An Integrated Framework for Wildfire Evacuation in a Damaged Transportation Network

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ABSTRACT: This study proposes an agent-based modeling (ABM) framework for wildfire evacuation in damaged transportation settings to support effective evacuation planning. While many existing studies applied ABM to community-based transportation evacuation planning during various types of natural hazards, the application of ABM to wildfire evacuation has been much less studied. In addition, most ABM evacuation simulations did not account for the probabilistic nature of incidents, nor did they examine the vulnerability of critical transportation components. This study fills the gap by proposing an integrated framework that incorporates hazard modeling, vulnerability assessment, behavioral analysis, and ABM to simulate wildfire evacuation in a damaged transportation network. The proposed framework is illustrated with the City of Santa Clarita, California impacted by the Rye Fire to demonstrate its applicability to a real-world community. The study results include the time-varying number of (a) vehicles successfully evacuated and (b) vehicles in the transportation network showing how damaged transportation settings could affect traffic congestion during a wildfire evacuation.

1. INTRODUCTION

The severity and duration of wildfires are anticipated to rise in the future as a result of changes in climate and land use (Cova et al., 2005). As more people are moving to the wildland-urban interface (WUI), wildfire activity poses an even greater threat to human lives and properties and challenges emergency preparation (Lee et al., 2022; Ma et al., 2022). Evacuation is an important way of reducing human losses during a wildfire incident; yet a massive evacuation can increase the traffic burden and congestion significantly. Reduced transportation capacity resulting from wildfire-induced bridge damage may further exacerbate traffic congestion. To account for substantial uncertainties in traffic conditions and human behaviors, wildfire evacuation simulation can be an effective means of emergency management and evacuation planning.

In recent years, agent-based modeling (ABM) has gained great attention in traffic modeling and evacuation planning due to its ability to capture both individual and collective behaviors in a dynamic complex system (Cimellaro et al., 2017; D'Orazio et al., 2014; Epstein, 1999; Feng et al., 2020; Mas et al., 2012). While many existing studies applied ABM to community-based transportation evacuation planning during various types of natural hazards, wildfire evacuation has been less studied (Grajdura et al., 2020) due to the complexity of rapidly changing and highly uncertain microenvironmental conditions during wildfires. Most existing wildfire evacuation studies do not consider fire analysis or simply utilize elementary hazard modeling in their evacuation models (Kuligowski et al., 2022; Stasiewicz and Paveglio, 2021) by assuming that all residents have already been forced to evacuate their community simultaneously. However, weather analysis and fire propagation models are necessary components for a wildfire evacuation simulation to account for spatiotemporally varying evacuation orders and consequent evacuee behaviors.

Some researchers have attempted to combine hazard models with ABM to create more realistic evacuation simulations. For example, Beloglazov et al. (2016) developed a wildfire evacuation model by combining spatiotemporal fire-front with evacuation trigger modeling and ABM. However, this model still lacked vulnerability analysis, and most parameters in the model were assumed or determined based on expert opinions, which made it hardly reproducible. Given that many parts of a transportation system are vulnerable to fires, their physical damage and the associated reduction in traffic carrying capacity due to fires should be considered in a community-based evacuation model so as to better represent traffic conditions and 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.

To fill the research gaps in the literature, this study proposes an integrated framework that incorporates hazard modeling, vulnerability assessment, evacuee response modeling, traffic simulation, and ABM to simulate wildfire evacuation in a damaged transportation network. The simulation results can be used to identify the critical parts of the transportation network for pre-fire risk mitigation actions, aimed at improving evacuation efficiency.

2. FRAMEWORK DEVELOPMENT

This study proposes an ABM framework for wildfire evacuation in damaged transportation settings. The framework integrates wildfire simulation and vulnerability assessment with ABM to adequately represent both human responses during an evacuation and time-dependent network functionality in microscopic traffic simulation. As shown in Figure 1, the framework consists of four modules: wildfire simulation, vulnerability assessment, evacuee response model, and traffic simulation. The first module evaluates the spatiotemporal probability of wildfire occurrence and generates representative wildfire scenarios in probability space. Fire Area Simulator (FARSITE) is used to simulate a time-dependent fire-front movement for each scenario and feed 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 an online survey results to predict individual evacuee behaviors as a fire-front approaches. The fourth module simulates traffic conditions by updating traffic demand and capacity at every time step. These four components allow us to track the movement of all residents and vehicles in a damaged transportation setting.

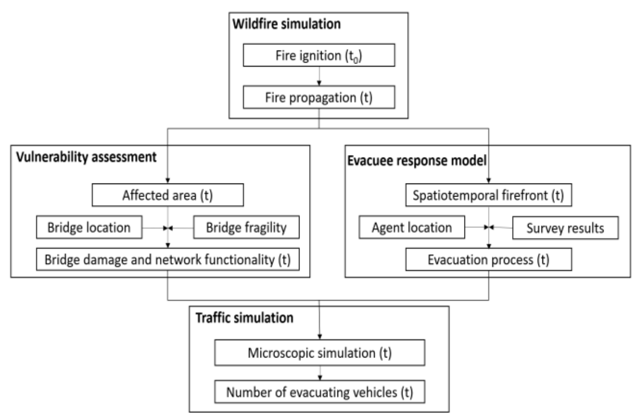

Figure 1: The proposed ABM framework for wildfire evacuation in damaged transportation settings.

Given that the primary mode of mobility in wildfire prone areas is private vehicles, this study focuses on capturing vehicle use and vehicular traffic without considering pedestrian behaviors. The final results include time-dependent traffic maps to identify the critical parts of transportation network that are the most vulnerable to wildfires and have the potential to cause traffic congestion during an evacuation. Additionally, the total number of evacuating vehicles during a given time period is obtained, which can 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 spatio-temporally varying fire probabilities in the study region and generates representative wildfire scenarios. The second stage simulates wildfire growth for each scenario and records time-dependent fire-front that will be fed into the subsequent modules.

In the first stage, a community of interest and its surrounding areas are defined and divided into small grids (e.g., 1km x 1km) to find the probabilities of fire that can be propagated into the community. As shown in Equations 1-3, a generalized additive logistic regression is employed to construct a wildfire probability estimation model. This model can account for spatiotemporal dependence and non-linear relationship between independent and dependent variables (Preisler et al., 2004).

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

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

$$P\big(L_f\big) = P\big(L_f|f\big) * P(f) \tag{3}$$

where $P(f)$ = the ignition probability; $f(\cdot)$ = 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; bi = the burning index; $P\big(L_f|f\big)$ = the conditional probability of an ignition turning into a large fire; and $P\big(L_f\big)$ = the unconditional probability that a large fire occurs at a given cell and on a given day of year.

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 dataset 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 having a specific ignition location and time, wildfire growth is simulated to generate spatiotemporal fire-front and time-dependent fire map. Because FARSITE has an iterative simulation structure allowing time-dependent inputs, it can model wildfire growth under heterogeneous weather, fuel, and topography conditions, which produces more accurate simulation results compared to the other software programs. Since the prediction accuracy of fire growth at every time step is key to effective wildfire evacuation modeling, FARSITE is used in the fire growth modeling of this study despite its relatively high computational costs.

2.2. Vulnerability assessment

Bridges are vital yet susceptible elements in a transportation system during wildfire incidents. Damage from fires can greatly decrease bridge safety and restrict traffic flow. As the post-fire traffic capacity of bridges is crucial in evaluating the movement of people and vehicles during evacuation, understanding bridge functionality during fires is essential for evacuation planning and management. Therefore, this module includes the vulnerability assessment of bridges to determine the reduced flow capacity of a transportation system during wildfire incidents.

Bridge vulnerability is often assessed using fragility curve, which can be constructed analytically through structural analyses and evaluations, experimentally based on testing results, or empirically based on post-disaster reconnaissance data. In some cases, multiple approaches are combined to develop a fragility curve. This study assumes that bridge damage level depends only on bridge material and uses a simple relationship between them as shown in Figure 2. In this study, five damage levels (DLs) are 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 bridges (Peris-Sayol et al., 2017). It should be noted that this relationship is conditioned on any exposure to fire. This simple relationship should be replaced with a bridge fire fragility curve once it becomes available.

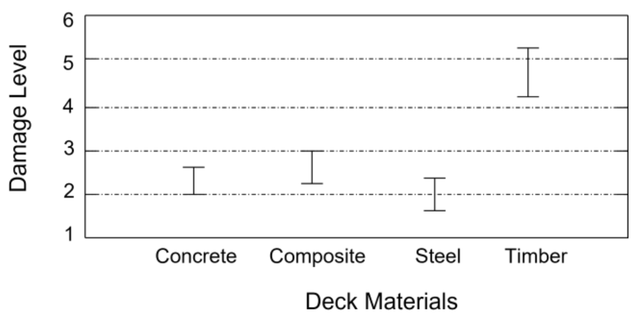

Figure 2: Relationship between type of deck material and bridge damage level (adapted from Peris-Sayol et al., 2017).

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. A specific set of bridges ($B' \subset B$) located in the current wildfire perimeter experiences a certain damage level, which is determined based on the relationship between deck material and DL. This relationship is not deterministic because of uncertainties. Thus, the DL of a bridge in the subset B' is a random variable and is determined through Monte Carlo simulation (MCS). Bridge damage results in reduced traffic flow capacity and subsequently affects the flow capacity of the link where the bridge is located, as shown in Table 1.

Table 1: Link damage state and the associated traffic carrying capacity (adapted from Shiraki et al., 2007).

Link Damage Level	*Capacity (%)*	*Free Flow Speed (%)*
Superficial damage	*100*	*100*
Slight damage	*100*	*75*
Partial damage	*75*	*50*
Massive damage	*50*	*50*
Structural collapse	*0*	*0*

2.3. Evacuee Response Model

This module aims to mathematically model and simulate individual responses during evacuation by considering a series of three events: evacuation trigger, decision delay, and preparation time. External stimuli, such as evacuation alerts, warnings, and orders, serve as evacuation triggers. Spatiotemporal fire-front data from Module 1 is used to estimate the timing of each trigger at every location within the community. Depending on individual risk-averse attitudes and characteristics, their responses to these triggers may vary. Decision delay and preparation time are also taken into account when simulating individual responses, as these factors may depend on individual awareness, beliefs, and priorities.

We conducted an online survey of residents in wildfire-prone areas in the United States, specifically in California, Oregon, and Colorado, to investigate their evacuation behavior and to develop quantitative relationship between individual characteristics and their responses during evacuation (Lee and Ma, 2022). These models will have a significant impact on traffic congestion and bottlenecks in Module 4.

2.4. Traffic Simulation

Module 4 performs traffic simulation by combining the results from Module 2 (the reduced functionality of the transportation network) and Module 3 (the elevated travel demand patterns) to predict traffic conditions during evacuation. An activity-based microscopic traffic simulation is performed using the Simulation of Urban Mobility (SUMO) software because of its accessibility and flexibility.

This module utilizes an ABM to simulate the behavior of each evacuee as an agent. Individual characteristics and decision rules are assigned to each agent based on the survey results obtained from Module 3 (Lee and Ma, 2022). These agents determine their departure time, evacuation route, and destination before entering the transportation network. Real-time information (e.g., fire-damaged bridges and traffic congestion) may not be available to the agents who prefer to use traditional maps during an evacuation, which may affect their ability to choose optimal evacuation routes. The ABM tracks the spatiotemporal movements of each agent at every time step.

The traffic simulation incorporates dynamic updates on link capacity and individual agent locations to predict traffic flows at the individual level and capture traffic dynamics considering the collective actions of agents. The ABM framework provides time-dependent traffic maps to identify critical and vulnerable parts of the transportation network that have a high potential for causing congestion during evacuation. Additionally, the simulation results provide the total number of evacuating agents during a given time period, which can inform retrofit decisions on bridges to minimize human losses during a wildfire evacuation.

3. ILLUSTRATIVE EXAMPLE

The proposed ABM framework is demonstrated using the City of Santa Clarita, California. Santa Clarita is located in Los Angeles County and has a population of 228,673 as of 2020. The Rye Fire is chosen as a scenario wildfire event, which broke out on December 5th, 2017, and threatened over 1,000 homes in the city. During the fire, about 1,300 homes were placed under evacuation orders, and both directions of Highway 5 were closed. Uncertainties in all four modules are considered and propagated throughout the framework to simulate evacuation during the Rye Fire.

Figure 3 shows the comparison between the simulated fire perimeter during the first day of the Rye Fire (December 5th, 2017) and the actual Rye Fire perimeter. The simulation is limited to the first day because the evacuation order was lifted that evening and further wildfire growth simulation is not needed for evacuation estimation. The similar propagation direction of the simulated and actual fires (see Figure 3) suggests that the model is able to simulate fire growth successfully until human intervention occurrs.

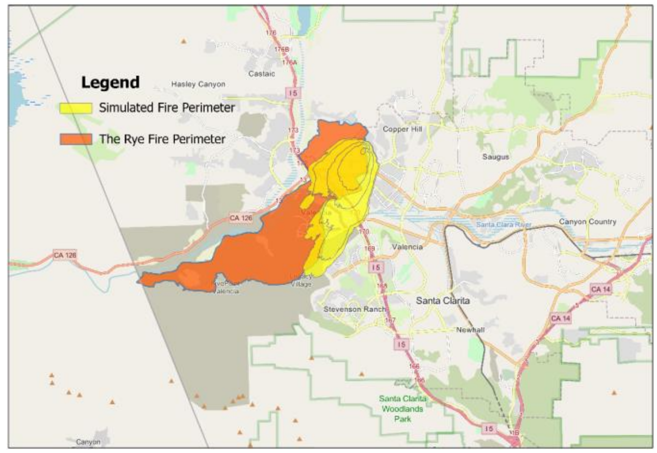

Figure 3: Comparison between the simulated fire perimeter (only during the first burning day) and the Rye Fire perimeter.

As shown in Figure 4, 11 bridges are located within the simulated fire perimeter. It is assumed that the damage level of a bridge is normally distributed with a mean value shown in Figure 2 and a coefficient of variation of 0.3. Using MCS, the damage level of each bridge is randomly sampled from the respective normal distribution. To highlight the impact of damaged bridges on traffic disruption during a wildfire evacuation, one of the extreme scenarios among infinitely many possible ones is considered in this case study: 5 bridges (Bridges 2, 6, 7, 9, 10) experience DL5, while the others are not damaged.

In the third module of the proposed framework, the evacuee response model is simulated to reflect diverse individual behaviors and responses during an evacuation. To apply the evacuee response model developed based on the survey data (Lee and Ma, 2022) to the case study, detailed information about the properties and characteristics of individual residents and households in the community is required. Whereas demographic information is available from the Census dataset, some of the key explanatory variables needed to estimate their evacuation timing or the use of real-time navigation (e.g., risk attitude, wildfire evacuation experience) are often not available. Thus, in this case study, we generate a synthetic population of the City of Santa Clarita.

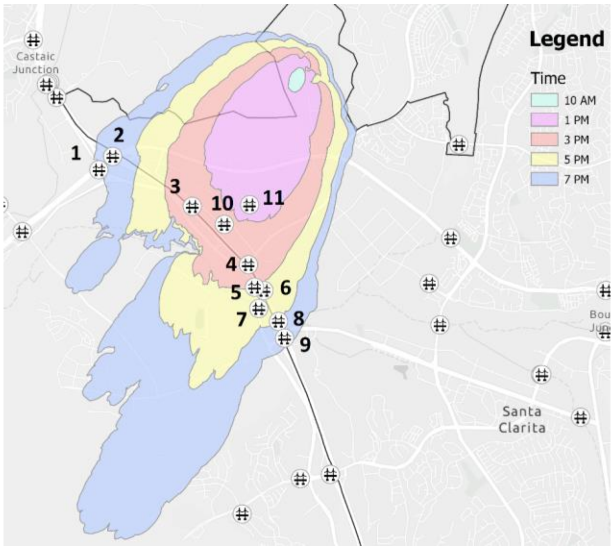

Figure 4: The locations of bridges within the simulated fire perimeter.

The synthetic population of the city is generated at the census-tract level using PopGen. The synthetic population consists of 83,558 households and 246,830 residents that closely match the marginal distributions of key characteristics of the true population. Each individual in the synthetic population is given a unique ID number and assumed to be in the same household as those with the same ID number. Each household is randomly assigned to a residential building in the same census tract, and individuals who work full-time or part-time are randomly assigned to workplaces. It is assumed that each household forms a decision group and shares the same evacuation decision during the evacuation process.

The third module generates evacuation timing, decision delay time, preparation time, and final destination for all synthetic households based on the survey results (Lee and Ma, 2022). However, public transportation and returning traffic are not considered in this module. Therefore, the following assumptions are made: (a) households without vehicles are assumed to use hypothetical vehicles for evacuation, and (b) if some of the household members at the workplace bring cars and no vehicles are available for the remaining household members at home, hypothetical vehicles are assigned to the household members at home. These hypothetical vehicles can be replaced with public transportation and ride-sharing in future studies. A total of 162,705 vehicles (actual and hypothetical) are used during the wildfire evacuation. The vehicles that are about to depart are recorded and considered in estimating traffic demand in the fourth module at every time step.

The agent-based traffic simulation is performed using SUMO. The network capacity from Module 2 and traffic demand from Module 3 are updated at every time step and used as input data in SUMO. The binary logistic regression model is used to classify evacuees as navigation users or non-navigation users. In the simulation, navigation users take the fastest routes, while non-navigation users take the shortest routes but not the fastest route as they may rely on familiar routes or conventional maps without real-time information. The results of this module include the locations of all vehicles at every second during the evacuation process, the time series of the number of vehicles in the transportation network, the number of vehicles that successfully evacuated, average speed, etc.

4. RESULTS AND DISCUSSION

Figure 5 shows the cumulative number of vehicles that have departed, have evacuated, and are 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 were lifted (11:00 pm). The black curve in Figure 5 has a series of steps because the fire perimeters are recorded at discrete time points (i.e., 10 am, 1 pm, 3 pm, 5 pm, and 7 pm). The results show that about three-quarters of vehicles triggered by the updated fire perimeter enter the network within 45 minutes, which aligns with our previous survey results (Lee and Ma, 2022) that around 75% of the respondents reported that their evacuation preparation time would be less than 45 minutes. The number of vehicles in the transportation network (i.e., the red curve in Figure 5) increases in the first 45 minutes of each step but gradually decreases as vehicles reach their final destinations or leave the network. Generally, most vehicles triggered by the previous fire perimeter are evacuated successfully before the next fire perimeter is updated. Severe congestion is observed specifically between 1 pm and 5 pm due to elevated travel demand and massive bridge damages. Although two bridges (Bridges 2 and 9) are severely damaged after 5 pm (see Figure 4), their impact is minimal possibly because the previously damaged bridges located on I-5 already created congestion. Finally, the smooth blue curve in Figure 5 indicates a stable evacuation rate throughout the simulation.

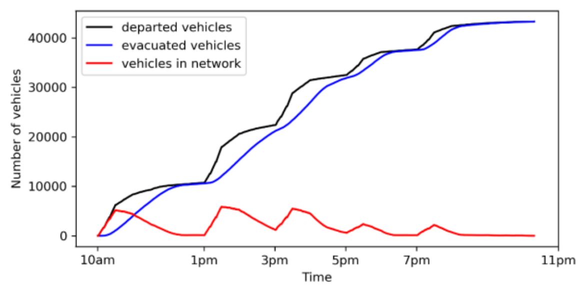

Figure 5: The cumulative number of vehicles that have departed and evacuated and the number of vehicles currently in the transportation network.

The ABM framework has the advantage of tracking the locations and travel speeds of individual vehicles at every second, which helps identify when and where severe traffic congestion occurs. Figure 6 shows a traffic map at 10:36 am, the time when severe traffic is first observed. The red colors in Figure 6 indicate that the network segments in red experience heavy traffic and should be considered for pre-fire risk mitigation efforts to facilitate wildfire evacuations in the future. In addition, the vulnerability assessment in the framework can identify bridges that are most likely to experience severe damage. This information will provide useful guidance for transportation risk managers or local government officials about which parts of the transportation network are vulnerable to fires and cause severe congestion during a wildfire evacuation. While the results of this case study are specific to the Rye Fire, by taking a fully probabilistic approach, the framework can provide quantitative data to support more effective pre-fire mitigation actions that can be applied to a wide range of plausible wildfire scenarios.

Figure 6: Traffic map at 10:36 am (average speed of 15.6 mph).

5. CONCLUSIONS

Effective community-based transportation evacuation planning is an important issue for state and local policymakers 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 study 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. ABM allowed the framework to generate both disaggregated-level and aggregated-level outputs. By combining the aggregated-level outputs with the disaggregated-level ones, we can assess the overall network performance during an evacuation while identifying bottlenecks and the critical network segments that may experience heavy congestion. The proposed framework also introduced damaged traffic settings to the evacuation process and showcased how the reduced network capacity impacted evacuation efficiency, especially when combined with the elevated travel demand.

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 of this model. Future works 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 detour due to road closure, and (e) taking a fully probabilistic approach.

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