Integrating Human Behavior Modeling into a Probabilistic Wildfire Egress Planning Framework

Marilia A. Ramos[a], Mohammad Pishahang[a,b], Andres Alfredo Ruiz-Tagle Palazuelos[c], Enrique Andrés Lopez Droguett[a,b], and Ali Mosleh[a]

[a] The B. John Garrick Institute for the Risk Sciences, University of California Los Angeles, USA, Email: *marilia.ramos@ucla.edu*, *mosleh@ucla.edu*

[b] Department of Civil and Environmental Engineering, University of California Los Angeles, USA, Email: *mh.pishahang@ucla.edu*, *eald@g.ucla.edu*

[c] Department of Mechanical Engineering, University of Maryland, College Park, USA, Email: *aruiztag@umd.edu*

Abstract: Wildland Urban Interface (WUI) can be defined as "the zone of transition between unoccupied land and human development." The communities in these areas are particularly vulnerable to wildfires that start and propagate in wildlands. Numerous efforts have been undertaken to address the dangers of wildfires, including building more resilient infrastructures, advancing techniques for extinguishing fires and exploring the possibilities of controlled fires. Associated with these efforts is the pressing need to ensure the safe evacuation of communities in WUI once they are threatened by wildfires. Evacuation modeling and planning is a challenging and complex problem. It involves human decisions and actions concerning if, when, and how to evacuate; directly impacting the traffic flow during the evacuation. Furthermore, the available time for a community to evacuate is a dynamic element: it changes according to the fire progression, which, in turn, depends on vegetation, weather, among other factors. The models for traffic and fire progression have advanced considerably in the past years. Human behavior modeling during wildfire evacuations has also received significant attention, leveraging existing studies for other natural hazards, such as hurricanes. However, these are mainly developed as standalone, qualitative approaches rather than integrated into a complete egress framework that accounts for traffic modeling and wildfire progression. This paper discusses the challenges of modelling human behavior during evacuations. It further presents the method adopted for integrating human behavior model into the evacuation planning tool WISE (Wildfire Safe Evacuation). WISE calculates the probability of successful evacuations through a framework that incorporates human behavior, traffic, and fire progression models using Bayesian Networks, Agent-Based models, real-world socio-demographic data, and Geographic Information System. Finally, the paper showcases the impact of the socio-demographic profile of different communities on a safe evacuation probability.

1. INTRODUCTION

The United States (U.S.) Fire Administration defines WUI as "the zone of transition between unoccupied land and human development. It is the line, area or zone where structures and other human development meet or intermingle with undeveloped wildland or vegetative fuels". Wildfires pose a significant threat to many communities in WUI areas worldwide. In the U.S., more than 46 million residences in 70,000 communities are at risk for WUI fires, and the WUI area grows by approximately 2 million acres per year [1].

Management of WUI fire risks is a pressing challenge that requires a multi-disciplinary approach. A position paper by The International FORUM of Fire Research Directors [2] recognizes four major focus areas for addressing the hazards of WUI fires. First, designing structures to be more resistant to ignition in WUI fires, known as hardening. Second, aspects related to WUI Firefighting. Third, environmental issues related to both suppressing WUI fires, as well the exposure to products of combustion from WUI fires. Finally, emergency management. On emergency management, they highlight the importance of evacuation planning and research on evacuation protocols. They state the need of i) the utilization of human behavior research to develop effective and evidence-based emergency communication strategies for communities in the WUI, ii) standardized protocols for emergency communication and iii) a better understanding of the likelihood of residents responding to notification and adopting the desired behavior. Despite the awareness of wildfire threats for WUI communities and the need for robust evacuation plans, many communities do not have a strong strategy in place. A 2021 investigation by a Californian News Network [3], which requested evacuation plans from 27 communities at greatest risk of fire using Cal Fire's designation, found that only 22% of them have a robust evacuation plan that is available to the public.

Evacuation planning is inherently dependent on multiple interrelated factors. First, it needs to consider the fire dynamics of the wildfires that may pose a threat to a community. The fire dynamics depend on the area's vegetation, environmental conditions, topography, and other elements that may change throughout the year and may be affected in the medium future by climate change. Second, it must assess the routes capacities considering the size of the community and time they need to leave the danger zone. Many existing WUI communities do not sufficiently meet evacuation-related travel needs, including suburbs built with only one road in and out [4]. Thirdly, it ought to be human-centered, and recognize that human behavior plays a considerable role during the evacuation process. Human behavior includes how people receive and respond to the cues about the need to evacuate, how and when they decide about whether to evacuate, which actions they take before evacuating, which intermediary stops they may take, and to which direction they travel.

Considerable advances have been made for the development and integration of fire dynamics and evacuation routes models into WUI evacuation models. The incorporation of human behaviour into evacuation models is, however, still incipient. Evacuee's behavioral aspects have been scarcely tackled [5], and data on how people behave during wildfires is limited [6]. When integrated into evacuation models, individuals in the at-risk population are many times assumed to randomly start evacuating according to a selected distribution [7]. Social scientists and fire science researchers have attempted to close this gap mainly through studies aiming at understanding the factors the impact households' decisions on whether to evacuate, including socio-demographic factors. The real impact of some of the factors is still inconclusive, such as the presence of children in the household [8]. Nonetheless, the increasing body of research on these factors is a considerable step into the direction of more realistic models of wildfire evacuation.

This paper presents a framework for including human behavior into a wildfire evacuation model. The Wildfire Safe Egress planning (WISE) simulation platform integrates fire dynamics, human behavior, and traffic models in a GIS-based environment. This paper focused on the human behavior model of WISE, whereas an accompanying paper by Pishahang et al. [9] in this conference proceedings describe other aspects of the platform. WISE adopts an agent-based approach to communities' evacuation and leverages existing research on human decision-making during wildfires evacuation. Section 2 presents an overview of research and challenges of modeling human behaviors. Section 3 introduces WISE with a focus on the human behavior aspects. A case study is presented in Section 4, followed by the conclusions.

2. MODELING HUMAN BEHAVIOR IN WILDFIRE EVACUATIONS

A wildfire evacuation operation can be considered successful if all the people threatened by the fire hazard are safely and orderly evacuated. Ideally, individuals should have sufficient time to gather their belongings and direct themselves to pre-defined shelters, friends or relatives houses, and other safe locations before the threat reaches the community, and without risks posed by traffic jams. Reality, however, can highly differ from the ideal scenario. Most likely, individuals need to traverse long traffic jams before reaching a safe location. For instance, several miles of traffic congestion off the Malibu area, Southern California, U.S., could be seen as people were fleeing the Woolsey Fire in 2018 [10]. When fleeing the fast-moving Camp Fire, in 2018, some people from the city of Paradise, in Northern California, abandoned their cars and continued the evacuation on foot. Tragically, seven died in their vehicles [11]. The conditions for evacuating are even more challenging for vulnerable people. A report from the Auditor of the State of California [12] found that the county that includes Paradise had not adequately prepared to protect people with “access and functional needs”. Despite advances in partnering between California communities and local disability organizations to develop better plans to alert, evacuate and shelter vulnerable populations, plenty of weak spots remain.

Possible solutions to the abovementioned challenges refer not only to infrastructure improvement, e.g. more and better roads, and reliable communication channels. The logistical challenges during an evacuation are highly tighten to human behavior and decision-making. For instance, on the one hand, if people evacuate all at once when an evacuation was planned as a phased one, roads’ capacity will be exceeded, resulting in traffic congestions. On the other hand, the fear of being stuck in a traffic jam during an evacuation affects peoples’ decision on whether to evacuate. The rate of non-compliant people, i.e., people that receive a mandatory evacuation order but do not leave, is not negligible. In fact, a recent study [13] on the evacuations during 11 wildfires in California between 2017 and 2019 pointed that non-compliance rate ranged from 3 to 13%. The same study pointed that the shadow evacuations, i.e., individuals who did not receive the order but did evacuate, ranged from 29 to 75%. Shadow evacuations add a challenge to evacuation planning concerning traffic and roads’ capacity.

Issues related to shadow evacuations point to the impact and, consequently, importance of analysis of *when* people decide to evacuate, rather than only *whether* people decide to evacuate. In the opposite spectrum to shadow evacuations, late evacuations are also a serious safety concern. A late evacuation can put people at risk of being caught by the fire-front or being exposed to dangerous amounts of radiant heat. Despite the dangers of delaying the decision to evacuate, a significant portion of people consistently display waiting behaviors or even plan to wait and assess the risk when faced with wildfire in the future [14].

Modelling thus *which decisions* individuals take during wildfire evacuations, *when* these decisions are taken, and *which factors* impact individuals’ decisions, is crucial for evacuation planning and real-time activities. The sub-sections 2.1 and 2.2 discuss evacuees’ decisions and influencing factors. It focuses on the main aspects that were used as a foundation for WISE. For a more complete literature review, the reader is referred [4] and [15].

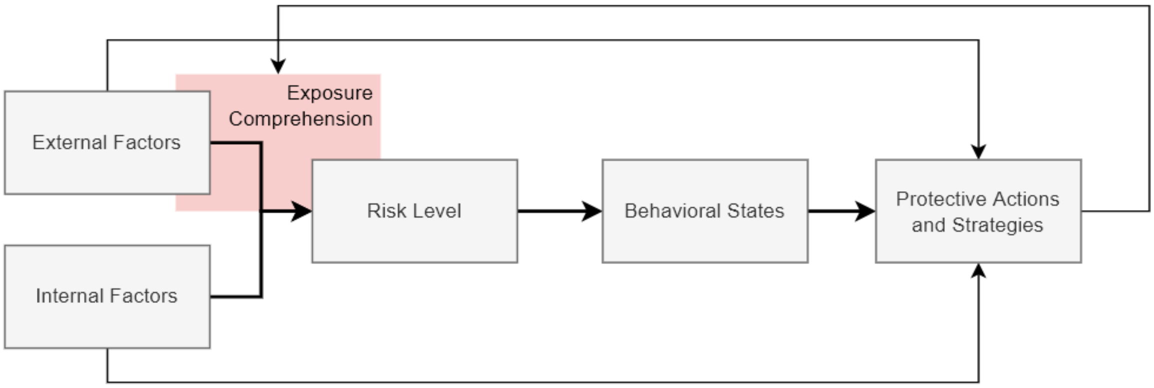
2.1 The Decisions

Decision-making in response to threats of environmental hazards is a well-established line of research. The Protective Action Decision Model (PADM) [16–18] is a widely applied model, especially in North America (e.g. by the U.S. Federal Emergency Management Agency (FEMA) [19]).

The PADM identifies three critical predecision processes (reception, attention, and comprehension of warnings or exposure, and interpretation of environmental/social cues)--that precede all further processing. These processes are an input to three core perceptions: threat perceptions, protective action perceptions, and stakeholder perceptions. These perceptions become the basis of protective action decision-making, in which decision-makers consider whether a real threat exists, the need for protective action, available protective options, the best protective alternative and the timing of its implementation. This process, in turn, generates behavioral responses including information search, protective response, and emotion-focused coping. Information search continues as a feedback loop involving decision-makers assessing the adequacy of information, identifying information sources and channels and establishing its required timing. This loop continues until there is sufficient certainty to allow householders to make decisions about appropriate protective actions [18]. The PADM may not be directly applicable to all contexts. For instance, [20] proposes the addition of long-run hazard adjustments (property maintenance and preparation, equipping for fire-fighting and self-protective actions) as a factor influencing evacuating or remaining to better represent the Australian wildfire evacuation context.

Lovreglio et al. [21] used the PADM as a framework for wildfire evacuation decision making model (Figure 1). The behavioral states, in this context, are: i) Normal State, in which the individual does no change their normal activities, ii) Investigative State, in which the individual investigate the existence of the threat), iii) Vigilant state, in which the individual may start preparing to evacuate, or "wait and see", and the iv) Protective State, in which the individual applies a protection strategy. The protective actions and strategies for wildfire evacuation adopted by the authors are based on extensive body of literature: Leave or Stay. The latter is divided into Defend or Shelter in Place (SIP). The final householder behavior can be the result of a combination of these three strategies as the decision-making could be dynamic over time.

Figure 1: Framework of wildfire evacuation decision making model based on the PADM [21]



2.2 The Influencing Factors

A large body of research on wildfire evacuation decision-making focuses on identifying the factors that impact households' decision to evacuate. Some of these studies associate the factors to the decision-making stages to PADM, e.g. [22]. Toledo et al. [15] present a review of the factors affecting evacuation propensity identified in the literature for various types of events, including wildfires, hurricanes, and chemical fire, and Kuligowski et al. [6] discusses several of these factors. This section presents a brief overview of the factors, and the reader is referred to those references for in-depth discussions.

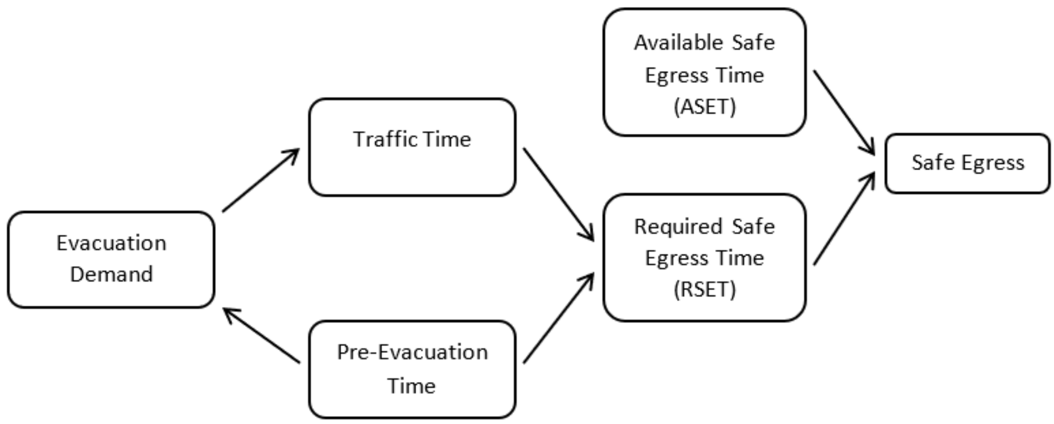
- **Evacuation plan:** The literature indicates that having a plan to evacuate influenced the decision to evacuate during a fire event; whereas having a plan to stay or performing mitigation actions to reduce the risks of wildfire led to decisions to stay and defend;
- **Previous experiences:** experiencing property damage from a previous wildfire and evacuating in previous disasters may increase the probability that households would evacuate in future events. However, experience with previous alarms deemed as unnecessary may lead to lower probabilities of evacuation;
- **Warning and cues:** Receiving mandatory or voluntary orders may increase` the probability of evacuating, especially if they were provided by a trusted source. Also, receiving advice from neighbors, friends and family influenced the decision on whether to evacuate, as well as visual cues such as visible smoke, embers, flames;
- **Gender:** Some studies link men to a higher likelihood to stay and defend;
- **Age:** Older individuals were linked to a higher likelihood to stay and defend;
- **Income level:** Lower income level are linked to a higher likelihood to stay and defend
- **Residence time:** long-term residents and having pets or livestock are associated with lower probability of evacuating.

Despite advances using post-wildfire surveys and other methods, existing studies do not provide information about (1) the impact of each factor on the protective action decision (i.e. how much a single parameter changes the probability to choose one strategy over another); or (2) the combined impact of several factors through a multivariate analysis (i.e. what is the probability of choosing a strategy given a set of factors). [21]

3. INTEGRATION OF HUMAN BEHAVIOR MODELING INTO THE WISE PLATFORM

The WISE framework integrates a human decision model, a traffic model, and wildfire dynamics model for estimating the probability that a community safely evacuates when in danger by a wildfire. The likelihood of safe evacuation is calculated by probabilistically comparing two competing parameters: (i) the Available Safe Egress Time (ASET), which determines the total amount of time before the fire reaches a community's border; and (ii) the Required Safe Egress Time (RSET), that determines the time a community needs to safely evacuate. These variables are modeled through a Bayesian Belief Network (BBN) (**Figure *2***) . WISE adopts an agent-based approach for estimating the time for community members to evacuate, based on their socio-demographic profile. The different times are inputted to the agent-based traffic model through a Monte Carlo simulation of a Poisson distribution. Then, a traffic model considers routes the evacuee may choose, while considering every road segment. Finally, the RSET is estimated as the summation of the pre-evacuation time and the travel time for each agent (member of the community). These elements are integrated into the BBN along with the Available Safe Egress Time (ASET) for calculating the likelihood of safe evacuation of the community (**:**). WISE is implemented as a web-based software platform, allowing users to have a practical egress assessment in a visual GIS-based environment. The reader is referred to the accompanying paper by Pishahang et al. [9] in this conference proceedings for further details on WISE model.

Figure 2: Bayesian Belief Network of the wildfire evacuation process modeled by WISE [23]

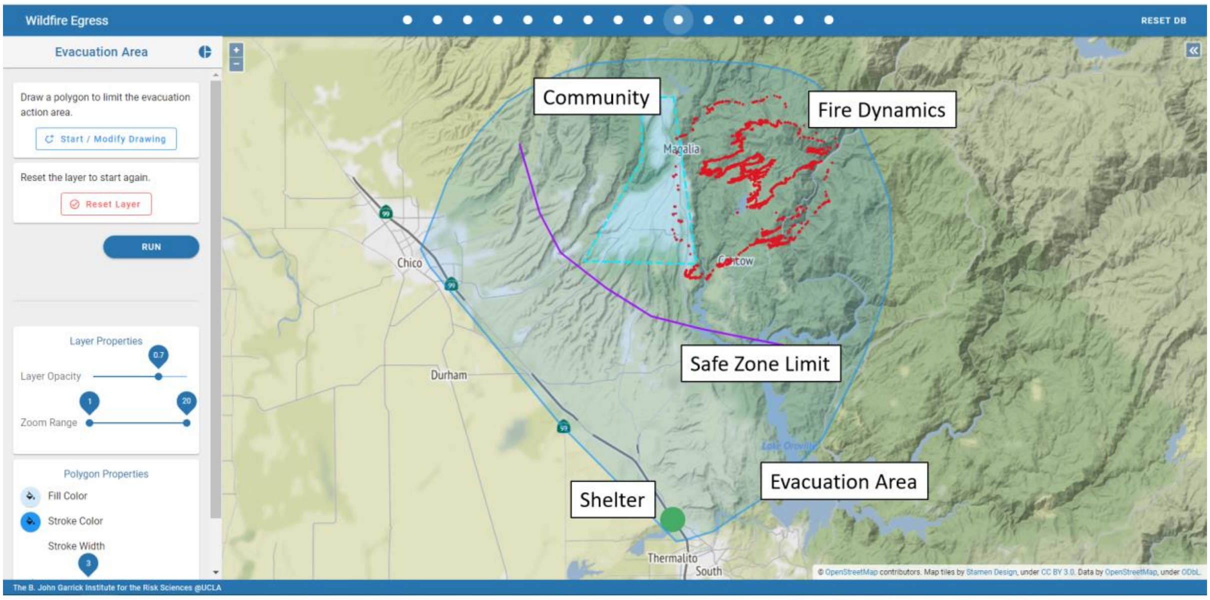


WISE takes as user inputs (illustrated in **Figure *3***):

1. The fire dynamics: Wise is fire simulator agnostic. Therefore, any wildfire simulation solution, e.g. FlamMap [24], can be used: the only required data is a raster file containing the fire arrival time for each pixel. The fire dynamics provide an input to the ASET: The ASET is assumed to be the time for the fire to first reach the community boundary. This is a conservative assumption, indicating that individuals who do evacuate after the fire has first reached the community are not considered as being *safely* evacuated.
2. Community boundaries: The user defines the community to be evacuated by drawing a polygon over the map.
3. Evacuation trigger and trigger failure: The initial trigger for community awareness about the need to evacuate is an evacuation warning, or the fire proximity (whichever happens first). In case of an official evacuation warning, the notice may fail to reach all the population. In this case, the user can input a failure probability.
4. Safe zone limit: The user can inform where the evacuees could be considered as safe from the fire hazard. Only after crossing this limit, the community will be assumed as having “safely evacuated”. The RSET is thus the time for the community to reach the safe zone limit.

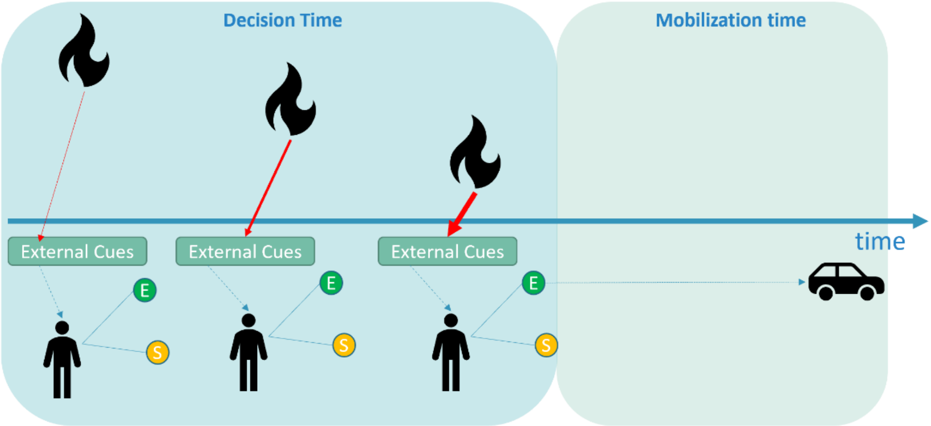
5. Shelter location: The shelter location indicates to which direction the evacuees will be directed. Thus, the shelter does not need to be a specific place with high capacity to guarantee to accept all the evacuees.

Figure 3: WISE Platform Egress Planning Scenario Setting [9]



Human decision-making is modeled in two moments in the evacuation process: the Evacuation Decision Time (EDT) and the Mobilization Time. These time variables constitute the Pre-Evacuation Time to be integrated into the WUI Evacuation Model (Figure 2). During the evacuation, individuals decide whether they should evacuate depending on external cues and internal factors. Therefore, the decision to evacuate or to stay is not taken at one point in time only. Indeed, as the external factors (such as the fire distance to the community) are dynamic, these decisions are a function of time (Figure 4).

Figure 4: Illustration of decision time and mobilization time

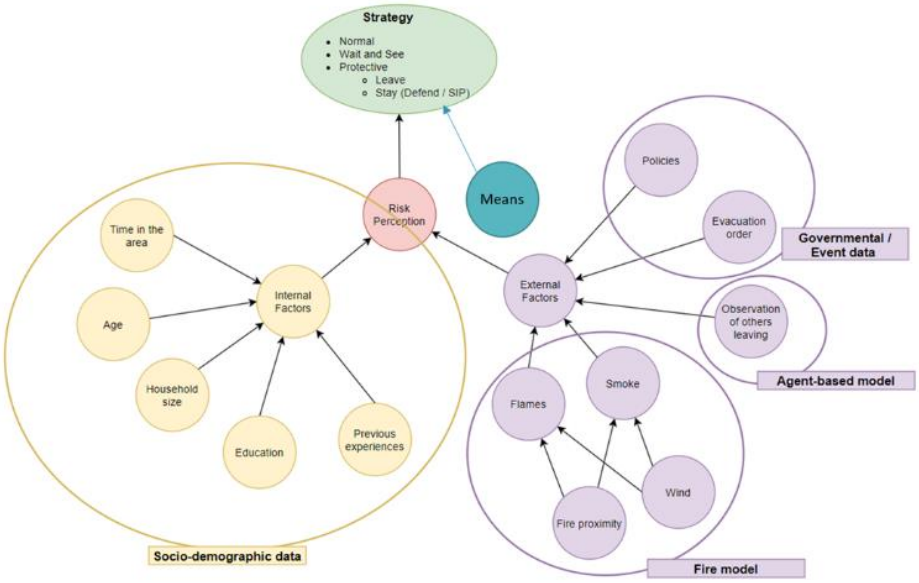


As discussed in Section 2.2., during an evacuation, an agent may assume different strategies: wait and see, shelter in place (SIP), stay and defend, or evacuate. WISE simplifies these strategies as “stay” or “evacuate.” Therefore, there is no differentiation between an agent that is sheltering in place and one that is waiting and collecting more information before making a decision.

The EDT is the time it takes for an agent to decide to evacuate after receiving and acknowledging a "trigger," which may be an official evacuation alert or visual cues about the need to evacuate (e.g., flames, smoke, neighbors evacuating). Note that the agent may also decide not to evacuate - this decision is modeled as an agent that takes "infinite" time to decide to evacuate, i.e., they will not choose to evacuate until the simulation reaches its end.

An agent's decision to evacuate, at any point in time, is a function of the agent's Risk Perception (RP), (in a similar approach to the PADM), and the Agent's Means (AM). The RP is a function of Internal Factors (IF) and External Factors (EF). The AM is related to the agent's financial and physical means to evacuate, such as car ownership, means for paying for accommodation, and possibilities of missing workdays. Figure 5 illustrated the conceptual framework for the agents' strategies choices and influencing factors. Note that the factors presented in the Figure are not exhaustive and should serve as a reference only.

Figure 5: Conceptual model of the agents' evacuation decisions and influencing factors



Two main challenges arise when incorporating a human behavior model into WISE. First, the lack of consensus on the factors that influence evacuees' decisions to stay or leave. Second, and more important, the lack of data. Despite information concerning whether some factors makes a household more prone to stay or to leave, there is no sufficient data on the quantitative impact on their probability, nor on the time it will take for them to take one of these decisions. In fact, time is rarely addressed in the literature.

The EDT was thus simplified for the current stage of the egress model development and implementation. It adopts an agent-based model using the concept of "penalties". The Pre-Evacuation time is estimated as a function of the time it takes for agents to be aware of the need to evacuate, the time for them to decide on the evacuation, and the time for them to start evacuating:

$$T_{\text{pre-evacuation}} = T_{\text{awareness}} + T_{\text{decision}} + T_{\text{mobility}}$$

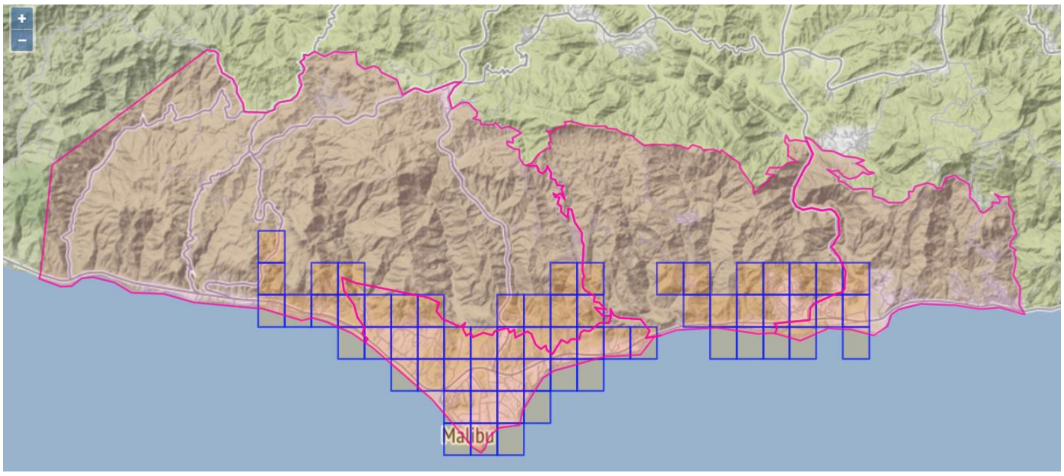
For each of these time variables, agents receive a penalty according to socio-demographic profile.

3.1 The Socio-Demographic Profile

The socio-demographic profile of the residents of the community to be evacuated are estimated through the combination of two data sources. First, U.S. Census tracts are used to define a population. Then, WorldPop [1] is used to estimate the population count within cells of 1km x 1km, plotted on top of the census tract. Figure 6 presents the tracts (in pink), and the cells (in blue). The advantage of using the U.S. Census Tracts is that it allows using the CDC Social Vulnerability Index (SVI) data [25], [26]. The SVI indicates the relative vulnerability of every U.S. Census tract. It ranks the tracts on 15 social factors, and further groups them into four related themes. The tracts are considered homogeneous, i.e., the socio-demographic profile is the same for the agents of the cells within the same tract. The socio-demographic profile of each cell is then estimated using WorldPop and SVI data

The SVI factors for which the literature indicates an impact on the evacuation decision and mobilization times, and for which there is data available, are used to represent the internal factors and the agents' means.

Figure 6: Combination of WorldPop data and U.S. Census tracts in WISE



3.2 The Awareness Time

Awareness time is a critical aspect of pre-evacuation time. The initial trigger for community awareness is an evacuation warning, or the fire proximity (whichever happens first). In addition to official evacuation alerts, a community may learn about the upcoming wildfire through different communication channels, including TV programs, social media, telephone, and informing the neighbors face to face.

In case of an official evacuation warning, the notice may fail to reach all the population. In this case, the user can input a failure probability. Figure 7 and **Figure 8** illustrate the modeling of the awareness time. In **Figure 7**, it is considered that an official warning is sent to the population with a probability of failure P_{FW}. In this case, a proportion of the community $Pop_W = 1\text{-}P_{FW}$ is alerted when the warning is sent, T_{Warn}. **Figure 8** illustrates the case where there is no official warning.

WISE assumes a linear distribution of the information throughout the community, representing the awareness that is obtained through the visualization of neighbors leaving, neighbors alerting each other, or information obtained by social media and television.

Figure 7: Awareness time with official warning

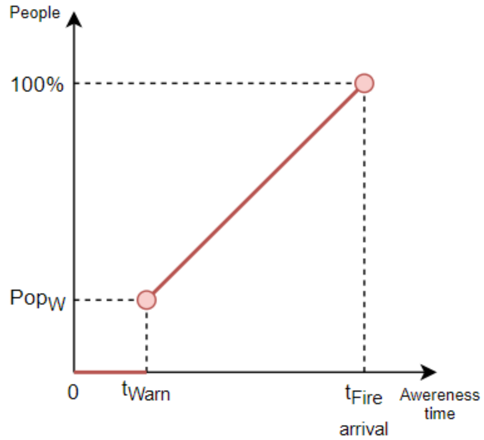
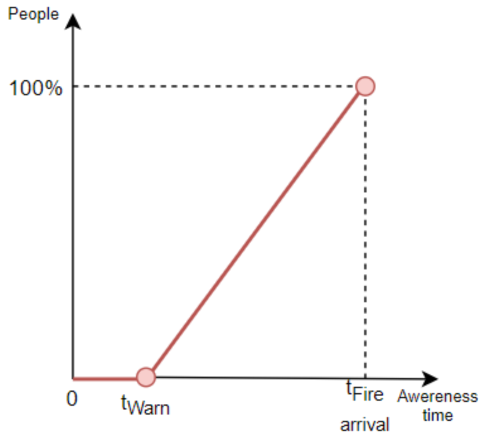


Figure 8: Awareness time without official warning



3.3 The Penalties

For determining the penalties, the model leverages the study performed by Grajdura et al. [27] on awareness, departure, and preparation time in wildfire evacuations, collected through post-wildfire survey, as shown in **Table 1**. The category concerning "no vehicles at the household" was selected as representative of the "No Means" factor.

Note that these estimates were collected for a rapid fire (Camp Fire). Rapidly advancing fire scenarios pose more challenges concerning the evacuation of the population, and they require a faster decision and evacuation. The validity of these penalties to other scenarios must be further investigated. Furthermore, it is known that other factors impact the households' decision-making during evacuation scenarios. However, data was not available for those factors.

Table 1: Time penalties adopted at first version of WISE

Category	Penalty (min)			
	Awareness	Decision	Mobility	Total
Elderly (60 years +)	34	37	30	101
Disability			30	30
Income is less than 50k/year	23	37		60
Low English Proficiency	29			29
No vehicles at the household				1000

4. CASE STUDY

This section presents an application of WISE to the Camp Fire. The Camp Fire was a deadly and extremely destructive wildfire that happened in Northern California in November 2018. The Camp Fire was selected as a test case due to its recency and severity, availability of data on the fire progress and communities' evacuation, and the access to firefighters who served in this disaster. The following describes the main inputs to the case study:

1. The fire dynamics: The Camp Fire was simulated in FlamMap, with parameters that result for the fire progression as close as possible to reality. The report by the National Institute of Standards and Technology (NIST) was used as reference for the fire progression [28].

2. Community boundaries: The city of Paradise was selected as the community to be evacuated.
3. Evacuation trigger and trigger failure: The awareness trigger time was set to one hour before the fire entered the city. Also, the warning system failure probability is assumed to be one, i.e., the population becomes aware of the need to evacuate following a linear distribution starting one hour before the fire enters Paradise. This is consistent with the real-life events in which the official evacuation warnings failed to reach the population successfully

The simulation results indicates that the probability of a safe evacuation (SAFE) in this scenario would be of 16%, i.e., 16% of the population could safely evacuate before the fire would reach the city of Paradise. This result is consistent with the reports from the firefighters that served the Camp Fire, as they indicated that nearly 20% of the residents had evacuated when the fire first arrived at Paradise city.

A sensitivity analysis was performed for ASET and the warning system parameters. The results showed that if the community had 2 hours to egress in the same situation, more than 40% of the population could leave the danger zone before the fire reaches the borders of the city. Furthermore, if the warning probability would have been 0.5, i.e., if 50% of the population were aware of the need to evacuate by an official warning, the SAFE would be of nearly 49.64%.

Sensitivity analysis was also performed for the time penalties for the socio-demographic factors, as presented in Table 2, aiming at analyzing how sensible the complete model is the human behavior model The initial condition for the sensitivity analysis was of an ASET of 2 hours, resulting in a SAFE of 41.69%. The overall penalties were modified, increasing or decreasing the extra time that individuals belonging to the groups defined in Table 1 would need to safely evacuate. The results indicate that WISE is highly sensitive to the human behavior model and its parameters. Although a quantitative validation of these results is challenging due to the lack of real-world data concerning evacuees' behaviors, it is qualitatively consistent with the literature and the knowledge on the human behavior impact on the success of an evacuation operation.

Table 2: Sensitivity analysis of demographic parameters and warning system

<table>
<tr><th>SAFE for Initial Conditions</th><th colspan="2">Modified Parameter</th><th>SAFE</th><th>Change %</th></tr>
<tr><td rowspan="6">41.69</td><td rowspan="4">Penalties</td><td>Reduce time penalties for population without vehicle by a factor of 10</td><td>58.47</td><td>40%</td></tr>
<tr><td>Reduce time penalties for population without vehicle by a factor of 20</td><td>69.54</td><td>67%</td></tr>
<tr><td>Increase time penalties by a factor of 2</td><td>22.03</td><td>-47%</td></tr>
<tr><td>Increase time penalties by a factor of 10</td><td>6.16</td><td>-85%</td></tr>
<tr><td rowspan="2">Warning Failure Probability (Initial: 1)</td><td>0.8</td><td>44.2</td><td>6%</td></tr>
<tr><td>0.5</td><td>49.64</td><td>19%</td></tr>
</table>

5. CONCLUSION

A first validation of the WISE model through the Camp Fire test case demonstrates that the WISE framework and the corresponding software platform provide a good foundation and unique opportunity for risk-informed, model and data-based evacuation planning. The modular approach to WISE makes it a flexible platform for enhancing the underlying model.

Future work on WISE includes further calibration and validation using information from several past wildfires and advancing the following aspects of the human behavior model. First, a more explicit consideration of the internal factors and their impact on the individuals risk perception can be added.

This can be achieved through access to post-wildfire surveys, integration of elements analyzed for other emergency evacuations such as hurricanes, and subject matter expert judgment. Second, the impact of other agents' actions (evacuating) on the ego agent can be added in future extensions. This impact is well recognized in the literature. Thirdly, the awareness time is, at the current version, modeled as a linear distribution. Other distributions can be explored considering the distances between houses (affecting awareness due to neighbors leaving or neighbors direct communication) and access to social media in different communities. Finally, it is recognized in the literature that humans tend to make intermediate stops when evacuating, e.g., for picking up relatives. This can be added to the model, in addition to the time of the evacuation. For example if the evacuation takes place during the day, parents may stop at schools to pick up their children.

The model and software platform were aimed at assessing, at this stage, the probability of success of an WUI evacuation. Granularity could be added to certain parts of the model so that it could be used for decision-making prior and during evacuations. Example are: i) Localization of the most vulnerable populations for reinforcement of evacuation efforts, ii) Decision on when to warn certain communities considering the time it takes for those communities to evacuate, iii) Identification of the best routes for evacuation with further consideration of the human behavior (e.g., intermediate stops), iv) Comparison between different evacuation strategies, e.g., phased evacuation and total evacuation.

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