Impact of Timing in Post-Warning Prepositioning Decisions on Performance Measures of Disaster Management: A Real-Life Application

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ABSTRACT

This research analyzes the impact of timing of post-warning and pre-disaster stock prepositioning decisions in disasters with an advance warning, such as hurricanes. From the warning time to the landfall time, disaster planners receive updated information regarding the hurricane's trajectory and the potential target region iteratively. The planners should decide when the best trigger time (TT) is to start the preparedness activities (prepositioning stocks of emergency goods). The quality of a given TT is evaluated concerning two performance measures: (i) the total logistics cost in the preparedness and response phases; and (ii) the minimum response time (RT) needed to transfer goods from the response facilities to affected areas in the response phase.

A stochastic optimization model is designed to determine the best TT, preparedness decisions, and response operations. The computational complexity of the model is reduced using a graph-theoretic conversion. We test the converted model on experimental data based on major hurricanes from 2001 to 2017 on the United States southeastern coast. Sensitivity analysis of the model shows that delaying TT makes a non-linear reduction in the total logistics cost and non-linear increment in the shortest possible RT. The optimal TT makes the best compromise between the total logistics cost and the speed of the response operations, according to the preference of disaster planners.

Keywords: Disaster relief; Preparedness; Response; Disaster warning; Stochastic optimization.

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1. INTRODUCTION

The consequences of recent hurricanes in the U.S. have demonstrated that human societies suffer from an insufficient capacity to cope with their destructive force and aftermath. The disaster management cycle is a process whereby governmental and non-governmental organizations manage disasters, comprises four sequential phases: mitigation, preparedness, response, and recovery (Altay and Green, 2006; Besiou et al., 2014; Tomasini and Van Wassenhove, 2009, Ghorbani-Renani et al., 2020). This research focuses on prepositioning decisions in the preparedness phase and analyzes their impacts on the response phase operations. Prepositioning before disasters is a reliable method to serve the affected people in the response phase. The number and locations of response facilities, the inventory levels, and the optimal sourcing decisions are determined in the preparedness phase. The main focus of this research is on inventory prepositioning in the case of predictable, rapid-onset disasters such as hurricanes.

1.1. Prepositioning

An appropriate relief stock prepositioning neutralizes the adverse impact of disasters and directly (or indirectly) determines the effectiveness of mitigation, preparedness, and response phases. However, various reasons make stock prepositioning ineffective: (1) the prepositioned inventories of response facilities is affected by disasters; (2) the response facilities are wrongly located far from affected areas; (3) the prepositioned inventories of the response facilities are inaccessible as the distribution infrastructure network is disrupted; and (4) the level of the prepositioned inventories is less than the required demand. Improving prepositioning decisions is one of the functions of the Federal Emergency Management Agency (FEMA). Some scholars criticize prepositioning strategies because they require high investment and incurs holding costs, including costs of product expiration due to lack of inventory turnover (Whybark, 2007). While some useful preparedness strategies can help us reduce resources gobbled in prepositioning (e.g., investing in capabilities), we cannot entirely eliminate the prepositioning. Immediately after a disaster, it takes time to procure supplies and distribute them to the affected people. That is why only response facilities can guarantee a quick response (Kunz et al., 2014). In the inventory prepositioning for disasters such as hurricanes, there is a prior notice (so-called warning time) and ample preparation time. After warning issuance and before the disaster landfall, FEMA would like to know “when” is the best time to start moving right relief items to the right places, while minimizing the total logistics cost and minimizing the response time (RT). RT represents the time needed to transfer the prepositioned items to the affected areas after the landfall (in the response phase). The lack of sufficient financial resources is always a severe issue for FEMA (Flavelle and Wasson, 2017). Therefore, the minimization of logistics cost is crucial as it accounts for 60%–80% of the disaster management costs (Van Wassenhove, 2006). Also, RT is critical because FEMA's ultimate purpose is to serve the affected people as soon as possible. In this research, following the FEMA distribution network, we determine the best trigger time (TT) for preparedness activities while analyzing the tradeoffs between the logistics costs (in the preparedness and response phases) and RT (in the response phase).

1.2. Hurricane

This paper mainly focuses on hurricanes, but its findings can be applied to any other predictable disasters that may strike with prior notice. Since 1851, hurricanes have stricken 19 states in the U.S. mainland. According to their wind speed, central pressure, and wind damage potential, hurricanes are classified into five categories. Hurricanes with a wind speed of 111 miles per hour or higher (Categories 3–5) are considered major. According to the National Oceanic and Atmospheric Administration (NOAA), on average, 17.7 hurricanes hit the U.S. per decade, and 6 of them are of the major category and hugely disrupt societies (U.S. Hurricane Strikes by Decade, 2018). For example, Category-5 Hurricane Matthew (formed on September 28, 2016, and dissipated on October 10, 2016) left more than 1650 fatalities and costed over $10.58 billion. Further, in 2017, three Category-4 hurricanes made landfall in the U.S. This research focuses on hurricanes because of the destruction they cause at such a massive scale and so frequently.

According to FEMA, hurricanes are seasonal. The Atlantic and the Eastern Pacific hurricane season runs from June 1 and May 15, respectively, and ends on November 30. The National Hurricane Center (NHC) issues a forecast advisory five days before a hurricane landfall to predict its location, intensity, and landfall time. All this information is updated and issued every 6 hours (Pacheco and Batta, 2016). We consider the dynamic updates of hurricanes' forecast advisory in our problem.

1.3. FEMA logistics network structure for prepositioning

Depending on the types of disasters, different nations implement different prepositioning strategies. FEMA has a distribution network, as illustrated in Figure 1. Some scholars such as Balcik and Beamon (2008), Horner and Downs (2010), Afshar and Haghani (2012), Bozorgi-Amiri et al. (2013), Galindo and Batta (2013), and Pacheco and Batta (2016) describe the structure of the FEMA network slightly different from the description in this study. This study follows the network structure exactly as described by the members of FEMA on their official website:

a) Main Distribution Centers (MDCs): The MDCs are permanent distribution centers that are geographically dispersed in the U.S.: six in the continental U.S. (Atlanta, GA; Berryville, VA; Ft. Worth, TX; Frederick, MD; San Jose, CA (Moffett Field); Cumberland, MD) and three in the U.S. territories (Guam, Hawaii, and Puerto Rico) (McBride-Davis, 2008; Afshar and Haghani, 2012). At the MDCs, FEMA keeps millions of tons of inventory of life-saving emergency commodities as a part of the Initial Response Resources (IRR). The majority of the capacity of the MDCs is allocated to the six primary items, which are considered central to the IRR concept: 1) water, 2) meals, 3) cots, 4) tarps, 5) blue roofing sheeting, and 6) blankets. Other items, such as generators and hygiene kits, known as secondary items (Pedraza-Martinez and Van Wassenhove, 2011; Stauffer et al., 2016), are also available at the MDCs. In recent years, items for toddlers and infants, as well as durable medical equipment, are also considered as added requirements to expand the IRR (FEMA Factsheet, 2011).

b) Pre-staging Areas (PSAs): The inventory of goods is transported from MDCs to the temporary PSAs in anticipation of a disaster. In this process, the items with a primary demand (such as water, food, and medicines) are prioritized. Different emergency items require different storage and transportation requirements. Therefore, they are usually stored and transported separately (Vanajakumari et al., 2016). In the U.S. and Canada, multi-purpose large arenas and stadiums are designed to be used for locating PSAs and temporarily storing relief items (Vanajakumari et al., 2016). For example, during Hurricane Katrina, Camp Beauregard in central Louisiana was pre-staged by FEMA (Cooper and Block, 2007).

c) Staging Areas (SAs): Once the disaster strikes, disaster logisticians determine and transport an appropriate amount of inventory from PSAs to SAs based on the exact location and magnitude of the disaster in the affected population centers.

d) Point of Distribution (POD): PODs are the places where the affected people stay or take shelter. The last-mile delivery is the movement of goods from SAs to PODs. To avoid further complexity, the last mile delivery is not considered in this research. Further information regarding the last mile delivery can be found in works by Afshar and Haghani (2012), Noyan (2012), Sodhi and Tang (2014), and Vanajakumari et al. (2016). Figure 1 shows the scope of this research aligned with the FEMA distribution network and the timeline of the investigated operations.

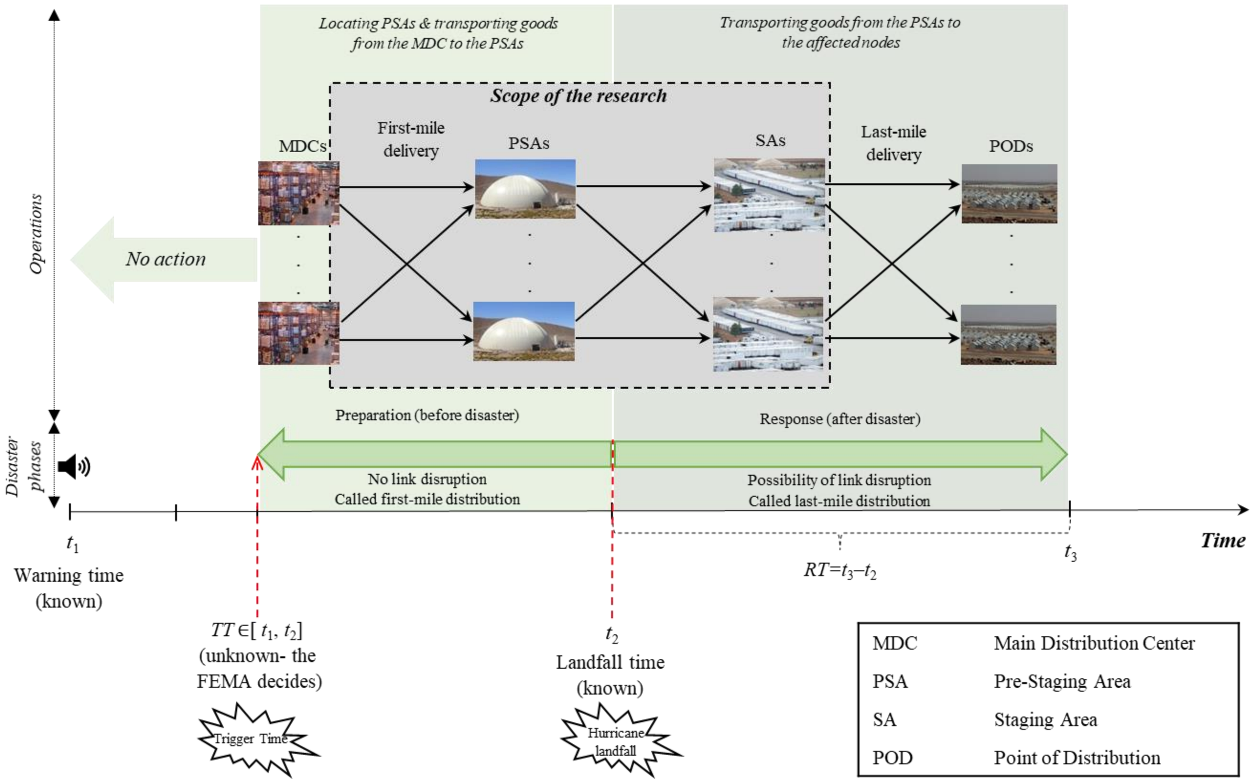


Figure 1. The structure of the FEMA distribution network and timeline of the operations considered in the research.

1.4. Scope and research questions

Disasters can be divided into two categories: rapid and slow-onset disasters (Apte, 2009). In this research, we focus on rapid-onset disasters with prior warnings such as hurricanes. We study the demand for primary items (such as food, water, and medicines) that are urgent to stabilize victims and increase their survival chances. The distribution network used in this paper is aligned with the FEMA structure. As shown in Figure 1, FEMA does not take any action after warning issuance until TT. After TT, the preparedness activities are initiated. Considering t_2 as the estimated landfall time, the whole preparedness activities (such as selecting PSA locations and transferring goods from the nearest MDC to the PSAs) should be accomplished in $[TT, t_2]$ interval. After the landfall, at time t_2, goods are transported from located PSAs to affected areas in the form of response operations. Assuming that RT is the response time considered by FEMA, the response operations should be accomplished by time $t_3 = t_2 + RT$. Approximately, five days before the landfall, the National Hurricane

Center (NHC) starts to issue advisories that can help decision-makers about the preparedness activities (NHC, 2012; Paul and Zhang, 2019). This means $t_2 - t_1 = 5$ (days) for hurricanes and FEMA has at most 5 days for preparedness operations ($TT \in [t_1, t_2]$). We consider the maximum length of the preparedness phase (i.e., $t_2 - t_1$) as a parameter to be more aligned with spatial characteristics of disasters and their corresponding target areas. This makes the proposed model applicable to all predictable disasters in different geographies. Without loss of generality, we assume that we have enough information about the time of hurricane landfall (i.e., time t_2 is known). The choice of TT affects the scope of preparedness activities and the quality of the response operations.

By approaching the landfall time (increasing TT), NHC releases more information about the movement track of a hurricane, and a better estimation exists about its potential landfall locations. At first glance, increasing TT may look beneficial for FEMA because it reduces the size of the area that is threatened by the hurricane and should be covered by the FEMA preparedness activities (a cost reduction). A better estimate of the potential landfall locations may help FEMA locate PSAs closer to those locations (an RT reduction). This paper shows that increasing TT is not always beneficial and should not be considered the best policy by FEMA. We develop a stochastic optimization model to concurrently optimize TT, preparedness activities, and response operations in the disaster management cycle. The decisions made in the preparedness phase answer the following questions:

- When is the best time to start preparedness activities (TT)? This decision determines the target region's size and location that is predicted to be affected by the hurricane and should be covered in the preparedness phase. Also, TT determines the total time available to preposition emergency goods.
- What are the best number, location, and inventory for the PSAs established in the target region in the preparedness phase?
- What is the best transportation plan to transfer emergency goods from MDCs to PSAs within the available time?

In the ***response phase***, the following questions are answered:

- What is the best transportation plan to fulfill demands in the affected region through undamaged PSAs and transportation roads within a fixed RT?
- What is the minimum possible RT to complete the response operations?

Two stochastic optimization models are suggested to solve the problem. Initially, the problem is formulated as a conventional transportation model, which is computationally complicated. Then, the problem is converted to a multi-stage network using a graph-theoretic conversion. Based on the new network, we develop an innovative scenario-based model and solve it using CPLEX 12.9. Moreover, running the model on real-life data and different combinations of TT and RT results in useful insights that answer the following research questions:

- When is the best TT for preparedness activities (establishing and filling PSAs)?
- How does TT affect the total logistics cost in both preparedness and response phases?
- How does TT impact the efficiency of the response operations that is measured by RT?

This paper explains the literature review and contribution of this research in Section 2. Section 3 first describes the case study and then defines it in the form of an academic problem. Sections 4 and 5 formulate and solve the defined problem, respectively. Section 6 analyzes the problem to extract practical insights for policymakers. Section 7 conducts some sensitivity analyses based on realistic data and presents some important observations. Finally, the paper is concluded in Section 8.

2. LITERATURE REVIEW

Holguin-Veras et al. (2011) review a broad spectrum of studies in the humanitarian logistics in (i) short-term response and recovery, where life-to-death and urgent decisions are of importance, and (ii) long-term restoration decisions and assistance where operational efficiency is in priority. As the focus of this research is the preparedness and response phases of the disaster management cycle, in this literature review, we have focused on the papers that study preparedness and response operations of disasters separately, hierarchically, or simultaneously. Specially, we focus on the papers that study location-inventory decisions. First, the related literature's main research streams have been introduced and then compared and contrasted with this research. Finally, we explain the main contributions of this research to the literature.

2.1. Preparedness phase

In the context of prepositioning relief supplies in the preparedness phase, several studies (Balcik and Beamon, 2008; Mete and Zabinsky, 2010; Rawl and Turnquist, 2010; Campbell and Jones, 2011; Duran et al., 2011; Doyen et al., 2012; Noyan, 2012; Bozorgi-Amiri et al., 2013; Galindo and Batta, 2013; Hong et al., 2015; Uichanco, 2015; Salman and Yucel, 2015; Alem et al., 2016; Moreno et al., 2018; Aslan and Celik, 2019; and Sanci and Daskin, 2019) focus on location-inventory decisions for prepositioning of response facilities along with incorporating practical characteristic such as varying lead time, fleeting size of vehicles, and uncertainties in demands. A majority of these papers consider general or rapid-onset disasters, such as earthquakes, in their models. However, there are few studies (Regnier, 2008; Rawl and Turnquist, 2010; Galindo and Batta, 2013) focus on hurricanes, and some studies (Alem et al., 2016; Moreno et al., 2018) focus on floods and landslides with advanced warnings. For example, Regnier (2008) uses stochastic models of the hurricane movement to propose a model that finds the optimal time for the hurricane evacuation under incomplete information. Rawl and Turnquist (2010) propose a model to optimize location-inventory decisions for response facilities and response distribution under the uncertainty of if/where hurricane landfall occurs. Galindo and Batta (2013) propose a methodology to optimize the relief propositioning decisions considering the fact that the disaster may damage the located supplies. To tackle the problems that arise from floods and landslides, Alem et al. (2016) propose a stochastic model to rapidly supply humanitarian aids to victims in the presence of challenges such as scarcity of critical items and lack of information about the exact locations and number of casualties. Moreno et al. (2018) present a mathematical model to optimize the decisions related to response facility location, emergency routing, and fleet sizing. Their innovation lies in incorporating one response vehicle on multiple trips. All studies in this field deal with the location-inventory decisions in the preparedness phase but do not follow the FEMA network structure. Also, they do not consider the time limitation exists to complete preparedness activities. Along with optimizing location-inventory decisions in the preparedness phase, the contribution of this research to this stream is to consider and optimize TT and study its impacts on the efficiency of imminent response operations and the associated performance measures.

2.2. Response phase

Afshar and Haghani (2012) and Vanajakumari et al. (2016) study positioning of temporary facilities operating in the response phase. They follow the FEMA distribution network structure focusing on hurricanes. These studies primarily focus on locating temporary facilities or transferring items to the affected areas after disasters. As these studies do not consider preparedness activities in their problems, their proposed models cannot be used to analyze the impact of TT on RT. We fill this gap through this research.

2.3. Integration of preparedness and response phases

The integration among organizations involved in humanitarian operations increases its efficiency and effectiveness (Jahre et al., 2016). Yücel et al. (2018) integrate the mitigation (through the fortification and structural strengthening of highway components) and response phases. Our research focuses on the integration between the preparedness and response phases. Similarly, Rawls and Turnquist (2010, 2011, and 2012), Döyen et al. (2012), Pacheco and Batta (2016), Tofighi et al. (2016), and Ni et al. (2018) integrate the preparedness and response phases. Therefore, this research is closer to the papers in this category. Rawls and Turnquist (2010, 2011), Döyen et al. (2012), and Tofighi et al. (2016) do not study TT and its impacts on the related metrics before and after a disaster. Their models are applicable for disasters with no warning, such as earthquakes. However, studying TT is practically critical for disasters with an ample warning time, such as hurricanes. For making relevant assumptions about TT, Rawls and Turnquist (2012), Pacheco and Batta (2016), and Ni et al. (2018) are the closest studies to this research. Therefore, they are described in further detail as follows:

Rawls and Turnquist (2012) incorporate a dynamic inventory allocation model to their location-inventory problem in the case of hurricanes. The demand is uncertain, and the objective function is minimizing the expected logistics cost. They study the decisions in both the preparedness (i.e., the location, capacity, and inventory of response facilities) and response (i.e., the transportation of goods from the response facilities to the affected sites) phases. Rawls and Turnquist (2012) propose a dynamic model that makes dispatching decisions for goods at several time steps with updated demand data. The model is tested on a case in North Carolina. Rawls and Turnquist (2012) assume that TT is fixed and exogenously given. Unlike this research, their model neither makes any decision on TT nor analyzes its impacts on the preparedness and response operations.

Pacheco and Batta (2016) propose a model to determine the best time to start preparedness operations. The preparedness operations include the stock prepositioning and re-prepositioning of emergency goods. They intend to ensure that there is sufficient inventory in the response facilities to fulfill the demand in the response phase. Still, they do not consider response operations in their model. Therefore, the impact of TT selection on the efficiency of the response operations (such as the minimum RT) and the tradeoff between the minimum RT and the total logistics cost cannot be investigated using their model. Additionally, in contrast to reality, Pacheco and Batta (2016) assume that the size of the target region is fixed and does not shrink with time. These two gaps will be filled in this paper. NHC documents show that the location and size of the target region is a function of TT. In other words, if FEMA delays TT, the level of uncertainty regarding the moving direction of hurricanes is reduced, but less time is left for the preparation.

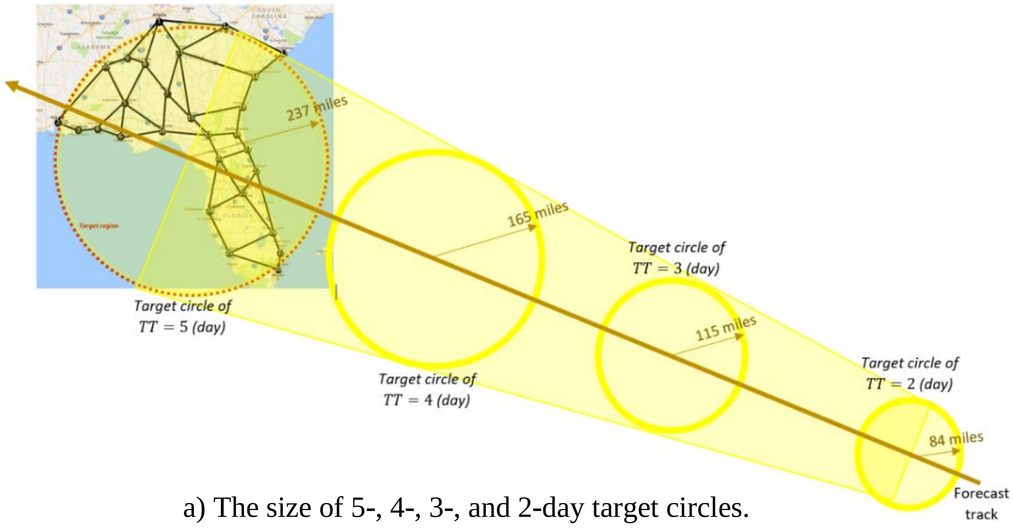
Ni et al. (2018) propose an integrated model that makes the preparedness (i.e., the location and inventory of PSAs) and response (i.e., the transportation of goods from PSAs to stricken nodes) decisions, simultaneously. Similar to this research, they consider demand uncertainty and the possibility of disruption in the response facilities and linking roads. Ni et al. (2018) assume that TT is fixed and exogenously given. Unlike Ni et al. (2018), we consider TT as a decision variable and examine its impacts on the preparedness and response phases in this research. In summary, this research contributes to the literature in the following ways:

- Incorporating the fact that the size of the target region - that should be covered in the preparedness phase - is a function of TT and dynamically shrinks over time;
- Analyzing the impacts of TT on the total logistics cost (in the preparedness and response phases) as the most significant practical objective function during disasters (due to the budget concerns of FEMA);
- Analyzing the impact of TT on the minimum RT in the response phases, which is the second-important performance measure to minimize the suffering level of the affected people;
- Investigating the tradeoff between the total logistics cost and the minimum RT in disasters. This tradeoff should be compromised in TT selection based on the priorities and risk attitude of decision-makers.

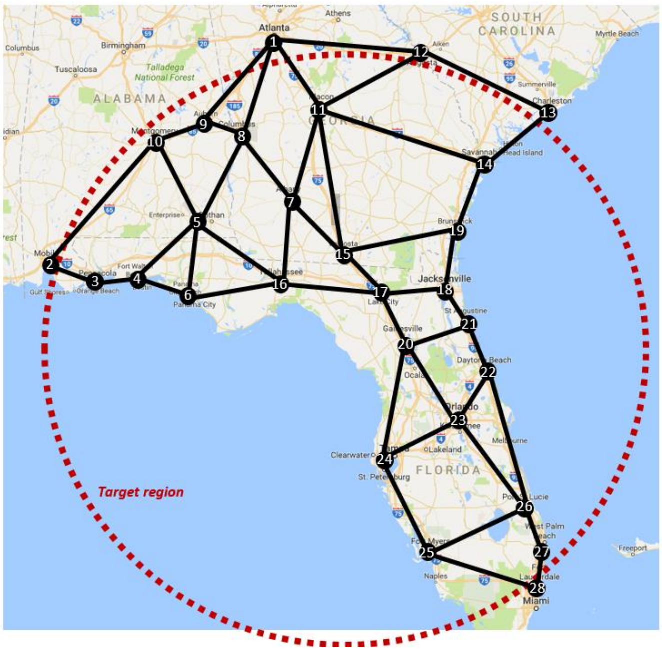
3. PROBLEM DEFINITION

In the problem description, we focus on hurricanes as disasters threatening all coastal states of the U.S. Assume that a hurricane has been formed in the Atlantic Ocean. The tropical storms and hurricanes usually move very slowly with a known speed, and uncertainty is mainly related to their direction of movements. Therefore, the arrival time of hurricanes to the coastal area is almost known. Their moving trajectories and destinations are still stochastic and represented by a target circle instead of a single point. As time passes and the hurricane approaches the coastlines, uncertainty about the direction of movement of the hurricane decreases by gathering more information, and the target circle shrinks (NHC, 2017). Figure 2 illustrates the geographical region that is predicted to be stricken by the hurricane according to NHC's forecast. This region is composed of a known number of population centers (represented by nodes) threatened by the hurricane. The initial reports from NHC contain a 5-day forecast cone for the hurricane's projected trajectory but are continuously updated every 6 hours. The cone is formed by a set of target circles along the forecast track. The size of these circles is set as the two-thirds of historical official forecast errors over a 5-year sample (NHC, 2017). As seen in Figure 2a, the circle radius defines the 5-day, 4-day, 3-day, and 2-day forecasts in 2017 for the Atlantic basins is 237, 165, 115, and 84 miles, respectively. The dashed red circle in Figure 2b represents the target circle of the 5-day forecast. This target circle includes several population centers represented by solid black nodes on the map. The hurricane may strike any of these nodes inside the target circle. In Figure 2b, links represent the transportation roads between pairs of nodes. In this research, we refer to this network as a "relief network (G)."

After NHC issues the hurricane warning, FEMA has five days to prepare for the hurricane (the preparedness phase). TT is the moment when FEMA starts preparedness activities in the target region and varies between 0 (warning moment or five days before the landfall) to 4 (one day before the landfall) days. Options shorter than a day before the landfall are not considered as TT because when a hurricane is expected to make landfall in less than a day, efficient preparation is difficult (Morrice et al., 2016). Determining an appropriate TT is challenging for FEMA because of the following conflicting facts. The radius (or size) of the target circle shrinks over time according to further information gathered by NHC. This fact changes the number, location, and inventory of PSAs that should be located in the preparedness phase. For late TTs (i.e., when the preparedness activities are started late), the size of the target region that should be covered by located PSAs is smaller, leading to locating a smaller number of PSAs and prepositioning a smaller amount of inventory.



a) The size of 5-, 4-, 3-, and 2-day target circles.



b) The relief network of the 5-day target circle.

Figure 2. The target circles of the case study on the southeast coast of the U.S.

On the other hand, for late TTs, the time available to transfer emergency goods from MDCs to located PSAs is short. This time limitation restricts the potential nodes that can be used to locate PSAs. It may also adversely affect the response operations' efficiency (such as RT) after the hurricane. Appropriate selection of TT is crucial to make a tradeoff between its positive and negative impacts on the activities in the preparedness and response phases. After TT, FEMA starts to locate PSAs in the target region to keep emergency goods (Hurricane Sandy, FEMA After-Action Report, 2013). The population centers (or nodes) are the candidate locations to preposition PSAs. The following decisions (starting with "D") are made in the preparedness phase of a disaster by FEMA:

D1: When is the best time to trigger preparedness activities (i.e., TT)?

D2: How many PSAs should be located in the target circle?

D3: Where are the best places to locate the PSAs?

D4: How much inventory should be stored in each PSA? The inventories of located PSAs are transported from the closest MDC located in the continental U.S.

D5: What are the best transportation paths to transfer goods from the closest MDC to the located PSAs?

Each transportation path is a sequence of links/roads that originates from the MDC, passes through several intermediate nodes, and finally ends at a located PSA. When the hurricane makes landfall, the inventories stored in PSAs will be used to fulfill the demands materialized at the stricken nodes in the response phase. The following decisions are made in the response phase:

D6: How much inventory should be transported from each PSA to each stricken node?

D7: Which transportation paths should be used to transport inventories from PSAs to stricken nodes?

This paper proposes a stochastic optimization model to make the above decisions and analyze the tradeoff between disaster-related performance measures (i.e., the total logistics cost and RT). In this model, demands at stricken nodes (i.e., population centers) are stochastic variables with given distribution functions, and the uncertainty in the trajectory of the hurricane (i.e., the location of the target region) is considered through probable scenarios.

The objective function of the model is to minimize the total logistics cost. This objective function aligns with the humanitarian budget concerns in pre- and post-disaster phases (Balcik et al., 2016). In this research, we focus on a single emergency good as different agencies handle emergency goods (e.g., FEMA and American Red Cross), and they require diverse storage and transportation requirements. Therefore they are usually stored and transported separately (Vanajakumari et al., 2016). According to FEMA, the response operations should be accomplished at most 24 hours after landfalls (Florida, 2005). RT shows the time required for response operations. In other words, RT represents the time interval needed to transfer emergency goods from prepositioned PSAs to stricken nodes. A quick response (or a short RT) is critical in the aftermath of disasters (Balcik and Ak, 2014). The impact of choosing TT (in the preparedness phase) on RT (in the response phase) will be analytically investigated in the paper.

Hurricanes may damage the PSAs related to the stricken nodes or disrupt some of the transportation roads (links) ending at stricken nodes. Therefore, the inventory of PSAs located at unstricken nodes and undisrupted roads can only be used in the response phase. Since the focus of the paper is on strategic level decisions, large-scale uncertainties such as disruption in located PSAs and road infrastructure are considered in the decision-making process. Small fluctuations, such as uncertain transportation times, are ignored. In the next section, a conventional transportation model is developed for the problem, and its computational complexity is discussed. The solution approach proposed to reduce its computational complexity is addressed in Section 5.

4. MODEL FORMULATION

In this section, we develop a model to make the preparedness (regarding location-inventory of the PSAs) and response (regarding transferring inventories from located PSAs to stricken nodes) decisions for a given relief network simultaneously. TT and RT are considered fixed parameters in the model. The model is solved for a wide range of TT and RT values to analyze their impacts on the total cost and each other.

The relief network is represented by a directed graph $G(N, E)$ where N is the set of nodes (indexes of n_M, n_P, and n_D are used to represent the MDC, PSAs, and stricken/demand nodes. Intermediate nodes are represented by n, $\acute{n}$, and n'' indexes), and E is the set of links (index of e is used to represent links). The location, held inventory, and transportation decisions for PSAs are made by variables x_{n_P}, y_{n_P}, and $z_e^{\overrightarrow{(n_M, n_P)}}$. Binary variables $w_e^{\overrightarrow{(n_M, n_P)}}$ are defined to ensure that preparedness activities are doable in $TT = t$.

This model includes several uncertainties in the preparedness phase: (i) uncertainty in the demand locations depends on the movement trajectory of the hurricane, and (ii) uncertainty in the demand quantities depends on the severity of the hurricane. The demand for emergency goods will only materialize at nodes (population centers) stricken by the disaster. We do not know exactly which nodes the disaster strikes inside the target circle in the preparedness phase. We also have no complete information about the amount of demand materialized at the stricken nodes. To address the uncertainties in the demand locations, we define a set of scenarios. In the case that $TT = t$ (day), a set of locations is defined for the center of the t-day target circle according to the movement trajectories of historical hurricanes: $L^t = \{l\}$ (will be explained in detail in Section 7.1). The set of nodes located inside the target circle that is centered at $l \in L^t$ is represented by N^l. We consider 1 to q^{Max} severity levels for the hurricane. In severity level q $(= 1, 2, \dots, q^{Max})$, q number of nodes inside the target circle are stricken simultaneously by the hurricane, and the demand for emergency goods is materialized at these nodes. Therefore, $S^t = \{s\}$ includes all possible scenarios for the stricken nodes (or the locations of the demands) and has $|S^t| = \sum_{l=1}^{|L^t|} \sum_{q=1}^{q^{Max}} \binom{|N^l|}{q}$ members. N^s represents the set of stricken/demand nodes in scenario $s \in S^t$. For each scenario of stricken nodes $s \in S^t$, a set of scenarios for disrupted roads is defined as $R^s = \{r\}$. Set R^s includes all subsets of links ending at the stricken nodes of s that can be disrupted simultaneously by the hurricane. To avoid infeasible models, disrupted roads of each $r \in R^s$ should be selected in such a way as not to isolate any stricken node. E^r includes the set of disrupted roads in scenario $r \in R^s$. Variables $\acute{z}_e^{r,\overrightarrow{(n_P, n_D)}}$ identify the transportation decisions from PSAs to demand nodes and binary variables $\acute{w}_e^{r,\overrightarrow{(n_P, n_D)}}$ controls their feasibility in $RT = \acute{t}$.

The demand quantity at a stricken node is considered a random variable with a given distribution function, F. Information of past hurricanes is used to determine the distribution function. For a given $TT = t$ and $RT = \acute{t}$, the conventional mathematical model that is developed to make ***D2-D7*** decisions for the relief network is as follows (for more detail about the notation, refer to Table A1 of Appendix A):

Min		$\sum_{n_P \in N} f_{n_P}^t x_{n_P} + \sum_{n_P \in N} h_{n_P}^t y_{n_P} + \sum_{n_P \in N} \sum_{e \in E} v^t d_e z_e^{\overrightarrow{(n_M,n_P)}} + \frac{1}{\sum_{s \in S^t} \lvert R^s \rvert} \sum_{s \in S^t} \sum_{r \in R^s} \left(\sum_{n_P \in N} \sum_{n_D \in N^s} \sum_{e \in E} v^r d_e \acute{z}_e^{r,\overrightarrow{(n_P,n_D)}} \right)$	(1)
Preparedness operations	*Locating PSAs*	$y_{n_P} \leq M x_{n_P}$ $\quad (\forall n_P \in N)$	(2)
	Pre-disaster transportation	$\sum_{e \in E \mid e = \overrightarrow{(n, n')}} z_e^{\overrightarrow{(n_M,n_P)}} = \sum_{\acute{e} \in E \mid \acute{e} = \overrightarrow{(n', n'')}} z_{\acute{e}}^{\overrightarrow{(n_M,n_P)}}$ $\quad (\forall n_P, n' \in N \mid n' \neq n_P \text{ and } n_M)$	(3)
		$y_{n_P} = \sum_{e \in E \mid e = \overrightarrow{(n, n_P)}} z_e^{\overrightarrow{(n_M,n_P)}}$ $\quad (\forall n_P \in N)$	(4)
	TT limitation	$z_e^{\overrightarrow{(n_M,n_P)}} \leq M w_e^{\overrightarrow{(n_M,n_P)}}$ $\quad (\forall n_P \in N, e \in E)$	(5)
		$\sum_{e \in E} d_e w_e^{\overrightarrow{(n_M,n_P)}} \leq d_t x_{n_P}$ $\quad (\forall n_P \in N)$	(6)
Response operations	*Post-disaster transportation*	$\sum_{n_D \in N^s} \sum_{e \in E \mid e = \overrightarrow{(n_P, n)}} \acute{z}_e^{r,\overrightarrow{(n_P,n_D)}} \leq y_{n_P} \left(1 - \gamma_{n_P}^s\right)$ $\quad (\forall s \in S^t, r \in R^s, n_P \in N)$	(7)
		$\sum_{e \in E \mid e = \overrightarrow{(n, n')}} \acute{z}_e^{r,\overrightarrow{(n_P,n_D)}} = \sum_{\acute{e} \in E \mid \acute{e} = \overrightarrow{(n', n'')}} \acute{z}_e^{r,\overrightarrow{(n_P,n_D)}}$ $\quad (\forall n_P \in N, s \in S^t, r \in R^s, n_D \in N^s, n' \in N)$	(8)

		$\sum_{n_P \in N} \sum_{e \in E \mid e=(\overrightarrow{n,n_D})} \acute{z}_e^{r,(\overrightarrow{n_P,n_D})} \geq F_{n_D}^{-1}(\theta)\gamma_{n_D}^s$ $(\forall n_P \in N, s \in S^t, r \in R^s, n_D \in N^s)$	(9)
	RT limitation	$\acute{z}_e^{r,(\overrightarrow{n_P,n_D})} \leq M\acute{w}_e^{r,(\overrightarrow{n_P,n_D})}$ $(\forall n_P \in N, e \in E, s \in S^t, r \in R^s, n_D \in N^s)$	(10)
		$\sum_{e \in E} d_e \acute{w}_e^{r,(\overrightarrow{n_P,n_D})} \leq d_{\acute{t}}\gamma_{n_D}^s$ $(\forall n_P \in N, e \in E, s \in S^t, r \in R^s, n_D \in N^s)$	(11)
	Road disruption	$\acute{w}_e^{r,(\overrightarrow{n_P,n_D})} \leq \gamma_e^r$ $(\forall e \in E, s \in S^t, r \in R^s, n_P \in N, n_D \in N^s)$	(12)
Variables		$\acute{w}_e^{r,(\overrightarrow{n_P,n_D})}, w_e^{(\overrightarrow{n_M,n_P})}, \ x_{n_P} \in \{0,1\}$ $(\forall e \in E, s \in S^t, r \in R^s, n_P \in N, \ n_D \in N^s)$	(13)
		$\acute{z}_e^{r,(\overrightarrow{n_P,n_D})}, z_e^{(\overrightarrow{n_M,n_P})}, \ y_{n_P} \geq 0$ $(\forall e \in E, s \in S^t, r \in R^s, n_P \in N, n_D \in N^s)$	(14)

In the model, we assume that the closest MDC is located at node n_M of the relief network. The objective function (1) minimizes the total logistics cost in the relief network for given $TT = t$ and $RT = \acute{t}$. The first and second term in (1) corresponds to the locating cost of PSAs in the target circle and the inventory holding cost of emergency goods in the PSAs. The third term in (1) calculates the transportation cost of transferring goods from the MDC to PSAs (pre-disaster transportation cost). The prepositioning decisions of PSAs are made in the post-warning and pre-disaster time interval in which stricken nodes (and demand locations) and roads disrupted by the hurricane are unknown. The scenarios defined in the model address this uncertainty. The fourth term in (1) corresponds to the average transportation cost of transferring inventories from located PSAs to stricken nodes in all scenarios (post-disaster transportation cost).

According to constraint (2), the inventory of emergency goods can only be stored at nodes where a PSA is located. In the pre-disaster process of transporting goods from the MDC to the located PSAs, the total inflow should be equal to the total outflow at the intermediate nodes (constraint (3)). Constraint (4) ensures that the inventory of a PSA equals the total amount of goods transferred to its corresponding node during the preparedness phase. Based on constraints (5) and (6), the maximum distance that the emergency goods can move throughout the relief network from the MDC to located PSAs is consistent with TT selection (d_t shows the maximum distance that can be traveled by the vehicles carrying emergency goods within $TT = t$). Constraints (5) ensures that the variable $w_e^{(\overrightarrow{n_M,n_P})}$ is 1 for all links used in transferring goods from the MDC to the PSA located at node *n*. The binary variables $w_e^{(\overrightarrow{n_M,n_P})}$ are needed in constraint (6) to control the transportation distance of goods from the MDC to PSAs. After the hurricane, the total outflow from the PSAs of unstricken nodes in each scenario cannot be more than their inventories (constraint (7)).

Since $1 - \gamma_{n_P}^s$ would be zero for each scenario's stricken nodes, the total outflow of these nodes would be zero. In the process of transferring goods from PSAs to stricken nodes, the total inflow should be equal to the total outflow at the intermediate nodes in each scenario (constraint (8)). Based on constraint (9), the total inflow to each stricken node in each scenario should be sufficient to fulfill its demand with θ probability. In this constraint, the demand that is materialized at the stricken node n_D is a random variable with F_{n_D} cumulative distribution function and θ is called the service level that represents the fulfillment rate of the demand. Constraint (9) is the simplified form of a reliability inequality that preserves the service level ($Probability\ (Total\ inflow \geq demand) \geq \theta$). θ represents the risk aversion level of decision-makers concerning the uncertainty in the demand quantity. Additionally, constraints (10) and (11) ensure that the transportation of emergency goods from located PSAs to stricken nodes is doable within RT in each scenario. According to this constraint, the maximum distance that the emergency goods can move throughout the relief network from located PSAs to stricken nodes is not more than $d_{\acute{t}}$ ($d_{\acute{t}}$ shows the maximum distance that can be traveled by the vehicles carrying emergency goods within $RT = \acute{t}$). Constraint (12) ensures that only undisrupted roads (the roads for which $\gamma_e^r = 1$) can be used in the process of transferring goods from PSAs to stricken nodes. Constraints (13) and (14) determine the type of variables in the model (e.g., binary and continuous). In this model, we assume that the capacity of PSAs is large enough for any amount of storage. This assumption is legitimate because, as mentioned in Section 1, FEMA usually uses large pre-constructed buildings such as arenas and stadiums to locate PSAs.

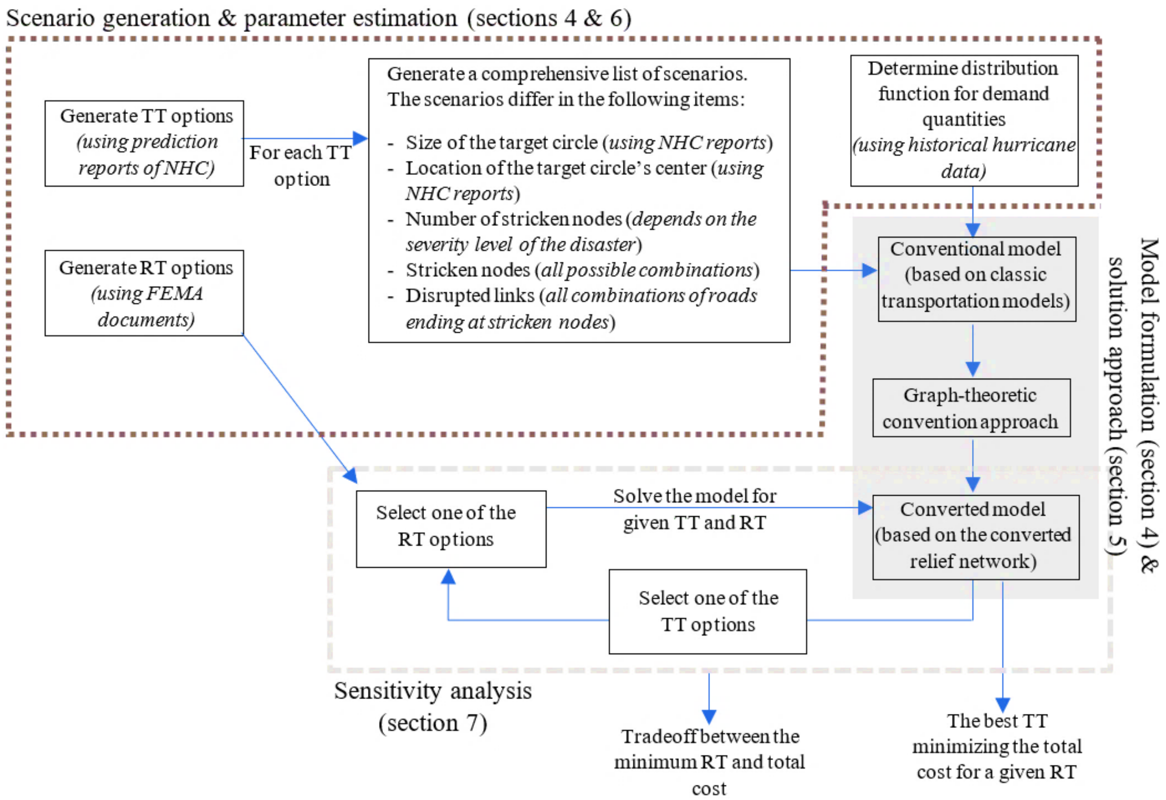


Figure 3. The steps of generating scenarios, modeling, solving, and analyzing results.

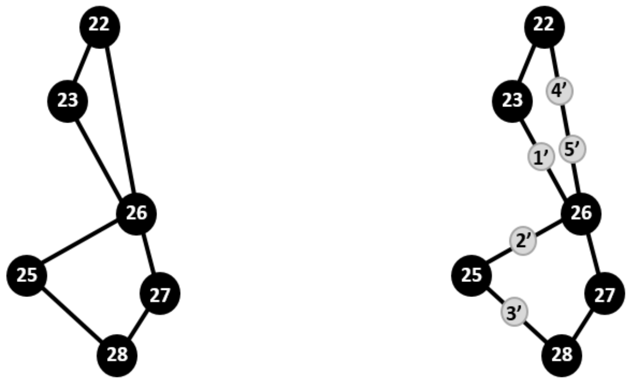
Model (1-14) is a scenario-based mixed integer programming with $|N| + |E|.|N| + (\sum_{\forall s \in S^t} \sum_{\forall r \in R^s} |E|.|N|.|N^s|)$ number of binary variables for given $TT = t$ and $RI = \acute{t}$. For the 5-day target circle in Figure 2b, this conventional model has more than five million binary variables (even when we ignore the disruption possibility of links). Having such a considerable number of binary variables makes Model (1-14) unsolvable for real-size large-scale relief networks. Thus, a graph-theoretic conversion approach is proposed in Section 5 to reduce the number of binary variables in the model. Figure 3 illustrates the steps of generating scenarios, modeling, solving, and analyzing results.

5. SOLUTION APPROACH

The stochastic nature of prepositioning problems prompts scholars to use stochastic optimization techniques to control such dynamic environments (Klibi et al., 2013 and 2018). Since the stochastic model developed in the previous section is computationally complicated, an innovative graph-theoretic conversion approach is developed in this section to formulate and solve the problem more efficiently. This approach results in linear mixed-integer programming with a rational number of binary variables that make it solvable for life-scale problems. The CPLEX 12.9 optimization studio software is used to solve this new model for a case problem on the southeastern coast of the United States.

5.1. Step 1 – Unify the relief network

In this step, we define a New Distance Unit (NDU) in the relief network based on the lengths of links/roads. The NDU is the maximum possible distance according to which the lengths of all links can be estimated as its integer coefficients with high accuracy. Then, by inserting dummy nodes on the links of the relief network, we discretize each link to smaller links with the length of one NDU. We explain this step using a sample sub-network of the case relief network shown in Figure 4. Figure 4a shows this sub-network in which $d_{(\overrightarrow{n_{22},n_{23}})} = d_{(\overrightarrow{n_{23},n_{22}})} = d_{(\overrightarrow{n_{26},n_{27}})} = d_{(\overrightarrow{n_{27},n_{26}})} = d_{(\overrightarrow{n_{27},n_{28}})} = d_{(\overrightarrow{n_{28},n_{27}})} = 1$ (NDU). As the length of these links is equal to 1 (NDU), there is no need to insert any dummy nodes. In this sub-network, there are links with the length of 2 (NDU), such as $d_{(\overrightarrow{n_{26},n_{23}})} = d_{(\overrightarrow{n_{23},n_{26}})} = d_{(\overrightarrow{n_{26},n_{25}})} = d_{(\overrightarrow{n_{25},n_{26}})} = d_{(\overrightarrow{n_{25},n_{28}})} = d_{(\overrightarrow{n_{28},n_{25}})} = 2$ (NDU). We must insert a dummy node in the middle of these links; these nodes are identified by $n_{1'}$, $n_{2'}$ and $n_{3'}$ in Figure 4b. The length of link (n_{22}, n_{26}) is equal to 3 (NDU). Therefore, two dummy nodes should be inserted on the link to split it into three shorter links with the same length of 1 (NDU); these nodes are shown by $n_{4'}$ and $n_{5'}$ in Figure 4b. In the resultant network (so-called ***unified relief network***), the length of all links is equal to 1 (NDU). The unified relief network has $|N|$ real and $|\widehat{N}|$ dummy nodes.



a) The original sub-network. b) The unified sub-network.

Figure 4. The process of unifying a sample sub-network.

5.2. Step 2 – Construct a multi-stage relief network based on the unified relief network

In this step, we exploit the unified relief network constructed in Step 1 to create a multi-stage relief network ($\acute{G}$), which will be the foundation of our new model. The multi-stage relief network comprises $D_t + D_{\acute{t}} + 1$ stages. D_t and $D_{\acute{t}}$ show the number of NDU that exists inside d_t and $d_{\acute{t}}$, respectively. As explained in Section 4, d_t shows the maximum distance that the inventory of the MDC can mobilize through the relief network toward the located PSAs after $TT = t$ and before the landfall. Moreover, $d_{\acute{t}}$ shows the maximum distance that the inventory of the PSAs can mobilize through the relief network toward the affected nodes during $RT = \acute{t}$. There is only one node in stage 1 of $\acute{G}$. This node represents the closest MDC to the target region of the hurricane. In the case study of Figure 2, the node in stage 1 is node 1 (Atlanta City), which contains one MDC. Stages 2 to D_t and $D_t + 2$ to $D_t + D_{\acute{t}}$ include $|N| + |\widehat{N}|$ nodes. In these stages, there is a node corresponding to each node in the unified relief network. In stages $D_t + 1$ and $D_t + D_{\acute{t}} + 1$, there are $|N|$ nodes corresponding to the nodes in the original relief network. Figure 5 illustrates the multi-stage relief network that is constructed based on the unified relief network of Figure 4b. In Figure 5, it is assumed that the closest MDC is located at node 22.

We consider a link between node n in stage i and node $\acute{n}$ ($n \neq \acute{n}$) in stage $i+1$ ($i = 1, 2, 3, \dots, D_t + D_{\acute{t}}$) of the multi-stage relief network if there is a link between the corresponding nodes of n and $\acute{n}$ in the unified relief network. Black arrows in Figure 5 show these links in the multi-stage network. For example, there is a back arrow from node n_{22} in stage 2 to node n_{23} in stage 3 of the multi-stage network. This is because nodes n_{22} and n_{23} are connected through a link in the unified network of Figure 4b. Since the length of all links in the unified network is 1 (NDU), the moving of flow between the nodes of two successive stages in the multi-stage network corresponds to the travel of 1 NDU in the original relief network. The PSAs can be located at the nodes of stage $D_t + 1$ and the MDC is in stage 1. The fact that there are D_t number of black links between stages 1 and $D_t + 1$ ensures that the maximum movement distance from the MDC to the located PSAs (in the preparedness phase) cannot be more than D_t (NDU) or d_t (mile). Having stages in $\acute{G}$ helps control the movement distance (and the transportation time) of goods in the network without defining binary variables. There is a link between node $n \in N$ in stage i and node $n \in N$ in stage $i+1$ ($i = 1, 2, 3, \dots, D_t + D_{\acute{t}}$) of the multi-stage relief network. The blue arrows in Figure 5 show these links. The flow in these links represents that the emergency items are kept at node $n \in N$, and no movement happens in the original relief network.

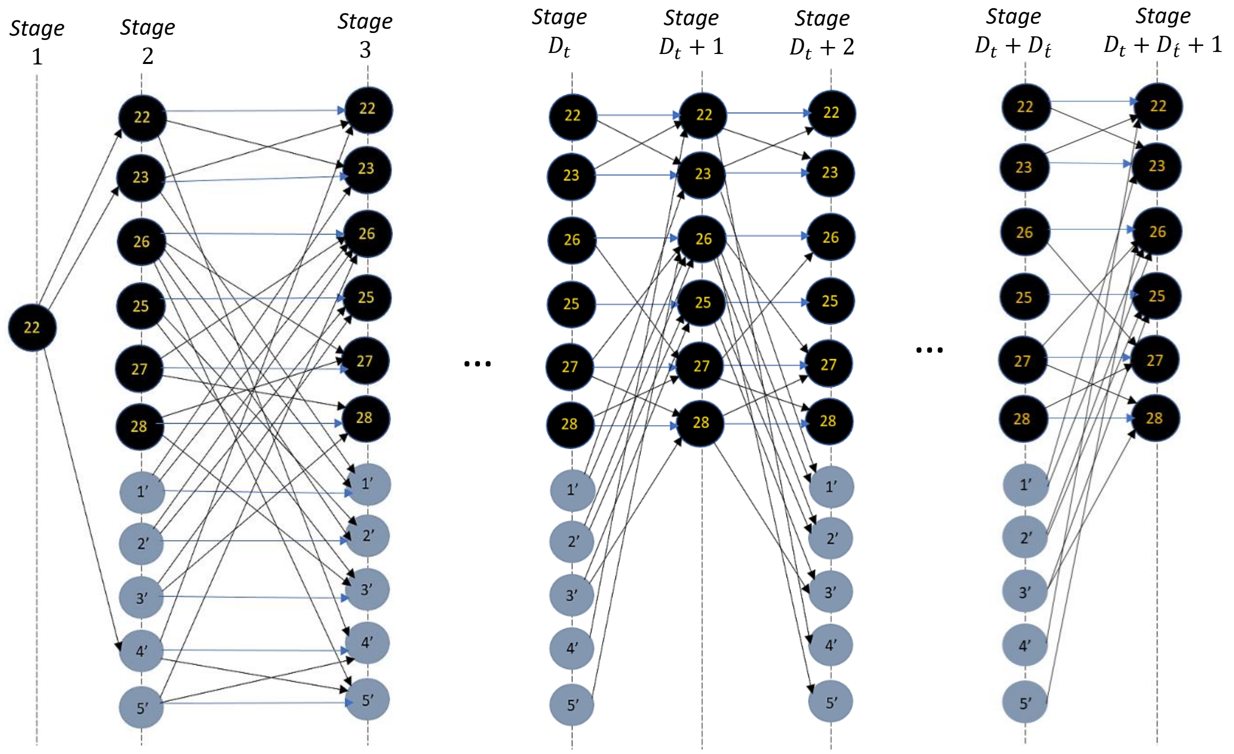


Figure 5. The multi-stage relief network ($\acute{G}$) constructed based on the unified relief network of Figure 4b.

In the rest of this section, we explain how the flow transactions between the stages of the multi-stage relief network determine the decisions that should be made in the original relief network (*D*1-*D*7). Positive inflow to node $n \in N$ in stage $D_t + 1$ of the super-relief network corresponds to locating one PSA at node n of the original network (*D*2 and *D*3), and its inventory is equal to the maximum inflow to this node in all scenarios (*D*4). The movement paths of flow from the node of stage 1 to the nodes of stage $D_t + 1$ determines the best transportation paths to transfer goods from the closest MDC to the located PSAs (*D*5). Flow transactions from the nodes in stage $D_t + 1$ to the nodes in stage $D_t + D_{\acute{t}} + 1$ demonstrates the transportation of the emergency items from the located PSAs to the stricken nodes in the response phase (*D*7). Having $D_{\acute{t}} + 1$ stages between the located PSAs and stricken nodes indicate that the maximum traveling distance of goods from the nodes in stage $D_{\acute{t}} + 1$ (the located PSAs) to the nodes in stage $D_t + D_{\acute{t}} + 1$ (the stricken nodes) is $D_{\acute{t}}$ (NDU) or $d_{\acute{t}}$ (mile). Total inflow to node $n \in N$ in stage $D_t + D_{\acute{t}} + 1$ of the multi-stage relief network represents the total inventory transferred from the located PSAs to the corresponding node of node n in the original network to fulfill its demand (*D*6).

5.3. Step 3 – Develop an optimization model using the multi-stage relief Network

In this step, we develop an optimization model utilizing the multi-stage relief network $\acute{G}(\acute{N},\acute{E})$ constructed in Step 2 (see notation in Table A2 of Appendix A):

Min		$\sum_{n_P\in\acute{N}^{(D_t+1)}} f^t_{n_P} x_{n_P} + \sum_{n_P\in\acute{N}^{(D_t+1)}} h^t_{n_P} y_{n_P} + \sum_{i=1}^{D_t}\sum_{e\in\acute{E}^{(i)}} v^t z_e + \frac{1}{\sum_{s\in S^t}\lvert R^s\rvert}\sum_{s\in S^t}\sum_{r\in R^s}\left(\sum_{i=D_t+1}^{D_t+D_{\acute{t}}}\sum_{e\in\acute{E}^{(i)}} v^r \acute{z}^r_e\right)$	(15)
Preparedness	*Locating PSAs*	$y_{n_P} \le M x_{n_P} \quad (\forall n_P \in \acute{N}^{(D_t+1)})$	(16)
	Pre-disaster transportation	$\sum_{e=(\overrightarrow{n,\acute{n}})\in\acute{E}^{(i)}} z_e = \sum_{\acute{e}=(\overrightarrow{\acute{n},n''})\in\acute{E}^{(i+1)}} z_{\acute{e}} \quad (\forall \acute{n} \in \acute{N}^{(i+1)}\ i = 1,2,\dots,D_t - 1)$	(17)
		$y_{n_P} \ge \sum_{e=(\overrightarrow{\acute{n},n_P})\in\acute{E}^{(D_t)}} z_e \quad (\forall n_P \in \acute{N}^{(D_t+1)})$	(18)
Response	*Post-disaster transportation*	$\sum_{e=(\overrightarrow{n_P,\acute{n}})\in\acute{E}^{(D_t+1)}} \acute{z}^r_e \le y_{n_P}(1-\gamma^s_{n_P}) \quad (\forall n_P \in \acute{N}^{(D_t+1)}, s\in S, r\in R^s)$	(19)
		$\sum_{e=(\overrightarrow{n,\acute{n}})\in\acute{E}^{(i)}} \acute{z}^r_e = \sum_{\acute{e}=(\overrightarrow{\acute{n},n''})\in\acute{E}^{(i+1)}} \acute{z}^r_e \quad (\forall \acute{n} \in \acute{N}^{(i+1)}\ i = D_t+1,\ \dots,\ D_t + D_{\acute{t}} - 1,\ s\in S, r\in R^s)$	(20)
		$\sum_{e=(\overrightarrow{n,n_D})\in\acute{E}^{(D_t+D_{\acute{t}})}} \acute{z}^r_e \ge F^{-1}_{n_D}(\theta)\gamma^s_{n_D} \quad (\forall n_D \in \acute{N}^{(D_t+D_{\acute{t}}+1)}, s\in S, r\in R^s)$	(21)
	Road disruption	$\acute{z}^r_e \le M\gamma^r_e \quad (\forall e \in \acute{E}^{(i)}\ i \in \{D_t+1,\ \dots,\ D_t+D_{\acute{t}}\}, s\in S, r\in R^s)$	(22)
Variables		$x_{n_P} \in \{0,1\} \quad (\forall n_P \in \acute{N}^{(D_t+1)})$	(23)
		$y_{n_P},\ z_e \ge 0 \quad (\forall n_P \in \acute{N}^{(D_t+1)}, e\in\acute{E}^{(i)}\ i = 1,\ \dots,\ D_t)$	(24)
		$\acute{z}^r_e \ge 0 \quad (\forall e \in \acute{E}^{(i)}\ i = D_t+1,\dots,D_t+D_{\acute{t}},\ s\in S, r\in R^s)$	(25)

Objective function (15) minimizes the total logistics cost in the relief network (i.e., the sum of locating, inventory holding, and pre- and post-disaster transportation costs), for the given $TT = t$ and $RT = \acute{t}$. Constraint (16) ensures that only nodes that contain a PSA can keep the emergency inventory. In the process of transferring goods from the MDC in stage 1 to the located PSAs in stage $D_t + 1$, the total inflow should be equal to the total outflow at the intermediate nodes, constraint (17). Based on constraint (18), the inventory of a PSA located at node $n \in \acute{N}^{(D_t+1)}$ is equal to the total goods transferred to the node from the nodes of the previous stage (D_t). According to constraint (19), the total outflow from the PSAs of unstricken nodes in each scenario cannot be more than their inventories. The inventories of the PSAs located at the stricken nodes are not used to fulfill demands because they may be damaged by the disaster. In the process of transferring goods from the PSAs in stage $D_t + 1$ to the stricken nodes in stage $D_t + D_{\acute{t}} + 1$, the total inflow should be equal to the total outflow at the intermediate nodes, constraint (20). According to constraint (21), the total inflow to the stricken nodes in the last stage of the network should be sufficient to fulfill their demands and meet the service level (θ). In the process of transferring items from the PSAs to the stricken nodes in the response phase, only undisrupted roads can be used, constraint (22). Model (15-25) is a scenario-based stochastic optimization that is formulated as a linear mixed integer programming with only $|N|$ binary variables, much less than the original model (1-14). This new model makes the computational time of the converted model (15-25) significantly less than the conventional model (1-14). In Section 7, the converted model is solved using CPLEX 12.9 Optimization Studio software on a Dell computer with Windows 10, an Intel i7 processor, and 8 GB of installed RAM.

6. ANALYTICAL RESULTS

Analyzing Model (15-25) reveals the following insights that apply to any relief network and any emergency good (see Appendix B for proofs). These results help us answer research question (iii), discussed in Section 1, by determining the relationship between TT and the efficiency of response operation that is measured by RT (see new notation in Table A3 of Appendix A).

Proposition 1 – The minimum requirement (the number of PSAs and the total inventory) needed for disaster preparedness: *For a given* $TT = t$ *and* $l \in L^t$*, the minimum number of PSAs that should be located in the target circle* l *(denoted by* ϑ_l*) and the minimum inventory that should be stored in the PSAs (denoted by* ξ_l*) are as follows (*$l \in L^t$*):*

a) If the target circle of $TT = t$ *and* $l \in L^t$ *does not include the whole relief network (*$|N^l| < |N|$*), then the minimum number of PSAs that should be located in the preparedness phase is 1 (*$\vartheta_l = 1$*). If the target circle includes the whole relief network (*$|N^l| = |N|$*), then the minimum number of PSAs would be* $\vartheta_l = q^{Max} + 1$.

b) The minimum amount of inventory that should be stored in PSAs in the preparedness phase is $\xi_l = \underset{s\in S^l, r\in R^s}{MAX}\left(\sum_{\forall n_D\in N^s} F_{n_D}^{-1}(\theta)\right)$.

This proposition determines the minimum preparedness level (the minimum number of PSAs and the minimum amount of inventory) needed for hurricanes at given $TT = t$ and $l \in L^t$. The outcomes of this proposition are used in the next proposition to determine the range of RT that can be provided in the response phase.

Proposition 2 – The range of RT can be provided in the response phase: *For a given* $TT = t$ *and* $l \in L^t$*, all feasible RTs that can be provided in the response phase are in* $[RT^{Min}, RT^{Max}]$ *interval. Any* $RT < RT^{Min}$ *is infeasible and any* $RT > RT^{Max}$ *is useless and does not reduce the total inventory or the number of PSAs. The value of* RT^{Min} *and* RT^{Max} *depends on the structure of the network but* $d_{RT^{Min}}$ *(the maximum distance that can be traveled within* RT^{Min}*) and* $d_{RT^{Max}}$ *(the maximum distance that can be traveled within* RT^{Max}*) never gets less than* $\check{d}$ *and larger than* $\hat{d}$*, respectively:*

- $\check{d} = \underset{s\in S^l, r\in R^s}{MAX} d_r^{Min}$ *where* $d_r^{Min} = \underset{n_D\in N^s}{MAX}\left(\underset{n_P\in N-N^s}{MIN} d(n_P, n_D)\right) s \in S^l \text{and } r \in R^s$,
- *In the case that* $N^O = N - N^l \neq \emptyset$, $\hat{d} = \underset{n_P\in N^O}{MIN}\left(\underset{s\in S^l, r\in R^s, n_D\in N^s}{MAX} d(n_P, n_D)\right)$. *When* $N^O = \emptyset$, $\hat{d} = \underset{n_P\in N^l}{MAX}\left(\underset{s\in S^l, r\in R^s, n_D\in N^s}{MAX} d(n_P, n_D)\right)$.

A short RT is essential in the disaster management to minimize the suffering of affected people during disasters. In Proposition 2, RT^{Min} determines the shortest time interval in which the response operations can be accomplished for given $TT = t$ and $l \in L^t$. Intuitively, we expect that delaying the preparedness operations (i.e., larger TTs) results in acquiring more accurate information about the location of the target circle that reduces the size of the target circle. Having more accurate information about the target circle leads to better preparedness activities and better post-disaster response operations (i.e., a smaller RT^{Min}). However, in the next proposition, we show that the expected RT^{Min} is a non-decreasing function of $TT = t$.

Proposition 3 – Expected RT^{Min} is a non-decreasing function of $TT = t$: *Late reaction of emergency management agencies such as FEMA to acquire more information about the movement trajectory of the hurricane may reduce their expected ability to provide short RTs after disasters.*

This result answers research question (iii) and shows that increasing TT in the preparedness phase reduces the average shortest RT, expected RT^{Min}, that can be provided in the response phase. The expected RT^{Min} for a given $TT = t$ represents the average of RT^{Min} over all possible target circles of $TT = t$ centered at $l \in L^t$. To calculate RT^{Min} for a given $l \in L^t$, we started with solving Model (15-25) for the target circle that is centered at $l \in L^t$ and the lowest possible value for RT. Iteratively, we increased the value of RT a time unit. RT^{Min} for a given $l \in L^t$ is the smallest RT that makes the model feasible.

7. EMPIRICAL OBSERVATIONS

This section analyzes the interaction between the total logistics cost and TT to answer research question (ii). Along with the analytical results of Section 6, this numerical analysis provides a comprehensive view regarding the tradeoff between the total logistics cost and RT^{Min}. This tradeoff helps us answer research question (i) and provides guidelines for practitioners to select the best TT.

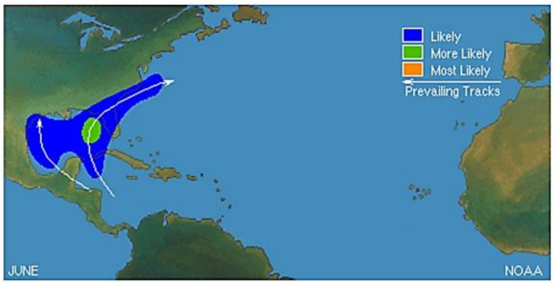
7.1. Experimental Setting

We test the optimization model for a target circle in parts of Florida, Georgia, Alabama, and South Carolina as they have experienced the highest number of hurricane in the nation since 1851. The experimental parameters are fivefolds:

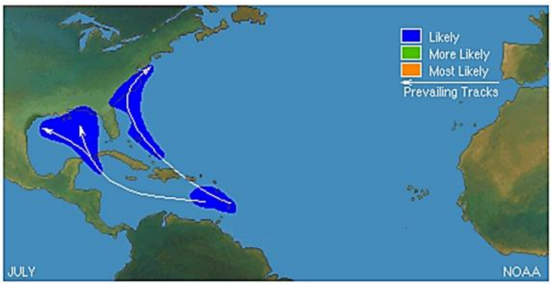
Releif network: The circles in Figure 2a demonstrate the size of the target circle for different TTs. The black nodes in Figure 2b illustrate the population centers inside the 5-day target circle. The distance between these nodes represents the driving distance between their corresponding population centers in Google Maps.

Logistics costs: We preposition medical kits as the emergency items in the target circle. The sensitivity of results for food and water with different cost components is analyzed. Unit inventory holding cost is a percentage of the purchase cost, which varies between 18% and 35% (Kiefer, 2012). According to Kiefer (2012), it comprises the cost of money (15%), storage cost (4%), obsolescence and spoilage cost (1%), and insurance cost (0.5%). Since FEMA is a non-profit organization, taxes are not accounted for it. Overall, we consider 20.5% of the total value of the inventory as its annual inventory-holding cost. Based on Alibaba's wholesale price, the purchase price of a medical kit is \$140. We assume that the transportation cost for a unit of medical kit per mile has not changed significantly over the recent decade. Therefore, we consider it to be \$5.8E-04 (Rawls and Turnquist, 2010). Since FEMA usually uses large pre-constructed buildings such as arenas and stadiums to locate PSAs, the locating cost includes preparedness cost of buildings for storage. Similar to Vanajakumari et al. (2016), we assume that the average fixed locating cost is \$4708. The materialized demand in landfall nodes is proportional to their populations.

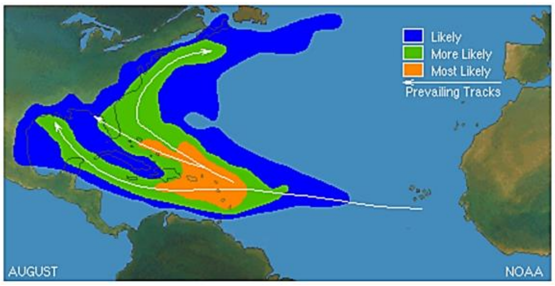
Demands: Table C1 of Appendix C summarizes some of the most recent hurricanes in the U.S., their landfall areas, the total population of the landfall areas at the landfall time, and the total population affected by the hurricanes (EM-DAT, 2017). Using the historical data, we computed the ratio of the affected population in the affected areas. As seen in the last column of Table C1, the minimum and maximum ratios are equal to 0.005% to 76%, respectively. Therefore, we assume that the ratio of the affected people in each landfall area is a random variable following a continuous uniform distribution of U~ [0%, 76%].



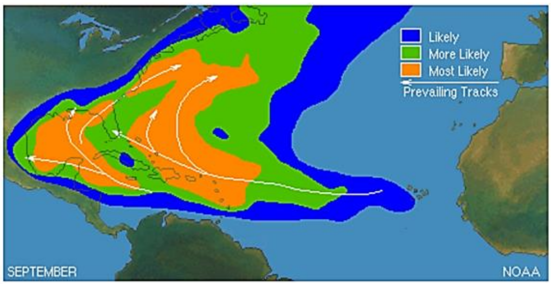
a) Prevailing tracks in June.



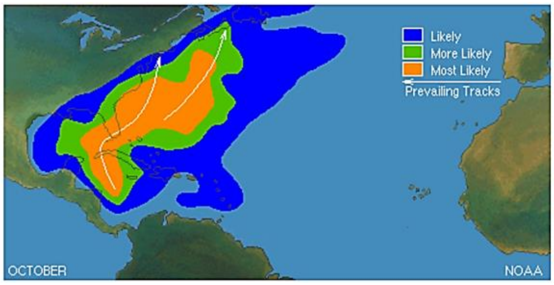
B) Prevailing tracks in July.



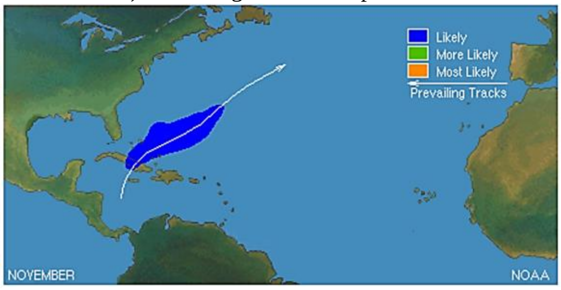
c) Prevailing tracks in August.



D) Prevailing tracks in September.



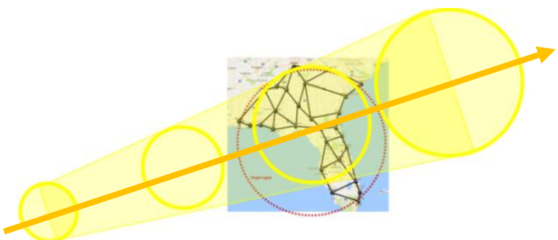
e) Prevailing tracks in October.



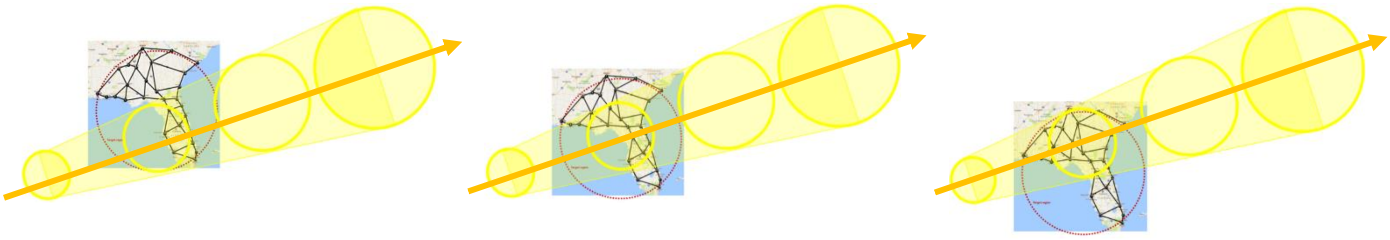
F) Prevailing tracks in November.

Figure 6. Prevailing tracks in the eastern tropical Atlantic.

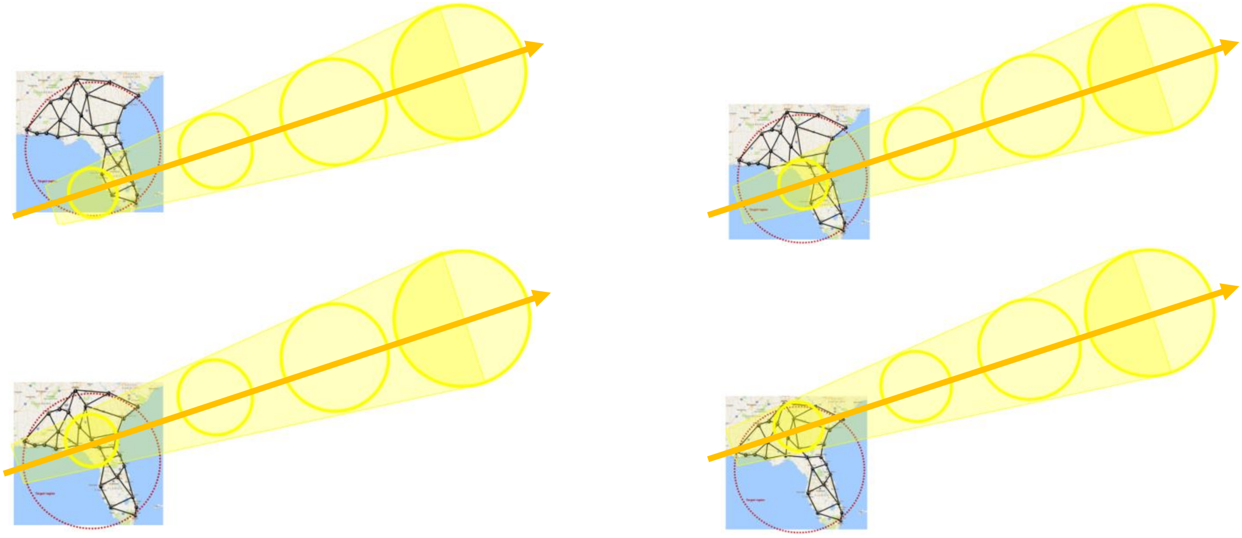
Transportation: Due to emergency disaster operations, we assume that 16 hours of driving is possible per day to transfer emergency goods from the MDC to PSAs and from PSAs to stricken nodes (two drivers are used on each truck. Each of them drives 8 hours and the truck travels 16 hours per day). This leaves enough extra time for loading and unloading trucks, tentative traffic on roads or loading and unloading stations, or daily maintenance operations. In the case study, we assume that there is an unlimited number of trucks to accomplish transportation needs. Having a limited number of trucks may prolong transportation times and the required RT to accomplish the response operations. We assume an unlimited number of trucks to ensure that the whole increase in RT^{Min} is because of delaying TT and not resource limitations.



a) Possible locations for the 4-day target circle.



b) Possible locations for the 3-day target circle.



c) Possible locations for the 2-day target circle.

Figure 7. The 4-, 3-, and 2-day target circles considered in the first movement trajectory.

Hurricane trajectories: The NDU used to construct the unified and multi-stage relief network is 50 miles. We consider several trajectories for the hurricane movement. The wind belt in a hurricane's location determines its trajectory. In the eastern part of tropical Atlantic, all hurricanes move toward the west by easterly trade winds. Migration of storms toward the northwest around the high subtropical results in hurricanes on the east coast of the U.S. Further, they move toward the northeast by the westerlies and merge with mid-latitude frontal systems (Movement of Hurricanes, 2010). The figures of NHC (2017) illustrate the zones of origin and tracks for different months during the hurricane season (see Figure 6). These figures only depict average conditions. Hurricanes can originate in different locations and travel different paths, but these figures provide an efficient view of the average hurricane paths. Using these figures, we categorize three average trajectories for hurricanes in the investigated area of this study:

1) *The first movement trajectories:* Thess trajectories are observed at the beginning and end of the hurricane season when hurricanes mostly form in the Caribbean Sea and pass through the investigated area, moving toward the northeast.
2) *The second movement trajectories* : These trajectories are observed in the middle of the hurricane season when hurricanes mostly form in the Atlantic Ocean and pass through the investigated area, moving toward the northwest.
3) *The third movement trajectories:* These trajectories are also observed in the middle of the hurricane season when hurricane may turn northeastward on their ways, guided by the westerlies.

We solve the model for these three average movement trajectories and different sizes of the target circle (between 5- to 1-day target circles) for each trajectory. We consider several locations for the center of each target circle to consider possible variations in the movement angle of the hurricane in each trajectory. The locations ($|L^{t=1\ days}| = 2$, $|L^{t=2\ days}| = 3$, and $|L^{t=3\ days}| = 4$) considered for the 4-, 3-, and 2-day target circles in the first movement trajectory are shown in Figure 7. We considered three severity levels for the hurricane (i.e., $q^{Max} = 3$). As an example, for the second location of the 3-day target circle the number of nodes equals thirteen ($|N^l| = 13$). The number of scenarios defined for stricken nodes in severity level 1, 2, and 3 is $\binom{13}{1} = 13$, $\binom{13}{2} = 78$, and $\binom{13}{3} = 286$, respectively. To explain the approach used to define link disruption scenarios, we consider $s = \{n_{24}\}$ as an example. For this stricken node scenario, six scenarios can be defined for disruption of roads ending at the stricken node: $L^s = \{\{(n_{24}, n_{20})\}, \{(n_{24}, n_{23})\}, \{(n_{24}, n_{25})\}, \{(n_{24}, n_{20}), (n_{24}, n_{23})\}, \{(n_{24}, n_{20}), (n_{24}, n_{25})\}, \{(n_{24}, n_{23}), (n_{24}, n_{25})\}\}$. Having more than two disrupted roads will isolate the stricken node and make the model infeasible. Figures D1 and D2 of Appendix D include the same information for the second and third movement trajectories.

7.2. Total Logistics Cost Respect to RT at a Given TT

Figure 8 shows the average logistics cost components - including the locating cost of PSAs, inventory-holding cost, pre-disaster transportation cost, and post-disaster transportation cost - and their changes with respect to RT at TT = 0, 1, and 1.5 (day) in the first hurricane trajectory (for other TTs and trajectories, the results are the same). The results in Figure 8 are for a specific emergency good (medical kits). For other emergency goods (e.g., water, food, and tents), the inventory holding and transportation costs would be different. Even the locating cost of PSAs may be different if we focus on a different disaster-prone region. No matter what the cost components of the investigated emergency goods are, the same trends of changes are expected in the average logistics cost components with respect to RT. Increasing RT leads to greater values for d_{RT} (d_{RT} shows the maximum distance that can be traveled by the vehicles of emergency goods within RT). Therefore, the inventories stored in PSAs can be mobilized for longer distances in the relief network after the landfall and can be used by a higher number of nodes to fulfill their demands (if the disaster strikes them). This leads to a smaller number of PSAs and less total inventory in the relief network. Less inventory amount necessitates fewer transportation needs before a disaster from the MDC to PSAs (pre-disaster transportation). Longer distances between PSAs and stricken nodes increase the transportation cost after the disaster (post-disaster transportation). As expected, for a given TT, having a shorter RT in the response phase leads to the following changes in the logistics cost components:

- Locating cost of PSAs increases.
- Inventory holding cost of emergency goods increases.
- Pre-disaster transportation cost increases.
- Post-disaster transportation cost decreases.

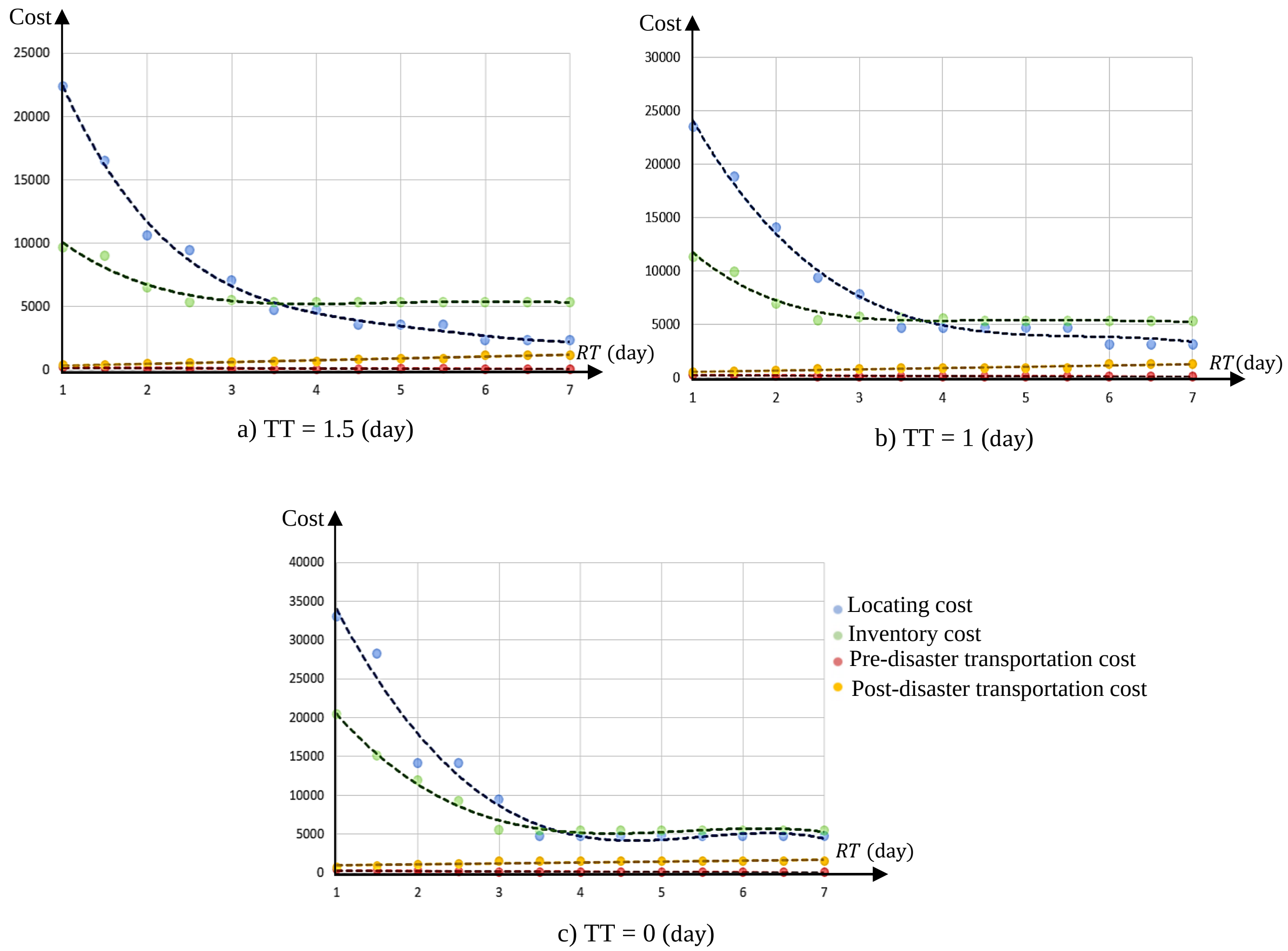
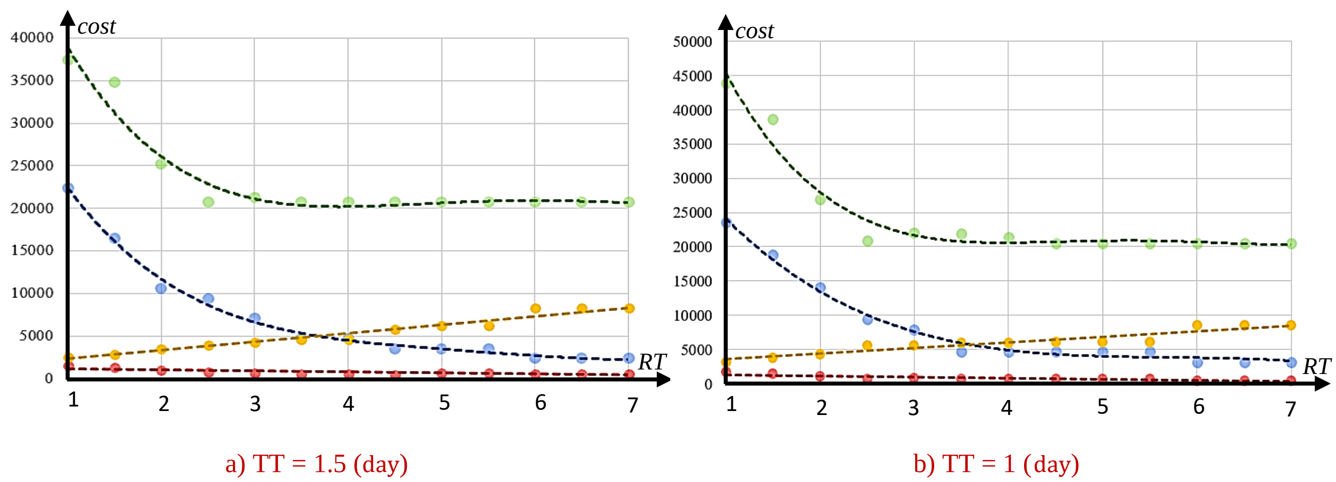
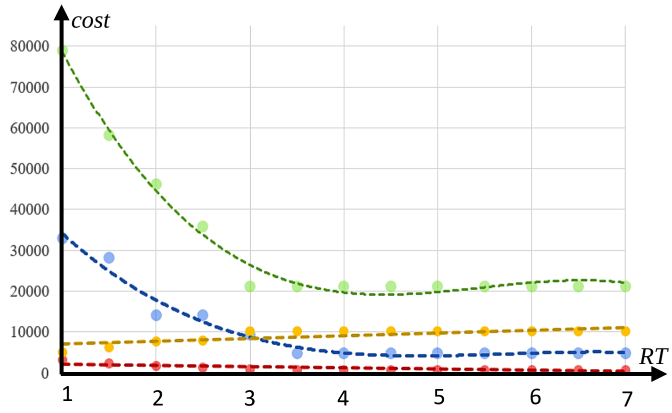


Figure 8. The logistics cost components of medical kit with respect to RT for TT=0, 1, and 1.5 (day).

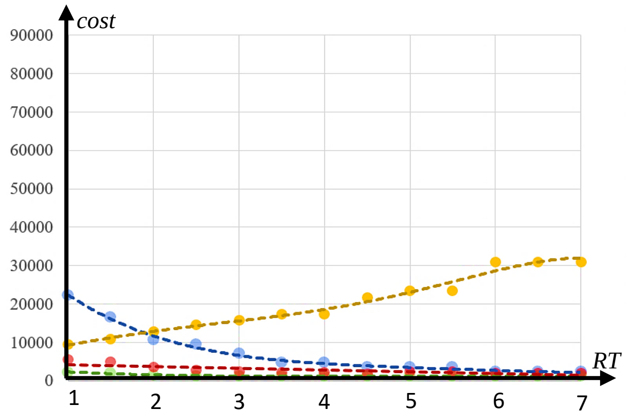
Figures 9 and 10 show the average logistics cost components for food and water. Water is assumed to be in units of 10 gallons and food is supplied in the form of meals-ready-to-eat (MREs) in units of 10 meals. Following Rawl and Turnquist (2010), the purchase costs for a unit of water and food are \$6.48 and \$54.2 and the transportation costs are \$0.3E-02 and \$0.04E-02, respectively. Figures 9 and 10 illustrate the sensitivity results by representing the variations in the logistics cost components of food and water with respect to RT at TT = 0, 1, and 1.5 (day).



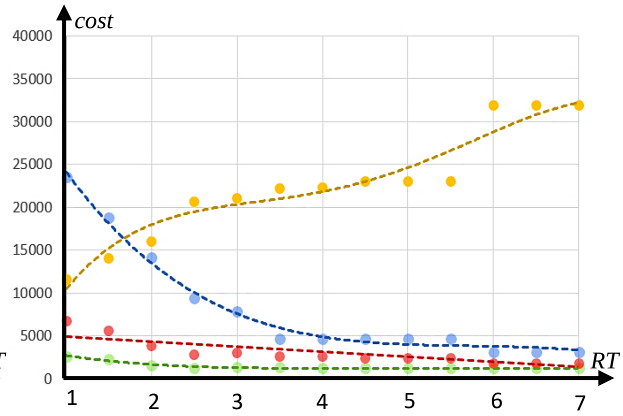


c) TT = 0 (day)

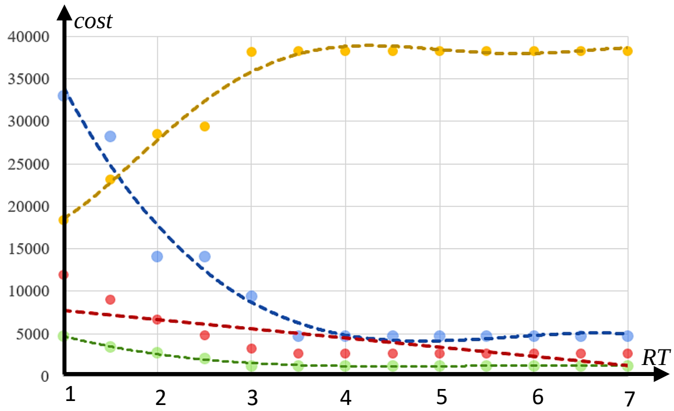
Figure 9. The logistics cost components of food with respect to RT for TT=0, 1, and 1.5 (day).



a) TT = 1.5 (day)



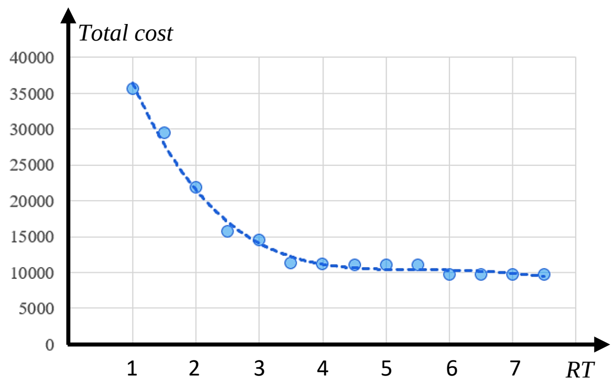
b) TT = 1 (day)



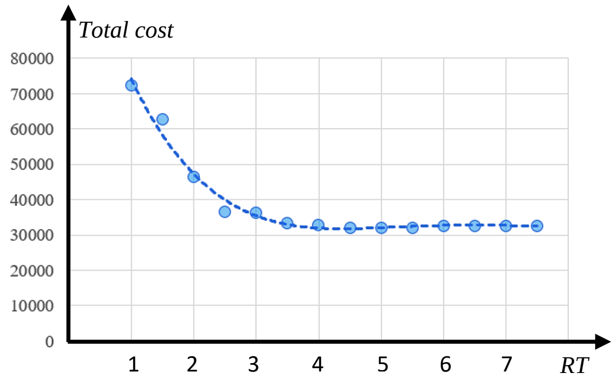
c) TT = 0 (day)

Figure 10. The logistics cost components of water with respect to RT for TT=0, 1, and 1.5 (day).

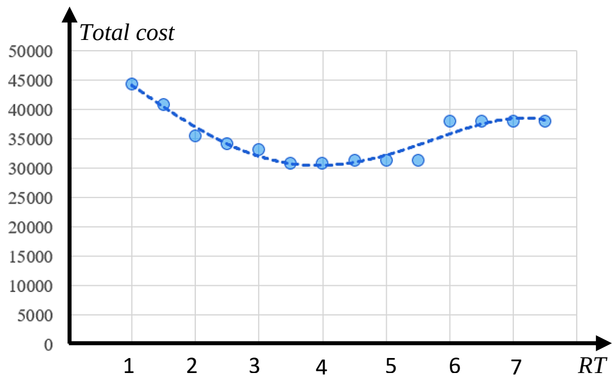
As seen in the figures, the trend of changes in the logistics cost components is the same for these three emergency goods. However, the reactions of the total logistics cost to RT increment depend on the magnitude of the cost components. As seen in Figure 11, considering cases where the contribution of locating and inventory costs in the total logistics cost is higher than the transportation cost (e.g., medical kit and food), the total logistics cost of emergency goods is a non-increasing of RT. For inexpensive emergency goods (e.g., water), increasing RT has non-monotonic impacts on their total logistics costs. This happens because the contribution of the transportation cost in the total logistics cost of these goods is high and increasing RT boosts the post-disaster transportation cost.



a) Medical kit



b) Food

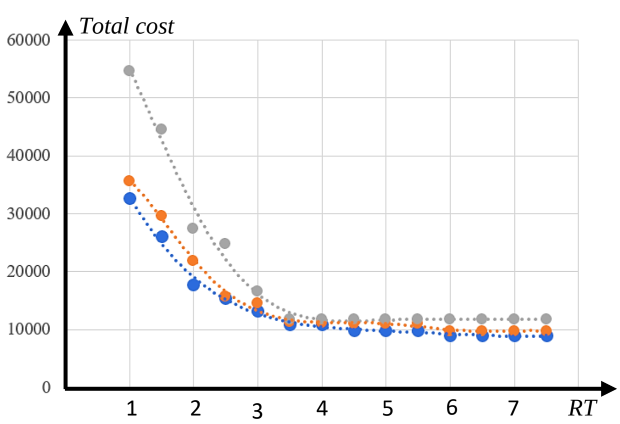


b) Food

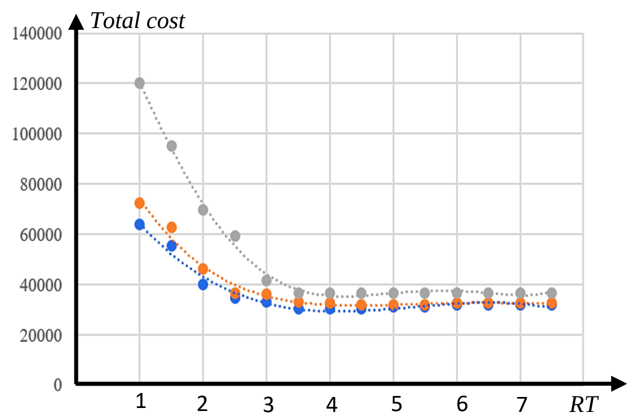
Figure 11. The total logistics cost components of emergency goods with respect to RT at TT=1 (day).

7.3. Total Logistics Cost with Respect to TT

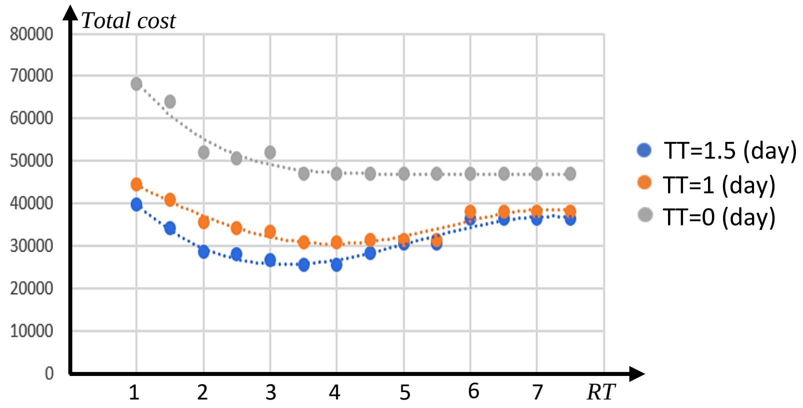
Figure 12 shows that the average total logistics cost is a non-increasing function of TT. Although these results are for the medical kit, food and water, the same trend of variations is expected for all emergency goods because the area of the target circle is larger when the preparedness activities are initiated earlier (at small values of TT). Covering demand in a larger target circle requires locating more PSAs and transporting and storing a higher amount of inventory. As seen in Figure 12, the reduction that delaying preparedness activities (increasing TT) makes in the total logistics cost is more significant in shorter RTs.



a) Medical kit



b) Food



c) Water

Figure 12. The total logistics cost for different TTs.

7.4. Tradeoff Between Total Logistics Cost and RT^{Min}

Section 7.3 numerically demonstrated that the average total logistics cost is a non-increasing function of TT. Section 6 shows that the expected minimum RT in the response phase of disasters (the expected RT^{Min}) is a non-decreasing function of TT. The combination of these two results demonstrates that:

Observation 1 - TT of the preparedness phase has two conflicting impacts on disaster management operations. Increasing TT reduces the expected total logistics cost (a positive impact) and increases the expected $\mathrm{RT}^{\mathrm{Min}}$ ***(a negative impact).***

As TT decreases in the preparedness phase, the average total logistic cost will increase. This observation indicates that disaster management agencies such as FEMA should start preparedness activities as late as possible to incur lower logistics cost. As TT increases in the preparedness phase, the expected RT^{Min} in the response phase will increase. The expected RT^{Min} for a given $TT = t$ represents the average RT^{Min} over all possible target circles of $TT = t$ centered at $l \in L^t$. FEMA should start preparedness activities as soon as possible to minimize the expected shortest possible RT in the response phase.

Figure 13 shows this tradeoff for the medical kit (there are similar tradeoffs for other emergency goods). It illustrates how postponing preparedness operations for 1.5 days (TT = 1.5) reduces the total logistics cost of disasters by 40% without making a significant increment in the expected minimum RT (expected RT^{Min}) of the response operations. This choice of TT seems to be a sage and non-risky advice for disaster managers to postpone preparedness operations for 1.5 days. Any extra delay in initiating the preparedness activities will significantly increase RT^{Min} in response to a small reduction in the total logistics cost. We use the fitted function of $\Pi_1(TT)$ to represent the relationship between the normalized RT^{Min} and TT for the medical kit. Similarly, $\Pi_2(TT)$ demonstrates how the normalized logistics cost will decrease by increasing TT. The results of comparing these two functions are summarized below:

Observation 2 - The TT value for which $\Pi_1(TT^*) = \Pi_2(TT^*)$ is called the fair TT and is shown by TT^*. At $TT = TT^*$, the normalized values of the humanitarian (RT^{Min}) and economic (total logistics cost) performance measures are the same. By selecting a TT in $[0, TT^*]$ interval, a higher weight will be given to the humanitarian performance measure. In contrast, by choosing a TT in $[TT^*, 5]$ interval, a higher weight will be given to the economic performance measure.

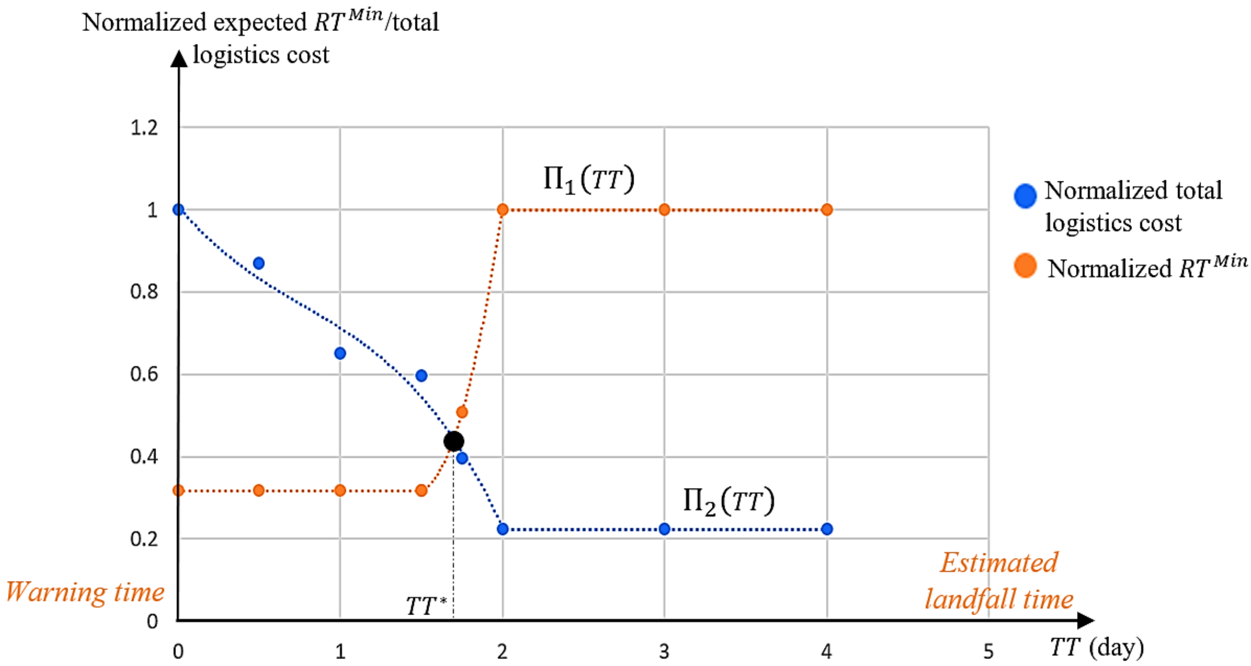


Figure 13. The tradeoff between the average total logistics cost and the average RT^{Min}.

8. CONCLUSION

This research focuses on prepositioning and transferring emergency goods in the preparedness and response phases of disasters with a prior warning, such as hurricanes (the recovery phase that includes the repairing process of disrupted roads and facilities is not included). This research is based on two key terms: the trigger time (TT) and response time (RT). TT represents the number of days that preparedness activities are started after the disaster warning. RT is the time interval required to transfer goods from the response facilities to the affected population centers after the disaster. The paper develops a stochastic optimization model to select the best TT in the preparedness phase by analyzing its contradictory impacts on the disaster management's efficiency measurement (e.g., minimizing RT and minimizing the total logistics cost). This paper demonstrates that the expected minimum RT is a non-decreasing function of TT, and the average total logistics cost is a non-increasing function of TT. This demonstrates a tradeoff between the total logistics cost and the expected shortest possible RT in the disaster management operations. The optimal TT selection in the preparedness phase is crucial to compromise these two competing aspects of disaster management. According to the results of this study, the most practical managerial insights for disaster managers are as follows:

- If disaster management agencies such as FEMA intend to minimize the expected total logistics cost, they should start preparedness activities as late as possible (such as TT = 4 (days) in hurricanes).
- In case that disaster management agencies such as FEMA aim to maximize the speed of response operations after a disaster (or minimize the expected RT^{Min}), they should start preparedness activities as soon as possible (such as TT = 0 (days) in hurricanes).
- Selecting any TT between the extremes mentioned above balances the total logistics cost and the speed of response operations (or RT^{Min}). Further, the best TT selection depends on the preferences of decision-makers.

Through fitting functions of $\Pi_1(TT)$ and $\Pi_2(TT)$ to represent changes in the normalized expected RT^{Min}

and total logistics cost concerning TT, we showed that:

- Selecting $TT = TT^*$ for which $\Pi_1(TT^*) = \Pi_2(TT^*)$ leads to a fair solution that gives the same weight to the humanitarian (RT^{Min}) and economic (total logistics cost) performance measures in the disaster management operations;
- Selecting $TT < TT^*$ prioritizes the humanitarian (RT^{Min}) performance measures in the disaster management operations;
- Selecting $TT > TT^*$ prioritizes the economic (total logistics cost) performance measures in the disaster management operations;

The study ignores resource limitations in calculating RT^{Min}. Resource limitations, such as having limited transportation fleets after disasters, make real values of RT^{Min} even longer than RT^{Min} calculated in this paper. This makes the tradeoff between TT and RT^{Min} sharper than what is represented in this paper. Analyzing the impacts of resource limitations on RT^{Min} and its tradeoff with TT can be an interesting future research component for this study.

The focus of this study is on hurricanes; however, the developed models are applicable to all predictable disasters with an advance warning such as floods, tornadoes, and tsunamis. To apply the models for other types of predictable disasters, we need to adjust the variation range of TT and the scenario sets of L^t and S^t for the new disaster. According to the NHC reports, the range of TT for hurricanes varies between 0 (warning moment or five days before the landfall) to 4 (one day before the landfall) days. This range can be different for other disasters. Also, uncertainty in demand locations are considered in the models through defining scenario sets of L^t and S^t. Set L^t is determined according to the historical movement trajectories of the disaster and S^t depends on the size of the disaster's target circles. Both of them may vary based on the type of disaster and the geographical location of the investigated region.

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REFERENCES

Aflaki, A., A.J. Pedraza-Martinez. 2016. Humanitarian funding in a multi-donor market with donation uncertainty. *Production and Operations Management* **25**(7) 1274–1291.

Afshar, A., A. Haghani. 2012. Modeling integrated supply chain logistics in real-time large-scale disaster relief operations. *Socio-Economic Planning Sciences* **46**(4) 327–338.

Alem, D., A. Clark, and A. Moreno. 2016. Stochastic network models for logistics planning in disaster relief. *European Journal of Operational Research*, **255**(1) 187-206.

Altay, N., W.G. Green III. 2006. OR/MS research in disaster operations management. *European Journal of Operational Research* **175**(1) 475–493.

Apte, A. 2009. Humanitarian logistics: A new field of research and action. Foundations and Trends in Technology. *Information and Operations Management* **3**(1) 1–100.

Aslan, E., and M. Çelik. 2019. Pre-positioning of relief items under road/facility vulnerability with concurrent restoration

and relief transportation. *IISE Transactions*, **51**(8) 847-868.
Balcik, B., D. Ak. 2014. Supplier selection for framework agreements in humanitarian relief. *Production and Operations Management* **23**(6) 1028–1041.
Balcik, B., B.M. Beamon. 2008. Facility location in humanitarian relief. *International Journal of Logistics: Research and Applications* **11**(2) 101–121.
Balcik, B., C.D.C. Bozkir, O.E. Kundakcioglu. 2016. A literature review on inventory management in humanitarian supply chains. *Surveys in Operations Research and Management Science* **21**(2) 101–116.
Besiou, M., A.J. Pedraza-Martinez, L.N. Van Wassenhove. 2014. Vehicle supply chains in humanitarian operations: Decentralization, operational mix, and earmarked funding. *Production and Operations Management* **23**(11) 1950–1965.
Bhattacharya, S., S. Hasija, L.N. Van Wassenhove. 2014. Designing efficient infrastructural investment and asset transfer mechanisms in humanitarian supply chains. *Production and Operations Management* **23**(9) 1511–1521.
Bozorgi-Amiri, A., M.S. Jabalameli, S.M.J. Mirzapour Al-e-Hashem. 2013. A multi–objective robust stochastic programming model for disaster relief logistics under uncertainty. *OR Spectrum* **35**(4) 905–933.
Campbell, A.M., P.C. Jones. 2011. Pre-positioning supplies in preparation for disasters. *European Journal of Operational Research* **209**(1) 156–165.
Cooper, C., R. Block. 2007. Disaster: Hurricane Katrina and the Failure of Homeland Security, Times Books. 1st edition, New York.
Döyen, A., N. Aras, G. Barbarosolu. 2012. A two-echelon stochastic facility location model for humanitarian relief logistics. *Optimization Letters* **6**(6) 1123–1145.
Duran, S, M.A. Gutierrez, P. Keskinocak. 2011. Pre–positioning of emergency items for CARE. *Interfaces* **41**(3) 223–237.
EM-DAT. 2017. The International Disaster Database. 2017. http://www.emdat.be/, last visited on 24 August 2017.
FEMA Factsheet. 2011. Logistics Management Directorate. Available online on https://www.fema.gov/pdf/media/factsheets/2011/lmd.pdf, last visited on 16 November 2018.
Flavelle, C., E. Wasson. 2017. FEMA was almost out of money as hurricane Irma threatened Florida. Available online on https://www.bloomberg.com/news/articles/2017-09-05/fema-is-almost-out-of-money-as-hurricane-irma-threatens-florida, last visited on 18 February 2018.
Florida. 2005. Logistics technical bulletin. In State Emergency Response Team. Available online on http://www.floridadisaster.org/Response/Logistics/2007/Documents/LTB%201-1.pdf, last visited on 18 February 2018.
FMCA. 2015. Federal Motor Carrier Safety Administration. Hours of service of drivers, Part 395: Maximum driving time for property-carrying vehicles; Part 395.3. Available online on https://www.fmcsa.dot.gov/regulations/title49/section/395.3, last visited on 24 August 2017.
Galindo, G., R. Batta. 2013. Prepositioning of supplies in preparation for a hurricane under potential destruction of prepositioned supplies. *Socio-Economic Planning Sciences* **47**(1), 20–37.
Ghorbani-Renani, N., A.D. Gonzalez, K. Barker, N. Morshedlou. 2020. Protection-interdiction-restoration: Tri-level optimization for enhancing interdependent network resilience. *Reliability Engineering and System Safety*. **199**, 106907
Pacheco, G. G., & Batta, R. (2016). Forecast-driven model for prepositioning supplies in preparation for a foreseen hurricane. *Journal of the Operational Research Society*, **67**(1), 98-113.
Holguin-Veras, J., M. Jaller, L.N. Van Wassenhove, N. Perez, T. Wachtendorf. 2012. On the unique features of post-disaster humanitarian logistics. Journal of Operations Management 30, 494-506.
Hong, X., M.A., Lejeune, N. Noyan. 2015. Stochastic network design for disaster preparedness, *IIE Transactions* **47**(4) 329–357.
Horner, M.W., J.A. Downs. 2010. Optimizing hurricane disaster relief goods distribution: Model development and application with respect to planning strategies. *Disasters* **34**(3) 821–844.
Hurricane Sandy FEMA After-Action Report. 2013. Available online on https://www.fema.gov/media-library-data/20130726-1923-25045-7442/sandy_fema_aar.pdf, last visited on 24 August 2017.
Jahre, M., M.J. Kembro, T. Rezvanian, O. Ergun, S.J. Hapnes, P. Berling. 2016. Integrating supply chains for emergencies and ongoing operations in UNHCR. *Journal of Operations Management* **45**(1) 57–72.
Kiefer, D. 2012. The Million Dollar Question: The true cost of carrying inventory. Available online on http://k3s.com/wp-content/uploads/2012/05/True-cost-of-carrying-inventory.pdf, last visited on 24 February 2017.
Klibi, W., S. Ichoua, A. Martel. 2013. Prepositioning emergency supplies to support disaster relief: a stochastic programming approach. Cirrelt-2013-19. Available online on https://www.cirrelt.ca/DocumentsTravail/CIRRELT-FSA-2013-19.pdf, last visited on 19 December 2018.
Klibi, W., S. Ichoua, A. Martel. 2018. Prepositioning emergency supplies to support disaster relief: a case study using stochastic programming. *INFOR: Information Systems and Operational Research* **56**(1) 50–81.
Kunz, N., G. Reiner, S. Gold. 2014. Investing in disaster management capabilities versus pre-positioning inventory: A new approach to disaster preparedness. *International Journal of Production Economics* **157**(1) 261–272.
McBride-Davis, V.L. 2008. Responding logistically to future natural and man-made disasters and catastrophes. Available online on http://www.dtic.mil/dtic/tr/fulltext/u2/a478576.pdf, last visited on 16 November 2018.
Mete, H.O., Z.B. Zabinsky. 2010. Stochastic optimization of medical supply location and distribution in disaster management. *International Journal of Production Economics* **126**(1) 76–84.
Moreno, A., D. Alem, D. Ferreira, and A. Clark. 2018. An effective two-stage stochastic multi-trip location-transportation model with social concerns in relief supply chains. *European Journal of Operational Research*, **269**(3) 1050-1071.
Morrice, D.J., P. Cronin, F. Tanrisever, J.C. Butler. 2016. Supporting hurricane inventory management decisions with consumer demand estimates. *Journal of Operations Management* **45**(1) 86–100.

Movement of Hurricanes. 2010. Steered by the global winds. Available online on http://ww2010.atmos.uiuc.edu/(Gh)/guides/mtr/hurr/mvmt.rxml, last visited on 17 November 2018.

National Hurricane Center. 2012. Saffir-Simpson Hurricane Wind Scale. Available online on http://www.nhc.noaa.gov/aboutsshws.php, last visited on 24 August 2017.

National Hurricane Center. 2017. Tropical Cyclone Climatology. Available online on http://www.nhc.noaa.gov/ climo/, last visited on 17 November 2018.

Ni, W., J. Shu, M. Song. 2018. Location and Emergency Inventory Pre-Positioning for Disaster Response Operations: Min-Max Robust Model and a Case Study of Yushu Earthquake **27**(1) 160–183.

Noyan, N. 2012. Risk-averse two-stage stochastic programming with an application to disaster management, *Computers and Operations Research* **39**(3) 541–559.

Paul, J. A., & M. Zhang. 2019. Supply location and transportation planning for hurricanes: A two-stage stochastic programming framework. *European Journal of Operational Research*, 274(1), 108-125.

Pedraza-Martinez, A.J., L.N. Van Wassenhove. 2011. Field Vehicle Fleet Management in Humanitarian Operations: A Case-Study Based Approach. *Journal of Operations Management* **29**(5) 404–421.

Rawls, C.G., M.A. Turnquist. 2010. Pre–positioning of emergency supplies for disaster response. *Transportation Research: Part B* **44**(4) 521–534.

Rawls, C.G., M.A. Turnquist. 2011. Pre-positioning planning for emergency response with service quality constraints. *OR Spectrum* **33**(3) 481–498.

Rawls, C.G., M.A. Turnquist. 2012. Pre-positioning and dynamic delivery planning for short–term response following a natural disaster. *Socio-Economic Planning Sciences* **46**(1) 46–54.

Regnier, E. (2008). Public evacuation decisions and hurricane track uncertainty. *Management Science*, 54(1), 16-28.

Salman, F. S., and E. Yücel. 2015. Emergency facility location under random network damage: Insights from the Istanbul case. *Computers & Operations Research*, **62**, 266-281.

Sanci, E., and M. S. Daskin. 2019. Integrating location and network restoration decisions in relief networks under uncertainty. *European Journal of Operational Research*.

Sodhi, M.S., C.S. Tang. 2014. Buttressing supply chains against floods in Asia for humanitarian relief and economic recovery. *Production and Operations Management* **23**(6) 938–950.

Stauffer, J.M., A.J. Pedraza-Martinez, L.N. Van Wassenhove. 2016. Temporary hubs for the global vehicle supply chain in humanitarian operations. *Production and Operations Management* **25**(2) 192–209.

Tofighi, S., S.A. Torabi, S.A. Mansouri. 2016. Humanitarian logistics network design under mixed uncertainty. *European Journal of Operational Research* **250**(1) 239–250.

Tomasini, R., L.N. Van Wassenhove. 2009. Humanitarian logistics, Basingstoke, UK, Palgrave MacMillan, Taylor & Francis, Ltd.

Vanajakumari, M., S. Kumar, S. Gupta. 2016. An integrated logistic model for predictable disasters. *Production and Operations Management* **25**(5) 791–811.

Van Wassenhove, L.N. 2006. Blackett memorial lecture humanitarian aid logistics: Supply chain management in high gear. *Journal of the Operational Research Society* **57**(5) 475–489.

Whybark, D.C. 2007. Issues in managing disaster relief inventories. *International Journal of Production Economics* **108**(1–2) 228–235.

Uichanco, J. 2016. A robust model for pre-positioning emergency relief items before a typhoon with an uncertain trajectory. Submitted *to Manufacturing & Service Operations Management.*

U.S. Hurricane Strikes by Decade. 2018. National Hurricane Center, the National Oceanic and Atmospheric Administration (NOAA). Available online on https://www.nhc.noaa.gov/pastdec.shtml, last visited on 18 February 2018.

Yücel, E., F.S. Salman, I. Arsik. 2018. Improving post-disaster road network accessibility by strengthening links against failures. *European Journal of Operational Research* **269**(1) 406–422.

APPENDIX A

List of Abbreviations:

AOML	Atlantic Oceanographic and Meteorological Laboratory
FEMA	Federal Emergency Management Agency
IRR	Initial Response Resource
MDC	Main Distribution Center
NDU	New Distance Unit
NHC	National Hurricane Center
NOAA	National Oceanic and Atmospheric Administration
NWS	National Weather Service
POD	Point of Distribution
PSA	Pre-staging Areas
RT	Response time
SA	Staging Areas
TT	Trigger time

Table A1 includes the notation used in the conventional model of Section 4.

Table A1: The notation of the conventional model.

Sets	
N	The set of nodes in the original relief network. Indexes of n_M, n_P, and n_D are used to represent the MDC, PSAs, and demand nodes. Intermediate nodes are represented by n, $\acute{n}$, and n''.
$E = \{e\}$	The set of links/edges in the original relief network
$L^t = \{l\}$	The set of locations for the center of the t-day target circle
$S^t = \{s\}$	The set of scenarios for the stricken/demand nodes when TT is t
N^s	The set of stricken/demand nodes in scenario $s \in S^t$
$R^s = \{r\}$	The set of scenarios for disrupted roads when the hurricane strikes the nodes of $s \in S^t$
E^r	The set of disrupted roads in scenario $r \in R^s$ ($s \in S^t$)
S^l	The set of all scenarios for the stricken nodes in the target circle centered at $l \in L^t$
N^l	The set of nodes located inside the target circle that is centered at $l \in L^t$
Variables	
x_{n_P}	1 if a PSA located at node $n_P \in N$; 0 otherwise
y_{n_P}	The total inventory stored in the PSA located at node $n_P \in N$
$z_e^{(\overrightarrow{n_M, n_P})}$	The total amount of emergency goods transported from the MDC located at node n_M through link $e \in E$ to be stored at node $n_P \in N$ as a PSA
$\acute{z}_e^{r,(\overrightarrow{n_P, n_D})}$	The total amount of emergency goods of the PSA located at node $n_P \in N$ that flows through link $e \in E$ to fulfill the demand materialized at node $n_D \in N^s$ in scenario $r \in R^s$
$w_e^{(\overrightarrow{n_M, n_P})}$	1 if link $e \in E$ is used in the process of transferring emergency goods from the MDC located at node n_M to the PSA located at node $n_P \in N$
$\acute{w}_e^{r,(\overrightarrow{n_P, n_D})}$	1 if link $e \in E$ is used in the process of transferring items from the PSA located at node $n_P \in N$ to the stricken node $n_D \in N^s$ in scenario $r \in R^s (s \in S^t)$
Parameters	
t	The selected TT in the preparedness phase
$\acute{t}$	The selected RT in the response phase
$q\ (= 1, 2, \dots, q^{Max})$	The severity level of the hurricane that is represented by the number of nodes that can be stricken simultaneously by the hurricane inside the target circle
v^t	The cost of transporting a unit of good in a distance unit in the preparedness phase when $TT = t$
v^r	The cost of transporting a unit of good in a distance unit in the response phase when scenario $r \in R^s$ happens
d_e	The length of link $e \in E$
$f_{n_P}^t$	The fixed cost of locating a PSA at node $n_P \in N$ when $TT = t$
$h_{n_P}^t$	The cost of keeping a unit of inventory in the PSA located at node $n_P \in N$ when $TT = t$
n_M	The node of the relief network that includes the MDC
$\gamma_{n_D}^s$	1 if node $n_D \in N^s$; 0 otherwise
γ_e^r	1 if link $e \in E^r$; 0 otherwise
θ	The ratio of the demand that is expected to be fulfilled at the stricken nodes (called the service level)
F_{n_D}	The cumulative distribution function for the demand that is expected to materialize at node $n_D \in N$ when stricken by disasters
d_t	The maximum distance that the inventory of the MDC can be mobilized through the relief network toward the located PSAs when TT is equal to t
$d_{\acute{t}}$	The maximum distance that the inventory of the PSAs can be mobilized through the relief network toward the stricken nodes when RT is equal to $\acute{t}$

Table A2 includes the notation used in the converted model of Section 5.

Table A2: The notation of the converted model.

Sets	
$\acute{N}$	The set of nodes in the multi-stage relief network. Indexes of n_M, n_P, and n_D are used to represent the nodes in the 1st (the MDC), $D_t + 1$th (PSAs), and $D_t + D_{\acute{t}} + 1$th (stricken nodes) stage. Indexes of n, n', and n'' to represent the nodes in the rest of stages (intermediate nodes)
$\acute{E}$	The set of links/edges in the multi-stage relief network. Indexes of e and e' are used to represent the links of the multi-stage relief network
$\acute{N}^{(i)}$	The set of nodes in stage i ($i = 1, 2, \dots, D_t + D_{\acute{t}} + 1$) of the multi-stage relief network
$\acute{E}^{(i)}$	The set of links originating from the nodes of stage i and ending at the nodes of stage i+1, $i = 1, 2, \dots, D_t + D_{\acute{t}}$
$S^t = \{s\}$	The set of scenarios defined to represent stricken nodes when TT is t. Each scenario includes a set of nodes in stage $D_t + D_{\acute{t}} + 1$ that may be stricken concurrently by the disaster

$R^s = \{r\}$	The set of scenarios defined to represent disrupted roads when the hurricane strikes the nodes of $s \in S^t$
Variables	
x_{n_P}	1 if a PSA located at node $n_P \in \acute{N}^{(D_t+1)}$; 0 otherwise
y_{n_P}	The total inventory stored in the PSA located at node $n_P \in \acute{N}^{(D_t+1)}$
z_e	The total amount of emergency goods transported through link $e = \left(\overrightarrow{n,\acute{n}}\right)$ of the multi-stage network ($n \in \acute{N}^{(i)}$ and $\acute{n} \in \acute{N}^{(i+1)}$ $i = 1, 2, \dots, D_t$)
$\acute{z}_e^r$	The total amount of emergency goods transported through link $e = \left(\overrightarrow{n,\acute{n}}\right)$ of the multi-stage network in scenario $r \in R^s$ ($n \in \acute{N}^{(i)}$ and $\acute{n} \in \acute{N}^{(i+1)}$ $i = D_t + 1, \dots, D_t + D_{\acute{t}}$),
Parameters	
t	The selected TT in the preparedness phase
$\acute{t}$	The selected RT in the response phase
d_t	The maximum distance that the inventory of the MDC can be mobilized through the relief network toward the located PSAs when TT is equal to t
$d_{\acute{t}}$	The maximum distance that the inventory of the PSAs can be mobilized through the relief network toward the stricken nodes when RT is equal to $\acute{t}$
D_t	The number of NDU exists inside d_t
$D_{\acute{t}}$	The number of NDU exists inside $d_{\acute{t}}$
v^t	The cost of transporting a unit of good in a distance unit in the preparedness phase when $TT = t$
v^r	The cost of transporting a unit of good in a distance unit in the response phase when scenario $r \in R^s$ happens
$f_{n_P}^t$	The fixed cost of locating a PSA at node $n_P \in \acute{N}^{(D_t+1)}$ when $TT = t$
$h_{n_P}^t$	The cost of keeping a unit of inventory in the PSA located at node $n_P \in \acute{N}^{(D_t+1)}$ when $TT = t$
$\gamma_{n_D}^s$	1 if node $n_D \in \acute{N}^{(D_t+D_{\acute{t}}+1)}$ is one of the stricken nodes in scenario $s \in S^t$; 0 otherwise
γ_e^r	1 if link e is one of the disrupted roads in scenario $r \in R^s$; 0 otherwise
θ	The ratio of the demand that is expected to be fulfilled at the stricken nodes (called the service level)
F_{n_D}	The cumulative distribution function for the demand that is expected to materialize at node $n_D \in \acute{N}^{(D_t+D_{\acute{t}}+1)}$ when stricken by disasters

Table A3 includes the new notation used in the analytical results of Section 6.

Table A3: The new notation of the analytical results.

Notation	
ϑ_l	The minimum number of PSAs that should be located in the target circle $l \in L^t$
ξ_l	The minimum inventory that should be stored in the PSAs for the preparedness of the target circle $l \in L^t$
RT^{Min}	The minimum threshold for feasible RTs that can be provided for the target circle of $l \in L^t$ in the response phase
RT^{Max}	The maximum threshold for feasible RTs that can be provided for the target circle of $l \in L^t$ in the response phase
$d_{RT^{Min}}$	The maximum distance that can be traveled within RT^{Min}
$d_{RT^{Max}}$	The maximum distance that can be traveled within RT^{Max}
$\check{d}$	The lower bound for RT^{Min}
$\hat{d}$	The upper bound for RT^{Max}

APPENDIX B

This appendix includes the proofs of the propositions in Section 6.

Proof of Proposition 1.

a) In the case that the target circle of $TT = t$ and $l \in L^t$ does not include the whole relief network, we divide the nodes of the relief network into two subsets: the subset of nodes inside the target circle (N^l) and the subset of nodes outside the circle ($N^O = N - N^l$).

   Defining $\acute{d} = \underset{n_P \in N^O}{\text{MIN}}\left(\underset{n_D \in N^l}{\text{MAX}}\left(d_{(n_P,n_D)}\right)\right)$, all the PSAs should be located at nodes inside the target circle when $d_{\acute{t}} < \acute{d}$. Since the disaster may strike any node inside the target circle, the located PSAs of this case can be damaged by the disaster. Considering q^{Max} as the maximum severity level for the disaster, at most q^{Max}

number of nodes can be stricken concurrently by the disaster. Therefore, the number of located PSAs should be greater than or equal to $q^{Max}+1$ to ensure that always there is an undamaged PSA to support stricken nodes. Increasing RT in a way that $d_{\acute{t}} \geq \acute{d}$, there is at least one node outside that target circle ($\exists n \in N^{o}$) that can support the stricken nodes inside the circle within $RT \leq \acute{t}$. Since the nodes outside the target may not be stricken by the disaster, having a single PSA is enough ($\vartheta_l = 1$).

In the case that the target circle of $TT = t$ includes the whole relief network, $N^{O} = \emptyset$. Therefore, all the located PSA are always inside the target circle and can be damaged by the disaster. According to the logic explained above for $d_{\acute{t}} < \acute{d}$, at least $q^{Max}+1$ number of PSAs should be located in the preparedness phase.

b) Each located PSA has a covering circle including all nodes of the relief network that their distance from the PSA is less than or equal to $d_{\acute{t}}$. If the PSA is located at node n_P, the covering circle of the PSA would be $CC_{n_P}^{RT=\acute{t}} = \{\forall n_D \in N |\, d_{(n_P,n_D)} \leq d_{\acute{t}}\}$. The value of $\left|CC_{n_P}^{RT=\acute{t}}\right|$ shows the usability of its inventory. Lower usability for the inventories of the PSAs leads to higher inventory in the network. Because there is some unused inventory in some of the scenarios. The covering circle of a PSA expands by increasing RT and the usability of its inventory increases: $\left|CC_{n_P}^{RT=\acute{t}}\right| \leq \left|CC_{n_P}^{RT=t''|t''>\acute{t}}\right|$. The highest usability happens when the RT is high enough to make the usability equal to $|N|$. In this case, there is no unused inventory in the network, and the total inventory drops to the maximum demand realized in the scenarios, $\underset{s\in S^l, r\in R^s}{\text{MAX}}\left(\sum_{n_D\in N^s} F_{n_D}^{-1}(\theta)\right)$.

□

Proof of Proposition 2.

Each node $n \in N^l$ in the target circle of $TT = t$, and $l \in L^t$ has a supply circle centered at node n with the radius of $d_{RT=\acute{t}}$. When node n is stricken, the demand for node n can only be fulfilled by a PSA located at one of the unstricken nodes exists inside its supply circle. The supply circle of scenario $r \in R^s$ ($s \in S^l$) is the union of the supply circles of the scenario's stricken nodes. This supply circle is feasible if there exists at least one unstricken node inside the supply circle of each stricken node of that scenario. The minimum RT, for which the supply circle of scenario $r \in R^s$ becomes feasible is $d_r^{Min} = \underset{n_D\in N^s}{MAX}\left(\underset{n_P\in N-N^s}{MIN} d(n_P,n_D)\right)$. For feasibility with respect to all scenarios, RT should be large enough to make a feasible target circle for each scenario: $RT \geq \underset{s\in S^l, r\in R^s}{MAX} d_r^{Min}$ or $\check{d} = \underset{s\in S^l, r\in R^s}{MAX} d_r^{Min}$.

$\hat{d}$ is the shortest RT that minimizes the disaster preparedness:

- According to Proposition 1, the minimum number of PSAs that should be located when $N^{O} \neq \emptyset$ is 1, and this PSA will be outside the target circle. The longest distance needed to transfer emergency goods from the PSA located at node $n_P \in N^{O}$ to the stricken nodes of scenarios is equal to $\underset{s\in S^l, r\in R^s, n_D\in N^s}{MAX} d(n_P,n_D)$. Therefore, the minimum RT needed to locate a PSA outside the target circle would be the RT, for which d_{RT} is $\underset{n_P\in N^{O}}{MIN}\left(\underset{s\in S^l, r\in R^s, n_D\in N^s}{MAX} d(n_P,n_D)\right)$.
- According to Proposition 1, the minimum number of PSAs that should be located when $N^{O} = \emptyset$ is $q^{Max} +$

1 and the minimum total inventory is $\underset{s\in S^l,r\in R^s}{MAX}\left(\sum_{n_D\in N^s} F_{n_D}^{-1}(\theta)\right)$. Also, all of these PSAs will be inside the target circle. Therefore, in the scenario with the highest demand, the inventory of all PSAs should be transferred to the stricken nodes of that scenario to fulfill their demands. The longest distance between the potential locations of the PSAs ($\forall n \in N^l$) and the stricken nodes of scenarios ($\forall r \in R^s, s \in S^l$) is $\underset{n_P\in N^l}{MAX}\left(\underset{s\in S^l,r\in R^s,n_D\in N^s}{MAX} d(n_P, n_D)\right)$. Therefore, the maximum RT needed to transfer goods from any PSA inside the target circle to any stricken nodes cannot be larger than the RT for which d_{RT} is $\underset{n_P\in N^l}{MAX}\left(\underset{s\in S^l,r\in R^s,n_D\in N^s}{MAX} d(n_P, n_D)\right)$.

As an example, consider the following small sample relief network (Figure B1). The dashed circle shows a sample target circle of $TT = t$ and $l \in L^t$ that includes three nodes (n_1, n_2, and n_3). The highest severity level for the disaster is $q^{Max} = 2$. The set of scenarios that can be defined for stricken nodes of l is $S^l = \{s1 = \{n_1\}, s2 = \{n_2\}, s3 = \{n_3\}, s4 = \{n_1, n_2\}, s5 = \{n_1, n_3\}, s6 = \{n_2, n_3\}\}$. For simplicity, we assume that all roads are fortified and there is no disruption possibility.

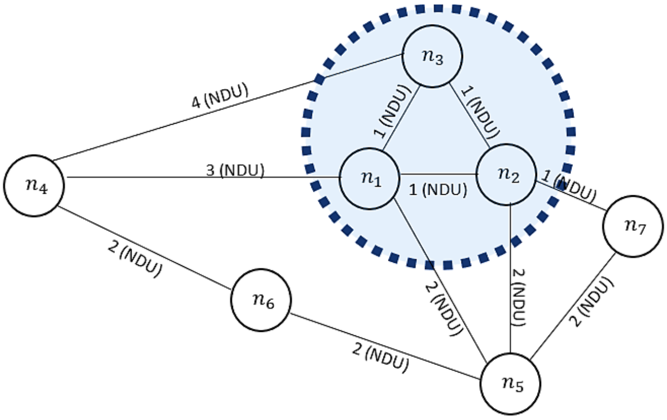


Figure B1: A small sample relief network.

In this relief network, for $\forall s \in S^l$, we have $d_s^{Min} = \underset{n_D\in N^s}{MAX}\left(\underset{n_P\in N-N^s}{MIN} d(n_P, n_D)\right) = 1$. This means that $\check{d} = \underset{s\in S^l}{MAX}\, d_s^{Min} = 1$. In this case, by locating three PSAs at nodes n_1, n_2, and n_3, we can complete the response operations in an RT for which $d_{RT} = 1$ (NDU).

To calculate $\hat{d}$, we focus on the case in which $N^O \neq \emptyset$ ($N^O = \{n_4, n_5, n_6, \text{and } n_7\}$). For the nodes of N^O, we have:

- For node n_4, $\underset{s\in S^l,n_D\in N^s}{MAX} d(n_4, n_D) = 4$
- For node n_5, $\underset{s\in S^l,n_D\in N^s}{MAX} d(n_5, n_D) = 3$
- For node n_6, $\underset{s\in S^l,n_D\in N^s}{MAX} d(n_6, n_D) = 5$
- For node n_7, $\underset{s\in S^l,n_D\in N^s}{MAX} d(n_6, n_D) = 2$

Therefore, $\hat{d} = \underset{n_P\in N^O}{MIN}\left(\underset{s\in S^l,r\in R^s,n_D\in N^s}{MAX} d(n_P, n_D)\right) = 2$. This means that by locating a single PSA at node n_7, we can minimize the preparedness activities. In this case, we can complete the response operations in an RT for which $d_{RT} = 2$ (NDU).

Proof of Proposition 3.

The value of $TT = t$ determines which nodes of the relief network can be considered as candidate locations for PSAs in the preparedness phase. The candidate locations reside in a region centered at the MDC, and there is a path with the length of less than or equal to $d_{TT=t}$ between the nodes of this region and the MDC, $\{\forall n_P \in N |\ d_{(n_M,n_P)} \leq d_{TT=t}\}$. By delaying the preparedness activities (increasing TT and reducing $d_{TT=t}$), the size of the region shrinks, and the candidate locations concentrate around the MDC. This concentration of PSA candidate locations around the MDC does not impact RT^{Min} of few scenarios in which the target circle of $TT = t$ is centered around the MDC. For scenarios in which the target circle of $TT = t$ is centered far from the MDC, the distances between the candidate locations of PSAs and the candidate stricken/demand nodes that are located inside the target circles significantly increase. Increasing distances boosts RT^{Min} for these scenarios. Therefore, the expected value of RT^{Min} increases.

By reducing $d_{TT=t}$, the average distance between the candidate locations of PSAs and the other nodes of the network as candidate demand locations increases. Therefore, higher traveling distance and consequently higher RT^{Min} will be needed after the disaster. The main purpose of locating PSAs is to make stocks of emergency goods closer to the stricken nodes. Increasing TT mitigates the role of PSAs by making them closer to the MDC.

APPENDIX C

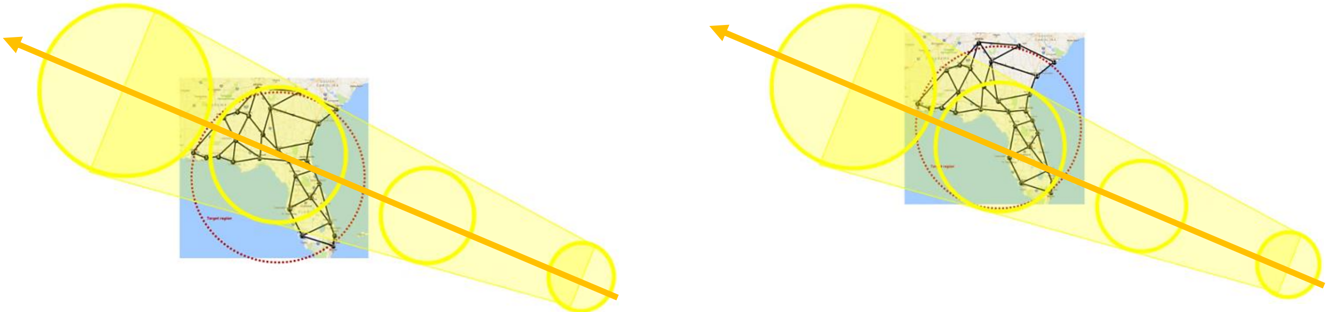
This table includes the list of the most recent hurricanes in the United States, their landfall areas, the total population of the landfall areas at the landfall time, and the total affected population in the hurricanes (EM-DAT, 2017).

Table C1: The historical data for some of the hurricanes in the United States over the recent century.

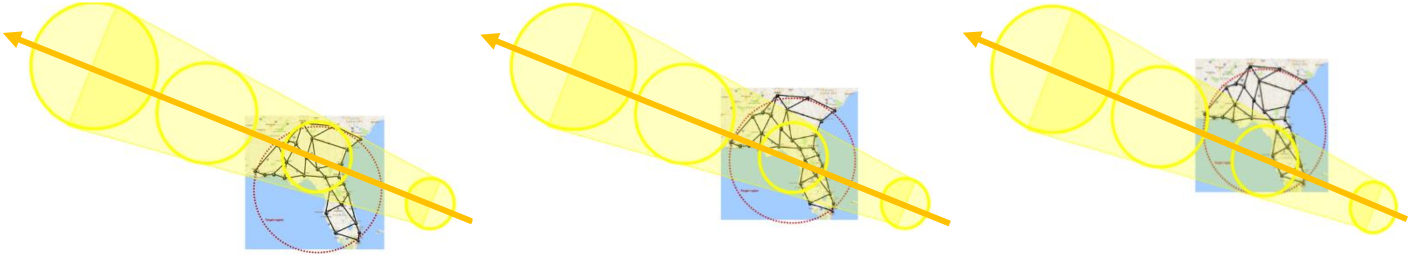
Year	*Hurricane*	*Landfall areas*	*Landfall areas' population*	*Affected people population*	*Affected people ratio*
2017	Irma	Florida Keys islands, Monroe, South Florida, Jacksonville	6,015,052	70,000	1.16%
2017	Harvey	Eastern Texas: Rockport, Corpus Chrsti, Port Lavaca, Cypress	2,057,518	480,024	23.33%
2015	Joaquin	South Carolina, North Carolina	15,294,000	800	0.0052%
2014	Iselle	Big Island (HI)	186,738	834	0.54%
2012	Isaac	Port Fourchon (LA) & Southwest Pass (LA)	155,628	60,000	38.5%
2012	Debby	Steinhatchee (FL) & Panama City (FL)	53,500	17,010	31.8%
2011	Irene	Outer Bank (NC), Little Egg Inlet (NJ), & Brooklyn (NY)	2,619,387	370,000	14.12%
2008	Ike	Galveston (TX) & Palestine (TX)	306,833	200,000	65.18%
2006	Ernesto	Mainland (FL), Wilmington (NC), & Oak Island (NC)	120,906	146	0.12%
2005	Wilma	Florida Keys (FL) & Naples (FL)	101,676	30,000	29.5%
2005	Rita	Johnson Bayou (LA) & Sabine Pass (TX)	396,493	300,000	75.7%
2005	Katrina	Buras – Triumph (LA), South Eastern Louisiana (LA), & Meridian (MS)	1,285,241	500,000	38.9%
2004	Jeanne	Hutchinson Island (FL), Sewall's Point (FL), Stuart (FL), & Port Saint Lucie (FL)	248,071	40,000	1.61%
2004	Frances	Fort Pierce (FL), West Palm Beach (FL), Hutchinson (FL), Sewall's Point (FL), Jensen Beach (FL), Port Salerno (FL), Florida Peninsula (FL), Tampa (FL), & St. Marks (FL)	1,446,462	500,000	34.56%
2004	Charley	St. Vincent Island (FL), Cayo Costa (FL), & Punta Gorda (FL)	552,681	30,000	5.4%
2003	Isabel	Cape Hatteras (NC), Cape Lookout (NC), Ocracoke Island (NC), Western Virginia (WV), & Western Pennsylvania (PA), Pittsburg (PA)	2,113,916	225,000	10.6%
2002	Isidore	Grand Isle (LA)	434,767	13,200	3.03%
2001	Allison	Alligator Point (FL) & St. Marks (FL)	1,082,277	172,000	15.89%

APPENDIX D

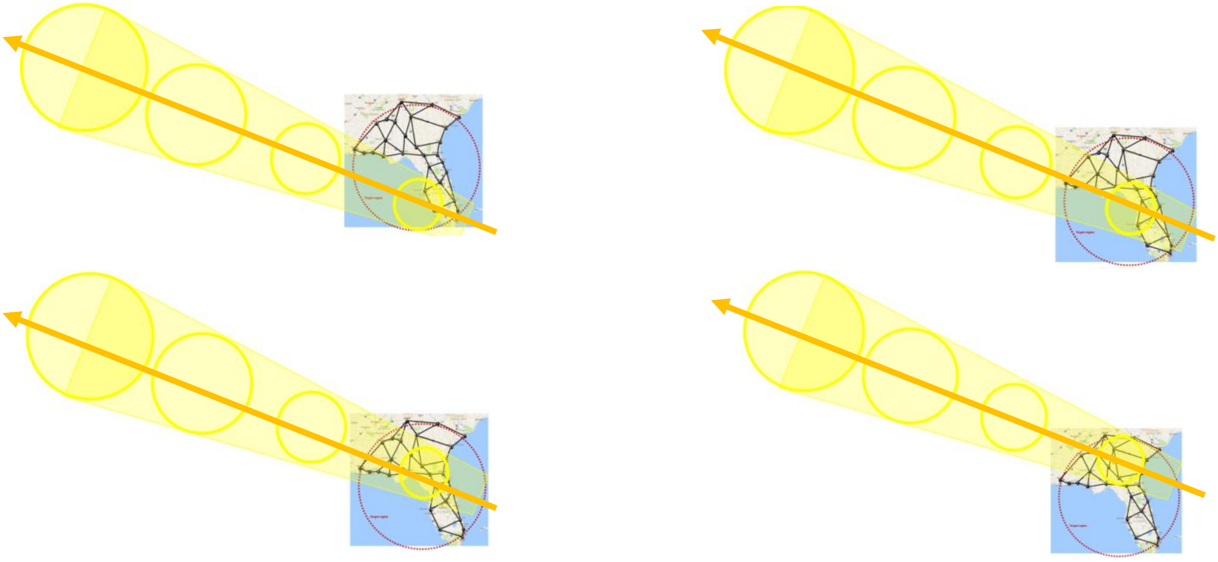
The locations considered for the 4-, 3-, and 2-day target circles on the second and third movement trajectories are shown in Figures D1 and D2.



a) Locations of the 4-day target circle.

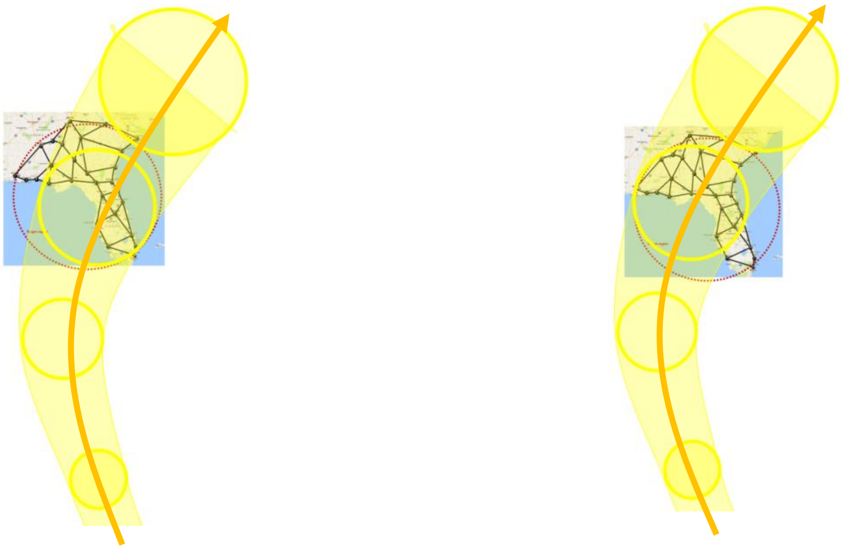


b) Locations of the 3-day target circle.

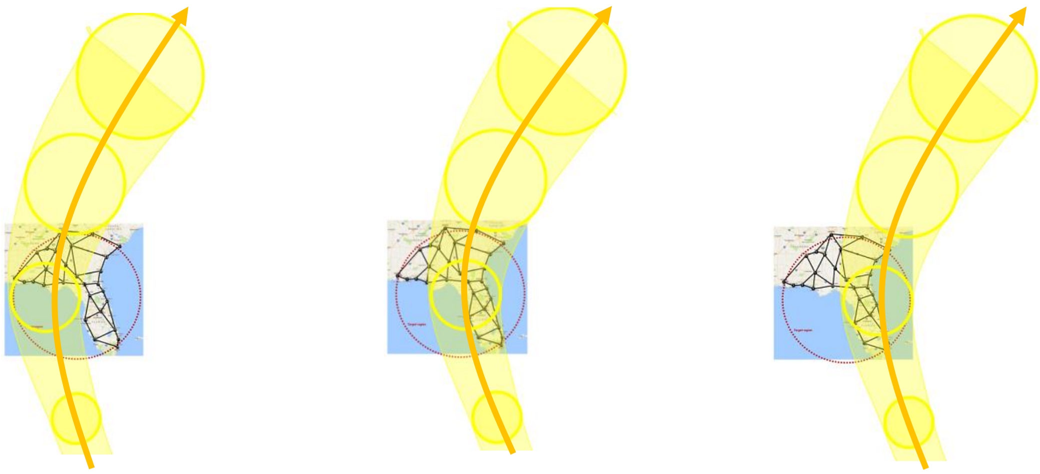


c) Locations of the 2-day target circle.

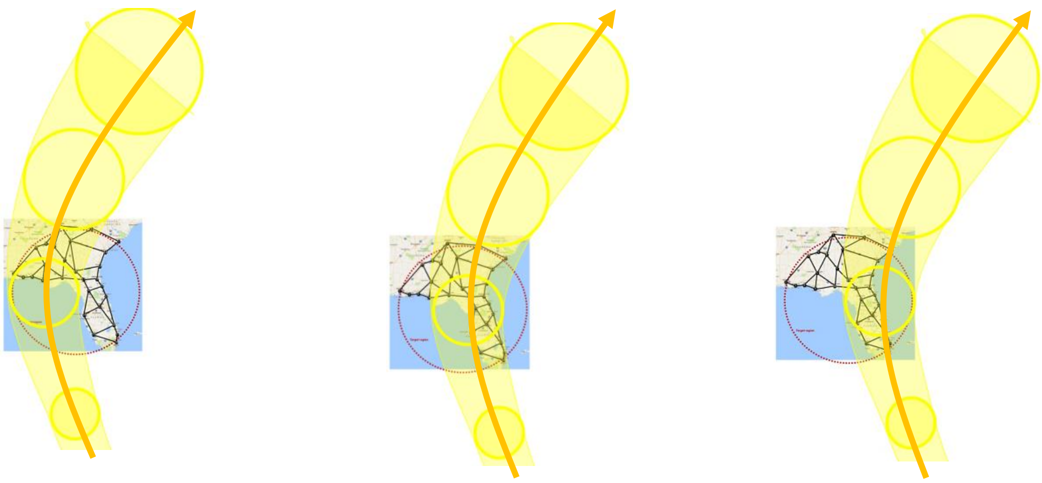
Figure D1. Locations of the 4-, 3-, and 2-day target circles in the second hurricane trajectory.



a) Locations of the 4-day target circle.



b) Locations of the 3-day target circle.



c) Locations of the 2-day target circle.

Figure D2. Locations of the 4-, 3-, and 2-day target circles in the third hurricane trajectory.