International Journal of Disaster Risk Reduction 99 (2023) 104126

Contents lists available at ScienceDirect

International Journal of Disaster Risk Reduction

journal homepage: www.elsevier.com/locate/ijdrr

GIS-based methodology for prioritization of preparedness interventions on road transport under wildfire events

Erica Arango [a,*], Maria Nogal [b], Hélder S. Sousa [a], José C. Matos [a], Mark G. Stewart [c]

[a] *Department of Civil Engineering, ISISE, ARISE, University of Minho, Guimarães, Portugal*
[b] *Department of Materials, Mechanics, Management & Design. Technical University of Delft, Delft, Netherlands*
[c] *School of Civil & Environmental Engineering. University of Technology Sydney, NSW, Australia*

ARTICLE INFO

Keywords:
Wildfires
Extreme events
Transport networks
Road infrastructure
Decision-making
Exposure
Preparedness
Resilience

ABSTRACT

Climate change is leading to a rise in the occurrence and intensity of wildfires, exacerbated by the growing encroachment of communities into the natural environment, posing challenges to our global capacity to respond to wildfires. During wildfire events, road transport infrastructure becomes crucial for the evacuation of people and accessibility to an emergency by first responders. Nevertheless, resilience management of transportation infrastructure affected by wildfires is poorly considered, despite its relevant role and high exposure to wildfires. Therefore, this study proposes a new methodology to estimate the priority level for wildfire preparation by combining exposure and criticality of road transportation infrastructure to wildfire hazards with consideration of different wildfire categories. The analysis is conducted at the system level considering interdependencies and redundancies among infrastructure components and using a geographic information system (GIS) to automate the modelling process and visualization of results. The proposed methodology is applied to a case study in the Leiria region of Portugal, demonstrating its utility in prioritizing economic resources and decision-making for areas requiring preparation. This approach can serve as a resilience-based tool for decision-making, supporting the implementation of effective adaptation strategies to enhance wildfire resilience.

1. Introduction

Society has reached a certain level of resilience to wildfires due to a long tradition of fire events (e.g., China 1987; Australia 1961; Portugal 2003). However, this level of resilience may not be sufficient to cope with recent extreme wildfire events (EWE), or bushfires, as reflected by their associated high societal cost. For instance, the Camp Fire that occurred in Butte County (California) in 2018 destroyed more than 18,000 buildings and claimed 85 lives [1]. EWE are fires with significantly high characteristic values, such as intensity, size, and spread speed [2] that make suppression exceptionally challenging leading to severe and unexpected impacts, such as those that occurred in Australia in 2019–2020; Chile in 2016; Portugal in 2017, the USA in 2021, and Canada in 2023. There is evidence that climate change is influencing the frequency and intensity of wildfires and other natural catastrophes [3–6]. For instance, bushfire projections in Australia predict that by 2050 the number of days with a very extreme risk of bushfires can increase by a factor of four to five compared to 1990 [7]. Climate change has been linked to more extended fire seasons, i.e., the fire season is no longer associated exclusively with the summer months but may happen at any time of the year. Therefore, the effects of climate change are

* Corresponding author.
E-mail addresses: ericaaarango@gmail.com, id9253@alunos.uminho.pt (E. Arango), M.Nogal@tudelft.nl (M. Nogal), sousa.hms@gmail.com (H.S. Sousa), jmatos@civil.uminho.pt (J.C. Matos), Mark.Stewart@uts.edu.au (M.G. Stewart).

https://doi.org/10.1016/j.ijdrr.2023.104126
Received 28 March 2023; Received in revised form 24 October 2023; Accepted 6 November 2023
Available online 14 November 2023

becoming more important [8,9]. This new generation of wildfires leads to more extensive and destructive fires in regions already susceptible to such events and emerges in areas where societies had not previously encountered similar phenomena. For instance, in Europe, wildfires used to be concentrated mainly in the Mediterranean area. Nowadays, an increasing trend of wildfires is advancing toward central and northern Europe. Therefore, countries such as Ireland, Sweden, and The Netherlands are already unexpectedly facing these events. Wildfire propensity is also exacerbated by other factors, such as current land use problems, e.g., rural abandonment and low-density urbanization, which contribute to landscape-scale fuel accumulation and, consequently, more severe wildfires [10].

Wildfire management has traditionally been based on suppression, i.e., extinguishing the fire, and risk rather than preparedness and resilience [11]. Aiming at zero wildfire risk is not possible and a paradigm change is required in terms of wildfire management towards a resilience-based approach [12–14]. Nonetheless, there is an important lack of methods with a focus on the preparation of the critical infrastructure for wildfire hazards, so they can maintain their functionality supporting a resilient society. This is discussed in more detail in Section 2.

To address the indicated gap, this study proposes a GIS-based methodology to estimate the priority level for the intervention of road transportation infrastructures to prepare for wildfires. The methodology combines a novel exposure measure and a criticality raking to capture the individual circumstances of each road in the context of wildfires at the asset level and to provide the importance of each road within the context of the system, respectively. The approach considers a complete range of wildfire hazards (including normal fires and EWE) to support decision-making and allow the prioritizing of economic resources. Unlike other studies, the methodology is quantitative, is not data-intensive, and with an adequate level of fidelity to support decision-makers in wildfire management toward resilience. It incorporates social, physical, and environmental factors without involving high data requirements or high computational costs. The framework is developed from a resilience-based perspective (for a detailed discussion between the resilience-based approach and risk-based approach see Ref. [15]), meaning that the system should be prepared, respond, and recover from any wildfire category independently of the occurrence probability. Therefore, following a resilience-based approach, the methodology does not consider the probability of man-made or naturally occurring wildfire events that bring unpredictability to the problem. The method proposes a system-level analysis, considering interdependencies and redundancies among the road system, thus, accounting for important resilience-related aspects, such as adaptability and redundancy. The framework is focused on road infrastructure, as it is one of the most essential factors for the safety and resilience of communities in the case of wildfires. The geographic information system (GIS) is used to automate the modelling process and visualization of results.

Therefore, the novelties of this paper rely on the novel exposure metric and its integration with road criticality, enabling the establishment of a priority ranking for preparedness interventions. This allows interventions to be strategically designed to target roads with higher priority, offering an effective decision-making tool to enhance wildfire resilience. This methodology is not presented as a tool for resilience assessment, but it helps improve the resilience of the road network to wildfires. The study aims to 1) develop a GIS method for prioritizing interventions for preparedness against wildfire hazards at a system level. This method is based on novel exposure measures that account for the characteristics of the new extreme wildfire regime; 2) applies the method to a real case study in the Leiria region of Portugal; and 3) reflects on its application to support decision-making processes at two stages: emergency management and long-term planning.

2. Preparedness of road networks for wildfires

In the field of road transport infrastructure, the study of wildfire management is focused on risk-based approaches, i.e., based on known and measurable threats, where the main attention is on evacuation (e.g. Refs. [16–20]). It is also assumed enough suppression capacity to adequately manage the wildfires. While this approach can be adequate to deal with normal fires (those fires where suppression is sufficient to quickly control them), the impacts of events over the last two decades show that it is not sufficient when it comes to EWE [21]. In this section, the limitations and challenges derived from the suppression-related assumption and risk-based approaches are explained.

Issue I: Lack of tools to address the preparedness of critical infrastructures for wildfires. Suppression has been the cornerstone of wildfire management, while preparedness has been considered through research into early warning systems once the fire is initiated (e.g. Ref. [22]) and emergency management (e.g. Refs. [19,23,24]). In comparison, aspects such as prevention and protection, which are essential to reduce the impact of wildfires, have received less attention. According to Ref. [25], one of the main reasons for the persistence of the suppression approach is the lack of methods to identify and evaluate preparedness interventions, i.e., prevention and protection through adaptation measures. Therefore, there is a clear need for tools to support the preparedness of road networks for wildfires, particularly in the presence of the new generation of EWE. In that sense, adopting a resilience perspective may yield better results in developing a plan for unforeseen disruptive events because resilience takes a broader approach that emphasizes the system's ability to cope with the unexpected at all levels [26].

Approaching concepts such as exposure, vulnerability, and criticality from a resilience perspective could be essential when assessing the interventions to improve wildfire resilience. According to ISO Guide 73 [27], exposure is defined as the extent to which an asset is subject to an event according to its location, whereas vulnerability considers the inherent qualities of the assets resulting in susceptibility to a risk source. The inherent characteristics of a road regarding fire refer to aspects such as pavement properties and road structural layout. When the focus of the study is on users' safety, it is unacceptable that drivers use roads surrounded by flames, then, the concept of vulnerability becomes less relevant than exposure. In addition, growing evidence suggests that the extent of disaster risk associated with extreme hazards is more influenced by exposure than by vulnerability [28]. On the other hand, criticality is the quantification of losing or damaging certain road segments or components [29], i.e., the more critical the road link, the more severe the consequences (e.g. social, economic, environmental, health impacts) [30]. Consequently, exposure can be related to hazard identification and its causes at the asset level, and criticality with the consequence at the system level. Both concepts are of high relevance to improve the capacity of road transport networks to cope with different wildfire intensities, i.e., enhance the resilience of the system.

The criticality of road transport networks has been extensively studied, specifically in risk assessments [31,32]; also referred to as vulnerability analysis [33–35]. There are criticality assessments that implement different criteria such as topology (e.g. Ref. [36]), travel time increase (e.g. Ref. [37]), accessibility loss (e.g. Ref. [38]), traffic flow congestion (e.g. Ref. [39]), and disruption of the supply chain (e.g. Ref. [40]). Recent literature reviews on criticality analysis can be found at Refs. [41,42]. On the other hand, despite the many studies developed on wildfire risk, little attention has been paid to assessing wildfire exposure. For instance, in Ref. [43] a guide for determining communities' exposure to wildfires based on a rule of thumb is presented. In terms of more scientific methods, in Ref. [44] wildfire exposure is evaluated using simulations, which have significant drawbacks related to the difficulties described in Issue II.

Issue II: The problem of risk-based methods for capturing EWE behavior. Existing risk-based methods analyze wildfire behavior and impact, such as fire ignition probability [45–47], risk mapping [48,49], forecasting [50–52], and spatial analysis of the factors related to the fire phenomenon [53–55], within which qualitative methods can be distinguished (e.g. Refs. [56–59]). A recent literature review of wildfire behavior modelling can be found in Ref. [60]. These methods have two main limitations; (i) they have difficulties capturing the dynamics of extreme wildfire events (EWE), which are increasingly often out of line with expectations. The risk-based methods are usually built upon historical records (e.g. Refs. [61–63]) and do not consider the effects of the new EWE regime. EWE has unpredictable behavior and therefore high uncertainty. For instance, according to official reports, the wildfire in Pedrogão Grande (Portugal) 2017 was not anticipated by emergency services in Portugal or Europe [64]. It occurred unexpectedly during late Spring, i.e., with the expected less favorable weather conditions for such an event. Despite significant efforts in suppression and detection, wildfire management results were not favorable in the case of Portugal. Wildfire management is a complex process that involves various components, such as prevention, protection, detection, suppression, and recovery. Therefore, the limitation lies in the focus on only two of the five crucial components of wildfire management, which also reinforces Issue I; and (ii) these methods are increasingly categorical for a specific scenario (e.g., a particular ignition point) and data-intensive, but with insufficient capacity to extrapolate other scenarios or conditions. Examining a single scenario of hazard-specific conditions requires copious amounts of information, for this reason, very specific scenarios are usually analyzed. However, analyzing a limited number of fire events to derive predictions is not conclusive enough due to the large uncertainty of such a complex event that depends on many variables.

From a resilience perspective, focusing on the system capacity is necessary rather than predicting the wildfire occurrence. Consequently, exposure assessment can provide valuable information in that regard. To the best of the authors' knowledge, there is no quantitative framework that differentiates the level of wildfire exposure of a road according to its location, i.e., depending on the surrounding elements. Similarly, there is also a lack of tools to prioritize preparedness interventions by jointly assessing criticality and exposure.

3. Methodology

The methodology includes aspects related to the causes and consequences of normal and EWE based on an analysis of the exposure and criticality of road transport networks, respectively. The analysis in this study consists of two main components; (I) an assessment at the asset level, which examines the exposure of each road to wildfires, considering its location within the natural and built environment; and (II) an evaluation at the network level, which focuses on determining the criticality of each road in ensuring uninterrupted mobility. In this sense, criticality considers the interdependencies and redundancies of the road system.

There are many interrelated factors involved in the phenomenon of EWE. The proposed methodology accounts for different domains to comprise many of these influential factors. It considers social factors (e.g., road transport demand, land use), physical factors (e.g., buildings, road, and energy infrastructure), environmental factors (e.g., type of vegetation, rivers), and coping capacity of the communities (e.g., the existence of fire stations and other barriers). These domains are quantitatively combined. Social consequences

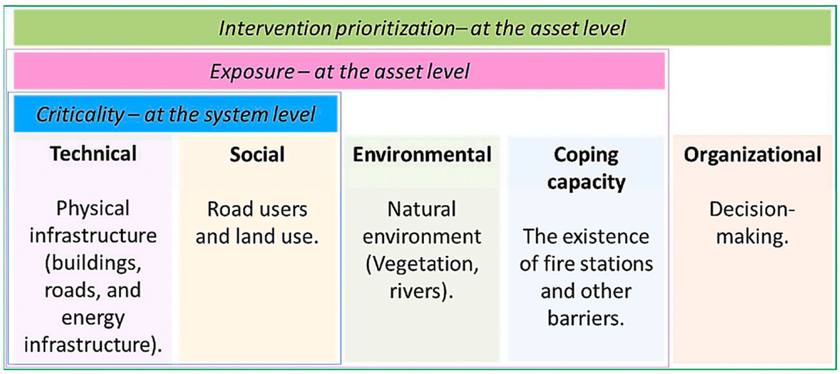

Fig. 1. Domains involved in the methodology for prioritization intervention.

are included; however, the environmental consequences are not considered in this analysis. The combination of these domains provides a global perspective and relevant information about the system to stakeholders, as shown in the discussion of results (Section 6). Fig. 1 summarizes the conceptualization of the methodology.

3.1. Exposure analysis

This section presents a novel methodology that facilitates the comparison of two roads or targets situated in different natural and built environments, assessing their exposure to various types of wildfires without considering associated ignition points. For instance, when comparing Road 1, surrounded by pastures and a river at a distance of 2 km, with Road 2, encompassed by a Eucalyptus plantation and a firebreak of 4 m width along the road: Which road is more exposed to a fire event? Or which road would be reached by the fire first? Also, how long would it take to reach the roads under a given wildfire category? Hereinafter, the burning sources, and fire extinguishers are referred to as sources and barriers, respectively. To answer these questions, two concepts are defined, the Equivalent Fire Distance (EFD) and FIRe Arrival Time (FIRAT). EFD provides a fictitious distance to answer the first two questions. It translates the surrounding conditions of a road or target involving sources and barriers of different nature to an equivalent scenario where there is a unique source, the reference source. The transformation, which is based on the rate of spread of the different sources and barriers, facilitates the comparison of different assets. FIRAT is an exposure measure that provides the average time for a random fire to reach a target (e.g., assets) based on the wildfire conditions and surrounding sources and barriers with the ability to feed or extinguish the fire. In that sense, FIRAT helps answer the third question.

For the sake of clarification, Fig. 2 compares the exposure level of a road with varied surroundings and two ignition points A and B. In (I) the real system is shown with several types of sources and barriers on each side of the road. From each ignition point, the fire travel time can be calculated as the sum of the propagation times for each of the sources and barriers for a given wildfire condition. This will allow the comparison between Point A and B. Alternatively, the equivalent system (II) shows how all the sources are homogenized in terms of a reference source, thus combining them into an equivalent measure. That means that areas on the right and left sides of the road can be compared. In this case, we observe that ignition point B is more critical as $B_{equiv.}$ is closer than $A_{equiv.}$ The FIRAT can be calculated considering the equivalent distances and the rate of spread of the reference source under a given wildfire condition, providing the same results obtained for the real system.

It is important to highlight that EFD is independent of both the wildfire conditions and the location of the fire ignition. Similarly, FIRAT is not associated with the location of the ignition point, as will be explained below. This stands as the primary distinction from the fire travel time used by other authors, e.g. Ref. [65], which needs the definition of a specific ignition point. In this approach, the ignition point holds no relevance because adopts a scenario-free perspective. As a result, regardless of where the fire originates, the fire sources and barriers will ultimately determine the progression of the fire.

The homogenization also makes it possible to consider 7 different categories of fire conditions from normal to extreme wildfires, as shown in Table 1, where each fire category is briefly defined. Several parameters are associated with a given wildfire category, such as fireline intensity, flame length, and Rate of Spread (ROS). Given the goal of the proposed approach, the ROS parameter is used. ROS is a measure of how fast the fire is propagated from its source. This propagation rate is quantified in units of distance over time (e.g., m/s).

Note that for a given fire category, f, the ROS varies with the burning source, i. For instance, $ROS_{i=grassland}^{f=1} = 15$ m/s (according to

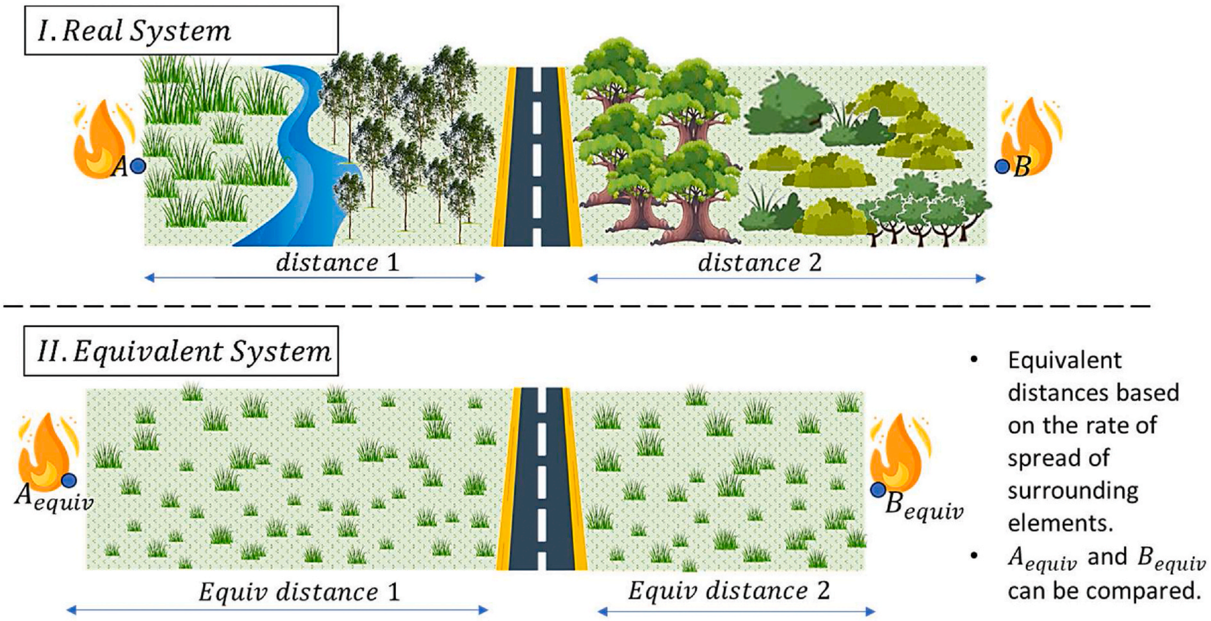

Fig. 2. Schematic representation of the logic behind EFD and FIRAT.

Table 1
Wildfire event classification based on fire behavior. Adapted from [2].

Fire Categories		Fire Type	Description	ROS (m/min)
Normal fires	1	Surface Fire	Walking fire in the lowest vegetation layer	5_a – 15_b
	2	Surface Fire	Walking fire in the lowest vegetation layer	15_a – 30_b
	3	Surface/Flying fire	Burning and glowing vegetation particles are carried by the wind (Spotfire)	20_c – 50_d
	4	Surface Fire - Crowning likely	Crowning likely depending on vegetation type and stand structure	50_c – 100_d
EWE	5	Crown fire	Either wind - or plume-driven. Spotting plays a relevant role in fire growth. Possible fire breaching across an extended obstacle to local spread. It has chaotic and unpredictable fire spread	150_c – 250_d
	6	Plume-driven/ Firestorm	Highly turbulent fire. Chaotic and unpredictable fire spread. Spotting, including long-distance, plays a relevant role in fire growth. Possible fire breaching across an extended obstacle to local spread	250–300
	7	Firestorm	Plume-driven, highly turbulent fire. Area-wide ignition and firestorm development non-organized flame fronts because of extreme turbulence/vorticity and massive spotting	>300

Note: [a] Forest and shrubland; [b] grassland; [c] forest; [d] shrubland and grassland.

Table 1). For a given target, e.g., a bridge, a road, or a building, the FIRAT associated with a fire category f, is calculated as the ratio of the Equivalent Fire Distance, *EFD*, and the characteristic ROS as follows.

$$FIRAT^{f} = \frac{EFD_{ref}}{ROS_{ref}^{f}}, \tag{1}$$

where ROS_{ref}^{f} is the ROS associated with a reference type of burning source for a fire category f, obtained from the fire classification in Table 1. EFD_{ref} is a measure that combines the distances from all the closest burning sources and barriers (included in the same group, S) to the target expressed in terms of a reference type of burning source. Fire barriers are understood as those that inhibit the fire advance due to the lack of sufficient fuel to support the spread of wildfires. Note that the fire approach time associated with the most extreme wildfire category is at least 30 times shorter than the mildest fire category. Thus, the higher the FIRAT value, the less exposed the target is.

One of the main challenges that an exposure assessment to wildfires poses is the consideration of different fire sources and barriers, each with a different fire spread capacity. Therefore, it is a source/barrier factor proximity that indicates the distance to fuels or dangerous flammable materials or fire breaks. To combine them, it is proposed the EFD that is calculated as Eq. (2),

$$EFD_{ref} = \Lambda_{i \in S} \, W_i d_i \tag{2}$$

where Λ is an aggregator operator that combines the sources and barriers analyzed. For each source or barrier $i \in S$, its physical distance to the target element, d_i. The distance is normalized by the ratio W_i which is calculated as the ratio of the ROS of a reference source, ROS_{ref}^{f}, and the ROS of a source or barrier i, that is,

$$W_i = \frac{ROS_{ref}^{f}}{ROS_i^{\,f}} \tag{3}$$

Note that $ROS_i^{\,f}$ in the case of barriers is low, or even zero. To avoid computational overflow, it is recommended to assume a very small number rather than a zero value. This normalization allows comparing different distances of several sources or barriers from the point of view of their capacity to spread the fire. The aggregator operator can be the average or minimum of all the S distances or others, depending on the information's purpose. Whereas the average value offers a global perspective of the target exposure concerning all the surrounding sources and barriers, the minimum value focuses on the most critical scenario for the target (i.e., how close it is to a source of fire propagation). This choice mainly depends on the study objectives.

To summarize, the FIRAT is calculated as a distance divided by a propagation velocity. This distance refers to the distance between the study target and the most critical element of its type, e.g., between two pasture areas, it will be the closest one. Therefore, FIRAT is scenario-free (resilience-based approach), whereas traditional methods using fire travel time put the focus on the ignition point. These methods are risk-based and consider a concrete hazard scenario (their limitations are discussed in Section 2, Issue II).

ROS is used as the basis for the methodology because it is one of the most important parameters of wildfire behavior, which in turn allows considering the different fire categories for FIRAT assessment. ROS is easily related to distance units and combined with the homogenization process, allows consideration of several sources and barriers in the exposure analysis, including fuel and infrastructure types. ROS base values should reflect the specific conditions of the analyzed case and be estimated by experts. In some cases, estimating the ROS associated with some infrastructure types, such as gas stations and power plants, can be challenging. The ROS values used in Eq. (3), are assumed to be constant and spread similarly in all directions. Eq. (3) permits expressing all the sources in terms of the reference value ROS_{ref}^{f}. Therefore, W_i informs about the impact of different sources in a straightforward manner for each fire category.

Nonetheless, ROS is associated with significant uncertainty given wildfire dynamics. Therefore, ROS values can be altered by factors, such as wind direction and speed, humidity, and topography [66]. Researchers such as [67], and [68] recommend altering the ROS values by a factor between 2 and 3 to consider wildfires under windier and drier conditions, as well as the effect of an upslope fire. Therefore, this correction factor can be applied to the calculation of the EFD and FIRAT. Underestimating them will yield conservative values; nevertheless, it will ensure that the measures/decisions taken based on this information are the safest for users. It is possible to consider a variability range for the ROS parameter to obtain more accurate results. The EFD can be given by a confidence interval varying, for instance, between 1 and 3 m.

The exposure assessment procedure is summarized in the following seven steps.

1. Hazard definition. The input data correspond to the definition of the study target (e.g., a bridge, a road), fire propagation sources, and barriers that can affect the object of study. In addition, it is necessary to contemplate a classification that allows considering the different fire categories, in this case, the classification developed by Tedim et al. [2] as given in Table 1 is suggested.
2. ROS values identification $\left(ROS_i^f\right)$. Establishing the ROS for the different sources and barriers for a selected fire category, considering the source and zone characteristics.
3. Reference object definition $\left(ROS_{ref}^f\right)$. Select one of the fire propagation sources previously identified as a reference object.
4. ROS ratio estimation (W_i) using Eq. (3).
5. Distances calculation (d_i). A distance measure between fire propagation sources/barriers and the target.
6. EFD calculation, using Eq. (2).
7. FIRAT estimation using Eq. (1) for the selected fire category.

3.2. Criticality analysis

The wildfire consequences are considered from a criticality analysis focused on the human-related aspects. This analysis considers the topological characteristics of a road network to evaluate connectivity based on the relative locations and configurations of roads (henceforth referred to as links for traffic analysis purposes) and nodes. One link corresponds to each road direction, i.e., a two-way road corresponds to two links. The nodes are defined as the road characteristics change, intersections, and places of entry or exit of users. The traffic demand and the network performance regarding travel time are also considered. The annual average daily traffic (AADT) is used to assess how a wildfire event can affect the capacity of the road network to meet the demand under regular operation. However, during an emergency, the demand may well vary, and this is a topic for future research.

The proposed criticality analysis consists of measuring the change in the total travel cost of the traffic network, usually expressed in terms of travel time, as a result of the degradation of the network. It is conducted through a traffic assignment model, whose underlying idea is that traffic flow spreads through the network in such a way that drivers optimize their travel time, i.e., they try to reduce their

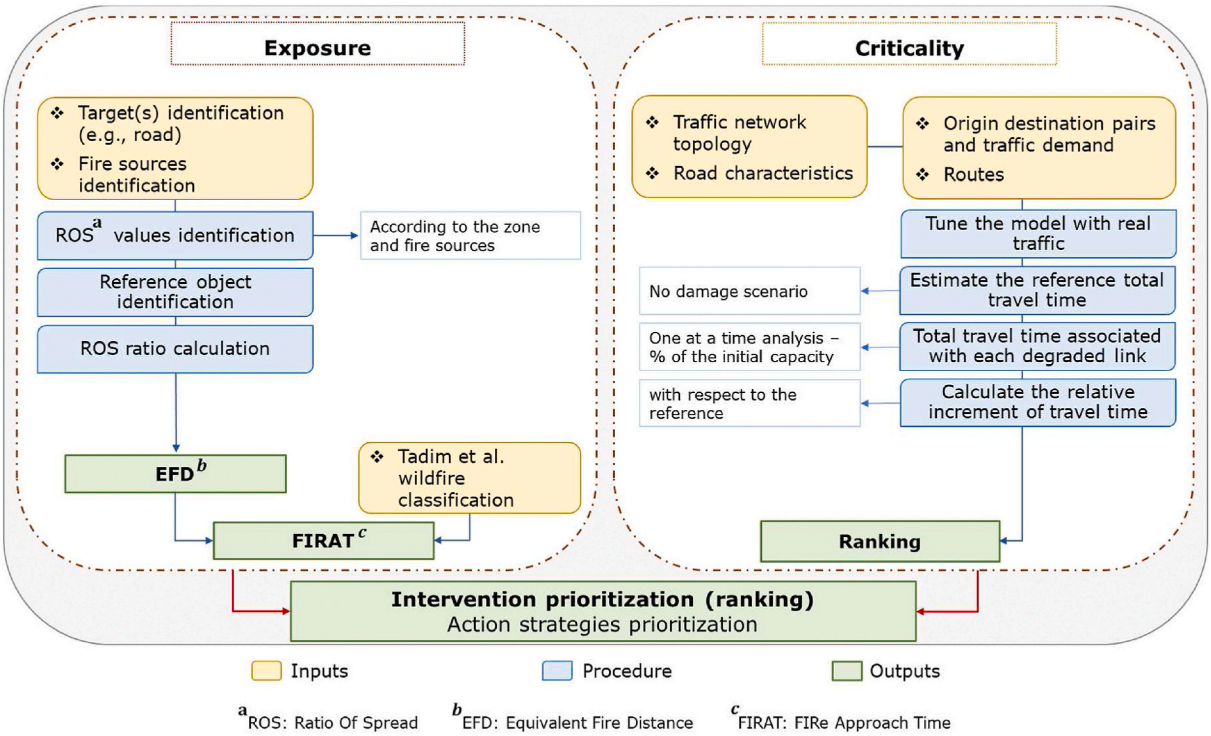

Fig. 3. Methodology scheme for prioritization of preparedness interventions on road transport systems affected by wildfires.

travel time as much as possible. Given that the travel time of a road is a function of its saturation degree, the analysis requires optimization at a network level. This allows the consideration of the behavior of all users in the network and the influence of roads affected by wildfires on non-affected roads because of users changing their routes.

The new traffic flow distribution through the network caused by the affected areas is assessed by a stochastic traffic assignment model, which permits introducing the biased perception of users who may not have perfect information about the situation [69]. The results allow the identification and classification of critical links in the network based on the relative increase in travel time caused by link damage.

The criticality assessment procedure is summarized in six steps.

1. Inputs definition. The network topology, origin, and destination (OD) pairs, routes, road characteristics, and traffic demand.
2. Tune the traffic model.
3. Estimate the reference total travel time (no damage scenario).
4. One-at-a-time analysis. Estimation of the total travel time associated with each damaged link.
5. Calculate the relative increment of travel time regarding the reference cost.
6. Rank the links from the most to the least critical ones.

3.3. Intervention prioritization methodology

The final output of the framework is the ranking of the priority level for preparedness interventions, which is obtained by combining the two main analyses: exposure and criticality analyses. Both analyses are combined following a risk-inspired approach, which involves normalizing the results of each analysis between 0 and 1. The homogenized values are then multiplied and the intervention priority ranking of all the links is obtained. It allows for identifying those roads with high exposure and criticality values,

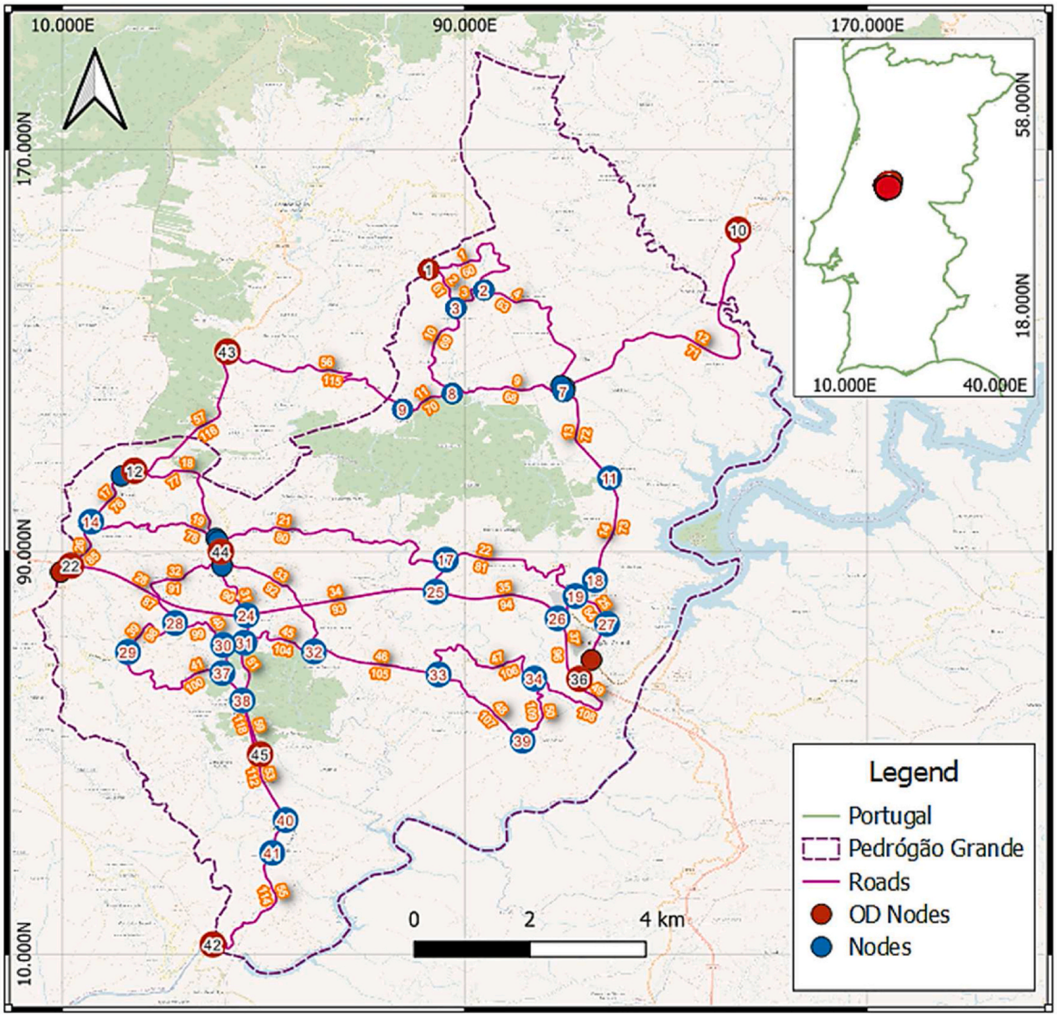

Fig. 4. Portugal Case study - Pedrógão Grande traffic network, defined by nodes and roads (links). Red-shadowed nodes are the origin and destination (OD) nodes. Source of background: Google Maps

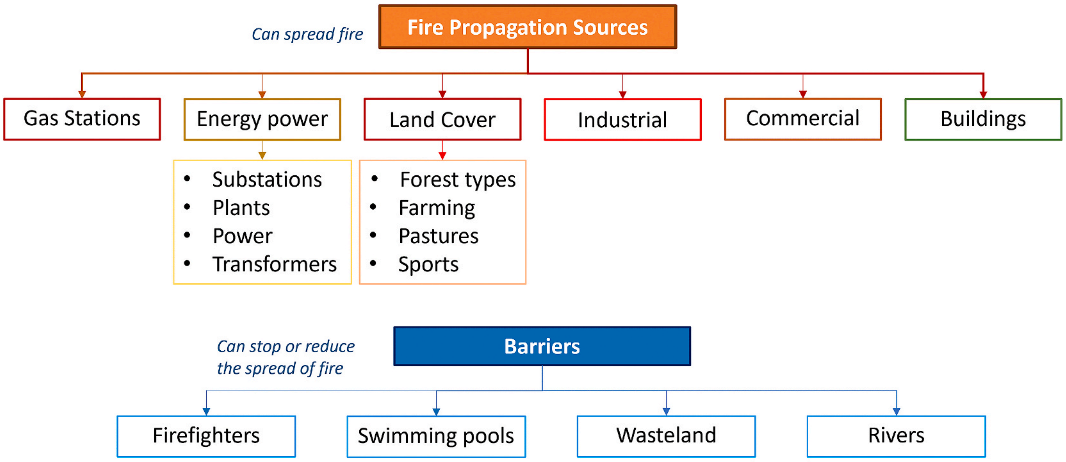

Fig. 5. The fire spread sources and barriers.

dismissing those with either low criticality or low exposure. The new ranking provides valuable information for decision-makers regarding where to implement actions to improve the wildfire resilience of the system. Fig. 3 summarizes the complete framework.

4. Pedrógão Grande traffic network. Case study

4.1. Case description

Pedrógão Grande is a Portuguese municipality in the Leiria District, Central Region, and inter-municipal community of Leiria, as

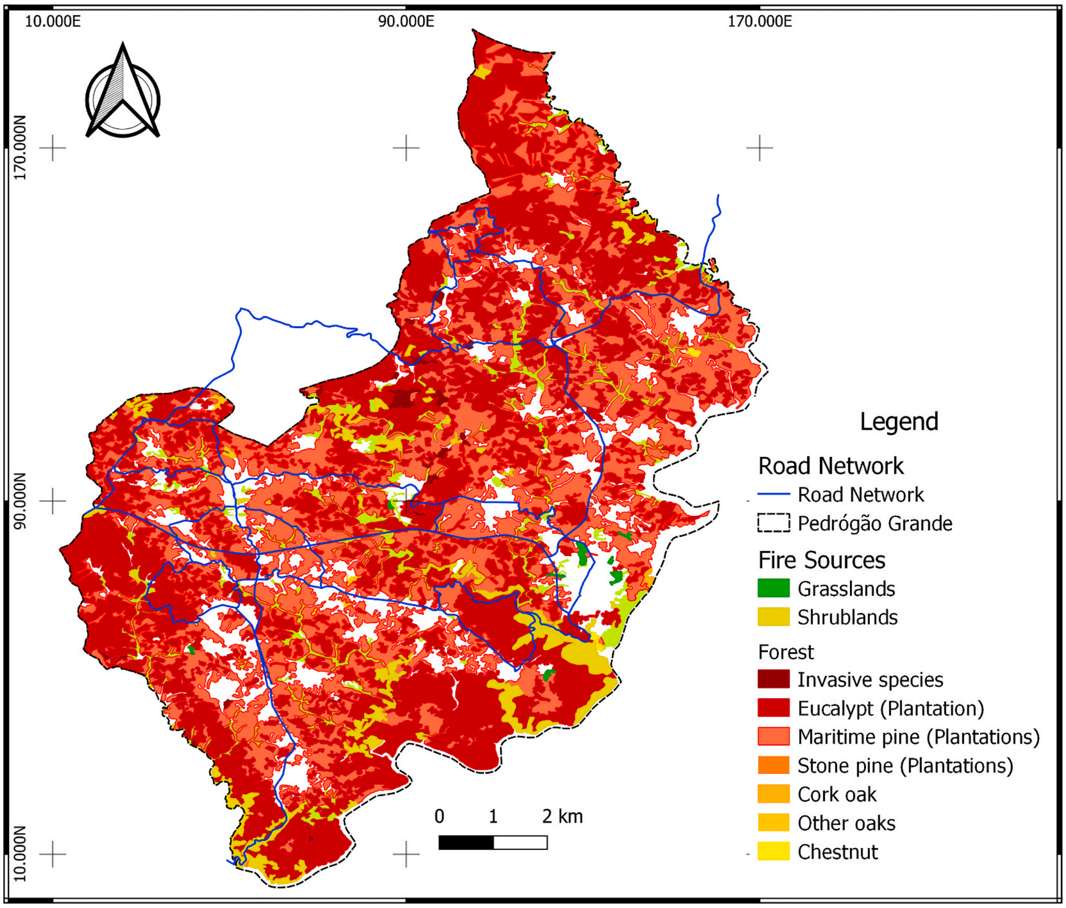

Fig. 6. Fire propagation sources (forest) considered for Pedrógão Grande, Portugal.

Table 2
ROS values for spread and barrier source – assumptions or observations.

	Spread sources	ROS (m/min)	References	Assumptions/Observations
Bases	Grassland	50	Cruz et al. [75]	All values were taken in 10 % Humidity and 20 km/h Wind condition.
	Shrublands	25		
	Dry eucalypt forest	12		
	Pine plantations	7.0		
	Wet eucalypt forest	1.2		
Fire Barriers	Wastelands	0.5	Scott and Burgan [74]	They are assumed as elements that do not spread fire, i.e., fulfill a barrier's function.
	Rivers	0.5		
	Swimming pools	0.5		
	Fire stations	0.5–0.8		
Forest	Invasive species	50	"Invasoras.pt" [77]	It is assigned the same ROS as grass due to the existence of Cortaderia Selloana, a species with high propagation speed.
	Shrublands	35	Assembleia da República [64]	This vegetation type is assumed to be large-scale plantations and therefore can increase fine flammable fuels at a landscape scale [78]. The mean values of models built with previous information in this area were used.
	Eucalypt (plantation)	25		
	Maritime pine (plantation)	30		
	Stone pine (plantation)	33		These values are established from the base values and expert judgment.
	Cork oak	12		
	Other oaks	12		
	Chestnut	7		
	Hardwoods trees	7		
Other activities	Farming	25	Assembleia da República [73] Teixeira [79] Scott and Burgan (2005) [74]	Farming is assumed to be combustible and therefore spread the fire (based on previous fires in this area). Additionally, a high ROS value is assigned for the farming type, which is mostly corn and sunflowers.
	Gas stations	200	ARIA Technologies (2009) EPA CEPP (1998) [80–82]	Assuming an average damage radius of 200 m (taken from ARIA 23952–January 22, 2003–93 - LA COURNEUVE) and a 1 min to reach it, consider an imminent explosion.
	Industrial (lumbermen and furniture relative activities)	450	Al-Hajj et al. [83]	Assuming 3 km of heavy damage, recorded on the Beirut (Vancouver) blast and 400s to reach that fire radius according to Chen et al. (2010) and Lin and Wu (2018).
	Substations and Power plants	250	Ahumada and Lillis (2021) Dominion Energy (2022) BLANC et al. [84–86]	An average explosion radius of 250 m is assumed, and 1 min is considered to reach that radius for the most critical scenario.
	Commercial	170	Office of Civil Defense [87]	A blast radius of 804 m according to the reference and a time of 284 s is assumed according to Chen et al. (2010); and Lin and Wu (2018).
	Sports	25		Assuming that they are mostly grass fields or green areas such as pastures.
	Buildings	7.2	Cousins et al. [88] Thomas, Heron, and Baker [89]	Assuming fire-spread mechanisms between buildings with non-combustible claddings through non-fire-rated roofs or wall openings use a critical separation distance for a broken window of 18 m and 2.5 min to reach that length.

shown in Fig. 4. It is one of the richest councils in natural heritage [70]. This municipality gained international recognition due to the large wildfire that devastated its surroundings in June 2017 and resulted in the loss of 64 lives and 153 injuries.

The transport network of the study area is mostly composed of primary roads and therefore they are busy and important within that region and for the country. Due to the large amount of information, only the most relevant data from the case study is shown in the main body of the paper. The interested reader is referred to Appendix A for further details.

4.2. Exposure analysis

In this case study, the targets are the links of the road network. The fire propagation and barrier sources are given in Fig. 5. They were mostly defined from the available information in Open Street Maps through QGIS, free and Open-Source Software. The information on fuel type was obtained from the land use and occupation chart for Continental Portugal, in its most recent version (2018 version). It provides a set of geographic data that represents the thematic mapping of land use and occupation, available as Linked Open Data in DGT [71].

The collected data shows that the study area is characterized by a low presence of urbanized areas (<5 %) relative to areas with infrastructure, equipment, and public space. It exhibits a discontinuous built fabric with scattered built areas and a dispersed population. On the other hand, there is also a low presence of shrublands (<5 %), from 0 to 3 % of the land use corresponds to pastures and from 10 to 20 % to agriculture. The forest is the most representative land use and occupation class of the territory >60 %. The forest is formed by several species, predominantly maritime pine, eucalyptus, and cork oak plantations [72], as shown in Fig. 6.

Farming land is also considered a fire propagation source because agriculture is not always well maintained in non-combustible conditions. It means the grass is allowed to grow under the crops, or wheat or similar crops are dried before harvest. This was demonstrated in the 2017 wildfire event, where crops were one of the largest sources of fire spread [73]. On the other hand, sources that could directly affect the target (roads) or considerably increase the fire propagation speed in the event of an explosion are also considered, such as gas stations, power plants, substations, and industrial, commercial, and residential buildings. Explosion and propagation considerations are detailed in the last column of Table 2.

Three barriers are considered; (I) wasteland, such as gravel pits, arid deserts, dunes, and rocky outcrops; (II) land covered by open water bodies, such as lakes and rivers, see Ref. [74]. Only the highest order rivers are considered, from order three onwards, according to Strahler's stream order; and (III) the existence of firefighter's brigades and other water bodies, such as swimming pools that can serve as backup for firefighters. Other sources and barriers considered are shown in Appendix A-Figure A. 1

For the ROS assignment, the propagation sources were classified by activity into three main groups, namely: (I) forest (fuel type), (II) barriers, and (III) other activities. In the first group, the Australian guide of fire spread rate prediction for different fuel types [75] was taken as a basis and complemented with the information reported in the analysis of data related to the fires that occurred in Pedrógão Grande [64], combined with expert judgment. It was necessary to review and complement the information because the forest conditions in Portugal are different from those in Australia, where for example, the eucalyptus forests are natural, while in Europe they correspond mostly to plantations [21,76], which significantly changes the ROS value. While for dry eucalypt forest, the ROS value may correspond to 12 m/min, a forest plantation is more flammable and increases the fine flammable fuels on a landscape scale [21] doubling the ROS value (25 m/min). This was established according to the 2017 post-fire report in this area [64].

In the case of fire barriers, since they prevent the fire advance, their ROS value is assumed to be close to zero. For those sources that can directly affect the target (road links) or considerably increase the speed of fire propagation in the explosion event, it is necessary to consider a blast or damage radius with the respective reach time to set it in terms of propagation speed. The ratio and blast times are obtained from scientific literature and reports. For example, for gas stations, assuming an imminent explosion, it is considered 200 m of danger radius and a time of 1 min for the fire to spread in that radius, obtaining a ROS value of 200 m/min. All the values and corresponding assumptions to the propagation source groups are synthesized in Table 2. The ROS values provided in Table 2 can be used as a basis for other application cases. Nevertheless, it is important to review and update them according to the characteristics of the case study. ROS values of bases and forest groups were taken in 10%–20 % humidity and 10–20 km/h wind conditions. Other factor such as soil moisture is assumed to be similar throughout the study area.

On the other hand, no significant variations in slope were observed that could be considered as differentiating factors in the case study. Therefore, they are not considered, as they do not alter the priority ranking. Note that these factors depend on the case study and should be analyzed in all cases to avoid underestimation of ROS values. The ROS value of grassland is selected as the reference object due to convenience for later steps in the use of the fire classification in Table 1. By applying Eq. (3), the ROS ratio of each source and barrier can be estimated. For instance, the ROS value of the eucalypt (plantation) is 25 m/min. Therefore, its ROS ratio (W_i) is 2 with respect to the reference ROS (ROS_{ref}), which means that it takes double the time compared to the grassland (reference object) to reach the target object under the same fire conditions.

On the other hand, to estimate the real distances between the roads to the fire propagation sources and barriers, the coordinates provided by QGIS are used. In this case, only the closest source of each type has been considered, based on the assumption that the wildfire will reach the target road by the closest sources. For instance, for the other activities group, the sources could affect all links within the explosion range assumed in each case. Finally, using Eq. (2), the equivalent distance of each fire propagation and barrier source can be obtained for each link.

The used aggregation is the average equivalent distance. $FIRAT^{f}$ is obtained by applying Eq. (1), considering the obtained EFD_{ref} of each target and the characteristic ROS value for each fire category using Table 1.

4.3. Criticality analysis

The proposed approach has been implemented to determine the criticality of the traffic network in Pedrógão Grande, Portugal. The data relating to the traffic network was provided by *'Infraestruturas de Portugal. S.A.'*, a public company managing the largest stock of assets in Portugal [90]. The information consists of the node coordinates, links, link lengths, link free-flow speed, link flow, and road typology. Also, the demand associated with each OD (origin-destination) pair and the set of routes connecting each OD pair. The Pedrógão Grande network consists of 118 links and 45 nodes as shown in Fig. 4.

The Bureau of Public Roads (BPR) function [91] is used to estimate the travel time of link a as a function of its saturation degree, that is,

$$t_a = t_a^0 \left[1 + m \left(\frac{v_a}{v_a{}^{max}} \right)^b \right] \tag{4}$$

where m and b are positive parameters, t_a^0 is the free-flow travel time, $v_a{}^{max}$ is the link capacity to provide a certain service level, and v_a is the travel flow of link a. The link capacity is obtained based on the speed limit, as proposed by Leong and Tan [92], obtaining link capacities in the range of values between 1100 and 1700 vehicles/hr/lane. The BPR parameters were selected depending on the road type from Mtoi and Moses [93], m as 0.26 and 0.32, and b as 8.4 and 6.87 for primary and secondary roads, respectively.

The stochastic traffic assignment model proposed by Ref. [94] is used in this case. The so-called C-logit Stochastic User Equilibrium (SUE) model allows the introduction of the biased perception of users through the parameters θ, which is related to the dispersion of the network, and β to the users' preference for routes with multiple alternatives. This model provides more dispersed traffic flow patterns than the deterministic models. The latter concentrates traffic flow only on those routes with the minimum travel time, which is not realistic. It has been assumed $\theta = 1.2$ and $\beta = 1$, which are common values. See Ref. [95] for the sensitivity analysis of these parameters. Nonetheless, other traffic assignment models can be used (e.g., the well-known Beckmann's user equilibrium model [96]). An optimization process is applied to tune the traffic model with the observed traffic data, i.e., the AADT. The difference between the observed link flow and the flow given by the C-logit SUE model is minimized to determine the demand associated with each OD pair. Subsequently, the model is refined by eliminating routes with a demand of fewer than 150 vehicles per day. As a result, 113 routes are considered for a total of 25 OD pairs (see Appendix A- Table A.2). The incorporation of an additional criticality factor based on proximity to population centers can be added.

With the characteristics of the traffic network and observed demand, the reference total travel time is calculated as depicted in Fig. 7. This is assumed as a no-damage scenario and the baseline for the one-at-a-time analysis. During the criticality analysis, link by link is penalized by considering 1 % of the initial capacity and 100 times the free-flow travel time, thus, simulating that the link is canceled. The traffic assignment model will avoid assigning traffic flow to the link given the excessive travel time associated. The links are not fully removed because this would imply re-define the entire network and re-calculate the existing routes every time. The impact on the total travel time of the network, when each link is canceled, is assessed using the workflow depicted in Fig. 6. In this sense, the

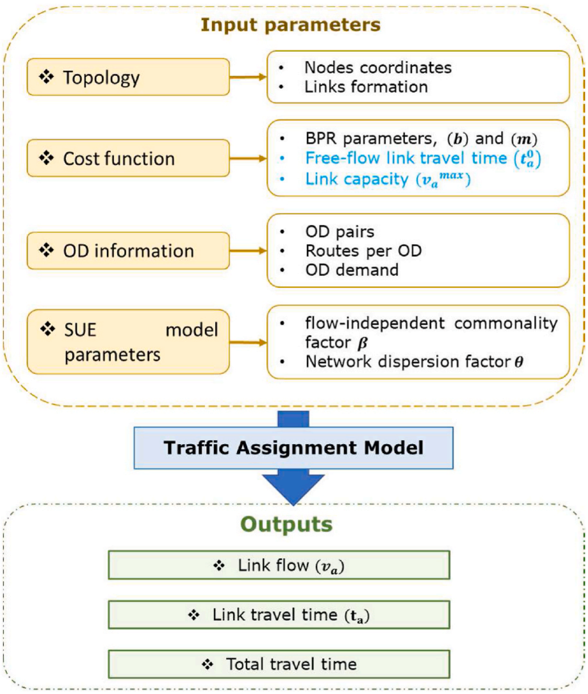

Fig. 7. Input parameters and output of the traffic assignment model. The inputs in blue color change with each damage scenario

most critical links causing the largest increment of the travel time at a network level are identified.

5. Results

5.1. Exposure analysis

Due to the extension of the case study, only the obtained values for the most important 13 roads (26 links) are shown in Table 3, those 13 roads correspond to the 10 most exposed and the 3 least exposed roads. The detailed results for the complete network links can be consulted in Appendix A-Table A.1. The exposure map of the road network for the case study is shown in Fig. 8 , which reflects the information in Table 3.

Table 3
Fire approach time - FIRAT (min) of the selected set of links for the Pedrógão Grande traffic network.

Road	EFD (m)	Fire	Cat. 1	Cat.2	Cat.3	Cat.4	Cat.5	Cat. 6	Cat. 7
		ROS	15 m/min	30 m/min	50 m/min	100 m/min	250 m/min	300 m/min	>300 m/min
10–69	76.9	5.13		2.56	1.54	0.77	0.31	0.26	0.15
17–76	62.1	4.14		2.07	1.24	0.62	0.25	0.21	0.12
32–91	37.8	2.52		1.26	0.76	0.38	0.15	0.13	0.08
39–98	25.9	1.73		0.86	0.52	0.26	0.10	0.09	0.05
40–99	55.8	3.72		1.86	1.12	0.56	0.22	0.19	0.11
42–101	39.4	2.63		1.31	0.79	0.39	0.16	0.13	0.08
43–102	21.1	1.41		0.70	0.42	0.21	0.08	0.07	0.04
47–106	1.4	0.09		0.05	0.03	0.01	0.01	0.00	0.00
48–107	68.0	4.53		2.27	1.36	0.68	0.27	0.23	0.14
50–109	65.4	4.36		2.18	1.31	0.65	0.26	0.22	0.13
1–60	48034.9	3202.33		1601.16	960.70	480.35	192.14	160.12	96.07
41–100	27758.9	1850.59		925.30	555.18	277.59	111.04	92.53	55.52
55–114	50062.35	3337.49		1668.74	1001.25	500.62	200.25	166.87	100.12

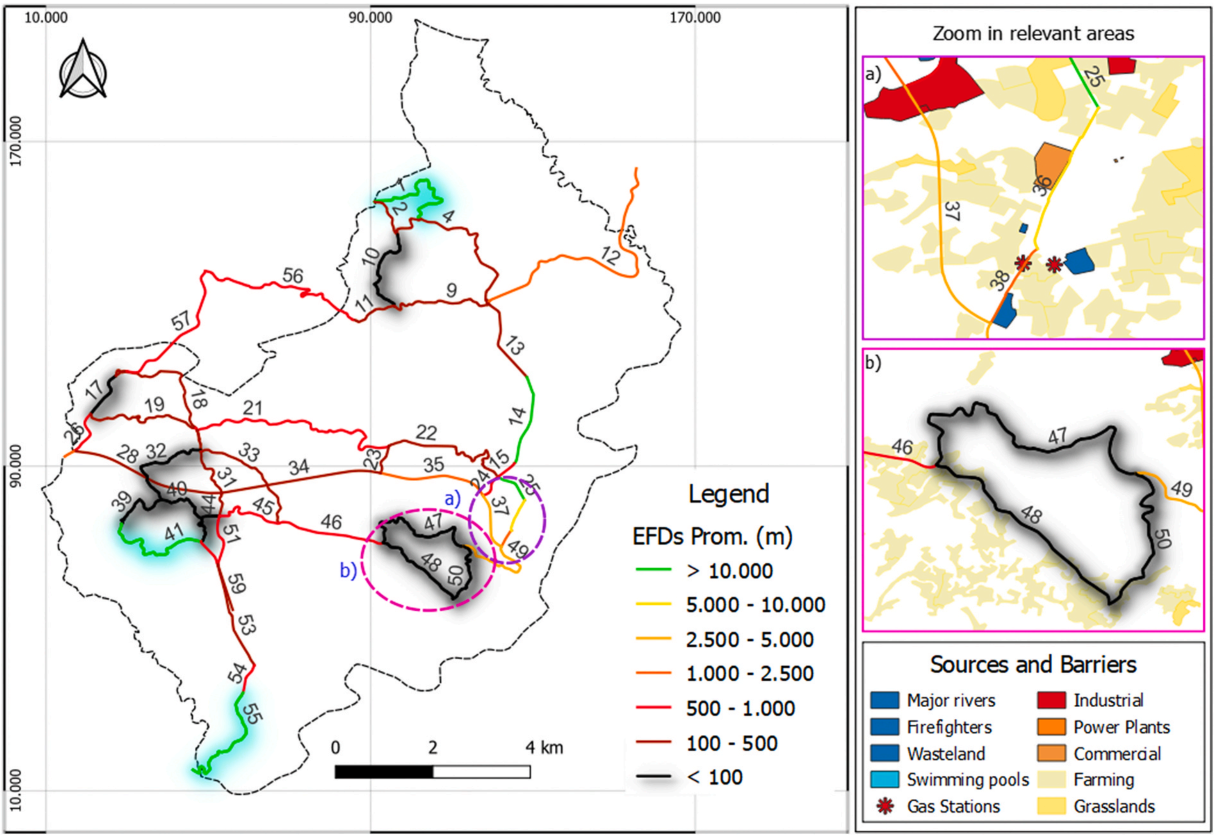

Fig. 8. Equivalent Fire Distances – EFD for Pedrógão Grande Road network (m). Reference burning source: grassland.

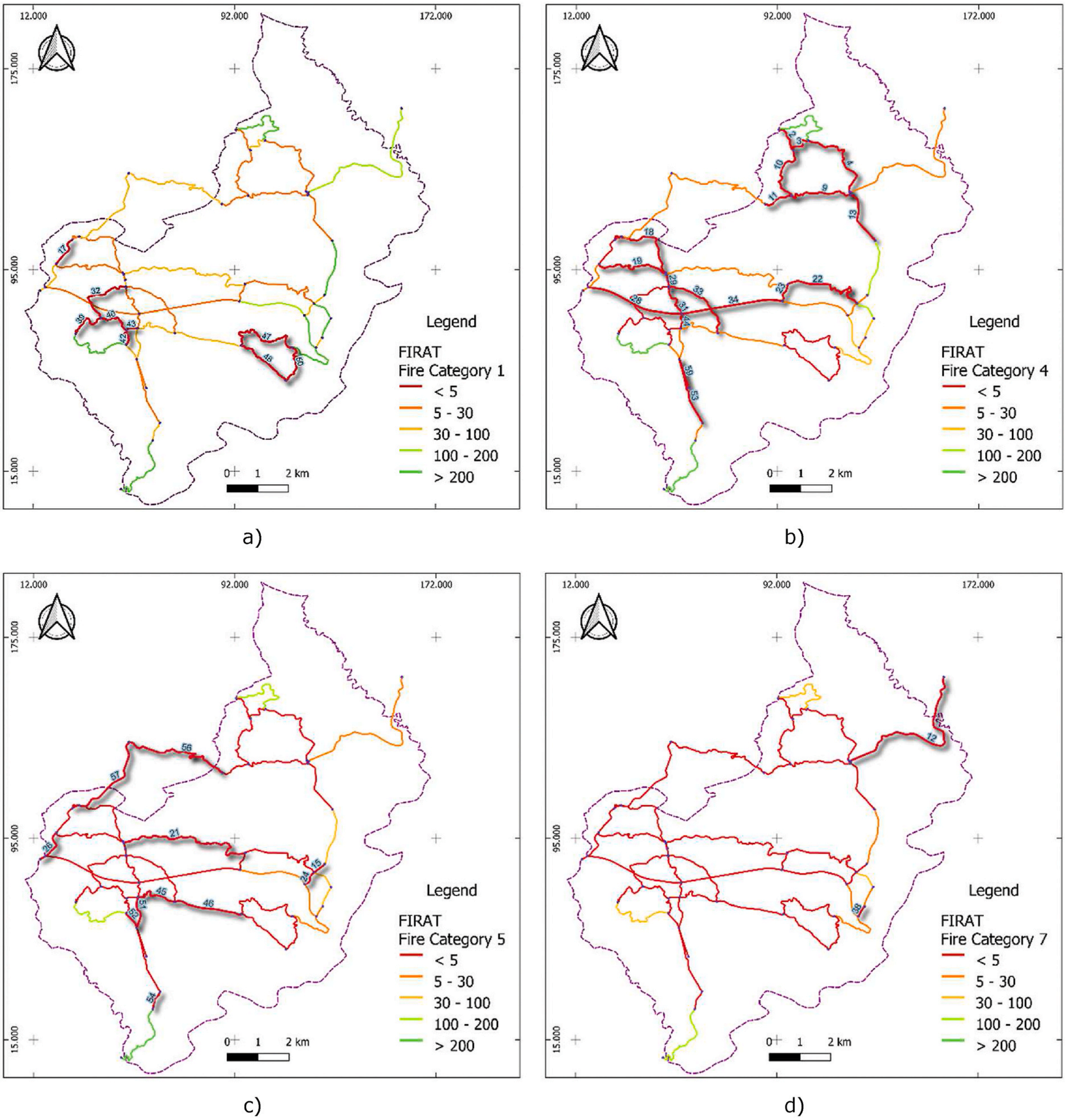

Fig. 9. Fire Approach Time – FIRAT for Pedrógão Grande traffic network (in minutes). Normal fires: a) Fire Category 1, b) Fire Category 4. EWE: c) Fire category 5 and d) Fire category 7. The new links falling into the group with a FIRAT<5 min when changing the fire category are highlighted with a thicker red line.

The results showed that the most exposed road segments in terms of equivalent fire distance, EFD,are roads 10–69, 17–76, 32–91, 39–98, 40–99, 42–101, 43–102, 47–106, 48–107 and 50–109, which have an *EFD* smaller than 100 m (highlighted black lines in Fig. 8). Those roads are close to industrial zones, farming, forests (such as Eucalyptus, and Maritim pine), shrublands, and gas stations, and mainly because those roads do not have any nearby barriers. The roads with the largest *EFD* are 1–60, 41–100, and 55–114, which show values greater than 10 km (highlighted green lines in Fig. 8). The general *EFD* evaluation for the entire transportation network of Pedrógão Grande is shown in Fig. 8. The information is provided per road because, in this procedure (exposure analysis), it is not necessary to distinguish each link direction but rather to consider their location and propagation sources around them. Opposed to the criticality analysis, for which such distinction is necessary.

The importance of considering barriers to reducing fire exposure can be seen for example, in roads 36, 37, and 38 (Fig. 8 a). Their proximity to barriers (blue sources) reduces the EFD value and counteracts the exposure to sources such as gas stations, industrial areas, and crops. On the contrary, roads 47, 48, and 50, which do not have any nearby barriers, are some of the most exposed road

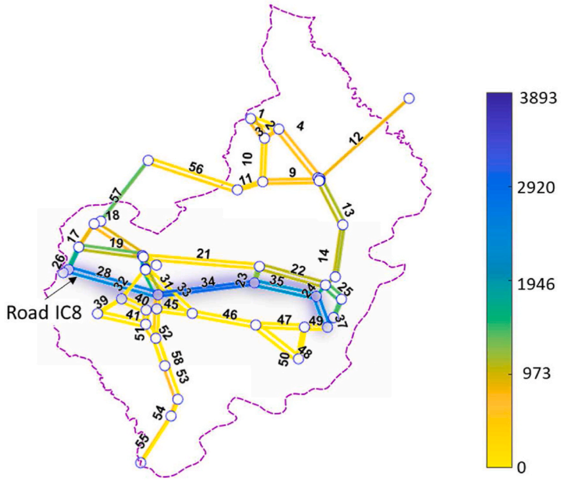

Fig. 10. Link flow distribution of the Pedrógão Grande traffic network for normal operation, expressed in Passenger Car Unit/h (PCU/h).

segments, as shown in Fig. 8 b.

In terms of fire arrival time, FIRAT, since it depends on ROS and *EFD*, the exposure ranking is maintained. Therefore, the exposure ranking can be calculated in terms of fire distance with the *EFD*, with no need to determine the FIRAT. However, the FIRAT adds relevant information to support decision-making, because it indicates the available response time in the case of a given fire category, as shown in Fig. 9. This observation can be divided into two groups, normal fires, which include fires of categories 1 to 4, and extreme wildfire events, which include fires of categories 5 to 7. For the first group, it is observed that moving from a fire category 1 to category 2 can significantly affect 8 additional roads within the most exposed ones, resulting in a total of 26 roads with less than 5 min for the fire to reach them and 18 additional roads, for a total of 66 with a FIRAT between 5 and 30 min. When compared to a fire category 4, the number of the most exposed roads (i.e., less than 5 min for the fire arrival) almost quadruples concerning category 1 (see the additional links from one category to another highlighted in red in Fig. 9).

These and other variations of exposure are easily identifiable in Fig. 9 a - d, in which each figure corresponds to a different fire category. Fig. 9 shows categories 1, 4, 6, and 7, for more detailed results (all fire categories), see Appendix A- Figure A. 2. The FIRAT range of the network is reduced from 55.6 h (fire category 1) to 3.3 h for fire category 5, 2.8 h for category 6, and 1.7 h for category 7.

Note that the exposure level considers the proximity to fire sources and barriers, expressed in terms of EFD. This distance can be translated to time (FIRAT) depending on the fire conditions through the ROS values. Therefore, the FIRAT is a temporal measure of the exposure level when the area surrounding a link is burning under a certain fire regime. This does not imply that the entire studied area must be subjected to the same fire category. For instance, if the North area has a fire category 4, the FIRAT of the roads in this area will respond to Fig. 8b, while the rest of the studied area can have no wildfires at all.

5.2. Criticality analysis

Regarding the criticality analysis, Fig. 10 illustrates the traffic flow distribution for the reference scenario associated with normal operation. The network includes important national, and complementary roads, especially Road IC8 which supports the national road network. This is adequately reflected in the traffic flow distribution in Fig. 10.

As a result of the one-at-a-time analysis, it can be seen how the total travel time is affected when reducing each link's capacity compared with the baseline travel time as depicted in Fig. 11.

In Fig. 11 the darker colours refer to those links that are essential for network connectivity, such as links 93–34, with a relative increment of the total travel time of 10^{13}. This value represents a significant connectivity loss that collapses the network. Meanwhile, the lighter colours indicate those links that have redundancy or are not associated with many users and therefore less essential for network connectivity. This is reflected in the criticality of the network shown in Fig. 12, in which it can be observed that the 6 most critical links are 93–34, 86, 57, 72, and 73, mainly due to the number of users and no alternate routes. In contrast, the 4 least critical ones correspond to links 113, 114, 117, and 118. Fig. 12 depicts the criticality of each link in the Pedrógão Grande traffic network, where the most critical links are identified by their link numbers.

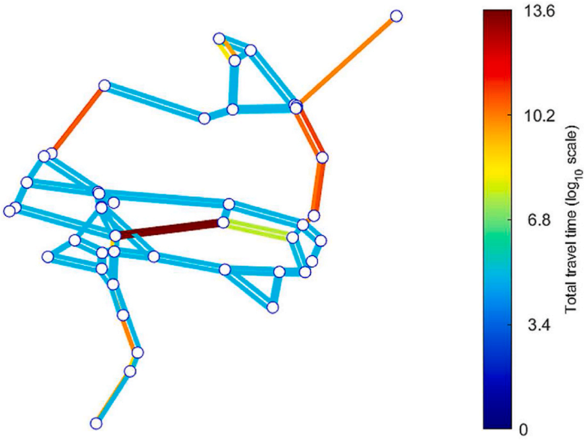

Fig. 11. Relative total travel time increment of the Pedrógão Grande traffic network when reducing each link's capacity, expressed in a $\log_{10}$ scale.

6. Discussion

Finally, the combination of the two previous analyses makes it possible to identify roads with high exposure and criticality values, discarding those with low criticality or low exposure. The obtained results are shown in Fig. 13, providing the classification of the roads in the network based on their priority for preparedness actions (i.e., prevention, protection, adaptation). The ranking is given in 4 groups from Low to Extreme priority, (i.e., Low <0.25, Medium 0.25–0.5, High 0.5–0.75, and extreme >0.75). In that sense, it is possible to observe that against any wildfire intensity (normal or EWE), the main corridor formed by the roads 27–86, 28–87, 34–93, 35–94, and 37–95, would be one of the most affected (central links highlighted in red color in Fig. 13), i.e., roads that should be better prepared and increase the wildfire resilience. These roads are classified from high to extreme priority as they connect the zone from east to west through 10.5 km in length (which communicated Pedrógão Grande with other municipalities such as Figueiró dos Vinhos) and are associated with the largest number of users within the case study (1061 users/hr).

This corridor divides the zone into two different priority areas. The Northwest area has medium-priority roads because of their proximity to high-exposure fire propagation sources and connectivity but low traffic demand. Road 57-116 (4.24 km long) is the exception in this area (highlighted in red in the northwestern zone, Fig. 13), classified as an extreme priority road since its interruption would affect around 711 users/hr and there are no nearby alternative routes. As well as the corridor formed by roads 12–71, 13–72, 14–73, and 15–74 with 12 km in length (highlighted in red in the northeastern zone, Fig. 13), that connects the northeast and center of the case study, i.e., isolates Pedrógão Grande from the northern municipalities. This corridor has exposed roads close to exposure sources such as gas stations and eucalyptus but also compromises the traffic demand of the network because, although it does not have a high number of users, there are no nearby alternative routes in case of evacuation.

The southern zone, with roads such as 33 (of 3 km), 39 (of 1.6 km), and 45–50 (of 1.7 km), highlighted in cyan color in Fig. 13, presents high exposure values due to their proximity to the sources, but low demand due to the low number of users associated with these routes, and vice versa (e.g., link 55 of 1.5 km, highlighted in cyan color in Fig. 13). The low demand makes them less critical, and therefore, they do not require priority attention. While roads such as 47–106, 48–107, and 50–109 are highly exposed due to their proximity to shrublands and eucalyptus and lack nearby extinction barrier, their classification as secondary roads with fewer associated users results in low and medium priority. Roads such as 40, 42, and 43, with a low criticality level because they are small and secondary roads, have a high priority level. This is due to their high exposure because even with the existence of nearby barriers, they are located in industrial areas and close to a power substation. However, some links are classified with high exposure and criticality, which makes them links with extreme priority. For example, road 44, which is extremely exposed due to its proximity to a gas station, is also one of the roads with the highest number of associated users (most critical). The roads with low exposure and criticality are 1, 112, 113, 114, 117, and 118. More examples of extreme priority are roads 12, 13, 14, and 15, close to crops, buildings, and gas stations.

When combining both analyses, the differences between route directions (links) are evident due to their criticality level. Therefore, there are some roads with different priority levels depending on the direction, for example, on roads 2–61 (Fig. 13 a), one direction (2) is of high priority while the other direction (61) is of extreme priority because of the number of users associated. One of the roads with the most drastic differences is 53–112 (Fig. 13 c), which has extreme priority in one direction (high number of users/hr) while it is of low priority in the other direction. Other examples are links 42–101, 51–110, and 54–113 (Fig. 13 b), among others. In these cases, the adaptation of the link with the highest priority of intervention will benefit the road and therefore the wildfire resilience of the entire

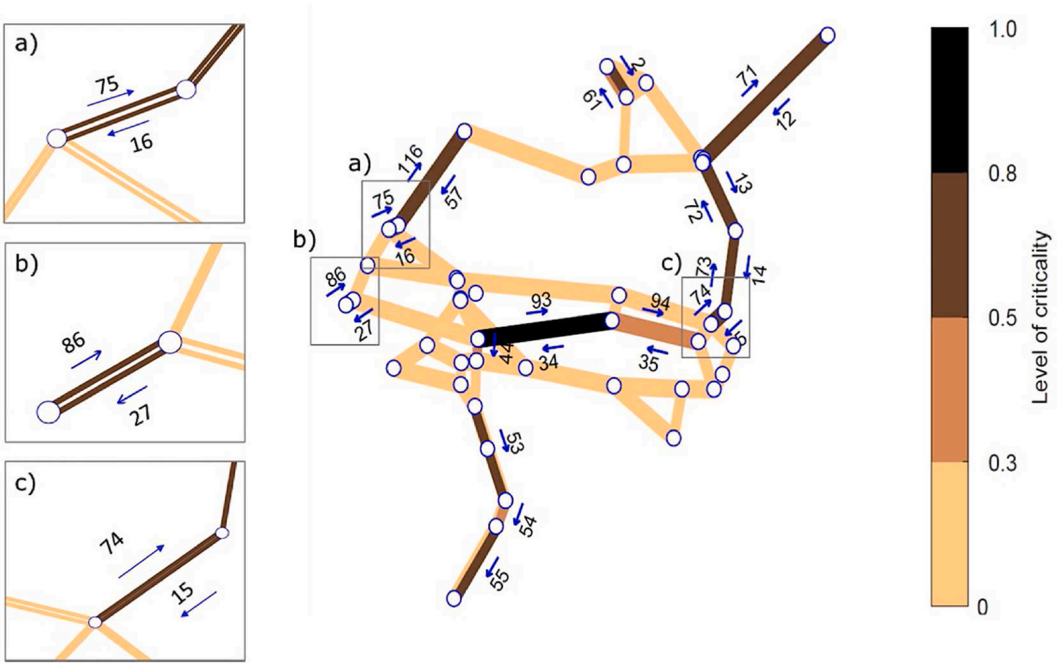

Fig. 12. Ranking of critical links for the Pedrógão Grande traffic network.

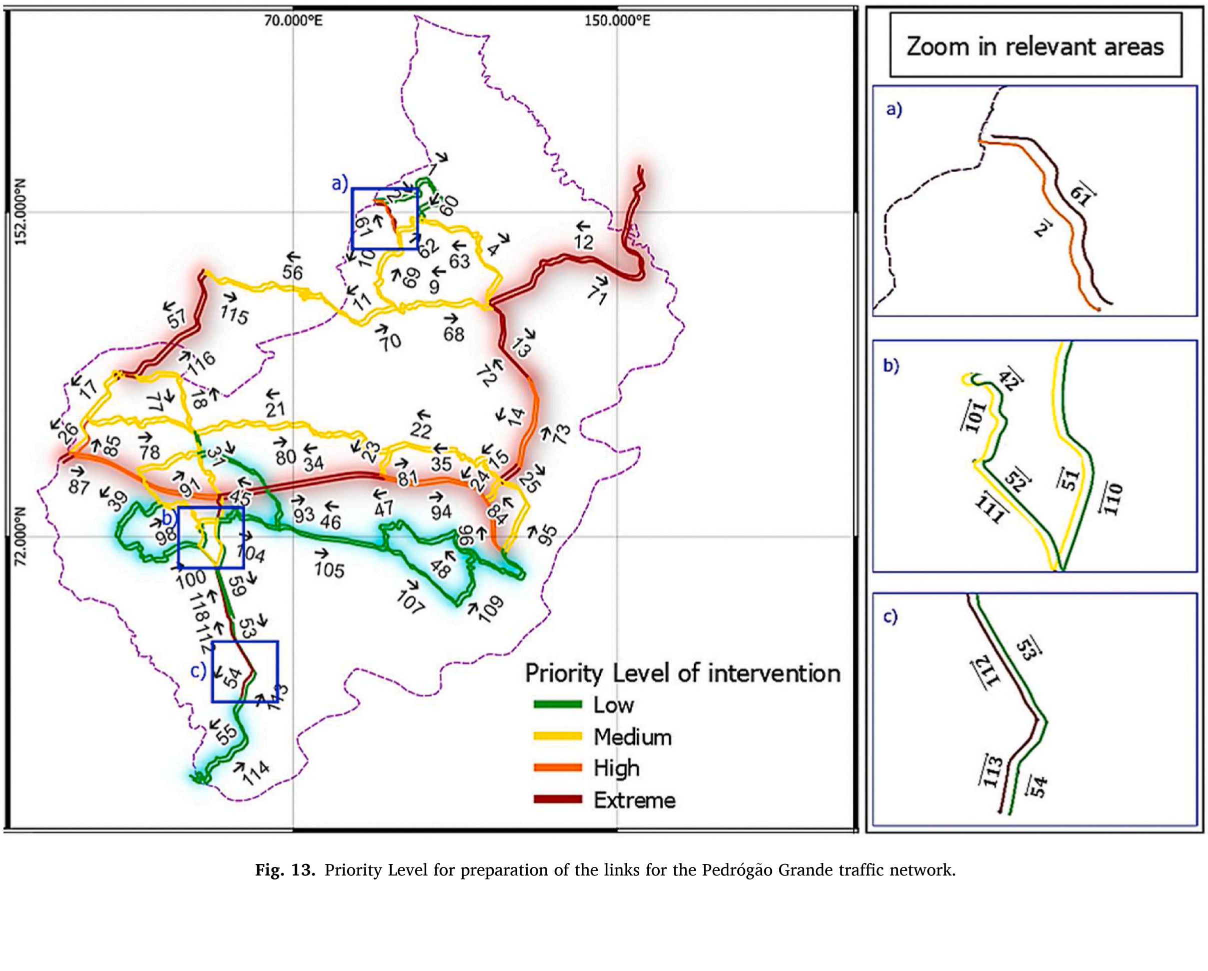

Fig. 13. Priority Level for preparation of the links for the Pedrógão Grande traffic network.

network.

For this case study, factors affecting the spread of wildfires, such as geography favoring adverse weather conditions (e.g., wind gusts) and the topography have not been considered. The influence of these orographic conditions may vary from zone to zone, increasing or decreasing exposure in some areas. However, in the analyzed case, the orographic conditions (flat orography, without physical barriers that promote specific wind directions) were not considered differentiating factors. Thus, they have been neglected because they would modify the EFD and FIRAT equally on all roads, maintaining the ranking order. In other case studies with more irregular orography, the FIRAT should reflect these conditions, penalizing the steepest areas. These will be considered in future work, along with a criticality analysis including several links affected at the same time.

7. Conclusions

This paper proposes a novel approach to address the lack of works on critical infrastructure preparedness for wildfire risks. The methodology provides a ranking of the assets according to their priority for preparedness intervention to improve the wildfire resilience of the system. This is done through a combination of exposure and criticality analyses. The proposed methodology allows the exposure classification of the roads of a traffic network based on the closest exposure sources (fire propagation sources and barriers), as well as the fire approach time (FIRAT) associated with different wildfire categories including both normal and extreme fires. It also provides the link ranking in terms of criticality considering not only the network topology but also the associated traffic demand.

The information provided from this framework is practitioner-oriented and can be of great relevance for stakeholders (i.e., emergency first responders, infrastructure managers, and policymakers) to support decision-making and improve the response in the face of a given wildfire event. It can be used for strategic planning using the priority level map for resource investment and prioritization, not only because it clearly shows the priority areas and roads to act on, but also because FIRAT maps associated with different fire categories can support evacuation time management. Besides, these analyses support the creation of policies for the minimization of wildfire impact, prevention, and adaptation to combat wildfires and improve road network management. Also, the methodology can be used for the assessment of the effectiveness of different actions to reduce the network criticality (e.g., construction of alternative roads), as well as to reduce exposure through the creation of more barriers and vegetation management (e.g., combining the vegetation with larger ROS, which allows rapid-fire advance, with more fire-resistant vegetation). This will be explored in future works.

Other advantages of the approach are the immediate visualization of the impact of potential actions, facilitating the understanding of the results. It is easy to use and understand for any user type. Compared to detailed-scenario analysis, this framework is a non-detailed tool (it is easily applicable), upgradeable to any type of system (e.g., buildings), requiring minimal data (mostly available from open data sources), and is not computationally demanding. Despite that, the outputs provide a general overview of the system's criticality and exposure for supporting decision-making and prioritizing resources. Since the approach is based on a resilience perspective, it identifies the parts of the network that would be most affected under a wildfire event (moderate to large magnitude) avoiding the consideration of the fire probability occurrence and therefore the associated uncertainty. It includes many relevant parameters, such as natural and man-made exposure sources and barriers, structures, and connectivity of the road network, and the traffic conditions capturing the economic characteristics of the studied area. This allows the evaluation of different types of policies, from infrastructure management at an asset or system level to ecological or environmental management.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Data availability

Data will be made available on request.

Acknowledgments

This work was partly financed by FCT/MCTES through national funds (PIDDAC) under the R&D Unit Institute for Sustainability and Innovation in Structural Engineering (ISISE), under reference UIDB/04029/2020, and under the Associate Laboratory Advanced Production and Intelligent Systems ARISE under reference LA/P/0112/2020. This work is financed by national funds through the Foundation for Science and Technology (Fundação para a ciência e tecnologia, FCT, Portugal), under grant agreement 2020.05755.BD attributed to the first author.

Appendix A

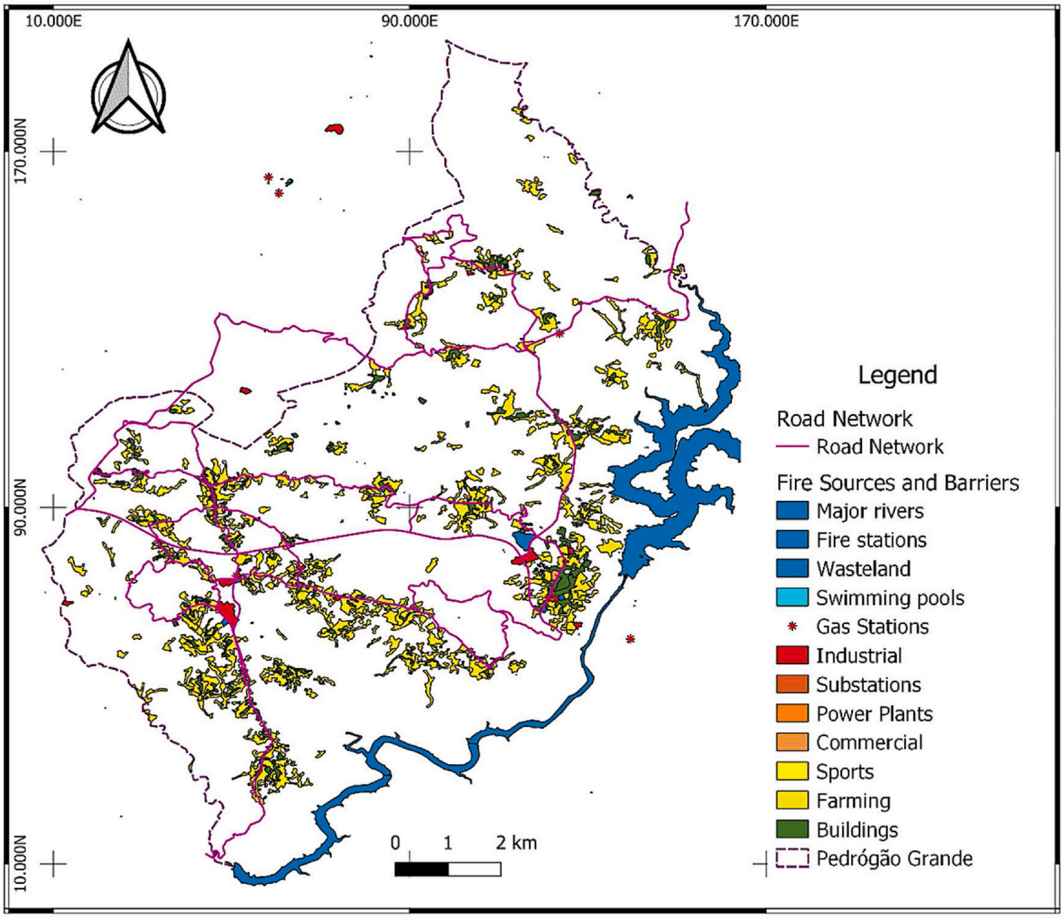

Fig. A. 1. Fire propagation sources and barriers considered for Pedrógão Grande, Portugal.

Table A. 1
Fire approach time - FIRAT (min) for Pedrógão Grande traffic network

Link	EFD (m)	Fire ROS	Cat. 1 15 m/min	Cat.2 30 m/min	Cat.3 50 m/min	Cat.4 100 m/min	Cat.5 250 m/min	Cat. 6 300 m/min	Cat. 7 >300 m/min
1	48,034,9	3202,33		1601,16	960,70	480,35	192,14	160,12	96,07
2	447,8	29,85		14,93	8,96	4,48	1,79	1,49	0,90
3	475,4	31,69		15,85	9,51	4,75	1,90	1,58	0,95
4	204,3	13,62		6,81	4,09	2,04	0,82	0,68	0,41
5	389,3	25,95		12,98	7,79	3,89	1,56	1,30	0,78
6	222,9	14,86		7,43	4,46	2,23	0,89	0,74	0,45
7	261,1	17,41		8,70	5,22	2,61	1,04	0,87	0,52
8	287,7	19,18		9,59	5,75	2,88	1,15	0,96	0,58
9	112,3	7,49		3,74	2,25	1,12	0,45	0,37	0,22
10	76,9	5,13		2,56	1,54	0,77	0,31	0,26	0,15
11	360,1	24,00		12,00	7,20	3,60	1,44	1,20	0,72
12	2104,7	140,31		70,16	42,09	21,05	8,42	7,02	4,21
13	216,7	14,44		7,22	4,33	2,17	0,87	0,72	0,43
14	11,818,6	787,91		393,95	236,37	118,19	47,27	39,40	23,64
15	803,8	53,59		26,79	16,08	8,04	3,22	2,68	1,61
16	319,3	21,29		10,64	6,39	3,19	1,28	1,06	0,64
17	62,1	4,14		2,07	1,24	0,62	0,25	0,21	0,12
18	305,9	20,40		10,20	6,12	3,06	1,22	1,02	0,61
19	268,9	17,92		8,96	5,38	2,69	1,08	0,90	0,54
20	526,7	35,12		17,56	10,53	5,27	2,11	1,76	1,05
21	530,4	35,36		17,68	10,61	5,30	2,12	1,77	1,06
22	325,4	21,69		10,85	6,51	3,25	1,30	1,08	0,65

(continued on next page)

Table A. 1 (*continued*)

Link	EFD (m)	Fire ROS	Cat. 1 15 m/min	Cat.2 30 m/min	Cat.3 50 m/min	Cat.4 100 m/min	Cat.5 250 m/min	Cat. 6 300 m/min	Cat. 7 >300 m/min
23	352,7	23,51		11,76	7,05	3,53	1,41	1,18	0,71
24	516,9	34,46		17,23	10,34	5,17	2,07	1,72	1,03
25	16,223,6	1081,58		540,79	324,47	162,24	64,89	54,08	32,45
26	804,4	53,63		26,81	16,09	8,04	3,22	2,68	1,61
27	1053,8	70,25		35,13	21,08	10,54	4,22	3,51	2,11
28	390,3	26,02		13,01	7,81	3,90	1,56	1,30	0,78
29	468,6	31,24		15,62	9,37	4,69	1,87	1,56	0,94
30	193,4	12,90		6,45	3,87	1,93	0,77	0,64	0,39
31	135,9	9,06		4,53	2,72	1,36	0,54	0,45	0,27
32	37,8	2,52		1,26	0,76	0,38	0,15	0,13	0,08
33	250,1	16,67		8,34	5,00	2,50	1,00	0,83	0,50
34	119,7	7,98		3,99	2,39	1,20	0,48	0,40	0,24
35	1627,1	108,47		54,24	32,54	16,27	6,51	5,42	3,25
36	8355,6	557,04		278,52	167,11	83,56	33,42	27,85	16,71
37	4101,6	273,44		136,72	82,03	41,02	16,41	13,67	8,20
38	1498,6	99,91		49,95	29,97	14,99	5,99	5,00	3,00
39	25,9	1,73		0,86	0,52	0,26	0,10	0,09	0,05
40	55,8	3,72		1,86	1,12	0,56	0,22	0,19	0,11
41	27,758,9	1850,59		925,30	555,18	277,59	111,04	92,53	55,52
42	39,4	2,63		1,31	0,79	0,39	0,16	0,13	0,08
43	21,1	1,41		0,70	0,42	0,21	0,08	0,07	0,04
44	246,6	16,44		8,22	4,93	2,47	0,99	0,82	0,49
45	506,9	33,79		16,90	10,14	5,07	2,03	1,69	1,01
46	665,1	44,34		22,17	13,30	6,65	2,66	2,22	1,33
47	1,4	0,09		0,05	0,03	0,01	0,01	0,00	0,00
48	68,0	4,53		2,27	1,36	0,68	0,27	0,23	0,14
49	3973,0	264,87		132,43	79,46	39,73	15,89	13,24	7,95
50	65,4	4,36		2,18	1,31	0,65	0,26	0,22	0,13
51	724,1	48,27		24,14	14,48	7,24	2,90	2,41	1,45
52	669,3	44,62		22,31	13,39	6,69	2,68	2,23	1,34
53	407,1	27,14		13,57	8,14	4,07	1,63	1,36	0,81
54	882,0	58,80		29,40	17,64	8,82	3,53	2,94	1,76
55	50,062,3	3337,49		1668,74	1001,25	500,62	200,25	166,87	100,12
56	822,3	54,82		27,41	16,45	8,22	3,29	2,74	1,64
57	913,3	60,89		30,44	18,27	9,13	3,65	3,04	1,83
58	249,5	16,64		8,32	4,99	2,50	1,00	0,83	0,50
59	243,5	16,23		8,12	4,87	2,43	0,97	0,81	0,49

Table A. 2
Origin-destination pair nodes, demand, and the number of routes considered for the Pedrógão Grande traffic network.

Origin Node	Destination node	D_{pq} (users/hour)	No. of routes
1	35	390	5
1	36	438	5
10	22	251	5
10	36	290	5
10	22	250	5
12	36	550	5
12	43	653	1
22	35	370	5
22	36	1061	5
22	43	431	5
23	35	222	5
23	36	600	5
23	42	672	5
10	1	285	5
36	1	537	5
22	10	603	5
36	10	223	5
36	12	687	5
43	12	711	1
23	22	329	1
35	22	591	5
36	22	888	5
43	22	541	5
35	23	422	5
36	23	605	5

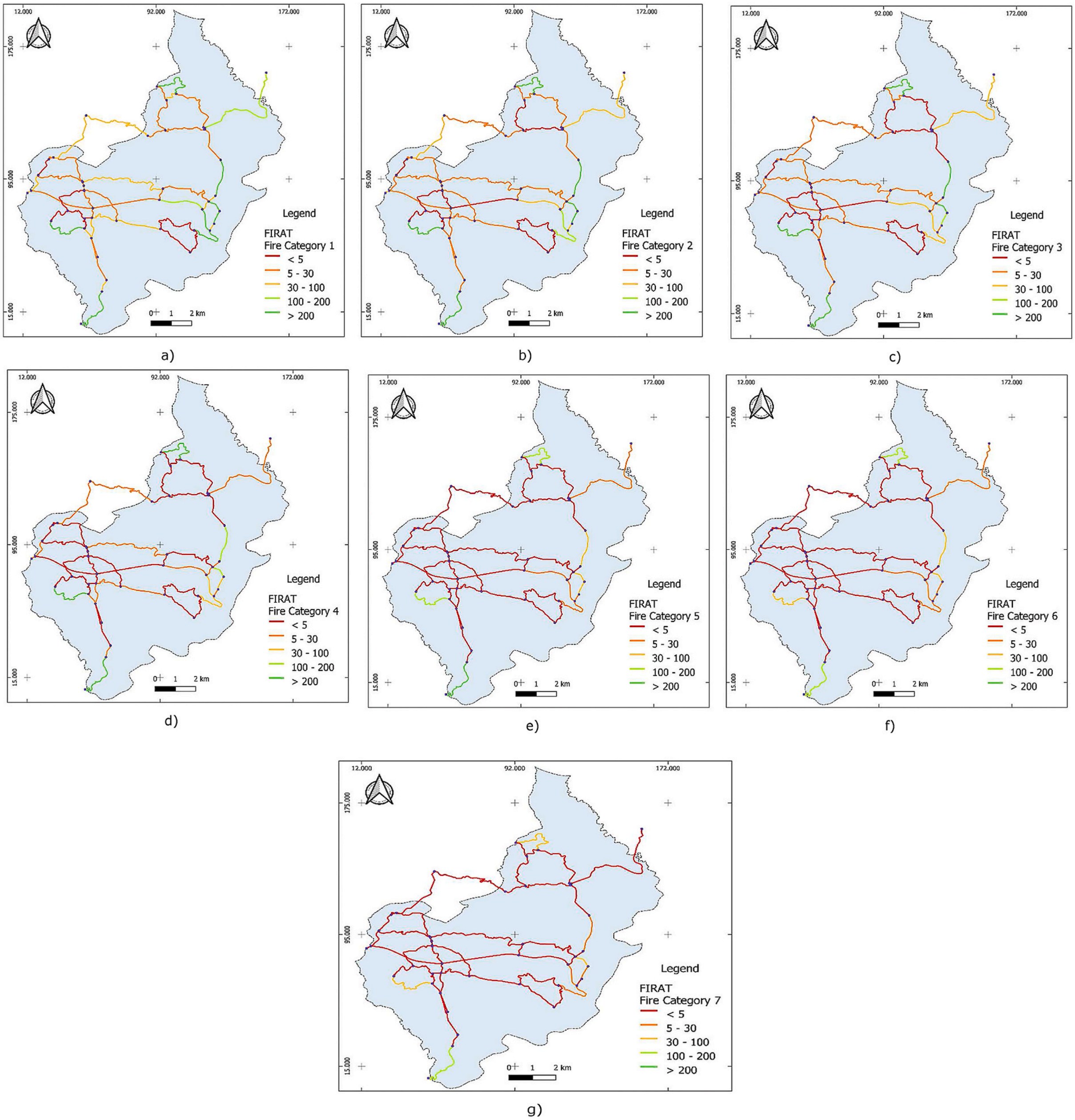

Fig. A. 2. Fire Approach Time - FIRAT for Pedrógão Grande traffic network (in minutes). a) - d) Fire category 1–4, 'Normal fires' e) - g) Fire category 5–7 'extreme wildfire event'.

References

[1] A. Rosenthal, E. Stover, R.J. Haar, Health and social impacts of California wildfires and the deficiencies in current recovery resources: an exploratory qualitative study of systems-level issues, PLoS One 16 (3 March) (2021).

[2] F. Tedim, et al., Defining extreme wildfire events: difficulties, challenges, and impacts, Fire 1 (1) (2018) 1–28.

[3] D.M.J.S. Bowman, G.J. Williamson, J.T. Abatzoglou, C.A. Kolden, M.A. Cochrane, A.M.S. Smith, Human exposure and sensitivity to globally extreme wildfire events, Nat. Ecol. Evol. 1 (3) (Feb. 2017) 1–6, 2017 13.

[4] J. Ruffault, T. Curt, N.K. Martin-Stpaul, V. Moron, R.M. Trigo, "Extreme wildfire events are linked to global-change-type droughts in the northern Mediterranean," Nat, Hazards Earth Syst. Sci. 18 (3) (Mar. 2018) 847–856.

[5] G. Di Virgilio, et al., Climate change increases the potential for extreme wildfires, Geophys. Res. Lett. 46 (14) (Jul. 2019) 8517–8526.

[6] A.P. Williams, et al., Observed impacts of anthropogenic climate change on wildfire in California, Earth's Future 7 (8) (Aug. 2019) 892–910.

[7] C. Lucas, K.J. Hennessy, G.A. Mills, J.M. Bathols, Bushfire Weather in Southeast Australia Recent Trends and Projected Climate Change Impacts; Consultancy Report Prepared for the Climate, Institute of Australia, Melbourne, Vic, 2007, https://doi.org/10.25919/5e31c82ee0a4c.

[8] A. Buscarino, M. Frasca, L.V. Gambuzza, P. Hovel, Chimera states in time-varying complex networks, Phys. Rev. E - Stat. Nonlinear Soft Matter Phys. 91 (2) (Dec. 2014).

[9] I. Zambon, A. Cerdà, P. Cudlin, P. Serra, S. Pili, L. Salvati, Road network and the spatial distribution of wildfires in the Valencian community (1993–2015), Agric. For. 9 (5) (May 2019) 100, https://doi.org/10.3390/agriculture9050100, 2019, Vol. 9, Page 100.

[10] O. Viedma, J. Quesada, I. Torres, A. De Santis, J.M. Moreno, "Fire severity in a large fire in a Pinus pinaster forest is highly predictable from burning conditions, Stand Structure, and Topography," Ecosystems 18 (2) (Mar. 2015) 237–250.

[11] F. Tedim, V. Leone, G. Xanthopoulos, A wildfire risk management concept based on a social-ecological approach in the European Union: fire Smart Territory, Int. J. Disaster Risk Reduc. 18 (Sep. 2016) 138–153.

[12] F. Moreira, et al., Wildfire management in Mediterranean-type regions: paradigm change needed, Environ. Res. Lett. 15 (1) (Jan. 2020), 011001.

[13] A. Ganteaume, R. Barbero, M. Jappiot, E. Maillé, Understanding future changes to fires in southern Europe and their impacts on the wildland-urban interface, J. Saf. Sci. Resil. 2 (1) (Mar. 2021) 20–29.

[14] M. Castellnou, et al., Empowering strategic decision-making for wildfire management: avoiding the fear trap and creating a resilient landscape, Fire Ecol 15 (1) (Dec. 2019) 1–17.

[15] M. Nogal, A. O'Connor, Resilience assessment of transportation networks, in: Routledge Handbook of Sustainable and Resilient Infrastructure, 2018.

[16] T.J. Cova, D.M. Theobald, J.B. Norman, L.K. Siebeneck, Mapping wildfire evacuation vulnerability in the western US: the limits of infrastructure, Geojournal 78 (2013) 273–285.

[17] T. Toledo, I. Marom, E. Grimberg, S. Bekhor, Analysis of evacuation behavior in a wildfire event, Int. J. Disaster Risk Reduc. 31 (Oct. 2018) 1366–1373.

[18] A.W. Dye, J.B. Kim, A. McEvoy, F. Fang, K.L. Riley, Evaluating rural Pacific Northwest towns for wildfire evacuation vulnerability, Nat. Hazards 107 (1) (May 2021) 911–935.

[19] S. Grajdura, S. Borjigin, D. Niemeier, Fast-moving dire wildfire evacuation simulation, Transport. Res. Transport Environ. 104 (Mar. 2022), 103190.

[20] E. Kuligowski, Evacuation decision-making and behavior in wildfires: past research, current challenges and a future research agenda, Fire Saf. J. 120 (Mar. 2021), 103129.

[21] A. Duane, M. Castellnou, L. Brotons, Towards a comprehensive look at global drivers of novel extreme wildfire events, Clim. Change 165 (3) (Apr. 2021) 1–21, 2021 1653.

[22] V. Kotroni, et al., DISARM early warning system for wildfires in the eastern mediterranean, Sustain. Times 12 (16) (Aug. 2020) 6670, 2020, Vol. 12, Page 6670.

[23] S.D. Wong, J.C. Broader, J.L. Walker, S.A. Shaheen, Understanding California wildfire evacuee behavior and joint choice making, Transportation (Apr. 2022) 1–47.

[24] A.M. Stasiewicz, T.B. Paveglio, Preparing for wildfire evacuation and alternatives: exploring influences on residents' intended evacuation behaviors and mitigations, Int. J. Disaster Risk Reduc. 58 (May 2021), 102177.

[25] R.D. Collins, R. de Neufville, J. Claro, T. Oliveira, A.P. Pacheco, Forest fire management to avoid unintended consequences: a case study of Portugal using system dynamics, J. Environ. Manag. 130 (Nov. 2013) 1–9.

[26] M. Nogal, A. O'Connor, Resilience Assessment of Transportation Networks, Routledge Handb. Sustain. Resilient Infrastruct., Jan. 2018, pp. 199–215.

[27] ISO, ISO Guide 73:2009 Risk Management — Vocabulary, the International Organization for Standardization, 2009.

[28] UNISDR. Global Assessment Report on Disaster Risk Reduction: Making development sustainable, the future of disaster risk management, United Nations Office for Disaster Risk Reductio, Geneva, Switzerland, 2015. https://www.undrr.org/publication/global-assessment-report-disaster-risk-reduction-2015.

[29] J. Dowds, karen Sentoff, J. Sullivan, L. Aultman-Hall, Transportation Network Data Requirements for Assessing Criticality for Resiliency and Adaptation Planning. A Research Report from the National Center for Sustainable Transportation about the National Center for Sustainable Transportation, Vermont, 2017. Retrieved from, https://escholarship.org/uc/item/8t60z813.

[30] K. Rebello, et al., Testing a criticality framework for road networks in Auckland, New Zealand, Int. J. Disaster Resil. Built Environ. 10 (1) (Apr. 2019) 36–51.

[31] B. Martinez-Pastor, M. Nogal, A. O'Connor, R. Teixeira, Identifying critical and vulnerable links: a new approach using the Fisher information matrix, Int. J. Crit. Infrastruct. Prot. 39 (Dec. 2022), 100570.

[32] S. Yang, et al., Criticality ranking for components of a transportation network at risk from tropical cyclones, Int. J. Disaster Risk Reduc. 28 (Jun. 2018) 43–55.

[33] R.A. El-Rashidy, S.M. Grant-Muller, An assessment method for highway network vulnerability, J. Transport Geogr. 34 (2014).

[34] H. Seppänen, P. Luokkala, Z. Zhang, P. Torkki, K. Virrantaus, Critical infrastructure vulnerability—a method for identifying the infrastructure service failure interdependencies, Int. J. Crit. Infrastruct. Prot. 22 (2018), https://doi.org/10.1016/j.ijcip.2018.05.002.

[35] M. Nogal, O. Morales Nápoles, A. O'Connor, Structured expert judgement to understand the intrinsic vulnerability of traffic networks, Transport. Res. Part A Policy Pract. 127 (2019).

[36] K. Mahajan, A.M. Kim, Vulnerability assessment of Alberta's provincial highway network, Transp. Res. Interdiscip. Perspect. 6 (Jul. 2020), 100171, https://doi.org/10.1016/j.trip.2020.100171.

[37] J. Rozenberg, C. Briceno-Garmendia, X. Lu, L. Bonzanigo, H. Moroz, "Improving the Resilience of Peru's Road Network to Climate Events," Improv. Resil. Peru's Road Netw. To Clim. Events, The World Bank, 2017.

[38] J.M. Moratalla, S.R. Uma, Probabilistic assessment of road accessibility under cascading hazards, Int. J. Disaster Risk Reduc. 91 (Jun. 2023), 103692.

[39] L.G. Mattsson, E. Jenelius, Vulnerability and resilience of transport systems - a discussion of recent research, Transport. Res. Part A Policy Pract. 81 (Nov. 2015) 16–34.

[40] C. Colon, S. Hallegatte, J. Rozenberg, Criticality analysis of a country's transport network via an agent-based supply chain model, Nat. Sustain. 4 (3) (2021).

[41] B.A. Jafino, J. Kwakkel, A. Verbraeck, Transport network criticality metrics: a comparative analysis and a guideline for selection. https://doi.org/10.1080/01441647.2019.1703843, Mar. 2019 vol. 40, no. 2, pp. 241–264.

[42] S.A. Hassan, H.A. Amlan, N.E. Alias, M.A. Ab-Kadir, N.S.A. Sukor, Vulnerability of road transportation networks under natural hazards: a bibliometric analysis and review, Int. J. Disaster Risk Reduc. 83 (Dec. 2022), 103393.

[43] J. Beverly, et al., FireSmart: wildfire exposure assessment: A planning tool for identifying values at risk and prioritizing mitigation effort. Guide of FireSmart Canada, 2018. https://firesmartcanada.ca/wp-content/uploads/2022/01/FS_ExposureAssessment_Sept2018-1.pdf.

[44] M. Salis, et al., Application of simulation modeling for wildfire exposure and transmission assessment in Sardinia, Italy, Int. J. Disaster Risk Reduc. 58 (2021).

[45] D. Li, T.J. Cova, P.E. Dennison, Setting wildfire evacuation triggers by coupling fire and traffic simulation models: a spatiotemporal GIS approach, Fire Technol. 55 (2) (Mar. 2019) 617–642.

[46] L.F. De Castro Galizia, M. Rodrigues, Modeling the influence of eucalypt plantation on wildfire occurrence in the Brazilian savanna biome, For 10 (10) (Sep. 2019) 844, 2019, Vol. 10, Page 844.

[47] C. Campos-Vargas, D. Vargas-Sanabria, Assessing the probability of wildfire occurrences in a neotropical dry forest. https://doi.org/10.1080/11956860.2021.1916213, Jun. 2021 vol. 28, no. 2, pp. 159–169.

[48] W. You, et al., Geographical information system-based forest fire risk assessment integrating national forest inventory data and analysis of its spatiotemporal variability, Ecol. Indicat. 77 (Jun. 2017) 176–184.

[49] A. Hysa, F.A.T. Başkaya, "A GIS based method for indexing the broad-leaved forest surfaces by their wildfire ignition probability and wildfire spreading capacity," Model, Earth Syst. Environ. 5 (1) (Mar. 2019) 71–84.

[50] J. Yang, et al., Predicting wildfire occurrence distribution with spatial point process models and its uncertainty assessment: a case study in the Lake Tahoe Basin, USA, Int. J. Wildland Fire 24 (3) (2015) 380–390, 24(3) 380-390.

[51] M. Naderpour, H.M. Rizeei, F. Ramezani, Forest fire risk prediction: a spatial deep neural network-based framework, Rem. Sens. 13 (13) (Jun. 2022) 2513, https://doi.org/10.3390/rs13132513, 2021, Vol. 13, Page 2513.

[52] P. Sun, Y. Zhang, A probabilistic method predicting forest fire occurrence combining firebrands and the weather-fuel complex in the northern part of the Daxinganling Region, China, Forests 9 (7) (2018) 1–19.

[53] Z. Wang, H.T. Vo, M. Salehi, L.I. Rusu, C. Reeves, A. Phan, "A large-scale spatio-temporal data analytics system for wildfire risk management," GeoRich 2017 - 4th Int. ACM Work, Manag. Min. Enriched Geo-Spatial Data, Conjunction with SIGMOD (2017) 19–24. May 2017.
[54] J. San-Miguel-Ayanz, et al., "Forest Fires in Europe, Middle East and North Africa 2017," EUR 29318 EN, Publications Office of the European Union, Luxembourg, 2017, https://doi.org/10.2760/27815.
[55] D. Prieto Herráez, M.I. Asensio Sevilla, L. Ferragut Canals, J.M. Cascón Barbero, A. Morillo Rodríguez, A GIS-based fire spread simulator integrating a simplified physical wildland fire model and a wind field model. https://doi.org/10.1080/13658816.2017.1334889, Nov. 2017 vol. 31, no. 11, pp. 2142–2163.
[56] M. Asori, D. Emmanuel, G. Dumedah, Wildfire hazard and risk modelling in the northern regions of Ghana using GIS-based multi-criteria decision-making analysis, J. Environ. Earth Sci. 10 (11) (Nov. 2020) 11–26, https://doi.org/10.7176/JEES/10-11-02.
[57] A. Tiwari, M. Shoab, A. Dixit, GIS-based forest fire susceptibility modeling in Pauri Garhwal, India: a comparative assessment of frequency ratio, analytic hierarchy process and fuzzy modeling techniques, Nat. Hazards 105 (2) (Jan. 2021) 1189–1230.
[58] C.A. Schultz, L.F. Miller, S.M. Greiner, C. Kooistra, A qualitative study on the US forest service's risk management assistance efforts to improve wildfire decision-making, For 12 (3) (Mar. 2021) 344, 2021, Vol. 12, Page 344.
[59] S. Costafreda-Aumedes, C. Comas, C. Vega-Garcia, Human-caused fire occurrence modelling in perspective: a review, Int. J. Wildland Fire 26 (12) (Dec. 2017) 983–998.
[60] J. Silva, et al., A systematic review and bibliometric analysis of wildland fire behavior modeling, Fluid 7 (12) (2022).
[61] C. Vitolo, C. Di Napoli, F. Di Giuseppe, H.L. Cloke, F. Pappenberger, Mapping combined wildfire and heat stress hazards to improve evidence-based decision making, Environ. Int. 127 (Jun. 2019) 21–34.
[62] M.-A. Parisien, et al., Applications of simulation-based burn probability modelling: a review, Int. J. Wildland Fire 28 (12) (Oct. 2019) 913–926.
[63] M. Rodrigues, A. Jiménez-Ruano, D. Peña-Angulo, J. de la Riva, A comprehensive spatial-temporal analysis of driving factors of human-caused wildfires in Spain using Geographically Weighted Logistic Regression, J. Environ. Manag. 225 (Nov. 2018) 177–192.
[64] CTI, Análise e apuramento dos factos relativos aos incêndios que ocorreram em Pedrógão Grande, Castanheira de Pera, Ansião, Alvaiázere, Figueiró dos Vinhos, Arganil, Góis, Penela, Pampilhosa da Serra, Oleiros e Sertã" Comissão Técnica Independente, Assembleia da República, Lisboa Portugal, 2017.
[65] M.A. Finney, Fire growth using minimum travel time methods, Can. J. For. Res. 32 (8) (2002).
[66] A.L. Sullivan, J.S. Gould, Wildland fire rate of spread, Encycl. Wildfires Wildland-Urban Interface Fires (2019) 1–4.
[67] F. Pimont, J.L. Dupuy, R.R. Linn, Coupled slope and wind effects on fire spread with influences of fire size: a numerical study using FIRETEC, Int. J. Wildland Fire 21 (7) (2012).
[68] P.M. Fernandes, Upscaling the estimation of surface-fire rate of spread in maritime pine (Pinus pinaster Ait.) forest, IForest 7 (2) (2014).
[69] M. Nogal, "Mathematical Methods for Traffic Prediction" (PhD Thesis), Universidad de Cantabria, 2012. https://www.tdx.cat/bitstream/handle/10803/56317/TesisMNM.pdf.
[70] PGM, Pedrógão Grande - Património Natural, Pedrógão Grande Municipality, 2022 [Online]. Available: https://shorturl.at/giHRS. (Accessed 4 May 2022).
[71] DGT, Carta de Uso e Ocupação do Solo para 2018, DGT, 2018 [Online]. Available: https://www.dgterritorio.gov.pt/Carta-de-Uso-e-Ocupacao-do-Solo-para-2018. (Accessed 23 February 2022).
[72] DGT, Análises temáticas: Uso e ocupação do solo em Portugal continental, 2020 [Online] Available: https://www.dgterritorio.gov.pt/sites/default/files/publicacoes/folheto_cos_lq.pdf. (Accessed 26 February 2022).
[73] Assembleia da República, Avaliação dos Incêndios ocorridos entre 14 e 16 de outubro de 2017 em Portugal Continental, Comissão Técnica Independente, Assembleia da República, Lisboa Portugal, 2018.
[74] J.H. Scott, R.E. Burgan. Standard Fire Behavior Fuel Models: A Comprehensive Set for Use with Rothermel's Surface Fire Spread Model." General Technical Report-RMRS-GTR-153, United States Department of Agriculture, Forest Service, Rocky Mountain Research, Station, 2005, p. 72. https://www.fs.usda.gov/rm/pubs_series/rmrs/gtr/rmrs_gtr153.pdf.
[75] M.G. Cruz, J.S. Gould, M.E. Alexander, A.L. Sullivan, W.L. McCaw, S. Matthews, Empirical-based models for predicting head-fire rate of spread in Australian fuel types, Aust. For. 78 (3) (Jul. 2015) 118–158.
[76] R. Brus, et al., Extent, distribution, and origin of non-native forest tree species in Europe, Scand. J. For. Res. 34 (7) (Oct. 2019) 533–544.
[77] Invasoras.pt, Mapa de avistamentos | Plantas Invasoras em Portugal [Online]. Available: https://invasoras.pt/pt/mapeamento. (Accessed 25 January 2022).
[78] D. Heron, G. Thomas, J. Cousins, B. Lukovic, R. Schmid, Modelling Fire-Spread in and Around Urban Centres, Fire Service Commission - Geological & Nuclear Sciences, New Zealand, 2003.
[79] M. Teixeira, Análise crítica e prospetiva da exploração agrícola Herdade do Pedrógão, Universidade de Lisboa, Lisboa, 2016. http://hdl.handle.net/10400.5/12108.
[80] ABC News, Petrol Station Gutted by Fire at Riverton North of Adelaide, ABC News, 2015.
[81] ARIA Technologies, Petrol Station Accidents France, 1958 - 2007, Boulogne-Billancourt, France, 2009.
[82] EPA CEPP, Risk Management Program Guidance for Propane Storage Facilities (40 CFR PART 68), Chemical Emergency Preparedness and Prevention Office, United States, 1998.
[83] S. Al-Hajj, H.R. Dhaini, S. Mondello, H. Kaafarani, F. Kobeissy, R.G. DePalma, Beirut ammonium nitrate blast: analysis, review, and recommendations, Front. Public Health 9 (Jun. 2021) 661.
[84] R. Ahumada, R. Lillis, "CA Power Substation Fire Spreads to Building," Fire Damaged an Electrical Substation, Then Spread to a Building in Downtown Sacramento that Resulted in a Six-Block Blackout, 2021 [Online]. Available: https://rb.gy/rm3u6. (Accessed 26 January 2022).
[85] Dominion Energy, Substation fires [Online]. Available: https://firstresponder.domsafety.com/topic/substation-fires/, 2022. (Accessed 26 January 2022).
[86] R. Blanc, et al.. Guide for Transformer Fire Safety Practices. Report 537, Working Group A2.33, CIGRE publication, 2013. https://docplayer.net/12159548-Guide-for-transformer-fire-safety-practices.html.
[87] Office of Civil Defense, Personal & Family Survival, Department of Defense - U.S.A, 1963. https://files.eric.ed.gov/fulltext/ED062591.pdf.
[88] J. Cousins, D. Heron, S. Mazzoni, G. Thomas, D. Lloydd, Estimating Risks from Fire Following Earthquake, Fire Service Commission, New Zealand, 2002.
[89] G. Thomas, D. Heron, G. Baker, Implementation of Urban Fire Spread Model as NZFS Tools, 2008. Wellington, New Zealand.
[90] J. Morgado, J. Amado, N. Carlos, M. Pinheiro, The development of multi-asset performance indicators for the management of the Portuguese road and rail networks, in: Towards a Resilient Built Environment - Risk and Asset Management, 2019, pp. 1643–1650.
[91] HCM, Highway Capacity Manual, National Academy of Sciences, 2000.
[92] L.V. Leong, K.Y. Tan, Volume-delay function in trip assignment, Appl. Mech. Mater. 802 (Oct. 2015) 351–356.
[93] E.T. Mtoi, R. Moses, Calibration and evaluation of link congestion functions: applying intrinsic sensitivity of link speed as a practical consideration to heterogeneous facility types within urban network, J. Transport. Technol. 4 (2) (2014) 141–149.
[94] Z. Zhou, A. Chen, S. Bekhor, C-logit stochastic user equilibrium model: formulations and solution algorithm. https://doi.org/10.1080/18128600903489629, Jan. 2010 vol. 8, no. 1, pp. 17–41.
[95] M. Nogal, D. Honfi, Assessment of road traffic resilience assuming stochastic user behaviour, Reliab. Eng. Syst. Saf. 185 (May 2019) 72–83.
[96] M. Beckmann, C.B. McGuire, C.B. Winsten, Studies in the Econ. Transport. 226 (1956) in Report/Paper Numbers.