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Evacuation behavior of affected individuals and households in response to the 2018 Attica wildfires: From empirical data to models

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A R T I C L E I N F O

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A B S T R A C T

The objective of this paper is to analyze the household response behavior of road users during community evacuations in response to the 2018 Attica wildfires in Greece. To achieve this objective, empirical data were obtained from a questionnaire survey completed by residents from the affected areas by the wildfires of the East Attica in 2018. The design of the survey questionnaire was guided by the Protective Action Decision Model – PADM. Logistic regression models and machine learning techniques such as random forests were developed to identify the critical factors influencing the decision to evacuate or not, as well as the mode choice during evacuation. Findings reveal that the perception of risk, age, years in residence, the number of adults up to 65 years of age in residence, the attempt to obtain information before evacuation, gender, the existence of a prior warning, the number of minors in residence, the level of education and income were the most critical factors to the decision to evacuate during the wildfire. Regarding the mode choice, the most critical factors were the existence of an available vehicle, age, the attempt to obtain information before the evacuation and the perception of risk.

1. Introduction

Natural hazards and extreme events can have a dramatic impact on citizens' well-being and the economy (Pel et al., 2012). Also, they can often lead to the loss of human lives. Natural hazards include volcanic eruptions, earthquakes, tsunamis, hurricanes, floods and fires; man-made disasters are caused by industrial and nuclear accidents, chemical leaks and military or terrorist activities. In recent years, particularly due to climate change, there has been an increase in the frequency and intensity of extreme weather events worldwide that create natural hazards and therefore the urgent need to evacuate areas with large populations. Hazards vary greatly in their characteristics, such as warning times, duration, immediacy, spatial and temporal extent of impacts and so on. All of this has a significant impact on the planning of an emergency response. However, in all cases, effective management of the transport system is vital in order to facilitate the evacuation of affected populations and the movement of civil protection personnel and equipment (Perry and Lindell, 2003).

The inability to predict the exact circumstances of a disaster means that the proposed evacuation and transport plans need to be adapted and evaluated in a wide range of scenarios with regard to the nature of the event and its impact on the transport system (Urata and Hato, 2012). Modeling of transportation systems is necessary to support the development of such plans, with the models possibly being used in civil protection control and decision-making centers during a disaster (Brachman and Church, 2009; McLennan et al., 2019).

The supply of the transport system may be affected during an event through the closure of one or more roads and the closure of public transportation (Taylor and Freeman, 2010). However, a number of traffic management strategies that increase the supply of the network can also be implemented, such as granting of one or more lanes of traffic from the opposite current, known as contraflow (Wolshon, 2008).

The impact of demand can be more complex and difficult to predict. Therefore, understanding the demand for travel during disasters, especially when evacuations take place, is vital for effective risk management (van der Gun et al., 2016). The normal traffic activity and driving habits of network users may be completely different during a disaster, which is why community evacuation studies use different estimates than usual for different traffic sizes (Ni, 2006). These depend on the nature and extent of the event, the information and instructions provided to the

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population and the locations and activities carried out by household members at the start of the event. Interactions and dependencies between the behaviors of different household members, as well as with others in the extended family and social network, are also extremely important and may dictate mobility patterns (Singh et al., 2021, Urata and Hato, 2012). For example, in an evacuation, adults may first need to pick up dependent children or other people who need help before evacuating. These tasks can be assigned to specific members of the household, based on their physical or social proximity to people in need of assistance, vehicle availability and so on (Liu et al., 2014a).

Murray-Tuite and Wolshon (2013), in their research on travel demand during the evacuation, defined 4 stages in modeling namely “who” is evacuating and the factors influencing the decision to evacuate/stay, the trip generation, the destination selection and network distribution for each trip, and the mode choice during evacuation. Questions about who evacuates and what factors influence the evacuation decision are often discussed, mainly in social sciences, but more recently also by engineers.

Folk et al. (2019), Lovreglio et al. (2019a), McLennan et al. (2019), and Strahan and Gilbert (2021) have reviewed the literature on wildfire evacuation decisions, whereas Huang et al. (2016) conducted a statistical meta analysis of hurricane evacuation decisions, and Thompson et al. (2017) reviewed evacuation decisions for a variety of threats. According to Table 1, some factors were frequently found to have a specific effect on the evacuation decisions (e.g., gender, risk perception, existence of pets etc.), while others (e.g., age, income, education etc.) were found to have inconsistent effects in different researches/case studies.

The mode choice during evacuation, highly depends on the required distance to safety and the associated travel time. However, these characteristics vary significantly for the different types of threat. Hurricane evacuations often have warnings from several hours to multiple days before landfall and evacuees rely mostly on vehicles to find shelters which could be several kilometers away from the danger zone or staying with family or friends much further away from the impacted areas (Wang et al., 2016). On the other hand, wildfires usually have more localized impacts and, in some cases, people can evacuate on foot (Wong et al., 2020).

In addition to the type and characteristics of the threat, important factors when choosing an evacuation mode are the place where someone is at the time of the evacuation order (e.g., at work, or in residence), their available options (e.g., the availability of a vehicle) as well as their willingness to drive under the specific conditions. A survey by (Wu et al., 2012) on evacuation due to Hurricanes Katrina and Rita found that only 11% of the people who owned a car decided not to use it for evacuation, 71% of whom evacuated in a friend’s or relative’s vehicle and 28% otherwise. According to a summary of their findings from previous surveys, this figure does not exceed 13%.

For households with access to at least one personal vehicle, the question arises as to how many vehicles each household will use and what kind of vehicles they will be. According to Lindell et al. (2019b) Section 6.5, the median number of evacuating vehicles per household for United States hurricanes is 1.38, with a range from 1.25 to 1.70. However, the variation across local jurisdictions is more substantial—ranging from 1.10 to 2.15 across counties in Hurricane Lili. Wong et al. (2020) found that during three wildfires in California between 2017 and 2019, a large number of individuals used three or more personal vehicles to evacuate (number ranging from 8.6% to 16.5%). They also found that 54.1% to 68.5% of evacuating households had at least two or more spare seats available over all their evacuating vehicles.

Given the frequent catastrophic fires that Greece faces every year, it is necessary to carry out research to develop appropriate evacuation plans for areas that are susceptible to wildfires (Veeraswamy et al., 2018). This research could help examine the resiliency of transportation systems in traffic volumes caused by evacuation and propose improvements that may be required. The most complex process of such research is calculating the demand for travel, since it depends not only on the size of the population and its spatial distribution, but also on the behavior of people and the critical decisions they make during the threat.

The purpose of this paper is to investigate the evacuation behavior of individuals and households from communities in response to wildfires using the 2018 Attica wildfire as a case study. More specifically, this paper will focus on the critical factors influencing the decision to evacuate or not and the factors influencing the evacuation mode choice decision.

In order to carry out this research, empirical data were collected from residents of areas affected by the 2018 Eastern Attica wildfires. The data were collected using a questionnaire that was adapted from studies of responses to tsunami (Lindell et al., 2015) and flash flood (Lindell et al. (2019a) hazards. The data were processed using statistical as well as machine learning algorithms.

2. Methods

2.1. *The Eastern Attica wildfire*

On July 23, 2018 two wildfires occurred in the region of Eastern Attica in Greece. One of them evolved rapidly and it soon threatened the residential areas of Neos Voutzas and Mati, a popular tourist destination for locals, 40 km from Athens (Fig. 1). The majority of the residents and visitors of these areas were either unofficially informed about the wildfire by observing the approaching flames, or informed by neighbors and people evacuating nearby. An official evacuation order was never issued, so the decision whether to evacuate, the destination and route of the evacuation, remained up to the affected people. Some chose to evacuate using their cars, while others chose to evacuate on foot to the closest beaches or other areas they considered safe.

The road network of the affected area consists of 4% primary (1800 vehicles/lane/hour), 3% secondary (1800 vehicles/lane/hour), 8% tertiary (800 vehicles/lane/hour), 83% residential and 2% unclassified roads. During the event, more than 1200 vehicles tried to evacuate the area in <2 h. At the same time, there was an additional demand coming from the Rafina Harbor of approx. 300 vehicles/hour. The traffic impact of the evacuation was a 70% increase of the usual volume to capacity ratio, leading to a congested network (Lekkas et al., 2018). More than 100 people died and dozens of others were injured during the wildfire.

2.2. *The questionnaire survey*

The questionnaire is based on the Protective Action Decision Model (PADM—Lindell, 2018; Lindell and Perry, 2012), which is a multistage model that is based on findings from decades of research on people’s responses to environmental hazards and disasters. The PADM integrates the processing of information received from environmental cues (e.g., observation of smoke and flames), social cues (e.g., observations of others evacuating), and social warnings consisting of *messages* (usually about the threat and protective actions) from sources (authorities, news media, and peers) transmitted through communication channels (ranging from broadcast media to face-to-face communication). Those who receive this information experience three critical predecision processes (reception, attention, and comprehension of the information) that produce perceptions of the threat’s certainty, severity, immediacy, and duration. This information also produces perceptions of protective actions (e.g., their effectiveness in protecting persons and their impediments to implementation) and perceptions of stakeholders (people who can provide additional information and assistance). In turn, these perceptions generate an information search strategy when the situation is uncertain or a protective action decision making as the pressure for action increases. The effectiveness of these strategies depends on situational impediments and facilitators.

The questionnaire is divided into three main sections covering a total of 40 questions. The questionnaire’s first section consists of questions

Table 1
Factors that influence the evacuation/stay decision in various types of threat.

Factor	Effect	Wildfire	Hurricane/Storm	Flood	Tsunami	General
Risk perception	↑	(Alsnih et al., 2005; Lovreglio et al., 2019b; McLennan et al., 2015; McNeill et al., 2016; Mozumder et al., 2008; Strahan et al., 2018; Strawderman et al., 2012)	(Dow and Cutter, 2000; Meyer et al., 2013; Perry and Lindell, 1991; Ricchetti-Masterson and Horney, 2013; Whitehead et al., 2000)	(Perry et al., 2006; Tobin et al., 2011)		
Official warning sources	↑	(Fischer et al., 1995; Lovreglio et al., 2019b; McCaffrey et al., 2018; Strahan et al., 2018; Strawderman et al., 2012)	(Baker, 1995; Burnside, 2006; Burnside et al., 2007; Huang et al., 2012; Lamb et al., 2012; Rosenkoetter et al., 2007a; West and Orr, 2007)	(Drabek, 1969; Drabek and Stephenson, 1971)		(Gray-Graves et al., 2011)
Evacuation order	↑	(McCaffrey et al., 2018; Mozumder et al., 2008)	(Dixit et al., 2012; Fu et al., 2007; Hasan et al., 2010; Petrolia and Bhattacharjee, 2010; Reininger et al., 2013; Rincon et al., 2001)			(Gray-Graves et al., 2011)
Gender (women)	↑	(Alsnih et al., 2005; Cohn et al., 2006; Eriksen et al., 2010; Handmer and O'Neill, 2016; Haynes et al., 2010; McLennan et al., 2011; Mozumder et al., 2008; Paveglio et al., 2014; Whittaker et al., 2016, 2013; Whittaker and Handmer, 2010)	(Cahyanto and Pennington-Gray, 2014; Elliott and Pais, 2006; Huang et al., 2012; Meyer et al., 2013; Morss et al., 2016; Reininger et al., 2013; Riad et al., 1999; Rosenkoetter et al., 2007b; Smith and Mccarty, 2009)			
Age	↑and↓	(Alsnih et al., 2005; Lovreglio et al., 2019b)	(Baker, 1979; Cahyanto et al., 2014; Christensen et al., 2013; Meyer et al., 2013; Morss et al., 2016; Reininger et al., 2013; Willigen et al., 2005)			
Race (Caucasian)	↑		(Reininger et al., 2013; Riad et al., 1999; Zhang et al., 2004)			(McClure et al., 2011)
Homeownership	↑↓	(Paveglio et al., 2014)	(Hasan et al., 2012; Meyer et al., 2013; Riad et al., 1999; Solís et al., 2010)		(Charnkol and Tanaboriboon, 2006)	
Emotional attachment to property/community	↓	(Cohn et al., 2006; McLennan et al., 2015, 2013, 2011; McNeill et al., 2016)				
Duration of residence	↓	(Alsnih et al., 2005; Benight et al., 2004; Mozumder et al., 2008)	(Adeola, 2008; Horney et al., 2010; Riad et al., 1999)			
Higher education	↑and↓		(Hasan et al., 2010; Paul, 2012; Reininger et al., 2013; Thiede and Brown, 2013; Zhang et al., 2004)	(Arieh et al., 2016)	(Charnkol and Tanaboriboon, 2006)	
Higher Income	↑,↓ and -	(Paveglio et al., 2014)	(Aguirre, 1991; Burnside, 2006; Cahyanto et al., 2014; Christensen et al., 2013; Dixit et al., 2008; Elliott and Pais, 2006; Hasan et al., 2010; Meyer et al., 2013; Murray-Tuite et al., 2012; Reininger et al., 2013; Willigen et al., 2005; Zhang et al., 2004)	(Arieh et al., 2016; Perry and Lindell, 1991)		
Children in household	↑	(Fischer et al., 1995; McLennan et al., 2011; McNeill et al., 2016)	(Hasan et al., 2012, 2010; Smith and Mccarty, 2009; Solís et al., 2010) (Bateman and Edwards, 2002; Hasan et al., 2012, 2010; Smith and Mccarty, 2009; Solís et al., 2010)	(Arieh et al., 2016; Heath et al., 2001)		
Disabled members	↓		(Willigen et al., 2002)			
Pets and livestock	↓	(McLennan et al., 2011; McNeill et al., 2016; Mozumder et al., 2008; Tibbits and Whittaker, 2007; Whittaker et al., 2020)	(Brackenridge et al., 2015; Petrolia and Bhattacharjee, 2010; Solís et al., 2010; Whitehead et al., 2000)	(Heath et al., 2001)		
Having a plan to evacuate	↑	(McLennan et al., 2015; Paveglio et al., 2014)	(Burnside et al., 2007; Lazo et al., 2015)			
Having a plan to stay and defend	↓	(Lovreglio et al., 2019b; McLennan et al., 2013, 2012, 2011; Tibbits and Whittaker, 2007)				
Concern for safety of belongings	↓		(Aguirre, 1991)			
Perceived physical readiness	↓	(McLennan et al., 2014, 2011; McNeill et al., 2016)				
Persuasion of close others	↑	(McLennan et al., 2011; Whittaker et al., 2016)	(Adeola, 2008; Hasan et al., 2010)			
Previous experience	↑,↓ and -	(Cohn et al., 2006; Mozumder et al., 2008; Strawderman et al., 2012)	(Adeola, 2008; Arlikatti et al., 2006; Cahyanto et al., 2014; Hasan et al., 2012, 2010; Huang et al., 2012; Lazo et al., 2010; Lindell et al., 2011, 2005; Matyas et al., 2011; Rincon et al., 2001; Sharma and Patt, 2012; Solís et al., 2010; Tinsley et al., 2012)		(Charnkol and Tanaboriboon, 2006)	
Warning fatigue	↓	(Whittaker and Handmer, 2010)				

(*continued on next page*)

Table 1 (*continued*)

Factor	Effect	Wildfire	Hurricane/Storm	Flood	Tsunami	General
						(LeClerc and Joslyn, 2015; Mackie, 2014)

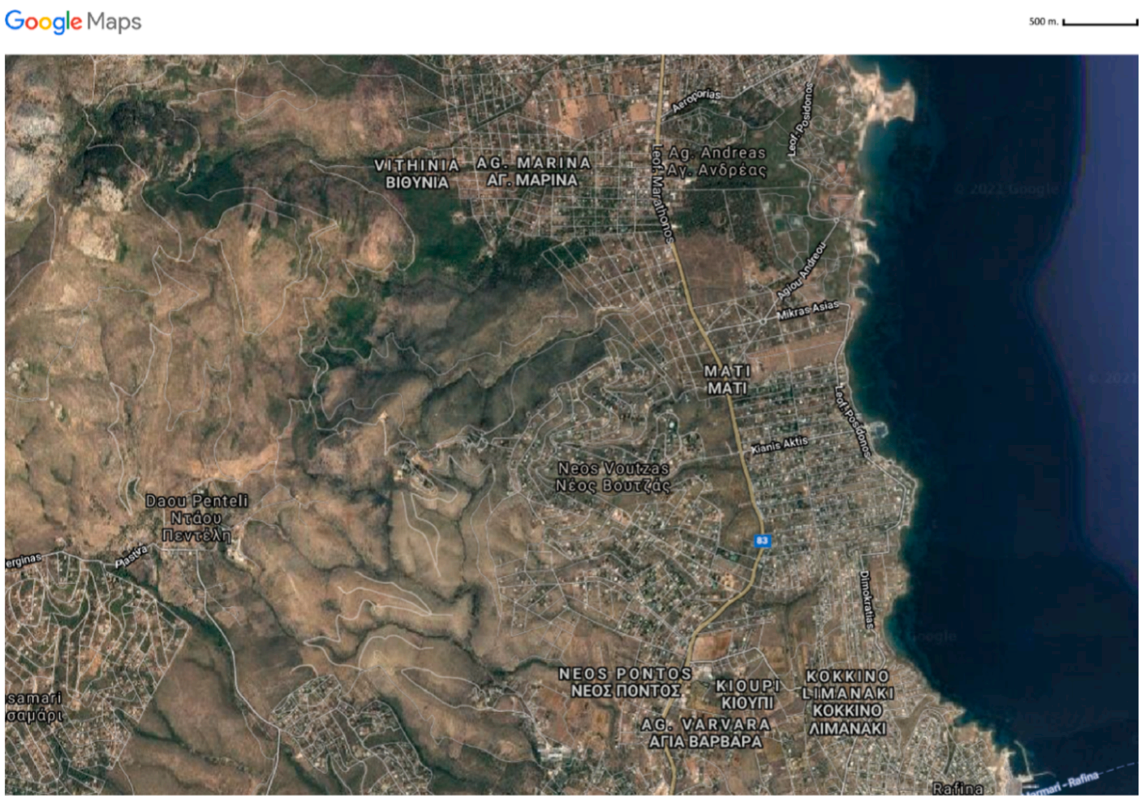

Fig. 1. Affected region of 2018 Eastern Attica wildfire. (Google Maps, xxxx)

concerning a description of the events before and during the wildfire. More specifically, there are questions about how the respondents received a warning of the fire, their evacuation decision, and the logistics of their evacuation. The second section of the questionnaire consists of questions related to the respondents' intended responses to a future wildfire threat, given their recent experience, feelings and actions they have taken to prevent this possibility. Finally, the third and final section of the questionnaire asked about demographic characteristics such as gender, age, educational level, marital status and annual family income. This information provides an assessment of the sample's representativeness and supports an examination of the correlation between demographic characteristics and other questionnaire replies. The average questionnaire completion time was 15 min.

The survey took place during April and May 2020. Due to COVID 19 pandemic restrictions, all questionnaires were collected in an online survey. The sample consists of 152 completed questionnaires. However, one response with inconsistent answers was deleted from the analysis. It is difficult to estimate the exact population that was affected by the wildfires since the wildfires covered only parts of areas in which demographic data are available and because these areas have many vacation homes. The area of interest for this research mainly consists of the residential areas of Neos Voutzas and Mati that have an estimated combined population of 3000 people. For a 90% confidence level, the margin of error for a sample size of 151 and a population size of 3000 is about 6.5%. Potential participants were approached through social media groups of the affected communities and through emails to local businesses and organizations. A summary of the sample demographic characteristics and its comparison to data from the National Statistic Agency can be found in Table 2.

The analysis of the questionnaires revealed some important univariate data, a summary of which is shown in Tables 3 and 4. These data indicate that the majority of respondents (86%) tried to evacuate their residence after the ignition of the wildfire. Women reported a statistically significantly higher evacuation rate (91.4%) than men (80%); $z = 2.011$, $p = 0.048$ (two proportion z test).

Table 2
Survey sample summary statistics.

Variable	Distribution in sample	Distribution in population
Gender	Female 46.4%, Male 53.6%	Male 53.1% Female 46.9%
Age	18–29: 23.2%, 30–49: 35.1%, 50–69: 34.4%, 70+: 7.3%	18–29: 17.3%, 30–49: 40.7%, 50–69: 28.7%, 70+: 13.3%
Marital Status	Married: 55.6%, Unmarried: 31.1%, Divorced: 7.9%, Widowed: 5.3%	Married: 49.6%, Unmarried: 39.6%, Divorced: 6.7%, Widowed: 4.1%
Type of ownership	Tenant: 17.2%, Owner: 82.8%	Tenant:21.4%, Owner: 78.6%
Education	High school or lower: 23.2%, Some college/trade school: 17.2%, University: 39.7%, Masters or PhD: 19.9%	–
Income	Low: 42.4%, Medium: 44.4%, High: 13.2%	–

Table 3
Critical variables in the event.

Variable	Distribution in sample	
Evacuated	Yes: 86.1% (n = 130)	No: 13.9% (n = 21)
First information about the wildfire	Saw the flames coming: 68.2% (n = 103)	Other: 31.8% (n = 48)
Evacuation rate, by age group		
18–29	Yes 88.6% (n = 31)	No: 11.4% (n = 4)
30–49	Yes 83% (n = 44)	No: 17% (n = 9)
50–69	Yes 84.6% (n = 44)	No: 15.4% (n = 8)
70+	Yes 100% (n = 11)	No: 0% (n = 0)
Evacuation rate, by gender	Female: 91.4% (n = 74)	Male: 80% (n = 56)
Available vehicle	Yes: 90.8% (n = 118)	No: 9.2% (n = 12)
If yes, did you use it?	Yes: 83.9% (n = 99)	No: 16.1% (n = 19)
Caught inside the wildfire at any moment	Yes: 53.6% (n = 70)	No: 46.4% (n = 60)
If evacuated with family vehicle	Yes: 47.5% (n = 47)	No: 52.5% (n = 52)
If evacuated some other way (e.g., on foot)	Yes: 74.2% (n = 23)	No: 25.8% (n = 8)
Mode choice, by age group		
18–29	Own vehicle: 54.8% (n = 17)	Other: 45.2% (n = 14)
30–49	Own vehicle: 79.5% (n = 35)	Other: 20.5% (n = 9)
50–69	Own vehicle: 84.1% (n = 37)	Other: 15.9% (n = 7)
70+	Own vehicle: 90.9% (n = 10)	Other: 9.1% (n = 1)

Table 4
Respondents' expectations of their behavior in a future wildfire.

Variable	Without official evacuation order:	With official evacuation order:
Likelihood of evacuating	1.86/5	4.45/5
Planned destination	Yes: 68.9%	No: 31.1%
Planned route	Yes: 63.6%	No: 36.4%
Planned number of vehicles	One: 65.6%	All: 34.4%

The proportion of those who used a vehicle to evacuate (76.2%), is significantly lower than the proportion of those who had an available vehicle when evacuating (90.8%); $z = 3.172$, $p = 0.002$ (two proportion z test). This suggests that the availability of a vehicle is not the only factor that affects the mode choice during wildfire evacuation. Moreover, the proportion of people that were caught by the wildfire if evacuating with a family vehicle (47.5%) is significantly lower than proportion of people that were caught by the wildfire if evacuating on foot (74.2%); $z = 2.604$, $p = 0.014$ (two proportion *z* test). It's clear that evacuation on foot was related to being caught in the fire and was consequently more dangerous.

Additionally, a paired-samples *t*-test was conducted to compare expectations (Not at all likely = 1 to Extremely likely = 5) of evacuating when an evacuation order has been issued in a future wildfire. There was a significant difference in the scores for evacuation order ($M = 4.45$, $SD = 0.98$) and no evacuation order ($M = 1.86$, $SD = 1.00$) scenarios; $t(150) = 23.43$, $p < 0.001$. These results suggest that the issuance of an official evacuation order plays a critical role in residents' decision to evacuate.

In the 18–29 age group, 45% chose to evacuate on foot—compared to 20% in the 30-49age group, 16% in the 50–69 age group, and 9% in the 70+ age group. It is therefore likely that the older the age, the higher the evacuation rate in private vehicles. The age groups with the highest rates of evacuation were those 70+ (100%), followed by those younger than 29 years old (88.6%), whereas the age groups with the lowest evacuation rates were the 30–49 group (83%) and 50–69 group (84.6%).

Finally, 65.6% of respondents said that in a future wildfire they would choose to use only 1 vehicle as opposed to the remaining 34.4% who said they would try to evacuate with all available vehicles in the family.

2.3. Models

The questionnaire responses, after being encoded as variables into a dataset, are used in logistic regression and random forest models in order to predict the behavior of road users and to sort the most important factors affecting their decisions. More specifically, the models were created to predict the decision to evacuate or stay as well as the evacuation mode choice as they are the two of the most critical decisions affecting evacuation travel demand.

Logistic regression is often used in transport research that assesses the linear relationship of specific factors on an outcome. Then, through an appropriate transformation, the probability of this outcome's occurrence is calculated. The utility function of logistic regression is given by the relationship:

$$Ui = a0 + a1x1 + a2x2 + \cdots + anxn \tag{1}$$

where Ui, the utility function of event I, $x_1 \ldots x_n$ the variables of the problem, a_0, the constant representing the influence of factors not included as variables in the mathematical model and $a_1 \ldots a_n$, the coefficients of variables. The probability of the outcome *i* occurring is given by the relationship:

$$Pi = eUi/(1 + eUi) \tag{2}$$

An important indicator of a predictor variable's importance is its odds ratio, which is the ratio of the probability of the event occurring (in the ratio's numerator) to the probability of it not occurring (in the ratio's denominator). If, therefore, *P* represents the probability of the event occurring and 1-P the probability of it not occurring, then the odds ratio is *P*/(1-*P*). The odds ratio is typically reported in logarithmic form as:

$$logit(P) = lnP/(1-P) = \beta 0 + \beta 1x1 + \cdots + \beta nxn \tag{3}$$

More recently, random forest algorithms have been introduced to the field of evacuation behavior modeling (Zhao et al., 2021). The random forest algorithm is an ensemble method that trains several decision trees in parallel with bootstrapping followed by aggregation, jointly referred as bagging (Breiman, 2001). Bootstrapping indicates that multiple decision trees are trained in parallel on different subsets of the training dataset using different subsets of available features. Bootstrapping ensures that each individual decision tree in the random forest is unique, which reduces the overall variance of the random forest classifier. For the final decision, the random forest classifier aggregates the decisions of individual trees; consequently, it exhibits good generalization. A random forest classifier tends to outperform most other classification methods in terms of accuracy without issues of overfitting. Like a decision tree classifier, a random forest classifier does not need feature scaling. Unlike a decision tree classifier, a random forest classifier is more robust to the selection of training samples and noise in training dataset.

The output of the model for each individual in a classification problem is the mode (the class appearing most frequently) of the decision tree classifiers (Bonaccorso, 2017):

$$\widehat{y} = argmax(d_i(\overline{x})), \tag{4}$$

where $d_i(x)$ represents the output of the i^{th} decision tree. In contrast to simple decision trees, which provide simple classification rules that can also be applied manually in each of their nodes, random forests are not so easy to interpret, due to their complexity. Although a feature importance metric (based on feature permutation,) can be estimated for each of the independent variables, they are generally considered as a black-box approach (Aurélien Géron, 2019).

2.4. Variables

In the preprocessing phase, variables with zero or very little variation and variables with a correlation of more than $r = 0.50$ were removed. Table 5 shows the variables taken into account in the modeling of the decision to evacuate and the mode choice.

Regarding evacuation mode, out of 130 people who evacuated, 29 evacuated on foot, 99 evacuated with their own vehicle and 2 used the "other" option of the questionnaire to explain that someone passing by picked them up from the street while evacuating on foot. Accordingly, we merged the responses into two categories: "Vehicle" (99 responses) and "Other" (31 responses).

Q7a, Q7b, Q7c, Q7d and Q7e are the dummy variables created to represent the answers of Q7. Each dummy variable has only 2 possible answers (Yes = 1, No = 0), indicating if the associated check box in the questionnaire was checked or not. The dummy coding was also applied to questions 8–11. Moreover, the variable "prior warning" gets the value Yes (=1) if respondents were warned about the wildfire by face-to-face, by voice call/SMS or by TV/radio. Otherwise, if the first source of information about the wildfire was seeing the wildfire coming or seeing people evacuating, the variable gets the value No (=0).

Finally, the variable "perceived risk" is calculated as the average of each respondent's scores (1 to 5) on the four questions—*After you received any wildfire warnings, how likely did you think it was that it would: a) severely damage or destroy many homes in your community, b) injure or kill many people in your village if they did not evacuate, c) severely damage or destroy your home, d) injure or kill you or your family if you did not evacuate?*

Table 5
Variable definitions.

Variable	Description	Values
evacuated	Did you evacuate the place you were in when he was threatened by the fire?	No (0), Yes (1)
Evacuation mode	How did you evacuate your area?	Vehicle (0), Other (1)
years in community	How many years do you live in the community you live in now?	Num
years in residence	How many years do you live in your current residence?	Num
ownership status	Do you rent or own the residence where you live?	Rent (0), Own (1)
age	How old are you?	Num
gender	What's your gender?	Male (0), Female (1)
marital status	What's your marital status?	Unmarried, Married, Divorced, Widowed
children in residence	Existence of minors in residence	No (0), Yes (1)
household under18	How many people in your residence are under 18?	Num
household 18to65	How many people in your residence are 18–65 years old?	Num
household over65	How many people in your residence are over 65 years old?	Num
income	Which of the following categories best describe your household's annual income before tax?	<25.000 (1), 25.000–50.000 (2), >50.000 (3)
education	Which of the following reflects the level of training you have completed?	Elementary, High School, High School, Private College, University, Master's/Doctorate
prior warning	Existence of a previous warning	No (0), Yes (1)
perceived risk	Perception of the risk of fire	Num
Q7: Did you get advice from someone to take refuge in a safer location?		
Q7a	No	No (0), Yes (1)
Q7b	Yes, from some authority (e.g., police)	No (0), Yes (1)
Q7c	Yes, from a friend, relative or neighbor.	No (0), Yes (1)
Q7d	Yes, from the media	No (0), Yes (1)
Q7e	Other	No (0), Yes (1)
Q8: Did you try to get more information from someone before you decided to evacuate?		
Q8a	no	No (0), Yes (1)
Q8b	yes, from friends, family, neighbors.	No (0), Yes (1)
Q8c	Yes, from the authorities (e.g., police)	No (0), Yes (1)
Q8d	Yes, from the media.	No (0), Yes (1)
Q11: Did you take any other action before evacuating?		
Q11a	I've collected essentials.	No (0), Yes (1)
Q11b	I tried to protect my property.	No (0), Yes (1)
Q11c	I tried to track down members of my family who weren't with me.	No (0), Yes (1)
Q11d	I tried to warn others.	No (0), Yes (1)
Q11e	no	No (0), Yes (1)
Q11f	I tried to transport members of my family to a safe area on more than one route.	No (0), Yes (1)
Q12-available vehicle	Did you have a vehicle (e.g., car, motorcycle, etc.) available when deciding whether to evacuate?	No (0), Yes (1)

3. Results

3.1. Evacuation decision

The dependent variable selected for the evacuate/stay models was the "evacuated" variable indicating whether the respondent decided to evacuate the place where they were located. In order for the variables not to contain bias, only those that describe events that preceded the evacuation decision were selected, meaning that variables from questions 11, 12 and 13 (mode) were omitted from the model.

Due to the skewed distribution of responses on the dependent variable (130 evacuated, 21 didn't) an oversampling strategy was followed in which responses were respondents had stated that they did not evacuate the area, were randomly repeated in the training set. After oversampling, 130 positive and 50 negative responses emerged. This strategy was considered necessary in order to make it easier for the models to identify negative responses. The resulting 72% evacuation rate for the oversampled data yields a 60% baseline for chance prediction. Before its implementation, the models tended to classify all the responses to the positive class since in that way the overall accuracy exceeded 86%. The models were checked using 10-fold cross validation and the resulting statistical characteristics of the logistic regression and random forest models predicting the evacuation decision can be found in Table 6.

Table 7 shows in detail the factors selected from the logistic regression model along with their associated beta coefficients, standard errors, z values, p values and odds ratios. The effect of the factors operating in favor of evacuation is considered positive.

In the random forest model, the importance of the variables was calculated through the metric "Mean Decrease in Accuracy". This metric quantifies the importance of a variable by measuring the change in forecast accuracy when the values of the variable are converted randomly compared to the original observations. The 10 most important variables that came up in the model are shown in Fig. 2.

3.2. Mode choice

For the mode choice models, the dependent variable was evacuation

Table 6
Statistical characteristics of evacuation decision for logistic regression and random forest models.

	Logistic Regression	Random Forest
Accuracy	80.6%	94.4%
Kappa	48.0%	86.0%
Sensitivity	90.8%	96.9%
Specificity	54.0%	88.0%
Precision	83.7%	95.5%
F measure	87.1%	96.2%
AUC	72.4%	96.0%

Table 7
Logistic regression model for predicting evacuate/stay decision.

Variable	β	Std. error	z value	p-value	exp (β)
Intercept	−6.55	1.55	−4.22	< 0.001	0.001
Risk perception	0.93	0.20	4.59	< 0.001	2.54
Income	1.48	0.40	3.75	< 0.001	4.41
Tip for evacuation from friend/ relative/neighbor (Q7c-Yes)	2.25	0.66	3.42	< 0.001	9.46
Tried to obtain additional information before the evacuation decision (Q8a-No)	−1.41	0.48	−2.95	0.003	0.24
Age	0.03	0.02	2.07	0.039	1.03
Number of minors in residence	−0.29	0.16	−1.75	0.080	0.75
Type of home ownership	−1.10	0.67	−1.64	0.102	0.33
Gender	0.66	0.42	1.58	0.114	1.93

mode and all the variables in Table 5 were taken into account. As noted earlier, 99 of the 130 evacuees (76%) traveled by car, so the baseline for chance prediction is 64%. The models were checked with the method of 10-fold cross validation. Resulting statistical characteristics of the logistic regression and random forest models predicting the mode choice can be found in Table 8.

The low values of kappa coefficient and specificity of the logistic regression model indicate a poorer performance with respect to these indicators of model fit and an inability to identify users that did not use their own vehicles to evacuate. The random forest model has consistently better statistical characteristics since it manages to predict both classes satisfactory.

In the random forest model, the importance of the variables was calculated again through the "Mean Decrease in Accuracy" metric. The 5 most important predictors are shown in Fig. 3. These are the availability of a vehicle, the respondent's age, the attempt to obtain information before evacuation, the perception of risk, and family income.

4. Discussion

Our logistic regression model for predicting evacuation decisions indicates that higher risk perception ($p < .001$) affects the evacuation decision positively. This outcome agrees with the literature from Table 1 (Alsnih et al., 2005; McCaffrey et al., 2018, McLennan et al., 2015; McNeill et al., 2016; Mozumder et al., 2008; Strahan et al., 2018; Strawderman et al., 2012). The same applies to "advice from close others" ($p < .001$) (McLennan et al., 2011; Whittaker et al., 2016). Both of these results are consistent with research on evacuation from other rapid onset disasters such as tsunamis (Lindell et al., 2015) and flash floods (Lindell et al., 2019) as well as slow onset disasters such as hurricanes (Baker, 1991; Huang et al., 2016). On the other hand, trying to obtain more information before deciding ($p = .003$), known as "milling" (Wood et al., 2018) has a negative effect on evacuation decisions. Since most of the respondents were informed about the wildfire by seeing the flames coming, there was no need to "wait and see" if they were at risk (McCaffrey et al., 2018).

Some demographic variables positively affected the evacuation decision—higher income ($p < .001$) and age ($p = .039$). Paveglio et al.

Table 8
Statistical characteristics of mode choice logistic regression and random forest model.

	Logistic Regression	**Random Forest**
Accuracy	79.2%	89.2%
Kappa	38.0%	69.7%
Sensitivity	89.9%	93.9%
Specificity	45.2%	74.2%
Precision	84.0%	92.1%
F measure	86.8%	93.0%
AUC	76.4%	91.0%

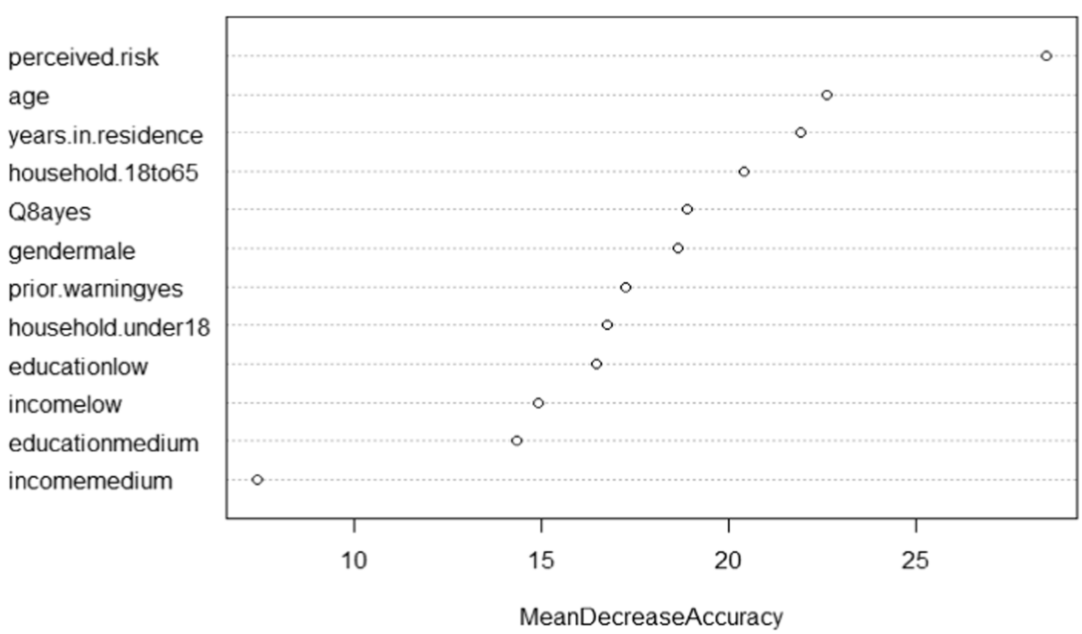

Fig. 2. Variable importance of evacuation decision final random forest model.

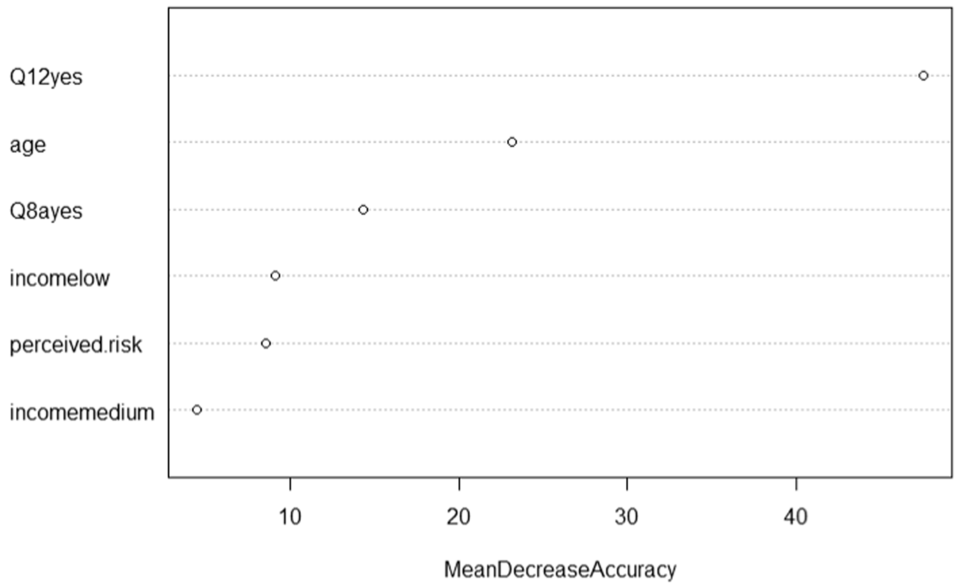

Fig. 3. Variable importance of mode choice final random forest model.

(2014), in their study of evacuation preferences among Northwest Montana residents, also found that people with a higher income were more likely to evacuate. However, an expanded review on studies dealing with other natural hazards, shows mixed results for the effect of income on the evacuation decision(Aguirre, 1991; Burnside, 2006; Cahyanto et al., 2014; Christensen et al., 2013; Dixit et al., 2008; Elliott and Pais, 2006; Hasan et al., 2010; Meyer et al., 2013; Murray-Tuite et al., 2012; Reininger et al., 2013; Willigen et al., 2005; Zhang et al., 2004). Research that studies the influence of age on evacuation, also presents conflicting results (Baker, 1979; Cahyanto et al., 2014; Christensen et al., 2013; Meyer et al., 2013; Morss et al., 2016; Reininger et al., 2013; Willigen et al., 2005). These conflicting results are consistent with Baker's (1991) conclusion that demographic variables have small and inconsistent effects on hurricane evacuation decisions. Huang et al. (2016) confirmed Baker's conclusion and proposed that this might be because the effects of demographic variables on evacuation decisions are mediated by psychological variables such as respondents' perceptions of the threat, protective actions, and other stakeholders.

The variable "children in residence" that describes the presence of minors in a household, was not selected as a significant predictor of the evacuation decision by our model. Instead, the variable "number of minors" ($p = .080$) has a negative effect on the decision to evacuate, although it does not meet the conventional level of statistical significance ($p < .05$). Most of the studies that found significant effects for the presence of children reported that this raises evacuation rates (Fischer et al., 1995; McLennan et al., 2011; McNeill et al., 2016) so the result seems to contradict the literature. A possible explanation could be the very short notice of the specific event, as larger families did not have enough time to prepare and assemble for evacuation. Gathering scattered family members has a large effect on household behavior and can delay departure times (Liu et al., 2012). Of course, another explanation is that this is a chance result, so further research is needed to determine if it can be replicated.

Finally, homeownership and gender appear to have effects that are consistent with previous studies (Paveglio et al., 2014; Whittaker et al., 2016, 2013), with homeownership ($p = .10$) being negatively related and gender ($p = .11$) being positively related to evacuation. However, both variables fail to meet conventional level of statistical significance (homeownership $p = .10$; gender $p = .11$), which is consistent with the hurricane research findings about the small and inconsistent effects of demographic variables (Baker, 1991; Huang et al. (2016). Consequently, statistical meta analyses should be conducted to assess these variables' effect sizes.

The machine learning approach presented some minor and some major differences compared to the logistic regression model in terms of selection and importance of variables. Firstly, according to the random forest model, receiving a tip from a friend/relative/neighbor, was not an important predictor of the decision to evacuate. Instead, the variable "prior warning", that describes the existence of a prior warning by any information channel (e.g., radio/TV) except seeing the respondents seeing flames with their own eyes or seeing people nearby evacuating, was selected. Another variable that is missing from the random forest selection of variables was homeownership. On the other hand, a number of variables were selected by the random forest model and not the logistic regression model. Specifically, the random forest model indicates that duration of residence in the household and the number of adults under 65 in household appear to strongly influence the decision to evacuate, whereas education has a weaker influence (see Fig. 2).

Regarding evacuation mode choice, the logistic regression model did not perform as well as the random forest model and did not produce any significant results; therefore it is not discussed further. On the contrary, the random forest model confirmed our expectation that the availability of a vehicle is not the only factor that affects the mode choice during wildfire evacuation (see 2.2). This conclusion is also supported by the findings of several studies of hurricane evacuations (Bian et al., 2019; Deka and Carnegie, 2010; Murray-Tuite and Wolshon, 2013; Wu et al., 2012) that have found that other variables such as age and income also are related to evacuation mode choice.

Even though the most important factor for predicting the mode choice, according to our model, is indeed the availability of a vehicle, age also appears to play a significant role as it was also proposed in our initial statistical analysis (see 2.2). Income, risk perception and attempt to obtain additional information also appear to have a weak effect on the mode choice.

According to Wu et al. (2012) age is negatively related to owning a vehicle and therefore positively related to carpooling when evacuating. Additionally, it associated with smaller evacuation distances and travel times. Liu et al. (2014b) used rule-based classification methods to predict mode choices in large-scale no-notice evacuations. However, sociodemographic characteristics were not important predictors of mode choice in their model. Instead, the availability of vehicles in the household, the individual's usual commute habits, and the responsibility to pick up a child were only used as predictors. Several other studies of evacuations (Bian et al., 2019; Deka and Carnegie, 2010;

Murray-Tuite and Wolshon, 2013) measured the behavior of evacuees regarding their evacuation mode choice, but did not identify the critical factors that affect this choice.

As in Zhao et al. (2021), the random forest models outperformed the logistic regression ones in both of the cases where they were implemented. Stoltzfus (2011) has argued that the significance of the factors resulting from the random forest algorithms is much more reliable than that of logistic regression ones since logistic regression is based on numerous assumptions. There is always the risk that some interaction between variables will not be detected and therefore some bias will be incorporated in the model that will lead to wrong choice of factors. Logistic regression also assumes simple linear dependency relationships between independent and dependent variables. This is often good, because the results it produces are easy to interpret. However, such simple relationships can underfit the data by failing to predict the dependent variables as well as the random forest model. Of course, the downsides of the random forest algorithm are that it is more difficult to explain the effect of individual factors and that it does not completely eliminate the possibility of overfitting the sample data.

5. Study limitations

During the process of the analysis, we came across a number of possible limitations of our work. First of all, the size of the examined sample, while adequate considering the difficulties of reaching the residents (COVID-19 restrictions, large number of vacation homes), was relatively small so there was only suficient statistical power to detect moderately large effects. Another possible limitation of our research is that it is based on self-reported data that cannot be independently verified and could contain some bias (e.g., exaggeration, selective memory etc.), especially if we consider the time passed since the event (20 months). Additionally, data from the hypothetical case study introduced in Table 4 could also have a social desirability bias or even a bias driven by respondents' willingness to highlight the lack of state's preparedness and its importance.

6. Conclusion

In this work, we assessed the critical decisions of evacuees in communities under the emergence of wildfires, namely their evacuation decision and mode choice. The data necessary to carry out the analysis were collected through a questionnaire completed by residents of areas affected by the fires of East Attica in 2018. The data were modeled using logistic regression and random forests. Findings reveal that random forests provide more accurate predictions than logistic regression. The most significant factors that influence the decision to evacuate were perceived risk, age, number of years in residence, number of adults under 65 in household, milling (the attempt to obtain additional information before deciding), gender, number of minors in household, education and income. Regarding the mode choice, the most important factors were the availability of a vehicle, respondent age, milling, and risk perception.

Future work would benefit from collecting and analyzing larger sample data that, when combined with O-D information, would have far-reaching implications for evacuation management. Accurate and reliable evacuation decision models can contribute to the calibration of behavioral traffic models and simulation platforms. These tools can be used to evaluate alterative traffic management strategies in critical evacuation situations for improving the resilience of communities to natural and manmade hazards.

7. Contribution

Wang H. designed the questionnaire. Katzilieris K. conducted the survey, the statistical analysis and contributed to the paper writing. Vlahogianni E. designed the modeling, contributed to the paper writing and had the overview of the entire paper. All authors reviewed the final manuscript.

CRediT authorship contribution statement

Katzilieris Konstantinos: Investigation, Formal analysis, Writing – original draft, Writing – review & editing. **I. Vlahogianni Eleni:** Methodology, Supervision, Writing – review & editing. **Haizhong Wang:** Writing – review & editing, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

Wildfire Evacuation Questionnaire

1. In what community/village were you located when the 2018 Attica wildfire threatened it?__________________
2. What was your first source of information about the wildfire? (Check one)
☐ I saw people near me evacuating (go to Q5)
☐ I saw the wildfire coming (go to Q5)
☐ I was warned face to face (go to Q3)
☐ I was warned by voice telephone or text message (go to Q3)
☐ I was warned by radio or TV (what station?) ____________________ (go to Q3)
☐ Other (please explain) ____(go to Q3)

3. Who provided your first information about the wildfire? (Check one)
☐ An authority (e.g., a police officer) ☐ A friend, relative, neighbor, or coworker
☐ A radio or TV announcer ☐ Someone else (please explain)
____

4. What information did you receive from that first source? (Check all that apply)
☐ What was the threat (i.e., a wildfire) ☐ Which areas would be affected
☐ What protective action to take (e.g., evacuation) ☐ Which areas would be safe/where to go
☐ Where to get assistance in evacuating ☐ Where to get additional information
☐ Other (please explain)
____

5. After you received the first information about the wildfire, from which other sources did you receive information? (Check all that apply)
☐ I saw the wildfire coming ☐ I saw people near me evacuating
☐ I received information face to face ☐ I received information by telephone call
☐ I received information by radio ☐ I received information by TV
☐ I received information by text message ☐ I received information by email
☐ I received information by Internet ☐ I received information by social media
☐ Other (please explain) _____________________________

6. After you received any wildfire warnings, how likely did you think it was that it would…

	Not at all likely			Almost certain	
a. severely damage or destroy many homes in your community?	1	2	3	4	5
b. injure or kill many people in your village if they did not evacuate?	1	2	3	4	5
c. severely damage or destroy your home?	1	2	3	4	5
d. injure or kill you or your family if you did not evacuate?	1	2	3	4	5

7. Were you advised by anyone to evacuate to a safer location? (Check all that apply)
☐ No ☐ Yes, by an authority (e.g., police officer) ☐ Yes, by a friend, relative, or neighbor
☐ Yes, by news media ☐ Yes, by others (please explain) ________________________________

8. Did you try to get more information from anyone before deciding to evacuate? (Check all that apply)
☐ No ☐ Yes, friends, relatives, neighbors ☐ Yes, authorities (e.g., police)
☐ Yes, news media ☐ Yes, other sources (please specify)
____

9. Did you evacuate from the place where you were when threatened by the wildfire? (Check one)

☐ Yes, I evacuated *before* an official evacuation order was issued (go to Q11)
☐ Yes, I evacuated *after* receiving an official evacuation order (go to Q10)
☐ No, I stayed where I was and continued what I was doing (go to Q17)
☐ No, I stayed where I was and waited for additional information (go to Q17)
☐ No, I stayed to protect property (go to Q17)
☐ No, I took some other action (Please explain, then go to Q17)

____

10. How much time did you wait after you were warned until you evacuated? _______________minutes

11. Did you do anything else before you evacuated? (Check all that apply.)
☐ Packed an emergency kit ☐ Tried to protect my property
☐ Tried to find separated family members ☐ Tried to warn others
☐ Other (please explain)

____

12. Did you have a motor vehicle (e.g., car, truck, or motorcycle) available when you were deciding whether to evacuate?
☐ No ☐ Yes

13. How did you evacuate? (Check all that apply.)
☐ By foot ☐ My own vehicle ☐ Friend/neighbor's vehicle ☐ Public transportation
☐ Emergency vehicle (e.g., police car) ☐ Other (please explain)

____

14. When you evacuated, did you go to a different community than where you were when you were warned about the wildfire? ☐ No (go to Q17) ☐ Yes (go to Q15)

15. To which community/place did you go?

____

16. To which of the following places did you go when you evacuated? (Check all that apply)
☐ The home of a relative ☐ The home of a friend
☐ An official shelter ☐ A public location (e.g., park)
☐ A church ☐ Other (please explain)

____

17. Were you caught in the wildfire at any time during this event? ☐ No ☐ Yes

18. Which of the following did you have on hand before the wildfire? (Check all that apply.)
☐ 3 day supply of water ☐ 3 day supply of non-perishable food
☐ Emergency kit filled with supplies ☐ Family emergency plan
☐ Battery powered radio ☐ Predetermined place to evacuate

19. How likely do you think it is that in the next 10 years a *wildfire* will...

	Not at all likely				Extremely likely
a. cause major damage to property in your community	1	2	3	4	5
b. injure or kill community residents if they do not evacuate?	1	2	3	4	5
c. cause major damage to your home?	1	2	3	4	5
d. injure or kill you or members of your family if you do not evacuate?	1	2	3	4	5

20. How often do you …

	Daily	Weekly	Monthly	Yearly	Never
a. think to yourself about wildfires?	1	2	3	4	5

b. talk to other people about wildfires? 1 2 3 4 5

21. To what extent does the risk of *future* wildfires make you feel…	**Not at all**			**Very great extent**	
a. worried	1	2	3	4	5
b. nervous	1	2	3	4	5
c. fearful	1	2	3	4	5
d. angry	1	2	3	4	5
e. frustrated	1	2	3	4	5
f. annoyed	1	2	3	4	5

22. How likely do you think it is that each of the following will happen after a *wildfire* begins but before your home is threatened…	**Not at all likely**			**Extremely likely**	
a. you will receive an accurate forecast of fire arrival time at your home	1	2	3	4	5
b. you will receive an official evacuation warning	1	2	3	4	5
c. you can prepare to evacuate	1	2	3	4	5
d. you can evacuate to a safe location	1	2	3	4	5

23. To what extent have you received information about wildfire hazard in this area from...	**Not at all**			**Very great extent**	
a. print media (newspapers, magazines, brochures)?	1	2	3	4	5
b. electronic media (broadcast and cable radio and TV)?	1	2	3	4	5
c. Internet (e.g., news media websites, emergency management websites)?	1	2	3	4	5
d. social media (e.g., Facebook, Twitter)?	1	2	3	4	5
e. discussions with peers (friends, relatives, neighbors, coworkers)?	1	2	3	4	5
f. meetings with community groups?	1	2	3	4	5
g. meetings with state and local emergency management authorities?	1	2	3	4	5

24. How likely are you to take each of the following actions if you are at home when a wildfire *approaches your area*?	**Not at all likely**			**Extremely likely**	
a. Evacuate before an official evacuation order is issued for my area	1	2	3	4	5
b. Evacuate as soon as I hear an official evacuation order for my area	1	2	3	4	5
c. Stay to protect property even if I receive an official evacuation order	1	2	3	4	5
d. Stay to see if the risk is great even if I receive an official evacuation order	1	2	3	4	5

25. If you receive an official evacuation order decide to evacuate from your home for a wildfire, how will you do it?
☐ Car ☐ Foot ☐ Bicycle ☐ Other_________________________

26. If you plan to evacuate by car, how many cars do you plan to take? _____________cars

.

27. Have you planned where to go if you evacuate from your home for a wildfire ☐ No ☐ Yes

28. Have you planned what route to take if you evacuate from your home for a wildfire ☐ No ☐ Yes

29. How long will it take you to prepare to evacuate (e.g., gather family members, grab emergency kit) for a wildfire?_____ minutes

30. How long *after you leave the house* will it take you to reach safety using your preferred evacuation route for a wildfire _____ minutes

31. Have you done any of the following to prepare for a wildfire?

	No	Haven't done but plan to do	Yes
a. managed vegetation	1	2	3
b. made my house more fire resistant	1	2	3
c. prepared a family emergency plan	1	2	3
d. obtained information about what to do during wildfire threats	1	2	3
e. obtained information about where to go during a wildfire evacuation	1	2	3
f. obtained an emergency toolkit for wildfire threats	1	2	3

32. How many years have you lived in: _____ The community you live in now _____ Your current residence

33. Do you rent or own the home where you now live? ☐ Rent ☐ Own
34. How old are you? ______years

35. What is your gender? ☐ Male ☐ Female ☐ Prefer to self-describe

36. What is your marital status? ☐ Married ☐ Single ☐ Divorced ☐ Widowed
37. How many people in your household are: ____ Less than 18 years ____18-65 years ____ Over 65 years

38. Which of the following categories best describes your yearly household income before taxes?
☐ Less than €25,000 ☐ €25,001 - €50,000 ☐ €50,001 - €75,000
☐ €75,001 - €100,000 ☐ Over €100,000

39. Which best reflects the highest level of education you 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.)

40. Do you have any other comments about household evacuation preparedness?

____
____
____
____
____

Thank you for participating in this survey.

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