Mixed Methods Approaches to Wildfire Evacuation: Modeling Behavior, Simulation, and Equity

By

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Abstract

This dissertation presents several aspects of short-notice wildfire evacuation, using empirical findings from the 2018 Camp Fire in Butte County, California. I examine the manner and timing in which people find out about and begin evacuating in a short notice wildfire. Using these findings, I build a simulation model of such a disaster, and examine different worst-case scenarios. Lastly, I use thematic analysis to reveal findings from first-person interviews with fire evacuees.

This topic is important due to the prevalence of wildfires in California and the chance of future no/short-notice wildfires occurring in the future. In particular, the Camp Fire was extremely deadly and destructive. It is imperative that I study these large-scale events to improve response and planning. In this dissertation, I rely on data from two post-evacuation surveys as well as interview data taken at post-fire shelters. This unique dataset allows us to answer several questions about this specific event. I use the qualitative findings to add context to the quantitative results.

The first paper addresses the timing of awareness, departure, and preparation in short and no-notice wildfire events. Much of the literature has focused on the timing of when people choose to stay at their property, but no literature to my knowledge empirically analyzes awareness and departure in a short or no-notice evacuation. I also analyze the evacuation notice data sent out during the 2018 Camp Fire event. I find that quicker awareness is associated with higher income, smartphone ownership, seeing the fire firsthand, and familiarity with the local evacuation plans. Departure times were delayed for those living in the community longest, among other findings.

The second paper addresses how to simulate a short or no-notice wildfire evacuation by building an agent-based model. I use empirical data to inform the timing of when evacuees become notified of the disaster and begin to depart. I use this model to study different worst-case scenario outcomes, namely delayed awareness time, limited smartphone access, and reduced vehicle access. I find that these scenarios lead to longer evacuation times. This model provides a strong basis for future wildfire-related scenario modeling.

The final paper shares qualitative interview findings from 26 in-person shelter interviews post Camp Fire. These interviews share information on several areas of evacuee experience from evacuation through a month post-evacuation. By centering accounts from those living in shelters, I gain a new perspective unique to disadvantaged communities. I coded the interviews based on several topics: evacuation, evacuation traffic conditions, fears/problems, financial aid/assistance, finding out about the fire, and shelter/housing.

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Chapter 1. Introduction

Wildfires are catastrophic events likely to increase in frequency with global climate change. Climate change brings higher temperatures, higher winds, lower humidity, and higher Forest Fire Danger Index (FFDI), which are all associated with more wildfire fatalities (Blanchi et al., 2014). With greater population living in disaster-prone areas like the wildland-urban interface (WUI), evacuation efficiency safety becomes even more important (Wolshon and Marchive, 2007). The outcome of an evacuation depends on many complicating factors including information quality and dissemination, warning time, response time, route choice, traffic flow, etc. (Pel et al., 2010).

The wildland-urban interface (WUI) is the area where population overlaps with undeveloped vegetation (Schoennagel et al., 2017). Because this area consists of two disparate regions: one under-developed with large amounts of wildfire fuel, the other densely populated, this interface is a natural concern for wildfire safety. Much of the research on wildfire evacuation traffic modeling focuses on these regions for this very reason- it is where developed meets the undeveloped, often forested land with a high fire potential. These areas are where people are at the highest risk for wildfires, since they are often in the path of wildfires. Additionally, the number of exits and amount road infrastructure have not kept pace with the rapid population growth in these areas, creating more vulnerability particularly in the North American West (Cova et al., 2013). A recent review of California wildfires from 2017 to 2019 found numerous areas of improvement in communication, evacuation, and sheltering that are much needed for modern wildfires (Wong, Broader, & Shaheen, 2020).

A no-notice, or short-notice disaster is one which cannot be predicted, while an advance-notice disaster is sometimes forecasted weeks ahead of time, giving residents a large time horizon to make decisions. A wildfire is an example of a no-notice disaster, which precipitates a sudden, or no-notice evacuation. In such instances, there may or may not be a notification, requiring people to make acute decisions in a matter of hours or less, as compared to days or even weeks for advance-notice disasters such as hurricanes, albeit there being uncertainty in both types of disasters.

Given the population, semi-remote geography, and lack of road infrastructure, fast-moving wildfires in the WUI especially pose a large threat to human life and property. In such events, whole towns may need to be evacuated in a short amount of time, making evacuation notifications, departure time, and route choice extremely important, even life or death. It is imperative that in planning for such events, projected to become commonplace in the future, that policymakers and local planners are able to take into consideration the rich behavioral aspects of residents while evacuating. Traditional assumptions about destination and route choice may not apply in such no-notice situations; people may move randomly just to avoid the wildfire instead of following a planned path. People also may gather at intermediate destinations, or staging areas, before they move on to final destinations. All of these factors affect proper planning for no-notice wildfires and must be considered in order to take the best precautions.

The November 2018 Camp Fire is an example of a fast-moving WUI fire which tragically killed 85 people, and its data is used in this dissertation to inform the development of a decision-making tool to evaluate evacuation strategies.

2018 Camp Fire

The 2018 wildfire season was the most destructive in California's history, burning nearly 2 million acres with over 100 fatalities. In particular, the November 2018 Camp Fire in Northern

California was the deadliest and most destructive wildfire in the state of California and the deadliest for the past 100 years in the United States, destroying 14,000 residences while burning for over two weeks (Lam, 2019). The Camp Fire occurred in the Sierra Nevada foothills of Butte County, northeast of the city of Chico in Northern California, in the communities of Paradise, Magalia, Yankee Hill, Pulga, and Concow. The wind speed was 40 to 60 mph for at least nine hours of the day of the fire and the proceeding day, causing the fire spread extremely quickly, at an estimated rate of one football field per second (Belles, 2019). A map of the location of the Camp Fire and its location with respect to the rest of California can be seen below in Figure 1.

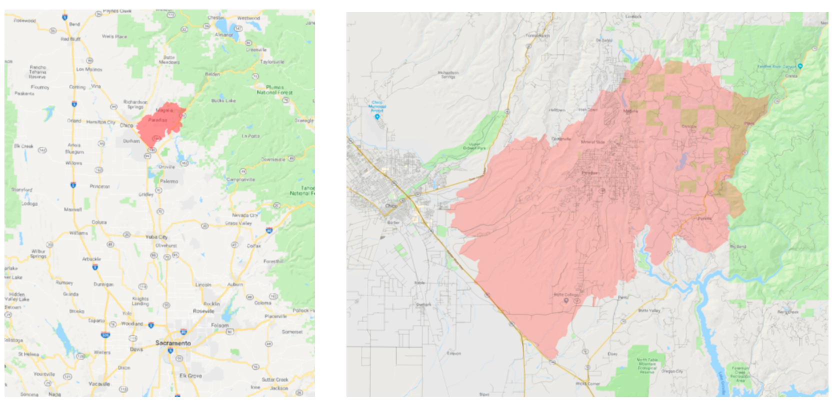

Figure 1: Camp Fire 3-day Burn Scar

The Camp Fire started at 6:30 am on a Friday as a result of a malfunction on an aging and faulty electrical transformer maintained by the local utility company, Pacific Gas & Electric (PG&E). Coincidentally, in the days preceding the morning of November 8th, PG&E had notified its customers that it might shut down power as a precautionary measure due to forecasted high winds in the foothills. When the power eventually was shut down on the day of the Camp Fire, many residents believed that PG&E was simply following its safety protocol for high winds, with no idea that there was a fast-moving wildfire heading their way and spreading very rapidly. The emergency alert system, Code Red, was an opt-in service run by Butte County's Office of Emergency Management (OEM). With little warning time and a fast-moving fire, thousands of people did not have adequate time to prepare to evacuate. In fact, many were forced to immediately evacuate after waking up to smoke, with no time to even receive let alone process an evacuation text or phone call. Inevitably, evacuation routes were marked with extreme traffic congestion, downed power lines, abandoned vehicles, and approaching flames, causing many to abandon their vehicles and seek safety afoot.

This dissertation describes evacuee experiences in large-scale, short-notice wildfire evacuations and the unique challenges these individuals face. These events are especially important to California and the broader American West, where there is considerable risk of these large-scale disasters in the future. Despite this risk, there are also considerable research gaps regarding dire wildfire evacuations, of which the 2018 Camp Fire is an example. My study focuses on the transportation-related aspects of these evacuations, which will be required to undertake future planning for these types of wildfires.

This dissertation follows the following format:

- Literature Review on large-scale no-notice and short-notice wildfires
- Statistical analysis of the timing of when evacuees become aware of and depart in a short-notice wildfire
- An agent-based simulation model of the 2018 Camp Fire, with several dire scenarios and outcomes.
- Qualitative analysis of first-person interviews, revealing findings across different time horizons of evacuee experience.

Contributions to Literature

My dissertation makes these contributions to the literature:

- A novel and new analysis of empirical data from a short-notice wildfire event is examined
- Improved understanding of human evacuation behavior in no-notice and short-notice wildfires. I find several aspects which affect awareness of this type of disaster; income, being aware of evacuation plans, race, smartphone ownership, and the manner in which a person finds out about the disaster all impact awareness. Smartphone ownership, length of residence, and receiving an evacuation notice all affect departure time. Home insurance, length of residence, receiving an evacuation notice, and how a person finds out about the disaster all impact the time an evacuee takes before evacuating. These variables can be used in future no-notice and short-notice disaster research to more accurately model human behavior.
- I deploy an agent-based simulation model which is also a new addition to the field, and model several dire wildfire evacuation scenarios, many of which have never been simulated for this type of disaster. I show that many of the critical scenarios lead to longer evacuation times and more trapped evacuees.
- Lastly, my empirical tracking of inequalities and injustices for wildfire evacuations using mixed methods is also new and makes an important addition to the disaster inequality field. This work is also important in that it centers evacuee experiences within the mixed methods framework.

Chapter 2. Literature Review

This literature review first addresses evacuation modeling, then focuses on evacuations in wildfires. Next I cover two important aspects of wildfire evacuation modeling, trigger modeling and traffic modeling. I review the literature on agent-based modeling for evacuation, as well as different parts of evacuation modeling such as destination and route choice. Lastly, I address human behavior in wildfire evacuation and identify areas for future research.

Evacuation Modeling

Traffic modeling is an important part of evacuation planning and emergency management, with regard to a priori planning and in real time management of an unfolding disaster (Wolshon and Marchive, 2007) (Chiu et al., 2007). There are several literature reviews addressing general evacuation modeling (Murray-Tuite and Wolshon, 2013a; Pel et al., 2012). While these reviews include some reference to wildfire evacuation studies, none focus solely on wildfires, and much of the research covered has been on hurricanes (Huang, Lindell, & Prater, 2016; Wilmot & Mei, 2004; Wolshon, Urbina, Wilmot, & Levitan, 2005a, 2005b). This introduction aims to be a brief summary and is not an exhaustive review of evacuation traffic modeling.

Evacuation models can be macroscopic (traffic flows), mesoscopic, and microscopic (individual vehicles). Macroscopic models are used for large scale evacuations and can answer how long it takes to evacuate an area (Bayram, 2016). Microscopic models are used by traffic engineering and are more detailed; mesoscopic models are macroscopic models with disaggregated parts (Bayram, 2016). Evacuation traffic modeling can be split broadly into the travel demand stage and the traffic assignment stage (Intini et al., 2019; Southworth, 1991). Within the travel demand stage, there is the trip generation step, trip distribution step, and modal split. Trip generation is composed of two further steps: the stay/evacuate decision and the time at which the evacuee decides to leave, known as the departure time decision (Intini et al., 2019). The mode choice assumptions largely depend on the disaster, for example distance to safety, affected population, available options, etc. (Murray-Tuite and Wolshon, 2013a). Note that the trip distribution and destination choice are later covered in-depth in the literature review for the second paper.

Traffic assignment can use a static or dynamic framework; it is composed of two steps, route choice and traffic simulation. Background traffic may or may not be considered (Intini et al., 2019). For route choice, some studies assume that evacuees are myopic and choose the least congested links or are restricted to certain routes by emergency personnel (Cova and Johnson, 2002), while some assume use shortest route or most familiar route.

Hazard analysis, vulnerability analysis, behavior analysis, and shelter analysis are all important parts that determine traffic assignment (Bayram, 2016). Warnings and information are also an important part of evacuation, as they influence the number of people evacuating, from where they evacuate, and where they end up going (Murray-Tuite and Wolshon, 2013a). Evacuations can be classified as “with notice”, “short-notice” and “no-notice”. In no-notice situations, evacuees are typically assumed to seek refuge from the threat first, then head to a final destination (Bayram, 2016). I elaborate on the distances between these notice levels in Chapter 3.

Wildfire Evacuation

The evacuation decision, mode choice, destination, and intermediate stops are all inter-related when modeling evacuation decisions for wildfires (Toledo et al., 2018). A joint model of these decisions should consider the order and hierarchy of the various decisions and the way one choice affects others; to do this, some researchers suggest an integrated model instead of modeling each decision separately (Toledo et al., 2018). A recent paper investigated choice dimensions of wildfire evacuations, developed portfolio choice models to jointly model these dimensions; they found joint preferences to exist among several evacuation facets such as time of day, geography, and type of route (Wong, Broader, et al., 2020).

One non-wildifre paper that with a joint model of departure and travel times used data from Hurricane Sandy (Gehlot et al., 2018). To do this, the authors use a joint discrete-continuous framework and find that unobserved factors that increase the departure time of an evacuee also decrease the probability of an individual traveling for more than 3 hours (Gehlot et al., 2018). The authors suggest the use of other joint decisions like departure time-route choice and departure time-destination choice, and checking the transferability of the results using a different type of disaster (Gehlot et al., 2018). Since wildfire evacuations are usually at a smaller geographic scale than hurricane evacuations, household-level travel demand modeling is typical (Cova and Johnson, 2002; Li et al., 2019; Wolshon and Marchive, 2007).

Trigger Modeling

Much of the literature on traffic modeling for wildfire evacuation uses trigger modeling (Cova, Thomas et al., 2005; Dennison et al., 2007; Li et al., 2019, 2017, 2015). An evacuation trigger point is a certain geographic feature, such as a river or road, that will prompt an evacuation once fire crosses it (Cova, Thomas et al., 2005). These trigger points can be decided ahead of time, during a wildfire, or if the wildfire is fast-moving, there may be no time to identify the trigger points. In their 2005 paper, Cova et al. estimate evacuation trigger buffers by combining geographical and fire-related data such as wind speed and amount of fuel, and estimated wildfire path (Cova, Thomas et al., 2005).

The comprehensive Wildland-Urban Interface (WUIVAC) model determines when residents should evacuate and potential evacuation routes by creating evacuation trigger buffers (Dennison et al., 2007). Topography as well as historical fuel and weather inputs are taken into consideration to create worst case scenario wildfires for the case study communities of Julian and Whispering Pines, California. They model eight different fire directions for Julian, each resulting in its own evacuation route profile. The WUIVAC model is very valuable for strategic evacuation planning since it provides the worst-case trigger points ahead of time, which can be very helpful in fast-moving wildfire, giving people more time for decision-making (Dennison et al., 2007). The authors suggest that in evacuation planning, evacuation routes be selected that would not be cut off by these trigger buffers during a worst-case wildfire.

Researchers in 2015 developed a household-level evacuation approach that combined trigger modeling (ArcGIS) with fire spread modeling (FLAMAP) (Li et al., 2015). Their research looks at how to divide up households into evacuation zones based on the current road network, evacuation behavior, and parameters of the wildfire. One assumption they make is that there is no traffic congestion in such an evacuation, and state that this assumption should be investigated in the future. The authors used 18 different wildfire scenarios, randomized evacuation response times, and a combination of shortest path or alternate path route choice (Wolshon and Marchive, 2007).

More recently, evacuation triggers have been predicted by using microscopic traffic simulations (Li et al., 2019). By estimating the travel demand of a threatened area and the dynamics of an oncoming fire, researchers are able to back out where and when triggers should be set. To estimate travel demand, assumptions such as all households evacuating based on an assumed departure time distribution, will take the shortest path, and that the road network will not be affected by the approaching wildfire must be made (Li et al., 2019). The authors note that these assumptions should hold for a WUI scenario, where there is typically a sparse road network, limiting potential options for route choice.

Wildfire Traffic Modeling

One of the first wildfire traffic modeling studies to use a microscopic traffic model looked at individual WUI neighborhood evacuations at the household level (Cova and Johnson, 2002). Researchers use a scenario generator (trip generation, departure time, destination choice) and the commercial microscopic traffic simulator Paramics (traffic flow, route choice) to simulate wildfire evacuation of neighborhoods in a fire-prone area of Salt Lake City, Utah (Cova and Johnson, 2002). Also using Paramics, Church et al. (2002) conducted neighborhood-level analysis of wildfire vulnerable communities in California (Church and Sexton, 2002). Using this setup, it is possible to see how changing the road network affects evacuation travel times. The authors found that development density, road network attributes, and geographical features can hinder the ability of some communities to evacuate (Cova and Johnson, 2002). A recent wildfire simulation model of the WUI in Berkeley, California incorporated past wildfire survey data to develop a data-driven model to be used at low cost to agencies (Zhao and Wong, 2021).

From a recent review of the literature (Intini et al., 2019), evacuation is often separated into travel demand and traffic assignment. For the travel demand stage, which consists of the trip generation step (stay or evacuate), trip distribution step (destination choice), and modal split, a trip-based or activity-based framework can be used. The main difference between these two frameworks is that for short-notice evacuations the activity-based framework may be preferable since it includes intermediate trips in a situation where people may be doing much gathering of family members (Murray-Tuite and Wolshon, 2013a; Murray-tuite and Mahmassani, 2004); evacuees in wildfires have been shown to make many intermediate trips (Toledo et al., 2018).

The choice to stay or evacuate depends on the dynamics of the wildfire in question. Some people can safely stay and defend their home without fear of losing their life, but in other cases due to the wildfire's speed or wind carrying embers, it becomes evident that everybody must leave. The choice to stay or evacuate is important to estimate the evacuation demand, and can be modeled through random utility models (logit structures) or descriptive methods (cross-classification, regression analysis) (Intini et al., 2019). A recent paper used a revealed preference dataset of the 2017 Southern California wildfires to compare using the conventional random utility maximization versus regret minimization (Wong, Chorus, et al., 2020). Despite the results favoring the random utility maximization, regret was found to exist with respect to route and mode choice.

Conversely, departure time, or the time at which people begin evacuation, can be modeled through either empirical methods or activity-based approaches. The empirical methods are similar to the departure curves that are used for hurricanes, where it is assumed a certain proportion of the population leaves at different times after the issue of an evacuation warning, but this would depend on the speed of the oncoming wildfire and other factors (Pel et al., 2012).

Both the leave/stay and departure time decisions are largely dependent on the communication of the severity of the disaster and evacuation orders (van der Gun et al., 2016).

The distribution step can be modeled using descriptive models (gravity models), random utility models, or activity models. For no-notice or short-notice evacuations, the final destination is sometimes of little importance, as long as evacuees can leave the threatened zone (Lindell and Prater, 2007). For wildfires, mode split modeling usually assumes people will take private vehicles or be picked up by emergency personnel (Intini et al., 2019). The mode split can be modeled by descriptive methods, random utility models, or activity models. It is noted that the descriptive and random utility approaches can be combined with wildfire models to account for road network disturbances and that (Intini et al., 2019). Activity models are employed through microsimulation and probabilistic approaches such as Monte Carlo (Intini et al., 2019). Multi-modality and its relation to departure time and the progressing wildfire/disaster is an under-studied area of wildfire evacuation modeling and deserves additional research.

Moving onto the traffic assignment stage, a dynamic approach is recommended since the wildfire will likely be affecting the road network over time (Beloglazov et al., 2016; Pel et al., 2012; van der Gun et al., 2016). The elements of the traffic assignment stage are route choice algorithm, background traffic, and the traffic simulation tool (Intini et al., 2019). Route choice can take a deterministic or a stochastic approach. The stochastic approach is more realistic for wildfires because it allows for en-route decision-making (Pel et al., 2010). The issue of changing routes en-route and the relation to destination choice are covered more thoroughly in the subsequent literature review. Furthermore, background traffic should be included in evacuation modeling so as to not underestimate congestion (Intini et al., 2019). It can be included by adding another OD matrix, or through by using an activity based approach.

Agent-based wildfire evacuation simulation

Several wildfire simulations in the literature integrate evacuation with traffic simulation using agent-based simulation (Beloglazov et al., 2016; Scerri et al., 2010; Wolshon and Marchive, 2007). These kinds of models are important because they can be used either for planning or real-time use during a wildfire (Intini et al., 2019). Typically, these studies have at least three modules- one for wildfire modeling, another for traffic modeling, and another for behavior modeling- which all combine to create the overall evacuation model. Some studies include more advanced modules, and these are discussed below.

Studying WUI wildfire evacuations of neighborhood subdivisions, researchers sought to understand from a traffic flow analysis perspective, the synergies between the factors that Cova et al. (2002) found important: housing density, road network, and geographical features, plus wildfire threat urgency (Wolshon and Marchive, 2007). The authors used simulation tool CORSIM and model evacuation directly from individual houses in a Salt Lake City suburban subdivision. They used random assignment of response time among households using 30 minute, 1 hour, and 2 hour periods, and also randomly assigned the number of vehicles to each household. They do not take into consideration the dynamics of the fire, which they note would likely affect response time (Wolshon and Marchive, 2007).

In this study, two types of route choice strategies were used: shortest path and alternate path. The latter consists of half of the vehicles choose a longer route if they encounter congestion. The results showed a need to spatio-temporally spread the loading of demand within a capacity constrained network in order to reduce the number of vehicles unable to escape, which is similar to other types of hazards (Wolshon and Marchive, 2007). The authors suggest increasing lead time through earlier notifications and controlling the level of evacuation travel demand through less dense housing stock.

Another agent-based simulation for wildfire evacuation called BLOCKS was created to show the Australian public the impact of their evacuation decisions on evacuation outcomes (Scerri et al., 2010). It consists of three modules: fire spread, human behavior, and traffic evacuation. Individuals are modeled as agents with demographic attributes as well as variables like panic level, access to vehicle, number of family members, and visibility and choose to either evacuate or shelter in place (Scerri et al., 2010). Agents simulate human behavior by either choosing to stay and protect their home or evacuate to a pre-determined location using the shortest path algorithm.

Dynamic factors, or the time-dependent relationships between wildfire progression, evacuation triggers, and individual behavior- were included by Beloglazov et al. (2016) in a more complex detailed simulation evacuation model. This agent-based model includes a wildfire simulator, behavior model, and a microscopic traffic simulator (Beloglazov et al., 2016). The effect of people in close proximity to an evacuation trigger, and the perceived severity of the threat may vary based on personality, hence the authors include behavior groups to account for this heterogeneity (Beloglazov et al., 2016).

In this approach, the wildfire simulation, behavior categorization, and destination modeling are first completed. From here, the wildfire simulation and behavior categorization inform the evacuation trigger modeling. The resultant evacuation triggers by area together with the behavior/personality type inform the departure time modeling, resulting in the origins and departure times by vehicle. These origins, destinations from the destination modeling step, and road network all are inputs to the eventual traffic simulation. Finally, this simulation produces the vehicle trajectories, or the how, when, and where residents evacuate. Lastly, these trajectories, combined with the spatio-temporal fire front from the wildfire simulation, go into the risk analysis and assessment. Varying the ignition points of the initial wildfire, the authors run the whole model for different ignition scenarios. The results show a statistically significant difference from using the dynamic factors model when compared to simply a static model. This shows that it will be important for future models in include dynamic factors, which provide needed explanation for the complex, interconnected processes of evacuation.

For future study, the authors suggest several directions such as sensitivity and comparison of the simulation results to different behavioral aspects like vehicle occupancy or timing of the warning and response time, among many others (Beloglazov et al., 2016). Taking into consideration the changing of routes due to road blockages/congestion as well as gathering behavior and preference for well-known places like highways and shopping malls are also important areas that can be explored to create more realistic evacuation simulations. Future research is needed to assess the extent of evacuation preparation time for rapid-onset hazards, such as fast-paced wildfires and tsunamis (Golshani et al., 2019, 2018; Wang et al., 2016).

Destination and Route Choice in No-Notice Evacuations

There is a lack of data on no-notice evacuations, hence there is not much research on proximate and ultimate destinations and how they affect traffic flow and evacuation operations. Most research focuses on advance-notice disasters, particularly hurricanes, which do not incorporate the proximate/ultimate destination choice aspect. Advanced-notice studies typically assume a single destination, which is based on either evacuees minimizing distance/travel time, locations of friends' and relatives' homes, speed of the hazard, established evacuation plans, and/or traffic conditions on the network (Southworth, 1991).

Much of this literature examines evacuation overnight accommodation. From least to most preferred, these options include shelter, hotel/motel, and friends'/relatives' home, , etc. (Lindell et al., 2011; Murray-Tuite et al., 2012; Sorensen, 2000; Wu et al., 2012). In the case of the Camp Fire evacuation, many evacuees actually ended up staying overnight in proximate destinations, such as the Chico Walmart parking lot, for several days or even weeks due to extremely congested roads, not knowing where to go, and because it had a sense of familiarity (Romero, 2018).

When residents evacuate in a no-notice disaster, traditional trip distribution modeling work differently in the sense that destinations are not selected ahead of time, since people may take routes haphazardly, trying to avoid the hazard as safely and quickly as possible, without a destination in mind (Pel et al., 2012). This rerouting behavior is best captured using the en-route and hybrid route choice models, which determines the destination while the evacuee is escaping, based on the route they take (Pel et al., 2012). Eventually, evacuees escape the risk, reaching safety and terminating their evacuation route; this terminus is the proximate destination, first defined by Barrett et al. (2000) in their development of a dynamic hurricane evacuation model (Barrett et al., 2000). The proximate, or intermediate, destination can be defined in three different ways:

- the nearest point beyond the risk area
- the point beyond the risk area with the shortest travel time

- the point beyond the risk area with the least perceived cost (Barrett et al., 2000; Lindell and Prater, 2007)

Following the en-route/hybrid route choice assumption for no-notice evacuations, evacuees do not “choose” their proximate destination, but rather end up there based on the route they took. Evacuees still need to go to their ultimate destination, or where they will stay until the risk subsides and they can return to their homes or place of work, etc. (Lindell and Prater, 2007). The ultimate destinations are considered to be shelters, friends and family’s homes, hotels/motels, etc. However, in their review article on evacuation transportation modeling, Murray-Tuite et al. note that the proximate/ultimate destination idea is not based on empirical evidence (Murray-Tuite and Wolshon, 2013a).

As described above, for no-notice disasters, destination choice can be thought of as a product of route choice, which may be haphazardly chosen to avoid the threat. Re-routing behavior to avoid the threat can bring the evacuee to a safe location that was not intended at the outset of the evacuation. En-route and hybrid route choice models allow for flexibility in the evacuee’s route, especially the ability to account for degradation of the road network due to the developing hazard and dynamic changes in the network due to traffic control measures taken by emergency responders to improve the ongoing evacuation (Pel et al., 2012).

Destination & Route Choice: Examples from the Literature

Using stated preference data for a no-notice disaster in the Chicago metropolitan area, Golshani et al. (2018) considered the relationship between departure time and destination choice (ultimate) using a discrete–continuous joint model structure (Golshani et al., 2018). Specifically, they use a multinomial logit (MNL) model for the destination choice, an accelerated hazard model to estimate departure time choice, and a copula-based modeling approach to capture interrelations. This study is mainly focused on the classification of destination types and their interrelation with departure time, rather than the spatial distribution of destinations and their effect on the road network. This study does not take into consideration the proximate-ultimate destination issue. The authors point to several areas of future research, such as incorporating mode choice and accounting for on-route infrastructure failure and its impact on final destination choice resulting in the re-routing behavior of evacuees (Golshani et al., 2018).

Several destination choice models use zone-based aggregated methods. In a short-notice disaster traffic simulation, Wang et. al (2014) use TAZ's to estimate destinations, where the number of evacuees destined for a certain TAZ is proportional to the amount of housing stock within a given TAZ (Wang et al., 2014). The portion of evacuees without vehicles were assumed to go to nearby shelters, which had assumed locations.

Wilmot et al. (2006) use a trip distribution gravity model and intervening opportunity model to see how well these models reproduce observed evacuation destination choices at an aggregated level (Wilmot et al., 2006). The authors stress the importance of using dynamic trip distribution models to account for congestion and consideration of the location of destinations with regard to the path of the hazard (Wilmot et al., 2006). In another aggregated study, a MNL model is estimated where the outcomes are different TAZ-destination zones formed by their hurricane risk (Cheng et al., 2008). Some attributes of TAZ's that affected destination choice were racial breakdown, total populations, city density, highways, and hotels. Both of these studies considered hurricanes, but they were still included because of their focus on destination choice.

The use of pre-determined destinations in no-notice evacuation modeling is also commonly used. Studying a tsunami, Charnkol et. al examine the preference of private and public shelters, but do not consider proximate vs. ultimate decisions or any spatial aspect of destinations (Charnkol et al., 2007). Assuming that an emergency network planner can route evacuees to certain destinations, Chiu et. al (2007) propose a network transformation which solves for destination, traffic assignment, and departure schedule simultaneously (Chiu et al., 2007). Considering the short notice evacuation planning problem using a capacitated network flow optimization approach, Lim et. al (2012) also use pre-determined destination nodes to which evacuees are routed (Lim et al., 2012). Hsu et al. assume that people do not choose a destination but just choose a familiar route, without switching it at any point, and that route brings them to pre-determined shelter locations (Hsu and Peeta, 2013). Na et al. (2019) assign evacuees to pre-determined shelters locations based on the shortest path algorithm and the extent of their hazard-induced injuries in an agent-based simulation (Na and Banerjee, 2019).

To account for spatial correlation in destination choice for a tsunami evacuation, Parady et al. (2016) estimated a spatially correlated logit model of evacuation destination choice using empirical data (Parady and Hato, 2016). Some factors they found to affect destination choice were OD distance, OD altitude difference, building density, and number of shelters. There have not been any empirical studies on the proximal-ultimate destination/route choice process, other than the literature mentioning this as a concern in no-notice events. This issue was first discussed by Lindell et al. (2007), in reference to private vehicle behavior in hurricanes (Lindell and Prater, 2007).

Understanding destination choice is important because knowing how people disperse during no-notice events allows us to ensure that their movement does not interfere with the evacuation of others or the movement of emergency personnel. Destination choice during evacuation is a critical factor which affects the spatial and temporal distribution on the network, which itself can be changing dynamically as the hazard unfolds. Better understanding of this destination choice behavior can reduce the proclivity of gridlocks which can cause longer evacuation times and loss of life in some hazards. This has important implications for disaster management and evacuation planning. Lastly, this topic contributes to the knowledge base of wildfire-specific evacuations, of which there is markedly less research than for other types of disasters.

Destination & Route Choice: Examples from the Wildfire Evacuation Literature

In their review of wildfire evacuation modeling in the wildland-urban interface (WUI), Intini et al. (2019) explain that random utility models are typically used to simulate destinate choice, based on their respective utility (Intini et al., 2019). Using a microscopic traffic simulation of wildfire evacuation, Beloglazov et al. (2016) model destination selection simply based on distance, with an evacuee choosing the nearest destination to their origin beyond the risk zone (Beloglazov et al., 2016). The authors do not take into account proximate vs. ultimate destinations. Modeling neighborhood wildfire evacuations in the WUI, Cova et al. (2002) also use the closest assignment method, choosing destinations within a pre-defined set of shelters and exits (Cova and Johnson, 2002). Similarly, in a study which examined subdivision-level wildfire evacuation, destinations, or “exits” were pre-determined (Wolshon and Marchive, 2007).

Information on proximate destinations was collected in a revealed preference survey after a wildfire in Haifa, Israel. Toledo et. al (2018) found that for those residents that evacuated, the proximate destinations were 57% houses of someone else, 17% to public places, 18% other, and

8% work or school (Toledo et al., 2018). Of these evacuees, 52% had proximate destinations within the city of Haifa, 20% to the larger Haifa metropolitan area, and 28% further away (Toledo et al., 2018). Unfortunately, this study did not collect information on ultimate destinations.

Bridging Engineering and Human Behavior in Wildfire Evacuation

In the wildfire literature there are two disjoint areas: engineering and human behavior. Many behavior studies come from social disciplines while the evacuation and transportation research are couched in engineering. Although some engineering models aim to include these behavioral aspects, in general both sides have not recognized that the human behavior aspects and transportation aspects are inextricably coupled (Lovreglio et al., 2019). Apart from this dichotomy, there is also the issue of the much larger body of evacuation research devoted to hurricanes, which may or may not be applicable to wildfire evacuations.

Even though wildfires are increasingly common with climate change and WUI population growth, the majority of the existing evacuation behavior literature focuses on disasters which have a period of notice beforehand, namely hurricanes. In a literature review of 83 peer-reviewed evacuation behavior articles from varying disciplines between 1961 and 2016, 59 of the studies analyzed hurricanes, while only 3 looked at wildfires (the remainder being 14 floods, 5 tsunami, 2 volcano eruptions) (Thompson et al., 2017). This indicates that a majority of the evacuation behavior research has been on hurricanes, rather than wildfires, although this study did exclude qualitative and theoretical papers.

Despite the traditional focus on hurricane evacuation, there have been three very recent articles which focus on the gaps in wildfire evacuation literature. First, Intini et. al (2019) thoroughly reviewed suggested methods to use in traffic modeling for wildfire evacuation. This study focused on the appropriate traffic modeling techniques to use for wildfire evacuation, many of which have been referenced earlier in this chapter. This paper took an engineering-focused approach and did not include much of the social science research that has been done on wildfire evacuation.

The second pertinent recent article, by Lovreglio et al. (2019), tries to bridge this gap by developing a mathematical framework that engineers can use that incorporates human behavior simulation (Lovreglio et al., 2019). The main areas of human behavior that this paper focuses on are the evacuate/stay and defend your property decision and departure time. Finally, recent review article compared hurricane and wildfire behavior modeling literature and built a provisional qualitative framework for individual decision-making in wildfires (Folk et al., 2019). This article mostly focused on the stay/leave decision again, and notes that an area of future study are the factors that affect the wildfire evacuation decisions of route choice and final destination choice (Folk et al., 2019).

Chapter 3. Awareness, departure, and preparation time in no-notice wildfire evacuations[1]

Wildfires are catastrophic events likely to continue to increase in frequency with global climate change. One in three U.S. homes is now located within the wildland urban interface (WUI), increasing the risk of catastrophic loss significantly (Radeloff et al., 2018). With nearly 2 million acres burned and over 100 fatalities, the 2018 California wildfire season was the most destructive in the state's history, at the time of this paper's submission. One of the fires that year, the Camp Fire, was also the deadliest and most destructive wildfire in the state and the deadliest in the past 100 years nationally (California Department of Forestry and Fire Protection, n.d.). The Camp Fire alone resulted in 85 fatalities and destroyed some 14,000 residences while burning for over two weeks (Lam, 2019). Wind speeds of 40 to 60 mph were observed for at least nine hours the day of the fire resulting in extremely fast spreading fire spread, at an estimated rate of one football field per second (NOAA, 2020).

The Camp Fire started around 6:30 am on a Thursday (November 8th) as a result of electrical transmission lines owned by the local utility company, Pacific Gas & Electric (PG&E) (California Department of Forestry and Fire Protection, 2019). With little warning time and an unusually fast-moving fire, there was virtually no time for thousands of people to prepare to evacuate. In fact, many were forced to immediately evacuate after waking up to smoke and embers, with little time to receive, let alone process an alert. Inevitably, evacuation routes were

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[1] This chapter should be cited as Grajdura, S., Qian, X., Niemeier, D., 2021. Awareness, departure, and preparation time in no-notice wildfire evacuations. Saf. Sci. 139, 105258. https://doi.org/ 10.1016/j.ssci.2021.105258

marked by traffic congestion, downed power lines, abandoned vehicles, and approaching flames, causing many to leave their vehicles and seek safety afoot.

No-notice events are complicated to manage for authorities and residents alike; authorities may struggle to communicate quickly with the population, while residents have limited time between notification and evacuation decisions. In a crisis, the timing of each decision cascades to affect the next decision. One of the major challenges in evacuation planning is understanding the behavior underpinning these decision-making points (Folk et al., 2019) and how authorities can incorporate this knowledge into planning and simulation of response-phase evacuation behavior (Veeraswamy et al., 2018).

In this paper I draw on a unique dataset of surveys and interviews collected online and at evacuation shelters shortly after the November 2018 Camp Fire. I examine the factors that influence the time at which people become aware of an oncoming wildfire (the awareness time). How the timing of awareness related to departure time is also a topic of interest. I analyze the range of factors that affect individuals' choice of departure time and, in turn, the preparation time, or the span of time between fire awareness and departure.

The paper begins with a review of the literature on no-notice evacuations and wildfire evacuation behavior. From there, I describe the data and lay out the empirical models measuring awareness time, departure time, and preparation time, as well as the independent variables used in each estimation. I then present the results of these models and discuss the major findings and their implications for no-notice wildfire evacuation research and wildfire evacuation planning. I conclude with a summary of the findings, limitations, and suggestions for future research.

Literature Review

There are a number of detailed literature reviews of evacuation modeling (Bayram, 2016; Murray-Tuite and Wolshon, 2013a; Pel et al., 2012) as well as quite a few recent reviews of wildfire evacuation modeling (Intini et al., 2019) and behavior (Folk et al., 2019; McCaffrey et al., 2018; McLennan et al., 2019). My intent in this section is to highlight the important gaps in the knowledge using these resources. I begin with a few key definitions. A no-notice evacuation occurs when there is an unpredictable disaster that necessitates rapid evacuation, with little or no prior warning (Chiu et al., 2007). Advanced-notice evacuations, in contrast, occur for forecasted events such as floods and hurricanes, in which there is ample time, sometimes weeks, for public officials to adequately warn the public (Golshani et al., 2019). A wildfire is considered a no-notice event if it is moving quickly and there is little preparation time for evacuation. Some of the major ways in which advance notice (e.g., hurricanes) varies from no-notice (e.g., wildfires) evacuations are the much longer warning times, better prediction of the affected areas, and the potentially viable choice to stay and protect one's home (McCaffrey et al., 2018).

Advanced warning events provide expanded window of time in which to gather information and make decisions. Evacuation departure times for advanced notice events like hurricanes often follow behavioral response curves and mathematical models from post-evacuation surveys (Fu et al., 2008). These modeled response curves take into account timing of the evacuation notice, the time-dependent characteristics of the event (e.g., a hurricane), and household characteristics (Fu et al., 2008). Comparatively, there is little behavioral research on no-notice events; this is in large part associated with the difficulty of acquiring data (Golshani et al., 2019). There is even less research looking specifically at no-notice wildfires (McCaffrey et al., 2018). The next section reviews the relevant literature regarding behavior in both no-notice events and wildfires. These two areas are important to understand the research gaps that this manuscript targets.

Evacuation in No-Notice Disasters

It is reasonable to assume that human behavior during wildfire no-notice evacuations plays a significant role in evacuation outcomes. However, most of what is understood about no-notice wildfire evacuations focuses narrowly on the decision to choose to evacuate (Folk et al., 2019). This focus makes sense, since departure time, or the time at which a respondent leaves the evacuation origin, is a key factor affecting successful evacuation outcomes (Beloglazov et al., 2016). Last minute evacuations tend to result in greater numbers of fatalities (Haynes et al., 2010). Wildfires in particular require sufficient time to avoid both flames, flying debris and smoke as well as to ensure that vehicles do not conflict with emergency and/or fire response teams (McCaffrey et al., 2018). To understand the other potential elements playing a role in departure times, I have to look at no-notice evacuations for events other than wildfires.

Stated preference surveys of decision-making under hypothetical disasters provide some indication of the factors that influence departure time, including evacuation warnings, socio-economics, and environmental factors (Golshani et al., 2019). For instance, gathering scattered family members (e.g., children) has a large effect on household behavior and can delay departure times (Liu et al., 2012). When family gathering and mode choice are accounted for in no-notice evacuation modeling for hypothetical disasters, the results produce starkly different evacuation times (Liu et al., 2014).

Models using stated preference data have been developed both for system-wide no-notice evacuation with joint decision-making (Chiu et al., 2007) and hierarchically, with evacuees first choosing to evacuate and then choosing a route (Hsu and Peeta, 2013). Golshani et al (2018) used a joint model to look at the relationship between departure time and destination choice and found that similar factors affect both departure and destination. Some decisions, like destination choice, may not even be made as evacuees simply aim to reach safety without a specific destination in mind (Pel et al., 2012).

One of the limitations of this body of research is that much of the work is based on stated preferences surveys of hypothetical no-notice disasters, while both stated and revealed preference data are important for disaster management planning and simulation for no-notice events (Murray-Tuite and Wolshon, 2013b), there are several issues associated with using stated-preference data. The most obvious is that how someone may plan to act in a hypothetical situation may be wildly different than how they respond in a real-world situation (Train, 2009). Second, the way a hypothetical situation is constructed may differ from the manner in which a real-life disaster event unfolds. The research addresses the gap in understanding using observational data collected shortly after the no-notice event, which allows us to better understand behavior in wildfires, an important aspect to disaster planning.

Wildfire Evacuation Behavior

The outcome of a wildfire evacuation depends on many complicating factors but is highly influenced by the quality of information received and the dissemination tactics that are used to "spread the word." Approximately 11% of wildfire fatalities in Australia between 1900 and 2008 were due to a lack of, or late evacuation warning (Haynes et al., 2010). In a review of North American and Australian wildfire evacuation behavior, people were more likely to search for information than to prepare to evacuate after unclear warnings (McLennan et al., 2019). With normal communication patterns often disrupted by power shutdowns, understanding how to communicate with sufficient lead times in the WUI communities is critical (Taylor et al., 2003).

The Protective Action Decision Model (PADM) was developed to understand how people are alerted to a disaster, and then how they choose to protect themselves in a disaster situation (Lindell and Perry, 2004). The framework is divided into cues (environmental, social, and information) which in turn lead to a pre-decision process, credible threat and risk assessment, and lastly a protective action decision (Lindell and Perry, 2004). In the protective action decision stage of the PADM model, age, gender, and income have all been found to be important factors of decision-making (Folk et al., 2019). When analyzing findings from the 2009 Victoria bushfires, Mclennan et. al found that, of those reportedly being highly vigilant and aware of the oncoming fires early on, 42% choose to evacuate and 58% stayed to defend (Mclennan et al., 2011). One highly relevant study examining the choice of whether to evacuate during a no-notice wildfire found that after accounting for perceived risk, household characteristics such as the number and age of children and presence of elderly effect evacuation rates (Toledo et al., 2018).

Even after accounting for communication efforts, research suggests that earlier departure times are often associated with environmental triggers such as smoke, flames and embers, family concerns, a higher perceived threat of the fire, and warnings from others, all of which serve as significant motivators for departures (McLennan et al., 2013). When there is uncertainty of the level of threat and there is a prior commitment to a plan of action, the decision to stay is usually because it was already part of the plan of action and the decision to leave is associated with realizing the gravity of the threat (McLennan et al., 2012). Departure modeling from wildfire events use evacuation order timing and typically assume exogenous S-curves to arrive at a distribution across time (Church and Sexton, 2002; Cova et al., 2011; Cova and Johnson, 2002; Dennison et al., 2007; Tweedie et al., 1986; Wolshon and Marchive, 2007). Departure S-curves were originally developed for hurricanes, but have been found to be generally applicable for other disasters, including certain types of wildfires (Murray-Tuite and Wolshon, 2013a). More recent models have incorporated dynamic sub-models to capture elements such as wildfire physics, behavior, and traffic flow (Beloglazov et al., 2016). Refining even further, Ronchi et. al (2019) created an integrated framework for WUI evacuations which incorporated wildfire propagation, pedestrian response, and traffic modeling to allow for dynamic fire vulnerability mapping (Ronchi et al., 2019).

Despite the recent literature additions, gaps in understanding remain on the effect of behavior on departure delays, even after receiving an evacuation warning (McLennan et al., 2019). Strahan et al.'s (2018) recent work suggest there may even be different evacuation archetypes, such as the Responsibility Denier, Considered Evacuator, and Experienced Independents, and these archetypes are associated with varying departure times (Strahan et al., 2018). Other recent conceptual models identify socio-demographics, environmental and social cues, previous experience, and familial responsibilities, among others, to be of paramount importance in the decision to evacuate in a WUI wildfire (Folk et al., 2019).

The length of time a resident lived in an area also affected their concern around wildfire events and potential home damage (Mozumder et al., 2008). Those living in an area for longer periods had stronger beliefs around personal safety than those living in the same area for shorter time (Benight et al., 2004). Among socio-demographic variables, age has been found to affect wildfire perception and behavior (Mclennan et al., 2011; Mozumder et al., 2008), while gender seems to affect willingness to evacuate and evacuation decisions. Men are less likely to evacuate or evacuate later than women (Eriksen et al., 2010; Mclennan et al., 2011; Mozumder et al., 2008; Paveglio et al., 2014; Whittaker et al., 2016, 2013). Income has been shown to effect household concern and evacuation behavior, with higher income households more likely to evacuate (Mozumder et al., 2008; Paveglio et al., 2014).

Whether or not someone is capable of receiving a warning is also important. In their review of the 2009 Victorian Bushfires, Mclennan et. al found that those who received information face to face were more likely to evacuate (Mclennan et al., 2011), but personal communication devices, such as smartphones, are also influential in evacuation decisions (Mesmer and Bloebaum, 2012). I use these important findings of previous research to guide the questions and methodology.

Research Question

There is an important gap in the literature on the range of factors that determine how and when residents become aware of a no-notice wildfire, and how this awareness time affects departure time during an actual no-notice wildfire evacuation. Furthering the understanding in this area is important because in no-notice wildfires, there can be little to no time for official warnings to be sent before evacuation must begin. Generally, I expect that those with earlier awareness times will also have earlier departures, and that if residents find out about the wildfire sooner, then they will have longer preparation periods to pack and gather belongings before evacuating. I hypothesize that younger, wealthier, more educated residents with smartphones will have earlier awareness and departure times and longer preparation times, and consistent with previous literature, that home insurance status and residence tenure will affect awareness, departure, and preparation times. Likewise, I expect being aware of community evacuation plans and having received an evacuation order would be associated with earlier awareness and departures, and longer preparations.

This study is aimed at improving understanding of the relationships between wildfire awareness time, official alert time, and departure time in no-notice wildfire evacuations and the socio-economic factors I preview above. To do this, I model awareness time, departure time, and preparation time for the 2018 Camp Fire, a large-scale no-notice wildfire, using unique data from surveys conducted closely following the evacuation. I find that the manner in which residents become aware of the wildfire, the socio-demographics, familiarity with evacuation plans, age, smartphone ownership, length of residency, among other factors influence the three dimensions of awareness, preparation, and departure.

Data Description

Study Area

The Camp Fire took place in the Sierra Nevada foothills of Butte County California, northeast of the city of Chico, near the Feather River Canyon (Figure 2). The largest town destroyed during the Camp Fire was Paradise, although the smaller communities of Magalia, Butte Creek Canyon, Pulga, and Concow were also affected. The area is heavily forested, with a population of about 38,000 residents. The roads in the area were built along old gold mining trails and orchard paths that were paved haphazardly over the years to allow the area to grow and develop, resulting in several miles of dead-end roads and only four main evacuation routes (St. John et al., 2018). The 2008 Humboldt Fire motivated the 2015 reconfiguration of the main evacuation route, Skyway, as a one-way out of town in the event of an evacuation. Paradise had detailed evacuation plans by zone. This zone by zone evacuation was practiced as a drill in 2016;

however, emptying the entire town and surrounding communities at once was never planned nor practiced (St. John et al., 2018).

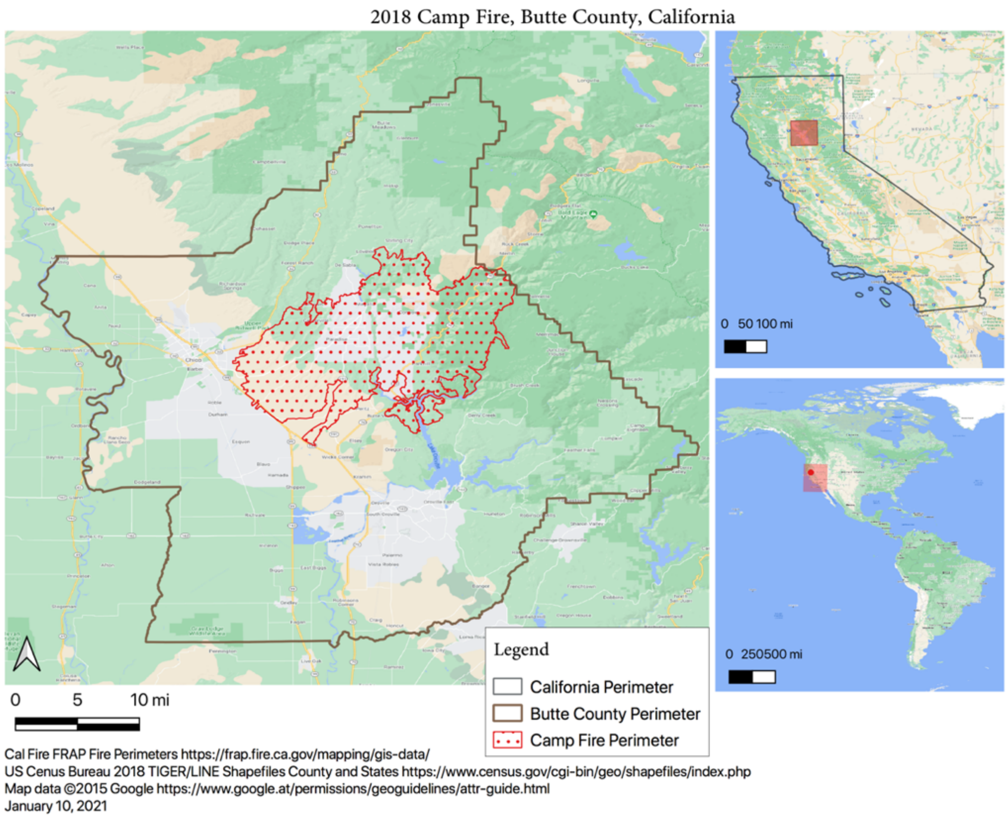

Figure 2: Camp Fire Study Area

Data

The research team gathered first-person interviews and surveys in the weeks following the November 8th, 2018 Camp Fire. In-person surveys were conducted using an intercept method at local Red Cross shelters in the cities of Chico and Gridley, California as well as the Butte County Disaster Recovery Center in Chico, California. The Red Cross shelters were set up specifically for Camp Fire evacuees in the days and weeks following the Camp Fire, and the researchers were given access to enter the shelters and conduct surveys. In total, 133 in-person surveys were conducted November 28^{th} through December 19^{th}, 2018. The survey consisted of 51 questions, both multiple choice and short-answer and covered several areas including socio-demographics, evacuation decision-making, evacuation communications, familiarity with existing evacuation plans, and post-evacuation housing (Table 1).

I also distributed the survey online December 3^{rd} 2018 through January 4^{th}, 2019. The survey was administered through the local Camp Fire survivor Facebook groups and notices were distributed through advertisements in local newspapers and radio stations. In total, 373 surveys were collected online; 109 of these surveys were blank or only partially completed. I eliminated these surveys, bringing the total online surveys to 264. Between the in-person and usable online surveys, the complete sample size is 397, 34% of collected in person, and 66% collected online. Among the online and shelter groups, I noticed several differences, significantly that the shelter group consisted of a lower-income, higher proportion non-white, older respondents and a higher proportion of male respondents.

The 133 shelter residents who took the survey also participated in extended interviews which consisted of open-ended questions, allowing the individual to freely share their experience. The interviews covered the same topics of the survey, the only difference was that the questions were framed in an open-ended manner to get the person's unique perspective of evacuation events. I believe this experiential dimension to the human subjects research greatly enriched the understanding of the Camp Fire evacuation beyond simply the survey questions.

The survey and interview data offers several important advantages for this analysis. Since I asked several questions in the survey that require recent memory of the course of evacuation events, it was advantageous that I was able to collect survey responses quickly, in a matter of weeks, after the disaster event. Disaster surveys have largely taken place several months after the event. In their recent review on evacuation from natural disasters, Thompson et al. tabulated the timing of post-disaster interviews and surveys from the literature. Data collection efforts ranged from days to as much as 5 years after a disaster had taken place, with only about 12% taking place within 1-3 months of the events and about 10% within a month. (Thompson et al., 2017). Another advantage was the access to the Red Cross shelters, giving us the chance for face to face discussions with evacuees. This offers a much deeper understanding of the data by providing context and understanding of the behavioral evacuation process that would otherwise be absent from the research in evacuation dynamics (Haghani, 2020). Lastly, by intercepting individuals at the Red Cross shelters, I also ensured that we were capturing a representative sample of evacuees, and not only those who had online access to the survey.

Descriptive Statistics

Demographically, the sample is predominantly white, non-Hispanic, and female, and is balanced across age, education, income, and household size. The dataset's racial makeup closely matches that of the region: the data is 85% white and 6% Hispanic, while the town of Paradise is 90% white and 7% Hispanic by the 2018 American Community Survey (ACS) 1 year estimates ((“Am. Community Surv.,” 2018). The survey respondents were largely females – as noted earlier, this is driven by the online respondents (78% female) - while Paradise is an estimated 53% female.

I asked evacuees how they first found out there was a fire. Nearly half, 45%, reported that they saw the fire firsthand, either by flames, embers, or smelling smoke and looking outside. The next most common way of being alerted to the fire was receiving the information firsthand by someone else, which accounted for about 26% of the responses, followed by those reporting that first notice came via a received call or non-official text (17%), 7% reported hearing online (Facebook, Twitter, etc.), and 4% reported noticing by TV or radio. The least common way of being alerted to the fire was through an official evacuation notice, accounting for just 1% of the sample. When asked if residents were aware of the local evacuation plans for their community, 57% reported knowledge of the local zonal evacuation plans.

Table 1: Descriptive Statistics

Variable	Value
Race	American Indian/Alaska Native = 1.4% (5), Asian = 1.6% (6), White = 84.6 % (307), Two or more races = 9.4% (34), Other = 3.0% (11)
Hispanic	Yes = 5.7% (20), No = 94.3 % (330)
Age	18-34 = 15.2% (60), 35-54 = 35.7% (141), 55-64 = 27.6% (109), 65+ = 21.5% (85)
Gender	Male= 34.2% (135), Female = 64.8% (256), Other = 1% (4)
Education	Less than high school = 5.1% (20), High school graduate = 15.1% (59), 2 year degree = 14.3% (56), Some college = 32.4% (127), 4 year degree = 20.4% (80), Master's/Professional = 11.4% (45), Doctorate = 1.3% (5)
Income	Less than $10,000 = 9.3% (35), $10,000-$14,999 = 12.5% (47), $15,000-$24,999 = 9.1% (34), $25,000-$34,999 = 11.7% (44), $35,000-$49,999 = 11.5% (43), $50,000-$74,999 = 17.1% (64), $75,000-$99,999 = 12% (45), $100,000-$149,999 = 11.2% (42), $150,000+ = 5.6% (21)
Household	1 member = 23.4% (93), 2 members = 36.2% (144), 3 members = 20.2% (80), 4+ members = 20.2% 80
Time at residence	Less than 1 year = 17.8% (70), 1-3 years = 22.6% (89), 3-5 years = 11.4% (45), 5-10 years = 15.7% (62), 10-15 years = 8.6% (34), 15+ years = 23.9% (94)
Smartphone	Yes = 85.9% (340), No = 14.1% (56)
Found out about fire	Saw fire firsthand = 44.6% (175), In person by somebody = 26.3% (103), Call or Text = 17.1% (67), Online = 6.9% (27), TV or Radio = 3.8% (15), Official Evacuation Notice = 1.3% (5)
Aware of local evacuation plans	Yes = 57% (209), No = 43% (157)

Note: Not all questions have the full sample size of 397 individuals

I also included questions regarding the evacuation sequence of events such as finding out about the fire, when respondents received an evacuation notice, and when they departed. From this information (Figure 3), it is clear that receipt of official notices followed reported awareness and departure times. The green line in Figure 3 represents the time at which residents received an evacuation notice, if they did in fact receive one at all. In the sample, only 19% of respondents reported receiving an evacuation order at any time on November $8^{th.}$.

The second data source are the Butte County Office of Emergency Management (OEM) Code Red logs, which were obtained through a Freedom of Information Act (FOIA) request. These data include the time official messages were sent out, the message content, and the proportion of each distribution method (phone, text, email, etc.), including the proportion of people reached. There were 44 total alerts from the morning of November 8 until the afternoon of November 10^{th}, 2018, 15 of which were recall attempts. A recall attempt is when an original message is sent again, in hopes of reaching the people who were not reached in the original message. These messages are displayed by the black line in Figure 3. It is important to note that not all residents were subscribed to the Code Red emergency notification system, which was an opt-in system. In Butte County, with a population of 229,000, only about 132,000 phone numbers and emails were in the Code Red subscription (Moffitt, 2019). In addition to the meager opt-in levels, as much as 40% of the Code Red calls did not go through (Moffitt, 2019). The lack of call pass through was exacerbated by the lack of cellular service as a result of the burning of fiberoptic cables. Although I consider this an important topic, I do not delve into who received and who did not receive Code Red notifications and why, partially because data on who had opted-in seems to be unavailable. I only know if a person received or did not receive a Code Red notification, not whether they were subscribed to the service or not.

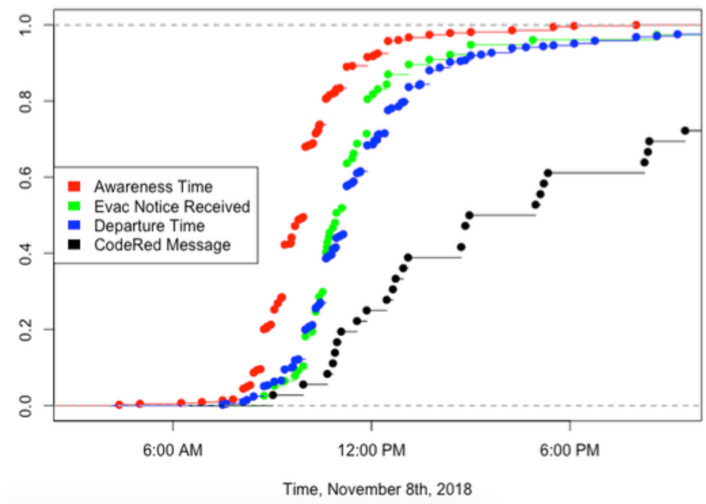

Figure 3: Cumulative Response Curves for Awareness Time, Time Received Evacuation Notice, Departure Time, and Code Red Messaging

Spatial Visualization of Survey

In Figure 4 below, I see a spatial-temporal visualization of the evacuation process showing how respondents were alerted to the fire, and the 98% of respondents identifying when they were first alerted to the fire (first alert), the 21% of respondents receiving official notification (official notification), and the 99% of respondents who shared their departing time (departure). I present this information in hourly intervals, from 6:00 AM through 2:00 PM the day of the fire.

Most of the residents were first alerted to the fire between 6 AM and 8 AM. The majority of respondents were first alerted to by seeing it firsthand or were alerted by other people. For those who did receive official notifications, displayed in the third column, the notifications mostly occurred within the hours of 6:00 AM to 12:00 PM. When I examine the spatial distribution of the notification locations, they are most concentrated in a long north-south strip passing through the city of Paradise. The spatial distribution is very different from that of the first alert locations, which means that the notification system was insufficient for reaching fire victims.

The time at which respondents reported evacuating generally lagged the time at which they report being alerted to the fire. For instance, compare the density of respondents reporting departing at 6AM-7AM and the number reporting first being alerted to the fire at 6AM-7AM. This visualization makes it clear that there was a very short time gap between when respondents reported their first alert and when they reported departing. In the next section, I examine the range of factors influencing awareness time, preparation time, and departure time.

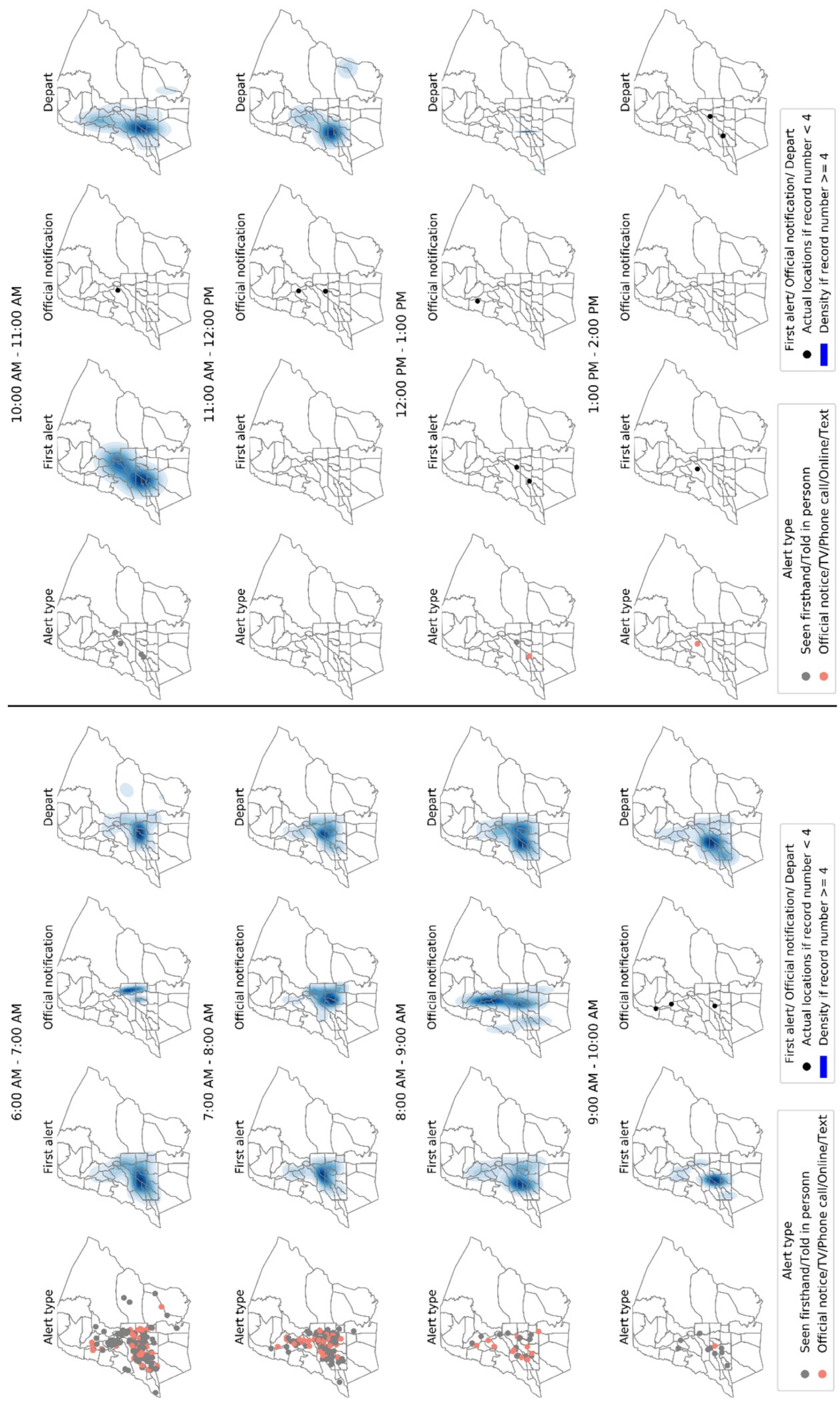

Figure 4: Data Visualization of First Alert, Official Notice, and Departure

Modeling Approach

I approach the modeling by formulating several critical objectives. I want to understand the factors that play an important role in: 1) how quickly people become aware of a no-notice disaster; 2) once they are aware of the fire, the time they take to prepare for departure, and finally 3) the actual departure time. I model both preparation time and departure time because I hypothesize that the factors related to preparation time are different from the factors associated with departure time.

In the first model, I ask the question *what affects awareness time in a no-notice wildfire evacuation?* The independent variables are derived from the literature and from the in-depth interviews. A summary of the variables is given in Table 2. I specify an ordinary least squares model in which the outcome is awareness time, a continuous variable measured in minutes,

$$t\_aware_i = \beta_0 + \beta_i X_i + \epsilon_i \qquad (1)$$

where *t_aware* is a continuous variable representing awareness time measured in minutes from 6:00 AM on November 8th, 2018; the fire began sometime between 6:15-6:30 AM, and 6 AM is a convenient benchmark. The intercept, β_0 can be interpreted as the awareness time when all continuous numeric independent variables are equal to zero, and all categorical variables are at their reference value. X_i is a vector of independent variables, and ϵ_i is the normally distributed error term. The index *i* represents each individual in the survey.

The departure time model is specified as,

$$t\_depart_i = \beta_0 + \beta_i X_i + \epsilon_i \qquad (2)$$

where t_depart is a continuous variable denoting the time individuals began their evacuation departure, as measured in minutes from 6:00 AM. β_0 is the constant representing the departure time when all independent variables are at their reference level, X_i is a vector of independent variables, and ϵ_i is the error term.

Finally, preparation time is calculated as the difference between awareness and departure times, $t\_prep_i = t\_depart_i - t\_aware_i$, as measured in minutes,

$$t\_prep_i = \beta_0 + \beta_i X_i + \epsilon_i \qquad (3)$$

where t_prep is a continuous variable, measured in minutes. β_0 is the sample's preparation time when all other variables are at their reference level, X_i is a vector of independent variables, and ϵ_i is the error term. In this model, a positive coefficient on an independent variable signifies more time elapsed between finding out about the fire and evacuating.

For the modeling, I constructed a number of variables (Table 2) based on sample size and critical features of the literature, the interviews, and the knowledge of the region. For example, I suspected that both income and age would play an important role in how easily and quickly alerts were received and evacuations undertaken. Similarly, I expected those owning smartphones have access to more evacuation information, those owning homes to behave differently from renters, and those residing in the area for longer to exhibit differences in their choice of departure time.

Table 2: Definitions of Analysis Variables

Variable	Description
t_aware	the time at which an individual became aware that there was a fire
t_depart	the time at which an individual starts evacuation
t_prep	the difference between t_aware and t_depart
age	Age <65 = 0 Age 65+ =1
gender	1=male, 0=female
income	< $50,000 = 0 , $50,000+ =1
educ	1.) Less than high school =0, High school and above = 1, 2.) Less than high school =1, High school =2. Above high school =3
white	individual is white (1=yes, 0=no)
smartphone	owns smartphone=1, no smartphone=0
insurance	has home insurance=1, no insurance=0
reside	how long an individual has lived in the community <15 yrs =0, 15+ yrs =1
findout	indicates how people became aware of the fire 1.) Phone call/SMS, Online, Evac Notice, TV/Radio =0, Told in-person =1, Sees firsthand (ie smoke, flames) =2 2.) Phone call/SMS, Online, TV/Radio =0, Evac notice =1, Told in-person=2, Sees firsthand (ie smoke, flames) =3
evacnotice	received official evacuation notice =1, no notice =0
plans	awareness of town evacuation plan before fire (not aware=0, aware=1)
num_modes	number of evacuation modes taken (ranging from one mode to four modes)
hh	number of household members, <4 members =0, 4+ members =1
num_evac	number of individuals evacuated with, including self (1= alone, 2-3, 4+)

Since this research breaks new ground, I took the perspective that variables should be considered from both a traditional statistical perspective (e.g., p-values and stepwise inclusion) as well as whether or not the variable had practical importance. I also collapsed levels for categorical variables that were consistent with the literature, but did not rise to statistical significance.

Results

Each of the three of the model's F statistics are statistically significant (p<0.01), indicating that each specified model is superior to an intercept-only model (Table 3). The awareness model specification is displayed in the second column of Table 3. There are nine independent variables included in this model: age, race, income, education level, household size, smartphone ownership, how the person found out about the fire, awareness of community evacuation plans, and receipt of evacuation notice. Of these independent variables, age 65+ (p<0.0001), race (p=0.033), income (p=0.0012), smartphone ownership (p=0.0061), finding out about the fire through firsthand observation (p=0.013), and awareness of community evacuation plans (p=0.0076) were all statistically significant at the 5% significance level or better. The adjusted R^2 value is 0.183.

Recall that the outcome in all three models is measured in minutes from 6:00 AM on the day of the fire. A negative coefficient indicates an earlier awareness time and a positive coefficient a later time. Starting with the effect of seeing the fire on awareness time, I find the coefficient is negative and statistically significant. This indicates that those who observed the fire firsthand were aware of the fire earlier than those who found out about the fire via phone/SMS, online, evacuation notice, or by TV/radio. Likewise, those with higher incomes (above $50,000) tended to have earlier awareness times. I see the same results for smartphone ownership, awareness of the community's wildfire evacuation plans, and whether or not the respondent was white. The only variable that is statistically significant with a positive coefficient is whether or not the respondent was over the age of 65, indicating later fire awareness for this age group.

Table 3: Modeling Results

Variable	Awareness time (min)	Departure time (min)	Preparation time (min)
Findout: Told in person[1]	-7.053 (9.128)		
Findout: Saw firsthand	-19.936** (7.941)		
Income greater or equal to $50,000	-23.480*** (7.160)		
Awareness time (min)		0.743*** (0.091)	
Smartphone	-29.083*** (10.529)	-37.414* (19.300)	-21.628 (18.886)
Education: High School[2]			47.689 (31.301)
Education: Above High School			8.903 (28.476)
Reside 15+ years		34.481** (14.891)	30.566** (14.223)
Aware of evac plans	-18.679*** (6.946)	17.651 (13.362)	10.578 (12.483)
Number of evac modes		3.757 (18.451)	
Home Insurance			33.547** (13.652)
Age 65+	33.855*** (8.511)	8.569 (16.261)	-2.281 (15.055)
4+ household members	-1.597 (8.733)		
White	-20.481** (9.554)	-29.799 (18.653)	
Gender (male)			23.342* (13.193)
Received evac notice	-0.409 (8.896)	39.932** (17.527)	47.141*** (16.176)
Education: High School or above	11.088 (16.073)	28.633 (30.071)	
Findout: Evac notice		-82.587 (68.281)	-91.264* (55.140)
Findout: Told in person		-21.333 (17.409)	-21.463 (16.036)
Findout: Saw firsthand		5.205 (15.356)	4.876 (14.281)
Constant	173.990*** (18.959)	124.656*** (45.631)	46.406 (33.047)
Observations	306	325	321
R^2	0.209	0.255	0.105
Adjusted R^2	0.183	0.226	0.070
Residual Std. Error	57.562 (df=295)	113.337 (df=312)	104.707 (df=308)
F Statistic	7.817*** (df=10; 295)	8.905*** (df=12; 312)	3.012*** (df=12; 308)
Note: *p<0.10, **p<0.05, ***p<0.01, (Robust standard errors)			

[1.] The FINDOUT variables have alternative specifications depending on the model. The awareness time model uses three options: phone call/text/TV/radio/online/evacuation notice, told in person, and see fire firsthand, where phone call/text/TV/radio/online/evacuation notice is the base level in the model. In the two remaining models, I use four options: phone call/text/TV/radio/online, evacuation notice, told in person, and see fire firsthand, again where the first option is the base level in the model. [2.] The EDUCATION variable is used in the awareness and departure models. The levels of education are less than high school or high school and above. In the preparation time model, the education levels specified are less than high school, high school, and above high school. In both cases, less than high school is the base level.

The results of the departure time model (third column of Table 3) included ten independent variables: age, race, education level, smartphone ownership, time living at residence, how the person found out about the fire, fire awareness time, awareness of community evacuation plans, number of evacuation modes, and receipt of evacuation notice. Variables which are statistically significant include smartphone ownership (p=0.053), time living at residence (p=0.021), awareness time (p<0.0001), and receipt of evacuation notice (p=0.023). The adjusted R^2 of the model is 0.226.

Awareness time is statistically significant in this model, with a positive coefficient estimate; this implies that a later awareness time is associated with a later departure, and vice versa. Smartphone ownership has a large, negative effect (-37.41), indicating that smartphone ownership is correlated with a much earlier departure time. Conversely, living in the community for 15 years or longer and receipt of an evacuation notice have large positive coefficients, indicating much later departure times for longer term residents and for those who received an official evacuation notice.

The preparation time model (fourth column of Table 3) includes nine independent variables: age, gender, education level, smartphone ownership, time living at residence, home insurance, how the person found out about the fire, awareness of community evacuation plans, and receipt of evacuation notice. Of these regressors, I find gender (p=0.078), time living at residence (p=0.032), alert by evacuation notice (p=0.099), receipt of evacuation notice (p=0.0038), and home insurance (p=0.015) to be statistically significant. This model has the least explanatory power, with an adjusted R^2 of 0.070. Being male (gender =1), having home insurance, living in the community for at least 15 years, and receiving an evacuation notice are all associated with longer preparation times. Conversely, finding out about the fire by evacuation notice is associated with shorter preparation times.

Discussion

Awareness time

The modeling indicates that age, race, and income all have a large and significant effect on when someone is first alerted to the wildfire, which is consistent with Folk et. al's (2019) work on the (PADM). Age had a strong effect on awareness timing, with a later awareness time approaching 34 minutes for those age 65 or older compared to those younger than 65. This particular case study is a good example of the importance is understanding the effects of age on evacuation behavior; Paradise and the surrounding area evolved over time to be a largely retirement community (Rinker, 2018). From the first-person interviews, I found that many older evacuees were not employed, and were not awake early or preparing for work when the fire first started (~ 6:30 AM). The model makes clear that quicker awareness times were associated with firsthand observation. The results also suggest that when community demographics are older, evacuation alerts might need to be structured differently. A recent study examining behavior in the 2018 Hokkaido Eastern Iburi earthquake and ensuing tsunami also found increased age to inhibit awareness and evacuation in a sudden disaster which they attribute to a decrease in mental and physical health (Arimura et al., 2020). Similarly, looking at the propensity to evacuate the 2016 wildfire in Haifa, Toledo et. al found statistically different evacuation rates between those aged 13 18 and those 55 and older, with the latter having a lower rate (Toledo et al., 2018).

Income was associated with quicker awareness times, with those making $50,000 or more alerted to the fire approximately 23 minutes sooner than those making less than $50,000. This finding coincides with the literature that shows income is an important factor, particularly in the choice of protecting one's home, although it is important to also note that conflicting results have been shown on the effect of income and the choice of whether to evacuate or not (Folk et al., 2019). Among very low to very high income groups, Toledo et. al found those with reported high income to have statistically different, and higher, evacuation rates than all other groups (Toledo et al., 2018). It is possible that the earlier awareness time of higher-income residents could be influencing their higher evacuation rates. White residents were alerted to the fire about 20 minutes earlier than non-white residents. To my knowledge, there is little research on how race affects the pre-decision and credible threat and risk assessment steps (Folk et al., 2019).

A smartphone had a large effect on awareness time, with those owning smartphones finding out about the fire roughly 29 minutes earlier that those who did not. This is expected since personal communication devices have been shown to be important in replicating realistic evacuation behavior, serving as a source of information and its dissemination (Mesmer and Bloebaum, 2012). This finding is intuitive in that even if a resident finds out about the fire by other means, the smartphone provides an essential information-gathering tool.

In the in-person interviews, I found that many residents saw the fire firsthand or smelled smoke, then quickly checked their phones to gather more information on the situation. The data also suggest smartphone ownership is related to income: of the 56 respondents who did not own smartphones, 77% earned less than $50,000 annually. Despite the smartphone being vital to finding out quickly, this technology is not failsafe during evacuations. Apart from the only 30% of the population enrolled in the CodeRed emergency alert system, numerous cell towers were destroyed in the Camp Fire, rendering cell phones useless (Moench, 2019; St. John et al., 2018).

Lastly, I find that knowing community evacuation plans beforehand was associated with an earlier awareness time, by about 19 minutes. This shows that even though the zonal evacuation plan did not go as planned, those who were aware of the evacuation plans still became aware of the fire sooner. This could possibly be due to these residents being more attentive to wildfire conditions or having a stronger understanding of the community landscape and built environment.

Departure Time

As I hypothesized, awareness time directly affects departure time. The positive coefficient indicates that an earlier awareness time is associated with an earlier departure time, and vice versa. This result seems reasonable; turning to the PADM model, credible threat and risk assessment is the first step in an evacuation. However, I find other factors temper this direct relationship. Again, smartphone ownership is important in determining departure time, even when controlling for awareness time. Owning a smartphone is associated with a 37 minute earlier departure time, all else constant. Through the in-person interviews, there were several anecdotal stories of residents checking Facebook only to discover that friends and loved ones were in dire situations, which spurred them, in turn, to start to evacuate.

A longer tenure of residence (15 years or more) led to a later departure time, of about 34 minutes. Anecdotally, long-time residents that I interviewed spoke of being accustomed to wildfires as a routine occurrence, and they did not suspect this particular wildfire to be any more dangerous than previous fires. Residents spoke of being reluctant to leave their homes, since they had previously dealt with several fires in the past, with no issues, and had already taken protective measures at their residences. This finding is supported by the literature, in which preparation and experience are important driving factors in deciding whether to remain and protect a home (Folk et al., 2019; McLennan et al., 2012). In their behavior study of tsunami evacuees, Arimura et. al (2020) found home ownership to negatively influence evacuation response, which they theorize is due to home owners having more confidence in the durability and resilience of their homes, as compared to renters (Arimura et al., 2020).

Holding all other factors constant, receiving an evacuation notice was associated with a later departure time. This result is surprising since evacuation notices would tend to spur quicker evacuation. However, I think this result has more to do with the timing of the evacuation notices and those who opted into the CodeRed alerts, and less to do with the alerts motivating people to begin evacuating. It is estimated that only 30% of the population were enrolled in this program (St. John et al., 2018). It is important to keep in mind that evacuees may have received the evacuation notice even after they had already begun their evacuation. Anecdotally, several people I interviewed said they received evacuation notices only after they safely reached their final destination or received the CodeRed alert as they were already beginning to evacuate. This could have been due to the fact that the Camp Fire took down 17 cell towers in the area, disabling cell reception for thousands of evacuees (Moench, 2019).

If I look at the sequence of the CodeRed alerts on November 8th, a clear pattern emerges. Figure 5 (leftside) shows the cumulative layout of alerts on that day, while Figure 5 (rightside) shows a k-means clustering of the alerts with 5 clusters. I apply this method to the CodeRed data in order to understand how CodeRed alerts were distributed. Looking at the distribution of the CodeRed alerts, I can see that the alerts are clustered later in the morning, at least much later than the average awareness time of 8:00 AM (Figure 3) and just ten minutes earlier than the average sample departure time of 9:33 AM (Figure 3). The standard deviation of the awareness time is 71 minutes, or a little over an hour, making the majority of the sample already aware of the fire by 9:11 AM, the mean of the earliest cluster in Figure 5. This means that the CodeRed alerts were not at all useful in notifying people of the oncoming fire. Similarly, the median departure time, or the time at which half of the sample had already evacuated, was 9:00 AM, so over half of the sample had already departed by the morning CodeRed cluster mean at 9:11 AM. As I observed with awareness time, the evacuation notice had little noticeable effect on encouraging evacuation departures.

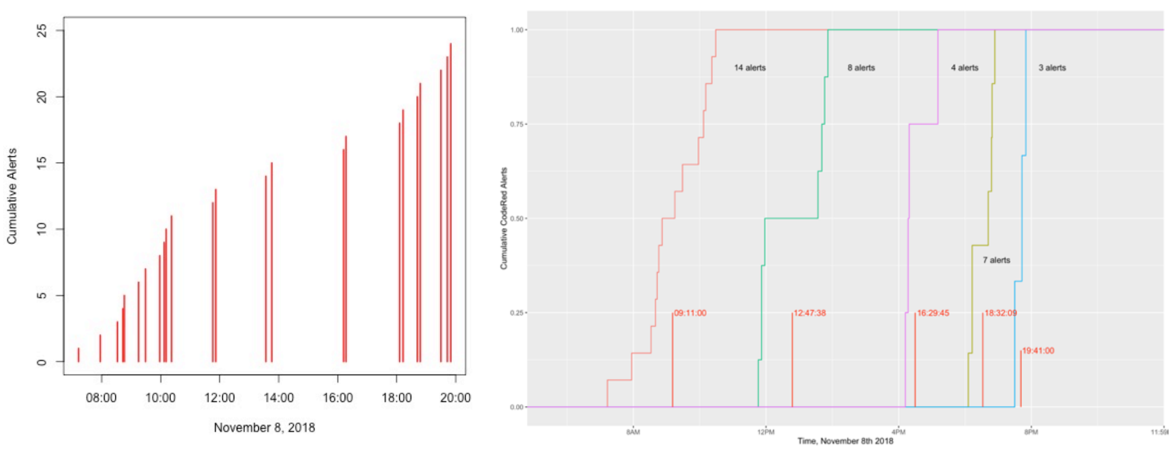

Figure 5: Distribution of CodeRed Alerts in Time

Preparation Time

Similar to departure time, residence tenure is an important factor in determining the length of preparation time. Those living in the community 15 or more years delayed their departure for upwards of a half an hour, holding all else constant. Based on the interviews, it appears that the underlying rationale is similar to that of departure time; those living longer in the community are more accustomed to the seasonal wildfires that happen in this region of California. This comfort with wildfires can cause these individuals to delay leaving, hoping for minimal damages.

Gender has a surprising role in the difference between the awareness and departure times; men tend to have a longer delay time, all things equal, than women, by 23 minutes. In the in-person interviews, I heard from men who chose to stay and defend their homes, while evacuating the rest of their family. These men ended up departing at a later time, only after realizing their homes could not be saved. Having homeowner's insurance also had delayed departures by about 34 minutes; I assume this result emerges because homeowners have a bigger incentive to defend their home than non-homeowners. Attachment to home and community and a desire to protect one's property are also important elements in the protective action decision during a wildfire (Folk et al., 2019).

Being alerted to the fire by evacuation notice was associated with a shorter preparation period, approximately 91 minutes (p=0.099). As discussed earlier, the official CodeRed notifications came much later than the average awareness time. It makes sense that those who found out about the wildfire through CodeRed would have a later than average awareness time, which in turn constrained the amount of time available for preparation. Meanwhile, those who indicated they received CodeRed (the question asks if they received a notification at any point on November 8th, not only one that alerted them to the existence of the fire) experienced longer preparation periods by 47 minutes (p=0.00383). The differing effects on preparation time of finding out by an evacuation notice versus receiving an evacuation notice at any point during the evacuation is an area for future research.

These findings have several implications regarding improving wildfire safety programs and household safety education. Authorities should consider evacuation plans specifically for a worst-case scenario in which a fast-moving, no-notice wildfire outpaces their abilities to adequately notify the population by traditional forms of evacuation notices. Planning must address the possibility of cell towers going dark, severely affecting cellular service of evacuees. Since most residents I report on were alerted to the fire by seeing the fire or smelling the smoke firsthand, education programs must teach people how to make quick evacuation decisions in the absence of a centralized alert system. In this way, householders can incorporate these scenarios into their personal disaster preparation planning.

Operations must also consider the socio-demographics and other details of their communities in developing future plans; I found marked differences across age, income, race, home insurance, and residence tenure. Authorities should be sensitive to these community dynamics and work to incorporate these aspects into future plans. Targeted education could be another way of accounting for more at-risk demographics. Carrying out these measures will in no doubt create more robust preparation in case of no-notice events.

Conclusion

In this paper, I investigate the factors and relationships between the different stages of no-notice wildfire evacuation decision-making, specifically awareness time, or when people found out about the fire, departure time, and preparation time. To my knowledge, there has been little empirical research that looks at the timing of when people find out about a wildfire, and how that in turn affects their evacuation departure time in a no-notice wildfire event. To date, most of the scholarship in this space has focused on disasters more broadly, or has developed theoretical frameworks for wildfire evacuations. In the protective action decision stage of the PADM model, age, gender, and income have all been found to be important factors of decision-making (Folk et al., 2019); this paper fills an important gap in linking these factors to the timing of decision-making activities.

The major findings include the following:

- The manner in which evacuees become aware of the no-notice wildfire has a significant effect on when they are first alerted to a fire and then, how long they take preparing before departure. Those observing the fire in person had earlier awareness times while those finding out by evacuation notice had less preparation time, largely because alerts were generally sent out later.
- Socio-demographics of evacuees play an important role in the timing of when they become aware of an approaching fire. White residents and those making $50,000 or more annually had significantly earlier awareness times. Older residents, age 65 and older, had significantly later awareness times.
- Having a smartphone makes a significant difference in terms of both awareness and departure times. Those with smartphones had much earlier awareness and departure times.
- The time at which people find out about the wildfire had a large and significant effect on their departure time in the no-notice wildfire event. Earlier awareness times denoted earlier departure times, and vice versa.
- How long a person has lived in the community plays an important role in choosing the departure time. Residents with tenure of 15 years or more had significantly later departure times, and took significantly longer to depart after finding out about the fire.
- Home insurance was associated with longer times until departure. Identifying as male also was significantly associated with longer preparation times.
- Receipt of official evacuation notices, in this case CodeRed, was surprisingly associated with later departure and longer preparation times. Since I do not have data on who was

opted-in to the CodeRed program, it is difficult to say decidedly if there were unobserved characteristics about those opted in to the program, or if the CodeRed notifications did indeed cause residents to behave in a way that delayed their time to departure.

Our analysis offers several important lessons in the overlapping areas of wildfire evacuation, evacuee behavior, and no-notice evacuation management and planning. First, the issue of race, income, and age have strong effect on awareness time, which means that these factors should be taken into consideration when planning for no-notice disasters.

Secondly, awareness time is associated with departure time. In order to give people ample time to prepare and depart at a reasonably safe time, I need to improve the awareness time across the distribution of evacuees. It is unclear how to best do this, but as the results show, people found out about this disaster in several ways, and not just evacuation notifications as much of the literature uses as a benchmark. At the minimum, better formal evacuation notice would be helpful. There is little question that improvements to the wildfire notification system are critically needed to combat no-notice events. In the study, formal evacuation notices, on average, arrived much later than firsthand observation of the fire progress. An individual that received a formal evacuation notice, at any time, was actually associated with a longer preparation time and a later departure time than those who did not receive notifications. It is unclear if this is due to lack of clarity in the notifications or other factors unique to that opt-in group of notification receivers. It is important to include smartphone access - and lack thereof - into evacuation management strategies, since I found them to have a large effect on both time of awareness and departure.

While the empirical findings can be extrapolated to other communities and incorporated into pre-event and real-time evacuation planning and traffic modeling, care should be taken. The results are endemic of the Camp Fire, and the external validity should be taken into account. That is not to say that none of the findings can be extrapolated, but more post-disaster surveys of similar wildfire events should be taken, along with pre-disaster surveys in high-probability wildfire areas.

The findings do have limitations which deserve attention. First, the analysis did not consider the geographical location of residents at the time of their awareness and departure, nor their location in reference to the dynamic location of the wildfire. Individuals nearer the fire would likely have earlier awareness and departure times, due to their proximity to imminent danger. In order to account for these spatial effects, I experimented with dummy variables corresponding to different evacuation zones. However, due to the grouping of the observations relative to the starting point of the fire, I did not find that including this aspect of the fire was advantageous, and the results were not statistically significant. Therefore, I did not account for the response varying with spatial heterogeneity for the three models. Since I did not account for the spatial component in the models, it is possible that observables such as race, age, and income varied spatially. Future work should address why awareness of the no-notice disaster varied significantly across race, income, and age. More should be done in evacuation management to account for these factors.

Another limitation to this study is that only evacuation survivors were interviewed; those 88 people who perished in the Camp Fire were not included in the sample. Since these individuals were not able to be included, the sample is biased towards those who did survive. In this case, I should be careful in how I interpret these findings. Further research should tackle the decision-making that did lead to unsuccessful evacuations, if possible. Finally, I did not take into consideration the choice sets of each individual, nor allow for it in the modeling framework. It is possible that some individuals would have preferred to depart sooner, but were unable to for lack of vehicle, or other reasons. The framework and survey instrument did not allow for such detail, yet this detail was captured in the qualitative interviews. Recent work studying evacuee behavior in dwelling fires showed that the larger the disaster, the worse individuals' recall ability; since this data is based on post-disaster surveys of recalled information, there is a possibility that evacuees' accounts are not perfectly accurate (Hulse et al., 2020).

To conclude, no-notice wildfires are a large threat that have dire consequences for human life, especially for those living in the WUI. With these events being a relatively new phenomenon that has the potential to increase in frequency with climate change, it is important that I make pre-event plans as realistic as possible (Murray-Tuite and Wolshon, 2013b). Empirical data is a powerful tool which can be leveraged to make no-notice wildfire planning more realistic, effective, and in turn safer.

Chapter 4. Fast-moving dire wildfire evacuation simulation[2]

Introduction

Extreme and no-notice disasters, those events with little to no official warning, pose a significant threat to human life. As for other natural disasters, climate change means that wildfires, which are especially dangerous and destructive, are intensifying, increasing in frequency, and producing greater destruction and loss of life (Pierre-Louis and Popovich, 2018). Climate change also brings higher temperatures, higher winds, lower humidity, drier fuels, and higher Forest Fire Danger Indices (FFDI), all of which are associated with increased wildfire fatalities (Blanchi et al., 2014), especially in the wildland-urban interface (WUI) where evacuation efficiency and safety are critical (Wolshon and Marchive, 2007).

Much of the wildfire evacuation research focuses on ideal and favorable conditions for evacuation, not extreme and dire events like that of the 2018 California Camp Fire (Cova, et al., 2021). At the time, this fire was the deadliest U.S. fire in the previous 100 years. The interest is in the fast-moving, no notice wildfire events within the WUI, where developed land meets undeveloped, often forested land with a high fire potential (Naiem et al., 2010; Zhang & de Farias, 2007; Cova and Johnson, 2002). In many of these areas, the number of exits and roadway infrastructure has often not kept pace with rapid population growth, which increases

[2] Grajdura, Sarah, Sachraa Borjigin, and Deb Niemeier. 2022. "Fast-Moving Dire Wildfire Evacuation Simulation." *Transportation Research Part D* 104:103190. doi: 10.1016/j.trd.2022.103190.

vulnerability (Cova et al., 2021). Modeling human response to these events can be complicated since decisions will be made quickly and without much deliberation because time is of the essence (P.M. Murray-Tuite et al., 2012).

California Camp Fire, 2018

The November 8th, 2018 Camp Fire in Butte County, Northern California was the most destructive and deadly wildfire in California history to date (NIST, 2021). The meteorological settings influenced the severity, including a windstorm moving downhill in drought conditions, which made the fire travel incredibly fast (Brewer and Clements, 2020). The town of Paradise was the largest town that was decimated, along with the communities of Magalia, Centerville, Concow, Yankee Hill, Pulga, Butte Creek Canyon, and Berry Creek in the Sierra Nevada foothills. The speed of the fire complicated the evacuation since residents needed to begin evacuating right away in some cases, causing severe road congestion as about 50,000 people began evacuating nearly simultaneously. The evacuation was dire for many, with some evacuees leaving their vehicles as the flames approached and traffic congestion stopped them from evacuating fast enough (Lin and La Ganga, 2018; Nicas et al., 2018). Downed satellite communication infrastructure rendered most mobile phones useless during the evacuation, further complicating the process (Pogash and Chen, 2019).

I create an agent-based evacuation model (ABM) that simulates a short-notice, extreme, fast-moving wildfire evacuation. I use data directly derived the 2018 Camp Fire in Northern California, United States. The research interest is in the inter-relationships between urban factors, socio-economics and evacuation outcomes for extreme wildfire events. For the purposes of the study, the outcomes I am most interested in are the travel time and the evacuation outcome. The data from the Camp Fire are likely to be representative for other extreme wildfires. The results show that it is imperative that in planning for such extreme events, policymakers and local planners take into consideration the interconnected behavioral aspects of residents while both creating and executing evacuation plans.

Literature Review

A no-notice disaster is one that cannot be predicted in advance and provides little to no time for official notification. I distinguish no-notice events from short-notice disasters, which allow for short but reasonable public notification time. In the case of the Camp Fire, the distinction between a no-notice and short-notice fire event blurred for many residents. There were significant failures in the public awareness system, a rapid cell tower failure, and extremely quick and unpredictable fire dynamics.

In wildfires specifically, hazards such as flying debris, flames, and smoke, further complicate evacuations (McCaffrey et al., 2018). Fire and wind hazards coupled with reduced reaction time make the traditional paradigm of evacuation decision-making - a cascading series of clear choices around departure time, destination choice, and route choice- unlikely to hold (Pel et al., 2012). The beginning of a no-notice evacuation process is set once an evacuee becomes aware of the oncoming fire. Denoting this as “awareness time”, Grajdura et al. (2021) found that there existed a relationship between being white, having higher incomes, increased smartphone ownership, and younger ages and finding out about a fire sooner.

The departure time for a no-notice wildfire event is also not entirely predictable. The usual methods of modeling departure time using pre-determined distributions and S curves for departure time (Church and Sexton, 2002; Cova et al., 2013; Cova and Johnson, 2002; Dennison et al., 2007; Murray-Tuite and Wolshon, 2013; Tweedie et al., 1986; Wolshon and Marchive, 2007; Church and Sexton, 2002) are likely not applicable in this type of disaster. Looking at simultaneous and staged evacuation departures, Chen and Zhen investigated the effects of road connectivity and population density on evacuation time with an agent-based model. Departure strategies were contingent on the road network connectivity and population density, with lower density areas performing better with simultaneous evacuations and high density gridded areas performing better with staged evacuations (Chen and Zhan, 2008). Instead of purely staged or simultaneous evacuation, evacuees' departure timing likely depends on a host of factors, such as the fire dynamics, interactions with other evacuees, and individual characteristics, among other factors (Golshani et al., 2019a; Grajdura et al., 2021; McLennan et al., 2013). Much of the wildfire evacuation research looks at the decision to remain on property versus the decision to leave (Toledo et al., 2018; Folk et al., 2019), however in a dire wildfire event, it may quickly become evident to evacuees that staying is not an option and everyone must leave or find shelter.

Several models attempt to capture the dynamic complexity that evacuees face while modeling how the wildfire develops and interacts with the built environment (Beloglazov et al., 2016; Ronchi et al., 2019), but some of these models leave out characteristics of a dire wildfire scenario. For example, in the Camp Fire, residents began rapidly abandoning cars as a result of gridlocked conditions and the approaching fire. Some evacuees reported being forced to switch from their vehicles to walking; most were picked up by other evacuees (John et. al, 2018). In short, knowledge of the evacuation decision-making process and how it relates to the built environment and environmental conditions in a dire wildfire is a gap in the literature.

Agent-Based Modeling in Wildfire

I take advantage of ABMs to simulate scenarios in the research and thus, it is worth briefly commenting on some of the advantages and usages of ABMs more generally. ABM's have several advantages over most simulation approaches, especially for the wildfire evacuation and decision-making processes, and have been used to explore complicated wildfire risk management strategies (e.g., Paveglio and Prato, 2012). The agent-based models allow for the integration of various forms of data (Crooks and Heppenstall, 2012), the specification of different classes of agents with heterogeneous behavior, and can accommodate agent adaptability, experience learning, complex behavior, and communication (Bonabeau, 2002; Crooks and Heppenstall, 2012). Outcomes from past wildfire evacuation ABM's include improving prediction of response time (Chen and Zhan, 2008), estimating the number of sheltered or refused agents (Sun and Turkan, 2020), and approximating net wildfire losses (Paveglio and Prato, 2012). Agents within the ABM framework are highly customizable, which is useful for wildfire evacuation modeling. Information such as number of vehicles, housing density, household evacuation response time (Wolshon and Marchive, 2007), panic level (Scerri et al., 2010), demographic information (age, gender, health, energy, etc.), and time-dependent relationships between wildfire progression, evacuation triggers, and individual behaviors (Beloglazov et al., 2016) can be incorporated as agent attributes. By linking spatial data to the ABM system, more realistic evacuation scenarios can be developed (Sun and Turkan, 2020).

Methods

I combine statistical modeling of a post-disaster survey to inform the ABM simulation. The Camp Fire post-disaster survey was deployed both in-person and online in the months following the disaster. This resulted in 397 total surveys, two thirds collected online and one third in-person at long-term disaster recovery shelters. Survey topics ranged from resident characteristics and socio-demographics to their communications and decision-making at various points of the evacuation. The descriptive statistics of the survey (Table 4) mirror the local community demographics well, with the exception of sex, in which the survey represents markedly more female: 78% female vs. 53% in the local population (U.S. Census Bureau, 2019).

Table 4: Data Overview

Variable	**Value**
Race	American Indian/Alaska Native = 1.4% (5), Asian = 1.6% (6), White = 84.6 % (307), Two or more races = 9.4% (34), Other = 3.0% (11)
Hispanic	Yes = 5.7% (20), No = 94.3 % (330)
Age	18-34 = 15.2% (60), 35-54 = 35.7% (141), 55-64 = 27.6% (109), 65+ = 21.5% (85)
Gender	Male= 34.2% (135), Female = 64.8% (256), Other = 1% (4)
Education	Less than high school = 5.1% (20), High school graduate = 15.1% (59), 2 year degree = 14.3% (56), Some college = 32.4% (127), 4 year degree = 20.4% (80), Master's/Professional = 11.4% (45), Doctorate = 1.3% (5)
Income	Less than $10,000 = 9.3% (35), $10,000-$14,999 = 12.5% (47), $15,000-$24,999 = 9.1% (34), $25,000-$34,999 = 11.7% (44), $35,000-$49,999 = 11.5% (43), $50,000-$74,999 = 17.1% (64), $75,000-$99,999 = 12% (45), $100,000-$149,999 = 11.2% (42), $150,000+ = 5.6% (21)
Household	1 member = 23.4% (93), 2 members = 36.2% (144), 3 members = 20.2% (80), 4+ members = 20.2% 80
Time at residence	Less than 1 year = 17.8% (70), 1-3 years = 22.6% (89), 3-5 years = 11.4% (45), 5-10 years = 15.7% (62), 10-15 years = 8.6% (34), 15+ years = 23.9% (94)
Smartphone	Yes = 85.9% (340), No = 14.1% (56)
Found out about fire	Saw fire firsthand = 44.6% (175), In person by somebody = 26.3% (103), Call or Text = 17.1% (67), Online = 6.9% (27), TV or Radio = 3.8% (15), Official Evacuation Notice = 1.3% (5)
Aware of local evacuation plans	Yes = 57% (209), No = 43% (157)

Note. Adapted from "Awareness, departure, and preparation time in no-notice wildfire evacuations", Grajdura, S. et al., 2021. Safety Science, *139*, p. 105258.

ABM Specification

The review of wildfire studies suggests mode of transportation, fire behavior, the roadway and housing network, as well as the evacuee social demographic information are key features determining evacuation behavior. I can realistically capture behavior using the Camp Fire survey and GIS allows for seamless integration of the road and housing networks to identify escape routes. Specific to the case of rapid-onset hazards such as fast-paced wildfires, earthquakes, and tsunamis, the literature has noted the importance of using evacuation preparation times (Golshani et al., 2019b; Shabanpour et al., 2018; Wang et al., 2016). I also include this aspect by capturing delays in departure timing along with several other empirical factors, using a published theoretical model of the 2018 Camp Fire (Grajdura et al., 2020).

Specifying the ABM

I use NetLogo, a free and open-source programming language and integrated development environment for agent based modeling, to create customizable agents and the geographies specific to the case study. I specify different types of agents representing evacuees and the built environment they will traverse. In NetLogo, agents that move around in the environment are called "turtles"; in the model, both the evacuees and the fire are turtle agents. "Patch" agents create the environment in which turtles move. Here, the road, building network, and road-building connector GIS files are reflected as patch agents.

To scale the model, I use 200 evacuee agents in the model. This allows us to reduce model run time and expand the scenarios while still capturing the dominate evacuee trends. I do not include traffic congestion effects in the model largely because there were only two or three available routes and all were similarly congested. I note that future work should expand on the congestion effects to generalize the work to more complicated roadway networks. I model the fire using a fixed start location and randomized wind direction and speed.

The ABM assigns properties to the agents based on community socio-demographics (age, sex, income, etc.). The goal of each evacuee-agent is to successfully evacuate by traveling along the road-network and arriving at a shelter without encountering a road segment that is blocked by the growing fire. Agents are randomly assigned to locations and each agent's origin on the road network is chosen as the nearest road network node to the origin building's centroid. Figure 6 below represents the visual model at initialization. Since I assign socio-demographics before randomly assigning each agent to a building and hence origin, I maintain the socio-demographic profile of the community.

At the beginning of each simulation, I calculate each evacuee agent's awareness and departure times using their socio-demographic information, which I outline in the following section. Once the nearest shelter is selected, the shortest path is determined using the A* search algorithm (Hart et al., 1968). The A* algorithm is a best-first search algorithm often used in path finding applications. If an evacuee encounters a blocked road network link on the selected evacuation path, the agent restarts the A* algorithm to find a new available shelter and evacuation route. If the second evacuation route also becomes blocked, I assume the agent becomes trapped and does not reach a shelter. In reality, this evacuee may seek a non-designated shelter location (e.g., an area that offers some safety or a parking lot).

Figure 6: ABM Initialization. Green represent evacuees in vehicles, white represent carless evacuees, yellow represent pre-determined shelter locations, pink lines represent the road network.

Defining Agent Attributes

I use the non-parametric classification and regression tree (CART) to identify the variables most influential in predicting three progressive elements of evacuation progress: awareness time, the departure time, and the total evacuation travel time. I measure these times in minutes from 6:00 AM to coincide with the start of the Camp Fire. The candidate variables are listed below in Table 5. The results provide the attributes that I use to characterize agents in the ABM. CART uses recursive partitioning to describe an outcome based on independent variables. The data size is relatively small and the work is among the first of its kind, so I do not use training data. Pruning is performed by minimizing the cross-validated error. I run the CART method for each of three times: awareness, depart, and total travel time.

Table 5: ABM Variables

Variable	Description
Travel time	Length of time from departing to reaching a shelter
Awareness time	Time at which an individual became aware of the fire
Depart	Time at which an individual starts evacuating
Age	Age < 65 = 0, Age 65+ = 1
Gender	1 = male, 0 = female
Income	Less than $50,000 = 0, $50,000 or above = 1
Education	Less than high school = 0, High school and above = 1
White	Race is white (1= Yes, 0 = No)
Smartphone	Owns smartphone = 1, No smartphone = 0
Reside	Community residence (<15 years = 0, 15+ years = 1)
Method of finding out	Phone call, SMS, online, evacuation notice, TV, or radio = 0, told in-person = 1, sees firsthand (i.e., smoke, flames) = 2
Evacuation notice	Received official evacuation notice (Yes = 1, No = 0)
Plans	Awareness of town evacuation plan before fire (Yes = 1, No =0)
Num_modes	Number of evacuation modes taken
Household_size	Household size (< 4 members = 0, 4 + members = 1)

Note. Adapted from "Awareness, departure, and preparation time in no-notice wildfire evacuations", Grajdura, S. et al., 2021. Safety Science, *139*, p. 105258.

The regression tree for awareness time indicates that age, income, smartphone ownership, and gender are the most important variables in predicting the time at which people were alerted to the wildfire (Figure 2). Those below age 65 with an income over $50,000 had earlier, on average, awareness times, as shown in the leftmost path of the decision tree. The rightmost path, consisting of age over 65, no smartphone, and female experienced the longest times before being alerted to the fire, over twice as long as the earliest cohort.

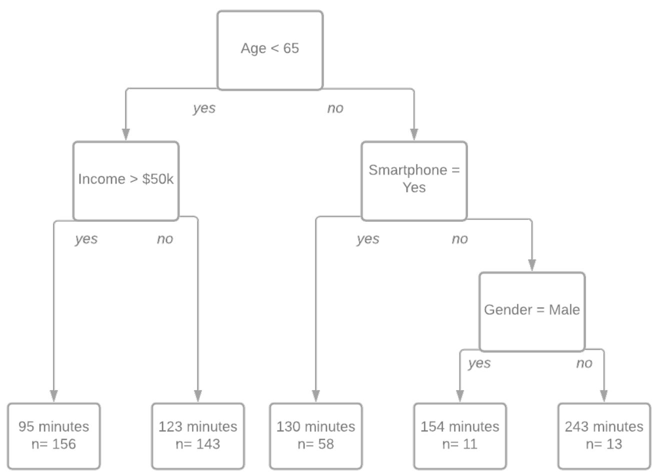

Figure 7: Pruned Awareness Time Decision Tree

As might be expected, the leaves of the regression decision tree predicting departure time (Figure 3) consists of various values of awareness time. Those with an awareness time less than 175 minutes from 6:00 AM (8:55 AM), have on average the earliest departure times of 193 minutes (9:13 AM). Those with the latest awareness times greater than 315 minutes (12:15 PM) have the latest average departure time, 550 minutes (3:10 PM).

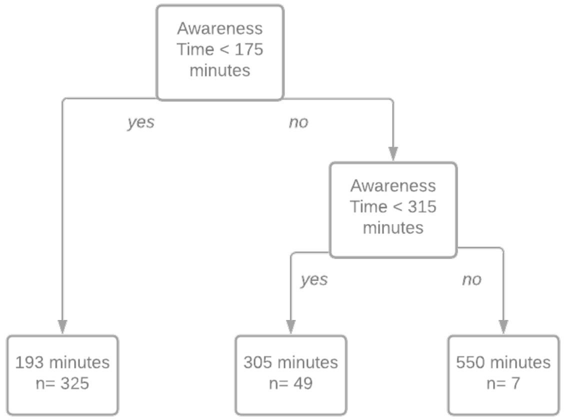

Figure 8: Pruned Departure Time Decision Tree

For the total travel time (Figure 9), if the departure time is greater than 349 minutes, I move to the left in the tree, otherwise I move to the right. To the right we see “findout4=0,1” indicating the person was alerted to the wildfire by means other than observing it firsthand (see Table 2 for other possible options); if this is true, I move left and end at a total travel time of one to two hours, representing 5% of the sample. If not, I move right, and end at less than one hour, which represents 4% of the sample. In the remaining leftward branches of the decision tree in Figure 9, the other deciding independent variables include departure time, awareness time, and receiving an evacuation notice. One clear finding in these results is that in fast moving fire situations, awareness is key to faster evacuations.

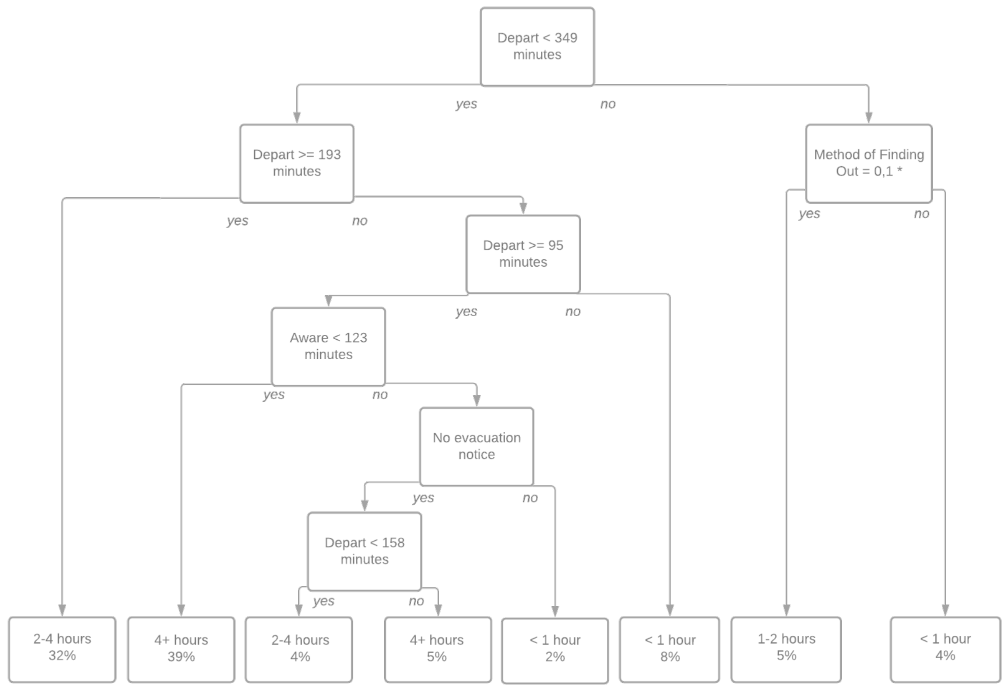

Figure 9: Pruned Total Travel Time Decision Tree. (*Method of Finding out about the fire = 0 or 1 refers to finding out by SMS, phone call, TV, radio, online, told in person, or an evacuation notice)

The ABM agents possess attributes such as sex, race, and age and prior to evacuation, each agent must also have an awareness and a departure time. To determine the awareness and departure times for each agent within the ABM, I use ordinary least squares (OLS) (eq 1 and 2). To estimate the coefficients, I use the survey data and variables derived from the CART analysis (eq 3 and 4). The dependent variables, departure and awareness time (in minutes), are continuous and measured from 6:00 AM, where *i* represents an individual agent, and μ is normally distributed. I use the regression specification and randomly assign values for the independent variables using the survey to assign attributes to each agent (Table 6).

Table 6: Equations for Departure time and Awareness time

Time	Equation
Departure time (DT)	Eq. (1) $\beta_0 + \beta_1 Awareness\ time_i + \beta_2\ Reside_i + \beta_3 Sex + \beta_4 Evacnotice_i + \mu_i$
Awareness time (AT)	Eq. (2) $\beta_0{}' + \beta_1{}' Age_i + \beta_2{}'\ Income_i + \beta'_3 Smartphone_i + \beta'_5 Findout_i + \beta'_6 Sex + \mu'_i$
Estimated DT	Eq. (3) $86.8 + 0.864 * Awareness\ time_i + 35.7 * Reside_i + 26.2 * Sex + 20.6 * Evacnotice_i$
Estimated AT	Eq. (4) $150 + 30.4 * Age_i - 28.0 * Income_i - 18.7 * Smartphone_i - 3.36 * Findout_{toldinperson\ i} - 21.0 * Findout_{firsthand\ i} + 0.107 * Sex$

Scenarios

I created a base scenario and four basic simulation scenarios (Table 7). The base scenario represents the Camp Fire evacuation conditions using empirical survey data from the evacuation, and represents the actual evacuation as closely as possible. For the base scenario, I run 499 simulations where all input variables are from the survey data. I ran these simulations to better understand the potential for variation within the model, namely variations in awareness, departure, and travel times. I expect more variation in travel time (compared to awareness and departure time), since it is an outcome variable and not calculated for the ABM input.

Scenario 1 simulates a loss in communication capabilities. During the Camp Fire, the fire decimated several regional cell towers. This made evacuee smartphone use nearly impossible. To simulate this, I use varying levels of the variable smartphone ownership. In Scenario 2, I model delays in wildfire awareness and Scenario 3 explores the effects of varying the evacuation speed of agents. Variability in agent speeds allows us to simulate different combinations of modes. For example, at least 7% of the survey respondents reported needing multiple modes such as a stranger's vehicles, police vehicles, and/or walking during their evacuation due to vehicle breakdowns or traffic jams. Finally, the integrated Scenario 4 cuts across evacuation elements by varying amounts of smartphone and vehicle use, combined with varying delays in awareness timing.

Table 7: Scenarios and cases

Scenario	Case
Base	All independent variable values from survey data
1. Communication loss	Vary smartphone use from 0 to 100%
2. Awareness delay	Vary from 30 to 120 minutes
3. Decrease vehicle access	Vary vehicle access from 0 to 100%
4. Integrated: combination of low smartphone, less vehicles, and awareness time delays	Case 1: 20% of community has smartphones, 50% vehicles, 50% pedestrians
	Case 2: 0% of community has smartphones, 50% vehicles, 50% pedestrians
	Case 3: 20% of community has smartphones, 30% vehicles, 70% pedestrians
	Case 4: 0% of community has smartphones, 30% vehicles, 70% pedestrians
	Case 5: 20% of community has smartphones, 50% vehicles, 50% pedestrians, delay awareness by 1 hour
	Case 6: 0% of community has smartphones, 50% vehicles, 50% pedestrians, delay awareness by 1 hour
	Case 7: 20% of community has smartphones, 30% vehicles, 70% pedestrians, delay awareness by 1 hour
	Case 8: 0% of community has smartphones, 30% vehicles, 70% pedestrians, delay awareness by 1 hour

Results

The primary interest is in total travel time and the associated variability; that is, how long does it take to fully evacuate everyone, and what is the uncertainty around that time. Here, I present the total travel time outcomes for two scenarios: the base scenario and the integrated Scenario 4 simulations. I have provided an extended discussion of the awareness and departure time simulations and the outcomes of the single element Scenarios 1-3 in the Supplemental Material.

Base Scenario Results

When I examine the probability density function for travel time (Figure 10), I see two distinct distributions. The first distribution, which I refer to as the shorter travel time distribution, peaks initially at 100 minutes (1 hour 40 minutes) with smaller peaks at 250 minutes (4 hours 10 minutes) and 430 minutes (7 hours 10 minutes). This curve captures early evacuees (agents) with shorter travel times. The second, longer travel time curve has a much smaller first peak falling between 175 minutes (nearly 3 hours) and 225 minutes (3 hours 45 minutes) and another peak around 460 minutes (7 hours 40 minutes). It is important to note that the fatter tail extending past 700 minutes (11 hours 40 minutes) suggests a possible outcome of evacuees with very long travel times. The later distribution also has less variation vertically than the earlier curve, suggesting many similar travel time outcomes among agents.

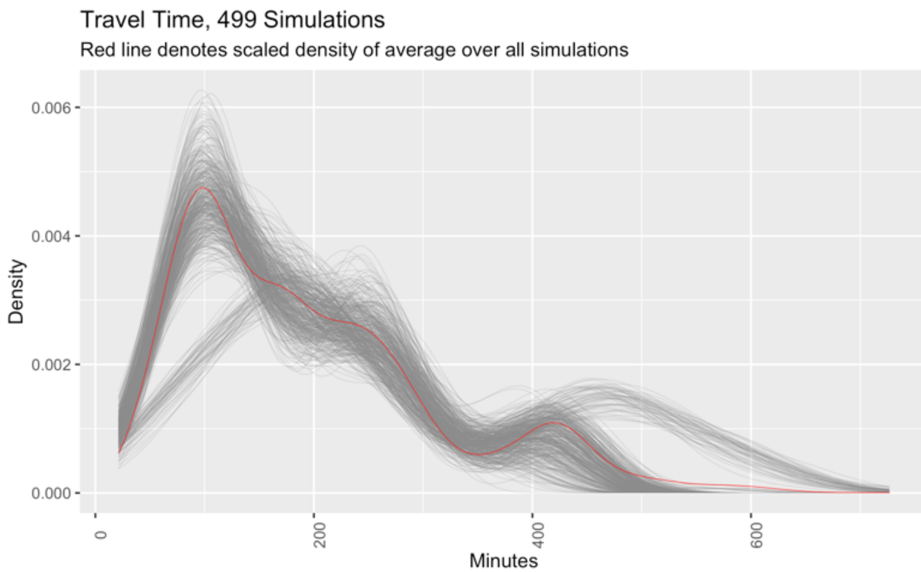

Figure 10: Travel Time (Probability Density) for the Base Scenario, 499 Simulations

In Figure 11, the blue cdf represents the shorter travel time distribution and red represents the longer travel time distribution. At the 50% evacuated mark, the shorter travel time curve is roughly an hour shorter than the longer travel time curve. Comparing the 75th percentiles for both curves, the shorter travel time curve reaches this percentile at about 250 minutes (4 hours 10 minutes) on average, while the longer travel time curve is about 425 minutes (7 hours 5 minutes) on average, nearly three hours later. Recall that these simulations represent possible outcomes, not actual or a complete set of outcomes. I have some ideas about why there are two groups of evacuees shown in red and blue – those with significantly shorter travel times and those with longer travel times, which I outline in the discussion section.

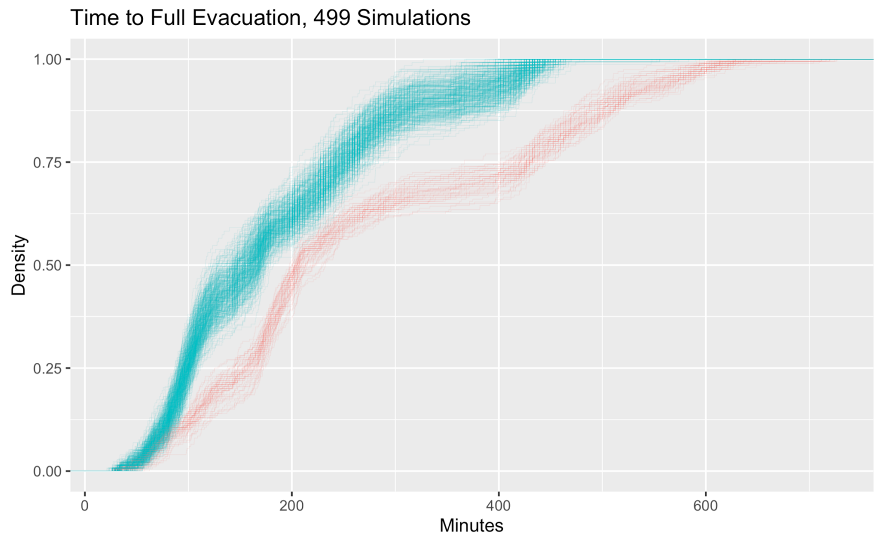

Figure 11: Time to Full Evacuation (Cumulative Density) for the Base Scenario, 499 Simulations

Finally, I investigated the relationship between the departure time and the total travel time (Figure 12), where the darker blue color represents a higher density of agents across simulations. The highest density of departing agents occurs at about 200 minutes (9:20 AM) with travel time outcomes of around 100 minutes (1 hour 40 minutes). Most of the agents depart between 175 and 225 minutes (8:55am-9:45am) and travel between 100 and 300 minutes (1 hour 40 minutes - 5 hours). Combinations of early departure time- long travel time, late departure time, short travel time, or late departure and long travel time are less common. However, the departure time is not highly correlated with travel time. There are agents who depart both early (before 9AM) and very late (after 11AM) that have travel times under both an hour and over 8 hours, respectively.

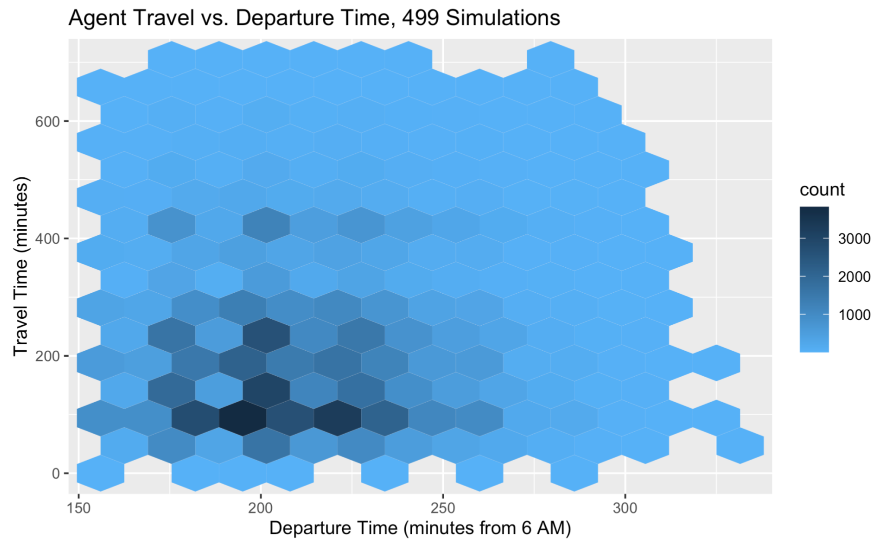

Figure 12: Agent Travel Time vs. Departure Time for the Base Scenario, 499 Simulations

Integrated Scenario Results

To capture potential policy levers and/or socio-economic indicators, I create a combination of integrated worst-case conditions representing: 0 to 20% smartphone use, 30 to 50% vehicle access, and either no delay or a one-hour delay in awareness time. This produces eight different cases, which serve as a benchmark to examine how various factors can influence total time outcomes. The travel time pdf's (top panel of Figure 13) differ considerably from the base scenario pdf. All eight cases have peaks occurring later than the base in terms of travel time. The intensity (or number of agents evacuating) is also lower; larger numbers of agents have travel times to the right of the peak, exceeding even 500 minutes (8+ hours). In the second panel, the distribution of travel times for each case increasing travel times with greater variability in comparison to the base scenario. I also clearly see the departure time shifts right most dramatically for Cases 5 through 8 which all have about an hour delay.

In the last two panels, I consider trapped evacuees. The number of trapped agents in each case is higher than in the base scenario, although not by much. In particular, cases 3, 7, and 8 have the highest number of trapped agents. These results suggest that there can be a large number of evacuees on foot. The potential outcomes show that under a variety of worst case conditions – constrained cellphones, awareness time delays, and lack of vehicle access -, the evacuation outcomes are much worse than outcomes produced by consideration of only one of the individual factors (See Supplement Material).

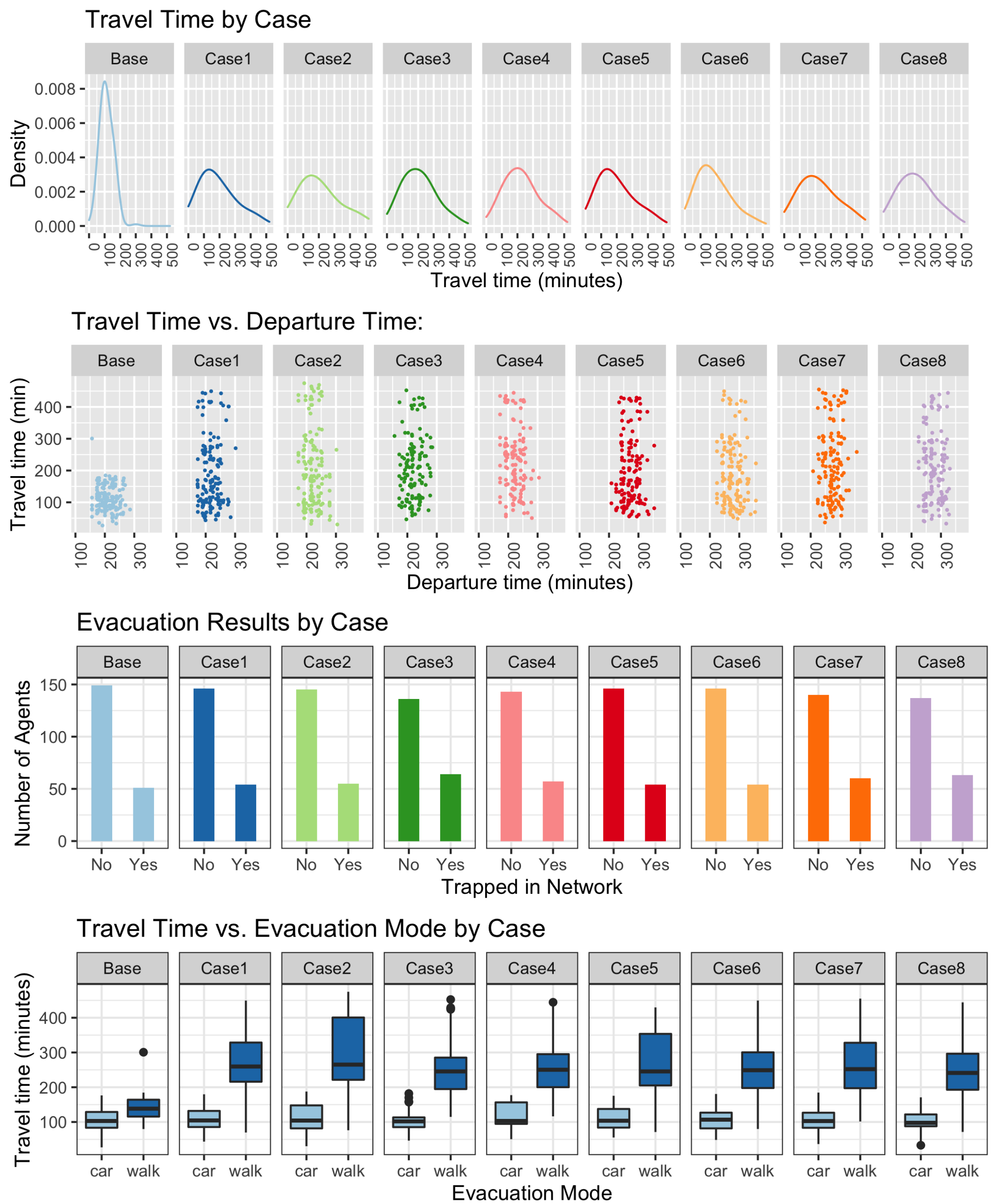

Figure 13: Scenario 4 Combination Results

Finally, I compare the results from the integrated scenario with the other scenario results and with the base scenario. Several of the scenario cases result in larger peaks than the average base scenario (black line in Figure 14), indicating more people with shorter travel times.

However, several scenario cases show long and thick tails and peaks beyond 3 hours, indicating greater numbers of evacuees with longer travel times. Scenario 4, the integrated scenario shown in purple in Figure 14, exhibits some of the longest travel times, falling below the black line with shorter departures, but then has a rather fat tail exhibiting departure times well above the average.

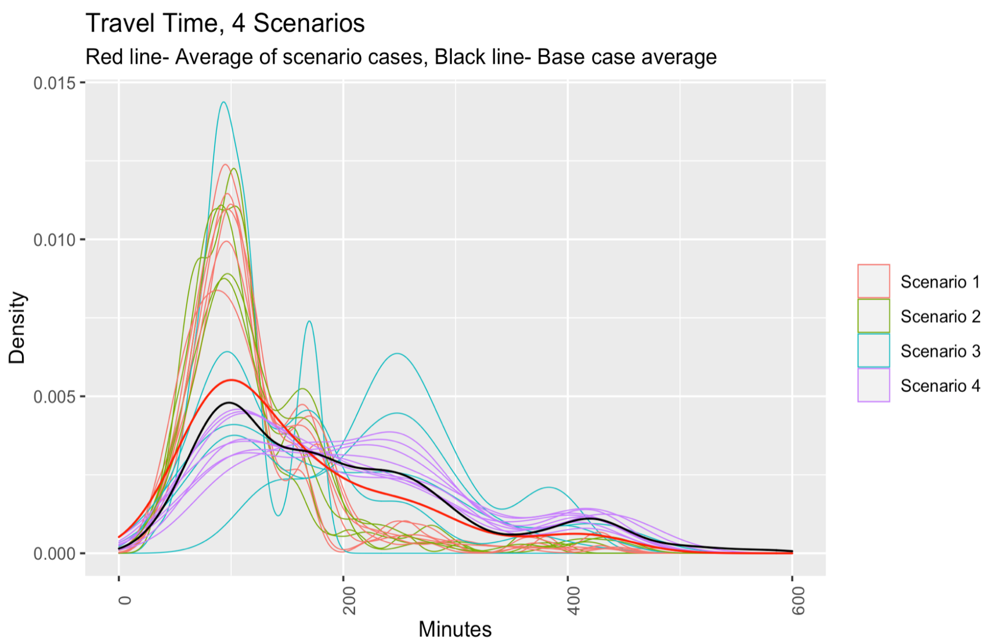

Figure 14: Travel Time (Probability Density) Comparison Among Scenarios

Notably, several of the Scenario 4 cases (Figure 15) follow the averaged base scenario (black) quite closely, especially cases 1, 5, and 6. All of these cases have 50% vehicle use, but varying amounts of smartphone ownership and delays. Cases 3, 4, and 8 differ considerably from the base scenario, with large peaks above those of the base scenario. These cases all share a low level of vehicle use (30%).

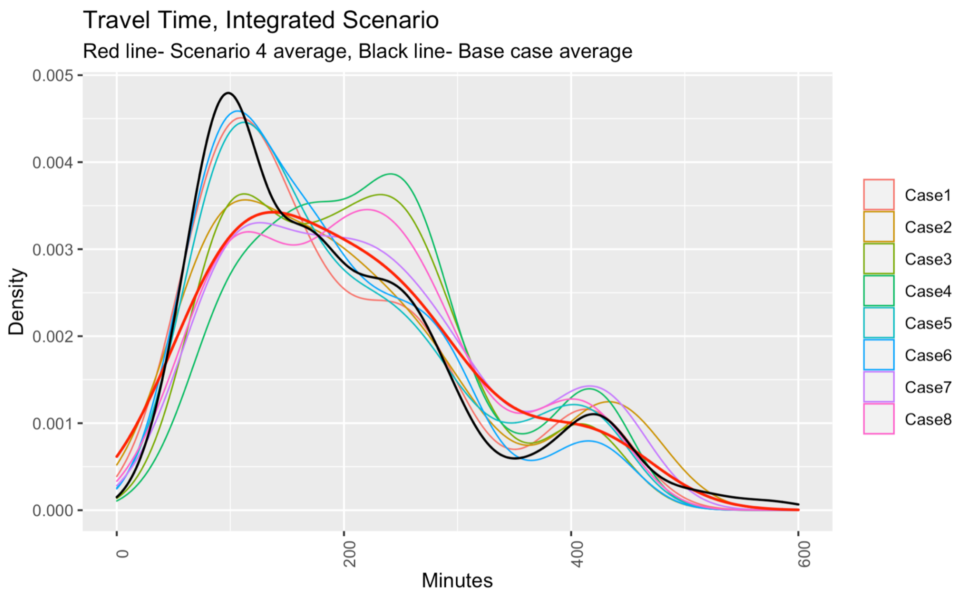

Figure 15: Travel Time (Probability Density) for Scenario 4 Cases

Discussion

The results provide several critical insights on evacuation times and factors such as access to cell phones, awareness time, and the availability of a vehicle. I saw that many of the scenarios produced large variations, which shows the potential for travel time uncertainty in any given evacuation. The number of evacuees at any given awareness time varied by as much +/- 41% from the mean at any point in time in the base scenario. For example, at 100 minutes since the beginning of the fire, where the density of evacuees could range from 21% below to 27% above the mean, strategies that increase the number of evacuees should be prioritized. I also observed tail spread in awareness, departure, and travel time distributions, signifying there will be groups of evacuees who need assistance in evacuating such that their travel times become closer to the average. Potential tools could include more robust backup notification systems that are independent of smartphones or landlines since, as the Camp Fire illustrated, these communication tools may not always be available.

Travel Time Patterns

One result in need of further reflection is the existence of two distributions in the travel time simulation (Figures 10-11). The only factor that differed between the two groups was the percentage of trapped agents. While only 70.1% of the agents in the blue (shorter average travel time) group reached a shelter, 99.9% of the red (longer average travel time) group reached a shelter. This is somewhat counterintuitive, since the red group exhibits longer evacuation times. I would expect more agents in this group to be trapped in the road network.

To investigate further, I mapped the final locations of the agents in a cartesian coordinate system, using the NetLogo output data for each agent (Figure 16). The maps in Figure 16 are not to scale, but are used as tools to offer a general understanding of spatial relations in this context. The final locations of all agents (trapped and not trapped) are shown in the top left panel; the outlying points are the shelters, while inner clustered purple dots are trapped agents. I can compare the final locations among those trapped and not trapped in the bottom row of Figure 16; the bottom left figure shows the final shelter allocations and the bottom right figure shows the density of the trapped agents.

Pooling across all scenarios, the ending locations of the 11,600 agents of the red outlier group are spaced mostly among shelters (top right of Figure 16), if I compare to the bottom two figures. This corroborates the finding that those in the outlier red group were less likely to be trapped, despite having a longer evacuation travel time. It is possible that agents with the longer travel times had to change their shortest selected path to another route as they evacuated. Despite longer travel time and lower trapped rates, longer evacuations also carry risks such as encountering traffic congestion, smoke inhalation, and running out of gas. It is important to note that I did not build these complexities into the model.

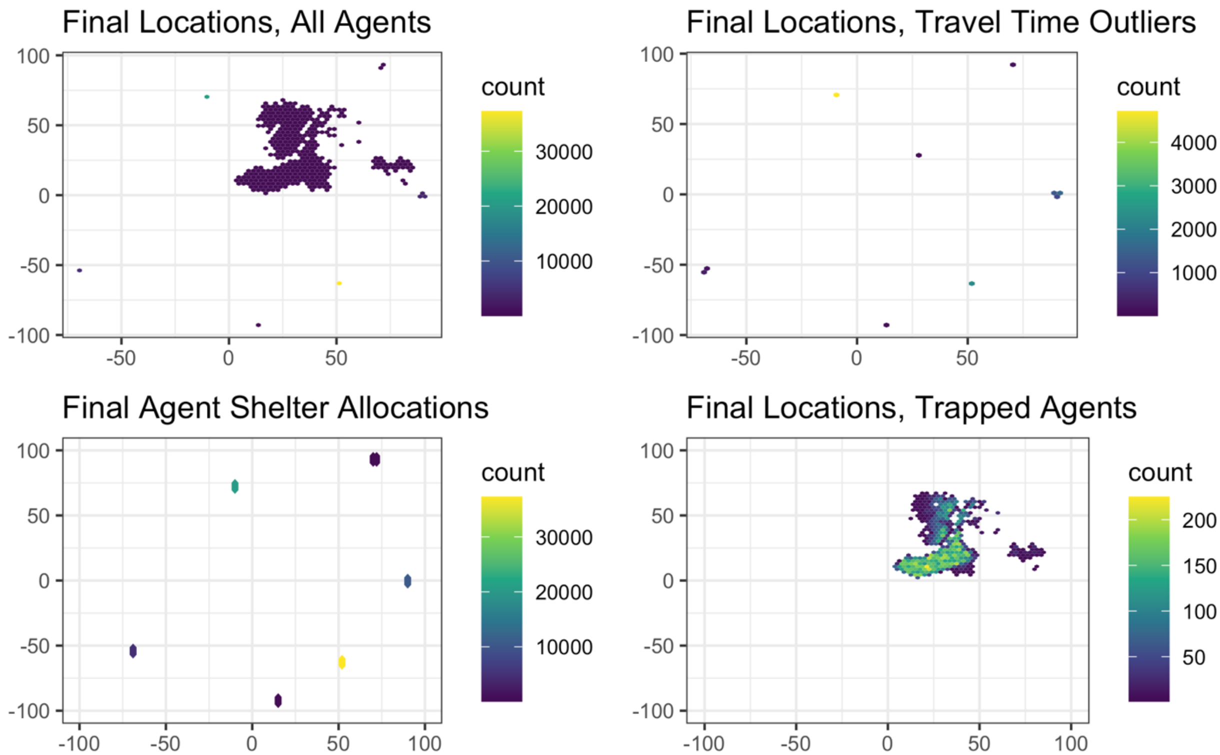

Figure 16: Final locations of all agents (top left). Final locations of outlier red group (top right). Origins of trapped and not trapped agents (bottom row)

In the worst-case integrated scenario, combining vehicle accessibility and cellphone access with delays in awareness produces very different patterns in evacuation outcomes, including much longer travel times and more trapped agents (Figures 13-15). In particular, cases 3, 4, 8 had noticeably higher peaks denoting longer travel times. All of those cases had vehicle use limited to 30%. Not surprisingly, this suggests that vehicle access and by turn, speed of evacuation are very important in estimating the final travel time of evacuees. If these scenarios were to be combined with traffic congestion, I might see even more extreme time durations.

Agent Characteristics and Outcomes

I also examined the characteristics of trapped agents across the base and integrated scenarios (Table 8). I do not see large differences among trapped and not trapped agents in the base scenario. However, in the Integrated Scenario, I do see differences. I find greater numbers of trapped elderly agents and fewer trapped less men relative to women. I also find those not trapped are more likely to be wealthier and have a slightly more education. Surprisingly, those with smartphones are slightly more likely to end up trapped than those without smartphones.

Table 8: Trapped Agent Characteristics Comparisons

Characteristic	Base Scenario		Integrated Scenario	
	Trapped	Not Trapped	Trapped	Not Trapped
Awareness Time	No difference	No difference	No difference	No difference
Departure Time	No difference	No difference	No difference	No difference
Age 65+	No difference	No difference	24.5%	20.98%
Male	No difference	No difference	32.1%	34.8%
Income $50k+	No difference	No difference	44.9%	47.9%
High School Ed+	No difference	No difference	92.6%	94.6%
Smartphone	No difference	No difference	10.4%*	9.8%*
White	No difference	No difference	85.9%	84.6%
Reside 15+ years	24.9%	25.2%	23.9%	25.5%
Find Out Other	29.73%	30.0%	29.7%	30.0%
Find Out In Person	25.87%	26.0%	27.3%	25.5%
Find Out Firsthand	44.4%	43.9%	42.9%	44.4%

*Varied in the Integrated Scenario

I also considered trends among those agents who were first to clear the area in the base and integrated scenarios. To study these early arrivals, I created a new variable, arrival time, denoting the time that an agent clears the area or reaches a shelter. The arrival time is found by summing the departure and travel times (both in minutes). I designate those agents arriving within the first quartile of arrival times as “Early” and all others “Late”, which is the same convention I use in Table 9 below.

In the base scenario, average arrival time was 12:46 PM for the sample and 11:13 AM for the early arrivals. For the Integrated Scenario, the average arrival time was 1:30 PM for the sample, but 12:05 PM for the early arrivals. In both the Base and the Integrated Scenario, early arrival agents are proportionally younger, more female, and higher incomes. More of the early arrival agents also have smartphones and are newer to the community. Those who found out about the fire in person are almost 10 percentage points more likely to be part of the early arrival group.

The largest differences, however, relate to income, with those making over $50,000 annually much more likely to be part of the early arrival cohort, in both the Base and Integrated Scenarios. This finding is not altogether surprising given the large effects that income have been found to exhibit on evacuee behavior (Yabe and Ukkusuri, 2020). The mechanism by which higher income residents manage clear the area quicker deserves more attention in future research.

Table 9: Early Arrival Evacuee Characteristics

Characteristic	Base Scenario		Integrated Scenario	
	Early	All Others	Early	All Others
Awareness Time	Mean 7:50 AM	Mean 8:03 AM	Mean 8:28 AM*	Mean 8:50 AM*
Departure Time	Mean 9:16 AM	Mean 9:35 AM	Mean 9:49 AM	Mean 10:15 AM
Age 65+	14.0%	24.7%	17.0%	22.3%
Male	23.8%	37.5%	27.1%	37.4%
Income $50k+	58.0%	43.3%	56.5%	44.9%
High School Ed+	No difference	No difference	No difference	No difference
Smartphone	89.1%	84.9%	14.38%*	8.26%*
White	No difference	No difference	86.0%	84.2%
Reside 15+ years	12.7%	29.1%	16.8%	28.5%
Find Out Other	28.6%	30.6%	No difference	No difference
Find Out In Person	32.4%	23.9%	32.2%	23.1%
Find Out Firsthand	39.0%	45.5%	38.7%	46.4%

*Varied in the Integrated Scenario

Model Validation

Finally, I compared the reported travel times across the post-disaster survey data and the scenario simulation results pooled over all cases within a scenario (Table 10). Average travel time across all cases are binned into less than one hour, 1-2 hours, 2-4 hours, and over four hours, with survey data in the top row. The base scenario greatly underestimates the number of evacuees taking under an hour to evacuate, by more than twenty percentage points, and overestimates all longer times. This signifies that the model is somewhat conservative and to focus on the comparisons between the scenarios, rather than the absolute estimates.

On average, the other scenarios underestimate the proportion of evacuees completing their travel in less than an hour, relative to the survey data. A possible reason for this is since the agents only traveled at two different speeds, I was not able to model the possibility of some agents early on in the evacuation traveling faster in relation to other evacuees due to less congestion. Another possibility is that I programmed the agents to calculate a second evacuation route if their route was blocked, but in reality evacuees may have just driven around an obstacle in the road or shared a ride with another vehicle, instead of taking a completely different route. The communication loss and awareness delay scenarios also greatly overestimate the proportion of evacuees taking 1-2 hours, by more than a factor of 2, suggesting that despite the loss of a cell tower, some communication was still possible among the survey respondents.

Table 10: Travel Time Comparisons, Averaged over all Cases Within Scenarios

	< 1 hour	**1-2 hours**	**2-4 hours**	**4+ hours**
Survey*	27.2% (115)	20.1% (85)	23.4% (99)	29.3% (124)
Base Scenario	4.60%	30.9%	34.6%	30.0%
Communication loss	8.90%	59.0%	26.1%	6.00%
Awareness delay	9.6%	57.9%	26.8%	5.74%
Decrease vehicle access	4.93%	35.4%	31.8%	27.9%
Integrated	3.16%	26.9%	36.7%	33.3%

*Based on 423 responses (29 no answer)

Conclusion

In this study, I develop an agent-based simulation model of a dire no-notice wildfire evacuation to test the effects limited or lost communication capabilities, delays in fire awareness, and decreased vehicle access. The outcomes of interest include evacuation travel time and the number of agents trapped in the road network. Using a post-disaster survey dataset from the 2018 Camp Fire, I use decision tree methods and linear regression to derive awareness time and departure time inputs for the simulation model. I randomize both socio-demographic and evacuation inputs as well as spatial variables such as fire spread and agent origin based on local building data. Agents are constrained to the road network and travel to the nearest shelter using the shortest path algorithm, which is updated if the fire overtakes a road segment on their path.

Although the model takes advantage of data from Paradise, California and the surrounding communities, the framework could be used to develop similar models for other locations by incorporating relevant geographic data (road network, building polygons, etc.). In this sense, the ABM approach can be used in disaster pre-planning, taking into account the socio-demographics and perceived evacuation data of a community. The survey results are robust and the specific equations I use to calculate awareness and departure times may be transferable. The findings regarding travel time, smartphone use, awareness delay, vehicle access, and trapped agents certainly are.

Limitations

Despite the findings of the study, I would be remiss to not discuss the limitations as well. First, the reported data come from surveys. Respondent perceptions of and answers about awareness and departure times may be incorrectly remembered. Although this is a possibility, I consider the richness of the post-disaster survey data to generally be a benefit in the analysis.

Since this data was collected after the 2018 Camp Fire, there could be concerns regarding the external validity of the data, model, and results in relation to other wildfires or even other no-notice disasters. For this reason, I suggest researchers consider this when interpreting the results and applying them to other disaster scenarios. Elements of the ABM, e.g., fire spread and removal of road links from the network, may not be directly applicable to other no-notice disaster evacuation scenarios. A simplification that I made is that the fire spread model is not identical to the actual fire spread of the Camp Fire. By assuming a start location and randomized speed and wind direction in the model, I greatly simplified the dynamics of the wildfire event. Future work should aim at developing a more realistic fire spread model with higher resolution.

Another simplification I took in developing the ABM was to not include traffic congestion effects, which might make the model more generalizable in terms of evacuations and traffic patterns. The 2018 Camp Fire had limited exit roads for evacuation and experienced extreme congestion. As a result, I did not see the need to add a congestion element. Finally, I did not include interactions between agents in the model, which are important part of modeling evacuation behavior (Liu et al., 2014, 2012; Marom and Toledo, 2021). I know from the surveys that many people gathered with family members or friends. Others abandoned their vehicles and entered strangers' cars. Some evacuees did not go directly to shelters either, but stayed safe in large empty parking lots while the town burned around them. Future work should begin to include some of this more complicated evacuation behavior.

To conclude, more research is needed to meet the challenges of planning for dire and short-notice wildfire evacuations which pose a grave threat to many communities around the world, particularly those living in the WUI. This agent-based simulation model sheds light on the complexities in planning for such events using empirical data from a dire wildfire, the 2018 Camp Fire. I address communication loss, fire awareness delays, and vehicle access, all aspects of which complicated the 2018 Camp Fire evacuation. The work offers new insights into modeling and planning for such dire wildfire evacuation scenarios. This serves as a first step in modeling evacuee behavior and evacuation dynamics which I hope to build upon with future research.

Chapter 5: Wildfire Evacuees, Equity, and Justice[3]

Introduction

California has experienced numerous large wildfires in the past 10 years, with record levels of destruction. Since 2015, the state has had seven of the top ten largest wildfires on record occur (Di Liberto, 2020). These disastrous events are especially dangerous for human life, with damaging effects to human health, the environment, and economy, and are often the result of expedience. Take, for example, the historical land use paradigm that California has employed during its history which has relied heavily on fire suppression, rather than prescribed burns and indigenous wildfire practices, often exacerbating large wildfire events (Christianson, 2015). Convenience, rather than fire risk, often dictates construction in the built environment. For example, housing in the Oakland hills was based on the location of old logging roads, not taking into consideration the area's historical predilection for burning (Simon and Dooling, 2013). Building in these kinds of high-risk areas inevitably necessitates considerable fire suppression, and in fact the main driver of fire suppression efforts is the protection of homes (Plantinga et al., 2020). Research studying the effects of a changing climate and housing on diverse California landscapes' fire risk found that human infrastructure was consistently responsible for more fire ignitions and structure loss across scenarios, even more so than climate (Syphard et al., 2019). The research is clear that much of the wildfire management work goes into protecting higher value homes and wealthier neighborhoods (Plantinga et al., 2020). Fire agencies are simply more

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responsive to the prevention of wildfires in higher socio-economic status communities (Anderson et al., 2020). Federally funded housing buyout programs have been historically found to occur in wealthier counties, with minorities receiving less aid (Nelson and Molloy, 2021).

Yet, it is the most vulnerable hit the hardest in climate change-fueled disaster events (Tol et al., 2004). Here, I use vulnerability not simply a static state triggered by a disaster, but as a state of being brought about by historical political, environmental, economic, and demographic factors that manifest in certain populations as broad social inequalities (Collins, 2008). Although most people living in high-risk wildfire areas are socio-economically secure, 10% of housing stock in such areas are considered to be highly socially vulnerable (Wigtil et al., 2016). Census tracts consisting of majority Black, Hispanic, or Native American populations have a 50% higher chance of wildfire than majority White census tracts (Davies et al., 2018). Many lower socio-economic residents live in rented housing, where renters are prohibited from modifying landscapes to mitigate fire hazards and are not usually protected by home fire insurance (Collins, 2008). This population is understandably the most at risk for displacement following a wildfire.

Warming temperatures place additional stress on California's electricity infrastructure, which in turn can increase wildfire risk (Sathaye et al., 2013). In Northern California, the process of de-energizing portions of the electrical grid on high wildfire risk days carries the risk of disproportionate power losses to vulnerable people (Abatzoglou et al., 2020). Policies such as shelter in place (SIP) and evacuation inherently depend on an individual's resources, and these practices are unequal to vulnerable groups (Fu, 2013). Collins characterizes this as two sides of the same coin; a *marginalization* of the vulnerable, and a *facilitation* of safety for those with resources, resulting in differential risks (Collins, 2008).

The study responds to the equity considerations by investigating the ways in which a large wildfire event affects vulnerable populations, from evacuation through several months post-evacuation. In particular, I am interested in how evacuees navigate housing and who is displaced and where evacuees eventually settle. This information is most important for fire professionals, planners, and government officials to proactively improve equity across wildfire evacuation, acute post-disaster housing, aid distribution, and long-term housing. I draw on surveys undertaken of evacuees of the 2018 Camp Fire three to five weeks after the evacuation, and again eight months post-evacuation. Using a mixed method-approach, I integrate the survey data with contextual information from first-person interviews. I document equity considerations ranging from evacuation, short-term housing, and displacement. I argue that short-notice wildfires in particular pose a significant and complex threat to the most vulnerable, and that their nuanced relationship with the built environment creates hardship that persists over time. In particular, for the Camp Fire, I show that lower-income residents who capitalized on lower-cost housing in the Paradise area struggle to find new housing given the high cost of housing in California and lack of insurance funds for renters. I find inequities across pre-evacuation, evacuation, sheltering, and displacement among lower-income, the elderly, renters, and the homeless. Inequities are exacerbated by aid and shelter policies, which I must update to better serve these vulnerable communities in the face of future wildfires.

Key Literature

I begin by defining equity, equality, justice, vulnerability and finally resilience; these terms are ubiquitous when referring to people and natural disasters, yet have vastly different meanings (Ikeme, 2003). Equity is the fair distribution of benefits and costs (Karner et al., 2020). Comparatively, equality is a weaker term that relates solely to the equal distribution of resources.

An illustrative example of this difference would be the equal imposition of traffic fines across socio-demographics (equality), while equity would be imposing progressively rated fines that accommodate lower-income earners. Stronger yet is the theorization of justice. Mimi Sheller argues that "transportation justice" cannot be taken in isolation and must be considered more broadly (Sheller, 2018), comprising "accessibility, bodily freedom of movement, equitable infrastructure, and spatial designs that support the rights of movement" (Sheller, 2018).

Vulnerability is connected to three linked realms: root causes, dynamic pressures, and unsafe conditions (B. Wisner et al. 2004). The root or underlying causes refer to the wide historical, political, economic, demographic, and environmental factors that produce unequal distributions of resources among people. While unsafe conditions may involve both the spatial location and the characteristics of the built environment, they also include fragile livelihoods, resource dependency, inadequate incomes, legal and political inequities, and a lack of preparedness for emergencies (B. Bolin with L. Stanford 1998).

Resilience focuses on the ability of a community to withstand changes. A 2017 World Bank study defines socioeconomic resilience as the measure of a local economy's ability to minimize the impact of asset losses on well-being, or the ratio of asset losses to well-being losses (Hallegate et al., 2017). Investments in resilience can theoretically stabilize an economy in the event that a natural disaster occurs. For example, research exploring communities susceptible to wildfire found that social cohesion greatly improves wildfire response and in turn, resiliency (Prior and Eriksen, 2013). Critics claim that this positivist approach to resilience does not always include equity nor justice and recent participatory research shows that the conceptualizations of resiliency change depending on the local community (Ensor et al., 2021).

The literature provides us with examples of inequities at different time horizons of disasters. However, there is no broad survey which documents inequities during several stages of wildfires. This paper aims to fill this gap and provide a reference for other researchers, emergency management planners, and policy-makers in considering social equity in pre-planning and post-disaster work.

The 2018 Camp Fire

At the time of the fire, the Camp Fire was the deadliest and most destructive wildfire in the state and the deadliest in the past 100 years and nationally, with 85 fatalities and 14,000 structures burned (CAL-FIRE, n.d.; Lam, 2019). The fire started from electrical transmission lines around 6 AM, when many residents were asleep or just leaving for work. Fueled by the Jarbo Winds, high-speed winds in the Feather River canyon induced higher winds in nearby canyons. Wind speeds of 40 to 60 mph were observed for at least nine hours the day of the fire, resulting in extremely fast fire spread, at an estimated rate of one football field per second (NOAA, 2020).

Although the City of Paradise had a well-planned evacuation zone system, wind speeds made the preparations inadequate. Several evacuees were trapped in their vehicles, some joining other evacuees or inhabiting empty parking lots while the fire raged. The alert system was ineffective. Notifications were sent out late and very few people received the notices due to downed cellular towers (Grajdura et al., 2021a). The roads became extremely congested. Evacuation times soared to more than four hours for many residents. Around 50,000 evacuees flooded local shelters, hotels, and apartments. The recorded number of dead was 85, with the average age of 72 years old and 75% those perished being seniors (Butte County Grand Jury, 2019).

Local History

Butte County lies in the northern part of the California Central Valley and stretches eastward into the Sierra Nevada foothills. The region lies in the drainage basins of the Sacramento and Feather Rivers, and Butte Creek. Humans have inhabited this area west of the Sierra Nevada mountains since at least 2000 BC (Clark, 2021). The Concow, Konkow, or Konkow Maidu people originally inhabited the City of Paradise and its surrounding areas. Like other native California tribes, the Konkow Maidu used planned burns to manage forest overgrowth and promote use of plants that would grow after burns (Hankins, 2008).

The Paradise area, particularly Magalia, was intensively mined for gold through the 1890s (*Magalia District*, 1976). In 1903, the Butte County railroad was constructed, extending south of Chico to Magalia and later to Stirling City (Figure 17), primarily serving mines and sawmills. The modern-day Skyway Road, a main evacuation route, runs parallel to this railway, highlighted in yellow. In Figure 1 below, we can see the now abandoned Southern Pacific railroad along which Skyway follows.

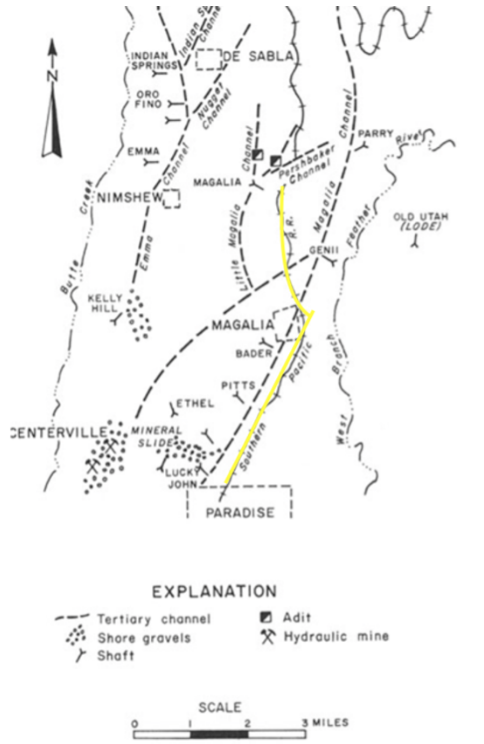

Figure 17. Sketch Map of Magalia District, Butte County. The northern part of the Butte Creek district is also shown. The channels are not all of the same geologic age.

Figure 17: Paradise and Magalia Area, circa 1905

In the 1800s and early 1900s, local housing plans emulated dense small Main Street towns, largely organized around the mining industry. When the mining activities mostly ceased by the 1930's, many of the mining properties eventually became subdivisions (*Magalia District*, 1976). Local ranchers or developers bought land, subdividing it further and selling it off as smaller parcels.

In the 1960's, the region saw a large expanse of subdivision development. For example, in 1969 the Concow Camelot Development transitioned an old ranch settlement into 1.4 acre lots (Mauch, 2015). Roads that were previously only sparsely used for mining or ranch access were paved and used for residents to access their new properties. The main message here is that these settlements took advantage of road access that was convenient, and a number of these same settlements would later be destroyed by the Camp Fire. By 1966, Paradise was home to some 20,000 residents, and in 1979 was incorporated as a town (McDonald, n.d.). By 2000, the city's population stood at about 26,000. Between 2000 and 2010, Paradise suffered two major fires.

In June 2008, the Humboldt Fire burned the southwest portion of Paradise requiring mass evacuations. The following month, fires from the larger Butte Lightning Complex fire threatened the area, resulting in 60,000 acres burned, 200 lost homes, one death and several injuries (Butte County Grand Jury, 2009). The 2008/2009 Grand Jury report ordered additional evacuation routes be implemented into the General Plan 2030, expressing concern for other foothill communities after evacuees were stuck in gridlocked mountain roads.

This study examines how wildfire events affect vulnerable populations, from evacuation through several months post-evacuation. Despite a history of wildfires, the city of Paradise and its surrounding communities were not designed with wildfire evacuation as a priority and grew exponentially during the 1960s and 1970s as retirees sought more affordable housing (Newberry, 2019). The 2018 Camp Fire was the most significant wildfire event experienced to date, and I will show how an efficient development strategy using mining and ranching roads produced a long-term hardship that will almost certainly persist over time.

Methods and Data

I use a mixed methods approach, combining qualitative interviews and quantitative survey data to examine inequity issues at stages of evacuation. Although the research design for the mixed methods sections is quantitatively dominant (Johnson et al 2007), I use qualitative data to contextualize this study. This combination results in a richer understanding of the data and results. I divide the study into three different time horizons: evacuation, immediate sheltering post-evacuation, and long-term post-evacuation to facilitate the study of equity issues (Table 11).

I define the evacuation period as the time of first alert (e.g., visually, by a neighbor or through formal channels) to the wildfire through the time at which evacuees depart their residence taking an evacuation route using their primary evacuation mode(s). After evacuation, I consider the range of immediate sheltering issues, including acquiring more permanent shelter, establishing communication, and other issues that evacuees deal with immediately after reaching safety and up to about six weeks following evacuation. The long-term period covers evacuee experiences about two to eight months post-disaster.

Table 11: Study Time Horizons

Period	Topics	Data Sources
Evacuation	Awareness of fire, Evacuation orders, Pre-evacuation communications and preparation, Departure, Evacuation mode, Evacuation route, Traffic conditions, Evacuation problems, etc.	At-Evacuation Survey and Shelter Interviews
Immediate Sheltering (0-6 weeks post-fire)	Short-term shelter, Aid, etc.	At-Evacuation Survey and Shelter Interviews
Long-term (2-8 months post-fire)	Longer-term housing, Displacement, etc.	Post-Evacuation Follow-up Survey

At-Evacuation Survey Data

In the two to six weeks following the Camp Fire, I deployed a survey in two ways: online through local newspapers, radio stations, Facebook support groups, and in-person at local Red Cross shelters in Gridley and Chico, California. I gathered information such as where respondents lived prior to evacuation as well as demographic data (e.g., household income). I collected 513 at-evacuation survey responses. I tabulate summary statistics in Table 12. The sample was mostly white, older, and female. The income distribution ranged from very low to relatively high. There are areas within Paradise and the surrounding communities with a very low median income of less than $20,000 annually. In fact, the 2018 average income of $49,270 for Paradise was below the federal average of $60,293 and the California average of $71,228 ("Am. Community Surv.," 2018).

Table 12: At- Evacuation Survey Summary Statistics

Variable	**Survey Value**
Race	Amer. Indian/Alaska Native = 1.4% (5), Asian = 1.6% (6), White = 84.6 % (307), Two or more races = 9.4% (34), Other = 3.0% (11).
Hispanic	Yes = 5.7% (20), No = 94.3 % (330).
Age	18-34 = 15.2% (60), 35-54 = 35.7% (141), 55-64 = 27.6% (109), 65+ = 21.5% (85).
Sex	Male = 34.2% (135), Female = 64.8% (256).
Education	Less than high school = 5.1% (20), High school graduate = 15.1% (59), 2-year degree = 14.3% (56), Some college = 32.4% (127), 4-year degree = 20.4% (80), Master's/Professional = 11.4% (45), Doctorate = 1.3% (5).
Income	Less than $10,000 = 9.3% (35), $10,000-$14,999 = 12.5% (47), $15,000-$24,999 = 9.1% (34), $25,000-$34,999 = 11.7% (44), $35,000-$49,999 = 11.5% (43), $50,000-$74,999 = 17.1% (64), $75,000-$99,999 = 12.0% (45), $100,000-$149,999 = 11.2% (42), $150,000+ = 5.6% (21).
Household	1-member = 23.4% (93), 2-members = 36.2% (144), 3-member = 20.2% (80), 4+ members = 20.2% (80).
Time at residence	Less than 1 year = 17.8% (70), 1-3 years = 22.6% (89), 3-5 years = 11.4% (45), 5-10 years = 15.7% (62), 10-15 years = 8.6% (34), 15+ years = 23.9% (94).
Owns smartphone	Yes = 85.9% (340), No = 14.1% (56).
Alerted to Fire Via	Saw fire firsthand = 44.6% (175), Told in-person = 26.3% (103), Call or Text = 17.1% (67), Online = 6.9% (27), TV or Radio = 3.8% (15), Official Evacuation Notice = 1.3% (5).

Note. Table 12 has been adapted from Grajdura, S. et al., 2021. Safety Science, *139*, p. 105258.

At-Evacuation Shelter Interview Data

In addition to the survey data, in the two to six weeks post-disaster I also conducted 26 semi-structured qualitative interviews with Red Cross shelter residents who were willing to share their experiences. In these interviews, I gathered information relating to their evacuation process, immediate and short-term housing prospects, and future housing plans. The sample statistics (Table 13) lean towards mostly male (72%) and lower-income individuals, with 46% making $15,000 a year or less and 75% earning $25,000 or less. Of the interviewees, 28% owned their home, 52% rented, and the remaining 20% lived with family or were homeless.

I first went through all interviews to identify main themes based on the broad interview topics similar to all participants. Then I went through a second time and applied these codes to the interviews. Based on the topics of the guided interviews, I coded the interviews with nine codes using Dedoose software (Table 14).

Table 13: Shelter Interview Summary Statistics

Variable	**Survey Value**
Race	Amer. Indian/Alaska Native = 3.85% (1), Asian = 0% (0), White = 61.5% (16), Two or more races = 34.6% (9).
Age	18-34 = 11.5% (3), 35-54 = 30.8% (8), 55-64 = 34.6% (9), 65+ = 23.1% (6).
Sex	Male = 72% (18), Female = 28% (7).
Education	Less than high school = 15.4% (4), High school graduate = 23.1% (6), 2-year degree = 15.4% (4), Some college = 26.9% (7), 4-year degree = 19.2% (5), Master's/Professional = 0% (0), Doctorate = 0% (0).
Income	Less than \$10,000 = 29.2% (7), \$10,000-\$14,999 = 16.6% (4), \$15,000-\$24,999 = 29.2% (7), \$25,000-\$34,999 = 8.33% (2), \$35,000-\$49,999 = 12.5% (3), \$50,000-\$74,999 = 4.17% (1), \$75,000-\$99,999 = 0% (0), \$100,000-\$149,999 = 0% (0), \$150,000+ = 0% (0).
Time at residence	Less than 1 year = 42.3% (11), 1-3 years = 7.66% (2), 3-5 years = 19.2% (5), 5-10 years = 15.4% (4), 10-15 years = 3.84% (1), 15+ years = 11.6% (3).
Housing	Own = 28% (7), Rent = 52% (13), With family/friends = 12% (3), Other = 8% (2).

Table 14: Interview Thematic Codes

Code	Description	Excerpts
Finding out	How people first found out about the fire	66
Evacuating	Descriptions of people evacuating	235
Traffic conditions	Perceptions of traffic conditions on evacuation route	89
Fears and problems	General fears/problems encountered post-disaster	129
Communication	Descriptions of important communication	80
Shelter/Housing	Descriptions of post-evacuation housing	94
Financial aid/Assistance	Description of money or aid received	31
Blame	Who is to blame/what could have been done differently	43
Future plans	Description of evacuees' future plans	23
Other	Other important information not in another code	82

Post-Evacuation Follow-up Survey Data

The post-evacuation follow-up survey was sent to those who agreed to provide a contact method in the at-evacuation survey 8 months post-evacuation. I sent the follow-up survey to 253 people of which 103 responded, bringing the response rate to 41%. The follow-up sample is mostly white, middle-aged, female, highly educated, of higher income home owners (Table 15).

Table 15: Post Evacuation Survey Summary Statistics

Variable	Survey Value
Race	Amer. Indian/Alaska Native = 1.1% (1), Asian = 1.1% (1), White = 88.8% (79), Two or more races = 5.6% (5), Other = 3.4% (3)
Age	18-34 = 7.0% (7), 35-54 = 45% (45), 55-64 = 30% (30), 65+ = 18% (18).
Sex	Male = 21% (21), Female = 79% (79).
Education	Less than high school = 0% (0), High school graduate = 4.04% (4), 2-year degree = 17.2% (17), Some college = 31.3% (31), 4-year degree = 24.2% (24), Master's/Professional = 20.2% (20), Doctorate = 30.3% (3).
Income	Less than \$10,000 = 3.1% (3), \$10,000-\$14,999 = 6.2% (6), \$15,000-\$24,999 = 6.2% (6), \$25,000-\$34,999 = 9.2% (9), \$35,000-\$49,999 = 8.2% (8), \$50,000-\$74,999 = 18.6% (18), \$75,000-\$99,999 = 18.6% (18), \$100,000-\$149,999 = 18.6% (18), \$150,000+ = 11.3% (11).
Time at residence	Less than 1 year = 13.2% (13), 1-3 years = 21.2% (21), 3-5 years = 10.1% (10), 5-10 years = 23.2% (23), 10-15 years = 9.1% (9), 15+ years = 23.2% (23).
Housing	Own = 62.6% (57), Rent = 30.8% (28), With family/friends = 2.2% (2), Other = 4.4% (4).

Geocoding and Regression Trees

Spatial information is available from both the at-evacuation and post-evacuation surveys. I geocoded this information, using it to provide context for evacuee displacement. Nearly a year after the fire, half of all evacuees who were property owners were still living in Butte County, with about a third residing in Chico (Chase and Hansen, 2019). I build upon this analysis by examining the residential decisions associated with renters and other vulnerable groups.

I geocoded original pre-fire addresses, the length of residence at the time of the survey, and last place information. Using this information, I derived the distance that individuals traveled in the 8 months after the Camp Fire. I also calculated the distance between the 1) the original location and the last location the person had stayed prior to receiving the 8-month post-evacuation survey, and 2) the original location and the location they were currently staying at the time of the 8 month post-evacuation survey. It should be noted that evacuees may have stayed at numerous places between taking the at-evacuation survey and the post-evacuation survey; I collected information on the last place in which they stayed. I refer to this displacement period, Displacement 1, as the "short term" and the 8 months period as Displacement 2, the "long-term."

For the analysis, I am interested in the variables influencing evacuee displacement. For this I use classification and regression tree (CART), a non-parametric method, to identify the variables most influential in predicting evacuee displacement. The method uses recursive partitioning to describe an outcome based on independent variables. In this case, because the outcome, displacement, is a continuous variable, I build two regression tree models, one for short-term and long-term displacements, respectively. The potential independent variables are shown in Table 16. Since the sample is small and my work is among the first of its kind, I do not use training data. Combining these methods with my qualitative findings from the immediate sheltering period enriches the analysis.

Table 16: CART Independent Variables

Variable	Description
Income	<= $50,000 = 0, $50,000+ = 1
Age	Age < 65 = 0, Age 65+ = 1
Reside	Community residence (<15 years = 0, 15+ years = 1)
White	Race is white (1= Yes, 0 = No)
Smartphone	Owns smartphone = 1, No smartphone = 0
Education	Less than high school = 0, High school and above = 1
Sex	1 = male, 0 = female
Household size	Household size (< 4 members = 0, 4 + members = 1)
Insurance	0= No insurance, 1 = Has insurance
Places	Number of different locations an evacuee has stayed at in first month post-fire

Results

In this section I present the evacuation period thematic analysis results as well as the short and long-term displacement results. I begin with a presentation of the evacuation issues that were identified in the interviews. I then present the short-term displacement results coupled with the immediate sheltering interview results, because aspects such as ability to acquire financial assistance, greatly affected the displacement patterns I observe post-evacuation. Last, I present the long-term displacement results.

Evacuation Shelter Interviews

The interviews with sheltered evacuees elicited a number of important themes with respect to how they were alerted to the approaching fire (Table 17). None of the 26 interviewees received a formal evacuation warning by phone call, email, or text by the official system, Code Red. This is consistent with prior research indicating that Code Red alerts did not affect the time at which people became aware of the fire or began evacuating (Grajdura et al., 2021b). Many interviewees carried on with morning routines, unaware of the fire, running errands around town when they suddenly became mired in the evacuation gridlock and were never able to return home. One newspaper delivery man reported calling 911 to verify the fire and was informed nothing was wrong, only to be met by flames minutes later.

Table 17: Evacuation Themes from Qualitative Data

Theme
Lack of formal emergency notification
Hesitation to begin evacuating
Role of property manager at mobile home parks
Alerting friends and neighbors
Unconventional evacuation (mode, route, etc.)
Haphazard evacuation decision-making
Extreme traffic conditions

One elderly renter noted, “How did I first find out about the fire? When the ember started falling down on top of the house.” Several shelter evacuees I interviewed noted that despite finding out about the fire, they did not see reason to begin evacuating. Some had medical issues that took precedence or were quite familiar with wildfires and chose to wait and see, not knowing the severity of the situation.

One unexpected theme in the interviews was the role of the property manager in rented apartments and in manufactured home parks, in which about 65% of the interviewees lived. Some interviewees expressed dismay and surprise that their property manager had evacuated without notifying residents of the immediate danger. One elderly resident of a manufactured home park who lived alone describes:

> “None of my other neighbors, on either side of me were there. Everybody panicked and left…Even the manager of the complex... Didn't even go around telling people. He just hopped in his truck and took off.”

At another complex, the property manager played a critical role in alerting residents by circulating around the mobile home park shouting at residents. One interviewee who indicated that he had just had open heart surgery and was unable to drive was alerted to the fire because of the manager’s actions. There were several other examples of people alerting and helping others in their community, especially the elderly. These altruistic actions likely saved many peoples’ lives who would have not have otherwise started evacuating.

Once underway, very few of the respondents drove directly to their destination, which is how most conventional evacuation models expect people to behave. Several of the interviewees recounted picking up neighbors and strangers along the way who were in imminent danger. Many respondents evacuated by some combination of walking, biking, or driving four-wheelers –and were later picked up by other evacuees in vehicles. One man who was living off-grid in the foothills rode a four-wheeler for 36 hours after most people had been evacuated. After sending his family on an evacuation route, he went to go check on an elderly family friend, who did not want to leave his burning house. The man saved his friend but ended up being trapped for two days within the burning forest and suffered serious burns.

The evacuation was a deeply traumatic experience for most interviewees, trying to escape quickly with the chance of being overcome by fast-moving flames and avoiding the constant rain of embers, not to mention downed power lines, burning cars, and other obstacles. As one evacuee describes:

> "On both sides, you were going down the middle between the flames, walls of flames. And the trees weren't burning like you would think of normally because the fire was up at height and blowing sideways. So, when they caught fire, they caught fire at the bottom all the way to the top, all at once. Just hit it like that, then boom, they would go up."

Lacking clear direction for safe evacuation and having to haphazardly navigate were also common themes. Interviewees described their evacuation plan aligning more with simply trying to escape the fire than having a specific route in mind. They report being forced to stay overnight in empty parking lots. This feeling of not knowing what was to come next echoed through the post-evacuation period as many evacuees struggled to find a stable housing situation in the days and months following the evacuation.

Displacement 1: Short-term

When I use the survey data to model initial displacement, (i.e., where evacuees initially stay post-evacuation), I find that the number of locations an evacuee has stayed at in the first month post-disaster, and income are highly influential in the short-term displacement of evacuees (Figure 18). Those who stayed at five or less locations in the first month after evacuating had on average the smallest displacements, as shown in the leftmost path of the decision tree. The rightmost path, consisting of those who had stayed at more than five different locations in the span of a month, with incomes less than $50,000, experienced on average the largest displacements, about 15 times farther than the left-most cohort. Those staying at more than five locations with an income over $50,000 averaged a short-term displacement of 80 miles.

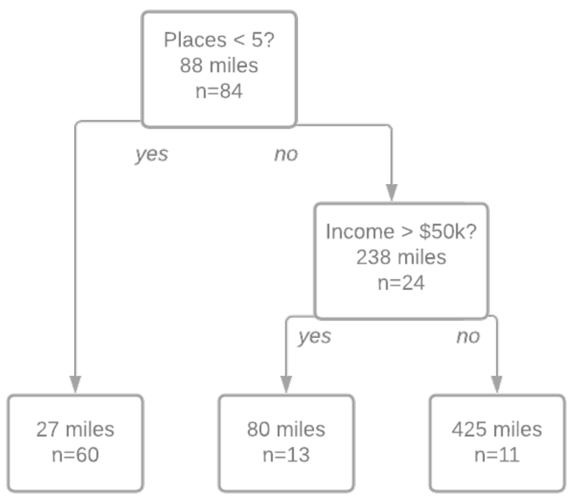

Figure 18: Short-term Evacuee Displacement Regression Tree

Both the in-person shelter interviews and survey responses support the finding that those who lived at fewer locations with higher incomes relocated in closer proximity to their original residence. When I examine displacement distance by income groups (Table 18), it is clear that a large proportion of higher-income evacuees (33%) displaced to a new residence within 10 miles of their original home; this compares to a mere 18% of those earning less than $50,000.

Similarly, I see greater numbers of higher income evacuees (44%) living between 10 and 30 miles from their original residence, compared to 32% of lower income evacuees.

In fact, half of the lower income evacuees locate in the short-term more than 30 miles from their home; this compares to just 22% of higher income evacuees. The proportion of low-income evacuees living more than 400 miles away (11%) from their original home is staggering compared to the 1.9% of the higher income group living at this distance. The results suggest that higher income evacuees having the means to remain closer, while lower income evacuees end up moving further out from their original home. I speculate that this is likely due to a search for affordable housing and/or co-locating with family.

Table 18: Measuring Evacuee Income and Displacement (miles)

Income and Displacement 2-8 months		
Distance (mi)	<$50k	$50k+
[0,10)	17.9%	33.3%
[10,30)	32.1%	44.4%
[30,100)	35.7%	13.0%
[100,200)	0.0%	5.6%
[200,400)	3.6%	1.9%
[400+)	10.7%	1.9%
	N=28	N=54

When I look at the themes that arose around relocation issues in the interviews (Table 19), these support the model suggesting that wealthier people who stayed at fewer locations had more options available to them to stay closer to their original home. Most of the shelter interviewees were lower income, with over 75% earning less than $35,000 a year (compared to 60% earning $50,000 or more from the at-evacuation survey results). While there is some obvious self-selection in the shelter interview sample (shelter evacuees are often those who lack other housing prospects or are hindered by the availability of funds), it is clear that from the moment they evacuated to a shelter, evacuees were concerned about housing.

Table 19: Immediate Sheltering Period Themes from Qualitative Data

Theme
Difficulty securing shelter first few nights post-evacuation
Transportation challenges while living at shelter
Non-evacuated homeless in shelters
Difficulty securing permanent housing (apartment, trailer, house, etc.)
Concern over being kicked out of the shelter
Shelter health conditions
Concern over pets
Financial aid inadequate for low-income evacuees

Evacuees that I interviewed were generally unsure about where to go initially for short-term housing, and most reported that once they escaped imminent danger, they gathered at local gas stations and chain stores like Walmart and Costco. Many ended up staying overnight at the Walmart parking lot or other box store parking lots after the initial evacuation. Some evacuees drove from place to place searching for a place to stay, e.g., a shelter or hotel room. One evacuee notes the following after staying in a parking lot for a few nights:

> “We didn't know where we were going to go, none of us did.
> We were like, ‘What do we do?’ We were just living here,
> we didn't have nowhere to go, don't know if we're going to
> lose our stuff, and we don't know where we're going.”

Interviewees reported finding out about shelters as a temporary relocation option through word of mouth, the radio, and online. However, those who stayed in shelters found themselves moving from several different shelters in the several weeks following the Camp Fire, as several Red Cross and other smaller centers were closed and consolidated into one main shelter, the Silver Dollar Fairgrounds in Chico, California. Once evacuees arrived at a shelter, mobility was limited, especially for those without a vehicle or who had lost a vehicle in the fire. One interviewee explained how the buses offered by the shelters were not conducive to daily transportation, proving especially challenging for those evacuees with disabilities needing frequent access to hospitals.

One controversial issue was the presence of homeless people from Chico and surrounding areas, living at the shelters among the evacuees. Stakeholders and local officials found handling the existing homeless population while expanding service for the new, displaced evacuees very challenging (Spearing and Faust, 2020). Many evacuees felt it was unfair that homeless people were benefitting from the services meant solely for Camp Fire evacuees. However, many did not mind sharing resources, and considered themselves to be homeless as well.

Combining the difficulty of securing housing and the uncertainty of shelter stays, interviewees expressed genuine concern over becoming homeless themselves. This anxiety was exacerbated by evacuees waiting for the (slow) distribution of insurance money and trailers from the Federal Emergency Management Agency (FEMA). Despite the Red Cross assuring evacuees that nobody would be kicked out prematurely, interviewees struggled with rumors that people would be forced to leave without adequate notice. This spurred some evacuees to attempt to find temporary housing on their own. Others voiced fears of needing to return to the shelter in the future:

> "And then they want us to get temporary housing so when our money runs out, then what are we going to do? We're going to come back here?... We're not leaving until we get our money or they give us housing."

Interviewees also expressed concern over the health conditions in shelters. In the first few weeks after the evacuation, the norovirus spread to four different shelters housing evacuees, infecting more than 150 people (Thomas, 2018). Others expressed concerns about the air quality in shelters. In the month following the evacuation, Butte County's air quality was the worst in the world, posing significant health consequences (Turkewitz and Richtel, 2018). Since by design shelters are open air with many people sleeping in a large room, and doors open during the day, the shelters did not provide much protection against the unhealthy air quality.

Displacement 2: Long-term

Here, recall that I refer to long-term displacement as the point of residence at eight months. In the modeling of long-term displacement (Figure 19), we see that if the evacuee is not white, they have taken residence fairly close (within 21 miles) of their original residence. If the evacuee is white, younger than 65 and has moved more than three times, they take housing on average around 117 miles from their original residence. Those younger than 65 and having moved less than three times end up much further from their original residence (on average 248 miles). Finally, evacuees older than 65 end up with an average long-term displacement is 307 miles.

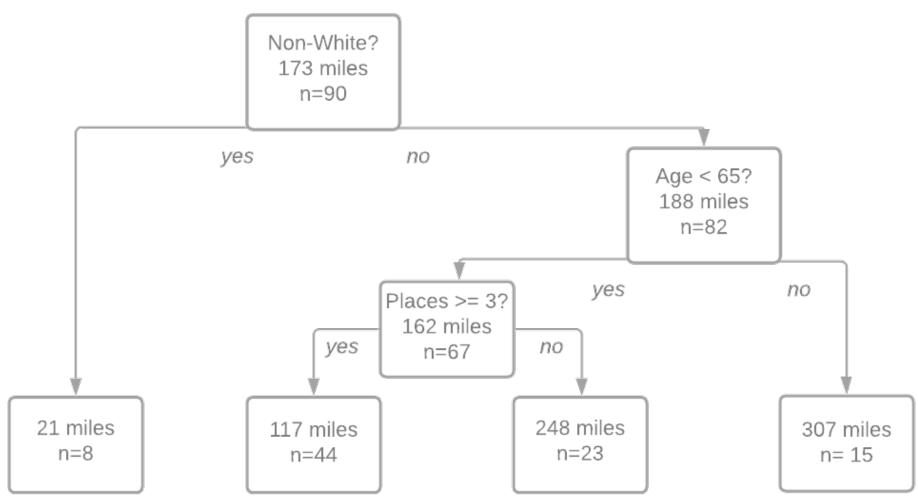

Figure 19: 8 Month Evacuee Displacement Regression Tree

When we look at short-term and long-term displacement by age (Table 20), we see fewer young evacuees living within 10 miles of their original home. This might reflect a stabilizing of work and home, which is more feasible as time goes on. For example, insurance and FEMA money may have been distributed, providing more latitude on where to live. Some have argued that evacuees moving further away may be retired and have less reason to stay in the area, as well as the financial means to move to a more distant residence (Chase and Hansen, 2019).

Table 20: Displacement by Evacuee Age

Displacement	**Short-term (<8 months)**		**Long-term (>8 months)**	
Distance (mi)	**<Age 65**	**Age 65+**	**<Age 65**	**Age 65+**
[0,10)	31.80%	11.10%	21.90%	11.80%
[10,30)	40.90%	33.30%	45.20%	11.80%
[30,100)	18.20%	38.90%	16.40%	47.10%
[100,200)	3.00%	5.60%	1.40%	11.80%
[200,400)	3.00%	0.00%	5.50%	0.00%
[400+)	3.00%	11.10%	9.60%	17.60%
	N=66	N=18	N=73	N=17

Discussion

The results suggest that there are some practical steps that can be taken to address and improve inequities in post-disaster displacement. For example, improved plans for staging areas and longer-term shelters and housing options should be a top priority for aiding vulnerable people. In the short-term, it was traumatic for vulnerable evacuees to continue moving from shelter to shelter. If centralized shelters were kept open for at least eight to ten months post-disaster, it would allow processing of aid funds and help to assist in stable housing. The results suggest that it is critical for all fire-prone communities to have long-term permanent shelter plans in place before a wildfire occurs.

Research into the planning of shelters for the Camp Fire specifically found that the transient nature of evacuees was a significant challenge to providing adequate shelter and resources (Spearing and Faust, 2020). From the view of the evacuees, there was not adequate information about where to go or how to find help. Again, if towns or regions could have one consolidated area for the staging (arriving of evacuees after evacuating) and pre-planned long-term shelter infrastructure in place, there could be improved information sharing.

As part of improved shelter logistics, it is imperative for cities and towns with sizeable homeless populations to account for possibility of additional occupants including the existing homeless population, incoming evacuee population, and for people who were homeless already in the burned area and had to evacuate. I found disabled evacuees faced more constrained challenges regarding housing, which is supported by the literature (Gartrell et al., 2020). All of these groups of people have different needs and timelines for procuring short term housing. This should be part of pre-planning operations for wildfire evacuation sheltering infrastructure.

Interestingly, income was not a deciding factor of evacuee longer-term displacement, yet it was in short-term displacement. One of the challenges voiced by the interviewees in the short-term was the difficulty in using monetary aid from FEMA or other organizations toward rent in a sustainable way. Because many did not have insurance or own a home, the amount of aid was less, if they received any at all. As one person points out:

> “FEMA divides the world pretty much into the homeowners with insurance and everybody else. So, I'm kind of in one of the favored few category. Not few, but a lot of people here didn't have insurance.

They lost everything."

Many found it challenging to procure an apartment with aid funds, especially since the local prices increased after the Camp Fire. However, some of the interviewees also stated that landlords would not accept their aid as income, barring them from signing a lease. In this sense, the shelters not only served as shelter in the plainest sense, but also serve as a place that affords people to live for free while they work and save money, and rebuild their lives. There was also considerable fear about having to return to the shelter if they chose to rent and were not able to afford rent or ran out of money. In the longer run, these issues may have been addressed, which is why I do not see income as a deciding factor in displacement.

One success story was a man who was able to take advantage of a special promotion at local bank offering loans with no credit check for Camp Fire survivors to purchase a recreational vehicle (RV). The man was very proud because this was the first loan he had ever taken out in his life, and had expressed surprise that more evacuees were not taking advantage of this offer, which proved to be truly life-changing for him. It is likely that others were unaware that this offer existed or were perhaps too uncomfortable accepting this offer with a low income. Better communication of aid possibilities to those in shelters could be life-changing by helping secure temporary housing, may it be an RV or apartment.

One clear finding for both the short-term and long-term displacement is that the number of locations an evacuee resides at in the first few months is an important predictor of displacement. However, in the short-term, more locations (> 5) is associated with more distant displacements, and in the long-term, having more locations (>3) is associated with less displacement distance. I suspect that in the short-term, more locations suggests limited options.

That is, someone who is forced to stay at several locations in a short period of time due to a lack of other options. Research has shown that indeed renters have more freedom in the short-term, but to permanently relocate depends on several aspects like transportation, employment, distance to family, and savings, not to mention the availability of rentals (Peacock et al., 2017). In the long-term, I see age becomes more prominent than the number of places someone stays at during the first few months in displacement distance.

Finally, housing plays a critical role in providing safety for evacuees. One of the natural disaster displacement equity issues is the right for someone to stay or proximate to their original residence. Not only did some evacuees lose their home, but they were also unable to rent or purchase a new home in the surrounding area due to surging housing prices and other challenges (Peloton, 2020). Complicating this issue is the well-documented housing shortage in California, intensified by the low interest rates (Kamin, 2021). Providing short-term shelter for some 50,000 evacuees does pose practical challenges for local policymakers facing a large shock to their infrastructure (Spearing and Faust, 2020). A new initiative between FEMA and the Department of Housing and Urban Development (HUD) aims to improve case management and housing procurement specifically for vulnerable groups post-disaster, in part due to the continuing challenges Camp Fire evacuees face (Dreier, 2022).

Conclusion

Dire and fast-moving wildfires can result in entire towns evacuating within hours. This was the case in the 2018 Camp Fire. By researching the local environmental history, analyzing first-person evacuee interviews, and using decision tree methods with longitudinal survey data, I investigate the range displacement-related equity and justice issues wildfire evacuees face. I find inequities throughout the evacuation to resettlement period. As the disaster progresses, these inequities change.

Specifically, I find that during the pre-evacuation period, vulnerable evacuees may not receive formal notifications to evacuate, may hesitate to evacuate, and may try help other vulnerable evacuees if possible. I also found property managers of mobile home parks to be important information disseminators. Vulnerable people may experience unconventional evacuation routes due to various reasons, such as not owning a car or having a medical condition.

Securing shelter for the first several nights post-evacuation is challenging for vulnerable populations. Temporary housing is difficult to achieve on a low income, especially with extremely low availability and in instances where FEMA aid is not accepted. Shelters had issues with accommodating local homeless people. Many vulnerable people felt uninformed and unsure when shelters would close and feared they would also become homeless. Finding a permanent housing solution felt out of reach for the most vulnerable, with worries about not being able to pay higher rents, and needing to return to the shelter.

I find that income heavily impacts evacuee displacement, with higher income earners being able to settle closer to their original home in both the short and long-term. In the short-term, younger evacuees had shorter displacements, which equalized somewhat in the long run, with more people both young and old moving over 400 miles away.

Estimating displacement using regression tree methods, the “shelter hopping” activity I observe becomes a main predictor of evacuee displacement, along with income in the short-run and with race and age in the long-run. “Shelter hopping” is more common among lower-income populations, who struggle to find temporary or permanent housing and are shuttled between shelters amid shelter consolidations.

The unequal conditions that natural disasters bring are just a symptom of existing societal inequities. However, governments, planners, and emergency managers need to develop plans that address these inequalities in a way that is respectful of all residents. Evacuation modeling that accommodates many of the unconventional behavior that vulnerable evacuees might experience should be studied further. It is imperative that communities develop shelter infrastructure that can accommodate large crowds given a mass evacuation for long periods of time.

Chapter 6: Conclusion

Wildfires in the American West will be an integral part to this region's future, in addition to several other regions around the world. To date there has been limited empirical research on no-notice and short-notice wildfire evacuations. This dissertation aimed to investigate the characteristics of human response to a short/no-notice, fast-moving wildfire, both in the short-term evacuation and in the longer term.

Investigating the human response to such a wildfire, I found that awareness, preparation, and departure times varied across the evacuee population. Factors found to impact these timings were linked to socio-demographic and other characteristics. This information can be applied to future wildfire evacuation modeling research, by incorporating new variables such as smartphone access and residence tenure and to estimate awareness and departure times. It can also be used by those planners dealing with wildfire preparedness to estimate the times at which to give adequate notice in a no/short-notice event.

The agent-based simulation model with scenarios specific to a dire no/short-notice wildfire event is useful as a framework for future wildfire evacuation models and can be easily customized to other locations. It incorporates empirical behavior into the model, and allows for a high level of customizability. It also addresses the location of where evacuees may become trapped in an evacuation. I find that in all scenarios, travel times are increased and awareness delays and limited vehicle access increase the number of trapped agents. This information is important for future planning for dire wildfire events.

Lastly, this dissertation addresses equity and justice at different stages of wildfire evacuation. This research is unique in that it centers evacuee experiences and presents results for different time periods of the disaster. The results indicate inequalities amid evacuations, sheltering, and eventual displacement. These aspects must be incorporated into disaster planning for these large-scale wildfire events in the American West.

Beyond this research, there is much more empirical data to be collected during and after wildfire evacuation. Survey data directly from evacuees provides important insight into what must be improved to provide adequate aid to vulnerable groups. Policies affecting wildfire evacuees should also be explored to determine optimal policy actions to increase equitable evacuations and post-evacuations. Further research should also improve upon the simulation model presented, adding complexity in evacuee movements such as mode sharing, mode switching, and congestion effects.

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