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A data-driven approach to improving evacuation time estimates during wildfires for communities with part-time residents in the wildland-urban interface

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ABSTRACT

Wildfires pose a significant threat to the residents living in the wildland-urban interface. Computerized modeling of wildfire evacuation could facilitate protective action decision-making and improve wildfire public safety. This study aims to leverage different types of data, traffic simulation model, and geographic information systems to develop a data-driven wildfire evacuation model to improve evacuation time estimates in resort areas. Specifically, we take into account household vehicle ownership data and the occupancy rate of second homes based on a variety of data in model construction. We used the Tahoe Donner neighborhood in Truckee, California in the case study and derived a series of evacuation time estimates. The results indicate that the evacuation time estimates vary significantly with the mean number of vehicles per home and second homes' occupancy rate in resort areas. The proposed method could help incident commanders better understand the dynamics of travel demand of the fire-prone communities with part-time residents during wildfire evacuation and increase their situational awareness.

1. Introduction

Wildfire is a natural hazard that impacts both human communities and the ecosystem in many regions [1]. Due to the dry climate and fuel accumulation, wildfire poses a significant threat to the residents who live in the wildland-urban interface (WUI) in the western US [2]. Researchers have found a trend of larger and more frequent wildfires in the western US in the past few decades [3]. For example, in the 2020 fire season, California has experienced several top 20 largest fires in its history: the August Complex Fire, the Santa Clara Unit (SCU) Lightning Complex Fire, the Sonoma–Lake–Napa Unit (LNU) Lightning Complex Fire, the North Complex Fire, and the Creek Fire [4]. Wildfire has caused significant loss of life and property in the western US in recent fire seasons. For example, the Camp Fire in Butte County, California destroyed 18,804 structures and killed 85 people in November 2018; the North Complex Fire caused a loss of 2352 structures and 15 lives in August 2020 [5]. Despite the increasing wildfire risk, the WUI population has been growing rapidly in the past few decades [6]. These trends pose a significant challenge for wildfire management in the US.

With the rapid population growth in the WUI, many fire-prone communities that have a limited number of egresses in the American west could have evacuation difficulty during wildfires [7,8]. When a wildfire approaches a WUI community and threatens life and property, incident commanders (ICs) need to issue protective action recommendations (PARs) to the population at risk. The PARs include evacuation and shelter-in-place, and evacuation is the primary PAR in the US [9]. Wildfire evacuation is a complex process, and

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ICs need to consider a variety of factors such as fire spread, evacuation route systems (ERS), and evacuation traffic before they could make effective PARs [10].

Traffic simulation has been widely used in wildfire evacuation modeling to improve public safety [11–13]. Previous research on wildfire evacuation modeling typically focuses on the households in fire-prone WUI communities and assumes that all the dwelling units are occupied by people in the fire season [11–14]. However, little research has examined how to account for those unoccupied homes in resort areas in wildfire evacuation modeling. We aim to leverage different types of data, traffic simulation model, and geographic information systems (GIS) to develop a data-driven wildfire evacuation model and improve evacuation time estimates (ETEs) for resort areas so as to improve wildfire public safety and increase community resilience. Specifically, a variety of data will be used to more accurately model evacuation travel demand, which makes this study a typical data-driven application in the field of wildfire evacuation. The novelty of this study is as follows. First, we present a data-driven approach to modeling evacuation travel demand in resort areas. Second, we develop a series of evacuation scenarios to test the developed evacuation model.

This article has the following implications. First, the wildfire evacuation model constructed in this study could be directly used by emergency managers to develop a better understanding of potential issues during a wildfire evacuation in resort areas. Second, the constructed evacuation model could be used by emergency managers or evacuation practitioners to develop evacuation plans for resort areas. Lastly, the proposed data-driven method in this study could not only make full use of existing data to improve the accuracy of ETEs but also shed light on how to incorporate other types of data to further improve wildfire evacuation modeling.

The remainder of this article is organized as follows. Section 2 provides a review of wildfire evacuation modeling literature. The study area and relevant datasets compiled for this study are introduced in Section 3. Section 4 presents the proposed methods, and the results are included in Section 5. Finally, we give a further discussion on the research topic and conclude with future research directions.

2. Background

Traffic simulation was first employed to study evacuation in nuclear power plant emergencies [15,16]. The classic transport model is characterized by four steps: trip generation, trip distribution, modal split, and assignment [17]. Evacuation is the process of moving the population threatened by a hazard from the risk area to safe places [18]. Traffic simulation has been widely used in evacuation modeling in the past few decades [15,19]. In the US, private vehicle is the primary transportation mode during mass evacuations [20], and Southworth [21] formulated evacuation modeling as a five-step process: 1) trip generation; 2) departure time modeling; 3) destination selection; 4) route selection; and 5) the setup, analysis, and revision of the plan. With the rapid development of transport modeling, traffic simulation models have been used to study mass evacuations in different types of hazards such as hurricane [22,23], wildfire [11,12], and tsunami [24].

Traffic simulation models can be divided into macroscopic, mesoscopic, and microscopic models based on the level of detail [19,25,26]. Microscopic traffic simulation models can include detailed individual driving behaviors and vehicle movements and have enjoyed great popularity in wildfire evacuation modeling [11–13,27]. Note that the risk area in a wildfire evacuation is usually much smaller than that in a hurricane evacuation. Thus, although microscopic traffic simulation is characterized by heavy computation [28], it is still feasible to use it in wildfire evacuation modeling. Recently, the coupling of different computer models such as fires spread, trigger, and traffic simulation models has become a popular trend in wildfire evacuation modeling [11,13,27]. Additionally, recent research also reveals the importance of incorporating behavioral research into wildfire evacuation modeling [25]. This trend is also consistent with the notion that we should employ an interdisciplinary approach to modeling evacuation [29].

Different metrics can be derived from traffic simulations to evaluate evacuation effectiveness, and some popular metrics include total evacuation time, total travel time, total travel distance, and total evacuation exposure [30,31]. The total evacuation time is also termed network clearance time, and it usually includes mobilization time, vehicle travel time, and queueing delay time [32]. ETE has been widely used as a metric to measure evacuation effectiveness in evacuation research [28,33]. In a wildfire evacuation, we need to ensure that the evacuees could travel to safe places before the fire approaches the community at risk [10,34]. Additionally, ETE can also be further integrated with the lead time derived from fire spread models to construct some more complex metrics for wildfire evacuation such as the direness score [35]. Note that some complex evacuation evaluation metrics such as exposure count rely on fire spread and microscopic traffic simulation models and can be computationally prohibitive if evacuation researchers and practitioners are to consider the randomness of many input parameters.

Wildfire evacuation modeling involves the steps summarized by Southworth [21]; and every step could affect the accuracy of the evacuation model. Among these steps, evacuation travel demand modeling plays a significant role in the computation of ETEs. Evacuation travel demand modeling has drawn significant research attention in the past few decades [19,21,26,36]. However, it is still a challenge to accurately model evacuation travel demand [28]. One primary reason is that we lack the necessary human movement data [28]. Although recent data-driven research has revealed that cellphone data could be used to derive human movement patterns at a reasonable cost [37], such data has privacy issues and can rarely be acquired for evacuation modeling in the US and many other countries. Note that the methods to model evacuation travel demand could vary from one type of hazard to another. For example, hurricane evacuation usually involves a larger risk area, and evacuation modelers will use larger evacuation zones (e.g., traffic analysis zones, zip code zones, or census tracts/blocks) and relevant socio-economic data to generate evacuation travel demand [38,39]. Since wildfire evacuation usually involves a smaller population when compared with hurricane evacuation, evacuation modelers could use fine-grained household location data to generate evacuation demand [13]. In an early study , Cova and Johnson [12] used a US Geological Survey (USGS) digital orthophoto quad (DOQ) and some CAD data from the local planning agency to manually code a total of 250 home locations and road network for wildfire evacuation modeling in the Emigration Canyon community to the east of

Salt Lake City, Utah. Similarly, Wolshon and Marchive [14] used a total of 753 residential parcels to generate evacuation traffic in the Summit Park neighborhood near Salt Lake City, Utah. Another recent study done by Li, Cova, and Dennison [13] also used 744 residential parcels to generate evacuation traffic and estimate evacuation time for the Town of Julian in San Diego County, California. Besides residential parcel data, address point data is also widely available in many municipal, county, and state governments and could also be used to generate trips in wildfire evacuation modeling [11,40]. Note that it is usually assumed that all the homes are occupied and can be used to generate evacuation travel demand in previous studies [12]. This assumption will be effective for those WUI communities that are not located in resort areas. However, since there are many second homes in the WUI communities in resort areas, we need to take into account the occupancy rate of these second homes during the fire season so as to better model evacuation travel demand and derive more accurate ETEs. Although the importance of considering second homeowners and tourists in evacuation modeling has been highlighted in previous evacuation literature [41,42], relevant research on this topic is scarce. This study will contribute to the evacuation modeling literature by developing a data-driven approach to improving ETEs for resort communities.

Different types of data (e.g., high-resolution satellite imagery, the aerial imagery from unmanned aerial vehicles (UAVs), and social media data) have been used in disaster research in the past few years [43]. The data from various sensors or social media can be generated at a great speed, and such streaming data has been widely used in wildfire evacuation research [44,45]. Although different types of data have been widely used in wildfire evacuation research, little research has been conducted on data-driven wildfire evacuation modeling in resort areas. For example, the occupancy type of the parcels and the occupancy rate of second homes have not been used in previous evacuation modeling studies. This study aims to fill this gap by employing a variety of data to design and implement a wildfire evacuation model for the WUI communities in resort areas.

3. Data

3.1. Study area

Many WUI communities in the western U.S. are located in fire-prone areas and have a limited number of egresses, which places the residents at risk during wildfires [8]. We used the Tahoe Donner neighborhood in the Town of Truckee, California as our study site. Truckee is an incorporated town with a population of 16,180 (2010 Census) in Nevada County, California. As shown in Fig. 1, the town is located in the northern Sierra Nevada, and Tahoe Donner is a high-density neighborhood in the northwestern part of the town. The Mediterranean climate in the Sierra Nevada area is characterized by a wet winter and a dry summer [46]. The Tahoe Donner neighborhood is surrounded by a large amount of flammable vegetation. The dry summer, proximity to flammable vegetation, and frequent wildfire ignitions make Tahoe Donner a typical fire-prone community in the American West. In addition, this neighborhood also has many second homes. Since Truckee is close to many attractions (e.g., Lake Tahoe) and attracts a large number of tourists every year, the occupancy rate of the second homes in this area can vary significantly with time during the fire season. For example, the occupancy rate can be very high on weekends or holidays. Lastly, the Tahoe Donner neighborhood only has two egresses in its ERS. Thus, wildfire poses a significant risk to the local residents in this neighborhood in the fire season. The potential large evacuation travel demand and the limited capacity of the ERS also pose a challenge to emergency managers in wildfire evacuation planning and management.

3.2. Data compilation

This study focuses on using a variety of data to design and implement a wildfire evacuation model for WUI communities in resort areas. The primary datasets used in this study are listed in Table 1. Open data usually refers to free, publicly available data and has enjoyed great popularity in scientific research in recent years [47–49]. Note that while most of the data used are open data, four datasets (occupancy type, field survey, evacuation route, and road data) acquired from the Town of Truckee are not open data. The compiled datasets include relevant socio-economic data and the datasets of the built environment (e.g., the ERS). The following subsections provide more details on these datasets.

3.2.1. Socio-economic data

Socio-economic data has been widely used to study social vulnerability in disaster research [50]. In this study, we employ parcel occupancy and household vehicle ownership data to derive household travel demand in evacuation modeling. The parcel occupancy

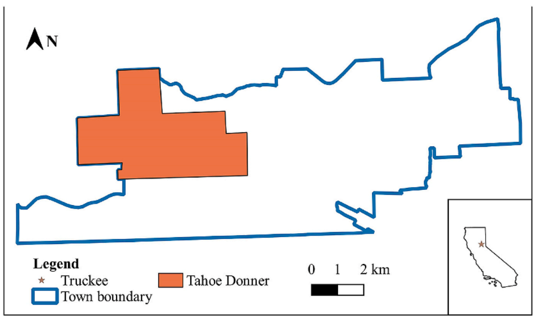

Fig. 1. The location of the Tahoe Donner neighborhood.

Table 1
The primary datasets compiled for this study.

Dataset Name	Source	Year
Parcel occupancy type data	The Town of Truckee	2019
Vehicle ownership data	American Community Survey	2014–2018
Tahoe Donner field survey data	The Town of Truckee	2019–2020
Raw parcel data	Nevada County Assessor's Office	2019
Residential parcel data	Nevada County Assessor's Office	2019
Road data	The Town of Truckee	2019
Road data	OpenStreetMap	2019
Evacuation route data	The Town of Truckee	2019
Neighborhood boundary data	The Town of Truckee	2019
Truckee boundary data	The Town of Truckee	2019

type dataset was derived based on residential trash and recycling charges from the Town of Truckee. Parcel occupancy type data can be subsequently joined to the residential parcel polygon data through parcel identifications (IDs). The value of this dataset lies in that it will allow evacuation modelers to assign trips for each household based on its occupancy type. This practice will significantly improve the accuracy of the model (especially in resort towns such as Truckee).

Another important dataset is the household vehicle ownership data in the comparative housing characteristics dataset (2014–2018 estimates) from the American Community Survey (ACS). The vehicle ownership data is listed in Table 2. This dataset can be used to determine the number of trips generated by each household [13]. Note that this dataset is open data and is available for most of the areas in the US. The household vehicle ownership data can be used to estimate the mean number of vehicles for each home in Tahoe Donner in subsequent evacuation travel demand modeling.

3.2.2. Built-environment-related data

Three types of datasets related to the built environment were compiled from different sources. First, a residential parcel dataset was acquired from the Assessor's Office of Nevada County, CA, and it includes a total of 12,708 residential parcels. Unlike the large-scale evacuations caused by hurricanes, wildfires evacuations usually impact a smaller geographic area. Thus, compared with hurricane evacuation modeling, wildfire evacuation modeling requires finer-grained data to generate evacuation travel demand so that we can study the patterns of evacuation traffic in a smaller study area. High resolution parcel-level data could be used to generate evacuation travel demand at the household level in the WUI [40]. This dataset can be integrated with other socio-economic data such as household vehicle ownership data to estimate evacuation travel demand in the evacuation model. We employ this dataset to construct the evacuation model because it is more recent and includes the detailed location information that could be used to generate household-level evacuation travel demand in the evacuation model.

Additionally, we also compiled two datasets related to the road network. Specifically, we compiled a road dataset from the Town of Truckee. This road dataset includes the detailed speed limit information for each road. Another road dataset comes from the OpenStreetMap project because MATSim uses OpenStreetMap data as the input road network data. Compared with authoritative data, OpenStreetMap data can often be obsolete and inaccurate [51]. Thus, we used the speed limit information from the authoritative road data to update the speed limit for each road in the OpenStreetMap road data to improve its quality. Lastly, we also compiled the evacuation route data from the Town of Truckee, and this dataset includes the primary evacuation routes in the local evacuation plan.

3.2.3. Field survey data

A series of field surveys in Tahoe Donner were conducted by local stakeholders from June 30th, 2019 to September 27th, 2020 in the Tahoe Donner neighborhood. Specifically, as shown in Fig. 2, a total of 395 residences were included in the surveys. The selection of the residences was based on the local stakeholders' knowledge about this area and can be representative of the households in this neighborhood. The surveys were conducted between 6:30 a.m. and 7:15 a.m. on the weekends or holidays, and the local police department counted the number of vehicles for each residence in the map in person during each survey. The occupancy rate and the average number of vehicles of the homes in the sample were recorded in the surveys. As shown in Fig. 3, the occupancy rate reaches its peak (58.3%) on July 4th, 2020 (Independence Day). The overall occupancy rate ranges from 37.5% to 58.3% in the fire season, while the average number of vehicles per home ranges from 2.4. to 2.7. Note that the field surveys only provide the overall occupancy rates for all types of residences. The occupancy rate and average number of vehicles from the field surveys can be used to estimate evacuation travel demand.

Table 2
The vehicle ownership data from ACS.

Number of Vehicles	Occupied Housing Units	Percent
No vehicles available	132	2.2%
1 vehicle available	1260	20.9%
2 vehicles available	2514	41.7%
3 or more vehicles available	2122	35.2%
Total	6028	100%

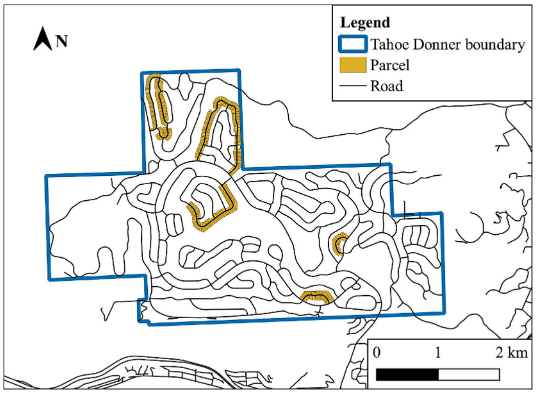

Fig. 2. The parcels used in the field surveys.

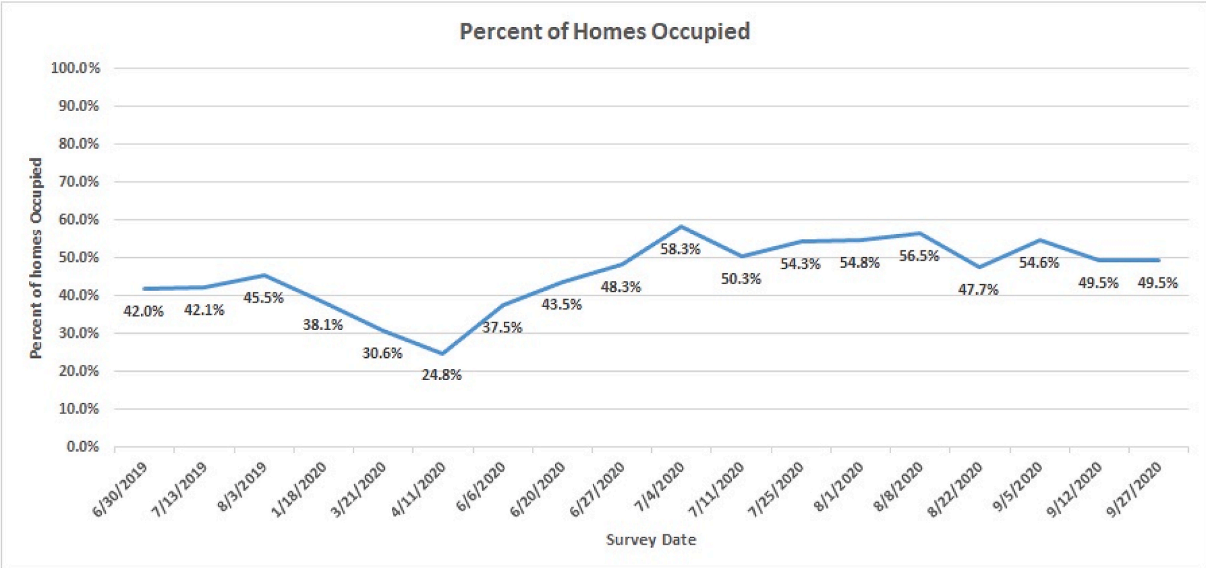

Fig. 3. The percentage of homes occupied in the field surveys.

3.3. *Data processing*

We used the QGIS software to join parcel occupancy type data to residential parcels based on parcel IDs. Table 3 lists the number of residential parcels for each occupancy type. These summaries were derived in QGIS. Specifically, the residential parcels (N = 5859) are divided into four groups: primary home, second home, vacant parcel, and unknown parcel. Note that 70.5% of the homes in this neighborhood are second homes. Thus, we need to take into account the occupancy rate of the second homes when developing a wildfire evacuation model for Tahoe Donner. We examined the residential parcels without any occupancy type information and found that most of them are mobile homes. Based on the stakeholders' local knowledge, the 205 parcels in the unknown group will be treated as primary homes in evacuation traffic simulation. The data shows that Tahoe Donner is a high-density neighborhood with many second homes.

Table 3
The number of homes by occupancy type in Tahoe Donner.

Occupancy type	Count	Percent
Primary home	1229	21.0%
Second home	4130	70.5%
Vacant	295	5.0%
Unknown	205	3.5%
Total	5859	100%

4. Methods

4.1. Data-driven evacuation modeling

We employ a data-driven approach to design and implement the evacuation model. The primary goal of this proposed data-driven method is that we leverage a variety of data to improve wildfire evacuation modeling and better mimic the reality. Our proposed method is characterized by the use of a variety of data in different steps. Note that we need to take into account the following three factors in constructing data-driven evacuation models. First, the data used should be able to improve wildfire evacuation modeling. Second, the data should be readily available in local governments or could be acquired from other sources at a relatively low cost, which will ensure that the proposed method could be applied to other fire-prone communities. Additionally, since we employ a microscopic traffic simulator to perform evacuation simulations for different scenarios, it is computationally intensive to process and analyze the large model outputs to derive the ETEs [52,53].

We use the household vehicle ownership data from ACS to estimate the mean number of vehicles of each household in Tahoe Donner. This ACS dataset includes 6028 housing units in Truckee, and 2122 of them have three or more vehicles available. Since we do not know the exact mean number of vehicles for this group, we assume that the mean number of vehicles for this group (n) could range from 3 to 5. Excel was used to perform the calculation. As shown in Table 4, we used 0.5 as the interval to derive a range of values and computed the mean number of vehicles for all the households (N = 6028) accordingly. The final results range from 2.1 to 2.8. Note that if we use $n = 2.1$ to generate trips in the evacuation model, it could be an underestimation of the total evacuation travel demand. Since the likelihood that n is larger than 5 is very small in reality, $n = 2.8$ could be considered as the upper bound to be used to generate trips for each household in subsequent evacuation traffic simulation. Although some research has shown that households may not use all the vehicles in the evacuation [54], we assume all vehicles will be used so as to consider the worst case scenarios in evacuation planning.

We employ a variety of data to implement the evacuation model, and the flowchart of the whole procedure is shown in Fig. 4. First, we derive residential parcels based on parcel type. Then, we use occupancy type, occupancy rate, and household vehicle ownership data to calculate evacuation travel demand for the study area. Specifically, as shown in Table 5, we use occupancy type data to divide the residential parcels into four categories. We employ occupancy rate data to randomly select a set of second homes as the occupied second homes. Those parcels in the "unknown" category are also considered occupied based on the stakeholders' local knowledge. Then, we use the mean number of vehicles (n) derived from the household vehicle ownership data and a Poisson distribution to randomly generate a number of vehicles for each occupied residence. Once evacuation travel demand is generated, we proceed to specify the egresses based on the ERS. Then we use a microscopic traffic simulation model to perform evacuation traffic simulation and derive the ETE. Specifically, we calculate the time when the first vehicle departs (t_1) and when the last vehicle leaves the risk area

Table 4
The estimated mean number of vehicles based on the household vehicle ownership data.

# of Vehicles	# of Vehicles	Count	Percent	Mean Number of Vehicles (n)
No vehicles available	0	132	2.2%	–
1 vehicle available	1	1260	20.9%	–
2 vehicles available	2	2514	41.7%	–
3 or more vehicles available	3	2122	35.2%	2.10
	3.5	2122	35.2%	2.28
	4	2122	35.2%	2.45
	4.5	2122	35.2%	2.63
	5	2122	35.2%	2.80

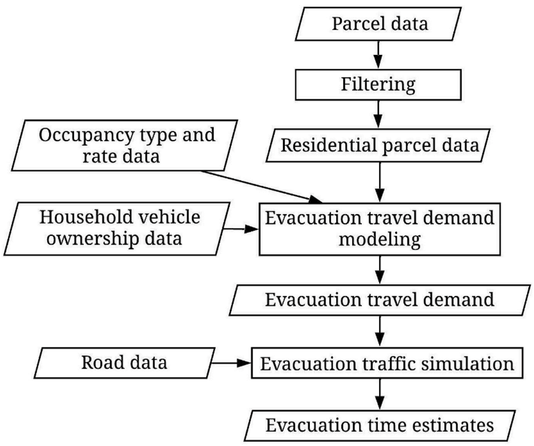

Fig. 4. The flowchart of the evacuation modeling procedure.

Table 5
Generating household evacuation travel demand based on occupancy type.

Occupancy type	Occupancy rate	Mean # of vehicles
Primary home	100%	*n* vehicles (ACS)
Second home	*r* (0%–100%)	*n* vehicles (if occupied)
Vacant	0	0 vehicle
Unknown	100%	*n* vehicles

(t_2), and the derived ETE is t_2-t_1. This process is repeated *N* times for each evacuation scenario, and we will derive *N* different ETEs. Note that the distribution of the occupied second homes and the number of vehicles for each residence vary in each simulation. We do not consider the randomness in the spatial distribution of primary vs secondary homes in our model because this dataset is derived from the most recent tax and utility data and usually does not change dramatically within a short period of time. We use the total ETE because it is a widely used metric for evaluating evacuation effectiveness. The total ETE can be directly affected by the evacuation travel demand. This study focuses on a data-driven approach to improving evacuation travel demand modeling. We have added two new input parameters (occupancy type and rate) to the evacuation model, which makes the model more complex and computationally intensive. Additionally, because we are using a microscopic traffic simulation model and the Tahoe Donner neighborhood is larger than most of the neighborhoods used in previous studies, it will be computationally prohibitive to derive some more complex evacuation evaluation metrics if we are to take into account the stochastic nature of the input parameters.

The implementation of the method is as follows. We use an open-source microscopic traffic simulation package MATSim [55] and its evacuation library to implement the evacuation model and perform evacuation traffic simulation. The MATSim traffic simulator is implemented in Java, and evacuation modelers could customize the code to add extra functionalities [55]. The road network data is downloaded directly from OpenStreetMap, and the JOSM software and its MATSim plugin are used to code the road network for MATSim. Specifically, we use the authoritative road data from Truckee to correct the speed limit information of each road in the OpenStreetMap data. The centroids of the residential parcels were extracted and saved as a vector format file (shapefile). Trips will be generated from each parcel location randomly based on the mean number of vehicles per household (*n*) in this file during the evacuation. Specifically, the residential parcel location dataset has a column that includes the occupancy type information, and we could apply different occupancy rates (*r*) for the second homes. Although residents' evacuation behaviors in hurricanes have been thoroughly studied [56], relevant research on people's evacuation behaviors in resort communities during a wildfire evacuation is scarce [41,57]. Relevant evacuation research has shown that departure time can be modeled with statistical distributions such as lognormal or Weibull distributions [58–60]. Thus, we use a lognormal distribution to model departure times, and it is assumed that all evacuees will choose the closest egress and the shortest path during their evacuation. Note that we use these assumptions for computational convenience, and they do not affect the generalizability of the proposed evacuation model. If more detailed evacuation behavior data is available, we can use the data to further improve the model. The user can provide a risk area polygon as the input, and all the people within the risk area will be evacuated during the wildfire evacuation. In this study, we use a risk area polygon that covers the whole Tahoe Donner neighborhood. Once the evacuation simulation is finished, the program will produce an event file that includes all the event information of each individual vehicle (e.g., a vehicle enters and leaves a link) during the evacuation. Finally, we could use Java and relevant MATSim libraries to process the event files and derive ETE information for each evacuation scenario.

Besides ETEs, we also derive the vehicle count information for each road link and map out the information to help ICs improve their situational awareness. Specifically, first, we use Java and relevant MATSim libraries to parse the vehicle trajectory data to derive the vehicle count information for every road link in each run of the simulation for a specific scenario at time t. Second, we aggregate the vehicle count information to derive the average vehicle count for each link for each evacuation scenario. Then we join the vehicle count information to the road link dataset in QGIS based on the common road link identification and map out the vehicle count information for each road link.

4.2. Experimental design

In this study, it is assumed that the whole Tahoe Donner neighborhood needs to be evacuated due to a fast-spreading wildfire and the two egresses will not be blocked by the fire during the evacuation. As shown in Fig. 5, Tahoe Donner has two primary egresses in its local evacuation plan: A (Alder Creek Rd) and B (Northwoods Blvd). Alder Creek Rd connects Tahoe Donner to Highway 89, and Northwoods Blvd is connected to Interstate highway 80.

We design a set of evacuation scenarios based on the data compiled for this study. Specifically, we use the mean number of vehicles per home (*n*) and the second homes' occupancy rate (*r*) as the primary variables in our experimental design. First, we need to use a series of occupancy rates for the second homes in Tahoe Donner. The overall occupancy rates for different *r* values are listed in Table 6. Based on the occupancy rate data from the field surveys, we use six different values for occupancy rate *r* (10%–60% with an interval of 10%) in the experiment. Additionally, since most previous evacuation modeling studies did not consider the occupancy rate of second homes, we also compute the ETEs for a 100% occupancy rate such that we can compare the results. Note that a 100% occupancy rate of the second homes will make our proposed evacuation model close to those in previous studies because previous evacuation models do not have occupancy type and rate parameters [11–13].

As for the mean number of vehicles per household (*n*), it is estimated to range from 2.1 to 2.8 based on the field survey data. We use 2.1–2.8 with an interval of 0.1 for *n* in the experiment. Although a significant amount of research has been done on hurricane evacuation behaviors in the U.S., relevant research on residents' evacuation behaviors in resort communities during wildfires is still

Fig. 5. The evacuation zone used in this study.

Table 6
Overall occupancy rates derived from the occupancy rates of second homes in Tahoe Donner.

Occupancy rate (r) for second homes	# of occupied units	Overall occupancy rate
10%	1847	31.5%
20%	2260	38.6%
30%	2673	45.6%
40%	3086	52.7%
50%	3499	59.7%
60%	3912	66.8%
70%	4325	73.8%
80%	4738	80.9%
90%	5151	87.9%
100%	5564	95.0%

scarce. Previous evacuation research has shown that departure time can be modeled with statistical distributions such as lognormal or Weibull distributions [54,58,59]. Thus, we use a lognormal distribution [55] to model departure times: $\ln(t) \sim N(\mu, \sigma^2)$ (unit: s) and assume that all evacuees will leave within 60 min after the evacuation order is issued. The expected value of the departure time is 1800 s (30 min), and the variance is 360,000 s^2. We choose to use this departure time distribution because this could be a short-notice evacuation scenario and can be used as a baseline for wildfire evacuation planning. The key parameters are summarized in Table 7, and we will perform evacuation traffic simulation for a total of 56 different evacuation scenarios. We can derive the number of simulations for each scenario based on the following equation [61]:

$$N = z_{\alpha/2}^2 \sigma^2 / D^2$$

where N is the number of simulations, $z_{\alpha/2}$ is the standard Z-score, σ is the estimated standard deviation, and D is desired margin of error. We need to run the simulation at least 16 times with the following parameters: $\alpha = 0.05$ (at the 95% confidence level),

Table 7
The evacuation scenarios used in the experiment.

Departure time distribution (unit: second)	Occupancy rate (r)	Mean # of vehicles (n)
($\mu = 7.442$, $\sigma = 0.325$)	10%–60%, 100%	2.1–2.8

$\sigma = 10$ min, and $D = 5$ min. Since it is computationally intensive to perform microscopic traffic simulation [28], we choose to run each scenario 30 times ($N = 30$) in this study. Finally, we derive the statistics of the ETEs for each evacuation scenario.

We map out the vehicle count information for each road link for the following six scenarios (See Table 8): 1) n = 2.1, r = 10%; 2) n = 2.1, r = 60%; 3) n = 2.1, r = 100%; 4) n = 2.8, r = 10%; 5) n = 2.8, r = 60%; 6) n = 2.8, r = 100%. We aggregate the vehicle count data of 30 simulation runs for each scenario and map out the average vehicle count information for each road link at the time when 50% of the vehicles have left the risk area.

5. Results

We performed evacuation traffic simulation in MATSim for different evacuation scenarios and derived a series of ETEs. The detailed results for each run of the traffic simulation are stored in a text file. The total size of the results of the 56 scenarios is about 28 GB, and the total computation time for 1680 simulation runs was about 10 h. The boxplots of the total ETEs for different scenarios are shown in Fig. 6, and the detailed statistics (the mean value, standard deviation, and confidence interval at the 95% confidence level) of the derived ETEs are listed in Appendix B. The results indicate that the ETEs vary significantly with the occupancy rate of second homes (r) and the mean number of vehicles per home (n). For example, according to the field survey data, the maximum overall occupancy rate on July 4th is 58.31%. The corresponding occupancy rate of second homes is approximately 50%. The derived ETEs can range from 420 min (n = 2.1) to 564 min (n = 2.8). If n is fixed (e.g., n = 2.1), the derived ETEs can range from 226 min

Table 8
The evacuation scenarios used for mapping out the vehicle count information.

Scenario	Mean # of vehicles (n)	Occupancy rate (r)	Input time (t) (min)
1	2.1	10%	80
2	2.1	60%	170
3	2.1	100%	242
4	2.8	10%	106
5	2.8	60%	226
6	2.8	100%	323

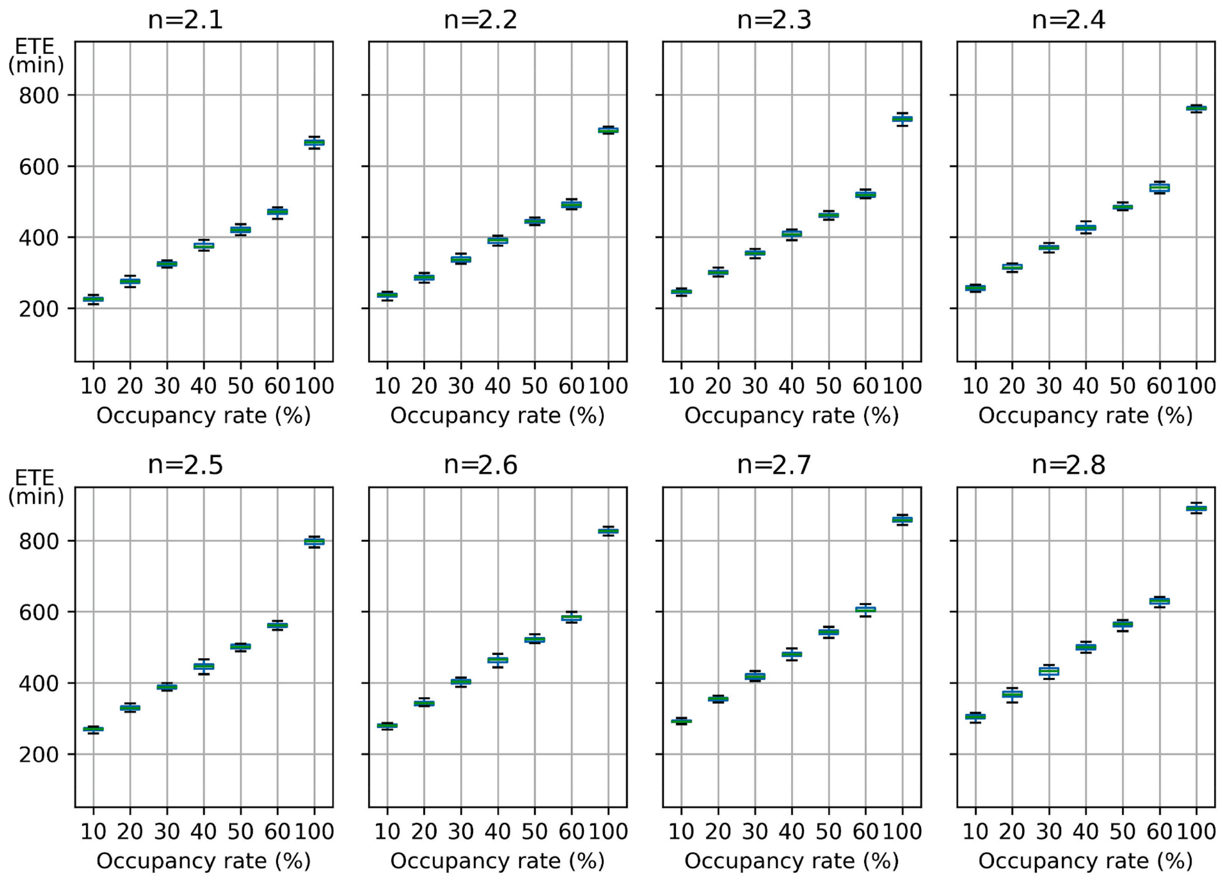

Fig. 6. The derived ETEs for different evacuation scenarios.

(r = 10%) to 470 min (r = 60%). If all the second homes are occupied (r = 100%, n = 2.1), it could take about 667 min to evacuate the whole Tahoe Donner neighborhood. The results have shown that our proposed model can better reflect real evacuations when compared with previous models that do not consider the occupancy type and rate of second homes in resort areas. Note that the assumptions for the derived ETEs in Fig. 6 are all the residents are at home, the evacuation compliance rate is 100%, and all the residents will evacuate within 60 min. Although this assumption is very unlikely in reality, evacuation planners and incident commanders also need to take into account these extreme evacuation scenarios in evacuation planning [35]. Additionally, it should also be noted that the field surveys were conducted on weekends or holidays, and the derived ETEs on weekdays could be lower than those on weekends or holidays.

Relevant research on residents' evacuation behavior in the WUI communities has shown that many residents may choose to stay and protect their homes [62,63]. Additionally, many residents in the neighborhood may not be at home in the daytime. Thus, we also derived the ETEs needed for 95%, 75% and 50% of the vehicles to leave the risk area, and the results are shown in Figs. 7–9, respectively. The detailed statistics are listed in Appendix C. These ETEs could be useful when only a proportion of the households participate in the evacuation. Note that the values of input parameters used in this study do not affect the generalizability of the proposed method. If more detailed population distribution and evacuation behavior data is available, evacuation researchers and practitioners can change the input parameters for the proposed model to derive more accurate ETEs. In summary, the simulation results indicate that it will take a long time to evacuate the residents in Tahoe Donner when the occupancy rate is high. Thus, the emergency manger can have significant difficulty evacuating the residents in Tahoe Donner if a fast-moving fire threatens this community. Moreover, the results also show that it is necessary to take into account the occupancy rate of the second homes in wildfire evacuation modeling and planning for resort areas.

The vehicle count information of the road links for the six evacuation scenarios are shown in Figs. 10 and 11. Specifically, Fig. 10 A-C show the results of scenarios 1–3, respectively, and the results of scenarios 4–6 are shown in Fig. 11 A-C, respectively. The results indicate that traffic congestion will occur on the Northwoods Blvd under the assumption that all evacuees will use the closest egress and the shortest path during the evacuation. The reason is that a larger proportion of the homes are closer to egress B in Fig. 5. Egress A (the Alder Creek Rd) is underused with this assumption. Moreover, more evacuation traffic will be on the Northwoods Blvd when there is a larger evacuation travel demand (i.e., a larger *n* or *r*). The inclusion of vehicle count information can help the ICs better understand the dynamics of evacuation traffic.

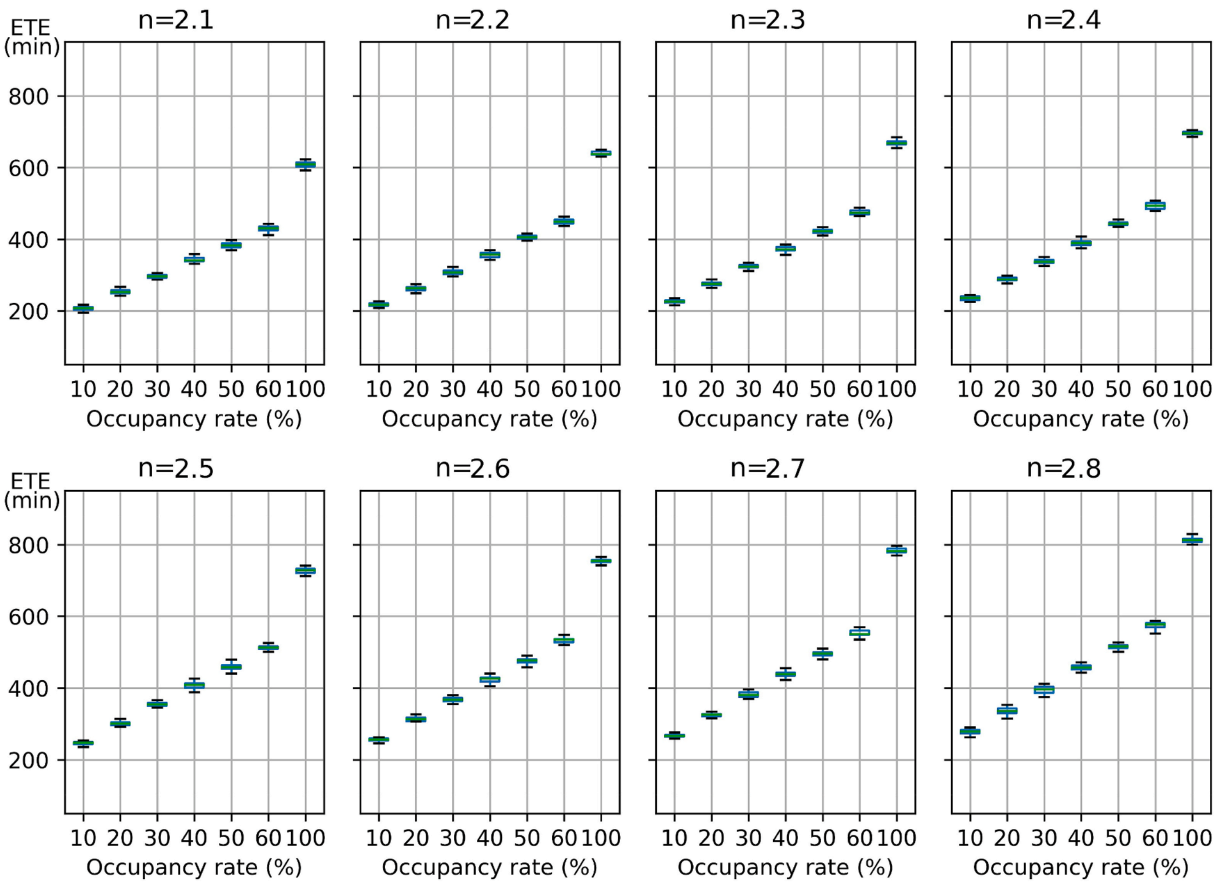

Fig. 7. The derived time needed for 95% of the vehicles to leave the risk area.

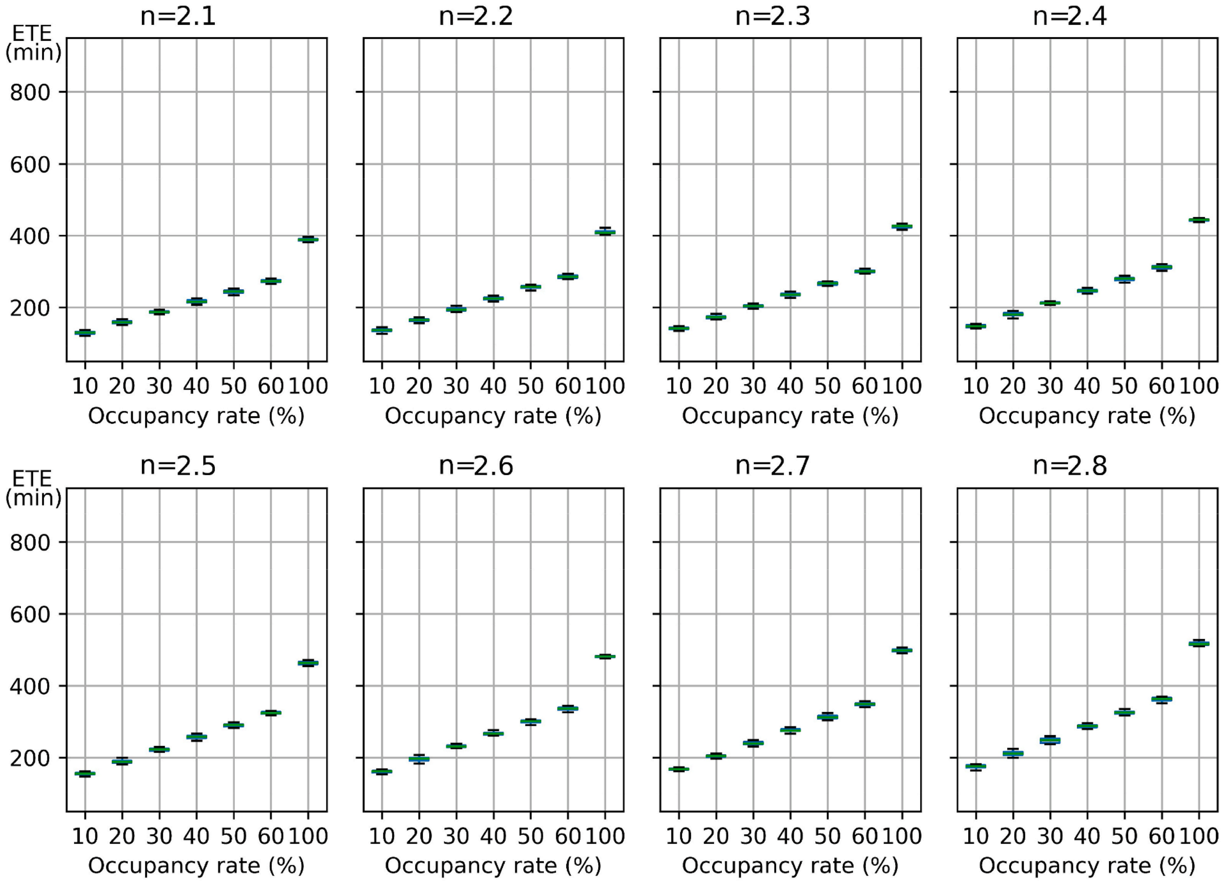

Fig. 8. The derived time needed for 75% of the vehicles to leave the risk area.

6. Discussion

In this study, we leveraged a variety of data to construct the wildfire evacuation model and improve ETEs in the Tahoe Donner neighborhood in Truckee, CA. Our proposed data-driven evacuation model can be used by the WUI communities in resort areas for evacuation planning. Evacuation practitioners could use the results of this study to better understand the dynamics of evacuation travel demand during the fire season and improve the local evacuation plans accordingly. We were faced with several challenges in data-driven wildfire evacuation modeling research. We need to address these challenges before we can use the proposed model operationally.

The first challenge lies in data availability. This study is based on a set of assumptions. For example, it was assumed that all evacuees will depart from their homes and the participation rate is 100%. However, a wildfire evacuation in reality could be more complex and very different from these assumptions. Thus, it is important that we further leverage different types of data to narrow the gap between our knowledge and the real-world evacuation so that we could build an evacuation model that could better reflect the reality. When using different datasets to improve wildfire evacuation modeling, we need to seek a balance among many factors such as cost, effectiveness, and applicability. For example, although we could use household surveys to collect data to estimate the distribution of daytime population, this method is costly and we may still have difficulty in deriving an accurate estimate of the spatio-temporal distribution of the population in a study area. Although big data has enjoyed great popularity in the past few years, we still have data scarcity issues in wildfire evacuation modeling. For example, we used the ACS data and the field survey data to estimate the mean number of vehicles for each household in the study area, and we lack relevant data that could more accurately estimate this parameter. Although we used the most recent occupancy type information derived from tax and utility data, the COVID-19 pandemic has significantly changed human mobility patterns and could also change occupancy types because many people move from cities to rural areas during the pandemic. Additionally, the occupancy rate of second homes is based on field survey data in this study. However, the occupancy rate of second homes and the population distribution in resort areas can be very dynamic, and evacuation modelers need high spatial and temporal resolution human mobility data to better estimate evacuation travel demand.

One limitation of this study is that we did not have household survey data and use them to derive the parameters (e.g., the departure time distribution, the compliance rate, and the number of vehicles used by each household) for the evacuation model. We could collect the above-mentioned data via household surveys to further improve the evacuation model in the next step. Another limitation is that we did not consider the tourists in hotels. Additionally, some secondary homes can also be rented out to tourists via websites

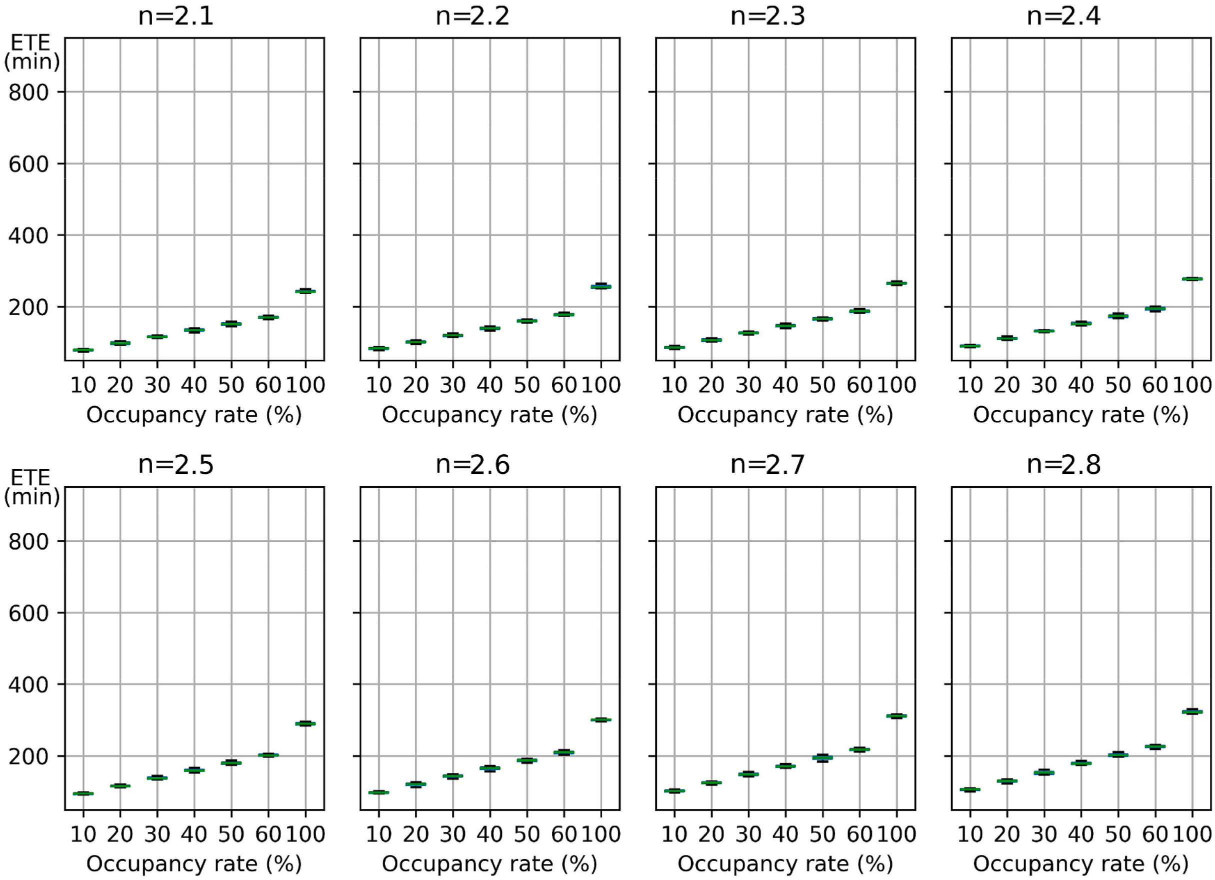

Fig. 9. The derived time needed for 50% of the vehicles to leave the risk area.

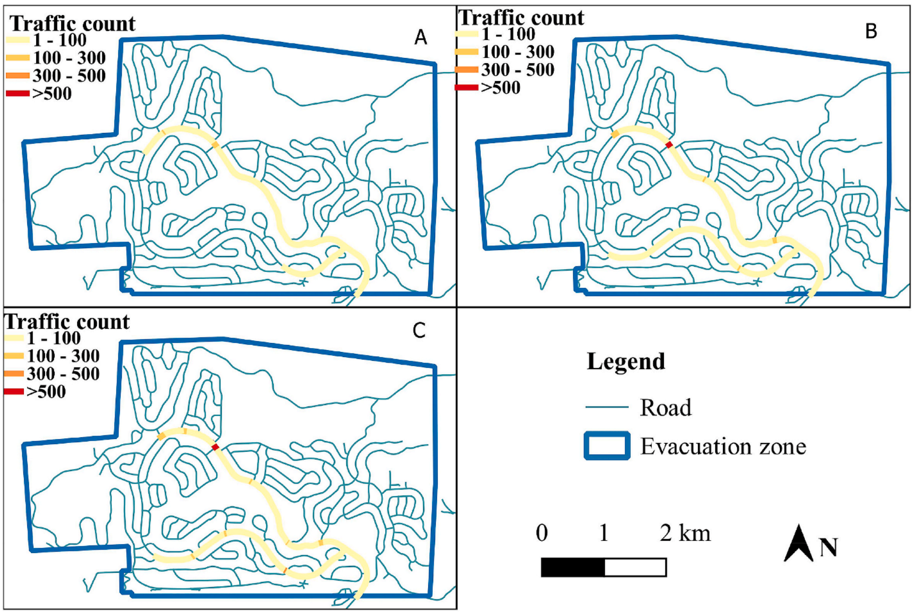

Fig. 10. The distribution of the evacuation traffic in three different evacuation scenarios (n = 2.1).

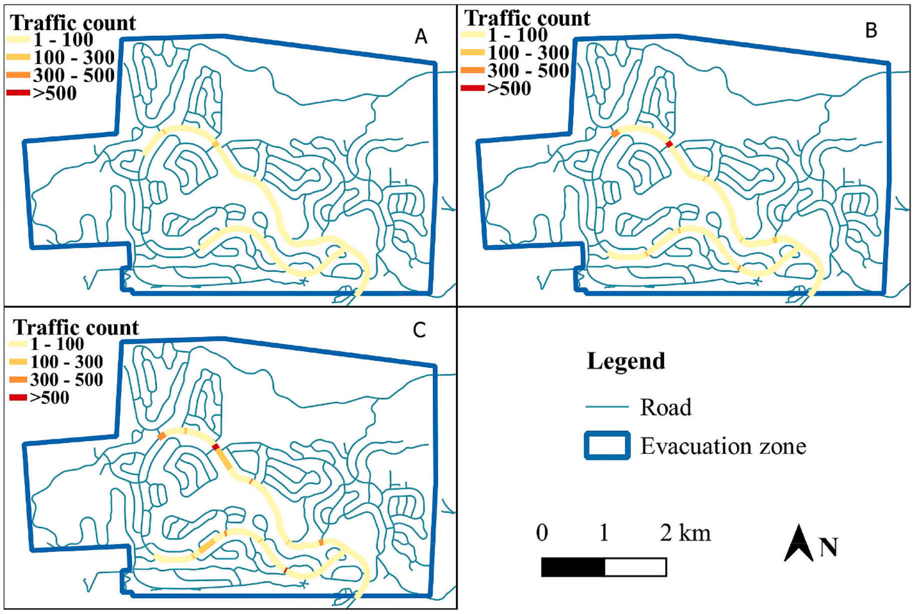

Fig. 11. The distribution of the evacuation traffic in three different evacuation scenarios (n = 2.8).

such as Airbnb. These tourists can also significantly increase the ETEs during the tourist season [42]. The tourists and many second homeowners can have very different characteristics (e.g, the number of vehicles) and evacuation behaviors (e.g., protective action selection, destination selection, and route selection) during a wildfire evacuation. These differences can have significant impacts on the ETEs derived from traffic simulation models. However, the tourists and second homeowners may not be included in traditional household survey data (e.g., the ACS data). We need to collect relevant data to further study the tourists and second homeowners' evacuation behavior. Lastly, we only considered evacuation traffic within the community and assumed there is no traffic congestion at the egresses because of the lack of destination choice data. We will need to collect more data to model destination choice in the future.

Recent research has shown that relevant data such as cellphone location data could be used to study people's evacuation behavior in disasters [64]. However, such high-resolution location data is rarely available to evacuation researchers and practitioners in the US due to privacy issues [65] or the high cost. Coarse-resolution cellphone location data has also been widely used by researchers to study human mobility in recent years [37]. Big data can provide a new avenue to improve evacuation travel demand modeling. Further research could focus on investigating if high-resolution (e.g., GPS data) or coarse-resolution cellphone data (e.g., the number of persons within the service area of each cellphone tower) could be acquired to estimate diurnal population distribution and improve wildfire evacuation modeling.

Another challenge in integrating different types of data to improve wildfire evacuation modeling is data management. Evacuation analysts/modelers need to have a variety of data to perform evacuation analysis/modeling to facilitate the ICs' decision-making. However, data management in the US is decentralized due to the organization of the government agencies, which poses a significant challenge to evacuation management. Since there is no one-stop data portal in Truckee, it was time-consuming to compile different datasets used in this study. Furthermore, other issues such as data inconsistency will emerge when we integrate these data for one specific application because different datasets are managed by different agencies. It should be noted that many large wildfires could spread across multiple cities/counties, which poses a significant challenge to wildfire evacuation researchers and practitioners. In such large fires, evacuation researchers and practitioners will be better off if relevant data could be provided efficiently so that they could leverage these data directly in computer models to help improve situational awareness and facilitate protective action decision-making. Nowadays, many local and state government agencies have access to Web GIS platforms such as ArcGIS Online and have the capacity to publish spatial data as web services that are based on open standards such as Web Map Service (WMS) and Web Feature Service (WFS). More research should be conducted on developing a better cyberinfrastructure for data-driven wildfire evacuation modeling.

Besides the above-mentioned aspects about data, another challenge in wildfire evacuation modeling lies in the coupling of different computer models. Although this study does not focus on coupling different computer models to model wildfire evacuation, this has become a popular trend in recent years [11,13]. One of the reasons model coupling in wildfire evacuation modeling is challenging is that each model is usually implemented as a separate piece of software and it is technically difficult to integrate them into one piece of software at the source code level. One alternative is to integrate the results of each model to do relevant computations. Another issue in model coupling lies in that very few open-source coupled evacuation models are available at this moment, which hinders the adoption of these new coupled models in wildfire evacuation practices. Lastly, recent research has shown has that coupled wildfire evacuation models can be used to derive some new evacuation effectiveness metrics such as the direness score [35]. Further research could focus on developing a suite of open-source tools for data-driven wildfire evacuation modeling to derive more meaningful metrics for measuring evacuation effectiveness in resort areas.

Lastly, this study used a few representative evacuation scenarios in the experimental design. From a wildfire evacuation planning perspective, it would be meaningful if we could derive the results for all possible scenarios based on available data. However, this will not be feasible due to the heavy computation. We could include a few more parameters to construct more evacuation scenarios and employ high-performance computing (HPC) to calculate the ETEs for each scenario. For example, if a fire is approaching the community very fast and the residents do not have enough time to evacuate to safe areas, a shelter-in-place order should be issued for some residents. In this case, we need to take into account different types of protective actions during the evacuation. Eventually, we could derive a large table that lists the ETEs for different parameters, which could be used by the ICs to look up the ETEs for a specific evacuation scenario with a given set of parameters. Another alternative is that we could use deploy the coupled evacuation model in an HPC environment so that ICs could provide input parameters to the model and derive ETEs from the model directly. Recently, cloud computing has enjoyed great popularity in geospatial sciences [66]. Thus, modern commercial cloud computing platforms such as Amazon Web Services (AWS), Google Cloud, and Microsoft Azure Cloud could be used to host the evacuation model as a web service and derive ETEs for the ICs. Additionally, future research could also examine how to model a staged evacuation in the study area. In most cases, ICs will issue evacuation orders in a staged manner, and the residents who are closer to the fire front will be evacuated earlier. It would be useful to compare the results in this study with those derived from a staged evacuation. However, note that a staged evacuation involves many parameters, and we need to further customize the evacuation model before we could perform a meaningful staged evacuation simulation.

7. Conclusion

We employ a data-driven approach to design and implement a wildfire evacuation model for resort areas in this study. Although we used one neighborhood in the case study, the proposed approach could be used by many similar WUI communities in the US to improve the ETEs derived from evacuation modeling. The proposed method could help emergency managers, emergency planners, and other stakeholders develop a better understanding of the dynamics of the travel demand in resort areas in wildfire evacuation and improve wildfire public safety. Additionally, this study also sheds light on how to better manage and integrate different types of data to further improve wildfire evacuation modeling.

Compared with previous research, this study focuses on integrating different types of data to improve wildfire evacuation modeling for resort areas and provides a different perspective. Based on the findings in this study, future research could focus on the following aspects. First, we could further explore how to leverage big data (e.g., GPS data and social media data) and different computer models to build a data-driven, coupled wildfire evacuation model that can take into account household evacuation behavior, the dynamics of evacuation travel demand, and fire spread. Second, more research should be conducted to explore how to better use open data in wildfire evacuation modeling. Lastly, we also need to explore how to use modern computing technologies such as cloud computing and Web GIS to make the developed evacuation models more accessible.

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.

Data availability

The authors do not have permission to share data.

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Appendix A

The traffic count data in field surveys in the Tahoe Donner (TD) neighborhood.

Date	Occupied Dwellings by Percentage	Average number of Vehicles per Occupied Dwelling	Notes
6/30/2019	41.96%	2.6	1st weekend of July 4th Week
7/13/2019	42.13%	2.4	
March 8, 2019	45.45%	2.5	
1/18/2020	38.14%	2.4	Martin Luther King Weekend
3/21/2020	30.60%	2.4	Covid-19
November 4, 2020	24.83%	2.4	Covid-19 Saturday

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Date	Occupied Dwellings by Percentage	Average number of Vehicles per Occupied Dwelling	Notes
June 6, 2020	37.47%	2.4	
6/20/2020	43.46%	2.5	Father's Day weekend
6/27/2020	48.34%	2.4	Pre-4th weekend
April 7, 2020	58.31%	2.7	4th of July
November 7, 2020	50.33%	2.4	Post 4th of July
7/25/2020	54.32%	2.5	
January 8, 2020	54.77%	2.6	
August 8, 2020	56.54%	2.5	
8/22/2020	47.67%	2.5	North Bay Fires, Smoke Issues in local area
May 9, 2020	54.55%	2.6	Labor Day Weekend
December 9, 2020	49.45%	2.5	Smoke Issues
9/27/2020	49.45%	2.5	Sunday, Red Flag No. Cal.,
Summary	45.99%	2.5	Running over-all average

Appendix B

The statistics of the derived total ETEs for different evacuation scenarios.

n	r (%)	Mean (100%)	SD (100%)	Confidence Interval (p = 0.95)
2.1	10	225.57	6.28	(223.32, 227.82)
2.1	20	275.7	7.24	(273.11, 278.29)
2.1	30	324.03	6.54	(321.69, 326.37)
2.1	40	375.13	7.57	(372.42, 377.84)
2.1	50	419.5	8.2	(416.56, 422.44)
2.1	60	470.2	8.78	(467.06, 473.34)
2.1	100	666.77	8.29	(663.8, 669.73)
2.2	10	236.63	5.52	(234.66, 238.61)
2.2	20	286.43	6.57	(284.08, 288.79)
2.2	30	336.8	7.7	(334.04, 339.56)
2.2	40	389.83	7.64	(387.1, 392.57)
2.2	50	444	6.92	(441.52, 446.48)
2.2	60	491.83	7.75	(489.06, 494.61)
2.2	100	700.87	7.6	(698.15, 703.59)
2.3	10	246.4	5.14	(244.56, 248.24)
2.3	20	301.2	6.21	(298.98, 303.42)
2.3	30	354.57	7.36	(351.93, 357.2)
2.3	40	408.7	7.14	(406.14, 411.26)
2.3	50	462.17	6.6	(459.81, 464.53)
2.3	60	519.6	6.95	(517.11, 522.09)
2.3	100	730.9	9.01	(727.68, 734.12)
2.4	10	256.83	5.84	(254.74, 258.92)
2.4	20	314.7	6.96	(312.21, 317.19)
2.4	30	369.13	6.45	(366.82, 371.44)
2.4	40	426.33	7.99	(423.47, 429.19)
2.4	50	484.77	7.94	(481.92, 487.61)
2.4	60	539.8	9.97	(536.23, 543.37)
2.4	100	763	7.95	(760.16, 765.84)
2.5	10	269.3	5.23	(267.43, 271.17)
2.5	20	329	5.96	(326.87, 331.13)
2.5	30	388.07	5.95	(385.94, 390.2)
2.5	40	446.5	9.83	(442.98, 450.02)
2.5	50	501.47	8.25	(498.51, 504.42)
2.5	60	561.33	7.66	(558.59, 564.08)
2.5	100	797.27	8.09	(794.37, 800.16)
2.6	10	279.43	5.22	(277.56, 281.3)
2.6	20	342.27	7.72	(339.5, 345.03)
2.6	30	402.9	7.03	(400.38, 405.42)
2.6	40	463.6	8.62	(460.52, 466.68)
2.6	50	521.1	7.01	(518.59, 523.61)
2.6	60	582.6	7.66	(579.86, 585.34)
2.6	100	826.9	7.38	(824.26, 829.54)
2.7	10	291.9	4.87	(290.16, 293.64)
2.7	20	355.47	5.78	(353.4, 357.54)

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n	r (%)	Mean (100%)	SD (100%)	Confidence Interval (p = 0.95)
2.7	30	417.47	7.9	(414.64, 420.29)
2.7	40	479.57	9.92	(476.02, 483.11)
2.7	50	543.17	10.89	(539.27, 547.06)
2.7	60	603.97	9.93	(600.41, 607.52)
2.7	100	858.2	7.48	(855.52, 860.88)
2.8	10	303.9	6.91	(301.43, 306.37)
2.8	20	367	9.98	(363.43, 370.57)
2.8	30	431.87	11.02	(427.92, 435.81)
2.8	40	499.67	7.9	(496.84, 502.49)
2.8	50	563.7	7.88	(560.88, 566.52)
2.8	60	628.6	9.31	(625.27, 631.93)
2.8	100	891.27	8.43	(888.25, 894.28)

Appendix C

The statistics of the derived ETEs for different evacuation scenarios.

n	r (%)	Mean (95%)	SD (95%)	Mean (75%)	SD (75%)	Mean (50%)	SD (50%)
2.1	10	206.73	5.77	129.9	4.23	79.57	2.24
2.1	20	252.5	6.82	158.9	3.99	98.2	2.41
2.1	30	296.57	6.15	186.7	3.58	115.8	2.37
2.1	40	343.17	6.98	216.2	4.33	134.57	2.79
2.1	50	383.37	7.5	243.6	4.67	151.87	3.12
2.1	60	429.67	8.33	272.87	3.97	170.3	2.65
2.1	100	608.87	7.82	388.37	4.04	242.43	2.84
2.2	10	216.83	5.31	136.1	3.76	83.6	2.09
2.2	20	262.2	6.13	164.7	3.98	101.63	2.57
2.2	30	308.17	7.17	193.93	4.45	120.23	2.6
2.2	40	356.57	7.21	224.47	3.73	139.8	2.71
2.2	50	405.77	6.5	256.57	3.81	160	2.46
2.2	60	449.4	7.28	285.3	4.09	178	2.63
2.2	100	639.93	7.18	408.57	4.15	255.27	3
2.3	10	225.87	4.68	141.6	3	86.67	2.23
2.3	20	275.57	5.9	172.97	3.96	106.8	2.48
2.3	30	324.37	6.86	203.8	4.16	126.8	2.66
2.3	40	373.7	6.71	235.53	4.22	146.93	2.83
2.3	50	422.43	6.17	266.57	3.67	165.93	2.39
2.3	60	474.93	6.48	300.3	3.46	187.37	2.41
2.3	100	667.43	8.58	425.3	4.45	265.3	3.09
2.4	10	235.27	5.51	147.6	3.85	90.37	1.92
2.4	20	288.1	6.61	180.67	4.49	111.4	2.36
2.4	30	337.63	6.24	212.3	3.49	131.83	2.2
2.4	40	389.9	7.5	245.87	4.44	152.77	2.86
2.4	50	443.13	7.31	279.2	4.69	173.93	3.37
2.4	60	493.37	9.24	311.63	5.01	194.37	3.45
2.4	100	696.93	7.42	443.7	4.24	277.27	2.69
2.5	10	246.8	4.98	155.23	3.56	94.8	1.63
2.5	20	301.23	5.67	188.83	4.08	115.97	2.09
2.5	30	355	5.61	222.77	3.46	138.07	2.55
2.5	40	408.3	9.29	257.13	5.16	159.83	3.23
2.5	50	458.33	7.68	289.4	4.93	180.4	3.57
2.5	60	512.9	7.23	324.33	3.78	202.27	2.72
2.5	100	728.23	7.65	462.97	4.51	289.23	3.04
2.6	10	256	5.07	160.57	3.72	98.07	2.03
2.6	20	313.37	7.19	196.43	5.1	121.17	2.7
2.6	30	368.57	6.55	231.33	4.28	143.8	3.01
2.6	40	423.97	8.06	266.83	4.5	166.1	3.18
2.6	50	476.27	6.72	300.43	3.9	187.23	2.81
2.6	60	532.43	7.03	335.97	4.57	209.53	3.21
2.6	100	755.1	6.89	481.2	3.88	300.4	2.53
2.7	10	267.4	4.49	167.7	3.49	102.43	1.89
2.7	20	325.53	5.38	204.13	3.9	125.3	2.39
2.7	30	381.83	7.27	239.73	4.46	148.9	3.12

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n	r (%)	Mean (95%)	SD (95%)	Mean (75%)	SD (75%)	Mean (50%)	SD (50%)
2.7	40	438.57	9.14	275.73	5.26	171.3	3.27
2.7	50	496.5	10.2	312.77	5.99	194.87	3.99
2.7	60	551.9	9.26	348.67	4.86	217.43	3.29
2.7	100	783.83	7.04	498.1	4.44	311.07	3.08
2.8	10	278.4	6.46	174.87	4.75	106.2	2.58
2.8	20	336	9.42	210.87	6.1	129.8	3.21
2.8	30	395.17	10.45	247.93	6.51	152.97	3.94
2.8	40	457.03	7.44	287.47	4.31	178.9	3.02
2.8	50	515.3	7.32	325.13	4.85	202.5	3.05
2.8	60	574.37	8.65	362.4	4.48	225.83	2.97
2.8	100	813.9	7.94	517.1	4.47	322.8	3.21

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