Science of the Total Environment 899 (2023) 165704

Contents lists available at ScienceDirect

Science of the Total Environment

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

Review

Integrated wildfire danger models and factors: A review

Ioannis Zacharakis, Vassilios A. Tsihrintzis *

Centre for the Assessment of Natural Hazards and Proactive Planning & Laboratory of Reclamation Works and Water Resources Management, School of Rural, Surveying and Geoinformatics Engineering, National Technical University of Athens, 9 Heroon Polytechniou St., Zographou 15780, Athens, Greece

ARTICLE INFO

Editor: Paulo Pereira

Keywords:
Integrated wildfire danger rating systems
Forest fire danger modeling
Wildfire driving factors
Machine learning in fire science
GIS and remote sensing in fire modeling
Climate change extremes

ABSTRACT

Wildfires have been systematically studied from the early 1950s, with significant progress in the applied computational methodologies during the 21st century. However, modern methods are barely adopted by administrative authorities, globally, especially those considering probabilistic models concerning human-caused fires. An exhaustive review on wildfire danger studies has not yet been performed. Therefore, the present review aims at collecting and analyzing integrated modeling approaches in estimating forest fire danger, examining the driving factors, and evaluating their influence on fire occurrence. The main objective is to propose the top performing methods and the most important risk factors for the development of an Integrated Wildfire Danger Risk System (IWDRS). Studies were classified based on the applied technique, i.e., geographic information systems, remote sensing, statistics, machine learning, simulation modeling and miscellaneous techniques. The conclusions of each study concerning the relative importance of model input variables are also reported. Online search engines such as 'Scopus', 'Google Scholar', 'WorldWideScience', 'ScienceDirect' and 'ResearchGate' were used in relevant literature searches published in scientific journals, manuals and technical documentation. A total of 230 studies were gathered with a selected subset being evaluated in a meta-analysis process. Machine learning techniques outperform average classic statistics, although their predictability relies heavily on the quantity and the quality of the input data. Geographic information systems and remote sensing are considered valuable yet supplementary tools. Modeling techniques apply best to fire behavior prediction, while other techniques referenced in the current review are potentially useful but further investigation is needed. In conclusion, wildfire danger is a function of seven thematic groups of variables: meteorology, vegetation, topography, hydrology, socio-economy, land use and climate. Ninety-five explanatory drivers are proposed.

1. Introduction

In recent years, the frequency of extreme phenomena, such as heat waves and droughts, has been augmented rapidly, due to human-caused climate change, leading to an increase in wildfire occurrences and burn severity (Barriopedro et al., 2011; Batelis and Nalbantis, 2014; Abatzoglou and Williams, 2016; Boer et al., 2017; European Environment Agency, 2017; Fernandez-Anez et al., 2021). Particularly, regions with Mediterranean-type climate have been identified as highly fire-prone (Keeley, 2012), as extreme temperatures, strong winds and insufficient precipitation depths during the summer period have been proved to severely affect forest fire incidents (Founda and Giannakopoulos, 2009; Hernandez et al., 2015; Fernandes et al., 2016; Ruffault et al., 2017). Furthermore, land use fragmentation and land-use changes have been reported as a major fire driver in Mediterranean-type climate areas (Costafreda-Aumedes et al., 2018; Rodriguez et al., 2018).

Flannigan et al. (2005) considered four main factors that contribute to fire activity: fuel condition, climate-meteorology, ignition agents and humans. The condition of fuels, mostly described by Dead Fuel Moisture Code (DFMC) and Live Fuel Moisture Code (LFMC) based on the water presence in living or dry vegetation, has been considered as one of the major factors related to forest fires (Byram, 1959; McArthur, 1967; Keetch and Byram, 1968; Van Wagner, 1974; Deeming et al., 1977; Fosberg et al., 1981; Andrews, 1986; Rothermel, 1986; Burgan et al., 1998; Sharples et al., 2009). Among the two of the most applied approaches in estimating fuel moisture content, which include field sampling and remote sensing techniques, the latter has been thoroughly documented in the respective literature and has been the most common in fire science (Yebra et al., 2013).

Climate, meteorology, and vegetation have been at the core of almost every environmental fire danger risk system across the world, as high temperature, low relative humidity, inadequate precipitation or periods

* Corresponding author.
E-mail addresses: john_zacharakis@mail.ntua.gr (I. Zacharakis), tsihrin@survey.ntua.gr, tsihrin@otenet.gr (V.A. Tsihrintzis).

https://doi.org/10.1016/j.scitotenv.2023.165704
Received 17 March 2023; Received in revised form 18 July 2023; Accepted 20 July 2023
Available online 23 July 2023
0048-9697/

of drought, as well as strong winds and low fuel moisture content have been proved to be the most critical and necessary factors in fire occurrence (Houghton et al., 1996; Keane et al., 2001; Schlobohm and Brain, 2002). However, environmental fire danger rating systems and indices have been proved quite inadequate and outdated in fire ignition probability estimation (Zacharakis and Tsihrintzis, 2023), in terms of accuracy and validity. Some of the main reasons include the randomness of fire incidents as well as the complexity of causative factors, as most of the incidents are related to human activities, while the same variables may contribute to a totally different extent throughout different environments (Leone et al., 2009; Liu et al., 2012; Camia et al., 2013). A slightly different approach considers fire as a hierarchy of conditions related to biomass and its availability to burn, fire spread and ignition sources, documented as the hypothesis of four switches which have to occur at the same time for a fire event to happen (Archibald et al., 2009; Bradstock, 2010).

To the best of the authors' knowledge, this is the first complete attempt to gather, classify, analyze, and evaluate most of the widely applied methodologies and techniques in modeling integrated wildfire danger at a global level. Additionally, the emphasis of this review is on estimating the relative use, importance, and impact of both environmental factors (such as meteorology, vegetation, topography, hydrology, climate) and social factors (such as demography, employment, land-uses). Thus, this review focuses on studies on modeling and rating integrated fire danger, which consists of fire ignition and spread (Chuvieco et al., 2004) and includes both environmental and human factors; however, studies covering fire vulnerability, fire behavior, factors driving large fires and/or methods for estimating fire drivers are covered to the extent of being related to fire danger estimation. In more detail, models with methods and equations referring to fire vulnerability, fire severity or fire behavior are beyond the scope of this review; however, important conclusions concerning fire drivers and the relation between fire danger and fire vulnerability, fire severity or fire behavior are included. For example, defining how variables drive an already burning fire as well as the combustion properties of a fuel are not considered; however, remarks on fuel properties that lead to an uncontrollable fire of great intensity are taken into account, as arsonists might choose areas of this kind of vegetation leading to an increased fire danger. Hence, this review emphasizes prevention and pre-fire conditions, and all included studies, even those not strictly bound to fire danger modeling were scrutinized in this perspective. Consequently, the objectives of this review article are: (1) to collect, categorize and analyze the main scientific modeling approaches in estimating integrated forest fire danger; (2) to examine the factors related to forest fire incidents; (3) to evaluate the methods and the risk factors used in the included studies; and (4) to propose the top performing methods and the most important risk factors for the development of an Integrated Wildfire Danger Rating System (IWDRS). The terminology used in the current review is discussed in paragraph 3.1.

2. Material and methods

As the current article focuses on integrated fire danger modeling, literature was examined according to the following criteria: (1) studies must be papers published in scientific journals or technical documents supporting fire agency policies; (2) studies must contain systems or indices that focus on fire danger estimation; (3) studies must include social (or human) variables as driving factors or stochastic modeling. Since there are already reviews concerning fire danger modeling (e.g., Cruz and Alexander, 2010; Ganteaume et al., 2013; Rivera et al., 2012; Miller and Ager, 2013; Yebra et al., 2013; Parisien et al., 2019; Jain et al., 2020), the collection of such articles was the starting point of the present study. Then, the cited literature of the mentioned reviews was collected and scrutinized. In addition, online search engines such as 'Scopus', 'Google Scholar', 'WorldWideScience', 'ScienceDirect' and 'ResearchGate' were used, focusing on the following keywords: forest fire danger modeling; human caused fires; wildfire ignition probability; wildfire spread; machine learning in wildfires; wildfire simulation; fire danger and remote sensing. The time range of this review expands from 1957 to 2023, with more than two thirds of the included studies published in the last 20 years.

The research was conducted from September 2022 to February 2023 and the selection procedure followed the next steps: (1) the titles of the studies were compared with the above keywords; (2) those that matched were examined by their respective abstract; (3) those that their abstracts fulfilled the selection criteria mentioned above were included. Furthermore, filters such as 'year of publication' and 'reviews' were applied as needed. A total of 330 studies were included and presented in groups, based on the applied method, in the following categories: (1) Geographic Information Systems, Remote Sensing and Image Analysis; (2) Basic Statistic; (3) Machine Learning; (4) Simulation; and (5) Miscellaneous. However, since the terminology concerning fire science is complex and commonly misused, an extra section with discussion about general concepts in fire science is included in this review, based on European and international terminology. Lastly, the current review follows the PRISMA 2020 guidelines as presented in Fig. 1 (Page et al., 2021).

3. Results and discussion

3.1. General concepts

In fire science, there is often a confusion between the usage of terms, as agencies, researchers and decision makers define them differently according to local perspective. Therefore, it was considered necessary to provide definitions – according to the international literature – related to the core topics discussed in the present review. The included terms are relative to theoretical and scientific concepts rather than software, tools and techniques. The following sources were used: Merrill and Alexander, 1987; Simard, 1991; MOF, 1997; GFMC-FAO, 1999; NWCG, 2003; Hardy, 2005; Chuvieco et al., 2010; EUFOFINET, 2012. The basic definitions are included in Table 1, while the complete terminology can be found in the Supplementary Material (SM) file, in Table SM1.

3.2. Modeling methodologies and spatiotemporal distribution

In the current section, modeling methodologies based on the applied technique are presented, with emphasis on input variables and results. A selected number of the total included studies is presented in Table SM2, summarizing references, variables, methods, and conclusions. The geographical distribution of the included studies is presented in Fig. 2. Most studies were conducted in the USA and Europe, followed by Australia and Canada, i.e., regions prone to forest fires. The available funding for scientific research and civil protection mechanisms must also be considered for explaining the geographical distribution of the studies.

Accordingly, the temporal evolution of the conducted studies is presented in Fig. 3. It is obvious that most of the included studies come from the 21st century. Furthermore, the time range could be divided into the following eras based on dominant methodologies: (i) 1957–1985: deterministic models and simple regression techniques; (ii) 1985–2005: GIS and Passive Remote Sensing; (iii) 2005–2011: Simulation techniques; (iv) 2011–2023: Active Remote Sensing and Machine Learning (Fig. 3). Hence, new technologies, mostly related to computational performance, spatial resolution of sensors and greater storage capacities, have stimulated wildfire science. The number of input parameters has increased in recent decades, as well as their estimation accuracy, mostly due to the improvements in remote sensing sensors and the development of machine learning techniques, with the first allowing the acquisition of more detailed data and the second incorporating and analyzing efficiently greater volumes of data. Calculations are much more complex in modern systems, especially regarding of machine learning

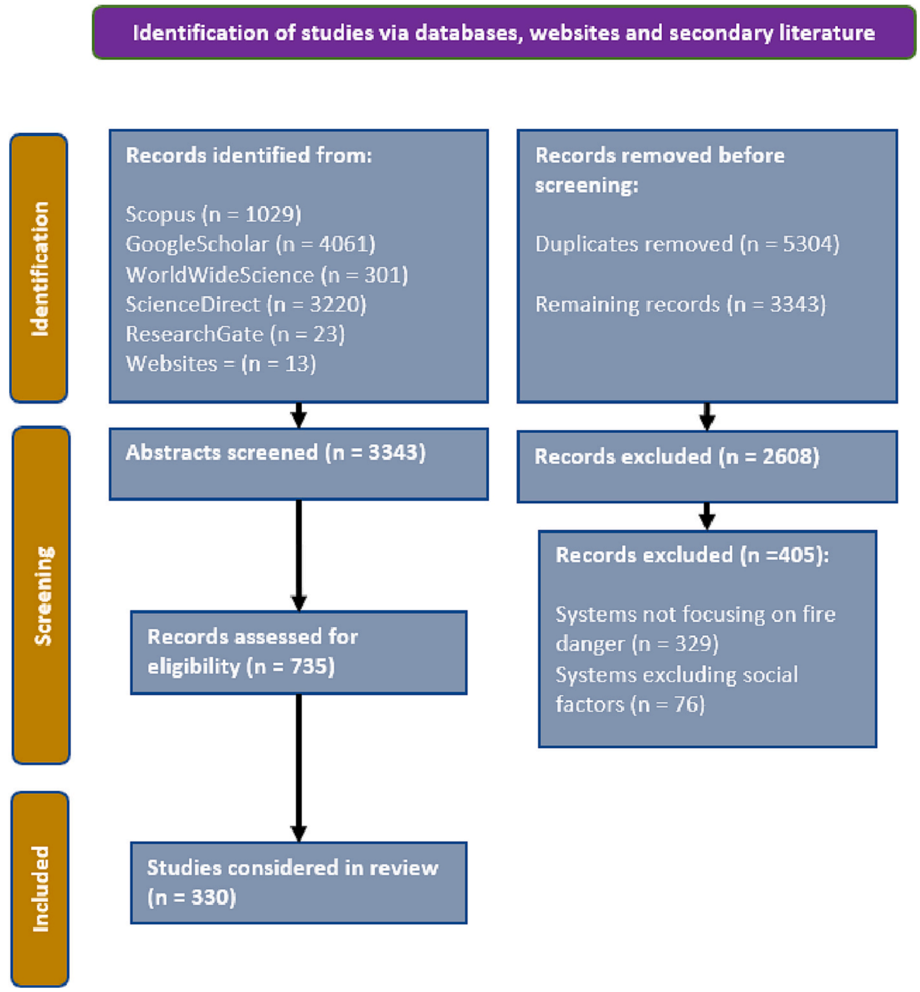

Fig. 1. The selection of scientific references based on PRISMA methodology (Page et al., 2021).

methodologies and Active Remote Sensing data. Nevertheless, few countries have incorporated modern techniques in their official forest fire danger rating systems, as discussed in Section SM3.

3.3. Geographic information systems (GIS) and remote sensing (RS)

In the first group of studies, several methods including geographic information and earth observations related to wildfires occurrence are described. GIS technology as well as remote sensing techniques have been applied to some extent in most of the described studies in the other sections of this review; however, in the following lines, the included studies make use of GIS and RS to define (sub-)indices, codes or procedures related to fire risk components, such as the estimation of fuel moisture content, the overlaying of geospatial data, classification of fuels/vegetation, and parameter proximity and topology. However, as Chuvieco and Congalton (1989) stated, "*the use of GIS presupposes the presence of a previous theory which makes it possible to combine the variables in a meaningful and efficient way*"; hence, defining the significance of each sub-component or variable incorporated in fire risk modeling, as the assignment of weights to each parameter depends on expert judgments or techniques like the Analytical Hierarchy Process (AHP), Multi-Criteria Decision Support (MCDS) methods, expert meetings or forums like the Delphi method, and stochastic approaches as discussed in following sections.

One of the early research projects, which focused on the Mediterranean coast of Spain, combined satellite images captured by Landsat Multispectral System Scanner, and GIS processing techniques. Specifically, to estimate fire hazard and behavior, Chuvieco and Congalton (1989) included the following: 16 vegetation species produced by maximum likelihood classification in GIS environment from satellite images; elevation; slope and aspect produced from digital terrain modeling (DTM) using GIS; and distance to roads, trails, campsites and housing, creating buffer zones in GIS with radii of 50 m for roads and 150 m from trails. After assigning weights based on relative literature, the model performed well in fire hazard estimation, although poor results were achieved for fire behavior estimation, mostly because parameters related to wind were excluded. A more integrated approach was adopted by Chuvieco and Salas (1996) in mapping fire danger, creating three indices for each group of variables: i) weather danger index, which included ignition probability expressed by slope-aspect-illumination from DTM, temperature and relative humidity, as well as wind data from stations using interpolation and extrapolation techniques; ii) fuel hazard, which incorporated ignition probability and fuel types based on the BEHAVE System and the products of Landsat satellite imagery; and iii) human risk, which combined GIS proximity analysis (buffer zones) with statistical data concerning burned areas. All variables were included in a raster file with 30 m × 30 m grid resolution. The model was partially validated, as the Spanish institution in charge of forest fire defense reports concluded to a 96% accuracy of the weather danger component, while the fuel hazard component was considered as accurate as the BEHAVE System, which has been reported to perform fine (Andrews, 1986).

Both Chuvieco et al. (1999) and Adaktylou et al. (2020) included variables, such as topography, vegetation, weather, and accessibility to

Table 1
Basic definitions used in the review.

Term	Description	Source
Fire danger	1] Describes factors affecting inception, spread and resistance to control and subsequent fire damage; often expressed as index	NWCG, 2003
	2] The sum of fire ignition and fire propagation	Chuvieco et al., 2010
	3] A general term used to express an assessment of both fixed and variable factors of the fire environment that determine the ease of ignition, rate of spread, difficulty of control, and fire impact; often expressed as an index	GFMC-FAO, 1999
Fire model	1] A computer program which, with given information, will predict the rate of spread of a fire from a point of origin 2] A computer model which, with given information, will predict the spread of fire as influenced by meteorological conditions, fuel characteristics, and topography	GFMC-FAO, 1999
Fire risk	The chance that a fire might start, as affected by the nature and incidence of causative agents	Hardy, 2005
Fuel model	A mathematical representation of fuel properties within a specified location, often used to predict and plot likely fire spread and intensity	EUFOFINET, 2012
Fuel type	A group of fuels that will respond to fires in a similar way	EUFOFINET, 2012
Human-caused fire	Any wildland fire (usually in the context of wildfire causes) caused by human carelessness or malicious use of fire	Merrill and Alexander, 1987 & GFMC-FAO, 1999
Ignition probability	1] The beginning of flame production or smouldering combustion; the starting of a fire	Merrill and Alexander, 1987
	2] The initiation of combustion	EUFOFINET, 2012
	3] Chance that a firebrand will cause an ignition when it lands on receptive fuels	GFMC-FAO, 1999
Wildfire	1] Any unplanned and uncontrolled wildland fire which regardless of ignition source may require suppression response, or other action according to agency policy. 2] Any free burning wildland fire unaffected by fire suppression measures which meets management objectives	GFMC-FAO, 1999

human infrastructure, and attributed weights by pairwise comparisons, based on expert opinions (EO) or on relative literature. A similar approach was adopted by Mazzeo et al. (2022) in Italy, using MCDS for weight assignment to the following variables: satellite data/products, including CORINE land cover (Bossard et al., 2000), Normalized Difference Vegetation Index (NDVI) for fuel moisture (Tucker, 1979) and fire identification images; weather forecasts (for temperature, due point temperature and wind); as well as slope and aspect. Hessburg et al. (2007) assigned weights using the AHP and expert judgments, creating a decision-support system in Utah, USA for evaluating wildfire danger as a function of three elements: fire hazard, which incorporated fuel models, canopy bulk density and canopy base height; fire behavior, which included spread rate, flame length, fireline intensity and crown fire potential; and risk of ignition using Palmer Drought Severity Index (PDSI), Keetch and Byram Drought Index (KBDI), NDVI and Lightning Strike possibility.

Remote sensing applications in fire science are numerous, mainly associated with fuel load and moisture content, fire risk mapping, fire detection, rate of spread and burn severity (e.g., Yebra et al., 2013; Veraverbeke et al., 2018; Szpakowski and Jensen, 2019; Chuvieco, 1997; Gale et al., 2021). Two types of remote sensing sensors have been applied to fire science: passive using sensors, which measure the reflected microwave energy or the radiated energy (mostly thermal emissions); and active using sensors, which transmit their own radiation in the form of pulses and capture the returned reflectance.

Passive Remote Sensing techniques relying on capturing the existing reflectance of an object, such as analysis of satellite images, have been proved to be very useful in cases where no field measurements exist; however, data preprocessing is necessary before including them into a model. Gonzalez-Alonso et al. (1997) describe analytically some of the basic preprocesses, such as radiometric and reflectance calibration, atmospheric and geometric corrections, masking, and index calculations and classification. Furthermore, passive remote sensing techniques are often critical in image analysis; thus, indices based on the reflectance of the observed objects (i.e., spectral signatures) have been proposed by researchers. The medium infrared band of approximately from 1 μm to 2.5 μm has been noticed as the most sensitive to changes in fuel moisture content, and this is a crucial parameter for short term fire danger estimation (Jensen, 1983; Rock et al., 1986; Westman and Price, 1988; Hunt and Rock, 1989; Chuvieco et al., 1999; Desbois et al., 1997). Among the most well-known indices in the aforementioned spectrum, which have been directly related to chlorophyll content in the leaves and indirectly related to water content in the leaves (Broge and Leblanc, 2001; Blackburn, 2002; Yebra et al., 2013) are: the NDVI, which is used in a great number of studies mainly as a fuel moisture content proxy (Tucker, 1979; Paltridge and Barber, 1988; Burgan, 1996; Chuvieco et al., 1999; Gonzalez-Alonso et al., 1997; Burgan et al., 1998; Wulder, 1998; Lopez et al., 2002; Chuvieco et al., 2003; Sudiana et al., 2003; Huesca et al., 2009; Qi et al., 2012; Mazzeo et al., 2022); the Relative and Visual Greenness (RG and VG, respectively) produced by historical NDVI values (e.g., Burgan and Hartford, 1993; Burgan et al., 1998; Newnham et al., 2011); and the Normalized Difference Infrared Indices (NDII) which vary depending on the included satellite band (Hardisky et al., 1983; Stow et al., 2006; Roberts et al., 2006).

When it comes to fuel moisture codes, although Dead Fuel Moisture Content (DFMC) is empirically determined from weather, fuel diameter and biochemical compositions through statistical modeling (Viney, 1991; Ager et al., 2010), Live Fuel Moisture Content (LFMC) estimation can be harder, as plants apply different strategies for surviving through periods of drought (Viegas et al., 2001). For the first one, the following indices, which have been widely applied, are presented in descending performance order: Cellulose Absorption Index (CAI), Lignin-Cellulose Absorption Index (LCAI), Normalized Difference Tillage Index (NDTI) and Shortwave-Infrared Normalized Difference Residue Index (SINDRI) (van Deventer et al., 1997; Nagler et al., 2000; Daughtry et al., 2005; Serbin et al., 2009). Dead fuel moisture codes have been also developed in environmental forest fire danger rating systems (Zacharakis and Tsihrintzis, 2023). In the second one, both burned area and large fires have been correlated to LFMC (Schoenberg et al., 2003; Dennison and Moritz, 2009), using either statistical approaches (Dennison et al., 2005; Garcia et al., 2008; Peterson et al., 2008; Caccamo et al., 2012) or deterministic models (Zarco-Tejada et al., 2003; Colombo et al., 2008; Yebra and Chuvieco, 2009). Near infrared indices, such as the Normalized Difference Water Index (NDWI) or those mentioned above, have been proved to be useful in estimating LFMC (Hardy and Burgan, 1999; Dennison et al., 2005; Yebra et al., 2008).

Gale et al. (2021) divided fuel attributes based on their vertical position, and more specifically in overstory, understory, surface, and bark fuel, as well as their condition, i.e., dead or live fuel and fuel model. Overstory main attributes, like canopy cover and height, have been modeled with reasonable accuracies, using statistical and machine learning techniques alongside with remote sensing methods (Heiskanen et al., 2011; Pierce et al., 2012; Palaiologou et al., 2013; Korhonen et al., 2017). Nevertheless, the other three types of fuel attributes have merely been modeled using passive remote sensing, as the reflectance of the understory, surface and bark fuel is interrupted by the canopies of the

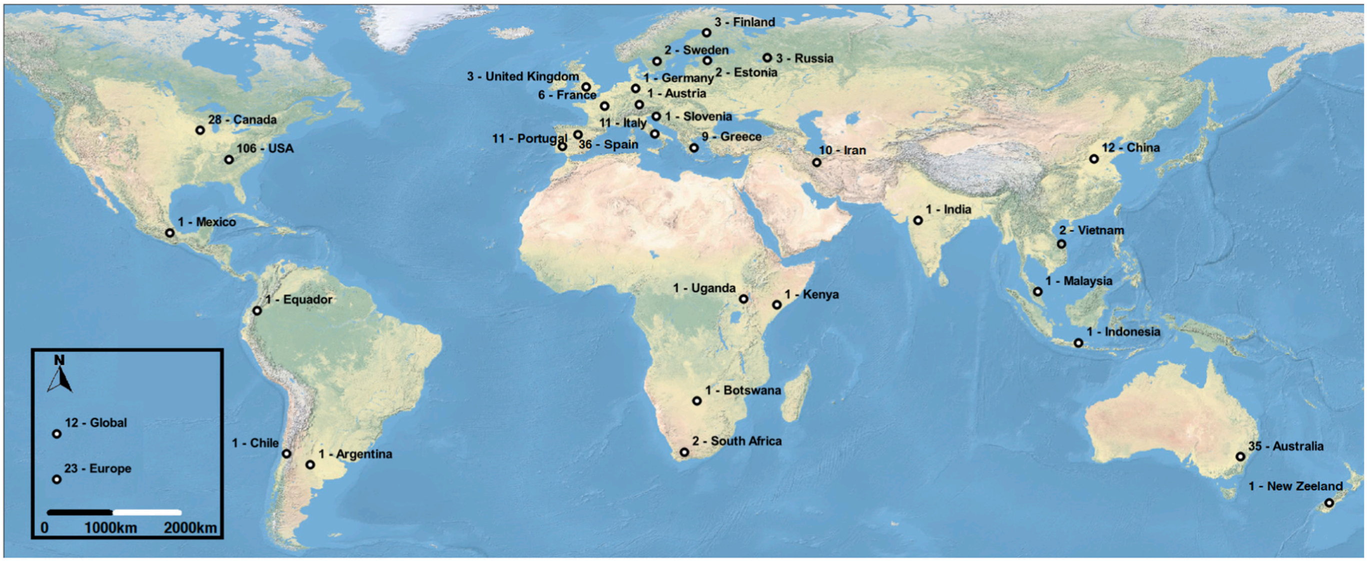

Fig. 2. Geographical distribution of included studies.

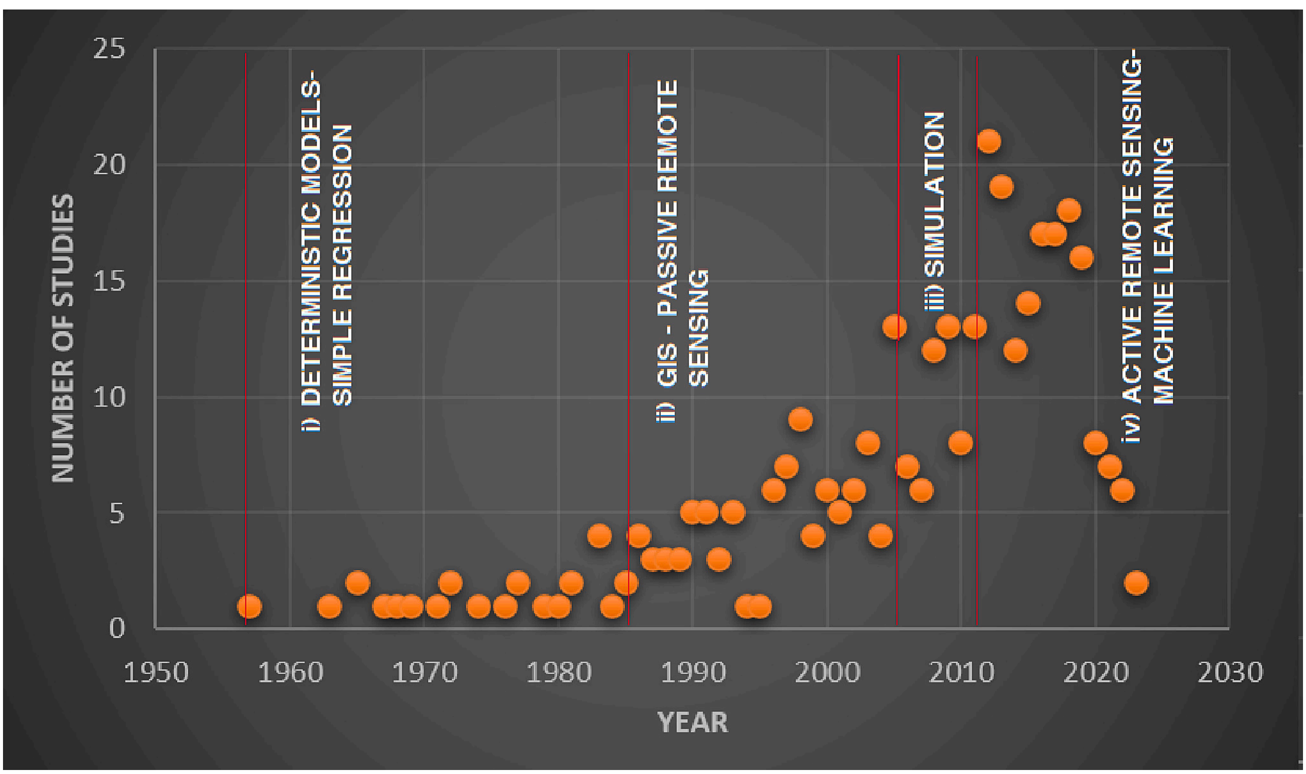

Fig. 3. Temporal distribution of main included studies.

trees (Campbell et al., 2018; Szpakowski and Jensen, 2019; Gale et al., 2021). These fuels are mostly modeled by active remote sensing techniques (usually LiDAR). Furthermore, at narrow fuel scale, mostly in stand inventories, plots and especially on individual trees or shrubs, LiDAR data techniques are considered as a reliable alternative to photogrammetric methods (Allgöwer et al., 2006).

In more detail, LiDAR has been applied in fuel mapping, individual tree analysis as well as in estimating canopy biophysical characteristics, such as bulk density, depth, volume and biomass, as well as leaf density indices (Côté et al., 2011; Seielstad et al., 2011; Béland et al., 2014; Pimont et al., 2015), approximating accuracies of 87 to 95%, especially when combined with high resolution images (Holmgren and Persson, 2004; Mutlu et al., 2008; Ferraz et al., 2009; Duff et al., 2013; Spits et al., 2017). Filippelli et al. (2019) compared LiDAR and photogrammetric point clouds for mapping forest structure in pre-fire conditions, concluding to strong correlations concerning canopy metrics, although the used method was not statistically significant in all models. Low density LiDAR with at least 1 pulse per m^2 returns can accurately describe typical forest metrics such as tree density, basal area and dominant species at plot level, meaning that costly and less accurate field measurements can be replaced at great extent (Ferraz et al., 2009; Jakubowksi et al., 2013); however, low density LiDAR has been less accurate in mixed forests (Palomino and Silva, 2021). Luo et al. (2018) proposed a method for direct estimation of crown base height from

LiDAR data in mixed forests with field validation and root mean squared error of 1.62 m, concluding that taller trees lead to less credible results. Strong relations were noticed among overstory structure, surface fuels, species richness, LiDAR data, canopy fuels and fire activity (Yavari and Sohrabi, 2019; Hudak et al., 2016). Heisig et al. (2022) integrated passive and active remote sensing data (satellite and LiDAR) with field measurements and wind data for producing custom fuel models and mapping wildfire hazard through fire spread simulation in North Germany, achieving an accuracy of 0.971 for fuel classification with the use of LiDAR and 0.73 for canopy base height. LiDAR has also contributed to the creation of accurate digital terrain models, as in Fernández-Alonso et al. (2017), who combined topographic and fuel variables derived from LiDAR measurements, proving the first as the second most important set of variables and linking lower canopy base heights to high severity fire. Lin et al. (2021) combined topographic variables and fuel properties in Dajiaxi Working Centre-Taiwan, based on Sikkink et al. (2009) fuel guide, producing two scale models from LiDAR data with relative error of 38%.

Passive and active remote sensing data mesh has also been widely applied recently for relating fire severity and vegetation structure, mostly combining indices such as the Normalized Burn Ratio (NBR), differenced NBR (dNBR), relative Normalized Burn Ratio (RdNBR), Relativized Burn Ratio (RBR), as well as indices related to field sampling techniques such as the Composite Burn Index (CBI) (e.g., Key and Benson, 2006; Allen and Sorbel, 2008; Parks et al., 2014; Viedma et al., 2020; Fernández-Guisuraga et al., 2021; Fernández-Guisuraga et al., 2022; Fernández-Guisuraga and Fernandes, 2023). Skowronski et al. (2020) used passive and active remote sensing methods introducing 11 variables related to canopy bulk density (CBD), varying in terms of height, position (ladder, mid or canopy fuels) and extremes defining 20 CBD classes. In the Pinelands National Reserve, New Jersey, consisting of *Pinus* and *Quercus* species overstories, shrub oaks mid-stories and Ericaceous shrubs understories with a layer of fast-decomposing leaf litter, they discovered that the mid CBD to canopy CBD ratio was the most important variable positively correlated to fire severity. Other important variables were max and ladder CBD, negatively correlated to total CBD as far as pre-fire conditions are concerned. In terms of post-fire, total, max and ladder CBD were negatively associated (Skowronski et al., 2020). Overall, pre-fire landscape was more heterogeneous in lower severity classes with horizontal and vertical diversity being inversely related to higher fire severities (Skowronski et al., 2020).

Viedma et al. (2020) analyzed the spatial variability of fire severity in Yeste-Spain, using three groups of explanatory variables: pre-fire vegetation composition, vegetation structure from LiDAR metrics and burning conditions (fire propagation, weather, and topography). Burned vegetation consisted of mixed pine forests (*Pinus pinaster*, *Pinus halepensis* and *Pinus nigra*) as well as shrublands (*Juniperus oxucedrous* and *Arbutus unedo*). Two satellite imageries were utilized for the calculation of fire severity indices: Sentinel 2A and Landsat 8 OLI combined with CBI from field sampling. Pre-fire vegetation structure was incorporated alongside with other biophysical variables, i.e., Leaf Area Index (LAI) and Photosynthetically Active Radiation (fPAR), as well as LiDAR data; The Canopy Relief Ratio (CRR) and the density of height bins were calculated as in Parker and Russ (2004) and Kindt and Coe (2005), respectively (Viedma et al., 2020). Fuel models were used from the Canadian Promytheus classification framework and thresholds of vegetation coverage were assigned accordingly, while other data related to burning conditions and fire behavior were also used in a statistical analysis using Boosted Regression Trees. The analysis was performed on the inserted data, revealing that CBI was more related with NBR than with the other indices, producing slightly more accurate results for Sentinel 2 rather than Landsat 8 (Viedma et al., 2020). Fire severity increased in medium to high LAI values for dNBR, RBR and in low fPAR for RdNBR. LAI and fPAR were found to be very important, also in shrublands with sporadic pines, followed by mixed pine forests and plain shrublands (Viedma et al., 2020). Heterogeneous stands with short trees but tall shrubs were severely burned, while fuel models were overall less significant. Burning conditions contributed the most, followed by LiDAR metrics and pre-fire vegetation (Viedma et al., 2020).

Fernández-Guisuraga et al. (2021) combined LiDAR metrics, Sentinel 2 images (at 10 m resolution) and field sampling with broadband land surface albedo (bLSA) data of pre-fire stands for spatializing fire severity and estimating wall-to-wall dNBR in Sierra de Cabrera (northwest Spain). Field data were used for calculating CBI aiming to validate dNBR results (Fernández-Guisuraga et al., 2021). The ecosystem consisted of gorse, heath, and broom shrublands, dominated by *Genista hystrix* Lange, *Erica australis* L., and *Genista florida* L., respectively, and *Pinus sylvestris* and *Quercus pyrenaica* forests (Fernández-Guisuraga et al., 2021). The vegetation structure, which consisted of high-density canopies with great fuel continuity, caused extreme fire behavior in oak and pine stands, while in shrubs the bLSA proved to be the most important driver (Fernández-Guisuraga et al., 2021). The most important variable for the global model was high canopy volumes rather than topography (Fernández-Guisuraga et al., 2021). Although LiDAR metrics could not significantly relate shrub ecosystems, the authors highlighted their great potential in modeling three-dimensional canopy volume (Fernández-Guisuraga et al., 2021). A similar approach was applied to Sierra del Teleno (northwest Spain) by Fernández-Guisuraga et al. (2022). The ecosystem was dominated by *Pinus pinaster*, *Quercus pyrenaica* and *Quercus ilex* trees, with understory of Ericaceae and Cistaceae. Furthermore, LiDAR metrics and Landsat 7 images were incorporated (Fernández-Guisuraga et al., 2022). Key LiDAR and Landsat ETM+ variables, which maximize AGB prediction performance, were selected as in Kane et al. (2015), applying a Random Forests (RF) regression model. Shrublands were masked using NDVI. The authors predicted wildfire severity based on pre-fire AGB estimates, incorporating dNBR calculations in the RF regression model, while CBI was calculated from field data for model validation (Fernández-Guisuraga et al., 2022). The authors confirmed the essential role of pre-fire AGB as a fire severity driver for wildfire areas dominated by forest, as also in Avitabile et al. (2012), Fernandes et al. (2015) and Viedma et al. (2015). The authors highlighted that individual pre-fire AGB for the overstory and understory forest layers led to higher predictive results rather than total AGB (Fernández-Guisuraga et al., 2022). Nevertheless, RF regression produced rather inaccurate results for understory AGB (Fernández-Guisuraga et al., 2022). Horizontal fuel continuity, distribution of fuel loads and canopy openness are also highly related to fire severity, as shown in central Portugal (Fernández-Guisuraga et al., 2022). The authors used LiDAR metrics of various return densities per strata and proved that higher surface fuel load, horizontal and vertical continuity of surface fuel and overstory increased fire severity (Fernández-Guisuraga et al., 2022). The role of RF was also important in previous studies; however, a more in-depth analysis can be found in the machine learning section of this review. Moreover, despite the strengths of LiDAR methods briefly mentioned so far, three main limitations have been documented: the signal cannot penetrate the surface (Jakubowksi et al., 2013), thence litter estimations are not credible; the vertical accuracy is about 30 cm missing very fine surface fuels (Hopkinson et al., 2005); and dense foliage downgrades the signal, underestimating the under-canopy vegetation (Dubayah and Drake, 2000). Price and Gordon (2016) found strong relations to field measurements and LiDAR data in elevated and lower canopy cover, with not that accurate results. Finally, LiDAR systematically underestimates lower canopy cover and surface fuel (Price and Gordon, 2016).

An alternative to statistical models for fuel moisture content estimation through remote sensing are (bio)-physical models such as the Radiative Transfer Models (RTMs), which simulate the reflectance of vegetation as a function of its biophysical properties, with the latter being retrieved from passive remote sensing data (Zarco-Tejada et al., 2003; Colombo et al., 2008; Yebra et al., 2013). More information concerning RTM models can be found in Gates et al. (1965), Thomas et al. (1971), Jacquemoud and Baret (1990), Kuusk (1991), Curran et al.

(1992), Hosgood et al. (1994), Fourty et al. (1996), Asner (1998), Dawson et al. (1998), Kuusk (2001), Ma et al. (2013), and He et al. (2013). Single RTM models have been mostly applied to homogeneous vegetation (as in agricultural crops) rather than mixed and multi-layered forests (Jacquemoud, 1993; Jacquemoud et al., 1995). However, in the latter cases, the coupling of RTMs has been proved more accurate and representative, as in Sichuan province, China, where field data of forest canopy leaves and grasses were gathered, and parameters such as Leaf Area Index and crown coverage were measured with camera systems (Quan et al., 2017). Chlorophyll content, leaf area, EWT, dry matter content and FMC were approximated from field samples, while both NDVI and NDII indices produced from Landsat 8 OLI were calculated and used instead of multispectral bands in reducing noises (Quan et al., 2017). Quan et al. (2017) found that LAI and DMC extremes did not respond simultaneously as also reported in Mediterranean grasslands and shrublands (Yebra et al., 2008), although Equivalent Water Thickness (EWT) was correlated with chlorophyl content (Féret et al., 2011). The important role of dry matter/leaves parameter was identified by RTMs, as changes in its quantity and distribution affects more the live fuel moisture content rather than water stress (Jolly et al., 2014), while its contribution to FMC was greater than fresh leaves, and produced more accurate results (Riaño et al., 2005a). Nevertheless, actual measurements are necessary for validating and acquiring realistic results with high accuracies (Combal et al., 2003; Riaño et al., 2005b) although field measurements related to canopy biophysical properties make an important source of error, even though a priori knowledge of some of the characteristics of the targeted species can facilitate and enhance the inversion of RTMs (Jacquemoud et al., 1995).

3.4. Basic statistical methods

The current section includes the most common statistical approaches in fire danger estimation, including regression analysis, Bayesian-based methods, statistical tests, timeseries trend tests and collinearity tests. Almost all methods in the current review use at a certain extend statistical methods (i.e., in data processing, variable collinearity tests, timeseries trend tests, and regression analyses); however, in this section only studies that rely on statistics for building the predictive model are discussed. Machine learning techniques are analyzed in a following section.

One of the first studies related to fire ignition probability was conducted by Martell et al. (1987) for Kirkland Lake, Ontario. Linear logistic regression was applied using the Fine Fuel Moisture Content (FFMC), the Duff Moisture Code (DMC), the Build Up Index (BUI) and the Fire Weather Index (FWI), which are all components of the Canadian Forest Fire Danger Rating System (CFFDRS), meaning that actual data for social factors were not immediately incorporated. FFMC was best related to human caused fire, DMC and BUI performed well in fire incidents close to recreation, miscellaneous and industrial uses, while FWI was proven most suited to incendiary fires. A similar approach was applied by Kourtz and Todd (1991) as the three CFFDRS components were incorporated into the Quebec Prediction Program, which was designed for 100,000 km^2 of forest land divided in $0.25^\circ \times 0.25^\circ$ grid (500 km^2). The program handled historical weather records and fire reports for fire season. FFMC, DMC and Initial Spread Index (ISI) were combined, forming an ignition index. Poisson distribution was used for describing the expected number of fires in a cell and a gamma distribution for the mean number of fires. The accuracy of the program was close to the estimations of expert individuals in the field. Balling et al. (1992) also used a proxy index – specifically the Palmer Drought Severity Index – incorporating monthly weather records for Yellowstone National Park, alongside fire reports from 1895 to 1990. The correlation of the main weather coefficients was concluded using Spearman rank test and Pearson product moment. Among the main findings, precipitation of the two preceding years was strongly related to land area burned, while PDSI was found as an accurate proxy for temperature and precipitation combined.

An early study integrating social and environmental factors related to fire occurrence was conducted by Julio (1990) in central Chile. The study area was divided into risk zones, defined based on climate, meteorology, fire occurrence reports, vegetation, topography, and population density. Multiple linear regressions were applied for the creation of a general model with five independent variables: temperature, relative humidity, wind speed, drought, and seasonality (period of the year). Sub-models for each zone were also defined. Another approach integrating social and environmental factors, which had a great impact on fire science, was developed by Cardille et al. (2001). Data for the 1985–1995 period was used and the study area in the Upper Midwest USA was covered by two resolution grids: a 10×10 km^2 and a 5×5 km^2. Input variables were classified as: biotic which included land cover; abiotic which included water body density, mean March–June precipitation and mean maximum August temperature; and human-based which included rail and road density, distance to city and forest as well as population density. The results from the applied generalized linear regression model showed that areas with higher population and road density as well as closer to non-forest land cover were in greater fire danger, while human settlements and land use were the most important correlates of fire patterns at both resolutions.

A great number of studies focusing on Spain, which is a fire prone country, have also integrated social and environmental variables into a predictive model. Vilar del Hoyo et al. (2010) and Costa et al. (2011) applied general additive models for predicting fire danger in Spain. The first one considered distance to roads and rails, wildland urban interface (WUI), meteorological data as well as topography for the creation of a 1×1 km^2 voxel based model for daily fire danger estimation, which reached an average accuracy of 92%, while the second incorporated population and road density, percentage of dominant trees (conifer, eucalyptus, broad-leaves), phytomass, slope and monthly values of temperature and rain depth, with the first three considered as the most important. Martínez et al. (2009) and Costafreda-Aumedes et al. (2018) used logistic regression for Spanish Mainland and Balearic Islands forests; the first one included 29 variables with 13 of them found to be significant, reaching accuracies between 76.2% and 85.4%, while the second one emphasized road and population density, distance to urban, recreational and water areas, topography and land use. The study area was split to Atlantic and Mediterranean. Martínez et al. (2009) found the partitioning of agricultural land to be the most important for fire risk, followed by livestock concentrations, unemployment and rural exodus between 1950 and 1991. Costafreda-Aumedes et al. (2018) reported that: elevation was the most important variable for both types of regions; wildlands land cover affected mostly the Atlantic type; distance to roads and urban areas affected mostly the Mediterranean regions; and the fire season should begin earlier, in February.

A more geographic approach was adopted by Chuvieco et al. (2012) and Rodriguez et al. (2018). They used geographically weighted regression for fire danger modeling, with the first study reaching an accuracy of 87% for human-caused fires and 64.2% for lightning-caused fires. The second one incorporated Wildland-Agricultural Interface (WAI), WUI, demographic potential, distance to power lines, forest tracks, paths and natural areas, railroad length and the Standardized Precipitation-Evapotranspiration Index (SPEI) using a dataset from 1988 to 1992 and 2006–2010 recorded on a 10×10 km^2 grid. Rodriguez et al. (2018) found that the SPEI, which was the only climatic variable considered, was important in all generalized linear model testing, concluding on the significance of climatic variables as an arsonist might choose the most favorable climatic conditions to start a fire. In addition, there are other studies supporting the importance of climatic factors. Westerling et al. (2003) used linear regression and showed that the previous two-year precipitation is important in following fire seasons, especially in areas covered by fine fuel. Westerling et al. (2006) found that shorter periods of snow-cover and/or extended drought augment fire risk in mountainous areas. Westerling and Bryant (2008), using logistic regression and incorporating simulation results from the basic climatic scenarios, predicted an increase in large fires by 10% to 40% until 2099. Koutsias et al. (2012) used weather timeseries from Greece for the period 1894–2010 and, after processing using Mann-Kendall trend test, Spearman rank correlation test and ordinary least squares regressions, found that temperature is strongly auto-correlated with fire trends, agreeing with Aldersley et al. (2011) that climate might overweight human factors in fire risk estimation. Eventually, Barbero et al. (2015) concluded on the increase of large fires for the 2041 to 2070 period (with burned areas greater than 5000 ha) using stepwise regression for PDSI, Fosberg's Index and the components of CFFDRS and NFDRS (National Fire Danger Rating System; USA) for data sets from 1971 to 2000.

3.5. Machine learning techniques

The advance in modern computing technology enhanced the creation of data-centric algorithms and methods capable of handling large volumes of data to find an accurate solution to a complex problem. These methods of Artificial Intelligence, known by the term 'Machine Learning' (ML), have been increasingly applied in forest and wildfire science (Jain et al., 2020). In the present section, a brief description of studies applying ML techniques is presented, focusing on the accuracy and comparison of each method-model as well as on the input variables and their relative significance in wildfire occurrences. Nevertheless, analyzing the theoretical background related to each ML technique is out of the scope of the present study.

ML has been widely utilized in forest fuel characterization. Riaño et al. (2005a) used Artificial Neural Networks (ANN) for predicting equivalent water thickness and dry matter content of leaf samples. Riley et al. (2014) used Random Forests (RF) for producing fuel type charts in Oregon (USA). López-Serrano et al. (2016) found ML techniques, such as Support Vector Machines (SVM), K-Nearest-Neighbor (KNN) and RF, more accurate than Multiple Regressions for biomass estimation in Mexico, with RF outperforming the other methods if optimization is not used. Self-Organizing Maps (SOM) is a common approach for fire weather modeling, including meteorological indices (Crimmins, 2006; Sanabria et al., 2013; Lagerquist et al., 2017; Nauslar et al., 2019).

Blouin et al. (2016) and Bates et al. (2017) modeled lightning ignition probability, with the first using only RF and the latter one combining RF, Classification and Regression Trees (CART) and other statistical approaches in Canada and Australia, respectively. Maximum Entropy (MaxEnt) has been often used for future fire probability projections (Moritz et al., 2012; Batllori et al., 2013; Li et al., 2017; Davis et al., 2017; Stroh et al., 2018). Fire occurrence has been modeled in several studies by ANN, as in Vega-Garcia et al. (1996), achieving accuracies in the range of 78% to 85% in Alberta-Canada, while in studies by Alonso-Betanzos et al. (2002, 2003) in Galicia-Spain, accuracies reached 79%, incorporating parameters like temperature, relative humidity, precipitation, and fire history. Vasilakos et al. (2007) included three fire indices in their ANN model in Lesvos island, Greece. Dutta et al. (2013) compared ten types of ANN for monthly fire-occurrence modeling, concluding to 'Elman RNN', while ANN outperformed SVM in predicting the number of fires in Sakr et al. (2011) model with input variables of relative humidity and precipitation.

Gholamnia et al. (2020) compared various ML techniques, i.e., RF, ANN, Decision Trees (DT), Least Angle Regression (LARS), SVM, Multilayer Perceptron (MLP), SOM, DM Neural, Radial Basis Function (RBF), D-mine Regression (DR) along with LR, for wildfire susceptibility in North Iran, concluding that the top performing methods were RF, SVM, LARS and ANN, while the less accurate results were produced by LR. The input variables comprised: topography, including slope, aspect, elevation, topographic wetness index, landforms, and plan curvature; hydrology, including distance to streams and annual rainfall; meteorology such as annual temperature, wind effect, and potential solar radiation; and human-based such as land use, distance to villages-roads, recreational areas as well as vegetation-NDVI. The most important variable for the aforementioned model was the aspect. MLP along with SVM were also applied by Sayad et al. (2019) in central Canada, incorporating NDVI, Leaf Area Index (LAI) as in Chen and Black (1992), Thermal Anomalies (TA) and Land Surface Temperature (LST) in their model. RF were also used on Liguria-Italy in three variations using k-fold cross validation, including slope, north-east angles from aspect, distance to roads, urban areas, pathways, and crops (Tonini et al., 2020). Predictions were more accurate for winter months, although they were overall good except for the year 2017 mop up phase of fire suppression, concluding that changes in the surrounding conditions can seriously affect the accuracy of the model.

Researchers have often used ML for estimating the relative importance of each driving factor for wildfire occurrence. Vacchiano et al. (2018) used MaxEnt method in Aosta Valley in the Italian Alps with fire ignition data of a 15-year period, which included the following variables: temperature and precipitation extremes for warmest-coldest-wettest-driest periods, elevation, slope, cosine of aspect minus 225 degrees as a proxy for evapotranspiration (according to Franklin and Tolonen, 2000), heat load index as a proxy for solar radiation (as in McCune and Keon, 2002), distance from main roads-buildings, number of grazing domestic animals and number of enterprising with grazing animals. The results showed that summer fires occurred at lower elevations, higher mean temperatures, and greater distance from infrastructures than in winter ignitions, while generally, most ignitions occurred in agricultural and forest land, due to negligence. Elevation, distance to infrastructure, max temperature of the warmest month, average temperature of the driest quarter of the year as well as precipitation total of the wettest and driest months were the most important variables. In the same study area, the Standardized Precipitation Evapotranspiration Index was also noted to be important (Castagneri et al., 2015). Xu et al. (2006) also corroborated that higher elevation leads to lower fire incidents, while the results of Vacchiano et al. (2018) concerning the influence of infrastructure density and landscape fragmentation have also been widely confirmed in earlier studies (Catry et al., 2009; Martínez et al., 2009; Vilar del Hoyo et al., 2010; Narayanaraj and Wimberly, 2012; Oliveira et al., 2012; Arndt et al., 2013). Tehrany et al. (2019) used a hybrid ML technique, which combined LogitBoost and DT for North Vietnam, including: topography (i.e., slope, elevation and aspect) as in Pradhan et al. (2007), Gao et al. (2011), Ghobadi et al. (2012), Parisien et al. (2012), Motazeh et al. (2013), Bassett et al. (2015), Kane et al. (2015) Pourtaghi et al. (2015), and Nami et al. (2018); land use and NDVI as in Chuvieco et al. (2004) and Nepstad et al. (2008); distance to residential areas as in Le et al. (2014); meteorology (i.e., precipitation, temperature, wind speed and relative humidity) as in Drobyshev et al. (2012) and Jolly et al. (2015). The most important variables were NDVI, slope and elevation, while LogitBoost ensemble proved to be superior with 89.7% followed by SVM and KLR (87.2% and 86.2%, respectively).

Furthermore, Hong et al. (2018) constructed two RF and two SVM models with and without optimization feature selection, in Dayu County-China, identifying fire incidents from MODIS historic data set, including 13 variables: elevation, slope, aspect and curvature for topography; soil cover type, heat load index and NDVI for vegetation; precipitation for climatic factors; distance to rivers and roads as well as land use for human factors. No multicollinearity was found for the variables, which were classified based on natural breaks, while weights were assigned using the Certainty Factor, and for feature selection, genetic algorithms were applied. The most important variables were NDVI, slope, elevation, and distance to road network. RF outperformed SVM both with and without optimization. Elia et al. (2020) used ANN and Logistic Regression in estimating wildfire probability in Italy, including land cover, tree cover percentage, relative humidity, maximum temperature and wind speed, roads, rails, settlement locations, population, fire climatic index, elevation, and slope. The last three were the most important variables, except for the Alpine region where forest cover was the most significant. The accuracy of the ANN model ranged from 0.68 to 0.83 outperforming the logistic regression model. Reyes-Bueno and Loján-Córdova (2022) used Logistic Regression, Multivariate Adaptive Regression Splines (MARS) and Logistic Model Trees (LMT) in modeling fire susceptibility in Loja-Ecuador. Parameters included NDVI and NDMI for fuel moisture content, accessibility from the economic center and roads, elevation, and distance from rivers and anthropic zones. NDMI, elevation and accessibility to roads were the most significant variables, while MARS and LMT outperformed Logistic Regression.

The performance of Machine Learning techniques was also tested against deterministic models, as in Leuenberger et al. (2018). In more detail, the deterministic model, which was first proposed by Verde and Zezere (2010) and further improved by Parente and Pereira (2016), was compared to RF and Extreme Learning Machine (ELM) in Portugal, including the following input variables: elevation, slope, aspect, and land cover. The deterministic model produced similar results to the two ML models; however, the latter two underestimated the susceptibility of the south-west part of the study area. The most important variables were low density and mixed forests from land cover.

ML has been applied to sociological drivers by Delgado et al. (2018), who used Bayesian Networks (BN) for understanding the motivation of arsonists. They used datasets from Spain, combined the results of Shye (1985), Viegas and Soeiro (2007) and Sotoca et al. (2013), and constructed five archetypes for arsonist profiles (i.e., slight negligence, gross negligence, impulsive, profit and revenge), integrating ten variables related to the crime itself and 15 to the arsonist profile. The results showed that most fires from arson are ignited in spring, on days of high level of risk. Arsonist characteristics include: age of 46 to 60, living in couple (without children), having a handwork job, elementary level of education with medium income, and living in towns relatively close to the incident.

Adab (2017), Bisquert et al. (2012), Goldarag et al. (2016) and Elia et al. (2020) corroborated that ML techniques outperform simple statistical methods (e.g., regression), while other researchers (e.g., Stojanova et al., 2012; Vecín-Arias et al., 2016; Cao et al., 2017) found that RF outperform other common ML techniques (such as ANN, SVM, KNN) and regression methods. RF is also one of the most common techniques alongside with MaxEnt for estimating the relative importance of each input variable in fire occurrence (Aldersley et al., 2011; Chingono and Mbohwa, 2015; Masrur et al., 2018; Mansuy et al., 2019); however, the importance of each factor differs significantly from region to region, with larger fires being connected to climatic drivers and smaller ones to anthropogenic ones (Jain et al., 2020).

3.6. Simulation-based modeling

Simulation has been commonly used in computing fire likelihood and behavior, mostly using a deterministic approach that assumes fire geometry as a spreading line-fire (Rothermel, 1972; Albini, 1976; Van Wagner, 1977; Anderson, 1983; Rothermel, 1983; Alexander, 1985; Andrews, 1986; Finney, 1998; Finney, 2005; Andrews et al., 2007; Tymstra et al., 2010). Some of the most used fire growth models, such as FARSITE-USA, Promytheus-Canada, FlamMap (Finney, 2006), Burn-P3 (Parisien et al., 2005), BurnPro (Davis and Miller, 2004) and Landis (Yang et al., 2008), incorporate fuel characteristics (such as land cover, flammable biomass, unburnable areas and fuel models), topography (mostly elevation, slope and aspect), and weather (commonly temperature, relative humidity, wind speed and direction as well as precipitation) in producing ignition locations, fire perimeters, fire likelihood, and fire behavior maps (Parisien et al., 2019). Simulation models offer the ability to examine several scenarios for estimating fire ignition and spread in fine resolution and accuracy by altering and combining differently the input variables (Parisien et al., 2019).

The USA system 'FARSITE' – one of the early systems – was implemented for simulating fire growth using the Huygens' principle (Finney, 1998), assuming each vertex as a source of an independent expansion in the shape of an ellipse (as in Van Wagner, 1969). Fire propagation is modeled using Richard's technique of the vertices of the fire perimeter polygon (Richards, 1990), while many other models have been incorporated in the system, including Rothermel (1972), Albini (1976) and Van Wagner (1977, 1993). Input data are divided in spatial (i.e., elevation, slope, aspect, fuel model, canopy cover, crown height, canopy base height and canopy bulk density), and weather (such as temperature, relative humidity, precipitation, wind speed and direction and cloud coverage). Dead fuel moisture content is estimated via NFDRS and BEHAVE components. A similar approach is applied in the Canadian System 'Prometheus' for fire propagation (Tymstra et al., 2010); however, instead of the BEHAVE and NFDRS system components, the respective of Canadian Forest Fire Behavior Prediction System (CFFBPS) is used. The inputs of the system include required ones (such as fuel type and weather data), and optional (such as topography). The 16 CFFBPS standard fuel types are incorporated in the form of grids, from which additional characteristics can be defined, such as grass curing, crown geometry and coverage (Tymstra et al., 2010). Other geographic layers, such as lakes and roads, can be inserted as break lines and the outputs of the system consist of the geographic values of vertex points, CFFBPS outputs, perimeter length and polygon area.

Furthermore, FlamMap was developed for extending the capabilities of the systems used in FARSITE, emphasizing landscape level characterization of fuel hazard, integrating GIS technologies (Finney, 2006). Input data are inserted in a single landscape file type, incorporating raster grids of the environmental variables, such as topography, fuel model, canopy geometry, and wind speed and directions. Fire growth is estimated using the Minimum Travel Time (MTT) (Finney, 2002). Ignition points can either be inserted or generated randomly (Finney, 2006). Another simulating tool emphasizing wildfire susceptibility is 'Burn-P3' introduced by Parisien et al. (2005). Fire occurrences, fuel types (as in the Prometheus System), daily noon weather inputs and ecological units are inserted in the system. Ignition and burning conditions are calculated statistically, while fire growth is estimated deterministically. The model was validated by Parisien et al. (2005) using three scenarios, approximating the historic fire distribution, but slightly overestimating the fire size. Burn-P3 can produce fire distribution and burn probability at fine quality beforehand – opposed to common statistics – although a large data volume and computations are required (Parisien et al., 2005).

Yang et al. (2008) combined spatial point process modeling of historic fire occurrences, MTT algorithm for simulating fire spread using BEHAVEPlus (Andrews et al., 2005) and CFFBPS, and LANDIS design for examining vegetation types that are prone to burn, considering the influence of topography, human factors and spread patterns in South Missouri and North Arkansas-USA. Vegetation type, elevation, slope, aspect, distance to roads-municipalities, population density and ownership data sets were used as input variables. The simulation of 390 fires and CART techniques showed that proximity to roads and municipalities mostly affected fire occurrence, while burn probability was lower in valleys and low elevation, and higher on moderate slopes. Burn probability was higher in open woodland, followed by grassland, mixed forest and deciduous forest, while topography mostly affected burn patterns rather than fire occurrences. In Sardinia, Salis et al. (2014) simulated 100,000 fire events, using historic ignition data, average monthly weather data (computed from daily records), land cover from CORINE, topography, crown characteristics as well as fire suppression capacity, as indicated in Terradas et al. (1998), Schoennagel et al. (2008), and Brotons et al. (2013). Greater relationships were found based on statistical tests for high maximum temperature and wind, as well as average wind mostly from northwest, north and southwest directions, while the most affected areas of highly value and resources were the WUI areas.

Finney et al. (2011) used the MTT algorithm, deploying the 'FSim' software at 30 m resolution, for accounting spatio-temporal variations with the same input variables in USA Fire Planning Units (https://www.

nwcg.gov/term/glossary/fire-planning-unit-fpu, Accessed 1 November 2022). They used, however, the classification of dead fuels and the Energy Release Component (ERC) from NFDRS. The results were statistically tested with historic reports, finding that burn probabilities tended to be higher with much larger fire size in the simulation model. FSim was also applied by Thompson et al. (2013) in Montana and Colorado for estimating burning probability and area burned in Highly Valued Resources and Assets (HVRA) areas. They used similar input variables and ERC calculations for weather data at 90 m resolution. A polygon-based approach was applied by digitizing the perimeters of areas likely to be ignited to determine where fire is likely to spread; these were named 'firesheds' in analogy to watersheds. Although the burning likelihood varied significantly, smaller firesheds were found to have greater likelihood to be totally burned, while areas at distances less than one km from firesheds accounted for 72% of the expected HVRA area burned. In Spain, Alcasena et al. (2016, 2017) used FlamMap to evaluate wildfire exposure of HVRA and estimate economic losses, by incorporating the required inputs from Finney (2006). Canopy fuel metrics were measured by LiDAR systems as proposed by Mutlu et al. (2008) and wind data were spatially distributed using WindNinja software (Forthofer et al., 2014). Historic ignition locations were also inserted for simulating the burn probability, the conditional flame length, fire size and crown fire activity at 20 m resolution. The highest burn probability was found in highly urbanized areas and areas with cereal crops, *Pinus nigra* afforestation and Mediterranean oak forests.

Another simulating tool – developed in Australia – called PHOENIX RapidFire, incorporates fuel, topography, and weather, having the advantage of including firebrand transport and ignition to fire spread (Tolhurst et al., 2008; Paterson and Chong, 2011; Pugnet et al., 2013). The main fire behavior models consist of CSIRO southern grassland fire spread model (Cheney and Sullivan, 1997) and McArthur Mark5 forest fire behavior model (McArthur, 1967; Noble et al., 1980) with a slight modification (Jenkins et al., 2019). PHOENIX RapidFire was used in Albury, Australia, by Jenkins et al. (2019) running a total of 600 scenarios and 163,200 fires, concluding that weather severely affected fire size in contrast to planting design. However, PHOENIX RapidFire was also used in Cavaillon, France, with very high-resolution fuel inputs of 1 m and simulations at 5, 10, 15 and 20 m achieving accurate predictions of fire spread, although not quite accurate fire shapes (Pugnet et al., 2013). The outputs of PHOENIX RapidFire have been included in ML techniques for estimating potential house loss (Duff and Penman, 2021). Nevertheless, another simulating tool named Spark was selected in 2020 as the next Australian operational bushfire spread simulator by the Australasian Fire and Emergency Services Authorities Council (Hilton et al., 2022). Spark includes ignition conditions, rate of spread equations and fire spread simulator with the latter two being separated, meaning that user-defined models for fire behavior can be inserted due to the modularity of the system (Hilton et al., 2019; Hilton et al., 2022). Spark supports movement of fire perimeter, transport of firebrands and ground level pressure, while input and output data are in GIS formats (Hilton et al., 2022). Spark incorporates: meteorological data such as dry bulb air temperature, dew point temperature, relative humidity, wind speed and direction; initial fire conditions such as position and fire front; and topographical data in the form of digital elevation model and basic land covers (Swedosh et al., 2018). For validating Spark's accuracy, historic fire events were reconstructed using 30 m resolution data (Swedosh et al., 2018). Although Spark is sensitive to input data quality and further improvement is feasible – the accuracy was high overall – with an average score of 0.462 (Swedosh et al., 2018).

Simulation modeling has also been applied on a global scale, mostly for assessing the influence of climate change on wildfires. Specifically, Krause et al. (2014) used the Earth System Model (Giorgetta et al., 2013) to simulate global changes in lightning occurrence and its effects on wildfires under climate change. They integrated the Arora and Boer (2005) algorithm as the product of available biomass, fuel moisture and ignition source. Three climatic periods were selected: (i) pre-industrial (1850–1874); (ii) present-day (1980–2004); (iii) future projections of RCP26-RCP45-RCP85 (2070–2094). The model predictions were coherent to real data (derived from http://thunder.nsstc.nasa.gov, Accessed 1 November 2022) with tropical areas being affected more by lightning. However, significant inaccuracies occurred in low flash-rate areas. Although other effects of climate change have greater impact on wildfires, the lightning occurrence should not be neglected in wildfire danger modeling (Krause et al., 2014). Fire growth, fuel load, burned area and wildfire emissions under climate change were simulated by Knorr et al. (2016) at global scale, using a combination of LPJ-GUESS-SIMFIRE tools, integrating maximum Nesterov Index values (Nesterov, 1949). In this study, RCP4.5 and RCP8.5 were used to simulate climate change effects, while five scenarios were executed for human population evolution. Knorr et al. (2016) concluded that higher fire risk is expected in warmer areas, in savannahs under woody thickening and litter turnover, as well as due to climatic and demographic changes. Finally, Loehman et al. (2017) used FireBGGv2 to simulate interactions of wildland fire, pine beetle and pine blister rust.

3.7. Miscellaneous

In the present section, studies combining the aforementioned approaches, or applying ad-hoc methods that cannot be categorized are discussed. These following studies chose a combination of techniques in the scope of creating an integrated system rather than comparing their respective accuracy as in earlier paragraphs of the current review.

A common issue in modeling neighborhood events, like wildfire ignition and spread, is the spatial autocorrelation, which is often omitted by researchers, although it may affect significantly burn probability estimation (Reed et al., 1998; Dormann et al., 2007; Koutsias et al., 2012; Mishra et al., 2016; Portier et al., 2018). Chou et al. (1993) elaborated a logistic model for estimating fire occurrence probability in San Jacinto Mountains-California (USA), incorporating GIS techniques for the delimitation of geographical units, the proximity analysis for structures, roads and trails, as well as fuel models from NFDRS, annual precipitation and temperature data. Neighborhood effects were evaluated using Moran's autocorrelation index (Moran, 1948), finding that shrub vegetation had the higher autocorrelation values. Chou et al. (1993) concluded that spatial autocorrelation must be inserted in wildfire modeling, as it strongly affects burn effectiveness. Wang et al. (2016) created a framework for the evaluation of climate change impacts on fire regimes in British Columbia-Canada for the 2080s via simulations with Burn-P3 including correlation and autocorrelation tests using Pearson (1895) and Moran (1948), respectively. Topography, wind and fire zone grids, 17 fuel types from CFFBPS and ignition locations, which were estimated by logistic regression and historical data, were incorporated in the model. Fuels were the most important parameter, followed by weather and ignition, corroborating Peterson's (2002) results concerning the reduction in flammability by the establishment of long-lived species.

A less common approach, yet more accurate for estimating burn probability, combines fuel mapping techniques with simulation modeling. Burgan (1996) calculated Visual Greenness and Relative Greenness Indices from remote sensing data to produce a fine 30 m resolution fuel map and use it in simulations with FARSITE. Mallinis et al. (2016) integrated: remote sensing data, object-based image analysis (OBIA) and Random Forests for fuel mapping; GIS techniques for topographic data and wildfire transmission; and simulation modeling with FlamMap for fire risk estimation. Xofis et al. (2020) implemented: a fire danger index integrating OBIA with ML algorithms, concluding to RF for extracting fuel types and canopy characteristics; simulation modeling with FlamMap; and GIS kernel density analysis for quantifying pyric history data for a 40-year period as well as buffer zone analysis for calculating distance from roads and settlements. Both Mallinis et al. (2016) and Xofis et al. (2020) conclude to finer scale products leading to enhanced accuracies compared to simple techniques such as logistic regression, or to predefined fuel types/models. A more complex approach was adopted by Scott et al. (2012) in Jackson, Wyoming, USA, using a Monte Carlo simulation (FSim) for estimating annual burn probability and the expected annual burned area in the WUI for prescribed natural fires. The following procedure was applied for the inputs of the simulation model: (i) ten fuel models were mapped based on Scott and Burgan (2005) classification; (ii) historic weather data from 1990 to 2010 were incorporated in ERC calculations while two ignition location grids were produced by logistic regression as in Vilar del Hoyo et al. (2008) and Vilar del Hoyo et al. (2011), one for human and one for lightning caused fires, with independent variables concerning vegetation type, elevation, potential solar radiation, topographic position index and distance to roads and trails; (iii) non-ignition locations were produced by GIS techniques. The simulation of more than 30,000 fires showed that early-season fires burned longer while the expected annual WUI area burn peaked in July.

Srivastava et al. (2013) divided the driving factors to causative or to anti-causative, i.e., those increasing or decreasing, respectively, the fire danger probability. Vegetation types, distribution of animal population road and settlement network, tourism zones and grazing areas were assumed as causative factors while water bodies, firelines, anti-poaching camps, checkposts and watch towers were assumed as anti-causative factors. Remote sensing techniques were applied to satellite images for fuel type flammability layer, GIS techniques were used for the quantification of input factors and the significance of each factor was extracted by pair-wise comparisons via 'OSIRIS' software. The final model was calibrated with logistic regression using data for a 15-year period. Another approach used for model calibration was applied by Abdollahi et al. (2018) by comparing the daily values of surface temperature and precipitable water as well as the values of an 8-day period of NDVI and NDWI with the respective average ones for the whole study area. In cases where a pixel value exceeded the average one, fire danger increased for the pixel. The initial model consisted of statistically analyzed historical human and lightning fire occurrence data, soil and vegetation data produced by remote sensing techniques as well as natural subregions and road network integrated in the model by GIS proximity analysis. Hong et al. (2019) showed that the combination of GIS techniques, Weights of Evidence (WOE) method and AHP produces enhanced accuracies. In the integrated model, slope, elevation, NDVI (for fuel moisture) annual rain, wind speed, land use and proximity to rivers, roads and human settlements were incorporated, while the most fire-prone areas were located at elevations greater than 600 m and for NDVI greater than 0.3 in forests.

Rebuilding historic fire regimes based on stratigraphic charcoal and tree ring records has led to important conclusions, related to fire occurrence, climatic fluctuations, and human activities (Clark, 1989; Swetnam, 1993; Larsen, 1996; Loope and Anderton, 1998; Veblen et al., 2003). More details are included in Section SM2.

Vegetation flammability has also been studied as one of the main wildfire drivers. In more detail, Fares et al. (2017) highlighted the characteristics of live Mediterranean vegetation in relation to flammability in terms of biochemical and moisture content. He also presented the main approaches in estimating vegetation characteristics including field, laboratory experiments and remote sensing techniques. A list of 60 vegetation types were elaborated based on fire expert opinions (Xanthopoulos et al., 2012), while the Vegetation Quality Index (VQI) was used in identifying the quality of vegetation in terms of three parameters: fire risk, soil erosion and drought resistance (Basso et al., 2000). García-Llamas et al. (2019) examined different satellite imagery data sources (Landsat 7, MODIS and Meteosat) in terms of estimating biophysical properties related to fuel conditions and their effect on fire severity in Sierra del Teleno (northwest Spain). They also used a combination of dNBR and CBI indices for identifying fire severity. They estimated fuel loads and moisture content, the two main biophysical variables, using proxy variables: VARI and Actual Evapotranspiration (AET) for the first, and water deficit for the latter one. AET was estimated from two sources, with MODIS providing more influential trends for fire severity (García-Llamas et al., 2019). Overall, biophysical parameters were confirmed for their important role in fire severity, with fuel moisture estimated from VARI being the most important driver; however, the available fuel load was found more significant than the fuel moisture (García-Llamas et al., 2019). In addition, biogenic volatile organic compounds (BVOC) in leaves were indicated as flammability drivers enhancing ignition (Owens et al., 1998; De Lillis et al., 2009) with increased flammability in species emitting isoprenoids, e.g., *Pinus halepensis*, *Pinus Brutia*, *Quercus Ilex*, and others (Dimitrakopoulos, 2001). Leaves with higher surface area-to-volume ratios ignite quicker because of greater contact area for pyrolysis (Gill and Moore, 1996) creating low bulk-density fuel-beds that permit air flows to penetrate, mostly in broadleaves as curvy leaves burn at higher pace.

The last group of studies included in the present review concerns the new Australian Fire Danger Rating System (AFDRS), which replaced the McArthur Fire Danger Index in September 2022, in Australia (Van Wagner, 1987; Marsden-Smedley et al., 1999; Mills and McCaw, 2010; Cube Management Solutions (Cube), 2014; Cruz et al., 2015; Burrows et al., 2018; Grootemaat et al., 2019; Matthews et al., 2019a, 2019b; Sauvage et al., 2019). More details are included in Section SM3.

3.8. Factors affecting fire incidents

In the previous section, the main factors used as input in fire modeling were referenced and analyzed in terms of their importance in fire risk assessment, with an emphasis on modeling methodologies, results, input data and validating feedback. The purpose of the current section is to propose and present in a compact and brief manner the independent driving factors involved mainly in fire danger, as well as to a certain extent in fire behavior, fire severity, according to the referenced literature. All the included variables in the current section are confirmed to have an influence on fire danger, although there is still room for improvement. In cases of highly dependent variables used interchangeably in the included literature, the authors of the present review included all of them, as no hard evidence proving one variable over the other existed. However, these variables should not be included together due to their very high correlations (for example, the relative humidity and the dew point temperature).

Furthermore, the main "shell" of the core equation that describes fire danger in an integrated wildfire danger rating system is defined based on the proposed and arranged variables. Hence, the driving factors (also mentioned as fire variables, or fire agents) were classified in thematic categories, defined according to literature used in this review and others (Ganteaume et al., 2013; Plucinski, 2012; Costafreda-Aumedes et al., 2018; Hesseln, 2018; Zacharakis and Tsihrintzis, 2023). Seven major thematic groups of variables are proposed: meteorology, vegetation, topography, hydrology, socio-economy, land use, and climate. However, not all classes have the same impact on fire danger. Therefore, fire danger can be estimated based on a function of the proposed thematic groups of variables with their respective weights, according to the following relation:

$$f_{FD} = f_v(m, v, tg, h, se, lu, c) \bullet f_w() \pm f_e() \quad (1)$$

where f_{FD} is the fire danger function, f_v is the function connecting the variables, f_w is the weight function, m corresponds to meteorology, v to vegetation, tg to topography, h to hydrology, se to socio-economy, lu to land use, c to climate, and f_e is an error function. In other words, fire danger is the dot product of a variable function with the respective weight function increased or decreased according to an error function. The process of providing the exact mathematical expression of Eq. (1) is highly related to national or local characteristics and peculiarities; consequently, defining global standards would be rather inappropriate and inaccurate, especially within the frame of this review. The set of variables is included in Table SM3. Finally, every variable inserted in the variables function is in fact a function of space (x,y,z) and time (t), as follows:

$$m = f_m(x, y, z, t) \quad (2)$$

$$v = f_v(x, y, z, t) \quad (3)$$

$$tg = f_{tg}(x, y, z, t) \quad (4)$$

$$h = f_h(x, y, z, t) \quad (5)$$

$$se = f_{se}(x, y, z, t) \quad (6)$$

$$lu = f_{lu}(x, y, z, t) \quad (7)$$

$$c = f_c(x, y, z, t) \quad (8)$$

3.9. Limitations

Wildfire modeling is a broad and complex scientific discipline concerning very diverted areas of the global sphere. Both deterministic and stochastic factors, related in a fuzzy rather than precise manner, characterize wildfire incidents, while the exact number of variables, their autocorrelation as well as their importance can only be ad-hoc approximated for each case study. Therefore, in the current section, the basic limitations of the present review are briefly discussed.

3.9.1. Methodologies

A plethora of methodologies and techniques were reported in this review; however, their thematic classification was not straightforward, and some compromises had to be made, for example, including a miscellaneous category at the end of the respective section. Furthermore, not all the reported methods led to equivalent results, as for example, GIS was used for data analysis and visualization while machine learning was applied for creating equations with explanatory variables. Additionally, not all selected studies included clear and analytical description of the methodologies applied.

3.9.2. Variables-factors

Each study focuses on a specific number of factors, ranging from 1 to 43 variables, rarely explaining the reason for their selection in terms of both quality and quantity. Moreover, different methods are used for collecting data describing the selected factors, leading to deviations in accuracy and to uncertain conclusions about their significance in fire danger. Furthermore, variables are often replaced or mixed with indices leading to imprecise count of inserted variables in the evaluation process of this review.

3.9.3. Validation

A very significant procedure omitted in some of the studies is related to the evaluation of each methodology. Common issues are related to the insufficient sample, the limited area scale and even the total neglect of a validating procedure.

3.9.4. Spatio-temporal Scales

Systematic *w*ildfire studying commenced in the late 1950s, with the most recent reaching the year 2023. Therefore, despite the technological and scientific advances that occurred during the mentioned timeline, the conclusions alongside their respective importance in future wildfire danger estimation should be accordingly adjusted. In addition, several studies include multi-temporal data expanding to decades, while others are limited to short periods (a month or two). Accordingly, the final outputs of the reported literature differ from small land plots to the earth itself. The differentiation both in spatial scale and in geography results in less trustworthy conclusions, as driving factors of wildfires have different impact and variance per region. Local practices and customs also define diverted patterns of fire ignitions; therefore, the conclusions of each study have different significance.

Finally, the current review attempted to include as many methodologies and variables as possible, rather than emphasizing on a specific approach or group of variables, although all of them could not possibly have been included and analyzed in a single article.

4. Meta-analysis of selected studies

As the aforementioned studies are quite divert, a meta-analysis was undertaken and is presented in the current section, aiming to define a rating procedure. This analysis was based on the following ten established criteria:

- *System accuracy*: it is according to the validation procedure of each study and is measured as a percentage. Lower threshold matches the top performing Environmental Fire Danger Rating Systems (Zacharakis and Tsihrintzis, 2023). Higher accuracy results in higher grade.
- *Output resolution*: it refers to the spatial resolution of the final product of each model-system and is measured in km^2. In Europe, 30×30 km is approximately the size of a metropolitan area, while 1×1 km is approximately the size of a small municipality.
- *Variable accuracy*: it is defined in spatial resolution of input data. Although the variables introduced in each study have different units, all of them have spatial reference, and therefore, the respective accuracy can be defined in meters. Thresholds were defined based on output resolutions and the minimum variable unit which refers to a single tree (less than 20 m).
- *Number of included variables*: it refers to the input variables of each model. Greater numbers lead to finer accuracies to a certain extent, but (auto-)correlation issues may arise.
- *Variable significance*: it is defined by the weight or the correlation to fire danger of the included variables; studies defining which variables are more important or strongly correlated to fire danger make greater contribution to fire science.
- *Case study size*: it is defined according to a classification proposed for the purposes of this meta-analysis. The size of each case study reflects the accuracy of the final output, as more complexity is added and the contribution of each input is more significant in larger areas; thus, the input data describe less sufficiently larger areas.
- *Sample size*: it refers to the data used for the validation procedure of each model. Studies with validating procedures require a sample which reflects on the accuracy of the model. The thresholds refer, mostly, to the number of fire incidents that occurred in areas with the size classification used in the 'case study size' criterion of the present meta-analysis.
- *Data time span*: multitemporal data increase the predictability of each model. The thresholds were chosen based on the reviewed studies.
- *Climatic variety index (CVI)*: models refer to areas of different size and variant climate. Thus, an ad-hoc index, combining the size and the climatic classes according to Köppen-Geiger classification was introduced and computed for each case study area as follows:

$$CVI = \frac{C + A}{C_{max} + A_{max}} \quad (9)$$

where C is the number of climate classes, and A is the size of the selected area, while C_{max} is the maximum number of climate classes (here C_{max} equals 22 which refers to USA climate classes), and A_{max} is the area size class which refers to the smaller areas (here A_{max} equals 6). From two areas with the same number of climate classes, the smaller one indicates more variability, thus less accurate results as the driving forces that cause a climatic differentiation are likely to be excluded from the smaller area despite their impact on it. Higher index values show greater variability and less accuracy. The thresholds of areas by size classification are: 10^4, $5*10^4$, 10^5, $5*10^5$,

10^6, $5*10^6$. Other classifications can also be used.

- *Relevance to fire danger rating*: it is defined according to the scope of each study. The included studies can be divided in three categories in relevance to fire danger: those that estimate immediately fire danger; those that estimate a parameter of fire danger (such as fire susceptibility); and those that estimate a variable related to a parameter or fire danger. The grades are high, medium, and low, respectively, with respective grade values 2, 1 and 0.

The thresholds of each class were defined by the authors based on current technology, data sources and modeling practices; hence they can be modified as needed. Furthermore, the inclusion of weights per criterion could be promising but were omitted in the current meta-analysis for simplicity as the scope is rather generic. Studies omitting or not clearly stating the value for a certain criterion were marked with 0. Grades start from 0 and end to 1, 2 or 3 based on the number of ranges in each criterion. The overall rating is the sum of the criteria, as presented in Table SM4, while the respective rating scale for each criterion is presented in Table SM5. However, this rating concerns only the relevance and the importance of each study in estimating fire danger, modeling performance and variable inclusion and significance rather than the respective scientific quality.

In the top performing studies, researchers have included at least 10 variables in their models and the respective case studies were limited in size, meaning that their methods should be carefully tested in regions that differ in size and geography. Finally, these studies were adequately validated and included multitemporal data of fine resolution.

5. Conclusions

Integrated fire danger modeling techniques and wildfire driving factors are presented. GIS, RS, and IA techniques have been widely applied as their capability of remotely handling, combining, analyzing and extracting information from large volumes of geospatial data could not be neglected from any modern Integrated Wildfire Danger Rating System. However, each input factor as well as its respective importance must be determined by a separate method. Pairwise comparisons, Multi-Criteria Decision Methods, Analytical Hierarchy Process, and similar techniques have been commonly used.

Statistical approaches, such as the logistic regression, are the most applied ones for being simple, straightforward and to a certain extent accurate. The selection of input variables and their relative importance can also be defined through statistics. Machine Learning (ML) methods consist of a more accurate and data-driven set of techniques, with Random Forest (RF) being generally the most accurate (as standalone) in fire danger modeling and at the same time capable of finding the relative importance of each input variable. Nevertheless, both statistical and mostly ML methods require a large volume of historic data of fire occurrences and their accuracy is much related to their quantity and their quality. Furthermore, since stochastic models are based on data from past periods, which are not always homogeneous, their predictive ability under dynamic phenomena – such as climate change – can be questioned. Consequently, their applications should be limited to calibration and validation rather than the construction of fire danger models.

Simulation techniques have been produced using deterministic approaches for estimating quite accurately fire behavior and fire susceptibility, although very often the results are exaggerated. Nevertheless, for estimating fire danger, simulation techniques must be combined with stochastic approaches, leading to similar problems as mentioned above. Pure simulation techniques ignore social and economic parameters, as they emphasize landscape characteristics. Other techniques mentioned in the current study can be useful for evaluating causative factors, their significance and/or their autocorrelation, as well as for calibrating the main model.

Concerning the variables related to fire danger, the most essential category, which is rarely omitted in any fire model, is vegetation, in which fuel types, fuel moisture contents and plant geometries are included, followed by meteorology consisting of temperature, relative humidity, precipitation and wind speed. Topographic variables, and mostly elevation, slope, and aspect, are also of great importance, as well as proximity to infrastructures (roads, railroads, urban areas, power lines, and recreational or touristic areas) and WUI. The rest of the variables must be considered according to if their relation to the application region is strong, based on the cited literature and the local fire history.

In conclusion, the approach for building an Integrated Wildfire Danger Rating System (IWDRS) should rely on both deterministic (mostly related to the core of the system functionality) and stochastic methods (mostly used for validation and calibration). A complete and up-to-date geospatial and temporal dataset concerning vegetation, topography, land uses, and georeferenced social and economic parameters should be constructed as the foundation of an IWDRS for the area of interest, in which calculating processes should transform inputs to fire danger vulnerability maps. Finally, the model prediction ability should be monitored and conserved throughout the years following its development, which has been rarely applied in the respective literature.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. A graduate scholarship to Ioannis Zacharakis by the Research Committee of the National Technical University of Athens is greatly appreciated.

CRediT authorship contribution statement

Ioannis Zacharakis: Conceptualization, Investigation, Methodology, Validation, Formal analysis, Data curation, Visualization, Writing – original draft. **Vassilios A. Tsihrintzis:** Conceptualization, Investigation, Methodology, Validation, Resources, Project administration, Supervision, Writing – review & editing.

Declaration of competing interest

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

Data availability

All data are included in the paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2023.165704.

References

Abatzoglou, J.T., Williams, A.P., 2016. Impact of anthropogenic climate change on wildfire across western US forests. Proc. Natl. Acad. Sci. U. S. A. 113 (42), 11,770–11,775. https://doi.org/10.1073/pnas.1607171113.

Abdollahi, M., Islam, T., Gupta, A., Hassan, Q.K., 2018. An advanced forest fire danger forecasting system: integration of remote sensing and historical sources of ignition data. Remote Sens. 10 (6), 923. https://doi.org/10.3390/rs10060923.

Adab, H., 2017. Landfire hazard assessment in the Caspian Hyrcanian Forest ecoregion with the long-term MODIS active fire data. Nat. Hazards 87 (3), 1807–1825. https://doi.org/10.1007/s11069-017-2850-2.

Adaktylou, N., Stratoulias, D., Landenberger, R., 2020. Wildfire risk assessment based on geospatial open data: application on Chios, Greece. ISPRS Int. J. Geo-Information 9 (9), 516. https://doi.org/10.3390/ijgi9090516.

Ager, A.A., Vaillant, N.M., Finney, M.A., 2010. A comparison of landscape fuel treatment strategies to mitigate wildland fire risk in the urban interface and preserve old forest structure. For. Ecol. Manag. 259 (8), 1556–1570. https://doi.org/10.1016/j.foreco.2010.01.032.

Albini, F.A., 1976. Computer-based Models of Wildland Fire Behavior: A user's Manual. Intermountain Forest and Range Experiment Station, Forest Service, US Department of Agriculture (Available here (accessed 01 November 2022)).
Alcasena, F.J., Salis, M., Naulsar, N.J., Aguinaga, A.E., Vega-García, C., 2016. Quantifying economic losses from wildfires in black pine afforestations of northern Spain. For. Policy Econ. 73, 153–167. https://doi.org/10.1016/j.forpol.2016.09.005.
Alcasena, F.J., Salis, M., Ager, A.A., Castell, R., Vega-García, C., 2017. Assessing wildland fire risk transmission to communities in northern Spain. Forests 8 (2), 30. https://doi.org/10.3390/f8020030.
Aldersley, A., Murray, S.J., Cornell, S.E., 2011. Global and regional analysis of climate and human drivers of wildfire. Sci. Total Environ. 409, 3472–3481. https://doi.org/10.1016/J.SCITOTENV.2011.05.032.
Alexander, M.E., 1985. Estimating the length-to-breadth ratio of elliptical forest fire patterns. In: Proc. 8th Conf. Fire and Forest Meteorology, pp. 287–304 (Available here (accessed 01 November 2022)).
Allen, J.L., Sorbel, B., 2008. Assessing the differenced normalized burn ratio's ability to map burn severity in the boreal forest and tundra ecosystems of Alaska's national parks. Int. J. Wildland Fire 17 (4), 463–475. https://doi.org/10.1071/WF08034.
Allgöwer, B., Calogine, D., Camia, A., Cuiñas, P., Fernandes, P., Francesetti, A., Séro Guillaume, O., 2006. Methods for Wildland Fuel Description and Modelling: Final Version of the State of the Art. https://doi.org/10.13140/RG.2.1.2318.4487.
Alonso-Betanzos, A., Fontenla-Romero, O., Guijarro-Berdiñas, B., Hernández-Pereira, E., Canda, J., Jimenez, E., Soto, J.L.L., Muñiz, S., Paz-Andrade, C., Paz-Andrade, M.I., 2002. A neural network approach for forestal fire risk estimation. Technical report. In: Proceedings of the 15th European Conference on Artificial Intelligence, ECAI'2002, Lyon, France, July 2002 (Available here (accessed 25 October 2022)).
Alonso-Betanzos, A., Fontenla-Romero, O., Guijarro-Berdiñas, B., Hernández-Pereira, E., Andrade, M.I.P., Jiménez, E., 2003. An intelligent system for forest fire risk prediction and firefighting management in Galicia. Expert Syst. Appl. 25 (4), 545–554. https://doi.org/10.1016/S0957-4174(03)00095-2.
Anderson, H.E., 1983. Predicting wind-driven wildland fi re size and shape. In: USDA For. Serv. Res. Pap. INT-305 (Available here (accessed 01 November 2022)).
Andrews, P.L., 1986. BEHAVE: Fire Behaviour Prediction and Fuel Modelling System: BURN Subsystem, Part 1, Vol. 194. US Department of Agriculture, Forest Service, Intermountain Research Station. https://doi.org/10.2737/INT-GTR-194.
Andrews, P.L., Bevins, C.D., Seli, R.C., 2005. BehavePlus fire modeling system, version 4.0: User's Guide. Gen. Tech. Rep. RMRS-GTR-106 Revised, 106. Department of Agriculture, Forest Service, Rocky Mountain Research Station, Ogden, UT. https://doi.org/10.2737/RMRS-GTR-106, 132p.
Andrews, P.L., Finney, M.A., Fischetti, M., 2007. Predicting wildfires. Sci. Am. 297, 46–55. https://doi.org/10.1038/SCIENTIFICAMERICAN0807-46.
Archibald, S., Roy, D.P., van Wilgen, B.W., Scholes, R.J., 2009. What limits fire? An examination of drivers of burnt area in Southern Africa. Global Change Bio. 15 (3), 613–630. https://doi.org/10.1111/j.1365-2486.2008.01754.x.
Arndt, N., Vacik, H., Koch, V., Arpaci, A., Gossow, H., 2013. Modeling human-caused forest fire ignition for assessing forest fire danger in Austria. iForest 6, 315–325. https://doi.org/10.3832/ifor0936-006.
Arora, V.K., Boer, G.J., 2005. Fire as an interactive component of dynamic vegetation models. J. Geophys. Res. 110, G02008. https://doi.org/10.1029/2005JG000042.
Asner, G.P., 1998. Biophysical and biochemical sources of variability in canopy reflectance. Remote Sens. Environ. 64 (3), 234–253. https://doi.org/10.1016/S0034-4257(98)00014-5.
Avitabile, V., Baccini, A., Friedl, M.A., Schmullius, C., 2012. Capabilities and limitations of Landsat and land cover data for aboveground woody biomass estimation of Uganda. Remote Sens. Environ. 117, 366–380. https://doi.org/10.1016/j.rse.2011.10.012.
Balling Jr., R.C., Meyer, G.A., Wells, S.G., 1992. Relation of surface climate and burned area in Yellowstone National Park. Agric. For. Meteorol. 60 (3–4), 285–293. https://doi.org/10.1016/0168-1923(92)90043-4.
Barbero, R., Abatzoglou, J.T., Larkin, N.K., Kolden, C.A., Stocks, B., 2015. Climate change presents increased potential for very large fires in the contiguous United States. Int. J. Wildland Fire 24 (7), 892–899. https://doi.org/10.1071/WF15083.
Barriopedro, D., Fischer, E.M., Luterbacher, J., Trigo, R.M., García-Herrera, R., 2011. The hot summer of 2010: redrawing the temperature record map of Europe. Science 332 (6026), 220–224. https://doi.org/10.1126/science.1201224.
Bassett, M., Chia, E.K., Leonard, S.W.J., Nimmo, D.G., Holland, G.J., Ritchie, E.G., Clarke, M.F., Bennett, A.F., 2015. The effects of topographic variation and the fire regime on coarse woody debris: insights from a large wildfire. For. Ecol. Manag. 340, 126–134. https://doi.org/10.1016/j.foreco.2014.12.028.
Basso, F., Bove, E., Dumontet, S., Ferrara, A., Pisante, M., Quaranta, G., Taberner, M., 2000. Evaluating environmental sensitivity at the basin scale through the use of geographic information systems and remotely sensed data: an example covering the Agri basin (Southern Italy). Catena 40 (1), 19–35. https://doi.org/10.1016/S0341-8162(99)00062-4.
Batelis, S.C., Nalbantis, I., 2014. Potential effects of forest fires on streamflow in the Enipeas river basin, Thessaly, Greece. Environ. Process. 1 (1), 73–85. https://doi.org/10.1007/s40710-014-0004-z.
Bates, B.C., Dowdy, A.J., Chandler, R.E., 2017. Classification of Australian thunderstorms using multivariate analyses of large-scale atmospheric variables. J. Appl. Meteorol. Climatol. 56 (7), 1921–1937. https://doi.org/10.1175/JAMC-D-16-0271.1.
Batllori, E., Parisien, M.A., Krawchuk, M.A., Moritz, M.A., 2013. Climate change-induced shifts in fire for Mediterranean ecosystems. Glob. Ecol. Biogeogr. 22 (10), 1118–1129. https://doi.org/10.1111/geb.12065.
Béland, M., Baldocchi, D.D., Widlowski, J.L., Fournier, R.A., Verstraete, M.M., 2014. On seeing the wood from the leaves and the role of voxel size in determining leaf area distribution of forests with terrestrial LiDAR. Agr. For. Met. 184, 82–97. https://doi.org/10.1016/j.agrformet.2013.09.005.
Bisquert, M., Caselles, E., Sánchez, J.M., Caselles, V., 2012. Application of artificial neural networks and logistic regression to the prediction of forest artificial fire danger in Galicia using MODIS data. Int. J. Wildland Fire 21 (8), 1025. https://doi.org/10.1071/WF11105.
Blackburn, G.A., 2007. Wavelet decomposition of hyperspectral data: a novel approach to quantifying pigment concentrations in vegetation. Inter. J. Rem. Sens. 28 (12), 2831–2855. https://doi.org/10.1080/01431160600928625.
Blouin, K.D., Flannigan, M.D., Wang, X., Kochtubajda, B., 2016. Ensemble lightning prediction models for the province of Alberta, Canada. Int. J. Wildland Fire 25 (4), 421–432. https://doi.org/10.1071/WF15111.
Boer, M.M., Nolan, R.H., Resco De Dios, V., Clarke, H., Price, O.F., Bradstock, R.A., 2017. Changing weather extremes call for early warning of potential for catastrophic fire. Earth's Future 5 (12), 1196–1202. https://doi.org/10.1002/2017EF000657.
Bossard, M., Feranec, J., Otahel, J., 2000. CORINE Land Cover Technical Guide: Addendum 2000, vol. 40. European Environment Agency, Copenhagen (Available here (accessed 10 February 2023)).
Bradstock, R.A., 2010. A biogeographic model of fire regimes in Australia: current and future implications. Global Ecol. Biogeo. 19 (2), 145–158. https://doi.org/10.1111/j.1466-8238.2009.00512.x.
Broge, N.H., Leblanc, E., 2001. Comparing prediction power and stability of broadband and hyperspectral vegetation indices for estimation of green leaf area index and canopy chlorophyll density. Rem. Sens. Environ. 76 (2), 156–172. https://doi.org/10.1016/S0034-4257(00)00197-8.
Brotons, L., Aquilué, N., De Cáceres, M., Fortin, M.J., Fall, A., 2013. How fire history, fire suppression practices and climate change affect wildfire regimes in Mediterranean landscapes. PLoS One 8 (5), e62392. https://doi.org/10.1371/journal.pone.0062392.
Burgan, R.E., 1996. Use of remotely sensed data for fire danger estimation. In: EARSel Advances in Remote Sensing, 4, pp. 1–8 (Available here (accessed 07 October 2022).
Burgan, R.E., Hartford, R.A., 1993. Monitoring vegetation greenness with satellite data, Vol. 297. US Department of Agriculture, Forest Service, Intermountain Research Station. https://doi.org/10.2737/INT-GTR-297.
Burgan, R.E., Klaver, R.W., Klaver, J.M., 1998. Fuel models and fire potential from satellite and surface observations. Int. J. Wildland Fire 8 (3), 159–170. https://doi.org/10.1071/WF9980159.
Burrows, N., Gill, M., Sharples, J., 2018. Development and validation of a model for predicting fire behaviour in spinifex grasslands of arid Australia. Int. J. Wildland Fire 27 (4), 271–279. https://doi.org/10.1071/WF17155.
Byram, G.M., 1959. Combustion of forest fuels. In: Forest Fire: Control and Use, pp. 61–89 (Available here (accessed 30 May 2022)).
Caccamo, G., Chisholm, L.A., Bradstock, R.A., Puotinen, M.L., Pippen, B.G., 2012. Monitoring live fuel moisture content of heathland, shrubland and sclerophyll forest in south-eastern Australia using MODIS data. Int. J. Wildland Fire 21, 257–269. https://doi.org/10.1071/WF11024.
Camia, A., Houston Durrant, T., San-Miguel-Ayanz, J., 2013. Harmonized classification scheme of fire causes in the EU adopted for the European Fire Database of EFFIS. In: Vol. 25923 of EUR - Scientific and Technical Research. Publications Office of the European Union. https://doi.org/10.2788/86859.
Campbell, M.J., Dennison, P.E., Hudak, A.T., Parham, L.M., Butler, B.W., 2018. Quantifying understory vegetation density using small-footprint airborne lidar. Remote Sens. Environ. 215, 330–342. https://doi.org/10.1016/j.rse.2018.06.023.
Cao, Y., Wang, M., Liu, K., 2017. Wildfire susceptibility assessment in southern China: a comparison of multiple methods. Int. J. Disast. Risk Sci. 8 (2), 164–181. https://doi.org/10.1007/s13753-017-0129-6.
Cardille, J.A., Ventura, S.J., Turner, M.G., 2001. Environmental and social factors influencing wildfires in the Upper Midwest, United States. Ecol. Appl. 11 (1), 111–112. https://doi.org/10.1890/1051-0761(2001)011[0111:EASFIW]2.0.CO;2.
Castagneri, D., Bottero, A., Motta, R., Vacchiano, G., 2015. Repeated spring precipitation shortage alters individual growth patterns in scots pine forests in the Western Alps. Trees 29, 1699–1712. https://doi.org/10.1007/s00468-015-1250-z.
Catry, F.X., Rego, F.C., Bacao, F., Moreira, F., 2009. Modelling and mapping wildfire ignition risk in Portugal. Int. J. Wildland Fire 18, 921–931. https://doi.org/10.1071/WF07123.
Chen, J.M., Black, T.A., 1992. Defining leaf area index for non-flat leaves. Plant Cell Environ. 15 (4), 421–429. https://doi.org/10.1111/j.1365-3040.1992.tb00992.x.
Cheney, N.P., Sullivan, A.L., 1997. Grassfires: Fuel, Weather and Fire Behaviour. CSIRO Publishing, Collingwood, Australia (Available here (accessed 27 February 2023)).
Chingono, T.T., Mbohwa, C., 2015. Fire hazard modelling in Southern Africa. In: Proceedings of the World Congress on Engineering and Computer Science, San Francisco, Calif (Available here (accessed 18 October 2022)).
Chou, Y.H., Minnich, R.A., Chase, R.A., 1993. Mapping probability of fire occurrence in San Jacinto Mountains, California, USA. Environ. Manag. 17 (1), 129–140. https://doi.org/10.1007/BF02393801.
Chuvieco, E., 1997. A Review of Remote Sensing Methods for the Study of Large Wildland Fires, 192. Megafires project ENV-CT96-0256, Spain (Available Here (accessed 07 October 2022)).
Chuvieco, E., Congalton, R.G., 1989. Application of remote sensing and geographic information systems to forest fire hazard mapping. Remote Sens. Environ. 29 (2), 147–159. https://doi.org/10.1016/0034-4257(89)90023-0.
Chuvieco, E., Salas, J., 1996. Mapping the spatial distribution of forest fire danger using GIS. Int. J. Geogr. Inf. Syst. 10 (3), 333–345. https://doi.org/10.1080/02693799608902082.
Chuvieco, E., Deshayes, M., Stach, N., Cocero, D., Riaño, D., 1999. Short-term fire risk: foliage moisture content estimation from satellite data. In: Remote Sensing of Large

Wildfires. Springer, Berlin, Heidelberg, pp. 17–38. https://doi.org/10.1007/978-3-642-60164-4_3.
Chuvieco, E., Allgöwer, B., Salas, J., 2003. Integration of physical and human factors in fire danger assessment. In: Wildland Fire Danger Estimation and Mapping: The Role of Remote Sensing Data, pp. 197–218. https://doi.org/10.1142/9789812791177_0007.
Chuvieco, E., Cocero, D., Riano, D., Martin, P., Martınez-Vega, J., De La Riva, J., Pérez, F., 2004. Combining NDVI and surface temperature for the estimation of live fuel moisture content in forest fire danger rating. Remote Sens. Environ. 92 (3), 322–331. https://doi.org/10.1016/j.rse.2004.01.019.
Chuvieco, E., Aguado, I., Yebra, M., Nieto, H., Salas, J., Martín, M.P., Zamora, R., 2010. Development of a framework for fire risk assessment using remote sensing and geographic information system technologies. Ecol. Model. 221 (1), 46–58. https://doi.org/10.1016/j.ecolmodel.2008.11.017.
Chuvieco, E., Aguado, I., Jurdao, S., Pettinari, M.L., Yebra, M., Salas, J., Hantson, S., de la Riva, J., Ibarra, P., Rodrigues, M., Echeverris, M., Azqueta, D., Roman, M.V., Bastarrika, A., Martinez, S., Recondo, C., Zapico, E., Martínez-Vega, F.J., 2012. Integrating geospatial information into fire risk assessment. Int. J. Wildland Fire 23 (5), 606–619. https://doi.org/10.1071/WF12052.
Clark, J.S., 1989. Effects of long-term water balances on fire regime, north-western Minnesota. J. Ecol. 77, 989–1004. https://doi.org/10.2307/2260818.
Colombo, R., Meroni, M., Marchesi, A., Busetto, L., Rossini, M., Giardino, C., Panigada, C., 2008. Estimation of leaf and canopy water content in poplar plantations by means of hyperspectral indices and inverse modeling. Remote Sens. Environ. 112, 1820–1834. https://doi.org/10.1016/j.rse.2007.09.005.
Combal, B., Baret, F., Weiss, M., Trubuil, A., Mace, D., Pragnere, A., Wang, L., 2003. Retrieval of canopy biophysical variables from bidirectional reflectance: using prior information to solve the ill-posed inverse problem. Remote Sens. Environ. 84 (1), 1–15. https://doi.org/10.1016/S0034-4257(02)00035-4.
Costa, L., Thonicke, K., Poulter, B., Badeck, F.W., 2011. Sensitivity of Portuguese forest fires to climatic, human, and landscape variables: subnational differences between fire drivers in extreme fire years and decadal averages. Reg. Environ. Chang. 11 (3), 543–551. https://doi.org/10.1007/s10113-010-0169-6.
Costafreda-Aumedes, S., Vega-Garcia, C., Comas, C., 2018. Improving fire season definition by optimized temporal modelling of daily human-caused ignitions. J. Environ. Manag. 217, 90–99. https://doi.org/10.1016/j.jenvman.2018.03.080.
Côté, J.F., Fournier, R.A., Egli, R., 2011. An architectural model of trees to estimate forest structural attributes using terrestrial LiDAR. Environ. Model. Softw. 26, 761–777. https://doi.org/10.1016/j.envsoft.2010.12.008.
Crimmins, M.A., 2006. Synoptic climatology of extreme fire-weather conditions across the Southwest United States. Int. J. Climatol. 26 (8), 1001–1016. https://doi.org/10.1002/joc.1300.
Cruz, M.G., Alexander, M.E., 2010. Assessing crown fire potential in coniferous forests of western North America: a critique of current approaches and recent simulation studies. Int. J. Wildland Fire 19 (4), 377–398. https://doi.org/10.1071/WF08132.
Cruz, M.G., Gould, J.S., Alexander, M.E., Sullivan, A.L., McCaw, W.L., Matthews, S., 2015. Empirical-based models for predicting head-fire rate of spread in Australian fuel types. Aust. For. 78 (3), 118–158. https://doi.org/10.1080/00049158.2015.1055063.
Cube Management Solutions (Cube), 2014. Improving our National Danger Rating System, Concept Document, National Fire Danger Rating Working Group, Version 1.0 (Available here (accessed 26 February 2023)).
Curran, P.J., Dungan, J.L., Macler, B.A., Plummer, S.E., Peterson, D.L., 1992. Reflectance spectroscopy of fresh whole leaves for the estimation of chemical concentration. Remote Sens. Environ. 39, 153–166. https://doi.org/10.1016/0034-4257(92)90133-5.
Daughtry, C.S.T., Hunt Jr., E.R., Doraiswamy, P.C., McMurtrey III, J.E., 2005. Remote sensing the spatial distribution of crop residues. Agron. J. 97, 864–871. https://doi.org/10.2134/agronj2003.0291.
Davis, B., Miller, C., 2004. Modelling wildfire probability using a GIS. In: 'Proceedings of the 2004 Annual ASPRS Conference', 23–28 May 2004, Denver, CO. American Society for Photogrammetry and Remote Sensing, Denver, CO, USA (Available here (accessed 01 November 2022)).
Davis, R., Yang, Z., Yost, A., Belongie, C., Cohen, W., 2017. The normal fire environment-modelling environmental suitability for large forest wildfires using past, present, and future climate normals. For. Ecol. Manag. 390, 173–186. https://doi.org/10.1016/j.foreco.2017.01.027.
Dawson, T.P., Curran, P.J., Plummer, S.E., 1998. LIBERTY—modeling the effects of leaf biochemical concentration on reflectance spectra. Remote Sens. Environ. 65 (1), 50–60. https://doi.org/10.1016/S0034-4257(98)00007-8.
De Lillis, M., Bianco, P.M., Loreto, F., 2009. The influence of leaf water content and isoprenoids on flammability of some Mediterranean woody species. Int. J. Wildland Fire 18, 203–212. https://doi.org/10.1071/WF07075.
Deeming, J.E., Burgan, R.E., Cohen, J.D., 1977. The National Fire-Danger Rating System–1978. USDA Forest Service, Intermountain Forest and Range Experiment Station, General Technical Report INT-39, Ogden, Utah (63 pp).
Delgado, R., González, J.L., Sotoca, A., Tibau, X.A., 2018. Archetypes of wildfire arsonists: an approach by using Bayesian networks. For. Fire. https://doi.org/10.5772/intechopen.72615.
Dennison, P.E., Moritz, M.A., 2009. Critical live fuel moisture in chaparral ecosystems: a threshold for fire activity and its relationship to antecedent precipitation. Int. J. Wildland Fire 18, 1021–1027. https://doi.org/10.1071/WF08055.
Dennison, P.E., Roberts, D.A., Peterson, S.H., Rechel, J., 2005. Use of normalized difference water index for monitoring live fuel moisture. Int. J. Remote Sens. 26, 1035–1042. https://doi.org/10.1080/0143116042000273998.
Desbois, N., Deshayes, M., Beudoin, A., 1997. Protocol for fuel moisture content measurements. In: Chuvieco, E. (Ed.), A Review of Remote Sensing Methods for the Study of Large Wildland Fires. Departamento de Geografía, Universidad de Alcalá, Alcalá de Henares, pp. 61–72 (Available here (accessed 07 October 2022)).
van Deventer, A.P., Ward, A.P., Gowda, P.H., Lyon, J.G., 1997. Using thematic mapper data to identify contrasting soil plains to tillage practices. Photogramm. Eng. Remote. Sens. 63, 87–93 (Available here (accessed on 24 May 2023).
Dimitrakopoulos, A.P., 2001. A statistical classification of Mediterranean species based on their flammability components. Int. J. Wildland Fire 10, 113–118. https://doi.org/10.1071/WF01004.
Dormann, F.C., McPherson, M.J., Araújo, B.M., Bivand, R., Bolliger, J., Carl, G., Wilson, R., 2007. Methods to account for spatial autocorrelation in the analysis of species distributional data: a review. Ecography 30 (5), 609–628. https://doi.org/10.1111/j.2007.0906-7590.05171.x.
Drobyshev, I., Niklasson, M., Linderholm, H.W., 2012. Forest fire activity in Sweden: climatic controls and geographical patterns in 20th century. Agric. For. Meteorol. 154–155, 174–186. https://doi.org/10.1016/jagrformet.2011.11.002.
Dubayah, R.O., Drake, J.B., 2000. Lidar remote sensing for forestry. J. For. 98 (6), 44–46. https://doi.org/10.1093/jof/98.6.44.
Duff, T.J., Penman, T.D., 2021. Determining the likelihood of asset destruction during wildfires: modelling house destruction with fire simulator outputs and local-scale landscape properties. Saf. Sci. 139, 105196 https://doi.org/10.1016/j.ssci.2021.105196.
Duff, T.J., Bell, T.L., York, A., 2013. Predicting continuous variation in forest fuel load using biophysical models: a case study in south-eastern Australia. Int. J. Wildland Fire 22, 318–332. https://doi.org/10.1071/WF11087.
Dutta, R., Aryal, J., Das, A., Kirkpatrick, J.B., 2013. Deep cognitive imaging systems enable estimation of continental-scale fire incidence from climate data. Sci. Rep. 3 (1), 3188. https://doi.org/10.1038/srep03188.
Elia, M., D'Este, M., Ascoli, D., Giannico, V., Spano, G., Ganga, A., Colangelo, G., Lafortezza, R., Sanesi, G., 2020. Estimating the probability of wildfire occurrence in Mediterranean landscapes using artificial neural networks. Environ. Impact Assess. Rev. 85, 106474 https://doi.org/10.1016/j.eiar.2020.106474.
European Environment Agency, 2017. Climate Change, Impacts and Vulnerability in Europe 2016. An Indicator-based Report (Available here (accessed 07 October 2022)).
European Forest Fire Network (EUFOFINET), 2012. European Glossary for Wildfires and Forest Fires (Available here (accessed 07 November 2022)).
Fares, S., Bajocco, S., Salvati, L., Camarretta, N., Dupuy, J.L., Xanthopoulos, G., Corona, P., 2017. Characterizing potential wildland fire fuel in live vegetation in the Mediterranean region. Ann. For. Sci. 74, 1–14. https://doi.org/10.1007/s13595-016-0599-5.
Féret, J.B., François, C., Gitelson, A., Asner, G.P., Barry, K.M., Panigada, C., Jacquemoud, S., 2011. Optimizing spectral indices and chemometric analysis of leaf chemical properties using radiative transfer modeling. Remote Sens. Environ. 115 (10), 2742–2750. https://doi.org/10.1016/j.rse.2011.06.016.
Fernandes, P.M., Fernandes, M.M., Loureiro, C., 2015. Post-fire live residuals of maritime pine plantations in Portugal: structure, burn severity, and fire recurrence. For. Ecol. Manag. 347, 170–179. https://doi.org/10.1016/j.foreco.2015.03.023.
Fernandes, P.M., Barros, A.M.G., Pinto, A., Santos, J.A., 2016. Characteristics and controls of extremely large wildfires in the western Mediterranean Basin. J. Geophys. Res. Biogeosci. 121 (8), 2141–2157. https://doi.org/10.1002/2016jg003389.
Fernández-Alonso, J.M., Vega, J.A., Jiménez, E., Ruiz-González, A.D., Álvarez-González, J.G., 2017. Spatially modeling wildland fire severity in pine forests of Galicia, Spain. Eur. J. For. Res. 136, 105–121. https://doi.org/10.1007/s10342-016-1012-5.
Fernandez-Anez, N., Krasovskiy, A., Müller, M., Vacik, H., Baetens, J., Hukić, E., Cerda, A., 2021. Current wildland fire patterns and challenges in Europe: a synthesis of national perspectives. Air Soil Water Res. 14 https://doi.org/10.1177/11786221211028185 (11786221211028185).
Fernández-Guisuraga, J.M., Fernandes, P.M., 2023. Using pre-fire High Point cloud density LiDAR data to predict fire severity in central Portugal. Remote Sens. 15 (3), 768. https://doi.org/10.3390/rs15030768.
Fernández-Guisuraga, J.M., Suárez-Seoane, S., García-Llamas, P., Calvo, L., 2021. Vegetation structure parameters determine high burn severity likelihood in different ecosystem types: a case study in a burned Mediterranean landscape. J. Environ. Manag. 288, 112462 https://doi.org/10.1016/j.jenvman.2021.112462.
Fernández-Guisuraga, J.M., Suárez-Seoane, S., Fernandes, P.M., Fernández-García, V., Fernández-Manso, A., Quintano, C., Calvo, L., 2022. Pre-fire aboveground biomass, estimated from LiDAR, spectral and field inventory data, as a major driver of burn severity in maritime pine (Pinus pinaster) ecosystems. For. Ecosyst. 9, 100022 https://doi.org/10.1016/j.fecs.2022.100022.
Ferraz, A., Bretar, F., Jacquemoud, S., Gonçalves, G., 2009. The Role of Lidar Systems in Fuel Mapping. INESC, Coimbra, Portugal (Available here (accessed 10 February 2023).
Filippelli, S.K., Lefsky, M.A., Rocca, M.E., 2019. Comparison and integration of lidar and photogrammetric point clouds for mapping pre-fire forest structure. Remote Sens. Environ. 224, 154–166. https://doi.org/10.1016/j.rse.2019.01.029.
Finney, M.A., 1998. FARSITE: Fire Area Simulator – Model Development and Evaluation. USDA For. Serv. Res. Pap. RMRS-RP-4, 47p. https://doi.org/10.2737/RMRS-RP-4.
Finney, M.A., 2002. Fire growth using minimum travel time methods. Can. J. For. Res. 32 (8), 1420–1424. https://doi.org/10.1139/x02-068.
Finney, M.A., 2005. The challenge of quantitative risk analysis for wildland fire. For. Ecol. Manag. 211, 97–108. https://doi.org/10.1016/J.FORECO.2005.02.010.
Finney, M.A., 2006. An Overview of FlamMap Fire Modeling Capabilities (Available here (accessed 01 November 2022)).

Finney, M.A., McHugh, C.W., Grenfell, I.C., Riley, K.L., Short, K.C., 2011. A simulation of probabilistic wildfire risk components for the continental United States. Stoch. Env. Res. Risk A. 25 (7), 973–1000. https://doi.org/10.1007/s00477-011-0462-z.

Flannigan, M.D., Logan, K.A., Amiro, B.D., Skinner, W.R., Stocks, B.J., 2005. Future area burned in Canada. Clim. Change 72 (1–2), 1–16. https://doi.org/10.1007/s10584-005-5935-y.

Forthofer, J.M., Butler, B.W., Wagenbrenner, N.S., 2014. A comparison of three approaches for simulating fine-scale surface winds in support of wildland fire management. Part I. Model formulation and comparison against measurements. Int. J. Wildland Fire 23 (7), 969–981. https://doi.org/10.1071/WF12089.

Fosberg, M.A., Rothermel, R.C., Andrews, P.L., 1981. Moisture content calculations for 1000-hour timelag fuels. For. Sci. 27 (1), 19–26 (Available here (Accessed 09 October 2022).

Founda, D., Giannakopoulos, C., 2009. The exceptionally hot summer of 2007 in Athens, Greece— a typical summer in the future climate? Glob. Planet. Chang. 67 (3–4), 227–236. https://doi.org/10.1016/j.gloplacha.2009.03.013.

Fourty, Th., Baret, F., Jacquemoud, S., Schmuck, G., Verdebout, J., 1996. Leaf optical properties with explicit description of its biochemical composition: direct and inverse problems. Remote Sens. Environ. 56, 104–117. https://doi.org/10.1016/0034-4257(95)00234-0.

Franklin, S.B., Tolonen, M., 2000. Temporally-explicit models of fire and forest. Plant Ecol. 146, 145–168. https://doi.org/10.1023/A:1009891610140.

Gale, M.G., Cary, G.J., Van Dijk, A.I.J.M., Yebra, M., 2021. Forest fire fuel through the lens of remote sensing: review of approaches, challenges and future directions in the remote sensing of biotic determinants of fire behaviour. Rem. Sens. Environ. 255, 112282 https://doi.org/10.1016/j.rse.2020.112282.

Ganteaume, A., Camia, A., Jappiot, M., San-Miguel-Ayanz, J., Long-Fournel, M., Lampin, C., 2013. A review of the main driving factors of forest fire ignition over Europe. Environ. Manag. 51, 651–662. https://doi.org/10.1007/s00267-012-9961-z.

Gao, X., Fei, X., Xie, H., 2011. Forest fire risk zone evaluation based on high spatial resolution RS image in Liangyungang Huaguo Mountain scenic spot. In: Spatial Data Mining and Geographical Knowledge Services (ICSDM), 2011 IEEE International Conference on. IEEE, pp. 593–596. https://doi.org/10.1109/ICSDM.2011.5969116.

Garcia, M., Chuvieco, E., Nieto, H., Aguado, I., 2008. Combining AVHRR and meteorological data for estimating live fuel moisture content. Remote Sens. Environ. 112, 3618–3627. https://doi.org/10.1016/j.rse.2008.05.002.

García-Llamas, P., Suárez-Seoane, S., Taboada, A., Fernández-García, V., Fernández-Guisuraga, J.M., Fernández-Manso, A., Calvo, L., 2019. Assessment of the influence of biophysical properties related to fuel conditions on fire severity using remote sensing techniques: a case study on a large fire in NW Spain. Int. J. Wildland Fire 28 (7), 512–520. https://doi.org/10.1071/WF18156.

Gates, D.M., Keegan, H.J., Schleter, J.C., Wiedner, V.R., 1965. Spectral properties of plants. Appl. Opt. 4, 11–20 (Available here (accessed 24 May 2023).

Ghobadi, G.J., Gholizadeh, B., Dashliburun, O.M., 2012. Forest fire risk zone mapping from geographic information system in northern forests of Iran (case study, Golestan province). Int. J. Agric. Crop Sci. 4, 818–824 (Access here (accessed 18 October 2022).

Gholamnia, K., Gudiyangada Nachappa, T., Ghorbanzadeh, O., Blaschke, T., 2020. Comparisons of diverse machine learning approaches for wildfire susceptibility mapping. Symmetry 12 (4), 604. https://doi.org/10.3390/sym12040604.

Gill, A.M., Moore, P.H.R., 1996. Ignitibility of Leaves of Australian Plants. CSIRO Division of Plant Industry, Canberra (Available here (accessed 24 May 2023).

Giorgetta, M.A., Januriyadi, N.F., Kazama, S., Moe, I.R., Kure, S., 2013. Climate and carbon cycle changes from 1850 to 2100 in MPI-ESM simulations for the coupled model Intercomparison project phase 5. J. Adv. Model. Earth Syst. 5, 572–597. https://doi.org/10.1002/jame.20038.

Glossary of Fire Management Terminology (GFMC-FAO), 1999. Wildland Fire Management Terminology (Available here (accessed 07 November 2022)).

Goldarag, Y.J., Mohammadzadeh, A., Ardakani, A.S., 2016. Fire risk assessment using neural network and logistic regression. J. Ind. Soc. Remote Sens. 44 (6), 885–894. https://doi.org/10.1007/s12524-016-0557-6.

Gonzalez-Alonso, F., Cuevas, J.M., Casanova, J.L., Calle, A., Illera, P., 1997. A forest fire risk assessment using NOAA AVHRR images in the Valencia area, eastern Spain. Int. J. Remote Sens. 18 (10), 2201–2207. https://doi.org/10.1080/014311697217837.

Grootemaat, S., Runcie, J., Matthews, S., Kenny, B., Hollis, J., 2019. Australian fire danger rating system research prototype: live trial results. In: Proceedings for the 6th International Fire Behaviour and Fuels Conference, April 29–May 3, 2019, Sydney, Australia. International Association of Wildland Fire, Missoula, Montana, USA (Available here (accessed 26 February 2023)).

Hardisky, M.A., Klemas, V., Smart, R.M., 1983. The influence of soil salinity, growth form, and leaf moisture on the spectral radiance of Spartina alterniflora canopies. Photogramm. Eng. Remote. Sens. 49, 77–83 (Available here (accessed 09 October 2022).

Hardy, C.C., 2005. Wildland fire hazard and risk: problems, definitions, and context. For. Ecol. Manag. 211 (1–2), 73–82. https://doi.org/10.1016/j.foreco.2005.01.029.

Hardy, C.C., Burgan, R.E., 1999. Evaluation of NDVI for monitoring live moisture in three vegetation types of the Western U.S. Photogramm. Eng. Remote. Sens. 65, 603–610 (0099-1112/99/6505-603, Available here (accessed 10 October 2022).

He, B., Quan, X., Xing, M., 2013. Retrieval of leaf area index in alpine wetlands using a two-layer canopy reflectance model. Int. J. Appl. Earth Obs. Geoinf. 21, 78–91. https://doi.org/10.1016/j.jag.2012.08.014.

Heisig, J., Olson, E., Pebesma, E., 2022. Predicting wildfire fuels and hazard in a central European temperate forest using active and passive remote sensing. Fire 5 (1), 29. https://doi.org/10.3390/fire5010029.

Heiskanen, J., Rautiainen, M., Korhonen, L., Mõttus, M., Stenberg, P., 2011. Retrieval of boreal forest LAI using a forest reflectance model and empirical regressions. Int. J. Appl. Earth Obs. Geoinf. 13, 595–606. https://doi.org/10.1016/j.jag.2011.03.005.

Hernandez, C., Drobinski, P., Turquety, S., 2015. How much does weather control fire size and intensity in the Mediterranean region? Ann. Geophys. 33 (7), 931–939. https://doi.org/10.5194/angeo-33-931-2015.

Hessburg, P.F., Reynolds, K.M., Keane, R.E., James, K.M., Salter, R.B., 2007. Evaluating wildland fire danger and prioritizing vegetation and fuels treatments. For. Ecol. Manag. 247 (1–3), 1–17. https://doi.org/10.1016/j.foreco.2007.03.068.

Hesseln, H., 2018. Wildland fire prevention: a review. Curr. For. Rep. 4 (4), 178–190. https://doi.org/10.1007/s40725-018-0083-6.

Hilton, J., Bally, J., Sullivan, A., Swedosh, W., Sparkes, D., Clark, N., 2022. Australia's national operetional bushfire spread simulator. In: IAWF Fire & Climate 2022 Conference (Available here (accessed 27 February 2023)).

Hilton, J.E., Swedosh, W., Hetherton, L., Sullivan, A., Prakash, M., 2019. Spark User Guide 1.1.2. CSIRO, Australia (Available here (accessed 27 February 2023)).

Holmgren, J., Persson, Å., 2004. Identifying species of individual trees using airborne laser scanner. Remote Sens. Environ. 90 (4), 415–423. https://doi.org/10.1016/S0034-4257(03)00140-8.

Hong, H., Tsangaratos, P., Ilia, I., Liu, J., Zhu, A.X., Xu, C., 2018. Applying genetic algorithms to set the optimal combination of forest fire related variables and model forest fire susceptibility based on data mining models. The case of Dayu County, China. Sci. Total Environ. 630, 1044–1056. https://doi.org/10.1016/j.scitotenv.2018.02.278.

Hong, H., Jaafari, A., Zenner, E.K., 2019. Predicting spatial patterns of wildfire susceptibility in the Huichang County, China: an integrated model to analysis of landscape indicators. Ecol. Indic. 101, 878–891. https://doi.org/10.1016/j.ecolind.2019.01.056.

Hopkinson, C., Chasmer, L.E., Sass, G., Creed, I.F., Sitar, M., Kalbfleisch, W., Treitz, P., 2005. Vegetation class dependent errors in lidar ground elevation and canopy height estimates in a boreal wetland environment. Can. J. Remote. Sens. 31 (2), 191–206. https://doi.org/10.5589/m05-007.

Hosgood, B., Jacquemoud, S., Andreoli, G., Verdebout, J., Pedrini, A., Schmuck, G., 1994. The JRC Leaf Optical Properties Experiment (LOPEX'93), Eur. Commiss. Directorate—General XIII, Telecommun, Inf, Market and Exploitation of Res., L-2920, Belgium, CL-NA-16095-EN-C (Available here (accessed 24 May 2023)).

Houghton, J.T., Meira-Filho, L.G., Callander, B.A., Harris, N., Kattenberg, A., Maskell, K., 1996. Climate Change 1995: The Science of Climate Change. Cambridge University Press, New York (Available here (accessed 17 March 2023)).

Hudak, A.T., Bright, B.C., Pokswinski, S.M., Loudermilk, E.L., O'Brien, J.J., Hornsby, B. S., Klauberg, C., Silva, C.A., 2016. Mapping forest structure and composition from low-density LiDAR for informed forest, fuel, and fire management at Eglin Air Force Base, Florida, USA. Can. J. Remote. Sens. 42, 411–427. https://doi.org/10.1080/07038992.2016.1217482.

Huesca, M., Litago, J., Palacios-Orueta, A., Montes, F., Sebastián-López, A., Escribano, P., 2009. Assessment of forest fire seasonality using MODIS fire potential: a time series approach. Agric. For. Meteorol. 149 (11), 1946–1955. https://doi.org/10.1016/j.agrformet.2009.06.022.

Hunt Jr., E.R., Rock, B.N., 1989. Detection of changes in leaf water content using near- and middle-infrared reflectances. Remote Sens. Environ. 30 (1), 43–54, 0034-4257/89. https://doi.org/10.1016/0034-4257(89)90046-1, 0034-4257/89.

Jacquemoud, S., 1993. Inversion of the PROSPECT + SAIL canopy reflectance model from AVIRIS equivalent spectra: theoretical study. Remote Sens. Environ. 44, 281–292. https://doi.org/10.1016/0034-4257(93)90022-P.

Jacquemoud, S., Baret, F., 1990. PROSPECT: a model of leaf optical properties spectra. Remote Sens. Environ. 34 (2), 75–91. https://doi.org/10.1016/0034-4257(90)90100-Z.

Jacquemoud, S., Baret, F., Andrieu, B., Danson, F.M., Jaggard, K., 1995. Extraction of vegetation biophysical parameters by inversion of the PROSPECT+ SAIL models on sugar beet canopy reflectance data. Application to TM and AVIRIS sensors. Remote Sens. Environ. 52 (3), 163–172. https://doi.org/10.1016/0034-4257(95)00018-V.

Jain, P., Coogan, S.C., Subramanian, S.G., Crowley, M., Taylor, S., Flannigan, M.D., 2020. A review of machine learning applications in wildfire science and management. Environ. Rev. 28 (4), 478–505. https://doi.org/10.1139/er-2020-0019.

Jakubowksi, M.K., Guo, Q., Collins, B., Stephens, S., Kelly, M., 2013. Predicting surface fuel models and fuel metrics using Lidar and CIR imagery in a dense, mountainous forest. Photogramm. Eng. Remote. Sens. 79, 37–49 (0099-1112/13/7901–37, Available here (accessed 10 October 2022)).

Jenkins, M., Price, O., Collins, L., Penman, T., Bradstock, R., 2019. The influence of planting size and configuration on landscape fire risk. J. Environ. Manag. 248, 109338 https://doi.org/10.1016/j.jenvman.2019.109338.

Jensen, J.R., 1983. Biophysical remote sensing. Ann. Assoc. Am. Geogr. 73, 111–132. https://doi.org/10.1111/j.1467-8306.1983.tb01399.x.

Jolly, W.M., Hadlow, A.M., Huguet, K., 2014. De-coupling seasonal changes in water content and dry matter to predict live conifer foliar moisture content. Int. J. Wildland Fire 23, 480–489. https://doi.org/10.1071/WF13127.

Jolly, W.M., Cochrane, M.A., Freeborn, P.H., Holden, Z.A., Brown, T.J., Williamson, G.J., Bowman, D.M., 2015. Climate-induced variations in global wildfire danger from 1979 to 2013. Nat. Commun. 6 (1), 1–11. https://doi.org/10.1038/ncomms8537.

Julio, G., 1990. Diseño de índices de riesgo de incendios forestales para Chile. Bosque 11 (2), 59–72. https://doi.org/10.4206/bosque.1990.v11n2-06.

Kane, V.R., Cansler, C.A., Povak, N.A., Kane, J.T., McGaughey, R.J., Lutz, J.A., Churchill, D.J., North, M.P., 2015. Mixed severity fire effects within the rim fire: relative importance of local climate, fire weather, topography, and forest structure. For. Ecol. Manag. 358, 62–79. https://doi.org/10.1016/j.foreco.2015.09.001.

Keane, R.E., Burgan, R.E., Wagtendonk, J.V., 2001. Mapping wildland fuels for fire management across multiple scales: integrating remote sensing, GIS, and biophysical modelling. Int. J. Wildland Fire 10, 301–319. https://doi.org/10.1071/WF01028.
Keeley, J.E., 2012. Fire in mediterranean climate ecosystems—a comparative overview. Israel J. Ecol. Evol. 58 (2–3), 123–135 (Available here (accessed 24 August 2022).
Keetch, J.J., Byram, G.M., 1968. A Drought Index for Forest Fire Control. USDA Forest Service, Southeast Forest Experiment Station Research Paper SE-38, Ashville, NC (32 pp, Available here (accessed 05 January 2022).
Key, C.H., Benson, N.C., 2006. Landscape assessment (LA). In: FIREMON: Fire Effects Monitoring and Inventory System, 164, LA-1 (Available here (accessed 20 May 2023)).
Kindt, R., Coe, R., 2005. Tree diversity analysis. In: A Manual and Software for Common Statistical Methods for Ecological and Biodiversity Studies. World Agroforestry Centre (ICRAF), Nairobi. ISBN 92-9059-179-X. (Available here (accessed 20 May 2023)).
Knorr, K., Jiang, L., Arneth, A., 2016. Climate, CO_2 and demographic impacts on global wildfire emissions. Biogeosciences 13 (1), 267. https://doi.org/10.5194/bg-13-267-2016.
Korhonen, L., Hadi Packalen, P., Rautiainen, M., 2017. Comparison of Sentinel-2 and Landsat 8 in the estimation of boreal forest canopy cover and leaf area index. Remote Sens. Environ. 195, 259–274. https://doi.org/10.1016/j.rse.2017.03.021.
Kourtz, P.H., Todd, J.B., 1991. Predicting the Daily Occurrence of Lightning-caused Forest Fires, Vol. 112 (Available here (accessed 21 December 2022).
Koutsias, N., Xanthopoulos, G., Founda, D., Xystrakis, F., Nioti, F., Pleniou, M., Arianoutsou, M., 2012. On the relationships between forest fires and weather conditions in Greece from long-term national observations (1894–2010). Int. J. Wildland Fire 22 (4), 493–507. https://doi.org/10.1071/WF12003.
Krause, A., Kloster, S., Wilkenskjeld, S., Paeth, H., 2014. The sensitivity of global wildfires to simulated past, present, and future lightning frequency. J. Geophys. Res. Biogeosci. 119, 312–322. https://doi.org/10.1002/2013JG002502.
Kuusk, A., 1991. The hot spot effect in plant canopy reflectance. In: Photon-Vegetation Interactions: Applications in Optical Remote Sensing and Plant Ecology, pp. 139–159. https://doi.org/10.1007/978-3-642-75389-3_5.
Kuusk, A., 2001. A two-layer canopy reflectance model. J. Quant. Spectrosc. Radiat. Transf. 71 (1), 1–9. https://doi.org/10.1016/S0022-4073(01)00007-3.
Lagerquist, R., Flannigan, M.D., Wang, X., Marshall, G.A., 2017. Automated prediction of extreme fire weather from synoptic patterns in northern Alberta, Canada. Can. J. For. Res. 47 (9), 1175–1183. https://doi.org/10.1139/cjfr-2017-0063.
Larsen, C.P.S., 1996. Fire and climate dynamics in the boreal forest of northern Alberta, Canada, from AD 1850 to 1989. The Holocene 6, 449–456. https://doi.org/10.1177/095968369600600407.
Le, T.H., Nguyen, T.N.T., Lasko, K., Ilavajhala, S., Vadrevu, K.P., Justice, C., 2014. Vegetation fires and air pollution in Vietnam. Environ. Pollut. 195, 267–275. https://doi.org/10.1016/j.envpol.2014.07.023.
Leone, V., Lovreglio, R., Martín, Martínez, J. & Vilar, L., 2009. Human factors of fire occurrence in the Mediterranean. In: Chuvieco, E. (Ed.), Earth Observation of Wildland Fires in Mediterranean Ecosystems. Springer, Berlin Heidelberg, pp. 149–170. https://doi.org/10.1007/978-3-642-01754-4_11.
Leuenberger, M., Parente, J., Tonini, M., Pereira, M.G., Kanevski, M., 2018. Wildfire susceptibility mapping: deterministic vs. stochastic approaches. Environ. Model. Softw. 101, 194–203. https://doi.org/10.1016/j.envsoft.2017.12.019.
Li, S., Hughes, A.C., Su, T., Anberree, J.L., Oskolski, A.A., Sun, M., Ferguson, D.K., Zhou, Z., 2017. Fire dynamics under monsoonal climate in Yunnan, SW, China: past, present and future. Palaeogeogr. Palaeoclimatol. Palaeoecol. 465, 168–176. https://doi.org/10.1016/j.palaeo.2016.10.028.
Lin, C., Ma, S.E., Huang, L.P., Chen, C.I., Lin, P.T., Yang, Z.K., Lin, K.T., 2021. Generating a baseline map of surface fuel loading using stratified random sampling inventory data through cokriging and multiple linear regression methods. Remote Sens. 13 (8), 1561. https://doi.org/10.3390/rs13081561.
Liu, Z., Yang, J., Chang, Y., Weisberg, P.J., He, H.S., 2012. Spatial patterns and drivers of fire occurrence and its future trend under climate change in a boreal forest of Northeast China. Glob. Chang. Biol. 18 (6), 2041–2056. https://doi.org/10.1111/j.1365-2486.2012.02649.x.
Loehman, R.A., Keane, R.E., Holsinger, L.M., Wu, Z., 2017. Interactions of landscape disturbances and climate change dictate ecological pattern and process: spatial modeling of wildfire, insect, and disease dynamics under future climates. Landsc. Ecol. 32 (7), 1447–1459. https://doi.org/10.1007/s10980-016-0414-6.
Loope, W.L., Anderton, J.B., 1998. Human vs. lightning ignition of presettlement surface fires in coastal pine forests of the upper Great Lakes. Am. Midl. Nat. 206–218. https://doi.org/10.1674/0003-0031(1998)140[0206:HVLIOP]2.0.CO;2.
Lopez, A.S., San-Miguel-Ayanz, J., Burgan, R., 2002. Integration of satellite sensor data, fuel type maps and meteorological observations for evaluations of forest fire risk at the pan-European scale. Int. J. Remote Sens. 23, 2713–2719. https://doi.org/10.1080/01431160110107761.
López-Serrano, P.M., López-Sánchez, C.A., Álvarez-González, J.G., García-Gutiérrez, J., 2016. A comparison of machine learning techniques applied to Landsat-5 TM spectral data for biomass estimation. Can. J. Remote. Sens. 42 (6), 690–705. https://doi.org/10.1080/07038992.2016.1217485.
Luo, L., Zhai, Q., Su, Y., Ma, Q., Kelly, M., Guo, Q., 2018. Simple method for direct crown base height estimation of individual conifer trees using airborne LiDAR data. Opt. Express 26 (10), A562–A578. https://doi.org/10.1364/OE.26.00A562.
Ma, H., Zhang, H., Ying, W., Fang, D., 2013. Cross-flow heat transfer in fixed bed. Heat Mass Transf. 49, 753–759. https://doi.org/10.1007/s00231-013-1120-4.
Mallinis, G., Mitsopoulos, I., Beltran, E., Goldammer, J.G., 2016. Assessing wildfire risk in cultural heritage properties using high spatial and temporal resolution satellite imagery and spatially explicit fire simulations: the case of Holy Mount Athos, Greece. Forests 7 (2), 46. https://doi.org/10.3390/f7020046.
Mansuy, N., Miller, C., Parisien, M.A., Parks, S.A., Batllori, E., Moritz, M.A., 2019. Contrasting human influences and macro-environmental factors on fire activity inside and outside protected areas of North America. Environ. Res. Lett. 14 (6), 064007 https://doi.org/10.1088/1748-9326/ab1bc5.
Marsden-Smedley, J.B., Rudman, T., Pyrke, A., Catchpole, W.R., 1999. Buttongrass moorland fire-behaviour prediction and management. Tasforests 11, 87–99 (ISSN 1033-8306).
Martell, D.L., Otukol, S., Stocks, B.J., 1987. A logistic model for predicting daily people-caused forest fire occurrence in Ontario. Can. J. For. Res. 17 (5), 394–401. https://doi.org/10.1139/x87-068.
Martínez, J., Vega-Garcia, C., Chuvieco, E., 2009. Human-caused wildfire risk rating for prevention planning in Spain. J. Environ. Manag. 90 (2), 125–1241. https://doi.org/10.1016/j.jenvman.2008.07.005.
Masrur, A., Petrov, A.N., DeGroote, J., 2018. Circumpolar spatio-temporal patterns and contributing climatic factors of wildfire activity in the Arctic tundra from 2001–2015. Environ. Res. Lett. 13 (1), 014019 https://doi.org/10.1088/1748-9326/aa9a76.
Matthews, S., Fox-Hughes, P., Grootemaat, S., Hollis, J.J., Kenny, B.J., Sauvage, S., 2019a. Australian Fire Danger Rating System: Research Prototype, NSW Rural Fire Service, Lidcombe, NSW, 384pp. (Available here (accessed 26 February 2023)).
Matthews, S., Sauvage, S., Grootemaat, S., Hollis, J.J., Kenny, B., Fox-Hughes, P., 2019b. Implementation of models and the forecast system for the Australian fire danger rating system. In: Proceedings of the 6th International Fire Behaviour and Fuels Conference, Sydney, Australia, Vol. 29 (Available here (accessed 26 February 2023)).
Mazzeo, G., De Santis, F., Falconieri, A., Filizzola, C., Lacava, T., Lanorte, A., Marchese, F., Nolè, G., Pergola, N., Pietrapertosa, C., Satriano, V., 2022. Integrated satellite system for fire detection and prioritization. Remote Sens. 14 (2), 335. https://doi.org/10.3390/rs14020335.
McArthur, A.G., 1967. Fire Behaviour in Eucalypt Forests (Available here (accessed 10 December 2021)).
McCune, B., Keon, D., 2002. Equations for potential annual direct incident radiation and heat load. J. Veg. Sci. 13, 603–606. https://doi.org/10.1111/j.1654-1103.2002.tb02087.x.
Merrill, D.F., Alexander, M.E., 1987. Glossary of Forest Fire Management Terms. Canadian Committee on Forest Fire Management. National Research Council of Canada, Ottawa, ON, Canada (Available here (accessed 07 November 2022).
Miller, C., Ager, A.A., 2013. A review of recent advances in risk analysis for wildfire management. Int. J. Wildland Fire 22 (1), 1–14. https://doi.org/10.1071/WF11114.
Mills, G.A., McCaw, W.L., 2010. Atmospheric Stability Environments and Fire Weather in Australia: Extending the Haines Inde (Available here (accessed 26 February 2023)).
Ministry of Forests (MOF), 1997. Glossary of Forest Terms. Ministry of Forests. Province of British Columbia, Canada (Available here (accessed 07 November 2022)).
Mishra, N.B., Mainali, K.P., Crews, K.A., 2016. Modelling spatiotemporal variability in fires in semiarid savannas: a satellite-based assessment around Africa's largest protected area. Int. J. Wildland Fire 25 (7), 730–741. https://doi.org/10.1071/WF15152.
Moran, P.A.P., 1948. The interpretation of statistical maps. J. R. Stat. Soc. Ser. B 37, 243–251. https://doi.org/10.1111/j.2517-6161.1948.tb00012.x.
Moritz, M.A., Parisien, M.A., Batllori, E., Krawchuk, M.A., Van Dorn, J., Ganz, D.J., Hayhoe, K., 2012. Climate change and disruptions to global fire activity. Ecosphere 3 (6), 1–22. https://doi.org/10.1890/ES11-00345.1.
Motazeh, A.G., Ashtiani, E.F., Baniasadi, R., Choobar, F.M., 2013. Rating and Mapping Fire Hazard in the Hardwood Hyrcanian Forests Using GIS and Expert Choice Software Acknowledgement to Reviewers of the Manuscripts Submitted to Forestry Ideas in 2013:141 (Access here (accessed 18 October 2022)).
Mutlu, M., Popescu, S.C., Stripling, C., Spencer, T., 2008. Mapping surface fuel models using lidar and multispectral data fusion for fire behavior. Remote Sens. Environ. 112 (1), 274–285. https://doi.org/10.1016/j.rse.2007.05.005.
Nagler, P.L., Daughtry, C.S.T., Goward, S.N., 2000. Plant litter and soil reflectance. Remote Sens. Environ. 71, 207–215. https://doi.org/10.1016/S0034-4257(99)00082-6.
Nami, M.H., Jaafari, A., Fallah, M., Nabiuni, S., 2018. Spatial prediction of wildfire probability in the Hyrcanian ecoregion using evidential belief function model and GIS. Int. J. Environ. Sci. Technol. 15 (2), 373–384. https://doi.org/10.1007/s13762-017-1371-6.
Narayanaraj, G., Wimberly, M.C., 2012. Influences of forest roads on the spatial patterns of human- and lightningcaused wildfire ignitions. Appl. Geogr. 32, 878–888. https://doi.org/10.1016/j.apgeog.2011.09.004.
National Wildfire Coordinating Group (NWCG), 2003. Glossary of Wildland Fire Terminology (Available here (accessed 07 November 2022)).
Nauslar, N.J., Hatchett, B.J., Brown, T.J., Kaplan, M.L., Mejia, J.F., 2019. Impact of the North American monsoon on wildfire activity in the southwest United States. Int. J. Climatol. 39 (3), 1539–1554. https://doi.org/10.1002/joc.5899.
Nepstad, D.C., Stickler, C.M., Filho, B.S., Merry, F., 2008. Interactions among Amazon land use, forests and climate: prospects for a near-term forest tipping point. Philos. Trans. R. Soc. B 363 (1498), 1737–1746. https://doi.org/10.1098/rstb.2007.0036.
Nesterov, V.G., 1949. Combustibility of the Forest and Methods for its Determination (in Russian). USSR State Industry Press.
Newnham, G.J., Verbesselt, J., Grant, I.F., Anderson, S.A., 2011. Relative greenness index for assessing curing of grassland fuel. Remote Sens. Environ. 115 (6), 1456–1463. https://doi.org/10.1016/j.rse.2011.02.005.

Noble, I.R., Gill, A.M., Bary, G.A.V., 1980. McArthur's fire danger meters expressed as equations. Aust. J. Ecol. 5 (2), 201–203. https://doi.org/10.1111/j.1442-9993.1980.tb01243.x.

Oliveira, S., Oehler, F., San-Miguel-Ayanz, J., Camia, A., Pereira, J.M.C., 2012. Modelling spatial patterns of fire occurrence in Mediterranean Europe using multiple regression and random forest. Forest Ecol. Manag. 275, 117–129. https://doi.org/10.1016/j.foreco.2012.03.003.

Owens, M.K., Lin, C.D., Taylor, C.A., Whisenant, S.G., 1998. Seasonal patterns of plant flammability and monoterpenoid content in Juniperus ashei. J. Chem. Ecol. 24, 2115–2129. https://doi.org/10.1023/A%3A1020793811615.

Page, M.J., McKenzie, J.E., Bossuyt, P.M., Boutron, I., Hoffmann, T.C., Mulrow, C.D., et al., 2021. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ 2021 (372), n71. https://doi.org/10.1136/bmj.n71.

Palaiologou, P., Kalabokidis, K., Kyriakidis, P., 2013. Forest mapping by geoinformatics for landscape fire behaviour modelling in coastal forests, Greece. Int. J. Remote Sens. 34, 4466–4490. https://doi.org/10.1080/01431161.2013.779399.

Palomino, A.F., Silva, F.R.Y., 2021. Fuel modelling characterisation using low-density LiDAR in the Mediterranean: an application to a natural protected area. Forests 12 (8), 1011. https://doi.org/10.3390/f12081011.

Paltridge, G.W., Barber, J., 1988. Monitoring grassland dryness and fire potential in Australia with NOAA/AVHRR data. Remote Sens. Environ. 25 (3), 381–394. https://doi.org/10.1016/0034-4257(88)90110-1.

Parente, J., Pereira, M.G., 2016. Structural fire risk: the case of Portugal. Sci. Total Environ. 573, 883e893. https://doi.org/10.1016/j.scitotenv.2016.08.164.

Parisien, M.A., Kafka, V.G., Hirsch, K.G., Todd, J.B., Lavoie, S.G., Maczek, P.D., 2005. Mapping Wildfire Susceptibility With the BURN-P3 Simulation Model (Available here (accessed 01 November 2022)).

Parisien, M.A., Snetsinger, S., Greenberg, J.A., Nelson, C.R., Schoennagel, T., Dobrowski, S.Z., Moritz, M.A., 2012. Spatial variability in wildfire probability across the western United States. Int. J. Wildland Fire 21, 313–327. https://doi.org/10.1071/WF11044.

Parisien, M.A., Dawe, D.A., Miller, C., Stockdale, C.A., Armitage, O.B., 2019. Applications of simulation-based burn probability modelling: a review. Int. J. Wildland Fire 28 (12), 913–926. https://doi.org/10.1071/WF19069.

Parker, G.G., Russ, M.E., 2004. The canopy surface and stand development: assessing forest canopy structure and complexity with near-surface altimetry. For. Ecol. Manag. 189, 307–315. https://doi.org/10.1016/J.FORECO.2003.09.001.

Parks, S.A., Dillon, G.K., Miller, C., 2014. A new metric for quantifying burn severity: the relativized burn ratio. Remote Sens. 6 (3), 1827–1844. https://doi.org/10.3390/rs6031827.

Paterson, G., Chong, D., 2011. Implementing the Phoenix fire spread model for operational use. In: Surveying and Spatial Sciences Conference (p. 111), Wellington, New Zealand (Available here (accessed 27 February 2023)).

Pearson, K., 1895. VII. Note on regression and inheritance in the case of two parents. Proc. R. Soc. Lond. 58 (347–352), 240–242. https://doi.org/10.1098/rspl.1895.0041.

Peterson, G.D., 2002. Contagious disturbance, ecological memory, and the emergence of landscape pattern. Ecosystems 5 (4), 329–338. https://doi.org/10.1007/s10021-001-0077-1.

Peterson, S., Roberts, D.A., Dennison, P.E., 2008. Mapping live fuel moisture with MODIS data: a multiple regression approach. Remote Sens. Environ. 112, 4272–4284. https://doi.org/10.1016/j.rse.2008.07.012.

Pierce, A.D., Farris, C.A., Taylor, A.H., 2012. Use of random forests for modelling and mapping forest canopy fuels for fire behavior analysis in Lassen Volcanic National Park, California, USA. For. Ecol. Manag. 279, 77–89. https://doi.org/10.1016/j.foreco.2012.05.010.

Pimont, F., Dupuy, J.L., Rigolot, E., Prat, V., Piboule, A., 2015. Estimating leaf bulk density distribution in a tree canopy using terrestrial LiDAR and a straightforward calibration procedure. Remote Sens. 7, 7995–8018. https://doi.org/10.3390/rs70607995.

Plucinski, M.P., 2012. A Review of Wildfire Occurrence Research. Bushfire Cooperative Research Centre, Melbourne, Vic., Australia (Available here (accessed 09 November 2022).

Portier, J., Gauthier, S., Robitaille, A., Bergeron, Y., 2018. Accounting for spatial autocorrelation improves the estimation of climate, physical environment and vegetation's effects on boreal forest's burn rates. Landsc. Ecol. 33 (1), 19–34. https://doi.org/10.1007/s10980-017-0578-8.

Pourtaghi, Z.S., Pourghasemi, H.R., Rossi, M., 2015. Forest fire susceptibility mapping in the Minudasht forests, Golestan province, Iran. Environ. Earth Sci. 73, 1515–1533. https://doi.org/10.1007/s12665-014-3502-4.

Pradhan, B., Suliman, D.H.B.M., Awang, A.B.M., 2007. Forest fire susceptibility and risk mapping using remote sensing and geographical information systems (GIS). Disaster Prev Manag 16, 335–344.

Price, O.F., Gordon, C.E., 2016. The potential for LiDAR technology to map fire fuel hazard over large areas of Australian forest. J. Environ. Manag. 181, 663–673. https://doi.org/10.1016/j.jenvman.2016.08.042.

Pugnet, L., Chong, D., Duff, T., Tolhurst, K., 2013. Wildland–urban interface (WUI) fire modelling using PHOENIX Rapidfire: a case study in Cavaillon, France. In: Proceedings of the 20th International Congress on Modelling and Simulation, Adelaide, Australia, pp. 1–6 (Available here (accessed 27 February 2023)).

Qi, Y., Dennison, P.E., Spencer, J., Riaño, D., 2012. Monitoring live fuel moisture using soil moisture and remote sensing proxies. Fire Ecol. 8 (3), 71–87. https://doi.org/10.4996/fireecology.0803071.

Quan, X., He, B., Yebra, M., Yin, C., Liao, Z., Li, X., 2017. Retrieval of forest fuel moisture content using a coupled radiative transfer model. Environ. Model. Softw. 95, 290–302. https://doi.org/10.1016/j.envsoft.2017.06.006.

Reed, W.J., Larsen, C.P.S., Johnson, E.A., MacDonald, G.M., 1998. Estimation of temporal variations in historical fire frequency from time-since-fire map data. For. Sci. 44 (3), 465–475. https://doi.org/10.1093/forestscience/44.3.465.

Reyes-Bueno, F., Loján-Córdova, J., 2022. Assessment of three machine learning techniques with open-access geographic data for forest fire susceptibility monitoring—evidence from southern Ecuador. Forests 13 (3), 474. https://doi.org/10.3390/f13030474.

Riaño, D., Ustin, S.L., Usero, L., Patricio, M.A., 2005a. Estimation of fuel moisture content using neural networks. In: Mira, J., Álvarez, J.R. (Eds.), IWINAC 2005: Artificial Intelligence and Knowledge Engineering Applications: A Bioinspired Approach, Vol. 3562. Springer, Berlin, Heidelberg, pp. 489–498. https://doi.org/10.1007/11499305_50. Lecture Notes in Computer Science.

Riaño, D., Vaughan, P., Chuvieco, E., Zarco-Tejada, P.J., Ustin, S.L., 2005b. Estimation of fuel moisture content by inversion of radiative transfer models to simulate equivalent water thickness and dry matter content: analysis at leaf and canopy level. IEEE Trans. Geosci. Remote Sens. 43 (4), 819–826. https://doi.org/10.1109/TGRS.2005.843316.

Richards, G.D., 1990. An elliptical growth model of forest fire fronts and its numerical solution. Int. J. Numer. Math. Eng. 30, 1133–1149. https://doi.org/10.1002/nme.1620300606.

Riley, K.L., Grenfell, I.C., Finney, M.A., Crookston, N.L., 2014. Utilizing Random Forests Imputation of Forest Plot Data for Landscape-level Wildfire Analyses. Imprensa da Universidade de Coimbra, Coimbra. https://doi.org/10.14195/978-989-26-0884-6_67 (2014. ISBN 978-989-26-0884-6 (PDF)).

Rivera, J.D.D., Davies, G.M., Jahn, W., 2012. Flammability and the heat of combustion of natural fuels: a review. Combust. Sci. Technol. 184 (2), 224–242. https://doi.org/10.1080/00102202.2011.630332.

Roberts, D.A., Peterson, S., Dennison, P.E., Sweeney, S., Rechel, J., 2006. Evaluation of Aibone Visible/Infrared Imaging Spectrometer (AVIRIS) and Moderate Resolution Imaging Spectrometer (MODIS) measures of live fuel moisture and fuel condition in a shrubland ecosystem in southern California. J. Geophys. Res. 111, GO4S02 https://doi.org/10.1029/2005JG000113.

Rock, B.N., Vogelmann, J.E., Williams, D.L., Vogelmann, A.F., Hoshizaki, T., 1986. Remote detection of forest damage: plant responses to stress may have spectral "signatures" that could be used to map, monitor, and measure forest damage. Bioscience 36 (7), 439–445. https://doi.org/10.2307/1310339.

Rodriguez, M., Jiménez-Ruano, A., Peña-Angulo, D., De la Riva, J., 2018. A comprehensive spatial-temporal analysis of driving factors of human-caused wildfires in Spain using geographically weighted logistic regression. J. Environ. Manag. 225, 177–192. https://doi.org/10.1016/j.jenvman.2018.07.098.

Rothermel, R.C., 1972. A Mathematical Model for Predicting Fire Spread in Wildland Fuels. USDA Forest Service Research PaperINT-115, Odgen, UT (Available here (accessed 01 November 2022)).

Rothermel, R.C., 1983. How to Predict the Spread and Intensity of Forest and Range Fi Res. USDA For. Serv. Gen. Tech. Rep. INT-143. https://doi.org/10.2737/INT-GTR-143.

Rothermel, R.C., 1986. Modeling Moisture Content of Fine Dead Wildland Fuels: Input to the BEHAVE Fire Prediction System (No. 359). US Department of Agriculture, Forest Service, Intermountain Research Station. https://doi.org/10.2737/INT-RP-359.

Ruffault, J., Moron, V., Trigo, R.M., Curt, T., 2017. Daily synoptic conditions associated with large fire occurrence in Mediterranean France: evidence for a wind-driven fire regime. Int. J. Climatol. 37 (1), 524–533. https://doi.org/10.1002/joc.4680.

Sakr, G.E., Elhajj, I.H., Mitri, G., 2011. Efficient forest fire occurrence prediction for developing countries using two weather parameters. Eng. Appl. Artif. Intell. 24 (5), 888–894. https://doi.org/10.1016/j.engappai.2011.02.017.

Salis, M., Ager, A.A., Finney, M.A., Arca, B., Spano, D., 2014. Analyzing spatiotemporal changes in wildfire regime and exposure across a Mediterranean fire-prone area. Nat. Hazards 71 (3), 1389–1418. https://doi.org/10.1007/s11069-013-0951-0.

Sanabria, L.A., Qin, X., Li, J., Cechet, R.P., Lucas, C., 2013. Spatial interpolation of McArthur's Forest Fire Danger Index across Australia: observational study. Environ. Model. Softw. 50, 37–50. https://doi.org/10.1016/j.envsoft.2013.08.012.

Sauvage, S., Fox-Hughes, P., Matthews, S., Kenny, B., Hollis, J., Grootemaat, S., Jakob, D., Su, C.H., Eizenberg, N., Steinle, P., 2019. A preliminary climatology of the Australian Fire Danger Rating Prototype. In: Proceedings for the 6th International Fire Behavior and Fuels Conference (Available here (accessed 26 February 2023)).

Sayad, Y.O., Mousannif, H., Al Moatassime, H., 2019. Predictive modeling of wildfires: a new dataset and machine learning approach. Fire Saf. J. 104, 130–146. https://doi.org/10.1016/j.firesaf.2019.01.006.

Schlobohm, P., Brain, J., 2002. Gaining an Understanding of the National Fire Danger Rating System. National Wildfire Coordinating Group, PMS, p. 932 (Available here (accessed 30 November 2021)).

Schoenberg, F.P., Peng, R., Huang, Z., Rundel, P., 2003. Detection of non-linearities in the dependence of burn area on fuel age and climatic variables. Int. J. Wildland Fire 12, 1–6. https://doi.org/10.1071/WF02053.

Schoennagel, T., Smithwick, E.A., Turner, M.G., 2008. Landscape heterogeneity following large fires: insights from Yellowstone National Park, USA. Int. J. Wildland Fire 17 (6), 742–753. https://doi.org/10.1071/WF07146.

Scott, J.H., Burgan, R.E., 2005. Standard Fire Behaviour Fuel Models: A Comprehensive Set for Use With Rothermel's Surface Fire Spread Model. USDA Forest Service General Technical Report RMRS-GTR-153, Rocky Mountain Research Station, Fort Collins, Colorado, USA (Available here (accessed 04 November 2022)).

Scott, J.H., Helmbrecht, D.J., Parks, S.A., Miller, C., 2012. Quantifying the threat of unsuppressed wildfires reaching the adjacent wildland-urban interface on the Bridger-Teton National Forest, Wyoming, USA. Fire Ecol. 8 (2), 125–142. https://doi.org/10.4996/fireecology.0802125.

Seielstad, C., Stonesifer, C., Rowell, E., Queen, L., 2011. Deriving fuel mass by size class in Douglas-fir (*Pseudotsuga menziesii*) using terrestrial laser scanning. Remote Sens. 3, 1691–1709. https://doi.org/10.3390/rs3081691.
Serbin, G., Daughtry, C.S., Hunt Jr., E.R., Brown, D.J., McCarty, G.W., 2009. Effect of soil spectral properties on remote sensing of crop residue cover. Soil Sci. Soc. Am. J. 73 (5), 1545–1558. https://doi.org/10.2136/sssaj2008.0311.
Sharples, J.J., McRae, R.H., Weber, R.O., Gill, A.M., 2009. A simple index for assessing fuel moisture content. Environ. Model. Softw. 24 (5), 637–646. https://doi.org/10.1016/j.envsoft.2008.10.012.
Shye, S., 1985. Nonmetric multivariate models for behavioural actions systems. In: Canter, D.V. (Ed.), Facet Theory: Approaches to Social Research. Springer Verlag, New York, pp. 97–148 (ISBN-13: 978-1461295372).
Sikkink, P.G., Lutes, D.C., Keane, R.E., 2009. Field Guide for Identifying Fuel Loading Models. https://doi.org/10.2737/RMRS-GTR-225.
Simard, A., 1991. Fire severity, changing scales, and how things hang together. Int. J. Wildland Fire 1 (1), 23–34 (Available here (accessed 07 November 2022).
Skowronski, N.S., Gallagher, M.R., Warner, T.A., 2020. Decomposing the interactions between fire severity and canopy fuel structure using multi-temporal, active, and passive remote sensing approaches. Fire 3 (1), 7. https://doi.org/10.3390/fire3010007.
Sotoca, A., González, J.L., Fernández, S., Kessel, D., Montesinos, O., Ruíz, M.Á., 2013. Perfil del incendiario forestal español: Aplicación del perfilamiento criminal inductivo. Anuario de Psicología Jurídica 23 (1), 31–38. https://doi.org/10.5093/aj2013a6.
Spits, C., Wallace, L., Reinke, K., 2017. Investigating surface and near-surface bushfire fuel attributes: a comparison between visual assessments and image-based point clouds. Sensors 17. https://www.mdpi.com/1424-8220/17/4/910/pdf (accessed 10 October 2022).
Srivastava, S.K., Saran, S., de By, R.A., Dadhwal, V.K., 2013. A geo-information system approach for forest fire likelihood based on causative and anti-causative factors. Int. J. Geogr. Inf. Sci. 28 (3), 427–454. https://doi.org/10.1080/13658816.2013.797984.
Stojanova, D., Kobler, A., Ogrinc, P., Ženko, B., Dzeroski, S., 2012. Estimating the risk of fire outbreaks in the natural environment. Data Min. Knowl. Disc. 24 (2), 411–442. https://doi.org/10.1007/s10618-011-0213-2.
Stow, D., Madhura, N., Kaiser, J., 2006. Time series of chaparral live fuel moisture maps derived from MODIS satellite data. Int. J. Wildland Fire 15, 347–360. https://doi.org/10.1071/WF05060.
Stroh, E.D., Struckhoff, M.A., Stambaugh, M.C., Guyette, R.P., 2018. Fire and climate suitability for woody vegetation communities in the southcentral United States. Fire Ecol. 14 (1), 106–124. https://doi.org/10.4996/fireecology.140110612.
Sudiana, D., Kuze, H., Takeuchi, N., Burgan, R.E., 2003. Indonesian Forest Fire–A Quantitave Assessment. 12th Indonesian Scientific Meeting, Osaka University, September 2013 (Access here (accessed 28 June 2022)).
Swedosh, W., Hilton, J., Miller, C., 2018. Spark Evaluation – 0.9.7: Comparison of Wildfire Rate of Spread Models Implemented within the Spark Framework to Historical Reconstructions of Wildfire Events (Available here (accessed 27 February 2023)).
Swetnam, T.W., 1993. Fire history and climate change in giant sequoia groves. Science 262, 885–889. https://doi.org/10.1126/science.262.5135.885.
Szpakowski, D.M., Jensen, J.L., 2019. A review of the applications of remote sensing in fire ecology. Remote Sens. 11, 2638. https://doi.org/10.3390/rs11222638.
Tehrany, M.S., Jones, S., Shabani, F., Martínez-Álvarez, F., Tien Bui, D., 2019. A novel ensemble modeling approach for the spatial prediction of tropical forest fire susceptibility using LogitBoost machine learning classifier and multi-source geospatial data. Theor. Appl. Climatol. 137 (1), 637–653. https://doi.org/10.1007/s00704-018-2628-9.
Terradas, J., Lloret, F., Trabaud, L., Pascual, J.P., 1998. Risk Factors in Wildfires Along the Mediterranean Coast of the Iberian Peninsula: Fire Management and Landscape Ecology (Available here (accessed 02 November 2022)).
Thomas, J.R., Namken, L.M., Oerther, G.F., Brown, R.G., 1971. Estimating leaf water content by reflectance measurements. Agron. J. 63, 845–847. https://doi.org/10.2134/agronj1971.00021962006300060007x.
Thompson, M.P., Scott, J., Kaiden, J.D., Gilbertson-Day, J.W., 2013. A polygon-based modeling approach to assess exposure of resources and assets to wildfire. Nat. Hazards 67 (2), 627–644. https://doi.org/10.1007/s11069-013-0593-2.
Tolhurst, K., Shields, B., Chong, D., 2008. Phoenix: development and application of a bushfire risk management tool. Aust. J. Emerg. Manag. 23 (4), 47–58 (Available here (accessed 27 February 2023).
Tonini, M., D'Andrea, M., Biondi, G., Degli Esposti, S., Trucchia, A., Fiorucci, P., 2020. A machine learning-based approach for wildfire susceptibility mapping. The case study of the Liguria region in Italy. Geosciences 10 (3), 105. https://doi.org/10.3390/geosciences10030105.
Tucker, C.J., 1979. Red and photographic infrared linear combinations for monitoring vegetation. Remote Sens. Environ. 8 (2), 127–150. https://doi.org/10.1016/0034-4257(79)90013-0.
Tymstra, C., Bryce, R.W., Wotton, B.M., Taylor, S.W., Armitage, O.B., 2010. Development and Structure of Prometheus: the Canadian Wildland Fire Growth Simulation Model. Natural Resources Canada, Canadian Forest Service, Northern Forestry Centre Information Report NOR-X-417. (Edmonton, AB) (Available here (accessed 01 November 2022).
Vacchiano, G., Foderi, C., Berretti, R., Marchi, E., Motta, R., 2018. Modeling anthropogenic and natural fire ignitions in an inner-alpine valley. Nat. Hazards Earth Syst. Sci. 18 (3), 935–948. https://doi.org/10.5194/nhess-18-935-2018.
Van Wagner, C.E., 1969. A simple fire growth model. For. Chron. 45, 103–104 (Available here (accessed 01 November 2022).
Van Wagner, C.E., 1974. Structure of the Canadian Forest Fire Weather Index, Vol. 1333. Environment Canada, Forestry Service, Ontario. Available here (accessed 25 November 2021).
Van Wagner, C.E., 1977. Conditions for the start and spread of crown fire. Can. J. For. Res. 7, 23–24 (Available here (accessed 01 November 2022).
Van Wagner, C.E., 1987. Development and Structure of the Canadian Forest Fire Weather Index System, Vol. 35 (Available here (accessed 26 February 2023).
Van Wagner, C.E., 1993. Prediction of crown fire behaviour in two stands of jack pine. Can. J. For. Res. 23, 442–449. https://doi.org/10.1139/x93-062.
Vasilakos, C., Kalabokidis, K., Hatzopoulos, J., Kallos, G., Matsinos, Y., 2007. Integrating new methods and tools in fire danger rating. Int. J. Wildland Fire 16 (3), 306–316. https://doi.org/10.1071/WF05091.
Veblen, T.T., Kitzberger, T., Raffaele, E., Lorenz, D.C., 2003. Fire history and vegetation changes in northern Patagonia, Argentina. In: Fire and Climatic Change in Temperate Ecosystems of the Western Americas. Springer, New York, NY, pp. 265–295. https://doi.org/10.2307/2657194.
Vecín-Arias, D., Castedo-Dorado, F., Ordóñez, C., Rodríguez-Pérez, J.R., 2016. Biophysical and lightning characteristics drive lightning-induced fire occurrence in the central plateau of the Iberian Peninsula. Agric. For. Meteorol. 225, 36–47. https://doi.org/10.1016/j.agrformet.2016.05.003.
Vega-Garcia, C., Lee, B.S., Woodard, P.M., Titus, S.J., 1996. Applying neural network technology to human-caused wildfire occurrence prediction. AI Appl. 10, 9–18 (Available here (accessed 17 October 2022).
Veraverbeke, S., Dennison, P., Gitas, I., Hulley, G., Kalashnikova, O., Katagis, T., Kuai, L., Meng, R., Roberts, D., Stavros, N., 2018. Hyperspectral remote sensing of fire: state-of-the-art and future perspectives. Remote Sens. Environ. 216, 105–121. https://doi.org/10.1016/j.rse.2018.06.020.
Verde, J.C., Zezere, J.L., 2010. Assessment and validation of wildfire susceptibility and hazard in Portugal. Nat. Hazards Earth Syst. Sci. 10, 485e497. https://doi.org/10.5194/nhess-10-485-2010.
Viedma, O., Quesada, J., Torres, I., De Santis, A., Moreno, J.M., 2015. Fire severity in a large fire in a Pinus pinaster forest is highly predictable from burning conditions, stand structure, and topography. Ecosystems 18, 237–250. https://doi.org/10.1007/s10021-014-9824-y.
Viedma, O., Chico, F., Fernández, J.J., Madrigal, C., Safford, H.D., Moreno, J.M., 2020. Disentangling the role of prefire vegetation vs. burning conditions on fire severity in a large forest fire in SE Spain. Remote Sens. Environ. 247, 111891 https://doi.org/10.1016/j.rse.2020.111891.
Viegas, D.X., Piñol, J., Viegas, M.T., Ogaya, R., 2001. Estimating live fine fuels moisture content using meteorologically based indices. Int. J. Wildland Fire 10, 223–240. https://doi.org/10.1071/WF01022.
Viegas, E., Soeiro, C., 2007. Perfis psicossociais dos incendiários portugueses. In: Propostas para aprevençao. Jornadas sobre Investigación Criminal de Incendios Forestales, marzo 2007, Santiago de Compostela. https://doi.org/10.5093/aj2013a6.
Vilar del Hoyo, L., Isabel, M.P.M., Vega, J.M., 2008. Empleo de técnicas de regresión logística para la obtención de modelos de riesgo humano de incendio forestal a escala regional. Boletín de la Asociación de Geógrafos Españoles. Available here (accessed 22 December 2022).
Vilar del Hoyo, L., Woolford, D.G., Martell, D.L., Martín, M.P., 2010. A model for predicting human-caused wildfire occurrence in the region of Madrid, Spain. Int. J. Wildland Fire 19 (3), 325–337. https://doi.org/10.1071/WF09030.
Vilar del Hoyo, L., Martín Isabel, M.P., Martínez Vega, F.J., 2011. Logistic regression models for human-caused wildfire risk estimation: analysing the effect of the spatial accuracy in fire occurrence data. Eur. J. For. Res. 130 (6), 983–996. https://doi.org/10.1007/s10342-011-0488-2.
Viney, N.R., 1991. A review of fine fuel moisture modelling. Int. J. Wildland Fire 1, 215–234. https://doi.org/10.1071/wf9910215.
Wang, X., Parisien, M.A., Taylor, S.W., Perrakis, D.D., Little, J., Flannigan, M.D., 2016. Future burn probability in south-central British Columbia. Int. J. Wildland Fire 25 (2), 200–212. https://doi.org/10.1071/WF15091.
Westerling, A.L., Bryant, B.P., 2008. Climate change and wildfire in California. Clim. Chang. 87 (1), 231–249. https://doi.org/10.1007/s10584-007-9363-z.
Westerling, A.L., Gershunov, A., Brown, T.J., Cayan, D.R., Dettinger, M.D., 2003. Climate and wildfire in the western United States. Bull. Am. Meteorol. Soc. 84 (5), 595–604 (Available here (accessed 05/10/2022).
Westerling, A.L., Hidalgo, H.G., Cayan, D.R., Swetnam, T.W., 2006. Warming and earlier spring increase western US forest wildfire activity. Science 313 (5789), 940–943. https://doi.org/10.1126/science.1128834.
Westman, W.E., Price, C.V., 1988. Spectral changes in conifers subjected to air pollution and water stress: experimental studies. IEEE Trans. Geosci. Remote Sens. 26 (1), 11–21.
Wulder, M., 1998. Optical remote-sensing techniques for the assessment of forest inventory and biophysical parameters. Prog. Phys. Geogr. 22, 449–476 (Available here (accessed 9 October 1998)).
Xanthopoulos, G., Calfapietra, C., Fernandes, P., 2012. Fire hazard and flammability of European forest types. In: Moreira, F., Arianoutsou, M., Corona, P., De las Heras, J. (Eds.), Post-fire Management and Restoration of Southern European Forests. Springer, Dordrecht, pp. 79–92. https://doi.org/10.1007/978-94-007-2208-8_4.
Xofis, P., Tsiourlis, G., Konstantinidis, P., 2020. A fire danger index for the early detection of areas vulnerable to wildfires in the eastern Mediterranean region. Euro-Mediterr. J. Environ. Integr. 5 (2), 1–13. https://doi.org/10.3390/f7020046.
Xu, D., Shao, G., Dai, L., Hao, Z., Tang, L., Wang, H., 2006. Mapping forest fire risk zones with spatial data and principal component analysis. Sci. China, Ser. E: Technol. Sci. 49 (S1), 140–149. https://doi.org/10.1007/s11434-006-8115-1.

Yang, J., He, H.S., Shifley, S.R., 2008. Spatial controls of occurrence and spread of wildfires in the Missouri Ozark Highlands. Ecol. Appl. 18, 1212–1225. https://doi.org/10.1890/07-0825.1.

Yavari, F., Sohrabi, H., 2019. Estimation of available canopy fuel of coppice oak stands using low-density airborne laser scanning (LIDAR) data. In: Advances in Remote Sensing and Geo Informatics Applications: Proceedings of the 1st Springer Conference of the Arabian Journal of Geosciences (CAJG-1), Tunisia 2018. Springer International Publishing, pp. 171–173. https://doi.org/10.1007/978-3-030-01440-7_40.

Yebra, M., Chuvieco, E., 2009. Generation of a species-specific look-up table for fuel moisture content assessment. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 2, 21–26. https://doi.org/10.1109/JSTARS.2009.2014008.

Yebra, M., Chuvieco, E., Riaño, D., 2008. Estimation of live fuel moisture content from MODIS images for fire risk assessment. Agric. For. Meteorol. 148, 523–536. https://doi.org/10.1016/j.agrformet.2007.12.005.

Yebra, M., Dennison, P.E., Chuvieco, E., Riano, D., Zylstra, P., Hunt Jr., E., Danson, F., Qi, Y., Jurdao, S., 2013. A global review of remote sensing of live fuel moisture content for fire danger assessment: moving towards operational products. Remote Sens. Environ. 136, 455–468. https://doi.org/10.1016/j.rse.2013.05.029.

Zacharakis, I., Tsihrintzis, V.A., 2023. Environmental Forest fire danger rating systems and indices around the globe: a review. Land 12 (1), 194. https://doi.org/10.3390/land12010194.

Zarco-Tejada, P.J., Rueda, C.A., Ustin, S.L., 2003. Water content estimation in vegetation with MODIS reflectance data and model inversion methods. Remote Sens. Environ. 85, 109–124. https://doi.org/10.1016/S0034-4257(02)00197-9.