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Temporal-Spatial Analysis of Emergency Evacuation Traffic

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by

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A Thesis Submitted to the College of Engineering Department of Civil Engineering
in Partial Fulfillment of the Requirements for the Degree of
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TEMPORAL-SPATIAL ANALYSIS OF EMERGENCY EVACUATION TRAFFIC

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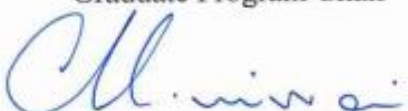_____
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Abstract

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Mass evacuations, particularly those at a statewide level, represent the largest single-event traffic movements that exist. These complex events can last several days, cover thousands of miles of roadway, and include hundreds of thousands of people and vehicles. Often, they are also marked by enormous delay and congestion and are nearly always criticized for their inefficiency and lack of management. However, there are no standardized methods by which to systematically quantify traffic characteristics at the proper scale. This paper describes research to develop and apply an analytical method to measure and describe statewide mass-evacuations in a practical, cost-effective manner. The research methods are based on simple, yet widely available, and easily understood traffic count datasets that support both qualitative and quantitative analyses. By spatially and temporally arranging sensor-based statewide traffic volume data from Hurricane Irma (2017), Michael (2018), Tubbs Fire (2017), and Thomas Fire (2018) evacuations, these methods were able to describe and address several key questions about these events. The methods described herein estimate the start and end of the auto-based evacuation, the loading and peaking characteristics of traffic, and the total number of vehicles used in the evacuation process, as well as the effective start and end of the auto-based reentry. Among the key findings of this work were that the Hurricane Irma and Michael evacuations began several days before landfall, peaking two to three days prior to the storm, suggesting a

heightened perception of risk; and that the Thomas and Tubbs fire evacuations traffic were impacted by subsequent fires nearby. It is expected that state departments of transportation and emergency management officials would be able to reproduce the procedure presented here to analyze future evacuations.

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Chapter I

Introduction

Mass evacuations, particularly those at a statewide level, represent single-event traffic movements that can occur. These complex transportation events can last several days, span thousands of miles of roadway, and include hundreds of thousands of people and vehicles traveling with vital urgency. Often, they are also plagued by enormous travel delay and congestion and are nearly always criticized for their inefficiency and lack of management. However, there are few studies quantitatively examine such events to objectively asses what travel conditions were actually like. Typically, opinions are based on media reports that tend to sensationalize poor operations and focus strictly on areas that are performing poorly.

Unfortunately, there are many reasons why mass evacuations tend to be comprehensively studied. Obviously, they are large and complex, but another is that there are no standardized methods by which to systematically quantify traffic characteristics at the proper scale. There are few indicators, apart from a lack of fatalities and the amount of vehicles moved, to determine if any evacuation was "effective" or not. Instead, outside of media reports, emergency managers and transportation professionals often work under general assumptions that an evacuation was effective if people were able to get out of danger and no one drowned in their homes.

Purpose Statement

To provide a basis of measurement and comparison, the study describes research undertaken to examine and assess evacuation characteristics. More importantly, the study illustrates methods to measure and quantify evacuations in an unbiased, practical, and repeatable fashion that is both intuitive and beneficial to state officials. The research methods are based on simple, yet widely available, and easily understood traffic count datasets. Traffic volume counts

serve as a fundamental parameter of traffic measurement, but they can yield enormous insights into the ebb and flow of daily commutes and when, where, how much, and how fast people are able to move during an evacuation. These wide area, long term vehicle count can also be used to illustrate the movement of evacuees after the hurricane to better understand how many vehicles were impacted, when the recovery began, and even how long it took based on when the traffic patterns returned to normal.

Objectives

Based on these ideas, the objectives of the research are to spatially and temporally quantify key aspects of the evacuation and reentry process in Florida and California during the record-setting 2017 and 2018 hurricane and wildfire seasons, specifically:

(i) When did the auto-based evacuation make a measurable impact on traffic (when did it noticeably start)?

(ii) What were the loading characteristics of the evacuating traffic on the network?

(iii) What was the peak evacuation volume and when did it occur?

(iv) When did the auto-based evacuation conclude?

(v) How many vehicles were used in the evacuation?

(vi) When did the reentry begin?

(vii) When did reentry effectively conclude?

These objectives are achieved through the observation and analysis of roadway volumes collected from ground-based sensors (predominately, magnetic-loop detectors) during

hurricanes and wildfires of 2017-2018 evacuations and reentries in the State of Florida and California. These two events provide a unique opportunity to study the evacuation phenomenon because they are among the largest in the history of the united States; they affected nearly all of the major metropolitan population centers of the state; and traffic volumes are recorded on geographic scale and at levels of fidelity rarely achieved in prior evacuation studies.

Research Contribution

The scientific contribution of this work is that it demonstrates a straightforward and reproducible methodology to measure the auto-based evacuation response and reentry of an area. The proposed methods demonstrated in this paper have a significant practical value for state transportation and/or emergency management agencies seeking to quickly and accurately assess evacuation characteristics. This research also expands the literature by providing insights into the less-often-studied topic of evacuation reentry timing and participation. Finally, it creates a set of aggregate evacuation parameters that can be used to calibrate evacuation planning and simulation models making the paper a valued reference for future research studies.

Delimitations and Assumptions

This study required to filter and set boundaries for the acquired data, since in many of these natural disasters there is always a margin of error because of the sensors in the region being affected. The acquired full real time data that contained region location, naming, and volume information, such as county names, latitudes, longitudes, speed, volume, among others. This data was filtered among those sensor-based regions that were unavailable because of the disaster. For example, during Michael there were many sensors on the west coast of the State of Florida that were not recording data, assuming that these sensors were either malfunctioning because of the weather, connection breakage, or damaged.

Limitations

Analysts tend to focus on how the evacuation progressed over time giving importance to the topography and infrastructure of the region. The primary limitations that analysts or researchers cannot modify, or change is the current transportation network. The network was considered and designed for the highest demand, which is most likely not a massive evacuation. This study considered the current network, how state's current and past plans, and most importantly how the current evacuations took place.

Background

Natural disasters have always been an issue for many countries, according to the Natural Hazard Project of the Department of Regional Development and Office of Foreign Disaster Assistance/U.S. Agency for International Development, natural disasters are "naturally occurring physical phenomena caused by rapid or slow onset events which can be geophysical, hydrological, climatological, meteorological, or biological" (**International Federation of Red Cross and Red Crescent Societies, n.d.**). Hurricanes are natural disasters that affect the day-to-day climate through strong winds and heavy storms, hurricanes are base under a category from 1 to 5. These hurricanes form when there is warm ocean water, the weather is moist and humid. While the humid air flows up where there is low pressure over the warm ocean water, then the water is released from the air as it starts to rotate creating the clouds of the storm shown in Figure 5. Wildfires on the other hand, are phenomenon that are unpredictable when it comes to location, time, and direction; this is because wildfires depend on the speed of the winds and heat temperature. Figure 6 shows the prone areas for wildfires to occur in the State of California.
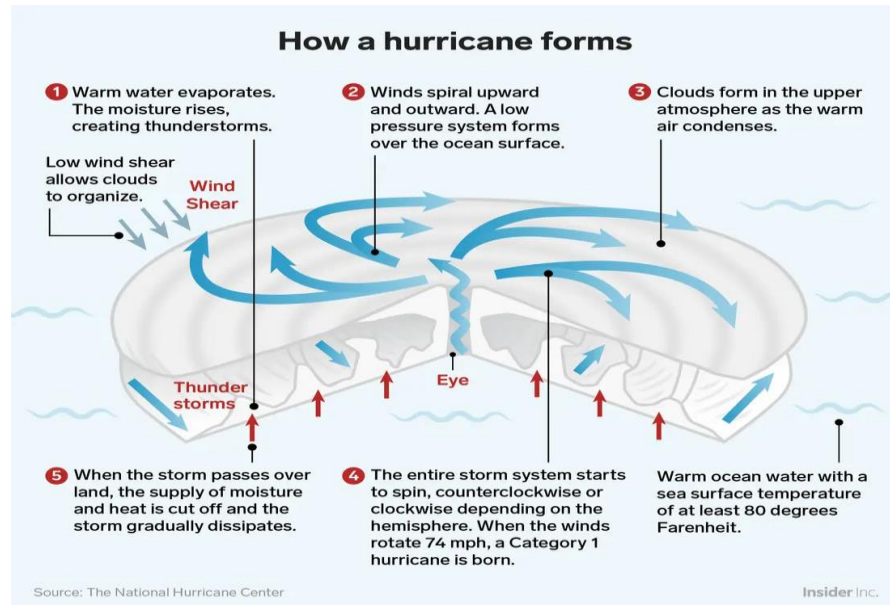
Figure 1. How are hurricanes or tropical cyclones formed. Source: The National Hurricane Center. Retrieved on January 20th, 2018.

Florida and California have their season of danger and precautions, which leads to evacuations. In 2017, California suffered from four wildfires that spread through Southern California leaving more than 30 structures destroyed through its path (Alvarez & Santora, 2017). This also includes about 200,000 people had little time to prepare during the 2017 Ventura, California wildfire. In 2017, Florida suffered from a category 4 hurricane with maximum wind speed of 130 miles per hour destroying about 25% of homes in the Florida Keys, flooding all of the coasts in Florida and leaving more than three million Floridians without power (Wall Street Journal, 2017). Those two states have a lot in common; their evacuations consist on large capacity movements because both are heavy populated states. Even though Florida's 2017-hurricane evacuation was considered the biggest evacuation in the United States history, California's wildfire destruction and deaths have been marked in history.

Fundamentally, surface transportation seeks to find a balance between supply and demand. An increase in the number of vehicles on a road (demand) subsequently leads to an increase in congestion and travel time (price), assuming the supply of roads does not change. This concept is universal in traffic analysis. In general, the supply of roads is typically governed by daily commuting traffic. That is to say, the number of roads servicing an area is usually a function of the number of daily commuters needing access to this area. In theory, as the number of commuters grow over time, so too should the number/capacity of roads. The delicate balance between travel supply and demand leaves communities vulnerable to sudden and drastic increases in demand. A spike in demand can lead to excessive congestion with the potential to cause network wide gridlock. Such situations occur during road maintenance or special events but are most consequential during emergency evacuations. Because roads are design for daily commuter traffic, the increase in demand caused by the evacuating public and the potential for subsequence gridlock, is a serious problem for transportation officials.

The 2017 evacuation of Hurricane Irma has been referred to as the largest evacuation in the history of the nation with approximately 6.5 million Floridians under mandatory or voluntary evacuation orders **(Marshall, 2017)**. Hurricane Irma impacted nearly the entire peninsula and its high-powered winds, storm surge, and uniquely unpredictable path caused havoc on the Florida roadways. Ultimately, Hurricane Irma made two landfalls within the state of Florida. The first was near Cudjoe Key in the lower Florida Keys, on September 10th, 2017 at approximately 9:10 AM ET as a Category 4 hurricane with sustained winds of 130 mph (209 kph) as shown in Figure 1. The second landfall was at approximately 3:35 PM ET near Marco Island, just south of Naples, FL as a Category 3 hurricane with winds of 115 mph (161 kph) **(Jansen, 2017)**. The storm left approximately 6.7 million homes (65 percent of the state),

without power **(O'Connor, 2017)**. Hurricane Irma was attributed to taking the lives of 75 Floridians and costing an estimated $49 billion **(Wile, 2017)**. The lower Florida Keys remained closed to non-residents for approximately three weeks following the storm **(Associated Press, 2017)**.
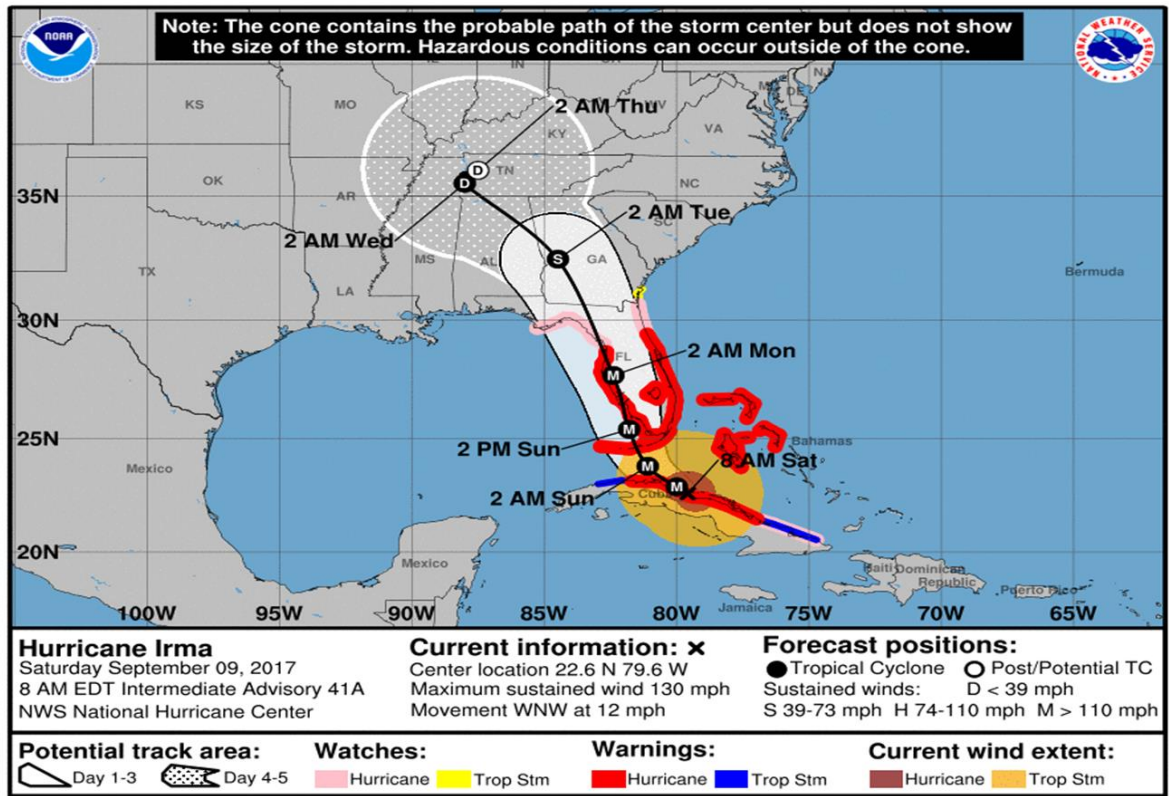
Figure 2. This figure illustrates the projected track of Hurricane Irma. Picture created by the National Oceanic and Atmospheric Administration, U.S. Department of Commerce. Retrieved on December 5th, 2017.

Hurricane Michael was category 5 hurricane that made landfall near Mexico Beach, Florida on October 10th, 2018 at approximately 12:30 P.M. With sustained wind speeds of 155 mph (250 kpm), Hurricane Michael was the strongest storm by wind speed to strike the mainland U.S. since hurricane Andrew in 1992 **(Beven, Berg, & Hagen, 2019)**. Hurricane Michael was directly responsible for 16 deaths and approximately $25 billion in damage. In total, 21 counties

issued evacuation orders, of which 12 held mandatory orders in place **(Haddad, 2018)**. However, initial reports suggested Hurricane Michael would make landfall as category 3 hurricane, which may have had an impact on evacuation participation rates leading up to landfall as shown in Figure 3 **(Roberson, 2018)**. Hurricane Michael's intensity projections 54 hours before landfall forecast a Category 1 or Category 2 storm **(United States, National Oceanic and Atmospheric Administration (NOAA), Nation Hurricane Center, 2018)**.
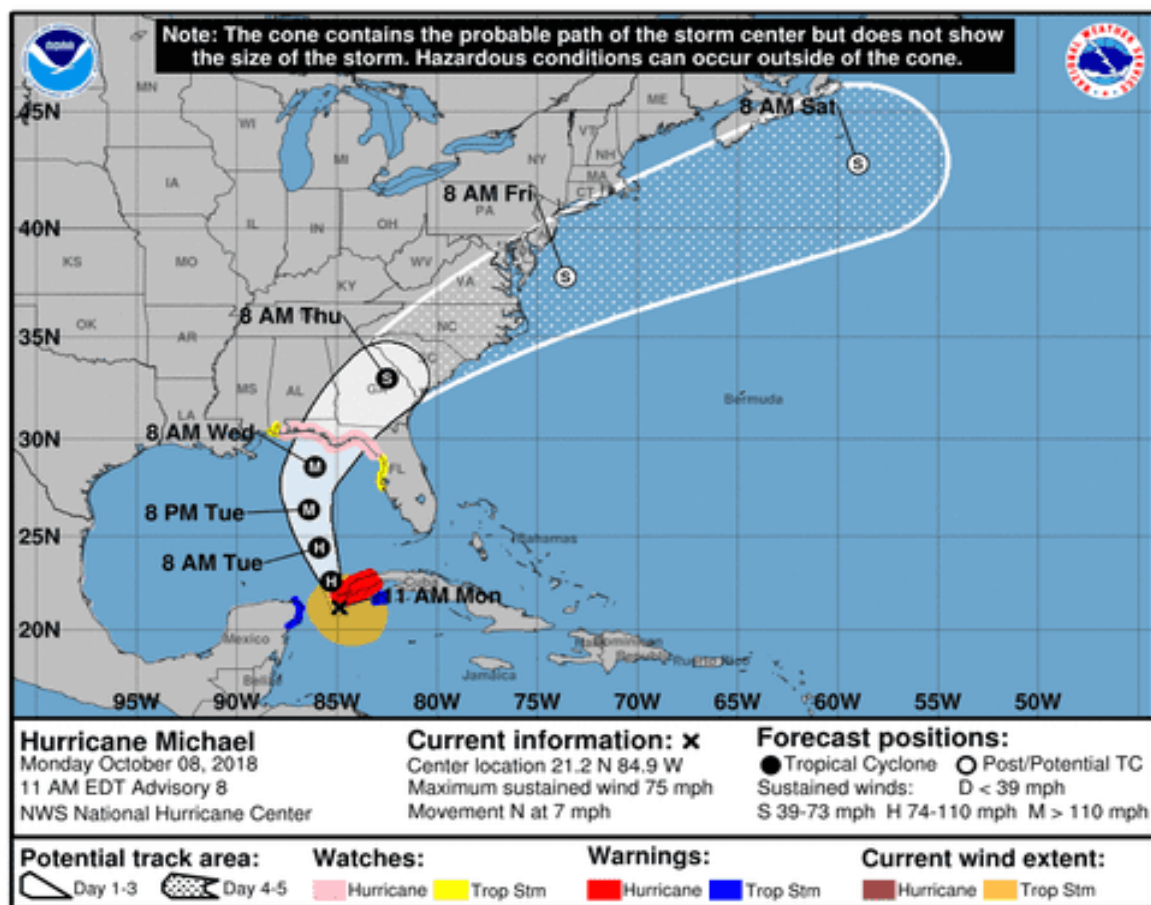
Figure 3. This figure illustrates the projected track of Hurricane Micheal. Source: National Oceanic and Atmospheric Administration (NOAA), U.S. Department of Commerce. Retrieved on January 21st, 2019.

Wildfires are generally formed by a high and low pressure usually occurs in mountainous areas as shown in Figure 6 and Figure 7. Normally anyone can start a fire with three simple things: fuel, oxygen, and heat. Wildfires tend to occur naturally with dry and weather and droughts, where green vegetation turns into bone-dry (flammable fuel), with warm temperatures (combustion), the strong winds that spreads the fire, and the last ingredient is a spark that can be caused by lighting, downed power line, cigarette, among others **(Wolters, 2019)**. The National Geographic states that an "average of 72 thousand wildfires cleared an average of 7 million acres of the United States" each year since 2000 **(Wolters, 2019)**. This is said to be double the number of acres burnt by wildfires in the previous decade. As population increase causing the additions of homes to the rural and wilderness areas, and the with the climatology changes change making the U.S. hotter and drier every year, the more wildfires will occur. According to the Environmental Protection Agency, wildfires are classified as natural disasters, but about 15 percent of these occur on their own instead of human causes **(Wolters, 2019)**
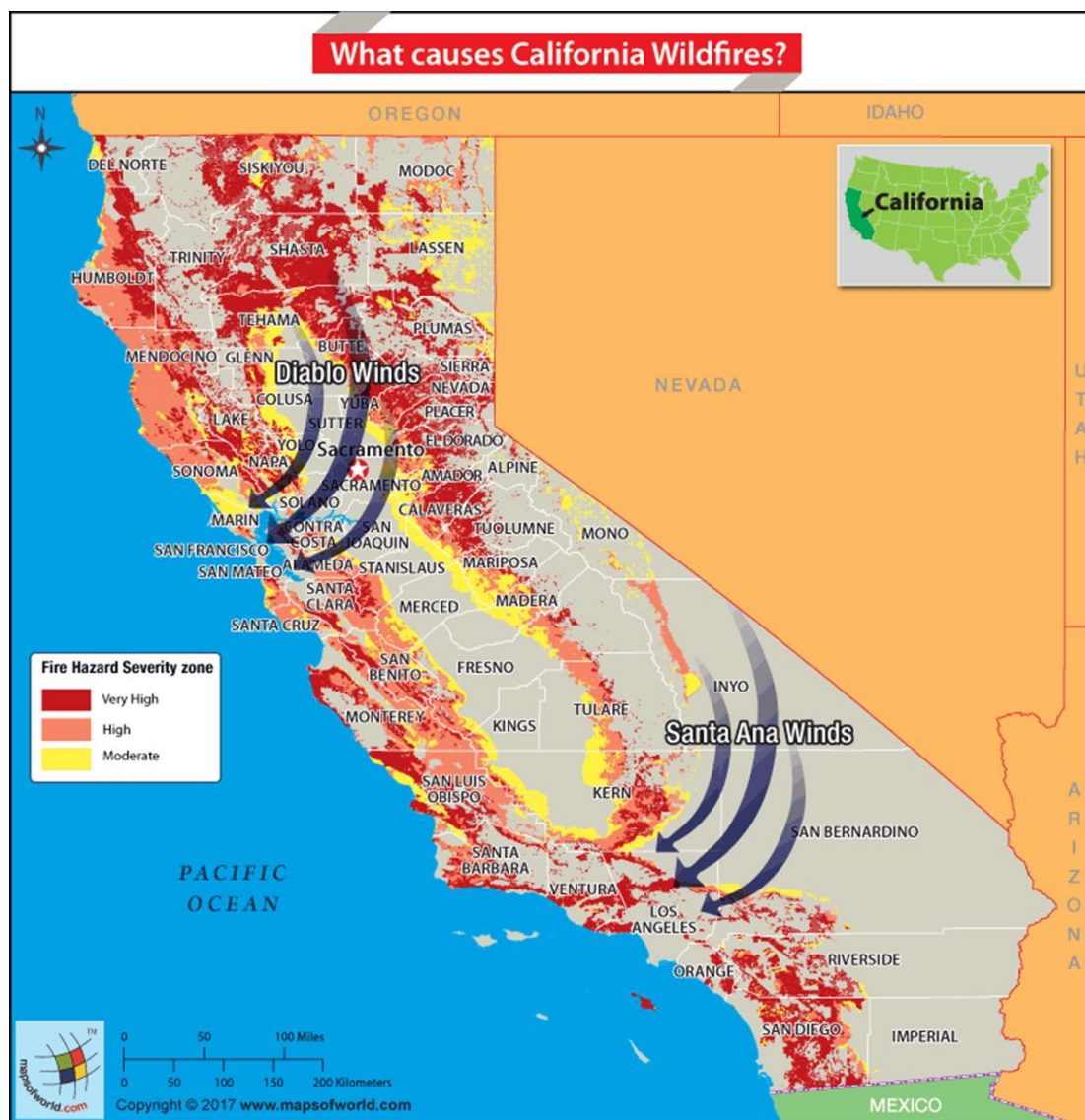
Figure 4. The severity of fire hazard zones across the State of California. Source: Copyright: Maps of the World

Winds whip up fierce California fires

Hot, dry winds (known as Santa Anas in Southern California and Diablos in Northern California) often whip up roaring fires across the state. They usually begin when winds circulate around a high-pressure area over Nevada or Utah.

1 Santa Ana winds
Winds can gust to **80 mph** in the mountains and passes.

2 Compressed air
Cool air descends from the high deserts and warms as it descends toward the coast.

3 Coastal regions
Air squeezes through canyons, fanning fires.

HOT, DRY VALLEYS

SOURCE National Weather Service; Storm Prediction Center
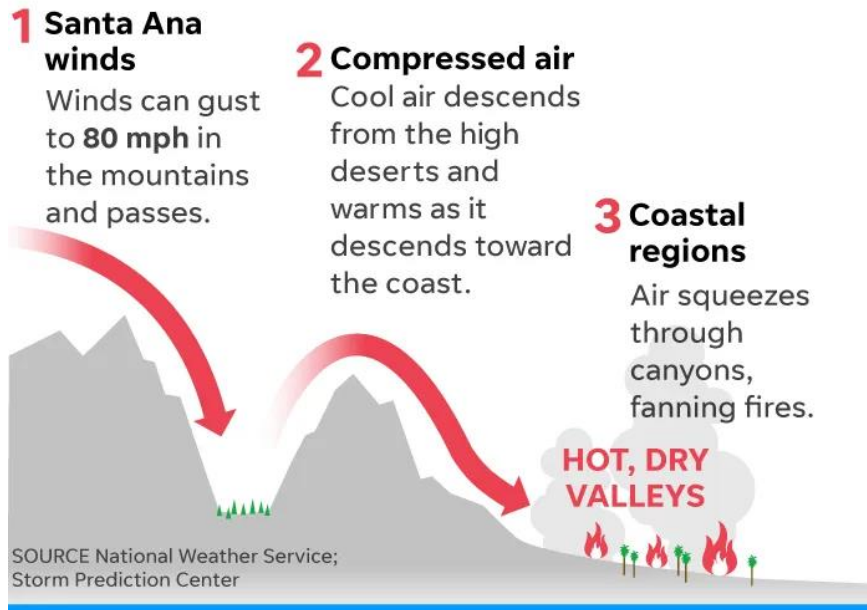
Figure 5. This figure illustrates how wildfires are formed in California. Source: National Weather Service; Storm Prediction Center and USA Today. Retrieved on June 13th, 2019.

One of the most destructive wildfires California had in 2017 was Tubbs Fire. 2017 Tubbs Fire has been under investigation since 2017, this fire started October 8th, 2017 around 9:45 p.m. and the fire was fully contained on October 31st, 2018. Tubbs Fire destroyed and damaged about six thousand structures and caused about 22 deaths as shown in Figure 3 (Cal Fire, 2018). This wildfire is categorized as the first most destructive fire in California, until 2018 Thomas Fire occurrence. The Tubbs fire started about a quarter mile north of Santa Rosa and began spreading south west of Santa Rosa as shown in Figure 3, eventually reaching Santa Rosa by 3:00 a.m. on October 9th. More information and timeline on the spread of the Tubbs Fire in the Appendix.
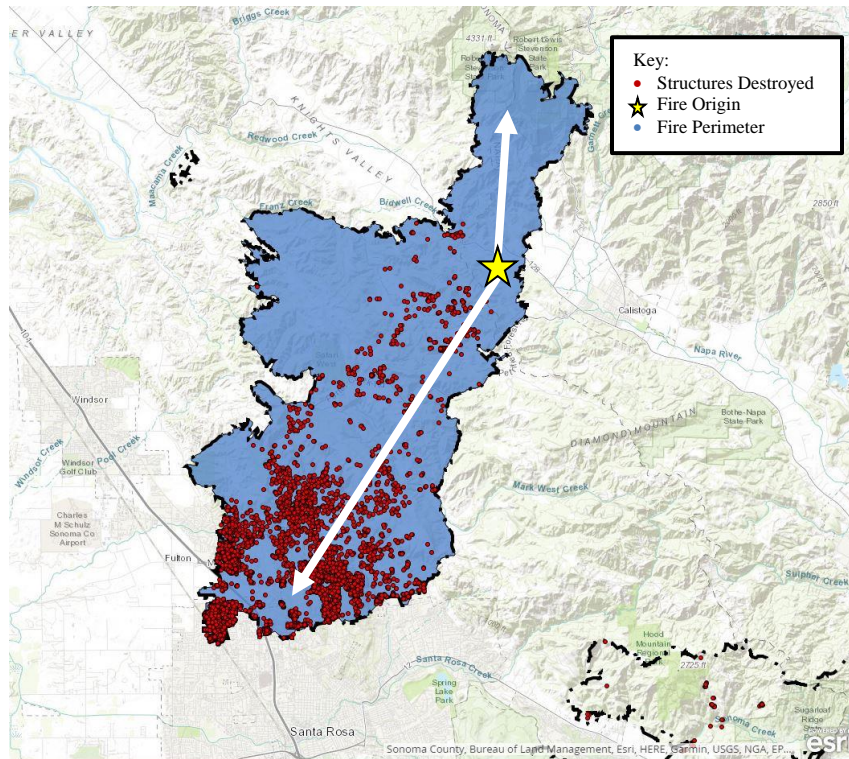
Figure 6. This figure illustrates the destruction and spreading of the Tubbs fire in the Napa and Sonoma County. Source: The Bureau of Land Management, Esri, HERE, Garmin, USGS, NGA, EPA, USDA, NPS and Cal Fire. Retrieved on June 13th, 2019.

The largest wildfire in California's history and in 2018 was the Thomas Fire that started on November 4th, 2018 and the fire was fully contained on December 15th, 2018. Thomas Fire caused about 15 deaths and about two thousand structures were damaged becoming the largest wildfire in California's history **(Cal Fire, 2018)**. Cal Fire estimated that about 177 million dollars were spent to fight the Thomas Fire from spreading and containment **(Helsel, 2017)**. According to Sommer, the growth of population has been spreading to more fire-prone areas in the State of California **(Sommer, 2017)**. As shown in the figure 4, the fire began on north of Santa Paula, then started spreading quickly to Ventura, and finally start threatening Ojai Valley on December 13th, 2018.
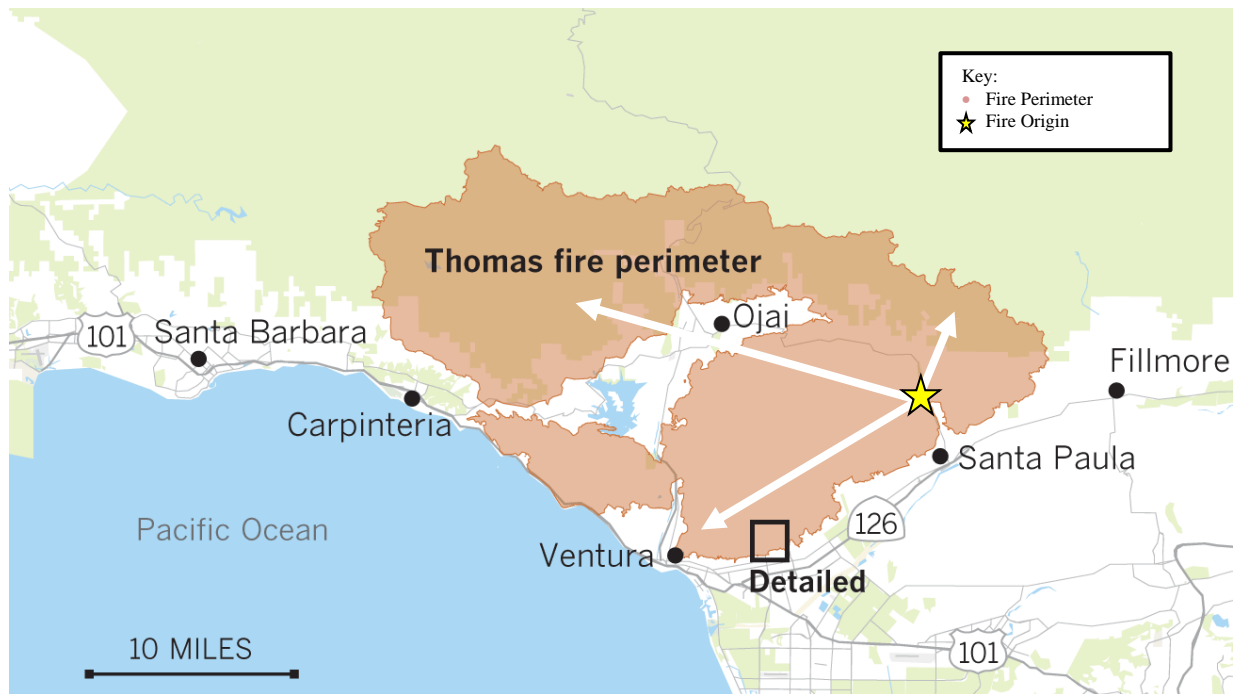
Figure 7. This figure illustrates the progression of the Thomas Fire in 2018. Source: Ventura County, Mapzen, OpenStreetMap. Map perimeter updated as of 4 a.m. on Dec. 11. Retrieved on June 10th, 2019.

Chapter II

Review of the Relevant Literature

The design, implementation, planning, and research of evacuations in Florida and California are very significant to the residences of this state and the future of keeping our population safe from any global climatological events that may occur. The overall topic of using the sensor-based data and developing a quantifying system from a temporal and spatial analysis is to be analyze how the evacuation plan was effective, how evacuees move over time and quantifying the amount of time that was take to evacuate after or before evacuation orders as well as for the reentry. Given the issue observing how effective were the orders, evacuations, and reentry plans in order to evacuate a big population in a short amount of time.

Understanding the impact of Hurricane Irma, Michael, and Wildfires on the evacuation process within Florida and California can provide insights for future storms and evacuation events. The fundamentals for the analysis, the supply and demand of vehicles and roads is universal within the transportation sciences. Therefore, the results and insights gained here can benefit future traffic, urban, and disaster management planners. The State of Florida has not seen any major destruction as seen during Hurricane Irma in 2017 and Michael in 2018, since Hurricane Andrew in 1992. Similarly, California has not had a major wildfire disaster with numerous fatalities since the Cedar Fire (San Diego County) in 2003. This analysis will help FDOT and LADOT be better prepared for a massive evacuation when time is needed. Also educate residents how traffic works, especially how the preparations for selecting evacuation routes. For the development of this research, several areas of prior literature in specific regions, special events and emergency planning, sensor-based and empirical studies on manual traffic

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control were read and implemented in this study. The following sections of this chapter will discuss these elements in further detail.

Traffic Analysis and Modeling Literature

The spatial and temporal patterns tend to help explore the traffic volume patterns of some secondary and low volume roadways that occurred in Florida during Hurricane Irma. This study matches the study done in Louisiana during Hurricane Katrina, which the researchers collected hourly traffic volume at each station for all of August 2005 (Wolshon & McArdle, 2011). According to Wolshon and McArdle, "statistical testing was also used to quantitatively discern the volume patterns associated with the evacuation and reentry" of the volume collected. Statistical testing was valuable when there was low traffic routine volume or considerably volume variation (Wolshon & McArdle, 2011). Through the Flow Rate versus Days statistical graph analysis are used to determine the different peaks that suggest different traffic situations. Westbound traffic volume lanes of Louisiana State Highway 28 (LA 28) shows that the "traffic counts on secondary roads had volume peaks starting and ending later could suggest a travel time lag as evacuees moved north" (Wolshon & McArdle, 2011). The study observes the traffic patterns that includes the origin and destination while using the location and direction of the evacuees. In addition, this observation done by Wolshon and McArdle studied the volumes around the cities and major roads, such as the ones done in this analysis.

Many studies identify evacuation volumes to compare the volumes from the previous week of the evacuation, such as Li, Ozbay, Bartin, Iyer, and Canegie's research from 2013. This paper's methodology consisted in using automatic traffic count data from the toll booths during Hurricane Irene to develop empirical response curves for a single county in New Jersey (Li, Ozbay, Bartin, Iyer, & Carnegie, Empirical Evacuation Response Curve During Hurricane Irene

in cape May County, New Jersey, 2013). This is similar to our graphical analysis for the counties in Florida and California, volumes were used and directions from the sensor-based data. Also, the studies identifies the evacuation traffic starting about six hours before the mandatory evacuation order for the barrier islands, which our analysis considers a good variable to quantify the amount of evacuees in both the evacuation and reentry. In addition, the overall quick response to a mandatory evacuation order was detected during the observed time, which they assumed that it could be due to the large tourist population in the area (Li, Ozbay, Bartin, Iyer, & Carnegie, Empirical Evacuation Response Curve During Hurricane Irene in cape May County, New Jersey, 2013). Li and Ozbay furthered their research in their spatial exposure and data that contained weigh-in-motion stations and historical travel time data (Li & Ozbay, Hurricane Irene Evacuation Traffic Patterns in New Jersey, 2014). As a result of this data, the analyst observed that the overall evacuation took approximately 36 hours where the evacuation traffic was mostly shown near the shore, inclining that the evacuees moved west instead of north along the shore (Li & Ozbay, Hurricane Irene Evacuation Traffic Patterns in New Jersey, 2014). In comparison to Hurricane Sandy, the volumes were lower than Hurricane Irene's, but with similar spatial patterns (Li, Ozbay, & Bartin, Effects of Hurricanes Irene and Sandy in New Jersey: Traffic Patterns and Highway Disruptions During Evacuations, 2015).

Li et al. developed a system for communities threatened by hurricanes that computed the Evacuation Time Estimates (ETEs) (Lindell & Prater, Critical Behavioral Assumptions in Evacuation Time Estimate Analysis for Private Vehicles: Examples from Hurricane Research and Planning, 2007). This computation requires analysts to create sophisticated models of evacuation flows (Lindell & Prater, Critical Behavioral Assumptions in Evacuation Time Estimate Analysis for Private Vehicles: Examples from Hurricane Research and Planning, 2007).

This study presents the "principal behavioral variables affecting hurricane ETEs, which provides recommendations and describes the available empirical data relevant to the ETE models" for future research and more effective analytical methods (Lindell & Prater, Critical Behavioral Assumptions in Evacuation Time Estimate Analysis for Private Vehicles: Examples from Hurricane Research and Planning, 2007).

The prior studies related to the amount of time residents were away from the evacuation zones have yet not been studied, except for the study done by Lindell, Kang, and Prater in their Natural Hazard publication. Their study concluded that Hurricane Lili (Category 4), the second costliest and strongest hurricane in 2002, where the average duration of time away from home was approximately two and half days (Lindell, Kang, & Prater, the Logistics of Household Hurricane Evacuation, 2011), whereas Hurricane Katrina (Category 5) in 2005, the average was about two weeks (Wu, Lindell, & Prater, 2012). This proposes that the amount of time residents are away can vary in many different situations and states, which could be consider by the amount of damage, emergency response ability, and utilities to the households.

Meteorologists have found a pattern by analyzing all hurricanes that have gone or gotten close to Florida and most of them have taken the path of the coasts (East and West) or center of the state coming from the south and affecting the entire state. According to Brian Wolshon (P.h.D., P.E.) and Ben McArdle, "this trend is expected to continue as a global climatological patterns are forecast to result in a long-term period of highly active and threatening tropical weather within the Atlantic Basin", this was written for Hurricane Katrina regional evacuation and with this in mind the FDOT and the state government need an ultimate evacuation plan for the most massive and threatening hurricane possible (Wolshon & McArdle, 2011). With this previous research, this study is able to investigate the patterns taken from the biggest hurricane

evacuation that the state of Florida has ever had and pass along the information to make specific arrangements and improvements.

There are categorizations of different traffic conditions such as contraflow, maximum and minimum flow volumes. For Hurricane Katrina the statistical data analysis on the Wolshon's paper, states that "maximum sustainable flow under evacuation conditions are important because they are often used" (Wolshon B. , Empirical Characterization of Mass Evacuation Traffic Flow, 2008). This study consists of using detector data to investigate different aspects of an evacuation for future planning, as seen in many other studies. In addition, the "forecast that the times were required to clear locations on the basis of combinations of population size, the response rate, and the available roadway capacity" are important to the categorization of different traffic conditions (Wolshon B. , Empirical Characterization of Mass Evacuation Traffic Flow, 2008). Wolshon used this data collected during Hurricane Katrina to evaluate how well the Highway Capacity Manual (HCM) maximum capacities matched the detector reported flows for the different roadway networks in Louisiana. The different types of roadway networks consist in contraflow freeway segments, freeways operating in the normal direction, four-lane arterial roadways, and two-lane arterials. The conclusion to this study was that the maximum flows on these types of roadways were lower than the theoretical values of the HCM (Wolshon B. , Empirical Characterization of Mass Evacuation Traffic Flow, 2008).

Evacuations are needed in a state of emergency; hurricanes that form close to Florida are most likely to develop into extremely strong hurricanes with wind speed of more than 90 mph. In the case of an evacuation, the state government declares publicly a state of emergency when hurricanes are a category 4 or more. According to Boyd, Wolshon, and Heerden, understanding the relationship between emergency communication and response is important for "disaster

planning and response" (Wolshon & McArdle, 2009). In Florida Governor Rick Scott communicated that Florida was in a state of emergency after predictions were given that hurricane Irma was going to make its course through the entire peninsula, from the Keys to Tallahassee. Similarly, to the impact that the states' warning announcements made on the spatial and temporal movement of the evacuation traffic in Louisiana, Florida's warnings of different evacuation zones impacted the spatial and temporal movement of the evacuation traffic (Wolshon, Boyd, & Heerden, 2009). The impact that Florida had through these announcements were bigger than Louisiana's because Florida has only one way to evacuate when the announcements stated that the populations needed to be away from the coasts. Since Florida is a peninsula, the only way to evacuate for such a massive dangerous hurricane is north, were how the population evacuated from East to West and South to North by the predictions of the meteorologists, states announcements, and the media can be analyzed. Many people stayed in their homes rather than evacuate and "the role of effective risk communications, both long term and immediately prior to landfall, cannot be emphasized" when there is a higher risk of losing people during such a major evacuation in Florida, California, and North Carolina. Communication is extremely important during emergency evacuations that "[n]ot only can accurate information mean the difference between life and death, [but] it can provide reassurance [and guidance] that response and recovery are truly underway" (Federal Emergency Management Agency). The type of governor evacuation order is "emerged as a statistically significant predictor of evacuation behavior and expectation notice" as said in previously in this paper (Thompson, Garfin, & Silver, 2016).

Through global climatological patterns, studies have found that there will be a "long-term period of highly active and threatening tropical weather" (Wolshon & McArdle, 2009). According to this paper, about 36-38 hours are needed to evacuate the population in New Orleans through the traffic volumes analysis, which is also what the Corps of Engineers (CoE) estimated to be 72 hours. Just as the traffic volume data was used in the New Orleans Hurricane analysis, on the Irma analysis helps illustrate the effects of the Irma evacuation plan on the "roadway infrastructure in both spatial and temporal terms" (Wolshon & McArdle, 2009). The temporal analyses evaluate the "movement of traffic over time to assess the apparent starting and ending times of the evacuation, estimated travel time, the impact of contraflow operations, and the relationship of these parameters to [the] routine conditions" (Wolshon & McArdle, 2009). Temporal pattern has an evacuation timeline and temporal traffic movements across the state of Florida, this will keep track of the storm compared to the traffic volumes shown in the dataset that was acquired. Similarly, the time that residents take to get from the threat zone to the safe zone shows when the evacuation needs to begin and end; it also predicts if the evacuation was effective or not. As it states the "primary goal of many transportation agencies is to measure and minimize travel time in evacuations" (Wolshon & McArdle, 2009). Our investigation and data acquire the idea of an "Evacuation flow", where the evacuation volume flow volume "increased above and returned to (or went below)" the normal historical average. On the other hand, the spatial analyses evaluates the "impact of the extent of traffic dispersion" and "its terms of roadway functional classification and in contrast to the evacuation" to the prior year (Wolshon & McArdle, 2009).

Analyzing graphs for spatial-temporal patterns can suggest many traffic situations as well, it is helpful to show conditions at particular points and times along the routes (Wolshon & Dixit, Traffic Modeling and Simulation for Regional Multimodal Evacuation Analysis, 2012). The method of organizing the traffic volume versus day/time of the data set was done by the analysis that Wolshon and Dixit put together in the Hurricane Katrina evacuation research papers. According to Wolshon and Dixit, "[e]arly studies to apply to traffic simulation for evacuation were limited in their geographical scales and time duration", this will help the research be more specific when helping FDOT (Wolshon & Dixit, Traffic Modeling and Simulation for Regional Multimodal Evacuation Analysis, 2012).

After Hurricane Andrew there were many researchers that analyzed the "maximum hourly rate on a uniform roadway section during a given time under prevailing" (Dixit & Wolshon, 2014). According to Dixit and Wolshon, there are two measures that are introduced "maximum evacuation flow rates (MEFR)" and "maximum sustainable evacuation flow rates (MSEFR)" (Wolshon & Dixit, Traffic Modeling and Simulation for Regional Multimodal Evacuation Analysis, 2012). MEFR is "found to peak to a maximum value for a brief period and then drop[s] to flow rates that are able to be sustained for several hours as inflow is sufficient to saturate the evacuation route" (peak max shown in the graphs of this analysis) and MSEFR is "defined as sustainable flows that are observed for greater than or equal to one hour" (Dixit & Wolshon, 2014). The reasons for these capacity drops are hypothesized by Brilon et al. (2005) to be bottlenecks and different driver behavior. Bottlenecks are defined as "[t]he flow at the point under investigation [that] remains fluent until the section between this point and the bottleneck is filled with congested flow" subsequently "the maximum flow will be the bottleneck's capacity". On the other hand, different driver behavior is defined as the "drivers [that are] in

fluent traffic accept shorter headways since they expect to be able to pass the vehicles in front", "[o]nce they have given up this idea, they switch to a more safety-conscious style of driving and keep longer headways" (Dixit & Wolshon, 2014).

Analyzing graphs for spatial-temporal patterns can suggest many traffic situations as well, it is helpful to show conditions at particular points and times along the routes (Wolshon & Dixit, Traffic Modeling and Simulation for Regional Multimodal Evacuation Analysis, 2012). The method of organizing the traffic volume versus day/time of the data set was done by the analysis that Wolshon and Dixit put together in the Hurricane Katrina evacuation research papers. According to Wolshon and Dixit, "[e]arly studies to apply to traffic simulation for evacuation were limited in their geographical scales and time duration", this will help the research be more specific when helping FDOT (Wolshon & Dixit, Traffic Modeling and Simulation for Regional Multimodal Evacuation Analysis, 2012).

South Miami coastal evacuations for Hurricane Irma were done on Wednesday, September 6th, 2017, prior to the landfall on Saturday the 9th and mandatory evacuation warnings were communicated on Thursday the 7th. When evacuating from coast areas in Florida, there are not many alternatives for routing the population, just like evacuating from the Keys, Miami Beach, Palm Beach areas, and among others can only take certain evacuation routings. These areas have a very particular geographic shape and roadway network for entering and exiting these zones (Sadri, Ukkusuri, Ph.D., Murray-Tuite, Ph.D., & Gladwin, Ph.D., 2014). These barrier islands on the coast are "relatively low-elevation islands [that] lie off much of the Atlantic and Gulf Coastline and expose large numbers of their residents to storm surge risk from hurricanes" (Sadri, Ukkusuri, Ph.D., Murray-Tuite, Ph.D., & Gladwin, Ph.D., 2014). Many of our analysis that end up with high traffic volume are due to these areas on the coast of the state

of Florida, since evacuees tend to delay their departure from when the evacuation orders are given, which causes "traffic surges [that] occur resulting in gridlock on several evacuation routes" (Sadri, Ukkusuri, Ph.D., Murray-Tuite, Ph.D., & Gladwin, Ph.D., 2014). The meaning of evacuation orders are to "allow clearance time for traffic to get past bottlenecks like bridges and roads with limited traffic capacity" (Sadri, Ukkusuri, Ph.D., Murray-Tuite, Ph.D., & Gladwin, Ph.D., 2014).

California's wildfire impacts have left many deaths and damage across the State of California. California has two unique winds that occur at the end of the year called the Diablo Winds and the Santa Ana Winds, since vegetation is dried out from the summer season these winds will pick up and wildfires will start appearing. Since California is a desert state, the dry heat affects the winds and create these fires. According to Beloglazov, Almashor, Abebe, Richter, and Barton Steer, the biggest factor in these traffic analysis models are "the departure time of evacuees – the time when they leave their point of origin- which depends on their awareness, beliefs and priorities". The reason for these models to be analyzed are in general for any type of evacuation, the resident's behaviors have a heavy effect on the congestion of any roadway system (Beloglazov, Almashor, Abebe, Richter, & Barton Steer, 2016). This is where the spatial and temporal patterns take place, depending on those behaviors and decision making after the influence of mass media, governors' announcements, and department of transportation evacuation routes.

Every state has their own mechanism and planning associated to their specific topography, population, demand, and infrastructure. Li, Cova, and Dennison's study is on a GIS Model for traffic analysis. The purpose of this study is to "improve on previous methods by coupling fire and traffic simulation models to set triggers", which will allow analysts and

planners to estimate the time needed to evacuate using a traffic simulation model (Li, Cova, & Dennison, Setting Wildfire Evacuation Trigger Coupling Fire and Traffi Simulation Models: A Spatiotemporal GIS Application, 2018). The literature presents that the "time required to guarantee that 95% of the evacuating residents arrive at the safe area as a fire approaches a community is estimated at 160 minutes for one scenario but 292 minutes if the travel demand is doubled" (Li, Cova, & Dennison, Setting Wildfire Evacuation Trigger Coupling Fire and Traffi Simulation Models: A Spatiotemporal GIS Application, 2018).

Conversely, the studies done in the California region are observing the critical zones of danger through geographical information systems (GIS). According to Chou, two of the "hypothetical spatial strategies of prescribed burning were evaluated in terms of their effectiveness in reducing the danger to the district from fire and producing a more desirable spatial pattern" in case of an evacuation (Chou, 2007). This study was analyzing the data of the Idyllwild 7-5 minutes quadrangle in the Southern region of California where a probability model was constructed (Chou, 2007). This probability model included vegetation, topography, precipitation, temperature, proximity to buildings and transportation to generate the distribution of fire to occur (Chou, 2007).

The creation of evacuation warning zones for wildfires characterized by data-driven spatial modeling is important in the literature and methods behind the purpose. As stated in Li's dissertation, from the University of Utah, "[i]n wildfire evacuation practices, incident commanders use prominent geographic features (e.g., rivers, roads, and ridgelines) as trigger points, such that when a fire crosses a feature, the selected protective action recommendation will be issued to the residents at risk" (Li D. , Modeling Wildfire Evacuation As Coupled Human-Environmental System Using Triggers, 2016). This study examines the "dynamics of evacuation

timing by coupling wildfire spread modeling, trigger modeling, reverse geocoding, and traffic simulation to model wildfire evacuation as a coupled human-environmental system" (Li D. , Modeling Wildfire Evacuation As Coupled Human-Environmental System Using Triggers, 2016). The research also explores the spatiotemporal dynamics behind evacuation timing by coupling fire and traffic simulation models, where the integration of the two analysis sets triggers to the wildfire evacuation based on the estimated evacuation times through simulation and planning (Li D. , Modeling Wildfire Evacuation As Coupled Human-Environmental System Using Triggers, 2016). In addition to the broad analysis, Li proposes a model for wildfire evacuation that is a spatiotemporal GIS framework to couple fire and traffic simulation models to set triggers during such event (Li D. , Modeling Wildfire Evacuation As Coupled Human-Environmental System Using Triggers, 2016). Similarly, to our analysis and transportation knowledge, Li states that "with the increase of evacuation travel demand, more evacuees will be exposed to fire risk" (Li D. , Modeling Wildfire Evacuation As Coupled Human-Environmental System Using Triggers, 2016). This delays the evacuation causing the exposure to the fire rapidly spreading.

Similarly, to many studies done for different countries a great example is the study conducted by Zang, Lim, and Shaples, where they modeled spatial patterns of wildfire occurrence in South-Eastern Australia. This study consists of identifying the exact locations of future occurrences, many U.S. wildfire studies have been done for location of future, but no traffic analysis for the movement of residents out of the risk area. Their research shows that "wildfires are most likely to occur in mountainous areas, forests, savannahs, and lands with high vegetation coverage, and are less likely to occur in grasslands and shrublands" (Zhang, Lim, & Sharples, 2015). More studies similarly to Zang's is the forest risk fire maps in a GIS open source

application created by Teodoro and Duarte in Portugal (Teodoro & Duarte, 2012). Municipalities in Portugal are required to produce a forest fire risk map annually by the Portuguese Forest Authority (Teodoro & Duarte, 2012).

Micah Brachman, a student from the University of California - Santa Barbara, researched the assumptions related to the empirical data from survey of people in Santa Barbara (Brachman, 2012). Similar to what Brachman mentions in her study that there are mathematical models related to the hazard conditions of the regions, road topology, and population characteristics, there is a need to challenge those mathematical methods and assumptions with real time data (Brachman, 2012). Even though Brachman challenges through surveys, our research overlaps with the idea of whether residents choose to "stay-or-go" when they are living in a mandatory evacuation area. Brachman's analysis uses survival analysis to "analyze empirical evacuation route data and determine which wayfinding strategies were employed by Jesusita Fire evacuees" (Brachman, 2012).

Many literatures focus on the development of a certain methodology to identify different areas of planning and analysis in different evacuation situations. According to the study presented in Church and Cova's literature, their "Critical Cluster Model", which can be used "to identify small areas or neighborhoods which have high ratios of population to exit capacity" (Chruch & Cova, 2000). This model can be used to produce maps of evacuation risks or susceptibility in a GIS (Geographical Information Systems) system (Chruch & Cova, 2000).

The empirical knowledge and previous experience of different studies and analysis help planning for evacuation easier, but in the case of population growth the real meaning and purpose of effective and successful evacuation. Han, Yuan, and Urbanik II's study presents different

measures of effectiveness (MOE) for evacuation (Han, Yuan, & Urbanik II, 2007). The MOEs presented where from different literatures previously done, which were "implicitly assumed or explicitly defined" and an optimization of the MOEs is compiled and presented depending on different situations (Han, Yuan, & Urbanik II, 2007).

On the other hand, population growth and residential areas expansion is a primary concern when it comes to infrastructure and planning for an effective evacuation. Cova, Theobald, Norman III, and Siebeneck's study analyzed different communities and locations of wildfire histories that have a pattern. According to this study, the pattern consists in sharing "a unique vulnerability in that all residents may not be able to evacuate in scenarios with short warning" (Cova, Theobald, Norman III, & Siebeneck, 2011). This study helps pinpoint the areas of vulnerability with the wind patterns during certain time of the year in the west coast, especially in California.

Another important observation in wildfire evacuations is the ability to consider the fire management area of an evacuation. McCaffrey, Rhodes, and Stidham's studied four different communities in the United States "where some alternative to mass evacuation during a wildfire was being considered" (McCaffrey, Rhodes, & Stidham, 2013). The results of this study is rather interesting because while there are residents interested in increasing safety and reducing uncertainty for emergency responders tend to think that the best approach is a mass evacuation (McCaffrey, Rhodes, & Stidham, 2013). On the other hand, those who were interested in the same, but for "homeowners tend to think that alternative responses were valid option" (McCaffrey, Rhodes, & Stidham, 2013). This is one of the mayor differences that hurricane and wildfire evacuations have, the use of emergency responders is a primary concern and priority to these communities.

California has limited studies on wildfires, the demand is related more towards the environmental factors rather than the transportation impacts. On the other hand, Australia and many foreign countries have studied other factors and impacts of a wildfire, such as engaging and preparing the homeowners in these events. According to a group of researchers starting with Stephens and Adams, California and many other states in the U.S. should learn from the studies done in Australia (Stephens, et al., 2009). The researchers imply that "U.S. society has attempted to accommodate many of the natural hazards inherent to the landscapes that we inhabit; by examining the Australian model, we may approach a more sustainable coexistence with fire as well" (Stephens, et al., 2009).

The graphical analysis of this research can be related to that of Wolshon, Archibald, and McNeil's. There are many factors that are included in such graphs that help reflect the day of the week and the time of day variations. These variations during evacuations show a distorted increase during an evacuation and re-entry, but a distorted decrease during the disasters. According to Archibald and McNeil, "[g]raphing traffic against time provides insights into how much variation occurs in these patterns and helps to identify disruptions", such as congestion assumptions. These assumptions are related to bottlenecks, construction downstream, closed exit ramps, accidents, among others (Archibald & McNeil, 2012). In these graphical analyses the use of conservation of flow to estimate vehicles evacuated are important because the "traffic counts can be used to estimate the population evacuated" (Archibald & McNeil, 2012). As explained in the previous sections, the use of traffic recorders or detectors count the number of vehicles that pass-through a given location over a specific period of time. As stated in this literature, when acquiring enough counters, the analysis of the traffic demand of the evacuation can be gathered to "pinpoint exactly how many vehicles left a given area in the specified period" (Archibald &

McNeil, 2012). This connects back to what our study's procedure will be on, analyzing graphicly the change in volume over time given the analyst the opportunity to evaluate the disruptions and illustrate how effective are the evacuation announcements from the moment residents decide to evacuate.

The equations from the Archibald and McNeil's study is shown below to calculate the change in vehicle count, number of evacuees, percentage occupancy of seasonal units, number of people in each and the percentage calculated (Archibald & McNeil, 2012).

1.	How the change in vehicle count for an area can be calculated using the inbound and outbound counts:

$$\Delta n = \sum all\ counters\ (Inbound\ Count - Outbound\ Count)$$

2.	Finding the number of evacuees using the number of vehicles that evacuated (Δn), assuming that the number of vehicles per household is the same for the residents and the visitors:

$$Number\ of\ Evacuees = |\Delta n|\ x\ \frac{(People\ per\ Household)}{(Vehicles\ per\ Household)}$$

3.	Identifying the percentage occupancy of seasonal units and the number of people in each:

$$Total\ Population$$
$$= Permanent\ Residents$$
$$+ \%occupancy\ (\#seasonal\ units)\ x\ Visitors\ per\ unit$$

4.	Calculating the percentage evacuated using the number of evacuees and the total population of the region:

$$\%Evacuated = \frac{(Number\ of\ Evacuees)}{(Total\ Population)}$$

Due to population growth and urban development expansion during the past decade, analysts consider evacuations to start to become more difficult. According to Pel, Bliemer, and Hoogendoorn, "the frequency and intensity of natural disasters [have] been increasing over the past decades"; their conclusion is based on two studies that were done by William H. Hooke in 2000 and Ross T. Newkirk 2001, (Pel, Bliemer, & Hoogendoorn, 2012). These studies focused on many regions in the world and summarized in giving importance in investing on "efficient disaster management strategies" for hazard prone regions, (Pel, Bliemer, & Hoogendoorn, 2012). There are different factors to consider for a successful evacuation, such as "warning time, response time, information and instructions dissemination procedure, evacuation routes, traffic flow conditions, dynamic traffic control measures, etc." (Pel, Bliemer, & Hoogendoorn, 2012). This is the guidance towards the tempo-spatial analysis considering government announcements for mandatory and voluntary evacuations. In addition, Pel, Bliemer, and Hoogendoorn suggested that "the speed, intensity, and track of a hurricane or wildfire inappropriately [has] not effect on travel demand" of the region during evacuations (Pel, Bliemer, & Hoogendoorn, 2012). There are many models like the model shown in this study that gives a conceptual framework of a repeated binary logit model to calculate the amount of people that evacuated and stayed.

A review of the literature has shown that currently there is no way to effectively compare evacuations and re-entries, as well as traffic coverages through the area(s) that were evacuated. Managing reentry can be challenging. In contrast to evacuation where destinations are dispersed, in reentry, traffic converges to the area(s) that were evacuated. These areas may have suffered damage, have debris issues, and utility outages (Zhang, Wolshon, Herrera, & Parr, 2019). These parameters observed will help government agencies to be prepared. Numerous studies have reportedly low compliance with official reentry plans: 38% for Hurricane Ike (Siebeneck,

Lindell, Prater, Wu, & Huang) , 46.4% returning on or after scheduled return date for Hurricane Rita (Siebeneck & Cova, An Assesment Return Entry Process for Hurricane Rita 2005.), and no studies for wildfires reentry. Assuming that the reason there is a lack of studies done for reentries during wildfire events is because of the great damage to property that this natural disaster causes. Considering this relatively low compliance, it is important for researchers to investigate and agencies to understand when evacuees will return and the volume in which they do so. The use of this spatial-temporal analysis and literature will help the four phases of disaster management: mitigation, preparedness, response, and recovery. This study uses aggregate data to improve this understanding.

Chapter III

Methodology

Broadly, the research methodology utilized traffic count data taken from across the state of Florida and California to investigate the auto-based evacuation response and reentry of communities from both Hurricane Irma (2017), Michael (2018), Tubbs Fire (2017), and Thomas Fire (2018). The first part of the methodology was to process traffic count data used in the analysis. The second part of the methodology discussion demonstrates how this data was used to estimate the start and end of the auto-based evacuation, the loading and peaking characteristics of the auto-based evacuation, and the total number of vehicles used in the evacuation process, as well as the effective start and end of the auto-based reentry.

Data Collection and Processing

The SunGuide program gathers roadway data from across the State of Florida. Traffic counts are reported hourly and archived for analysis. There are 255 SunGuide locations; each provides bidirectional hourly counts. For the analysis of the hurricane Irma evacuation, data was collected, cataloged, and processed for a 36-day period beginning August 27th, 2017 and ending October 1st, 2017. The analysis of Hurricane Michael encompasses the same locations and included a 14-day period that began October 1st, 2018 and concluded October 14th, 2018.

The evacuation analysis focuses on five general regions of Florida: Naples, the Florida Keys, Southeast Florida, and Tampa were analyzed during the Hurricane Irma evacuation and sections of the Florida Panhandle were investigated for the hurricane Michael evacuation. Naples and the Florida Keys were included in the analysis because hurricane Irma made landfall in both regions. Southeast Florida was included in the analysis because this region of Florida is the most heavily populated and was directly in the path of Hurricane Irma, as previously shown Figure 8.

The Tampa region was also included in the analysis because it too is heavily populated and was Irma's path. Unlike Irma, Hurricane Michael showed a consistent and ultimately accurate storm path projection, leading to the evacuation being focused in the panhandle region. For this reason, only one analysis zone was investigated for Hurricane Michael.

The SunGuide data collection sites were selected to encompass each of the five regions, similar to the way a cordon line identifies the inner and outer limits of a region. The SunGuide locations and analysis regions were provided in Figure 8. Given the relative location of each count station, directional counts were classified as "inbound", into the region, or "outbound", out of the region. Drawing a cordon line around a major city, a net increase in the number of inbound vehicles would be expected in the morning, while the opposite would be expected in the afternoon, for a normal commute. As such, it should also be expected that the number of vehicles entering the region in the morning should be approximately equal to the number exiting in the evening. A failure to maintain this equilibrium would result in an overall net increase or decrease of vehicles within the cordoned area. However, during an evacuation, this pattern is broken resulting in the number of vehicles exits significantly outnumbering vehicle entries.

Figure 8. SunGuide Data Collections and Analysis Regions.

Similarly, the Performance Measurement Systems (PEMs) Data Source is a Caltrans (State of California) system that collects and organizes all of the detectors in an area where these detectors are installed. The assumed limits chosen for the wildfire data analysis in this study are near the areas where there was mandatory evacuations in a state road that had reliable data points. Tubbs Fire data was collected, classified, and processed for a 36-day period beginning October 1st, 2017 and ending November 5th, 2017 northeast of Santa Rosa, CA. The analysis of Thomas

Fire evacuation encompasses the west coast of Los Angeles locations and included a 26-day period that began November 27th, 2018 and concluded December 22nd, 2018.

The evacuation analysis focuses on four counties of California: Napa, Somona, Ventura, and Santa Barbara were analyzed during the Tubbs Fire and Thomas Fire evacuations. These regions were included because of the locations of the fires and because these fires were the biggest destructive fires in 2017 and 2018, as previously shown Figure 9 and 10. The PEMs data collection sites were selected to encompass each of the four regions, similar to the way a cordon line identifies the inner and outer limits of a region. The PEMs locations and analysis regions were provided in Figure 9 and 10. Given the relative location of each count station, directional counts were classified as "inbound", into the region, or "outbound", out of the region. Drawing a cordon line around a major city, a net increase in the number of inbound vehicles would be expected in the morning, while the opposite would be expected in the afternoon, for a normal commute similar to the hurricane evacuations. Similarly to the hurricane "inbounds" and "outbounds", it should also be expected that the number of vehicles entering the region in the morning should be approximately equal to the number exiting in the evening. A failure to maintain this equilibrium would result in an overall net increase or decrease of vehicles within the cordoned area. However, during an evacuation, this pattern is broken resulting in the number of vehicles exits significantly outnumbering vehicle entries.
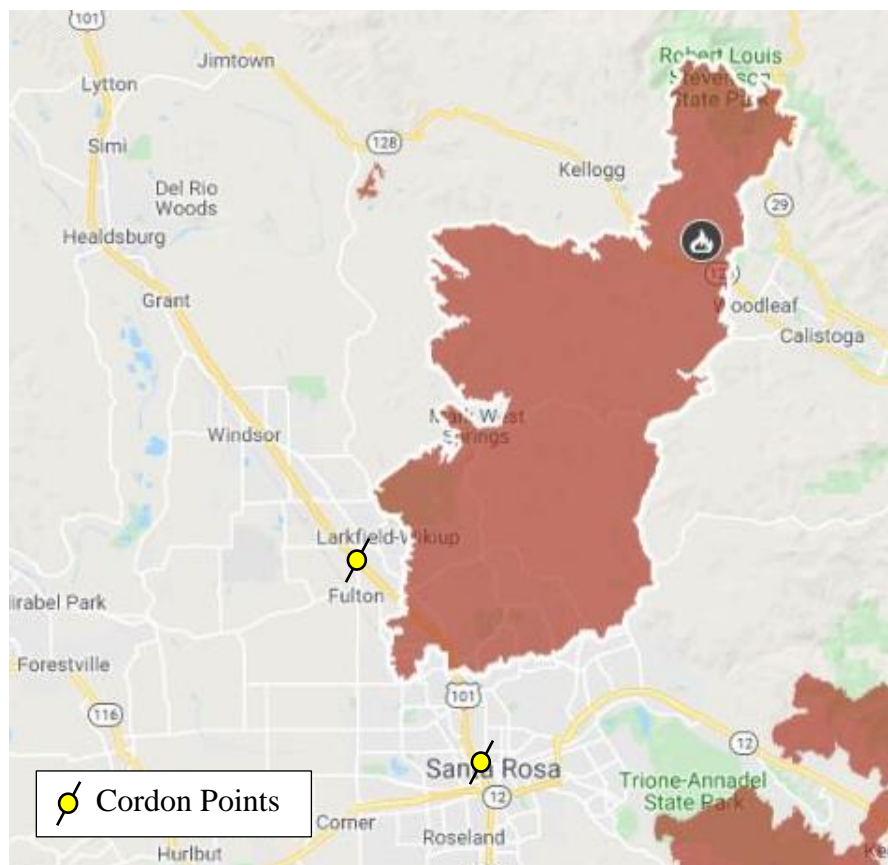
Figure 9. Tubbs Fire (2017) PEMs detector for data collection shown as a yellow symbol.
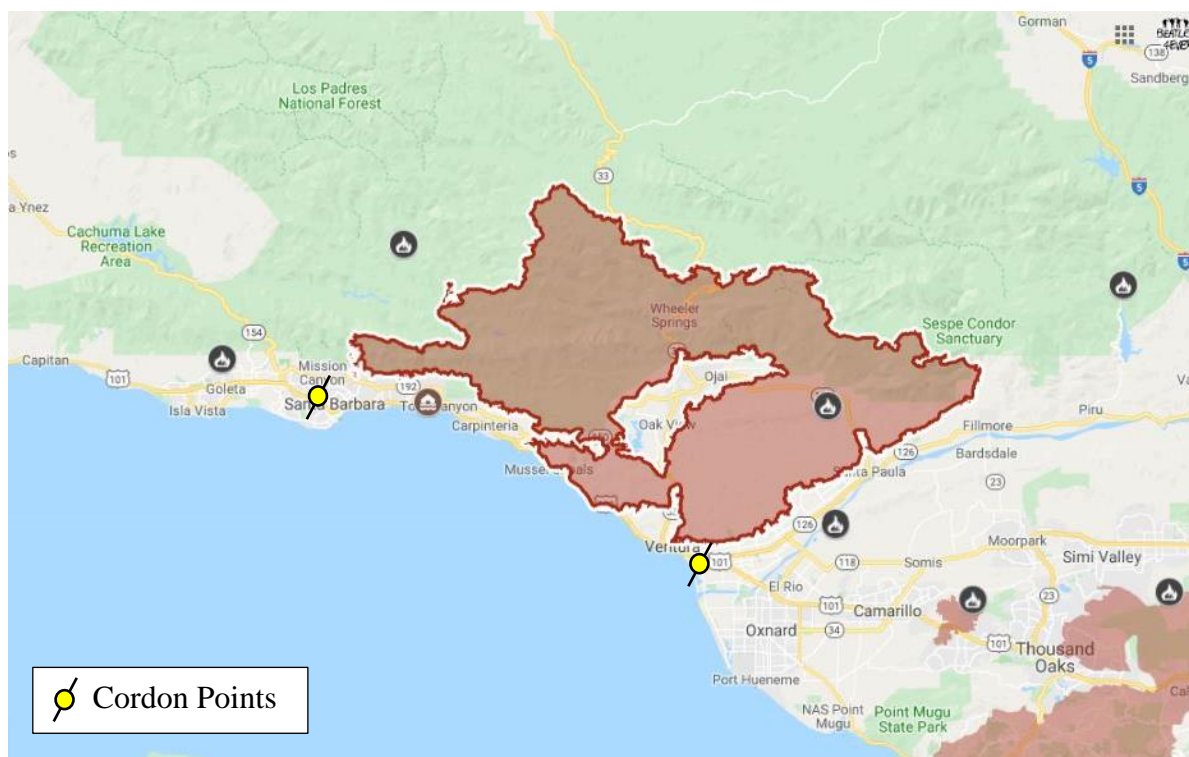

Figure 10. Thomas Fire (2018) PEMs detector for data collection shown as a yellow symbol.

Evacuation Analysis

Fundamentally, the change in the number of vehicles within a defined cordon boundary can be measured by adding the number vehicles crossing a cordon line into the area and subtracting the number of vehicles exiting. This simple method can determine the change in the number of vehicles within the boundary area. By establishing a cordon line around an evacuating city or region, it is possible to estimate the net change in vehicles, i.e., the number of evacuating vehicles. Let the number of vehicles entering an evacuation area A from location i along the cordon line for area A, over time interval t, be represented by IN_{it}^A. Likewise, let the number of vehicles exiting A at i, during t, be represented by the variable OUT_{it}^A. The start of the evacuation is noted as τ and the recovery time, after the evacuation and reentry of A, as T. The net change in vehicles can be calculated at any time t, as Δ_t^A in Equation 1:

$$\Delta_t^A = \sum_{i=1}^{I}(IN_{it}^A - OUT_{it}^A) \tag{1}$$

In practice, roadway detectors along major routes capture the number of vehicles passing in each direction $(IN_{it}^A - OUT_{it}^A)$. A cordon line can be delineated by connecting detector locations to encompass a city or region. In general, daily commuting patterns tend to result in approximately the same number of vehicles entering and exiting a region during any 24-hour period $IN_{it}^A = 0 = \sum_{t=1}^{24} \sum_{i=1}^{I}(IN_{it}^A - OUT_{it}^A)$. While seasonal variations or special circumstances often occur that violate this assumption, the daily equilibrium tends to remain relatively in balance. Determining the approximate time an evacuation begins (τ) and recovery ends (T) has been a significant challenge for emergency managers. However, as the traffic pattern changes over time, the imbalance caused by the evacuation in favor of outbound vehicles becomes evident i.e. $\sum_{t=1}^{24} \Delta_t^A < 0$. While it remains, difficult to estimate the precise time at which the

evacuation begins and recovery ends, due to the stochastic nature of driving patterns and behaviors, this research shows, to the hour, when the traffic pattern deviated from a typical commuting regimen. Therefore, this research defines the start of the auto-based evacuation τ and the recovery time (the end of the reentry) T as the start and end times corresponding to a net loss in vehicles that is inclusive of the hurricanes landfall time, t_1.

The total number of evacuating vehicles for area A is calculated as the minimum value of the cumulative Δ_t^A. The clearance point of the auto-based evacuation (t_{cp}) is the time at which the cumulative Δ_t^A reaches its minimum value (i.e., when the most evacuees have exited the cordoned area. For a hurricane evacuation, the clearance point typically occurs before or at landfall ($\tau < t_{cp} \leq t_l$). The clearance time (t_{ct}) is the duration between the start of the evacuation and the clearance point ($t_{ct} = t_{cp} - \tau$). The peak evacuation traffic is seen when Δ_t^A reaches a minimum value. The peak evacuation hour t_p, is the hour that sees Δ_t^A reach a minimum value. This minimum could then be considered the peak evacuation exit volume of the area. Evacuation peak demand flow rate and evacuation peak hour factor can also be calculated, if the detectors report 15-minut count intervals or shorter.

By considering the maximum value of the cumulative Δ_t^A as 100 percent of the auto-base evacuation demand, then t_{ct} represents the clearance time for 100 percent of the auto-based evacuees. It is therefore possible to estimate the clearance time for any proportion of the auto-based evacuation. For example, the clearance time corresponding to 90 percent of the auto-based evacuation t_{ct90} is the time at which 90 percent of the cumulative Δ_t^A minimum is achieved. In this fashion, it is possible to estimate vehicle exit rates and id travel time data is available, these exit rates could be adjusted to estimate vehicle-loading rates.

Chapter IV

Results

Descriptive Statistics

The results focused on the development and analysis of figures that show Δ_t^A and the cumulative Δ_t^A for the Florida and California communities affected by hurricanes Irma and Michael as well as the wildfires. These figures were used to determine the total number of evacuating vehicles, start of the auto-based evacuation (τ), and end of the recovery period (T), clearing point (t_{cp}), the peak evacuation volume (Δ_t^A minimum) and hour (t_p). The results also discussed the development of evacuation time estimate curves, which show the cumulative percent evacuating each region over time. For these curves, it was possible to estimate the 90 percent clearance time t_{ct90}, 50 percent clearance time t_{ct50}, etc. Finally, the results show how data collected from the evacuation of the Florida Keys was used to substantiate prior survey results from the region.

Evacuation Figures for Florida Hurricanes

Figure 9 shows the evacuation and reentry traffic resulting from Hurricane Irma evacuation of the Naples, FL region. The primary y-axis displays Δ_t^A, the number of evacuated vehicles hourly. The secondary y-axis displays the cumulative number of evacuating vehicles for all time periods between the start of the evacuation (τ) and end of reentry (T). The x-axis is time, in hours. Landfall t_l is shown with a thick vertical line for September 10th, 2017 at 15:00 when the storm made landfall on Marco Island, FL. The figure shows a typical example week traffic pattern to demonstrate the disparity between the evacuation and routine conditions. In general, the daily traffic shows a morning peak of traffic entering the region ($IN_{it}^A > OUT_{it}^A$) and an afternoon peak where the vehicles are leaving the region ($IN_{it}^A > OUT_{it}^A$) . The evacuation

traffic shows net losses in the number of vehicles prior to landfall and net increases, post landfall, representing re-entry. The maximum traffic demand periods during both the evacuation and reentry are shown on the figure as the peaks and valleys of the evacuation traffic line. The figure shows these points of interest. It is important to note that the cordon line, which encircled the Naples Region, did not constitute a true cordon, as data for many smaller roads were not available. However, the cordon likely captures the vast majority of evacuees. Naples saw a net decrease of 123,202 vehicles in the days leading up to the storm. The evacuation of Naples began approximately 126 hours before the landfall and concluded 122 hours later (just for hours before the eye wall of the storm crossed onto Marco Island). This was unexpected finding and suggests the unpredictable path may have delayed the decision of whether and when to evacuate. The peak evacuation demand occurred 28 hours before landfall at 11:00 and the reentry process took 169 hours (over seven days) to conclude.
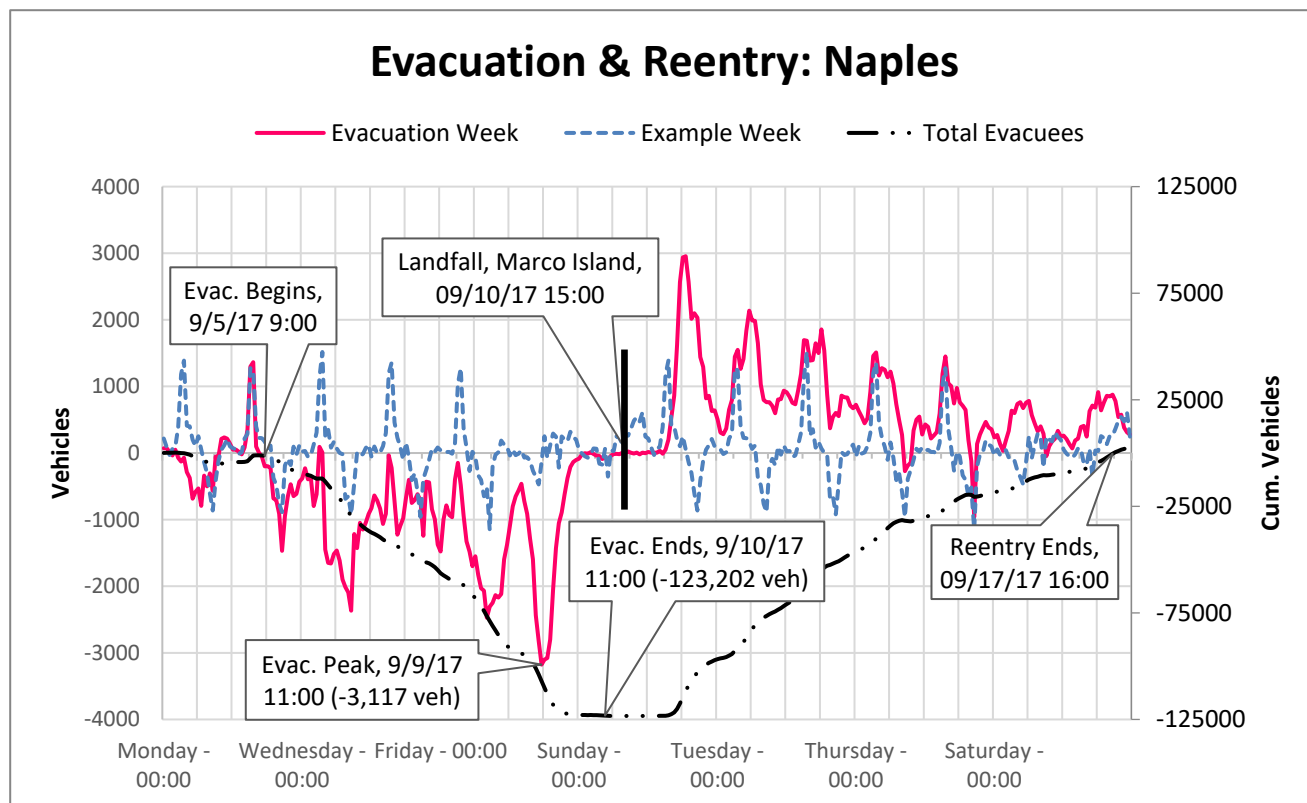

Figure 11. Naples Evacuation and Reentry Traffic Analysis

The figure for the Florida Keys is shown in Figure 10. unlike the other four regions, the Florid Keys have only one primary evacuation route and therefore the analysis represents data collected from only one detector location. The analysis found that 40,731 vehicles crossed the cordon line, not to return until after the storm. The evacuation began approximately 120 hours before landfall (on Cudjoe Key Sept. 10, 2017 at 9:00) and concluded 108 hours later. The peak evacuation demand occurred 89 hours before landfall at 16:00. The reentry of the 40,731 vehicles required 484 hours or 20 days and four hours after landfall. This was likely because many residents of the lower keys were not permitted to return home for several days.

Figure 11 shows the evacuation figure for Southeast Florida. This cordon line included nine detector locations along the major highways and freeways exiting a region. Again, it was not possible to conduct a true cordon, as many lower capacity streets were not available for analysis. Southeast Florida saw 276,052 vehicles leave the area in the days leading up to the storm. The evacuation began 95 hours before landfall on Cudjoe Key and concluded 62 hours later. The peak demand occurred 66 hours before landfall at 15:00. The analysis also found that 20,282 vehicles (7.35 percent) actually entered Southeast Florida, after it had cleared. That is to say after the cumulative change in volume reached its minimum value before landfall, over 20,000 vehicles travelled into and stayed in Southeast Florida as an evacuation destination. This was likely a combination of two reasons: 1) Southeast Florida has the largest, therefore many people would have friends and family in the area, marking it a desirable destination after the storm's path had changed. 2) It was likely that some evacuees, after seeing the updated projections returned home before the storm made landfall. The evacuation reentry took seven days and 23 hours (191 hours) to complete.
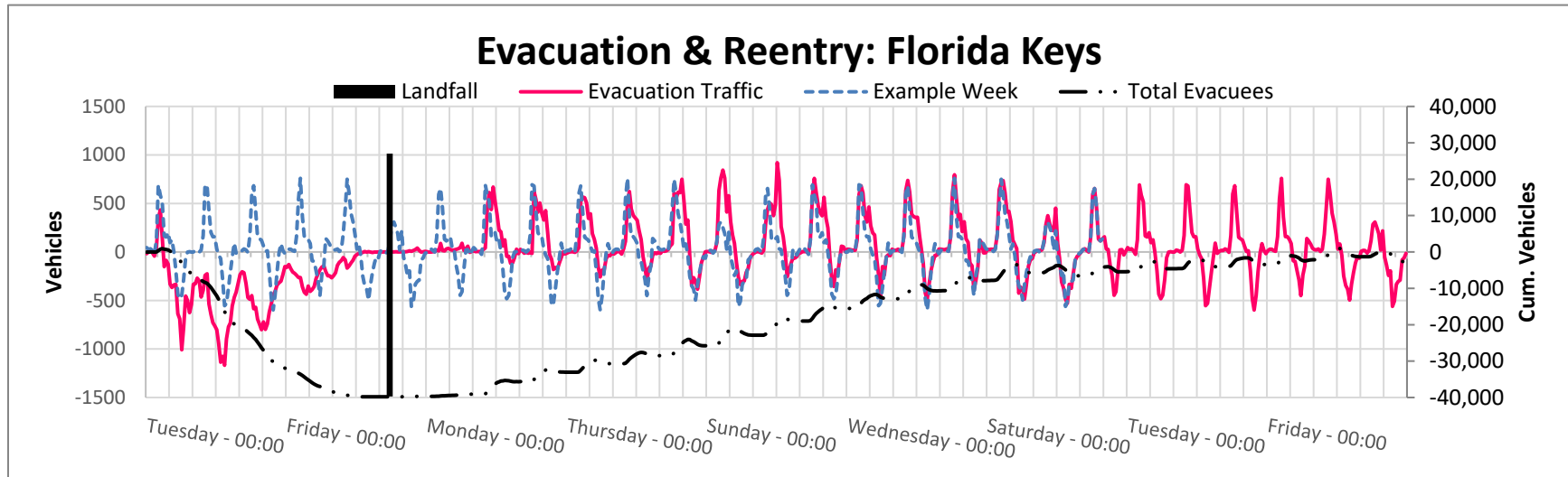
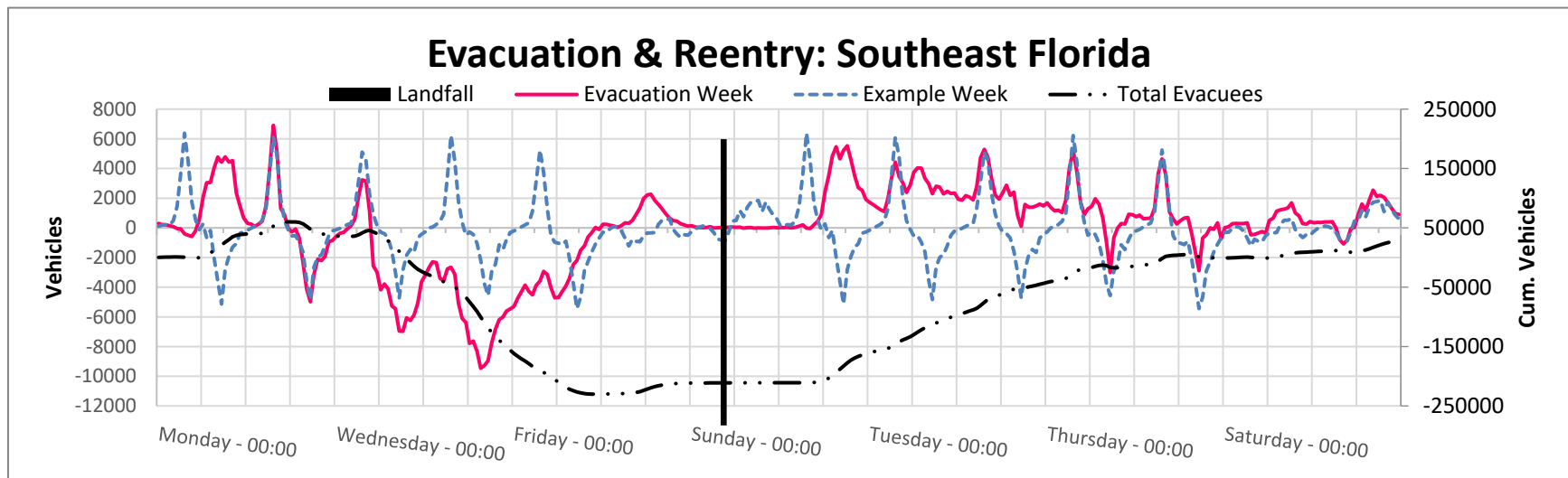Figure 12. Florida Keys Evacuation and Reentry Traffic Analysis.

Figure 13. Southeast Florida Evacuation and Reentry Traffic Analysis.

Figure 12 shows the evacuation plot for the Tampa Region of Florida. The Tampa area cordon included nine detector locations. In the days leading up to the evacuation. Tampa experienced a net increase in vehicles between Tuesday morning and the start of the evacuation on the following Friday afternoon. The number of vehicles within the Tampa region increased by 20,768 over this period. This may suggest Tampa was a desirable evacuation destination prior to the storm's path change or it could simply be residents returning from the Labor Day break on September 4th, 2017. In either event, the Tampa area experienced a net loss of 135,080 vehicles by the time Hurricane Irma made landfall. The evacuation began approximately 47 hours before landfall and concluded 57 hours later (10 hours after the storm reached Cudjoe Key). The peak evacuation demand occurred just 21 hours prior to landfall at 10:00 and the reentry took just four days and four hours (100 hours) to complete.

Figure 13 shows the evacuation from Hurricane Michael in the Florida Panhandle Region. Its cordon line consisted of seven detector locations on the major exit routes of the area. Severe damage to the power grid resulted in the loss of service to many of the data collection sites. Leading up to and after the storm's landfall. Detector failure began at midnight of October 10,2018 and continued (on and off) until the data collection period ended. This shown in the figure as a yellow overlay depicting times of poor data quality. Prior to the data collection failure, 16,370 vehicles were recorded during the evacuation 13 hours before landfall. At the time of landfall, the remaining detectors indicated that 18,302 vehicles had exited. However, these additional exits were recorded while nearly half of the seven detector locations were inoperable. In reality, it is likely the evacuation encompassed more than 20,000 vehicles. Still, the auto-based evacuation began 187 hours prior to landfall. Due to the detector error, it was not possible to determine the exact time of the clearance point but based on the data available it may have

occurred just two hours prior to landfall. No estimate for the evacuating vehicles could return.

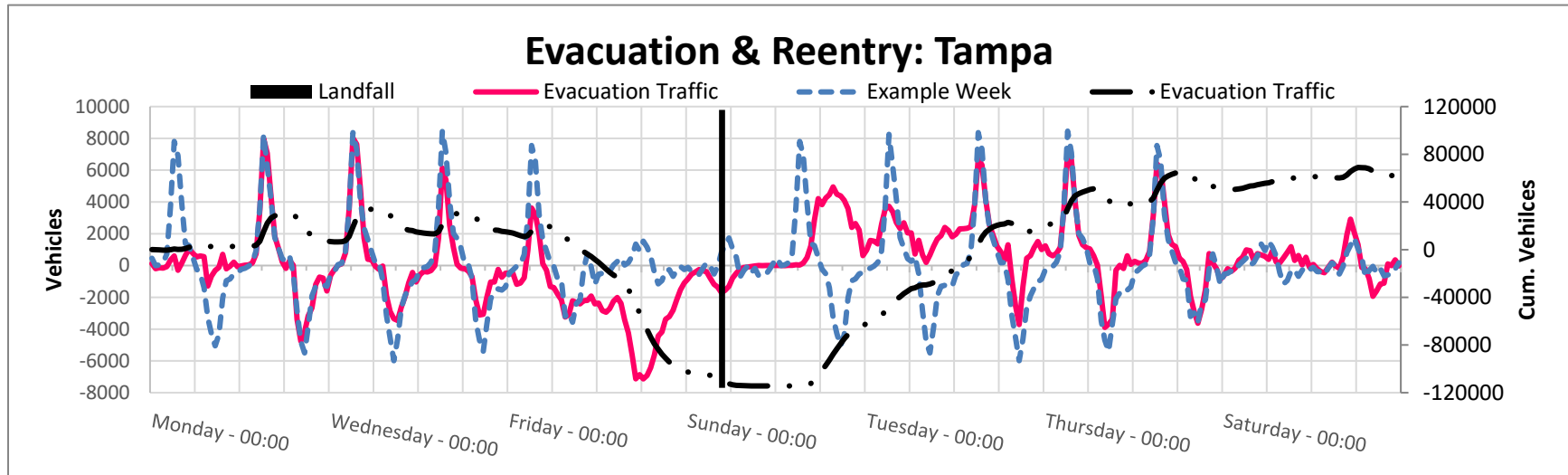The evacuation peaked 42 hours before landfall at 8:00.

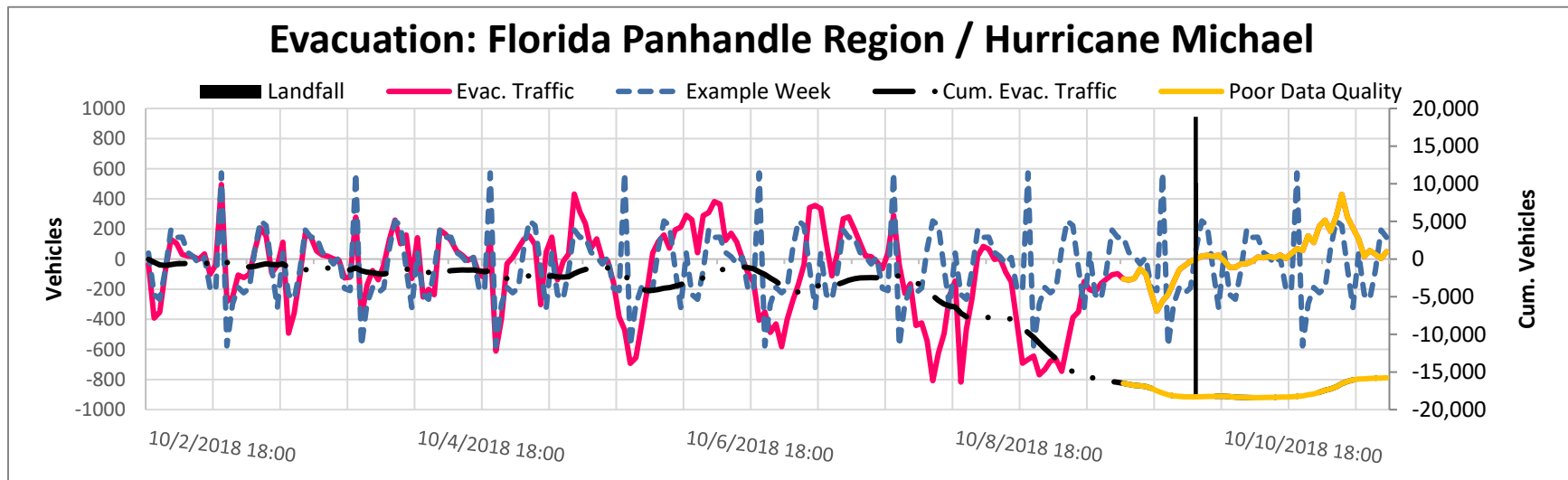Figure 14. Tampa Evacuation and Reentry Traffic Analysis.

Figure 15. Florida Panhandle Region Evacuation from Hurricane Micheal Traffic Analysis.

Evacuation and Reentry Time Estimates

Figure <mark>7</mark> shows the evacuation time estimates for the five study regions. The y-axis shows the cumulative percent of vehicles exiting the cordoned area. The x-axis shows the number of hours, which have elapsed since the start of the evacuation $(T - \tau)$. From this figure, the evacuation clearance time may be estimated for any cumulative percent evacuated. For example, the time needed to evacuate 50 percent of the residents of the Florida Keys was 34 hours. Likewise, 99 percent of evacuees in the Naples Region were able to clear the area within 104 hours, as compared to the last one percent, which required an additional 18 hour. The figure also presents a comparison of the exiting rate and by extension the loading rate for each region. The figure suggests that Southeast Florida and the Tampa region mobilized quickly as compared to the Florida Keys and Naples Region. However, regions showing slower mobilization began comparatively earlier than those with longer loading rates did. The mobilization in response to Hurricane Michael, on the other hand spanned several days before spiking two days prior to landfall. This was likely because the projected storm path did not deviate much in days leading up to landfall. This could have allowed residents in coastal areas to evacuate earlier. However, as the storm approached, it rapidly intensified. These later forecasts were likely the cause of large evacuation response closer to landfall and the resulting spike in network loading. With the exception of the Florida Keys, the evacuation reentry generally tended to be more gradual than the evacuation itself. The Florida Keys experienced severe damage resulting from the storm which led to curfews, travel restrictions, and ultimately the prolonged reentry curve shown in the figure. Half of the population of Southeast Florida that evacuated by vehicle did so within 23 hours after the evacuation began. However, it was not for another 120 hours that half of the population reentered. Therefore, the average evacuee from Southeast Florida was displaced for up to five days. Using this same approach, 50 percent of

the Naples auto-based evacuees were displaced for 120 hours as well. The displacement time for

the 50th percentile of the auto-based evacuees from the Tampa Region was only 64 hours whereas

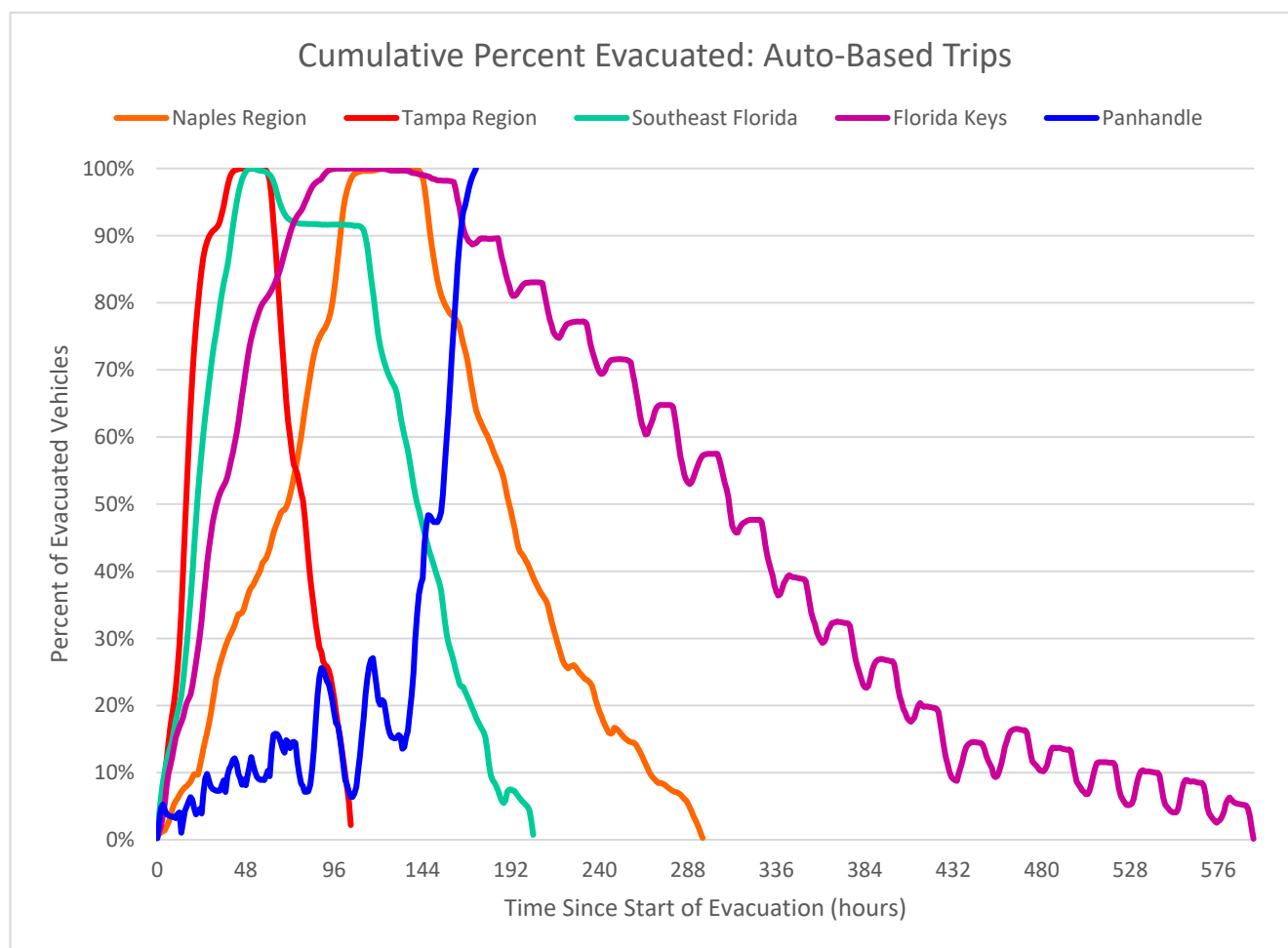the average Florida Keys resident was displaced for 278 hours, over 11.5 days.

Figure 16. Evacuation Time Estimates

Summary Results

Table 1 provides summary data, pulled from each region's evacuation figure as well as the evacuation time estimate analysis. The table shows that Southeast Florida experienced the largest net loss in vehicles. This was expected as this region has the highest population and was likely to see the greatest number of evacuees. In general, the evacuations began several days before the storm made landfall. However, Tampa did not begin to evacuate substantially until 47 hours before landfall. It is likely that the Tampa evacuees did not make their decisions to evacuate until much later because the storm was originally predicted to hit the Southeast Florida and only have a marginal impact in the Tampa area. The evacuation from Hurricane Michael shows evacuees leaving the region over one week in advance of the storm. The Florida Keys, Southeast Florida and the Panhandle saw the peak evacuation hour, two to three days in advance of the landfall. This is a significant finding because it suggests that hurricane warnings and evacuation notification were taken seriously and acted upon. However, Naples and Tampa did not experience peak demand until 28 and 21 hours before the storm arrived, respectively. Again, this was likely because of the shifting storm track. Tampa experienced the fastest reentry time of just four days and four hours after landfall. Naples and Southeast Florida had similar recovery times of just over a week. The Florida Keys required more than 20 days for the traffic patterns to recover. This was likely because the keys were the hardest hit and access was restricted to the lower keys for nearly three weeks. The clearance time was provided for when 50 percent, 90 percent, 99 percent, and 100 percent of evacuees exited the region. The table shows Naples and the Florida Keys has the longest clearance times from Hurricane Irma. It is not likely coincidental that these two regions were also the hardest hit by the storm. The clearance time for Hurricane Michael was estimated to be significantly longer than any region impacted by Irma. The

extended clearance time may suggest that while some evacuees decided to leave early, others departed only once the storm had intensified. This likely resulted in a two-phase evacuation, one for those who evacuated as a result of the first storm projection and one for those who decided to evacuate after the second. Southeast Florida and Tampa had significantly shorter clearance times despite evacuating more vehicles. This was likely because these areas have more, higher capacity roads and freeways and their evacuations started much later when compared to the other regions.

Table 1. Summary of Hurricane Evacuation Analysis

Regions	Total Veh	All Times Shown Relative to Landfall						
		Evac. Initiated (τ)	Peak Hours (t_p)	Evac. Reentry (T)	Clearance time (t_{ct})			
					50%	90%	99%	100%
FL Keys	40,731	5d, 0hr	3d, 17hr	20d, 4hr	34	73	92	104
S.E. FL	276,052	2d, 23hr	2d, 18hr	7d, 1hr	23	42	48	53
Naples Region	123,202	5d, 6hr	1d 4hr	7d, 1hr	68	97	104	122
Tampa Region	130,407	1d, 23hr	0d, 21hr	4d, 4hr	17	30	41	47
FL Panhandle (Michael)	16,370	7d, 19hr	1d, 18hr	N/A*	156	166	173	185*

*exact value not able to be determine.

Comparison with Survey Results

In response to the active hurricane seasons of 2004 and 2005, the Florida State Legislators authorized the development of regional evacuation studies. Contracting with Florida's Regional Planning Councils, the Statewide Regional Evacuation Study Program (SRESP) was developed to support and update local government emergency management plans. As part of the SRESP, a series of stated choice surveys were conducted to better understand evacuation modeling and shelter planning. The behavior assumptions collected as part of that

survey were: evacuation rate, out-of-county trips, type of refuge, percent of available vehicles, and evacuation timing. Surveys were conducted with 400 residents in each of the Florida's 67 counties.

To demonstrate further the application of the proposed methodology, the results of the SRESP surveys were analyzed to estimate the auto-based evacuation response of a Category 4 hurricane landfall in the lower keys. These results were then compared to the values generated by Hurricane Irma (a Category 4 hurricane that made landfall on Cudjoe Key). The analysis first investigated the number of evacuating vehicles predicted by the SRESP while the second assessed the evacuation timing curve results. The 2017 Census data were used to calculate the number of site-built and mobile homes of the Florida Keys region. Then the SRESP survey results were used to estimate the evacuation participation rate, percent of the vehicles used, and the number of available vehicles. Through this process, the number of evacuating vehicles could be estimated for a hypothetical storm. Further, the SRESP forecast three evacuation timing scenarios (fast response, normal response, and slow response). These scenarios represent a 24-hour mobilization time for evacuees. However, based on the results already discussed, the evacuation of the Florida Keys took several days.

Table 2 shows the estimated number of vehicles evacuating the Florida Keys because of a Category 4 hurricane landfall in the lower keys. To remain consistent with Hurricane Irma, these results assume a Category 4 scenario for Key West and the Lower Keys, a Category 3 storm in the middle keys, and a Category 2 storm in the Upper Keys. The analysis suggests up to approximately 53,781 vehicles may be used during the evacuation. The analysis of the Hurricane Irma results found 40,731 vehicles. A number of factors likely contributed to the more than 10,000 vehicle disparity between the predicted value and the observed. The most significant

of which was the SRESP study stating, "the planning assumptions for the evacuation rates are the maximum probable rates" (Baker, 2010). Therefore, the evacuation values estimated by the SRESP survey represent the upper limit of evacuees from any storm likely to affect the region. In this sense, the SRESP was accurate in that planning values were not surpassed by the Irma evacuation and were reasonably accurate. In addition, the SRESP results were based om surveys conducted in 2007 and 2008, nearly ten years before hurricane Irma. Updated survey results might lead to more accurate predictions.

Table 2. SRESP Estimate of the Number of Vehicles Evacuating the Florida Keys

Keys Region	Households [1]		Evac. Rate [2]		Vehicles Use Rate [2] Error! Reference source not found.		Vehicles. Avail.[3]	Evac. Vehicles	
	Built	Mobile	Built	Mobile	Built	Mobile		Built	Mobile
Upper	15,789	1,886	50%	75%	75%	80%	1.8	10,658	2,037
Middle	6,929	1,338	70%	85%	75%	80%	1.8	6,548	1,638
Lower	7,459	1,373	80%	95%	75%	80%	2.6	11,637	2,714
West	15,714	2,859	80%	95%	80%	85%	1.5	15,086	3,463
								Total Vehicles =	53,781

[1] U.S. Census Bureau QuickFacts: Monroe County, Florida. (2018). Retrieved from https://www.census.gov/quickfacts/monroecountyflorida

[2] Baker, E. (2010). Statewide Regional Evacuation Study Program: Volume 2-11 South Florida Region Regional Behavioral Analysis. Retrieved from United States, Florida Division of Emergency management, South Florida Regional Planning Council: http://www.sfrpc.com/SRESP Web/Vol2-11.pdf

[3] Downs, P., Prusaitis, S., Germain, J., & Baker, J. (2010). Statewide Regional Evacuation Program: Volume 3-11 South Florida Region Regional Behavioral Survey Report. Retrieved from United States, Florida Division of Emergency Management, South Florida Regional Planning Council: https://www.sffrpc.com/SRESP Web/Vol3-11.pdf

Figure 8 shows the three evacuation planning curves developed as part of the SRESP and the cumulative percent of vehicles evacuating the Florida Keys during Hurricane Irma. The x-axis displays the number of hours relative to government issued, mandatory evacuation orders.

The three planning curves represent a slow, normal, and fast evacuation response scenario. However, each was complete within a 24-hour period. This was done within the SRESP to estimate a severe shift in storm forecast that prompts a shortened window of evacuation. Again, representing the more severe conditions which are still probable to occur. In addition, the curve resulting from Hurricane Irma was based on the number of vehicles exiting the region, not the number of vehicles loading on the road network. Therefore, the planning curves do not account for travel time between residents' homes and the detector location. The figure shows that over 20 percent of the residents evacuating the Keys did so before mandatory evacuation orders were in place. However, the response curves predicted from the SRESP survey show this value to be 10 percent. In general, the SRESP survey estimated the most severe evacuation projections in term s of the number of evacuees and loading, that could reasonably expected to occur. Therefore, the values estimated by the SRESP were likely reasonable. It was not unreasonable to assume that if Irma's intensity projection were fixed in the days leading up to landfall, that an additional 20,000 vehicles may have been used during the evacuation.
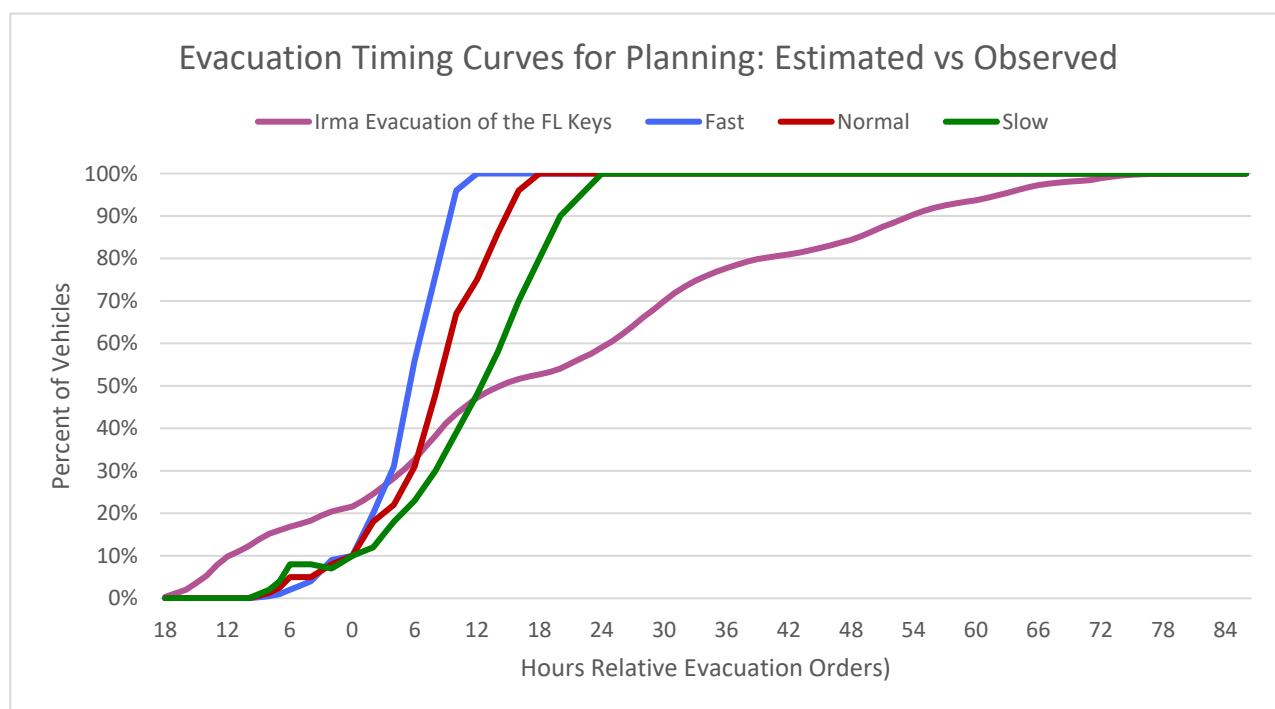

Figure 17. Evacuation Timing Curves for the Florida Keys

Evacuation Figures for California Wildfires

Figure 20 shows the evacuation and reentry traffic resulting from Tubbs Fire evacuation of the Napa and Somona County, CA region. The primary y-axis displays Δ_t^A, the number of evacuated vehicles hourly. The secondary y-axis displays the cumulative number of evacuating vehicles for all time periods between the start of the evacuation (τ) and end of reentry (T). The x-axis is time, in hours. Landfall t_l is shown with a thick vertical line for October 8th, 2017 at 19:00 when the fire broke out between Kellogg and Calistoga, CA. The figure shows a typical example week traffic pattern to demonstrate the disparity between the evacuation and routine conditions. In general, the daily traffic shows a morning peak of traffic entering the region ($IN_{it}^A > OUT_{it}^A$) and an afternoon peak where the vehicles are leaving the region ($IN_{it}^A > OUT_{it}^A$). The evacuation traffic shows net losses in the number of vehicles prior to the start of the fire and net increases, post fire, representing re-entry. The maximum traffic demand periods during both the evacuation and reentry are shown on the figure as the peaks and valleys of the evacuation traffic line. The figure shows these points of interest. It is important to note that chosen detectors, which are located near the evacuation zones, did not constitute the only access to the evacuation, as data for many smaller roads were not available. However, the chosen detectors likely capture the vast majority of evacuees. Part of Somona and Napa counties saw a net decrease of 43,000 vehicles in the days after the fire started. The evacuation began approximately 48 hours after the fire started and the evacuation did not conclude since there was not enough information to evaluate the reentry. The peak evacuation demand occurred 10 hours after the fire broke out. This was unexpected finding and suggests that since the location were the fire start is in a vegetated area the closest residential area is southwest with about 6.38 miles away from the origin of the fire. The reentry start was not able to be evaluated through the traffic analysis since

residents are not going to return to burnt properties where everything is considered to be lost.

Figure 18 shows the nearby fires that caused an increase in traffic prior to the start of the fire.

Figure 18. Fires nearby the Tubbs Fire that occurred either prior or subsequently after Tubbs Fire.
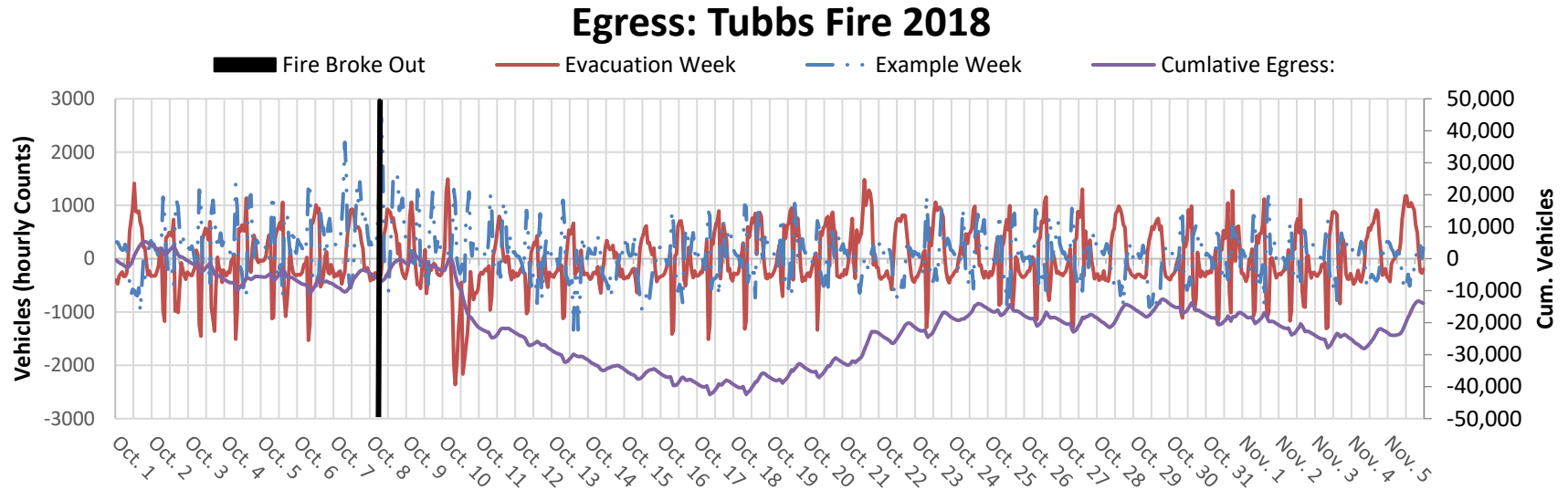
Figure 19. Napa and Somona County Evacuation and Reentry Traffic Analysis for Tubbs Fire (2017)
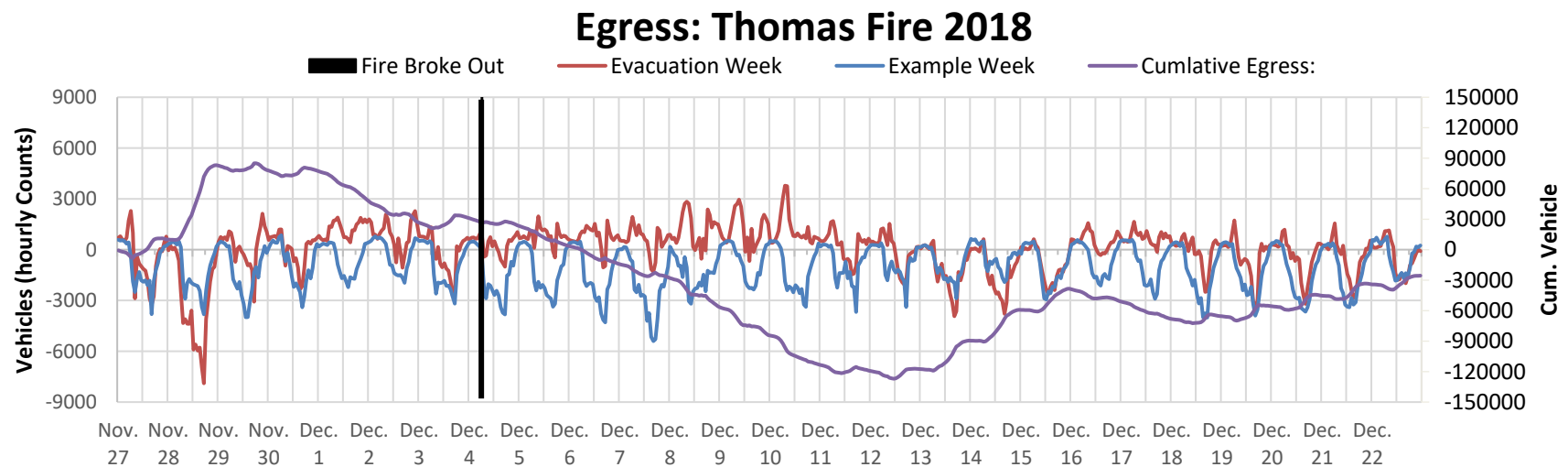

Figure 20. Santa Barbara and Ventura County Evacuation and Reentry Traffic Analysis for Thomas Fire (2018)

Figure 21 shows the evacuation and reentry traffic resulting from Thomas Fire (2018) evacuation of the Ventura and Santa Barbara County, CA region. The primary y-axis (Δ_t^A), secondary y-axis (evacuation beginning: τ; end of reentry: T), x-axis (t – hours), fire start (t_l) for December 4th, 2018 when the fire broke out west of Steckle Park in the area of Los Angeles, CA. The figure shows a typical example week traffic pattern to demonstrate the disparity between the evacuation and routine conditions. The evacuation traffic shows net losses in the number of vehicles prior to the start of the fire and net increases, post fire, representing re-entry. The maximum traffic demand periods during both the evacuation and reentry are shown on the figure as the peaks and valleys of the evacuation traffic line. The figure shows these points of interest. It is important to note that chosen detectors, which are located near the evacuation zones, did not constitute the only access to the evacuation, as data for many smaller roads were not available. However, the chosen detectors likely capture the vast majority of evacuees.

Part of Ventura and Santa Barbara counties saw a net decrease of 120,000 vehicles in the days after the fire started. The evacuation began approximately 2 days and 3 hours after the fire started and the evacuation did not conclude since there was not enough information to evaluate the reentry. This was unexpected finding and suggests that since the location were the fire start is in a vegetated area the closest residential area is Santa Paula with about 5 miles away from the origin of the fire. Figure 19 shows the nearby fires that caused an increase in traffic prior to the start of the fire. The peak evacuation demand occurred 3 days after the fire broke out and the reentry process was not able to be determine since the graphs do not show vehicles volumes. The reentry start was not able to be evaluated through the traffic analysis since residents are not going to return to burnt properties where everything is considered to be lost. Figure 19 shows

the nearby fires that caused an increase in traffic prior to the start of the fire. According to

Shatkin, more than 4,000 firefighters were needed to extinguish the Thomas Fire (Shatkin, 2017).

Table 2 provides summary data of the traffic analysis illustrated in Figures 21.

Table 3. Summary of Wildfire Evacuation Analysis

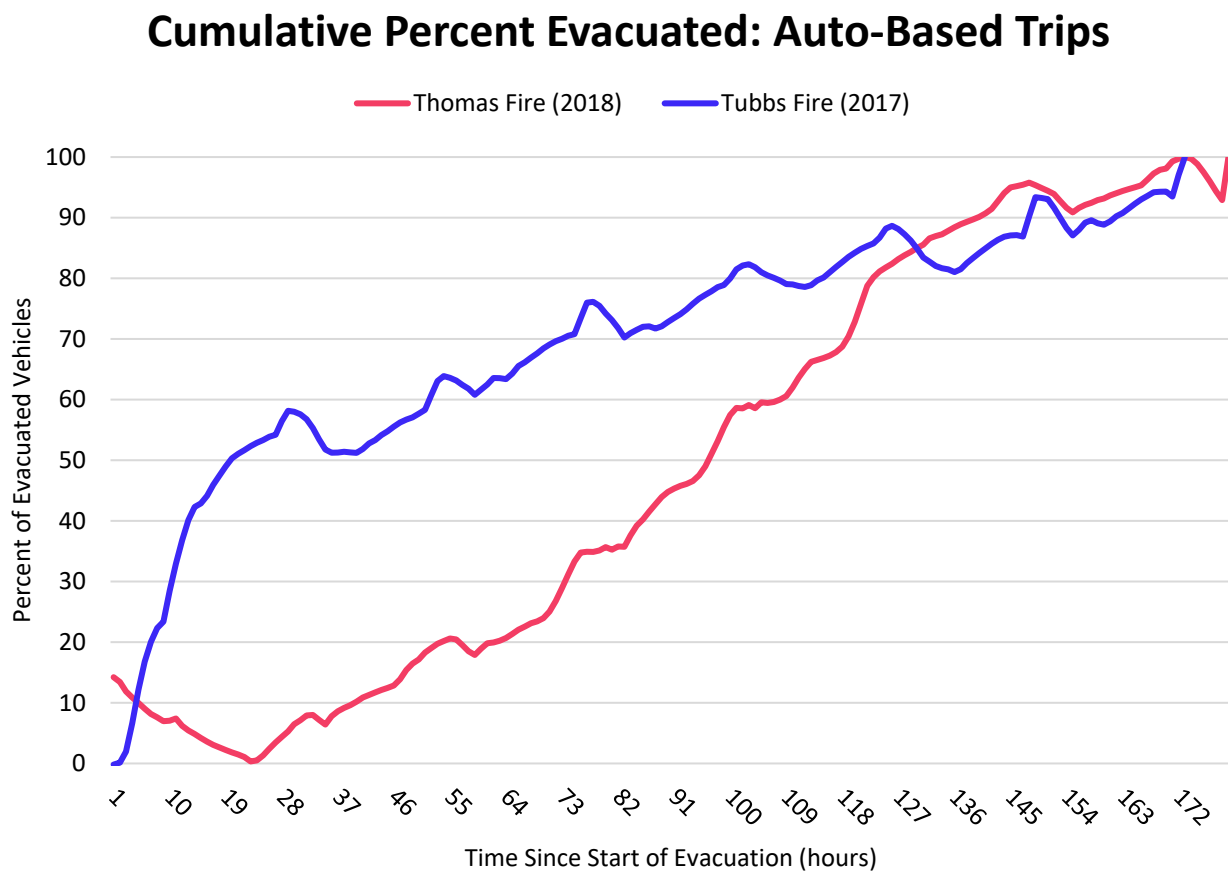| Regions	All Times Shown Relative to Fire Start		
	Evac. Initiated (τ)	Peak Hours (t_p)	Evac. Reentry (T)
Tubbs Fire (2017)	1d, 23hr	0d, 10hr	N/A*
Thomas Fire (2018)	2d, 3hr	3d, 0hr	N/A*

*exact value not able to be determined

Figure 21. Cumulative Percentage of Auto-Based trips comparing Tubbs and Thomas Fires in the state of California

Figure 21 shows the cumulative percent of evacuated vehicles since the start of the evacuation. Since the analysis does not include a true cordon line, but a screen line point, the cumulative amounts of vehicles evacuating are not accurate. However, the actual time shown in the following graph is accurate for time it took the vehicles to exit the area. The graph does not show the reentry event because the reentry data was not available for analysis since the data is not reliable. Tubbs Fire evacuation order and real evacuation event was effective, Figure 21 shows that the 30 percent of the vehicles started evacuating within 10 hours. On the other hand, Thomas Fire evacuation about 30 percent of the vehicles evacuated within 73 hours of the start of the evacuation, vehicles took longer to evacuate compared to Tubbs Fire.

Figure 22. Fires nearby the Thomas Fire that occurred either prior or subsequently after Thomas Fire.

Chapter V

Discussion, Conclusions, and Recommendations

Often, the perceived success of an evacuation, or lack thereof, is based on media reports, anecdotal observation or, worse, rumors and social media discussion. In reality, a highly effective evacuation could be assumed a failure because of a few limited but highly visible areas of congestion. This has suggested the need for a better way to describe and assess large statewide evacuations in more systematic and objective ways. Unfortunately, this is not easy to accomplish because there are few, if any, data records or performance measures generated that accurately and effectively describe the conditions of these events. In fact, there is no standardized methodology to quantify the characteristics of an evacuation that is transferable and repeatable between state departments of transportation.

Fortunately, there are many commonly used data measures for analyzing routine transportation conditions. The intent of this work was to adapt and apply them to develop a method capable of describing mass evacuations. In fact, these methods can also be applied to describe evacuation reentry traffic patterns; a historically lightly studied area in practice and research. The results of this effort showed these methods could be quite effective to illustrate statewide temporal and spatial trends of traffic movement as well as infer evacuee behavioral responses and threat interpretation.

Results of the application of the research methodology showed that the evacuations from Hurricane Irma and Michael began several days before landfall. They further suggest that Michael evacuees, presumably in low-lying coastal regions prone to flooding, began evacuating as much as seven days before landfall. Similarly, vulnerable residents in Florida Keys started their evacuations five days before Hurricane Irma's landfall with nearly 20 percent departing

prior to the mandatory evacuation order. This observation was unexpected because prior survey results suggested that a two-day loading was most likely (Baker, 2010). In general, the evacuations peaked two to three days before landfall and between the hours of 8:00 AM and 3:00 PM confirming prior research that suggested a preference for morning departures (Lindell, Murray-Tuite, Wolshon, & Baker, 2019). In addition, the largest reentry time relative to landfall for these 5 regions was 20 days, it can be concluded that since the region was the Florida Keys is a vulnerable region in the state of Florida than most regions because of the infrastructures and possible flooding and destruction took longer for the residents to travel back to their origin. From an emergency preparedness standpoint, these trends are positive and suggest an increased civic awareness of hazard risk perception.

The research also found that half of the auto-based evacuees from Southeast Florida and the Naples region were displaced for up to five days. The 50th percentile displacement time for Florida Keys residents, which evacuated by car saw significantly longer displacement times of over 11 days. When comparing stated choice survey results taken from Florida Keys' residents, the predicted participation rates suggested an upper bound of evacuating vehicles that was reasonably accurate to the Hurricane Irma evacuation; given the uncertain path and intensity of the storm.

The wildfire application with the research methodology showed that the evacuations from Thomas Fire and Tubbs Fire began shortly after the mandatory evacuation announcement was published. With the dry environment that the state of California has the fire spreads quickly and for safety evacuees need to make a quicker decision than those evacuees in the state of Florida. Tubbs Fire had about 43,000 vehicles that evacuated between October 17th and October 18th, while there was about 90% of the fire being contained. Tubbs fire mandatory evacuation

announcement were given a day after the fire broke out and people did not evacuate until about 23 hours following the orders, on the emergency preparedness perception, the residents were proactive and quickly on the evacuation orders given when dealing with a rapidly fire spread. Thomas Fire mandatory evacuation announcement for Ventura County was announced December 4th in the evening and about 87,000 residents evacuated between Tuesday and Thursday. On the other hand, while the fire started spreading to Santa Barbara County, their government officials announced to start evacuating the area on December 21st at 9:00 PM and about 95,000 residents evacuated shortly after (Guerin, 2017). Thomas Fire's mandatory evacuation was given within 24 hours following the fire start and immediately after, the residents evacuated within 10 hours of the evacuation orders.

These two phenomena have several differences in terms of intensity, paths, resident's preparedness, and traffic pattern. Hurricane Irma and Michael had very different paths which affected their evacuation patterns before and during the time evacuation occurrence. These paths changed the trajectory of the evacuees on their destination, similarly to the traffic pattern of evacuees, the fires surrounding the area affected the traffic pattern of the evacuees in the state of California for both wildfires. The intensity of both hurricanes were unique which affected the times the evacuees decided to evacuate, however the wildfires had no sign of any affected times before the evacuation started. By comparison, the evacuation orders were communicated differently in both cases. The hurricane mandatory evacuations were given about 3-5 days in advance, which made many residents decide their destination depending on the predicted path of the storm and evacuated between 5-7 days prior to landfall. Wildfires' mandatory evacuations were given within a day after the fire and minimal containment started, which is the analysis shows that as soon as the orders were given residents evacuated immediately. In addition, the

categorized start of the evacuation on both fires were within 24 hours of the evacuation orders. Since the results did not show effects of the pre evacuation events for the wildfires but showed that as soon as the announcements were communicated, the assumption is that evacuees waited for the evacuation orders. On the other hand, the hurricane analysis did show that residents evacuated ahead of time, which was categorized as the pre evacuation traffic. In addition, the quick response of the wildfire cases compared to the hurricane cases is related to the intensity, region, access, and spread of the both phenomenon.

Reentry could not be predicted or categorized in any of the Hurricane Michael and California wildfire analysis or data because of limited access as well as inconsistent acquired data for detectors. There are some assumptions that can made for the wildfire evacuations since there were a couple of fires that took place around the studied regions. The analysis shows that there was an in-flow number of vehicles during the reentry but were not totaling to the commutative numbers of vehicles that were presented before the fire broke out. On the other hand, Hurricane Michael's reentry analysis and data set showed that the acquired information was not reliable since the detectors that were considered were working correctly before and some time during the storm.

Recommendations

This research provides a system for state departments of transportation and emergency management officials to analyze future auto-based evacuations. The method also facilitates parametric comparisons between evacuation events, an area needed to continue to evolve and improve evacuation practice. Standardize measures for hurricane evacuations are needed to facilitate systematic evaluations of performance. Future researchers could build upon methods presented here to develop a level-of-service (LOS) analysis for emergency evacuations. This

would be similar to the way the highway Capacity Manual uses the standardized collection and processing of freeway densities for its LOS evaluations. With additional research, the methods laid out in this paper could also lead to a more comprehensive understanding of evacuation traffic processes and behavioral responses to improve their planning and management.

References

Abu-Orf, M., Bowden, G., & Pfrang, W. (2014). *Wastewater Engineering, Treatment and Resource Recovery.* New York: McGraw-Hill Education .

Alvarez, L., & Santora, M. (2017). *"Hurricane Irma Barrels Toward U.S., Threatening to Engulf Florida".* The New York Times.

Archibald, E., & McNeil, S. (2012, July). Learning from Traffic Data Collected Before, During, and After a Hurricane. *IATSS Research*, 1-10. Retrieved from https://www.sciencedirect.com/science/article/pii/S0386111212000222?via%3Dihub

Associated Press. (2017, October 2). *"Curfew Lifted in Florida Keys 3 Weeks After Hurricane Irma.".* Retrieved from U.S. News & World Report, U.S. News & World Report: www.usnews.com/news/best-states/florida/articles/2017-10-02/curfew-lifted-in-florida-keys-3-weeks-after-hurricane-irma

Baker, E. (2010). *Statewide Regional Evacuation Study Program: Volume 2-11 South Florida Region Regional Behavioral Analysis.* Retrieved from (United States, Florida Division of Emergency management, South Florida Regional Planning Council): http://www.sfrpc.com/SRESP Web/Vol2-11.pdf

Beloglazov, A., Almashor, M., Abebe, E., Richter, J., & Barton Steer, K. C. (2016). Simulation of Wildfire Evacuation with Dynamic Factors and Model Composition. *Simulation Modelling Practice and Theory 60*.

Beven, J. L., Berg, R., & Hagen, A. (2019). *National Hurricane Center: Tropical Cyclone Report: Hurricane Michael (AL142018).* United States, National Oceanic and Atmospheric Administration (NOAA), Nation Hurricane Center.

Boyd, E., Wolshon, B., & Heerden, I. (2014). *Risk Communication and Public Response During Evacuations: The New Orleans Experience of Hurricane Katrina.* Taylor Francis Online.

Brachman, M. L. (2012). *Modeling Evacuation Vulnerability.* ProQuest LLC.

Cal Fire. (2018). *Top 20 Most Destructive California Wildfires.* Los Angeles: State of California.

CalTrans. (2018). CalTrans PeMS Database. Los Angeles, CA, U.S.: California Department of Transportation.

Cambridge University Press. (n.d.). Retrieved from Cambridge Dictionary: https://dictionary.cambridge.org/us/dictionary/english/wildfire

Chou, Y. H. (2007). *Management of wildfires with a geographical information system.* International Journal of Geographical Information System.

Chruch, R. L., & Cova, T. J. (2000). *Mapping Evacuation Risk on Transportation Networks Using a Spatial Optimization Model.* Elsevier Science Ltd.

Cova, T. J., Theobald, D. M., Norman III, J. B., & Siebeneck, L. K. (2011). *Mapping wildfire evacuation vulnerability in the western US: the limits of infrastructure.* Springer US.

Dixit, V., & Wolshon, B. (2014). *Evacuation Traffic Dynamics.* Louisiana: Transportation Research Part C.

Downs, P., Prusaitis, S., Germain, J., & Baker, J. (2010). *Statewide Regional Evacuation Program: Volume 3-11 South Florida Region Regional Behavioral Survey Report.* Retrieved from United States, Florida Division of Emergency Management, South Florida Regional Planning Council: https://www.sffrpc.com/SRESP Web/Vol3-11.pdf

Federal Emergency Management Agency. (n.d.). *Communicating in an Emergency.* Retrieved

   from FEMA:

   https://training.fema.gov/emiweb/is/is242b/student%20manual/sm_03.pdf

Florida Division of Emergency Management. (n.d.). *Disaster Preparedness Maps*. Retrieved

   from Florida Disasters: https://floridadisaster.org/plan--prepare/disaster-

   preparedness-maps/

Haddad, K. (2018, October 10). *List of Mandatory Evacuation Zones in Florida Ahead of*

   Hurricane Michael. Retrieved from

   https://www.clickondetroit.com/weather/hurricane/list-mandatory-evacuation-zones-

   in-florida-ahead-of-hurricane-Michael

Han, L. D., Yuan, F., & Urbanik II, T. (2007). *What Is An Effective Evacuation Operation?*

   American Society of Civil Engineers.

Helsel, P. (2017, December 22). *U.S. News Southern California's Thomas Fire Now Largest in*

   State History. Retrieved from NBC News:

   https://www.nbcnews.com/storyline/western-wildfires/southern-california-s-thomas-

   fire-now-largest-state-history-

   n832296#targetText=The%20Thomas%20Fire%20has%20destroyed,so%20far%2C%20t

   he%20agency%20said.

International Federation of Red Cross and Red Crescent Societies. (n.d.). Retrieved from Types

   of Disasters: Definition of hazard: https://www.ifrc.org/en/what-we-do/disaster-

   management/about-disasters/definition-of-hazard/

Jansen, B. (2017, September 10). *"Timeline: Hurricane Irma's Progress to Monster Storm.".*
Retrieved from USA Today, Gannett Satellite Information Network:
www.usatoday.com/story/news/2017/09/10/timeline-hurricane-irma-fluctuating-
strgrowing-stronger-weaker-crashed-into-caribbean-islands-florid/651421001/

KPCC Staff. (2017, September 25). Canyon Fire Prompts evacuations, Backs Up Traffic on
Anaheim-Area Freeways. *Southern California Public Radio (SCPR).*

Lai, K. R., Watkins, D., & Wallance, T. (2017, December 8). Where the Fires Are Spreading. *The
New York Times.*

Li, D. (2016). *Modeling Wildfire Evacuation As Coupled Human-Environmental System Using
Triggers.* ProQuest LLC.

Li, D., Cova, T. J., & Dennison, P. E. (2018). *Setting Wildfire Evacuation Trigger Coupling Fire
and Traffi Simulation Models: A Spatiotemporal GIS Application.* Springer US.

Li, J., & Ozbay, K. (2014). *Hurricane Irene Evacuation Traffic Patterns in New Jersey.* Natural
Hazards Review.

Li, J., Ozbay, K., & Bartin, B. (2015). *Effects of Hurricanes Irene and Sandy in New Jersey: Traffic
Patterns and Highway Disruptions During Evacuations.* Natural Hazards.

Li, J., Ozbay, K., Bartin, B., Iyer, S., & Carnegie, J. (2013). *Empirical Evacuation Response Curve
During Hurricane Irene in cape May County, New Jersey.* Transportation Research
Record.

Lindell, M. K., & Prater, C. S. (2007). *Critical Behavioral Assumptions in Evacuation Time
Estimate Analysis for Private Vehicles: Examples from Hurricane Research and
Planning.* Journal of Urban Planning and Development.

Lindell, M. K., Kang, J. E., & Prater, C. S. (2011). *the Logistics of Household Hurricane Evacuation.* Natural Hazards.

Lindell, M. K., Murray-Tuite, P., Wolshon, B., & Baker, E. J. (2019). *Large-scale Evacuation: The Analysis, Modeling, and Management of Emergency Relocation from Hazardous Areas.* New York: Taylor and Francis.

Marshall, A. (2017). *4 Maps That Show the Gigantic Hurricane Irma Evacuation*. Retrieved from https://www.wired.com/2017/09/4-maps-show-gigantic-hurricane-irma-evacuation

McCaffrey, S., Rhodes, A., & Stidham, M. (2013). *Wildfire evacuation and its alternatives: perspectives from four United States' communities.* International Journal of Wildland Fire.

Miller, H. J., & Wentz, E. A. (2008). *Representation and Spatial Analysis in Geographic Information Systems.* Annals of the Association of American Geographers.

National Oceanic Atmosphere Administration. (n.d.). *IRMA Graphics Archive*. Retrieved from NOAA: https://www.nhc.noaa.gov/archive/2017/

O'Brien, D. W. (n.d.). *Evaluating Data for the Purpose of Wildland Fire Evacuation Planning.* Washington: Clark County Fire District 3.

O'Connor, A. (2017, December 4). *"Florida's Hurricane Irma Recovery: The Cost, The Challenges, The Lessons.".* Retrieved from Insurance Journal: www.insurancejournal.com/news/southeast/2017/11/30/472582.htm.

Pel, A. J., Bliemer, M. C., & Hoogendoorn, S. P. (2012). *A Review on Travel Behavious Modelling in Dynamic Traffic Simulation for Evacuations.* Springer US. Retrieved June 8, 2019

Potts, K. E., Bennett, R. M., & Rajabifard, A. (2013). *Spatially Enabled Bushfire Recovery.* Springer Netherlands.

Roberson. (2018, October 8). *Hurricane Michael: First Florida Evacaution Ordered in Gulf County, Others in Panhandle.* Retrieved from https://www.tallahassee.com/story/news/2018/10/08/hurricane-michael-florida-evacaution-gulf-county-panhandle-wakulla-bay-mandatory/1567904002

Sadri, A. M., Ukkusuri, Ph.D., S. V., Murray-Tuite, Ph.D., P., & Gladwin, Ph.D., H. (2014). *Hurricane Evacuation Routing Strategy from Miami Beach: Choice of Major Bridges.* Miami: Transportation Research Record.

Sommer, L. (2017). As California's Population Grows, People Are Moving Into More Fire-Prone Areas. *National Public Radio.*

Stephens, S. L., Adams, M. A., Handmer, J., Kearns, F. R., Leicester, B., Leonard, J., & Moritz, M. A. (2009). *Urban–Wildland Fires: How California and Other Regions of the US Can Learn From Australia.* IOP Science.

Teodoro, A. C., & Duarte, L. (2012). *Forest Fire Risk Maps: A GIS Open Source Application – A Case Study In Norwest of Portugal.* international Journal of Geographical Information Science.

Thompson, R. R., Garfin, D. R., & Silver, R. C. (2016). Evacuation from Natural Disasters: A Systematic Review of the Literature. *Risk Analysis / Volume 37, Issue 4.*

U.S. Census Bureau QuickFacts: Monroe County, Florida. (2018). Retrieved from https://www.census.gov/quickfacts/monroecountyflorida

United States, National Oceanic and Atmospheric Administration (NOAA), Nation Hurricane

    Center. (2018). Retrieved from MICHAEL Graphics Archive: 5-day Forecast Track, Initial

    Wind Field and Watch/Warning Graphic:

    https://www.nhc.noaa.gov/archive/2018/MICHAEL_graphics.php?product=5day_cone

    _with_line_and_wind

Wile, R. (2017, September 11). *"Hurricane Irma, Harvey: AccuWeather's Economic Cost*

    Estimate | Money.". Retrieved from Time, Time: time.com/money/4935684/hurricane-

    irma-harvey-economic-cost/

Wolshon, B. (2008). *Empirical Characterization of Mass Evacuation Traffic Flow.* New Orleans:

    Transportation Research Record: Journal of the Transprtation Research Board.

Wolshon, B., & Dixit, V. V. (2012). *Traffic Modeling and Simulation for Regional Multimodal*

    Evacuation Analysis. New Orleans: Inderscience Enterprise Ltd.

Wolshon, B., & McArdle, B. (2009). *Temporospatial Analysis of Hurricane Katrina Regional*

    Evacuation Traffic Patterns. New Orleans: Journal of Infrastructure Systems ASCE.

Wolshon, B., & McArdle, B. (2011). *Traffic Impacts and Dispersal Patterns on Secondary*

    Roadways during Regional Evacuations. New Orleans: Natural Hazards Review ASCE.

Wolshon, B., Boyd, E., & Heerden, I. V. (2009). *Risk Communication and Public Response*

    During Evacuations: The New Orleans Experience of Hurricane Katrina. Louisiana: M.E.

    Sharpe, Inc.

Wolters, C. (2019, August 9). *National Geographic*. Retrieved from Climate 101: Wildfires:

   https://www.nationalgeographic.com/environment/natural-disasters/wildfires/

Wu, H.-C., Lindell, M. K., & Prater, C. S. (2012). *Logistics of Hurricane Evacuation in hurricanes Katrina and Rita.* Transportation Research Part F.

Zhang, Y., Lim, S., & Sharples, J. J. (2015). *Modelling Spatial Patterns of Wildfire Occurance in South-Eastern Australia.* Journal Geomatics, Natural Hazards and Risk.
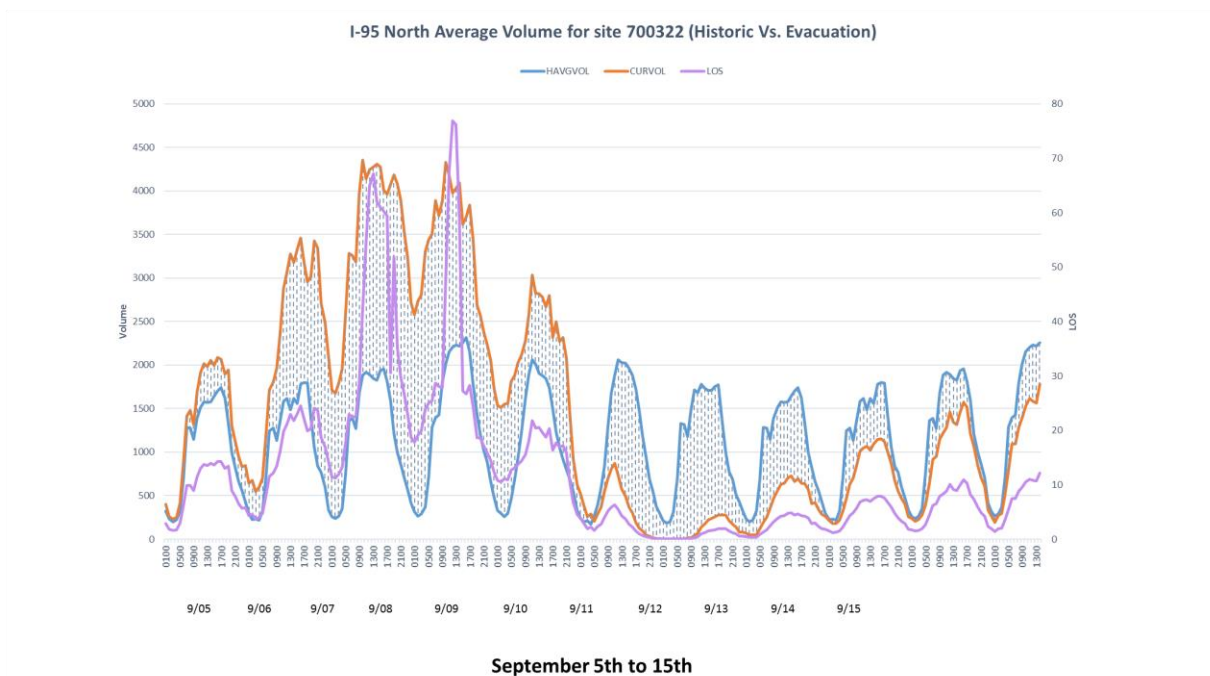
Appendix A

Hurricane Irma (2017) and Hurricane Michael (2018)
Graphical Illustrations per Detectors

Examples of the micro analysis on the Irma evacuation by sites, congested, not congested, with either high or low volumes:
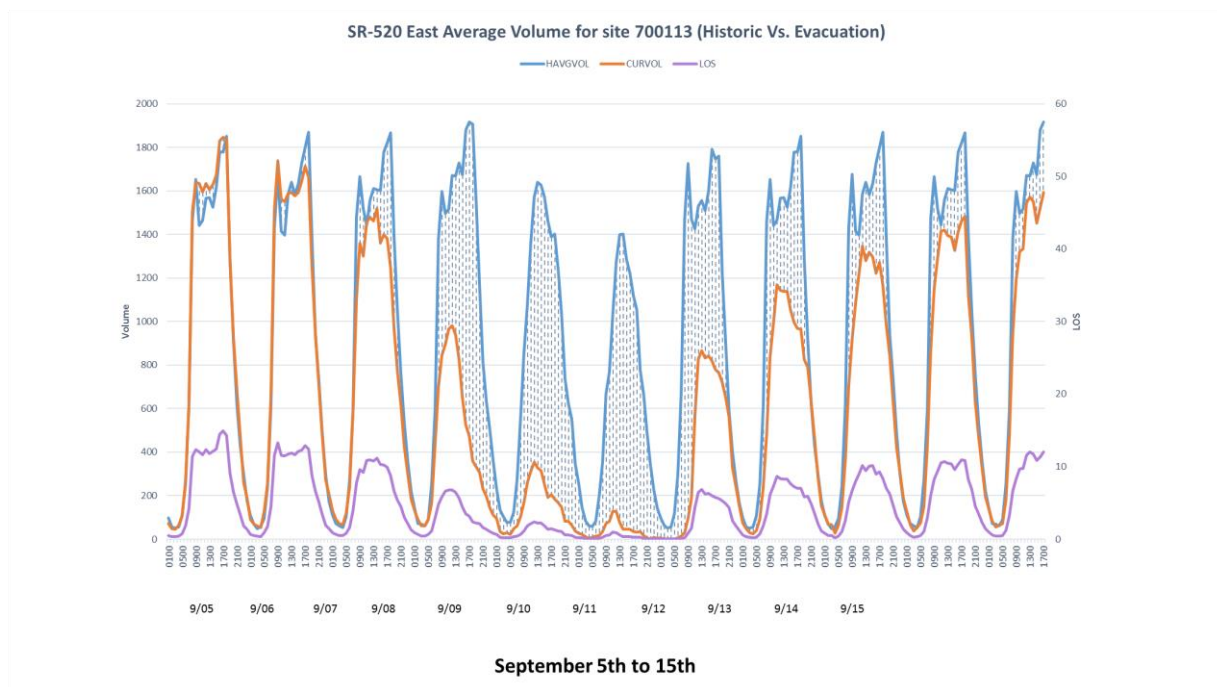
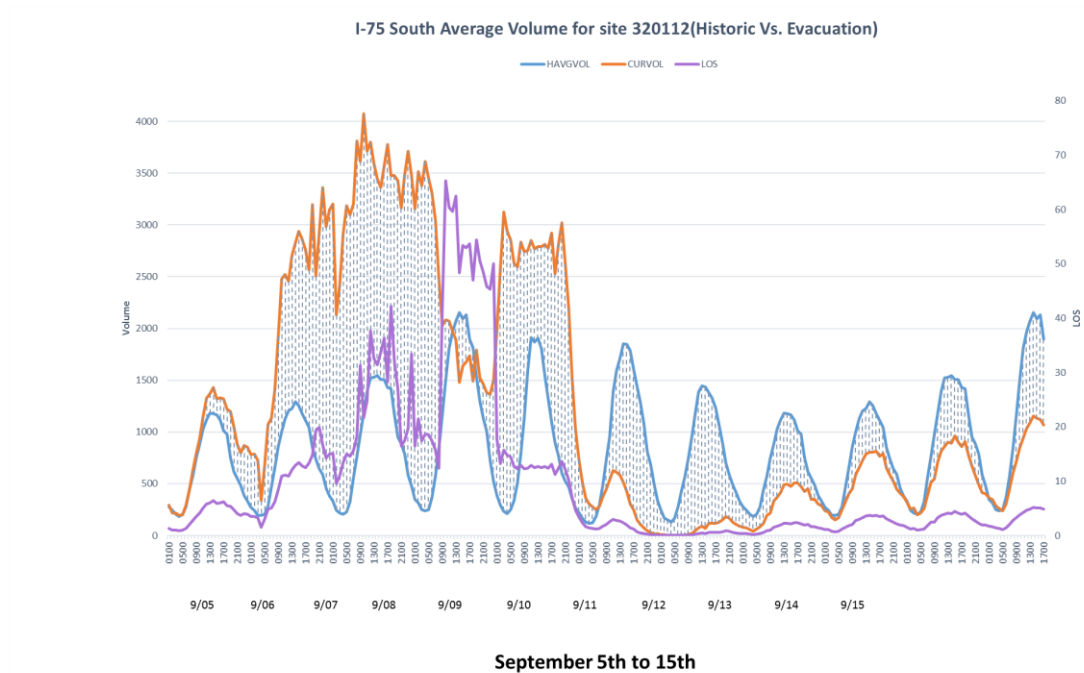A high volume not congested during evacuation:
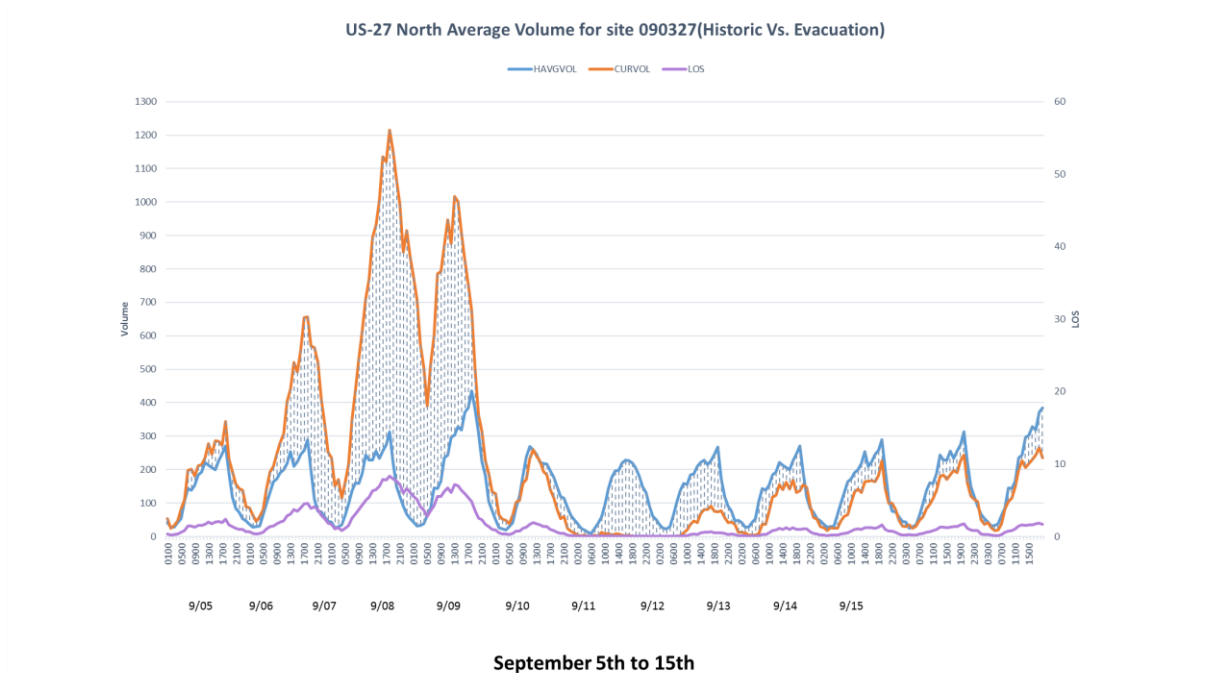
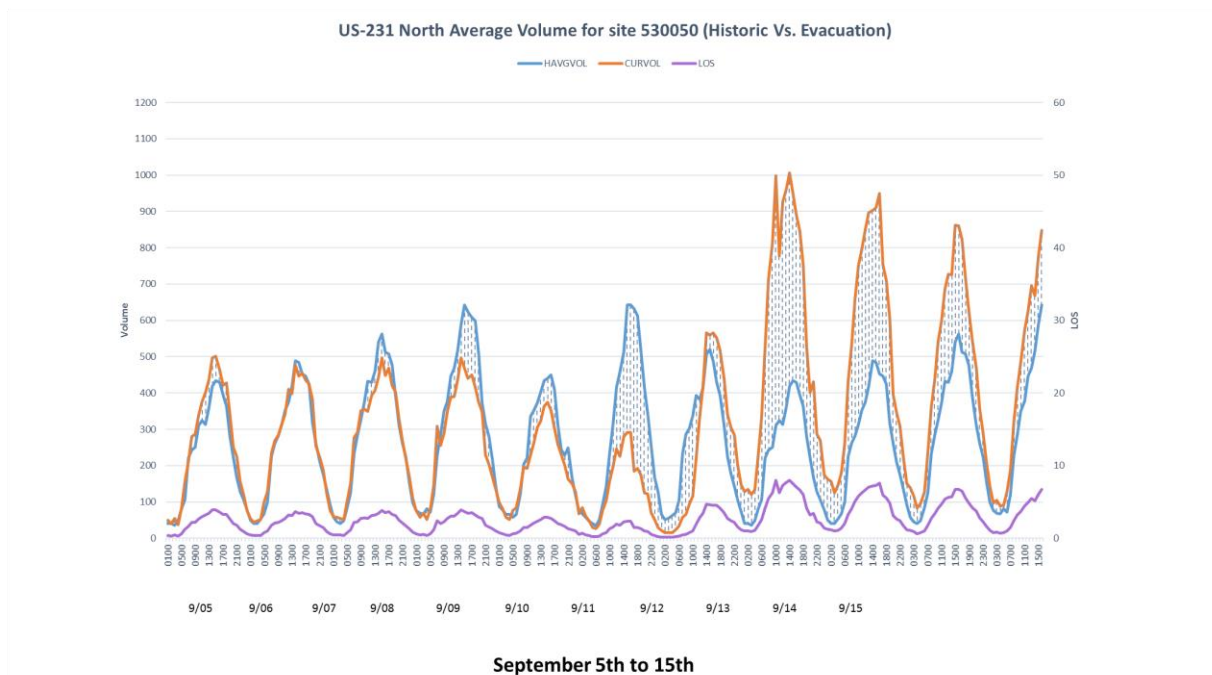A high volume congested during evacuation:

A low volume not congested during evacuation:
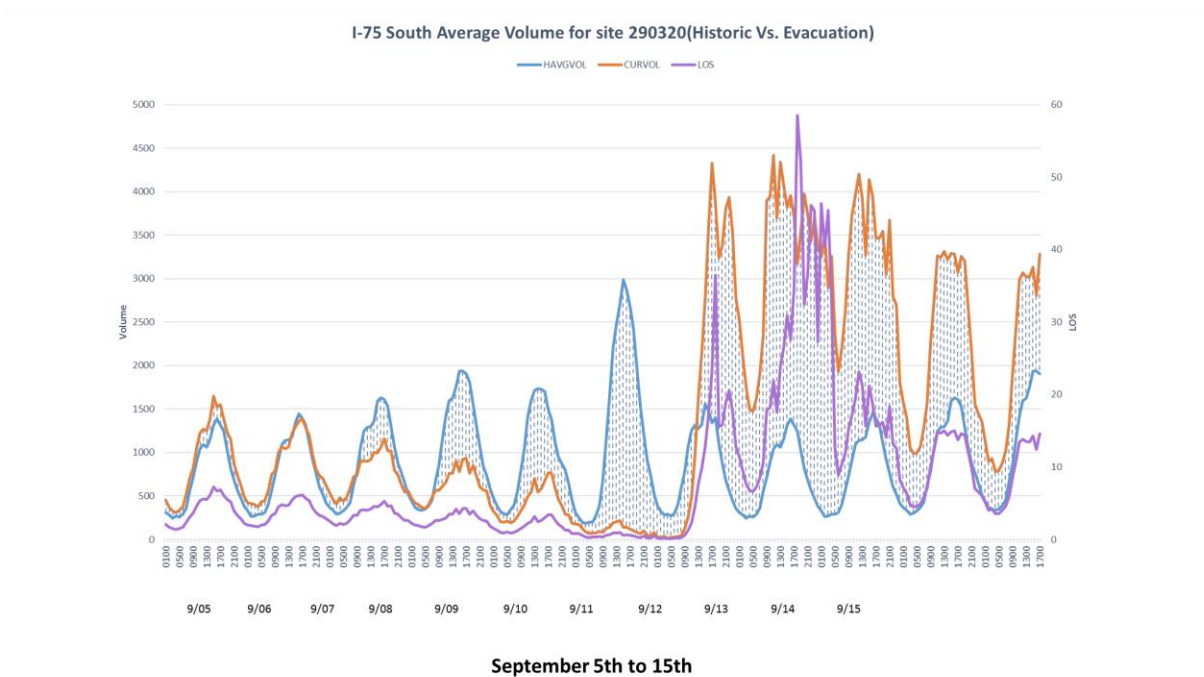

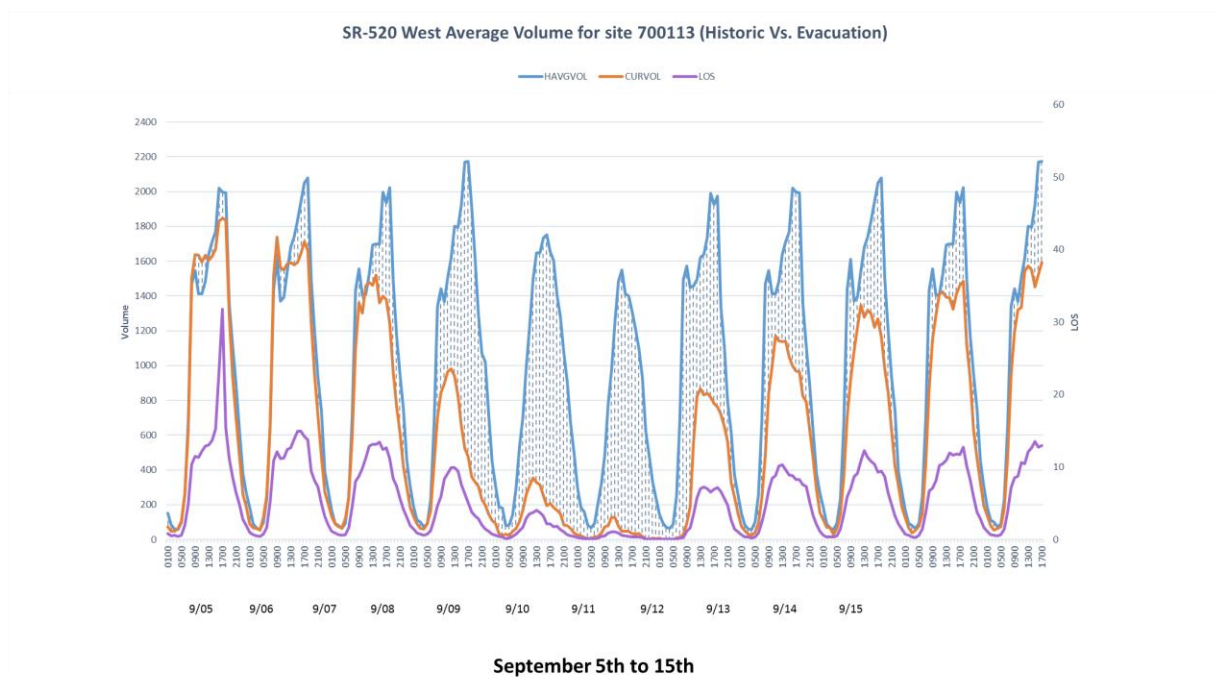A low volume congested during evacuation:

A high volume not congested during re-entry:
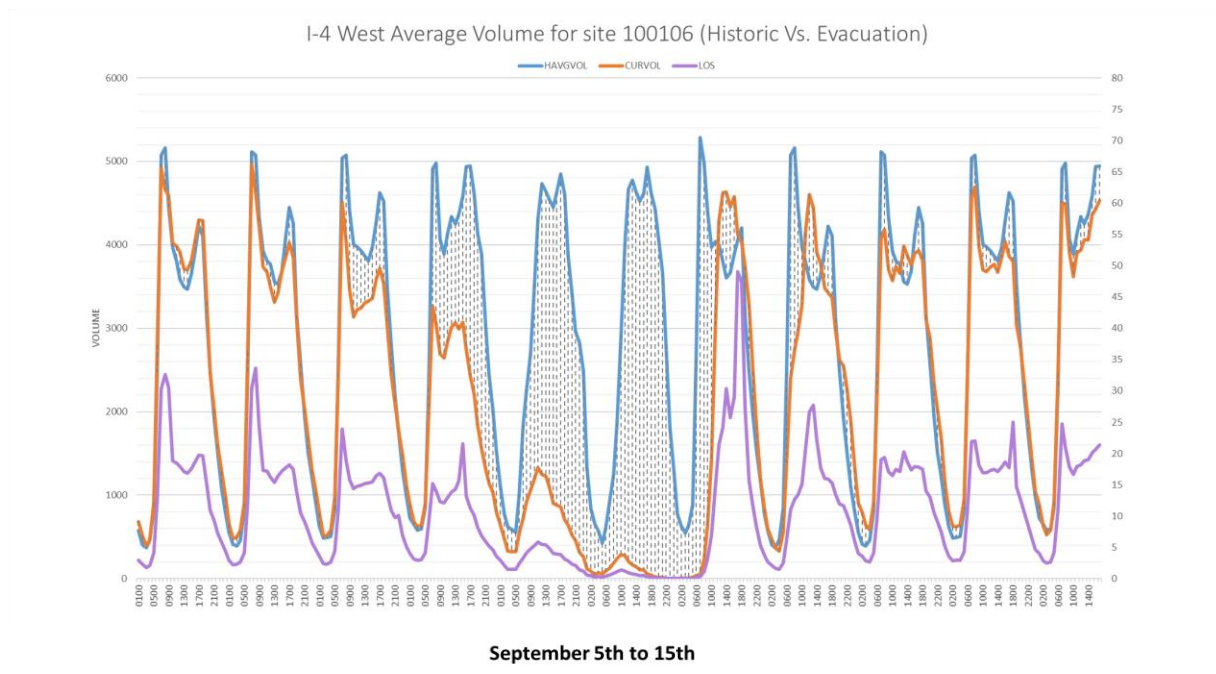

A high volume congested during re-entry:

A low volume not congested during re-entry:

A low volume congested during re-entry:

Appendix
Tubs Fire (2017) and Thomas Fire (2018)
Graphical Illustrations per Detectors

Outbound Regional Traffic: Tubbs Fire 2017
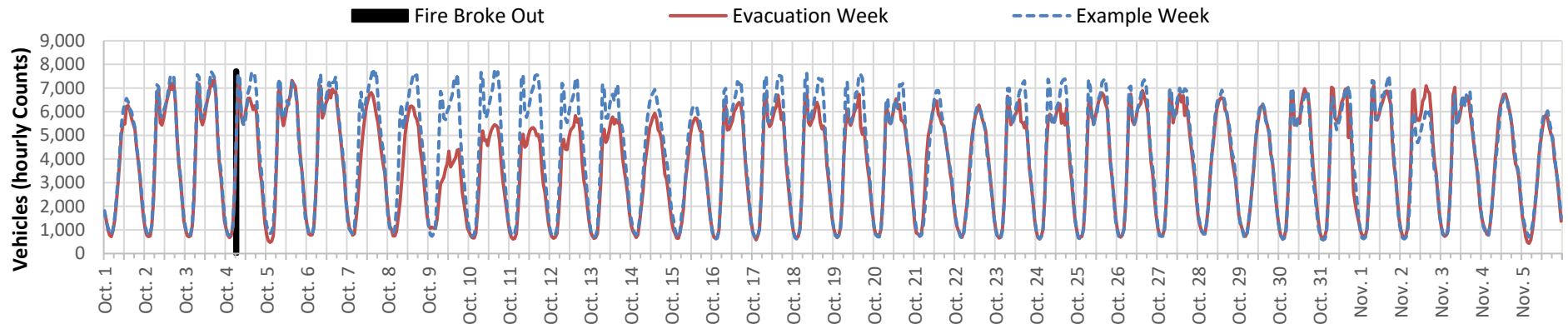
Inbound Regional Traffic: Tubbs Fire 2017
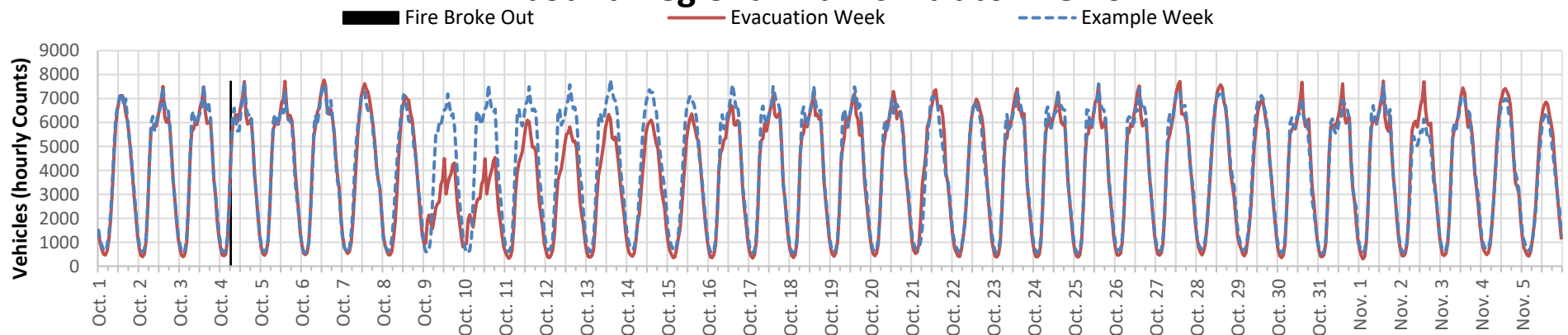
Egress: Tubbs Fire 2017
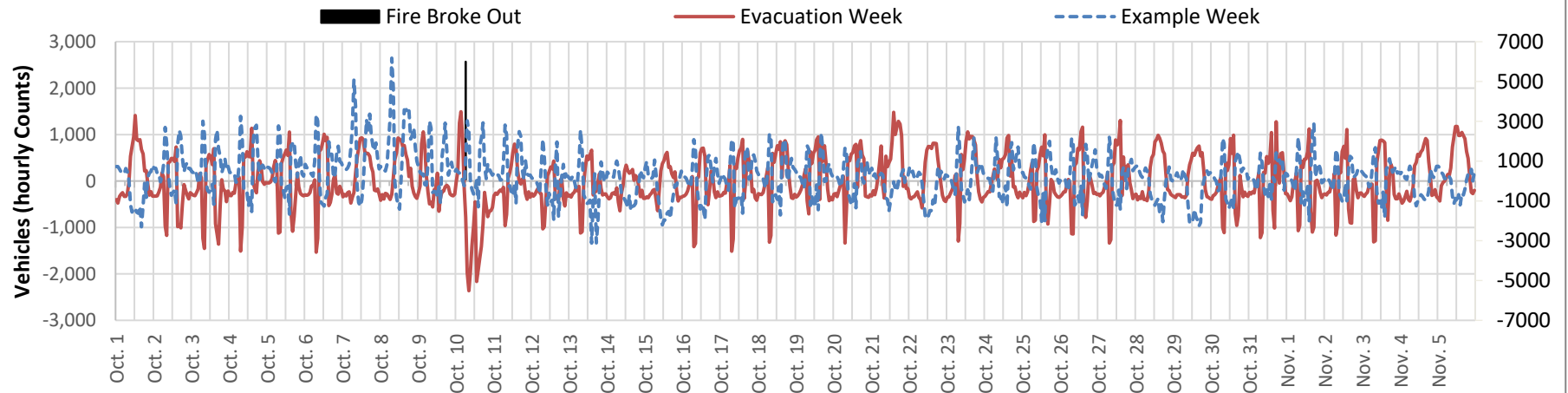
Cumlative Egress: Tubbs Fire 2017
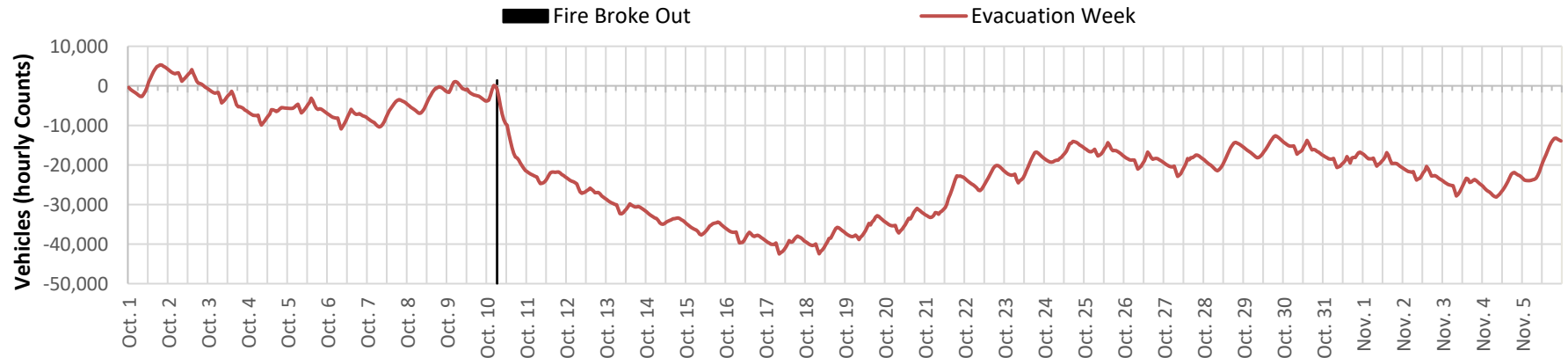
Inbound Regional Traffic: Thomas Fire 2018

■ Fire Broke Out ——— Evacuation Week ——— Example Week

Outbound Regional Traffic: Thomas Fire 2018

■ Fire Broke Out ——— Evacuation Week ——— Example Week
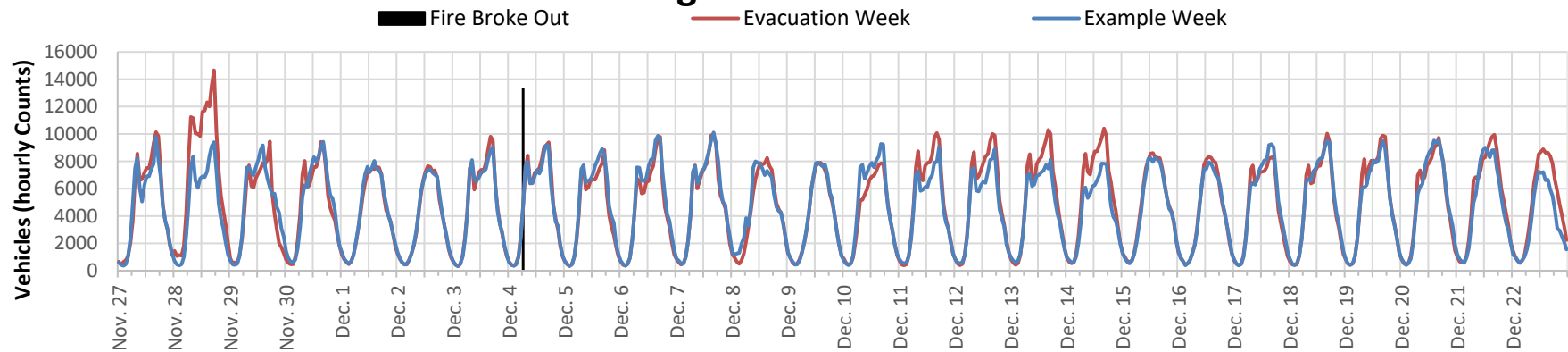
Egress: Thomas Fire 2018
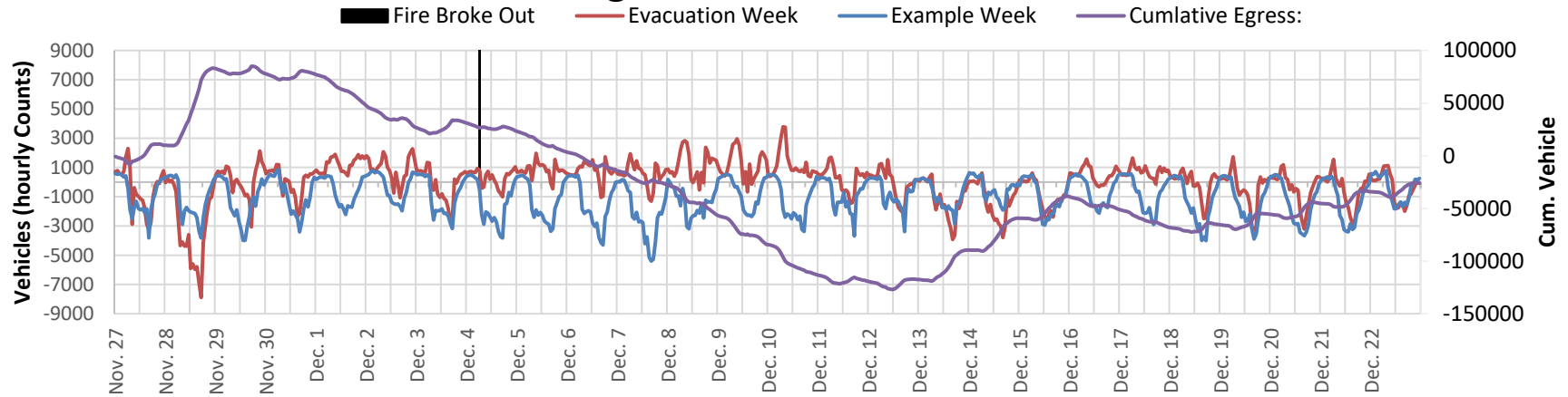
Cumlative Egress: Thomas Fire 2018

Appendix C
Maps and Figures

Location
of fire

San
Francisco

CALIFORNIA

Los
Angeles

SHOWN ON MAP
Destroyed structures
visible in satellite imagery
Deaths

Extent of the Tubbs fire
on Oct. 10

N

The Tubbs fire started
on Oct. 8 around
9:43 p.m.

Approximate edge of fire at
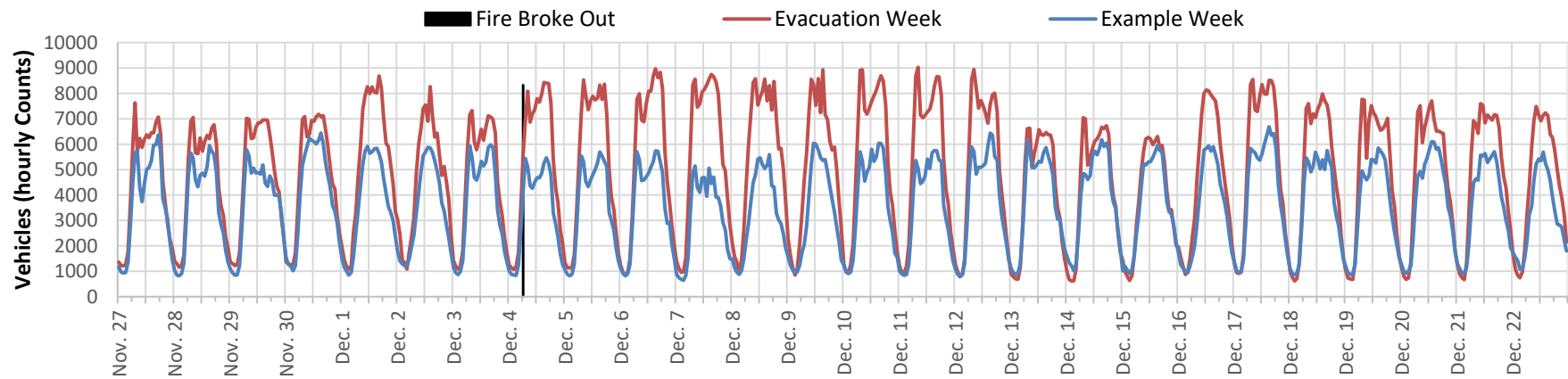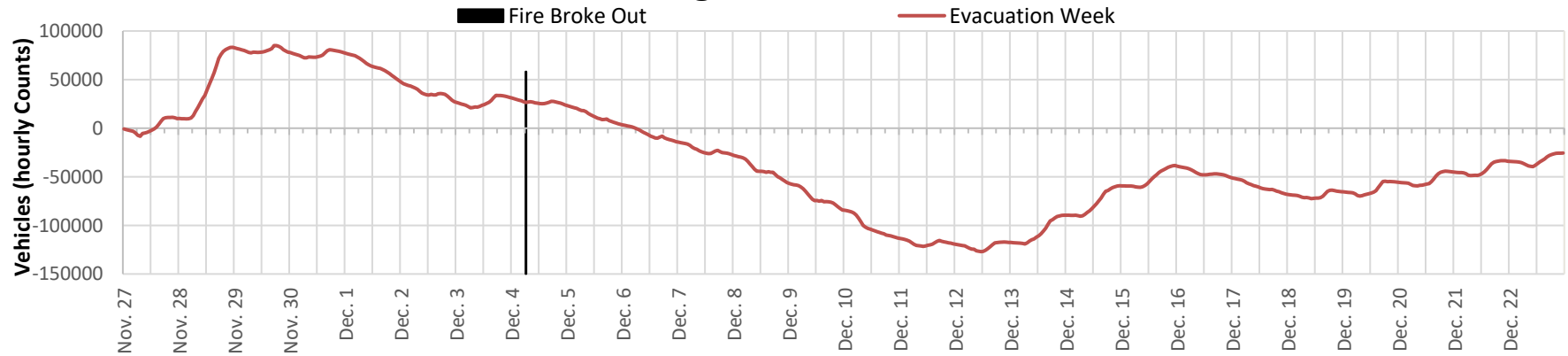**10:30 p.m.**

TO CALISTOGA

11 p.m.

At 10:52 p.m., firefighters called for
a mandatory evacuation of all of
Porter Creek Road and Petrified
Forest Road.

Petrified Forest Road

Michael Dornbach, 57,
died while visiting family
and friends in the area.

At 11:58 p.m., firefighters
called for an evacuation of the
entire area between Calistoga
and Santa Rosa.

HALF MILE

Porter Creek Road

12 a.m.

1 a.m.

At 1:12 a.m., firefighters
warned that the fire would
reach eastern Santa Rosa
within an hour.

Monte Kirven, 81,
died at home.
Veronica McCombs,
67, died at home.

Lynne Powell, 72,
died while fleeing
her home.

Carmen Berriz, 75, died in a
backyard pool in the arms of her
husband, who survived.

2 a.m.

Sharon Robinson,
79, died at home.

Mike Grabow, 40,
died at home.

3 a.m.

Arthur Grant, 95, and **Suiko
Grant**, 75, died in their wine
cellar.

Christina Hanson, 27,
who used a wheelchair,
died at home.

CITY LIMITS

FOUNTAINGROVE

LARKFIELD-WIKIUP

Donna Halbur, 80, died
in her garage. **Leroy
Halbur**, 80, died on the
driveway.

Carmen McReynolds,
82, died in her garage.

101

Valerie Evans, 75, died while
trying to save her dogs.

Carol Collins-Swasey, 76,
died in her house.

Marilyn Ress, 71, died
in her bedroom.

Linda Tunis, 69, died in her
home in a mobile-home
community.

Karen Aycock,
56, died in her
bathroom.

COFFEY
PARK

60 MILES TO
SAN FRANCISCO

101

SANTA ROSA