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

FINAL PROJECT REPORT

by

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16. Abstract

The main goal of this project was to support effective evacuation planning by developing an agent-based modeling (ABM) framework for wildfire evacuation in damaged transportation settings. More specifically, the framework integrates wildfire simulation and vulnerability assessment with ABM to adequately represent both human behaviors during an evacuation and time-dependent network functionality in microscopic traffic simulation. The framework predicts traffic conditions during an evacuation and identifies the critical parts of the transportation network for pre-fire risk mitigation actions aimed at improving mobility during a wildfire evacuation. The proposed framework is illustrated with the City of Santa Clarita, affected by the Rye Fire, to demonstrate its applicability to a real community. The contribution of this project is twofold: (a) The framework incorporates an advanced wildfire hazard modeling and vulnerability assessment to improve the accuracy of wildfire evacuation in damaged transportation settings; and (b) This project constructs an evacuee response model based on a stated preference survey to predict individual evacuees' behaviors as a firefront approaches.

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SI* (Modern Metric) Conversion Factors

APPROXIMATE CONVERSIONS TO SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
°F	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	°C
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa

APPROXIMATE CONVERSIONS FROM SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
°C	Celsius	1.8C+32	Fahrenheit	°F
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

*SI is the symbol for the International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380. (Revised March 2003)

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LIST OF ABBREVIATIONS

ABM:	Agent-based modeling
ACS:	American Community Survey
AIC:	Akaike Information Criterion
BDL:	Bridge damage level
BI:	Burning index
BIC:	Bayesian Information Criterion
DL:	Damage level
FARSITE:	Fire Area Simulator
FBFM40:	40 Scott and Burgan Fire Behavior Fuel Models
gridMET:	Gridded Surface Meteorological Dataset
HC:	Hill climbing
LDL:	Link damage level
MCS:	Monte Carlo Simulation
MTT:	Minimum Travel Time
MTurk:	Mechanical Turk
PNW:	Pacific Northwest
PUMS:	Public Use Microdata Sample
RAWS:	Remote Automatic Weather Station
SR:	Synthetic reconstruction
SUMO:	Simulation of Urban Mobility
TRANSIMS:	Transportation Analysis and Simulation System
WUI:	Wildland-urban interface

EXECUTIVE SUMMARY

Wildfires pose an increasing threat to residents in the Pacific Northwest (PNW) region as more people are moving to the wildland-urban interface. In addition, increasing frequency and magnitude of wildfires induced by climate change will greatly intensify wildfire threat to humans, the built environment, and ecosystem in the PNW region. While many state- and local-level initiatives are under way to mitigate wildfire risks, it is not possible to completely remove such risks because of substantial inherent uncertainties. In this case, evacuation is the most important and effective method to reduce human losses during a wildfire event. While it seems easy to achieve the main goal of evacuation (i.e., moving people at risk to safer places), human behaviors during an evacuation are highly unpredictable, and the elevated travel demand due to simultaneous evacuation may lead to traffic congestion, both of which endanger human lives.

Bridge damage induced by fires and the associated reduction in traffic carrying capacities further complicate this problem. Therefore, wildfire evacuation simulation can be an effective experimental means for emergency management and evacuation planning because its costs are low and it identifies bottlenecks and critical points for traffic congestion during an evacuation.

The main goal of this project was to support effective evacuation planning by developing an agent-based modeling (ABM) framework for wildfire evacuation in damaged transportation settings. More specifically, the framework integrates wildfire simulation and vulnerability assessment with ABM to adequately represent both human behaviors during an evacuation and time-dependent network functionality in microscopic traffic simulation. The framework predicts traffic conditions during an evacuation and identifies the critical parts of the transportation network for pre-fire risk mitigation actions aimed at improving mobility during a wildfire evacuation.

This goal is well aligned with the PacTrans theme of "providing data driven solutions for the diverse mobility challenges in the Pacific Northwest." To achieve the goal, the project performed an online survey of residents in wildfire-prone communities in the United States to collect information on human behaviors during a wildfire evacuation, which was subsequently used to characterize individual evacuees' decision sequences in the ABM. Other types of data (e.g., weather and vegetation patterns, topography, transportation network, and building/ population distribution) were also collected to perform wildfire simulation, vulnerability assessment, and traffic simulation. In this context, the project contributed to one of the PacTrans special topic areas, “data-driven solutions in transportation.” The proposed framework was illustrated with the City of Santa Clarita, affected by the Rye Fire, to demonstrate its applicability to a real community. In summary, the contribution of this project is twofold:

a) The framework incorporates an advanced wildfire hazard modeling and vulnerability assessment to improve the accuracy of wildfire evacuation in damaged transportation settings; and

b) This project constructed an evacuee response model based on a stated preference survey to predict individual evacuees’ behaviors as a firefront approaches.

CHAPTER 1. INTRODUCTION

1.1. Background and Motivation

Recent wildfires in the Western United States have highlighted the destructive effects of wildfires on property, people, and the environment. The 2018 Camp Fire was the deadliest and most destructive wildfire in California's history, resulting in 85 fatalities and more than 18,000 buildings destroyed (Syphard et al., 2022). In 2020, the Western United States experienced more than 100 fires, which affected approximately 8.2 million acres of land (Keeley and Syphard, 2021). Moreover, according to the U.S. Forest Service, a billion acres of land across the United States are at risk of catastrophic wildfires. A recent increase in the frequency and severity of wildfires in the United States is partly attributed to global climate change, which may induce an increase in heatwaves and prolonged dry periods (Cova et al., 2005). Coupled with climate change effects, rapid population growth and residential development at the wildland-urban interface (WUI) have greatly exacerbated property destruction and human/economic losses induced by wildfires (Lee et al., 2022; Ma et al., 2022).

Having seen the 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. As part of this effort, a variety of community-level wildfire protection plans have been proposed and implemented by federal, state, and local government agencies. The plans include zoning regulation, fire department support, adequate water supply and flow for firefighting, road improvement for facilitated access, and public education and outreach (Communities Committee, 2004). In WUI areas, individual homeowners adopt wildfire risk mitigation actions, including the use of nonflammable or ignition-resistant materials, the installation of dual-pane windows or fire sprinklers, vegetation fuel treatment, etc. While wildfire risks can be mitigated through these proactive actions, residual risks always exist because of 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. For example, while most tsunami risk reduction measures were destroyed during the 2011 Great East Japan Earthquake/Tsunami, rapid evacuation saved approximately 90 percent of the total population at risk from the tsunami (Mas et al., 2012). 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. Therefore, effective community-based transportation evacuation planning has become a critical issue in disaster emergency and risk management.

1.2. 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 flows during the evacuation process (e.g., Kisko and Francis, 1985; Burkard et al., 1993). However, most of them assumed homogenous behaviors among evacuees because of the 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 have incorporated 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 because of 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 actions and interactions 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 on 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 by 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 effects 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 by using videotape analysis.

Many other studies have 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 the traffic environment (Chen and Zhan, 2014).

Specifically, hurricane evacuation has been well studied, due in part to 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). Because of 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. Therefore, 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, they have constructed regression models based on survey data or have developed ABM-based evacuation models based on the assumption that all residents have already been forced to evacuate their community.

Several researchers have 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 by using the 2011 Great East Japan earthquake event with a magnitude of 9.0 Mw. The proposed evacuation model was integrated with a numerical simulation of a 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 in an 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 a spatiotemporal 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 on the basis of 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 the evacuation process during the event. 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.

1.3. Goal

The main goal of this project was 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 project developed an integrated framework that incorporates hazard modeling, vulnerability assessment, evacuee response modeling, and traffic simulation to predict traffic conditions during an evacuation and to identify critical parts of the transportation network for pre-fire risk mitigation actions. The contribution of this project is twofold:

a) The framework incorporates an advanced wildfire hazard modeling and vulnerability assessment to improve the accuracy of wildfire evacuation in damaged transportation settings; and
b) This project constructed an evacuee response model based on a stated preference survey to predict individual evacuees' behavior as a firefront approaches.

Effective community-based transportation evacuation planning is an important issue for state and local policy makers in communities at great risk of wildfires in the United States.

Evacuation is considered to be the second line of defense if the first course of defense (i.e., wildfire countermeasures) cannot prevent wildfire risks to communities. Underestimation of this issue and ineffective planning could result in catastrophic human losses during a wildfire. The evacuation simulation model may assist a well-developed evacuation plan and ultimately could save lives.

1.4. Report Overview

The remainder of this report is organized as follows. Chapter 2 describes an ABM-based framework for wildfire evacuation in damaged transportation settings and explains the modules in the framework in more detail. In Chapter 3, online survey data collection and analyses are introduced and used to support an evacuee response model, which is one of the modules of the proposed framework. The fourth chapter illustrates the proposed framework with the City of Santa Clarita, California, affected by the 2017 Rye Fire, and the case study results are presented. Finally, we conclude with a general discussion of the findings and limitations of this project.

CHAPTER 2. FRAMEWORK DEVELOPMENT

The project developed 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 2.1, the framework consists of four modules: wildfire simulation, vulnerability assessment, evacuee response modeling, 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 bridge vulnerability 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.

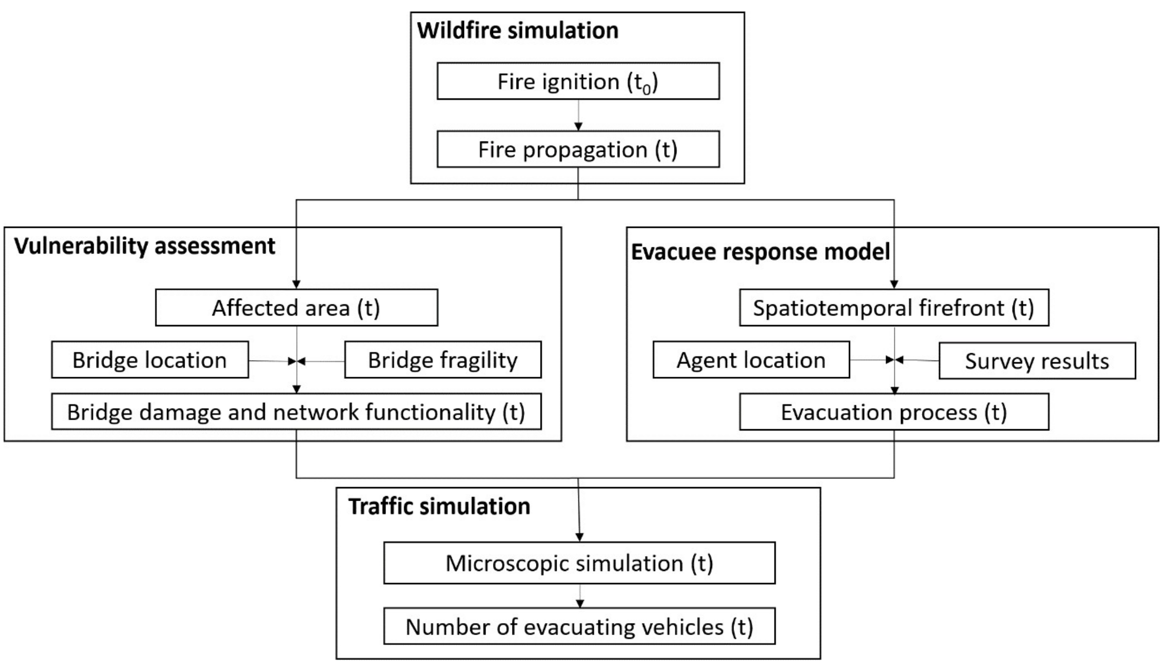

Figure 2.1 The proposed ABM framework for wildfire evacuation in damaged transportation settings

All the variables considered in the framework are updated at a fixed time step: each bridge's damage state and traffic carrying capacity are updated on the basis of fire propagation measured at every time step; each agent updates its state during an evacuation; and microscopic traffic simulation coupled with ABM is performed on the basis of 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). Therefore, the framework focuses on capturing vehicle use and vehicular traffic without considering pedestrian behaviors. The final results are time-dependent traffic maps to identify the critical parts of transportation network that are the most vulnerable to wildfires and that have the greatest potential for causing traffic congestion during an evacuation. Moreover, the total number of evacuating vehicles during a given time period is also obtained as a final result, which could be used to determine the bridges that need to be strengthened to minimize human losses during wildfire evacuation.

2.1. Wildfire Simulation

The wildfire simulation module consists of two stages: wildfire probability estimation and growth modeling. The first stage estimates spatiotemporally varying fire probabilities in the study region and generates representative wildfire scenarios. The second stage simulates wildfire growth for each scenario and records the time-dependent firefront, which 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., 1km x 1km) 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: human causes (e.g., power lines, equipment failure and accidental ignitions, smoking, fireworks, campfires, arson) and natural causes. Population density, urban development, distance to a 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., 2013). To simplify the wildfire occurrence probability model, all the grid-specific human factors are encapsulated into a single location factor, for example (x, y) in equations 1-3. The model also includes temporally varying factors such as the day of year, relative humidity, temperature, wind speed, and burning index (BI). BI is used to indicate the difficultly of containing a fire and provides a good seasonal profile (Preisler et al., 2004).

A generalized additive logistic regression is employed to construct a wildfire probability estimation model to account for spatiotemporal dependence and the 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 report, a large fire is defined as a fire that has burned areas greater than 100 acres (Preisler et al., 2004). Fire ignition is an important factor in wildfire simulation, but fire cannot propagate and develop into a large fire without appropriate environmental and weather conditions, such as a burning fuel bed, convective heating influenced by wind, moisture content, etc. Thus, the unconditional probability that a large fire occurs at a given cell and on a given day of year, $P(L_f)$, is the product of the ignition probability, $P(f)$, and the conditional probability of an ignition turning into a large fire, $P(L_f|f)$. The logistic regression models for estimating these probabilities are expressed mathematically as follows:

$$logit(P(f)) = f_1(t) + f_2(x, y) + f_3(r_{max}, r_{min}) + f_4(t_{max}, t_{min}) + f_5(ws) + f_6(bi) \quad (1)$$

$$logit(P(L_f|f)) = f_7(t) + f_8(x, y) + f_9(r_{max}, r_{min}) + f_{10}(t_{max}, t_{min}) + f_{11}(ws) + f_{12}(bi) \quad (2)$$

$$P(L_f) = P(L_f|f) * P(f) \quad (3)$$

where

$f(\cdot)$ = the non-parametric smooth function;

t = the day of year;

x = the latitude;

y = the longitude;

r_{max} and r_{min} = the maximum and minimum relative humidity;

t_{max} and t_{min} = the maximum and minimum temperature;

ws = the average wind speed; and b

i = the burning index.

As shown in equations 1 and 2, all the weather-related variables and the burning index are spatiotemporally varying factors, which means that the probabilities are spatially and temporally explicit.

To estimate the models shown in equations 1 and 2, 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 because of the 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). Therefore, 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 (Brillinger et al., 2003; Preisler et al. 2004). The probability 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

$$P(E_A|E_B) = \frac{P(E_B|E_A)P(E_A)}{P(E_B)} \tag{4}$$

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

$$P(E_A|E_B) = p_r = \frac{p_a}{p_a+(1-p_a)r} \tag{5}$$

where p_a = the probability that a fire occurred at voxel k. Equation 5 can be then written as Equation 6 through elementary algebra transformation.

$$logit(p_r) = logit(p_a) - \log(r) \tag{6}$$

To generate a set of representative wildfire scenarios, traditional clustering algorithms (e.g., k-means) can be used to cover a wide range of plausible scenarios based on historical data. Specifically, the k- means clustering algorithm divides a data set into a number of clusters and selects a representative scenario from each cluster by utilizing Euclidean distance between the time series.

In the second stage, for each representative wildfire scenario with a specific ignition location and time, wildfire growth is simulated to generate a spatiotemporal firefront and time-dependent fire map. Wildfire growth is mostly dependent on topography, as well as environmental and weather conditions. In this study, the Fire Area Simulator (FARSITE), a widely used wildfire simulation program now included in FlamMap 6, was used. FARSITE utilizes the Huygens principal (Richards, 1990), in which 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 than the other software programs. However, FARSITE is computationally inefficient: FARSITE simulation times can be over 10 times longer than those of the other programs, which limits its use when a large and complex wildfire is simulated or a large suite of fires is generated.

On the other hand, other widely used wildfire simulation software programs, such as FlamMap, FSPro, and FSim, model wildfire growth on the basis of the Minimum Travel Time (MTT) method developed by Finney (2002). MTT is a simplified, raster-based fire growth model that searches 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. Because this method holds weather and fuel conditions constant over time, its simulation results are not as precise as those of FARSITE. However, MTT greatly reduces simulation time. Because the prediction accuracy of fire growth at every time step is key to effective wildfire evacuation modeling, FARSITE was used in the fire growth modeling of this study despite its relatively high computational costs.

The major weather inputs for FARSITE include temperature, relative humidity, precipitation, wind speed, and wind direction. Hourly weather data are collected for all grids in the study region to capture spatiotemporal characteristics. Additionally, 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. For each representative wildfire scenario, the spatiotemporal firefront and fireline intensity are generated and fed into a vulnerability assessment (Module 2) and evacuee response model (Module 3). In the vulnerability assessment, both firefront and fireline intensity are useful in identifying the locations and severity of damaged bridges, while the spatiotemporal firefront is used in the evacuee response model to estimate the timing of evacuation trigger and departure time.

2.2. Bridge Vulnerability Assessment

Bridges are one of the most critical but vulnerable components in a transportation network during a wildfire event. Because of structural damage, the post-fire safety of bridges may be reduced significantly, and in order to maintain their safety, the allowable traffic flows of bridges are often controlled or regulated. Because the post-fire traffic flow capacities of bridges play an integral role in assessing the flow capacity of a transportation network and subsequently evaluating the movement of people and vehicles during an evacuation, it is imperative to understand the post-fire functionalities of bridges in evacuation planning and management. Therefore, in this module, the vulnerability of bridges should be assessed to estimate the reduced flow capacity of a transportation system during a wildfire event.

Bridge vulnerability is often assessed using a fragility curve. A fragility curve represents the conditional probability that the damage state of an element or an entire bridge will exceed a specific damage state given a hazard intensity level (e.g., peak ground acceleration for earthquakes, wind speed for hurricanes and tornadoes) (Masoomi and van de Lindt, 2016; Rosowsky and Ellingwood, 2002). A fragility curve is often constructed analytically on the basis of structural analyses and evaluations, experimentally on the basis of testing results, or empirically on the basis of post-disaster reconnaissance data. In some cases, multiple approaches are combined to develop a fragility curve. Extensive studies have been conducted to develop seismic and hurricane fragility curves, whereas fire fragility curves have been much less studied. Peris-Sayol et al. (2017) collected information on 154 bridge fire cases from existing literature, news, and bridge management authorities and concluded that the bridge deck material, structural system, and the causes of the fire (e.g., cars, trucks, wildfires) had statistically significant impacts on bridge damage level.

Specifically, timber bridges were the most vulnerable to fires, and tanker truck collisions caused the most severe damage to bridges. Naser (2021) used machine learning algorithms to predict the vulnerability and damage states of bridges when they were subjected to extreme loading events. However, limited data availability was a major issue that hindered the performance of the algorithms. Moreover, fire intensity was not included as an explanatory variable in either model, which is necessary information in constructing a fire fragility curve (Naser, 2021; Peris-Sayol et al., 2017).

Fire intensity induced by wildfire is usually less than that caused by a truck collision. The collision of a fuel tanker results in hydrocarbon fires (burning of fuel). If fuel spillages are involved, the temperature may reach up to 1000°C within the first few minutes of ignition, thus causing substantial structural damage (Kodur et al., 2017; Sobanjo and Thompson, 2013). While such a car or truck collision resulting in significant damage to a bridge may be caused by smoke-induced visibility issues during wildfire evacuation, this cause of bridge fire was not considered in this project because of a lack of information about the quantitative causal relationship between visibility issues due to wildfires and such collisions. The probabilistic relationship between fire intensity and bridge state has yet to be explored in any depth.

Chan et al. (2000) conducted experiments and showed that the compressive strength of concrete may decrease up to 50 percent and 80 percent when the concrete is exposed to 600°C and 800°C, respectively. Although other researchers have also demonstrated that the structural capacity of a bridge decreases by increasing fire temperature and exposure time, the experimental results have not been sufficient to construct a fire fragility curve because of different laboratory settings and limited results. Therefore, this project assumed that bridge damage level depends only on bridge material and used a simple relationship between them, as shown in figure 2.2. Five damage levels (DLs) were considered, including superficial damage (DL2), slight damage (DL3), partial damage (DL4), massive damage (DL5), and structural collapse (DL6), in addition to no damage (DL1). The mean damage levels are 2.3, 2.6, 2.0, and 4.8 for concrete, composite, steel, and timber bridge, respect;tively (Peris-Sayol et al., 2007). This simple relationship should be replaced with a bridge fire fragility curve once it becomes available.

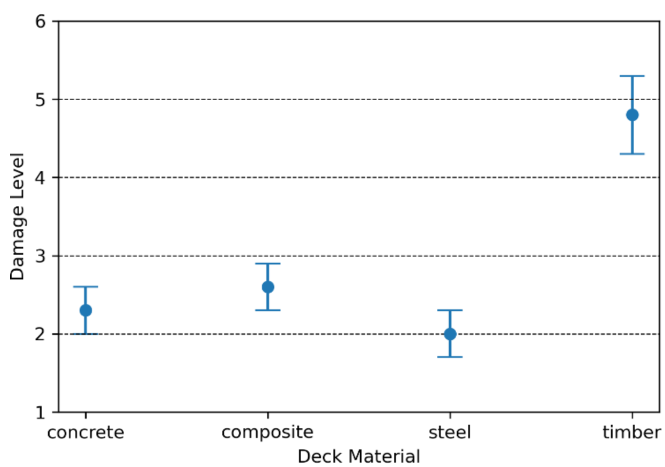

Figure 2.2 Relationship between type of deck material and bridge damage level (adapted from Perios-Sayol et al., 2017)

After each representative wildfire scenario is simulated in FARSITE, the time-dependent wildfire perimeter is overlaid with a bridge map to identify the bridges affected by wildfire at every time step. The bridge map includes the locations of all bridges (B) in the study region as well as their structural systems, deck materials, number of lanes, traffic flow capacities, etc. A specific set of bridges ($B' \subset B$) located in the current wildfire perimeter experiences a certain damage level. The DL of each bridge in the subset B' is determined on the basis of the relationship between deck material and DL (cf., figure 2.2).

This relationship is not deterministic because of uncertainties; see the range of DL associated with each type of deck material. Therefore, the DL of a bridge in the subset B' is a random variable and is determined through a Monte Carlo simulation (MCS).

Bridge damage will result in reduced traffic flow capacity and subsequently will affect the flow capacity of the link where the bridge is located. The bridge damage levels (BDL) realized from the previous step are used to estimate the link damage level (LDL) through the empirical equation below (Shiraki et al., 2007):

$$LDL = \sqrt{\sum_{i=1}^{n}(BDL_i)^2} \tag{7}$$

where n = the total number of bridges located in the link and BDL_i = the damage level for the i^{th} bridge. The values of LDL are translated into the estimates of link traffic flow capacities, as shown in table 2.1.

The reduced flow capacities of the links attacked by wildfires will be incorporated into the traffic simulation in Module 4 to simulate evacuation process in damaged transportation settings. While vehicle re-routing due to blocked roads or smoke-induced visibility can be another obstacle that reduces the flow capacity of the transportation network, these factors were not considered in this project.

Table 2.1 Link damage state and the associated traffic carrying capacity (adapted from Shiraki et al., 2007)

Link Damage Level	LDL Lower Bound	LDL Upper Bound	Capacity (%)	Free Flow Speed (%)
Superficial damage	0.00	0.50	100	100
Slight damage	0.50	1.00	100	75
Partial damage	1.00	1.50	75	50

Massive damage	1.50	3.00	50	50
Structural collapse	3.00	∞	0	0

2.3. Evacuee Response Model

In the fourth module, traffic demand is estimated at the individual evacuee, household, or vehicle level. Thus, in this module, individual responses and behaviors during evacuation are 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 an information update procedure. Individual evacuees start to evacuate at different points in time even when they are exposed to the same level of a 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 was 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 area and suggests that 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, events that 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 by 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, then one of the stimuli is activated, and the evacuee's response is simulated on the basis of his/her risk attitudes and characteristics through an MCS. The departure time is not immediately after the timing of the evacuation trigger but may be delayed because of 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., 2015). 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 the 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 is introduced in Chapter 3.

2.4. Traffic Simulation

The reduced functionality of a transportation network (Module 2) can endanger human lives when combined with elevated travel demand patterns (Module 3) during an evacuation. Module 4 performs 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 that models each evacuee as an agent is often adopted in microscopic traffic simulation and is more appropriate for regional evacuation modeling because of its high computational burden. Given that wildfire evacuation is often limited to the community or county level, activity-based microscopic traffic simulation has been widely used in previous wildfire evacuation studies (Cova and Johnson, 2002; Grajdura et al., 2020; Mancheva et al., 2019).

In this study, the activity-based microscopic traffic simulation was performed within ABM. Various ABM software programs 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 because of 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 enter the transportation network and choose their evacuation routes using their routing selection method (i.e., the results from Module 3). Some agents who do 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 damaged bridges, traffic congestion, etc. Therefore, the spatiotemporal movements of individual agents are 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 the microscopic traffic simulation to predict traffic flows at the level of individual agents and to capture traffic dynamics that consider collective actions among the agents. The ABM framework for wildfire evacuation in damaged transportation settings provides time-dependent traffic maps to identify the critical parts of the transportation network that are the most vulnerable to wildfires and have the greatest potential for causing traffic congestion during an evacuation. Moreover, the total number of evacuating agents during a given period are also obtained as a final result, which could be used to determine the bridges that need to be strengthened to minimize human losses during a wildfire evacuation.

CHAPTER 3. DATA COLLECTION AND ANALYSES

3.1. Data Collection

The project team conducted an online survey of residents in wildfire-prone areas, specifically in California, Oregon, and Colorado, that have experienced major wildfire events and evacuations in the past several years to capture their diverse behaviors before and during a wildfire evacuation.

Participants were recruited through Amazon Mechanical Turk (MTurk) between April and May 2022. MTurk, a platform where crowdworkers can be recruited, was used in this project because of its high- quality data at a reasonable cost (Owens and Hawkins, 2019). The inclusion criteria for participating in the survey were residents living at the study site who were at least 18 years of age. A total of 1,312 participants responded to the survey, but 459 responses were considered invalid because they did not meet the following criteria: (a) participants should pass all attention checks; (b) participants should provide the same answers to two identical questions during the survey; and (c) the combined number of elder people and children in a household should be less than or equal to the total number of people in the household.

In the final sample of 853 participants, 47 percent of the respondents were female, and 53 percent of the respondents were male. The age group between 30 and 39 years old comprised the highest proportion in the sample, whereas only 19.5 percent of the population at the study site was in this age group according to the Census data (U.S. Census Bureau, 2021). The percentage of the respondents whose annual household income was less than $100,000 was greater than the percentage from the Census data. Such differences were observed because younger and lower-income people generally use MTurk as a means of earning extra money. The demographic characteristics of the sample and the Census data are presented in table 3.1.

The online survey consisted of a set of closed-ended quantitative and qualitative questions, including demographic information, property location, car ownership, mobility issues, risk perception, previous experience with wildfire and other natural hazards, and the series of their evacuation actions. The survey also asked a question about the method that participants would utilize in selecting an evacuation route (e.g., familiar route, conventional map, real-time map, etc.) to investigate their routing selection in Module 4. All study protocols were approved by the Washington State University Institutional Review Board before the survey commenced.

Table 3.1 Demographic characteristics and census data

Characteristics	Classes	Sample (%)	Census (%)	p-value
Gender	Female	47%	50.2%	0.0770*
	Male	53%	49.8%	0.1245
Age (years)	18 – 29	24.6%	19.9%	0.0014**
	30 – 39	36.2%	19.5%	<0.0001***
	40 – 49	19.6%	17.9%	0.2174
	50 – 59	12.3%	17.6%	<0.0001***
	60 – 69	6.2%	14.7%	0.0340**
	>= 70	1.1%	10.4%	0.0902*
Education	Less than a high school diploma	0.2%	15.1%	<0.0001***
	High school diploma or equivalent	14.9%	42.2%	<0.0001***
	Associate degree	8.8%	8.0%	0.2871
	Bachelor's degree	59.3%	21.7%	<0.0001***
	Graduate degree	15.8%	13.1%	0.0052***
Ethnicity	Caucasian	66.5%	64.6%	0.0689*
	Asian	12.5%	12.3%	0.7708
	African American	5.5%	5.3%	0.5457
	American Indian, Alaska Native, Native Hawaiian or Other Pacific Islander	1.5%	1.2%	0.5938
	Two or more races	5.9%	4.7%	0.1380
	Other races	8.1%	11.9%	<0.0001***
Annual household income before taxes	Less than $49,999	28.7%	33.2%	<0.0001***
	$50,000 to $99,999	49.4%	28.4%	<0.0001***
	$100,000 to $199,999	17.0%	26.2%	<0.0001***
	Over $200,000	5.9%	12.2%	<0.0001***

*p < 0.1; **p < 0.05; *** p < 0.01

3.2 Data Analyses

To identify statistically significant explanatory variables that influence individual decisions about evacuation and peoples' preference as to whether to use real-time navigation during an evacuation, we performed binary logistic regression analyses based on the survey data. A logistic regression model is a special type of generalized linear model and projects a linear function to a value between 0 and 1. Because the output bounded between 0 and 1 is used to estimate the probability of an event occurring, binary logistic regression has been widely used for estimating discrete choice preferences, such as insurance purchases (Lee and Li, 2021; Lee et al., 2022) and evacuation decisions (Kuligowski et al., 2022). For example, in this project, an individual could decide whether to evacuate, and a decision variable would take two values, 1 (evacuate) or 0 (do not evacuate), which were mutually exclusive and collectively exhaustive.

The independent variables considered at the initial step of estimating the regression models were the variables describing the characteristics of individual participants and their households, and these are summarized in Appendix A. We first considered all independent variables that are shown in Table 3.1 and Appendix A. Then the regression model was estimated by using a stepwise backward regression approach. It began with all the independent variables, and at each step the least significant variables were eliminated 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 of greater than a 5 percent 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 Bayesian Information Criterion (BIC).

3.3 Survey Results and Discussion

During a wildfire, individual evacuation can be triggered by various external stimuli, such as an official announcement (e.g., mandatory or voluntary evacuation order) or physical cues (e.g., smoke, flames, or embers). Understanding the responses of evacuees to various evacuation triggers is important in estimating evacuation time and traffic demand in the proposed ABM framework. Table 3.2 shows the frequency distribution of the main external stimuli that could trigger evacuation during a wildfire. As shown in table 3.2, 38.8 percent of respondents said they would evacuate after either a Level 1 (i.e., evacuation alert that a wildfire threat is in the area) or Level 2 (i.e., evacuation warning that there is a high probability of a need to evacuate) announcement. These were followed by "evacuation without any official announcement but after knowing that there would be a wildfire threat from news and/or neighbors" (29.8 percent), and "evacuation with a mandatory evacuation order (Level 3)" (27.8 percent). Only 3.6 percent of respondents said they would wait until smoke or flames/embers were observed or would stay and defend.

Table 3.2 Frequency distribution of evacuation trigger

Evacuation Trigger	Count	Percentage
Evacuate without any official announcement	254	29.8%
Evacuate with a voluntary evacuation order	331	38.8%
Evacuate with a mandatory evacuation order	237	27.8%
Evacuate after smoke is observed	11	1.3%
Evacuate after flames/embers are observed	5	0.6%
Stay and defend	15	1.8%

For illustration purposes, this study categorized respondents into two groups based on their evacuation triggers. Respondents who said they would evacuate without official announcement or in response to a voluntary evacuation order were categorized as early evacuees. The delayed evacuation group included the respondents who would evacuate after receiving a mandatory evacuation order, evacuate after observing physical cues, or choose not to evacuate. Thus, 68.6 percent of respondents were classified in the early evacuation group, while the rest (31.4 percent) were in the delayed evacuation group.

Table 3.3 summarizes the binary logistic regression results of evacuation timing, where the dependent variable takes values between 0 (the delayed evacuation group) and 1 (the early evacuation group). The survey results indicated that the respondents with higher incomes would prefer to wait or stay and defend. This may be explained by the findings of McCaffrey et al. (2018), that staying and protecting peoples' properties during a wildfire could actually reduce economic losses, and that there could be a trade-off between personal safety and the desire to protect their properties. The positive effect of past wildfire evacuation experiences on early evacuation may indicate that these respondents lived in high wildfire-prone areas and could be more aware of the importance of early evacuation. The tendency to use real-time navigation routinely may indicate the respondents' level of familiarity with their community: the positive coefficient of this variable can be interpreted that the respondents with a lower level of familiarity with their community would prefer evacuating early because of the fear of having to take a detour as a result of road closures or severe congestions. The respondents who owned three or more personal automobiles, owned both pets and livestock, or lived alone said they would be less likely to evacuate in advance.

Table 3.3 Logistic regression results of evacuation timing

Variable	Estimated coefficient	Wald chi-square	p-value
Intercept	0.6906	3.3195	0.0009
Education: High school diploma or equivalent	-0.5674	-2.7181	0.0066
Household income: 100k - 200k	-0.3681	-2.0209	0.0433
Household income: over 200k	-0.5024	-2.0589	0.0395
Household size: 1 person	-0.7043	-3.2263	0.0013
The number of cars per household: 3 or more	-0.8329	-3.3490	0.0008
Animals: both pets and livestock	-0.8279	-2.3767	0.0175
Real-time navigation: use under normal conditions	0.3840	2.1103	0.0348
Homeowners insurance: fully insured	0.4884	2.9268	0.0034
Wildfire evacuation: more than once in the past 10 years	0.6992	3.2844	0.0010

These results are consistent with Toledo et al. (2018), who found that household size, the presence of animals, income, and fire risk have a significant impact on individual evacuation decisions. However, their findings regarding the positive impact of age and the presence of children on early evacuation were not significant in our case. The negative effect of the presence of animals was also supported by Mozumder et al. (2008). Moreover, the respondents who had full coverage homeowners' insurance said they would be more likely to be early evacuees. This is partly because people who fully insure their properties generally have a higher risk-averse attitude and thus tend to evacuate early.

Actual departure time may be delayed because of decision delay and preparation for evacuation. Because decision delay time was hard to know through the stated preference survey, only evacuation preparation time was considered in this project. As presented in table 3.4, about two-thirds of the respondents said they expected that evacuation preparation time would be less than 30 minutes. Only 5 percent of the respondents said they would spend more than two hours preparing for evacuation, partly because they might need extra time to move their livestock to shelter, evacuate with elderly or disabled family members, or find a ride (when the household did not have a car). Another uncertain factor in the evacuation decision process is destination choice. As summarized in the frequency distribution of evacuation destinations shown in table 3.5, individuals may have a number of destination choices. About half of the respondents said they would choose to stay at someone else's house (e.g., friends, family members, and relatives) after a wildfire evacuation, which was quite close to the survey results (i.e., 57 percent of the 446 respondents) of Toledo et al. (2018). More than one-quarter of the respondents said they would prefer to stay at hotels, and only about 10 percent of the respondents would chose public shelters as their destinations. These findings were not consistent with the findings of Sorensen and Sorensen (2009), that the final destinations of the residents in the evacuation zones for the 2007 San Diego Fire were a relative's home (43.6 percent), friend's home (27.6 percent), hotel/motel (11 percent), and public shelter (4.9 percent). While the percentages were different, the levels of preference found in these two studies were consistent.

Table 3.4 Frequency distribution of evacuation preparation time

Preparation time	Count	Percentage
< 10 mins	132	15.5%
11 mins - 20 mins	174	20.4%
21 mins - 30 mins	230	27.0%
31 mins - 45 mins	97	11.4%
46 mins - 60 mins	87	10.2%
1h - 2h	90	10.6%
> 2h	43	5.0%

Table 3.5 Frequency distribution of evacuation destination

Destination	Count	Percentage
Friend or family member's house	437	51.2%
Hotel	244	28.6%
Public shelter	84	9.8%
Secondary residence	35	4.1%
Portable vehicle	20	2.3%
Rental house	21	2.5%
Others	12	1.4%

Evacuees may use real-time navigation as a route-optimization tool during an evacuation, which could potentially improve evacuation efficiency. However, to the best of the authors' knowledge, few studies have investigated the key factors that influence the use of real-time navigation during an evacuation and how its use affects the evacuation process. Table 3.6 presents the binary logistic regression results of real-time navigation use during an evacuation. As expected, the respondents who used real-time navigation routinely said they would be more likely to use it in determining evacuation routes. The respondents who owned their properties or had experienced wildfire damage to their properties over the past decade would be less likely to use real-time navigation during an evacuation. This may be partly because they may have lived in their communities longer than the rest of the respondents and were more familiar with the neighborhood and local region, which would allow them to determine evacuation routes by themselves rather than relying on navigation. This interpretation aligns with the finding that the respondents who had full-time jobs would prefer using real-time navigation during an evacuation, as they would be relatively less likely to spend time outside or be familiar with their communities. Risk-seeking respondents said they would be less likely to utilize real-time navigation, which was consistent with our expectation that the people having risk-averse attitudes would not be willing to take a risk (e.g., unexpected delay due to road closure or traffic congestion) during an evacuation.

Table 3.6 Logistic regression results of real-time navigation use during an evacuation

Variable	Estimated coefficient	Wald chi-square	p-value
Intercept	-0.9563	-4.4295	<0.0001
Employment: full time	0.4029	2.2211	0.0263
Homeownership: with mortgage	-0.6373	-3.6248	0.0003
Homeownership: free and clear	-0.6938	-3.4582	0.0005
Navigation use: routinely	0.8897	4.6480	<0.0001
Property damage due to past wildfires: yes	-0.9340	-4.2415	<0.0001
Safety risk attitude: risk-averse	-0.2163	-2.4418	0.0144

CHAPTER 4. CASE STUDY: THE CITY OF SANTA CLARITA, CALIFORNIA

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, and its 2020 population was 228,673. This city was selected because many homes in Santa Clarita were in the 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 was the Rye Fire, which broke out on December 5, 2017, and endangered over 1,000 homes in the city.

During the fire, about 1,300 homes were affected by the evacuation order, and both directions of Highway 5 were closed.

While the ABM framework can adopt both scenario-based and probabilistic approaches, in this case study, we specifically took a scenario-based approach for illustration purposes. Although the scenario- based approach was adopted in this case study, uncertainties in all four modules were still considered and propagated throughout the framework to simulate evacuation during the Rye Fire.

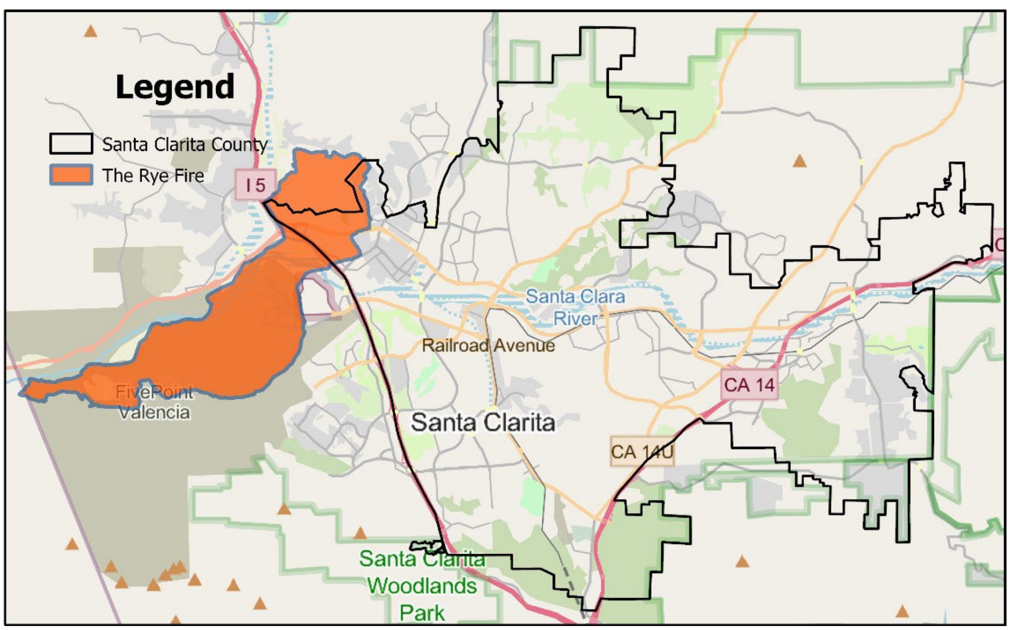

Figure 4.1 The City of Santa Clarita affected by the Rye Fire

4.2. Procedure

4.2.1. Module 1. Wildfire Simulation

To estimate spatiotemporally varying fire probabilities in the study region, potential fires that ignited outside the City of Santa Clarita but could propagate into the city were considered. Given that the largest wildfire in California history scorched more than 1 million acres, a total of 31 zip codes around the city were defined as the study region for estimating wildfire ignition probabilities. Once the wildfire occurrence probability map was constructed, representative wildfire scenarios were generated to simulate wildfire growth. Since a scenario-based approach was taken in this case study, we present only the procedure for generating a wildfire occurrence probability map and simulating wildfire growth from the known ignition location and time.

The required inputs to the wildfire occurrence probability estimation models (see equations 1 -3) included gridded daily climate data (i.e., the maximum and minimum temperature, the maximum and minimum relative humidity, average wind speed, and burning index) and gridded topographic and fuel layers. 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 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. 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 2.1, to address the issues with imbalanced data, 435 no-fire voxels were first randomly sampled, which was 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. Although the accuracy of the current model was 74.4 percent, there are multiple ways to improve its accuracy: (a) a longer climate data period (e.g., collected during the period between 1979 and 2021) could be used; and (b) additional gridded human factors such as population density, urban development, and distance to the freeway could be included in the estimation model rather being encapsulated into a single location factor.

While the wildfire occurrence probability map constructed through the estimation model could be used to generate a set of representative scenarios through the k-means clustering algorithm, this case study adopted a scenario-based approach. Therefore, the ignition time and location of the Rye Fire were used as the starting point for wildfire growth simulation. The required inputs to FARSITE included 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) system located throughout the United States, while all raster files were downloaded from the LANDFIRE program. The 40 Scott and Burgan Fire Behavior Fuel Models (FBFM40) does not support fire spread into urban and suburban areas, which was not the case during the Rye Fire.

Therefore, in the case study, we replaced urban and suburban development (NB1) with low load, dry climate timber-grass-shrub (TU1) to allow the fire to propagate into urban and suburban areas.

The simulated fire perimeter during the first burning day (December 5, 2017) was compared with the Rye Fire perimeter, which is shown in figure 4.2. 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 required additional assumptions about human suppression efforts in order to stop the fire. While FARSITE had limitations in simulating the Rye Fire from its ignition to full containment, the similar propagation direction of both simulated and actual fires (see figure 4.2) indicated that the model had the capability to simulate fire growth successfully until human intervention.

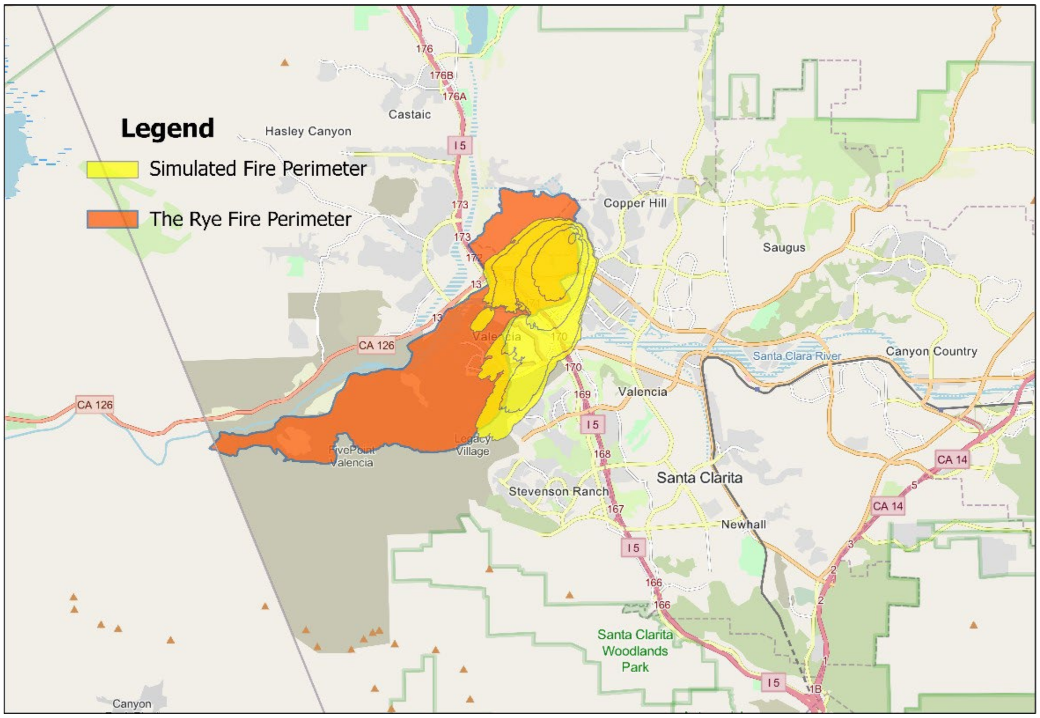

Figure 4.2 Comparison between the simulated fire perimeter (only during the first burning day) and the Rye Fire perimeter

4.2.2. Module 2. Bridge Vulnerability Assessment

As shown in figure 4.3, 11 bridges were located within the simulated fire perimeter. The deck materials of all these bridges are summarized in table 4.1. The relationship presented in figure 2.2 was used to estimate each bridge's damage level. It was assumed that the damage level of a bridge was normally distributed with a mean value as shown in figure 2.2 and a coefficient of variation of 0.3. Using MCS, the damage level of each bridge was randomly sampled from the respective normal distribution. To highlight the impacts of damaged bridges on traffic disruption during a wildfire evacuation, one of the extreme scenarios among infinitely many possible ones was considered in this case study: five bridges experienced massive wildfire damages (DL5). Based on table 2.1, wildfire damage subsequently reduced the traffic capacities of massively damaged bridges by 50 percent. Such reduced traffic capacities were fed into Module 4 and combined with increased traffic demand at each time step. For example, between 1:00 pm and 3:00 pm on December 5th, Bridge 10 was severely damaged and lost its capacity by 50 percent. Then the reduced capacity of this bridge was incorporated into traffic simulation in Module 4.

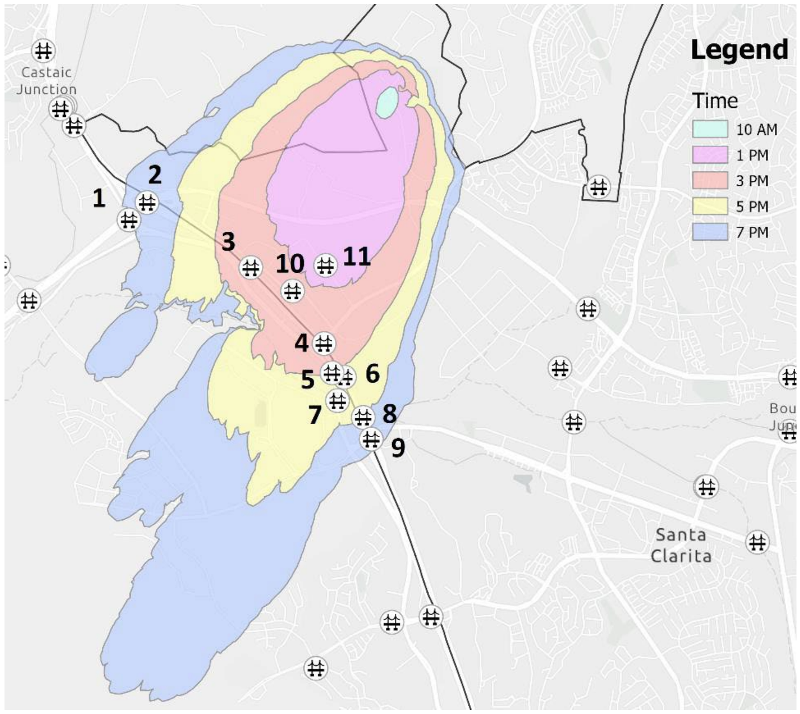

Figure 4.3 The locations of bridges within the simulated fire perimeter

Table 4.1 Bridge deck materials and damage levels

Bridge ID Number	Deck Material	Damage Level
1	Prestressed concrete continuous	DL1
2	Prestressed concrete continuous	DL5
3	Concrete continuous	DL1
4	Concrete continuous	DL1
5	Concrete continuous	DL1
6	Concrete continuous	DL5
7	Steel	DL5
8f	Prestressed concrete continuous	DL1
9	Prestressed concrete continuous	DL5
10	Concrete	DL5
11	Concrete	DL1

4.2.3. 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 from 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 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, by 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 percent shape length were labeled as multifamily residential buildings. The ratio of 30 percent was determined on the basis of the 2019 U.S Census Bureau American Housing Survey, which found that 31.4 percent of housing in the U.S. was 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 on the basis of the survey data and results described in Chapter 3. First, the evacuation timings of all synthetic households in the city were determined on the basis of the binary logistic regression model summarized in table 3.3.

Explanatory variables in the logistic regression model for evacuation timing included education level, household income, household size, the number of vehicles, homeowners' insurance status, navigation use, the presence of animals, and past evacuation experience. Whereas the first five characteristics of synthetic households had already been realized during the synthetic population generation, the last three properties of each household were not known because these properties are often not available from the U.S. Census data. Therefore, 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 were 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, note that this assumption may have introduced bias due to representative issues (Hung and Wang, 2022; Seebauer et al., 2017). The regression model predicted that 57,879 households would be in the early evacuation group, categorizing 69.3 percent of the synthetic households as early evacuees. This rate was consistent with the survey results that 68.6 percent of the respondents would be willing to evacuate before receiving a mandatory evacuation order.

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, two buffer zones were created to generate two types of evacuation triggers: a 2-mile buffer around the updated firefront was used to trigger the evacuation of the early evacuation group, and a 0.5-mile buffer was used to initiate the evacuation of the delayed evacuation group. The actual departure time could be delayed because of 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 that affect the delay time and their statistical relationship because of the abstract nature of major parameters. Therefore, in this study, the delay time of each household mainly due to evacuation preparation was randomly sampled from the histogram of preparation time shown in table 3.4.

The evacuation destinations of the synthetic households are also uncertain. As presented in table 3.5, 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 4.4 shows the three schools that were located within the city but outside the fire perimeter. These schools were considered public shelters in the case study. In the survey (c.f., table 3.5), 9.8 percent of the respondents reported that public shelters would be their final destinations. Therefore, 9.8 percent of the households that decided to evacuate were randomly selected, and their final destinations were randomly assigned to one of the three public shelters. Three major community exits, shown in figure 4.4, were assigned to the households whose final destinations were not public shelters. As such, this case study used only the histogram of destination choices in determining the final destinations of the synthetic households. In future studies, a regression model will be developed to relate household characteristics to destination choices. Moreover, future studies will allow the households to choose the closest shelter or exit rather than randomly assigning final destinations to the households.

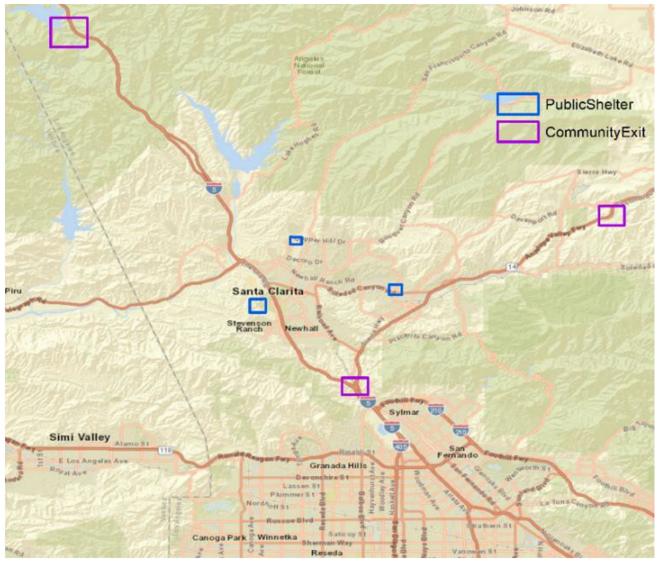

Figure 4.4 Final destination locations

This module generated the evacuation timing, decision delay and preparation time, and final destination of all synthetic households based on the survey results and ultimately determined their actual departure times. However, public transportation and returning traffic (e.g., the vehicles that would return to home) were not considered in this module. Thus, the following additional assumptions were made: (a) the households that did not own a vehicle but still would like to evacuate, used hypothetical vehicles to evacuate; and (b) if some of the household members at the workplace brought cars and no vehicles were available for the remaining household members at home, hypothetical vehicles were assigned to the household members at home. These hypothetical vehicles can be replaced by public transportation and ride-sharing in future studies. Finally, a total of 162,705 vehicles (both actual and hypothetical vehicles) were used during a wildfire evacuation. At every time step, the vehicles that were about to depart were recorded and considered in estimating traffic demand in the fourth module.

4.2.4. Module 4. Traffic Simulation

The agent-based traffic simulation was performed by using SUMO. The vehicle-only transportation network in the City of Santa Clarita is illustrated in figure 4.5. 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, by using the binary logistic regression model of the use of real-time navigation, some evacuees were classified as navigation users and others were classified as non-navigation users. In the traffic simulation, only navigation users took the fastest routes. Non-navigation users took 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 numbers of vehicles that successfully evacuated, average speed, etc.

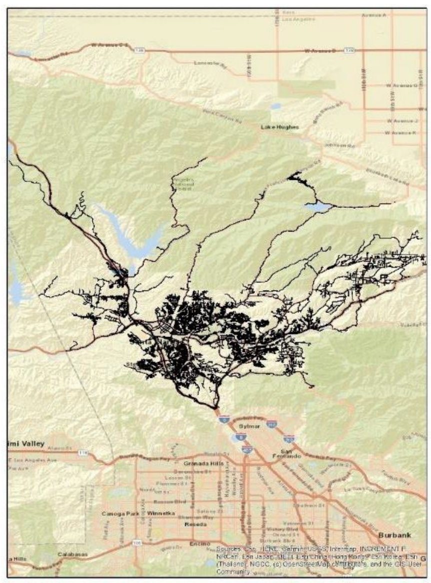

Figure 4.5 Vehicle-only transportation network in the City of Santa Clarita

4.3. Results and Discussion

The proposed framework was illustrated with the Rye Fire, which affected the City of Santa Clarita in December 2017. The procedure and results from each module are summarized as follows. The first module generated a wildfire occurrence probability map for the study region and simulated the growth of the Rye Fire from its ignition point at 9:32 am on December 5, 2017. Fire perimeters were recorded at 10:00 am, 1:00 pm, 3:00 pm, 5:00 pm, and 7:00 pm on the same day. The fire perimeter at 7:00 pm was 3,187 acres. The fire growth simulation was terminated at 7:00 pm because all evacuation orders were lifted the evening of December 5th.

Because of the limited capability of FARSITE to model suppression and barrier effects, the simulated fire perimeter was a bit different from the actual one, while the propagation directions of both actual and simulated fires were similar. The second module estimated the locations, timing, and severity levels of damaged bridges within the evacuation zones. Among infinitely many plausible scenarios, we considered a specific scenario where five out of 11 bridges were massively damaged. Although concrete and steel bridges are generally not extremely vulnerable to fires, it is highly possible that these types of bridges might have reduced capacity due to blockage resulting from fire-induced landslides or fallen trees/rocks, smoke-induced limited visibility, etc. Because of safety concerns and visibility issues, road or bridge closures can be announced by authorities. For example, during the actual Rye Fire, both directions of Highway 5 near Magic Mountain in Valencia were closed on December 5th. Therefore, the bridge damage scenario considered in the case study was one of the worst-case scenarios but was still plausible. The third module generated a synthetic population in the City of Santa Clarita. On the basis of the survey results and the binary logistic regression models, the evacuation triggers and final destinations of all households in the affected region were determined. Combined with the time-dependent fire-front movement obtained from the first module, the evacuation timings of all households were determined, which were subsequently used as time-dependent traffic demand in the traffic simulation. Finally, in the last module, traffic simulation was implemented during the evacuation process (from 9:30 am to 11:00 pm on December 5, 2017) to capture the locations of all vehicles at every second.

Figure 4.6 presents the cumulative number of vehicles that had departed, the cumulative number of vehicles that had evacuated, and the number of vehicles currently in the transportation network at every second during the entire evacuation period from wildfire ignition (9:30 am) to the time after all evacuation orders had been lifted (11:00 pm). Because the fire perimeters were recorded at discrete time points (i.e., 10:00 am, 1:00 pm, 3:00 pm, 5:00 pm, and 7:00 pm), the black curve in figure 4.6 has a series of steps, which indicates the timings of evacuation triggers. About three-quarters of vehicles that were triggered by the updated fire perimeter entered the network within 45 minutes, which aligned with the survey, in which about 75 percent of the respondents reported that their evacuation preparation time would be less than 45 minutes. Similarly, the number of vehicles in the transportation network (i.e., the red curve in figure 4.6) increased in the first 45 minutes of each step but gradually decreased after some of the vehicles had arrived at the final destinations and were out of the network. Generally, most of the vehicles triggered by the previous fire perimeter had evacuated successfully before the fire perimeter was updated at the next time step. However, given that a relatively higher number of vehicles evacuated between 1:00 pm and 3:00 pm, some vehicles still remained in the network even after the next fire perimeter had been updated. Consequently, by being combined with the vehicles just departing, the vehicles remaining in the network caused severe traffic congestion. This can also be observed in figures 4.7 and 4.8. Finally, a smooth blue curve in figure 4.6 indicates that the evacuation rate was stable throughout the simulation.

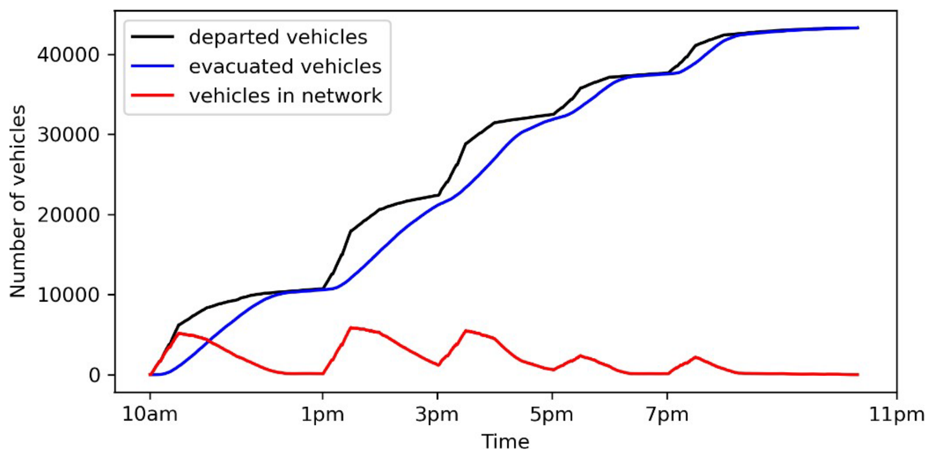

Figure 4.6 The cumulative number of vehicles that have departed and evacuated and the number of vehicles currently in the transportation network

In the SUMO traffic simulation, a vehicle that was trapped at same location for a certain amount of time was teleported to the next available edge on its route. Thus, the teleported vehicle could be treated as one that was stuck in severe traffic congestion. As shown in figure 4.7, the cumulative number of teleported vehicles increased drastically between 10:00 am and 12:00 pm and between 3:00 pm and 5:00 pm, which implies severe congestion in the network. Similar results can be observed in the time series of average speed displayed in figure 4.8. Congestion first appeared when residents were informed of the outbreak of the Rye Fire and started the evacuation. Initial traffic congestion decreased once most of the residents who were triggered by the first fire perimeter had evacuated successfully. Whenever an updated fire perimeter triggered the evacuation of some of the remaining residents, the average speed decreased dramatically in the first 45 minutes of each step, which is consistent with figure 4.5. Severe congestion was observed specifically between 1:00 pm and 5:00 pm because of elevated travel demand and massive bridge damages. Although two bridges (bridges 2 and 9) were severely damaged after 5:00 pm, their impact was minimal, possibly because the previously damaged bridges located on I-5 had already created congestion.

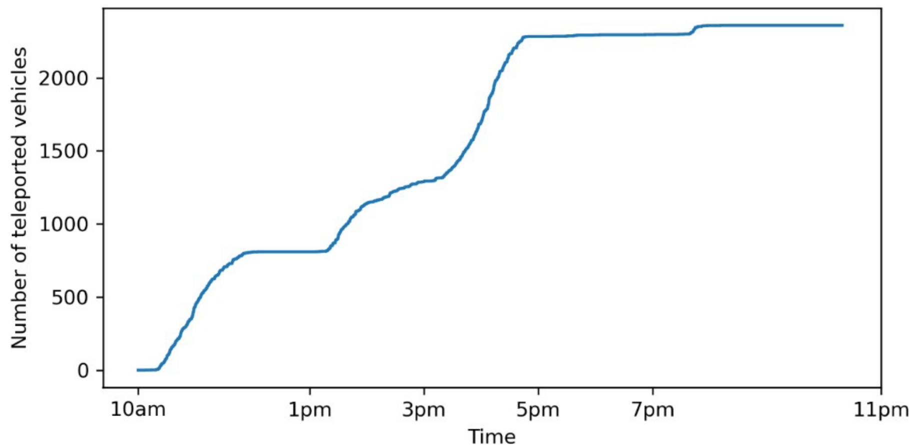

Figure 4.7 The cumulative number of vehicles stuck in traffic

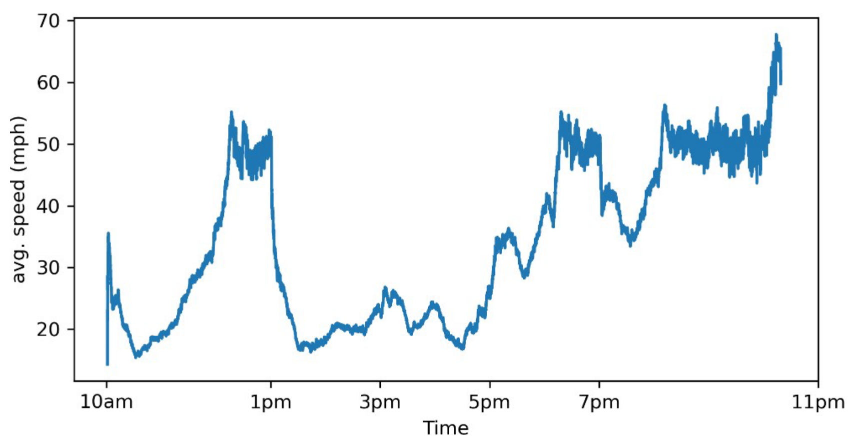

Figure 4.8 Time series of average speed

One advantage of using the ABM framework is to track the locations and travel speeds of individual vehicles at every second to help identify when and where severe traffic congestion will occur and provide quantitative data to support risk-informed decision-making. Figures 4.9 and 4.10 show traffic maps at 10:36 am (i.e., the time when severe traffic was first observed) and at 8:11 pm (i.e., the time when high average speed was observed), respectively. In figure 4.9 the network segments in red experienced heavy traffic and should be considered in pre-fire risk mitigation efforts to facilitate wildfire evacuations in the future. Most congestion problems were resolved, as shown in figure 4.10, where all major highways and arterial roads have blue colors. The results from this framework can be further used in identifying the critical parts of the transportation network during a wildfire evacuation. For example, figures 4.7 and 4.8 show the periods when severe congestion occurred. By observing a series of traffic maps (e.g., figures 4.9 and 4.10) during these time periods, the network segments that would experience or cause severe congestion can be identified. Additionally, through the vulnerability assessment, the bridges that would have the highest chance of being severely damaged can be identified. Such information will provide useful guidance for transportation risk managers or local government officials about which parts of the transportation network are vulnerable to fires or would cause (or experience) severe congestion during a wildfire evacuation. As pre-fire mitigation actions, the identified network components and segments can be retrofitted or expanded, while alternative routes are constructed, aimed at facilitating evacuation during a wildfire event. Since the results of this case study were generated only under the effect of the Rye Fire, such information on pre-fire mitigation actions may not be comprehensive. By taking a fully probabilistic approach, however, the framework can provide quantitative data to support more effective pre-fire mitigation actions that can be applicable to a wide range of plausible wildfire scenarios

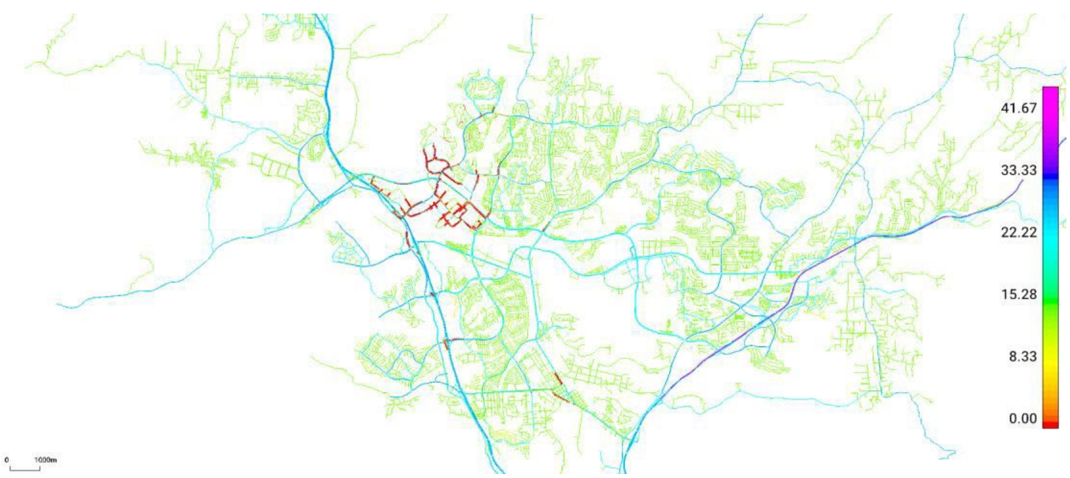

Figure 4.9 Traffic map at 10:36 am (average speed of 15.6 mph)

Figure 4.10 Traffic map at 8:11 pm (average speed of 56.3 mph)

CHAPTER 5. CONCLUSIONS, LIMITATIONS, AND FUTURE RESEARCH DIRECTION

Effective community-based transportation evacuation planning is an important issue for state and local policy makers at great risk of wildfires in the United States. Evacuation is considered to be the second line of defense if the first course of defense (i.e., wildfire countermeasures) cannot prevent wildfire risks to communities. Underestimation of this issue and ineffective planning could result in catastrophic human losses during a wildfire. An evacuation simulation model may assist a well-developed evacuation plan and ultimately could save human lives.

This project proposed an ABM framework for wildfire evacuation in damaged transportation settings by integrating wildfire simulation, 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. As part of the project, we conducted an online survey of residents in wildfire-prone areas in California, Colorado, and Oregon to understand highly unpredictable human behaviors during an evacuation. The survey results were used as a basis for determining key characteristics of the synthetic population so that the ABM framework could capture individual behaviors during a wildfire evacuation. ABM allows the framework to generate both disaggregated-level outputs (e.g., the location and speed of individual vehicles at every second) and aggregated- level outputs (e.g., the cumulative number of vehicles that have departed or evacuated, the number of vehicles that are currently in the network or stuck in traffic, time series of average travel speed). By combining the aggregated-level outputs with the disaggregated-level ones, we can assess overall network performance during an evacuation while identifying bottlenecks and the critical network segments that may experience heavy congestion. The proposed framework also introduces damaged traffic settings to the evacuation process and showcases how the reduced network capacity impacts evacuation efficiency, especially when combined with elevated travel demand.

The main contributions of this project include (a) the incorporation of an advanced wildfire hazard modeling and vulnerability assessment to improve the accuracy of wildfire evacuation in damaged transportation settings, and (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. However, the project has a number of limitations that may hinder its accuracy or wide applicability.

First, public transportation and returning traffic were not considered. Second, the evacuation zone was determined by using two buffers (2-mile and 0.5-mile buffers herein) estimated from the simulated fire perimeters, which may not reflect real-world situations. Third, the scenario-based approach only shows the estimated traffic demand and capacity under a specific what-if scenario. To account for uncertainties throughout the entire framework and generate an expected network functionality, a fully probabilistic approach is necessary. Finally, the evacuation destination was randomly assigned on the basis of 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, we will release most of the restrictive assumptions and address the current limitations listed above. Future work will include (a) introducing public transportation and returning traffic, (b) modeling carpool behavior to remove hypothetical vehicles, (c) determining evacuation zones based on the combined effect of wind and fire propagation directions, (d) modeling vehicle detours due to road closures, and (e) taking a fully probabilistic approach.

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APPENDIX A:
SURVEY DATA ON INDIVIDUAL AND HOUSEHOLD CHARACTERISTICS

Characteristics	Cla sse s	Frequency
Employment	Employed, working 40 or more hours per week	70.0%
	Employed, working less than 40 hours per week	16.6%
	Not employed	6.1%
	Retired	2.6%
	Disabled, not able to work	0.9%
	Others	3.8%
Mode of commuting	Personally owned car, truck, or van	60.8%
	Personally owned motorcycle	11.0%
	Public transportation (e.g., bus, streetcar subway)	6.2%
	Carpool	0.8%
	Shared ride (e.g., Uber, Lyft)	1.6%
	Taxicab	1.6%
	Personally owned bicycle	1.8%
	Walk	2.1%
	Work from home	10.9%
	Other	3.2%
Decision-making role	Primary decision-maker	22.6%
	Sole decision-maker	42.1%
	Share decision-making roles equally with others	30.8%
	Providing input to another decision-maker	3.6%
	Other	0.9%
Family Size	1	14.5%
	2	18.3%
	3	22.2%
	4	34.2%
	5 or more	10.8%
Property ownership	Own without mortgage	26.4%
	Own with mortgage	36.0%
	Rent	34.6%
	Other	3.0%
Presence of children	Y	55.5%
	N	44.5%
Presence of elderly	Yes	27.7%
	No	72.3%
Special need required	Yes	26.0%
	No	74.0%
Number of vehicles owned	None	9.8%
	1	57.0%
	2-3	23.2%
	3 or more	10.0%

Characteristics	Classes	Frequency
Homeownership duration	Less than 1 year	4.6%
	1 – 3 years	19.8%
	3 – 5 years	22.3%
	5 – 10 years	24.7%
	10 – 15 years	10.6%
	More than 15 years	18.1%
Animal ownership	None	24.5%
	Pet only	66.4%
	Livestock only	3.9%
	Both pet and livestock	5.3%
Internet access	Yes	1.2%
	No	98.8%
Smartphone access	Yes	2.1%
	No	97.9%
Use of real-time navigation routinely	Yes	76.3%
	No	23.7%
Homeowners insurance status	Not insured	20.8%
	Under insured	24.5%
	Fully insured	54.7%
Past evacuation experience	None	51.6%
	Once	19.0%
	2-3 times	21.9%
	4-5 times	5.6%
	More than 5 times	1.9%
Past wildfire-induced property damage	Yes	27.9%
	No	72.1%
Disaster plan	No plan	44.9%
	Have a plant but not written	34.8%
	Written plan	20.3%