MARITIME TRANSPORTATION RESEARCH AND EDUCATION CENTER
TIER 1 UNIVERSITY TRANSPORTATION CENTER
U.S. DEPARTMENT OF TRANSPORTATION

Evacuation Behavior and its Mobility Impacts in Coastal Communities from Across the Nation

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December 2023
FINAL RESEARCH REPORT
Prepared for:
Maritime Transportation Research and Education Center

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Acknowledgements

This material is based upon work supported by the U.S. Department of Transportation under Grant Award Number 69A3551747130. The work was conducted through the Maritime Transportation Research and Education Center at the University of Arkansas.

Disclaimer

The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented herein. This document is disseminated in the interest of information exchange. The report is funded, partially or entirely, by a grant from the U.S. Department of Transportation's University Transportation Centers Program. However, the U.S. Government assumes no liability for the contents or use thereof.

Abstract

Mass evacuations, especially at the statewide level, present formidable challenges in traffic management, often characterized by extensive delays and congestion. This paper introduces an innovative analytical method designed for the cost-effective measurement and comprehensive description of such large-scale evacuations. By utilizing straightforward and widely available traffic count datasets, the research delves into critical aspects of evacuation scenarios, addressing key questions pertaining to events like Hurricane Irma and Michael in Florida, as well as Tubbs and Thomas Fire evacuations in California. The analytical approach enables the estimation of the onset and conclusion of auto-based evacuations, understanding loading and peaking traffic characteristics, and determining the total number of vehicles involved in the evacuation process. Additionally, it delineates the effective start and end of the auto-based reentry phase.

Building upon prior efforts to quantify evacuation impacts, this research is unique in its dual investigation of hurricane evacuations in Florida and wildfire evacuations in California. By encompassing these distinct scenarios, the study offers valuable insights that contribute to a more comprehensive understanding of the complexities involved in large-scale evacuations. The findings not only enhance our preparedness and response strategies for future events but also provide a versatile framework that can be adapted by state departments of transportation and emergency management officials for diverse evacuation scenarios.

1. Introduction

Mass evacuations, particularly at the statewide level, constitute singular traffic events with intricate dynamics. These elaborate transportation scenarios, spanning several days and covering vast networks of roadways, involve hundreds of thousands of individuals and vehicles urgently seeking safety. Unfortunately, these operations are often marred by significant travel delays, congestion, and persistent criticism for their perceived inefficiency and lack of effective management. Regrettably, there is a scarcity of comprehensive studies that quantitatively analyze these events to objectively evaluate the actual travel conditions. Opinions are typically shaped by media reports that tend to sensationalize shortcomings, focusing primarily on areas experiencing difficulties.

The lack of in-depth studies on mass evacuations can be attributed to their sheer size and complexity, compounded by the absence of standardized methods to systematically quantify traffic characteristics at an appropriate scale. Few indicators, aside from the absence of fatalities and the number of vehicles moved, are available to determine the effectiveness of an evacuation. Consequently, emergency managers and transportation professionals often rely on general assumptions, considering an evacuation successful if people evacuate danger zones and no fatalities occur in homes.

Purpose Statement:

This study aims to establish a foundation for measurement and comparison by examining and assessing evacuation characteristics. More crucially, it illustrates methods for unbiased, practical, and repeatable measurement beneficial to state officials. Leveraging simple yet widely available traffic count datasets, the research focuses on traffic volume counts as a fundamental parameter, providing insights into daily commutes, the dynamics of evacuation movements, and the subsequent return to normalcy after a disaster.

Objectives:

Based on these considerations, the research seeks to spatially and temporally quantify key aspects of the evacuation and reentry process during the record-setting 2017 and 2018 hurricane and wildfire seasons in Florida and California. These objectives include determining the initiation and conclusion of auto-based evacuations, loading characteristics, peak evacuation volume, the number of vehicles involved, and the timelines for reentry effectiveness.

These objectives are accomplished through the observation and analysis of roadway volumes collected from ground-based sensors, predominantly magnetic-loop detectors, during the 2017-2018 hurricanes and wildfires in Florida and California. These events, among the largest in the history of the United States, provide a unique opportunity to study evacuations due to their widespread impact on major metropolitan population centers and the extensive recording of traffic volumes on a geographic scale, reaching levels of fidelity rarely achieved in previous evacuation studies.

Research Contribution:

This work makes a significant scientific contribution by demonstrating a straightforward and reproducible methodology for measuring auto-based evacuation responses and reentries. The proposed methods offer practical value for state transportation and emergency management agencies seeking rapid and accurate assessments of evacuation characteristics. Additionally, the research expands the literature by providing insights into the less-studied topic of evacuation reentry timing and participation. Lastly, it establishes a set of aggregate evacuation parameters useful for calibrating evacuation planning and simulation models, making the paper a valuable reference for future research studies.

Delimitations and Assumptions:

This study necessitated the filtration and setting of boundaries for acquired data, acknowledging the inherent margin of error due to sensor issues during natural disasters. Real-time data, including region location, naming, and volume information, was collected and filtered based on sensor availability in regions affected by disasters, such as during Hurricane Michael on the west coast of Florida.

Limitations:

Analysts typically concentrate on the progression of evacuations over time, emphasizing the topography and infrastructure of the region. Primary limitations, beyond the control of analysts or researchers, include the inherent constraints of the current transportation network. Designed for routine demand, the network may not be optimized for massive evacuations. This study considers the existing network, the state's current and past plans, and, most importantly, how current evacuations took place.

Background:

Natural disasters pose ongoing challenges for many nations. According to the Natural Hazard Project by the Department of Regional Development and the Office of Foreign Disaster Assistance/U.S. Agency for International Development, these events are defined as "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, categorized from 1 to 5, significantly impact daily climates with strong winds and heavy storms. Formation depends on warm ocean water, moist and humid weather, and low-pressure systems, illustrated in Figure 1. On the other hand, wildfires are unpredictable phenomena affected by wind speed and temperature. Prone areas in California are depicted in Figure 2.

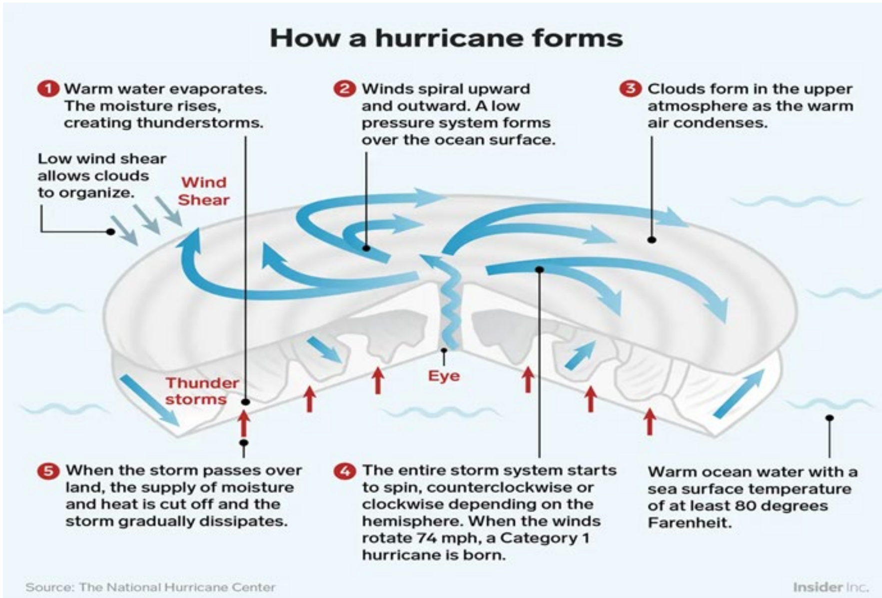


Figure 1: How are hurricanes or tropical cyclones formed (National Hurricane Center. Retrieved on January 20th, 2018)

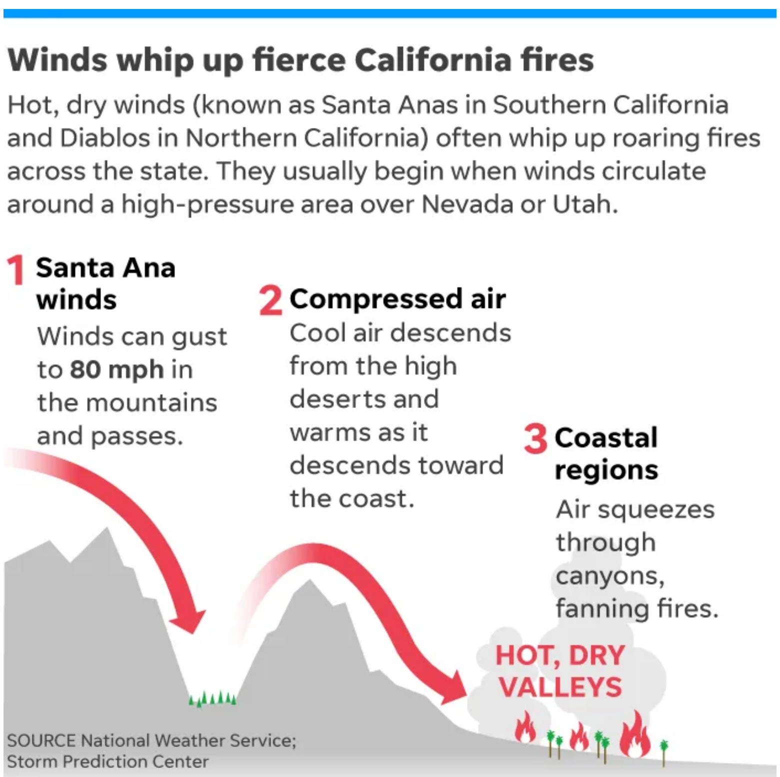


Figure 2: This figure illustrates how wildfires are formed in California. Source: National Weather Service; Storm Prediction Center and USA Today. Retrieved on June 13th, 2019.

Florida and California face recurring dangers, leading to evacuations. In 2017, California experienced four wildfires, causing destruction and displacing over 200,000 people (Alvarez & Santora, 2017). The same year, Florida encountered a category 4 hurricane, affecting millions of residents and causing substantial damage (Wall Street Journal, 2017). Both states, with their densely populated areas, handle large-scale evacuations. While Florida's 2017 hurricane evacuation set a historical record, California's wildfires left an enduring impact on its history.

Surface transportation strives to balance supply and demand. Increased demand, reflected in a higher number of vehicles on roads, leads to congestion and longer travel times. This concept is critical during emergency evacuations, where the sudden surge in demand can overwhelm transportation infrastructure, causing gridlock. The 2017 Hurricane Irma evacuation, involving approximately 6.5 million Floridians, marked the largest evacuation in U.S. history (Marshall, 2017). Hurricane Michael in 2018, a category 5 hurricane, resulted in 16 deaths and significant damage (Beven, Berg, & Hagen, 2019). Figures 3 and 4 display key moments in these events.

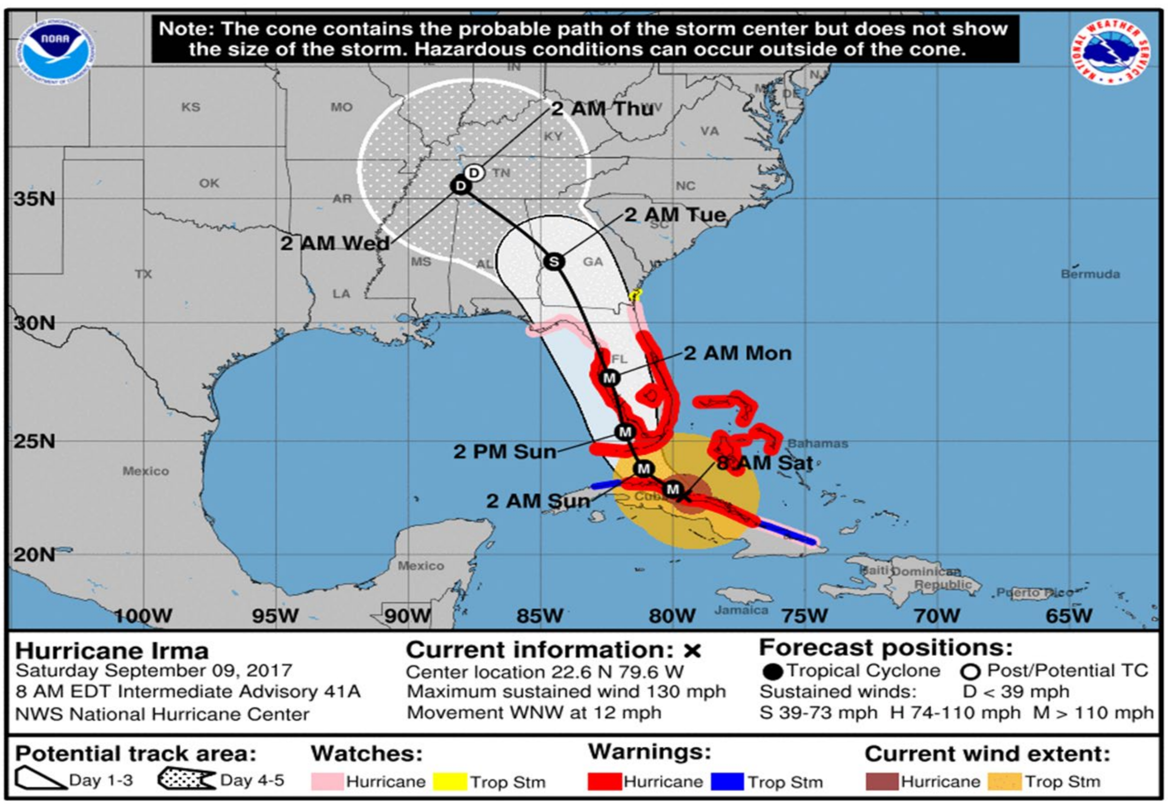


Figure 3: This figure illustrates the projected track of Hurricane Irma. (National Oceanic and Atmospheric Administration, U.S. Department of Commerce. Retrieved on December 5th, 2017).

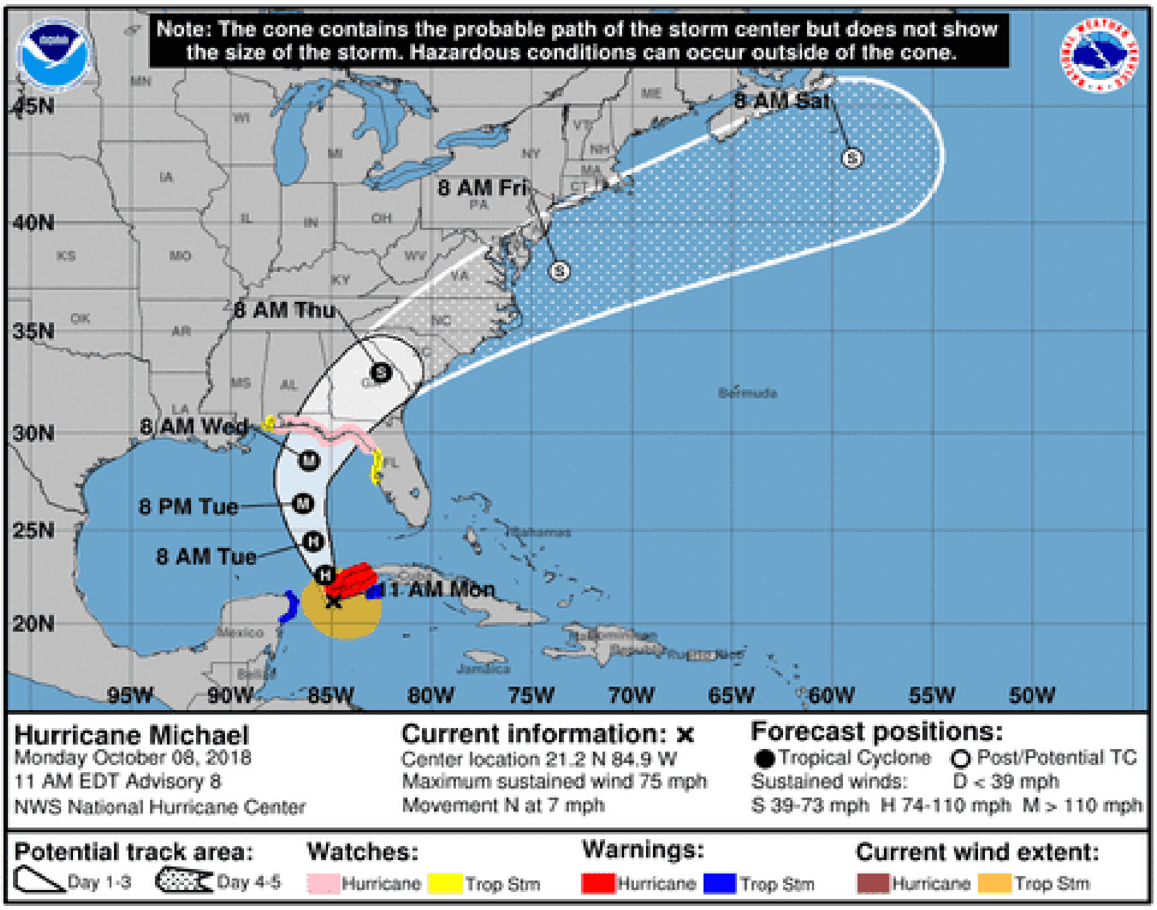


Figure 4: This figure illustrates the projected track of Hurricane Micheal. Source: National Oceanic and Atmospheric Administration (NOAA), U.S. Department of Commerce. Retrieved on January 21st, 2019.

Wildfires, influenced by pressure differentials, terrain, and climatic conditions, occur unpredictably. Anyone can ignite a fire with fuel, oxygen, and heat. Dry weather and droughts contribute to natural wildfires, with approximately 72,000 wildfires burning 7 million acres yearly since 2000 (Wolters, 2019). Increasing population and climate change escalate wildfire frequency. Tubbs Fire in 2017 and Thomas Fire in 2018, California's most destructive wildfires, caused numerous casualties and extensive damage (Cal Fire, 2018). Figures 3 and 4 depict the spread and impact of these fires.

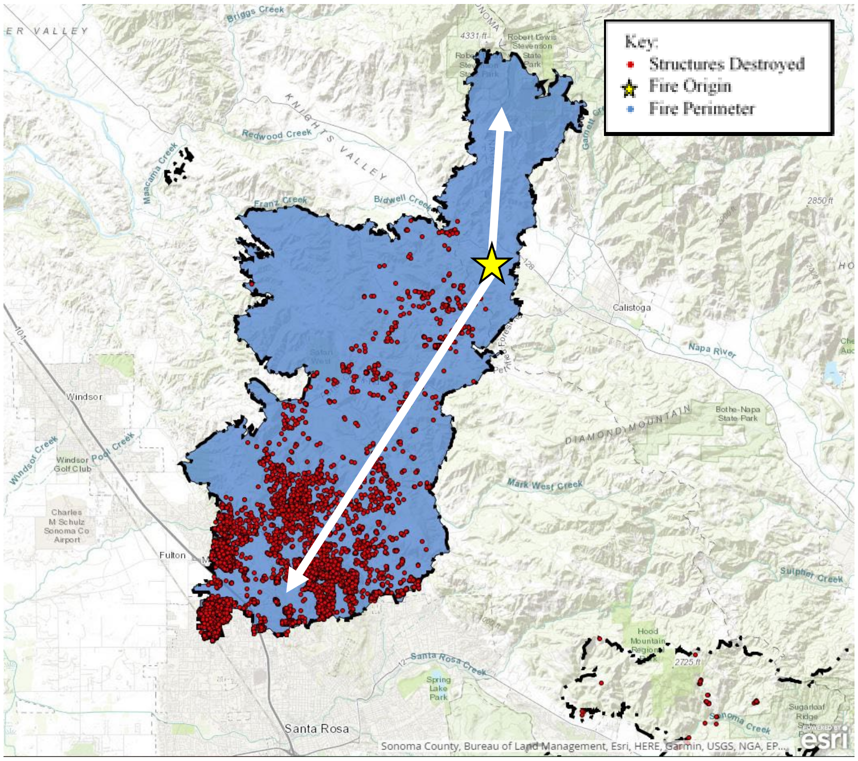


Figure 5: This figure illustrates the destruction and spreading of the Tubbs fire in the Napa and Sonoma County. Source: The Bureau of Land Management, Esri, HERE, Garmin, USGS, NGA, EPA, USDA, NPS and Cal Fire. Retrieved on June 13th, 2019.

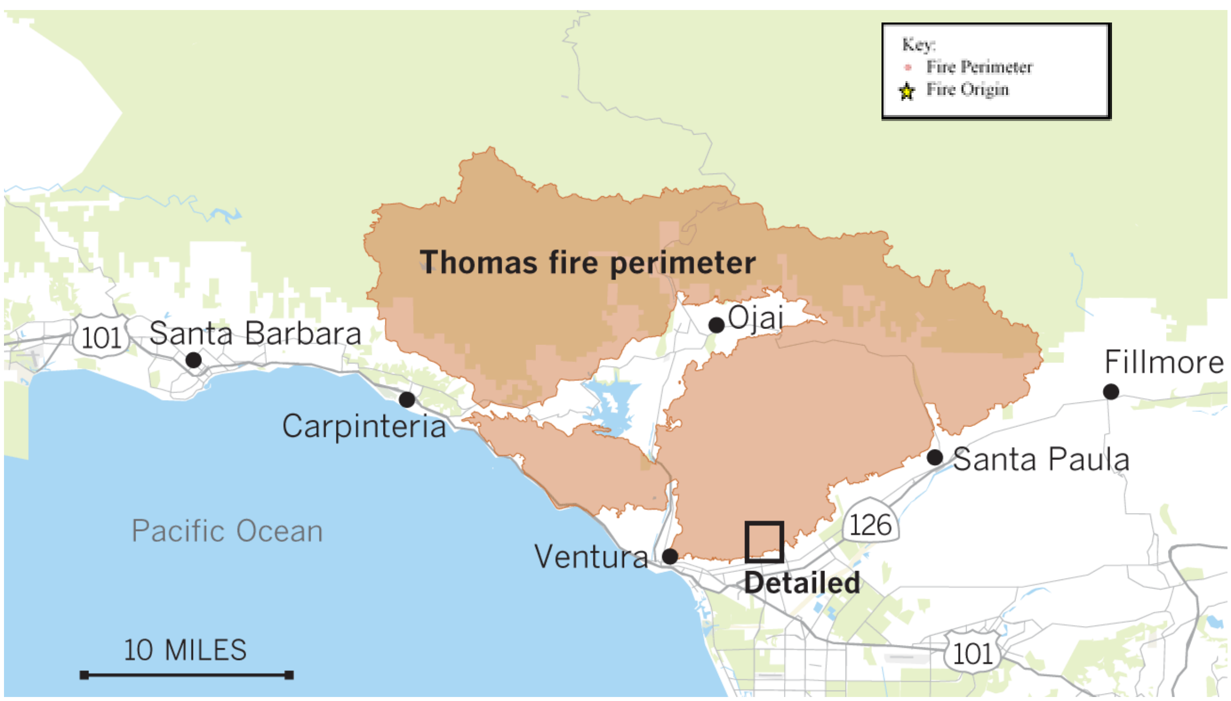


Figure 6: This figure illustrates the progression of the Thomas Fire in 2018. Source: Ventura County, Mapzen, OpenStreetMap. Map perimeter updated as of 4 a.m. on Dec. 11. Retrieved on June 10th, 2019.

2. Literature Review

The design, implementation, planning, and research of evacuations in Florida and California are paramount for the safety of residents in the face of potential global climatological events. This study focuses on utilizing sensor-based data and developing a quantifying system through temporal and spatial analysis to assess the effectiveness of evacuation plans. The evaluation includes analyzing how evacuees move over time, quantifying the time taken for evacuation and reentry, and assessing the overall efficacy of orders and plans for evacuating large populations promptly. Understanding the impact of natural disasters, such as Hurricanes Irma and Michael, and wildfires on evacuation processes in Florida and California provides valuable insights for future emergency events. The analysis considers fundamental concepts in transportation sciences, particularly the balance between the supply and demand of vehicles and roads, offering insights applicable to traffic, urban planning, and disaster management.

Florida, having not witnessed significant destruction since Hurricane Andrew in 1992, and California, without a major wildfire disaster with numerous fatalities since the Cedar Fire in 2003, highlight the importance of this analysis for the Florida Department of Transportation (FDOT) and Los Angeles Department of Transportation (LADOT) in enhancing preparedness for massive evacuations. The research draws on prior literature, encompassing specific regions, special events, emergency planning, sensor-based studies, and empirical analyses of manual traffic control. Various aspects, including traffic analysis and modeling literature, spatial and temporal patterns, evacuation volumes, and evacuation time estimates (ETEs), contribute to a comprehensive understanding of evacuation dynamics.

For instance, studies like those conducted during Hurricane Katrina in Louisiana (Wolshon & McArdle, 2011) and Hurricane Irene in New Jersey (Li et al., 2013) provide valuable insights into traffic patterns, evacuation volumes, and empirical response curves. These studies aid in evaluating the effectiveness of evacuation plans and informing future strategies. Moreover, evacuation flow analyses, maximum sustainable flow rates, and the impact of bottleneck conditions on evacuation routes (Dixit & Wolshon, 2014) enhance the understanding of traffic conditions during evacuations. The relationship between emergency communication and response is emphasized, with studies highlighting the significant role of effective risk communication in encouraging evacuations (Wolshon & McArdle, 2009).

Spatial-temporal patterns, as observed in Hurricane Katrina evacuations, offer critical information on evacuation timelines, traffic movements, and route conditions (Wolshon & Dixit, 2012). These patterns help in categorizing different traffic conditions, optimizing evacuation routes, and improving traffic simulation models for regional multimodal evacuation analysis. Furthermore, the study addresses unique challenges in coastal evacuations, such as those observed in South Miami during Hurricane Irma, where limited alternative routes exacerbate traffic congestion. The impact of evacuation orders on traffic surges and the importance of clearance time for bottleneck areas, like bridges and roads with limited capacity, are highlighted (Sadri et al., 2014).

In California, the study delves into the unique wildfire challenges, considering the influence of Diablo and Santa Ana Winds. The departure time of evacuees, influenced by awareness, beliefs, and priorities, becomes a critical factor in traffic analysis models (Beloglazov et al., 2016). States implement unique mechanisms and plans for evacuations based on their specific topography, population, demand, and infrastructure. Li, Cova, and Dennison's study focuses on a GIS model for traffic analysis, aiming to enhance previous methods by integrating fire and traffic simulation models to establish triggers. These triggers enable analysts and planners to estimate evacuation times during wildfire events (Li, Cova, & Dennison, 2018). Notably, the literature suggests that the time required to ensure 95% of evacuating residents reach a safe area as a fire approaches varies based on travel demand scenarios, emphasizing the critical role of effective planning (Li, Cova, & Dennison, 2018).

In California, studies concentrate on critical zones using geographical information systems (GIS) to assess hypothetical spatial strategies, such as prescribed burning, for reducing fire danger. Chou's research in the Southern region evaluates the effectiveness of these strategies through a probability model considering factors like vegetation, topography, and proximity to buildings (Chou, 2007). Li's dissertation emphasizes the importance of establishing evacuation warning zones using data-driven spatial modeling, incorporating geographic features as triggers to issue protective action recommendations (Li D., 2016). This comprehensive approach combines wildfire spread modeling, trigger modeling, reverse geocoding, and traffic simulation to create a spatiotemporal GIS framework for wildfire evacuation (Li D., 2016).

Analyzing evacuation dynamics, Li D. highlights that increased evacuation demand exposes more evacuees to fire risk, leading to delayed evacuations and heightened danger (Li D., 2016). Similar international studies, such as Zang, Lim, and Sharples' examination of wildfire occurrence in South-Eastern Australia, focus on identifying future fire locations but lack a thorough analysis of evacuation traffic (Zang et al., 2015). Brachman's research challenges mathematical evacuation models by incorporating real-time data from surveys, specifically examining residents' decisions to "stay-or-go" during mandatory evacuation orders (Brachman, 2012). Studies like Church and Cova's Critical Cluster Model aim to identify high-risk areas for evacuation, providing a GIS-based tool for mapping evacuation risks (Church & Cova, 2000). The need to challenge mathematical methods with real-time data is reinforced by Brachman's emphasis on validating assumptions using survey data (Brachman, 2012). Additionally, Han, Yuan, and Urbanik II propose measures of effectiveness (MOEs) for evacuation, considering different scenarios and optimizing MOEs based on varied situations (Han, Yuan, & Urbanik II, 2007).

Population growth and urban development further complicate evacuation planning. Pel, Bliemer, and Hoogendoorn stress the increasing frequency and intensity of natural disasters, advocating for efficient disaster management strategies (Pel, Bliemer, & Hoogendoorn, 2012). However, their studies suggest that the speed, intensity, and track of hurricanes or wildfires do not necessarily impact travel demand during evacuations (Pel, Bliemer, & Hoogendoorn, 2012).

While evacuation studies are well-established, reentry remains challenging, with low compliance observed in various disasters. Researchers must explore the factors influencing evacuees' return to damaged areas. Zhang, Wolshon, Herrera, and Parr highlight the importance of spatial-temporal analysis in understanding reentry patterns, aiding in all phases of disaster management (Zhang et al., 2019). This study utilizes aggregate data to enhance comprehension and improve disaster management strategies across mitigation, preparedness, response, and recovery phases.

3. 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.

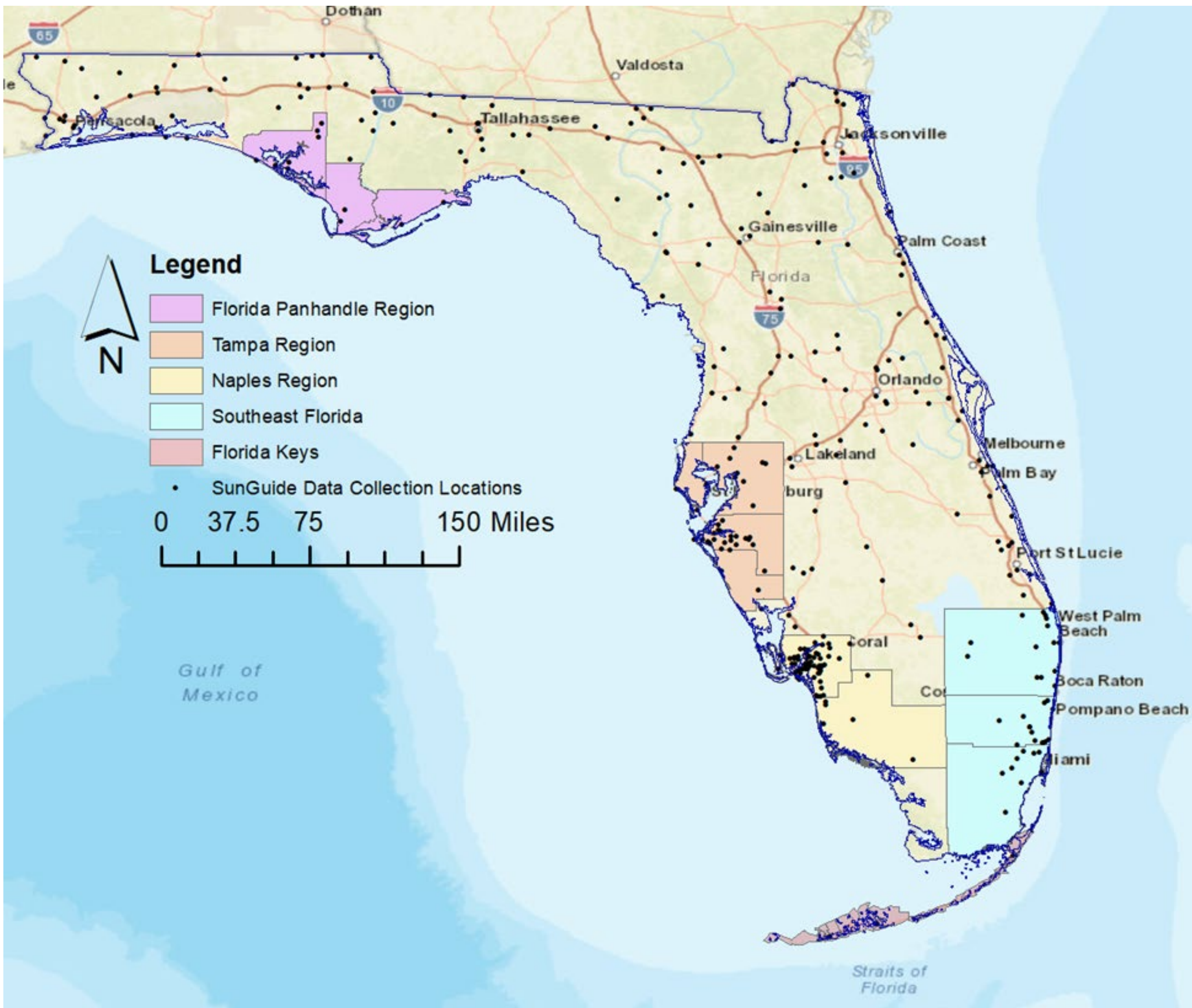


Figure 7. SunGuide Data Collections and Analysis Regions.

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.

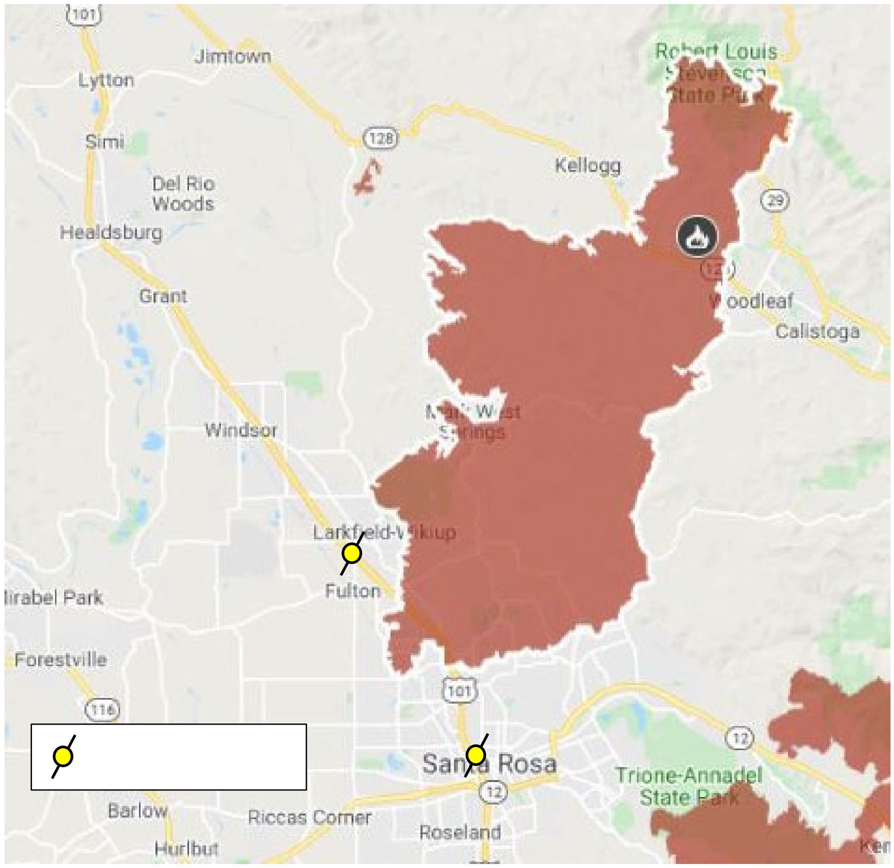


Figure 8. Tubbs Fire (2017) PEMs detector for data collection shown as a yellow symbol.

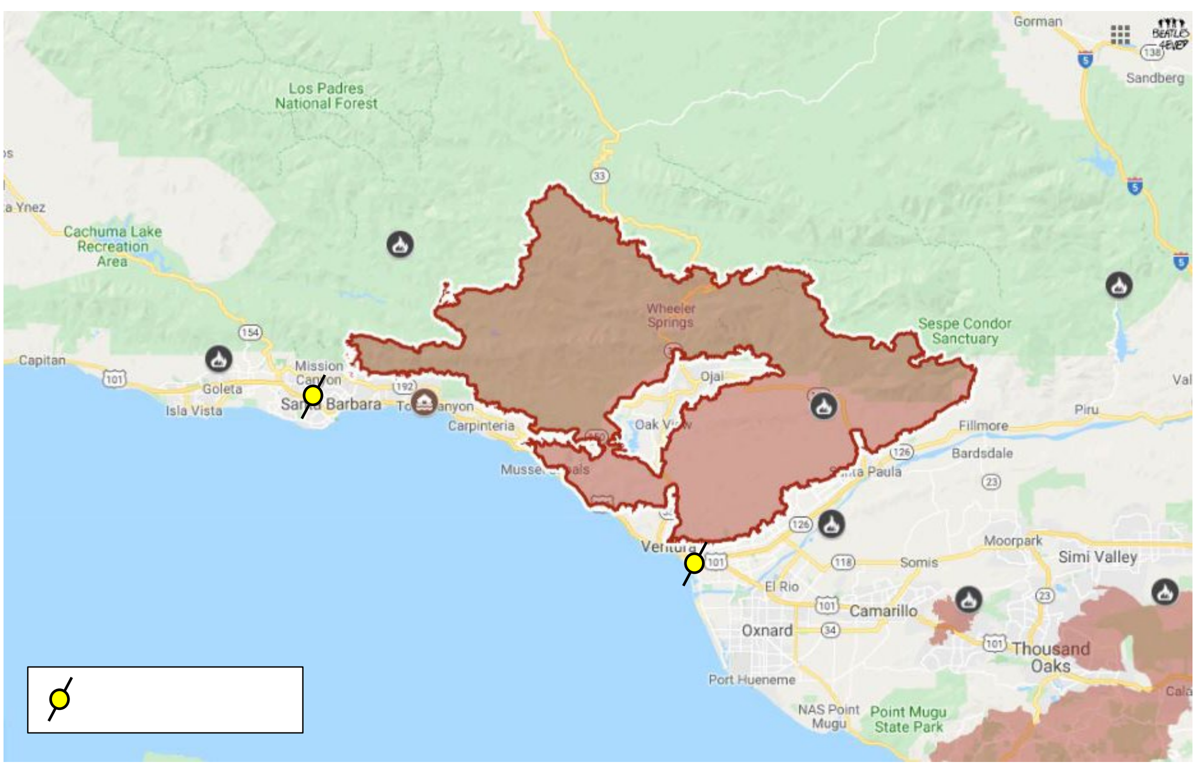


Figure 9. Thomas Fire (2018) PEMs detector for data collection shown as a yellow symbol.

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:

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

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 $IN_{it}^{A} = 0 = \Sigma_{t=1}^{24}\Sigma_{i=1}^{I}(IN_{it}^{A} - OUT^{A})$. 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. $\Sigma_{t=1}^{24}\,\Delta_t^A < 0$. 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.

4. RESULTS AND DISCUSSION

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^Aminimum) 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 10 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 ($IN_{it}^A > OUT^A$) . 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.

The figure for the Florida Keys is shown in Figure 11. 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 12 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

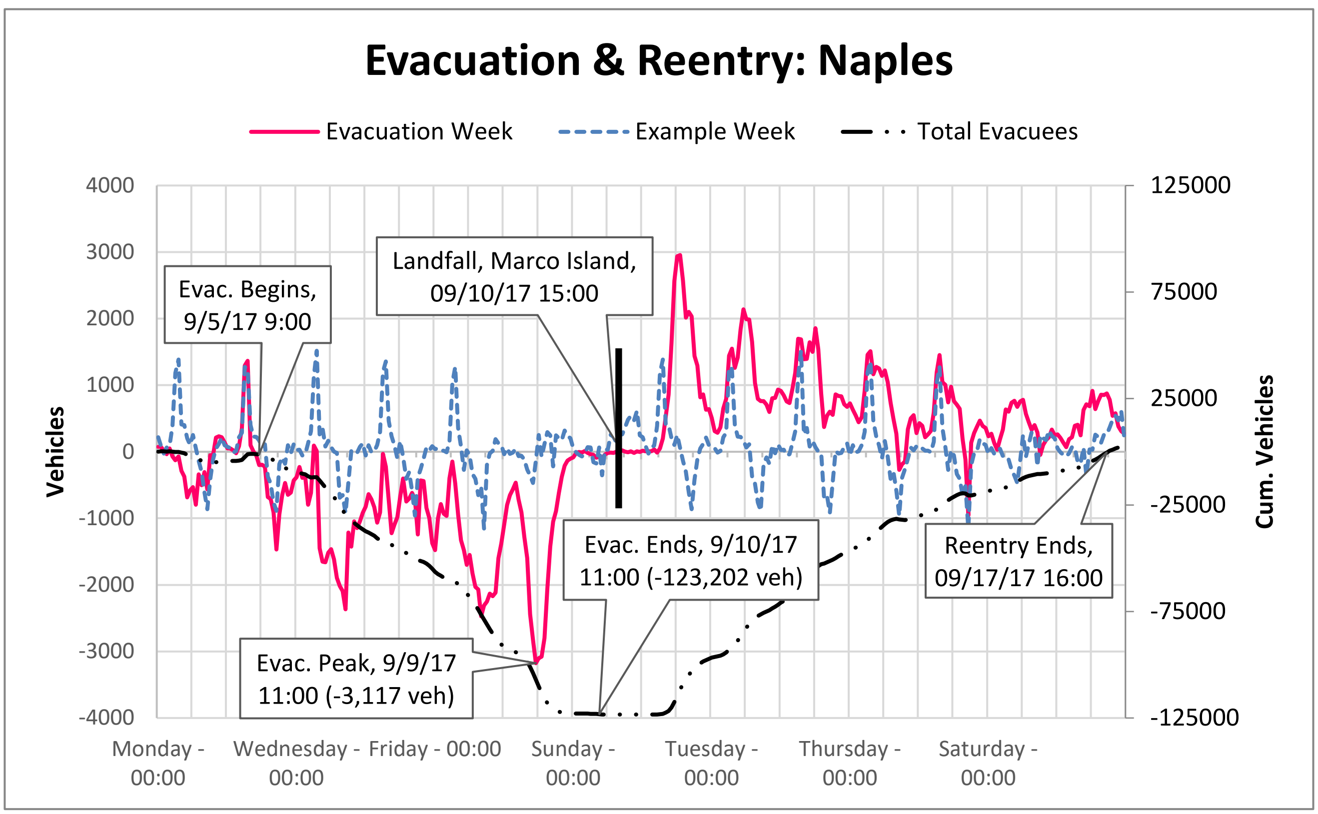


Figure 10: Naples Evacuation and Reentry Traffic Analysis

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.

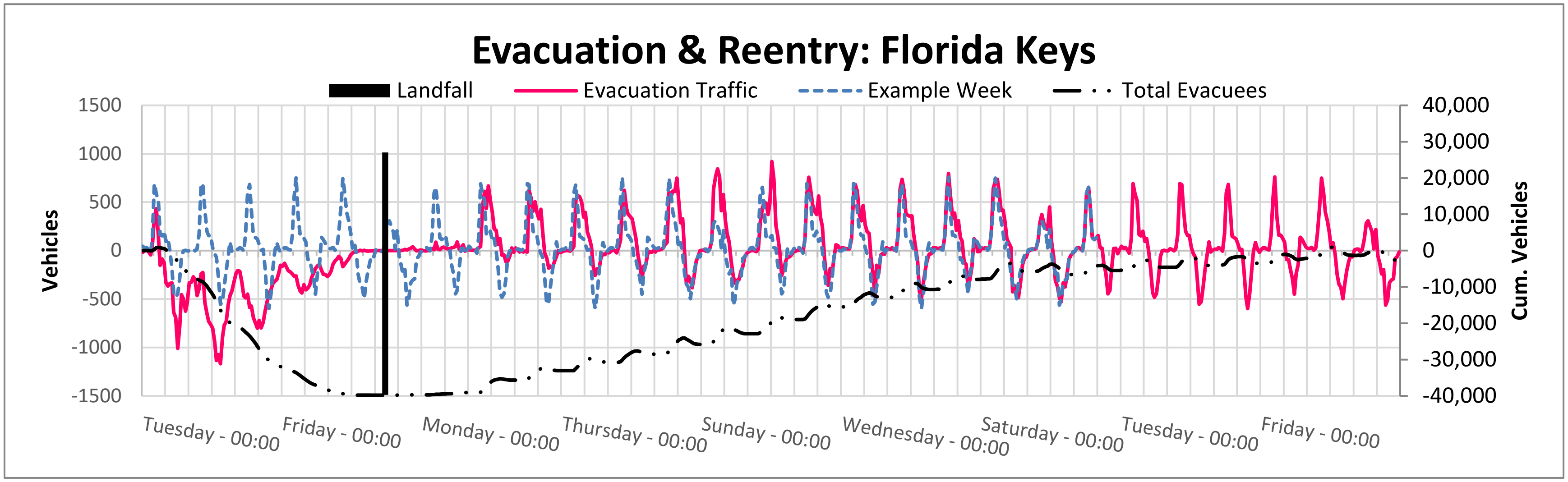


Figure 11: Florida Keys Evacuation and Reentry Traffic Analysis.

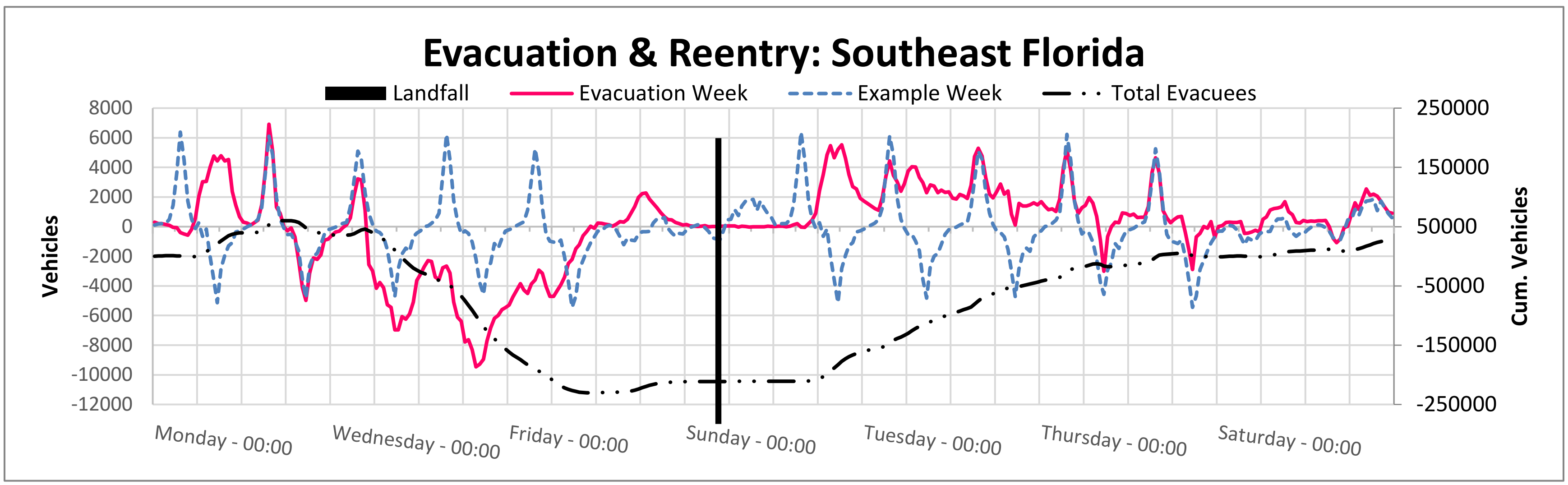


Figure 13 shows the evacuation plot for the Tampa Region of Florida. The Tampa area cordon included nine detector locations. In the days leading up to the evacuation. Tampa experienced a net increase in vehicles between Tuesday morning and the start of the evacuation on the following Friday afternoon. 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 14 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.

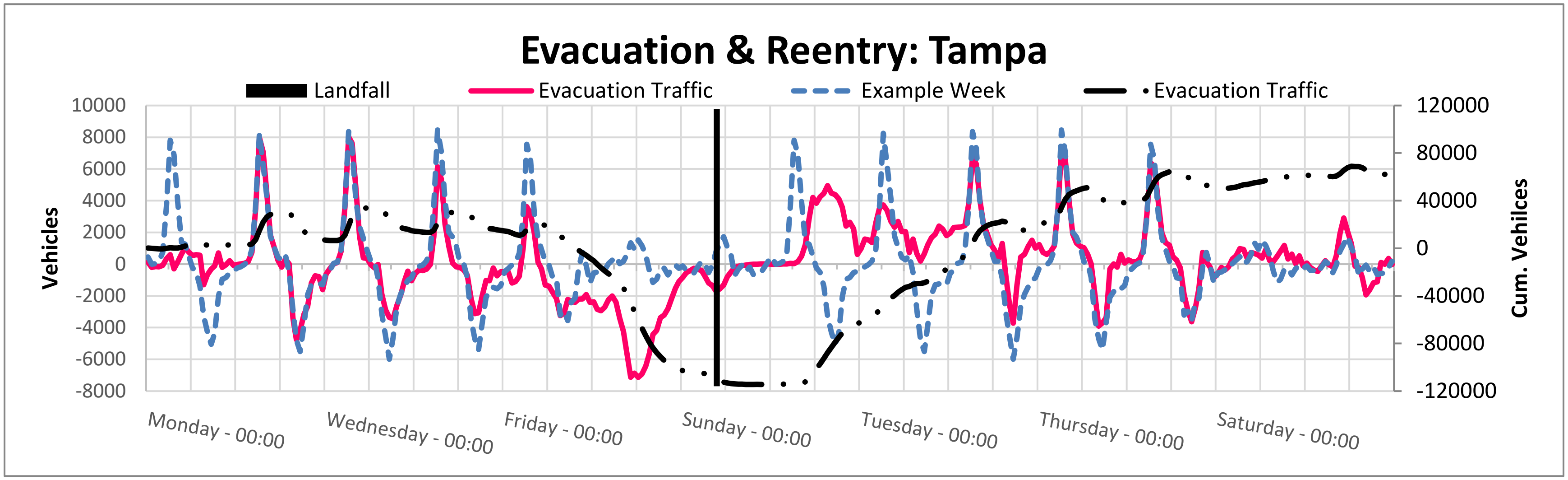


Figure 13: Tampa Evacuation and Reentry Traffic Analysis.

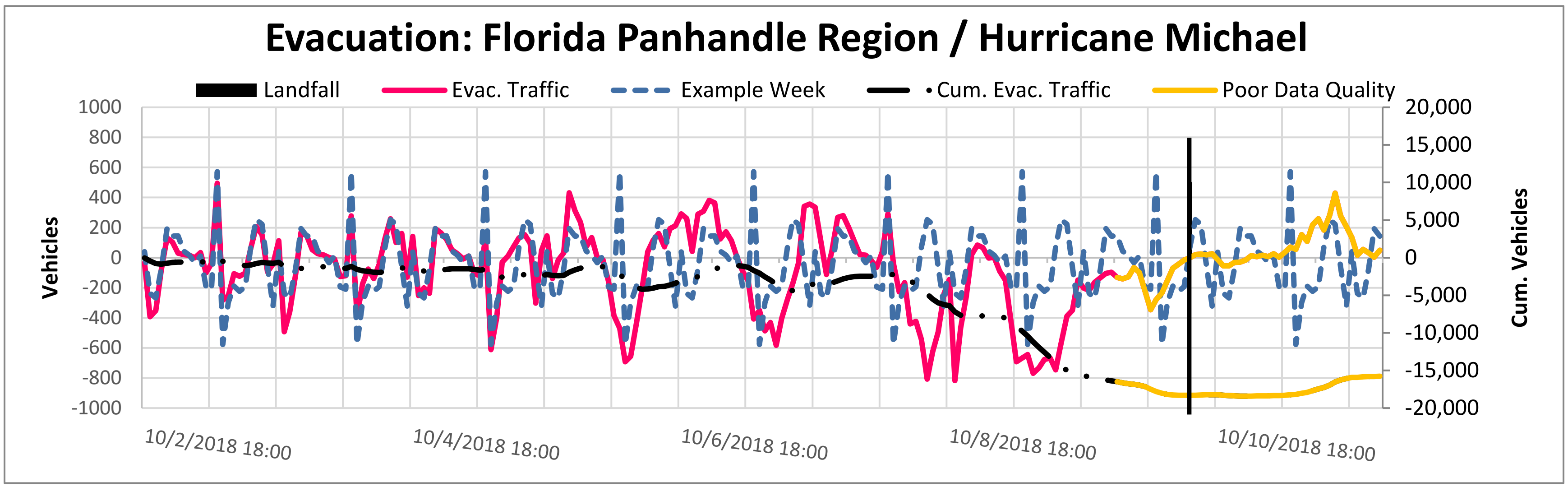


Figure 14: Florida Panhandle Region Evacuation from Hurricane Michael Traffic Analysis.

Evacuation and Reentry Time Estimates

Figure 15 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.

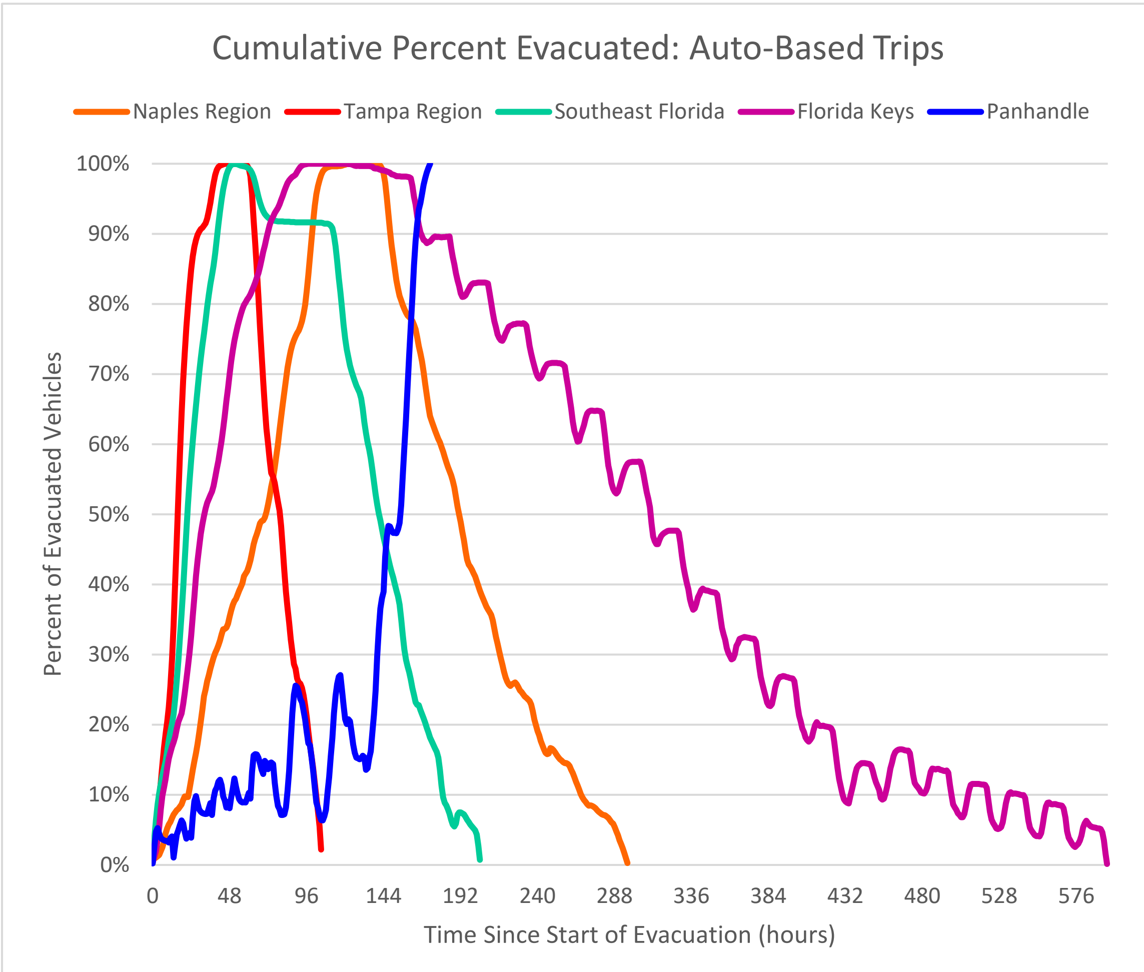


Figure 15: Evacuation Time Estimates

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

		All Times Shown Relative to Landfall						
Regions	**Total Veh**	**Evac. Initiated (τ)**	**Peak Hours (t_p)**	**Evac. Reentry (T)**	**Clearance time (t_{ct})**			
					0%	**0%**	**9%**	**00%**
FL Keys	40,731	5d, 0hr	3d, 17hr	20d, 4hr	4	3	2	04
S.E. FL	276,052	2d, 23hr	2d, 18hr	7d, 1hr	3	2	8	3
Naples Region	123,202	5d, 6hr	1d 4hr	7d, 1hr	8	7	04	22

Tampa Region	130,407	1d, 23hr	0d, 21hr	4d, 4hr	7	0	1	7
FL Panhandle (Michael)	16,370	7d, 19hr	1d, 18hr	N/A*	56	66	73	85*

*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]		Vehicles. Avail.[3]	Evac. Vehicles	
	Built	Mobile	Built	Mobile	Built	Mobile		Built	Mobile
Upper	15,789	1,886	0%	75%	5%	80%	1.8	10,658	2,037
Middle	6,929	1,338	0%	85%	5%	80%	1.8	6,548	1,638
Lower	7,459	1,373	0%	95%	5%	80%	2.6	11,637	2,714
West	15,714	2,859	0%	95%	0%	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 16 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.

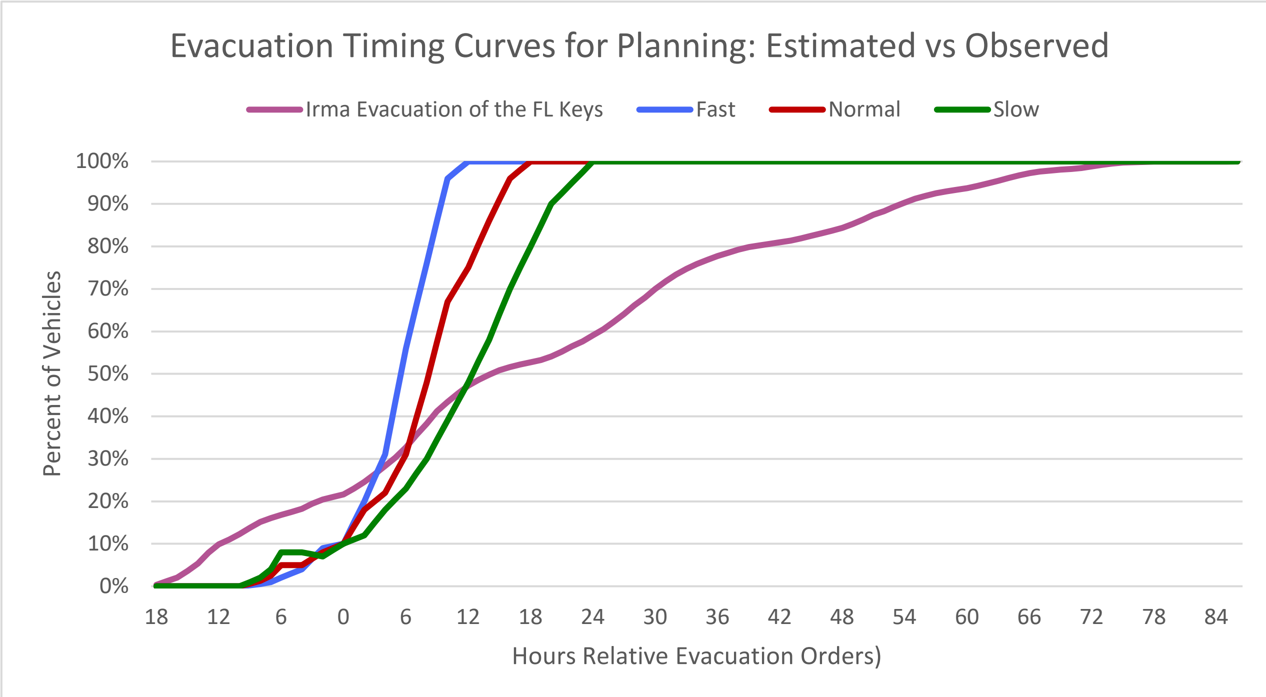
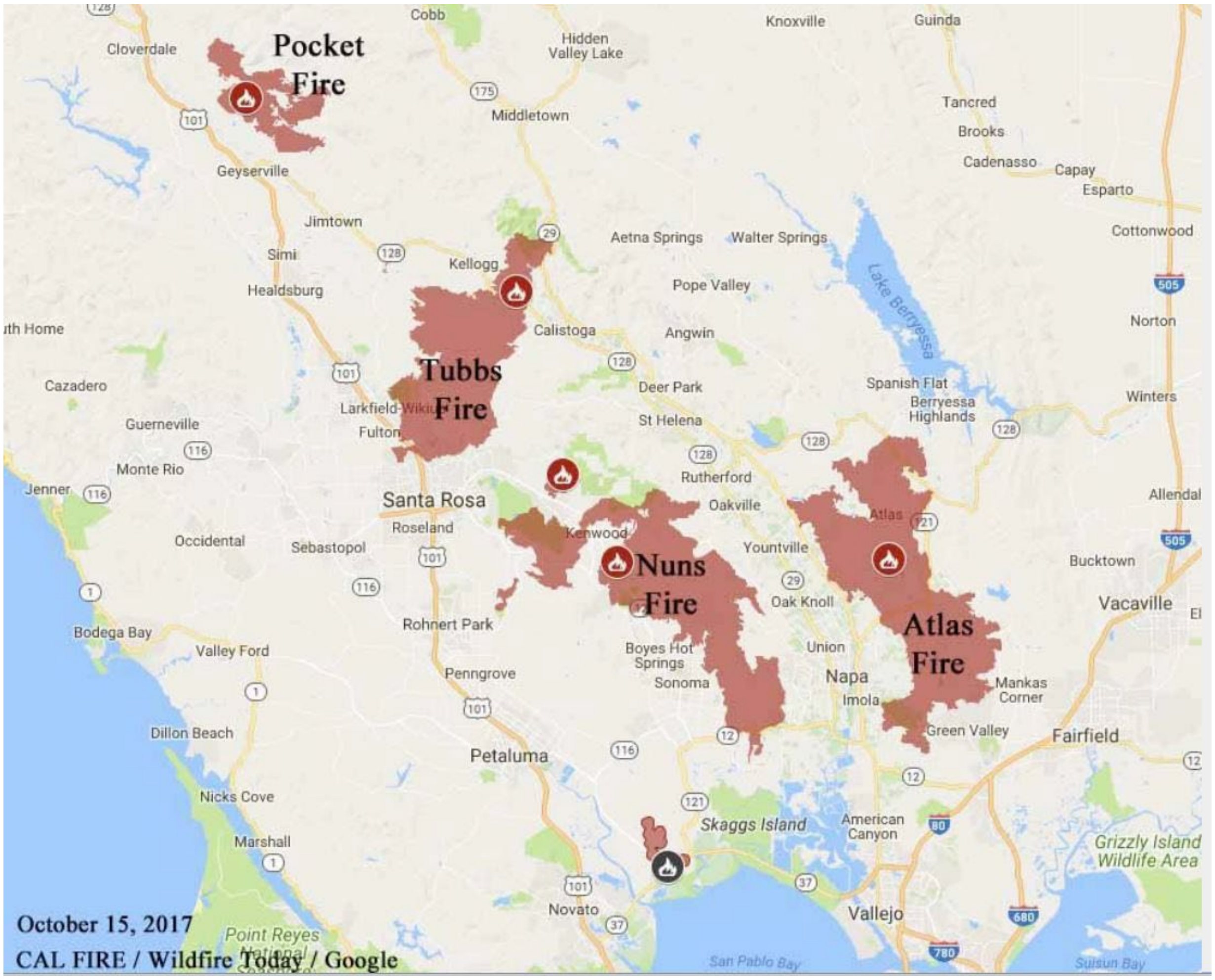


Figure 16. Evacuation Timing Curves for the Florida Keys

Evacuation Figures for California Wildfires

Figure 18 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 ($IN_{it}^A > OUT^A$). 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.


Pocket Fire
Tubbs Fire
Nuns Fire
Atlas Fire
Santa Rosa
Napa
Petaluma
Vallejo
Calistoga
Sonoma
Vacaville
Fairfield
October 15, 2017
CAL FIRE / Wildfire Today / Google

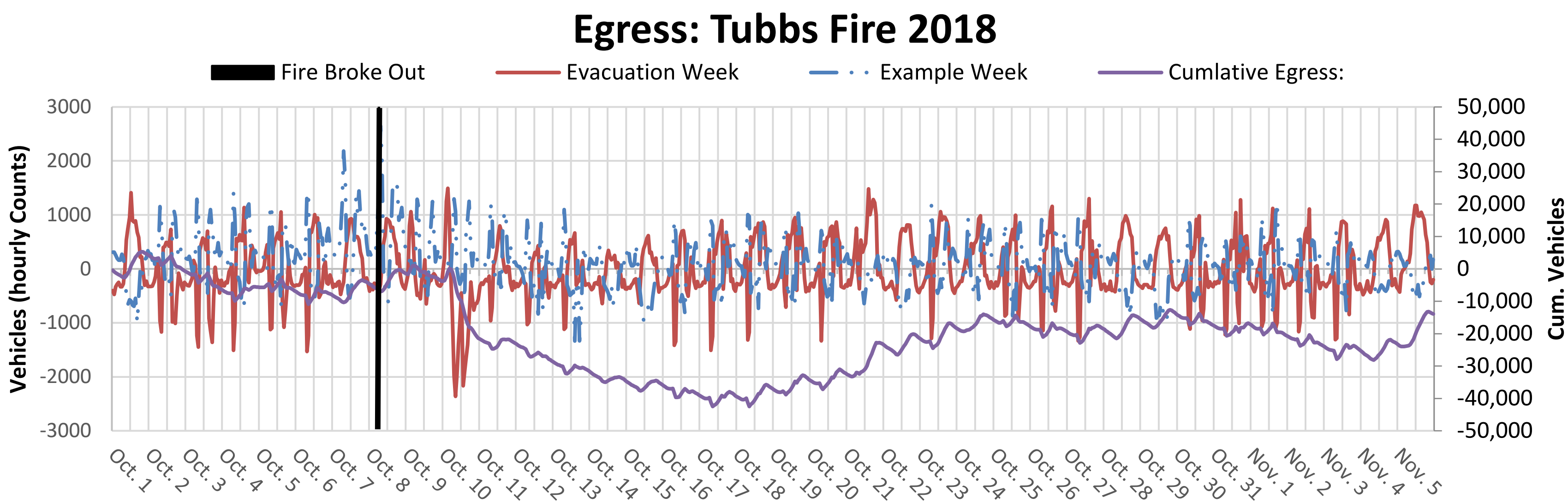


Figure 18: Napa and Somona County Evacuation and Reentry Traffic Analysis for Tubbs Fire (2017)

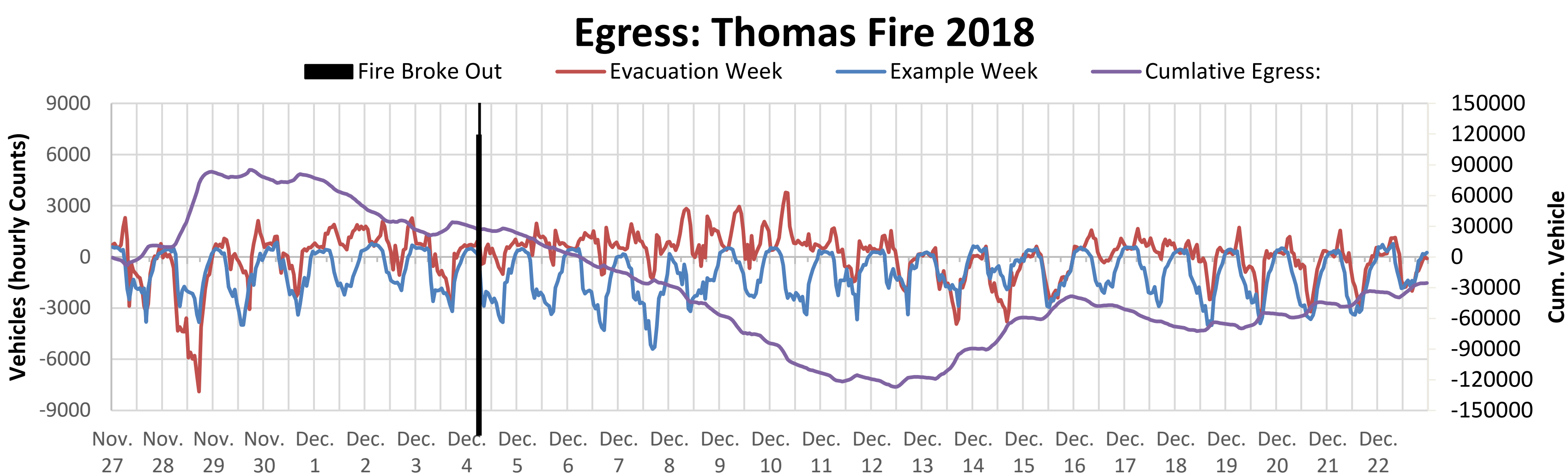


Figure 19 shows the evacuation and reentry traffic resulting from Thomas Fire (2018) evacuation of the Ventura and Santa Barbara County, CA region. The primary y-axis (Δ_t^A), secondary y-axis (evacuation beginning: τ; end of reentry: T), x-axis (t – hours), fire start (t_l) for December 4th, 2018 when 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

	All Times Shown Relative to Fire Start		
Regions	**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

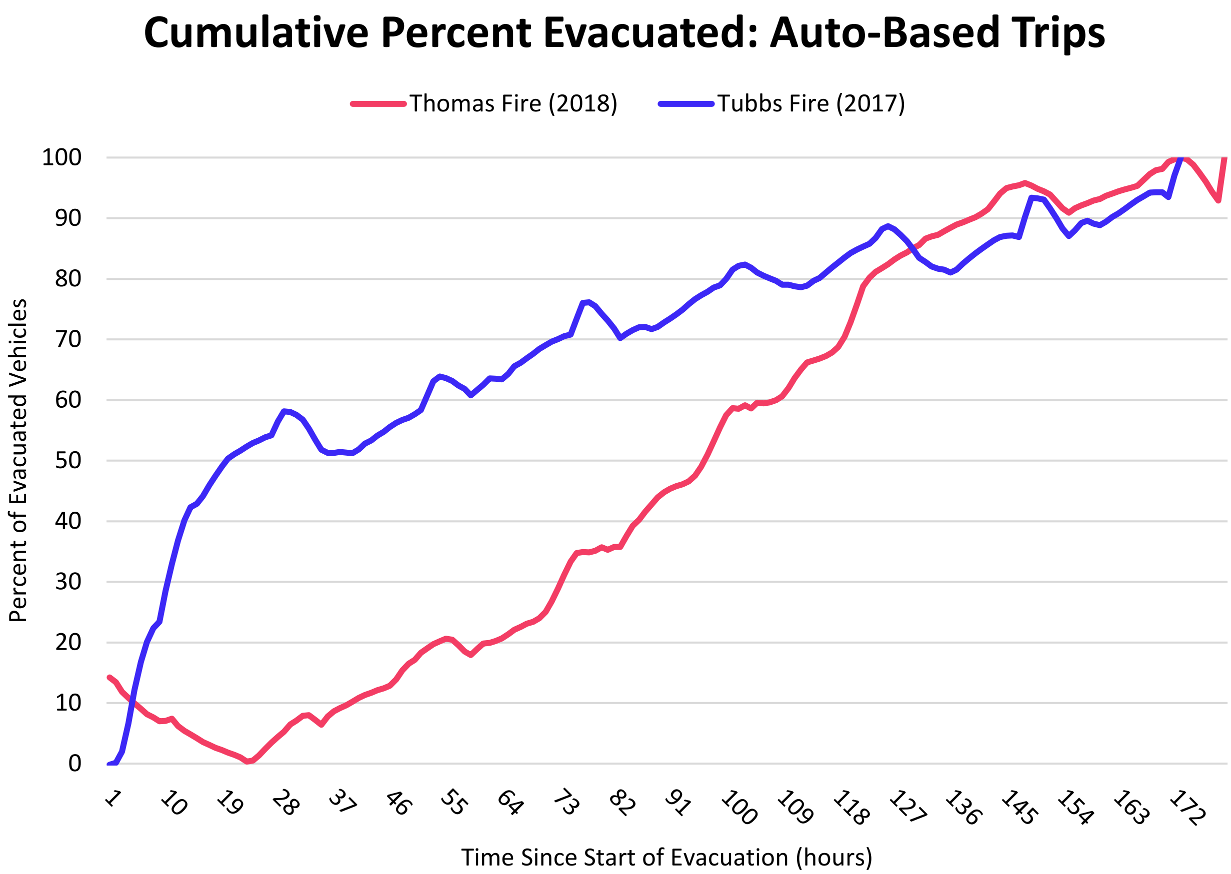


Figure 20. Cumulative Percentage of Auto-Based trips comparing Tubbs and Thomas Fires in the state of California

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.

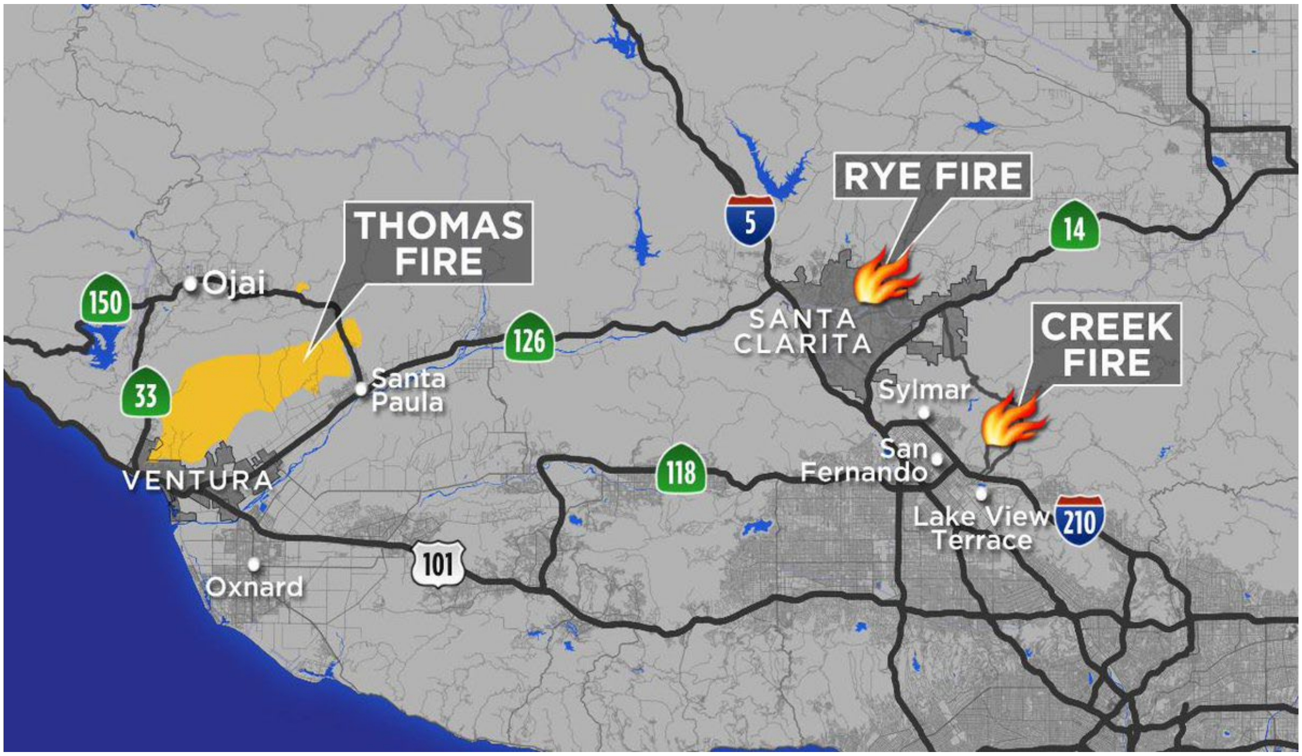


Figure 21: Fires nearby the Thomas Fire that occurred either prior or subsequently after Thomas Fire.

5. 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.

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