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An interdisciplinary agent-based multimodal wildfire evacuation model: Critical decisions and life safety

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ABSTRACT

This article applies an interdisciplinary agent-based model (ABM) of wildfire evacuation to the devastating 2018 wildfire in Mati, Greece, where the second-deadliest wildfire of the 21st century took place. This model integrates the natural hazard system (wildfire propagation) with the sociotechnical response system comprising social (population response) and engineered (transportation network and shelter location) components. The research objective is to investigate the effects on wildfire casualties of the risk area population's decisions about (1) whether to leave and how long to wait (i.e., departure time); (2) what transportation mode to use (e.g., walking or driving); and (3) how fast to travel. Analysis of several evacuation scenarios shows that the absence of children, multi-modal travel, staged evacuation, and increased shelter capacity lead to a more successful wildfire evacuation. These analyses can help emergency managers improve the effectiveness of their communities' wildfire evacuation plans.

1. Introduction

1.1. Background

Wildfires throughout the world have resulted in human casualties, property damage, and environmental destruction (Beloglazov et al., 2016). The magnitude of the 2016 Fort McMurray Canada fire (May, 2016) and the 2016 Haifa Israel fire are powerful reminders of how wildfires affect communities – tens of thousands of people were forced to evacuate in each event (Folk et al., 2019). California experienced a significant number of fatalities because of wildfires in 2017 and 2018 (e.g., Camp and Woolsey fires) (Tierney, 2018), as well as in 2019 (e.g., Ranch, Kincade, Maria, Eagle, Hillside). In total, recent California wildfires burned approximately 1.48 million acres and destroyed over 30,000 structures (Wong et al., 2020). Among these, the Camp Fire in Paradise CA was one of the most devastating events, extending over an area of 62,053 ha (153,336 ac), resulting in the loss of 18,804 structures, 85 civilian fatalities, and \$16.5 billion in damage (Lam, 2018).

Researchers have identified five factors that influence wildfire impacts on human society. First, global climate change is producing warmer temperatures, earlier snow-melt, and longer dry seasons, making wildfires more likely (Jolly et al., 2015; Liu et al., 2010). Second, human intervention – over-suppression of wildfire from the natural cycle – resulted in cumulative flammable fuel across large

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areas in the forest that leads to severer wildfires (USDA, 2003). Third, development continues to expand into the wildland–urban interface (WUI), producing increased exposure to deaths and injuries (Toman et al., 2013), as well as property destruction (Dodson, 2010). Fourth, many structures in the WUI are built with flammable materials, making it impossible to safely shelter in-place (Cova et al., 2009). Fifth, WUI communities have inadequate evacuation preparedness – especially evacuation route systems (ERSs) that have inadequate capacity or, in extreme cases, only a single exit that could be blocked by fire (Cova and Johnson, 2002). The first and second factors require a global reduction in carbon emissions and wildfire fuel management, whereas the third can be managed through better land use practices and the fourth can be addressed by better building construction practices (Lindell et al., 2006). However, the fifth factor requires an improved understanding of when and how those at risk respond to wildfires and, especially, take critical evacuation decisions that affect their life safety.

There have been extensive studies of wildfire-related evacuation dynamics—all of which converge to predict wildfire impacts on communities (Chen and Zhan, 2008). In the past, social scientists tended to focus on people's protective action decisions and ignored other behavioral aspects of evacuation (Lindell and Perry, 1992; Lindell and Prater, 2007a). In contrast, transportation engineers tended to focus on modeling vehicular travel through road networks but based their analyses on assumptions about people's evacuation behavior rather than on empirical data. More recently, evacuation studies have integrated social science with transportation engineering into a sociotechnical response model (Lindell et al., 2019; Trainor et al., 2013; Murray-Tuite et al., 2021; Kuligowski, 2020).

Evacuation modelers increasingly recognize that local authorities face a dilemma when deciding about evacuations. One goal is to clear the risk area before the arrival of hazardous conditions. However, they often lack any information about the length of time needed to clear the risk area, so they must make an evacuation decision while being uncertain about when, or even if, hazardous conditions will reach their community. A timely decision requires the decision maker to understand two chains of events—one for the environmental hazard and the other for the community response (Lindell et al., 1985; Lindell and Perry, 1992; Mileti, 1975). In the case of wildfires, the environmental hazard chain of events can be characterized by the projected progress of the fire front due to fuel, terrain, and meteorological conditions (Bayham et al., 2020). Next, the projected exposures provide the decision information that Incident Commanders can use in emergency assessments for protective actions such as sheltering in-place and evacuation. Specifically, these exposure projections can serve as the basis for evacuation triggers (Cova et al., 2017), that are derived from evacuation decision arcs used for hurricanes (Lindell and Prater, 2007b).

Once Incident Commanders have selected protective action recommendations (PARs) using decision aids such as evacuation triggers, they can disseminate those PARs through communication channels such as broadcast media to households in threatened communities. People can then mobilize their response resources (e.g., clear vegetation around structures, pack bags, and secure the home) and seek additional information – "milling" (Wood et al., 2018) – before deciding how to respond (Lindell and Perry, 2012; Lovreglio et al., 2020, 2019). The time required to complete all of these steps – an evacuation time estimate (ETE) – is a function of four ETE components (Urbanik et al., 1980; Lindell et al., 2019): $t_T = f(t_d, t_w, t_p, t_e)$, where t_T is a household's total clearance time, t_d is the authorities' warning issuance delay time, t_w is the household's warning receipt time, t_p is the household's preparation (mobilization) time, and t_e is the household's evacuation travel time. Households vary in the duration of their t_w and t_p, so the first three ETE components form a cumulative distribution known as the household evacuation departure time curve. This distribution, also known as an ERS loading function, is an input to a computational algorithm for modeling flows of evacuating vehicles (or persons, in the case of pedestrian evacuations) through the ERS to produce the fourth time component (t_e). Evacuation travel time is then determined by the ERS's network geometry and link capacities, as well as by the number of vehicles and their speeds on their chosen routes to their selected destinations.

Recent reviews have produced summaries of hurricane evacuation data for first three ETE components (Lindell et al., 2021, 2020) but comparable data for wildfires are limited and scattered. Specifically, there appear to be only five studies that have reported ETE components for wildfires and even those are analysts' assumptions rather than empirical data collected from evacuees in the aftermath of wildfires – (Cova and Johnson, 2002; Beloglazov et al., 2016; León and March, 2017; Veeraswamy et al., 2018; Li et al., 2019a).

1.2. Research objectives

There does not appear to be any previous research on wildfire evacuation modeling that has simultaneously considered the effect of both evacuation strategy and modal choice on the reduction of wildfire fatalities. Therefore, it is necessary to examine the way in which staged evacuation and travel mode choice can be integrated within evacuation modeling techniques such as ABMs while simulating appropriate pedestrian dynamics to better capture the real-world scenarios. We select Mati, Greece, where the second-deadliest wildfire in the 21st century took place (Blandford, 2019), as the test-bed for an ABM analysis. The objectives of this research are to -

- create an interdisciplinary ABM framework that integrates the natural hazard system (wildfire propagation) with social (population response) and engineered (transportation network and shelter location) system components,
- assess the effects of evacuees' socio-psychological and physical characteristics on evacuation effectiveness, and
- investigate the impact of travel-related variables (i.e., milling time, travel speed) on estimates of wildfire casualties.

These analyses will help emergency managers to develop improved household evacuation plans and increase their communities' wildfire resilience.

Table 1
Wildfire evacuation assumptions (P = Poisson distribution, R = Rayleigh distribution, N = Normal distribution; all models implicitly assumed t_d = 0 and no evacuation shadow. * Implied; ** Pedestrian evacuation).

	Participation rate	Departures time	Vehicles/ household	Evacuation routes	Evacuation destinations	Travel speed
Cova and Johnson (2002)	100%	P ($\lambda = 5 - 25$)	P($\lambda = 0.5 - 3.0$)	Myopic choice	Nearest	Unspecified
Beloglazov et al. (2016) Fire visible	40%	0 + R (M = 10)	1.5	Shortest*	Nearest	Speed limit
Beloglazov et al. (2016) 2-h warning	30%	10 + R (M = 20)	1.5	Shortest*	Nearest	Speed limit
Beloglazov et al. (2016) 6-h warning	10%	20 + R (M = 30)	1.5	Shortest*	Nearest	Speed limit
León and March (2017) 24-h warning	100%	P ($\lambda = 2$)	P ($\lambda = 2$)	Shortest	Nearest	20 kph
Li et al. (2019b) Case 1	100%	N(M = 40 m, SD = 20 m)	P ($\lambda = 2$)	Shortest	Nearest	64 kph hwy, 40 kph res
Li et al. (2019b) Case 2	100%	N(M = 40 m, SD = 20 m)	P ($\lambda = 4$)	Shortest	Nearest	64 kph hwy, 40 kph res
Veeraswamy et al. (2018) Pedestrian	100%	30 s–16 m	0**	Shortest	Nearest	0.85–1.1 m/s

2. Literature review

In general, threatened communities are expected to begin evacuating from a wildfire as soon as they receive warnings directly from authorities via emergency notification systems, indirectly through the news media via TV and radio broadcasts and internet sites, or from peers through channels such as face-to-face conversation of or electronic communication. These warning messages contain information about the wildfire hazards (e.g., initial detection, evacuation trigger, fire front arrival) and, especially, what type of evacuation procedure – simultaneous or staged – they should follow (Lindell, 2018). In response to such exposure projections, people reassess their perceptions of the amount of time before arrival of hazardous conditions based on environmental cues and social sources, and then choose different types of protective responses – either to “stay and defend" or “evacuate". However, previous wildfire studies were limited to simpler research assumptions such as 100% evacuation rate with people traveling at normal speed limit (see Table 1). For evacuation, authorities often provide transportation support; however, evacuees in developed countries typically use their own vehicles, which requires authorities to provide traffic management. People overwhelmingly choose vehicles for large-scale evacuations such as hurricanes, whereas a multiple modes – vehicular and pedestrian – are feasible for small-scale evacuations such as many flash floods and tsunamis, and some wildfires (Mostafizi et al., 2019b). With these characterizations, the following sections provide a detailed literature review about how the natural hazard system (wildfire propagation) influences the sociotechnical response system components (e.g., population response, transportation network, shelter location).

2.1. Wildfire modeling

Wildfire spread determines the complexity of the sociotechnical system’s responses. The fact that risk area residents might not be aware of a wildfire’s presence or its direction and speed until it is too late to successfully evacuate can lead to a great loss of life (Anguelova et al., 2010). Thus, it is essential to incorporate computerized models of wildfire propagation into the modeling process (Li et al., 2019a). In past decades, approaches such as fire growth models have been developed to model the complex spatiotemporal wildfire process. For example, the Rothermel fire behavior model (Rothermel, 1972) has been widely used in a number of computerized and manual models such as FlamMap (Finney, 2006) and FARSITE (Finney, 1998) for modeling wildland spread dynamics. The FlamMap program uses inputs from GIS to analyze spatial variability in fire behavior in a landscape-level analysis (Finney, 2006). In addition, fire propagation in the landscape is assessed by the minimum fire travel time model (Finney, 2002) and the cellular automata (CA) model (Clarke et al., 1994).

2.2. Sociotechnical system response to wildfires

One significant challenge in wildfire response is that the highly dynamic nature of wildfires means that PARs can change in short order (Cova et al., 2011). Although early evacuation has proven to be the least risky strategy for wildfire response (Zhang et al., 2020), it is not the only feasible protective action. Paveglio et al. (2008) conducted a qualitative analysis to identify feasible evacuation alternatives. One of the most common alternatives to evacuation is to “Stay and Defend", which can range from 10–13% (Veeraswamy et al., 2018) to 20% (Paveglio et al., 2014) of the risk area population. One major impediment to evacuation is uncertainty about wildfire spread, which significantly influences the probability of evacuation (McLennan et al., 2012). The effect of uncertainty is reduced when authorities issue mandatory rather than voluntary evacuation orders (Baker, 1991). Mozumder et al.

(2008) used mail survey data to better understand the evacuation intentions of residents in East Mountain, New Mexico. They found that risk perception related to previous exposure to wildfires, and concern about the availability of evacuation shelters and the safety of pets or livestock significantly affect residents' evacuation decisions. Blanchi et al. (2018) used quantitative analysis to examine the experiences of those who sheltered in the Black Saturday bushfires. They found that evacuation behavior was influenced by the fire propagation process, house construction, and the neighboring landscape. This study's results highlight the efficacy of better hazard education in reducing life loss because a house is likely to become untenable faster than anticipated by its residents, leading to an increased exposure to the wildfires. A recent review of wildfire evacuation studies conducted in North America and Australia from 2005–2017 (McLennan et al., 2019) yielded conclusions that are consistent with research on other hazards (Lindell, 2018). Specifically, they found evidence of "milling" in which people delay their evacuations until additional information confirms the initial warning. In Australia, people generally accepted the "Stay and Defend" strategy before the 2009 Black Saturday fires took place. However, the "Stay or Go" policy was discouraged after those fires, and in turn, the Australasian Fire and Emergency Service Authorities Council (AFAC) recommended early evacuation (Kuligowski, 2020). Another study described the factors affecting residents' behavior within the framework of the Protective Action Decision Model (PADM) (McCaffrey et al., 2018). They concluded that there are two types of people during wildfires: people inclined to evacuate and people inclined to stay. Their results indicate that factors such as evacuation efficacy, preparedness knowledge, and general risk attitude plays a significant role in influencing a resident's decision to either evacuate or not. The authors found that an increase in evacuation efficacy by one unit predicts a 52% reduction in the likelihood of a household staying and defending.

2.3. Managing the wildfire response

A major challenge in a wildfire management is to how to get as many people as possible – ideally all – out of the danger zone as quickly and safely as possible. Therefore, it is necessary to take into considerations how different evacuation management strategies influence the overall ETEs. To illustrate, authorities implemented a staged evacuation when evacuating Los Alamos residents from a 2002 wildfire (Chen and Zhan, 2014). The apparent success of staged evacuation in that event motivated other jurisdictions to adopt this strategy. For example, during a South Carolina hurricane evacuation, authorities found staged evacuation to relieve traffic congestion and thus were able keep the evacuation clearance time to a minimum (Farrell, 2005). In addition, Wolshon et al. (2006) documented New Orleans officials' use of staged evacuation as Hurricane Katrina approached in 2005. However, there remains a research gap because there have been no investigations into whether staged evacuation is more effective than simultaneous evacuation in a wildfire.

It is well documented that the duration of milling time as people engage in warning confirmation and evacuation preparation has a great impact on mortality rates during a disaster (Wang et al., 2016). Milling time is especially influenced by warning messages' specificity and completeness (Council et al., 2006). Specifically, people seek to confirm authorities' warning messages by surveying their immediate environment. If there are no environmental cues of the hazard, they are less likely to take prompt protective action (Perry, 1979). All these detrimental factors may put the affected population at a higher risk during as the highly dynamic nature of wildfires necessarily mean that residents will have a less preparation time in comparison to other hazard agents such as hurricanes (Kang et al., 2007; Lindell and Prater, 2007a) or nuclear power plant accidents (Wood et al., 2018). There is also a need to consider how vulnerable population segments such as children influence overall evacuation efficacy (Zoraster et al., 2010). The fact that children have a higher degree of susceptibility to injury because of their misperceptions about the level of risk and dependence on others for decision-making practice (Sperling, 2008) necessarily means that families with children require more milling time before they are both prepared and willing to evacuate. In addition, children are more susceptible to wildfire hazard than adults as they have a slower walking speed because of their small size, higher respiratory rates, and other factors (Martin et al., 2006). With all these characterizations, children require extra attention, and intervention strategies designed with them in mind, to help families with children evacuate successfully.

Toledo et al. (2018) illustrated how the number and types of vehicles that households choose for evacuation can influence the evacuation travel time and, in turn, the number of fatalities. Those authors found that most people used private vehicles (92%) and, thus, only a small percentage used public transportation or evacuated on foot. These results are similar to those from other disaster research that also found a strong predilection for private vehicles compared with other transportation modes (Lindell et al., 2019). In addition, modal split data provide information about evacuees' movement through the road network using transportation modes that differ in size and capacity. It is important to account for these behaviors in the wildfire studies since vehicles take more space on the roads than people evacuating by foot.

The availability of evacuation accommodations is also important in determining disaster impacts because the proper location and allocation of emergency shelters for those who cannot stay with peers or in commercial facilities can greatly improve evacuation efficiency and thus effectively reduce fatalities (Mostafizi et al., 2019a). For example, evacuation studies have found a relationship between congestion and evacuation time (Jonkman et al., 2009; Zhang et al., 2013). Later, Zhao et al. (2017) performed a case study analysis of Beijing's Jinzhan Town that demonstrated how evacuation shelter area influences the evacuation time. Mas et al. (2013) used a stochastic simulation of the initial spatial distribution of residents and evacuation milling time to evaluate the capacity–demand relation at tsunami evacuation shelters in Peru. Their results emphasized the importance of evaluating shelter capacity to enable authorities to develop strategies for ensuring adequate accommodations for the affected population. However, analyses regarding the influence of shelter capacity on mortality rates have mostly examined hurricane and flood evacuations, which neglects the assessment of route choice during wildfires.

Travel speed influences the mortality rate as slower travel speed will increase the overall ETE leaving people exposed to the wildfire arrival. Porzycki et al. (2018) conducted experiments on fire evacuation within a tunnel to analyze the variation in evacuee's travel speed when exposed to artificial, non-toxic smoke. Results show that evacuation travel speed is influenced by evacuees' attitudes and their familiarity with the environment. With this in view, Wood and Schmidtlein (2013) considered three running and three walking speed to better capture the mixed mobility of tsunami zone residents. Recently, Wahlqvist et al. (2021) considered a reasonably conservative range of walking speeds (0.7–1.0 m/s) to characterize pedestrian movement and adjusted vehicle speed based on a speed–density relationship (Ronchi et al., 2020). However, there have not been any studies that examined how a range of travel speeds affects the mortality in a wildfire.

3. Methodology: Interdisciplinary agent-based wildfire evacuation model (I-ABWEM)

In past decades, approaches such as linear programming (LP), simulation, and heuristic algorithms have been widely employed to model different components of wildfire evacuation systems (Pillac et al., 2016; Srinurak et al., 2016). The shortcoming of these methods is that they lack the capacity to model the unique behaviors of different individuals during the wildfire, and thus fail to fully incorporate the potential interaction effects among evacuees (Wang et al., 2016). Specifically, there are many heuristic models of evacuation behavior (e.g., Pillac et al. (2007); Kinsey et al. (2019)) that have provided interesting insights into the human decision-making process during a disaster, but they often work at a relatively macroscopic level and therefore do not incorporate microscopic factors characterized by the complexity of diverse components, as well as varied and nonlinear interactions among individuals (Malleson et al., 2009). Modeling community responses to wildfires requires the coupling of two highly complex, dynamic phenomena: an environmental hazard and a human community (Assaf, 2010). Environmental hazards are characterized by uncertainty about speed of onset, impact magnitude, and scope and duration of impact. Similarly, human behaviors during wildfire are characterized by a significant degree of apparent randomness, subjectivity, fuzziness, and ambiguity. Due to their complexity, people's responses can only infrequently be described by simple mathematical equations. Moreover, disaster responses are characterized by many uncertainties regarding the time of warning receipt, duration of milling, and choice of protective action (often shelter in-place vs. evacuation). In the latter case, there is uncertainty about evacuees' departure times, travel mode (including the number of evacuating vehicles), travel route, destination, and accommodations. These variables are often difficult, and frequently impossible, for traditional methods to represent adequately. To address these limitations, agent-based models (ABMs) are used to model dynamic and complex systems in which people's decision processes are involved (Mostafizi et al., 2019a).

An ABM is an object-oriented modeling procedure that simulates actions and interactions of both individual and collective entities in order to understand system behavior as a whole (Dawson et al., 2011). For example, Nagarajan et al. (2012) developed a multi-agent model that can analyze the warning dissemination process. Paruchuri et al. (2002) adopted an ABM to analyze unmanaged traffic flow, whereas Chen et al. (2006) simulated the collective behavior of evacuees' traffic flow. Liu et al. (2008) modeled group evacuation incorporating dynamic route choice. Uno and Kashiyama (2008) proposed a multi-agent model that measures casualties to people and damage to infrastructure. Poulos et al. (2018) analyzed an evacuation strategy that minimizes casualties during natural hazards. The fact that ABMs can easily capture heterogeneity, randomness, and interactions at the agent level is the primary motivation behind this work.

We developed an interdisciplinary agent-based wildfire evacuation model (I-ABWEM) using NetLogo (North et al., 2006). The I-ABWEM platform has five different modules for (1) population distribution, (2) transportation network, (3) evacuation shelter locations, (4) fire spread, and (5) data visualization. These modules incorporate the data files required to address both systems of the interdisciplinary approach: natural and sociotechnical. For example, to estimate fatalities, we first characterize the demand (e.g., the risk area population's time-dependent rate of evacuation), identify the supply (i.e., the road network), and then calculate the number of people who successfully evacuate to shelters (Cova et al., 2013). In this study, the simulations are bound with evacuees' social-demographic characteristics, which are translated to the risk area residents' warning reception, evacuation decisions (e.g., stay or evacuate), and departure time. In turn, the decision to evacuate influences choices of evacuation modes and travel speed (which, in the case of pedestrian evacuation, represents the physical ability of the evacuee). We then integrate all these complex spatiotemporal processes with fire arrival time to estimate the number of fatalities. As an example, Fig. 1 displays the results of one wildfire evacuation scenario and the data files used to analyze it.

The model begins with wildfire propagation to analyze the speed of onset, as well as the magnitude and areal extent of the threat. It continues with residents' threat recognition and risk assessment that influence their evacuation decisions. Data on evacuation decisions and ETE components provide the evacuation transportation models with information about vehicles' rate of entry into the ERS. The model continues with an assessment of the impacts of this vehicular demand on the ERS through the evacuees' choices of transportation modes, destinations, and routes of travel. The model shows how local authorities can manage evacuation demand through the implementation of different traffic (e.g., staged or simultaneous evacuation), and shelter capacity management strategies (Lindell et al., 2019; Toledo et al., 2018).

3.1. Natural hazard system model

Fig. 2 provides a schematic view of the Mati 2018 wildfire that shows the chronology of fire front propagation. This wildfire ignited on Penteli mountain in the afternoon of 13 July, 2018. High temporal image data produced from FlamMap[1] indicates the

[1] https://www.firelab.org/project/farsite

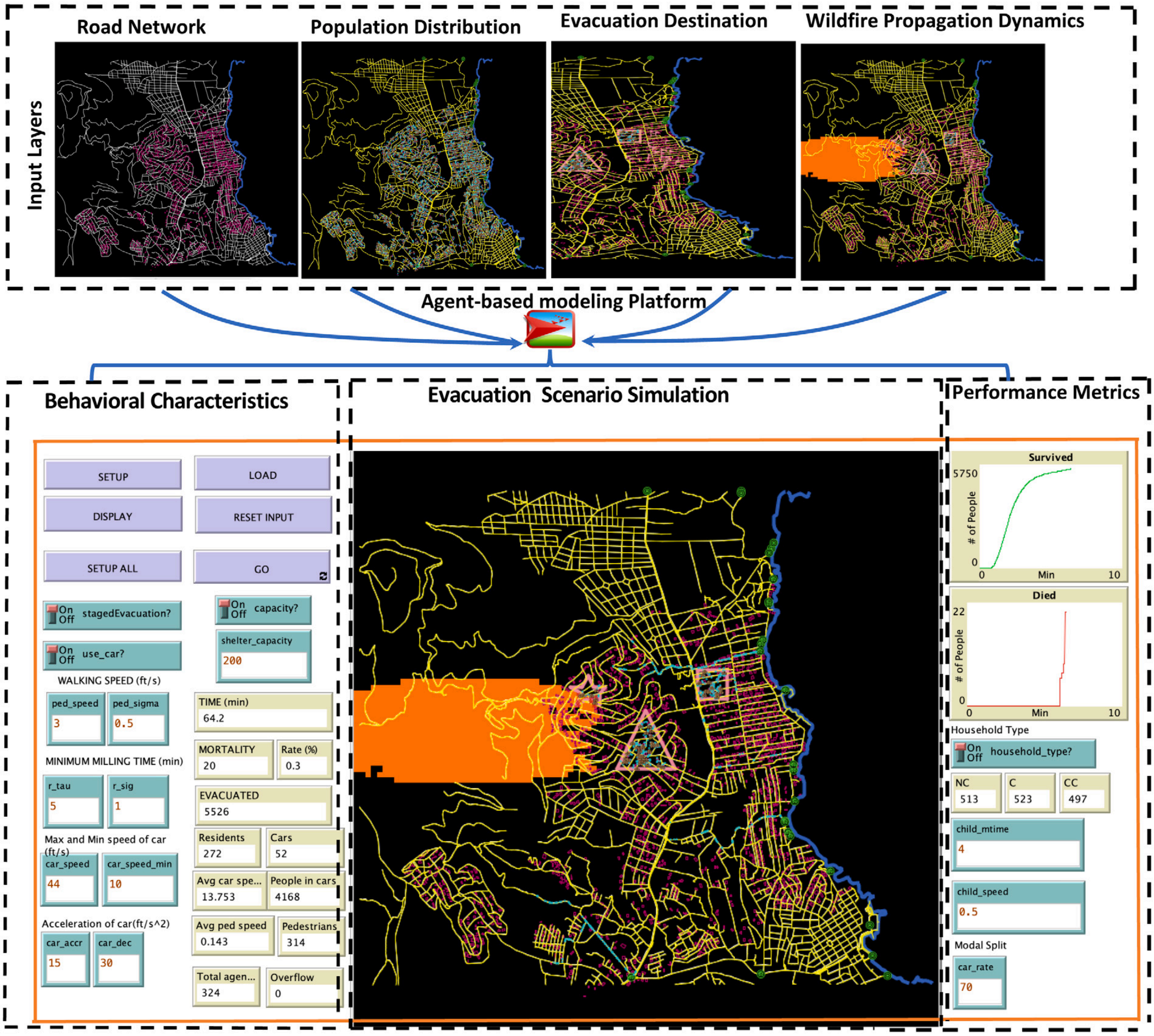


Fig. 1. The agent-based wildfire evacuation model of Mati, Greece in Netlogo. The left panel lists controllable system variables such as evacuation mode split, evacuation strategy, and behavioral and physical aspects of the risk area residents. Evacuation dynamics are displayed in the GUI in the middle panel, which shows the movement of cars and pedestrians through the ERS, along with the fire propagation (orange color) and priority areas selected for staged evacuation (pink colored geometric shapes). The right panel contains the evacuation results in terms of the number of wildfire fatalities. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

time when the fire front (in the form of smoke or hot gases with temperature up to 800°c) (Haynes et al., 2020; Kotroni et al., 2019) has reached an agent's location (either in car or on foot), at which point the agent is counted as a fatality. Several spatial inputs were provided to the FlamMap, such as wind speed (40 km/h), temperature (31°C), and relative humidity (40%) (Xanthopoulos and Athanasiou, 2019). All these environmental features, coupled with topographic profile of the terrain (i.e., down-slope characteristics of the eastern region of Attica) incorporated into the FlamMap model, made it possible to simulate the rapid fire spread as observed during the event. Available online resources such GIS maps or visual descriptions from European Union, Forest Fires Emergency Response Coordination Centre (ERCC) (EU (2021), ArcGIS (2021), ReliefWeb (2021)) were used to validate the fire propagation model.

3.2. Sociotechnical system model

This section discusses the traffic simulation, evacuation demand, and the road network supply.

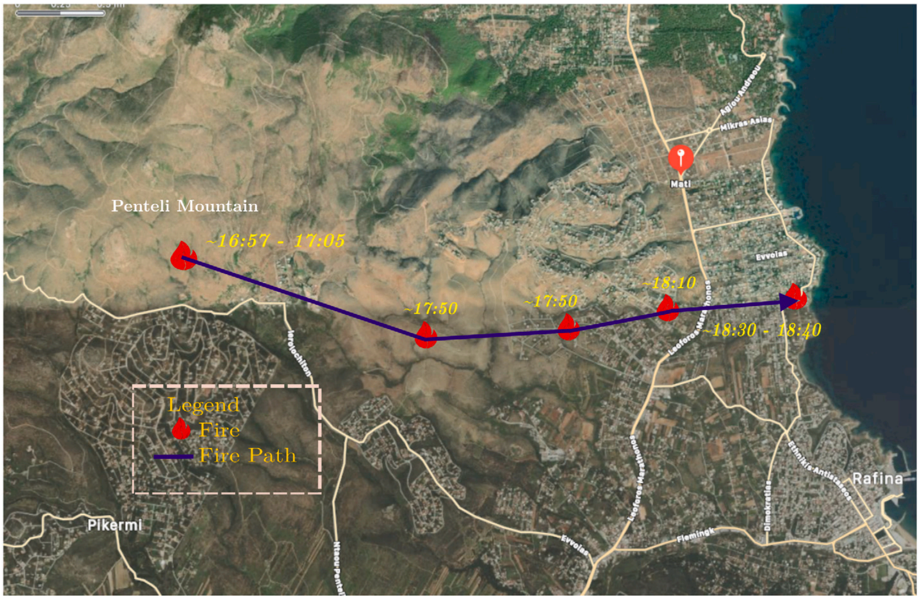


Fig. 2. A schematic view of the general region affected by the 2018 Attica fire showing major roads to the village of Mati. Fire symbols represent only general areas affected by the fire delineating an approximate path the fire followed. Note: From Apple Maps, by Apple.

3.2.1. Wildfire evacuation decision-making process

In this paper, we consider "stay-at-home" or "evacuate" as the alternatives available to vulnerable individuals. However, the decision-making process for selecting one of these alternatives is complex, as residents' evacuation participation can differ based on their environmental contexts and personal characteristics (Lindell, 2018). To capture such complex interactions, we define the evacuation decision (ED) during a wildfire event as follows,

$$\mathrm{ED} = f(\mathcal{X} | \bigcup_{n\in\mathbb{Z}} \theta_n) \tag{1}$$

where θ is the effect of explanatory variable $\mathcal{X}$. Some variables may remain unobserved, so we denote them as $\mathcal{X}_u$ and the observed variables as $\mathcal{X}_o$. Thus, Eq. (1) can be rewritten as Eq. (2) as follows

$$\mathrm{ED} = f(\mathcal{X}_o | \bigcup_{i\in\mathbb{Z}} \theta_{io}, \mathcal{X}_u | \bigcup_{i\in\mathbb{Z}} \theta_{iu}) \tag{2}$$

To better understand the implication of the explanatory variables, we express Eq. (2) in a multivariate polynomial form as follows

$$\mathrm{ED} = \sum_{i\in Z}^{n} \beta_{io} \mathcal{X}_{io}^{\omega_{io}} + \sum_{j\in Z}^{m} \beta_{ju} \mathcal{X}_{ju}^{\omega_{ju}} \tag{3}$$

where $\{\beta, \omega\} \in \theta$.

However, we cannot model the unobserved variables due to lack of information, so we replace those variables in Eq. (3) with a constant parameter β_o, which is their average effect, as illustrated in Eq. (4)

$$\mathrm{ED} = \sum_{i\in Z}^{n} \beta_{io} \mathcal{X}_{io}^{\omega_{io}} + \beta_o \tag{4}$$

Now to account for the likely possibility that the observed variables will not predict ED perfectly, we add a disturbance term ζ to the Eq. (4). Therefore, the Eq. (4) takes the form of Eq. (5) as

$$\mathrm{ED} = \sum_{i\in Z}^{n} \beta_{io} \mathcal{X}_{io}^{\omega_{io}} + \beta_o + \zeta \tag{5}$$

In turn, this probability function becomes the logistic regression function in Eq. (6)

$$\Pr(\mathrm{ED} = 1 | \mathcal{X}_{io}) = \frac{\exp(\sum_{i\in Z}^{n} \beta_{io} \mathcal{X}_{io}^{\omega_{io}} + \beta_o)}{1 + \exp(\sum_{i\in Z}^{n} \beta_{io} \mathcal{X}_{io}^{\omega_{io}} + \beta_o)} \tag{6}$$

The likelihood function for this model can then be illustrated as in Eq. (7)

$$\log L = \prod_{i=1}^{n} \left(\frac{e^{\sum_{i\in Z}^{n} \beta_{io} \mathcal{X}_{io}^{\omega_{io}} + \beta_o}}{1 + e^{\sum_{i\in Z}^{n} \beta_{io} \mathcal{X}_{io}^{\omega_{io}} + \beta_o}} \right)^{y_i} \times \left(\frac{e^{\sum_{i\in Z}^{n} \beta_{io} \mathcal{X}_{io}^{\omega_{io}} + \beta_o}}{1 + e^{\sum_{i\in Z}^{n} \beta_{io} \mathcal{X}_{io}^{\omega_{io}} + \beta_o}} \right) \tag{7}$$

3.2.2. Departure time

A number of studies have analyzed departure time distributions for different types of hazards (e.g., hurricane, tsunami, earthquake) (Lindell et al., 2019; Wang et al., 2016; Mostafizi et al., 2019a). There are two different ways in which the I-ABWEM simulates the departure time distribution:

- Staged Evacuation: A staged (or phased) evacuation is one in which authorities decide to evacuate different areas in sequence instead of having everyone evacuate at once (i.e., simultaneous evacuation). Staged evacuation is encouraged to reduce congestion during evacuation and thus reduce loss of life (Li et al., 2015). For the present study, several factors, such as population distribution and likelihood of exposure to fire propagation, are considered to identify areas that are given priority for evacuation. In the selected area, evacuees are assumed to begin their evacuation immediately after receiving an evacuation warning.
- Simultaneous evacuation: Simultaneous evacuation denotes the scenario in which evacuees in the affected area are advised to depart at a time. Following Wang et al. (2016), we model the uncertainty in departure time during the wildfire as the Rayleigh distribution in Eq. (8)

$$P(t) = \begin{cases} 0 & 0 < t < t_o + \tau \\ 1 - e^{\frac{-(t-t_0-\tau)^2}{2\sigma_t^2}} & t > t_o + \tau \quad \text{or} \quad \Pr(\text{ED}|X_{io}) > \xi \end{cases} \tag{8}$$

where t is the departure time after the wildfire initiation; t_o denotes the time warning is received about the occurrence of the wildfire; τ is the delay time (i.e., minimum milling time) that an evacuee incurs in process of information-gathering, evacuation decision-making, and logistical preparation; σ_t is a scale parameter; ξ is a marginal evacuation value above which the evacuee will make the decision to evacuate (Hsu and Peeta, 2013). τ, ξ, and σ_t can vary with the characteristics of the wildfire and the community.

3.2.3. Evacuation mode choice

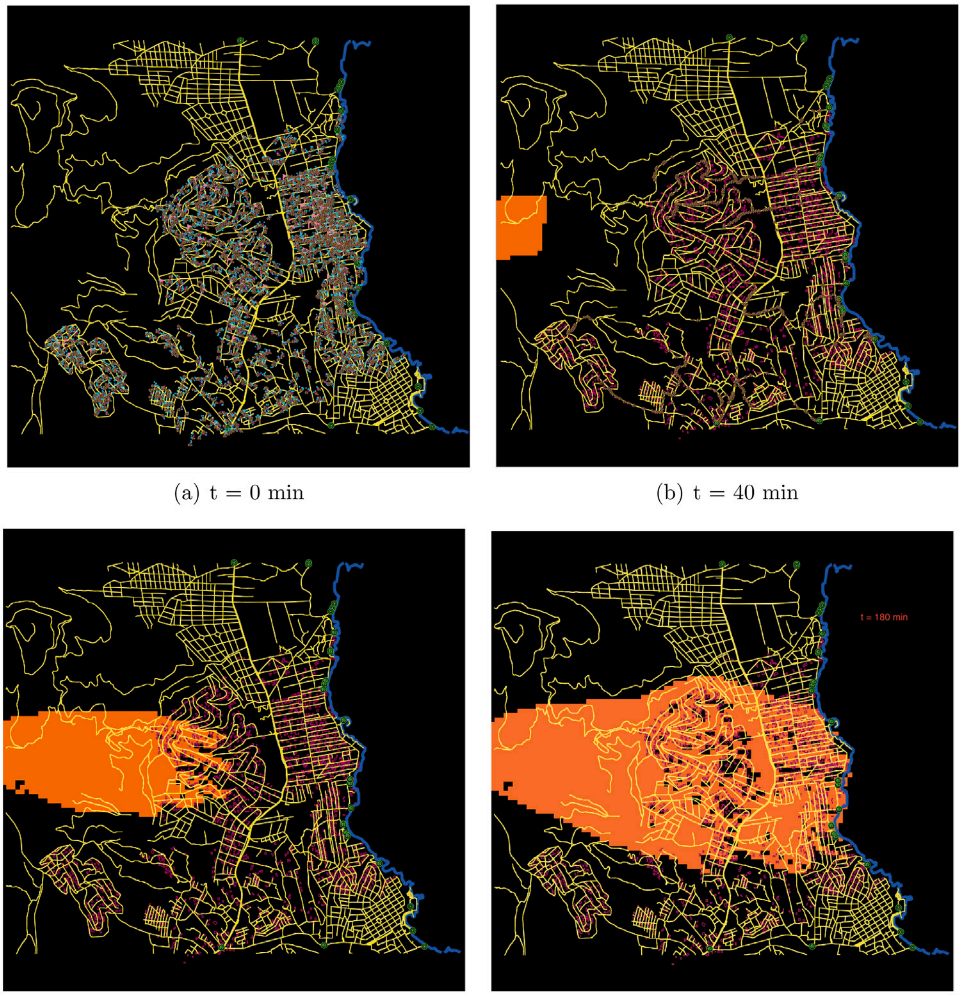
Mode choice was examined in two scenarios: a pedestrian-based evacuation and a vehicle-based scenario that assumed a maximum two persons per vehicle, which approximates the typical number of occupants in hurricane evacuations (Lindell et al., 2019). To incorporate car–car interaction, car speeds are modeled in this research based on how dense the traffic is in the road network. For example, they will decelerate as they approach the preceding vehicle in line and will accelerate if there is no vehicle immediately ahead (Wang et al., 2016). These considerations capture the emotional state a driver experiences during the evacuation process (Tisue and Wilensky, 2004). Speed values in the range of 5–50 mph are simulated to describe the whole picture from congested to the initial free-flow road network. As for the pedestrian-based evacuation, an array of scenarios (e.g., fast-, moderate-, slow-walking; jogging) is considered to generate travel speed distributions ranging $3.5 - 5.0$ ft/s (1.1–2.0 m/s) (Wang et al., 2016). To illustrate, average walking speed for a fast-walking agent is 5.0 ft/s, whereas for the speed for a slow-walking agent is 3.0 ft/s (Fraser et al., 2014). Link capacities were adjusted as needed for an “over-crowding" factor. If the proportion of the population evacuating on foot is greater than the capacity of the roads or trails through which people evacuate, walking speed decreases by a value of δ (Durst et al., 2014). In our research, we take the value of δ in ranging from $10 - 17\%$ (Moussaïd et al., 2010; Seyfried et al., 2005).

3.2.4. Evacuation route system

The ERS was defined by extracting the Mati transportation network from Open Street Map and saving it as an OSM file. A suite of available Python packages including MAPbox (Acharya and Raje, 2000) and EarthPy (Wasser et al., 2019) was used to produce high resolution Google Earth imagery of the study area and then examined to identify evacuation routes (see Fig. 3) (Lekkas et al., 2018). The simulation assumes that agents will choose from the available transportation modes (i.e., driving or walking) and follow the road network to the nearest evacuation shelter. In addition, all traffic is assumed to be outbound from the fire zone.

3.2.5. Evacuation shelters

Based on available literature reviews (Vallianou et al., 2020; Blandford, 2019), this study assumed twenty-seven evacuation destinations that were located outside of the wildfire impact zone (i.e., closer to the seashore). Spatial locations of the evacuation shelters are marked as green in Fig. 3. For the sake of brevity, a more granular overview of how the evacuation shelters are selected in this study is provided in Appendix A. Evacuation shelters are effective in reducing the number of casualties if they can withstand different types of hazards (Mostafizi et al., 2019a). This study varied the capacity of evacuation shelters as either limited- or unlimited- capacity (Goto et al., 2012). To reduce computational complexity, adequate parking capacity is also assumed for each of these shelters. Evacuees’ (both pedestrian and car users) search for the nearest shelter is modeled by the shortest path algorithm (Deng et al., 2012). This algorithm is repeated if an evacuee reaches an already-full shelter and needs to search for the next closest shelter.



(a) t = 0 min (b) t = 40 min

(c) t = 80 min (d) t = 180 min

Fig. 3. Snapshots of model simulation at different stages of the wildfire event, at (a) $t = 0$ min shows where the initial population (cyan), shelters (green) are distributed; (b) $t = 40$ min shows the movement of evacuees either by car (blue) or on foot (purple); and (c)–(d) wildfire engulfs the city at about $t = 80$ min to $t = 180$ min, causing casualties (orange). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

3.3. General applicability of the I-ABWEM model for evacuation risk assessment

The I-ABWEM can be explained by a set of formal definitions. Based on the vector data of household locations, road networks, shelters, and fire propagation model, we first construct a spatial geometric network $N(H, S, Z)$ where H denotes the set of origin nodes (households) likely to be affected by the wildfire at time t, S represents the set of destination nodes (shelters), $Z_{z=1,2,\ldots,z} \subset N$ defines an area where Z represents the set of zonal areas divided for the staged-based evacuation strategy, and a set K of nodes (assembly points) $(H \notin K, S \notin K)$ together with a set L of arcs among the nodes. The sizes of H, S and K are taken as e, f, g, respectively, such that $h = 1, 2, 3, \ldots, e; s = 1, 2, 3, \ldots, f; k = 1, 2, 3, \ldots.., g$. Considering $T = t_0, t_1, \ldots..., t_n$ to be the set of times over which the developed model is simulated, the algorithm is then executed as follows:

- In response to the fire front's projected progression, authorities consider two types of strategies: staged or simultaneous evacuation. Based on the chosen evacuation strategy, the authorities issue a warning at time ϖ_k^{φ} to the risk area population Z_z indicating that the fire front will arrive at their location in φ hours:

  $$\varpi_z^{\varphi} = \min_t \{t : Z_z \cap \varsigma_{t+\varphi} \neq \emptyset\}, t \in T$$

  where ς_t is the set of points affected by the wildfire at time t.
- Considering P to be the total population of the designated evacuation zone (either staged or simultaneous), we then estimate the number of people deciding to evacuate $\rho \in P$ based on Eq. (6). Those who decide to evacuate then choose whether to

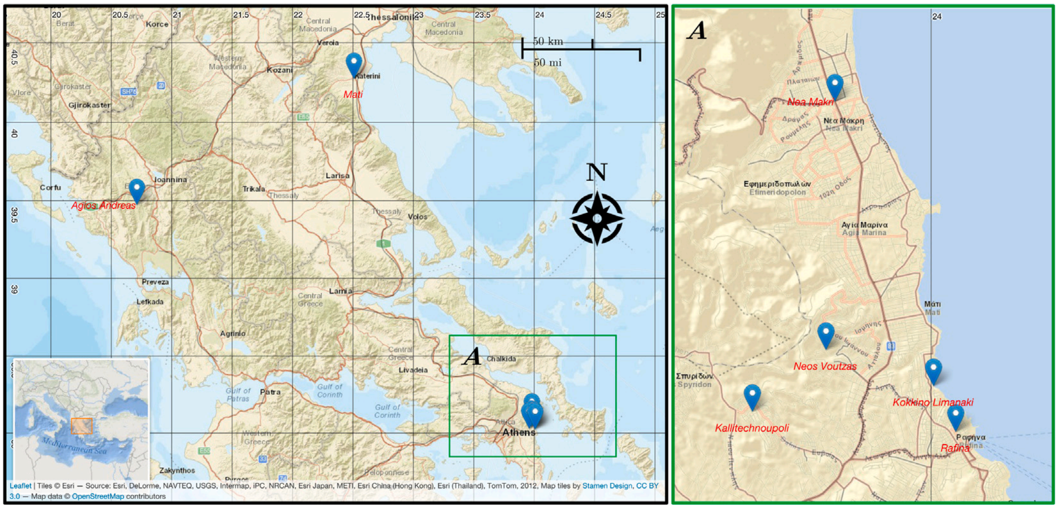


Fig. 4. Map of Mati, Greece and data collection sites.

evacuate on foot or in a vehicle. For those choosing a vehicle, we apply the vehicle assignment as a function λ that maps people to vehicles such that $\lambda : \rho \rightarrow V$, where V is a set of vehicles. In addition, we consider appropriate measures to simulate pedestrian dynamics (i.e., walking speed, overcrowding factor, and child presence).

- Evacuees choose a shelter based on the objective of minimizing their evacuation distance. The I-ABWEM applies the Dijkstra algorithm to construct a distance matrix $D(d_{hs})$ for the set H and S whose objective is to minimize the evacuation distance as follows:

$$D = \sum d_{hs} = \sum \min(l_{hk}, l_{sk}) \qquad h\forall H, s\forall S, k\forall \mathcal{K} \tag{9}$$

where d_{hs} represents the shortest distance between origin node h and destination node s, l_{hk} denotes the arc's length from node h to node k and l_{ks} is the arc's length from node k to node s. An evacuation shelter is then chosen after analyzing whether there is enough capacity ($C_{d_{hs}}$) remaining to accommodate the number of individuals likely to access the evacuation zone:

$$\sum C_{hs} = e, \quad \text{subject to} \quad C_{hs} = \begin{cases} 0 & C_{hs} > \rho_{d_{hs}} \\ 1 & C_{hs} < \rho_{d_{hs}} \end{cases} \tag{10}$$

If evacuees find the chosen shelter overcrowded, the I-ABWEM reapplies Eq. (9), (10) to reroute the evacuees to the next available shelter.

4. Results and analysis

4.1. Study area and data

Mati, Greece is a village located 40 km from Athens on the east coast of the Attica region, Fig. 4 shows the relative location of the Mati area in the world map. Mati is a popular tourist destination with hotels, restaurants, beaches, and recreational activities. Mati, which is close to the Rafina harbor on the Aegean Sea, can be accessed through Marathonos Avenue to the west.

In July 2018, Mati experienced wildfires that were second only to the 2009 Black Saturday bushfires in Australia (Palaiologou et al., 2019). The flames trapped and burned people inside their houses and cars within a few meters from the beach causing 100 confirmed deaths and in excess of 600 injuries. The wildfires also affected areas adjacent to Mati (e.g., the cities of Rafina and Marathonas (Fig. 5)), with about 3,200 hectares burned that included forests and residential buildings (Lekkas et al., 2018). We limited our study to Mati, which suffered the most damage in terms of deaths and severe damage in significant social infrastructures such as electricity and water networks.

A survey of households in the area collected data on variables identified in previous wildfire evacuation studies as determinants of the evacuate decision (Sorensen et al., 2009; McLennan et al., 2019). These variables included a number of pre-event and sociodemographic variables, as well as the types of warnings received (both the first warning and any subsequent warnings) and environmental cues observed (flames, embers and smoke) before deciding on a particular protective action – to stay or evacuate. In addition, respondents were asked whether they had received any evacuation training, their degree of risk perception at the time of that decision, and their choice of transportation mode (and the reason for that choice). Appendix B lists the questionnaire items used in the data analyses.

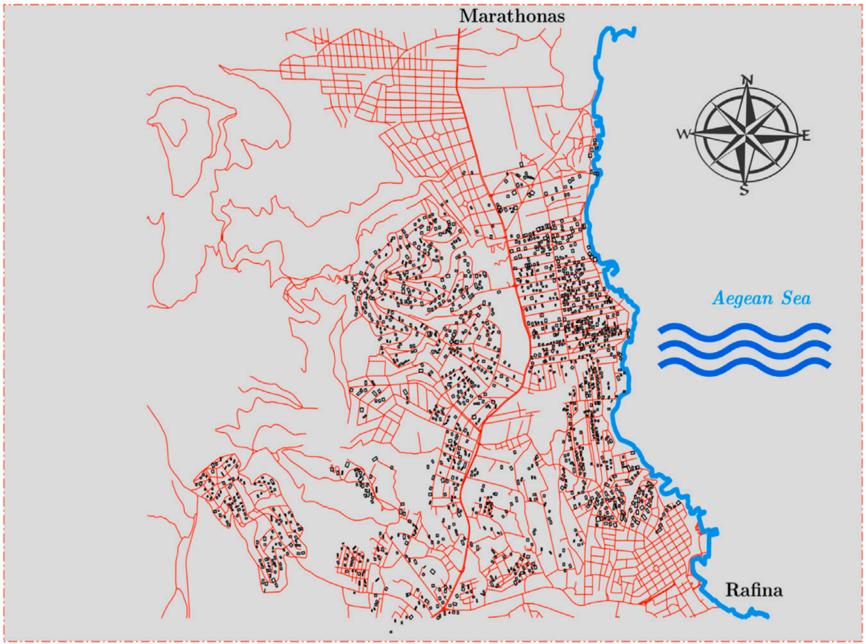


Fig. 5. Mati's evacuation map: it provides an overview of the road network with black dots representing the household locations.

Table 2
Input Parameters for the I-ABWEM Model.

Model parameters	Data source and mapping	Data range
Choice of mode	Q: Did you have a motor vehicle (e.g., car or motorcycle) available when you were deciding whether to evacuate? Q: How did you evacuate?	Varied in sensitivity analyses
Population distribution	GIS data layers – Census data	Constant
Evacuation intent	Provided by emergency management	To the edge of hazard zone
Fire front propagation speed	Computed using FARSITE (Srivas et al., 2016)	Constant
Background traffic	Calculated based on Section 3.2.1	Varied in sensitivity analyses

Questionnaires were revised based on extensive literature review and later were translated to Greek. The survey was administered during the first wave of COVID-19 pandemic in April 2020. Due to the prevalent pandemic restrictions, all questionnaires were collected though an online platform following the Dillman et al. (2014)'s procedure. As most homes within the wildfire affected area were destroyed, careful consideration was taken while sending out the questionnaire so as to collect a representative sample of individuals who experienced the wildfire. To illustrate, the survey participants' spatial extent ranged from the wildfire's origin (Agios Andreas) to the locations where it had the most impact in terms of fatalities and disruption to the transportation network (e.g., Kallitechnoupoli, Neos Voutzas). Fig. 4 displays the locations of the survey respondents. The final sample of 152 participants was mostly (53.3%) female, had a median age of $30--49$ years, and a median income of 25,001€- 50,000€. The participants were also predominantly married (55%) and most owned their homes (79.6%) at the time of the fire. Most respondents (72.4%) had 10 or more years tenure in the area. This sample was similar to Greece's 2011 census data (Greece, 2011) in terms of gender composition (52.5% female) and age (median of 41.3 years). Further, appropriate statistical analysis and visual interpretation were performed in order to draw conclusions from the data collected through the survey. Specifically, 90.8% of respondents owned a car at the time of the wildfire, but only 76.2% of them used their vehicles to evacuate (statistically significant difference at 95% confidence level).

To systematically analyze evacuation times, a baseline model was run first to replicate the real Mati event – simultaneous evacuation without any official notice from authorities, 76.2% of the residents traveling by car to the nearest shelter without considering if the shelter is at full capacity, and wildfire propagating with actual environmental conditions (e.g., wind speed (40 km/h), temperature (31°C), and relative humidity (40%)), followed by runs that increased, decreased, or eliminated each evacuation demand or supply variable individually as detailed in Table 2.

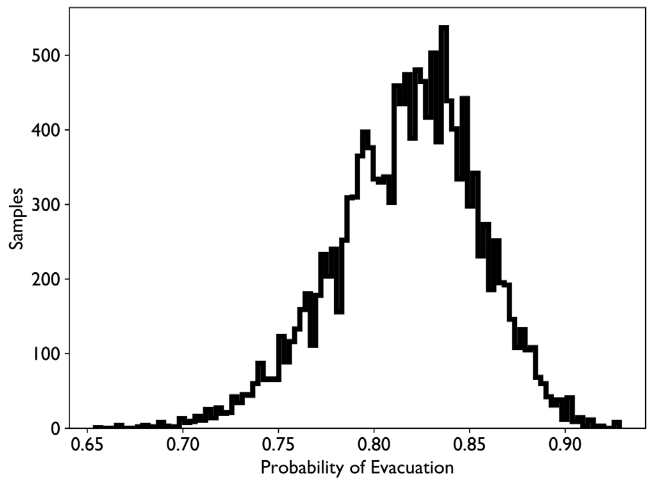


Fig. 6. Probability distribution for evacuation based on Markov Chain Monte Carlo simulation.

Table 3
Binomial logistic regression of multiple factors on evacuation decision (evacuate or stay) (n=152); coefficients that are marginally significant (at 0.05 or 0.10) are included.

	Coeff. (β)	Standard error	p-value	Exp(β)
Prior awareness of fire risk	1.1871	0.652	0.069*	3.277
Had an evacuation plan for wildfires	0.8245	0.483	0.088*	2.280
Constant	1.1159	0.321	0.001**	3.052

Factors such as choice of evacuation strategy, milling time, and travel speed were used to assess evacuation effectiveness (Wang et al., 2016). The decisive influence of these variables on evacuation life safety motivated sensitivity analyses of these factors' effects on the evacuation mortality. All of this study's analyses use Monte Carlo simulation to account for stochasticity in the model, regression equations for each of the evaluation criteria are provided in Appendix C. The following variables were tested for the analyses:

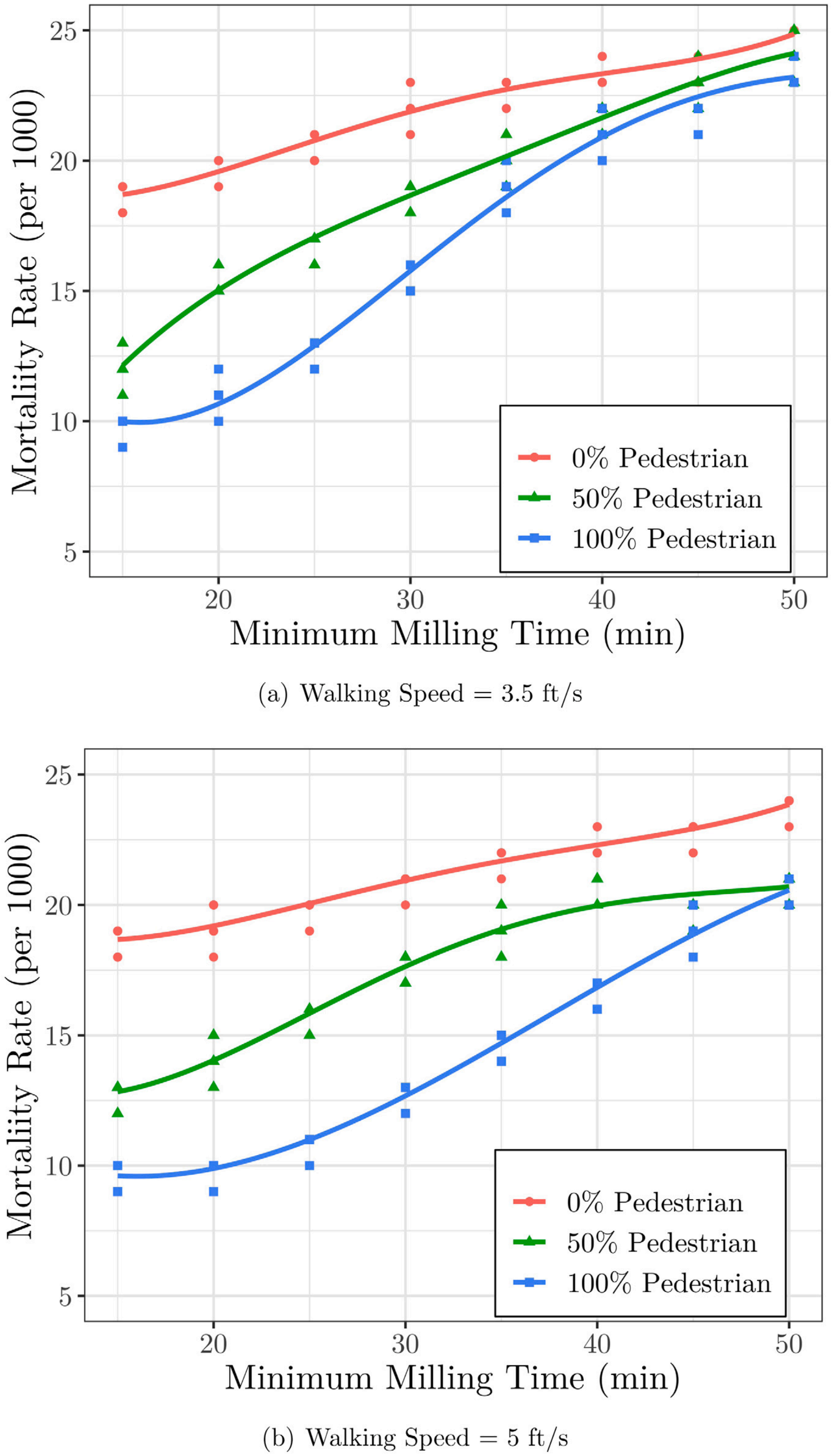
- Staged evacuation is the baseline case and simultaneous evacuation is the alternate case;
- Child absence is the baseline case and child presence is the alternate case;
- Milling time is assumed to be zero in the baseline case and a randomly assigned departure time based on a Rayleigh distribution with a range of 15 to 50 min departure time in the alternate case;
- Shelter capacity is modeled by assigning evacuees to the closest evacuation shelter without considering shelter overflow in the baseline case and considering capacity constraint in the alternate;
- Mode choice is assumed to be pedestrian-only for all evacuees in the baseline case and car-only for the address with available cars based on Census data in the alternate case;
- Various walking speeds (3.5 ft/s, 4.5 ft/s, and 6.5 ft/s) and driving speeds (5–50 mph) are considered.

4.2. Overall evacuation risk based on natural and sociotechnical systems of wildfire events

4.2.1. Analysis of evacuation decisions

The overwhelming majority (86%) of the people in the threatened area evacuated. This high percentage of evacuees attenuated the variance in the dependent variable and, in turn, its correlations with the explanatory variables. Because of this artifactual limitation, we used a less stringent significance level–$p = 0.10$ in exploratory analyses of the effects of 20 variables on survey respondents' evacuation decisions. Table 3 indicates that prior awareness of fire risk significantly predicted evacuation decisions (β= 1.19, $p < 0.1$), as did possession of a prior evacuation plan (β= 0.82, $p = 0.09$). That is, the odds of evacuation are more than 3.2 times higher for each one-unit increase in prior awareness of fire risk. There are similar results for the influence of having a pre-incident wildfire evacuation plan, which replicate previous wildfire studies (Kuligowski et al., 2021; Lovreglio et al., 2020) that found evacuation decisions were predicted by risk perception variables but not demographic variables. As noted earlier, there were no warnings issued by authorities (e.g., police, emergency managers) during the Mati wildfire event, so people took protective actions based on environmental cues (i.e., seeing the wildfire first-hand) (Lekkas et al., 2018).

We then performed a Markov Chain Monte Carlo simulation based on Eq. (7) to estimate the posterior probability of evacuation (see Fig. 6) that can be described by $\mathcal{N} \sim (0.82, 0.03)$ (two-sided Kolmogorov–Smirnov test, p-value $< 2.2e - 16$). These results are integrated into the I-ABWEM model to provide an estimate of how many people evacuated as well as a definitive departure time distribution.



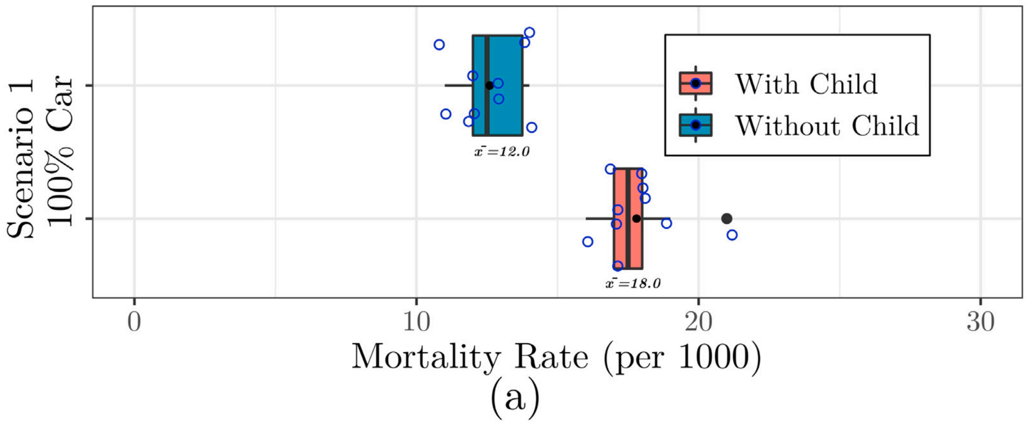
(a) Walking Speed = 3.5 ft/s

(b) Walking Speed = 5 ft/s

Fig. 7. Mortality rate based on ranges in minimum milling time for walking speed of (a) 3.5 ft/s, (b) 5 ft/s.

4.2.2. Influence of milling time on evacuation effectiveness

The results in Fig. 7 show that milling time has a positive influence on disaster mortality (note that the dependent variable is plotted on the horizontal axis rather than the vertical axis). As indicated earlier, milling time is modeled by the modified Rayleigh



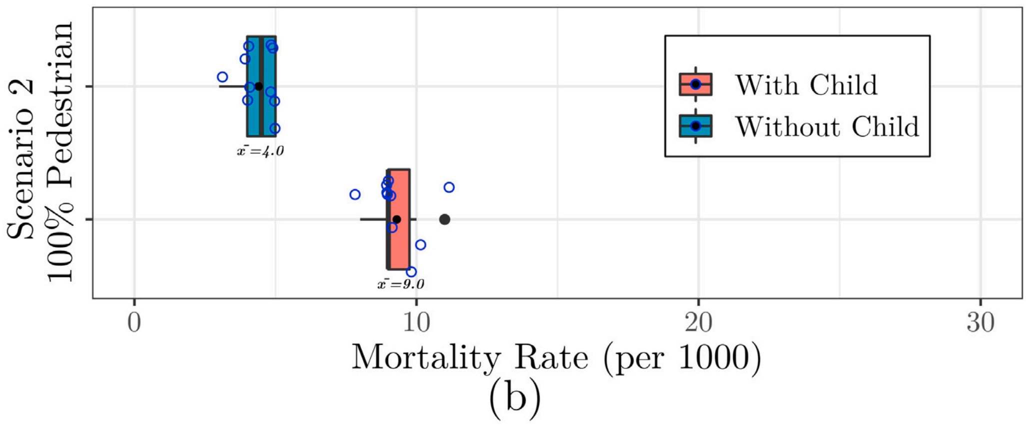


Fig. 8. Effect of child-presence on mortality rate on the Mati network, here $\bar{x}$ refers to average mortality rate for each scenario.

distribution in Eq. (8) that has three parameters – τ, σ, and ξ where τ represents the minimum delay time, σ is the scale parameter, and ξ is threshold value as a measure of risk perception. Values of τ, σ, and ξ can vary depending the adopted evacuation strategy (e.g., staged or simultaneous evacuation) and evacuation mode choice (Mostafizi et al., 2019b). However, for simplicity, only the impact of τ on evacuation effectiveness was assessed in the present analysis while ξ, σ were kept constant at 0.2 and 0.5, respectively, in accordance with Hsu and Peeta (2013). To capture stochasticity in human decision-making process during evacuation, eight simulation runs were conducted for each scenario - 0% pedestrian, 50% pedestrian, and 100% pedestrian. Regression analysis is then applied to characterize the trend of the simulated mortality rate.

Fig. 7 shows how mortality rate varies as minimum milling time, τ, ranges from 15 – 50 minutes. Two average walking speeds were considered: 3.5 ft/s (1.1 m/s) and 5 ft/s (1.5 m/s). For both cases, mortality rate increases with minimum milling time. In addition, mortality rate increases with the percentage of evacuees evacuating by foot (see Fig. 7a and 7b). Specifically, a milling time of 20 minutes when walking speed is 5 ft/s, produces a 48% decrease in the mortality rate during the 100% pedestrian-based evacuation in comparison to the 0% pedestrian-based scenario. However, there is a smaller difference in the mortality rate when milling time reaches 40 minutes, for by that time the wildfire has progressed far enough into the affected area. This highlights the need for early evacuation decisions during such extreme events.

4.2.3. Influence of child-presence in household on evacuation effectiveness

Fig. 8 shows that having the presence of children increases the mortality rate as children tend to decrease evacuees' walking speed. We perform ten simulation runs to account for stochasticity in the evacuation scenario with the presence of children characterized by two effects: (1) milling time, and (2) evacuation speed is decreased (for both vehicle- and pedestrian-based evacuation) by 50%. When 100% vehicle-based evacuation is adopted and children are present, the average mortality rate reaches 18; whereas it remains below 12 when children are absent – a 30% decrease in the mortality rate. On the other hand, for a 100% pedestrian-based evacuation scenario, the absence of children produces a 52% decrease in the mortality rate. The presence of children is less sensitive in the 100% vehicle-based scenario, because in this case travel speed is unaffected and more people reach the shelters safely. Both cases, however, capture the variation in the mortality rate with and without child-presence. These results underscore the importance of providing targeted messaging to households with children about appropriate evacuation behavior (i.e., *early* preparedness to stay and defend or to evacuate early).

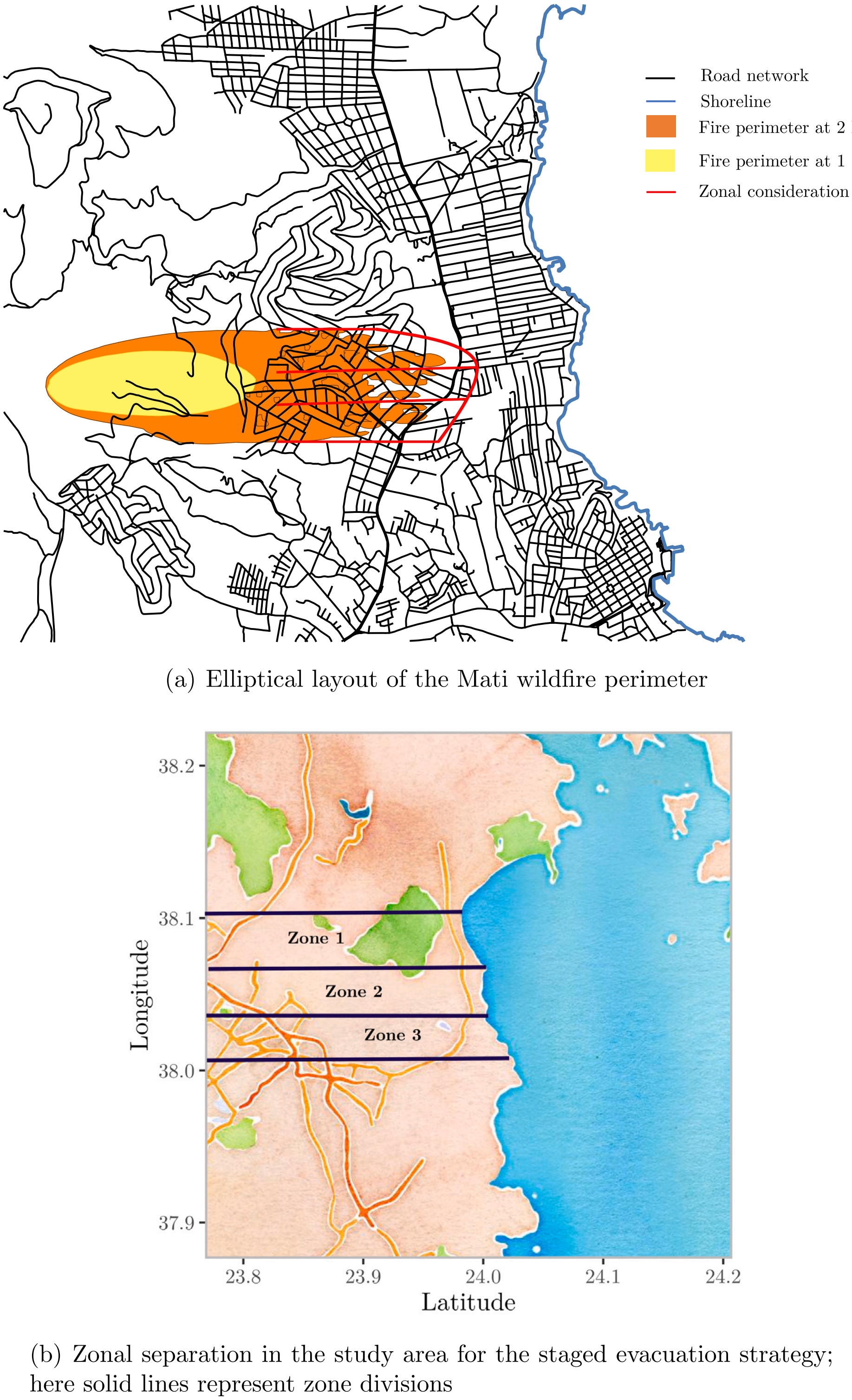


Fig. 9. Zoning for staged evacuation in Mati, Greece.

4.3. Overall evacuation risk based on engineered-system components of wildfire events

4.3.1. Staged evacuation or simultaneous evacuation?

Fig. 9 shows how the risk area is divided into three arbitrary zones while considering several factors, such as population distribution (Greece, 2011) (i.e., identifying areas from which the Mati evacuation traffic originates) and likelihood of exposure

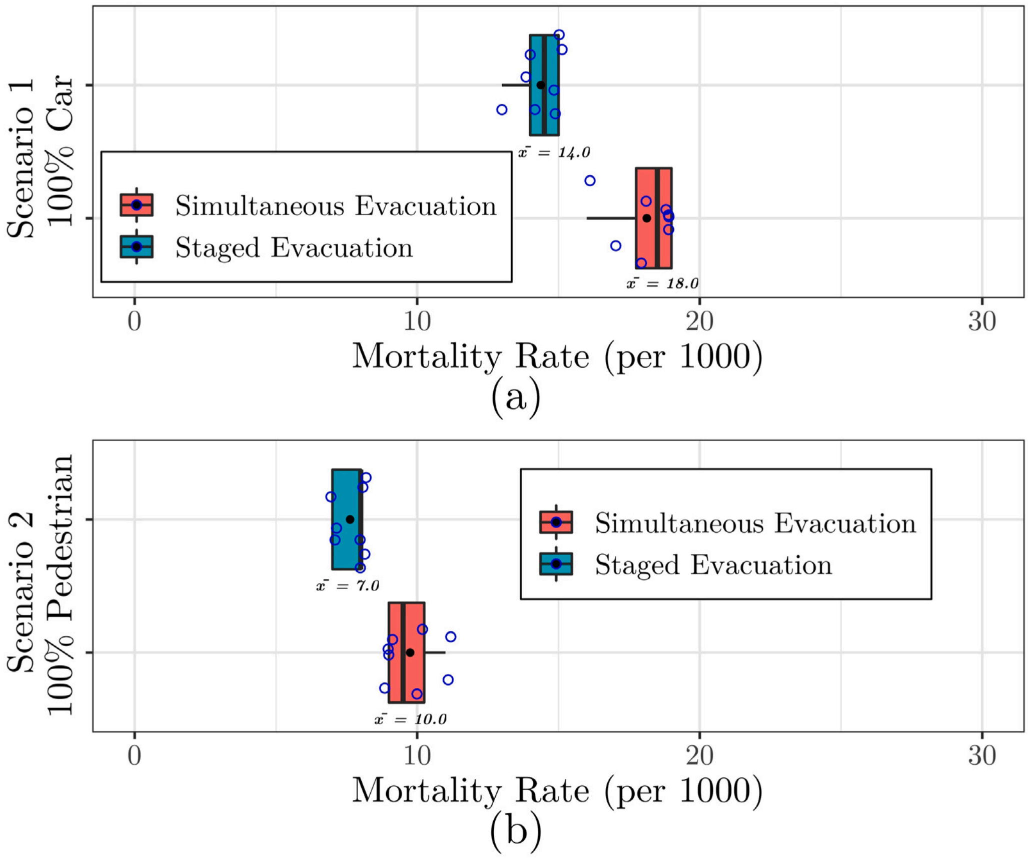


Fig. 10. Efficacy of different evacuation strategies for the Mati network.

to fire propagation. Although the affected area could be divided into a different number of zones, we chose three zones because that number is arguably large enough to make a difference (one zone would be a simultaneous evacuation) but small enough to avoid confusion among the risk area population. In addition, the choice of three zones was also dictated by the fact that Mati wildfire was propagating towards the shore in an asymmetrical ellipse (as illustrated in Fig. 9(a)). Therefore, the staged evacuation strategy is implemented by the three zones detailed in Fig. 9(b), in which Zone 1 is advised to evacuate first, followed by Zone 2, and then Zone 3. By contrast, the simultaneous evacuation strategy assumes that warnings are disseminated to all zones at the same time and all vehicles or residents initiate the evacuation process following Eq. (8).

Fig. 10 displays the results of ten simulation runs performed for each scenario (i.e., simultaneous and staged evacuation) to account for stochasticity. Fig. 10 shows that the two evacuation strategies differ in effectiveness. Specifically, a 100% vehicle-based evacuation yields an average mortality rate of 18 per thousand for a simultaneous evacuation but a 22% decrease to a value of 14 per thousand for a staged evacuation. These results are consistent with those of other studies concluding that simultaneous evacuation over a short travel distance is not recommended since this will create bottlenecks resulting in increased travel times (Spiess, 1990). Similar results are found when 100% pedestrian evacuation is implemented. For simultaneous evacuation, the average mortality rate is 10 per thousand, which drops to 7 per thousand if staged evacuation is implemented.

For both scenarios (vehicle- and pedestrian-based), congestion is lower during staged evacuation than in simultaneous evacuation, since there are a fewer evacuees in the road network at any given time. Of course, these evacuation scenarios assume ideal conditions that do not explicitly simulate traffic signals or complex driving behaviors under high traffic density. However, these factors would have a greater adverse effect on simultaneous evacuation than on staged evacuation, supporting previous conclusions that staged evacuation is likely to be the preferable evacuation strategy (Spiess, 1990). Nonetheless, future research should continue to examine the effects of different variables on the effectiveness of staged evacuation.

4.3.2. Multimodal evacuation: walk or drive?

Fig. 11 shows how a split in mode choice affects the mortality rate. Specifically, as the percentage of pedestrians increases from $0-50\%$, the car mortality rate decreases exponentially by a factor of 3.4. This result can be attributed to the reduction of congestion that traps people in their vehicles as the fire front overtakes them. On the other hand, we observe an approximately linear increase in the pedestrian mortality rate with an increase in the percentage of pedestrians. This result can be attributed to the mobility advantage

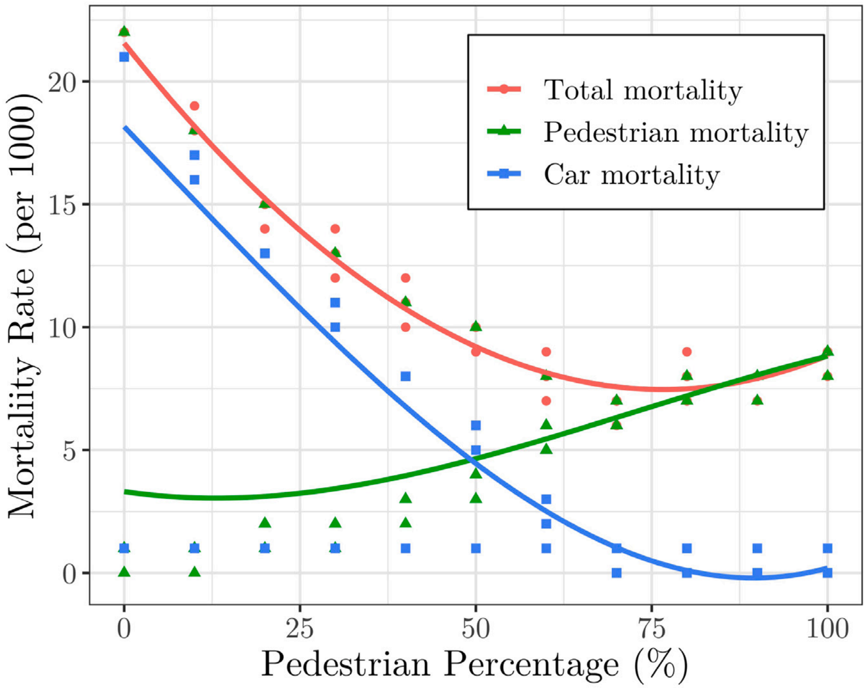


Fig. 11. Variation in evacuation risk in terms of mortality rate based on different modal choice; here V_{walk} = 3.5 ft/s and τ = 10 is considered. Here eight simulation runs were performed to capture the stochastic evacuation process and regression line represents the trend of mortality rate obtained from simulation.

that driving offers over walking. The net effect of these two mortality curves is that the total mortality rate is minimized when the pedestrian percentage is 70%, after which there is a slight increase in mortality because the pedestrian mortality rate continues to rise after the car mortality rate has reached a minimum. These observations are in line with the findings from Spiess (1990), which indicate that increasing the number of vehicles on the road increases traffic congestion, especially on roads and bridges that lead to evacuation shelters. These results are also consistent with events in the Mati wildfire, where people were seen abandoning their cars in the streets as the overcrowded road network lacked the capacity to accommodate excessive vehicle demand (Vallianou et al., 2020). This result suggests that evacuation managers should carefully examine pedestrian evacuation so they can encourage pedestrian evacuation in the areas where it is appropriate.

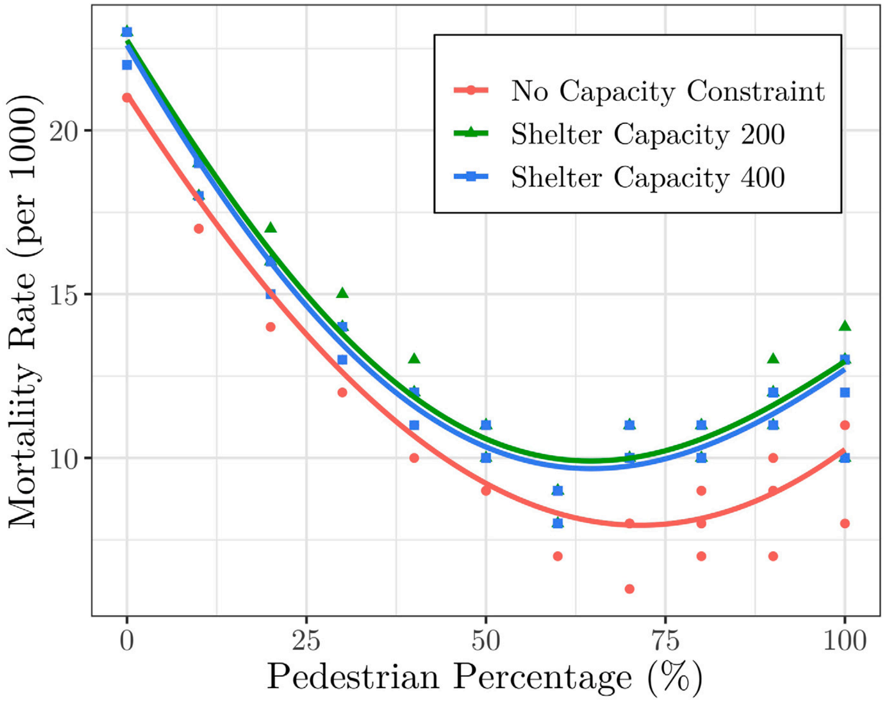
4.3.3. Influence of shelter capacity on evacuation effectiveness

Given the assumption that all residents within a community will travel to the same shelters using the shortest evacuation route, two evacuation scenarios are examined to see how shelter capacity influences the mortality rate: Scenario 1 - walking speed of 6 ft/s and maximum driving speed of 35 mph; and Scenario 2 - walking speed of 3.5 ft/s and maximum driving speed of 20 mph. For demonstration purposes, this study examined the effects of three different shelter capacities on the mortality rate based on eight simulation runs for each of these cases – 200 evacuees, 400 evacuees, and an unlimited number of evacuees. The results in Fig. 12 suggest that evacuation shelters' capacity constraints produce bottlenecks that propagate upstream into the burn area. Such information can help emergency managers anticipate the number of people who might be stranded along different sections of highway if the evacuation route becomes impassible. These results are similar to those in Section 4.3.2; as capacity increases we see a reduction in the mortality rate but the amount of the reduction varies with mode split. Specifically, when pedestrian percentage is limited to 50% for the first evacuation scenario, there is a 17% increase in the mortality rate when shelter capacity is limited to 200 in comparison to when there have been no capacity-constraint. In addition, initially we see a decrease in the mortality rate as the pedestrian percentage increases, reaching a minimum when it is 70%; however, the mortality rate increases beyond that minimum because, increasing congestion leaves an increasing number of people exposed to the advancing fire front.

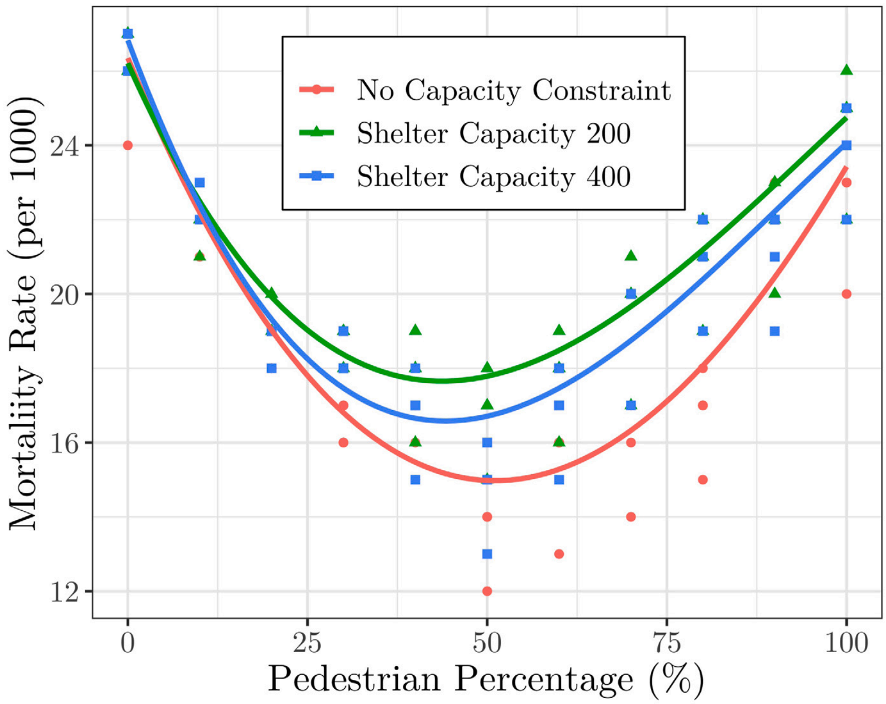
As for the second scenario, mortality reaches a minimum at 50% pedestrian evacuation, after which it increases due to increasing congestion. If there is an inadequate traffic management plan for the road users (e.g., contraflow, emergency shoulder use, appropriate way-finding system) (Zhang et al., 2017), evacuee movement slows – increasing the possibility of a large number of people stranded along the evacuation routes. These observations are consistent with Mitsopoulos et al. (2020), which explains that many evacuees were trapped in congestion that developed in narrow streets during vehicular evacuation attempts.

4.3.4. Influence of travel speed on evacuation effectiveness

Fig. 13 Panel a shows how walking speed affects mortality rate when evacuees' walking speeds are assumed to follow a normal distribution (Wang et al., 2016). Three different mean walking speeds are considered: u = 3.5 ft/s (1.1 m/s), 4.5 ft/s (1.4 m/s), and

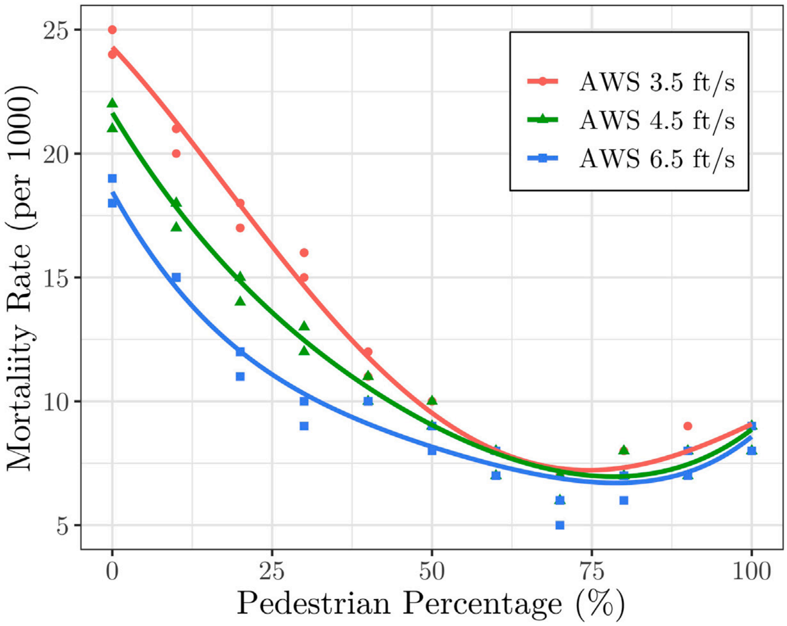


(a)

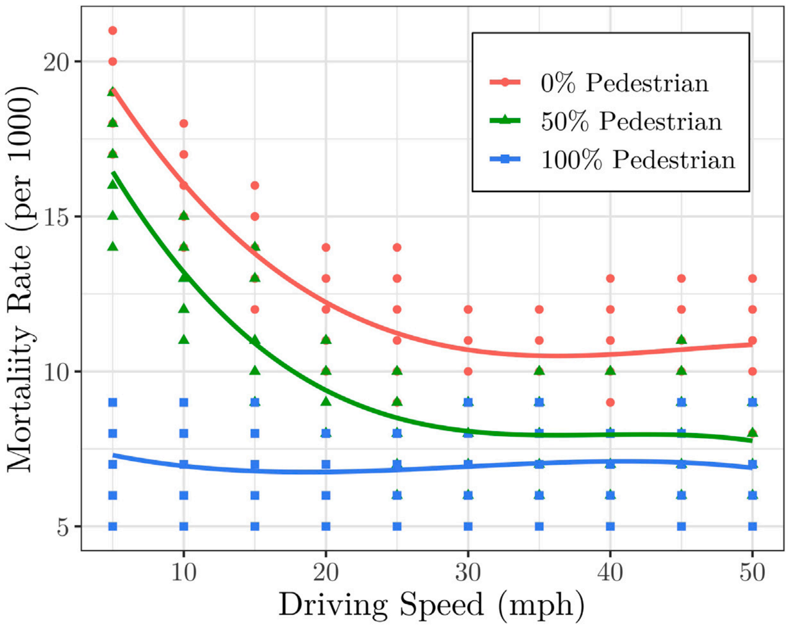


(b)

Fig. 12. Impact of shelter capacity on overall evacuation risk: (a) V_{walk} = 6 ft/s and maximum driving speed = 35 mph; (b) V_{walk} = 3.5 ft/s and maximum driving speed = 20 mph. The regression lines indicate the changes in average mortality rate for different percentages of pedestrian evacuation.



(a) Mortality rate based on ranges in waling speed (AWS is average walking speed) with maximum driving speed of 5 mph



(b) Impact of maximum driving speed on mortality ($\tau = 15$ min)

Fig. 13. Impact of travel speed on mortality, The regression lines indicate the changes in mortality rate averaged for different travel speeds.

6.5 ft/s (2.0 m/s). As one would expect, mortality rate decreases as walking speed increases. For example, as pedestrian percentage reaches 20%, the mortality rate decreases by a factor of 0.3 when pedestrian speed increases from 3.5 – 6.5 ft/s. However, from a 70% pedestrian percentage upward, the mortality rate increases because increasing congestion reduces the number of people who successfully evacuate.

Fig. 13 Panel b shows how driving speed affects mortality rate when walking speed is kept constant at 6.5 ft/s. Specifically, mortality decreases as driving speed increases to 25 mph (40 kph), but further increases in driving speed have a negligible effect for all mode splits except 100% pedestrian (a situation in which driving speed is obviously irrelevant). Moreover, this effect is compounded by an increase in the pedestrian evacuation percentage, implying that there is also a reduction in vehicular traffic that reduces the mortality rate.

5. Conclusions and future research

The frequent occurrence of wildfires throughout the world produces casualties, property damage, and environmental destruction. Although evacuations cannot reduce property damage and environmental destruction, they can reduce casualties. Thus, it is necessary to develop effective evacuation modeling and simulation systems that will help authorities to identify more effective evacuation management strategies. This paper describes the development of a wildfire evacuation ABM in NetLogo that models people's behavior during different situations. On the one hand, the results, and the conclusions drawn from those results, are approximations. On the other hand, they defined by real world circumstances (Dillon et al., 2015). To illustrate, we synthesize an evacuee's sociotechnical response to wildfires to obtain an accurate estimate of the number of evacuees as well as a definitive departure time distribution. With all these assumptions to replicate the real world conditions of the Mati wildfire, this study's results show –

- Both pedestrian walking speed and vehicle driving speed reduce mortality rates, but the effects of these variables depend upon the values of other variables;
- Targeted messaging in the form of focus group discussion or other appropriate strategies should be provided to households with children to promote pre-incident evacuation planning;
- Staged evacuation can achieve a significant reduction in mortality compared to a simultaneous evacuation,
- The lowest mortality can be achieved when there is a modal split between vehicular and pedestrian evacuation. In the Mati case, this occurs when 70% of evacuees choose to walk and 30% choose to drive,
- Improved shelter capacity–allocation schemes can significantly reduce mortality.

These results provide valuable insights into appropriate evacuation strategies in which elected officials, emergency managers, and city planners seek to reduce the potential loss of life from wildfires.

Future research should investigate the impact of strategically placing evacuation shelters (e.g., shelter-in-refuge (Cova et al., 2017)) on mortality, as well as conducting analyses to see if the distance of these shelters from household locations influences residents' evacuation mode choice. Further analyses should examine the effects of additional variables on evacuation effectiveness. These variables can be categorized as supply management and demand management strategies (Lindell et al., 2019). The supply management strategies include (a) access control to prevent traffic from entering the risk area, (b) turn restrictions and signal timing modifications to avoid delays caused by cross-traffic, (c) police manual control at intersections to adapt to changing traffic flows, and (d) contraflow that converts inbound lanes to use by outbound traffic. Unfortunately, these supply management strategies depend on the availability of an adequate number of trained traffic control personnel for their implementation. Consequently, they are feasible only if authorities have enough forewarning so they can mobilize and dispatch those traffic control personnel to the incident scene. In addition to the evacuation mode choice strategy studied here, demand management strategies include warning households to (a) evacuate only if they are in an area that authorities have designated as being at risk, (b) wait to leave until the time designated by authorities (avoid early departures from downstream locations), (c) leave at the time designated by authorities (avoid late departures from upstream locations), and (d) take the evacuation routes that authorities recommend for their area. Households' noncompliance with these recommendations, which has been documented in numerous evacuations, can adversely affect evacuation success. For example, the evacuation of households outside the officially designated risk area – known as evacuation shadow – can produce queues that propagate upstream and cause those in the risk area to be overtaken by the hazard. Evacuation shadow has been documented in response to a wide range of hazards since the nuclear power plant accident at Three Mile Island (Zeigler et al., 1981). Future studies should also pay special attention to collecting a diverse sample that includes people who face less severe wildfire threats (e.g., those on the lateral fringes of the fire propagation path) to ensure that there is adequate variation in the dependent variable. In many cases, a distribution in which 50 percent of the respondents have evacuated will have the best chance of correctly detecting statistically significant predictors of evacuation. To develop a more realistic and effective evacuation strategy in the event of a wildfire, future research should also include scenarios in which residents begin their evacuations in their car but abandon them to walk to safety when congestion becomes prevalent along the evacuation routes. As for the modeling perspective, future research endeavors should include incorporating the thermal shielding advantage (Li et al., 2017) vehicle users may experience to see if such consideration affects the number of casualties during a wildfire event. In addition, fire propagation model should include data about critical level of exposure duration (Reinhardt, 2000) to provide a more realistic casualty estimation.

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Appendix A. Evacuation shelter locations

Fig. A.14 provides an overview of evacuation shelter locations considered for the simulation purpose. While selecting each of these locations, several considerations were taken into account which are as follows -

- Evacuation shelter is located beyond the wildfire propagation zone. Panel A in Fig. A.14 contains such example shelters.
- Evacuation shelter is along the shore and beyond that (see Panel B in Fig. A.14). As the Mati fire picked up speed due to strong wind-push from the mountain of Penteli, people tried to evacuate towards the sea (Haynes et al., 2020). There were even instances where people were rescued by boats at a distance of kilometers from the shores (Xanthopoulos and Athanasiou, 2019).

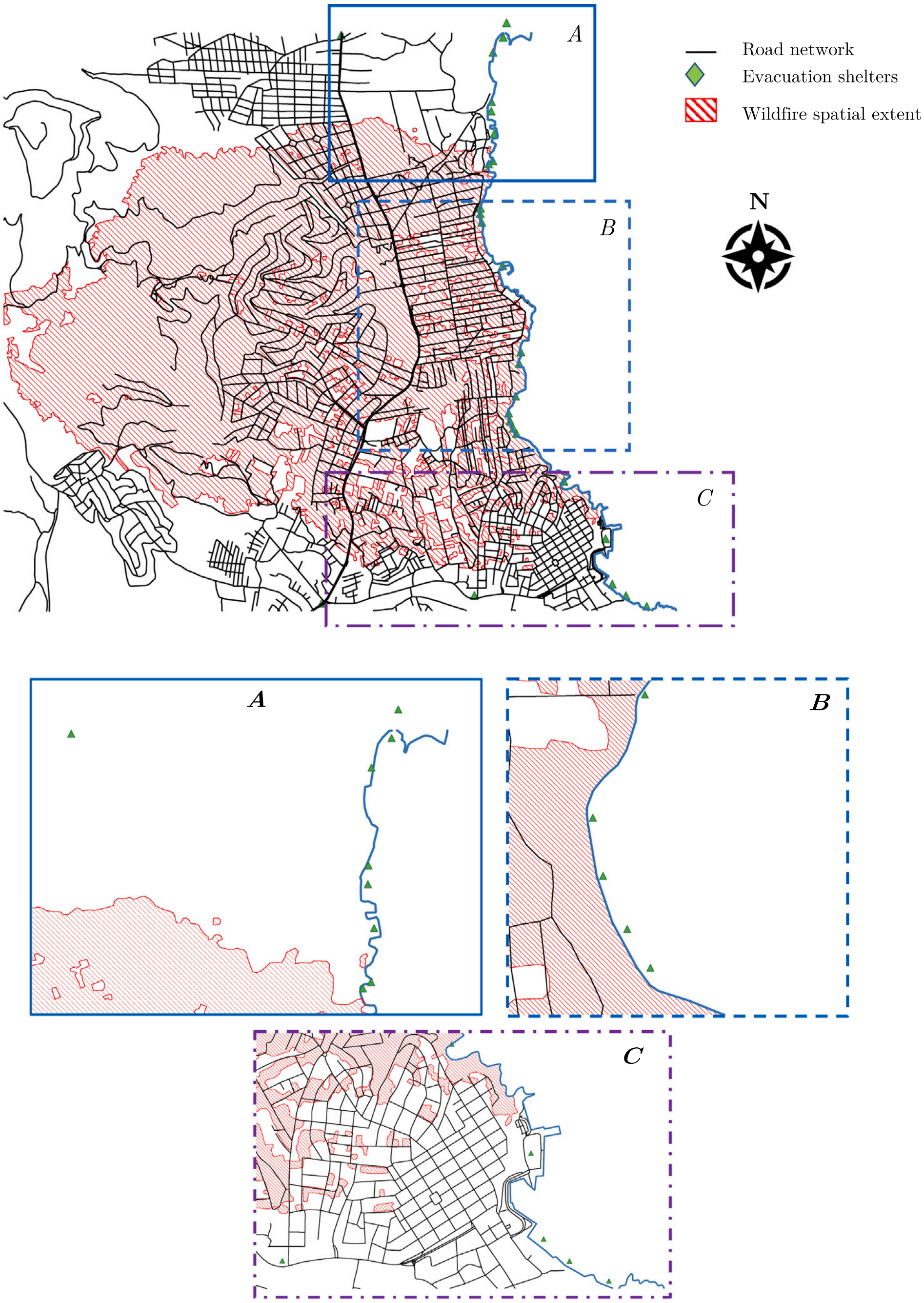

Fig. A.14. Locations of evacuation shelters in Mati, Greece.

Appendix B. Survey questionnaire items

See Table B.4.

Table B.4
Survey items used in data analysis.

Item	Item text	Scale or response options
Preparation for wildfires	*Did you have a household emergency plan for wildfires in place before the Mati fire?*	3 day supply of water; supply of non-perishable food; Emergency kit; Battery powered radio
Prior awareness of fire risk	*Before the Mati fire, did you know that wildfires could be a problem in your community?*	Yes, No
Length of residence	*How long had you lived at that residence (at the time of the 2018 Mati fire)?*	Less than 1 year; 1–2 years; 3–4 years; 5–10 years; 10+ years
Income	*Which of the following categories best describes your yearly household income before taxes?*	less than 25,000€; 25,001€- 50,000€; 50,000€+
Risk perception at time of decision	*At that moment you decided what to do, how likely did you think it was that it would – (1) severely damage or destroy many homes in your community? (2) injure or kill many people in your village if they did not evacuate? (3) severely damage or destroy your home? (4) injure or kill you or your family if you did not evacuate?*	1 (No. likely) to 5 (extremely likely)
Gender	*What is your gender?*	Male; Female; other
Education	*What is the highest level of education you have completed?*	Elementary school (Grade 1–5)/Junior high or middle school (Grade 6–8)/High school (Grade 9–12); Some college/trade school; College degree (2 or 4 year degree); Graduate degree (Master, Ph.D., etc.)
Martial status	*What is your marital status?*	Married; single; Divorced; Widowed
Presence of children	*How many people in your household are less than 18 years?*	1–4
Age	*How many years old are you?*	0–29; 30–49; 50–69; 70+

Appendix C. Regression equations

See Table C.5.

Table C.5
Coefficients for Regression line equations.[a].

	Scenario	α	β_1	β_2	R^2
Fig. 7a	0% pedestrian	92.30	1.62	−0.001	0.96
	50% pedestrian	28.97	3.56	−0.023	0.98
	100% pedestrian	9.85	3.27	−0.011	0.97
Fig. 7b	0% pedestrian	100.85	0.88	0.001	0.95
	50% pedestrian	24.89	3.92	−0.040	0.91
	100% pedestrian	46.84	0.21	0.030	0.98
Fig. 11	Total mortality	132.20	−2.27	0.020	0.98
	Pedestrian mortality	18.90	0.01	0.003	0.25
	Car mortality	113.24	−2.28	0.011	0.79
Fig. 12a	No capacity constraint	130.72	−2.28	0.020	0.98
	Shelter capacity 200	140.28	−2.38	0.020	0.97
	Shelter capacity 400	137.78	−2.48	0.040	0.97
Fig. 12b	No capacity constraint	159.77	−2.58	0.020	0.91
	Shelter capacity 200	155.52	−1.87	0.020	0.87
	Shelter capacity 400	157.67	−2.16	0.020	0.88
Fig. 13a	AWS 3.5 ft/s	109.38	−1.87	0.010	0.96
	AWS 4.5 ft/s	131.51	−2.31	0.020	0.98
	AWS 6.5 ft/s	143.34	−2.35	0.010	0.78
Fig. 13b	0% pedestrian	135.74	−3.78	0.050	0.81
	50% pedestrian	114.13	−3.64	0.050	0.79
	100% pedestrian	44.25	−0.16	0.002	0.02

[a]Note: Here, α = intercept; β_1, β_2 = coefficient.

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