Review

Human-caused fire occurrence modelling in perspective: a review

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Abstract. The increasing global concern about wildfires, mostly caused by people, has triggered the development of human-caused fire occurrence models in many countries. The premise is that better knowledge of the underlying factors is critical for many fire management purposes, such as operational decision-making in suppression and strategic prevention planning, or guidance on forest and land-use policies. However, the explanatory and predictive capacity of fire occurrence models is not yet widely applied to the management of forests, fires or emergencies. In this article, we analyse the developments in the field of human-caused fire occurrence modelling with the aim of identifying the most appropriate variables and methods for applications in forest and fire management and civil protection. We stratify our worldwide analysis by temporal dimension (short-term and long-term) and by model output (numeric or binary), and discuss management applications. An attempt to perform a meta-analysis based on published models proved limited because of non-equivalence of the metrics and units of the estimators and outcomes across studies, the diversity of models and the lack of information in published works.

Introduction

Wildfire is a major disturbance in many parts of the world and its incidence is growing due to climate change (Liu *et al.* 2010; Wotton *et al.* 2010; Moriz *et al.* 2012). More than 30% of the world's land mass already has significant and recurrent fire activity, though remote sensing has shown Africa and Latin America to be the most active fire areas (Chuvieco *et al.* 2008). According to the Food and Agriculture Organization of the United Nations (FAO 2010), which compiled a wildfire database with records from 64 countries (60% of the world's wildlands), an annual average of 487 000 wildfires occurred during 2003–2007. Worldwide, more than 90% of fires are linked directly or indirectly to intentional and unintentional human actions, power lines and machinery (FAO 2007). These fires are usually termed 'human-caused fires' (HCFs). In contrast, 'natural fires' are those originating from natural causes such as lightning, spontaneous ignition, volcanic eruptions and earthquakes.

HCFs often display broadly identifiable spatial and temporal patterns, which led researchers in the 1950s to believe that

wildfire occurrences could be modelled. At that time, Crosby (1954) argued that '*Fire occurrence can be predicted*' and Bruce (1963), convinced that fire ignitions could be analysed by mathematical methods, asked '*How many fires* [occur]*?*' New models of fire occurrence appeared during the following decades. Donoghue and Main (1985) produced the first study focusing on HCF occurrence. It was soon recognised that forecasting these fire occurrences could provide important information for prevention programs (Altobellis 1983; Donoghue *et al.* 1987), optimising resource allocation in strategic firefighting (Martell *et al.* 1987; Dlamini 2010) and generally guiding forest and fire policies (Stolle *et al.* 2003; Chas-Amil *et al.* 2010). With the development of the field and the widening of the goals of modelling, definitions for what the different authors meant by fire occurrence have often required clarification. Here we abide by the concept as it was defined and used early in the wildfire literature (Haines *et al.* 1983; Martell *et al.* 1987) because this has been the predominant view in most papers published since. A fire occurrence is 'one fire event occurring

in a specific place within a specific period of time' (Romme 1980). Fire occurrence, according to the definition in the *Fire Management Glossary* by Merrill and Alexander (1987), is 'the number of fires started in a given area over a given period of time', a definition also adopted by FAO (updated January 2005). Fire occurrence measures ignitions or fire starts, and is a process modelled separately from fire spread, which may or may not take place after ignition depending on environmental conditions. Fire occurrence deals with absolute numbers, whereas the related concepts of fire frequency or fire incidence are expressed as averages (Merrill and Alexander 1987). Averages and return intervals are crucial in disturbance ecology, for instance, but absolute numbers and shorter time spans are needed for operational decisions in fire management. Another source of confusion may arise from the fact that early works also referred to 'the probability or chance of fire starting determined by the presence and activities of causative agents (i.e. potential number of ignition sources)' as 'fire risk', or 'human risk' if the causative agents were humans (Merrill and Alexander 1987). The term 'fire risk' was used to describe the probability of HCF occurrence until 2005, when the term aligned with the broader definition and terminology in the risk analysis field (Finney 2005; Chuvieco *et al.* 2010, 2014; Miller and Ager 2013). Nowadays, the term 'risk' is generally used to describe the chance of loss, determined from estimates of likelihood and associated outcomes (likelihood, intensity and effects) (Miller and Ager 2013). We have avoided using 'human risk' throughout our review, but we caution that ignoring it when looking for 'human-caused fire occurrence' in a literature search would miss a lot of early work.

Consequently, the aim of this review is to analyse the developments in the field of HCF occurrence modelling. Modellers have tried to identify which environmental and socioeconomic factors influence fire occurrence by using many techniques for many different goals. Our main goal is to identify the relevant variables and best methods to explain and anticipate fires and evaluate the level of achievement reached by modellers in fulfilling forest and fire management and civil protection needs, investigating the alignment of background motivations from modellers with management demands.

For this purpose, we have considered research papers published in English in widely available scientific journals, as well as widely circulated reports published in the 1950s and '60s (when publishing in scientific journals was not as common as it was later on). A total of 152 research papers were found between the first (Crosby 1954) and the last (Papakosta and Straub 2016), and all are listed in Table S1, available as Supplementary material to this paper, with descriptive information on the contents. The largest number of HCF papers was published between 2012 and 2016, with an average of 14 studies per year.

This review compilation considers general HCF occurrence modelling (42 studies), but also work done on specific human-related causes, like arson (Donoghue and Main 1985; Vasconcelos *et al.* 2001; Prestemon and Butry 2005; Juan *et al.* 2012; Penman *et al.* 2013; Serra *et al.* 2013, 2014; Abt *et al.* 2015; Collins *et al.* 2015) and negligence (Vasconcelos *et al.* 2001; Juan *et al.* 2012; Serra *et al.* 2013, 2014; Abt *et al.* 2015; Collins *et al.* 2015), as well as livestock-related (Ruiz-Mirazo *et al.* 2012) or debris fires (Donoghue and Main 1985). A reliable classification of the specific causes (human or natural) is not always available (FAO

2007). Consequently, we have also considered research papers that include ignitions from any cause or those that do not specify the ignition source, but only if they state that human activity is the predominant causal factor for ignitions in the study area (100 studies).

Background motivations

Most previous work specifies at least a generic purpose for building models, but very few provide examples of practical applications or guidelines for the implementation of their fire occurrence outputs, suggesting that the link between research and management needs to be strengthened. A few models (5) are limited to testing the significance of certain variables, such as soil profile data (Levi and Bestelmeyer 2016) or roads (Narayanaraj and Wimberly 2012). The goal most commonly stated across studies (55) is fire prevention, including mainly forest and fuel treatments, and planning for risk reduction and damage mitigation. Then come goals related to supporting decisions or strategies and policies for general fire, forest or land management (33). Another background motivation is fire suppression: deployment, pre-suppression planning, firefighting efficiency, and optimisation of human resources and funds (24). Climate change effects on vegetation covers and fire regimes (11) have received attention only recently (mainly in 2009–2016). Some studies explore the link between fire occurrence and fire danger rating to develop early warning systems (7). Ecological or conservationist goals are scarce (5) and quite restricted in time (2007–2009). At least 10 studies seem to pursue the testing of novel techniques without mentioning any specific or generic goal.

In order to test the alignment of these background motivations from modellers with management demands, we have analysed summaries of fire management strategies in the regions with more fire occurrence publications, southern Europe (56 publications), and North America (United States, 33, and Canada, 16). It is widely recognised in these regions that quantitative risk assessment is the basis for all fire management activities (FAO 2011; Miller and Ager 2013; WFLC 2017). However, the complexity of fire risk estimation has also been highlighted; the 34th meeting of the European Commission expert group on forest fires (Barcelona, Spain, 2015), including civil protection authorities from 22 countries, demanded cooperation in setting basic common criteria to determine medium and high fire risk areas (European Commission 2015). Since fire risk is a combination of likelihood, intensity and effects, where fire likelihood includes ignition probability and burn probability (Miller and Ager 2013), models developed for ignition probability using fire occurrence data within risk frameworks certainly do serve management needs. However, as comprehensive national risk frameworks are either not developed or formally applied by administrations and agencies in most fire-affected countries, fire occurrence models are not routinely used, and authors are bound to state generic purposes in their papers.

Temporal span for modelling

The motivations in these studies set the frame for the temporal span for modelling: the segregation of previous works into short-term (daily, weekly and monthly studies, 43 papers, 47 models)

or long-term (seasonal, annual and longer time ranges of several years, 109 papers, 134 models) responded to the stated goals for model building. Improved detection, preparedness, pre-attack planning and suppression predominate in short-term models (Haines *et al.* 1970; Martell *et al.* 1989; Bradstock *et al.* 2009; Wotton *et al.* 2010; Papakosta and Straub 2016), whereas long-term models are usually built for fire prevention, landscape fuel treatments, forest management, land-use planning and civil protection (Cardille and Ventura 2001; Koutsias *et al.* 2010; Gralewicz *et al.* 2012*a*; Oliveira *et al.* 2012; Abt *et al.* 2015).

Accordingly, the temporal dimensions for fire observations may be daily (Crosby 1954; Haines *et al.* 1983; Alonso-Betanzos *et al.* 2003; Lozano *et al.* 2007; Albertson *et al.* 2009; Wotton *et al.* 2010; Padilla and Vega-Garcia 2011; Sakr *et al.* 2011), monthly (Preisler *et al.* 2004; Boulanger *et al.* 2014) or yearly (Todd and Kourtz 1991; Prestemon and Butry 2005; Hu and Zhou 2014; Karouni *et al.* 2014). However, longer time-spans of several years are the most frequent (Pew and Larsen 2001; Chuvieco *et al.* 2008; Avila-Flores *et al.* 2010; Gonzalez-Olabarria *et al.* 2011; West *et al.* 2016). Within a given year, fire occurrence levels may be constant (e.g. central Africa) or differ seasonally (e.g. United Kingdom, Albertson *et al.* 2009) – there is a well-defined seasonality in some regions with a high peak of fire occurrence in summer (Ager *et al.* 2014), whereas in others there are two well-defined peaks of fire frequency, for example in early winter and summer (Martell *et al.* 1989). Accordingly, some models only consider fire observations recorded during a fire season defined by the period with the highest number of fires (Haines *et al.* 1970; Vega-Garcia *et al.* 1995, 1996; Dickson *et al.* 2006; Vilar *et al.* 2010).

Considering the amount of attention given in the past to long-term models for general fire prevention, and fire and forest planning and policy, and their general maturity, it would be expedient to widen the focus for the future to the development of short-term applications with operational potential. Daily models have been rarely used because most agencies in fire-affected countries have treated the landscape as uniformly high-risk (Boulanger *et al.* 2012, 2014), operating under full suppression policies (all fires aggressively fought until extinguished, anywhere and under all weather conditions). However, paradigms are changing to allow for managed or prescribed fire (let-burn policies), budgets are constrained in the current economic recession, wildland–urban interfaces are expanding and climate introduces uncertainties, all of which increase the need for short-term fire occurrence prediction (Costafreda-Aumedes *et al.* 2016*a*).

Sources of ignition data

HCF occurrence models rely on the analysis of historical data to describe past HCF patterns or to predict future events. Fire events are usually investigated, reported and recorded in databases by national forest or fire departments, agencies or administrations, and usually include the fire start location, date and time, and cause, which are the basis for wildfire occurrence modelling (Finney 2005). However, undetected, unreported or missing fires are a common problem in many countries, because of a lack of managerial resources and peak fire loads, differing policies on minimum reporting of fire size or fire start location in remote underpopulated regions with low values at risk (Lefort *et al.* 2004). When field-collected fire records are unavailable, fire occurrence can be estimated from remote sensing sources such as burned area products or hotspots (Venevsky *et al.* 2002; Vadrevu *et al.* 2006; Maingi and Henry 2007; Chuvieco *et al.* 2008; Garcia-Gonzalo *et al.* 2012; Marques *et al.* 2012; Zhang *et al.* 2013; Li *et al.* 2014; Bedia *et al.* 2015; Ancog *et al.* 2016). All models built from remote sensing data have had to consider a certain minimum fire size because of technical limitations in sensor spatial or spectral resolution, including, for example, fires >400 ha (Preisler and Westerling 2007; West *et al.* 2016), fires >0.25 ha (Stolle *et al.* 2003) or fires >0.1 ha (Miranda *et al.* 2012). In these cases, precise ignition locations have a degree of uncertainty – after ignition, determined by causative agent activity and fine fuel state, fires spread and grow to a final size determined by topography, fuels, winds and suppression efforts, masking fire start location. Many remote sensing sources are currently available, besides those previously used, for future fire occurrence collection, such as the Wildfire Automated Biomass Burning Algorithm (Schmidt *et al.* 2002) developed for GOES-13, GOES-15, Meteosat-10 or the MTSAT-1R/-2, or Land Surface Temperature, and Thermal Anomalies and Fire available in the MODIS Collections 5 and 6 products: MOD11/MYD11 (Wan *et al.* 2002), MOD14/MYD14 (Giglio 2010), MCD45A1 (Giglio *et al.* 2009) and MOD21/MYD21 (Hulley *et al.* 2014). However, some fires may be missing from these algorithms, as thresholds used to minimise the number of false detections cause some fires to be deleted (Giglio *et al.* 2003).

Spatialising ignition data

Fire occurrence refers to the number of fires in a spatial unit for a certain time span. Spatial unit types depend on the source of fire data and associated location uncertainty, but it is commonplace for authors to spatially aggregate ignitions within regular grids (pixels, quadrats) or within irregular administrative divisions (areal units such as districts, provinces, townships).

Estimations of the actual number of ignitions in a prediction unit or in a certain time span have been provided on occasions (García Diez *et al.* 1994, 1999; Cardille *et al.* 2001; Knorr *et al.* 2014; Plucinski *et al.* 2014; Xiao *et al.* 2015), though not in the majority of the works. Fires are rare events (Vega-Garcia *et al.* 1995), and increasing resolutions across temporal and spatial scales multiplies no-fire observations for a same number of fire observations. Accepting that fires are rare events and that rarely more than one fire takes place in the temporal and spatial unit under study allows a binary dependent variable to be used. Fire occurrence can be modelled as absence or presence of fire (coded 0 or 1), and most research papers have focused on this binary prediction of wildfires (Andrews *et al.* 2003; Reineking *et al.* 2010; Zhang *et al.* 2010, 2016; Arndt *et al.* 2013; Pan *et al.* 2016). Many HCF occurrence models are probabilistic; their output is the probability that 'at least one fire occurs', ranging from 0 to 1. By classifying the output of such models with a cut-off value, predicted *v.* observed values can be used to test predictive performance. The choice of modelling fire occurrence as a binary (at least one fire) or numerical variable (number of fires) determines most modelling methods.

Only a few recent studies have been able to analyse the spatial-specific location of each event as a point pattern in a certain location and date (Yang *et al.* 2007; Juan *et al.* 2012; Liu *et al.* 2012; Miranda *et al.* 2012; Fuentes-Santos *et al.* 2013; Serra *et al.* 2013, 2014; Costafreda-Aumedes *et al.* 2016*b*). Spatially explicit point process models have so far been considered as statistical tools to analyse space (–time) structures of wildfires, but not to model such spatial structures. For instance, Ripley's K function has been used to describe spatial structures, or configurations, of such point patterns. However, the use of such model schemas combined with variables related to fire occurrence can result in very powerful predictive tools, and these models hold the greatest potential for the future in terms of resolution, as their spatial unit for prediction is adimensional (a point instead of a spatial unit for prediction).

Driving risk factors of HCF occurrence

The probability of a fire starting depends on the presence and activity of ignition sources and the conditions within the environment where fires occur (Merrill and Alexander 1987). Environmental factors with high variability in time are often called 'temporal' factors, and are mainly derived from weather or weather-driven indices related to drought or vegetation moisture, both influencing ignitability. However, a few temporal variables are related to ignition pressure by humans, such as day of the week. Factors derived from physiography, land cover or human socioeconomic variables (e.g. census data), are often termed as 'spatial' or 'geographic' variables, and they either have inherent low temporal variability or data that are infrequently updated and often unavailable. Most are related to ignition pressure by human presence and activities, but some also influence ignitability, such as fuel type.

Some studies only consider either 'temporal' or 'spatial' variables, or specific sub-groups (i.e. only weather, only landscape structure) for input variables (Plucinski 2012). Across the abundant research conducted thus far, many spatial and temporal factors have been tested and been found to be related to, or to be able to explain, HCF occurrence. The technique used for the analysis (Verdú *et al.* 2012; Rodrigues *et al.* 2016; Vilar *et al.* 2016*a*) and the local values of the variables in each study area (Argañaraz *et al.* 2015) influence variable selection and behaviour in a model. However, the analysis of spatial and temporal variables selected in most studies for short-term (Table 1) and long-term HCF modelling (Table 2), shows coincidences in variables and their signs

Table 1.   List and behaviour of the most influential variables for short-term fire occurrence prediction

Weather and danger	Physiography	Vegetation / fuel	Human-related	Other
Mean and max. temperature (+)	Elevation (−)	Shrubs (+)	Dist. to roads (−)	Holidays (+)
Min. temperature (−)	Aspect (+)	Grasslands (+)	Road density (+)	Weekend (+)
Precipitation (−)		Wetlands (−)	Dist. to settlements (−)	Workday (−)
Relative humidity (−)			Urban areas (−)	Fire history (+)
Wind Speed (+)			Dist. to railroads (−)	
FFMC (+)				
FWI (+)				
DMC (+)				
DC (+)				
ISI (+)				
BUI (+)				
McArthur (+)				

Table 2.   List and behaviour of the most influential variables for long-term fire occurrence prediction

Weather and danger	Physiography	Vegetation / fuel	Human-related	Other
Mean and max. temperature (+)	Elevation (−)	Wildland–urban interface (+)	Distance to roads (−)	Winter (−)
Annual precipitation (+)	Slope (−)	Forest–agriculture interface (+)	Road density (+)	Spring and summer (+)
Fire-season precipitation (−)	Topographic roughness (+)	Wildland–agriculture interface (+)	Distance to settlements (−)	Date maximum NDVI (−)
Non-fire season precipitation (+)		Forest–grassland interface (+)	Population density (+)	Recent fires (+)
Days with precipitation (−)		Forests (+)	Building density (+)	Holiday (+)
Days without precipitation (+)		Coniferous (+)	Distance to railroads (−)	
		Broadleaves (−)	Railroad density (+)	
		Shrublands (+)	Distance to recreational areas (−)	
		Grasslands (+)	Protected areas (+)	
		Agriculture (+)	Per capita GDP (+)	

(positive or negative relationship to fire occurrence), which allow us to summarise some global patterns.

Predictors for short-term studies

As should be expected when considering combustion requirements within the environment, significant variables in the short term models reflect weather conditions that cause downward changes in fuel moisture and, consequently, upward changes in fuel availability. Temporal variables drive short-term models. High mean and maximum temperatures (Alonso-Betanzos *et al.* 2003; Preisler *et al.* 2004; Carvalho *et al.* 2008, 2010; Vilar *et al.* 2010; Magnussen and Taylor 2012; Bedia *et al.* 2014; Karouni *et al.* 2014; Najafabadi *et al.* 2015), low precipitation (Albertson *et al.* 2009; Vasilakos *et al.* 2009; Zhang *et al.* 2010; Plucinski *et al.* 2014; Guo *et al.* 2016a) and low relative humidity (Alonso-Betanzos *et al.* 2003; Padilla and Vega-Garcia 2011; Chang *et al.* 2013; Karouni *et al.* 2014) favour fires and are often used in models.

However, fire science has developed methods to estimate the decrease in moisture content caused by weather on litter and fine fuels, medium compact organic layers and deep organic soil layers or heavy fuels for fire danger rating (Dimitrakopoulos *et al.* 2011). Fire danger is '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' (FAO 2005) Some well-established fire danger rating indices used in many countries are the three Codes (Fine Fuel Moisture Code, FFMC; Duff Moisture Code, DMC; Drought Code, DC) and Indices (Initial Spread Index, ISI; Built-Up Index, BUI; Fire Weather Index, FWI) of the Canadian Forest Fire Weather Index System (Van Wagner 1987), the Energy Release Index in the United States' National Forest Fire Danger Rating System (ERC, Bradshaw *et al.* 1983), the Forest Fire Danger Index by McArthur (FFDI, McArthur 1967) and the Keetch–Byram Drought Index (KBDI, Keetch *et al.* 1968). Of these, we found a very frequent use of FFMC (Cunningham and Martell 1973; Martell *et al.* 1989; Vega-Garcia *et al.* 1995; Wotton *et al.* 2010; Lee *et al.* 2012; Boulanger *et al.* 2014; Li *et al.* 2014; Beccari *et al.* 2015), DC (Wotton *et al.* 2003, 2010; Carvalho *et al.* 2008; Drever *et al.* 2009; Bedia *et al.* 2014) and DMC (Martell *et al.* 1987; Todd and Kourtz 1991; Wotton *et al.* 2003; Magnussen and Taylor 2012), FWI (Haines *et al.* 1983; Martell *et al.* 1987; Vega-Garcia *et al.* 1996; Carvalho *et al.* 2010; Reineking *et al.* 2010; Ager *et al.* 2014; Beccari *et al.* 2015; Papakosta and Straub 2016), ISI (Haines *et al.* 1970, 1983; Vega-Garcia *et al.* 1995; Li *et al.* 2014), FFDI (Bradstock *et al.* 2009; Penman *et al.* 2013; Plucinski 2014; Plucinski *et al.* 2014), KBDI (Prestemon and Butry 2005) and ERC (Andrews *et al.* 2003).

The Canadian FFMC and FWI were the significant danger variables most often selected across the short-term models analysed (17 and 13 instances in 47 models), with raw weather variables such as precipitation (13) and temperature (24). The Canadian FWI indices and codes accounted for half the variables across all the models analysed (57 of 128 weather-related significant variables in 47 models). Among the spatial or geographic variables, elevation (11 models) and distance to

roads (8) were the most relevant. Non-specific land-cover classes were occasionally included in some models, indicating specific regional or local conditions (e.g. two models linked to 'dense forest' and two to 'grasslands'), but spatial variables generally had scarce representation in these models. In some short-term models (7), temporal variables related to specific months (e.g. August and September, Vasilakos *et al.* 2009) or holidays (e.g. weekends and public holidays, Plucinski *et al.* 2014) were included. Outdoor recreation activities occur more frequently during public or summer holidays (Mandallaz and Ye 1997; Prestemon and Butry 2005; Albertson *et al.* 2009; Plucinski *et al.* 2014), and weekends (Prestemon and Butry 2005; Albertson *et al.* 2009; Plucinski *et al.* 2014). The fact that outdoor recreation is especially popular in spring (Martell *et al.* 1989; Albertson *et al.* 2009) and summer (Martell *et al.* 1989; Vilar *et al.* 2010; Ager *et al.* 2014) matches human activities with the most favourable seasons for ignition in many countries. It has been suggested (Plucinski 2014) that legal regulations on fire use or total bans on use of fire should be a relevant managerial factor reducing human ignition pressure on regulated days. However, total bans on fire use have often proven ineffective, when not directly counterproductive to prevent wildfires (FAO 2007), suggesting that it is preferable to establish appropriate legal and technical measures to control the misuse of fire and to achieve other land-use goals (Morgera and Cirelli 2009). Many countries have systems in place to grant fire permits under stipulated conditions. To the best of our knowledge, this factor has not been considered before, perhaps because fire permits are usually granted outside the fire season upon which fire occurrence models focus. Also, these data may be difficult to obtain, as regulations and conditions vary locally, but the legal fire-use status of a given day should be a relevant variable to consider in the future.

Predictors for long-term studies

Weather variables also play a role in long-term studies (134 models), but averaged over a meaningful fire-pattern period, like several years used for planning, or a season (Chou 1992; Preisler and Westerling 2007; Jiang *et al.* 2012; Verdú *et al.* 2012; Chas-Amil *et al.* 2015). High evapotranspiration (Badia-Perpinyà and Pallares-Barbera 2006; Xiao *et al.* 2015) and insolation (Heat Load Index, Lozano *et al.* 2007; Yang *et al.* 2015) increase the probability of human-caused ignition. Annual or seasonal temperature and precipitation variables abound (Pew and Larsen 2001; Amatulli *et al.* 2006; Prasad *et al.* 2008; Oliveira *et al.* 2012; Faivre *et al.* 2014; Xiao *et al.* 2015; Ancog *et al.* 2016), with drought estimations (e.g. Palmer Drought Severity Index, Preisler and Westerling 2007; Miranda *et al.* 2012) and climatic classifications in the 127 models analysed. Summer precipitation has a fire-inhibiting factor (Prasad *et al.* 2008; Parisien and Moritz 2009; Turco *et al.* 2014; Barreal and Loureiro 2015). However, annual precipitation, and especially spring precipitation, is related to an increase in HCFs (Cardille *et al.* 2001; Krawchuk *et al.* 2009; Avila-Flores *et al.* 2010; Oliveira *et al.* 2012; Hu and Zhou 2014; West *et al.* 2016; Bashari *et al.* 2016). Precipitation in spring increases vegetation biomass, especially in fine fuels like grasses or shrubs, which may be available later to burn. Weather conditions favourable to

fire occur mainly in summer (Albertson *et al.* 2009; Badia *et al.* 2011; Ager *et al.* 2014), but also happen at other times of the year when fuels are dry, such as early or late winter in some regions (Maingi and Henry 2007; Reineking *et al.* 2010; Zhang *et al.* 2010). In Europe (Reineking *et al.* 2010; Ganteaume *et al.* 2013), for example, fires have two well-defined peaks, one higher in summer, and another lower in winter. These peaks may be associated with specific fire causes, such as arson, agricultural burnings and accidental fires, which are more frequent in summer (Ganteaume *et al.* 2013), and fires caused by shrub removal for regenerating pastures and feeding livestock in winter and early spring (DeWilde and Chapin 2006). Nevertheless, in most long-term models, weather-climate variables (177 variables) are less important than spatial variables linked to human patterns of landscape use (230 land-use and interface variables and 288 related to access, population and infrastructure in 134 models).

Elevation and slope were most often included in spatial models (69 instances out of the 109 topography-related variables in 134 models). Usually, lower elevation (Kalabokidis *et al.* 2007; Sebastián-López *et al.* 2008; Kwak *et al.* 2012; Narayanaraj and Wimberly 2012; Liu and Wimberly 2015) and smaller slope gradient (Preisler *et al.* 2004; Syphard *et al.* 2008; Dondo Bühler *et al.* 2013; Oliveira *et al.* 2014; Argañaraz *et al.* 2015) increase HCF occurrence. Since surface temperature and humidity are affected by terrain, these may be reflecting climatic conditions. As HCFs tend to occur in lowlands and gentle slopes, where the population tends to cluster, topographic variables may also be proxies for human presence and activity or potentially favourable topographic positions for roads. However, this depends on the fire cause. González-Olabarria *et al.* (2015) found that fires related to pasture burning and forest work are mainly located in mountain areas. Arson (Vasconcelos *et al.* 2001) and negligent fires (Juan *et al.* 2012; Serra *et al.* 2013) occur most often on flat or moderate slopes.

Urban, forest and agricultural land uses coexist and intermix in these anthropic landscapes, and interfaces between them seem to favour HCF occurrence in those models that have taken them into consideration (63 interface out of 230 land-use variables) (Vilar del Hoyo *et al.* 2011; Faivre *et al.* 2014; Duane *et al.* 2015; Mishra *et al.* 2016; Modugno *et al.* 2016; Rodrigues *et al.* 2016). Configuration metrics have not been applied as extensively (only 13 variables) as composition or land-cover variables, but fire-prone landscapes often present high fragmentation (Martínez *et al.* 2009; Ruiz-Mirazo *et al.* 2012; Martínez-Fernández *et al.* 2013) and non-complex shapes linked to the artificial boundaries set by humans (Henry and Yool 2004; Gralewicz *et al.* 2012b; Costafreda-Aumedes *et al.* 2013).

Undoubtedly, the prevalent factors in the long term analysis of HCFs are those related to the population, dwellings and access networks (288 variables in 134 models). The location of human activities is highly dependent on site-related variables that determine the number and distribution of human sources of ignition. Human presence can be analysed from explicit spatial factors such as proximity to, or density of, infrastructure such as roads (Dickson *et al.* 2006; Yang *et al.* 2008, 2015; Gralewicz *et al.* 2012b; Hegeman *et al.* 2014; Syphard and Keeley 2015; Zhang *et al.* 2016; Mhawej *et al.* 2016; Vilar *et al.* 2016b), tracks (Pew and Larsen 2001; Romero-Calcerrada *et al.* 2008, 2010;

Rodrigues *et al.* 2014), trails (Syphard *et al.* 2008; Vilar del Hoyo *et al.* 2011; Arndt *et al.* 2013) and railways (Sturtevant and Cleland 2007; Guo *et al.* 2015; Alcasena *et al.* 2016), all of which are associated with an increase in fire occurrence. For example, in Spain (MAGRAMA 2015), the United States (Morrison 2007) and south-eastern Australia (Penman *et al.* 2013), more than half of HCFs start along road systems. They act as conveyers for arsonists, careless drivers and campers according to Morrison (2007). HCFs occur most often near settlements (Pew and Larsen 2001; Romero-Calcerrada *et al.* 2008; Yang *et al.* 2008; Liu *et al.* 2012; Wu *et al.* 2014) or highly built-up areas (Sturtevant and Cleland 2007; Chas-Amil *et al.* 2015).

Regarding socioeconomic indicators, population density is the most commonly used indicator in relation to the occurrence of HCFs (Prasad *et al.* 2008; Kwak *et al.* 2012; Dondo Bühler *et al.* 2013; Mundo *et al.* 2013; Knorr *et al.* 2014; Alcasena *et al.* 2016; Nunes *et al.* 2016) (96 significant variables in the models analysed). High population densities are related to high wildfire occurrence in general. However, studies on high population density in large urban areas, such as those by Gonzalez-Olabarria *et al.* (2011) for north-eastern Spain, Argañaraz *et al.* (2015) for Argentina, and Beccari *et al.* (2015) for northern Italy, found low fire occurrence. This may have been caused by the lower availability of fuel to support HCFs in highly developed urban areas (Syphard *et al.* 2007, 2009; Price and Bradstock 2014). Donoghue and Main (1985) observed an increase of HCF occurrence related only to non-metropolitan population density. In intensive agricultural areas, as the number of farmers (Martínez *et al.* 2009; Koutsias *et al.* 2010) and small landholders (Stolle *et al.* 2003) increases, the number of HCFs increases. González-Olabarria *et al.* (2015) have found that the distribution of arson, smokers, powerlines and camp fires in North Eastern Spain occur near coastal areas, where the population density is higher.

Productive activities on the land, especially agriculture, also seem to be related to wildfire occurrence. Croplands (Catry *et al.* 2009; Vasilakos *et al.* 2009; Gallardo *et al.* 2016) or proximity to agricultural plots (Vasconcelos *et al.* 2001) are associated with a higher probability of HCF ignitions. Martínez *et al.* (2009), Rodrigues and de la Riva (2014) and Rodrigues *et al.* (2014) found that the density of agricultural machinery in Spain, as a proxy for intensive land use, is related to HCF occurrence. When considering livestock production, livestock density (goats, sheep, cattle) is often directly associated with HCF occurrence (33 variables in the 134 long-term models) (Martínez *et al.* 2009; Oliveira *et al.* 2012; Boubeta *et al.* 2015) but the relationship is non-linear. Dlamini (2010) and Romero-Calcerrada *et al.* (2008) concluded that intermediate livestock densities were associated with an increased occurrence of HCFs in Swaziland and central Spain respectively. Shrub removal by fire for pasture regeneration tends to be performed in rural areas with a lower population density than and further away from metropolitan areas (Cardille *et al.* 2001; Stolle *et al.* 2003; Sitanggang *et al.* 2013; Zhang *et al.* 2013).

Outdoor recreational activities (Romero-Calcerrada *et al.* 2008, 2010; Vilar del Hoyo *et al.* 2011) have been found to be associated with a higher probability of HCF ignitions. Proximity to campgrounds (Pew and Larsen 2001; Gonzalez-Olabarria *et al.* 2011; Mann *et al.* 2016) or fishing areas (Chang *et al.* 2013;

Table 3.   Techniques that have been selected in at least two studies of HCF occurrence modelling, by temporal span and type of fire dependent variable (binary or multiple fire occurrence)

Bold text indicates techniques used in more than five studies

Short-term (daily)		Long-term (annually or longer)	
Binary occurrence (31 studies)	Number of fires (14 studies)	Binary occurrence (81 studies)	Number of fires (34 studies)
Logistic regression (14)	**Poisson regression (6)**	**Logistic regression (40)**	**Poisson regression (10)**
Multiple linear regression (3)	Autoregressive regression (2)	**Classification and Regression Trees (CART) (6)**	**Multiple linear regression (9)**
Artificial neural network (2)	Multiple linear regression (2)	**Inhomogeneous Ripley's K function (6)**	Negative binomial model (4)
		Multiple linear regression (6)	Generalised additive models (3)
		MaxEnt (5)	Geographically weighted regression (2)
		Boosted regression trees (4)	Zero-inflated models (2)
		Random forest model (3)	
		Weights of evidence (3)	
		Bayesian belief network (2)	
		Geographically weighted logistic model (2)	

Sitanggang *et al.* 2013) is often related to negligent or careless fires. The relationship between HCFs and population density varies depending on the ignition cause. For instance, Narayanaraj and Wimberly (2012) concluded that fire ignitions occurred in low population density areas because their fires were linked to hiking, camping and hunting in public forests that are located far from highly populated areas.

Additionally, HCFs have been modelled by including other variables (29) related to economic and educational levels of the population, which are highly relevant for the design of awareness and prevention campaigns. Wildfire occurrence has been found to relate to social level (Mercer and Prestemon 2005; Vadrevu *et al.* 2006; Oliveira *et al.* 2012; Dondo Bühler *et al.* 2013; Chas-Amil *et al.* 2015), poverty levels (Dondo Bühler *et al.* 2013), gross domestic product per capita (Chuvieco *et al.* 2008; Guo *et al.* 2016*a*, 2016*b*, 2016*c*), unemployment (Mercer and Prestemon 2005; Prestemon and Butry 2005; Martínez *et al.* 2009; Oliveira *et al.* 2012; Dondo Bühler *et al.* 2013; Chas-Amil *et al.* 2015; Nunes *et al.* 2016), age (Koutsias *et al.* 2010; Martínez-Fernández *et al.* 2013; Nunes *et al.* 2016) or literacy level (Vadrevu *et al.* 2006). Law enforcement as a preventive factor has been included in the models from two perspectives: as police presence (Mercer and Prestemon 2005; Prestemon and Butry 2005), which discourages arson before it happens; and as the number of prosecutions and convictions after it has happened (Donoghue and Main 1985).

HCF occurrence modelling methods

The first fire occurrence models started with linear regression (Crosby 1954; Haines *et al.* 1970, 1983; Altobellis 1983), modelling the number of natural fires and HCFs together. In the second half of the 1980s, Donoghue and Main (1985) and Martell *et al.* (1987) respectively introduced the Generalised Logistic Models of binary logistic regression for the HCF binary occurrence and Poisson logistic regression for predicting the number of HCFs. Both methods have been frequently applied since then (Liu and Zhang 2015; Levi and Bestelmeyer 2016; Marchal *et al.* 2017), as they are easy to use and understand (Chang *et al.* 2013). In subsequent years, models evolved in

parallel to mathematical applications, analysis and modelling techniques, computing power and increased availability of spatial datasets, thereby increasing the number of fire occurrence studies. Complex techniques such as Classification and Regression Trees (CARTs, Amatulli *et al.* 2006; Sitanggang *et al.* 2013; Karouni *et al.* 2014; Argañaraz *et al.* 2015), Artificial Neural Networks (ANNs, Vasconcelos *et al.* 2001; Sakr *et al.* 2011; Ruiz-Mirazo *et al.* 2012), Support Vector Machines (SVMs, Rodrigues and De la Riva 2014) or Generalised Additive Models (GAMs, Penman *et al.* 2013) have been introduced as alternatives to traditional statistical methods, especially when dealing with large databases, non-linear patterns and variables that are highly correlated or not normally distributed. Currently, the observation that fires often occur in aggregated or clustered patterns has led to non-parametric models that include the spatiotemporal relations between ignitions (Yang *et al.* 2007; Beccari *et al.* 2015). Table 3 shows the distribution of the most used methods, organised by temporal span and dependent variable. Fig. 1 displays the temporal emergence of techniques in recent decades, grouped by output or dependent variable: binary (*a*) or number of fires (*b*). In total, 22 different techniques have been applied to short-term prediction for operational purposes, and 34 to long-term models for planning, but logistic regression are prevalent in both, followed by Poisson regression and multiple linear regression. At the daily scale, ANNs have also been frequently used.

Additionally, this methodological evolution has increased HCF prediction accuracy. Bar Massada *et al.* (2013) suggested that the outcomes of different modelling techniques should be compared or combined to produce ensemble predictions and improve accuracy. Whereas the linear regression model by Altobellis (1983) showed an accuracy of 0.27 for all fire causes (number of fires), the Poisson mixed-model by Boubeta *et al.* (2015) reached an accuracy of 0.86 for HCFs. Padilla and Vega-Garcia (2011) obtained predictive accuracies ranging from 0.474 to 0.826 for 53 ecoregions in Spain with a logit model (binary output). However, different techniques often yield similar results with the same input data, suggesting limitations in the data or the independent variables, not in the models (Bar Massada *et al.* 2013).
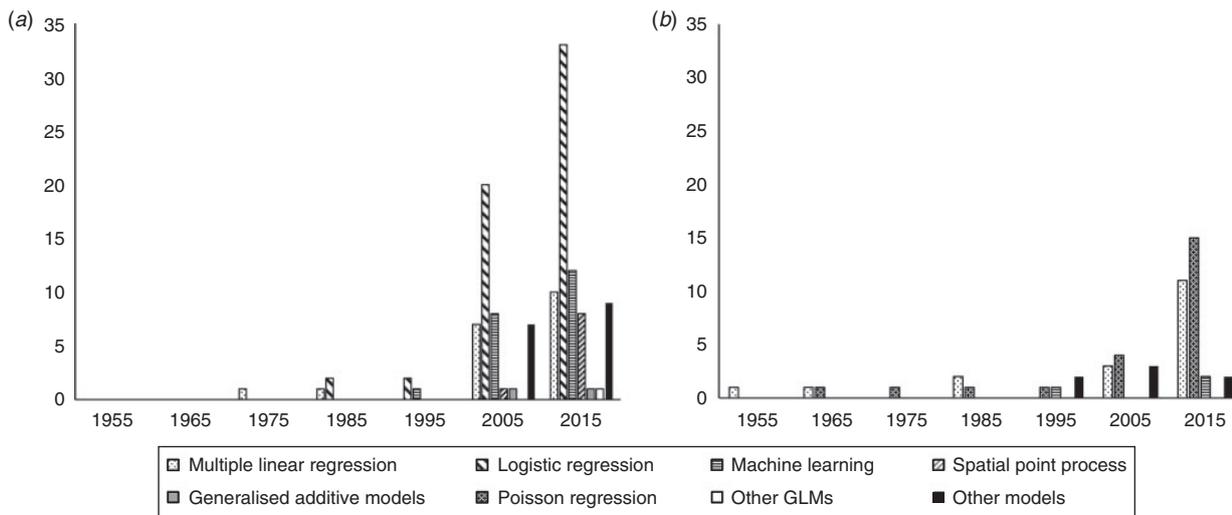
Fig. 1. Evolution of emerging techniques for binary models (*a*) and for numeric models (number of human-caused fires) (*b*).

Whatever the output type of these models (binary or numeric), published results generally include the description of a 'predictive' best model with its diagnostics (criteria for model selection). Model outputs are only occasionally mapped to provide a visual representation of probability levels in the study area (Martínez *et al.* 2009). Validation of predictive capacity with independent datasets is uncommon, though some previous works offer classification tables of observed and predicted responses, or receiver operating characteristic (ROC) curves (Mercer and Prestemon 2005; Penman *et al.* 2013; Levi and Bestelmeyer 2016). Fits too specific for the databases used in model development and poor generalisation capacity may be a problem in many non-validated models, proposed as 'explanatory'; most authors provide inferences about relevant predictors that are supposed to have a causal influence on fire occurrence, because they assume their models have explanatory power. However, the most commonly used techniques – ordinary or generalised linear models, logistic and Poisson regression models – all suffer from multicollinearity problems, so they are unreliable, according to the discussion on predictive and explanatory models by MacNally (2000), unless 'exhaustive search' or 'all-models' schemas are used.

On the question, then, of what methods perform better, we should probably conclude that those applied most often are not necessarily more commendable, unless multicollinearity is controlled and predictive capacity proved. Techniques claiming to be robust with respect to multicollinearity, like artificial neural networks, should be given more attention.

A meta-analysis approach

As part of this systematic review, we attempted to provide a quantitative summary of the 181 HCF models through a statistical synthesis or meta-analysis. Combining the results of these HCF models would require them to be conceptually identical comparable studies (O'Rourke 2007) dealing with a common process, in this case the probability of a HCF.

However, across the 152 documents analysed, identical procedures were not followed, i.e. the dependent variable was either binary (fire yes or no) or numeric (number of fires). For the short-term analyses, 22 modelling techniques and 109 variables were used, and, for the long-term analyses, 34 techniques and 378 variables were used. Original databases of observations for analysis were never available, as only best models obtained with their significant variables were described in publications, documented with a wide range of diagnostic measures of goodness-of-fit and predictive power.

Table 1, supported by Table S1, shows the diverse nature of the studies considered in this review, highlighting the difficulty of obtaining sets of homogeneous model cases to perform a meta-analysis. The synthesis proved difficult because of non-equivalence of the metrics and units of the estimators and outcomes across studies, the estimation of very diverse models, and the lack of information in study reports. In order to obtain comparable models, we started by selecting the most commonly used techniques in the short term and long-term logistic regression and Poisson model groups with the same or similar prediction unit size. For each model, we listed its parameters (coefficients), value, standard error or *P*-value, prediction unit size (base) and number of observations used in adjusting the model. There were not enough comparable models in the short term group, or Poisson long-term group. Among the logistic regression models for long-term planning, we could only perform a meta-analysis for some of the regression coefficients (variables). We considered three regression coefficients using the same metrics and measurement units – elevation (m), slope (%) and distance to urban areas (km) – to perform three distinct meta-analyses with 6, 3 and 3 studies respectively (see Table 4). It should be noted that, within the three sets of studies, we had a large variability in the coefficient values and standard errors, thereby suggesting the presence of heterogeneity in these meta-analysis approaches.

We used random-effect meta-analyses (Whitehead 2002; Borenstein *et al.* 2009) rather than fixed-effect models because

Table 4. Overview of studies selected for each meta-analysis

	Studies	Variable	Coefficient	s.e.	Units	Base
Meta-analysis I	Guo *et al.* (2016*a*)	Elevation	−0.0019	0.0001	m	Points
	Guo *et al.* (2016*c*)		−0.0034	0.0005		
	Kalabokidis *et al.* (2007)		−0.4940	0.2380		
	Narayanaraj and Wimberly (2012)		−0.0010	0.0002		
	Zhang *et al.* (2013)		−0.0010	0.1770		
	Zhang *et al.* (2016)		0.0030	0.0001		
Meta-analysis II	Kalabokidis *et al.* (2007)	Slope	0.1110	0.0420	%	Points
	Narayanaraj and Wimberly (2012)		−0.0139	0.0031		
	Zhang *et al.* (2013)		−0.4000	0.0100		
Meta-analysis III	Pan *et al.* (2016)	Distance to urban	−1.1710	0.5080	km	Pixels
	Pew and Larsen (2001)		−0.0200	0.0040		
	Pew and Larsen (2001)		−0.0210	0.0030		

we envisaged having uncontrolled between-studies variation as well as the possibility of being able to generalise our results to other statistically similar populations. Thus, we expected to estimate a particular coefficient for each study $\hat{\theta}_i$, and assumed that each of these values were random realisations of a common unknown coefficient θ. We also computed a measure of heterogeneity for each meta-analysis to assess the validity of our assumption (Borenstein *et al.* 2009). In particular, for each meta-analysis we considered the significance of the statistic Q (a Q-test) (Whitehead 2002), and we used the I^2 statistic as a quantitative measure of true heterogeneity or between-studies variability (Borenstein *et al.* 2009). Moreover, we considered a restricted maximum likelihood estimator for between-studies variability $\hat{\tau}^2$, since it is approximately unbiased and quite efficient (Viechtbauer 2005).

All the meta-analyses were computed using the *metafor* statistical package (Viechtbauer 2010) for the *R* statistical environment (R Foundation for Statistical Computing, Vienna, Austria, see http://www.r-project.org, accessed 3 February 2017).

Table 5 shows the results of the Q-test, the values of $\hat{\tau}^2$ and $\hat{I}^2$, and the estimated coefficient $\hat{\theta}$ for the three random-effect meta-analyses. This highlights that, for two meta-analyses (elevation and slope), we should reject the assumption of homogeneity and accept the presence of uncontrolled between-studies variability, although, for the other meta-analysis (distance to urban areas), we can assume homogeneity. Despite this result, we have also assumed a random-effect approach for this variable (distance to urban areas) because this result in a more conservative test and the outcomes of both approaches were, in any case, virtually the same. Moreover, only the resulting estimated coefficient value for the distance to urban areas meta-analysis was significant and larger than zero; estimated coefficients for elevation and slope were not significant. A particular problem when evaluating these results is the small number of studies per meta-analysis, and the high variability between studies in terms of coefficient values and standard error, which make the evaluation of these results difficult and their generalisation somewhat limited. However, the results for distance to urban areas (km) are a promising example of the potential that meta-analysis has, though more cooperation for harmonisation in models, temporal range, predictive units,

Table 5. Results of the *Q*-test (degrees of freedom between brackets), the values of $\hat{\tau}^2$ (between-studies variability) and the statistic $\hat{I}^2$ (proportion of between-studies variability with respect to total variability), the estimated effect-size $\hat{\theta}$, and corresponding *P*-value for the three random-effect meta-analyses

	Q (d.f.)	*P*-value	$\hat{\tau}^2$	$\hat{I}^2$(%)	$\hat{\theta}$	*P*-value
Elevation	1532.2 (5)	<0.0001	8.4×10^{-6}	99.57	−0.0008	0.5828
Slope	1373.5 (2)	<0.0001	0.074	99.85	−0.1026	0.5049
Distance to urban	5.1 (2)	0.0755	0.000	0.30	−0.0207	<0.0001

variables and metrics is needed among researchers in the field before a global characterisation of fire occurrence is possible.

Conclusions and recommendations

The reasonably large quantity of HCF occurrence models published (181 models in 152 published documents) indicates this fire science topic has reached a good level of development, especially in Europe and North America. In recent years, the People's Republic of China has become the country with the second largest number of studies, behind Spain. The most active world fire areas (Africa and Latin America) still require modelling efforts. We found that few studies have focused on these most active fire regions largely ignored by research (Chuvieco *et al.* 2008; Krawchuk *et al.* 2009; Knorr *et al.* 2014; Bedia *et al.* 2015), where wildfire databases are not even available (FAO 2010). Improving global wildfire databases in terms of fire location and causes of ignition is essential to have a global diagnosis of HCF occurrence around the world. Remote sensing can be a valuable tool in fire data acquisition when field-collected fire records are unavailable, though these sources are not free from limitations linked to technical thresholds. Remote sensing cannot provide information on causality as this requires field investigation, but reducing the high rates of unknown cause in fire registries in order to build models focused on specific causes should be a global fire management goal, with potential for more efficient risk mitigation.

Once the models are developed, links to management need to be strengthened, and specific capacities demonstrated. For

example, fire suppression resources are often challenged by simultaneous occurrences of fires (Molina-Terrén and Cardil 2015), but daily fire load can be predicted in advance by fire occurrence models, identifying areas where fires are most likely to occur. The explanatory and predictive capacity of fire occurrence models is not yet widely used in management applications, though some fire management systems have made provisions for their use (Chuvieco *et al.* 2010), partly because comprehensive national risk assessment frameworks are lacking in most fire-affected countries, if not all. Demands for strategic planning and operational applications will continue to increase, as paradigms are changing to allow for managed or prescribed fire (let-burn policies), budgets are increasingly constrained, wildland–urban interfaces are expanding and climate change introduces uncertainties.

What are the most appropriate variables and methods for applications in forest and fire management and civil protection? There are many good choices available. The first wildfire occurrence models were simple and did not predict very well, then, logistic regression models were introduced and became commonly used, and, over the years, they have been joined by more complex methodologies, such as CARTs, ANNs, SVMs, GAMs and other parametric and non-parametric models, all with good accuracies, but little managerial use. Model complexity and model perception as a black box (e.g. for ANN) with lack of adequate technical transference may partly explain this lack of use of some novel techniques. Models based on point pattern analysis hold the greatest potential for the future in terms of resolution, but they are not yet as developed and technically accessible as traditional statistical models, which in turn have to be controlled for multicollinearity problems.

HCF occurrence models include many different predictors, according to model goals that set different time ranges: they are either operational (short-term, mainly daily time ranges) or aim to influence planning (long-term, mainly a period of several years). Weather-related variables drive the daily operational models, but some fire danger rating indices have proved optimal for integrating weather conditions conducive to fires, particularly FFMC and FWI, present in the majority of studies conducted. Over the long-term, HCFs tend to be associated with accessible and populated areas, close to houses and their socioeconomic activities (both productive and leisure locations), interfaces and fragmented landscapes.

Models and predictors, though, vary locally and heavily depend on causative agents, so more studies stratified by cause or fire-prone activities are a research need, since they are scarce.

A quantitative summary of HCF models results through a meta-analysis reveals this diversity of techniques, variables and units used, and spatiotemporal dimensions (time frame and prediction spatial units). However, original databases are not available in published work. Data availability and some normalisation in terms of the spatial units and variables used, as well as their metrics and units, would improve comparability among studies and meta-analysis potential.

In closing, future research into fire occurrence should seek deeper knowledge on causality, improving global wildfire databases, novel model development, some normalisation in techniques, metrics and units, and better integration of fire occurrence within risk assessment frameworks for improved transference to management. Fire occurrence models may be useful inputs to managerial applications in fire prevention, forest and fuel treatments, media campaigns, planning for risk reduction and damage mitigation, supporting decisions or strategies and policies for general fire, forest or land management, fire suppression efficiency, deployment optimisation and pre-suppression planning, optimisation of human resources and budgets, and, lastly, for modelling climate change effects on vegetation covers and fire regimes.

Conflicts of interest

The authors declare that they have no conflicts of interest.

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