CSIRO PUBLISHING

International Journal of Wildland Fire **2017**, *26*, 983–998
https://doi.org/10.1071/WF17026

Review

Human-caused fire occurrence modelling in perspective: a review

Sergi Costafreda-Aumedes[A,D], *Carles Comas*[B] and *Cristina Vega-Garcia*[A,C,E]

[A]Department of Agriculture and Forest Engineering, University of Lleida, Alcalde Rovira Roure 191, 25198, Lleida, Spain.
[B]Department of Mathematics, University of Lleida, Agrotecnio Center, Carrer Jaume II 69, 25001, Lleida, Spain.
[C]Forest Sciences Center of Catalonia, Crta. Sant Llorenç de Morunys, km 2, 25280, Solsona, Lleida, Spain.
[D]Department of Agri-food Production and Environmental Sciences, University of Florence, Piazzale delle Cascine 18, 50144, Florence, Italy.
[E]Corresponding author. Email: cvega@eagrof.udl.cat

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.

Additional keywords: meta-analysis, predictive models, space–time patterns, wildfire.

Received 2 August 2016, accepted 27 September 2017, published online 8 December 2017

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.* 2016*a*) 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.* 2012*b*; 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.* 2012*b*; Hegeman *et al.* 2014; Syphard and Keeley 2015; Zhang *et al.* 2016; Mhawej *et al.* 2016; Vilar *et al.* 2016*b*), 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).

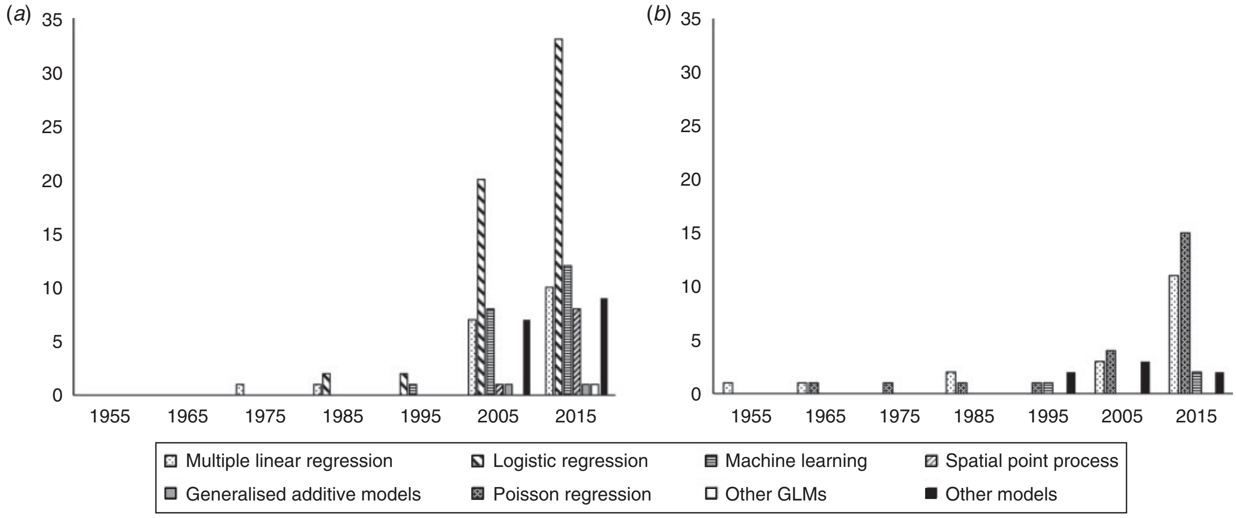

Fig. 1. Evolution of emerging techniques for binary models (*a*) and for numeric models (number of human-caused fires) (*b*).

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.

Acknowledgements

We acknowledge with gratitude the useful contributions of the three anonymous reviewers and the Associate Editor of this review paper. This research article received a grant for its linguistic revision from the Language Institute of the University of Lleida in 2017.

References

Abt KL, Butry DT, Prestemon JP, Scranton S (2015) Effect of fire prevention programs on accidental and incendiary wildfires on tribal lands in the United States. *International Journal of Wildland Fire* **24**, 749–762. doi:10.1071/WF14168

Ager AA, Preisler HK, Arca B, Spano D, Salis M (2014) Wildfire risk estimation in the Mediterranean area. *Environmetrics* **25**, 384–396. doi:10.1002/ENV.2269

Albertson K, Aylen J, Cavan G, McMorrow J (2009) Forecasting the outbreak of moorland wildfires in the English Peak District. *Journal of Environmental Management* **90**, 2642–2651. doi:10.1016/J.JENVMAN.2009.02.011

Alcasena FJ, Salis M, Nauslar NJ, Aguinaga AE, Vega-García C (2016) Quantifying economic losses from wildfires in black pine afforestations of northern Spain. *Forest Policy and Economics* **73**, 153–167. doi:10.1016/J.FORPOL.2016.09.005

Alonso-Betanzos A, Fontenla-Romero O, Guijarro-Berdiñas B, Hernández-Pereira E, Inmaculada Paz Andrade M, Jiménez E, Luis Legido Soto J, Carballas T (2003) An intelligent system for forest fire risk prediction and fire fighting management in Galicia. *Expert Systems with Applications* **25**, 545–554. doi:10.1016/S0957-4174(03)00095-2

Altobellis AT (1983) A survey of rural population density and forest fire occurrence in the south, 1956–1970. USDA Forest Service, Southern Forest Experiment Station, Research Note SO-294. (New Orleans, LA, USA)

Amatulli G, Rodrigues MJ, Trombetti M, Lovreglio R (2006) Assessing long-term fire risk at local scale by means of decision tree technique. *Journal of Geophysical Research. Biogeosciences* **111**, G04S05. doi:10.1029/2005JG000133

Ancog RC, Florece LM, Nicopior OB (2016) Fire occurrence and fire mitigation strategies in a grassland reforestation area in the Philippines. *Forest Policy and Economics* **64**, 35–45. doi:10.1016/J.FORPOL.2016.01.002

Andrews PL, Loftsgaarden DO, Bradshaw LS (2003) Evaluation of fire danger rating indexes using logistic regression and percentile analysis. *International Journal of Wildland Fire* **12**, 213–226. doi:10.1071/WF02059

Argañaraz JP, Gavier Pizarro G, Zak M, Landi MA, Bellis LM (2015) Human and biophysical drivers of fires in semiarid Chaco Mountains of central Argentina. *The Science of the Total Environment* **520**, 1–12. doi:10.1016/J.SCITOTENV.2015.02.081

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. doi:10.3832/IFOR0936-006

Avila-Flores D, Pompa-Garcia M, Antonio-Nemiga X, Rodriguez-Trejo DA, Vargas-Perez E, Santillan-Perez J (2010) Driving factors for forest fire occurrence in Durango State of Mexico: a geospatial perspective. *Chinese Geographical Science* **20**, 491–497. doi:10.1007/S11769-010-0437-X

Badia A, Serra P, Modugno S (2011) Identifying dynamics of fire ignition probabilities in two representative Mediterranean wildland–urban interface areas. *Applied Geography* **31**, 930–940. doi:10.1016/J.APGEOG.2011.01.016

Badia-Perpinyà A, Pallares-Barbera M (2006) Spatial distribution of ignitions in Mediterranean periurban and rural areas: the case of Catalonia. *International Journal of Wildland Fire* **15**, 187–196. doi:10.1071/WF04008

Bar Massada A, Syphard AD, Stewart SI, Radeloff VC (2013) Wildfire ignition-distribution modelling: a comparative study in the Huron–Manistee National Forest, Michigan, USA. *International Journal of Wildland Fire* **22**, 174–183. doi:10.1071/WF11178

Barreal J, Loureiro ML (2015) Modelling spatial patterns and temporal trends of wildfires in Galicia (NW Spain). *Forest Systems* **24**, e022. doi:10.5424/FS/2015242-05713

Bashari H, Naghipour AA, Khajeddin SJ, Sangoony H, Tahmasebi P (2016) Risk of fire occurrence in arid and semi-arid ecosystems of Iran: an investigation using Bayesian belief networks. *Environmental Monitoring and Assessment* **188**, art531. doi:10.1007/S10661-016-5532-8

Beccari A, Borgoni R, Cazzuli O, Grimaldelli R (2015) Use and performance of the Forest Fire Weather Index to model the risk of wildfire occurrence in the Alpine region. *Environment and Planning. B, Planning & Design* **0**, 1–19. doi:10.1177/0265813515596448

Bedia J, Herrera S, Gutiérrez JM (2014) Assessing the predictability of fire occurrence and area burned across phytoclimatic regions in Spain. *Natural Hazards and Earth System Sciences* **14**, 53–66. doi:10.5194/NHESS-14-53-2014

Bedia J, Herrera S, Gutiérrez JM, Benali A, Brands S, Mota B, Moreno JM (2015) Global patterns in the sensitivity of burned area to fire-weather: implications for climate change. *Agricultural and Forest Meteorology* **214–215**, 369–379. doi:10.1016/J.AGRFORMET.2015.09.002

Borenstein M, Hedges LV, Higgins JPT, Rothstein HR (2009) 'Introduction to Meta-Analysis.' (Wiley: Padstow, UK)

Boubeta M, Lombardía MJ, Marey-Pérez MF, Morales D (2015) Prediction of forest fires occurrences with area-level Poisson mixed models. *Journal of Environmental Management* **154**, 151–158. doi:10.1016/J.JENVMAN.2015.02.009

Boulanger Y, Gauthier S, Burton PJ, Vaillancourt MA (2012) An alternative fire regime zonation for Canada. *International Journal of Wildland Fire* **21**, 1052–1064. doi:10.1071/WF11073

Boulanger Y, Gauthier S, Burton PJ (2014) A refinement of models projecting future Canadian fire regimes using homogeneous fire regime zones. *Canadian Journal of Forest Research* **44**, 365–376. doi:10.1139/CJFR-2013-0372

Bradshaw LS, Deeming JE, Burgan RE, Cohen JD (1983) The 1978 National Fire-Danger Rating System: Technical Documentation. USDA Forest Service, Intermountain Forest and Range Research Station, General Technical Report INT-169. (Ogden, UT, USA)

Bradstock RA, Cohn JS, Gill AM, Bedward M, Lucas C (2009) Prediction of the probability of large fires in the Sydney region of south-eastern Australia using fire weather. *International Journal of Wildland Fire* **18**, 932–943. doi:10.1071/WF08133

Bruce D (1963) How many fires? Fire Control Notes 24, 45–50. Available at https://www.fs.fed.us/fire/fmt/fmt_pdfs/024_02.pdf [Verified 7 February 2016]

Cardille JA, Ventura SJ (2001) Occurrence of wildfire in the northern Great Lakes Region: effects of land cover and land ownership assessed at multiple scales. *International Journal of Wildland Fire* **10**, 145–154. doi:10.1071/WF01010

Cardille JA, Ventura SJ, Turner MG (2001) Environmental and social factors influencing wildfires in the Upper Midwest, United States. *Ecological Applications* **11**, 111–127. doi:10.1890/1051-0761(2001)011[0111:EASFIW]2.0.CO;2

Carvalho A, Flannigan MD, Logan K, Miranda AI, Borrego C (2008) Fire activity in Portugal and its relationship to weather and the Canadian Fire Weather Index System. *International Journal of Wildland Fire* **17**, 328–338. doi:10.1071/WF07014

Carvalho A, Flannigan MD, Logan KA, Gowman LM, Miranda AI, Borrego C (2010) The impact of spatial resolution on area burned and fire occurrence projections in Portugal under climate change. *Climatic Change* **98**, 177–197. doi:10.1007/S10584-009-9667-2

Catry FX, Rego FC, Bação FL, Moreira F (2009) Modeling and mapping wildfire ignition risk in Portugal. *International Journal of Wildland Fire* **18**, 921–931. doi:10.1071/WF07123

Chang Y, Zhu Z, Bu R, Chen H, Feng Y, Li Y, Hu Y, Wang Z (2013) Predicting fire occurrence patterns with logistic regression in Heilongjiang Province, China. *Landscape Ecology* **28**, 1989–2004. doi:10.1007/S10980-013-9935-4

Chas-Amil ML, Touza J, Prestemon JP (2010) Spatial distribution of human-caused forest fires in Galicia (NW Spain). *Ecology & Environment* **137**, 247–258. doi:10.2495/FIVA100221

Chas-Amil ML, Prestemon JP, Mcclean CJ, Touza J (2015) Human-ignited wild fire patterns and responses to policy shifts. *Applied Geography* **56**, 164–176. doi:10.1016/J.APGEOG.2014.11.025

Chou YH (1992) Management of wildfires with a geographical information system. *International Journal of Geographical Information Systems* **6**, 123–140. doi:10.1080/02693799208901900

Chuvieco E, Giglio L, Justice C (2008) Global characterization of fire activity: toward defining fire regimes from Earth observation data. *Global Change Biology* **14**, 1488–1502. doi:10.1111/J.1365-2486.2008.01585.X

Chuvieco E, Aguado I, Yebra M, Nieto H, Salas J, Martín MP, Vilar L, Martínez J, Martín S, Ibarra P, de la Riva J, Baeza J, Rodríguez F, Molina JR, Herrera MA, Zamora R (2010) Development of a framework for fire risk assessment using remote sensing and geographic information system technologies. *Ecological Modelling* **221**, 46–58. doi:10.1016/J.ECOLMODEL.2008.11.017

Chuvieco E, Aguado I, Jurdao S, Pettinari ML, Yebra M, Salas J, Hantson S, de la Riva J, Ibarra P, Rodrigues M, Echeverría M, Azqueta D, Román MV, Bastarrika A, Martínez S, Recondo C, Zapico E, Martínez-Vega FJ (2014) Integrating geospatial information into fire risk assessment. *International Journal of Wildland Fire* **23**, 606-619. doi:10.1071/WF12052

Collins KM, Price OF, Penman TD (2015) Spatial patterns of wildfire ignitions in south-eastern Australia. *International Journal of Wildland Fire* **24**, 1098–1108. doi:10.1071/WF15054

Costafreda-Aumedes S, Garcia-Martin A, Vega-Garcia C (2013) The relationship between landscape patterns and human-caused fire occurrence in Spain. *Forest Systems* **22**, 71–81. doi:10.5424/FS/2013221-02685

Costafreda-Aumedes S, Cardil A, Molina D, Daniel S, Mavsar R, Vega-Garcia C (2016*a*) Analysis of factors influencing deployment of fire suppression resources in Spain using artificial neural networks. *iForest – Biogeosciences and Forestry* **9**, 138–145. doi:10.3832/IFOR1329-008

Costafreda-Aumedes S, Comas C, Vega-Garcia C (2016*b*) Spatio-temporal configurations of human-caused fires in Spain through point patterns. *Forests* **7**, art185. doi:10.3390/F7090185

Crosby JS (1954) Fire occurrence can be predicted. USDA Forest Service, Central States Forest. Experiment Station, Technical Paper 143. (Columbus, OH, USA)

Cunningham AA, Martell DL (1973) A stochastic model for the occurrence of man-caused forest fires. *Canadian Journal of Forest Research* **3**, 282–287. doi:10.1139/X73-038

DeWilde L, Chapin FS (2006) Human impacts on the fire regime of interior Alaska: Interactions among fuels, ignition sources, and fire suppression. *Ecosystems* **9**, 1342–1353. doi:10.1007/S10021-006-0095-0

Dickson BG, Prather JW, Xu Y, Hampton HM, Aumack EN, Sisk TD (2006) Mapping the probability of large fire occurrence in northern Arizona, USA. *Landscape Ecology* **21**, 747–761. doi:10.1007/S10980-005-5475-X

Dimitrakopoulos AP, Bemmerzouk AM, Mitsopoulos ID (2011) Evaluation of the Canadian fire weather index system in an eastern Mediterranean environment. *Meteorological Applications* **18**, 83–93. doi:10.1002/MET.214

Dlamini WM (2010) A Bayesian belief network analysis of factors influencing wildfire occurrence in Swaziland. *Environmental Modelling & Software* **25**, 199–208. doi:10.1016/J.ENVSOFT.2009.08.002

Dondo Bühler M, de Torres Curth M, Garibaldi LA (2013) Demography and socioeconomic vulnerability influence fire occurrence in Bariloche (Argentina). *Landscape and Urban Planning* **110**, 64–73. doi:10.1016/J.LANDURBPLAN.2012.10.006

Donoghue LR, Main WA (1985) Some factors influencing wildfire occurrence and measurement of fire prevention effectiveness. *Journal of Environmental Management* **20**, 87–96.

Donoghue LR, Simard AJ, Main WA (1987) Determining the economic relationship between law enforcement activities and arson wildfires: a feasibility study in Arkansas. *Journal of Environmental Management* **25**, 377–393.

Drever CR, Bergeron Y, Drever MC, Flannigan M, Logan T, Messier C (2009) Effects of climate on occurrence and size of large fires in a northern hardwood landscape: Historical trends, forecasts, and implications for climate change in Témiscamingue, Québec. *Applied Vegetation Science* **12**, 261–272. doi:10.1111/J.1654-109X.2009.01035.X

Duane A, Piqué M, Castellnou M, Brotons L (2015) Predictive modelling of fire occurrences from different fire spread patterns in Mediterranean landscapes. *International Journal of Wildland Fire* **24**, 407–418. doi:10.1071/WF14040

European Commission (2015) Minutes of the 34th DG ENV and DG JRC meeting of the European Commission expert group on forest fires, 16–17 March 2015, Barcelona, Spain. Available at http://ec.europa.eu/transparency/regexpert/index.cfm?do=groupDetail.groupDetailPDF&groupID=416 [Verified 24 November 2017]

Faivre N, Jin Y, Goulden ML, Randerson JT (2014) Controls on the spatial pattern of wildfire ignitions in Southern California. *International Journal of Wildland Fire* **23**, 799–811. doi:10.1071/WF13136

Finney MA (2005) The challenge of quantitative risk analysis for wildland fire. *Forest Ecology and Management* **211**, 97–108. doi:10.1016/J.FORECO.2005.02.010

FAO (2007) Fire management global assessment 2006. A thematic study prepared in the framework of the Global Forest Resources Assessment 2005. Food and Agriculture Organization of the United Nations, Forestry Paper 151. (Rome, Italy)

FAO (2010) Global Forest Resources Assessment 2010 – Main report. Food and Agriculture Organization of the United Nations, Forestry Paper 163. (Rome, Italy)

FAO (2011) Wildfire Prevention in the Mediterranean. A key issue to reduce the increasing risks of Mediterranean wildfires in the context of climate change. Food and Agriculture Organization of the United Nations, Position paper. Second Mediterranean Forest Week. (Avignon, France)

FAO (2005) Wildland Fire Management Terminology. Food and Agriculture Organization of the United Nations, Forestry Paper 70. (Rome, Italy)

Fuentes-Santos I, Marey-Pérez MF, González-Manteiga W (2013) Forest fire spatial pattern analysis in Galicia (NW Spain). *Journal of Environmental Management* **128**, 30–42. doi:10.1016/J.JENVMAN.2013.04.020

Gallardo M, Gómez I, Vilar L, Martínez-Vega J, Martín MP (2016) Impacts of future land use/land cover on wildfire occurrence in the Madrid region (Spain). *Regional Environmental Change* **16**, 1047–1061. doi:10.1007/S10113-015-0819-9

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. *Environmental Management* **51**, 651–662. doi:10.1007/S00267-012-9961-Z

García Diez EL, Soriano LR, De Pablo Dávila F, Garcia Diez A (1994) An objective forecasting model for the daily outbreak of forest fires based on meteorological considerations. *Journal of Applied Meteorology* **33**, 519–526. doi:10.1175/1520-0450(1994)033<0519:AOFMFT>2. 0. CO;2

García Diez EL, Rivas Soriano L, de Pablo F, García Diez A (1999) Prediction of the daily number of forest fires. *International Journal of Wildland Fire* **9**, 207–211. doi:10.1071/WF00003

Garcia-Gonzalo J, Zubizarreta-Gerendiain A, Ricardo A, Marques S, Botequim B, Borges JG, Oliveira MM, Tomé M, Pereira JMC (2012) Modelling wildfire risk in pure and mixed forest stands in Portugal. *Allgemeine Forst- und Jagdzeitung* **183**, 238–248.

Giglio L (2010) MODIS Collection 5 Active Fire Product User's Guide Version 2.4. Technical Report, University of Maryland, MD, USA. Available at http://modis-fire.umd.edu/products.asp [Verified 30 June 2017]

Giglio L, Descloitres J, Justice CO, Kaufman YJ (2003) An Enhanced Contextual Fire Detection Algorithm for MODIS. *Remote Sensing of Environment* **87**, 273–282. doi:10.1016/S0034-4257(03)00184-6

Giglio L, Loboda T, Roy DP, Quayle B, Justice CO (2009) An active-fire based burned area mapping algorithm for the MODIS sensor. *Remote Sensing of Environment* **113**, 408–420. doi:10.1016/J.RSE.2008.10.006

Gonzalez-Olabarria JR, Mola-Yudego B, Pukkala T, Palahi M (2011) Using multiscale spatial analysis to assess fire ignition density in Catalonia, Spain. *Annals of Forest Science* **68**, 861–871. doi:10.1007/S13595-011-0082-2

González-Olabarria JR, Mola-Yudego B, Coll L (2015) Different factors for different causes: analysis of the spatial aggregations of fire ignitions in Catalonia (Spain). *Risk Analysis* **35**, 1197–1209. doi:10.1111/RISA.12339

Gralewicz NJ, Nelson TA, Wulder MA (2012*a*) Spatial and temporal patterns of wildfire ignitions in Canada from 1980 to 2006. *International Journal of Wildland Fire* **21**, 230–242. doi:10.1071/WF10095

Gralewicz NJ, Nelson TA, Wulder MA (2012*b*) Factors influencing national scale wildfire susceptibility in Canada. *Forest Ecology and Management* **265**, 20–29. doi:10.1016/J.FORECO.2011.10.031

Guo F, Innes JL, Wang G, Ma X, Sun L, Hu H, Su Z (2015) Historic distribution and driving factors of human-caused fires in the Chinese boreal forest between 1972 and 2005. *Journal of Plant Ecology* **8**, 480–490. doi:10.1093/JPE/RTU041

Guo F, Su Z, Wang G, Sun L, Lin F, Liu A (2016*a*) Wildfire ignition in the forests of southeast China: identifying drivers and spatial distribution to predict wildfire likelihood. *Applied Geography* **66**, 12–21. doi:10.1016/J.APGEOG.2015.11.014

Guo F, Wang G, Su Z, Liang H, Wang W, Lin F, Liu A (2016*b*) What drives forest fire in Fujian, China? Evidence from logistic regression and Random Forests. *International Journal of Wildland Fire* **25**, 505–519. doi:10.1071/WF15121

Guo F, Selvalakshmi S, Lin F, Wang G, Wang W, Su Z, Liu A (2016*c*) Geospatial information on geographical and human factors improved anthropogenic fire occurrence modeling in the Chinese boreal forest. *Canadian Journal of Forest Research* **46**, 582–594. doi:10.1139/CJFR-2015-0373

Haines DA, Main WA, Johnson VJ (1970) Relation between the U.S. National Fire Danger Rating System spread component and fire activity in the lake States. Research Paper NC-41 US Department of Agriculture, Forest Service, North Central Forest Experiment Station. Available at https://www.fs.usda.gov/treesearch/pubs/10562 [Verified 7 February 2016]

Haines DA, Main WA, Frost JS, Simard AJ (1983) Fire-danger rating and wildfire occurrence in the northeastern United States. *Forest Science* **29**, 679–696.

Hegeman EE, Dickson BG, Zachmann LJ (2014) Probabilistic models of fire occurrence across National Park Service units within the Mojave Desert Network, USA. *Landscape Ecology* **29**, 1587–1600. doi:10.1007/S10980-014-0078-Z

Henry M, Yool S (2004) Assessing relationships between forest spatial patterns and fire history with fusion of optical and microwave remote sensing. *Geocarto International* **19**, 25–37. doi:10.1080/10106040408542304

Hu T, Zhou G (2014) Drivers of lightning- and human-caused fire regimes in the Great Xing'an Mountains. *Forest Ecology and Management* **329**, 49–58. doi:10.1016/J.FORECO.2014.05.047

Hulley G, Veraverbeke S, Hook S (2014) Remote sensing of environment thermal-based techniques for land cover change detection using a new dynamic MODIS multispectral emissivity product (MOD21). *Remote Sensing of Environment* **140**, 755–765. doi:10.1016/J.RSE.2013.10.014

Jiang Y, Zhuang Q, Mandallaz D (2012) Modeling large fire frequency and burned area in Canadian terrestrial ecosystems with Poisson models. *Environmental Modeling and Assessment* **17**, 483–493. doi:10.1007/S10666-012-9307-5

Juan P, Mateu J, Saez M (2012) Pinpointing spatio-temporal interactions in wildfire patterns. *Stochastic Environmental Research and Risk Assessment* **26**, 1131–1150. doi:10.1007/S00477-012-0568-Y

Kalabokidis KD, Koutsias N, Konstantinidis P, Vasilakos C (2007) Multivariate analysis of landscape wildfire dynamics in a Mediterranean ecosystem of Greece. *Area* **39**, 392–402. doi:10.1111/J.1475-4762.2007.00756.X

Karouni A, Daya B, Chauvet P (2014) Applying decision tree algorithm and neural networks to predict forest fires in Lebanon. *Journal of Theoretical and Applied Information Technology* **63**, 282–291.

Keetch JJ, Control F, Byram GM, Physicist P (1968) A drought index for forest fire control – a drought index for forest fire control. USDA Forest Service, Southeastern Forest Experiment Station, Research Paper SE-38. (Asheville, NC, USA)

Knorr W, Kaminski T, Arneth A, Weber U (2014) Impact of human population density on fire frequency at the global scale. *Biogeosciences* **11**, 1085–1102. doi:10.5194/BG-11-1085-2014

Koutsias N, Martínez-Fernández J, Allgöwer B (2010) Do factors causing wildfires vary in space? Evidence from geographically weighted regression. *GIScience & Remote Sensing* **47**, 221–240. doi:10.2747/1548-1603.47.2.221

Krawchuk MA, Moritz MA, Parisien MA, Van Dorn J, Hayhoe K (2009) Global pyrogeography: The current and future distribution of wildfire. *PLoS One* **4**, e5102. doi:10.1371/JOURNAL.PONE.0005102

Kwak H, Lee W-K, Saborowski J, Lee S-Y, Won M-S, Koo K-S, Lee M-B, Kim S-N (2012) Estimating the spatial pattern of human-caused forest fires using a generalized linear mixed model with spatial autocorrelation in South Korea. *International Journal of Geographical Information Science* **26**, 1589–1602. doi:10.1080/13658816.2011.642799

Lee SY, Chae HM, Park GS, Ohga S (2012) Predicting the potential impact of climate change on people-caused forest fire occurrence in South Korea. *Journal of the Faculty of Agriculture, Kyushu University* **57**, 17–25.

Lefort P, Leduc A, Gauthier S, Bergeron Y (2004) Recent fire regime (1945–1998) in the boreal forest of western Quebec. *Ecoscience* **11**, 433–445. doi:10.1080/11956860.2004.11682853

Levi MR, Bestelmeyer BT (2016) Biophysical influences on the spatial distribution of fire in the desert grassland region of the southwestern USA. *Landscape Ecology* **31**, 2079–2095. doi:10.1007/S10980-016-0383-9

Li X, Zhao G, Yu X, Yu Q (2014) A comparison of forest fire indices for predicting fire risk in contrasting climates in China. *Natural Hazards* **70**, 1339–1356. doi:10.1007/S11069-013-0877-6

Liu Z, Wimberly MC (2015) Climatic and landscape influences on fire regimes from 1984 to 2010 in the western United States. *PLoS ONE* **10**, e0140839. doi:10.1371/JOURNAL.PONE.0140839

Liu D, Zhang Y (2015) Research of regional forest fire prediction method based on multivariate linear regression. *International Journal of Smart Home* **9**, 13–22. doi:10.14257/IJSH.2015.9.1.02

Liu Y, Stanturf J, Goodrick S (2010) Trends in global wildfire potential in a changing climate. *Forest Ecology and Management* **259**, 685–697.

Liu Z, Yang J, Chang Y, Weisberg PJ, He HS (2012) Spatial patterns and drivers of fire occurrence and its future trend under climate change in a boreal forest of Northeast China. *Global Change Biology* **18**, 2041–2056. doi:10.1111/J.1365-2486.2012.02649.X

Lozano FJ, Suárez-Seoane S, de Luis E (2007) Assessment of several spectral indices derived from multi-temporal Landsat data for fire occurrence probability modelling. *Remote Sensing of Environment* **107**, 533–544. doi:10.1016/J.RSE.2006.10.001

Mac Nally R (2000) Regression and model-building in conservation biology, biogeography and ecology : the distinction between – and reconciliation of – 'predictive' and 'explanatory' models. *Biodiversity and Conservation* **9**, 655–671. doi:10.1023/A:1008985925162

Magnussen S, Taylor SW (2012) Prediction of daily lightning- and human-caused fires in British Columbia. *International Journal of Wildland Fire* **21**, 342–356. doi:10.1071/WF11088

MAGRAMA (2015) 'Los incendios forestales en España.' (Ministry of Agriculture Food and Environment: Area of Defense Against Forest Fires: Madrid, Spain)

Maingi JK, Henry MC (2007) Factors influencing wildlife occurrence and distribution in eastern Kentucky, USA. *International Journal of Wildland Fire* **16**, 23–33. doi:10.1071/WF06007

Mandallaz D, Ye R (1997) Prediction of forest fires with Poisson models. *Canadian Journal of Forest Research* **27**, 1685–1694. doi:10.1139/X97-103

Mann ML, Batllori E, Moritz MA, Waller EK, Berck P, Flint AL, Flint LE, Dolfi E (2016) Incorporating anthropogenic influences into fire probability models: effects of human activity and climate change on fire activity in California. *PLoS ONE* **11**, e0153589. doi:10.1371/JOURNAL.PONE.0153589

Marchal J, Cumming SG, McIntire EJB (2017) Exploiting Poisson additivity to predict fire frequency from maps of fire weather and land cover in boreal forests of Québec, Canada. *Ecography* **40**, 200–209. doi:10.1111/ECOG.01849

Marques S, Garcia-Gonzalo J, Botequim B, Ricardo A, Borges JG, Tome M, Oliveira MM (2012) Assessing wildfire occurrence probability in *Pinus pinaster* Ait. stands in Portugal. *Forest Systems* **21**, 111–120. doi:10.5424/FS/2112211-11374

Martell DL, Otukol S, Stocks BJ (1987) A logistic model for predicting daily people-caused forest fire occurrence in Ontario. *Canadian Journal of Forest Research* **17**, 394–401. doi:10.1139/X87-068

Martell DL, Bevilacqua E, Stocks BJ (1989) Modelling seasonal variation in daily people-caused forest fire occurrence in Ontario. *Canadian Journal of Forest Research* **19**, 1555–1563. doi:10.1139/X89-237

Martínez J, Vega-Garcia C, Chuvieco E (2009) Human-caused wildfire risk rating for prevention planning in Spain. *Journal of Environmental Management* **90**, 1241–1252. doi:10.1016/J.JENVMAN.2008.07.005

Martínez-Fernández J, Chuvieco E, Koutsias N (2013) Modelling long-term fire occurrence factors in Spain by accounting for local variations with geographically weighted regression. *Natural Hazards and Earth System Sciences* **13**, 311–327. doi:10.5194/NHESS-13-311-2013

McArthur AG (1967) Fire behaviour in eucalypt forests. Australian Forestry and Timber Bureau, Leaflet 107. (Canberra, ACT, Australia)

Mercer DE, Prestemon JP (2005) Comparing production function models for wildfire risk analysis in the wildland–urban interface. *Forest Policy and Economics* **7**, 782–795. doi:10.1016/J.FORPOL.2005.03.003

Merrill DF, Alexander ME (1987) 'Glossary of Forest Fire Management Terms', 4th edn. (National Research Council of Canada, Canadian Committee on Forest Fire Management: Ottawa, ON, Canada)
Mhawej M, Faour G, Abdallah C, Adjizian-Gerard J (2016) Towards an establishment of a wildfire risk system in a Mediterranean country. *Ecological Informatics* **32**, 167–184. doi:10.1016/J.ECOINF.2016.02.003
Miller C, Ager AA (2013) A review of recent advances in risk analysis for wildfire management. *International Journal of Wildland Fire* **22**, 1–14. doi:10.1071/WF11114
Miranda BR, Sturtevant BR, Stewart SI, Hammer RB (2012) Spatial and temporal drivers of wildfire occurrence in the context of rural development in northern Wisconsin, USA. *International Journal of Wildland Fire* **21**, 141–154. doi:10.1071/WF10133
Mishra NB, Mainali KP, Crews KA (2016) Modelling spatiotemporal variability in fires in semiarid savannas: a satellite-based assessment around Africa's largest protected area. *International Journal of Wildland Fire* **25**, 730–741. doi:10.1071/WF15152
Modugno S, Balzter H, Cole B, Borrelli P (2016) Mapping regional patterns of large forest fires in wildland–urban interface areas in Europe. *Journal of Environmental Management* **172**, 112–126. doi:10.1016/J.JENVMAN.2016.02.013
Molina-Terrén DM, Cardil A (2015) Temperature determining larger wildland fires in NE Spain. *Theoretical and Applied Climatology* **125**, 295–302. doi:10.1007/S00704-015-1511-1
Morgera E, Cirelli MT (2009) Forest fires and the law – a guide for national drafters based on the fire management voluntary guidelines. Food and Agricultural Organization of the United Nations. (Rome, Italy)
Moritz MA, Parisien M-A, Batllori E, Krawchuck MA, van Dorn J, Ganz DJ, Hayhoe K (2012) Climate change and disruptions to global fire activity. *Ecosphere* **3**, 1–22.
Morrison PH (2007) Roads and Wildfires. Pacific Biodiversity Institute. (Winthrop, WA, USA)
Mundo IA, Wiegand T, Kanagaraj R, Kitzberger T (2013) Environmental drivers and spatial dependency in wild fire ignition patterns of northwestern Patagonia. *Journal of Environmental Management* **123**, 77–87. doi:10.1016/J.JENVMAN.2013.03.011
Najafabadi ATP, Gorgani F, Najafabadi MO (2015) Modeling forest fires in Mazandaran Province, Iran. *Journal of Forestry Research* **26**, 851–858. doi:10.1007/S11676-015-0107-Z
Narayanaraj G, Wimberly MC (2012) Influences of forest roads on the spatial patterns of human- and lightning-caused wildfire ignitions. *Applied Geography* **32**, 878–888. doi:10.1016/J.APGEOG.2011.09.004
Nunes AN, Lourenço L, Meira ACC (2016) Exploring spatial patterns and drivers of forest fires in Portugal (1980–2014). *The Science of the Total Environment* **573**, 1190–1202. doi:10.1016/J.SCITOTENV.2016.03.121
O'Rourke K (2007) An historical perspective on meta-analysis: dealing quantitatively with varying study results. *Journal of the Royal Society of Medicine* **100**, 579–582. doi:10.1177/0141076807100012020
Oliveira S, Oehler F, San-Miguel-Ayanz J, Camia A, Pereira JMC (2012) Modeling spatial patterns of fire occurrence in Mediterranean Europe using multiple regression and random forest. *Forest Ecology and Management* **275**, 117–129. doi:10.1016/J.FORECO.2012.03.003
Oliveira S, Pereira JMC, San-Miguel-Ayanz J, Lourenço L (2014) Exploring the spatial patterns of fire density in Southern Europe using Geographically Weighted Regression. *Applied Geography* **51**, 143–157. doi:10.1016/J.APGEOG.2014.04.002
Padilla M, Vega-Garcia C (2011) On the comparative importance of fire danger rating indices and their integration with spatial and temporal variables for predicting daily human-caused fire occurrences in Spain. *International Journal of Wildland Fire* **20**, 46–58. doi:10.1071/WF09139
Pan J, Wang W, Li J (2016) Building probabilistic models of fire occurrence and fire risk zoning using logistic regression in Shanxi Province, China. *Natural Hazards* **81**, 1879–1899. doi:10.1007/S11069-016-2160-0
Papakosta P, Straub D (2016) Probabilistic prediction of daily fire occurrence in the Mediterranean with readily available spatio-temporal data. *iForest – Biogeosciences and Forestry* **9**, e1–e9. doi:10.3832/IFOR1686-009
Parisien M-A, Moritz MA (2009) Environmental controls on the distribution of wildfire at multiple spatial scales. *Ecological Monographs* **79**, 127–154. doi:10.1890/07-1289.1
Penman TD, Bradstock RA, Price O (2013) Modelling the determinants of ignition in the Sydney Basin, Australia: implications for future management. *International Journal of Wildland Fire* **22**, 469–478. doi:10.1071/WF12027
Pew KL, Larsen CPS (2001) GIS analysis of spatial and temporal patterns of human-caused wildfires in the temperate rain forest of Vancouver Island, Canada. *Forest Ecology and Management* **140**, 1–18. doi:10.1016/S0378-1127(00)00271-1
Plucinski MP (2012) A review of wildfire occurrence. (Bushfire Cooperative Research Centre: East Melbourne, Vic., Australia)
Plucinski MP (2014) The timing of vegetation fire occurrence in a human landscape. *Fire Safety Journal* **67**, 42–52. doi:10.1016/J.FIRESAF.2014.05.012
Plucinski MP, McCaw WL, Gould JS, Wotton BM (2014) Predicting the number of daily human-caused bushfires to assist suppression planning in south-west Western Australia. *International Journal of Wildland Fire* **23**, 520–531. doi:10.1071/WF13090
Prasad VK, Badarinath KVS, Eaturu A (2008) Biophysical and anthropogenic controls of forest fires in the Deccan Plateau, India. *Journal of Environmental Management* **86**, 1–13. doi:10.1016/J.JENVMAN.2006.11.017
Preisler HK, Westerling AL (2007) Statistical model for forecasting monthly large wildfire events in Western United States. *Journal of Applied Meteorology and Climatology* **46**, 1020–1030. doi:10.1175/JAM2513.1
Preisler HK, Brillinger DR, Burgan RE, Benoit JW (2004) Probability based models for estimation of wildfire risk. *International Journal of Wildland Fire* **13**, 133–142. doi:10.1071/WF02061
Prestemon JP, Butry DT (2005) Time to burn: modelling wildland arson as an autoregressive crime function. *American Journal of Agricultural Economics* **87**, 756–770. doi:10.1111/J.1467-8276.2005.00760.X
Price O, Bradstock R (2014) Countervailing effects of urbanization and vegetation extent on fire frequency on the wildland–urban interface: disentangling fuel and ignition effects. *Landscape and Urban Planning* **130**, 81–88. doi:10.1016/J.LANDURBPLAN.2014.06.013
Reineking B, Weibel P, Conedera M, Bugmann H (2010) Environmental determinants of lightning- *v.* human-induced forest fire ignitions differ in a temperate mountain region of Switzerland. *International Journal of Wildland Fire* **19**, 541–557. doi:10.1071/WF08206
Rodrigues M, de la Riva J (2014) An insight into machine-learning algorithms to model human-caused wildfire occurrence. *Environmental Modelling & Software* **57**, 192–201. doi:10.1016/J.ENVSOFT.2014.03.003
Rodrigues M, de la Riva J, Fotheringham S (2014) Modeling the spatial variation of the explanatory factors of human-caused wildfires in Spain using geographically weighted logistic regression. *Applied Geography* **48**, 52–63. doi:10.1016/J.APGEOG.2014.01.011
Rodrigues M, Jiménez A, de la Riva J (2016) Analysis of recent spatial–temporal evolution of human driving factors of wildfires in Spain. *Natural Hazards* **84**, 2049–2070. doi:10.1007/S11069-016-2533-4
Romero-Calcerrada R, Novillo CJ, Millington JDA, Gomez-Jimenez I (2008) GIS analysis of spatial patterns of human-caused wildfire ignition risk in the SW of Madrid (Central Spain). *Landscape Ecology* **23**, 341–354. doi:10.1007/S10980-008-9190-2
Romero-Calcerrada R, Barrio-Parra F, Millington JDA, Novillo CJ (2010) Spatial modelling of socioeconomic data to understand patterns of human-caused wildfire ignition risk in the SW of Madrid (central Spain).

Ecological Modelling **221**, 34–45. doi:10.1016/J.ECOLMODEL.2009.08.008

Romme WH (1980) Fire frequency in subalpine forests of Yellowstone National Park. In 'Proceedings of the Fire History Workshop'. (Eds MA Stockes, JH Dieterich) General Technical Report RM-81, US Department of Agriculture, Forest Service, Rocky Mountain Forest and Range Experiment Station, pp. 27–30. (Tucson, AZ, USA)

Ruiz-Mirazo J, Martínez-Fernández J, Vega-García C (2012) Pastoral wildfires in the Mediterranean: Understanding their linkages to land cover patterns in managed landscapes. *Journal of Environmental Management* **98**, 43–50. doi:10.1016/J.JENVMAN.2011.12.017

Sakr GE, Elhajj IH, Mitri G (2011) Efficient forest fire occurrence prediction for developing countries using two weather parameters. *Engineering Applications of Artificial Intelligence* **24**, 888–894. doi:10.1016/J.ENGAPPAI.2011.02.017

Schmidt CC, Prins EM, Feltz J (2002) The GOES wildfire automated biomass burning algorithm processing system. Presented at the AGU Spring Meeting, Washington, DC, 28–31 May 2002.

Sebastián-López A, Salvador-Civil R, Gonzalo-Jiménez J, SanMiguel-Ayanz J (2008) Integration of socio-economic and environmental variables for modelling long-term fire danger in Southern Europe. *European Journal of Forest Research* **127**, 149–163. doi:10.1007/S10342-007-0191-5

Serra L, Juan P, Varga D, Mateu J, Saez M (2013) Spatial pattern modelling of wildfires in Catalonia, Spain 2004–2008. *Environmental Modelling & Software* **40**, 235–244. doi:10.1016/J.ENVSOFT.2012.09.014

Serra L, Saez M, Mateu J, Varga D, Juan P, Díaz-Ávalos C, Rue H (2014) Spatio-temporal log-Gaussian Cox processes for modelling wildfire occurrence: the case of Catalonia, 1994–2008. *Environmental and Ecological Statistics* **21**, 531–563. doi:10.1007/S10651-013-0267-Y

Sitanggang IS, Yaakob R, Mustapha N, Ainuddin AN (2013) Predictive models for hotspots occurrence using decision tree algorithms and logistic regression. *Journal of Applied Sciences* **13**, 252–261. doi:10.3923/JAS.2013.252.261

Stolle F, Chomitz KM, Lambin EF, Tomich TP (2003) Land use and vegetation fires in Jambi Province, Sumatra, Indonesia. *Forest Ecology and Management* **179**, 277–292. doi:10.1016/S0378-1127(02)00547-9

Sturtevant BR, Cleland DT (2007) Human and biophysical factors influencing modern fire disturbance in northern Wisconsin. *International Journal of Wildland Fire* **16**, 398–413. doi:10.1071/WF06023

Syphard AD, Keeley JE (2015) Location, timing and extent of wildfire vary by cause of ignition. *International Journal of Wildland Fire* **24**, 37–47. doi:10.1071/WF14024

Syphard AD, Radeloff VC, Keeley JE, Hawbaker TJ, Clayton MK, Stewart SI, Hammer RB (2007) Human influence on California fire regimes. *Ecological Applications* **17**, 1388–1402. doi:10.1890/06-1128.1

Syphard AD, Radeloff VC, Keuler NS, Taylor RS, Hawbaker TJ, Stewart SI, Clayton MK (2008) Predicting spatial patterns of fire on a southern California landscape. *International Journal of Wildland Fire* **17**, 602–613. doi:10.1071/WF07087

Syphard AD, Radeloff VC, Hawbaker TJ, Stewart SI (2009) Conservation threats due to human-caused increases in fire frequency in Mediterranean-climate ecosystems. *Conservation Biology* **23**, 758–769. doi:10.1111/J.1523-1739.2009.01223.X

Todd JB, Kourtz PH (1991) Predicting the daily occurrence of people-caused forest fires. Forestry Canada, Petawawa National Forestry Institute, Information Report PI-X-103. (Chalk River, ON, Canada)

Turco M, Llasat M-C, von Hardenberg J, Provenzale A (2014) Climate change impacts on wildfires in a Mediterranean environment. *Climatic Change* **125**, 369–380. doi:10.1007/S10584-014-1183-3

Vadrevu HP, Eaturu A, Badarinath KVS (2006) Spatial distribution of forest fires and controlling factors in Andhira Pradesh, India, using satellite datasets. *Environmental Monitoring and Assessment* **123**, 75–96. doi:10.1007/S10661-005-9122-4

Van Wagner CE (1987) Development and structure of the Canadian Forest Fire Weather Index System, Forestry Technical Report 35. (Chalk River, ON, Canada)

Vasconcelos MJP, Silva S, Tomé M, Alvim M, Cardoso Pereira JM (2001) Spatial Prediction of Fire Ignition Probabilities: Comparing Logistic Regression and Neural Networks. *Photogrammetric Engineering and Remote Sensing* **67**, 73–81.

Vasilakos C, Kalabokidis K, Hatzopoulos J, Matsinos I (2009) Identifying wildland fire ignition factors through sensitivity analysis of a neural network. *Natural Hazards* **50**, 125–143. doi:10.1007/S11069-008-9326-3

Vega-Garcia C, Woodard PM, Titus SJ, Adamowicz WL, Lee BS (1995) A logit model for predicting the daily occurrence of human caused forest-fires. *International Journal of Wildland Fire* **5**, 101–111. doi:10.1071/WF9950101

Vega-Garcia C, Lee BS, Woodard PM, Titus SJ (1996) Applying neural network technology to human-caused wildfire occurrence prediction. *AI Applications* **10**, 9–18.

Venevsky S, Thonicke K, Sitch S, Cramer W (2002) Simulating fire regimes in human-dominated ecosystems: Iberian Peninsula case study. *Global Change Biology* **8**, 984–998. doi:10.1046/J.1365-2486.2002.00528.X

Verdú F, Salas J, Vega-García C (2012) A multivariate analysis of biophysical factors and forest fires in Spain, 1991–2005. *International Journal of Wildland Fire* **21**, 498–509. doi:10.1071/WF11100

Viechtbauer W (2005) Bias and efficiency of meta-analytic variance estimators in the random-effects model. *Journal of Educational and Behavioral Statistics* **30**, 261–293. doi:10.3102/10769986030003261

Viechtbauer W (2010) Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software* **36**, 1–47. doi:10.18637/JSS.V036.I03

Vilar L, Woolford DG, Martell DL, Martin MP (2010) A model for predicting human-caused wildfire occurrence in the region of Madrid, Spain. *International Journal of Wildland Fire* **19**, 325–337. doi:10.1071/WF09030

Vilar L, Camia A, San-Miguel-Ayanz J, Martín MP (2016*a*) Modeling temporal changes in human-caused wildfires in Mediterranean Europe based on land use–land cover interfaces. *Forest Ecology and Management* **378**, 68–78. doi:10.1016/J.FORECO.2016.07.020

Vilar L, Gómez I, Martínez-Vega J, Echavarría P, Riaño D, Martín MP (2016*b*) Multitemporal modelling of socio-economic wildfire drivers in central Spain between the 1980s and the 2000s: comparing generalized linear models to machine learning algorithms. *PLoS ONE* **11**, e0161344. doi:10.1371/JOURNAL.PONE.0161344

Vilar del Hoyo L, Martín Isabel MP, Martínez Vega FJ (2011) Logistic regression models for human-caused wildfire risk estimation: analysing the effect of the spatial accuracy in fire occurrence data. *European Journal of Forest Research* **130**, 983–996. doi:10.1007/S10342-011-0488-2

Wan Z, Zhang Y, Zhang Q, Li Z (2002) Validation of the land-surface temperature products retrieved from Terra moderate resolution imaging spectroradiometer data. *Remote Sensing of Environment* **83**, 163–180. doi:10.1016/S0034-4257(02)00093-7

West AM, Kumar S, Jarnevich CS (2016) Regional modeling of large wildfires under current and potential future climates in Colorado and Wyoming, USA. *Climatic Change* **134**, 565–577. doi:10.1007/S10584-015-1553-5

WFLC (2017) Challenges and opportunities. The science analysis of the National Cohesive Wildland Fire Management Strategy. (Wildland Fire Leadership Council) Available at https://cohesivefire.nemac.org/challenges-opportunities [Verified 21 June 2017]

Whitehead A (2002) 'Meta-analysis of controlled clinical trials.' (Eds S Senn, V Barnett) (Wiley: Chichester, UK) . doi:10.1002/0470854200

Wotton BM, Martell DL, Logan KA (2003) Climate change and people-caused forest fire occurrence in Ontario. *Climatic Change* **60**, 275–295. doi:10.1023/A:1026075919710

Wotton BM, Nock CA, Flannigan MD (2010) Forest fire occurrence and climate change in Canada. *International Journal of Wildland Fire* **19**, 253–271. doi:10.1071/WF09002

Wu Z, He HS, Yang J, Liu Z, Liang Y (2014) Relative effects of climatic and local factors on fire occurrence in boreal forest landscapes of northeastern China. *The Science of the Total Environment* **493**, 472–480. doi:10.1016/J.SCITOTENV.2014.06.011

Xiao Y, Zhang X, Ji P (2015) Modeling forest fire occurrences using count-data mixed models in Qiannan Autonomous Prefecture of Guizhou province in China. *PLoS One* **10**, 1–12. doi:10.1371/JOURNAL.PONE.0120621

Yang J, He HS, Shifley SR, Gustafson EJ (2007) Spatial patterns of modern period human-caused fire occurrence in the Missouri Ozark Highlands. *Forest Science* **53**, 1–15. doi:10.1142/9789812706713_0001

Yang J, He HS, Shifley SR (2008) Spatial controls of occurrence and spread of wildfires in the Missouri Ozark highlands. *Ecological Applications* **18**, 1212–1225. doi:10.1890/07-0825.1

Yang J, Weisberg PJ, Dilts TE, Loudermilk EL, Scheller RM, Stanton A, Skinner C (2015) Predicting wildfire occurrence distribution with spatial point process models and its uncertainty assessment: a case study in the Lake Tahoe Basin, USA. *International Journal of Wildland Fire* **24**, 380–390. doi:10.1071/WF14001

Zhang ZX, Zhang HY, Zhou DW (2010) Using GIS spatial analysis and logistic regression to predict the probabilities of human-caused grassland fires. *Journal of Arid Environments* **74**, 386–393. doi:10.1016/J.JARIDENV.2009.09.024

Zhang H, Han X, Dai S (2013) Fire occurrence probability mapping of northeast China with binary logistic regression model. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* **6**, 121–127. doi:10.1109/JSTARS.2012.2236680

Zhang Y, Lim S, Sharples JJ (2016) Modelling spatial patterns of wildfire occurrence in south-eastern Australia. *Geomatics, Natural Hazards & Risk* **5705**, 1–16. doi:10.1080/19475705.2016.1155501