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Emergency Shelter Resource Allocation and Location Analysis

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Emergency Shelter Resource Allocation and Location Analysis

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ABSTRACT

This paper formulates a mixed-integer facility location model to optimize emergency shelter location and resource allocation based on a set of existing candidate shelters. This model minimizes network access time between an affected census block and a potential emergency shelter, the operating costs of a shelter as a function of shelter capacity, and the cost of not accommodating all evacuees with emergency shelter capacity at the planning stage. A sensitivity analysis of the model examines the impact of the model parameters, finding that assumptions about the number of evacuees and the importance of providing capacity for all evacuees at the planning stages significantly impact solutions. The results indicate that there is room for additional efficiency in prioritizing resource allocation to emergency shelters in a comprehensive plan. Even under the most extreme modeling circumstances (half of the population seeking shelter) only 78% of candidate shelters are recommended to be in operation, due to a spatial mismatch between population and shelter capacity. The sensitivity analysis and case study show that not only does the total number of shelters vary under different scenarios, but also the distribution in the sizes of recommended shelters. A case study for the state of Connecticut was conducted for a category 4 hurricane storm surge affecting the entire coastline of the state to demonstrate applicability of the model and potential uses of the results.

INTRODUCTION

According to the U.S. National Oceanic and Atmospheric Administration (NOAA) there were 1,484 deaths caused by a hurricane between 1940 and 2013 with 1,168 of those occurring between 2000 and 2013 (NOAA 2015a). Although some reports suggest different figures, there is no doubt that hurricanes continue to pose a significant danger and that deaths can be decreased significantly with strategic emergency planning. Between the years 1900 and 2005 the average annual normalized damage from hurricanes in the U.S. is approximately $10 billion. Between 1996 and 2005 the US experienced the second highest cost for hurricane damages during a 10-year period (Pielke 2008). The deadly and costly storms that have occurred in the last 15 years have increased the urgency for planning and preparing for such disasters. Preparation for hurricanes and tropical storms requires the coordination of many emergency services within a highly uncertain and unpredictable context. An aspect of this preparation is planning for evacuation shelters for coastal communities. These shelters serve as places of refuge and may serve as distribution centers for emergency supplies in the days immediately following a storm. Plans for emergency shelters may suffer from fragmentation due to jurisdictional issues, lack of data and the use of qualitative and subjective methodologies in creating the network of shelters and logistical hubs.

The eastern coast of the United States faces an average of 4.2 hurricanes per year, with 2.3 of those being a Category 3 or higher, based on data between 1966 and 2009 (NOAA 2015b). Many of these storms affect the southeastern part of the United States and accordingly, this region of the country has extensive hurricane preparedness and evacuation plans. Hurricane Katrina was the costliest disaster in the United States when it made landfall in August of 2005 in the southeastern part of the US. Hurricane Katrina was responsible for more than 1,800 lives lost, $125 billion in expenditures, and more than 250,000 displaced residents (Houston et al. 2006).

Hurricane Katrina was an unfortunate reminder of the importance of hurricane preparedness in minimizing the number of casualties and providing immediate relief to survivors. Although the chances of a hurricane hitting the northeastern part of the United States are much less than the Gulf Coast, Hurricane Sandy demonstrated the danger posed to the northeastern U.S. Hurricane Sandy made landfall on the evening of October 29th in 2012 in southern New Jersey near Atlantic City. As the storm moved parallel to southeastern United States, Sandy was a category 1 hurricane and when it made landfall it was a post tropical cyclone with hurricane force winds up to 80 miles per hour. Hurricane Sandy took the lives of 162 people, caused 8.5 million people to lose power, and caused widespread flooding in New Jersey, New York, and Connecticut. The storm damaged or destroyed hundreds of thousands of houses and buildings, forcing over 23,000 people to seek temporary shelter (U.S. Dept. of Homeland Security 2013).

This paper describes a decision support model for the allocation of resources to opening and maintaining a network of evacuation shelters in the event of a hurricane. A case study along the southern coast of Connecticut is presented to illustrate the utility and potential efficiencies of the model. The model for emergency shelter location is designed to minimize access costs and shelter operating costs while maximizing the number of evacuees that are accommodated. It is important that these facilities are located such that access to the shelters is equally distributed across populations, geographies and modes of access. Elderly persons, people with disabilities, people who are impoverished, and people who don’t own a vehicle should receive special consideration but are not in the model presented in this paper. These populations will be the focus of subsequent investigations.

The following sections of this paper consists of a literature review section summarizing research covering emergency preparedness and response. The third section describes the

formulation of the mixed-integer facility location model generated in this paper. The fourth section discusses the results of a sensitivity analysis. The sensitivity analysis is followed by a case study application for the coastline of Connecticut. The final section summarizes the results and describes future research avenues.

LITERATURE REVIEW

Hurricane preparedness has become a heavily researched topic since Hurricane Katrina in 2005. A significant amount of this research has focused on the southeastern part of the United States because of the higher probability of a hurricane making landfall in this region. There are many aspects of emergency preparedness and response that have been studied including prepositioning of relief supplies (Rawls and Turnquist 2010; Lodree et al. 2012; Mete and Zabinsky 2010; Roh et al. 2015), evacuation route planning (Murray-Tuite and Wolshon 2013; Sorenson 2000; Pel et al. 2012), emergency shelter location (Yushimito et al. 2012; Horner and Downs 2007; Bayran et al 2015;(Kongsomsaksakul et al. 2005; Ng et al. 2010; Beamon and Balcik 2008), and supply movement after a storm (Hanghani and Oh 1996; Ozdamar et al. 2004; Sheu 2007).

An important part of hurricane preparedness is positioning commodities and resources such as food, water, medical kits, and emergency generators in places that are close to affected areas without being in the affected areas and potentially being damaged by the storm. Rawls and Turnquist (2010) develop a model to determine the location and amount of supplies that should be prepositioned based on the probability of different strengths of storms arriving in different locations. Their model is a two stage stochastic mixed integer program in which the first stage decisions are made considering uncertain future events including demand variations and damages to the network. The second stage decision is made after these uncertain future events are known and involves the distribution of commodities from distribution centers to the affected

areas. Lodree et al. (2012) develop a model very similar to Rawls and Turnquist with the exception that their model is tailored to big box retailers. Like Rawls and Turnquist (2010), their model is a two-stage stochastic programming model, however, during the first stage of their model emergency commodities to be distributed from a manufacturer to the retailer is determined rather than the location and capacity of distribution centers. The second stage involves transshipments among retailers in addition to direct shipments from the manufacturer to retailers in affected areas. Mete and Zabinsky (2010) describe a similar stochastic model adapted to medical supplies and ensuring hospitals have sufficient inventory to deal with injured people. In the second stage of their model detailed vehicle assignments and routing is determined in addition to the amount of supplies being shipped between hospitals and medical supply warehouses. Roh et al. (2015) develop a model determining the location of relief supply warehouses worldwide to improve response time for nations that have experienced a natural disaster.

One aspect of hurricane preparedness that can eliminate or reduce the number of casualties and the number of people that need to be rescued is evacuation route planning. There are many specific areas within evacuation planning and operations, including forecasting of evacuation travel demand, the distribution and assignment of demand to road networks, and strategies to access and increase capacity of evacuation networks (Murray-Tuite and Wolshon 2013). In order to generate estimates of the number of people evacuating and where they are evacuating from it is helpful to know what influences people’s decision to evacuate. There is an extensive amount of statistical analysis and research that has been performed that is summarized in reviews (Murray-Tuite and Wolshon 2013; Sorenson 2000). Another important behavior is route choice and traveler behavior in evacuation conditions. Pel, Bliemer, and Hoogendoorn

(2012) provide an extensive review of mathematical models that model evacuation behavior including the time to evacuate, the destination choice, and the route choice. Increasing the capacity of the network strategies include contraflow operations, use of road shoulders, modified traffic control, and use of transit (Murray-Tuite and Wolshon 2013).

Optimization models that determine the locations of emergency shelters and supply distribution centers are typically based on the facility location problem but minimize travel time and minimize human suffering rather than myopically minimizing transportation costs. Yushimito, Jaller, and Ukkusuri (2012) develop a model that determines the location of supply distribution centers based on a specified number of facilities to be located. Their model uses Voronoi diagrams to determine a set of locations for shelters that minimizes a social cost while ensuring all demand points are covered. Horner and Downs (2007) take a different approach in determining the locations, minimizing shipping costs rather than minimizing social costs. Their model determines the location of distribution centers while minimizing the transportation costs between the supply warehouses and the distribution centers and the distribution centers and neighborhoods. Bayram et al. (2015) develop a model that determines the location of emergency shelters while considering evacuation traffic assignment. Their model minimizes the path evacuees must take rather than social costs or transportation costs. Kongsomsaksakul et al (2005) focus on determining the location of evacuation shelters by developing a bi-level program. The upper level is a location model that determines where emergency planners should locate emergency shelters and the lower level models evacuees' decision of where to evacuate to and what route they will take to get to the shelter. The upper level minimizes the total evacuation time in the network whereas the lower level minimizes the evacuees' individual evacuation time. Ng, Park, and Waller (2010) develop a bi-level model very similar to Kongsomsaksakul et al.

(2005) except their model assigns evacuees to specific shelters in the upper level and the lower level only models the route the evacuees take to reach their assigned shelters. Each of these four models discussed determines the location of supply distribution centers or emergency shelters while maximizing coverage and minimizing either shipping distance or travel time. Balcik and Beamon (2008) evaluate performance measurements for emergency supply relief chain compared to commercial supply chains and consider factors unique to relief supply chains such as supplies not reaching people in an acceptable amount of time.

Haghani and Oh (1996) develop a multi-objective, multimodal network flow model that can be used by federal and state authorities for the movement of supplies after a storm. Their model can be used to determine detailed routing and scheduling for various modes of transportation, load plans for each mode of transportation, and delivery schedules for various commodities at certain destinations. Ozdamar et al. (2004) develop a hybrid model of the multi-period multi-commodity network flow problem and a multi-period vehicle routing problem for multiple modes of transportation that considers time-varying demand and regenerates a plan for each time period that incorporates new supply and new requests for supplies. Sheu (2007) presents a model with a component that predicts the relief demand using a dynamic relief demand forecast model using fuzzy techniques. In the final phase of the model an optimization model is applied to distribute relief commodities from relief distribution centers to affected areas (Sheu 2007). This paper adapts concepts from the established literature and evaluates a large set of existing emergency shelters and the utility of maintaining these shelters in the event of an emergency rather than identifying where new shelters should be placed. Uncertainty in evacuee characteristics is accommodated through the inclusion of a penalty for not accommodating all evacuees – allowing the analyst to explore solutions that are not driven by a requirement to

accommodate a demand for shelter that is likely to be based on rough estimation. Further, the model's simplicity allows for rapid, simple sensitivity analysis to evaluate several scenarios and policy alternatives.

PROBLEM FORMULATION

A facility location model is formulated minimizing the total fixed costs of opening and operating shelters, the total distance traveled between census block centroids and emergency shelters, and the number of people not provided shelter capacity at the planning stage. The results of this model will identify shelters that should be maintained and utilized opened and estimate the number of people that will travel from each affected census block to each emergency shelter. The formulation of the facility location model with the associated descriptions is provided below including the necessary sets and indices, data and parameters, objective function and constraint set.

Sets and Indices

The following sets are used:

$i \in I$	census block centroids within storm surge boundary
$j \in J$	candidate shelter locations

Set I contains census blocks that are within Sea, Lake, and Overland Surges from Hurricanes (SLOSH) zones which are determined by the National Weather Service (NOAA 2015c). Set J are potential hurricane shelters that can include schools, senior centers, churches, town recreational centers, etc. as given by the Connecticut Dept. of Emergency Management and Homeland Security (DEHMS).

Data and Parameters

d_i	evacuees originating at census block centroid *i*
b_j	capacity of shelter *j*
f_j	fixed cost of operating a shelter at *j* based on the shelter's capacity
c_{ij}	travel cost between census block *i* and potential shelter *j*
M	scalar for facility constraint
Ψ	scalar that penalizes evacuees not accommodated by a shelter

The parameter d_i is a predetermined or assumed percentage of the total number of people living in each affected census block based on existing models such as Fu and Wilmot (2004) or local policy. The parameter b_j is the number of people a candidate shelter can accommodate and is based on the square footage of useable spaces (American Red Cross 2002). The parameter f_j is the opening and operating cost of a potential shelter (assumed for this paper a function of the capacity of the shelter). The parameter c_{ij} is the travel cost between census blocks and shelters. This cost is equal to the network distance (in miles) between *i* and *j* multiplied by the value of evacuees time ($) divided by the speed at which a person evacuates (mph). The scalar M is a suitably large scalar used to limit the flow of evacuees only to those shelters that are opened. The scalar Ψ is a penalty for any evacuees not provided shelter and is in units of dollars per person not assigned.

Decision Variables

The decision variables used in this model are:

$$y_j = \begin{cases} 1 & \text{if shelter is opened at } j \\ 0 & \text{otherwise} \end{cases}$$

x_{ij} The number of evacuees traveling from block *i* to shelter *j*

Formulation

The objective function is:

$$\sum_{j\in J} f_j y_j + \sum_{i\in I}\sum_{j\in J} c_{ij}x_{ij} + \Psi\left(\sum_{i\in I}\left(d_i - \sum_{j\in J} x_{ij}\right)\right)$$

$$(1)$$

The objective function defined above minimizes three components, all in units of cost in dollars. The first component is the total fixed cost of opening and operating the set of selected shelters. The second component minimizes the travel/access cost for evacuees between the residence census block and the emergency shelter to which they are assigned. The third component captures the cost of being unable to accommodate all evacuees with shelter capacity.

The objective function is constrained by the following:

$$\sum_{j \in J} x_{ij} \leq d_i \qquad \forall\, i \in I \tag{2}$$

$$x_{ij} \leq y_j M \qquad \forall i \in I, \forall j \in J \tag{3}$$

$$\sum_{i \in I} x_{ij} \leq b_j \qquad \forall j \in J \tag{4}$$

$$y_j \in \{0,1\} \qquad \forall j \in J \tag{5}$$

$$x_{ij} \in \mathbb{Z}^+ \qquad \forall i \in I, \forall j \in J \tag{6}$$

Constraint 2 ensures that the amount of evacuees from block *i* assigned to shelter *j* is less than or equal to the evacuee demand of block *i*. Constraint 3 limits assigning evacuees only to shelters that are selected to be opened. Constraint 4 ensures that the number of evacuees assigned to a shelter does not exceed the capacity of that shelter. Constraint 5 restricts the variable that determines whether a shelter is opened at candidate location *j* to being binary. Lastly, constraint 6 limits the variable for the number of people assigned to each shelter from each census block to nonnegative integer values.

The proposed model is formulated as a mixed integer program and is coded in GAMS and solved utilizing CPLEX. GAMS is a high level modeling system for mathematical programing and optimization and the CPLEX solver is used to solve complex linear programs and mixed integer programs.

Datasets

Table 1 displays information about the datasets used for the model formulation with basic descriptive statistics provided in Figure 1.

Table 1 Datasets Used for Sets and Indexes

Sets/Indices	Source:	Date:
Census Blocks	US Census Bureau	2010
Candidate Shelter Locations	CT Dept. of Emergency Management and Homeland Security (DEMHS)	May 1st 2015

SENSITIVITY ANALYSIS

The proposed model is demonstrated using census blocks in Connecticut determined to be within a Category 4 hurricane surge zone and the set of candidate shelters for this scenario as determined by Connecticut Dept. of Emergency Management and Homeland Security (DEHMS). Using ArcGIS, category 4 SLOSH zones are overlaid on census blocks to determine the census blocks that contain surge zones and therefore require consideration for evacuation shelters. Figure 1 shows the towns (in blue) that contain blocks that are affected by a category 4 storm surge (shown in red) in addition to the location of candidate shelters.

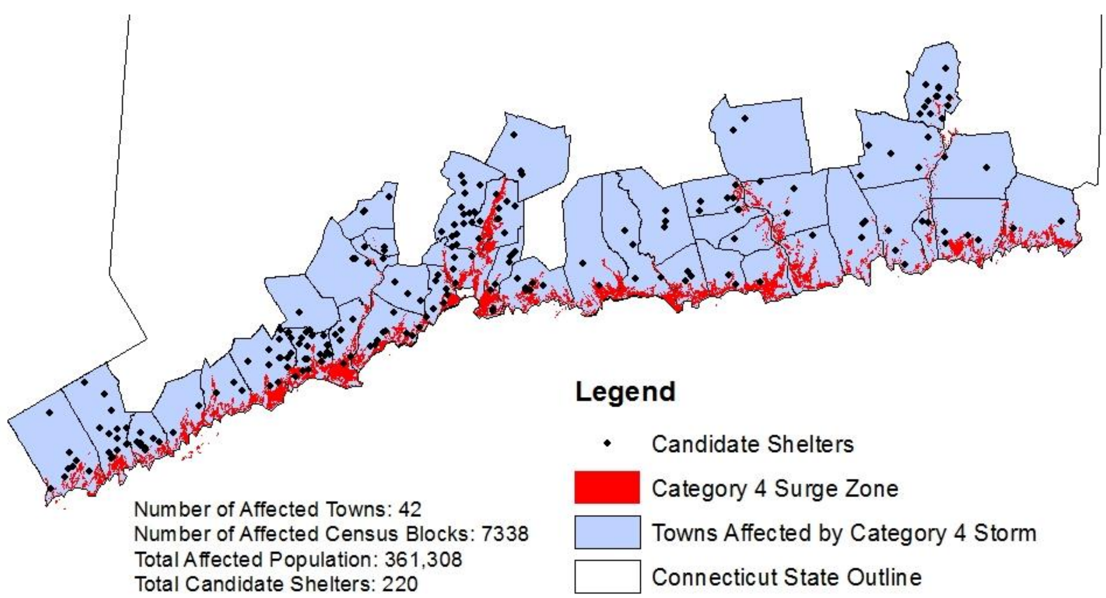


Figure 1 Map of case study region.

As visible in Figure 1, some shelters are located within a surge zone, which may impact their ability to accommodate evacuees. In follow-on research the authors will explore a stochastic version of the model that accounts for the possibility that shelters may too be damaged during a hurricane and therefore incapable of accommodating evacuees.

There are 7338 census blocks that contain a category 4 SLOSH zone. This case study considers 220 potential emergency shelters in towns that contain affected blocks. The capacity of these shelters is based on 20 square feet of space per evacuee which is within the range of the recommended amount of space by the American Red Cross for hurricane shelters (American Red Cross 2002). Operating costs were not available for each individual shelter and per discussions with Connecticut DEMHS personnel, it was determined that a majority of the labor to open and operate an emergency shelter is done by volunteers. For this example the operating cost is estimated to be $20 per person including the cost of food and water for the length of time the shelter is open. While this value is subject to debate, the sensitivity analysis revealed that the ratio of unaccommodated evacuee penalty to operating cost that is important and that for analysis to be meaningful, that ratio must be greater than 1.1.

The sensitivity analysis presented in Figures 2 and 3 shows the relationship between the speed of evacuation, the value of evacuees' time, the assumed percentage of the population affected by a category 4 hurricane that will need shelter and the value of unaccommodated evacuee penalty. Sensitivity is presented as the impact on the number of evacuees not accommodated and the total number of shelters opened. The analysis assumes the following default parameter values: the value of people's time at $10/hour, an evacuation speed of 20 mph, 10% of the affected population is in need a shelter, and the penalty for unaccommodated evacuation demand is $30 per person.

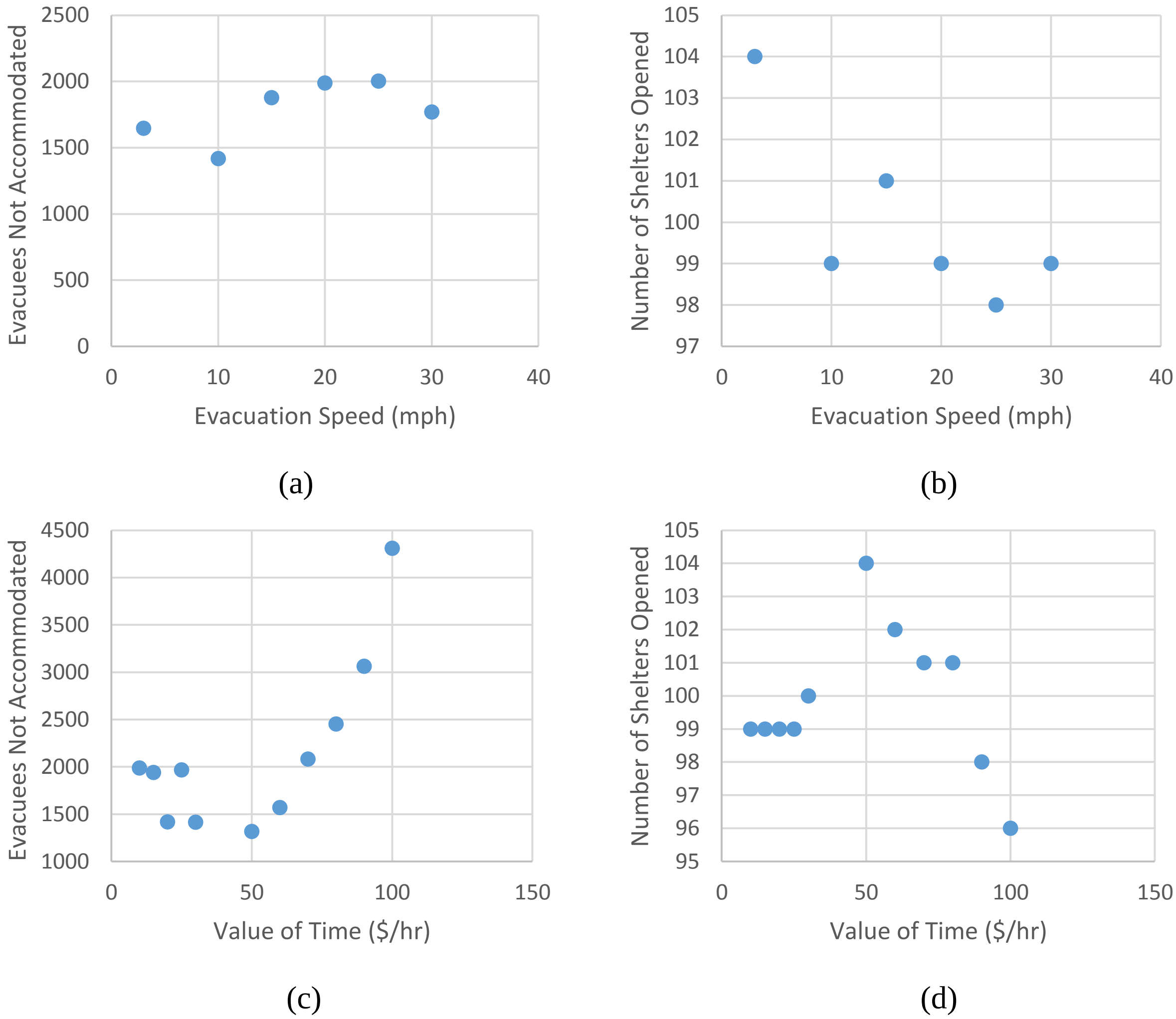
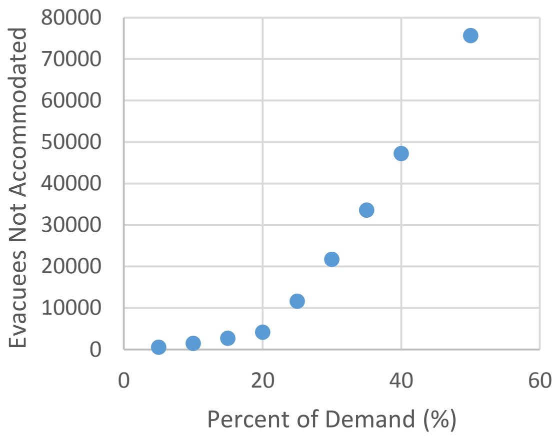


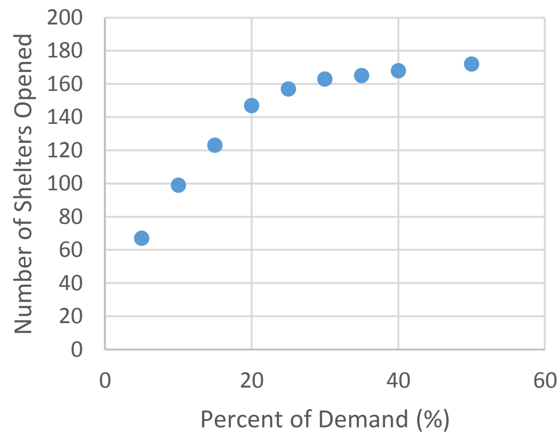
Figure 2 Evacuees not accommodated and number of shelters opened as a function of evacuation speed (a) and (b) and the value of evacuees' time (c) and (d).

The range of evacuation speeds in Figures 2(a) and 2(b) was chosen to represent possible modes of evacuation – a speed of 3 mph would focus on those walking to shelter, 10-15 mph those using transit or driving in urban traffic conditions and 30 mph those utilizing suburban/rural roads to reach the shelters. The evacuation demand not accommodated remains relatively constant over the range of evacuation speeds, with no obvious relationship. An explanation for the drop off in Figure 2(a) between 25mph and 30mph is that travel costs are decreasing because an evacuee can travel a further distance in less time and additional shelter capacity becomes reachable. However the number of shelters opened decreases markedly when access speeds are

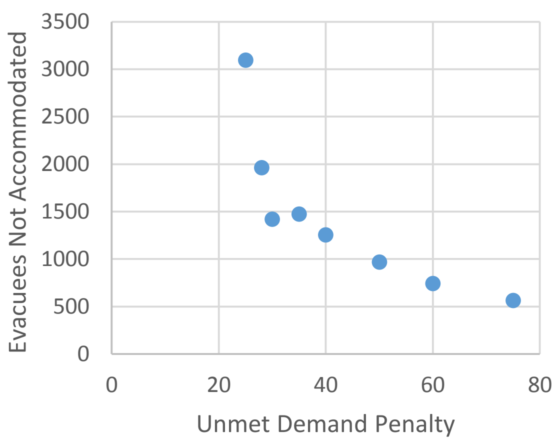
much higher – as would be expected when planning for walking vs. auto access. This suggests that an analysis allowing for multiple access modes may be warranted and is being considered for future study. Figure 2(c) shows that when the value of time is low (less than $50/hour) the penalty for not accommodating demand and the operating cost of a shelter have a stronger influence than the travel cost.



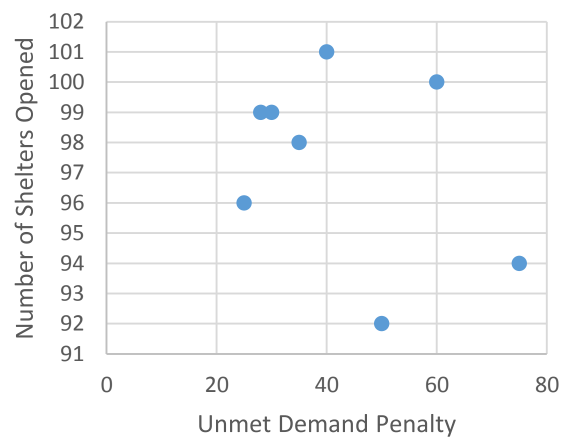
(a)



(b)



(c)



(d)

Figure 3 Evacuees not accommodated and number of shelters opened as a function of percentage of affected population in need of shelter (a) and (b) and penalty for unmet demand (c) and (d).

Figures 3(a) and 3(b) demonstrate the effects of capacity on the system. Naturally, as the assumed percentage of the population needing to evacuate rises the number of unaccommodated individuals rises – dramatically so when the number of evacuees exceeds the total capacity of the shelters in the system. This is illustrated in 3(a) with the exponential rise in evacuees not accommodated once the assumed percentage of population needing shelter exceeds 30%. Interestingly, in Figure 3(b), the total number of shelters plateaus at just under 180 facilities – much less than the 220 currently within the DEMHS plan. This suggests that even in extreme situations there is the opportunity to target resources on a smaller set of shelter locations and still provide capacity for accommodating evacuation needs. This finding is likely due to a spatial mismatch between shelter capacity and population and the reasonable expectation that evacuees will be unlikely to travel long distances within this network for shelter and would instead choose other evacuation options.

Figures 3(c) and 3(d) portray the effects of changing the penalty for unaccommodated evacuees (unmet demand). The number of evacuees not accommodated decreases exponentially as shown in Figure 3(c). This is an intuitive result – the more emphasis evacuation planners place on accommodating all possible evacuees should result in fewer evacuees being unaccommodated. Figure 3(d) suggests that the value of the unmet demand penalty doesn't have a definitive effect on the number of shelters opened - this finding is explored further in the case study and detailed in Figure 5.

Table 2 shows the number of shelters opened when changing the percentage of the population in need of shelter. When conducting the sensitivity analysis of the travel speed, value of people's time, and the percentage of the population in need of shelter, the maximum and minimum number of shelters opened occurs when changing the percentage in need of shelter.

As Table 2 shows there is not a situation when all of the potential shelters are opened, even when 50% of the population is in need of shelter. This is noteworthy because 50% of the affected population is almost 23,000 more people than the 220 candidate shelters can theoretically accommodate (157,909 people).

Table 2 Number of Shelters Opened

Total Shelters Opened	% of Population in Need of Shelter	Evacuation Travel Speed	Value of Evacuee's Time	Penalty for Unmet Demand
172	50%	20 mph	$10/hour	$30/person
168	40%	20 mph	$10/hour	$30/person
163	30%	20 mph	$10/hour	$30/person
147	20%	20 mph	$10/hour	$30/person
99	10%	20 mph	$10/hour	$30/person
67	5%	20 mph	$10/hour	$30/person

Of practical concern is the shelters themselves that are opened in each of the analyses. Thirty-four combinations of parameters were analyzed and each resulted in a unique solution. Combinations include evacuation speeds between 3 mph and 30 mph, value of people's time between $10 per hour and $100 per hour, the percentage of the affected population needing shelter between 5% and 50%, and the penalty for unmet demand ranging between 25 and 75.

The results indicate that certain shelter locations deserve priority in evacuation planning. Figure 4 maps 47 shelters that are deemed most critical (shown in green) and were opened in all of the 34 scenarios in the sensitivity analysis. The 42 shelters shown in red were never opened in any of the trials with the 131 other shelters falling within the ranges depicted in Figure 4. This information can serve as the basis for a prioritization scheme in allocating resources to evacuation shelter preparedness.

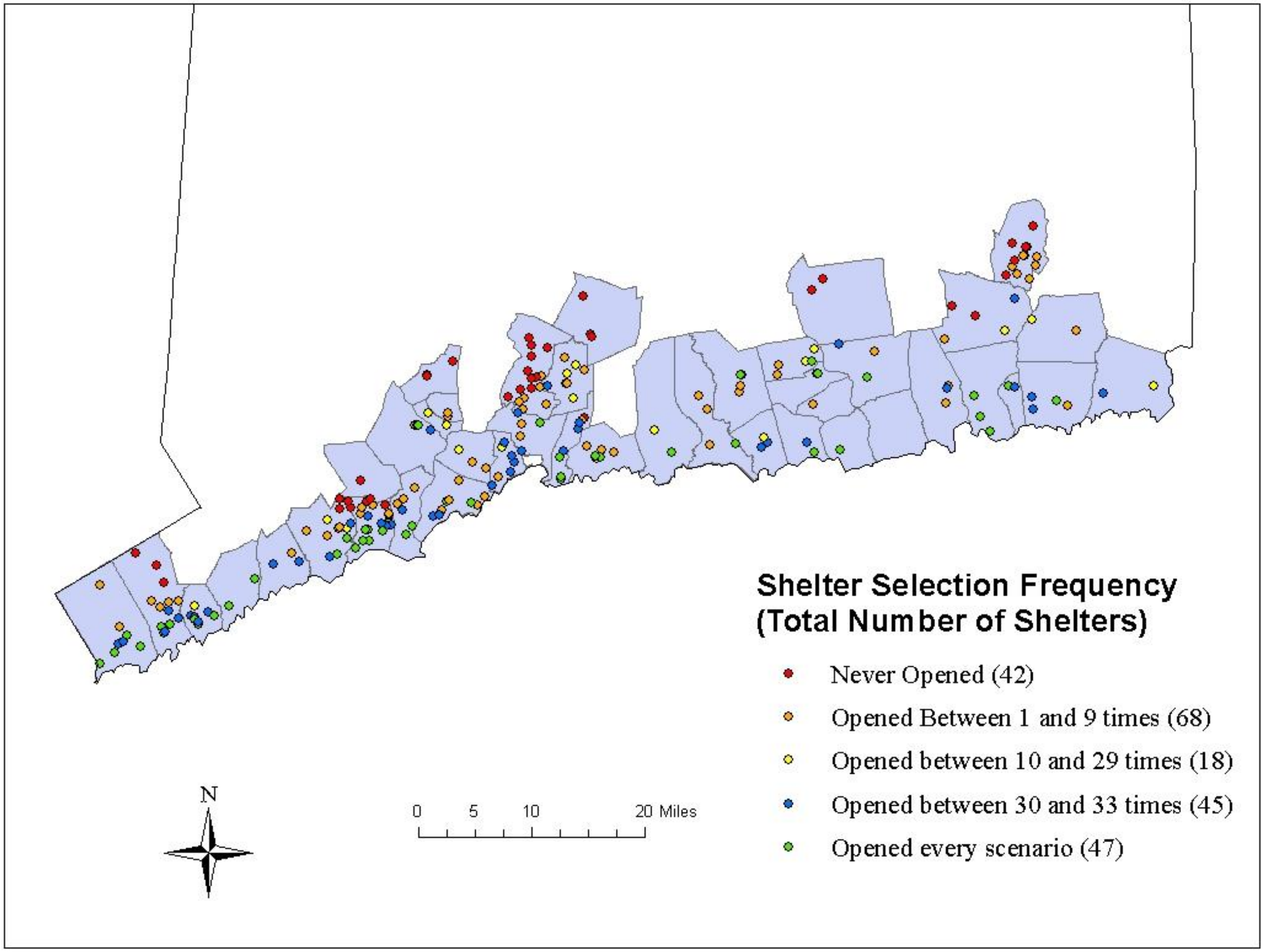


Figure 4 Shelter prioritization.

CASE STUDY

A case study is presented to look at a single application of the model in more detail using the same datasets as the sensitivity analysis. Focus is given to the distribution of shelter sizes across assumed values of unserved demand penalty. Assumed parameter values are shown in Table 3.

Table 3 Assumed Values for Case Study

Parameter	Value
Evacuation travel speed	20 mph
Value of evacuees' time	$20 per hour
Percentage of affected population in need of shelter	10%

The travel speed is assumed to be 20 mph, a reasonable average speed considering that the majority of the affected in Connecticut are in suburban areas. The value of people's time was assumed to be $20 per hour which is slightly more than the living wage per person in Connecticut of $19.08 (Henry and Frederickson 2014). For his analysis it assumed that 10% of the affected population need shelter which is what was experienced by evacuation managers during Hurricane Sandy. The relationship between the number of shelters opened, the size distribution of shelters and the value of the penalty for unserved demand is shown below in Figure 5 which is based on data shown in Table 4.

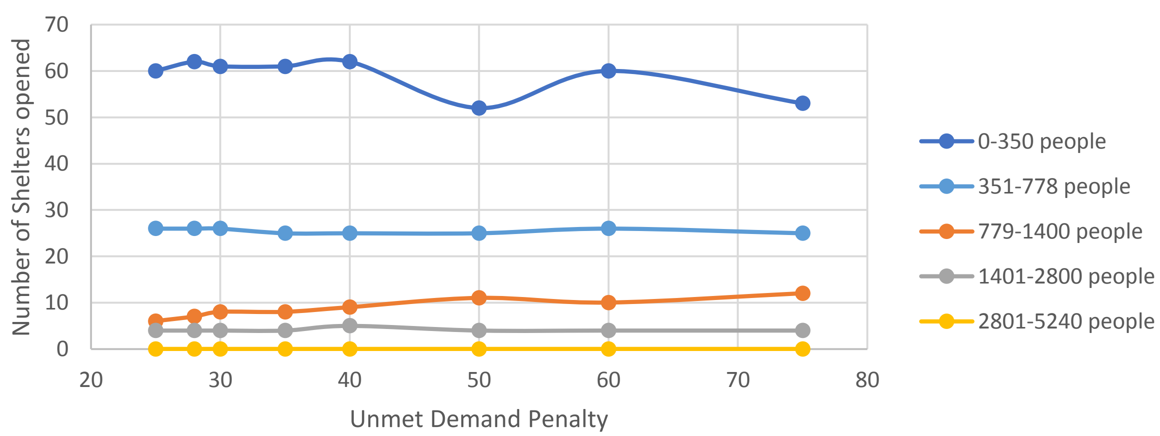


Figure 5 Number of shelters opened when changing unmet demand penalty.

Table 4 Data for Figure 5

Unmet Demand Penalty	25	28	30	35	40	50	60	75	
Size of Shelter	**Number Of Shelters Opened**								**Number of Candidate Shelters**
0-350	60	62	61	61	62	52	60	53	**102**
351-778	26	26	26	25	25	25	26	25	**48**
779-1400	6	7	8	8	9	11	10	12	**41**
1401-2800	4	4	4	4	5	4	4	4	**23**
2801-5240	0	0	0	0	0	0	0	0	**6**
Total Opened- All Sizes	**96**	**99**	**99**	**98**	**101**	**92**	**100**	**94**	

Figure 5 shows the number of shelters opened divided into 5 categories based on the size of the shelter. The categories are divided following the Jenks natural breaks classification method (Jenks and Caspall 1971). The far right column in Table 4 shows how many possible shelters are available in each of the five categories.

As the penalty for unmet demand increases fewer smaller shelters are opened and more medium-sized are utilized. This is not surprising – as the emphasis on accommodating as many evacuees as possible increases, larger capacity facilities are able to do so more effectively in a resource-constrained context. This finding is important – the emphasis evacuation planners place on the various aspects of the problem have an impact not only on the total number of planned shelters, but the size distribution of shelters within that total number.

Figure 6 maps the results of this case study, with the not-surprising result of clustered shelters in dense population areas. Interestingly, there are towns with no shelters located within town boundaries. An extension of this model will be to consider that each town must have at least one shelter opened within its boundaries. A further extension will explore the impacts of requiring evacuees to be assigned to a shelter within their town, regardless of access distance/cost. The latter extension is in line with the manner in which emergency information is organized and distributed in Connecticut, which is primarily a function of the town of residence.

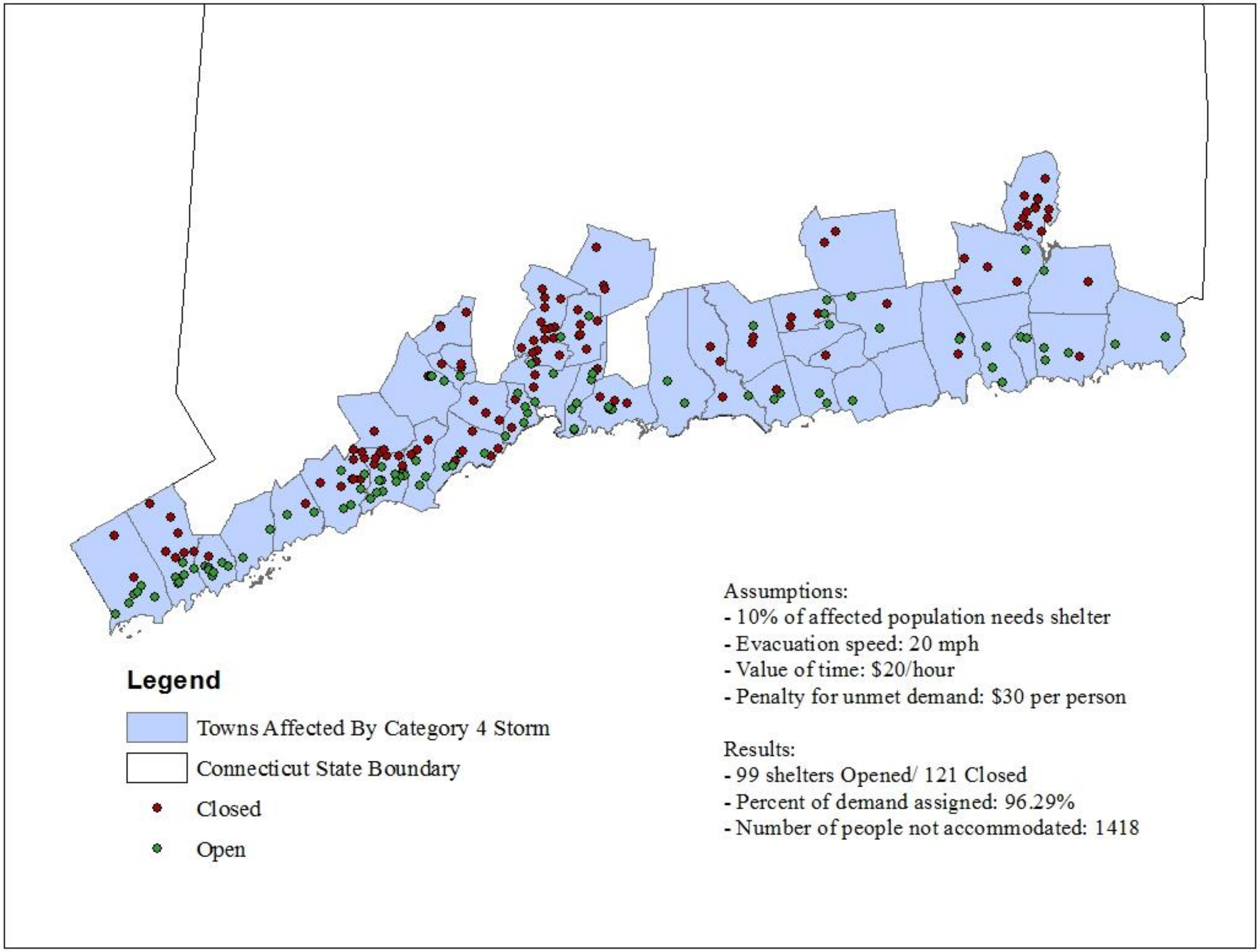


Figure 6 Results for sample scenario.

CONCLUSION

This paper formulates a facility location model to inform emergency shelter planning based on a set of candidate shelters. The sensitivity analysis conducted on this model suggests that the model captures tradeoffs between the competing objectives of providing shelter capacity to as many people as possible in as efficient a manner as possible in a resource-constrained context. An important takeaway is that the maximum number of shelters opened within the model (172) is significantly less than the total number of candidate shelters. There is opportunity to focus resources on a smaller set of shelters and still achieve the goals of evacuation planning. This result also suggests that a spatial mismatch between shelter demand and supply may exist and new candidate locations need to be considered. The sensitivity analysis also revealed that certain shelters should receive higher priority in any strategy, as they were opened in every (or a vast majority) of scenarios. A key objective of this paper is to understand how the penalty for unmet demand affects the distribution of shelter sizes. The case study demonstrated in this paper is a (thankfully improbable) category 4 hurricane storm surge in the state of Connecticut. While the chances of this occurring are very low, it represents a worst case scenario and potential starting point for examining shelter planning and resource allocation decisions. Future research will include similar application for category 1-3 storms. Future extensions will explore stochastic version of the model that integrates storm scenario probabilities and the possibility that shelters may too be damaged to accommodate evacuees.

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DISCLAIMER
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EMERGENCY FACILITY LOCATION MODEL WITH STOCASTIC COMPONENT

ABSTRACT

This paper formulates a mixed-integer facility location model with a stochastic component to optimize emergency shelter location and resource allocation based on a set of existing candidate shelters. This model minimizes network access time between an affected census block and a potential emergency shelter, the operating costs of a shelter as a function of shelter capacity, and the cost of not accommodating all evacuees with emergency shelter capacity at the planning stage. In this paper, 9 scenarios were generated for Connecticut, varying storm severity and location of landfall. In these scenarios developed, the percentage of the population in need of shelter and the capacity of shelters varied depending on the severity of the storm and location of landfall. This stochastic element is included in the model to determine which shelters should be opened based on the probability of the different scenarios occurring. The application of the model including the stochastic element can be used by emergency planners because of the high level of uncertainty associated with the severity of a hurricane and location of landfall. A comparison of the results of the deterministic model and the stochastic model is presented in this paper.

INTRODUCTION

According to the U.S. National Oceanic and Atmospheric Administration (NOAA) there were 1,484 deaths caused by a hurricane between 1940 and 2013 with 1,168 of those occurring between 2000 and 2013 (NOAA 2015a). Although some reports suggest different figures, there is no doubt that hurricanes continue to pose a significant danger and that deaths can be decreased significantly with strategic emergency planning. Between the years 1900 and 2005 the average annual normalized damage from hurricanes in the U.S. is approximately $10 billion. Between 1996 and 2005 the US experienced the second highest cost for hurricane damages during a 10-year period (Pielke 2008). The deadly and costly storms that have occurred in the last 15 years have increased the urgency for planning and preparing for such disasters. Preparation for hurricanes and tropical storms requires the coordination of many emergency services within a highly uncertain and unpredictable context. An aspect of this preparation is planning for evacuation shelters for coastal communities. These shelters serve as places of refuge and may serve as distribution centers for emergency supplies in the days immediately following a storm. Plans for emergency shelters may suffer from fragmentation due to jurisdictional issues, lack of data and the use of qualitative and subjective methodologies in creating the network of shelters and logistical hubs.

The eastern coast of the United States faces an average of 4.2 hurricanes per year, with 2.3 of those being a Category 3 or higher, based on data between 1966 and 2009 (NOAA 2015b). Many of these storms affect the southeastern part of the United States and accordingly, this region of the country has extensive hurricane preparedness and evacuation plans. Hurricane Katrina was the costliest disaster in the United States when it made landfall in August of 2005 in the southeastern part of the US. Hurricane Katrina was responsible for more than 1,800 lives lost, $125 billion in expenditures, and more than 250,000 displaced residents (Houston et al. 2006).

Hurricane Katrina was an unfortunate reminder of the importance of hurricane preparedness in minimizing the number of casualties and providing immediate relief to survivors. Although the chances of a hurricane hitting the northeastern part of the United States are much less than the Gulf Coast, Hurricane Sandy demonstrated the danger posed to the northeastern U.S. Hurricane Sandy made landfall on the evening of October 29th in 2012 in southern New Jersey near Atlantic City. As the storm moved parallel to southeastern United States, Sandy was a category 1 hurricane and when it made landfall it was a post tropical cyclone with hurricane force winds up to 80 miles per hour. Hurricane Sandy took the lives of 162 people, caused 8.5 million people to lose power, and caused widespread flooding in New Jersey, New York, and Connecticut. The storm damaged or destroyed hundreds of thousands of houses and buildings, forcing over 23,000 people to seek temporary shelter (U.S. Dept. of Homeland Security 2013).

This paper describes a decision support model for the allocation of resources to opening and maintaining a network of evacuation shelters in the event of a hurricane. The model includes a stochastic element to capture the uncertainty of the location and severity of a storm. The stochastic element determines which shelters should be opened based on the probability of different severities of storms and different locations of landfall. A case study along the southern coast of Connecticut is presented to illustrate the utility and potential efficiencies of the model. Based on historical storms making landfall along the southern coast of Connecticut, 9 storm scenarios were developed for storms ranging between a tropical storm and a Category 2 hurricane that made landfall in three regions of Connecticut. The scenarios developed vary the percentage of the population in need of shelter as well as the capacity of the shelters based on the severity and location of landfall. Because evacuations need to begin long before the exact location and severity of the storm is known, the stochastic component captures this uncertainty

and determines who should evacuate to which shelter based on the probability of the 9 different scenarios occurring.

The following sections of this paper consists of a literature review section summarizing research covering emergency preparedness and response. The third section describes the formulation of the mixed-integer facility location model with a stochastic component generated in this paper. The fourth section discusses the case study that the model was applied for. The final section summarizes the results and describes the achievements of this model.

LITERATURE REVIEW

Hurricane preparedness has become a heavily researched topic since Hurricane Katrina in 2005. A significant amount of this research has focused on the southeastern part of the United States because of the higher probability of a hurricane making landfall in this region. There are many aspects of emergency preparedness and response that have been studied including prepositioning of relief supplies with a stochastic component (Rawls and Turnquist 2010; Lodree et al. 2012; Mete and Zabinsky 2010; Roh et al. 2015; Rennemo et al. 2014; Ahmadi et al. 2015), evacuation route planning (Murray-Tuite and Wolshon 2013; Sorenson 2000; Pel et al. 2012), emergency shelter location (Yushimito et al. 2012; Horner and Downs 2007; Bayran et al 2015;(Kongsomsaksakul et al. 2005; Ng et al. 2010; Beamon and Balcik 2008), and supply movement after a storm (Hanghani and Oh 1996; Ozdamar et al. 2004; Sheu 2007).

An important part of hurricane preparedness is positioning commodities and resources such as food, water, medical kits, and emergency generators in places that are close to affected areas without being in the affected areas and potentially being damaged by the storm. A significant amount of the research conducted related to positioning supplies include a stochastic component related to storm severity, location of impact, and potential damage to infrastructure including roads and supply warehouses. Rawls and Turnquist (2010) develop a model to

determine the location and amount of supplies that should be prepositioned based on the probability of different strengths of storms arriving in different locations. Their model is a two stage stochastic mixed integer program in which the first stage decisions are made considering uncertain future events including demand variations and damages to the network. The second stage decision is made after these uncertain future events are known and involves the distribution of commodities from distribution centers to the affected areas. Lodree et al. (2012) develop a model very similar to Rawls and Turnquist with the exception that their model is tailored to big box retailers. Like Rawls and Turnquist (2010), their model is a two-stage stochastic programming model, however, during the first stage of their model emergency commodities to be distributed from a manufacturer to the retailer is determined rather than the location and capacity of distribution centers. The second stage involves transshipments among retailers in addition to direct shipments from the manufacturer to retailers in affected areas. Mete and Zabinsky (2010) describe a similar stochastic model adapted to medical supplies and ensuring hospitals have sufficient inventory to deal with injured people. In the second stage of their model detailed vehicle assignments and routing is determined in addition to the amount of supplies being shipped between hospitals and medical supply warehouses. Roh et al. (2015) develop a model determining the location of relief supply warehouses worldwide to improve response time for nations that have experienced a natural disaster. Rennemo et al. (2014) use a three-stage mixed-integer stochastic programming model for the distribution of relief goods. The first stage determines which local distribution centers (LDC) should be opened and the quantity of relief supplies should be stocked in the distribution center. The second stage of their model deals with vehicle routing decisions based on supply demand in affected area and capacity of vehicles at each LDC. The third stage includes information about routes determined in stage 2 being

inoperable. Rennemo et al. (2014) solve their three stage model by including stochastic components for demand, vehicles available for supply delivery, and the condition of the transportation network. Similar to Rennemo et al. (2014), Ahmadi et al. (2015) develop a stochastic two-stage model in order to determine where distribution centers should be located and vehicle routing decisions based on uncertainty in where a disaster might occur and what components of a transportation network might not be usable after a disaster.

One aspect of hurricane preparedness that can eliminate or reduce the number of casualties and the number of people that need to be rescued is evacuation route planning. There are many specific areas within evacuation planning and operations, including forecasting of evacuation travel demand, the distribution and assignment of demand to road networks, and strategies to access and increase capacity of evacuation networks (Murray-Tuite and Wolshon 2013). In order to generate estimates of the number of people evacuating and where they are evacuating from it is helpful to know what influences people's decision to evacuate. There is an extensive amount of statistical analysis and research that has been performed that is summarized in reviews (Murray-Tuite and Wolshon 2013; Sorenson 2000). Another important behavior is route choice and traveler behavior in evacuation conditions. Pel, Bliemer, and Hoogendoorn (2012) provide an extensive review of mathematical models that model evacuation behavior including the time to evacuate, the destination choice, and the route choice. Increasing the capacity of the network strategies include contraflow operations, use of road shoulders, modified traffic control, and use of transit (Murray-Tuite and Wolshon 2013).

Optimization models that determine the locations of emergency shelters and supply distribution centers are typically based on the facility location problem but minimize travel time and minimize human suffering rather than myopically minimizing transportation costs.

Yushimito, Jaller, and Ukkusuri (2012) develop a model that determines the location of supply distribution centers based on a specified number of facilities to be located. Their model uses Voronoi diagrams to determine a set of locations for shelters that minimizes a social cost while ensuring all demand points are covered. Horner and Downs (2007) take a different approach in determining the locations, minimizing shipping costs rather than minimizing social costs. Their model determines the location of distribution centers while minimizing the transportation costs between the supply warehouses and the distribution centers and the distribution centers and neighborhoods. Bayram et al. (2015) develop a model that determines the location of emergency shelters while considering evacuation traffic assignment. Their model minimizes the path evacuees must take rather than social costs or transportation costs. Kongsomsaksakul et al (2005) focus on determining the location of evacuation shelters by developing a bi-level program. The upper level is a location model that determines where emergency planners should locate emergency shelters and the lower level models evacuees' decision of where to evacuate to and what route they will take to get to the shelter. The upper level minimizes the total evacuation time in the network whereas the lower level minimizes the evacuees' individual evacuation time. Ng, Park, and Waller (2010) develop a bi-level model very similar to Kongsomsaksakul et al (2005) except their model assigns evacuees to specific shelters in the upper level and the lower level only models the route the evacuees take to reach their assigned shelters. Each of these four models discussed determines the location of supply distribution centers or emergency shelters while maximizing coverage and minimizing either shipping distance or travel time. Balcik and Beamon (2008) evaluate performance measurements for emergency supply relief chain compared to commercial supply chains and consider factors unique to relief supply chains such as supplies not reaching people in an acceptable amount of time.

Haghani and Oh (1996) develop a multi-objective, multimodal network flow model that can be used by federal and state authorities for the movement of supplies after a storm. Their model can be used to determine detailed routing and scheduling for various modes of transportation, load plans for each mode of transportation, and delivery schedules for various commodities at certain destinations. Ozdamar et al. (2004) develop a hybrid model of the multi-period multi-commodity network flow problem and a multi-period vehicle routing problem for multiple modes of transportation that considers time-varying demand and regenerates a plan for each time period that incorporates new supply and new requests for supplies. Sheu (2007) presents a model with a component that predicts the relief demand using a dynamic relief demand forecast model using fuzzy techniques. In the final phase of the model an optimization model is applied to distribute relief commodities from relief distribution centers to affected areas (Sheu 2007).

This paper adapts concepts from the established literature and evaluates a large set of existing emergency shelters and the utility of maintaining these shelters in the event of an emergency rather than identifying where new shelters should be placed. The model in this paper includes a stochastic component similar to model's discussed above to determine which shelters should be opened for storms of different severity making landfall in different locations. Uncertainty in evacuee characteristics is accommodated through the inclusion of a penalty for not accommodating all evacuees – allowing the analyst to explore solutions that are not driven by a requirement to accommodate a demand for shelter that is likely to be based on rough estimation.

PROBLEM FORMULATION

A facility location model is formulated minimizing the total fixed costs of opening and operating shelters, the total distance traveled between census block centroids and emergency shelters, and the number of people not provided shelter capacity at the planning stage. The results of this model will identify shelters that should be maintained and utilized and estimate the number of people that will travel from each affected census block to each emergency shelter. The formulation of the facility location model with the associated descriptions is provided below including the necessary sets and indices, data and parameters, objective function and constraint set.

Sets and Indices

The following sets are used:

$i \in I$	census block centroids within storm surge boundary
$j \in J$	candidate shelter locations
$s \in S$	storm scenarios varying location of severity of storms

Set *I* contains census blocks that are within Sea, Lake, and Overland Surges from Hurricanes (SLOSH) zones which are determined by the National Weather Service (NOAA 2015c). Set *J* are potential hurricane shelters that can include schools, senior centers, churches, town recreational centers, etc. as given by the Connecticut Dept. of Emergency Management and Homeland Security (DEHMS). Set *S* contains storms scenarios that were developed based on the paths and frequency of historical storms and the return periods of storms. The process for developing these scenarios is explained later in this section.

Data and Parameters

d_{is}	evacuees originating at census block centroid *i* in scenario *s*
b_{js}	capacity of shelter *j* in scenario *s*
f_j	fixed cost of operating a shelter at *j* based on the shelter's capacity
c_{ij}	travel cost between census block *i* and potential shelter *j*
ρ_s	probability of scenario *s* occurring
M	scalar for facility constraint
Ψ	scalar that penalizes evacuees not accommodated by a shelter

The parameter d_{is} is a predetermined or assumed percentage of the total number of people living in each affected census block based on existing models such as Fu and Wilmot (2004) or local policy. The parameter b_{js} is the number of people a candidate shelter can accommodate, unique to each scenario, and is based on the square footage of useable spaces (American Red Cross 2002). The parameter f_j is the opening and operating cost of a potential shelter (assumed for this paper a function of the capacity of the shelter). The parameter c_{ij} is the travel cost between census blocks and shelters. This cost is equal to the network distance (in miles) between *i* and *j* multiplied by the value of evacuees time ($) divided by the speed at which a person evacuates (mph). The parameter ρ_s is the probability scenario *s* will occur and the process of generating scenarios is discussed in Section 3.6. The scalar M is a suitably large scalar used to limit the flow of evacuees only to those shelters that are opened. The scalar Ψ is a penalty for any evacuees not provided shelter and is in units of dollars per person not assigned.

Decision Variables

The decision variables used in this model are:

$$y_j = \begin{cases} 1 & \text{if shelter is opened at } j \\ 0 & \text{otherwise} \end{cases}$$

x_{ijs} The number of evacuees traveling from block *i* to shelter *j* during scenario *s*

Formulation

The objective function is:

$$\sum_{j\in J} f_j y_j + \sum_{i\in I}\sum_{j\in J}\sum_{s\in S} c_{ij} x_{ijs}\rho_s + \Psi\left(\sum_{i\in I}\sum_{s\in S}\left(d_{is}\rho_s - \sum_{j\in J} x_{ijs}\right)\right) \qquad (1)$$

The objective function defined above minimizes three components, all in units of cost in dollars. The first component is the total fixed cost of opening and operating the set of selected shelters. The second component minimizes the travel/access cost for evacuees between the residence census block and the emergency shelter to which they are assigned. The third component captures the cost of being unable to accommodate all evacuees with shelter capacity.

The objective function is constrained by the following:

$$\sum_{j\in J} x_{ijs} \le d_{is} \qquad \forall\, i \in I, \forall s \in S \qquad (2)$$

$$x_{ijs} \le y_j M \qquad \forall i \in I, \forall j \in J, \forall s \in S \qquad (3)$$

$$\sum_{i\in I} x_{ijs} \le b_{js} \qquad \forall j \in J, \forall s \in S \qquad (4)$$

$$y_j \in \{0,1\} \qquad \forall j \in J \qquad (5)$$

$$x_{ijs} \in \mathbb{Z}^+ \qquad \forall i \in I, \forall j \in J, \forall s \in S \qquad (6)$$

Constraint 2 ensures that the amount of evacuees from block *i* assigned to shelter *j* in scenario *s* is less than or equal to the evacuee demand of block *i* for scenario *s*. Constraint 3 limits assigning evacuees only to shelters that are selected to be opened. Constraint 4 ensures that the number of evacuees assigned to a shelter does not exceed the capacity of that shelter in scenario *s*. Constraint 5 restricts the variable that determines whether a shelter is opened at candidate location *j* to being binary. Lastly, constraint 6 limits the variable for the number of people assigned to each shelter from each census block in each scenario to nonnegative integer values.

The proposed model is formulated as a mixed integer program and is coded in GAMS and solved utilizing CPLEX. GAMS is a high level modeling system for mathematical programing and optimization and the CPLEX solver is used to solve complex linear programs and mixed integer programs.

Datasets

Table 1 displays information about the datasets used for the model formulation.

Table 5 Datasets Used for Sets and Indexes

Sets/Indices	Source:	Date:
Census Blocks	US Census Bureau	2010
Candidate Shelter Locations	CT Dept. of Emergency Management and Homeland Security (DEMHS)	Feb. 11th 2016

Scenario Development

A stochastic element is included in the model developed in this paper in order to determine which shelters should be opened for storms of different severities and different locations. For this paper, scenarios were developed for the southern coast of Connecticut based on historical storm records organized by NOAA. The state of Connecticut was divided into three sections as shown in Figure which also shows the location of landfall of historical tropical storms and hurricanes.

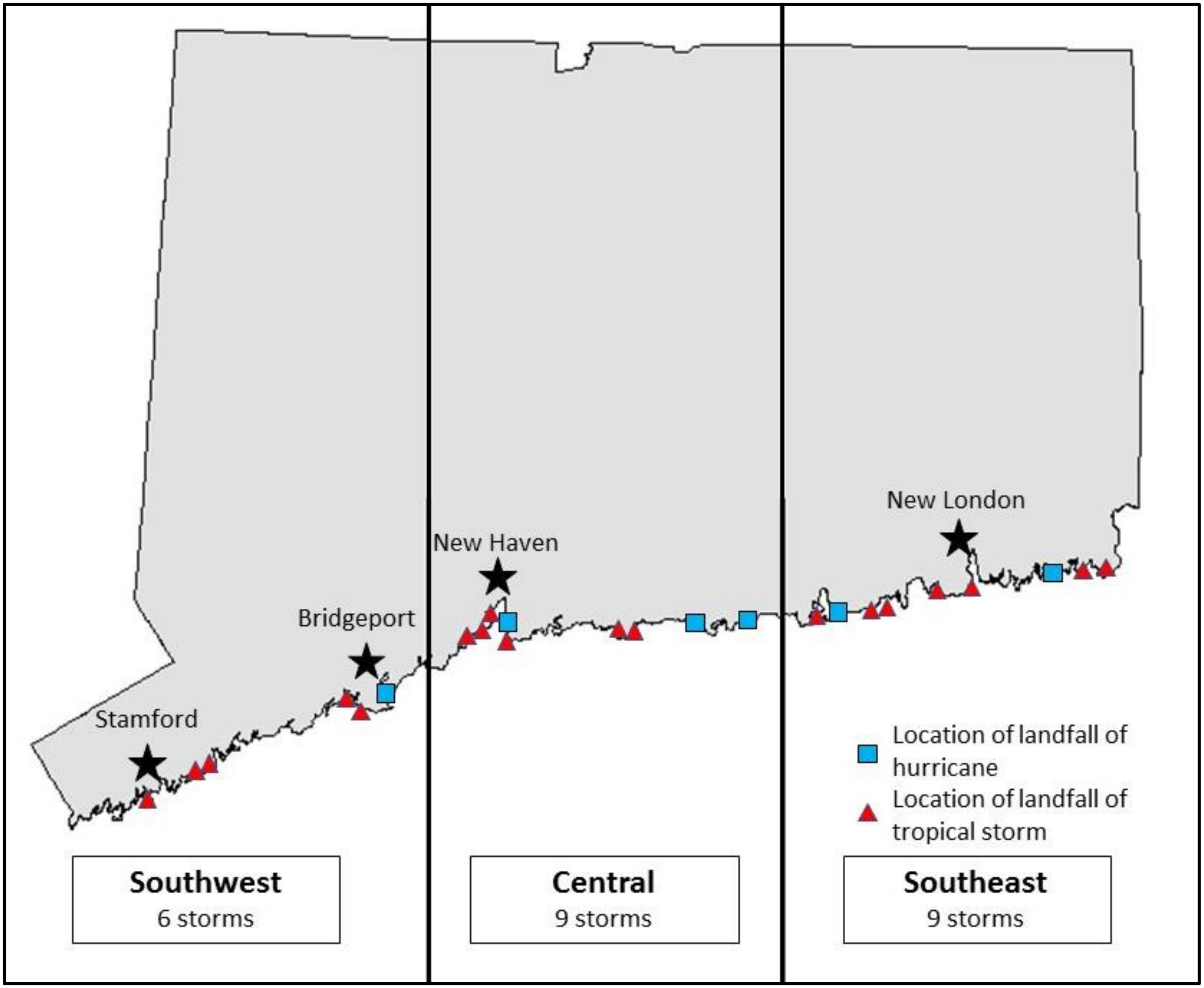

Figure 1: Map of Scenario Development

In order to determine the probability of a storm making landfall in each of the three zones, the number of times the eye of a storm passed through one of these three zones on the coast of Connecticut was counted. Figure shows the location and severity of storms used to create scenarios.

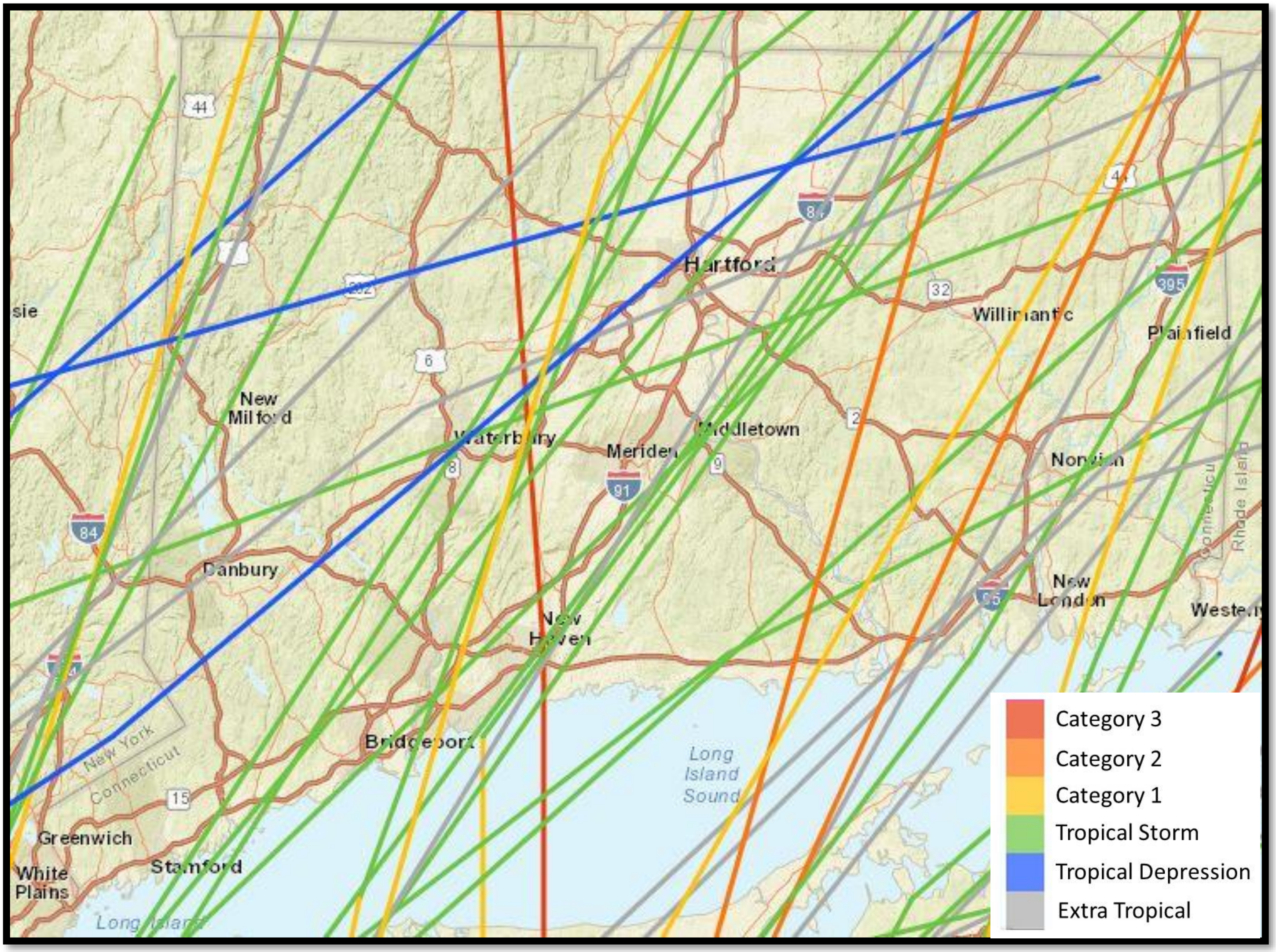

Figure 2: Location and Severity of Historical Storms

Based on this map, between 1851 and 2016 there have been 6 occurrences when the eye of a storm passed through the coastline of the southwest region, 9 occurrences for the central region, and 9 occurrences for the southeast region.

In addition to the frequency of where a storm makes landfall the return periods of tropical storms, category 1 hurricanes, and category 2 hurricanes were used to calculate the probability of a storm of various severities making landfall in one of the three zones in Connecticut. The return period for a tropical storm is 8 years, 17 years for a category 1 hurricane, and 39 years for a category 2 hurricane. Keim et al. (2007); Glowacki (2013). Nine different scenarios were developed based on three severities of storms and three different locations for landfall in Connecticut. Table 6 shows the calculated probability for each scenario.

Table 6: Probability of Scenario Occurring

		Location of Landfall		
		Southwest	Central	Southeast
Severity of Storm	Tropical Storm	14.92%	22.38%	22.38%
	Cat 1 Hurricane	7.02%	10.53%	10.53%
	Cat 2 Hurricane	3.06%	4.60%	4.60%

Regarding how the scenarios affected the inputs to the model, the number of evacuees in need of shelter and the capacity of shelters changed depending on the scenario. The operating cost and travel cost were the same for all scenarios. Table 7 shows the percentage of the population within one of the three zones that will require shelter for the three different severities of storms.

Table 7: Percentage in Need of Shelter for Scenarios

Eye of the storm makes landfall in Southwest zone			
	Southwest	**Central**	**Southeast**
Tropical Storm	20%	15%	10%
Cat 1	25%	20%	15%
Cat 2	30%	25%	20%

Eye of the storm makes landfall in Central zone			
	Southwest	**Central**	**Southeast**
Tropical Storm	15%	20%	15%
Cat 1	20%	25%	20%
Cat 2	25%	30%	25%

Eye of the storm makes landfall in Southeast zone			
	Southwest	**Central**	**Southeast**
Tropical Storm	10%	15%	20%
Cat 1	15%	20%	25%
Cat 2	20%	25%	30%

The general idea of what is shown in the above tables is that the zone in which the storm makes landfall has the highest percentage in need of shelter with the zone next to the landfall zone has 5% less in need of shelter. When a tropical storm occurs, the landfall zone has 20% of its population in need of shelter; when a category 1 hurricane occurs 25%; and when a category 2 hurricane occurs 30%.

The capacity of the shelter is also altered depending on the severity and location of a storm but is a little simpler than the percentage of population in need of shelter. Information was obtained about which shelters have backup emergency generators from DEMHS and was used to alter the available capacity for the 9 scenarios developed. If a shelter is located in the landfall zone and does not have a backup generator it is assumed 50% of the shelter's capacity is available for a tropical storm. For the same situation 0% of the shelter's capacity is available for a category 1 and 2 hurricane. If a shelter has a backup generator, 100% of its capacity is available regardless of where the storm makes landfall or the severity of the storm.

CASE STUDY

The case study in this paper solves the model described twice, once as a deterministic problem and once as stochastic problem. The proposed model is demonstrated for the southern coast of Connecticut using census blocks that are within a Category 2 hurricane surge zone and a set of candidate shelters from the Connecticut Dept. of Emergency Management and Homeland Security (DEMHS). Using ArcGIS, category 2 SLOSH zones, shown in red in Figure 3, are overlaid with census blocks to determine blocks that would be affected. These blocks are used for set I in the proposed model.

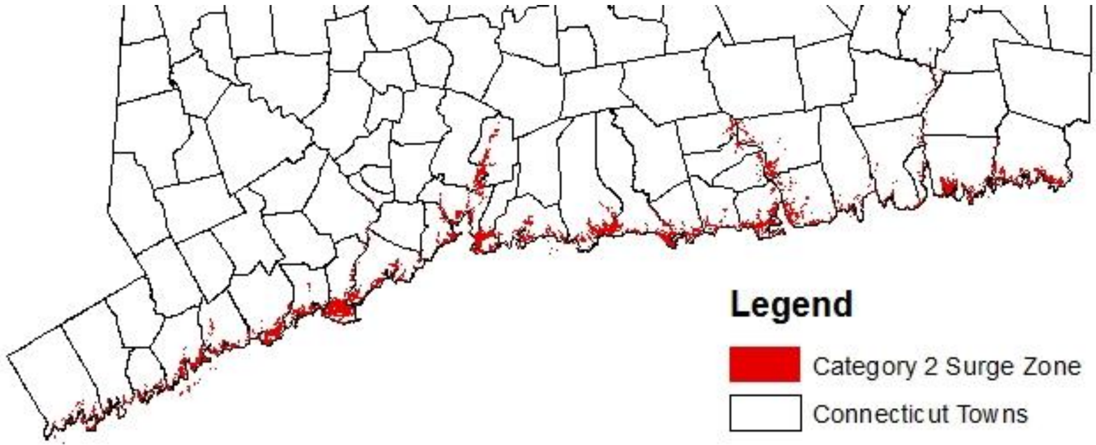

Figure 3: Map of Surge Zones

There are 1,697 census blocks that contain a Category 2 SLOSH zone with a total population of 143,208 permanent residents. In the deterministic problem the total demand was 29,354 people (20% of the affected population) whereas in the stochastic problem the population in need of shelter ranged between 20,736 and 38,620 people depending on the scenario. There are 591 candidate shelters in the entire state of Connecticut that were used to determine a candidate set of shelters, for memory reasons only 272 shelters were used for set *J*. ArcGIS was used to find the 35 closest shelters to each affected census block which resulted in the 272 shelters that are in set *J*. The capacity of these shelters is based on 20 square feet of space per evacuee which is within the range of the recommended amount of space by the American Red Cross for hurricane shelters (American Red Cross 2002). The total capacity of all 272 shelters is 132,680. Operating costs were not available for each individual shelter and per discussions with Connecticut DEMHS personnel, it was determined that a majority of the labor to open and operate an emergency shelter is done by volunteers. For this example the operating cost is estimated to be $20 per person including the cost of food and water for the length of time the shelter is open. The assumed values for the various parameters in the model are shown in the table below.

Assumed Values for Case Study

Parameter	**Value**
Evacuation travel speed	20 mph
Value of evacuees' time	$20 per hour
Penalty for not accommodating demand	$100,000 per person

The travel speed is assumed to be 20 mph, a reasonable average speed considering that the majority of the affected in Connecticut are in suburban areas. The value of people's time was assumed to be $20 per hour which is slightly more than the living wage per person in Connecticut of $19.08 (Henry and Frederickson 2014). The deterministic problem assumes that 20% of the affected population needs shelter which is what was experienced by evacuation managers during Hurricane Sandy. It also assumes that 100% of the capacity of the emergency shelters is available to evacuees. The stochastic problem contains 9 different storm scenarios with the demand of each census block and the capacity of each shelter varying for each scenario as described in Section 3.6 of this paper.

The deterministic problem resulted in 100 shelters being utilized with 100% of the demand assigned to a shelter. The stochastic problem was first run with a penalty for not accommodating demand equal to 100,000 which resulted in 186 shelters being utilized with 100% of the demand assigned to a shelter in all 9 scenarios. There are 96 shelters that were opened both in the deterministic problem and in the stochastic problem which means that only 4 shelters were opened in the deterministic example but not in the stochastic example. There are 90 shelters that were opened in the stochastic example but not in the deterministic which leaves 82 shelters that were never opened. Figure 4 shows which shelters were opened only in the deterministic problem (shown in yellow), only in the stochastic problem (shown in green), which ones were opened in both problems (shown in purple), and which shelters were not utilized at all (shown in red).

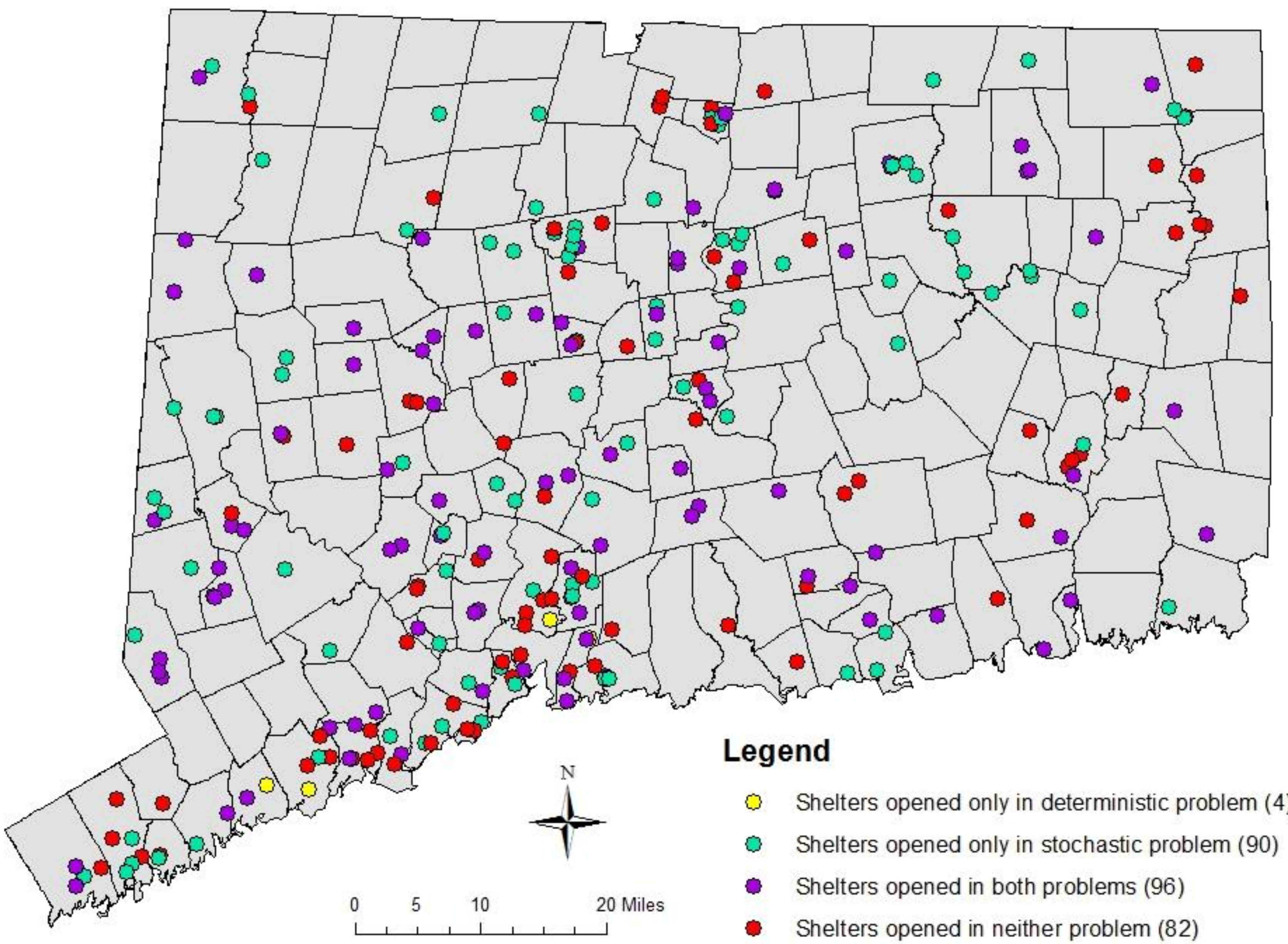

Figure 4: Shelters opened in deterministic and stochastic problems

The stochastic problem was run a second time with a penalty for not accommodating demand decreased from 100,000 to 10,000 to see how the results would differ. This resulted in 71 total shelters being opened but only between 9% and 18% of evacuees accommodated depending on the scenario. Although this resulted in fewer shelters being opened, saving on operating and opening costs, a very large percentage of evacuees where not assigned to a shelter. In this situation it was cheaper for the model to not accommodate evacuees rather than opening and operating shelters. Figure provides information about which shelters were opened only when the penalty was 100,000 (shown in blue), the shelters opened only when the penalty was 10,000 (shown in green), shelters that were open when the penalty was 100,000 or 10,000 (shown in purple), and the shelters that were opened in neither situation (shown in red).

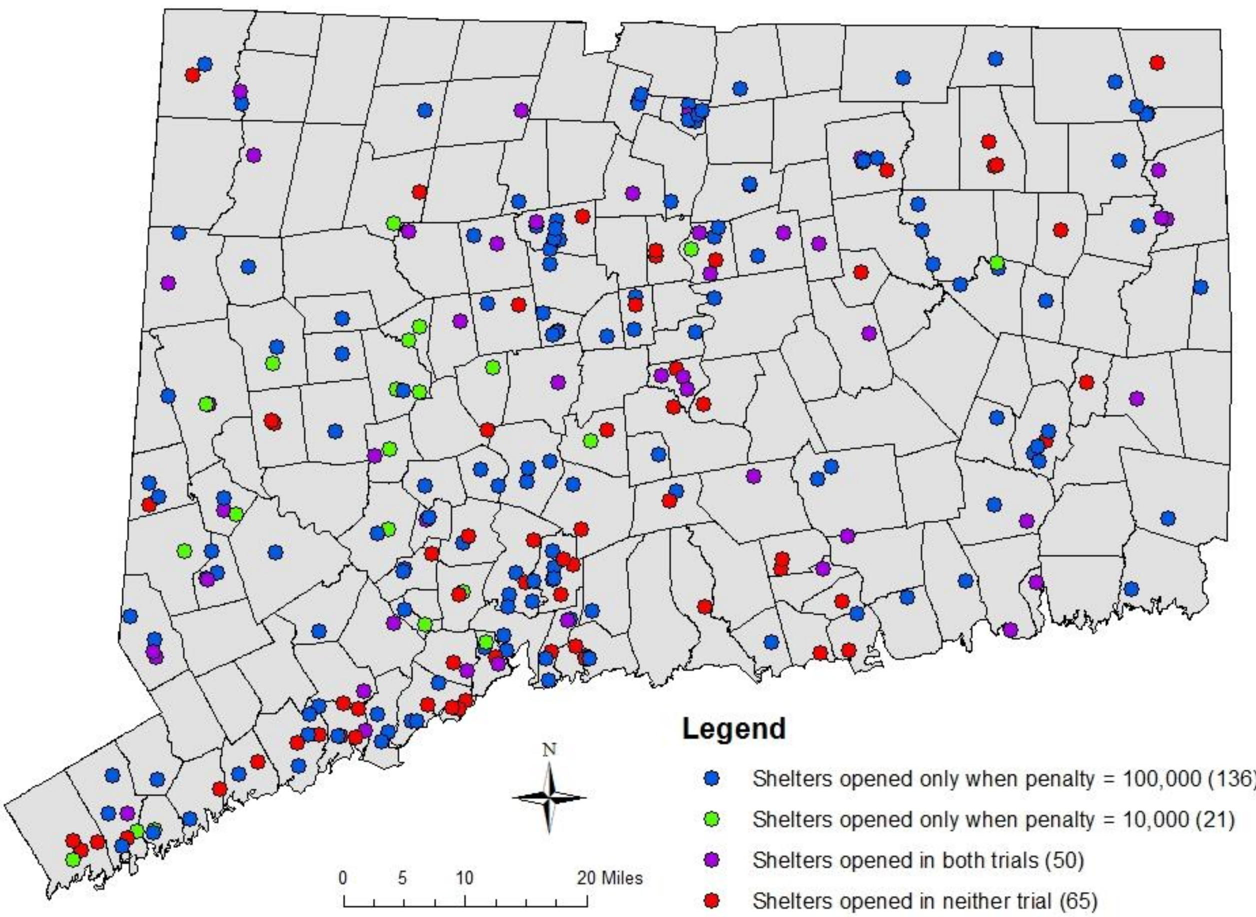

Figure 5: Shelters opened when changing the penalty for not accommodating evacuees

CONCLUSION

This paper formulates a facility location model with a stochastic component built in to inform emergency shelter planning. The stochastic component was included to determine which shelters should be utilized in a hurricane evacuation plan given the high degree of uncertainty of the severity and location of a hurricane or tropical storm. In the case study the model was solved for a deterministic and stochastic example. The deterministic problem shows what shelters should be opened assuming a Category 2 storm affecting the entire southern coast of Connecticut equally. The solution of the deterministic problem can be used for short term response once the location and severity of a storm is known. The stochastic problem shows what shelters should be utilized considering 9 different scenarios varying storm severity and location of landfall and the probability of those scenarios occurring in addition to varying percentage of affected population in need of shelter and the capacity of shelters. The solution to the stochastic problem can be used for long term emergency planning because it represents the solution based on various severity of storms making landfall in various areas. In both the deterministic and stochastic examples, shelters close to the affected census blocks were not utilized whereas shelters in the northern part of the state were utilized. The reason for this could be that the travel cost component of the model isn't influencing the solution as much as the other two components of the model. This paper develops a model that can be used by emergency planners for long term emergency planning (stochastic problem) and used in the response to a specific storm.

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