WISE: A Probabilistic Wildfire Safe Egress Planning Framework and Software Platform

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

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

[b] The B. John Garrick Institute for the Risk Sciences, University of California Los Angeles, USA, Email: mariliar@g.ucla.edu, mosleh@g.ucla.edu

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

Abstract: Wildfire is a significant threat to many communities in Wildland Urban Interface (WUI) areas and ensuring an efficient evacuation of these communities in case of wildfire is a pressing challenge. Wildfire evacuation modeling consists of three main layers: fire model, human decision-making, and traffic models. Thus, an efficient evacuation planning requires a comprehensive understanding of each of these layers and their mutual interactions. This paper presents a framework for probabilistic evacuation planning in the case of wildfires: the Wildfire Safe Egress (WISE) framework, which integrates a human decision model, a traffic model, and wildfire dynamics modeling for estimating the probability that a community safely evacuates when in danger by a wildfire. The evacuation success is calculated through a comparison between two competing variables. The Available Safe Egress Time (ASET) determines the total amount of time before the fire reaches a community's borders. This variable depends on the wildfire dynamics. The Required Safe Egress Time (RSET) determines the amount of time a community needs to evacuate safely. The RSET considers population distribution, demographic characteristics, warning system timing and its reliability, available roads network, and the traffic travel times. These variables are modeled in a Bayesian Belief Network (BBN). Next, a Monte Carlo simulation of a Poisson process defined by the community's socio-demographic profile generates the evacuation demand curve. Finally, the traffic model is developed through agent-based modeling of evacuees' mobilization on the roads network. The final node of the BBN estimates the probability of a successful evacuation. Having a realistic estimation of this probability helps decision-makers and stakeholders to plan evacuation time, routes, and strategies to mitigate the consequences of a wildfire on a community considering different scenarios. This framework is implemented as a web platform, allowing users to have a practical egress assessment in a visual GIS-based environment.

1. INTRODUCTION

Wildfires pose a significant threat to many communities in Wildland Urban Interface (WUI) areas worldwide. According to the National Interagency Fire Center, in 2021 there were 58,985 wildfires in the U.S., burning about 7.1 million acres [1]. Wildfires cause property damage, assets loss, human casualties, and environmental destruction every year and can be considered one of the most significant natural hazards affecting many communities, especially in California. In the last decade, extreme drought combined with other factors caused more frequent and severe wildfire incidents in California. Indeed, more than 2 million properties in California were considered at high to extreme wildfire risk in 2021, the largest number of properties of any U.S. state [2].

Wildfire risk management comprises several aspects, ranging from wildfire prevention, mitigating wildfires consequences, and ensuring communities' safe evacuation when in danger of a wildfire. The latter, wildfire egress planning, is an active multi-disciplinary research area. Yet, ensuring the safety of WUI communities in case of wildfires is a complex task. It requires a deep understanding of the wildfire dynamics and spread mechanisms, human decision-making processes, transportation systems, among many other related subjects. These topics have been studied extensively by researchers. Indeed, transportation engineers tend to focus on vehicular traffic modeling of evacuation. They mainly concentrate on the available roads network to predict the travel time for the community members during evacuation. Agent-based modeling [3, 4, 5] is the most common methodology used to simulate traffic systems. Such algorithms provide the researchers with a foundation to compare different evacuation strategies [6], simulate multi-modal evacuation models [7], and offer new technologies like cellular data collection to track the evacuees [8]. In contrast, social scientists have focused on human behavior and decision-making processes in emergencies [9, 10, 11].

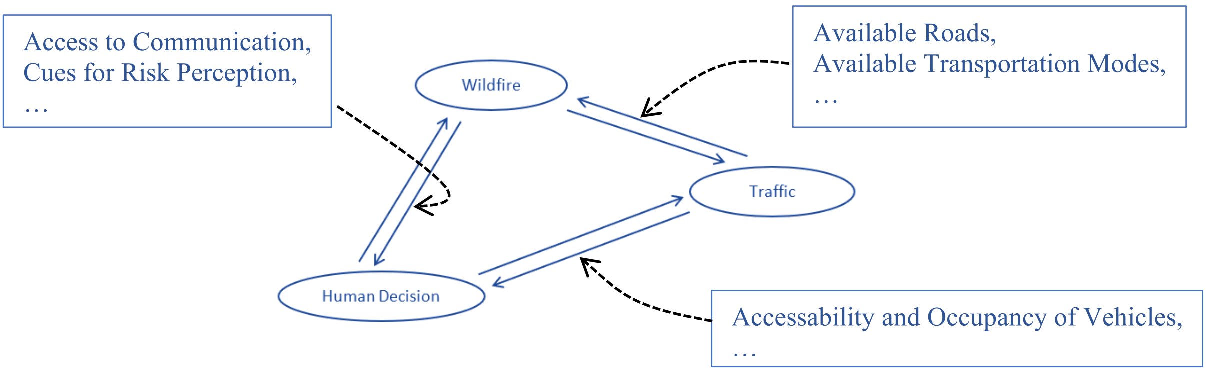
Despite recent efforts to converge these two essential aspects of wildfire evacuation [12, 13], no framework implements all elements (i.e., fire model, human decision-making, and traffic models) into a complete wildfire egress planning process in a unified probabilistic manner. This paper addresses this challenge by filling the current gap by proposing a comprehensive methodology for wildfire evacuation planning. An accompanying paper by Ramos et al. [14] in the conference proceedings discusses the human behavior model and pre-evacuation time calculations in more detail.

2. WILDFIRE SAFE EGRESS (WISE) MODEL

Wildfire egress planning consists of three main layers: fire dynamics, human decision-making, and traffic model. Wildfire dynamics are mainly affected by the available vegetations as fuel, weather conditions, and topography of the area. The human decision layer depends on the population distribution, demographic characteristics of the society, and the quality of the warning systems. Finally, the traffic model is a function of road network configurations, the available transportation modes, and weather conditions, among many other factors.

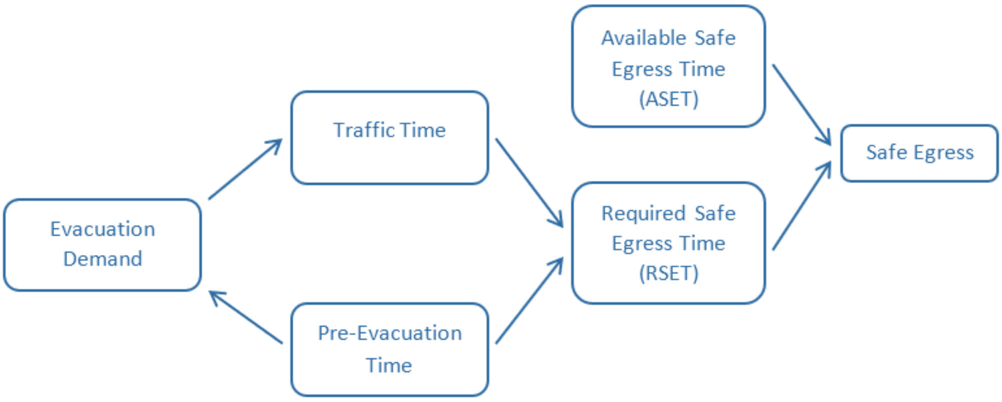
Together, these three layers form a complex system in which the components have tight interactions. In Indeed, wildfires can directly affect the human decision layer. For instance, the visual appearance of the fire or the smoke may encourage people to evacuate faster or to shelter in place. The fire can also affect the communication infrastructures and cause delays in the evacuation process. On the other hand, people may decide to perform actions to decrease fire expansion rate or to suppress the fire. Therefore, the fire dynamics can be affected by human decisions. Wildfire also interacts with traffic as it may change the availability of some roads or transportation modes, and the traffic congestion could cause problems in the fire suppression mission. The interaction between human decisions and traffic is also significant. For example, departure time, selected transportation mode, and the occupancy of the cars directly impact the traffic. The traffic congestion status, in its turn, impacts the human decision on the evacuation timing and route. Figure 1 illustrates the flow of data among these three layers.

Figure 1: Flow of Data and Interactions Among the Main Elements Wildfire Egress



A robust evacuation planning framework requires a comprehensive analysis of all these layers as well as their interactions. To address such a challenge, the WISE framework is underpinned by a Bayesian Belief Network (BBN) in which the components and their dependencies are modeled in a probabilistic manner. Figure 2 presents the BBN's main nodes (i.e., random variables). The pre-evacuation time determines the evacuation demand curve (departure times), affecting the traffic model. The traffic model and the pre-evacuation time form the Required Safe Egress Time (RSET). On the other hand, the fire dynamics determine the Available Safe Egress Time (ASET). It also provides flexibility to the analysts should they want to create and compare different evacuation scenarios. Finally, the probability distribution characterizing the likelihood and uncertainty of a successful evacuation scenario is obtained from the RSET and ASET nodes.

Figure 2: Bayesian Belief Network Model of Wildfire Evacuation Process.

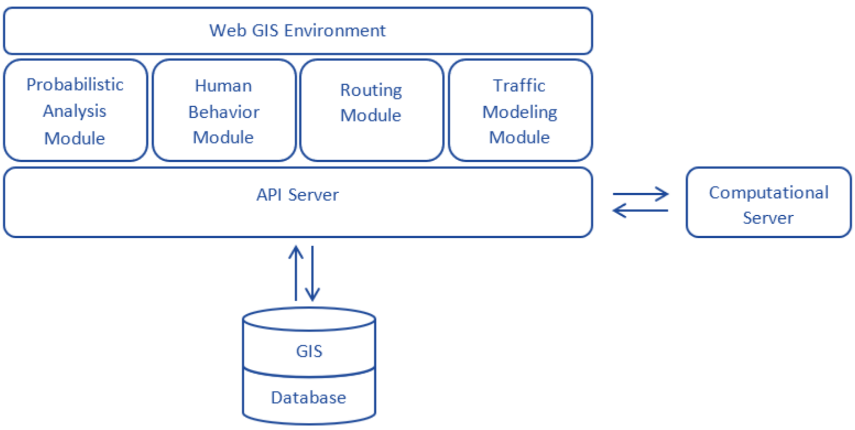


3. THE WISE PLATFORM IMPLEMENTATION

The WISE framework is implemented using web technologies. Figure 3 shows the architecture, components, and modules of the platform. In this paper, the WISE platform is calibrated and tested for the state of California in the United States. However, the methodology and the workflow remain the same for any other geographical locations. All the datasets are collected in a PostGIS database at the lowest layer. The complete California roads network, gridded population distribution, and demographic tracts are stored in different database tables. An Application Programming Interface (API) server is the main backend module that interacts with the PostGIS database and a separate computational server.

The frontend is developed as a web application and runs inside a browser. A web GIS environment offers a user-friendly graphical interface to create the evacuation scenarios, run simulations, and visualize the results. Several modules are implemented for different tasks in the application, including probabilistic analysis, human behavior analysis, routing, and traffic modeling. These modules receive user inputs from the GIS environment, communicate with the API server, and generate the results. Most of the heavy computations, such as finding the optimum path (route) between two points, are performed inside the database and the computational server.

Figure 3: WISE Platform Architecture.



In the WISE platform, the user first creates a specific evacuation scenario. Each scenario consists of five main elements: fire, community, safe zone limit, shelter, and warning system. All these elements are explained with more details in the following sections.

3.1. Fire Dynamics Simulation

The WISE platform is fire simulator agnostic. Therefore, any wildfire simulation solution which generates the compatible format can be used: the only required data for fire dynamics is a raster file containing the fire arrival time for each pixel. For example, the pilot and validation process described in this paper were obtained based on results from wildfire simulations with FlamMap [15]. By importing the fire dynamics file into the platform, the model is stored in the database, and a representation of the fire will show on the map. This fire model helps the user to define the endangered community. Moreover, the fire model determines ASET parameter.

3.2. Community

The community is defined by drawing a polygon on the map. Then, the platform queries the population of grid cells inside this polygon. The characterization of the community merges two data sources for better defining the population count and the profile of the population – which are used to model human behavior. First, U.S. Census tracts are used to define a population. Then, WorldPop [16] is used to estimate the population count within cells of 1km x 1km.

3.3. Shelter & Safe Zone Limit

A shelter point is another essential part of the egress scenario. 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. The shelter location is combined with a safe zone limit to estimate when and where the evacuees are safe from the dangers of the fire. The user draws a polyline on the map, which separates the safe zone from the endangered zone. Although the shelter point is still used as the destination for all evacuees, only the travel time before crossing the safe zone limit will be considered part of RSET.

3.4. Warning System

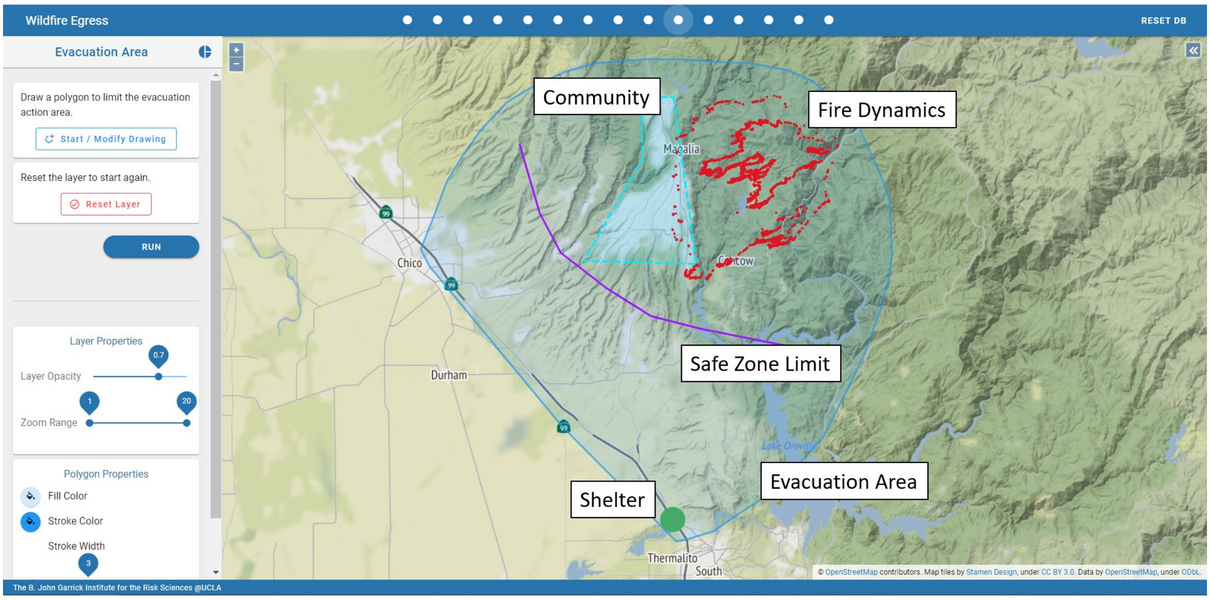
As discussed in previous sections, awareness time is a critical part of pre-evacuation time. The initial trigger for community awareness is an evacuation warning, or the fire proximity (whichever happens first). In addition to official evacuation alerts, a community may learn about the upcoming wildfire 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. If we assume that an official warning is sent to the population with a probability of failure P_{FW}, a proportion of the community $Pop_W = 1 - P_{FW}$ is alerted when the warning is sent, T_{warn}. WISE assumes a linear distribution of the information throughout the community, representing the awareness that is obtained through the visualization of neighbors leaving, or neighbors alerting each other, or information obtained by social media and television.

3.5. Evacuation Area

Each agent is modeled as a random point inside the community, and the platform identifies optimum routes between the origin and the shelter point. The routing process is done inside the PostGIS database. Therefore, for each agent, the server needs to perform heavy calculations among every single road segment in California. If the purpose is to do routing and the WUI area around a small city, there is no need to search through all streets in cities far from the area in danger. Therefore, another configuration is added into the scenario creation: the user defines the interested area in which all the egress mission will be performed. Consequently, not only the routing algorithms will perform significantly faster, but also the evacuation area is explicitly isolated from other places. Figure 4 shows an example of an egress planning scenario.

Figure 4: WISE Platfprm Sample Egress Planning Scenario Setting.



4. MODELING and SIMULATION FLOW

The fire spread model is the first input to the platform. The model is used to calculate the available safe egress time and is required to model the human behavior. After importing the fire spread model, an endangered community can be defined by drawing a polygon, which is used for the population extraction in the community and its socio-demographic characteristics from the database. The evacuation warning system is another input required for human behavior modeling. The pre-evacuation stage is then estimated through human awareness, decision, and mobility times.

The pre-evacuation time determines the average amount of time that an agent (i.e., evacuee) with a given socio-demographic profile takes before evacuation. However, not all agents start evacuation travel together. Therefore, one must employ a simulation method to generate random departure times for different agents. WISE uses Monte Carlo simulation from a Poisson process for this purpose. Assuming that every agent spends t_0 minutes before evacuation, the evacuation rate is $1/t_0$. This means that for the specific group of agents, one agent starts to travel on average every $1/t_0$ minutes. Then, the evacuation demand can be modeled through a Poisson distribution with this parameter. For each agent in that group, we can sample a random number from such probability distribution. Thus, every agent will have a random departure time so that the average departure time of the whole group is approximately t_0. The human behavior model and pre-evacuation time calculations are discussed in more detail in an accompanying paper by Ramos et al. [14] in this conference proceedings.

The WISE platform uses an agent-based method for traffic time modeling. The exact origin point of each evacuee is not known, but the destination of all evacuees is the shelter point. WISE generates random points inside the community polygon for every agent. Then, the optimum route the evacuee may choose is calculated using the shortest path routing algorithms. Note that the shortest path does not imply the shortest distance. Every road segment has a traffic cost based on attributes such as road type, number of lanes, and the segment length. The routing algorithm finds a list of connected road segments from origin to destination with the minimum total cost. PgRouting [17] is the routing engine used in WISE, and it performs all the calculations inside the PostGIS database. Although database-level routing is somewhat slower than some other routing options, it provides great opportunities for the platform.

The first and the most important benefit of this approach is that the costs of the road segments can be modified dynamically during the simulations. Thus, when some agents are in the same road segment together, WISE automatically increases the traffic cost of that segment, and the next agents will search the optimum routes using the modified costs. Consequently, it is possible to appropriately model traffic congestions. These traffic jams will increase the travel time for corresponding agents and directly affect the probability of a successful egress mission.

The last section of the egress planning is a comparison between the Required Safe Egress Time (RSET) and the Available Safe Egress Time (ASET). RSET is calculated as the summation of the pre-evacuation time and the traffic time for each agent. On the other hand, ASET depends on the fire dynamics and determines the amount of time the community has before the fire enters the community polygon. Both RSET and ASET are simulated and presented as histograms. Subtracting the RSET from the ASET results in the surplus safe egress time, SAFE, that the community will have for evacuating from the wildfire. The result explains the proportion of the agents who could evacuate safely, and the agents who needed more time for safe evacuation. It is important to note that analysts are able to easily change parameters in the model and run simulations to understand the important components and the general mechanism of the evacuation mission for their scenarios of interest. Figure 5 presents the workflow described in this section.

5. CALIBRATION AND CASE STUDY

To ensure that WISE can represent realistic evacuation simulations, its parameters were calibrated using the Camp Fire as a test case. Camp Fire was a deadly and extremely destructive wildfire in November 2018 and caused at least 85 civilians' fatalities. 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 opportunity we had to evaluate the proposed model with the first-hand knowledge and experience of the firefighters who served in this disaster.

First, the Camp Fire was simulated in FlamMap. WISE then estimated the probability of safe evacuation of the Paradise community. A first calibration was performed to adjust the model such that it could realistically represent the wildfire and evacuation process as described in the National Institute of Standards and Technology report [18]. The results of the calibrated model were discussed with the firefighters for validation. The firefighters provided the WISE development team with many details of the Camp Fire evacuation scenario and their observations. Based on their first-hand experiences, the community was informed about the approaching wildfire almost one hour before the fire reached the city. They reported that nearly 20% of the residents had evacuated when the fire first arrived at Paradise city.

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 of the Camp Fire in WISE shows that, with the defined scenario, almost 16% of the community could evacuate safely before the fire touches the borders of the city, a result near to the 20% indicated by the firefighters.

After calibration, many different scenarios were created to evaluate the effect of each parameter in the results. The sensitivity analysis was performed for ASET, different socio-demographic parameters, and the warning system parameters. Figure 6 shows 15 scenarios in which the only changing parameter is ASET. The graph shows that for the given case study, if the community has one hour for egress, only 16% of the population can evacuate safely before the fire reaches the community. However, if the community had 4 hours to evacuate in the same situation, more than 88% of the population could leave the danger zone before the fire reaches the borders of the city. The same graph demonstrates that in 6.5 hours, almost all the community could be safely evacuated.

These results demonstrate the impact of ASET in a successful evacuation. ASET is tightly linked to the trigger for community evacuation. Although Camp Fire was an extremely fast-moving wildfire, the absence of a successful evacuation warning system played an essential role in losing the most appropriate time for evacuation. Proper infrastructure for detecting the fire in its early stages, evaluating the fire dynamics, and informing the civilians, could provide the community with more time for safe egress. As shown in figure 6, only 3 additional hours for evacuation would increase the safe egress rate of the community by almost 72%.

Figure 5: WISE simulation flow.

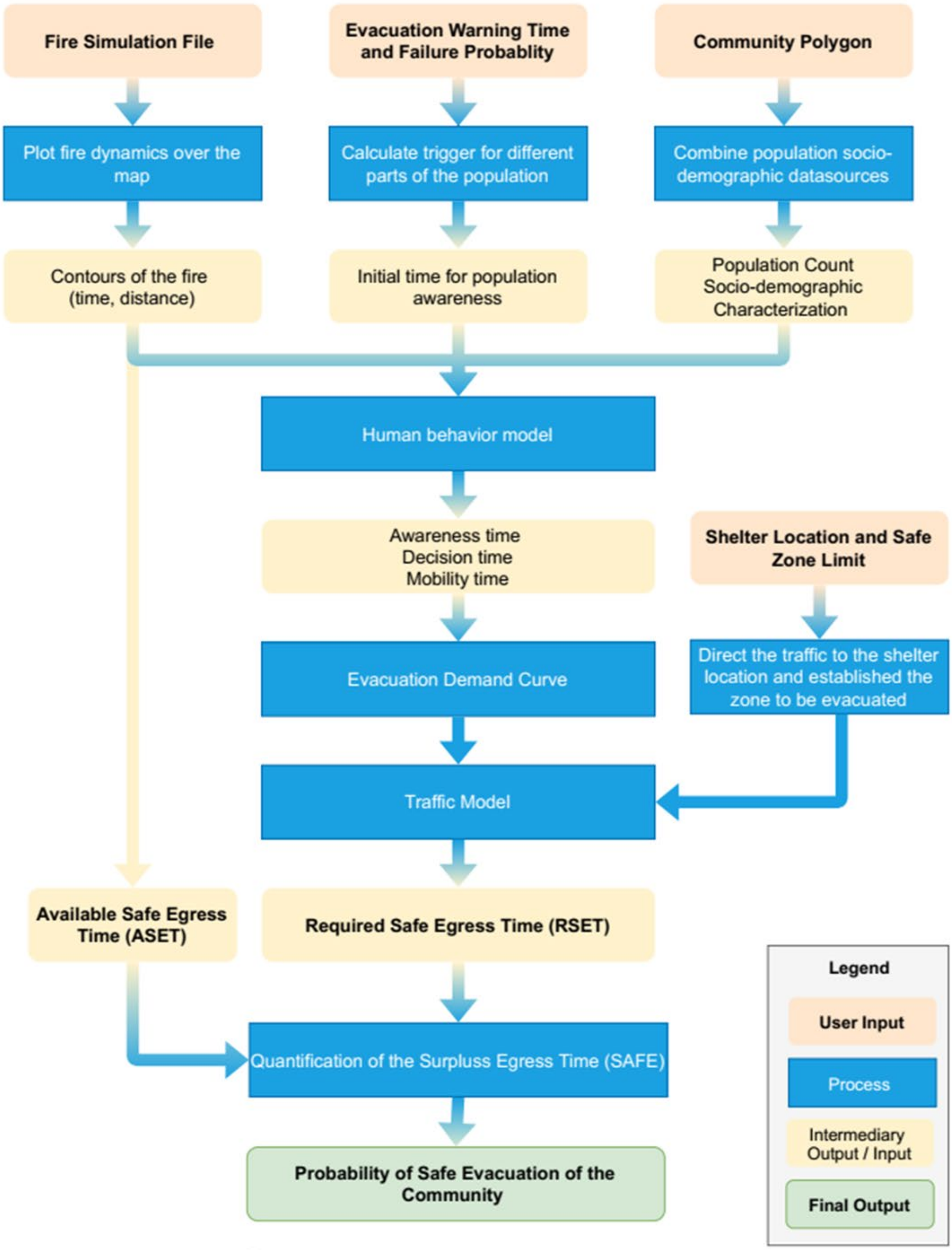


Figure 6: Sensitivity analysis of ASET.

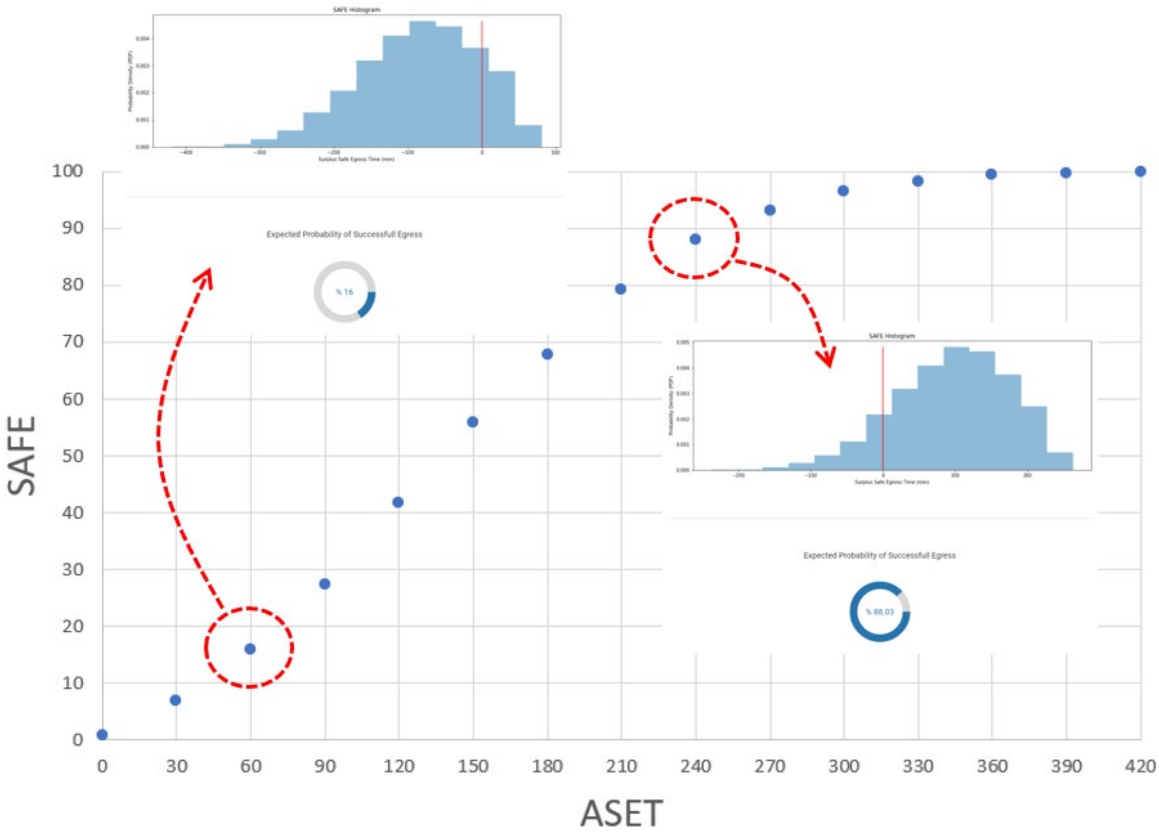


Table 1 provides the sensitivity analysis results for the warning system failure probability. This table assumes the same scenarios as Figure 6 with 120 minutes available for safe egress time as the initial condition. It also assumes that initially the warning system failed completely. The table illustrates that if the warning system does its mission for 50% of the community's population, the safe egress rate increases by 19%. Therefore, the proper functioning of the warning system has a significant effect on the safe egress rate of a community.

Table 1: Sensitivity analysis of the warning system.

SAFE for Initial Conditions: Warning Failure Probability 1.0	Modified Parameter	SAFE After Change	Change %
41.69	0.8	44.2	6%
	0.5	49.64	19%

6. CONCLUSIONS

The unprecedented integration of fire dynamics, traffic modeling, and human behavior modeling for WUI fire evacuation in one platform is an essential step towards more realistic evacuation models. Various methods have been proposed for wildfire risk assessment, focusing on each of these components separately, but few address the issue considering all these layers. The WISE platform addresses this issue and fills the existing gap. A first validation of the WISE model through the Camp Fire test case successfully demonstrated that the framework and the platform provide a unique opportunity for risk-based, model and data-based realistic evacuation planning.

The WISE development is a work in progress. However, the modular approach to WISE makes it a flexible platform for enhancing the underlying model. In the first stage, the objective was to develop a general framework and the corresponding modeling infrastructure to address the wildfire evacuation in WUI areas. Future work may focus on additional topics to improve each part of the model.

The model can be enhanced with more explicit consideration of various human behavior factors and their impact on the human risk perception. This can be achieved through post-wildfire surveys, and elements analyzed for other emergency evacuations such as landslides, flooding, and hurricanes. Moreover, the evacuation scenario creation procedure is simplified in the current version of the model. Identifying multiple shelters instead of a single one, and considering the time of day (or night) for evacuation will lead to more realistic models. Also, the transportation module could include multi-modal transportations as not all evacuees use personal vehicles to evacuate. For instance, the municipality may offer buses to expediate the evacuation of the people in some regions. Moreover, evacuees may have intermediate stops on their way before evacuation. Considering such more complex evacuation scenarios will increase the precision of the simulations.

Acknowledgements

The research forming the basis for this paper was sponsored by Pacific Gas and Electric Company (PG&E). The WISE development team would like to express their special gratitude to Mr. Jon Eric Thalman and Mr. Paul McGregor and to the PG&E fire safety specialists Mike Weaver, Rob Cone, Mike Webb, David Hawks, and Donovan Lee for important insights on identifying the relevant attributes impacting the WUI communities evacuation and calibration of the model.

References

[1] National Interagency Fire Center, *"Fire Information (Statistics: Wildfires and Acres)"* [Online]. Available: https://www.nifc.gov/fire-information/statistics/wildfires. [Accessed 11.02.2022].
[2] Verisk, *"Verisk Wildfire Risk Analysis"* [Online]. Available: https://www.verisk.com/insurance/campaigns/location-fireline-state-risk-report/. [Accessed 11.02.2022].
[3] A. Harris, P. Roebber and R. Morss, *"An agent-based modeling framework for examining the dynamics of the hurricane-forecast-evacuation system"*, International Journal of Disaster Risk Reduction, vol. 67, (2022).
[4] B. Wolshon, Z. Zhang, S. Parr, B. Mitchell and J. Pardue, *"Agent-based Modeling for Evacuation Traffic Analysis in Megaregion Road Networks"*, Procedia Computer Science, vol. 52, pp. 908-913, (2015).
[5] H. Suk Na and A. Banerjee, *"Agent-based discrete-event simulation model for no-notice natural disaster evacuation planning"*, Computers & Industrial Engineering, vol. 129, pp. 44-55, (2019).
[6] X. Chen and F. Zhan, *"Agent-based modelling and simulation of urban evacuation: relative effectiveness of simultaneous and staged evacuation strategies"*, J. Oper. Res. Soc., vol. 59, pp. 25-33, (2008).
[7] M. Siam, H. Wang, M. K. Lindell, C. Chen, E. I. Vlahogianni and K. Axhausen, *"An interdisciplinary agent-based multimodal wildfire evacuation model: Critical decisions and life safety"*, Transportation Research Part D: Transport and Environment, vol. 103, (2022).
[8] B. Melendez, S. Ghanipoor Machiani and A. Nara, *"Modelling traffic during Lilac Wildfire evacuation using cellular data"*, Transportation Research Interdisciplinary Perspectives, vol. 9, (2021).
[9] S. Vaiciulyte, L. M. Hulse, A. Veeraswamy and E. R. Galea, "Cross-cultural comparison of behavioural itinerary actions and times in wildfire evacuations", Safety Science, vol. 135, (2021).
[10] E. Kuligowski, *"Evacuation decision-making and behavior in wildfires: Past research, current challenges and a future research agenda"*, Fire Safety Journal, vol. 120, (2021).

[11] S. Grajdura, X. Qian and D. Niemeier, *“Awareness, departure, and preparation time in no-notice wildfire evacuations”*, Safety Science, vol. 139, (2021).
[12] E. Ronchi and S. Gwynne, *“Computational Evacuation Modeling in Wildfires”*, Encyclopedia of Wildfires and Wildland-Urban Interface (WUI) Fires. Springer, no. 121, (2019).
[13] E. Ronchi, S. M. Gwynne, G. Rein, P. Intini and R. Wadhwani, *“An open multi-physics framework for modelling wildland-urban interface fire evacuations”*, Safety Science, vol. 118, pp. 868-880, (2019).
[14] Marilia Ramos el al. “Integrating Human Behavior Modeling into a Probabilistic Wildfire Egress Planning Framework”, Proceedings of the probabilistic Safety Assessment and Management PSAM 16, (2022)
[15] M. Finney, *“FlamMap”* [Online]. Available: https://www.firelab.org/project/flammap.
[16] A. Sorichetta, G. Hornby and F. Stevens, *“High-resolution gridded population datasets for Latin America and the Caribbean in 2010, 2015, and 2020”*, Sci Data, vol. 2, p. 150045, (2015).
[17] PgRouting contributors, *“PgRouting”* [Online], Available: https://pgrouting.org.
[18] A. Maranghides, E. Link, W. Mell, S. Hawks, M. Wilson, W. Brewer, C. Brown, B. Vihnaneck and W. D. Walton, *“A Case Study of the Camp Fire – Fire Progression Timeline (NIST Technical Note 2135)”* U.S. Department of Commerce, National Institute of Standards and Technology, (2021).