Center for Accessibility and Safety for an Aging Population

Florida State University

In Partnership with Florida A&M University and University of North Florida

RESEARCH FINAL REPORT

Senior Community Resilience: Assessing the Interdependencies between Critical Transportation Infrastructures and Implications on Aging People's Households

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Final Report

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16. Abstract

There are increasing number of aging populations in the State of Florida for whom safe, reliable and accessible transportation is a very significant issue. This is highly dependent on the performance of Florida's roadways and critical assets such as bridges, critical facilities such as hospitals and other relevant structures. Their performance becomes especially critical in the presence of extreme events such as hurricanes where the connectivity between the critical structural and transportation assets, and the roadway network play a vital role in providing safety, reliability and accessibility to all roadway users including aging populations. Central to this challenge is the need to identify the interdependencies between these vital elements, and their effects on the aging people's communities and households, which is a very challenging problem. This problem becomes even more challenging since the aging populations are identified as one of the cohorts with a heightened vulnerability to climate change. In order to respond to this challenge, this project presents a holistic approach based on the implementation of Geographical Information Systems-based novel models that study the interdependencies between power lines, roadways, critical facilities such as hospitals and bridges with a focus on demographics and socioeconomics. These models can provide solutions to handle the high risk associated with these disruptions, reduce their effect on the aging people's communities, and therefore improve the community resilience. Realistic case studies are built and used to evaluate the differences in mitigation strategies for different types of roadway-related disruptions based on the impact point/area, the weather conditions (i.e., wind and rain), the aging population living in the affected area, and duration/type of the event.

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List of Abbreviations

Accessibility Decrease Index (ADI)
Congested Travel Time (CGT)
Convolutional Neural Network (CNN)
Geographic Information Systems (GIS)
Emergency Medical Services (EMS)
Emergency Response Travel Time (ERTT)
Florida Department of Transportation (FDOT)
Florida Geographic Data Library (FGDL)
Florida Statewide Transportation Network Model Structure (FSUTMS)
Florida State University (FSU)
Florida A&M University (FAMU)
Free Flow Travel Time (FTT)
Hazards United States (HAZUS)
Institute of Electrical and Electronics Engineers (IEEE)
Kernel Density Estimation (KDE)
Maximum Likelihood (ML)
Metropolitan Planning Organization (MPO)
National Bridge Inventory (NBI)
Origin-Destination (OD)
Sea, Lake, and Overland Surge from Hurricanes (SLOSH)
Spatial Autoregressive Model (SAR)
Spatial Errors Model (SEM)
Storm Surge Heights (SSH)
System Average Interruption Frequency Index (SAIFI)
Tampa Bay Regional Planning Model (TBRPM)
University of North Florida (UNF)

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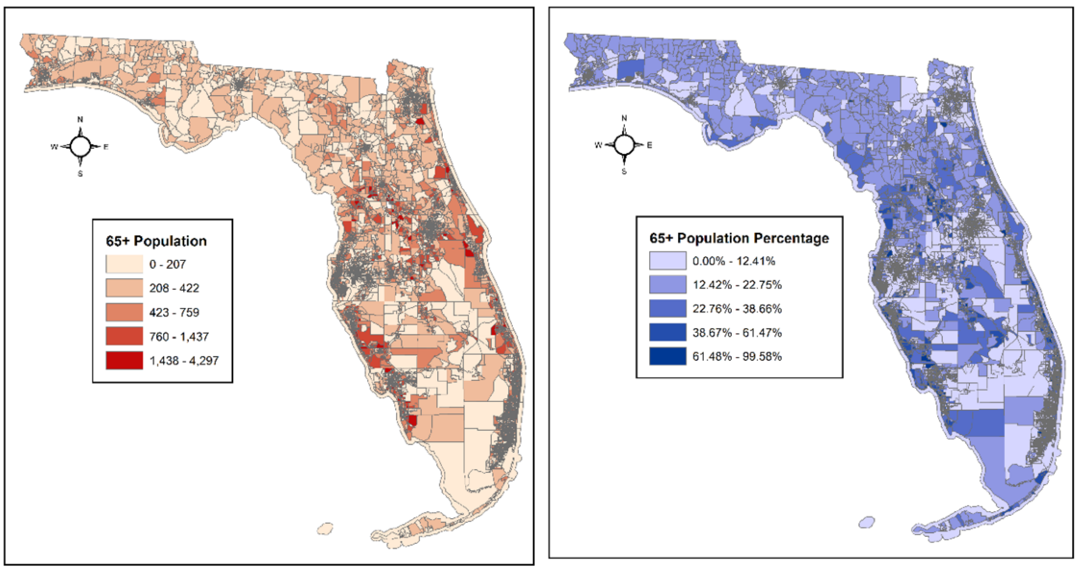
Abstract

There are increasing number of aging populations in the State of Florida for whom safe, reliable and accessible transportation is a very significant issue. This is highly dependent on the performance of Florida's roadways and critical assets such as bridges, critical facilities such as hospitals and other relevant structures. Their performance becomes especially critical in the presence of extreme events such as hurricanes where the connectivity between the critical structural and transportation assets, and the roadway network play a vital role in providing safety, reliability and accessibility to all roadway users including aging populations. Central to this challenge is the need to identify the interdependencies between these vital elements, and their effects on the aging people's communities and households, which is a very challenging problem. This problem becomes even more challenging since the aging populations are identified as one of the cohorts with a heightened vulnerability to climate change. In order to respond to this challenge, this project presents a holistic approach based on the implementation of Geographical Information Systems-based novel models that study the interdependencies between power lines, roadways, critical facilities such as hospitals and bridges with a focus on demographics and socioeconomics. These models can provide solutions to handle the high risk associated with these disruptions, reduce their effect on the aging people's communities, and therefore improve the community resilience. Realistic case studies are built and used to evaluate the differences in mitigation strategies for different types of roadway-related disruptions based on the impact point/area, the weather conditions (wind and rain), the aging population living in the affected area, and duration/type of the event.

Chapter 1 Background and Motivation

The urgent need to understand and study the interdependencies among the elements of civil infrastructure systems has been receiving extra attention recently. However, the interdependencies between structural assets (e.g., vital connectors such as bridges, critical facilities such as hospitals), environment (e.g., trees), power grid and roadway networks, and their effects on aging people's households and communities have not been studied before. Florida is an essential state to provide such an aging population-focused interdependency assessment, especially considering the fact that 17.34% of the state population in 2010 was 65 years and older, being the second highest nationally. The 65+ population of the State of Florida is 3,259,602 as of 2010 whereas the ratio of the 65+ population to the total state population is 17.33%. Figure 1.1 shows the spatial distribution of 65+ populations for the State of Florida (both counts and percentages) at the population block group level. It is important to note that neither number of people nor percentage of these people in the block group is adequate to properly reflect the possible effect of the existing population. Evaluating only 65+ population count would disguise those sparsely populated blocks that are highly populated in terms of 65+ residents. On the other hand, evaluating only the 65+ population percentages (65+/Total Population) would disguise those highly populated blocks that have relatively fewer 65+ residents.

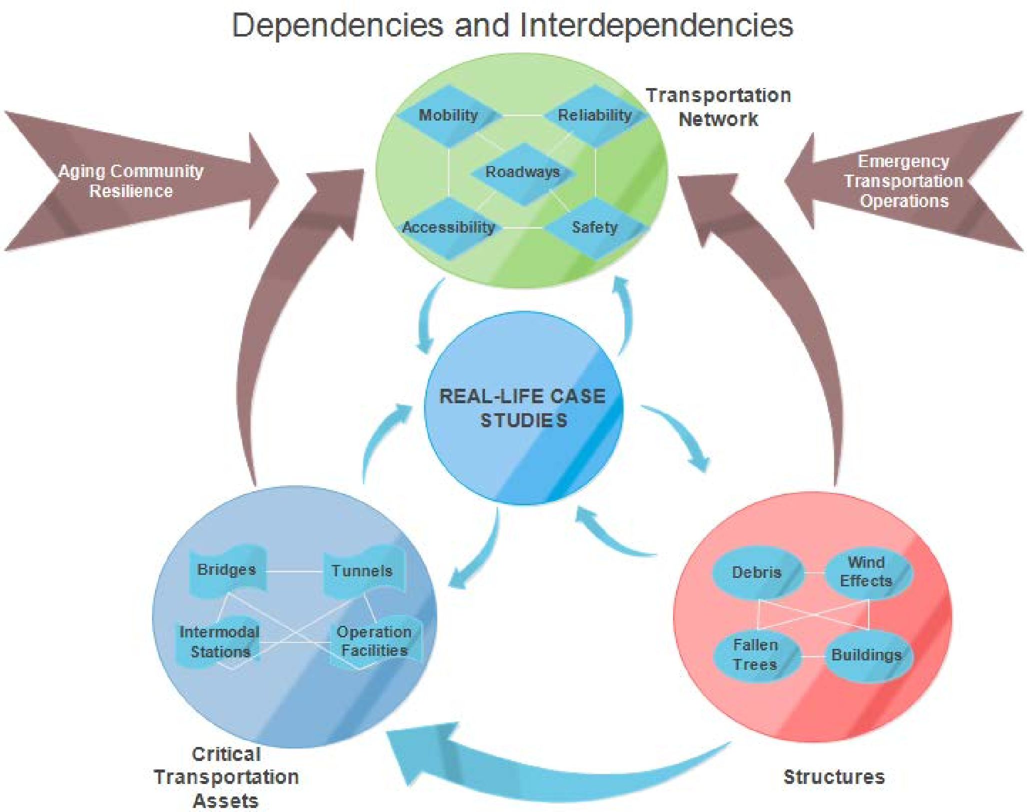
Moreover, the Baby boomer generation, people born after the World War II, will substantially increase the percentage of the 65+ population in the whole nation as well as in Florida. The 65+ population growth is even faster in Florida, with those age 65 and older expected to comprise 41% of the state population by 2030. This implies that Florida will have an even higher number of 65+ population in the future considering the fact that the present day 65+ population percentage in the State of Florida is already higher than the national average. As such, the evaluation of the interdependency between the structures, trees, transportation connectors, power and roadway networks with respect to 65+ populations will become even more important. This study will focus on the 65+ populations in order to represent the aging populations; however, this approach can be applied for other adult age groups as well.



(a) 65+ Population Counts (b) 65+ Population Percentages

Figure 1.1. Spatial Distribution of Aging 65+ Populations

In addition, community resilience has become a key planning and policy issue both at the federal, state and local levels. An efficient transportation system is critical to enhance the ability of a community to recover from any disruptions. In this context, transportation assets such as bridges, tunnels, facilities such as hospitals are critical since they help providing safe and reliable access for transportation to the public. The efficiency of a transportation system depends on the accessibility and availability of these facilities through the available roadway network. This indicates that the dependencies between them become vital in order to achieve high transportation efficiency and performance while serving the public, especially those that live in rural areas and/or small communities. In addition, the multiple dependencies between transportation assets, facilities and roadways create the interdependencies among these interconnected elements. Since these facilities are also necessarily limited in number, identifying and assessing these interdependencies is a major concern for agencies. This issue becomes even more complex when other structural, power-related or environmental elements are also considered. For example, the adverse effect of structural or tree debris on the roadways and power lines can be extremely critical during emergency transportation operations (i.e., loss of capacity and performance), which creates an extra level of dependency between the structures, trees, power lines and the roadway network. The overall dependencies and interdependencies are presented in Figure 1.2 in the context of aging-focused transportation operations. For a state like Florida, any dependency and interdependency that can elevate the effect of disruptions on the communities may be devastating, especially when aging populations are considered due to their potential cognitive, physical and mental limitations and health problems that can adversely affect their driving and wayfinding skills. Therefore, aging people may have a greater need for an efficient transportation system that is robust to disruptions than other adult age groups.



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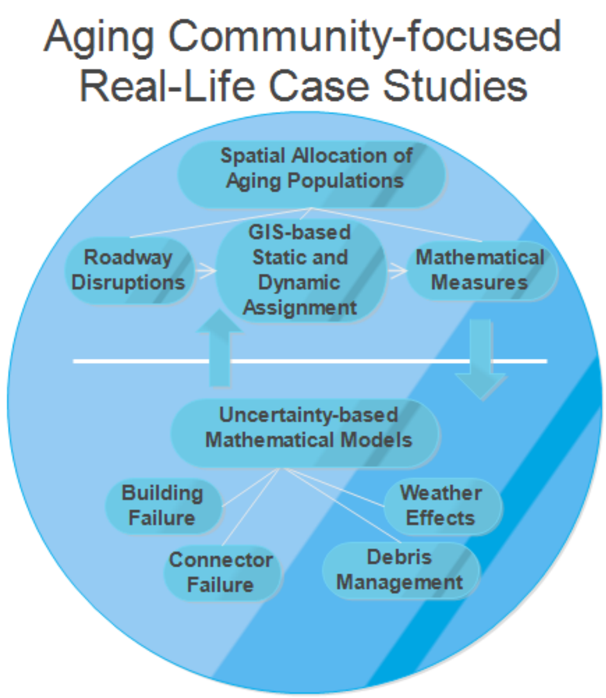


(b)

Figure 1.2. Aging Population-focused Dependencies and Interdependencies

One of the most important challenges of the transportation operations is reducing the harm and alleviating the suffering a disruption causes to its victims. A significant component of this challenge is maximizing the accessibility to the critical facilities such as intermodal facilities and emergency shelters, especially for vulnerable populations such as aging and/or people with special needs. Any disruption (either at the facility level or on the roadway network) will make this inaccessibility problem even worse, especially for the aging people, for whom any extra incurred time may be life threatening. Four examples of dependencies in the context of transportation accessibility are presented as follows:

(1) The closure or loss of a roadway section or a single lane on the pre-determined evacuation route due to debris (structural or fallen trees) may drastically increase the travel time needed to reach the emergency shelters, which may have vital consequences for aging people. This clearly shows the importance of extensively studying the dependencies so that the effect of such a disruption on the aging communities and households (urban or rural) can be minimized.

(2) Mass evacuations have known to cause severe traffic jams. It will be ideal if unnecessary and shadow evacuations can be avoided, especially for the aging populations who may have mobility issues or who may suffer significantly during the actual evacuation. An important interdependency problem herein is to analyze the safety of buildings subjected to hurricanes, and to estimate the necessary volume of evacuation, with the goal of avoiding unnecessary and shadow evacuations. Therefore, severe traffic jams and suffering of aging population could be minimized by studying this interdependency problem.

(3) The effect of bridge damage (due to a disruption such as flooding in the event of a heavy rain) on the performance of the transportation network is critical since bridges are naturally the vital connectors that are used extensively by the public. Therefore, another dependency that should be clearly assessed is the effects of the structural bridge damage on the roadway closures. This will help reducing the risk associated with the structural failure of a bridge, and providing safety to the public, including the aging people's households and communities.

(4) Florida's emergency relief operations were significantly affected by these hurricanes such as Irma, which substantially flooded roadways, toppled trees and utility poles, taking power, cable, and phone lines with the 80 to 100 mph sustained winds. This led to the inability of the affected infrastructure components (i.e., roadways and power lines) to effectively cope with random and dynamic changes and a lack of available plans in enacting adequate emergency response measures. Such shortfalls have translated into critical electricity and transportation networks-related resilience deficiencies while amplifying vulnerabilities and exposing gaps in planning and response. Public works crews had to clear these downed trees and utility poles so that other emergency vehicles, such as ambulances, fire, and supply trucks could use these roadways. Also, power restoration crews were significantly slowed down by the closure or loss of roadway sections because of debris, such as fallen trees, particularly in the cases in which the removal of the trees was under the jurisdiction of public works rather than power restoration crews. Such lack of coordination was one of the main reasons for delays in handling the power outage-related problems, rippling through entire cities until fixed.

The main goal of the project is developing Geographic Information Systems-based models in order to (a) enhance resilience, safety and accessibility for aging people's communities and households, (b) improve the preparedness of these households and communities for and recovery from disruptions. In doing so, conventional approaches will separately deal with facilities, trees, bridges, and transportation networks affected by disruptions (e.g., day-to-day disruptions such as congestion and accidents, or emergency disruptions such as flooding or debris due to hurricanes). A major contribution of this project is to model interdependencies of these components, to greatly enhance prediction capabilities, and thereby to provide assistance in the context of community resilience.

This report contains four chapters. Chapter 1 provides the background and motivation for the problem.

Chapter 2 focuses on a two-step methodology to identify the impact of Hurricane Hermine on the City of Tallahassee, the capital of Florida. The regional and socioeconomic variations in the Hermine's impact were studied via spatially and statistically analyzing power outages. First step includes a spatial analysis to illustrate the magnitude of customers affected by power outages together with a clustering analysis. This step aims to determine whether the customers affected from outages are clustered or not. Second step involves a Bayesian spatial autoregressive model in order to identify the effects of several demographic, socioeconomic and transportation-related variables on the magnitude of customers affected by power outages.

Chapter 3 evaluates the accessibility of emergency response facilities, such as police stations, fire stations and hospitals in the City of Tallahassee, the capital of Florida, was extensively studied using real-life data on roadway closures during Hurricane

Hermine. A new metric, namely Accessibility Decrease Index (ADI), was proposed, which measures the change in ERTT before and in the aftermath of a hurricane such as Hermine.

Chapter 4 focuses on the senior community resilience, which is assessed through the accessibility of seniors to hospitals after bridge damage caused by hurricane events. Pinellas County in the Tampa Bay area is used as case-study. The following results are presented: (i) exposure probabilities for hurricane events at bridge locations; (ii) bridge damage state functions and damage state rating assignments using historical data from the National Bridge Inventory (NBI) database; (iii) identification of bridges at risk to hurricane-induced damage; (iv) bridges identified as serving areas (census districts) with dense population of aging people; and (v) the estimated effects of bridge closures on mobility and resilience of the aged population, based on accessibility to hospitals by using congested and free flow travel times obtained from traffic assignment modeling.

Chapter 2 Assessment of the Hurricane-induced Power Outages from a Demographic, Socioeconomic, and Transportation Perspective

Natural disasters have devastating effects on the infrastructure, and disrupt every aspect of daily life in the regions they hit. To alleviate problems caused by these disasters, first an impact assessment is needed. As such, this chapter focuses on a two-step methodology to identify the impact of Hurricane Hermine on the City of Tallahassee, the capital of Florida. The regional and socioeconomic variations in the Hermine's impact were studied via spatially and statistically analyzing power outages. First step includes a spatial analysis to illustrate the magnitude of customers affected by power outages together with a clustering analysis. This step aims to determine whether the customers affected from outages are clustered or not. Second step involves a Bayesian spatial autoregressive model in order to identify the effects of several demographic, socioeconomic and transportation-related variables on the magnitude of customers affected by power outages. Results showed that customers affected by outages are spatially clustered at particular regions rather than being dispersed. This indicates the need to pinpoint such vulnerable locations, and develop strategies to reduce hurricane-induced disruptions. Furthermore, the increase in the magnitude of affected customers were found to be associated with several variables such as the power network and total generated trips as well as the demographic factors. The information gained from the findings of this study can assist emergency officials in identifying critical and/or less resilient regions, and determining those demographic and socioeconomic groups which were relatively more affected by the consequences of hurricanes than others.

2.1 Introduction

Natural disasters such as hurricanes have devastating effects on the infrastructure, and disrupt every aspect of daily life in the regions they hit. Communities living in these regions suffer from the adverse consequences of hurricanes; therefore, emergency officials are responsible to find solutions in order to alleviate the problems caused by these disasters. Although a sizable number of major hurricanes have struck the U.S. Gulf States such as Florida previously, several areas of this hurricane-prone region have never seen landfalls in the last thirty years. For example, Hurricane Hermine was the first hurricane to make landfall in Florida on September 2nd, 2016 since Hurricane Wilma in 2005, and was the first hurricane to directly hit Apalachee Bay since Hurricane Alma in 1966 [1]. As a result of Hurricane Hermine, a large region in the Northwest Florida endured power outages, food shortages, and roadway disruptions [2]. At a local level, Hermine left 100,000 residents without power in the City of Tallahassee, the capital of Florida, knocking out trees, power lines and shutting down stores and businesses for days [1, 2, 3]. In addition, this region was also affected adversely by the Hurricane Irma recently.

Previous studies have investigated the effects and consequences of hurricanes through spatial and statistical models. For example, a spatial and statistical analysis was conducted in [4] to predict the treefalls during a hurricane using several predictors such as precipitation, roadway density, and wind speed via a hierarchical Bayesian model. Authors identified regions which possess higher risk of treefalls based on varying wind speeds. Moreover, it was shown that roadway density and wind speed were the most important variables affecting the treefall probability. The power system performance and power outages, on the other hand, has been of significant interest in the literature regarding the adverse consequences of hurricanes. For example, the power system performance and power outages were investigated by [5] during five hurricanes at South and North Carolina in the United States. Authors examined the number of outages, affected customers, and the geographic distribution of disruptions as well as the type of failed power system components. The magnitudes of disruptions were found to be highly correlated with the maximum wind speed. Environmental factors were also used to predict the number of hurricane-related power outages, which were stated to be essential to prepare the power system prior to a hurricane landfall [6-8]. A two-phase estimation model was proposed using different environmental characteristics such as elevation, land cover, soil, precipitation, and vegetation characteristics in addition to speed and duration of winds [8]. Results showed that inclusion of environmental characteristics and two-phase modeling substantially increased the prediction accuracy compared to previous models. The importance of environmental factors (e.g. soil characteristics, elevation, etc.) on the power outage were previously shown by [6].

To predict power outages and duration of these outages, researchers proposed various approaches such as negative binomial regression [9], generalized additive models [10], spatial generalized mixed models [11], and random forest methods [7]. For instance, a random forest model approach was adopted in [7] using variables such as wind speed, wind duration, protection of power system, power system components, length of power lines, soil characteristics, precipitation, land slope, elevation, and land cover. They found that wind characteristics, precipitation, and soil characteristics (e.g. soil moisture level, etc.) were most effective variables on the duration of power outages. In general, we observed that the power outage prediction studies usually relied on some common variables. These variables can be listed as hurricane characteristics (e.g. wind speed and duration, precipitation), geographical characteristics (e.g. land cover, elevation, soil type and features, vegetation, tree type), and power system characteristics (e.g. system components, electricity poles, power line lengths, protective systems).

The assessment of different aspects of hurricane impact has been as important as predicting power outages. For example, $410 million loss was estimated for State of Virginia through simulating various hurricane scenarios that will lead workforce losses due to absence [12]. In addition to economic loss, several studies paid attention to vulnerability and resilience of different demographic and socioeconomic groups as well as impacts of hurricanes and power outages on these groups [13-16]. For instance, Congressional Research Services' report on the impact of the Hurricane Katrina showed that the poor and African American population suffered the most due to the storm [14]. Considering this important association between demographics/socioeconomics and hurricane impact, A social vulnerability index was developed for coastal communities using factors such as race, age, gender, and socioeconomic status, which also showed social vulnerability is driven by these factors [15]. Another study focused on daily power outages rather than hurricane-induced ones [17]. This study examined the community resilience to daily power outages considering a few socioeconomic and transportation-related variables such as the disadvantage of Native Americans, distance to the nearest hospital, and distance to the major roadway. Authors have also used a spatial regression approach using these variables in order to interpret the outlying reasons behind the daily power outage durations.

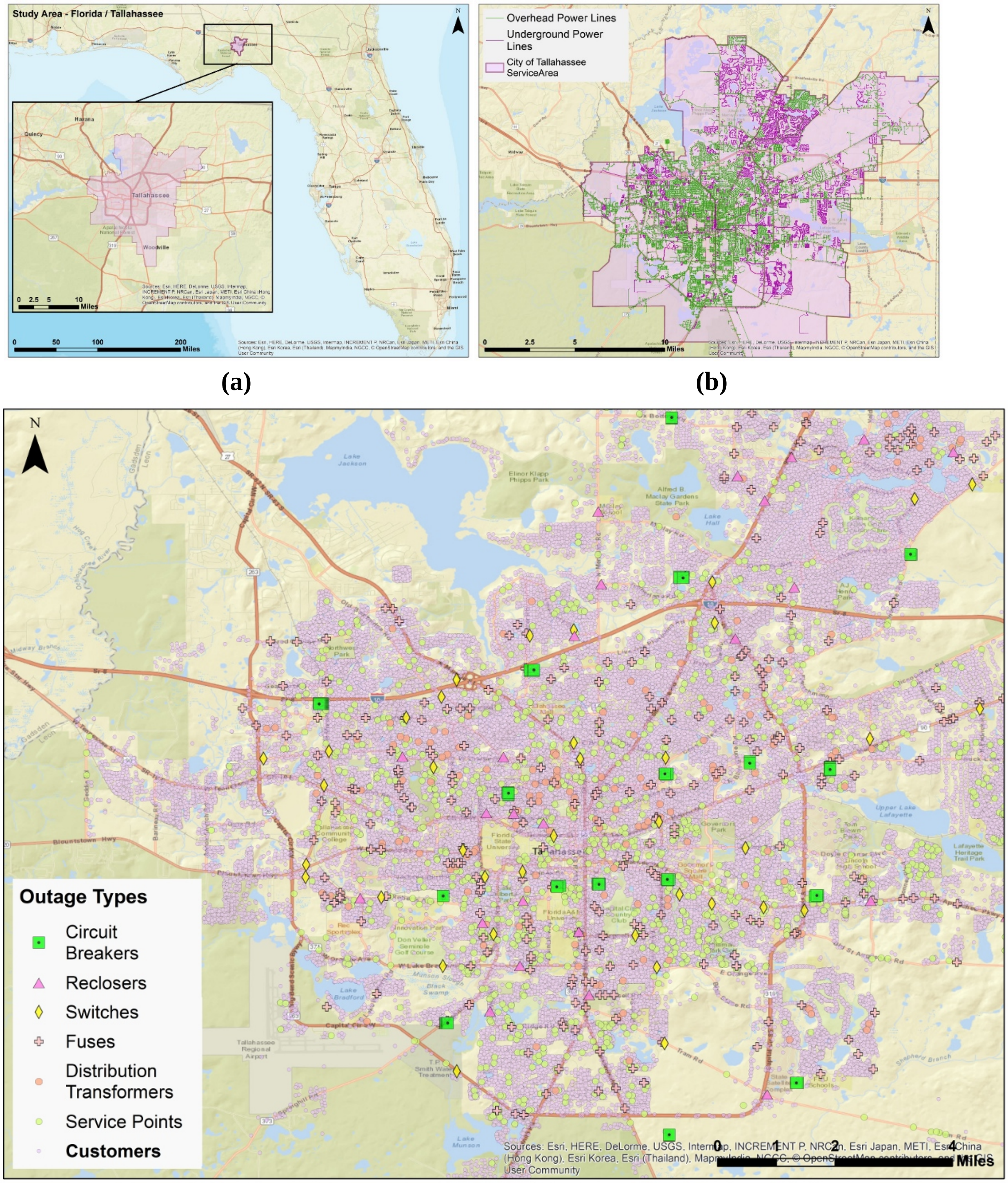
In this study, we investigated the impact of Hurricane Hermine both on the City of Tallahassee infrastructure and the communities of the city. The prominent consequence of the hurricane –power outages, was examined spatially and statistically in order to comprehend the regional variations of Hermine's impact on the different demographic and socioeconomic groups. This analysis also led to the identification of the factors such as the type of powerlines or wind speed which drive the magnitude of this impact. In order to perform this, a two-step approach was adopted. First step includes (a) a spatial analysis to illustrate the magnitude of customers affected by power outages in different regions, and (b) a Spatial Autocorrelation analysis based on Moran's I index [18, 19] together with a clustering analysis based on Anselin Local Moran's I index [20, 21]. The spatial analysis was conducted in order to determine the spatial distribution of the customers affected from outages. Second step involves a statistical analysis to model the number of customers affected by power outages over the total population (i.e., percentage of affected customers) using several variables related to demography, socioeconomics, power system components (e.g. underground/overhead powerlines), roadway disruptions, and transportation. Note that, in this study, the objective is to assess the impact of Hurricane Hermine on the Tallahassee communities rather than attempting to predict the locale of power outages. That is, we use demographic, socioeconomic, and transportation-related variables in order to answer the following question: Where and why post-hurricane treatments and remedies of the city agencies should focus?

2.2 Case Study Area and Data Description

This section presents a case study application in the City of Tallahassee, the capital of Florida, which was hit by Hurricane Hermine on September 2nd, 2016 (Figure 2.1a). Tallahassee is also a home to two universities, and has a population of 190,894, which makes it a mid-size city and a considerable urban region. In this chapter, several datasets were used to conduct the proposed case study application. These datasets include those that are related to the city infrastructure (power lines, failed power system components and roadway closures due to fallen trees, provided by the City of Tallahassee – Figure 2.1b, Figure 2.1c and Figure 2.2, respectively), 2010 Census data [22] (census block groups - Figure 2.2), and maximum measured wind speeds at weather stations in Tallahassee [23] (Figure 2.2).

The City of Tallahassee is a full-service municipality providing essential services to the region: electric, gas, water solid waste, sewer, public works, airport, mass transit, etc. It was one of the first public utilities in the U.S. to implement a full-scale Automated Metering Infrastructure in 2009. Power outage data was gathered through the “ping” operation for the power network, which identifies the outages. “Ping” data contains unresponsive devices (e.g., circuit breakers, reclosers, fuses, switches, transformers and service points), and the following information: the feeder they belong to, dispatch remarks, time of outage, time of restoration, duration for the outages and number of customers affected. The restoration covers a time frame from September 1st to September 10th, 2016, affecting 60,928 customers [1]. The failed power system components were used to calculate number of customers affected by power outage at each U.S. census population block group. Note that the failure of these components result in different outcomes in the context of affected customers. For instance, service point failures usually indicate one or a few number of customers suffering from the outage. Failure of circuit breakers, on the other hand, affects a large number of customers since these components serve multiple power lines connected to many customers.

Roadway closures were identified through online requests and requests through a mobile app called DigiTally [24], which are both maintained by the City of Tallahassee. DigiTally establishes a platform to connect residences directly with City of Tallahassee, which helps communicating more effectively and efficiently to resolve issues in the community. Through these systems, residents can file requests for any issues and monitor others. During Hurricane Hermine, 776 roadway closures/disruptions due to tree failures were reported in a one week window. Note that, although this may not be the whole roadway closures that happened as a result of fallen trees, the City of Tallahassee officials have ensured the research team that this dataset included all the major roadway closures the city has experienced. The total number of roadway closures together with the average duration of closure were determined for each U.S. census population block group, and then used in the Bayesian spatial autoregressive model. A flowchart illustrating overall methodology is provided in Figure 2.3.



(c)

Figure 2.1. Overview of the study area and data (a) study area, (b) power infrastructure, (c) customers and failed components of the power infrastructure

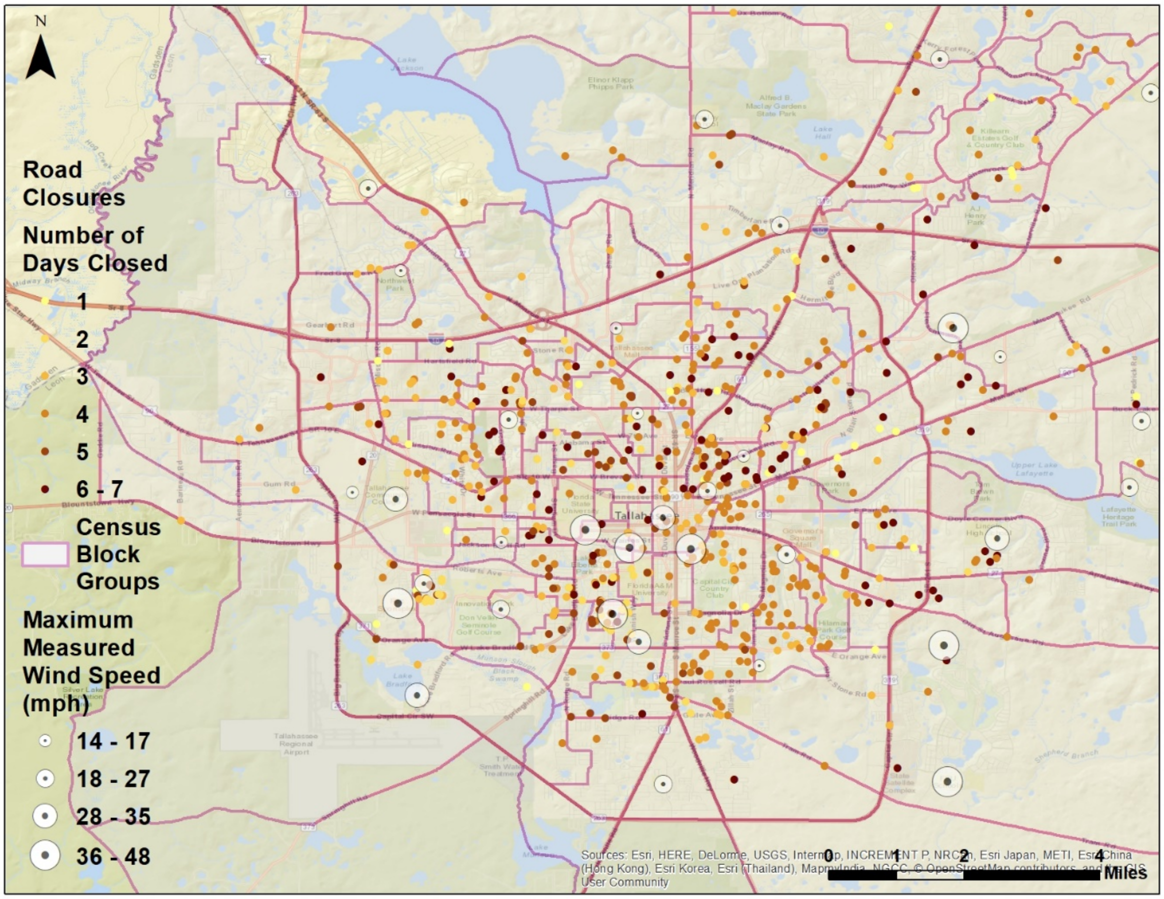


Figure 2.2. U.S. Census population block groups, hurricane related roadway closures due to fallen trees and maximum wind speed measurements at weather stations

<u>2.3 Methodology</u>

This study consists of two different methodological approaches to investigate the impact of Hurricane Hermine both on the infrastructure and the communities of the City of Tallahassee: spatial and statistical analyses. Spatial analyses include: a) mapping the affected customers, b) determining the density distribution of the magnitude of power outages using a kernel density estimation (KDE)-based approach, c) identifying the spatial autocorrelation (using Global Moran's I index) between power outage magnitudes of affected customers to discover whether there is a clustering pattern or not, and d) illustrating those power outage clusters using the Local Moran's I index, if there is a clustering pattern identified by the Global Moran's I index. Following the spatial analysis, a statistical modeling approach was utilized to comprehend the intricacy of the power outages. As such, a Bayesian spatial autoregressive model was adopted to conduct a statistical analysis due to its advantage in modeling spatially distributed datasets which possess inherent spatial correlation between observations. This type of Bayesian modeling approach was preferred due to its power when sample size is relatively small [25, 26]. A flowchart illustrating overall methodology is provided in Figure 2.3.

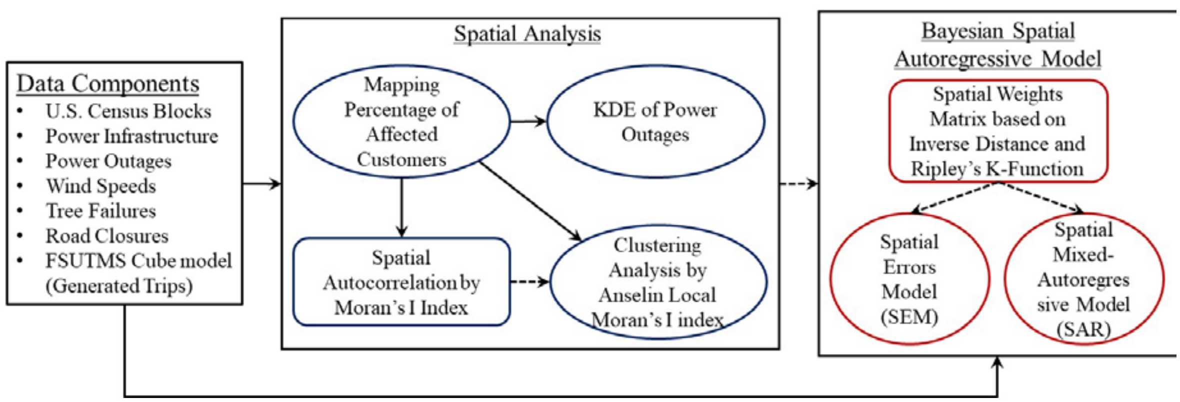
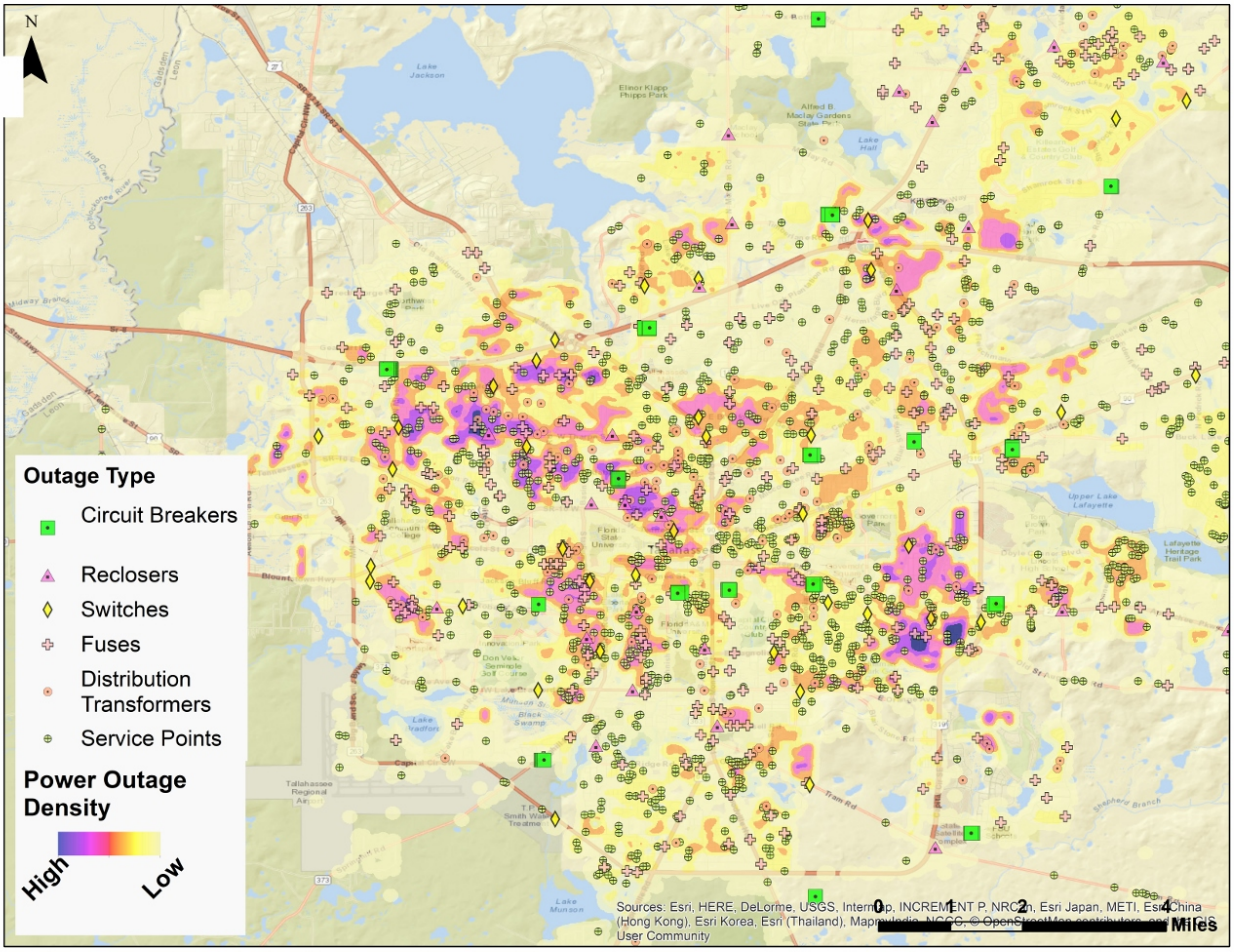


Figure 2.3. Methodology flowchart

2.3.1 Spatial Analysis

The power outage data revealed the spatial distribution of affected customers. This information was used to obtain the power outage density map shown in Figure 2.4. Figure 2.4a shows the failed power system components along with the power outage densities throughout the study region. Figure 2.4b, on the other hand, displays how roadway closures and the power outage densities are related. It is clear from the figures that a direct relationship between roadway closure intensity and the elevated power outage density exists since roadway closures, particularly those with longer durations, were more frequent at those regions with high outage densities. The power outage density was calculated based on the spatial distribution of affected customers using a kernel density estimation (KDE) approach [27] in ArcGIS software [28]. This was followed by determining the total number of affected customers in each census block group to be able to observe the regional variation of the power outages in the city. As such, two different metrics were calculated: 1) total number of affected customers, and 2) total number of affected customers divided by the total population of each census block group (i.e. percentage of affected customers). Identifying the affected customers in each census block group provided a visual basis to compare different regions in terms of the impact of the hurricane. A Spatial Autocorrelation analysis was conducted based on Moran's I index [18, 19] to determine whether there is a spatial clustering pattern for customers affected from outages. This was followed by a clustering analysis which was conducted based on Anselin Local Moran's I index [20, 21] in order to identify those census block group clusters based on the magnitude of affected customers. Both analyses were conducted using the ArcGIS software [28]. This spatial analysis aimed to highlight those regions which compel special attention for post-hurricane treatments (e.g. improving infrastructure, building redundant systems, providing generators, etc.). In addition, findings pinpoint the critical locations city can focus on in order to alleviate future outage problems. The regional variations of power outages in the City of Tallahassee are provided in the Results section.


N
Outage Type
Circuit Breakers
Reclosers
Switches
Fuses
Distribution Transformers
Service Points
Power Outage Density
High
Low
Sources: Esri, HERE, DeLorme, USGS, Intermap, INCREMENT P, NRCan, Esri Japan, METI, Esri China (Hong Kong), Esri Korea, Esri (Thailand), MapmyIndia, NGCC, © OpenStreetMap contributors, and the GIS User Community
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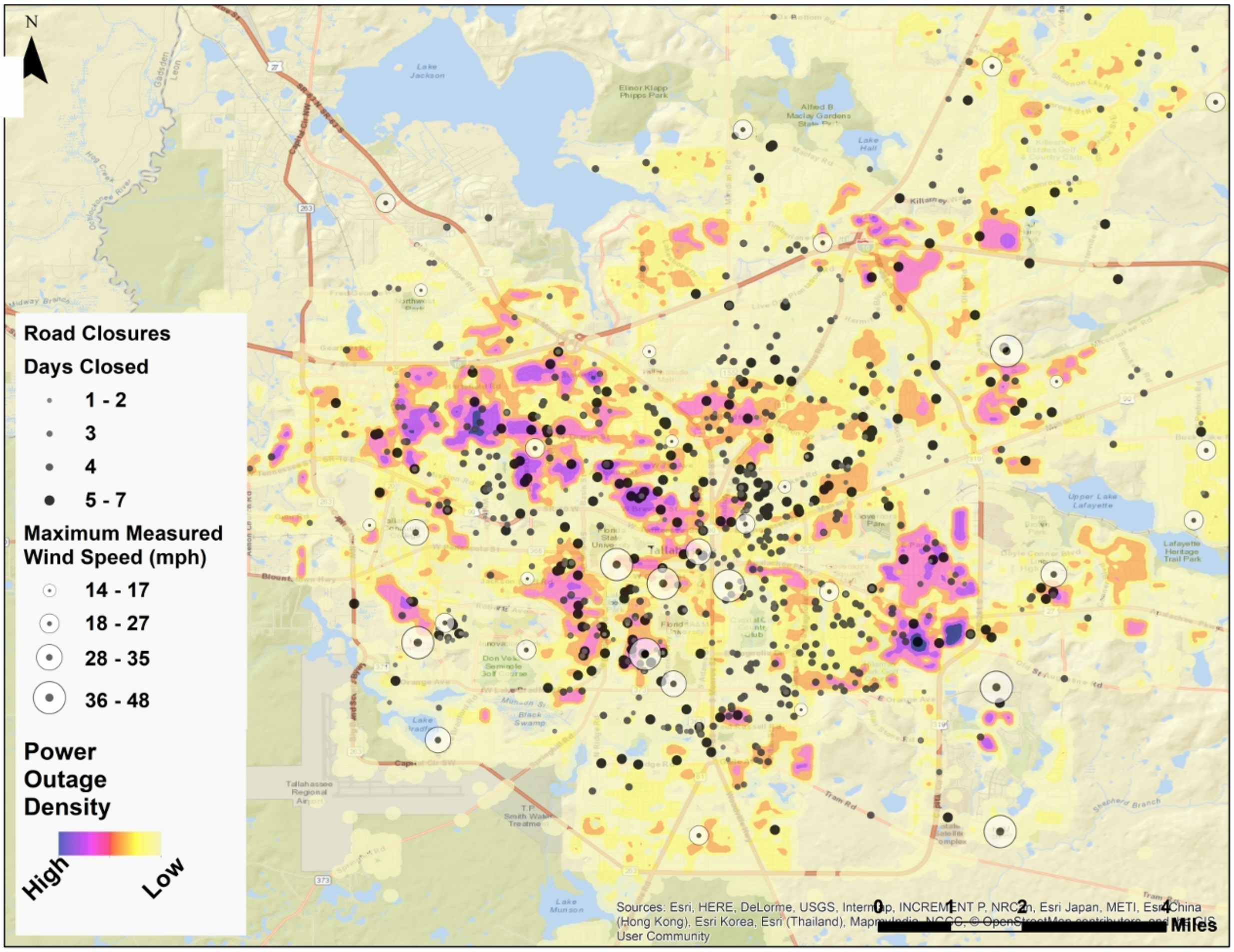


(b)

Figure 2.4. Power outage density along with (a) failed power system components, and (b) road closures

2.3.2 Bayesian Spatial Autoregressive Model

Bayesian spatial autoregressive modeling was used to assess the impact of hurricane on the different demographic and socioeconomic groups as well as to identify factors such as type of powerlines or wind speed which drive the magnitude of this impact. The necessity of implementing spatial autoregressive model arose from the spatial autocorrelation analysis (Moran's I) conducted for the residuals obtained from ordinary least squares analysis [18, 19]. Findings of this analysis are provided in the Results section.

The demographic and socioeconomic variables were provided in the U.S. Census data [22] whereas power outages and roadway closures were provided by the City of Tallahassee. Moreover, maximum wind speeds at weather stations were collected from WeatherSTEM [23], and the total generated trips at census block groups were obtained from the Capital Region Cube model [29, 30]. The list of candidate variables for the model together with their descriptive statistics and definitions are provided in Table 2.1. The correlations between these candidates were tested using Pearson correlation coefficient measure (Figure 2.5), and highly correlated variables such as percentage of white and African-American population were identified. Then, the potential models were investigated, and the final model along with its variables was determined. Note that the dependent variable of the analysis is total number of affected customers over the total population (i.e. percentage of affected customers). This metric is similar to the "System Average Interruption Frequency Index" (SAIFI) proposed by IEEE [31]; however, the denominator in this chapter is total population rather than total customers given in SAIFI.

The spatial autoregressive modeling is a particular approach applicable to spatially distributed datasets which possess an inherent spatial correlation between observations. This type of data is known to produce systematically varying residuals when implemented with models that disregard spatial relations between observations (i.e. generalized linear models) [32]. The reason behind the Bayesian approach was as follows: (a) the sample size of the study data was relatively small (N=160), and (b) the constant variation of errors and normality assumption inherent to maximum likelihood (ML) estimation was relaxed. The Bayesian and ML approaches are known to result in similar estimates when sample size is large enough (N>200) [25, 26]. However, one of the advantages of Bayesian models is observed when there is this aforementioned small sample size problem, which prevents making consistent and accurate estimates using the ML approach [25]. In this study, there are 160 census block groups used to model the power outages, which compels the use of Bayesian approaches rather than ML-based ones [26]. Furthermore, the Bayesian extension of spatial autoregressive model introduces the concept of spatial heterogeneity which relaxes the assumptions of normality and constant variation of errors. A detailed description and discussion on the Bayesian inference can be found in [33]. The structure of Bayesian spatial autoregressive model is given below [34]:

$$y = \rho \boldsymbol{W_1} y + \boldsymbol{X}\beta + u \tag{1}$$

$$u = \lambda \boldsymbol{W_2} u + \epsilon$$

$$\epsilon \sim N(0, \sigma^2 V)$$

$$V = diag(v_1, v_2, \dots, v_n)$$

where y is an n by 1 vector of observations, $\boldsymbol{X}$ is n by k matrix of model variables, β is k by 1 vector of variable coefficients, $\boldsymbol{W_1}$ and $\boldsymbol{W_2}$ are n by n row-standardized (rows sum to 1) spatial weights matrices also known as contiguity matrices involving the distance relations between observations and having zeros in diagonal. ρ and λ are the spatial autoregressive parameters, ϵ is normally distributed error term with zero mean and non-constant variance with different values for each observation through V. The magnitudes of v_i which introduce spatial heteroscedasticity via non-constant variance were estimated by the Bayesian approach.

The Bayesian modeling approach compels the identification of prior distributions for parameters based on the prior knowledge about the variables and their parameters. However, this prior knowledge is generally not available, and prior distributions are chosen for convenience rather than any prior information about the actual parameter distributions. The posterior distributions of parameters are determined based on these prior distributions [33]. The Bayesian specification of the model as used in this study is given below [34]:

$$\beta \sim N(c, T) \tag{2}$$

$$\sigma \sim (1/\sigma)$$

$$r/v_i \sim ID\ \chi^2(r)/r$$

$$r \sim \Gamma(m, k)$$

where a normal prior was introduced to β and a diffuse prior was introduced into σ. Variance terms v_i, are fixed and they were estimated based on the informative prior distribution of $\chi^2(r)/r$ with gamma distributed parameter r.

There are two special models that can be derived based on the general model specification given in Equation 1 through the imposed restrictions on spatial weights matrices. First model involves setting W_1 to zero which creates spatially correlated disturbances with a classical regression model, or the so-called spatial errors model (SEM). Setting W_2 to zero, on the other hand, produces a mixed regressive – spatial autoregressive model (SAR) which is also known as the spatial lag model [35]. We tested the general proposed model as well as these two special models in order to identify the best fitting model to the used data.

Table 2.1. Descriptive Statistics and Definitions of Candidate Variables

Variables	Min.	Max.	Mean	Med.	St.D.	Definition
White %	0.003	0.972	0.607	0.656	0.263	Percentage of white population
African American %	0.011	0.981	0.328	0.266	0.266	Percentage of African American population
Young (18-) %	0	0.427	0.186	0.197	0.086	Percentage of 18 years and younger population
Aging (65+) %	0	0.591	0.102	0.092	0.078	Percentage of 65 years and older population
Average Family Size	0	4	2.856	3	0.548	Average family size in a census block group
Above Poverty %	0	1.487	0.723	0.761	0.297	Percentage of people living above poverty level
Below Poverty %	0	1.117	0.225	0.139	0.24	Percentage of people living below poverty level
College Degree %	0	0.417	0.16	0.156	0.081	Percentage of people with at least college degree
Use of Car for Transportation %	0	0.857	0.447	0.452	0.164	Percentage of people relying on private cars for transportation
Use of Public Transportation %	0	0.142	0.008	0	0.021	Percentage of people using public transportation for travel purposes
Median Family Income	0	16	5.837	5.045	3.599	Median income of families living in a census block group (divided by 10,000)
Zero Vehicle Ownership %	0	0.404	0.032	0.015	0.051	Percentage of people with no vehicle ownership
Number of Road Closures	0	28	4.869	3	5.199	Total number of road closures within the census block group
Average Day Roads Closed	0	5	1.854	1.991	1.173	Average duration of road closures (days)
Total Length of Underground (UG) Power Lines	0	63	6.049	3.049	8.728	Total length of underground power lines (divided by 10,000)
Total Length of Overhead (OH) Power Lines	0.061	30	8.641	7.752	5.4	Total length of overhead power lines (divided by 10,000)
Total Length of Power Lines	2.053	698	146.899	118.2	106.2	Total length of power lines
Maximum Wind Speed	14	47	24.519	22	9.447	Maximum wind speed measured during hurricane
Total Generated Trips / Total Population	0	44	3.642	1.985	5.152	Total daily travels generated in a census block group over total population
Abbreviations	Min: minimum, Max: maximum, Med: Median, St.D.: standard deviation					

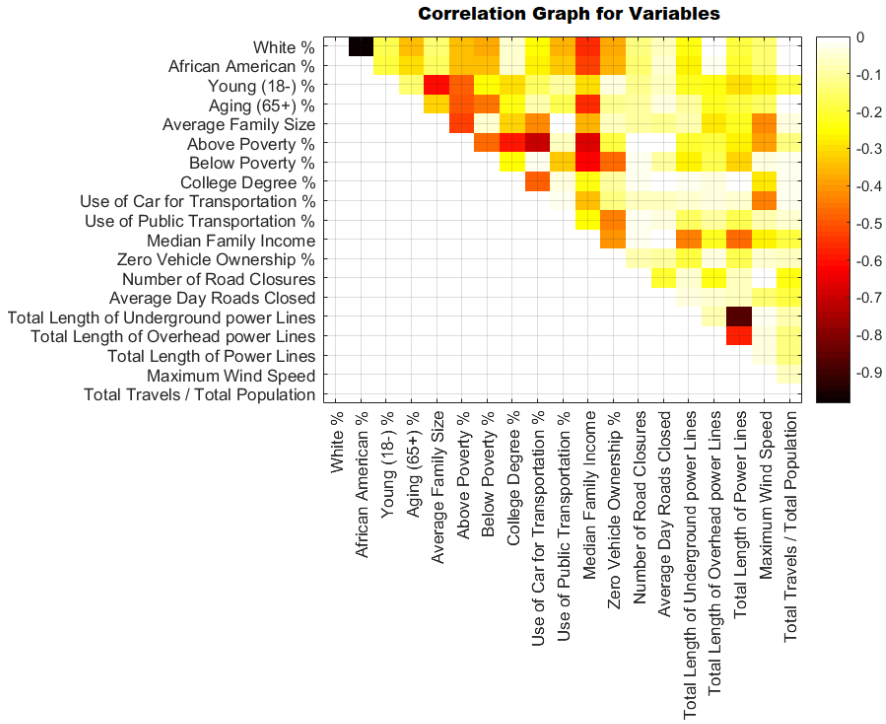


Figure 2.5. Correlation chart of candidate variables

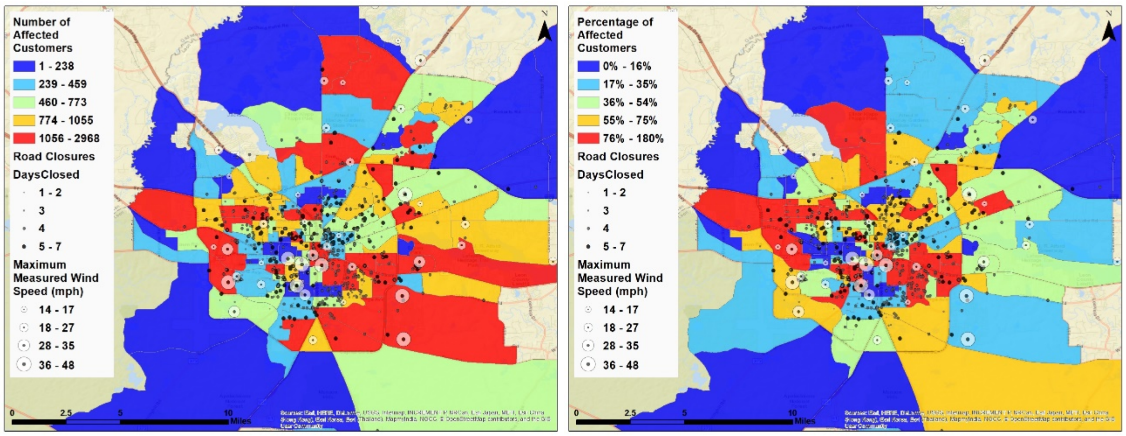
2.4 Results

2.4.1 Spatial Analysis Results

The first step of the analysis involves the spatial investigation of power outages induced by the Hurricane Hermine. The analysis was conducted to identify those critical locations which were affected the most. In order to achieve this, the total number of customers affected by outages in each census block group was determined, and two metrics –total number of affected customers and percentage of affected customers– were calculated (Figure 2.6). Figure 2.6a and Figure 2.6b display a slight variation due to the normalization by the total population living in the census block groups. Figure 2.6a shows that power outages were more or less spread over the City of Tallahassee. It is observed that there were customers highly affected by the outages in the whole city. Figure 2.6b, on the other hand, shows that the power outages were mostly clustered in the Northwest and Mid-

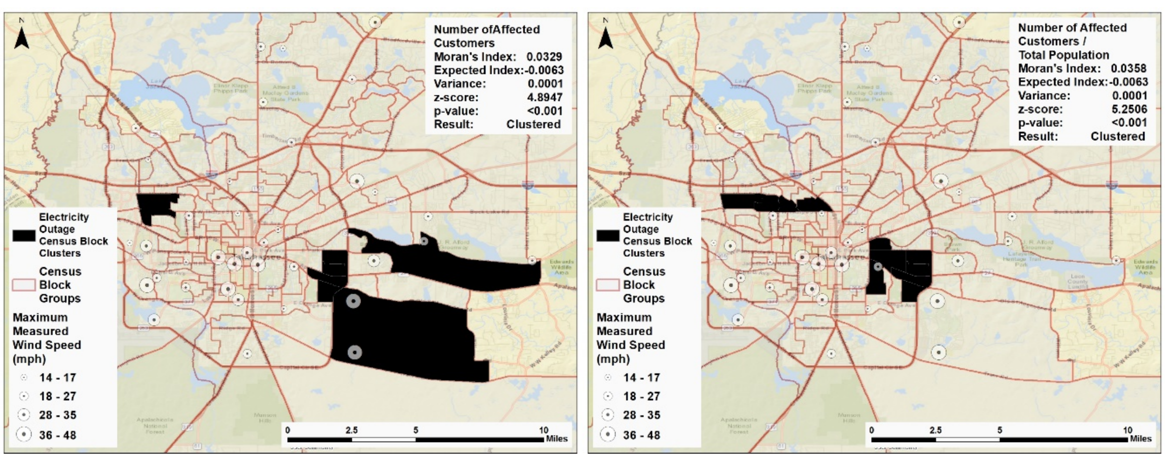
Southeast of the City of Tallahassee when the focus is on the percentage of affected customers. Note that red regions have relatively decreased in the Southeast compared to Figure 2.6a. This means that even though there is a substantial number of affected customers in the Southeast Tallahassee, the number of affected customers are not that high compared to the total population. Furthermore, roadway closures were displayed along with the affected customers in both maps. It is apparent from the maps that there is a higher concentration of roadway closures in those regions with elevated percentage of affected customers. This indicates a close relationship between roadway closures and power outages, which is expected since fallen trees are the most prominent cause of these two disruptions. Nevertheless, roadway closure can also stem from damages inflicted to the power system components. For instance, similar to fallen trees, fallen electricity poles or other failed power feeder lines can also lead to roadway closures. Furthermore, power outages can also affect traffic signalization of the city which would further cripple the transportation network and cause closure of roadways due to safety concerns.

Figure 2.7a and Figure 2.7b, on the other hand, demonstrate the spatial clustering of census block groups based on the magnitude of affected customers. Although the visual inspection of Figure 2.6a and Figure 2.6b does not show a clustering pattern, spatial autocorrelation (Global Moran’s I) and clustering analysis (Local Moran’s I) results disclosed that there is a clustering pattern based on both number of affected customers and percentage of affected customers. For instance, Figure 2.7a revealed that there is a high clustering of number of affected customers in the Mid-Southeast Tallahassee and a smaller region in the Northwest Tallahassee. This clustering pattern shifted westward when percentage of affected customers is considered, as shown in Figure 2.7b. This type of visualization of the outage data can be helpful for the city officials to pinpoint those critical locations for post-hurricane treatments. However, there is a need for more concrete statistics-based analyses in order to verify these results, which will be presented in the next section.



(a) **(b)**

Figure 2.6. Spatial distribution of power outages in each census block group together with wind speed measurements (a) total number of affected customers, (b) total number of affected customers over total population



(a) **(b)**

Figure 2.7. Spatial Autocorrelation and Local Moran’s I results (a) total number of affected customers, (b) percentage of affected customers

2.4.2 Spatial Autoregressive Model Results

To assess the necessity for a spatial autoregressive model, Moran's I statistics was calculated first for the residuals of an ordinary least squares analysis. The result for this analysis (Moran's I: 0.18, Moran' I statistics: 4.76 > 1.96, hypothesis of no spatial correlation rejected) clearly showed that there is an inherent spatial relationship between observations that cannot be captured by non-spatial models. This finding indicates that a linear (or non-linear) model which disregard a spatial correlation between observations is not appropriate for the data used in this study. Given the need for spatial models, we created the spatial weights matrix required for spatial model. As such, we first identified the distance that provides the highest spatial correlation between observations through a Ripley's K function approach [36], which resulted in 6.25 miles. Then, a spatial weights matrix was created by using this distance (6.25 mi) as threshold value. The spatial relationship between observations was conceptualized by the inverse distance method.

In this chapter, three spatial autoregressive models were tested, namely; general, SAR, and SEM models in order to find the best fitting approach through checking the statistical significance of spatial autoregressive model parameters ρ and λ [34]. Table 2.2 shows that parameters of both SAR and SEM model are statistically significant at a 5% significance level, while parameters of the general model are not significant. This finding indicates that SAR or SEM model is more appropriate than the general model. A further examination was conducted to check the spatial correlation between residuals of the SAR model. Spatial autocorrelation analysis indicated that there still exists a spatial dependence in the residuals of SAR model implying that spatial correlation between observations are not fully captured. Therefore, SEM model appears to fit the study data better than SAR model. Nevertheless, we presented results for both models in order to show a better picture of the spatial model findings.

Result of the spatial autoregressive modeling shows that most of the variables (9 out of 12) have statistically significant effects on the percentage of affected customers at a significance level of 10% (Table 2.3). Moreover, both approaches (SEM and SAR) appear to produce similar results. “Aging (65+) %” variable reveals that the higher the percentage aging population living in a census block, the higher the percentage of affected customers. This finding implies that the regions commonly populated by aging residents were highly affected by the power outages. Another interesting finding is that percentage of affected customers increases by the increasing “Average Family Size.” This means that census block groups where larger families are living suffered power outages more significantly than other locations. This assessment also holds for “College Degree %” and “Car Use for Transportation %”.

“Median Family Income”, on the other hand, discloses a different pattern due to its’ negative coefficient. That is, higher median family income seems to be associated with decreasing percentage of affected customers. One explanation for this finding might be the fact that higher income families usually prefer in newly developed/developing parts of the city, where the infrastructure is relatively new and/or power lines are under the ground. For example, the coefficient of “Total Length of Overhead Power Lines” shows that the longer the overhead power lines, the higher the percentage of affected customers. The effect of “Total Length of Underground Power Lines”, on the other hand, is very small and not statistically significant even though it has a positive coefficient. Figure 2.1b shows that underground lines are more frequent at newly developed/developing areas than other parts of the city due to the ease of deployment of underground lines at newly developing areas. Consequently, regions that have overhead lines rather than underground lines appear to be more vulnerable to hurricanes, which is logical and expected.

Total number of roadway closures within each census block group and average duration of these closures directly reflect the impact of the hurricane, and in turn, there is a substantial association between power outages and these variables. A substantial amount of power outages could actually be a result of fallen trees on the power lines. As such, the higher the number of roadway closures and duration of these closures, the higher the number of percentage of affected customers. Similarly, “Maximum Wind Speed” variable is used as a measure to quantify the magnitude of the Hurricane Hermine. Surprisingly, the effect of wind speed is not as firm as the effect of roadway closures since it is not statistically significant. This means that, at the very least, there is a high variation in the effect of maximum measured wind speed on the power outages. This indicates that the maximum wind speed of the hurricane is relatively less effective by itself, and probably environmental factors such as presence of trees and poor infrastructure elevate the severity and disruptiveness of the hurricane. In other words, failed power components might be already in bad condition which would not be able to withstand even low to moderate wind speeds while components in good condition or with redundancy endured higher wind speeds without failing. Indeed, the power outages were mostly observed at periphery of the city where power system redundancy was questionable. Around the city center, on the other hand, power system redundancies seemed to prevent total outage despite higher wind speeds. Consequently, although wind speed may directly affect the failure of individual system components such as switches and feeders, failure of a system is more likely to be triggered by the combination of several factors (e.g. state-of repair, redundancy, wind speed). From a transportation point of view, results show that the regions which generate more trips were more affected by the power outages as “Total Generated Trips / Total Population” variable has a positive coefficient. This is critical since the total generated trips generally reflect the magnitude of travels starting from a zone and usually residential areas generate higher number of trips. Therefore, disruptions in these areas prolong the recovery period after the hurricane, and in turn further cripple the economic and social life in the city. Nonetheless, it is important to note that the city center is observed to be relatively less affected by outages. This indicates that city may still be functioning since major government or business offices might not be as severely affected as the residential areas, which would enhance the economic recovery efforts. Therefore it is critical to pay particular attention to the power system components in and around facilities such as governmental offices and big businesses. However, overall resilience of the city depends on the well-being of the citizens since people are the engines of the disaster response and recovery efforts which bring about importance of power system resilience in the residential areas.

Table 2.2. Spatial Model Parameter Significance

Parameters	General *(p level)*	SAR *(p level)*	SEM *(p level)*
ρ	0.393 *(0.144)*	0.523 *(0.011)*	-
λ	0.207 *(0.601)*	-	0.703 *(0.004)*

Table 2.3. Bayesian Spatial Autoregressive Model Results

Variables	SEM			SAR		
	β	*p*	*p < 0.1*	*β*	*p*	*p < 0.1*
Intercept	-0.286	0.06	✓	-0.506	0.00	✓
Young (18-) %	-0.196	0.29	×	-0.345	0.15	×
Aging (65+) %	0.845	0.01	✓	0.815	0.01	✓
Average Family Size	0.077	0.08	✓	0.074	0.08	✓
College Degree %	0.518	0.05	✓	0.575	0.04	✓
Car Use for Transportation %	0.320	0.03	✓	0.376	0.01	✓
Median Family Income	-0.012	0.10	✓	-0.014	0.05	✓
Number of Road Closures	0.007	0.07	✓	0.007	0.06	✓
Average Day Roads Closed	0.063	0.00	✓	0.060	0.00	✓
∑ Length of OH Power Lines	0.010	0.02	✓	0.011	0.01	✓
∑ Length of UG Power Lines	0.001	0.40	×	0.001	0.46	×
Maximum Wind Speed	0.002	0.22	×	0.002	0.20	×
∑ Generated Trips / ∑ Population	0.007	0.06	✓	0.007	0.05	✓
λ	0.703	0.00	✓	-	-	
ρ	-	-		0.523	0.01	✓
Number of observations: 160, Number of variables: 12						
Abbreviations	β: estimated coefficient mean, p: p value, ∑: Total, SEM: Spatial error model, SAR: Spatial mixed-autoregressive model					

2.5 Conclusions

In this study, the hurricane-induced power outages were investigated spatially and statistically in order to comprehend the regional variations of the hurricane's impact on the city infrastructure as well as different demographic and socioeconomic groups. This is performed through analyzing the data based on the adverse consequences of a recent Hurricane Hermine that hit the City of Tallahassee. Spatial analysis was performed in order to identify the highly-affected areas based on the "percentage of affected customers" metric. Spatial autoregressive modeling, on the other hand, provided critical information about the association between the magnitude of affected customers and several variables related to demographics, socioeconomics, infrastructure, transportation, and hurricane characteristics.

The information gained by such investigation of hurricane-induced power outages can assist emergency officials in identifying critical and less resilient regions, and determining those demographic and socioeconomic groups which were more affected by the adverse consequences of the hurricane. For example, the analysis showed that the higher the percentage of aging (65+) residents, the higher the percentage of affected customers. This indicates the need for addressing those problems related to infrastructure and power system components at those regions where more 65+ populations live. Another critical finding is that the magnitude of power outages appeared to be increasing in regions which generate more trips. This is critical since the total generated trips generally reflect the magnitude of travels starting from a zone, and usually residential areas generate higher number of trips. In addition, the roadway infrastructure also appears to be crippled in those regions. For a more resilient community, this transportation perspective should be considered, and disruptions in these areas should be prevented in order to maintain the economic and social quality of life in the city.

There are several limitations of this study. For example, there were not enough number of weather stations to find the maximum measured wind speeds to cover the whole study area, and there were a number of census block groups without wind speed measurements. Therefore, measurements of the wind stations closest to these census block groups were used in the analysis. This assumption might have created some errors related to estimating the effect of maximum wind speed on the magnitude of power outages. Furthermore, hurricane-related roadway closures were obtained from the online requests and the DigiTally database, which mainly shows online requests from the city residents. Therefore, it is possible that there may be other locations which were not reported online by the residents. This might be a drawback of data source in terms of reflecting the actual extend of roadway closures. Moreover, the impact of only Hurricane Hermine was investigated in this study due to data availability. However, as a future study, the impact of Hurricane Irma will be investigated and compared with the findings of this study if and when the data for this recent hurricane is available to the authors.

Chapter 2 References

1. Berg R (2016) Hurricane Hermine Tropical Cyclone Report . AL092016.
2. Morris K, Johnson A (2016) Workshop on the Hurricane Hermine After Action Report. https://cms.leoncountyfl.gov/coadmin/agenda/Workshops/ws120161213.pdf.
3. SERT (2017) State Emergency Response Team. In: Florida Div. Emerg. Manag. http://www.floridadisaster.org/eoc/hermine2016/. Accessed 7 May 2017.
4. Demiroluk S, Ozbay K (2015) Bayesian Spatial Modeling and Risk Mapping of Downed Trees along the Roadways Using Data from Hurricanes Irene and Sandy. In: Transportation Research Board 94th Annual Meeting. pp 1–23.
5. Davidson RA, Liu H, Sarpong IK, et al (2003) Electric Power Distribution System Performance in Carolina Hurricanes. Nat Hazards Rev 4:36–45.
6. Quiring SM, Zhu L, Guikema SD (2011) Importance of soil and elevation characteristics for modeling hurricane-induced power outages. Nat Hazards 58:365–390 . doi: 10.1007/s11069-010-9672-9.
7. Nateghi R, Guikema SD, Quiring SM (2014) Forecasting hurricane-induced power outage durations. Nat Hazards 74:1795–1811 . doi: 10.1007/s11069-014-1270-9.
8. Mcroberts DB, Quiring SM, Guikema SD (2016) Improving Hurricane Power Outage Prediction Models Through the Inclusion of Local Environmental Factors. Risk Anal. doi: 10.1111/risa.12728.
9. Liu H, Davidson RA, Rosowsky D V., Stedinger JR (2005) Negative binomial regression of electric power outages in hurricanes. J Infrastruct Syst 11:258–267 . doi: 10.1061/(ASCE)1076-0342(2005)11:4(258).
10. Han SR, Guikema SD, Quiring SM (2009) Improving the predictive accuracy of hurricane power outage forecasts using generalized additive models. Risk Anal 29:1443–1453 . doi: 10.1111/j.1539-6924.2009.01280.x.
11. Liu H, Davidson RA, Apanasovich T V. (2008) Spatial generalized linear mixed models of electric power outages due to hurricanes and ice storms. Reliab Eng Syst Saf 93:897–912 . doi: 10.1016/j.ress.2007.03.038.
12. Akhtar R, Santos JR (2013) Risk-based input-output analysis of hurricane impacts on interdependent regional workforce systems. Nat Hazards 65:391–405 . doi: 10.1007/s11069-012-0369-0.
13. Lindell MK, Prater CS (2003) Assessing Community Impacts of Natural Disasters. Nat Hazards Rev 4: . doi: https://doi.org/10.1061/(ASCE)1527-6988(2003)4:4(176).
14. Gabe T, Falk G, McCarty M, Mason VW (2005) Hurricane Katrina: Social-demographic characteristics of impacted areas . RL33141 CRS.
15. Bjarnadottir S, Li Y, Stewart MG (2011) Social vulnerability index for coastal communities at risk to hurricane hazard and a changing climate. Nat Hazards 59:1055–1075 . doi: 10.1007/s11069-011-9817-5.
16. Bian R, Wilmot CG (2017) Measuring the vulnerability of disadvantaged populations during hurricane evacuation. Nat Hazards 85:691–707 . doi: 10.1007/s11069-016-2598-0.
17. Liévanos RS, Horne C (2017) Unequal resilience: The duration of electricity outages. Energy Policy 108:201–211 . doi: 10.1016/j.enpol.2017.05.058.
18. Ord JK, Getis A (1995) Local Spatial Autocorrelation Statistics: Distributional Issues and an Application. Geogr Anal 27:286–306 . doi: 10.1111/j.1538-4632.1995.tb00912.x

19. Koenig WD (1999) Spatial autocorrelation of ecological phenomena. Trends Ecol Evol 14:22–26 . doi: 10.1016/S0169-5347(98)01533-X.
20. Anselin L (1995) Local indicators of spatial association-LISA. Geogr Anal 27:93–115 . doi: 10.1111/j.1538-4632.1995.tb00338.x.
21. McCullagh M (2006) Detecting hotspots in time and space. In: International Symposium & Exhibition on Geoinformation. Subang Jaya, Selangor, Malaysia, pp 1–18.
22. U.S. Census Bureau (2010) 2010 US Census Blocks in Florida. Website: Florida Geographic Data Library. http://www.fgdl.org/metadataexplorer/explorer.jsp. Accessed 1 Oct 2015.
23. WeatherSTEM (2017) https://www.weatherstem.com/. http://leon.weatherstem.com/. Accessed 1 Jan 2017.
24. DigiTally (2017) DigiTally. City Tallahassee. http://www.talgov.com/Main/digitally.aspx. Accessed 1 Jan 2017.
25. Dunson DB (2001) Commentary: Practical advantages of Bayesian analysis of epidemiologic data. Am J Epidemiol 153:1222–1226 . doi: 10.1093/aje/153.12.1222.
26. De Winter JC, Dodou D, Wieringa PA (2009) Exploratory Factor Analysis With Small Sample Sizes. Multivariate Behav Res 44:147–181 . doi: 10.1080/00273170902794206.
27. Brunsdon C (1995) Estimating probability surfaces for geographical point data: An adaptive kernel algorithm. Comput Geosci 21:877–894 . doi: 10.1016/0098-3004(95)00020-9.
28. ESRI (2014) ArcGIS Desktop: Release 10.2 [Computer program].
29. Citilabs (2016) Cube Software [Computer program]. http://www.citilabs.com/. Accessed 1 Jan 2016.
30. FSUTMS (2017) Statewide and Regional Models. http://www.fsutmsonline.net/index.php?/model_pages/model_pages/. Accessed 1 Aug 2017.
31. IEEE (2012) Guide for Electric Power Distribution Reliability Indices. New York.
32. LeSage JP (1997) Bayesian Estimation of Spatial Autoregressive Models. Int Reg Sci Rev 20:113–129.
33. Gelman A, Carlin JB, Stern HS, et al (2003) Bayesian Data Analysis, 2nd edn. CRC Press, London.
34. LeSage JP (1999) The Theory and Practice of Spatial Econometrics. http://www.rri.wvu.edu/webbook/lesage/spatial/wbook.pdf.
35. Anselin L (2002) Under the hood: Issues in the specification and interpretation of spatial regression models. Agric Econ 27:247–267 . doi: 10.1111/j.1574-0862.2002.tb00120.x.
36. Gatrell AC, Bailey TC, Diggle PJ, Rowlingson BS (1996) Point Spatial application pattern analysis geographical epidemiology. Trans Inst Br Geogr 21:256–274.

Chapter 3 Measuring the Accessibility of Critical Facilities in the Presence of Hurricane-related Roadway Closures and an Approach for Predicting Future Roadway Disruptions

Roadway closures magnify the adverse effects of disasters on people since any type of such disruption increases the emergency response travel time (ERTT), which is of central importance for the safety and survival of the affected people. Especially in the State of Florida, high winds due to hurricanes, such as the Hurricane Hermine, lead to notable roadway disruptions and closures that compel special attention. As such, in this chapter, the accessibility of emergency response facilities, such as police stations, fire stations and hospitals in the City of Tallahassee, the capital of Florida, was extensively studied using real-life data on roadway closures during Hurricane Hermine. A new metric, namely Accessibility Decrease Index (ADI), was proposed, which measures the change in ERTT before and in the aftermath of a hurricane such as Hermine. Results clearly show those regions with reduced emergency response facility accessibility and roadways under a disruption risk in the one-week window after Hermine hit Tallahassee. City officials can pinpoint these critical locations for future improvements, and identify those critical roadways, which are under a risk of disruption due to the impact of the hurricane. This information can be utilized to improve emergency response plans by improving the roadway infrastructure and providing alternative routes to public.

3.1 Introduction

Roadway closures magnify the adverse effects of disasters on people since any type of such disruption increases the emergency response travel time (ERTT), which is of central importance for the safety and survival of the affected people. An emergency response plan, therefore, should include strategies to evaluate the conditions of existing roadway networks during and in the aftermath of disasters such as hurricanes (e.g., many strategies have been developed to alleviate the suffering of public after the infamous Hurricane Katrina). Within such plans, the available transportation network should be evaluated with respect to disasters using historical data and/or predictions in order to assess the roadway conditions, and identify the critical locations. Especially in the State of Florida, high winds due to hurricanes, such as the Hurricane Hermine, lead to notable roadway disruptions and closures. Even the lower strength storms may still be strong enough to adversely affect the transportation network (i.e., roadway disruptions and closures due to fallen trees, which will definitely cripple the emergency response operations. Focusing on this accessibility-based analysis is especially critical since providing necessary aid to hurricane victims in a timely manner can alleviate possible adverse consequences of hurricanes.

Previous research shows that transportation accessibility has been a special interest, especially given the advances in computational power that has enabled the analysis of more computationally complex problems. Numerous studies have focused on the accessibility of critical facilities such as supermarkets [1], nursing homes [2], health care facilities [3, 4], multimodal facilities [5], and shelters [6]. These studies take advantage of Geographical Information Systems (GIS)-based tools to perform accessibility analysis. However, to the authors' knowledge, there has not been a study that focused both on emergency facility accessibility based on real-life disaster data and prediction of future roadway disruptions. As such, the objective of this study was twofold. First, accessibility of emergency response facilities such as police stations, fire stations and hospitals in the City of Tallahassee, the capital of Florida, was extensively studied using real-life data on roadway closures due to Hermine. This was achieved by the temporal reconstruction of the reported roadway closures on the Tallahassee roadway network in the one-week window after Hermine hit Tallahassee. Furthermore, new metric, namely Accessibility Decrease Index (ADI), was proposed, which measures the change in ERTT before and in the aftermath of a hurricane such as Hermine. That is, ADI value is equal to the ratio between ERTT before and after a hurricane. As a result of this approach, regions with reduced emergency response facility accessibility were identified. In order to calculate the ADI values, eight minutes threshold value was selected for after-hurricane ERTT based on the existing literature [7-10]. For those regions with after-hurricane ERTT values higher than this threshold, ADI scores were calculated and illustrated since these regions are critical for emergency response. To calculate travel time between two locations, there are different available costs such as distance, and static and dynamic congested travel time. However, in this study, it is assumed that actual travel time for emergency vehicles such as police, fire and rescue, and emergency medical services (EMS) is very close to the free flow time (FFT) considering that all vehicles should yield to emergency vehicles by law.

Second, hurricane-related roadway disruption probabilities were estimated for major roadways, which are usually utilized as evacuation or emergency response routes. Note that the recent improvements in the technology increased the availability of the satellite images. This fact along with the development of image recognition techniques led to many studies in the literature in the context of satellite images data extraction [11, 12]. The concept of Convolutional Neural Network (CNN) was introduced in 1997 [13]. Unfortunately, the computational power of computers was not sufficient at the time, and it took twenty more years for the CNN to become one of the most popular techniques in the machine learning field. Please see [14] for more information on CNN. Recent studies have also showed the incredibly high accuracy of CNN for a high number of classifiers [15]. Lately, CNN was also used to extract data from satellite images for land usage classification [16], updating road data information [17], and for high wind risk analysis [18-21]. In the current research, we used CNN and satellite images to investigate the hurricane-related roadway disruption probabilities by recognizing and classifying tree types along major roadways, calculating their fragility to wind speeds. Those results can be used for analyzing critical roadways, which can be disrupted by tree failures. City officials can pinpoint these critical locations for future improvements and enhancing emergency response plans.

3.2 Study Area, Hurricane Hermine and Data

The City of Tallahassee, the capital of Florida, being the most populated city in the Leon County, hosts 286,272 people, and is home to two major universities and a community college. The urbanized area of Tallahassee has a population of 190,894 according to the US Census estimate [22]. The City of Tallahassee is a full service municipality providing essential services to the region: electric, gas, water solid waste, sewer, public works, airport, mass transit, etc. During emergency situations and disasters, the City of Tallahassee recognizes that a transportation system functions as a whole, and requires that each piece work together at all levels (i.e. institutional and operational) so that the system runs safely and efficiently.

Tallahassee was hit by Hurricane Hermine in September, 2016. Hermine provoked disruptions in all services in Tallahassee from 10:00 PM of September 1st, 2016 to 4:00

AM of the next day September 2nd, affecting thousands of customers. Tallahassee radar images [23, 24] show the time and path of Hermine as in Figure 3.1. Please refer to the Hermine report by NHC at [25] for detailed information. Maximum speeds reached during Hurricane Hermine varied for different parts of the city (Figure 3.2a). These high wind speeds resulted in fallen trees and roadway disruptions in Leon County (Figure 3.2a). The roadway closure data is provided by the City of Tallahassee, through a mobile app called Digitally [26]. It is a tool that connects residences directly with City of Tallahassee staff in order to resolve issues more effectively and efficiently. Users can file requests for any issues and monitor others. During Hurricane Hermine, 776 roadway closures were reported due to fallen trees in a one-week window (Figure 3.2b). Note that, 7th day closures shown in Figure 3.2b do not indicate that those closures occurred on 7th day, but correspond to closures which exist until 7th day. In case of an emergency, police (law enforcement), fire and hospital response teams are dispatched to locations of the emergency. In Tallahassee, five hospitals, thirteen fire stations, and fourteen police stations are ready to serve the public (Figure 3.2c) [27].

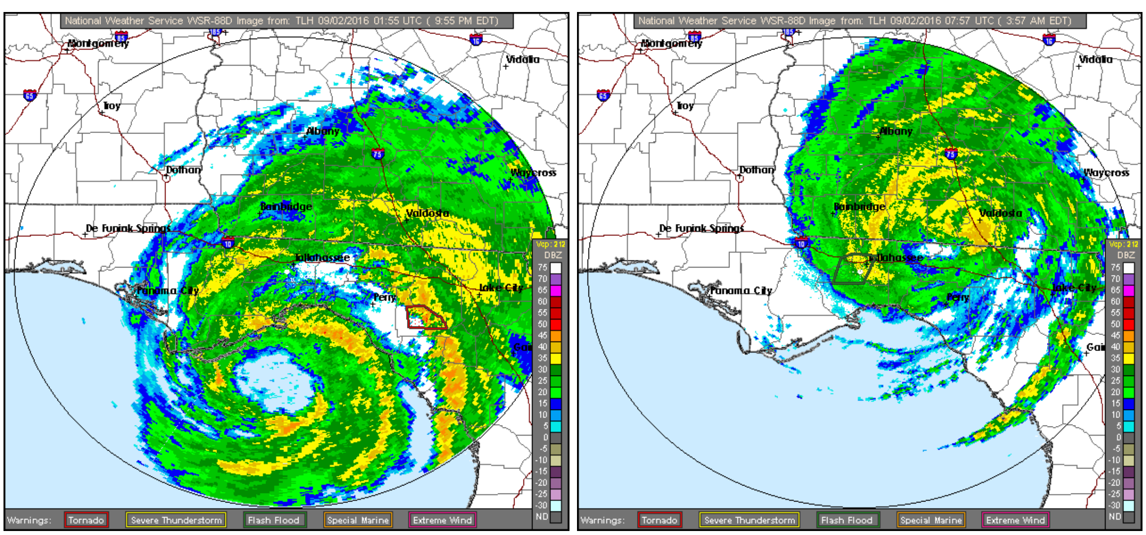
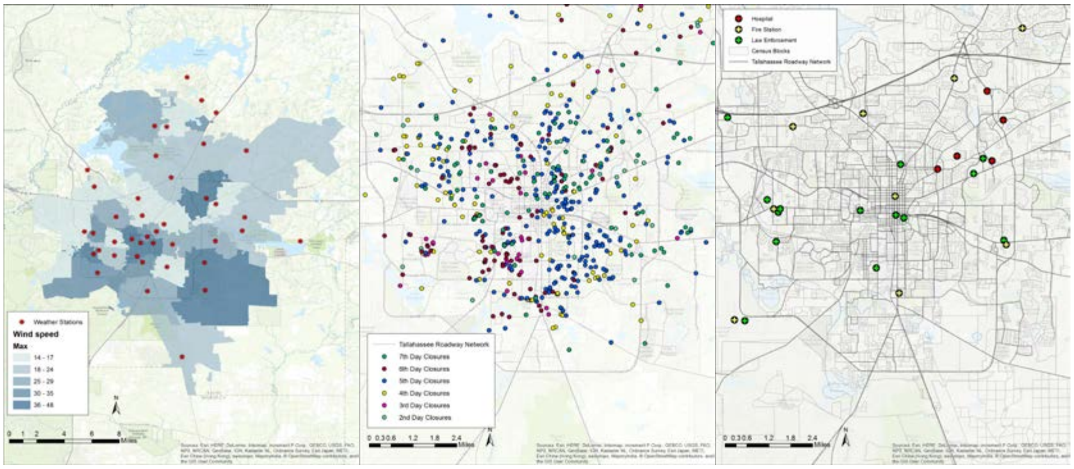


Figure 3.1. Hurricane Hermine Path over Tallahassee, FL from 09/01/16 to 09/02/16



(a) **(b)** **(c)**

Figure 3.2. Study Area (a) Wind Speeds by U.S. Census Blocks during Hermine (b) Roadway Closures (c) U.S. Census Blocks and Emergency Response Facilities

3.3 Methodology

3.3.1 Accessibility of Emergency Response Teams

Following the temporal reconstruction of the events related to the Tallahassee transportation network (e.g., roadway closures due to fallen trees), the ArcGIS "Network Analyst" tool was used to measure the transportation accessibility from police stations (law enforcement), fire stations, and hospitals. Three components were identified as part of the approach: (a) origins: police stations, fire stations, and hospitals, (b) destinations: U.S. Census block centroids, and (c) the roadway network. To find the least cost paths between origins and destinations (O-D pairs), an ArcGIS "OD Matrix" analysis was performed. Travel of the emergency vehicles was assumed to originate at the origin locations, and end at the census block centroids, based on the least cost path. It was assumed that actual travel time for emergency vehicles such as police, fire and rescue or emergency medical services (EMS) is very close to the free flow time (FFT) considering that all vehicles should yield to emergency vehicles by law. A threshold value for the response time was selected based on the literature, which states that emergency response time should not exceed approximately eight minutes [7-10]. For one week period, travel times were derived to identify the transportation accessibility metric considering each days' roadway closures in the city. For the census blocks with more than eight minutes accessibility and roadway closures due to fallen trees, travel times were compared to daily free flow time. For this purpose, a new metric, namely Accessibility Decrease Index (ADI), was proposed. ADI value is equal to the ratio between emergency response travel time (ERTT) before and after a hurricane event as defined in Equation 1, which is always bigger than 1. Note that, ADI values were not calculated for the locations where ERTT after the hurricane is still lower than the 8 minutes threshold duration, which indicates that those locations still have acceptable emergency response time. This analysis revealed those regions which has critical emergency response problems due to inaccessibility during and after the Hurricane Hermine.

$$ADI = f(x) = \begin{cases} \dfrac{ERTT_{after}}{ERTT_{before}}, & ERTT_{after} > 8\ minutes \\ N/A \quad , & ERTT_{after} \leq 8\ minutes \end{cases} \tag{1}$$

3.3.2 Sensitivity Analysis for Estimation of Roadway Disruption Probability

The estimation of roadway disruption probability is a multi-step problem. The first step was to take satellite image as an input, and recognize all trees that can affect roadways during a hurricane (Note that Figure 3.3a shows a typical satellite image for the analysis used in this study). The CNN methodology was utilized in order to recognize the trees from these satellite images. It was assumed that the trees that should be taken into consideration were in 10 meters from the center of the road. To start with, two separate CNN were trained to identify the number and types of trees around the roadways. The first CNN-1 was used to recognize the trees from the satellite image while the second CNN-2 identified the tree type selection from the pre-selected images identified by CNN-1. The training set was composed of 8,000 images for CNN-1 and 2,000 for CNN-2. The size of the images was 76x76 RGB pixels. The training pictures were manually selected from the City of Tallahassee satellite images. Two networks were tested on the 10% of the images and exceeded 97% and 93% accuracy for the CNN-1 and CNN-2, respectively.

The second step was to classify the selected trees based on their species. According to City of Tallahassee, there are four common tree species in Tallahassee namely lobby pine, shortleaf pine, sweetgum, and live oak. The third step was to approximate the geometric and structural characteristics of these trees. Color thresholding method was used to calculate the crown diameter [28, 29]. The crown diameter was used to approximate the other tree parameters (e.g. weight of the crown, height of the crown, etc.) necessary to calculate failure probability and data from [30] was used for this task. The next step was to estimate the tree fragility curves for all recognized trees. Several studies have been published on the probability estimation of tree failure induced by high winds [31-34]. In this study, the model given in Equation 2 was used for the failure probability estimation. The model involves one failure damage mode which is failure by rupture. Figure 3.3b, Equation 2, Equation 3, and Equation 4 illustrate the procedure used for failure calculation. The wind model [35] is described by Equation 2:

$$V_z = b\left(\frac{z}{10}\right)^{\alpha} V \qquad (2)$$

where b and α are constants, z is the height of tree measured from the ground, and V is the wind speed at 10 meters above the ground. The equal wind speed was assumed along the crown of the tree. Equation 3 characterizes the maximum force moment caused by the wind speed, where the forces F_1 and F_2 are caused by wind speed V_z, and F_3 represents the force produced by the weight of the crown, Δx is a initial deflection produced by forces F_1 and F_2.

$$M = F_1 \cdot h_1 + F_2 \cdot h_2 + F_3 \cdot \Delta x \quad (3)$$

The failure is considered when Equation 4 is satisfied:

$$\sigma_r < \sigma \quad (4)$$

where σ is the maximum stress in the cross section of the tree caused by the moment M and σ_r is the modulus of rupture, which depends on the specie of the tree. The Monte Carlo simulation was applied in order to calculate the fragility curves for each tree. Figure 3.3c shows examples of fragility curves for the Shortleaf Pine. The final step was to calculate the probability of roadway disruption. Based on the fragility curves developed for each particular tree, the overall probability of roadway disruption, P_r, was calculated, where P_r is the occurrence probability of at least one of the N events $P(E_i)$, and each event represents a failure of a tree along the roadway segment (Equation 5). Note that, the calculated probability corresponds to probability of at least one tree failure along a roadway segment, and this probability was referred as the roadway disruption probability. However, failure of a tree does not necessarily indicate a roadway closure since the fallen tree may or may not block the roadway. Therefore, the calculated probability was called the “disruption probability” rather than “closure probability.”

$$P_r = 1 - \prod_{i=1}^{N} \left(1 - P(E_i)\right) \quad (5)$$

where P_r is the roadway segment's disruption probability, $i = 1, \ldots, N$ and N is the total number of trees along that roadway segment, and $P(E_i)$ is the probability of failure of tree i.

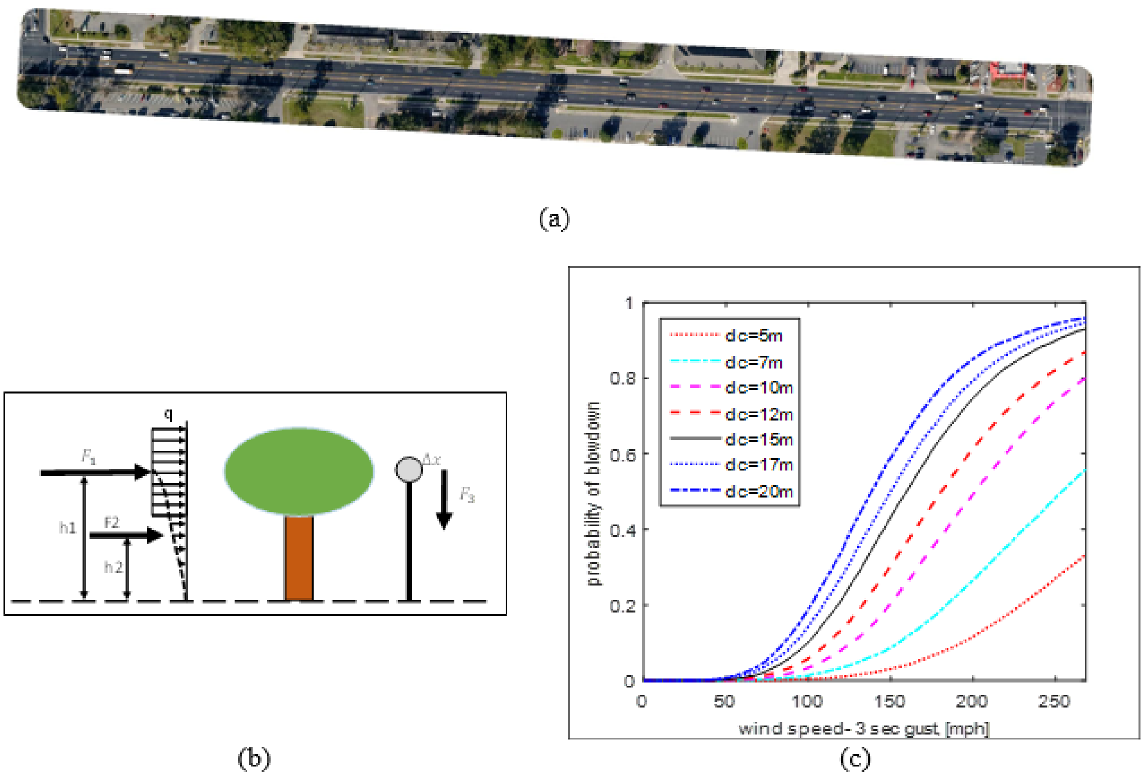


Figure 3.3. (a) A satellite image after classifying trees, (b) Tree failure model (c) Probability of roadway disruption for Shortleaf Pine.

3.4 Results

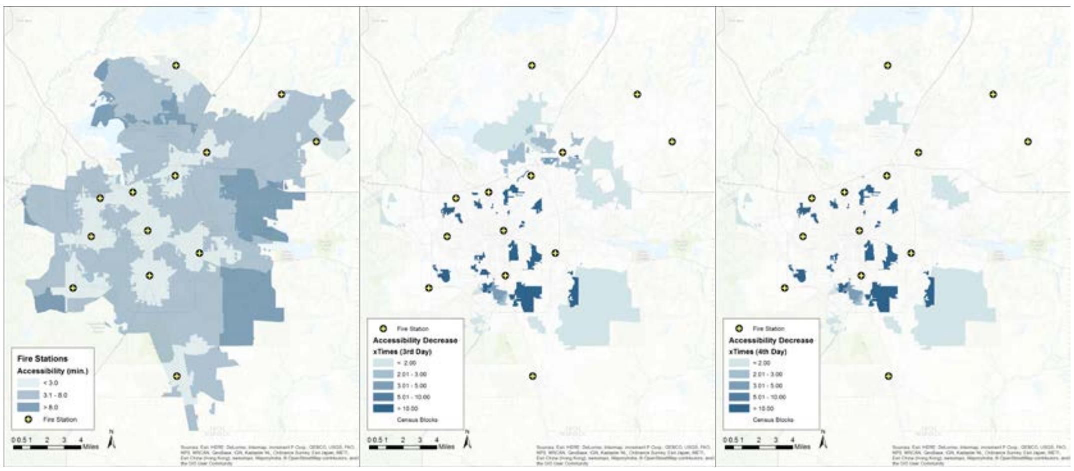
3.4.1 Accessibility of Emergency Response Teams

Figure 4a shows the free flow travel times from fire stations to census blocks. Major portions of the Southeast Tallahassee and Eastern Tallahassee appear to experience emergency response travel times (ERTT) greater than eight minutes. Note that, these locations are 'major' geographically speaking, but not as 'major' demographically speaking. Southeast Tallahassee is a growing residential zoning area, available for future developments, drawing high attention for investors. Even without the focus on emergency response planning, those regions might be considered for future improvements (e.g., building a new fire station) to decrease the emergency response time. Rest of the maps in Figure 4 displays the change in the ERTTs. Note that, all the highlighted census blocks are the ones that have eight minutes or more travel times from fire stations. Accessibility decrease index (ADI) in these maps shows the amount of change in the emergency response travel time before and after the hurricane event. For instance, if the free flow travel time from one station to a census block was 5 minute before hurricane and 15 minutes after the hurricane (due to roadway closures), the ADI equals to three (15/5=3). Note that, there were no road closures in Day 1 since the hurricane hit the city later in the evening of Day 1. Also note that, since Day 2 and Day 3 roadway conditions were almost identical, the analysis results were shown from Day 3 (Figure 4, Figure 5 and Figure 6).

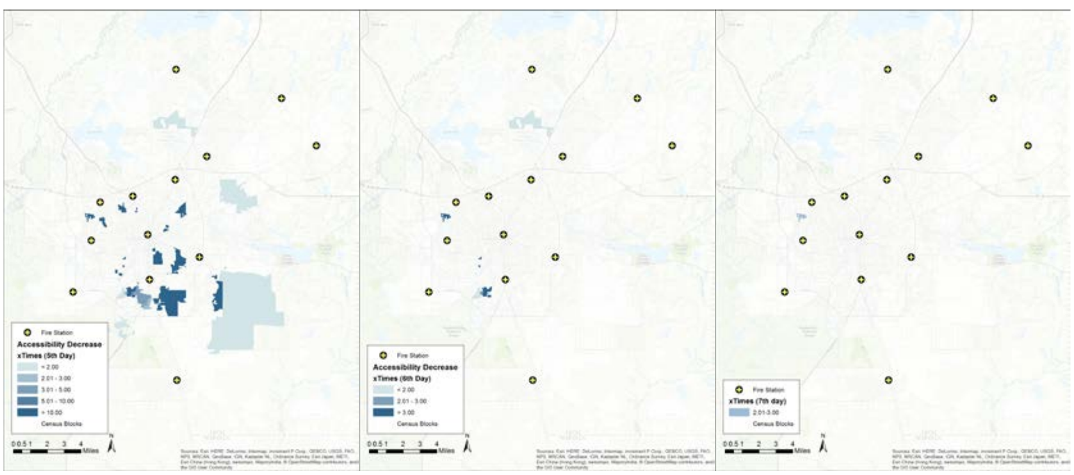
Figure 4b shows that there are pockets of census blocks experiencing significant changes in ERTTs, and a significant decrease in accessibility for Day 3, two days after the Hermine hit Tallahassee. In the northeastern southeastern sections of the city, ADI was less than two times. Pockets with ADI values larger than ten were observed mostly in local roadways where residential townhouses are located. Note that Tallahassee has regions that heavily inhabit trees with different types and heights all over the city. Figure 4c shows a clearance in the north and northeastern part in terms of ERTT value on Day 4. This is since the roadways were cleared from trees, ERTTs for fire stations returned to normal in those sections of the city. Pockets with ADI larger than ten have still experienced higher travel times since Day 3. Between Day 4 and Day 5, there was a slight change in ERTT from fire stations to census blocks. Roadway closures still led to inaccessibility in Day 5 for those pockets with the highest ADI. Recall that, those areas are located around neighborhoods with townhouses and local streets (mostly two-lane), which are more prone to roadway closures due to fallen trees than major highways. On Day 6 and Day 7 (Figure 4e and f), ERTTs for fire stations returned to daily levels as Figure 4a shows.

Figure 5a shows that major sections of the north, northeast and southeast of Tallahassee experience ERTTs above eight minutes. Similar to the previous analysis, these sections are also open to further development even without considering emergency response. Observing Fig. 5, the northern Tallahassee seems to be struggling in terms of accessibility to police stations in the whole one-week window. Since there was not a present police station in the southern Tallahassee, residences experienced reduced accessibility compared to accessibility to fire stations (Figure 4) until Day 7 (Figure 5f). Note that, the accessibility may be better in real life since police vehicles may already be on patrol in the communities. However, under emergency conditions such as hurricanes, roadways may be closed or disrupted, and hence they may not be able to patrol the area. Northern Tallahassee experienced the same problem, and ERTTs did not return to normal until Day 7. Pockets with the highest ADIs eventually returned to normal conditions on Day 6 (Figure 6e). Those regions might be considered for infrastructure improvements or new landscape developments in order to manage tree failures.

Unlike fire and police stations, hospitals are heavily clustered in a certain area. This might be disadvantageous for certain regions even under normal conditions. As Figure 6 shows, a major portion of the City of Tallahassee experiences accessibility problems related to hospitals. Due to this critical inaccessibility, numerous pockets of census blocks were observed to have high ADI values. Day 4 shows that the closest pockets to the northernmost hospital were in a better shape in terms of roadway closures compared to Day 3. On Day 5 (Figure 6d), a clear improvement was observed in ERTTs from hospitals to census blocks in the northern and northeast sections of Tallahassee. South of Tallahassee still had small pockets of census blocks with high ADIs. Figure 6f shows that even 7 days after hurricane, those parts were still experiencing a lack of accessibility to hospitals.

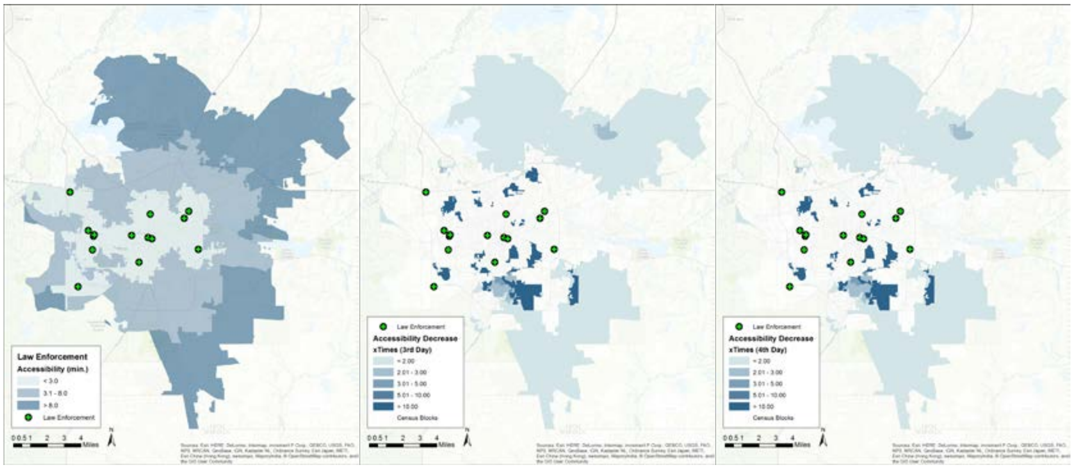


a) **b)** **c)**



d) **e)** **f)**

Figure 3.4. Accessibility for Fire Stations



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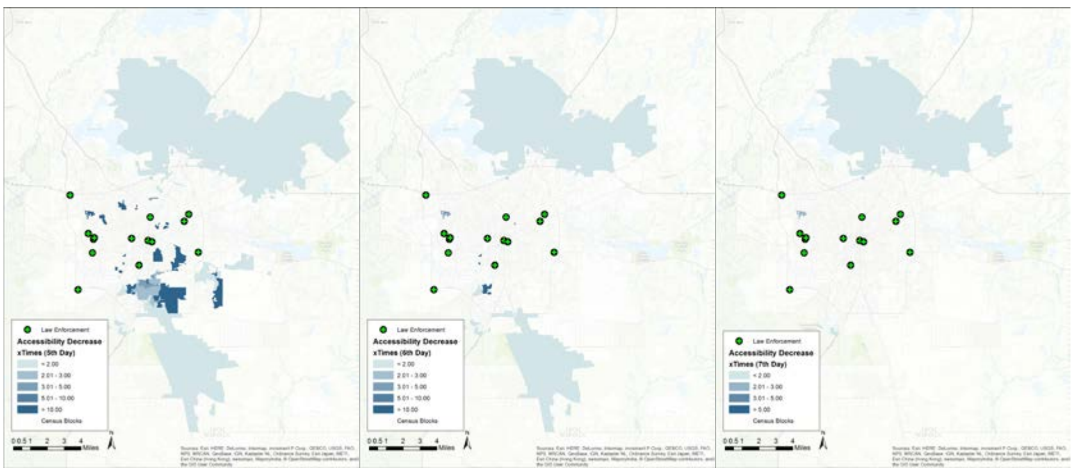
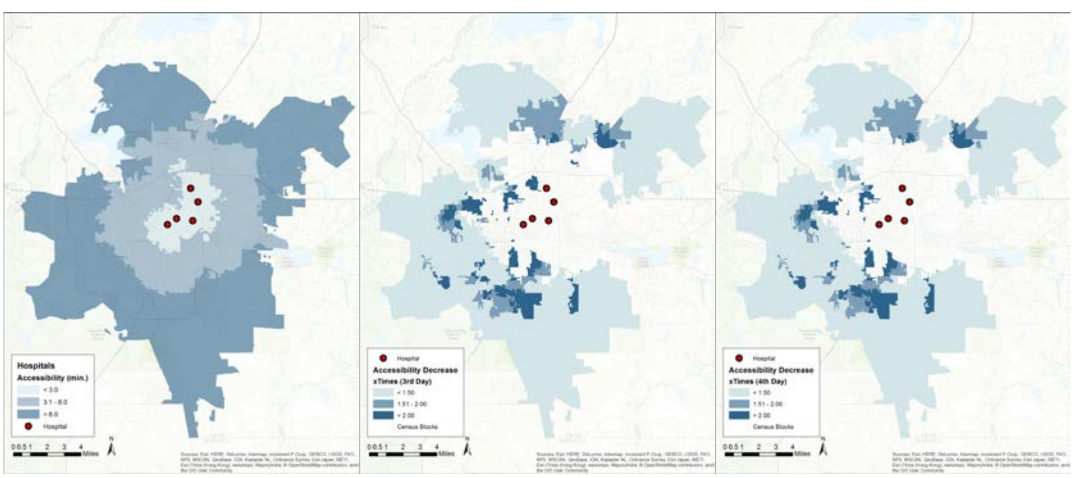
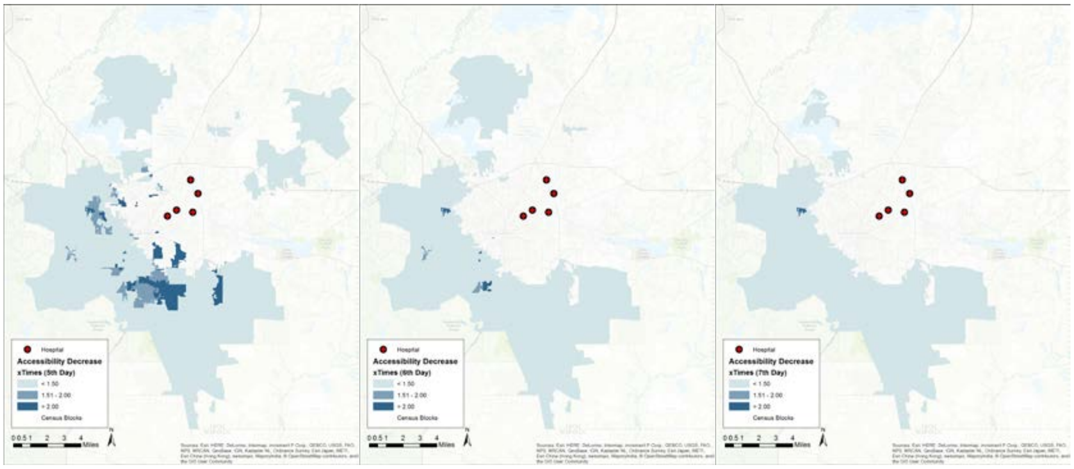


d) **e)** **f)**

Figure 3.5. Accessibility for Law Enforcement (Police Stations)



a) **b)** **c)**

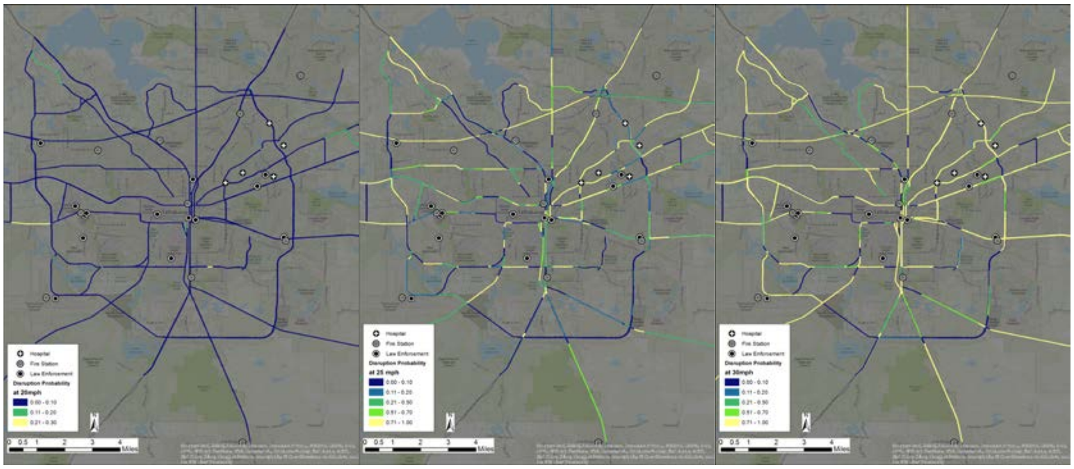


d) **e)** **f)**

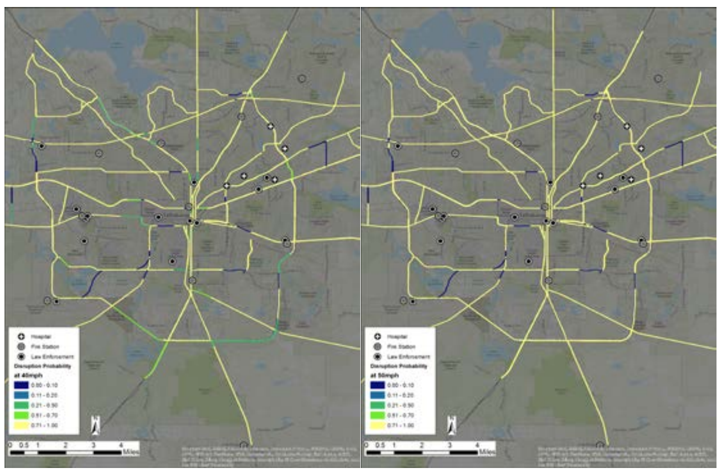
Figure 3.6. Accessibility for Hospitals

3.4.2 Sensitivity Analysis for the Estimation of Roadway Disruption Probability

As Figure 3.2a clearly shows, Hermine hit different section of the town with different wind speeds. Wind speeds were ranging between 14 mph to 48mph, which caused 776 roadway closures all over the town (Figure 3.2b). Note that wind speed data was collected through 43 weather stations [36] around the city as shown in Figure 3.2a. It should also be noted that a different Hurricane can have different path than Hurricane Hermine. In order to propose a more scalable approach, this section presents a sensitivity analysis for estimating possible roadway disruptions. The analysis was conducted using 435 roadway sections to estimate the roadway disruption probabilities based on the proposed CNN methodology. Note that, these sections are demarcated by intersections, and individual satellite images was extracted for each roadway section. In order to show the usefulness of this approach, five major highway corridors were selected: (1) I-10, which starts from the City of Jacksonville in the east, passing through Tallahassee and continuing west towards the City of Pensacola, (2) US-90 which lies parallel to I-10, passing through the downtown Tallahassee, (3) US-319, which extends from Georgia along the Gulf Coast through downtown Tallahassee, (4) US-27, which begins in the southern Florida and extends to the Georgia State border, and (5) SR-263, or Capital Circle SW, which encircles Tallahassee. Note that, probability of roadway disruption would increase with the increasing number of trees along the roadway section. Figure 3.7a shows the disruption probability for a 20 mph wind speed. For all the major highways, probability is below 0.10. Only one roadway has a probability of disruption between 0.20 and 0.30. When wind speed increased to 25 mph, roadways around hospitals started experiencing roadway disruption probabilities of 0.70 to 1.00 (Figure 3.7b). With the 30 mph wind speed, 90% of the major roadways around emergency response facilities experienced a probability of roadway disruption of at least 0.70. Capital Circle South, lying from west to east at the bottom of the figures, do not have substantially high roadway disruption probability until 40 mph, which is mostly different than other major roadways. This might be due to the fact that shoulders and sections along this roadway do not have substantial number of trees like other major roadways, or shoulders may be more than enough in terms of length so that a fallen tree cannot affect the roadway. Right after the hurricane, this roadway section (Capital Circle South) can be a safe passage for emergency response. In the western sections of the city, where fire stations and police stations are clustered, major roadways have experienced high probabilities of roadway disruption with 40 mph wind speed. City officials might consider providing alternative routes for the emergency response possibilities for future hurricanes in these locations. 50 mph wind speed, as shown in Figure 3.7e, causes 95% of the major roadway sections to have probabilities higher than 0.70. This also indicates the need to have emergency plans and strategies to find the safest and fastest routes for efficient emergency response operations.



a) **b)** **c)**



d) **e)**

Figure 3.7. Roadway Disruption Probabilities on the Major Highways of Tallahassee

3.4.3 Comparison of Predicted Roadway Disruptions and Roadway Closures Reported During Hurricane Hermine

The proposed prediction model was utilized in order to find the roadway disruption probabilities of roadway segments under different wind speeds experienced during hurricane Hermine. To do this, first, each roadway segment was assigned the 95th percentile wind speed measured at the weather station closest to that roadway segment. Based on these wind speeds, roadway disruption probability of each roadway segment was found and roadways were mapped based on this probability (Figure 3.8). Following, a kernel density estimation (KDE) [10] approach was utilized to find the roadway closure density in the City of Tallahassee, which produced a closure density surface. Visual inspection of the Figure 3.8 indicates that there is a substantially strong spatial relationship between high closure density locations and roadway disruption probabilities. That is, the relationship trend implies that the higher the closure density, the higher the disruption probability. It is worth noting that there are roadway segments (a) with high disruption probability where closure density is relatively smaller and (b) with low disruption probability where high closure density is observed. However, note that the roadway closure data is obtained from DigiTally app [26] which is composed of user reported roadway closures. Therefore, the roadway closure data at hand does not represent all of the closures experienced during the hurricane (particularly local roadways are overrepresented due to the immediate access of the residents to these roadways). Moreover, the predicted probabilities are roadway disruption probabilities rather than closure probabilities. That is, a disruption may or may not lead to a closure which would not be reflected by the closure data. Nevertheless, Figure 3.8 still illustrates a significant spatial relationship between closure density and roadway disruption probability.

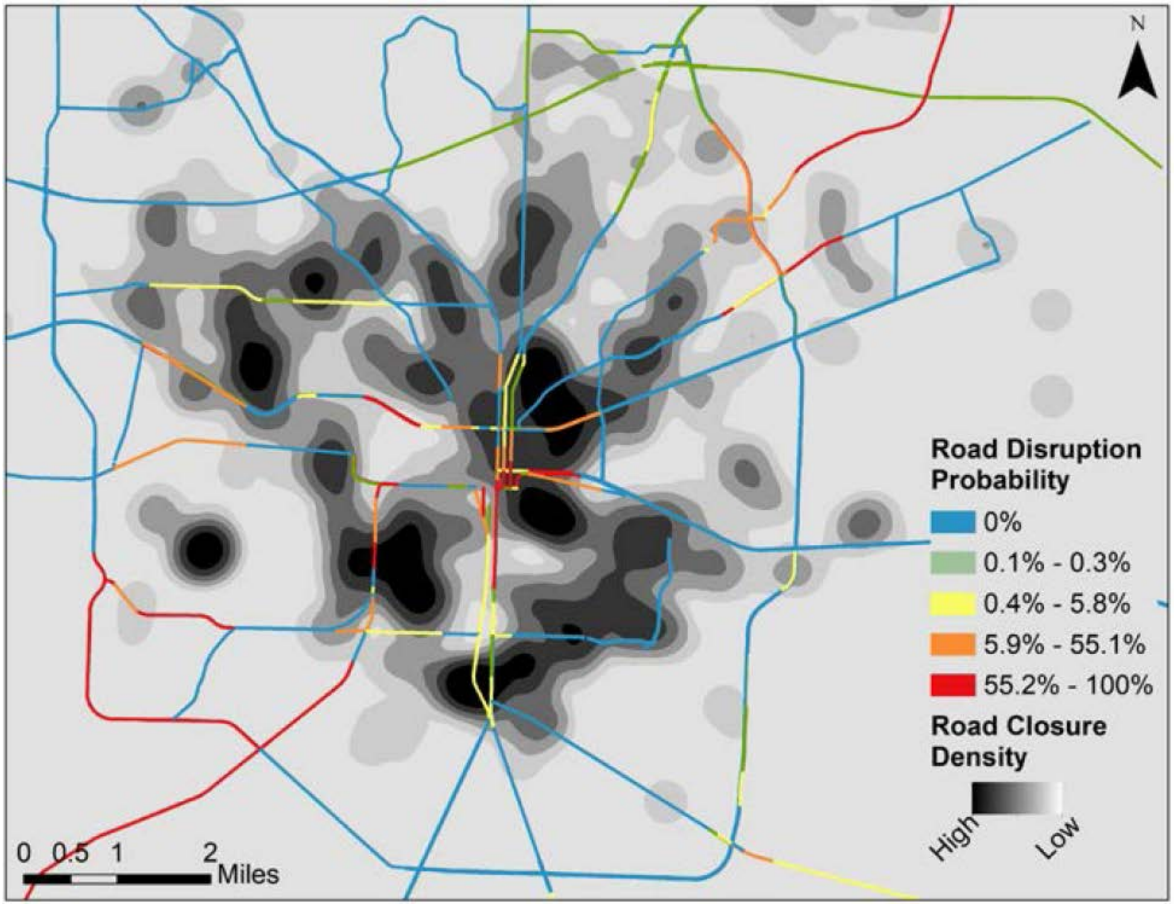


Figure 3.8. Comparison between disruption probability and reported closures

3.5 Conclusions

This study presents a GIS-based methodology to assess and analyze the accessibility to critical emergency facilities (e.g., police stations, fire stations and hospitals) in the context of roadway disruptions due to disasters such as hurricanes. A new metric, namely Accessibility Decrease Index (ADI), was proposed, which measures the change in the emergency response travel time (ERTT) before and in the aftermath of a hurricane such as Hermine. ADIs were used to identify those regions with reduced accessibility to emergency facilities in the aftermath of Hermine. In order to propose a more scalable approach, which can help city officials planning for future hurricanes, a tree failure modeling approach was also presented in order to estimate the probability of hurricane-related roadway disruptions under different hurricane wind speeds based on a Convolutional Neural Network (CNN)- and satellite image-based approach.

City officials can pinpoint the identified critical locations for future improvements (i.e., landscaping modifications to eliminate the threat of fallen trees, and roadway geometry modifications), and enhancing emergency response plans (i.e., providing alternative routes to emergency response crews). Officials might consider having such plans in place for future hurricanes in the critical sections of the city depending on the facility type. There may be other alternatives such as patrolling emergency services, or establishing new emergency response facilities in these sections. Note that any suburban location close to the city can also be supported by these activities. However, this study focused only on the City of Tallahassee, and the proposed approach can be extended to other locations. Another caveat of this study is as follows: If roadway sections get longer, the probability of roadway disruption substantially increases with more trees along these sections. Therefore, as a future work, shorter and/or equal-length roadway sections can be considered to increase the accuracy and reliability of the proposed approach. Future work also will focus on the effect of tree failures on downed power lines in addition to roadways, which will definitely be a more comprehensive analysis to solve disruption-related problems in the aftermath of a hurricane.

Chapter 3 References

1. Widener MJ, Farber S, Neutens T, Horner MW (2015) Spatiotemporal accessibility to supermarkets using public transit: An interaction potential approach in Cincinnati, Ohio. J Transp Geogr 42:72–83 . doi: 10.1016/j.jtrangeo.2014.11.004.
2. Saliba D, Buchanan J, Kington RS (2004) Function and Response of Nursing Facilities During Community Disaster. Am J Public Health 94:1436–1441 . doi: 10.2105/AJPH.94.8.1436.
3. Islam MS, Aktar S (2011) Measuring physical accessibility to health facilities--a case study on Khulna City. World Heal Popul 12:33–41 . doi: 10.12927/whp.2011.22195.
4. Ulak MB, Kocatepe A, Ozguven EE, et al (2017) Geographic Information System – Based Spatial and Statistical Analysis of Severe Crash Hotspot Accessibility to Hospitals. Transp Res Rec J Transp Res Board 2635:90–97 . doi: 10.3141/2635-11.
5. Ozel H, Ozguven EE, Kocatepe A, Horner MW (2016) Aging Population-Focused Accessibility Assessment of Multi-Modal Facilities in Florida. Press Transp Res Rec J Transp Res Board 1–29 . doi: 01590023.
6. Kocatepe A, Ozguven EE, Ozel H, et al (2016) Transportation Accessibility Assessment of Critical Emergency Facilities : Aging Population-focused Case Studies in Florida. In: Zhou J, Salvendy G (eds) Human Aspects of IT for Aged Population: Design for Aging. pp 407–417.
7. Blackwell TH, Kaufman JS (2002) Response time effectiveness: Comparison of response time and survival in an urban emergency medical services system. Acad Emerg Med 9:288–295 . doi: 10.1197/aemj.9.4.288.
8. Pons PT, Markovchick VJ (2002) Eight minutes or less: Does the ambulance response time guideline impact trauma patient outcome? J Emerg Med 23:43–48 . doi: 10.1016/S0736-4679(02)00460-2.
9. Pons PT, Haukoos JS, Bludworth W, et al (2005) Paramedic response time: Does it affect patient survival? Acad Emerg Med 12:594–600 . doi: 10.1197/j.aem.2005.02.013.
10. Ulak MB, Kocatepe A, Konila Sriram LM, et al (2018) Assessment of the hurricane-induced power outages from a demographic, socioeconomic, and transportation perspective. Nat Hazards 1–20 . doi: 10.1007/s11069-018-3260-9.
11. Castelluccio M, Poggi G, Sansone C, Verdoliva L (2015) Land Use Classification in Remote Sensing Images by Convolutional Neural Networks. arXiv Prepr arXiv150800092 1–11.
12. Albert A, Kaur J, Gonzalez M (2017) Using convolutional networks and satellite imagery to identify patterns in urban environments at a large scale, https://arxiv.org/abs/1704.02965.
13. Lawrence S, Giles CL, Ah Chung Tsoi, Back AD (1997) Face recognition: a convolutional neural-network approach. IEEE Trans Neural Networks 8:98–113 . doi: 10.1109/72.554195.
14. Simard PY, Steinkraus D, Platt JC (2003) Best practices for convolutional neural networks applied to visual document analysis. Seventh Int Conf Doc Anal Recognition, 2003 Proceedings 1:958–963 . doi: 10.1109/ICDAR.2003.1227801.
15. Krizhevsky A, Sutskever I, Geoffrey E. H (2012) ImageNet Classification with Deep Convolutional Neural Networks. Adv Neural Inf Process Syst 25 1–9 . doi: 10.1109/5.726791.

16. Zhu Y, Newsam S (2015) Land use classification using convolutional neural networks applied to ground-level images. In: Proceedings of the 23rd SIGSPATIAL International Conference on Advances in Geographic Information Systems - GIS '15. ACM Press, New York, New York, USA, pp 1–4.
17. Costea D, Leordeanu M (2016) Aerial image geolocalization from recognition and matching of roads and intersections, https://arxiv.org/abs/1605.08323.
18. Powell MD, Houston SH, Amat LR, Morisseau-Leroy N (1998) The HRD real-time hurricane wind analysis system. J Wind Eng Ind Aerodyn 77–78:53–64 . doi: 10.1016/S0167-6105(98)00131-7.
19. Vickery P, Skerlj P, Twisdale L (2000) Simulation of hurricane risk in the US using empirical track model. J Struct Eng 126:1222–1237 . doi: 10.1061/(ASCE)0733-9445(2000)126:10(1222).
20. Amirinia G, Jung S (2017) Buffeting response analysis of offshore wind turbines subjected to hurricanes. Ocean Eng 141: . doi: 10.1016/j.oceaneng.2017.06.005.
21. Kakareko G, Jung S, Vanli OA, et al (2017) Hurricane loss analysis based on the population-weighted index. Front Built Environ 3:46 . doi: 10.3389/FBUIL.2017.00046.
22. Census US (2016) Population and Housing Unit Estimates. https://www.census.gov/programs-surveys/popest/data/tables.2016.html.
23. AccuWeather (2017) Tallahassee, FL Radar. https://www.accuweather.com/en/us/tallahassee-fl/weather-radar.
24. NDAA (2017) NWS radar image from Tallahassee, FL. https://radar.weather.gov/radar.php?rid=tlh.
25. Hermine H, Berg R (2016) National Hurricane Center Tropical Cyclone Report.
26. DigiTally (2017) DigiTally. In: City Tallahassee. http://www.talgov.com/Main/digitally.aspx. Accessed 1 Jan 2017.
27. U.S. Census Bureau (2015) 2010 US Census Blocks in Florida. In: Florida Geogr. Data Libr. http://www.fgdl.org/metadataexplorer/explorer.jsp. Accessed 15 Jan 2015.
28. Stiles WS (1959) Color Vision: The Approach through Increment-Threshold Sensitivity. Proc Natl Acad Sci U S A 45:100–114 . doi: 10.2307/90200.
29. Deng YB, Shiota T, Shandas R, et al (1993) Determination of the most appropriate velocity threshold for applying hemispheric flow convergence equations to calculate flow rate: selected according to the transorifice pressure gradient. Digital computer analysis of the Doppler color flow convergence . Circulation 88:1699–708.
30. McPherson EG, van Doorn NS, Peper PJ (2016) Urban tree database and allometric equations. Albany, CA: U.S. Department of Agriculture, Forest Service, Pacific Southwest Research Station.
31. Baker CJ, Bell HJ (1992) Aerodynamics of urban trees. J Wind Eng Ind Aerodyn 44:2655–2666 . doi: 10.1016/0167-6105(92)90057-H.
32. Gardiner BA (1994) Wind and wind forces in a plantation spruce forest. Boundary-Layer Meteorol 67:161–186 . doi: 10.1007/BF00705512.
33. Stacey GR, Belcher RE, Wood CJ, Gardiner BA (1994) Wind flows and forces in a model spruce forest. Boundary-Layer Meteorol 69:311–334 . doi: 10.1007/BF00708860.
34. Asner GP, Goldstein G (1997) Correlating Stem Biomechanical Properties of Hawaiian Canopy Trees with Hurricane Wind Damage1. Biotropica 29:145–150 . doi: 10.1111/j.1744-7429.1997.tb00018.x.

35. ASCE (2010) Minimum design loads for buildings and other structures. ASCE Stand 608 . doi: 10.1061/9780784412916.
36. WeatherSTEM (2017) WeatherSTEM.

Chapter 4 Senior Community Resilience with a Focus on Critical Transportation Infrastructure: An Accessibility-based Approach to Healthcare

The importance of bridges to mobility in transportation is well known. However, the identification of bridges that influence senior mobility has not been evaluated. This is imperative because of human frailties associated with aging. In this chapter, senior community resilience is assessed through accessibility of seniors to hospitals after bridge damage caused by hurricane events. Pinellas County in the Tampa Bay area is used as case-study. The following results are presented: (i) exposure probabilities for hurricane events at bridge locations; (ii) bridge damage state functions and damage state rating assignments using historical data from the National Bridge Inventory (NBI) database; (iii) identification of bridges at risk to hurricane-induced damage; (iv) bridges identified as serving areas (census districts) with dense population of aging people; and (v) the estimated effects of bridge closures on mobility and resilience of the aged population, based on accessibility to hospitals by using congested and free flow travel times obtained from traffic assignment modeling. Findings showed that: (i) 66 bridges prone to hurricane-induced damage were observed to affect 140 selected aging population areas; (ii) bridge closures resulted in about 15% and 75% increase in free flow and congested travel times, respectively; (iii) complete loss of accessibility to hospitals for some aging-dense zones; and (iv) resilience indexes of 0.94 and 0.81 were computed for free flow and congested travel times, respectively. These results which highlight significant loss in senior accessibility to hospitals, emphasize the need for policy discussions on the capabilities of highway bridges for efficient senior mobility.

4.1 Introduction

Transportation infrastructure are essential components of intermodal facilities and important to the reliability, accessibility and resilience of communities. The damage of civil bridge infrastructure poses a major threat to the overall resilience of communities [1]. With the increasing impact of climate change on the environment, different countries and states stand the chance of being vulnerable to natural disasters such as hurricanes, tornadoes and floods.

Recent occurrences of Hurricanes Harvey and Irma have created a stronger sense of awareness for safety during hurricane events, especially for the aging population. Hurricane Irma reported deaths of which many victims were the elderly (65 years and over) in the communities. From 2004 to 2006, five major hurricanes hit the state of Florida that left catastrophic devastations along their paths. The impacts of these hurricanes led to the damage of bridges and civil infrastructure in the state with the most significant being the damage of the I-10 Escambia Bay Bridge. The quantified cost of damage of bridges within the two years were reported as amounting to about $500 million [2]. Natural and man-made hazards have been postulated to have a synergistic effect in the event of failure. Their impacts have led to road posting and bridge closures for serviceability and structural review due to physical damage and the consequent disruption of the transportation network [3-5]. Bridge closures have also been determined to have enormous implications on transportation user cost at the regional level [6].

Bridge elements such as sign structures, movable bridge elements, trusses and railings have been considered to have high extent of damage in the event of hurricanes [7]. With the growing concern for climate change (sea level rise and unexpected storms) and its implication, the risk of hurricane induced floods in Florida is high as most of its cities are at low elevations. Bridges located in high tides and tropical storm zones have experienced unseating of decks, undermining of approach slabs, and deterioration of slope protections, channels, culverts, footing and walls. Probabilities of scouring, vessel collision and advanced deterioration have been reviewed by past research to ascertain the likelihood of occurrence of hurricanes and other hazards and their respective impacts [2, 8, 9].

The concept of community resilience can be explained by the capacity for social units to mitigate hazards, contain its effects after the occurrence, and strategically recover to normal levels of activity [10-12]. As we near 2050, it is expected that the oldest age categories will grow in both numbers and proportions. This changing age structure of the population will affect both families and society [13]. This indicates the need for more resilient communities for the seniors. Resilient communities are unequivocally vital to the safety of a society with a gradually increasing aging population. Recent literature based on the 2010 Census indicates that Florida had the highest percentage of people 65 years and over, representing 17.3% of the total population of the state [14].

Several studies have also revealed the aging population's need for shelters during hazard events [15, 16] while many others have cited the disproportionate effects of disasters on frail older adults; records from the Hurricane Katrina indicated that 49% of those who died were over the age of 75 years [17]. To compound the situation, about 80% of older adults presently have at least one chronic condition such as heart disease, cancer, diabetes, or stroke, while 50% have at least two [18]). Congestion during evacuation activities means that majority of nursing homes and assisted-living facilities would have to shelter in place. Asking the elderly to sit in a bus and making them stay on the road for hours is not the best for their health. This means post-disaster emergency management must enable easy and safe access to healthcare facilities. Road closures or bridge damages can lead to travel delays and increased fatalities among the more frail aging population. The need for building and maintaining infrastructure of relevance to the aging population cannot be overstated. Resilient communities are essential in ensuring the safety and well-being of individuals living in the community, especially during hazard events. Previous studies in this field include research on the role of interdependencies in community resilience [19] and a place-based model for evaluating community resilience [20].

The primary focus of this chapter is to assess senior community resilience by considering the physical transportation infrastructure within the communities. The chapter investigates three issues regarding community resilience, with a focus on bridge infrastructure: (1) the identification of coastal bridges susceptible to hurricane damage; (2) the expected damage condition/states evaluation of the exposed bridges focusing on critical bridges significant to aging mobility; and (3) the development of performance measures for the assessment of the impact of the closures of selected bridges on senior mobility. Using historical condition data from NBI, these effects are evaluated at the network level for the case study region. The above is further explained with a developed resilience index.

4.2 Methodology

In order to achieve the goals for this chapter, the analysis followed these sequential steps: (i) computing exposure probabilities for categorical hurricane events at bridge locations; (ii) developing and applying damage state functions in allocating damage states to bridges using both historical and NBI data fields; (iii) identifying bridges at risk to hurricane-induced damage; (iv) identifying the bridges affecting aging-dense areas; and (v) estimating the effects of bridge closures to aging mobility and resilience through accessibility to hospitals based on congested and free flow travel times obtained from traffic assignment modeling. The framework for bridge selection illustrated in Figure 4.1.

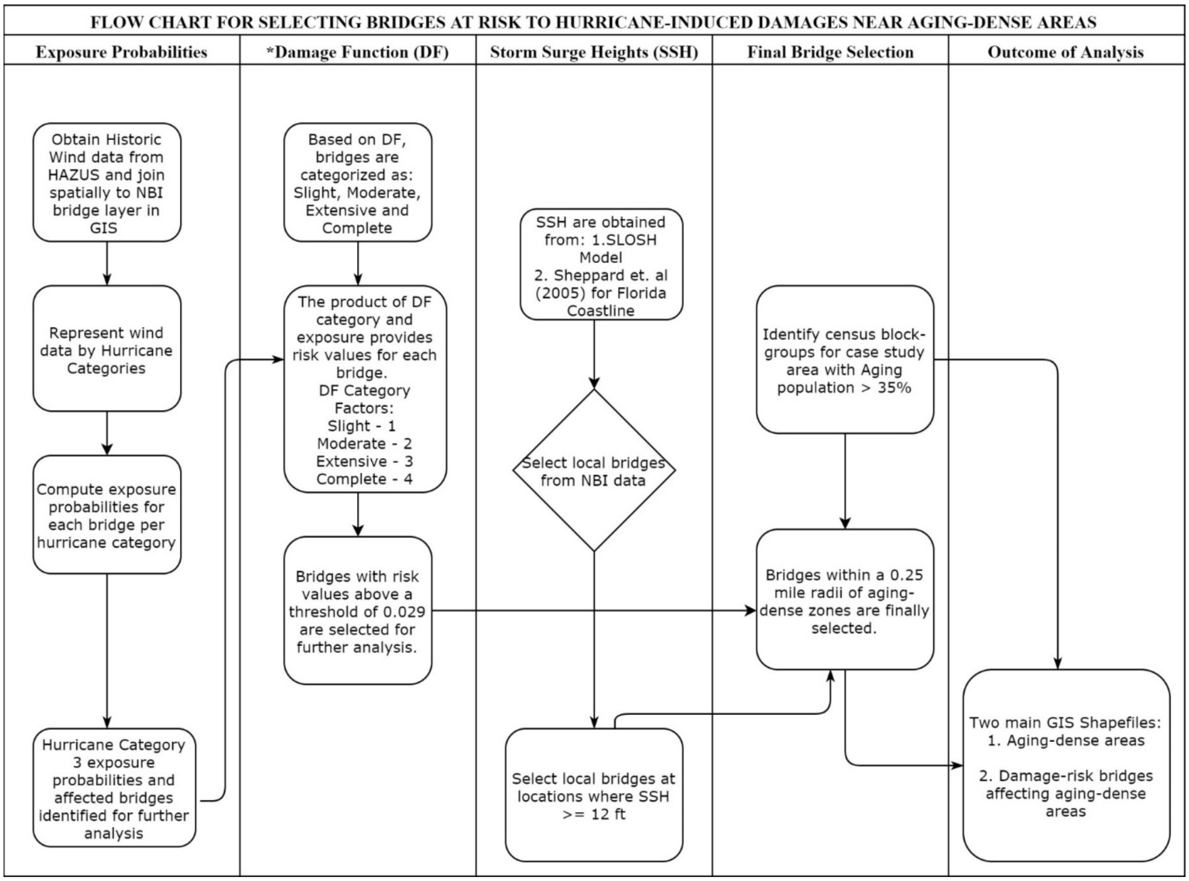


Figure 4.1. Framework for identifying damaged bridges critical to aging-dense areas

4.2.1 Computing Exposure Probabilities for Categorical Hurricane Events at Bridge Locations

Coastal bridges have been identified as critical during storm surges and wave loadings resulting from hurricane events. Many studies have therefore focused on the vulnerability of coastal bridges to storm surges and wave loading, and consequences in terms of agency and user costs [6, 21-23].

To forecast the occurrence of hurricanes based on historical records, the number of storm arrivals at an exact coastal location in a single year is being modeled as Poisson distribution. In this chapter, more specific attention was given to Category 3 Hurricanes due to Florida's coast being prone to such storms and the resulting debilitating effects on physical infrastructure and mobility. Using Hazards United States (HAZUS) software wind data [24], the exposure probabilities (Figure 4.2) were thus estimated. Wind speeds assigned to each census tract were categorized using the well-known Saffir-Simpson Hurricane Wind Scale from the National Hurricane Center. Number of storms arriving at a location in one year is defined as:

$$P_n = \frac{\lambda^n \exp(-\lambda)}{n!} \tag{1}$$

$$F_T(t) = P(T \leq t) = 1 - exp[-\lambda t] \tag{2}$$

where

P_n - probability of n number of storms occurring in a year, and

λ - mean rate of storms per year

$F_T(t)$ – cumulative distribution function of an exponential random variable, T, and t is a random variable representing a given period

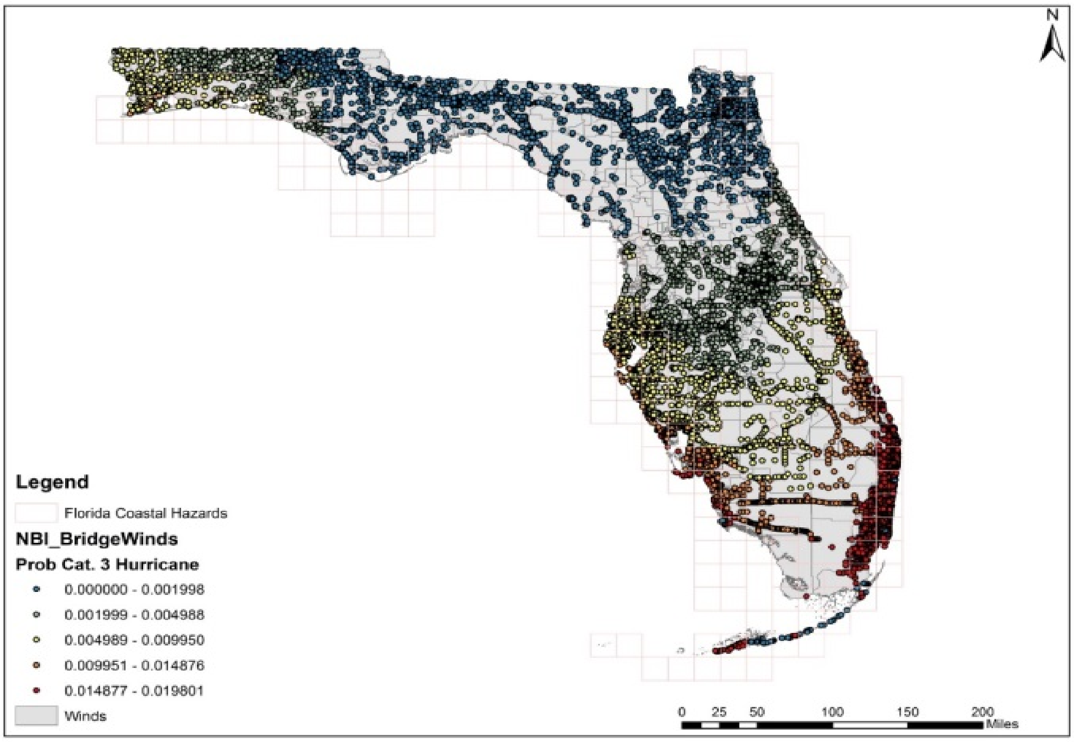


Figure 4.2. Map indicating Hurricane category 3 exposure probabilities for NBI bridges in the State of Florida

4.2.2 Developing and Applying Damage State Functions in Allocating Damage States to Bridges Using both Historical and NBI Data Fields

In assessing the performance of bridges in the case study region, pertinent prior studies on the impact of different hurricanes on bridges in different states of the country were consulted, to evaluate operational and traffic characteristics. The levels of damage were assessed through probability analysis in addition to the engineering expert decision making to predict the expected damages to bridges in the region. Different coded fields (Figure 4.3) from NBI database were also utilized for the analysis. The database fields such as deck ratings, superstructure ratings, substructure ratings, culvert and channel ratings, are evaluated along with other explanatory variables such as age, location of bridge, type of bridge (fixed or movable), waterway adequacy, and traffic characteristics. From the data, damages are categorized into slight, moderate, extensive or complete levels based on the categories previously developed [2]. Table 4.1 is a qualitative description of the bridge damage states.

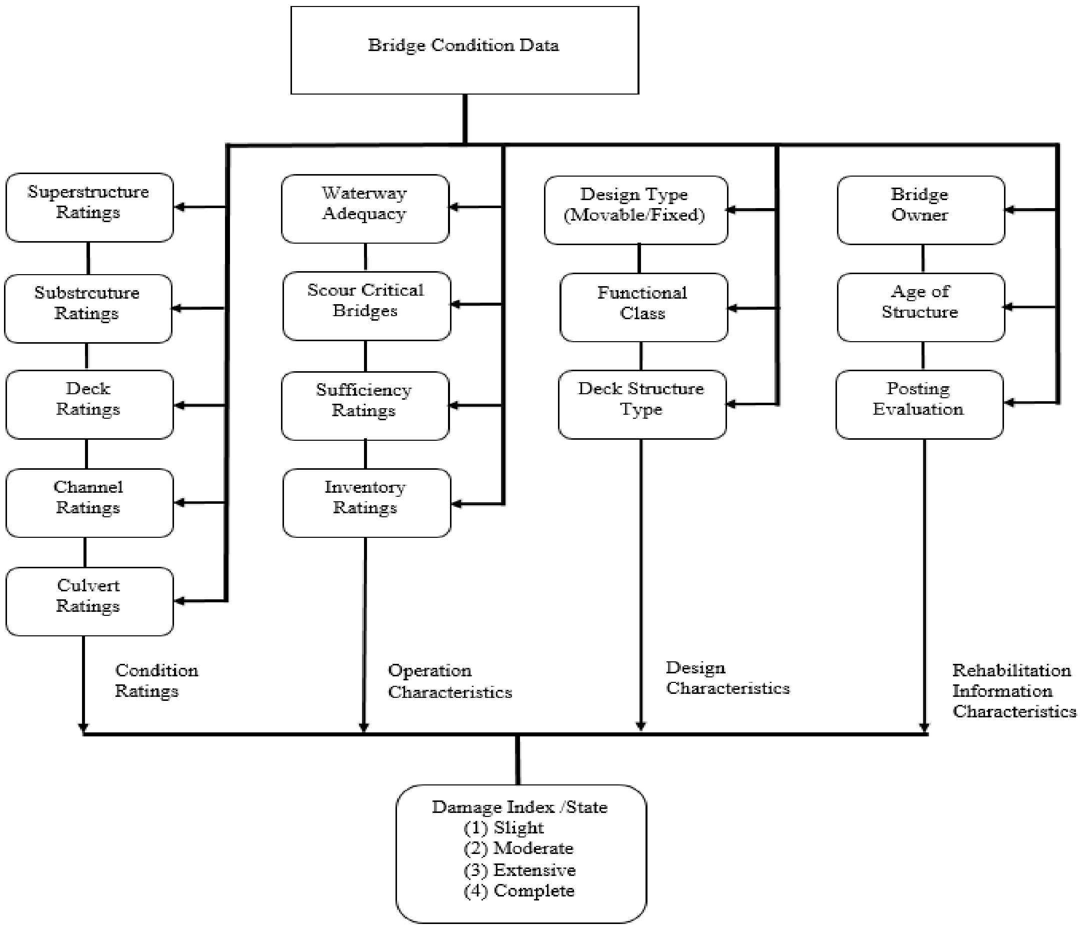


Figure 4.3. NBI fields selected for computing bridge damage states

A total of 82 damaged bridges from Florida, Louisiana, Mississippi and Alabama were used in mapping out the damage state of bridges in the case study region of this research. There were 25% of the bridges categorized as movable bridges, with the remaining being fixed bridges of different types. Based on an extensive review of damage history, the movable bridges are expected to suffer different levels of impact ranging from damage of elements such as the operator facility, failure of gates, signals and motors due to wind, and storm impacts to mechanical and electrical faults. On the other hand, fixed bridges are anticipated to fail through unseating of decks, scouring, failure of slope protection and abutments as well as pier and column failure due to barge collision.

Table 4.1. Qualitative Damage State Descriptions Defined by Amending HAZUS for Typical Hurricane-Induced Bridge Damage

Damage state	Hazard Type	Description
Slight	Hurricane (Bridges)	Debris (tree logs, boats etc.) insignificant scour, minor damage to channel, and damage to non-structural elements such as street lights, luminaires, lamps, mounted lights, small signs, and railing. Poses no serious structural problem. Structure may need minor repairs. Minor damages such as loss of sign panels, twisting of luminaires, etc. Poses no serious structural problem. Structure may need minor repairs
	Hurricane (Sign Structures)	Minor damages such as loss of sign panels, twisting of luminaires, etc. Poses no serious structural problem. Structure may need minor repairs
Moderate	Hurricane (Bridges)	Washouts at embankments/approach slabs and damage to slope protection system. Overtopping due to flood (deck/slab or culvert) and significant scour. Moderate damages including undermining, to abutments, columns, piles, caps, footings, channel, and bulkhead. Moderate damages to fenders, navigational lights, warning gates, traffic signals, operator facilities, electrical conduit, cables, PLCs, transformers, and equipment. Poses serious structural/functional problems. Structure is repairable.
	Hurricane (Sign Structures)	Loss of horizontal members, and minor cracks on foundation. Moderate damage to horizontal, vertical members, or foundation. Poses serious structural/functional problems. Structure is repairable.
Extensive	Hurricane (Bridges)	Extensive damage to culvert, deck, superstructure, substructure, and pertinent bridge elements. Structure is repairable. Poses serious structural/functional problems. May require full replacement of structural component(s).
	Hurricane (Sign Structures)	Extensive damage to panels, chords, trusses, and foundation. Poses serious structural/functional problems. Structure is repairable. May require full replacement of structural component(s).
Complete	Hurricane (Bridges)	Severe damage to all or critical structural and non-structural components. Structure needs to be completely replaced.
	Hurricane (Sign Structures)	Severe damage to all or critical structural components. Structure needs to be completely replaced.

A number of NBI fields were selected to assess the individual bridge operational characteristics and ratings. Four key variables were found to be statistically-correlated to the damage states of bridges based on the movable bridge data. These fields with correlation coefficient of 30% and higher were the superstructure condition rating, substructure condition rating, posting evaluation, and scour critical condition. For fixed bridges, the key fields which were observed to have high correlation with levels of damage were the deck condition rating, superstructure condition rating, substructure condition rating, inventory rating, deck geometry evaluation, and scour critical condition. To assign the level of damage of bridges some assumptions were made, and steps followed, summarized as follows:

1. Bridge damage states were categorized based on the type of bridge (either fixed or movable).
2. Bridges with unknown foundations are expected to suffer the worst damage (either complete or extensive).
3. Non-waterway bridges as well as bridges which are not scour critical are ranked based on the inventory and operational characteristics (deck, superstructure and substructure ratings).
4. Bridges without deck, superstructure and substructure such as culverts and channels are assigned damage states based on other significant NBI fields.
5. Bridges could be assigned two damage states based on certain special characteristics.

Table 4.2 represents the initial list of NBI fields used in the damage state assessment of bridges.

Table 4.2. NBI fields considered for bridge damage state assessment

NBI Field	Operational Characteristics
Owner	State, County, Local
Functional Class	Interstate / Non-Interstate
Age	Old (>=50yrs) / New(<50yrs)
Year Reconstructed	Recent / Previous
Waterway Adequacy	Adequate / Inadequate
Scour Critical Bridges	High (>3) / Low (<=3)/ Unknown Foundation
Type of Service	Highway / Railroad, Interchange
Kind of Material	Wood /Timber, Steel, Concrete
Type of Design	Fixed / Movable
Condition ratings (Deck, Superstructure, Substructure)	High (>4) / Low (<=4)
Channel and Channel Protection Rating	High (>7) / Low (<=7)
Culverts Rating	High (>8)/ Low (<=8)
Minimum Vertical Underclearance	Adequate / Inadequate
Sufficiency Rating	High (>50%)/ Low (<=50%)
Status	Functionally Adequate / Inadequate

4.2.3 Discussion for Damage State Analysis

From the analysis, it is observed that a total number of 1162 bridges out of the 1393 fixed bridges are expected to be subjected to slight or moderate damage conditions. The two damage states which amount to 83% of the entire inventory were found to be in consonance with the evaluation made by previous studies [4, 25] where many bridges were estimated as slight or moderate damage levels. Further results indicated that the remaining bridges have equal likelihood of experiencing extensive or moderate damages with each damage state amounting to 8% of the entire bridge count. It is noteworthy to state that about 87 bridges were classified to experience either complete or extensive damage state because of their peculiar characteristics. A total of 313 culverts were identified from the inventory with about 88% of them suffering slight damage while the rest experience other damage states as follows: 11% subjected to moderate damage state; 14% being extensive, and 12% complete damage levels, respectively.

For the 21 recorded movable bridges, about 19% of them were expected to be impacted slightly, 32% of the movable bridges suffering extensive to complete damage levels, with 26% being extensive and 23% with complete damage.

4.2.4 Identifying Bridges at Risk to Hurricane-induced Damage

Bridges at risk to hurricane-induced damages were identified by combining bridge damage states with exposure probabilities. Storm surge heights (SSH) based on data from a previous Florida study [25] and the Sea, Lake, and Overland Surge from Hurricanes (SLOSH) model [26] were also used to identify local bridges at risk to damage. The SLOSH model is a computerized model developed by the National Weather Service (NWS) to estimate storm surge heights and winds resulting from historical, hypothetical, or predicted hurricanes.

Local bridges at locations where SSH were greater than or equal to 12 feet were identified as being at risk to damage. The threshold of 12 feet was chosen since storm surge heights above that level are known to cause inundations, while SLOSH model outputs indicated that SSH for the case study area were mostly in the selected range. Aging-dense zones were selected as census block groups with over 35% of the total population being 65 years old and above. All identified bridges within a quarter-mile radius to these locations were then selected as those having a direct influence on mobility to and from the aging-dense zones. The results are shown in Figure 4.4.

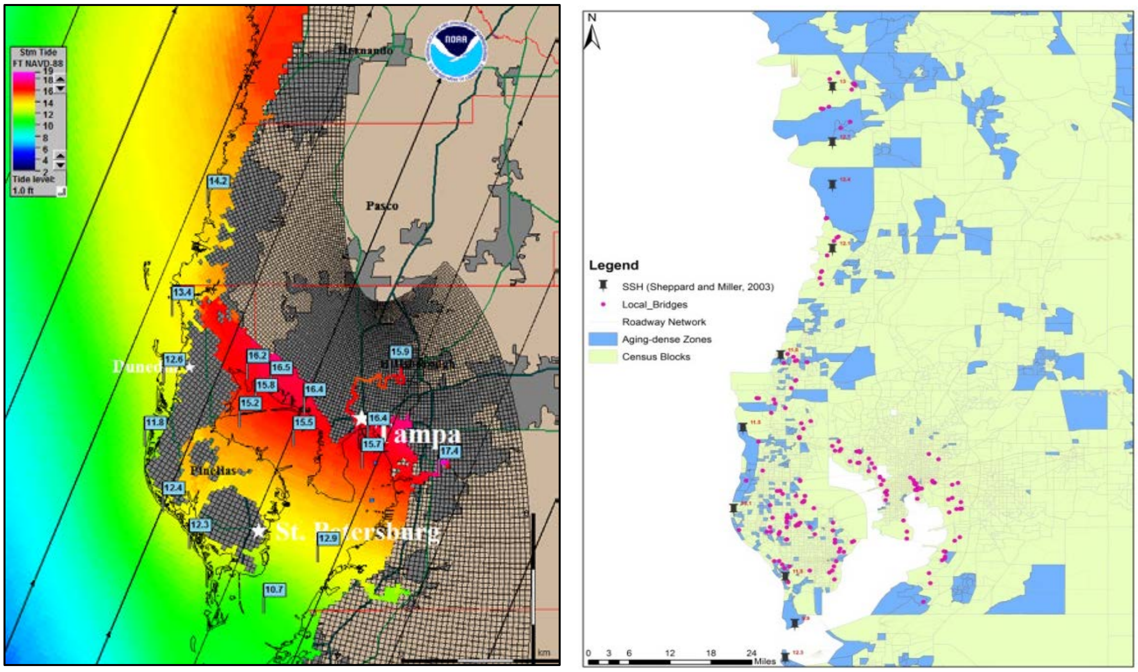


Figure 4.4. SSH from SLOSH model and selected local bridges based on SSH threshold for the Tampa Bay area

4.2.5 Computing Resilience

Accessibility is used as a mobility measure in estimating the effects of bridge damages on commute of aged population to hospitals. This measure is expressed as the least cost (travel time) between origins (aging-dense zones) and destinations (hospital facilities) prior to and after the hurricane events. The approach is executed through the use of Environmental Systems Research Institute (ESRI)'s ArcGIS software, applying the closest facility extension. A similar concept was noted as being adopted in literature for determining geographic access to cancer care [27]. In our study, travel time data was based on the Tampa Bay Regional Planning Model (TBRPM) provided by the Florida Department of Transportation (FDOT)'s District 7 Metropolitan Planning Organization (MPO). The model was exported into ArcGIS and used to obtain origin-destination matrices for both free flow travel time (FFT) and congested travel times (CTT) with the aid of the network analyst extension. Resilience was computed by combining measures of functionality and recovery times for bridge closure events as illustrated in Figure 4.5.

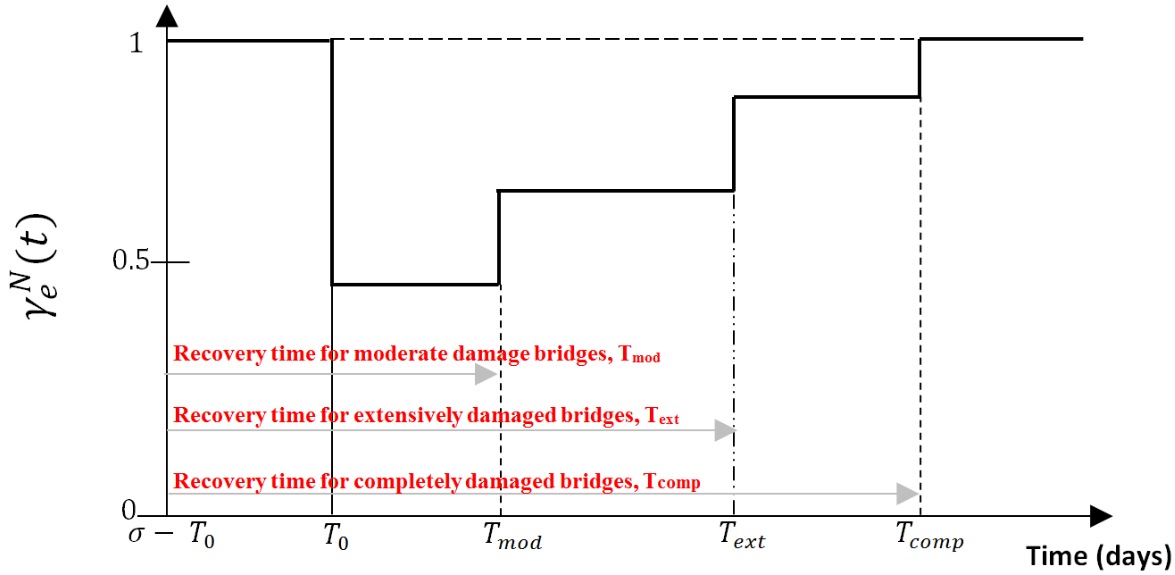


Figure 4.5. Resilience based on bridge damage states used in this chapter

Functionality Measure:

$$\gamma_e^N(t) = \frac{Acc_i^T(t)}{Acc_i^T(t\_dis)} \tag{3}$$

where:

$Acc_i^T(t)$ – minimum travel time for ith O-D prior to hazard

$Acc_i^T(t\_dis)$ – minimum travel time for ith O-D after hazard

N – transportation network

Resilience

$$R = 1 - \frac{1}{\bar{T}} \int_0^{\bar{T}} (1 - \gamma_e^N(t))dt \tag{4}$$

where:

$\bar{T}$ – mean time to recovery in days

4.3 Case Study for Accessibility Analysis

The general area for Tampa Bay, the case study, is an area prone to hurricane strikes and storm surges. The Tampa Bay is a vast natural harbor and estuary which is linked to the Gulf of Mexico on the west central coast of Florida. The specific county for this case study is Pinellas County.

4.3.1 Data Set

Information for hospital facilities, census block groups, and Florida coastal hazards demarcations were obtained from Florida Geographic Data Library (FGDL). The NBI bridges shapefile was obtained from ESRI, while roadway shapefile and Tampa Bay Regional Planning Model (TBRPM), were retrieved from the Florida Standard Urban Transportation Model Structure (FSUTMS). The hospital shapefile contained attributes for hospital facility locations and capacities (number of beds) for the case study area. The census block groups also contained various demographic details for each block group division within the jurisdiction. The coastal hazards dataset contained cartographic representation of the coastal counties in the State of Florida that are vulnerable to coastal erosion and inundation from sea level rise or storm surge. The database file and its associated layers are utilized by coastal managers to comprehensively assess hurricane induced storm surge hazards along the coast of Florida. Figure 4.6 shows the area with the hospitals and damaged bridges.

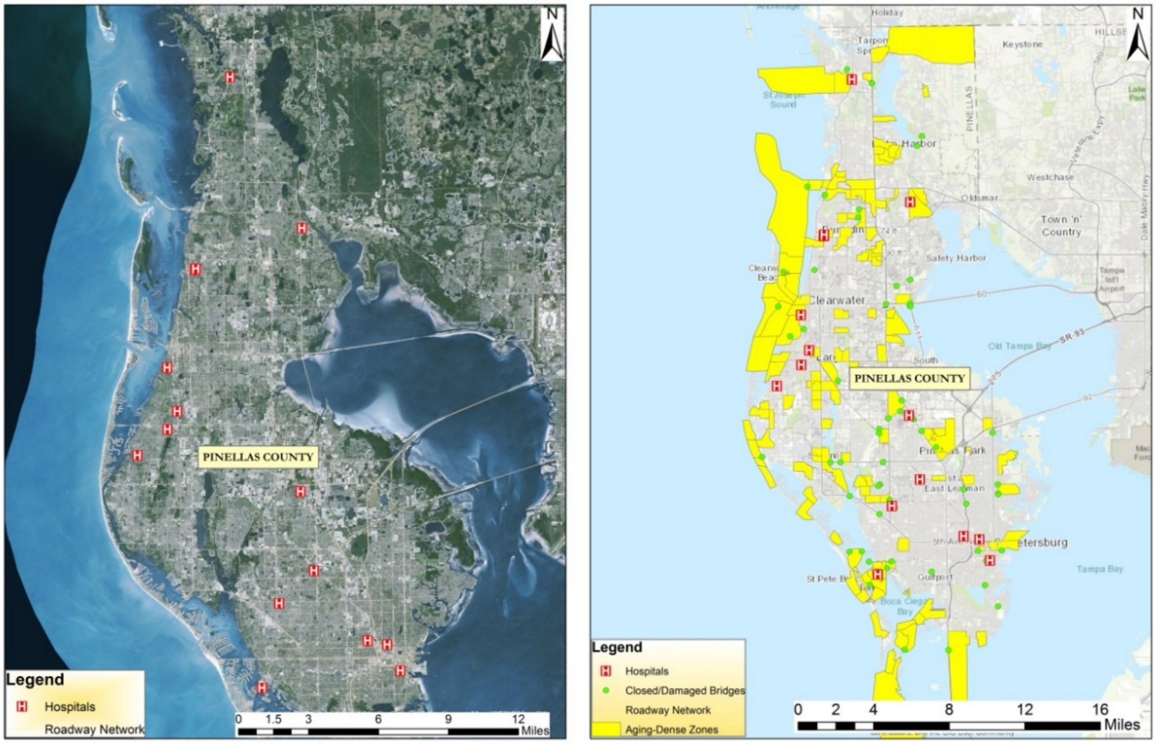


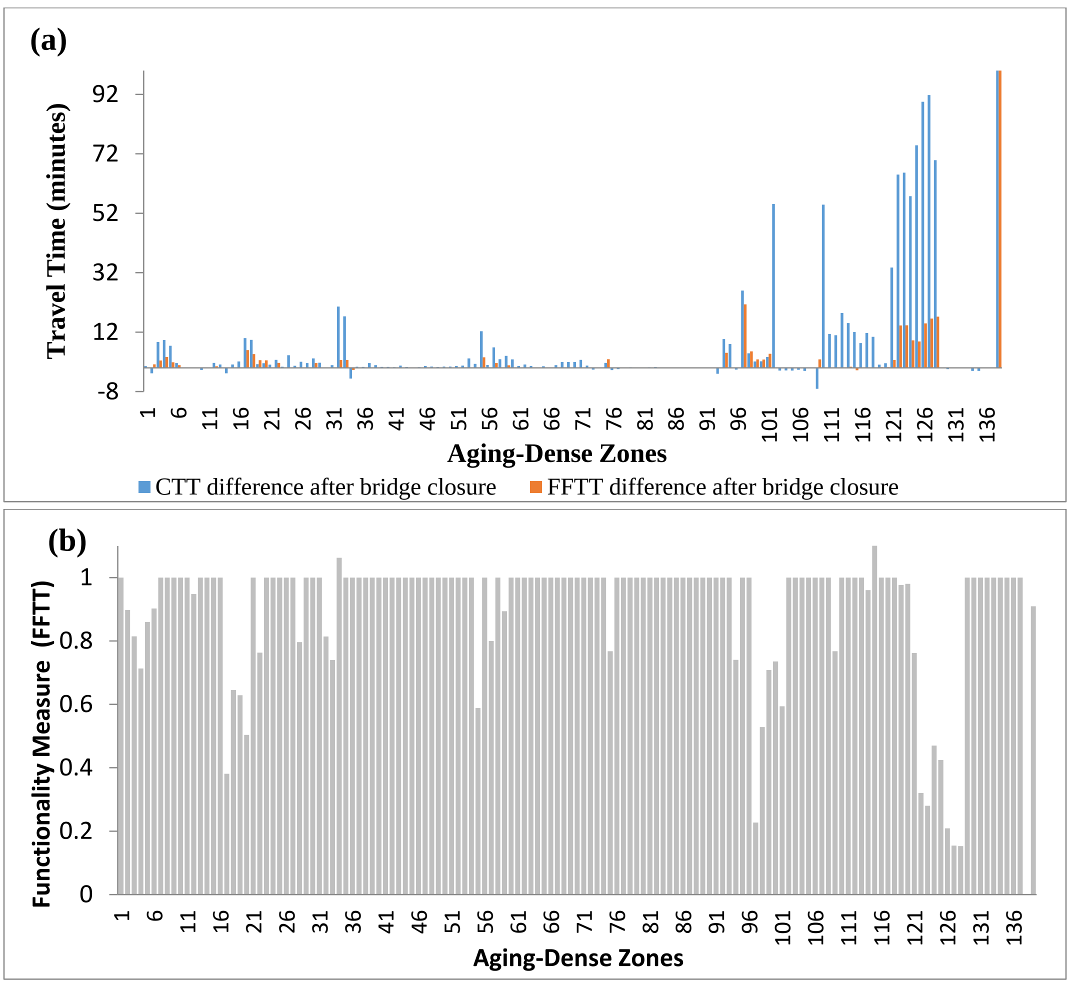
Figure 4.6. Maps showing Pinellas County with the locations of hospitals and expected damaged bridges near to aging-dense zones.

4.4 Results and Discussion

The accessibility analysis for this study included the selection of 140 census block groups that were identified as aging-dense zones, with these zones serving as incident areas. It has been previously indicated in this chapter that 66 bridges critical to the mobility of the above-mentioned zones are at risk of closure during a Category 3 Hurricane. Also, 15 designated hospital locations were identified, serving as facilities of interests for accessibility analysis. The scenarios adopted in this study assumes that the identified-at-risk bridges are damaged during the storm, hence, remains closed after the hurricane event for repair activities which are envisaged to take lengthy periods. Furthermore, as normal activities resume, accessibility of seniors to primary healthcare, expected to be affected, is evaluated. The network analysis methodology used in this study is quite rigorous since resilience is measured based on the senior accessibility to healthcare under normal road network functionality, compared with senior healthcare accessibility during closures of the identified bridges.

In the network analysis, the TBRPM is utilized to initially capture FFT and CTT for the Pinellas County for the base model (without bridge closures). The network is then modified to capture the damaged bridges within the TBRPM environment and re-analyzed until a new equilibrium is reached hence adequately representing FFT and CTT during bridge closures. The closest facility analysis tool in network analyst (an extension in ArcGIS) is then used to obtain the minimum times for each aging-dense area to access healthcare prior to and after the hurricane event. Figure 4.7 depicts the effects of bridge closures on the travel times between the aging population zones and the hospitals. There was an observed increase from about 900 to 1100 minutes and from about 1200 to 2100 minutes, for the FFT and CTT, respectively. This indicates travel time increases of about 15% and 75% for FFT and CTT, respectively. Furthermore, an additional total travel distance of 52.85 miles was observed for FFT and CTT.

The mean travel times after bridge closures increased from 6.6 to 7.76 minutes and from 8.43 to 15.1 minutes for FFT and CTT, respectively. Figure 4.7a represents changes in minimum travel time after bridge closures for each aging-dense zone. Figures 4.7b and 4.7c are derived from equation 3, and account for functionality computed as the ratios of minimum travel times for each trip, prior to and after bridge closures. It is observed that while many age-dense zones did not record changes in FFT as observed in Figure 7b, Figure 4.7c indicates significant changes for CTT resulting from the effects of congestion on travel. This is because post-hazard recovery involves an increase in roadway demand leading to significant impact of bridge closures on network travel time. Such conditions warrant the prioritization and rapidity of bridge restoration activities in order to ensure that the emergent health needs of the aging population are met. Results shown in Figure 4.8 indicate minimum travel times and routes to various hospitals based on FFT and CTT for both the base model (Figures 4.8a and 4.8b) and interrupted network (Figures 4.8c and 4.8d). The color variations seen indicate the minimum travel times from the centroids to the nearest hospital.



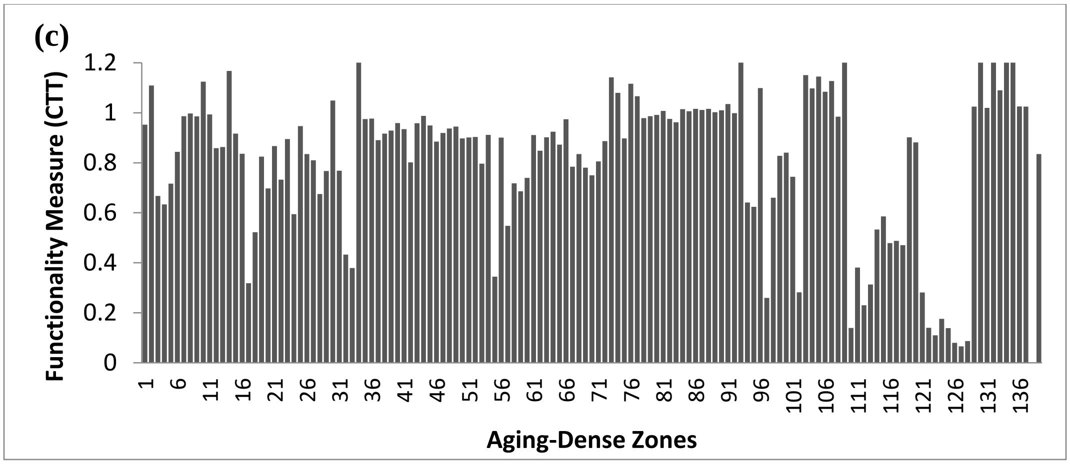


Figure 4.7. Results indicating differences in FFT and CTT prior to and after bridge closures, as well as FFT and CTT based functionality measures.

While FFT accessibility maps (Figures 8a and 8c) show some similarities, bridge closures are observed to significantly affect accessibility of the aging population to hospitals. This difference is further evident when comparing CTT accessibility maps (Figures 4.8b and 4.8d). These results support findings in Figure 4.7. Additionally, three aging-dense zones were observed as being without access to hospitals after bridge closures. These are seen on the South boundary of Pinellas County and are highlighted green in Figures 4.8c and 4.8d.

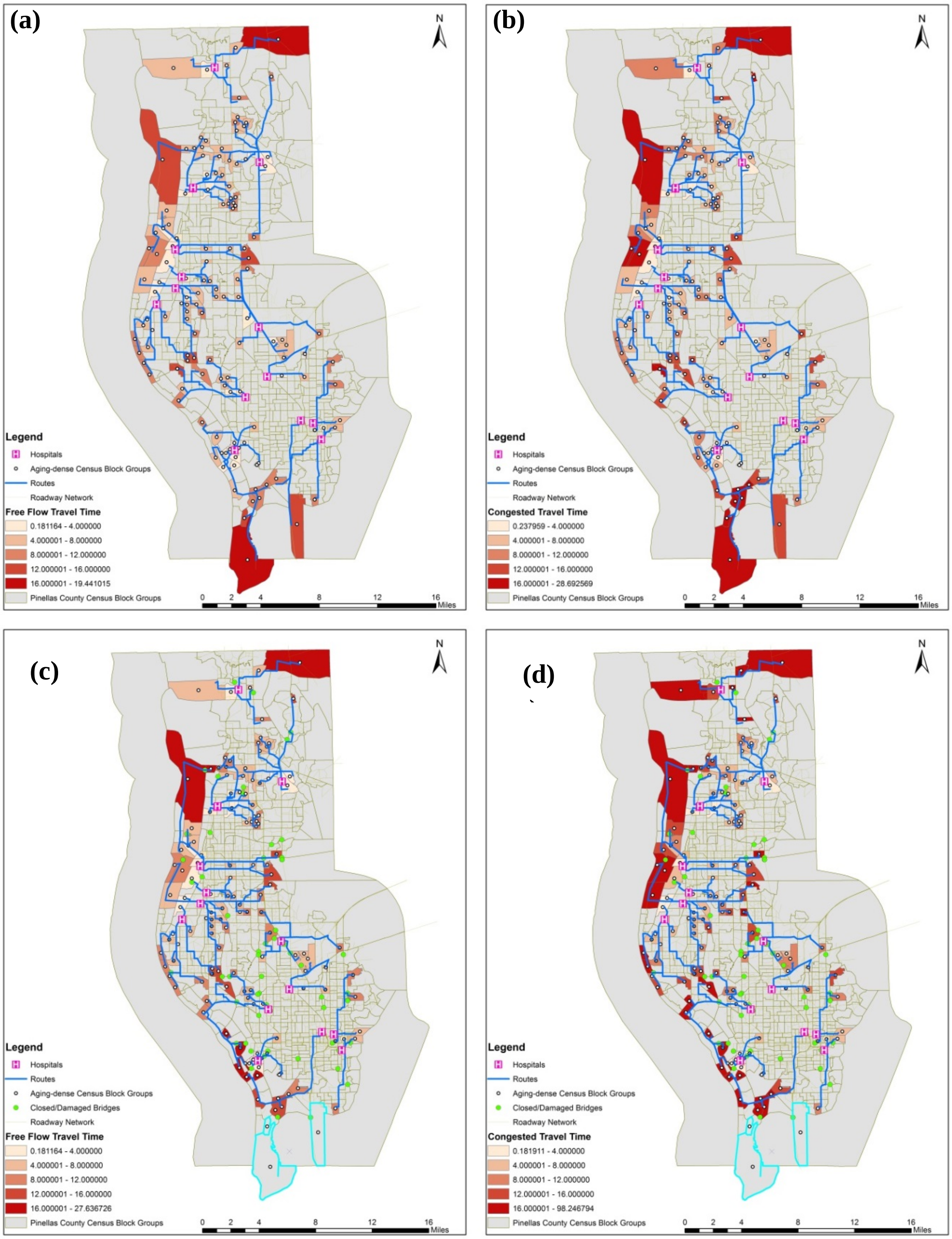


Figure 4.8. Minimum FFT and CTT to hospitals for each aging-dense location: a.), b.) base network and c.), d.) bridge closure-network

Resilience indexes for the bridges were based on the functionalities computed from FFT and CTT using equation 3, as well as the expected bridge recovery times after bridge damages. The damage states for the 66 identified bridges were considered as moderate, extensive, and complete levels; slightly damaged bridges were not taken into account in this study as those bridges are normally not expected to undergo total closures. In computing resilience index, it is expected that in most cases, moderately-damaged bridges will be restored before those bridges with extensive and finally, the restoration of completely-damaged bridges. Computations included the re-evaluation of the traffic assignment model for network functionality improvement after bridge restoration for each damage state. The resulting resilience index scaled from 0 to 1 is computed based on equation 4, with 1 representing a perfectly functional network and zero otherwise. It is expected that six days after all bridges are closed, moderately damaged bridges will be restored, and this results in functionality improvement from 0.87 to 0.94 considering FFT, and from 0.57 to 0.83 considering the CTT. Extensively-damage bridges are expected to open 30 days after the hurricane event, resulting in functionality increase from 0.94 to 0.96, and 0.83 to 0.85, respectively, considering FFT and CTT. All bridges are expected to be restored 29 days after extensively damaged bridges are opened. The resilience index for this study was computed as 0.94 and 0.81 for FFT and CTT respectively, implying significant loss in senior mobility hence the need for mitigation measures.

4.4 Conclusions

This chapter has presented an accessibility-based approach to healthcare for evaluating senior community resilience with a focus on bridge damages. The research approach adopted included the identification of bridges which are at high risk to damage as a result of Category 3 Hurricane events by computing wind exposure probabilities at each bridge location, assigning damage states to bridges by using NBI attribute fields and historic data, and finally identifying local bridges subjected to high storm surge heights during hurricanes. The adopted approach was based on previous studies which identified bridge damages to areas of high-wind exposure probabilities. The essence of this study was to provide an approach for identifying at-risk bridges by utilizing available data sources on hurricane winds, storm surge heights, operational characteristics (from NBI) of previously damaged bridges due to hurricanes, and NBI characteristics of bridges presently located in coastal areas exposed to categorical hurricanes. Furthermore, the importance of the identified bridges to aging-dense zones was evaluated as well as the effects of bridge closures to aging population accessibility to hospitals.

Results indicated that 66 bridges were of specific interest (using proximity analysis) to areas with a high percentage of aging population. Movable bridges were identified as being very vulnerable during hurricanes. Accessibility analysis was modeled based on closest facility analysis by using the identified 140 aging-dense zones and 15 hospitals as origins (incident locations) and destinations (facilities), respectively. Significant increases in minimum travel time to hospitals were observed for both free flow travel time (FFT) and congested travel times (CTT). This was more evident for CTT due to congested roadway conditions, yielding a resilience index of 0.81 compared to 0.94 from FFT. Aging population accessibility to hospitals is of utmost importance due to human frailties that come with age, and because some age dense zones were more affected than others in this study. The need for increased financial investment in maintaining and reinforcing both state and locally maintained bridges are requisite for efficient senior mobility. With the population of those 65 years and above on the increase, this need is timely. Increase in roadway travel times, reduced functionalities, and decreased resilience communicated through this study highlights that senior members are affected by bridge closures.

The authors recommend that further studies which entail the application of more precise recovery times for affected bridges are undertaken to improve the computation of a more rigid resilience index which will help to communicate the effects of bridge closures on community resilience. Various transportation agencies are also encouraged to develop and maintain a database to document hazard-induced bridge damages and post-disaster recovery activities (especially recovery times). This will contribute to identifying the extent of bridge damage, evaluate recovery efforts, and enhance mitigation measures and/or rapidity during post-hazard recovery.

Chapter 4 References

1. Zhang, P., & Peeta, S. (2011). A generalized modeling framework to analyze interdependencies among infrastructure systems. *Transportation Research Part B: Methodological*, *45*(3), 553-579.
2. Sobanjo, J. O., & Thompson, P. D. (2013). Development of risk models for Florida's bridge management system. Florida State University, Technical Report BDK83 977-11. Accessed May 12, 2017 from https://ntl.bts.gov/lib/47000/47800/47813/FDOT-BDK83-977-11-rpt.pdf
3. FDEM (Florida Division of Emergency Management) 2006b Hurricane Task Force Report. WWW document, http://www.floridadisaster.org/documents/HurricaneTaskForceReport.pdf
4. Padgett, J., DesRoches, R., Nielson, B., Yashinsky, M., Kwon, O. S., Burdette, N., & Tavera, E. (2008). Bridge damage and repair costs from Hurricane Katrina. *Journal of Bridge Engineering*, *13*(1), 6-14.
5. Salman, A. M., & Li, Y. (2016). Age-dependent fragility and life-cycle cost analysis of wood and steel power distribution poles subjected to hurricanes. *Structure and Infrastructure Engineering*, *12*(8), 890-903.
6. Twumasi-Boakye, R., & Sobanjo, J. O. (2017). Evaluation of transportation user costs based on simulated regional network models. *Transportation Research Record: Journal of the Transportation Research Board*, No. 2612, 2017, pp. 121–131. http://dx.doi.org/10.3141/2612-14
7. Inkoom, S., Sobanjo, J. O., Thompson, P. D., Kerr, R., & Twumasi-Boakye, R. (2017). Bridge Health Index: Study of Element Condition States and Importance Weights. *Transportation Research Record: Journal of the Transportation Research Board*, (2612), 67-75.
8. Xu, L., & Brown, R. E. (2008, July). A hurricane simulation method for Florida utility damage and risk assessment. In *Power and Energy Society General Meeting-Conversion and Delivery of Electrical Energy in the 21st Century, 2008 IEEE* (pp. 1-7). IEEE.
9. Thompson, P., Sobanjo, J., & Kerr, R. (2013). Modeling the risk of advanced deterioration in bridge management systems. *Transportation Research Record: Journal of the Transportation Research Board*, (2360), 52-59.
10. Bruneau, M., Chang, S. E., Eguchi, R. T., Lee, G. C., O'Rourke, T. D., Reinhorn, A. M., ... & Von Winterfeldt, D. (2003). A framework to quantitatively assess and enhance the seismic resilience of communities. *Earthquake spectra*, *19*(4), 733-752.
11. Bruneau, M., & Reinhorn, A. (2007). Exploring the concept of seismic resilience for acute care facilities. *Earthquake Spectra*, *23*(1), 41-62.
12. Zorn, C. R., & Shamseldin, A. Y. (2015). Post-disaster infrastructure restoration: A comparison of events for future planning. *International Journal of Disaster Risk Reduction*, *13*, 158-166.
13. Ortman, J. M., Velkoff, V. A., & Hogan, H. (2014). *An aging nation: the older population in the United States* (pp. 25-1140). United States Census Bureau, Economics and Statistics Administration, US Department of Commerce.

14. Howden, Lindsay M., and Julie A. Meyer. "Age and sex composition: 2010." *2010 Census Briefs, US Department of Commerce, Economics and Statistics Administration. US CENSUS BUREAU* (2010).
15. Gibson MJ. We can do better: lessons learned for protecting older persons in disasters. Washington (DC): AARP; 2006. http://assets.aarp.org/rgcenter/il/better.pdf.
16. Fernandez, L. S., Byard, D., Lin, C. C., Benson, S., & Barbera, J. A. (2002). Frail elderly as disaster victims: emergency management strategies. *Prehospital and disaster medicine*, *17*(2), 67-74.
17. Brunkard, J., Namulanda, G., & Ratard, R. (2008). Hurricane katrina deaths, louisiana, 2005. *Disaster medicine and public health preparedness*, *2*(4), 215-223. doi: https://doi.org/10.1097/DMP.0b013e31818aaf55
18. Centers for Disease Control National Center for Health Statistics, 2004, The State of Aging and Health in America 2004, http://www.cdc.gov/aging/pdf/State_of_Aging_and_Health_in_America_2004.pdf
19. Cimellaro, G. P., Solari, D., Renschler, C. S., Reinhorn, A. M., & Bruneau, M. (2013). Community resilience index integrating network interdependencies. In *Structures Congress 2013: Bridging Your Passion with Your Profession* (pp. 1789-1799).
20. Cutter, S. L., Barnes, L., Berry, M., Burton, C., Evans, E., Tate, E., & Webb, J. (2008). A place-based model for understanding community resilience to natural disasters. *Global environmental change*, *18*(4), 598-606.
21. Maxey, D. (2006, August). Emergency Repair of the I-10 Bridge Over Escambia Bay. In *FICE/FDOT Design Conference, Orlando, Fla*.
22. Padgett, J. E., Spiller, A., & Arnold, C. (2012). Statistical analysis of coastal bridge vulnerability based on empirical evidence from Hurricane Katrina. *Structure and infrastructure engineering*, *8*(6), 595-605. doi: http://dx.doi.org/10.1080/15732470902855343
23. Stearns, M., & Padgett, J. E. (2011). Impact of 2008 Hurricane Ike on bridge infrastructure in the Houston/Galveston region. *Journal of Performance of Constructed Facilities*, *26*(4), 441-452. doi: http://dx.doi.org/10.1061/(ASCE)CF.1943-5509.0000213
24. Vickery, P. J., Skerlj, P. F., Lin, J., Twisdale Jr, L. A., Young, M. A., & Lavelle, F. M. (2006). HAZUS-MH hurricane model methodology. II: Damage and loss estimation. *Natural Hazards Review*, *7*(2), 94-103. doi: https://doi.org/10.1061/(ASCE)1527-6988(2006)7:2(94)
25. Sheppard, D. M., & Miller Jr, W. (2003). *Design storm surge hydrographs for the Florida coast* (No. 4910 45-04-920). url: http://www.fdot.gov/research/Completed_Proj/Summary_STR/FDOT_BC354_70_rpt.pdf

26. Jelesnianski, C. P., Chen, J., & Shaffer, W. A. (1992). *SLOSH: Sea, lake, and overland surges from hurricanes* (Vol. 48). US Department of Commerce, National Oceanic and Atmospheric Administration, National Weather Service.
27. Onega, T., Duell, E. J., Shi, X., Wang, D., Demidenko, E., & Goodman, D. (2008). Geographic access to cancer care in the US. *Cancer*, *112*(4), 909-918.