Title
Developing Transportation Response Strategies for Wildfire Evacuations via an Empirically Supported Traffic Simulation of Berkeley, California

Authors
Zhao, Bingyu
Wong, Stephen D

Publication Date
2021-08-10

DOI
10.1177/03611981211030271

Developing Transportation Response Strategies for Wildfire Evacuations via an Empirically Supported Traffic Simulation of Berkeley, California

Pre-Print

Transportation Research Record

August 2021

https://doi.org/10.1177/03611981211030271

Bingyu Zhao, Ph.D.
UC Berkeley

Stephen D. Wong, Ph.D.
UC Berkeley
University of Alberta

Note: Small differences in language will exist between this version and the final published journal article

Developing Transportation Response Strategies for Wildfire Evacuations via an Empirically Supported Traffic Simulation of Berkeley, California

Bingyu Zhao
Postdoctoral Researcher
University of California, Berkeley
Civil and Environmental Engineering
Berkeley, California 94720
Email: bz247@berkeley.edu

Stephen D. Wong
Incoming Assistant Professor
University of Alberta
Civil and Environmental Engineering
Email: stephenwong@ualberta.ca
https://orcid.org/0000-0002-3638-3651

Published Online: August 10, 2021

Funding Statement: SB 1 grant from the University of California Institute of Transportation Studies, the Graduate Research Fellowship Program (National Science Foundation), and the Dwight D. Eisenhower Transportation Fellowship Program (Federal Highway Administration).

Open-source Code: https://github.com/cb-cities/spatial_queue

ABSTRACT

Government agencies must make rapid and informed decisions in wildfires to safely evacuate people. However, current evacuation simulation tools for resource-strapped agencies largely fail to compare possible transportation responses or incorporate empirical evidence from past wildfires. Consequently, we employ online survey data from evacuees of the 2017 Northern California Wildfires (n=37), the 2017 Southern California Wildfires (n=175), and the 2018 Carr Wildfire (n=254) to inform a policy-oriented traffic evacuation simulation model. We test our simulation for a hypothetical wildfire evacuation in the wildland urban interface (WUI) of Berkeley, California. We focus on variables including fire speed, departure time distribution, towing of items, transportation mode, GPS-enabled rerouting, phased evacuations (i.e., allowing higher-risk residents to leave earlier), and contraflow (i.e., switching all lanes away from danger).

We found that reducing household vehicles (i.e., to 1 vehicle per household) and increasing GPS-enabled rerouting (e.g., 50% participation) lowered exposed vehicles (i.e., total vehicles in the fire frontier) by over 50% and evacuation time estimates (ETEs) by about 30% from baseline. Phased evacuations with a suitable time interval reduced exposed vehicles most significantly (over 90%) but produced a slightly longer ETEs. Both contraflow (on limited links due to resource constraints) and slowing fire speed were effective in lowering exposed vehicles (around 50%), but not ETEs. Extended contraflow can reduce both exposed vehicles and ETEs. We recommend agencies develop a communication and parking plan to reduce the number of evacuating vehicles, create and communicate a phased evacuation plan, and build partnerships with GPS-routing services.

Keywords: Evacuations, Traffic Simulation, California Wildfires, Transportation Policy, Behavior, Contraflow**,** Phased Evacuations

1. INTRODUCTION

Recent large-scale wildfire evacuations in California have exposed significant challenges for governments in increasing evacuation compliance, decreasing congestion, and ensuring equity. In many of these events, public agencies (e.g., transportation, transit, emergency management) lacked resources to deploy for a transportation response (1). These challenges are likely to extend to other wildland-urban interface (WUI) evacuations across North America. Without adequate funding, staff, and research ability, governments need practice-ready strategies to successfully evacuate residents in wildfires. One positive direction in the field has been the development of wildfire evacuation models, including traffic simulation models (2) that have sometimes been coupled with fire spread models and trigger buffer models (e.g., (3)). Despite these new integrated models, two key limitations remain in the wildfire evacuation simulation field. First, choice-making and behavior (e.g., transportation mode choice, destination choice) in wildfire evacuation simulations is often assumed or estimated based on expert knowledge, not actual behavior from post-disaster surveys or data. Second, traffic simulations for wildfires often fail to compare transportation strategies for evacuations. Effective and cost-efficient policies are crucial for ensuring safe evacuations.

To begin addressing these two key limitations, we developed several research questions:

1. What behavioral assumptions in simulations could be replaced by previously collected evacuation data?
2. What key factors should be integrated into traffic simulations to balance realism, computational complexity, and generalizability?
3. What transportation responses/strategies could be simulated and how might responses/strategies differ?

To answer these questions, we developed a spatial-queue-based traffic simulation that integrates post-disaster wildfire survey data from three wildfires - the 2017 Northern California Wildfires, the 2017 Southern California Wildfires, and the 2018 Carr Wildfire - for several evacuation choices. Using this simulation, we compare and contrast different fire speeds, departure times, towing demand, transportation mode splits, rerouting participation rates (i.e., GPS-guided routing based on real-time traffic conditions), phased evacuation times (i.e., time-based zone releases of evacuees), and contraflow options (e.g., switching all lanes to evacuate away from the fire). These fire behavior and policy parameters are tested in hypothetical wildfire incidents in the Berkeley Hills. We investigate the results for each scenario and provide recommendations for the different responses and strategies.

2. LITERATURE REVIEW

2.1 Wildfire and No-Notice Evacuation Behavior

During wildfire evacuations, individuals must make a number of complex choices including their decision to evacuate or stay/defend, departure timing, transportation mode, route choice, shelter/accommodation type, destination, and reentry timing. The wildfire evacuation behavior literature (see review in (4)) has focused predominantly on the decision to evacuate or stay (5,6). In many cases (e.g., (7,8)), this literature employs discrete choice models to isolate influential variables in the decision to evacuate or stay including defending behavior of property (see (9) for more work on alternatives to evacuations). One important improvement over the years has been the collection of post-disaster wildfire evacuation survey data to inform these models, e.g., (6–8,10,11,1). However, much less work has focused on decisions during the evacuation process (e.g., route, destination) (11,12), as noted in (13). Other work, such as (14), notes that behavior such as extra-trip making, mobilization time, and background traffic can also impact evacuations. Moreover, alternative transportation strategies such as the sharing economy (e.g. (15–17)) may be feasible under certain wildfire evacuation circumstances, changing the potential modal split and sometimes increasing social equity. Altogether, the literature lacks in several areas: 1) fully understanding evacuee behavior, and 2) having enough survey data for most or all choices in wildfire evacuations. In addition, survey data has yet to be fully integrated into evacuation simulation models as behavioral variables are currently created via assumptions, expert opinions, and/or hypothesized statistical distributions.

Apart from the wildfire specific studies referenced above, no-notice or short-notice evacuation under other types of hazards (e.g., truck attack, flash flood, or general emergency situations) have long attracted researchers' attention (18–21). Research in this area can be categorized into two types. The first type focuses on understanding the evacuation demand, such as participation rates, origin locations, departure times, and destination locations (22). The second type analyzes operational strategies to accomplish the evacuation safely and efficiently (23). On the demand side, compared to early, self-organized evacuations, no- or short-notice evacuations are often characterized by excess levels of stress and uncertainties associated with dire situations (20,24). As a result, evacuees' behaviors might differ from their response to long-notice evacuations. In addition, short-notice evacuations also have distinct phases (e.g., anticipation, warning, displacement, notification, and return and recovery) (24). Different evacuation behaviors are associated with each phase. Surveys and statistical models have been used to elicit qualitative and quantitative insights on the evacuation behavior parameters, such as the reasons and ratios of people choosing to stay in shelters, hotels, or with family/friends (22,24). It is also recognized that different behavior parameters are interconnected and correlated, and models with correlation structures have been used to capture their joint distribution (22). On the operational side, challenges for safely evacuating people correspond to traffic assignment tasks, with some additional features and constraints. Different algorithms have been used to optimize the evacuation process, from bus scheduling, to family trip-chain arrangements, to optimum traffic assignment (21,23,25).

2.2 Wildfire Evacuation Strategies

Wildfire evacuation strategies have been largely developed following guidance and lessons learned from other types of disasters (e.g., hurricanes, tsunamis). The focus of most strategies for wildfire evacuations has been on evacuation efficiency (e.g., reducing evacuation time estimates [ETEs] or total travel time), given the speed and short notice of wildfires. Generally, these metrics are aimed to 1) improve the network capacity through strategies of contraflow (e.g., switching some or all lanes of a roadway to flow away from a hazard) or new infrastructure or 2) optimize the utilization of the network by evacuees through strategies such as phased evacuation, which reduces peak demand on the roadway by spreading out evacuees temporally. Some examples in literature offer more details of how the strategies can be implemented in a wildfire evacuation context. Contraflow was studied in (14), where locations were determined by iteratively turning the excess road capacity in the opposite direction of road links. (26) proposed a phased-evacuation strategy where those closer to danger should leave first (Innermost First Out, InFO), while (27) tested all phase sequences in a road network with four evacuation zones. A lane-based intersection-control plan was proposed in (28) to reduce crossing and merging conflicts at intersections for wildfire evacuations. However, one key limitation of many of these strategies is the need for a significant amount of personnel and coordination to implement (e.g., intersection control in (29)). Moreover, some metrics to determine strategy efficiency can be misleading as ETEs are sensitive to the departure of the last vehicle from the evacuation zone (30). Despite work on different transportation strategies in evacuations (63), a comprehensive study that compares relative gains of each type of strategy specifically for wildfire evacuation remains absent from the literature.

2.3 Wildfire Evacuation Simulations and Strategies

Traffic modeling and simulations have been widely used to test wildfire evacuation scenarios and strategies (Table 1), from simple hypothetical network (27,29), to small communities with tens to hundreds of households (31,32) to a large town/city (33). Most studies run off-the-shelf microscopic simulation software, such as SUMO (33) and Paramics (29,31). Certain non-microsimulation quick calculations are also proven to be useful in estimating the evacuation delays and finding bottlenecks, such as the simplified manual calculations in (29) and adjusted four-step models used by (14). Model inputs (network and travel demand) are usually sourced from a variety of venues, such as the OpenStreetMap (OSM), digitized aerial imagery, planning documents, and census data. Vehicles follow either a fixed route to the closest exits or routes that periodically update based on evolving traffic conditions during the evacuation. Probably due to the complexity of the problem as well as the emerging nature of the evacuation process, most wildfire-evacuation-related studies use one-shot assignment rather than optimization-based formulation, with exceptions for simplified networks, such as in (28) and (34). Model outputs typically include aggregated metrics such as ETEs, fire exposure (e.g., (27)), or spatially or temporally disaggregated link-level congestion status (e.g., (14,33)). In many evacuation studies across hazards, agent-based models are widely adopted in the evacuation simulations (35–37). These types of models are frequently leveraged to investigate the changes in evacuation performance metrics in parametric studies by focusing on detailed evacuation choices, such as departure time, route, and destination.

TABLE 1 Key Models for Wildfire Evacuations

Traffic Simulation Models for Wildfire Evacuations							
Reference	**Model Characteristics**					**Metrics**	**Strategies or Scenarios**
	Demand Generation	**Departure Time**	**Destination and Routing Choices**	**Simulation Type**	**Network + Demand Data Source**		
(31)8/11/2021 8:14:00 AM	250 homes; vehicles per household follows Poisson distribution (mean: 0.5-3 vehicles/household)	Household departure time follows Poisson distribution (mean: 5-25 minutes)	Dynamically updated least-cost routes to closest exits	Microscopic (Paramics)	Digitized aerial image and planning documents (Emigration Oak, UT)	Clearance time, mean vehicle travel time, evacuation time of each household (disaggregated)	Adding new infrastructure; varying demand rate and departure delay
(29)*	Not required; 30-150 vehicles per zone used for testing the clearance time on the hypothesized network	Not required; uniformly generated within 15 minutes; used for testing the clearance time on the hypothesized network	Various static routing (minimize total travel distance, minimize merging or balanced); destinations solved endogenously with routes	Microscopic (Paramics) and manual capacity analysis	Hypothesized (9 to 25 intersections); digitized aerial image of 20 intersections (Salt Lake City, UT)	Clearance time, total travel distance, number of merges	Reducing intersection merge/cross delays via turn restrictions (lane-based routing); varying demand rate, signal timing and numbers of exits
(34)*	Three levels of evacuation demand: 1,794, 3,558, and 5,692. Background traffic and evacuees are in total 47,300	Optimum departure time solved endogenously with routes	System-optimal dynamic traffic assignment; destinations solved endogenously with routes	Mesoscopic (DYNASMART-P) for network loading	Simplified extracted network (Fort Worth, TX)	Network clearance time, total and average trip time	Time-dependent staging policy for each origin; varying evacuation demand
(32)	1.5-5 vehicles per node, randomly assigned to 753 nodes	All departure finish by 30 minutes (urgent), 1 hour (medium), or 2 hours (slow)	Fixed “shortest” path or dynamically updated “fastest” path to pre-designated exits	Microscopic (CORSIM)	Digitized aerial photograph (Summit Park, Salt Lake City, UT)	Clearance time, fatalities, link level max. queue length	Varying demand rate, departure time (urgency), & incorporating rerouting
(27)*	Grid network: 20-80 vehicles per block; Ring network: same vehicle density as the grid network; real network of 1-8 vehicles per household for 485 households	Set zonal departure time interval: hypothesized network: 1 minute; real network: 1 or 4 minutes	Dynamically updated fastest route to any exit; all exits are linked as one destination zone.	Microscopic (Paramics)	Hypothesized (grid, ring); digitized aerial image (San Marcos, TX)	Clearance time	Staggering departure of zones; varying demand rate

(14)	All households in 8 evacuation districts with background traffic; auto ownership from US Census (2000)	Not available (static)	Shelters (15%), Friends or families' home (60%), hotels (15%), out of county (10%)	Adjusted four-step with static multiclass assignment	Planning documents of main roads for fire-prone neighborhoods (Colorado Spring, CO)	Clearance time, link-level congestion (volume-to-capacity)	Restricting the egress routes to evacuees; blocking the entrance to evacuation zones; conducting contraflow
(38)	Total population of about 9,000. 85% participate in the evacuation, 1.5 people per vehicle trip	Evacuees react to visual triggers & official warnings, both related to dynamic fire front; decision and preparation delay	Static routing to closest exits	Microscopic (SUMO) with trigger model	Open Street Maps (OSM); census population; registered household addresses (Dandenong Ranges, Australia)	Clearance time, fire exposure count	Conducting phased evacuation with dynamic triggering, varying fire ignition locations and weather conditions
(33)	Uniformly distributed along residential/service roads (23,635 vehicles for Paradise, 12,212 for Mill Valley)	S-shaped cumulative departure	Fixed "shortest" path or periodically updated "fastest" path to any exit; all exits are linked as one destination zone.	Microscopic (SUMO) 1 second time step is used).	OSM (Paradise, CA and Mill Valley, CA)	Link-level speed, arrival curve, average trip-time	Closing roads; conducting contraflow, varying departure time concentration; varying demand rate, and rerouting

* Emergency evacuations, not specific to wildfire evacuations

Other Key Literature Related to Simulations of Wildfire Evacuations

Reference	**Type of Model or Analysis**	**Goal or Aim of Study**
(39)	Fire spread modeling (FlamMap), fire-spread network modeling, and shortest path analysis (altogether known as the Wildland-Urban Interface Evacuation model)	Calculate evacuation trigger buffer a small community (Julian, California) and determine trigger zones
(40)	Wildland-Urban Interface Evacuation model (WUIVAC)	Apply data from the 2003 Cedar Fire in southern California to develop trigger buffers and compare results to the event timeline to find possibly improvements
(41)	Network and spatial data analysis (critical cluster model)	Identify fire-prone communities with minimal egress opportunity in western U.S.
(3)	Household-level model for trigger buffers and fire-spread modeling (FlamMap)	Determine evacuation trigger buffers (ETBs), recommended evacuation departure times (REDTs), and a ranking of households based on lead time
(42)	Review of evacuation models	Understand and review the scale, applicability, and interactions of fire, pedestrian, and traffic models
(2)	Review of traffic models for wildfire evacuations	Understand and review the traffic models based on relation to fire spread, spatial and demographic factors, temporal issues, and intended application and identification of 22 traffic models and applications
(43)	Controlled behavior experiment and regression models	Determine the collective evacuation decision of communities under different disaster likelihoods and shelter availabilities

2.4 Evacuation issues in other disasters

Evacuation strategies in wildfire emergencies can sometimes be different compared to other disasters, due to characteristics of fire hazards. For example, time for advanced warnings in wildfire evacuations (hours) are often shorter than those for hurricanes and flooding (often with at least 24 hours in advance), but longer than tsunami evacuations (minutes in advance or no warnings at all). The spatial extent of evacuations for each hazard are also different, where the distances of evacuation trips include local sheltering (e.g., tsunamis), within-region evacuations (e.g., wildfires), and out-of-state evacuations (e.g., hurricanes). These spatial temporal differences along with the difference in risks (63) alters evacuation behavior and the most efficient and effective transportation response strategies. For example, compared with wildfire evacuations when cars are the predominant mode of transport, tsunami evacuations are usually multi-modal, involving both vehicular traffic and pedestrian traffic as people need to rapidly move to safety (35). Tsunami evacuation destinations also tend to be closer in distance (to inland location or vertical shelters), due to the minimal time to evacuate (36). Hurricane evacuations benefit from a longer period of advanced warning (e.g., usually days in advance), but the spatial extents of the evacuation trips are also the largest, sometimes requiring evacuations of over 100 miles to another state (44,45). This can lead to large-scale transportation responses that span multiple states. While wildfires often require more rapid evacuations compared to hurricanes, they also tend to impact a smaller land area, threaten less people, and require shorter trips to reach a safe destination. Consequently, wildfire evacuation transportation responses must be deployed faster than hurricane responses, but they can also be more complex and time-intensive compared to tsunami evacuations.

Other types of disasters, such as nuclear power plant failures, chemical accidents, and hazardous material accidents, also require evacuations. In nuclear power plant failures (e.g., the Three Miles Island (TMI) nuclear accident, USA [1979] and the Fukushima nuclear disaster, Japan [2011]), individuals evacuated lived in specific distances from the source of the accident. For example, residents within several to tens of miles radius of the accident were ordered to evacuate in past events (46,47). Since the direction of radioactive material plays a critical role, the strategies employed could be parallel to those of wildfires. However, shelter-in-place strategies (e.g., staying inside and reducing air flow into a building) are more common for these disasters than wildfires. It should also be noted that the temporal length of evacuations from these types of disasters is highly variable (46,48), which indicates that different evacuation strategies from a range of natural hazards could be used. Altogether, the unique characteristics of hazards influences the most effective transportation response strategies to improve evacuation outcomes. However, strategies developed for one disaster could be effective for another disaster with similar spatiotemporal characteristics. To test this possibility for wildfire evacuations, we considered a number of strategies across hazards to begin developing a suite of evacuation strategies that are most effective for wildfires.

3. METHODOLOGY

To address some gaps presented in the literature review and taking cues from (2), we developed a survey-informed dynamic (spatial-queue) traffic simulation to evaluate evacuation performance (time efficiency, evacuee safety) under different fire, human behavior, and transportation response scenarios. The details of each component are introduced below in Figure 1 and following sections.

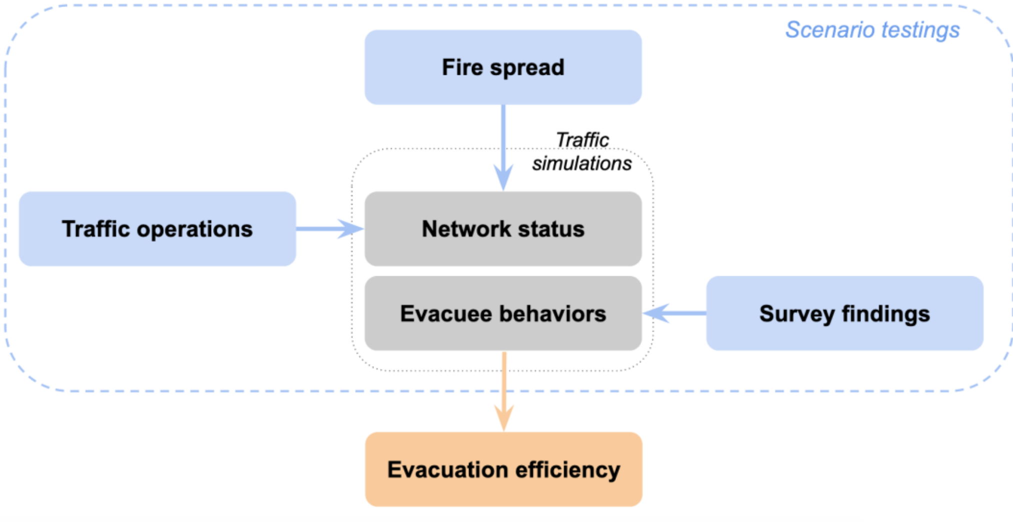

Figure 1. Study framework

3.1 Spatial-Queue-Based Dynamic Traffic Simulation Model

We use a spatial-queue-based traffic model to simulate the evacuation process. We chose this over popular microscopic simulators that implement car-following and lane-changing because the spatial-queue-based model is less data intensive and is easier to program from scratch. The simulator tracks individual vehicles through a vehicle routing module, a spatial-queue-based link model, and an intersection model that prevents cross conflicts. The simulation runs at a time step of 1 second, capturing detailed temporal traffic conditions, though not sub-link, sub-node or sub-second behavior (e.g., interaction of multiple vehicles inside an intersection). At the beginning of the simulation (or when rerouting is required), the routing module computes for the fastest path using Dijkstra's Algorithm (49), based on the free flow speed (initial route) or average travel speed in the past 20 seconds (subsequent rerouting). Vehicle routes are updated every 10 seconds for those following real-time traffic updates similar to location-based direction services (e.g., Google Maps, Apple Maps, Waze). Queues and spillbacks are simulated by the link model, which requires a vehicle to spend at least the free flow travel time on a link, before joining a queue at the end. When the end of the queue, formed by vehicles with some physical length, reaches the upstream end of the link, no more vehicles can enter (spillback). Link flow capacity is assumed to be 1,900 vehicles/(hour×lane). Discretized into one-second time steps, link capacities are imposed in a flip-coin probability manner, with the probability of a queuing vehicle leaving the current link or entering the next link being 0.53 vehicles/(second×lane). At each 1-second time step, the node model moves vehicles at the front of each link to the next link, as long as 1) it satisfies the inflow capacity of the next link and the outflow capacity of the current link, and 2) it does not conflict with other vehicles moving through the intersection at that time step (e.g., from perpendicular direction, left-turns). Vehicles entering an intersection are assumed to have equal priority except roundabouts (higher priority). All intersections are modeled as non-signalized (e.g., due to power failures).

3.2 Scenario Development

This research compares the effectiveness of different evacuation response/policy options via scenario testing with controlled variables. In this section, the set of fixed inputs and variable scenarios will be explained.

3.2.1 Road Network

The hypothesized evacuation occurs in the hilly northeast area of Berkeley. Most of the roads in the study area are one-way-per-direction residential roads (Figure 2(b)). On-street parking is common, creating many narrow choke points that prohibit two-way flow. However, off-street parking is often recommended by the city on a red flag warning day (50). Figure 2(b) highlights a few main evacuation routes. Among all possible routes leading away from the fire, Marin Avenue is the straightest (no curve), but is also the steepest (maximum gradient over 30%). The other two roads labeled in Figure 2(b) (i.e., Spruce Avenue and Euclid Avenue), are also frequently used by residents. A distinct feature of the road network in the Berkeley Hills compared to other wildfire evacuation study is that the road network here is "funnel-shaped." Apart from the major egress roads shown in Figure 2(b), there are many smaller roads that lead to safe areas. These roads can serve as the evacuation route for a small number of vehicles that are routed off the main roads, while also allowing for emergency access vehicles to go uphill if major roads are used for contraflow operations. We also note that nearly all roads in the area are flanked by densely grown trees and brush, which pose substantial fire risk and a high chance for toppled trees on roadways.

The road network for the study area was obtained from the OSM. The study area is defined to be the city of Berkeley plus a 6.2-mile (10 km) buffer area, given wildfire evacuation trips are usually short (1,14). To reflect slower driving on narrow, hilly roads, a discount factor of 0.8 was applied on the speed limit. After processing the OSM data, a directed node-and-link-based road network for the study area was obtained (Figure 2). The large and complex network consists of 15,294 nodes and 37,951 links.

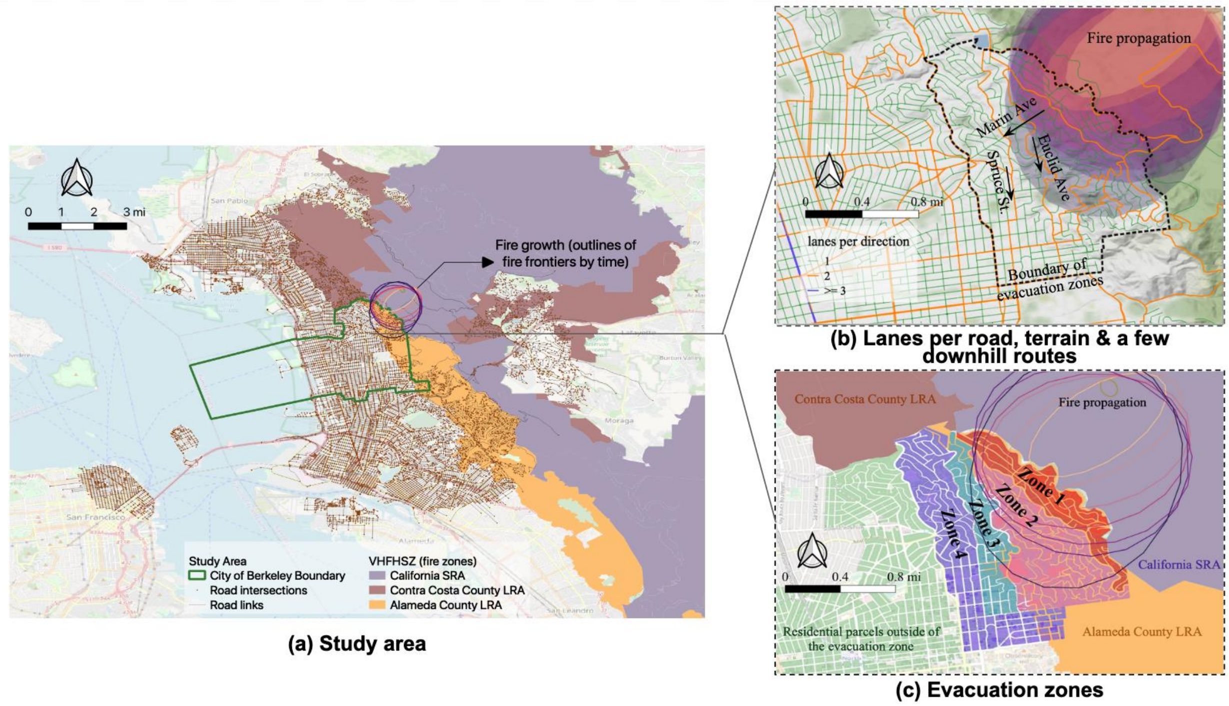

Figure 2. Map of the study area, road network, evacuation zones and fire hazard severity zones. (a) The whole study area; (b) terrain map and numbers of lanes per road in the evacuation zone; (c) four evacuation zones. (LRA: local responsible area; SRA: state responsible area. VHFHSZ: very high fire hazard severity zone)

3.2.2 Fire Propagation

The Berkeley Hills area borders Tilden Regional Park and mostly falls within the California Department of Forestry and Fire Protection (Cal Fire) Very High Fire Hazard Severity Zones (VHFHSZ, Figure 2). A hypothesized fire is ignited at a transmission tower 0.9 miles northeast of the Berkeley Hills area (coordinate: 37.910399, -122.249261). Fire spread can be modeled by software such as FlamMap or the Wildland-Urban Interface Fire Dynamics Simulator (WFDS) (39,51). However, WUI fire spread is difficult to model due to non-uniform buildings, defensible space, and vegetation. Consequently, data from a nearby and real fire case (1991 Oakland Hills Fire) was borrowed. Both sites are located on the east hillside of the East Bay Hills with similar weather patterns, land topology, vegetation, and housing density. An elliptical fire growth model was fitted to a georeferenced map of the Oakland Hills Fire (Figure 3) (52). The hypothesized fire starts shortly before 11:00 am on a weekend, same as the Oakland Hills Fire. All households are assumed to be at home. These two critical assumptions were used to constitute a "worse-case" scenario. Evacuation orders are sent out 15 minutes after the onset of the fire (reasonable estimate for an urban fire), starting the evacuation. Future work will be necessary to integrate wildfire modeling with traffic simulations to produce more realistic evacuation models.

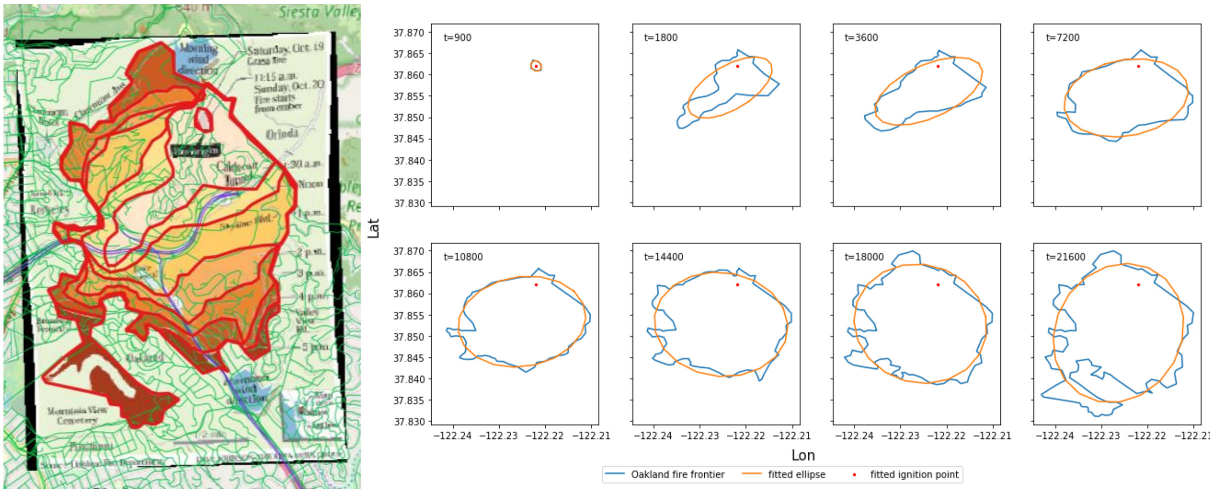

Figure 3. (a) Chronological view of the development of the 1991 Oakland Hills Fire (via Oakland Fire Department from georeferenced image by (52)). (b) Fitting elliptical curves to the observed fire frontier.

3.2.3 Evacuation Zone

Based on fire location, evacuation orders are issued to an assumed area within Berkeley bounded by several major streets (Hearst Avenue on the south, the Shattuck-Sutter-Arlington corridor on the west and the city boundary on the east and north). To add land development realism, a parcel map was obtained for the evacuation area, where each parcel is home to one to five households depending on the land use code (53,54). This accounts for 7,438 households. For simplicity, areas west of Shattuck Avenue (i.e., downtown Berkeley) and south of Hearst Avenue (i.e., University of California, Berkeley campus) are assumed as temporary safe locations. For this study, we generated a random list of origin-destination pairs, where 30%, 30%, 30%, and 10% of the vehicles evacuate to destinations within 1-2 miles, 2-3 miles, 3-4 miles, and 5 or more miles. Our local focus stems from our survey data that found upwards of two-thirds of evacuees remained within their county of origin. The treatment of destination choices is simplistic, as evacuees' destinations could be influenced multiple factors (e.g., availability of shelters, proximity to resources, safety of the destination). Moreover, we did not ask for exact destinations (by address or traffic analysis zone) in our survey and these destinations will require more robust datasets such as mobile phone traces. With this limitation in mind, the results of this study focus on the first half of the evacuation trip (e.g., the time to reach 1 mile away from the evacuation zone or the distance/time exposed to the fire). Time to the destination is not reported, as this does not provide any additional about risk to the evacuee.

3.2.4. Transportation Response Scenarios

We tested a range of wildfire evacuation scenarios, which can be categorized into three groups: hazard (fire speed), evacuation behavior (departure time, towed vehicle demand, transportation mode choice, GPS-enabled rerouting), and policies/responses (phased evacuation, contraflow). For a set of scenario variables, a base case value was chosen for comparison. Details of each scenario are given in Table 2.

Several post-disaster surveys of individuals impacted by California wildfires in 2017 and 2018 were used to define some scenario variables, as discussed in Table 2 (1). For example, mode choice with a focus on vehicles per household was used as a key behavioral parameter. About 41% to 45% of evacuees depending on wildfire used two vehicles to evacuate. Moreover, an additional 9% to 17% of evacuees depending on wildfire used three or more vehicles to evacuate. Even small increases of vehicles on the roadway could significantly increase congestion during a wildfire. For route decision-making, only between 8% and 19% of evacuees depending on fire used GPS navigation. This behavior is particularly interesting given that 78% to 87% of respondents overall had access to in-vehicle or smartphone navigation. This result may be influenced by shorter evacuations during wildfires (about two thirds evacuated within county) and/or evacuees' greater knowledge of route options. Finally, between 6% and 21% of evacuees depending on fire towed items while evacuating (e.g., boats, trailers, or towing personal vehicles using recreational vehicles). Towed items generally increase congestion, take additional space on narrow mountain roads, and reduce traffic throughput. Individuals likely wanted to protect their processions from the fire, leading them to tow items during the evacuation. Additional details and a thorough discussion of these choices and more are provided in (1).

TABLE 2 Descriptions of Scenarios

Category	**Options (Baseline Value Underlined)**	**Description**
Hazard Scenario		
Fire speed	"Slow": Basecase ROS × 0.5 "Normal": 1991 Oakland Hills Fire rate of spread (ROS) "Fast": Basecase ROS × 2	• Wildfire speed depends on fuel type, wind speed, humidity, land topology, etc. • The baseline case uses the fire speed in the 1991 Oakland Hills Fire (Figure 3(b)) • Alternative cases assume the fire speed to be halved (e.g., with proper fuel management and/or firefighting, favorable weather) or doubled (e.g., poor fuel management and/or challenged firefighting, unfavorable weather)
Evacuee Behavior		

Departure time	"Fast": 20 min ± 10 min <u>"Medium": 40 min ± 20 min</u> "Slow": 60 min ± 30 min	• Cal Fire emphasizes the importance preparing and taking swift action in a wildfire ("Ready, Set, Go!") • The planned departure times assumed as a truncated normal distribution (i.e., truncated around the mean at ± one standard deviation) • Vehicles will leave automatically if fire reaches residents' location regardless of the planned departure time • The baseline case assumes the planned departure time to be the medium level *~N(40min, 20min)*, truncated at 20 min and 60 min. • The alternative cases assume shorter or longer departure times
% household towing item	0% <u>10% (approximated survey)</u> 25%	• Normal vehicles assumed to take 26 ft. on the road, invert of typical jam density (94) • Towed vehicles assumed to take 50 ft. of space (normal vehicle plus a 24 ft. trailer/recreational vehicle) • Survey results indicated that between 6% and 21% of households took towed vehicles during their evacuation • It is assumed each household tows a maximum of one item irrespective of the number of evacuating vehicles • The baseline case assumes 10% households tow an item • The alternative case assumes 0% and 25% households tow an item
# vehicles per household for evacuation	"Low": 1 vehicles/household <u>44%/43%/13% households leave with 1/2/3 vehicles (approximated survey)</u> "High": 3 vehicles/household	• Survey results indicated that *approximately* 36-45%/41-45%/9-17% of households (depending on wildfire case) evacuate with 1/2/3 vehicles and this is taken as the baseline (12,621 vehicles in total for our case) • Alternative scenarios assume the number of vehicles per household to be one (7,438 vehicles in total) or three (22,358 vehicles in total) • Other forms of transportation (i.e., bus, rail, biking, walking) are converted to single vehicle households for simplicity
% vehicles rerouting	0%	• Survey results indicated that 91% to 93% of the evacuees have smartphones but only

with real time traffic information	15% (approximated survey) 50% 100% 15%, but lost connection to real-time data in 6 minutes 15%, but lost connection to real-time data in 30 minutes 50%, but lost connection to real-time data in 6 minutes 50%, but lost connection to real-time data in 30 minutes	between 8% and 19% of people followed GPS directions during the evacuation (depending on wildfire case study) • It is assumed updated routing information will be available every 10 seconds based on the average link traversal time in the past 20 seconds • Individuals that may reroute without perfect information are not considered • The baseline scenario assumes 15% people follow dynamic updated fastest path while the rest do not update their route • Three alternative scenarios assume different percentages of vehicles that dynamically update their path • Four alternative scenarios assume the connectivity to the real-time routing information is interrupted 10 or 30 minutes after the start of the evacuation (e.g., cell tower losing power)
Policy Scenario		
Phased evacuation time interval	0 min 15 min 30 min 60 min	• Evacuation area is divided into four zones based on distance to the fire origin (Figure 2) • Zone boundaries are all secondary or tertiary roads (i.e., important roads in the residential area) • Baseline case assumes "no phased evacuation": vehicles in four zones have the same mean departure time • Alternative scenarios vary the time interval in the mean departure time of vehicles in each of the four evacuation zones
Contraflow	No contraflow Short-distance contraflow on selected roads (Figure 4) Long-distance contraflow	• Contraflow roads now switch all lanes in the evacuation direction • Baseline case assumes "no contraflow" • Roads were identified based on long traffic queues from the baseline simulation and local knowledge of primary routes in the area • Alternative scenarios assume a short-distance or a long-distance contraflow

3.3. Limitations

In addition to the assumptions described in the prior section, we note several key limitations here. First, the surveys exhibit self-selection bias as they were opt-in. We attempted to reduce this bias through a wide distribution across multiple agencies and news sources. Participants also skewed wealthier with more vehicles, due to the online distribution, and the sample sizes for the surveys were small. Additional survey limitations are described in further details in (1). The survey data also has measurement error, leading us to choose approximate values for the model. Finally, we note that we used survey data from other locations to develop the scenarios for the Berkeley Hills, as a major fire has not occurred recently in the Berkeley Hills. Despite this possible mismatch of traffic, social, climate, and cultural factors, the surveys and our study area were similar based on fire risk (WUI zones), housing type (mostly single-family residences) and income level (high income level). Future work is needed to apply modeling across more geographies and collect more survey data to increase generalizability.

There are limitations regarding the network representations. For example, even though the city recommends off-street parking on a red flag day, the compliance is not guaranteed. This is a major issue hindering evacuation, as the road network in the study area (as well as many other high-risk sites beyond this study) is quite windy and narrow. Also, there are critical intersections where left-turns block other movements or where two traffic streams merge. Evacuation efficiency could be significantly improved if these critical intersections can be correctly managed (e.g., forming undisrupted evacuation routes (55)). However, such strategies usually require optimization techniques to be formulated and are not included in this study. We also note that our network does not consider the impacts of vehicle breakdowns or emergency vehicles (which need to travel uphill towards the fire). However, since contraflow is not instituted on all uphill routes, emergency vehicles would find alternative roads to access the fire or those in needs. The network analysis also assumes that most evacuees will not travel far distances, which is supported by the survey data. However, mass evacuations over 100,000 people may require a better understanding of destinations and shelter types (along with the suitability of these locations) for the simulation.

Regarding traffic models, due to data availability and coding efficiency considerations, sub-link behaviors in the model (e.g., lane-changing aggressive drivers) were not included. The node model is not detailed enough to investigate within-intersection events. We remove signaling for simplicity, since so few nodes in the study area are signalized. The “fastest” path assumption is limited as evacuees likely do not have full knowledge of congestion, choosing detours to circumvent congestion. Research has also shown that other factors impact routing beyond shortest path (11,56). Pedestrian-vehicle interactions are not considered, evacuees are assumed to leave via a vehicle (overestimating congestion), and individuals rerouting without perfect information are not considered.

For the scenarios, interactions of different strategies are not considered due to the already large numbers of studied variables, despite possible correlated effects (57). Incidents such as fallen trees blocking the roads are not considered. A shelter-in-place option is not considered. We assume 100% of residents are home and 100% of evacuees will leave even though research has shown compliance of mandatory evacuation orders around 90% (11). This oversimplification is chosen to model both a disadvantageous scenario for congestion, but also an ideal outcome (in terms of compliance to mandatory evacuation orders) for public safety agencies. We also note that we oversimplify the evacuation process (one trip per household, with no trip-chaining). Past research has demonstrated that evacuees may take multiple stops before reaching the destination. For example, (6) found that people make 1.1 intermediate stops on average based on post-wildfire surveys in Haifa, Israel. Families with children make more intermediate stops, at 1.5 on average. (58) also argued that trip-chaining helped explain certain travel behaviors (e.g., evacuating towards the fire area), which avoids overly optimistic travel time predictions. In the simulation case study presented in this paper, trip chains are not considered (e.g., child pickup or helping carless individuals). However, the considered scenario, namely a weekend morning when all residents are at home, is likely to imply an equally disadvantageous demand level. First, additional trips such as child pickup or return home from work are usually happening during work hours, which coincides with the time that most residents are away from home in the residential neighborhood. Second, during wildfire events, there are usually orders in place that prevents people from entering the fire zone.

Apart from excluding trip-chaining, we also simplify the model by not including surrounding vehicles (i.e., background traffic), multiple pre-evacuation trips by households, or post-evacuation trips. We also did not consider shadow evacuations (i.e., evacuation of individuals who did not receive a mandatory evacuation order), which is a limitation. More data is needed to determine the extent of shadow evacuations, especially in cases where evacuation orders are delivered effectively and on-time. We also note that specific vulnerable population evacuations were not considered. For instance, in zip code area 94708, which covers most of the evacuation area, there are 2,850 Old-Age, Survivors, and Disability Insurance (OASDI) beneficiaries (59). Agencies with local knowledge should make these populations a priority. The destination choice in the simulation is based on the notion that most wildfire evacuations are short-distance trips. Destinations for each simulated vehicle are randomly sampled according to the trip distance distribution obtained from the survey. Three random variables are used, and results indicate that stochasticity in destination locations only have minor impacts on the results. Future work is necessary to also consider how shelter locations could be incorporated into the modeling.

Most critically, simulations are not perfect representatives of real-life behavior. The number of factors, random events, and governmental decisions would be nearly impossible to model. We acknowledge that our simulation, while incorporating past behavioral data, could be continuously improved with greater realism. This might also include how demographic characteristics impact the decision to evacuate or stay/defend (see (6–8,11,13)). Though, most of these studies have found that risk perceptions, not demographics, are better predictors of choice. Regardless, integrating discrete choice analyses with this simulation framework is a logical next step. Finally, the simulation framework is not straightforward for agencies to use directly due to the lack of an interactive dashboard. Efforts are being made to make the code and data open-sourced, as discussed in Section 3.4. Our aim is to produce a workable simulation model that is a stepping stone for more behaviorally driven research.

3.4 Simulation Reproducibility

Reproducibility is defined as the ability to confirm the results of a previous experiment by means of another similar experiment (60), and it is a crucial criterion in ensuring the credibility of scientific results. (60) categorized reproducibility into four levels, from being able to reproduce the results using the same data and model, to reproducing the results based on general descriptions of the model specifications. The model presented in this paper is based on computer simulations. Efforts to ensure reproducibility include:

1. **Stating model specifications and key assumptions in detail in the methodology section (Section 3).** Based on these specifications, the results can be verified and reproduced in other simulation software;
2. **Conducting repeated experiments with random seeds as shown in the results section (Section 4).** Despite the minor differences in each random experiment, the magnitude and overall conclusions of the results were largely unchanged;
3. **Providing open-sourced simulation code.** To ensure that the results and conclusions are reproducible by future researchers, the simulation code is open-sourced, and data inputs are available upon request.

4. RESULTS

We begin with presenting the baseline case for the wildfire simulation. Figure 4 shows the simulated congestion status at two specific time steps for the baseline case. Each road link is colored by vehicle density, while each road node is represented by pre-departed vehicles. Figure 4(a) shows results at 45 minutes since giving out the evacuation order. The traffic is visibly heavier than Figure 4(b), which is at 1 hour and 45 minutes after giving out the evacuation order. We note that the most congested roads are often branch roads merging into key routes (e.g., the roads leading to Marin Avenue).

For each scenario shown in Table 2, the alternatives are compared against the base scenario, while fixing all other strategies to their respective baseline values (underlined values in Table 2). Three random repetitions are conducted to reduce the influence of random variabilities on the outcomes. Two evacuation related metrics are shown in detail:

- **Safe Vehicles:** Total number of vehicles that have reached at least one mile away from the evacuation zone;
  - Designates vehicles reaching safe location;
  - Can derive evacuation time estimates;
- **Exposed Vehicles:** Number of vehicles within in the fire frontier;
  - Identifies vehicles overtaken by the fire (i.e., potential risk or danger);
  - Does not necessarily signify fatalities.

The metrics are plotted over time for the baseline and each comparison scenario. Other summary statistics are given in Table 3, including time of exposed vehicles and average distance from the fire frontier.

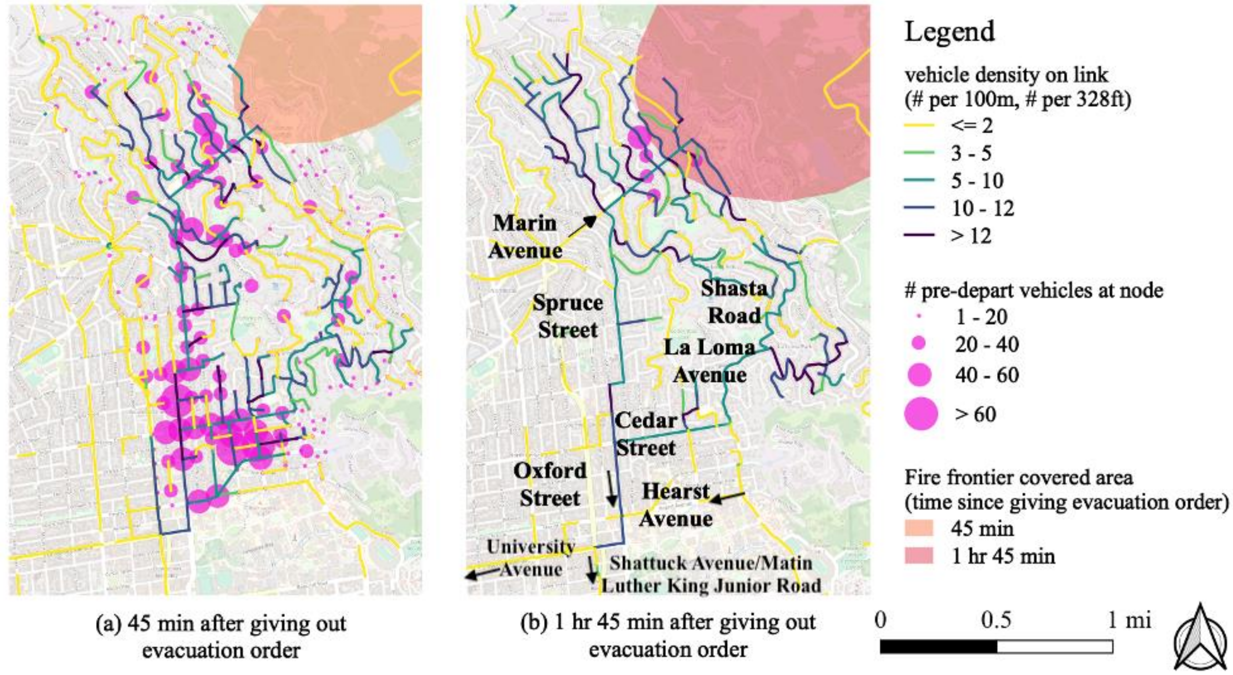

Figure 4. Results from the spatial-queue-based traffic simulation, including the vehicle density on each road link and number of pre-depart vehicles (either because of the delay in departure or being blocked from the first link). (a) Results at 45 minutes since the evacuation order is given out (1 hour since the ignition of the fire); (b) Results at 1 hour and 45 minutes since the evacuation order is given out (2 hours since the ignition of the fire);

4.1 Fire Speed

We first vary the fire speed to reflect potential changes in weather conditions, firefighting, and/or fuel management. In the baseline case, fire overtook the first vehicle at 14 minutes after the evacuation order was given (Figure 5(a)). The number of exposed vehicles reached its peak of 782 vehicles at 2.3 hours. Compared to the baseline, this metric decreases by 56% if the fire speed can be reduced to half (e.g., through effective firefighting, fuel management, weather, etc.) or increases by 55% if the fire speed doubles. Figure 5(b) shows safe vehicles and the associated ETEs. Fire speed only minimally influences ETEs since most vehicles depart before the fire reaches their households in all scenarios. Additional work will need to identify how departure time and mobilization time is influenced by fire speed, especially given the role of speed in challenging evacuations in past wildfires (1).

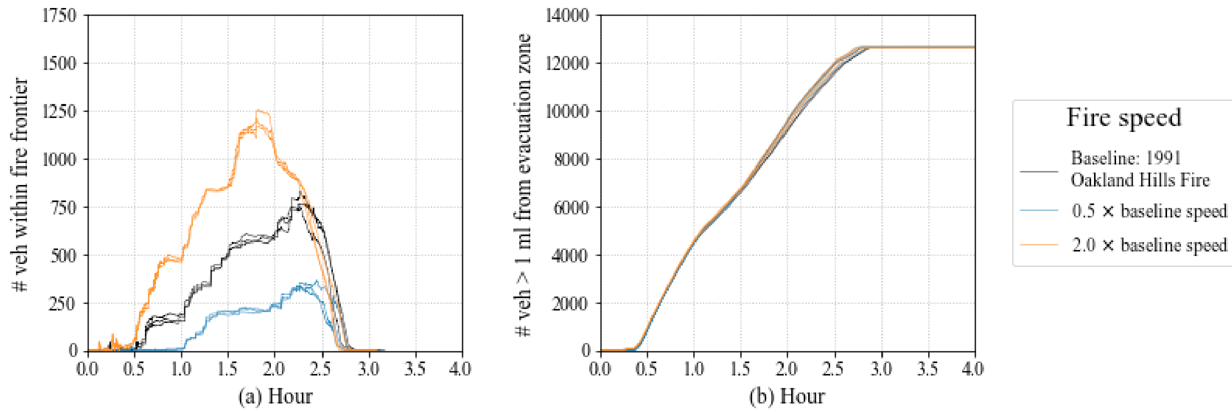

Figure 5. The impact of fire speed on (a) exposed vehicles; (b) number of safe vehicles.

4.2. Departure Timing

The three departure time scenarios ("fast", "medium" and "slow", Table 2) represent departure times after receiving the evacuation order. Scenarios perform similarly for exposed vehicles (Figure 6(a)), possibly due to relatively close means for all three cases (20, 40 and 60 minutes). The number of exposed vehicles in the "fast" departure scenario grows ahead of the other two cases due to earlier buildup of queues on Marin Avenue (a key local route).

Figure 6(b) shows both the cumulative number of vehicles that started the evacuation (dashed line) and safe vehicles. We note that the dashed line for the cumulative distribution function (CDF) does not follow a truncated normal function, since some vehicles cannot enter fully saturated links. The "fast" case is the most efficient in ETEs, showing the benefit in early departure. However, the magnitude of the time savings of a 20-minute earlier departure is minimal. Compared with Section 4.4 (phased evacuation), more gradual departure times (without staggering the departure spatially) alleviate less congestion.

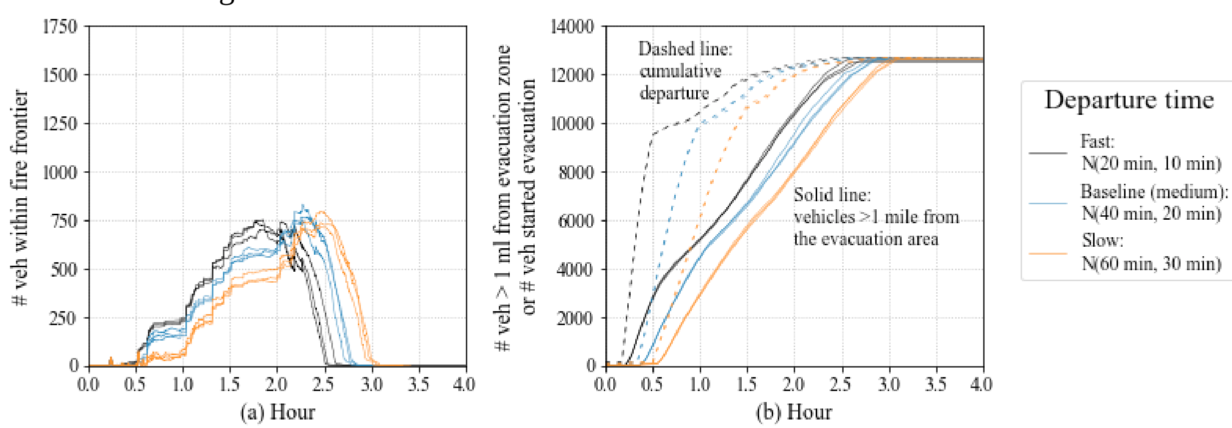

Figure 6. The impact of departure delays on (a) exposed vehicles; (b) safe vehicles.

4.3 Towing

Normal vehicles are assumed to take 26 ft of space on road, the invert of typical jam density (94) with towed items taking an additional 24 ft (approximate trailer length). Assuming the percentage of households towing items is 0% or 25%, the simulation results in -5% and 8% changes in the total vehicle length compared to the baseline

(10% households take towing items). The maximum number of exposed vehicles changed by -3% and 5% compared to the baseline, while the ETEs changed by -7 minutes and +4.2 minutes, a rather small change compared to other scenarios.

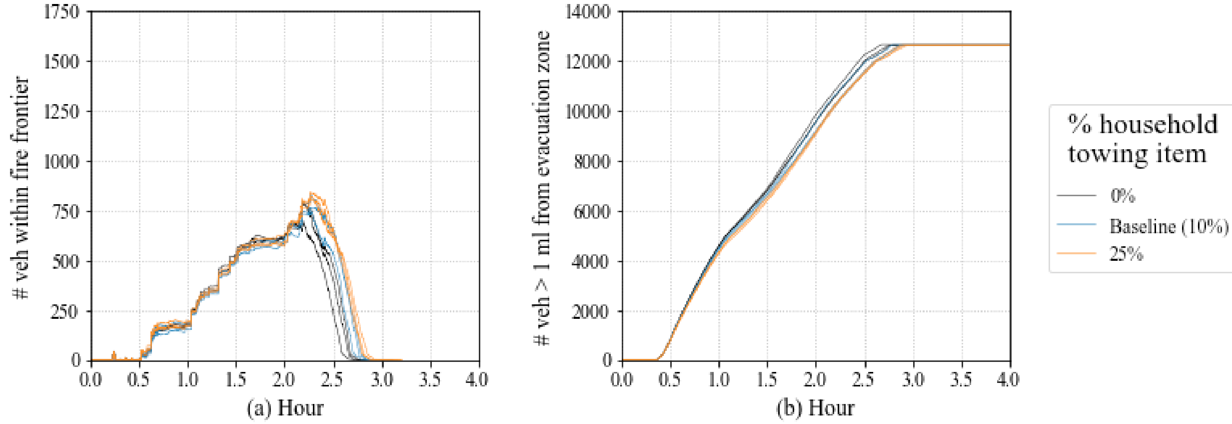

Figure 7. The impact of towing items on (a) exposed vehicles; (b) safe vehicles.

4.4 Transportation Mode Split

Evacuating households often use multiple vehicles to take belongings, family members, and pets or to remove the vehicle from danger (61), leading to more congestion. Our baseline case sets the household vehicles for evacuation according to the survey (about 1.7 per household), resulting in 782 exposed vehicles (about 6% of the total demand) and an ETE of about 3 hours. If all households evacuate with only one vehicle, the maximum number of exposed vehicles falls to 245 (about 3% of the total demand) and the ETE is cut to 1.9 hours. If all households evacuate with three vehicles, exposed vehicles reach 2,497 (11% of the total demand). Only 19,953 vehicles can reach the safe area in 4 hours (89% of the total demand in this scenario).

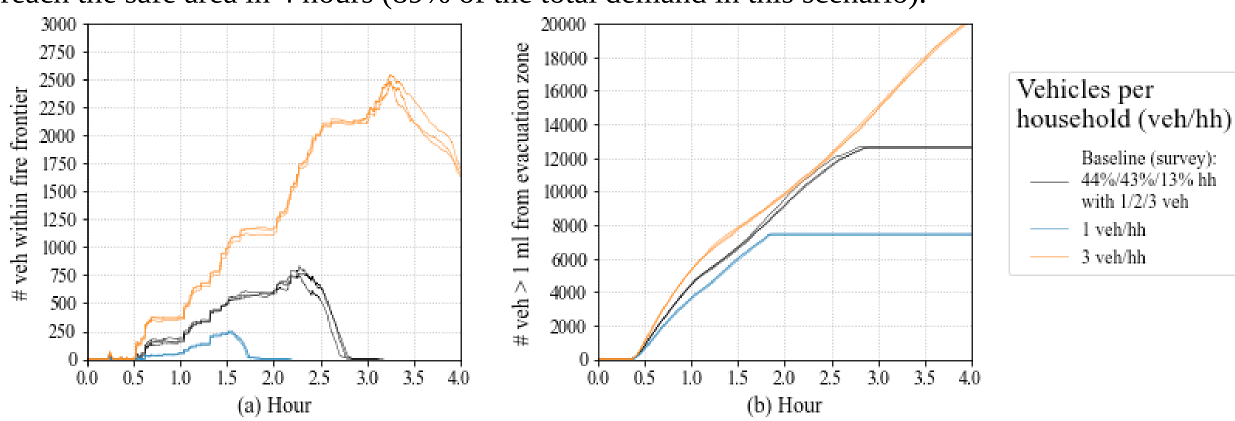

Figure 8. The impact of number of vehicles per household on (a) exposed vehicles; (b) safe vehicles. Note the scales are different.

4.5 Real-Time Traffic Information for Rerouting

Rerouting can theoretically relieve congestion by distributing the traffic to other roads. The black lines in Figure 9(a) presents baseline results with 15% rerouting (similar to the survey). The orange, blue and green curves correspond to scenarios where 0% (no information), 50% (strong access to rerouting information), and 100% (theoretically equivalent to automated vehicles [AVs]) of the drivers reroute. Compared to baseline, the exposed vehicles change by +20%, -51% and -

89%, respectively. Figure 9(b) shows that the alternative scenarios can also reduce the ETEs to 3.2, 2.1 and 1.2 hours compared to 2.9 hours in the baseline case.

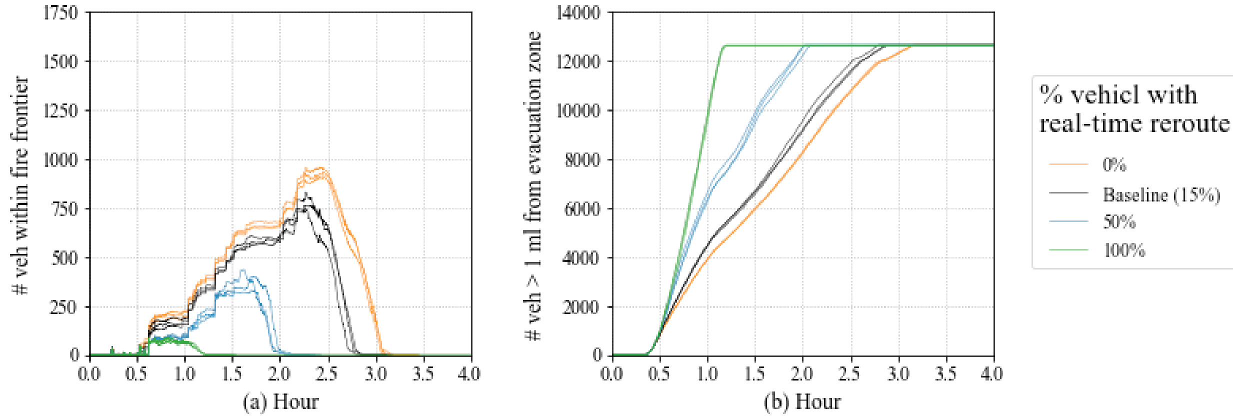

Figure 9. The impact of vehicle rerouting on (a) exposed vehicles; (b) safe vehicles.

However, rerouting may not be a safe option due to road closures or connectivity challenges, as was the case of the Camp Fire (62). We further explored this scenario in the simulation and the results are shown Figure 10. In Figure 10, results of two levels of real-time routing participation rate (15% and 50%) and three levels of interruption timing (no interruption, interrupt at 30 minutes and 6 minutes) are plotted. In the base case (black curves), 15% of vehicles follow real-time routing information, and such information is available throughout the evacuation process. Comparatively, the orange and red curves show the results when the connection to the real-time information is interrupted at 30 minutes or 6 minutes. Unless the connectivity is lost at a very early stage, the influence on evacuation efficiency is minimal (orange curve almost coincides with the base curve). The reasoning is that the total number of rerouting vehicles (15%) is relatively small. For these vehicles, many are routed away from the congested roads at the beginning and are not adjusted significantly during the evacuation. This can be seen in Figure 11(a), where the thickness of the lines indicates the numbers of vehicles using each link throughout the entire simulation and the color indicates the percentages of rerouting vehicles. We note that the percentage of rerouting vehicles on the congested roads (thick lines) is lower (less than 5%) than the scenario average of 15% rerouting. As a result, interrupting rerouting after congestion starts to form will not alleviate or worsen congestion significantly. However, if rerouting is interrupted at the beginning of the simulation (e.g., the red curve in Figure 10), the vehicles with rerouting capabilities are not able to avoid the congestion, since delays have not started to form when they are planning their routes. The results of a loss of connectivity early in the evacuation are very similar to results without rerouting (orange curve in Figure 9). For higher usage of real-time rerouting (50% of vehicles using real-time rerouting, blue/green/purple curves in Figure 10), the impact of losing such information is clearer. As shown in Table 3, if the connection to the real-time information is lost at 30 minutes while 50% of the evacuees are trying to follow it for routing, the number of exposed vehicles increases by almost 100 compared to the no interruption case, while the total exposed time (vehicle-hours) increases by over 50%. Figure 11(b) also illustrates this. Since evacuation efficiency is dominated by the congestion on a few routes, significant improvements could be made if vehicles on these congested routes could have used real-time rerouting to seek an alternative route.

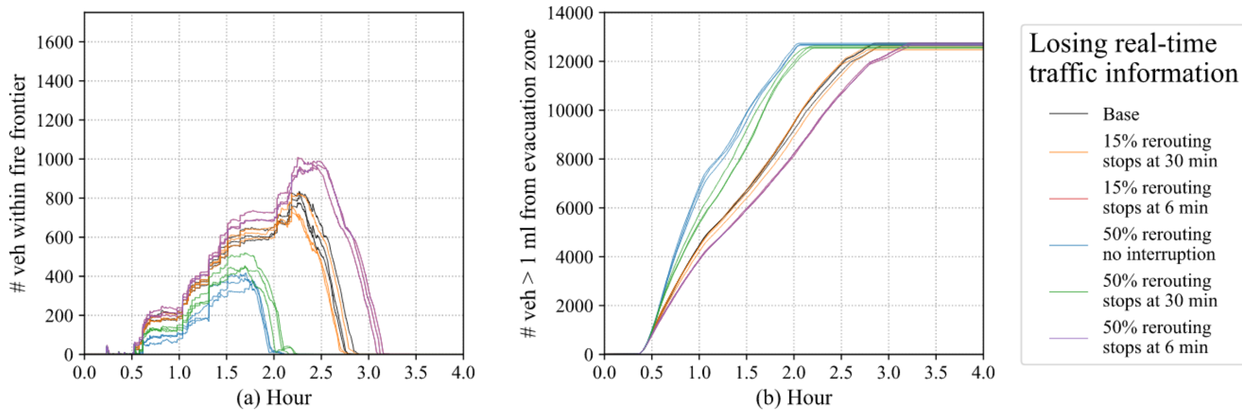

Figure 10. The impact of interrupting real-time routing at different stages of the evacuation.

Figure 11. Total numbers of vehicles using each link (thickness) and percentages of vehicles with real-time rerouting on each link (color scale). (a) 15% of all evacuees follow real-time traffic information; (b) 50% of all evacuees follow real-time traffic information.

4.6 Phased Evacuation

Phased evacuations often improve congestion by reducing the maximum instantaneous traffic load and increases overall safety by prioritizing residents in greater danger (63). We tested phasing by altering time intervals between the mean departure time of different evacuation zones (Figure 12). Figure 12(a) shows exposed vehicles for different phased evacuation intervals. By giving a 15-minute priority to each of the evacuation zones closer to the fire (blue curve), exposed vehicles reduce by 78%. If the phase interval increases to 30 minutes (green curve), exposed vehicles reduce by 94%. However, if the phase interval becomes too large (e.g., 60 minutes, orange curve), some vehicles may leave too late and be overcome by the fire, increasing exposed vehicles slightly compared to the 30-minute case. Figure 12(b) shows safe vehicles differ minimal from baseline for phase intervals of 15 minutes and 30 minutes. However, when the phase interval becomes 60 minutes, the network is underutilized (characterized by flat lines).

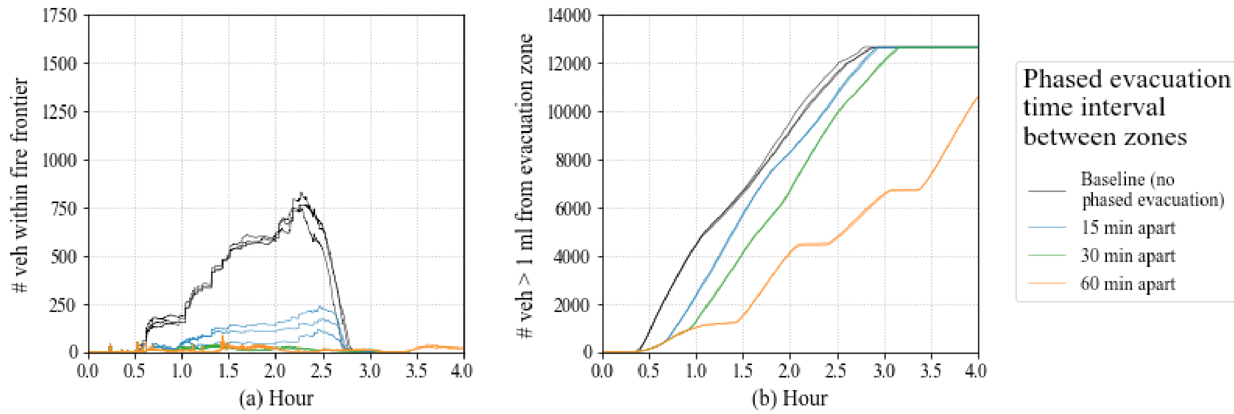

Figure 12. The impact of phased evacuation on (a) exposed vehicles; (b) safe vehicles.

4.7 Contraflow

In this study, the locations of contraflow were identified based on inspecting the bottlenecks in Figure 4, centerline markings, and local knowledge of downhill routes as:
For short-distance contraflow, resources are assumed to be limited and the strategy could only be implemented along the key egress routes to slightly beyond the evacuation boundary:

- West side downhill routes (3.7 miles long, extending 0.5 mile outside of the evacuation zone): Marin Avenue → Spruce Street → Oxford Street; and
- East side downhill routes (1.9 miles long): Shasta Road → Glendale Avenue → La Loma Avenue → Cedar Street → Euclid Avenue → Le Conte Avenue → Hearst Avenue (→ join the westside contraflow routes at Oxford Street).

When there are sufficient personnel and time, contraflow roads can be extended to local highways. In this scenario, the contraflow strategies are also implemented following roads:

- Shattuck Avenue and Martin Luther King Junior Way, from University Avenue till CA-24 (2.7 miles).
- University Avenue, from Shattuck Avenue till I-80 (2.2 miles).

Figure 13(a) shows a reduction of 53% of exposed vehicles after implementing contraflow to the evacuation zone boundary. In the extended contraflow scenario, the number of exposed vehicles reduced by 73% compared to the baseline. In Figure 13(b), the number of safe vehicles and ETE does not change substantially when the evacuation lanes terminate close to the evacuation boundary. In fact, this is in accordance with the characteristics of contraflow: it helps absorb more vehicles from branch roads to the contraflow lanes, thus making it faster for the vehicles to outrun the fire. However, in an urban setting, the downstream (sink) capacity is still limited by the end of the contraflow roads, leading to vehicle queues downstream of the contraflow roads. By extending the contraflow lanes to a further distance away from the evacuation zone, it is possible to reduce the queue spillback into the evacuation zone, making it faster for vehicles to leave the dangerous area.

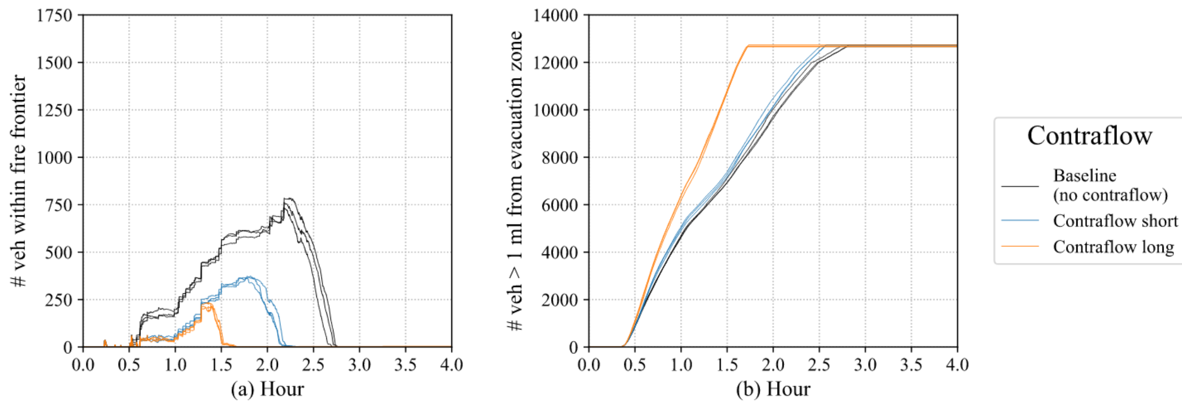

Figure 13. The impact of contraflow on (a) exposed vehicles; (b) safe vehicles.

4.8 Summary of Findings

Four summary statistics are given in Table 3 for comparison: 1) exposed vehicles; 2) ETE; 3) amount of time exposed vehicles were in the fire frontier; and 4) average distance from fire. The time for all vehicles to complete the evacuation is not shown, as the evacuation destinations were picked at random and sometimes constitute long trip times.

Based on summary statistics in Table 3, phased evacuations with 30-minute departure time interval, >50% vehicle rerouting, personal vehicle reduction (1 vehicle per household) and instituting contraflow beyond the evacuation zone boundaries are the most effective strategies. These strategies can greatly reduce the load of the traffic temporally (phased evacuations), spatially (rerouting and contraflow), and overall (personal vehicle reduction). Each strategy has limitations: phased evacuations require strict adherence to mandatory orders, vehicle rerouting requires real-time information from power and cell sources and quick detection of road closures, personal vehicle reduction requires significant education and a willingness to give up an expensive asset, and contraflow requires planning efforts and is labor-intensive during its execution.

Some strategies (e.g., slowing fire speed, phased evacuation with less time intervals between zones, selective contraflow) have less impact on ETEs but still lead to moderate reductions in exposed vehicles. Reducing fire speed provides more time for slower households to leave. We found that rapid phasing, compared to more drawn-out phasing, overloads the network too quickly and is not as effective as other phasing intervals. Contraflow over a short length also removes individuals quickly from the fire area, but downstream congestion still leads to high ETEs. Several strategies, such as changing towing behavior and speeding up departure times, lead to minimal reductions in both exposed vehicles and ETEs. The worst case among all scenarios studied is to evacuate with three vehicles per household. This represents the highest evacuation demand on a network with limited capacity and is detrimental in all metrics evaluated.

The above simulation results are based on the series of scenarios and assumptions as stated in Sections 3.2 and 3.3. In reality, situations that deviate from these assumptions might happen and lead to changes in the outcomes. For example, depending on the time and day of the incident, there may be less people at home compared to the current assumption. This will reduce the evacuation demand, effectively leading to less challenging evacuation situations similar to the effect of vehicle reduction. Also, it has been suggested that people may make multiple trips during the evacuation (6,58). This has the potential to increase the overall ETE and conflicts at intersections, for example. Other factors that will affect evacuation outcomes include shadow evacuations, the presence of pedestrians sharing the road network, vehicle breakdowns, emergency vehicles traveling in the opposite direction, transportation of vulnerable populations, and public transit usage. In addition, the resilience and operations of the infrastructure may also impact the overall evacuation efficiency. For instance, signals that are not optimized may create long queues of traffic backing up (64). However, as the signalized intersections in the study area are mostly out of the evacuation zone, it may not significantly affect evacuation metrics, such as the fire exposure time. Realistically, multiple disadvantageous scenarios may happen at the same time, such as a fast-moving fire that damages the communication and navigation infrastructure, causing difficulties in coordinating contraflow operations between emergency personnel and/or evacuee challenges in accessing real-time routing information.

TABLE 3. Summary of Evacuation Efficiency Metrics under Different Strategy Scenarios.

	Evacuation Efficiency Metrics					
	Exposed Vehicles		**Evacuation Time Estimate (ETE)**		**Total Time of Exposed Vehicles**	**Distance from Fire**
	Max # veh in fire frontier at the same time (veh);	% change from baseline	Time (hrs), all vehicles reach safety, 1 ml from evac zone;	% change from baseline	Total veh-hours fire frontier (veh-hrs)	Min. average distance to the fire frontier (miles)
Baseline						
Baseline	782	-	2.9	-	954	0.6
Fire speed						
×0.5 (slower)	342	-56%	2.8	-1%	350	0.8
×2 (faster)	1,209	+55%	2.8	-2%	1,569	0.5
Departure time						
Less delay	729	-7%	2.7	-5%	910	0.4
More delay	747	-4%	3.1	+7%	906	0.6
% towed vehicles						
0%	757	-3%	2.8	-4%	885	0.7
25%	821	+5%	3.1	+2%	906	0.6

# vehicles per household for evacuation						
1	245	-69%	1.8	-36%	129	0.9
3	2,497	+219%	>4	>+40%	5,057	0.4
% vehicles rerouting with real-time traffic information						
0%	943	+20%	3.2	+11%	1,320	0.6
50%	381	-51%	2.1	-28%	279	0.8
100%	86	-89%	1.2	-58%	35	0.7
15%, stop at 6 min	979	+25%	3.1	+7%	1,430	0.6
15% stop at 30 min	771	-1%	2.8	-3%	974	0.6
50%, stop at 6 min	979	+25%	3.1	+7%	1,430	0.6
50%, stop at 30 min	474	-39%	2.1	-28%	411	0.8
Phased evacuation time difference between bands						
15 min	173	-78%	2.9	+2%	188	0.8
30 min	49	-94%	3.2	+10%	35	0.8
60 min	80	-90%	>4	>+40%	40	0.7
Contraflow						
Short contraflow	367	-53%	2.6	-10%	310	0.8
Long contraflow	209	-73%	1.7	-41%	84	0.9

5. POLICY RECOMMENDATIONS

The modeling results point to clear opportunities for emergency management and transportation agencies to reduce wildfire evacuee risk and improve ETEs. In Table 4, we present each of the transportation responses, their priority, and possible recommendations for agencies to pursue. We note that many strategies will require careful planning and substantive communication with residents. Indeed, informational and educational campaigns (not infrastructure or operational changes) that attempt to nudge behavior may be the most cost-effective strategy to improve evacuation outcomes.

TABLE 4: Policy Recommendations for Transportation and Hazard Responses and Strategies

<table>
<tr><th>Transportation/ Hazard Response</th><th>Priority</th></tr>
<tr><td>1. Slowing Fire Speed</td><td>Moderately Recommended</td></tr>
<tr><td colspan="2">Description
Slowing fire speed will reduce the number of vehicles in the fire frontier and allow for longer mobilization times, especially for vulnerable populations who might need more time to evacuate. However, slowing fire speed requires very quick and rapid response to the hazard or longer-term fuel management strategies (e.g., fuel breaks), which may not be feasible for some jurisdictions. Moreover, the typology, land development, and weather conditions may make fire suppression nearly impossible, placing firefighters or aircrafts at risk.

Recommendations for Emergency Management and Transportation Agencies
Manage fuels and create fire breaks by reducing highly flammable vegetation in high-risk areas (e.g., near powerlines) and along roadways
Develop rapid detection systems for wildfires (e.g., cameras, sensors, physical lookouts, crowdsourced information, drones)
Work with homeowners and landowners through education, funding, and enforcement to create defensible space, fire resistant structures, and backup water storage systems
Feasibility
Fire spread depends on the weather, topology, and fuel. Studies have shown that fuel management such as Fuel Reduction Burning (FRB) can effectively slow down the rate of head fire spread (65). Also, structures that are separated by sufficient distances or have defensible space around them can help stop or slow down fire (66). Smart technologies are also maturing and have been adopted in practice, such as using fire cameras combined with Artificial Intelligence (AI) to rapidly detect fire and smoke at early stage (67). The benefits of slowing fire spread are clear, but actions will require substantial effort by agencies and residents. Agencies should work on community preparedness and prescribed burning. Residents should conduct actions for the residence (e.g., clean gutters, use fire resistant roofing and exterior in high-risk areas). Economically, however, this can be difficult for low-income communities (e.g., metal roofing can be 5-10 times more expensive than asphalt roofing materials), indicating equity challenges.</td></tr>
<tr><td>2. Reducing Departure Delays</td><td>Moderately Recommended</td></tr>
<tr><td colspan="2">Description
Reducing the departure time lag between receiving a mandatory evacuation order and evacuating can help remove at-risk people more quickly. However, this strategy alone is not enough to sufficiently reduce evacuation risk. Moreover, some individuals, such as individuals with a physical disability, may need extra assistance and additional time to evacuate.

Recommendations for Emergency Management and Transportation Agencies</td></tr>
</table>

- Issue mandatory evacuation orders as quickly as possible to ensure enough time for individuals to mobilize and leave, especially individuals with access and functional needs (AFN)
- Encourage residents to create go-bags that speed up the mobilization process
- Include in mandatory evacuation orders an approximate amount of time they should spend mobilizing that is long enough to prepare but also short enough to evacuate individuals quickly

Feasibility
Reduction in departure delay can be achieved through improving pre-event preparedness and giving evacuation orders in a timely and clear manner. Cal Fire and local agencies have made efforts in improving this preparedness with the public-facing website readyforwildfire.org that disseminates "Ready, Set and Go" information (68). For alert systems, most local areas are gradually adopting state-of-the-art software, such as Code Red, and/or updating their Wireless Emergency Alert (WEA) system. However, issues remain in disseminating information quickly, in multiple languages, with adequate direction, and to enough people (1). Reducing evacuation delay is attainable, but based on recent experience, a robust communication system (along with correct decision-making from officials) is needed.

3. Reducing the Amount of Towing	Minimally Recommended

Description
Additional mobile assets (e.g., trailers, boats, motorhomes) create more demand, but this increase is minimal to moderate. A reduction in towing leads to some gains across evacuation metrics. However, mobile assets tend to be expensive, making them a higher priority for protection.

Recommendations for Emergency Management and Transportation Agencies
- Encourage residents in high-risk areas with mobile assets to gain wildfire (e.g., disaster) insurance
- Suggest to residents to hook up and prepare mobile assets ahead of potential fire danger to reduce mobilization time
- Develop plans for parking areas outside of potential evacuation zones for residents to take mobile assets during high fire danger weather (i.e., pre-disaster trip-making)

Feasibility
There is currently little information on agency regulation or recommendations regarding towing vehicles, so its current feasibility is hard to assess. Based on the Federal Highway Administration (FHWA) highway statistics of 2019, the ratio of trailers versus automobiles (all privately owned) in the fire-prone states California, Nevada, Oregon, and Washington were 0.16, 0.18, 0.22 and 0.20, respectively (69). The values are within range of the simulation inputs (0-25%) in this study. Trailer usage in places with large farm animals may be higher and planning for their safe evacuation might be more crucial.

4. Reducing Number of Evacuating Vehicles	Highly Recommended

Description
The travel demand from multiple vehicle households greatly increases exposed vehicles and ETEs. By reducing the number of vehicles taken by households, congestion will be greatly diminished and allow evacuees to reach their destinations more quickly. Reducing vehicles is highly recommended for all jurisdictions but this strategy will require significant and proactive educational campaigns.

Recommendations for Emergency Management and Transportation Agencies

- Recommend to residents to take as few vehicles as possible (i.e., enough to transport people and key belongings) through an educational and informational campaign
- Suggest to resident to pre-pack vehicle(s) in advance such that space is used efficiently in vehicles
- Encourage evacuees taking more than one vehicle to provide their extra space to carless individuals and other vulnerable populations to improve equitable outcomes
- Develop an equitable insurance framework for protecting vehicles of residents in high-risk fire areas
- Develop plans for parking areas outside of potential evacuation zones for residents to take additional vehicle during high fire danger weather (i.e., pre-disaster trip-making)

Feasibility

Based on data from 1990-2010, the WUI is the fastest growing land use type in the contiguous United States (70). With mostly single-family houses in the WUI (71), private vehicle are the primary mode of transport in such areas. In the Berkeley Hills area (most of which belongs to zip code 94708), the average household size is 2.3, but there are nearly 2 vehicles per household on average. As a result, carpooling would be considered less attractive given the high car-ownership. Israel, for example, having lower car ownership than the United States, was reported to use 0.89 vehicles per household for evacuation (6). The benefits of vehicle reduction during evacuations are well understood in the literature, and there is already some development of education campaign by agencies. For example, Marin County in California advocates on its website that “every seat should be filled” and that evacuees should “assist elderly or disabled neighbors” and “carpool with neighbors to reduce traffic” (72,73). (57) noted the difficulty in vehicle reduction and compared this to the “prisoner’s dilemma”, where residents would have to forsake personal properties (vehicles and belongings that could not be taken) for the overall benefit of reduction in traffic. One important possibility is that auto insurance could help to reduce the financial loss of vehicles if they are left at the residence. Some auto insurance policies cover wildfire damage but not all people can afford this comprehensive coverage. In terms of parking capacity in the study area, there are nearly 1,400 off-street parking spots owned and operated by the City of Berkeley, including three garages and two surface parking lots in Downtown Berkeley, South Berkeley, and the Elmwood district (74). There are also over 1,400 parking spaces at the North Berkeley and Ashby stations for Bay Area Rapid Transit (BART) (75). In addition, the above totals do not count for parking owned by companies, employers, or private operators. Other parking structures, such as those on the nearby University of California, Berkeley campus, can also provide additional space for the pre-evacuation of vehicles. For other cities, a similar crude validation can be used to estimate the feasibility of a pre-evacuation parking strategy.

5. Increasing GPS-Based Rerouting	Highly Recommended

Description
Higher rates of rerouting led to significant reductions in exposed vehicles and ETEs. Even smaller percentages of rerouting (15%) were far more effective than other potential transportation strategies. Despite these benefits, a rerouting strategy will have to ensure that GPS-guided directions are available, accurate, and followed by evacuees.

Recommendations for Emergency Management and Transportation Agencies

- Partner with GPS mapping services (e.g., Google Maps, Apple Maps, Waze) and auto manufacturers with GPS guidance to ensure that systems with be operational in a disaster
- Update mapping services through official or crowdsourced information of blocked routes (i.e., downed powerlines, trees) and current fire location
- Work with and require utilities to have backup generators for key communication services (e.g., high-speed mobile Internet) to ensure GPS directions are available
- Produce pre-disaster information related to GPS guidance to evacuees and encourage usage of services, even for short evacuations
- Encourage services to default applications to reroute in an evacuation, rather than remain on the current route
- Consider future integration of wildfire evacuation information to automated vehicles (AVs)
- In the long-term, develop vehicle-to-everything (V2X) technologies that can exchange information and compute real-time routes without relying on vulnerable communication infrastructures (e.g., cell towers)

Feasibility
Real-time rerouting is an effective strategy in all scenarios studied in the simulation. However, its feasibility is dampened by several challenges. First, real-time rerouting services are mostly provided by private companies. While many have shown strong willingness to assist (e.g., Google hazard map showing real-time closures), companies have yet to develop robust partnerships with agencies. Second, GPS systems need to be paired with transmission infrastructure (e.g., cell towers) to communicate with the central server about current positions. However, cell towers and other communication infrastructures have been susceptible to power outages, losses of backhaul fibers, and structure damages from wildfires (76). In 2020, California Public Utilities Commission issued a new decision for major wireless providers to have 72 hours of backup power and build new communication resiliency and emergency operations plans (77). Other opportunities for ensuring communication include the use of short-range equipment to act as temporary stations (e.g., using drones to relay wireless signals in (78)). However, these innovations are still largely conceptual. Finally, people may not choose real-time routing guidance during an evacuation, opting instead for routes that are shorter, have less fire danger, and high-quality pavement conditions (12). Altogether, real-time routing requires improvements to enhance V2G (vehicle to grid) infrastructure and V2V (vehicle to vehicle) infrastructure to support more secure and robust communication to make rerouting feasible (79–82).

6. Phasing Evacuations	Highly Recommended
Description Depending on the phasing time difference (and size of phased zones), a phased evacuation strategy can be effective in improving evacuation outcomes on its own. However, phasing requires significant pre-planning activity and active communication with residents before and during the evacuation, making it difficult to implement. Moreover, the characteristics of the wildfire may make a phased evacuation impossible, as the fire may overcome non-evacuated zones. Recommendations for Emergency Management and Transportation Agencies • Research, develop, and widely distribute phased evacuation plans that create reasonable time bands (e.g., approximately 30 minutes for a highly urban fire) • Use known boundaries and easy to identify landmarks and roads to set evacuation zones for phasing • Maintain a relatively small number of potential zones to reduce confusion in the evacuation process and reduce the number of messages sent to evacuees • Convey emergency evacuation orders and warnings by zones • Prepare for contingencies (i.e., changes in time bands) if the fire spread is faster or slower than expected Feasibility Dividing the fire-prone area into zones is an effective way to move as few people as needed to safe areas (83). In practice, agencies can construct evacuation zones based on both natural (e.g., vegetation type) and human factors (e.g., landmarks, clearly defined roads) (84,85). The initial research can be done as a desktop study, as the vegetation coverage map, the road network map, and other geospatial information can be readily obtained from sources such as the LANDFIRE program and OpenStreetMap. During the development stage, refinement can be made through meetings with the emergency responders and the wider community (14). Prior to wildfires, residents need to be informed of their zones, potentially through letters sent to homeowners and renters or announcements via online neighborhood hubs such as Nextdoor. Interactive zone maps for the jurisdiction can also be created easily using tools such as ArcGIS online (e.g., Berkeley Evacuation Zone Map from (86)). During the wildfire, geo-coded alerts can be sent to residents in targeted zones. For example, alerts can be sent to the residents in specific areas through FEMA's Integrated Public Alert & Warning System (IPAWS) system through multiple pathways using commercial software (87,88). However, reliability of the software could be problematic, as previous technical difficulties have been reported (89). Lastly, zone-based phased evacuation may not work as planned if the fire spreads too quickly. In such case, public agencies may need to use a variety of communication tools (e.g., radios, phone calls, social media platforms, person-to-person interactions) to keep evacuees informed (62).	
7. Instituting Contraflow	Moderately Recommended

Description
Contraflow strategies can reduce the exposed vehicles from the fire frontier. Extending the contraflow operation beyond the immediate boundary of the evacuation zone can help to further improve the ETEs. However, contraflow tends to be an expensive procedure that requires significant pre-planning, time to executive, and personnel. For resource-strapped or smaller agencies, contraflow may not be a viable option.

Recommendations for Emergency Management and Transportation Agencies

- Develop contraflow plans that focus on highly congested roads, arterials, and neighborhoods with few exits to maximize effectiveness and minimize resource needs
- Notify evacuees ahead of time of the plan to switch lanes to flow in the opposite direction
- Consider potential turning or merging conflicts when designing contraflow routes
- Pre-plan traffic operations (e.g., changing signals to prioritize traffic away from the fire) and consider congestion-reducing mechanisms near the end of the contraflow to minimize bottlenecks and upstream queuing in the fire frontier

Feasibility
The practicality and benefits of contraflow has been demonstrated mainly in hurricane evacuations. However, its success is heavily dependent on proper planning and execution. Early studies pointed out several factors that might prevent contraflow from achieving its optimum outcome. On the planning level, limitations include the cost of planning and infrastructure changes, safety implications, confusion caused by evacuees' unfamiliarity to the arrangement, and reduced access for service and emergency vehicles (90). On the operational level, especially on urban roads/arterials, challenges remain in identifying contraflow links analytically, disseminating contraflow information timely, and maintaining traffic flow through reversed lanes and intersections (91). However, it has been shown that simple and inexpensive actions, such as providing enough entrance capacity and carrying out merges after the evacuation area, can greatly improve contraflow efficiency (92,93).

6. CONCLUSIONS

In this study, we developed a spatial-queue-based dynamic traffic simulation model that incorporated behavioral data from post-disaster wildfires in California. This simulation model was applied to a wildfire evacuation case in the Berkeley Hills Area of Berkeley, California. To incorporate realism, we considered a range of variables including fire speed, departure time, destination choice, mode choice, number of towed vehicles, queuing, rerouting, and two policy strategies (e.g., contraflow, phased evacuation). We aimed to produce a data-driven model that could identify possible transportation response strategies for agencies with minimal time, funds, resources, or knowledge to respond to a wildfire evacuation. Compared to other evacuation models, the incorporation of behavioral data, focus on policies and strategies, and realistic details (e.g., dynamic routing, parcel level data, complicated street network) signify an important step for the field.

We found strong indications that phased evacuations, vehicle rerouting, and reduction in personal vehicles were the most effective strategies for reducing the number of exposed vehicles in the fire frontier and/or the evacuation time estimate (ETE). Implementing these strategies, while challenging, would not be unrealistic for small and/or poorly resourced emergency management and transportation agencies. The strategies would require substantial pre-disaster communication and accurate, timely messaging during the wildfire. Contraflow for an extended length beyond the evacuation boundary was also found to be effective in reducing ETEs and exposed vehicles. However, this strategy would be potentially hard to implement for resource-strapped agencies if guidance is required at every intersection. A vehicle rerouting strategy may also require new partnerships with GPS-based mapping platforms (e.g., Google Maps, Apple Maps, Waze). In addition, the phased evacuation results showed that too small or too large of time intervals would be less efficient, suggesting a need for thoughtful planning. We also found moderate improvements in evacuation outcomes for implementing contraflow (for short lengths under resource constraints) and slowing fire speed *for our case study*. In combination with other strategies, these responses may prove to be highly useful under different conditions (e.g., for a different road network).

Given the level of details that the simulation can support (e.g., road network, vehicle behavior), there are many assumptions involved that have been documented extensively in Section 3 and offer broader application. Specifically, the intended application of this simulation is for preparedness analysis and reconnaissance of real events, where reasonable assumptions can be made based on local knowledge or post-event surveys. For example, for many resource-strapped communities in the WUI area, it is imperative to understand the most cost-effective precautionary measures and implement corresponding policies. This best-working strategy is likely to be different for each community, thus a flexible simulation model framework such as the one presented in this paper becomes valuable. The model can be adapted to incorporate local knowledge-based assumptions to find the critical policy scenario specific to the local context. For post-event reconnaissance, (64) presented the application of a similar framework in Paradise, CA to simulate the Camp Fire evacuation. In that study, the assumptions were made according to the field interviews with local officials. Consequently, the modeling approach in this paper demonstrates the applicability of the simulation framework to analyze alternative scenarios and gain valuable lessons from reconstructing past events.

However, more research is needed on this topic based on the limitations of the paper. For example, the model could use additional realism through better post-disaster data (including verification with mobile phone data) and integration with a fire spread model. The model also requires application across more jurisdictions in California, in North America, and globally for generalizability assessments. Most critically, work is needed to link this model to a transit-based evacuation model that better incorporates the needs of vulnerable populations and includes data on how vulnerable populations make decisions in wildfire evacuations. With increasing frequency and size of wildfire evacuations, realistic and practice-oriented models that incorporate behavioral realism will become even more critical to ensure that *all people* are safe.

7. ACKNOWLEDGEMENTS

This study was made possible via an SB 1 grant from the University of California Institute of Transportation Studies, the Graduate Research Fellowship Program (National Science Foundation), and the Dwight D. Eisenhower Transportation Fellowship Program (Federal

Highway Administration). We thank the many agencies and community organizations across California for distributing the surveys and Professor Kenichi Soga, Professor Susan Shaheen, and Professor Joan Walker from the University of California, Berkeley for their support. We express our gratitude to the anonymous reviewers for their time and valuable advice on improving the quality of this paper.

8. AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: B. Zhao, S. Wong; data collection: S. Wong; modeling: B. Zhao; analysis and interpretation of results; draft manuscript preparation, results review, and final approval: all authors.

9. REFERENCES

1. Wong SD, Broader JC, Shaheen SA. Review of California Wildfire Evacuations from 2017 to 2019 [Internet]. University of California Institute of Transportation Studies; 2020 Mar. Available from: https://escholarship.org/uc/item/5w85z07g

2. Intini P, Ronchi E, Gwynne S, Pel A. Traffic modeling for wildland-urban interface fire evacuation. Journal of Transportation Engineering Part A: Systems. 2019;145(3):1–15.

3. Li D, Cova TJ, Dennison PE. A household-level approach to staging wildfire evacuation warnings using trigger modeling. Computers, Environment and Urban Systems. 2015 Nov 1;54:56–67.

4. McLennan J, Ryan B, Bearman C, Toh K. Should We Leave Now? Behavioral Factors in Evacuation Under Wildfire Threat. Fire Technol [Internet]. 2018 Jul 17 [cited 2018 Oct 3]; Available from: https://doi.org/10.1007/s10694-018-0753-8

5. Mozumder P, Raheem N, Talberth J, Berrens RP. Investigating intended evacuation from wildfires in the wildland-urban interface: Application of a bivariate probit model. Forest Policy and Economics. 2008 Aug;10(6):415–23.

6. Toledo T, Marom I, Grimberg E, Bekhor S. Analysis of evacuation behavior in a wildfire event. International Journal of Disaster Risk Reduction. 2018 Oct;31:1366–73.

7. Lovreglio R, Kuligowski E, Gwynne S, Strahan K. A modelling framework for householder decision-making for wildfire emergencies. International Journal of Disaster Risk Reduction. 2019 Dec 1;41:101274.

8. McCaffrey S, Wilson R, Konar A. Should I Stay or Should I Go Now? Or Should I Wait and See? Influences on Wildfire Evacuation Decisions. Risk Analysis. 2018 Jul 1;38(7):1390–404.

9. Paveglio TB, Boyd AD, Carroll MS. Wildfire evacuation and its alternatives in a post-Black Saturday landscape: Catchy slogans and cautionary tales. Environmental Hazards. 2012 Mar 1;11(1):52–70.

10. Strahan K. Factors influencing householder self-evacuation in two Australian bushfires. 2017 [cited 2018 Oct 3]; Available from: http://researchbank.rmit.edu.au/view/rmit:162093

11. Wong SD, Broader JC, Walker JL, Shaheen SA. Understanding California Wildfire Evacuee Behavior and Joint Choice-Making. 2020 May 1 [cited 2020 Jun 4]; Available from: https://escholarship.org/uc/item/4fm7d34j

12. Wong SD, Chorus CG, Shaheen SA, Walker JL. A Revealed Preference Methodology to Evaluate Regret Minimization with Challenging Choice Sets: A Wildfire Evacuation Case Study. Travel Behaviour and Society. 2020 Jul 1;20:331–47.

13. Kuligowski E. Evacuation decision-making and behavior in wildfires: Past research, current challenges and a future research agenda. Fire Safety Journal. 2020 May 3;103129.

14. de Araujo MP, Lupa MR, Casper CT, Waters B. Wildfire Evacuation Scenario in Colorado. Transportation Research Record: Journal of the Transportation Research Board. 2014 Jan;2430(1):133–44.

15. Wong S, Shaheen S. Current State of the Sharing Economy and Evacuations: Lessons from California. 2019 Jun 1 [cited 2019 Jun 27]; Available from: https://escholarship.org/uc/item/16s8d37x

16. Wong SD, Broader JC, Shaheen SA. Can Sharing Economy Platforms Increase Social Equity for Vulnerable Populations in Disaster Response and Relief? A Case Study of the 2017 and 2018 California Wildfires. Transportation Research Interdisciplinary Perspectives. 2020 May 1;5:100131.

17. Wong SD, Walker JL, Shaheen SA. Role of Trust and Compassion in Willingness to Share Mobility and Sheltering Resources in Evacuations: A Case Study of the 2017 and 2018 California Wildfires. 2020 Feb 1 [cited 2020 Feb 28]; Available from: https://escholarship.org/uc/item/1zm0q2qc

18. Murray-Tuite PM, Mahmassani HS. Transportation Network Evacuation Planning with Household Activity Interactions. Transportation Research Record. 2004 Jan;1894(1):150–9.

19. Noh H, Chiu Y-C, Zheng H, Hickman M, Mirchandani P. Approach to Modeling Demand and Supply for a Short-Notice Evacuation. Transportation Research Record. 2009 Jan;2091(1):91–9.

20. Vorst HCM. Evacuation models and disaster psychology. Procedia Engineering. 2010;3:15–21.

21. Lim GJ, Zangeneh S, Reza Baharnemati M, Assavapokee T. A capacitated network flow optimization approach for short notice evacuation planning. European Journal of Operational Research. 2012 Nov;223(1):234–45.

22. Golshani N, Shabanpour R, Mohammadian A (Kouros), Auld J, Ley H. Analysis of evacuation destination and departure time choices for no-notice emergency events. Transportmetrica A: Transport Science. 2019 Nov 29;15(2):896–914.

23. Shahparvari S. Possibilistic scheduling routing for short-notice bushfire emergency evacuation under uncertainties_ An Australian case study. 2016;22.

24. Cohn PJ, Carroll MS. Evacuation Behavior during Wildfires: Results of Three Case Studies. 2006;10.

25. Murray-Tuite PM, Mahmassani HS. Model of Household Trip-Chain Sequencing in Emergency Evacuation. Transportation Research Record. 2003 Jan;1831(1):21–9.

26. So SK, Daganzo CF. Managing evacuation routes. Transportation Research Part B: Methodological. 2009;44(4):514–20.

27. Chen X, Zhan FB. Agent-based modelling and simulation of urban evacuation: relative effectiveness of simultaneous and staged evacuation strategies. Journal of the Operational Research Society. 2008 Jan 1;59(1):25–33.

28. Cova TJ, Johnson JP. A network flow model for lane-based evacuation routing. Transportation Research Part A: Policy and Practice. 2003 Aug;37(7):579–604.

29. Cova TJ, Johnson JP. A network flow model for lane-based evacuation routing. Transportation Research Part A: Policy and Practice. 2003 Aug;37(7):579–604.

30. Cova TJ, Johnson JP. Microsimulation of Neighborhood Evacuations in the Urban–Wildland Interface. Environment and Planning A: Economy and Space. 2002 Dec;34(12):2211–29.

31. Cova TJ, Johnson JP. Microsimulation of Neighborhood Evacuations in the Urban–Wildland Interface. Environment and Planning A: Economy and Space. 2002 Dec;34(12):2211–29.

32. Wolshon B, Marchive III E. Emergency Planning in the Urban-Wildland Interface: Subdivision-Level Analysis of Wildfire Evacuations. Journal of Urban Planning and Development. 2007 Mar 1;133(1):73–81.

33. Chen Y, Yusef Shafi S, Chen Y. Simulation Pipeline for Traffic Evacuation in Urban Areas and Emergency Traffic Management Policy Improvements. 2020 Feb; Available from: http://arxiv.org/abs/2002.06198

34. Sbayti H, Mahmassani HS. Optimal Scheduling of Evacuation Operations. Transportation Research Record. 2006 Jan 1;1964(1):238–46.

35. Wang H, Mostafizi A, Cramer LA, Cox D, Park H. An agent-based model of a multimodal near-field tsunami evacuation: Decision-making and life safety. Transportation Research Part C: Emerging Technologies. 2016 Mar;64:86–100.

36. Mas E, Suppasri A, Imamura F, Koshimura S. Agent-based Simulation of the 2011 Great East Japan Earthquake/Tsunami Evacuation: An Integrated Model of Tsunami Inundation and Evacuation. Journal of Natural Disaster Science. 2012;34(1):41–57.

37. Parikh N, Hayatnagarkar HG, Beckman RJ, Marathe MV, Swarup S. A comparison of multiple behavior models in a simulation of the aftermath of an improvised nuclear detonation. Auton Agent Multi-Agent Syst. 2016 Nov;30(6):1148–74.

38. Beloglazov A, Almashor M, Abebe E, Richter J, Steer KCB. Simulation of wildfire evacuation with dynamic factors and model composition. Simulation Modelling Practice and Theory. 2016 Jan 1;60:144–59.

39. Dennison PE, Cova TJ, Mortiz MA. WUIVAC: a wildland-urban interface evacuation trigger model applied in strategic wildfire scenarios. Natural Hazards. 2007;41:181–99.

40. Larsen JC, Dennison PE, Cova TJ, Jones C. Evaluating dynamic wildfire evacuation trigger buffers using the 2003 Cedar Fire. Applied Geography. 2011 Jan 1;31(1):12–9.

41. Cova TJ, Theobald DM, Norman JB, Siebeneck LK. Mapping wildfire evacuation vulnerability in the western US: the limits of infrastructure. GeoJournal. 2013 Apr 1;78(2):273–85.

42. Ronchi E, Rein G, Gwynne SMV, Intini P, Wadhwani R. Framework for an integrated simulation system for Wildland-Urban Interface fire evacuation. In 2017 [cited 2020 Jul 23]. p. 119–34. Available from: http://lup.lub.lu.se/record/1840add0-243c-40b1-a60c-e7f7e2be3b51

43. Nguyen C, Schlesinger KJ, Han F, Gür I, Carlson JM. Modeling Individual and Group Evacuation Decisions During Wildfires. Fire Technol [Internet]. 2018 Sep 21 [cited 2018 Oct 3]; Available from: https://doi.org/10.1007/s10694-018-0770-7

44. Chen X, Meaker JW, Zhan FB. Agent-Based Modeling and Analysis of Hurricane Evacuation Procedures for the Florida Keys. Nat Hazards. 2006 Jul;38(3):321–38.

45. Stephen Wong SS. Understanding Evacuee Behavior: A Case Study of Hurricane Irma. 2018 [cited 2021 Mar 31]; Available from: https://escholarship.org/uc/item/9370z127

46. Cutter S, Barnes K. Evacuation behavior and Three Mile Island. Disasters. 1982;6(2):116–24.

47. Akabayashi A, Hayashi Y. Mandatory evacuation of residents during the Fukushima nuclear disaster: an ethical analysis. Journal of Public Health. 2012 Aug;34(3):348–51.

48. Do XB. Fukushima Nuclear Disaster displacement: How far people moved and determinants of evacuation destinations. International Journal of Disaster Risk Reduction. 2019 Feb;33:235–52.

49. Kumar K. Dijkstra Priority Queue [Internet]. 2020 [cited 2020 Jul 19]. Available from: https://github.com/cb-cities/sp

50. City of Berkeley. Red Flag Warning for the Berkeley Hills [Internet]. 2020 [cited 2021 Mar 31]. Available from: https://www.cityofberkeley.info/City_Manager/Press_Releases/2020/2020-10-20_Red_Flag_warning_for_the_Berkeley_hills.aspx

51. United States Forest Service. Wildland-Urban Interface Fire Dynamics Simulator (WFDS) [Internet]. 2013 [cited 2020 Jul 19]. Available from: https://www.fs.fed.us/pnw/fera/wfds/simulation_models.shtml

52. Ryan D. Map of Oakland Hills Fire [Internet]. 2013 [cited 2020 Jul 19]. Available from: http://djjr-courses.wikidot.com/soc128:project13-fires

53. Alameda County Assessor's Office. The Assessor's Use Codes [Internet]. 2005 [cited 2020 Jul 19]. Available from: https://www.acgov.org/MS/prop/useCodeList.aspx

54. Alameda County Data Sharing Initiative. Parcels [Internet]. 2020 [cited 2020 Jul 19]. Available from: https://data.acgov.org/

55. Xie C, Turnquist MA. Lane-based evacuation network optimization: An integrated Lagrangian relaxation and tabu search approach. Transportation Research Part C: Emerging Technologies. 2011 Feb;19(1):40–63.

56. Brachman ML, Church R, Adams B, Bassett D. Wayfinding during a wildfire evacuation. Disaster Prevention and Management: An International Journal. 2019 Jan 1;29(3):249–65.

57. Chen YY, Yusef Shafi S, Chen YY, Shafi SY, Chen YY. Simulation Pipeline for Traffic Evacuation in Urban Areas and Emergency Traffic Management Policy Improvements [Internet]. Feb, 2020. Available from: http://arxiv.org/abs/2002.06198

58. Pel AJ, Bliemer MCJ, Hoogendoorn SP. A review on travel behaviour modelling in dynamic traffic simulation models for evacuations. Transportation. 2012 Jan;39(1):97–123.

59. Social Security Administration. OASDI Beneficiaries by State and ZIP Code [Internet]. 2019 [cited 2021 Mar 31]. Available from: https://www.ssa.gov/policy/docs/statcomps/oasdi_zip/2019/ca.html

60. Dalle O. On reproducibility and traceability of simulations. In: Proceedings of the 2012 Winter Simulation Conference (WSC). 2012. p. 1–12.

61. Lindell M, Murray-Tuite P, Wolshon B, Baker EJ. Large-scale evacuation. New York: Routledge; 2019.

62. Comfort L, Soga K, Stacey M, McElwee M, Ecosse C, Dressler G, et al. Collective Action in Communities Exposed to Recurring Hazards [Internet]. Natural Hazards Center; 2019 [cited 2020 Jul 25]. Report No.: QR300. Available from:

https://hazards.colorado.edu/quick-response-report/collective-action-in-communities-exposed-to-recurring-hazards

63. So SK, Daganzo CF. Managing evacuation routes. Transportation Research Part B: Methodological. 2010 May;44(4):514–20.

64. Soga K, Comfort L, Zhao B, Lorusso P, Soysal S. Integrating Traffic Network Analysis and Communication Network Analysis at a Regional Scale to Support More Efficient Evacuation in Response to a Wildfire Event [Internet]. Berkeley, USA: University of California Institute of Transportation Studies; 2021 Mar [cited 2021 Mar 31]. Available from: https://berkeley.app.box.com/s/4y0uozbbtz5zwcct34fh4bvuga46a9t4

65. McCarthy GJ, Tolhurst KG, Victoria, Fire Management. Effectiveness of broadscale fuel reduction burning in assisting with wildfire control in parks and forests in Victoria. East Melbourne: Dept. of Natural Resources and Environment; 2001.

66. Hakes RSP, Caton SE, Gorham DJ, Gollner MJ. A Review of Pathways for Building Fire Spread in the Wildland Urban Interface Part II: Response of Components and Systems and Mitigation Strategies in the United States. Fire Technol. 2017 Mar;53(2):475–515.

67. Alchera Inc. Alchera [Internet]. 2020 [cited 2020 Mar 31]. Available from: https://alcherainc.com/en/

68. Cal Fire. Wildfire is coming... Are you ready? [Internet]. 2019 [cited 2020 Mar 31]. Available from: https://www.readyforwildfire.org/prepare-for-wildfire/ready-set-go/

69. FHWA. Highway Statistics 2019. Trailer and semi-trailer registrations. [Internet]. 2020 [cited 2020 Nov 28]. Available from: https://www.fhwa.dot.gov/policyinformation/statistics/2019/

70. Radeloff VC, Helmers DP, Kramer HA, Mockrin MH, Alexandre PM, Bar-Massada A, et al. Rapid growth of the US wildland-urban interface raises wildfire risk. Proc Natl Acad Sci USA. 2018 Mar 27;115(13):3314–9.

71. Thomas DS, Butry DT. Areas of the U.S. wildland–urban interface threatened by wildfire during the 2001–2010 decade. Nat Hazards. 2014 Apr;71(3):1561–85.

72. Firesafe Marin. Wildfire Evacuation Checklist. Marin County [Internet]. 2019 [cited 2021 Nov 28]. Available from: https://www.firesafemarin.org/images/documents/resources/evac/FIRESafe_MARIN_Evacuation_Checklist.pdf

73. Firesafe Marin. Wildfire Evacuation Preparedness [Internet]. 2020 [cited 2020 Nov 28]. Available from: https://www.firesafemarin.org/evacuation

74. City of Berkeley. Off Street Parking (Garages & Lots [Internet]. 2020 [cited 2021 Mar 31]. Available from:

https://www.cityofberkeley.info/Public_Works/Transportation/Off_Street_Parking_(Garages_and_Lots).aspx

75. BART. 2015 BART Station Profile Study [Internet]. Bay Area Rapid Transit; 2015. (Station Profiles - Home Origins). Available from: https://www.bart.gov/sites/default/files/docs/StationProfile2015_HomeOriginOnePagers_rev0629.pdf

76. Anderson S, Barford C, Barford P. Five Alarms: Assessing the Vulnerability of US Cellular Communication Infrastructure to Wildfires. In: Proceedings of the ACM Internet Measurement Conference. 2020.

77. California Public Utilities Commission (CPUC). CPUC Requires Wireless Companies to Better Serve Customers in Emergencies [Internet]. 2020 [cited 2021 Mar 31]. Available from: https://docs.cpuc.ca.gov/PublishedDocs/Published/G000/M343/K979/343979403.PDF

78. Xie Y, Liu X-Y, Kong L, Wu F, Chen G, Vasilakos AV. Drone-Based Wireless Relay Using Online Tensor Update. 2016;8.

79. Abuelela M, Olariu S. Taking VANET to the clouds. 2010;8.

80. Flötteröd Y-P, Erdmann J. Dynamic Reroute Modeling for Emergency Evacuation: Case Study of Brunswick City, Germany. 2018;11.

81. Elbery A, Hassanein HS, Zorba N, Rakha HA. VANET-Based Smart Navigation for Emergency Evacuation and Special Events. In: 2019 IEEE 24th International Workshop on Computer Aided Modeling and Design of Communication Links and Networks (CAMAD) [Internet]. Limassol, Cyprus: IEEE; 2019 [cited 2020 Nov 24]. p. 1–6. Available from: https://ieeexplore.ieee.org/document/8858502/

82. Han R, Tolan M, McCloskey R, Cleary F. A NOVEL EMERGENCY EVACUATION ALGORITHM FOR VEHICLES BASED ON VEHICLE-TO-VEHICLE (V2V) COMMUNICATION. 2019;10.

83. FEMA. Planning Considerations: Evacuation and Shelter-in-Place Guidance for State, Local, Tribal, and Territorial Partner [Internet]. 2019 [cited 2021 Mar 31]. Available from: https://www.fema.gov/sites/default/files/2020-07/planning-considerations-evacuation-and-shelter-in-place.pdf

84. Wilmot CG, Meduri N. Methodology to Establish Hurricane Evacuation Zones. Transportation Research Record. 1922;9.

85. Wong S, Martin I, Halpern J. KENSINGTON EVACUATION RESEARCH PROJECT FINAL REPORT. 2020;124.

86. City of Berkeley. Wildfire Evacuation [Internet]. 2020 [cited 2021 Mar 31]. Available from: https://www.cityofberkeley.info/WildfireEvacuation/

87. FEMA. Integrated Public Alert & Warning System. Federal Emergency Management Agency [Internet]. 2020 [cited 2021 Mar 31]. Available from: https://www.fema.gov/emergency-managers/practitioners/integrated-public-alert-warning-system

88. OnSolve. CodeRED for IPAWS [Internet]. 2020 [cited 2021 Mar 31]. Available from: https://www.onsolve.com/landing/codered-for-ipaws/

89. Todd Z, Trattner S, McMullen J. Ahead of Camp Fire Anniversary, New Details Emerge of Troubled Evacuation. PBS - Frontline [Internet]. 2019 Oct 25; Available from: https://www.pbs.org/wgbh/frontline/article/camp-fire-anniversary-new-details-troubled-evacuation/

90. Wolshon B. “One-Way-Out”: Contraflow Freeway Operation for Hurricane Evacuation. Nat Hazards Rev. 2001 Aug;2(3):105–12.

91. Tuydes H, Ziliaskopoulos A. Tabu-Based Heuristic Approach for Optimization of Network Evacuation Contraflow. Transportation Research Record. 2006;12.

92. Theodoulou G, Wolshon B. Alternative Methods to Increase the Effectiveness of Freeway Contraflow Evacuation. Transportation Research Record. 2004 Jan;1865(1):48–56.

93. Lim E, Wolshon B. Modeling and Performance Assessment of Contraflow Evacuation Termination Points. Transportation Research Record. 2005;11. \

94. May, A.D. (1990), Traffic Flow Fundamentals, Prentice Hall, Englewood Cliffs, NJ.