MODELING WILDFIRE EVACUATION AS A COUPLED

HUMAN–ENVIRONMENTAL SYSTEM

USING TRIGGERS

by

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ABSTRACT

Wildfire is a common hazard in the western U.S. that can cause significant loss of life and property. When a fire approaches a community and becomes a threat to the residents, emergency managers need to take into account both fire behavior and the expected response of the threatened population to warnings before they issue protective action recommendations to the residents at risk. In wildfire evacuation practices, incident commanders use prominent geographic features (e.g., rivers, roads, and ridgelines) as trigger points, such that when a fire crosses a feature, the selected protective action recommendation will be issued to the residents at risk. This dissertation examines the dynamics of evacuation timing by coupling wildfire spread modeling, trigger modeling, reverse geocoding, and traffic simulation to model wildfire evacuation as a coupled human-environmental system.

This dissertation is composed of three manuscripts. In the first manuscript, wildfire simulation and household-level trigger modeling are coupled to stage evacuation warnings. This work presents a bottom-up approach to constructing evacuation warning zones and is characterized by fine-grain, data-driven spatial modeling. The results in this work will help improve our understanding and representation of the spatiotemporal dynamics in wildfire evacuation timing and warnings. The second manuscript integrates trigger modeling and reverse geocoding to extract and select prominent geographic features along the boundary of a trigger buffer. A case study using a global gazetteer

GeoNames demonstrates the potential value of the proposed method in facilitating communications in real-world evacuation practice. This work also sheds light on using reverse geocoding in other environmental modeling applications. The third manuscript explores the spatiotemporal dynamics behind evacuation timing by coupling fire and traffic simulation models. The proposed method sets wildfire evacuation triggers based on the estimated evacuation times using agent-based traffic simulation and could be potentially used in evacuation planning.

In summary, this dissertation enriches existing trigger modeling approaches by coupling fire simulation, reverse geocoding, and traffic simulation. A framework for modeling wildfire evacuation as a coupled human-environmental system using triggers is proposed. Moreover, this dissertation also attempts to advocate and promote open science in wildfire evacuation modeling by using open data and software tools in different phases of modeling and simulation.

TABLE OF CONTENTS

LIST OF TABLES

Tables

LIST OF FIGURES

Figures

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A Ph.D. is not the end but just the start of the journey. “The way ahead is long; I see no ending, yet high and low I will search with my will unbending”.

CHAPTER 1

INTRODUCTION

1.1 Background

Wildfire is a common hazard in the western U.S. due to dry climate and seasonal drought, and studies have shown that the number of wildfires has increased in recent decades (Dennison, Brewer, Arnold, & Moritz, 2014; Westerling, Hidalgo, Cayan, & Swetnam, 2006). With the rapid population increase in the Wildland-Urban Interface (WUI) (Hammer, Radeloff, Fried, & Stewart, 2007; Hammer, Stewart, & Radeloff, 2009; Theobald & Romme, 2007), defined as the region where urban and wildland areas intermix (Stewart, Radeloff, Hammer, & Hawbaker, 2007), wildfires pose significant risks to residents and property (Hammer et al., 2009). Public safety in the WUI has attracted significant attention from a variety of perspectives (Cova, 2005; Haas, Calkin, & Thompson, 2013; Haight, Cleland, Hammer, Radeloff, & Rupp, 2004; Lampin-Maillet et al., 2010; Wolshon & Marchive, 2007).

When a fire approaches a community, an incident commander (IC) needs to issue relevant protective action recommendations (PARs) to the threatened residents so as to ensure public safety (Cova, Dennison, & Drews, 2011; Paveglio, Carroll, & Jakes, 2008). The 2012 wildfire season is one example where a large number of residents were evacuated due to wildfire risks across many events. Figure 1.1 shows a wildfire

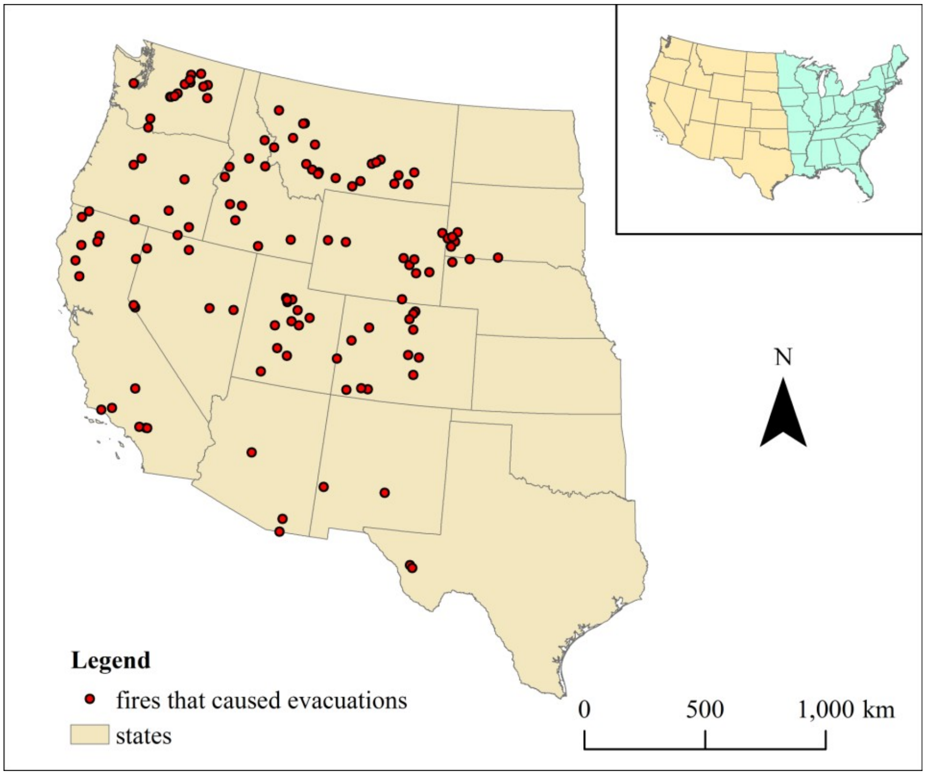

Figure 1.1 2012 wildfire evacuation map in the western U.S.

evacuation map for the western U.S. in the 2012 wildfire season. This map was produced based on the data collected from reports of evacuations in the media. There were more than 100 fires in total that caused evacuations. The largest evacuation was caused by the Waldo Canyon fire in Colorado Springs, in which over 32,000 residents were evacuated (Wineke, 2012).

Due to the continual loss of life and property caused by wildfires in the WUI, a significant amount of research has been conducted on wildfire risks in recent years. One line of research, which is the emphasis of this dissertation, is wildfire evacuation triggers. Wildfire evacuation triggers are prominent geographic features whereby wildfire evacuations will be recommended for the residents or firefighters in the path of the wildfire if the fire crosses these features (Cova, Dennison, Kim, & Moritz, 2005). The previously proposed trigger modeling method uses fire spread modeling and geographic information systems (GIS) to generate buffers around the location of the threatened assets based on the estimated evacuation times needed by the threatened population to travel to safer places (Cova et al., 2005). The past few years have witnessed the development of various applications using this trigger modeling method, e.g., community evacuation planning (Dennison, Cova, & Moritz, 2007; Larsen, Dennison, Cova, & Jones, 2011), firefighter evacuation (Cova et al., 2005; Fryer, Dennison, & Cova, 2013), and pedestrian evacuation (Anguelova, Stow, Kaiser, Dennison, & Cova, 2010) in the wildlands.

1.2 Research objectives

This dissertation aims to improve our understanding of the complexity of wildfire evacuation both spatially and temporally by coupling fire spread and evacuation models. Specifically, this work supplements and improves the previously proposed trigger modeling method in both methodology and application, so as to develop a better understanding of how to use trigger modeling to gain more insight on evacuation timing and warning and facilitate communications during evacuations. The three primary objectives are listed as follows.

First, this work aims to apply trigger modeling at a finer scale (at the household level) and explore whether new knowledge can be gained by integrating fine-grain trigger modeling with fire spread modeling to stage evacuation warnings.

Second, this work explores how to associate trigger buffers generated by trigger modeling with real-world prominent geographic features. As noted, ICs use prominent geographic features as trigger points to facilitate communications and evacuation timing but existing approaches conclude with a rasterized polygon that represents a trigger buffer (i.e., detecting the moment the fire crosses the buffer boundary can be difficult). Bridging the gap between trigger modeling and how trigger points are used in real-world applications will make trigger modeling more effective.

Third, this dissertation aims to set wildfire evacuation triggers by coupling wildfire and traffic simulation models. Traffic simulation is used to estimate the total evacuation time needed by the threatened residents for a safe evacuation. The coupling of the evacuation traffic system with wildfire spread could further improve the applicability of trigger modeling in real-world evacuation practices because the critical input value of estimated evacuation time would be derived in a more systematic manner. As noted by Urbanik (2000), different factors and scenarios could be used to perform a sensitivity analysis and calculate more accurate evacuation time estimates (ETEs). We need to take into account uncertainty to evaluate the earliest, most, and latest probable time of fire arrival against earliest, most, and latest probable ETEs.

In summary, the goal of this work is to improve our understanding and representation of the complex wildfire evacuation process by coupling models developed to represent human and environmental systems. This dissertation aims to advance current wildfire evacuation modeling and simulation using an interdisciplinary approach, which could also shed light on evacuation studies on other hazards.

1.3 A coupled human-environmental system framework

Wildfire is an integral part of the earth system and impacts and is impacted by other systems like human communities and ecosystems (Moritz et al., 2014). Thus, when studying wildfire, we need to take into account the interactions between wildfire and other systems. As noted by Lindell (2013), evacuation modeling should take into account both hazards and the people to be evacuated. With the rapid advancement of computerized modeling and simulation, the coupling of the hazard model and the model of evacuation traffic has begun to emerge in modeling evacuations caused by different hazards in the past few years (Lämmel, Grether, & Nagel, 2010; Mas, Suppasri, Imamura, & Koshimura, 2012). In wildfire evacuation modeling, the question of how to couple models that represent the fire and the evacuation of the threatened population to better understand this complex process is also on the research frontier (Beloglazov, Almashor, Abebe, Richter, & Steer, 2016).

Wildfire evacuation concerns both human and environmental systems, which are composed of many subsystems, as shown in Figure 1.2. The human systems primarily involve the ICs and evacuees' behaviors during the evacuation process, e.g., the ICs' risk perception and protective action selection, the timing of evacuation warnings, evacuees' risk perception process, evacuees' decision-making and departure times, and the evacuation traffic. The environmental systems can be divided into two categories: the natural and built environments. Fire spread is the primary natural environmental system, which is related to vegetation cover, topography, and weather conditions. The evacuation route systems are the built environment. Thus, wildfire evacuation process can be characterized as a complex coupled human-environmental system (CHES).

Trigger modeling takes into account both fire spread and the evacuation of the threatened population, as calculating a trigger point requires both an estimate of the available time to act, as well as the time it will take for the community to complete any

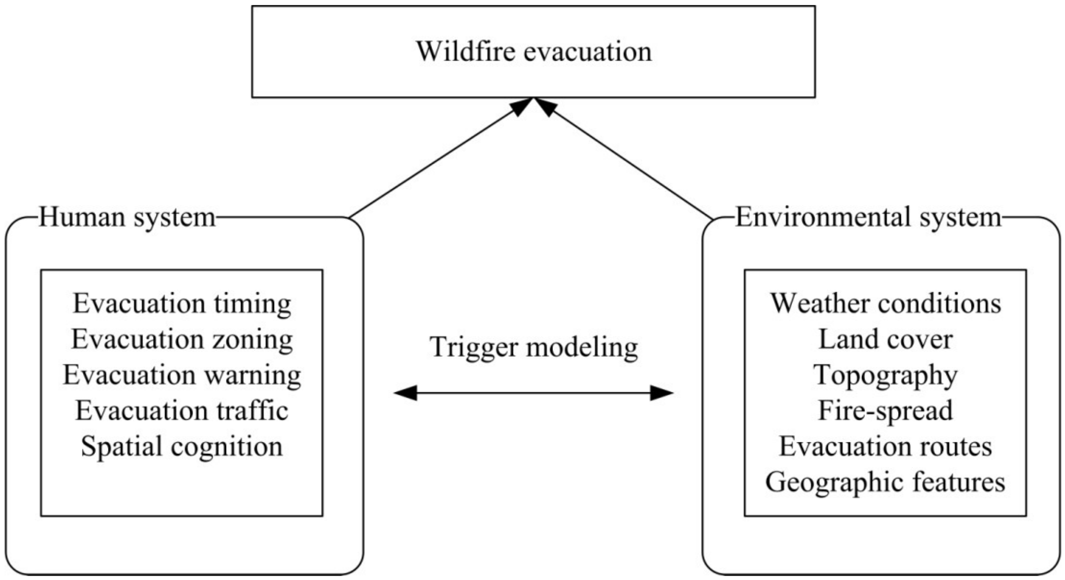

Figure 1.2 A CHES framework for wildfire evacuation

protective actions. The estimated evacuation time of the population at risk is used as the input time for trigger modeling, and fire spread modeling and GIS are used to create a temporal buffer around the population at risk. This coupling can be used to help develop a better understanding of evacuation timing. Moreover, trigger modeling is also an evacuation warning mechanism. When a fire crosses the boundary of a trigger buffer, the predefined protective action will be issued by the ICs to the threatened population in the path of the fire. Lastly, when trigger buffers are associated with prominent geographic features, communicating trigger points and detecting when they are crossed can be more easily improved.

1.4 Study area

Dense flammable fuels (e.g., chaparral), seasonal drought, and the Santa Ana wind make the WUI communities in southern California extremely vulnerable to wildfire risk during the fire seasons (Keeley, Safford, Fotheringham, Franklin, & Moritz, 2009). The study site of this dissertation is Julian—a census-designated place (CDP) located in the east of San Diego County, California. As shown in Figure 1.3, Julian is surrounded by a large amount of fuels (short grasses and shrubs) and has only a limited number of egress points, making it a site representative of many exurban fire-prone communities in the American West.

1.5 Organization of the dissertation

The remaining dissertation is organized into four chapters. The next three chapters represent three standalone research articles on trigger modeling based on the proposed

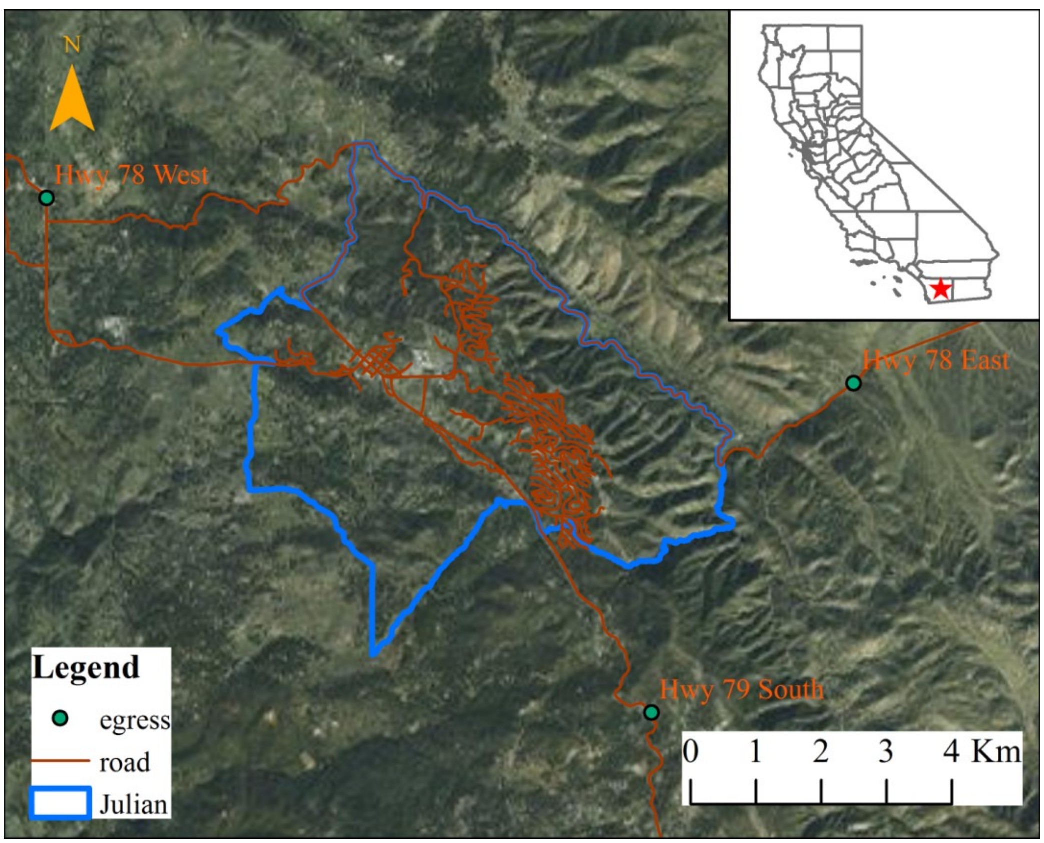

Figure 1.3 The map of Julian, California

CHES framework. The three articles demonstrate the couplings of different systems and use different modeling and analysis methods. The structure of this dissertation is shown in Figure 1.4.

Chapter 2 proposes a method that integrates fire spread modeling and household-level trigger modeling to construct evacuation warning zones and stage evacuation warnings. This chapter focuses on the coupling of fire spread and household evacuation. From a CHES perspective, fire spread is an environmental system, while household evacuation is a human system. Trigger modeling is used to couple these two systems, which produces the staged evacuation warnings that could help the ICs develop a better understanding of wildfire risk and improve evacuation decision-making.

Chapter 3 extends trigger modeling by integrating it with reverse geocoding so that prominent geographic features are associated with generated trigger buffers. Reverse

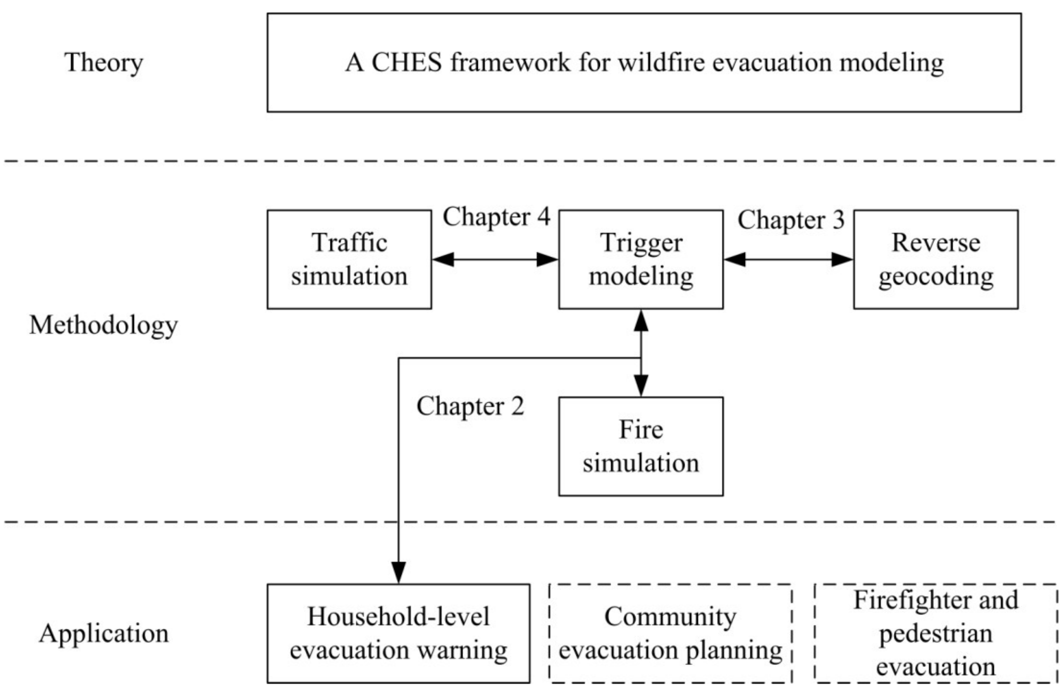

Figure 1.4 The structure of the dissertation

geocoding associates a geographic feature with a given pair of geographic coordinates. Since prominent geographic features concern spatial cognition and communications during evacuations, the data structure and algorithm given in this chapter make trigger modeling more applicable in real-world wildfire evacuation practices.

The focus of Chapter 4 is coupling wildfire and traffic simulation models to set evacuation triggers. Specifically, microscopic traffic simulation performed at the household level is employed to estimate the total evacuation time of the communities in Julian area. The estimated evacuation times are used as the input for trigger modeling, and a statistical method is proposed to model and represent the uncertainty of evacuation time in the coupling process. Then fire and traffic simulation models are coupled to evaluate the value of the generated probability-based trigger buffers.

Finally, Chapter 5 summarizes the three articles and future research directions in this field. Specifically, the conclusion section accents the couplings of human and environmental systems from a CHES perspective. This dissertation lays a foundation for a more comprehensive research of modeling wildfire evacuation as a CHES in the future.

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CHAPTER 2[1]

A HOUSEHOLD-LEVEL APPROACH TO STAGING WILDFIRE EVACUATION WARNINGS USING TRIGGER MODELING

2.1 Abstract

Wildfire evacuation trigger points are prominent geographic features (e.g., ridges, roads, and rivers) utilized in wildfire evacuation and suppression practices, such that when a fire crosses a feature, an evacuation is recommended for the communities or firefighters in the path of the fire. Recent studies of wildfire evacuation triggers have used Geographic Information Systems (GIS) and fire spread modeling to calculate evacuation trigger buffers around a location or community that provide a specified amount of warning time. Wildfire evacuation trigger modeling has been applied in many scenarios including dynamic forecast weather conditions, community-level evacuation planning, pedestrian evacuation, and protecting firefighters. However, little research has been conducted on household-level trigger modeling. This work explores the potential uses of wildfire evacuation trigger modeling in issuing household-level staged evacuation warnings. The method consists of three steps: 1) calculating trigger buffer for each

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household; 2) modeling fire spread to trigger the evacuation of all households; and 3) ranking households by their available (or lead) time, which enables emergency managers to develop a staged evacuation warning plan for these homes. A case study of Julian, California is used to test the method's potential and assess its advantages and disadvantages.

2.2 Introduction

Wildfires are a growing hazard in the western U.S. (Dennison, Brewer, Arnold, & Moritz, 2014) and pose significant risks to households in the Wildland-Urban Interface (WUI), defined as the area where residential development and wildlands meet (Davis, 1990). Wildfires cause significant losses of life and property in the western U.S. every year, and public safety for the communities vulnerable to wildfires has attracted significant research attention (Brenkert–Smith, Champ, & Flores, 2006; Cova, 2005; McCaffrey & Rhodes, 2009; Paveglio, Carroll, & Jakes, 2008). Increasing trends in fire activity in the American West have coincided with rapid population growth in WUI areas (Theobald & Romme, 2007). These dual trends have become a challenge for public safety.

When wildfire approaches a community, common protective actions for the residents include evacuation or shelter-in-place, which can be further classified into shelter-in-home and shelter-in-refuge (Cova, Drews, Siebeneck, & Musters, 2009). If enough time is available, evacuation provides a high level of life protection to threatened residents because they will be clear of the risk area. Shelter-in-place may be adopted when the residents are trapped by a rapidly spreading fire or when homeowners want to stay to protect property (Handmer & Tibbits, 2005). Although the government policy in Australia offers homeowners a choice to stay and defend their homes (McLennan, Cowlishaw, Paton, Beatson, & Elliott, 2014; McNeill, Dunlop, Heath, Skinner, & Morrison, 2013), evacuation is the primary protective action in the U.S. Selecting appropriate protective action remains a challenge for emergency managers because they need to take into account both the hazard dynamics and population distributions. Hazard assessment is generally performed to determine the immediacy and impact of the hazard, while population monitoring is conducted to inform decision makers of the population vulnerable to the hazard (Lindell, Prater, & Perry, 2006). Protective action decision making is typically done at the spatial scales of communities or regions, but further research may be needed for variation in hazard at finer scales such as that of the household.

Protective action selection is influenced to a large degree by timing—how much time is available for the residents to take action, and how much time is needed for the best option to be safe and effective? In practice, incident commanders (ICs) usually use prominent geographic features as trigger points to time protective-action recommendations. For example, when a fire crosses a ridgeline, evacuation recommendations may be issued to residents in the fire’s path (Cook, 2003). In order to better understand the mechanism of wildfire evacuation triggers and facilitate wildfire evacuation decision-making, Cova, Dennison, Kim, and Moritz (2005) proposed a method that uses geographic information systems (GIS) and fire spread modeling to delimit a trigger buffer around a vulnerable geographic asset. Trigger modeling has been applied to create evacuation trigger buffers for firefighters (Cova et al., 2005; Fryer, Dennison, & Cova, 2013), and predefined communities (Dennison, Cova, & Mortiz, 2007; Larsen, Dennison, Cova, & Jones, 2011). However, little research has been conducted in setting triggers at the household level to help define evacuation warning zones. Moreover, fire spread rates influence evacuation decision making and the timing of protective-action recommendations (Kim, Cova, & Brunelle, 2006). Existing applications of trigger modeling neglect the modeling of wildfire spread toward a trigger buffer, and integrating fire spread modeling with trigger modeling may improve situational awareness during wildfire evacuations.

The aim of this study is to perform trigger modeling at the household level and to use fire spread modeling to recommend departure times and associated staged evacuation warning zones. The first question concerns the spatial scale of trigger modeling: can trigger modeling be performed at the household level and what are the advantages and disadvantages of this scale? The second question is: can fire spread modeling and household-level trigger modeling be integrated to develop staged evacuation warning zones and recommended departure times at the most detailed scale? The rest of this paper is organized as follows. Section 2.3 provides a literature review of evacuation modeling and planning, fire spread modeling, and trigger modeling. Section 2.4 presents the three steps of the proposed method as well as the principles and theories underlying them. A case study of Julian, California is given in section 2.5, and section 2.6 ends the paper with discussions and conclusions.

2.3 Background

2.3.1 Trigger modeling

The raster data model represents the world with a regular grid and is a fundamental spatial data model in GIS (Chang, 2012). Trigger modeling uses a raster data model to represent the landscape and then employs fire spread modeling and GIS to create a buffer using the shortest path algorithm around a given location (P) with a given time (T) (Cova et al., 2005). Dennison et al. (2007) formulated trigger modeling into a three-step model—the Wildland Urban Interface Evacuation (WUIVAC) model. In the first step, the FlamMap software package is used to calculate the spread rates of the fire in eight cardinal and ordinal compass directions. The second step calculates fire travel times between adjacent raster cells and constructs a directional fire travel-time network. The third step reverses the arcs between adjacent cells and performs shortest path calculation using Dijkstra's algorithm (Dijkstra, 1959) from a given location P with a given time interval T. It is important to note that the input P can be geographic objects at different scales, for example, the position of a firefighter or a firefighting crew, a house, a road, or a community. When P is the location of a firefighter or a house surrounded by fuels, it can be represented with one raster cell, while when P is a road or a community, it can be represented by a raster polyline or polygon. The input time interval T is the required evacuation time for the residents or firefighters at P, and it can be estimated using evacuation traffic simulation.

Cova et al. (2005) used trigger modeling to create trigger buffers for a fire crew's location, and another study conducted by Anguelova, Stow, Kaiser, Dennison, and Cova (2010) applied trigger modeling in pedestrian evacuation scenarios in wildland areas.

These studies have demonstrated the potential of trigger modeling for small geographic scale scenarios. Dennison et al. (2007) performed trigger modeling at the community level using historic maximum wind-speeds to show how trigger modeling can be used for strategic community-level evacuation planning.

The shape of trigger buffer depends on fuels, wind, and topography (Dennison et al., 2007), and a study by Larsen et al. (2011) used varied wind speed and direction to create nested, dynamic trigger buffers for a community using the 2003 Cedar Fire as a scenario. Fryer et al. (2013) used varied wind speed, wind direction, and fuel moisture to create a series of trigger buffers for firefighting crew escape routes using travel times calculated for different modes. It should be noted that the size and shape of trigger buffers can be affected by fuel moisture, wind speed, and wind direction (Fryer et al., 2013), and this should be taken into account.

2.3.2 Fire spread modeling

Fire behavior is determined by the fire environment, which includes topography, fuel, weather, and the fire itself (Pyne, Andrews, & Laven, 1996, p. 48). Computerized modeling of wildfire spread has a long history (Rothermel, 1983), and fire spread models developed in the past few decades can be categorized into physical, semiphysical and empirical models (Sullivan, 2009a, 2009b). The Rothermel fire spread model (Rothermel, 1972), a semiphysical model based on energy conservation principles and calibrated with empirical data, has been widely used in various fire modeling systems such as BEHAVE (Andrews, 1986), FlamMap (Finney, 2006), and FarSite (Finney, 1998). The elliptical fire shape model proposed by Van Wagner (1969) models fire spread rates for head fire, flank fire, and back fire using an elliptical shape and has enjoyed great popularity in fire simulation. After fire behavior parameters are derived from fire spread models, fire growth models are utilized to propagate the fire across the landscape. The minimum fire travel time algorithm is used to propagate fire in FlamMap (Finney, 2002), while an algorithm based on Huygens' principle is used in FarSite (Finney, 1998). Other fire propagation models include Delaunay triangulation and shortest path algorithms (Stepanov & Smith, 2012), and Cellular Automata (CA)-based models (Clarke, Brass, & Riggan, 1994). Recently developed fire models have begun to include complex interactions between fire and weather by coupling an atmospheric prediction model with a fire spread model (Clark, Coen, & Latham, 2004; Coen, 2005; Coen et al., 2013).

The past few decades have witnessed the application of fire spread modeling in various fields, such as wildlife habitat preservation (Ager, Finney, Kerns, & Maffei, 2007) and wildfire risk evaluation (Carmel, Paz, Jahashan, & Shoshany, 2009). However, research on using fire spread modeling in wildfire evacuation is scarce. Postevent studies of wildfire evacuations have revealed the significant value of fire progression in understanding evacuation timing (Kim et al., 2006), and in this regard, fire spread modeling has a great potential in improving situational awareness and facilitating decision making in wildfire evacuations when it is integrated with evacuation modeling.

2.3.3 Evacuation modeling and planning

Evacuation is defined as the process of moving people from risk areas to safer areas and can decrease the loss of life and property when a natural or technological hazard becomes a threat to residents (Lindell, 2013). However, it was not until the midtwentieth century that evacuation became a research topic (Quarantelli, 1954). In the U.S., the Three-Mile Island nuclear incident in the 1970s attracted significant attention from research domain and became a milestone for modern evacuation studies (Cutter & Barnes, 1982). Numerous studies have been conducted on emergency evacuations in the past few decades and can be categorized into two types: behavioral and engineering studies (Murray-Tuite & Wolshon, 2013). Behavioral studies focus on public response and decision making (e.g., risk perception, evacuation decision making, and departure times) during emergency evacuations and on relevant socio-economic or psychological factors that influence behavior (Dash & Gladwin, 2007; Lindell & Perry, 1992; Lindell & Perry, 2003). The engineering perspective focuses on transportation modeling and simulation techniques, and evacuation traffic simulation has enjoyed great popularity in the past few decades (Sheffi, Mahmassani, & Powell, 1982; Southworth, 1991). A growing trend in this field is to combine the social science and engineering perspectives in an interdisciplinary direction (Murray-Tuite & Wolshon, 2013; Trainor, Murray-Tuite, Edara, Fallah-Fini, & Triantis, 2012).

Behavioral studies conducted on wildfire evacuation reveal that ICs and evacuees have different concerns during anticipation, warning, displacement, return and recovery phases (Cohn, Carroll, & Kumagai, 2006). Specifically, the ICs are concerned about evacuation timing—when to impose evacuation orders (Cohn et al., 2006), which is an important leverage point in the evacuation process. Warning compliance refers to the percentage of residents who choose to evacuate after they are given an evacuation warning and relies on people's perception of the risk (Lindell et al., 2006). Previous research revealed that evacuation warnings have a significant effect on evacuation timing

(Sorensen, 1991), and thus determining the timing of warnings is an important problem in evacuation planning.

Cova and Church (1997) used nodes and arcs to represent the transportation network and evaluate spatial evacuation vulnerability to wildfire using the critical cluster model (CCM) in Santa Barbara, California. It should be noted that this line of research quantifies the imbalance and contradiction between the rapid residential development in the WUI and the insufficient capacity of the transport infrastructure for evacuations and can be used to enlighten future community planning (Cova, 2005). The past several years have witnessed the application of microscopic traffic simulations to estimate evacuation travel times and test the effectiveness of neighborhood wildfire evacuation plans (Cova & Johnson, 2002; Wolshon & Marchive III, 2007). These studies use population data to generate evacuation travel demand and perform traffic simulations but do not take into account the progression of wildfire and its impact on evacuation timing. Postevent studies on wildfire evacuations have revealed that fire progression determines the timing of evacuation orders issued for the threatened residents (Kim et al., 2006). In this regard, incorporating fire progression into modeling and simulation becomes a necessity if we are to address the critical questions of who should be evacuated and when.

Risk areas refer to the geographic areas threatened by a natural or technological hazard (Lindell, 2013), and risk area delineation has attracted a significant amount of research attention in the past few years (Arlikatti, Lindell, Prater, & Zhang, 2006; Zhang, Prater, & Lindell, 2004). Staged evacuation is defined as the evacuation practice in which the risk area is divided into evacuation warning zones, and these zones are evacuated in a progressive manner (Chen & Zhan, 2008). The strength of staged evacuation strategy over simultaneous evacuation lies in that it can relieve traffic congestion and reduce total evacuation time when the evacuation travel demand significantly exceeds the capacity of the transportation network (Chen & Zhan, 2008). Another advantage of staged evacuation is that it can minimize the disruption of nonthreatened residents. Note that the advantages of staged evacuation are realized only if evacuees comply with the stages. It should also be noted that dividing the risk area into evacuation warning zones is the premise for staged evacuation. Existing studies usually establish evacuation warning zones prior to the study using aggregate data such that they are a given (Chen & Zhan, 2008; Sorensen, Carnes, & Rogers, 1992; Southworth, 1991; Wilmot & Meduri, 2005). This top-down approach is characterized by "risk area-evacuation zone-traffic simulations" and has been the dominant paradigm in evacuation modeling and simulation in the past few years. Although evacuation zoning has been examined (Murray-Tuite & Wolshon, 2013), it is still an under-researched subfield in emergency management. With the rapid development of computing power, modeling and simulation at the individual level have become a popular trend (Bonabeau, 2002), which provides a good opportunity to research staged evacuation zoning using a bottom-up approach.

2.4 Methods

In general, wildfire evacuations are conducted at a relatively small geographic scale from a few households up to a few thousand. Trigger modeling has been applied at the community scale, but this work aims to perform trigger modeling at a more detailed scale to examine household-level evacuation warning timing and zoning. Figure 2.1 is a conceptual representation of the proposed method. The red polygons represent fire

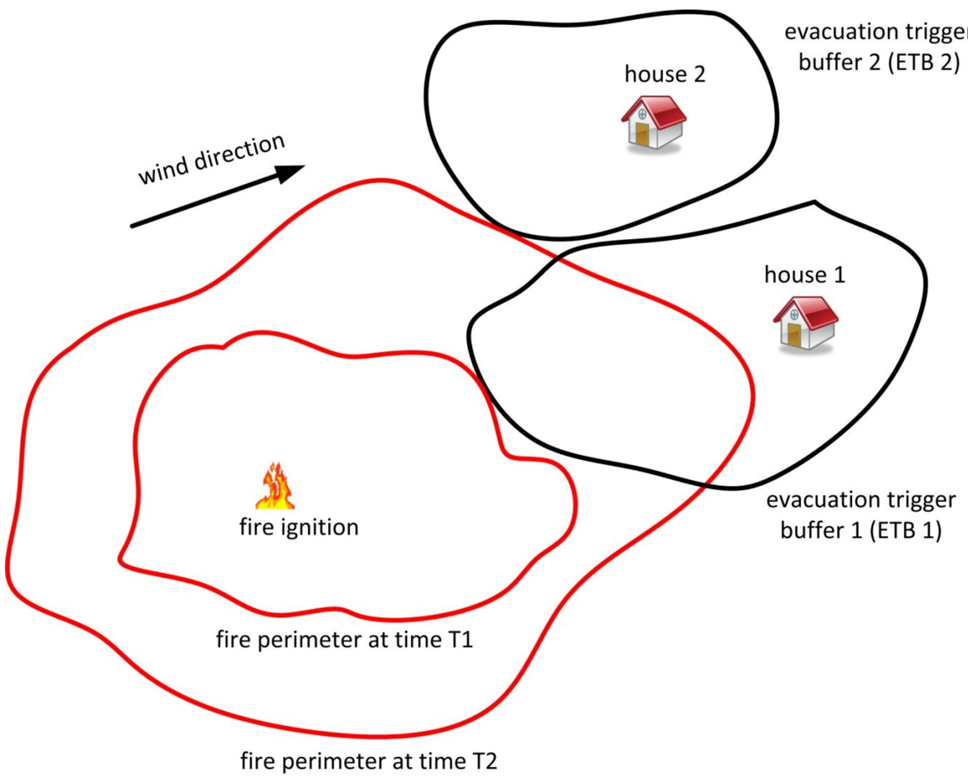

Figure 2.1 A conceptual representation of the method

perimeters, while the black polygons represent evacuation trigger buffers (ETBs) for houses 1 and 2, respectively. Note that the shape of the fire perimeter is skewed in the same direction as the wind, while the two ETBs are skewed in the opposite direction of the wind to offer the same amount of warning time if fire should approach from that direction (i.e., a trigger buffer is a fire travel-time isochrone). The fire shown crosses the boundary of ETB 1 at time T1, so household 1 should be notified to evacuate at T1. Similarly, household 2 should be notified to evacuate at T2.

Given a series of sparsely distributed exurban households H = $\{h_1, h_2,\ldots,h_n\}$ and an estimated evacuation time for each household ET = $\{et_1,et_2,\ldots, et_n\}$, trigger modeling can be used to create ETBs B = $\{b_1, b_2,\ldots,b_n\}$ for each household with relevant wind direction, wind speed, and fuel moisture. If the fire spread process has *m* time steps T =

$\{t_1, t_2, \ldots, t_m\}$, and the spreading fire crosses the boundary of ETB b_i at time t_j, then household h_i should be warned to evacuate. These residents should have at least et_i before the fire reaches their residence. With the progression of the fire, the recommended evacuation departure time (REDT) for each household h_i can be derived and can be represented by REDT = $\{redt_1, redt_2, \ldots, redt_n\}$. Then, the derived evacuation departure times REDT can be used to group the households into staged evacuation warning zones Z = $\{z_1, z_2, \ldots, z_k\}$. An emergency manager could use these zones to issue staged evacuation warnings when the households are threatened by wildfire.

The proposed method is formulated into a three-step process, and the workflow of the method is shown Figure 2.2. In the first step, trigger modeling is performed using the household locations, evacuation times for households, elevation, aspect, slope, vegetation cover, wind direction, wind speed, and fuel data as the inputs. The output of the first step is a set of ETBs, which can be used as inputs in the second step—fire spread modeling. Fire spread modeling uses the same set of environmental inputs, and the evacuation notifications are triggered when the fire crosses the boundary of the ETB of each household. The output of the second step is a set of REDTs for the households. In the third step, the REDTs of the households are used to divide the households into different evacuation warning zones.

2.4.1 Step 1: household-level trigger modeling

In the first step, trigger modeling is performed at the household level to generate the ETBs based on the estimated evacuation time. Evacuation time in this specific context refers to the time taken by a household from warning initiation to the time the household

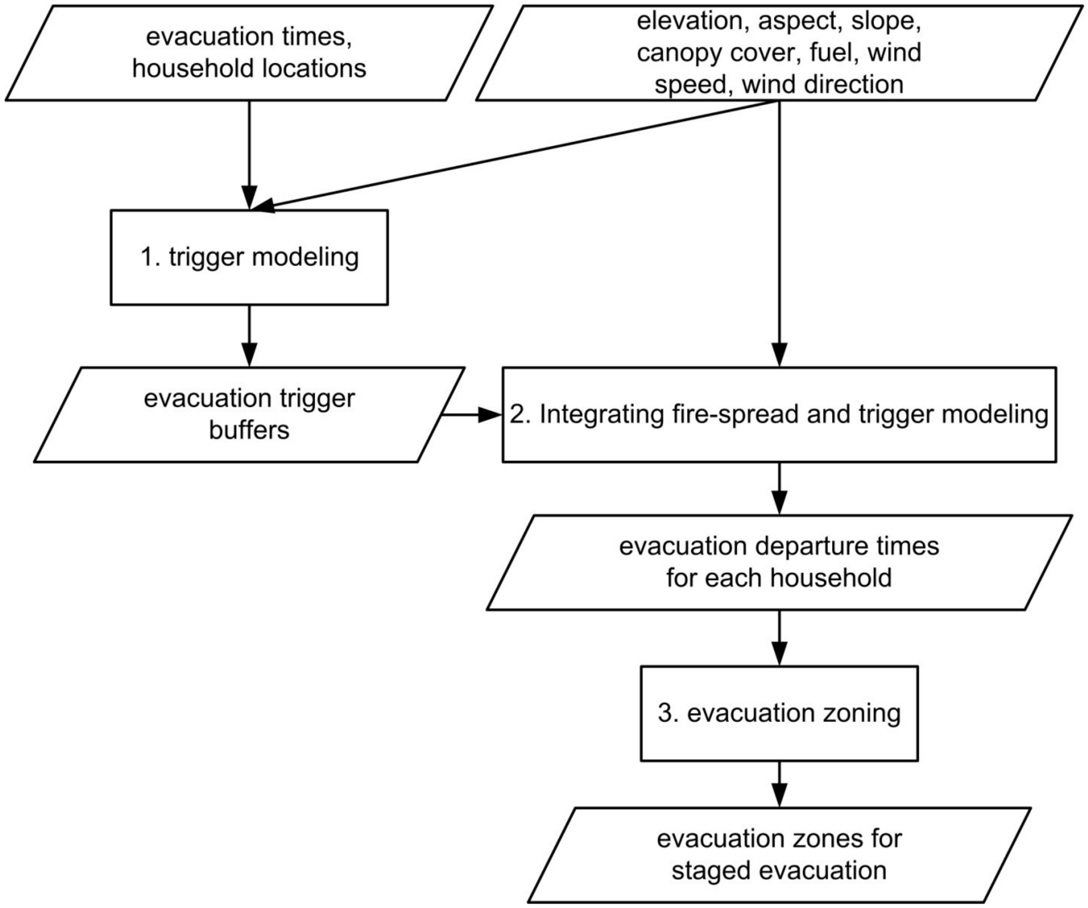

Figure 2.2 Workflow of the research method

arrives at safety (Lindell, 2008). The input time for trigger modeling is the estimated evacuation time for the target population. The inputs can be divided into two groups: one group that includes topography (elevation, slope, and aspect), vegetation (fuel and canopy cover), and weather (wind direction and speed) data that is used for fire spread modeling, and a second group that includes household locations and estimated evacuation times.

In order to facilitate trigger modeling, the three-step process proposed by Dennison et al. (2007) is used to create ETBs for the households, as shown in Figure 2.3. The first step employs a fire spread modeling software package (FlamMap) that uses the topography, vegetation, and weather inputs to calculate fire spread rates (Finney, 2006).

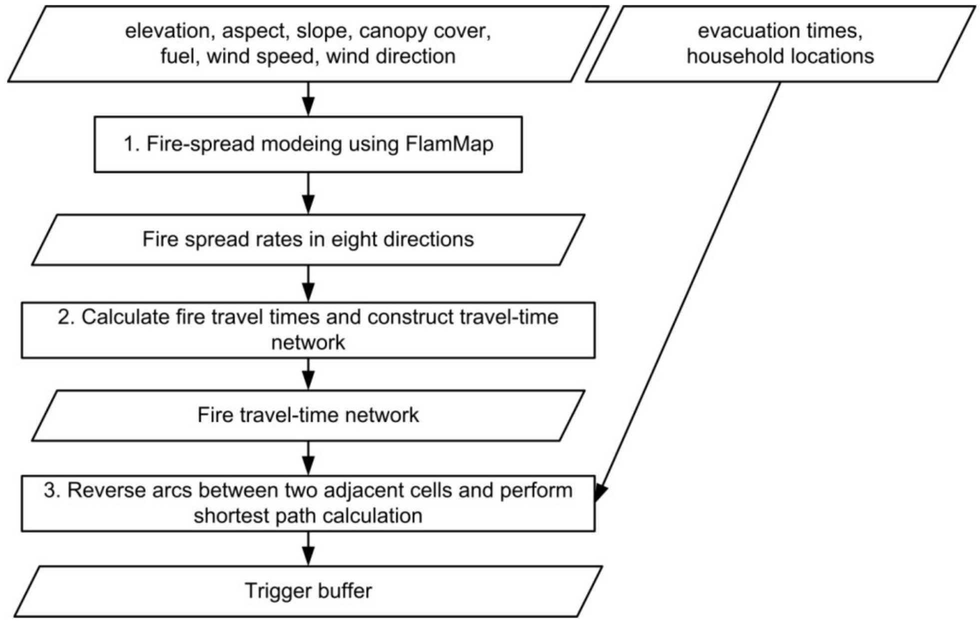

Figure 2.3 Workflow of trigger modeling

The second step uses the derived fire spread rates in eight cardinal and ordinal compass directions to calculate the travel times between orthogonally and diagonally adjacent raster cells, which are then used to construct a fire travel-time network. In this network, the arcs are directional and the weight of an arc denotes the fire travel time from one cell to its neighbor in that specific direction. In the third step, all the arcs in the network are reversed and Dijkstra's algorithm (Dijkstra, 1959) is employed to traverse from a given cell containing a household until the accumulated travel time reaches a specified constraint time, in this case the estimated evacuation time. In this manner, a set of household-level ETBs can be derived using trigger modeling.

2.4.2 Step 2: integrating fire spread with trigger modeling

After the generation of trigger buffers for the households, fire spread modeling can be performed to trigger the evacuation warnings for households based their corresponding ETBs. When the spreading fire on the landscape reaches the boundaries of the ETBs, those households should be notified to evacuate. When ICs use triggers in practice, they need to first estimate the evacuation times needed for the threatened population before they set triggers (Cova et al., 2005).

The first step can generate an ETB $b \in B$ for each household $h \in H = \{h_1, h_2, \ldots, h_n\}$. Moreover, the spatial data used in fire spread modeling can also be used in FlamMap to generate a minimum fire travel time (MFTT) map, which is a raster map where the value for each cell within the map represents the MFTT it takes from the ignition cell to every raster cell in the landscape. The MFTT algorithm produces a travel-time network that depicts the shortest path that fire might take between the ignition and each raster cell in the landscape. We should note that the MFTT and Dijkstra's algorithm used in fire growth modeling and trigger modeling both calculate the shortest path in a travel-time network and thus have taken into account the worst-case scenario (i.e., fire taking the most rapid path), which is of critical significance in evacuation timing. The resulting MFTT map can be used to trigger the evacuation of the households using their ETBs and obtain the REDT for each household.

The algorithm used for calculating the REDTs for the households is shown in Table 2.1. The MFTT map is used to simulate the fire spread across the raster landscape. The fire at the ignition point starts at time 0 (in minutes), which is also used as the starting time for the simulation. In the algorithm initialization, all households are added to a set that have not been warned (or triggered) to evacuate. As the fire progresses, the algorithm will search for the ETBs that are being crossed by the fire and record the household, as well as the time when fire crosses the boundary of its ETB. When a

Table 2.1 Algorithm for calculating recommended evacuation departure times

```
tMax = getMaxTime(MFTTMap)          // get the maximum fire travel time
setHousehold = getHouseholds()       // a set of households to be evacuated
triggerBuffers = getTriggerBuffers()  // get the trigger buffer for each household
mapHouseholdEvactime  = NULL         // record each household
For t From 0 To tMax                 // iterate t from 0 to the maximum value
  For cell In MFTTMap                // iterate each cell in the MFTT map
    If cell == t                     // if the value of the cell is equal to t
      For household In setHousehold              // for each household in the set
        If cell Is In triggerBuffer[household]    // if the cell is within the buffer
          setHousehold.remove(household)          // remove household from the set
          mapHouseholdEvactime.insert(household, t)  // add the household
```

household has been triggered to evacuate, it is eliminated from the household set. The REDTs derived are relative to the fire ignition time and are also in minutes. Eventually, the REDTs for all the households are derived, which can be used to group the households into different evacuation warning zones in the next step.

2.4.3 Step 3: evacuation zoning

This step aims to develop bottom-up evacuation warning zones using the REDTs of the households according to above-mentioned procedures. Evacuation zoning should take into consideration both the REDTs and the spatial configuration of the households. In other words, the households with similar REDTs should be grouped into one zone, and the households in geographic proximity to each other should be included in one zone. At this point the zoning problem is transformed to a clustering problem with spatial constraints—the REDTs can be used as attributes and the household locations can be used to measure spatial closeness. Assunção, Neves, Câmara, and da Costa Freitas (2006) put forward the Spatial "K"luster Analysis by Tree Edge Removal (SKATER) algorithm to cluster spatial features by partitioning a minimum spanning tree (MST) constructed using the features, which has been proved to be effective in clustering spatial features efficiently. Thus, the SKATER algorithm can be used to partition the households into different evacuation warning zones based on their departure times as well as their spatial configuration.

When given a set of features, the SKATER algorithm requires that a connectivity graph be constructed using contiguous or proximal relationships. In this context, each node in the graph represents a household, and the value of edge between two features denotes the dissimilarity of REDTs. In the context of household evacuation zoning, the households are point features and proximity measurements between two households can be used to construct the connectivity graph. For example, K Nearest Neighbors (KNN) method can be used to define proximity based on the Euclidean distance between households. After the construction of connectivity graph, the SKATER algorithm prunes edges with high dissimilarity and uses Prim's algorithm to derive a MST, which is a spanning tree with the minimum sum of dissimilarities over all the edges. Since sub-trees can be derived by cutting the tree at suitable places, the clustering problem is transformed to an optimal graph partitioning problem. The sum of intracluster squared deviations is used as an objective function in the optimization process, which reflects the intra-cluster homogeneity and should be minimized. It should be noted that the MST partitioning problem is NP-hard, and therefore a heuristic method is employed in SKATER to perform the tree partitioning at a relatively low computational cost (Assunção et al., 2006). After the partitioning of the MST, the households are divided into different groups, which can be used as staged evacuation warning zones.

Since topography, fuel, and weather determine fire behavior and thus can determine the size and shape of the trigger buffer generated by trigger modeling (Dennison et al., 2007), the REDTs derived in the second step may not strictly reflect the distance decay principle. For example, if the REDT of household h_1 is smaller than that of household h_2, it means h_1 should be evacuated earlier than h_2. However, h_2 may be closer to the fire front compared to h_1 because they may differ in terms of topography, fuel, and weather. This influences the shape and size of the trigger buffer and can result in inconsistency between their distances to the fire front and their REDTs. In this regard, the evacuation warning zones derived directly using clustering method based on the REDTs need to be adjusted using prominent geographic features. The purpose of adjustment is to establish evacuation warning zones that are easily identifiable by the threatened residents and can be conveniently and effectively communicated to the public by ICs in issuing actual warnings. Common geographic features used to establish evacuation zone boundaries include roads, neighborhoods and other prominent physiographic (rivers) and cultural features (landmarks). Zip codes, or other administrative zones, can also be used to construct evacuation warning zones when a hazard threatens a large geographic area, but they are relatively rare in wildfire evacuations because most are performed for smaller areas. Finally, it should be noted that the results of this step are a series of delineated evacuation warning zones with REDT for each zone, which can be used to issue warnings to threatened residents and facilitate staged evacuation.

2.5 Case study

Flammable vegetation types, seasonal drought, and Santa Ana winds have made the fire-prone communities in southern California extremely vulnerable to devastating wildfires (Westerling, Cayan, Brown, Hall, & Riddle, 2004). Wildfires have caused significant losses in life and property in the past few decades in this area (Rogers, 2005). The devastating 1991 Tunnel Fire in Oakland/Berkeley cost 2475 homes and 25 lives, and the 2003 Cedar Fire in San Diego caused the loss of 2232 homes and 14 lives (Rogers, 2005). Public safety in these fire-prone communities in southern California has attracted a significant amount of attention in the past few years (Cova, 2005; Stephens et al., 2009). In the case study, Julian, a census-designated place (CDP) in San Diego County, California, is our study site. As noted by Dennison et al. (2007), Julian is relatively isolated from the metropolitan areas and is surrounded by large areas of fuels, making it a good case study for wildfire evacuation studies. A total number of 62 sparsely distributed households located in the southwest portion of Julian were selected, and the map for the distribution of these households is shown in Figure 2.4. The household locations were derived by calculating the centroids of the residential parcels in Julian using the 2010 parcel data downloaded from the GIS agency of San Diego County—SanGIS. Other vector road network and Julian boundary data were also obtained from SanGIS. Python and the ArcGIS Python library ArcPy were used to transform household location data into raster cells. The raster data were at 30 m resolution and the study area contains 500 × 500 raster cells. A 2003 fuel map at 30 m resolution from the Fire and Resource Assessment Program (FRAP) at California Department of Forestry and Fire Protection was used as the fuel data. The compiled fuel data use the 13 Anderson (1982)

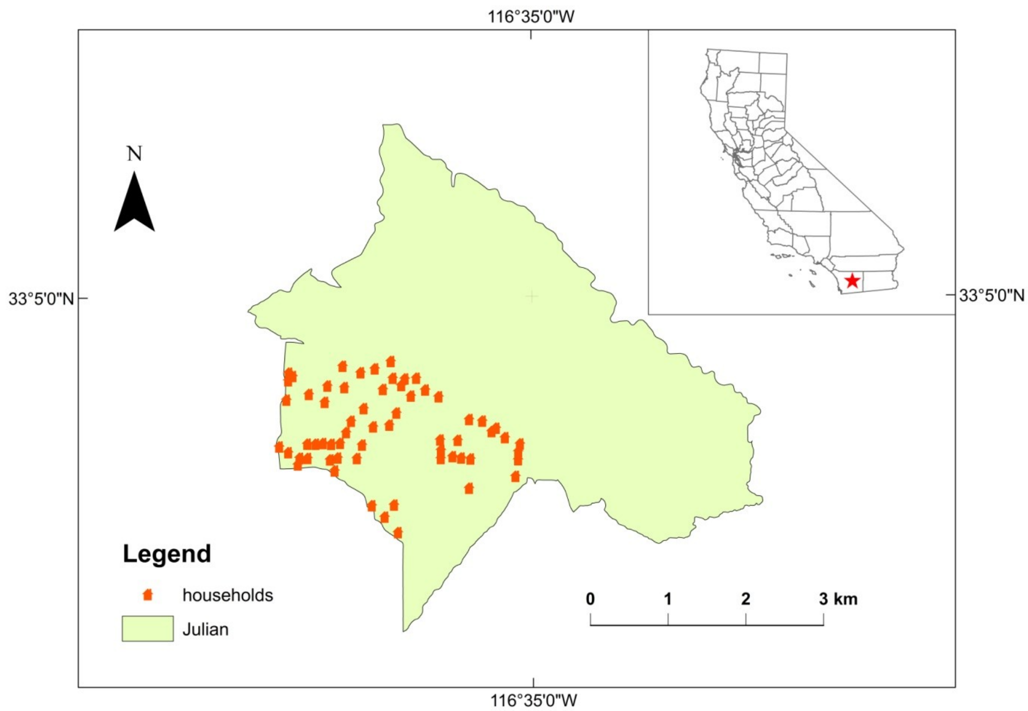

Figure 2.4 Sparsely distributed households in Julian, California

fuel models and include 11 flammable fuel types and 3 unburnable fuel classes. The 30 m resolution digital elevation model (DEM) data obtained from the United States Geological Survey (USGS) was used to calculate aspect and slope data using the GIS software package ArcGIS.

Different software packages and programming languages were used to implement the proposed method as a loosely coupled system (Brown, Riolo, Robinson, North, & Rand, 2005). It was assumed that 1 h is sufficient for each household to evacuate to a safe area, and thus the input time for trigger modeling was set to 1 h. The wildfire spread modeling software package FlamMap was used to perform wildfire spread modeling and get the maximum spread rates, maximum spread direction, elliptical parameters for calculating directional fire spread, and MFTT map. The programming language C++ was used to create ETBs for each household in the first step and simulate the "fire triggers evacuation" process in the second step because it has good computational efficiency and its object-oriented programming (OOP) characteristics can favor the reusability of the code in the future. Since the SKATER clustering algorithm has been implemented in ArcGIS, ArcGIS was used to cluster the households into different groups based on their spatial locations and REDTs. Finally, Python was used to adjust the derived groups based on road segments to get the final evacuation warning zones, and ArcGIS was used to map the zones constructed using the proposed method.

In order to better understand the characteristics of the proposed method, different fire ignition points and varying wind speeds were used for fire spread and trigger modeling. Specifically, 3 ignition points located 3 miles away from the centroid of the households were used, and 2 wind speeds (16 and 32 km/h) were used for each ignition point. In total, 6 scenarios were used to evaluate the proposed method, as shown in Table 2.2. Wind directions were set from the ignition point towards the households, which denotes the worst-case scenario in terms of the risk imposed by the fire to the households. The map in Figure 2.5 illustrates the experiment design. The centroid of the households

Table 2.2 Scenarios for fire spread and trigger modeling

Scenario	Ignition	Wind direction	Wind speed (km/h)
1	west	west	16
2	west	west	32
3	southwest	southwest	16
4	southwest	southwest	32
5	south	south	16
6	south	south	32

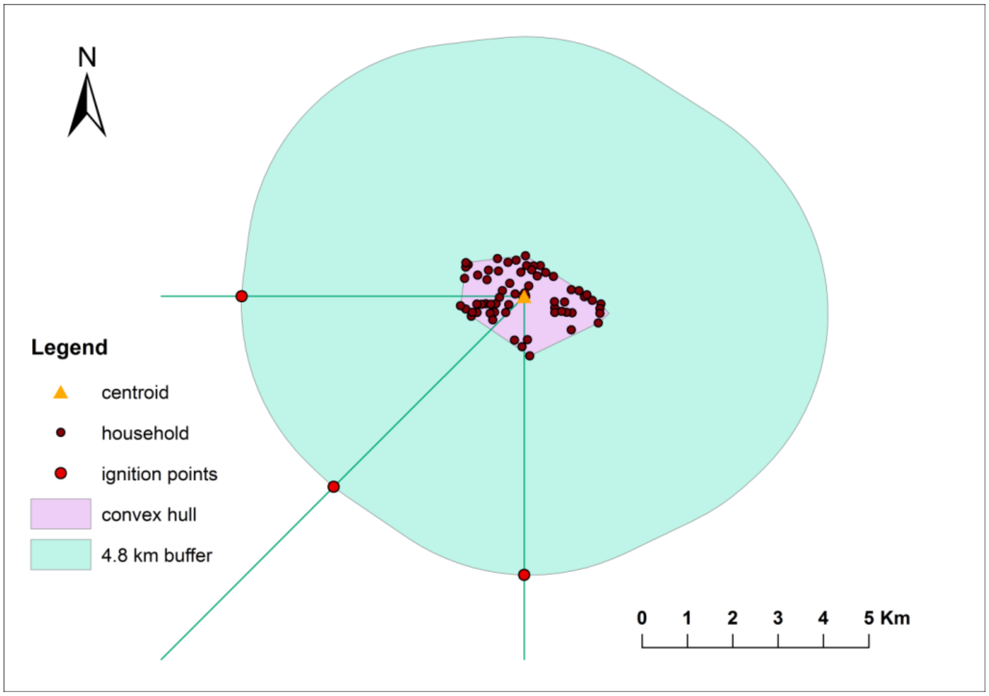

Figure 2.5 Map for the case study design

was calculated, and a 4.8 km (3 miles) buffer was created around the convex hull of the households using ArcGIS. The three ignition points were placed on the boundary of the buffer to the west, southwest, and south of the centroid.

The results of the 6 scenarios were derived using the proposed method, and Figure 2.6 shows the clustering results for scenarios 1 and 2 using the group analysis tool in ArcGIS. Specifically, KNN was used as the spatial constraints and 8 neighbor households were used to determine the group one household will fall in. The number of groups was set as 2, 3, and 4, respectively, for each scenario, and the results for the group analysis are listed in Table 2.3. The geographic scale of the study area is relatively small, thus we can use road segments as the building blocks for evacuation warning zones, which is common in exurban wildfire evacuations. From the overlaid road network, we can note that the households are naturally clustered by road segments, and using road segments to adjust

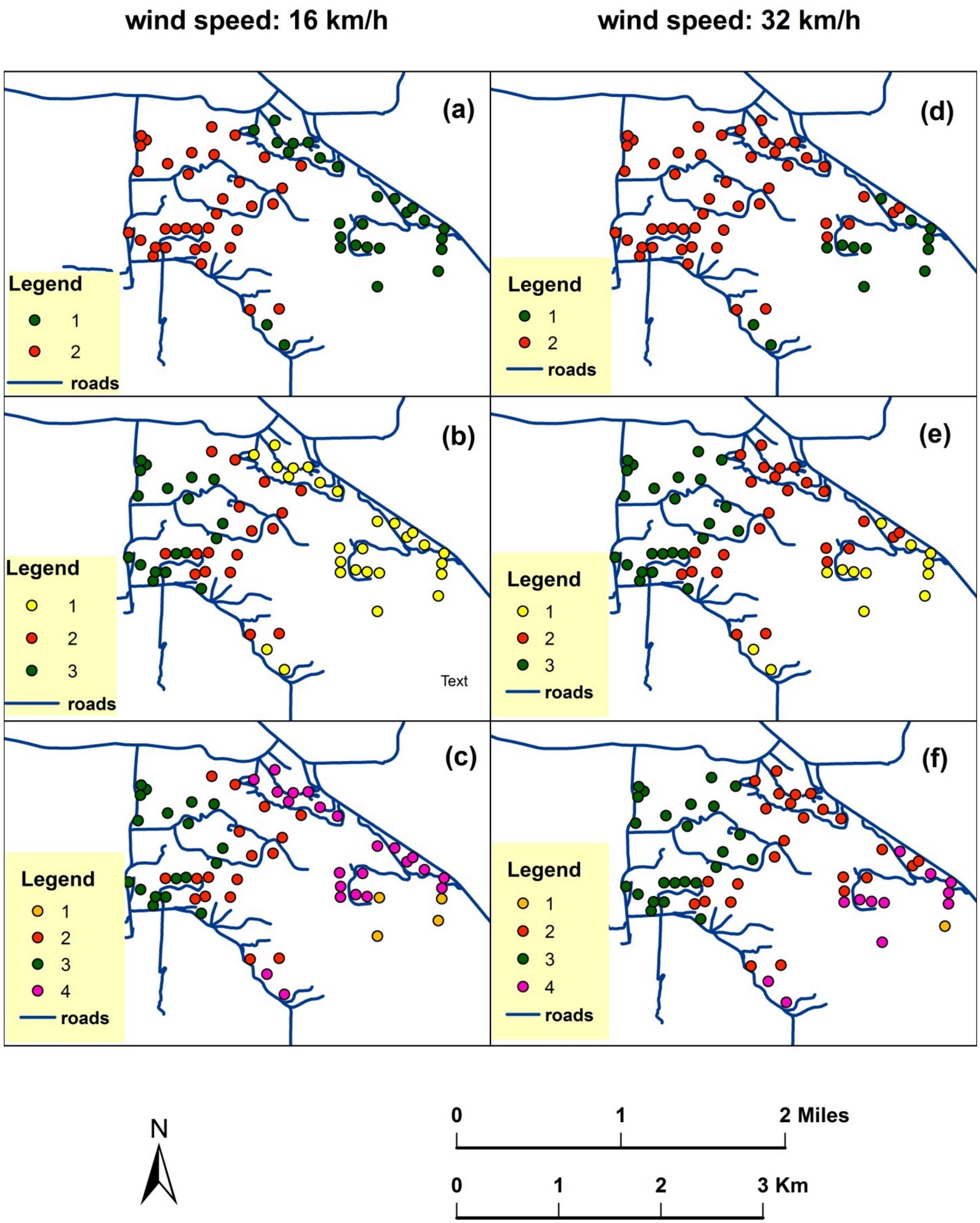

Figure 2.6 Group analysis for scenarios 1 and 2

Table 2.3 Results of group analysis

Scenario (groups)	Group ID	Count	Mean (min)	Std. Dev.	Min (min)	Max (min)
1 (2)	1	27	307	43	255	458
	2	35	206	37	127	277
1 (3)	1	27	307	43	255	458
	2	17	236	18	216	277
	3	18	176	25	127	208
1 (4)	1	4	387	41	361	458
	2	17	236	18	216	277
	3	18	176	25	127	208
	4	23	293	24	255	340
2 (2)	1	13	111	18	94	166
	2	49	72	12	49	91
2 (3)	1	13	111	18	94	166
	2	25	82	6	73	91
	3	24	61	7	49	71
2 (4)	1	1	166	0	166	166
	2	25	82	6	73	91
	3	24	61	7	49	71
	4	12	106	8	94	118
3 (2)	1	25	386	48	336	522
	2	37	285	34	225	356
3 (3)	1	4	480	29	452	522
	2	37	285	34	225	356
	3	21	368	23	336	429
3 (4)	1	4	480	29	452	522
	2	15	319	17	285	356
	3	21	368	23	336	429
	4	22	263	22	225	302
4 (2)	1	6	153	23	130	190
	2	56	98	12	75	121
4 (3)	1	6	153	23	130	190
	2	31	89	7	75	99
	3	25	109	7	98	121
4 (4)	1	2	185	6	179	190
	2	31	89	7	75	99
	3	25	109	7	98	121
	4	4	138	6	130	147
5 (2)	1	5	1243	47	1174	1293
	2	57	1066	38	944	1157
5 (3)	1	5	1243	47	1174	1293
	2	10	1005	24	944	1027
	3	47	1079	25	1045	1157

Table 2.3 Results of group analysis (continued)

Scenario (groups)	Group ID	Count	Mean (min)	Std. Dev.	Min (min)	Max (min)
5 (4)	1	5	1243	47	1174	1293
	2	10	1005	24	944	1027
	3	14	1102	18	1082	1157
	4	33	1069	21	1045	1126
6 (2)	1	9	406	24	384	455
	2	53	352	13	310	378
6 (3)	1	9	406	24	384	455
	2	21	364	5	358	378
	3	32	344	10	310	359
6 (4)	1	6	391	10	384	414
	2	21	364	5	358	378
	3	32	344	10	310	359
	4	3	434	15	418	455

the zones will make issuing emergency warnings more convenient. Based on the structure of the road network and the spatial configuration of the households, six roads with names were chosen and one road with the name “Deer Lake Park Rd” was split into two parts because the households along it fall into two natural clusters. Table 2.4 gives the seven clusters of households grouped by their closest road segment, and the spatial configuration of the grouped households is shown in Figure 2.7. Then these road-segment household groups were used to adjust the results of the group analysis—voting was performed within each road-segment group, and the group is assigned with the most popular evacuation group ID of the households. The final adjusted evacuation warning zones for the six scenarios are shown in Figures 2.8-2.10. After adjusting the zones, heterogeneity is eliminated within each zone and the zones become homogenous. The final adjusted results also demonstrate that the spatial configuration of evacuation warning zones can reflect the spread direction of the fire. For example, the zones in Figure 2.8 are arranged from the west to the east, which corresponds to the wind direction in scenario 1 and 2; the zones in Figure 2.9 are arranged from the southwest to the northeast; and the zones in Figure 2.10 are arranged from the south to the north. Thus, wind direction can influence the spatial configuration of the zones.

Table 2.4 The number of households by road segment

Road name	Number of households
6th Street	12
Van Duesan Road	11
Old Cuyamaca Rd	9
Slumbering Oaks Trl	8
Pine Hills Rd	4
Deer Lake Park Rd segment 1 (north)	14
Deer Lake Park Rd segment 2 (south)	4
Total number of households	62

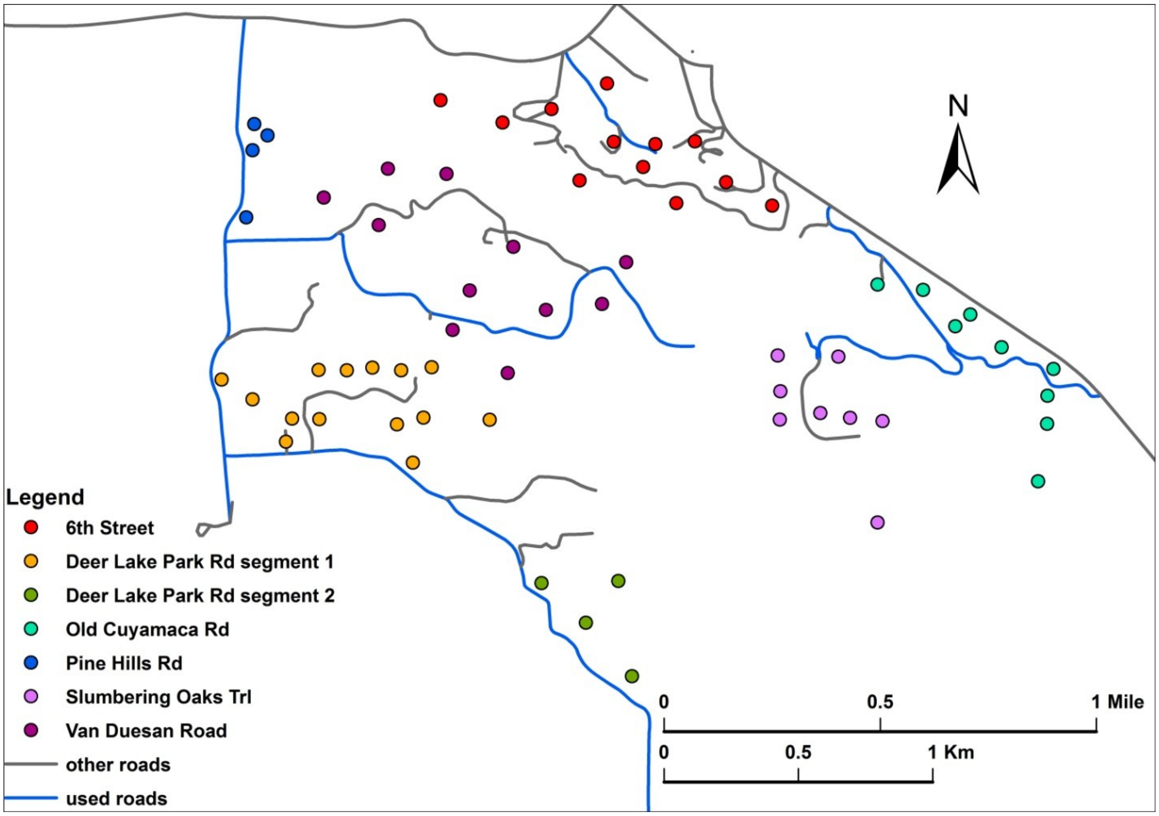

Figure 2.7 Households grouped by road segments

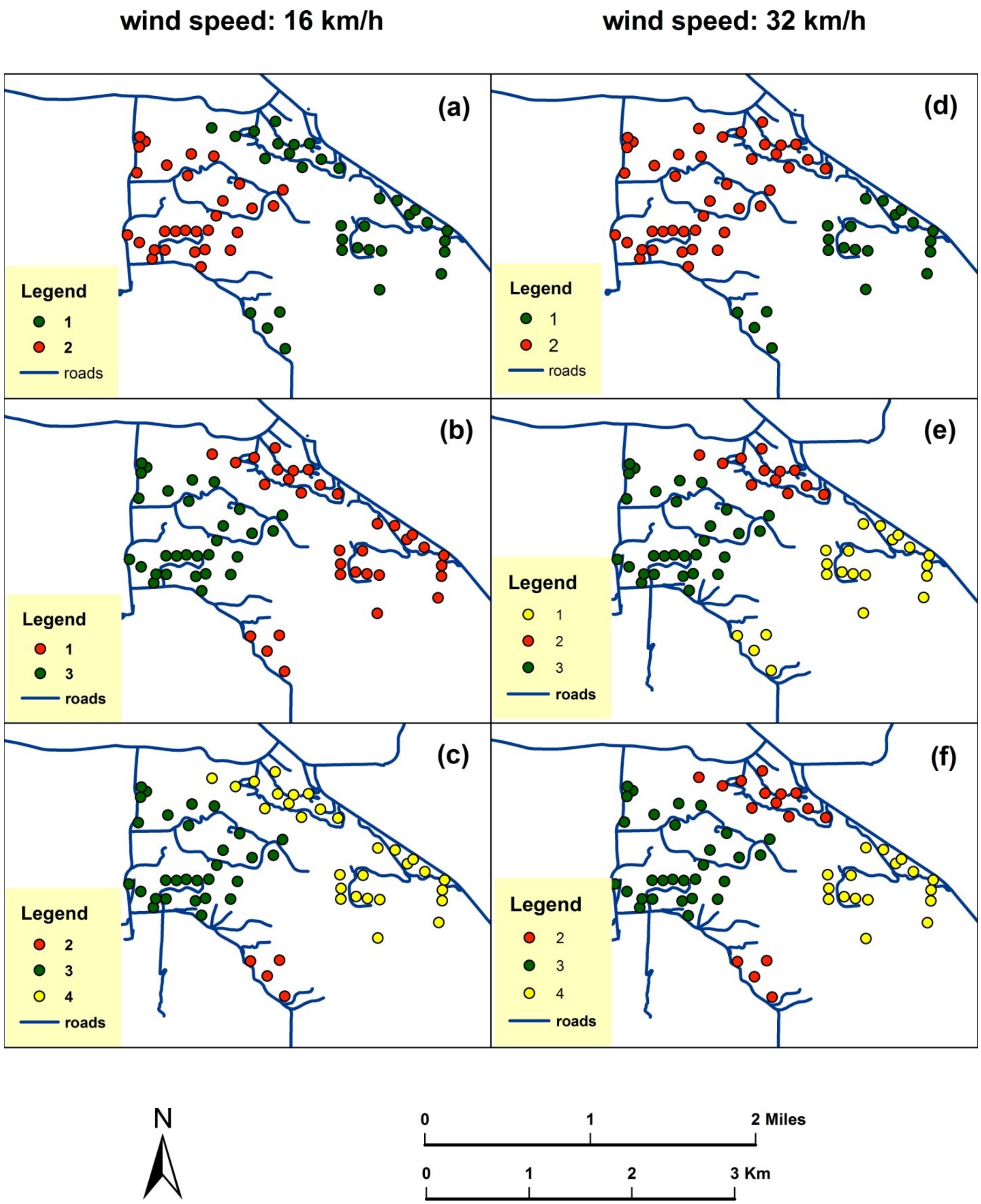

Figure 2.8 Adjusted zones using road segments for scenarios 1 and 2

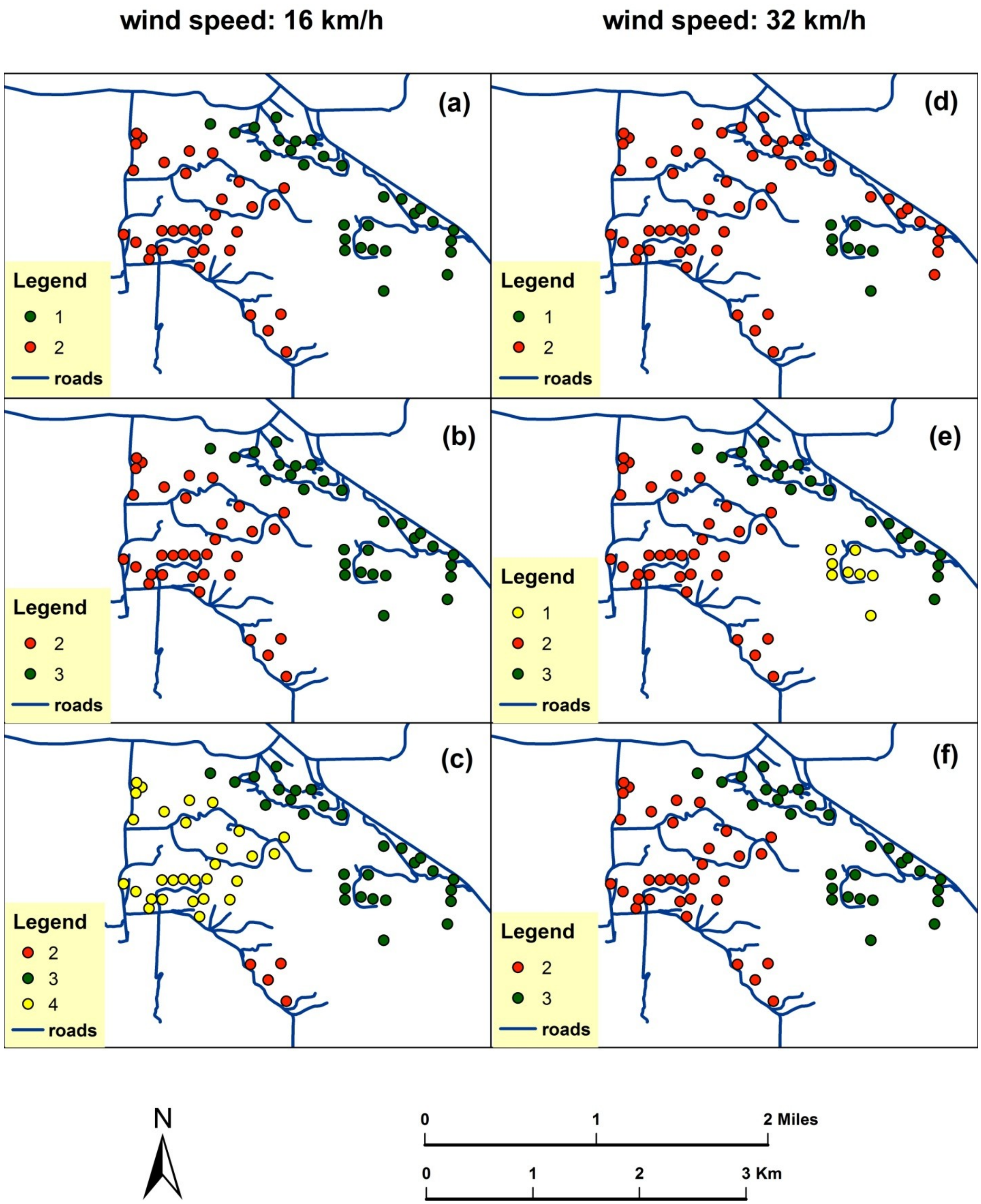

Figure 2.9 Adjusted zones using road segments for scenarios 3 and 4

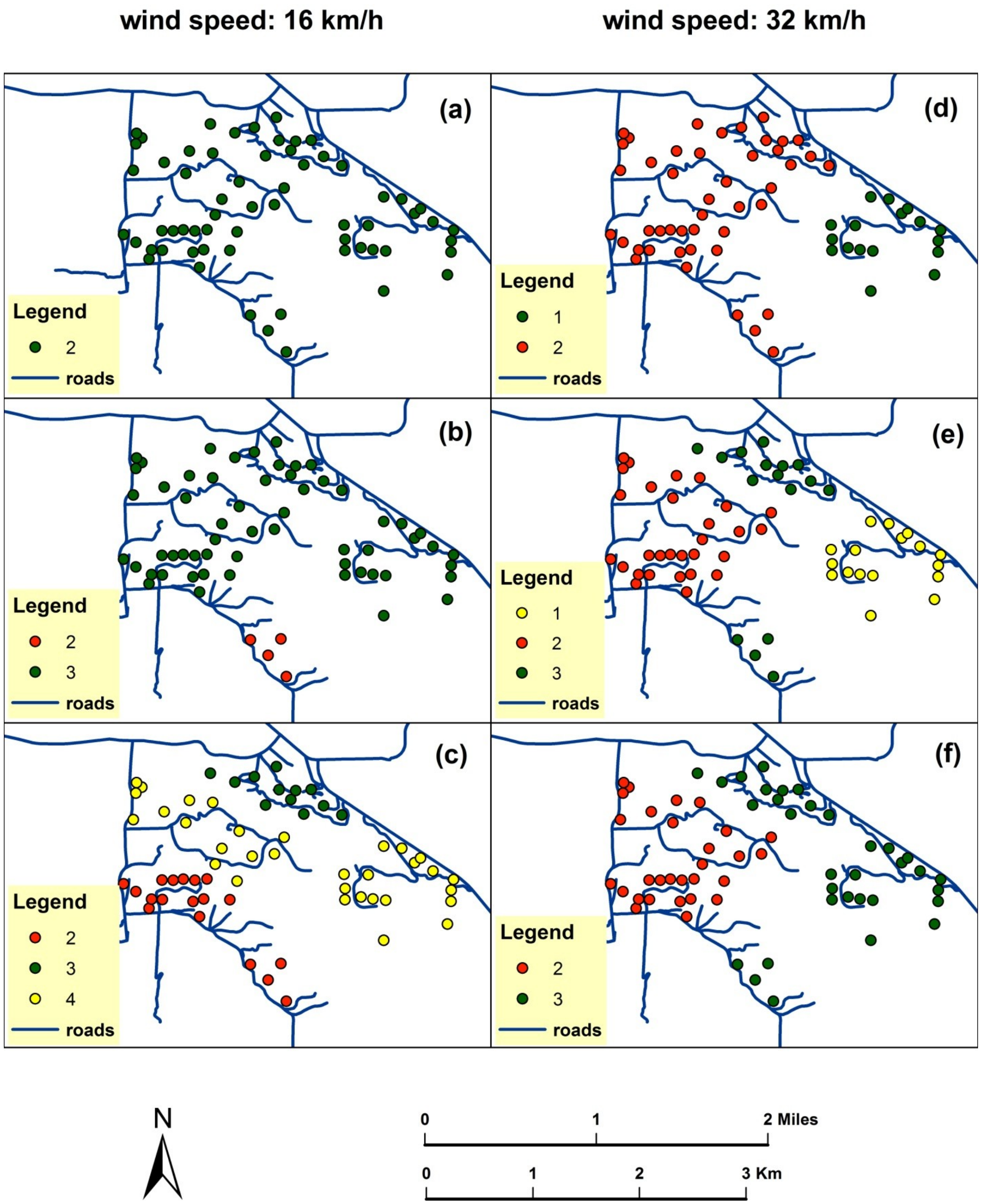

Figure 2.10 Adjusted zones using road segments for scenarios 5 and 6

2.6 Discussion and conclusion

Wildfire evacuation is a complex spatiotemporal process, which involves the progression of the fire and the evacuation of the at-risk population to safe areas. In order make sound warning decisions, ICs need to take into account many factors during evacuation, e.g., the direction and speed of fire progression, the population at risk, estimated evacuation traffic demand, and shelter selection. The complexity of the evacuation process can overwhelm ICs and poses significant problems for effective decision making (Drews, Musters, Siebeneck, & Cova, 2014). Postevent studies on fire progression and the timing of protective action recommendations during wildfire evacuations can help improve our understanding of the evacuation process and provide guidance for future evacuations (Kim et al., 2006). In this regard, simulations can be performed to help increase situational awareness and facilitate decision making during wildfire evacuations. This work presents a method that employs fire spread modeling and household-level trigger modeling to tackle wildfire evacuation warning timing and staged zoning from the IC's perspective. Several implications from this study are summarized as follows.

First, this study demonstrates that household-level wildfire evacuation trigger modeling is technically feasible. However, this finer-grain modeling and simulation costs significantly more computationally, and the necessity of performing modeling and simulation at the finer level should be determined before any endeavors are conducted. The value of performing trigger modeling at the household level is two-fold: first, for those isolated households in rural areas, household trigger modeling can be used to facilitate emergency warning at a very detailed level. Second, when household-level triggers are integrated with fire spread, ICs can develop a better understanding of timing evacuation warnings and managing travel demand. This work focuses on the second implication and demonstrates how the integration of household trigger modeling and fire spread modeling can facilitate evacuation warnings and staged zoning. However, the first implication is equally important and has great potential in evacuation warning practice. With modern warning technologies like the reverse 911 system, household-level warning has become popular (Strawderman, Salehi, Babski-Reeves, Thornton-Neaves, & Cosby, 2012). Household-level trigger modeling is a means of controlling evacuation timing based on the MFTT it will take for the fire to reach a specific household. Estimating the REDTs for sparsely distributed household in the WUI holds promise to improve emergency notification and warning at the household level, thereby improving public safety while minimizing the disruption of households that are not at risk. Future work could focus on using WebGIS to implement the trigger modeling on the server side, while using the most recent mobile computing to provide relevant emergency warning and notification at the client side (web or mobile client). This has been called "geo-targeted warnings" and it represents a significant research challenge in issuing public warnings to people with location-based devices like cellphones (Aloudat, Michael, Chen, & Al-Debei, 2014; National Research Council, 2013). Moreover, modern sensor web technologies have capabilities to retrieve data from sensors and process the data in a near real-time manner (Chen, Di, Yu, & Gong, 2010). These sensor web technologies can be used to detect fire progress in wildfire evacuations and have great potential in facilitating decision making when they are integrated with trigger modeling.

Second, integrating fire spread and trigger modeling is a central contribution of this paper. This work uses a loosely coupled strategy to build the system. For example, the software package FlamMap is used to perform fire spread modeling, and ArcGIS is employed to accomplish group analysis and construct evacuation warning zones. This loosely coupled strategy has limitations when it comes to sensitivity analysis and will bring inconvenience to decision makers in wildfire evacuation, and more efforts should be devoted to building a tightly coupled system so as to facilitate the use of the method. Specifically, relevant open source libraries can be borrowed to couple the systems at the source code level, which could bring great convenience to decision making in wildfire evacuations.

Third, this work examines building wildfire evacuation warning zones by using a risk-based, bottom-up approach that integrates fire spread and household-level wildfire trigger modeling, which proves to be applicable to staged evacuation planning. The geographic scales of evacuations vary with different hazard agents. For example, hurricane evacuations are usually performed at the country, state, or regional level, while wildfire evacuations are generally conducted at the community scale. The geographic scale of hazard agents determines the size of the risk area and the population at risk, which will eventually influence the size of evacuation warning zones. This study illustrates the use of road segments in delineating evacuation warning zones at the finer scale. The strength of using road segments lies in that people have great familiarity with the road names around them, which will significantly facilitate people's perception of the risk area during the warning process. Traditionally, the ICs will estimate fire progress and then divide the risk area into evacuation warning zones using prominent geographic features. In this top-town method, the determination of the order of the evacuation warning zones is determined by the spatial configuration of the zones relative to the fire, and the staged evacuation warnings are sent to the zones merely based on the ICs' situational awareness. Taking the evacuation scenario in the case study as an example, the ICs can delineate the zones using road segments and send out warnings accordingly, but they cannot specify when to send warnings to each zone. The proposed method can generate evacuation warning zones with their corresponding REDTs, and the zones are aggregated and constructed based on the computation of the REDT for each household. Thus, the ICs can not only delineate the zones using prominent features, but also specify the REDT for each zone and recommend staged evacuation warnings accordingly. Thus, the proposed method makes a contribution to existing methods.

Lastly, the assumptions used for fire propagation and trigger modeling should be taken into account. The MFTT and Dijkstra's algorithm are employed for fire propagation modeling and trigger modeling, and they use the same data structure and both calculate the shortest path in a fire travel-time network. Fire propagation models can have different implications for different contexts. In the context of wildfire evacuation, the implication of using shortest path algorithms in a fire travel-time network is that fire propagates in the fastest manner in the landscape, which ensures that worst-case scenarios are considered in evacuation planning (i.e., the case with the least time available to take protective action). Fire travel times in modeling fire spread have significant implications because the speed of fire propagation directly influences evacuation timing. If fire growth from shortest path algorithms is faster than reality, the generated REDTs will have smaller values and the households will be evacuated earlier than they should be, which could result in unnecessary disruption. Conversely, if the fire forecast propagates slower than reality, late evacuation could occur and the households will be placed in danger during evacuation (Handmer & Tibbits, 2005). Thus, the accuracy of fire propagation models should be taken into consideration. Finney (2002) compared fire-perimeter growth using MFTT with that from FarSite simulations, and the results indicate that the two methods can produce identical fire-growth expansions. Future work can use other fire propagation methods in the proposed method and compare their results with that of shortest path algorithms. Another assumption taken in our trigger modeling is that 1 h is sufficient for the households to safely evacuate. Although traffic congestions in exurban areas during wildfire evacuation is less likely to happen than in larger regional evacuations (e.g., hurricanes), poor design of the evacuation route systems may still result in the residents' inability to evacuate (Cova, Theobald, Norman III, & Siebeneck, 2013). For example, road closures caused by the fire can influence households' evacuation route choice and their evacuation times. As a result, traffic simulation could be performed in future work to further examine this assumption.

This study integrates fire spread with trigger modeling and presents a novel simulation-based, bottom-up approach to establishing staged wildfire evacuation warning zones and warnings. This work also provides a road map for integrating different systems and can shed light on how to use simulation-based methods for wildfire evacuation decision making. Trigger modeling is highly sensitive to environmental factors and the evacuation zoning process is also sensitive to clustering methods. Thus, sensitivity analysis needs to be conducted in future work to evaluate how sensitive the proposed method is when input variables vary so as to help develop a better understanding of it (Lindell, 2008). Simulation-based sensitivity analysis has enjoyed great popularity in spatial modeling and simulation in the past few years (Crosetto, Tarantola, & Saltelli, 2000) and can be used to perform sensitivity analysis for the proposed method. We should note that a tightly coupled system needs to be implemented before hundreds of thousands of simulations can be run for sensitivity analysis. Moreover, since fire spread and trigger modeling are computationally intensive, modern parallel computing techniques will be employed to accomplish simulation-based sensitivity analysis. Finally, the principles for evacuation warning zone establishment still remain unclear at this moment due to the scarcity of research on evacuation zoning. These endeavors will perfect the proposed method and help develop a better understanding of wildfire evacuation warning timing and zoning.

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CHAPTER 3

SETTING WILDFIRE EVACUATION TRIGGERS USING REVERSE GEOCODING

3.1 Abstract

Wildfire evacuation trigger points are prominent geographic features (e.g., ridge lines, rivers, and roads) utilized in timing evacuation warnings. When a fire crosses a feature, a predefined evacuation warning is issued to the communities or firefighters in the path of the fire. Existing studies on trigger modeling have used fire spread modeling and geographic information systems (GIS) to create a raster buffer around a community or firefighter crew with the estimated evacuation time as the input. Current buffers generated by trigger modeling have limited utility because they are not explicitly tied to real-world geographic features, making it difficult to determine when a fire has crossed a trigger buffer. This work aims to address this limitation by using reverse geocoding to set prominent triggers that have more value to emergency managers. The method consists of three steps: first, trigger modeling is performed to calculate a trigger buffer; second, online reverse-geocoding is employed to retrieve geographic features proximal to the buffer boundary; third, a procedure is used to select geographic features that represent viable trigger points. A case study of Julian, California is presented using the proposed method, and the GeoNames online reverse-geocoding service is used to test the method.

The results demonstrate that the proposed method results in more salient trigger points that would have value to emergency managers in real emergencies. An important finding is that a feature will have more value as a trigger point when it is close to the trigger buffer boundary and fire front.

3.2 Introduction

The wildland urban interface (WUI) is defined as the area where urban settings and wildlands meet (Radeloff et al., 2005; Stewart, Radeloff, Hammer, & Hawbaker, 2007). Most people move from urban areas to the WUI for rural amenities (Davis, 1990), and the past few decades have witnessed rapid WUI population growth in the American West (Hammer, Stewart, & Radeloff, 2009; Theobald & Romme, 2007). At the same time, the occurrence of and area burned by wildfires has grown, corresponding to an increase in drought severity in many regions (Dennison, Brewer, Arnold, & Moritz, 2014). Wildfires pose a significant threat to WUI residents, and improving public safety in these areas has received considerable research attention (Brenkert–Smith, Champ, & Flores, 2006; Cova, 2005; Cova, Dennison, & Drews, 2011; Mell, Manzello, Maranghides, Butry, & Rehm, 2010).

When an advancing fire becomes a threat to the residents of a community, protective actions may need to be taken to ensure public safety. Common protective actions in wildfires include evacuation and shelter-in-place (SIP) (Cova, Drews, Siebeneck, & Musters, 2009). When threatened residents have enough time to evacuate to safer places, incident commanders (ICs) tend to recommend this option to maximize public safety, but when a fire advances too fast and the residents do not have enough time for evacuation, SIP may be recommended so that the residents will not be trapped en route (Cova et al., 2011). To aid in timing protective action recommendations (PARs), prominent geographic features (e.g., ridge lines, rivers, and roads) may be used as triggers, such that when a fire crosses a feature, a PAR will be issued to threatened residents or firefighters in the fire's path (Cook, 2003; Cova, Dennison, Kim, & Moritz, 2005). A key characteristic of effective trigger points is *prominence*, as it improves the chance that a triggering event is readily detected by decision makers.

Existing trigger research uses fire spread modeling and geographic information systems (GIS) to model and set triggers (Cova et al., 2005). Fire spread models simulate the spread of fire over time and space from an ignition point. In trigger modeling, modeled fire spread rates can be used to create a fire travel-time graph, and the graph can be traversed from the threatened geographic assets outwards to generate a trigger buffer for a specific estimated evacuation time. Initial work has been conducted to examine the sensitivity of trigger modeling with varying weather inputs (Fryer, Dennison, & Cova, 2013; Larsen, Dennison, Cova, & Jones, 2011). However, little research has been done on the problem of identifying prominent geographic features to use as trigger points. Reverse geocoding, the reverse process of geocoding, can be used to associate place names with geographic coordinates, and has potential in associating geographic features with the modeled trigger buffers. The goal of this research is to bridge the gap between trigger modeling and real-world trigger points by incorporating reverse geocoding. Specifically, the research questions to be addressed include: 1) how can reverse geocoding be used to identify prominent geographic features to be used as real-world trigger points? 2) How can the features retrieved from reverse geocoding be used as trigger points in wildfire evacuation practices?

The remainder of this article is organized as follows. Section 3.3 gives an introduction to related work in trigger modeling and reverse geocoding. Section 3.4 introduces the research methods, and section 3.5 presents a case study of the methods applied to Julian, California. Finally, section 3.6 provides an in-depth discussion about the computational efficiency of the method and the saliency of the features, and section 3.7 concludes the article by summarizing the strengths and weaknesses of the proposed method along with future research directions.

3.3 Background

3.3.1 Trigger modeling

Trigger points are prominent geographic features used by ICs in wildfire evacuations as a warning mechanism to facilitate communications and evacuation timing. Existing trigger modeling uses the raster data model to represent the landscape (Cova et al., 2005). The raster data model represents the earth surface with a set of regular cells and is widely used to represent spatial phenomena such as topography and vegetation in GIS (Goodchild, 1992). Trigger modeling employs fire spread modeling and GIS to create a trigger buffer around the geographic asset where the threatened population is located. The geographic assets can be viewed at different scales (e.g., community, house, road, and fire crew). Accordingly, assets at different geographic scales can be represented as a raster cell, raster polyline, or raster polygon. The current trigger modeling method has been formulated into a three-step process by Dennison, Cova, and Moritz (2007). In the first step, the fire spread modeling software FlamMap is employed to calculate fire spread rates within a raster cell in eight directions under varying assumptions regarding fuel, wind, and humidity. FlamMap uses mathematical equations developed by Rothermel (1972) to calculate the fire spread rate in one direction using the fire shape model developed by Anderson (1983) to generate the two-dimensional spread rates (Finney, 2006). The second step constructs a network by connecting the centroids of orthogonally and diagonally adjacent raster cells to represent fire travel times between adjacent cells. A fire travel-time graph is derived with the nodes and edge weights representing the raster cells and the travel times, respectively. In the third step, the travel times between two adjacent cells are reversed, and the Dijkstra shortest path algorithm (Dijkstra, 1959) is employed to traverse the graph from the input raster feature outwards until the accumulated travel time reaches the input time constraint. The output of trigger modeling is a raster trigger buffer around the threatened asset for a specific input time (e.g., estimated evacuation time).

Previous studies have demonstrated that trigger modeling may have great potential in a variety of applications. Cova et al. (2005) used trigger modeling to create buffers for the location of a fire crew along the road using the 1996 Calabasas Fire scenario in southern California and demonstrated how trigger modeling could be used to protect firefighters in an operational context. Another study conducted by Fryer et al. (2013) demonstrated the potential use of trigger modeling in avoiding firefighter entrapment in the wildlands using the 2007 Zaca Fire in southern California. Dennison et al. (2007) used trigger modeling to create buffers around the Julian area in San Diego County, California, which could be used for strategic community evacuation planning. Trigger buffers were also calculated for evacuation routes in Julian in this study. Another community-level study conducted by Larsen et al. (2011) examined the feasibility of trigger modeling in the context of fire perimeters in the 2003 Cedar Fire in San Diego, California. This study found that trigger modeling could overestimate fire spread when generating trigger buffers, which could result in early evacuations when trigger buffers are used in issuing evacuation warnings. Anguelova, Stow, Kaiser, Dennison, and Cova (2010) applied trigger modeling to examine pedestrian wildfire risk and their results indicate that trigger modeling may have great potential in protecting pedestrians during wildfires in the wilderness. Recently, trigger modeling was also applied at the household level to stage wildfire evacuation warnings (Li, Cova, & Dennison, 2015). The size and shape of trigger buffers depend on various inputs used for trigger modeling such as input estimated evacuation times, topographic inputs (digital elevation model (DEM), aspect, and slope), environmental inputs (fuel type and cover), and weather inputs (wind speed, fuel moisture, and wind direction) (Dennison et al., 2007). Uncertainty associated with these inputs, for example, in weather inputs, can create a range of trigger buffers (Fryer et al., 2013).

3.3.2 Geocoding and reverse geocoding

Georeferencing, defined as the general process of relating information to geographic location (Hill, 2009), is an important concept in geographic information systems (GIS). Geocoding, an important georeferencing technique, usually refers to relating addresses or place names to geographic coordinates (Goldberg, Wilson, & Knoblock, 2007). Geocoding has been widely used in various applications such as public health (Krieger, 1992; Krieger et al., 2002; Rushton et al., 2006), crime (Andresen, 2006;

Ratcliffe, 2004), and traffic accident studies (LaScala, Gerber, & Gruenewald, 2000; Loo, 2006). In these studies, addresses are usually available, and the researchers use geocoding to get the geographic locations of the subjects, crime incidents, or traffic accidents to examine the geographic distribution of the phenomena and relevant socioeconomic or environmental factors. Geocoding quality and its impacts on spatial analysis have attracted substantial research attention in the past few years (Bonner et al., 2003; Zandbergen, 2008; Zandbergen, 2009; Zandbergen, 2011; Zandbergen, Hart, Lenzer, & Camponovo, 2012). Specifically, widely agreed-upon metrics for evaluating geocoding quality include positional accuracy, completeness, and repeatability (Zandbergen, 2008). Positional accuracy refers to the displacement between a geocoded point to the “true” feature in the real world; completeness (or match rate) is usually defined as the percentage of input records that were successfully geocoded; and repeatability reflects how sensitive the geocoding results are to changes in factors like input baseline data and associated matching algorithms (Zandbergen, 2008). Reverse geocoding is a process that relates geographic features to given geographic coordinates (Kounadi, Lampoltshammer, Leitner, & Heistracher, 2013). Existing studies on reverse geocoding mainly focus on privacy issues (Kounadi et al., 2013; Krumm, 2007).

Geocoding/reverse geocoding can be generally categorized into two types: conventional and online geocoding/reverse geocoding (Roongpiboonsopit & Karimi, 2010). Conventional geocoding/reverse geocoding practices are usually conducted by GIS professionals using existing software (e.g., ArcGIS), and users can have more control on the reference data and geocoding/reverse geocoding methods. Online geocoding/reverse geocoding services are usually provided by commercial companies or agencies as web services, and users can send requests according to predetermined format and receive results from these services. Compared to conventional offline geocoding/reverse geocoding, online services can be readily integrated into software systems developed on different platforms or in different programming languages. This platform and programming language-transparent feature has increased the popularity of online geocoding/reverse geocoding services. A number of studies have been conducted to evaluate the quality of online geocoding services (Karimi, Sharker, & Roongpiboonsopit, 2011; Roongpiboonsopit & Karimi, 2010). These studies employed the same metrics in evaluating offline geocoding quality to assess the quality of online geocoding services. Existing research on online reverse geocoding usually focuses on the accuracy of these services in urban areas (McKenzie & Janowicz, 2015). For example, a study by Kounadi et al. (2013) examined the accuracy and privacy issues of using different online reverse geocoding services in crime studies.

3.4 Methods

Existing trigger modeling is a computation-based approach that takes into account both fire spread and the response of the threatened population. Reverse geocoding could be potentially used to associate geographic features with trigger buffers in a computational manner. In this section, a three-step method that integrates trigger modeling and reverse geocoding is presented (Figure 3.1). In the first step, trigger modeling is performed for the threatened population. The outputs from this step are evacuation trigger buffers (ETBs) for specific input evacuation times. These raster

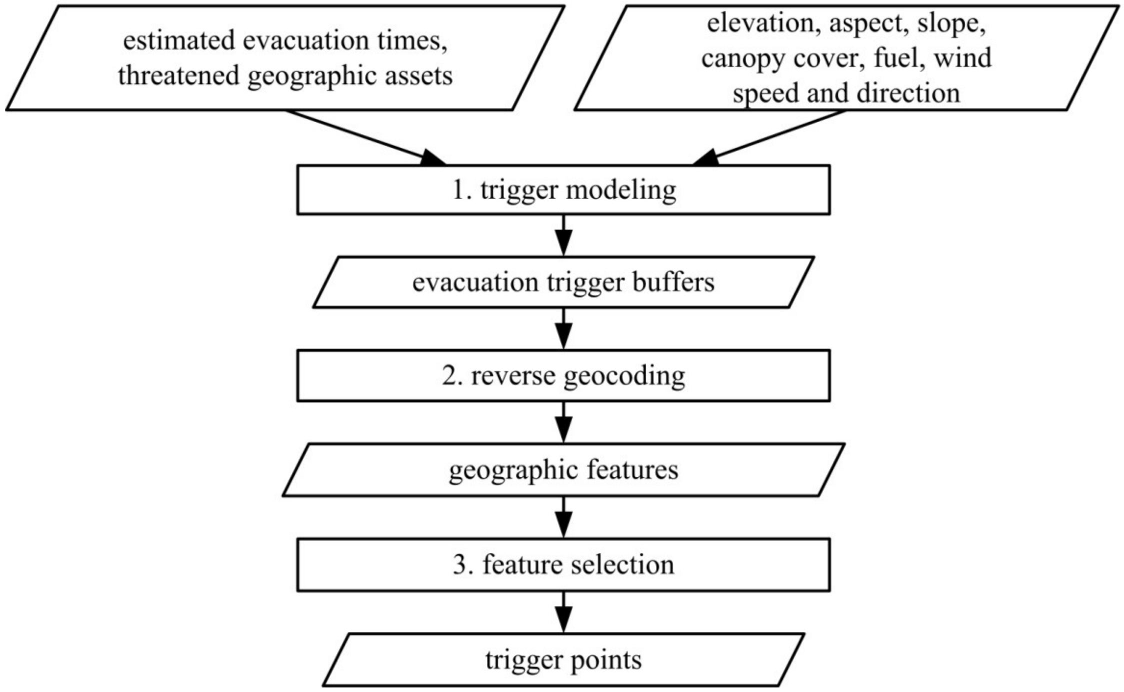


Figure 3.1 Workflow of the three-step method

buffers are used as the input in the second step where reverse geocoding is used to retrieve geographic features around the boundary of the buffer. Specifically, online reverse geocoding services are used to perform this operation because they are platform and system-independent and readily available. In the third step, the retrieved geographic features are selected according to the constraints of estimated evacuation times imposed by the ICs. The uncertainty in the input times is taken into account and modeled to select features as trigger points. The following subsections describe each step in more detail.

3.4.1 Step 1: trigger modeling

In the first step, trigger modeling is performed to create buffers around the geographic location where the threatened population or assets are located (Dennison et al., 2007). This method is based on the raster data model, and the input data can be categorized into five groups: land cover data (fuel types and canopy cover), topographic data (DEM, slope, and aspect), weather inputs (moisture, wind speed, and wind direction), threatened assets (firefighter crew, community, road, house, etc.), and estimated evacuation times. Since trigger modeling is based on the raster model, all the input spatial data rely on the same spatial resolution and geographic extent. The threatened asset locations in vector format are converted to raster data and then coregistered with the other raster data. In the field of fire spread modeling, fuel characteristics such as height, size, loading, and arrangement are assigned based on fuel model classes, using systems described by Anderson (1982) or more recently by Scott and Burgan (2005). Remote sensing image classification can be used to assign discrete fuel models to continuous fuel properties across raster space, creating a fuel map.

Figure 3.2 outlines the three-step process of trigger modeling. In the first step, all the input data are imported into FlamMap, and fire spread modeling is performed to calculate fire spread rates in eight cardinal and ordinal compass directions for each raster cell (Figure 3.2(a)). The second step uses the spread rates to compute the fire travel times between the centroids of orthogonally and diagonally adjacent raster cells to construct a fire travel-time graph. As shown in Figure 3.2(b), the centroids of the raster cells are the nodes, and the weights for the arcs are the travel times The arcs are directed because fire spread rates within one raster cell differ in each direction due to wind, fuel, and topography. In the third step, the directional arcs derived in the second step are reversed, and the Dijkstra (1959) shortest path algorithm is used to traverse from the input location cells until the accumulated travel time reaches the input time. This process is illustrated in Figure 3.2(c), which shows the resulting raster trigger buffer.

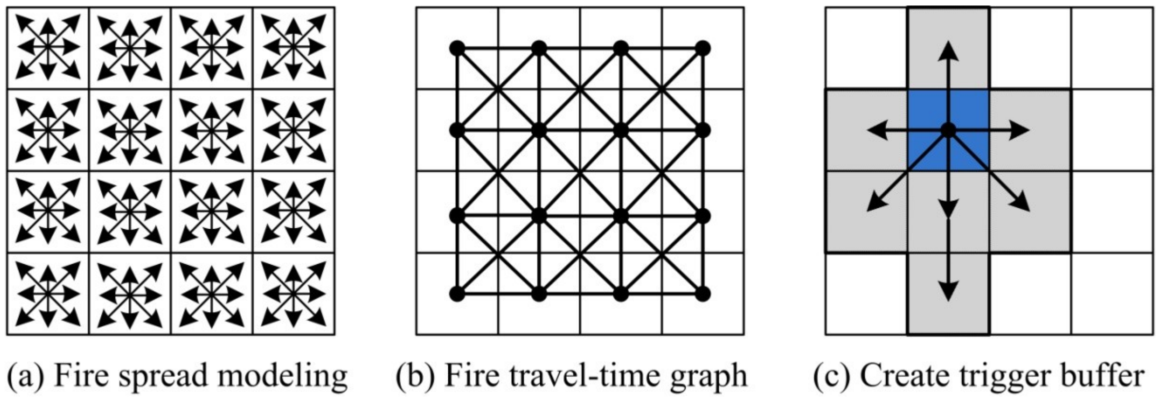
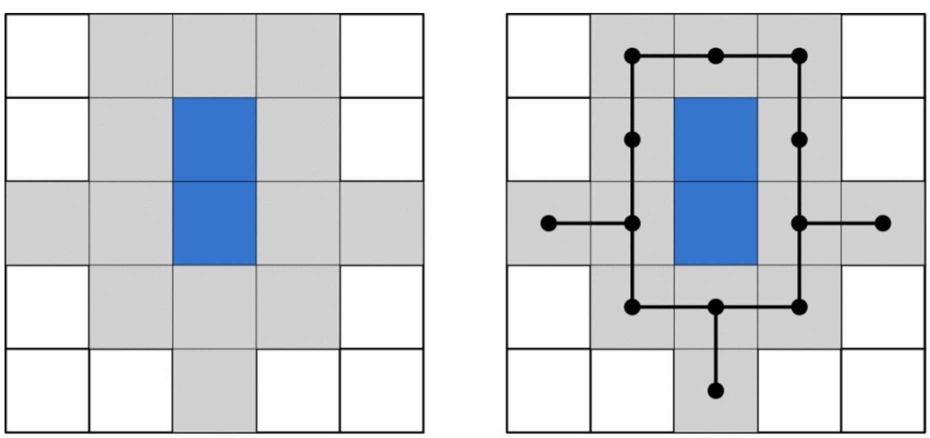


Figure 3.2 The three-step trigger modeling process

3.4.2 Step 2: reverse geocoding

Reverse geocoding can be considered as a basic spatial query operation in GIS. Users provide a point with geographic coordinates as the input, and the reverse-geocoding process retrieves the nearest geographic feature from a spatial database. Online reverse geocoding services usually take one pair of geographic coordinates (latitude and longitude) as the input, whereby they return a feature name as well as its location as the output. However, in many real-world applications, the input can be other geometries instead of simple points, e.g., line features and polygon features. These complex features must be split into points before they can be processed by online reverse geocoding services. Miller and Wentz (2003) point out that GIS provides various representation and analytical capabilities to solve problems and that spatial representation determines the analytical methods used for the spatial analysis. Thus, when reverse geocoding is integrated with trigger modeling, the spatial representation employed in the latter is taken into account. Specifically, the centroids of the boundary cells are the vertices, while orthogonally adjacent cells are connected by edges. A boundary cell is defined as a cell in the ETB that has at least one neighbor that does not fall within the ETB. As shown in Figure 3.3(a), the blue cells are inside cells, while the gray ones boundary cells. Figure 3.3(b) shows the graph representation of the boundary cells. Note that only orthogonally adjacent boundary cells are connected and each vertex can have four neighbors at most. Thus, the graph is a sparse graph and the adjacency list representation should be used.

As noted earlier, the trigger is represented as a raster buffer around the input raster feature. From a modeling and computation perspective, PARs should be issued when the fire crosses the boundary. However, prominent geographic features are widely used in fire suppression and evacuation warnings to improve communication. Thus, we need to use the buffer boundary as the input to the reverse geocoding process to identify proximal geographic features. Specifically, the centroids of the boundary cells of the buffer, coined query points in this context, are extracted, and these points are then used as the input for reverse geocoding. An algorithm for extracting the query points and constructing the graph is given in Table 3.1. Note that edges only exist between one



(a) Boundary of ETB (b) Graph for ETB boundary

Figure 3.3 Illustration of boundary cells and the graph representation

Table 3.1 Algorithm for extracting query points from an ETB

```
G = (V, E)                                          // a graph for storing boundary cells
ETB = readData( )                                   // read data and ETB is a N by N array
For i From 0 To N-1                                 // iterate each row
    For j From 0 To N-1                             // iterate each column
        If isBoundaryCell(ETB(i, j) ) Is True       // if the cell is a boundary cell
            G.addVertex(ETB(i, j))                  // add the cell to the vertex list
            For neighbor In ETB(i, j).getNeighbors( )  // iterate each neighbor cell
                If isBoundaryCell(neighbor) Is True    // if it is a boundary cell
                    G.addVertex(neighbor)              // add it to the vertex list
                    G.addEdge(ETB(i, j), neighbor)     // add the edge to the list
                    G.addEdge(neighbor, ETB(i, j))     // add the edge to the list
                EndIf
            EndFor
        EndIf
    EndFor
EndFor
```

boundary cell and its four orthogonally adjacent boundary cells (Figure 3.3). Thus, the edges are based on the spatial relationship between boundary cells.

Figure 3.4 demonstrates the process of extracting query points from the ETB generated by trigger modeling using the above algorithm. Specifically, Figure 3.4(a) shows an ETB generated by the trigger modeling around the given input geographic feature. Note that in this case, the input feature is a raster cell, which could represent a firefighter crew or a house located in the WUI. Large-scale features like communities or roads can be represented using a set of contiguous raster cells. Trigger buffers are usually skewed because of the wind and the variability of topographic factors. The ETB in Figure 3.4(a) is generated using uniform topographic factors, and its skewedness is due to the direction and speed of the wind. Figure 3.4(b) illustrates the extracted boundary cells, and their centroids serve as the query points for reverse geocoding.

In order to use these query points as input to retrieve geographic features via

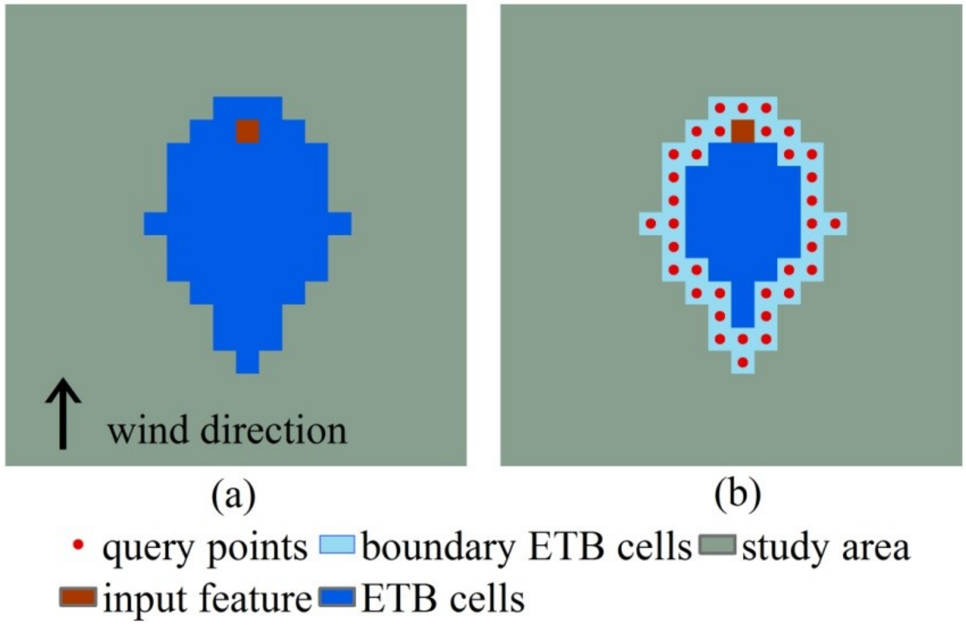
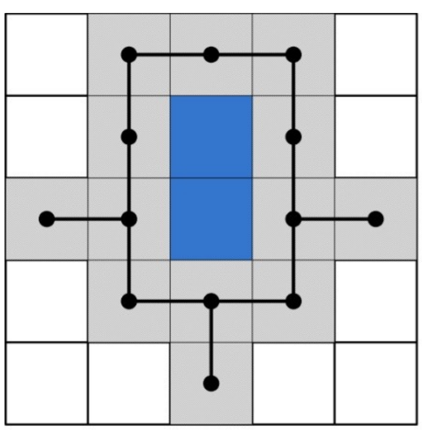


Figure 3.4 Extracting query points from ETB

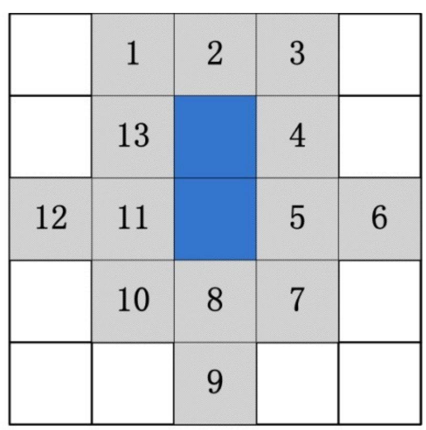
reverse geocoding, a graph traversal operation needs to be performed so as to transform the two-dimensional boundary to a linear sequence. Breadth first search (BFS) and depth first search (DFS) are two popular graph traversal methods (Cormen, Leiserson, Rivest, & Stein, 2009). Since the edges in this context denote spatial adjacency, they will have the same weights. The BSF begins the search from a given staring vertex *s* and finds all vertices that are at distance *d* from *s* before it finds the vertices that are at a distance d+1, while the DFS will search the graph as deep as possible and then traverse other branches. In this context, if the top left boundary cell is chosen as the starting vertex, the BFS will traverse the graph in two directions, while the DFS will search the graph along one direction. Thus, a DFS is chosen to arrange the query points in a sequential order in one direction. The DFS method starts with the top left boundary cell in the graph and finds the neighbor boundary vertices from its four neighbor cells. Note that when it searches its four neighbor cells, it starts from its parent vertex and continues to search the rest of the cells in a clockwise manner. In this way, the whole DFS will traverse the graph in a clockwise order. After the DFS, the two-dimension boundary of the ETB can be transformed into a linear sequence based on the spatial relationships between the cells. An example given in Figure 3.5 shows the DFS of the graph. Specifically, Figure 3.5(a) shows the graph and Figure 3.5(b) illustrates the results after DFS with each number denoting the traversal order for each boundary node. After the DFS, a linear sequence of vertices is derived that can be used as the query points for reverse geocoding. The features derived from reverse geocoding for each query point are stored for further analysis. The detailed DFS algorithm is given in Table 3.2.

3.4.3 Step 3: feature selection

The generated trigger buffer is usually skewed due to the variability in the input data. Previous studies on trigger modeling have revealed that the size and shape of trigger buffers depend on the inputs such as wind speed and direction (Dennison et al., 2007; Larsen et al., 2011). However, little research has focused on the uncertainty in the input



(a) Boundary of ETB



(b) Graph traversal

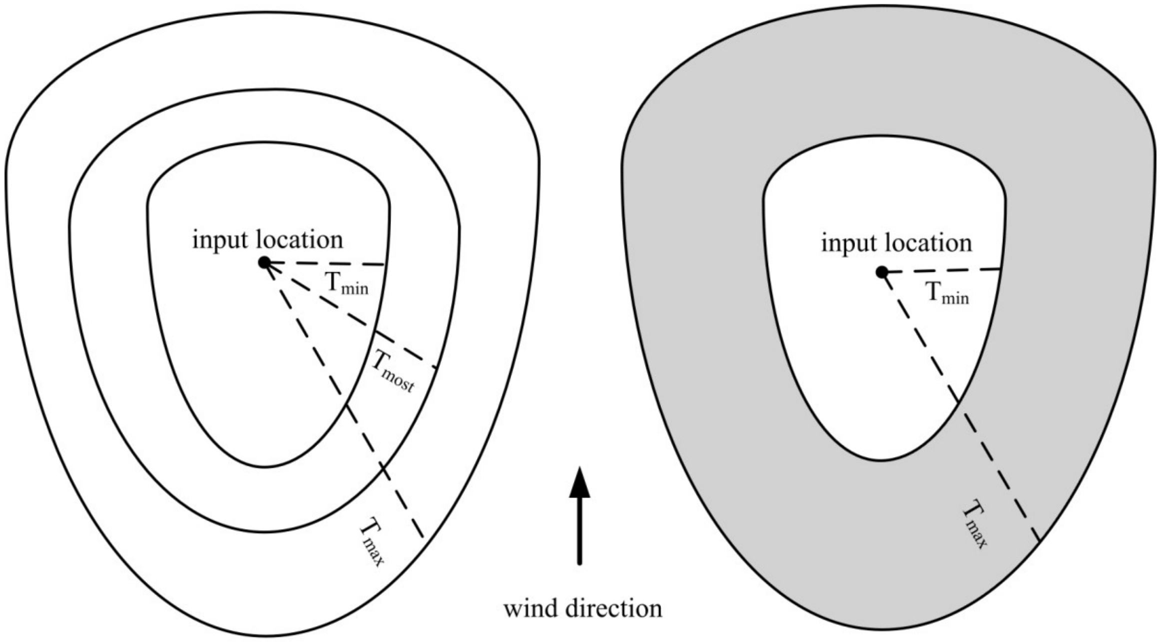
Figure 3.5 An example of DFS of the graph

Table 3.2 The DFS algorithm for graph traversal

```
G = (V, E)                          // a graph that represents boundary cells
ReverseGeocoder                     // a reverse geocoder
resultFeatures = { }                // the final feature set for the vertices
For vertex In V                     // initialize the vertices in the graph
    vertex.setColor('white')   // initialize each vertex to 'white' (unvisited)
    vertex.setParent(null)      // set the parent vertex for each vertex to null
EndFor
t = 0                               // initialize visit time to 0
startVertex = G.getStartVertex( )
Function DFSVisit(startVertex)      // a function for depth first traversal
     startVertex.setColor('gray')        // set the vertex to 'gray' (being visited)
     t  += 1                             // increase the current visit time by 1
     startVertex.setDiscoveryTime(t)  // set the discovery time to t
     For nextVertex In startVertex.getNeighbors( ) // get the neighbors
          If nextVertex.getColor( ) == 'white' // if the neighbor vertex is not visited
             nextVertex.setParent(startVertex   // set the parent vertex of each neighbor
             DFSVisit(nextVertex)      // search each unvisited neighbor recursively
          EndIf
     EndFor
     startVertex.setColor('black')     // set the status of the vertex to 'black' (visited)
     t += 1                            // increase the visit time by 1
     startVertex.setFinishTime(t)    // set the finish time to the current visit time
EndFunction
SortedV = sortByDiscoveryTime (V)   // sort the vertices by their discovery times
For vertex In SortedV                   // iterate each vertex in V
     features = List( )       // create a list to store the features from reverse geocoders
     geoLocation = getGeoLocation(vertex)     // get the geographic coordinates
     feature = ReverseGeocoder.reverseGeocode(geoLocation)   // retrieve feature
     features.append(feature)                // append the feature to the list
     resultFeatures[vertex] = features      // add the features for each vertex
EndFor
```

time for trigger modeling. As noted, trigger modeling needs an estimated evacuation time for the threatened population as the input. When trigger modeling is integrated with reverse geocoding, the uncertainty in the input time should be taken into account. Figure 3.6 illustrates the feature selection process. Assume that the IC's most probable evacuation time estimate (ETE) for a threatened community is T_{most} and the derived trigger buffer for it can be denoted ETB(T_{most}). Given that T_{most} is usually estimated using evacuation traffic simulation or simply based on the IC's estimate, the actual time T could fall within a range [T_{min}, T_{max}], where T_{min} denotes the minimum probable ETE while T_{max} the maximum probable ETE. As noted, the ETB calculated by trigger modeling is a time buffer and the size of the ETB will increase with the increase of the input time. So when T_{min}, T_{most}, and T_{max} are all given, three ETBs can be generated respectively using trigger modeling, as shown in Figure 3.6(a). Note that ETB(T_{most}) is used as the input for reverse geocoding to extract the geographic features along its boundary. The spatial space for [T_{min}, T_{max}] can be derived by subtracting ETB(T_{min}) from ETB(T_{max}). Figure 3.6(b) shows the derived ring area that can be used for feature selection. All the features within the ring area could be used as trigger points, and when the fire crosses them, the threatened residents will have time $T \in [T_{min}, T_{max}]$ to evacuate to safer places.

The algorithm for the feature selection process is shown in Table 3.3. Note that the ETB subtraction operation is to subtract one small ETB from a large one, and it is based on the raster data model. Moreover, the derived geographic features in the reverse geocoding step are points with geographic coordinates, and coordinate transformation needs to be performed to examine the spatial relationship between the features and the derived selection space in this step. All the features falling within the selection space are reserved and could be used as trigger points. The uncertainty in input times for trigger modeling is transformed to a two-dimensional selection space and this time-space transformation enables feature selection and can help the ICs develop a better understanding of input time uncertainty in setting triggers during wildfire evacuations.



(a) ETBs for T_{min}, T_{most}, and T_{max} (b) Valid ring area for feature selection

Figure 3.6 Illustration of the feature selection process

Table 3.3 Algorithm for feature selection

Input: T_{most}	// the input time for trigger modeling
T_{min}	// the lower bound
T_{max}	// the upper bound
resultFeatures = List( )	// a list to store the selected features
ETB(T_{most}) = TriggerModeling(T_{most})	// create the ETB for time T_{most}
ETB(T_{min}) = TriggerModeling(T_{min})	// create the ETB for time T_{min}
ETB(T_{max}) = TriggerModeling(T_{max})	// create the ETB for time T_{max}
SelectionSpace = ETB(T_{max}) - ETB(T_{min})	// create selection space
features = ReverseGeocoding (ETB(T_{most}))	// get geographic features
For feature **In** features	// for each geographic feature
If feature **Is** Within SelectionSpace	// if the feature falls within the space
resultFeatures.append(feature)	// add the feature to the final result set
EndIf	
EndFor	

3.4.4 Implementation of the method

This subsection introduces the implementation of the method. For the first step in the proposed method, the three-step trigger modeling procedure is used to create ETBs for the threatened geographic assets. As mentioned above, the software FlamMap is used for fire spread modeling, and then a C++ program is used to construct the fire travel time network and perform shortest path analysis to calculate the ETBs. The second step—reverse geocoding—can employ either manual reverse geocoding or online reverse geocoding services. The latter can be conveniently integrated into various information systems and has enjoyed great popularity in the era of mobile computing. Moreover, such online services also relieve users from compiling reference data and handling all the technical details in many reverse geocoding practices. Since many services are managed by commercial companies and it is costly to maintain these services, many services will have limitations on the number of requests per day the users can make for free. Note that the users can always pay a certain fee to access unlimited service. When users make a request using these online services, the input geographic coordinates contained in the Hypertext Transfer Protocol (HTTP) request are extracted by these services, and the nearest feature is retrieved from the spatial databases and returned to the user in either an Extensible Markup Language (XML) or JavaScript Object Notation (JSON) format. The returned files in these structured formats can be easily interpreted by most programming languages, which makes such web services popular in modern software systems. Thus, online reverse geocoding is used in this work. Specifically, the service used is GeoNames, which is a global geographic database that contains millions of various geographic features. The GeoNames “findNearby” reverse geocoding application program interface

(API) can return the nearby feature for an input geographic point in XML or JSON format. Python was used to implement the proposed method. Two open source Python libraries were used in the implementation: the Universal Transverse Mercator (UTM) library was used to perform map projection between geographic and UTM coordinates and the PyShp library was used to save the final selected features into a shapefile format file.

3.5 Case study

With a combination of flammable vegetation (e.g., chaparral) and extreme weather conditions (Santa Ana winds), southern California has become one of the most vulnerable areas to wildfires in the U.S. Wildfires have caused significant losses of life and property in this area (Rogers, 2005). The area chosen for the case study is located in Julian—a census-designated place (CDP) in the east of San Diego County, California. The 2003 Cedar fire occurred in this area and caused 26 fatalities and the loss of thousands of buildings. Specifically, the Julian downtown area and the Whispering Pines and Kentwood communities were included as the threatened residential area in this case study. The selected residential area is surrounded by grass, shrub, and tree fuel types and can represent many fire-prone communities in the American West. As shown in Figure 3.7, the residential area used as the input for trigger modeling is a raster polygon. The administrative boundary dataset of Julian was acquired from the GIS department of San Diego County (SanGIS). The fuel, DEM, aspect, slope, and canopy cover data were downloaded from the LANDFIRE project, an open data portal that provides national datasets used in wildfire-related studies in the U.S. (Rollins, 2009).

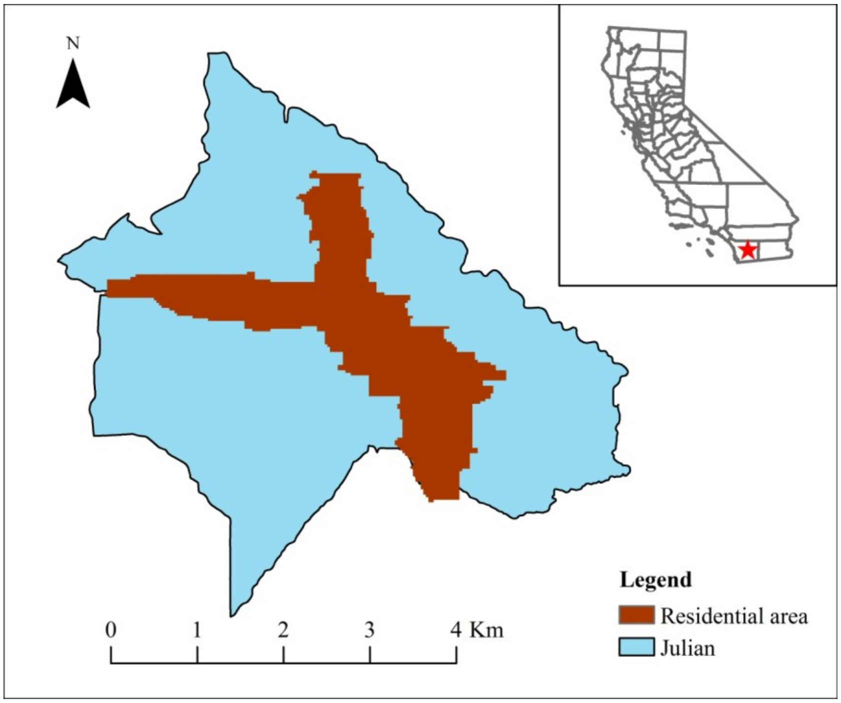


Figure 3.7 Map of Julian, California

All the data acquired from LANDFIRE are at 30 m resolution, and the datasets include 1500×1500 raster cells and cover Julian and its surrounding area. Specifically, the fuel data in this study use the 13 Anderson fuel models (Anderson, 1982). Burnable fuel model 1 (short grass), 2 (timber), and 5 (brush) account for 58.4%, 22.6%, and 7.8%, respectively, while unburnable fuel model 91 (urban) and 99 (barren) are 2.7% and 4.2%, respectively. These fuel models account for 95.8% of all raster cells. The environmental parameters listed in Table 3.4 were used as the input for fire spread modeling.

Table 3.4 Environmental parameters for fire spread modeling

Wind direction	Wind speed (km/h)	Dead fuel moisture (%)			Live fuel moisture (%)	
		1 h	10 h	100 h	Wood	Herbaceous
Northwest	16	5	5	5	65	65

The input ETEs T_{min}, T_{most}, and T_{max} for trigger modeling were set to 75 min, 90 min, and 105 min, respectively. The selection space was calculated by subtracting the 75 min ETB from the 105 min ETB. As shown in Figure 3.8(a), the ETBs for input evacuation times of 75 min, 90 min, and 105 min were mapped in different colors around the Julian residential area. Figure 3.8(b) shows the boundary of the 90 min ETB, which was used to derive the query points for reverse geocoding. A total number of 1,023 query points were employed to retrieve geographic features using the GeoNames reverse geocoding service, and 28 unique features were derived as the results, which are shown as points in Figure 3.8(c). In the final step, the selection space was generated by subtracting the 75 min ETB from the 105 min ETB, which is shown as the blue area in Figure 3.8(d). Five features fall within the constructed selection space, as shown in Figure 3.8(d).

The features derived from GeoNames include various types of natural and man-made features, such as a populated place, mine, school, park, reservoir, and stream. These derived features could be potentially used as valuable trigger points. Note that the final five features derived using the proposed method could be potentially used as trigger points to provide residents with 75 ~ 105 min for their evacuation, assuming the real fire's rate-of-spread (ROS) does not exceed the modeled ROS. Features that fall between the selection space and the residential area could be used as trigger points for an ETB generated using an evacuation time less than 75 min; and those falling out of the selection space could be potentially used for an ETB derived using an input time greater than 105 min. Table 3.5 lists the five features in Figure 3.8(d). Specifically, the GeoNames feature identification (ID), name, and feature class are included for each feature.

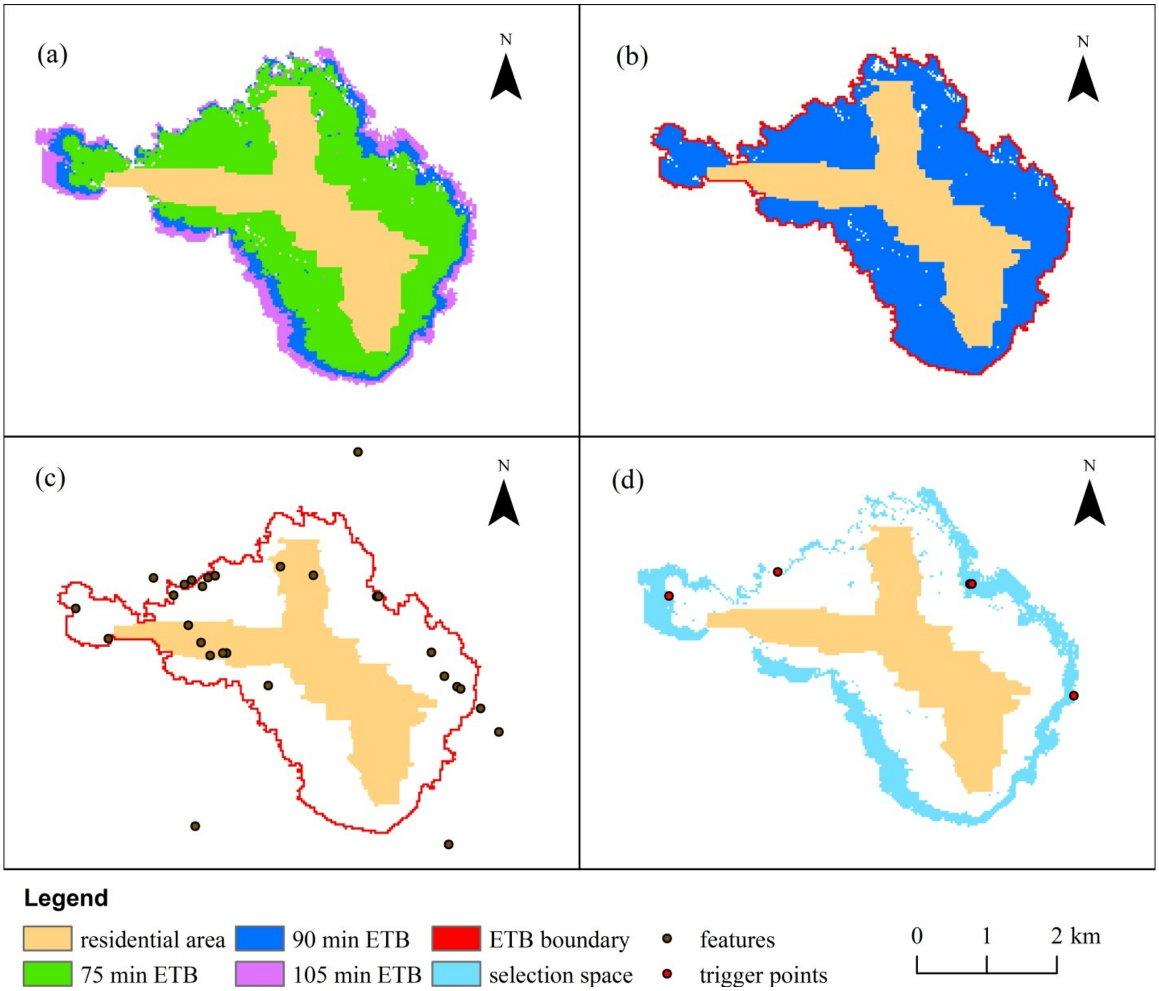


Figure 3.8 Maps of ETBs and the retrieved geographic features

Table 3.5 Retrieved geographic features from GeoNames

GeoNamesID	Name	Feature class
5345692	El Dorado Mine	spot building farm
5346201	Ella Mine Group	spot building farm
5337485	Cimarron Elementary School	spot building farm
5345212	Eastwood Creek	stream lake
5363094	Keystone Pilot Mine	spot building farm

3.5.1 Feature prominence

One issue related to the value of using derived features as trigger points is saliency, which refers to the degree to which a feature can be identified from its surrounding environment and used by nearby firefighters for communication and navigation purposes during wildfire evacuations. We performed a viewshed analysis for the four derived features in Table 3.5. The feature "Ella Mine Group" was excluded because it is very close to "El Dorado Mine". As shown in Figure 3.9, when a feature is used as a trigger point, the nearby firefighters located within the viewshed could easily detect it when the fire crosses the trigger point. This could also help firefighters communicate with others about the whereabouts of the fire and facilitate evacuation

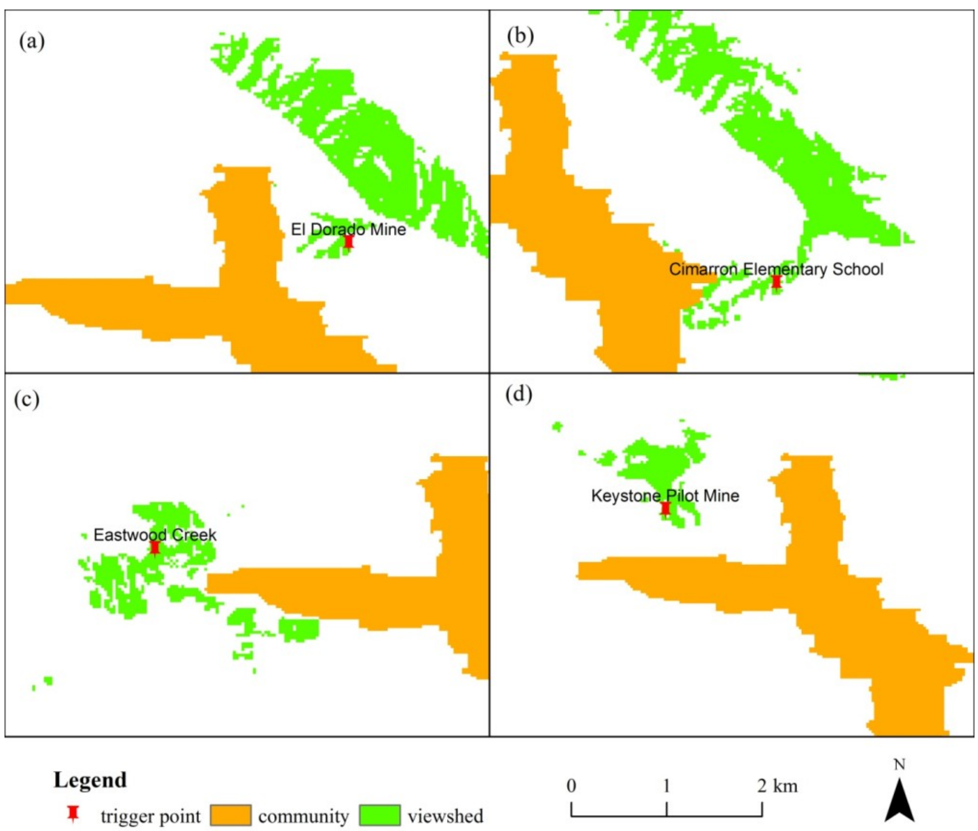


Figure 3.9 Results of viewshed analysis for the trigger points

warnings. From a visibility perspective, “Eastwood Creek” could be more effective than others because its viewshed covers a larger area that falls between the feature and the community. Note that viewshed analysis does not take into account the obstacles (e.g., smoke, trees, and buildings) between the firefighters and the trigger point, and more research should be conducted on this topic to develop a more complete set of metrics for feature prominence. Moreover, another aspect of saliency is about people’s spatial perception, and more empirical studies should be done to further examine how to use prominent geographic features as trigger points to support communications and navigation during wildfire evacuations.

3.5.2 Spatial configuration

In order to demonstrate the potential use of a derived trigger point from GeoNames, we selected the Eastwood Creek as a trigger point for three wildfire scenarios, as shown in Figure 3.10. Wildfire simulation was performed for each ignition point using the same environmental inputs listed in Table 3.4. The fire arrival and lead times for the ETBs and trigger point calculated using fire simulations are listed in Table 3.6. Fire arrival time contours were created to better illustrate the spatial relationships between fire perimeters (the numbers denote fire travel times) and the trigger point as well as their impacts on evacuation timing, as shown in Figure 3.11. In scenario 1 (Figure 3.11(a) and (b)), the modeled fire reached the community before it crossed the trigger point, which implies that this feature was not useful for this scenario. In scenario 2 (Figure 3.11(c)), when the fire crosses the trigger point, the residents should have about 70 min to evacuate before the fire reaches the community. In scenario 3 (Figure 3.11(e) and (f)) the lead time

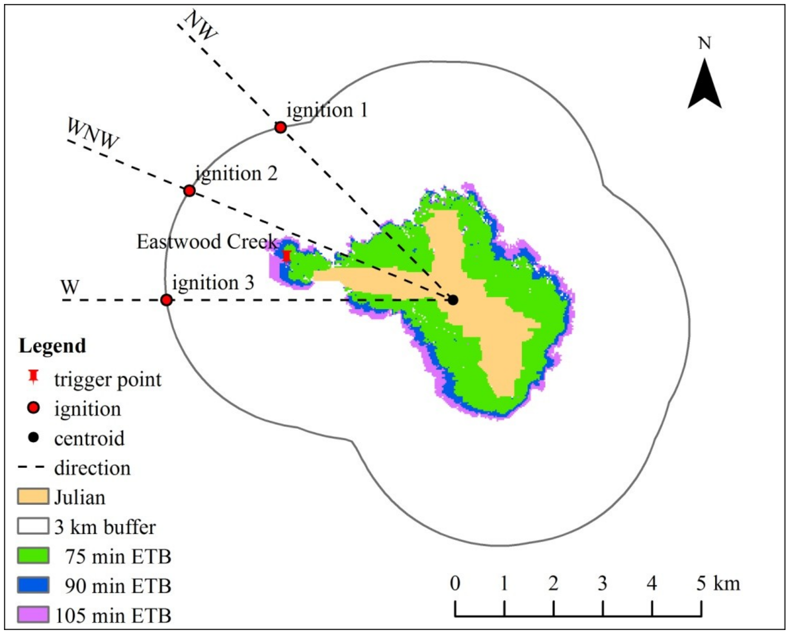


Figure 3.10 Three scenarios for evaluating the method

when the fire crosses the trigger point is 42 min, which may lead to insufficient warning time to evacuate. Note that the trigger point is located to the east of the boundary of the 90 min ETB, which results in less lead time when it is used to trigger an evacuation warning, as shown in a larger scale map of scenario 2 in Figure 3.11(d). From the spatial configurations of fire perimeters, ETBs, and the trigger point, we can come to two conclusions. First, a trigger point has more value when it is close to the buffer boundary. Second, a trigger point has more value when it is closer to the fire front because wildfires can spread around a point feature. Thus, the ICs should use the retrieved features that are closer to the boundary of the ETB and the fire front as trigger points in wildfire evacuations. Another finding from the case study is that when retrieving features to set trigger points, we cannot simply reply on the geographic distance because the fire perimeters are usually skewed. Thus, all computations should be conducted in a space characterized by fire travel times rather than a simple Euclidean space.

Table 3.6 Fire arrival and lead times from wildfire simulations

Fire arrival time (lead time)/min	Ignition 1	Ignition 2	Ignition 3
105 min ETB	420 (105)	239 (103)	239 (105)
90 min ETB	437 (88)	253 (89)	256 (88)
75 min ETB	458 (67)	269 (73)	270 (74)
Trigger point	538 (-13)	272 (70)	302 (42)
Community	525 (0)	342 (0)	344 (0)

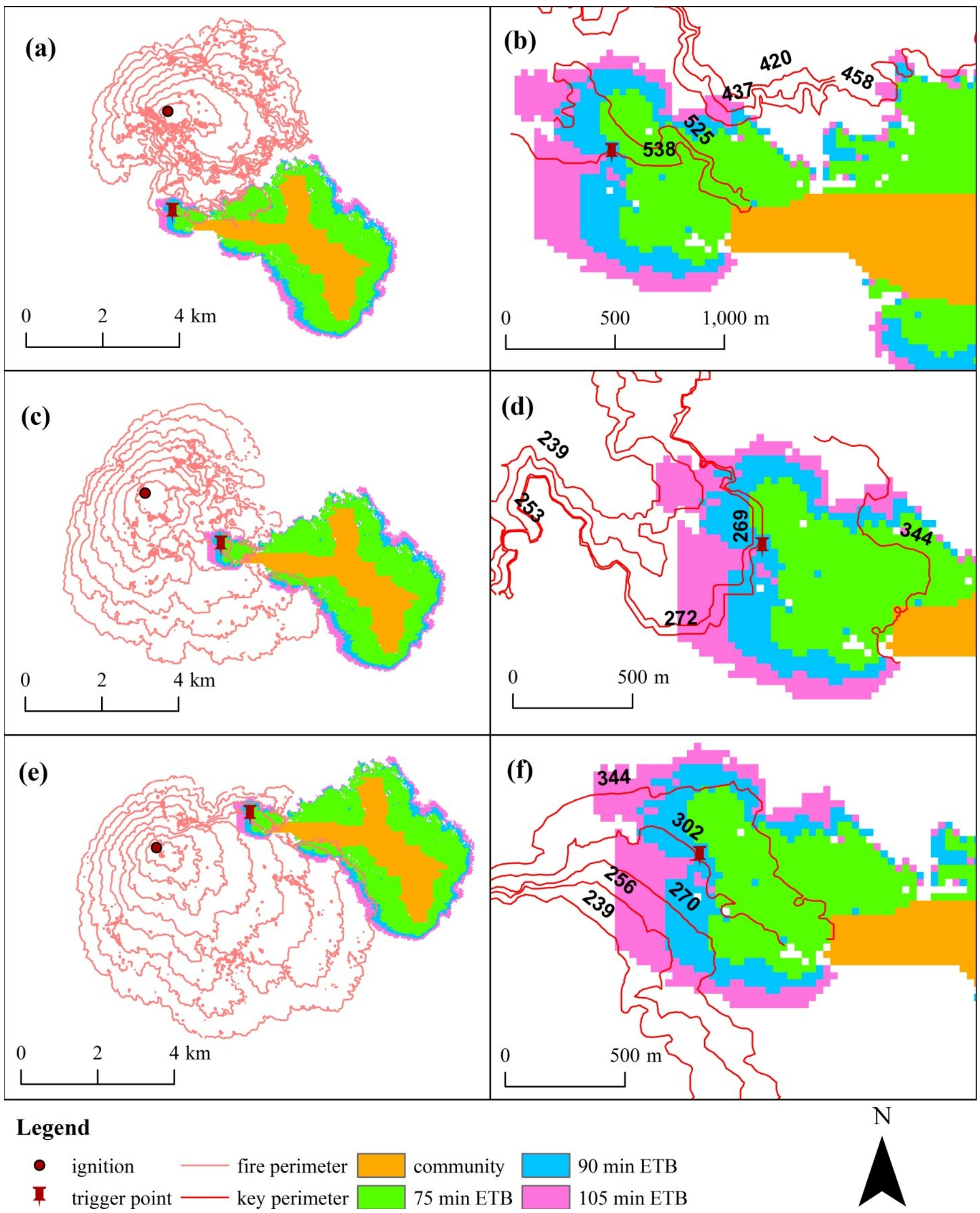


Figure 3.11 Fire perimeters for the three scenarios

3.5.3 Computational efficiency

In the above case study, the centroids of all the boundary cells were used as the query points. Since it is computationally intensive to retrieve features from online reverse geocoding services, adjustments should be made to reduce the number of query points when we employ the proposed method to set trigger points for operational use purposes in wildfire evacuations. The centroid of the residential area was used to divide the study area into four quadrants. The proposed method can transform the centroids of the boundary cells of the ETB to a linear sequence of query points, which enables users to sample the query points using different intervals, as shown in Figure 3.12. We also visualized the distance between each query point and its corresponding feature, which reveals that the spatial configuration of the features will influence the efficiency the query process. The details of the analyses are listed in Table 3.7. Note that 15 out of 18 features can be retrieved using only 78 query points, which reveals that we could use query points at resolutions coarser than 30 m since the feature density in this area is low. Moreover, we calculated the average computation time for each scenario by repeating the query process 10 times (Table 3.7) using a server with a two-core 2.3 GHz CPU, 4 GB memory, and stable network access in the university data center. The results reveal that the computation can be significantly reduced by selecting the query points close to the fire front and using larger sampling intervals. Moreover, parallel computing can also be used to speed up the computation. Thus, the proposed method for feature retrieval can also be effectively tailored for operational use. In terms of the computation time consumed for the whole method, the trigger modeling process is more time-consuming because a separate software package FlamMap is used to calculate fire spread rates.

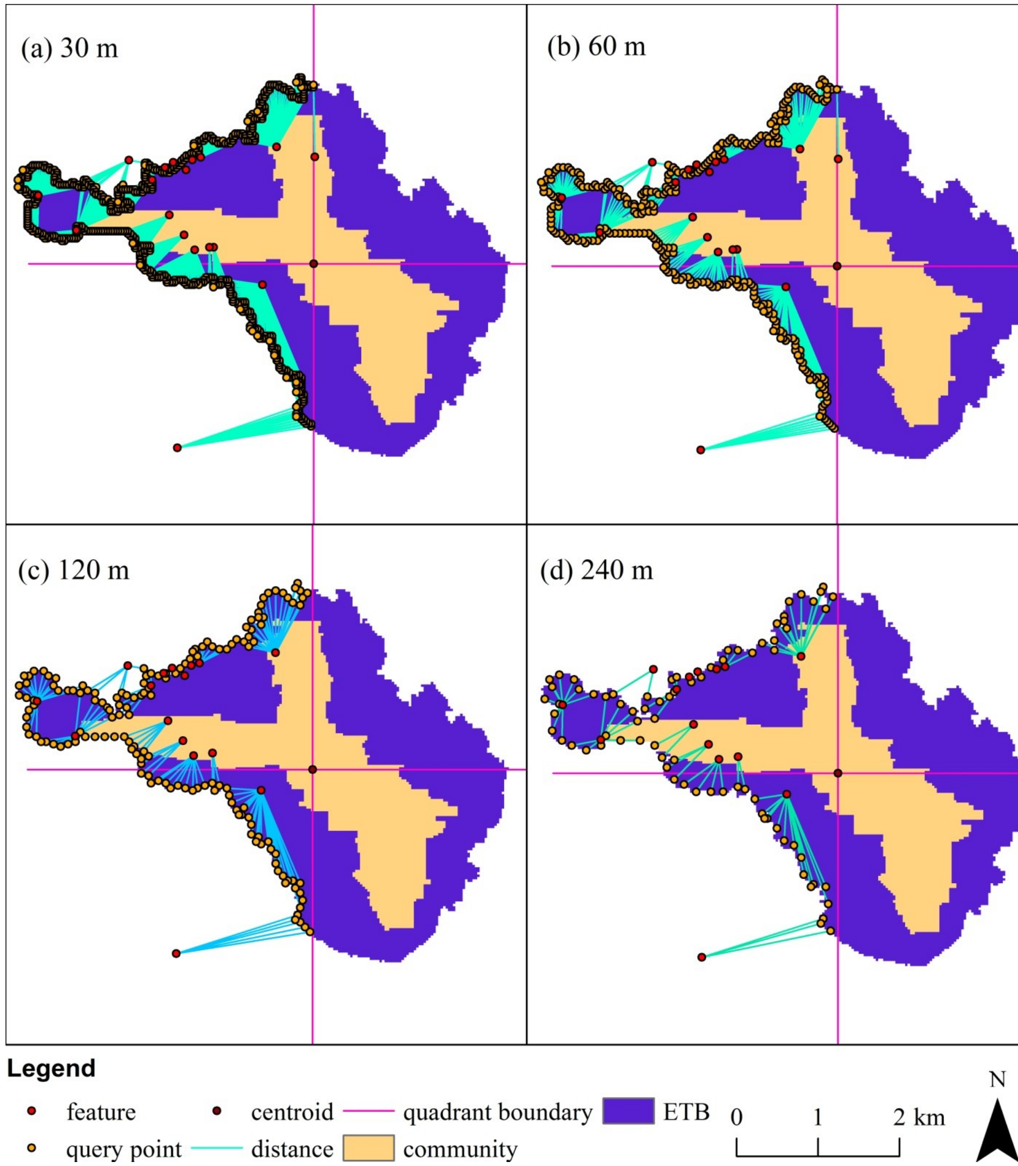


Figure 3.12 Reverse geocoding results for sampled query points

Table 3.7 Reverse geocoding results for different sampling intervals

Sampling interval	Number of query points	Number of features	Computation time (s)
1	612	18	198.67
2	306	18	98.8
4	154	16	49.4
8	78	15	26.1

3.6 Discussion

This section includes further discussions on several problems and implications concerning the proposed method. First, the method in this work involves the coupling of trigger modeling and reverse geocoding. Specifically, trigger modeling can be considered as a reverse fire spread modeling process, and the ignition is from the input residential area in the case study. In terms of data model in GIS, trigger modeling is based on the raster data model and the calculation of the ETB is based on the shortest path algorithm performed over a constructed fire travel-time graph. Since reverse geocoding is based on vector points, conversion between vector and raster model is used to fill the gap between trigger modeling and reverse geocoding. Specifically, when an ETB is given as the input for reverse geocoding, the centroids of its boundary cells are extracted and used as the query points. After the geographic features are derived using reverse geocoding, these features are converted to raster cells and used in the third step of the method to select the features that can satisfy the evacuation time constraints. Note that a graph is used to represent the boundary of the ETB and the DFS graph traversal algorithm is employed to search the graph and derive an array of query points that are spatially adjacent. These practices align with the model and data structure utilized in trigger modeling. Since a variety of data used in fire spread modeling are in raster format, it is simple to perform raster-based fire spread modeling and the computation involved is acceptable. However, compared to the vector data model, the raster model lacks representational accuracy. Thus, future work could be conducted to examine the feasibility of using the vector model in trigger modeling and compare the difference between the two models in the generated ETBs.

Second, this work uses a publicly available online reverse geocoding service to retrieve geographic features around the boundary of the ETB. With the popularity of cloud computing, software as a service (SaaS) is being widely adopted in geospatial cyber-infrastructure (Yang et al., 2011; Yang, Raskin, Goodchild, & Gahegan, 2010). As noted, online reverse geocoding services can be integrated into various information systems with ease. However, the black-box characteristics of these online services pose challenges in various applications. For example, accuracy and privacy have been considered significant concerns for using online geocoding services in crime studies (Kounadi et al., 2013). In the context of trigger modeling, the accuracy of these online services is important, while privacy may not be a big concern. Specifically, the importance of the accuracy of these services lies in that the accuracy of the locations of the derived features that are used as trigger points could determine the evacuation timing for the residents at risk during wildfire evacuation. Thus, further study should be done to examine the accuracy of these online reverse geocoding services to help develop a better understanding of them before they are used in real-world practices. Another direction for future research is to examine the spatial distribution of prominent geographic features in the WUI and its surrounding wildland area so as to evaluate the potential of using these features as trigger points in these areas.

Third, the geographic features retrieved from online reverse geocoding services are represented as geographic points, and the proposed method selects the features as trigger points based on the spatial relationship between them and the selection area calculated using the input time range. Note that a point can effectively represent small scale geographic features like a building but cannot represent features like rivers and roads with an accepted level of accuracy. Thus, we also need to take into account spatial representation when using features as trigger points. The feature retrieved from GeoNames is a point feature, while Eastwood Creek should be represented as a polyline feature. Note that when a linear feature is used as a trigger point, its orientation and the spatial relationship between it and the fire perimeters also influence its effectiveness. It is also worth mentioning that the features that could be used as trigger points could be at a very fine scale and may not be readily available from existing data sources. A digital gazetteer is defined as a collection of geographic names with their footprints and descriptions (Goodchild & Hill, 2008; Hill, 2000). GeoNames is a global gazetter, but the footprints of the features are points. As a matter of fact, in a typical digital gazetteer, the footprints of geographic features are no longer restricted to points but also can be represented using polylines and polygons. Thus, further research could be conducted to examine how to design and build a digital gazetteer to support trigger modeling. Specifically, the features derived from a gazetteer could be points, polylines, and polygons, which will involve more complex spatial analysis during the feature selection step. More efforts could be made in future work to compile detailed geographic data and build a special web service for trigger modeling. Local emergency managers could work with their planning departments to inventory prominent geographic features that could be used as trigger points and use them in evacuation planning.

Fourth, further research needs to be done to further examine the uncertainty associated with the input time for trigger modeling. In this work, 15 min was used to derive a time range to demonstrate the effectiveness of the proposed method. The input time for trigger modeling is usually based on the time needed for the safe evacuation of the threatened population (Cova et al., 2005). Trigger buffers generated using different input times could be associated with different PARs. For example, if the input time is larger than the time needed by the residents or firefighters to evacuate to safe places, the generated trigger buffer could serve as an ETB; otherwise it could be associated with SIP. Thus, more work needs to be done to model the uncertainty in the input time. When estimating evacuation times for a threatened WUI community, traffic simulation could be employed to achieve the goal (Cova & Johnson, 2002; Wolshon & Marchive III, 2007). And the model proposed by Lindell (2008) could be modified and leveraged to take into account findings from empirical studies and calculate the ETEs. Thus, evacuation traffic simulation could be performed to model the uncertainty in the input time from a statistical perspective, which will further improve trigger modeling.

3.7 Conclusion

The proposed method provides a means of associating the ETBs generated by trigger modeling with geographic features in the real world. The case study reveals that features close to buffer boundary and the fire front may have more value when used as trigger points. Also, salient features may also have more value because they make it much easier for officials (or residents) to detect when the trigger event has occurred. The proposed method can be used for both setting trigger points long before any actual fire occurs (strategic) and setting trigger points during a fire (operational) application. This supplements the existing trigger modeling method and makes it more applicable in real-world evacuation scenarios.

In conclusion, this work presents a method that supplements current trigger modeling by associating geographic features with the ETBs generated by trigger modeling, and the case study demonstrates the feasibility of the method for strategic and operational uses in wildfire evacuations. Note that the method represents a preliminary attempt toward making trigger modeling more applicable in real-world practices and could be further improved in the aspects mentioned in the discussion section. It is also worth mentioning that this line of research involves the use of prominent geographic features in exurban areas and may also be potentially employed in wilderness landmark-based navigation and search and rescue (SAR) (Duckham, Kulik, & Worboys, 2003; Millonig & Schechtner, 2007; Zhu & Karimi, 2015). Future work can focus on above-mentioned aspects so as to develop a better understanding of using salient geographic features to facilitate communications and navigation during wildfire evacuations.

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CHAPTER 4

SETTING WILDFIRE EVACUATION TRIGGERS BY COUPLING FIRE AND TRAFFIC SIMULATION MODELS: A SPATIOTEMPORAL GIS APPROACH

4.1 Abstract

Wildfire evacuation triggers are prominent geographic features utilized in wildfire suppression and evacuation practices, and when an approaching fire crosses a feature, an evacuation warning is issued to the communities or firefighters in the path of the fire. Current wildfire trigger modeling methods consider the evacuation time as an input from a decision maker and use fire spread modeling to create a trigger buffer around a threatened population. This paper extends the current trigger modeling method by coupling fire and traffic simulation models to set triggers using a spatiotemporal GIS framework. A key aspect of this framework is that evacuation time is estimated from traffic simulation models rather than expert judgment. A three-step method is proposed to couple the two models and evaluate the generated trigger buffers. The first step is to use traffic simulation to estimate a range of evacuation times for the threatened community. The second step calculates the cumulative probabilities for distinct evacuation times and generates probability-based trigger buffers. The last step evaluates the value of the generated buffers by coupling fire and traffic simulation models to examine the spatial

configurations of evacuation traffic and fire perimeters. A case study of Julian, California is used to test the proposed method. The results indicate that the proposed method improves the dynamic representation of evacuation traffic and fire spread during wildfire evacuations, which could help improve our understanding of wildfire evacuation timing and decision making. Finally, the paper concludes with the strengths and limitations of the proposed method, as well as future research directions.

4.2 Introduction

Wildfires are a common hazard in the western U.S. due to seasonal precipitation variability and frequent droughts, and studies have shown that the number of wildfires has increased in recent decades (Dennison, Brewer, Arnold, & Moritz, 2014; Westerling, Hidalgo, Cayan, & Swetnam, 2006). The Wildland-Urban Interface (WUI) is defined as the area where urban areas and wildlands meet or intermix (Stewart, Radeloff, Hammer, & Hawbaker, 2007). In the American West, with the rapid population increase in the WUI, wildfires pose a significant risk to many residents (Hammer, Stewart, & Radeloff, 2009), and public safety has become an increasing concern for fire-prone WUI communities (Brenkert–Smith, Champ, & Flores, 2006; Cova, 2005; Cova, Theobald, Norman, & Siebeneck, 2013; Paveglio, Carroll, & Jakes, 2008). Recommending timely and effective protective actions to the public is important when wildfires threaten life and property. The most common protective actions in wildfires include evacuation and shelter-in-place, and the latter can be further classified into shelter-in-refuge and shelter-in-home (Cova, Drews, Siebeneck, & Musters, 2009). In the U.S., shelter-in-place recommendations are rare, and evacuation is the primary protective action (Drews, Musters, Siebeneck, & Cova, 2014).

In the U.S., first responders are responsible for both wildfire suppression and evacuation when a fire poses a threat. Incident commanders (ICs) need to take into consideration the fire, the population in the risk area, as well as the evacuation route systems to evaluate the risk before they issue the most effective protective action notices to the residents at risk. Evacuating the right residents at the right time is a critical and challenging problem. Evacuating the residents too early might cause unnecessary community disruption and adversely affect the credibility of emergency managers if the fire does not ultimately threaten the evacuated residences, due to either successful fire suppression or the change of weather. Conversely, if the residents are evacuated too late, they could be placed in danger because they might not have enough time to safely leave the threat area (Handmer & Tibbits, 2005).

The reason evacuation timing is a complex problem in wildfire evacuation is two-fold. On one hand, the clearance time for communities at risk must be estimated before ICs can issue evacuation orders to the threatened residents. The total network clearance time is composed of the authorities' warning receipt time, the households' warning receipt time, preparation time, and vehicular travel time (Lindell, 2008). On the other hand, ICs have to estimate the available time for communities to evacuate before any orders can be made. The available time in this context refers to the time the residents have before the fire approaches the residences, which is primarily determined by fire progression rates. Thus, the complexity of evacuation timing puts decision makers in a difficult situation when they have to issue evacuation orders.

In wildfire suppression and evacuation, it is a common practice to use prominent geographic features such as ridges and rivers as trigger points (Cook, 2003). When a fire crosses a feature, the community or firefighters in the path of the fire will be notified to evacuate. A wildfire evacuation trigger is a timing mechanism that takes into account both spatial and temporal dimensions of the risk fire poses to the residents. Current trigger modeling methods employ fire spread modeling to calculate the fire spread rates and then use geographic information systems (GIS) methods to derive a buffer around a place *P* with a given time *T* using the shortest path algorithm (Cova, Dennison, Kim, & Moritz, 2005). If a fire crosses the boundary of the trigger buffer, the residents in the path of the fire should be notified to evacuate, and they will have time *T* for their safe evacuation. Trigger modeling can play a significant role in helping the ICs develop a better understanding of evacuation timing. However, the previously proposed method assumes that the total evacuation time *T* is given as an input from a decision maker, and time *T* could be estimated based on a more systematic method.

Wildfire evacuations occur in both time and space, and modern GIS has the capability to model complex spatiotemporal processes (Goodchild, 2013; Kwan, Richardson, Wang, & Zhou, 2015; Miller & Shaw, 2015; Yuan, Nara, & Bothwell, 2014). Traffic simulation has been widely used to estimate evacuation time in evacuation modeling for decades (Southworth, 1991) and can be used to estimate the input evacuation time *T* for trigger modeling. This purpose of this research is to couple fire and traffic simulation models by using a spatiotemporal GIS framework to improve our understanding of wildfire evacuation timing and better support evacuation decision-making. Specifically, the research questions to be addressed include: 1) how can the uncertainty in the evacuation time be modeled and represented when we couple fire and traffic simulation models to set triggers? 2) Will the estimated evacuation times from traffic simulation have value when they are used as the input for trigger modeling to create evacuation trigger buffers? 3) How can we evaluate the value of trigger buffers generated using the estimated evacuation times?

The remainder of this paper is organized as follows. Section 4.3 provides a literature review of evacuation traffic simulation, wildfire spread and trigger modeling, and spatiotemporal GIS. The proposed method is presented in section 4.4, and a case study of Julian, California is given in section 4.5. Finally, sections 4.6 and 4.7 end this paper with conclusions and future research directions.

4.3 Background

4.3.1 Evacuation traffic simulation

The traditional four-step demand model—trip generation, trip distribution, mode split, and traffic assignment—has been widely used in transportation planning to evaluate and balance demand and supply so as to build better transport systems (de Dios Ortúzar & Willumsen, 2001). Based on transportation planning models, Southworth (1991) formulated regional evacuation modeling 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 deals with modeling the number of trips that will be generated from the origins over a given duration of time (Pel, Bliemer, & Hoogendoorn, 2012). Note that the risk area should be delineated before we perform travel demand modeling (Wilmot & Meduri, 2005). In general, there are two kinds of travel demand models in evacuations: sequential travel demand modeling and simultaneous travel demand modeling (Pel et al., 2012). Sequential travel demand approaches involve modeling travelers' departure time choice, which is accomplished 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 (Cova & Johnson, 2002). "S-shaped" departure time curves have been widely used in travel demand modeling in evacuation studies (Lindell & Prater, 2007a). For example, Tweedie, Rowland, Walsh, Rhoten, and Hagle (1986) used a Rayleigh probability distribution function to approximate the mobilization time. The simultaneous travel demand models usually utilize some specific binary logit models to calculate the share of households that choose to evacuate over time, and the accuracy of these models relies on the utility functions used in evacuation decision-making modeling (Pel et al., 2012).

In general, traffic simulation models can be categorized into macroscopic, mesoscopic, and microscopic based on their levels of detail (Pel et al., 2012). With the rapid development of computing power, microscopic traffic simulation has enjoyed great popularity in evacuation modeling and simulation in recent years (Chen, Meaker, & Zhan, 2006; Cova & Johnson, 2002). The primary advantage of microscopic traffic simulation is that it can model detailed behaviors concerning the activity of a vehicle agent over the road network, which can be used to discover new knowledge concealed by macroscopic approaches (Chen & Zhan, 2008). Han, Yuan, and Urbanik (2007) put forward a four-tier measures of effectiveness (MOE) framework for evacuation: 1) evacuation time; 2) individual travel time and exposure time; 3) time-based risk and evacuation exposure; and 4) time-space-based risk and evacuation exposure. These MOEs could be derived by analyzing the results from a microscopic evacuation traffic simulation. Note that this work focuses on using traffic simulation to estimate the evacuation time of a community to provide input for trigger modeling.

4.3.2 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. Wildfire spread modeling includes several key steps: fuel type modeling, fire behavior modeling, and fire growth modeling. Different fuels are categorized into fuel models based on their physical characteristics. A fuel model usually includes its unique identification (ID) and key values for relevant physical characteristics for calculating fire behavior (e.g., fuel load, and fuel bed depth) (Anderson, 1982). Note that different countries usually develop and use different fuel model systems. In the U.S., two widely used fuel model systems are the 13 Anderson Fuel Models (Anderson, 1982) and the 40 Scott and Burgan Fuel Models (Scott & Burgan, 2005). The Rothermel fire behavior model (Rothermel, 1972), a semiphysical model that uses mathematical equations calibrated by empirical experiments to model rate of spread and fire intensity, has been widely used in many fire modeling software systems, e.g., FlamMap (Finney, 2006) and FarSite (Finney, 1998). The elliptical fire shape model has been widely used to model fire spread rates on a two-dimensional plane (Van Wagner, 1969). Fire growth models are used to model the propagation of fire in the landscape, and growth models include the minimum fire travel time model (Finney, 2002) and the cellular automata (CA) model

(Clarke, Brass, & Riggan, 1994). Wildfire simulation has been widely used in a variety of applications, e.g., wildfire management (Alexandridis, Russo, Vakalis, Bafas, & Siettos, 2011), wildfire risk assessment in the WUI (Massada, Radeloff, Stewart, & Hawbaker, 2009), and evaluation of wildfire risk on wildlife habitat (Ager, Finney, Kerns, & Maffei, 2007).

Wildfire evacuation triggers are agreed-upon prominent geographic features in the landscape, which are used by emergency managers to issue evacuation orders or take other emergency response measures should a fire cross one (Cook, 2003; Cova et al., 2005). Typical wildfire evacuation triggers include prominent features like ridge lines, rivers, and roads. Based on the trigger mechanism in hurricane evacuations, Cova et al. (2005) introduced the idea of modeling triggers in wildfire evacuations and proposed a method that uses fire spread modeling and GIS to set triggers. Dennison, Cova, and Moritz (2007) formulated trigger modeling into a three-step model: 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 (Dijkstra, 1959). Previous studies have shown that trigger modeling could be potentially used in protecting firefighter crews (Cova et al., 2005; Fryer, Dennison, & Cova, 2013), community evacuation planning (Dennison et al., 2007; Larsen, Dennison, Cova, & Jones, 2011), and pedestrian safety protection in the wildlands (Anguelova, Stow, Kaiser, Dennison, & Cova, 2010). Note that the previously proposed trigger modeling method considers the evacuation time as a given input from a decision maker, and the work herein examines how to employ traffic simulation to estimate the evacuation time.

4.3.3 Spatiotemporal GIS

GIS was designed and used to store, manage, process, and analyze static spatial data in the early stages of its development (Chang, 2012). However, many geographic phenomena are complex spatiotemporal processes, which calls for more advanced GIS capabilities to model and represent both the spatial and temporal dimensions of these phenomena (Langran & Chrisman, 1988). Space-time modeling and representation in GIS can be generally divided into two categories: the discrete and the continuous view (Peuquet, 2001). The discrete view focuses on representing and modeling the movements of discreet objects in the space over time, and this line of research is characterized by time geography (Hägerstraand, 1970), which has enjoyed great popularity in mobility studies in the past few years (Miller & Shaw, 2015). Specifically, in the context of wildfire evacuation, the evacuees can be represented as moving objects within the road network over time. The continuous view concerns representing objects as attributes attached to a location (Peuquet, 2001). In this regard, wildfire spread and trigger buffer can be represented and modeled as a raster polygon with fire travel time as an attribute. This work focuses on developing a GIS framework to study the space-time coupling of fire and traffic simulation models for trigger modeling. Recent years have witnessed the development of many space-time methods that support spatiotemporal queries (Pultar, Cova, Yuan, & Goodchild, 2010; Pultar, Raubal, Cova, & Goodchild, 2009; Yuan, 2001), and these methods could be employed to perform spatiotemporal queries and computation in the model coupling process in this work.

4.4 Research method

Spatial representation to a large degree determines the methods used in subsequent modeling and analysis practices (Miller & Wentz, 2003). Trigger modeling uses the raster data model to represent the landscape. Figure 4.1(a) illustrates wildfire spread modeling, in which the fire starts from the ignition point and spreads outwards to create a series of perimeters. 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 trigger buffer, as shown in Figure 4.1(b). If a trigger buffer is generated for a given input time *T*, the threatened population in the input residential area will have time *T* to evacuate to safe places when a fire crosses the boundary of the buffer. Note that this 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

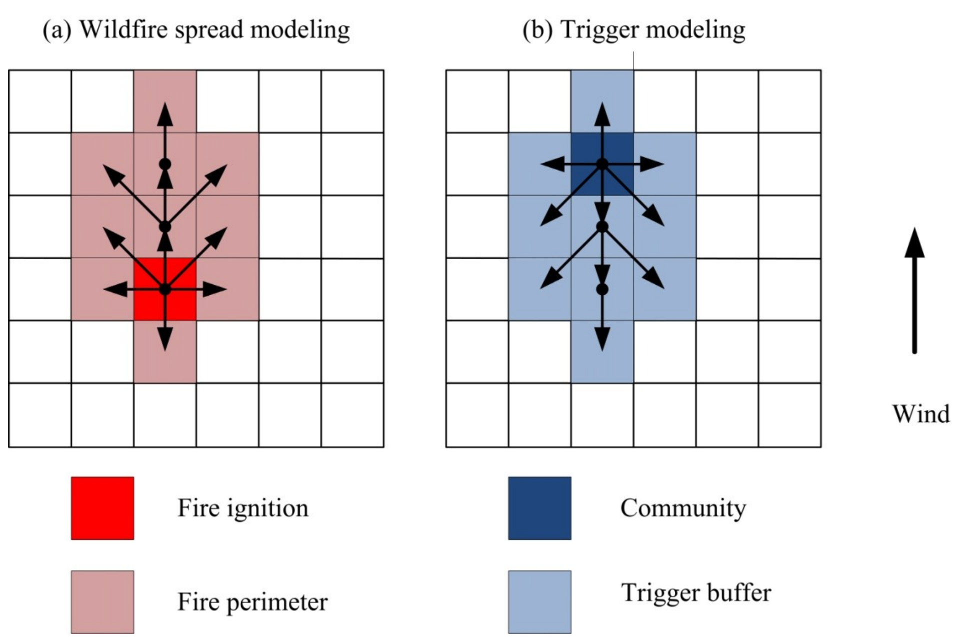


Figure 4.1 Illustration of wildfire spread and trigger modeling

direction, while the trigger buffer is skewed in the opposite direction. Similar to the time-space convergence concept in transport geography (Janelle, 1969), wildfire spread and trigger modeling are based on time distance rather than Euclidean distance (Gatrell, 1983). In the context of community wildfire evacuation, the ICs need to make protective-action selections based on how much time is available before the fire reaches the threatened communities and how long it will take for the safe evacuation of the threatened population. Thus, evacuation timing plays a significant role in the ICs' evacuation decision making.

Wildfire evacuation occurs in both space and time. When a fire approaches a community and becomes a threat to the residents, relevant protective action recommendations may be issued. From a wildfire risk perspective, trigger modeling can be considered as an evacuation timing and warning mechanism based on fire risk. Yuan (1997) 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 two 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 used to couple fire and traffic simulation models, as shown in Figure 4.2. Evacuation traffic takes place in the road network, which is a constrained geographic space. The estimated evacuation times are used as the input for trigger modeling. As for fire spread modeling, geographic distance between two adjacent raster cells is converted to fire travel times in different

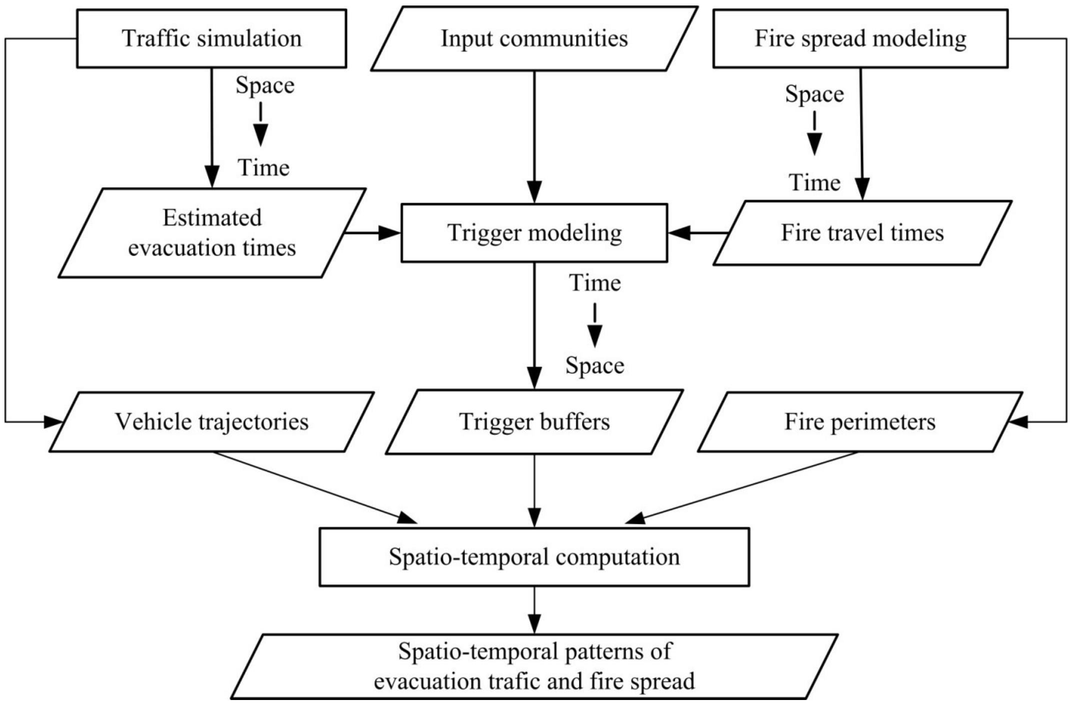


Figure 4.2 A spatiotemporal GIS framework for model coupling

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 account both evacuation and fire travel times. After the buffers are generated, fire and traffic simulation models are coupled to perform spatiotemporal computation and reveal the spatiotemporal patterns of evacuation traffic and fire spread. The following three subsections introduce the detailed steps of the coupling process.

4.4.1 Step 1: estimate evacuation time using traffic simulation

In the first step, traffic simulation is performed to estimate the evacuation time of a fire-prone community. Specifically, microscopic traffic simulation is used for evacuation time estimation. Based on the five-step evacuation modeling procedure proposed by Southworth (1991), the workflow for estimating evacuation time is shown in Figure 4.3. Since wildfire evacuations are usually at a smaller geographic scale than hurricane evacuations, household-level travel demand modeling has enjoyed great popularity (Cova & Johnson, 2002; Wolshon & Marchive, 2007). Thus, household data are used to generate evacuation travel demand. Since the exact number of vehicles for each household is unknown, a statistical distribution is usually used to assign a number to each household as the number of vehicles, e.g., the Poisson distribution (Cova & Johnson, 2002). Thus, a Poisson distribution is used 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 estimating evacuation time. It is assumed that all the households will choose to 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

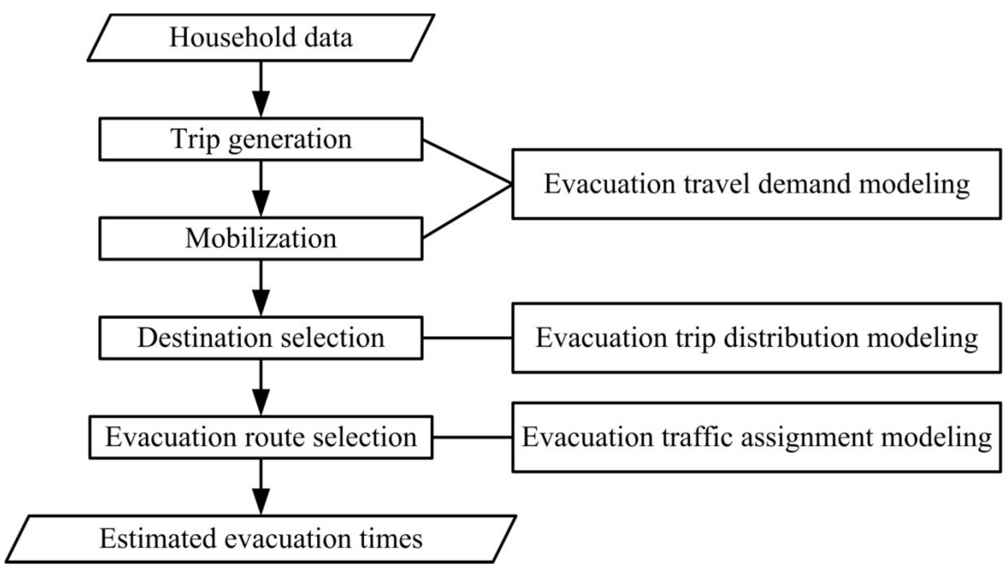


Figure 4.3 Workflow of traffic simulation

will choose the closest egress. Finally, the assumption used for route selection is that all the evacuees will choose the shortest path.

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. (2007) point out that the evacuation time to 95% population evacuated is more practically meaningful compared to a complete 100% evacuation rate. Thus, the evacuation times when 50%, 75%, 95%, and 100% of the population have arrived at the destination are calculated to evaluate the value of the estimated evacuation times as input for trigger modeling. And the four estimated evacuation times are denoted with T_{50}, T_{75}, T_{95}, and T_{100}, respectively, as shown in Figure 4.4. For a given evacuation scenario, trip distribution and traffic assignment could be considered constant, and the evacuation travel demand will vary in each run of the simulation. Finally, *n* sets of four estimated evacuation times can be derived from *n* runs of simulation, and these evacuation times are used as the input to create trigger buffers in trigger modeling. Note that many traffic microsimulators have the capabilities to

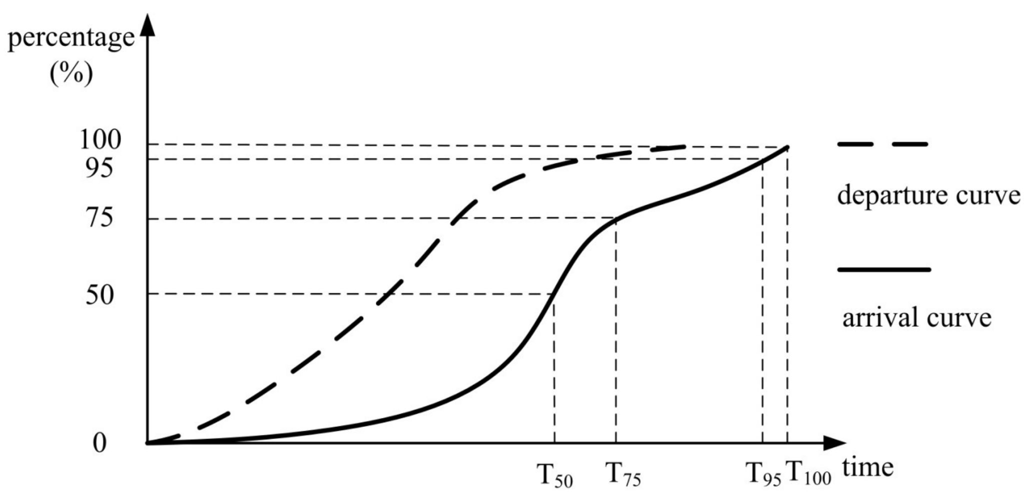
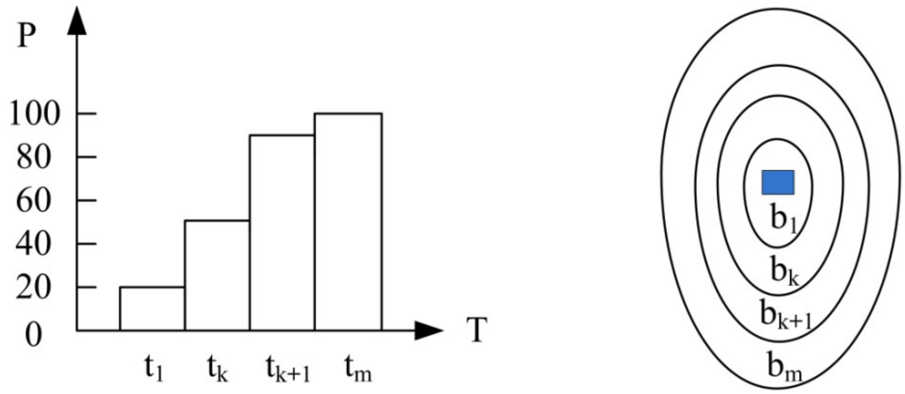


Figure 4.4 Illustration of the four estimated evacuation times

simulate the traffic using second as the time step. The final estimated evacuation times are converted to minutes since the temporal resolution for fire spread and trigger modeling is a minute.

4.4.2 Step 2: generate probability-based trigger buffers

In this step, the estimated evacuation times from Step 1 are aggregated and then used to generate probability-based trigger buffers. Note that since there could be repeated values in the n input evacuation times, the total number of unique evacuation times m should be no larger than n ($1 \leq m \leq n$). All the m distinct estimated evacuation times for a specific scenario are sorted in an ascending order and can be denoted with a set $T_e = \{t_1, \ldots, t_m\}$. Let f_k ($1 \leq k \leq m$) be the cumulative frequency of evacuation time 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 Figure 4.5(a). In this way, a trigger buffer b_k is associated with a probability value p_k. As shown in Figure 4.5(b), the probability of the outmost trigger buffer b_m is p_m = 100%. We need to associate the generated trigger buffer surface with the evacuation traffic simulation when interpreting the results. For any evacuation time $t_k \leq t_{k+1}$ ($1 \leq k <$ m), the generated trigger buffer b_k will fall within b_{k+1}. For the outmost surface b_m, all the trigger buffers generated fall within it, 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 surface b_1 as the trigger buffer in this evacuation scenario, the probability that it can ensure the successful completion of the evacuation will be p_1.



(a) Cumulative probability (b) Probability-based trigger buffers

Figure 4.5 Illustration of probability-based trigger buffers

The three-step procedure for trigger modeling is used to create trigger buffers, as shown in Figure 4.6 (Dennison et al., 2007). First, the fire spread modeling software package FlamMap is used to calculate the fire spread rates in eight directions for each raster cell. Second, the fire spread rates are used to compute the travel times between adjacent raster cells and construct a fire travel-time graph. Note that the nodes are the centroids of the cell and the weights of the edges denote the travel time from one node to its neighbor in that direction. Third, the edges in the graph are reversed and the Dijkstra (1959) 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*. Note that a trigger buffer is represented by a raster polygon around the community. 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 evacuation time and 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.

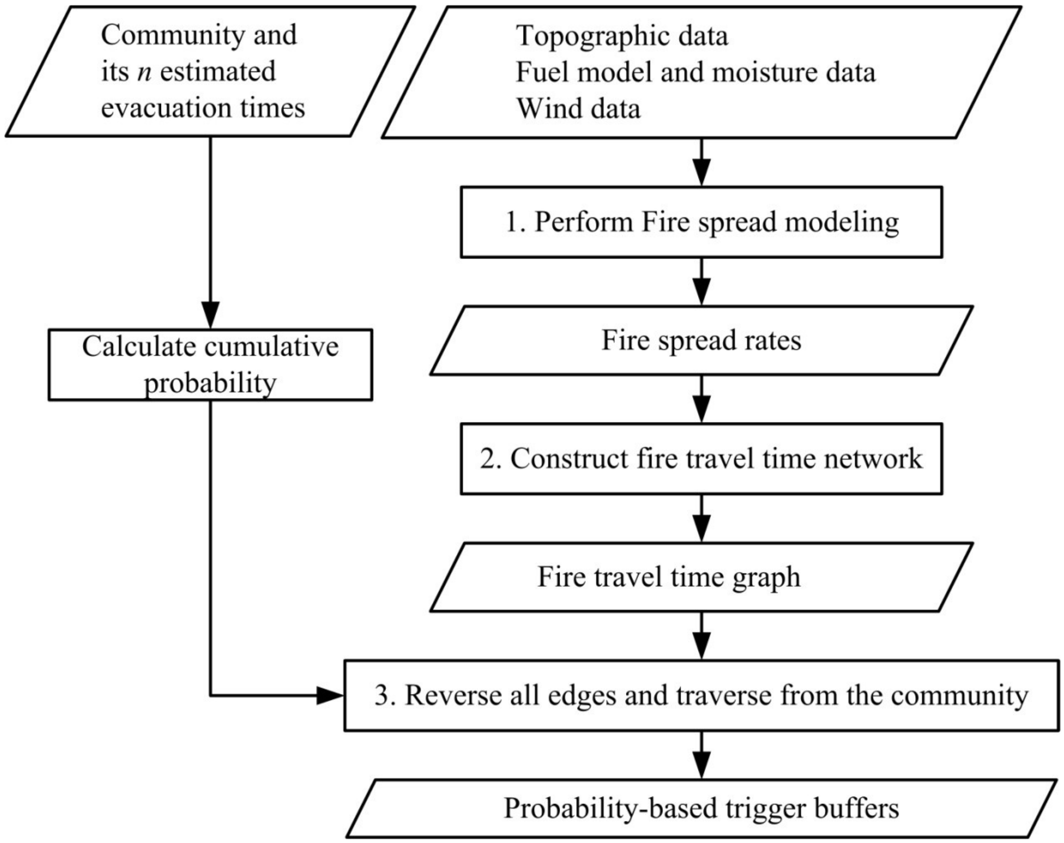


Figure 4.6 Workflow of creating probability-based trigger buffers

4.4.3 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 trigger buffers generated in Step 2. The conceptual diagram of the evaluation procedure is given in Figure 4.7. 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, and 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 to construct a fire simulator. 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.

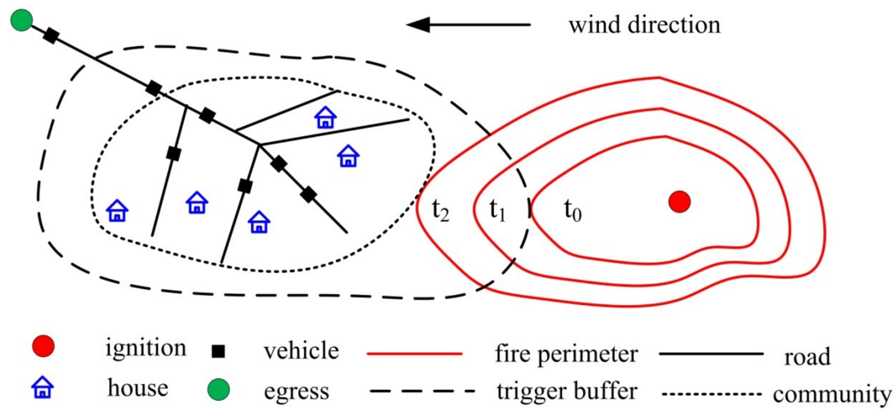


Figure 4.7 Conceptual diagram of the evaluation procedure

After evacuation warnings are sent out, vehicles start to depart from the household origins and travel towards the egress nodes. In order to better evaluate the value of the generated trigger buffers, wildfire simulation is used to examine the spatial relationship between fire front and the vehicles en route. Beloglazov, Almashor, Abebe, Richter, and Steer (2016) used person-threat distance to measure evacuees' exposure to fire risk during the evacuation process. 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 en route at time step t_2 when the fire reaches the community is calculated, as shown in Figure 4.7. The trajectory of a vehicle v can be represented with a series of points with corresponding times $TP(v) = \{tp_1, \ldots, tp_1\}$. 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 model 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. In this way, we could develop a better understanding of the potential use of the estimated evacuation times in trigger modeling.

4.5 Case study

Southern California is one of the areas that are 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 Figure 4.8, there are three 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.

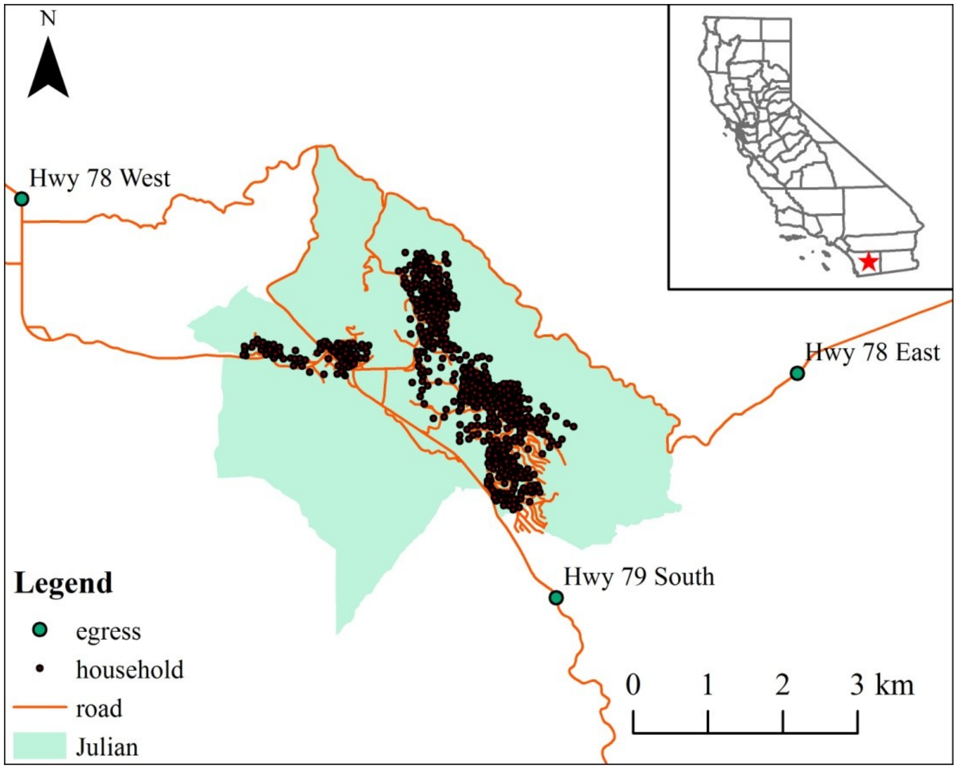


Figure 4.8 Map of Julian, California

Coding of the road network used to take a significant amount of time and efforts (Cova & Johnson, 2002). With the development of traffic simulators, existing road GIS data from various sources can be readily used in modern traffic simulation software. In this study, the evacuation module of an open-source traffic microsimulation software package named MATSim was used to perform traffic simulation and estimate the evacuation time (Lämmel, Grether, & Nagel, 2010). The road network data were from OpenStreetMap, a crowd-sourcing open data initiative with millions of contributors all over the world (Haklay & Weber, 2008). OpenStreetMap uses points, polylines, and polygons to represent various geographic features. Relevant tags are used to organize various attributes, and users can retrieve attributes from a feature record conveniently. The data from OpenStreetMap can be readily used in MATSim (Goetz & Zipf, 2012).

The downloaded road data were edited using an open-source tool named Java OpenStreetMap Editor (JOSM) and its MATSim plugin. Specifically, the speed limits of the highways and residential roads were set to 17.882 m/s (40 mph) and 11.176 m/s (25 mph), respectively, during the network coding process.

Egress points will also be the nodes on the road network and will be used as destination nodes. Points of egress could be derived from a specific local evacuation plan or from previous evacuation practices. 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. (Wolshon & Marchive, 2007), 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. Specifically, the mean values used for the Poisson distribution were 2, 3, and 4. As for the departure times, two normal distributions with different standard deviations were used. As shown in Table 4.1, six scenarios with different combinations of travel demand and departure time profiles were used. 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 the evacuation times. Note that the normal distribution is used for computation convenience, and use of this specific distribution does not affect the generalizability of the method.

Table 4.1 Parameters for different evacuation scenarios

Scenario	λ	μ (min)	σ (min)	earliest (min)	latest (min)
1	2	40	5	0	80
2	2	40	20	0	80
3	3	40	5	0	80
4	3	40	20	0	80
5	4	40	5	0	80
6	4	40	20	0	80

The calculated evacuation time estimates (ETEs) as well as their cumulative probabilities are listed in Table 4.2. Note that we calculated the evacuation times when 50%, 75%, 95%, and 100% of the evacuees have arrived at the safe areas for each scenario. We also summarized the minimum, mean, maximum, and standard deviation of the evacuation times for each case. The corresponding cumulative probability values are shown in the parentheses. These estimated evacuation times can be used as the input for trigger modeling to generate trigger buffers, and each trigger buffer will be associated with the probability that it could ensure the successful completion of that evacuation for that specific scenario.

Relevant data for fire spread modeling were prepared beforehand. These data 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 wildfire studies (Rollins, 2009). The spatial resolution of all the 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

Table 4.2 Cumulative probabilities for four ETEs (unit: min) in six scenarios

Scenario		1	2	3	4	5	6
T_{50}	min	75(1%)	78(4%)	106(1%)	105(1%)	137(1%)	139(2%)
	mean	81.5(64%)	82.3(56%)	113.4(53%)	112.4(52%)	145.1(58%)	144.3(55%)
	max	88(100%)	88(100%)	122(100%)	119(100%)	155(100%)	151(100%)
	sd	2.6	2.4	3.5	2.7	3.2	2.7
T_{75}	min	111(2%)	113(2%)	159(1%)	158(1%)	209(1%)	210(1%)
	mean	118.7(55%)	119.1(56%)	169(52%)	168.1(51%)	219.4(58%)	218.8(63%)
	max	127(100%)	128(100%)	182(100%)	179(100%)	233(100%)	229(100%)
	sd	3.5	3.4	4.6	3.8	4.4	4.0
T_{95}	min	139(1%)	141(2%)	201(1%)	200(1%)	266(1%)	268(1%)
	mean	148.6(56%)	148.7(58%)	213.6(55%)	212.7(53%)	278.9(57%)	278.4(57%)
	max	159(100%)	160(100%)	229(100%)	227(100%)	295(100%)	292(100%)
	sd	4.4	4.2	5.5	4.9	5.5	5.1
T_{100}	min	146(1%)	148(1%)	211(1%)	211(2%)	280(1%)	282(1%)
	mean	156(53%)	156.2(52%)	224.8(54%)	223.9(51%)	293.8(57%)	293.3(57%)
	max	167(100%)	168(100%)	241(100%)	239(100%)	311(100%)	308(100%)
	sd	4.6	4.3	5.7	5.2	5.8	5.4

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 wood and herbaceous fuel moistures were set to 65%.

The generated probability-based trigger buffers for scenario 1 are shown in Figure 4.9. When the fire crosses the boundary of the outmost 88 min trigger buffer in Figure 4.9(a), the probability that the lead time could ensure the successful completion of the evacuation in which 50% of the evacuees have arrived at the safe areas for this case is 100%; if we use the minimum 75 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 100%

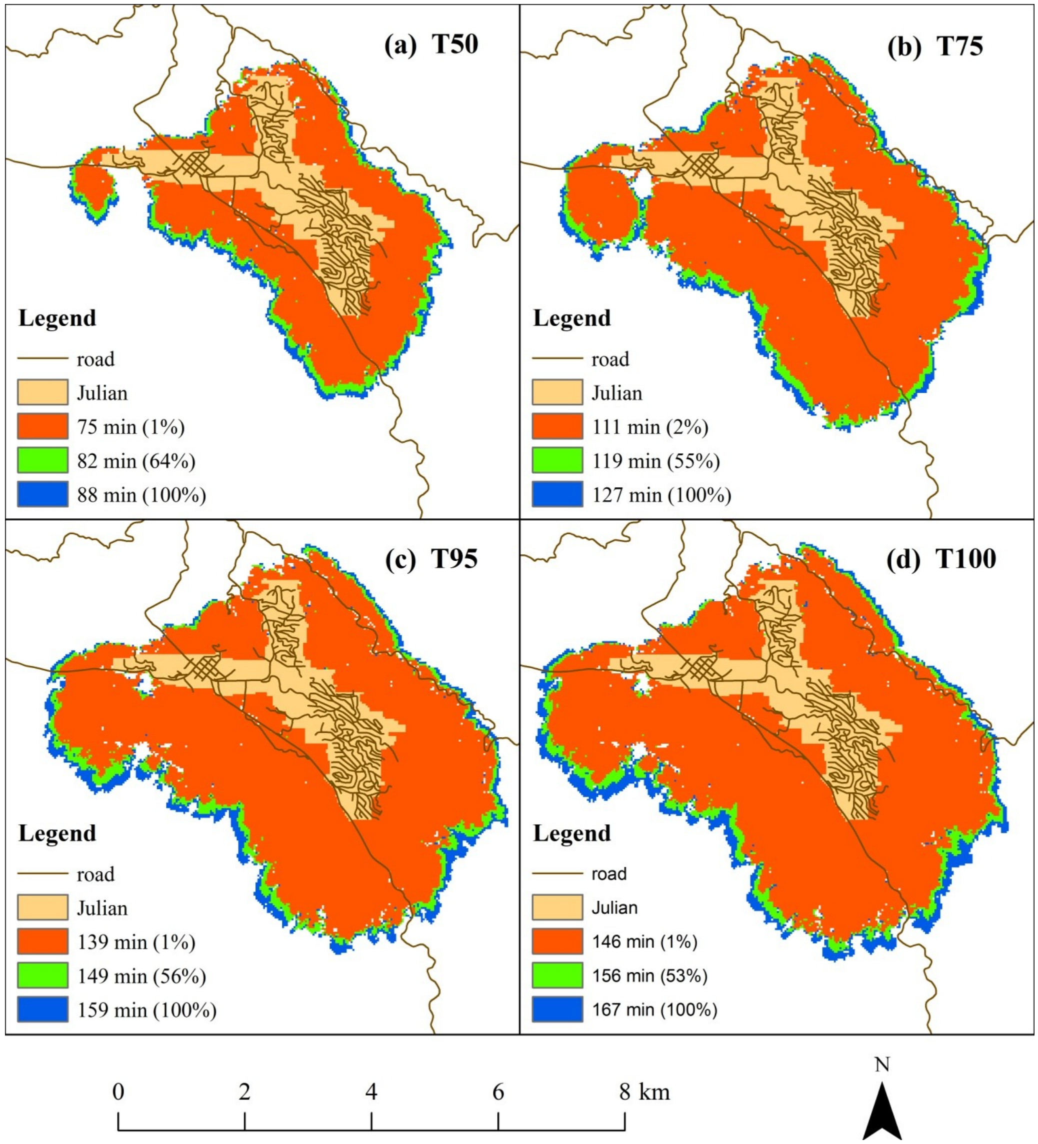


Figure 4.9 Generated probability-based trigger buffers for scenario 1

evacuation is 167 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 Figure 4.10. The evacuation times and sizes of trigger buffers increase with the increase of evacuation travel demand. For scenarios with the same travel demand, the speed of evacuation has little influence on the total evacuation time. We constructed a fire simulator using the fire spread rates from FlamMap and the shortest path algorithm and employed wildfire simulation to evaluate the value of the derived trigger buffers in Figure 4.10. As shown in Figure 4.11 (the numbers in the map denote fire travel times), the fire ignition point is located 4 km from the boundary of the residential area. Note that the fire perimeters are skewed downwind and the trigger buffers are skewed upwind. When the fire reaches the boundary of a trigger buffer at time t_0, the threatened residents are warned to evacuate; when the fire reaches the boundary of the community at time t_2, the residents are in the midst of evacuation and the person-threat distances at this moment were calculated. The calculated fire travel times are shown in Table 4.3. Note that time T denotes the input times for trigger modeling and the maximum evacuation times from Table 4.2 were used. The time $t = t_2 - t_0$ computed from fire simulation aligns with the input time T. The locations of the en route vehicles were extracted at time t from the results of traffic simulation and the person-threat distances were computed. Table 4.4 gives the statistics of the person-threat distances for one run of the 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 times for T_{100} are used for trigger modeling, all 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).

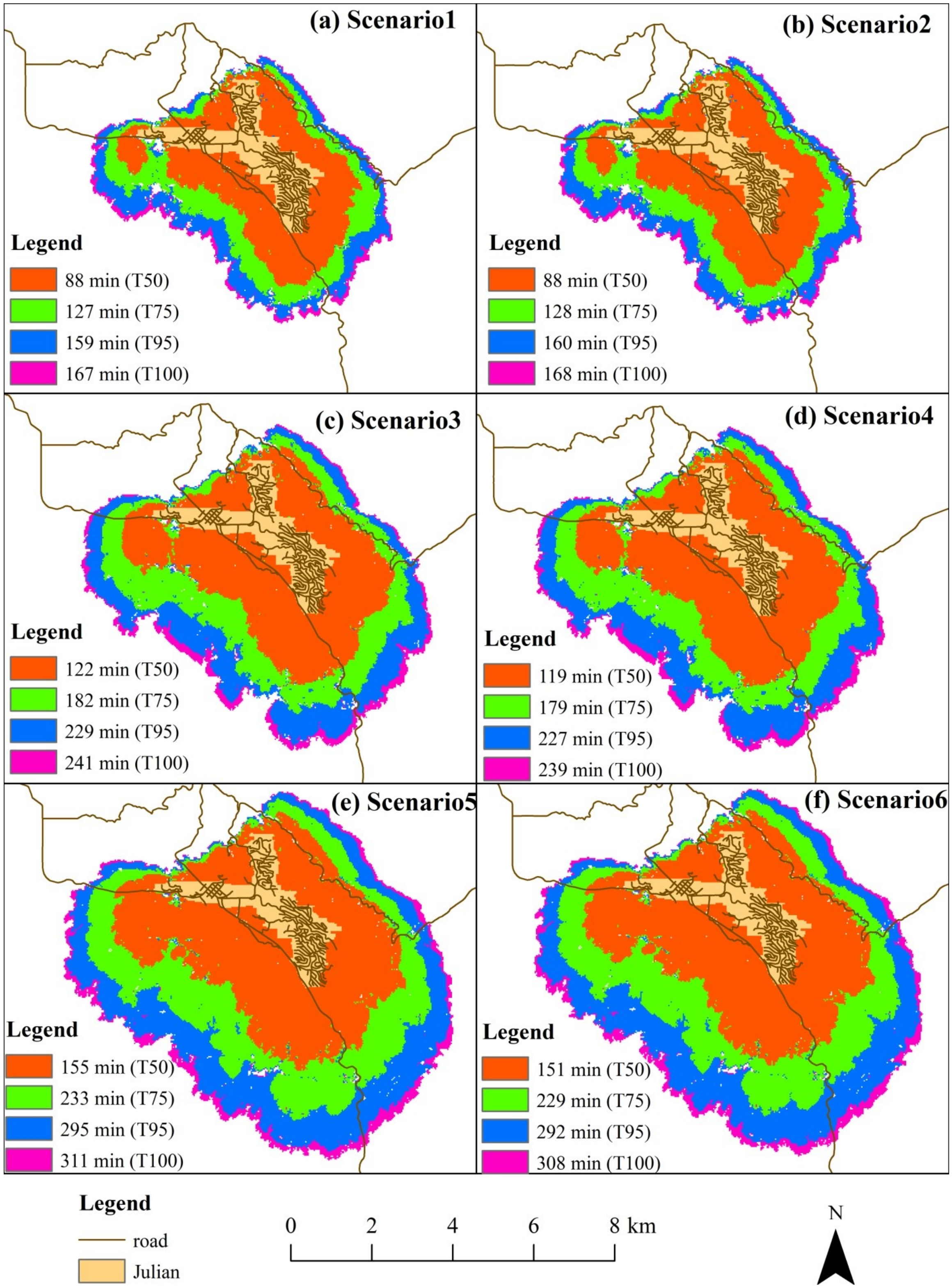


Figure 4.10 Trigger buffers generated using 100% evacuation times for six scenarios

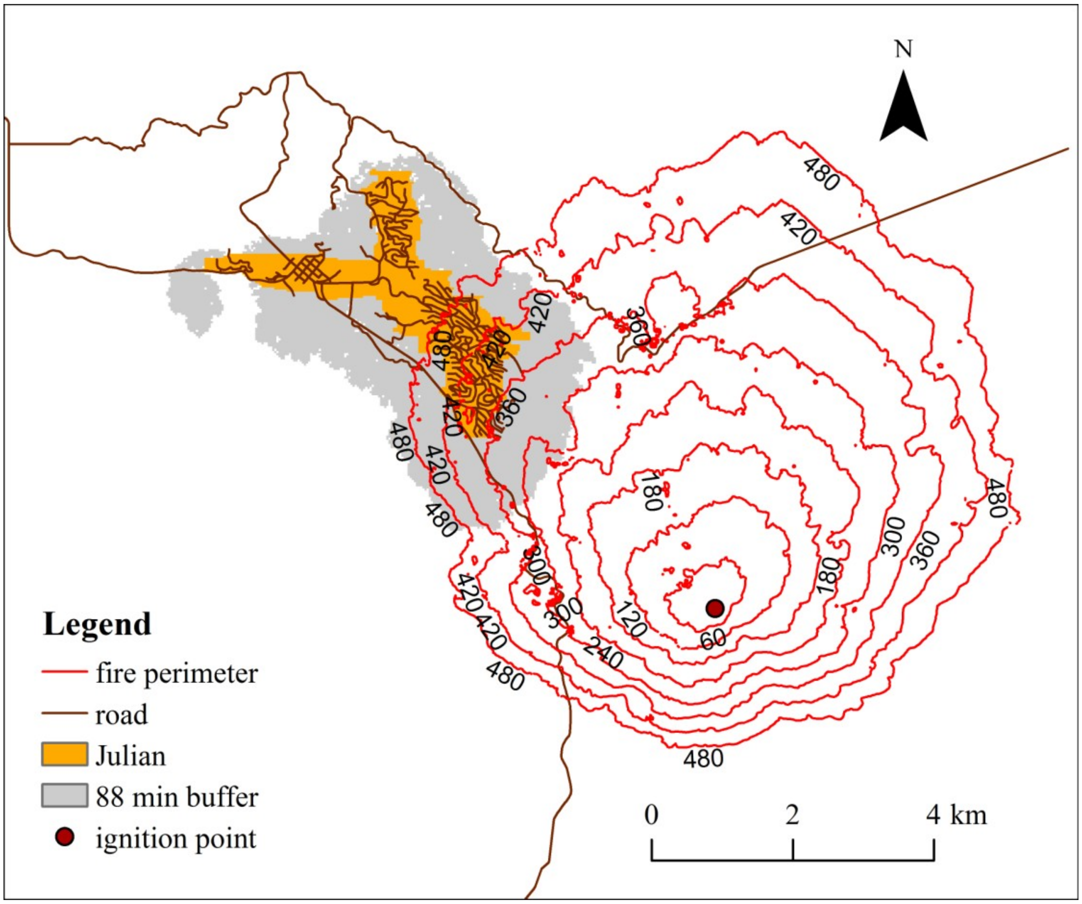


Figure 4.11 Fire perimeters from wildfire simulation

Table 4.3 Derived fire travel times from fire simulation (unit: min)

Scenario		1	2	3	4	5	6
T_{50}	T	88	88	122	119	155	151
	t_0	264	264	230	233	196	200
	t_2	351	351	351	351	351	351
	t	87	87	121	118	155	151
T_{75}	T	127	128	182	179	233	229
	t_0	227	224	169	173	119	122
	t_2	351	351	351	351	351	351
	t	124	127	182	178	232	229
T_{95}	T	159	160	229	227	295	292
	t_0	193	193	122	124	57	60
	t_2	351	351	351	351	351	351
	t	158	158	229	227	294	291
T_{100}	T	167	168	241	239	311	308
	t_0	185	185	112	114	41	47
	t_2	351	351	351	351	351	351
	t	166	166	239	237	310	304

Table 4.4 Person-threat distances for different scenarios in one run (unit: m)

Scenario		1	2	3	4	5	6
T_{50}	min	2,106.9	2,106.9	1,778.6	2,078.7	1,778.6	1,778.6
	mean	3,187.0	3,232.3	2,940.7	3,013.6	2,813.1	2,838.4
	max	9,457.6	9,457.6	9,457.6	9,457.6	9,400.7	9,457.6
	sd	1,507.9	1,554.8	1,298.9	1,260.1	1,105.6	1,089.7
T_{75}	min	2,574.7	2,810.8	2,574.7	2,574.7	2,574.7	2,574.7
	mean	4,100.3	4,564.6	3,776.9	3,650.5	3,267.7	3,233.2
	max	9,457.6	9,457.6	9,457.6	9,400.7	9,400.7	9,457.6
	sd	1,933.6	1,998.9	1,816.2	1,746.5	1,491.0	1,464.1
T_{95}	min	9,692.8	9,692.8	9,692.8	9,692.8	8,935.8	6,827.2
	mean	9,692.8	9,692.8	9,692.8	9,692.8	9,198.0	8,045.2
	max	9,692.8	9,692.8	9,692.8	9,692.8	9,457.6	9,457.6
	sd	0	0	0	0	195.6	737.0
T_{100}	min	9,692.8	9,692.8	9,692.8	9,692.8	9,692.8	9,692.8
	mean	9,692.8	9,692.8	9,692.8	9,692.8	9,692.8	9,692.8
	max	9,692.8	9,692.8	9,692.8	9,692.8	9,692.8	9,692.8
	sd	0	0	0	0	0	0

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 mapped out in Figures 4.12-4.14. The vehicles were aggregated at the link level and the vehicle counts for the links were also visualized. The maps indicate that for each scenario more en route evacuees are closer to the fire front when small trigger buffers are used. 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

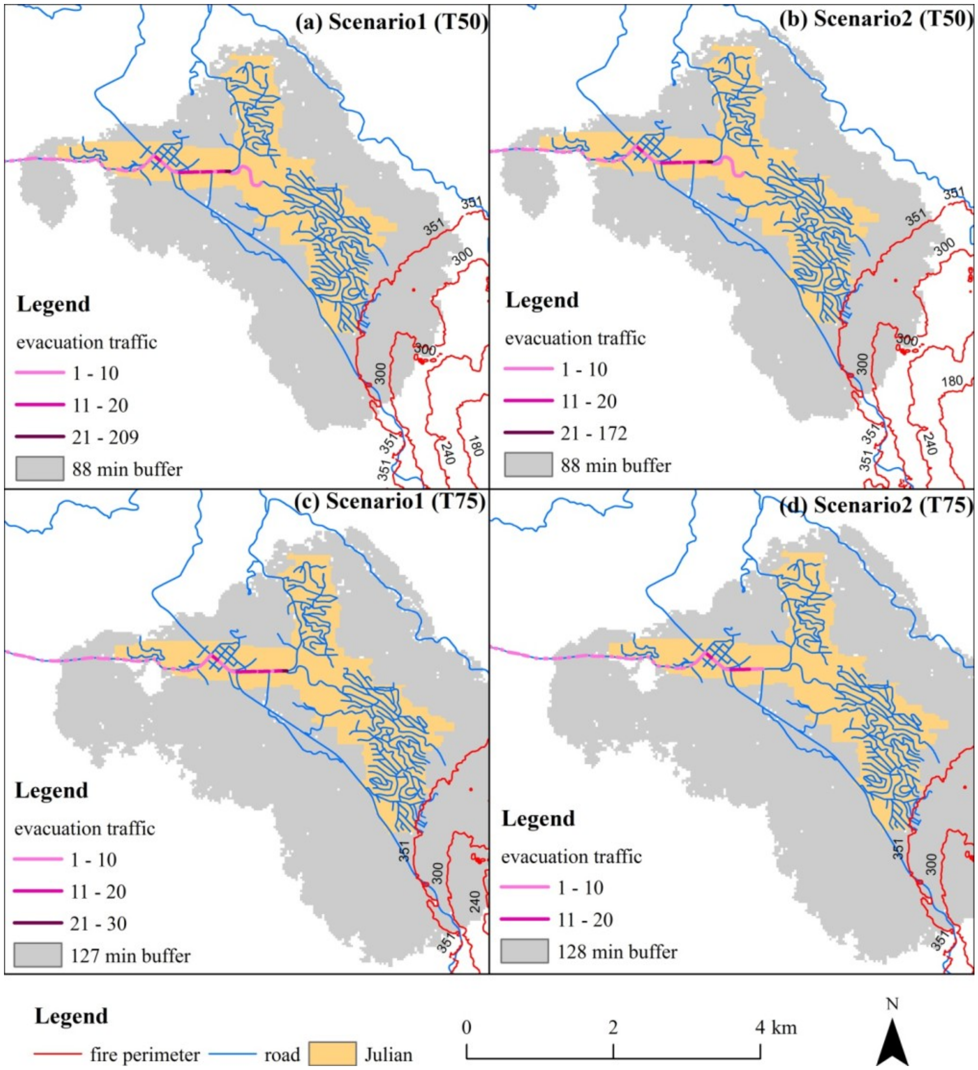


Figure 4.12 Evacuation traffic for scenario 1 and 2

exposed to the fire risk. If the congested link is located close to the fire front, the fire could trap the evacuees en route and cause deaths. Moreover, with the increase of evacuation travel demand, more evacuees will be exposed to fire risk. The results from 100 runs of traffic simulation for each scenario were aggregated to obtain all the links that have evacuation traffic when the fire reaches the community. As shown in Figures 4.15-4.17, the above-mentioned findings are still very evident for all the links with evacuation traffic in the 100 runs of traffic simulation.

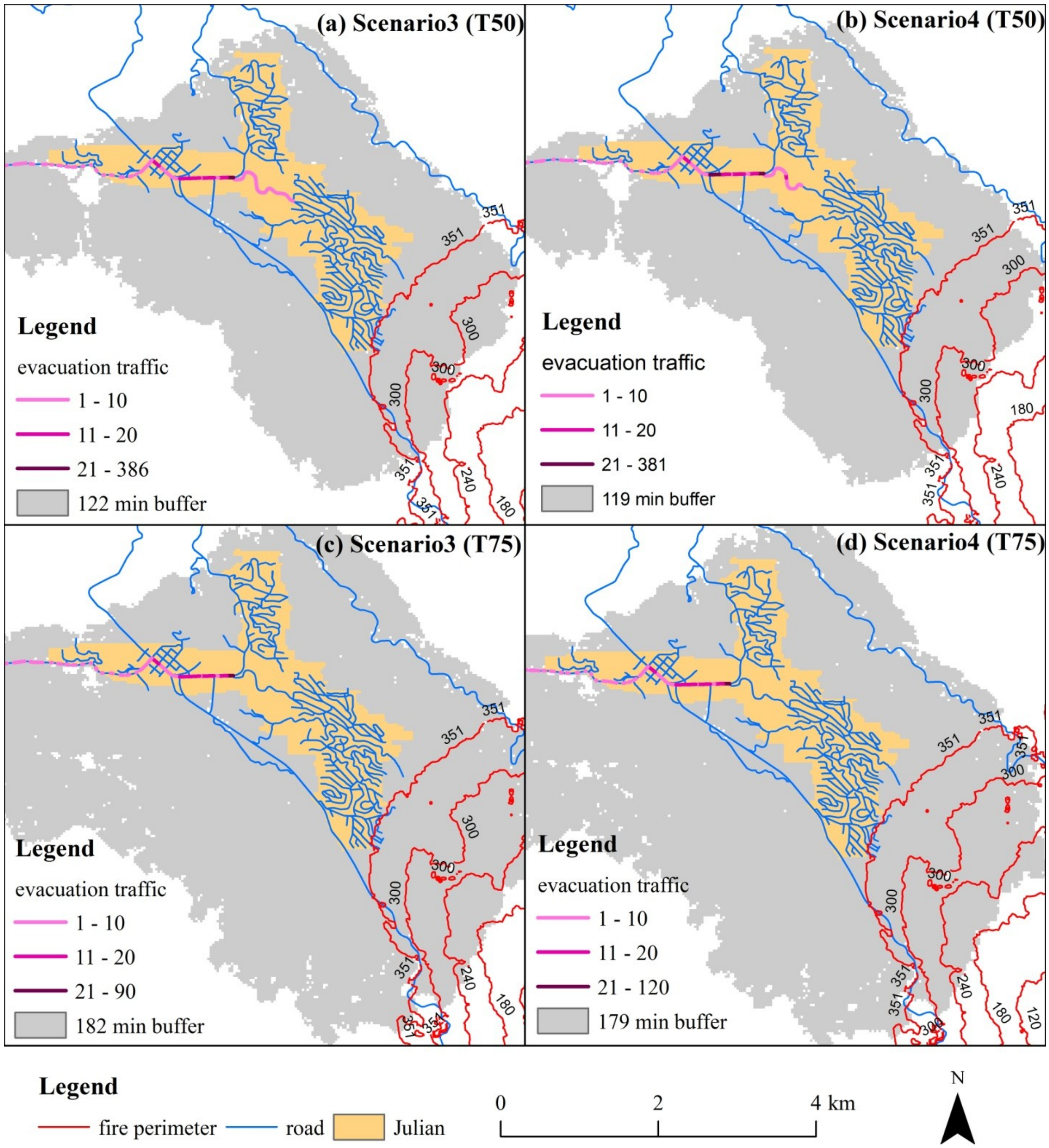


Figure 4.13 Evacuation traffic for scenario 3 and 4

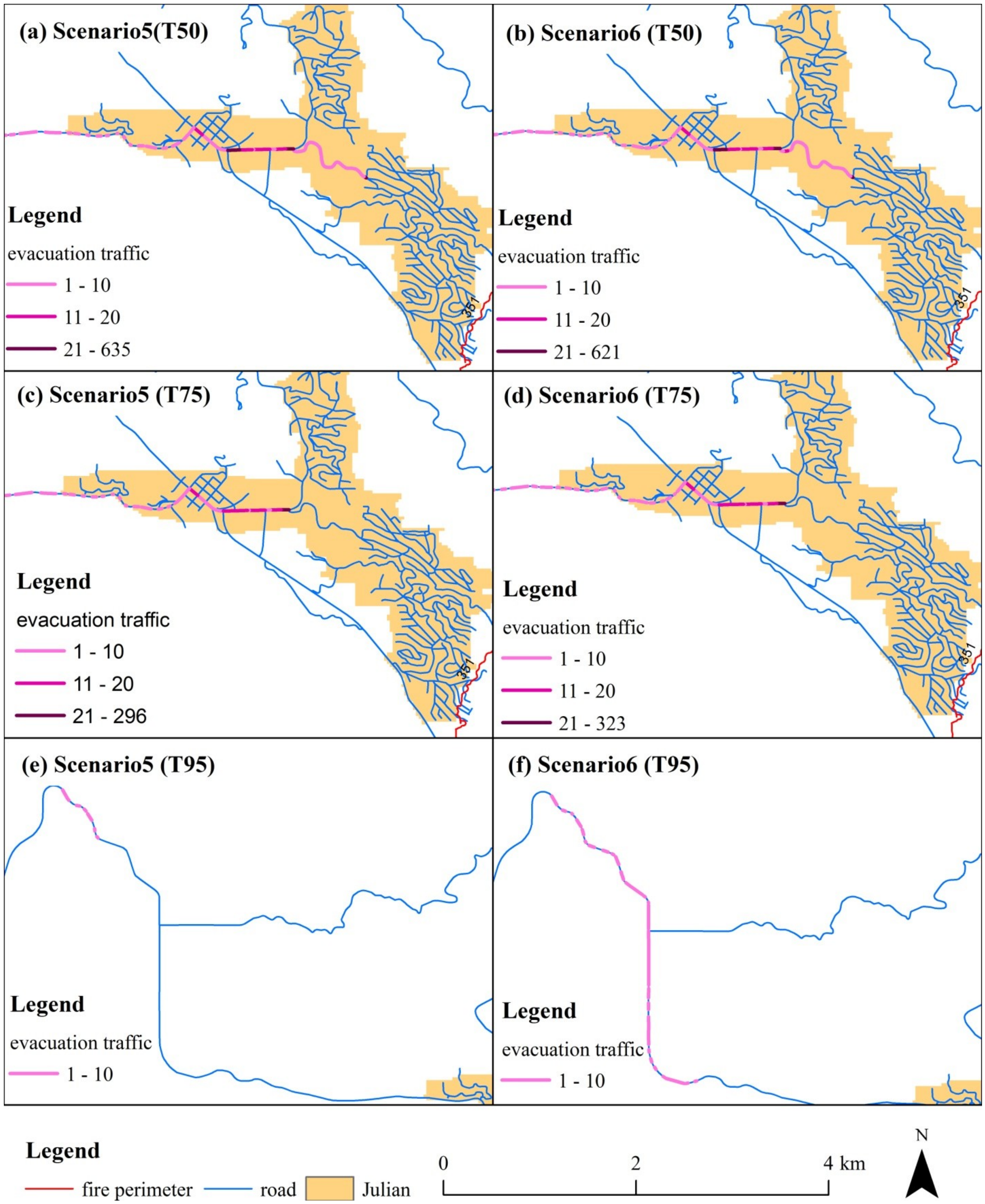


Figure 4.14 Evacuation traffic for scenario 5 and 6

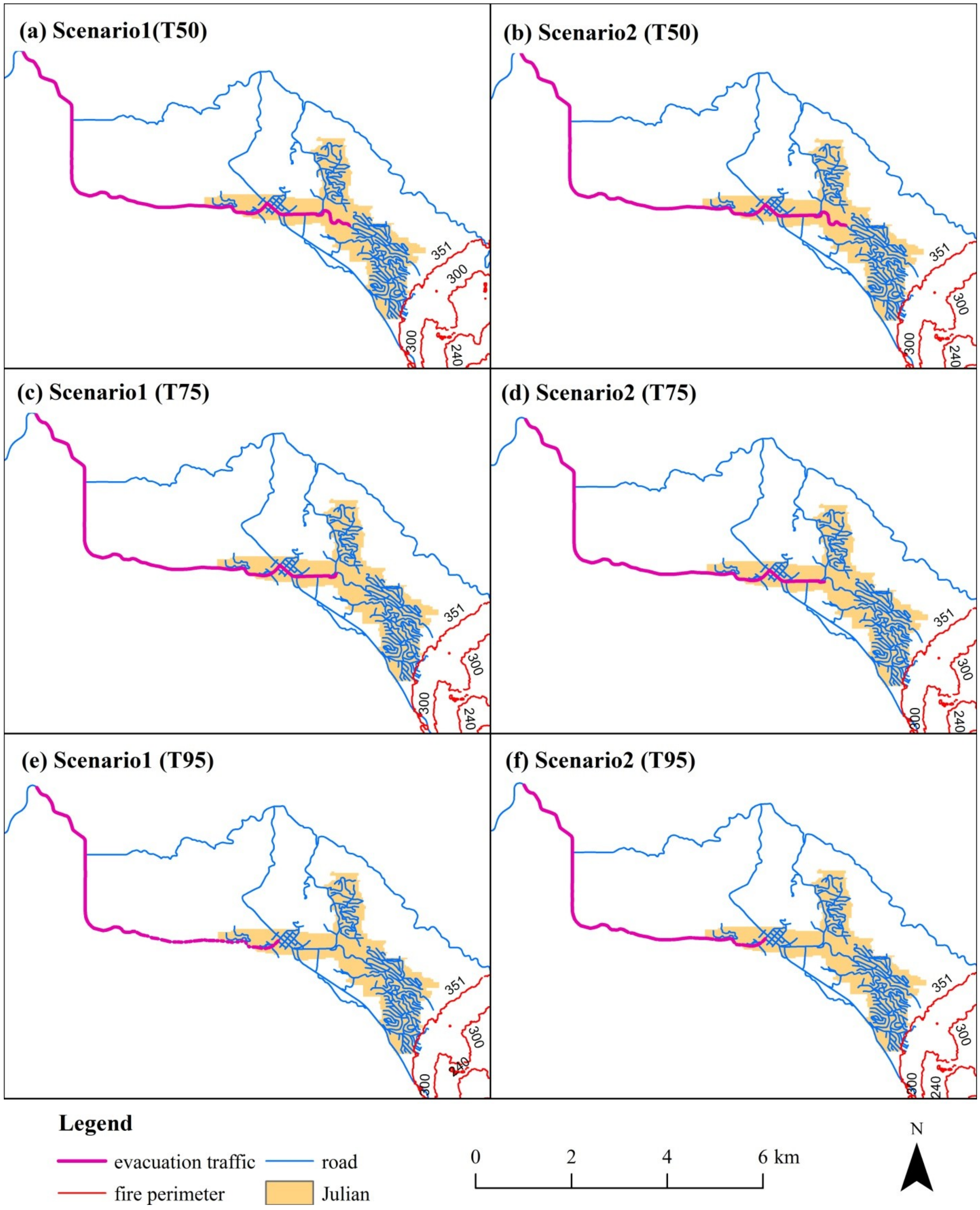


Figure 4.15 Links with evacuation traffic for scenario 1 and 2

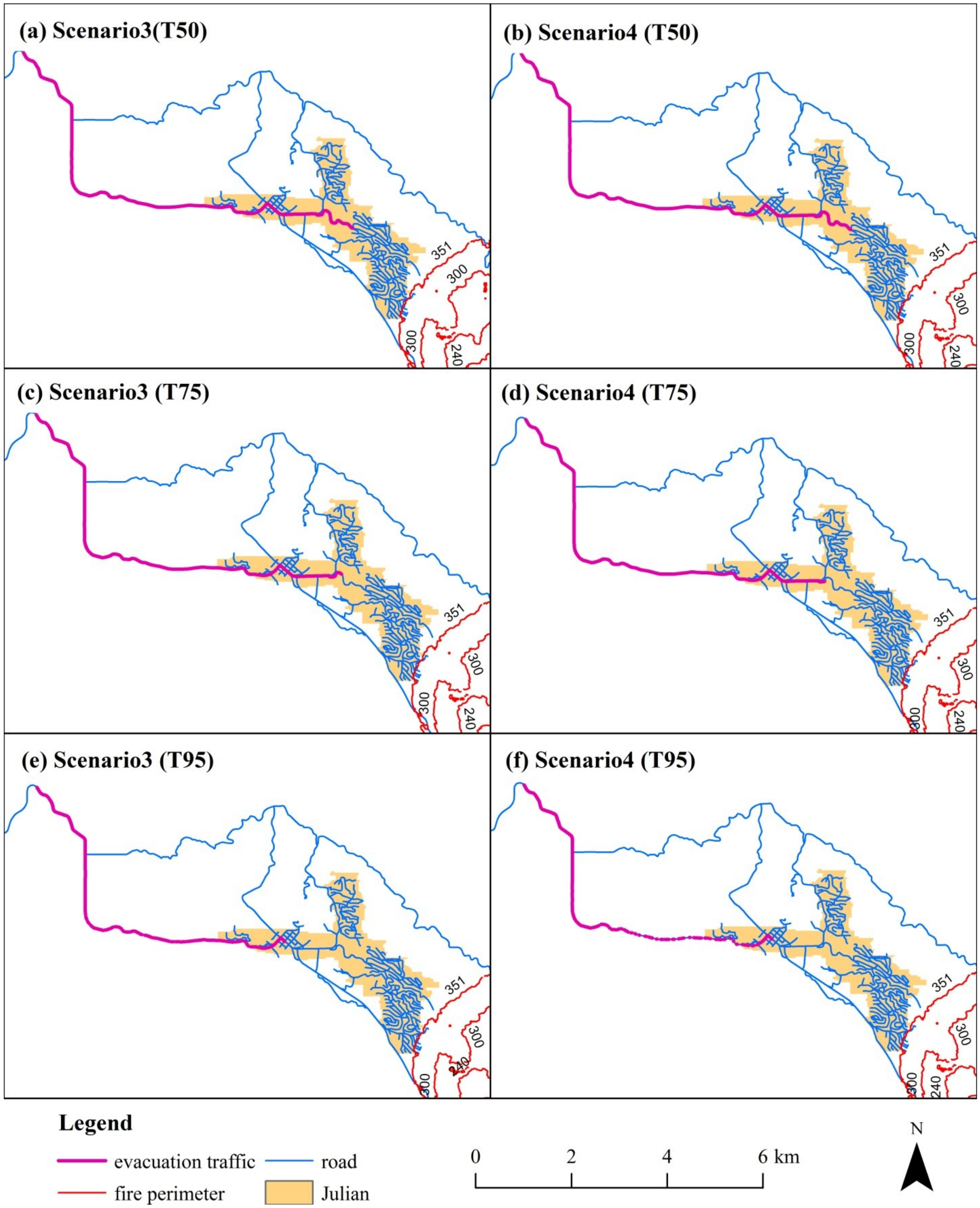


Figure 4.16 Links with evacuation traffic for scenario 3 and 4

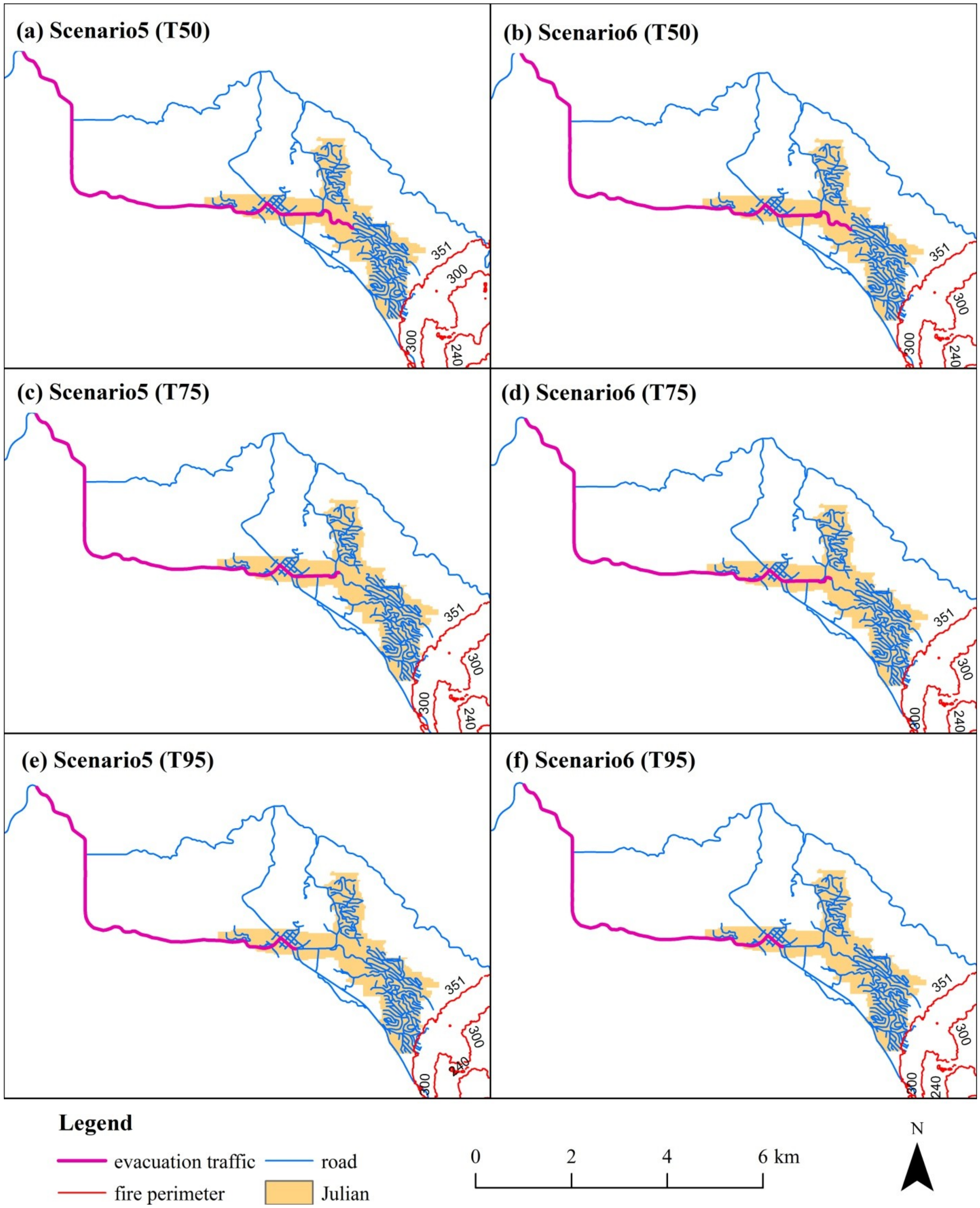


Figure 4.17 Links with evacuation traffic for scenario 5 and 6

4.6 Discussion

This work presents a spatiotemporal GIS framework that enables coupling fire and traffic simulation models to set triggers. The method could provide a spatial perspective on evacuation timing by taking into account both evacuation traffic and fire spread. The ICs could have a better understanding of evacuation timing through this method. Previous studies have examined the influence of the structure of the road network on wildfire evacuation risk (Church & Cova, 2000; Cova & Church, 1997). The results in this study reveal that we could better reveal the dynamics of evacuation traffic and fire spread in wildfire evacuations when we couple fire and traffic simulation models to set triggers. The interdisciplinary nature of this work 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 during traffic simulation, which cannot consider all possible spatiotemporal patterns of the evacuation traffic during wildfire evacuations. Note that complete compliance and a normal distribution of distribution of departure times are used for computation convenience. Evacuation departure times are a function of warning receipt and household preparation (Lindell, 2008). Future work could focus on taking into account more findings (e.g., evacuation shadow) from empirical studies to better estimate evacuation time (Lindell, Kang, & Prater, 2011; Murray-Tuite & Wolshon, 2013; Wu, Lindell, & Prater, 2012). Specifically, more factors could be taken into account to better model evacuation travel demand. For example, the distribution of the population differs significantly during the day time and at night

(Kobayashi, Medina, & Cova, 2011), and in the case study, we made the assumption that all the evacuees are at home. This could be a typical evacuation scenario in the night time. People may involve in many activities in the day time, e.g., driving to work, picking up children from school, and going to the grocery store. Recent years have witnessed the popularity of activity-based analysis and modeling in transportation studies (Miller & Shaw, 2015). Note that MATSim supports activity-based traffic simulation (Bekhor, Dobler, & Axhausen, 2011), 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 (Lindell & Prater, 2007a). However, note that departure time profiles can vary from one incident to another. Even in the same geographic area, a curve function that is the best fit to the empirical data from one case may not be a good fit for other cases. Thus, different departure curves could be used for estimating evacuation time in future work.

Second, it is assumed that the residents in the whole residential area receive warnings at the same time during the evacuation. However, staged evacuation is very popular in real-world evacuations because the fire could be suppressed by the firefighters and the wind might also change its direction. Thus, more work should be conducted to further examine the impacts of staged evacuations on the total evacuation time of the communities. 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 (Arlikatti et al., 2006; Zhang et al., 2004). Compared with hurricane risk areas, it is more difficult to define risk areas in wildfire evacuations because wildfire can come from any direction for those households surrounded by fuels. Protective action warnings in wildfire evacuations are sent out dynamically with the spread of the fire (Kim, Cova, & Brunelle, 2006). The dynamic nature of risk area delineation in wildfire evacuations makes it a challenge to perform staged evacuation traffic simulations. A recent study by Beloglazov et al. (2016) used staged evacuation strategies in wildfire evacuation simulation based on very different set of assumptions. Future work could explore the impacts of staged evacuation strategies on evacuation time estimation in trigger modeling.

Third, more research should be conducted to examine how to associate trigger buffers with 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 the residences or the evacuation route systems, an evacuation order could make the residents trapped en route. In this case, a shelter-in-place order should be issued. Thus, protective action selection relies on evacuation timing—whether the threatened population 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 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, Dennison, and Drews (2011) presented 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 manager make evacuation decision, 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 (Lindell & Prater, 2007b). These should also be taken into account in protective action selection modeling.

Lastly, with the popularity of open science in various disciplines, more efforts should be devoted to examining how to promote open science in wildfire evacuation modeling. Open science could be considered as an extension of the open source software initiative in scientific research. Specifically, Sui (2014) argues that open science in the field of GIS should include the openness in data, software, hardware, standards, research collaboration, publication, funding, and education/learning. As for wildfire evacuation modeling, open science should primarily focus on open data, open model, open software, and open research collaboration at this moment. In this work, open data were used for the case studies. Future work could focus on developing a WebGIS system to publish the generated trigger buffers, which could potentially facilitate training and education in wildfire evacuations. As for open model and software, the previously proposed trigger modeling procedure employs the FlamMap software for fire spread modeling and a separate C program to generate trigger buffers. Although FlamMap is free to the public, it is not open-source. This limitation makes it difficult for the users to integrate fire spread modeling into their software systems. Studies have shown that the open-source library fireLib can be effectively used for fire spread modeling (Bogdos & Manolakos, 2013; Sousa, dos Reis, & Pereira, 2012). Thus, some open-source fire spread modeling libraries like fireLib should be employed to implement trigger modeling to improve the reusability and scalability of the model. The traffic simulation tool MATSim is an open-source project, which makes it convenient to take into account the above-mentioned factors by customizing the functionalities in MATSim. Finally, since wildfire evacuation modeling is an interdisciplinary field, more efforts should be made to encourage collaboration among researchers with different backgrounds.

4.7 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 taken into consideration under the spatiotemporal GIS framework. This could facilitate more complex spatiotemporal computation to further examine the dynamics of evacuation traffic and fire spread in wildfire evacuations in future work. Second, the proposed method takes into account the uncertainty in evacuation time and represents the uncertainty using the probability-based trigger buffers, which can reflect the uncertainty induced by the departure time and travel demand distribution. When the ICs use the proposed method to set triggers, the trigger buffers that include evacuation time information for the evacuation traffic 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 in this work could be potentially be used by the ICs to facilitate evacuation planning and evacuation decision-making in wildfires. The proposed method could be 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 estimated evacuation times from evacuation traffic simulation as the input, the ICs could develop a better understanding of evacuation timing when they use 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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CHAPTER 5

CONCLUSION

5.1 Summary

Wildfire evacuation is a complex human-environmental process that occurs in space and time and involves environmental dynamics and human decision making. This complexity makes it a challenge to model and simulate this process as a coupled system. This dissertation represents a preliminary step in establishing a coupled human-environmental system (CHES) framework for wildfire evacuation modeling and simulation. This work models wildfire evacuation as a CHES by coupling wildfire spread modeling, trigger modeling, reverse geocoding, and traffic simulation. The contributions of the three chapters are summarized as follows.

Chapter 2 applies trigger modeling at a finer scale (at the household level) and integrates it with fire spread modeling to stage evacuation warnings. First, this work couples fire simulation with evacuation modeling, which represents the frontier of current evacuation research. The notion of coupling the hazard model with the evacuation model has enjoyed great popularity in the past few years (Lämmel, Grether, & Nagel, 2010). The nature of emergency evacuation is a CHES, which calls for more interdisciplinary collaboration between physical hazard modelers and transportation evacuation modelers. Second, trigger modeling is used to identify the changing set of threatened households as a fire approaches a community, in addition to deriving their recommended evacuation departure times. Specifically, the mechanism of how trigger modeling can be used for evacuation warning and departure timing is modeled. The definition of trigger modeling highlights how a fire triggers a predefined protective action warning as its proximity to households in a community increases. This work implements this process by incorporating dynamic fire simulation into trigger modeling, which makes an important contribution to the existing trigger literature. Third, this work performs trigger modeling at the household level and aggregates the household-level departure times to construct evacuation zones and stage evacuation warnings. Agent-based modeling (ABM) refers to the process of capturing the emergent phenomena of a system from fine-grain modeling of the individual agents (Bonabeau, 2002). This bottom-up approach reflects the spirit of agent-based modeling and enables the discovery of new knowledge in this field at a more detailed level. Fourth, GIS provides an important platform for model coupling in this work. The raster data model is employed to couple fire simulation and trigger modeling. In summary, Chapter 2 makes a contribution to the wildfire evacuation literature by coupling the fire simulation model with the evacuation trigger model and demonstrates to address a familiar problem in a novel manner—staging household-level evacuation warnings.

Chapter 3 employs reverse geocoding to retrieve prominent geographic features along the boundary of modeled trigger buffers to use them as trigger points. In real-world wildfire evacuation and suppression practices, trigger points are usually prominent geographic features (e.g., ridges, rivers, and roads) because emergency managers need to know when the fire crosses the trigger. This work bridges the gap between trigger modeling that produces polygons and how trigger points are actually identified in practice, which makes trigger modeling more applicable in real-world applications. The data structure and algorithm given in this work associate a trigger buffer with proximal geographic features along its boundary. Moreover, the feature selection process takes into consideration the uncertainty in the evacuation time for trigger modeling and employs map algebra to construct a selection space to obtain the features and use them as trigger points. The procedure also takes into account the resolution and accuracy of the raster data model used in trigger modeling. This chapter extends and improves the previously proposed trigger modeling method by adding a functionality to use reverse geocoding to obtain prominent geographic features to set trigger points.

Chapter 4 couples fire and traffic simulation models to set wildfire evacuation triggers under a spatiotemporal GIS framework. This chapter employs spatiotemporal modeling to model and represent space and time in fire spread and evacuation traffic processes that occur in different spaces (i.e., landscape versus road network). Traffic simulation is used to estimate the evacuation time of a community and provides the estimated evacuation times as the input for trigger modeling. Fire simulation is employed to calculate fire spread rates for each raster cell to create trigger buffers in trigger modeling. This chapter provides a space-time perspective for trigger modeling and makes a contribution to the theoretical underpinnings of trigger modeling with the notion of a probability based trigger buffer (i.e., trigger points can be assigned a probability of providing enough time to clear an area for a given set of modeling assumptions). The coupling of these two models takes into account the uncertainty in evacuation time but not the uncertainty in the fire spread rates. This work sheds light on the coupling of human and environmental systems in wildfire evacuation modeling.

The three chapters that make up this dissertation involve couplings of different human and environmental systems. GIS plays a significant role in modeling and representing the spatiotemporal processes in these systems. This CHES perspective can help improve our understanding of the complexity in wildfire evacuation. More importantly, the CHES framework enables us to discover new knowledge that would be difficult to obtain using traditional modeling methodologies. Note that the three chapters are connected by the theme of trigger modeling. Future work could build on the findings in these three chapters by including more complexity found in human and environmental systems.

5.2 Future work

The interdisciplinary nature of this dissertation provides a fruitful avenue to identify novel research questions for future research. The following paragraphs provide some ideas for future work and then list the key components towards building a more comprehensive CHES framework for wildfire evacuation modeling and simulation.

Chapter 2 demonstrates the potential use of trigger modeling in staging evacuation warnings at the household level. Future research following this chapter is planned as follows. First, more work should be done to further examine how to integrate the hazard model with evacuation models at the source code level and develop relevant tools to facilitate the use of the integrated model. The existing trigger modeling procedure involves the use of the FlamMap software and a separate C program (Cova, Dennison, Kim, & Moritz, 2005), which has limitations in deploying trigger modeling on supercomputers or cloud computing platforms for batch processing. Second, more efforts should be made to explore how to design and build evacuation zoning systems for household-level evacuation analysis, modeling, and planning. Although previous studies on evacuation zoning have reached a consensus on some important principles for evacuation zoning systems (e.g., using prominent geographic features to delimit evacuation zones to facilitate communications), this area remains an under-researched field in emergency management (Murray-Tuite & Wolshon, 2013). One potential use of evacuation zoning systems is to issue warnings to the threatened population in staged evacuations, which could reduce traffic congestions in large scale evacuations (Wilmot & Meduri, 2005). However, existing evacuation zoning systems are established at very coarse scales and do not support household-level warnings, which could be very common for those sparsely distributed households in exurban areas, as demonstrated in Chapter 2. Thus, more research should be conducted to design and build better wildfire evacuation zoning systems. Modern technologies in spatial database and WebGIS can be employed to establish more robust evacuation zoning systems. Third, the proposed household-level trigger modeling model could also be used to design and develop geo-targeted warning systems. Note that geo-targeted warning systems are location-based and thus should be closely related to evacuation zoning systems. Moreover, mobile computing can also be incorporated into geo-targeted warning systems to facilitate evacuation warnings during wildfires.

Chapter 3 uses reverse geocoding to retrieve prominent geographic features along the boundary of the generated trigger buffers to use them as trigger points. This work bridges the gap between trigger modeling and how trigger points are used in real-world applications. Future work to be conducted is listed as follows. First, metrics for evaluating the quality of digital gazetteers or online reverse geocoding services should be defined. Note that general metrics like accuracy can be used in various applications, while special metrics for trigger modeling (e.g., feature types) should also be defined. Second, existing online gazetteer or reverse geocoding services should be evaluated using the developed metrics. It is always important to compare and evaluate the existing available services before we start to design and implement new services. Third, if existing services cannot satisfy our needs, a special digital gazetteer for trigger modeling should be designed and developed to support the use of trigger modeling in evacuation communications and warnings. Spatial database and WebGIS can be leveraged to implement a gazetteer specially designed for trigger modeling. Finally, more empirical studies should be conducted to explore how incident commanders choose and use prominent geographic features as trigger points. This line of research focuses on human beings' spatial cognition and communications, which are complex human systems that we should take into account. Overall, Chapter 3 falls within the field of geographic information retrieval (GIR) (Jones & Purves, 2008). Note that existing gazetteer or reverse geocoding services usually use points to represent geographic features, which has limitations in representing linear features (e.g., roads, and rivers) or large polygon features. Thus, this should be taken into account if we are to design and implement a special digital gazetteer for trigger modeling.

Chapter 4 models and represents the uncertainty in the total evacuation time of a threatened community to set triggers by coupling fire and traffic simulation models. This is a typical coupling of an environmental and a human system. Future research should focus on the following aspects. First, more work needs to be done to further examine how to represent the uncertainty of the evacuation time from traffic simulation in trigger modeling. Only six scenarios were used in Chapter 5, and we need to take into account more factors for a more accurate estimation of evacuation time. Furthermore, more work should be conducted to examine how to use traffic simulation and trigger modeling for protective action selection modeling during wildfire evacuations. Cova, Dennison, and Drews (2011) conducted preliminary work on this topic, and future work could follow this line of research and model protective action selection in a more thorough manner.

In summary, the future research directions mentioned above could further improve wildfire evacuation modeling and simulation methodologically. Furthermore, all the findings in these three chapters should be synthesized to further couple fire spread modeling, trigger modeling, traffic simulation, and reverse geocoding to model the whole evacuation process as a CHES, which will make a significant contribution to natural hazards studies. This research direction emphasizes the coupling of different models, which calls for more interdisciplinary collaboration. More importantly, a CHES framework should be developed to cover the principles involved in the coupling process, which include, but are not limited to, systems thinking, model composition, spatiotemporal representation and modeling, and software design and implementation. This CHES framework will not only advance wildfire evacuation modeling and simulation but also shed light on evacuation studies on other hazards.

5.3 References

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