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Evaluating driving behavior patterns during wildfire evacuations in wildland-urban interface zones using connected vehicles data

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ABSTRACT

Wildfire risk is increasing all over the world, particularly in the western United States and the communities in wildland-urban interface (WUI) areas are at the greatest risk of fire. Understanding the driving behavior of individuals to evacuate fire-affected WUI areas is important as the evacuees may encounter low visibility and difficult driving conditions due to burning material and steep topography. This study investigates the driving behavior patterns of individuals during historical wildfire events in rural and urban areas with mandatory evacuation orders using a connected vehicle dataset. This dataset provides the geolocation and timestamp of vehicles' hard-braking (HB) and hard-acceleration (HA) events. The comparative analysis of the data demonstrated that the reported HA & HB event patterns were consistent in representing the varying driving behavior in response to the changing driving conditions and the depiction of the temporal and spatial impact of the fire in all studied areas. Moreover, the HB event dataset located critical traffic congestion points and the HA event dataset revealed the hurried response of evacuees on the exiting routes as a result of short-notice evacuation. In addition, significant differences in driving behavior patterns were noticed between rural and urban areas.

1. Introduction

A wildfire is an uncontrolled fire that breaks out in a natural environment such as forests, grasslands, or prairies and poses a serious threat to property, lives and the integrity of the ecosystem. It spreads quickly in the presence of high winds, severe drought, steep topography and dry vegetative fuels. Unfortunately, these conditions are becoming more common because of climate change, especially in the western United States [1,2]. According to U.S. Fire Administration (USFA), the United States had an estimated annual average of 1,344,100 fires resulting in 3190 civilian deaths, 16,225 injuries, and $14.7 billion in direct property loss each year between 2008 and 2017 [3]. Additionally, widespread wildfires can cause mass evacuations, that may result in societal disturbance, long-term infrastructure damage, and evacuee and responder injuries or fatalities [4–6]. Statistics show that between 1980 and 2007, there were an average of 20 evacuations per year in Canada with some years recording as many as 53 evacuations [7]. Moreover, in recent years the state of California witnessed more than one million people evacuate their neighborhoods and about 30,000 structures destroyed due to fire incidents [8].

Due to the unpredictable nature of fires, including their direction, intensity, and the release of firebrands and smoke, the driving behavior of evacuating traffic during fire incidents becomes crucial. It poses risks to health and safety, as it can lead to reduced visibility [9,10]. In addition, the time available to evacuate a given area plays a significant role in defining the aggressive nature of the drivers. During the 2018 California Camp Fire, thousands of people had very little time to prepare to evacuate since the extremely fast-spreading fire allowed for very little warning. Many were compelled to flee their homes as soon as they awoke to smoke and fire, and several people abandoned their cars and sought safety on foot because of traffic jams and approaching flames [11–13]. Furthermore, the communities living close to the undeveloped wildland or vegetative fuels, forming wildland-urban interface (WUI) zones, are at the greatest risk of fire due to the proximity of flammable vegetation and limited exit routes [14–16]. In the United States, WUI areas account for only 10 % of the total land area but are the origin of approximately 32 % of all wildfires [17]. Between 1990 and 2010, these areas grew by 33 % in land area and saw a 41 % increase in new

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residences [18]. Moreover, it is expected that these zones will continue to expand significantly, especially in the intermountain west states of the United States, increasing the risk to human lives [14].

Therefore, the driving behavior of the individuals evacuating a neighborhood affected by wildfire needs to be investigated, especially that of people living in WUI zones with exit options limited by surrounding vegetative fuels and steep topography. Recently, connected vehicle data has become available that enables researchers to investigate the driving behavior of individuals during historical wildfire events requiring the mandatory evacuation of the residents [19]. The dataset contains lane-level precision hard-braking (HB) and hard-acceleration (HA) data of vehicles to assess the aggressive driving behavior patterns of evacuating traffic, along with identification of traffic congestion points and fire impact areas in a road network.

Considering that the collection of evacuation behavior data is mostly reliant on social science-based stated preference or revealed preference surveys, there are concerns regarding their accuracy and implementation. This type of qualitative dataset provides an opportunity to investigate the driving behavior patterns of evacuees in historical wildfire events and to incorporate key findings in evacuation behavior models and traffic simulation tools. The social-science-based survey techniques have also been criticized for their failure to comprehend descriptive data on evacuation response, self-selection bias for targeting a specific group of people and restricting response options [8,20], and uncertainty of event recounting behavior in the post-disaster surveys [21,22]. Currently, the majority of the research on wildfire evacuation focuses on identifying the factors that impact the household's decision to evacuate or not, with a few focusing on wait-and-see decisions. More research is needed to improve our understanding and provide further validation of the current findings [23].

Furthermore, the traffic simulation models that need an aggregate level of traffic data i.e. macroscopic models as well as the models that need individual vehicle level data i.e. microscopic models both have to rely on assumptions resulting from these human behavioral studies as currently there is no comprehensive data available on the driving behavior parameters needed for these models in the events of wildfire evacuation [23]. More specifically, the driving parameters needed for microscopic traffic modeling are more specific to individual vehicle behavior about car-following, lane-changing and gap acceptance [24]. Inaccurate assumptions about evacuee driving behavior can underestimate evacuation performance and force emergency officials to employ ineffective traffic management strategies [23]. There is currently limited data available on the effect of traffic conditions (such as urban or rural roads, or congestion points), environmental factors related to WUI fires (such as weather, firebrands, and smoke), and the information on the impact of temporal and spatial progression of fire on driving behavior characteristics for wildfire evacuation [22,25].

Thus, expanding on our previous study and findings [26], this paper investigates the human driving behavior patterns under various wildfire hazards needing evacuation, based on the connected vehicle dataset (supplied by Wejo), and contributes to the existing literature on evacuation behavior modeling. In addition, this paper contributes to the fields of wildfire evacuations by understanding the impacts of factors such as traffic conditions, environment, and temporal and spatial progression of fire, on driving behavior characteristics for wildfire evacuation.

The rest of the paper is organized as follows: Section 2 reviews relevant literature on past research efforts and the need for this study. The case studies investigated for this research are described in Section 3 while Section 4 presents the overall research framework consisting of data collection, data processing and comparative analysis of the data. The discussion of the results and conclusion are presented in Section 5.

2. Literature review

2.1. Surveys and evacuation behavior models

Over the years, researchers have used different methodologies to understand and predict the behavior of individuals evacuating because of various kinds of disasters. These studies have primarily relied on qualitative analysis techniques such as stated preference and revealed preference surveys to determine the factors that are used to develop various evacuation behavior models and to simulate such behaviors in various traffic simulation tools [23]. These surveys have helped in identifying several key factors that can affect the decision-making process of the evacuee, especially in the event of a fire. Among these factors, the warning time to evacuation is found to be critical in defining the response of the evacuees, particularly for wildfires where they have to look out for burning flames, flying debris and smoke, and to avoid conflict with emergency responders [21,27–30]. The response of the local authorities and emergency responders is also considered crucial in defining the evacuation behavior of the residents. It has been observed that the issuance of pre-evacuation warnings and clear instructions from emergency officials can help evacuees to make contemplative decisions about the fire risk and leave the affected area safely [31–36]. The traffic infrastructure and population density of the area impacted by the fire are also regarded as significant to the evacuation effort. High-density neighborhoods during short-notice evacuations can lead to increased traffic congestion and longer queue lengths on departing routes, which can put the lives of stranded evacuees in danger [37–41]. Moreover, population characteristics such as household size, income, education level, car and housing ownership, ethnicities as well as prior experience with mass evacuations can also highly influence the evacuation rate [42–44].

To determine these factors, stated preference surveys are conducted in the pre-disaster phase using numerous data collection techniques where a diverse group of respondents is asked about their intended plan of action in the case of a potentially hazardous event. Survey respondents are presented with various hypothetical scenarios and are asked to choose between different preferences that can result in a certain desirable or undesirable outcome. Mozumder et al. evaluated the impact of official evacuation orders in a WUI area using a mail-based survey and forecasted that the sample respondents are more likely to evacuate under a mandatory evacuation order than under a voluntary evacuation order [42]. In another study, Stasiewicz et al. conducted a stated preference survey in another WUI area, which included full-time and part-time occupied residences, and asked them about the likelihood of staying to defend their property rather than evacuating the affected area in the event of a wildfire. They discovered that full-time residents are more inclined to stay and defend their property than part-time residents who intend to evacuate immediately [45]. Auld et al. also conducted an internet-based survey by sending out emails to individuals in Chicago, USA, to inquire how they would react to various imaginary no-notice evacuation scenarios. They predicted that the residents would move to shelter locations under moderate threat levels and would seek out relatives and friends under high threat levels [44]. This type of survey provides researchers with an opportunity to analyze the preferred responses of individuals under various hazard scenarios. However, the data obtained in these surveys may not always be exactly representative of how people would act in a real emergency situation, because the respondents are subject to a hypothetical scenario and they may have limited knowledge about the true risk associated with the actual hazard [44,46,47].

Therefore, researchers conduct post-disaster revealed preference surveys with people who were impacted by an actual hazard to learn about the factors that influenced their choices and to compare how people in different geographic regions respond to the fire hazard. McCaffrey et al. conducted a mail survey in two distinct areas in the United States that were affected by wildfire to determine if evacuees behaved differently than non-evacuees while seeking information. The study's findings revealed that evacuees consistently sought information more actively than non-evacuees and placed a greater emphasis on using interactive information sources. However, the assessment of pre-fire information needs varied between the two communities, indicating that experiences with fire may have an impact on their views [48]. In another study, Vaiciulyte et al. undertook a cross-cultural survey on wildfire evacuation in France and Australia. The study's findings showed that while the actions that make up behavioral itineraries were identical between the two locations, there were regional differences in the mean number of actions and the time to evacuation due to geographic and cultural factors [49]. The significance of the difference in geographic regions is also found in another multiple region study by Wong et al. who found that joint-choice decision-making during a wildfire evacuation is highly dependent on the context and the geography and may result in different choices [50]. This implies that while there may be some similarities in the way people behave during various wildfire disasters, each wildfire event should be evaluated in the context of geographical differences as this has a substantial influence on people's decision-making process.

Due to the complexity of human behavior under hazardous scenarios, several evacuation behavior models and techniques have been developed to simulate decision-making behavior during an emergency situation. Earlier studies employed descriptive analysis techniques to identify the traits and perceptions of respondents and their actions in response to messages and information about evacuation [48,51,52]. In recent years, several discrete choice models have been developed to examine how various factors may affect a certain choice or behavior. Toledo et al., Lovreglio et al., Kuligowski et al. and Walpole et al. used binary choice models to evaluate the variables that influenced people's decision to leave or stay while accounting for demographic conditions, official orders, and risk perception [53–56]. McCaffrey et al. and Wong et al. built latent class choice models (LCCM) to extend the binary logit model to account for unobservable classes of individuals and identified a separate evacuation class and a defend class based on beliefs and attitudes about wildfire risk [27,50]. Mozumder et al. analyzed respondents' probability of evacuation and their subjective belief structure regarding wildfire risk using a bivariate probit model [42]. In addition to discrete choice models, multinomial logistic models have been used to examine the various decisions people make while determining whether to remain and protect their property or leave a community [27,57,58]. A hybrid choice model was developed by Lovreglio et al. that created a single latent variable of risk by combining external elements (e.g. physical cues), internal factors (e.g. demographic data) and risk indicators (e.g. the perception of harm or death) [22]. Walpole et al. employed logistic regression analysis to evaluate the influences on waiting behavior during evacuation [56]. To obtain further insights into perceptions and experiences that are challenging to capture through surveys, researchers have also utilized qualitative approaches (e.g. interviews and focus groups) to examine and elicit aspects that impact evacuation behavior [59,60].

Studies have also emphasized the importance of the transportation system in defining the evacuation behavior, as fire propagation often results in vehicular evacuation in WUI areas. It has been asserted that a vast majority of evacuees use private vehicles for evacuation [53,61], Dow and Cutter found that 25 % of households use two or more cars to evacuate while Kang et al. found that an average of 1.62 cars are used by each household for the evacuation [61,62]. So, researchers have adopted geographic information system (GIS) mapping techniques to locate spatial effects of fire and have used traffic simulations and fire spread models. In these models, evacuation behavioral assumptions such as whether to stay or evacuate, warning and response times, route choice, evacuation modes, and traffic flow conditions are modeled into the traffic simulation platforms for the analysis and planning of emergency evacuations [63–65]. In the case of wildfire, these studies have used trigger point modeling to determine the timing of evacuation considering the characteristic of the fire [66], calculating clearance times from neighborhoods using machine learning techniques to simulate evacuee decision-making [67], and incorporating fire propagation and warning dynamics into simulation models [68]. Over the years, various traffic simulation platforms have been developed to describe and predict traffic flow conditions during evacuations for various types of hazards such as MASSVAC [69], NETVACl [70], TEDSS [71], DYNEV [72], IMDAS [73], OREMS [74], CEMPS [75]. In recent years, researchers have adopted well-established microscopic and macroscopic traffic simulation tools for detailed analysis of evacuation behavior. These include PARAMICS [76], VISSIM [77], CORSIM [78], AIMSUM [79], and TransCAD [24] which employ different car-following behaviors, lane-change, and gap-acceptance models, giving opportunity for researchers to model various type of evacuation scenarios [80]. Intini et al., 2019 provided a detailed review of different traffic simulation models used in the evacuation studies [81].

To understand the behavior of people evacuating in their personal vehicles and to model such behavior, it is important to understand that driving is a complex and dynamic task requiring the drivers to continuously monitor the surrounding environment and make cognitive judgments at a high traveling speed [82]. Driving becomes more challenging at traffic intersections, junctions, and signalized roadways where queuing of vehicles and rapid stopping can urge drivers to use brakes and accelerate quickly. This can disrupt traffic flow and create congestion [83]. In the event of a wildfire in WUI area, fire propagation can create a broken transportation link that is impassable to vehicles or produce smoke spreading from the fire front at varying distances that can influence the drivers' behavior [81]. Therefore, the driving task imposes varying levels of workload on the driver and increases the driver's stress level during an unexpected event [84]. Several studies have found that drivers tend to exhibit more aggressive behavior during emergency evacuations. This behavior is characterized by increased speeds, higher rates of acceleration and deceleration, shorter headways, and frequent instances of rapid emergency braking [85–87].

2.2. Data sources

In recent years, the extensive use of sensors, including GPS devices in various modes of transportation and mobile phones, has generated a large amount of data on human mobility. This data has become a crucial component of smart cities, providing detailed information on location, speed, and travel times. Independent third-party companies compile crowdsourced data to deliver real-time traffic information, enhancing transportation planning and management. Examples include Waze [88], INRIX [89], TomTom [90], HERE [91]. The availability of this data is revolutionizing our understanding of human mobility patterns, providing valuable insights for improving evacuation strategies and emergency response in urban environments. This dataset has been utilized in various studies, demonstrating its versatility and value in understanding evacuation dynamics. For instance, Xu et al. employed the dataset to delve into evacuation routing behavior, while Zhao et al. utilized it to estimate wildfire evacuation decision and departure timing. These studies showcase the broad applicability of the dataset in exploring different aspects of evacuation processes, providing valuable insights for optimizing routing strategies and enhancing decision-making during evacuation events [92,93]. Moreover, with the advancement in automobile technology in recent years, modern vehicles are now equipped with sensors that record temporal and spatial information about the vehicle, the driver, and the surrounding environment [94]. Data from these sensors can be used to study and analyze the behavior of drivers under special events [95]. These connected vehicles are capable of profiling driver behavior related to vehicle speed and braking and acceleration habits based on their steering wheel angle, accelerometer, and brake-pedal operations [96]. This vehicle-probe data is collected by vehicle embedded sensors and transmitted to automobile manufacturers and shared with several third-party connected vehicle data processing companies [19,97] for aggregation and cleansing of data. The processed data is then shared with vehicle manufacturers, state agencies, researchers and technology developers [98].

Wejo, a connected vehicle data provider, has partnered with multiple world-leading automobile manufacturers that collect vehicle HB and HA data from vehicle onboard sensors [19]. The vehicle records a data point whenever a driver applies a HB, or a HA and each data-point consists of a unique anonymous identifier with the timestamp and geographic location of a HB or a HA event. In this dataset, the geographic location of the data-point is recorded within a 3-m radius with an accuracy of 95 %, and the data-point for a HB or a HA event is recorded when the vehicle decelerates or accelerates over 2.77 m/s^2 respectively. Although this anonymized connected vehicle dataset has only recently become available to researchers and technology developers to look at historical driver behavior patterns at locations of interest, several researchers have already tested Wejo's HB and HA event datasets. Desai et al. used Wejo's historical data to correlate vehicle crash data and HB data at interstate highway work zones [99]. In another study, researchers used HB data to look at driving behavior patterns at signalized corridors to identify dilemma zones and the identification of construction zones along high-speed roadways [100]. Saldivar-Carranza et al. utilized Wejo's HA data to analyze the variation in the behavior of drivers by changing left-turn phasing at traffic signals [20].

3. Case studies

This section reports the timeline of the wildfire events studied in this paper along with the background of the study areas, their vulnerability to fire incidents and the measures taken by the state and local authorities to control such incidents.

3.1. The Knolls Fire in Utah

Utah is one of the most wildfire-prone states in the United States, witnessing 800 to 1000 wildfires annually [101]. In 2020, the state saw a record-breaking wildfire season with 1547 fires, with 1202 of those fires (78 %) caused by humans [102,103]. This paper selected Saratoga Springs, a city in Utah affected by a human-caused wildfire event, named the "Knolls Fire," on June 28, 2020, which damaged 12 homes and destroyed one house [104]. Saratoga Springs is one of the fastest-growing cities in Utah and, as per the 2020 census, has a population density of around 1625 people/sq. mi [105]. The city is surrounded by Utah Lake on the eastern border and Lake Mountain on the western border with State Route 68 (SR-68) also called "Redwood Road" serving as the main exit corridor for the city.

According to the city's 2017 multi-hazard mitigation plan, between 1999 and 2017 the city experienced 12 wildfires on Lake Mountain, posing wildfire hazards to residences, businesses and infrastructure. The city is at risk from several factors that contribute to the rapid spread of fire. These factors include severe drought conditions, high winds and vegetation on Lake Mountain, that can serve as fuel for the spread of fire. During the city's development period, the city's administration implemented several mitigation measures to reduce the impact of fire, including laying down pressurized water lines, installing fire hydrants and constructing fire breaks to minimize the spread of fire [106]. The State of Utah has an Emergency Operation Plan (EOP) that establishes a comprehensive statewide all-hazard approach to provide consistent incident management and state response to any emergency or disaster event and support local authorities when needed [107]. Furthermore, the city also has a Community Emergency Response Team (CERT) that prepares residents for hazards that may impact the area and train them in basic disaster response skills such as fire safety, rescue and disaster medical operations [108].

The Knolls Fire erupted between 2:00 p.m. and 2:30 p.m. on June 28, 2020, east of Lake Mountain and south of Saratoga Springs and spread quickly towards the city driven by 60 mph gusting winds. Mandatory evacuation orders were issued for more than 3100 homes or 13,000 residents, i.e. almost one-third of the population of the city [109–111]. The evacuation began at 2:45 p.m., initially in the southern neighborhoods of the city, and residents were forced to evacuate their homes with very short notice in the midst of high winds, smoke and dust. Later in the afternoon, all residents who lived south of Grandview Boulevard on the west side of Redwood Road were asked to evacuate their homes because of the rapid spread of the fire [111,112]. The following day, with the help of 200 firefighters, the fire was contained by 25 %, and the residents were allowed to return to their homes with a post-fire evacuation warning [104,113,114]. A visual representation of the fire event is illustrated in Fig. 1.

3.2. The Cameron Peak Fire & The East Troublesome Fire in Colorado

In Fall 2020, the state of Colorado in the United States witnessed the two largest wildfires in its history: The Cameron Peak Fire & The East Troublesome Fire. The fires led to the evacuation of thousands of people in the state, particularly several towns in Larimer & Grand counties [115,116]. Both Larimer and Grand counties contain communities that are considered as WUI areas and are at a greater risk of catastrophic wildfires. Annually, the wildfire event count reaches around 22 in Larimer County and around 8.3 in Grand County [117,118]. Each county has detailed emergency preparedness plans to prepare authorities and residents for future wildfire events and hazard mitigation plans to reduce these events. They also have emergency operation plans to provide coordinated response and support to local authorities in controlling various types of natural and human-caused disasters [119,120].

For this study, we selected the towns of Granby and Grand Lake in Grand County and the town of Estes Park in Larimer County that were forced to evacuate because of the Cameron Peak and East Troublesome fire events. These are three different-sized towns, with Estes Park having a population density of 865 people/sq. mi. and Granby and Grand Lake having a population density of 164 people/sq. mi. and 397 people/sq. mi. respectively [105]. The towns of Estes Park and Grand Lake serve as major accommodation locations and key access points to the Rocky Mountain National Park, one of the most-visited national parks in the United States attracting millions of visitors annually [121,122]. According to the 2021 Larimer County multi-jurisdictional hazard mitigation plan, the town of Estes Park is considered to have one of the highest WUI risk index ratings in Larimer County [117]. While, according to the Grand County 2020 multi-hazard mitigation plan, the town of Granby contains 1793 people within high-risk and 1306 people within medium-risk WUI communities. Correspondingly, the town of Grand Lake contains 1578 people within medium-risk WUI communities [118].

The East troublesome Fire ignited on October 14, 2020, in Grand County near north-central Colorado spreading toward Rocky Mountain National Park. It experienced an extensive growth on October 21, growing from 30,000 acres to 170,000 acres in about 24 h [123,124]. On October 21, 2020, the Grand County Sheriff's Office announced mandatory evacuation orders for the town of Grand Lake as the fire moved east toward the town and the entire area was at risk of fire. Both lanes of U.S. Highway 34 were turned southbound to move the evacuation traffic south toward the town of Granby and an evacuation center was opened at the Inn at Silver Creek in Granby [125–128]. The next day, the town of Granby was also asked to evacuate as the fire moved closer to the town and U.S. Highways 34 and 40 were closed for inbound traffic to speed up the process of evacuation [129,130]. In Larimer County, the Cameron Peak Fire, which ignited on August 13, 2020, near Chambers Lake, Colorado, and the East troublesome fire came closer to the town of Estes Park on October 22, 2020. So, the state governor announced mandatory and voluntary evacuation orders for various neighborhoods in the town creating traffic jams on all exiting routes [131–133]. The west side of Rocky Mountain National Park was closed on October 21, 2020, because of the spread of the East Troublesome Fire

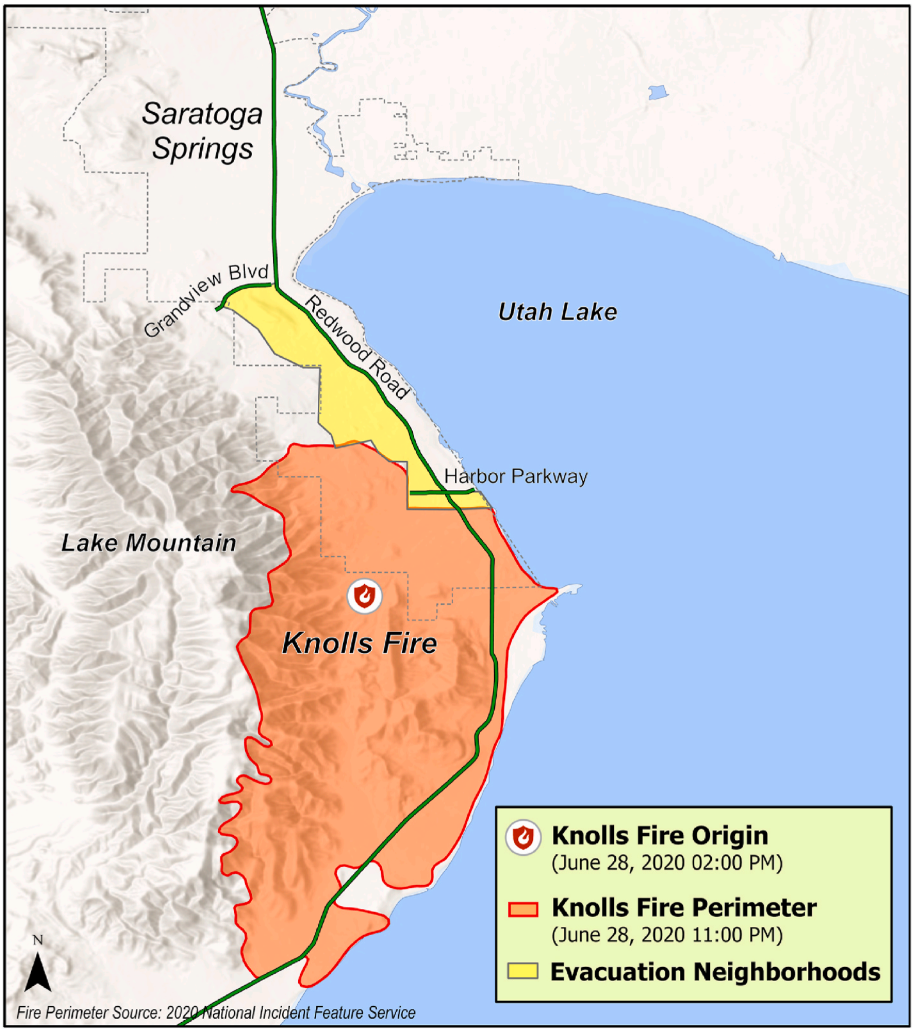


Fig. 1. 2020 Knolls fire.

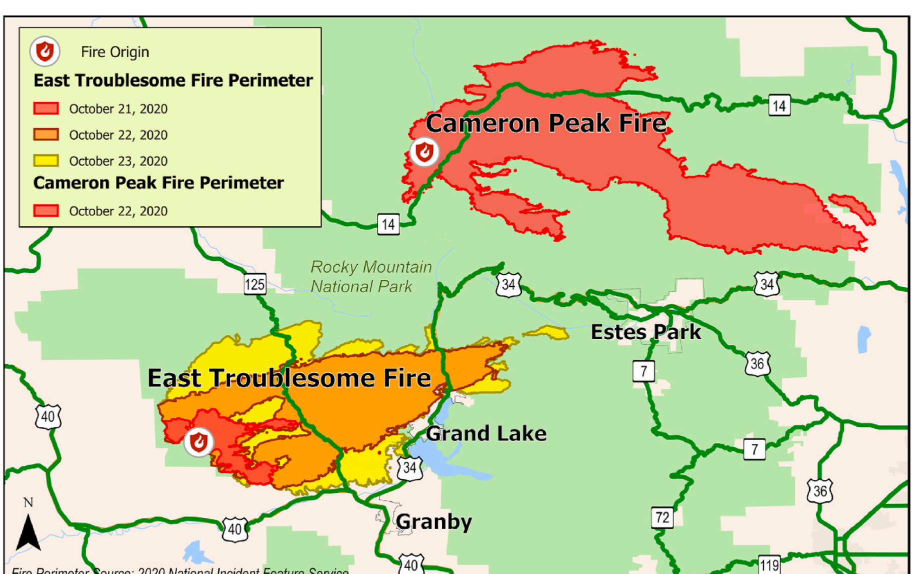


Fig. 2. 2020 east troublesome & cameron peak fires.

towards Grand Lake [134]. The following day, the entire park was closed as the fire spread towards Estes Park and the visitors were not permitted to enter there [130–135]. Later, the impact of the two fires was dampened slowly each day by the arrival of snow allowing the Coloradoans to return to their neighborhoods in multiple phases [136–138]. A visual representation of the fire events is illustrated in Fig. 2.

4. Data collection and analysis

This section presents a comprehensive research framework consisting of data collection, processing, and analysis of driving events data for all case study areas. The research workflow is displayed in Fig. 3. The main elements in this research include the following:

1) Data collection, specifying the raw data collected for this study.
2) Data processing, describing how the raw data is processed to extract useful information.
3) Data analysis, presenting the comparative analysis of raw data for each case study area.

4.1. Data collection

For the selected study areas, the connected vehicle driving events data (i.e. hard-braking and hard-acceleration) provided by Wejo Data Services, Inc. were used to analyze the behavior of drivers in a mass evacuation. To analyze the extent of aggressive driving in the selected wildfire evacuation cases, the period of data collection consisted of evacuation as well as non-evacuation time frames to allow us to evaluate the behavior of drivers under varying driving conditions. Considering that Saratoga Springs in Utah was evacuated on June 28, 2020, data was collected for the period of June 20–30, 2020. The three towns in Colorado were evacuated on October 21, 2020, (Grand Lake) and October 22, 2020 (Granby and Estes Park), so data was collected from three days in September and five days in October as detailed in Table 1. During data collection, homogeneous periods were not feasible to be selected due to evaluation of two different fire incidents, each characterized by varying ignition dates and evacuation orders. In Saratoga Springs, the evacuation orders were issued on the same day the fire started, while in Colorado, a significant time span elapsed before issuance of evacuation orders following the fires' ignition.

Table 1
Driving events data collection.

S No.	City	Fire event	Date of evacuation	Data collection period
1	Saratoga Springs, UT, USA	Knolls Fire	June 28, 2020	June 20, 2020–June 30, 2020
2	Grand Lake, CO, USA	East Troublesome Fire	Oct. 21, 2020	Sept. 23, 2020–Sept. 25, 2020, Oct. 21, 2020–Oct. 25, 2020
3	Granby, CO, USA	East Troublesome Fire	Oct. 22, 2020	Sept. 23, 2020–Sept. 25, 2020, Oct. 21, 2020–Oct. 25, 2020
4	Estes Park, CO, USA	Cameron Peak Fire & East Troublesome Fire	Oct. 22, 2020	Sept. 23, 2020–Sept. 25, 2020, Oct. 21, 2020–Oct. 25, 2020

The data was delivered in smaller parcels consisting of around 14,000 JSON files to Amazon Web Services (AWS) S3 cloud storage which were stored in the local storage using the AWS Command Line Interface (CLI). The raw data extracted from JSON files consisted of

Table 2
Key driving events data attributes.

S No.	Data attributes	Definitions
1	Datapoint ID	Records a unique data-point whenever a vehicle applies a HB or a HA event.
2	Captured date & time	Records the time and date of the event when a data-point is recorded in Universal Coordinated Time (UTC).
3	Time zone offset	Records the location time zone offset for the data-point. The time zone offset of (UTC- 6 h) was used for all study areas for the collected data period.
4	Latitude	Provides the North-South positioning of the vehicle on the Earth's surface.
5	Longitude	Provides the East-West positioning of the vehicle on the Earth's surface.
6	Acceleration change type	Signifies a HA event when a vehicle detects an acceleration of over 2.77 m/s^2 or a HB event when a vehicle detects a deceleration of over 2.77 m/s^2.

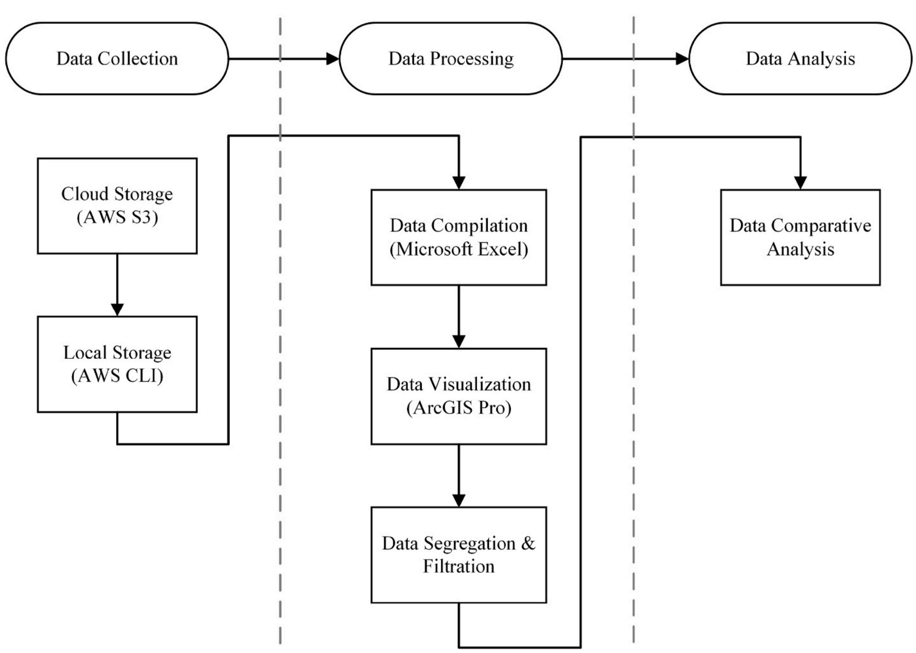


Fig. 3. Overall research framework.

67,527 occurrences of driving events, involving 4508 unique vehicles, from three towns in Colorado. Similarly, the Utah dataset included 89,630 occurrences of driving events from 1845 unique vehicles, based on device IDs. In the manuscript, only the data relevant to the study area was reported, as filtering was necessary. The key attributes of the data used for processing & analysis are listed in Table 2.

4.2. Data processing

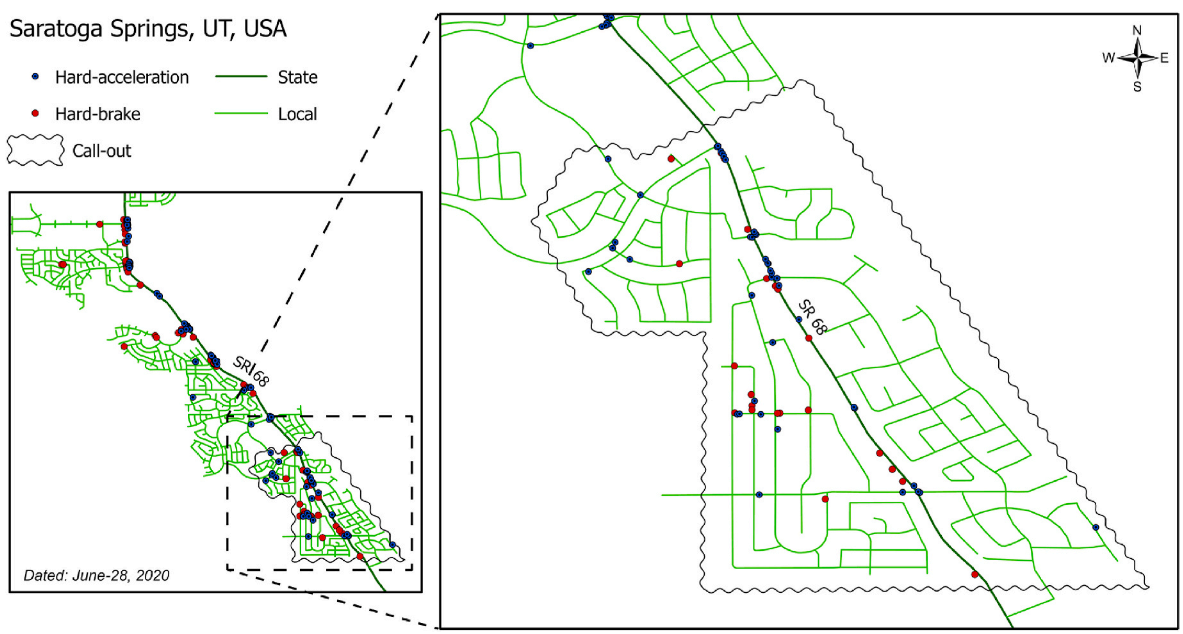
The dataset was pre-processed. First, the stored JSON files were converted to CSV files, formatted, and compiled together in MS Excel software. To visualize the processed tabular data, it was imported into the ArcGIS Pro version 2.8 software which is a well-established GIS application used for visually analyzing a dataset [139]. The location attributes of the data (i.e. latitude and longitude) were used to create a feature class of the whole dataset. Then, the data was separated and filtered to ensure that the data was contained within the research region and within the considered time frame of the study. The geographical attributes were utilized to segregate the data for each city and the temporal attributes were used to filter out the data for the timeline under consideration. Additionally, all data points in each city that were outside the investigated area's perimeter were omitted from the study.

4.3. Data analysis

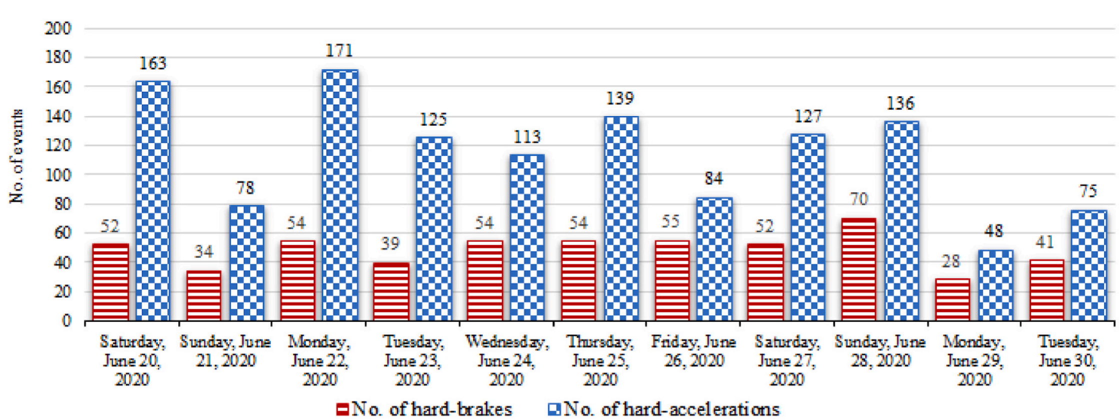
4.3.1. Descriptive statistical analysis

The study area analyzed for Saratoga Springs city consisted of 5 miles of SR-68 between mile markers 25 & 30 along with the residential neighborhoods evacuated during the 2020 Knolls Fire as illustrated in Fig. 4(a), where each red and blue marker represents an occurrence of a HB or a HA event, respectively. As can be seen in Fig. 4(b), the analysis of the data for this city revealed that the day of evacuation (June 28, 2020) observed almost twice as many HA events and more than twice HB events as the reference day the week before (June 21, 2020, also Sunday). This suggests that the residents reacted aggressively to the short-notice evacuation orders and drove their vehicles with higher acceleration and deceleration rates to safely exit the impacted region from the fire, as discussed previously in the literature.

It was also observed that throughout the study period, the southern neighborhoods of the city, that were initially asked to evacuate, observed the highest number of HB & HA events on the day of evacuation as noted in Table 3 and depicted in the call-out drawn in Fig. 4(a).



(a)



(b)

Fig. 4. Saratoga Springs, UT, USA (a) driving-events map (b) driving-events data.

Table 3
Call-out area daily driving events.

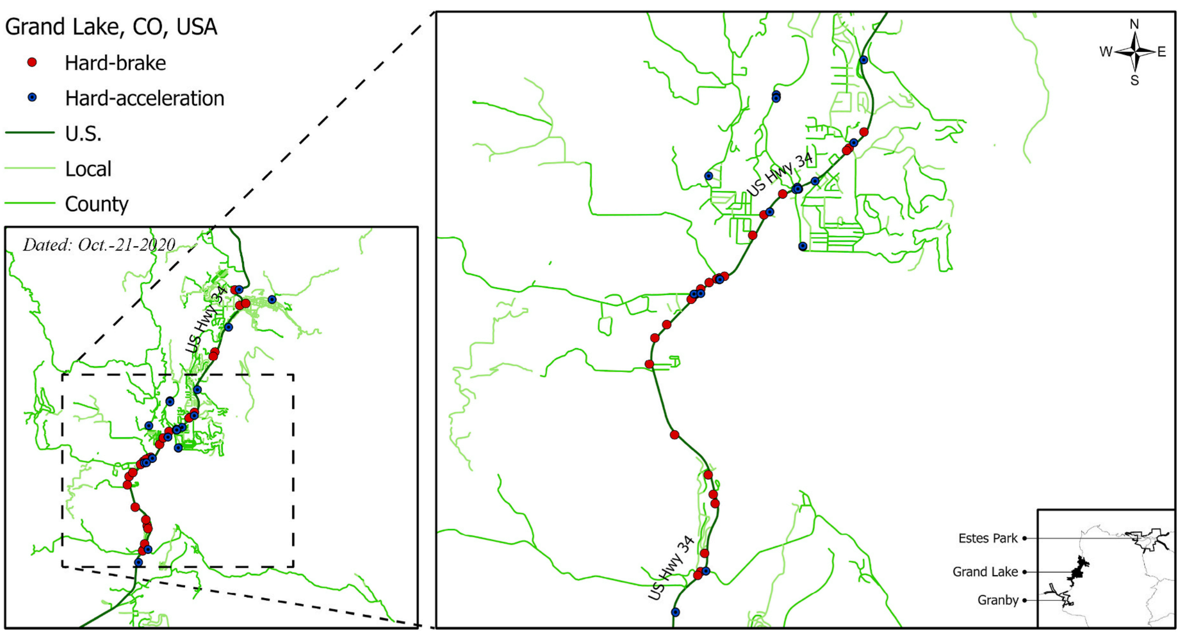
Date	No. of hard-brakes	No. of hard-accelerations
Saturday, June 20, 2020	17	30
Sunday, June 21, 2020	11	19
Monday, June 22, 2020	8	39
Tuesday, June 23, 2020	7	28
Wednesday, June 24, 2020	10	27
Thursday, June 25, 2020	7	21
Friday, June 26, 2020	9	14
Saturday, June 27, 2020	7	18
Sunday, June 28, 2020	24	41
Monday, June 29, 2020	3	10
Tuesday, June 30, 2020	5	15

The call-out area represents a specific region within the total evacuation zone which was initially significantly impacted by the fire and its effects were particularly pronounced. By identifying and examining this area separately, insights were obtained concerning the specific challenges and dynamics associated with the evacuation process in a heavily affected region.

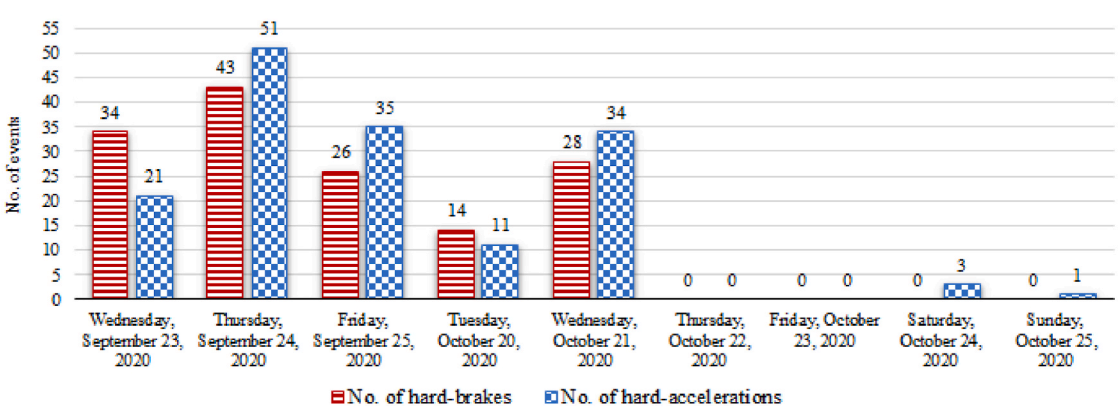
Additionally, the southern neighborhoods observed almost 83 % of the day's HB and 73 % of the day's HA events during the evacuation period (2:45 p.m. to 7:00 p.m.). This highlights the significant temporal and spatial impact of the fire and the subsequent hurried evacuation driving behavior in the affected neighborhoods. Furthermore, the data evaluation also revealed that the traffic intersections are critical congestion points where the highest number of driving events are observed. This implies that vehicles formed queues at the intersections requiring drivers to apply HB to stop the vehicle and then HA to leave the area quickly, as previously noted in the literature. The driving event data for this city demonstrates the driving behavior of people evacuating the city on very short notice out of fear for their lives, as supported by the studied case reported in the previous section.

The data for the three towns in the state of Colorado were analyzed, including the Grand Lake area consisting of neighborhoods along U.S. Highway 34 (mile marker 5 to 17) and the Granby area consisting of neighborhoods along U.S. Highway 40 (mile marker 207 to 216), U.S. Highway 34 (mile marker 0 to 3), and State Highway 125 (mile marker 0 to 3). The Estes Park area consisted of neighborhoods along U.S. Highway 34 (mile marker 54 to 70), U.S. Highway 36 (mile marker 1 to 7) and State Highway 7 (mile marker 0 to 7).

Starting with the evacuation of Grand Lake, it was observed that the



(a)



(b)

Fig. 5. Grand Lake, CO, USA (a) driving events map (b) driving events data.

majority of evacuation day driving events occurred on U.S. Highway 34 traffic traveling south towards Granby as was reported in the previous section and illustrated in Fig. 5(a). The increasing occurrence of HA events for vehicles traveling south in particular demonstrates the urgency of evacuees to leave the affected area. Secondly, since both lanes of U.S. Highway 34 were used to reduce congestion during the evacuation, a high increase in HB events was not observed as detailed in Fig. 5 (b). Another reason for the lack of significant increase in driving events during evacuation might be that the town received fewer visitors because the west side of Rocky Mountain National Park towards Grand Lake was closed for visitors on the evacuation day.

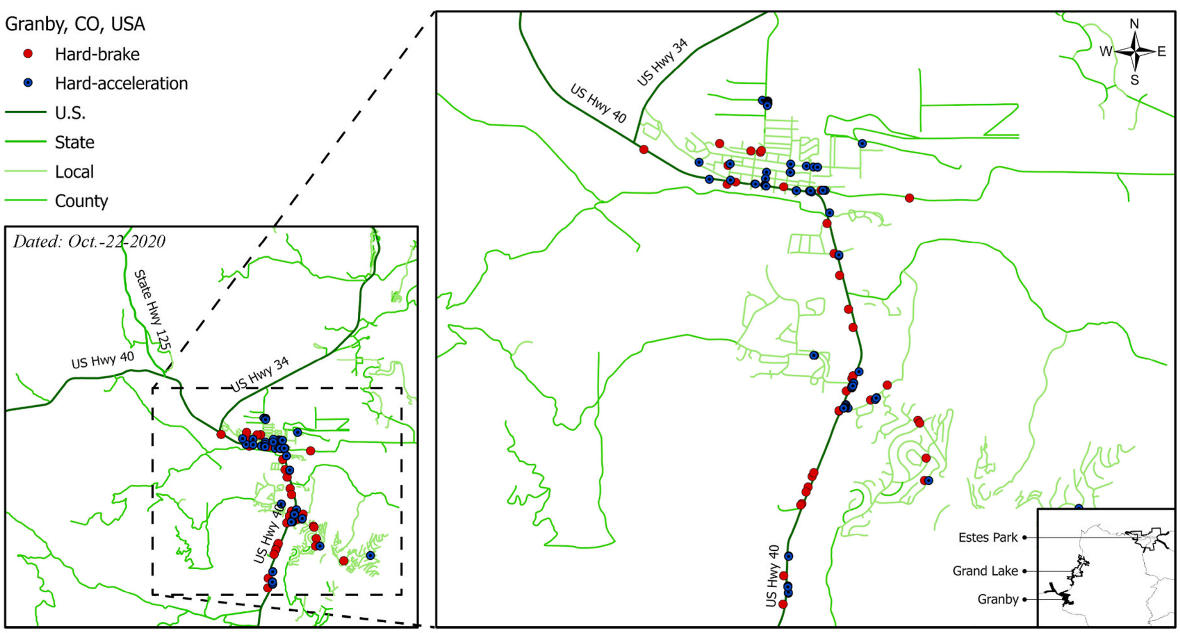
In Granby, we observed an increase in driving events on October 21 & 22 particularly HA events as depicted in Fig. 6(b). One likely reason for the increase in such events was the rushed arrival of evacuees from Grand Lake on October 21 to shelter in Granby as explained earlier and later all residents of Granby and Grand Lake evacuated the town using a southbound route on October 22 leading to congestion on the exiting route. Fig. 6(a) further gives evidence that all driving events within the close proximity of the town were reported either in the center of the town or the traffic leaving south on U.S. Highway 40 away from the fire-impacted paths in the north (State Highway 125 and U.S. Highway 34).

The analysis of the data for Estes Park showed the formation of clusters of HA and HB events on all major exiting routes, particularly U. S. Highways 34 & 36, and State Highway 7 during the evacuation period as depicted in Fig. 7(a). This suggests that congestion and stop-and-go traffic situations were observed at traffic intersections and junctions, as reported in the previous section. Secondly, the reporting of reduced number of driving events in the study period October 20–22, 2020 as detailed in Fig. 7(b) suggests that the town received fewer visitors due to the closure of Rocky Mountain National Park in this period, as previously reported in the literature.

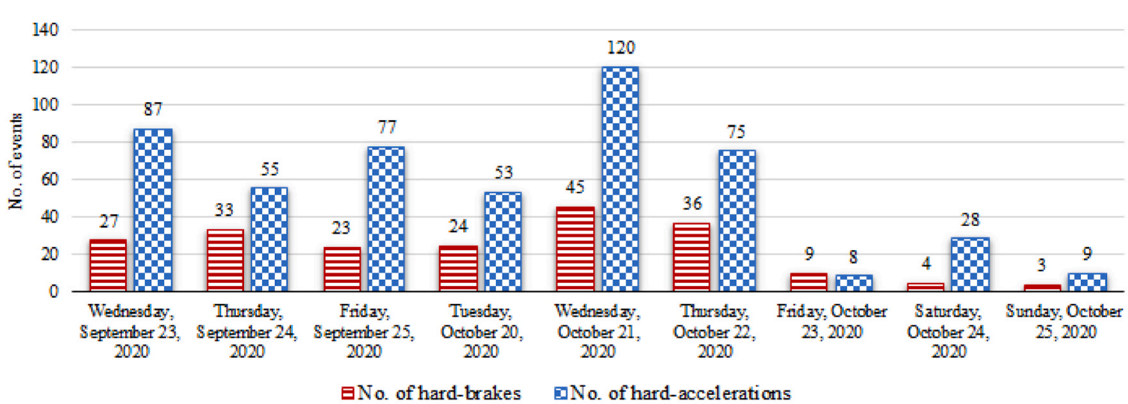
Finally, the comparison of the data for the three towns of Colorado showed the least number of driving events for many days following the day of evacuation in the study period demonstrating the state of evacuated towns as explained previously.

4.3.2. Independent samples statistical analysis

To further explore differences in driving patterns before and after the fire events, an independent sample *t*-test was conducted for the selected study incidents. The dataset for the three Colorado towns exhibited intermittent records, attributed to the extended nature of the Cameron Peak Fire and East Troublesome Fire. Given the extended duration of

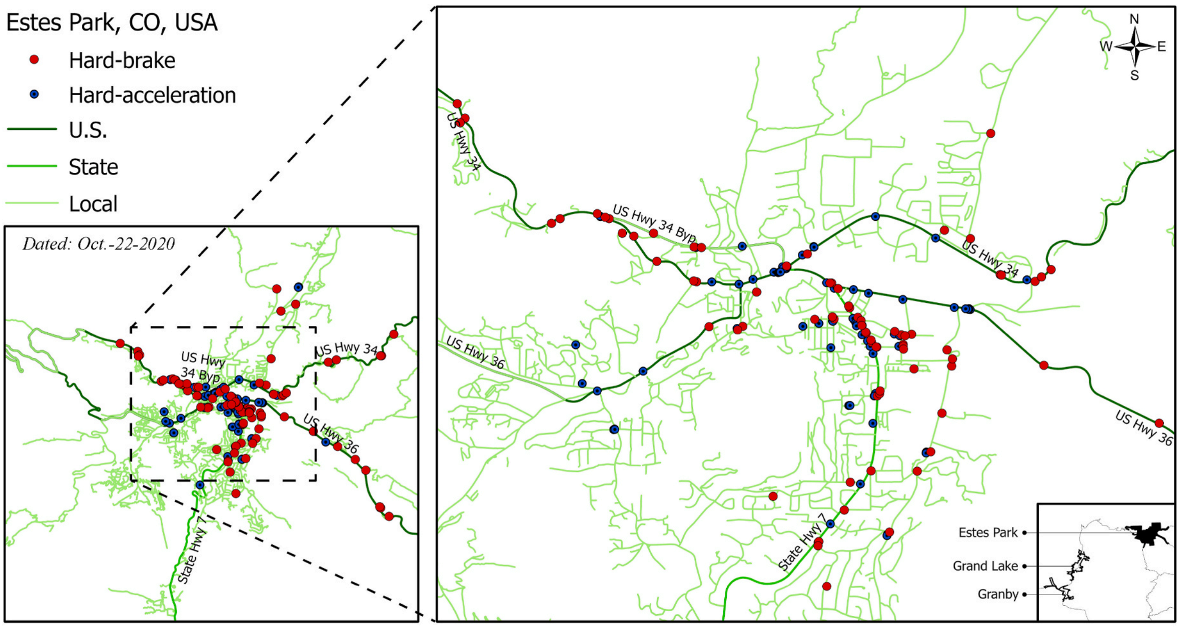


(a)

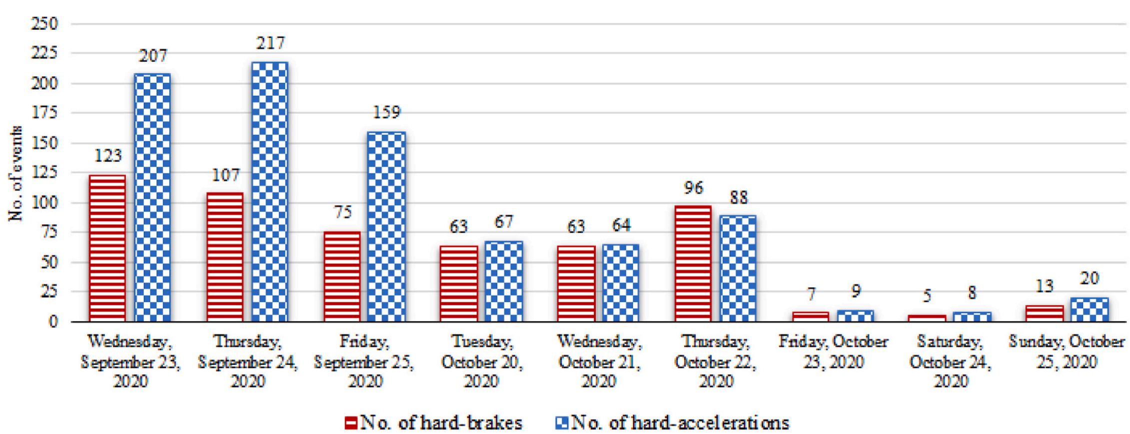


(b)

Fig. 6. Granby, CO, USA (a) driving events map (b) driving events data.



(a)



(b)

Fig. 7. Estes Park, CO, USA (a) driving events map (b) driving events data.

these events, defining the evacuation driving period precisely posed certain complexities. Consequently, this study chose to focus on the Utah Knolls Fire, utilizing a continuous dataset spanning from June 20th to June 30th.

Utilizing the date and time stamps within the dataset, hourly data was extracted from the study area for analysis of both HA and HB activities. In this particular instance, considering the Knolls Fire started at 2:30 p.m., data prior to 2 p.m. on June 28th, 2020, was categorized as the pre-evacuation period for analysis, while driving events occurring after 3 p.m. on June 28th were designated as the evacuation period. To enhance comprehension of the daily driving patterns, the HA and HB events within the study area were segmented using pivot tables, organized by hourly intervals (see Tables 4 and 5, respectively).

Following data processing, it became evident that limitations existed within the records, particularly within the 12 a.m.–5 a.m. timeframe for most days. This led to a specific focus on data points from 6 a.m. until midnight, forming the basis for a comprehensive statistical analysis. Additionally, to minimize potential seasonal effects, especially considering the impact of various weekdays on driving behavior, the dataset for the week before the evacuation order, beginning on June 21st at 3 p.

Table 4
Pivot table on hard accelerations for the Knolls fire in Utah.

Count of HA	Date						
Time of day	6/20	6/21	6/22	6/23	6/28	6/29	6/30
6:00 a.m.	0	0	2	18	0	4	3
7:00 a.m.	12	2	5	18	6	1	2
8:00 a.m.	9	1	2	4	4	1	3
9:00 a.m.	18	5	1	5	6	8	1
10:00 a.m.	10	19	7	4	10	5	2
11:00 a.m.	4	2	10	5	2	3	13
12:00 p.m.	8	3	7	3	15	1	6
1:00 p.m.	5	0	19	3	6	5	3
2:00 p.m.	13	4	3	3	13	2	8
3:00 p.m.	9	24	30	6	20	1	1
4:00 p.m.	9	1	15	13	20	2	21
5:00 p.m.	22	8	18	16	22	6	12
6:00 p.m.	11	1	14	16	1	3	0
7:00 p.m.	13	0	2	6	8	1	0
8:00 p.m.	13	3	8	1	0	4	0
9:00 p.m.	3	0	1	2	2	0	0
10:00 p.m.	2	1	20	1	1	1	0
11:00 p.m.	0	0	0	0	0	0	0

Table 5
Pivot table on hard brakes for the Knolls fire in Utah.

Count of HB	Date						
Time of day	6/20	6/21	6/22	6/23	6/28	6/29	6/30
6:00 a.m.	0	0	2	0	0	1	1
7:00 a.m.	2	2	2	5	0	1	3
8:00 a.m.	7	6	1	0	2	0	6
9:00 a.m.	5	0	2	3	1	1	0
10:00 a.m.	1	0	1	0	2	4	4
11:00 a.m.	2	1	2	1	2	2	8
12:00 p.m.	2	1	0	1	8	0	3
1:00 p.m.	2	1	2	1	1	1	1
2:00 p.m.	3	1	3	2	8	2	5
3:00 p.m.	9	7	8	6	8	3	1
4:00 p.m.	1	1	10	3	19	0	8
5:00 p.m.	5	3	2	7	11	4	1
6:00 p.m.	5	1	11	4	2	3	0
7:00 p.m.	4	1	3	1	4	2	0
8:00 p.m.	1	2	3	1	0	4	0
9:00 p.m.	1	4	1	1	0	0	0
10:00 p.m.	2	2	1	0	1	0	0
11:00 p.m.	0	1	0	0	0	0	0

m., was utilized as the foundation for the pre-evacuation data group. An equivalent number of observations were intentionally chosen for direct comparison with the evacuation group, resulting in a simplified pivot table format.

The grey-shaded numbers above represent the data analyzed for both HA and HB events. To determine the appropriate type of *t*-test for the data, F-tests were conducted for both events, as shown in Table 6.

Based on Tables 6 and it can be seen that the P value for HA F-test stands at 0.089, thereby not allowing the null hypothesis to be rejected, necessitating the application of the equal variance *t*-test. Conversely, the HB events yield a P value of 0.021 from the conducted F-test, warranting the null hypothesis's rejection and prompting the usage of a *t*-test with unequal variance (see Table 7).

Table 6
F-test on hard accelerations and hard brakes for the Knolls fire in Utah.

F-Test Two-Sample for Variances	Hard-Accelerations		Hard-Brakes	
	Pre-evacuation	Evacuation	Pre-evacuation	Evacuation
Mean	7.6923	5.0513	2.6923	2.9231
Variance	59.9555	38.5236	7.3238	14.2834
Observations	39	39	39	39
df	38	38	38	38
F	1.5563		0.5128	
$P(F \leq f)$ one-tail	0.0887		0.0213	
F Critical one-tail	1.7167		0.5825	

Table 7
t-Test on Hard Accelerations for The Knolls Fire in Utah.

t-Test: Two-Sample Assuming Equal Variances	Pre-evacuation	Evacuation
Mean	7.6923	5.0513
Variance	59.9555	38.5236
Observations	39	39
Pooled Variance	49.2395	
Hypothesized Mean Difference	0	
df	76	
t Stat	1.662	
$P(T \leq t)$ two-tail	0.1006	
t Critical two-tail	1.9916	

Table 8
t-Test on Hard Brakes for The Knolls Fire in Utah.

t-Test: Two-Sample Assuming Unequal Variances	Pre-evacuation	Evacuation
Mean	2.6923	2.9231
Variance	7.3239	14.2834
Observations	39	39
Hypothesized Mean Difference	0	
df	69	
t Stat	−0.31	
$P(T \leq t)$ two-tail	0.7574	
t Critical two-tail	1.9949	

The evaluation of driving behaviors before and after the fire provides a notable trend showing that in the wake of the fire, there is an evident reduction of around two events per hour in the count of hard accelerations within the study area. This shift corresponds logically with the anticipated decrease in vehicular activity following the fire event. Within this study's context, the possibility of HA and HB events deviating from the norm, either occurring less or more frequently, remains a factor that cannot be wholly disregarded. As such, the selection is made for a two-tail statistical analysis. The calculated two-tail P value rests at 0.100, a value situated within the 89 % confidence interval of the analysis. This implies a subtle yet perceptible statistical significance or a potential trend. It is noteworthy, however, that the study did not uncover statistically significant findings at the 95 % confidence level.

To enhance the findings of this study, it becomes essential to acquire a comprehensive count of vehicles operations in the study area, along with the total miles traveled. Unfortunately, owing to the pause in traffic monitoring by the Utah Department of Transportation and the alteration of traffic signals to stop signs, no records are available encompassing the overall number of vehicles in transit during that period. Leveraging the potential records from the ATSPM system is anticipated to alleviate the occurrence of multiple zeros through the inclusion of non-connected vehicle data. This adjustment is poised to substantially enhance the analysis's precision. With a substantial increase in traffic during the evacuation day, an anticipation of heightened hard accelerations during the evacuation hours emerges. However, the numbers are likely to decrease once a majority of the population completes the evacuation, leading to a subsequent decline in HA events compared to regular days.

Table 8 provides the results of t-Testing concerning HB events prior to and following the fire incident. No distinct statistical significance materializes in the comparison of these periods. Notably, the average frequency of HB events remains consistent before and after the fire (2.69 per hour and 2.92 per hour, respectively). The P value linked with the t-Tests on HB events stands at 0.757, indicating the absence of statistical significance. The potential for a more robust analysis beckons with access to comprehensive data on the total number of vehicles and overall miles traveled. Such data could potentially offer refined data processing pathways. The presence of multiple zeros within the dataset could likely have shaped the data pattern of the analysis. In anticipation of heightened traffic during the evacuation day, a projection of escalated hard brake incidents during evacuation hours takes shape. Subsequently, as a majority of the population completes the evacuation, a decrease is foreseen, leading to a subsequent decline in HB events compared to regular days.

5. Conclusions and future work

This paper evaluated the human driving behavior in four historical wildfire evacuations in different regions where residents were subjected to varying evacuation conditions and investigated the aggressive driving behavior patterns of vehicles during evacuation using a connected vehicle dataset correlated with the chronology of the actual events. The connected vehicle data reported the geolocation of vehicles applying HB or HA at a certain time and date. This allowed researchers to objectively look at HB and HA patterns of vehicles evacuating a hazardous situation and analyze how it represents the traffic behavior across the timeline of reported events. The key findings from the comparative data analysis are provided as follows:

1) The evaluation of the driving event data for all the selected case studies revealed that individuals' driving behavior patterns change as they are exposed to changing driving conditions throughout the course of all the wildfire events. This is evidenced by the change in HB and HA patterns of the vehicles in all wildfire events.
2) The comparative analysis of the data for all cases emphasized the importance of evacuation warning time in defining the aggressive nature of drivers. We observed increased occurrences of HA events on the evacuation routes and the heavily impacted areas, indicating the urgency of evacuees to leave the fire-impacted area, as they are exposed to challenging driving conditions on a short notice evacuation.
3) The traffic intersections and junctions are critical congestion points during the evacuation, with clusters of HB events forming in all study areas, implying the creation of vehicular queues and traffic delays on the evacuation routes.
4) With the visualization of the temporal and spatial spread of HB and HA events provided by the connected vehicle database during non-evacuation and evacuation periods, as well as the precise position of these traffic events on the roadways and high-impact areas during fire evacuation for the rural and urban case study areas, evacuation patterns in rural and urban areas were observed to be significantly different which are recommended to plan differently accordingly.
5) The statistical analysis of HA and HB events in Knolls Fire, Utah, showed a discernible shift in driving behavior before and after the fire incident. However, the analysis relying solely on connected vehicle data does not reveal statistically significant trends for HB events.

Due to the lack of availability of driver behavior data during wildfire evacuations and the uncertainty associated with the use of stated or revealed preference surveys, this study provides researchers and emergency responders valuable findings which can be applied to model evacuation scenarios and driver behaviors on the modeling platforms. This includes incorporating traffic congestion locations and the geographic, temporal and spatial context of the fire incident. Therefore, the driving parameters for microscopic traffic modeling about car-following and gap acceptance can be modified for emergency evacuation modeling incorporating the aggressive driving behavior of individuals at critical congestion points in the study network under various scenarios.

However, the analysis of the data is limited to conducting a qualitative and comparative assessment of the historical hazardous events with the reported incidents information due to the unavailability of other comprehensive datasets about driving behavior and relatively low penetration rates of connected vehicles. Thus, additional studies are needed to investigate the effectiveness of integrating such datasets into evacuation traffic simulation modeling. Future studies may conduct quantitative analysis of this dataset to compare the results with other available sets of data about driving behavior. Additionally, revealed preference surveys may also be carried out in the studied cases to compare the results of this study and identify what factors affect the evacuation.

Author statement

Salman Ahmad: Formal analysis, Methodology, Writing – original draft, Visualization, Investigation; Hafiz Usman Ahmed: Investigation, Writing – review & editing; Asad Ali: Investigation, Visualization, Writing – review & editing; Xinyi Yang: Investigation, Writing – review & editing; Ying Huang: Conceptualization, Methodology, Writing – review & editing, Funding Acquisition, Advising and Mentoring; Mingwei Guo: Investigation, Visualization, Writing – review & editing; Yihao Ren: Investigation, Writing – review & editing; Pan Lu: Writing – review & editing, Funding Acquisition, Advising and Mentoring.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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