UNDERSTANDING AND MANAGING WILDFIRE RISKS TO RESIDENTIAL COMMUNITIES AND SUPPLY CHAIN NETWORKS

By

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Abstract

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Wildfire has become an increasing threat to humans, the built environment, and ecosystems in the United States. Several factors contribute to such an increase in wildfire risk, including climate change, rapid population growth and infrastructure development at the wildland-urban interface, and accumulated fuels from past wildfire management practices. Increases in wildfire activity have resulted in substantial human and economic losses in the past decade. For example, the 2023 Hawaii wildfires razed more than 2,200 homes and businesses while tragically claiming the lives of at least 115 individuals. A series of California wildfires in 2015, 2017, and 2018 resulted in direct economic losses of $4.8 billion, $18 billion, and $26.3 billion, respectively. In addition to the direct economic losses, the 2018 California wildfires disrupted many supply chain systems, which propagated across the regional economy and induced $88.6 billion in direct losses. These recent wildfires have underscored the urgent need for understanding, assessing, and managing wildfire risks to residential communities and supply chains. To this end, this dissertation aims at understanding and managing wildfire risks to humans, properties, and the regional economy, with a particular focus on residential communities and supply chain networks.

To advance our understanding of various proactive and emergency activities, this dissertation begins by examining homeowners' decisions on wildfire-related proactive actions, such as home hardening, vegetation treatment, and homeowners insurance, through an online survey and subsequently assesses the effect of these actions on the process of housing recovery. Next, this dissertation shifts its focus towards individual behaviors during wildfire events, encompassing their preferences and decisions made during wildfire evacuations. This entails the study of factors like evacuation triggers and timing, as well as a series of en-route decisions made by evacuees in wildfire-prone areas, all gathered through an online survey. Based on the survey results, data-driven models are developed for predicting evacuees' behaviors during wildfires. Furthermore, this dissertation integrates these data-driven predictive models with wildfire simulations, vulnerability assessment, and traffic simulation to construct a comprehensive agent-based modeling (ABM) framework for wildfire evacuations under damaged transportation settings. The framework is designed to simulate traffic conditions during a wildfire evacuation and identifies the critical parts of the transportation network for pre-fire risk mitigation actions aimed at improving mobility during a wildfire evacuation.

To assess wildfire risk to a supply chain network, this dissertation also proposes a probabilistic wildfire risk assessment framework. It provides rigorous probabilistic descriptions of wildfire ignition likelihood and growth, interaction between supply chain components and wildfire, consequent component damage, and network-level performance reduction. Then, a hypothetical forest-residuals-to-sustainable-aviation-fuel supply chain network is utilized as an illustrative example to demonstrate the capability and applicability of the proposed framework. The proposed framework can be used as a planning tool to evaluate network performance subject to a set of what-if scenarios and the effect of pre- and post-wildfire risk mitigation measures.

Overall, this dissertation provides valuable insights into understanding the inherent drivers behind individual's preference for both wildfire proactive actions and evacuation decisions. This information can lay the foundation for improving community resilience by helping policymakers and stakeholders increase participation rates in proactive actions and improve responsiveness to evacuation orders. Moreover, the simulation tools and quantitative frameworks developed in this dissertation provide valuable support to stakeholders and policymakers in predicting post-wildfire performance and implementing more effective pre-event mitigation strategies. These adaptable tools and frameworks show potential for broader applications across various domains, including water distribution networks, transportation systems, and electric power grids, making them valuable assets in addressing the complex challenges posed by dynamic and interconnected systems.

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CHAPTER ONE: INTRODUCTION

1.1 Background

Wildfire risk has increased significantly in recent years and is expected to grow across many parts of the United States (Balch et al. 2017). Eight out of the top ten costliest wildfires in the United States occurred between 2017 and 2020 (Insurance Information Institute 2020), with notable examples in California (e.g., the Carr Fire, the Woolsey Fire, and the Camp Fire, all of which occurred in 2018 and destroyed over 20,000 structures in California). Climate change may play an important role in increasing the frequency and severity (in terms of fire size and duration) of wildfire. The average global surface temperature has risen by 0.14℉ per decade since 1880, resulting in reduced winter precipitation, drier soil and vegetation, and longer summer dry seasons (Pausas and Keeley 2021), all of which can be observed in the Western United States (Westerling et al. 2011). Under changing climate, more wildland-urban interface (WUI) areas have become fire-prone environments, and thus more houses in the WUI are exposed to wildfire danger. Moreover, growing population and human activities in the WUI have altered the environment and increased the exposure of human and high value assets to wildfire, making the problem even more complicated and severe (Westerling et al. 2011; Moritz et al. 2014; Smith et al. 2016). One-third of residential buildings in the USA are located in the WUI (Wisch and Yin 2019), and 4.5 million U.S. homes are at high to extreme risk of wildfire (Verisk 2019). Due to increased exposure in wildfire-prone areas, the small historical fires (e.g., Awbrey Hall Fire Oregon 1990) that did not cause significant economic losses could pose much greater risks if they were to occur today, as demonstrated by Wisch and Yin (2019). Moreover, as clearly shown in the Inland Northwest of the United States (Hessburg et al. 2005, Calkin et al. 2015), the active wildfire suppression during the last century has allowed for fuel accumulation and changed fire regimes.

Escalated wildfire activity and exposure have posed considerable threats to human lives, properties, and the regional economy. For example, the 2016 Great Smoky Mountains wildfires, also known as the Gatlinburg wildfires, caused $911 million in direct economic losses. The 2018 Camp Fire, the deadliest and most destructive wildfire in California's history, caused at least 85 fatalities and more than 18,000 building destruction. Similar trends have also been observed in other parts of the United States: according to the records in National Fire and Aviation Management (FAM) and National Interagency Fire Center (NIFC), more than 63,000 structures have been destroyed by wildfires since 2015, accounting for approximately 71% of the structures that were destroyed by wildfires in 2005-2020 (Barrett, 2020). Wildfire losses can be classified into direct losses and indirect losses. Wildfire direct losses include suppression cost, the damages to buildings, critical infrastructure, and natural resources, and fatalities/injuries, all of which can be directly quantified. On the other hand, wildfire indirect losses include impact on human well-being, and reduced outputs and revenue arising from wildfire-induced disruptions to the flows of goods and services (Zybach et al. 2009, Thomas et al. 2017).

Reducing Direct Losses from Wildfires

Wildfire risk management action is a first step towards reducing direct losses. Individual homeowners can take various types of mitigation efforts (e.g., home hardening, vegetation treatment) to protect their lives and properties from wildfires: Home hardening makes the structure itself more resistant to embers and flames, thus reducing the risk of ignition; on the other hand, vegetation treatment creates a defensible space around the house, mitigating the risk of fire intrusion and providing a buffer zone. Another important proactive measure that homeowners can take is purchasing homeowners insurance, which provides coverage for damage to structures and personal belongings caused by wildfires and smoke. It helps homeowners in alleviating excessive financial burdens from repair/reconstruction costs following a wildfire event. In the past two decades, extensive studies have investigated the effects of homeowner mitigation efforts (McGee and Russell, 2003; McFarlane et al. 2011; McCaffrey, 2008). However, most of them have focused on a single type of mitigation action and have not evaluated the combined effect of various mitigation efforts on structural damage and post-disaster recovery process, which is essential for assessing their roles in community resilience. Moreover, there has been only a limited number of studies that quantitatively evaluate the impact of homeowners insurance on houses and communities affected by wildfires. This dearth of quantitative analysis on homeowners insurance has led to the underestimation or oversight of its significance in numerous community resilience planning studies. Therefore, it is crucial to gain insights into the potential factors influencing various proactive actions (e.g., home hardening, vegetation treatment, and homeowners insurance) taken by homeowners to manage wildfire risks and understand the role of such actions in the process of housing recovery.

Although individual-level proactive actions are effective ways of mitigating wildfire risk, it is not possible to completely remove such risks due to substantial inherent uncertainties in its activity. In this case, evacuation is the most important and effective method to reduce human losses during a wildfire event. For example, while the majority of tsunami risk reduction measures were destroyed during the 2011 Great East Japan Earthquake/Tsunami, timely evacuation saved approximately 90% of the total population at risk from the tsunami (Mas et al., 2012). While evacuation is considered one of the most effective means of ensuring human safety in the case of residual risks from natural hazards (Mas et al. 2012), many homeowners do not perceive evacuation as the most effective means in the case of wildfires because they believe they can protect their properties better by staying and fighting the fire themselves (McLennan et al. 2013, Mutch et al. 2011). However, due to the fast and unpredictable movement of fires, there is a great risk for individuals who evacuate late or refuse to evacuate. For example, 70 out of 85 fatalities during the 2018 Camp Fire were found inside or immediately outside of their properties, and 8 were trapped on the road during the evacuation (Ramsey et al. 2020). Therefore, a comprehensive understanding of the underlying factors that influence individual evacuation preferences and behaviors can help authorities make more effective emergency plans and reduce human losses in future wildfire events.

Moreover, evacuation process may be complicated in the real world due to public panic and traffic congestion created by exit route shortages when massive evacuation orders are issued simultaneously, which can greatly jeopardize human lives (Cova et al., 2005). Numerous studies have been conducted to develop transportation evacuation simulation models for a variety of natural hazard events. Most of the early works used static analysis at the macro or meso scale (Zhan and Chen, 2008). In recent decades, evacuation modeling has benefited from microscopic traffic simulation, owing to the advancement of computer technology and its capabilities to simulate traffic flow at the individual vehicle level (Benjaafar et al., 1997; Hamacher and Tjandra, 2002). Among these approaches, agent-based modeling (ABM) has received great attention due to its advantages in capturing individual and collective behaviors in a dynamic complex system (Mas et al., 2012; D'Orazio et al., 2014). However, most of the studies using ABM in evacuation simulations have not been integrated with natural hazard modeling, thus developing their models based on the assumption that all (or a certain portion of) the residents have already been forced to evacuate their community. To overcome these restrictive assumptions and achieve a more accurate prediction of traffic conditions during a wildfire evacuation, it is necessary to develop an integrated approach that combines hazard modeling, vulnerability assessment, evacuee response modeling, and traffic simulation.

Understanding Indirect Losses from Wildfires

While the direct impact of wildfires on humans, structures, and natural resources induces substantial economic losses, supply chain disruptions during and following a wildfire event (i.e., indirect economic losses herein) also account for a large portion of total wildfire-induced economic losses. As revealed by Wang et al. (2021), the total economic losses from the 2018 California season were estimated to be $148.5 billion, including $27.7 billion of direct economic losses and $88.6 billion of indirect economic losses (about 60% of the total economic losses) primarily due to supply chain disruptions. Similarly, economic losses from the 2017 California wildfires totaled $180 billion, which was significantly attributed to disrupted wine supply chains (AccuWeather, 2017). Regional and national supply chains are highly interconnected one another, and disruptions to one supply chain can propagate to others. Given that headquarters and distribution facilities of many shipping and wholesale companies (e.g., Amazon, Costco) are located on the west coast (Cosgrove, 2018) which includes high wildfire risk areas, wildfire may result in extensive delays and significant expenses in supply chain systems in the United States. Therefore, wildfire risk assessment for supply chain operation is an important aspect in reducing wildfire-induced regional and/or national economic impact.

In the past two decades, an extensive literature has assessed wildfire risk to humans, ecosystems, and the built environments (Scott et al. 2013; Thompson et al. 2011; Tutsch et al. 2010), but most of them have focused on component-level damage assessment and summed them up to estimate an aggregated level of damage and losses. Very little research has been conducted to develop an integrated wildfire risk assessment framework which quantifies wildfire likelihood, severity, and consequences and has the ability to account for cascading effects in estimating network-wide risks. Moreover, to the best of my knowledge, an integrated wildfire risk assessment framework has not been developed for a supply chain system to estimate its direct and indirect impacts on system performance.

1.2 Research Objectives

This dissertation aims at understanding and managing wildfire risks to humans, properties, and the regional economy, with a particular focus on residential communities and supply chain networks. To accomplish this goal, the following research tasks have been conducted:

1. Investigate the potential factors that may affect homeowner proactive actions for managing wildfire risks and the role of such actions in the housing recovery by conducting an online survey of residents in wildfire-prone areas.

2. Examine the critical factors that influence evacuee preferences and behaviors during wildfires. Establish empirical predictive models for their evacuation-related decisions using both statistical and machine-learning approaches.

3. Develop an agent-based modeling framework for wildfire evacuation in damaged transportation settings aimed at predicting traffic conditions during an evacuation and identifying the critical parts of transportation network for pre-fire risk mitigation actions.

4. Propose an integrated wildfire risk assessment framework for a supply chain network which probabilistically quantifies the effect of wildfire-related disruption on network functionality.

1.3 Dissertation Organization

This dissertation is divided into two parts. The first part focuses on managing wildfire risks to residential communities by investigating individual-level wildfire risk management actions (Chapter 2), establishing empirical predictive models for wildfire evacuation decisions (Chapter 3), and developing an agent-based simulation framework for wildfire evacuation (Chapter 4). The second part focuses on understanding wildfire risks to a supply chain network probabilistically (Chapter 5).

The remainder of this dissertation consists of five chapters, followed by a list of references. Chapter two investigates homeowner decisions on wildfire-related proactive actions and the effects of such actions on housing recovery based on a post-wildfire online survey and analysis of homeowners in multiple counties at high to extreme risk of wildfire in California and Washington. Chapter three identifies crucial factors that affect individual evacuee response to staged evacuation orders and constructs predictive models for en-route evacuation decisions based on a stated-preference online survey distributed to California, Oregon, and Colorado states. Chapter four develops an ABM simulation framework that predicts traffic conditions during a wildfire evacuation, particularly in damaged transportation settings. Chapter 5 proposes a probabilistic framework for quantifying wildfire risk to a supply chain network and illustrates it with a hypothetical sustainable aviation fuel supply chain network located in the Pacific Northwest region. Finally, Chapter 6 summarizes the findings that are detailed in the previous chapters and discusses future directions for the research.

CHAPTER TWO: UNDERSTANDING HOMEOWNER PROACTIVE ACTIONS FOR MANAGING WILDFIRE RISKS

2.1 Background

As part of wildfire risk reduction efforts, since the early 1900s, the U.S. federal and local governments have developed and implemented a variety of community-level wildfire protection plans. In the early stages, these policies were intended to reduce the consequences of wildfire by suppressing fires in an efficient and timely manner (Yin 2018). Wildfire policies have since evolved, and community-level efforts have placed more emphasis on reducing the likelihood of wildfire by removing fuel accumulation in high-risk areas (Yin 2018). For example, the Butte County Fire Prevention Program recently added multiple risk management activities such as pre-fire strategies and tactics, vegetation management (i.e., clearing fuels around communities and along roadways and evacuation routes), and fire break zones (Butte County 2021). The federal and local governments also enforce compliance with defensible space laws and regulations and home hardening to reduce property-level risk. To increase wildfire awareness and educate homeowners about wildfire risk reduction actions and evacuation preparedness, educational workshops and brochures are also provided as part of community-level efforts (Haines et al. 2004). Such additional components have been added because there has been an increasing awareness that, unlike other types of natural hazards, the probability of ignition, the rate of fire propagation, and the consequences of wildfire (all of which constitute wildfire risk) can be reduced by human efforts. Community Wildfire Protection Plans (CWPPs) are tailored to specifically address a community's unique conditions and risks related to wildfire (USFA, 2020) and have helped nearly 4,800 communities in the U.S. WUI in identifying their priorities for the protection of life, property, and critical infrastructure (Communities Committee 2004; Jakes and Sturtevant 2013).

In addition to community-level wildfire risk management actions, individual homeowner proactive actions are also vitally important for enhancing community resilience. As described in Figure 1, there are two types of proactive actions that homeowners can take prior to a wildfire event: individual-level risk reduction actions and homeowners insurance.

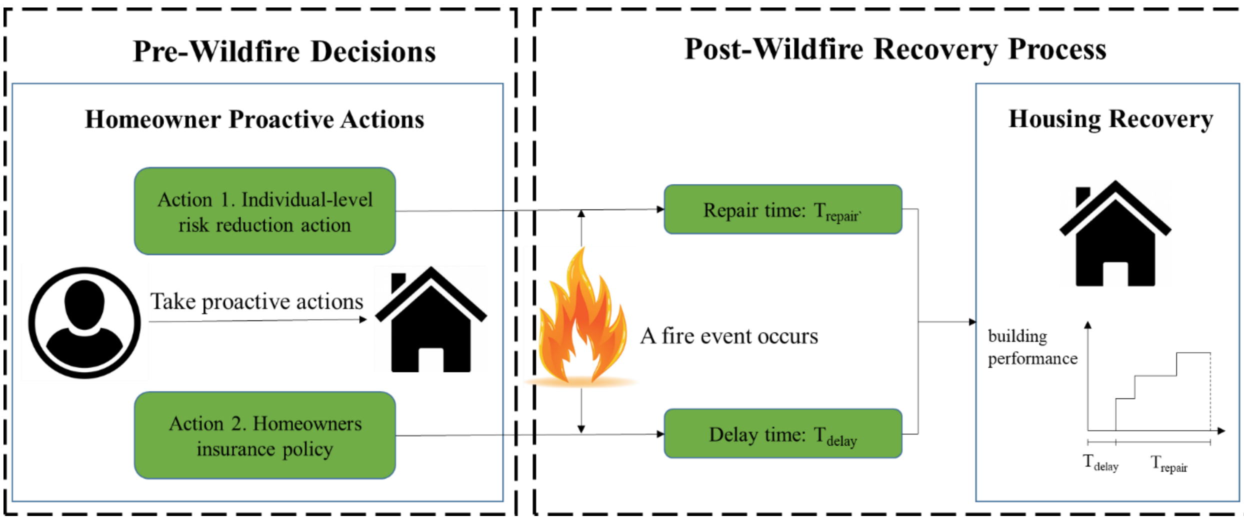


Figure 2.1 Role of homeowner proactive actions in the post-wildfire housing recovery process

2.1.1 Proactive action 1: individual-level risk reduction actions

In response to wildfire incidents, individual responsibility plays an important role in reducing the likelihood of ignition and combustion of an individual house and removing potential ignition sources around the house. It has been demonstrated that structure-level wildfire risk can be significantly decreased by reducing its ignition vulnerability to firebrands and flames (i.e., home hardening) and creating defensible spaces surrounding a house (Communities Committee 2004; Syphard et al. 2014). Home hardening involves the use of non-combustible or ignition-resistant siding and trim, installing Class A fire-resistant roof assembly, and installing dual pane windows and/or fire sprinklers, all of which decrease the likelihood of ignition and combustion of an individual house. Designing and maintaining defensible space is also important given that the presence of flame and firebrand ignitions within 131' (or 40 m) of a structure would highly increase the chance of home ignition (Alexandre et al. 2016). Defensible space creates the buffer between a house and surrounding vegetation to slow the spread of wildfire and protect the house from fire. For example, the U.S. National Fire Protection Association (NFPA) defines three home ignition zones based on the distance from the exterior point of a house (NFPA 2021): immediate zone, intermediate zone, and extended zone, which are the areas of 0–5′, 5–30′, and 30′–100′ from the furthest attached exterior of the house, respectively. The NFPA suggests various risk reduction actions that should be taken for each zone ranging from removing flammable material to vegetation treatment (e.g., thinning tree canopies, spacing trees). The abovementioned individual-level risk reduction actions not only protect a house from wildfire but also affect the vulnerability of neighboring houses. Evans et al. (2015) found that such individual-level efforts can reduce the average home hazard by 20%.

The extent of structural damage induced by wildfire depends on various factors that include property-level parameters and landscape factors such as vegetation management, fuel characteristics, and topography. To gain knowledge about the relationship between wildfire risk mitigation actions and the associated structural damages, several studies (Moore 1981; Radtke 1983; Syphard et al. 2012, 2017; Penman et al. 2014; Alexandre et al. 2016) have recently investigated the effects of individual-level risk reduction actions on building damage and its survival rate. As most of them have utilized computer-based simulation or laboratory experiments, until recently, existing wildfire risk mitigation actions have been driven by limited empirical studies that are based on restrictive assumptions on fire behavior, thus resulting in highly theoretical "best practices" (Syphard and Keeley 2019). Without having the actual damage and response dataset, it is nearly impossible to predict the best proactive plan. Hence, post-wildfire surveys and field studies are necessary to collect observations and validate simulation and/or laboratory results. While several researchers have attempted to conduct post-wildfire field surveys on schools and hospitals (Schulze et al. 2020), channel environment (Benda et al. 2003), etc., few studies have collected post-wildfire structural damage sustained by houses.

Extensive studies have been conducted to examine factors that influence wildfire mitigation actions taken by homeowners (e.g., McGee and Russell 2003; Schulte and Miller 2010; McFarlane et al. 2011; Ghasemi et al. 2020; Faulkner et al. 2009). Common factors identified as the key variables affecting homeowner mitigation decisions include property type and value, financial availability, mortgage situation, risk perception and attitude, previous experience with wildfire and other natural hazards, etc. For example, there is considerable evidence that people who have experienced natural disasters are more inclined toward taking risk mitigation actions (Peacock 2003; Ge et al. 2011; Lindell and Perry 2012). McGee and Russell (2003) suggested that several attributes of homeowners, including previous experiences with wildfires, involvement in agriculture and with the local fire brigade, and their social network, contributed to mitigation behavior, while wildfire preparedness within the community was affected by "a culture of self-reliance, experience with fires as part of farming, and social cohesion." The attributes of mitigation measures (such as costs and perceived efficacy) also play a key role in homeowner decisions (Winter and Fried 2000; McCaffrey 2008; Collins 2009). In addition to the characteristics of homeowners, communities, and mitigation measures, the spillover effect (normally termed as neighbor decisions) is also identified as one of the main factors affecting mitigation decisions given that wildfire risk is interdependent (Shafran 2008, 2010; Butry and Donovan 2008; Taylor 2019; Dickinson et al. 2020; Warziniack et al. 2019). If a structure ignites and burns due to flame or firebrand, the burning structure could become a new source of firebrand generation and threaten adjacent structures (Suzuki et al. 2014). Thus, one's mitigation behavior affects the risk levels of the neighboring environment and vice versa. For example, unmitigated properties or public lands adjacent to the property would reduce the willingness of owners to take mitigation actions, as they believe the efficacy of their own mitigation actions would be low (Brenkert-Smith et al. 2006, 2012). Inversely, mitigation actions taken by neighbors can cause the free-rider problem (NFPA 2020) also highlighted the importance of collaborative actions between neighbors to reduce their shared risk. As such, homeowner mitigation decisions have been well studied in the past two decades. However, many of them have focused on a single type of mitigation action and have not related these actions to housing damage and recovery, which is necessary for assessing their roles in community resilience.

2.1.2 Proactive action 2: homeowners insurance

Homeowners insurance, which covers damages to structures and personal belongings induced by wildfire and smoke, is another important proactive action that homeowners can take in case their properties are damaged by residual wildfire risks (Lee and Li 2021; J. Zhao et al. 2020a). It helps policyholders in alleviating excessive financial burdens from repair/ reconstruction costs following a high-consequence wildfire event by transferring risks to a third party and over time (Pelling 2003). With sufficient insurance coverage, homeowners may receive reliable and timely claim payments that enable the expedited recovery processes of houses, and in turn, the community as a whole. The role of catastrophe risk insurance (e.g., earthquake insurance or flood insurance which is not covered by homeowners insurance and requires a separate endorsement) has been well investigated in several studies (Hazell 2001; Kunreuther and Pauly 2006; Paudel 2012; Charpentier 2014), but most of these studies have taken a qualitative approach to assessing its effect on community resilience. Due in part to the lack of quantitative assessment of catastrophe insurance, the effect of insurance has often been underestimated or neglected in many community resilience planning studies. While a limited number of studies have developed either theoretical or statistical models for the insurance purchase behavior of forest owners and/or homeowners through experimental economics and survey (McKee et al. 2004; Gan et al. 2014), most of these studies have considered only binary variables in their model (i.e., purchase insurance or not). However, given that homeowners with a mortgage (i.e., over 70% of the U.S. population) are required to purchase homeowners insurance, insurance coverage limits play a more significant role in housing recovery than insured status does. In many cases, uninsured and underinsured homeowners are low- (and middle-) income residents who are identified as economic and socially vulnerable groups in society (Eriksen and de Vet 2020; Priest et al. 2005; Mockrin et al. 2015), and therefore their post-disaster financial availabilities may greatly affect community resilience. Moreover, few studies have attempted to relate homeowner purchasing behavior to their financial availability following a hazard event (J. Zhao et al. 2020a).

To address the significant research gaps identified above, this paper examines potential factors that may affect homeowner proactive actions for managing wildfire risks and the role of such actions in the housing recovery. To achieve the goal, a post-wildfire online survey of homeowners was conducted in multiple counties at high to extreme risk of wildfire in California and Washington. Based on the online survey results, we identified the key factors that contributed most to homeowner decisions about each proactive action and estimated a set of logistic regression models in order to relate the characteristics of houses and homeowners to their willingness to invest in the proactive action. Then, the effect of proactive actions on the housing recovery process was explicitly modeled by assessing (a) the effect of homeowners insurance policy on delay time

(T_{delay}), and (b) the effect of individual-level risk reduction actions on housing repair time (T_{repair}); see Figure 2.1. The rest of this paper is organized as follows. Section 2.2 describes the investigation methods including the online survey data collection method and statistical analyses. In Section 2.3, the results obtained from the data analyses are discussed. Finally, Sect 2.4 presents summary and conclusions.

2.2 Investigation Methods

2.2.1 Research questions

This study is motivated by the following research questions:

1. What factors affect homeowner proactive actions for managing wildfire risks?

2. How do the proactive actions taken prior to a wildfire event affect the housing recovery process following the event?

To answer the research questions, this study uses a quantitative approach to identifying independent variables that are likely to influence homeowner proactive actions for managing wildfire risks and assessing their impacts on the housing recovery processes through an online survey. The quantitative models developed based on the survey data will provide federal/local government with preliminary insights into how to motivate homeowners to take proactive actions and which proactive action could be more effective in expediting the housing recovery process.

2.2.2 Data collection

To collect data used to support quantitative models, we conducted an online survey of homeowners in California and Washington where at least one wildfire event occurred in the past five years. The affected areas were identified by being overlaid with the layer containing wildfire perimeters in the past five years in ArcMap. Participants were recruited in January 2021 by Qualtrics research service, a professional organization that uses prequalified respondents to achieve significant response rates for the purpose of validity. While online convenience sampling was used to recruit participants, these samples collected by Qualtrics panels could be demographically and politically representative, as demonstrated in Boas et al. (2020). The inclusion criteria for participating in this survey were to be homeowners in the study area (Figure 2.2) who were at least 18 years of age and whose houses were damaged by at least one wildfire event (i.e., house experienced at least a minor damage state due to wildfire) in the past five years. Since the survey was designed to assess the effect of pre-wildfire proactive actions on post-wildfire house damage and delay time, homeowners whose houses were not damaged by wildfires were excluded. Figure 2.2 shows the study areas and the number of valid survey responses received from each area.

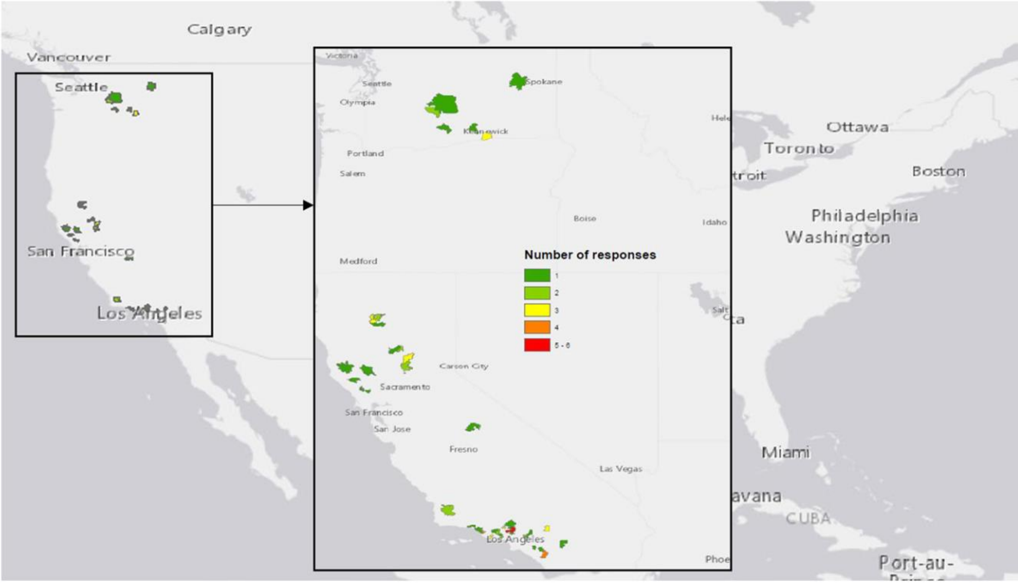


Figure 2.2 Study areas and the number of survey responses received from each area

In the study area, about 30,000 structures (i.e., the estimated total population size) were damaged or destroyed by major wildfires. Based on the approach to determining sample size presented in Krejcie and Morgan (1970), 64 responses were a sufficient sample size to generate a 90% confidence interval and 10% margin of error (MoE), while 95 sample size was required for 95% confidence interval and 10% MoE. We collected 85 responses from the study area and excluded five invalid responses if the answers to the survey questions did not meet the following requirements: (a) one's mortgage balance should be less than or equal to his/her property value; (b) the dwelling coverage limit should be less than or equal to his/her property value; and (c) given the dwelling and content coverage limits, the insurance premium and deductible should be within a reasonable range. After the exclusion, total 80 valid responses (71 responses from California and 9 responses from Washington) generated a 93% confidence interval and 10% MoE. Although 10% MoE may be considered large, there was a barrier to increasing the sample size because (a) only homeowners who experienced at least minor wildfire damage to their houses in the past five years could participate in this survey, and (b) convenience sampling was used.

To enable participants to clearly understand the four possible damage states (i.e., none, minor damage, major damage, and destroyed) sustained by a house due to wildfire, a detailed information page describing the damage states was provided at the beginning of the survey. The page presented the images of a house experiencing each damage state along with a detailed description as illustrated in Table 2.1. The online survey consisted of a set of closed-ended quantitative and qualitative questionnaires, including demographic information; property type and value; risk perception/attitude; previous experience with wildfire and other types of natural hazards; homeowners insurance policy; homeowner financial availability, mortgage situation; proactive actions taken at the time of the most recent wildfire event; and time to initiate and complete the recovery of their houses. Moreover, participants were encouraged to have their homeowners insurance policy documents (the policies they held at the time when their properties were damaged by the most recent wildfire) at hand so that they could answer the questions related to their insurance policies, such as dwelling/content coverage limit and deductible, additional living expenses (ALE) coverage limit, and annual insurance premium. All study protocols were approved by the Washington State University Institutional Review Board before the study commenced (IRB #18084).

Table 2.1 Damage state description (Butte County GIS 2021)

None	Minor	Extensive	Collapse
	 	 	 
Surrounding vegetation burnt; no-damage to structure	Nonstructural damage; minor structural damage	Extensive damage to structure; partially collapsed	Complete destruction

2.2.3 Statistical analysis

The data were analyzed in two steps. First, to investigate the first research question, we assessed the effects of independent variables on homeowner decisions about two different types of proactive actions and identified the key variables that should be included in the logistic regression models. Then, to address the second research question, we constructed the quantitative relationship between homeowner proactive actions and the delay and repair times of a damaged house and examined their impact on the housing recovery process.

2.2.3.1 Regression models for proactive actions

To identify key variables affecting each type of proactive action (i.e., individual-level risk reduction actions and homeowners insurance), we performed a logistic regression analysis for each action based on the survey data. The independent variables considered at the initial step of estimating the regression models were the variables describing the characteristics of house/property and homeowners and are summarized in Table 2.2 and Appendix A. We first coded all these independent variables as dummy variables to analyze qualitative data such as categorical representation (e.g., house damage state, demographic information). As a homeowner had decided whether or not to take a certain type of proactive action before his/her property was damaged by the most recent wildfire, a decision variable can take only two values, 1 (take action) or 0 (do not take action), which are mutually exclusive and collectively exhaustive. Thus, the probability (p) that an individual homeowner had taken a certain type of proactive action is expressed by the following logistic regression equation:

$$p = \frac{e^{\boldsymbol{\beta X}}}{1+e^{\boldsymbol{\beta X}}} \tag{2.1}$$

in which $\boldsymbol{\beta}$ = the vector of coefficients for independent variables; and X = the vector of independent variables. Higher p indicates a higher probability that a homeowner had taken the proactive action. The regression model for each proactive action was estimated using a backward stepwise regression approach. It began with all the independent variables and at each step gradually eliminated the least significant variables from the regression model until only statistically significant variables were left in the model. At each step, the Wald Chi-Square Test was used to select the variable that should be eliminated: the variable with a p value greater than a 5% level of significance was eliminated. This process was repeated until all the remaining variables did not meet the specified level for elimination. The final model obtained from this approach was compared with the models with more independent variables (obtained from the previous steps) and was found to be the optimal one based on the Akaike Information Criterion (AIC) and/or Bayesian Information Criterion (BIC).

First, logistic regression models were estimated for two types of individual-level risk reduction actions (i.e., home hardening and defensible space), respectively. The survey asked participants to indicate the types of individual-level risk reduction actions they took before their properties were damaged by the most recent wildfire and then classified them into two categories: home hardening (e.g., use of non-combustible or ignition-resistant siding and trim, installation of Class A fire-resistant roof assembly, installation of multi-pane windows or ideally tempered glass, installation of fire sprinklers) and defensible space (e.g., design and maintenance of the immediate, intermediate and/or extended zones). Hence, the dependent variables for the regression models were whether or not home hardening or defensible space was adopted at the time of the most recent wildfire.

A logistic regression model for homeowners insurance was also estimated, where the dependent variable was binary: a homeowner purchased or did not purchase homeowners insurance at the time when his/her property was affected by the most recent wildfire. However, as explained in Sect. 2.1, a binary logistic regression model for insurance purchase could be meaningful only if homeowners can fully decide whether to buy insurance based on their preference. However, about 70% of U.S. households have a mortgage, and lenders require homeowners with a mortgage to insure houses to protect their investment. Consequently, these homeowners do not have much room to decide whether or not to purchase homeowners insurance.

However, they may have more freedom to choose insurance coverage (although some lenders still have minimum requirements for dwelling coverage). Moreover, insurance coverage plays a critical role in estimating the financial availability of homeowners following a wildfire event. If a house is not fully insured, homeowners still experience financial hardship and tend to delay house recovery until they obtain financing. In light of this, in addition to the binary logistic regression model for insurance purchase, homeowner decisions about insurance policy were also investigated. Homeowners insurance policy includes four types of coverage: dwelling, personal property, additional living expenses (ALE), and liability protection. The survey did not include any questions pertinent to liability protection because the study focused on structural damage to the house, attached structure, and personal property, and the associated economic losses. Dwelling coverage is the main component of homeowners insurance policy, and the other two coverages are often determined by the percentages of the selected dwelling coverage, such as 50% to 70% of dwelling coverage for personal property and 20% of dwelling coverage for ALE. Thus, a linear regression model for dwelling coverage limit (the dependent variable) was estimated. The ordinary least squares approach was used to estimate unknown coefficients, and then a stepwise backward approach with t-tests was used to eliminate insignificant independent variables.

2.2.3.2 Quantitative relationship between proactive actions and housing recovery

To quantitatively assess the impacts of individual-level wildfire risk reduction actions and homeowners insurance on the housing recovery processes, we examined the relationship between proactive actions and variables related to house damage and recovery. First, we investigated how homeowner risk reduction actions taken prior to a wildfire event affected post-wildfire damage states. Four different groups of homeowners were considered as independent variables:

homeowners without any risk reduction actions, with home hardening only, with defensible space only, and with both actions. The frequency distributions of house damage state (minor damage, major damage, and destroyed) for each group were constructed. In this study, the houses that had been already hardened before homeowners bought them were not considered because many homeowners were not likely to be aware of structural hardening adopted before they moved in.

We also assessed the effect of insurance on housing recovery by considering homeowner repairing decisions, post-wildfire financial availability, and delay time as dependent variables. The participants were divided into three groups, including Group A (homeowners with full dwelling coverage), Group B (underinsured homeowners), and Group C (uninsured homeowners). Then, for these three groups, homeowner repairing decisions given a housing damage state were compared. Moreover, several questions about homeowner post-wildfire financial situation were asked during the survey, including homeowner out-of-pocket expenses and financial hardship they experienced due to a wildfire event, and the most helpful financial source for them to recover from wildfire-induced damage. The relationships between independent variables (three groups of homeowners) and dependent variables were constructed. Lastly, in this study, delay time was defined as the time between wildfire containment and the initiation of the house repair/reconstruction process. It can be induced by many different impeding factors, such as post-disaster inspection; engineering mobilization and review/redesign; financing; contractor mobilization and bid process; and permitting (Lee et al., 2019; Zhao et al., 2020). Specifically, financing delay was calculated as the sum of the time required for homeowners to secure funding sources and the time due to delayed payments associated with insurance, loan, or government assistance. To estimate the total delay time, the survey question also asked participants about the time taken to initiate their structural (house) repair/reconstruction process since the wildfire in the community had been contained. Then, we examined how delay time was impacted by the insurance coverage limit.

2.3 Results and Discussions

The demographic characteristics of the sample are presented in Table 2.2. Sixty percent of the participants were male, and 40% of them were female. The age group between 30 and 39 years old comprised the highest proportion in the sample, and 68.75% of the respondents were Caucasian. The majority of the respondents (60%) attended college. At the time when their properties were damaged by the most recent wildfire, 72.5% of the respondents were employed, and 43.75% of the respondents reported an annual household income before taxes of $25,000 to $99,999, followed by $100,000 to $149,999 (22.5%) and less than $24,999 (17.5%). Census demographic data (in percentage) are also summarized in Table 2.2. The sample mean of each demographic characteristic was compared with its population mean through a hypothesis testing approach to demonstrate if the collected sample could represent the population well. The p values are summarized in Table 2.2. For most of the demographic characteristics, the null hypothesis that there was no significant difference between the population mean and sample mean was accepted, which implies the representativeness of the collected sample. However, at the 5% significance level, the null hypothesis was rejected for age and educational background.

Table 2.2 Demographic characteristics and census data

Characteristics	Classes	Sample percentage	Census percentage	p_value
Gender	Male	60%	49.5%	0.0604
	Female	40%	50.5%	0.0604
Age (years)	18 – 29	22.50%	19.3%	0.4978
	30 – 39***	41.25%	17.4%	<0.0001
	40 – 49	21.25%	19.8%	0.7536
	50 – older***	15.00%	43.4%	<0.0001
Education	Less than high school degree***	5%	17.7%	<0.0001

	High school degree or equivalent***	35%	48.2%	<0.0001
	Associate degree***	11.25%	8.3%	0.0005
	Bachelor's degree	33.75%	16.6%	0.1363
	Master's degree***	13.75%	6.1%	<0.0001
	Professional degree***	0%	1.9%	<0.0001
	PhD degree**	1.25%	1%	0.0015
Employment	Employed, working 1 – 39 hours per week	31.25%	26.7%	0.3856
	Employed, working 40 or more hours per week	41.25%	36.2%	0.3647
	Not employed or retired	27.5%	37.1%	0.0596
Ethnicity	Caucasian	68.75%	72.3%	0.4980
	Asian	6.25%	6.28%	0.9912
	African American	6.75%	2.95%	0.2292
	Native American/Hawaiian/Pacific Islander*	8.75%	1.68%	0.0290
	Others*	9.5%	16.8%	0.0473
Annual household income before taxes	Less than $24,999	17.5%	20.5%	0.4849
	$25,000 to $99,999	43.75%	52.5%	0.1209
	$100,000 to $149,999	22.5%	15.0%	0.1144
	$150,000 to $199,999	7.5%	6.3%	0.6866
	Over $200,000	8.75%	5.7%	0.3403

*p<0.05; **p<0.01; ***p<0.001

2.3.1 Key factors affecting homeowner proactive actions

This subsection identifies independent variables that are likely to influence homeowner proactive actions for managing wildfire risks to answer the first question specified in Sect. 2.1.

2.3.1.1 Individual-level risk reduction actions

Based on the survey results, 65% of the respondents adopted home hardening, while 58.75% of the respondents adopted defensible space. As shown in Table 2.3, the key independent variables that affected decisions to adopt home hardening were homeowner age, household income, total wealth, and willingness to invest in individual-level wildfire risk mitigation actions. It should be noted that some of these actions (e.g., siding, asphalt roof shingles, dual pane windows) could have been taken for aesthetic purposes or simply to replace worn items. However, given that homeowner willingness to invest in wildfire risk mitigation actions was identified as one of the most statistically significant factors, the results imply that many homeowners took such actions to harden homes. There was no significant evidence to claim that age was correlated with other key independent variables (i.e., their willingness to invest in risk mitigation actions, household income, and total wealth). Homeowner decisions about home hardening obtained from the survey were plotted against the simulated ones from the regression model in Figure 2.3. It showed 80% accuracy in estimating decision variables. The logistic regression results for defensible space are summarized in Table 2.4. Satisfaction with the surrounding environment (e.g., scenic beauty, proximity to recreation, privacy) was identified as the only variable that significantly affected homeowner decisions to design and maintain defensible space surrounding their homes. Seventy percent of the simulated results from the regression model for defensible space matched the survey results. As presented in Table 2.4, the variables describing the characteristics of homeowners and houses did not have any statistically significant impacts on homeowner decisions about defensible space. It can be interpreted that, in this survey, homeowners perceived defensible space as a proactive action to mitigate wildfire risks to the surrounding environment rather than a house itself, whereas home hardening was adopted to protect their houses from wildfires. We also performed a regression analysis for homeowners who adopted both types of wildfire risk mitigation actions and summarize the results in Table 2.5. While the level of their confidence in the structural resistance of the houses against wildfire had a negative impact on their decisions, prior experience with natural hazards encouraged them to take both actions. Moreover, people who purchased homeowner insurance showed higher probability of adopting both risk mitigation actions. This result is consistent with other studies (e.g., Meldrum et al. 2019) revealing that risk reduction decisions and insurance decisions could be jointly determined.

Additionally, we performed a hypothesis test to see if a wildfire-related policy could be one of the key independent variables affecting homeowner proactive action. Considering that only California requires homeowners living in the State Responsibility Area (SRA) to create a 100 ft defensible space, we set up the null hypothesis that there was no significant difference in the ratios of homeowners creating defensible space between California and Washington (which does not have such policy). The null hypothesis was accepted, which indicated that the requirement for defensible space in SRA did not affect the ratio of homeowners creating defensible space significantly. Given that only 9 responses were collected from Washington, however, this result cannot be generalized to the entire population or other types of wildfire-related policies.

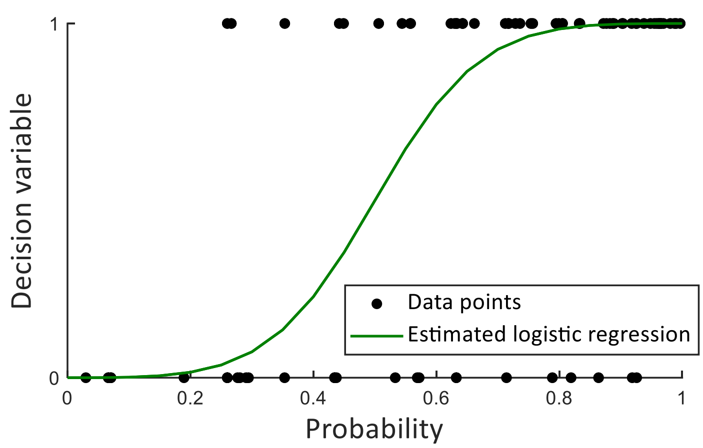


Figure 2.3 Comparison of homeowner decisions about home hardening between simulated and survey results

Table 2.3 Logistic regression results of homeowner decisions about home hardening (95% confidence interval)

Variable	Estimated coefficient	Wald chi-square	p-value
Intercept	0.5270	0.6111	0.5412
Age	-0.7946	-2.8978	0.0038
Homeowner willingness to invest in individual-level wildfire risk mitigation actions	0.7825	3.0941	0.0020
Household income	-0.4100	-2.1754	0.0296
Homeowner total wealth	0.4382	2.5510	0.0107

Table 2.4 Logistic regression results of homeowner decisions about defensible space (95% confidence interval)

Variable	Estimated coefficient	Wald chi-square	p-value
Intercept	-1.2465	-1.9622	0.0497
Satisfaction with surrounding environment	0.5221	2.6573	0.0079

Table 2.5 Logistic regression results of homeowner decisions about both actions (95% confidence interval)

Variable	Estimated coefficient	Wald chi-square	p-value
Intercept	-1.8668	-1.2222	0.2216
Confidence in house resistance against wildfire	-0.7371	-2.2582	0.0239
Prior experience with natural hazards	1.9349	2.2212	0.0270
Insurance purchase	2.5730	2.3372	0.0194

2.3.1.2 Homeowners insurance

The survey data indicated that 80% of the respondents had homeowners insurance in place at the time of the wildfire. As presented in Table 2.6, the homeowner mortgage balance and neighbor proactive actions were identified to have statistically significant impacts on homeowner decisions about insurance purchases. Considering that homeowners with a mortgage were required to purchase homeowners insurance, the finding that a positive mortgage balance was the most significant factor in this regression model was well-supported. In addition, we also examined the independent variables that might affect homeowner decisions about insurance policy (more specifically dwelling coverage limit) through linear regression analyses. The results are summarized in Table 2.7. As expected, property value had the greatest impact on homeowner decisions about dwelling coverage limits. Interestingly, the other two independent variables (i.e., age and household income) in the regression model were also the key variables that were likely to affect homeowner decisions about home hardening (see Table 2.3). Given that the binary regression model for insurance purchase does not reflect homeowner preference appropriately, homeowner age and household income can be considered the two most statistically significant factors affecting homeowner decisions to take proactive actions.

Table 2.6 Logistic regression results of homeowner decisions to purchase homeowners insurance (95% confidence interval)

Variable	Estimated coefficient	Wald chi-square	p-value
Intercept	-1.0227	-1.5580	0.1192
Homeowner mortgage balance	0.8715	2.5757	0.0100
Neighbor proactive actions	1.4021	2.1651	0.0304

Table 2.7 Linear regression results of homeowner decisions about dwelling coverage limit (95% confidence interval)

Variable	Estimated coefficient	t	p-value
Intercept	-0.8940	-1.543	0.128
Age	0.4260	2.519	0.014
Property Value	0.5231	5.558	<0.001
Household income	0.2421	2.626	0.011

2.3.2 Effect of proactive actions on postfire housing recovery

This subsection quantitatively assesses the impacts of pre-wildfire proactive actions on the housing recovery processes to answer the second question specified in Sect. 2.1.

2.3.2.1 Individual-level risk reduction actions

We assessed the effect of individual-level wildfire risk reduction actions on house damage state. Only 12.5% of the respondents did not take any pre-wildfire risk reduction actions (i.e., either home hardening or defensible space) at the time when their houses were affected by the most recent wildfire. As shown in Table 2.8, 60% of the homeowners without any risk reduction actions experienced minor structural damage to their houses, while 40% of their houses were destroyed by a fire. The vast majority (87.5%) of the respondents adopted at least one individual-level wildfire risk reduction action. To determine whether there was a statistical relationship between mitigation action and structure damage state, the null and alternative hypotheses were defined as follows:

$\boldsymbol{H_0}$**:** There is no relationship between mitigation action and structural damage state.

$\boldsymbol{H_a}$**:** There is a relationship between mitigation action and structural damage state.

Table 2.8 Frequency distributions of house damage states: with and without individual-level wildfire risk reduction actions

Mitigation actions	Minor damage (%)	Major damage (%)	Destroyed (%)
Without mitigation (12.5%)	60	0	40
Defensible space only (22.5%)	56	11	33
House hardening only (28.75%)	65	22	13
With both mitigation (36.25%)	67	10	21

The chi-square statistic was 6.3317, and the p value was not significant (0.3897), indicating that the null hypothesis was not rejected. Given that the chi-square test is very sensitive to sample size, however, it is hard to conclude that there is no relationship between these two variables.

More specifically, homeowners who adopted only fuel treatment in defensible space had similar house damage state distribution as those who did not adopt any mitigation actions. Minor structural damage comprised the highest proportion (56%), followed by destroyed (33%) and major damage (11%). Based on the results, it was not clear if designing and maintaining defensible space was effective in reducing wildfire damage to a house. It might be because defensible space reduces the chance of firebrand ignitions in the surrounding environment rather than mitigating wildfire consequences if a home has already ignited. Since homeowners who did not experience home ignition were screened out at the beginning of the survey, the reduced chance of ignition (i.e., the efficacy of defensible space) was not captured in the survey results. The result was also consistent with our interpretation that defensible space was perceived by homeowners as a proactive action to mitigate wildfire risks to the surrounding environment rather than reducing post-wildfire house damage (see Sect. 2.3.1.1). On the other hand, homeowners who adopted only home hardening or both types of mitigation actions were less likely to experience a destroyed damage state (i.e., 13% and 21%, respectively) compared to those who adopted only defensible space or none of these actions. Hence, it can be inferred from the results that home hardening could be a more effective action to reduce wildfire damage to a house.

2.3.2.2 Homeowners insurance

First, we examined the effect of insurance on homeowner repairing decisions. Among the three groups, Group B (underinsured homeowners) comprised the highest proportion of the participants, followed by Group A (homeowners with full dwelling coverage) and Group C (uninsured homeowners). Table 2.9 summarizes the repairing decisions of these three groups. While the damage state distributions of the three groups were similar, Group C homeowners were much less likely to repair their houses, especially when the houses were completely destroyed. It should be noted that it would be possible that Group C homeowners were more likely to be seasonal or second homeowners and were not willing to rebuild their homes that were not their primary residences. However, the result generally suggested that insurance could ensure homeowners to be financially secure following a wildfire event and help them repair their houses. Hence, it can be expected that a community with a higher insurance take-up rate (and more homeowners having full coverage) would have a higher rate of housing repair after a wildfire event.

Table 2.9 Comparison of repairing decisions between three groups

Group	Damage state	Repair (%)	No repair (%)

Group A (28.75%)	Minor damage (65.2%)	80	20
	Major damage (26%)	100	0
	Destroyed (8.7%)	100	0
Group B (51.25%)	Minor damage (68.2%)	86	14
	Major damage (9.8%)	100	0
	Destroyed (22%)	56	44
Group C (20%)	Minor damage (60%)	63	38
	Destroyed (40%)	0	100

Group A: Fully-insured homeowners; Group B: underinsured homeowners; Group C: uninsured homeowners

We also assessed the effect of homeowners insurance on the financial availability of homeowners following a wildfire event because their post-wildfire financial situation determines the financing delay time of the housing recovery process as well as repairing decisions. First, we estimated homeowner out-of-pocket expenses by measuring the difference between their estimated total wealth (including housing equity, vehicles, retirement, life insurance, fixed-income investment, managed assets, common stock and mutual fund shares, liquid assets, farms, business equity in other real estates, and net worth) prior to and following a wildfire event. The out-of-pocket expenses of the three groups were compared in Figure 2.4a. As expected, Group A experienced the least out-of-pocket expenses ($23,913), which indicated that full dwelling coverage reduced the financial burden of Group A homeowners following a wildfire event. However, contrary to our expectation, the mean value of the out-of-pocket expenses of Group B ($125,000) was much higher than the mean value of Group C ($35,938). It may be because most of the homeowners in Group C decided not to repair their damaged houses due to lack of financial availability as shown in Table 2.9, and thus their out-of-pocket expenses could not necessarily reflect repair/reconstruction costs. On the other hand, higher portion of the homeowners in Group B decided to repair their houses because they received payment from insurance companies. They still had to pay deductibles and the remaining repair/reconstruction costs that were not covered by homeowners insurance, which induced higher out-of-pocket expenses. Therefore, it would not be wise to conclude that homeowners insurance was not effective in reducing the financial burden of underinsured homeowners.

The effectiveness of homeowners insurance in post-wildfire financial situation was further supported by the survey results. Fifty percent of Groups A and B homeowners (who had either full or partial insurance coverage) indicated that insurance was the most helpful financial source for them to recover from the wildfire event, followed by loans (23.43%), government assistance (18.75%), and other sources (7.82%), while 62.5% of Group C homeowners reported government assistance as the most helpful financial source. Participants were also asked to answer a question about the type of financial hardship they experienced due to wildfire damage (e.g., mortgage default, mortgage forbearance, selling their properties, and huge loan or debt). As shown in Figure 2.4b, only 25% of Group C homeowners responded that they did not experience any financial hardship after experiencing wildfire, while homeowners who did not report any financial hardship in Groups A and B were 43.5% and 31.7%, respectively. Moreover, Groups A and B homeowners answered that, on average, 75.38% of repair/reconstruction costs were covered by insurance. All these results supported the effectiveness of homeowners insurance in reducing post-wildfire homeowner financial burden.

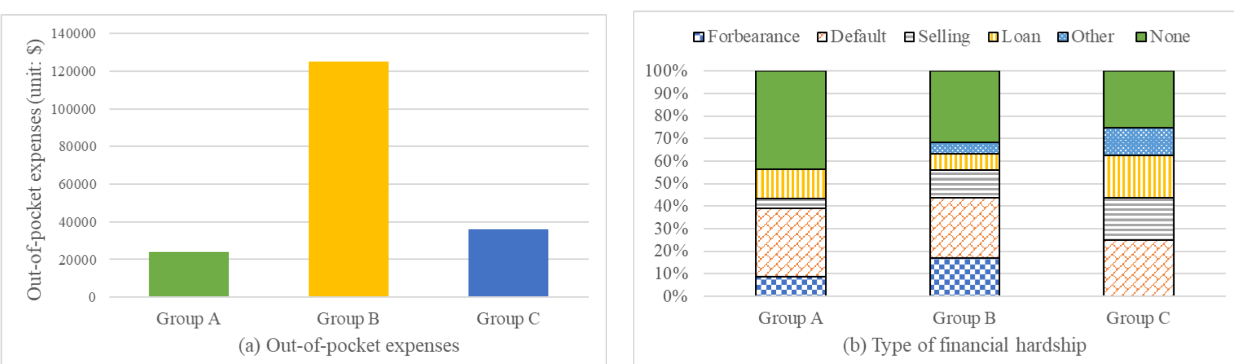


Figure 2.4 Comparison of financial situation between three groups

Moreover, the effect of homeowners insurance on delay time (Tdelay) was examined. The mean values of the delay time of Group A (8.1 months) and Group B (8.9 months) were longer than the mean value of Group C (6.8 months), which was contrary to our common belief. Since delay time was not only induced by lack of financing but also induced by other impeding factors and only a limited number of Group C homeowners repaired their damaged properties, this result might not be able to capture the effect of homeowners insurance on the delay time. In this regard, we further quantified the effect of different types of financial sources on financing delay time (which was defined as the time between claim application and payment). However, government financial aid showed a shorter delay time (3.05 months), followed by homeowners insurance (3.21 months) and loans (3.23 months). In conclusion, the findings of this study indicated that homeowners insurance did not reduce financing delay, while it encouraged homeowners to repair their damaged houses by relieving the financial burden from repair/reconstruction costs.

2.4 Summary, limitations, and conclusions

This study conducted a post-wildfire online survey and statistical analyses of homeowners living in multiple counties at high to extreme risk of wildfire in California and Washington to understand homeowner decisions on wildfire-related proactive actions and the effect of such actions on the housing recovery. The online survey was targeted at homeowners in these counties whose properties were damaged by wildfires in the past five years. The survey results revealed that homeowner age and household income were the common key independent variables affecting homeowner decisions about both home hardening and homeowners insurance, while the only key independent variable in the regression model for defensible space was satisfaction with the surrounding environment. Although the survey results indicated that home hardening was found to be more effective in reducing wildfire damage to a house than defensible space did, it would not be wise to generalize this conclusion due to the limited sample size. Moreover, the results clearly implied that the effect of homeowner insurance on post-wildfire financial availability was significant, and homeowners with higher coverage limits were more likely to repair their damaged properties. However, contrary to our initial expectation that homeowners with full coverage might receive expedited claim payments that could speed up the housing recovery processes, its effect on reduced financing delay was not supported by the findings. The results from this study can provide guidance to federal/local government on (a) how to motivate homeowners to adopt proactive actions by identifying the key factors affecting homeowner decisions (i.e., the answer to the first research question in Sect. 2.2.1), and (b) how to effectively enhance community resilience by understanding the effect of proactive actions on housing recovery process (i.e., the answer to the second research question).

There are some limitations and room for improvement in this study that could be addressed in future research. First, to generalize the results, the sample size needs to be increased, and the collected sample should be able to represent the general population. Considering that the conclusions were drawn from the homeowners whose houses sustained at least minor wildfire damage, the results and conclusions of this study cannot be applied to the houses that survived a wildfire without any damage. It should be noted that the comparison between the samples that reported wildfire-induced structural damage and the samples that did not report any wildfire-induced damage could provide further insight into the effect of pre-wildfire proactive actions on house survivability. Second, this study assumed that the survey respondent was representative of his or her household or primary decision-maker and used the individual-level variables (e.g., age, gender, education, employment) to predict household-level proactive mitigation actions—home hardening, defensible space, and homeowners insurance—in the logistic regression models. Given that this assumption may introduce bias due to representative issues (Hung and Wang 2022; Seebauer et al. 2017), future studies should address this issue by restricting the predictors to household-level variables or by conducting an in-depth interview with all members of a household. Third, post-wildfire reconnaissance surveys can be conducted to better quantify the effects of individual-level risk reduction actions on structural damage to houses, and in turn, the repair time of houses. These results will greatly complement the results obtained from the online survey because the impact of defensible space on wildfire risks to houses was not clearly quantified in this study. Moreover, based on our content validity, some respondents seemed to have difficulty quantifying their total wealth, property values, expenditures, economic losses, among others. Therefore, in-depth individual interviews with homeowners will also be helpful to provide sufficient information and guidance on such quantification processes to interviewees.

CHAPTER THREE: UNDERSTANDING EVACUATION BEHAVIOR DURING WILDFIRES: EXPLORING KEY FACTORS AFFECTING EVACUEE BEHAVIORS AND DEVELOPING PREDICTIVE MODELS FOR DECISION-MAKING

3.1 Background

In recent decades, wildfires have posed an increasingly serious threat to human lives and properties. While proactive actions can be taken to manage wildfire risk, residual risks always exist due to substantial uncertainties. A comprehensive understanding of the underlying factors that influence individual evacuation preferences and behaviors can help authorities make more effective emergency plans and reduce human losses in future wildfire events. The utilization of quantitative models that leverage empirical data to analyze wildfire behaviors and decision-making is particularly important in the development of effective emergency strategies for responding to wildfires. Quantitative models offer valuable insights into the triggers that prompt individuals to initiate evacuations and the various factors that shape evacuees' decisions concerning evacuation timing, destination selection, and the utilization of GPS navigation systems. By integrating these quantitative models into traffic and evacuation simulation, authorities can develop more effective evacuation plans and strategies that take into account the complex and dynamic nature of human behavior during emergencies. These models can also be used to identify potential bottlenecks and congestion points in evacuation routes, allowing them to make informed decisions about traffic flow management and evacuation routes. While important and promising, quantitative models for wildfire evacuation behavior still lack extensive investigation.

This chapter investigates the factors that influence evacuee preferences and behaviors during wildfires and develops quantitative predictive models to understand their decision-making processes during an evacuation. The study begins with a comprehensive literature review of wildfire evacuation behavior and the existing quantitative models in this domain. Following that, we describe the data collection methodology, which involved a stated preference survey targeting residents with physical addresses in California, Oregon, and Colorado. The statistical models are then used to identify the key factors affecting evacuee behaviors and decisions, focusing on evacuation timing, destination selection, and GPS navigation usage. Then, a set of quantitative predictive models for these key factors is constructed using a range of machine learning (ML) approaches. Finally, to showcase the practical applicability of the predictive models, we used these models in simulating evacuations during the Tick Fire, which broke out on October 24th, 2019 near Santa Clarita, California, and compared the simulation results with the actual evacuation situations during this fire. This chapter concludes by summarizing the key findings, addressing the limitations of the study, and providing recommendations for future research in this field.

3.2 Literature Review

3.2.1 Wildfire evacuation behavioral studies: identification of key factors affecting evacuation

Wildfire evacuation is a complex process involving multiple factors that affect evacuee preferences, behaviors, and decisions. A significant number of studies (Christianson et al. 2019, McGee et al. 2019) have attempted to collect qualitative data through focus group discussions and interviews to identify key factors influencing evacuee decisions during a wildfire. For example, Taylor et al. 2005 conducted focus group discussions with residents who had been impacted by wildfires and examined the role of official information in the evacuation decision-making process. Cohn et al. 2006 performed interviews with both residents and public safety officials and highlighted the crucial role of information in an emergency evacuation. In addition, several researchers have studied the impact of social context and preparedness policies on individual evacuation behaviors based on the data collected from either focus group discussions or individual interviews (Cote and McGee 2014, Goodman and Proudley 2008).

In addition to qualitative data, which primarily rely on verbal expressions gathered from focus group discussions or individual interviews, several studies (Koksal et al. 2019, Mozumder et al. 2008, Roberson et al. 2012) have conducted mail and web-based surveys to collect quantitative data on evacuation preferences and behaviors, where most of the responses were coded numerically. McCaffrey et al. 2018 conducted a mail survey of homeowners in the United States, and based on the survey results, they suggested that the perceived efficacy of an action (evacuate or stay to defend), risk attitudes, and different cues to act (e.g., official warnings, physical cues, and social cues) were the key drivers of evacuation decisions in the protective action decision model (PADM). Strahan et al. 2019 and Edgeley and Paveglio 2019 also supported this finding. Although these studies have provided insight into the underlying factors that influence evacuation decisions, they were more likely to focus on the subjective aspects of evacuee characteristics, such as their beliefs, perceptions, and risk attitudes. However, this type of data, typically gathered through surveys or interviews, may not be ideal for use by state or local policymakers. These policymakers generally rely on demographic characteristics of the general public, which are collected through census surveys, and may not have access to the same level of subjective information as the researchers do.

Several researchers have included more objective features in the survey and experimental designs to investigate their role in wildfire evacuation decisions. For example, Toledo et al. 2018 conducted a web survey shortly after a large-scale wildfire event to examine the relationship between individual characteristics and evacuation behaviors. The objective independent variables considered in this study included household size, presence of children, elderly, pets, and car ownership. Similarly, Kuligowski et al. 2022 investigated a suite of objective information characterizing evacuees, while also considering subjective factors such as the pre-event perception of safety and risk. A combination of objective and subjective factors has facilitated a more thorough understanding of evacuation decisions. A systematic review conducted by McLennan et al. 2019 provided a comprehensive overview of both qualitative and quantitative studies on this subject, thereby offering a more complete understanding of the issue.

The literature on wildfire evacuation preferences suggests conflicting evidence regarding the characteristics that significantly impact such preferences. For example, the effect of age on evacuation preferences has been found to be contradictory across different studies (Toledo et al. 2018, Grajdura et al. 2021, Katzilieris et al. 2022, Stasiewicz et al. 2021). Similarly, the impacts of income level (Toledo et al. 2018, Kuligowaski et al. 2022, Walpole et al. 2020), home ownership (Kuligowski et al. 2022, Katzilieris et al. 2022), and the presence of physical cues (McCaffrey et al. 2018, Kuligowski et al. 2022, Walpole et al. 2020) on evacuation preferences have also yielded inconsistent findings across various studies. These contradictory findings highlight the need for more empirical data to better understand individual evacuation behaviors during wildfire events.

3.2.2 Quantitative models for wildfire evacuation behaviors

There is a large body of research on mathematical, statistical, and computational models that use quantitative data to simulate and predict evacuation process during a wildfire. Their primary purpose is to provide decision-makers with a better understanding of the potential outcomes of different evacuation strategies and to identify the most effective and efficient ways to evacuate populations at risk. Cova and Johnson 2002 were among the first to study wildfire evacuation at the microscopic level. Other studies in this area have focused on identifying wildfire evacuation trigger points to facilitate a more organized and systematic evacuation process (Cova et al. 2005), evaluating emergency preparedness in WUI communities (Wolshon and Marchive 2007), and examining the impact of dynamic factors on wildfire evacuation simulation (Beloglazov et al. 2016). In recent years, there has been increasing interest in incorporating traffic simulation, both at the microscopic and mesoscopic levels, into wildfire evacuation studies. Several studies developed integrated frameworks for simulating wildfire evacuations and determining feasible evacuation plans (Ronchi et al. 2019, Wahlqvist et al. 2021). A review conducted by Intini et al. 2019 provided further instances of the use of traffic simulation in wildfire evacuation studies and emphasized the need for behavioral input to improve the performance of evacuation assessments.

There are relatively few studies that have focused on quantitative behavioral models for wildfire evacuation. Most quantitative models have utilized latent class analysis or logit models for evacuation decisions based on data collected from surveys. These studies have typically considered only binary choices: either to evacuate or to stay (Mozumder et al. 2008, Toledo et al. 2018, Kuligowski et al. 2022, Kuligowski et al. 2020, Walpole et al. 2020, Wong et al. 2022). Several studies have expanded the range of decision options beyond two levels, including three or more alternatives (e.g., evacuate, wait, or stay) and have utilized multinomial analysis to identify the key drivers of these decisions (McCaffrey et al. 2018, Edgeley et al. 2019, Stasiewicz and Paveglio 2021). Grajdura et al. 2021 and Grajdura et al. 2022 specifically modeled individual awareness time and preparation time by employing a linear regression model and non-parametric classification and regression tree (CART). However, only a limited number of studies have investigated other types of decisions pertaining to wildfire evacuation, such as route selection, means of transportation, GPS navigation use, and destination choice (Katzilieris et al. 2022, Wong et al. 2020b). While these en-route choices have a significant impact on the outcome of an evacuation, they have not received sufficient attention in the existing literature, which highlights the need for more detailed quantitative models for wildfire evacuation decisions.

In addition to traditional statistical models, ML techniques have been widely utilized in evacuation modeling (Liu et al. 2011, Wang et al. 2019, X. Zhao et al. 2020b) and travel mode choices (Cheng et al. 2019, Hagenauer and Helbich 2017, Lhéritier et al. 2019). However, the application of ML approaches in the context of wildfire evacuation has been relatively limited, with only a few notable exceptions. Katzilieris et al. 2022 and Xu et al. 2023 employed a ML approach to creating a predictive model for binary evacuation decisions. Their studies demonstrated the potential of integrating ML techniques into wildfire evacuation behavior studies, highlighting the possibilities for leveraging the power of ML in this context. In comparison to traditional statistical modeling, ML techniques can offer distinct advantages in effectively managing intricate relationships between variables, particularly their nonlinear interactions. Moreover, ML-based predictive models for evacuation behaviors have the potential to seamlessly integrate with other high-dimensional data and models for fire analysis and traffic simulations.

3.2.3 Research gaps and objectives

The existing literature reveals a gap pertaining to the range of factors influencing evacuation preferences, behaviors, and decisions. This gap underscores insufficient knowledge on the subject and the need for more empirical evidence. Moreover, the majority of previous research has focused on binary wildfire evacuation decisions. However, during an evacuation, evacuees make a range of decisions, encompassing evacuation timing (i.e., compliance with staged evacuation orders), route selection, choice of transportation mode, destination choice, and GPS navigation use. Specifically, the utilization of GPS navigation is a pivotal factor in traffic simulation, as it enhances evacuation efficiency significantly by optimizing routes, relative to individuals who select a familiar route (Zhao and Wong 2021). Despite such potential benefits, there is a scarcity of studies that have investigated the critical factors that influence the use of GPS navigation during evacuations, to the best of the authors' knowledge. Finally, the utilization of ML-based predictive modeling specifically for wildfire evacuation behaviors is currently limited, despite the presence of complex relationships among key variables influencing evacuee decisions and behaviors.

This chapter addresses these research gaps and presents unique contributions to the current body of literature on wildfire evacuation in multiple aspects. Firstly, this chapter explores crucial characteristics that influence evacuee responses to staged evacuation orders, moving beyond simplistic binary decisions regarding evacuation timing, such as "evacuate" or "stay." The results can be used in tailoring evacuation strategies and communication efforts. Secondly, this study collects data and develops data-driven predictive models for various en-route choices during a wildfire evacuation. Specifically, the effect of GPS navigation usage on evacuation timing and efficiency, which has not been thoroughly investigated, is studied comprehensively in this paper. GPS navigation can help individuals receive real-time information on road conditions and congestion and be advised on the optimal route to take. The use of GPS navigation not only improves evacuation efficiency at the individual level but also changes the overall traffic mobility at the transportation network level (Zhao and Wong 2021). However, the survey conducted by Wong et al. 2020a revealed that only a small percentage of evacuees (8% to 19%) actually utilized GPS during evacuation in California. Further exploration of the factors influencing the utilization of GPS navigation would assist authorities in promoting its adoption during evacuations. Finally, considering the scarcity of quantitative models in the current literature, the ML-based predictive models developed in this study can bridge the gap between behavioral study and traffic demand estimation, which can have significant value in facilitating wildfire evacuation simulations for modeling and tracking individual agent behaviors and decisions.

3.3 Methodology: Data Collection and Analyses

This chapter aims to identify factors affecting evacuee preference, behavior, and decisions during a wildfire and to develop a series of predictive models that could best describe and simulate future evacuee behaviors. To achieve these objectives, we first collected both qualitative and quantitative data through a web-based stated preference survey of residents with physical addresses in California, Oregon, and Colorado. These states have undergone major wildfire evacuation events in the past years. Then, conventional statistical analyses were used to identify the key factors influencing evacuee preferences, behaviors, and decisions, which were subsequently used as major input variables in the predictive models. Various ML algorithms were tested and compared to find the best predictive models with the highest performance. Finally, the predictive models were used to estimate the evacuation decisions of the synthetic population in Santa Clarita, California. Figure 3.1 illustrates the methodology workflow and the modeling components. Specifically, data collection and model construction (Sections 3.3 and 3.4) are described in the green box. The predictive models are then combined with wildfire and traffic simulation in the illustrative example (Section 3.5) to demonstrate their applicability to a comprehensive wildfire evacuation simulation. By doing so, the methodology can provide more accurate traffic demand inputs for evacuation planning, taking into consideration the diverse range of individual behaviors and inherent heterogeneity among evacuees.

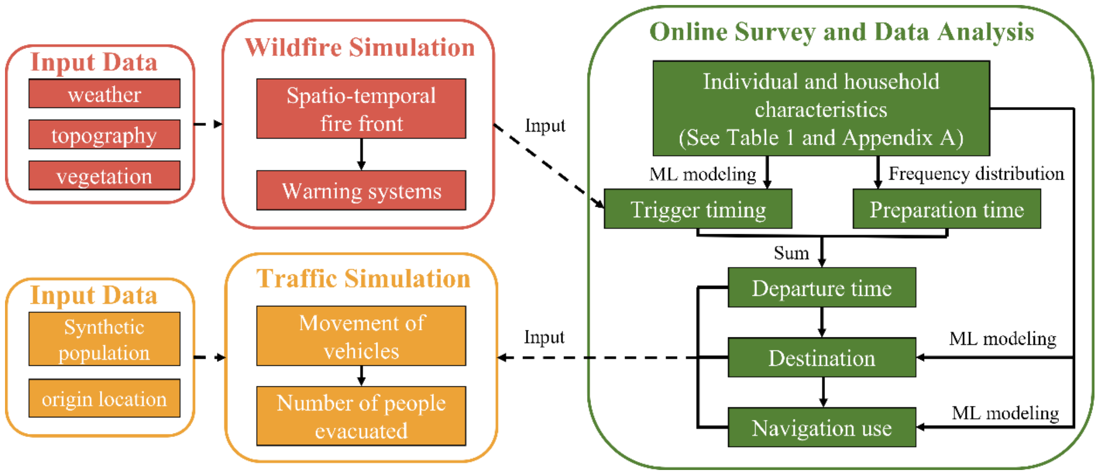


Figure 3.1 The overall methodology for constructing and applying the quantitative predictive models for wildfire evacuation decisions

3.3.1 Data collection: a web-based stated preference survey

We conducted a web-based stated preference survey of residents in wildfire-prone areas of the United States, specifically in California, Oregon, and Colorado, which have experienced major wildfire events and evacuations in the past several years. The survey aimed to capture the diverse behaviors of residents prior to and during a wildfire evacuation. According to the United States Department of Agriculture (USDA) Forest Service Wildfire Risk to Communities program (USDA 2022), on average, these states are at a higher risk of wildfire than 96%, 74%, and 66% of the United States, respectively. The survey was conducted online through Amazon Mechanical Turk (MTurk) between April and May 2022. MTurk, a platform where crowdworkers can be recruited for various tasks, was used in this study because of relatively high-quality data at a reasonable cost (Owens and Hawkins 2019). To be eligible to participate in the survey, individuals should be residents living in the study area and should be at least 18 years old. However, since 2018, there has been increasing concern about data quality issues associated with MTurk, primarily attributed to the presence of "bots" (computer programs that automatically complete tasks) and "farmers" (individuals using server farms to bypass MTurk location restrictions). This study addressed these concerns by incorporating specific criteria to ensure data quality and reliability. As suggested by Chmielewski & Kucker 2020 and Kennedy et al. 2020, the following validation checks were implemented: (a) attention check: participants should pass all attention checks; (b) consistency check: participants should provide the same answers to identical questions throughout the survey; (c) logical check: the total number of elder individuals and children residing in a household should not exceed the total number of individuals in the household, as cross-verified through two distinct questionnaires; and (d) IP address check: responses should be verified to originate from US IP address and should not be identified as virtual private servers (VPS) users based on an IP lookup tool (https://rkennedy.shinyapps.io/IPlookup/). This tool (Kennedy et al.2020) utilized the IP Hub (https://iphub.info/) service. A total of 1,312 participants completed the survey, but 554 responses were considered invalid because they failed to meet at least one of the validation checks. Thus, a final dataset consisted of 758 valid responses.

The online survey consisted of a set of closed-ended quantitative and qualitative questions designed to elicit information about respondents' demographics, property, car ownership, mobility issues, risk perception, previous experience with natural disasters, and a series of potential evacuation-related actions. Major factors characterizing participants and their households are summarized in Appendix B. This survey also asked a question about the method a respondent would utilize in selecting an evacuation route (e.g., familiar route, conventional map, GPS navigation map, etc.) to investigate their routing selection, which has not been thoroughly examined in previous studies.

All study protocols were approved by the Washington State University Institutional Review Board before the survey began. To mitigate potential survey response biases, this survey included a question on the individual's decision-making role within their household. This question could address the issue of whether a participant's responses reflected household-level preferences, behavior, and decisions. This is in line with previous studies (Hung and Wang 2022, Seebauer et al. 2017) that suggested the importance of ensuring that the survey respondents were representative of their household or primary decision-maker. A total of 723 respondents answered that they actively participated in the household decision-making process. Only those respondents were included in the statistical analyses and predictive model construction.

3.3.2 Identification of key factors affecting wildfire evacuation preferences and behaviors through regression analyses

To identify statistically significant explanatory variables that influence individual behaviors and decisions about wildfire evacuation, we first performed regression analyses based on the survey data. As the dependent variables (e.g., evacuation timing, destination choice, and the use of GPS navigation) were all discrete in nature, logit models were used in identifying key factors affecting these dependent variables.

In this study, the evacuee's decision to use GPS navigation during an evacuation and their destination choice were modeled as binary variables. Binary logistic regression (BLR) analysis was utilized to identify the explanatory variables that significantly influence these decisions. BLR is a widely used method for estimating discrete choice preferences, such as insurance purchases (Lee et al. 2022, Lee and Li 2021) or simple evacuation decisions (Kuligowski et al. 2022). As shown in Eq. 3.1 and Eq. 3.2, the logit operator in the BLR models projects a linear function to a value between 0 and 1, which can be used to estimate the probability (p) that an individual chooses one of the alternatives:

$$logit(p) = \ln\left(\frac{p}{1-p}\right) = \boldsymbol{\beta X} \quad (3.1)$$

$$P(Y = 1|\boldsymbol{X}) = \frac{\exp(\boldsymbol{\beta X})}{1+\exp(\boldsymbol{\beta X})} \quad (3.2)$$

where $\boldsymbol{\beta}$ = the estimated vector of coefficients for explanatory variables; $\boldsymbol{X}$ = the vector of explanatory variables; and Y = the dependent variable.

At the initial step of estimating the BLR models for the use of GPS navigation during an evacuation and destination choice, the explanatory variables ($\boldsymbol{X}$) considered were all the variables describing various characteristics of individual respondents and their households as summarized in Table 3.1 and Appendix B. The BLR models were then estimated using a backward stepwise elimination approach (Steyerberg et al. 2004). The initial model included all explanatory variables, and at each step, the least statistically significant variables were gradually eliminated from the model. The elimination of variables was determined using the Wald Chi-Square Test, with a p-value threshold of 5%. This process was repeated until none of the remaining variables met the specified level for elimination. The final model obtained through this approach was compared to the models with more explanatory variables and was determined to be the optimal one based on the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC).

Previous research on evacuation behavior has treated evacuation timing as a binary decision (either staying or evacuating) (Toledo et al. 2018, Kuligowski et al. 2022, Walpole et al. 2020). However, in the United States, there are typically three stages of wildfire evacuation orders, such as Evacuation Watch, Evacuation Warning, and Evacuation Order, that guide individual evacuation decisions. Therefore, it is essential for understanding and modeling various evacuee responses to different stages of evacuation orders to improve evacuation simulation accuracy and ultimately develop more efficient emergency planning. In this study, individual evacuation timing is modeled as a multi-class decision, and these categorical variables are inherently ordinal. Thus, the ordered logistic regression (OLR) was used to take into account the ordered nature of the categorical outcomes. OLR model assumes proportional odds, implying that the effects of the explanatory variables on the log-odds of each category relative to the next one are the same for all categories as expressed in Eq. 3.3 (Williams and Quiroz 2020):

$$log\left(\frac{p_1(X)+p_2(X)}{\sum_{i=3}^{N} p_i(X)}\right) - log\left(\frac{p_1(X)}{\sum_{i=2}^{N} p_i(X)}\right) = log\left(\frac{p_1(X)+p_2(X)+p_3(X)}{\sum_{i=4}^{N} p_i(X)}\right) - log\left(\frac{p_1(X)+p_2(X)}{\sum_{i=3}^{N} p_i(X)}\right) \qquad (3.3)$$

Based on the proportional odds assumption, for a multi-class decision with K alternatives, only one coefficient vector β can be estimated, and the conditional probabilities of an individual taking each alternative given an independent vector X are expressed by (Williams 2018):

$$P(y = 1|\boldsymbol{X}) = 1 - \frac{exp\,(\boldsymbol{X\beta}-\tau_1)}{1+exp\,(\boldsymbol{X\beta}-\tau_1)} \qquad (3.4)$$

$$P(y = j|\boldsymbol{X}) = \frac{exp\,(\boldsymbol{X\beta}-\tau_j)}{1+exp\,(\boldsymbol{X\beta}-\tau_j)} - \frac{exp(\boldsymbol{X\beta}-\tau_{j-1})}{1+exp(\boldsymbol{X\beta}-\tau_{j-1})} \quad j = 2, \dots, K-1 \qquad (3.5)$$

$$P(y = K|\boldsymbol{X}) = \frac{exp\,(\boldsymbol{X\beta}-\tau_{K-1})}{1+exp\,(\boldsymbol{X\beta}-\tau_{K-1})} \qquad (3.6)$$

where τ_1 = the threshold points for two consecutive alternatives that shall be estimated with $\boldsymbol{\beta}$ at the same time. Similar to the process used for the BLR models, the statistically significant explanatory variables were selected through a backward stepwise elimination approach.

3.3.3 Predictive model development using machine learning techniques

While traditional statistical analyses have been widely used in the literature, they have limitations in terms of accuracy when used to make predictions. ML approaches, on the other hand, have outperformed traditional statistical analyses in many fields and have received increasing attention. However, the data-driven nature and black box aspect of most ML approaches limit the understanding of causal effects. To address these limitations, this study proposes a combination of statistical regression analyses and ML approaches to construct predictive models with a smaller set of significant features and acceptable accuracy. This combination can serve as a bridge between behavioral study and traffic demand modeling and provide a detailed traffic demand estimation tool that helps policymakers understand the potential actions of individuals at both the aggregate and disaggregate levels during future wildfire evacuations.

In Section 3.2, the key variables influencing individual wildfire evacuation decisions were identified using the backward stepwise elimination approach. Since the logit model converts a linear combination of regressors to probability, it may not be robust enough to capture potential nonlinearity between independent and dependent variables, ML approaches can be more effective at modeling such nonlinearity. In this study, various ML approaches were used to construct predictive models that can estimate individual responses during a wildfire evacuation. The approaches tested in this study include random forest (RF), support vector machine (SVM), K-nearest neighbors (KNN), and naïve Bayes (NB). These models have commonly been employed to make prediction for discrete choices and have recently been applied in evacuation studies, showing higher accuracy when compared to traditional statistical analyses (Katzilieris et al. 2022, Wang et al. 2019, Xu et al. 2023). For both the statistical models and the ML approaches, the full dataset was split into two sets: 70% of the data used for training and the remaining 30% used for testing. The model was trained on the training set, and its performance was evaluated on the testing set. The average accuracy score was calculated by repeating this process five times to increase its robustness.

3.4 Survey Data Analyses and Discussions

3.4.1 Descriptive statistics

Of the initial group of 1,312 participants, only 723 individuals passed the validation criteria (see Section 3.1) and indicated active participation in their household decision-making process. Of this final sample, 47.2% of them were female. The age group between 30 and 39 years old comprised the highest proportion in the sample, while this group made up only 19.5% of the population in the study sites according to the Census data (U.S. Census Bureau 2023). The percentage of the respondents (47.9%) whose annual household income was between $50,000 and $99,999 was much higher than the one (28.4%) from the Census data. These differences may be due to the fact that younger and lower-income individuals generally use MTurk as a means of earning additional income. The demographics of the sample are shown in Table 3.1.

Table 3.1 Demographic characteristics of the sample

Characteristics	Classes	Percentage (%)
Gender	Female	47.2%
	Male	52.8%
Age (years)	18 – 29	23.1%
	30 – 39	35.5%
	40 – 49	20.2%
	50 – 59	13.3%
	60 – 69	6.8%
	>= 70	1.1%
Education	Less than a high school diploma	0.6%
	High school diploma or equivalent	15.4%
	Associate degree	10.0%
	Bachelor's degree	58.5%
	Graduate degree	15.5%
Ethnicity	Caucasian	68.4%
	Asian	12.0%
	African American	4.9%
	American Indian, Alaska Native, Native Hawaiian or Other Pacific Islander	1.4%
	Two or more races	5.7%
	Other races	7.6%
Annual household income before taxes	Less than $49,999	28.6%
	$50,000 to $99,999	47.9%
	$100,000 to $199,999	17.6%
	Over $200,000	5.9%

During a wildfire, individual evacuation can be triggered by various external stimuli/cues, such as official announcements from authorities (e.g., mandatory or voluntary evacuation order) or physical cues (e.g., smoke, flames, or embers) (McCaffrey et al. 2018, Beloglazov et al. 2016). Evacuation orders are often issued in a staged manner. For example, in California, an evacuation warning may be issued for an area potentially at risk of wildfire but not yet in imminent danger, advising residents to be prepared to evacuate. If the fire presents a more immediate threat, a mandatory evacuation order may be issued, which most residents are likely to follow. However, some may hesitate to evacuate under a mandatory order and instead wait until they observe physical cues or choose to stay and defend their properties. Table 3.2 shows the frequency distribution of the main external stimuli that may trigger their evacuation during a wildfire. As shown in Table 3.2, 38.6% of respondents would be willing to evacuate when either level 1 (i.e., evacuation alert that a wildfire threat is in your area) or level 2 (i.e., evacuation warning that there is a high probability of a need to evacuate) evacuation be announced. It is followed by "evacuation without any official announcement but after knowing that there would be a wildfire threat from news and/or neighbors" (30.7%), and "evacuation with a mandatory order (level 3)" (27.4%). Only 3.3% of respondents would wait until smoke or flames/embers are observed or stay and defend.

Table 3.2. Frequency distribution of evacuation trigger

Evacuation Trigger	Count	Percentage
Evacuate without any official announcement	222	30.7%
Evacuate with a voluntary evacuation order	279	38.6%
Evacuate with a mandatory evacuation order	198	27.4%
Evacuate after smoke is observed	9	1.2%
Evacuate after flames/embers are observed	4	0.6%
Stay and defend	11	1.5%

The evacuation preparation time can be defined as the combination of decision delay (the time between receiving evacuation trigger and deciding to start preparation) and preparation delay (the time spent gathering family members, packing necessary items, etc.). The distribution of evacuation preparation time was separated based on the evacuation timing group, as presented in Table 3.3. The immediate group includes individuals who intended to evacuate without any official announcement. The voluntary group includes individuals who would respond to either level 1 or level 2 evacuation order, and the mandatory group contains individuals who would evacuate under level 3 evacuation order. The results suggest that the immediate group reported the highest proportion of preparation time ranging from 11 minutes to 20 minutes, while the voluntary and mandatory groups showed the highest proportion of preparation time from 21 minutes to 30 minutes and 31 minutes to 60 minutes, respectively. Overall, the respondents who were more responsive to the evacuation orders tended to have shorter evacuation preparation times, implying a higher level of awareness and readiness prior to a wildfire.

Table 3.3 Frequency distribution of evacuation preparation time

	< 10 mins	11 mins – 20 mins	21 mins – 30 mins	31 mins – 60 mins	> 60 mins
Immediate	56(25.2%)	57(25.7%)	52(23.4%)	36(16.2%)	21(9.5%)
Voluntary	34(12.2%)	49(17.6%)	88(31.5%)	63(22.6%)	45(16.1%)
Mandatory	18(9.1%)	27(13.6%)	46(23.2%)	62(31.4%)	45(22.7%)

The selection of an evacuation destination is a crucial factor in evacuation modeling. Table 3.4 presents the frequency distribution of evacuation destination, which revealed that among the respondents, 52% planned to evacuate to the house of a friend or relative, while 28.8% intended to go to a hotel or motel, 8.9% planned to evacuate to a public shelter, and 4.3% intended to evacuate to a secondary residence.

Table 3.4 Frequency distribution of evacuation destination

Evacuation Destination	Count	Percentage
Friend or family member's house	376	52%
Hotel or motel	208	28.8%
Public shelter	64	8.9%
Secondary residence	31	4.3%
Others	44	6%

Homeowners insurance can serve as a financial safeguard for homeowners in the event of property damage caused by a wildfire (Lee et al. 2022). According to McCaffrey et al. 2018, individuals may weigh the trade-off between financial security and personal safety when making evacuation decisions. Thus, the potential relationship between financial security and personal safety was examined through a contingency table (i.e., Table 3.5) displaying the frequencies of combinations of insurance status and evacuation triggers. Insurance status was classified into three categories: fully insured, underinsured, and no insurance. The results in Table 3.5 show that 46% of respondents who would evacuate after observing physical cues or chose to stay and defend did not have homeowner insurance. On the other hand, fully insured homeowners were more likely to evacuate earlier, which aligns with the findings of McCaffrey et al. 2018 and Lee et al. 2022. These results suggest that having greater insurance coverage may alleviate concerns about financial burden from repair/reconstruction costs following a wildfire event, thereby increasing their responsiveness to evacuation triggers. Therefore, it is reasonable to conclude that insurance status may influence evacuation decisions and timing.

Table 3.4 Contingency table for insurance status and evacuation preference

Evacuation triggers	No insurance	Underinsured	Fully insured	Sum
Evacuate without any official announcement	24 (11%)	35 (16%)	163 (73%)	222
Evacuate with a voluntary evacuation order	58 (21%)	79 (28%)	142 (51%)	279
Evacuate with a mandatory evacuation order	52 (26%)	51 (26%)	95 (48%)	198
Evacuate with physical cues OR stay and defend	11 (46%)	4 (17%)	9 (38%)	24

In addition, there is evidence in the literature that past experience with natural disasters can have a positive effect on individual evacuation preferences. Lovreglio et al. 2020 found that previous evacuation experience was positively associated with evacuation preferences, and Mozumder et al. 2008 showed that previous wildfire damage experience had a similar positive impact on evacuation decisions. We also collected both wildfire damage experience and previous evacuation experience through the online survey to examine their impact on evacuation preferences. The results are summarized in Table 3.6.

Table 3.5 Contingency table for past evacuation experience and past damage experience

	Property damage experience	No property damage experience
Evacuation experience	185	155
No evacuation experience	8	375

As shown in Table 3.6, of the 340 respondents who had previously evacuated, 185 reported their past property damage experience, while the remaining 155 respondents did not. Those who had evacuated in the past but did not experience any damage might have perceived their evacuation as unnecessary, while those who experienced damage might likely view it as necessary. This inference is reasonable because property damage typically results from direct contact with fire front and damaged properties are likely to have been subject to a mandatory evacuation order. This inference is based on the assumption that most survey respondents had experienced at most one wildfire event in the past several years and that property damage and evacuation experiences had occurred during the same wildfire event. These assumptions are justifiable as the majority of the study sites where respondents resided had experienced no more than one major wildfire event in the past several years.

In this study, all the respondents were reclassified into three groups: 375 respondents without previous experience of both wildfire damage and evacuation, 193 respondents who may have realized that evacuation was necessary based on their previous experience, and 155 respondents with past experience of unnecessary evacuation. The frequencies of combinations of evacuation triggers and past experience are presented in Table 3.7. The results indicate that respondents with no past experience or experience of unnecessary evacuation were more likely to wait for an official evacuation order, including both voluntary and mandatory orders. In contrast, those with past experience of effective evacuation were more likely to evacuate early. The results suggest that effective evacuation experience can encourage early evacuation in the future, highlighting the importance of effective staged evacuation orders to avoid unnecessary evacuations for residents.

Table 3.6 Frequency distribution of evacuation trigger versus past experience

Past experience	Immediate	Voluntary	Mandatory	Physical cues OR stay	Sum
No experience	65 (17%)	162 (43%)	133 (35%)	15 (4%)	375
Unnecessary evacuation	46 (30%)	65 (42%)	41 (26%)	3 (2%)	158
Effective evacuation	111 (58%)	52 (27%)	24 (12%)	6 (3%)	193

3.4.2 Statistical analysis results

An OLR analysis was first performed to identify key drivers affecting various evacuation triggers. The four evacuation decision classes were considered: (a) evacuation before an official announcement (i.e., early evacuation); (b) voluntary evacuation; (c) mandatory evacuation; and (d) late or no evacuation (i.e., after observing physical cues, or decide to stay and defend). Late and no evacuees were grouped into a single class, as the results of this study were used to advance an understanding of how individuals respond to official announcements.

Table 3.8 summarizes the OLR results for evacuation triggers, where the dependent variable was categorized into 3 (early evacuation), 2 (voluntary evacuation), 1 (mandatory evacuation), and

0 (late or no evacuation). The reference alternative chosen for comparison is 0 (late or no evacuation). Out of the 22 variables as listed in Table 3.1 and Appendix B, the final optimal model had 6 key independent variables. The results suggest that respondents who had full insurance coverage were more likely to evacuate early, which aligned with our findings observed in Table 3.5. Individuals with higher levels of education exhibited a greater responsiveness to evacuation orders. Moreover, respondents with past effective evacuation experiences (see Tables 3.6 and 3.7) tended to have earlier evacuation timing in future wildfire events. The positive coefficient of financial risk preference indicates that the respondents who were more tolerant of financial risk were more likely to evacuate early. In addition, the tendency to routinely use GPS navigation may serve as an indicator of the respondent's unfamiliarity with their community: the positive coefficient of this variable can be interpreted that the respondents who were less familiar with local area preferred evacuating early due to concerns about potential detours resulting from road closures or severe congestions. The results also suggest that households with predetermined evacuation plans for wildfires tended to evacuate late, possibly implying that the plans increased their confidence in executing a quick evacuation.

Table 3.7 Ordered logistic regression results of evacuation timing (0: late or no evacuation; 1: mandatory evacuation; 2: voluntary evacuation; and 3: evacuation before an official notification)

Variable	Estimated coefficient	Wald chi-square	p-value
Education: bachelor's degree or higher	0.5462	3.178	0.001
GPS-navigation: use routinely	0.3448	1.962	0.050
Homeowners insurance: fully insured	0.3748	2.495	0.013
Effective evacuation experience: yes	0.4226	3.756	<0.001
Disaster evacuation plan: yes	-0.3160	-2.161	0.031
Financial risk preference	0.3052	3.642	<0.001
Threshold point: Late or Stay/Mandatory	-2.7036		
Threshold point: Mandatory/Voluntary	0.9922		
Threshold point: Voluntary/Immediate	0.6403		

The use of GPS navigation was identified as one of the significant factors affecting evacuation timings through the OLR analyses (see Table 3.8). Based on the results of the online survey, 35% (252) of respondents indicated that they would be willing to use GPS navigation during an evacuation. Since the intention to use GPS navigation during an evacuation is a binary choice, a binary logistic regression model was used to identify significant factors affecting their preferences.

Table 3.8 Binary logistic regression results of GPS navigation use during an evacuation

Variable	Estimated coefficient	Wald chi-square	p-value
Intercept	-0.9177	-3.747	<0.001
Employment: full time	0.4185	2.098	0.036
Homeownership: own a house	-0.6563	-3.793	<0.001
Household member with special need: yes	-0.5526	-2.383	0.017
Navigation use: use routinely	0.9159	4.295	<0.0001
Effective evacuation experience: yes	-0.3560	-2.570	0.010
Safety risk preference	-0.2488	-2.446	0.014

Table 3.9 presents the binary logistic regression results of GPS navigation use during an evacuation. As expected, the individuals who routinely used GPS navigation were more likely to use it in determining evacuation routes. The respondents who owned their properties or experienced effective wildfire evacuations were less likely to use GPS navigation during an evacuation. It could be partly because they might have lived in their communities longer than the rest of the respondents (e.g., renters, seasonal house owners) and were more familiar with the neighborhood and local region, which made them determine evacuation routes by themselves rather than relying on navigation. This interpretation can be aligned with the finding that the respondents who had full-time jobs preferred using GPS navigation during an evacuation, as they were relatively less likely to spend time outside or be familiarized with their communities. Risk-seeking respondents were less likely to utilize GPS navigation, which was consistent with our expectation that the people having risk-averse attitudes might not be willing to take a risk (e.g.,

unexpected delay due to road closure or traffic congestion) during an evacuation. Interestingly, the results revealed that respondents who had household member(s) with special needs exhibited a lower likelihood of utilizing GPS navigation during evacuations. This finding can be attributed to the likelihood that families with special needs have established pre-planned evacuation routes and strategies customized to meet their specific requirements. Additionally, households with special needs members may prioritize direct communication channels with emergency responders or local authorities which can provide real-time information and guidance tailored to their unique circumstances.

The impact of past effective evacuation experience on the intention to use GPS navigation during a wildfire evacuation (Table 3.11) can be particularly highlighted when it is compared with their usage habits (Table 3.10). For the respondents who had no past evacuation experience, the frequency of using GPS navigation during an evacuation only changed by 26% from their normal usage. However, it was found that the individuals who had past evacuation experience preferred not to use navigation during an evacuation even though they used it daily. In particular, for those who experienced effective evacuation in the past, the frequency of using navigation dropped from 91% in normal conditions to 19% during an evacuation. This significant change in frequency among individuals with past evacuation experience highlights the negative effect of past experience on the intention to use GPS navigation during an evacuation. The results suggest that, while the use of GPS navigation is perceived as an effective action during an evacuation, those with past evacuation experience may be more likely to rely on their previous evacuation routes, especially if they effectively evacuated in the past.

Table 3.9 Contingency table for past effective evacuation experience and GPS navigation use under normal conditions

	Navigation use: Yes	Navigation use: No
No experience	257 (69%)	118 (31%)
Unnecessary evacuation	126 (81%)	29 (19%)
Effective evacuation	176 (91%)	17 (9%)

Table 3.10 Contingency table for past effective evacuation experience and GPS navigation use during an evacuation

	Navigation use: Yes	Navigation use: No
No experience	165 (43%)	210 (56%)
Unnecessary evacuation	64 (32%)	105 (68%)
Effective evacuation	37 (19%)	156 (81%)

During wildfire evacuations, the decision of where to evacuate to is also crucial, specifically in regard to the willingness of individuals to evacuate to public shelters. Policymakers should have a good estimate of the expected number of individuals using public shelters to determine the number and capacity of these shelters and allocate appropriate resources to them. Thus, only binary decision variables, evacuation to public shelters or to other places (e.g., friend's or relative's house, hotel, secondary residence, portable vehicle, rental house), were considered in a logit model. Binary logistic regression for destination choice revealed three statistically significant explanatory variables (i.e., home ownership, regular use of navigation, and past effective evacuation experience). However, due to an imbalanced dataset in which only 8.9% of respondents expressed a willingness to choose public shelters, the model categorized all individuals as evacuating to other places. These findings suggest that traditional statistical analysis may not serve as an effective predictive model for destination choice. Therefore, Section 3.3 presents the use of ML approaches as a possible solution to address such limitation associated with imbalanced dataset.

3.4.3 Predictive model comparison and accuracy

As discussed in Section 3.2, four evacuation triggers were considered to mimic real-world staged evacuation response. The dataset was found to be severely imbalanced given that only 3.4%

of respondents were in the late or no evacuation group. To address this imbalance, the number of data points in the late or no evacuation group was upsampled to 233 data points, which was roughly equivalent to one third of the total data points. Consistent with the results from Katzilieris et al. 2022, the classifier with the highest accuracy was RF, which showed an accuracy of 64% when all 24 features (that are shown in both Table 3.1 and Appendix B) were considered. By including only six significant independent variables identified by the OLR model as described in Table 8, its average accuracy was 59% (i.e., a 5% decrease), which highlights the significant impacts of those six variables. Table 3.12 shows the confusion matrix obtained from the RF model with 5-fold cross validation. While the confusion matrix does not indicate a high overall accuracy, it reveals that that diagonal elements (representing correct predictions) have relatively high values. This suggests that the model performs better than random chance and exhibits some level of predictive capability. Its comparison with the OLR model can be found in Table 3.13.

Table 3.11 Average confusion matrix for evacuation timing using random forest (5-fold cross validation)

		Predictive values			
		0	1	2	3
True values	0	71	0	0	0
	1	5	20	24	10
	2	6	21	37	19
	3	3	8	19	37

0: late or no evacuation; 1: mandatory evacuation; 2: voluntary evacuation; and 3: early evacuation

Similarly, the significant imbalance was an issue for evacuation destinations. As discussed in Section 4.2, the logistic regression model classified all individuals into the majority group (i.e., evacuation to other places), thereby failing to account for the diversity in the selection of evacuation decisions. To address this issue, the minority group (evacuation to public shelters) was randomly upsampled to the same size as the majority group (evacuation to other places). The resulting dataset included 659 upsampled data points in the minority group and 659 original data points in the majority groups. Using this dataset, binary logistic regression identified 13 statistically significant independent variables, including age, gender, household size, home ownership, the presence of children, car ownership, routinely use of navigation, insured status, past effective evacuation experience, evacuation plan, confidence in property, and risk preferences for personal safety and financial safety respectively. RF was determined as the optimal classifier for these 13 selected features, yielding an average accuracy of 99%.

Table 3.13 summarizes the comparison of the prediction accuracies of logistic models and various ML algorithms for evacuation trigger, destination choice, and GPS navigation use during evacuation. As shown in Table 3.13, ML algorithms outperformed logistic regressions. It should be noted that the accuracies of predicting evacuation timing and the preference of using GPS navigation are relatively low for both logistic regression analysis and ML approaches. This indicates a significant level of uncertainty inherent in individual decision-making, particularly when faced with hypothetical wildfire events. To enhance the accuracy of prediction, it is recommended to conduct a post-evacuation revealed preference survey or present more specific hypothetical wildfire scenario to respondents.

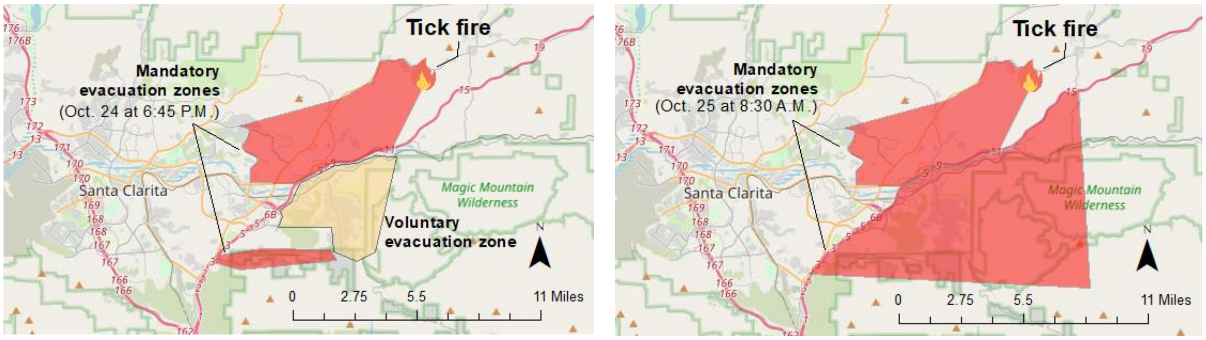
Table 3.12 A comparison table showing the prediction accuracies of regression and machine learning models for wildfire-evacuation-related decisions

Methods	Evacuation trigger	Evacuation destination	Navigation use
Logistic regression	56%	68%	68%
Random forest	**59%**	**99%**	67%
Support vector machine	43%	66%	**70%**
Naïve Bayes	42%	64%	69%
K-nearest neighbors	56%	94%	64%

For the evacuation preparation time, both statistical analyses and ML algorithms showed low performance, with an accuracy of merely 28%, which was only slightly superior to pure random guessing (based on the 5 preparation time slots). This indicates that there is significant randomness associated with preparation time during evacuation. Therefore, it is suggested that random sampling from the frequency distribution with respect to each evacuation timing group, as shown in Table 3.3, be used to represent preparation time in traffic simulations. While random sampling may introduce substantial uncertainty at the level of individual preparation times, it is expected to provide a good representation of the overall frequency distribution at a larger or aggregated level.

3.5 Illustrative example: Tick Fire evacuation

To showcase their practical applicability, a historical wildfire, the Tick Fire burned near Santa Clarita, California, was used as an illustrative example in this paper. The Tick Fire broke out on October 24th, 2019 and was contained on October 31st, 2019. Although the burned area was only 18.7 square kilometer, more than 10,000 residential structures were threatened and over 40,000 residents were forced to evacuate. As shown in Figure 3.2, mandatory and voluntary evacuation orders were issued at 6:45 p.m. on October 24th, and the mandatory evacuation orders were then extended to a larger area at 8:30 a.m. on October 25th. The evacuation orders were partially lifted at 8 a.m. on October 26th, indicating that the fire was under control in the affected area (Wikimedia Foundation 2022).



(a) (b)

Figure 3.2 Areas under evacuation orders on (a) Oct. 24th, 2019 and (b) Oct. 25th, 2019

As illustrated in Figure 3.2, a staged evacuation order was issued as a result of the Tick Fire. To consider individuals who evacuated before receiving an official announcement, we assumed that the evacuation order had three levels, as depicted in Figure 3.3. In addition to the mandatory and voluntary evacuation zones specified by the authorities during the Tick Fire, an alerting zone was assumed. This zone represented areas where residents were aware of the wildfire outbreak but had not yet received any official announcement. This zone was subject to the mandatory evacuation on October 25th but had not yet received any evacuation orders as of October 24th.

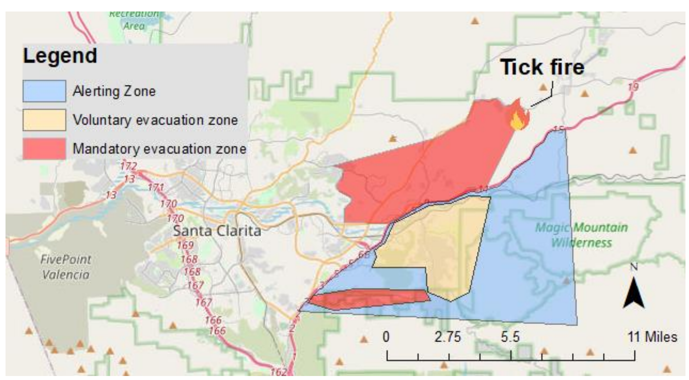


Figure 3.3 Areas under three levels of evacuation orders on Oct. 24th, 2019

A population synthesizer, PopGen, was implemented to generate a synthetic individual-level dataset in the Santa Clarita area. PopGen is a software program that produces synthetic populations while controlling and matching both individual- and household-level attribute distributions (Bar-

Gea et al. 2009, Konduri et al. 2016, Ye et al. 2016). The synthetic population was drawn from the Public Use Microdata Sample (PUMS) collected by the U.S. Census Bureau's American Community Survey (ACS), holding similar marginal distribution of individual and household characteristics to the actual marginal distributions of the population in the study area. Using the synthetic population in combination with predictive models offers a significant benefit as it enables the generation of individual-level evacuation decisions and their corresponding traffic demand. Such information can provide a more thorough understanding of the consequences of various evacuation order strategies.

The generated synthetic population consisted of 25,192 households and 51,045 residents with no significant difference from the marginal distributions of the true population's key characteristics (e.g., household size, household income, the presence of children, age, gender, race, education, and employment status). To relate each household to its home, the locations, types, and dimensions of all buildings in the Santa Clarita area were obtained from the OpenStreetMap (OSM) building layer, one of the major sources that provides network input for traffic modeling and simulations (Zhao et al. 2021). Buildings were classified into residential buildings and commercial buildings. The residential buildings having the top 30% shape area were classified as multifamily residential buildings (such as condominiums and apartments). The ratio of 30% was determined based on the 2019 American Housing Survey conducted by the U.S. Census Bureau that 31.4% of housing in the U.S. were multifamily housing. The remaining structures were labeled as single-family houses. The overlap between the OSM building layer and the evacuation zone layers was used to identify the residents exposed to different levels of evacuation orders. A total of 12,883 residential structures were identified in the evacuation zones, including 9,001 structures in the mandatory evacuation zone, 3,258 structures in the voluntary evacuation zone, and 624 structures in the wildfire alert zone (see Figure 3.3). All synthetic households in the census tract were randomly assigned to residential buildings in the same census tract. Similarly, all individuals who worked full-time or part-time were randomly assigned to workplaces (i.e., commercial buildings). Single-family buildings were only allowed to be assigned one household, while multi-family buildings were assigned multiple households. As a result, 9,244 households were subject to the mandatory evacuation order, affecting a total of 19,348 residents. The voluntary evacuation order impacted 2,276 households (4,925 residents), and the alerting evacuation impacted only 527 households (1,105 residents).

As described in Section 3.3, individual and household characteristics were used to predict residents' evacuation decisions. The distribution of the predicted individual responses to each level of evacuation order can be seen in Figure 3.4. Similar to the survey responses, approximately 5% of the synthetic residents were classified as the “late or no evacuation” group. Most of the synthetic residents preferred to wait until a mandatory evacuation order was issued: approximately 56% of the synthetic residents who received a voluntary evacuation order would evacuate; and 21% of the synthetic residents, who had not received any evacuation order but had been alerted to the presence of the threatening wildfire, chose to evacuate. Out of 25,378 synthetic residents who were subjected to evacuation alert or orders in the case study region, 3,773 synthetic residents (15% of the exposed population) were predicted to use GPS navigation during an evacuation.

When compared with real-world evacuation information, the number of synthetic evacuees (i.e., 21,747) was much smaller than the number of evacuees during the Tick Fire reported in the news (i.e., 40,000). This discrepancy can be explained by two reasons. First, the simulation was conducted during the initial phase of the fire incident, specifically when the evacuation orders were issued between October 24th and 25th, while, in reality, the Tick Fire was contained on October 31st, 2019. As the fire grew and the evacuation order was updated, the exposed population was expected to increase as well. Another reason can be the limitations of stated preference surveys. Responses collected in a hypothetical fire case may differ from actual behavior during a real event, particularly for those who have not previously experienced an evacuation.

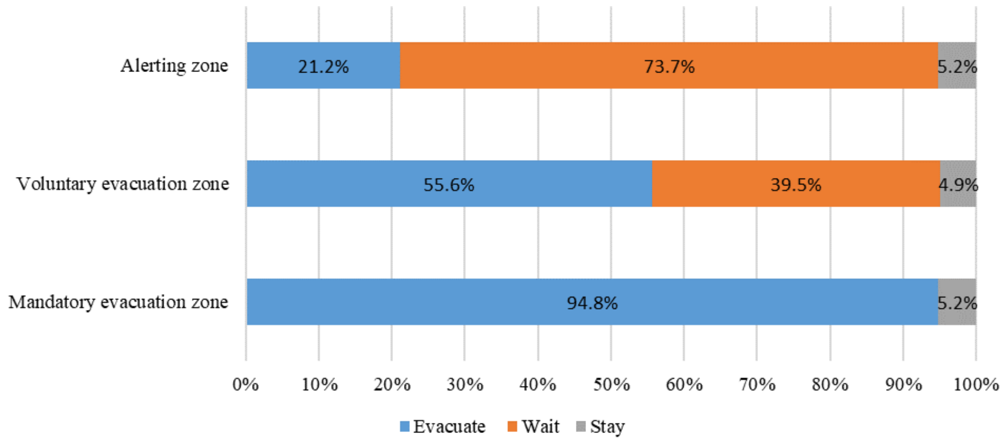


Figure 3.4 Predicted individual responses to three levels of evacuation orders

During the Tick Fire evacuation, two public shelters were opened on October 25th. Approximately 400 residents evacuated to one of the public shelters (Block 2019), which suggests that about 2% of the exposed residents evacuated to public shelters based on that assumption that the other shelter also admitted a similar number of residents. This percentage is higher than the one estimated by the predictive model (0.6%). One potential reason for this discrepancy is that the number of synthetic evacuees was only half of the number of actual evacuees. Another reason is the timing of the evacuation order; the Tick Fire evacuation order was issued at 7 p.m., and night evacuations might have presented additional challenges to find a place to stay and altered individual preferences. Additionally, the number of survey respondents who preferred to evacuate to public shelters was small, which made it difficult to characterize their preferences. The accuracy of the prediction can potentially be improved by a more expansive dataset including a greater number of responses indicating a preference for evacuating to a public shelter.

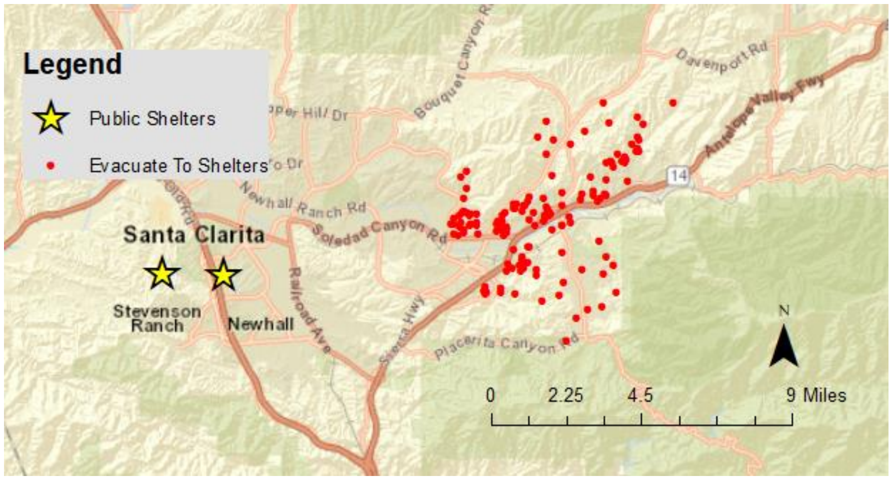


Figure 3.5 The locations of available public shelters during the Tick Fire (marked with yellow stars) and the locations of synthetic residents evacuating to public shelters (marked with red dots)

In addition to the aggregated information, the simulation results of this illustrative example include detailed, disaggregated information. Figure 3.5 shows the initial locations of the synthetic individuals choosing public shelters as their final destinations (marked with red dots). The locations of the public shelters during the Tick Fire evacuation are marked with yellow stars in Figure 3.5. From this figure, one can infer that, during the Tick Fire, most of the residents who evacuated to available public shelters would likely use the Soledad Canyon Road. By extending this analysis and taking a fully probabilistic approach, emergency planners can use such disaggregated information to conduct a pre-event analysis for more effective evacuation planning through traffic simulation and to improve traffic mobility during an evacuation.

3.6 Conclusions, Limitations, and Future Research Directions

This study collected data and developed empirical data-driven models for various en-route choices during a wildfire evacuation. First, we conducted a web-based stated preference survey of residents in California, Oregon, and Colorado to collect empirical data and understand highly unpredictable human behaviors during an evacuation. Contrary to the prevailing assumption in existing literature, which typically considers binary evacuation decisions (evacuate or stay), this paper examined evacuee responses to different levels of evacuation orders and provided insight into effective staged evacuation planning. The survey results indicated that a significant majority of respondents exhibited a heightened level of responsiveness to evacuation orders. However, there were notable variations in evacuation timing depending on factors such as education level, regular use of GPS navigation, prior effective evacuation experience, home insurance status, financial risk preferences, and the presence of a pre-determined disaster evacuation plan. The study also investigated (1) individual preferences regarding evacuation destinations, specifically the intention to evacuate to public shelters, and (2) their preference for using GPS navigation during evacuation. The findings revealed that a minority of respondents (less than 10%) opted for evacuation to public shelters, while 35% of respondents expressed their willingness to utilize GPS navigation during evacuations. These empirical data can inform decisions regarding the provision and capacity of such shelters, facilitating the allocation of necessary resources. Furthermore, these findings can assist authorities in promoting the adoption and utilization of GPS navigation systems during evacuations, ultimately improving evacuation efficiency. These aspects have received limited attention in the field but have practical implications for transportation evacuation planning. Finally, through comparative analysis, it was observed that ML algorithms outperformed conventional statistical logistic regression models in accurately predicting individual decision-making during evacuations. Thus, we utilized the ML-empowered predictive models in simulating the evacuation preferences, behaviors, and decisions of synthetic residents in the Santa Clarita area during the Tick Fire and demonstrated how the simulation results could be used to estimate evacuation decisions at the aggregated and disaggregated level and ultimately help policymakers design effective evacuation planning.

There are some limitations and areas for improvement in this study that should be addressed in future research. First, the statistical analyses and predictive model construction were based on the online survey results collected from residents in California, Colorado, and Oregon. Including other states having high wildfire risks would help further generalize the results of this work. Second, this study heavily relied on the stated preference survey results, which could introduce biases as respondents' stated preferences may not match their actual behaviors in real-world situations. Revealed preference surveys can address these biases in future studies. Third, a limited number of responses indicating a preference for evacuating to a public shelter made it challenging to capture the key factors influencing such preferences. Collecting a larger number of responses in future studies could increase the accuracy of the prediction. Finally, due to the limited availability of detailed evacuation information, the predictive models were mainly validated against real-world data only at the aggregated level. By conducting post-event interviews with individuals regarding their evacuation decisions at the parcel level, we can improve our understanding of evacuee decisions and their actual geographic distribution and further validate the predictive models at the individual level.

CHAPTER FOUR: AGENT-BASED MODELING FRAMEWORK FOR WILDFIRE EVACUATION IN DAMAGED TRANSPORTATION SETTINGS

4.1 Introduction

Having seen enormous economic and human losses that wildfires have caused over the past decades, the federal and local governments, researchers, engineers, and the public have paid increasing attention to wildfire risk management. While wildfire risks can be mitigated through both community- and individual-level proactive actions, residual risks always exist due to substantial uncertainties in wildfire risk assessment. In this case, evacuation is the most important and effective method to reduce human losses during a wildfire event. However, in the real world, mass panic and traffic jams caused by exit route shortages under simultaneous evacuation orders may complicate the simple and straightforward goal of evacuation that moves people at risk to safer places, thereby jeopardizing human lives (Cova et al., 2005). The fact that the residents in Paradise, California who tried to escape the 2018 Camp Fire got caught in a deadly traffic jam revealed that road systems were not designed for such an urgent evacuation during a hazard event. This problem can be extended to other communities at great risk of wildfires in the United States. Thus, effective community-based transportation evacuation planning has become an emergent issue in disaster emergency and risk management. Underestimation of this issue and ineffective planning could result in catastrophic human losses during a wildfire. Evacuation simulation models may assist a well-developed evacuation plan and ultimately could save human lives.

The objective of this chapter was to enhance community-based evacuation planning through the development of a novel agent-based modeling (ABM) framework. This framework assesses wildfire exposure and vulnerability within the traffic network, considering traffic mobility during evacuations while considering potential road closures caused by wildfires. The proposed framework serves as a valuable simulation tool, aiding policymakers and stakeholders in making informed decisions regarding pre-event retrofitting and mitigation strategies aimed at enhancing traffic mobility in the event of future wildfires.

4.2 Literature Review

A considerable amount of research has been carried out to develop transportation evacuation simulation models during various types of natural hazard events. Early works of emergency evacuation utilized macroscopic traffic simulations to capture dynamic network flow during evacuation process (e.g., Kisko and Francis, 1985; Burkard et al., 1993). However, most of them assumed homogenous behaviors among evacuees due to a high computational cost and estimated evacuation time at the macro or meso scale. Since the mid-1990s, advanced computer technology has enabled the utilization of microscopic traffic simulations in emergency evacuation models so as to simulate traffic flows at the individual vehicle level (Benjaafar et al., 1997; Hamacher and Tjandra, 2001). Moreover, several studies started incorporating the individual evacuees' behaviors during disasters into behavioral-based microscopic traffic simulation models. During an evacuation, individual behavior plays a critical role in evacuation process because it significantly affects pre-movement phases, reaction time, decisions to evacuate, and evacuation phases, thus affecting total evacuation time (D'Orazio et al., 2014). Using the parameters describing each evacuee's characteristics (e.g., start location, physical ability, reaction time, transportation mode, route choice mechanism, vehicle speed, etc.), individual and collective behaviors can be captured in dynamic traffic simulations at the micro scale (Sinuany-Stern and Stern, 1993).

In recent years, agent-based modeling (ABM) has received great attention due to its advantages in capturing individual and collective behaviors in a dynamic complex system (Epstein, 1999; Mas et al., 2012; D'Orazio et al., 2014; Cimellaro et al., 2017; Feng et al., 2020). ABM is one of the heuristic computational models that can simulate the action and interaction of individual agents for the purpose of finding system movement trends. In ABM, each evacuee (or vehicle) is modeled as an autonomous agent who has his/her own characteristics and follows specific decision rules. Individual agents make decisions based on interactions with other agents and the environment as well as localized knowledge (Chen and Zhan, 2014). Thus, ABM can model individual agents' behaviors simultaneously and capture their collective behavior subsequently in a dynamic system. A large number of studies have employed ABM in modeling evacuation. Pan (2006) investigated human behaviors during an earthquake event using basic concepts of psychology and sociology and incorporated them into multi-ABM for the egress analysis of a multi-story university building. Chen and Zhan (2014) utilized ABM to incorporate the effect of individual drivers' behaviors on traffic flow in three different road structures. D'Orazio et al. (2014) modeled the post-earthquake evacuation patterns of building occupants using videotape analysis.

Many other studies applied ABM to community-based transportation evacuation planning during various types of natural hazards, as it is straightforward to formulate decision rules in driving (e.g., acceleration, deceleration, land change, etc.) and traffic environment (Chen and Zhan, 2014). Specifically, hurricane evacuation has been well studied due in part to an advanced pre-event warning and relatively accurate hurricane trajectory prediction. On the other hand, wildfire evacuation has been much less studied (Grajdura et l., 2020; McCaffrey et al., 2018). Due to rapidly changing microenvironmental conditions (e.g., wind speed and direction) during wildfires, people are often forced to evacuate with short or no notice, and unnecessary evacuation occurs frequently. Thus, weather analysis and wildfire propagation prediction should be incorporated into the evacuation simulation to improve its accuracy. However, most existing studies have not accounted for hazard analysis (or have utilized very elementary hazard modeling) in their evacuation models (Kuligowski et al., 2022; McCaffrey et al., 2018; Mozumder et al., 2008; Stasiewicz and Paveglio, 2021). Rather, most of these studies constructed regression models based on survey data or developed ABM-based evacuation models based on the assumption that all residents have already been forced to evacuate their community.

Several researchers combined hazard models with ABM to represent more realistic evacuation situations. Mas et al. (2012) proposed an integrated ABM to estimate tsunami/earthquake evacuation patterns and validated this model using the 2011 Great East Japan earthquake event having a magnitude of 9.0 Mw. The proposed evacuation model was integrated with a numerical simulation of tsunami to estimate tsunami propagation and the associated start time of evacuation. While this model had a hazard modeling component, it did not perform the vulnerability assessment of a transportation system under earthquake/tsunami loading. Cimellaro et al. (2017) utilized ABM to simulate building evacuation during an earthquake event. The model first performed a numerical structural analysis of a building to estimate structural responses to a wide range of possible earthquake ground motion intensities and incorporated human anxiety and behavior under emergency. However, the vulnerability analysis in this study was limited to a single building, and therefore cannot be used to simulate a community-based evacuation process. Beloglazov et al. (2016) developed a wildfire evacuation model combining spatio-temporal firefront with evacuation trigger modeling and ABM. Although this model is one of the most comprehensive wildfire evacuation models, it still lacks a vulnerability component. In addition, the data and parameters used in the trigger and behavioral modeling were assumed or determined based on expert opinions, which made them hardly reproducible. Given that many parts of a transportation system are vulnerable to natural hazards, their physical damage and the associated reduction in traffic carrying capacity due to a hazard event should be considered in a community-based evacuation model so as to better represent traffic conditions and evacuation process during the event (Ma & Lee, 2023; Lee & Ma). To this end, the conventional ABM should be integrated with hazard analysis and vulnerability assessment of a transportation system while being supported by reproducible, quantitative data.

The main goal of this study is to support effective evacuation planning by developing an ABM framework for wildfire evacuation in damaged transportation settings. To fill the research gaps in the literature, this study develops an integrated framework that incorporates hazard modeling, vulnerability assessment, evacuee response modeling, and traffic simulation to predict traffic conditions during an evacuation and identify the critical parts of the transportation network for pre-fire risk mitigation actions. The contribution of this study is threefold: (a) the framework incorporates an advanced wildfire hazard modeling and vulnerability assessment to improve the accuracy of wildfire evacuation in damaged transportation settings; (b) this study introduces a novel approach by generating representative wildfire events within the domain of probability space, which enables the evaluation of evacuation performance while quantifying uncertainties inherent to hazardous events; and (c) this study constructs an evacuee response model based on a stated preference survey to predict individual evacuees' behavior as a firefront approaches.

4.3 Framework Development

This study develops an ABM framework for wildfire evacuation in damaged transportation settings aimed at predicting traffic conditions during an evacuation and identifying the critical parts of transportation network for pre-fire risk mitigation actions. The framework integrates wildfire simulation and vulnerability assessment with ABM to adequately represent both human behavior during an evacuation and time-dependent network functionality in microscopic traffic simulation. More specifically, as illustrated in Figure 4.1, the framework consists of four modules: wildfire simulation, vulnerability assessment, evacuee response model, and traffic simulation. The first module evaluates the spatiotemporal probability of wildfire occurrence and generates representative wildfire scenarios in probability space. FARSITE simulates a time-dependent fire-front movement for each scenario and feeds that information into the subsequent modules. The second module performs a road closure assessment to evaluate wildfire-induced changes in traffic capacity. The third module constructs an evacuee response model based on a stated preference survey to predict individual evacuees' behaviors in response to fire propagation. The fourth module simulates traffic conditions by updating traffic demand and capacity at every time step.

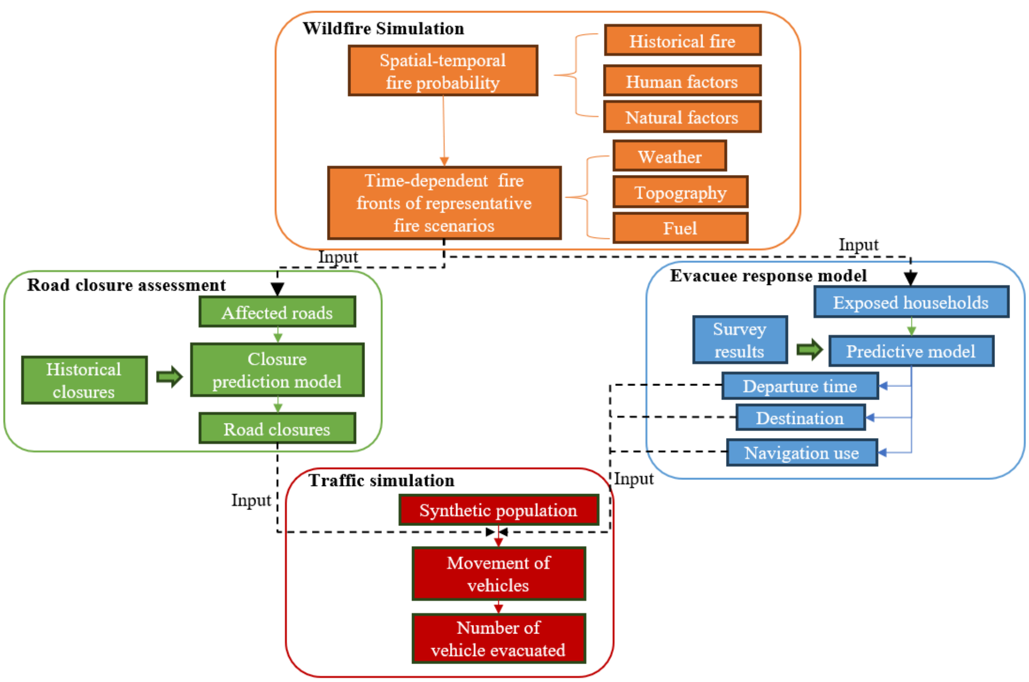


Figure 4.1 The proposed ABM framework for wildfire evacuation in damaged transportation settings

All the variables considered in the framework are updated at a fixed time step: road closure status and its traffic carrying capacity are updated based on fire propagation measured at every time step; each agent updates its state during an evacuation; and microscopic traffic simulation coupled with ABM is performed based on the time-dependent network functionality and the updated locations of all agents. Private vehicles are the primary form of mobility for people living in wildfire prone areas (Beloglazov et al., 2016). We therefore focus on capturing vehicle use and vehicular traffic in our modeling without considering pedestrian behaviors. Final results are time-dependent traffic maps to identify the critical parts of transportation networks that are the most vulnerable to wildfires and have great potential for causing traffic congestion during an evacuation. Moreover, the total number of evacuating vehicles during a given time period will also be obtained as a final result, which could be used to determine the road segments that constrain evacuation performance.

4.3.1 Wildfire simulation

As illustrated in Figure 4.1, the first module within this framework pertains to wildfire simulation. This module is responsible for quantifying the inherent uncertainties associated with wildfire occurrences and generating a set of representative wildfire scenarios within the probability space. These scenarios serve as crucial inputs for the subsequent modules, forming the foundational basis for the entirety of the simulations. This module consists of two stages: wildfire probability estimation and growth modeling. The first stage estimates spatio-temporally varying fire probabilities in the study region and generates representative wildfire scenarios. The second stage simulates wildfire growth for each scenario and records time-dependent firefront that will be fed into the subsequent modules. In the first stage, a community of interest and its surrounding areas are defined and divided into small grids (e.g., 4km x 4km) to find the probabilities of fire that can be propagated into the community. A model for estimating fire probability should consider two main causes of wildfire, including human causes (e.g., power lines, equipment failure and accidental ignitions, smoking, fireworks, campfires, arson) and natural causes. Population density, urban development, distance to freeway, railway or power lines, etc. can be used to estimate the occurrence rate of human-caused fires (Massada et al., 2012; Rodrigues and De la Riva, 2014), whereas weather and topographic factors (e.g., wind, temperature, relative humidity, landcover, elevation, slope) may affect the occurrence rate of nature-caused wildfires (Finney et al., 2011; Massada et al., 2012). In this study, the distance between the centroid of a gird cell to transmission lines, major roads, picnic/camp cite, the latitude and longitude of the centroid of a grid, the canopy cover ratio, and the population density in a grid were considered as the spatial related variables that incorporate both human-related and natural-related spatial diversity. On the other hand, temporal variation was encapsulated into a single indicator, energy release component (ERC), which can be considered as a composite fuel moisture index that reflects both live and dead fuel variability.

A generalized additive logistic regression is employed to construct a wildfire probability estimation model to account for spatiotemporal dependence and non-linear relationship between independent and dependent variables (Preisler et al., 2004). Since the wildfire probability estimation models are used to generate representative wildfire scenarios that trigger mass evacuation, the unconditional probability of a fire occurring and turning into a “large fire” should be estimated. In this study, a large fire is defined as a fire that has burned areas greater than 100 acres (Preisler et al., 2004). The unconditional probability that a large fire occurs at a given cell and a specific ERC value, $P(F_l|erc, x, y)$, is the product of the ignition probability, $P(F|erc, x, y)$, and the conditional probability of an ignition turning into a large fire, $P(F_l|F, erc, x, y)$. The generalized additive logistic regression models for estimating these probabilities are expressed mathematically by Eq. 4.1-4.3.

$$logit(P(F|erc,x,y)) = f_1(erc) + f_2(x,y) + f_3(pd_{x,y}) + f_4(delec_{x,y}, dsite_{x,y}) + f_5(cc_{x,y}) + f_6(droad_{x,y}) \quad (4.1)$$

$$logit(P(F_l|F,erc,x,y)) = f_7(erc) + f_8(x,y) + f_9(pd_{x,y}) + f_{10}(delec_{x,y}, dsite_{x,y}) + f_{11}(cc_{x,y}) + f_{12}(droad_{x,y}) \quad (4.2)$$

$$P(F_l|erc,x,y) = P(F_l|F,erc,x,y) * P(F|erc,x,y) \quad (4.3)$$

where $f(\cdot)$ = the non-parametric smooth function; erc = the ERC; x = the latitude; y = the longitude; $pd_{x,y}$ = the population density of a grid; $delec_{x,y}$ and $dsite_{x,y}$ = the distance from the centroid of a grid to the nearest transmission line and the nearest picnic/camp site ; $cc_{x,y}$ = the canopy cover ratio of a grid; and $droad_{x,y}$ = the distance from the centroid of a grid to the nearest major road. It should be noted that the non-parametric smooth functions $f(\cdot)$ are deterministic across the study area once fitted by the historical wildfire events.

To estimate the models shown in Equations 4.1, historical wildfire data should be utilized. However, most of the voxels (i.e., each grid on a given day) do not have any historical fires due to fine spatiotemporal scale. For example, it is highly probable that there has been no fire in a specific square-kilometer grid on a given day (say September 1st). Thus, a subsampling method can be used to solve the issue and create a balanced subset by randomly sampling a ratio r of no-fire voxels to estimate the ignition probability $P(F|erc,x,y)$(Brillinger et al., 2003; Preisler et al. 2004). The probability of an event that a fire occurred at voxel k (E_A) conditioned on the event that voxel k was selected in the subset (E_B) can be expressed as:

$$P(E_A|E_B) = \frac{P(E_B|E_A)P(E_A)}{P(E_B)} \quad (4.4)$$

where $P(E_A|E_B)$ = the wildfire occurrence probability predicted by the balanced subset, which can also be expressed by p_r:

$$P(E_A|E_B) = p_r = \frac{p_a}{p_a+(1-p_a)r} \tag{4.5}$$

where p_a = the probability that a fire occurred at voxel k. Equation 4.5 can be then written as Equation 6 through elementary algebra transformation.

$$logit(p_r) = \ logit(p_a) - \log(r) \tag{4.6}$$

The estimation of the conditional probability for an ignition turning into a large fire $P(F_l|F, erc, x, y)$ is straightforward and was assessed solely from the voxels associated with wildfire events. Therefore, the application of the sub-sampling strategy for probability estimation, as used for ignition probabilities, is unnecessary in this case.

Based on the spatial-temporal occurrence probability of large wildfires, calculated through Eq. 4.1-4.6, a set of representative wildfire scenarios can be generated at the centroids of geographic grid clusters and ERC percentile groups to encompass a wide range of plausible events. This approach efficiently captures the inherent uncertainty of wildfires while controlling computational complexity. The geographic grid clusters consist of closely located grids, representing clusters on the spatial scale, while the ERC percentile groups serve as clusters on the temporal scale. The probability of a representative wildfire scenario, which combines a geographic grid cluster and an ERC percentile group, can be calculated using Eq. 4.7. It should be noted that this probability reflects the likelihood of at least one wildfire occurring within those grids with all the ERCs falling within the ERC percentile group. Thus, it is calculated as the complementary event of no wildfires occurring under such circumstances.

$$P(F_l|C, E) = 1 - \prod_{erc\in EP} \prod_{x\in C_x} \prod_{y\in C_y} (1 - P(F_l|x, y, erc)) \tag{4.7}$$

where C=the geographic grids cluster, D =the day of a year, E=the ERC percentile group, C_x, C_y=the latitudes and longitudes of the centroids of the all the grid cells within the geographic grids cluster.

In the second stage, the ignition locations of the representative wildfire scenarios were assumed to be the centroids of the geographic grid clusters, wildfire growth was then simulated to generate spatiotemporal firefront and time-dependent fire map. Wildfire growth is mostly conditioned on topography as well as environmental and weather conditions. In this study, the Fire Area Simulator (FARSITE), that is a widely used wildfire simulation program now included in FlamMap 6, is used. FARSITE utilizes Huygens principle (Richards, 1990), where small elliptical wavelets are formed around the perimeter of the fire (i.e., firefront) at the current time step, and the outer edge of these wavelets becomes a new firefront at the next time step. Because an iterative simulation structure allows time-dependent inputs, FARSITE has the ability to model wildfire growth under heterogeneous weather, fuel, and topography conditions, which produces more accurate simulation results compared to the other software programs. However, FARSITE is computationally inefficient: FARSITE simulation time could be over 10 times longer than the other programs, which limits its usage when simulating a large and complex wildfire or generating a large suite of fires. On the other hand, other widely used wildfire simulation software programs, such as FlamMap, FSPro, and FSim, model wildfire growth based on the Minimum Travel Time (MTT) method developed by Finney (2002). MTT is a simplified raster-based fire growth model searching for the minimum travel time among the nodes of a grid. Fire shape is created by contouring the nodes with the same minimum travel time. Since this method holds weather and fuel conditions constant in time, its simulation results are not as precise as FARSITE. However, MTT greatly reduces simulation time. Since the prediction accuracy of fire growth at every time step is key to effective wildfire evacuation modeling, FARSITE is used in the fire growth modeling of this study despite its relatively high computational costs.

A set of grid-specific raster-based topographic inputs (e.g., elevation, slope, and aspect) and fuel property inputs (e.g., canopy cover, fuel mode, canopy stand height, canopy base height, and canopy bulk density) are collected and used as inputs for wildfire growth modeling. Additionally, hourly weather data including temperature, relative humidity, precipitation, wind speed, and wind direction are collected for a representative Remote Automated Weather Station (RAWS) in the study region to capture temporal characteristics. For each representative wildfire scenario, the spatiotemporal firefront is generated and fed into vulnerability assessment (Module 2) and evacuee response model (Module 3) to identify the locations of closed road segments and estimate the timing of evacuation trigger and departure time.

4.3.2 Traffic network vulnerability assessment

Traffic networks play a pivotal role in facilitating evacuations, forming the foundation for transporting individuals to safe locations. The assessment of post-wildfire road capacities holds significant importance, as it directly influences the evaluation of transportation network performance during evacuations. Understanding how traffic networks function after a wildfire event is vital for effective evacuation planning and management. As such, this module aims to conduct a vulnerability assessment of roads to estimate the diminished flow capacity of the transportation system in the event of a wildfire.

Traditionally, roads have been considered non-combustible materials, largely immune to physical damage in wildfire situations. However, practical challenges like reduced visibility and smoke-related health concerns often lead to road closures during these events. In this module, road closure occurrences are addressed, and a predictive model is developed based on historical data encompassing fire and road closure incidents.

The vulnerability assessment in this study specifically focuses on road closures resulting from direct or indirect impacts caused by wildfires. The dataset was compiled from 30 major wildfire events that took place between 2015 and 2022 in the western United States. Table 4.1 presents the chosen wildfire events, while Figure 4.2 depicts the locations of all affected roads. All road locations and attributes were extracted from the OSM road layer. The selected wildfire events resulted in 18,581 impacted road segments, of which 1,427 segments experienced closures during these events. To address the issue of imbalance, closed road segments were up-sampled to match the number of non-closed road segments, resulting in a dataset containing 37,162 road segments. The road properties considered in constructing the road closure predictive model include road type, whether it is a one-way road, its maximum speed limit, the number of other roads crossing under it, and the presence of bridges or tunnels on the segment. The Random Forest (RF) model was selected as the road closure assessment model due to its higher accuracy (97%) compared to traditional logistic regression (70.5%). The pre-trained RF model, utilizing the up-sampled dataset, will then be applied to the impacted road segments from representative wildfire scenarios to identify potential road closures.

Table 4.1 Selected major wildfire events in the western U.S.

Fire	**Acres**	**Year**	**Fire**	**Acres**	**Year**
Dixie	963405	2021	Camp	153336	2018
Bootleg	413717	2021	Rough	151547	2015
Creek	379883	2020	Archie creek	131596	2020
LNU Lightning Complex	363220	2020	Dolan	124310	2020
Claremont-Bear	318777	2020	Woolsey	96949	2018

Thomas	281894	2017	Evans canyon	75693	2020
Carr	229651	2018	Rocky	69438	2015
Pearl hill	223731	2020	Tamarack	67054	2021
Monument	223127	2021	Loyalton	56477	2020
Caldor	221786	2021	Archer mountain	48879	2017
Beachie creek	193566	2020	Earthstone	42253	2017
Chetco bar	191242	2017	Slinkard	40142	2017
Cold spring	189912	2020	Sobenchain	32671	2020
Range 12	176610	2016	Bobcat	30024	2020
Holiday farm	173393	2020	Mill	3935	2022

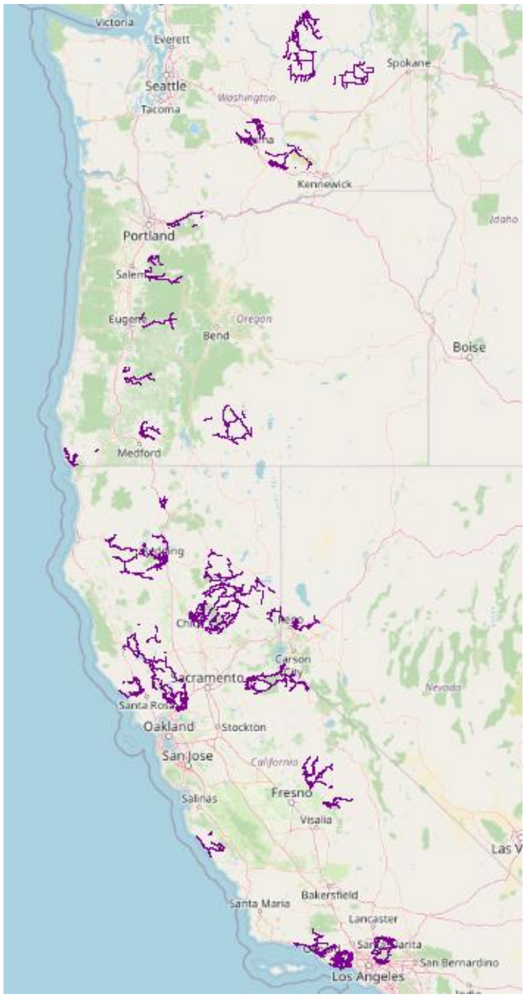


Figure 4.2 Locations of impacted roads during selected major wildfire events

4.3.3 Evacuee response model

In the fourth module, traffic demand will be estimated at the individual evacuee, household, or vehicle level. Thus, in this module, individual responses and behaviors during evacuation will be modeled and simulated. Similar to the classic four-step transportation planning model consisting of demand estimation, destination choice, mode choice, and trip assignment, evacuation modeling generally includes evacuation decision, traffic mode split, destination choice, departure time estimation, and information update procedure. Individual evacuees start to evacuate at different points in time even when they are exposed to the same level of wildfire threat. Evacuation behavior is a key factor in realistically simulating evacuation at the community level and can be defined by a set of actions of individuals and external stimuli during an evacuation (D'Orazio et al., 2014).

To mathematically model an individual's evacuation behavior, a series of three events is considered in this project: evacuation trigger, decision time delay, and preparation time (Mas et al., 2012). First, four types of external stimuli serve as evacuation triggers for evacuees. An evacuation alert (Level I) lets people know that a wildfire threat is in their areas and suggests they consider evacuation in the event that it becomes necessary. An evacuation warning (Level II) indicates the high probability of a need to evacuate. An evacuation order (Level III) asks people to evacuate within a specified time period. A large portion of people may respond to these three levels of evacuation, but some people may wait until a firefront is within visible range of their initial locations (Mas et al., 2012). As such, evacuation triggers, which can actually induce an individual evacuee's response, may depend on his or her risk-averse attitude and other characteristics and should be identified and explicitly incorporated into evacuation modeling. The timing of each evacuation trigger can be estimated using the spatiotemporal firefront obtained from Module 1. For example, if the distance between the firefront and the initial location of an evacuee is within a specific threshold, one of the stimuli is activated, and the evacuee's response is simulated based on his/her risk attitudes and characteristics through MCS. The departure time is not immediately after the timing of the evacuation trigger but may be delayed due to decision delay and preparation. Decision delay may occur if household members (or a group of people who plan to evacuate together) need to make a collaborative decision to evacuate. Decision delay may also depend on an evacuee's awareness, beliefs, and priorities (Beloglazov et al., 2016). Preparation time is also an evacuee-specific parameter.

We conducted an online survey of residents in wildfire-prone areas in the United States to investigate their evacuation behavior and to develop quantitative relationship between individual characteristics and their responses during evacuation. These models will have a significant impact on traffic congestion and bottlenecks in Module 4. More detailed information on survey data collection and analyses was introduced in Chapter four, and the resultant model was adopted in this study as the evacuee evacuation decision prediction algorithm.

4.3.4 Traffic simulation

The reduced functionality of a transportation network (Module 2) can endanger human lives when combined with the elevated travel demand patterns (Module 3) during an evacuation. Module 4 will perform traffic simulation by combining Module 2 results with Module 3 results to predict traffic conditions during an evacuation and identify the critical parts of the transportation network for pre-fire risk mitigation actions. Travel demand modeling for wildfire evacuation can be generally classified into trip-based and activity-based approaches (Intini et al., 2009). The reference unit for the trip-based approach is origin-destination pairs, and the total demand is estimated at the aggregated level. This approach is usually adopted in macroscopic traffic simulation and is more suitable for evacuations involving large geographic areas. On the other hand, the activity-based approach modeling each evacuee as an agent is often adopted in microscopic traffic simulation and is more appropriate for regional evacuation modeling due to its high computational burden. Considering that the wildfire evacuation is often limited to the community or county level, activity-based microscopic traffic simulation has been widely used in existing wildfire evacuation studies (Cova and Johnson, 2002; Grajdura et al., 2020; Mancheva et al., 2019).

In this study, the activity-based microscopic traffic simulation is performed within ABM. There are various ABM software programs that have been used in evacuation studies. NetLogo, a java-based program, was used by Grajdura et al. (2020) to model wildfire evacuations. Cova and Johnson (2002) used Paramics, which is a commercial traffic simulation software, in simulating wildfire evacuation. Transportation Analysis and Simulation System (TRANSIMS) and Simulation of Urban Mobility (SUMO) are also widely used software programs in evacuation planning and simulation (Beloglazov et al., 2016; Lopez et al., 2018; Yin et al., 2014). SUMO was chosen to perform traffic simulation in the fourth module of this framework due to its accessibility and flexibility.

Each evacuee in the community is modeled as an agent and based on the survey results obtained from Module 3, individual characteristics and decision rules are assigned to each agent and considered in ABM. In the ABM, individual agents determine their actual departure time, evacuation route, and destination prior to departure. After the agents depart from their point of origin (i.e., the results from Module 3), they will enter the transportation network and choose their evacuation routes using their routing selection method (i.e., the results from Module 3). Some agents who will not use real-time maps may not be able to select the optimal evacuation routes because they will not have any real-time information, such as the locations of closed roads due to fire, traffic congestion, etc. As such, the spatiotemporal movements of individual agents will be recorded at every time step.

The traffic carrying capacities of the links (i.e., the results from Module 2) are also dynamically updated as fire propagates over time. Dynamic updates on link capacity and individual agents' locations are incorporated into microscopic traffic simulation to predict traffic flows at the level of individual agents and capture traffic dynamics considering collective actions among the agents. The ABM framework for wildfire evacuation in damaged transportation settings will provide time-dependent traffic maps to identify the critical parts of the transportation network that are the most vulnerable to wildfires and have great potential for causing traffic congestion during an evacuation. Moreover, the total number of evacuating agents during a given time period will also be obtained as a final result, which could be used to determine the bridges that need to be strengthened in order to minimize human losses during a wildfire evacuation.

4.4 Illustration example: the city of Santa Clarita, California

4.4.1 Introduction

To illustrate the application of the proposed ABM framework to a real-world community, the City of Santa Clarita, California was selected as an illustrative example. The City of Santa Clarita is located in northwestern Los Angeles County in California as shown in Figure 4.3, and its 2020 population was 228,673. This city was selected because many homes in Santa Clarita were in WUI and at high wildfire risk, and thus it had a high potential for a mass wildfire evacuation. One of the recent fires affecting the City of Santa Clarita is the Tick Fire which broke out on October

24th, 2019, and endangered over 10,000 structures in the city. During the fire, about 40,000 people were affected by the evacuation order.

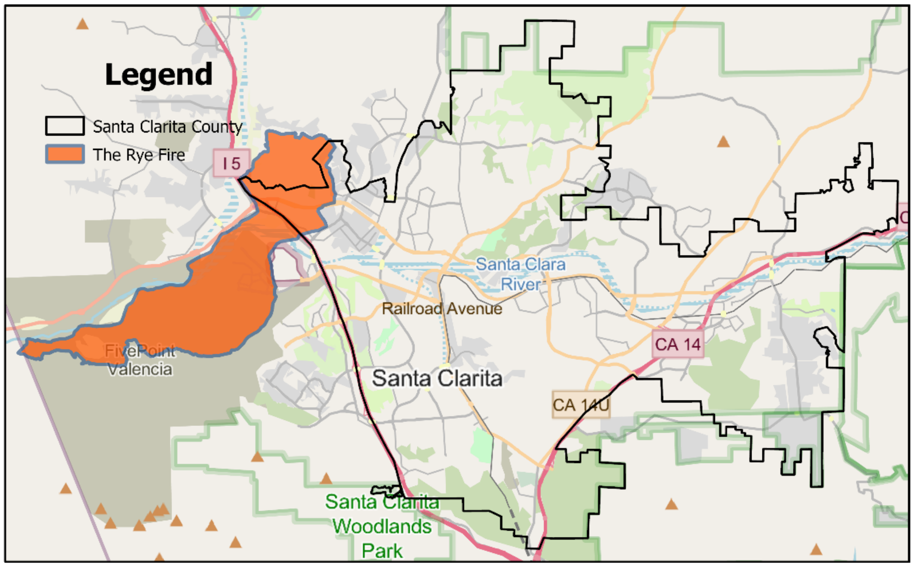


Figure 4.3 The City of Santa Clarita affected by the Rye Fire

4.4.2 Module 1: wildfire simulation

The first stage of the wildfire simulation module is to generate the spatiotemporally varying fire probabilities in the study region as shown in Eq. 4.1-4.6. The required inputs for the wildfire occurrence probability estimation models (see Equations 4.1-4.2) include gridded daily climate data (i.e., the ERC), the gridded human factors (i.e., population density, distances from grid centroid to the closest major roads, camp/picnic sites, and transmission lines.) and gridded topographic and fuel layer. The University of Idaho Gridded Surface Meteorological Dataset (gridMET, Abatzoglou, 2012), daily high-spatial resolution (~4 km) climate data collected since 1979, was used for the climate data. The gridded human factors were generated by utilizing OSM data. The gridded topographic and fuel data available from the LANDFIRE program had a spatial resolution of 30 meters and were used as the input in constructing the wildfire occurrence probability estimation model. Given that the largest wildfire in California history scorched more than 1 million acres, historical wildfire events within 31 zip codes (i.e., 2739905 acres) around the city were collected for estimating wildfire ignition probabilities. During the period between 2002 and 2021, there were 5,288,820 voxels. Among them, only 435 voxels had historical fire events that burned areas greater than 100 acres, while the remaining 5,288,385 voxels did not have any large fires. As described in Section 4.3.1, to address the issues with imbalanced data, 435 no-fire voxels were first randomly sampled, which is a subsampling method. Then, the subset consisting of 435 fire voxels and 435 no-fire voxels was divided into training and testing sets to construct the wildfire occurrence probability estimation model. The accuracy of the ignition probability model yields 80% prediction accuracy while the conditional probability of an ignition turning into a large fire model yields 75.2% accuracy. There are multiple ways to improve its accuracy, such as including longer climate data (e.g., collected during the period between 1979 and 2021).

The wildfire occurrence probability map constructed through the estimation model can be used to generate a set of representative scenarios. In this study, the evacuation simulation was primarily focused on mass evacuation at the early wildfire outbreak stage, since this stage pose great challenge to the network performance, the area including and around the Santa Clarita city and been divided into 24 4km*4km grid cells (94,888 acres). The whole area was divided into 6 sub-clusters with each sub-cluster including four grid cells. Six ERC percentile groups were considered including 0th-40th percentile, 40th-60th percentile, 60th-80th percentile, 80th-90th percentile, 90th-97th percentile, 97th-100th percentile. For each of the spatial centroid and each ERC percentile group, one representative wildfire scenario was generated based on the spatial-temporal occurrence probability map with a probability centroid over the sub-cluster at spatial scale and ERC percentiles at temporal scale. The location of the spatial sub-clusters and their centroids can be found in Figure 4.4. The probability of each representative wildfire scenario can be found in Table 4.2, where the row and column represent the cluster and the ERC percentile group of the representative events respectively.

Table 4.2 Probability of representative wildfire scenarios (i.e., $P(F_l|C, EP)$)

	0^{th} - 40^{th}	40^{th} - 60^{th}	60^{th} - 80^{th}	80^{th} - 90^{th}	90^{th} - 95^{th}	95^{th} - 100^{th}
1	0.61%	0.34%	0.52%	0.23%	0.26%	0.65%
2	0.15%	0.09%	0.14%	0.06%	0.07%	0.18%
3	0.24%	0.14%	0.22%	0.10%	0.11%	0.28%
4	0.34%	0.18%	0.28%	0.12%	0.14%	0.34%
5	0.43%	0.23%	0.35%	0.16%	0.18%	0.44%
6	0.32%	0.18%	0.28%	0.12%	0.14%	0.35%

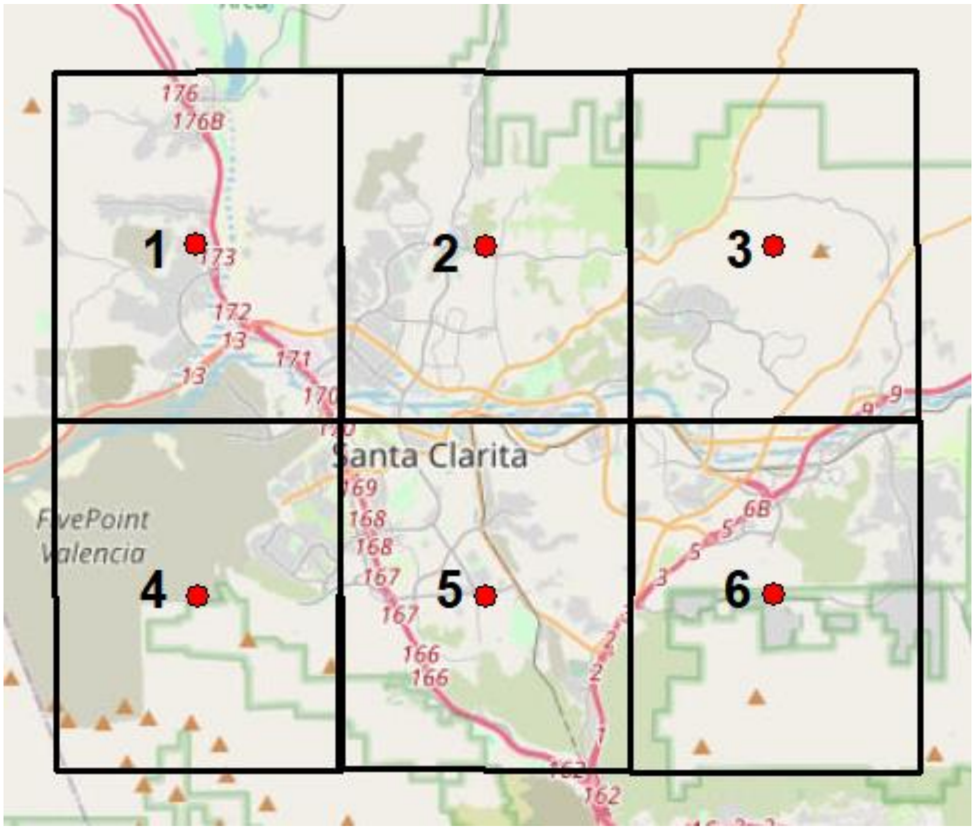


Figure 4.4 Clusters and their centroids

The ignition location of each representative wildfire event was designated as the spatial centroid of the sub-cluster it represented. The required inputs to FARSITE include hourly weather data and a set of raster files (elevation, slope, aspect, fuel model, canopy cover, stand height, canopy base height, and canopy bulk density). The hourly weather data were available from the Remote Automatic Weather Station (RAWS) located throughout the United States, while all raster files were downloaded from the LANDFIRE program. It should be noted that the hourly data used to simulate the representative wildfire event utilized hourly weather data from historical weather records. The date of the hourly data been used was determined by locating the date with the same ERC been chosen as the representative ERC within the ERC percentile group. Since 40 Scott and Burgan Fire Behavior Fuel Models (FBFM40) does not support fire spread into urban and suburban areas, which was not true when compared with the historical wildfire events in Santa Clarita area (i.e. Tick Fire, Rye Fire). Therefore, in the case study, we replaced urban and suburban development (NB1) with short, sparse dry climate grass (GR1) to allow the fire to propagate into urban and suburban areas.

In order to validate the simulation performance of the wildfire simulation algorithm, the simulated fire perimeter during the first burning day of the Rye Fire (December 5, 2017) was compared with the actual perimeter, which is shown in Figure 4.5. Due to the limited capability of FARSITE to model suppression and barrier effect, the simulated fire perimeter was a bit different from the actual one while the propagation directions of both actual and simulated fires were similar. Only the first day simulated fire perimeter was considered herein because the evacuation order was lifted the evening of the first burning day and further wildfire growth simulation was unnecessary for estimating evacuation. Moreover, a lack of a suppression model in FARSITE requires additional assumptions about human suppression efforts in order to stop the fire. While FARSITE has limitations in simulating the Rye Fire from its ignition to full containment, the similar propagation direction of both simulated and actual fires (see Figure 4.5) indicates that the model had the capability to simulate fire growth successfully until human intervention got involved.

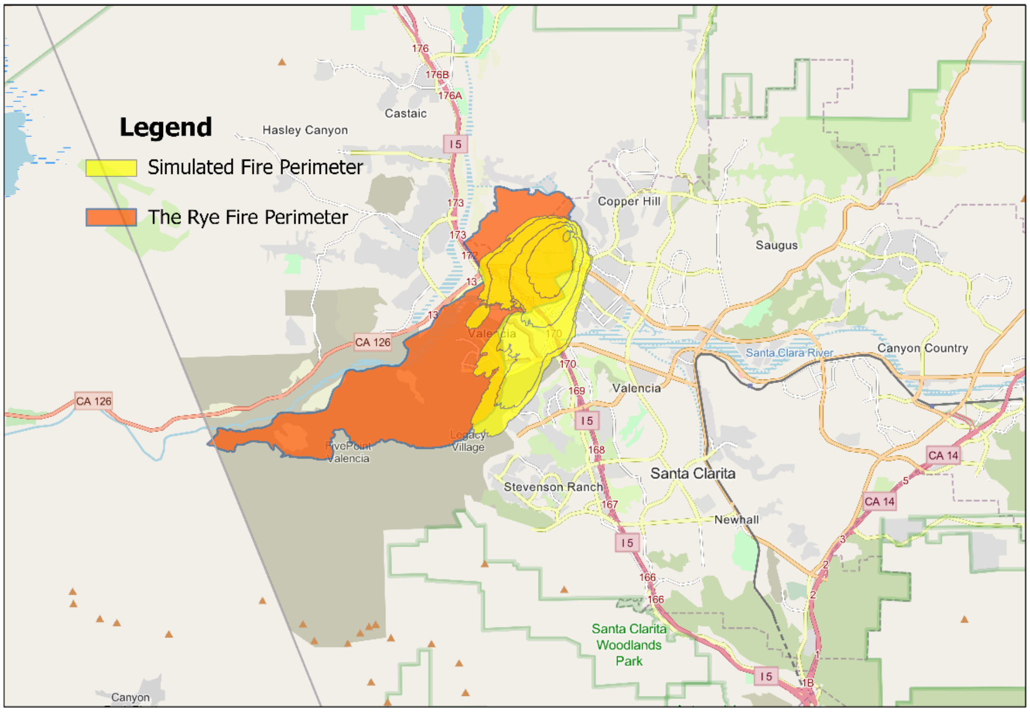


Figure 4.5 Comparison between the simulated fire perimeter (only during the first burning day) and the Rye Fire perimeter

4.4.3 Module 2: network vulnerability assessment

The location of the impacted roads by all of the representative wildfire events can be found in Figure 4.6 shown as black links. The attributes of the roads were extracted from the OpenStreetMap (OSM) road layer, including the road type, road access restriction (one-way or both way), maximum allowing speed, layer (vertical relationships between crossing or overlapping), bridge, and tunnel. The attributes of the impacted road segments were processed and evaluated by the network vulnerability model estimated through the historical closures described in section 4.3. Among the 3623 road segments that were impacted by the representative events, 54 road segments were predicted as closed, shown as the red segments in Figure 4.6. The reduced capacity of the network for each representative wildfire event was then incorporated into the traffic simulation in module 4.

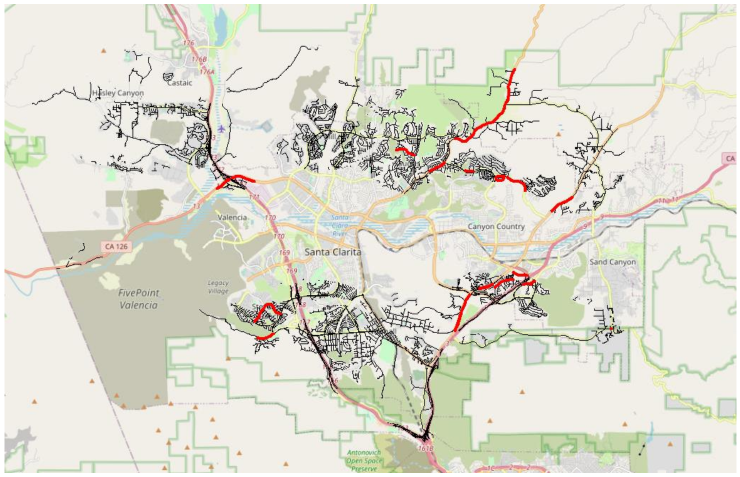


Figure 4.6 Impacted roads and predicted closed roads (black: impacted roads; red: closed roads)

4.4.4 Module 3: evacuee response model

In the third module of the proposed framework, the evacuee response model was simulated to reflect diverse individual behaviors and responses during an evacuation. To apply the evacuee response model developed based on the survey data to the case study, detailed information about the properties and characteristics of individual residents and households in the community was required. Whereas demographic information is available from the Census dataset, some of the key explanatory variables needed to estimate their evacuation timing or the use of real-time navigation (e.g., risk attitude, wildfire evacuation experience) are often not available. Thus, in this case study, we generated a synthetic population for the City of Santa Clarita.

Two standard approaches to generating a synthetic population are synthetic reconstruction (SR) and hill climbing (HC) (Namazi-Rad et al., 2014). The SR approach is a traditional method for generating a synthetic population based on both disaggregated- and aggregated-level data. By assuming that disaggregated-level data (i.e., seed data) can fully represent the target population, this approach samples individuals with the required sociodemographic characteristics from the true population in the study area, which is typically extracted from Census data, using a weighting technique. The HC approach is an optimization algorithm that maximizes an objective function. It starts with a random selection of units from the seed population and iteratively replaces them until improvement becomes negligible (Namazi-Rad et al. 2014). While both approaches are capable of generating reliable synthetic populations relative to the true population's marginal distributions (Jain et al. 2016), the SR approach was adopted in this study because user-friendly and well-developed software programs are available.

First, we used PopGen to generate a synthetic population in the City of Santa Clarita at the census-tract level. PopGen is a software program that produces synthetic populations while controlling and matching both individual- and household-level attribute distributions (Bar-Gera et al. 2009; Konduri et al., 2016; Ye et al. 2009). The seed population was adopted from the Public Use Microdata Sample (PUMS) produced by the U.S. Census Bureau, which was a small portion of the true population (including both households and individuals) without identification. The marginal distributions of the control population characteristics in the study area were available from the Census Bureau’s American Community Survey (ACS). The generated synthetic population consisted of 83,558 households and 246,830 residents with no significant difference from the marginal distributions of the true population’s key characteristics (e.g., household size, household income, the presence of children, age, gender, race, education, and employment status). All individuals in the synthetic population were given a unique ID number so that the individuals having the same ID number were assumed to be in the same household.

To relate each household to its home, the locations, shapes, and dimensions of all buildings in the City of Santa Clarita were obtained from the OpenStreetMap database. Buildings were classified into residential buildings and commercial buildings. The residential buildings having the top 30% shape length were labeled as multifamily residential buildings. The ratio of 30% was determined based on the 2019 U.S Census Bureau American Housing Survey that 31.4% of housing in the U.S. were multifamily housing. For each census tract, all synthetic households in the census tract were randomly assigned to residential buildings in the same census tract. Similarly, all individuals who worked full-time or part-time were randomly assigned to workplaces (i.e., commercial buildings).

After allocating individuals to their households, homes, and workplaces, it was assumed that each household formed a decision group and shared the same evacuation decision during the evacuation process. Then, the evacuee response modeling for each household was constructed based on the survey data and results described in Section 4.3. The evacuation timings of all synthetic households in the city were determined based on the fitted RF model. The explanatory variables for the evacuation timing included education, insured status, routinely use of navigation, past effective evacuation experience, disaster plan, financial risk preference. Whereas the first two characteristics of synthetic households were already realized during the synthetic population generation, the last four properties of each household were not known because these properties were often not available from the U.S. Census data. Thus, using MCS, these properties of each household were randomly sampled from the histograms of the survey results (see Appendix A). Additionally, some of these explanatory variables are individual-level variables (e.g., education and the use of real-time navigation). This study assumed that the survey respondent was representative of his or her household or primary decision-maker and used the individual-level variables to predict household-level evacuation decisions. However, it should be noted that this assumption may introduce bias due to representative issues (Hung and Wang, 2022; Seebauer et al., 2017). The results indicated 21.1% synthetic households intended evacuate without official order, 34.2% synthetic households intended evacuate under voluntary evacuation order, 39.7% synthetic households intended evacuate under mandatory evacuation order, and 5% synthetic households intended to stay or evacuate after observing physical cues (i.e., embers, smokes, flames).

By combining the wildfire growth simulation results from Module 1, the evacuation times of all households were determined. At every time step, once a new firefront was updated, three buffer zones were created to generate three types of evacuation triggers: a 2-mile buffer around the updated firefront was used to trigger the evacuation of the immediate evacuation group (evacuate without official order); a 1-mile buffer was used to trigger the evacuation of the voluntary evacuation group, and a 0.5-mile buffer was used to initiate the evacuation of the mandatory evacuation group. The actual departure time may be delayed due to decision delay and preparation. While the time associated with evacuation delay is affected by various evacuee- and household-specific parameters (e.g., awareness, risk attitudes, priorities, and beliefs), it is difficult to identify key independent factors affecting the delay time and their statistical relationship because of the abstract nature of major parameters. Thus, in this study, the delay time of each household mainly due to evacuation preparation was randomly sampled from the frequency distribution of preparation time shown in Table 4.3. It should be noted that another 0.2-mile buffer was created to simulate the case when fire front is too close to the household, and they need to departure immediately no matter how long they need to finish package and preparation.

Table 4.3 Frequency distribution of evacuation preparation time

	< 10 mins	11 mins – 20 mins	21 mins – 30 mins	31 mins – 60 mins	> 60 mins

Immediate	56(25.2%)	57(25.7%)	52(23.4%)	36(16.2%)	21(9.5%)
Voluntary	34(12.2%)	49(17.6%)	88(31.5%)	63(22.6%)	45(16.1%)
Mandatory	18(9.1%)	27(13.6%)	46(23.2%)	62(31.4%)	45(22.7%)

The evacuation destinations of the synthetic households are also uncertain. As presented in Appendix B, households may have a number of destination choices, including someone else's house, hotel, public shelter, secondary residence, portable vehicle, and rental house. In this case study, it was assumed that public shelters were located in the City of Santa Clarita, while other destinations were located outside the city. Figure 4.7 shows the three schools that are located within the city. These schools were considered public shelters in the case study. The intention to evacuate to the public shelter was evaluated based on the fitted regression model as described in section 3.4.3, the explanatory variables considered including age, gender, household size, home ownership, the presence of children, car ownership, routinely use of navigation, insured status, past effective evacuation experience, evacuation plan, confidence in property, and risk preferences for personal safety and financial safety respectively. Similar to the evacuation timing, the majority decision among all the adult household members were determined as the household level decision, the results evaluated 362 households (0.4%) intended to evacuate to public shelters. their final destinations were randomly assigned to one of the three public shelters. Three major community exits shown in Figure 4.7 were assigned to households whose final destinations were not public shelters.

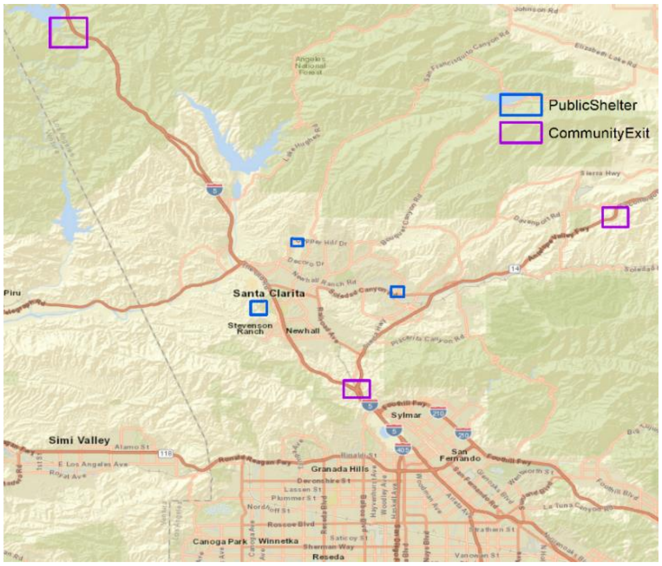


Figure 4.7 Final destination locations

In addition to assessing evacuation timing and destination preferences, this module also examined individuals' inclinations towards utilizing GPS navigation during evacuations. The adoption of GPS navigation can facilitate access to real-time travel information, allowing individuals to dynamically adjust their routes to circumvent traffic congestion while evacuating. Much like other choices related to evacuation, households in which a majority of adult members expressed an intent to employ GPS navigation would indeed proceed to do so during an evacuation event. The prediction of GPS navigation usage was achieved through the application of a fitted SVM model, as discussed in section 3.4.3. The model incorporated a range of explanatory variables, including employment status, property ownership, whether household members with spatial needs, routine navigation usage, past evacuation experience, and their safety risk attitudes. Within the 83,558 synthesized households, the SVM model projected that 10,971 of them would opt for GPS navigation during the evacuation process, constituting approximately 13.1% of the total population.

This module facilitated the generation of evacuation timing, departure time, GPS navigation usage, and final destination determinations for all synthetic households based on the survey results. It's important to note, however, that this module did not consider public transportation. To address this limitation, supplementary assumption was introduced. This assumption assumed that households without vehicle ownership yet desiring to evacuate would utilize hypothetical vehicles for the evacuation process. Given that this applied to only 4,142 (5%) of the synthetic households, the impact of this assumption on the overall number of vehicles within the network and simulation performance remains marginal. In forthcoming investigations, these hypothetical vehicles could potentially be replaced by public transportation or ride-sharing alternatives. Finally, a total of 166,069 vehicles (both actual and hypothetical vehicles) were used during a wildfire evacuation. At each time increment, the module captured and documented the impending departures of vehicles, a crucial facet that was factored into the estimation of traffic demand within the subsequent fourth module.

4.4.5 Module 4: traffic simulation

The agent-based traffic simulation was performed using SUMO. The vehicle-only transportation network in the City of Santa Clarita is illustrated in Figure 4.8. At every time step, the network capacity (i.e., the output from Module 2) and traffic demand (i.e., the output from Module 3) were updated and used as input data in SUMO. In SUMO, vehicles were considered autonomous agents, and their actions and interaction were simulated during a wildfire evacuation. Moreover, the evacuees were classified as navigation users and non-navigation users as described in section 4.4.4. With the GPS-navigation device, the navigation users can access the real-time map and reoptimize their route at every 180 simulation seconds and reroute if any faster routes were identified. The non-navigation users, on the other hand, will only take the shortest (but not the fastest) routes because they chose familiar routes or relied on conventional maps during an evacuation without having real-time information. The results from this module were the locations of all vehicles at every second during the evacuation process, the time series of the number of vehicles in the transportation network, the number of vehicles that successfully evacuated, average speed, etc.

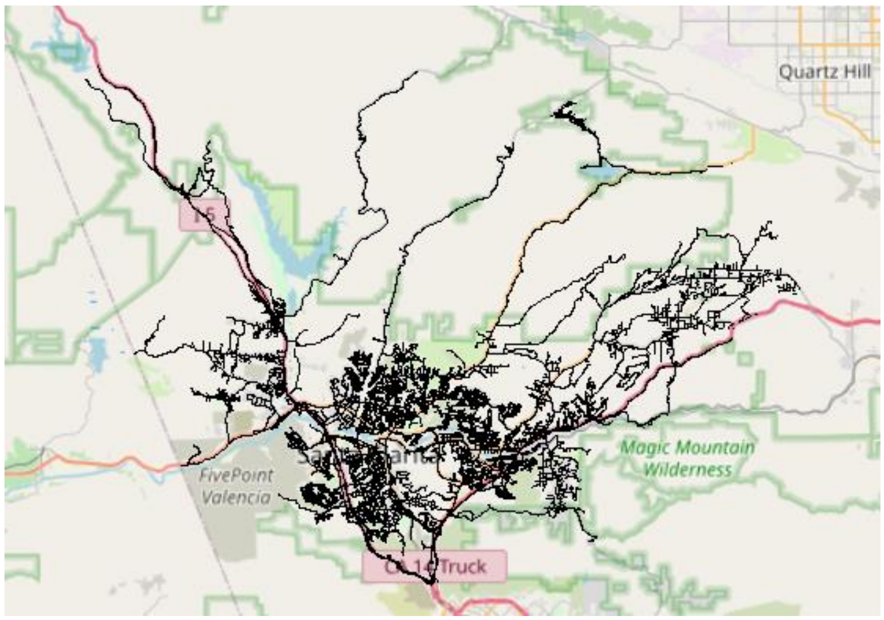


Figure 4.8 Vehicle-only transportation network in the City of Santa Clarita

4.4.6 Results and discussions

The proposed framework was demonstrated using the City of Santa Clarita as a case study. The procedure and outcomes of each individual module are outlined below. Through the first module, a probability map was created to illustrate the likelihood of wildfire occurrences across the study region. This map was then employed to determine the ignition locations and corresponding probability of representative wildfire events. The propagation of the representative wildfire events was then simulated through FARSITE. For each of these events, the assumption was made that the fire initiation occurred at 9 am and ceased propagation at 8 pm. It's crucial to clarify that the conclusion of the simulation doesn't necessarily denote complete fire containment. The simulation timeframe was selected to model network performance in scenarios where no- or short-notice was given. Beyond this timeframe, human intervention was expected to play a role, and the accuracy of the simulation derived from FARSITE was projected to diminish. With the second module, the focus shifted to estimating the temporal and spatial specifics of road closures. Moving on to the third module, a synthetic population was generated for the City of Santa Clarita. The evacuation decisions of the synthetic population were determined based on survey findings and machine learning predictive models. The models facilitated the identification of evacuation triggers, eventual destinations, and the utilization of GPS navigation for all households within the affected region. By integrating this information with the time-dependent fire-front movement obtained from the first module, the evacuation timings for all households were established. These timings subsequently served as time-varying traffic demand inputs for the traffic simulation. Finally, the fourth module executed a traffic simulation during the evacuation process to capture the movement of all evacuated vehicles at every second.

Utilizing the pre-trained road closure assessment model discussed in Section 4.3.2, we are able to assess the closure probability of all road segments within the vehicle-only road network of Santa Clarita city if they were enclosed by wildfire perimeters, as shown in Figure 4.9. The illustration discloses a pattern where residential and minor roads are less prone to road closures, in contrast to several major roads and highways, which exhibit a higher likelihood of being subjected to closures. This observed trend can be attributed to the elevated traffic volume and speed restrictions typically associated with these prominent road categories. The comprehensive closure probability map serves as a valuable resource for policymakers and stakeholders, affording a holistic perspective on network accessibility when confronted with the threat of wildfires.

Additionally, it provides a pre-event outlook on prospective road closures, offering insights into potential impacts caused by forthcoming wildfire incidents. This array of information empowers decision-makers to formulate well-informed strategies and plans, effectively managing and mitigating the ramifications of wildfires on Santa Clarita city's transportation infrastructure.

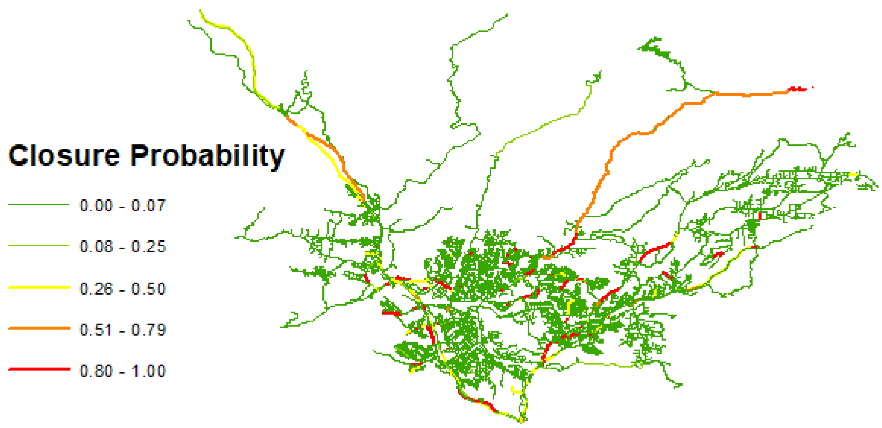


Figure 4.9 road closure probability of road segments in Santa Clarita

To illustrate the presence of both spatial and temporal variations in the collective evacuation performance, graphical representations were crafted. These figures, shown in Figure 4.10 and 4.11, portray the average cumulative count of vehicles traversing the network across geographical grid clusters and Emergency Response Coordination (ERC) percentile groups, respectively, at each second. For the computation of the average cumulative vehicle count across clusters, the cumulative vehicle count for each time step was multiplied by its associated conditional probability, as determined by Equation 8. Correspondingly, the average cumulative vehicle count across ERC percentile groups was computed by utilizing the conditional probability derived from Equation 9. This approach enabled the visualization of the dynamic changes in evacuation performance both in terms of geographical locations and ERC percentile groupings.

$$P(E_i|C_j, fire) = \frac{P(E_iC_j|fire)}{\sum_i P(E_iC_j|fire)} \quad (4.8)$$

$$P(C_j|E_i, fire) = \frac{P(E_iC_j|fire)}{\sum_j P(E_iC_j|fire)} \quad (4.9)$$

Where $P(E_i|C_j, fire)$ = the probability of a fire outbreak under E_i EP group if the fire will occur in cluster C_j. $P(C_j|E_i, fire)$ = the probability of a fire outbreak within cluster C_j if the fire will occur under E_i EP group. $P(E_iC_j|fire)$ = the probability of a fire outbreak under E_i EP group and within cluster C_j if the fire will occur in the Santa Clarita area.

Figure 4.10 (a) presents a comparison of the average cumulative number of vehicles entering the network across distinct geographic grid clusters on a per-second basis. Figure 4.10(b) illustrates the comparison of the average cumulative evacuation rate. This evacuation rate is defined as the ratio between the cumulative number of vehicles that have successfully reached their destination and the total number of vehicles that departed the area by the end of the simulation. The traffic simulation extends beyond the termination of fire-front updates (i.e., 8pm), allowing all evacuation vehicles adequate time to exit the network. As shown in Figure 4.10b, in clusters C1, C2, and C5, the majority of the evacuation vehicles entered the network within the first 3 hours of the evacuation process. This pattern can be attributed to the spatial arrangement of residential structures. Clusters C1, C2, and C5 exhibit a high potential for experiencing abrupt or urgent evacuation scenarios, emphasizing the necessity for enhanced awareness and preparedness among residents in these regions. Furthermore, revealed by Figure 4.10a, clusters C2 and C5 exhibit the highest volume of evacuations when compared to the remaining clusters. The comparisons in Figure 4.11 underscore the significance of clusters C2 and C5 in terms of their vulnerability to wildfire risks. Their higher exposure serves as a reminder of the critical need for tailored mitigation strategies and heightened vigilance to ensure the safety and preparedness of the residents inhabiting these areas.

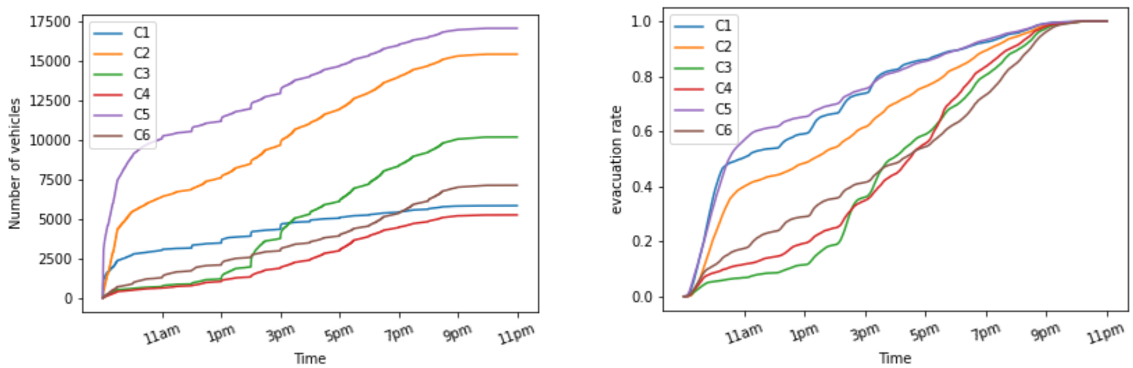


Figure 4.10(a) Average cumulative number of vehicles entered the network; and (b) Average cumulative rate of evacuation

In the SUMO traffic simulation, a vehicle that is trapped at same location for a certain amount of time is teleported to the next available edge on its route. Thus, the teleported vehicle can be treated as one that is stuck in severe traffic congestion. As shown in Figure 4.11, the average cumulative number of teleported vehicles were compared across different clusters. Clusters C3, C4, and C6 didn't experience large burdens during the evacuation process, mainly because the low number of vehicles entered the network at the initial stage. On the other hand, cluster C5 deploy the largest burden to the traffic network, nearly 15% of the vehicles entered the network within the first three hours after fire outbreak experienced severe traffic jam, indicating that the traffic demand in the first three hours exceed the network capacity. Clusters C2 and C1 only show minor traffic jam conditions compared with the cluster C5.

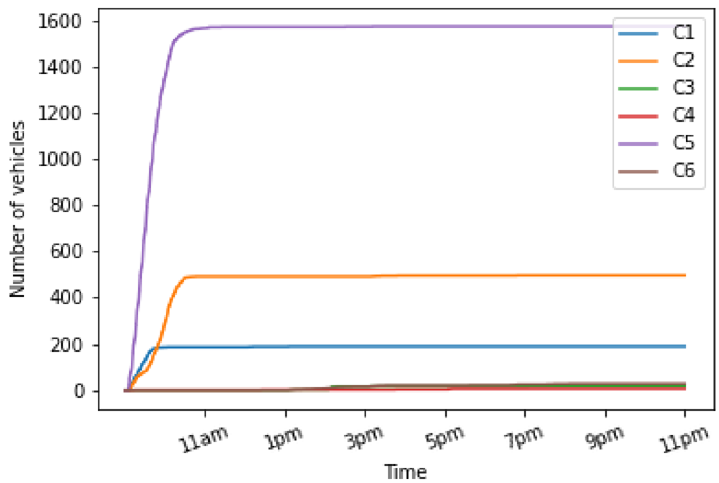


Figure 4.11 Comparison of average cumulative number of vehicles stuck in traffic across clusters.

Figure 4.12(a) presents the comparison between the average cumulative number of vehicles that entered the network across different EP groups. As expected, 0-40th, 40th-60th percentile groups show lowest impact in Santa Clarita City. However, 60th-80th and 80th-90th depict the highest number of vehicles entering the network implying the most significant impact in the network. While the ERC percentile reflects the degree of the fire-prone environment in the study region, its impact on the first day evacuation is not strictly following a linear relationship. This effect is possibly due to the wind condition at the fire day, which thus impacted the direction of the fire propagation. Figure 4.12(b) shows the average cumulative evacuation rate, EP2 percentile group were found to have the lowest rate of evacuation compared with other groups. Figure 4.12 revealed that the 60th-80th percentile group depicted the highest impact on the traffic performance if there is a fire occurred under such conditions.

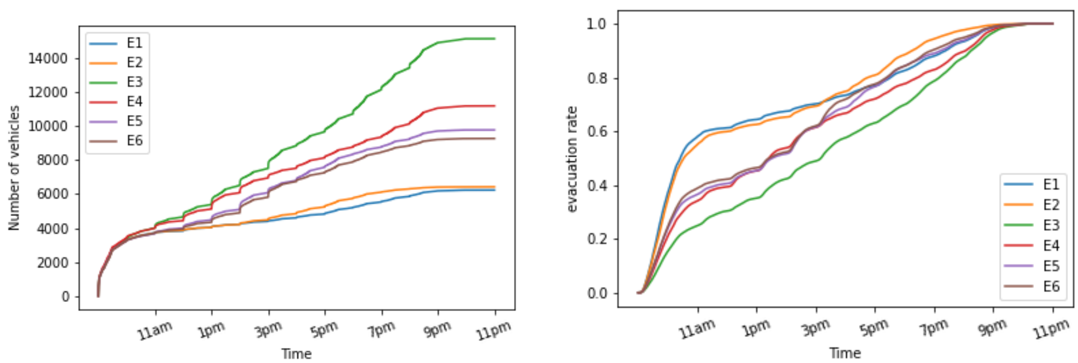


Figure 4.12(a) Average cumulative number of vehicles entered the network. (b) number of vehicles running in the network

Figure 4.13 shows the comparison of averaged cumulative number of vehicles stuck in the traffic between different ERC percentile groups. Though most of the vehicles didn't experience severe traffic jams when comparing the total number of vehicles that entered the network and the teleported vehicles. The traffic burden in the first three hours is severe, about 15% of evacuation vehicles stuck in the traffic during this time period, highlighting the importance of traffic management in the initial stage of evacuations.

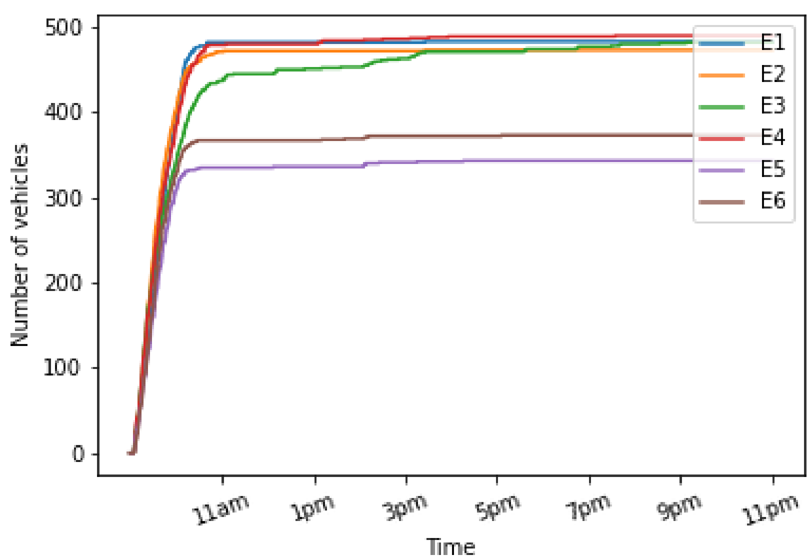


Figure 4.13 Comparison of average cumulative number of vehicles stuck in traffic across EP groups

Based on the cumulative number of vehicles plotted in Figures 4.10–4.13, the first three hours following the initial update of the fire front (i.e., 8 a.m.) show the most intensive traffic burdens, underscored by the steep increases in the cumulative number of teleported vehicles. Thus, the average cumulative time loss at every edge over the first three hours following a fire outbreak can be spatially plotted in Figure 4.14. The cumulative time loss is defined as the total number of seconds vehicles lost due to driving slower than desired summed up over all vehicles that passed this edge. The higher the value, the more vehicles are trapped in a long duration of traffic jam on the edge. This average cumulative time loss is a weighted average of the cumulative time loss calculated as equation 10, providing the potential for traffic jams if a fire occurs in the whole Santa Clarita area.

$$ATL_t = \sum_i \sum_j TL_{t,i,j} \frac{P\left(E_i C_j \middle| fire\right)}{\sum_i \sum_j P\left(E_i C_j \middle| fire\right)} \tag{4.10}$$

Where $P\left(E_i C_j \middle| fire\right)$ = the probability of a fire outbreak under E_i EP group and within cluster C_j if the fire will occur in the Santa Clarita area. $TL_{t,i,j}$ = the cumulative time loss on edge t within the first three hours of fire propagation for representative wildfire events occurred in cluster C_j under E_i EP group. ATL_t = the average cumulative time loss on edge t within the first three hours of wildfire propagation.

As illustrated in Figure 4.14, the majority of road segments within Santa Clarita city are anticipated to encounter minor slowdowns, characterized by time delays exceeding 100 seconds. Conversely, a subset of roads may encounter significant traffic congestion, resulting in time losses exceeding 5000 seconds, particularly evident in the southern and northwestern sectors of the city. The areas of pronounced congestion are distinctly demarcated in the figure, with road segments in these delineated zones shaded in gray if their average cumulative time loss falls below 1000 seconds. These highlighted regions distinctly emphasize the pronounced traffic congestion that is poised to transpire at the entry points to the highways, a consequence of the preference among the majority of evacuation traffic to utilize the highways owing to their heightened capacity and velocity. However, the swift flow of traffic along the highways inadvertently hinders the egress of traffic from the highway entrances, consequently engendering considerable delays within these road segments. Furthermore, this spatial visualization discerns an additional region of vulnerability, specifically pertaining to the residential zones situated to the northeast of the city. These residents face heightened susceptibility to the risk of wildfires due to the limited choices of evacuation routes available to them, thereby significantly augmenting the likelihood of delayed evacuations within the context of extensive evacuation scenarios. The spatial visualization of cumulative time loss offers policymakers and community managers a valuable tool for conducting pre-event assessments of network performance following an event. This aids in making informed pre-event mitigation choices, including the allocation of resources and the reinforcement or retrofitting of critical segments.

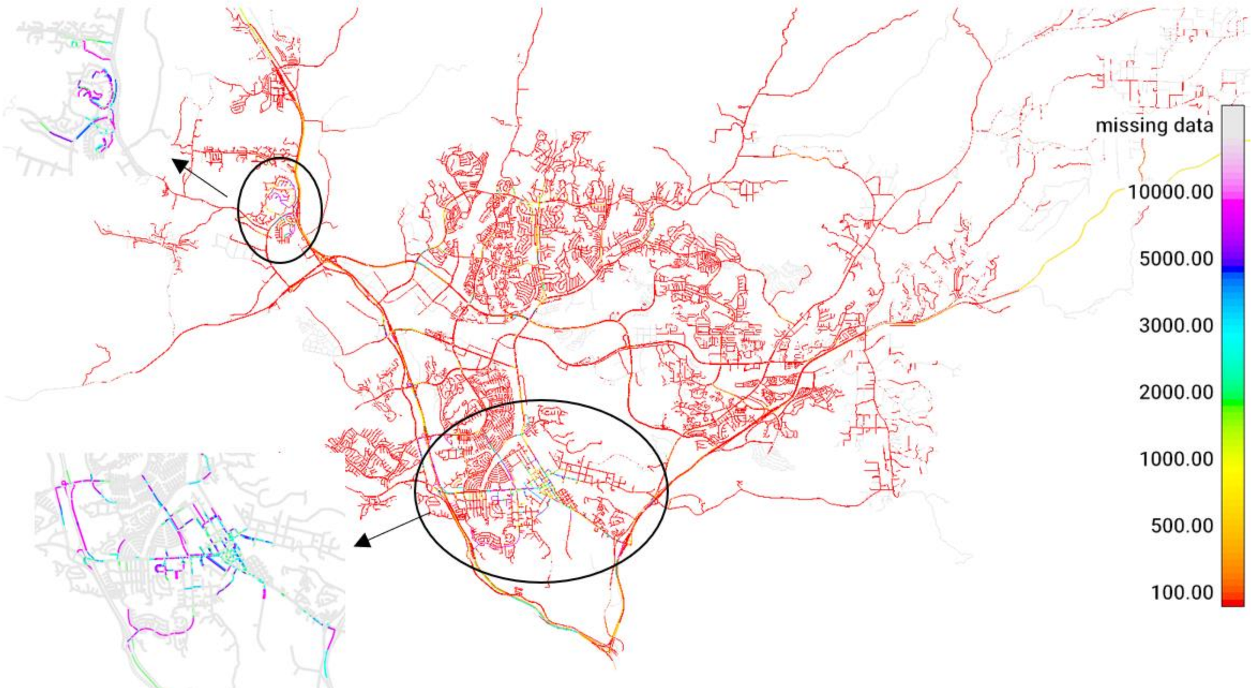


Figure 4.14 Spatial distribution of average cumulative time loss on edges

The spatial distribution of cumulative time loss can be further extended to the probability space and expressed as the annual expected time loss on every edge. The annual expected time loss can be estimated through Equation 4.11. The spatial distribution of the annual expected time loss is shown in Figure 4.15. The edges with a time loss greater than 500 seconds were colored to highlight the slow-down effects. Similar to the road segments highlighted in Figure 4.14, the south and northwest of Santa Clarita are expected to experience severe congestion under massive evacuations, indicating a constraint on the evacuation performance.

$$E(TL_e) = \sum_{i=1}^{I} \sum_{d=1}^{365} \sum_{j=1}^{J} TL_{e,C_i,E_j} P(F_l|C_i, E_j) P(E_j|d) \tag{4.11}$$

Where TL_{e,C_i,E_j} represents the time loss on edge e induced by the representative wildfire events at cluster C_i under EP groups E_j. I, J = the number of the clusters and EP groups respectively. d represents the d^{th} day of the year.

Figure 4.15 Spatial distribution of annual expected cumulative time loss on edges

4.5 Conclusions, limitations, and future research directions

Considering the high risk of wildfires in the United States, effective community-based transportation evacuation planning is a crucial issue for state and local policy makers. If wildfire risk to communities cannot be reduced by the first line of defense (i.e., wildfire countermeasures), evacuation is regarded as the second line of defense. Inadequate planning and underestimating this problem might lead to tragic human casualties during a wildfire. An effective evacuation plan may be aided by an evacuation simulation model, which could ultimately save lives.

This study proposed an ABM framework designed for wildfire evacuation within damaged transportation settings. This novel approach integrates wildfire simulation, network vulnerability assessment, evacuee response modeling, and traffic simulation. The aim is to forecast traffic conditions during an evacuation event and identify the critical segments of the transportation network that necessitate pre-fire risk mitigation measures. The utilization of ABM within this framework facilitates the generation of outputs at both a disaggregated level (for instance, individual vehicle locations and speeds at every second) and an aggregated level (including metrics such as the cumulative count of departed or evacuated vehicles, the quantity of vehicles currently within the network or ensnared in traffic, and time-series data depicting average travel speeds). By synergizing these aggregated-level outputs with the disaggregated ones, a comprehensive evaluation of network performance during an evacuation is achievable. Simultaneously, this amalgamation allows the identification of congestion bottlenecks and the critical network sections susceptible to substantial congestion. Additionally, this proposed framework introduces the integration of damaged traffic settings into the evacuation process. This facet underscores how the reduced network capacity consequent to damage affects evacuation efficiency, particularly when compounded by heightened travel demand.

The main contributions of this study include (a) the incorporation of an advanced wildfire hazard modeling and vulnerability assessment to improve the accuracy of wildfire evacuation in damaged transportation settings, (b) the development of a more comprehensive evacuee response model based on a stated preference survey to predict individual evacuees' behavior as a firefront approaches, and (c) evaluating the performance of evacuation under probability space.

However, the study has a number of limitations that may hinder its accuracy or wide applicability. First, public transportation and ride-sharing behavior were not considered. Second, the evacuation destination was randomly assigned based on the survey results, whereas in the real world, evacuees may choose the closest shelter or exit. To improve the accuracy of the model estimation and broaden its applicability, future works include (a) introducing public transportation, (b) modeling carpool behavior to remove hypothetical vehicles, and (c) determining evacuation zones based on the combined effect of wind and fire propagation directions.

CHAPTER FIVE: PROBABILISTIC WILDFIRE RISK ASSESSMENT METHODOLOGY AND EVALUATION OF A SUPPLY CHAIN NETWORK

5.1 Introduction

A supply chain network is a complex network system involving the whole process from the production of source materials to the delivery of a completed product to end-users. It is often modeled as a graph consisting of a set of nodes (e.g., feedstock, intermediate facilities, and demand nodes) and links (e.g., highway segments) and is spatially distributed over large geographic areas. All nodes and links in the supply chain network are highly interconnected because of functional interdependency between them. Thus, the failure of one or some of the nodes/links can lead to the failures of other parts of the network, which is known as cascading failure (Tang et al. 2016, Wang et al. 2016, Sun et al. 2020). Depending on the role of each node and link in the supply chain network, its failure impact on network performance varies greatly. For example, wildfire damage to highway bridges and segments could interrupt logistics and transportation activities. Certain types of feedstock nodes that are vulnerable to wildfire may not be recovered from wildfire damage in a short period of time, leading to a long-lasting negative impact on supply chain operations. Past wildfires have highlighted the significance of the impact of wildfire-damaged feedstocks on supply chain performance. The 2019 Amazon Rainforest wildfires caused large disruptions to the global supply chain in the pharmaceutical, timber, and meat industries because these industries heavily relied on raw materials from this area which were significantly destroyed by the fires. In Australia, national wool production was impacted by the 2019–2020 wildfires due to sheep losses. The honey production in New South Wales, Australia is expected to be 30% below the historical average for the next 10 years, because hives and field bees were attacked by the 2019–2020 wildfires (Lee et al. 2020). As such, wildfires have disrupted the performance of supply chain systems in many different industries and resulted in huge economic losses. Given that headquarters and distribution facilities of many shipping and wholesale companies (e.g., Amazon, Costco) are located on the west coast (Cosgrove 2018), wildfires may result in extensive delays and significant expenses in the supply chain systems in the United States. While it is important and promising to investigate wildfire risk to supply chain systems, this area of research is still in its infancy (Ma et al., 2022a; Ma et al., 2022b).

This chapter proposes an integrated wildfire risk assessment framework for a supply chain network that probabilistically quantifies the effect of wildfire-related disruption on network functionality. This chapter begins with a comprehensive review of wildfire hazard and risk analyses and supply chain risk assessment. To bridge the research gaps between these two fields identified in the literature review, this study proposes a probabilistic wildfire risk assessment framework which integrates wildfire hazard modeling, component-level vulnerability analysis, and network-level supply chain performance assessment. Multiple sources of uncertainties are propagated within the framework including the location and likelihood of wildfire ignition, wildfire spread rate and direction, and the level of component damage conditioned on fire intensity. Then, the proposed framework is illustrated with a hypothetical sustainable aviation fuel (SAF) supply chain network having feedstocks highly susceptible to wildfire located in the Pacific Northwest (PNW) region to demonstrate its applicability. As the proposed framework evaluates the expected network performance subject to a large number of wildfire scenarios, the results can be used as a planning tool to identify the most vulnerable network components and specify the target areas to effectively manage wildfire risks.

5.2 Literature Review

This study fills the research gaps between wildfire hazard/risk analyses and supply chain risk assessment by quantifying wildfire risks to a supply chain network through a probabilistic approach. This section will summarize current approaches and underscore the gaps in the existing body of work.

5.2.1 Wildfire hazard and risk analyses

A large body of theoretical and/or empirical wildfire hazard analyses has been conducted in the past two decades. Earlier works focused on assessing site-specific wildfire occurrence rates to produce a wildfire hazard map aimed at identifying and prioritizing areas of concern. Preisler et al. 2009 used a spatio-temporal nonparametric logistic regression model to estimate the probability of small wildfire occurrence and the conditional probability that a small fire will turn into a large fire given a small wildfire occurrence. By combining these two probabilities, the unconditional probability of large wildfire occurrence was assessed and used to develop a wildfire hazard map and predict the expected number of large fires in a given region over a specific period of time. Bradstock et al. 2010 developed a Bayesian logistic regression model to relate the Forest Fire Danger Index (FFDI) to large fire ignition probability based on historical records. As such, these studies primarily developed simple statistical models to find the relationship between explanatory variables and the probability of wildfire occurrence to account for uncertainties in nature and human factors. Finney et al. 2011 proposed an integrated large fire simulation (FSim) framework to quantitatively assess spatially varying wildfire risk. The simulation framework captured spatial characteristics in topography, fuel characteristics, and weather conditions while considering uncertainties at every stage of wildfire development, such as wildfire ignition, spread, and containment. The results from FSim included an annual burn probability map for the continental

United States and the fireline intensities and sizes of the simulated fires. The simulation and historical fire size distributions showed good agreement, while the simulated burn probabilities were “generally” consistent with historical values. This simulation model formed the basis of FSim wildfire risk simulation software which has been developed and periodically updated by the United States Department of Agriculture (USDA) and the United States Forest Service (USFS). A comprehensive review of burn probability modeling and its applications can be found in Parisien et al. 2019.

In recent years, various simulation software programs have been developed to model wildfire behavior and growth. The most widely used software programs include: the FlamMap fire mapping and analysis system; the Fire Area Simulator (FARSITE) fire growth simulation modeling system, which is now included in the recent version of FlamMap; the Fire Spread Probability (FSPro) model; and the FSim wildfire risk simulation software. These software programs have been extensively used by fire management specialists and USFS to evaluate wildfire risk and fuel treatment effects (Papadopoulos and Pavlidou 2011, Scott et al. 2013). While all these four software programs use the same fundamental wildfire behavior model (Rothermel 1972) and crown fire activity model (Rothermel 1991), they are different in their fire growth simulations and produce different formats of output. For example, FARSITE simulates fire growth through a wave-front propagation approach based on Huygen's principle (Richards 1990). In this fire growth simulation, small elliptical wavelets are formed around the perimeter of the fire (i.e., fire front) at the current time step, and the outer edge of these wavelets becomes a new fire front at the next time step. Because an iterative simulation structure allows time-dependent inputs, FARSITE has the ability to model wildfire growth under heterogeneous weather, fuel, and topography conditions, which produces more accurate simulation results compared to the other software programs.

However, FARSITE is computationally inefficient: FARSITE simulation time could be over 10 times longer than the other programs, which limits its usage when simulating a large and complex wildfire or generating a large suite of fires (Finney 2002). All the other three simulation programs (i.e., FlamMap, FSPro, and FSim) model wildfire growth based on the Minimum Travel Time (MTT) method developed by Finney 2002. MTT is a simplified raster-based fire growth model searching for the minimum travel time among the nodes of a grid. Fire shape is created by contouring the nodes with the same minimum travel time. Since this method holds weather and fuel conditions constant in time, its simulation results are not as precise as FARSITE. However, MTT greatly reduces its simulation time. While these three software programs use MTT in modeling fire growth, they have different simulation procedures and results. FSPro simulates wildfire growth for a given single ignition point under many weather scenarios and estimates the probability of a fire burning a given area over a specified period of time. Thus, FSPro does not produce fire sizes or shapes as its outputs. As described earlier, FSim is a more comprehensive wildfire analysis program involving weather data analysis and fire ignition, growth, and containment modeling. FSim generates the annual burn probability for a given area and the fireline intensities and sizes of the simulated fires. On the other hand, FlamMap simulates wildfire growth during the predefined burn period conditioned on a given ignition point or randomly generated ignition points. It generates conditional burn probabilities as well as final fire shapes and sizes under constant weather and fuel conditions (Scott et al. 2013).

Wildfire hazard analysis produces wildfire hazard maps and/or annualized burn probabilities, which can assist in identifying high-risk areas and facilitating decision-making efforts on minimizing risk in the identified areas. However, wildfire consequence analysis is also important in understanding the potential effect of wildfires on humans, the natural/built environment, and the regional economy. Several studies have attempted to assess wildfire consequences based on expert opinions. For example, Tutsch et al. 2010 proposed an approach to estimating forest fire consequences using a common metric. This study pointed out that measuring various consequences in different units (e.g., loss of market goods, endangered species, human losses) could be a primary challenge and established the relative importance of each consequence based on expert consultation and survey to measure an aggregated consequence through a common metric. However, this expert-opinion-based approach was qualitative, subjective, and highly dependent on the perceptions of the experts involved. An integrated wildfire risk assessment framework proposed by Scott et al. 2013 and Thompson et al. 2011 combined the results from burn probability maps, geospatial data of High Valued Resources and Assets (HVRAs), and expert-defined resource response functions to quantitively assess wildfire risks. Similar to Tutsch et al. 2010, both studies developed resource response functions based on expert opinion, which could introduce additional uncertainties and biases. Papakosta 2015 proposed Bayesian network (BN) models to probabilistically estimate economic losses due to wildfire-induced house and vegetation damages in the Mediterranean basin. The proposed BN models were constructed based on simple empirical relationships between independent variables (e.g., fire type, land cover, construction type, fire containment) and house/vegetation damage and accounted for uncertainties in fire hazard, house and vegetation exposure, and consequences. However, most of the random variables used in the BN models were assumed to be discrete, and the dependence structure between them was dependent heavily on data collected from various sources. In summary, many existing studies have developed the response functions either qualitatively or empirically, which have made the functions highly context-specific and less applicable to a general context. To generalize the procedure, the physical vulnerability of a component/resource and its interaction with fire should be quantified in constructing a response function. Moreover, most existing studies have not appropriately assessed the cascading effect of directly impacted components through the entire network, which would be critical for a network involving highly connected components. Rather, most existing studies have assessed component-level damages and summed them up to estimate an aggregated level of damage and loss. Very little research has been conducted to develop an integrated wildfire risk assessment framework which quantifies wildfire likelihood, severity, and consequences and has the ability to account for cascading effects in estimating network-wide risks.

5.2.2 Supply chain risk assessment

Supply chain risk assessment generally involves the calculation of the probability of an event and the potential consequences of the event and can be often classified into two categories: qualitative assessment, which is mostly based on expert opinions or simple rating scales; and quantitative assessment, which is based on empirical data and/or probabilistic models. To deal with vague, imprecise, and/or uncertain contexts associated with supply chain risk, qualitative approaches have been broadly adopted by many researchers (Cheng and Kam 2008, Jaffee et al. 2010, Kleindorfer and Saad 2005, Haimes et al. 2002, Cao et al. 2019, Nakandala et al. 2017). For example, Haimes et al. 2002 proposed a hierarchical holographic modeling framework consisting of eight phases that identified, prioritized, assessed, and managed risk scenarios of a large-scale system. In this framework, most of the tasks were performed primarily based on analysts' judgement. Several recent studies (Cao et al. 2019, Nakandala et al. 2017) have introduced fuzzy logic models to quantify vague or imprecise linguistic variables representing risk levels, but the degrees of membership and truth in the models were still subjective in nature.

Quantitative risk assessment numerically evaluates the impact of identified risks and uncertainties on supply chain performance and provides a quantitative basis for making decisions. Goh et al. 2007 provided a multi-stage stochastic model for supply chain networks operating under a variety of risks, such as uncertainties in supply, demand, exchange rate, and price. These risks were modeled as a multi-dimensional random variable vector and considered in a multi-stage stochastic convex programming where profit maximization and risk minimization were objective functions. However, the proposed model was designed for operational uncertainties and thus was not suitable for low-probability high-consequence (LPHC) events (e.g., extreme natural or man-made hazard events). Jenelius and Mattsson 2012 presented a grid-based approach to assessing the vulnerability of road networks. By dividing the whole study area into many uniformly shaped and sized cells and assigning distinctive weights and events to each cell, this approach accounted for spatial variability in network vulnerability and disruption impact. However, this study assessed disruptions to individual cells and failed to capture risk propagation throughout the networks. Dixit et al. 2020 used a simulation model to investigate the performance of a supply chain network in undisrupted and disrupted scenarios. In the case study where five independent risk scenarios were considered, the probability of occurrence and impact of each risk scenario was modeled by Bernoulli distribution and uniform distribution, respectively. The distribution models used in the evaluation of occurrence probability and impact were still not supported by any data.

The literature review shows that little research has been conducted to quantify the effect of LPHC events on supply chain performance. Due to the lack of understanding of natural hazard characteristics and/or physical interaction between hazard and network components, natural hazard modeling and vulnerability assessment have rarely been combined with supply chain analysis, aimed at evaluating the probability and consequences of a LPHC event. Moreover, to the best of the authors' knowledge, wildfire-caused supply chain disruption has not yet been quantitatively investigated in any depth. To fill the research gaps identified in wildfire hazard/ risk analyses and supply chain risk assessment, this study proposes a probabilistic wildfire risk assessment framework for a supply chain network which quantifies and accounts for uncertainties in wildfire likelihood, growth, and consequences and analyzes its cascading effects throughout the network. Contrary to other probabilistic approaches (e.g., Rodríguez-Martínez et al. 2020), the proposed framework will generate a large number of wildfire scenarios having various burn areas and perimeters and perform a network (i.e., supply chain) analysis for each scenario chosen. This approach will allow us to track the cascading effects of damaged nodes and links, assess network-level risks, and ultimately obtain the full probability distribution of wildfire impact on network performance (Ma et al., 2022a; Ma et al., 2022b).

5.3 Model Formulation

The changing environment and increased human-nature interaction have resulted in multiple sources of wildfire ignition and have introduced considerable uncertainties in the likelihood and location of wildfire ignition (Riley et al. 2013). Moreover, wildfire growth is affected by various site-specific (e.g., topography and fuel conditions) and highly variable (e.g., weather patterns and human containment ability) factors, all of which lead to uncertain fire behavior (Diao et al. 2020). Uncertainties in estimating the levels of fire-induced damage sustained by supply chain nodes (e.g., processor, refinery, short- and long-term storage, packing and distribution facility, feedstock node, and final destination node) and links (e.g., highway bridge and segment) add an extra layer of complexity to the prediction of post-wildfire supply chain performance. Therefore, in this paper, post-wildfire supply chain performance is expressed in probabilistic terms, acknowledging the substantial uncertainties that are inherent in wildfire ignition and growth as well as the structural responses of supply chain components.

Figure 5.1 illustrates a proposed probabilistic wildfire risk assessment framework which quantifies wildfire likelihood, growth, and consequences and accounts for cascading effects in estimating network-wide risks. The first module of the framework estimates site-specific large wildfire occurrence rates by combining historical fire records with weather data and generates the stochastic catalog of wildfires through Monte Carlo simulation (MCS). The stochastic catalog contains information about the occurrence times and locations of all the fires simulated based on the wildfire occurrence estimation model, which will be subsequently used as inputs to the next module. The second module is to simulate the growths of all the fires in the stochastic catalog based on weather conditions, topography, and fuel properties. The results from the second module include fire intensities during the burn period (i.e., the period from ignition to ultimate containment) and the shape and size of the burned area conditioned on each realized fire in the stochastic catalog. The third module is to estimate component-level damages induced by each fire. In this module, the hazard layers obtained from the first and second modules are overlayed with the vulnerability layer to estimate the spatial distribution of component-level physical damage and loss of functionality. In the fourth module, the locations and remaining capacities of the damaged components identified from the third module are incorporated into supply chain analysis to capture risk propagation throughout the network. By doing so, wildfire-caused supply chain disruption can be quantified in terms of post-wildfire unmet demand ratio (UDR) and total supply chain cost increase. Detailed descriptions and procedures for each module are introduced in the remainder of this section.

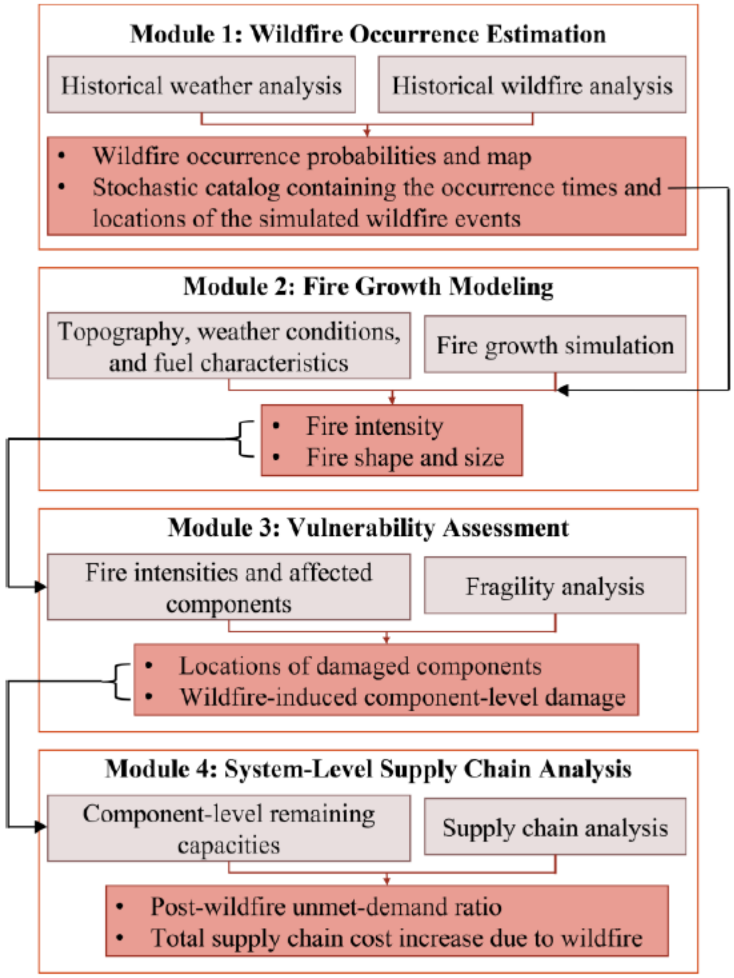


Figure 5.1 Four modules of the proposed probabilistic wildfire risk assessment framework

5.3.1 Wildfire occurrence estimation

The first module of the modeling framework is to estimate the site-specific large wildfire occurrence rates and generate the stochastic catalog of wildfires. In this paper, large wildfires refer to "fires that escape initial attack, irrespective of their actual size" (Finney et al. 2011). Thus, a large wildfire can occur when two conditions are satisfied: (a) a fire occurs at a certain location due to either human actions or natural forces, which is called wildfire ignition; and (b) under favorable burning conditions, the fire escapes from the initial ignition point and spreads over a large geographic area. This two-stage process is used to simulate large wildfire occurrences for a given area. The causes of wildfire ignition can be classified into two categories, including human causes (e.g., power lines, equipment failure, accidental ignitions, smoking, fireworks, campfires, and arson) and natural causes (e.g., lightning). The likelihood of human-caused ignition may be affected by (a) societal variables characterizing the variation of population and cultural/social context across landscapes; and (b) management variables that describe the influence of risk mitigation actions on fire occurrence and behavior (Massada et al. 2013, Prestemon et al. 2013, Rodrigues and Riva 2014). On the other hand, the likelihood of nature-caused ignition can be better explained by biophysical variables representing spatiotemporal variations in weather, topography, vegetation, and geology (Finney et al. 2011, Massada et al. 2013, Prestemon et al. 2013). While nearly 85% of wildfires are caused by human ignition in the United States (Joosse 2020, NPS 2021), a wildfire cannot be propagated and developed as a large fire without appropriate environmental and weather conditions, such as burning fuel bed, convective heating influenced by wind, and high-temperature, low-humidity conditions. Hence, this study considers only environmental and weather conditions in the two-stage process for large wildfire occurrence (Preisler et al, 2009, Bradstock et al. 2010, Finney et al. 2011, Scott et al. 2013, Dlamini 2010, Khakzad et al. 2018), which include the moisture contents of six fuel categories and wind speed and direction (Finney et al. 2011). This study uses an energy release component (ERC) as a composite fuel moisture index because daily variations in ERC are caused by changes in the moisture contents of both live and dead fuels (Finney et al. 2011). ERC is a National Fire Danger Rating System (NFDRS) index that represents the energy released within the flaming front at the head of a fire. Its unit is BTU/ft2, where BTU (British thermal unit) is a measure of heat energy and is commonly used in comparing energy sources or fuels. In this study, ERC for fuel model G

(ERC-G) is specifically used as it reflects dead fuel moisture contents for four time-lag classes (1 h, 10 h, 100 h, and 1000 h) as well as live herbaceous and live woody fuel moisture contents. Thus, ERC-G can be an indicator which can reflect both short- and long-term fluctuations of fuel moisture content induced by changes in weather conditions (e.g., precipitation, humidity, temperature) (Finney et al. 2011, Beth et al. 2003, USFS n.d.).

Previous studies have revealed that ERC has a strong positive relationship with large wildfire occurrence and intensity, confirming that ERC is a reliable indicator for predicting large wildfire occurrences (and intensities in the second module) (Andrews et al. 2003, Lindley et al. 2015, Riley et al. 2017). Fire managers and planners also use ERC values in daily staffing by combining the values with other NFDRS components. Based on historical ERC values and wildfire records for a given area, logistic regression (LR) models are estimated to develop a relationship between ERC and large wildfire occurrence probability (Finney et al. 2011). LR is a popular statistical model that belongs to the generalized linear model family. It can map a linear function to the scale of 0–1, and thus can be used to represent probability in this study. LR has been widely used in predicting wildfire occurrence from key factors or NFDRS indicators in the literature (Preisler et al. 2009, Massada et al. 2013, Barbero et al. 2014, Catry et al. 2009, Coldham et al. 2011, Mermoz et al. 2005).

In the two-stage process for estimating site-specific large wildfire occurrence rate, two logistic models are estimated: (a) the first model is used for estimating the conditional probability of wildfire ignition given an ERC value and mathematically expressed as Equation (5.1); and (b) the second model predicts the probability that wildfire is developed as a large fire conditioned on the ERC value associated with fire ignition, which is mathematically expressed as Equation (5.2).

$$P(f_{all}|erc) = \frac{e^{\beta_0+\beta_1 erc}}{1+e^{\beta_0+\beta_1 erc}} \tag{5.1}$$

$$P(f|erc_{f_{all}}) = \frac{e^{\beta_2+\beta_3 erc_{f_{all}}}}{1+e^{\beta_2+\beta_3 erc_{f_{all}}}} \tag{5.2}$$

where f_{all} = the wildfire ignition (including all sizes of wildfires); erc = the ERC value; $\boldsymbol{\beta}$ = the vector of logistic regression coefficients; f = the large wildfire occurrence; and $erc_{f_{all}}$ = the ERC value that has produced fire ignition. Therefore, the conditional probability of large wildfire occurrence given an ERC value, $P(f|erc)$, is calculated using Equations 5.1 and 5.2. It should be noted that these LR models vary by location due to site-specific environmental and weather conditions, thus resulting in a different set of LR models for each spatial unit of interest. Moreover, the probability that more than one large fire occurs on a particular day for each spatial unit is neglected in this study because (a) this probability is low, and (b) the effects of multiple fires on supply chain components are assumed to be the same as the effect of a single fire.

To estimate the annual probability of large wildfire occurrence for each spatial unit, plausible (or artificial) daily ERC values are produced through simulation. The measured weather data, which can be used to estimate dead and live fuel moisture contents and subsequently calculate daily ERC values, are available from Remote Automatic Weather Stations (RAWSs) located throughout the United States. The data from the RAWSs generally cover the past one to three decades, and therefore only 10 to 30 ERC values are available for each day of the year. Since such limited sample size is not sufficient for finding daily ERC value distributions, an upsampling method is often used to produce thousands of plausible ERC values on a particular day by capturing statistical properties observed in historical data (Finney et al. 2011). An easier way to produce plausible daily ERC values is to use a built-in tool provided by FireFamilyPlus, which is a widely used fire weather analysis software. However, this software tool requires users to define the thresholds of temperature, relative humidity, and wind speed, which could introduce subjectivity in making projection. This study uses a time series model in producing plausible daily ERC values to capture seasonal trend, natural variability, and temporal dependence between ERC values. For the purpose of illustration, the weather data recorded at the RAWS in Mt. Yoncalla, Oregon (Station ID 353043) are used to calculate historical ERC values and estimate a seasonal autoregressive model that predicts plausible daily ERC values (Box et al. 2015). Figure 5.2 shows the comparison of the simulated daily ERC values over an artificial year with the seasonal trend found in historical ERC values. The simulated values show a good agreement with the historical seasonal trend (R-squared value of 0.78), while the deviations around the trend represent natural variability in daily ERC values. Moreover, the autocorrelation of the ERC values is also captured well in the model. The detailed procedure for modeling the seasonal and daily variability in ERC values and producing plausible daily ERC values can be found in Finney et al. 2011.

The plausible daily ERC values over 5000 artificial years for each spatial unit are used as input variables in Equations (5.1) and (5.2) to simulate large wildfire occurrences on each day over a period of 5000 years. Subsequently, the annual rate of large wildfire occurrence conditioned on the spatial unit can be calculated from the expected number of simulated large wildfires per artificial year. As each spatial unit has its own set of LR models, the occurrence time and ignition location of each fire can be randomly sampled within the spatial unit through MCS. The occurrence time and ignition location of all the simulated large fires over the 5000 artificial years are recorded in the stochastic catalog for the region of interest. In other words, as shown in Figure 5.3, the stochastic catalog contains n fire events simulated over the 5000 artificial years, and each fire event has information about its occurrence time (i.e., day of the year) and ignition location. For each fire event, such information will be fed into the second module to simulate fire growth starting from the ignition point on the given day. In summary, the outputs from the first module include (a) a set of LR models for the study region, (b) a large wildfire occurrence map, and (c) the stochastic catalog, while only the information stored in the catalog will be directly utilized in the second module.

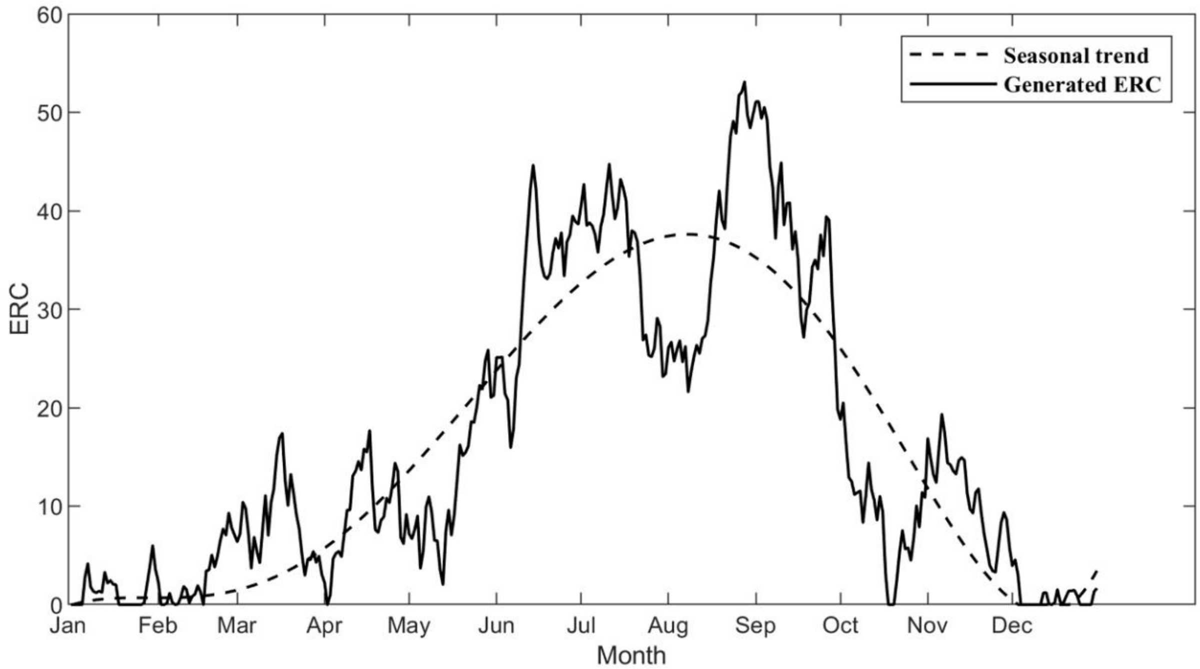


Figure 5.2 Comparison of the historical seasonal ERC trend with the simulated ERC values (Mt. Yoncalla, Oregon).

5.3.2 Fire growth modeling

The second module simulates the growths of all the fires in the stochastic catalog. Once the occurrence of a large wildfire has been simulated at a specific ignition point in the first module, its behavior is conditioned on fuel properties, topography, and weather conditions, all of which are site-specific. First, fuel types and fuel loading (i.e., the amount of vegetation in a given area) play an important role in fire behavior. Some fuel types burn more easily than others and can produce greater spotting distances. For example, the rate of a fire spread of high load, dry climate shrub

(SH5/145) can reach 3.02 km per hour at low moisture content level and midflame wind speed of 16.09 km/h, whereas under the same condition, the rate of high load, dry climate grass (GR7/107) can reach as high as 6.04 km per hour (Scott 2005). Closely packed fuels may induce higher fire spread rate and more extreme fire behavior than the fuels that are loosely packed. Topography (e.g., elevation, aspect, slope) should also be considered in predicting wildfire behavior. For example, slopes facing south are likely to receive more solar radiated heat, and therefore have warmer and drier conditions that north facing slopes do. It results in more fire activities and longer burn period in south-facing slopes. While topography and fuel characteristics change throughout the landscape, their temporal changes are relatively slow. Therefore, a landscape file used in various wildfire simulation software programs introduced in Section 5.2.1 is often developed based on static, time-invariant topography and fuel property data layers. For example, to develop a landscape file, FlamMap requires eight geospatial data layers which remain unchanged during simulation, including three topographic layers (i.e., elevation, slope, and aspect) and five fuel properties layers (i.e., fire behavior fuel models, canopy cover, canopy stand height, canopy base height, and canopy bulk density).

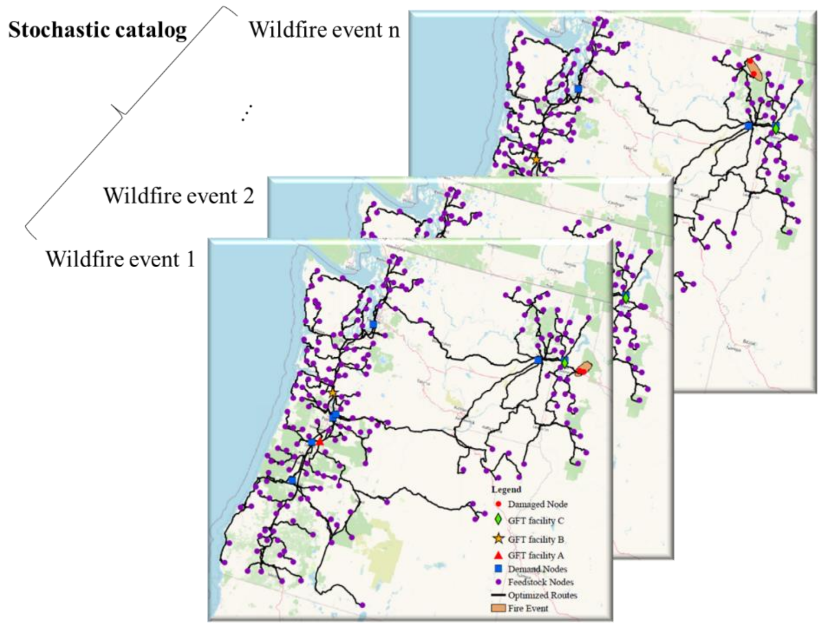


Figure 5.3 Schematic illustration of the stochastic catalog of wildfire events.

In addition to topography and fuel properties, weather conditions are also key factors in fire behavior and growth modeling. As weather conditions change over time and throughout the landscape, weather is one of the most uncertain factors in wildfire simulation and modeled as spatio-temporal random fields. In this study, weather is characterized by wind speed and direction as well as fuel moisture content. Wind is a driving force behind wildfire spread: wind speed affects fire spread rate, and wind direction may determine wildfire spread direction. Although both wind speed and direction are continuous random variables at a given spatial unit, for simplicity purposes, the ranges of these variables are divided into several classes as shown in Figure 5.4. Hence, they are modeled by joint discrete random variables with a joint probability mass function (PMF):

$$p_{W_s,W_d|m}(w_{s_i}, w_{d_i}|m) = P\left(W_s = w_{s_i} \cap W_d = w_{d_i}|m\right) \tag{5.3}$$

where w_s = the wind speed; and w_d= the wind direction. The joint PMF is conditioned on month, assuming it varies from month to month. Figure 5.4 shows the joint PMF of wind speed and direction in August, one of the most active months for wildfires, measured at the RAWS located in Gold Mountain, Washington (Station ID 452510). By considering monthly variable wind speed and direction, monthly wind patterns can be captured while obtaining sufficient number of samples (i.e., 30 or 31 datapoints per year over 10 to 30 years of historical records at a given RAWS) used in estimating joint PMF.

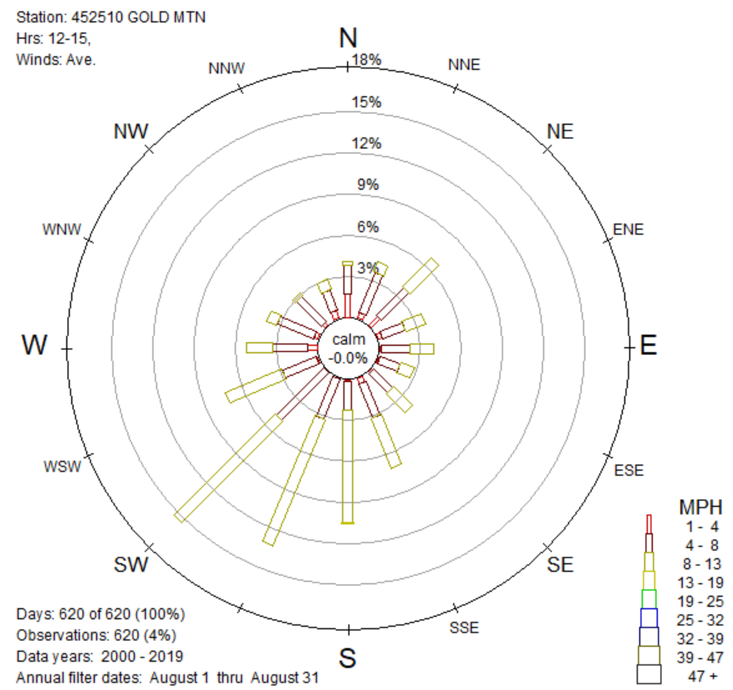


Figure 5.4 Joint probability mass function of wind speed and direction in August (Gold Mountain, Washington).

In combination with wind speed and direction, fuel moisture contents are also used in estimating fire behavior. Daily fuel moisture contents can be estimated from a look-up table (generated in the FireFamilyPlus software) that converts daily ERC values into the corresponding fuel moisture content. Using daily ERC values generated over 5000 artificial years for each spatial unit from the first module, daily fuel moisture content values can be calculated through the look-up table and used as input variables in wildfire simulation. In addition, fuel moisture contents also affect the length of active burn period, which is defined as “the portion of each day where fires are most active” (Finney et al. 2011, Fernandes et al. 2008, Leonard 2009). Although it is widely known that wildfire generally spreads faster during the afternoon hours partly due to higher temperature and drier fuel, the length of active burn period should be specified to perform wildfire growth simulation (specifically in the MTT algorithm) and ultimately determine the final fire size. In the proposed framework, only large-scale wildfires (in terms of final fire size) are considered, because small-scale wildfires may have minor consequences for a supply chain network which is often distributed over a large region. Given that most historical large-scale wildfires occurred when ERC values were above the 80th percentile (Finney et al. 2011), this study performs wildfire growth simulation only for above the 80th percentile of ERC. More specifically, if ERC value is at or above the 90th percentile, fuels easily burn, and fires can become serious and difficult to control. The 97th percentile is another threshold used to identify the most extreme fire danger conditions, where fires can move quickly and produce spot fires miles away. Spot fires are created when burning embers are lofted into the air and transported by strong winds. Accordingly, using the conditional PDF of ERC on a given day, f ERC|t (erc|t), ERC is discretized into three classes, including ERC1 (i.e., the 80th percentile ⩽ ERC1 < the 90th percentile), ERC2 (i.e., the 90th percentile ⩽ ERC2 < the 97th percentile), and ERC3 (i.e., the 97th percentile ⩽ ERC3), which represent mild, moderate, and extreme fire environments, respectively. In this study, the active burn period on a given day is assumed to be 1 h, 3 h, and 5 h per day for the ERC1, ERC2, and ERC3 classes (Finney et al. 2011).

As illustrated in this subsection, by combining the layers containing topography and fuel characteristics with spatio-temporal weather variables, the second module simulates fire growth and its intensities. Fireline Intensity (FI) is one of the most widely used wildfire intensity measures and represents the energy release per unit length of fire front per unit time (KW/m/s). As it shows high correlation with the flame length of wildfire, FI could indicate the ability of a wildfire to propagate and how hard it is contained, and thus is used in fire containment modeling (Keeley 2009). FI can also be used as an intensity measure for fragility functions in the third module to characterize a hazard intensity. As a result, the target outputs from the second module include (a) the FI values during the burn period, and (b) the shapes and sizes of the areas burned by each fire in the stochastic catalog.

5.3.3 Vulnerability assessment

In the third module of the proposed wildfire risk assessment framework, the spatial distributions of component-level physical damage and loss of functionality are estimated using fragility and loss analyses. First, for each simulated wildfire event in the stochastic catalog, the locations of damaged components are identified by overlaying the supply chain network layer (i.e., the exposure layer) with the layer containing the burned areas (i.e., the results from the second module). Then, fragility curves (i.e., the vulnerability layer) are used to estimate physical or structural damages to supply chain components, including major facilities (e.g., storages, preprocessors, refineries, distribution centers), feedstock nodes, demand nodes, and highway bridges/segments in the supply chain network. Fragility curve is widely used in probabilistic risk analysis of an engineering structure to represent the conditional probability that the damage state (DS) of an element or an entire structure will exceed a specific DS given a hazard intensity level (e.g., peak ground acceleration for earthquakes, wind speed for hurricanes and tornadoes) (Hasoomi and Van de Lindt 2016, Rosowsky and Ellingwood 2002). Fragility curve is often constructed analytically based on structural analyses and evaluations, experimentally based on testing results, or empirically based on post-disaster reconnaissance data. In some cases, multiple approaches are combined to develop a fragility curve (Biglari and Formisano 2020). A large number of studies have been conducted to develop seismic and hurricane fragility curves, whereas fire fragility curves have been much less studied. Figure 5.5(a) schematically illustrates the probability of reaching or exceeding each DS, such as minor damage (DS1), moderate damage (DS2), and severe damage (DS3), given a level of FI. After a FI value at a certain facility for a given wildfire event has been realized in the second module, it can be used to estimate the DS of the facility using a fragility curve. Since facilities interact with fire differently depending on facility age, structural type, construction material, etc., each facility has a distinctive fragility curve as shown in Figure 5.5(b). While FI is introduced as an intensity measure in this study, it can be replaced with other types of measures (e.g., fire load). After realizing the DSs of supply chain components for a given wildfire through MCS, the associated capacity reduction can be calculated using the loss functions relating DS to loss of functionality. Loss functions can be formulated either deterministically or probabilistically. Therefore, the outputs from the third module are (a) the locations of damaged components, and (b) the levels of damage and losses of functionality sustained by the damaged components following every wildfire event in the stochastic catalog.

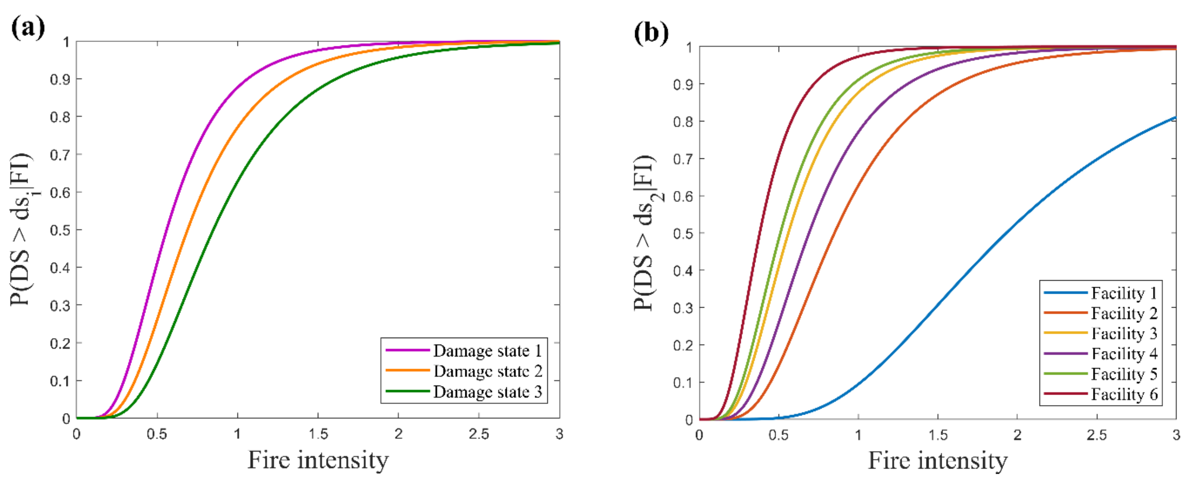


Figure 5.5 Fragility curves for (a) different damage states and (b) different facility types

5.3.4 Network-level supply chain analysis

In the fourth module, the reduced functionalities of the fire-damaged components are incorporated into supply chain optimization model to estimate the network-level supply chain performance reduction due to each simulated fire event in the stochastic catalog. Supply chain optimization problem can be mathematically formulated as a profit maximization or cost minimization problem. In this study, the objective function of the optimization problem is to minimize the total annual supply chain cost (TC) that consists of (a) the transportation costs including the cost of transporting commodities, the user-defined penalties that allow users to assign different weights on various types of roads based on their preferences (e.g., prefer arterial roads over local streets), and transloading costs (i.e., mode switching cost); and (b) the costs induced by user-defined unmet demand penalties for not meeting demand at the final destination nodes. Without the unmet-demand penalties, the optimal solution that minimizes the total annual cost will always be to transport nothing at all. Thus, the optimization problem for a simple supply chain network including three types of nodes (feedstock, processing facility, and demand nodes) can be mathematically formulated as:

$$Miminize\ \left\{\int\left(\sum_{fp} tc_{fp}\cdot x_{fp}(t)+\sum_{pd} tc_{pd}\cdot x_{pd}(t)+\ \sum_{d} U_d\cdot u_d(t)\right)dt\right\} \tag{5.4}$$

$$subject\ to$$

$$C_f(t)\cdot\left(1-\delta_f(t)\right)\geq\sum_{p\in P} x_{fp}\,(t) \text{ for each } f \tag{5.5-1}$$

$$C_p(t)\cdot\left(1-\delta_p(t)\right)\geq\sum_{f\in F} x_{fp}\,(t) \text{ for each } p \tag{5.5-2}$$

$$\sum_{f\in F} x_{fp}\,(t)\cdot S_p(t)\cdot\left(1-\delta_p(t)\right)\geq\sum_{d\in D} x_{pd}(t) \text{ for each } p \tag{5.5-3}$$

$$\sum_{d\in D} x_{pd}\,(t)\geq 0 \text{ for each } d \tag{5.5-4}$$

$$C_e(t)\cdot\left(1-\delta_e(t)\right)\geq x_e(t) \text{ for each } e \tag{5.5-5}$$

$$x_{ij}(t)\geq 0 \tag{5.5-6}$$

$$C_k(t) \geq 0 \tag{5.5-7}$$

$$0 \leq \delta_l(t) \leq 1 \tag{5.5-8}$$

Where F = the set of feedstock nodes; P = the set of processing facility nodes; D = the set of demand nodes; E = the set of transportation edges/links; tc_{ij} = the unit transportation cost to transport commodity from node i to node j; x_{ij} = the amount of commodity flow from node i to node j during t; U_d = the unit penalty for not meeting demand at destination used to prevent trivial solution (i.e., not transporting any commodity); u_d = the unmet demand at destination during t; C_k = the capacity at the node k; δ_l = the remaining capacity ratio at the node l which is used to reflect wildfire-induced loss of capacity/functionality; S_p = the conversion factor at the processing facility p; and x_e = the sum of all x the edge e.

For each wildfire event, the losses of functionalities/capacities of nodes and links are incorporated through δ_l in this optimization problem and affect the variables in Equation (5.4) to reoptimize transportation routes and network flow following an wildfire event. As described in Equations (5.4) and (5.5), optimal routes can be solved as a linear programming problem with the constraints of material, transportation, network flow capacity, etc. (Avami 2012, Huang et al. 2010, Kim et al. 2011). It should be noted that (a) the locations of the nodes are fixed in network layout optimization, while their remaining capacities change over time; and (b) the cascading effects of damaged nodes and links are propagated throughout the remaining network through the constraints (i.e., Equation 5.5) in the network-level supply chain analysis. Upon the completion of the optimization process, the UDR and total annual supply chain cost are recorded to measure post-wildfire supply chain performance given the wildfire event.

5.4 Illustrative Example: A Hypothetical Sustainable Aviation Fuel Supply Chain Network

In this study, a hypothetical forest-residuals-to-sustainable-aviation-fuel supply chain network is presented as an illustrative example to demonstrate the applicability of the proposed modeling framework and solution strategy. As shown in Figure 5.6, this hypothetical supply chain network is distributed across three states in the PNW region, including Washington, Idaho, and Oregon, which are at high risk of wildfire. Between 2015 and 2019, 23,606 wildfires were reported in the PNW region, accounting for 7.5% of all reported wildfires in the United States. The total burnt area as a result of those fires is about 32,400 square feet, accounting for 19.9% of the total burnt area during this time period in the United States. It indicates that a higher number of large-scale fires occurred in the PNW region compared to other parts of the United States, and there is a high probability that large-scale wildfires occur and disrupt supply chain networks in the PNW region. For example, based on our retrospective analysis, more than 20% of the feedstock nodes in this hypothetical supply chain network would have been damaged due to historical fires recorded between 2000 and 2019 in this region.

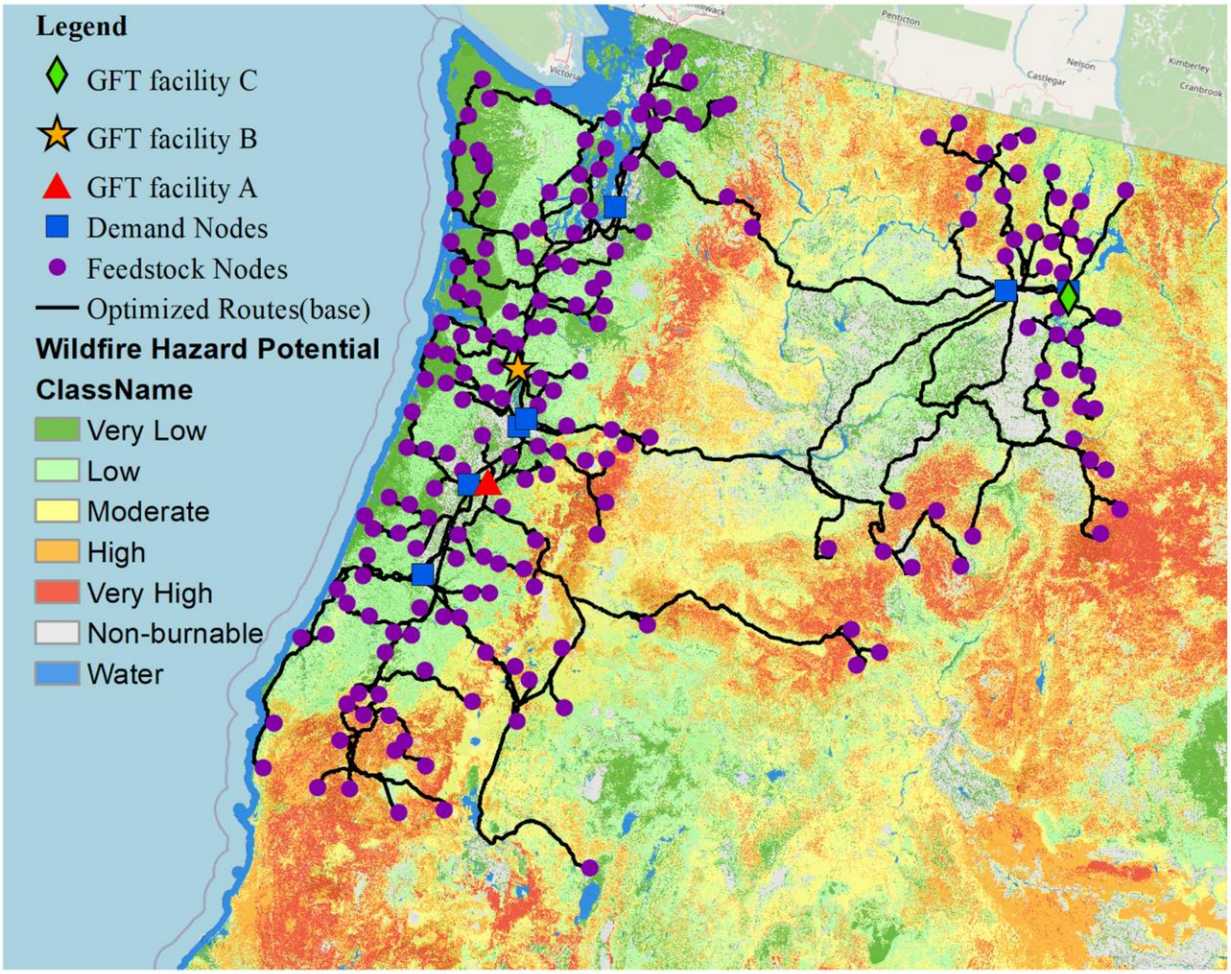


Figure 5.6 Geographical distribution of the supply chain network.

This SAF supply chain network consists of three types of nodes, representing feedstock nodes, processor nodes, and fuel destination nodes, as well as transportation links between them. In the supply chain network, forest residuals are used as the major raw materials for fuel production because they are abundant in the PNW region. Forest residuals are residues from forest harvesting and are typically burned on-site for disposal. In the network optimization, 198 feedstock nodes were selected based on their locations and capacities through the Freight and fuel Transportation Optimization Tool (FTOT) developed by the U.S. Department of Transportation Volpe Center (FTOT 2021, Lewis et al. 2019). These feedstock nodes can produce 1,993,281.5 metric tons of harvestable forest residuals per year. The forest residuals are converted into liquid fuels through a Gasification Fischer-Tropsch (GFT) pathway. The number and locations of GFT facilities were also determined using FTOT. Three GFT facilities are included in the optimized supply chain network layout as shown in Figure 5.6 and have the abilities to process 2,905,826.1 metric tons of harvestable forest residual per year. The final products produced by these facilities include jet fuel (267,286 kL per year) and road fuel (i.e., biodiesel) (178,190 kL per year), which are transported to airports and road fuel markets, respectively. In this optimized supply chain network, the total demand at all demand nodes (445,476 kL per year) are met.

As this supply chain network is distributed over a large geographic area, topography and fuel properties vary across the region of interest, making wildfire regimes spatially variable. The required ASCII layers containing topography and fuel property data for the study region were extracted from LANDFIRE dataset (www.landfire.gov) and were resampled to 270 m by 270 m. This cell size was selected because it required reasonable computational costs while being consistent with the cell size range that has been commonly used in existing studies (i.e., between 30 m and 270 m). On the other hand, to capture spatially variant wildfire frequency, the study region was divided into three zones based on the Wildfire Hazard Potential (Dillon et al. 2014) including (a) Zone A (i.e., the West Coast of Washington), (b) Zone B (i.e., the West Coast of Oregon), and (c) Zone C (i.e., Northeast Oregon, Northern Idaho, and Eastern Washington). Since this division was based on fire regimes, it was reasonable to assume that each zone had homogeneous weather conditions and wildfire occurrence rate. Thus, a single representative RAWS was selected for each zone considering the quality and completeness of the collected data and its distance to the supply chain system components (e.g., shorter distance is preferred). The historical daily observations of temperature, relative humidity, wind speed and direction, and precipitation were extracted from the representative RAWSs and were used to calculate historical ERC values. Subsequently, these ERC values were combined with the historical wildfire occurrence data available at the Fire & Aviation Management (FAMWEB) data warehouse to develop logistic regression models for large wildfire occurrence in each zone (see Equations (1) and (2)). To reduce computational cost, this study used a larger spatial unit in forecasting weather conditions and estimating wildfire occurrence rates as compared to the cell size (i.e., 270 m by 270 m) used in fire behavior modeling. It should be noted, however, that smaller size of spatial unit can better characterize weather conditions and wildfire occurrence rates.

Plausible ERC values over 5000 artificial years for each zone were generated as described in Section 5.3.1 and used to estimate the number of large wildfire occurrences in every artificial year. For each artificial year that had at least one large wildfire occurrence, fire ignition locations were randomly sampled with equal likelihood within each zone by assuming that all fires were independent. The occurrence times and locations of these realized fires were saved in the stochastic catalog. Combined with the ASCII layers containing topography and fuel property data, the behavior and growth of each wildfire were simulated using FlamMap (Finney 2006). FlamMap was selected in this study because of its ability to randomly generate multiple fires on the landscape and produce the final shapes and sizes of the burned areas as an output. Moreover, its computational efficiency made it possible to generate a large number of wildfires in the stochastic catalog to estimate the expected reduction in post-wildfire supply chain performance. Unlike Fsim, however, FlamMap does not have a fire suppression model to automatically stop a fire, and thus the final sizes and shapes of burned areas are sensitive to a user-defined maximum simulation time in minutes. In this study, the maximum simulation time was decomposed into the active burn period in a day and the number of days when wildfire burns (i.e., burning days). As described in

Section 5.3.2, the active burn period on a given day was assumed to be dependent on the ERC class of that day (i.e., 1 h, 3 h, and 5 h per day for the ERC1, ERC2, and ERC3 classes, respectively). To estimate the maximum number of burning days, the number of days that can generate a fire having the largest total burned area in history in the study region was calculated under the most extreme weather condition (i.e., the highest wind speed with the ERC3 class). Although it ensured that the potential largest burned area was matched with the actual one, it was a conservative assumption.

This case study considered the effect of wildfire on feedstock and GFT facility nodes. For simplicity purposes, the feedstock nodes located in the burned areas were assumed to completely lose their capacities (i.e., the amount of harvestable forest residuals is zero). Similarly, it was assumed that GFT facilities shut down if they were affected by a wildfire event. Given that industrial manufacturing and warehousing facilities are not physically vulnerable to fires due to their construction materials, the reduced functionality of a GFT facility during and following a wildfire event could be primarily caused by facility shutdown due to workforce safety (e.g., smoke-induced health issues), accessibility issues (e.g., essential transit route closure), etc. These factors may ultimately result in operational issues such as unmet demand and increased transportation time and costs due to detours. It should be noted, however, that wildfire could also affect different components and parts of the supply chain network: the functionalities of transportation links could be significantly reduced due to wildfire-induced structural damage, landslides, and rockfalls, or smoke-induced visibility issues. Moreover, manpower and truck shortages, fuel shortages, and intermodal transport accessibility issues during and following a wildfire event may greatly disrupt the supply chain network. Finally, for each wildfire, the reduced capacities of the damaged feedstock and facility nodes were incorporated into FTOT analysis to assess network-level supply chain performance reduction.

5.5 Results and discussion

Prior to a wildfire event, the hypothetical supply chain network meets total demand at all the destination nodes, and its total annual supply chain cost is estimated at $47.8 million. Since feedstock nodes were one of the most critical but vulnerable components in this SAF supply chain network, we first assessed the effect of wildfire-induced feedstock damages on feedstock availability. Figure 5.7 shows the histogram of annual feedstock losses due to wildfire damages, which accounts for uncertainties in weather conditions, and wildfire ignition and growth. As only a binary variable was used to represent the damage states of feedstock, uncertainty in vulnerability assessment was not taken into account. If a statistical relationship between wildfire intensity and multiple feedstock damage states becomes available based on empirical data, such uncertainty can be considered in the framework. The expected annual feedstock losses due to wildfires were 2383.1 metric tons, which was only 0.1% of the total annual harvestable forest residuals. As shown in Table 5.1, Zone C was the region contributing most to the expected feedstock losses, while feedstock nodes located in Zones A and B had relatively low probability of being exposed to wildfires. Although feedstock nodes were distributed over three zones relatively equally, their wildfire-induced damages and losses were different primarily because of inland climates: the Inland Northwest, also known as the Inland Empire, has drier condition, and less precipitation and higher temperature especially during the dry season may make wildfire worsen. Such difference in weather conditions can also be observed in historical ERC values in these three zones. As shown in Figure 5.8, the maximum historical ERC records in Zone C are 122% and 81% higher than the ones in Zones A and B, implying that large wildfire is more likely to occur and spread quickly in Zone C. Although wildfire effect on feedstock availability was insignificant in this supply chain network, wildfire risk could be reduced even further by including more feedstock nodes in Zones A and B in supply chain design. Reduced feedstock availability induced subsequent production loss, increased UDR, and ultimately increased total supply chain cost. Since such subsequent effects cannot be linearly and analytically formulated (see the numbers in Table 5.1), the propagation of damaged feedstock effects should be captured through the proposed framework. Moreover, while increase in UDR was slight, total supply chain cost increased significantly mainly due to high unmet demand penalty ($18,927/kL) and detours. However, this increase ($579,970 per year) was only 1.2% of the total annual cost, which indicated that this hypothetical supply chain network was not susceptible to wildfire risks.

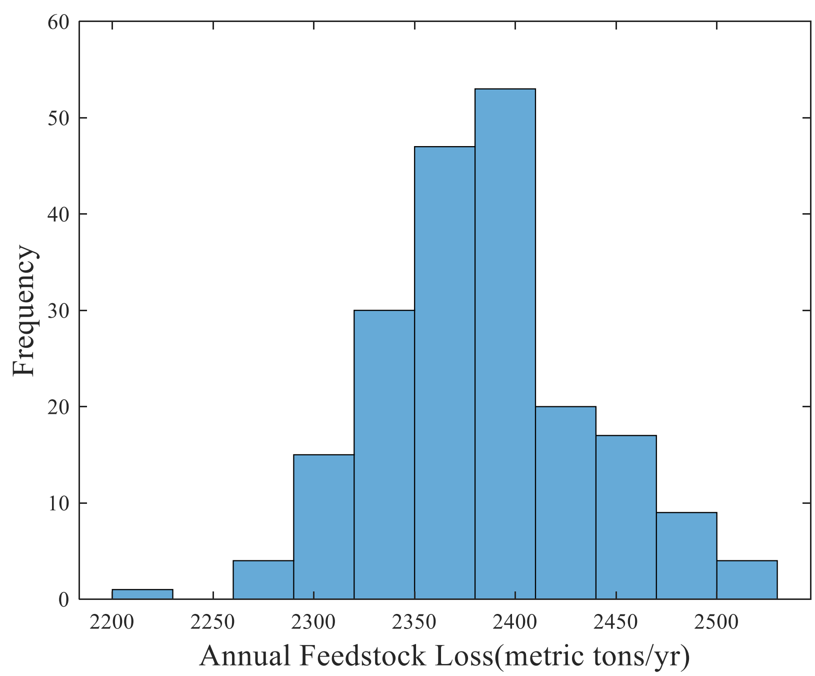


Figure 5.7 Histogram of annual feedstock losses (units: metric tons/year).

Table 5.1 Simulation results: expected changes in performance-related factors due to wildfire-induced feedstock damages.

	Zone A	Zone B	Zone C	Total
Annual feedstock losses (tons)	19.0	444.0	1,920.1	2,383.1
Annual production losses (kL)	3.8	90.5	511.6	605.9
Annual un-met demand ratio (%)	0.01	0.02	0.11	0.14
Annual supply chain cost increase ($)	4,696	105,807	469,467	579,970
Annual supply chain cost increase (%)	0.01%	0.22%	0.98%	1.21%

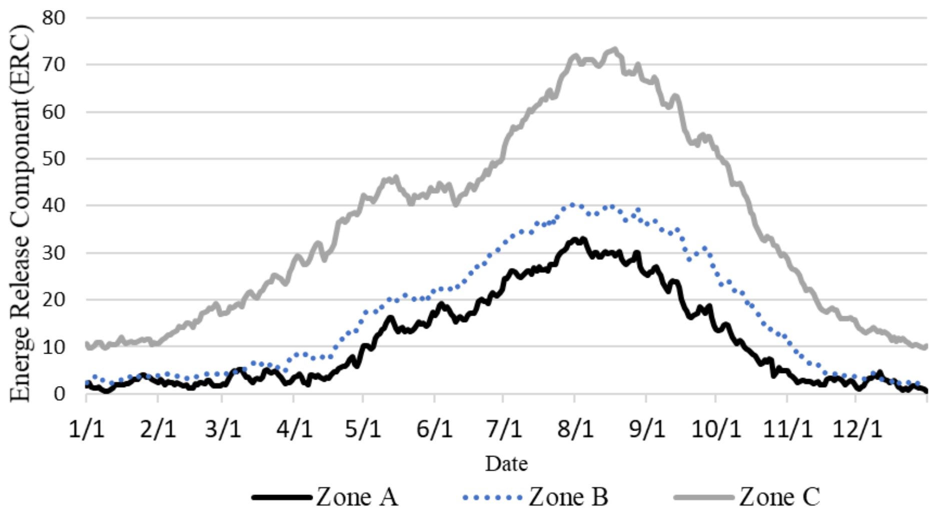


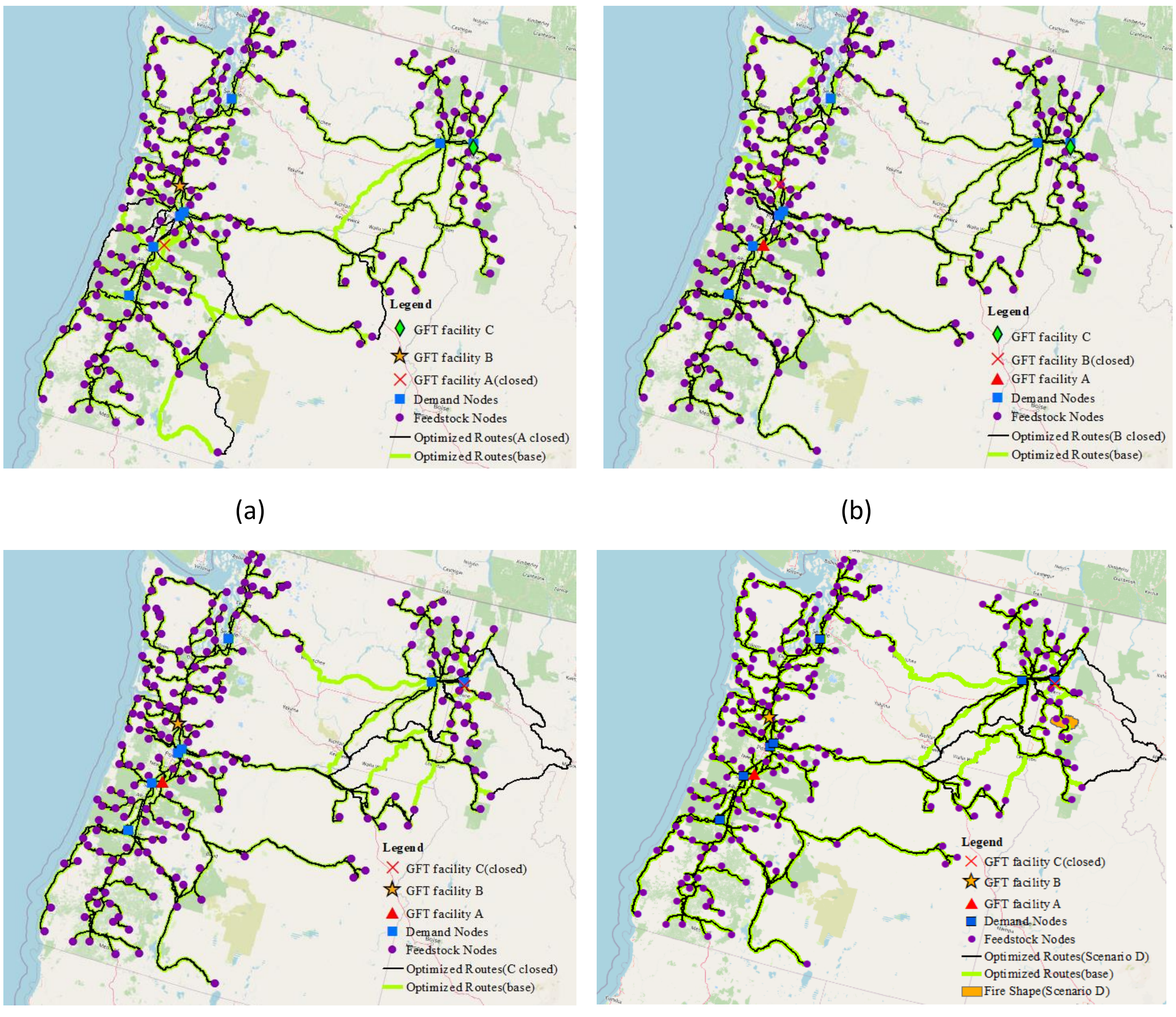
Figure 5.8 Comparison of the mean historical ERC values of the three zones

To validate the proposed risk assessment framework, the simulation results were compared with the expected changes in the four performance-related factors (shown in Table 5.1) induced by historical wildfires occurred over the past 20 years in the study region. By overlaying the fire-affected areas with the supply chain layout, the feedstock nodes affected by each historical fire were identified and used to estimate their propagation effects throughout the supply chain network. The expected reduction in feedstock availability due to historical wildfires was estimated at 1505.4 metric tons per year, while the expected increase in total supply chain cost was estimated at $358,320 per year. It indicated that the reduction in feedstock availability and total cost obtained from simulation results were overestimated at 59% and 62%, respectively. The reasons for such overestimation might include (a) the lack of historical data; (b) the assumption of uniform wildfire occurrence rate in each zone; (c) the use of constant weather conditions during the burn period; and (d) the approximation of fire containment modeling. First, in the validation process, we utilized only 20-year wildfire records to estimate the expected feedstock damages and supply chain performance reduction due to historical wildfires. Given that wildfire activity varies greatly from year to year, the dataset was not sufficient to capture such variance and represent the true effects of past wildfires on supply chain performance. Second, the assumption of uniform probability distribution of wildfire ignition within the same zone could contribute to inaccuracies in the simulation results. While it was a reasonable assumption in that the study area was divided into three zones based on FPU having similar environmental and weather conditions, dividing each zone into smaller spatial units would produce more accurate simulation results. Third, the use of constant weather conditions during the burn period generated an elliptical fire shape at every discrete time step which represented approximated fire size and direction. However, in the real world, the edges of fire shape are highly irregular due to substantially variable wind conditions along the edge. Such problem could be resolved by utilizing time-dependent weather conditions (i.e., pre-generated time-dependent fuel moisture and wind conditions). Finally, the approximation of fire containment used in the fire growth modeling was identified as the dominant source of the overestimation found in the comparison. Due to the lack of knowledge in fire containment and its highly uncertain nature (e.g., uncertainties in human activities, containment efforts, precipitation), in this study, the maximum simulation time in fire growth modeling was estimated based on the maximum wildfire size in the study area. It might overestimate the burn period and consequently increase the estimated wildfire risk. Improved containment modeling could greatly reduce uncertainties and result in more accurate simulation results. The effect of the aforementioned four sources of the overestimation on accuracy should be evaluated through sensitivity analyses and addressed in the assessment framework in future studies.

In addition to wildfire damages to feedstock nodes, wildfire-induced damages to GFT facilities were also considered in the case study. As shown in Figure 5.6, three GFT facilities A, B, and C are located in Northwest Oregon, South Puget Sound in Washington, and Northwest Idaho, respectively. The three facilities A, B, and C are capable of processing about 3 million metric tons of harvestable forest residual per year (i.e., the aggregate capacities of these three facilities), which is far greater than the total feedstock availability. Due to such redundant processing capacities, demands at final destination nodes could still be met even when one of the GFT facilities completely loses its capacity due to wildfires. Therefore, in this case study, the effect of the functionality loss of GFT facility on system performance was assessed by (a) increased total transportation cost and (b) increased total travel time.

For the purpose of illustration, three representative scenarios were considered to demonstrate the effect of facility shutdown on supply chain performance following a wildfire event. Scenarios A, B, and C represent the wildfire-induced closure of Facilities A, B, and C, respectively. It is because these facilities are located far apart from one another, and the probability that more than one facility will be simultaneously affected by wildfires is very low. Figure 5.9 (a) – (c) illustrate optimal routes for three different scenarios in addition to the base scenario (i.e., all the three facilities are open; see the green routes in each figure). As shown in Figure 5.9, facility closure induced re-routing and detours, therefore increasing total transportation time and cost. More specifically, Table 5.2 summarizes the total transportation time and costs for all these three scenarios and further specifies the transportation costs required to transport each type of commodity. For example, the total transportation cost for forest residuals represents the cost required to transport it from feedstock nodes to GFT facilities. As shown in Table 5.2, in comparison to the base scenario, total transportation costs for Scenarios A, B, and C increased by 18%, 14%, and 30% respectively, while total transportation times increased by 34.5%, 41.9%, and 192.8% respectively. Longer transportation time was expected in Scenario B compared to Scenario A, whereas the opposite behavior was observed in transportation costs. It is because Scenario B transported more commodities by rail than Scenario A did: one railroad car can transport more loads than a truck can, but at the same time, is slower (e.g., one railroad car can load 82 ton solid or 108 kL liquid with the average speed of 45 kmh, while a truck can load 24 ton solid or 30 kL liquid with the average speed of 80 kmh). As observed in Table 5.2, the costs required to transport forest residuals from feedstock nodes to the remaining GFT facilities contributed the most to the increase in the total transportation costs in all the three scenarios. The results also indicated that the closure of Facility C in Northwest Idaho had the most significant impact on supply chain performance because it processed most forest residuals from the feedstock nodes located in the eastern parts of the supply chain network. Therefore, constructing another GFT facility in the eastern parts may redistribute the burden of Facility C and subsequently reduce the negative effect of wildfire on supply chain system performance.

From Tables 5.1 and 5.2, wildfire-induced damages to the feedstock nodes and Facility C located in Zone C had the greatest impact on network-level performance. To assess the combined effect of destroyed feedstock and facility closure, Scenario D considered a series of wildfire events affecting two feedstock nodes (see the orange fire shape in Figure 5.9 (d)) and Facility C in Zone C in the same artificial year. In comparison to the closure of GFT facility C alone, the total transportation time decreased as a result of reduced commodity flow. On the other hand, the total supply chain cost ($71, 944, 548) increased due to the increased unmet demand at the final destination nodes in Zone C. As compared to the base scenario, the total scenario cost increased by 50.5%, including (a) a 24.9% rise in transportation cost owing to Facility C closure and the consequent detours; and (b) a 25.6% increase in unmet demand penalty due to the destroyed feedstock nodes.



(a) (b) (c) (d)

Figure 5.9 Optimal routes for four scenarios, including (a) GFT Facility A closure; (b) GFT Facility B closure; (c) GFT Facility C closure; and (d) GFT Facility C closure and feedstock damages

Table 5.2 Transportation costs and time for four scenarios

	Total cost ($)				Total time (hour)
	Total	Forest residual	Jet fuel	Road fuel	
Base scenario	47,792,195	44,216,801	2,941,664	633,713	408,303
Scenario A	56,297,579	52,016,870	2,844,828	1,435,864	549,177
Scenario B	54,611,535	50,836,126	3,106,508	668,884	579,283
Scenario C	62,350,385	57,284,058	3,332,436	1,733,873	1,195,358
Scenario D	59,692,706	54,894,348	3,173,278	1,625,079	1,113,328

Although the total recovery time of each facility is assumed to be one year which is consistent with the time interval used for the FTOT optimization, it depends on many factors such as the main causes of facility closure, post-wildfire available resources, etc. For example, facility capacity may be fully recovered immediately following wildfire containment (if this closure is induced by smoke-induced health issues or mandatory evacuation order) or upon the completion of restoration activities (when the closure is due to direct structural damage to the facility or essential transit route closure).

5.6 Conclusion

This paper proposes a probabilistic framework for quantifying wildfire risk to a supply chain network. The framework is designed to systematically account for uncertainties throughout all the phases of risk assessment and to estimate the expected post-wildfire functional loss of a supply chain network in terms of UDR, total supply chain cost, and total transportation time. The case study results showed that the hypothetical SAF supply chain in the PNW region met customer demands during and following a wildfire event, whereas total supply chain cost increased as a result of high unmet demand penalty and detours. Given that the feedstock nodes in the Inland Northwest were identified as the most vulnerable ones to wildfires, the inclusion of more feedstock nodes in the West Coast of Washington and the West Coast of Oregon could reduce wildfire risks.

The findings further 148ualtrghted that the closure of a single critical processor (Facility C) in the Inland Northwest dramatically increased transportation costs, suggesting that the construction of another processor in this zone could further reduce wildfire risk. Thus, the proposed framework can be used as a planning tool to evaluate network performance subject to a set of what-if scenarios that capture uncertainties in wildfire ignition, growth, and containment, component vulnerability, and network analysis, and the effect of pre- and post-wildfire risk mitigation measures. The framework can also be easily modified and applied to other types of natural hazards or other infrastructure systems.

The comparison between the results”from’historical wildfires and simulated wildfires indicated that the simulation results were overestimated due to the lack of data and several restrictive assumptions used in wildfire occurrence and growth modeling. To improve modeling accuracy, the identified sources of the overestimation in Section 5.5 should be addressed in future studies. Due to the underlying stationary assumption of topography and fuel conditions in the second module, the results of the proposed framework may have temporal stationarity issues. If a great change in climate pattern or fire regime is expected in the study area, the results will not be robust enough and may require re-estimation. Moreover, the case study assessed the effect of wildfire only on feedstock facilities and processor facilities for the purpose of simplicity. However, the proposed framework is designed to quantify wildfire disruptions to other supply chain components, such as major facilities, highway bridges and segments, and demand nodes. Thus, the authors will expand the current study to incorporate direct impacts on various network components as well as other indirect effect from wildfire (e.g., road closures or extensive delays due to landslides and/or rock falls following a wildfire event, or smoke-induced visibility and health issues from a wildfire event, fuel shortages, intermodal transport accessibility issues) to provide a more comprehensive framework.

CHAPTER SIX: SUMMARY AND CONCLUSIONS

6.1 Overview

Wildfire risk has significantly increased in recent decades, posing a greater threat to human lives, properties, and regional economies. This dissertation aims to understand, assess, and manage wildfire risks, with a particular focus on residential communities and supply chain networks. Specifically, to gain insights into individual residents' preferences and decisions about various proactive and emergency actions prior to and during a wildfire event, we conducted a set of online surveys, analyzed the data, and established quantitative models. These models have practical utility in the context of community resilience and traffic simulations, contributing to more effective wildfire risk management. Moreover, a simulation framework was proposed to replicate the responses and behaviors of evacuees during a wildfire event, specifically in damaged transportation settings. This framework can serve as a valuable tool for designing and testing the effectiveness of pre-fire risk mitigation strategies, enhancing the overall preparedness of communities facing the threat of wildfires. Finally, this dissertation developed a probabilistic framework that provided a quantitative means of evaluating wildfire risks to supply chain networks. It offers a comprehensive approach to identifying vulnerabilities and potential points of intervention within these networks, ultimately leading to reduction in wildfire risks.

6.2 Findings and Limitations

In Chapter 2, we assessed the factors driving individuals' preferences for adopting proactive measures and their effectiveness on post-wildfire recovery based on an online survey conducted after wildfire incidents. The results provided valuable insights federal and local governments to enhance community resilience. We found that homeowners' age and household income significantly affected their preference to adopt home hardening and purchasing homeowner insurance. Additionally, our findings highlighted the supreme effect of home hardening on reducing structural damage compared with constructing defensible space. Furthermore, we confirmed the significant effect of homeowner insurance on post-wildfire financial availability. However, we caution against generalizing our findings from this chapter due to the limited number of samples collected in the online survey. This study can benefit from a larger sample size that represents the general population and more in-depth individual interviews.

Chapter 3 investigated the factors impacting evacuee preferences and behaviors during wildfires. This investigation was based on a stated preference survey distributed in California, Colorado, and Oregon. The survey collected data on individuals' responses to staged evacuation orders and a series of en-route decisions. Additionally, we constructed a data-driven model to predict the evacuation decisions of individuals. This model was illustrated in the context of the Santa Clarita area during the Tick Fires, demonstrating how aggregated and disaggregated evacuation decisions can aid policymakers in designing effective evacuation plans. Findings from this chapter revealed that individuals' education level, regular use of GPS navigation, prior effective evacuation experience, homeowner insurance status, financial risk preferences, and the presence of a disaster evacuation plan impacted their responsiveness to different levels of evacuation orders. Since our study relied heavily on stated preference surveys, additional revealed preference surveys can alleviate the bias induced by the potential mismatch between stated preferences and actual behaviors. Moreover, our proposed predictive models can be further validated at the parcel level by conducting post-event interviews in the future.

Chapter 4 introduced a comprehensive evacuation simulation framework that integrates wildfire simulation, bridge vulnerability assessment, a data-driven evacuee response model, and ABM traffic simulation. We showcased the framework's capabilities through a case study in the Santa Clarita area, identified the vulnerable but critical role of the southern and northwest sectors of the city due to the excessive expected delays during wildfire evacuation events. The results highlighted the ability of the proposed framework to forecast traffic conditions during evacuation events and identified critical segments of the transportation network requiring pre-fire risk mitigation measures. It has the capability to simulate traffic movements at both aggregate and disaggregate level, offering a comprehensive assessment of network performance during evacuations under damaged transportation settings. The model's performance can be further enhanced by alleviating certain assumptions, such as incorporating public transportation and implementing a more realistic evacuation zone planning model in future work.

Chapter 5 focused on the development of an integrated wildfire risk assessment framework for supply chain networks. This framework encompasses wildfire occurrence estimation, wildfire growth and propagation simulation, vulnerability assessment, and network-level supply chain analysis. It serves as a planning tool to evaluate network performance under various what-if scenarios, capturing uncertainties in wildfire ignition, growth, containment, component vulnerability, network analysis, and the impact of pre- and post-wildfire risk mitigation measures on supply chain performance. The proposed framework was illustrated with the hypothetical SAF supply chain in the PNW region. The feedstock nodes in the inland Northwest were identified to be more vulnerable to wildfires in comparison to those on the west coast, and the closure of the processor facility at inland Northwest can dramatically reduce the functionality of the supply chain. It is worth noting that the proposed framework may have temporal stationary issues due to the stationary assumption of topography and fuel conditions. Re-estimation may be necessary if significant changes in the fire regime or climate patterns are observed. Furthermore, in future work, the framework's capabilities can be expanded to encompass both direct and indirect impacts on various components, in addition to feedstock and processing nodes.

In conclusion, the dissertation provides valuable information to policymakers and stakeholders on individual's preferences on both proactive actions and evacuation decisions. Such information can help federal/local governments increase the participation rates of proactive actions and the responsiveness to evacuation orders, which have the potential to increase community resilience. On the other hand, the simulation tools and quantitative frameworks developed in this dissertation can help stakeholders and policymakers forecast post-wildfire performances and make more effective pre-event mitigation measures. Furthermore, these adaptable tools and frameworks have the potential for broader applications in various domains, including water distribution networks, transportation systems, and electric power grids. As such, they represent valuable assets in addressing the complex challenges posed by dynamic and interconnected systems.

6.3 Future Works

Chapter 5 introduces a probabilistic supply chain wildfire risk assessment framework aimed at estimating the expected reduction in supply chain performance following a wildfire event. However, this model was developed based on several assumptions, including the static topographic and fuel conditions, and reliance on a constant ignition probability determined solely by the ERC calculated from a representative weather station. These assumptions may lead to robustness issues when confronted with significant changes in weather patterns and fire regimes. Moreover, the proposed framework has focused only on the direct impact of wildfire on the physical components of a supply chain system through a network analysis. However, wildfire may also disrupt supply chain operation and management indirectly. Highway bridges and segments may be closed or partially opened due to smoke-induced visibility issues, which could interrupt logistics and transportation activities. Facilities may be shut down to achieve workforce safety (e.g., smoke-induced health issues). Both direct and indirect effects of wildfire on various parts of supply chain, such as physical components, workers and drivers, should also be taken into account to properly estimate post-wildfire supply chain performance.

In future work, the framework can be enhanced by developing a machine learning-powered ignition probability model that utilizes Deep Neural Networks (DNNs) to assess the spatial-temporal probability of wildfire ignition, considering human, topographic, and meteorological variables. This improved probability estimation model can provide a dynamic update of wildfire potential by estimating spatial-temporal wildfire ignition probabilities for the next 16 days, using forecasted meteorological data obtained from the OpenWeather API. Additionally, the state-of-the-art Prithvi-100M burn scar model (Roy et al., 2023) can be leveraged to identify burn scars on the landscape from satellite images. This data can be used to retrieve information about burn scars and their recovery trajectory for historical wildfire events, for which only final perimeters are available. This information can be used to construct an empirical fragility curve for various components in the network, thereby enhancing the vulnerability assessment module.

Overall, the study aims to extend the framework introduced in Chapter 5 to dynamically update the expected wildfire risk for supply chains in a short time frame in the foreseeable future. This will provide timely evaluations to assist policymakers and stakeholders in improving their supply chain operation preparedness.

REFERENCES

Abatzoglou, J.T., (2012). Development of gridded surface meteorological data for ecological applications and modeling. International Journal of Climatology.

AccuWeather, (2017). AccuWeather predicts 2017 California wildfire season cost to rise to $180 billion. AccuWeather. Source: https://www.accuweather.com/en/weather-news/accuweather-predicts-2017-california-wildfire-season-cost-to-rise-to-180-billion/354369.

Alexandre PM, Stewart SI, Mockrin MH, Keuler NS, Syphard AD, Bar-Massada A et al (2016) The relative impacts of vegetation, topography and spatial arrangement on building loss to wildfires in case studies of California and Colorado. Landsc Ecol 31(2):415–430

Andrews, P. L., Loftsgaarden, D. O., & Bradshaw, L. S. (2003). Evaluation of fire danger rating indexes using logistic regression and percentile analysis. International Journal of Wildland Fire, 12(2), 213-226.

Avami, A. (2012). A model for biodiesel supply chain: A case study in Iran. Renewable and Sustainable Energy Reviews, 16(6), 4196-4203.

Balch, J. K., Bradley, B. A., Abatzoglou, J. T., Nagy, R. C., Fusco, E. J., & Mahood, A. L. (2017). Human-started wildfires expand the fire niche across the United States. Proceedings of the National Academy of Sciences, 114(11), 2946-2951.

Barbero, R., Abatzoglou, J. T., Steel, E. A., & Larkin, N. K. (2014). Modeling very large-fire occurrences over the continental United States from weather and climate forcing. Environmental research letters, 9(12), 124009.

Bar-Gera, H., K. Konduri, B. Sana, X. Ye, and R.M. Pendyala (2009) Estimating Survey Weights with Multiple Constraints Using Entropy Optimization Methods. Proceedings of 88th Annual Meeting of the Transportation Research Board, National Research Council, Washington, D.C.

Barrett, K. (2020). Wildfires destroy thousands of structures each year – Headwaters Economics. Headwaters Economics. Retrieved 11 November 2021, from https://headwaterseconomics.org/natural-hazards/structures-destroyed-by-wildfire/#methods

Beloglazov, A., Almashor, M., Abebe, E., Richter, J., & Steer, K. C. B. (2016). Simulation of wildfire evacuation with dynamic factors and model composition. Simulation Modelling Practice and Theory, 60, 144-159.

Benda L, Miller D, Bigelow P, Andras K (2003) Effects of post-wildfire erosion on channel environments, Boise River, Idaho. For Ecol Manag 178(1–2):105–119

Benjaafar, S., Dooley, K. and Setyawan, W., (1997). Cellular automata for traffic flow modeling. University of Minnesota. Retrieved from the University of Minnesota Digital Conservancy, http://hdl.handle.net/11299/155096.

Beth, L., TJ, B., LS, B., & WM, J. (2003, November). National standardized energy release component (ERC) forecasts. In 5th Symposium on Fire and Forest Meteorology.

Biglari, M., & Formisano, A. (2020). Damage probability matrices and empirical fragility curves from damage data on masonry buildings after Sarpol-e-zahab and bam earthquakes of Iran. Frontiers in built environment, 6, 2.

Block, B. (2019). Video: Evacuation centers provide relief for residents displaced by Tick Fire. Santa Clarita Valley Signal. https://signalscv.com/2019/10/video-evacuation-centers-provide-relief-for-residents-displaced-by-tick-fire. Accessed 15 February 2023

Boas TC, Christenson DP, Glick DM (2020) Recruiting large online samples in the United States and India: Facebook, mechanical turk, and 156ualtrics. Polit Sci Res Methods 8(2):232–250

Bradstock, R. A., Cohn, J. S., Gill, A. M., Bedward, M., & Lucas, C. (2009). Prediction of the probability of large fires in the Sydney region of south-eastern Australia using fire weather. International Journal of Wildland Fire, 18(8), 932-943.

Brenkert-Smith H, Champ PA, Flores N (2012) Trying not to get burned: understanding homeowners' wildfire risk–mitigation behaviors. Environ Manag 50(6):1139–1151

Brenkert-Smith H, Champ PA, Flores N (2006) Insights into wildfire mitigation decisions among wildlandurban interface residents. Soc Nat Resour 19(8):759–768

Brillinger, D. R., Preisler, H. K., & Benoit, J. W. (2003). Risk assessment: a forest fire example. Lecture Notes-Monograph Series, 177-196.

Burkard, R.E., Dlaska, K. and Klinz, B., (1993). The quickest flow problem. Zeitschrift für Operations Research, 37(1), pp.31-58.

Butry D, Donovan G (2008) Protect thy neighbor: investigating the spatial externalities of community wildfire hazard mitigation. For Sci 54(4):417–428

Butte County (2021) Fire Prevention. https://www.buttecounty.net/fire/Firefacilities/Prevention

Butte County GIS (2021) *Camp Fire information map*. ArcGIS. https://www.arcgis.com/apps/webappviewer/index.html?id=aadf4b961cd64eccb6287f277e95ab6c

Calkin, D. E., Thompson, M. P., & Finney, M. A. (2015). Negative consequences of positive feedbacks in US wildfire management. Forest Ecosystems, 2, 1-10.

Cao, Y., Wei, W., Huang, L., Qiao, H., & Du, J. (2019). Research on supply chain risk coping strategy based on fuzzy logic. Journal of Intelligent & Fuzzy Systems, 37(4), 4537-4546.

Catry, F. X., Rego, F. C., Bação, F. L., & Moreira, F. (2009). Modeling and mapping wildfire ignition risk in Portugal. International Journal of Wildland Fire, 18(8), 921-931.

Charpentier A, Le Maux B (2014) Natural catastrophe insurance: How should the government intervene? J Public Econ 115:1–17

Chen, X. and Zhan, F.B., (2014). Agent-based modeling and simulation of urban evacuation: relative effectiveness of simultaneous and staged evacuation strategies. In Agent-based modeling and simulation (pp. 78-96). Palgrave Macmillan, London.

Cheng, L., Chen, X., De Vos, J., Lai, X., & Witlox, F. (2019). Applying a random forest method approach to model travel mode choice behavior. Travel behaviour and society, 14, 1-10.

Chmielewski, M., & Kucker, S. C. (2020). An Mturk crisis? Shifts in data quality and the impact on study results. Social Psychological and Personality Science, 11(4), 464-473.

Christianson, A. C., McGee, T. K., & Whitefish Lake First Nation 459. (2019). Wildfire evacuation experiences of band members of Whitefish Lake First Nation 459, Alberta, Canada. Natural Hazards, 98(1), 9-29.

Cimellaro, G.P., Ozzello, F., Vallero, A., Mahin, S. and Shao, B., (2017). Simulating earthquake evacuation using human behavior models. Earthquake Engineering & Structural Dynamics, 46(6), pp.985-1002.

Cohn, P. J., Carroll, M. S., & Kumagai, Y. (2006). Evacuation behavior during wildfires: results of three case studies. Western Journal of Applied Forestry, 21(1), 39-48.

Coldham, D., Czerwinski, A., & Marxsen, T. (2011). Probability of Bushfire Ignition from Electric Arc Faults Final Report. Australia: HRL Technology Pty Ltd.

Collins TW (2009) Influences on wildfire hazard exposure in Arizona’s high country. Soc Nat Resour 22(3):211–229

Communities Committee, 2004. Preparing a community wildfire protection plan: a handbook for wildland urban interface communities. Communities Committee, et al. Available at: chromeextension://efaidnbmnnnibpcajpcglclefindmkaj/https://www.forestsandrangelands.gov/documents/resources/communities/cwpphandbook.pdf

Cosgrove, E. (2018). California widlfires endanger supply chain workers, displace businesses. Supply Chain Dive. Retrieved from https://www.supplychaindive.com/news/california-wildfires-logistics-effects/542110/.

Cote, D. W., & McGee, T. K. (2014). An exploration of residents' intended wildfire evacuation responses in Mt. Lorne, Yukon, Canada. The Forestry Chronicle, 90(4), 498-502.

Cova, T. J., Dennison, P. E., Kim, T. H., & Moritz, M. A. (2005). Setting wildfire evacuation trigger points using fire spread modeling and GIS. Transactions in GIS, 9(4), 603-617.

Cova, T. J., & Johnson, J. P. (2002). Microsimulation of neighborhood evacuations in the urban–wildland interface. Environment and Planning A, 34(12), 2211-2229.

Diao, T., Singla, S., Mukhopadhyay, A., Eldawy, A., Shachter, R., & Kochenderfer, M. (2020). Uncertainty aware wildfire management. arXiv preprint arXiv:2010.07915.

Dickinson KL, Brenkert-Smith H, Madonia G, Flores NE (2020) Risk interdependency, social norms, and wildfire mitigation: a choice experiment. Nat Hazards 103:1327–1354

Dillon, G. K., Menakis, J., & Fay, F. (2015). Wildland fire potential: a tool for assessing wildfire risk and fuels management needs. In R. E. Keane, M. Jolly, R. Parsons, & K. Riley (Eds.), Proceedings of the Large Wildland Fires Conference; May 19-23, 2014; Missoula, MT (pp. 60-76). RMRS-P-73, U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station, Fort Collins, CO.

Dixit, V., Verma, P., & Tiwari, M. K. (2020). Assessment of pre and post-disaster supply chain resilience based on network structural parameters with CvaR as a risk measure. International Journal of Production Economics, 227, 107655.

Dlamini, W. M. (2010). A Bayesian belief network analysis of factors influencing wildfire occurrence in Swaziland. Environmental Modelling & Software, 25(2), 199-208.

D'Orazio, M., Spalazzi, L., Quagliarini, E., & Bernardini, G. (2014). Agent-based model for earthquake pedestrians' evacuation in urban outdoor scenarios: Behavioural patterns definition and evacuation paths choice. Safety science, 62, 450-465.

Edgeley, C. M., & Paveglio, T. B. (2019). Exploring influences on intended evacuation behaviors during wildfire: What roles for pre-fire actions and event-based cues?. International journal of disaster risk reduction, 37, 101182.

Epstein, J. M. (1999). Agent-based computational models and generative social science. Complexity, 4(5), 41-60.

Eriksen C, de Vet E (2020) Untangling insurance, rebuilding, and wellbeing in bushfire recovery. Geograph Res

Evans A, Auerbach S, Miller LW, Wood R, Nystrom K, Loevner J et al (2015) Evaluating the effectiveness of mitigation activities in the wildland-urban interface. https://www.firescience.gov/projects/11-1-310/project/11-1-3-10_final_report.pdf

Faulkner H, Mcfarlane BL, Mcgee TK (2009) Comparison of homeowner response to wildfire risk among towns with and without wildfire management. Environ Hazards 8(1):38–51

Feng, K., Li, Q., & Ellingwood, B. R. (2020). Post-earthquake modeling of transportation networks using an agent-based model. Structure and Infrastructure Engineering, 16(11), 1578-1592.

Fernandes, P. M., Botelho, H., Rego, F., & Loureiro, C. (2008). Using fuel and weather variables to predict the sustainability of surface fire spread in maritime pine stands. Canadian Journal of Forest Research, 38(2), 190-201.

Finney, M. A., McHugh, C. W., Grenfell, I. C., Riley, K. L., & Short, K. C. (2011). A simulation of probabilistic wildfire risk components for the continental United States. Stochastic Environmental Research and Risk Assessment, 25, 973-1000.

Finney, M. A. (2006). An overview of FlamMap fire modeling capabilities. In P. L. Andrews, B. W. Butler (Eds.), Fuels Management-How to Measure Success: Conference Proceedings (pp. 213-220). Proceedings RMRS-P-41, vol. 41, US Department of Agriculture, Forest Service, Rocky Mountain Research Station, Fort Collins, CO.

Finney, M. A. (2002). Fire growth using minimum travel time methods. Canadian Journal of Forest Research, 32(8), 1420-1424.

FTOT (Freight and Fuel Transportation Optimization Tool), 2021 Retrieved from. https://github.com/VolpeUSDOT/FTOT-Public.

Gan J, Jarrett A, Gaither CJ (2014) Wildfire risk adaptation: propensity of forestland owners to purchase wildfire insurance in the southern United States. Can J for Res 44(11):1376–1382

Ge Y, Peacock WG, Lindell MK (2011) Florida households' expected responses to hurricane hazard mitigation incentives. Risk Anal Int J 31(10):1676–1691

Ghasemi B, Kyle GT, Absher JD (2020) An examination of the social-psychological drivers of homeowner wildfire mitigation. J Environ Psychol 70:101442

Goh, M., Lim, J. Y., & Meng, F. (2007). A stochastic model for risk management in global supply chain networks. European Journal of Operational Research, 182(1), 164-173.

Goodman, H., & Proudley, M. (2008). Social contexts of responses to bushfire threat (pp. 47-56). CSIRO Publishing, Melbourne, Australia.

Grajdura, S., Borjigin, S., & Niemeier, D. (2022). Fast-moving dire wildfire evacuation simulation. Transportation research part D: transport and environment, 104, 103190.

Grajdura, S., Qian, X., & Niemeier, D. (2021). Awareness, departure, and preparation time in no-notice wildfire evacuations. Safety science, 139, 105258.

Grajdura, S.A., Borjigin, S.G. and Niemeier, D.A., 2020, November. Agent-based wildfire evacuation with spatial simulation: a case study. In Proceedings of the 3rd ACM SIGSPATIAL International Workshop on GeoSpatial Simulation (pp. 56-59).

Hagenauer, J., & Helbich, M. (2017). A comparative study of machine learning classifiers for modeling travel mode choice. Expert Systems with Applications, 78, 273-282.

Haimes, Y. Y., Kaplan, S., & Lambert, J. H. (2002). Risk filtering, ranking, and management framework using hierarchical holographic modeling. Risk Analysis, 22(2), 383-397.

Haines TK, Renner CR, Reams MA, Granskog J (2004) The national wildfire mitigation programs database: state, county, and local efforts to reduce wildfire risk. In: Proceedings of the second international symposium on fire economics, planning, and policy: a global view, pp 19–22

Hamacher, H. W., & Tjandra, S. A. (2002). Earliest arrival flow model with time dependent capacity for solving evacuation problems. Pedestrian and Evacuation Dynamics, 267-276.

Hamacher, H. W., & Tjandra, S. A. (2001). Mathematical modeling of evacuation problems: A state of the art. In Pedestrian and Evacuation Dynamics (pp. 227-266). Springer, Berlin.

Hazell P (2001) Potential role for insurance in managing catastrophic risk in developing countries. Int Food Policy Res Institute (draft)

Hessburg, P. F., Agee, J. K., & Franklin, J. F. (2005). Dry forests and wildland fires of the inland Northwest USA: contrasting the landscape ecology of the pre-settlement and modern eras. Forest Ecology and Management, 211(1-2), 117-139.

Huang, Y., Chen, C. W., & Fan, Y. (2010). Multistage optimization of the supply chains of biofuels. Transportation Research Part E: Logistics and Transportation Review, 46(6), 820-830.

Hung LS, Wang C (2022) Integrating an intrahousehold perspective into climate change adaptation research. Environ Sci Policy 131:143–148

Insurance Information Institute (III) (2020) Fact + statistics: wildfires. https://www.iii.org/fact-statistic/ facts-statistics-wildfires

Intini, P., Ronchi, E., Gwynne, S., & Pel, A. (2019). Traffic modeling for wildland–urban interface fire evacuation. Journal of Transportation Engineering, Part A: Systems, 145(3), 04019002.

Jain, S., Ronald, N., & Winter, S. (2015, December). Creating a synthetic population: A comparison of tools. In Proceedings of the 3rd Conference Transportation Research Group, Kolkata, India (pp. 17-20).

Jaffee, S., Siegel, P., & Andrews, C. (2010). Rapid agricultural supply chain risk assessment: A conceptual framework. Agriculture and rural development discussion paper, 47(1), 1-64.

Jakes PJ, Sturtevant V (2013) Trial by fire: community wildfire protection plans put to the test. Int J Wildl Fire 22(8):1134–1143

Jenelius, E., & Mattsson, L. G. (2012). Road network vulnerability analysis of area-covering disruptions: A grid-based approach with case study. Transportation research part A: policy and practice, 46(5), 746-760.

Joosse, T. (2020). Human-sparked Wildfires Are More Destructive than Those Caused by Nature. American Association for the Advancement of Science. Retrieved from https://www.sciencemag.org/news/2020/12/human-sparked-wildfires-are-more-destructive-those-caused-nature

Katzilieris, K., Vlahogianni, E. I., & Wang, H. (2022). Evacuation behavior of affected individuals and households in response to the 2018 Attica wildfires: From empirical data to models. Safety Science, 153, 105799.

Keeley, J. E. (2009). Fire intensity, fire severity and burn severity: a brief review and suggested usage. International journal of wildland fire, 18(1), 116-126.

Kennedy, R., Clifford, S., Burleigh, T., Waggoner, P. D., Jewell, R., & Winter, N. J. (2020). The shape of and solutions to the Mturk quality crisis. Political Science Research and Methods, 8(4), 614-629.

Keow Cheng, S., & Hon Kam, B. (2008). A conceptual framework for analysing risk in supply networks. Journal of Enterprise Information Management, 21(4), 345-360.

Khakzad, N., Dadashzadeh, M., & Reniers, G. (2018). Quantitative assessment of wildfire risk in oil facilities. Journal of environmental management, 223, 433-443.

Kim, J., Realff, M. J., & Lee, J. H. (2011). Optimal design and global sensitivity analysis of biomass supply chain networks for biofuels under uncertainty. Computers & Chemical Engineering, 35(9), 1738-1751.

Kisko, T. M., & Francis, R. L. (1985). EVACNET+: A computer program to determine optimal building evacuation plans. Fire Safety Journal, 9(2), 211-220.

Kleindorfer, P. R., & Saad, G. H. (2005). Managing disruption risks in supply chains. Production and operations management, 14(1), 53-68.

Koksal, K., McLennan, J., Every, D., & Bearman, C. (2019). Australian wildland-urban interface householders' wildfire safety preparations: 'Everyday life'project priorities and perceptions of wildfire risk. International journal of disaster risk reduction, 33, 142-154.

Konduri, K. C., You, D., Garikapati, V. M., & Pendyala, R. (2016). Application of an enhanced population synthesis model that accommodates controls at multiple geographic resolutions. In Proceedings of the 95th annual meeting of the transportation research board, Washington, DC, USA (pp. 10-14).

Krejcie RV, Morgan DW (1970) Determining sample size for research activities. Educ Psychol Meas 30(3):607–610

Kuligowski, E. D., Zhao, X., Lovreglio, R., Xu, N., Yang, K., Westbury, A., et al. (2022). Modeling evacuation decisions in the 2019 Kincade fire in California. Safety science, 146, 105541.

Kuligowski, E. D., Walpole, E. H., Lovreglio, R., & McCaffrey, S. (2020). Modelling evacuation decision-making in the 2016 Chimney Tops 2 fire in Gatlinburg, TN. International journal of wildland fire, 29(12), 1120-1132.

Kunreuther H, Pauly M (2006) Rules rather than discretion: lessons from Hurricane Katrina. J Risk Uncertain 33(1–2):101–116

Lee, J.Y., & Li, Y. (2021) a first step towards longitudinal study on homeowners' proactive actions for managing wildfire risks. In: Natural hazards center quick response grant report series. Natural Hazards Center, University of Colorado Boulder, Boulder. https://hazards.colorado.edu/quick-response-report/a-firststep-towards-longitudinal-study-on-homeowners-proactive-actions-for-managing-wildfire-risks

Lee, J.Y., Zhao, J., Li, Y., & Yin, Y.J. (2019) Quantitative impact of catastrophe risk insurance on community resilience. In: Proceedings of the 13th international conference on applications of statistics and probability in civil engineering (ICASP13), Seoul, South Korea

Lee, H., Phoebe, S. Here's how wildfires will impact what Australians eat and wear, Bloomberg (13 January 2020). https://www.bloomberg.com/news/ articles/2020-01-11/here-s-how-wildfires-will-impact-what-australians-eat-and-wear

Lee, J. Y., Ma, F., & Li, Y. (2022). Understanding homeowner proactive actions for managing wildfire risks. Natural Hazards, 114(2), 1525-1547.

Lee, J.Y., & Ma, F. (2023). Agent-based modeling framework for wildfire evacuation in damaged transportation settings. The Pacific Northwest Transportation Consortium (PacTrans) Final Report. https://digital.lib.washington.edu/researchworks/handle/1773/49800.

Leonard, S. (2009). Predicting sustained fire spread in Tasmanian native grasslands. Environmental Management, 44, 430-440.

Lewis, K., Pearlson, M. N., Oberg, A., Gillham, O., Smith, S., Baker, G., & Vogel, A. (2019). Freight and Fuel Transportation Optimization Tool Technical Documentation: FTOT 2019.3 Public Release Version (No. DOT-VNTSC-FAA-19-06). John A. Volpe National Transportation Systems Center (US).

Lhéritier, A., Bocamazo, M., Delahaye, T., & Acuna-Agost, R. (2019). Airline itinerary choice modeling using machine learning. Journal of choice modelling, 31, 198-209.

Lindell MK, Perry RW (2012) The protective action decision model: theoretical modifications and additional evidence. Risk Anal Int J 32(4):616–632

Lindley, T. T., Murdoch, G. P., Schneider, K. J., Fenner, N. J., Smith, B. R., & Maxwell, C. (2015). A statistical analysis of energy release component for large wildland fires on the southern great plains. In Proceedings of the 11th Symposium on Fire and Forest Meteorology.

Liu, M., & Lo, S. M. (2011). The quantitative investigation on people's pre-evacuation behavior under fire. Automation in construction, 20(5), 620-628.

Lopez, P. A., Behrisch, M., Bieker-Walz, L., Erdmann, J., Flötteröd, Y. P., Hilbrich, R., … Wießner, E. (2018, November). Microscopic traffic simulation using SUMO. In 2018 21st International Conference on Intelligent Transportation Systems (ITSC) (pp. 2575-2582). IEEE.

Lovreglio, R., Kuligowski, E., Walpole, E., Link, E., & Gwynne, S. (2020). Calibrating the Wildfire Decision Model using hybrid choice modelling. International Journal of Disaster Risk Reduction, 50, 101770.

Ma, F., & Lee, J.Y. (2023). An integrated framework for wildfire evacuation in a damaged transportation network. In Proceedings of the 14th International Conference on Applications of Statistics and Probability in Civil Engineering (ICASP14), Dublin, Ireland.

Ma, F., Lee, J. Y., Camenzind, D., & Wolcott, M. (2022a). Probabilistic Wildfire risk assessment methodology and evaluation of a supply chain network. International Journal of Disaster Risk Reduction, 82, 103340.

Ma, F., Lee, J.Y., & Wolcott, M. (2022b). Probabilistic wildfire risk assessment for a supply chain system. In Proceedings of the 13th International Conference on Structural Safety and Reliability (ICOSSAR 2021-2022), Shanghai, China.

Mancheva, L., Adam, C., & Dugdale, J. (2019, May). Multi-agent geospatial simulation of human interactions and behavior in bushfires. In International Conference on Information Systems for Crisis Response and Management.

Mas, E., Suppasri, A., Imamura, F., & Koshimura, S. (2012). Agent-based simulation of the 2011 great east japan earthquake/tsunami evacuation: An integrated model of tsunami inundation and evacuation. Journal of Natural Disaster Science, 34(1), 41-57.

Masoomi, H., & van de Lindt, J. W. (2016). Tornado fragility and risk assessment of an archetype masonry school building. Engineering Structures, 128, 26-43.

Massada, A. B., Syphard, A. D., Stewart, S. I., & Radeloff, V. C. (2012). Wildfire ignition-distribution modelling: a comparative study in the Huron–Manistee National Forest, Michigan, USA. International journal of wildland fire, 22(2), 174-183.

McCaffrey, S., Wilson, R., & Konar, A. (2018). Should I stay or should I go now? Or should I wait and see? Influences on wildfire evacuation decisions. Risk analysis, 38(7), 1390-1404.

McCaffrey, S. (2008). Understanding public perspectives of wildfire risk. In: Martin, Wade E.; Raish, Carol; Kent, Brian, eds. Wildfire risk, human perceptions and management implications. Washington, DC. Resources for the Future: 11-22.

McFarlane, B. L., McGee, T. K., & Faulkner, H. (2011). Complexity of homeowner wildfire risk mitigation: an integration of hazard theories. International Journal of Wildland Fire, 20(8), 921-931.

McGee, T. K., Nation, M. O., & Christianson, A. C. (2019). Residents' wildfire evacuation actions in Mishkeegogamang Ojibway Nation, Ontario, Canada. International journal of disaster risk reduction, 33, 266-274.

McGee, T. K., & Russell, S. (2003). "It's just a natural way of life…" an investigation of wildfire preparedness in rural Australia. Global Environmental Change Part B: Environmental Hazards, 5(1), 1-12.

McKee M, Berrens RP, Jones M, Helton R, Talberth J (2004) Using experimental economics to examine wildfire insurance and averting decisions in the wildland–urban interface. Soc Nat Resour 17(6):491–507

McLennan, J., Ryan, B., Bearman, C., & Toh, K. (2019). Should we leave now? Behavioral factors in evacuation under wildfire threat. Fire technology, 55(2), 487-516.

McLennan, J., Elliott, G., Omodei, M., & Whittaker, J. (2013). Householders' safety-related decisions, plans, actions and outcomes during the 7 February 2009 Victorian (Australia) wildfires. Fire Safety Journal, 61, 175-184.

Meldrum JR, Brenkert-Smith H, Champ P, Gomez J, Falk L, Barth C (2019) Interactions between resident risk perceptions and wildfire risk mitigation: evidence from simultaneous equations modeling. Fire 2(3):46

Mermoz, M., Kitzberger, T., & Veblen, T. T. (2005). Landscape influences on occurrence and spread of wildfires in Patagonian forests and shrublands. Ecology, 86(10), 2705-2715.

Mockrin MH, Stewart SI, Radeloff VC, Hammer RB, Alexandre PM (2015) Adapting to wildfire: rebuilding after home loss. Soc Nat Resour 28(8):839–856

Moore HE (1981) Protecting residences from wildfires: a guide for homeowners, lawmakers, and planners, vol 50. US Department of Agriculture, Forest Service, Pacific Southwest Forest and Range Experiment Station

Moritz MA, Batllori E, Bradstock RA, Gill AM, Handmer J, Hessburg PF, Leonard J, McCaffrey S, Odion DC, Schoennagel T, Syphard AD (2014) Learning to coexist with wildfire. Nature 515(7525):58–66.

Mozumder, P., Raheem, N., Talberth, J., & Berrens, R. P. (2008). Investigating intended evacuation from wildfires in the wildland–urban interface: application of a bivariate probit model. Forest Policy and Economics, 10(6), 415-423.

Mutch, R. W., Rogers, M. J., Stephens, S. L., & Gill, A. M. (2011). Protecting lives and property in the wildland–urban interface: communities in Montana and southern California adopt Australian paradigm. Fire Technology, 47(2), 357-377.

Nakandala, D., Lau, H., & Zhao, L. (2017). Development of a hybrid fresh food supply chain risk assessment model. International Journal of Production Research, 55(14), 4180-4195.

Namazi-Rad, M. R., Mokhtarian, P., & Perez, P. (2014). Generating a dynamic synthetic population—using an age-structured two-sex model for household dynamics. PloS One, 9(4), e94761.

NPS (National Park Service). (2021). Wildfire Causes and Evaluations. NPS. Retrieved from https://www.nps.gov/articles/wildfire-causes-and-evaluation.html.

NFPA (National Fire Protection Association) (2021) Preparing homes for wildfire. NFPA. https://www.nfpa.org/Public-Education/Fire-causes-and-risks/Wildfire/Preparing-homes-for-wildfire

NFPA (National Fire Protection Association) (2020) Creating a community wildfire protection plan. Federal Emergency Management Agency.

Owens, J., & Hawkins, E. M. (2019). Using online labor market participants for nonprofessional investor research: A comparison of MTurk and Qualtrics samples. Journal of Information Systems, 33(1), 113-128.

Pan, X. (2006). Computational modeling of human and social behaviors for emergency egress analysis. Stanford University.

Parisien, M. A., Dawe, D. A., Miller, C., Stockdale, C. A., & Armitage, O. B. (2019). Applications of simulation-based burn probability modelling: A review. International journal of wildland fire, 28(12), 913-926.

Papakosta, P. (2015). Bayesian network models for wildfire risk estimation in the Mediterranean basin (Doctoral dissertation, Technische Universität München).

Papadopoulos, G. D., & Pavlidou, F. N. (2011). A comparative review on wildfire simulators. IEEE systems Journal, 5(2), 233-243.

Paudel Y (2012) A comparative study of public—private catastrophe insurance systems: lessons from current practices. Geneva Pap Risk Insur Issues Pract 37(2):257–285

Pausas JG, Keeley JE (2021) Wildfires and global change. Front Ecol Environ 19(7):387–395

Peacock WG (2003) Hurricane mitigation status and factors influencing mitigation status among Florida's single-family homeowners. Nat Hazard Rev 4(3):149–158

Pelling M (2003) The vulnerability of cities: natural disasters and social resilience. Earthscan, London

Penman TD, Collins L, Syphard AD, Keeley JE, Bradstock RA (2014) Influence of fuels, weather and the built environment on the exposure of property to wildfire. PLoS ONE 9(10):e111414

Prestemon, J. P., & Prestemon, J. P. (2013). Wildfire ignitions: a review of the science and recommendations for empirical modeling (p. 24). Asheville, NC, USA: US Department of Agriculture, Forest Service, Southern Research Station.

Preisler, H. K., Burgan, R. E., Eidenshink, J. C., Klaver, J. M., & Klaver, R. W. (2009). Forecasting distributions of large federal-lands fires utilizing satellite and gridded weather information. International Journal of Wildland Fire, 18(5), 508-516.

Preisler, H. K., Brillinger, D. R., Burgan, R. E., & Benoit, J. W. (2004). Probability-based models for estimation of wildfire risk. International Journal of Wildland Fire, 13(2), 133-142.

Priest SJ, Clark MJ, Treby EJ (2005) Flood insurance: the challenge of the uninsured. Area 37(3):295–302

Radtke KW (1983) Living more safely in the chaparral-urban interface. General Technique Report. GTRPSW-067. US Department of Agriculture, Forest Service, Pacific Southwest Forest and Range Experiment Station, Berkeley 51 p, 67

Ramsey, M. L., Murphy, M., & Diaz, J. (2020). The Camp Fire Public Report: A Summary of the Camp Fire Investigation. Butte County District Attorney, 1-92.

Richards, G. D. (1990). An elliptical growth model of forest fire fronts and its numerical solution. International journal for numerical methods in engineering, 30(6), 1163-1179.

Riley, K., & Thompson, M. (2016). An uncertainty analysis of wildfire modeling. Natural Hazard Uncertainty Assessment: Modeling and Decision Support, 191-213.

Riley, K. L., Abatzoglou, J. T., Grenfell, I. C., Klene, A. E., & Heinsch, F. A. (2013). The relationship of large fire occurrence with drought and fire danger indices in the western USA, 1984–2008: the role of temporal scale. International Journal of Wildland Fire, 22(7), 894-909.

Roberson, B. S., Peterson, D., & Parsons, R. W. (2012). Attitudes on wildfire evacuation: Exploring the intended evacuation behavior of residents living in two Southern California communities. Journal of Emergency Management, 10(5), 335-346.

Rodrigues, M., & De la Riva, J. (2014). An insight into machine-learning algorithms to model human-caused wildfire occurrence. Environmental Modelling & Software, 57, 192-201.

Rodríguez-Martínez, A., & Vitoriano, B. (2020). Probability-based wildfire risk measure for decision-making. Mathematics, 8(4), 557.

Ronchi, E., Gwynne, S. M., Rein, G., Intini, P., & Wadhwani, R. (2019). An open multi-physics framework for modelling wildland-urban interface fire evacuations. Safety science, 118, 868-880.

Rosowsky, D. V., & Ellingwood, B. R. (2002). Performance-based engineering of wood frame housing: Fragility analysis methodology. Journal of Structural Engineering, 128(1), 32-38.

Rothermel, R. C. (1991). Predicting behavior and size of crown fires in the Northern Rocky Mountains (Vol. 438). US Department of Agriculture, Forest Service, Intermountain Research Station.

Rothermel, R. C. (1972). A mathematical model for predicting fire spread in wildland fuels (Vol. 115). Intermountain Forest & Range Experiment Station, Forest Service, US Department of Agriculture.

Roy, S., Phillips, C., Jakubik, J., Fraccaro, P., Kumar, A., Avery, R., Ji, W., Zadrozny, B., & Ramachandran, R. (2023). Prithvi 100M burn scar. Hugging Face. https://huggingface.co/ibm-nasa-geospatial/Prithvi-100M-burn-scar.

Schulte S, Miller KA (2010) Wildfire risk and climate change: the influence on homeowner mitigation behavior in the wildland–urban interface. Soc Nat Resour 23(5):417–435

Schulze SS, Fischer EC, Hamideh S, Mahmoud H (2020) Wildfire impacts on schools and hospitals following the 2018 California Camp Fire. Nat Hazards 104(1):901–925

Scott, J. H., Thompson, M. P., & Calkin, D. E. (2013). A wildfire risk assessment framework for land and resource management.

Scott, J. H. (2005). Standard fire behavior fuel models: a comprehensive set for use with Rothermel's surface fire spread model. US Department of Agriculture, Forest Service, Rocky Mountain Research Station.

Seebauer S, Fleiß J, Schweighart M (2017) A household is not a person: consistency of pro-environmental behavior in adult couples and the accuracy of proxy-reports. Environ Behav 49(6):603–637

Shafran AP (2008) Risk externalities and the problem of wildfire risk. J Urban Econ 64(2):488–495

Shafran AP (2010) Interdependent security experiments. Econ Bull 30(3):1950–1962

Sinuany-Stern, Z., & Stern, E. (1993). Simulating the evacuation of a small city: The effects of traffic factors. Socio-Economic Planning Sciences, 27(2), 97-108.

Smith AMS, Kolden CA, Paveglio TB, Cochrane MA, Bowman DM, Moritz MA, Kliskey AD, Alessa L, Hudak AT, Hoffman CM, Lutz JA, Queen LP, Goetz SJ, Higuera PE, Boschetti L, Flannigan M, Yedinak KM, Watts AC, Strand EK et al (2016) The science of firescapes: achieving fire-resilient communities. Bioscience 66(2):130–146.

Stasiewicz, A. M., & Paveglio, T. B. (2021). Preparing for wildfire evacuation and alternatives: Exploring influences on residents' intended evacuation behaviors and mitigations. International Journal of Disaster Risk Reduction, 58, 102177.

Steyerberg, E. W., Borsboom, G. J., van Houwelingen, H. C., Eijkemans, M. J., & Habbema, J. D. F. (2004). Validation and updating of predictive logistic regression models: a study on sample size and shrinkage. Statistics in medicine, 23(16), 2567-2586.

Strahan, K. W., Whittaker, J., & Handmer, J. (2019). Predicting self-evacuation in Australian bushfire. Environmental Hazards, 18(2), 146-172.

Sun, J., Tang, J., Fu, W., Chen, Z., & Niu, Y. (2020). Construction of a multi-echelon supply chain complex network evolution model and robustness analysis of cascading failure. Computers & Industrial Engineering, 144, 106457.

Suzuki S, Brown A, Manzello SL, Suzuki J, Hayashi Y (2014) Firebrands generated from a full-scale structure burning under well-controlled laboratory conditions. Fire Saf J 63:43–51

Syphard, A. D., Keeley, J. E., Gough, M., Lazarz, M., & Rogan, J. (2022). What makes wildfires destructive in California?. Fire, 5(5), 133.

Syphard AD, Keeley JE (2019) Factors associated with structure loss in the 2013–2018 California wildfires. Fire 2(3):49

Syphard AD, Brennan TJ, Keeley JE (2017) The importance of building construction materials relative to other factors affecting structure survival during wildfire. Int J Disaster Risk Reduct 21:140–147

Syphard AD, Brennan TJ, Keeley JE (2014) The role of defensible space for residential structure protection during wildfires. Int J Wildland Fire 23(8):1165–1175

Syphard AD, Keeley JE, Massada AB, Brennan TJ, Radeloff VC (2012) Housing arrangement and location determine the likelihood of housing loss due to wildfire. PLoS ONE 7(3):e33954

Tang, L., Jing, K., He, J., & Stanley, H. E. (2016). Complex interdependent supply chain networks: Cascading failure and robustness. Physica A: Statistical Mechanics and its Applications, 443, 58-69.

Taylor MH (2019) Mitigating wildfire risk on private property with spatial dependencies. Strat Behav Environ 8(1):1–31

Taylor, J. G., Gillette, S. C., Hodgson, R. W., & Downing, J. L. (2005). Communicating with wildland interface communities during wildfire (No. 2005-1061). US Geological Survey.

Thomas, D., Butry, D., Gilbert, S., Webb, D., & Fund, J. (2017). The costs and losses of wildfires; a literature survey. US Department of Commerce, National Institute of Standards and Technology.

Thompson, M. P., Calkin, D. E., Finney, M. A., Ager, A. A., & Gilbertson-Day, J. W. (2011). Integrated national-scale assessment of wildfire risk to human and ecological values. Stochastic Environmental Research and Risk Assessment, 25(6), 761-780.

Toledo, T., Marom, I., Grimberg, E., & Bekhor, S. (2018). Analysis of evacuation behavior in a wildfire event. International journal of disaster risk reduction, 31, 1366-1373.

Tutsch, M., Haider, W., Beardmore, B., Lertzman, K., Cooper, A. B., & Walker, R. C. (2010). Estimating the consequences of wildfire for wildfire risk assessment, a case study in the southern Gulf Islands, British Columbia, Canada. Canadian Journal of Forest Research, 40(11), 2104-2114.

U.S. Census Bureau (2023). Age and Sex, 2021 America Community Survey 1-year estimates. https://data.census.gov/table?q=California&tid=ACSST1Y2021.S010. Accessed 26 May 2023

U.S. Census Bureau. (2021). American Community Survey. Retrieved from https://www.census.gov/programs-surveys/acs.

USDA. (2022). Wildfire Risk to Communities. https://wildfirerisk.org/explore. Accessed 5 February 2023

USFA (U.S. Fire Administration) (2020) Creating a community wildfire protection plan. Federal Emergency Management Agency.

USFS. (n.d.). Energy Release Component Fact Sheet. Retrieved March 29, 2021, from https://www.fs.usda.gov/Internet/FSE_DOCUMENTS/ stelprdb5339121.pdf.

Verisk. (2019). Wildfire risk analysis. https://www.verisk.com/insurance/campaigns/location-fireline-state-risk-report/

Wahlqvist, J., Ronchi, E., Gwynne, S. M., Kinateder, M., Rein, G., Mitchell, H., et al. (2021). The simulation of wildland-urban interface fire evacuation: The WUI-NITY platform. Safety science, 136,

Walpole, H. D., Wilson, R. S., & McCaffrey, S. M. (2020). If you love it, let it go: the role of home attachment in wildfire evacuation decisions. Environment systems and decisions, 40, 29-40.

Wang, D., Guan, D., Zhu, S., Mac Kinnon, M., Geng, G., Zhang, Q., ... & Davis, S. J. (2021). Economic footprint of California wildfires in 2018. Nature Sustainability, 4(3), 252-260.

Wang, K., Shi, X., Goh, A. P. X., & Qian, S. (2019). A machine learning based study on pedestrian movement dynamics under emergency evacuation. Fire safety journal, 106, 163-176.

Wang, Y., & Xiao, R. (2016). An ant colony based resilience approach to cascading failures in cluster supply network. Physica A: Statistical Mechanics and its Applications, 462, 150-166.

Warziniack T, Champ P, Meldrum J, Brenkert-Smith H, Barth CM, Falk LC (2019) Responding to risky neighbors: testing for spatial spillover effects for defensible space in a fire-prone WUI community. Environ Resour Econ 73(4):1023–1047

Westerling, A. L., Hidalgo, H.G., Cayan, D.R., & Swetnam, T.W. (2006). Warming and Earlier Spring Increase Western U.S. Forest Wildfire Activity. Science, 313(5789), 940–943.

Westerling AL, Bryant BP, Preisler HK, Holmes TP, Hidalgo HG, Das T, Shrestha SR (2011) Climate change and growth scenarios for California wildfire. Clim Change 109(S1):445–463.

Wikimedia Foundation. (2022). Tick fire. Wikipedia. https://en.wikipedia.org/wiki/Tick_Fire. Accessed 15 February 2023

Williams, R. A., & Quiroz, C. (2020). Ordinal regression models. SAGE Publications Limited.

Williams, R. (2018). Ordered logit models–basic & intermediate topics. University of Notre Dame.

Winter G, Fried JS (2000) Homeowner perspectives on fire hazard, responsibility, and management strategies at the wildland-urban interface. Soc Nat Resour 13(1):33–49

Wisch, R., & Yin, Y-J. (2019). Why are wildfires more destructive today? AIR Worldwide. https://www.air-worldwide.com/Blog/Why-Are-Wildfires-More-Destructive-Today-/. Accessed 26 May 2023

Wolshon, B., & Marchive III, E. (2007). Emergency planning in the urban-wildland interface: Subdivision-level analysis of wildfire evacuations. Journal of Urban Planning and Development, 133(1), 73-81.

Wong, S. D., Broader, J. C., Walker, J. L., & Shaheen, S. A. (2022). Understanding California wildfire evacuee behavior and joint choice making. Transportation, 1-47.

Wong, S. D, Broader, J. C, & Shaheen, S. A. (2020a). Review of California Wildfire Evacuations from 2017 to 2019. UC Office of the President: University of California Institute of Transportation Studies.

Wong, S. D., Chorus, C. G., Shaheen, S. A., & Walker, J. L. (2020b). A revealed preference methodology to evaluate regret minimization with challenging choice sets: a wildfire evacuation case study. Travel Behaviour and Society, 20, 331-347.

Xu, N., Lovreglio, R., Kuligowski, E. D., Cova, T. J., Nilsson, D., & Zhao, X. (2023). Predicting and Assessing Wildfire Evacuation Decision-Making Using Machine Learning: Findings from the 2019 Kincade Fire. Fire Technology, 59(2), 793-825.

Ye, X., Konduri, K., Pendyala, R. M., Sana, B., & Waddell, P. (2009). A methodology to match distributions of both household and person attributes in the generation of synthetic populations. In 88th Annual Meeting of the transportation research Board, Washington, DC.

Yin Y-J (2018) Are wildfire policies and preparedness helping or hurting risk? AIR Worldwide. https://www.air-worldwide.com/blog/posts/2018/5/are-wildfire-policies-and-preparedness-helping-or-hurti ng-risk/

Yin, W., Murray-Tuite, P., Ukkusuri, S. V., & Gladwin, H. (2014). An agent-based modeling system for travel demand simulation for hurricane evacuation. Transportation Research Part C: Emerging Technologies, 42, 44-59.

Zhan, F. B., & Chen, X. (2008). Agent-based modeling and evacuation planning. In Geospatial Technologies and Homeland Security (pp. 189-208). Springer, Dordrecht.

Zhao, B., & Wong, S. D. (2021). Developing transportation response strategies for wildfire evacuations via an empirically supported traffic simulation of Berkeley, California. Transportation research record, 2675(12), 557-582.

Zhao J, Lee JY, Li Y, Yin YJ (2020a) Effect of catastrophe insurance on disaster-impacted community: quantitative framework and case studies. Int J Disaster Risk Reduct 43:101387

Zhao, X., Lovreglio, R., & Nilsson, D. (2020b). Modelling and interpreting pre-evacuation decision-making using machine learning. Automation in Construction, 113, 103140.

Zybach, B., Dubrasich, M., Brenner, G., & Marker, J. (2009). US Wildfire Cost-Plus-Loss Economics Project: The "One-Pager" Checklist. Advances in Fire Practices', Fall.(Wildland Fire Lessons Learned Center) Available at https://www.wildfirelessons.net/HigherLogic/System/DownloadDocumentFile.ashx.

APPENDIX

APPENDIX A: INDEPENDENT VARIABLES THAT ARE LIKELY TO AFFECT A HOMEOWNER DECISION TO TAKE PROACTIVE ACTIONS

Independent variable	Coded Representation	Frequency
Property type	Single family house = 1	66.25%
	Others = 0	33.75%
Property construction material	Wood frame = 1	62.50%
	Others = 0	37.50%
Property value	<$49,999 = 1	13.75%
	$50,000-$99,999 = 2	8.75%
	$100,000-$199,999 = 3	15.00%
	$200,000-$299,999 = 4	11.25%
	$300,000-$399,999 = 5	12.50%
	$400,000-$499,999 = 6	7.50%
	$500,000-$749,999 = 7	17.50%
	$750,000-$999,999 = 8	8.75%
	$1,000,000-$1,499,999 = 9	3.75%
	>$1,500,000 = 10	1.25%
Remaining mortgage balance	<$49,999 = 1	38.75%
	$50,000-$99,999 = 2	18.75%
	$100,000-$199,999 = 3	16.25%
	$200,000-$299,999 = 4	7.50%
	$300,000-$399,999 = 5	11.25%
	$400,000-$499,999 = 6	5.00%
	$500,000-$749,999 = 7	2.50%
Personal belonging value	<$24,999 = 1	17.50%
	$25,000 - $49,999 = 2	13.75%
	$50,000 - $74,999 = 3	16.25%
	$75,000 - $99,999 = 4	10.00%
	$100,000 - $149,999 = 5	18.75%
	$150,000 - $199,999 = 6	6.25%
	$200,000 - $249,999 = 7	6.25%
	$250,000 - $349,999 = 8	3.75%
	$350,000 - $499,999 = 9	2.50%
	$500,000 - $749,999 = 10	1.25%
	>$750,000 = 11	3.75%
Surrounding satisfaction (an overall satisfaction of the vegetation cover, view, privacy, wildfire, etc.)	Very dissatisfied = 1	11.25%
	Somewhat dissatisfied = 2	22.50%
	Neither satisfied nor dissatisfied = 3	27.50%
	Somewhat satisfied = 4	18.75%
	Very satisfied = 5	20.00%
Willingness to pay for individual-level risk reduction actions ($/year)	<$249 = 1	27.50%
	$250-$499 = 2	30.00%
	$500-$749 = 3	17.50%
	$750-$999 = 4	5.00%
	$1,000-$1,499 = 5	12.50%
	$1,500-$1,999 = 6	3.75%

	>$2,000 = 7	3.75%
Willingness to pay for community-level risk reduction actions ($/year)	<$249 = 1	25.00%
	$250-$499 = 2	30.00%
	$500-$749 = 3	11.25%
	$750-$999 = 4	18.75%
	$1,000-$1,499 = 5	8.75%
	$1,500-$1,999 = 6	3.75%
	>$2,000 = 7	2.50%
Whether neighbors adopted mitigation actions	Yes = 1	60.00%
	No = 0	40.00%
Willingness to invest in individual- and/or community-level risk reduction actions	None = 1	17.50%
	Only one type of the actions = 2	40.00%
	Both types of the actions = 3	42.50%
Total wealth before a wildfire event	<$ 49,999 = 1	22.50%
	$50,000 - $99,999 = 2	10.00%
	$100,000 - $199,999 = 3	18.75%
	$200,000 - $299,999 = 4	12.50%
	$300,000 - $399,999 = 5	2.50%
	$400,000 - $499,999 = 6	7.50%
	$500,000 - $749,999 = 7	10.00%
	$750,000 - $999,999 = 8	5.00%
	$1,000,000 - $1,499,999 = 9	6.25%
	$1,500,000 - $1,999,999 = 10	3.75%
	$2,000,000 - $2,999,999 = 11	0.00%
	>$ 3,000,000 = 12	1.25%
Homeowner perceived probability that wildfire will occur in his/her community in the next 5 years	0% = 1	2.50%
	0%-1% = 2	1.25%
	1% - 4% = 3	2.50%
	5% - 9% = 4	2.50%
	10% - 19% = 5	12.50%
	20% - 39% = 6	13.75%
	40% - 59% = 7	22.50%
	60% - 79% = 8	17.50%
	80% - 100% = 9	22.50%
Homeowner perceived probability that his/her property will be damaged by a wildfire event	Highly unlikely = 1	3.75%
	Unlikely = 2	6.25%
	Neither likely nor unlikely = 3	35.00%
	Likely = 4	43.75%
	Highly likely = 5	11.25%
Homeowner self-assessment of preparedness for wildfire	1 (poorly prepared to take risk)	15.00%
	2	15.00%
	3	32.50%
	4	23.75%
	5 (well prepared to take risk)	13.75%
Entity who is responsible for paying for wildfire damage to house	Primarily government = 1	8.75%
	Government > Homeowner = 2	12.50%
	Government = Homeowner = 3	18.75%
	Government < Homeowner = 4	23.75%
	Primarily homeowner = 5	36.25%

Past experience with natural hazards	Yes = 1	78.75%
	No = 0	21.25%

APPENDIX B: SURVEY DATA ON INDIVIDUAL AND HOUSEHOLD CHARACTERISTICS

Characteristics	Classes	Frequency
Employment	Employed, working 40 or more hours per week	71.1%
	Employed, working less than 40 hours per week	16.3%
	Not employed	5.5%
	Retired	2.6%
	Disabled, not able to work	1.0%
	Others	3.4%
Mode of commuting	Personally owned car, truck, or van	63.4%
	Personally owned motorcycle	10.2%
	Public transportation (e.g., bus, streetcar subway)	5.7%
	Carpool	0.7%
	Shared ride (e.g., Uber, Lyft)	1.5%
	Taxicab	1.5%
	Personally owned bicycle	1.5%
	Walk	2.1%
	Work from home	10.9%
	Other	2.5%
Decision-making role	Primary decision-maker	23.8%
	Sole decision-maker	44.5%
	Share decision-making roles equally with others	31.7%
Family Size	1	16.3%
	2	19.2%
	3	21.4%
	4	32.6%
	5 or more	10.5%
Property ownership	Own without mortgage	24.8%
	Own with mortgage	37.8%
	Rent	35.0%
	Other	2.4%
Presence of children	Yes	54.5%
	No	45.5%
Presence of elderly	Yes	26.1%
	No	73.9%
Special need required	Yes	25.4%
	No	74.6%
Number of vehicles owned	None	9.5%
	1	57.2%
	2	23.9%
	3 or more	9.4%
Length of residency on the current property	Less than 1 year	4.8%
	1 – 3 years	19.9%
	3 – 5 years	21.6%
	5 – 10 years	25.0%
	10 – 15 years	11.1%
	More than 15 years	17.6%

Animal ownership	None	24.3%
	Pet only	66.5%
	Livestock only	3.5%
	Both pet and livestock	5.7%
Internet access	Yes	99.3%
	No	0.7%
Smartphone access	Yes	98.1%
	No	1.9%
Use of GPS-navigation routinely	Yes	77.3%
	No	22.7%
Homeowners insurance status	Not insured	20.0%
	Under-insured	23.4%
	Fully insured	56.6%
Past evacuation experience	None	53.0%
	Once	18.8%
	2 – 3 times	21.0%
	4 – 5 times	5.7%
	More than 5 times	1.5%
Past wildfire-induced property damage	Yes	26.7%
	No	73.3%
Disaster plan	No plan	46.5%
	Have a plan but not in a written form	34.4%
	Have a written plan	19.1%

APPENDIX C: “SELECTED” QUESTIONNAIRES FOR POST-WILDFIRE ONLINE SURVEY

Section 1: Pre-Screening Questions

Q1.1 Which category below includes your age?

Q1.2 What is the zip code of your house, condominium, mobile home, or manufactured home?

Q1.3 Did your property was damaged caused by wildfire in the past 5 years? If yes, which of the following categories best describes physical damage to your property due to wildfire?

Section 2: Demographic Questions

Q2.1 What gender do you identify as?

Q2.2 What is the highest level of school you have completed or the highest degree you have received?

Q2.3 Which of the following categories best describes your employment status at the time when the most recent wildfire attacked your property?

Q2.4 Which of the following categories best describes your ethnicity? Select all that apply.

Section 3: Property Information

Q3.1 Please specify your property type and ownership.

Q3.2 What was the main construction material of your damaged property?

Q3.3 How much was your estimated property (house) value (or a township assessment of property value) at the time when the wildfire attacked your property?

Q3.4 How much was your estimated personal belonging value at the time when the wildfire attacked your property?

Q3.5 How do you rate the surrounding of your property at the time when the most recent wildfire attacked your property?

Section 4: Individual-Level Proactive Action

Q4.1 Did you adopt any of the following risk reduction actions to protect your house from wildfire at the time when the most recent wildfire attacked your property? Select all that apply.

Q4.2 How much would you be willing to pay for individual-level fire risk mitigation actions listed in Question 4.1?

Q4.3 Did you hold any homeowner's insurance policy with wildfire coverage at the time when the most recent wildfire attacked your property?

Q4.4 What was your dwelling coverage (the coverage of your property value) limit at the time when the most recent wildfire attacked your property? Dwelling coverage limit is the maximum amount that your insurance policy paid for repairs or rebuilding.

Q4.5 How much was your dwelling deductible for natural hazards at the time when the most recent wildfire attacked your property? Dwelling deductible is the amount you paid out of pocket towards a covered claim for dwelling.

Q4.6 What was your content coverage (the coverage of your personal belongings) limit at the time when the most recent wildfire attacked your property? Content coverage limit is the maximum amount that your insurance policy paid for your personal belongings.

Q4.7 How much was your content deductible for natural hazards at the time when the most recent wildfire attacked your property? Content deductible is the amount you paid out of pocket towards a covered claim for content.

Q4.8 How much was your annual homeowner's insurance premium? In other words, how much was your annual homeowner's insurance payment at the time when the most recent wildfire attacked your property?

Q4.9 Did you file a claim with your insurance company for the wildfire damage at the time when the most recent wildfire attacked your property? In other words, did you request your insurance company to pay your loss/repair/reconstruction due to wildfire?

Q4.10 Was your insurance enough to cover your repair/reconstruction cost of damaged structure? If so, please choose yes. If not, please indicate the approximate percentage of repair/reconstruction cost that was covered by insurance.

Section 5: Financial availability Questions

Q5.1 How much total combined money did all members of your HOUSEHOLD earn at the time when the most recent wildfire attacked your property?

Q5.2 How much do you estimate for the **total combined economic losses** resulting from the most recent wildfire that attacked your property?

Q5.3 How much was the total claim payment received from the homeowner's insurance company following the most recent wildfire that attacked your property?

Q5.4 How much financial aid did you receive from the federal or local government following the most recent wildfire that attacked your property?

Q5.5 How long did it take to process the government assistance payment?

Q5.6 Which financial source you received was the most helpful for you to recover from the wildfire attack?

Q5.7 What types of financial hardship did you experience due to the most recent wildfire that attacked your property?

Section 6: Repair/ Reconstruction Questions

Q6.1 If your home was unfortunately damaged, did you rebuild or reconstruct your damaged home?

Q6.2 How long did you wait to initiate your structural (house) repair/reconstruction process since the wildfire in your community had been contaminated?

Q6.3 How long did it take to complete your structural (house) repair/reconstruction process since its initiation?

Section 7: Risk attitude and perception

Q7.1 How do you estimate the likelihood that a wildfire will attack your community in the next 5 years?

Q7.2 Please rate your confidence level about your property when it is exposed to wildfire.

Section 8: Additional Questions

Q8.1 Have you ever experienced damage to your house from natural hazards? if so, please specify.

Q8.2 Whom do you think have a responsibility for paying for your house/belonging damage from a wildfire?

APPENDIX D: “SELECTED” QESTIONNAIRES FOR WILDFIRE EVACUATION STATED PREFERENCE SURVEY

Section 1: Personal characteristics

Q1 Which category below includes your age?

Q2 What is the zip code of your residence?

Q3 What gender do you identify as?

Q4 What is the highest level of school you have completed or the highest degree you have received?

Q5 Which of the following categories best describes your employment status?

Q6 Which of the following categories your ethnicity? Select all that apply

Q7 What is your main mode of commuting (i.e., the main mode of transportation you use to travel to your place of work)?

Q8 What is your decision-making role in your household?

Section 2: Household characteristic

Q9 How many people live in your household including yourself?

Q10 What is your ownership of your current residence?

Q11 How many children do you have who live at home with you?

Q12 How many household members are 65 years and older?

Q13 Do you have any household members with special needs?

Q14 How many cars does your household have?

Q15 Does your household own pets or livestock?

Q16 Do you use In-Vehicle or Smartphone Navigation under normal conditions?

Q17 Do you have homeowners/renters insurance that covers wildfire damage to your house/apartment?

Section 3: Evacuation decision

Q18 What action would you take if a wildfire approaches your community?

Q19 How will you choose the evacuation route?

Q20 Where do you expect to stay temporarily until wildfire is completely contained and evacuation order is lifted?

Section 4: Risk perception and risk preference

Q21 How many times in the past 10 years did you evacuate your home/neighborhood/workplace (or other locations) because of a wildfire?

Q22 Has your household ever experienced property damage due to wildfire?

Q23 Does your household have a disaster plan for wildfires? A disaster plan lists how your household members will respond to disaster attacks.

Q24 How would you rate the level of wildfire risk in the area you live in?

Q25 How would you rate the level of confidence of your property if a wildfire hits your location?