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Drilling for disaster preparedness: Insights from a community wildfire evacuation exercise

Ann-Kristin Dugstad [a,1], Noureddine Bénichou [b], Maxine Berthiaume [b], Paul Geoerg [c,d,1], Steve Gwynne [a,e,f], Amanda Kimball [g], Kamryn Kubose-Peutz [e], Hui Xie [e,f], Enrico Ronchi [a,*], Max Kinateder [b,1]

[a] Lund University, Lund, Sweden
[b] National Research Council Canada, Ottawa, Canada
[c] Johanniter University of Applied Science, Berlin, Germany
[d] Vereinigung zur Förderung des Deutschen Brandschutzes e.V, Münster, Germany
[e] Movement Strategies Inc, UK
[f] University of Greenwich, London, UK
[g] Fire Protection Research Foundation, Quincy, MA, USA

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A B S T R A C T

Community evacuation exercises (or drills) are one approach residents and authorities use to train wildfire emergency procedures in the Wildland Urban Interface (WUI). This paper presents results from a drill performed in Roxborough Park, a WUI community in Colorado, USA, in 2024. Observer and self-report data were collected to derive resident preparatory actions, pre-travel, travel, and total evacuation times, as well as route choice and the drill's impact on their perceived preparedness. It took more than 28 minutes until 90 % of residents began traveling and more than 48 minutes until 90 % had completed their evacuation. Most of the participants reported following the instructions for the evacuation route, with a minority taking a shorter or more familiar route. The work underlines the value of drills for improving community disaster preparedness, providing data for developing/testing computational models, and deepening our understanding of human behavior in wildfire scenarios.

1. Introduction

As climate change intensifies and the Wildland-Urban Interface (WUI) continues to grow (in size and population), the number of wildfires requiring community evacuation has surged (Jolly, 2015; Intini et al., 2020; Christianson et al., 2024). For example, on average, wildfires caused 30 evacuations annually in Canada between 1980 and 2021, with the frequency and scale of evacuations increasing over time (Christianson et al., 2024). The 2023 fire season was particularly severe, with wildfires forcing approximately 232,000 Canadians to flee their homes (Jain et al., 2024). In California, over one million evacuees were documented between 2017 and 2019 (Wong et al., 2020b). Globally, multiple large-scale evacuations related to wildfires have been reported in the last two years alone - often in areas that were previously not impacted by wildfires; for example, Japan (Butler, 2025), South Korea (Young, 2025), Russia (Ostiller, 2024), Greece (Kalogeropoulos et al., 2024), South Africa (Press, 2024), and Algeria (McGarvey, 2023).

Given the urgency and complexity of the topic, understanding how community wildfire evacuations unfold is critical. A common representation of evacuations is through event timelines (Proulx, 2002). The concept of WUI Required Safe Egress Time (WRSET)

* Corresponding author.
E-mail address: enrico.ronchi@brand.lth.se (E. Ronchi).
[1] These authors contributed equally to this manuscript.

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splits an evacuation into several phases, including the time needed to detect, assess, and attempt to control a fire, the time for residents to receive evacuation orders, prepare their departure, move to their vehicles,[1] and then travel to and check into a place of safety (Ronchi et al., 2019). This breakdown allows studying and simulating WRSET components individually. For instance, depending on the scenario, the size of a community, or the distance needed to travel, the relative impact of pre-travel times and travel times on total evacuation duration may vary substantially.[2]

In recent years, several studies analyzed the spatio-temporal dynamics of community wildfire evacuations. Many of these use geospatial data and provide valuable insights into how a large number of people move in disasters. For example, one study derived cumulative travel times for the 2019 evacuation from the Kincade Fire (Zhao et al., 2022). Another study documented high evacuation rates even in neighborhoods outside the area under evacuation order during the 2023 McDougall Creek wildfire (Ha and Long, 2025). A recent study by Borody and Wong (2025) studied unplanned emergency evacuations in four Canadian communities during the 2023 wildfire season. The authors showed that departures times followed roughly S-shaped curves (Borody and Wong, 2025). Rohaert et al. accessed publicly available data from traffic counters to compare the dynamics of routine and evacuation traffic on California highways and found small but relevant differences in the speed-density relationships (Rohaert et al., 2023). However, while these studies provide valuable macroscopic understanding, more fine grained analyses into pre-travel and travel behavior are lacking due to the inherent limitations of the methods used. For instance, depending on the location, the quality and abundance of geospatial data can vary, particularly in remote and sparsely populated areas (Raei et al., 2025). In addition to technical and logistical challenges, there are also ethical and privacy related considerations that need to be taken into account (Wong et al., 2020b). That is, despite immense progress, fine-grained quantitative data related to human behavior during wildfire evacuation at the community scale remain scarce, particular with respect to pre-travel times (Kuligowski, 2021a). Yet, granular data are necessary to understand resident responses in detail and to validly generate pre-travel and travel times as an emergent output from computational simulation tools (Ronchi et al., 2023). In addition, describing evacuation timelines at the household level can provide valuable information to local emergency planners and other authorities, given that more aggregated information may not fully describe the variability in behavior that may occur during emergencies.

Indeed, timely evacuation is an essential strategy to minimize risks to the health of residents in the WUI and improve life safety (National Research Council of Canada, 2021; Kalogeropoulos et al., 2024). In turn, late or even dire evacuations have been linked to increased fatality rates (Cova et al., 2021; Kalogeropoulos et al., 2025; Haynes et al., 2010). Therefore, it is critical to ensure that communities are prepared to evacuate safely (e.g., through appropriate pre-travel actions) and know when and where to go (e.g., through timely departure and appropriate route choice) when they need to. This can be achieved by demonstrating that emergency evacuation procedures are effective, and that those who need to enact them, i.e., a community's residents and authorities, are familiar with said measures.

Community evacuation exercises (or drills for short) are one way for residents, first responders, and emergency managers to practice evacuation procedures as well as to assess and increase community preparedness. Drills can be classified as either announced - where the exact time and date are known to all participants, semi-announced - where some but not all details about the drills are shared beforehand (such as the date but not the exact time of day), and unannounced - where no information is shared with residents beforehand. Due to the scale, complexity, and required buy-in from residents, fully announced wildfire evacuation drills are rare. However, even announced and semi-announced drills are opportunities to collect empirical data to gain insight into evacuation dynamics and to validate simulation tools, although greater care needs to be shown in the veracity of such data and its subsequent use (Gwynne et al., 2020, 2023). In fact, drills can be considered an empirical model, that is a simplified representation of an actual emergency evacuation. As most models, drills have limitations, most importantly, whether or not they afford insights that can be generalized beyond their specific local context (Gwynne et al., 2020). The following specific biases may cause drill observations to differ from real events: Self-selection of participants: Volunteer participants of evacuation drills may differ from the community population overall (e.g., in terms of preparedness); drills are often conducted under optimal conditions (e.g., most residents likely at home when notified, good weather conditions). Nevertheless, there is a lack of empirical studies in this domain and it is therefore considered a field requiring further investigation (Haghani et al., 2024; Kuligowski, 2021b).

A range of empirical methods can be utilized to gather detailed data and assess performance during drills. These include self-report measures, accounts from human observers, automated traffic counters, aerial drones, and GPS trackers. Each method possesses strengths and weaknesses (see Dugstad et al. (2024) for a discussion). A combination of methods offers a holistic account of pre-travel and travel behavior and timing, enriched with detailed accounts from participants on their personal experiences, actions, and underlying motivations. This then allows for identifying the capacity of the road network and potential associated behavioral patterns (e.g., compliance (and lack thereof) with instructions) that may influence evacuation outcomes. In addition, combining several data collection methods allows for a systematic comparison against each other (Dugstad et al., 2025).

1.1. The present study

The main objectives of the present study are to (1) quantify pre-travel and travel times and to (2) describe route choice during a community evacuation drill. To address these questions, the present paper describes the result of a semi-announced community

[1] Private vehicles are by far the most common mode of transportation in WUI evacuations (Zehra and Wong, 2024)

[2] The terms "pre-travel time" and "travel time" are used throughout this paper; elsewhere these are also referred to as "pre-evacuation time" and "evacuation time"; The concept of "total evacuation time' is similar to "cumulative evacuation rates" used in other fields.

wildfire evacuation exercise conducted in Roxborough Park, Colorado, USA, in June 2024, where a variety of measures were employed to capture observational and self-report data. The concept of WRSET is then used to derive an evacuation timeline for the drill. This includes a pre-travel phase (including preparatory activities before deciding to evacuate) and a travel phase (once individuals or groups have started purposive movement toward safety), followed by results on in-transit actions and route choice. The paper then discusses the observational results in the context of the subjective experience of drill participants (e.g., in terms of perceived preparedness) and compares the findings to a previous drill (Gwynne et al., 2023).

2. Methodology

The following section describes the methodology, beginning with a general description of the community, its experience with wildfires and drills, and the residents who participated in the 2024 drill and research. Then the general data collection methods and processing are described, as well as key evacuation performance benchmark measures (pre-travel time, travel time, total evacuation time) as well as in-transit actions and route choice. Data collection related to the drill was reviewed and approved by the NRC Research Ethics Board (REB 2023-140).

2.1. Roxborough park, Colorado

Roxborough Park is situated in the WUI of Douglas County, Colorado, USA, southwest of Denver, and is considered to be in high wildfire risk area (Service, 2018). Developed in the 1970s, the community covers approximately nine square kilometers of heavily vegetated and hilly land. To the north, the community is neighboring another subdivision, which includes 250 homes that did not participate in the drill, and a golf course. Roxborough Park comprises 1057 mostly single-family homes with an estimated population of around 3,000. For more details, also see Kinateder et al. (2025).

Fig. 1 provides a community map, including locations relevant for research, such as evacuation gates (A, B, D, F), intersections (C, G), and the assembly point (H; the local fire station). The community is accessible via a single entrance and exit road (highlighted in red on the map). The community is equipped with four additional Emergency Egress Easements (EEE; black arrows on the map). EEEs are unpaved roads that are not used for routine traffic and provide additional evacuation routes. To the south, one EEE leads through densely forested areas to a neighboring town (south of point A in Fig. 1). To the north, two EEEs connect Roxborough park to a main road via another subdivision (highlighted in blue on the map). Throughout the community, signage indicates optimal evacuation routes. For analysis, four departure areas were defined and highlighted in color: north/red, east/blue, south/green, west/yellow. This differentiation allows testing whether (a) the home location of residents relative to the drill scenario (fire encroaching from the south) or (b) the evacuation routes would affect evacuation timing and route choice.

Since 2007, Roxborough Park has been recognized as a Firewise USA[3] community, reflecting its commitment to wildfire preparedness. The community's proactive approach began in 2003 with the establishment of the volunteer Fire Mitigation Committee. This committee collaborates with various agencies and researchers, exemplified by their coordination for the 2024 evacuation drill.

2.2. Previous drills

The Douglas County Office of Emergency Management facilitates wildfire evacuation exercises every five years with the community. In 2019, one of such drills was also observed by researchers (Gwynne et al., 2023). The 2019 drill followed a similar procedure to the 2024 drill (details below), with some noticeable differences. First, the 2019 drill was fully announced, i.e., residents were informed beforehand at what time the evacuation order would be issued. This had the effect that several participants evacuated before the drill began. Second, the data collection relied on manual observations and self-report data only and covered fewer observation points.

2.3. The community wildfire evacuation exercise

This section introduces the wildfire evacuation exercise, organized by the Douglas County Office of Emergency Management and the local community with support from the research team. Comprehensive information about the community collaboration and the procedures is available in the full report (Dugstad et al., 2024). A few weeks before the drill, residents were informed and encouraged to participate. The invitation included details about the drill, the associated research, and instructions on how to sign up. Importantly, residents had the option to enroll in the research independent from the drill, allowing them to participate in the drill without sharing their experience with the researchers. Those who registered *(were added to an emergency notification service database and received further information.)* Although residents were informed of the drill date, they were not told at what time the evacuation order would be issued, making it a semi-announced drill. Those who also enrolled in the research were also sent further details about the research, consent forms, and surveys. In addition, the research participants were instructed to put colored paper tags on their vehicles to indicate their area of origin in the community. These areas were defined according to their location relative to the nearest EEE (see the color codes in Fig. 1 and Dugstad et al., 2024; Kinateder et al., 2025).

[3] Firewise USA is a program that aims to educate and support WUI communities towards increasing their resilience to wildfires. For more information see: https://www.nfpa.org/education-and-research/wildfire/firewise-usa

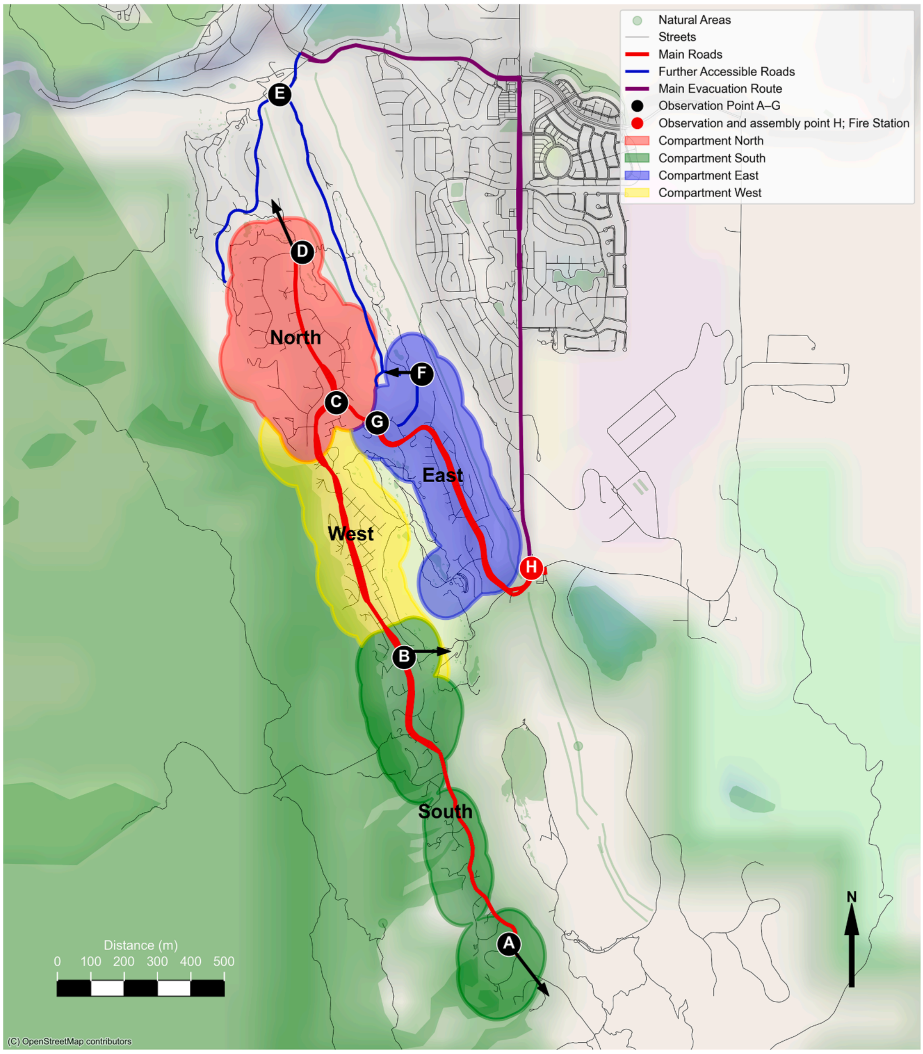


Fig. 1. Map of the community including the road network. The evacuation routes available during the drill are shown in red (main road) and blue (additional evacuation routes). For data analysis, four departure areas were defined and highlighted in color: north/red, east/blue, south/green, and west/yellow. Key observation points (A–H) include entries to EEEs (A, B, D, F), intersections (C, G), and the assembly point (H). EEEs at observation points A and B were closed during the drill. Map generated using OpenStreetMap (OpenStreetMap contributors, 2024) data and OSMnx (Boeing, 2017). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

An emergency notification database was used to provide further information to residents who had registered (Dugstad et al., 2024), and on June 29, 2024, at 9:00 a.m., evacuation orders were sent out via phone calls, voice messages, text messages, or email. In addition, emergency management officers knocked on drill participants' doors to communicate the evacuation order. The alert informed them of *(a wildfire approaching from the south and instructed them to evacuate the community using the northbound evacuation routes through the neighboring community and to gather at the local fire station.)* The drill scenario allowed for only two of the four EEEs to be accessible, imitating a real incident where evacuation routes might be blocked; only the two EEEs in the northern and eastern departure area were accessible (see Fig. 1). Upon arriving at the assembly point, residents could ask questions and submit surveys and postcards. *(After completion of the drill, residents were encouraged to explore the marked evacuation routes, including the EEEs.)* For further details regarding the organizational and logistical aspects of the drill, see (Dugstad et al., 2024; Kinateder et al., 2025).

2.4. Participants

A total of 128 households, that is, approximately 12 % of the community, registered 177 vehicles for the drill. On average, the participants were 66.33 years old (SD = 9.74 years) and had lived in Roxborough Park for approximately 11 years (SD = 9.04 years), with the mean duration of residence in their current home being about 10 years (SD = 8.40 years). Some participants reported having

Table 1
Data availability across evacuation and survey stages.

Stage	Count
Pre-Travel Time	125
Total Evacuation Time	132
Complete PTT and TET dataset	77
Postcards	90
Survey	108

a medical condition, such as heart or respiratory conditions, diabetes, or functional limitations (e.g., visual or hearing impairments, mobility-related disabilities). A more detailed overview of demographic data can be found in Appendix A and Dugstad et al. (2024).

2.5. Data collection methods

Human observers were placed at relevant locations throughout the community (see Fig. 1). Observers recorded arrival times at their observation points, either using a paper / pencil or a mobile phone-based note taking system.[4]

During the drill, participants also completed a postcard with questions that had been handed out prior to the drill documenting the timing of specific events, e.g., when they received the evacuation order, and the route taken. After the drill, participants completed a post-drill survey that included demographic information (e.g., age, gender, household size), perceived preparedness, and questions about their experience during the drill.

2.6. Data processing

The data produced by individual observers were pre-processed and aggregated into a single database. All data were cleaned and merged based on unique vehicle identifiers composed of Car ID and the color code of the departure area (e.g., car_01_green for the first vehicle from the southern departure area). To obtain timestamps for pre-travel time (PTT) and total evacuation time (TET), observations were parsed and aligned to a reference time of 09:00 a.m. local time on the day of the drill. All observed times were converted into minutes relative to the reference time and rounded to a consistent resolution for plotting and summary statistics. Only vehicles with complete observations, i.e. PTT and TET timestamps ($n = 77$) were retained for analysis. This ensured consistency in cumulative metrics but meant that 45 incomplete observations had to be discarded (see discussion and Appendix B for details). Table 1 gives an overview of the available data on PTT, TET as well as postcards and surveys.

2.7. Community evacuation benchmarks

2.7.1. Pre-travel time (PTT) and total evacuation time (TET)

Due to ethical and privacy considerations, PTTs were not measured at residents' homes. Instead, PTTs were approximated by measuring arrival times at the exits of each departure area and subtracting the estimated time needed to move from a home to the observation point (0.5 to 4 minutes; see Fig. 5):

$$\mathrm{PTT} = \mathrm{AT}_{\mathrm{obs}} - \mathrm{TT}_{\text{home-to-obs}} \tag{1}$$

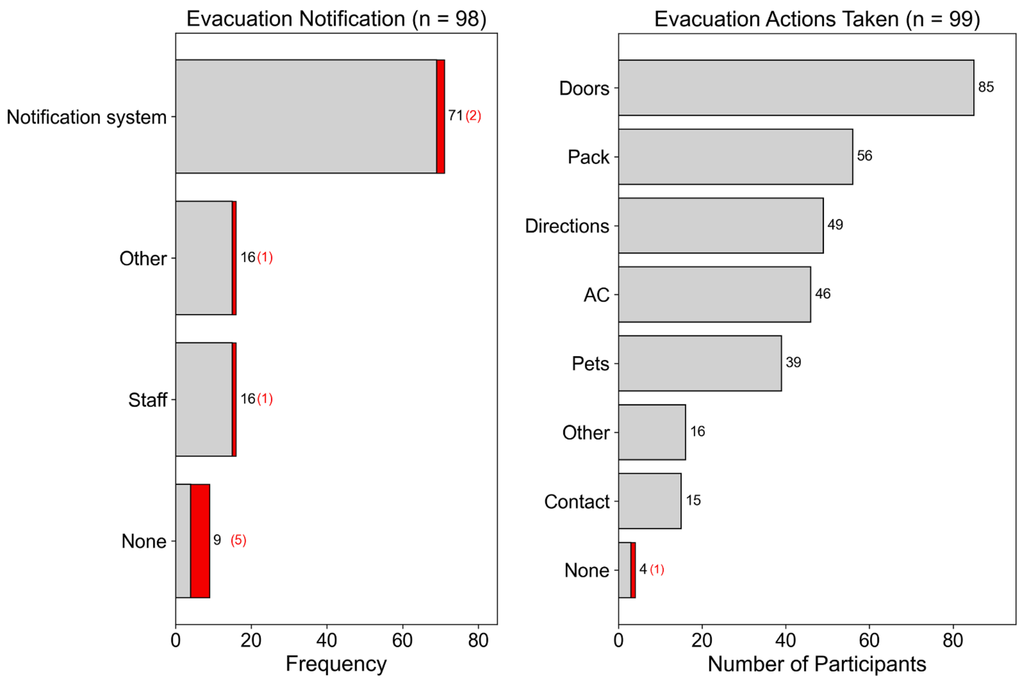
where PTT refers to the approximated pre-travel time, $\mathrm{AT}_{\mathrm{obs}}$ to the arrival time at the last observation point within a departure area, and $\mathrm{TT}_{\text{home-to-obs}}$ the estimated travel time from a home to the first point of observation. $\mathrm{TT}_{\text{home-to-obs}}$ estimates were 0.5 minutes for departure area north, 4 minutes for departure area east, 2 minutes for departure area south, and 1 minutes for departure area west. For further details on how these correction values were applied and for comparing pre-travel and total evacuation time distributions, see Appendix A, Fig. 10.

TET was measured at the assembly point (observation point H). In the context of the present study TET is the sum of pre-travel and travel time.

2.7.2. In-transit behavior and route choice

Each evacuee could potentially follow multiple routes to the assembly point (observation point H in Fig. 1). Assuming no observation point was traversed more than once during the evacuation, a finite set of possible routes can be defined. This assumption enables the identification of the minimum number of observation points required to monitor vehicle movements and unambiguously determine which routes were taken. To ensure comprehensive route coverage, all unique evacuation paths from each departure area to the assembly point, without repeating observation points, were first identified. This was achieved by applying a Depth-First Search

[4] For purposes beyond the scope of the present paper additional observation tools such as a drone and automated traffic counters were employed; see Dugstad et al. (2024)



(a) Reported sources of evacuation notification. (b) Actions performed.

Fig. 2. Self-report data (n = 98). (a) Channel of evacuation notification. (b) Actions taken during the pre-travel phase (multiple selections were possible). Note: Some participants gave contradictory responses (shown in red). For response options with contradictory answers, two counts are provided: (1) the total number of responses and (2) the number of contradictory responses. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

algorithm to an undirected graph representing the road network, which returned the following adjacency list (See Appendix C for algorithmic details and details on how the mapping was applied):

$$
\begin{aligned}
A &: \{B, H\}\\
B &: \{A, C, H\}\\
C &: \{B, D, G\}\\
D &: \{C, E\}\\
E &: \{D, F, H\}\\
F &: \{E, G\}\\
G &: \{C, F, H\}\\
H &: \{A, B, G, E\}
\end{aligned}
$$

Note that although the routes from observation points A and B to H were closed and not used in practice, these edges are included in the graph to reflect potential albeit unlikely route attempts. Based on this structure, a total of 48 unique evacuation paths were identified. These served as the basis for mapping the actual observed vehicle movements.

Assuming that each vehicle originated from one departure area (north, east, south, or west), all possible routes can be reconstructed by monitoring traffic at five observation points - nodes C (C was split into C1 and C2 since observers were positioned both ends of the intersection to track all route choices reliably), E, F and H (see Fig. 1 and Appendix C).

3. Results

Most residents received the evacuation order via the emergency notification system, with 73 of the 98 survey respondents reporting that they had received the notification (Fig. 2). The most common channels for this message were phone calls, followed by email and text messages. Seventeen residents reported that they were alerted by emergency management staff going from door to door, while sixteen residents received the notification through other channels. However, nine participants reported not receiving any evacuation notification and some gave contradictory responses (for example, selecting 'no' alongside specific notification sources in the survey, Fig. 2(a)).

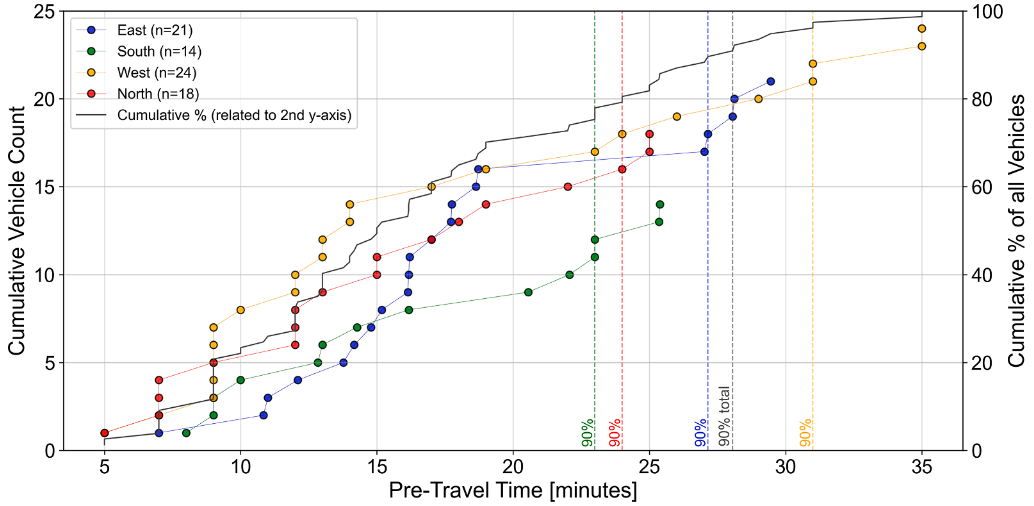


Fig. 3. Cumulative vehicle departures (pre-travel times) by departure area and overall percentage (solid black line related to the second y-axis) normalized by estimated travel time from the residence at 09:00 to the last observation point within a departure area. Vertical dashed lines indicate the time at which 90 % of vehicles from each area reached the observation point.

The following section describes pre-travel times and actions, followed by total evacuation times, route choice, and subjective experiences of participants during the drill. More detailed analysis and results on PTT and TET can be found in Appendix B.

3.1. Pre-travel phase

The participants performed a variety of preparatory actions before evacuating. These included *(closing doors and windows, packing personal items, checking directions, turning off air conditioning systems, and preparing pets for travel (see Fig. 2(b) and Dugstad et al. (2024)*. These responses indicate a relatively high engagement with evacuation protocols.

Of the 108 participants who completed the post-drill survey, most reported evacuating either individually (n = 42; 39 %) or with one other household member (n = 48; 44 %), with very few indicating larger household groups. In terms of vehicles used, 61 % of respondents (n = 66) reported using a single car, while 26 (24 %) used two vehicles. These numbers are broadly consistent with household sizes, but notable inconsistencies exist - such as participants claiming to have traveled alone while also reporting multiple cars - suggesting the possibility of separate departures by household members or reporting errors.

Fig. 3 shows cumulative PTTs. In general, most vehicles began traveling within 28 minutes after the evacuation notification was issued, with a notable increase between 09:08 and 09:18. This window marks the peak evacuation phase and reflects a common behavioral response across the community.

The dashed vertical lines in Fig. 3 indicate 90 % departure thresholds which can serve as calibration benchmarks for evacuation modeling and planning, helping to characterize typical pre-travel lag across different departure areas.

When broken down by departure area, the cumulative departure curves show that vehicles from the southern part had the fastest and most consistent early response, reaching the departure threshold of 90 % in about 23 minutes. The north followed closely, while the west began with a similar slope but plateaued earlier. South exhibited the slowest and most staggered progression.

3.2. Total evacuation time (TET)

Fig. 4 shows the cumulative number of unique vehicles that reached the assembly point (Observation point H), i.e., the indicator of TET.

The results reveal a steady increase in vehicle arrivals at the assembly point throughout the drill. By approximately 48 minutes, 90 % of vehicles had arrived. TETs were comparable for all but the southern departure area, where the first arrival was recorded approximately 20 minutes after the first arrivals in the other areas.

3.3. Overall evacuation timeline, individual variability, and outliers

In all departure areas, PTT represented a substantial part of the total evacuation time, even with the time shift correction to account for movement to the first observation point (Table 2). On average, pre-travel activities represented 53 % of the timeline, with marked differences between groups. Vehicles associated with the eastern departure area showed the highest proportion of time spent in pre-travel (54 %), while residents from the north and west tended to mobilize more quickly relative to their TET, with pre-travel times averaging just over 40 %.

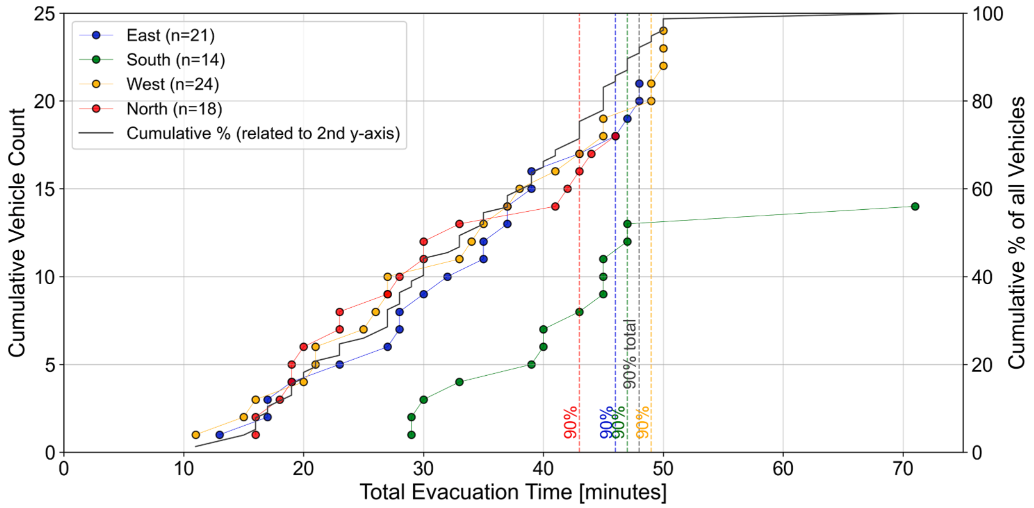


Fig. 4. Cumulative vehicle arrivals (TET) at the assembly point (Observation point H) grouped by departure area (color-coded groups) and overall percentage (solid black line related to the secondary y-axis); vertical dashed lines indicate the time at which 90 % of vehicles from each area reached the assembly point.

Table 2
PTT and TET time statistics by departure area.

Departure area	n	Travel Ratio	PTT [min]	TET [min]
North	18	0.49	15.2 ± 6.5 [5.5, 25.5]	29.3 ± 10.5 [16.5, 46.5]
East	21	0.37	21.9 ± 6.4 [11.0, 33.5]	36.8 ± 10.8 [17.0, 52.0]
South	14	0.57	18.5 ± 6.5 [10.0, 27.4]	43.6 ± 10.7 [31.0, 73.0]
West	24	0.49	18.3 ± 9.5 [6.0, 36.0]	34.7 ± 12.5 [12.0, 51.0]
Overall	77	0.47	18.6 ± 7.8 [5.5, 36.0]	35.6 ± 12.0 [12.0, 73.0]

Note: n = number of vehicles; Ratios represent the share of travel time relative to total evacuation time; PTT includes time shift corrections.

Individual evacuation timelines revealed wide variations in behavioral onset and travel duration. Fig. 5 presents individual-level evacuation timelines, decomposed into time shift (synchronization offset), pre-travel, and travel time components for each participating vehicle ($n = 77$). These components correspond to the time between the alert and departure (adjusted for location-based time shifts), and the duration from departure to exit point arrival, respectively. Color-coded car ID labels highlight the geographic origin (departure area) of each vehicle, facilitating the detection of systematic patterns. While several long pre-evacuation phases occurred in the northern and western departure areas, the times were more evenly distributed in other departure areas. These descriptive patterns suggest that both structural and behavioral drivers likely influenced the temporal characteristics of evacuation behavior.

Heterogeneity in PTT was evident at the individual level. For instance, while some participants (e.g., `car_37_green`) spent close to 80 % of their total evacuation time traveling, others (e.g., `car_39_orange`) departed much later and reached an exit relatively quickly, with travel accounting for only about one-third of their timeline.

The present analysis only included complete observations (i.e., vehicles with both PTT and TET; $n = 77$). However, several vehicles were recorded either at a single observation point within the community or at the assembly point, i.e., they either were not counted as evacuated or no PTT was measured. The 90 % PTT benchmark including all ($n = 125$) vehicles recorded was considerably longer, with a large number of outliers (58 min); see Appendix B for more detailed information about the influence of the sample size on benchmark thresholds).

3.4. *In-transit behavior and route choice*

Fig. 6 illustrates the probable routes taken during the drill of all observed vehicles ($n = 125$). Using the observed data and the known road network graph (see Section 2.7), the probable routes of the vehicles were derived by comparing the routes generated based on their recorded passage at the observation points with the most probable route they took (see Appendix C for the details of the mode). The results show that most of the residents traveled along the designated evacuation routes and to the assembly point via observation point E. With the notable exception of the northern departure area, the most probable path towards the assembly point was via observation points C and D. A relatively small proportion of residents also traveled to the assembly point via the main entry/exit road (i.e., from G to H).

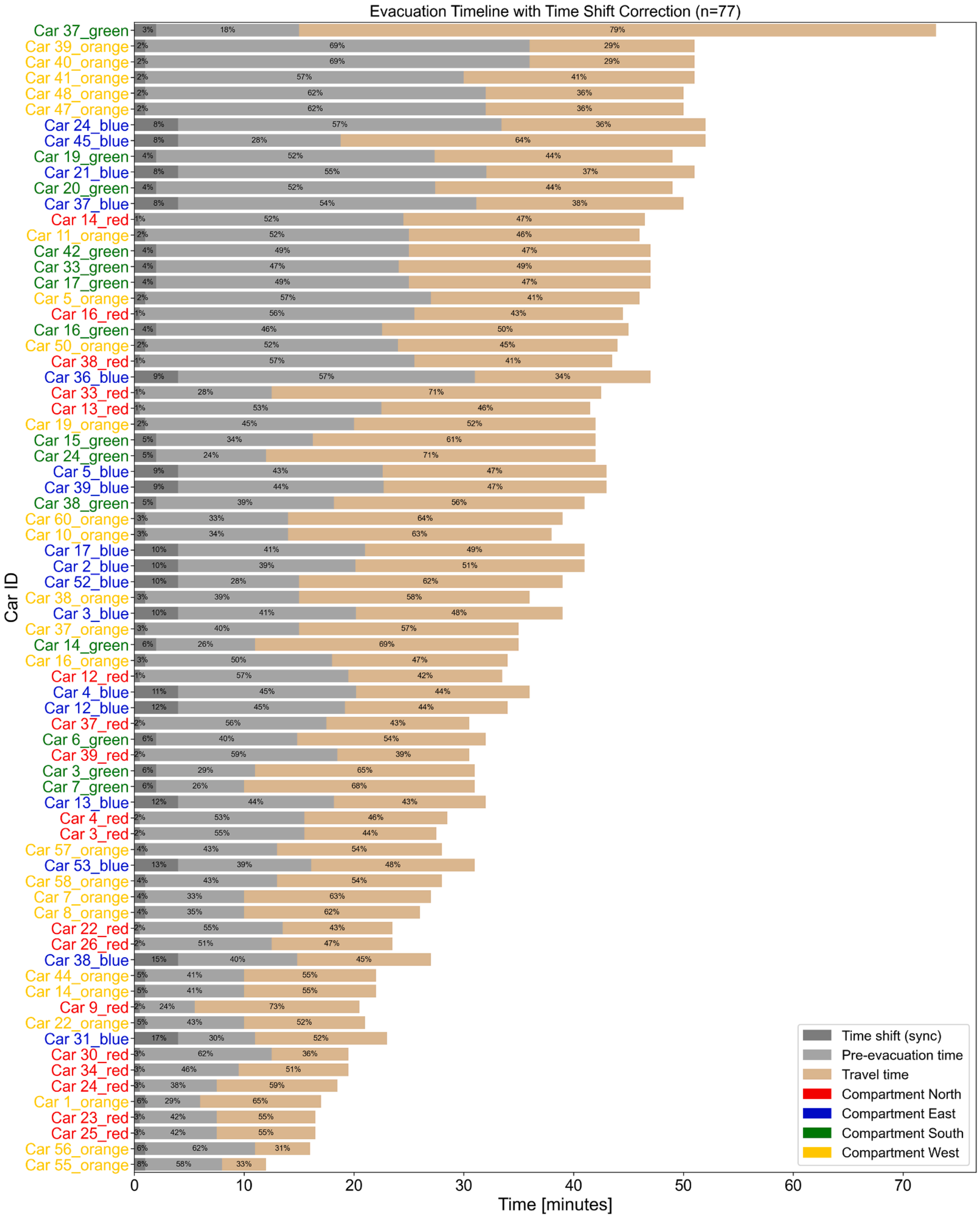


Fig. 5. Individual evacuation timelines ($n = 77$). Each bar represents one vehicle's evacuation process, broken down into three phases: time shift adjustment (dark gray), pre-travel time (light gray), and travel time (tan). Percentage labels indicate each phase's relative contribution to that vehicle's total evacuation time. Y-axis labels (Car IDs) are color-coded according to the assigned departure area: north (red), east (blue), south (green), and west (yellow). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Of the total of 125 vehicles, 48 (38.4 %) were not recorded at the assembly point (see Appendix B). These incomplete trajectories can have several possible explanations, such as residents deciding to not complete the evacuation drill (e.g., due to high traffic volume at the assembly point). However, lapses in data collection can also not be ruled out.

The self-reported data provides additional insights into the route choice behavior (Fig. 7(b)). Most of the participants ($n = 78$) indicated that they followed the instructions (that is, evacuated northbound). However, many also chose routes based on personal heuristics: 22 participants reported selecting the shortest route, and 12 preferred a familiar one. A smaller group ($n = 10$) selected "Other", which could reflect ad hoc decision-making or uncertainty about the assigned path. These results suggest a high overall level of compliance. Furthermore, most of the participants indicated that they completed the evacuation drill without stopping; however, some reported stopping at least once (Fig. 7(b)).

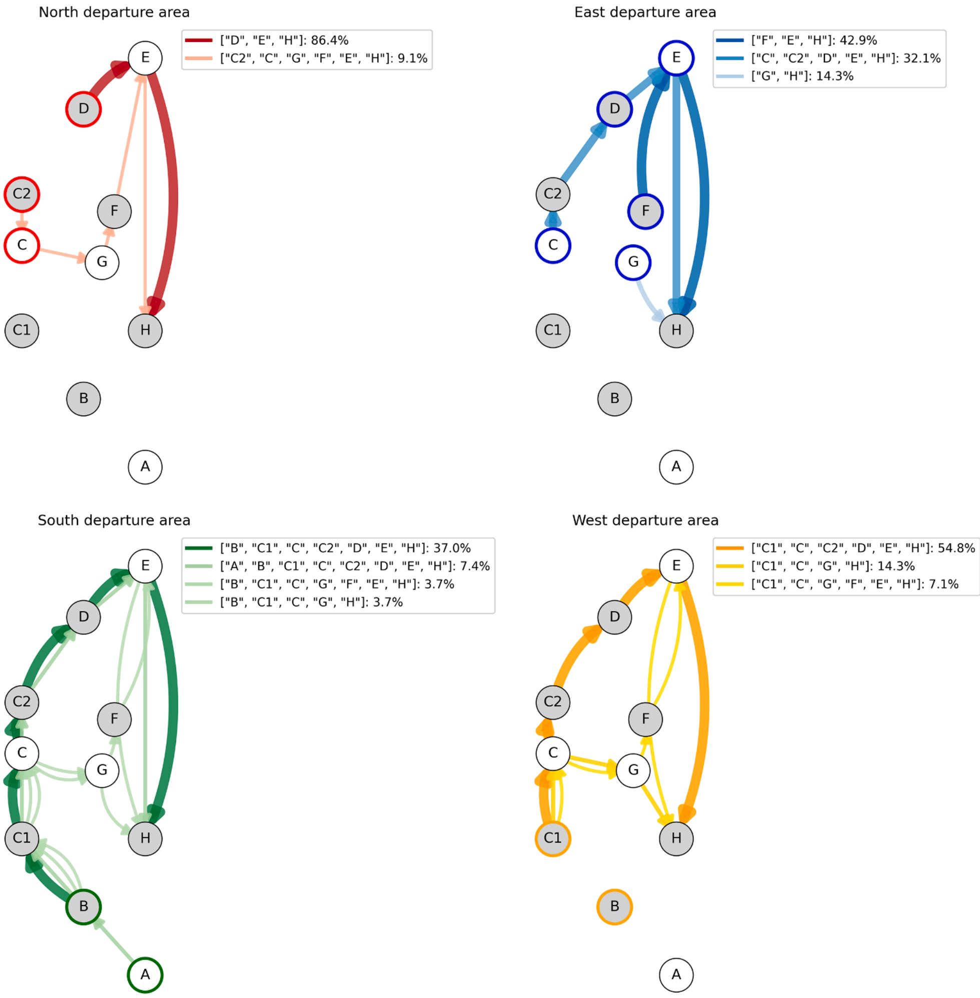


Fig. 6. Most probable route choices from the first observation points (highlighted with colored borders) to H (assembly point), mapped onto the observed pathways for each departure area. Arrow thickness represents the percentage of vehicles on each route. Nodes filled with gray indicate the presence of human observers. Differences from a full 100 % sum arise from vehicles that either failed to reach the assembly point H or took trajectories that could not be confidently assigned to a probable route. Note: For the eastern and western departure areas, two theoretically possible but not observed routes (from E to D and F) were excluded, as they went against the designated evacuation direction and were used exclusively by emergency services.

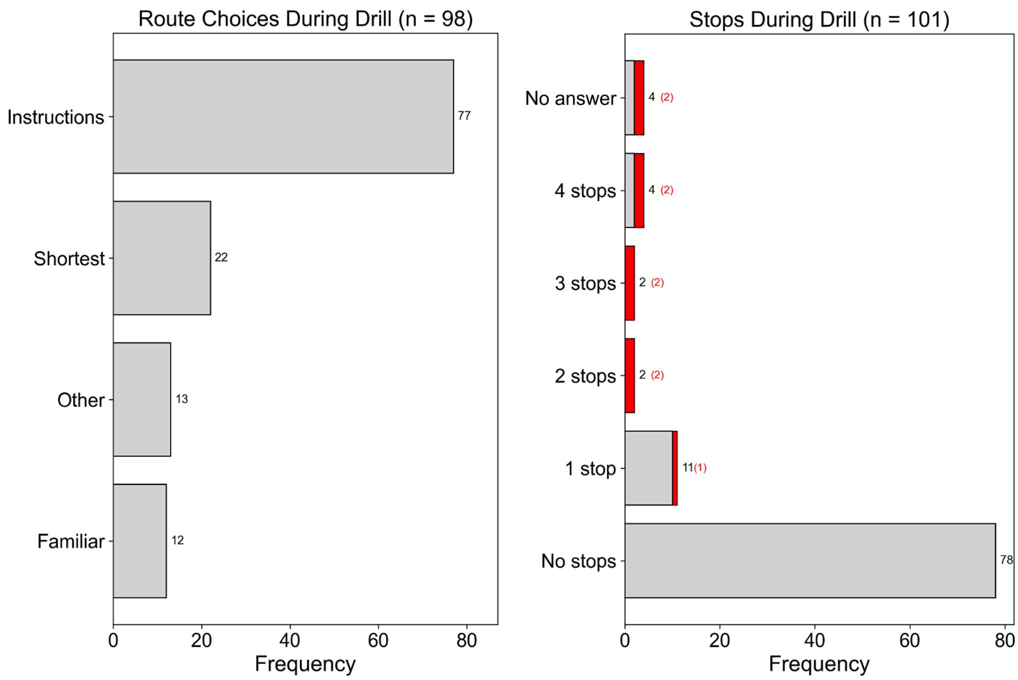
3.5. *Impact of the drill on perceived preparedness*

Fig. 8 shows self-reported preparedness before and after the drill, recorded on a 5-point Likert scale ranging from 1 (“Not at all”) to 5 (“Extremely”).

The drill increased perceived preparedness (Fig. 8). Before the drill, the average preparedness rating was 2.83 (SD = 0.82), with responses spread broadly across the lower end of the scale. This suggests that many participants considered themselves only moderately or poorly prepared before the exercise.

Following the drill, the average preparedness score increased to 3.65 (SD = 0.68). A paired t-test revealed a statistically significant increase in self-reported preparation after the drill, $t(75) = -7.546$, $p < 0.001$, $d = 0.844$. The direction of the sizable effect suggests that participants felt better-prepared post-drill. This shift was not only in the mean values but also in the consistency of the responses (i.e., reduced standard deviation), indicating that the drill not only boosted confidence but also helped align participants’ perceptions of what constitutes adequate preparedness. In other words, the exercise appeared to reduce the uncertainty and variability in perceived readiness.

These findings emphasize the effectiveness of evacuation drills in strengthening individual and community confidence. Where evacuation decisions can be sensitive and complex, such improvements and alignments in the perception of preparedness can contribute to life safety.



(a) Reasons for route choice. (b) Number of reported stops.

Fig. 7. Self-reported data on (a) route choice motivations and (b) stop behavior during the evacuation drill. Note: Contradictory responses - such as selecting “no stops” and multiple stop counts - are highlighted in red. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

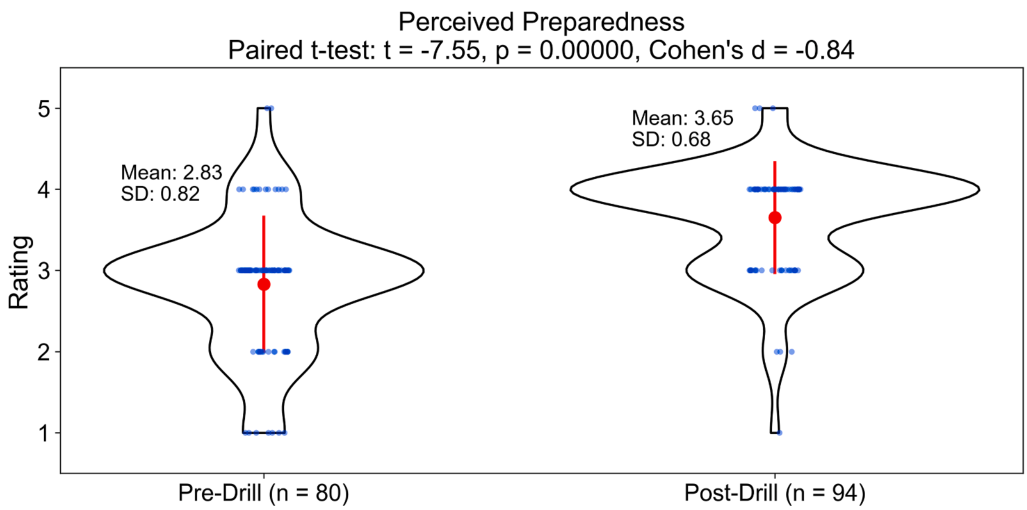


Fig. 8. Self-reported perceived preparedness before and after the evacuation drill. Participants rated their perceived preparedness for wildfire evacuation on a 5-point Likert scale of 1 (Not at all) to 5 (Extremely) both before the drill ($n = 94$) and after completing it ($n = 81$).

4. Discussion

Drills are an important tool for assessing and increasing community disaster preparedness. The findings from the 2024 Roxborough Park drill support this notion and provide additional detailed observations as well as insights for researchers and evacuation model developers. The section below discusses the results of Pre-Travel Times (PTT) and Total Evacuation Time (TET) and compares the findings to the drill observed in 2019, followed by a discussion of route choice and overall community preparedness.

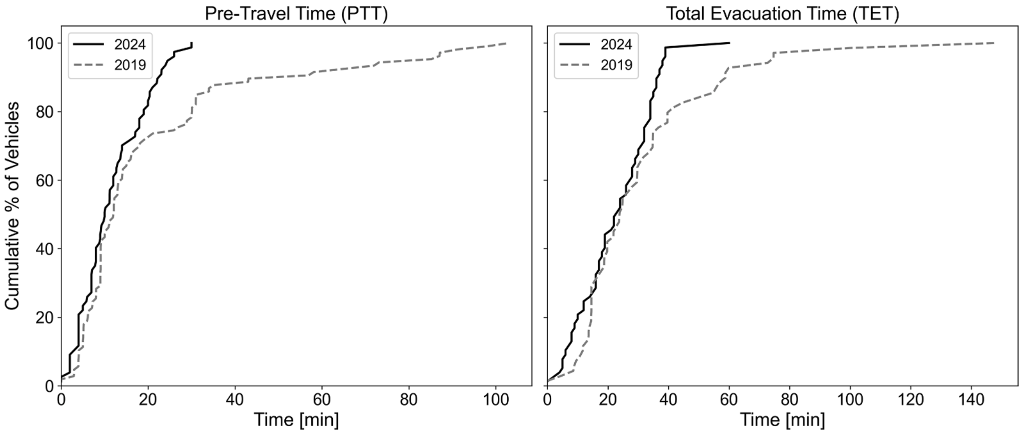


Fig. 9. Comparison of cumulative percentage PTT (left) and TET (right) curves for the 2019 and 2024 drill observations. Note that the timeshift is not available for the 2019-data; the time axis was normalized for each dataset individually such that time ($t = 0$) represents the moment of the first vehicle's departure (for PTT) or the first vehicle's arrival at the destination (for TET).

4.1. Pre-travel and travel times

This study provides insight into the evacuation dynamics of a WUI community of approximately 1000 homes. Previous work typically assessed TET during unplanned evacuations more coarsely, that is, describing departures over longer periods, e.g. Zhao et al. (2022) and Borody and Wong (2025).

The variability in TET was mainly driven by pre-travel actions (see Table 2 and Fig. 5). PTT varied not only between households, but also between departure areas, potentially reflecting differences in preparation, household composition, or information clarity. For example with respect to information clarity, some residents in the southern departure area reported that the evacuation order received by phone was incomprehensible, likely due to poor cell coverage in the area. Conversely, travel times were relatively consistent. Once on the road, most vehicles needed between eight and 20 minutes to reach the assembly point. This pattern reinforces that in the investigated community, the main driver of evacuation lag was the delay between alert and departure, rather than inefficiencies in route progression. The large proportion of PTT in the evacuation timeline suggests that interventions that target early action, such as clearer messaging, improved alerting, or community-level role activation, could reduce overall TET, particularly in the first 15–30 minutes after an evacuation order.

4.1.1. Comparison to 2019 drill

In 2019, a similar drill had been conducted and documented in the community (Gwynne et al., 2023). While there were notable differences between the 2019 and 2024 drills, for example with respect to evacuation notification (in 2019, the exact time of the evacuation notice had been communicated to residents prior to the drill), data collection (e.g., fewer human observers and no technology-based observation methods in 2019), and number of participants, a cautious qualitative comparison of the two events remains informative. Fig. 9 illustrates that the cumulative share of PTT and TET for both events were comparable, with steeper curves above the 80 % mark in the 2024 drill, indicating a somewhat more efficient evacuation in 2024. The overall similarity of the curves is indicative of the robustness of the results. However, two data points are not sufficient to assume the scalability of these findings.

4.2. Route choice

Most residents complied with the instructed evacuation procedures and traveled via the northbound evacuation routes. However, some did not choose the designated evacuation routes and followed the main road out of the community (Fig. 6). Closer inspection of the departure areas provides further nuance: In the northern part of the community (red areas), some residents first drove southbound despite being instructed to travel towards the north. This observation could be interpreted as anecdotal evidence for *movement to the familiar*, a known phenomenon in building evacuations, where occupants tend to move on familiar rather than on unknown egress paths (Sime, 1985). Indeed, some residents indicated that they chose either the shortest or more familiar routes (Fig. 7). In previous studies, familiarity with routes has been shown to correlate with chosen driving speeds (Colonna et al., 2016), which could influence travel duration during evacuations. However, more research is needed to evaluate to what degree movement to the familiar occurs during unplanned wildfire emergency evacuations.

As shown in Fig. 7(b), most participants ($n = 78$) reported that they did not stop on their way to the final assembly point. However, 19 participants reported making one or more stops, including some who reported making up to four stops. The specific nature of these stops was not captured, but they can indicate uncertainty, ad hoc route changes, or disengagement with drill objectives.

4.3. Implication for evacuation modeling

The observed variability in PTT, TET, and route choice has implications for developers who try to represent community wildfire evacuation timelines in computational models. Separating and simulating pre-travel and travel phases explicitly allows to represent heterogeneity in the different stages of the evacuation more accurately.[5] The proportions of PTT in TET might differ from case to case, for example when evacuees need to travel longer or shorter distances.

Accounting for behavioral variability in route choice is also critical. While the dominant trend showed high compliance with evacuation instructions and travel without detours, a non-negligible portion of participants deviated from the expected route or made discretionary stops (Fig. 7(b)). This can have critical implications for traffic flow, resource allocation, and communication planning in actual emergency scenarios. Models that assume full compliance or uniform travel behavior may risk underestimating congestion and uncertainty in real-world evacuations.

The present data can be used to provide benchmark data for WRSET estimations by providing insights into the overall evacuation process (e.g., arrival time curves) and information on traffic dynamics (e.g., flow at intersections, route choices)(Ronchi and Gwynne, 2019). However, implementation and generalization need to be done carefully, given the high variability in results and the scenario-dependent variables. For instance, only complete datasets - i.e., only vehicles with observations for both PTT and TET - were considered in the analysis. However, several vehicles ($n = 48$) were not recorded at the assembly area, suggesting that these residents either did not drive to the assembly point or were missed by observers. If these data were included in the analysis, the 90 % threshold for PTT would have only been reached after 58 minutes, i.e., 30 minutes later (see Appendix B). Further, while in the present study, 90 % was chosen as a cut-off criterion for PTT and TET, modeling exercises need to choose benchmarks carefully and based on requirements for their specific use case.

4.4. Implications for emergency planning

The present findings also have implications for emergency planning. For example, involving residents in a drill can reveal challenges in procedures (e.g., highlighting areas in the community that did not receive the evacuation notification) that may remain undetected during a tabletop exercise. In addition, drill may provide incentives to revisit assumptions (e.g., on route choice)

4.5. Local context and generalization of findings

Field observations provide local contextual information. Roxborough Park is a small and relatively affluent community in the WUI . However, the median age (66 years) of the drill participants was noticeably higher than the median age of the community (40.6 years).[6] Further, individuals who participated in the drill, are likely already well prepared for evacuation. and high levels of individual household preparedness. These factors - age, socioeconomic, and preparedness status - have been shown to impact evacuation outcomes (Naushirvanov et al., 2025; Sun et al., 2024; Wong et al., 2020a). Therefore, caution is warranted when generalizing findings from one particular case study, and it is critical to note that the observations are not representative for wildfire communities in general, nor the range of actual scenarios that might reasonably be faced by the community in question. For example, the observed timings may be overly optimistic given the level of prior preparedness and the availability of routes. This observation is true of all case studies and speaks to potential self-selection biases for drill participation in general. Despite these limitations, there are potential generalizable conclusions that can be drawn from this drill that may be applicable to communities similar to Roxborough Park, such as certain aspects of the survey responses. For instance, the increase of perceived preparedness after the drill appears to be generalizable, as there do not appear to be any reasons why this effect might be different in populations different from the study sample. One could even speculate that the observed effect is likely a conservative estimate of the true effect size, given that the volunteer participants were potentially more prepared prior to the drill than others. This very point suggests the importance in modelling community evacuation to supplement drill performance, where a multitude of scenario conditions might be examined. Precisely because of this, the data was captured in a modular manner (e.g., reflecting pre-evacuation delays, route use, etc.) allowing it to be recombined and repurposed to examine other scenarios in conjunction with other data-sets.

In addition, field observations provide a snapshot of a single event, and even if the comparison to the 2019 drill is reassuring, more research is needed to establish distributions or at least reasonable ranges for PTT, TET, and other evacuation performance parameters.

Announced and semi-announced drills are artificial scenarios that are meant to simulate emergency conditions. Several differences from an unplanned evacuation need to be highlighted though. The drill reported here occurred under optimal conditions (e.g., no actual emergencies, good weather, high visibility, and most residents at home when notified) with only a small proportion of the community participating. Those residents who participated likely were relatively well prepared (participating in the drill could be seen as an indicator of preparedness). Thus it is possible that similar to evidence from building evacuations (Kinateder et al., 2021), performance indicators reported here underestimate the duration of an unplanned evacuation, when conditions could include the presence of firebrands, reduced visibility and other challenges that could impact the awareness of residents that evacuation is necessary. Comparing the present study to observations from unplanned evacuations support this notion. For instance, the recently

[5] A recent study also argues that *notification time* should be modeled explicitly (Lawrence et al., 2025).

[6] See https://censusreporter.org/profiles/16000US0866197-roxborough-park-co/ for census data

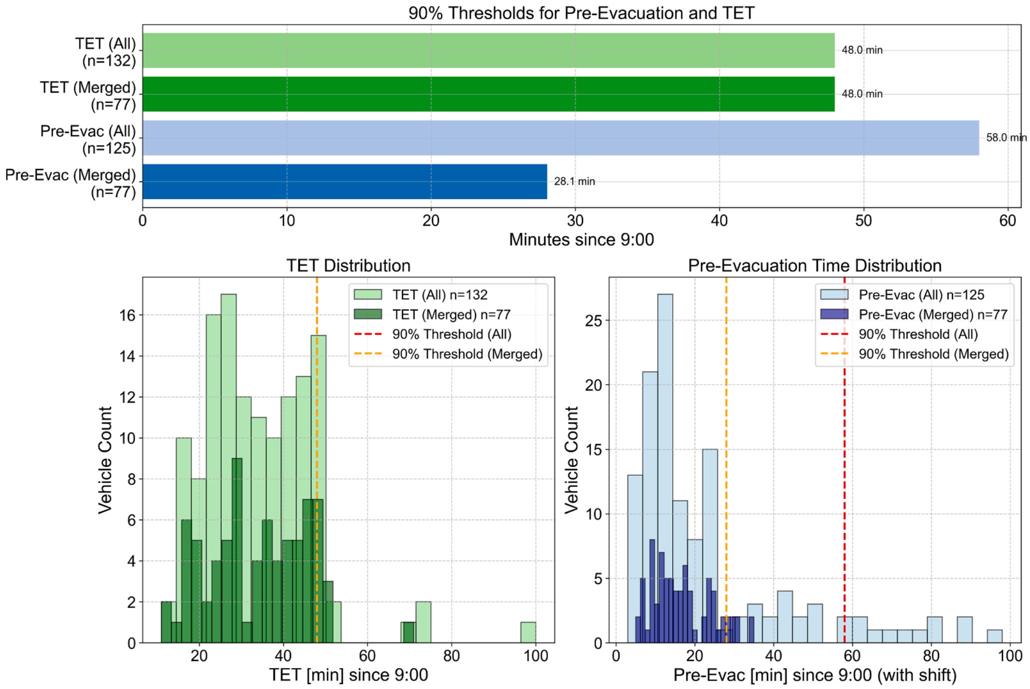


Fig. 10. Comparison of 90 % thresholds for PTTs and TETs. The top panel shows threshold times at which 90 % of vehicles had started (PTT) or completed (TET) evacuation, using both the full dataset and the merged subset with both timestamps ($n = 77$). The bottom panels show the distribution of PTT and TET times, highlighting the impact of using merged data and applying time shift corrections for observation-based PTT estimates.

reported findings on the departure times of Edson, British Columbia in 2023 followed a similar pattern to the TET reported here. However, the duration of that evacuation was noticeably longer (Borody and Wong, 2025). Similarly, self-report data on pre-travel times during the 2018 Camp Fire and the 2021 Marshall Fire reported significantly longer delays (Grajdura et al., 2021; Forrister et al., 2024).

Although immature and in need of guidance, drills are considered a useful source of data that can complement for instance post-incident analyses, particularly because they can be scheduled in advance, allowing researchers to plan and prepare accordingly for data collection (Dugstad et al., 2024). As any empirical method, drill observations have limitations, for example, due to their pre-planned nature, artificial scenarios, or self-selection of participants, the scenario conditions will not be identical to those in an actual incident. Despite this, they still can generate useful understanding of WUI evacuation dynamics that would otherwise be unattainable (Gwynne et al., 2020).

4.6. Technical limitations

Several technical limitations need to be taken into account. Firstly, there are inconsistencies between the observed number of vehicles across observation points (see Appendix B). Human observers may have missed vehicles or recorded timing inaccurately. Human observers were compared to other observation methods (e.g., automated traffic counters; see Dugstad et al., 2025). This evaluation showed that while human observers can overall be deemed reliable, there are differences in precision, accuracy and reliability. Secondly, the calculation method for PTT was based on assumptions that could be incorrect or represent an oversimplification. For example, a vehicle may have started on the very border of a given departure area and thus the added average for reaching this border would overestimate PTT; another vehicle may have needed longer than the assumed travel time from a home to the observation point. Thirdly, there were inconsistencies within the self-reported data. While a total of 108 surveys were completed, not all participants completed all items. For example, only 98 participants reported on their preparatory actions. In addition, there were occasions in which participants gave contradictory responses, such as indicating that they traveled alone but also with multiple vehicles. This noise in the data could potentially be attributed to issues in survey design (e.g., participants were not explicitly asked if they filled the survey as individuals or representatives of their household.) These mismatches highlight the importance of triangulating self-reported data with observational and tag-based records for accuracy in future drills or real-world analyses. Additionally, the logistics of the data collection itself could have impacted TET measurement, as participants spent time at the assembly point (e.g., to submit surveys) thus potentially impacting traffic. Finally, a critical limitation concerns the completeness of the presented observational dataset. While 125 vehicles provided pre-travel time data and 132 provided total evacuation time data, complete observations for both metrics were available for only 77 vehicles (61 % of PTT observations, 58 % of TET observations). This substantial proportion of incomplete observations introduces significant uncertainty into our evacuation timeline estimates. Fig. 10 illustrates the sensitivity of the presented results to this missing data. When analyzing only vehicles with complete observations (n = 77), the 90 % PTT threshold was reached at 28 minutes. However, when including all vehicles for which any PTT data were available (n = 125), this threshold extends to 58 minutes - a difference of 30 minutes that represents a doubling of the evacuation timeline. This sensitivity analysis reveals that our main results likely present an optimistic scenario, as residents who evacuated later were less likely to reach the assembly point. There are several potential explanations for this. Some residents may have chosen to avoid congested areas around the assembly point, particularly those departing later when traffic volumes were higher. Others may have disengaged from the drill objectives once they had practiced the evacuation procedure to their satisfaction. It also cannot be ruled out that observers may have missed recordings at the assembly point. However, a comparison of data collection methods revealed that human observers were overall reliable (Dugstad et al., 2025). In addition, this measurement challenge is not unique to drill-based studies but represents a fundamental tension in evacuation research: the most complete data collection occurs during controlled exercises, yet these exercises may systematically exclude the most vulnerable or reluctant evacuees whose behavior is most critical to understand in real emergencies. The range of estimates presented here (28–58 minutes for 90 % PTT) should therefore be interpreted as bounds rather than point estimates, with the understanding that actual wildfire evacuations may exhibit timing patterns closer to our inclusive scenario, particularly among populations with lower baseline preparedness or engagement.

5. Conclusion

More and more WUI communities are facing potential wildfire-related evacuations. The results reported here provide fine-grained insights into pre-travel actions and times as well as total evacuation times and route choice that can be of use for emergency planners, communities, and evacuation model developers. Most importantly, however, the findings support that the drill observed in Roxborough Park achieved its goals of training and assessing evacuation procedures. Although the efforts and preparations needed to conduct and document a drill can be considerable, the valuable insights gained and the enhanced community readiness make it undeniably worthwhile.

CRediT authorship contribution statement

Ann-Kristin Dugstad: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation; **Noureddine Bénichou:** Supervision, Project administration, Funding acquisition, Conceptualization; **Maxine Berthiaume:** Writing – review & editing, Visualization, Resources, Investigation, Formal analysis, Data curation; **Paul Geoerg:** Writing – review & editing, Writing – original draft, Visualization, Validation, Formal analysis, Data curation; **Steve Gwynne:** Writing – review & editing, Supervision, Methodology, Investigation, Funding acquisition, Conceptualization; **Amanda Kimball:** Supervision, Resources, Project administration, Investigation, Funding acquisition, Conceptualization; **Kamryn Kubose-Peutz:** Writing – review & editing, Investigation; **Hui Xie:** Writing – review & editing, Validation, Methodology; **Enrico Ronchi:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization; **Max Kinateder:** Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

Data availability

Data will be made available on request.

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Appendix A. Detailed demographic information

Table A.3 provides detailed demographic information shared by the participants.

Table A.3
Demographic information (n = 98). Note: "No answer" includes missing (blank) responses and "Prefer not to answer" responses. The frequency count and percentage for medical conditions and disability also include family members (i.e., not only participants).

Category	Variable	Frequency	Percentage	Contradictory
Area	North	18	18.37 %	0
	West	29	29.59 %	0
	South	20	20.41 %	0
	East	25	25.51 %	0
	No answer	6	6.12 %	0
Gender	Woman	55	56.12 %	0
	Man	42	42.86 %	0
	No answer	1	1.02 %	0
Household size	1 member	6	6.12 %	1
	2 members	81	82.65 %	0
	3 members	6	6.12 %	0
	4 members	4	4.08 %	0
	5 or more members	1	1.02 %	0
Household members under 18	Yes	2	2.04 %	0
	No	95	96.94 %	0
	No answer	1	1.02 %	0
Household members 18–65	Yes	46	46.94 %	0
	No	50	51.02 %	0
	No answer	2	2.04 %	0
Household members above 65	Yes	64	65.31 %	0
	No	32	32.65 %	0
	No answer	2	2.04 %	0
Type of residence	House	91	92.86 %	0
	Condo	7	7.14 %	0
Home ownership	Own	96	97.96 %	0
	Rent	1	1.02 %	0
	No answer	1	1.02 %	0
Residency	Full-time	96	97.96 %	0
	Part-time	2	2.04 %	0
Medical condition	Yes	23	23.47 %	1
	No	67	68.37 %	0
	No answer	8	8.16 %	0
Disability	Yes	9	9.18 %	2
	No	89	90.82 %	1

Appendix B. Additional information on evacuation time metrics

In this analysis, multiple timestamp sources were combined to reconstruct pre-travel behavior and total evacuation time at the unique Car ID level. Data were harmonized using a composite identifier consisting of the vehicle's Car ID and the reported departure area. All timestamps were aligned to a unified reference time of 09:00 on the day of the drill.

Pre-travel time was not directly measured due to ethical and privacy considerations that precluded tracking residents from their homes. Instead, the first observable activity was defined as the arrival time at a designated observation point within each departure area. These observation points, determined by the road network and observer locations, varied by group:

- South: Nodes A and B
- West: Nodes B and C
- North: Nodes C and D
- East: Nodes C, F, and H

For example, a vehicle leaving the southern departure area may have been observed at its first point of observation at 09:10 a.m. The derived PTT is then the time between the drill alert and the evacuee leaving their home. The approximated true time of when the resident left their home was calculated by subtracting the *estimated average travel time* from the home to the observation point. The estimated average travel time was calculated as follows: For each departure area, an equal distribution of homes along the routes leading to the observation point was assumed. The average distance from homes to the observation point can therefore be approximated as half the total route length. The average travel time to the closest exit is proportional to this distance. If two exits are available, the average travel time would be proportional to a quarter of the total route length. However, since each area was assigned one primary exit, we assume the average distance to the exit as half the total route length, and the travel time is therefore proportional to half the total travel time along the route. Given the road network, the average distance and travel time for each departure area (except the eastern) can be calculated as follows:

$$\text{Average Distance (km)} = \frac{\text{Total Route Length (km)}}{2}$$

$$\text{Average Travel Time (minutes)} = \frac{\text{Total Route Time (minutes)}}{2}$$

For the eastern departure area, the average distance and travel time are computed by considering the distances to the recommended exits (F and C) along three street segments: C-G, G-F, and G-H. The average distance to the nearest exit is calculated as

$$\frac{0.64}{2} + \frac{0.48}{2} + \frac{1.6}{2} = 1.85\,\text{km}$$

This reflects the average distance for homes along these streets, assuming they follow the recommendation to use exits F or C. The corresponding average travel time is calculated based on the proportional relationship between distance and travel time. For the example mentioned above (a vehicle observed leaving the southern departure area at 09:10 a.m.) this would mean that it assumed to have left the home 2 minutes earlier, thus its calculated PTT time would be 8 minutes.

- South: $-2\,\text{min}$
- West: $-1\,\text{min}$
- North: $-0.5\,\text{min}$
- East: $-4\,\text{min}$

The corrected PTT thus represents the estimated time each vehicle left a home.

TET was calculated as the duration between the reference time and the vehicle's final checkpoint timestamp, representing the completion of its evacuation route.

All values were converted to minutes and filtered for consistency. For comparative analysis, we retained only vehicles for which both a pre-evacuation timestamp and a TET timestamp were available ($n = 77$). This merged subset ensures a valid one-to-one comparison between departure and arrival times and allows the computation of 90 % thresholds within a consistent population (Fig. 10). Vehicles with only one of the two timestamps were retained in broader analyses but excluded from direct threshold comparisons.

Appendix C. Pathfinding approach for route enumeration

This appendix gives an overview on how the route network was derived from the observation points. Each observation point in the map (Fig. 1) is represented as a node in the network. To systematically identify all potential evacuation routes from each departure area to the designated assembly point (Node H), a Depth-First Search (DFS) algorithm tailored was used to extract all *simple paths* - that is, paths that do not revisit any node. This assumption reflects plausible evacuation behavior, where individuals avoid loops and redundant steps under time pressure.

The road network was represented as an undirected graph $G(V, E)$, where each node $v \in V$ corresponds to an intersection or observation point (e.g., A, B, C, …, H), and edges $e \in E$ denote the connecting road segments. Although some evacuation paths (e.g., from A and B to H) were closed during the drill, they were retained in the graph structure to allow a complete enumeration of possible (even if unused) evacuation paths.

Algorithm 1 DFS for finding all simple paths.

```
Input: Graph G(V, E), Start node s, End node e
Output: All simple paths from s to e
function DFS(G, s, e, path, paths)
    if s == e then
        Append path to paths
        return
    end if
    for each neighbor n of s in G do
        if n not in path then
            DFS(G, n, e, path ∪ {n}, paths)
        end if
    end for
end function
Initialize paths = {}
for each s in {A, B, C, D, E, F, G} do
    DFS(G, s, H, {s}, paths)
end for
return paths
```

The pseudocode shown in Algorithm 1 implements a recursive DFS routine that explores all acyclic paths from a given start node s to the fixed destination node e, set to Node H. The algorithm tracks the current path and appends it to a global list once the destination is reached. To ensure complete coverage of the network, the function is called once for each candidate origin node $s \in \{A, B, C, D, E, F, G\}$, reflecting the range of plausible community entry points into the road network.

The resulting enumeration of simple paths provided the candidate route set for inferring which itineraries participants most likely followed. Each vehicle's sequence of observation points (only a subset of which coincide with physical intersections) was matched to the candidate paths and assigned to one of three confidence classes:

- **Complete match** - the observed points fit a candidate path and *no* observer on that path failed to record the vehicle. Example: a blue car seen at F and H is a complete match with the path $F \to E \to H$; no observer was stationed at E, so no detection could be missed.
- **Semi-match** - the observed points fit a candidate path except that *one* intermediate observation point produced no detection. Example: a car from the eastern departure area (blue) seen at C_2 and H is a semi-match to $C_2 \to D \to E \to H$; the vehicle should have been spotted at D.
- **Low-probability match** - *two* observation points on the candidate path show no detection. Example: a car from the western departure area (yellow) recorded only at D and H could have traveled $C_1 \to C \to C_2 \to D \to E \to H$, missing detections at C_1 and C_2.

The routes shown in Fig. 6 are thus based on a matching between each recorded route and the most probable path that this recorded path would fit to.

References

Boeing, G., 2017. Osmnx: Python for street networks. https://github.com/gboeing/osmnx.
Borody, I., Wong, S.D., 2025. Evacuation and reentry curves for wildfire evacuations using network mobility data. Transp. Res. Rec. J. Transp. Res. Board , 03611981251331013https://doi.org/10.1177/03611981251331013
Butler, G., 2025. Thousands evacuated as Japan's biggest fire in decades continues to burn. BBC https://www.bbc.com/news/articles/c89ypkq72d0o.
Christianson, A.C., Johnston, L.M., Oliver, J.A., et al., 2024. Wildland fire evacuations in canada from 1980 to 2021. Int. J. Wildland Fire 33, WF23097. https://doi.org/10.1071/WF23097
Colonna, P., Intini, P., Berloco, N., Ranieri, V., 2016. The influence of memory on driving behavior: how route familiarity is related to speed choice. an on-road study. Saf. Sci. 82, 456–468.
Cova, T.J., Li, D., Siebeneck, L.K., Drews, F.A., 2021. Toward simulating dire wildfire scenarios. Nat. Hazard. Rev. 22 (3), 06021003.
Dugstad, A.-K., Berthiaume, M., Ronchi, E., Bénichou, N., Geoerg, P., Gwynne, S., Xie, H., Kubose-Peutz, K., Kimball, A., Kinateder, M., 2024. Data Collection in Wildfire Evacuation Drills. Technical Report 3264. Lund University, Department of Fire Safety Engineering. Lund, Sweden. https://portal.research.lu.se/en/publications/data-collection-in-wildfire-evacuation-drills.
Dugstad, A.-K., Berthiaume, M., Ronchi, E., Bénichou, N., Geoerg, P., Gwynne, S., Xie, H., Kubose-Peutz, K., Kimball, A., Kinateder, M., 2025. Comparing Behavioural Data Collection Methods for Wildfire Evacuation Drills. TBD.
Forrister, A., Kuligowski, E.D., Sun, Y., Yan, X., Lovreglio, R., Cova, T.J., Zhao, X., 2024. Analyzing risk perception, evacuation decision and delay time: a case study of the 2021 marshall fire in colorado. Trav. Behav. Soc. 35, 100729.
Grajdura, S., Qian, X., Niemeier, D., 2021. Awareness, departure, and preparation time in no-notice wildfire evacuations. Saf. Sci. 139, 105258.
Gwynne, S., Amos, M., Kinateder, M., Bénichou, N., Boyce, K., Natalie van der Wal, C., Ronchi, E., et al., 2020. The future of evacuation drills: assessing and enhancing evacuee performance. Saf. Sci. 129 (104767). https://doi.org/10.1016/j.ssci.2020.104767
Gwynne, S. M.V., Ronchi, E., Wahlqvist, J., Cuesta, A., Gonzalez Villa, J., Kuligowski, E.D., Kimball, A., Rein, G., Kinateder, M., Benichou, N., Xie, H., et al., 2023. Roxborough park community wildfire evacuation drill: data collection and model benchmarking. Fire Technol. 59 (2), 879–901. https://doi.org/10.1007/s10694-023-01371-1
Ha, H.J., Long, J.A., 2025. Measuring evacuation rates from mobility data during the mcdougall creek wildfire in british columbia, canada. Comput. Environ. Urban Syst. 119, 102286.
Haghani, M., Lovreglio, R., Button, M., Ronchi, E., Kuligowski, E., et al., 2024. Human behaviour in fire: knowledge foundation and temporal evolution. Fire Saf. J. 144. https://doi.org/10.1016/j.firesaf.2023.104085
Haynes, K., Handmer, J., McAneney, J., Tibbits, A., Coates, L., et al., 2010. Australian bushfire fatalities 1900–2008: exploring trends in relation to the 'prepare, stay and defend or leave early' policy. Environ. Sci. Policy 13 (3), 185–194. https://doi.org/10.1016/j.envsci.2010.03.002
Intini, P., Ronchi, E., Gwynne, S., Bénichou, N., et al., 2020. Guidance on design and construction of the built environment against wildland urban interface fire hazard: a review. Fire Technol. 56 (5), 1853–1883. https://doi.org/10.1007/s10694-019-00902-z
Jain, P., Barber, Q.E., Taylor, S., Whitman, E., Acuna, D.C., Boulanger, Y., Chavardès, R.D., Chen, J., Englefield, P., Flannigan, M., Girardin, M.P., Hanes, C.C., Little, J., Morrison, K., Skakun, R.S., Thompson, D.K., Wang, X., Parisien, M.S., 2024. Drivers and Impacts of the Record-Breaking 2023 Wildfire Season in Canada. Nat Commun. 15 (1), 6764. https://doi.org/10.1038/s41467-024-51154-7
Jolly, W., 2015. Climate-induced variations in global wildfire danger from 1979 to 2013. Nat. Commun. 6, 7537. https://doi.org/10.1038/ncomms8537
Kalogeropoulos, N., Mitchell, H., Kuligowski, E., Ronchi, E., Rein, G., 2024. Analyzing the Chances of Evacuation in the 2018 Mati Fire. In: Copernicus Meetings.
Kalogeropoulos, N., Mitchell, H., Kuligowski, E., Ronchi, E., Rein, G., 2025. Quantifying dire evacuations in case of wildfire using trigger boundaries and case study of the 2018 mati wildfire in greece. Saf. Sci. 181, 106691.
Kinateder, M., Byrne, R.M., Alexander, M., Geoerg, P., Ronchi, E., Berthiaume, M., Gwynne, S., Dugstad, A.-K., Kimball, A., Bénichou, N., 2025. The 2024 roxborough park wildfire evacuation drill - lessons learned after planning, running, and studying a community evacuation exercise. Proceedings of the 22nd ISCRAM Conference 118.
Kinateder, M., Ma, C., Gwynne, S., Amos, M., Benichou, N., 2021. Where drills differ from evacuations: a case study on canadian buildings. Saf. Sci. 135, 105114.
Kuligowski, E., 2021a. Evacuation decision-making and behavior in wildfires: past research, current challenges and a future research agenda. Fire Saf. J. 120, 103129. https://doi.org/10.1016/j.firesaf.2020.103129
Kuligowski, E., 2021b. Evacuation decision-making and behavior in wildfires: past research, current challenges and a future research agenda. Fire Saf. J. 120, 103129.
Lawrence, P.J., Filippidis, L., Veeraswamy, A., Blackshields, D., Marzoli, M., Marsella, S., 2025. Implementing notification strategies in the urbanEXODUS large-scale evacuation model. Saf. Sci. 187, 106854. https://doi.org/10.1016/j.ssci.2025.106854
McGarvey, E., 2023. Algeria wildfires: dozens killed and thousands evacuated. BBC https://www.bbc.com/news/world-africa-66292753.
National Research Council of Canada, 2021. National guide for wildland-urban-interface fires: Guidance on hazard and exposure assessment, property protection, community resilience and emergency planning to minimize the impact of wildland-urban interface fires - NRC Publications Archive. https://nrc-publications.canada.ca/eng/view/object/?id=3a0b337f-f980-418f-8ad8-6045d1abc3b3.

Naushirvanov, T., Elejalde, E., Kalimeri, K., Omodei, E., Karsai, M., Ferres, L., 2025. Evacuation patterns and socioeconomic stratification in the context of wildfires. EPJ Data Sci. 14 (1), 23.
OpenStreetMap contributors, 2024. Map of roxborough park, Colorado, USA. https://www.openstreetmap.org. Screenshot taken on May 21, 2024.
Ostiller, N., 2024. Authorities Declare State of Emergency in Russia's Novorossiysk as Wildfires Rage. The Kyiv Independent https://kyivindependent.com/authorities-declare-state-of-emergency-in-southern-russian-city-of-novorossiisk-as-wildfires-rage/.
Press, A., 2024. Wildfires force evacuations of South African coastal towns. Africanews https://www.africanews.com/2024/01/31/wildfires-force-evacuations-of-south-african-coastal-towns//.
Proulx, G., 2002. Movement of People: The Evacuation Timing. National Fire Protection Association, Quincy, MA. 3–13. pp. 3–342–3–366.
Raei, B., Kinateder, M., Bénichou, N., Gomaa, I., Wang, X., 2025. Are the data good enough? spatial and temporal modeling of evacuee behavior using GPS data in a small rural community. Int. J. Disaster Risk Reduct. 116, 105054.
Rohaert, A., Janfeshanaraghi, N., Kuligowski, E., Ronchi, E., et al., 2023. The analysis of traffic data of wildfire evacuation: the case study of the 2020 glass fire. Fire Saf. J. 141, 103909. https://doi.org/10.1016/j.firesaf.2023.103909
Ronchi, E., Gwynne, S., 2019. Computational evacuation modeling in wildfires. In: Manzello, S.L. (Ed.), Encyclopedia of Wildfires and Wildland-Urban Interface (WUI) Fires. Springer International Publishing, Cham, pp. 1–10. https://doi.org/10.1007/978-3-319-51727-8_121-1
Ronchi, E., Gwynne, S. M.V., Rein, G., Intini, P., Wadhwani, R., 2019. An open multi-physics framework for modelling wildland-urban interface fire evacuations. Saf. Sci. 118, 868–880. https://doi.org/10.1016/j.ssci.2019.06.009
Ronchi, E., Wahlqvist, J., Ardinge, A., Rohaert, A., Gwynne, S.M.V., Rein, G., Mitchell, H., Kalogeropoulos, N., Kinateder, M., Bénichou, N., Kuligowski, E., Kimball, A., et al., 2023. The verification of wildland–urban interface fire evacuation models. Natur. Hazar. 117 (2), 1493–1519. https://doi.org/10.1007/s11069-023-05913-2
Service, C. S.F., 2018. 2017 Colorado Wildfire Risk Assessment Update. Technical Report. https://coloradoforestatlas.org/customers/colorado/manuals/CO-WRA_2017_Final_Report.pdf.
Sime, J.D., 1985. Movement toward the familiar: person and place affiliation in a fire entrapment setting. Environ. Behav. 17 (6), 697–724.
Sun, Y., Forrister, A., Kuligowski, E.D., Lovreglio, R., Cova, T.J., Zhao, X., 2024. Social vulnerabilities and wildfire evacuations: a case study of the 2019 kincade fire. Saf. Sci. 176, 106557.
Wong, S.D., Broader, J.C., Shaheen, S.A., 2020a. 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. Transp. Res. Interdiscip. Perspect. 5, 100131.
Wong, S.D., Broader, J.C., Shaheen, S.A., et al., 2020b. Review of California wildfire evacuations from 2017 to 2019 . https://doi.org/10.7922/G29G5K2R
Young, J.Y., 2025. Wildfires Erupt in South Korea, Killing 4 and Forcing Thousands to Evacuate - The New York Times. The New York Times https://www.nytimes.com/2025/03/23/world/asia/south-korea-wildfires.html.
Zehra, S.N., Wong, S.D., 2024. Systematic review and research gaps on wildfire evacuations: infrastructure, transportation modes, networks, and planning. Transp. Plann. Technol. 47 (8), 1364–1398. https://doi.org/10.1080/03081060.2024.2348713
Zhao, X., Xu, Y., Lovreglio, R., Kuligowski, E., Nilsson, D., Cova, T.J., Wu, A., Yan, X., 2022. Estimating wildfire evacuation decision and departure timing using large-scale GPS data. Transp. Res. Part D Transp. Environ. 107, 103277. https://doi.org/10.1016/j.trd.2022.103277