Safety Emergency Science

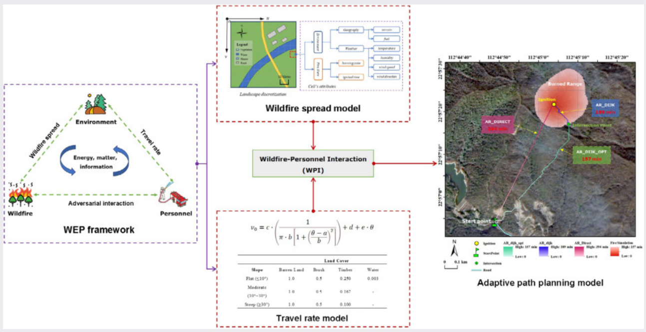
Research Article

Adaptive path planning for arriving at firelines in dynamic wildfires and complex landscapes

Zeren Gesang[1], Bo Yu[1,2], Jiasong Zhu[3,4,5,6], Wenyu Jiang[3,4,5,6,✉]

Cite this article: Gesang ZR, Yu B, Zhu JS, et al. *Safety Emergency Science*, 2025, **1**(1): 9590004. https://doi.org/10.26599/SES.2025.9590004

ABSTRACT: Timely deployment of firefighting efforts during the early stages of wildfires is essential to minimize disaster losses. However, complex landscapes and dynamic wildfire behaviors pose significant challenges to firefighters' rapid arrival at firelines. This paper introduces an adaptive path planning model designed to provide optimal routes in such dynamic environments. A "wildfire–environment–personnel" (WEP) framework was proposed to capture the spatiotemporal interactions among key elements of wildfire scenarios. By integrating a wildfire spread model and a firefighter travel model, the framework simulates the dynamic interplay between wildfires and personnel in wildland settings. A WEP-based model was tailored to calculate adaptive routes from the starting point to the dynamic fireline. Model validation was conducted with a wildfire-prone area in Foshan city as the study site. In an experimental scenario, our model demonstrated a significant advantage over traditional methods, reducing arrival time by more than 60% and accurately identifying the dynamic intersection point of the fireline. These findings underscore the model's potential for practical application in real-world wildfire suppression and rescue operations.



KEYWORDS: wildfire hazard; fire suppression; route planning; adaptive modeling; emergency response

1 Introduction

As global warming intensifies, the frequency and severity of extreme events such as heatwaves are increasing (IPCC, 2021), posing significant challenges to global forest fire prevention and control. From 2013 to 2022, the United States experienced an annual average of nearly 57,000 wildfires, which burned approximately 7 million acres of vegetation (NIFC, 2024). In the last 10 years, China has experienced an average of approximately 2 313 wildfires per year, resulting in approximately 33,000 hectares of overfire area and an annual average of 150 million RMB in economic losses (NBS, 2024). As of July 2023, the European Forest Fire Information System (EFFIS) reported that more than 230,000 hectares were burned by wildfires in the European Union (ESA, 2023). The United Nations Environment Programme (UNEP) predicts that climate and land use changes will exacerbate wildfire risks, with extreme fires projected to increase by 50% globally by 2100 (UNEP, 2022).

Wildfires have profoundly impacted ecosystems, economies, and public health. For example, Godfree et al. (2021) noted that the 2019–2020 Australian wildfires burned populations of more than 800 vascular plant species, posing a significant hazard to regenerative recovery and landscape scale. Van der Velde et al. (2021) estimated that Australian wildfires emit approximately 715 Tgs of CO_2, contributing to climate–carbon feedback loops. Bowd et al. (2019) demonstrated that wildfires also degrade soil by reducing essential nutrients such as phosphorus and nitrate, disrupting plant–soil–microbe interactions and diminishing forest productivity. Kozlov (2021) reported that smoke from wildfires containing toxic PM2.5 particles is linked to respiratory and cardiovascular diseases. These cascading impacts highlight the urgent need for improved wildfire management in the face of escalating climate risks.

Timely and effective containment of wildfires is critical for minimizing disaster losses. At present, firefighter-oriented fire suppression is the primary method for controlling wildfires (Andrews et al., 2003). Many scholars have focused on firefighter safety during complex wildfires. For example, Butler and Cohen

[1] Transportation Department of Tibet Autonomous Region, Tibet 850001, China. [2] Tibet Transportation Development Group, Tibet 850001, China. [3] College of Civil and Transportation Engineering, Shenzhen University, Shenzhen 518060, China. [4] Institute of Urban Smart Transportation & Safety Maintenance, Shenzhen University, Shenzhen 518060, China. [5] National Key Laboratory of Green and Long-Life Road Engineering in Extreme Environment, Shenzhen University, Shenzhen 518060, China. [6] MNR Key Laboratory for Geo-Environmental Monitoring of Great Bay Area, Shenzhen University, Shenzhen 518060, China.

✉ Corresponding author. E-mail: jiangwy@szu.edu.cn

Received: December 12, 2024; Revised: January 2, 2025; Accepted: January 8, 2025

(1998) developed a radiative heat transfer model to calculate the safe separation distance between firefighters and wildfires and recommended a minimum distance four times the height of the nearest flame. Later, Butler (2014) extended these models to account for convective heat transfer under conditions such as steep slopes and high winds. However, accurate estimation of flame height and safe distances during intense firefighting operations is challenging, increasing the likelihood of errors and the inability to predict fire dynamics effectively. To address these limitations, Campbell et al. (2017b) proposed a geospatial safety zone assessment method using high-resolution airborne LiDAR and vegetation models to calculate safe separation distances on the basis of heat transfer and injury mechanisms. This approach enables spatial suitability assessments for safety zones (SZs), providing emergency evacuation points for firefighters (Campbell et al., 2022). Furthermore, Campbell et al. (2019b) introduced the escape route index (ERI) to quantify the difficulty of personnel travel in wild land by considering geographic impediments such as dense vegetation and steep terrain. Higher ERI values indicate greater evacuation challenges and increased entrapment risks. While existing research emphasizes firefighter safety during wildfire suppression, it overlooks the challenge of rapid access to firelines in wildland scenarios where large firefighting vehicles are impractical. Complex landscapes and dynamic wildfires further complicate optimal route planning for timely fireline arrival.

Research on travel characteristics in complex landscapes has led to the development of various travel rate models (Alexander et al., 2005; Campbell et al., 2017a; Sullivan et al., 2020). The terrain is a key factor influencing travel speed. As one of the earliest models, Tobler's hiking function (THF) is widely used to estimate travel speed across different slopes in urban scenarios (Tobler, 1993). Fryer et al. (2013) subsequently adapted the THF for wild land firefighting scenarios. Butler et al. (2000) analyzed travel rates during two major wildfire events, South Canyon and Mann Gulch, to study the impact of slope on firefighter mobility. More recently, Campbell et al. (2019a) introduced a crowd-sourced data-driven model that employs a Lorentz distribution to describe the relationship between travel rates and slope. Surface vegetation is also a key factor influencing travel rates. Alexander et al. (2005) categorized vegetation types on the basis of wildfire fuel and studied travel rates under various vegetation conditions. Anguelova et al. (2010) analyzed the effects of common vegetation types on relative travel rates in southern California, USA, in response to pedestrian evacuation during wildfires. Surface soils also influence travel rates. Soule and Goldman (1972) examined energy loss due to different surface types via Pandolf's equation. Campbell et al. (2017b) utilized unmanned aerial vehicle (UAV)-based LiDAR data to develop a polynomial model linking environmental characteristics (e.g., terrain slope, vegetation density, surface roughness) to travel rates. These studies offer valuable insights for optimizing firefighter routes in wildlands. However, few methods account for the dynamic nature of wildfires, which can cause significant deviations between planned and actual routes.

To address the above research gap, an adaptive path planning model was implemented to optimize the route from the starting point to the dynamic fireline in wildfire scenarios. A wildfire scenario characterization framework named WEP (wildfire–environment–personnel) is developed to capture the spatiotemporal interactions among different elements. This framework overcomes the limitations of single-factor models by incorporating multifactor interactions, offering a novel approach to adaptive arrival route planning. Inspired by the WEP framework, a dynamic fire model was developed to simulate wildfire spread and travel. Subsequently, an adaptive path planning model was constructed to compute the route of the arriving fireline under dynamic wildfire conditions. Lingyun Mountain in Foshan city, an area that has experienced large-scale wildfires, was adopted as the study area to validate the usability and reliability of the model. The main contributions of this study are as follows:

(1) A wildfire scenario characterization framework (WEP) is proposed, which is novel for describing the spatiotemporal interactions of key elements in the wildfire landscape.

(2) A physically driven model is constructed to simulate the dynamic process of wildfire spread and personnel travel in a complex environment.

(3) An adaptive path planning model is implemented, enabling the arrival route from the starting location to the fireline in the varying landscape to be dynamically optimized.

2 Study area

In China, Guangdong Province is one of the regions most prone to wildfire. Between 2011 and 2021, nearly 2000 large wildfire incidents were recorded, causing significant economic losses of 38.618 million yuan (Jiang et al., 2024). Foshan city, a key economic hub in Guangdong Province, is home to abundant forestry resources, covering approximately 772 km^2 of forested land. Owing to extremely arid conditions and frequent human activities, Foshan faces long-term high wildfire risk. A notable fire incident named the "12·5 wildfire" occurred on December 5, 2019, on Lingyun Mountain, Foshan, as shown in Fig. 1. As the largest and longest wildfire in Guangdong Province in the past decade, this wildfire has burned approximately 9.20 km^2 of land and involved thousands of people in rescue efforts (Jiang et al., 2022a). Therefore, this wildfire was chosen as the study case to demonstrate how our model works. Various geographic data of this area, such as remote sensing imagery (Google, 2024), topographic data (GDC, 2024), and vegetation data (Zhang et al., 2023), have been collected to support subsequent modeling and analysis.

Quickly reaching the fireline is crucial for firefighters to arrive

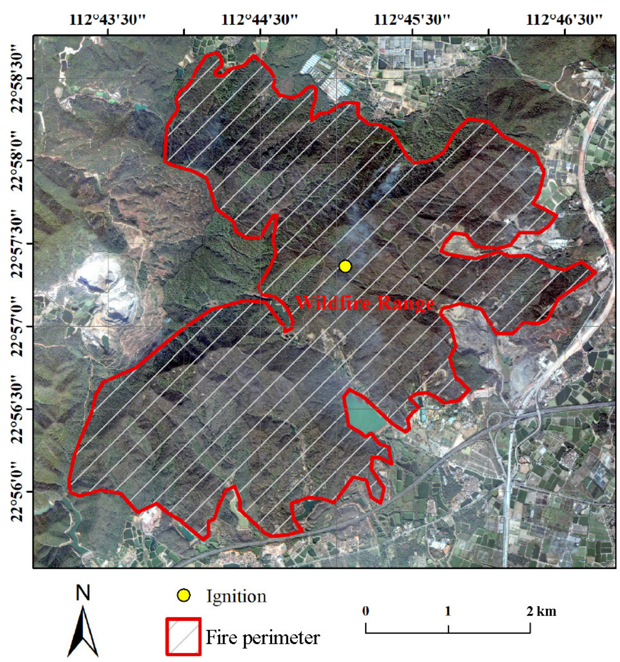


Fig. 1 "12·5 Wildfire" in Lingyun Mountain, Foshan city.

at the designated position and execute firefighting operations in a timely manner. However, current path planning heavily relies on expert experience or local guidance, which may overlook environmental complexity and result in significant deviations from the optimal route. In addition, a common and simple metric is necessary to evaluate the performance of different route strategies. Here, the arrival time T was defined as the metric, which represents the total travel time from departure point p_0 to fireline P_{fire}, as calculated via Eq. (1):

$$T = T_{\text{fire}} - T_0 \tag{1}$$

where T_{fire} is the moment when the personnel arrives at the intersection point $p_{\text{f}} \in P_{\text{fire}}$ of the fireline. T_0 is the moment when the personnel is at the starting point p_0. A smaller T indicates a more optimized path for firefighters to reach the fireline.

3 Methodology

3.1 Wildfire scenario characterization framework

Arrival route optimization in wildfire scenarios is a multifactorial problem requiring coupled modeling instead of a simple one-factor process. Inspired by the Public Safety Triangle (Fan, 2021), we developed a physically driven characterization framework, named “wildfire–environment–personnel” (WEP), to capture the spatiotemporal interactions among the key elements in the wildfire scenario, as illustrated in Fig. 2.

The WEP framework integrates three core components: the environment, wildfire, and personnel. The environment encompasses the landscape (e.g., topography, vegetation) and meteorological conditions (e.g., temperature, humidity, wind) in the landscape. The wildfire refers to a dynamic fire, whereas the personnel primarily involves firefighters engaged in fire suppression. These components closely interact through matter, energy, and information exchanges, which can be divided into three categories:

(1) Environment-wildfire interaction (EWI): The EWI describes the dynamics of wildfire spread in various environments, such as fire spread prediction (Finney, 1998; Jiang et al., 2022b, 2023) and special fire behaviors (Liu et al., 2021).

(2) Wildfire-personnel interaction (WPI): WPI involves the adversarial dynamics of fire suppression, such as critical extinction thresholds (Gleason, 2017; Hansen, 2012) and safe separation distances (Butler and Cohen, 1998; Campbell et al., 2017a).

(3) Personnel-environment interaction (PEI): PEI focuses on personnel travel characteristics in complex wildlands, such as travel rate models (Alexander et al., 2005; Campbell et al., 2017b).

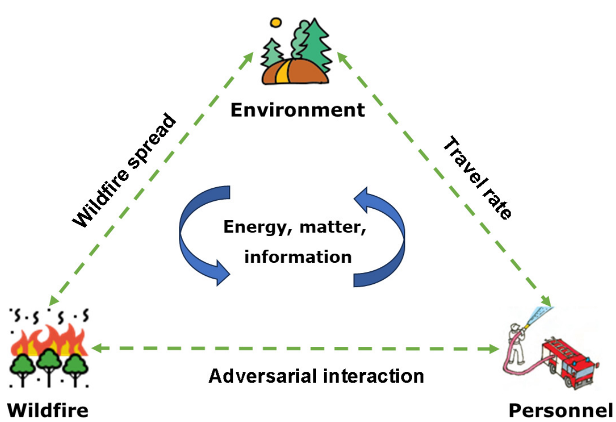


Fig. 2 “Wildfire–environment–personnel” (WEP) framework.

The WEP framework provides a novel foundation for optimizing firefighter arrival routes, addressing the limitations of single-factor models focused on PEIs only. The proposed WEP-based path planning model has the ability to quantitatively describe all interactions (PEI, WPI, and EWI), enabling adaptive optimization of the arrival route in a complex landscape. To complement this model, three submodels are developed and integrated: the wildfire spread model, travel rate model, and adaptive planning model.

3.2 CA-based wildfire spread model

Owing to their low complexity and high efficiency, cellular automata (CA) models have been widely used in wildfire spread prediction (Gharakhanlou and Hooshangi, 2021; Jiang et al., 2021; Mastorakos et al., 2023). Therefore, the CA-based WUI-fire model (Jiang et al., 2021) was adopted to simulate the spread of wildfires. This model has a high number of citations in Google Scholar and has been validated in many experiments and real wildfire cases, providing reliable support for the synthetic WEP-based model. Other models are also available to calculate the dynamics of wildfires, such as Farsite (Finney, 1998), BehavePlus (Frost et al., 2022), and WRF-SFIRE (Mandel et al., 2011). The adopted CA-based model contains three key components: spatial discretization, a spread rate function, and a state transfer function.

3.2.1 Spatial discretization

The spatial landscape is discretized into a collection of regular and closely spaced cells $C_{\text{f}} = \{C_{\text{f}}^0, C_{\text{f}}^1, \ldots, C_{\text{f}}^N\}$, where N denotes the number of cells. The attributes of each cell include the environment and the fire state, as shown in Fig. 3. The environmental factor contains geographic and weather elements that determine the characteristics of wildfire spread. The geographic element includes the terrain and fuel, whereas the weather element includes temperature (°C), humidity (%), wind speed (m/s), and wind direction (°). The fire state factor includes the burning state and ignition time. The burning state is used to describe four burning types: unburned (S_0), ignited (S_1), fully burned (S_2), and extinguished (S_3). The ignition moment t is an important parameter for describing the spread of a wildfire, which records the moment when the cell burning type changes from S_0 to S_1.

3.2.2 Spread rate function

To simulate the spread of a wildfire, it is necessary to calculate the spread rate in complex scenarios. Jiang et al. (2021) calculated the initial spread rate R_0 under different weather conditions, as defined in Eq. (2):

$$R_0 = a \cdot T + b \cdot V + c \cdot (100 - H) + d \tag{2}$$

where T, H, and V are the temperature (°C), humidity (%), and wind speed (m/s), respectively. a, b, c, and d are constants with values of 0.03, 0.05, 0.01, and −0.30, respectively. R_0 is further corrected to calculate the spread rate R in a more complex landscape, as defined in Eq. (3):

$$R = R_0 \cdot K_{\text{f}} \cdot K_{\text{s}} \cdot K_{\text{w}} \tag{3}$$

where K_{f}, K_{s}, and K_{w} are correction coefficients for the fuel type, slope, and wind direction, respectively. The value of R increases significantly in landscapes with highly flammable fuel, steep uphill slopes, or strong winds. More explanations of the model parameters can be found in the literature (Jiang et al., 2021).

3.2.3 State transfer function

To extrapolate the spread of wildfires, a state transfer function is

清華大学出版社 Tsinghua University Press | SciOpen

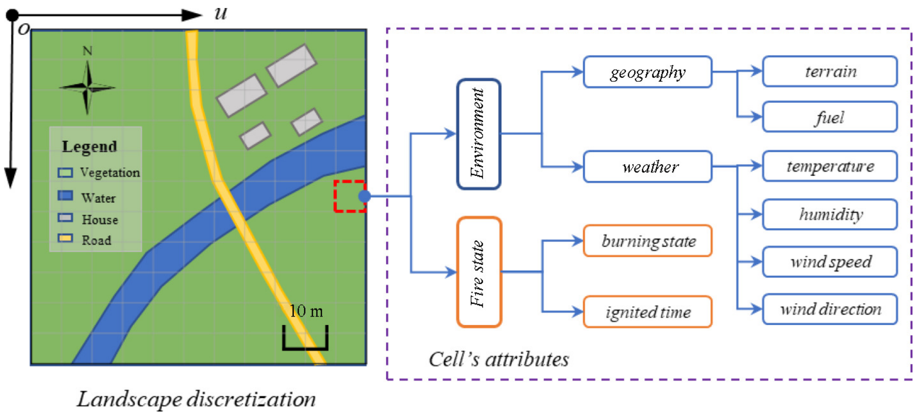


Fig. 3 Landscape discretization with regular cells.

crucial for defining the rules for transitions between different cell burning states. Here, the state transition of cell $C_{u,v}$ from S_0 to S_1 is defined in Eq. (4):

$$C_{u,v}^{t+\Delta t} = C_{u,v}^{t} + \frac{\sum R_{u,v}^{t} \Delta t}{L} \tag{4}$$

where L (m) is the geographical length of the cell. Only the cell in state S_2 has the ability to spread outward ($R > 0$), whereas cells in other states cannot ($R = 0$). $\Delta t = L/R_{\max}$ represents the minimum spread time. $R_{\max}$ is the maximum rate of all cells at the given moment T_{global}. Thus, Δt is a dynamic variable. The cell state is updated from S_0 to S_1 when $C_{u,v}^{t+\Delta t}$ is greater than a threshold C_{thr}. The further state transfer from S_1 to S_2 is determined by the spread rate R_{IN} within the cell, as defined by Eq. (5):

$$\Delta t_{\text{IN}} = L/R_{\text{IN}} \tag{5}$$

When all surrounding cells are noncombustible (e.g., the fuel type is the wasteland) or have ignited, the cell state changes from S_2 to S_3. Once the location p_{f0} and moment t_{f0} of ignition are determined, a minimum travel time algorithm (Finney, 2002) and the state transfer function are adopted to iteratively calculate the moment (from S_0 to S_1) when each cell is ignited. Finally, the wildfire spread map $T_{\text{f}} = \{t_{\text{f}}^{0}, t_{\text{f}}^{1}, \ldots, t_{\text{f}}^{N}\}$ (corresponding to the set C_{f}) is generated to quantitatively represent the dynamics of the wildfire.

3.3 Land- and slope-based travel rate model

The travel rate model is essential for quantifying firefighter travel characteristics, enabling the description of personnel movement under varying terrain and vegetation conditions. The slope-based model from (Campbell et al., 2019a) was adopted to calculate the rate of travel, which uses 136 million hiking trajectories in the Strava app to fit the Lorentz distribution function, as defined in Eq. (6):

$$v_0 = c \cdot \frac{1}{\pi \cdot b \left[1 + \left(\frac{\theta - a}{b}\right)^2\right]} + d + e \cdot \theta \tag{6}$$

where v_0 is the travel rate (m/s) and θ denotes the terrain slope (°). The model coefficients a, b, c, d, and e are −1.53, 14.04, 36.81, 0.32, and −0.0027, respectively. The model achieves a high correlation index ($R^2 =$ 0.985) between the predicted v_0 and actual values $v_0^{'}$, with an average absolute error of 0.078 m/s. This result demonstrates the excellent accuracy in predicting travel rates in wildland areas. Campbell et al. (2019b) extended the slope-based model by incorporating vegetation type $v = \varepsilon_v \cdot v_0$, where ε_v is the adjustment coefficient, accounting for both slope and fuel type, as described in Table 1.

Table 1 indicates that steep slopes and complex vegetation significantly hinder travel. For example, in arboreal areas with high slopes ($\theta = 15°$), the travel rate (~0.06 m/s) is approximately 1/10 that of barren land areas with gentle slopes ($\theta = 0°$, ~0.6 m/s). When integrated with the path panning algorithm, it becomes possible to compute the travel distances (m) and travel time (min) between any two locations in the wildfire landscape.

3.4 Adaptive route planning model

Dijkstra's algorithm (Gollapudi et al., 2022), which employs a greedy strategy, is a widely used method for path planning that iteratively identifies the minimum-loss path from a starting point to a destination. By integrating the travel rate model and wildfire spread model, an adaptive route planning model can be constructed to simulate the spatiotemporal movement of firefighters in complex wildfire scenarios. The primary calculation steps are as follows:

(1) Spatial discretization: Similar to the spatial discretization method outlined in Section 3.2.1, the area is divided into a collection of closely adjacent regular cells $C_{\text{p}} = \{c_1, c_2, \ldots, c_N\}$, where N is the number of cells and L is the cell length (m). Each cell has the attribute A_{p}, which includes travel-driven factors such as elevation (ele), surface type (sur), minimum arrival time (t_{p}), and azimuth θ, which corresponds to t_{p}. Notably, C_{p} shares the same spatial coordinate system as C_{f} from Section 3.2.1.

(2) Model initialization: Using the user-defined starting point, the corresponding cell $c_i \in C_{\text{p}}$ is selected. The sets $T_{\text{p}} = \{t_1, t_2, \ldots, t_N\}$ and $\theta_{\text{p}} = \{\theta_1, \theta_2, \ldots, \theta_N\}$ are updated, with $t_i =$ 0 and $\theta_i =$ 0. Here, T_{p} represents the shortest time required to reach any cell in the space from the starting point. If the starting and target points coincide, $t_{\text{p}} = 0$. θ_{p} stores the azimuth associated with the fastest arrival time t_{p}, enabling the derivation of trajectory coordinates $C_{\text{trajectory}}$, which correspond to the shortest path from c_i to any cell c_{p}.

(3) Path calculation: Identify the cell $c_{\min}$ with the minimum arrival time $t_{\min}$ from T_{p}. The travel rate model is used to

Table 1 ε_v under different slopes and land covers

Slope	Land cover			
	Barren land	Brush	Timber	Water
Flat (≤ 10°)	1.0	0.5	0.250	0.003
Moderate (10°–30°)	1.0	0.5	0.167	—
Steep (≥ 30°)	1.0	0.5	0.100	—

compute the travel time $t_0^{'}$ from $c_{\min}$ to nearby cells in the Moore neighborhood. Then, $T_{\rm p}$ with the minimum total elapsed time is updated as the new arrival moment, as defined in Eq. (7):

$$T_{\rm p} = \min\{T_{\rm p}, t_{\min} + t_0^{'}\} \tag{7}$$

After the calculation in Eq. (7), $c_{\min}$ is marked as a computed cell, which indicates that this cell will not be selected as $c_{\min}$ in the next iterations. The cell where $T_{\rm p}$ is updated is recorded as $c_{\rm update}$. The azimuth formed between $c_{\rm update}$ and $c_{\min}$ is defined as $\theta_{\min}$ (corresponding to the shortest path) and is then updated in the set $\theta_{\rm p}$.

(4) Spatiotemporal iteration: Step (3) is repeated until the selected cell $c_{\min}$ reaches the fireline $p_{\rm f} \in P_{\rm fire}$. This fireline is determined by $T_{\rm f}$, as described in Section 3.2.3. The arrival time $t_{\rm f}$ represents the shortest time to reach the fireline. Once arriving at the intersection point $p_{\rm f}$, firefighters stop advancing and initiate fire suppression. If the environment (e.g., wind speed or temperature) changes dynamically, the spread time $T_{\rm f}$ and the fireline at $t_{\rm f}$ of the wildfire will also shift, rendering $t_{\rm f}$ no longer optimal.

(5) Path optimization: Once the environmental parameters are fixed, $T_{\rm f}$ and $T_{\rm p}$ can be calculated via the wildfire spread and travel rate models, respectively. In the unified spatiotemporal system, $T_{\rm f}$ and $T_{\rm p}$ overlap at a spatial point where the arrival time $T_{\rm f}$ is minimized and defined as $t_{\rm f}$. This intersection point $p_{\rm f}$ (cell $c_{\rm f}$) is the dynamic arrival point on the fireline. To generate the shortest path, backtrack iteratively uses the azimuth set $\theta_{\min}$. Starting from the target cell $c_{\rm f}$, the previous arrival position $c_{\rm f}^{'}$ is located on the basis of the azimuth $\theta_{\rm f}$ corresponding to $c_{\rm f}$. The backward search for earlier positions $c_j^{'}$ via the azimuth θ_j associated with each path position c_j is subsequently iterated until the starting point c_i is reached. The resulting position set $R = \{c_i, C_j, c_{\rm f}\}$ represents the optimal route from c_i to fireline $c_{\rm f}$.

Existing path planning algorithms usually need to fix the starting point and target point first. For example, route planning in wildfire landscapes sets the current location as the starting point and fire ignition as the target point. However, wildfires are dynamically expanding as firefighters travel. The arrival point of a firefighter is no longer the preset target point (ignition) but the intersection point on the fireline. Comparatively, our model couples the wildfire factor to adaptively search for a dynamic fireline, enabling the planning of the optimal route in different wildfire scenarios.

4 Results and discussion

To validate the WEP-based model, two other route planning strategies are adopted for comparison. The first strategy, AR_DIRECT, follows a straight-line path directly connecting the starting point to the ignition point. The second, AR_DIJK, employs Dijkstra's optimization with fixed start and target points. The proposed model, defined as AR_DIJK_OPT, integrates dynamic environmental factors into the optimization process. Here, we simulate a wildfire scenario instead of adopting the real "12·5 wildfire" scenario to demonstrate the proposed model. This is due to the extreme complexity of real wildfires (over 1000 firefighters involved) and the fact that firefighter trajectory data are not recorded. In the simulated scenario, fire ignition was set at (112.751, 22.956), which is the same as the historical "12·5 wildfire" in Foshan city. The wind speed is set as 3 m/s with a south wind direction. The temperature was 24 °C, and the relative humidity was 20%. The route planning results of the above three strategies (AR_DIRECT, AR_DIJK, and AR_DIJK_OPT) are illustrated in Fig. 4.

In the simulated scenario, the AR_DIJK_OPT model demonstrated the best performance, achieving a travel time T of 157 min (green line). In contrast, the AR_DIRECT model required 394 min (red line), which means that AR_DIJK_OPT reduced the travel time by 60.2%. As the preset parameter, the endpoint of the AR_DIRECT model is the fire ignition point. Nevertheless, firefighters will cease traveling upon reaching the fireline to begin fire suppression operations. Therefore, the actual fireline arrival time T of the AR_DIRECT model is 377 min. Compared with the AR_DIRECT model, the AR_DIJK model also performs competitively (travel time T: 189 min, blue line and green line), saving 52.0% travel time. The primary difference between AR_DIJK and AR_DIJK_OPT lies in their target points, as both share identical core models (the travel rate model and Dijkstra's algorithm) and environmental parameters. Consequently, their route segments largely overlap. However, the AR_DIJK model does not account for the dynamics of wildfires (the red burned range). Therefore, the endpoint will be the intersection point (IP, green point) instead of the fire ignition point. When environmental parameters change (e.g., start point or wind direction), the location of the IP also shifts dynamically. The superiority of the AR_DIJK_OPT model is that it can adaptively recompute the new position of the IP, allowing for a more accurate representation of the firefighter's arrival process at the fireline. This adaptability provides efficient and dynamic path planning tailored to real-time wildfire conditions.

The performance improvement of the AR_DIJK_OPT model varies across scenarios, as it depends on specific environmental conditions, wildfire dynamics, and firefighter locations. Precisely quantifying this improvement is challenging. For example, when firefighters are closer to the fireline and in flat terrain, the difference in travel time T among the model strategies is minimal. Conversely, in more complex scenarios, the difference is pronounced. There is also variability between the model-estimated travel time T and the actual travel time $T^{'}$ in real wildfire scenarios, represented as $\Delta T = T - T^{'}$. Several factors contribute to this discrepancy, such as modeling errors and data errors. For example, the travel rate model is derived from crowdsourced hiking data (Campbell et al., 2019a), which differ from actual firefighter conditions. Firefighters generally travel faster under fire suppression scenarios, reducing the estimated T. In addition, coarse characterizations of combustible fuel properties (LANDFIRE, 2023), vegetation structure (Campbell et al., 2017a), and local microclimatic variations (Beer, 1991; Hilton and Garg, 2021) introduce discrepancies in simulated versus actual wildfire spread and personnel travel. Data assimilation is a promising way to eliminate the above model errors and has been adopted to improve the accuracy of fire spread prediction (Zhou et al., 2019). This method uses real-time wildfire data to dynamically correct the model output. However, it should be noted that complete real-time, even historical, data are not easy to obtain for practical fire suppression (Jiang et al., 2023). The construction of a comprehensive wildfire case dataset is essential for validating our WEP-based model and even advancing wildfire science. Although eliminating these errors is highly challenging and ΔT reveals biases in absolute T predictions, the AR_DIJK_OPT model remains superior to AR_DIJK from a relative perspective. This advantage also provides valuable decision-making assistance for fire commanders, emphasizing the practical utility of adaptive path planning in dynamic wildfire scenarios.

5 Conclusions

Rapid arrival at the fireline to conduct fire suppression is critical

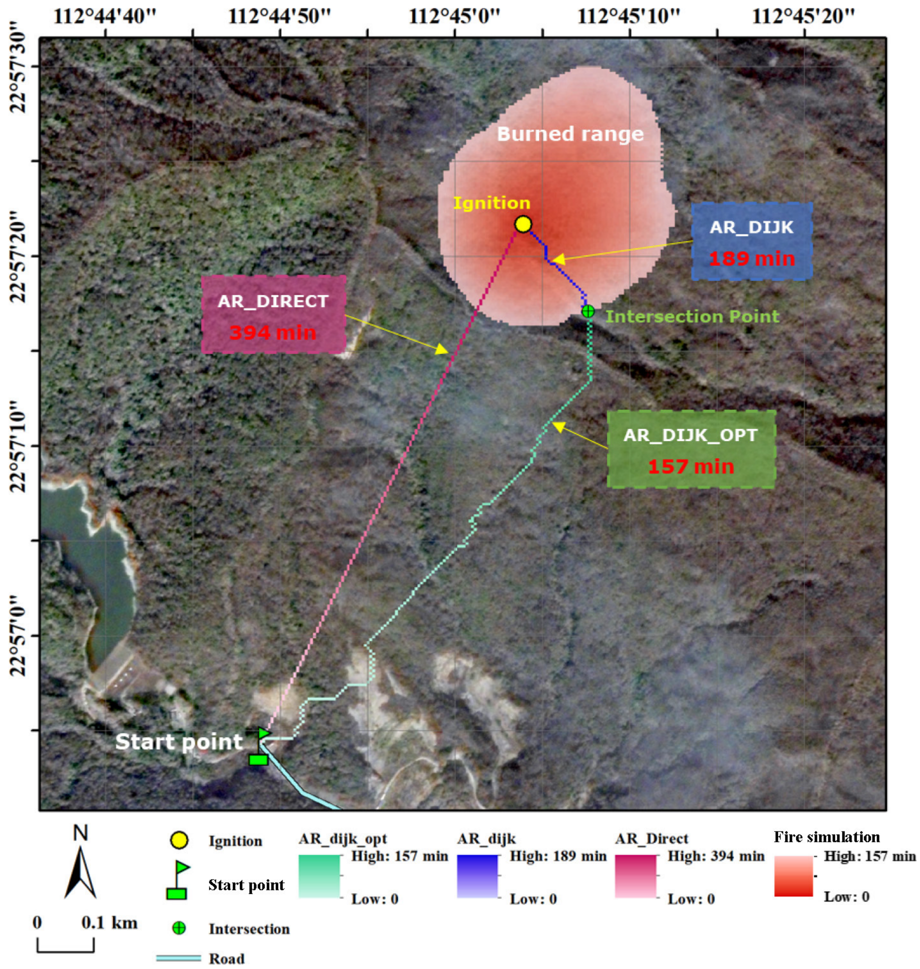


Fig. 4 Travel time T in different planning strategies.

for firefighters to contain wildfires in a timely manner. However, complex fire environments challenge optimal route planning. This study presents an adaptive path planning model that integrates wildfire dynamics and personnel travel to compute the optimal route to the evolving fireline. In a case study in Foshan city, the model reduced travel time by more than 60% compared with traditional algorithms, highlighting its potential for enhancing firefighting and rescue efficiency.

The proposed WEP-based model provides valuable insights for wildfire management. However, several limitations warrant further exploration. First, the model's accuracy depends on precise scene characterization. As the baseline models of the WEP-based model, both the wildfire spread model and travel rate model require high-quality input data (e.g., terrain and vegetation), improving the reliability and effectiveness of the target WEP-based model. LiDAR has potential as a high-quality data source because of its ability to generate dense point clouds (Campbell et al., 2017a). However, processing, storing, and semantically characterizing LiDAR data in complex wildfire scenarios remain challenging. Second, flame injury risk is a critical factor in route planning (Butler, 2014; Campbell et al., 2022; Dwyer, 2022). For example, the head fire burns more intensely, and suppression efforts typically focus on the fire flanks or rears. Further route planning should incorporate recommended suppression areas to avoid directing personnel into high-risk zones. Third, the travel rate model can be further refined. While it currently accounts for external environmental factors (e.g., terrain and vegetation), individual physiological factors are equally critical (Batista et al., 2020; Creagh and Reilly, 1997). In large-scale wildfire suppression, sustained high-intensity operations can impact physiological metrics, leading to variability in travel efficiency that should be accounted for in future models. Finally, it is worthwhile to develop a metric system to comprehensively evaluate model performance in path optimization. This system could encompass key metrics such as travel time (T), path length (L), average slope (S), and rate of slope change (ΔS).

Data availability

The data and source code can be addressed to the corresponding author.

Acknowledgements

This research was funded by the Guangdong Provincial Department of Science and Technology Key Area R&D Program Projects (No. 2022B0101020002).

Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

References

Alexander, M. E., Baxter, G. J., Dakin, G. R. 2005. Travel rates of Alberta wildland firefighters using escape routes. In: Proceedings of the 8th International Wildland Fire Safety Summit: Human Factors-Ten Years Later, Missoula, MT, USA, 12.

Andrews, P. L., Loftsgaarden, D. O., Bradshaw, L. S. 2003. Evaluation of fire danger rating indexes using logistic regression and percentile analysis. *International Journal of Wildland Fire*, **12**: 213.

Anguelova, Z., Stow, D. A., Kaiser, J., Dennison, P. E., Cova, T. 2010. Integrating fire behavior and pedestrian mobility models to assess potential risk to humans from wildfires within the U.S.–Mexico border zone. *The Professional Geographer*, **62**: 230–247.

Batista, M. M., Paludo, A. C., Gula, J. N., Pauli, P. H., Tartaruga, M. P. 2020. Physiological and cognitive demands of orienteering: A systematic review. *Sport Sciences for Health*, **16**: 591–600.

Beer, T. 1991. The interaction of wind and fire. *Boundary-Layer Meteorology*, **54**: 287–308.

Bowd, E. J., Banks, S. C., Strong, C. L., Lindenmayer, D. B. 2019. Long-term impacts of wildfire and logging on forest soils. *Nature Geoscience*, **12**: 113–118.

Butler, B. W. 2014. Wildland firefighter safety zones: A review of past science and summary of future needs. *International Journal of Wildland Fire*, **23**: 295.

Butler, B. W., Cohen, J. D. 1998. Firefighter safety zones: A theoretical model based on radiative heating. *International Journal of Wildland Fire*, **8**: 73.

Butler, B. W., Cohen, J. D., Putnam, T., Bartlette, R. A., Bradshaw, L. S. 2000. A method for evaluating the effectiveness of firefighter escape routes. In: Proceedings of the 4th International Wildfire Safety Summit, Edmonton, AB, Canada, 42–53.

Campbell, M. J., Dennison, P. E., Butler, B. W. 2017a. A LiDAR-based analysis of the effects of slope, vegetation density, and ground surface roughness on travel rates for wildland firefighter escape route mapping. *International Journal of Wildland Fire*, **26**: 884.

Campbell, M. J., Dennison, P. E., Butler, B. W. 2017b. Safe separation distance score: A new metric for evaluating wildland firefighter safety zones using lidar. *International Journal of Geographical Information Science*, **31**: 1448–1466.

Campbell, M. J., Dennison, P. E., Butler, B. W., Page, W. G. 2019a. Using crowdsourced fitness tracker data to model the relationship between slope and travel rates. *Applied Geography*, **106**: 93–107.

Campbell, M. J., Dennison, P. E., Thompson, M. P., Butler, B. W. 2022. Assessing potential safety zone suitability using a new online mapping tool. *Fire*, **5**: 5.

Campbell, M. J., Page, W. G., Dennison, P. E., Butler, B. W. 2019b. Escape route index: A spatially-explicit measure of wildland firefighter egress capacity. *Fire*, **2**: 40.

Creagh, U., Reilly, T. 1997. Physiological and biomechanical aspects of orienteering. *Sports Medicine*, **24**: 409–418.

Dwyer, G. 2022. Enacting safety: Firefighter sensemaking of entrapment in an Australian bushfire context. *International Journal of Disaster Risk Reduction*, **68**: 102697.

European Space Agency (ESA). 2023. Counting wildfires across the globe. Available at https://www.esa.int/Applications/Observing_the_Earth/Copernicus/Sentinel-3/Counting_wildfires_across_the_globe

Fan, C. S. 2021. *Public Safety and Emergency Management*. Science Press.

Finney, M. A. 1998. FARSITE: Fire Area simulator - Model development and evaluation. Research Paper RMRS-RP-4. Ogden, UT, USA: USDA Forest Service, Rocky Mountain Research Station.

Finney, M. A. 2002. Fire growth using minimum travel time methods. *Canadian Journal of Forest Research*, **32**: 1420–1424.

Frost, S. M., Alexander, M. E., Jenkins, M. J. 2022. The application of fire behavior modeling to fuel treatment assessments at army garrison camp williams, Utah. *Fire*, **5**: 78.

Fryer, G. K., Dennison, P. E., Cova, T. J. 2013. Wildland firefighter entrapment avoidance: Modelling evacuation triggers. *International Journal of Wildland Fire*, **22**: 883.

Geospatial Data Cloud (GDC). 2024. ASTER GDEM 30M. Available at https://www.gscloud.cn/sources/accessdata/310?pid=302

Gharakhanlou, N. M., Hooshangi, N. 2021. Dynamic simulation of fire propagation in forests and rangelands using a GIS-based cellular automata model. *International Journal of Wildland Fire*, **30**: 652–663.

Gleason, P. 2017. Lookouts, communications, escape routes, and safety zones. Available at https://www.fireleadership.gov/toolbox/documents/lces_gleason.html

Godfree, R. C., Knerr, N., Encinas-Viso, F., Albrecht, D., Bush, D., Christine Cargill, D., Clements, M., Gueidan, C., Guja, L. K., Harwood, T., et al. 2021. Implications of the 2019–2020 megafires for the biogeography and conservation of Australian vegetation. *Nature Communications*, **12**: 1023.

Gollapudi, S., Kollias, K., Panigrahi, D. 2022. The pit stop problem: How to plan your next road trip. In: Proceedings of the 30th International Conference on Advances in Geographic Information Systems, Seattle Washington, USA, 1–9.

Google. 2024. Google Earth. Available at https://earth.google.com/web/

Hansen, R. 2012. Estimating the amount of water required to extinguish wildfires under different conditions and in various fuel types. *International Journal of Wildland Fire*, **21**: 525.

Hilton, J., Garg, N. 2021. Rapid wind–terrain correction for wildfire simulations. *International Journal of Wildland Fire*, **30**: 410–427.

Intergovernmental Panel on Climate Change (IPCC). 2021. Climate change 2021: The physical science basis. Available at https://www.ipcc.ch/report/ar6/wg1/#SPM

Jiang, W. Y., Wang, F., Su, G. F., Li, X., Meng, Q. X., Wang, G. N. 2022a. Key technologies of emergency management informatization for forest fires. *China Safety Science Journal*, **32**(9): 182–191. (in Chinese)

Jiang, W., Qiao, Y., Su, G., Li, X., Meng, Q., Wu, H., Quan, W., Wang, J., Wang, F. 2023. WFNet: A hierarchical convolutional neural network for wildfire spread prediction. *Environmental Modelling & Software*, **170**: 105841.

Jiang, W., Qiao, Y., Zheng, X., Zhou, J., Jiang, J., Meng, Q., Su, G., Zhong, S., Wang, F. 2024. Wildfire risk assessment using deep learning in Guangdong Province, China. *International Journal of Applied Earth Observation and Geoinformation*, **128**: 103750.

Jiang, W., Wang, F., Fang, L., Zheng, X., Qiao, X., Li, Z., Meng, Q. 2021. Modelling of wildland-urban interface fire spread with the heterogeneous cellular automata model. *Environmental Modelling & Software*, **135**: 104895.

Jiang, W., Wang, F., Su, G., Li, X., Wang, G., Zheng, X., Wang, T., Meng, Q. 2022b. Modeling wildfire spread with an irregular graph network. *Fire*, **5**: 185.

Kozlov, M. 2021. How record wildfires are harming human health. *Nature*. Available at https://www.nature.com/articles/d41586-021-03496-1

LANDFIRE. 2023. 40 Scott and Burgan fire behavior fuel models. Available at https://www.landfire.gov/fbfm40.php

Liu, N., Lei, J., Gao, W., Chen, H., Xie, X. 2021. Combustion dynamics of large-scale wildfires. *Proceedings of the Combustion Institute*, **38**: 157–198.

Mandel, J., Beezley, J. D., Kochanski, A. K. 2011. Coupled atmosphere-wildland fire modeling with WRF 3.3 and SFIRE 2011. *Geoscientific Model Development*, **4**: 591–610.

Mastorakos, E., Gkantonas, S., Efstathiou, G., Giusti, A. 2023. A hybrid stochastic Lagrangian–cellular automata framework for modelling fire propagation in inhomogeneous terrains. *Proceedings of the Combustion Institute*, **39**: 3853–3862.

National Bureau of Statistics (NBS). 2024. China statistical yearbook. Available at https://www.stats.gov.cn/sj/ndsj/

National Interagency Fire Center (NIFC). 2024. National fire news. Available at https://www.nifc.gov/fire-information/nfn

United Nations Environment Programme (UNEP). 2022. Spreading like wildfire: The rising threat of extraordinary landscape fires. Report.

Available at https://www.unep.org/resources/report/spreading-wildfire-rising-threat-extraordinary-landscape-fires

Soule, R. G., Goldman, R. F. 1972. Terrain coefficients for energy cost prediction. *Journal of Applied Physiology*, **32**: 706–708.

Sullivan, P. R., Campbell, M. J., Dennison, P. E., Brewer, S. C., Butler, B. W. 2020. Modeling wildland firefighter travel rates by terrain slope: Results from GPS-tracking of type 1 crew movement. *Fire*, **3**: 52.

Tobler, W. 1993. Three presentations on geographical analysis and modeling. Techical Report. University of California, Santa Barbara, USA.

Van der Velde, I. R., van der Werf, G. R., Houweling, S., Maasakkers, J. D., Borsdorff, T., Landgraf, J., Tol, P., van Kempen, T. A., van Hees, R., Hoogeveen, R., et al. 2021. Vast CO_2 release from Australian fires in 2019–2020 constrained by satellite. *Nature*, **597**: 366–369.

Zhang, X., Liu, L., Zhao, T., Chen, X., Lin, S., Wang, J., Mi, J., Liu, W. 2023. GWL_FCS30: A global 30 m wetland map with a fine classification system using multi-sourced and time-series remote sensing imagery in 2020. *Earth System Science Data*, **15**: 265–293.

Zhou, T., Ding, L., Ji, J., Li, L., Huang, W. 2019. Ensemble transform Kalman filter (ETKF) for large-scale wildland fire spread simulation using FARSITE tool and state estimation method. *Fire Safety Journal*, **105**: 95–106.

Zeren Gesang received his B.S. degree in civil engineering from Southwest Jiaotong University in 2006 and his master degree in transportation engineering from Chang'an University in 2022. He is now a senior engineer in the Transportation Department of the Tibet Autonomous Region. His research interests include transportation safety and emergency management.

Wenyu Jiang received his B.S. degree from the School of Remote Sensing and Information Engineering, Wuhan University, in 2018 and his Ph.D. degree from the Department of Engineering Physics, Tsinghua University, in 2024. In 2023, he traveled to ETH Zurich, Switzerland, as a visiting scholar. He is currently an assistant professor at the College of Civil and Transportation Engineering, Shenzhen University, China, where his main research interests are in the areas of infrastructure safety monitoring, spatial intelligence, disaster prevention and mitigation, and emergency management.