuring supplies move from one location to another as efficiently as possible. Furthermore, all three forms of logistics have the strategic, tactical, and operational levels of decision making. Apte (2009) provides excellent definitions of the strategic, operational, and tactical levels of decision making for humanitarian logistics. Strategic level focuses on building infrastructure and pre-positioning supplies. Success in this level requires substantial funds in order to build and maintain infrastructure and purchase pre-positioning supplies. Operational level is the last-mile distribution of supplies, or the transportation of essential items from a warehouse or transfer point to the place of need. Tactical level bridges the gap between the strategic and operational levels with real-time resource management in regards to inventory, routing, distribution, and scheduling of deliveries (Apte 2009).

1.1.3 Donation of Gifts-in-Kind

GIK, donations of physical supplies or any donated items, are classified into three basic categories: governmental GIK, corporate (business) GIK, and individual GIK. The challenges surrounding GIK are not isolated to any one category, but typically shared among all three.

Governmental GIK usually occurs between governments of various countries, but it can also involve GIK from a government to a NGO. Typically, one country experiences a disaster of some kind and another country offers an in-kind gift, ranging from foodstuffs to military support (use of personnel and heavy transport equipment) which are negotiated between the governments and executed. A majority of the time no issues arise with governmental GIK.

When corporations donate GIK to humanitarian organizations, it is an example of corporate GIK. Large humanitarian organizations normally partner with corporations for a steady stream of donations, thus gaining access to vast quantities of supplies and allowing corporations to enjoy tax incentives on surplus inventory. The GIK are not limited to only supplies, as equipment is also sometimes offered by corporations or businesses.

Individual GIK results from individuals or groups of people donating gifts to humanitarian organizations. Items are second-hand or purchased goods shipped to disaster areas. They can also encompass service and individual volunteering (i.e. supply truck drivers), though this research does not focus on this specific type of GIK.

Examples of challenges with GIK illustrate its disruptive effect. Tomasini and Van Wassenhove (2004) cites a specific challenge during the 2002 South African food crisis when the United States provides an in-kind gift of food aid to the World Food Program (WFP) to distribute in Southern Africa. Parts of the GIK were genetically modified (GM) food and the African countries refused the aid because their economies are based mainly on conventional food products. Moreover, country leaders did not trust GM foods in general. At the time of rejection, a majority of the food aid was already either in African ports or in transit, so the GIK had to be warehoused and stored to prevent spoilage. In this case, cultural differences played a significant role in the rejection of the donation and caused storage issues at the African ports which delayed future inbound supplies for approximately a month and increased costs for all organizations involved.

Another challenge occurred during the response to the 2010 Haitian earthquake. In response to the significant truck shortage, business owners in the Dominican Republic donated 500 trucks to the Dominican Red Cross. Though various companies paid for all costs associated with the truck (driver and fuel), others did not and the Dominican Red Cross was responsible for paying drivers and purchasing fuel (Holguín-Veras et al. 2012c). This case highlights hidden costs that occasionally appear when receiving GIK. In the final example, Apte (2009) explains an instance during the 2005 Pakistani earthquake when donated tents arrived with missing pieces and either no assembly instructions or instructions in a foreign language. The tents were improperly used and caught fire, resulting in deaths. These examples show various challenges and impacts of GIK that humanitarian organizations face.

At the time of this publication, little research has been conducted on GIK specifically related to humanitarian relief and there has been no quantitative research on mitigating the impact of GIK to relief efforts. There is clearly a need for such work in this area.

1.2 Research Goal

The purpose of this thesis is to present a model that strategically pre-positions supplies and alleviates the impact of GIK by reserving warehouse storage space under uncertainty to reduce the burden of tactical level decisions during transition to the disaster response phase. The first research goal is to model GIK under uncertainty with a robust facility location model. The second research goal is to mitigate the impact of GIK on strategic level decisions.

1.3 Research Contributions

This study relates to current research in facility location, robust optimization, and humanitarian logistics. The study makes the following contributions:

1. Introduce models accounting for GIK in humanitarian disaster preparation and relief. There are many facility location models with demand uncertainty, but, to the author's knowledge, none involve GIK.
2. Demonstrate usefulness of the approach with a computational study. Although the computational study is on hurricanes, the approach is generalizable.

3. Examine impact of different objective functions on resulting pre-positioning decisions. This paper aims to show the contrasts between models and the effect of the objective functions.
4. Mitigate the impact of GIK at the strategic humanitarian relief planning level and provide insight to practitioners. To the author's knowledge there is no publication quantifying the mitigation of the impact of GIK in the planning stages of creating a humanitarian network.

Chapter 2 - Literature Review

This chapter provides information on relevant literature pertaining to the research topic, definitions, and how the current research differs from previously released publications. Chapter 2 begins with literature involving robust optimization, then discusses literature pertaining to facility location, and finally cites works that identify GIK issues.

2.1 Robust Optimization

Robust optimization (RO) is a different approach for solving optimization problems with uncertain parameters. In contrast to stochastic optimization, this method does not rely on probability distributions for the uncertain parameters. Instead, it seeks solutions that are feasible and perform well for any realization of the uncertain data in an uncertainty set. The uncertainty set and objective function are important modeling choices in any RO approach. This section discusses types of uncertainty sets, objective functions, general modeling structure, characteristics, and scenario-based robust optimization.

2.1.1 Types of Uncertainty Sets

RO utilizes many types of uncertainty sets. For the purposes of this research, emphasis is on the box, ellipsoidal, and scenario-based uncertainty sets. The uncertainty set is a set of deterministic values the uncertain parameter(s) can manifest when the uncertainty is realized. This realization is for all values or a single value during a specific scenario. The box uncertainty set was derived from the work of Soyster (1973). Framework surrounds a linear program with uncertain parameters a_j, center (mean or nominal) parameter value a, and a deflection value of ρ_j, with the uncertain set $\mathcal{U}$ being defined by the following:

$$\mathcal{U} = \{a_j : |a - a_j| \leq \rho_j \ \forall \ j\} \tag{1}$$

Equation (1) states that the realized value of the uncertain parameter a_j has to be within ρ_j of the value a generating the "box" for the uncertainty set. This uncertainty set creates a linear bound on the value a_j. The deflection value is derived from the percentage of uncertainty multiplied by the mean/nominal values (also a standard deviation). The uncertain value can either be increased or decreased to this deflection amount from the individual mean/nominal values. Ben-Tal and Nemirovski (1998) found that the box method produces a very conservative solution to models with uncertain parameters and, as a result, introduce the ellipsoidal uncertainty set. This method uses a safety parameter that is defined as the amount of uncertainty with respect to the deflection of the uncertain parameters; it is a value between zero and one representing the radius of the ellipse and the amount of accountable uncertainty. This method is non-linear and more computationally demanding than the box method (Bertsimas and Sim 2004). A special type of uncertainty set is a scenario-based approach for RO (similar to robust discrete optimization). Additional information on scenario-based uncertainty sets is included in Section 2.1.5.

In general, within the uncertainty set, RO utilizes the worst-case scenario for uncertain but bounded parameter(s) and optimizes the problem. A worst-case scenario is an uncertain parameter taking on its worst possible value within a defined bound. The outcome is a robust solution that is immunized to uncertainty. The distinct drawback to this approach is the possibility that solving for the worst-case scenario incurs an enormous cost and other impracticality leading to the rejection of the solution. This can be the case when utilizing the box uncertainty set. The ellipsoidal uncertainty set defines and bounds the uncertainty set away from the very conservative worst-case scenario. A model utilizing RO solves for each realized value of uncertainty producing a solution guaranteeing feasibility in the entire uncertainty set (robust feasible solution). For further details on uncertainty sets, the reader should reference Ben-Tal el al. (2009) and Bertsimas et al. (2011).

2.1.2 Types of Objective Functions

Typical objective functions in RO models are minimize maximum (minmax) cost and minmax regret functions or any similar minmax function. Ben-Tal and Nemirovski (1998) and Ben-Tal et al. (2004) apply minmax cost objective functions in showing different applications of RO and the utilization of the ellipsoidal uncertainty set. Assavapokee et al. (2008) presents a three stage minmax regret model using a scenario-based RO approach. An optimal solution to a robust problem with a minmax objective may not be the optimal solution for any individual realization of the uncertain parameters. Rather, the robust solution is not too far from optimal for all possible realizations.

2.1.3 Model Structure

The following illustration shows how to convert an uncertain linear program into its robust counterpart, adapted from Ben-Tal et al.'s (2009) linear programming model.

General linear programming model:

$$min\{c^T x: Ax \leq b\} \; where \; x, c \in \mathbb{R}^n, A \; is \; a \; m \times n \; constraint \; matrix \; and \; b \in \mathbb{R}^m \tag{2}$$

The robust counterpart to the linear program essentially introduces the uncertainty set to the problem and changes the objective function to a minmax to ensure feasibility.

General robust counterpart to the linear program:

$$min\{t: c^T x \leq t, Ax \leq b \; \forall \; (c, A, b) \in \mathcal{U}\} \; where \; \mathcal{U} \; represent \; the \; uncertainty \; set \tag{3}$$

All parameters (c, A, and b) can be uncertain and must belong to the uncertainty set $\mathcal{U}$. All robust models require that solutions be feasible for all values in $\mathcal{U}$. As stated in Section 2.1.2, any objective function can be used in robust models.

2.1.4 Characteristics of Robust Optimization

The increased usage of RO reveals some distinct issues in managing uncertainty. Bertsimas et al. (2011) explains three central issues surrounding RO: tractability, conservativeness, and flexibility. Tractability is highly dependent on how the uncertainty set is defined. Also, the nominal problem's tractability may not guarantee the tractability of the robust counterpart. Conservativeness is RO's ability to be immunized from the uncertain parameters in creating solutions. The level of conservativeness within the problem depends on the definition of the uncertainty set and allows the analyst to tweak the problem by choosing between robustness and performance. The flexibility of RO is shown not only by its multiple uses, but also by the multiple applications of building a model with the wide array of describing the uncertainty sets.

2.1.5 Scenario-Based Robust Optimization

This thesis uses a scenario-based approach which is very similar to robust discrete optimization. Scenario-based approach to RO utilizes a finite set of uncertain scenarios and provides a feasible solution over all scenarios. Kouvelis and Yu (1997) provide a basic overview of robust discrete optimization (scenario-based) approaches and definitions of different robustness criteria, including absolute robustness (minmax cost), robust deviation (minmax regret), and relative robustness (minmax relative regret). Assavapokee et al. (2008) creates an algorithm that solves a relaxation problem for both feasibility and optimality conditions of the main problem. The algorithm adds all scenarios that violate feasibility or optimality conditions of the relaxation problem and examines only a small subset of scenarios. The scenarios within the subset are in two categories: scenarios that maintain feasibility and scenarios that prove optimality. The authors prove the algorithm will terminate in a finite number of iterations and solve to optimality the minmax regret robust problem. The algorithm can also solve for the minmax relative regret. Bertsimas and Sim (2004) introduce a parameter Γ_i to the model's constraints adjusting the robustness based on the desired level of conservatism in the solution. This parameter controls the amount of robustness to an uncertain parameter in each scenario and the associated cost to the objective function; this is also known as the D-norm approach. Moreover, Goerigk and Schobel (2011) implement an algorithm that calculates less conservative robust solutions over a set of scenarios with the aim being to find "a solution which can be recovered to an optimal solution of a scenario (when it becomes known) with minimal recovery costs in the worst case." This approach can be used when there is an efficient method for solving the deterministic version of the problem and shows that the selection of the scenarios within the uncertainty set helps avoid solutions that are too conservative.

2.2 Facility Location

The set covering facility location class provides the basis for the models used in this paper. Covering models, in general, assign a facility to a location and satisfy demand up to a certain threshold or maximum distance/time traveled; all demand within this threshold is covered (Owen and Daskin 1998). There are two types of covering models: set covering and maximal covering (Daskin 1995, Owen and Daskin 1998). Set covering facility location models minimize the total cost of the system while maintaining a threshold of coverage, and maximal covering models maximize coverage given a set threshold of coverage and a fixed number of facilities. There are also two main categories of facility location problems: uncapacitated and capacitated. The models in this thesis fall in to the capacitated category. These problems typically have a large fixed cost for locating facilities. The capacity of a facility is defined in terms of physical space within the facility or the inbound and outbound flow through the facility. The capacitated facility location problem is the finite capacity version of the uncapacitated facility location problem (Verter 2011).

2.2.1. Facility Location Under Uncertainty

Facility location under uncertainty is a very important field of research to the logistics and humanitarian aid communities. Facility location is a strategic level decision for humanitarian organizations. Costs associated with location decisions are large and, most of the time, these decisions are extremely costly to change once implemented. Therefore, when demand or another parameter is uncertain, importance increases to model these long-term decisions with respect to that uncertainty. Snyder (2006) provides a great review of facility location under uncertainty and describes the two-stage nature of facility location models. Stage one determines the location of the facilities “here and now,” and stage two reacts to the realized uncertainty, in most cases some type of demand. The treatment of uncertainty in facility location problems is contained within two schools of thought, stochastic and robust location problems. Robust facility location problems are commonly solved with a scenario approach, either minimax cost or minimax regret modeling methods. With the consequential magnitude of cost in facility location, worst-case scenario for the uncertain parameter(s) is very impractical, so a “fractal target” approach is utilized (Snyder 2006). Essentially a threshold of 80, 85, or 90 percent of demand is satisfied within the coverage area.

2.2.2 Location-Inventory

Location-inventory models are used to simultaneously determine the location of facilities and the amount of inventory maintained at each facility. Daskin et al. (2002) explain that facility location and inventory problems are typically solved separately and often result in sub-optimality. A non-linear integer program is used to integrate both facility location and amount of inventory within each facility. In this model, Daskin et al. (2002) adopt the idea of risk pooling, which leads to an inventory cost savings for groups of facilities by combining both facility location and inventory management in a single model.

The concept of risk pooling allows retailers (in a system of distribution centers and retailers) to maintain a level of safety stock and act as distribution centers to other retailers in order to mitigate demand uncertainty (Shen et al. 2003). Shen et al. (2003) also combines both facility location and inventory management with risk pooling into one mixed integer non-linear model. Both these models utilize deterministic parameters for demand and supply, whereas Snyder et al. (2007) provides a stochastic location risk pooling model. Demand for this model is scenario-based with the scenarios following a normal distribution and supply remaining deterministic.

2.2.3 Pre-Positioning Aid in Humanitarian Relief

Balick and Beamon (2008) utilize a location-inventory model specifically for humanitarian relief. The model is a maximal covering location problem that has a mixed integer programming formulation with probabilistic disaster scenarios. The model seeks to maximize total expected demand covered subject to a total budget for pre- and post-disaster and upper and lower response time limits. Ultimately, the model provides decision makers with the locations of facilities and the amount to pre-position given a set of disaster scenarios. Another scenario formulation of a location-inventory problem is found in Görmez et al. (2010). This model utilizes the worst-case scenario of an Istanbul earthquake and, based on the model, determines the number of facilities and pre-positioned stock level. The problem utilizes a two-stage approach: the first stage locates the facilities and determines their capacities, and the second stage treats the facilities as demand points and assigns them to distribution centers. The author accounts for service disruptions by analyzing vulnerability levels at each demand site. Vulnerability level is the ratio of the population of the demand site to the total population. A higher vulnerability level means the demand point is high-risk and the program will bound the distance to a distribution center, ensuring the demand point is closer.

Rawls and Turnquist (2010) formulate a two-stage stochastic mixed integer program that pre-positions supplies and locates facilities within a discrete set of scenarios with probabilities of occurrence. The case study focuses on the hurricane threat in the Gulf Coast area of the United States. The first stage is under uncertainty and the decisions are the size, location, and number of facilities. The second stage is the realized demand and the distribution of available supplies based on the scenario. Because of the complexity of the problem the authors develop a heuristic called a Lagrangian L-shaped method. Salmerón and Apte (2009) create a strategic and resource allocation plan for humanitarian aid utilizing a two-stage stochastic optimization model. Along with the scenario-based problem with pre-positioning and warehouse location decisions, the two-stage model also takes into account means of transportation, relief personnel, medical facility, shelter, and rescue population decisions. This incorporation creates a very detailed strategic disaster planning model. Campbell and Jones (2010) introduce a pre-positioning location-inventory model that accounts for location risk as inventory is positioned closer to disaster locations. The unique aspect of this study is that risk and inventory levels are independent of scenarios. Galindo and Batta (2012) present a pre-positioning model that accounts for the destruction of the supplies during the disaster and increased logistics costs immediately after a hurricane. The authors include an amplified amount to the expected demand in order to mitigate demand uncertainty.

While most studies in pre-positioning humanitarian aid supplies utilize stochastic optimization to account for uncertainty, few have utilized robust optimization. This report introduces a strategic pre-positioning approach that uses a robust optimization technique that provides linear tractability with the protection against over conservatism akin to ellipsoidal uncertainty set.

2.3 Gifts-in-Kind

> *"Disaster response planning must consider the expected material convergence by designing operational procedures and analytical formulations that account for it"* Holguín-Veras et al. (2012b).

Holguín-Veras et al. (2012b) conducted an analysis of material convergence (the flow of all supplies and equipment, including GIK, to disaster areas), specifically unsolicited in-kind donations. The authors explain that this type of GIK has been problematic in all major disasters because unusable GIK arrive at a disaster site. The study reveals the overwhelming negative qualitative impact of GIK and that over 50 percent of received GIK are inapplicable to the disaster response. Destro and Holguín-Veras (2011) conduct a quantitative analysis of the impact of GIK using Hurricane Katrina as a backdrop. The authors study the flow of GIK from donor to disaster location and provide analysis of the flow of GIK after a disaster. Because GIK are an outlet from which to show genuine care and emotion in the face of a tragedy, many donors give in-kind donations but, regrettably, these gifts are often irrelevant, expired, or low quality and are burdensome to relief workers (Hechmann and Bunde-Birouste 2007). For instance, weeks after the 2004 tsunami, Sri Lanka's Colombo airport was inundated with humanitarian cargo; unfortunately, a majority of this cargo was GIK, which stymied operations at the airport and filled warehouses. These gifts were unsolicited and required significant manpower to categorize, so a majority of the items remained unclaimed for months after the disaster (Thomas and Fritz 2006). Holguín-Veras et al. (2012c) describe how news reports of scarce potable water in Haiti during the 2010 earthquake caused massive GIK water donations to the Dominican Red Cross, resulting in significant depreciation of local goods. The authors further explain that one donated bottle of water essentially is cost-equivalent to three or four bottles of local water. Moreover, the authors explain that Port-au-Prince was inundated with both cargo and GIK and that all shipments from the Dominican Republic ceased for five days.

As described in Chapter 1, Tomasini and Van Wassenhove (2004) explain the storage issues with in-kind donations during humanitarian crisis. Flandez (2012) is another example of a problematic storage issue concerning unsolicited in-kind donations and how they can complicate a crisis. The author proposes aid organizations should create more exclusive criteria with GIK, as well as inform donors of what constitutes responsible donating. Wachtendorf et al. (2010) provide a case study of Hurricane Katrina with respect to the qualitative impact of material convergence (GIK) in accordance with the social conditions surrounding disasters and catastrophes. Holguín-Veras et al. (2012a) identify the lack of research in material convergence (specifically GIK) and the urgent need to quantify the impact of this convergence.

There exist many studies qualifying the impact of GIK and few quantifying that impact. To the author's knowledge, this study is the first to mitigate the impact of GIK under uncertainty. The approach is to allocate space for GIK in warehouses during the preparation phase of the strategic planning process of a humanitarian organization. This method provides feasible solutions, under uncertainty, that satisfies demand and allocates space GIK.

Chapter 3 - Robust Facility Location Models

This chapter presents the problem statement of this paper and introduces the four robust facility location models that satisfy both uncertain demand and GIK donations for a prospective disaster location during the strategic level of decision making. In addition to the robust models, Chapter 3 presents four base models that satisfy only demand under uncertainty with a penalty for unsatisfied GIK and utilize the same robust facility location formulation as the robust models. Unsatisfied GIK is defined as not having space for GIK in a given warehouse. This chapter encompasses the problem statement, the formulation and description of the four robust facility location models, the description of the four base models, and the case study and data.

3.1 Problem Statement

A humanitarian organization wants to plan for the next hurricane disaster in the southeastern part of the United States, specifically the area encompassing the Atlantic and Gulf Coasts of the United States. The organization seeks to establish a strategic plan that involves placing warehouses with pre-positioned stocks in various candidate warehouse locations across the Southeast that will satisfy demand in any prescribed hurricane scenarios. These hurricane scenarios are derived from a sample of 15 hurricanes adapted from Rawls and Turnquist (2010), further explained in Section 3.3.3. This organization wants to include uncertainty in demand and GIK donations. Demand is split into three types of supply: potable water, meals-ready-to-eat (MRE), and medical kits. In every scenario, a demand region requires various amounts of the three types of supplies. Also, the region incites GIK donations from the rest of the United States. Exact origination of the donations is irrelevant, but these donations enter into the supply system for a demand region and the open warehouses must allocate space for the GIK in order to ensure adequate treatment and storage. Requirements dictate that the humanitarian organization knows where to place their warehouses in order to satisfy demand and GIK. The organization must also know how many pre-positioned supplies to purchase, the amount of supplies stored in each warehouse, how much space to allocate for GIK in each warehouse, and the total cost of establishing the strategic plan.

This problem requires a facility location model that guarantees satisfaction of both uncertain demand and GIK. The model must capture all costs associated with establishing a strategic facility location plan. These costs are divided into fixed costs and scenario-based costs. The following are fixed costs: warehouse infrastructure, pre-positioned supplies, and unused space for GIK storage. The scenario-based costs include: transportation cost of shipping supplies from warehouses to satisfy demand, transportation cost of shipping GIK from one warehouse to another (in the case where a warehouse is filled to capacity), and the handling cost of GIK. The creation of uncertainty sets for both demand and GIK resolves the uncertainty in the problem (Section 3.3.3). The next sub-section provides assumptions surrounding the problem before explanation of the model formulation in the next section.

3.1.1 Assumptions

1. Only one hurricane will strike the southeastern portion of the United States. There are no multiple or consecutive hurricane strikes.
2. No GIK donation can satisfy demand.
3. GIK are important and must be stored at all times.
4. GIK shipping information will be provided to public soon after the disaster strike. The humanitarian organization will identify all warehouses that have space for GIK and during the response phase, the organization will provide these locations for GIK shipments.
5. Demand for the three types of supplies is isolated to a demand node based on the scenario. Demand nodes represent the center mass of a region and all demand requirements are satisfied at this node.
6. The links between nodes are unaffected by the storms. Transportation routes remain clear after the storm and are only ground links (roads).
7. Warehouses are unaffected by the storms. Warehouses cannot be destroyed in a storm.
8. Candidate warehouse locations and demand regions can coexist on the same node if there is demand from that node.
9. If there is an open warehouse in a region that incites GIK donations, then GIK donations will arrive at that warehouse. Otherwise, GIK donations will arrive at warehouses that have allocated space for GIK.
10. Units of measurement for demand supplies and GIK are pallets. Pallets are stored in pallet racks at each warehouse.

3.2 Model Formulation

The four robust models described in this section are: minimize cost (MC), minimize mean scenario-based cost (MMSC), minimize maximum cost (MMC), and minimize maximum regret (MMR). All models seek to minimize a type of cost objective function while satisfying all demand and establishing space for GIK. All four models utilize the same indices, parameters, and decision variables.

Sets and Indices:

I	= Set of node locations for both candidate warehouse locations and demand regions; $i, j, r \in I$
S	= Set of supplies; $s \in S$
K	= Set of warehouse size categories; $k \in K$
H	= Set of scenarios; $h \in H$
N	= Set of hurricanes; $\eta \in N$

Parameters:

$\bar{d}_{rs}^{\eta}$	= Nominal demand at region r for supply s in number of pallets during hurricane η
$\tilde{d}_{rs}^{h}$	= Uncertain demand at region r for supply s in number of pallets from scenario h
$\bar{g}_{r}^{\eta}$	= Nominal incited GIK from region r in number of pallets during hurricane η
$\tilde{g}_{r}^{h}$	= Uncertain incited GIK from region r in number of pallets from scenario h
l_{ir}^{s}	= Cost per pallet of supply s to ship between warehouse location i and demand region r
B	= Cost per pallet of retaining warehouse space (pre-positioning) for GIK
β	= Cost per pallet of handling GIK
τ_{ij}	= Cost per pallet of GIK to ship between warehouse location i and warehouse j
f_k	= Fixed cost of establishing a warehouse the size of category k
c_s	= Cost per pallet of supply s
a_k	= Capacity of a category k warehouse
M	= Big M. Sufficiently large number

Decision variables:

w_{ik}	= 1 if warehouse location i in category k is open, 0 otherwise.
θ_i^1	= 1 if the allocated GIK storage space is greater than incited GIK from region r, 0 otherwise
θ_i^2	= 1 if the allocated GIK storage space is less than incited GIK from region r, 0 otherwise
q_{is}	= Total number of pallets warehouse i will store of supply s.
x_{ir}^{sh}	= Number of pallets warehouse i will store to demand region r of supply s in scenario h.
γ_i	= Total number of pallet spaces warehouse i will reserve for GIK.
y_{ir}^{h}	= Number of GIK pallets warehouse i will store for demand region r in scenario h.
z_{ij}^{h}	= Number of GIK pallets warehouse i will store for warehouse j in scenario h. This implies that warehouse j is collocated in region r ($r = j$) and warehouse j is unable to store the incited GIK from region r. Therefore, warehouse j will ship pallets of GIK to warehouse i for storage.

The variables w_{ik}, q_{is}, and γ_i are decisions made absent any scenario while variables x_{ir}^{sh}, y_{ir}^{h}, and z_{ij}^{h} are decisions dependent on a given scenario when demand and GIK amounts are realized. The model tries to minimize the total cost while maintaining feasibility in all scenarios in h. Feasibility in this case is the satisfaction of both demand and GIK where the warehouse location, quantity of supplies, and space allocated for GIK are sufficient for all scenarios. The uncertainty is modeled based on the scenario and discussed in Section 3.2.

The scenario-based decisions are the transportation decisions (x_{ir}^{sh}, z_{ij}^{h}) and the GIK storage decision (y_{ir}^{h}). The transportation decisions assign a cost per pallet for both supplies and GIK. The GIK transportation and storage decisions also assign a handling cost per pallet. The model minimizes all costs associated with transportation and handling for all scenarios. When $j = i$ (warehouse location and incited GIK demand region are the same) or region r does not have a warehouse, there is no transportation cost for GIK but a handling cost in the form of βy_{ir}^{h}.

The parameter values of infrastructure cost, procurement cost, transportation cost (l_{ir}^{s}), demand for all three types of supply, and warehouse capacities are derived directly from Rawls and Turnquist (2010). The space cost B represents the opportunity cost for not using the space for more pre-positioned goods or any other purpose for the humanitarian organization other than reserving space for GIK. The handling cost β is the specific cost of handling pallets of GIK. This cost incorporates worker cost and uncertainty attributed to the type of gift and weight of GIK pallets. The GIK transportation cost τ_{ij} includes the uncertainty in the type and weight of the gifts and the requirement to have a transportation asset dedicated to GIK shipment. The value of $\bar{g}_{r}^{h}$ is derived from the nominal demand. The nominal value of GIK can be no greater than the largest demand and no less than the smallest demand.

3.2.1 Minimize Cost Model

Objective Function:

$$\min \sum_{i\in I}\sum_{k\in K}(f_k w_{ik}) + \sum_{i\in I}\sum_{s\in S}(c_s q_{is}) + \sum_{i\in I}(B\gamma_i) + \sum_{i\in I}\sum_{r\in I}\sum_{s\in S}\sum_{h\in H}(l_{ir}^{s} x_{ir}^{sh}) + \sum_{i\in I}\sum_{j\in I}\sum_{h\in H}(\tau_{ij} + \beta) z_{ij}^{h} + \sum_{i\in I}\sum_{r\in I}\sum_{h\in H}(\beta y_{ir}^{h}) \qquad (4)$$

Subject to:

$$\sum_{s\in S} q_{is} + \gamma_i = \sum_{k\in K} a_k w_{ik} \ \ \forall\, i \in I \qquad (5)$$

$$\sum_{k\in K} w_{ik} \le 1\ \forall\, i \in I \qquad (6)$$

$$\sum_{i\in I} q_{is} \ge \tilde{d}_{rs}^{h}\ \forall\, r \in I, s \in S, h \in H \qquad (7)$$

$$\sum_{i\in I} x_{ir}^{sh} = \tilde{d}_{rs}^{h}\ \forall\, r \in I, s \in S, h \in H \qquad (8)$$

$$\sum_{r\in I} x_{ir}^{sh} \leq q_{is} \ \forall\, i \in I, s \in S, h \in H \tag{9}$$

$$\sum_{i\in I} \gamma_i \geq \tilde{g}_r^h \ \forall\, r \in I, h \in H \tag{10}$$

$$\sum_{i\in I} y_{ir}^h + \sum_{i\in I} z_{ij}^h = \tilde{g}_r^h \ \forall\, j = r, j, r \in I, h \in H \tag{11}$$

$$\sum_{r\in I} y_{ir}^h + \sum_{j\in I} z_{ij}^h \leq \gamma_i \ \forall\, i \in I, h \in H \tag{12}$$

$$\gamma_j - \sum_{k\in K} w_{jk}\tilde{g}_r^h \leq M\theta_j^1 \ \forall\, j = r, j, r \in I, h \in H \tag{13}$$

$$\tilde{g}_r^h\theta_j^1 \leq y_{ir}^h \ \forall\, j = r; j, r, i \in I, h \in H \tag{14}$$

$$\sum_{k\in K} w_{jk}\tilde{g}_r^h - \gamma_j \leq M\theta_j^2 \ \forall\, j = r, j, r \in I, h \in H \tag{15}$$

$$\sum_{i\in I} z_{ij}^h \geq \tilde{g}_r^h\theta_j^2 - \gamma_j \ \ \forall\, j = r, j, r \in I, h \in H \tag{16}$$

$$\sum_{i\in I} z_{ij}^h \leq \tilde{g}_r^h\theta_j^2 \ \forall\, j = r, j, r \in I, h \in H \tag{17}$$

$$\sum_{i\in I} z_{ij}^h \leq \sum_{k\in K} w_{jk}\tilde{g}_r^h \ \ \forall\, j = r, j, r \in I, h \in H \tag{18}$$

$$\sum_{j\in I} z_{ij}^h \leq \sum_{k\in K} w_{ik}M \ \ \forall\, i \in I, h \in H \tag{19}$$

$$z_{ii}^h = 0 \ \forall\, i \in I, h \in H \tag{20}$$

$$y_{jr}^h + \sum_{i\in I} z_{ij}^h \leq \tilde{g}_r^h\theta_j^1 + \tilde{g}_r^h\theta_j^2 \ \forall\, j = r, j, r \in I, h \in H \tag{21}$$

$$w_{ik}, \theta_i^1, \theta_i^2 \in \{0,1\} \ \forall\, i \in I, k \in K \tag{22}$$

$$q_{is} \in \mathbb{R}^+ \ \forall\, i \in I, s \in S \tag{23}$$

$$\gamma_i \in \mathbb{R}^+ \ \forall\, i \in I \tag{24}$$

$$x_{ir}^{sh} \in \mathbb{R}^+ \ \forall\, i, r \in I, s \in S, h \in H \tag{25}$$

$$y_{ir}^h \in \mathbb{R}^+ \ \forall\, i, r \in I, h \in H \tag{26}$$

$$z_{ij}^h \in \mathbb{R}^+ \ \forall\, i, j \in I, h \in H \tag{27}$$

The MC model's objective function seeks to minimize the total cost of six terms over all scenarios, the infrastructure cost of establishing warehouse w_{ik} with fixed cost f_k, the procurement cost c_s for quantity q_{is} in all warehouses, the per pallet space cost B for GIK quantity γ_i, the per pallet transportation cost l_{ir}^s of shipping supply quantity x_{ir}^{sh}, the per pallet transportation cost τ_{ij} plus the per pallet handling cost β for moving z_{ij}^h pallets of GIK between warehouses, and the per pallet handling cost β for holding y_{ir}^h pallets of GIK in warehouse i (4).

Constraint (5) is the facility capacity constraint ensuring that all supplies q_{is} and GIK γ_i held in warehouse i are equal to the total capacity a_k. This constraint allows all unused space in any open warehouse to be dedicated to GIK. The second constraint (6) ensures that only one category k of a facility can be open at any location i. Constraint (7) states that the sum of all warehouses with supply s must be greater than or equal to demand for the same supply at a given region r in scenario h. This ensures that the system wide stocks of supply s are sufficient to meet the demand in any scenario. The fourth constraint (8) states that the sum of the allocation decisions of the warehouses in i must satisfy demand for all supply s at region r in scenario h. In constraint (9) for a given warehouse location i, supply s, and scenario h, the sum of the allocation decisions over the regions must be less than the total amount of supply s in warehouse i. Constraint (10) for GIK is the same as constraint (7) but applicable for demand. Constraint (11) state that all storage and transportation decisions for GIK from region r or warehouse j ($j = r$), must be equal to the incited demand from region r. Constraint (12) for any given warehouse i the sum of all GIK storage decisions and transportation decisions to warehouse i must be less than its space allocated for GIK. The ninth constraint (13) identifies a breakpoint if the space allocated for GIK in warehouse j is greater than incited GIK from region r. Constraint (14) requires that if a warehouse j has enough space for the incited GIK in region j then it must support region r. Constraint (15) is the second breakpoint if incited GIK is greater than warehouse j's capacity. Constraint (16) is the GIK transportation decision for the amount of GIK above warehouse j's capacity. Constraint (17) is the upper bound for GIK transportation decisions and constraint (18) states that there can be no transportation decision if there is not an open origin warehouse. Constraint (19) states that a warehouse can only receive GIK from another warehouse if it is open. Constraint (20) states that no warehouse will transport GIK (z_{ij}^h) to itself. Constraint (21) states that the sum of all storage and transportation decisions are less than the incited GIK based on the breakpoint. If there is a warehouse in region r where there is incited GIK, then GIK will only arrive at that warehouse. From the warehouse, GIK is either stored or shipped to another warehouse. If no warehouse exists in the region with incited GIK, then all other warehouses with space will receive GIK based on the model. Constraints (22)-(27) are the non-negativity constraints for the decision variables.

A humanitarian organization will use this objective function if the organization is concerned about scenario-based costs. This objective function incorporates all the scenario-based costs in the objective value immunizing the model against all scenarios. A planner will use this fact to establish a pre-positioning network that is immunized to both parameter uncertainty and scenario realization. This is an extreme case of risk aversion for a humanitarian organization that wants to plan for all contingencies.

3.2.2 Minimize Mean Scenario-Based Cost Model

Objective Function:

$$\min \sum_{i\in I}\sum_{k\in K}(f_k w_{ik}) + \sum_{i\in I}\sum_{s\in S}(c_s q_{is}) + \sum_{i\in I}(B\gamma_i) + \frac{1}{|H|}\left(\sum_{i\in I}\sum_{r\in I}\sum_{s\in S}\sum_{h\in H}\left(l_{ir}^{s} x_{ir}^{sh}\right) + \sum_{i\in I}\sum_{j\in I}\sum_{h\in H}(\tau_{ij}+\beta)z_{ij}^{h} + \sum_{i\in I}\sum_{r\in I}\sum_{h\in H}\left(\beta y_{ir}^{h}\right)\right) \tag{28}$$

The MMSC model shares all the same constraints (5)-(27) as the MC model and shares the same goal of minimizing total cost, but a slight change to transportation cost is included in the objective function. This model minimizes the mean of the scenario-based costs. This model does not penalize for the cumulative total costs of transportation and GIK handling of all scenarios.

If an organization does not want to absorb the scenario-based costs of all scenarios, the organization may use the MMSC objective function. The cost added to the objective value is the mean of all the scenario-based costs, effectively assigning an equal probability to each scenario.

3.2.3 Minimize Maximum Cost Model

Objective Function:

$$\min p \tag{29}$$

Subject to:

$$p \geq \sum_{i\in I}\sum_{k\in K}(f_k w_{ik}) + \sum_{i\in I}\sum_{s\in S}(c_s q_{is}) + \sum_{i\in I}(B\gamma_i) + \sum_{i\in I}\sum_{r\in I}\sum_{s\in S}\left(l_{ir}^{s} x_{ir}^{sh}\right) + \sum_{i\in I}\sum_{j\in I}(\tau_{ij}+\beta)z_{ij}^{h} + \sum_{i\in I}\sum_{r\in I}\left(\beta y_{ir}^{h}\right)\ \forall\, h\in H \tag{30}$$

The MMC model also shares the same constraints as the previous two models with the exception of constraint (30). Constraint (30) states that the decision variable p is the maximum total cost of all the scenarios in H; the cost expression is similar to the objective function (4) of the MC model with the exception of the summation over h. This constraint isolates the costliest scenario while the objective function minimizes p, resulting in for all realized scenarios in H, that p is the maximum cost for the entire system.

A humanitarian organization will use this objective function to determine the minimum most costly scenario possible. This will establish the most an organization will pay for a solution that is feasible in all other scenarios. The MMC objective function is also a risk averse approach, but less costly than the MC model.

3.2.4 Minimize Maximum Regret Model

Objective Function:

$$\min R \tag{31}$$

Subject to:

$$R \geq \left(\sum_{i \in I} \sum_{k \in K} (f_k w_{ik}) + \sum_{i \in I} \sum_{s \in S} (c_s q_{is}) + \sum_{i \in I} (B\gamma_i) + \sum_{i \in I} \sum_{r \in I} \sum_{s \in S} (l_{ir}^s x_{ir}^{sh}) + \sum_{i \in I} \sum_{j \in I} (\tau_{ij} + \beta) z_{ij}^h + \sum_{i \in I} \sum_{r \in I} (\beta y_{ir}^h) \right) - R_h^* \ \forall\, h \in H \tag{32}$$

The MMR model introduces an additional constraint. Constraint (32) is the maximum regret for each scenario where R_h^* represents the scenario optimal solution cost. Regret is defined as the amount of increased total cost the results from the difference between the total cost of a scenario and the optimal solution cost of the same scenario R_h^*. All other constraints are the same as the MC and MMSC modes. The objective function seeks the minimize the maximum regret over all scenarios in H.

A humanitarian organization will opt for the MMR objective function if the organization is not seeking to be risk averse in the case of the MMC objective function. This minimizes the maximum regret for the current decision establishing the maximum possible feeling of regret for all scenarios. Organizations establish a base level of satisfaction utilizing the MMR objective function; any scenario realization other than the base level reduces regret, increasing satisfaction in terms of reducing costs.

3.2.5 Base Models

The four base models represent the MC, MMSC, MMC, and MMR models satisfying only demand and penalizing for unsatisfied GIK. Decision variables associated with GIK are discarded, retaining only decision variables affecting demand. The base models' constraints encompass constraints (6)-(9) and constraint (34) (replaced constraint (5)). The models do not allow warehouses to store GIK, so all GIK in every scenario incur a penalty. After the models generate a solution, a penalty cost P is added to the total cost for each pallet of unsatisfied GIK ($\tilde{g}_r^h$). P represents a per pallet cost that comprises the cost of ill-feelings from donors for unsatisfied GIK, cost of workers to handle unexpected GIK, and the cost of hasty placement of GIK. The purpose of these models is to provide models for comparison to the robust models presented in Sections 3.2.1-3.2.4.

Objective Function: Minimize cost model (BMC)

$$\min \sum_{i\in I}\sum_{k\in K}(f_k w_{ik}) + \sum_{i\in I}\sum_{s\in S}(c_s q_{is}) + \sum_{i\in I}\sum_{r\in I}\sum_{s\in S}\sum_{h\in H}\left(l_{ir}^{s} x_{ir}^{sh}\right) \tag{33}$$

Subject to:

$$\sum_{s\in S} q_{is} \leq \sum_{k\in K} a_k w_{ik} \ \ \forall\, i \in I \tag{34}$$

The calculation of the penalty cost for the BMC solution cost is:

$$\sum_{r\in I}\sum_{h\in H} P\tilde{g}_r^h$$

Objective Function: Minimize scenario-based cost (BMMSC)

$$\min \sum_{i\in I}\sum_{k\in K}(f_k w_{ik}) + \sum_{i\in I}\sum_{s\in S}(c_s q_{is}) + \frac{1}{|H|}\left(\sum_{i\in I}\sum_{r\in I}\sum_{s\in S}\sum_{h\in H}\left(l_{ir}^{s} x_{ir}^{sh}\right)\right) \tag{35}$$

The penalty cost for the BMMSC solution is:

$$\frac{1}{|H|}\left(\sum_{r\in I}\sum_{h\in H} P\tilde{g}_r^h\right)$$

Objective Function: Minimize maximum cost (BMMC)

$$\min p \tag{36}$$

Subject to:

$$p \geq \sum_{i\in I}\sum_{k\in K}(f_k w_{ik}) + \sum_{i\in I}\sum_{s\in S}(c_s q_{is}) + \sum_{i\in I}\sum_{r\in I}\sum_{s\in S}\left(l_{ir}^{s} x_{ir}^{sh}\right) + \sum_{r\in I}\sum_{h\in H} P\tilde{g}_r^h \ \ \forall\, h \in H \tag{37}$$

The penalty cost for the BMMC solution is the range of the penalty costs for all scenarios:

$$\left[\sum_{r\in I} P\tilde{g}_r^1, \ldots, \sum_{r\in I} P\tilde{g}_r^{30}\right]$$

Objective Function: Minimize maximum regret (BMMR)

$$\min R \tag{38}$$

Subject to:

$$R \geq \left(\sum_{i\in I}\sum_{k\in K}(f_k w_{ik}) + \sum_{i\in I}\sum_{s\in S}(c_s q_{is}) + \sum_{i\in I}\sum_{r\in I}\sum_{s\in S}\left(l_{ir}^s x_{ir}^{sh}\right) + \sum_{r\in I}\sum_{h\in H} P\tilde{g}_r^h\right) - R_h^* \;\forall\, h \in H \tag{39}$$

The BMMR solution utilizes the same penalty costs as the BMMC solution.

3.3 Case Study

This thesis presents a computational study to demonstrate the applicability of the previous models. The data for the study is adapted from Rawls and Turnquist (2010) and includes demand, demand and facility nodes, hurricane data, and costs. Three types of supply (water, MRE's, and medical kits) represent demand. The 30 cities across the southeast United States represent the demand and facility nodes. The data from 15 hurricanes represents the affected node(s) and demand amount for each type of supply. The cost data represents facility costs by size, supply cost, and supply transportation cost. This data is the foundation of the parameters used in the eight models previously described.

3.3.1 Rawls and Turnquist (2010) Case Study

The case study from Rawls and Turnquist (2010) centers on hurricanes in the Atlantic Basin of the United States and includes the following states: Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, and Texas. The data includes samples of 15 hurricanes (10 major, categories 3-5; and 5 minor, categories 1 and 2) that made landfall in the Atlantic Basin (between 2004 and 2007, data from the Atlantic Oceanographic and Meteorological Laboratory) and 30 demand-and-candidate facility nodes connected by 58 links. An open warehouse falls into a category of low, medium, or high, each with a cubic footage of 36,400, 408,200, or 780,000, respectively. Demand is categorized into three types of supply, potable water, MRE, and medical kits. For each hurricane event, the data describes the total demand for each supply type and affected nodes. The authors developed a total of 51 scenarios that included events of multiple hurricane strikes.

3.3.2 Robust Model Case Study

The case study of this thesis is comprised of 30 scenarios, two scenarios for each of the 15 hurricanes. The first scenario of each hurricane is the robust adaptation from hurricane data in Rawls and Turnquist (2010). The second scenario is a robust adaptation from the first scenario with either more regions affected or an increase in demand to at least one supply type or GIK. Table 3.1 shows Hurricane #1 from Rawls and Turnquist (2010) and the robust models' data. Both scenarios of the robust adaptation's values of demand and GIK come from within an uncertainty set that is based on the data from Rawls and Turnquist (2010). Scenario 1 of the robust adaptation comprises the robust values of demand from Rawls and Turnquist (2010) and Scenario 2, incorporating a second affected region while ensuring the total amount of demand for each supply type falls within the bounded regions of the uncertainty set. As previously described, nominal GIK values are derived from selecting a value that is between the highest and lowest nominal demand value of a single commodity in a scenario. This method is used to create the remainder of the 30 scenarios used in the robust models. All links exist between the 30 demand-and-facility nodes, resulting in a complete graph for the model. Links represent the distances between nodes, as shown in Figure 3.1 (links not shown in order to see all nodes). Rawls and Turnquist (2010) used cubic feet as the standard unit of measurement; all corresponding values are converted to pallets using a standard pallet measurement (L48"xW40"xH48"). Warehouse capacities, demand, and GIK unit of measurement is number of pallets. Costs, likewise, are converted to dollars per pallet for procurement and storage and dollars per pallet-mile for transportation costs.

Table 3.1: Scenario Creation Example

Hurricane Data	Scenario	Hurricane	Category	Node Affected	Water demand (pallets)	Food demand (pallets)	Medicine Kits demand (pallets)	GIK (Pallets)
Rawls and Turnquist (2010)	1	1	3	Houston, TX	948.94	820.28	10.88	N/A
Robust adaptation	1	1	3	Houston, TX	1016.72	734.35	11.42	310.00
Robust adaptation	2	1	3	Houston, TX	688.66	468.73	8.92	215.00
				Beaumont, TX	303.66	390.61	3.26	100.00

Node	City
1	Charlotte, NC
2	Wilmington, NC
3	Columbia, SC
4	Charleston, SC
5	Savannah, GA
6	Atlanta, GA
7	Nashville, TN
8	Jacksonville, FL
9	Live Oak, FL
10	Tallahassee, FL
11	Orlando, FL
12	Tampa,FL
13	Miami, FL
14	Key West, FL
15	Birmingham, AL
16	Mobile, AL
17	Biloxi, MS
18	Jackson, MS
19	Memphis, TN
20	Hammond, LA
21	New Orleans, LA
22	Baton Rouge, LA
23	Little Rock, AR
24	Ruston, LA
25	Beaumont, TX
26	Dallas, TX
27	Houston, TX
28	San Antonio, TX
29	Corpus Christi, TX
30	Brownsville, TX

Figure 3.1: Case Study Network

3.3.3 Data Uncertainty

In the robust models, both demand and GIK are uncertain and utilize a robust formulation to account for uncertainty. The robust uncertainty set used is motivated by the ellipsoidal and box uncertainty sets used by Ben-Tal and Nemirovski (1998), Ben-Tal et al. (2009) and Baron et al. (2011).

Notation and parameters:

Ω = Safety parameter between 0 and 1

ε_d = the percentage of robustness from the nominal value of demand

ε_g = the percentage of robustness from the nominal value of GIK

$\varepsilon_d \bar{d}_{rs}^{\eta}$ = the deflection value (standard deviation) of the nominal demand at region r for supply s during hurricane η

$\varepsilon_g \bar{g}_r^{\eta}$ = the deflection value (standard deviation) of the nominal GIK at region r during hurricane η

$\zeta_s = \begin{bmatrix} \left(\varepsilon_d \bar{d}_{1s}^{\eta}\right)^2 \\ \vdots \\ \left(\varepsilon_d \bar{d}_{rs}^{\eta}\right)^2 \end{bmatrix}$, ηx1 vector for each supply s, demand variance vector for hurricane η

$V = \begin{bmatrix} \left(\varepsilon_g \bar{g}_r^{\eta}\right)^2 \\ \vdots \\ \left(\varepsilon_g \bar{g}_r^{\eta}\right)^2 \end{bmatrix}$, ηx1 vector, the GIK variance vector for hurricane η

$\zeta_{s\eta}^*$ = the individual inverse demand variance value from the vector ζ_s^{-1} of supply s

V_η^* = the individual inverse GIK variance value from the vector V^{-1}

The starting point for creating the uncertainty sets for $\tilde{d}_{rs}^{h}$ and $\tilde{g}_{r}^{h}$ in each scenario is establishing the nominal values, $\bar{d}_{rs}^{\eta}$ and $\bar{g}_{r}^{\eta}$, and determining values of ε_d and ε_g. The nominal values are derived from the 15 hurricanes in Rawls and Turnquist (2010) where $\eta = \{1,2,\dots,15\}$, represent each of the hurricanes. In practice, the humanitarian organization would determine the desired level of robustness through parameters ε_d and ε_g. ε_d and ε_g are the percentages the uncertain values can shift about the nominal value. The amount of the shift is the deflection value $\varepsilon_d \bar{d}_{rs}^{\eta}$ or $\varepsilon_g \bar{g}_{r}^{\eta}$. The same organization must also determine the safety parameter Ω; this parameter determines the radius of the ellipse and the level of conservatism. $\Omega = 1$ is the maximum level of conservatism; the full ε_d or ε_g percent robustness is in effect for the problem (box uncertainty as described in Baron et al. (2011)). If $\Omega < 1$, then there is a reduction in conservatism. The variance vector for each type of supply and GIK for each of the 15 hurricanes (ζ_s, V) are created and the inverse of the values are assign to the parameters $\zeta_{s\eta}^{*}$ and V_{η}^{*}, respectively. The values assigned to $\zeta_{s\eta}^{*}$ and V_{η}^{*} become singletons. Equations (40) and (41) are the uncertainty set equations for demand and GIK. The equations are derived from the ellipsoidal uncertainty set equation from Baron et al. (2011), shown in Equation (42). In Equation (42), $\tilde{a}_i$ and $\bar{a}_i$ represent the uncertain and nominal parameter respectively with Ω_i as the safety parameter, C_i the covariance matrix, and x as decision variable. Equations (40) and (41) remove all decision variables and replace C_i under the radical with ζ_s. This removes the non-linearity, but retains the flexibility of the safety parameter.

To illustrate creating an uncertainty set assume $\varepsilon_d = 0.1$ (10 percent) and the nominal value of demand is 100. The deflection value is 10 $(0.1 \cdot 100 = 10)$. The deflection value is squared and placed in the ζ_s vector (for this illustration, the vector is 1x1) resulting in [100]; the inverse is $\left[\frac{1}{100}\right]$ with $\zeta_{s\eta}^{*} = \frac{1}{100}$. $\Omega = 0.75$, using Equation (40) results in the uncertain demand range of [92.5,107.5]. Section 3.3.3.1 provides another example for the process of creating the uncertainty set for potable water demand for Hurricane #1. The values between these bounds then derive each scenario. In every scenario no value for $\tilde{d}_{rs}^{h}$ or $\tilde{g}_{r}^{h}$ exists outside their bounds.

$$\bar{d}_{rs}^{\eta} - \frac{\Omega\sqrt{\zeta_{s\eta}^{*}}}{\zeta_{s\eta}^{*}} \le \tilde{d}_{rs}^{h} \le \bar{d}_{rs}^{\eta} + \frac{\Omega\sqrt{\zeta_{s\eta}^{*}}}{\zeta_{s\eta}^{*}} \tag{40}$$

$$\bar{g}_{r}^{\eta} - \frac{\Omega\sqrt{V_{\eta}^{*}}}{V_{\eta}^{*}} \le \tilde{g}_{r}^{h} \le \bar{g}_{r}^{\eta} + \frac{\Omega\sqrt{V_{\eta}^{*}}}{V_{\eta}^{*}} \tag{41}$$

$$\tilde{a}_i = \bar{a}_i \pm \frac{\Omega_i}{\sqrt{x^T C_i x}} C_i x \tag{42}$$

This method is a combination of the box and ellipsoidal method. The ellipsoidal method utilizes non-linear constraints in determining the uncertainty set. The uncertainty set derived in this paper utilizes the ellipsoidal method's concept of moving away from very conservative solutions to reasonably robust solutions with the manipulation of the safety parameter Ω. This method relaxes the non-linear constraint of the ellipsoidal method while still retaining the ellipsoidal quality of being subject to less than the full percentage deflection. Moreover, using the scenario-based approach allows for the computation of the uncertainty sets to happen separate from the optimization model, leading to a computationally tractable model. The uncertainty set derived in this paper is a subset of the box method described in Baron et al. (2011) if $\Omega < 1$. This method, because it is linear, follows closely to the box method, thus creating an interval of values for the uncertain parameters. With equal deflection parameters, the box method uncertainty set encompasses more values and contains the ellipsoidal uncertainty set (Baron et al. 2011). Because this paper's method is constructed similarly to the box method with ellipsoidal intervals, it is a superset of ellipsoidal method of this same problem.

3.3.3.1 Uncertain Data Creation Example

As described above, Hurricane #1, from Rawls and Turnquist (2010), affects the node at Houston, Texas, with the nominal water demand of 948.9375 pallets ($\bar{d}_{rs}^{\eta}$). $\varepsilon_d = 0.15$ and $\Omega = 0.8$ and ζ_1 represent the variance vector for water demand of all 15 hurricanes.

$$\zeta_1 = \begin{bmatrix} 2.03\mathrm{E}+04 \\ 5.19\mathrm{E}+04 \\ 1.23\mathrm{E}+05 \\ 1.34\mathrm{E}+07 \\ 9.30\mathrm{E}+06 \\ 1.65\mathrm{E}+05 \\ 5.95\mathrm{E}+04 \\ 3.72\mathrm{E}+05 \\ 1.79\mathrm{E}+05 \\ 8.37\mathrm{E}+05 \\ 4.13\mathrm{E}+06 \\ 5.36\mathrm{E}+07 \\ 1.31\mathrm{E}+06 \\ 8.29\mathrm{E}+05 \\ 3.20\mathrm{E}+06 \end{bmatrix}$$

The inverse of ζ_1 results in the vector ζ_1^{-1}.

$$\zeta_1^{-1} = \begin{bmatrix} 4.94E\text{-}05 \\ 1.93E\text{-}05 \\ 8.16E\text{-}06 \\ 7.46E\text{-}08 \\ 1.07E\text{-}07 \\ 6.05E\text{-}06 \\ 1.68E\text{-}05 \\ 2.69E\text{-}06 \\ 5.59E\text{-}06 \\ 1.19E\text{-}06 \\ 2.42E\text{-}07 \\ 1.87E\text{-}08 \\ 7.61E\text{-}07 \\ 1.21E\text{-}06 \\ 3.12E\text{-}07 \end{bmatrix}$$

At this point, isolating the value 0.0000494 in the first row of the ζ_1^{-1}vector results in the water demand multiplier for Hurricane #1 and assigned to the parameter ζ_{11}^{*}, $\eta = 1$ for Hurricane #1 and $s = 1$ for supply type 1 (water). The second row corresponds to water demand for Hurricane #2 and continues for the rest of the 15 hurricanes. The values of $\bar{d}_{rs}^{\eta}$, $\zeta_{s\eta}^{*}$, and Ω are entered in to the uncertainty set equation (Equation (40)) creating the bounds for the uncertain value $\tilde{d}_{rs}^{h}$. The water demand bounds for Hurricane #1 are $[835.065, 1062.81]$ pallets.

This process continues creating the uncertainty sets for food, medical kits, and GIK. The data is then used to derive the 30 scenarios that is the basis of the robust and base models. The next chapter presents the results of the computational study.

Chapter 4 - Computational Study Results

Chapter 4 consists of six sections: four sections presenting the results of each robust facility location model, one section presenting the four base models' results, one section comparing the robust models with the base models, and the final section discussing the insights from the robust models. All models are solved using ILOG OPL version 12.4 with a 1.50 GHz AMD A8-3500M APU computer (single core used) with 8.00 GB of RAM. All models are solved to within 0.05 percent of optimality.

4.1 Minimize Cost Model Results

Table 4.1 depicts the solution for the MC model. This solution has ten total warehouses, five large (14,625 pallet capacity), one medium (7,654 pallet capacity), and four small (683 pallet capacity). There is one specialized warehouse (storing only one of the three supply types or GIK) storing only water and four warehouses store all three supply types and GIK. All other warehouses store a combination of the supply types and GIK. The pre-positioned supply pallet totals for the entire system are: 51,514 for water, 23,202 for MRE, and 2,306 for medical kits. The space allocated for GIK encompasses a pallet capacity of 6,487.

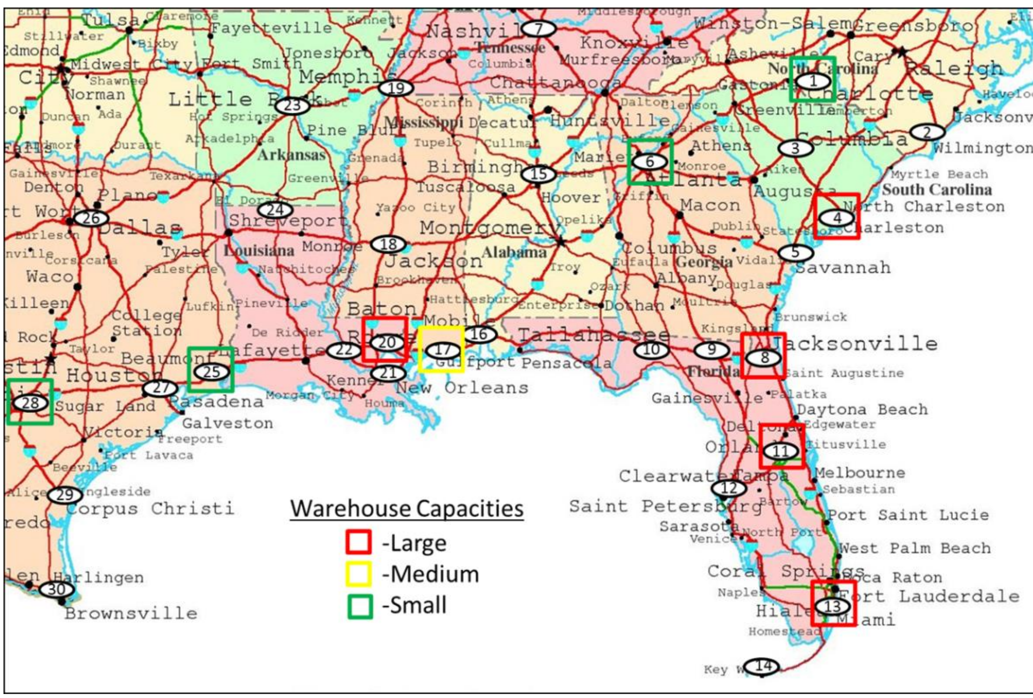
Table 4.1: MC Model Solution

Warehouse	Water (Pallets)	Food (Pallets)	Meds (Pallets)	GIK (Pallets)	Warehouse Capacity
Charlotte, NC	110	555	17	0	Small
Charleston, SC	10234	0	0	4391	Large
Atlanta, GA	0	494	189	0	Small
Jacksonville, FL	12052	2241	261	71	Large
Orlando, FL	14070	0	0	555	Large
Miami, FL	4880	8462	783	500	Large
Biloxi, MS	3335	3346	152	820	Medium
Hammond, LA	6150	7433	892	150	Large
Beaumont, TX	683	0	0	0	Small
San Antonio, TX	0	671	11	0	Small
Total # of pallets for supply and GIK	51514	23202	2306	6487	

Table 4.2 summarizes the cost breakdown of the model. The objective function value is $116.2 million with a majority ($107.6 million) of the total cost in the procurement cost. The procurement cost making up a large majority of the total cost is consistent in all the robust and base models. Figure 4.1 shows the map of the MC model solution.

Table 4.2: MC Model Cost Summary

Cost Type	Amount
Infrastructure Cost	$1,766,800.00
Procurement Cost	$107,633,660.01
GIK Space Cost	$486,547.73
Supply Transportation Cost	$5,971,345.35
GIK Transportation Cost	$24,000.00
GIK Handling Cost	$316,740.00
Total Cost	$116,199,093.09



Node	City
1	Charlotte, NC
2	Wilmington, NC
3	Columbia, SC
4	Charleston, SC
5	Savannah, GA
6	Atlanta, GA
7	Nashville, TN
8	Jacksonville, FL
9	Live Oak, FL
10	Tallahassee, FL
11	Orlando, FL
12	Tampa,FL
13	Miami, FL
14	Key West, FL
15	Birmingham, AL
16	Mobile, AL
17	Biloxi, MS
18	Jackson, MS
19	Memphis, TN
20	Hammond, LA
21	New Orleans, LA
22	Baton Rouge, LA
23	Little Rock, AR
24	Ruston, LA
25	Beaumont, TX
26	Dallas, TX
27	Houston, TX
28	San Antonio, TX
29	Corpus Christi, TX
30	Brownsville, TX

Figure 4.1: Map of MC Model Solution

4.2 Minimize Mean Scenario-Based Cost Model Results

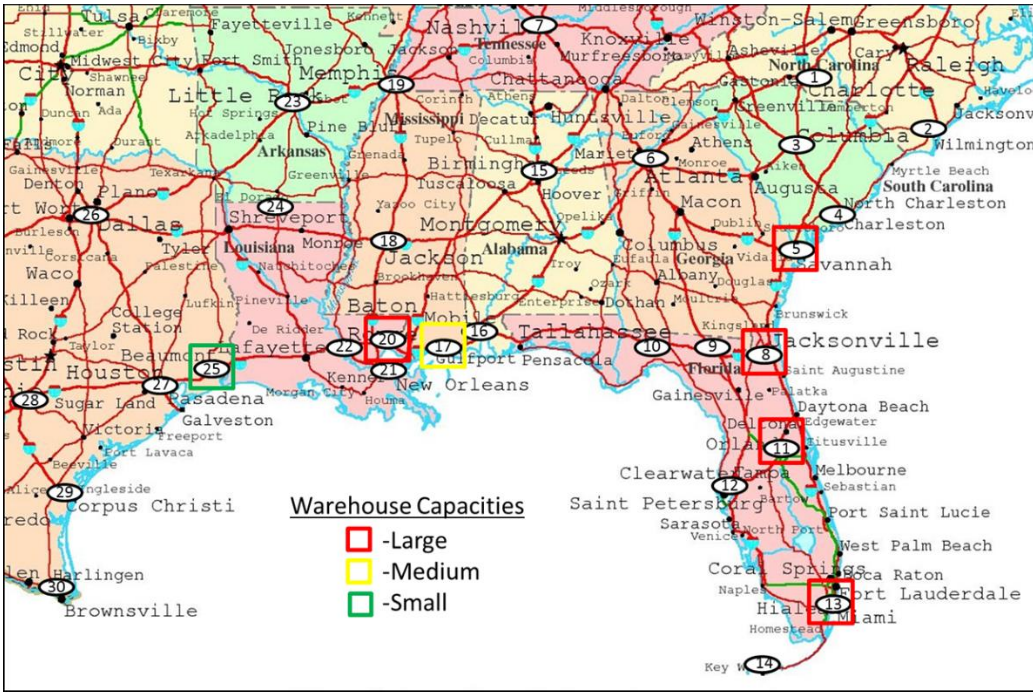
The MMSC model has a total of seven warehouses, five large, one medium, and one small. There are no specialized warehouses; five of the seven warehouses store all three supply types and GIK. Beaumont, Texas, and Orlando, Florida, store only water and GIK. Table 4.3 depicts the solution for the model, Table 4.4 shows the cost summary, and Figure 4.2 displays the map of the solution.

Table 4.3: MMSC Model Solution

Warehouse	Water (Pallets)	Food (Pallets)	Meds (Pallets)	GIK (Pallets)	Warehouse Capacity
Savannah, GA	12852	264	9	1500	Large
Jacksonville, FL	9544	4008	470	603	Large
Orlando, FL	14070	0	0	555	Large
Miami, FL	4880	8462	783	500	Large
Biloxi, MS	3335	3135	152	1032	Medium
Hammond, LA	6250	7333	892	150	Large
Beaumont, TX	583	0	0	100	Small
Total # of pallets for supply and GIK	51514	23202	2306	4440	

Table 4.4: MMSC Model Cost Summary

Cost Type	Amount
Infrastructure Cost	$1,708,000.00
Procurement Cost	$107,633,660.01
GIK Space Cost	$332,985.23
Supply Transportation Cost	$215,958.19
GIK Transportation Cost	$0.00
GIK Handling Cost	$10,591.33
Total Cost	$109,901,194.77



Node	City
1	Charlotte, NC
2	Wilmington, NC
3	Columbia, SC
4	Charleston, SC
5	Savannah, GA
6	Atlanta, GA
7	Nashville, TN
8	Jacksonville, FL
9	Live Oak, FL
10	Tallahassee, FL
11	Orlando, FL
12	Tampa,FL
13	Miami, FL
14	Key West, FL
15	Birmingham, AL
16	Mobile, AL
17	Biloxi, MS
18	Jackson, MS
19	Memphis, TN
20	Hammond, LA
21	New Orleans, LA
22	Baton Rouge, LA
23	Little Rock, AR
24	Ruston, LA
25	Beaumont, TX
26	Dallas, TX
27	Houston, TX
28	San Antonio, TX
29	Corpus Christi, TX
30	Brownsville, TX

Figure 4.2: Map of MMSC Model Solution

4.3 Minimize Maximum Cost Model Results

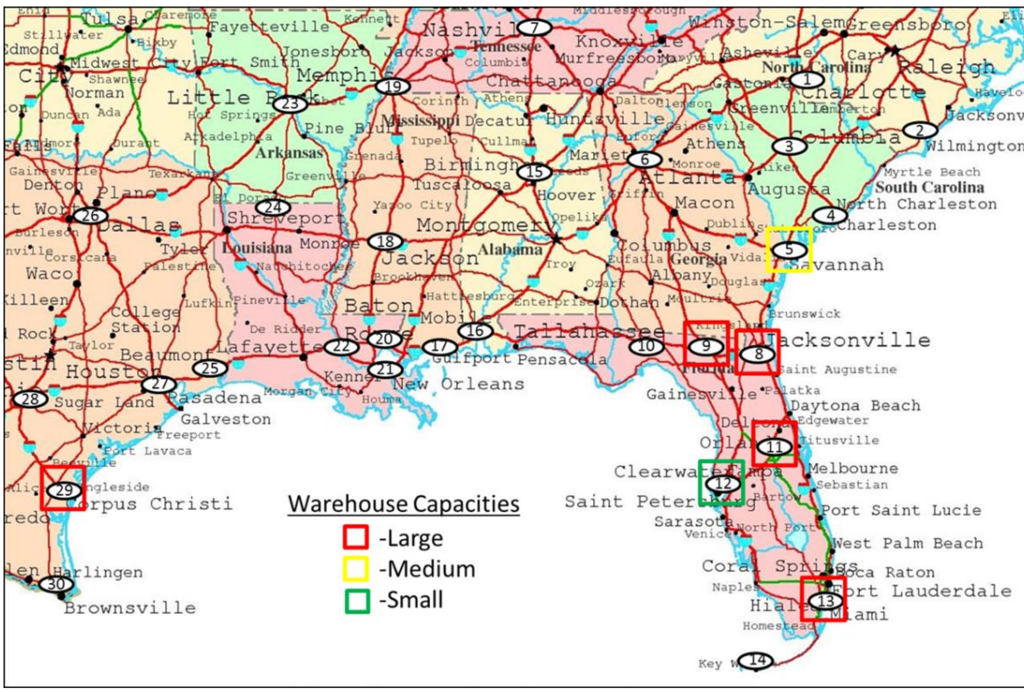
Table 4.5 summarizes the solution for the MMC model, with Figure 4.3 depicting the solution map. There are seven warehouses in this solution, five large, one medium, and one small. Two specialized warehouses store only water in Jacksonville and Tampa, Florida. Three warehouses store all pre-positioned supplies and GIK. The final two warehouses store a combination of pre-positioned supplies and GIK. Table 4.6 shows the cost summary for this model.

Table 4.5: MMC Model Solution

Warehouse	Water (Pallets)	Food (Pallets)	Meds (Pallets)	GIK (Pallets)	Warehouse Capacity
Savannah, GA	1993	4704	957	0	Medium
Jacksonville, FL	14625	0	0	0	Large
Live Oak, FL	12144	2176	305	0	Large
Orlando, FL	14070	0	0	555	Large
Tampa,FL	683	0	0	0	Small
Miami, FL	7923	3588	430	2685	Large
Corpus Christi, TX	77	12734	614	1200	Large
Total # of pallets for supply and GIK	51514	23202	2306	4440	

Table 4.6: MMC Model Cost Summary

Cost Type	Amount
Infrastructure Cost	$1,708,000.00
Procurement Cost	$107,633,660.01
GIK Space Cost	$332,985.23
Supply Transportation Cost	$740,976.76
GIK Transportation Cost	$0.00
GIK Handling Cost	$14,800.00
Total Cost	$110,430,422.01



Node	City
1	Charlotte, NC
2	Wilmington, NC
3	Columbia, SC
4	Charleston, SC
5	Savannah, GA
6	Atlanta, GA
7	Nashville, TN
8	Jacksonville, FL
9	Live Oak, FL
10	Tallahassee, FL
11	Orlando, FL
12	Tampa,FL
13	Miami, FL
14	Key West, FL
15	Birmingham, AL
16	Mobile, AL
17	Biloxi, MS
18	Jackson, MS
19	Memphis, TN
20	Hammond, LA
21	New Orleans, LA
22	Baton Rouge, LA
23	Little Rock, AR
24	Ruston, LA
25	Beaumont, TX
26	Dallas, TX
27	Houston, TX
28	San Antonio, TX
29	Corpus Christi, TX
30	Brownsville, TX

Figure 4.3: Map of MMC Model Solution

4.4 Minimize Maximum Regret Results

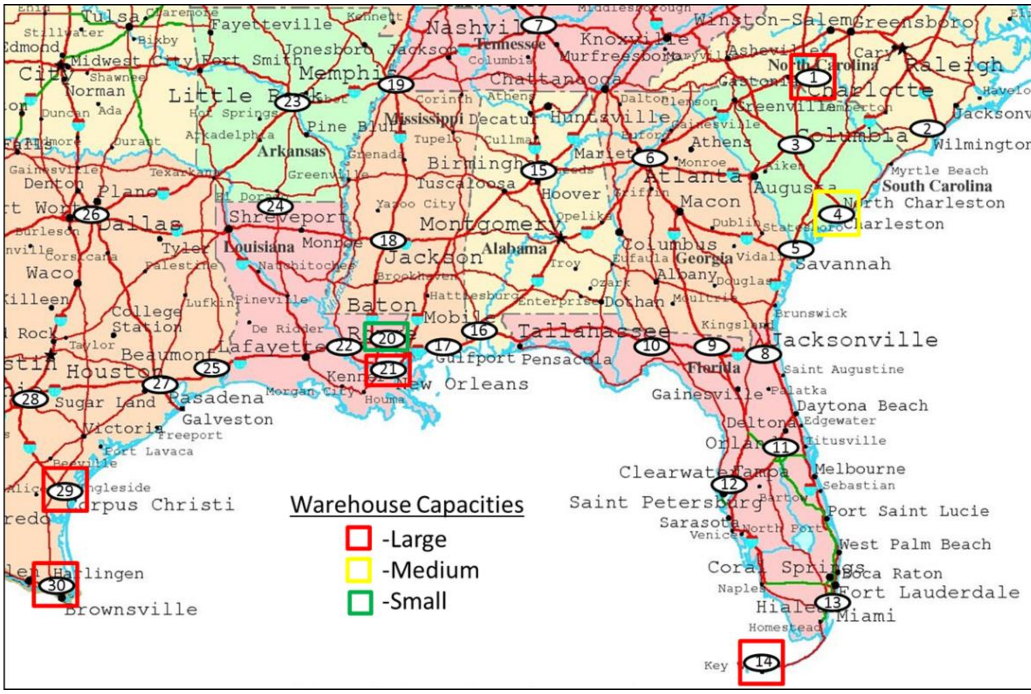
Like the MMC model, the MMR model has seven total warehouses with five large, one medium, and one small. One warehouse stores all pre-positioned supplies and allocates space for GIK. No other warehouse in this solution allocates space for GIK. Two specialized warehouses store only food. All other warehouses store a combination of pre-positioned supplies. Table 4.7 presents the solution for the MMR model, Table 4.8 shows the cost summary, and Figure 4.4 displays the map of the solution.

Table 4.7: MMR Model Solution

Warehouse	Water (Pallets)	Food (Pallets)	Meds (Pallets)	GIK (Pallets)	Warehouse Capacity
Charlotte, NC	12201	1920	505	0	Large
Charleston, SC	2101	1072	40	4440	Medium
Key West, FL	13570	1055	0	0	Large
Hammond, LA	0	683	0	0	Small
New Orleans, LA	0	14625	0	0	Large
Corpus Christi, TX	12865	0	1760	0	Large
Brownsville, TX	10777	3848	0	0	Large
Total # of pallets for supply and GIK	51514	23202	2306	4440	

Table 4.8: MMR Model Cost Summary

Cost Type	Amount
Infrastructure Cost	$1,708,000.00
Procurement Cost	$107,633,660.01
GIK Space Cost	$332,985.23
Supply Transportation Cost	$4,195.94
GIK Transportation Cost	$0.00
GIK Handling Cost	$1,910.00
Total Cost	$109,680,751.19



Node	City
1	Charlotte, NC
2	Wilmington, NC
3	Columbia, SC
4	Charleston, SC
5	Savannah, GA
6	Atlanta, GA
7	Nashville, TN
8	Jacksonville, FL
9	Live Oak, FL
10	Tallahassee, FL
11	Orlando, FL
12	Tampa,FL
13	Miami, FL
14	Key West, FL
15	Birmingham, AL
16	Mobile, AL
17	Biloxi, MS
18	Jackson, MS
19	Memphis, TN
20	Hammond, LA
21	New Orleans, LA
22	Baton Rouge, LA
23	Little Rock, AR
24	Ruston, LA
25	Beaumont, TX
26	Dallas, TX
27	Houston, TX
28	San Antonio, TX
29	Corpus Christi, TX
30	Brownsville, TX

Figure 4.4: Map of MMR Model Solution

4.5 Base Models Results

Table 4.9 shows the solution of the BMC model. The solution has 11 total warehouses, 4 large, 2 medium, and 5 small. Four small specialized warehouses store water in Houston, Texas; Mobile, Alabama; Savannah, Georgia; and Wilmington, North Carolina. Another small warehouse in Columbia, South Carolina, stores MRE and medical kits. All other warehouses store all three pre-positioned supplies. The objective value for this solution is $114.9 million, but the added penalty for unsatisfied GIK brings the total cost of the solution to $146.7 million. Table 4.10 presents the summary of the costs for the solution. Solution maps for the base models are located in Appendix C.

Table 4.9: BMC Model Solution

Warehouse	Water (Pallets)	Food (Pallets)	Meds (Pallets)	Warehouse Capacity
Wilmington, NC	683	0	0	Small
Columbia, SC	0	641	42	Small
Charleston, SC	13269	1250	106	Large
Savannah, GA	683	0	0	Small
Jacksonville, FL	7569	78	7	Medium
Orlando, FL	13662	867	96	Large
Miami, FL	4880	8951	794	Large
Mobile, AL	683	0	0	Small
Biloxi, MS	3254	3984	218	Medium
Baton Rouge, LA	6150	7431	1044	Large
Houston, TX	683	0	0	Small
Total # of pallets for supply	51514	23202	2306	

Table 4.10: BMC Model Cost Summary

Cost Type	Amount
Infrastructure Cost	$1,674,800.00
Procurement Cost	$107,633,660.01
Supply Transportation Cost	$5,636,744.95
Penalty Cost	$31,774,000.00
Total Cost	$146,719,204.96

The BMMSC model solution also has 11 total warehouses with the breakdown being five large and six small. All six small warehouses are specialized warehouses storing only water. All large warehouses are multi-commodity warehouses storing all three pre-positioned supplies. Table 4.11 shows the model solution. The total cost of the solution with penalties is $110.5 million the cost summary is shown in Table 4.12.

Table 4.11: BMMSC Model Solution

Warehouse	Water (Pallets)	Food (Pallets)	Meds (Pallets)	Warehouse Capacity
Wilmington, NC	683	0	0	Small
Charleston, SC	13014	1548	63	Large
Jacksonville, FL	8768	5053	605	Large
Orlando, FL	14580	39	6	Large
Miami, FL	4880	9158	587	Large
Mobile, AL	683	0	0	Small
Biloxi, MS	683	0	0	Small
Hammond, LA	683	0	0	Small
New Orleans, LA	683	0	0	Small
Baton Rouge, LA	6177	7404	1044	Large
Houston, TX	683	0	0	Small
Total # of pallets for supply	51514	23202	2306	

Table 4.12: BMMSC Model Cost Summary

Cost Type	Amount
Infrastructure Cost	$1,617,600.00
Procurement Cost	$107,633,660.01
Supply Transportation Cost	$192,709.51
Penalty Cost	$1,059,133.33
Total Cost	$110,503,102.85

Like the previous two models, BMMC model's solution has 11 warehouses. There are five specialized warehouses, all small. The rest of the warehouses are multi-commodity warehouses storing all or a combination of the pre-positioned supplies. Table 4.13 summarizes the BMMC model solution. The penalty cost for this solution will range between $71,000 (Scenario 25) and $4.4 million (Scenario 29) depending on the realized scenario as displayed in Table 4.14. The cost summary in Table 4.15 shows the range of the total cost of the BMMC solution subject to the minimum and maximum penalty costs. Before the penalty, the scenario that would result in the largest cost using the BMMC solution is Scenario eight.

Table 4.13: BMMC Model Solution

Warehouse	Water (Pallets)	Food (Pallets)	Meds (Pallets)	Warehouse Capacity
Wilmington, NC	8812	5798	15	Large
Charleston, SC	10574	3507	544	Large
Savannah, GA	11312	2734	579	Large
Atlanta, GA	0	683	0	Small
Nashville, TN	0	683	0	Small
Jacksonville, FL	0	484	0	Small
Orlando, FL	0	683	0	Small
Tampa,FL	14501	0	124	Large
Birmingham, AL	0	0	683	Small
Hammond, LA	0	321	362	Small
New Orleans, LA	6315	8310	0	Large
Total # of pallets for supply	51514	23202	2306	

Table 4.14: Scenario Penalty Costs

Scenario	Penalty Cost	Scenario	Penalty Cost	Scenario	Penalty Cost
1	$310,000.00	11	$1,115,000.00	21	$1,900,000.00
2	$315,000.00	12	$880,000.00	22	$1,600,000.00
3	$615,000.00	13	$347,000.00	23	$555,000.00
4	$625,000.00	14	$298,000.00	24	$705,000.00
5	$150,000.00	15	$175,000.00	25	$71,000.00
6	$191,000.00	16	$150,000.00	26	$85,000.00
7	$1,480,000.00	17	$1,100,000.00	27	$1,400,000.00
8	$1,806,000.00	18	$920,000.00	28	$1,650,000.00
9	$1,700,000.00	19	$1,000,000.00	29	$4,391,000.00
10	$1,540,000.00	20	$1,200,000.00	30	$3,500,000.00

Table 4.15: BMMC Model Cost Summary

Cost Type	Amount
Infrastructure Cost	$1,617,600.00
Procurement Cost	$107,633,660.01
Supply Transportation Cost	$742,285.64
Penalty Cost	$71,000.00-$4,391,000.00
Total Cost	$110,064,545.65-$114,384,545.65

The BMMR solution has 11 total warehouses with the same composition as the BMMSC and BMMC models; Table 4.16 shows the model's solution. Only two warehouses are specialized; all other warehouses hold multiple commodities. Depending on the scenario, the total cost of the solution can range from \$109.3 million to \$113.6 million as portrayed in Table 4.17. Like the BMMC solution, the scenario that would result in the largest regret using the BMMR solution is Scenario five.

Table 4.16: BMMR Model Solution

Warehouse	Water (Pallets)	Food (Pallets)	Meds (Pallets)	Warehouse Capacity
Charleston, SC	9891	4190	544	Large
Savannah, GA	9833	4771	21	Large
Live Oak, FL	292	0	218	Small
Tallahassee, FL	683	0	0	Small
Birmingham, AL	0	0	657	Small
New Orleans, LA	10655	3970	0	Large
Little Rock, AR	0	547	136	Small
Beaumont, TX	11633	2992	0	Large
Dallas, TX	393	0	289	Small
San Antonio, TX	8134	6437	54	Large
Brownsville, TX	0	295	387	Small
Total # of pallets for supply	51514	23202	2306	

Table 4.17: BMMR Model Cost Summary

Cost Type	Amount
Infrastructure Cost	\$1,617,600.00
Procurement Cost	\$107,633,660.01
Supply Transportation Cost	\$0.00
Penalty Cost	\$71,000.00-\$4,391,000.00
Total Cost	\$109,322,260.01-\$113,642,260.01

4.6 Analysis of Robust Models and Comparison to Base Models

The four robust models provide solutions that mitigate the impact of GIK by allocating warehouse space during the strategic planning period. Demand satisfaction and space allocation for GIK are equally important, resulting in the models creating feasible solutions satisfying both.

Constraints (7) and (10) are the requirements to satisfy demand and space for GIK. The result of these constraints is that the total amounts of pre-positioned supplies and space for GIK (Tables 4.1, 4.3, 4.5, and 4.7) in the solutions are either greater than or equal to the maximum amount required in any given scenario.

The objective function of the robust models presents four different goals of cost management, specifically in the scenario-based costs. The MC model minimizes the total scenario-based costs for the realized demand and GIK in all scenarios, generating a significant increase in supply transportation, GIK transportation, and GIK handling costs. The scenario-based costs in the MMSC model are the mean costs over all scenarios, substantially reducing costs resulting in a lower objective value than the MC model. The MMC model isolates the scenario that has the most expensive scenario-based cost, and the MMR model selects the scenario-based cost with the maximum regret. Depending on the requirements of the humanitarian organization, all four models are valid.

Coupled with the differing objective functions, the solutions of the robust models present unique approaches to mitigating GIK. The MC, MMSC, and MMC solutions have multiple warehouses allocating space for GIK, whereas the MMR solution only has one warehouse with space to store GIK. Both the MC and MMSC solutions spread warehouses along the Atlantic and Gulf Coast demand regions. These solutions focus on being close to, or in, demand regions, reducing the overall transportation costs for all scenarios. The MMC solution concentrates a majority of its warehouses in Florida and one each in both Georgia and Texas. This solution, like the MC and MMSC solutions, focuses on reducing scenario-based costs, specifically transportation costs. The MMR model presents a solution that centralizes the control of GIK to one location with the other warehouses solely focused on satisfying demand. The aforementioned model would rather pay to ship GIK than to allocate space in warehouses with pre-positioned supplies.

The analysis of the MMC and MMR solutions show they are the complement of each other in warehouse placement. The MMC solution has five warehouses in Florida and one each in both Georgia and Texas, leaving the middle and northeastern part of the network vacant. The MMR solution is the opposite with one warehouse each in Florida, North Carolina, and South Carolina, and two warehouses each in both Louisiana and Texas. Both solutions are willing to pay more in transportation costs than to place warehouses closer to demand nodes.

Compared with other robust solutions, a highlight of the MMR solution is it has the fewest warehouses in nodes subjected to hurricane strikes with only five warehouses exposed. The MMC solution has six warehouses exposed with both the MC and MMSC solutions having seven. With all robust solutions, at most two warehouses in any scenario have the potential of being in a hurricane.

The base models show the impact of not accounting for GIK through the penalty cost added to the total cost of the solutions. Establishing a plan for GIK as opposed to no GIK mitigation results in cost savings as evident by comparing the cost summaries of the MC solution to the BMC solution (Tables 4.2 and 4.10) and the MMSC solution to the BMMSC solution (Tables 4.4 and 4.12). The MMC and MMR solutions also have net savings, but the savings are scenario dependent. Table 4.18 depicts the total and penalty cost of the BMMC solution and compares the total costs in each scenario with the MMC solution total cost. The table highlights the scenarios that result in a net savings for the robust model. In all, 17 of the 30 scenarios result in cost savings for the MMC solution. Moreover, penalty costs greater than $920,000 (920 GIK pallets) result in the BMMC solution being more costly than the MMC solution (there are two scenarios with penalty costs less than $920,000 where the BMMC solution is more costly than the MMC solution). Table 4.19 portrays the same information as Table 4.18 for the BMMR and MMR solutions. The outcomes of 20 scenarios are cost savings for the MMR solution and the penalty cost threshold for cost savings is $555,000 (555 GIK pallets).

Without the penalty costs, the base models are less costly than the robust models. The BMC model has a cost savings of $1.3 million over the MC model, the BMMSC model versus the MMSC model, $0.5 million, BMMC versus MMC, $0.4 million, and BMMR versus MMR, $0.4 million. Any costs incurred for GIK must be greater than the aforementioned cost savings in the base models for the robust strategy to become attractive.

Table 4.18: BMMC and MMC Solution Cost Comparison

Penalty Cost	Total Cost	Scenario
$71,000.00	$109,322,773.32	25
$85,000.00	$109,336,779.67	26
$150,000.00	$109,460,704.06	5
$150,000.00	$109,705,734.08	16
$175,000.00	$109,763,249.16	15
$191,000.00	$109,533,257.76	6
$298,000.00	$109,624,499.04	14
$310,000.00	$109,660,889.10	1
$315,000.00	$109,678,282.20	2
$347,000.00	$109,687,272.60	13
$555,000.00	**$110,548,545.65**	**23**
$615,000.00	$109,962,700.01	3
$625,000.00	$109,978,218.22	4
$705,000.00	**$110,621,507.57**	**24**
$880,000.00	$110,326,867.39	12
$920,000.00	**$110,601,689.13**	**18**
$1,000,000.00	**$110,967,639.34**	**19**
$1,100,000.00	**$110,741,925.64**	**17**
$1,115,000.00	**$110,519,986.56**	**11**
$1,200,000.00	**$111,193,545.65**	**20**
$1,400,000.00	**$111,057,684.13**	**27**
$1,480,000.00	**$111,473,545.65**	**7**
$1,540,000.00	**$111,495,133.58**	**10**
$1,600,000.00	**$111,462,936.22**	**22**
$1,650,000.00	**$111,233,635.08**	**28**
$1,700,000.00	**$111,693,545.65**	**9**
$1,806,000.00	**$111,799,545.65**	**8**
$1,900,000.00	**$111,893,451.46**	**21**
$3,500,000.00	**$113,082,710.86**	**30**
$4,391,000.00	**$114,111,560.01**	**29**

Table 4.19: BMMR and MMR Solution Cost Comparison

Penalty Cost	Total Cost	Scenario
$71,000.00	$109,323,388.06	25
$85,000.00	$109,451,742.34	26
$150,000.00	$109,401,260.01	5
$150,000.00	$109,519,640.46	16
$175,000.00	$109,432,061.67	15
$191,000.00	$109,446,627.41	6
$298,000.00	$109,594,362.58	14
$310,000.00	$109,675,686.56	1
$315,000.00	$109,598,416.90	2
$347,000.00	$109,651,424.35	13
$555,000.00	**$113,543,493.06**	**23**
$615,000.00	**$110,017,493.25**	**3**
$625,000.00	**$109,927,956.48**	**4**
$705,000.00	**$113,156,450.34**	**24**
$880,000.00	**$110,369,595.84**	**12**
$920,000.00	**$110,814,772.12**	**18**
$1,000,000.00	**$111,073,571.02**	**19**
$1,100,000.00	**$110,962,791.84**	**17**
$1,115,000.00	**$110,595,849.60**	**11**
$1,200,000.00	**$110,520,315.15**	**20**
$1,400,000.00	**$111,023,174.93**	**27**
$1,480,000.00	**$112,114,119.72**	**7**
$1,540,000.00	**$112,073,131.21**	**10**
$1,600,000.00	**$111,980,080.21**	**22**
$1,650,000.00	**$111,369,111.65**	**28**
$1,700,000.00	**$112,059,712.83**	**9**
$1,806,000.00	**$111,729,085.65**	**8**
$1,900,000.00	**$112,712,270.15**	**21**
$3,500,000.00	**$114,412,848.38**	**30**
$4,391,000.00	**$114,825,524.58**	**29**

The base models have larger networks, in the number of warehouses, than the robust models, but the system-wide warehouse capacity is smaller. Table 4.20 shows the warehouse compositions of each model solution. Approximately half of the base models' networks encompass small warehouses and most of the robust models' networks are large warehouses (half the network in the MC solution is large warehouses). The smaller warehouses in the base models' solutions are the result of satisfying only demand and the majority large warehouses in the robust models' networks a result of allocating space for GIK. The robust models' and the base models' solution maps share some warehouse locations. The BMC and MC solutions share five warehouse locations; the BMMSC and MMSC solutions share five. The MMC solution shares all seven of its warehouse locations with its base model counterpart, while the regret models only share three. The solution maps of the base models place warehouses on, or relatively closer to, demand nodes than the robust models.

Table 4.20: Warehouse Compositions

Model	Warehouses		
	Small	Medium	Large
MC	4	1	5
BMC	5	2	4
MMSC	1	1	5
BMMSC	6	0	5
MMC	1	1	5
BMMC	6	0	5
MMR	1	1	5
BMMR	6	0	5

4.7 Insights

The comparison between the robust and base models illustrates that completely satisfying demand and allocating space for GIK does not have to change the strategic approach of a humanitarian organization. When accounting for GIK, there is a need for larger warehouses with an associated transportation plan for GIK if a warehouse is at capacity, as evident in the results of the robust models. The total costs of the MC and MMSC models show a cost savings compared to their base model counterparts. Likewise, the total costs of the MMC and MMR models show a net savings over their base model counterparts when the expected GIK donations are moderate to high (moderate donations are 555 pallets of GIK). Even with low GIK donations (low donations are less than 555 pallets of GIK) in the base model solutions (BMMC and BMMR), the cost increase of the MMC and MMR solutions is less than one-third of a percent over the base models, making the low GIK donation scenarios essentially cost neutral. In all scenarios, the robust models show either a similar cost or net savings compared to the total costs of the base models. The total cost comparison along with the similarities in solution maps makes the robust models a favorable choice over the base models.

The expected results for the robust models' solutions were multiple warehouses allocating space for GIK, as shown in the solutions of MC, MMSC, and MMC models. Contrary to the expectations, the MMR solution presents a single warehouse that stores GIK for all scenarios. Having a single warehouse allocate space for GIK allows the other warehouses to focus only on demand satisfaction. An insight to this observation is in the strategic planning period a humanitarian organization can shape where GIK show up after a disaster. The organization can distribute information about this warehouse to the public and reemphasize the information during a disaster with the help of media. Warehouses supporting the relief effort with pre-positioned supplies can have plans established to ship any received GIK to the earmarked warehouse for GIK. As simple and intuitive as it may be, this insight is a way to have complete demand focus in relief efforts while ensuring GIK will not hinder the operation.

The MMR solution is the most risk averse of the four robust models. Though the models do not include warehouse destruction or capacity degradation, the MMR solution exposes the least amount of warehouses in potential disaster areas. In all scenarios, the solution will have less regret in paying more in transportation costs than placing more warehouses in demand nodes. Humanitarian organizations may find this risk averse characteristic in the regret model appealing, because the solution minimizes the network's vulnerability to disaster. Unlike the MMR solution, the MMC solution is the most risk seeking of the four robust models with all seven of its warehouses in potential disaster areas. The MMR solution has the lowest transportation costs (both supply and GIK) in all scenarios. If a humanitarian organization is aggressively seeking to minimize their maximum cost (risk averse with respect to cost) and warehouse location is not a limiting criterion, then the MMC solution is a good fit.

Chapter 5 - Conclusion

This chapter comprises of two sections. The first section is the conclusion and recommendation and the second section provides limitations of the robust models and future research opportunities.

5.1 Conclusion and Recommendations

In the wake of every humanitarian disaster there are two significant forces, the demand for critical aid and the surge of GIK donations. Recent humanitarian disasters show the substantial impact of GIK during the response phase. Fifty percent of in-kind donations are irrelevant to the relief effort and a viable course of action for humanitarian organizations is proper treatment and storage. This thesis introduces a method to mitigate the impact of GIK by establishing a strategic policy of providing adequate space for unsolicited GIK donations. Additionally, it reveals that proper planning in the preparedness phase is critically important in any humanitarian operation.

This report finds that there are reasonable solutions for mitigating the impact of GIK during the preparedness phase. Utilizing robust facility location models, the work in this thesis shows that satisfying demand and mitigating GIK results in solutions with relatively smaller networks and net cost savings compared to models not accounting for GIK. Converting any demand centric humanitarian strategic model to include alleviating the impact of GIK will, depending on the scenario, either be cost neutral or cost saving. Four robust facility location models along with their base model counterparts were presented to illustrate mitigating the impact of GIK is at worst cost neutral.

The research in this paper recommends humanitarian organizations adopt one of the four robust models to mitigate the impact of GIK. The preferred model is the MMR model because it is the most risk averse (with respect to warehouse location) and establishes a dedicated warehouse for GIK, allowing the rest of the warehouses to focus on the relief effort. Another recommendation is for humanitarian organizations to increase public awareness of the donation locations in the network, especially in the MMR solution. By putting out information before donations start arriving, organizations begin the process of mitigating the burden of GIK.

5.2 Limitations and Future Work

The first limitation of this study is the lack of real-world scenarios. The destruction of transportation links, degradation of warehouse capacity, and the destruction of warehouses during storms are examples emphasizing the lack of real-world scenarios. Including aforementioned realities can significantly change the solutions of both the base and robust models in the transportation decisions, warehouse capacities, and location decisions. Moreover, the models do not include air transportation links for helicopters and cargo planes. Ground transportation will not be the only mode of transportation available during most crises.

A second limitation is capturing an accurate cost to reserve space for GIK in the robust models. This study requires complete demand and GIK satisfaction, so it is not plausible to associate the GIK space cost like an opportunity cost for pre-positioned supplies. The cost of reserving GIK space is the humanitarian organization's ability to display competency to donors by the safekeeping of all GIK. An accurate definition of this cost requires more research.

The final limitation is the GIK data. With the lack of accurate GIK donation records for Atlantic Basin hurricanes, the amount of GIK donations were selected arbitrarily between the highest and lowest demand values within a scenario. People donate during times of crisis and the donation amounts depend on the media coverage (Apte 2009). The deduction from this leads to a conclusion that a severe hurricane will incite more GIK donations than a minor hurricane based on the corresponding demand. Using this information, GIK were added to the scenarios. The accuracy of the GIK data is an obvious limitation in the models presented in this report and further research is require to alleviate this shortcoming.

This study leads to a few areas of future research. The first area of research is utilizing different uncertainty sets defining demand and GIK. Different uncertainty sets can reduce the conservatism the current models possess. A second area is more quantitative study on the level of devastation in a disaster and how that affects the donation of GIK. There is some study on the expected amount of in-kind donations to arrive after a disaster based on the devastation and the number of people affected, but more research is required. Third, create a rolling horizon model where the first year facility location decisions are permanent. This type of model will allow humanitarian organizations to establish long-term strategic plans that extend multiple years. Moreover, a rolling horizon model can expand to a dynamic model where at the end of every year the location decisions can change. Fourth, identify a utility function associated with GIK on the importance of allocating space versus the possible consequences of lost future donations and tie the utility function to the expected donation amounts. Finally, establish probabilities for the destruction of warehouses and transportation links between nodes, revealing real-world situations and requiring the entire system to account for disasters affecting the network.

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Appendix A - Parameter Information

Appendix A shows the parameter values utilized in the models of this paper. Cost per pallet-mile of water is \$0.11, food \$0.03, and medical packs \$0.03. Each are multiplied by the distance matrix in Tables A.4 and A.5 to determine the cost per pallet parameter l_{ir}^{s}. The cost per pallet-mile for GIK is \$1.00 and multiplying by the distance matrix results in the cost per pallet parameter τ_{ij}. The parameter B is \$75 per pallet and parameter β is \$10 per pallet. The penalty cost P is \$1000 per pallet. Table A.1 depicts fixed cost (f_k) and warehouse capacity (a_k) and Table A.2 depicts the procurement costs (c_s).

Table A.1: Fixed Costs and Warehouse Capacity

Warehouse size	Fixed Cost	Capacity (pallets)
Small	\$19,600.00	683
Medium	\$188,400.00	7654
Large	\$300,000.00	14625

Table A.2: Supply Procurement Costs

Supply Type	Cost per pallet
Water	\$238.89
Food (MRE)	\$3,468.94
Medical Kits	\$6,436.78

Table A.3 presents all 30 scenarios in the models presented. The scenarios encompass the specific hurricane, regions affected (r), and the realized values of $\tilde{d}_{rs}^{h}$ and $\tilde{g}_{r}^{h}$.

Table A.3: Scenarios

Scenario	Hurricane	Category	Regions affected (node)	Water demand (Pallets)	Food demand (Pallets)	Medical Kits demand (Pallets)	GIK (Pallets)
1	1	3	Houston, TX (27)	1016.72	734.35	11.42	310
2	1	3	Houston, TX (27)	688.66	468.73	8.92	215
			Beaumont, TX (25)	303.66	390.61	3.26	100
3	2	5	Biloxi, MS (17)	1626.75	1539.00	19.58	615
4	2	5	Biloxi, MS (17)	780.84	671.85	6.85	200
			Mobile, AL (16)	881.16	835.90	13.05	425
5	3	2	Charleston, SC (4)	2209.67	265.61	7.83	150
6	3	2	Charleston, SC (4)	1762.31	214.05	5.89	91
			Savannah, GA (5)	338.91	50.00	2.68	100
7	4	2	Charleston, SC (4)	25756.88	2367.09	87.00	1480
8	4	2	Columbia, SC (3)	704.93	640.60	13.05	406
			Charleston, SC (4)	18978.75	1249.95	50.03	900
			Savannah, GA (5)	2711.25	874.97	16.01	500
9	5	4	Baton Rouge, LA (22)	12200.63	1562.44	21.40	1200
			Miami, FL (13)	8676.00	1181.20	15.55	500
10	5	4	Baton Rouge, LA (22)	6778.13	781.22	10.88	500
			Hammond, LA (20)	2033.44	367.17	8.16	150
			New Orleans, LA (21)	1355.63	245.30	4.68	250
			Tampa, FL (12)	3389.06	546.85	6.53	325
			Miami, FL (13)	4880.25	624.98	9.03	315
11	6	3	Mobile, AL (16)	2494.35	2992.07	40.46	1115
12	6	3	Biloxi, MS (17)	1138.73	1124.96	15.70	430
			Mobile, AL (16)	1713.51	1874.93	21.05	450
13	7	2	Wilmington, NC (2)	1762.31	546.85	17.40	347
14	7	2	Wilmington, NC (2)	1491.19	453.11	14.14	298
15	8	1	Baton Rouge, LA (22)	4338.00	265.61	8.63	175
16	8	1	Baton Rouge, LA (22)	2169.00	148.43	4.35	90
			Hammond, LA (20)	677.81	25.00	1.41	35
			New Orleans, LA (21)	1287.84	93.75	2.72	25
17	9	5	New Orleans, LA (21)	1694.53	10468.33	1044.00	650
			Miami, FL (13)	1287.84	10155.84	783.00	450
18	9	5	New Orleans, LA (21)	1897.88	12499.50	1261.50	450
			Miami, FL (13)	1247.18	10702.70	1044.00	470
19	10	2	Corpus Christi, TX (29)	5422.50	1796.80	387.15	1000
20	10	2	Corpus Christi, TX (29)	6832.35	1968.67	456.75	1200
21	11	3	Wilmington, NC (2)	15183.00	2499.90	304.50	1900
22	11	3	Wilmington, NC (2)	12200.63	3062.38	250.13	1600
23	12	3	Orlando, FL (11)	51513.75	1102.46	95.70	555
24	12	3	Tallahassee, FL (10)	16267.50	156.24	16.31	350
			Orlando, FL (11)	26434.69	546.85	47.85	250
			Tampa, FL (12)	6778.13	335.92	32.63	105
25	13	3	Jacksonville, FL (8)	8133.75	132.81	10.98	71
26	13	3	Jacksonville, FL (8)	4338.00	78.12	6.53	40
			Orlando, FL (11)	2711.25	39.06	6.09	45
27	14	4	Biloxi, MS (17)	3253.50	1562.44	130.50	700
			Key West, FL (14)	2982.38	664.04	87.00	700
28	14	4	Biloxi, MS (17)	2169.00	859.34	87.00	800
			Mobile, AL (16)	1539.99	546.85	65.25	350
			Key West, FL (14)	1830.09	624.98	54.38	500
29	15	4	Charleston, SC (4)	10573.88	5468.53	543.75	4391
30	15	4	Charleston, SC (4)	8133.75	3906.09	348.00	2000
			Savannah, GA (5)	4880.25	2734.27	326.25	1500

Tables A.4 and A.5 show the mileage distance between each of the 30 cities.

Table A.4: Distance Matrix (1 of 2)

Distance	Charlotte, NC	Wilmington, NC	Columbia, SC	Charleston, SC	Savannah	Atlanta	Nashville	Jacksonville, FL	Live Oak, FL	Tallahassee	Orlando	Tampa	Miami	Key West	Birmingham
Charlotte, NC	0	198	91	207	252	243	407	383	464	481	525	580	724	887	391
Wilmington, NC	198	0	206	171	303	416	643	434	515	595	575	630	779	938	562
Columbia, SC	91	206	0	113	158	213	439	289	370	393	431	486	630	793	361
Charleston, SC	207	171	113	0	108	321	548	239	320	400	381	435	580	743	469
Savannah, GA	252	303	158	108	0	248	497	139	220	300	280	336	484	643	394
Atlanta, GA	243	416	213	321	248	0	249	323	273	268	445	456	668	821	152
Nashville, TN	407	643	439	548	497	249	0	588	520	490	682	703	903	1068	189
Jacksonville, FL	383	434	289	239	139	323	588	0	85	164	141	200	345	504	492
Live Oak, FL	464	515	370	320	220	273	520	85	0	82	177	191	397	555	380
Tallahassee, FL	481	595	393	400	300	268	490	164	82	0	260	274	480	639	302
Orlando, FL	525	575	431	381	280	445	682	141	177	260	0	84	229	394	562
Tampa,FL	580	630	486	435	336	456	703	200	191	274	84	0	280	425	602
Miami, FL	724	779	630	580	484	668	903	345	397	480	229	280	0	162	783
Key West, FL	887	938	793	743	643	821	1068	504	555	639	394	425	162	0	966
Birmingham, AL	391	562	361	469	394	152	189	492	380	302	562	602	783	966	0
Mobile, AL	573	739	537	642	540	328	447	405	322	244	497	515	720	879	259
Biloxi, MS	633	799	598	702	602	388	507	466	384	305	558	576	782	941	319
Jackson, MS	626	797	596	704	629	388	417	597	514	436	687	707	908	1072	238
Memphis, TN	617	799	606	580	631	390	211	729	615	536	806	839	1027	1203	238
Hammond, LA	728	893	692	796	696	483	546	560	478	399	652	671	876	1035	357
New Orleans, LA	711	881	676	784	684	470	534	548	466	387	640	658	864	1023	345
Baton Rouge, LA	769	935	733	837	737	524	587	602	519	441	694	712	918	1076	399
Little Rock, AR	754	935	744	852	766	525	348	864	750	672	944	974	1165	1339	373
Ruston, LA	775	945	744	848	777	529	515	745	662	584	837	855	1061	1220	386
Beaumont, TX	954	1119	918	1022	922	709	772	786	704	625	879	897	1102	1261	583
Dallas, TX	1034	1197	1004	1112	1029	786	663	997	914	836	1095	1107	1316	1471	636
Houston, TX	1040	1203	1005	1113	1006	800	782	871	788	710	969	981	1190	1345	668
San Antonio, TX	1235	1399	1200	1308	1202	997	940	1070	984	905	1164	1176	1385	1541	865
Corpus Christi, TX	1245	1410	1209	1313	1213	1000	986	1077	995	916	1170	1188	1393	1552	874
Brownsville, TX	1391	1556	1355	1459	1359	1146	1132	1224	1141	1063	1316	1334	1540	1698	1021

Table A.5: Distance Matrix (2 of 2)

Distance	Mobile	Biloxi	Jackson, MS	Memphis	Hammond, LA	New Orleans	Baton Rouge	Little Rock	Ruston, LA	Beaumont	Dallas	Houston	San Antonio	Corpus Christi	Brownsville
Charlotte, NC	573	633	626	617	728	711	769	754	775	954	1034	1040	1235	1245	1391
Wilmington, NC	739	799	797	799	893	881	935	935	945	1119	1197	1203	1399	1410	1556
Columbia, SC	537	598	596	606	692	676	733	744	744	918	1004	1005	1200	1209	1355
Charleston, SC	642	702	704	580	796	784	837	852	848	1022	1112	1113	1308	1313	1459
Savannah, GA	540	602	629	631	696	684	737	766	777	922	1029	1006	1202	1213	1359
Atlanta, GA	328	388	388	390	483	470	524	525	529	709	786	800	997	1000	1146
Nashville, TN	447	507	417	211	546	534	587	348	515	772	663	782	940	986	1132
Jacksonville, FL	405	466	597	729	560	548	602	864	745	786	997	871	1070	1077	1224
Live Oak, FL	322	384	514	615	478	466	519	750	662	704	914	788	984	995	1141
Tallahassee, FL	244	305	436	536	399	387	441	672	584	625	836	710	905	916	1063
Orlando, FL	497	558	687	806	652	640	694	944	837	879	1095	969	1164	1170	1316
Tampa,FL	515	576	707	839	671	658	712	974	855	897	1107	981	1176	1188	1334
Miami, FL	720	782	908	1027	876	864	918	1165	1061	1102	1316	1190	1385	1393	1540
Key West, FL	879	941	1072	1203	1035	1023	1076	1339	1220	1261	1471	1345	1541	1552	1698
Birmingham, AL	259	319	238	238	357	345	399	373	386	583	636	668	865	874	1021
Mobile, AL	0	64	191	398	158	146	199	463	339	384	591	468	664	675	821
Biloxi, MS	64	0	164	371	105	93	146	436	312	331	573	415	611	622	768
Jackson, MS	191	164	0	212	133	186	172	291	150	357	408	442	637	648	794
Memphis, TN	398	371	212	0	341	395	381	139	303	566	454	573	731	775	921
Hammond, LA	158	105	133	341	0	58	45	383	259	230	471	314	509	521	667
New Orleans, LA	146	93	186	395	58	0	80	441	296	294	526	351	546	555	701
Baton Rouge, LA	199	146	172	381	45	80	0	351	220	187	430	271	467	478	625
Little Rock, AR	463	436	291	139	383	441	351	0	170	408	315	434	592	641	788
Ruston, LA	339	312	150	303	259	296	220	170	0	232	254	308	470	515	661
Beaumont, TX	384	331	357	566	230	294	187	408	232	0	289	84	280	291	438
Dallas, TX	591	573	408	454	471	526	430	315	254	289	0	247	277	412	546
Houston, TX	468	415	442	573	314	351	271	434	308	84	247	0	199	211	357
San Antonio, TX	664	611	637	731	509	546	467	592	470	280	277	199	0	143	277
Corpus Christi, TX	675	622	648	775	521	555	478	641	515	291	412	211	143	0	161
Brownsville, TX	821	768	794	921	667	701	625	788	661	438	546	357	277	161	0

Table A.6 shows the characteristics of the 15 hurricanes used as backdrop of the models; it depicts the nominal values ($\bar{d}_{rs}^{\eta}$ and $\bar{g}_{r}^{\eta}$) and the initial regions affected.

Table A.6: Hurricane Characteristics

Hurricane	Regions affected (node)	Water Nominal	Food Nominal	Medicine Nominal	GIK Nominal
1	Houston, TX (27)	948.94	820.28	10.88	350.00
2	Biloxi, MS (17)	1518.30	1448.38	19.21	560.00
3	Charleston, SC (4)	2334.39	282.80	8.74	181.00
4	Charleston, SC (4)	24401.25	2643.64	81.78	1692.00
5	Baton Rouge, LA (22) Miami, FL (13)	20334.38	2767.08	36.69	1687.00
6	Mobile, AL (16)	2711.25	2871.76	38.08	1000.00
7	Wilmington, NC (2)	1626.75	506.23	15.66	324.00
8	Baton Rouge, LA (22)	4066.88	253.11	7.83	162.00
9	New Orleans, LA (21) Miami, FL (13)	2819.70	20780.42	2066.25	1040.00
10	Corpus Christi, TX (29)	6100.31	1757.74	407.81	1125.00
11	Wilmington, NC (2)	13556.25	2734.27	271.88	1750.00
12	Orlando, FL (11)	48802.50	984.34	97.88	630.00
13	Jacksonville, FL (8)	7640.30	125.00	12.42	80.00
14	Biloxi, MS (17) Key West, FL (14)	6070.49	2307.72	229.48	1477.00
15	Charleston, SC (4)	11929.50	6126.32	609.15	3921.00

Appendix B - Uncertainty Set

Appendix B presents the uncertainty sets for demand and GIK. Safety parameter Ω is set at 0.8 with the defections for demand and GIK (ε_d and ε_g) at 0.15.

B.1 Water Uncertainty Set

The uncertainty set for water demand is in section 3.3.3.1, Table B.1 shows the water demand bounds of all 15 hurricanes.

Table B.1: Water Demand Uncertainty Bounds

Hurricane	Robust Water Upper bound	Robust Water lower bound
1	1062.81	835.07
2	1700.50	1336.10
3	2614.51	2054.26
4	27329.40	21473.10
5	22774.50	17894.25
6	3036.60	2385.90
7	1821.96	1431.54
8	4554.90	3578.85
9	3158.06	2481.34
10	6832.35	5368.28
11	15183.00	11929.50
12	54658.80	42946.20
13	8557.14	6723.47
14	6798.95	5342.03
15	13361.04	10497.96

B.2 Food Demand Uncertainty Set

Food demand variance and inverse variance vectors.

$$\zeta_2 = \begin{bmatrix} 6.20E+03 \\ 1.93E+04 \\ 7.37E+02 \\ 6.44E+04 \\ 7.06E+04 \\ 7.60E+04 \\ 2.36E+03 \\ 5.90E+02 \\ 3.98E+06 \\ 2.85E+04 \\ 6.89E+04 \\ 8.93E+03 \\ 1.44E+02 \\ 4.91E+04 \\ 3.46E+05 \end{bmatrix}$$

$$\zeta_2^{-1} = \begin{bmatrix} 1.61\text{E-}04 \\ 5.17\text{E-}05 \\ 1.36\text{E-}03 \\ 1.55\text{E-}05 \\ 1.42\text{E-}05 \\ 1.32\text{E-}05 \\ 4.23\text{E-}04 \\ 1.69\text{E-}03 \\ 2.51\text{E-}07 \\ 3.51\text{E-}05 \\ 1.45\text{E-}05 \\ 1.12\text{E-}04 \\ 6.94\text{E-}03 \\ 2.04\text{E-}05 \\ 2.89\text{E-}06 \end{bmatrix}$$

The values of $\bar{d}^{\eta}_{rs}$, $\zeta^{*}_{s\eta}$, and Ω are entered in to the uncertainty set equation (Equation (40)) creating the bounds for the uncertain value $\tilde{d}^{h}_{rs}$, Table B.1 depicts the results.

Table B.2: Food Demand Uncertainty Bounds

Hurricane	Robust Food upper bound	Robust food low bound
1	918.71	721.85
2	1622.19	1274.57
3	316.74	248.87
4	2960.88	2326.41
5	3099.13	2435.03
6	3216.37	2527.15
7	566.98	445.48
8	283.49	222.74
9	23274.07	18286.77
10	1968.67	1546.81
11	3062.38	2406.15
12	1102.46	866.22
13	139.99	110.00
14	2584.65	2030.79
15	6861.48	5391.16

B.3 Medical Kit Uncertainty Set

Medical Kit demand variance and inverse variance vectors.

$$\zeta_3 = \begin{bmatrix} 5.63E+03 \\ 1.75E+04 \\ 3.64E+03 \\ 3.18E+05 \\ 6.40E+04 \\ 6.90E+04 \\ 1.17E+04 \\ 2.92E+03 \\ 2.03E+08 \\ 7.91E+06 \\ 3.52E+06 \\ 4.56E+05 \\ 7.34E+03 \\ 2.50E+06 \\ 1.76E+07 \end{bmatrix}$$

$$\zeta_3^{-1} = \begin{bmatrix} 1.78E\text{-}04 \\ 5.70E\text{-}05 \\ 2.75E\text{-}04 \\ 3.14E\text{-}06 \\ 1.56E\text{-}05 \\ 1.45E\text{-}05 \\ 8.57E\text{-}05 \\ 3.43E\text{-}04 \\ 4.92E\text{-}09 \\ 1.26E\text{-}07 \\ 2.84E\text{-}07 \\ 2.19E\text{-}06 \\ 1.36E\text{-}04 \\ 3.99E\text{-}07 \\ 5.67E\text{-}08 \end{bmatrix}$$

Using Equation (40) Table B.3 presents the bounds for medical kit demand.

Table B.3: Medical Kit Uncertainty Bounds

Hurricane	Robust Med upper bound	Robust Med low bound
1	12.18	9.57
2	21.51	16.90
3	9.79	7.69
4	91.59	71.97
5	41.10	32.29
6	42.65	33.51
7	17.54	13.78
8	8.77	6.89
9	2314.20	1818.30
10	456.75	358.88
11	304.50	239.25
12	109.62	86.13
13	13.91	10.93
14	257.02	201.95
15	31367.84	24646.16

B.4 Gifts-in-Kind Uncertainty Set

GIK variance and inverse variance vectors.

$$V = \begin{bmatrix} 2.76E+03 \\ 7.06E+03 \\ 7.37E+02 \\ 6.44E+04 \\ 6.40E+04 \\ 2.25E+04 \\ 2.36E+03 \\ 5.90E+02 \\ 2.43E+04 \\ 2.85E+04 \\ 6.89E+04 \\ 8.93E+03 \\ 1.44E+02 \\ 4.91E+04 \\ 3.46E+05 \end{bmatrix}$$

$$V^{-1} = \begin{bmatrix} 3.63\text{E-}04 \\ 1.42\text{E-}04 \\ 1.36\text{E-}03 \\ 1.55\text{E-}05 \\ 1.56\text{E-}05 \\ 4.44\text{E-}05 \\ 4.23\text{E-}04 \\ 1.69\text{E-}03 \\ 4.11\text{E-}05 \\ 3.51\text{E-}05 \\ 1.45\text{E-}05 \\ 1.12\text{E-}04 \\ 6.94\text{E-}03 \\ 2.04\text{E-}05 \\ 2.89\text{E-}06 \end{bmatrix}$$

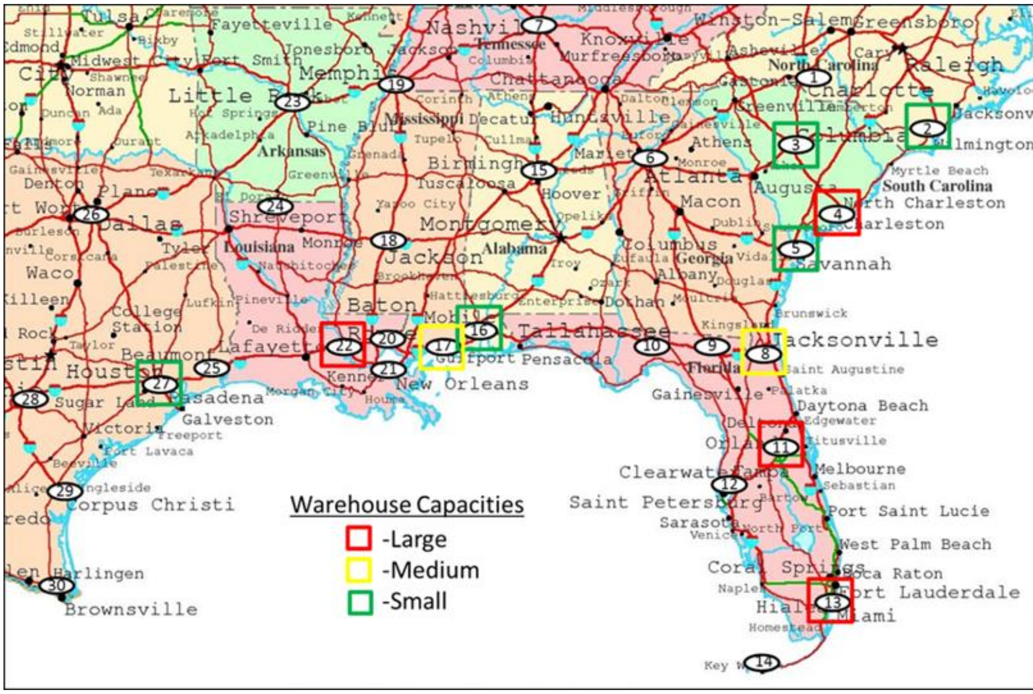
Using Equation (41) Table B.4 presents the bounds for GIK.

Table B.4: GIK Uncertainty Bounds

Hurricane	Robust GIK upper bound	Robust GIK upper bound
1	392.00	308.00
2	627.20	492.80
3	202.72	159.28
4	1895.04	1488.96
5	1889.44	1484.56
6	1120.00	880.00
7	362.88	285.12
8	181.44	142.56
9	1164.80	915.20
10	1260.00	990.00
11	1960.00	1540.00
12	705.60	554.40
13	89.60	70.40
14	1654.24	1299.76
15	4391.52	3450.48

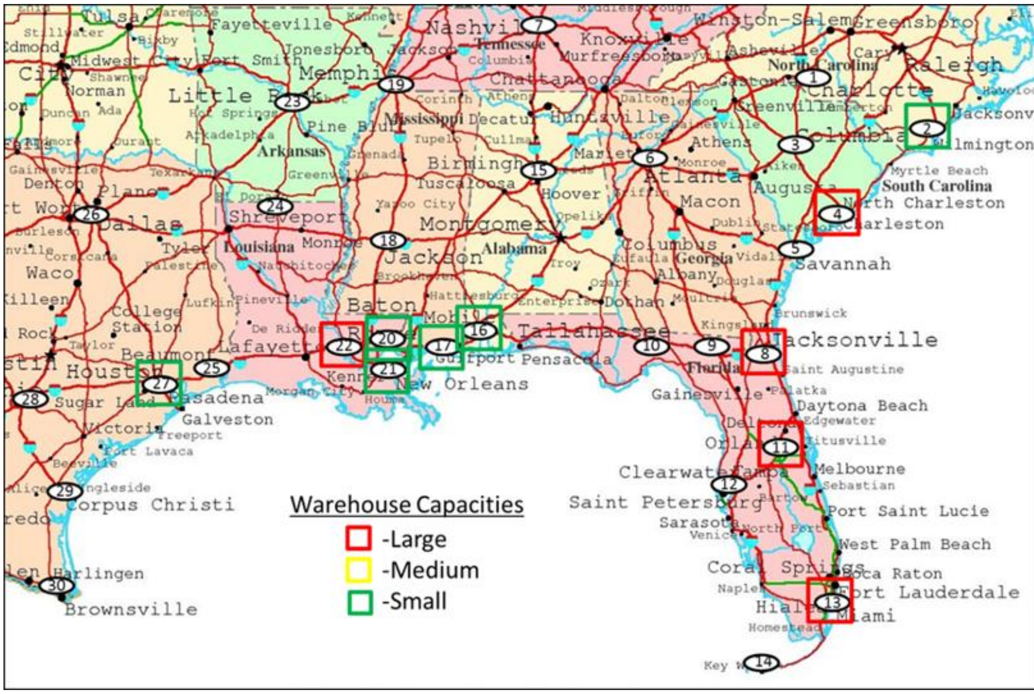
Appendix C - Base Models' Solution Maps

Figures C.1-C.4 depicts the solution maps of the BMC, BMMSC, BMMC, and BMMR models.



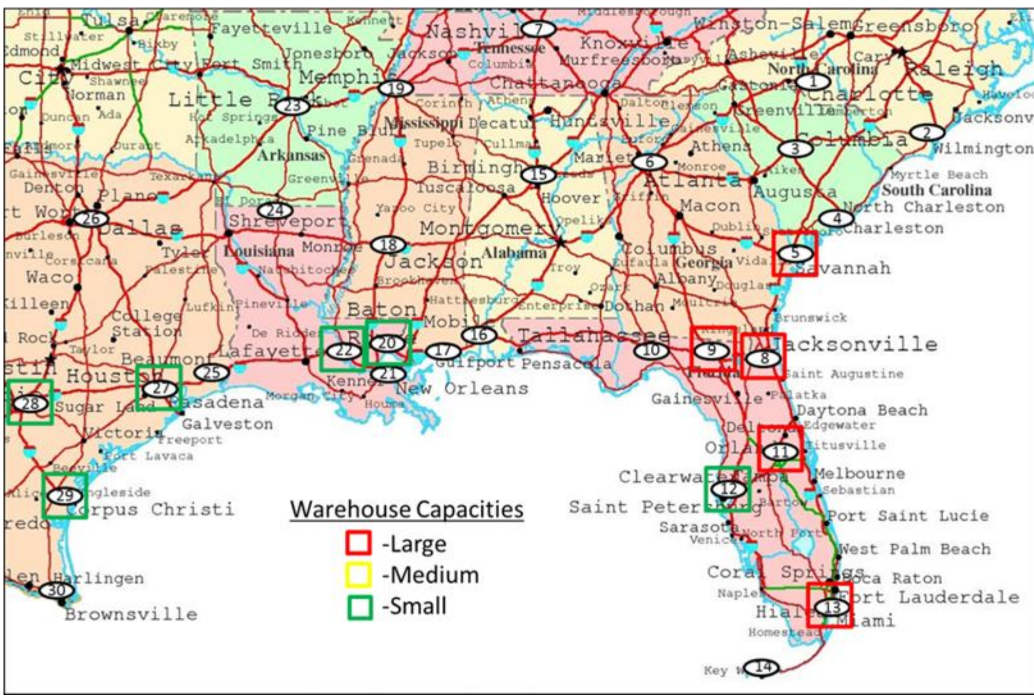
Node	City
1	Charlotte, NC
2	Wilmington, NC
3	Columbia, SC
4	Charleston, SC
5	Savannah, GA
6	Atlanta, GA
7	Nashville, TN
8	Jacksonville, FL
9	Live Oak, FL
10	Tallahassee, FL
11	Orlando, FL
12	Tampa,FL
13	Miami, FL
14	Key West, FL
15	Birmingham, AL
16	Mobile, AL
17	Biloxi, MS
18	Jackson, MS
19	Memphis, TN
20	Hammond, LA
21	New Orleans, LA
22	Baton Rouge, LA
23	Little Rock, AR
24	Ruston, LA
25	Beaumont, TX
26	Dallas, TX
27	Houston, TX
28	San Antonio, TX
29	Corpus Christi, TX
30	Brownsville, TX

Figure C.1: BMC Model Solution Map



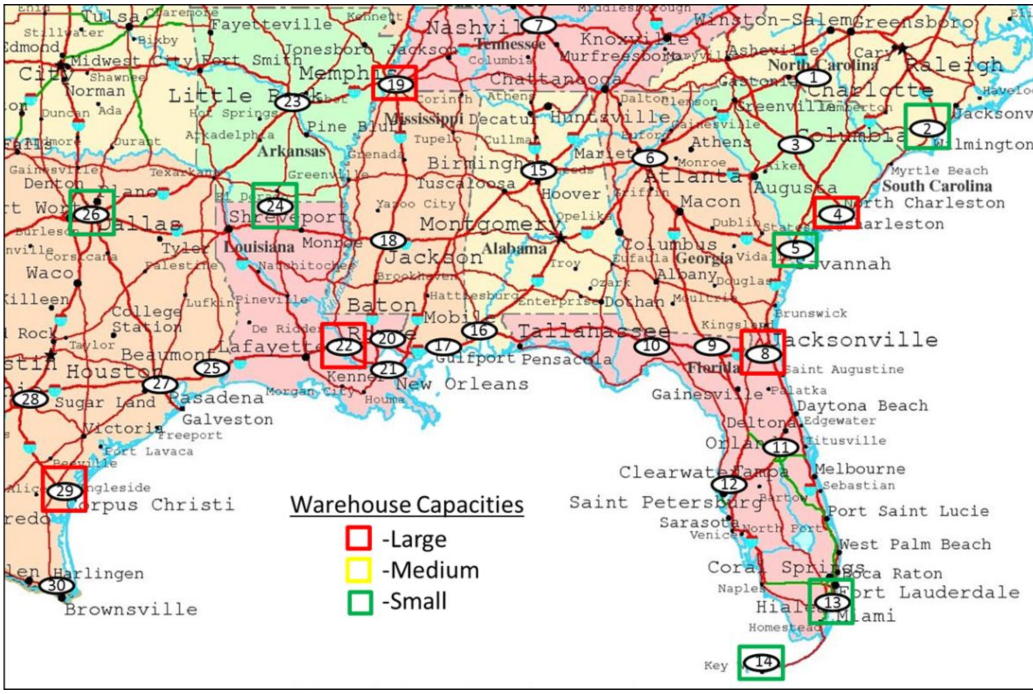
Node	City
1	Charlotte, NC
2	Wilmington, NC
3	Columbia, SC
4	Charleston, SC
5	Savannah, GA
6	Atlanta, GA
7	Nashville, TN
8	Jacksonville, FL
9	Live Oak, FL
10	Tallahassee, FL
11	Orlando, FL
12	Tampa,FL
13	Miami, FL
14	Key West, FL
15	Birmingham, AL
16	Mobile, AL
17	Biloxi, MS
18	Jackson, MS
19	Memphis, TN
20	Hammond, LA
21	New Orleans, LA
22	Baton Rouge, LA
23	Little Rock, AR
24	Ruston, LA
25	Beaumont, TX
26	Dallas, TX
27	Houston, TX
28	San Antonio, TX
29	Corpus Christi, TX
30	Brownsville, TX

Figure C.2: BMMSC Model Solution Map



Node	City
1	Charlotte, NC
2	Wilmington, NC
3	Columbia, SC
4	Charleston, SC
5	Savannah, GA
6	Atlanta, GA
7	Nashville, TN
8	Jacksonville, FL
9	Live Oak, FL
10	Tallahassee, FL
11	Orlando, FL
12	Tampa,FL
13	Miami, FL
14	Key West, FL
15	Birmingham, AL
16	Mobile, AL
17	Biloxi, MS
18	Jackson, MS
19	Memphis, TN
20	Hammond, LA
21	New Orleans, LA
22	Baton Rouge, LA
23	Little Rock, AR
24	Ruston, LA
25	Beaumont, TX
26	Dallas, TX
27	Houston, TX
28	San Antonio, TX
29	Corpus Christi, TX
30	Brownsville, TX

Figure C.3: BMMC Model Solution Map



Node	City
1	Charlotte, NC
2	Wilmington, NC
3	Columbia, SC
4	Charleston, SC
5	Savannah, GA
6	Atlanta, GA
7	Nashville, TN
8	Jacksonville, FL
9	Live Oak, FL
10	Tallahassee, FL
11	Orlando, FL
12	Tampa,FL
13	Miami, FL
14	Key West, FL
15	Birmingham, AL
16	Mobile, AL
17	Biloxi, MS
18	Jackson, MS
19	Memphis, TN
20	Hammond, LA
21	New Orleans, LA
22	Baton Rouge, LA
23	Little Rock, AR
24	Ruston, LA
25	Beaumont, TX
26	Dallas, TX
27	Houston, TX
28	San Antonio, TX
29	Corpus Christi, TX
30	Brownsville, TX

Figure C.4: BMMR Model Solution Map