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Lessons Learned From the 2018 Attica Wildfire: Households' Expectations of Evacuation Logistics and Evacuation Time Estimate Components

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Abstract. Despite the increase in frequency and intensity of wildfires around the world, little research has examined households' expectations of evacuation logistics and evacuation time estimate (ETE) components during such rapid-onset disasters. To address this gap, this study analyzes data from 152 household responses affected by the devastating 2018 wildfire in Mati, Greece where the second-deadliest wildfire of the 21st century took place. The questionnaire measured residents' expectations of how they would respond to a future wildfire. This includes the number of vehicles they would take, their evacuation destination and route choices, and their expected evacuation preparation and travel times. Explanatory variables include risk perceptions, wildfire preparedness, wildfire experience, and demographic characteristics. The univariate results reveal some similarities to, but also some differences from, expected evacuation logistics and ETE components in other natural hazards. Moreover, correlation and regression analyses show that expected evacuation logistics and ETE components are primarily related to wildfire preparedness actions. Comparison of this study's results with other rapid onset events such as tsunamis and hazardous material incidents, as well as longer onset events such as hurricanes, sheds light on household responses to wildfires. Emergency managers can use the similarities in results across studies to better prepare for wildfire evacuations.

Keywords: Wildfire evacuation, Evacuation logistics, Evacuation time estimation

1. Introduction

Frequent wildfires throughout the world are producing casualties, property damage, social and economic disruption, and environmental degradation [96]. Climate change is contributing to this recurrence of wildfires through increased fire-season fuel aridity [33]. Specifically, environmental changes such as longer dry seasons and heat waves have led to a substantial increase in the extent of forest areas that are prone to wildfires. In addition, rapid urbanization due to population growth

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in the Wildland-Urban-Interface (WUI, the area where households and infrastructure meet or lie within wildland vegetation) further exacerbates the problem by significantly increasing the amount of property at risk and the likelihood of human-caused ignition [75]. The prevalence of this issue in all regions of the world makes understanding household evacuation decision processes a focal point, as this will help emergency managers to better understand, plan, and improve the effectiveness of their communities' wildfire evacuation strategies [5, 83].

Gaps in knowledge about households' responses to imminent wildfire threats limits emergency managers' ability to address misconceptions through targeted messaging and to develop more effective traffic management strategies. To this end, evacuation modelers have sought to analyze the impact of wildfires on WUI populations and evacuation route systems (ERSs) using models such as WUI-NITY [77] and the Interdisciplinary Agent-based Wildfire Evacuation Model (I-ABWEM) [84]. Officials can take advantage of such simulation models to engage in pre-event planning that identifies the best evacuation start time, evacuation routes, and traffic management measures for an array of wildfire evacuation scenarios [38]. However, the credibility of such modeling approaches depends upon how effectively and accurately modelers can represent evacuees' responses to imminent wildfire threats [31]. In the absence of accurate data about evacuee behavior, forecasts of evacuation outcomes such as evacuation clearance time[1] are substantially affected by analysts' assumptions. As has been the case in evacuation analyses for nuclear power plant accidents [50] and hurricanes [53], these assumptions are user-defined model parameters or values randomly selected from an arbitrarily assumed statistical distribution [25] that substitute for empirical data about households' behavioral responses. These behavioral responses include households' evacuation departure times and their evacuation logisticsöevacuation modes, routes, destinations, and accommodations [41, 100, 102].

Most wildfire studies, although limited in comparison to studies of hurricanes [46, 56, 57] and tsunamis [61, 67–69], have focused on understanding evacuation decisions (e.g., stay-and-defend or evacuate) and emergent mobility patterns [26, 38]. However, it is also important to understand households' evacuation logistics because the number of evacuating vehicles, evacuation destinations, and evacuation routes are essential inputs to evacuation models.

Moreover, once households decide on their evacuation logistics, they can then either depart immediately or continue evacuation preparations by "milling" [98] (e.g., seeking warning confirmation and additional information and relaying warnings to others) and engaging in logistical preparation (e.g., gather all persons who would evacuate with you; pack items you would need while gone; shut off utilities, secure the home and leave [48]) before evacuating from their homes [52, 58, 59]. The time required to complete all of these stepsöan evacuation time estimate (ETE)öis a function of four components [49, 87]: $t_T = f(t_d, t_w, t_p, t_e)$, 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 evacuation prepa-

[1] Evacuation clearance time, the time required for a household to reach its evacuation destination, is the same as its Evacuation Time Estimate (ETE).

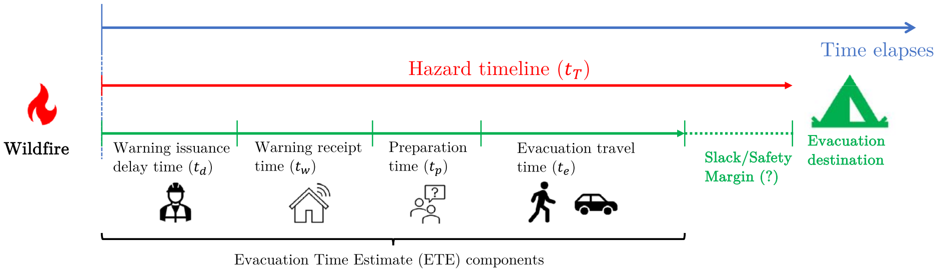

Figure 1. Chains of events for community response during a wildfire (adapted from Lindell and Perry [50], Fig. 4.1).

ration time, and t_e is the household's evacuation travel time–see Fig. 1, which is adapted from Lindell and Perry [50], Fig. 4.1. Households vary in their estimated values of t_w and t_p, which combine with t_d to determine their departure times. Specifically, households seek to reduce the probabilities of a false positive decision (evacuating for a wildfire that does not strike their home) and a false negative decision (failing to evacuate for a wildfire that does strike), by waiting as long as possibleöengaging in milling activities [98] until they think they have just enough time to evacuate before the wildfire front arrives [16]. The shorter their estimates of t_p and t_e, the longer they can wait after receiving a warning to reduce the probability of a decision error. A significant amount of research has demonstrated how households' expected responses to hypothetical hazard scenarios can provide reasonable predictions of evacuees' behavior in actual events [34, 36]. Such evacuation intentions data can allow evacuation analysts and emergency officials to develop effective evacuation strategies by using people's expectations about the time interval from their receipt of a warning, observation of environmental cues (e.g., the smell of burning, smoke proliferation, approaching flames), or observation of social cues (e.g., seeing others evacuating) until the time they leave their homes. In addition, empirical data on ETE components and evacuation logistics are essential inputs to computational algorithms for modeling flows of evacuating vehicles (or persons, in the case of pedestrian evacuations) through the evacuation route system (ERS) to estimate the evacuation travel times and, ultimately, evacuation clearance times.

Although there have been empirical studies of household evacuation behavior in large-scale evacuations (see the summary in Lindell et al. [49]), few studies have empirically analyzed households' expected evacuation logistics and ETE components for wildfire evacuations. Evacuees' expected number of evacuating vehicles affects evacuation clearance times because a large number of vehicles entering the ERS simultaneously slows travel speeds and increases the likelihood of evacuees being overtaken by the wildfire. Therefore, factors predicting the number of vehicles taken by each household, and the similarity of those factors to those identified in other evacuation surveys, will assist wildfire modelers who are constrained by sparse empirical data. Similarly, evacuees' evacuation routes and destinations

Table 1
Research Questions

Expectations of evacuation logistics	*RQ1*. What are the predictors of the number of cars that people plan to take in a wildfire evacuation? *RQ2*. What are the predictors of whether people have planned their wildfire evacuation destinations? *RQ3*. What are the predictors of whether people have planned their wildfire evacuation routes?
Expectations of ETE components	*RQ4*. What are the predictors of people's expectations about how long it will take for wildfire evacuation preparations? *RQ5*. What are the predictors of people's expectations about how long it will take for wildfire evacuation travel?

affect evacuation clearance times because many people going to the same destinations using the same routes will slow traffic or stop it altogether. Finally, excessive evacuation preparation times delay departure and increase the risk of being overtaken by a wildfire, whereas underestimates of evacuation travel time run the risk of delaying departures and also increase the risk of being overtaken by a wildfire. Consequently, the present study examines the five research questions in Table 1 about these dependent variables and the variables that influence them. The results are then compared to other evacuation studies to identify patterns of household response that emergency managers should expect in a wildfire.

1.1. Paper Organization

The next section provides a review of existing studies of households' wildfire evacuation logistics and evacuation preparedness. This is followed by a brief description of the study site in Sect. 3, and the results from statistical analyses in Sect. 4. Section 5 discusses this study's major findings, considering how they align with those from other evacuation studies; the study's limitations; and directions for future research on households' wildfire evacuation behavior. Finally, Sect. 6 presents concluding remarks related to wildfire evacuation research.

2. Literature Review

Past wildfire studies have focused on topics such as the household evacuation decision (i.e., evacuate or not) and evacuation movement modeling [26]. For example, some research has concluded that there are two types of responses to wildfires: some people are inclined to evacuate and others are inclined to stay, either because they do not think they are at risk or because they choose to shelter-in-place [63]. Additionally, factors such as perceived evacuation efficacy, preparedness knowledge, and general risk attitude significantly influence a resident's decision to evacuate or stay. Other wildfire studies have analyzed the effects of evacuees' socio-psychological and physical characteristics (e.g., walking or driving speed) on evacuation outcomes such as clearance times and mortality rates

Table 2
Demographic Comparisons Between Sample and Region

Variable	Sample	Greece population*
Median age	50	46
Female (%)	53	53
Home ownership (%)	80	74
Education, bachelor's degree or higher (%)	60	40
Median income	50, 000 €	16,235 €

*Regional data is from Greece [29]

[84, 90]. However, few studies have documented households' expectations about wildfire evacuation logisticsöespecially the number of vehicles taken, evacuation routes, and evacuation destinations [38]. There is a similar lack of data on expected ETE componentsöevacuation preparation and evacuation travel times. Given the limited wildfire data for some of these variables, the review below also examines evacuation data from hazards such as hurricanes and tsunamis.

2.1. Expected Evacuation Logistics

One survey of evacuation mode choice during a large wildfire in Haifa, Israel showed that only 10% of the respondents expected to evacuate alone, and an evacuating group had three individuals on an average [86]. As a result, the average number of evacuating vehicles per household was $M = 0.89$, which can be attributed to the fact that car ownership is lower in Israel than in the U.S. [38]. By contrast, hurricane evacuation studies in the U.S. have produced much larger estimates of vehicle use in evacuations. For example, Wu et al. [100] reported that households took an average of 1.38 cars (range = 1.25 to 1.70) in Hurricanes Katrina and Rita, but the average ranged from 1.10 to 2.15 in five local jurisdictions in Hurricane Lili [53]. However, hurricanes are slow-onset hazards that have much larger evacuation zonesöthe average evacuation distance for hurricanes ($M = 311$ km; range = 253 to 429 km [101]) substantially exceeds that for wildfires. In addition to the greater evacuation distance for hurricanes than for wildfires, cars are valuable assets that evacuees are motivated to preserve by evacuating them from danger [61]. Consequently, there might not be a difference in car use between hurricane and wildfire evacuations, at least in the U.S.

Residents who decide to evacuate during wildfires subsequently engage in evacuation preparations that include evaluating available options of accommodations in which they can stay until they return home. Predetermined choices in such contexts (i.e., choosing accommodations in advance) will help households achieve a higher probability of reaching safety before the arrival of hazardous conditions [84]. Therefore, it is necessary to understand how different social-psychological variables, wildfire experience, and demographic characteristics affect the evacuation decision making process. However, most wildfire studies have focused on the types of evacuation accommodations people choose during the event. For example, the majority of the evacuees chose relatives' (44%) or friends' homes (28%),

Table 3
Summary Statistics for Variables

Abbreviation	Description	Mean	SD
Expected evacuation logistics and ETE components			
No. of cars	Expected number of vehicles (1 = More than one car, 0 = One car)	0.86	0.38
Evac. dest	Planned destination (1 = Yes, 0 = No)	0.69	0.46
Evac. route	Predetermined evacuation route (1 = Yes, 0 = No)	0.64	0.48
Prep time	Expected evacuation preparation time (1 = <5, 2 = (5 to 10], 3 = (10 to 15] 4 = (15 to 30), 5 $\geq$ 30 min)	2.34	1.21
Travel time	Expected evacuation travel time (1 = <5, 2 = (5 to 10], 3 = (10 to 15] 4 = (15 to 30], 5 $\geq$ 30 min)	2.35	1.40
Risk perception			
Expected conseq	Expected consequences of a future wildfire "Not at all likely" (= 1) to "Extremely likely" (= 5)	3.58	1.27
Intrusive thoughts	Had thought about wildfires "Daily" (= 1) to "Never" (= 5)	2.50	1.19
Frequent discuss	Talked to others about wildfires "Daily" (= 1) to "Never" (= 5)	2.62	0.98
Fear	Felt worried, nervous, or fearful "Not at all" (= 1) to "Very much so" (= 5)	3.83	1.23
Anger	Felt angry, frustrated, or annoyed "Not at all" (= 1) to "Very much so" (= 5)	4.30	1.32
Wildfire preparedness			
Vegetation	Managed vegetation (1 = Yes, 0 = No)	0.62	0.49
Fire resistance	Increased home fire resistance (1 = Yes, 0 = No)	0.28	0.45
Family plan	Have family emergency plan (1 = Yes, 0 = No)	0.30	0.46
Wildfire info	Collect wildfire information (1 = Yes, 0 = No)	0.45	0.50
Dest. info	Obtain destination information (1 = Yes, 0 = No)	0.35	0.48
Emerg. kit	Prepared emergency kit (1 = Yes, 0 = No)	0.17	0.37
Wildfire experience			
Evac. experience	Evacuated in the 2018 fire (1 = Yes, 0 = No)	0.86	0.35
Pre plan	Had a family emergency plan (1 = Yes, 0 = No)	0.09	0.28

Table 3 continued

Abbreviation	Description	Mean	SD
Demographics			
Commun. tenure	Community tenure (1 = >20 years, 0 = otherwise)	0.62	0.48
Res. tenure	Residence tenure (1 = >20 years, 0 = otherwise)	0.46	0.50
Own home	Home ownership status (1 = Own, 0 = Rent)	0.83	0.38
Female	Female gender (1 = Female, 0 = Male)	0.54	0.50
Married	Marital status (1 = Married, 0 = otherwise)	0.56	0.50
Children	Number of children in the family (1 = Members aged < 18 years 0 = otherwise)	0.44	0.50
Elder	Number of elders in the family (1 = Members aged > 65 years 0 = otherwise)	0.47	0.50
Income	Income status (1 = >50,000€, 0 = otherwise)	0.13	0.34
Education	Education level (1 = Household with a bachelor's degree or higher, 0 = otherwise)	0.60	0.49

commercial facilities (hotels or motels, 11%), campgrounds or vacation homes (8%), or public shelters (5%) during the 2007 San Diego, California wildfires [85]. Later, evacuees from the 2017 Southern California wildfire reported their evacuation destinations as a peers' (i.e., friends' and family's) homes (74%), with the rest (26%) staying in commercial facilities [97]. These results are consistent with a summary that found most hurricane evacuees go to peers' homes (median Md = 62%; range 54% to 70%) and commercial facilities (Md = 27%; range = 16% to 32%), with public shelters (Md = 3%; range = 2% to 6%) as the least popular option [49]. Although Mileti et al. [66] provided some insights into the factors that influence people's decisions about evacuation accommodations and destinations, these decisions remain poorly understood in the context of a wildfire.

Hurricane studies have found that evacuation route choice is influenced by such factors as personal experience more than by pre-event educational materials, news media, or maps [49]. Other factors that influence hurricane evacuation route choice are the residents' familiarity with the at-risk area (i.e., due to their tenure in their community or current residence) or whether the emergency officials have provided recommendation about what route to follow Sadri et al. [80]. Understanding the basis for the evacuees' route choice is important because clearance times will increase if evacuees overload some routes and underutilize others. Such preimpact evacuation planningöidentifying and practicing an evacuation route in response to a warning, drill, or personal curiosityöhas been advocated as an essen-

Table 4
Pearson Correlation Matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. No. of cars	–												
2. Evac. dest.	− 0.11	–											
3. Evac. route	− 0.12	0.62	–										
4. Prep time	0.07	− 0.07	− 0.23	–									
5. Travel time	0.08	− 0.25	− 0.31	− 0.25	–								
6. Expected conseq.	− 0.12	0.05	− 0.02	0.07	0.04	–							
7. Intrusive thoughts	0.06	0.03	− 0.01	− 0.14	− 0.15	− 0.02	–						
8. Frequent discuss.	0.01	0.11	0.08	− 0.05	− 0.19	− 0.06	0.66	–					
9. Fear	− 0.09	− 0.05	− 0.07	0.10	0.15	0.32	− 0.37	− 0.19	–				
10. Anger	− 0.05	0.06	− 0.06	− 0.07	0.04	0.25	− 0.27	− 0.20	0.43	–			
11. Vegetation	0.03	0.12	0.14	− 0.05	− 0.23	− 0.24	− 0.03	0.06	− 0.17	− 0.04	–		
12. Fire resistance	− 0.01	0.00	0.07	− 0.02	0.10	− 0.03	− 0.04	− 0.04	0.04	0.12	− 0.09	–	
13. Family plan	− 0.08	0.28	0.22	0.01	− 0.05	0.10	− 0.05	0.02	− 0.02	0.01	− 0.02	0.05	–
14. Wildfire info.	− 0.10	− 0.02	0.13	− 0.06	− 0.18	− 0.16	0.02	0.05	0.00	− 0.06	0.00	− 0.06	0.14
15. Dest. info.	− 0.07	0.16	0.24	− 0.03	− 0.22	− 0.09	− 0.13	− 0.05	0.03	− 0.06	0.10	0.01	0.16
16. Emerg. kit	− 0.06	0.22	0.23	0.01	0.11	− 0.01	− 0.26	− 0.26	0.12	0.24	0.06	0.08	0.26
17. Evac. experience	0.02	− 0.18	− 0.17	0.07	0.27	− 0.13	− 0.02	0.06	− 0.03	0.04	− 0.09	− 0.02	− 0.09
18. Pre plan	0.03	− 0.05	0.04	0.03	0.04	− 0.03	0.02	0.16	− 0.01	0.03	0.00	0.13	0.32
19. Commun. tenure	− 0.04	− 0.14	− 0.11	0.02	− 0.03	0.05	0.15	− 0.04	− 0.04	− 0.12	− 0.08	0.03	− 0.06
20. Resid. tenure	− 0.06	− 0.06	− 0.01	0.20	− 0.02	− 0.04	0.15	0.05	− 0.04	− 0.12	− 0.11	0.05	− 0.05
21. Home owner.	0.07	0.00	0.06	0.13	− 0.02	− 0.18	0.15	0.21	− 0.18	− 0.11	0.04	0.01	− 0.09
22. Female	0.03	− 0.02	− 0.07	0.10	0.21	0.30	− 0.06	− 0.05	0.34	0.21	− 0.13	− 0.02	0.00
23. Married	0.09	− 0.05	− 0.07	− 0.02	0.00	0.03	− 0.09	− 0.17	0.03	0.06	− 0.07	0.05	0.09
24. HH with Child	− 0.02	0.04	0.03	− 0.13	− 0.01	0.16	− 0.02	− 0.05	0.23	0.19	− 0.05	0.14	0.10
25. HH with elders	− 0.10	0.06	0.08	0.13	− 0.02	0.01	− 0.02	0.00	0.13	0.00	0.12	0.03	− 0.03
26. Income	0.17	0.01	0.05	− 0.16	0.04	− 0.01	0.15	0.04	0.08	0.12	0.04	0.04	0.13
27. Education	− 0.03	− 0.03	0.05	− 0.04	− 0.01	0.02	0.12	− 0.19	0.04	0.04	0.15	− 0.06	0.01

Table 4
continued

	14	15	16	17	18	19	20	21	22	23	24	25	26	27
1. No. of cars														
2. Evac. dest.														
3. Evac. route														
4. Prep time														
5. Travel time														
6. Expected conseq.														
7. Intrusive thoughts														
8. Frequent discuss.														
9. Fear														
10. Anger														
11. Vegetation														
12. Fire resistance														
13. Family plan														
14. Wildfire info.	–													
15. Dest. info.	0.31	–												
16. Emerg. kit	− 0.01	0.16	–											
17. Evac. experience	− 0.12	− 0.19	− 0.08	–										
18. Pre plan	0.15	0.07	0.05	0.06	–									
19. Commun. tenure	0.02	0.00	− 0.09	0.02	0.01	–								
20. Resid. tenure	0.01	0.04	− 0.06	0.70	− 0.01	0.02	–							
21. Home owner.	0.13	0.04	0.17	0.22	0.39	0.03	0.01	–						
22. Female	− 0.07	− 0.23	− 0.09	− 0.07	0.04	0.03	0.01	0.06	–					
23. Married	− 0.08	− 0.15	0.11	− 0.01	0.00	− 0.02	0.05	− 0.01	0.08	–				
24. HH with Child	0.01	0.16	0.22	0.08	− 0.07	− 0.16	0.04	0.20	0.02	0.07	–			
25. HH with elders	− 0.10	0.06	0.05	0.14	0.22	0.22	0.08	0.01	− 0.08	− 0.03	0.05	–		
26. Income	0.16	− 0.12	0.02	− 0.09	0.07	− 0.11	0.05	0.07	0.09	− 0.09	− 0.05	0.02	–	
27. Education	− 0.04	− 0.06	0.14	0.06	0.02	0.02	0.05	0.35	0.05	0.07	0.12	0.09	0.01	–

Variables with $p < 0.01$ are underlined tial element to a successful evacuation [55, 94]. However, it remains to be determined if the findings from hurricane studies can be applied to wildfires. Much research (e.g., Grajdura et al. [28], Siam et al. [84]) has assumed that evacuees choose the shortest or fastest routes for wildfire evacuations (the User Equilibrium model) rather than the factors identified in post-disaster evacuation surveys [49]. This difference between modeling assumptions and real-world evacuation behavior [13] can reduce the accuracy of evacuation model outputsöespecially when evacuees will not divert from a congested primary route because they are unfamiliar with alternate routes [49]. It might be somewhat risky to make a last minute decision about an evacuation route during a slow-onset disaster such as a hurricane, but it could be extremely dangerous to make a last minute decision on an evacuation route during a rapid-onset event such as a wildfire [55]. Thus, there is an urgent need to analyze people's expected evacuation routes and the predictors of those routes.

2.2. Household ETE Components (t_p, t_e)

Very few studies have analyzed the variation in household preparation times (t_p) for wildfire evacuations. This ETE component typically denotes the time interval from a household's warning receipt to initiation of evacuation movement, where the warning is an advisory from an official warning source [79]. However, environmental cues such as smoke and flames can motivate people's evacuation preparations when official warnings are absent [45, 52]. In addition to milling [98] and logistical preparation [48], preparation time is influenced by a person's perception of a hazard's speed of onset. For example, people took almost 7.5 h to finish preparation tasks in Hurricanes Lili, Katrina, and Rita, whereas majority of the survey respondents evacuated 12 h after the National Hurricane Center issued a Hurricane Warning during Hurricane Ike in 2008 [35]. On the other hand, the majority of survey respondents expected to take no more than 2 h to prepare for evacuation from a radiological materials release from a nuclear power plant [56]. These nuclear power plant data are similar to two hazardous materials transportation incidents in which majority of people evacuated within 2 h to 6 h [76]. However, these time intervals are considerably greater than the 20-min first wave arrival time for a Cascadia Subduction Zone (CSZ) tsunami [13], where the median expected preparation times are approximately 10 min. These expected preparation times are consistent with actual preparation times during tsunamis. For example, 61% of American Samoa tsunami respondents reported leaving within 15 min [54]. Similarly, 45% of Palu Indonesia respondents reported leaving within 5 min, and 67% of them left within 10 min [91] and Harnantyari et al. [32] reported that 80% of their Palu respondents reported leaving the risk area within 30 min. These observations are similar to the 2015 Aotearoa/New Zealand study in which 7% expected to evacuate immediately and 63% expected to evacuate within 10 min [17]. Similarly, survey respondents in the west coast of Thailand reported spending between approximately 7–36 min before starting to evacuate during the 2004 Indian Ocean Tsunami [11]. However, a post-event study for the 2016 Aotearoa/New Zealand tsunami found people took longer than expected in response to a real eventö7% did evacuate without taking any other action, but only 36% evacuated within 10 min and only 52% evacuated within 30 min [7]. These results, on the other hand, are different from what is observed in a wildfire evacuation scenario. For example, Vaiciulyte et al. [89] observed that many individuals in a study conducted in Australia and the South of France took between 12 min and 34 min before beginning to evacuate, while a significant number of people spent between 15 min and 40 min in milling (e.g., calling friends and family, getting pets ready to leave, shutting windows). These contrasting findings highlight the potential for notable differences between expected and actual behavior that are due to the differences between respondents' assumed situational context when asked about a hypothetical threat and an actual threat. Other studies have assessed expected preparation times for hazardous materials releases. For example, a study of expected responses to a no-notice event such as a chemical spill found that 48% of the respondents expected to depart in the first 30 min after receiving a warning and the rest expected to leave within 180 min [27]. However, it remains unclear whether the research findings from these other hazards generalize to wildfires due to differences in hazard intensity and the amount of forewarning before hazard onset for hurricanes, tsunamis, and wildfires [70].

Similar to expected evacuation preparation time, research on expected evacuation travel time (t_e) is also mostly limited to tsunamis and hurricanes. For example, Arce et al. [1] reported that 53% of the households in Kamakura City, Japan expected to reach evacuation shelters within 30 min, while 14% expected to take more than 30 min and 33% did not know how long it would take. Moreover, Chen et al. [13] reported that 70% to 85% of CSZ residents expected evacuation travel times of 10 min or less, depending on location.

Although previous studies have examined the time that people spent during evacuation preparation and evacuation travel, there exists a gap in this knowledge for wildfires. Siam et al. [84] examined the evacuation process for the Mati, Greece wildfire, basing assumptions on data from Wang et al. [92], Mostafizi et al. [67], and Mostafizi et al. [69]. However, their assumptions were based on data from American tsunami-prone communities that may possess substantial differences in their risk perceptions, emergency preparedness, hazard experience, and demographic characteristics.

2.3. Predictors of Households' Expected Wildfire Evacuation Logistics and ETE Components

There is little research on the predictors of households' expected wildfire evacuation logistics, but there are some plausible categories of variables. Specifically, Lindell et al. [55] reported that expected preparation time for a tsunami evacuation was negatively correlated with receipt of hazard brochures and participation in hazard education meetings ($-0.10 \leq r \leq -0.25$), planned evacuation route ($r = -0.22$), knowledge of environmental cues to tsunami onset ($r = -0.22$), and expectations of car evacuation ($r = 0.20$). However, the only variable correlated with expected evacuation travel time was expected evacuation preparation time ($r = 0.29$). Moreover, Lindell et al. [42] reported that evacuation preparation times in the Uttarakhand floods were significantly correlated with education ($r = 0.18$), warning confirmation ($r = 0.36$) and information search ($r = 0.39$), preimpact preparation ($r = 0.45$), number of sources recommending evacuation ($r = 0.23$), and landslide expectation ($r = 0.16$). Also, Golshani et al. [27] found that expectations of later evacuation departure times were positively related to being disabled and larger household size, but negatively related to risk perception and being retired. In summary, these studies suggest that risk perceptions, emergency preparedness, hazard experience, and demographic characteristics are the most plausible explanatory variables for expected evacuation logistics and ETE components.

3. Method

3.1. Study Area

Mati is a Greek village located approximately 40 km from Athens on the east coast of the Attica region, see Fig. 2. It is popular among tourists because it offers hotel accommodations, beaches, and recreational activities. Mati is close to the Rafina harbor on the Aegean Sea and can be accessed by Marathonos Avenue to the west. Mati experienced a wildfire in July 13, 2018 that was the second deadliest in the 21st century, after Australia's 2009 Black Saturday bushfires [72]. The Mati wildfire originated at around 16:41 in a forested area on eastern slopes of Panteli mountain, which is about 20 km northeast of Athens' city center and 5 km from Attica's east coast. A very strong westerly wind blew for more than 10 h over Attica during the event, with wind gusts reaching 30 m/s to 34 m/s (67 mph to 76 mph) in the mountains. This wind interacted with the local topography to produce a downslope flow, warming temperatures to 39°C and lowering humidity to 19% prior to the onset of the wildfire [39]. These weather elements accelerated the fire spread through the WUI in Neos Voutzas and Mati within a time span of two h. The fire killed 104 people and seriously injured another 150. In addition to the high death toll, the wildfire destroyed 3000 houses, 305 vehicles, and 1,250 hectares of land [40].

3.2. Sample

A survey of 152 households in the area collected data on variables identified in previous evacuation studies as determinants of households' expected evacuation logistics and ETE components. Figure 2 displays the locations of the survey respondents who were contacted in April 2020 using an online platform following procedures recommended by Dillman et al. [19]. Because the majority of the homes in the wildfire impact area were destroyed, we took care to select respondents that would provide a representative sample of individuals who experienced the wildfire. Most of the respondents were from Mati (56%), followed by Neos Voutza (20%), Nea Makri (8%), Rafina (7%), Kokkino Limanaki (6%), Agios Andreas (2%), and Kallitechnoupoli (1%). They were slightly more likely (53%) to be female, had a median age of just over 50 years, and had a median income of

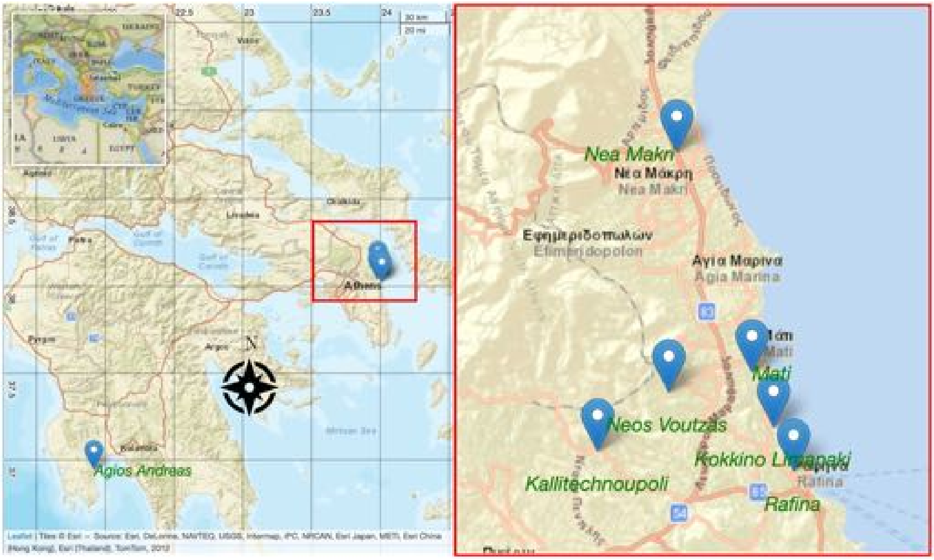

Figure 2. Map of Mati, Greece and survey data collection locations.

slightly less than €50, 000. The respondents were also predominantly married (55%), and most owned their homes (80%) at the time of the fire.

Table 2, which compares some of the sample demographics with available census data, shows the sample is reasonably representative of the population of these regions with respect to gender and home ownership. However, the respondents in this study are slightly older, somewhat more educated, and have much higher incomes than the Greek population in general. This over-representation of respondents who are more educated and affluent is consistent with other hazards surveys [8, 74]. Nonetheless, bias in any variable does not affect estimates of correlation coefficients unless it is so severe that it attenuates those variables' variances [51] and is likely to be completely irrelevant because the correlations of demographic variables with evacuation tend to be small and inconsistent [3, 34].

3.3. Survey Instrument

The questionnaire contained 39 items derived from recent research with other environmental hazards such as tsunamis [54, 91] and volcanoes [74, 94]. The expected evacuation logistics section asked respondents to report how many vehicles they expected to take when evacuating from a future wildfire (see Table 3 for item response categories); and if they had already planned where to go and what evacuation route they would take. In addition, there were asked about two expected ETE componentsötheir expected evacuation preparation time and evacuation travel time. Following Wei and Lindell [94], risk perception was measured by respondents' beliefs about the likelihood that there would be a wildfire in the next

10 years that would cause the following personal consequencesödamage in their community and to their home, and injury or death to community members and to family members. Respondents also reported the frequency of intrusive thoughts and discussions with others about wildfires, and their levels of fear (worried, nervous, fearful) and anger (angry, frustrated, or annoyed) about wildfire hazard. Wildfire preparedness was measured by asking respondents if they had prepared for a wildfire by (a) managing the vegetation around their home; (b) making their home more fire resistant; (c) preparing a family emergency plan; (d) obtaining information about what to do during wildfire threats; (e) obtaining information about where to go during a wildfire evacuation; and (f) obtained an emergency toolkit for wildfire threats. To assess respondents' hazard experience during the 2018 Mati wildfire, they reported if they evacuated, engaged in any evacuation preparations, and where they evacuated. The questionnaire concluded with questions about nine demographic variables: age, gender, marital status, number of people in their household in two age categories (<18 years and >65 years), highest level of education, annual household income, home ownership, residential tenure, and community tenure.

3.4. Analysis Procedures

Interdependencies among the variables in Table 3 were identified by computing the correlations among all of the dependent variables and explanatory variables. If two or more explanatory variables were significantly correlated with a dependent variable, the relative influence of each explanatory variable was assessed through regression analyses. The dichotomous dependent variables were tested using binomial logistic regression analysis whereas the ordinal dependent variables were analyzed by means of an ordered probit model. The regression analyses yielded estimates of marginal effects that explain the relative importance of each explanatory variable when holding the other explanatory variables constant [22, 93]. The marginal effect is the difference between the estimated probability of an event occurring when an indicator variable is zero and when it is one, while all other variables are held constant. The following results only report the average marginal effect across all observations, as each observation in the data has its own marginal effect.

These analyses produced 650 tests of correlation coefficients and 46 tests of regression coefficients, so the false positive (FP) rate is a concern [71]. Specifically, the expected number of false positives is FP $= \alpha \times n$, where FP is the number of false positive test results, α is the Type I error rate, and n is the number of statistical tests. Therefore, the expectation is that there will be approximately 35 false positives for $\alpha = 0.05$ but only $n = 7$ for $p < 0.01$. The best way to avoid inflation of this experiment-wise error rate is to use a procedure proposed by Benjamini and Hochberg [6]. They advocated that researchers (i) specify a false discovery rate (d) for the entire study, (ii) sort the p_i significance values for the individual tests in ascending order $1 \leq i \leq n$, and (iii) classify each $p_i \leq d \times i/n$ as statistically significant. When applied to evacuation surveys, this procedure generally yields a statistical significance level of $p < 0.01$, so this criterion is used in the following analyses.

4. Results

4.1. Univariate Analysis

Table 3 indicates that only about one-third of the respondents expect to take two or more cars in a future wildfire evacuation, and about two-thirds have planned their evacuation destination and the route they will take to that destination. Moreover, they expect to take approximately 8 min in evacuation preparations and another 8 min in evacuation travel time. The respondents had moderate levels of expected consequences of a future wildfire ($M = 3.58$), higher levels of fear ($M = 3.83$), and still higher levels of anger ($M = 4.30$). They had a moderate frequency of intrusive thoughts ($M = 2.50$) and discussions ($M = 2.62$) about a future wildfire. Their wildfire preparedness actions vary noticeably in popularity, ranging from 62% for managing vegetation to 17% for preparing an emergency kit. The respondents also vary noticeably in their wildfire experiences, ranging from 86% who evacuated in the Mati wildfire to the 9% who had a prepared a family emergency plan or had identified a place to evacuate.

As indicated in Fig. 3, 62% of the Mati respondents expected to take 10 min or less for evacuation preparations, 83% expected to complete those preparations within 15 min and 96% expected to complete preparations within 30 min. Moreover, as indicated in Fig. 4, 76% of the Mati residents expected complete their evacuation travel within 10 min, 89% expected their travel time to be 15 min or less and 98% expected this to be 30 min or less.

4.2. Correlation Analysis

As indicated in Table 4, the correlation analysis revealed five significant correlations among the evacuation logistics variables. The expected number of cars is not significantly correlated with any of the other variables, but a planned evacuation destination is positively correlated with a planned evacuation route ($r = 0.62$) and negatively correlated with expected evacuation travel time ($r = -0.25$). Moreover, having planned an evacuation route has significant negative correlations with expected evacuation preparation time ($r = -0.23$) and expected evacuation travel time ($r = -0.31$). Finally, expected evacuation preparation time is negatively correlated with expected evacuation travel time ($r = -0.25$). In addition, the risk perception variables have moderately strong correlations (average $|r| = 0.28$) but the wildfire preparedness items have extremely weak correlations (average $|r| = 0.08$) except for wildfire information with destination information ($r = 0.31$) and family plan with emergency kit ($r = 0.26$). Moreover, the risk perception variables generally had weak correlations with evacuation logistics and ETE components (average $|r| = 0.04$ and 0.09, respectively), as did the wildfire preparedness variables (average $|r| = 0.08$ and 0.04, respectively).

The correlation analysis identified only one correlation related to "RQ1: What are the predictors of the number of cars that people plan to take in a wildfire evacuation?". Specifically, income ($r = 0.17$) has the only significant correlation with the number of vehicles respondents expected to take in a wildfire evacuation. However, there are three significant correlations relevant to "RQ2: What are the predictors of whether people have planned their wildfire evacuation destinations?". Specifically, a planned evacuation destination is positively correlated with having prepared a family emergency plan ($r = 0.28$), collected information about evacuation destinations ($r = 0.16$), and prepared an emergency kit ($r = 0.22$). On the other hand, residents' prior experience during the 2018 Mati event is negatively associated ($r = -0.18$) with evacuation destination selection for a future wildfire. As for the"RQ3: What are the predictors of whether people have planned their wildfire evacuation routes?", this dependent variable has significant positive correlations with having prepared a family emergency plan ($r = 0.22$), collected information about evacuation destinations ($r = 0.24$), and prepared an emergency kit ($r = 0.23$).

In regard to "RQ4: What are the predictors of people's expectations about how long it will take for wildfire evacuation preparations?", this variable has two significant correlationsöa positive correlation with residence tenure ($r = 0.20$) and a negative correlation with household income ($r = -0.16$). Finally, there are five significant correlations regarding "RQ5: What are the predictors of people's expectations about how long it will take for wildfire evacuation travel?". Specifically, expected evacuation travel time is negatively correlated with the frequency of wildfire discussions ($r = -0.19$), managing vegetation ($r = -0.23$), wildfire information collection ($r = -0.18$), evacuation destination information collection ($r = -0.22$), but positively correlated with female gender ($r = 0.21$).

4.3. Regression Analyses

As the correlation analysis identifies only one variable having a significant correlation with the expected number of cars, there is no need to conduct regression analyses to control for the effects of other variables in addressing RQ1. However, the regression analysis for RQ2 in Table 5 shows that the significant predictors of whether respondents have planned their wildfire evacuation destinations are collecting information about potential evacuation destinations ($\beta = -0.12$), as well as evacuation experience ($\beta = -0.09$) and preparing an emergency kit ($\beta = 0.19$). Although wildfire information has a nonsignificant correlation coefficient, it has a significant regression coefficient ($\beta = -0.09$). Conversely, although family plan has a significant correlation coefficient, it has a non-significant regression coefficient. For RQ3, planning an evacuation route has four significant predictors, all of which are positive. These are preparing a family emergency plan ($\beta = 0.98$), collecting information about evacuation destinations ($\beta = 0.90$), and preparing an

Table 5
Regression Analyses

	RQ2: Evacuation destination		RQ3: Evacuation route	
Variable	β (SE)	B	β (SE)	B
Constant	0.29 (0.27)	0.09	0.40 (1.38)	0.02
Evac. experience	−0.12 (0.06)	−0.16	0.27 (0.19)	0.12
Expected conseq.	0.02 (0.04)	0.04	0.11 (0.21)	0.04
Frequent discuss.	0.05 (0.03)	0.14	0.06 (0.17)	0.03
Anger	0.03 (0.05)	0.05	−0.18 (0.22)	−0.07
Vegetation	0.10 (0.08)	0.10	−0.98 (0.49)	0.14
Fire resistance	−0.02 (0.08)	−0.02	0.56 (0.46)	0.09
Family plan	0.24 (0.08)	0.23	–	0.16
Wildfire info.	−0.09 (0.08)	−0.08	0.43 (0.41)	0.09
Dest. info.	−0.14 (0.08)	0.15	−0.90 (0.45)	0.16
Emerg. kit	−0.19 (0.11)	0.02	−0.69 (0.73)	0.08
AIC	138.06		151.99	

Variables significant at $p < 0.01$ are underlined
AIC Akaike information criterion

Table 6
Ordered Probit Model Results for ETE Components

	RQ4: Evacuation preparation time		RQ5: Evacuation travel time	
Variable	β (SE)	t-value	β (SE)	t-value
Evac. route	0.05 (0.19)	0.26	−0.76 (0.19)	−3.98
Frequent discuss.	0.02 (0.09)	0.25	−0.15 (0.09)	−1.68
Anger	0.01 (0.03)	0.33	−0.02 (0.12)	−0.17
Vegetation	−0.04 (0.18)	−0.22	−0.37 (0.18)	−2.03
Fire resistance	−0.05 (0.28)	−0.19	0.13 (0.20)	0.68
Wildfire info.	−0.05 (0.23)	0.22	−0.36 (0.18)	−1.19
Dest. info.	0.22 (0.20)	1.09	1.11 (0.21)	5.26
Emerg. kit	−0.16 (0.25)	−0.64	−0.48 (0.26)	1.83
Resid. tenure	0.42 (0.16)	2.63	−0.08 (0.17)	−0.47
Female	0.21 (0.17)	2.42	0.10 (0.17)	0.59
Income	−0.55 (0.22)	−2.43	0.25 (0.22)	1.14
μ_1	−0.64 (0.56)	−1.14	−2.49 (0.59)	−4.37
μ_2	0.25 (0.56)	0.46	−1.20 (0.57)	2.16
μ_3	0.90 (0.57)	1.59	−0.75(0.58)	−1.28
Log-likelihood	−216.47		−200.16	
McFadden's R^2	0.05		0.09	
AIC	464.94		432.32	

Variables significant at $p < 0.01$ are underlined

Table 7
Marginal Effects for RQ4: Expected Evacuation Preparation Time

	Marginal effects				
Variable description	< 5 min	5 min to 10 min	10 min to 15 min	15 min to 30 min	> 30 min
Evac. route	0.174	0.03	−0.07	−0.08	−0.04
Frequent discuss	0	0	0	0	0
Anger	0	−0.01	0.01	0.01	0
Vegetation	0.01	0.02	0	−0.01	0
Fire resistance	0.01	0	−0.01	0.07	0
Wildfire info	−0.01	0	0	−0.01	0
Emerg. kit	−0.07	−0.01	0.03	0.03	0.01
Dest. info	−0.07	−0.01	0.03	0.04	0.01
Resid. tenure	−0.14	−0.02	0.06	0.07	0.03
Female	−0.07	−0.01	0.03	0.04	0.01
Income	0.18	0.03	−0.07	−0.09	−0.03

emergency kit ($\beta = 1.69$). In addition, managing vegetation ($\beta = 0.69$) significantly predicted planning an evacuation route despite its non-significant correlation.[2]

For RQ4, Table 6 shows that there are the two significant predictors of residents' expected evacuation preparation time. These are residential tenure ($\beta = 0.42$) and income ($\beta = -0.55$). For RQ5, expected evacuation travel time has five significant predictors. These are having identified an evacuation route ($\beta = -0.76$), participating in frequent wildfire discussions ($\beta = -0.15$), managing vegetation ($\beta = -0.37$), and collecting wildfire information ($\beta = -0.36$). In addition, there is a significant regression coefficients for preparing an emergency kit ($\beta = -0.36$) even though it has a non-significant correlation coefficient. Conversely, obtaining destination information and female gender have non-significant regression coefficients even though they have significant correlations.[3]

[2] Binary logistic regression analysis was applied to identify the significant predictors for the expected number of cars to be taken in evacuation, planned evacuation destination, and planned evacuation route (RQ2–RQ3 in Table 1). The utility function Y for these three variables consist of systematic terms ($\beta Y_{\delta h}$) and a random term ($\xi_{\delta h}$). The vector Y in each of these functions represents household characteristics that influence their choices about evacuation logistics (δ) for that household (h). The error term (ξ) corresponds to the unobserved disturbances. The base outcomes for the three dependent variables are residents who planned to take one vehicle, or who have planned an evacuation destination or an evacuation route for a future wildfire.

[3] A fixed-parameter ordered probit model was used to analyze household ETE time components (5 min or less, 5 min to 10 min, 10 min to 15 min, 15 min to 30 min, and more than 30 min) because, unlike ordinary least squares regression that assumes equal intervals, the ordered probit model can account for unequal differences among the categories in the dependent variable [30]. The relationship between a dependent variable (i.e., preparation time or evacuation travel time) and its explanatory variables (i.e., respondent characteristics) is $Y_\varphi = \beta_\varphi X_\varphi + \xi_\varphi$, where Y_φ denotes the dependent variable coded as 0, 1, 2, 3, 4; β_φ is the vector of regression coefficients; X_φ is the vector of explanatory variables; ξ_φ is a normally distributed (zero mean and unit variance) error term. For a specific preparation time, a respondent can be associated with category n if $\mu_{n-1} < y < \mu_n$.

Furthermore, in addition to examining the combined impact of selected variables through ordered probit analyses for RQ4–RQ5, we present the individual effects of these variables to gauge the significance of each parameter (refer to Table 7, 8). As indicated in Table 7, the marginal effects for expected evacuation preparation time indicate that an unit increase in the number of people who had a predetermined evacuation route results in an average 0.17 increase in the probability for the respondents to take less than 5 min for evacuation preparation activities, a 0.03 increase to take between 5 min and 10 min, a 0.07 decrease to take between 10 min and 15 min, a 0.08 decrease to take between 15 min and 30 min, and a.04 decrease to take more than 30 min to finish evacuation preparations. In addition, a unit increase in residence tenure will lead to an average 0.14 decrease in the probability to take less than 5 min, a 0.02 decrease to take between 5 min and 10 min, a 0.06 increase to take between 10 min and 15 min, a 0.07 increase to take between 15 min and 30 min, and a 0.03 increase to take more than 30 min. Last, a unit increase in income will lead to an average 0.182 increase to take less than 5 min for evacuation preparation activities, a 0.03 increase to take between 5 min and 10 min, a 0.07 decrease to take between 10 min and 15 min, a 0.09 decrease to take between 15 min and 30 min, and a 0.03 decrease to take more than 30 min.

The marginal effects in Table 8 indicate that an unit increase in deciding on an evacuation route in advance leads to an average 0.03 increase to evacuate in less than 5 min, a 0.01 increase to evacuate in 5 min to 10 min, a 0.08 decrease to evacuate in 10 min to 15 min, a 0.08 decrease to evacuate in 15 min to 30 min, and a 0.03 decrease to evacuate in less than 30 min. Similarly, an unit increase in the frequency of residents' discussions about wildfire will result in an average 0.04 increase in the probability of taking less than 5 min in evacuation travel, a non-zero increase to evacuate in 5 min to 10 min, a 0.01 decrease to evacuate in 10 min to 15 min, a 0.01 decrease to evacuate in 15 min to 30 min, and a 0.01

Table 8
Marginal Effects for RQ5: Expected Evacuation Travel Time

	Marginal effects				
Variable description	< 5 min	5 min to 10 min	10 min to 15 min	15 min to 30 min	> 30 min
Evac. route	0.025	0.01	−0.08	−0.08	−0.03
Frequent discuss.	0.04	0	−0.01	−0.01	−0.02
Anger	0.05	0	−0.02	−0.02	−0.01
Vegetation	0.11	0.01	−0.03	−0.03	−0.01
Fire resistance	−0.07	−0.02	−0.01	0.02	0.01
Wildfire info.	0.09	0.01	−0.03	−0.03	−0.01
Emerg. kit	−0.20	−0.011	0.07	0.06	0.02
Dest. info.	0.32	0.10	−0.01	−0.03	−0.03
Resid. tenure	0.09	0.03	0	−0.01	−0.01
Female	−0.25	−0.08	0	0.03	0.02
Income	−0.25	−0.08	0	0.03	0.02

decrease to take more than 30 min. Similarly, an unit increase in managing vegetation around households will lead to a 0.11 increase in the probability of evacuating in less than 5 min, a 0.01 increase to evacuate in 5 min to 10 min, a 0.03 decrease to evacuate in 10 min to 15 min, a 0.03 decrease to evacuate in 15 min to 30 min, and a 0.01 decrease to evacuate in 30 min or greater. In addition, a unit increase in the collection of wildfire information beforehand results in a 0.10 increase in the probability of evacuating in < 5 min, a 0.10 increase to evacuate in 5 min to 10 min, a 0.03 decrease to evacuate in 10 min to 15 min, a 0.03 decrease to evacuate in 15 min to 30 min, and a 0.01 decrease to take more than 30 min. Last, an unit increase in assembling emergency kits results in an average 0.20 decrease in the probability of evacuating in less than 5 min, a 0.01 decrease to evacuate in 5 min to 10 min, a 0.07 increase to evacuate in 10 min to 15 min, a 0.06 increase to evacuate in 15 min to 30 min, and a 0.02 increase to take more than 30 min.

5. Discussion

5.1. Correlations among Evacuation Logistics and ETE Components

It is noteworthy that the expected number of cars is unrelated to other elements of evacuation logistics and ETE components. However, the other variables in these categories are consistently related. Specifically, planned evacuation destination and route are positively correlated ($r = 0.62$), indicatingöquite logicallyöthat people who have identified a safe destination have also planned a route to get there. Moreover, these two variables are negatively correlated with expected evacuation preparation time and expected evacuation travel time. The negative correlations with expected preparation time suggest that the respondents think, probably accurately, that planning an evacuation route and destination will eliminate milling about these issues when they decide to evacuate. However, the correlations with evacuation travel time are more difficult to explain. One possibility is that the resulting reduction in expected evacuation preparation time will allow them to leave earlier than their neighbors and, thus, avoid congestion on the evacuation route. Finally, the reason for the negative correlation between expected evacuation preparation time and evacuation travel time is unclear. One possible explanation is that people who think they can reach safety faster are willing to perform more evacuation preparation tasks. Since these explanations are speculative, they should be tested in future research.

5.2. Expected Number of Vehicles

Only 34% of the respondents planned to use more than one vehicle in a future wildfire evacuation which might have been affected by the large percentage (76% = 99 of the 130 survey participants [37]) using cars to evacuate during the Mati event and the best predictor of expecting to take multiple cars is higher income ($>$ 50,000 €)öboth of these findings are consistent with the number of cars actually taken in U.S. evacuations [49]. The desire to take multiple vehicles during an evacuation can be explained by people's desire to protect a valuable asset that, unlike the home and its furnishings, can be moved to safety [60, 61]. However, the additional vehicles increase traffic demand, which can cause traffic jams, and in turn, increase the possibility of being overtaken by hazardous conditions [95].

One practical contribution of the data on vehicle utilization is to help evacuation managers develop more effective traffic management strategies based on accurate traffic demand estimates. Knowing what proportion of the evacuees will take multiple vehicles avoids the error of overestimation (i.e., assuming two or more vehicles per household for all evacuees) or underestimation (assuming one vehicle per household for all evacuees). For example, Wood et al. [99] assumed an average of two cars per household in their simulation of tsunami evacuation. To provide even greater accuracy, future studies of wildfire evacuation should ask the number of registered vehicles available to be taken in addition to the number of vehicles that will be taken. This would allow wildfire studies to be compared to hurricane studies that have found 65% to 75% of registered vehicles are taken in evacuation [49].

5.3. Expected Evacuation Destination

Analyses related to RQ2 (What are the predictors of whether people have planned their wildfire evacuation destinations?) show that most respondents (69%) have identified an evacuation destination in anticipation of a future wildfire, which is identical to the percentage of CSZ residents who identified an evacuation destination in anticipation of a future tsunami [55].

Respondents' evacuation destination selection is positively related to their Wildfire preparedness actions. Specifically, households who have already collected information about evacuation destinations, developed a family emergency plan, or prepared an emergency kit are likely to have selected evacuation destinations in advance. These relationships are consistent with findings from earthquake studies that have reported that information seeking is related to other forms of preparedness [47, 64, 65].

Wildfire experience, on the other hand, has a negative association with selecting an evacuation destination in advance. In particular, the fact that 20% of the respondents were able to keep themselves out of the wildfire propagation pathway during the Mati event and reach safe places successfully may have induced a false sense of security, allowing them to avoid planning an evacuation destination for a future wildfire. These observations are consistent with other hazard studies that highlights the resident's such risk-tolerance behavior developing due to prior disaster experience [4]. In particular, Dillon et al. [20] found that people's responses to their experience depends on whether they interpret a near-miss as a "disaster that did not occur" or as a "disaster that almost happened".

5.4. Expected Evacuation Route

The results show that a majority of the respondents (64%) had already identified which route to take if they need to evacuate for a wildfire. This percentage is similar to the 70% of CSZ residents who had planned their tsunami evacuation routes [55] and is much higher than in Jakarta, where only 20% of the residents had planned a tsunami evacuation route [23]. Identifying an evacuation route in advance is important because it is likely to decrease expected preparation times as there would be no need for milling to identify an appropriate evacuation route. It is also important because it decreases the probability of choosing a dangerous route during an imminent threat [10]. However, wildfire and tsunami threats differ because a wildfire can typically approach a community from many different directions whereas tsunamis can only come from one direction. Consequently, WUI residents should identify multiple evacuation routes whereas tsunami inundation zone residents often need to identify only one. Thus, Mati residents should be encouraged to increase their rate of evacuation route planning beyond the current 64% rate. This is especially important because evacuation routes there are characterized by narrow roads that sometimes lead to dead ends where it was difficult to turn around during the 2018 wildfire [24].

Analyses for RQ3 (What are the predictors of whether people have planned their wildfire evacuation routes?) show that residents with planned evacuation routes expect to have shorter milling times and have shorter evacuation travel times. In turn, these will lead to a shorter evacuation clearance times that decrease the probability of being overtaken by hazardous conditions [13]. In addition, planned evacuation routes have many of the same correlates as planned evacuation destinations because these two elements of evacuation logistics are highly correlated ($r = 0.62$). Thus, a planned evacuation route is positively related to preparation of a family emergency plan, collecting destination information, and preparing an emergency kit. Such practices could be critical for a future wildfire because there was no distribution of hazard maps from government organizations showing areas with high-risk exposure to wildfire or any information about recommended evacuation routes before the 2018 Mati event [81].

5.5. *Expected Evacuation Preparation Time*

Figure 3 shows that Mati-area residents' expected evacuation preparation times are comparable to those of CSZ tsunami risk area residents [13]. Specifically, 62% of the Mati respondents expect to take 10 min or less for evacuation preparation, with 83% expecting to take 15 min or less for an average of $M = 8.3$ min. This is slightly shorter than than expected tsunami preparation times for in Lincoln City ($M = 8.8$ min), noticeably shorter than those in Coos Bay ($M = 10.2$ min), and significantly shorter than those in Crescent City ($M = 13.0$ min) and Commencement Bay ($M = 14.4$ min) [13]. The longer expected evacuation preparation times for the CSZ residents might be due to some respondents' inappropriate expectations of waiting for an official warning before evacuating from a local tsunami [55]. Conversely, it is also possible that the shorter expected evacuation preparation times for the Mati residents might indicate an effect of their recent evacuation experience, which the tsunami survey communities lacked.

Analyses regarding RQ4öWhat are the predictors of people's expectations about how long it will take for wildfire evacuation preparations?öshow that expected evacuation preparation time is negatively correlated with income and positively

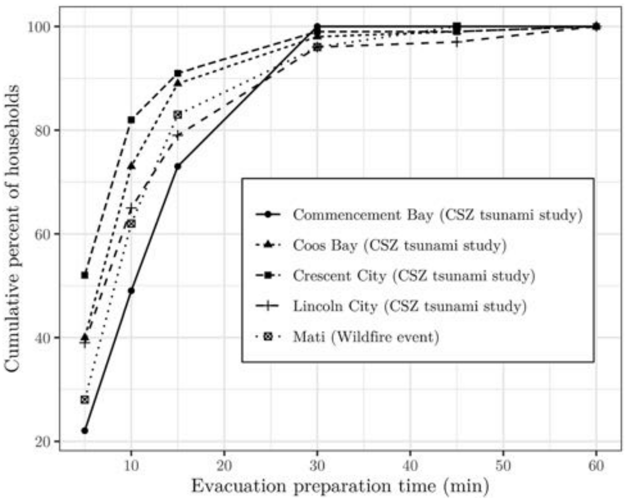

Figure 3. Expected Evacuation Preparation Time for Different Hazards.

correlated with residential tenure. The finding that Mati residents with higher income expect to take less time in evacuation preparation is consistent with tsunami research (e.g., Chen et al. [12]). One possible explanation for this finding is that those with higher incomes have greater access to disaster-related knowledge due to more frequent participation in social gatherings or greater interest in public affairs [78]. However, the nonsignificant correlation of education with evacuation preparation time casts doubt on this explanation. Thus, future research should examine other explanations for this correlation.

The positive correlation of expected evacuation preparation time with residential tenure is consistent with the extensive social networks that people tend to develop in their neighborhoods over the years [9]. In turn, the larger social networks would increase the number of people to whom they would consult in the milling process [98] and to whom they would relay warnings [42]. Other possible explanations for this correlation include the possibility that people with longer residential tenure have previous hazard experience that fostered a false sense of security that leads them to wait for stronger confirmation about the wildfire threat before evacuating [16]. Recent Greek wildfires in 2007 [62], 2009 [18], and 2012 [2]) may have contributed to a sense of *unrealistic optimism* [82] that they are unlikely to be affected by future wildfires. This would be consistent with research showing that a *near miss* can lead people to believe that they are not vulnerable to a disaster [21]. Indeed, some tsunami studies also support the conclusion that emergency preparedness can decrease after a disaster [73]. Ultimately, the crucial question is whether these expectations of evacuation preparation times are accurate. Consequently, future evacuation research should conduct experiments in which risk area residents are first asked to indicate their expected evacuation

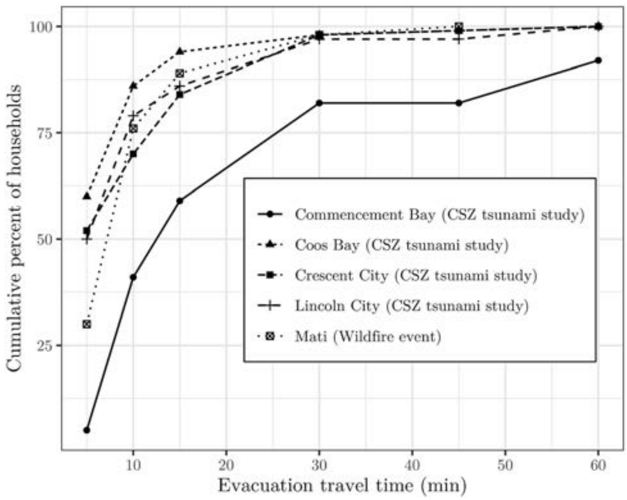

Figure 4. Expected Evacuation Travel Time for Different Hazards.

preparation times and then asked to actually perform the tasks that they would take in preparing for an evacuation. Comparison of the expected and actual preparation times would let evacuation analysts know whether expected evacuation preparation times are accurate and, if not, what would be the appropriate correction to apply to those estimates.

5.6. Expected Evacuation Travel Time

Figure 4 provides a comparison of Mati respondents' expected evacuation travel times with those of the four CSZ communities. Specifically, 89% of the Mati residents expected to complete their evacuation travel within 15 min. This is similar to the Chen et al. [13] report that 78% of CSZ residents expected to reach their evacuation destinations within 15 min, with an average of approximately 9.0 min in Lincoln City, $M = 9.5$ min in Coos Bay, and $M = 8.7$ min in Crescent City $M = 8.2$ min). Commencement Bay residents expected to take more than 23 min, but they are in a more densely populated urban area where there is a greater likelihood of traffic congestion that slows evacuation travel. Moreover, they are on the Puget Sound, which is far from the CSZ, so they would have much more time to evacuate before the arrival of the first wave from a CSZ tsunami. The similarity between the Mati wildfire respondents and the Pacific coast tsunami respondents may be due to the similarity in respondents' choice of evacuation destinations, which were within approximately 5 km, ($M = 4.5$ km in Mati, $M = 3.5$ km in Crescent City, and $M = 2.4$ km in Coos Bay).

The results in Table 6 show that expected evacuation travel times tend to be shorter for residents who have identified an evacuation destination ($r = -0.25$). Specifically, 93% of those who have identified an evacuation destination expect to reach their destinations within 15 min, whereas only 68% of those who have not identified an evacuation destination expect to evacuate this fast. Although 15 min might seem to be a very short time, one possible explanation might be that a car traveling at 50 kph (30 mph) can travel 12.5 m (7.5 min) in that time. Only vehicles traveling less than half that fast would be likely to be overtaken because wildfires only average about 25 kph [15].

Expected evacuation travel times also tend to be shorter for those who have engaged in wildfire preparedness practices such as obtaining wildfire information, engaging in frequent discussions with peers, managing vegetation around their homes, and preparing emergency kits. However, it is not entirely obvious why these variables are *negatively* correlated with expected evacuation travel times. One possibility is that people who have engaged in these wildfire preparedness practices have not only identified their evacuation routes but have also practiced those routes and, therefore, have shorter estimated evacuation travel times than those who have not. As is the case with expected evacuation preparation times, the crucial question is whether these estimates are accurate. Consequently, future wildfire evacuation research should ask WUI residents to report whether they have practiced those evacuation routes, as in Lindell et al. [55] and Wei and Lindell [94]. One limitation of this approach is that the resulting estimates of travel times under normal conditions are likely to lower than actual travel times on congested evacuation routes. Thus, future research should compare WUI residents' expectations of evacuation travel times with the results from ETE studies of wildfire evacuations to assess the accuracy of residents' estimates of evacuation travel times. Whether or not such analyses are conducted, local officials can reduce the likelihood of evacuation route congestion by explaining to local residents that they should leave early rather than waiting until the last minute because departure delays will overload evacuation routes and increase their likelihood of being overtaken by the wildfire.

6. Conclusions and Recommendations

The frequent occurrence of wildfires throughout the world produces casualties, property damage, and environmental destruction. However, there are fewer studies of evacuation from wildfires than from tsunamis and many fewer than from hurricanes. The neglect of wildfire evacuation is particularly acute when considering risk area residents' options for evacuation logistics (number of vehicles, planned destination, and planned route) and ETE components (expected evacuation preparation and travel times). In addressing this deficiency, this paper presents the results from 152 Mati-area respondents who experienced a devastating wildfire in which 104 people lost their lives. The survey instrument measured two types of dependent variables, expected evacuation logistics and ETE components, as well as four types of explanatory variablesöwildfire risk perception, wildfire preparedness actions, wildfire experience, and demographic characteristics. Correlation and regression analyses identified a number of explanatory variables for respondents' expected evacuation logistics and ETE components. These analyses support five conclusions and recommendations.

- Households having higher incomes ($>$ 50,000 €) are likely to use more vehicles to reach their evacuation destinations. This is quite likely due to wealthier households having more registered vehicles. Although this finding is consistent with previous research on large-scale evacuations [49], future wildfire research should include households with diverse socio-demographic characteristics to assess the percentage of registered vehicles that are taken in other wildfires. Regardless of the results of such research, local emergency managers should encourage households that plan to take multiple vehicles to leave early to reduce evacuation route congestion.
- Residents who have engaged in wildfire preparedness actions such as having obtained evacuation destination information, developed a family plan, and prepared an emergency kit are more likely to have identified an evacuation destination and evacuation route. Since this study only has cross-sectional data, it is not possible to definitively determine the direction of causality among these relationships [43]. However, in the absence of rigorous causal evidence, local emergency managers can encourage WUI residents to prepare by providing them with information about evacuation destinations and routes and also encouraging them to increase their preparedness by developing a family plan and preparing an emergency kit.
- Households with longer residential tenure expect to spend more time in evacuation preparationöperhaps due to previous near misses and false alarms. Thus, local emergency managers should encourage WUI residents to view near misses and false alarms as opportunities to practice their families' wildfire emergency plans.
- Although WUI residents' estimates of wildfire evacuation preparation and evacuation travel times are similar to those of tsunami zone residents, it is unclear how accurate those estimates are, due to possible discrepancies between households' evacuation intentions and later evacuation behavior. Kang et al. [36] found that there was a significant degree of correspondence between evacuation intentions and later evacuation behavior but the correspondence was not perfect. Consequently, local emergency managers should encourage WUI residents to practice their evacuation preparations to determine for themselves if their estimates are correct. If these households find that they have underestimated their preparation times, they should make advance preparations such as assembling Grab-and-go kits that will decrease their evacuation preparation times. In addition, households should practice their evacuation routes at times when they can expect the most congested conditions because this will give them more accurate estimates of evacuation travel times as a wildfire approaches.
- WUI residents who think about potential consequences of wildfire hazards or have greater hazard preparedness (e.g., managing vegetation around the house and preparing emergency kits) are more likely to have identified an evacuation route. This suggests that local emergency managers should frequently remind WUI residents about the need for evacuation preparedness during the wildfire

season. For example, some households have failed to plan evacuation routes and destination in advance. Thus, communities should distribute hazard brochures and conduct hazard education workshops to increase compliance with authorities' protective action recommendations.

The data from this study contribute to a better scientific understanding of the commonalities and differences in people's responses to different environmental hazards. In particular, they will provide a baseline for wildfire evacuation analysts to produce more accurate ETEs based on a realistic representation of evacuee behavior. These ''best estimate'' baseline analyses will provide a significant improvement over the current practice of using arbitrary hypothetical parameter inputs into their evacuation models [38].

Moreover, evacuation analysts should supplement their ''best estimate'' baseline models with sensitivity analyses that show the effects on their ETEs of plausible variation in the evacuation model's input variables (e.g., number of vehicles the at-risk individual will be using or evacuation preparation time distribution) [44]. Such sensitivity analyses are needed for emergency managers to adapt the baseline analysis to the conditions that exist at the time of an incident. In turn, the adjusted ETEs can be used as inputs to evacuation triggers [14] for deciding when to initiate evacuation warnings.

Despite this study's contributions, continuing research is needed to identify what types of protective action WUI residents choose during wildfires as well as how much they spent for each of those actions, what was the evacuation rate, and what was the modal split in the affected area, as well as any behavioral differences between households that successfully evacuated on their own and those who needed rescue efforts from emergency personnel [88]. Such studies could contribute to an assessment of WUI communities' wildfire evacuation plans and help emergency managers take life-safety related critical decisions more effectively.

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