University Transportation Research Center - Region 2

Final Report

Modeling Disaster Operations From An Interdisciplinary Perspective In The New York-New Jersey Area

Performing Organization: New York University

April 2016

Sponsor:
University Transportation Research Center - Region 2

University Transportation Research Center - Region 2

The Region 2 University Transportation Research Center (UTRC) is one of ten original University Transportation Centers established in 1987 by the U.S. Congress. These Centers were established with the recognition that transportation plays a key role in the nation's economy and the quality of life of its citizens. University faculty members provide a critical link in resolving our national and regional transportation problems while training the professionals who address our transportation systems and their customers on a daily basis.

The UTRC was established in order to support research, education and the transfer of technology in the field of transportation. The theme of the Center is "Planning and Managing Regional Transportation Systems in a Changing World." Presently, under the direction of Dr. Camille Kamga, the UTRC represents USDOT Region II, including New York, New Jersey, Puerto Rico and the U.S. Virgin Islands. Functioning as a consortium of twelve major Universities throughout the region, UTRC is located at the CUNY Institute for Transportation Systems at The City College of New York, the lead institution of the consortium. The Center, through its consortium, an Agency-Industry Council and its Director and Staff, supports research, education, and technology transfer under its theme. UTRC's three main goals are:

Research

The research program objectives are (1) to develop a theme based transportation research program that is responsive to the needs of regional transportation organizations and stakeholders, and (2) to conduct that program in cooperation with the partners. The program includes both studies that are identified with research partners of projects targeted to the theme, and targeted, short-term projects. The program develops competitive proposals, which are evaluated to insure the mostresponsive UTRC team conducts the work. The research program is responsive to the UTRC theme: "Planning and Managing Regional Transportation Systems in a Changing World." The complex transportation system of transit and infrastructure, and the rapidly changing environment impacts the nation's largest city and metropolitan area. The New York/New Jersey Metropolitan has over 19 million people, 600,000 businesses and 9 million workers. The Region's intermodal and multimodal systems must serve all customers and stakeholders within the region and globally.Under the current grant, the new research projects and the ongoing research projects concentrate the program efforts on the categories of Transportation Systems Performance and Information Infrastructure to provide needed services to the New Jersey Department of Transportation, New York City Department of Transportation, New York Metropolitan Transportation Council , New York State Department of Transportation, and the New York State Energy and Research Development Authorityand others, all while enhancing the center's theme.

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The modern professional must combine the technical skills of engineering and planning with knowledge of economics, environmental science, management, finance, and law as well as negotiation skills, psychology and sociology. And, she/he must be computer literate, wired to the web, and knowledgeable about advances in information technology. UTRC's education and training efforts provide a multidisciplinary program of course work and experiential learning to train students and provide advanced training or retraining of practitioners to plan and manage regional transportation systems. UTRC must meet the need to educate the undergraduate and graduate student with a foundation of transportation fundamentals that allows for solving complex problems in a world much more dynamic than even a decade ago. Simultaneously, the demand for continuing education is growing – either because of professional license requirements or because the workplace demands it – and provides the opportunity to combine State of Practice education with tailored ways of delivering content.

Technology Transfer

UTRC's Technology Transfer Program goes beyond what might be considered "traditional" technology transfer activities. Its main objectives are (1) to increase the awareness and level of information concerning transportation issues facing Region 2; (2) to improve the knowledge base and approach to problem solving of the region's transportation workforce, from those operating the systems to those at the most senior level of managing the system; and by doing so, to improve the overall professional capability of the transportation workforce; (3) to stimulate discussion and debate concerning the integration of new technologies into our culture, our work and our transportation systems; (4) to provide the more traditional but extremely important job of disseminating research and project reports, studies, analysis and use of tools to the education, research and practicing community both nationally and internationally; and (5) to provide unbiased information and testimony to decision-makers concerning regional transportation issues consistent with the UTRC theme.

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Principal Investigator(s):
Dr. Kaan Ozbay
Professor
City Smart Lab, Department of Civil & Urban Engineering
New York University
Brooklyn, NY 11201
Email: kaan.ozbay@nyu.edu

Dr. Satish Ukkusuri
Professor
Lyles School of Civil Engineering
Purdue University
West Lafayette, IN 47907
Tel: (765) 494-2296
Email: sukkusur@purdue.edu

Performing Organization:
New York University

Sponsor(s):
University Transportation Research Center (UTRC)

To request a hard copy of our final reports, please send us an email at utrc@utrc2.org

Mailing Address:

University Transportation Reserch Center
The City College of New York
Marshak Hall, Suite 910
160 Convent Avenue
New York, NY 10031
Tel: 212-650-8051
Fax: 212-650-8374
Web: www.utrc2.org

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Ph.D. Student, Transportation Program

Wei Hao*: Research Fellow*

Andriy Blagay: *Graphic Intern*

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16. Abstract

The objective of this research was to develop a systematic methodology to understand overall demand, destination type choice, and route choice decisions in the aftermath of a hurricane. It will consider transportation, social and other relevant factors such as actions of agencies dealing with emergency operations. Data collected from past hurricanes will be used to estimate and calibrate the evacuation demand and behavior models. This research is focused on the New York/New Jersey metropolitan area, and will utilize available data sources in this area to conduct the proposed work.

The research team proposed a data-driven research approach that "piggy-backed" on the new available social media and other electronic data, in addition to survey data. Major steps of our research methodology were:

1. Review literature related to hurricane demand with a focus on the choices of individuals in terms of departure time, mode, and destination.
2. Identify the effects of previous evacuation experience and familiarity with the transportation system in addition to other more commonly used factors such as type of socio-economic and demographic characteristics of evacuees and others.
3. Identify data sources especially rare data such as traffic data from recent hurricanes that can be used to capture the impact of traditional and non-traditional factors on the complex evacuee behavior.
4. Acquire data and estimate "agent based models" that can capture individual level interactions and homogeneities in the presence of rare yet catastrophic event of hurricanes
5. Compare the prediction of the proposed model with those of more traditional models of hurricane demand prediction.

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Executive Summary

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1 INTRODUCTION

1.1 Background

The United Nations International Strategy for Disaster Reduction (UN/ISDR) and the Centre for Research on the Epidemiology of Disasters (CRED) annually present official figures of the number of natural disasters and their impacts. Statistics from recent years show that the number of disasters has been increasing significantly. These events, and their devastating consequences, have highlighted the need for an efficient and responsive recovery after disasters. Hurricanes are one of the most dangerous and costly weather-related natural hazards in the United States (US). Considering the fatalities per natural hazard from 1981-2010, hurricanes were responsible on average for about 47 fatalities per year. This is one of the highest fatality rates, as compared to floods, lightning related events, and tornados. However, between 2004 and 2013 the average fatalities per year related to hurricanes increased to 108, which ranks hurricane and heat as the two most deadly natural hazards (NOAA 2014).

Between 2005 and 2008, hurricanes and in a smaller proportion tropical and subtropical storms, were responsible for 1,835 fatalities in the Atlantic basin (1,551 fatalities and monetary damage over $125.5 billion in the US) (Brown et al., 2010; Brennan et al., 2009; Frankin and Brown 2008; Beven et al., 2008). The most catastrophic hurricane in this time period was Hurricane Katrina (1500 deaths and around $81 billion in property damage in the US) (Beven et al., 2008). Hurricane Irene, the most recent one, was a large and destructive event which affected many regions from the Caribbean to the East Coast during the 2011 hurricane season. In its path, the hurricane was responsible for 56 deaths, and in the US the monetary losses were estimated at $15.6 billion, mainly in the East coast in New York, Vermont and New Jersey.

Considering its potentially devastating impacts and the importance of timely and effective evacuation before and during a hurricane, it is the responsibility of public agencies to understand all dimensions of an evacuation process. Since the public transportation system is vital for the evacuation of the population located within a risk region, comprehensive evacuation plans must integrate transportation theory with evacuation behavior theory. Lindell and Prater (2007) integrated social scientists' research on population behavior with transportation engineers' evacuation models. They classify models in three major groups: trip generation, departure timing, and destination/route choice.

Trip generation is related with understanding the question of whether or not to evacuate. Several researchers (Hasan et al., 2011; Dash and Gladwin, 2007; Lindell et al., 2005; Whitehead et al., 2000; Gladwin and Peacock, 1997) use statistical and econometric models to understand this decision, which is a function of variables related to households' socio-economic characteristics, household location, and hazard characteristics. Likewise, understanding departure timing allows the prediction of dynamic evacuee demand and the development of effective evacuation strategies. This phenomenon have been studied by some researchers (Hasan et al., in press; Fu and Wilmot 2004, 2006; Sorensen, 1990) using statistical and econometric models related with environmental, social, and demographic factors.

However, the destination choice of evacuees during hurricane evacuation requires assumptions and definitions to understand and model this choice. This topic has been only studied by a few researchers (Cheng et al., 2008; Modali, 2005; Chen, 2005; Mei, 2002; Barrett et al., 2000; Southworth, 1991). Three types of zonal-level models have been used to represent destination choice, i.e. gravity model (Modali, 2005; Chen, 2005), intervening opportunity model (Chen, 2005), and Multinomial Logit (MNL) models (Cheng et al., 2008). These models only consider houses of friends and relatives, and hotels as possible destinations. Likewise, they focus on zonal trip distribution without incorporating the choice among destination types and consider the percentage of evacuees traveling to each destination type as a given input.

A better understanding of how the household-level characteristics affect destination type choice is important for public agencies. Knowing the relationship between the household-level characteristics and destination type choice help public agencies 1) recognize public shelter demand and improve their locations and settings, 2) develop better evacuation notice per population segment giving advice on what destination types to choose, 3) develop cooperative programs with hotels guarantying some levels of demand, and 4) recognize the potential regions that are attractive for evacuees in order to anticipate traffic congestion. Likewise, a comprehensive hurricane evacuation model must consider all dimensions involved in this process and destination type choice is not an exception.

1.2 Research Objective

<u>The objective of this research is to develop a systematic methodology to understand overall demand, destination type choice, and route choice decisions in the aftermath of a hurricane</u>. It will

consider both transportation and social and other relevant factors such as actions of agencies dealing with emergency operations. Original data including traffic volume data, incident data and evacuation behavior survey data from past hurricanes will be used to estimate and calibrate the evacuation demand and behavior models, as well as new traffic data from Hurricanes Irene and Sandy in 2011. To the best of our knowledge this is the first model of its type found in hurricane evacuation modeling literature. Also, Hurricanes Irene and Sandy are among the major hurricanes in the Northeast areas, thereby allowing us to understand the determinants of different behavioral dimensions during hurricane evacuation.

1.3 Research Approach

We propose a data-driven research approach that will “piggy-back” on the new available social media and other electronic data, in addition to survey data. Major steps of our research methodology are:

1. Develop a summary of the recent literature related to hurricane demand with a focus on the choices of individuals in terms of departure time, mode and destination.
2. Identify the effects of previous evacuation experience and familiarity with the transportation system in addition to other more commonly used factors such as type of socio-economic and demographic characteristics of evacuees and others.
3. Identify data sources especially rare data such as traffic data from Hurricane Irene on NJ Turnpike that can be used to capture the impact of traditional and non-traditional factors on the complex evacuee behavior.
4. Acquire data and estimate “agent based models” that can capture individual level interactions and homogeneities in the presence of rare yet catastrophic event of hurricanes.
5. Compare the prediction of this new model with more traditional models of hurricane demand prediction.

This report is organized as follows. Chapter 2 provides an extensive review of the literature and explains the overall evacuation process, specifically within the context of understanding social network influences on evacuation decision making. Chapter 3 presents a comparative analysis of traffic incidents during Hurricanes Irene and Sandy which can affect the operational performance of the transportation systems during hurricanes. Chapter 4 analyzes evacuation behavior and constructed an evacuation response curve based on traffic data collected during Hurricane Irene in Cape May County, New Jersey. Chapter 5 investigates empirical evacuation traffic patterns based on traffic data collected during Hurricane Irene in New Jersey. Chapter 6 develops evacuation behavior models using post-Hurricane Irene and Sandy survey data. Chapter 7 summarizes this report and lists the major conclusions of this work.

2 LITERATURE REVIEW

This chapter provides an extensive review of the literature and explains the overall evacuation process, specifically within the context of understanding social network influences on evacuation decision making. In this chapter, we consider the complex process of hurricane evacuation in five broad categories: 1) evacuation timing behavior, 2) evacuation mobilization time, 3) evacuation destination choice, 4) evacuation routing strategy and 5) evacuation mode choice. First, we discuss the steps related to the overall hurricane evacuation process and the subsequent sections discuss in detail the existing research efforts regarding these general behavioral issues listed above.

2.1 Hurricane Evacuation in General

The overall process of evacuation is complicated in the coastal regions where the population growth is high but road network capacity growth is limited (Dow and Cutter 2002). Lindell *et al.* (2005) and Gladwin *et al.* (2007) presented the necessity of efficient evacuation management and planning for people in coastal regions is well recognized across stakeholders. In short-notice disasters like hurricanes, evacuation management agencies usually identify alternate evacuation routes depending on the expected path of the hurricane prior to the evacuation, and official routing recommendations are provided to evacuees. Evacuation orders are supposed to allow clearance time for traffic to get past bottlenecks like bridges and roads with limited traffic capacity. However, evacuees often delay departure and wind up leaving together and on similar routes showing synchronization in terms of their evacuation behavior (Wolshon 2002). Previous studies explored different governing factors such as hurricane trajectory and warning system, household locations and types, characteristics of the evacuees, etc. to explain the complex dynamic process of hurricane evacuation (Baker 1991, Gladwin *et al.* 2001, Urbina and Wolshon 2003, Gladwin *et al.* 2007, Lindell and Prater 2007b, Carnegie and Deka 2010).

2.2 Hurricane Evacuation Behavioral Modeling

2.2.1 Evacuation Timing Behavior

There are several studies on evacuation departure time where the main focus is to derive empirical distributions without the inclusion of different influential factors. The research by Lindell and

Prater (2007a) can be referred to for a detailed review on evacuation timing studies. However, as far as behavioral studies related to evacuation timing decisions are concerned, only a few attempts have been made in literature so far. Sorensen (1991) used path analysis for evacuation timing behavior and included a set of sequential decisions made over time with evolving hurricane forecasts in this process. This study considered ordinary least square (OLS) regression to capture the relationship between departure time and several significant variables.

A sequential logit choice model was developed by Fu and Wilmot (2004b) to capture the decision of whether to evacuate or not when each household reviews the conditions surrounding an approaching hurricane. Later in 2006, they developed a hazard-based model to understand evacuation decision with the evacuation timing decision jointly. One of the assumptions of the model is that the evacuation decision and the evacuation timing decision are made simultaneously and both decisions are influenced by similar influential variables. But this assumption may not be valid because although these two decisions are connected, the factors affecting these two decisions may be different. In addition to that, the model included the households who did not evacuate by considering the corresponding observations as right censored. This may overestimate the number of households who actually evacuate.

The above evacuation timing models (Sorensen 1991, Fu and Wilmot 2004b, Lindell and Prater 2007a) mostly included environmental, social and demographic factors. A hazard-based model to capture evacuation timing behavior was developed by Hasan *et al.* (2010). In terms of hurricane evacuation, the duration from the moment of receiving a hurricane warning to the moment of actual evacuation could be captured by hazard-based models. The hazard model developed in Hasan *et al.* (2010)provides valuable insights to understanding the temporal dynamics of the household's evacuation decision making process. In addition, they captured the heterogeneous risk response in the modeling framework by including random parameters in the model. The key focus of this study was to understand the causal factors that influence the evacuation timing decision by using data from Hurricane Ivan which affected the Caribbean and United States on September 2, 2004.

2.2.2 Evacuation Mobilization Time

From a different perspective, Dixit *et al.* (2008) explained different factors associated with the duration between the time that the evacuation decision is made and the time of evacuation by the evacuees of Hurricane Frances which passed the north of the Caribbean sea on August 24, 2004.

They referred this duration as the "mobilization time." The study showed how the impact of a previous hurricane affects the mobilization time in a subsequent hurricane by estimating the two models simultaneously. Previously, the mobilization time was defined as the difference between the time of departure and the time of warning receipt (Sorensen 1991). Some other studies referred mobilization time as the "evacuation delay," and revealed several factors affecting the delay by considering isolated hurricanes (Voght 1991, Heath *et al.* 2001, Stopher *et al.* 2005). Later in 2012, Dixit et al. (2008) used mobilization time to structurally model risk attitudes which can predict the total number of evacuees along with the associated departure time. Recently, Sadri *et al.* (2013a) introduced random parameters to understand this time gap between the decision to evacuate and the actual departure from the home or from the evacuation zone when the evacuation warning is applicable.

2.2.3 Evacuation Destination Choice

This section reviews the previous work related to hurricane evacuation destination choice and highlights the need for household level destination type choice models. Lindell and Prater (2007a) referred to the point in a given transportation network as the proximate destination, where the evacuee comes out of the risk area. They also refer to both the town/city and the type of accommodation, where evacuees will stay until they can return to their homes as the ultimate destination which was the focus in that study. On the other hand, Barrett *et al.* (2000) assumed the location, where an evacuee is predicted to seek safety or the evacuation location recommended in the evacuation plan as the ultimate evacuation destination. Southworth (1991) recognized that evacuees display dispersive nature in their destination selection being influenced by different factors: location of friends and relatives, the speed of the hazard, etc. Mei (2002) and Modali (2005) found no model of trip distribution for evacuations other than the Oak Ridge Emergency Management System (OREMS) package prior to their work. Wilmot *et al.* (2006) applied both a gravity model and an intervening opportunity model for the purpose of trip distribution during hurricane evacuation where the gravity model performed better. However, these models are only applicable to aggregated zones and further calibration is needed for each accommodation type. Cheng *et al.* (2008) developed two separate multinomial logit (MNL) models for hurricane evacuation destination choice at the zonal level, specifically for friends and relatives and hotel/motel choice.

As part of evacuation destination choice, homes of friends and relatives are the most preferred accommodation type, followed by hotels/motels (Smith and McCarty 2009). Public shelters are required for some types of emergencies (for example, nuclear power plant) and are critical resources for some evacuees despite their relative lack of use (Mileti *et al.* 1992). Public shelters as evacuation destination are preferred by lower income group of evacuees as revealed by previous studies (Moore *et al.* 1963, Mileti *et al.* 1992, USACE 2001). A recent study by Mesa-Arango *et al.* (2012) developed a household level hurricane evacuation destination type choice model that accounts for the utility differences among different destination options by using the Hurricane Ivan 2004 survey (Morrow and Gladwin 2005). In this study, a nested logit (NL) model has been developed where variables related to household location, socioeconomic characteristic, evacuation attributes, previous hurricane experience, and hurricane position, etc. were found to influence the choice of a type of destination.

2.2.4 Choice of Routing Strategy

In terms of emergency planning and network level analysis, a number of research efforts could be mentioned. For example, Wilmot and Mei (2004) differentiated between the relative accuracy of different forms of trip generation for evacuating traffic. Another study explained and offered guidance on the development of dynamic traffic models for hurricane evacuations by Barrett *et al.* (2000). Murray-Tuite and Mahmassani (2004) developed a way to predict delays and traffic densities while accounting for family gathering behavior in evacuations by using trip chain simulations. Robinson et al. (2009) evaluated the impact of incidents on the time to complete an evacuation of a large metropolitan area. Some research (Wolshon *et al.* 2005a, Wolshon *et al.* 2005b) focused on areas that are needed to be considered for a successful evacuation plan. Dixit *et al.* (2007) used microscopic modeling and introduced a process called “network breathing” for the external controls on entry and exit of evacuating vehicles into the evacuation network to improve overall outflow. Liu *et al.* (2006) developed a cell-based network model in order to determine optimal staging schemes to reduce congestion on an evacuation network by providing a more uniform distribution of demand. They assumed that the starting time for the evacuation of each staged zone could only be controlled.

As far as routing strategy during evacuation is concerned, Cova and Johnson (2003) developed a network flow model to identify optimal lane-based evacuation routing plans in a complex road network. The key idea was to reduce traffic delays at intersections in evacuations. Shen *et al.* (2008) proposed two models to address the highly uncertain and time-dependent nature of transportation systems during disruption. One of the models offered dynamic routing control in a stochastic time varying transportation network which routes the vehicles using the shortest path algorithm while accounting for the capacity of the links and delays due to congestion and they claimed that the proposed routing strategy minimizes evacuation time to the safety shelter locations. Lämmel and Flötteröd (2009) compared two different routing strategies in a multi-agent simulation of a real world evacuation environment. They claimed that the cooperative routing approach generates a substantially higher evacuation throughput than an alternative non-cooperative routing strategy. Chiu and Mirchandani (2008) showed that the route choice behavior of an evacuee, as opposed to selecting optimal routes, results in subsequent degradation of evacuation effectiveness. They introduced a FIR (Feedback Information Routing) strategy which could augment the evacuation effectiveness to an optimal situation. In this study, they applied an MNL-based route-choice Evacuation Route Choice Model (ERCM) that is calibrated by the stated preference approach. However, an important point they emphasized is the fact that ERCM is not intended to serve as an exact representation of the actual route-choice behavior during evacuation but to devise a plausible route choice behavior to show how actual route choice results in evacuation performance deviating from the optimal route choice behavior.

Existing literature suggests that few studies have addressed the routing decisions made by evacuees during a hurricane evacuation. A recent study by Robinson and Khattak (2010) revealed that the preferences of evacuees as to whether or not to detour from a route when faced with congestion are predictable and controllable by using ATIS (Advanced Traveler Information Systems). Stated preferences analysis indicates that drivers on the Hampton Roads, Virginia will be highly motivated to use an alternate route when longer than expected delays are observed on the intended route when ATIS information is available on alternate routes. The survey was intended to provide enough information to provide data for behavior based experiments, but it was not possible to ensure a representative sample of the population of the whole region. This is why they emphasized that a demographically accurate survey must be obtained before employing the results in a real world situation.

The research conducted by Wu *et al.* (2012) focused on household evacuation logistics in nine counties/parishes which conducted evacuations during Hurricanes Katrina and Rita. The study reported the choice of evacuation destination and route in different counties and presented the necessity of developing mathematically tractable models of household evacuation route choice. Murray-Tuite *et al.* (2012a) reported that many evacuees base their routing decisions on the belief that the selected route would be shortest and/or it is their usual or most familiar route during hurricane evacuation. Recently, Sadri *et al.* (2013c) developed a mixed logit model to understand the choice of routing strategies during hurricane evacuation by using data from Hurricane Ivan in 2004. The model identified and explained several important factors that influence the routing behavior of evacuees among three significant alternatives: selecting the usual route, following the routes recommended by emergency officials and possibly detouring or route switching. Another recent study explored the choice of major bridges for the evacuees from Miami Beach by using a random parameter logit-based approach (Sadri *et al.* 2013b).

2.2.5 Choice of Evacuation Mode

In addition, several studies discuss evacuation transportation modes in particular. Kang *et al.* (2007a) compared respondents' stated hurricane evacuation response with their actual behavior two years later during Hurricane Lili. Respondents were found to have accurate expectations about their actual evacuation behavior, information sources, evacuation transportation modes, number of vehicles taken, and evacuation shelter types. Lindell and Prater (2007a) revealed that those who are able to take personal vehicles were still largely assumed to have taken them, both from the citizen and management agency perspectives. They also recommended accounting for cars pulling boat trailers in hurricane evacuation modeling.

Other studies (Renne *et al.* 2008, Renne *et al.* 2009) investigated the needs for the carless and special needs populations who are dependent on others for transportation, such as, transit/emergency management agency, family, friends, neighbors, etc. Deka and Carnegie (2010) found a strong preference for private vehicle (84%) based on stated preference survey data and the choice of other modes depended on familiarity with a particular transit option and the unavailability of a personal vehicle. Wu *et al.* (2012), using hurricane Katrina/Rita data, confirmed that the most common way for households to evacuate is to take their own vehicles. According to this study, one exception is that older evacuees are less likely to have a registered vehicle and as a result they depend on carpooling rather than public transportation. They found only 11% of evacuees not taking their own cars, of which 71% rode with someone else and 28% used another form of transportation.

Wilmot and Gudishala (2013) found that approximately 96 % of the evacuees stated that they either used car or van to evacuate during Hurricane Gustav which affected Haiti on the August 25, 2008. Evacuees also used other modes of transportation, like bus (0.8%), sharing ride with someone else (2.8%), etc. Murray-Tuite *et al.* (2012b) developed a simultaneous optimization model that included multiple modes of transportation and found that the optimization model results indeed do not always correspond to evacuees' anticipated behavior. Another study pointed out that taking fewer vehicles during evacuation could reflect their concerns to keep the family close together, whereas taking more vehicles could indicate a desire to preserve personal property (Murray-Tuite *et al.* 2012a).

Villegas *et al.* (2013) investigated specific characteristics of tourists that influence their affective and cognitive responses to a hurricane warning message, and found that the method of transportation did not influence risk and fear perceptions except for tourists interviewed in the coastal sites. Lindell *et al.* (2011) reported that majority of evacuees (90%) traveled in their own vehicles, whereas 9% rode with peers and less than 1% used public transportation during Hurricane Lili which affected the Caribbean on September 21, 2002. According to their results, the average number of vehicles per household was 1.7, the average number of trailers per household was 0.35, and 7% of the households took high profile vehicles.

Liu *et al.* (2014) presented a framework to include both household-gathering behavior and mode choice in a no-notice emergency into an evacuation model to examine the effects of these two issues on evacuation efficiency and network performance. In this study, they considered a decision tree (DT) approach to model mode choice for no-notice evacuation situations. The model included individuals' gender, possession of a driver's license, access to a personal car, commute mode, commute distance, number of adults in the household, number of cars in the household, and child pick-up decision as input variables and the output variables are transport mode used in an evacuation, such as driving alone, taking public transit or taxi, and carpools.

Murray-Tuite and Wolshon (2013) presented a detailed review on the existing literature related to mode choice during evacuation and according to them, the mode of transportation to evacuate is likely to depend on a number of factors, such as characteristics of the disaster, required travel distance to reach safety, location of the evacuees at the time an order is given, and available options. However, to the best of the author's knowledge, this is the first attempt to model evacuees', non-household transportation mode choice behavior and the factors that influence the choice of a given mode, in a major hurricane.

2.3 Hurricane Evacuation and Social Influence

The overall hurricane evacuation process can be characterized as a complex process involving decision making at different levels of influence: individual, household, and community. Some important dimensions of the decisions involved in the evacuation process were discussed in Section 2.2 of this report.

Riad *et al.* (1999) identified 'social influence' as one the three social psychological processes combined with individual characteristics to influence the complex phenomenon of why people sometimes decide not to evacuate from a dangerous situation. According to this study, 'risk perception' and 'access to resources' are the two other processes in this regard. In addition to personal risk perception, social influences play an important role on individual's decision making process though individuals are finally responsible for their own decisions (Riad *et al.* 1999). Studies on hurricane evacuation (Baker 1991, Dash and Gladwin 2007) found that in addition to factors such as individual and household characteristics, risk level, evacuation orders, and storm threat, the personal risk perception was the most important factor in determining the evacuation decision. Hasan *et al.* (2010) found that the role of social influence on risk perception behavior is not directly addressed in the literature. However, it is possible that an individual's risk perception can be socially influenced as evacuation decisions spread from individual to individual thorough the social network configuration. Gladwin *et al.* (2007) concluded that, informal networks based on neighbors, co-workers, family members, and friends can influence the initiation of decision-making processes and the role of warning dissemination. The study also presented the necessary actions required by appropriate agencies and organizations to support social science research on the high-priority issues in the hurricane forecast and warning system.

Previous research suggests that individual's social ties have an impact on the disaster warning dissemination (i.e., content, source, and number of warnings received) and adaptation process (Clifford 1956). It is found that the greater the number of contacts and ties one has to the community, the more likely one is to receive information on evacuation recommendation (Perry

1979). Official warning messages sometimes provide vague information that are usually confirmed through other sources (i.e., through individual's social network) (Mileti and Beck 1975). It is generally agreed that kin relationships play more important role compared to community relationships in evacuation decision making. Perry (1979) however reasoned that when kin relationships are weak or absent, community contacts can serve similar function with respect to a model of evacuation behavior.

Characteristics of individual social network can be the predictors of evacuation patterns. For example, it is found that individuals who have smaller social networks are less likely to evacuate and vice versa (Drabek and Boggs 1968). Previous social science studies on hurricane evacuation also suggest that African American households typically possess more cohesive kinship and larger community networks compared to Caucasian communities and hence have a greater propagation of disaster warning information (Perry 1979). Previous research also found that ethnic groups such as African American households actively involve their elders within the kin network; which eventually contributes to a higher percentage of decisions to evacuate (Quarantelli 1985). Hasan *et al.* (2010) proposed a threshold model of social contagion to characterize the social influence in evacuation decision making process that was originally proposed in network science literature. This study suggested that individual social relationship can be thought of the combination of kin relationships (i.e., relatives) and community contacts (i.e., friends and neighbors) and both these relationships have influences on warning propagation and evacuation decisions.

2.4 Big Data in Disaster Management

Computing for disasters, a new research area, can potentially benefit the overall preparedness and resilience during natural disasters by collecting data and transforming data into usable and secured forms specifically for the emergency officials (CRA 2012). This requires examining multi-disciplinary areas and addressing challenges related to scope, scale, complexity and uncertainty. While previous studies suggested that 'systems approaches' will provide more success instead of individually exploring the new advances such as wireless communication, data fusion, embedded sensors, pattern recognition and so on (CRA 2003, Mason 2006, Sircar *et al.* 2009). Computing for disaster has the ability to increase the number of lives saved, improved quality of life for the injured people, accelerated economic recovery, creating new job sectors, etc. There are two major sources of big data: dedicated sensor networks (for example, earthquake detection using seismometers) and multi-purpose sensor networks (for example, social media such as Twitter using smartphones), both of them have demonstrated their usefulness in disasters such as the Tohoku Earthquake (Pu and Kitsuregawa 2013). According to this report, Big Data can essentially help in all four phases of disaster management: prevention, preparedness, response, and recovery.

Recently, Microblog service providers such as Twitter, Facebook, etc. are serving as potential source for handling relevant information during natural disasters or emergencies. Social media has the ability to reach the ground truth, sharing information, crowd sourcing as well as responses from different groups of social media users. In addition to the traditional sources of information such as television, newspaper, etc., social media offers ways to retrieve, produce and spread timely information during emergency events. Due to these additional features, social media has the potential to play an important role in the disaster preparation, warning, response and recovery. Crisis Informatics is the new area of studying human behavior and response during disaster by using social media data with increasingly pervasive information and communication technology (Palen *et al.* 2007). Social media data during crisis or natural disasters include studies like Virginia Tech shooting (Vieweg *et al.* 2008, Palen *et al.* 2009), Southern California wildfires (Hughes *et al.* 2008), major Earthquakes in China (Qu *et al.* 2009, Qu *et al.* 2011), Red River floods and Oklahoma grassfires (Vieweg *et al.* 2010) etc. from social networks like Facebook, Twitter, and image sharing service Flickr etc. Ukkusuri *et al.* (2014) recently provided new insights about using social media data in disaster response and emergency operations. This study analyzed microblogs related to 2013 Moore tornado in Oklahoma posted on Twitter and examined the actual public response and characteristics after the tornado, which can improve the understanding of the "the big picture" during critical situations. The nature of self-generating and sharing significantly accelerates the speed of information production and spreading and this is why social media, increasingly, is being considered as a means for emergency communications as it provides real-time content, sentiment, and trends of public attention and behavior.

2.5 Summary

This chapter provides an extensive review on the overall process of evacuation. Previous studies on evacuation behavior modeling are reviewed in five categories: 1) evacuation timing behavior, 2) evacuation mobilization time, 3) evacuation destination choice, 4) evacuation routing strategy and 5) evacuation mode choice. It is found that evacuation behaviors are affected by a variety of factors such as household location, evacuation attributes, hurricanes position, socioeconomic and demographic characteristic, environmental and social factors. Specifically, we have paid attention to the influences of social factors on evacuation decision making. The previous research shows that social influences play an important role on personal risk perception and on individual's decision making process. Additionally, there is a great potential of using social media, which offers ways to retrieve, produce and spread timely information, in the disaster preparation, warning, response and recovery.

This research report aims to develop a systematic methodology to fully understand evacuation demand and evacuation behaviors using empirical data collected in Hurricanes Irene and Sandy. The datasets used are more comprehensive and detailed than those of the previous studies. Collected traffic data include hourly toll plaza volume counts, weight-in-motion (WIM) traffic counts, and travel time data obtained from INRIX Inc. Additionally, stated preference telephone survey data collected for Jersey City/Newark Urban Areas Security Initiative region in Northern New Jersey are used. State-of-art statistical methods which could jointly replicate the decision making at different evacuation stages are used for evacuation behavior modeling.

3 COMPARATIVE ANALYSIS OF TRAFFIC INCIDENTS

Traffic conditions during the hurricane evacuation can be greatly influenced by traffic incidents. The frequency and duration of hurricane-related incidents such as flooding and downed trees increases dramatically during and after hurricanes (Xie *et al.* 2015). The changes in transportation systems caused by hurricane-related incidents can lead to traffic conditions which are significantly different from daily normal traffic conditions, and affect the reliability of the evacuation routes during the hurricane. Therefore, it is important for government agencies which are responsible for evacuation and emergency management to understand the influence of traffic incidents duration hurricanes. This chapter aims to examine the potential changes, with a focus on incidents, prior to, during, and after the hurricanes.

3.1 Data Sources

The incidents occurred during the Hurricanes Irene and Sandy were obtained from TRANSCOM. The data for Irene was extracted from August 2011 to September 2011 for New Jersey (NJ), and the data for Sandy were from October 2012 to December 2012 in New Jersey and to January 2013 in New York. The hurricane Irene affected NJ between August 27 and 29, 2011 and the hurricane Sandy affected NJ/NY areas between October 28 and 31, 2012. These incident data enable us to examine the characteristics of the incidents occurred prior to, during, and after each hurricane.

3.2 Overview of Traffic Incidents in Different Periods

Incidents including accidents, disabled vehicles, downed trees/poles, debris, flooding, and other weather related events were examined for each hurricane. TABLE 1 summarizes the number of incidents in each category analyzed. In total, 700 incidents were reported in the NJ roadway system during the 3-day of Irene in 2011. Likewise, there were 736 and 1,134 incidents during the hurricane Sandy reported in NJ and NY, respectively.

TABLE 1 Summary of incident data sets

Date set	Analysis Period	Accident	Disabled Vehicle	Debris	Downed Tree/Pole	Flooding	Weather Events
Data set for NJ Irene	Total (08/01/11 to 09/30/11)	1,428	295	166	330	759	429
	Irene (08/27/11 to 08/29/11)	50	4	8	222	367	49
Data set for NJ Sandy	Total (10/01/12 to 12/31/12)	2,408	580	196	460	158	107
	Sandy (10/28/12 to 10/31/12)	108	19	152	326	93	38
Date set for NY Sandy	Total (10/01/12 to 01/31/13)	8,511	3,609	952	369	94	203
	Sandy (10/28/12 to 10/31/12)	185	73	531	251	48	46

In order to highlight the impact of hurricanes on the incident occurrences, the number of incidents occurred in different periods were examined. The following FIGURE 1, FIGURE 2, and FIGURE 3 separately show the incidents occurred a week prior to a hurricane, during the hurricane, and a week post a hurricane in each area.

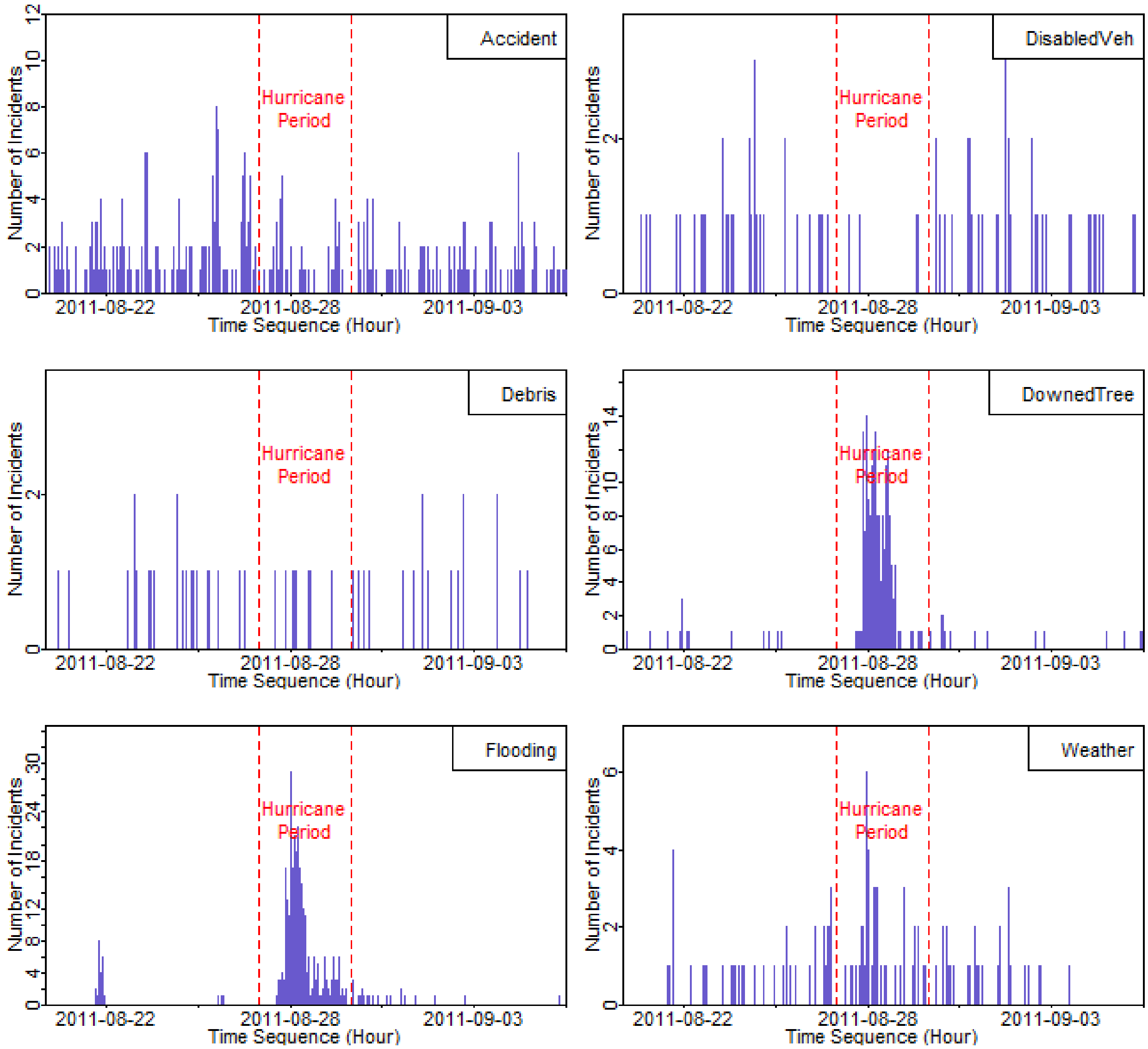


FIGURE 1 Incidents occurred in NJ road network prior to, during, and after Irene

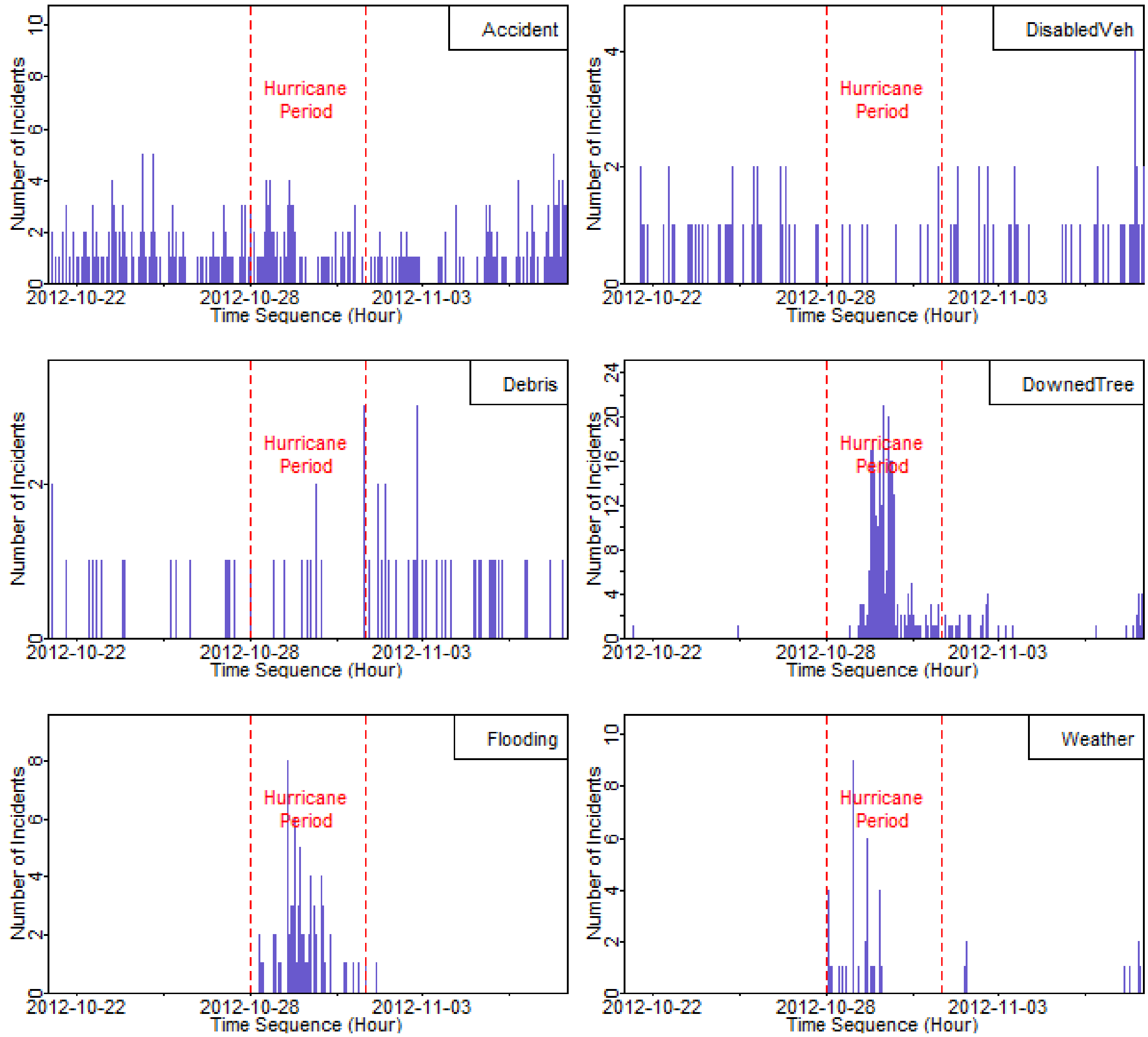


FIGURE 2 Incidents occurred in NJ road network prior to, during, and after Sandy

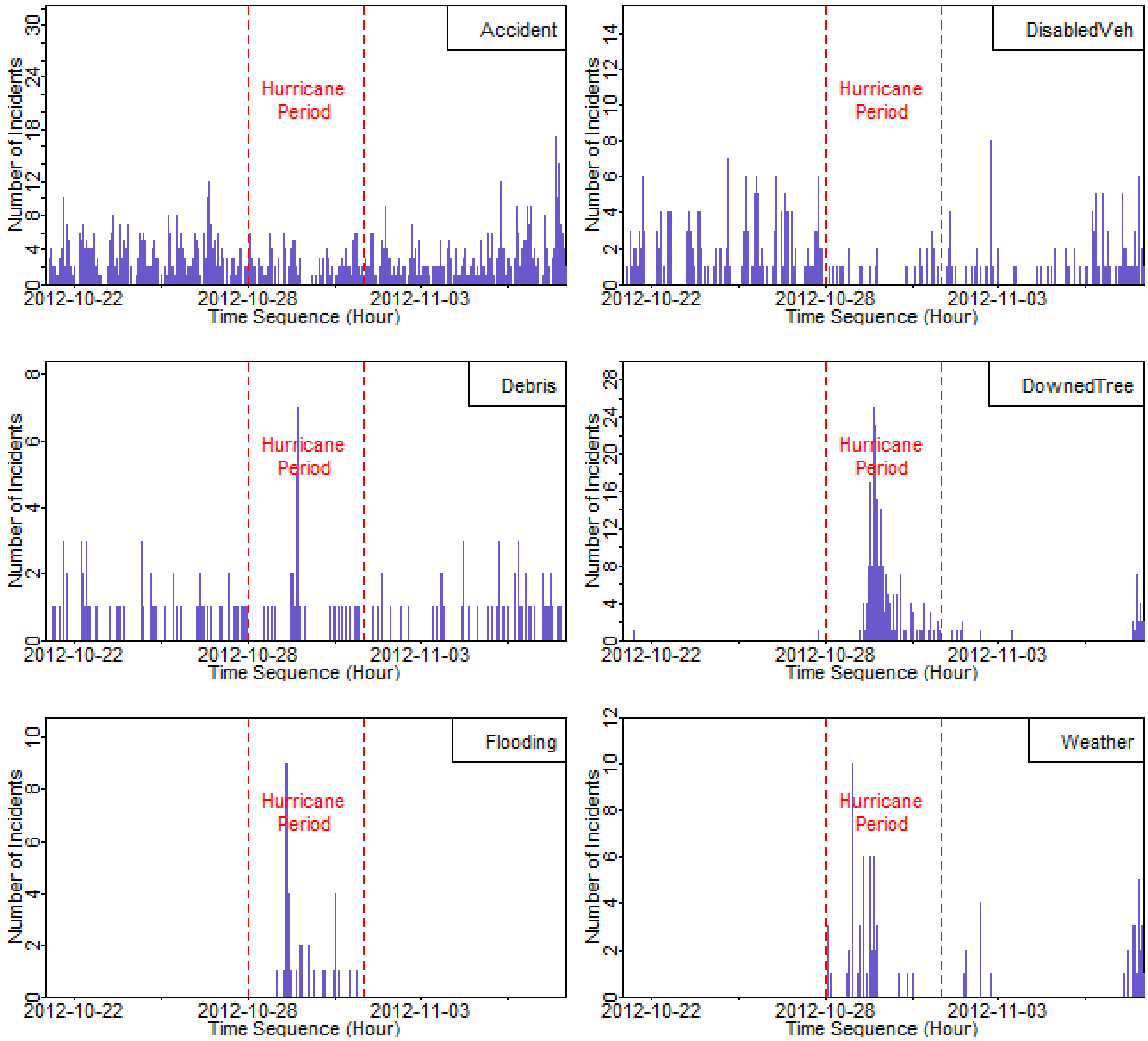


FIGURE 3 Incidents occurred in NY road network prior to, during, and after Sandy

As shown in FIGURE 4, there were notable changes during the hurricane Irene for the number of flooding, downed-tree incidents, and weather related events. The average number of flooding occurred in each day during the hurricane reached 74 compared with 2 incidents/day during pre- and post-hurricane periods. Another great increase was also seen for the downed-tree incidents. It was 5 and 4 incidents/day on average before and after the hurricane, but reached 123 incidents/day during the hurricane. The weather related incidents such as fog were also increased in the hurricane days: it reached 17 incidents/day during the hurricane but 6 and 4 incidents/day prior to and after the hurricane, respectively. During the hurricane period, the number of disabled-vehicle incidents in each day decreased to 2, but the pre- and post-hurricane periods were 5 and 6 incidents/day, respectively. Likewise, the accidents dropped from 28 to 17 during the hurricane period.

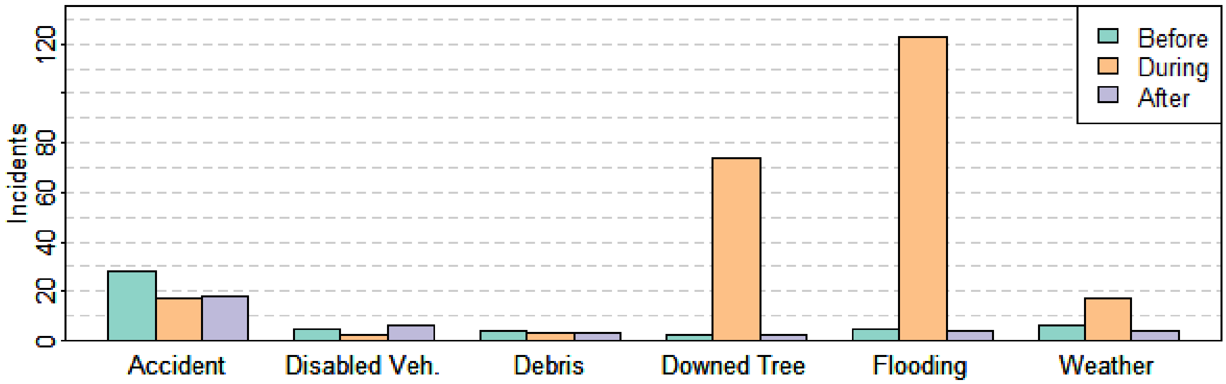


FIGURE 4 Average daily incidents occurred in NJ road network prior to, during, and after Irene

Similar to Irene, hurricane Sandy also led to significant impact on the incident occurrence. FIGURE 5 and FIGURE 6 illustrate the daily incidents of each category occurred prior to, during, and after the hurricane. This hurricane on average led to 108 and 84 downed-tree incidents daily in NJ and NY, respectively. Other than the notable increases in downed-tree incidents, flooding and weather related incidents were also greatly increased.

Similar to hurricane Irene, incidents associated with disabled vehicles decreased in both NJ and NY during Sandy. Incidents related to debris did not change too much in both areas. The number of reported accidents during each hurricane also barely did not change.

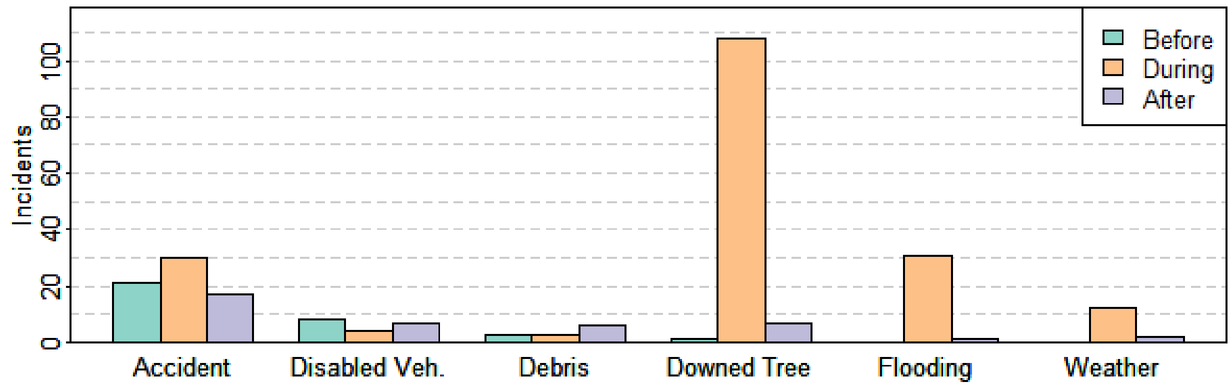


FIGURE 5 Average daily incidents occurred in NJ road network prior to, during, and after Sandy

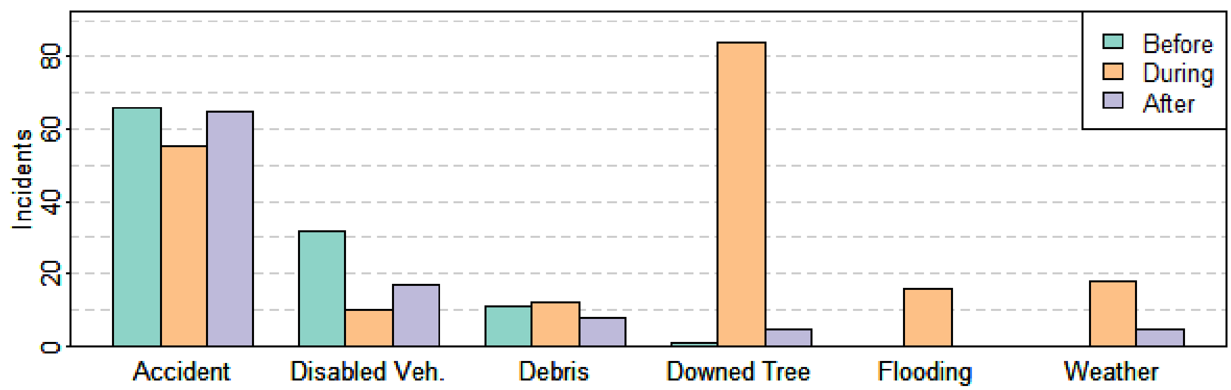


FIGURE 6 Average daily incidents occurred in NY road network prior to, during, and after Sandy

3.3 Incident Duration Analysis

Incident duration is a critical indicator for transportation agencies to examine their performance of handling emergency situations. Under hurricane conditions, the facilities, personnel and other resources might not be accessible immediately in some incidents. Thus, the removal of some incidents might be delayed. Comparing the incident durations under different scenarios can help reveal the challenges from certain type of incidents so that the agencies can further improve their countermeasures. Therefore, this section compares the incident durations prior to, during and post the hurricanes.

FIGURE 7, FIGURE 8, and FIGURE 9 show the average incident duration before, during, and after hurricane Irene in NJ. Notably, the durations associated with debris removal, downed tree, flooding, and weather greatly increased. The durations associated with accidents and disabled vehicles did not notably change.

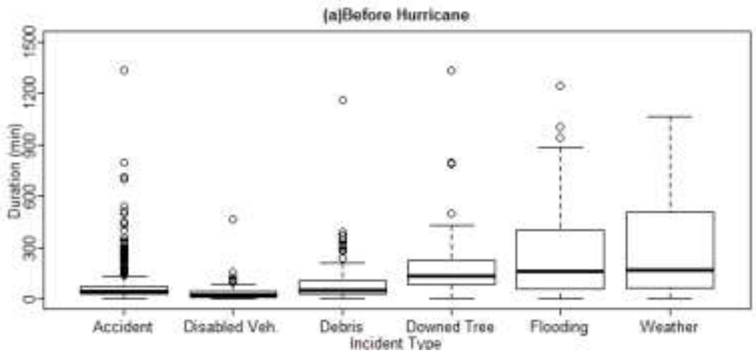


FIGURE 7 Average incident duration prior to Irene in NJ

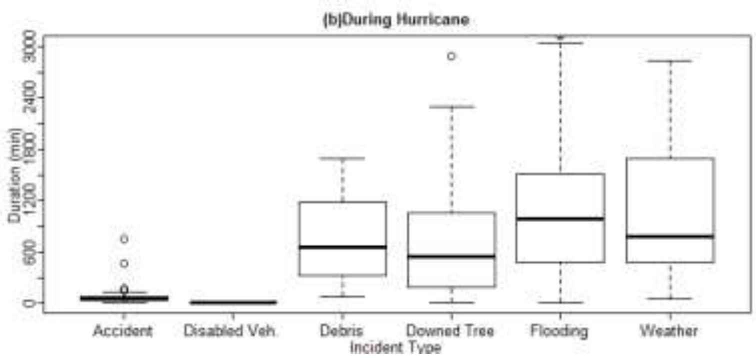


FIGURE 8 Average incident duration during Irene in NJ

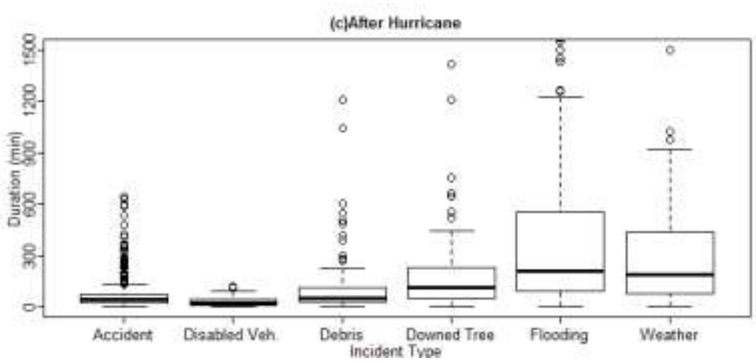


FIGURE 9 Average incident duration after Irene in NJ

Similarly, FIGURE 10, FIGURE 11, and FIGURE 12 show the average incident duration before, during, and after hurricane Sandy in NJ. Incidents including debris, downed tree, flooding, and weather events all had a longer durations during the hurricane.

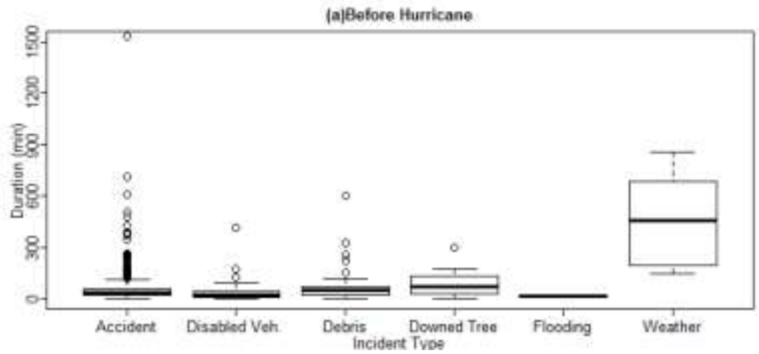


FIGURE 10 Average incident duration prior to Sandy in NJ

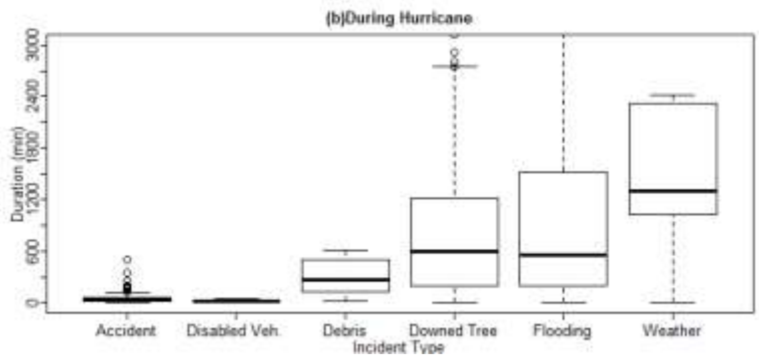


FIGURE 11 Average incident duration during Sandy in NJ

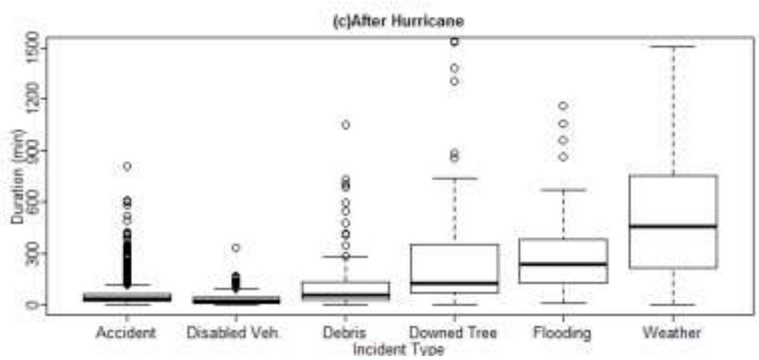


FIGURE 12 Average incident duration after Sandy in NJ

FIGURE 13, FIGURE 14, and FIGURE 15 show the average incident duration before, during, and after hurricane Sandy in NY. Unlike the hurricane's impact in NJ, only incidents including downed tree, flooding, and weather events had a significant increase in the duration.

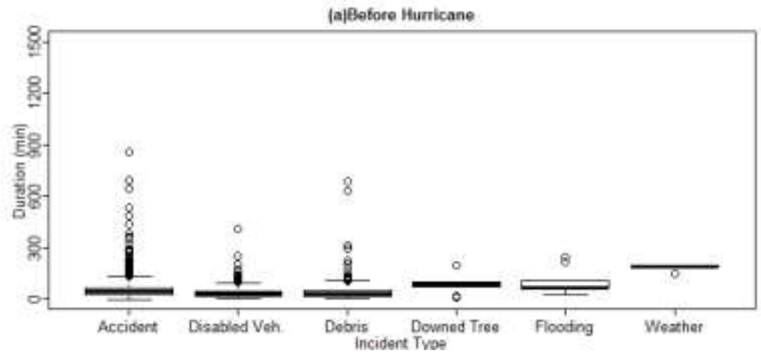


FIGURE 13 Average incident duration prior to Sandy in NY

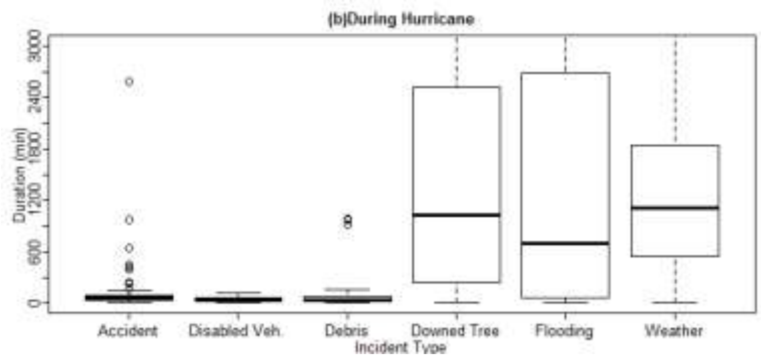


FIGURE 14 Average incident duration during Sandy in NY

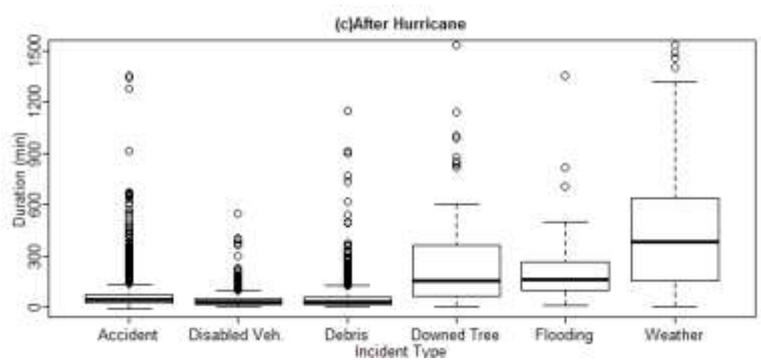


FIGURE 15 Average incident duration after Sandy in NY

FIGURE 16, FIGURE 17, and FIGURE 18 illustrate the spatial characteristics of the incident durations during each hurricane. It can be seen that hurricane Irene and Sandy had different impact on incidents occurred in different areas in NJ. This should be attributed to differences of the hurricanes.

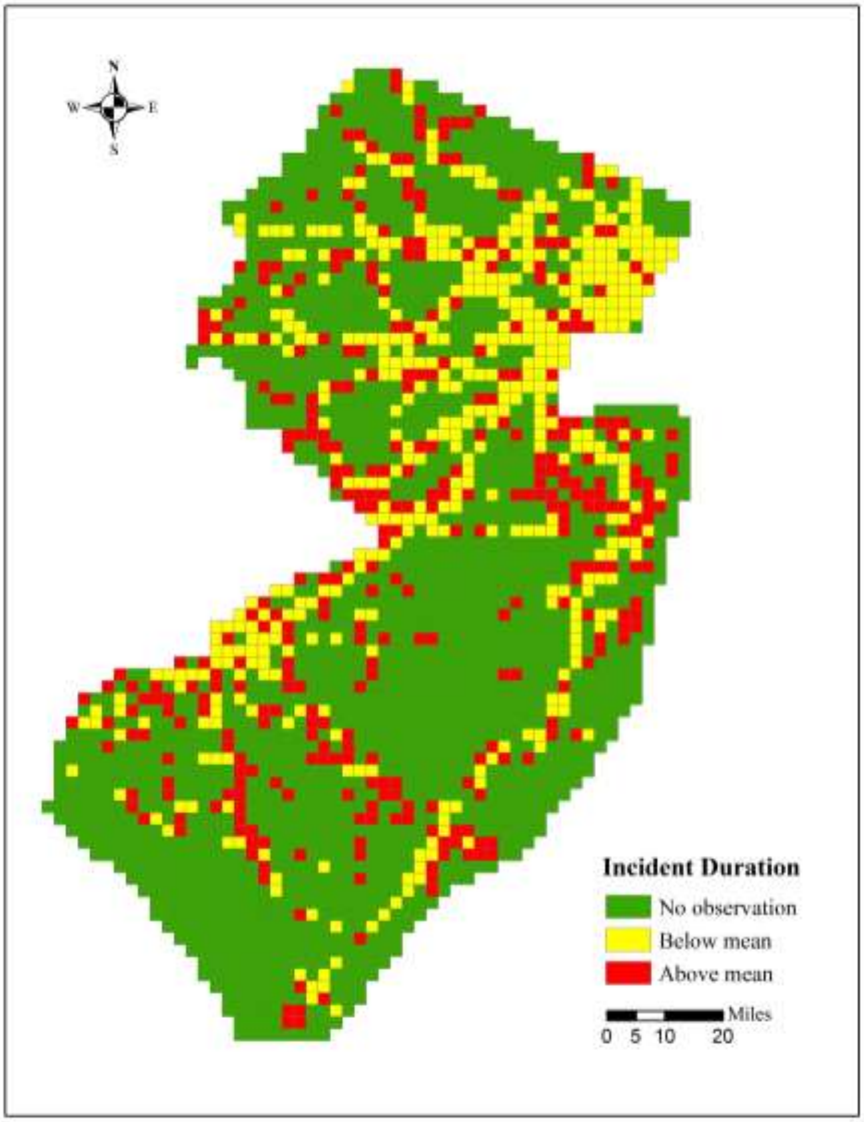


FIGURE 16 Durations of Irene incidents occurred in different region of NJ

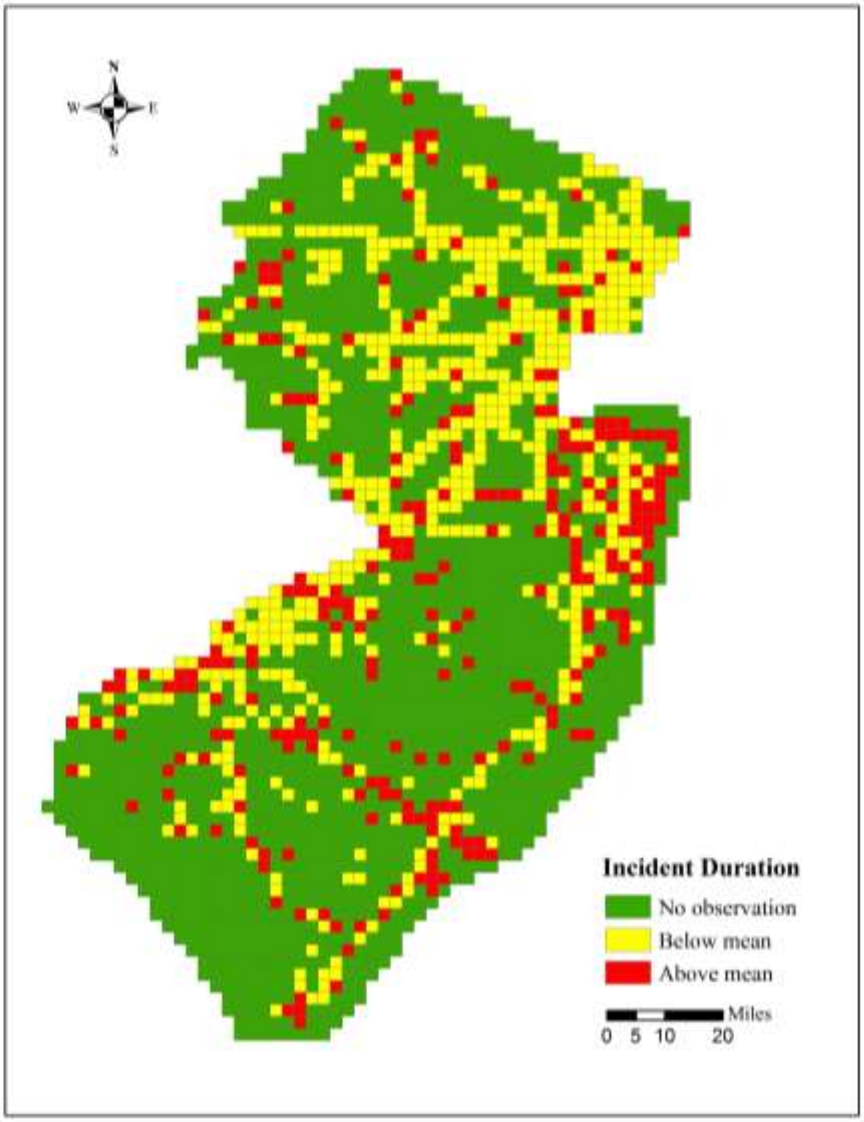


FIGURE 17 Durations of Sandy incidents occurred in different region of NJ

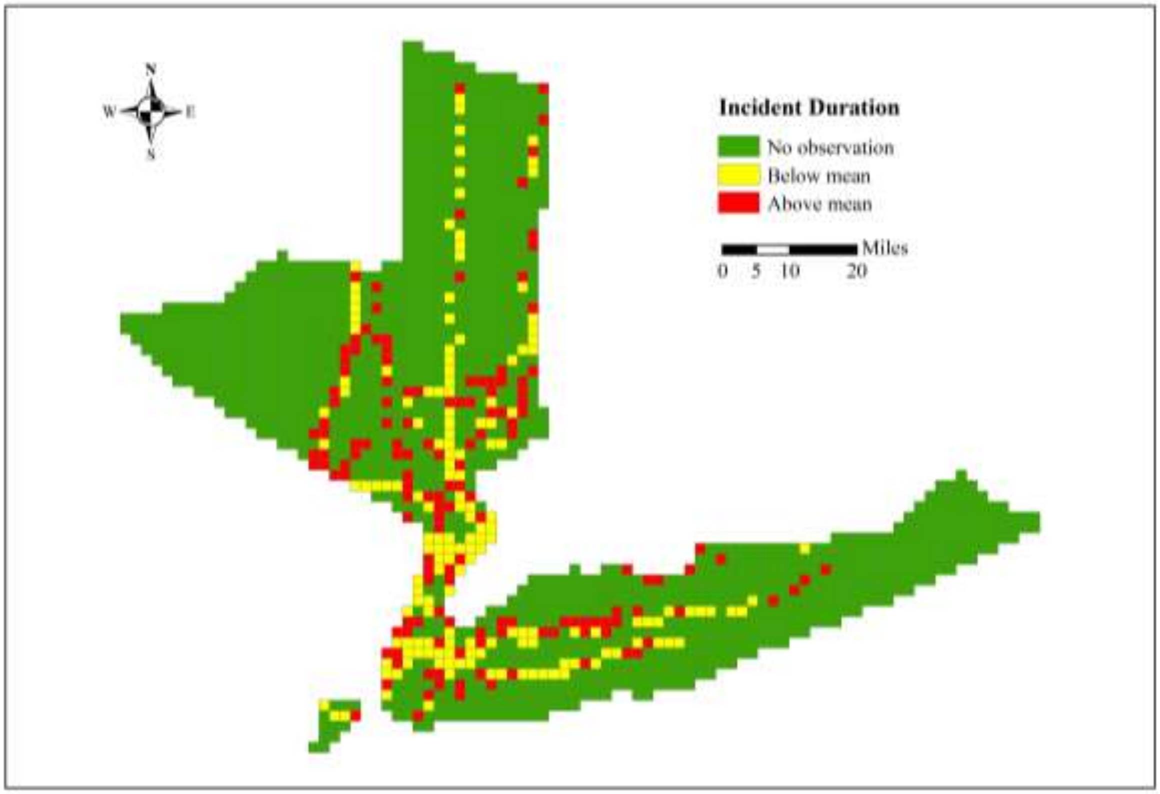


FIGURE 18 Durations of Sandy incidents occurred in different region of NY

In order to examine the factors that may affect the incident durations, a lognormal model is developed. A standard lognormal model assumes a linear relationship between the logarithm of incident durations and the vector of explanatory variables $\mathbf{X}$. In matrix form, it can be expressed as:

$$\begin{aligned} \mathbf{y} &= \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \\ \boldsymbol{\varepsilon} &\sim N(0, \sigma^2 \mathbf{I}) \end{aligned} \tag{1}$$

where $\mathbf{y}$ is the vector of logarithm of incident durations, $\mathbf{X}$ the vector of explanatory variables such as incident type, incident time and incident location, $\boldsymbol{\beta}$ the vector of regression coefficients to be estimated and $\mathbf{I}$ represents the identity matrix. The error term $\boldsymbol{\varepsilon}$ is assumed to be independent and identically distributed with mean zero and constant variance.

TABLE 2,

TABLE 3, and

TABLE 4 summarize the modeling results. Consistent with previous descriptive analysis, the downed tree incidents, flooding, and weather events significantly increased the incident duration. An incident occurred during and after the hurricane is more likely to have longer duration. Location, type of facility, and occurrence time will affect the incident durations.

TABLE 2 Modeling Results of Incident Durations under Irene in NJ

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-0.380	0.046	-8.220	0.000
TypeAccident (base)	---	---	---	---
TypeDebris	0.389	0.111	3.487	0.000
TypeDisabled	-0.632	0.086	-7.388	0.000
TypeDowned	0.944	0.095	9.902	< 2e-16
TypeFlooding	1.572	0.070	22.531	< 2e-16
TypeWeather	1.494	0.074	20.143	< 2e-16
Weekend	0.155	0.064	2.415	0.016
Night	0.196	0.075	2.625	0.009
PreIrene	0.451	0.092	4.925	0.000
DurIrene	1.155	0.093	12.471	< 2e-16
PostIrene	0.399	0.104	3.832	0.000
IntState	-0.373	0.051	-7.389	0.000
OtherCounty (base)	---	---	---	---
CountyCamden	-0.397	0.089	-4.470	0.000
CountyHunterd	0.607	0.185	3.274	0.001

TABLE 3 Modeling Results of Incident Durations under Sandy in NJ

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-0.575	0.037	-15.647	< 2e-16
TypeAccident (base)	---	---	---	---
TypeDebris	0.396	0.092	4.328	0.000
TypeDisabled	-0.564	0.057	-9.882	< 2e-16
TypeDowned	1.514	0.085	17.718	< 2e-16
TypeFlooding	1.814	0.111	16.394	< 2e-16
TypeWeather	2.328	0.130	17.877	< 2e-16
Weekend	0.102	0.052	1.984	0.047
Night	0.220	0.064	3.421	0.001
DurSandy	0.748	0.097	7.694	0.000
PostSandy	0.785	0.096	8.194	0.000
IntState	-0.193	0.043	-4.538	0.000
Tunnel	-0.487	0.266	-1.832	0.067
OtherCounty (base)	---	---	---	---
CountyHunterdon	0.480	0.240	2.000	0.046
CountyMonmouth	0.252	0.081	3.127	0.002
CountyOcean	0.219	0.107	2.046	0.041
CountyOrange	2.568	1.231	2.086	0.037
CountySalem	0.347	0.203	1.709	0.088

TABLE 4 Modeling Results of Incident Durations under Sandy in NY

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-0.435	0.018	-24.218	< 2e-16
TypeAccident (base)	---	---	---	---
TypeDebris	-0.276	0.035	-7.820	0.000
TypeDisabled	-0.509	0.021	-24.199	< 2e-16
TypeDowned	2.000	0.068	29.586	< 2e-16
TypeFlooding	1.524	0.110	13.847	< 2e-16
TypeWeather	2.480	0.084	29.691	< 2e-16
Weekend	0.067	0.022	2.987	0.003
Night	0.138	0.027	5.092	0.000
DurSandy	0.626	0.072	8.719	< 2e-16
PostSandy	0.657	0.065	10.177	< 2e-16
IntState	0.040	0.020	2.048	0.041
Tunnel	-0.353	0.144	-2.448	0.014
Bridge	-0.149	0.058	-2.560	0.010
OtherCounty (base)	---	---	---	---
CountyBronx	-0.151	0.044	-3.422	0.001
CountyChenango	1.728	0.718	2.407	0.016
CountyCortland	2.619	1.015	2.580	0.010
CountyDelaware	1.771	0.718	2.467	0.014
CountyJefferson	1.418	0.586	2.419	0.016
CountyNassau	-0.509	0.043	-11.899	< 2e-16
CountyNew York	-0.164	0.052	-3.175	0.002
CountyQueens	-0.339	0.036	-9.465	< 2e-16
CountyRichmond	-0.187	0.094	-1.977	0.048
CountySuffolk	-0.220	0.062	-3.556	0.000

4 EVACUATION RESPONSE CURVE: AN EMPIRICAL STUDY IN CAPE MAY COUNTY, NJ

The behavior analysis is a key component in evacuation modeling platform, and is also critical for public officials in deciding when to issue emergency evacuation orders. Such behavior is typically measured by an evacuation response curve that represents the proportion of total evacuation demand over time during evacuation.

This chapter is based on the our previous research (Li *et al.* 2013). We analyzed evacuation behavior and constructed an evacuation response curve based on traffic data collected during Hurricane Irene in Cape May County, New Jersey. Moreover, we also calibrated and compared the widely used S-curves with different mathematical functions and the state-of-art behavior models with empirical data. The results may benefit for evacuation planning in similar areas.

4.1 Introduction

Hurricane Irene crossed and affected much of the east coast of the United States in August 2011. In New Jersey, flood waters covered roadways and transit lines, high-speed wind took down trees and power lines, and caused significant damages and disruptions during the post-hurricane days. Fortunately, thanks to the proactive hurricane evacuation plans by state and local emergency authorities (Chen 2005), as well as early evacuation order declarations (Carnegie and Deka 2010), the evacuation process in New Jersey was relatively smooth with little traffic disturbance. More than one million people, including at least 90 percent of the residents in the most-impacted counties, left the New Jersey shore over 36 hours after the declaration of mandatory evacuation order.

This study investigates the time-dependent evacuation demand during Hurricane Irene in Cape May County, the southernmost county of New Jersey, using empirical data. Evacuation demand rate is typically estimated by using a so-called response or mobilization curve, which estimates the proportion of total demand beginning to evacuate within defined time intervals. These curves have been established either by expert judgment (Lewis 1985, Radwan *et al.* 1985, Tweedie *et al.* 1986, Cova and Johnson 2002), or by using mathematical models based on empirical evacuation behavior data (Fu and Wilmot 2004b, Fu *et al.* 2006, Fu and Wilmot 2006, Fu *et al.* 2007b, Hasan *et al.* 2010). Because of the environmental, social, and geographic factors (Baker 1991), evacuation response curves typically vary between different hurricane scenarios.

The objectives of this study are to construct the evacuation response curve in Cape May County, NJ using observed data collected during Hurricane Irene, and assess the state-of-art mathematical models with the constructed empirical response curve. Several features distinguish this study from the previous ones.

First, New Jersey is not a hurricane prone state such as Southeastern Atlantic or Gulf Coast states; Hurricane Irene was the first hurricane to directly hit the state since 1903. While a great deal of research focuses on hurricane prone states (Wolshon *et al.* 2005a), northern states along the Atlantic Coast receive insufficient attention. In addition, there is a high seasonal tourist population visiting and living along the New Jersey coast during the summer months. The total population of Cape May County can increase up to 850,000 in summer from 107,000 in winter. The behavioral patterns of residents have been well discussed in the literature (Baker 1991, Whitehead *et al.* 2000, Wolshon *et al.* 2005a, Dash and Gladwin 2007); however, much less is known about the empirical evacuation behavior of tourists (Baker 2000). The data in this study may contribute to this emerging research area.

Second, when modeling evacuation response behavior, the available models (Lewis 1985, Radwan *et al.* 1985, Tweedie *et al.* 1986, Cova and Johnson 2002, Fu and Wilmot 2004b, Fu *et al.* 2006, Fu *et al.* 2007a) are based on empirical data from hurricane prone states. However, whether such models are applicable to states with little hurricane experience is still unknown. In this study, the transferability of the models from hurricane prone states is also discussed by calibrating and comparing a number of mathematical functions presented in the literature (Radwan *et al.* 1985, Tweedie *et al.* 1986, Cova and Johnson 2002, Fu *et al.* 2006) with empirical data. The results may be valuable for evacuation modeling in similar areas.

Finally, the data used in this study come from automatic traffic counters, rather than from traditional post-hurricane surveys. Compared with post-hurricane surveys, traffic data yield more realistic results and avoid the general "problem of recall" in social science (Dash and Gladwin 2007). While much attention has been paid to hurricane evacuation behavior analysis, relatively few studies make use of real-world traffic data (Archibald and McNeil 2012). With the increasing number of sensors being deployed on our roadways, this study also illustrates how to introduce empirical data sources as a useful feedback to evacuation planning.

4.2 Data

Recently, a number of studies attempted to use traffic data to analyze evacuation behavior. For example, (Wolshon 2008) used volume data from automatic traffic counters in Louisiana to investigate empirical maximum evacuation traffic flow during Hurricane Katrina (2005) evacuation. Traffic data is generally preferable to data derived from post-hurricane evacuation surveys in terms of evacuation response curve modeling since the data provide more samples than post hurricane surveys, and since post hurricane surveys are expensive to conduct, and therefore have limited sample size (Southworth 1991). Also, traffic volume data such as electronic toll collection (ETC) data or sensor data do not have the general "problem of recall" in social science, where people may have difficulty in remembering their exactly hour by hour decisions during a hurricane (Dash and Gladwin 2007).

The data used in this study include hourly toll plaza volume counts on the Garden State Parkway (GSP). GSP is a statewide corridor in New Jersey, and is also the only major (limited access) northbound evacuation route from the shore area of Cape May County. The Cape May toll plaza is a one-way northbound (outbound) mainline barrier tollbooth located at mile marker 19.4 on GSP. In addition, the traffic data from southbound (inbound) Great Egg toll plaza were also collected to check the possible "background traffic" (non-evacuating traffic. Please see a detailed definition in next section). The Great Egg toll plaza is also a one-way mainline barrier tollbooth located at mile maker 28.8 on GSP.

The analyses included in this study are based on hourly traffic volumes from the Cape May toll plaza on GSP during August 24-28, 2011. This traffic primarily comes from Cape May peninsula and coastal barrier islands inside Cape May County, NJ. Thus, the traffic data can also be interpreted as samples of evacuees from all cross Cape May County, NJ. The location and photos of both tollbooths and detailed evacuation process are shown in FIGURE 19.

FIGURE 19 Toll plazas on GSP and Hurricane Irene evacuation process

4.3 Evacuation Traffic and Demand Response Curve

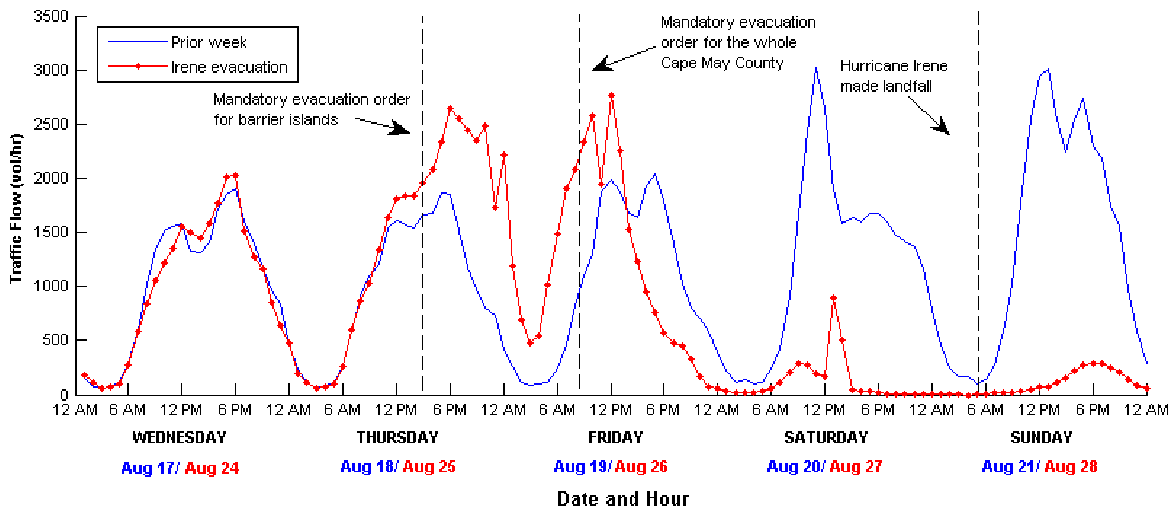
The temporal progression of Irene evacuation traffic is illustrated in FIGURE 20(a): the hourly traffic volume at Cape May toll plaza on GSP Northbound from Wednesday, August 24, through Sunday, August 28. The time stamps of mandatory evacuation orders and Hurricane Irene landfall time are shown as dashed vertical lines. As a reference, traffic flows for the same days during the prior week are also included in FIGURE 20(a), to illustrate typical traffic conditions.

In order to construct evacuation response curve, background traffic is needed to be eliminated by following the suggestions of (Urbanik 2000). "*Background traffic consists of vehicles that are present during an evacuation but are not associated with permanent residents, transients, special facility populations, or voluntary evacuees*". Note that the mandatory evacuation order of barrier islands issued in the afternoon of Thursday, August 25. FIGURE 20(b) shows the inbound traffic volumes at Great Egg toll plaza on GSP. It can be observed that there are no significant differences in traffic patterns between Thursday, August 25 and the same day of the prior week. Such traffic pattern shows that people still commuted to Cape May County in the morning, and possibly went back home as usual in the afternoon. Thus, when constructing the evacuation response curve, the regular commuting trips are eliminated from the traffic volume counts on Thursday, August 25. Such time-dependent commuting demand is assumed to have the same values as the same day of the prior week (Thursday, August 18). The significant reduction in traffic volume on Friday, August 25 in FIGURE 20(b) was caused by the restriction at the entrance. We assume that all of the traffic volume on Friday is due to the evacuation demand.

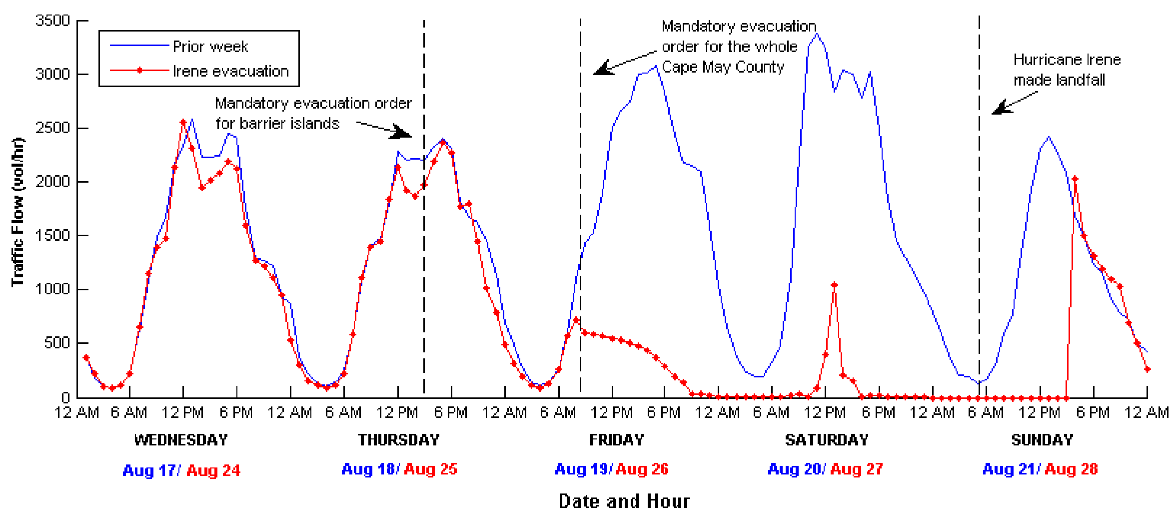
FIGURE 20(c) shows the evacuation response curve without background traffic derived from the Cape May toll plaza hourly traffic volumes during the evacuation. FIGURE 20(c) also includes the evacuation response curve with background traffic, and the cumulative demand curve based on the same day of the prior week.

The volume trend lines in FIGURE 20(a) show the Irene evacuation process in Cape May County. The process started around 9:00am on Thursday, August 25, when traffic volumes start to become significantly higher than the prior week's volumes. This increase in traffic volumes starts six hours before the mandatory evacuation order for the barrier islands. Approximately 6 percent of the evacuees had already evacuated by the time the mandatory evacuation order was issued. The major part of the evacuation, which comprised more than 85 percent of the evacuees, continued into the midnight of Friday, August 26. Less than 8 percent of the evacuees chose to evacuate on Saturday, August 27. In total, the duration of Irene evacuation in Cape May County was approximately 36 hours, and half of the total number of evacuees evacuated within 23 hours.

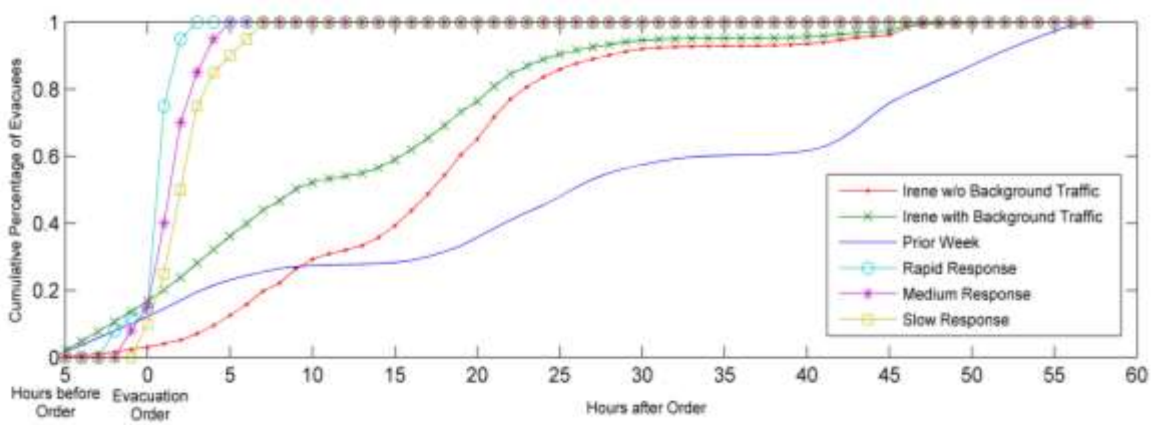
It can be observed in FIGURE 20(a) that the evacuees in Cape May County responded very quickly to the mandatory evacuation order. Traffic volumes increased significantly when the official mandatory evacuation order was issued. Two peak evacuation demand periods were observed around the start times of the mandatory evacuation for the shore areas (3:00pm, Thursday, August 25) and the whole county (8:00am, Friday, August 26), respectively. The quick evacuation response behavior is also illustrated graphically in FIGURE 20(c). Sharp upward changes in the slope of the curve represent increases in the evacuation rate following the mandatory evacuation notices. Moreover, it should be noted that because the evacuation order was well before landfall of Hurricane Irene (approximately 72 hours ahead of the storm), the empirical curve is much more spread out than the theoretical ones in FIGURE 20(c).



(a) Outbound traffic counts from Cape May toll plaza on GSP



(b) Inbound traffic counts from Great Egg toll plaza on GSP



(c) Irene evacuation response curves and theoretical curves

FIGURE 20 Irene evacuation traffic and demand response curves in Cape May County, NJ

The quick evacuation response behavior in Cape May County may have been due to the high tourist population. During the summer/hurricane season, more than 85 percent of the people in Cape May County are non-residents. As stated in Drabek (1996), tourists exhibited a faster response rate than that of permanent residents. One of the reasons is that tourists, especially day-trippers, do not have the responsibility of protecting their residences. Moreover, tourists usually stay together, thus it is quick for them to gather and evacuate, while residents may be scattered, as discussed in (Murray-Tuite and Mahmassani 2004). Tourists would instead first meet in a single location and then evacuate as a unit. This so-called household trip-chain sequencing may delay residents' evacuation departure times.

Several other factors may also affect the evacuation response behavior in Cape May County. One critical factor in evacuation behavior is evacuation experience. Residents of New Jersey, unlike Southeastern Atlantic Coast or Gulf Coast states, have relatively little or no hurricane evacuation experience. Prior literature (Baker 1991, Whitehead *et al.* 2000) found that people with no prior storm experience were more likely to evacuate than those with storm experience. For example, it was observed that without recent major hurricane history, 97 percent of people living in Pensacola and Pensacola Beach, Florida evacuated before Hurricane Frederic in 1979 (Baker 1991). Another factor that affects the evacuation response behavior is the location type (Baker 1991). The people who live in rural areas, especially along the shore, are more prone to evacuate than those who live in urban areas. For example, prior to Hurricane Andrew (1992) making landfall in South Florida, people in the Florida Keys decided to leave earlier than necessary. However many in urban areas in and around Miami decided not to leave at all, in part because of a perception of greater building safety in those areas (Drabek 1996).

4.4 Comparative Assessment of Evacuation Response Models

The hourly volume data at the Cape May toll plaza of GSP during Hurricane Irene are extremely valuable for modeling evacuation behavior and comparing with other estimates and responses. As seen in FIGURE 20(c), significant differences are observed between the theoretical evacuation response curves (Lewis 1985) and the empirical evacuation response curve from Hurricane Irene evacuation. In this section, four evacuation response models in the literature (Logit, Rayleigh, Poisson, and Sequential Logit) are reviewed and compared with the empirical evacuation response curve from Hurricane Irene.

4.4.1 Evacuation Response Model

4.4.1.1 Logit Function

The Logit function suggested by (Radwan *et al.* 1985) is the most common approach to model the hurricane evacuation response curve. It is used in some of the developed evacuation modeling software tools such as TEDSS (Hobeika *et al.* 1994) and MASSVAC (Hobeika and Kim 1998). The Logit function is shown in following equation:

$$P_t = 1/[1 + \exp[-\alpha(t - H)^2] \quad (2)$$

Where P_t is the percentage of the evacuees departed by time t, and α and H are model parameters to be calibrated. α gives the slope of the cumulative traffic loading curve, and H is half loading time: the time when half of the vehicles in the system are loaded onto the highway network.

4.4.1.2 Rayleigh distribution

The Rayleigh distribution was suggested by local civil defense officials to describe evacuation departure time (Tweedie *et al.* 1986). The Rayleigh distribution is shown in the following equation:

$$P_t = 1 - \exp[-0.5(t/\beta)^2] \quad (3)$$

Where P_t is the percentage of the evacuees departed by time t, and β is a parameter controlling the slope of the traffic loading curve.

4.4.1.3 Poisson distribution

The Poisson distribution is commonly used in queuing theory to describe the probability of n events occurring within a given time period. The distribution was proposed in (Cova and Johnson 2002) to model a random evacuation departure process. Poisson distribution is shown in the following equation:

$$P_t = \exp(-\gamma)\sum_{i=0}^{\lfloor t \rfloor}\frac{\gamma^i}{i!} \quad (4)$$

Where P_t is the percentage of the evacuees that have departed by time t, and γ is a parameter controlling the slope of the traffic loading curve.

4.4.1.4 Sequential Logit

A sensitivity analysis of evacuation probabilities was proposed in (Fu and Wilmot 2004b) and later improved by (Fu *et al.* 2006, Fu *et al.* 2007a). In the model, each random utility function U_i^n (utility of a household not evacuating at time t) and U_t^e (utility of a household evacuating at time t) are assumed to be composed of a systematic component V_t, and an error term ε_t (i.e. $U_t^n = V_t^n + \varepsilon_t$ and $U_t^e = V_t^e + \varepsilon_t$). Also the utility differences $U_t^n - U_t^e$ are assumed to be independently, logistically, distributed. Then, the probability of a household evacuating at time t given that it has not evacuated earlier is shown in the following equation:

$$P(t)_{e/n} = \frac{\exp(U_t^e)}{\exp(U_t^n) + \exp(U_t^e)} = \frac{\exp(V_t)}{1 + \exp(V_t)}$$
$$V_t = U_t^e - U_t^n = -2.292 + 1.018 * TOD1 + 2.123 * TOD2 + 1.949 * TOD3 + 2.111 * Order1 + 2.356 * Order2 + 0.019 * Speed - 1.748 * Ln(T) \quad (5)$$

The linear formulation was calibrated and validated in (Fu *et al.* 2007a). Where

TOD : the time of day - 1 for early morning (6am to 10am), 2 for middle day (10am to 4pm), and 3 for late afternoon (4pm to 8pm).

$Order$: evacuation order -1 for voluntary, 2 for mandatory.

$Speed$: hurricane speed (mph) and

$Ln(T)$: the natural logarithm of time T to hurricane landfall.

4.4.2 Model Comparison and Discussion

In order to compare the capabilities of the described evacuation response models, in terms of fitting the empirical data from Hurricane Irene, the first challenge is the parameter settings of each model. The values of parameters of each model are not fixed for different hurricane scenarios due to environmental, geographical, and social factors (Baker, 1991). For example, as stated in(Lindell and Prater 2007b), $\beta = 40$ provided the best fit of Rayleigh distribution to the empirical data in Tweedie et al., (1986), while the response curve in Hobeika and Kim (1998) and (Southworth and Chin 1987) was equivalent to a Rayleigh distribution with β = 45 and 74, respectively.

In this section, we first calibrate the parameter settings of each described model with empirical data from Hurricane Irene. Then the results of the calibrated models are compared to find the best fit model. Some recommendations and limitations of the evacuation response models are also discussed.

4.4.2.1 Statistical Measure

The Root Mean Square Error (RMSE) is used in this study to measure the difference between the model result and empirical data. RMSE is a frequently used measure of how close a fitted line is to data points. Specifically, in this study RMSE is the difference between the result of each model and empirical data. It can be mathematically represented as follows:

$$RMSE(\hat{s}) = \sqrt{E((\hat{s}-s)^2)} = \sqrt{\frac{\sum_{i=1}^{n}(\hat{s}_i - s_i)^2}{n}} \tag{6}$$

Where $\hat{s}$ is the fitted result from each model, s is the empirical data from Hurricane Irene, and n is the number of time interval (hours) in each S-curve. RMSE is thus the average distance of the empirical evacuation response curve from the fitted result of each model. The smaller the RMSE, the better fit of the model to the empirical data.

4.4.2.2 Model Calibration and Comparison

In this study, in order to calibrate each evacuation response model with empirical data, first the results of the model are calculated with different parameter settings. Then, RMSE values are used to compare each model result with the empirical data, as shown in FIGURE 21. The parameter setting with minimum value of RMSE is chosen as the calibrated one. Because the Sequential Logit model was calibrated and validated with empirical data from Hurricane Floyd and Hurricane Andrew, the parameter settings given in (Fu et al., 2007) are directly used in this study.

FIGURE 21 shows that improperly calibrated evacuation response models can have significant prediction error. The average errors of all three models fluctuate from less than

10 percent to as large as 60 percent in the Poisson distribution. The recommended parameter settings are $\alpha \in [0.1, 0.3]$ for the Logit function, $\beta \in [15, 20]$ for the Rayleigh distribution, and $\gamma \in [15, 20]$ for the Poisson distribution.

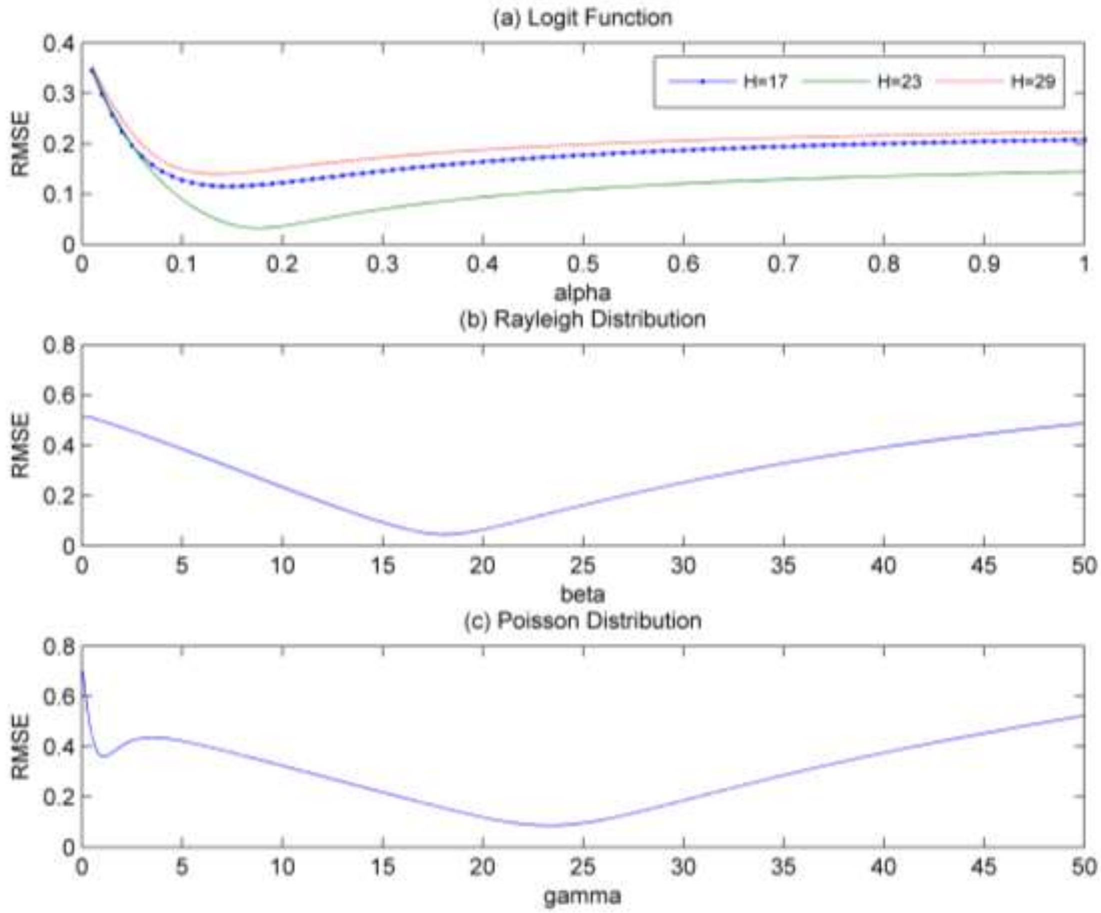


FIGURE 21 The parameter calibration of S-curve distributions

As seen in FIGURE 21, the Logit function yields a better fit compared with the other two distributions. As described above, the half loading time (H) of Hurricane Irene evacuation is 23 hours. When $H = 23$, it can be observed that the curve based on Logit function quickly converges and become stable. RMSE is between 15 percent and 20 percent on average, while less than five percent at its minimum. FIGURE 22 graphically shows the difference between each calibrated evacuation response model and the empirical response curve obtained from traffic data collected prior Hurricane Irene. The Logit and Rayleigh distributions fit empirical data better. RMSE of Logit and Rayleigh distribution are 3.21 percent and 4.77 percent, respectively. As a symmetric distribution, the Logit function fit the middle part of the empirical curve very well, as shown between hours 20 and 30, but underestimates the demand during the evacuation process following the mandatory evacuation order (between hours 10-20, and 30-40). While the Rayleigh distribution overestimates the demand during the early evacuation process (the first 24 hours), it generally underestimates the tail of the empirical curve.

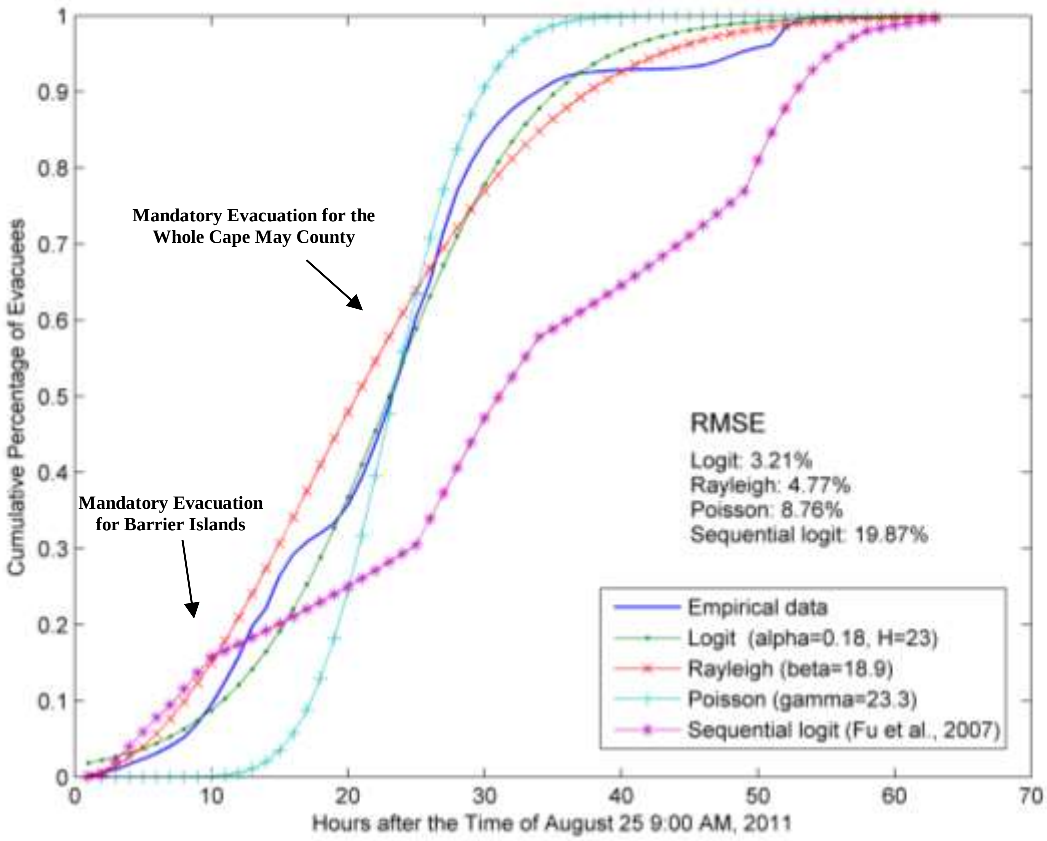


FIGURE 22 Comparison of calibrated models with observed data

However, the Logit function may increasingly misrepresent the empirical data with improper parameter settings of H, given the calibrated parameter α. As described in (Yazici and Ozbay 2008), α can be interpreted as the parameter that controls the behavior of evacuees, while H determines the half evacuation loading time or so-called clearance time ($2H$). The Logit density function is a symmetric distribution (Lindell and Prater 2007b), and therefore given the value of parameter α, different values of H can shift the S-curve in the horizontal direction and affect the calibration result. It can be observed in FIGURE 21 that the Logit function with $H = 23$ fits better to the empirical data compared with the other two models (where it is known that the half loading time is 23 hours during

Hurricane Irene evacuation). However, the half loading time is difficult to predict due to specific hazard conditions, geographical and social factors. A sensitivity analysis with different values of H is suggested when applying the Logit function in the context of hurricane evacuation planning.

4.4.2.3 Results Discussion

In summary, in part because of the quick response behavior of evacuees, the response curve during the multi-day Hurricane Irene evacuation process can still be considered as a general S-shape, instead of multi S-shapes, for Cape May County, New Jersey. The widely used S-curve models with Logit and Rayleigh functions also fit the empirical data well.

Moreover, the recommended parameter settings of S-curves for the case of Irene evacuation are also compared with other empirical studies. As summarized in Lindell and Pratel (2007), only a modest amount of empirical data have been used for calibrating and comparing evacuation response curves recommended by Lewis (1985). A recent study by Koshute (2012) evaluated Logit function vis-a-vis empirical evacuation response curves observed in six different hurricane scenarios. The results showed that Logit function with parameter $\alpha \in [0.4, 0.5]$ fitted better in general for all hurricane scenarios. Such parameter values are slightly higher than the recommended setting ($\alpha \in [0.1, 0.3]$) for Irene evacuation. However, the model parameter settings of empirical studies may also vary significantly, probably due to different environmental, geographical, and social factors. For example, $\beta = 117$ and 181 provided best fit of Rayleigh distribution for empirical evacuation departure time distributions of Texas gulf coast residents leaving from home or work (Lindell and Prater, 2007). The parameter settings are significantly different than our recommended range ($\beta \in [15, 20]$).

The state-of-art Sequential Logit model may not be transferable to other areas with little hurricane evacuation experience. FIGURE 22 shows that the calibrated Sequential Logit model does not perform well compared with empirical data from Hurricane Irene in New Jersey. One possible explanation is that, as concluded by (Hasan *et al.* 2013), the parameters of the evacuation choice models are only transferable over different hurricane contexts in similar hurricane prone regions. The studies that modeled evacuation behavior, including the recent studies about the transferability of such models (Hasan et al., 2013; Murray-Tuite et al., 2012; Fu et al., 2006), are usually based on empirical data from hurricane prone regions including Florida and the Gulf Coast states. Obviously, such studies are not usually conducted due to insufficient data in northern states such as New Jersey that have little hurricane experience. It may also be argued that while regions such as New Jersey are not at high-risk for hurricanes, areas with medium or low risks are sometimes more critical and may have significant damage potential due to insufficient planning and experience. Sound behavior models will still be required to bridge the gap between hurricane prone states and other states with little hurricane experience.

Clearly, with the increasing number of traffic sensors being deployed throughout our transportation system, this study is also a demonstration of the possible use of empirical data sources as an important feedback to evacuation planning process. Compared with post-hurricane surveys, data from automatic sensors have several advantages, including large sample size, low cost, and wide spatial distribution. Such data may provide benefits for other applications, such as the comparison between evacuation traffic pattern and regular weekend traffic pattern, which studied by (Archibald and McNeil 2012). Interestingly, they used sensor data and found that the evacuation traffic during Hurricane Irene in Delaware was very similar to the regular weekend traffic. Such a finding is reasonable for areas with a high tourist population.

The question of the similarity of hurricane evacuation traffic and the usual weekend shore traffic can also be studied using the observed data in this study. In this case, we compared the traffic data from the weekends before (Sunday, August 21) and after (Labor Day, Monday, September 5) with the hurricane with evacuation data (Friday, August 26). FIGURE 23 shows that the evacuees tended to be more risk-averse with 3-4 hours earlier departure time than regular weekends and holidays. The comparison shows that evacuation traffic is not totally unpredictable, and may benefit from traffic management, especially for those without prior emergency evacuation experience. However, this analysis is beyond the scope of this study and may be a subject for future work.

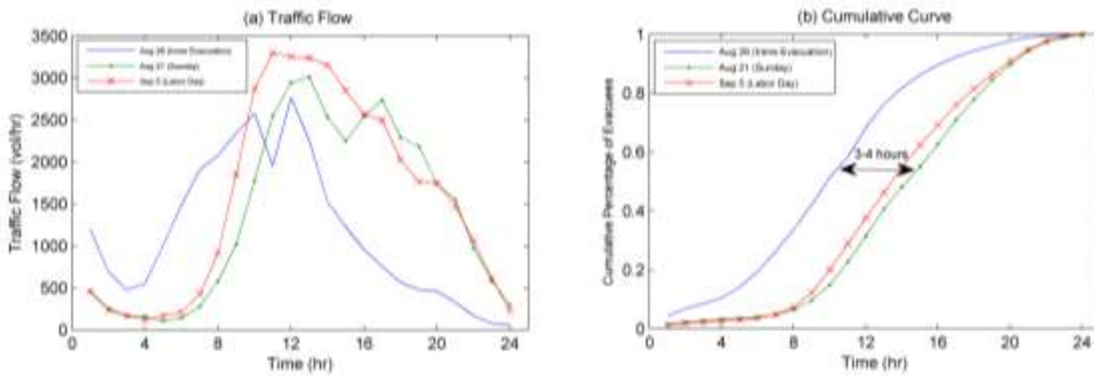


FIGURE 23 Traffic patterns during Irene evacuation and weekends

4.5 Summary

This case study analyzed the evacuation response curve during Hurricane Irene in Cape May County, New Jersey. The hourly toll plaza volume counts on the Garden State Parkway (GSP) were used for the analyses. Compared with traditional post-hurricane surveys, traffic volume data have several advantages, including large sample size, and avoiding the problem of recall in social science. The widely used so-called S-curves with different mathematical distributions (Logit, Rayleigh and Poisson) and state-of-art behavior model (Sequential Logit) are calibrated and compared with observed empirical data. The major conclusions of this study are as follows:

(a) The evacuees in Cape May County responded very quickly to the mandatory emergency order. Traffic volumes increased significantly when the official mandatory evacuation order was issued.

(b) The evacuation response curve is generally S-shaped with sharp upward changes in slope followed the issuance of mandatory evacuation notices. The sharp upward changes in the curve represent the quick evacuation response behavior observed during Hurricane Irene.

(c) The observed evacuation response behavior of the evacuees may have been partly caused by the high tourist population. Other factors such as little to no prior hurricane experience and limited evacuation routes may have also affected the observed evacuees' behavior.

(d) When comparing different evacuation response models, the calibrated S-curves obtained using Logit and Rayleigh functions are observed to fit the empirical data better. The better fit of S-curves is partly due to the quick response behavior of evacuees.

(e) The Sequential Logit model has not performed well when compared with empirical data. This is possible due to the fact that state-of-art behavior models based on empirical data from hurricane prone regions may not be transferable to states such as NJ with little or no previous hurricane experience.

(f) The empirical data can also be used for comparative analysis of traffic patterns during evacuation periods and regular weekdays/weekends. Our preliminary results show that the evacuation traffic pattern is similar to typical outbound traffic from the shore areas at the end of a summer weekend but with 3-4 hours earlier departure times.

The observed data from Hurricane Irene and calibrated parameter settings of evacuation response models may benefit evacuation planning in areas with similar circumstances as Cape May County, NJ. However, it should be noted that the findings of this study cannot be generalized since they are based on the analysis of a single set of data of evacuation behavior from a specific hazard condition in a particular area. A sensitivity analysis is recommended in other areas based on the calibrated models. Moreover, in order to have a reliable evacuation response model, more empirical data from different hurricane scenarios is required. This data should be used to better calibrate and compare current state-of-practice and state-of-art evacuation response models. In addition, when using traffic data for evacuation response behavior analysis, one limitation of such data is that the traffic volume may come from different counties or regions, and cannot be easily differentiated. In other words, the data may be a mixture of all evacuees from different counties or regions with separate evacuation orders, geographic, and social circumstances. However, such data could still benefit local highway agencies for emergency traffic management in terms of understanding similar hazard conditions.

Moreover, besides evacuation modeling, the behavior analysis is a much more fundamental issue for better understanding of the evacuation decision making process. In this study, we offer several tentative explanations for quick response behavior, which may be in part caused by an easily mobilized tourist population, lack of previous hurricane evacuation experience, and/or the nature of the location, which in this case a rural area with limited evacuation routes. However, such hypotheses still need additional rigorous tests supplemented with the individual information from a large sample of evacuees. The current traffic data does not contain such data. A possible future work can be to conduct evacuation behavior surveys among residents and tourists in Cape May County, New Jersey.

5 EVACUATION TRAFFIC PATTERNS: A CASE STUDY OF NEW JERSEY DURING HURRICANE IRENE

Understanding evacuation traffic characteristics is critical for public officials in employing emergency management strategies during an impending hurricane. This chapter is based on the our previous research (Li and Ozbay 2014, Li *et al.* 2015). We analyze empirical evacuation traffic patterns based on traffic data collected during Hurricane Irene (2011) in New Jersey. The results show that the most significant of the evacuation movements were located in the southern region of the state closest to the shore area. The vast majority of the evacuation traffic moved to the western regions, instead of traveling northbound along the vulnerable area. Moreover, the evacuation traffic patterns are similar to typical outbound traffic from the shore areas at the end of a summer weekend but with 3-4 hours earlier departure times. In addition, travel time data was used to identify the bottlenecks during Irene evacuation. The results show that the bottlenecks are generally merging areas with on/off ramps or interchanges.

5.1 Introduction

One of the main objectives of this study is to quantify and illustrate the empirical evacuation traffic patterns during Hurricane Irene in New Jersey. Such patterns include how people response to mandatory evacuation order and traffic conditions along the evacuation routes, such as congestions and bottlenecks. Several features distinguish this study from the previous ones.

First, the data used in this study comes from real-world traffic data, rather than from traditional post-hurricane surveys. The data includes hourly traffic volumes from highway toll plaza and Weight-in-Motion (WIM) stations, and historical travel time data collected by INRIX Inc. Compared with post-hurricane surveys, traffic data yield more realistic results and avoid the general “problem of recall” in social science. While much attention has been paid to hurricane evacuation behavior analysis, relatively few studies (Wolshon 2008, Archibald and McNeil 2012) make use of real-world traffic data.

Second, the behavioral reactions on travel time variability have been examined in the past couple of decades (Noland and Polak 2002). However, previous studies usually focus on the safety margin in daily travel behavior: the earlier departure time to compensate for possible traffic delays, especially the trips with deadlines, e.g. go to work or catch flights. Few previous studies examined the hurricane evacuation trips, which also have deadlines with "life-threatening" penalty, and high probable traffic delays. In addition, comparing with adaptive commuting behavior based on day-to-day learning of traffic conditions, the evacuees in New Jersey may not have sufficient evacuation experience to make rational decisions when hurricane happens. Thus, it is interesting to see the safety margin of people when disaster happens and no elements appear to be available for rational decision making.

Finally, the empirical bottlenecks are identified by comparing roadway travel time between evacuation and weekdays. Identification of bottlenecks is a critical component of emergency evacuation planning. However previous studies (Jha *et al.* 2004, Zou *et al.* 2005, Liu *et al.* 2008) usually use simulation techniques to determine the location and duration of bottlenecks along evacuation routes. Few studies investigated the empirical bottlenecks.

5.2 Spatial Evacuation Traffic Pattern in Statewide NJ

The major concern of this section is the spatial patterns of evacuation traffic prior Irene made landfall in statewide NJ. The vulnerable area of New Jersey to Hurricane Irene can be broadly divided into two geographic regions: northeastern NJ and the shore. Northeastern NJ lies within the New York City Metropolitan Area, and has the potential damage of storm surge and flooding.

While the shore, along the Atlantic Coast with 130 miles of coastline in the central-east and southeast, has its significant damage potential due to Nor'easters and tropical cyclones. In addition, high seasonal populations along the shore make hurricane evacuation an issue of critical concern for this region.

The analyses included in this section are based on hourly traffic volumes during Irene evacuation from the Weight-in-Motion (WIM) sites in statewide NJ. WIM sites are used for monitoring the heavy vehicles operating on roadways in North America. In addition to weight data of the heavy vehicles, WIM sites also collect a variety of traffic data, including traffic volume, speed, directional distribution, lane distribution, date and time of passage, axle spacing, and vehicle classification.

The spatial progression of Irene evacuation traffic is illustrated in FIGURE 24: the hourly traffic volume at each WIM site from Thursday, August 25, through Friday, August 26. As a reference, traffic flows for the same days during the prior week are also included, to illustrate typical traffic conditions. In addition to WIM data, the hourly traffic volumes from the Cape May and Gretna toll plazas on GSP are also included in FIGURE 24.

FIGURE 24 shows that the major evacuation happened in the shore region, the central-east and southeast region of the state closest the Atlantic Coast. In data sites 6-15, the traffic volumes during Irene evacuation are significantly higher than the prior week's counts. In addition, the evacuation traffic patterns at different locations also confirm the quick evacuation response behavior observed in Cape May County. The evacuation process started on Thursday, August 25, and the major part of the evacuation happened on Friday, August 26. Moreover, there was few evacuation traffic was observed in the data sites in northeast region of NJ. In other words, there no significant evacuation traffic from New York City was observed during Hurricane Irene.

Another observation in FIGURE 24 is that the major evacuation traffic moved to the western regions, instead of traveling northern area along the shore. For example, NJ-55 and GSP are two major evacuation outbound routes in Cape May County. However, westbound evacuation traffic along NJ-55 is 25,242, while the northbound traffic along GSP is only 14,450. This is partly because of the risk perception and proximity of evacuees along the shore. As stated by (Carnegie and Deka 2010), distance to threat is a critical factor affecting evacuation behavior. Evacuees preferred to choose the destinations and corresponding evacuation routes away from the potential risk.

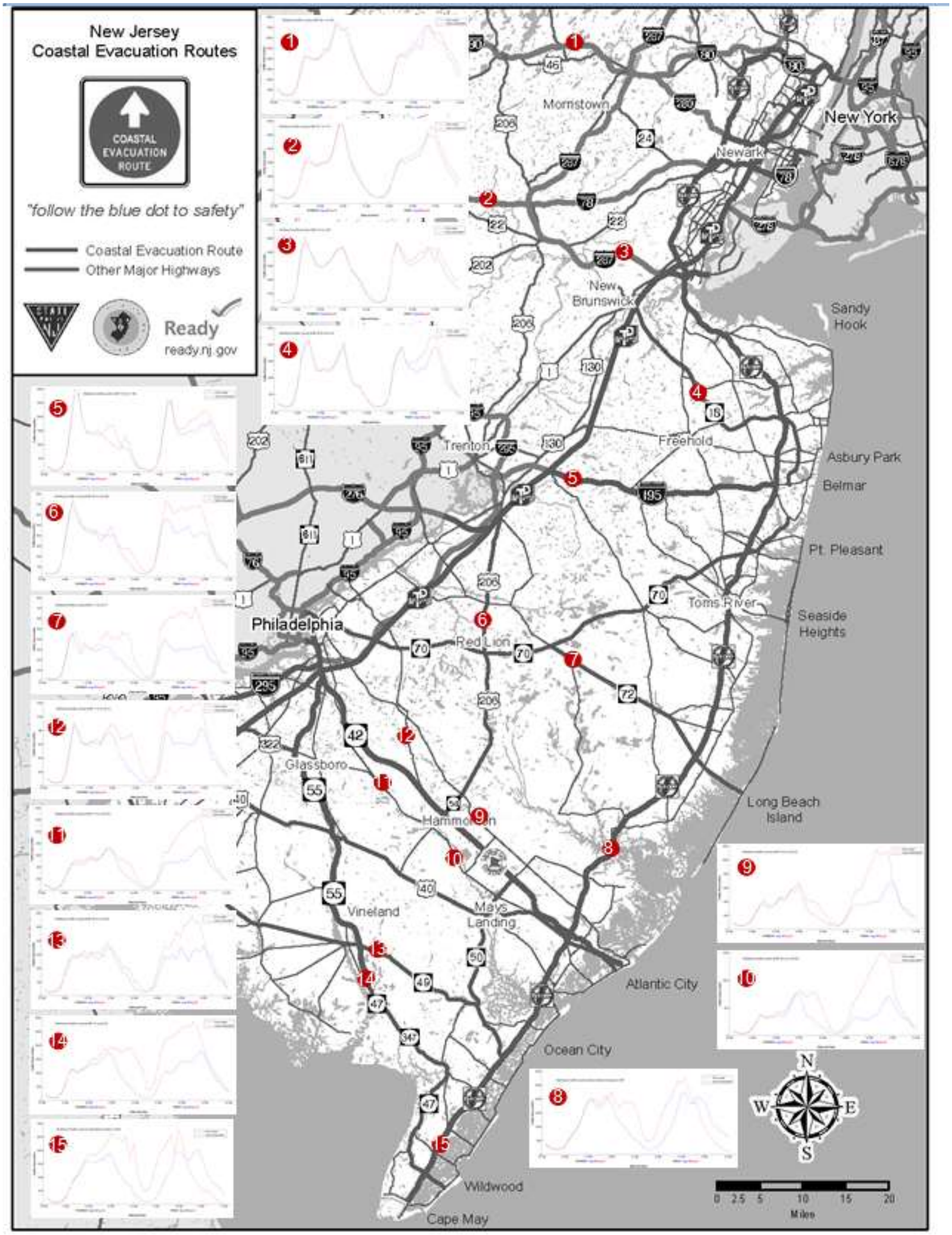


FIGURE 24 Irene evacuation traffic in statewide NJ

5.3 Evacuation safety margin

The quick evacuation response behavior can also be analyzed in terms of individual/household departure time choice. Generally when travelers make decisions on departure time to make sure of arriving destinations on time, e.g. go to work or catch flights, they prefer to departure earlier to compensate for possible delays caused by congested traffic. Such extra time for departure earlier is called safety margin (Gaver Jr 1968, Knight 1974).

The safety margin to uncertain travel times may also happen during hurricane evacuation. Because, on the one hand, evacuees have a deadline to leave the evacuation zones before the hurricane make landfall; on the other hand, evacuees probably also project that transportation system will be very congested based on the personal experience or media reports.

The differences between evacuation and daily trips are the penalties associated with late arrival at destinations. Hurricanes would bring "life-threatening" flooding while daily trips such as late arrival at work may only cost salary deductions. In addition, the daily departure time choice can be considered as adaptive behavior based on day-to-day learning of traffic conditions in transportation networks (Mahmassani and Chang 1986, Mahmassani and Jou 2000, Jotisankasa and Polak 2006). While people may not have sufficient evacuation experience to make rational decisions when disaster happens. Thus, it is interesting to see the safety margin when disaster happens and no elements appear to be available for rational decision making.

The differences of traffic patterns between Irene evacuation and weekends are illustrated in FIGURE 25: the comparison of traffic data from the prior weekends (Sunday, August 21) with the hurricane evacuation data (Friday, August 26). These data includes Toll Plaza, WIM station, and continuous volume data. In addition, the reason we compare Irene evacuation traffic with weekend traffic is that beach communities is dominated by tourists in summers. Usually daily trippers and weekly rentals are traveling to the beach on weekends and drive back home on Sundays. Thus the Sunday outbound traffic from the beach communities is often bumper to bumper with peak traffic demand.

FIGURE 25 shows that the evacuees tended to be more risk-averse with 1-4 hours earlier departure time than regular weekends in different data sites. The peak period on weekends is between 10 a.m. and 5 p.m., while during Hurricane Irene the peak period is between 7 a.m. to 1 p.m. Moreover, the data sites along the beach have larger safety margin than the sites in inland area. The value of safety margin decreased with the distance further to the Jersey shore. For example, in Cape May County the safety margin is 3-4 hours, and the value of the safety margin is reduced to 1-2 hours in the inland area. This may caused by the difference of risk perception and proximity of the evacuees. The evacuees along the shore area had larger safety margin probably because they perceived high risk/impact. The empirical evacuation safety margin during Hurricane Irene shows that evacuation traffic is not totally unpredictable, and may benefit from traffic management, especially for those without prior emergency evacuation experience.

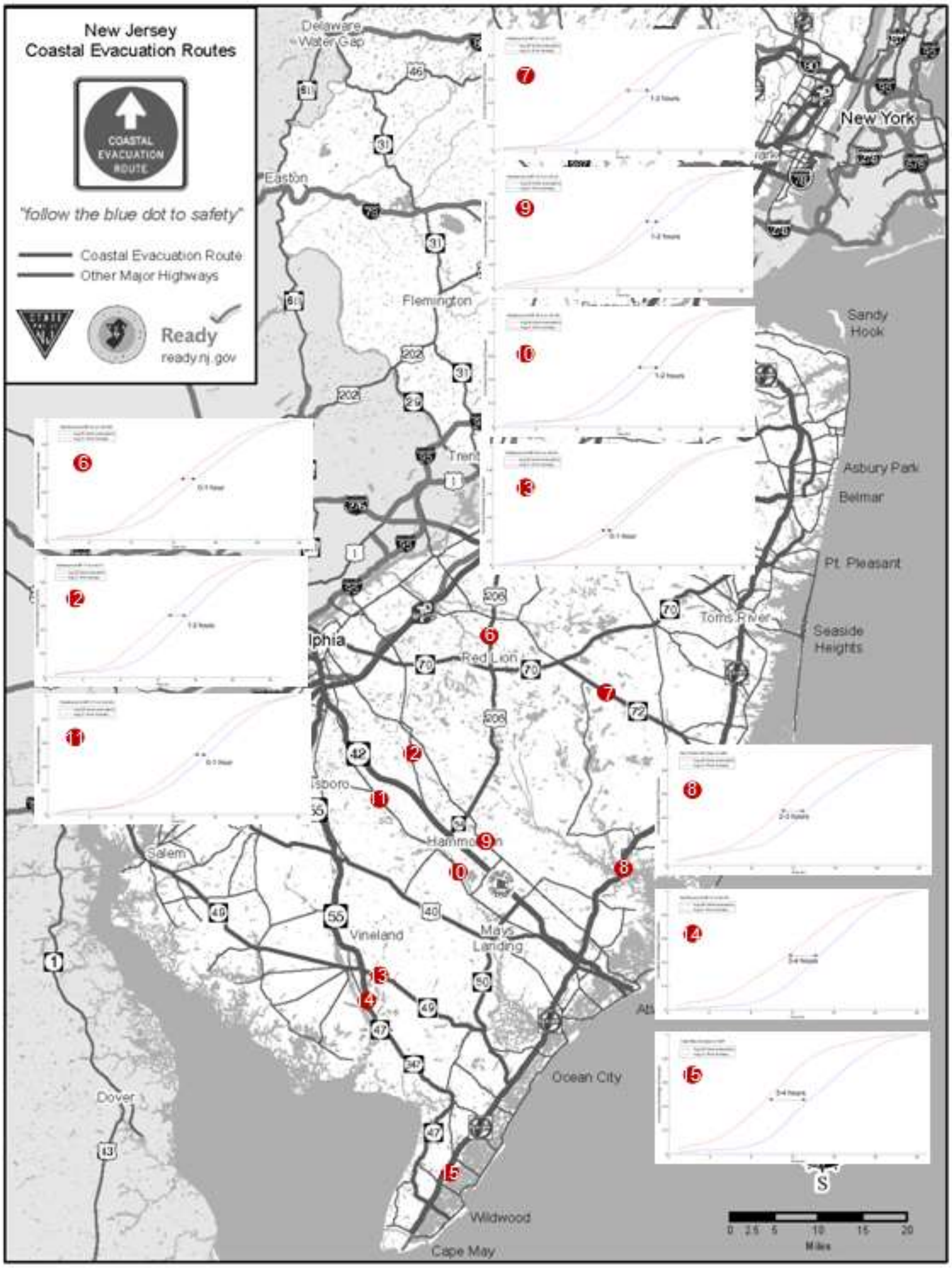


FIGURE 25 Difference of traffic patterns between Irene evacuation and weekends

5.4 Evacuation Bottlenecks

Identification of bottlenecks is a critical component of emergency evacuation planning for evaluating the traffic operations during an evacuation. Previous studies (Jha *et al.* 2004, Zou *et al.* 2005, Liu *et al.* 2008) usually use simulation techniques to determine the location and duration of bottlenecks along evacuation routes. But few studies investigate the empirical bottlenecks during hurricane evacuation.

The travel time during a hurricane evacuation is a persistent issue in many evacuation traffic analysis. The evacuation time from vulnerable area to safe zone is critical for public officials in emergency management. In addition, travel time is also a common indicator of evacuation performance by local and state governmental officials. In prior evacuation studies, probably because of insufficient data, the empirical evacuation travel time received insufficient attention.

In this section, the travel tie data collected by INRIX Inc was used in this study to identify traffic congestions and bottlenecks. INRIX is a software company which provides historical and real-time traffic information to business and individuals. The travel time data used in this study was collected from I-95 monitoring site which covers the major highways and arterials in New Jersey. For a specific section of road, INRIX data includes average speed and travel time in 5 minutes time interval.

FIGURE 26 shows the Irene evacuation bottlenecks in statewide NJ based on INRIX travel time. The bottlenecks refer to the links with 50% travel time increase by comparing Irene evacuation with the same time in the prior week. The bottlenecks firstly appeared in the afternoon of Thursday, Aug 25, along south part of GSP. Then on Friday, Aug 26, the bottlenecks spread to the north part of GSP and other major evacuation routes such as Atlantic City expressway. The worst network performance could be observed during 12:00 P.M. to 6 P.M on Friday, Aug 26. At the night period (6 P.M. to 9 P.M.) on Friday, Aug 26, the network congestion tailed away.

FIGURE 26 also illustrates that the bottlenecks during Irene evacuation are generally located in the merging areas. This is not surprising because freeway merging areas are critical segments causing congestions. When traffic volume increase, there are lots of conflicts (e.g. lane changing, vehicle merging, etc.) in merging areas. Actually ramp management is one of several functions performed on a daily basis but not receive sufficient attentions in emergency planning and management. Recent study (Foo *et al.* 2008) shows that ramp closure can be an effective tool in reducing traffic congestion and increasing efficiency on the road. Recently, (Machiani *et al.* 2013) also examined the ramp closures in no-notice evacuation management. The results show that *"ramp closures can speed the evacuation process by improving freeway flow. Blocking ramps could prohibit vehicles from entering freeways at their normal locations and mitigate the congestion experienced by evacuees".* This may be a good start to consider ramp management in emergency management, especially during hurricane evacuation.

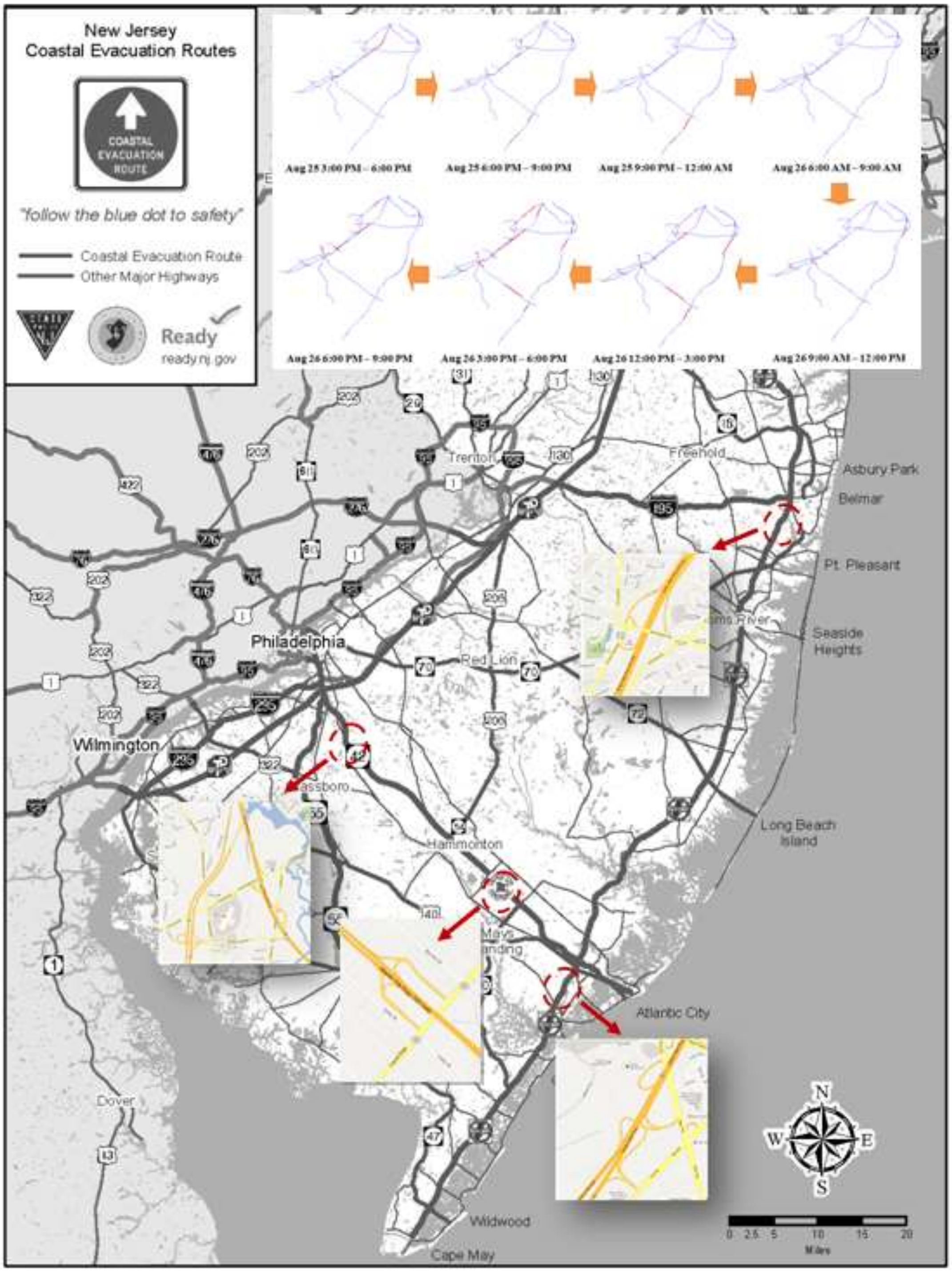


FIGURE 26 Bottlenecks in transportation network in southern New Jersey

5.5 Summary

This case study analyzed the evacuation traffic characteristics during Hurricane Irene in New Jersey. Different sources of real-world traffic data were used for the analyses. The data includes hourly toll plaza volume counts, Weight-in-Motion (WIM) traffic counts, and travel time data collected by INRIX Inc. Compared with traditional post-hurricane surveys, traffic data have several advantages, including large sample size, and avoiding the problem of recall in social science. The temporal and spatial evacuation traffic patterns were analyzed with empirical hourly traffic volume data, and bottlenecks were identified with travel time data. The major conclusions of this study are as follows:

(a) The most significant of the evacuation movements were on roads in the southern region of the state closest to the shore area. No significant evacuation traffic is observed in northern New Jersey.

(b) The vast majority of the evacuation traffic moved to the western regions, instead of traveling northbound along the shore area.

(c) The evacuation traffic pattern is similar to typical outbound traffic from the shore areas at the end of a summer weekend but with 3-4 hours earlier departure times.

(d) The bottlenecks during Irene evacuation are generally merging areas with on/off ramps or interchanges.

The observed empirical evacuation traffic patterns from Hurricane Irene may benefit evacuation planning in areas with similar circumstances as New Jersey. However, it should be noted that the findings of this study cannot be generalized since they are based on the analysis of a single set of data of evacuation behavior from a specific hazard condition in a particular area. Moreover, besides traffic data analysis, the behavior/psychological research is a much more fundamental issue for better understanding of the evacuation decision making process. In this study, we offer several tentative explanations for evacuation traffic patterns in NJ. However, such hypotheses still need additional rigorous tests supplemented with the individual information from a large sample of evacuees. The current traffic data does not contain such data. A possible future work can be to conduct evacuation behavior surveys among residents and tourists in statewide New Jersey.

6 MODELING EVACUATION BEHAVIOR UNDER HURRICANE CONDITIONS

6.1 Introduction

Hurricanes are among the most destructive natural disasters before which mass evacuations are highly likely. Especially in the post-Hurricane Irene and Sandy context, disaster preparedness has become a vital component of emergency management plans for many states in the Northeast United States that are vulnerable to flooding and other adverse effects of hurricanes (Bucci *et al.* 2013, NYC 2013). Accuracy of the early warning information and timeliness of the response systems play a crucial role in mobilizing people under risk (Baker 1991). In recent years, advanced information technologies enable decision-makers to evaluate risk factors and take necessary precautions hours before the storm makes landfall. However, mandatory evacuation orders by the authorities do not always mean the majority of people to start moving to safer places (Gladwin *et al.* 2001). Strong empirical evidence from literature shows that individual evacuation decisions are rather controlled by personal characteristics, features of the affected region and severity of the hurricane all of which need to be evaluated using statistical models.

A growing body of literature investigated the role of various factors in deciding whether to stay or to evacuate, mode, departure time, destination and route choice during evacuation. The majority of these studies were dedicated to identify the underlying factors in human decision-making. Statistical models that are employed to determine the significance of different factors are mostly calibrated using observed behavior in similar events. Parameters that are usually included in decision modeling are whether having a past experience in a similar disaster, proximity to coast, socio-economic and demographic characteristics. Although most of these models successfully mimic evacuation decisions and overall expected demand based on real world observed data, forecasting for life-threatening natural disasters such as hurricanes is generally very difficult. As pointed out by some recent studies, advanced statistical models can make an important improvement in accurate predictions for evacuation planning. For example it was showed that using models that allow including heterogeneity in model parameters to address the diverse causes behind the responses to survey questions can help better understanding evacuation decision (Hasan *et al.* 2010), or route choice during evacuation (Sadri *et al.* 2013c).

this chapter is based on our previous research (Yang *et al.* 2016). We aim to examine residents' evacuation behavior. It contributes to the existing literature by developing a structural equation modeling (SEM) approach to jointly analyze evacuation decision and destination choices based on stated preference data. A Telephone survey data collected for Jersey City/Newark Urban Areas Security Initiative region in Northern New Jersey was used as a case study. For detailed description of survey design and descriptive statistics of responses readers are referred to Carnegie and Deka (2010).

6.2 Research on Evacuation Behavior Modeling

Emergency evacuation behavior modeling in the literature can be grouped in two main categories: 1) Post-event studies and 2) Pre-event studies. The main advantage of post-event studies over pre-event studies is the observed behavior of the affected population under real evacuation situations. Most of these studies try to identify the chief reasons behind the evacuation decisions of people. The results obtained from post-event studies are usually considered as inputs for predicting future behavior of the respondents. However, for events with high degree of uncertainty, such as hurricanes, it is not always possible to generalize the findings from a single situation to future events (Murray-Tuite and Wolshon 2013). Pre-event studies, on the other hand, facilitate analyses of a wide range of hypothetical scenarios based on different assumptions about spatial contiguity and severity of the hurricane. The major concern regarding the findings in pre-event studies is the accuracy of the respondents' stated preferences with the actual behavior in a future real situation.

Baker (1995) compared hypothetical and actual hurricane evacuation behavior in Florida. The findings showed that logistic regression models using stated preference data precisely estimated the actual behavior of the respondents. In a more recent study, Kang *et al.* (2007b) found that a large portion of the population (80 per cent) who had stated that they would not evacuate actually did not evacuate during the Hurricane Lili. Same study also reported that 65 per cent of the users who had been expected to evacuate based on pre-event surveys did evacuate during the event. Murray-Tuite and Wolshon (2013) provided an excellent summary of research efforts in general evacuation transportation modeling including specific studies dealing with hurricanes.

Logistic regression models are widely used for predicting evacuation behavior. Whitehead *et al.* (2000) used telephone survey data from North Carolina to investigate evacuation decision-making of the respondents. Based on the survey data, the modeling results show that socio-economic characteristics along with the types of evacuation order played a key role in evacuation decision. As expected, in a voluntary evacuation order, people are more likely to stay and are not willing to go to a safer place compared to a mandatory evacuation order. Fu and Wilmot (2004a) used sequential logit models for estimating observed evacuation demand in Hurricane Andrew and concluded that their model produced reasonable prediction for the observed behavior. Brezina (2008) highlighted the reasons for not evacuating during Hurricane Katrina using a survey data that is collected immediately after the disaster. Logistic regression model results showed that in contrast with common belief that welfare effects (i.e. employment status) are not among the significant effects in evacuation decision. Gudishala and Wilmot (2013) used a sequential logit model for estimating evacuation behavior. The model was trained using a real evacuation data and then hypothetical scenarios were estimated from a stated choice data. Carnegie and Deka (2010) developed logistic regression models to evaluate evacuation decisions for different types of natural and man-made disasters. The results showed that socio-economic characteristics of the respondents play a more decisive role in evacuation in hurricanes compared to the other types of emergency conditions.

Random parameters models have been recently incorporated in the evacuation behavior context. Hasan *et al.* (2010) used mixed logit models to estimate evacuation decision by addressing unobserved heterogeneity of survey responses. The reported model results were found to be consistent with previous studies in terms of significance of factors and it was concluded that including parameter heterogeneity in modeling can contribute to more informed decision-making during emergency conditions.

Different modeling approaches employed to address risk-taking attributes and hierarchical nature of evacuation decision process. Dixit *et al.* (2012) developed a model that incorporates risk aversion for departure time choice during evacuation. The model presented in this study was stated as useful for authorities in distinguishing factors that are related to risk taking behavior of the population and take necessary action to motivate them for evacuation. Huang *et al.* (2012) analyzed household evacuation decision and departure time choice for Hurricane Ike using a Proactive-Action Decision Model. The results of this study showed that there is a hierarchical structure in evacuation decision, such that personal features play a role in deciding whether stay or to leave and storm characteristics and perceptions affect personal features.

TABLE 5 Summary of selected evacuation decision modeling literature gives a summary of selected literature on evacuation decision making along with data sources, sample sizes and modeling methodologies. All the existing studies modeled different evacuation behavior separately. The potential interactions among different evacuation behavior were not ignored. However, there is possibility that a person's choice of one thing will be conditional upon the choices of other things. Therefore, it is necessary to investigate the possible relationship between different evacuation behavioral responses.

TABLE 5 Summary of selected evacuation decision modeling literature

Author	Data Source	Sample Size	Modeling Methodology
Brezina (2008)	Survey of Hurricane Katrina Evacuees, New Orleans	680 respondents	Logistic Regression Analysis
Whitehead *et al.* (2000)	Telephone survey of North Carolina residents who were affected in Hurricane Bonnie	895 respondents	Logistic Regression Analysis for Evacuation Decision Multinomial Logit for Destination Choice
Gladwin *et al.* (2001)	Interview with Miami residents who were affected in Hurricane Andrew and Erin	954 respondents	Ethnographic Decision Tree Analysis
Fu and Wilmot (2004a)	Interview with people from Southwest Louisiana after Hurricane Andrew	428 households	Sequential Logit Model
Hasan *et al.* (2010)	Telephone survey of households that are affected in Hurricane Ivan	3,200 households	Mixed Logit Model
Dixit *et al.* (2012)	Interview with people from Southwest Louisiana after Hurricane Andrew	429 households	Utility maximization with risk aversion
Gudishala and Wilmot (2013)	Self-administered survey by mail in New Orleans area	300 households	Sequential Logit Model
Carnegie and Deka (2010)	Survey of four hypothetical disaster scenarios in Northern New Jersey including a hurricane scenario	2,218 interviews	Logistic Regression
Huang *et al.* (2012)	Mail survey of households in Houston- Galveston Study Area	200 households	Logistic Regression / Ordinary Least-squares Regression

6.3 Evacuation Behavior Survey

A random digit dial telephone survey was conducted between August and October of 2008 in northern New Jersey (*7*). It covers a large urban region consisting of Passaic, Bergen, Hudson, Morris, Essex, Middlesex and Union Counties. The total population of the region is approximately 4.5 million. In total, 2,218 households were interviewed with a set of questions related to their evacuation experience, disaster preparedness (including hurricane, industrial accident and catastrophic nuclear explosion), evacuation decision choices, evacuation destinations, and evacuation mode choices. In addition, a series of questions regarding the characteristics of the household and household members, such as income, vehicle ownership, family size etc. were asked.

TABLE 6 lists the major questions interviewed in the evacuation behavior survey. The survey data were cleaned by removing those without full responses. In total, 1,221 households provided valid responses to the interviewed questions. The responses were coded in TABLE 6. The number in the in the parenthesis indicates the number of responses for each question.

TABLE 6 Defining variables for the evacuation survey

Major Questions	Responses
Evacuation decision choice	very unlikely=0 (569); not very likely=1 (249); somewhat likely=2 (212); very likely=3 (191)
Evacuation destination	public shelter=1 (319); friend/relative's home=2 (518); hotel/motel=3 (140); others=4 (244)
Gender	male=0 (554); female=1 (667)
Evacuation experience	yes=0 (100); no=1 (1121)
Employment status	employed=0 (681); not employed=1 (540)
Risk perception	not affected=0 (178); affected=1 (1043)
Years of current residence	≤ 1 years = 0 (114); 1< years ≤ 10 = 1 (527); >10 years = 2 (580)
Type of residence	others=0 (319); house=1 (902)
House ownership	rent=0 (511); own=1 (710)
Age	age<65 is 0 (969); age≥65 is 1(252)
Household size	1 people =0 (262); ≥2 people =1 (959)
People under the age of 18	without =0 (779); with =1 (442)
Specific care needed	no =0 (1040); yes =1 (181)
Have pet	no =0 (795); yes =1 (426)
Educational level	≤ high school =0 (381); college and above =1 (840)
Household with vehicle	no =0 (217); yes =1 (1004)
Income level	<$2500 =1 (201); $25000~$50,000 =2 (216); $50,000~$100,000 =3 (298); ≥$100,000 =4 (292); Unreported =5 (214);
Distance to shore	distance in miles (1221)
Language of interview	English =0 (1076); Others =1 (145)
Marital status	others =0 (653); married =1 (568)
Race / ethnic background	White not Hispanic =0 (507); others =1 (714)

6.4 Methodology

The surveyed evacuation responses include non-negative count data and the outcome of a set of contributing factors. To model such count data, a number of discrete choice models can be considered. The following sections describe the models used in this study.

6.4.1 Structural Equation Modeling

Instead of modeling different aspects of evacuation behavior separately, an alternative interesting approach is to investigate whether one behavior/decision will affect the others. Specifically, whether the individuals' evacuation decisions will affect their choice of evacuation destination?

In order to address the aforementioned question, the structural equation modeling (SEM) approach is used in this study. In general, the structural equation modeling involves two components: a measurement model and a structural model. Former component describes how well the observed indicators measure the latent (unobserved) variables and the later one is used to relate all of the variables (both latent and manifest). FIGURE 27 shows the SEM model considered in this study. Some of the survey questions are considered to be explanatory variables that only affect the evacuation decision choices or evacuation destination choices whereas others (i.e. survey question k and h) are considered to be influential in both responses.

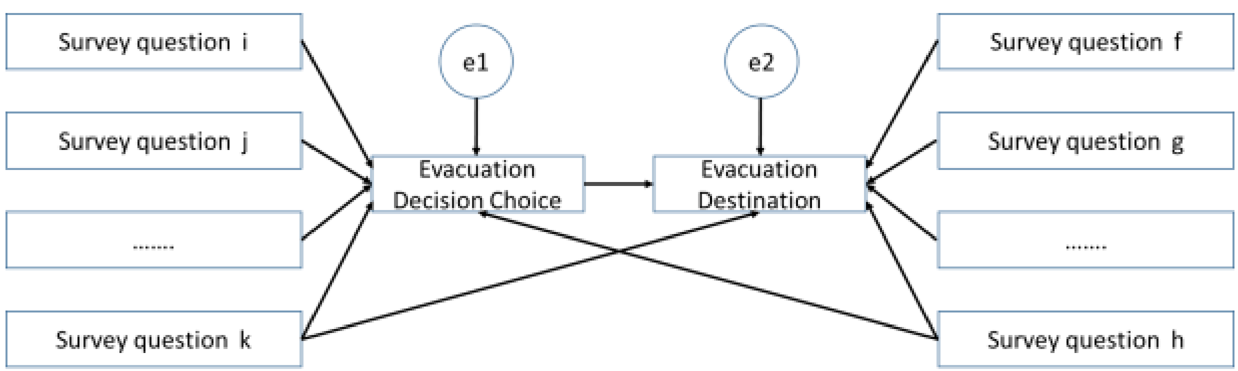


FIGURE 27. Example of a structural model examining evacuation decision behavior on evacuation destinations

The proposed model assumes that the evacuation decision choice will affect the choices of evacuation destination. In other words, if the individual chooses to evacuate, his/her choice to evacuation destination is bounded by certain options. The SEM approach can integrate different statistical modeling procedures into single statistical program, which provides us unparalleled flexibility in modeling other scenarios (if needed). Within the structural modeling framework, the individual components will be modeled in the following sections.

6.4.2 Modeling Evacuation Decision Behavior

The personal responses to the evacuation decision in the survey are described by four categorical answers, including very unlikely, not very likely, somewhat likely, and very likely. Thus these four choices can be considered as a discrete and ordinal response variable of the evacuation decision. Given the discrete natural order of the tendency of choice, the ordered probit regression (OPR) model is considered to capture the relationship between a list of exogenous factors and the interviewed person's evacuation decision choice. The modeling approach is described below.

Assume there is an unobserved latent continuous metric y_i^* underlying the observed tendency of evacuation decision y_i of the i^{th} interviewed person. y_i^* is assumed to depend linearly on the exogenous factors X_i plus a random error term ε_i as follows:

$$y_i^* = X_i^{'}\beta + \varepsilon_i \tag{7}$$

where y_i^* denotes the latent variable measuring the evacuation decision of the i^{th} interviewed person; X_i is a $k \times 1$ vector of observed non-random explanatory variables; β is a $k \times 1$ vector of unknown parameters; and ε_i is the random error term.

The latent variable y_i^* is mapped onto the observed variable y_i according to the following scheme:

$$y_i = j \ \text{ if } \ \tau_{j-1} < y_i^* \le \tau_j \quad \text{for } j = 1 \text{ to } J \tag{8}$$

where j is the observed tendency of evacuation decision of person i; y_i^* is dissected by $J-1$ thresholds into J partitions; τ_j's are constant and unknown threshold parameters to define partitions, denoted as $\tau_{j-1} < \tau_j$, $\tau_0 = -\infty$, and $\tau_J = +\infty$. The partitions are not in general equally spaced.

Defining evacuation decision of four levels according to the person' response to the question, equation (8) can be represented by the following decision model:

$$y_i = \begin{cases} 1 \quad if\ \tau_0 < y_i^* \le \tau_1 \quad \text{(Response = very unlikely)} \\ 2 \quad if\ \tau_1 < y_i^* \le \tau_2 \quad \text{(Response = not very likely)} \\ 3 \quad if\ \tau_2 < y_i^* \le \tau_3 \quad \text{(Response = somewhat likely)} \\ 4 \quad if\ \tau_3 < y_i^* \le \tau_4 \quad \text{(Response = very likely)} \end{cases} \tag{9}$$

Using the above equation (9) we can determine the cumulative probability of y_i as equation (10):

$$\Pr(y_i \le j) = \Pr(y_i^* \le \tau_j) = \Pr(X_i^{'}\beta + \varepsilon_i \le \tau_j) = \Pr(\varepsilon_i \le \tau_j - X_i^{'}\beta) = F(\tau_j - X_i^{'}\beta) \tag{10}$$

where F is the cumulative distribution function (CDF) of the unobserved error term ε_i.

Based on equation (10), the probability that the i^{th} person choosing j^{th} response level can be described by equation (11):

$$\Pr(y_i = j \mid X_i) = F(\tau_j - X_i^{'}\beta) - F(\tau_{j-1} - X_i^{'}\beta) \tag{11}$$

Given the assumption that the error term ε_i in equation (7) is independently distributed according to standard normal distribution $\varepsilon_i \sim N(0,1)$, then equation (7) represents the ordered probit model structure and the probability equation (11) can be specified as follows:

$$\Pr(y_i = j \mid X_i) = \Phi(\tau_j - X_i^{'}\beta) - \Phi(\tau_{j-1} - X_i^{'}\beta) \tag{12}$$

where Φ is the CDF of the standard normal distribution.

Specifically, the probability that the person is very unlikely to evacuate is:

$$\Pr(y_i = 1 \mid X_i) = \Phi(\tau_1 - X_i^{'}\beta) \tag{13}$$

The probability that the person is very likely to evacuate is:

$$\Pr(y_i = 4 \mid X_i) = 1 - \Phi(\tau_3 - X_i^{'}\beta) \tag{14}$$

We are concerned with how changes in the independent variables X_i translate into the probability of observing a particular level of severity. Equation (13) and (14) indicate that a positive coefficient β_k decreases $\Pr(y_i = 1 \mid X_i)$ and increases $\Pr(y_i = 4 \mid X_i)$, respectively. Alternatively, it can be said unambiguously that an increase in the variable implies the increases in the probability of deciding to evacuate under hurricane condition.

6.4.3 Modeling Evacuation Destination Choices

The individual responses regarding the evacuation destinations are described by a set of unordered discrete outcomes: public shelter =1, friend or relative's home = 2, hotel or motel = 3, and somewhere else = 4. Naturally, a multinomial logit (MNL) model is a suitable candidate to describe the relationships that may exist between the independent variables and the destination choices. In general, the MNL model aims to estimate a function that determines choice probabilities. Given one choice as a reference (i.e., public shelter), the probability of each choice π_{ij} is compared to the probability of the reference choice π_{iJ}. For choices $j = 1,2,...,J-1$, the log-odds of each choice is assumed to follows linear model:

$$\eta_{ij} = \log\left(\frac{\pi_{ij}}{\pi_{iJ}}\right) = X_i^{'}\alpha_j \tag{15}$$

where α_j is a $k \times 1$ vector of regression coefficients for each choice $j = 1,2,...,J-1$.

Based on equation (15), the probability of choosing i^{th} choice is $\pi_{ij} = exp\left(\eta_{ij}\right) \times \pi_{iJ}$. Note the fact that $\eta_{iJ} = 0$ and $\sum_{j=1}^{J} \pi_{ij} = 1$, we can obtain $\pi_{iJ} = 1 \Big/ \sum_{j=1}^{J} exp\left(\eta_{ij}\right)$. Therefore, the probability π_{ij} can be rewritten as follows:

$$\pi_{ij} = \frac{\exp\left(\eta_{ij}\right)}{\sum_{j=1}^{J}\exp\left(\eta_{ij}\right)} = \frac{\exp\left(X_i^{'}\alpha_j\right)}{\sum_{j=1}^{J}\exp\left(X_i^{'}\alpha_j\right)} \tag{16}$$

The MNL model is reduced to a logistic regression model if there are only two destination choices $J = 2$. For $J > 2$, the probability distributions of the destination choices are multinomial instead of binomial.

6.4.4 Bayesian Modeling Procedure

The structural equation model in this study was calibrated within the Full Bayesian context, which uses Monte Carlo Markov Chain (MCMC) sampling methods to estimate the parameters. The proposed model was constructed and implemented in the WinBUGS

("BUGS" stands for Bayesian inference using Gibbs sampling) statistical software. Such model estimation approach has been frequently used in travel behavior studies (Chikaraishi *et al.* 2009, Daly *et al.* 2012). MCMC approach draws samples from the posterior distribution and generates chains of random points. Once the distribution of the simulated chains is observed to converge to the target posterior distribution, full Bayesian estimates of the model parameters are obtained from the remaining iterations. The Brooks–Gelman–Rubin (BGR) statistic and trace plots of the chains can be used to check the convergence. The iterations up to the convergence point are excluded as burn-in samples and the remaining iterations are used for the posterior estimates. The accuracy of the posterior estimates is assessed by calculating the Monte Carlo error for each parameter. The Monte Carlo error is an estimate of the difference between the mean of sampled values and the true posterior mean. In general, an inference is considered to be reliable when the Monte Carlo error for each parameter of interest is less than about 5 percent of the sampled standard deviation (Burnham and Anderson 2002). In order to implement the Bayesian estimation procedure, prior distribution of each variable has to be defined. Since there is no known information about the distribution of each parameter, uninformative priors are considered. Usually, the normal distribution with zero mean and a large variance is used to define the prior distribution for the regression parameters. In addition, Gamma distribution [i.e., $Gamma(0.001,0.001)$] was used as the uninformative priors for other parameters such as the precision in specifying a normal distribution.

The Deviance information criterion (DIC) is used to assess the model fitting and complexity. DIC is calculated by the following equation:

$$DIC = \overline{D(\theta)} + p_D \tag{17}$$

where $D(\theta)$ represents the Bayesian deviance of the estimated parameter θ. $\overline{D(\theta)}$ is the posterior mean of $D(\theta)$, $\overline{D(\theta)} = E[D(\theta)] = -2\log[L(Y \mid \theta)]$. $p_D = \overline{D(\theta)} - D(\bar{\theta})$ defines the effective number of parameters and can be denotes as a measure of model complexity. $D(\bar{\theta})$ is the point estimate that describes how well the model fits the data and $L(Y \mid \theta)$ is the likelihood function. As a rule of thumb, a DIC difference of 10 would be used to rule out the model with the higher DIC (Gelman *et al.* 1996, Spiegelhalter *et al.* 2002).

6.5 Results and Discussion

Based on the defined variables in TABLE 6, the original data set was cleaned by removing those with missing values. In total, data related to 1,221 households were used for the final modeling analysis.

In order to specify the potential model structures, various relationships between response variables and independent variables have been explored. Those with small correlation coefficients have been excluded from initial consideration. Then an iterative procedure was employed to add/remove each variable to/from the candidate models. For the final evacuation decision choice model, seven variables, including gender, risk perception, age, education level, income level, distance to shore, and race / ethnic backgrounds, were specified in the final models. Other than the evacuation decision choice, other three variables namely, house ownership, evacuation experience, and employment status, were also included in the final model for evacuation destination choice. After a burn-in period of 20,000 iterations, we ran each chain (two chains in total for additional 10,000 iterations. Setting aside the results from the burn-in period, the estimated posteriors have been presented in TABLE 7. The accuracy of the estimation was verified as the Monte Carlo errors were less than 5 percent of the sampled standard deviation. The DIC for the structural equation model is 6038.94 (consisting of which Evacuation decision choice model DIC =2947.32 and evacuation destination choice model DIC=3091.62). No other model specifications were found to yield significantly smaller DIC value.

TABLE 7 Bayesian estimation results

Evacuation Decision Choice Model

Variable	mean	sd	2.5%	97.5%
β_1	0.106	0.067	-0.024	0.237
β_2	0.345	0.091	0.165	0.520
β_3	-0.278	0.083	-0.439	-0.116
β_4	-0.208	0.082	-0.368	-0.048
β_5	-0.088	0.117	-0.318	0.140
β_6	-0.262	0.114	-0.488	-0.043
β_7	-0.242	0.123	-0.487	-0.002
β_8	-0.140	0.119	-0.377	0.093
β_9	-0.341	0.051	-0.442	-0.242
β_{10}	0.486	0.071	0.348	0.627
c_1	-1.483	0.170	-1.829	-1.160
c_2	-0.857	0.168	-1.195	-0.535
c_3	-0.265	0.167	-0.600	0.054

Evacuation Destination Choice Model

Variable	mean	sd	2.5%	97.5%
$\alpha_{1,2}$	0.644	0.361	-0.043	1.362
$\alpha_{1,3}$	-0.821	0.495	-1.764	0.136
$\alpha_{1,4}$	-0.124	0.438	-0.989	0.734
$\alpha_{2,2}$	0.783	0.150	0.490	1.079
$\alpha_{2,3}$	0.785	0.215	0.369	1.206
$\alpha_{2,4}$	0.787	0.182	0.432	1.146
$\alpha_{3,2}$	0.580	0.271	0.057	1.115
$\alpha_{3,3}$	0.136	0.375	-0.606	0.861
$\alpha_{3,4}$	0.188	0.305	-0.400	0.789
$\alpha_{4,2}$	0.261	0.250	-0.228	0.752
$\alpha_{4,3}$	0.126	0.342	-0.537	0.810
$\alpha_{4,4}$	-0.169	0.287	-0.725	0.401
$\alpha_{5,2}$	0.052	0.218	-0.380	0.478
$\alpha_{5,3}$	-0.155	0.305	-0.742	0.461
$\alpha_{5,4}$	-0.370	0.247	-0.843	0.118
$\alpha_{6,2}$	0.448	0.155	0.148	0.750
$\alpha_{6,3}$	0.602	0.212	0.187	1.019
$\alpha_{6,4}$	-0.219	0.193	-0.602	0.158
$\alpha_{7,2}$	-0.976	0.315	-1.615	-0.400
$\alpha_{7,3}$	-0.674	0.424	-1.517	0.154
$\alpha_{7,4}$	-0.349	0.395	-1.141	0.427

Note:

β_1 - gender

β_2 - risk perception

β_3 - age

β_4 - education levels

β_5, β_6, β_7, β_8 - income

β_9 - distance to shore

β_{10} - race / ethic

c_1, c_1, c_1 - cutoff values

$\alpha_{1,i}$ - intercept

$\alpha_{2,i}$ - house ownership

$\alpha_{3,i}$, $\alpha_{4,i}$, $\alpha_{5,i}$ - evacuation decisions

$\alpha_{6,i}$ - with people under 18

$\alpha_{7,i}$ - evacuation experience

i - specific destination choice

The 95% Bayesian credible interval (BCI) was used to examine whether a variable is significant or not. This is defined the by the lower 2.5 percentile estimate and the upper 97.5 percentile estimate shown in the above table. If the estimated BCI covers zero, it suggests that the variable is not significant. Otherwise, the variable is considered to be significant. The estimation results in TABLE 7 show that females tend to be more likely to evacuate than males (reference group) as the posterior mean of gender is 0.106 (The lower bound (2.5 percentile) of its BCI is close to zero). If the person feels his/her family will be affected by the hurricane, his/her family is more likely to evacuate (β_2 =0.345). Elder person (age over 65) is less likely to evacuate than younger ones (reference group). These findings are consistent with Carnegie and Deka (2010). Interestingly, there is significant association between education levels and evacuation decision choices. $\beta_4 = -0.208$ suggests that the ones with college or higher education are less likely to evacuate than others (reference group). Though the sign of this variable is consistent with the findings of Carnegie and Deka (2010), they did not find it is significant. Other than β_6, the other three coefficients of income are not found to be significant in our study. This suggests that there is no significant difference between people with different income levels in terms of their evacuation decision choices. It was found that a family living close to shore is more likely to evacuate as β_9 is -0.976. The race/ethic background also affects the evacuation decisions. Compared to "White but not Hispanic" residents, others are more likely to evacuate.

The multinomial logistic regression model treated public shelters as the reference group and estimated three models for different destinations relative to public shelters. The standard interpretation of each estimated coefficient is that for a unit change in the explanatory variable, the logit of i^{th} destination choice relative to the reference group is expected to change by the corresponding estimate (in log-odds units) while holding all other variables in the model constant. For example, if the interviewed subject owns the house / apartment, the logit of choosing friend/relative's home, hotel/model, and other places as their destination in relative to public shelters is expected to increase 0.783, 0.785, and 0.787 unit respectively, given all other variables in the model are held constant. Likewise, if the family has members under 18, it is more likely to choose their friend / relative's home or hotel / motel as their destinations. Interestingly, previous experience with evacuation did not significantly change the logit of choosing friend/relative's home, hotel/model, or other places of destinations in relative to public shelters. The estimated $\alpha_{3,i}$, $\alpha_{4,i}$, and $\alpha_{5,i}$ examined the association between the evacuation decision choices and the evacuation destination choices. Other than $\alpha_{3,2}$, the results suggest that there was no obvious link between the evacuation decisions and destination choices. In other words, the subject' attitude to evacuate does not necessarily affect their choice of candidate destinations.

6.6 Summary

This section examined evacuation behavioral responses under hurricane conditions. The stated preferences for evacuation decision choices and evacuation destinations have been investigated based on a survey in New Jersey. A structural equation model has been developed to jointly model: (a) the potential factors that affect the choice behavior and (b) the relationship between the evacuation decision choices and the evacuation destination. It was found that age, education levels, distance to shore, and race/ethic background tend to affect the evacuation decisions. Nevertheless, gender and income levels did not significantly affect the decisions of evacuation. Regarding the evacuation destination choices, it was found that house ownership is a key factor that changes the preference of other types of destinations in relative to public shelters. The individuals who own the house/apartment are more likelihood to evacuate to their friend / relative's home as well as hotel. Evacuation experience did not significantly affect their choices of destinations. In addition, there was no strong relationship between evacuation decision choices and evacuation destination choices. In other words, whether or not individuals consider evacuating, there is no significant difference between choosing public shelters and other places.

Unlike other previous studies that modeled each evacuation behavior separately, this study offered a way to employ structural equation model for modeling different evacuation behavioral responses together. It suggests the need to consider the potential relationship between some response variables. However, this study is not free from limitations. First, the sample size of the survey should be further enlarged so that the heterogeneity of surveyed individuals across the state can be captured. A larger sample size will also be helpful in training the SEM models. Second, a comparative analysis with post-evacuation data collected after real hurricanes such as Sandy and Irene should be performed. Most of current surveyed population did not have experience of severe hurricanes in their local areas. Finally, other structural equation models can be considered by assuming different relationship among the contributing factors.

We have to mention that the SEM approach cannot test directionality in relationships. In other words, it requires users to hypothesize the causality (i.e., which evacuation behavior may affect the others). In addition, SEM requires well-specified measurement and conceptual models. The choice of variables and pathways will affect the SEM's ability to capture the sample covariance and variance patterns observed in field. Thus, the sensitivity of the model specification should be tested to help find more rational models.

7 CONCLUSIONS

This research report develops a systematic methodology to fully understand evacuation demand and evacuation behaviors using detailed data collected from the most recent Hurricanes Irene and Sandy. Collected traffic data include hourly toll plaza volume counts, Weight-in-Motion (WIM) traffic counts, and travel time data obtained from INRIX Inc. Additionally, stated preference telephone survey data collected for Jersey City/Newark Urban Areas Security Initiative region in Northern New Jersey are used. The findings of this research report can provide useful insights for government agencies to develop pre-hurricane evacuation plans as well as post-hurricane emergency management strategies.

An extensive review of the literature on the complex process of hurricane evacuation is presented in Chapter 2. Previous studies on evacuation behavior modeling are reviewed in five categories: 1) evacuation timing behavior, 2) evacuation mobilization time, 3) evacuation destination choice, 4) evacuation routing strategy and 5) evacuation mode choice. It is found that evacuation behaviors are affected by a variety of factors such as household location, evacuation attributes, hurricanes position, socioeconomic and demographic characteristic, environmental and social factors. Specifically, we pay attention to the influences of social factors on evacuation decision making. The previous research shows that social influences play an important role on personal risk perception and on individual's decision making process. Additionally, there is a great potential of using social media, which offers ways to retrieve, produce and spread timely information, in the disaster preparation, warning, response and recovery.

A comparative analysis of traffic incidents, which affected traffic operation during hurricanes, is conducted in Chapter 3. We found that, during the Hurricanes Irene and Sandy, there were notable changes in the number of flooding, downed-tree incidents, and weather related events as shown in FIGURE 4, FIGURE 5 and FIGURE 6. It is also found that the incident durations are likely to be extended during and after hurricanes according to modeling results in TABLE 2, TABLE 3 and TABLE 4. The changes in transportation systems caused by hurricane-related incidents can lead to traffic conditions which are significantly different from daily normal traffic conditions. Therefore, it is important for government agencies which are responsible for evacuation and emergency management to understand the influence of traffic incidents duration hurricanes.

In Chapter 4, using the traffic data during Hurricane Irene, the evacuation response curve is fitted for Cape May County, New Jersey. The evacuees in Cape May County responded very quickly to the mandatory emergency order during Hurricane Irene. According to FIGURE 20, Traffic volumes increased significantly when the official mandatory evacuation order was issued. This may have been partly caused by the high tourist population. The evacuation response curve is generally S-shaped with sharp upward changes in slope followed the issuance of mandatory evacuation notices. When comparing different evacuation response models, the calibrated S-curves obtained using Logit and Rayleigh functions are observed to fit the empirical data better, as shown in FIGURE 22.

The evacuation traffic patterns of New Jersey during Hurricane Irene are investigated in Chapter 5. According to FIGURE 24, the most significant of the evacuation movements were on roads in the southern region of the state closest to the shore area. No significant evacuation traffic is observed in northern New Jersey during Hurricane Irene. The vast majority of the evacuation traffic moved to the western regions, instead of traveling northbound along the shore area. As illustrated in FIGURE 25, the evacuation traffic pattern is similar to typical outbound traffic from the shore areas at the end of a summer weekend but with 3-4 hours earlier departure times. The bottlenecks during Irene evacuation are generally merging areas with on/off ramps or interchanges as shown in FIGURE 26.

In Chapter 6, evacuation behavior models are developed using post-Hurricane Irene and Sandy survey data. A novel structural equation model (SEM) has been developed to jointly model: (a) the potential factors that affect the choice behavior and (b) the relationship between the evacuation decision choices and the evacuation destination. The results of the SEM (TABLE 7) show that age, education levels, distance to shore, and race/ethic background tend to affect the evacuation decisions. Nevertheless, gender and income levels did not significantly affect the decisions of evacuation. Regarding the evacuation destination choices, it was found that house ownership is a key factor that changes the preference of other types of destinations in relative to public shelters. The individuals who own the house/apartment are more likelihood to evacuate to their friend / relative’s home as well as hotel. Evacuation experience did not significantly affect their choices of destinations. In addition, there was no strong relationship between evacuation decision choices and evacuation destination choices. In other words, whether or not individuals consider evacuating, there is no significant difference between choosing public shelters and other places.

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University Transportation Research Center - Region 2

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Region 2 - University Transportation Research Center
The City College of New York
Marshak Hall, Suite 910
160 Convent Avenue
New York, NY 10031
Tel: (212) 650-8050
Fax: (212) 650-8374
Website: www.utrc2.org