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Setting Wildfire Evacuation Triggers by Coupling Fire and Traffic Simulation Models: A Spatiotemporal GIS Approach

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Abstract. Wildfire evacuation triggers refer to prominent geographic features used in wildfire evacuation practices, and when a fire crosses a feature, an evacuation warning is issued to the communities or firefighters in the path of the fire. The existing wildfire trigger modeling methods consider evacuation time as an input from a decision maker and employ fire spread modeling and GIS to create a trigger buffer around a threatened asset. This paper substantially improves on previous methods by coupling fire and traffic simulation models to set triggers, which allows us to estimate evacuation time using a traffic simulation model rather than relying on expert judgment. Specifically, we propose a three-step method within a spatiotemporal GIS framework to couple these models and to evaluate the value of the generated trigger buffers. The first step uses traffic simulation to estimate the total evacuation time for a threatened community. The second step derives the cumulative probabilities for distinct evacuation times from multiple simulations and generates corresponding probability-based trigger buffers. In the last step, we evaluate the value of the generated buffers by coupling fire and traffic simulation models to examine the spatial configurations of fire perimeters and evacuation traffic. A case study of Julian, California is used to test the proposed method. The results from two evacuation scenarios with different travel demand indicate that a larger trigger buffer (more lead time) will be needed for higher levels of evacuation travel demand. For example, the time required to guarantee that 95% of the evacuating residents arrive at the safe area as a fire approaches a community is estimated at 160 min for one scenario but 292 min if the travel demand is doubled. The resulting framework advances the dynamic representation of evacuation traffic in wildfires and improves our understanding of wildfire evacuation timing and decision making. The paper concludes with a discussion of the strengths and limitations of the proposed method, as well as future research directions.

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1. Introduction

Wildfire is a common hazard in the American West due to fuel accumulation, seasonal precipitation variability, and frequent droughts. For this reason, the number and size of wildfires has increased in recent decades [1, 2]. The Wildland-Urban Interface (WUI) is defined as the region where wildlands and populated areas meet or intermix [3]. In the western U.S., with a rapidly growing WUI population, wildfires pose a significant risk to these residents [4], and public safety has become a concern for fire-prone WUI communities [5–8]. It is important to recommend timely and effective protective actions to the right population when a wildfire threatens life and property. Evacuation and shelter-in-place are the most common protective actions in wildfires, and the latter can be further divided into shelter-in-refuge and shelter-in-home [9]. Due to the ‘‘Stay and defend or leave early'' policy, ‘‘stay and defend'' is a popular protective action in wildfires in Australia [10, 11]. However, in the U.S., evacuation is the primary protective action, and shelter-in-place recommendations are rare [12, 13].

Incident commanders (ICs) must consider fire behavior, the population in the risk area, and the evacuation routing system to issue the most effective warnings to at-risk residents. Evacuating the right population at the right time is a critical and challenging problem. Evacuating residents too early might cause unnecessary community disruption, which can have adverse economic and social impacts. Conversely, late evacuation might lead residents to be trapped in-transit [14]. The reason evacuation timing is a complex problem is two-fold. On one hand, the total clearance time for a community at risk must be estimated before ICs can issue evacuation orders to the threatened residents. The total network clearance time includes the households' warning receipt time, preparation time, and vehicular travel time [15]. On the other hand, ICs also need to estimate the available time that communities have to take a protective action before the fire reaches the residences. This is primarily determined by the fire's ignition point, anticipated spread rate and direction. Thus, the complexity of evacuation timing requires decision makers to make accurate time estimates regarding both a human and natural system.

In wildfire evacuation practice, it is common to use prominent geographic features such as ridges, rivers and roads as trigger points to facilitate evacuation timing and warning [16]. For example, the firefighters used a ridge line as the trigger point above the Mountain Shadows Community in the Waldo Canyon Fire in Colorado on June 26, 2012 [17]. When a fire crosses a trigger point, the community or firefighters threatened by the fire will be notified to evacuate. Thus, wildfire evacuation triggers can be considered as an evacuation timing mechanism that takes into account both spatial and temporal dimensions of the risk fire poses to the residents, as well as the time it will take for the community to evacuate to safer places. Current trigger modeling methods employ fire spread modeling and geographic information systems (GIS) to derive a buffer around a place P with a given time T based on the shortest path algorithm [18–20]. If a fire crosses the boundary of the trigger buffer, the threatened residents should be notified to evacuate, and they will have time T for their evacuation. Trigger modeling can help ICs develop a better understanding of evacuation timing and the most effective trigger features [21]. However, one limitation of existing methods is that evacuation time T is treated as an input from a decision maker, and this parameter could be estimated using a more systematic method.

2. Background

2.1. Evacuation Traffic Simulation

Regional evacuation modeling was formulated by Southworth [22] as a five-step process: (1) trip generation; (2) evacuee mobilization; (3) destination selection; (4) evacuation route selection; and (5) evacuation plan setup, analysis, and revision. Travel demand modeling concerns modeling the number of trips generated from the origins in a given time period [23]. Risk area delineation should be performed before travel demand modeling [24]. In general, travel demand models in evacuations can be categorized into two types: sequential and simultaneous models [23]. Sequential travel demand methods model travelers' departure time choice by applying a response curve to determine the percentage of trips for each time interval. Certain probability distributions can be used for trip generation, e.g., the Poisson distribution [25]. "S-shaped" departure time curves have been widely used in evacuation travel demand modeling [26]. For example, Tweedie et al. [27] used a Rayleigh probability distribution function to estimate mobilization time. As for simultaneous travel demand models, some specific binary logit models are usually used to calculate the share of households that choose to evacuate over time, and the accuracy of these models often relies on the utility functions used in evacuation decision-making modeling [23]. Traffic simulation models can be divided into macroscopic, mesoscopic, and microscopic models based on their levels of detail [23]. With the rapid development of computing power, microscopic traffic simulation has enjoyed great popularity in evacuation modeling and simulation in recent years [25, 28]. The primary advantage of microscopic traffic simulation lies in that it can model the detailed behaviors of a vehicle agent over the road network, which can be used to discover new knowledge concealed by macroscopic approaches [29]. In this work, we use microscopic traffic simulation to estimate the total evacuation time of a community to provide input for trigger modeling.

2.2. Wildfire Spread and Trigger Modeling

Wildfire spread is a complex spatiotemporal process. Since it is not realistic to conduct experiments using a real fire to examine its impacts on other ecological or human systems, computerized modeling of wildfire spread can be used to perform simulations. The Rothermel fire behavior model [30], a semi-physical model that uses mathematical equations calibrated by empirical experiments to model fire spread rates and fire intensity, has been widely used in many fire spread modeling software systems, e.g., FlamMap [31] and FarSite [32]. The elliptical fire shape model has been widely employed to model fire spread rates on a two-dimensional plane [33]. Fire growth models such as the minimum fire travel time model [34] and the cellular automata (CA) model [35] can be used to model fire propagation in the landscape. Based on the mechanism of triggers in hurricane evacuations, Cova et al. [18] introduced the idea of modeling wildfire evacuation triggers and proposed a method to set triggers using fire spread modeling and GIS. Trigger modeling was formulated into a three-step procedure by Dennison et al. [19]: (1) fire behavior modeling; (2) construction of the fire travel-time graph; and (3) creation of trigger buffers using the Dijkstra's shortest path algorithm [36]. Previous studies have shown that trigger modeling could be potentially used in protecting firefighter crews [18, 20, 21], community evacuation planning [19, 37], wildfire evacuation warning [38], and pedestrian safety protection in the wildlands [39]. A recent study also examines how to use reverse geocoding and viewshed analysis to retrieve prominent geographic features and use them as trigger points during wildfire evacuation [21].

2.3. *Spatiotemporal GIS*

Many geographic phenomena are complex spatiotemporal processes, which calls for more advanced GIS capabilities to represent, model, and analyze both the spatial and temporal dimensions of these phenomena [40]. Space–time representation and modeling in GIS can be generally divided into two types: the discrete and the continuous view [41]. The discrete view represents and models the movements of discrete objects in the space over time, and this line of research is characterized by time geography [42], which has enjoyed great popularity in mobility studies in the past few years [43]. Specifically, the evacuees in wildfire evacuations can be represented as moving objects within the road network over time. The continuous view concerns representing objects as attributes attached to a location [41]. In this regard, wildfire spread and trigger buffer can be represented and modeled as a raster polygon with fire travel time as an attribute.

3. Research Questions

Protective-action triggers in environmental hazards take into account both human and environmental systems during an evacuation and can help us develop a better understanding of evacuation timing and warning [44]. This work focuses on developing a GIS framework to study the space–time coupling of fire and traffic simulation models for wildfire trigger modeling. Many space–time methods have been developed to support spatiotemporal queries [45–47], and these methods could be employed to perform spatiotemporal queries and computation in the model coupling process in this work.

The purpose of this research is to couple fire and traffic simulation models using a spatiotemporal GIS framework to improve our understanding of wildfire evacuation timing and decision support. Specifically, the research questions include: (1) How can the uncertainty in evacuation time estimates (ETEs) be represented when coupled fire and traffic models are used to set triggers? (2) How can we evaluate the value of trigger buffers generated using the ETEs derived from traffic simulation models? Addressing these questions will make a significant contribution to the theories and methodologies in wildfire evacuation modeling and help us develop a better understanding of wildfire evacuation from a system coupling perspective.

4. Methods

Spatial representation to a large degree determines the methods used in subsequent modeling and analysis [48]. The raster data model is used to represent the landscape in trigger modeling. As illustrated in Fig. 1a, the fire starts from the ignition point and spreads outwards to create a series of perimeters in wildfire spread modeling. In trigger modeling, the fire spread rates in eight directions for each raster cell are reversed and a fire travel time graph is constructed. Then a shortest path algorithm is performed to traverse the graph from the input community outwards to create a raster trigger buffer, as shown in Fig. 1b. Note that this

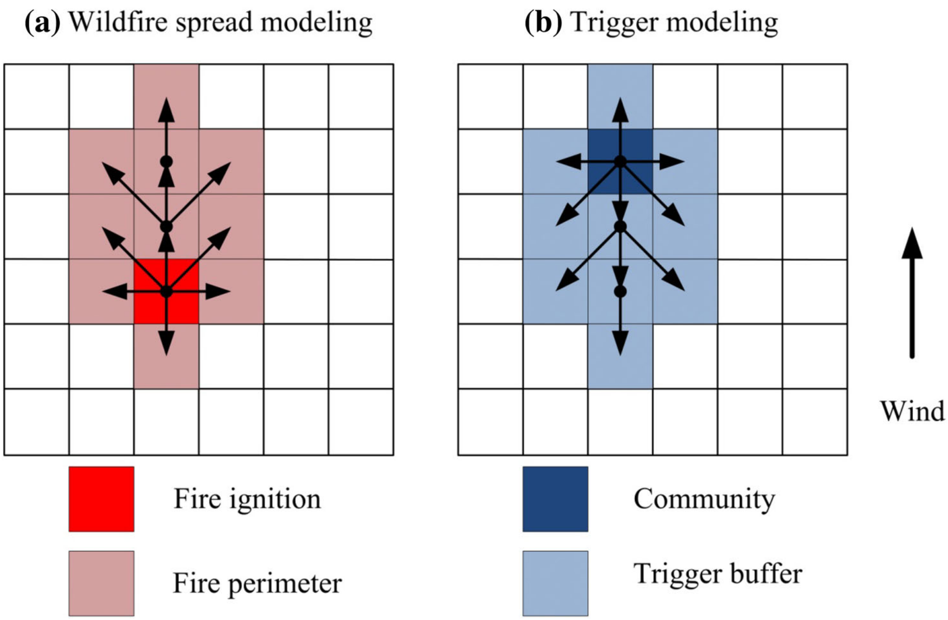

Figure 1. Illustration of wildfire spread and trigger modeling: (a) A demonstration of wildfire spread modeling; (b) A demonstration of trigger modeling [51]. Wildfire spread modeling uses the shortest path algorithm and the fire spread rates in eight different directions in one cell to derive fire travel times for each raster cell. Trigger modeling reverses edges in opposite directions and also employs the shortest path algorithm to create a raster buffer for a threatened community.

example assumes that uniform topographic and fuel model inputs are used, and the wind is from the south. Thus, the fire perimeter is skewed towards the wind direction, while the trigger buffer is skewed against the wind. In transportation geography, time–space convergence refers to the phenomenon that the travel-time between two places will decrease and distance will become less significant as a result of transport innovations [49]. Similar to the time–space convergence concept, wildfire spread and trigger modeling are based on fire travel time rather than Euclidean distance [50].

From a wildfire risk perspective, trigger modeling can be considered an evacuation timing and warning mechanism based on fire risk. Yuan [52] gives a summary of the spatiotemporal scales and sizes of resolution of different wildfire studies such as fire forecasting, analysis of fire phenomena, fire behavior/growth modeling, fire effect assessment, fire history, and fire management. The two key processes during wildfire evacuation include wildfire spread and the evacuation of the residents. These processes are both complex spatiotemporal processes, and we need to take into account their spatiotemporal scales as well as sizes of resolution when coupling them. In this work, a spatiotemporal GIS framework is proposed and used to couple fire and traffic simulation models, as shown in Fig. 2. Note

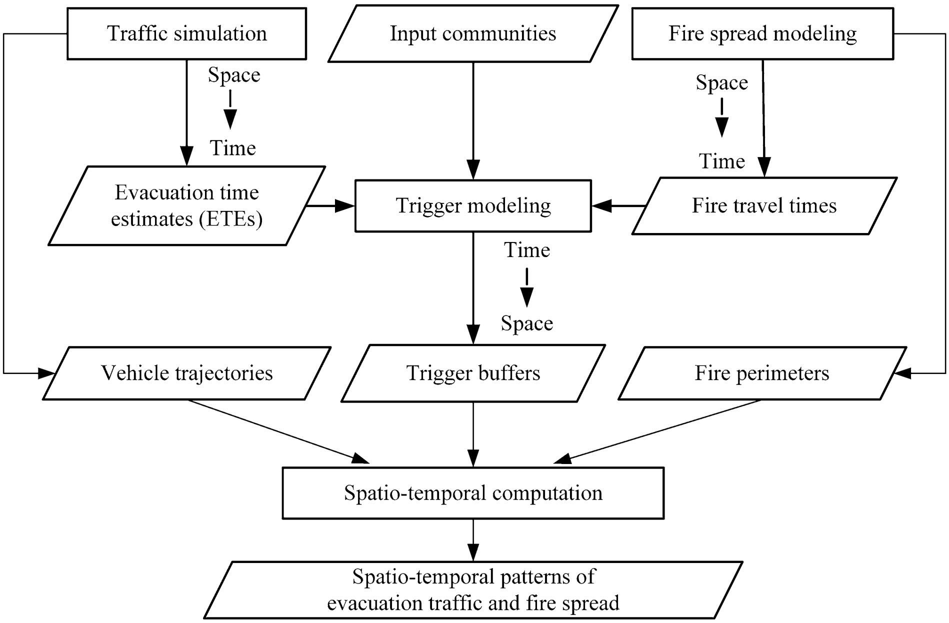

Figure 2. A spatiotemporal GIS framework for model coupling [51]. Traffic simulation is used to derive ETEs, which can be used as the input for trigger modeling. Fire spread rates and travel times can be calculated using fire spread modeling. Finally, we couple fire spread and traffic simulation models to examine the spatio-temporal patterns of fire spread and evacuation traffic.

that evacuation traffic takes place in the road network, which is a constrained geographic space. The ETEs derived from evacuation traffic simulation are used as the input for trigger modeling. As for fire spread modeling, the geographic distance between two adjacent raster cells is converted to fire travel times in different directions. Note that the spatial dimensions of fire spread and traffic simulations are converted to fire travel time and evacuation time, respectively. Then a time–space conversion is performed to generate a raster trigger buffer for a given input evacuation time *T*. Note that a trigger buffer is a time buffer and takes into consideration both evacuation and fire travel times. After the generation of the buffers, fire and traffic simulation models are coupled, and spatiotemporal computation is performed to reveal the spatiotemporal patterns of fire spread and evacuation traffic. The detailed steps are listed as follows.

4.1. Step 1: Estimate Evacuation Time Using Traffic Simulation

In the first step, microscopic traffic simulation is used to estimate the evacuation time of a fire-prone community. Based on the five-step evacuation modeling procedure proposed by Southworth [22], the workflow for this step is shown in Fig. 3. Since wildfire evacuations are usually at a smaller geographic scale than hurricane evacuations, household-level travel demand modeling is becoming more popular [25, 53]. Since the exact number of vehicles for each household is unknown, a statistical distribution can be used to assign the number of vehicles to each household, e.g., the Poisson distribution [25]. Thus, we use a Poisson distribution to generate the number of vehicles to randomly assign to each household (e.g., 0, 1, 2…n). Determining the departure time profiles is a prerequisite for evacuation time estimation. It is assumed that all the households will choose to

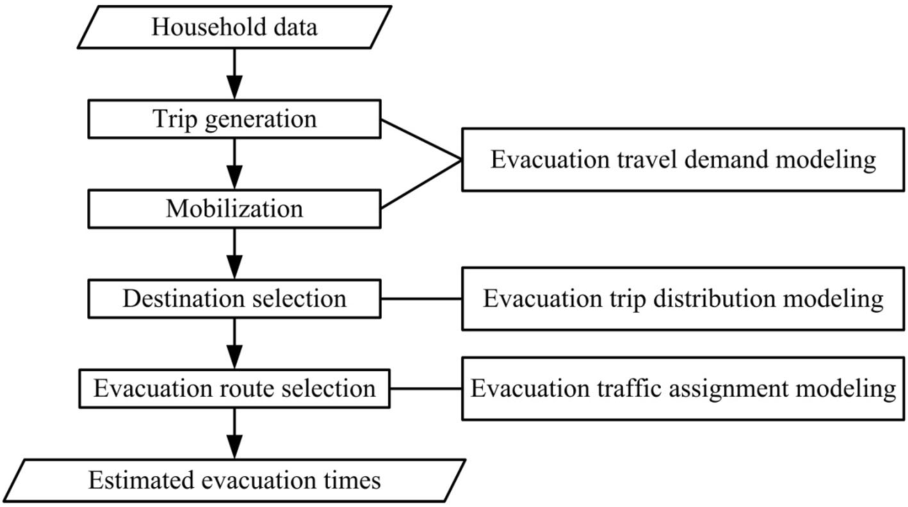

Figure 3. The workflow of traffic simulation [51]. We used a normal distribution to generate trips for each household and a Poisson distribution to generate the departure times.

evacuate after they receive the warnings and the departure time D follows a normal distribution $D \sim N(\mu, \sigma)$, where μ is the mean departure time and σ the standard deviation. As for destination selection, it is assumed that all the evacuees will choose the closest egress point. Finally, the assumption used for route selection is that all the evacuees will choose the shortest path, and this assumption is likely to hold in WUI areas with relatively sparse road networks.

The total evacuation time is defined as the time span from the start of the evacuation (when the evacuation warning is sent out) to the time when the last vehicle reaches the destination egress in the road network. Han et al. [54] point out that the evacuation time where 95% of the population is evacuated is more practically meaningful compared to a complete 100% evacuation rate, as the latter would put too much importance on the last departing vehicle. Thus, the evacuation times when 25, 50, 75, and 95% of the population have arrived at the destination are calculated and used as the input time for trigger modeling. The four ETEs are denoted with T_{25}, T_{50}, T_{75}, and T_{95}, respectively, as shown in Fig. 4. For a given evacuation scenario, n sets of four ETEs can be derived from n runs of traffic simulation. Note that many traffic microsimulators have the capability to simulate traffic using seconds as the time step. The final ETEs are converted to minutes since the temporal resolution for fire spread and trigger modeling is at the minute.

4.2. Step 2: Generate Probability-Based Trigger Buffers

In this step, the ETEs from Step 1 are aggregated to derive cumulative probabilities and then used to generate probability-based trigger buffers. Note that since there could be repeated values in the n input ETEs. All the m ($1 \leq m \leq n$) distinct ETEs for a specific scenario are sorted in an ascending order and can be denoted

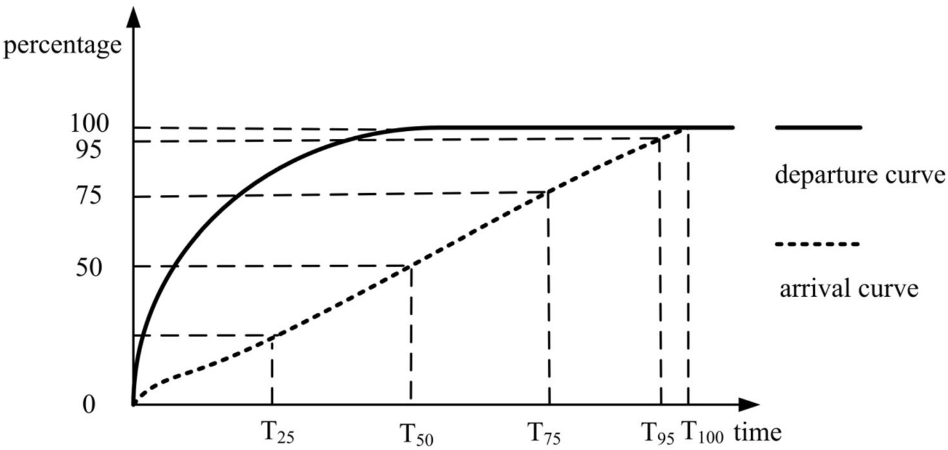

Figure 4. An illustration of the derived four ETEs [51]. Specifically, we calculate the time taken when 25, 50, 75, and 95% of the evacuees have arrived at the safe places during the evacuation for each run of traffic simulation. If we perform traffic simulation n times, we can derive n sets of these four ETEs.

with a set $T_e = \{t_1, \ldots, t_m\}$. Let f_k ($1 \le k \le m$) be the cumulative frequency of ETE t_k, and the probability that a trigger buffer b_k generated using t_k can ensure the successful completion of a specific evacuation is defined as $p_k = \frac{f_k}{n}$, as shown in Fig. 5a. In this way, a trigger buffer b_k is associated with a probability value p_k. As shown in Fig. 5b, the probability value associated with the outmost trigger buffer b_m is $p_m = 100\%$, which means that if it is used as the trigger buffer in wildfire evacuation, the probability that it could ensure the successful completion of an evacuation for the specific scenario will be 100%. However, if we use the innermost trigger buffer b_1 in this evacuation scenario, the probability will be p_1.

The three-step procedure for trigger modeling is used to create trigger buffers, as shown in Fig. 6 [19]. First, the fire spread modeling software package FlamMap is used to compute the fire spread rates in eight directions for each raster cell. Second, the fire spread rates are used to calculate the travel times between adjacent raster cells and construct a fire travel-time graph. Third, the edges in opposite directions are reversed and the Dijkstra [36] shortest path algorithm is used to traverse the graph from the community cells outwards until the accumulated fire travel time reaches the input evacuation time T. The trigger buffers will be a set of raster polygons around the community. The time distance between the boundary of a trigger buffer and the community depends on the fire travel time in that direction. Since fire spread rate is determined by many environmental factors (e.g., fuel model, topography, and wind), the shape of a trigger buffer is usually skewed.

4.3. Step 3: Evaluate the Value of the Generated Trigger Buffers

In this step, wildfire and traffic simulation models are coupled to evaluate the value of the generated trigger buffers. The conceptual diagram of the evaluation proce-

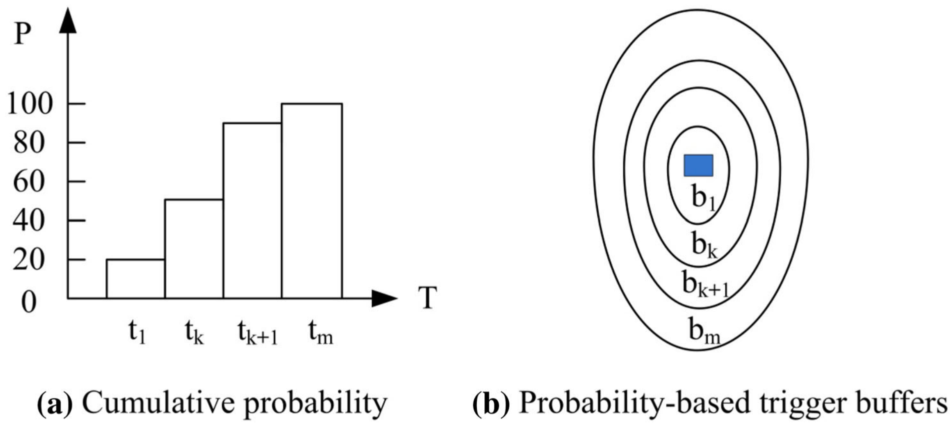

Figure 5. An illustration of the generated probability-based trigger buffers [51]. Note that the trigger buffer for each ETE is associated with a cumulative probability value, which denotes the probability that the trigger buffer can ensure the successful completion of the specific evacuation.

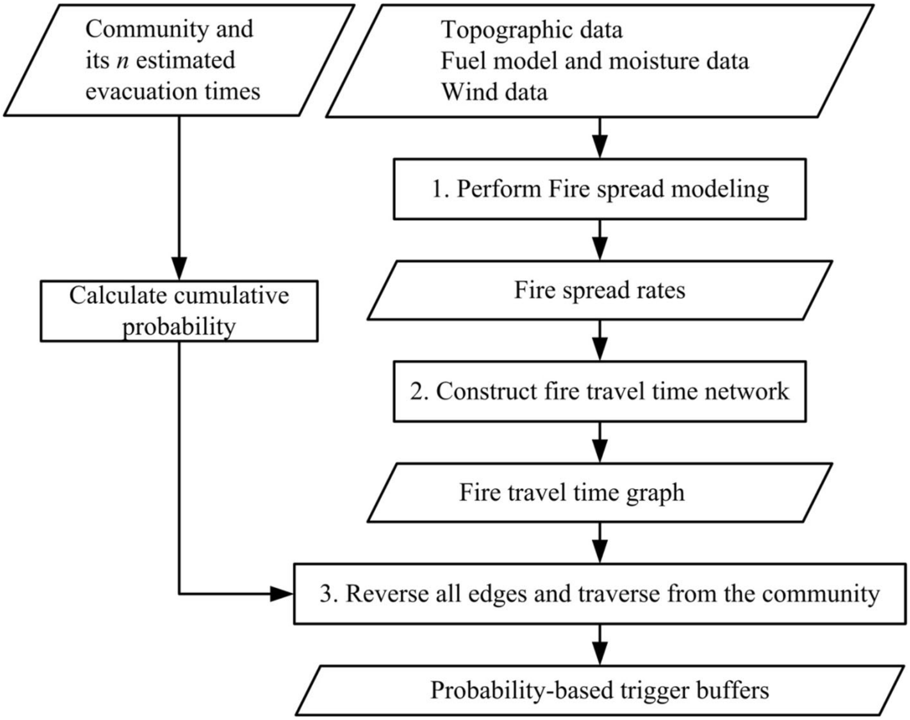

Figure 6. The workflow of creating probability-based trigger buffers [51]. The ETEs derived from traffic simulations have their corresponding cumulative probability values and are used as the input time for trigger modeling. A trigger buffer based on fire spread rates is generated for each input ETE, and thus each trigger buffer is also associated with a probability value.

dure is given in Fig. 7. The probability-based trigger buffers are used as input for this step. The fire perimeter for each time step can be computed from wildfire simulation. When the fire reaches the boundary of the evacuation trigger buffer at time t_0, the community at risk will be notified to evacuate. The same environmental inputs, fire spread rates, and shortest path algorithm are used for wildfire simulation. Note that when the fire reaches the community at time t_2, the fire travel time $t_2 - t_0$ should align with the input evacuation time T for the trigger buffer.

After evacuation warnings are sent out, vehicles start to depart from the household origins and travel towards the egress nodes. Fire and traffic simulation models are coupled to examine the spatial relationship between fire front and the vehicles in-transit. Beloglazov et al. [55] used person-threat distance to measure evacuees' exposure to fire risk during evacuation. In this work, the person-threat distance was also employed as a metric to evaluate the value of a trigger buffer. Specifically, the shortest distance between the fire front and the vehicles in-transit at time step t_2 when the fire reaches the community is calculated, as shown in

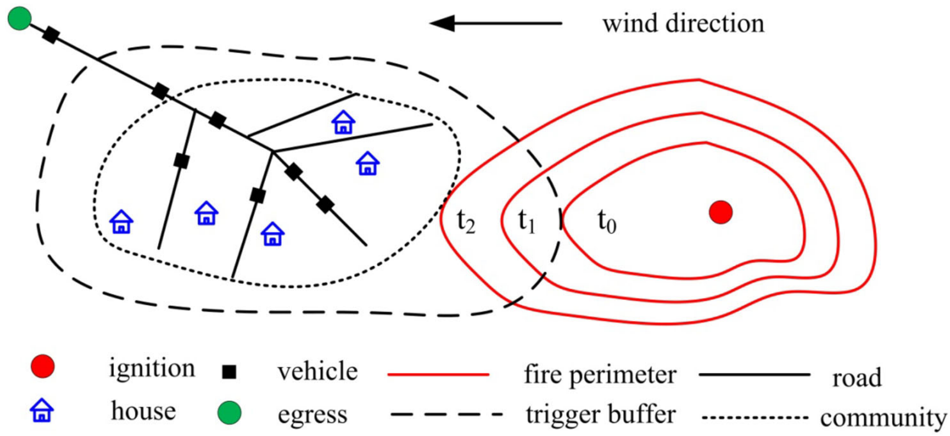

Figure 7. The conceptual diagram of the evaluation procedure [51]. The fire starts at the ignition and spread towards the community. When the fire reaches the trigger buffer at t_0, the residents will be notified to evacuate. The evacuation traffic will be mapped out when the fire reaches the community at t_2 to evaluate the effectiveness of the trigger buffer used during evacuation.

Fig. 7. The trajectory of a vehicle v can be represented with a series of points with corresponding times $TP(v) = \{tp_1, \ldots, tp_n\}$. Each element $tp \in TP$ includes time t and the location p and can be represented by $tp = (t, p)$. For each vehicle $v \in V$, we can derive the specific $tp = (t, p)$ when t is equal to t_2 and calculate the minimum distance between its location p and the fire front. Note that wildfire simulation is based on the raster data model and the shortest distance is the minimum Euclidean distance between the point p and the centroids of the raster cells that represent the fire front at time step t_2. The shortest distance could reflect the risk the fire poses to the closest evacuee when it reaches the community. If the distance is too small, the evacuee could be trapped by the fire; otherwise if the evacuee is very far from the fire front, it means that the trigger buffer used may lead to early evacuation. Moreover, we also extract the locations of the evacuees and aggregate them at the road link level at time t_2. If we map the results out, we can get a snapshot of the evacuation process such that we could more directly examine the spatial configuration of evacuation traffic and the fire front.

5. Case Study

Southern California is one of the areas that is most vulnerable to wildfires in the American West due to flammable fuels (e.g., chaparral), seasonal drought, and Santa Ana wind events. A case study was conducted to evaluate the value of the proposed method, and Julian, a census-designated place (CDP) in San Diego County, California, was chosen as the study site. Julian is surrounded by wildlands, and the evacuation route system only includes a few exits, which makes it representative of many high fire-risk and low-egress communities in the western U.S. As shown in Fig. 8, there are three primary exits in the evacuation route system—Highway 78 West, Highway 78 East, and Highway 79 South. The residential area used is composed of three communities: the Julian downtown area, the Whispering Pines community, and the Kentwood-in-the-pines community. The household locations were derived by extracting the centroids of the residential land parcels downloaded from the GIS department of San Diego County (SanGIS), and a total of 744 households in this area were used in this study.

In the case study, the evacuation module of an open-source traffic microsimulation software package named MATSim was used to perform traffic simulation and estimate evacuation time [56]. The road network data were compiled from OpenStreetMap, a crowd-sourcing open data initiative with millions of contributors all over the world [57]. Note that the data from OpenStreetMap can be readily used in MATSim [58]. Specifically, the downloaded road data were edited using an open-source tool named Java OpenStreetMap Editor (JOSM) and its MATSim plugin. The speed limits of the highways and residential roads were set to 17.882

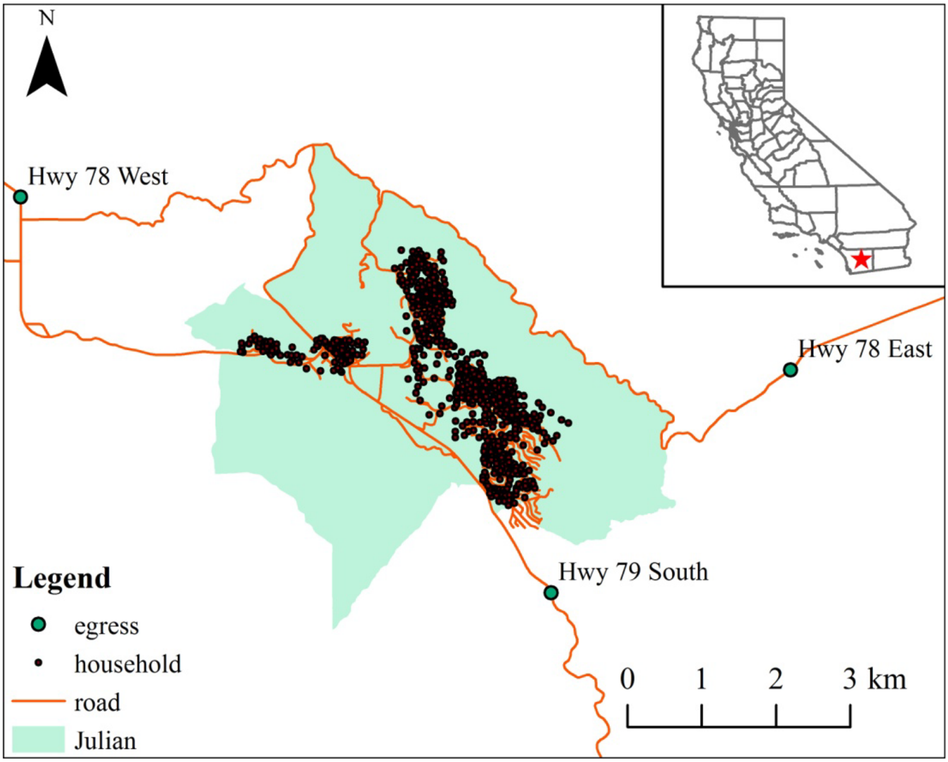

Figure 8. The map of Julian, California [51]. This study area is an isolated community surrounded by a large amount of fuels. The points denote household locations, and the road network is the evacuation route system during evacuation and has three major egresses.

m/s (40 mph) and 11.176 m/s (25 mph), respectively, during the network coding process. Note that the speed limits used are based on local regulations.

Egress points will also be the nodes on the road network and will be used as destination nodes. Household-level Origin–Destination (OD) demand in microsimulation will be determined by the locations of households and points of egress on the road network. In this case study, it is assumed that a fire will arrive from the southeast, and all residents will use the western egress (Highway 28 West) as their exit. MATSim uses the number of ‘‘persons’’ to denote the number of trips from one origin node. Since a personal vehicle is the primary transport mode in wildfire evacuations in the U.S. [53], a Poisson distribution number generator was implemented in Java to assign a random number to a household as the number of vehicles departing from this node. According to the American Community Survey (ACS) 2015 vehicle occupancy data (Appendix 1), the average household vehicle occupancy is close to 2. Thus, the mean value used for the Poisson distribution was 2. In addition, we also used a mean value 4 to create a scenario with a larger travel demand as a comparison. A normal distribution was used to generate the departure times, and the parameters are shown in Table 1. Note that λ denotes the mean value of the Poisson distribution for travel demand, and μ and σ are the mean value and standard deviation of the normal distribution for departure times. The traffic simulation was run 100 times for each scenario to estimate evacuation time. Note that only one iteration was performed for each simulation. We used the shortest path assumption and did not consider user equilibrium. The normal distribution was used for computation convenience, and use of this specific distribution does not affect the generalizability of the method.

The calculated ETEs as well as their cumulative probabilities are listed in Table 2. Specifically, we calculated the evacuation times when 25, 50, 75, and 95% of the evacuees have arrived at the safe areas for each scenario. We also computed the minimum, mean, maximum, and standard deviation of the ETEs as well as their corresponding cumulative probability values for each case. Relevant data for fire spread modeling primarily include vegetation cover data (fuel models), weather data (e.g., wind speed and wind direction), and topographic data (digital elevation model (DEM), slope, and aspect). The fuel model and topographic data were downloaded from LANDFIRE—a national open data initiative for fuel mapping [59]. The spatial resolution of all raster data used is 30 m. The residential raster polygon was acquired by combining the convex hull of the households and the raster cells with unburnable fuel model values around it. A south wind with speed 16 km/h (10 mph) was used for fire spread modeling in FlamMap. The 1 h, 10 h, and 100 h dead fuel moisture values used were 5%, and the live woody and herba-

Table 1
Parameters for Different Evacuation Scenarios

Scenario	λ	μ (min)	σ (min)	Earliest (min)	Latest (min)
1	2	40	20	0	80
2	4	40	20	0	80

Table 2
Cumulative Probabilities for Four ETEs (Unit: Minute)

Scenario	T_{25}	T_{50}	T_{75}	T_{95}
1				
Min	45 (1%)	78 (4%)	113 (2%)	141 (2%)
Mean	49 (64%)	82 (56%)	119 (56%)	149 (58%)
Max	53 (100%)	88 (100%)	128 (100%)	160 (100%)
SD	1.5	2.4	3.4	4.2
2				
Min	69 (4%)	139 (2%)	210 (1%)	268 (1%)
Mean	72 (74%)	144 (55%)	219(63%)	278 (57%)
Max	75 (100%)	151 (100%)	229 (100%)	292 (100%)
SD	1.3	2.7	4.0	4.2

ceous fuel moistures were set to 65%. The 5% dead fuel moisture is typical of daily lows in dead fuel moisture in fall in Southern California, and 65% live fuel moisture value is typical of seasonal lows reached annually in chaparral [60].

The generated probability-based trigger buffers for scenario 1 are shown in Fig. 9. When the fire crosses the boundary of the outmost 53 min trigger buffer in Fig. 9a, the probability that the lead time could ensure the successful completion of the evacuation in which 25% of the evacuees have arrived at the safe areas is 100%; if we use the minimum 45 min trigger buffer, the probability will be 1%. Thus, a trigger buffer with a larger probability value could better ensure the successful completion of the evacuation. Note that the maximum evacuation time for a 95% evacuation is 160 min and this buffer can ensure a safe evacuation for this scenario but might lead to earlier evacuation and cause unnecessary disruptions when it is used in wildfire evacuation practice. In this way, the uncertainty in evacuation time can be reflected directly by the probability values associated with the generated trigger buffers, which could help facilitate the ICs' decision making during wildfire evacuations.

The trigger buffers generated using the maximum evacuation times for different scenarios are displayed in Fig. 10. The ETEs and sizes of trigger buffers increase with the increase of evacuation travel demand. We employed wildfire simulation to evaluate the value of the derived trigger buffers in Fig. 10. As shown in Fig. 11, the fire ignition point is located 4 km from the boundary of the residential area. Note that the fire perimeters are skewed downwind and thus the trigger buffers are skewed upwind. The calculated fire travel times are shown in Table 3. Note that time T denotes the input time for trigger modeling and the maximum ETEs from Table 2 were used. The time $t = t_2 - t_0$ computed from fire simulation aligns with the input time T. The locations of the in-transit vehicles were extracted at time t from the results of traffic simulation, and the person-threat distances were also computed. Table 4 lists the statistics of the person-threat distances for one run of traffic simulation. For each scenario, the minimum person-threat distance increases when trigger buffers generated with larger input times are used (i.e., the risk to evacuating residents is reduced). When the maximum evacuation

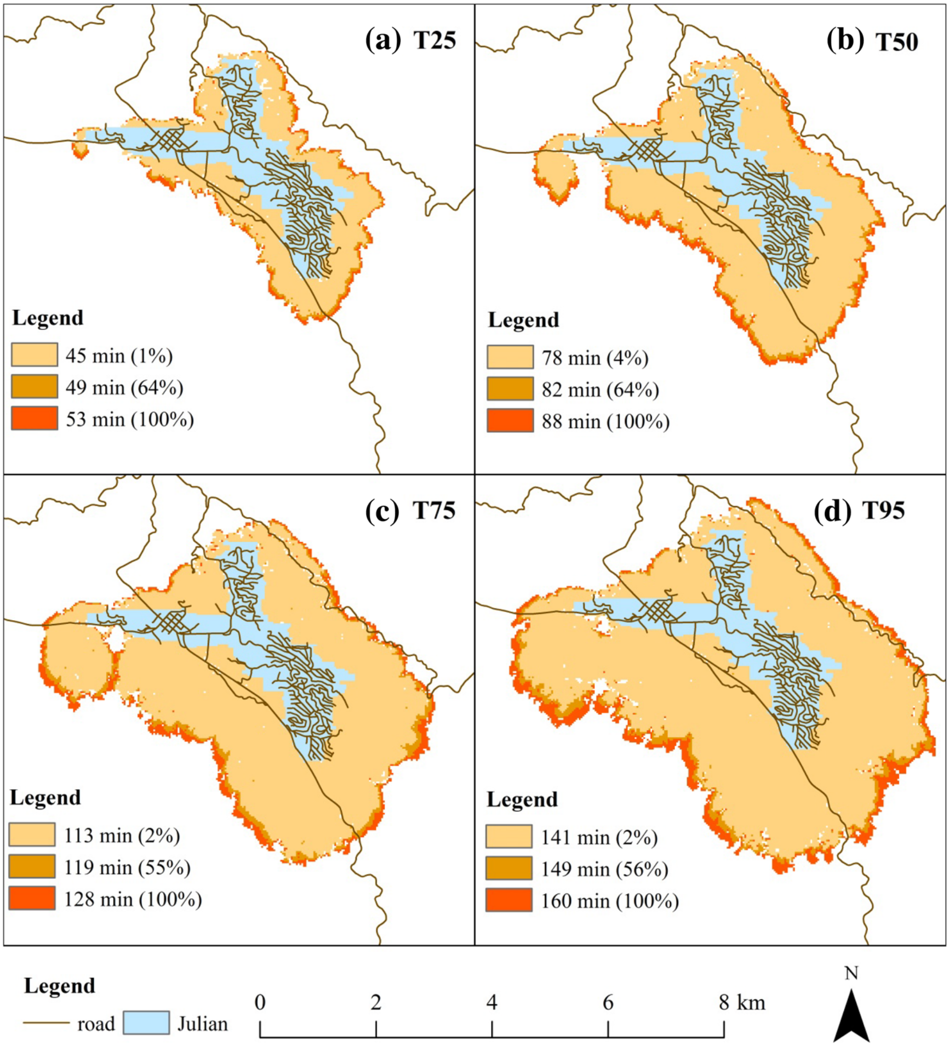

Figure 9. Generated probability-based trigger buffers for scenario 1. We computed the four ETEs for each simulation and mapped out the trigger buffers for the minimum, mean, and maximum ETE. The maximum ETE denotes the worst case in n simulations for a specific scenario, and the probability that its corresponding trigger buffer can ensure the successful completion of the evacuation is 100%.

times for T_{95} are used for trigger modeling, 95% of the evacuees have arrived at the safe area by the time the fire reaches the boundary of the community (i.e., the risk to the trailing evacuating residents is reduced).

In order to better reveal the dynamics of evacuation traffic and fire spread, the locations of the evacuees when the fire reaches the community were extracted and

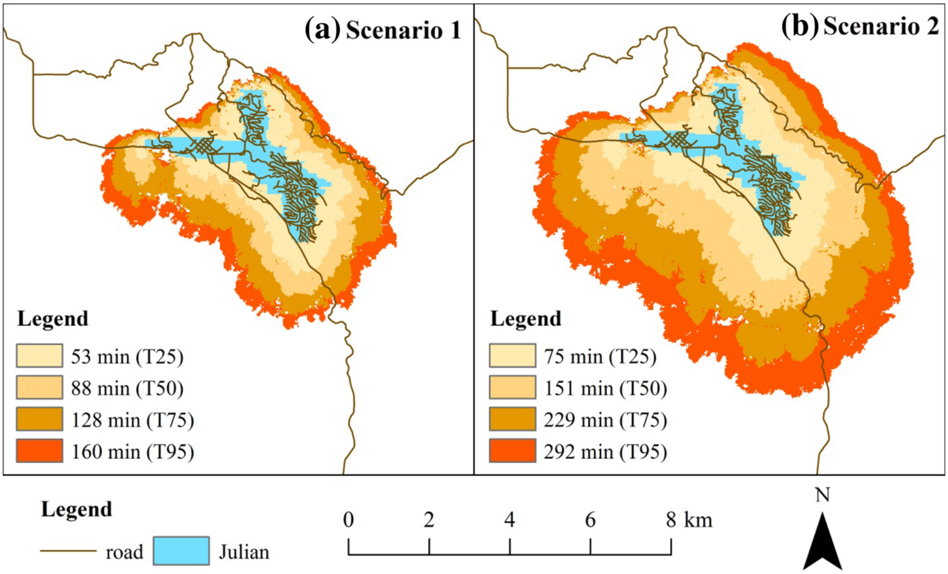

Figure 10. Trigger buffers generated using 100% evacuation times. We used the maximum ETEs in four set of ETEs to generate the trigger buffers for each scenario. Thus, the probability that these buffers can ensure the successful completion of the evacuation for each case is 100%.

mapped in Fig. 12. We aggregated the vehicles at the link level and visualized the vehicle counts of the links. The maps indicate that for each scenario more in-transit evacuees are closer to the fire front when small trigger buffers are used. For example, when the trigger buffers generated using T_{25} were used, many in-transit evacuees are located close to the fire front and could be potentially trapped by the fire; when larger buffers generated using T_{75} were used, fewer in-transit evacuees will be exposed to the wildfire risk. Another finding is that evacuation route system geometry will influence the evacuees' exposure to fire risk. For example, many vehicles will be put into a queue at these converging links and these links will become congested, resulting in the evacuees' being exposed to the fire risk. If the congested link is located close to the fire front, the fire could trap the evacuees in-transit and cause deaths. Moreover, a comparison of the two scenarios reveals that more evacuees will be exposed to fire risk with the increase of evacuation travel demand.

6. Discussion

The proposed method takes into account both evacuation traffic and fire spread and provides a spatial perspective on evacuation timing. The ICs could develop a better understanding of evacuation timing through this method. Previous studies

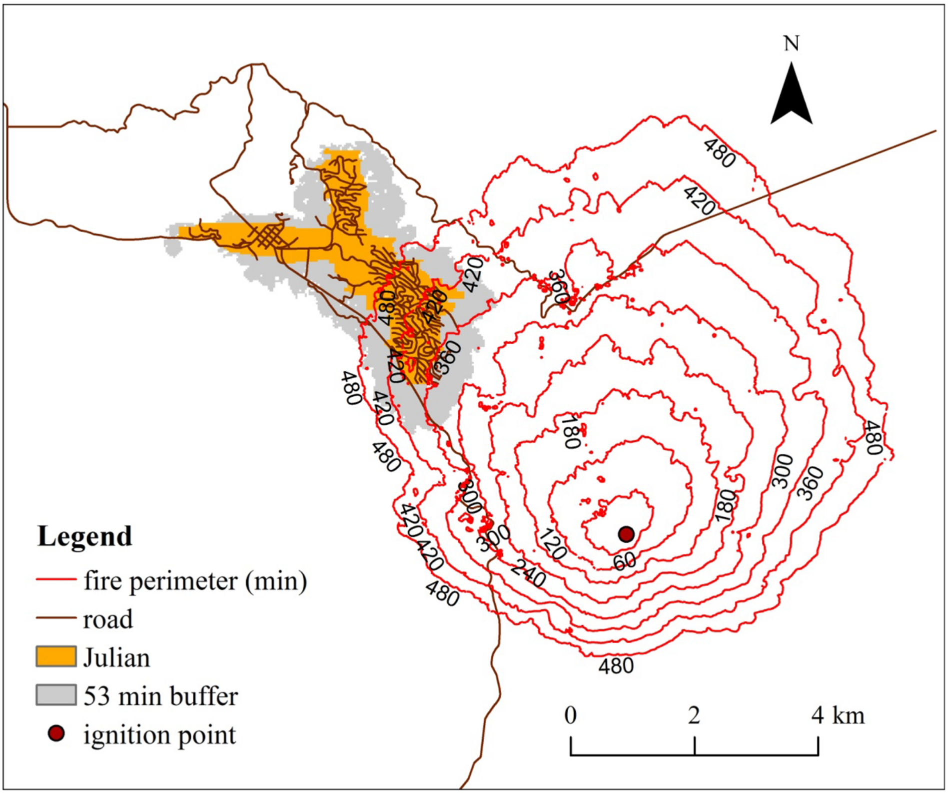

Figure 11. Fire perimeters from wildfire simulation [51]. We derived fire perimeters from wildfire simulation and overlaid the perimeters with other datasets. Note that the perimeters are skewed along the wind direction while the trigger buffer is skewed against the wind direction.

Table 3
Derived Fire Travel Times from Fire Simulation (Unit: Minute)

Scenario	T_{25}	T_{50}	T_{75}	T_{95}
1				
T	53	88	128	160
t_0	299	264	224	193
t_2	351	351	351	351
t	52	87	127	158
2				
T	75	151	229	292
t_0	277	200	122	60
t_2	351	351	351	351
t	74	151	229	291

Table 4
Person-Threat Distances for Different Scenarios in One Run (Unit: Meter)

Scenario	T_{25}	T_{50}	T_{75}	T_{95}
1				
Min	128	2107	2811	9693
Mean	168	3232	4565	9693
Max	290	9458	9458	9693
SD	38	1555	1999	0
2				
Min	128	1779	2575	6827
Mean	286	2838	3233	8045
Max	631	9458	9458	9458
SD	111	1090	1464	737

have examined the impacts of the structure of the road network on wildfire evacuation risk [61, 62]. The results in this study demonstrate that we could better reveal the dynamics of evacuation traffic and fire spread in wildfire evacuations when we couple the two models to set triggers. The interdisciplinary nature of this work also allows us to pursue answers to more questions concerning the complex dynamics of evacuation warning, evacuation traffic, and fire spread during wildfire evacuations. Future research can focus on the following four aspects.

First, some assumptions were made for traffic simulation, which cannot consider all possible spatiotemporal patterns of evacuation traffic during the evacuation. Note that complete compliance and a normal distribution of distribution of departure times are used for computation convenience. Evacuation departure times often depend on warning receipt and household preparation [15]. Thus, future work could take into account more findings (e.g., evacuation shadow) from empirical studies to better estimate evacuation time [63]. Specifically, more factors could be included to better model evacuation travel demand. For example, population distribution differs significantly during the day time and at night [64]. We made the assumption that all the evacuees are at home in the case study, which could be a typical evacuation scenario in the night time. People may involve in many other activities in the day time, e.g., driving to work, picking up children from school, and going to the grocery store. Thus, we also need to consider these activities to improve ETEs for day-time evacuations. Recent years have witnessed the popularity of activity-based analysis and modeling in transportation studies [43], and activity-based models can take into account these activities during evacuation. Note that MATSim supports activity-based traffic simulation [65], which could be used to model wildfire evacuation during the day time. Moreover, further studies should also be conducted to better model departure times. Many empirical studies use curves to model departure times [26, 66]. Thus, different departure curves could be used for estimating evacuation time in future work. And further research should also be conducted to examine the impacts of using different

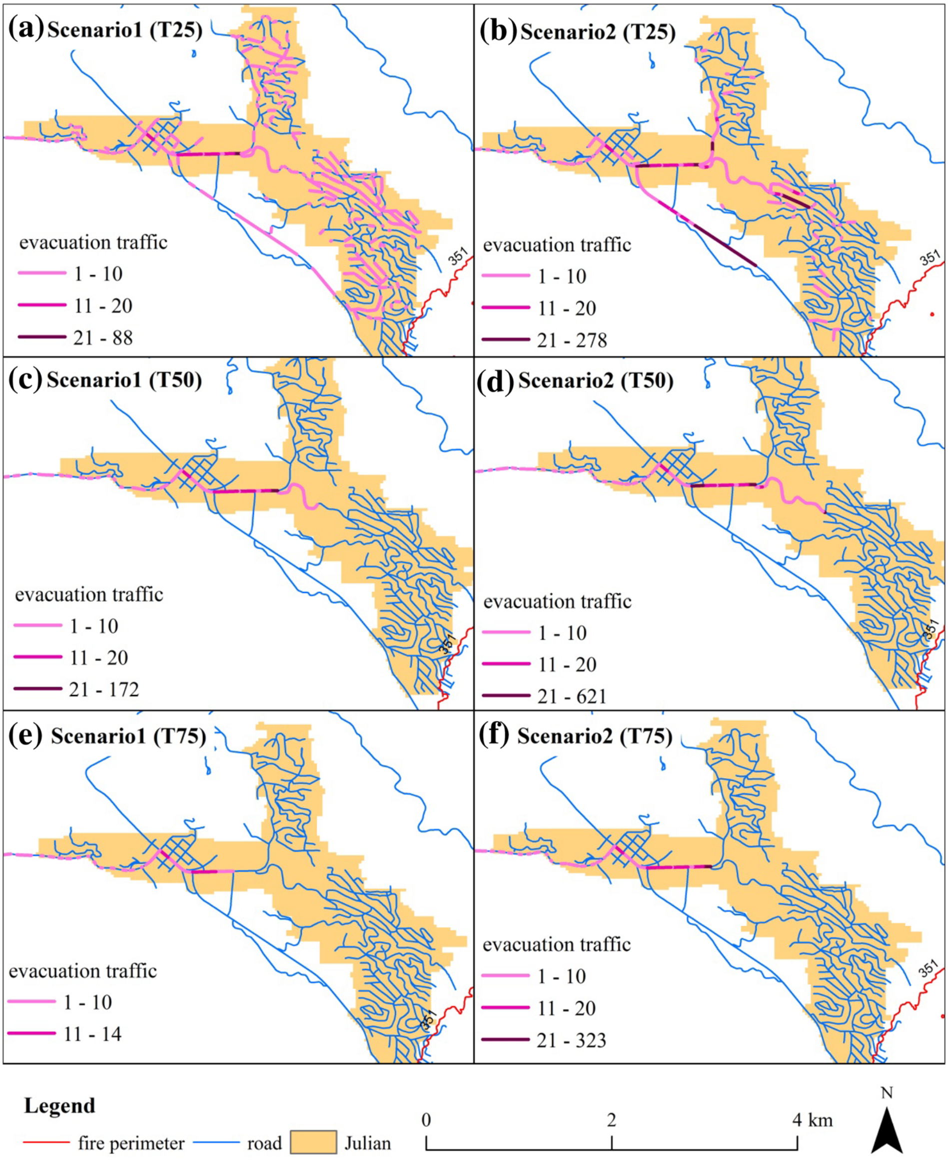

Figure 12. The evacuation traffic for scenario 1 and 2. The evacuation traffic when the fire reaches the community was mapped out separately for each scenario and overlaid with the fire perimeters and road network data. More vehicles will be located closer to the fire front for a larger evacuation traffic demand. And a larger buffer can provide more time for evacuation but might cause early evacuation and disruptions.

departure curves on evacuation timing and warning. Lastly, we used a shortest path assumption in the route choice modeling, and other agent route-choice behavior could be included in future work to evaluate the impacts of different assumptions (e.g., user equilibrium) on evacuation timing.

Second, it is assumed that all the residents in the study area receive warnings at the same time during the evacuation. However, staged evacuation is very popular in real-world wildfire evacuations because the fire could be suppressed by the firefighters and the wind might also change its direction. Note that risk area delineation is a key step towards performing staged evacuations. Risk area accuracy is an important issue in hurricane evacuations, and previous studies have examined the factors that influence people's perception of risk areas [67, 68]. Compared with hurricane risk areas, it is more difficult to define risk areas in wildfire evacuations because wildfire can come from any direction. Protective action warnings in wildfire evacuations are sent out dynamically with the spread of the fire [69]. The dynamic nature of risk area delineation in wildfire evacuations makes it a challenge to perform staged evacuation traffic simulations. Future work could explore the impacts of staged evacuation strategies on evacuation time estimation in trigger modeling.

Third, more research could be conducted to further examine how to associate trigger buffers with different protective action selections. Evacuation could maximize public safety and is the primary protective action during wildfire evacuations in the U.S. However, when the fire is too close to residences or evacuation route systems, an evacuation order could make the residents trapped in-transit. In this case, a shelter-in-place order should be issued instead. Thus, protective action selection relies on evacuation timing—whether the threatened residents will have enough time for their safe evacuation. In this regard, trigger modeling could be employed to create trigger buffers associated with different protective action recommendations. Note that evacuation traffic simulation can be used to estimate the probable worst-case and best-case evacuation time of a community given the assumptions used in the study (i.e., these extremes are subjective). The trigger buffer generated with the probable best-case evacuation time could be associated with a shelter-in-home order because it is difficult for the community to accomplish a safe evacuation within such a short time. On the contrary, the probable worst-case evacuation time could be used to create a trigger buffer for evacuation recommendation. Cova et al. [70] introduced an optimization-based model for protective action selection in wildfire evacuation. With more scenarios taken into account during evacuation traffic simulation, the proposed simulation-based method in this work could also be potentially tailored for protective action selection modeling. Moreover, when emergency managers make evacuation decisions, a false positive decision error can ensure public safety but will incur evacuation costs, reduce credibility, and decrease future warning compliance, while a false negative error (i.e., not evacuating residents when the threat impacts them) could cause loss of life and property [71]. These should also be taken into account in protective action selection modeling.

Lastly, wildfire smoke could significantly reduce visibility and cause accidents during an evacuation, which may slow down the whole evacuation process and make the evacuees trapped by the fire. We could take into account the impacts of smoke in wildfire evacuation modeling in future work. Researchers in public health have conducted a large body of research to examine people's exposure to wildfire smoke and its impacts on their health [72], and future work could also focus on evacuation planning and modeling in the context of exposure to wildfire smoke for vulnerable populations.

7. Conclusion

A spatiotemporal GIS framework to couple fire and traffic simulation models to set triggers during wildfire evacuation is presented. The key contributions of this work are as follows. First, the spatiotemporal scale and resolution of evacuation traffic and fire spread are considered under the spatiotemporal GIS framework. This could facilitate more complex spatiotemporal computation to further examine the dynamics of evacuation traffic and fire spread in future work. Second, the proposed method also takes into account the uncertainty in evacuation time estimation and represents the uncertainty using the probability-based trigger buffers, which can reflect the uncertainty induced by departure time and travel demand distribution. When the ICs use the proposed method to set triggers, the trigger buffers that include evacuation time information could help them make better decisions. Third, the proposed method geovisualizes the evacuation traffic when the fire reaches the community, which gives a spatial perspective on evacuation timing. The ICs could use this method to more directly examine the dynamics of evacuation traffic and fire spread, which could improve their situational awareness and facilitate their evacuation decision-making. The case study demonstrates the potential value of the trigger buffers generated using the proposed method, and the findings could potentially be used by the ICs to facilitate evacuation planning and evacuation decision-making in wildfires. Lastly, the proposed method could be also used to identify the population that is vulnerable to wildfire risk during evacuation and help emergency mangers and city planners adjust evacuation route systems or residential planning codes for hazard mitigation and emergency preparedness.

In summary, the proposed spatiotemporal GIS framework enriches the previous trigger modeling method by incorporating traffic simulation into trigger modeling. With the ETEs from evacuation traffic simulation as the input, the ICs could develop a better understanding of evacuation timing when using trigger modeling to set triggers in wildfire evacuation practices. Moreover, this work used open data in traffic simulation and trigger modeling, which lays a foundation for open wildfire evacuation modeling in future work.

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Appendix 1

See Table 5.

Table 5
The Vehicle Occupancy Data of Julian in 2015 from ACS

Category	Estimate	Percentage	SE
Total	508	100	81.21
Owner occupied	397	78.2	70.30
No vehicle available	0	0	7.27
1 Vehicle available	139	27.4	50
2 Vehicles available	164	32.3	55.76
3 Vehicles available	57	11.2	25.45
4 Vehicles available	37	7.3	26.67
5 or more vehicles available	0	0	7.27
Renter occupied	111	21.8	46.67
No vehicle available	0	0	7.27
1 Vehicle available	0	0	7.27
2 Vehicles available	85	16.7	39.39
3 Vehicles available	26	5.1	26.06
4 Vehicles available	0	0	7.27
5 or More vehicles available	0	0	7.27

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