DEVELOPMENT OF A COMPREHENSIVE NETWORK-BASED HAZARD EVACUATION MODEL: A CASE STUDY OF BALBOA ISLAND, CALIFORNIA

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Kevin D. Henry

Major Professor: Tim G. Frazier, Ph.D.
Committee Members: Raymond J. Dezzani, Ph.D.; Nathan J. Wood, Ph.D.
Department Administrator: Karen S. Humes, Ph.D.

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Authorization to Submit Thesis

This thesis of Kevin D. Henry, submitted for the degree of Master of Science with a Major in Geography and titled **"Development of a Comprehensive Network-based Hazard Evacuation Model: a Case Study of Balboa Island, California,"** has been reviewed in final form. Permission, as indicated by the signatures and dates below, is now granted to submit final copies to the College of Graduate Studies for approval.

Major Professor: ______________________________ Date: __________

Tim G. Frazier, Ph.D.

Committee Members: ______________________________ Date: __________

Raymond J. Dezzani, Ph.D.

______________________________ Date: __________

Nathan J. Wood, Ph.D.

Department Administrator: ______________________________ Date: __________

Karen S. Humes, Ph.D.

Abstract

A number of communities at risk to hazards that require evacuation, lack an understanding of evacuation capacity. Modeling to estimate clearance times provides insights into factors that affect evacuation, such as limited egress options, high population density, and evacuee mobility. This research use the island community of Balboa Island in the City of Newport Beach, California, to examine the interaction of these factors in a study of multi-modal, tsunami evacuation potential. A multi-modal evacuation model was developed that allows for exploratory analysis of potential tsunami evacuation scenarios. Incorporating evacuee response time, background traffic, shadow evacuation, and transit-dependent populations improves the model's representation of reality over traditional evacuation models that often underestimate clearance time. Results indicate a wide range of clearance times based on differing scenarios and strategies. Research results can be used to guide local emergency managers in the efforts to implement targeted mitigation strategies that reduce evacuation clearance time.

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Dedication

To my loving and supportive family: my parents, who instilled upon me a curiosity for knowledge and dedication to succeed; and my amazing wife, the driving force behind my studies. I can never thank you enough for your support, patience and motivation throughout this process.

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Chapter 1 – Introduction and Review of Literature

1.1 Introduction

Throughout the United States, many communities exist in areas exposed to natural hazards. In some cases, these areas house dense development with few access points to major roads. Additionally, many of these areas contain significant non-resident populations, including commuting employees and transient populations such as tourists (Wood, Ratliff, & Peters, 2013). In most planning processes, development planning is based on normal conditions, and under these conditions the transportation network can handle the overall traffic flow and intermittent congestion associated with resident and non-resident trips (Frazier, 2006). However, during a sudden-onset hazard event, abnormal traffic conditions may occur due to the simultaneous evacuation of all populations within the exposed area (Tamminga, Tu, Daamen, & Hoogendoorn, 2011). Limited egress potential from the development may lead to significant congestion during evacuation proceedings.

Evacuation can be vital component in mitigating the impacts of extreme events in areas exposed to natural hazards. Evacuation speed is a critical aspect, as populations must be removed from at-risk areas before hazard arrival to reduce potential for loss of life. Evacuation speed is determined by a number of factors, including local topography and development, infrastructure, local management, and individual risk perception (K. Dow & Cutter, 1998). These factors can all contribute to uncertainty towards how an evacuation scenario will unfold, and vary between study areas. Therefore, to understand an area's capacity to evacuate, the aforementioned characteristics unique to the area must be addressed to help in part to determine a community's vulnerability to natural hazards (Chakraborty, Tobin, & Montz, 2005).

Understanding a community's capacity to evacuate can provide insights into its degree of vulnerability to a hazard threat (Cova & Church, 1997). A baseline understanding of evacuation is a first step in effectively mitigating the impacts of many hazards, such as tsunamis, hurricanes, wildfire, and others. It can potentially point out the need for various mitigation strategies, and give context for future policy-making and planning practices. Because the magnitude and extent of a hazard can be uncertain, it may be useful to reference specific extreme events or projections when modeling. This sort of modeling may aid current planning practice, as traditionally evacuation-specific studies are not required, and instead only traditional traffic studies are performed (Frazier, 2006). The subsequent information gained can be placed in context with multiple potential hazard scenarios, such as potential scenarios based on past events and a worst-case scenario. Information gained from this contextual analysis can allow for a more comprehensive understanding of general hazard threats. This knowledge can provide more insight into planning and policy for a community (Cova & Church, 1997).

A common method for assessing an area's capacity to evacuate is through evacuation modeling. These models attempt to provide a representation a natural hazard evacuation scenario, utilizing concepts drawn from transportation research, risk analysis, sociology, and disaster management. Two main types of evacuation models exist: network-based models, and raster least-cost-path-based models. When modeling pedestrian evacuation from hazards where no infrastructure is present, or infrastructure is destroyed, least-cost-path-surface modeling is a useful method for determining of evacuation capacity (Wood & Schmidtlein, 2012). For scenarios that use a variety of modes of transit along existing transportation infrastructure, such as vehicular-based evacuation, network-based models can be used. For the purposes of this research, network-based evacuation models will be the focus and any mentions of 'evacuation modeling' refer to network-based evacuation.

Early evacuation models were systems that used an analysis of traffic patterns and network theory to determine an 'overall clearance time' (Sheffi, Mahmassani, & Powell, 1982), defined as the time required to fully evacuate from hazard zone. Contemporary models are slightly more complex, specifically in methodology for computing evacuation clearance time. In the past 5-10 years, case-based research has been conducted on hazard evacuations, such as vehicular evacuation of communities facing wildfire (Cova & Johnson, 2002), hurricane events (Chen, Meaker, & Zhan, 2006) and tsunamis (Goto et al., 2012; Mas, Suppasri, Fumihiko, & Koshimura, 2012; Wafda, Saputra, Nurdin, Nasaruddin, & Munadi, 2013). Other case studies have been performed with a specific spatial scale, but under no explicit type of hazard scenario (Chen & Zhan, 2006). Some prior modeling work has incorporated multiple modes of transportation, including pedestrian and vehicular modes (Goto et al., 2012; Mas et al., 2012; Wafda et al., 2013), and pedestrian and transit(Hana Naghawi & Wolshon, 2010). These vehicular- and pedestrian-based studies have followed the trend of employing pre-built traffic simulation software in an agent-based environment to determine evacuation clearance time.

Evacuation modeling can be a particularly difficult task because of the inherent complexity of hazard evacuations (Pel, Bliemer, & Hoogendoorn, 2012). Both the spatial and temporal scales of natural hazard evacuations can vary greatly, depending on the type of hazard, the characteristics of an individual event's, and the geography of the exposed area. In terms of

Evacuations have varying spatial and temporal scales, and modeling with local characteristics in mind is critical. Human behavior is also a problematic factor in modeling evacuation due to its unpredictability. Behavior can manifest itself in a number of concepts unique to evacuation. In past research, these complex concepts are not often addressed. Identifying the impacts of these real-world phenomena can improve the overall understanding of evacuation capacity by providing a more accurate representation of evacuation.

Because of the variety of factors that influence evacuations and the variability of each factor based on the study area and scenario, a holistic approach to model development is warranted. A flexible methodology will allow for the adjustment of model parameters to fit a desired scenarios and tests. Streamlined evacuation demand estimation and low computational requirements for traffic simulation allow users to obtain clearance times for a variety of scenarios relatively rapidly. These can be used to inform disaster management through testing different mitigation strategies, such as contraflow and alternative modes. Many evacuation modeling efforts fail to address the above examples of complex characteristics of hazard evacuations. Additionally, many models are created to test specific strategies, or provide results under one specific scenario. Because of the uncertain nature of extreme events and the potential benefits of scenario-based planning, an evacuation modeling methodology that can account for a variety of strategies, scenarios, and evacuating populations is required when modeling evacuation capacity. This work presents an evacuation modeling framework that addresses these limitations in current practice and presents methods for addressing real-world phenomena that should be incorporated to achieve accurate evacuation modeling.

1.2 Evacuation Modeling

Existing research that contributes to understanding hazard evacuations is diverse, and can incorporate transportation research, risk perception, computer science, mathematical theory, and stakeholder engagement. This work, both empirical and theoretical, presents various concepts of evacuation scenarios including topics such as evacuee behavior, hazard evacuation alerts, and evacuation strategies and policy (Abdelgawad & Abdulhai, 2009; Alsnih, Rose, & Stopher, 2005; Baker, 1991; K. Dow & Cutter, 1998; Fu, Wilmot, Zhang, & Baker, 2007; Lindell & Prater, 2007; Urbina & Wolshon, 2003; Wolshon, 2002). A separate vein of research is devoted to developing evacuation models (Murray-Tuite & Wolshon, 2013; Pel et al., 2012; Trainor, Murray-Tuite, Edara, Fallah-Fini, & Triantis, 2013). These models attempt to create an understanding of evacuation capacity, in general terms, or under a specific hazard evacuation scenario. Early evacuation models were systems that used an analysis of traffic patterns and network theory to determine an 'overall clearance time' (Sheffi et al, 1982). Contemporary models are slightly more complex, specifically in methodology for computing evacuation clearance time.

In addition to contributing to baseline vulnerability assessments, evacuation models can have the ability to test the effectiveness varying evacuation strategies. Because of this, they can be a useful tool for understanding how to mitigate the effects of natural hazards through better evacuation. Hazard mitigation can include structural improvement/defenses, policy and preparedness, and other forms of mitigation (Bruneau et al., 2003). Mitigation aimed at improving evacuation can be structural, such as evacuation shelters/towers and road network improvements, but also aimed at preparedness, such as improved hazard warning and evacuation order systems. Much of the recent work in evacuation modeling research has been focused on using evacuation models to analyze the effectiveness of varying evacuation strategies, including vertical evacuation (Wood & Schmidtlein, 2013), lane-based routing (Cova & Johnson, 2003), contraflow (Kim, Shekhar, & Min, 2008; Ren, Hua, Cheng, Zhang, & Ran, 2012), staged evacuations (X. Chen & Zhan, 2006), among others. Although the main goal of developing an evacuation model may be to understand an area's vulnerability to a natural hazard by estimating evacuation clearance time, the ability to test potential mitigation strategies is a useful byproduct. This sort of modeling may aid current planning practice, as traditionally evacuation studies are not required, and instead only traditional traffic studies are performed (Frazier, 2006). In exposed areas, evacuation modeling to understand vulnerability as well as potential mitigation strategies can be a useful if not mandatory task.

Evacuation modeling draws from theoretical frameworks of positivism and structuration. The process of evacuation modeling tends to follow a classic positivist scientific method with some exceptions in the case of validation and theory creation(Harvey, 1969). In the end, modeling addresses a specific problem or question related to community vulnerability, with the end goal of communication to inform management practices. Modeling draws from empirical data and uses quantitative geographic methods to understand evacuating populations and at-risk areas. With this information, less traditional methods can compound on base knowledge to further the analysis.

Structuration theory poses that the agency of humans and social structure are intertwined (Giddens, 1984). In the case of evacuation modeling, individual agency is a critical component in determining an area's evacuation capacity. Access to resources and socioeconomic characteristics determine not only an individual's ability to evacuate through transportation mode choice, but it influences the overarching systematic process of evacuation. Additionally, the social structure of the evacuating area creates patterns in individual agency based on the local geography. Structuration is an important theoretical framework that guides this research, as it places an importance on variations in individuals' agency and the social construct, in this case evacuation, which these variations influence.

Creating a general framework for modeling natural hazard evacuations can be a particularly difficult task because of the variety of scenarios that fall under the category of 'evacuation modeling', and the inherent complexity of hazard evacuations (Pel et al., 2012). Both the spatial and temporal scales of natural hazard evacuations can vary greatly, depending on the type of hazard, as well as an individual event's specific characteristics. Spatially, evacuations range from small areas (building evacuation) to large (hurricane evacuation), requiring action within minutes (fire, near-field tsunami) to days (hurricane). It is important to approach evacuation modeling from a local perspective, where model characteristics change in order to fit the at-risk area. In addition, human behavior is an important factor in modeling evacuation, giving rise to concepts such as: (1) shadow evacuation, a phenomenon the actual zone of evacuating population is much larger than the one ordered or intended by emergency management (Zeigler, Brunn, & Johnson, 1981); (2) intermediate trips, where family units meet in a central location before evacuating together, adding additional traffic potentially against the direction of evacuation (Murray-Tuite & Mahmassani, 2003); (3) evacuation decision, where a number of socioeconomic and psychological factors influence whether an at-risk individual decides to evacuate or not (Murray-Tuite & Wolshon, 2013), as well as the time before evacuees begin their evacuation. Some efforts have been made to incorporate human behavior into evacuation models, such as determining evacuation decisions as well as evacuation timing (Murray-Tuite & Wolshon, 2013). Human behavior in the face of evacuation influences the outcome of evacuation scenarios, and neglecting to include related components such as shadow evacuation in modeling practice can contribute to an inaccurate representation of an evacuation. However, it should be cautioned that relying on pre-programmed evacuee behavior in agent-based evacuation modeling methods can create flawed results, as assumptions must be made on seemingly unpredictable characteristics of human behavior (Epstein, 2011; Ormerod & Rosewell, 2009).

In most cases, the end goal of evacuation modeling is to obtain a value of overall clearance time (Sheffi et al., 1982). Using varying methodologies, clearance time is generally obtained through a combination of transportation forecasting, and traffic simulation typically using a four-step transportation model (Murray-Tuite & Wolshon, 2013; Pel et al., 2012). Each step of the four-step model contains components that aim to represent an evacuation scenario, and can be approached with varying methodology and can incorporate different theoretical and empirical knowledge of evacuation scenarios. The wide range of concepts that emerge in an evacuation scenario and the large number of methods for calculating evacuation clearance time have led to a large body of work reviewing modeling practices. Some of these works approach from a transportation research background (Murray-Tuite & Wolshon, 2013; Pel, et al., 2012, Southworth, 1991), others from a technical or computer-based perspective (Marcus, 1994; Zhang et al 2010; Gwynne et al. 1999), while others focus on building evacuations (Kuligowski and Peacock, 2005). Before attempting to develop an evacuation modeling framework, it is necessary to review current evacuation modeling methods for a number of reasons: (1) a synthesis approached from a comprehensive natural hazards research background can benefit evacuation research by providing more connection between modeling methods and hazard evacuation theory and empirical research. (2) A holistic review of potential evacuation modeling methodologies has not been made, as existing reviews tend to focus only on certain types of clearance time estimation, such as simulation, as well as only certain scenarios, such as vehicular or building evacuation. (3) A critique of the use of traditional transportation models in evacuation modeling raises potential issues in the accuracy of frequently employed evacuation models.

Network-based hazard evacuation modeling traditionally employs a four-step transportation model framework to determine evacuation clearance time. This can be further separated into two distinct processes: *travel demand estimation*, and *clearance time calculation*. In the four-step model four distinct problems are solved relating to the evacuation. The four steps are: (1) Trip Generation, (2) Trip Distribution, (3) Mode Choice and (4) Route Selection. When modeling transportation or evacuation scenarios, these steps are answered in succession, resulting in estimations of the location and characteristics of evacuating population, and the time required for them to reach safety.

In a four-step transportation model, a number of questions are answered:

- T*rip generation* determines who evacuates, and when they choose to evacuate.
- *Trip distribution* determines where the evacuees head.

- *Mode choice*, determines how the evacuees choose to evacuate.
- *Route selection*, determines what route the evacuee will take to his/her chosen destination (Pel et al., 2012).

In determining answers to these questions, various aspects of evacuation scenarios including evacuee behavior, event timing, and physical exposure should be considered. A number of assumptions are made in the four-step model, and should be based upon empirical information, which is then applied to the model through various methods. Depending on the specific evacuation scenario and study area, the assumptions made and the methodologies for determining the four steps will be altered slightly. Evacuation modeling research generally follows the four-step model, and focuses either on travel demand estimation, clearance time determination, or both. Because of the natural dichotomy in the evacuation modeling process, these two main components should be reviewed independently. Optimal methods for performing each task can be identified by taking such an approach.

1.2.1 Evacuation Demand Estimation

Evacuation demand modeling is a complex undertaking, and to estimate evacuating populations requires a large amount of data, or assumptions, if data is lacking (Murray-Tuite & Wolshon, 2013). Varieties of factors determine evacuating population, such as evacuee behavior and risk perception, disaster management practices, and the physical extent of the hazard. In general, evacuation demand sequentially determines characteristics of evacuating populations. Additionally, this process is traditionally performed at the household level (Pel et al 2012), as evacuation decision has been demonstrated to occur on a household scale (Dash and Gladwin 2007; Dow and Cutter 2000; Heath et al. 2001; Whitehead et al. 2000).

Trip generation determines who evacuates, and how long before they leave (Pel et al 2012). In transportation modeling, this step is an integral part of generating travel demand. The main goal of trip generation is to identify the total number of evacuees and their location in an evacuation zone. In addition, distinction between types of evacuee is identified. These types influence the evacuee's mode of transport, their evacuation behavior, and their evacuation destination (Lindell & Prater, 2007). Identification of the evacuation zone is generally required when performing scenario-specific based modeling. This can be identified by the physical exposure of a hazard, as well as adopted from existing emergency response planning areas

(ERPAs) determined by a local agency (Lindell & Prater, 2007). When identifying this zone, the concept of *shadow evacuation* can also be addressed.

Shadow evacuation is a term used to describe populations that lie outside, but adjacent to, a hazard zone and choose to evacuate during an extreme event. They may not be mandated to evacuate or at risk directly, but due to factors of risk perception and general human nature, these populations choose to evacuate (Dash & Gladwin, 2007; Gladwin, Gladwin, & Peacock, 2001; Murray-Tuite & Wolshon, 2013). Shadow evacuation can have a large impact on evacuations and overall clearance time, as the increased populations can create additional congestion and impede the entire evacuation process. The additional population from shadow evacuation is understood to be a real-world occurrence, and failure to address the concept will lead to inaccurate demand modeling and evacuation clearance time estimation. Shadow evacuation can be incorporated into an evacuation model by altering the assumed evacuation zone during trip generation (Murray-Tuite & Wolshon, 2013). This can be determined through survey methods or stakeholder engagement (Gladwin et al., 2001), and can also be tested by making an assumption that populations within x distance of evacuation zone will participate. In addition to boundary information for an evacuation zone, other information is needed to perform the evacuation model. Transportation network information, topographic information, and household-level boundaries provide the base data for an evacuation zone (Lindell & Prater, 2007; Wood & Schmidtlein, 2012).

Before identifying evacuees, total population within the evacuation zone must be identified. Population can be determined for each type of evacuee through various means. Residential and employee population can be obtained from census and business information, respectively. Transient populations have in the past been identified from local agency data of hotel rooms (Hobeika et al. 1994; Lindell et al. 2002), as well as campsites (Hobeika et al, 1994). Populations in group quarters should be identified separately from residential population, but can be determined from census data. Residents in institutionalized (i.e. correctional, nursing facilities) and non-institutionalized (student housing, military quarters) quarters should additionally be separated, as institutionalized populations require additional supervision and structure in evacuation (Wood et al., 2013) and both groups should be considered transit dependent in the context of the evacuation model due to their limited access to personal vehicles. An alternative to determining overall evacuating population is to instead determine the amount of evacuating households, and perform demand estimation at this scale. Many prior studies use this method

(Chen et al., 2006; Cova & Johnson, 2002; Lindell & Prater, 2007), and can be a justifiable scale for evacuation modeling, as studies show households generally gather before evacuation (Murray-Tuite & Mahmassani, 2003).

Additional transit dependent populations can be estimated from census data. Studies that identify these populations do not explain specific census variables that define individuals as transit dependent (Lindell, 2008; Hana Naghawi & Wolshon, 2010), but have noted that census-derived data tends to overestimate transit dependent population (Lindell & Prater, 2007). A previously proposed method determines transit dependent population through the below formula:

Transit Dependent Population (16+ within households) = Household Drivers - Autos Available

where

Household Drivers = Population Age 16 and over - Persons in Group Quarters

This is an inaccurate estimation in an evacuation scenario for a number of reasons: Population between ages 12 and 15 are considered transit dependent, despite potentially living in a household with access to a personal vehicle. In addition, this formula assumes each vehicle will only carry one driver, which has been found to be inaccurate in evacuation scenarios (Drabek, 1986; Lindell & Perry, 1992; Tierney, Lindell, & Perry, 2001). Finally, this information is only available at the census block group level, which can comprise an entire evacuation area in some circumstances. A simpler strategy for identifying transit-dependent populations in a study area is to acquire this data not at an individual scale, but at a household scale. American Community Survey (ACS) data of vehicles per household exists at the census block group level, which can be used to identify the number of transit dependent households within a census tract. This information can be used to inform assumptions about the amount of households evacuating by vehicles.

Assuming that the entire population exposed to a hazard will evacuate is not always valid. Depending on the specific hazard scenario it can be assumed that only a percentage of this population will choose to evacuate. For certain hazards, such as hurricanes, a resident's decision to evacuate is determined by their individual risk perception. Past research has shown that a large number of factors influence this. Few factors have been shown to decrease the likelihood of evacuation, such as frequent hazard experience (Anderson, 1968), longer length of residence, work requirements, and fear of looting. However, a vast number of other factors increase evacuation likelihood, such as degree of exposure to the hazard, hazard experience, demographic characteristics such as gender, presence of children, and race. Murray-Tuite and Wolshon (2013) performed a thorough evaluation of empirical or theoretical works to determine these factors' impact on evacuation decision. For some hazards, such as sudden-onset events, the timing of the hazard is a factor in determining the actual evacuating population (Barrett, Ran, & Pillai, 2000; Urbanik, 2000). For example, Klepeis et al. (2001) identified that while over 90% of populations in evacuation zones are at their homes between 10:00pm and 5:00am, less than 40% are at home between 11:00am and 3:00pm. However, evacuation modeling to a *worst-case scenario* provides a simpler solution to trip generation (Cova & Church, 1997). When modeling from a worst-case scenario approach, trip generation assumes that every occupied area within the evacuation zone (household, business, public place) will be fully evacuated. This is in many cases the scenario used for disaster management purposes. However, there is merit in modeling other potential scenarios to provide a more holistic understanding of evacuation capacity for planning purposes (Pearce 2001).

As mentioned, an additional step in trip generation used by many studies is determining the number of evacuating households and the population/vehicles in each. This step *must* be seen as a form of simulation, as unless empirical data for household population exists, deriving household-scale population from census data cannot be seen as accurate, as it violates issues of spatial analysis such as the modifiable areal unit problem (Openshaw, 1983). Lindell and Prater (2007) propose obtaining an average number of persons per residential household from census data and number of households. The mean persons per household or mean vehicles per household data are then typically used to inform a more specific travel demand estimation equation (Cova and Johnson, 2002; Lindell and Prater 2007).

For vehicular-based evacuees, the number of vehicles evacuating per household can also be used to inform demand estimation. In some cases, and with some assumptions of inaccuracy, vehicle registration data can be used. Chin and Southworth (1987) estimated that in daytime evacuations, 70% of registered vehicles will be used in an evacuation, and 90% in nighttime. Additionally, for sudden-onset hazard evacuations, 75% of registered vehicles will be used. In most areas, vehicle registration data generally does not exist at the required spatial scale for micro-scale evacuation models. Therefore, a number of methods exist to estimate this information. Cova and Johnson (2002) use a Poisson distribution to predict evacuees from a neighborhood. This type of distribution assumes that some homes will have no evacuating vehicles, most will have some and very few will have many. The mean number of vehicles, used as the mean of the Poisson distribution, can be adjusted to fit the time of the evacuation as well as the vehicle ownership of the study area. This method may be more useful in scenarios where the timing of the evacuation is important, such as sudden-onset hazard evacuation. Information from empirical surveys has also been used to identify vehicles per household (Kirstin Dow & Cutter, 2002), which can provide more accurate and better resolution data.

Another important concept to consider when performing trip generation is the modeling of *background traffic*. To account for background traffic, trips originating outside of the evacuation zone must also be generated, so that their impact on traffic flow the overall transportation network can be accounted for. Like shadow evacuation, failure to address this traffic will lead to an inaccurate representation of reality. Traffic generated from outside an evacuation model's study area will most likely always exist, and will potentially pass through the study area, influencing traffic flow. Background traffic can be determined based on real-world count data and traditional traffic flow information at the time of an evacuation event (Jha et al, 2004). Depending on the analysis method chosen for the evacuation model, background traffic may be incorporated differently. However, it will improve the accuracy of the evacuation model, as it will provide a better representation of real-world conditions during an evacuation event. Failure to incorporate background traffic and shadow evacuation into an evacuation model can create an underestimation of overall clearance time (Jha, Moore, & Pashaie, 2004; Murray-Tuite & Wolshon, 2013). Without background traffic, evacuating populations will not be impeded by other drivers on the network who are either evacuating to similar points, or traveling to other destinations.

Understanding *when* individuals evacuate is also called *response time*. There are multiple methods to approximate the response time of evacuees, including assumptions made based on empirical evidence, pre-evacuation surveys, judgment of human response (factor of risk perception), and modeling of the diffusion of emergency warnings (Southworth, 1991). Response time can be seen a function of the evacuee's mobility, risk perception, and the means by which the evacuation orders are sent. A general solution to model response time is to develop a response curve based on a statistical distribution, which can be used to track how much time has elapsed, and what percentage of the population has chosen to evacuate (Pel et al., 2012). This distribution will be employed in final evacuation model regardless of the methods chosen to perform the final analysis.

The specific distribution used to generate a response curve has varied throughout evacuation modeling research (Table 1). Regardless of the distribution type, the cumulative density function generally resembles an S-curve, where response is very low initially, and quickly begins to climb to reach near 100% before tapering off (Murray-Tuite & Wolshon, 2013). The shape of the curve can be adjusted to fit specific scenarios by altering two specific parameters. One parameter, *a*, determines the slope of the curve and influences the overall speed of response. The second parameter, *b*, is the point at which half of all evacuees have departed (Pel et al., 2012). Research shows that adjusting *b* does little to influence overall evacuation time, as it does not change the rate of departure (Ozbay and Yazici 2006, Pel et al., 2010). Adjusting *a* can influence congestion in the network, as having a rapid response rate can fill the network quickly and reduce network performance (Pel et al. 2010).

When a response curve has been created, it can be incorporated into an evacuation model by distributing response time values to the evacuating population, either on an individual basis or by incorporating the curve into an analytical analysis such as a traffic queue as an arrival rate function. An individual's response time not only adds to their personal clearance time, but it also can influence their route selection and can affect congestion within the evacuation zone. However, in evacuation conditions where a large population is attempting to traverse a network with significant bottlenecks, incorporating an evacuee response curve does little to impact the overall flow out of the network (Tamminga et al. 2011), and overall clearance time. For sudden-onset hazards from densely developed areas, including a response curve may only serve to affect individual evacuee clearance time, yet have no influence on overall clearance time.

Table 1. Departure Time Distributions Used in Evacuation Modeling

Response Time Distribution	Source
None (instantaneous departure)	Lewis 2001, (Chen et al., 2006),
Uniform	Liu et al. 2006, Yuan et al. 2006
Rayleigh	Tweedie et al. 1986
Poisson	Cova and Johnson, 2002
Weibull	Lindell; 2008
Sigmoid curve	Kalafatas and Peeta, Xie et al. 2010

In order to inform real-world practices and provide actionable information from evacuation modeling, the effectiveness of some types of disaster management strategies can be tested by adjusting trip generation. Staged evacuation and the timing of evacuation warnings can be explored by altering the shape of the response curve, or by creating multiple response curves and assigning them to specific areas of population (Chen and Zhan, 2006). In staged evacuation, exposed areas are evacuated in waves or stages. This strategy acts to help alleviate congestion and capacity issues, and provide a more efficient trip generation process. In a recent study, the impacts of evacuation staging were tested using traffic simulation, under in a number of different scenarios and transportation network structures. The results showed that staged evacuations can reduce overall clearance time, but only in densely populated grid-like urban areas (Chen and Zhan, 2006).

The second step of the four-step model, trip distribution, determines the evacuation destination, or safe zone chosen by the evacuee. For general hazards, this decision is influenced by a number of factors, including hazard severity, income (USACE, 2002), and a number of demographic and scenario-related factors that can influence whether an evacuee travels to a shelter, a hotel, or to a family member's residence (Mileti et al., 1992). This information originates through surveys or is derived from theory, similarly to traditional travel demand estimation. One strategy to estimate travel demand involves using surveyed or known responses that represent a sample of the evacuating population. However, this should always be seen as estimation, as much of the difficulty in modeling trip distribution again lies with the uncertainty of human behavior. In sudden-onset hazard scenarios, due to the danger and rapid response required, trips are generally distributed to the nearest point outside of the area directly exposed to the hazard (Cova & Johnson, 2002; Wood & Schmidtlein, 2012). However, other factors, including human behavior play a role in where evacuees will travel to in a sudden-onset hazard evacuation. A practice in emergency management is to determine where 'safe zones' are located under a specific scenario. These zones will most likely exist some distance away from the physical exposure zone of the hazard, in order to account for background traffic and where the individual evacuee deems is safe. For a more accurate evacuation scenario, trips can be distributed to a number of designated evacuation points. These may exist within local plan documents, or be identified as areas that can accommodate a large number of evacuating vehicles. Again, this decision is a factor of an evacuee's risk perception, but can be greatly influenced by emergency warnings and management. In past studies, areas beyond transportation network 'chokepoints' have been identified as evacuee destinations in the trip distribution step (Cova, 2002). For tsunami events, elevation can be used to identify trip distribution, as well as tsunami evacuation signage. Much work in evacuation research assumes that evacuees already are aware of the designated point of egress, and therefore model trip distribution without factoring risk perception and the impact of warning systems (X. W. Chen et al., 2006; Cova & Johnson, 2002). Future research on risk perception's influence on how evacuees choose where to evacuate from sudden-onset hazards could increase the accuracy of trip generation in evacuation modeling. Some understanding of evacuee destinations *beyond* the hazard zone is important when calculating clearance time, as these evacuees may still contribute to congestion beyond the hazard zone, which could contribute to congestion within the hazard zone. Many models assume a common main evacuation route along a major highway or high-capacity egress route (Chen and Zhan, 2006), yet an improved understanding of evacuee destination could potentially improve the realism of traffic assignment and congestion in the model.

Altering trip distribution has the power to explore mitigation strategies such as evacuation shelters, including vertical evacuation and storm shelters. For example, tsunami evacuation can be aided by structural mitigation such as vertical evacuation towers (Engstfeld et al., 2010). These structures act as evacuation shelters, and can easily be incorporated and tested in evacuation model, as they act as added trip distribution locations. These structures generally have a maximum capacity, however, which must be taken into account when modeling. Other strategies may be very case-specific, such as the creation of a pedestrian bridge. These act to modify the transportation network to provide increased variety of trip distribution.

Determining how an evacuee chooses to evacuate from a hazard is difficult aspect of evacuation modeling. In some cases, this determination is simplified, as only one mode is assumed available for evacuation due to the nature of the hazard. For example, some tsunami evacuation models assume pedestrian-only evacuation, as this the only mode of travel available due to infrastructure damage sustained from an offshore earthquake (Wood & Schmidtlein, 2012). Many evacuation modeling efforts addressing complex scenarios, such as hurricane evacuation, only incorporate personal vehicular transport (X. W. Chen et al., 2006; Murray-Tuite & Wolshon, 2013). However, this practice can lead to an inaccurate representation of reality and fails to address groups of evacuees without access to personal vehicles. In reality, hurricanes allow for evacuation through multiple modes of transport and an accurate model should incorporate a variety of modes of transport (Urbina & Wolshon, 2003). A majority of recent evacuation modeling works only model vehicular transportation (Chen et al., 2006; Cova & Johnson, 2002; Jha et al., 2004; Murray-Tuite & Wolshon, 2013). There are certain situations where the assumption that all evacuees will travel by personal vehicle can be valid, such as wildfire evacuations from suburban neighborhoods (Cova & Johnson, 2002). However, multi-modal evacuation modeling can account for potential marginalized populations, or identify alternative modes of evacuation. Transit-dependent populations may be more at-risk in an evacuation scenario due to their restricted access to vehicles, and instead rely on pedestrian or transit modes. A more comprehensive evacuation can incorporate multiple modes of transport, determined through a process similar to those used for trip generation; based on socioeconomic factors as well as demographic information about evacuees. For example, tourists, the elderly and institutionalized populations may not have access to a vehicle, and therefore must be addressed by providing an alternate mode choice. Overall, performing an assessment of the study area and identifying these populations when performing the mode choice step can improve the accuracy the model's estimate of clearance time. Neglecting to address alternate modes of transport can reduce the accuracy of the evacuation model and create a scenario that does not reflect real-world circumstances.

Little work has been undertaken to create a truly multi-modal evacuation model, although pedestrian/vehicular (Fang, Li, Li, Han, & Shaw, 2013) and transit/vehicular (Abdelgawad & Abdulhai, 2009) studies have been performed. Some works have addressed this, and have provided methodologies to model transit and bus evacuations, which affect the route selection and analytical portion of the evacuation model. Many traffic simulation software packages can model both pedestrian, vehicular and bus travel (Algers et al., 1997). Additionally, some of these packages can model interaction between modes by including extra rules for agent behavior (Algers et al., 1997). Utilizing the multi-modal modeling capabilities of such packages can help recreate a more realistic scenario and account for populations unable to evacuate by car.

Through mode choice, evacuation models can test strategies that provide alternate modes of evacuation. During historical evacuation events, such as Hurricane Katrina, estimates have identified upwards of 25-30% of evacuees without access transport (Urbina & Wolshon, 2003). This population may include lower-income, the elderly, tourists, and the institutionalized. This marginalized population makes up a considerable percentage of total evacuees, and may need additional support in the form of transit in order to evacuate successfully (Urbina & Wolshon, 2003). For example, extra shuttle service may be needed to transport this population. Optimal routes, shuttle capacity, number of shuttles, and timing of service are all factors that can influence the effectiveness of an evacuation shuttle (Bish, 2011). These shuttles can be implemented into an evacuation model in a number of ways. In traffic simulation models, 'shuttle agents' can be added with various parameters that address the above factors. In more analytical models, the shuttle evacuation must be translated into a more abstract impact, such as a reduction in number of evacuating vehicles.

1.2.2 Clearance Time Determination

In general, clearance time is determined through the final step of the four-step model, route selection. This requires some form of analytical or simulation tool to determine route selection and thereby obtain evacuation clearance time. This is operated within the transportation network of a study area, which can consist of information in the form of a network analysis, or in other cases anisotropic spatial analysis. The first three steps of the aforementioned four-step model can be incorporated into analysis by altering the network in the form of adding destinations as well as altering travel times based on response, as well as by adding demographic data. In the end, however, there are varieties of methods that can be used to obtain an understanding of evacuation time with the inclusion of various demographic, behavioral, and natural hazard characteristics. Decisions on which method to employ for analyses have been based on convenience (Desmet & Gelenbe, 2013), accessibility, and comprehension.

Travel demand-based modeling may prove to be a useful tool in situations where evacuation modeling is required, yet little knowledge of traffic assignment modeling exists, access to powerful analytical and simulation tools is not present, or critical areas of congestion have not been identified within a large study area. Travel demand modeling can help understand the congestion and traffic flows of large networks with little computational demand (Church & Cova, 2000; Cova & Church, 1997). Barrett et al. (2000) created a framework for estimating evacuation time using travel demand and dynamic traffic assignment techniques. These analyses provide an understanding of evacuation capacity, yet cannot estimate evacuation clearance time. Calculating clearance time is instead a deterministic problem, and requires some form of simulation of evacuees along a network under different scenarios of demand.

For network-based evacuation, traffic simulation using an agent-based approach is a popular approach to perform route selection and determine evacuation time. In agent-based modeling, individual agents (vehicles or pedestrians) traverse a network based on a set of rules for behavior. The type of behavior traditionally used in evacuation models has been simple car-following behavior (Chen et al., 2006; Chen & Zhan, 2006; Cova & Johnson, 2002; H. Z. Tu, Pei, Li, & Sun, 2012). In this method, agents (vehicles) follow the vehicle in front at a set speed limit, and maintain a specific safe distance. There are a variety of differing sets of assumptions that are associated with car-following models, leading to differences in the deterministic outputs of evacuation simulation (Olstam & Tapani, 2004). The differences in driver behavior have been found to impact overall clearance time, especially the mean gap and headway between vehicles (H. Tu, Tamminga, Drolenga, de Wit, & van der Berg, 2010; H. Z. Tu et al., 2012). Gaps between vehicles will most likely be smaller in evacuation scenarios, and therefore cannot be described as 'normal' car-following behavior (H. Tu et al., 2010). Adopting this type of simulation can potentially overestimate evacuation clearance time, as the queuing behavior and traffic flow may not be as optimal under normal driving conditions as it is in evacuation scenarios.

Traffic simulation has the capability to incorporate complex behavior determined by any number of factors associated with an evacuation event, such as slower response time, or faster and more reckless driving, yet few studies have attempted to simulate robust evacuee behavior. Agent-based evacuation simulation is generally successful in scenarios where inter-agent interaction is a critical aspect of the simulation (Lee & Pritchett, 2008). They are also simple to comprehend, and with the aid of traffic simulation software, simple to run. Modern software such as Paramics and VISSIM require input network model data, and behavior rules, and in the case of evacuation, a determined destination or destinations (Algers et al., 1997; Murray-Tuite & Wolshon, 2013). However, agent-based models are limited in their ability to be validated and verified (Ormerod & Rosewell, 2009). In this context, validation can be defined an assessment of accurately the model represents real-world processes, and verification can be defined as the process of determining if computational software correctly represents a model, and that equations are solver properly. Another minor drawback to these forms of simulation is that they require considerable processing power to run. However, current advances in computing power have made this drawback benign, and potentially are responsible for the ubiquitous use of simulation in the past ten years (Desmet & Gelenbe, 2013). Agent-based models are limited in these regards when compared to analytical solutions to network analysis, and any results must be accepted as deterministic and difficult to validate and verify.

Traffic simulation is also very saturated in terms of modeling software. Southworth (1991) compiled a list of common software packages, where pros and cons of each model were analyzed. Southworth makes a distinction between simulation types, from microsimulation to macrosimulation. The decision between which type of traffic simulation model to choose can be based on a number of factors, including available computational power, scale of study area, resolution of data, and others (Southworth, 1991). Reviews performed on evacuation modeling

(Murray-Tuite & Wolshon, 2013; Pel et al., 2011) tend to focus only on traffic simulation as a method of final analysis. However, other methods exist that can be used to determine evacuation clearance time, with potential situational benefits over traffic simulation.

Queuing analysis is an alternate method sometimes employed in traditional transportation modeling that can determine the impact of congestion points on overall clearance time. Queuing analysis is used to determine how long wait times are at a specific point in a network. Use of queuing analysis in an evacuation model assumes that the major determinate of clearance time is a choke point or single point of egress, which suffers from congestion issues. In certain areas with limited points of egress, such as islands or mountain communities, congestion in these locations may influence clearance time considerably. If congestion in these limited egress points turns out to be a large enough factor in impeding evacuation time, queuing theory can be a viable method of analysis. Queuing analysis is not frequently used in hazard evacuation modeling; however, it has been employed in building evacuation (Smith 1991, Bakuli and Smith 1996, Hasofer and Odigie 1996, Elms and Buchanan 1984). Queuing analysis of this type has fallen out of favor in recent times, due to issues with computational power and the rise of agent-based modeling; however some efforts have been made in the past decade (Desmet & Gelenbe, 2013).

A combination of the two aforementioned methods, network queuing simulation, can offer a more analytical approach to solving the deterministic problem of overall clearance time. Past studies (Lämmel & Flötteröd, 2009; Lämmel, Grether, & Nagel, 2010; Lammel & Nagel, 2009; Lämmel, Rieser, & Nagel, 2008, 2010; Lämmel, Rieser, Nagel, et al., 2010) have used a first-in, first-out (FIFO) queuing process simulation to route selection (Gawron, 1998). FIFO simulation differs from traditional queuing processes in that congestion is identified, and evacuees remain in the queue instead of being dropped. This allows the deterministic calculation of overall clearance time based on analytical queuing process methods (Lammel, 2008).

Other methods can also be used to obtain clearance time and model evacuation events that do not follow traditional transportation research methods. For example, research has been conducted on near-field tsunami evacuations that assume pedestrian evacuation as the only viable mode of transport, due to infrastructure damages from the nearby earthquake event that triggers the tsunami (Wood & Schmedtlin, 2013). Based on this infrastructure damage, traditional network analysis does not have as much utility, and instead anisotropic least cost-path modeling is used, giving speed weights to varying land covers and factoring elevation to determine travel time over terrain. The results of this method are a spatial distribution of pedestrian travel time to specified safe zones.

1.5 Research Questions and Goals

Understanding the evacuation capacity of a community can help to improve overall vulnerability assessments. Many methods exist for determining evacuation capacity, including social evacuation vulnerability analyses, network capacity analyses, evacuation demand estimations, and evacuation modeling. Evacuation modeling has potential to be informative for disaster management, as it can provide estimations of evacuation clearance time. Understanding evacuation clearance time in the context of hazard exposure scenarios provides thorough information about hazard vulnerability. However, clearance time results are determinate in nature, based on the methodology of demand estimation. Traditionally, these methods tend to misrepresent factors of evacuating populations leading to inaccurate clearance times. Additionally, traditional traffic simulation techniques for evacuation modeling are inadequate for determining evacuation clearance time from sudden-onset hazards for highly developed neighborhoods. The existing traffic simulation techniques are either intended for larger-area evacuations (Algers et al., 1997), or rely on pre-programmed human behavior in route selection and travel time estimation (Paramics, VISSIM). Therefore, a need to develop a comprehensive network-based sudden-onset hazard evacuation modeling framework exists, to estimate evacuation clearance time accurately for developed communities at risk to a variety of natural hazards.

To fill this gap, this research aims to create an evacuation modeling framework, building upon prior work, which addresses the limitations in current evacuation modeling methodologies when applied to network-based sudden-onset hazard evacuation. After thoroughly reviewing existing evacuation modeling literature, a need for improvements in both evacuation demand estimation and clearance time determination becomes apparent. In general, these models fail to address concepts from evacuation research, and when applied to sudden-onset natural hazard evacuation, do not accurately determine evacuation clearance time. Incorporating additional evacuating population in addition to residents, addressing alternate modes of transportation, and modeling background traffic and shadow evacuation can improve the overall demand estimation model to represent the exposed area. Utilizing the MATSim FIFO network queuing simulation environment helps to reduce the amount of assumptions and uncertainty that come with other traffic simulation packages that use normal driving behavior to determine travel time.

Additionally, network queuing simulation improves the utility of the model when attempting to identify areas of congestion. Lastly, existing modeling methodologies can be improved in their ability to inform disaster management. Creating a modeling framework that is flexible and easily repeated can allow for a variety of scenarios and mitigation strategy tests to be created within a study area. Not only can this give a comprehensive understanding of the evacuation capacity of an area, it can also provide results that demonstrate the impact of certain evacuation strategies or constrains for the area.

The comprehensive evacuation modeling framework was employed within the case study area to identify overall clearance time under a variety of scenarios, as well as overall clearance time using different evacuation strategies. These strategies were identified in order to prove the utility of the modeling framework, as well as demonstrate the ability of the framework to identify community evacuation capacity. Results from the scenario and strategy-based modeling were analyzed with local disaster management and stakeholders in mind. Presentation of results through stakeholder interaction is not a goal of this research, however modeling results are tailored in a way to facilitate informative and actionable information in relation to community evacuation capacity.

The research uses a case study area as an environment to develop and test a comprehensive network-based evacuation modeling framework. Additionally, overall evacuation clearance time was identified for the same study area, under a variety of scenarios. Clearance time under various disaster management and evacuation strategies was modeled and placed in context with the study area to identify affordances and constraints of each. General conclusions of disaster management practices can be made based on study-area specific conclusions identified through modeling results. This was performed in an effort to inform disaster management.

Based on prior research in evacuation studies and evacuation modeling, and the goals of this research, the following research questions can be answered:

1. Is queuing analysis a viable alternative to traffic simulation in determining evacuation clearance time?
2. How does accounting for non-residential evacuees in addition to residential evacuees affect overall clearance time estimation?
3. How do potential evacuation strategies contribute to, or inhibit overall clearance time?
4. Where do vulnerable populations exist within a spatial distribution of overall clearance time?

Chapter 2 – Evacuation Modeling Framework Development

2.1 Introduction

An important aspect in reducing loss of life from natural hazards involves the evacuation of populations from at-risk areas. A major part of planning for natural hazard evacuation is first understanding an area's capacity to evacuate. This can be achieved by creating and simulating a potential evacuation scenario through evacuation modeling. Having an understanding of potential evacuation scenarios can be useful for guiding local land use planning, development, as well as emergency management. Traditionally, evacuation modeling is performed using transportation modeling methodologies for travel demand forecasting. This can lead to an inaccurate representation of an evacuation scenario, as evacuations have unique characteristics not addressed by traditional transportation models. Neglecting these characteristics can lead to an underestimation of the total time required to evacuate at-risk population from a hazard zone. If one's goal is to provide a more accurate assessment of potential clearance times from extreme events, evacuation modeling should be approached as a unique exercise independent from traditional transportation modeling. An understanding of how these more complex factors of evacuation influence clearance time exists, yet is not often applied to evacuation modeling. In addition, applying a general transportation model on a case-by-case basis fails to address local characteristics that can have a large impact on an area's capacity to evacuate. Overall, a more holistic approach to evacuation modeling, and approaching the process not as a transportation problem but an *evacuation* problem can allow evacuation models to represent reality more accurately.

Incorporating the unique characteristics of a study area is critical when performing vulnerability assessments. Evacuation modeling to determine evacuation capacity should therefore adequately capture the socio-economic, infrastructural, and physical characteristics of the study area (Chakraborty et al., 2005). As this research aims to recreate evacuation scenarios through evacuation modeling, all potential evacuating populations should be addressed. This requires a variety of data sources including empirical, public, and private. Additionally, some assumptions must be made in order to capture other populations. The resulting framework built must be flexible and adaptable to different study areas to capture local characteristics of populations that influence evacuation demand. By analyzing socioeconomic characteristics and other local information, additional modes of evacuation may become apparent. The presence of transit-dependent populations, or the spatial scale of the study area may require modeling of pedestrian or shuttle-based evacuation instead of assuming vehicular evacuation and focusing solely on modeling this mode. Additionally, the characteristics of the transportation network should be highlighted when determining travel time, allowing for information relating to affordances and constraints of the network to be identified. Using a queuing network simulation environment allows for a more analytical calculation of travel time, and individual sections of the network where congestion problems occur can be identified.

Many methods exist to determine evacuation clearance time with a given evacuation demand. Network capacity and social evacuation vulnerability studies (Chakraborty et al., 2005; Cova & Church, 1997) have some utility, but are not adept at determining clearance time under different scenarios. Because one goal of this research is to solve a deterministic problem, how long it takes to move a given population demand across a network, some form of simulation is required. Many agent-based traffic simulation tools exist (Algers et al., 1997), most if not all use an imperfect simulation of human behavior as a main determinate of evacuee routing and thereby travel time. Queuing theory offers potential solutions in areas with limited egress, yet probabilistic queuing processes are not completely able to solve deterministic problems, instead assuming infinite flow of traffic (Smith, 1991). A potential solution is to perform a queuing simulation, where evacuee travel through one queue, or many queues in a network, is simulated based on queue service rates and arrival times (Gawron, 1998). This provides an analytically-rooted simulation that places less emphasis on evacuee behavior in determining travel time.

To address shortcomings in traditional evacuation models' ability to predict evacuation clearance time, this research presents a new methodological framework for a comprehensive network-based evacuation model. This model addresses local aspects that contribute to evacuation constraints or affordances and other concepts from theory that influence the evacuation potential of a community. The methodology can be split into two major components: demand estimation and clearance time determination. These two components are completed sequentially. Beginning with socioeconomic and geospatial data and under assumptions pertaining to the study area as well as desired scenario, evacuating populations (demand) can be identified. With this demand information, evacuation proceedings can be simulated along existing network infrastructure to determine evacuation clearance time for the study area.

The travel demand model developed under this work employs geographic information systems (GIS) tools in conjunction with socio-economic geospatial data to acquire a spatially explicit estimation of evacuating populations during a tsunami event. The demand modeling process uses a number of parameters that can be altered to estimate evacuating populations under a variety of scenarios, such as daytime versus overnight evacuations. Additionally, it incorporates variables such as employee population, transit-dependent population, and evacuee risk perception, which are underrepresented in past work, but critical factors of evacuation modeling. In some cases, estimating travel demand can alone suffice for a basic understanding of evacuation capacity (Chakraborty et al., 2005; Cova & Church, 1997; Lindell & Prater, 2007). In this model, it serves as an input into traffic simulation, which in conjunction with transportation network data, recreates the evacuation event and allows for an estimation of evacuation clearance time. Overall, the demand modeling framework presented in this research captures concepts not frequently addressed in evacuation modeling research, and provides the means for the most comprehensive estimation of evacuation demand yet in the field of research.

Traffic simulation serves to recreate an evacuation scenario by moving travel demand information across space within the constraints of a transportation network (Murray-Tuite & Wolshon, 2013). In this step, evacuee's trips, pre-determined from the travel demand model, are simulated. Travel time for this trip is recorded for each evacuating vehicle or evacuee, depending on the mode of transit. There are varieties of methods used to perform this traffic simulation, most of which employ agent-based simulation techniques focusing on modeling individual agents, in this case vehicles or evacuees. Traffic simulation models generally attempt to acquire an equilibrium state of traffic, meaning the most efficient combination of routes for all evacuees that achieves the shortest travel time on average for each evacuee. This assumes that evacuees will have perfect knowledge of the event, transportation network, and congestion as they evacuate. Researchers criticize the use of equilibrium in evacuation modeling, as evacuations are rare events (Murray-Tuite & Wolshon, 2013). The evacuation model in this study models both user equilibrium (re-routing) and non-equilibrium (shortest-path routing) to acquire best-case and worst-case clearance time results, respectively. The worst-case results can be seen as a scenario with little to no emergency response and traffic management. The best-case, equilibrium results can be seen as a scenario with the most effective management and routing in place to direct evacuees to safety in the shortest time possible. From this perspective, fewer assumptions are placed on the individual evacuee in determining their route, and instead placed upon traffic management and emergency response. Because the framework is focused on modeling smaller study areas with few evacuation routes, such traffic management is a possibility.

Additionally, there are inherent assumptions made when performing traffic simulation, as pre-defined rules for evacuee behavior are set before the simulation is performed. This is a limitation of traffic simulation, as these rules are difficult to validate statistically (Lindell & Prater, 2007; Ormerod & Rosewell, 2009; Pel et al., 2012). However, performing traffic simulation allows the model to account for interaction between individual evacuees and the network to account for congestion. Congestion can be a significant factor during sudden-onset network-based evacuation, and are therefore traffic assignment can provide extra insight into constraints on evacuation clearance time.

A first-in, first-out (FIFO) network queuing simulation model, MATSim, was chosen for traffic simulation because it makes fewer assumptions about evacuee behavior than other models, and its main method of simulation is grounded in queuing theory. Additionally, the use of network queuing simulation places focus on determining congestion within a transportation network. MATSim is an open-source Java programming-language package, with relatively robust documentation and simple setup. This potentially increases the audience for this study's evacuation model, as many other comparable traffic simulation software packages cost thousands of dollars and require expensive and rigorous training. MATSim also has relatively low computational requirements. For example, evacuation simulation for the case study area is performed in less than two minutes on a modern desktop machine.

This chapter of the research focuses on the development of a network-based evacuation modeling framework for sudden-onset hazards. By building upon past research and attempting to address its limitations, this work identifies and incorporates concepts and components that help provide a more accurate representation of an evacuation. These concepts included non-residential evacuee population, alternate modes of transit, background traffic, and shadow evacuation. After the baseline demand and simulation model was created, a sensitivity test was performed to identify the impact of various model components on overall evacuation clearance time for the study area. Conclusions are then made about how failure to incorporate these components leads to an inaccurate estimation of clearance time. Additionally, sensitivity testing can demonstrate the potential variance in evacuation clearance times based on different assumptions about evacuating populations.

2.2 Methods

2.2.1 Study Area

The selected area for evacuation model development is Balboa Island, located in the city of Newport Beach, in Orange County, California. The local geography of Balboa Island lends to a potentially complex evacuation, making it a viable study area under which to create a comprehensive evacuation modeling framework. The entirety of the island is exposed to far-field tsunami events, and is made up of dense residential development, with additional employee population, as well as a number of tourist visitors during the day, year-round. Balboa Island has only one point of egress from a tsunami, yet the entire island is less than a mile in length, and less than a square kilometer in area. The presence of high residential population, number of registered vehicles, and tourist population can lead to potential congestion issues during a tsunami evacuation, and provide opportunity to test a variety of model components in both the demand estimation and traffic simulation.

Balboa Island is not a census designated place (CDP), but instead has its boundaries deliniated by the physical extent of the island itself. Demographic data used was acquired from the 2010 U.S. Census and 2013 American Community Survey projections. The island containts 48 census blocks, with a total population of 2611. Business data, acquired from InfoGroup survey information, shows 158 business in operation on Balboa Island, with a total employee population of 741. Much of the analysis performed on the island was done at the parcel and household level. Parcel data was acquired from the City of Newport beach, and household totals were estimated from address data.

Table 2. Balboa Island demographic summary

Variable	Counts
Total Population	**2611**
Total Households	**1480**
Businesses	**158**
Residential Vehicles Available	≈2381 **μ = 1.6**
Boats	Small – **149** Large – **47**
Transit-dependent households	**58**

Tsunami inundation information is used to determine evacuation zones, safe zones, and evacuating popualtions. For the study area, tsunami inundation extent for two different scenarios was obtained. Firstly, the maximum tsunami exposure extent used by local and state agencies was obtained, in addition to a smaller tsunami exposure extent based on a potenteial scenario. This scenario was developed by modeling of a hypothetical event similar to that of the 1964 Alaskan earthquake (Ross, 2013). The use of both exposure extents can allow for the exploration of concepts of shadow evacuation, in addition to other analysis that can inform emergency management planning, which will be explored in Chapter 3 of this research. Balboa island lies entirely within both tsunami exposure extents (Figure 3).

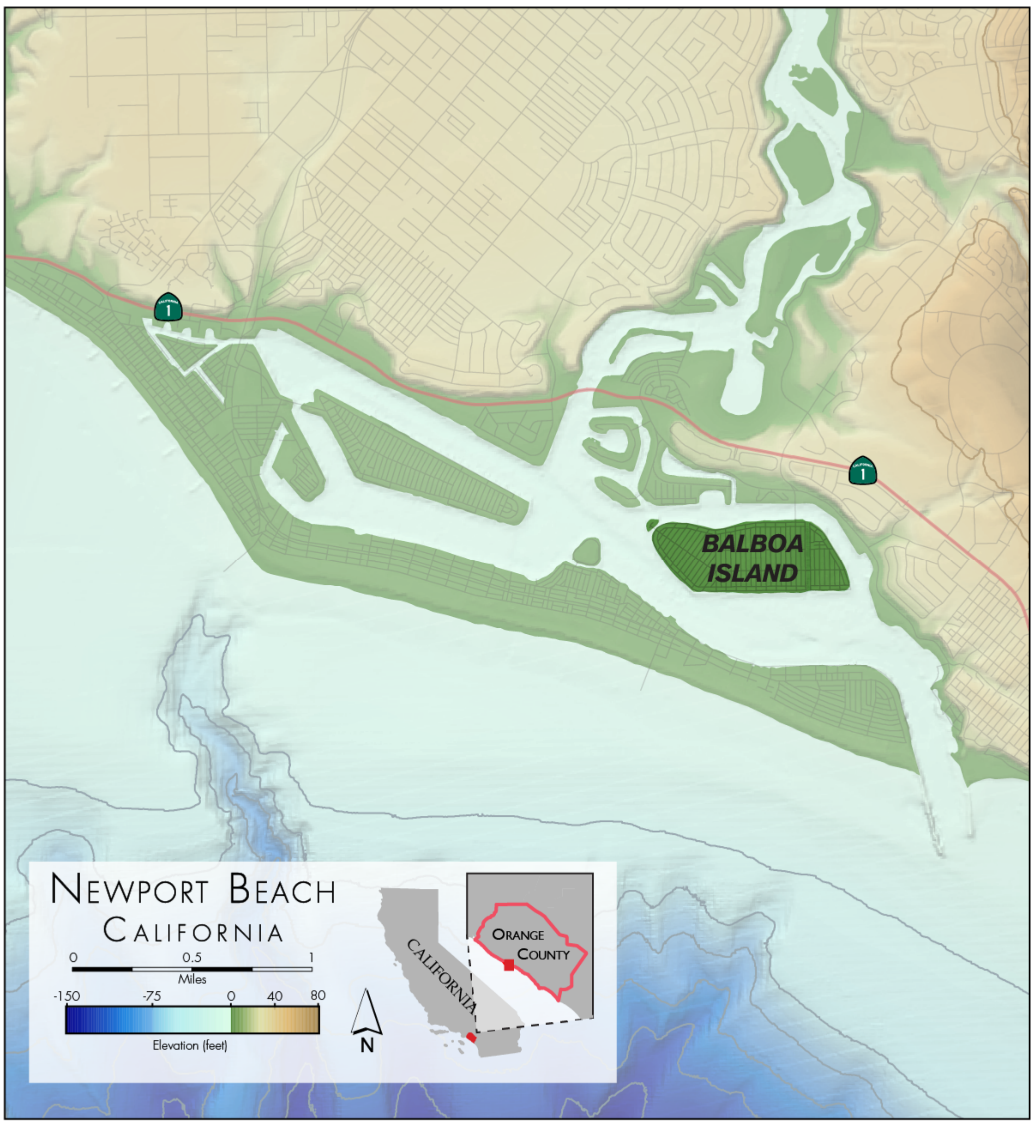

Figure 1. Topographic map of Balboa Island and surrounding area

Figure 2. Balboa Island tsunami exposure map

Balboa Island has a limited transportation network, consisting mainly of one-way streets and alleyways. Only three two-way streets exist on the island: Marine Avenue, the main commercial street which runs in a north-south direction, and connects the island to the mainland via a two-lane bridge, allowing for one lane of egress; Balboa Avenue, an east-west street that runs through half of the island, and Park Avenue, which runs east-west and connects the western extreme of the island to the eastern end. One-way streets and alleyways alternate along the entire island and run north-south, providing access to most of the residences on the island. Generally, these homes contain garages exiting to the alleywas. Evacuation from the island may be difficult due to high number of vehicles parked on all streets, including the main two-way roads. Egress from the island is limited to a two-lane bridge that leads to a traffic signal intersection with Bayside Drive. Marine Avenue continues to another traffic signal intersection with California State Route 1 (SR1). At this crossing, SR 1 provides access to areas along the coast to the north and south, and a major arterial road, Jamboree Rd. continues inland towards U.S. Interstate 405.

Figure 3. Balboa Island street map

The characteristics of the study area provide as an interesting case to explore the impact of background traffic and transit dependent populations on successful evacuation. The importance of background traffic in evacuation modeling can also be identified by identifying the impact of State Route 1 on congestion and evacuation time. The impact of performing shuttle-based evacuation to address transit-dependent populations can be identified by locating populations without a car, and including shuttle services in the overall evacuation model. These shuttles will follow two routes along the island, one route servicing the western portion and another servicing the eastern portion. These routes will terminate at a nearby shopping mall, serving as an evacuation staging point, as it is beyond potential inundation extents.

2.2.2 Travel Demand Estimation

The first step in performing an evacuation modeling assessment is to estimate travel demand. This provides information on the evacuating population, including where they are located, how they are choosing to evacuate (if at all), and where they are evacuating to. In the case of tsunami evacuation modeling, many of the answers to these questions are relatively straightforward. However, it is important to address the assumptions made in identifying answers to these questions

In the modeling framework presented by this research, trip generation and mode choice are determined through a demand model equation, performed for each parcel within the tsunami inundation zone. The model is adapted from Lindell and Prater (2007), who created an equation for hurricane evacuation demand. Many of the concepts are the same in the case of tsunami evacuation; however, parameter values will differ between hazards. Additionally, the equation differs depending on the mode of transit estimated. The general equation for vehicular demand (EV) applied to entire study area is:

$$EV= H*D*(1-TD_{veh})*(EVHH)*(1-S)*U+T*(B*EVB)+Tr$$

where H = # of households, D = proportion of participating households, TD = proportion of transit dependent residential households, EVHH = average number of evacuating vehicles per household, S = proportion of early evacuees, U = proportion of households that use primary evacuation routes, T = proportion of businesses open, B = # of businesses, EVB = average number of evacuating vehicles per business, and Tr = transient population.

Transit-dependent population, for the vehicular model, can be identified using ACS data on vehicle ownership per household. To obtain the proportion of transit dependent households for the above demand equation, TD is defined as:

$$TD = H_{NV}/H_{total}$$

where H_{NV} = households without access to a personal vehicle and H_{total} = total households.

When estimating pedestrian demand (EP), the overall demand equation is simplified slightly:

$$EP = P*D(1-TD)*(1-S)+T*(E*PE)+Tr$$

where P = total population, D = proportion of participating households, TD = proportion of transit dependent residential households, S = proportion of early evacuees, T = proportion of businesses open, E = employee population, PE = proportion of employees at business, and Tr = transient population.

In estimating pedestrian demand, transit-dependent population is defined differently, and is determined by the amount of population physically unable to evacuate on foot:

$$TD_{ped} = P_{NA}/P_{total}$$

where P_{NA} = non-ambulatory population and P_{total} = total population.

P_{NA} is a more difficult metric to determine, but can be derived from demographic age data, or more preferably from survey data. For the purposes of this study, pedestrian-based demand modeling was performed with no transit-dependent population. Modeling mixed pedestrian and shuttle-based evacuation is possible, but requires additional transportation network and a more robust simulation package that can incorporate interaction between vehicles and pedestrians.

The above demand estimation equations can function in a large study area, as employed in Lindell and Prater (2007). When applying the above demand equations to very small boundary units such as parcels to achieve a micro-scale simulation, certain parameters of the demand modeling equation must be handled differently than proposed in Lindell and Prater (2007). Specifically, proportional variables that are meant to be applied to large sample sizes of data must be dealt with differently when working at a parcel level, which in many cases only contains one household. Before running the demand model, data is gathered or assumptions are made for the parameters of these proportional and average variables (proportion of households deciding to evacuate, *D*; average vehicles per household, *EVHH*; average vehicles per business, *EVB*; proportion of early evacuees; *S*; proportion of businesses open *T*; and employee population, *E*). Because these values are simulated to acquire a high-resolution demand model, they must be randomized based on pre-determined distributions or probability. *D*, *T*, and *S*, are determined using a Boolean randomization based on a desired probability determined at the outset of demand modeling. For example, if the demand model is set to assume that 80% of the total population will choose to evacuate, the value of *D* will be randomized for each parcel, with zero or False occurring 20% of the time, and 1 or True occurring 80% of the time. For parameters that deal with averages such as *EVHH* and *EVB*, a Poisson distribution is used to randomize values distributed throughout the study area. The λ value for the distribution is determined by the overall mean. For example, census data demonstrates that households in Balboa Island own on average 1.3 cars. A randomized Poisson value is set for each household with $\lambda = 1.3$. Because of the high number of households in the study area, despite randomizing each household's vehicles separately, the total vehicles and vehicles per household match closely with the empirical data that exists at a higher spatial scale. This technique for estimating vehicle demand has been performed in prior evacuation modeling work (Cova & Johnson, 2002) and provides a relatively accurate simulation of where cars are located within the study area based on household numbers.

Incorporating business data to determine employee and tourist population can increase the accuracy of the demand model and provide the opportunity for multi-scenario modeling based on time of day of an evacuation event. Geo-located business data with number of employees can be used to associate the number of businesses and employees with parcel information. Estimation of evacuating vehicles from businesses is performed in a similar fashion to residential households. A Poisson random number generator is used with a λ value based on the average number of vehicles evacuating per business. This value is more difficult to generate from assumptions of the study area, as less data exists on vehicle ownership at a business level. Some insight can be gained from the amount of employees per business, which can allow assumptions to be made based on the number of vehicles used per employee.

Transient populations can be present in institutionalized and non-institutionalized group quarters, such as hospitals, correctional facilities, or dormitory housing. Tourists can also contribute to additional evacuees not originating from residential or employees. Methods for identified these populations can vary depending on the study area and the type of dwelling/evacuee. Past work has identified local visitor's bureau as a source of this information (Lindell and Prater 2007). For the study area, tourist population was identified cars occupying street parking, based on expert opinion informed by imagery data and in-person ground-truthing. Assumptions can be made on street occupancy based on time of day and season to create a desired tourist population scenario.

The areal extent of demand estimation is critical to consider before performing evacuation modeling. While simply estimating evacuation demand for a specific study area may suffice in some circumstances, neglecting to estimate additional evacuees from outside the study area may lead to an underestimation of congestion and clearance time. For example, the study area of Balboa Island shares potential evacuation routes with other developed areas on the mainland. These areas, also within potential maximum inundation zones, should be included in demand model estimation. This allows for the capture of background evacuees, and other potential shadow evacuees that may exist outside the study area, yet still impact congestion. To demonstrate the impact of these 'background' evacuees, a sensitivity test can be performed comparing evacuation model results of just Balboa Island with those that incorporate additional mainland evacuees.

In order to obtain values to input into the demand model, a number of socio-economic datasets with spatial information are required. All data must share the same datum and projected coordinate system to insure accurate spatial analysis. For the study area, data was recorded in or transformed to NAD1983, and projected in California Teal Albers Equal Area projection. Because network analysis is a major part of this study, choosing an equal area projection insures measurements and distances are consistent across the study area. The base data required is parcel boundary data, which is used in addition to an accurately geocoded list of addresses in point data form. Parcel data for Balboa Island was acquired from the City of Newport Beach, CA. Census block boundaries with census-level population data acquired from the U.S. Census Bureau are also necessary to obtain population counts for input in the pedestrian demand model. Only total population statistics are required, but population by age can also be helpful in determining transit-dependent populations. Data used for this study was acquired from the 2010 U.S. Census SF1. Vehicle ownership information is also useful to determine parameters in the demand model. Census Tract-level data is available from the U.S. Census American Community Survey (ACS). Vehicle ownership for Orange County, CA census tract 630.06 was acquired from the 2010 ACS.

For business information, geocoded InfoGroup survey data can be assigned to parcels to determine the number of businesses within the parcel. To prevent redundancy of households that are also registered as businesses, households that share an address with a business are removed from the total residential household count. Lastly, street network information is required to derive the number of street parking spaces available, which can be used to address non-resident non-employee population. Based on standards for street parking spot length, the number of parking spaces along streets can be determined based on segment length. These parking spots are converted into polygons, which will be populated with evacuating vehicles during traffic simulation to address tourist populations.

With all data compiled and in the correct datum and projection, data from various spatial scales can be assigned to each parcel within the study area to acquire evacuation demand. The end goal is an estimation of the number of households, businesses, total population, transit-dependent population, and number of vehicles for each parcel within the study area. This process must be seen as a simulation, with results interpreted as only estimates. Attempting disaggregate spatial data with 100% accuracy is not possible (Openshaw, 1983). However, creating a simulation of travel demand fits within the next step of traffic simulation, and provides extra spatial resolution to the analysis. Before performing demand estimation for each parcel, the number of households must be determined for each parcel. This can also be estimated from higher-level ACS data, or alternatively can be determined by removing known business addresses from the complete list of geocoded addresses to obtain the residential addresses of the study area. For the study area, this was done by associating both sets of data by physical address. The location of businesses obtained from geocoding was poor, and therefore businesses were associated to parcels based on joined address attributes, in lieu of joining the two datasets spatially. At this point, a simple spatial location query for each parcel can determine the number of residential addresses in the parcel, which can be added to each parcel as a new attribute. This same process is performed with businesses to determine the total number of businesses for each parcel. Likewise, the total employee population for each parcel can be obtained by adding the employee information from each business.

At this point of the demand estimation process, population location can be simulated iteratively throughout the study area (Cova, 2002). Initially, an estimate of total population and total dependent population can be made for each parcel, derived from census data. This is obtained by using the total population counts for a census block and distributing these totals randomly to parcels within the census block. The same process is performed to estimate transit-dependent population. With this information, the output mode of transport desired will determine the demand equation chosen. Before running the demand model, parameters are required for a number of variables of the equation, including proportion of households deciding to evacuate, D; average vehicles per household, $EVHH$; average vehicles per business, EVB; proportion of early evacuees; S; proportion of businesses open T; and E, employee population. Altering these parameters can allow for the creation of a scenario tailored to specific characteristics. For example, an evacuation beginning in the early hours of the morning will have zero for the proportion of early evacuees, as well as zero for T, the proportion of businesses open.

This portion of the demand estimation process is streamlined using a custom ArcGIS geoprocessing tool (Figure 6). This tool accepts the demographic and cadastral data inputs and outputs a parcel-level GIS dataset (Figure 5) with attributes of either number of vehicles or number of pedestrians, by using the above demand modeling equation and randomization techniques. Additionally, tourist population is estimated by modeling parking spots occupied by tourist vehicles. Adjustment of the evacuating area, which determines which parcels to perform the demand model estimation in, is performed by changing the evacuating zone polygon. The tool itself serves as the graphical interface for a Python programming language script, which performs the variety of geoprocessing, computational, and iterative tasks. The ArcGIS tool inputs can be altered to adjust parameter values for the demand model. This allows for rapid creation of multiple scenarios and assumptions for sensitivity testing.

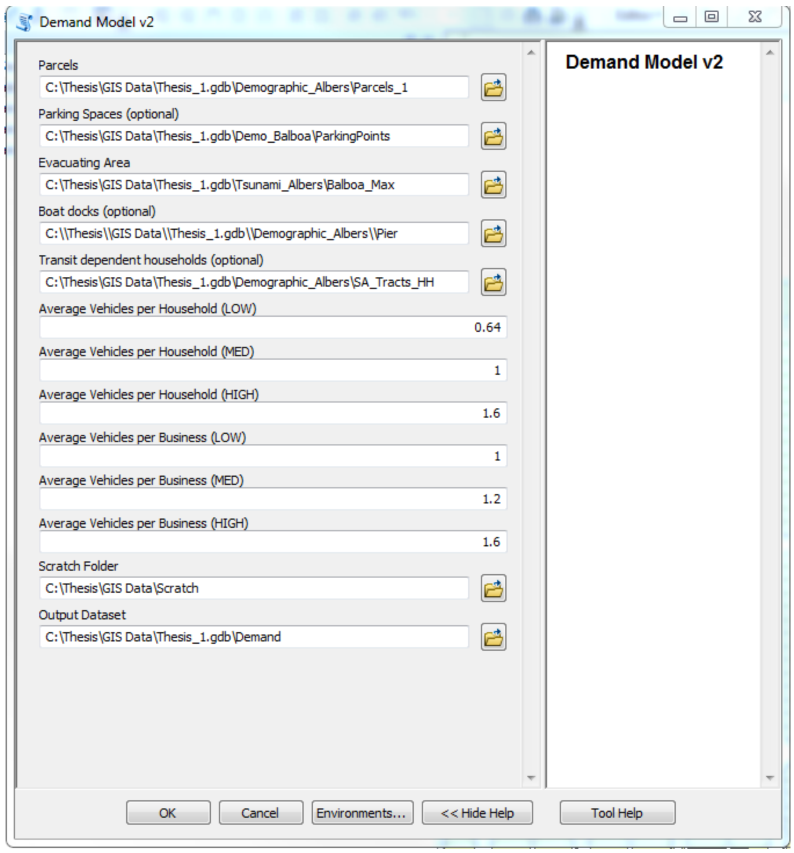

Figure 4. Custom ArcGIS geoprocessing tool with sample parameters

When using this tool, geoprocessing times for small study areas such as Balboa Island are minimal. This allows for modeling multiple evacuation scenarios using differing travel demand model outputs. For the study area, travel demand was estimated initially using a baseline scenario, or daytime evacuation during business hours. To test the sensitivity of the demand model to various changes in assumptions and parameter inputs, demand estimation can be repeated, altering one variable to either low or high in respect to the baseline.

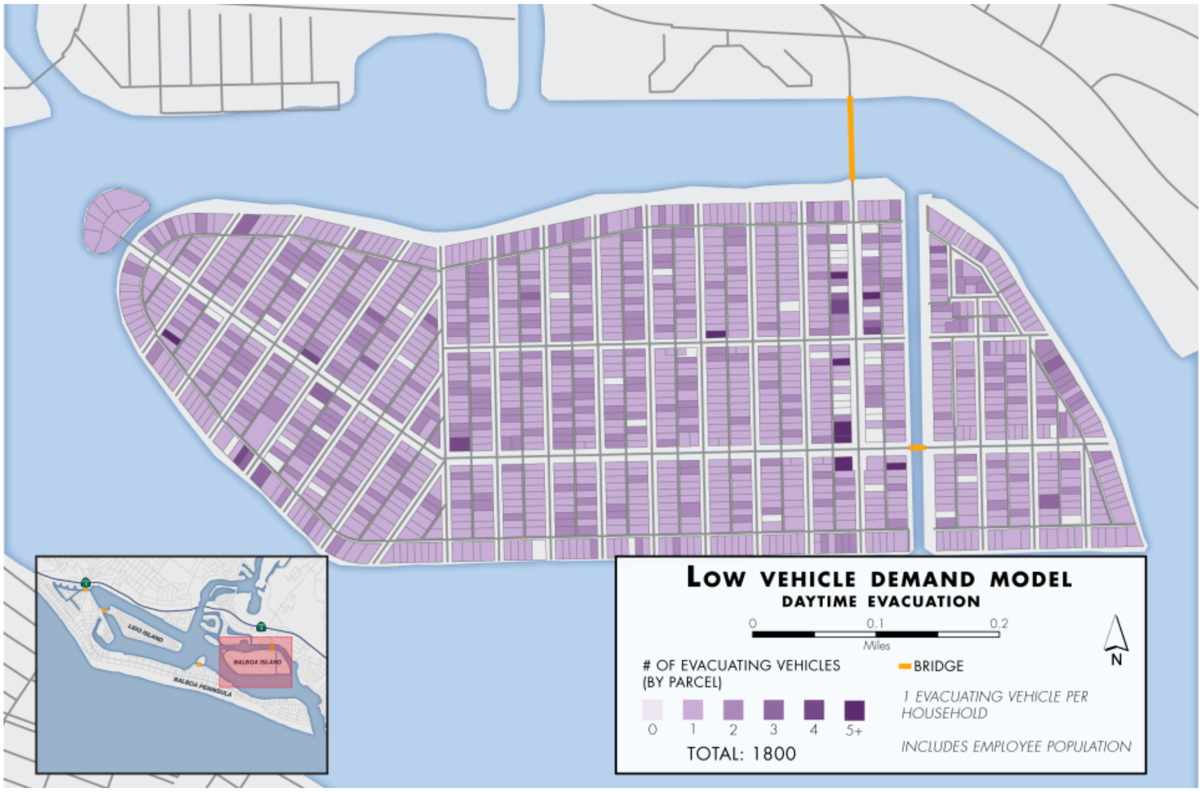

Figure 5. Sample evacuation demand modeling output.

2.2.3 Traffic Simulation

After acquiring a spatial distribution of evacuation demand, evacuation clearance time can be determined through traffic simulation. This portion of analysis determines evacuee route selection, identifying travel time for individual agents, which can be used to determine overall clearance time. With an understanding of each agent's travel time, overall clearance time can be determined as the time required for the *last* evacuee to exit the exposure zone. Many potential software packages can perform this analysis. Past modeling has used commercial traffic simulation software such as Paramics (Cova & Johnson, 2002), VISSIM (Chen et al., 2006; Chen & Zhan, 2006), as well as custom agent-based simulation (Goto et al., 2012; Madireddy, Medeiros, & Kumara, 2011; Mas, Adriano, & Koshimura, 2013; Mas et al., 2012).

Based on the limitations previously discussed with many agent-based traffic simulation packages, and the benefits of using a queuing process, a first-in, first-out queuing simulation environment was selected for the modeling framework. In this form of simulation, segments of the transportation network are given capacity values based on their length, number of lanes, and speed limits. Based on this capacity, only a set number of evacuee vehicles may enter a segment, until it has reached capacity. Agents must remain in a link for a set amount of time, based on the travel time of the link as well as if the proceeding link is uncongested (Lämmel, Grether, et al., 2010). Additional vehicles may only enter the segment once capacity becomes available by the means of another vehicle exiting the segment further along the transportation network (Lämmel, Rieser, & Nagel, 2010).

The MATSim traffic simulation package was selected because of a number of factors, lending to its utility for sudden-onset hazard evacuations. Additionally, it has been demonstrated as a viable simulation environment for evacuations (Lammel & Nagel, 2009; Lämmel, Rieser, & Nagel, 2010; Lämmel, Rieser, Nagel, et al., 2010). Lastly, an evacuation modeling-specific module, GIS-based Risk-Analysis-, Information-, and Planning-System for Regional Evacuation (GRIPS) has been developed for MATSim that aids in processing demand and network data for simulation.

MATSim evacuation simulation is built as an open-source Java programming language package. It offers a variety of transportation modeling tools (MATSim user guide), but most critically offers network queuing traffic simulation. MATSim is comprised of a variety of Java modules and *classes*, which must be run through either a command line or integrated development environment (IDE). There is a variety of methods to run MATSim, and choices may be up to the preference of the individual. The MATSim developers provide a tutorial and suggestions for setting up Java (Balmer, 2011). For this study, the Eclipse Integrated Development Environment (IDE) was used to manage workspaces of Java modules, classes, and libraries. Eclipse has the ability to checkout a number of Java packages, including MATSim, and easily updates these packages as improvements are made. Additionally, the GRIPS evacuation and OTFVIS (On-The-Fly Visualization) modules for MATSim can also be checked-out, increasing the utility of MATSim.

The GRIPS evacuation package provides a bridge between the GIS demand model data and MATSim, which requires data in Extensible Markup Language (XML) format to operate. It is used to synthesize spatial demand model and evacuation zone into traffic simulation. GRIPS requires three input datasets: population, network, and evacuation zone. Population must be in ESRI Shapefile format, and population counts for each feature must be within a attribute field titled ‘persons’, with a field type of Double. Because GRIPS only accepts one population field, differing scenarios must have unique shapefiles, and each scenario must have two shapefiles: one with vehicle totals and one with pedestrian totals as the ‘persons’ field.

GRIPS uses Open Street Map (OSM) data for network information. This data can either be exported from online OSM databases, or created using OSM editing software such as jOSM. In the case of the study area, existing OSM data was not completely correct, so it must be exported and then modified using jOSM (Figure 7). This network data can be edited using software such as jOSM to correct errors or to create hypothetical networks to test traffic management strategies such as contraflow, and infrastructural mitigation such as adding additional lanes or bridges. The evacuation zone data must also be in ESRI Shapefile format, and does not require any attributes, simply feature shape information.

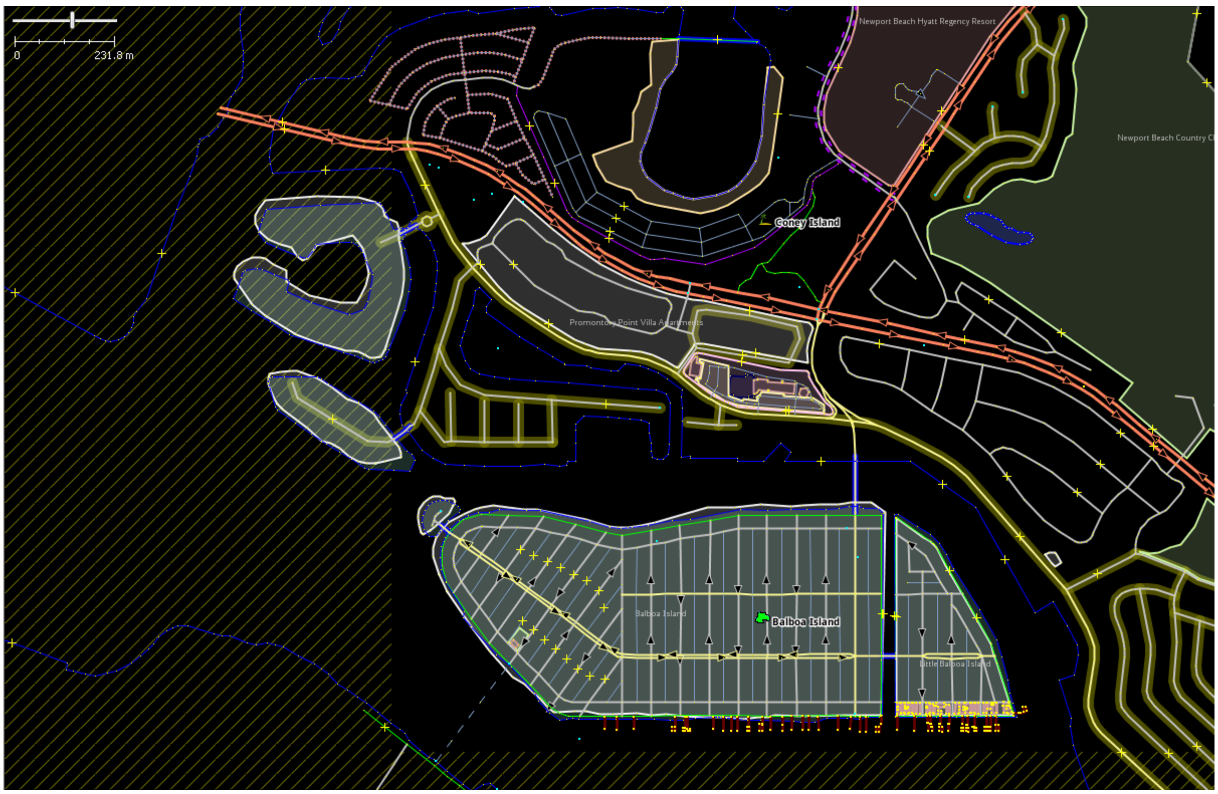

Figure 6. Open Street Map network data viewing in jOSM ediing software

Running the GRIPS Scenario Generator class creates geo-located trip origins from the input population shapefile. In this step, individual agents (either vehicles or pedestrians, depending on the demand model) are created for each polygon in the input demand file. Agent location is randomly distributed within each polygon. This is a critical distinction, as it demonstrates the merit in preforming micro-scale demand model estimation, as the level of accuracy in disaggregation will be slightly higher than simply allowing GRIPS to distribute population randomly within larger cadastral units such as census block groups.

GRIPS assigns starting times based on a Dirac delta distribution, which resembles other s-curves used for evacuee departure rate. As noted in Tamminga et al. (2011), departure rate distributions do little to impact overall clearance time in sudden-onset evacuation with limited egress flow. For the study area, no departure distribution was used, instead assuming traffic simulation begins with all evacuees exiting their households. The impacts of using a departure curve can be tested, however. A Dirac delta distribution can be used to add 'response time' to estimated evacuee demand. Using this distribution, few evacuees immediately respond, most evacuees respond relatively quickly, and the remaining evacuees slowly respond. Testing the impacts of a departure curve on overall evacuation clearance time can identify constraints of the study area, opportunities to improve evacuee risk perception, and the merits of including a departure curve in evacuation modeling for the study area.

The Scenario Generator then assigns destinations to evacuees. In this step, the nearest road segment that travels outside the evacuation zone based on Dijkstra's shortest path is selected. In MATSim, agents are no longer simulated the moment they reach their destination. For this reason, it is important not to use just the hazard exposure zone GIS data as the evacuation zone. Instead, a more general 'area of simulation' should be used. This way, evacuee traffic will continue to be simulated beyond the safe zone to account for any congestion that may build up from outside the safe zone. This simulation does not inflate the measurement of overall clearance time, as this value is recorded once the last evacuee exits the exposure zone, instead of their overall duration. Trip destinations should be assigned to major evacuation routes such as highways that lead well away from the hazard zone (Chen et al., 2006). When finished, the Scenario Generator class will create two data files, one describing the evacuating population and one for the network, in the .xml.gz format for use with the main MATSim package. This conversion is required, as MATSim cannot handle GIS datasets. They must first be converted into xml format (Figure 8). Lastly, GRIPS will create a custom MATSim configuration file, which controls most of MATSim's traffic simulation capability.

MATSim traffic simulations are initiated by creating a 'controller' Java class that references an XML configuration file, such as the one created by the GRIPS scenario generator class. When this controller class is run, MATSim performs the traffic simulation based on the parameters within the configuration file. Options are numerous within this file, and can use a wide variety of modules. For the purposes of this study, only the transit, traffic signal, and OTFVIS modules were used. Figure 9 depicts a section of a sample MATSim configuration.

```xml
<?xml version="1.0" encoding="utf-8" ?>
<!DOCTYPE population SYSTEM "http://www.matsim.org/files/dtd/population_v5.dtd">

<population>

<!-- ====================================================================== -->

    <person id="0" employed="no">
        <plan score="0.0" selected="yes">
            <act type="pre-evac" link="2388" x="-1.3124496669227993E7" y="3952983.277536612" end_time="00:00:00" />
            <leg mode="car">
            </leg>
            <act type="post-evac" link="el1" x="-1.3113012362333622E7" y="3963371.8241388625" end_time="00:00:00" />
        </plan>

    </person>

<!-- ====================================================================== -->

    <person id="1" employed="no">
        <plan score="0.0" selected="yes">
            <act type="pre-evac" link="3443" x="-1.3124953291835653E7" y="3953215.0591208674" end_time="00:00:00" />
            <leg mode="car">
            </leg>
            <act type="post-evac" link="el1" x="-1.3113012362333622E7" y="3963371.8241388625" end_time="00:00:00" />
        </plan>

    </person>

<!-- ====================================================================== -->
```

Figure 7. XML conversion of evacuation demand GIS data

```xml
<?xml version="1.0" ?>
<!DOCTYPE config SYSTEM "http://www.matsim.org/files/dtd/config_v1.dtd">
<config>

    <module name="global">
        <param name="randomSeed" value="4711" />
        <param name="coordinateSystem" value="Atlantis" />
    </module>

    <module name="network">
        <param name="inputNetworkFile" value="G:/MatSimTutorial/workspace4/myProject/TransitDependent/input/fixednetwork.xml" />
    </module>

    <module name="plans">
        <param name="inputPlansFile" value="G:/MatSimTutorial/workspace4/myProject/TransitDependent/input/tourist_mid.xml" />
    </module>

    <module name="scenario">
        <param name="useTransit" value="false" />
        <param name="useVehicles" value="true" />
        <!-- Set this parameter to true if signal systems should be used, false if not. -->
        <param name="useSignalsystems" value="true" />
        <!-- Set this parameter to true if lanes should be used, false if not. -->
        <param name="useLanes" value="true" />

    </module>
```

Figure 8. Sample MATSim configuration file structure

Incorporating transit (shuttles) and traffic signals requires additional data and configuration files. Transit vehicles require two specific configuration XML files: transit schedule and vehicle information. The transit vehicle information is similar to the evacuee population file in that it lists unique agents, in this case vehicles. It additionally defines the parameters for the transit vehicles, such as capacity, size, and access and egress time.

The transit schedule details the shuttle stop locations, shuttle routes, and which unique shuttle IDs follow what routes. The shuttle routes must list every link, in order, that the shuttle travels, which are referenced by a unique ID determined when the network is generated using the GRIPS scenario generator. To aid in determining these routes, the OTFVIS package can be run on the MATSim network file, where links can be interacted with to determine their ID. Scripting can aid in the creation of shuttle rout configuration files, as XML formatting is time-intensive if performed by hand in a text editor. For example, a Python script was created for the study area that parses through a CSV file that lists the links within a shuttle route and creates an XML file to be copied into the transit schedule configuration file. At this point, the respective configuration files must be referenced in the MATSim main configuration XML file, and the 'useTransit' parameter must be set to 'true' within the 'scenario' module configuration.

Traffic signals can be modeled by MATSim, again with proper configuration files that identify the location of the traffic signal, which links are governed by it, and the signal timing information. This can aid in the realism of the simulation, and help to capture congestion within the network during an evacuation. Traffic signal configuration is spread across three XML files, 'signal_control', 'signal_systems', and 'signal_groups'. Again, identifying link IDs using OTFVIS can help locate where traffic signals should be placed. Traffic signal modeling is not entirely robust with MATSim, but it instead determines how long links should be considered 'green', or traversable, and 'red', or blocked. The timing for each signal can be altered in the 'signal_control' configuration file. Consultation of the MATSim user guide is recommended, in addition to the traffic signal tutorial, to obtain the sample configuration files and an understanding of the complex XML structure of configuration files. Much like transit module, traffic signals configuration files must be referenced in the main MATSim configuration, and 'useSignalsystems' must be set to 'true' in the 'scenario' module configuration. Many more modules are available in MATSim, but for the evacuation modeling framework, these two are the only additional modules consulted.

MATSim simulation runs multiple iterations of traffic simulation, each successive iteration building upon the prior in route selection in an attempt to address learned driver behavior and achieve an 'optimal routing system' (Gawron, 1998). First iteration outputs can be used to demonstrate a worst-case scenario of traffic flow. In the first iteration, evacuee route selection is based strictly on a shortest path without congestion. Successive iterations should be used with caution, as perfect learned driver behavior and equilibrium demonstrate a best-case scenario, which is often not the case during evacuation. However, using this optimal routing simulation to represent efficient emergency traffic flow management can provide useful information to emergency managers and give an understanding of how to minimize congestion and improve clearance time. Using both the worst-case and best-case scenarios in conjunction can provide impetus for evacuation management. In general, by the 10th iteration an optimal state of routing tends to be achieved (Figure 10). For sensitivity testing, this iteration is used to represent a more accurate evacuation scenario. Some fluctuation occurs as traffic is rerouted in subsequent iterations, so a mean of clearance times should be used for overall clearance time starting with the 10th iteration.

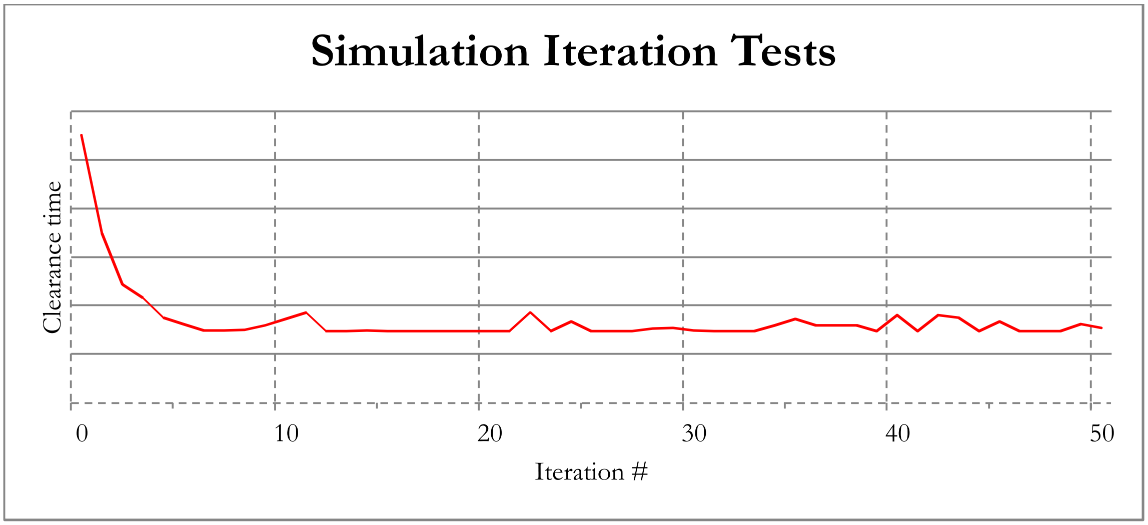

Figure 9. Plot of clearance time over multiple rerouting iterations

After MATSim is finished with simulation, a number of output data are created. The baseline file which contains information from each iteration is within an 'events' file. The events data records every agent's behavior, from basic events such as entering and exiting queues to more complex events such as waiting to board transit. This events file can be visualized in a number of means, either through the purchasable Senozon Via software, or with the on-the-fly visualization (OTFVIS) MATSim module. Visualization can be a useful tool to identify areas of congestion and overall patterns in evacuation. Additionally, it can be used to double check the accuracy of simulation. The events file also is used to identify the overall clearance time of the simulation. In order to obtain a singular value for overall evacuation clearance time, a specific node that represents the beginning of the safe zone can be identified by intersecting the network with the hazard zone. This node's unique ID can then be searched for in the events file. The latest recorded event of an evacuee leaving this node can be determined as the overall evacuation clearance time.

As the events file records the travel time of individual agents, and these agents have spatially explicit starting locations, a spatial distribution of clearance time can be obtained. However, a number of limitations and violations are associated with a spatial distribution of clearance time. Any maps created from this information should not be used to represent vulnerability in a traditional sense. Firstly, the location of evacuee origins is not necessarily accurate, as it was created using disaggregation of data and randomization. Secondly, the FIFO queuing simulation method of MATSim does not allow agents to leave a parcel until no agents are arriving in the adjacent link from further back in the queue. In a real world example, evacuees do not pause to allow vehicles onto the road network from alleyways or garages. The result of this is significantly higher average clearance time from parcels with a large number of evacuating vehicles, such as parcels with businesses or multiple households.

2.2.4 Sensitivity Testing

To test the sensitivity of the modeling framework to changes in assumptions, parameters, and components, a baseline input was created based on a specific scenario and general assumptions about the study area. Iteratively, each aspect of the demand model or traffic simulation can be increased, decreased, or turned off. Parameters in the demand model, such as average vehicles per parcel, a 'low', 'medium', and 'high' assumption can be tested to identify the sensitivity of the demand model to this parameter. See Table 2 for parameters tested and the values used for each test.

Table 3. Evacuation demand model parameter sensitivity test variables

Variable	Low	Baseline	High
Vehicles per Business (EVB)	1	$\lambda = 1.2$	$\lambda = 1.6$
Vehicles per Household (EVHH)	1	$\lambda = 1.2$ (75%)	$\lambda = 1.6$ (100%)
Tourist Population	None	Parking occupancy 100% - arterial roads 30% - other roads	Parking occupancy 100% - arterial roads 30% - other roads

Other components such as background traffic, shadow evacuation, and simulation extent can be tested to demonstrate the impact of their addition to the modeling framework. All results were compared based on the overall clearance time estimate. Results can demonstrate aspects of the demand model that are potentially weighted more in determining clearance time, or alternatively, demonstrate the predominant components of evacuation demand within the study area.

Table 4. Additional evacuation model component sensitivity testing

Variable	Sensitivity Test	Baseline
Departure Curve	Normal Distribution	Instantaneous departure
Transit-dependent population	Shuttle Simulation	No Simulation
Boat Evacuation	✓	X
Simulation extent	Hazard zone only	Hazard zone & Evacuation routes
Background evacuees	X	✓

2.3 Results

The above demand modeling methodology was performed for the study area, Balboa Island, under baseline conditions. Clearance time was obtained under the comprehensive evacuation modeling framework, which includes background traffic, shadow evacuation, transit-dependent populations, and simulation beyond the hazard extent. Once the baseline results were obtained, individual parameter and component sensitivity tests were performed to identify limitations of the model, study area, and the relevance of including complex evacuation-specific concepts.

Demand modeling

To test the impacts of demand model parameters, one singular randomization of baseline demand was performed. From this baseline, individual parameters were adjusted based on the weighting mentioned in the previous section. If new demand model simulations were performed for each sensitivity test, comparisons from the baseline would be invalid, as randomization could cause irregularities in the distribution of evacuation demand. By performing one randomization, the relative impact of each parameter can be correctly identified.

Initially, demand model sensitivity tests demonstrate that adjusting the average vehicles per household makes a larger impact on overall evacuating vehicles than the other parameters. This is most likely due to the characteristics of the study area, which is predominantly residential. The high estimate of vehicles per household represents that average *total* vehicles owned within the study area. This value is generally used in evacuation modeling to represent vehicular demand (Chen et al., 2006; Cova & Johnson, 2002). However, survey research demonstrates that roughly 75% of total vehicles will be used in a sudden-onset hazard evacuation. Lastly, low estimates assume only one evacuating vehicle per household. The wide range in resulting vehicular demand from residences demonstrates the variability in hazard evacuation scenarios, and potential for disaster management in terms of regulating vehicle usage. As the literature recognizes 75% as a general percentage for hazards similar in characteristics to the study area, the middle-range estimate for this parameter will be used for the baseline model.

Table 5. Evacuation demand model sensitivity test vehicle counts

Test Name	Evacuating Vehicles	Δ Baseline
Baseline	3485	0
Vehicles per Business (Low)	3397	-88
Vehicles per Business (High)	3575	+90
Vehicles per Household (Low)	2597	-888
Vehicles per Household (High)	5008	+1523
Tourist Population (Low)	3082	-403
Tourist Population (High)	3792	+307

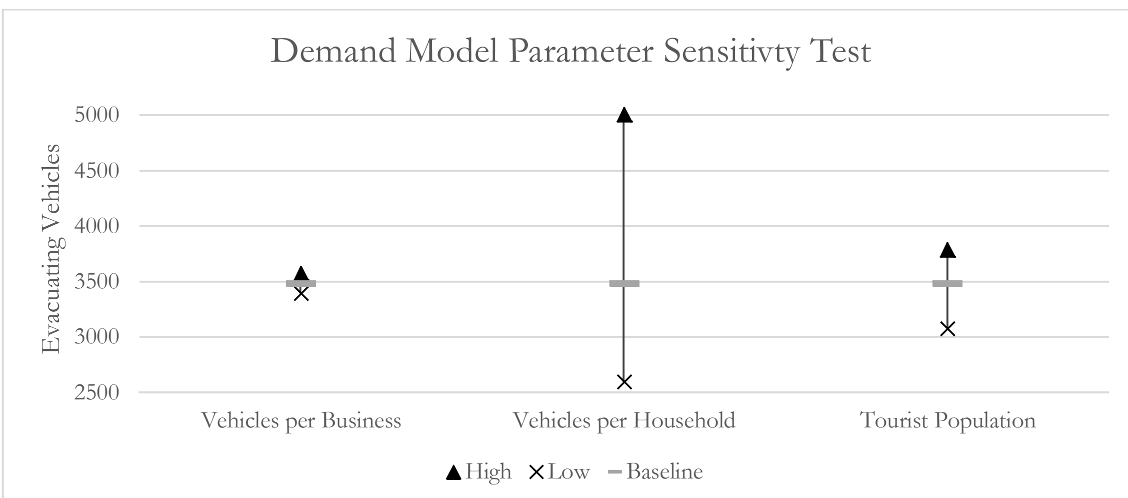

Figure 10. Plot of evacuation demand model sensitivity test results

Pedestrian demand modeling does not allow for sensitivity testing, as input parameters are basic population counts, and do not use any assumptions or averages. Scenario-based parameters such as residential and business occupancy rates can be altered to impact pedestrian demand, but this process would be used for scenario-based planning. This will be addressed in the following chapter of this research.

Evacuation Simulation

Demand model parameter estimates can be further tested through evacuation simulation to determine evacuation clearance time. Unfortunately, no recorded data of tsunami evacuation clearance time exists for the study area, so the accuracy of parameter estimates cannot be tested with empirical data. However, understanding the final impact on overall clearance time can provide some insight into the impact of parameter estimation. Seven (7) different traffic simulations were performed, one for baseline estimates, and an additional six to test both high and low estimations of average vehicles per business, households, and tourist populations.

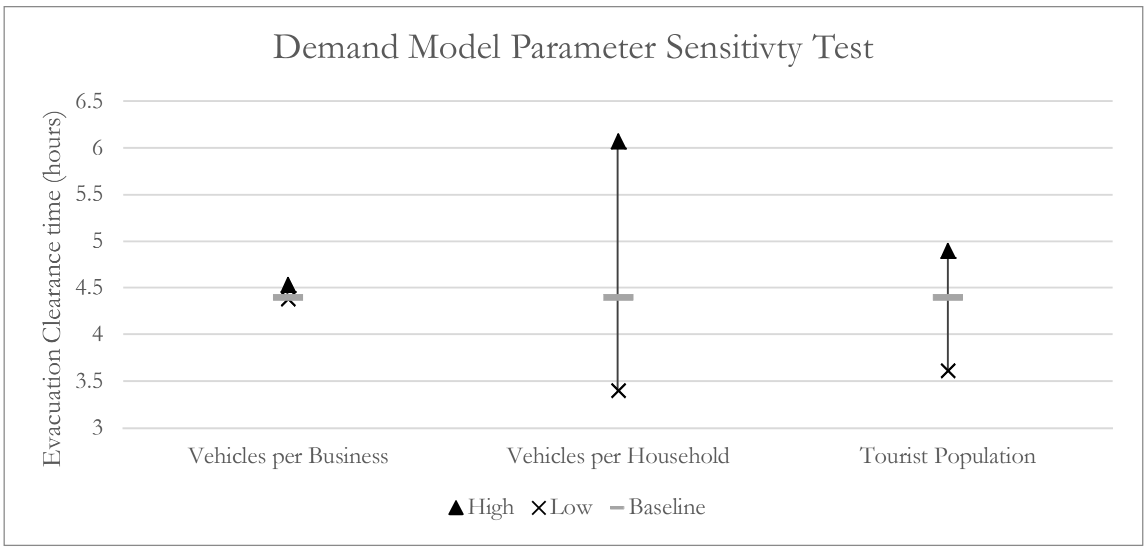

Figure 11**. Demand model sensitivity test results after traffic simulation**

Plotting clearance time of the various sensitivity tests generates similar results as when the total evacuating vehicle estimation is performed. This demonstrates the issue the study area may have with congestion and capacity to evacuate populations. Clearance time seems to have a direct correlation with the amount of evacuating vehicles estimated in travel demand. This correlation may differ between study areas, but demonstrates that MATSim simulation captures the increase in population and, to some extent, accurately simulates that added vehicles contributes to a larger overall clearance time.

Additional components that attempt to capture unaddressed concepts of evacuation of can be tested to provide an understanding of their impact on evacuation clearance time. When placed in context with the completed baseline model, which incorporates all components, some conclusions can be made about the merit of their inclusion. Some components are related to the demand estimation process, while others are used to alter the traffic simulation. Tests demonstrate that failing to include these components can result in an underestimation of overall clearance time. For all components, the amount of underestimation was minimal when compared to the overall clearance time. In total, components in baseline simulations account for 7.5% of the overall clearance time. However, when tested using worst-case evacuation demand scenarios (more evacuating vehicles), the underestimation increases. In a worst-case scenario, the additional components account for 11% of the overall clearance time. This is a logical increase, as many of the additional components attempt to capture increased congestion. The additional vehicles that are simulated in a worst-case scenario on top of additional components amplifies the presence of congestion.

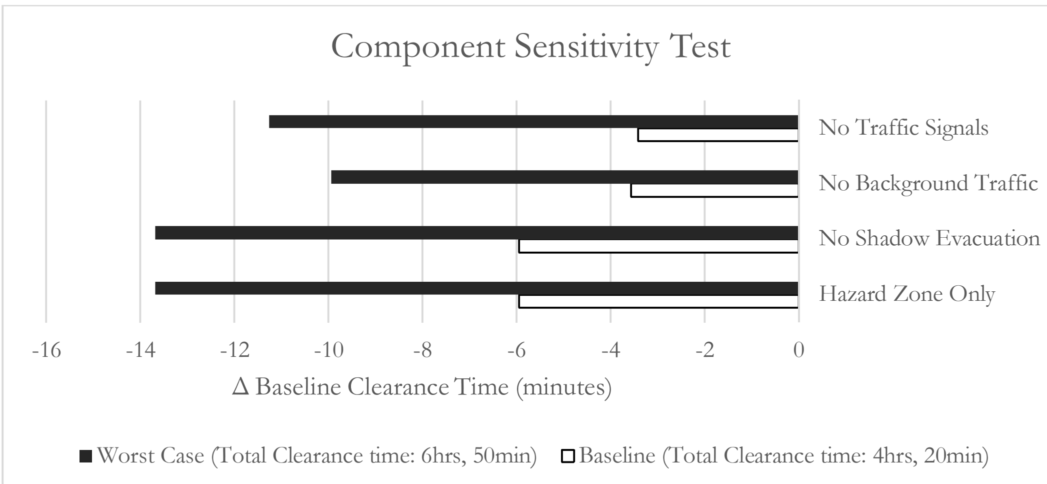

Figure 12. Additional model component tests after traffic simulation

Lastly, a sensitivity test of using a departure curve can be performed. For the study area, two separate simulations were performed under the same evacuation demand scenario. Under each simulation, a different distribution of evacuee departure times was applied to evacuees in the study area. The first test assumed instantaneous departure of evacuees. Making this assumption allows for a more general understanding of vulnerability, as it does not introduce another layer of randomization into the evacuation modeling. In this simulation, all evacuees begin at the same time, and only their location on the island can contribute to their location in the queue. To model a range of departure times, a distribution of starting times was assigned to the evacuating population. Results re-iterate findings from the literature that show evacuee departure distribution does little to impact the overall evacuation clearance time for sudden-onset evacuations with limited egress flow. Simulation of a departure curve contributed to a clearance time 5.3 minutes lower than the instantaneous departure simulation.

Table 6. Evacuee departure time curve sensitivity test results

Departure Timing	Overall Clearance Time	Δ Baseline (min)
Instantaneous Departure	4hrs, 20min	0
Normal Distribution	4hrs, 15min	-5

2.4 Discussion

Evacuation modeling is a complex task, which requires careful surveying of literature on human behavior, risk perception, analytical methods, and computing. The complexities in methodologies demonstrate the variety of applications of evacuation modeling, and the different fundamental fields of research that influence a given methodology. For natural hazard evacuations, little work has been performed attempting to synthesize various aspects of research to create an evacuation modeling framework that not only incorporates aspects of real-world evacuations, but also avoids limitations and assumptions that can undermine the accuracy of results. Early natural hazard evacuation modeling was approached as large-area, GIS-based vulnerability analyses (Chakraborty et al., 2005; Cova & Church, 1997). These analyses are generalized and not site-specific, and captured limitations in the transportation network and demographic characteristics of the area, but contribute little understanding to what a potential evacuation scenario may resemble. Prior natural hazards evacuation models tend to focus on residential evacuation (Chen et al., 2006; Chen & Zhan, 2006; Cova & Johnson, 2002, 2003), or evacuation from one site or compound (Jha et al., 2004). These models use agent-based traffic simulation packages that introduce assumptions of human behavior and micro-scale recreation of evacuation in attempts to improve the precision of results. However, by failing to incorporate broader concepts of evacuation that influence the evacuation demand and congestion, the accuracy of the results are limited.

The modeling framework proposed in this research attempts to capture the under-addressed concepts of evacuation to create a comprehensive evacuation model that can be employed in a variety of scenarios. In creation and testing of the framework, the merits of including concepts of shadow evacuation in demand modeling can be assessed. Additionally, improvements in traffic simulation's representation of reality can be identified by testing background traffic, simulation beyond the hazard zone, and simulation of traffic signals. Sensitivity of evacuation modeling to methods for estimating evacuation demand can also be identified. While some of the sensitivity tests only provide information in the context of the study area, the results demonstrate the validity in incorporating multiple concepts into the model, and reinforce the claim that a flexible and comprehensive model is necessary for understanding natural hazard evacuations.

2.4.1 Model Sensitivity

Demand model estimation is a critical component of evacuation modeling, as it generally is performed at the initial stages of modeling, and has an influence on results regardless of the method of determining clearance time. Many different equations and methods exist for identified evacuation demand, all which attempt some estimation of the evacuating populations in a given area under a certain hazard exposure scenario. What many demand estimation methods lack is the ability to capture unique characteristics of the study area. Some methods are tailored towards residential evacuation (Chen et al., 2006; Cova & Johnson, 2002), and do not present a method for capturing employee populations. Others focus on evacuating a very specific population (Jha et al., 2004). Others are performed in a large area and use averages and assumptions with the intention that demand modeling will be the only analysis of evacuation modeling (Lindell, 2008; Lindell & Prater, 2007). A more flexible demand model that can incorporate potential populations in a variety of study areas will provide a more accurate description of evacuating populations.

Adjusting parameters of the demand model gives insights to the characteristics of the study area, and specifically with residential demand, how determining the percentage of vehicles used has a large impact on overall results. Modeling residential demand based on overall vehicle ownership leads to a significantly longer evacuation clearance time than when modeling based on observed rates from the literature. When attempting to recreate a scenario representative of potential real-life evacuation, 75% vehicle usage rates may be more accurate, but potentially give an underestimation of clearance time. When modeling the high residential demand scenario of *all* registered vehicles, the total clearance time increases significantly. Inversely, a scenario of exactly one vehicle per household also significantly lowers the overall clearance time. These scenario-based results can be implemented for disaster management purposes, and will be discussed in the next chapter. For the study area, the assumptions of vehicles per business were made with little empirical data; instead, averages were adopted from residential statistics. The impact of adjusting this parameter was much less overall than residential demand, most likely due to study area characteristics. Tourist population was also identified based on anecdotal evidence and assumptions from imagery. The low sensitivity test of tourist demand tests the outcome of modeling if tourists are not included at all. For the study area, almost an hour of evacuation clearance time is attributed to tourist populations, demonstrating the significant impact of this subset of population. Medium and high estimates represent a proportion of street parking, and nearly all street parking respectively. These tests again provide more insights into the study area characteristics and the potential for worst-case scenarios in terms of tourist occupancy. For a more accurate model, tourist bureau information should be acquired to inform assumptions. Overall, the sensitivity testing of model parameters demonstrates the potential diversity of study area evacuation demand, and that some parameters may require additional focus depending on the study area.

Shadow evacuation & evacuation beyond the hazard zone are concepts that are not directly addressed in evacuation modeling. For the study area, these two concepts end up having similar impacts on overall clearance time. When modeling within the hazard zone only for the study area, evacuees are deemed safe upon crossing the bridge off Balboa Island. Modeling beyond the hazard zone, but not including shadow evacuation, creates the same effect. Because the bridge is the main constraint to the island, traffic that continues to the mainland, but with no constraints from shadow evacuation, will not meet congestion and slow evacuation from the island. The results from these two tests demonstrate the importance of both, and both in conjunction. Shadow evacuation cannot be modeled without modeling beyond the evacuation zone, and modeling beyond the evacuation zone may not alter results unless added population is contributing to traffic.

Background traffic and traffic signals help to improve the realism of the simulation. In theory, these two components are added factors of congestion and can almost be seen as constants in the study area. For the Balboa Island study area, their impact as a constraint to evacuation is minimal when compared to the bridge off the island. However, they create some congestion beyond the hazard zone, which based on clearance time results, can intermittently affect speed off the island. The model presented in this research proves the ability to incorporate these concepts and provides some justification for implementation in the study area, and in other areas these may be mandatory, depending if any other constraints exist in the road network.

Evacuee departure time is a commonly discussed topic for evacuation modeling (Murray-Tuite & Wolshon, 2013; Pel et al., 2012; Pel, Hoogendoorn, & Bliemer, 2010). Many different methods have been used to capture this phenomenon, and it is prevalent in evacuation modeling studies (Chen & Zhan, 2006; Cova & Johnson, 2002; Kalafatas & Peeta, 2009; Lewis, 2001; Lindell, 2008; Tweedie, Rowland, Walsh, Rhoten, & Hagle, 1986; Xie, Lin, & Waller, 2010). However, research demonstrates the minimal impact of departure time modeling in study areas similar to the Balboa Island study area (Tamminga et al., 2011). Results from sensitivity testing demonstrate that there is some reduction in clearance time from the highly congested island when evacuee departure is not instantaneous. Results demonstrate that it is worthwhile to include departure time, as it presents a more true-to-life recreation of evacuation. However, it makes spatial distributions of clearance time invalid due to the introduction of more randomization into the model, this time through assigning departure times based on a distribution. Overall, departure time should be introduced when modeling towards obtaining an accurate clearance time estimate, and only if significant data exists on evacuee behavior in the study area.

2.4.2 Model Limitations

The evacuation modeling framework has some limitations stemming from the difficult problem of recreating such a complex, deterministic scenario. In order to address the diverse population impacted by a natural hazard evacuation with limitations in data availability, general assumptions needed to be made about certain populations. Additionally, to simulate evacuation in a smaller area to identify constraints within a small island road network, disaggregation of spatial data through randomization was required. This leads to limitations in mapping evacuation clearance time at the scale of simulation. A more viable alternative would be to create 'evacuation-sheds', using similar methodologies of hydrologic analysis. By identifying common evacuation paths and choke points, overall clearance time for specific areas can be identified and mapped. Unfortunately, the entire study area is comprised of one single evacuation-shed. Therefore, the result with the most utility is a single measure of overall clearance time. The ability to repeat modeling for a variety of sensitivity tests improves the utility of these results, however.

2.5 Conclusion and Summary

A number of trends within contemporary evacuation modeling are problematic and can potentially lead to inaccurate estimations of clearance time. One cause of this inaccuracy is that models have discrepancies with real-world evacuation scenarios. This is partially due to the reliance on existing transportation modeling techniques that treat an evacuation model as a strictly transportation-related issue, to be solved by traditional transportation model. Although an evacuation model can be approached from a traditional four-step transportation model, it is a unique scenario with more complex concepts than generally seen in travel demand forecasting. Above-normal network use, irrational human behavior and potential infrastructure damage all contribute to the uniqueness of the scenario. Transportation models that use normal driving behavior can fail to address concepts of uncertainty or unfamiliarity with an extreme event and make assumptions about learned behavior (Lindell & Prater, 2007; Pel et al., 2012). A number of concepts such as background traffic and shadow evacuation also influence the network differently under an evacuation scenario. Major analytical components of evacuation modeling efforts rely solely on traffic simulation (Trainor et al., 2013), and much of the literature in evacuation modeling assumes that traffic simulation is now the obvious choice when creating an evacuation model (Abdelgawad & Abdulhai, 2009; Murray-Tuite & Wolshon, 2013; Pel et al., 2012). The reliance on traffic simulation software for evacuation modeling also brings up issues of validation and verification on top of inaccurate representations of evacuee behavior (Ormerod & Rosewell, 2009). This agent-based approach to traffic assignment modeling leads to shortcomings in accuracy and analytical power (Epstein, 2011; Galan et al., 2009), which can manifest themselves as inaccurate estimates of clearance time Alternative methodologies are worth exploring for a number of reasons, including ease of comprehension, case-by-case utility, as well as real-world accuracy. Another potential issue with evacuation modeling practice is the focus on solely modeling vehicular transport. While it may be the predominant mode for evacuation, ignoring transit-dependent populations can actually create an overestimation of clearance time. For example, some evacuees may not have access to a vehicle, or are non-ambulatory, thereby hindering their capacity to evacuate. Therefore, incorporating multiple modes of transport can provide a more accurate representation of reality. In addition, multiple modes may alleviate congestion on the road network, allowing for evacuation planning that is more comprehensive.

In general, adopting a universal transportation model for determining evacuation clearance time on a case-by-case basis will lead to inaccuracies. Characteristics of the specific hazard as well as the at-risk area should be addressed when creating an evacuation model, as its methodologies could change based on the spatio-temporal extent of the hazard as well as the physical, socio-economic, and infrastructural characteristics of the at-risk area. For example, methods of estimating clearance time may be viable in certain areas as opposed to others based on how many points of egress exist, proximity to the hazard, and social vulnerability of the population.

Chapter 3 – Applied Modeling for Disaster Management

3.1 Introduction

A major utility of evacuation modeling is its power in applied research. While some studies explore the theory and framework of modeling (Murray-Tuite & Wolshon, 2013; Trainor, Murray-Tuite, Edara, Fallah-Fini, & Triantis, 2013), the main body of work lies in applied modeling, either in case studies and vulnerability assessments (Chen et al., 2006; Church & Cova, 2000; Cova & Church, 1997; Cova & Johnson, 2002; Jha et al., 2004), or using modeling to explore management strategies (Campos, da Silva, & Netto, 2000; Chen & Zhan, 2006; Cova & Johnson, 2003). There is opportunity to inform disaster management practices through evacuation modeling, either by performing vulnerability assessments through evacuation capacity modeling, or by identifying the effect of mitigation strategies on reducing overall clearance time.

Predominantly, disaster management is focused on preparing and planning for worst-case scenarios (Pearce, 2003). However, a more comprehensive understanding of vulnerability from a scenario-based perspective may inform disaster management practices and identify the differential vulnerability of an area. In many cases, communities lack an understanding of evacuation capacity, forgoing evacuation modeling when performing traffic studies (Frazier, 2006). Community vulnerability to hazards and preparedness could be affected through applied evacuation modeling to inform decision-making. Applied evacuation modeling attempts to generate results aimed at presenting limitations in planning and potential solutions for disaster management. Initially, baseline understandings of the evacuation capacity of an area can serve as a starting point for modeling. This information can be built upon to explore more complex characteristics of potential evacuation, such as time-of-day scenarios. Additionally, evacuation modeling has the power to recreate future scenarios, or those under different management strategies or changes in population or infrastructure. These types of results can demonstrate planning practices to reduce overall clearance time and thereby reduce vulnerability.

Past research has used evacuation modeling to identify the potential of evacuation management strategies in a general sense. Cova and Johnson (2003) explored the effect of micromanaging traffic flow through lane-based routing. This form of management routes evacuees based on their destination using lane blockages through intersections in an attempt to reduce congestion. The modified evacuation model was employed in a gridded urban network, and lane-based routing served to reduce clearance times by up to 40%. The study demonstrated the merits of such traffic management, but employing such a complex strategy in a real-world application may be difficult. Another strategy, staged evacuation, was explored by (Chen & Zhan, 2006). Varying departure time stages were used in evacuation modeling to simulate staging of evacuees in an urban environment. Effectiveness of staging evacuation varied between strategies and types of networks, but the main conclusion was that staging does little to improve evacuation speed in areas with little congestion. However, in gridded networks, staging to reduce sudden surges in demand proved to reduce clearance time. Contraflow has been modeled frequently, both in macro- and micro-scale. These studies demonstrate the feasibility of contraflow modeling, as it can potential greatly improve capacity and traffic flow by creating additional lanes (Kalafatas & Peeta, 2009; Kim, Shekhar, & Min, 2008; Meng, Ling, & Cheu, 2008). However, usage of contraflow for planning purposes brings up other issues such as set-up time, and removal or reduction of ingress flow. Some studies have explored alternate or multi-modal evacuations (Bish, 2011; Hana Naghawi & Wolshon, 2010; H. Naghawi & Wolshon, 2012), which attempt to develop a modeling framework but are not directly applied in an attempt to improve evacuation clearance time.

The literature demonstrates the capability of evacuation models to inform disaster management. However, little applied modeling is performed by communities to improve the understanding of evacuation capacity and potential strategies. By using the evacuation modeling framework proposed in this research, a number of evacuation management strategies can be identified for a specific study area, with the express intent of informing disaster management practices to improve clearance time. First, the model can be used to obtain a comprehensive understanding of evacuation capacity, under a variety of different potential evacuation scenarios, including different time-of-day evacuations. Strategies of contraflow, pedestrian evacuation, and traffic routing can be tested for a study area that faces potential constraints to evacuation.

Alternate modes of evacuation, such as pedestrian, and in the case of the study area, boat evacuation, may serve to reduce overall and individual clearance time. Other modes, such as shuttle-based evacuation may be a necessity to address marginalized populations. Incorporating these modes of evacuation can improve the representative power of the model, and present potential strategies for disaster management.

The merit of hazard scenario-based planning can be explored by modeling under two different natural hazard scenarios, with differing extents of exposure. An interest in this sort of planning exists (Ross, 2013), but little understanding has been developed on the affordances and constrains of evacuating to specific scenarios, in lieu of using assumptions based on a worst-case scenario.

3.2 Methods

The evacuation modeling framework described in chapter two of this research was employed to recreate three different forms of evacuation scenarios in an attempt to inform planning and management: (1) holistic understanding of evacuation capacity; (2) potential management and mitigation strategies to reduce clearance time; and (3) planning for specific scenarios to prevent over-evacuation.

3.2.1 Study Area

Balboa Island was again be used as a study area to explore evacuation modeling from a planning perspective. The study area was initially selected as it is a community that is potentially vulnerable to tsunamis, mainly because of its low capacity to evacuate (Wood et al., 2013). Additionally, no past evacuation modeling was been performed for Balboa Island, presenting an opportunity to provide a comprehensive analysis of evacuation capacity. The study area's narrow transportation network and small size offers opportunity to explore alternate strategies for evacuation such as contraflow and pedestrian evacuation. Lastly, the study area lies completely within two separate tsunami scenario inundation zones, allowing for exploration of scenario-based evacuation management for the larger area surrounding Balboa Island.

3.2.2 Scenario-based Disaster Management

Using the flexible travel demand estimation, multiple evacuation scenarios were modeled to obtain a more comprehensive understanding of evacuation demand of the study area. Three different scenarios can be obtained that may help to better understand the vulnerability of the area to a tsunami threat. First, demand estimation techniques were used that attempt to recreate a *weekday* hazard evacuation scenario beginning in the late afternoon, where businesses are still open and a relatively large (60%) proportion of residents are at home. An *overnight* scenario was modeled, where 100% of residential population is accounted for, yet no employee or tourist population is present. Lastly, a *summer weekend* scenario was modeled, which attempts to capture a time when the highest potential population is present on Balboa Island. This includes maximum residential, business and tourist population. In real-world terms, this scenario could represent a weekend daytime evacuation during the summer. For the study area, this hypothetical scenario captures the highest amount of residential, employee, and tourist populations. See Table 6 for demand model parameters by scenario.

Table 7. Evacuation scenario demand model parameter values

Scenario	Average Vehicles per Household (EVHH)	Average Vehicles per Business (EVB)	Tourist Parking Occupancy
Weekday	1	1.2	100% - arterial roads 30% - other roads
Overnight	1.6	0	None
Summer Weekend	1.6	1.6	100% - arterial roads 50% - other roads

Clearance time was determined via MATSim traffic simulation. For the scenario modeling, the most accurate simulation is desired. Therefore, all additional components of the model were incorporated, including evacuation beyond the hazard zone, shadow evacuation, background traffic, and traffic signals. Shadow evacuation extent was determined by the maximum tsunami inundation zone exposure, and is manifested in areas of development on the mainland. The transportation network used for simulation was representative of present-day, normal conditions.

Additionally, the merits of planning for specific physical hazard scenarios can be identified by modeling evacuation demand based on two different exposure extents: a potential scenario loosely based upon historic events, and a maximum scenario used by local government for planning purposes. The hypothetical management strategy of limiting evacuees to only those within exposed areas can be tested by comparing results with and without the added population that lies within the maximum tsunami inundation zone.

The overall evacuation model was performed for both scenarios, each with differing spatial hazard exposure extents. This influences the demand model in that evacuating population and their destinations change with the hazard exposure zone. In the study area, a significant population on the mainland lies within the maximum tsunami inundation zone, but not the scenario zone. Subsequently, the traffic simulation will also differ due to changes in congestion and potential routes to safety. Performing the evacuation modeling provides outputs of overall clearance time for each scenario. These outputs were compared and placed into context with the temporal characteristics of the hazard. If the extra evacuating population serves to impede evacuation speed enough that clearance time is greater than tsunami arrival time, planning based on worst-case scenarios may prove to increase the vulnerability of some populations to smaller hazards.

3.2.3 Mitigation to Reduce Clearance Time

Potential strategies to reduce clearance time present themselves from analyzing the results of evacuation capacity. A useful tool in identifying constraints in the network is to visualize evacuation simulation in a geospatial environment. MATSim contains a sub-package for visualization, OTFVIS, which can replay evacuation modeling events. By visualizing the results, constraining factors can be identified in the network. Problematic segments of the network in terms of capacity can potentially be addressed through contraflow.

To model contraflow, the road network input was adjusted to reflect the additional lane of egress, and lack of an ingress lane. This was performed for MATSim networks using an open street map editor, such as jOSM. Lanes that are intended to be converted to contraflow must have the attribute 'oneway' added, with the value 'yes'. This converts the road segment into a one-way link. It is important to identify the topology of the road segment in question, as the one-way attribute reflects the directionality of the road segment. This must be reversed if the direction of one-way is representing ingress instead of egress. Additional lanes must also be added to the segment by adding a 'lanes' attribute with the respective number of lanes as the value. Contraflow was modeled in the study area by reversing the direction of the lanes in Park Avenue that travel away from the bridge, while Balboa Avenue and Marine Avenue were converted into one-way streets in the direction off the island, with an extra lane added for each to represent the additional contraflow lane. Additionally, contraflow was modeled for only the bridge on Marine Avenue, as it is demonstrated to be the major constraint to evacuation for the study area. Lastly, a contraflow scenario where the entirety of Marine Avenue is reversed was modeled.

Pedestrian evacuation, as a management strategy, can be implemented in MATSim. The GRIPS evacuation package only models vehicular or pedestrian modes in isolation, and cannot easily represent a mixed-modal scenario with interaction between two modes. Pedestrian evacuation is modeled along existing road networks, with different agent travel speeds and network capacity reflective of pedestrian travel. Pedestrian evacuation does respect the network, however, and does not allow travel across the entire landscape, through either homes or yards or swimming. When modeling a pedestrian evacuation, the demand model estimation is adjusted to capture individual population counts instead of using averages and assumptions, which drive the vehicular demand estimation.

Alternate modes of transit can also be addressed by the evacuation modeling framework. The impact of shuttle-based evacuation can be modeled by MATSim, and requires information on shuttle size and routes. MATSim has the capability to model agent interaction with shuttles, however the decision making process uses a set of behavioral rules that do not accurately represent evacuees who may require shuttle-based evacuation. Evacuees will board shuttles if they improve travel time over walking. However, in some circumstances such as the study area, evacuees that will necessitate shuttle-based evacuation most likely will not be ambulatory. However, there is still merit in modeling shuttles and shuttle-dependent populations. The shuttle's impact on the overall transportation network and congestion was identified for the study area, and shuttle-riding populations were addressed by removing them from the vehicular demand estimation.

In a similar manner, non-traditional modes of evacuation can be analyzed. For the study area, boat evacuation is a potential solution to reducing clearance time by lowering congestion. To identify boat evacuation, first the number of boat docks and available boats in the study area were identified from site visits and imagery. Then, households within a proximity to boat docks were determined. In a similar process to the overall demand estimation, boat-evacuating-households were randomly assigned iteratively for each boat within the study area. These households were then removed from vehicular demand estimation. This was performed under weekday demand conditions for the study area, and can be compared to the weekday results without boat evacuation to identify the reduction in overall clearance time.

3.3 Results

3.3.1 Scenario-based Disaster Management

Modeling of various scenarios based on the time of day can provide insights into the vulnerability of at-risk populations. The complex nature of the study area presents few scenarios without constraints to evacuation. Both weekday and overnight conditions have similar amounts of evacuating vehicles, and similar evacuation times. The summer weekend scenario has a considerably larger evacuating population, and thereby higher overall clearance time. The summer weekend scenario can be useful for planning purposes as it represents the maximum evacuation clearance time for planning goals. When these results are placed in the context of the physical hazard, more insights can be made (Figure 14). The expected arrival time for the modeled tsunami hazard exposure scenario is between 5.5 and 6 hours after the tsunami-generating earthquake occurs (Ross, 2013). On top of this, tsunami warning announcement may not occur immediately after the tsunami-generating event occurs. For the study area, worst-case scenarios of travel demand result in overall clearance time higher than the time allotted to evacuate before tsunami arrival. Additionally, overnight scenario clearance time is lower than tsunami arrival time, yet this does not factor evacuee response time. For overnight evacuation, a lag time might be expected between tsunami warning and evacuee departure time, in addition to the potential delay in tsunami warning announcement after the actual tsunami-generating event occurs. The results from the evacuation capacity modeling, in context with actual hazard exposure information, present a potential need for planning to reduce clearance time in the face of a hazard threat. The tsunami arrival time used for context assumes evacuation begins immediately after the tsunami-generating event occurs. In real-life situations, evacuations may not start until well after the tsunami is generated. Some lag time is expected for tsunami evacuation alerts to be given, and evacuations may not begin until one to one and a half hours have passed from the tsunami generating event.

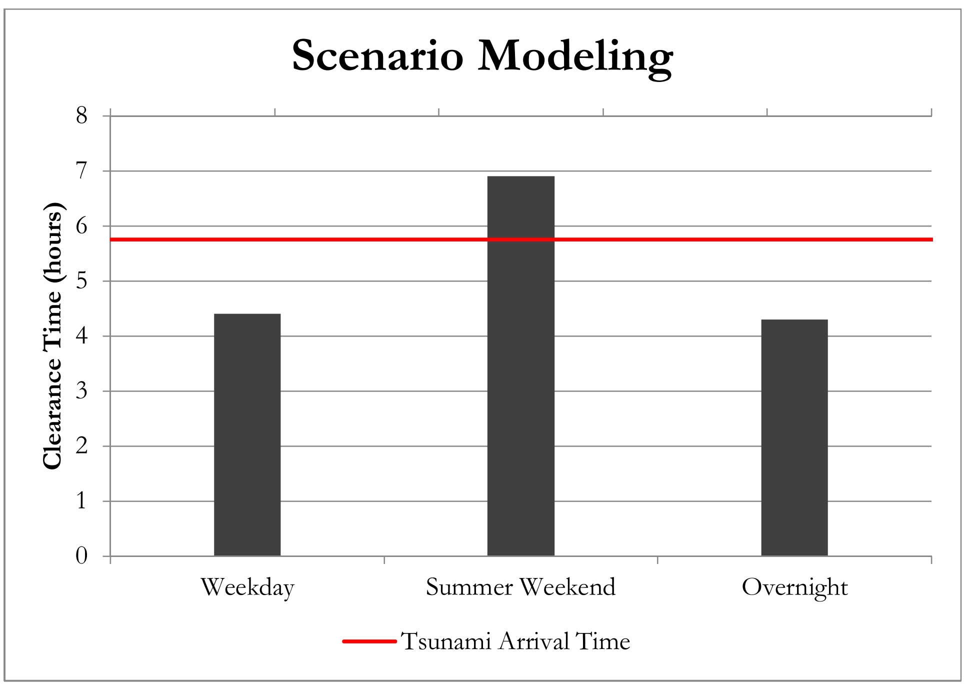

Figure 13. Clearance time estimation for evacuation scenarios

Prior results attempt to recreate a realistic evacuation scenario, and thereby incorporate shadow evacuation originating from the mainland that lie within maximum tsunami inundation zones. These populations may not be within a potential tsunami inundation zone loosely based upon a historic scenario (henceforth referred to as the 'scenario zone', and thus not technically required to evacuate. From behavioral studies, however, these populations do tend to evacuate (Murray-Tuite & Wolshon, 2013). A potential management strategy may restrict evacuation to those only within projected exposure zones. By limiting shadow evacuation and modeling only evacuees within the potential hazard zone, the merits of planning based on scenarios instead of to the maximum zone may become apparent.

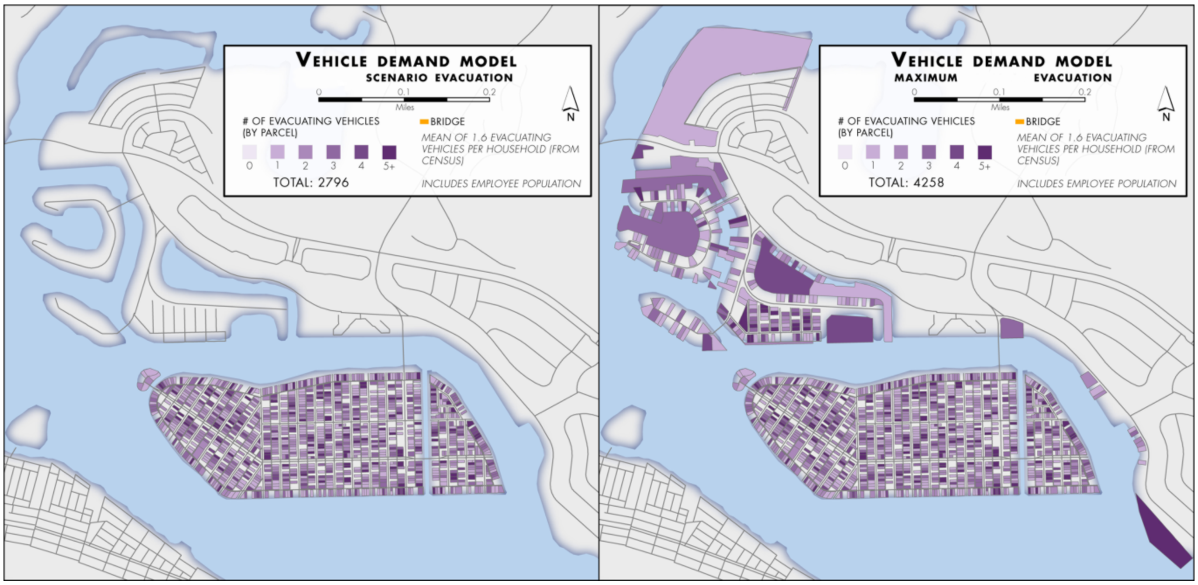

Figure 14. Demand modeling outputs for scenario zone and maximum tsunami exposure

Demand estimation demonstrates the difference in evacuating populations between the two hazard exposure zones (Figure 15). Balboa Island still contains a majority of the evacuating population due to the dense development and business population. Potential areas of extra congestion for evacuees from Balboa Island can be identified, as many of the major egress points from the maximum tsunami inundation zone are shared by the additional population not present in the scenario zone. Traffic simulation results demonstrate the relative impact of additional populations on overall clearance time. Under a maximum evacuation scenario, the clearance time for the study area, assuming proper traffic management, is under four and a half hours (4.4 hours). By contrast, clearance time for only populations exposed to the scenario tsunami is five minutes less. In all iterations of the traffic simulation, the final evacuee to reach safety originated from within the scenario zone, on Balboa Island. These results reflect the earlier test of using evacuation from only the hazard zone, when compared to the comprehensive model. These results also assume the evacuation order is issued immediately after the tsunami-generating earthquake occurs. In reality, many evacuation scenarios are not initiated until the conditions of the tsunami threat are more elucidated, reducing the time for full evacuation before tsunami arrival.

3.3.2 Mitigation to Reduce Clearance Time

Results from modeling potential management strategies demonstrate the potential for improvement in evacuation from the study area. Contraflow reduces the clearance time roughly by half, as it serves to increase capacity twofold. Pedestrian evacuation is considerably faster than vehicular evacuation, as it does not suffer from congestion issues and the total travel distance to safety is relatively short in walking terms (< 1 mile for most of the study area). When results are placed in context with tsunami arrival time, specifically summer weekend conditions, the benefits of mitigation are apparent (Figure 16). Pedestrian or contraflow strategies could allow complete evacuation before tsunami arrival. There are affordances and constraints that arise from each strategy, however.

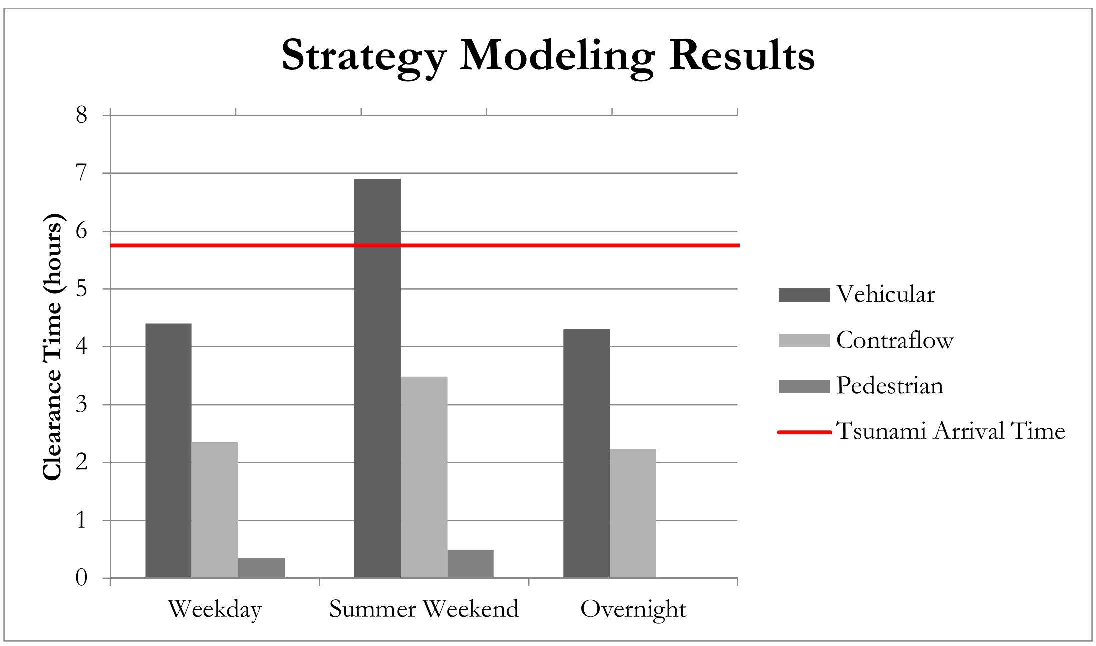

Figure 15. Evacuation management strategy modeling results

The resulting test of traffic signals can be used to identify the proper calibration for signal timing in the event of an evacuation. Results demonstrate the 'tipping point' of 1:5 ratio of green to red time for the major intersection with CA SR1. Under this scenario, congestion increases at this intersection to the point where it becomes more of impedance on traffic flow than the bridge on Balboa Island. More conservative ratios allow more flow off of the island, and serve to increase the clearance time slightly over the 1:1 baseline ratio, due to intermittent backups associated with background traffic and timing of arrival at intersections.

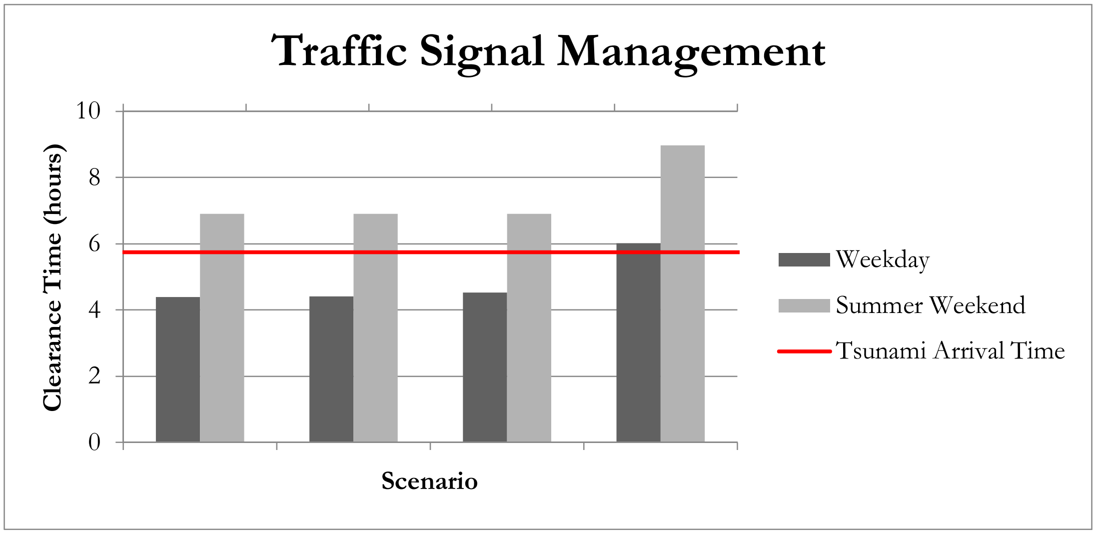

Figure 16. Traffic signal management modeling results

Multiple strategies for performing contraflow on the island exist. However, there are some limitations to implementation. Only three two-way roads exist on the island, and reversing one-way roads will limit evacuee egress from their homes. Results demonstrate that entire island contraflow is effective at reducing clearance time, but does not have any more influence than only reversing ingress lanes on Marine Ave, the major entry point into the island. Additionally, a strategy of contraflow on the entire island except for the bridge, allowing room for traffic to enter the island, does not reduce clearance time. This is because the bridge is still a constraining factor in the evacuation. In addition, modeling contraflow on only the bridge results in no reduction of clearance time, as Marine Avenue becomes the main constraint.

Pedestrian modeling results demonstrate that congestion issues that occur during vehicular evacuation are only minimally present during pedestrian evacuation. Summer weekend clearance times are slightly higher than weekday, roughly 10 minutes, indicating that the additional population demand contributes somewhat to congestion, but not significant enough to endanger populations. Mapped results of pedestrian evacuation times demonstrate how modeling seems to resemble a simple path-distance analysis (Figure 19). Evacuation time surfaces seem to follow a trend outward from the egress point of the island. While populations on either end of the island, especially the west end, are the most vulnerable in a pedestrian evacuation, when placed in context with the tsunami arrival time, their vulnerability is minimal so long as they are able to travel the required distance on foot.

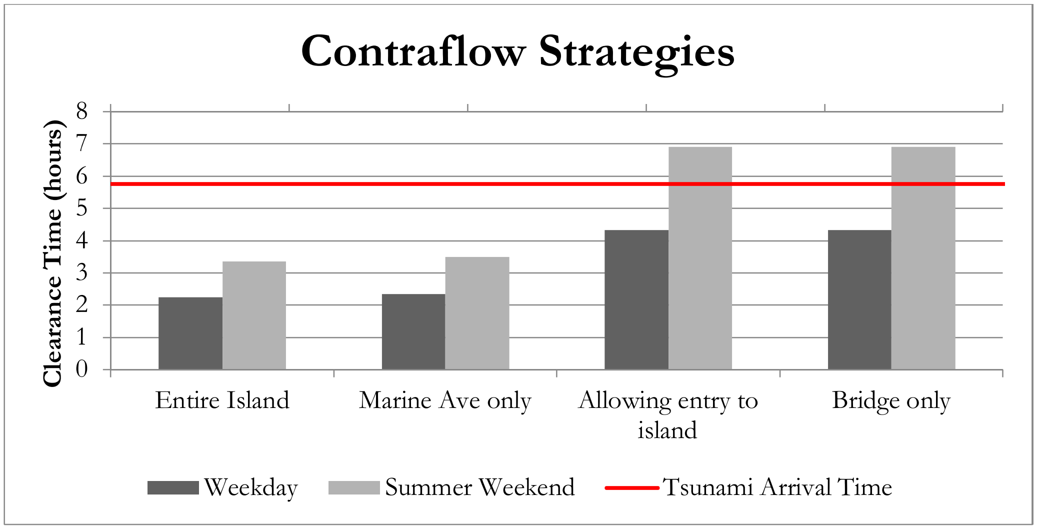

Figure 17. Comparison of differing contraflow planning impacts on clearance time

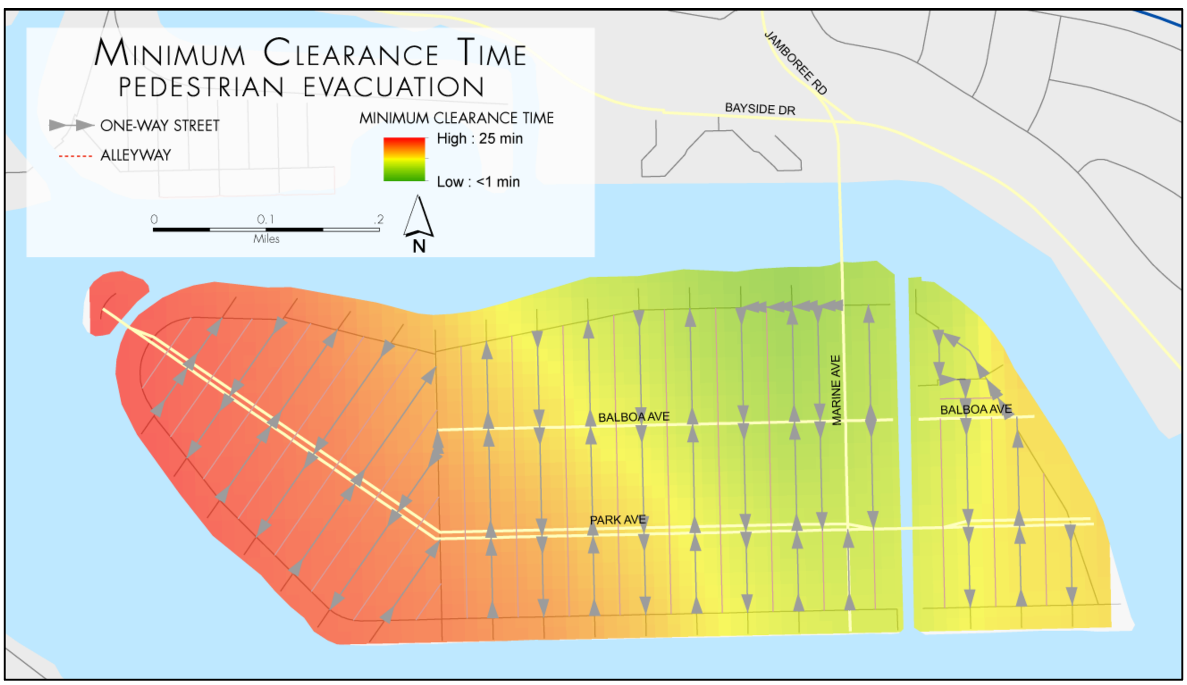

Figure 18. Local kernal estimation of mean evacuation times for pedestrian evacuation.

The impact of alternative modes of evacuation on overall clearance time can be determined by altering the demand model output, and simulating shuttles in the overall vehicular evacuation. Modeling boat evacuation resulted in less vehicular demand originating from the island, specifically 206 less vehicles. The impact on overall clearance time was a 14 minute reduction. Modeling evacuation shuttles to address transit-dependent populations in lieu of assuming these populations will evacuate in neighbor's vehicles also has a slight impact on overall clearance time. The requisite number of shuttles to address the estimated transit dependent population adds roughly 5 minutes to the overall clearance time. This is a relatively small number considering the estimated number of transit-dependent population was over 100 people. In the simulation, these shuttles are generally the last vehicles to leave the island, as the need to stop and pick up evacuees places them at the end of the queue to exit the island.

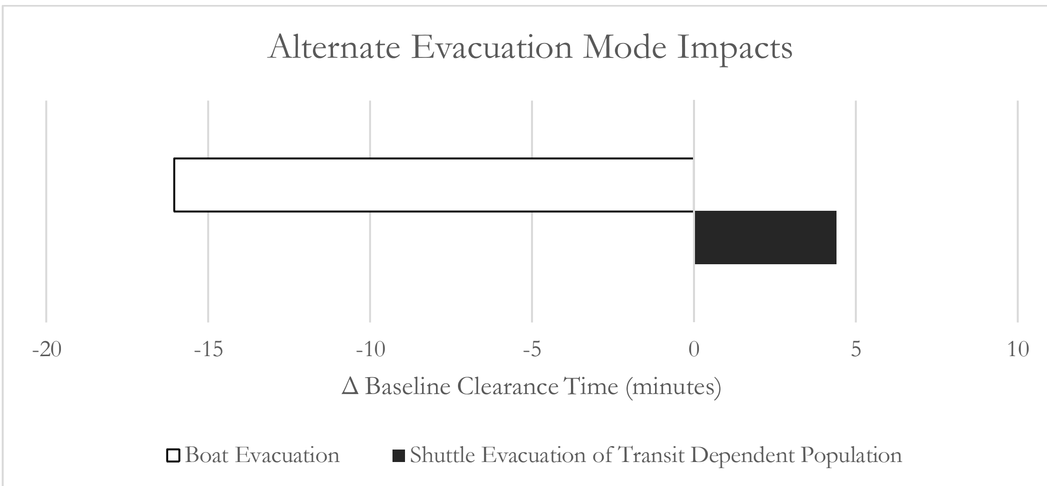

Figure 19. Impacts on overall clearance time from modeling alternate modes of transport.

3.4 Discussion

Evacuation modeling can be a powerful initial step in hazard mitigation planning. Modeling can contribute to an understanding of a community's vulnerability to a hazard by providing additional information in addition to traditional exposure assessments. Identifying the time required for exposed populations to evacuate, and strategies to reduce evacuation clearance time are useful pieces information for assessing the vulnerability of a community. A comprehensive understanding of evacuation capacity can inform disaster management and help reduce loss of life from potential hazards. The results from this work demonstrate a situation where performing scenario-based modeling and planning can lead to more informed and efficient disaster management. By understanding community vulnerability from a holistic perspective, management can be equipped with more tools to guide operations during extreme events.

It should be noted that this approach has shortcomings in addition to its benefits. The major constraint to scenario-based planning is the unpredictability of individuals. Multiple aspects of risk perception and awareness can influence individual behavior, including misinformation, lack of trust in local management, or fear and irrational behavior. In most cases, disaster management is performed based on worst-case scenarios in an attempt to capture, or at least remove assumptions on individual behavior. In the end, understanding community vulnerability and evacuation capacity under a variety of scenarios can serve to benefit planning practice. Management in order to create conditions tailored to precise scenarios is unlikely, yet comprehensive modeling provides an understanding of potential affordances and constraints of current evacuation plans. In the case study, results demonstrate potential over-evacuation if worst-case planning is used universally. Additionally, results provide suggestions for future management and ways to reduce vulnerability to, in this case, smaller hazards. Overall, scenario-based evacuation modeling can be a useful component in community vulnerability assessments, to represent a comprehensive description of vulnerability. The utility of this modeling framework is not necessarily for direct implementation into disaster management, but instead as a thorough description of vulnerability to inform disaster management and future planning. The more comprehensive understanding of community evacuation vulnerability in the context of multiple scenarios can guide future planning and the potential implementation of various mitigation strategies such as traffic control, vertical evacuation, and other network improvements such as additional lanes or widened bridges.

Testing of mitigation strategies creates even more information towards the evacuation capacity of the study area. Insights into planning can be gathered from testing of strategies that can reduce clearance time for the study area. Results specific to the study demonstrate that complete evacuation is possible under the worst-case scenario before tsunami waves arrive (~6 hours), provided proper traffic control and management is carried out (adequate traffic signal timing and re-routing). More intense mitigation strategies such as bridge widening or contraflow improve clearance time significantly. However, the results from testing contraflow must be interpreted with the limitations of such a strategy in mind. Contraflow would shut down any possible access to the island by emergency response, or residents returning to their homes before evacuating. This can potentially be avoided by performing some type of staged contraflow, where initially service onto the island is allowed, but after a certain time, contraflow is enacted and major flow off the island is potentially doubled. This type of strategy is more complex in terms of modeling, but the results from basic contraflow modeling demonstrate the potential validity of such a strategy. The most telling result is that pedestrian-only evacuation would require only thirty minutes for completion. This is due to a lack of congestion issues and the relatively short distance required to travel outside of the tsunami inundation zone (<1 mile average). However, attempting to force residents to evacuate on foot may also be a difficult or at least not-well-received strategy.

Boat evacuation, overall, does not have a significant impact on clearance time. However, it may reduce the vulnerability of some populations on the far western side of the island, where evacuation times are generally higher due to the location of evacuees in the queue that originate from these locations. Much like evacuee response time, boat evacuation influences individual evacuee clearance time. It may be considered a viable strategy do improve some resident's capacity to evacuate, but could require a considerable amount of management to prevent the boat evacuees from traveling to unsafe locations. The modeling of shuttles demonstrates the small impact that a shuttle can have on overall clearance time when compared to the amount of evacuees it can service. It can also help address assumptions that transit-dependent populations will receive assistance from nearby residents, which may not always be a valid assumption in evacuation scenarios. The major issue with shuttle-based evacuation, from a management standpoint, is that for the study area, shuttles cannot complete numerous iterations of service. Entering the island after the evacuation orders occur places shuttles at the back of the queue, thus giving these residents the highest individual clearance times and not allowing the shuttle to unload residents and return back to pick up more evacuees. Additionally, in a contraflow scenario, shuttle evacuation would not be possible, as no lanes for ingress would be available. The case study lacks a shuttle yard or space to stage shuttle evacuation, so off-island shuttle access would be required. Overall, alternate modes of evacuation can be potentially beneficial to individual evacuees, but when modeled next to a vehicular evacuation, they have little impact on overall clearance time.

3.5 Conclusion

Overall, the insights gained from evacuation modeling with the goal of applied results are numerous. Although results are very study-area specific and do not necessarily lead to any broad conclusions about evacuation management on a whole, this was not the goal of the chapter. The goal is to demonstrate the evacuation model's utility in an applied setting of a study area that had little to no knowledge of evacuation capacity beforehand. By beginning with a comprehensive evacuation modeling framework that attempts to address real-world phenomena of human behavior, confidence in the results increases. Disaster management and planning in the study area can benefit from the results given, as they provide a variety of answers to questions and solutions to problems, in a holistic context. The main limitations of the modeling process lie with the methodology and framework. Applied results are only limited by their scope of vision and the confidence in accuracy. However, because of the strong framework and thorough investigation of the study area, results can be presented with confidence and the hope that that they may inform disaster management planning for the study area, as well as future vulnerability analysis for communities with potential evacuation issues.

4. Thesis Summary and Conclusions

4.1 Summary

The goal of this thesis was to create a framework for performing accurate and comprehensive evacuation modeling to determine evacuation clearance time from extreme events. Specifically, this work aimed at incorporating under-addressed real-world phenomena that are known to have an impact on clearance time. Additionally, it attempted to identify overall clearance time using traffic simulation methods not frequently seen in prior research. While the modeling framework is tailored towards areas with potential congestion issues in the face of evacuation, the methods for identifying evacuating populations and traffic simulation can be applied to a vast number of hazard scenarios.

The thesis answers four distinct research questions to achieve the above goal:

1. Is queuing analysis a viable alternative to traffic simulation in determining evacuation clearance time?

By performing a holistic review of evacuation modeling methodologies and identifying potential simulation frameworks, queuing analysis was identified as a strong methodology for determining traffic flow. By using a traffic simulation framework built upon a FIFO queuing process, overall clearance time could be obtained for a number of deterministic scenarios, still relying on fundamentals of queuing analysis. By obtaining clearance time in this manner, issues associated with evacuee behavior-centric models were avoided, in addition to issues inherent with agent-based programming of human behavior.

2. How does accounting for non-residential evacuees in addition to residential evacuees affect overall clearance time estimation?

By incorporating shadow evacuation, background evacuation, business and transient populations in sensitivity testing, the impact of these populations, not normally incorporated into evacuation modeling, was identified. Overall, neglecting to incorporate these populations leads to an underestimation of overall evacuation clearance time. The modeling framework additionally demonstrates the ease in addressing these populations given the existence of certain datasets. The ability to incorporate business, transient, shadow and background populations shows the value of this modeling framework as a viable method for accurately estimating evacuating populations to determine clearance time.

3. How do potential evacuation strategies contribute to, or inhibit overall clearance time?

Taking advantage of the flexible nature of the framework provides the opportunity to employ the evacuation model in a case study area to identify contextual analysis of evacuation strategies. By altering the transportation network and evacuation demand, results for different scenarios can be obtained that represent the impact of strategies of contraflow, scenario-based evacuation zone enforcement, and alternate-modal evacuation. For the study area, contraflow reduced overall evacuation clearance time by roughly 50%. Limiting evacuation to scenario-based hazard zones demonstrated a slight improvement in overall clearance time compared to evacuating based on maximum inundation zones, which tends to be the default in evacuation management. Lastly, modeling pedestrian-only evacuation shows the potential congestion issues associated with vehicular evacuation that can lead to inflated individual travel times, in the context of the relatively short distance to safety. Pedestrian evacuation of densely developed areas can potentially alleviate congestion issues and in certain situations, such as tsunami evacuation, provide a much lower evacuation clearance time than vehicular evacuation.

4. Where do vulnerable populations exist within a spatial distribution of overall clearance time?

Because of the traffic simulation techniques used, a spatial distribution of vulnerable populations to vehicular evacuation is not achievable with any consistency or accuracy. However, results of pedestrian evacuation times can be mapped with some consistency and show that distance from safety tends to influence clearance time in a continuous surface (Figure 19).

4.2 Significance

Understanding evacuation capacity can provide an understanding of a community's vulnerability to hazards requiring evacuation. However, many communities lack an understanding of how transportation networks and development will influence residents and non-resident's ability to evacuate an area. Additionally, future development planning traditionally performs transportation modeling under normal, everyday conditions, and therefore the transportation network and development reflects these results. However, it is critical to understand this development's capacity during an evacuation, in order to reduce the area's vulnerability and potentially prevent loss of life in the event of a hazard evacuation. Performing accurate evacuation modeling is also critical, as past methodologies have been demonstrated in this work to misrepresent evacuation clearance time, as they fail to capture real-world concepts such as shadow evacuation, background population, and non-residential evacuees. The work in this thesis presents the limitations of prior evacuation modeling and provides solutions to fill gaps in modeling methodology to create a comprehensive evacuation modeling framework. The resulting methodology can be applied to future works and case studies to provide a better understanding of community evacuation capacity, vulnerability, and potential strategies to reduce loss of life from a failure to evacuate.

4.4 Future Research

The work presented in this thesis provides opportunities for further research and investigations into the complexities of evacuation modeling. The author plans to present the evacuation modeling framework in a condensed journal article, including sensitivity testing and case study results to demonstrate the validity of the framework. Additionally, the merits of pre-development evacuation modeling can be identified by applying the framework to another study area that faces potential congestion issues during wildfire evacuation. The comprehensive plan for this study area also increases the development, and potential evacuating population, while not improving the egress options and transportation network capacity. The overall clearance time under current conditions and planned conditions can be identified and compared to demonstrate the need for improved evacuation capacity when creating new development. This can potentially be identified *during* the planning process by performing evacuation modeling, preventing development that increases a community's vulnerability to a hazard by increasing the time require to evacuate.

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