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A REVIEW OF WILDFIRE OCCURRENCE RESEARCH

Matt P. Plucinski

CSIRO Ecosystem Science and CSIRO Climate Adaptation Flagship

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M.P. Plucinski

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Abstract

Wildfire occurrence statistics describe the presence and quantity of ignitions across spatial and temporal scales. Fire occurrence research is based on regional fire incidence data containing the time, location and cause of all fires within a defined area and time period. This research has also relied on other spatial and temporal data, including terrain, land cover, human geography, weather, and fire danger indices, in analyse and modelling.

Fire occurrence research has been undertaken to map ignition risks, investigate causal factors and develop predictive models. Ignition risk maps inform fire management operations and can be used to identify the best locations for fuel treatments and suppression resource bases. Some fire occurrence models have been developed to predict the probability of a fire day and estimate the number of daily ignitions that may occur within a fire management region. These predictions can be used by fire managers to set operational resourcing levels and locations which will optimise suppression effectiveness by allowing them to maximise resource availability and reduce response times. Fire occurrence models have been applied in recent research undertaken to predict the effects of climate change on fire regimes and fire risks.

Fire occurrence research has been undertaken in a variety of countries, mainly in North America and Europe. Much of the research has been published in recent years as datasets have become more available and computing technology has allowed more sophisticated analyses. Fire occurrence research papers have presented a variety of findings that reflect the diverse locations and regional nature of these works. Very little fire occurrence research has been undertaken in Australia. Undertaking such research in Australian regions will enhance knowledge of fire patterns and provide practical outputs that will benefit fire management.

Introduction

The term fire occurrence is used to describe the presence and frequency of fires within a finite time and space. Fire occurrence statistics account for all reported ignitions regardless of the area they burn or damage they cause. Historical fire data, incorporating timing, location and cause information for all incidents, is the basis of fire occurrence research (Finney 2005). Such data is typically sourced from fire and land management agency records and is analysed with other environmental and geographical variables relating to weather, vegetation, terrain, and land use.

Fire occurrence knowledge and predictions are important for a variety of fire management functions. Spatial fire occurrence research has been used to identify areas with high ignition risks (e.g.: Beverly *et al.* 2009; Cardille and Ventura 2001; Díaz-Delgado *et al.* 2004; Syphard *et al.* 2008) and has been used in broader wildfire risk analyses that also consider other measures, such as fire severity and the probability of an area being burned (e.g.: Finney *et al.* 2005; Martinez *et al.* 2009; Mercer and Prestemon 2005; Preisler *et al.* 2004; Weinstein and Woodbury 2006). Findings from spatial fire occurrence analyses can be used to target fire management actions, such as the identification of the best locations for fuel treatments and dynamic allocation of suppression resources (Dlamini 2010; Syphard *et al.* 2008; Wotton 2004; Wotton and Martell 2005). Spatial fire occurrence analyses can also be used to judge the effectiveness of prevention programs (Donoghue and Main 1985; Donoghue *et al.* 1987).

Temporal fire occurrence predictions are typically based on meteorological variables, such as weather, weather indices and fuel moisture models, and have been developed to predict ignitions within spatial units. During the fire season, daily fire occurrence predictions can be used to estimate the potential load on suppression resources that a fire management agency will face enabling them to plan levels of preparedness and manage resource locations (Haines *et al.* 1983; Tithecott 1992; Vilar *et al.* 2010b; Wotton 2004; Wotton and Martell 2005; Wotton *et al.* 2010). These actions help optimise suppression effectiveness by enabling planning that maximises resource availability and reduces response times, thereby increasing the probability of initial attack success (Podur and Wotton 2010; Todd and Kourtz 1990; Wotton *et al.* 2010).

Much of the research has been undertaken to address the specific issue of large fire occurrence (e.g.: Bermudez *et al.* 2009; Bradstock *et al.* 2009; Dickson *et al.* 2006; Drever *et al.* 2009; Hély *et al.* 2010; Mendes *et al.* 2010; Moreira *et al.* 2010; Preisler *et al.* 2009; Preisler *et al.* 2008; Preisler and Westerling 2007) concentrating on determining causal factors and prediction of the most significant fire events. However studies limited to large fires only consider conditions when suppression actions are unable to cope with the fire load. Fire occurrence research that incorporates all ignitions also considers the many fires where suppression has been successful. Some fire occurrence and large fire occurrence research has been undertaken to compare fire occurrence statistics with fire danger indices (Andrews *et al.* 2003; Haines *et al.* 1983; Padilla and Vega-García 2011; Preisler *et al.* 2004; Preisler *et al.* 2009; Viegas *et al.* 1999). This research also investigated other wildfire statistics such area burned, and numbers of fires that escape initial attack and become large for this reason.

Fire occurrence research has been undertaken at regional levels, utilising data from specific fire management zones. This research has been used to address regional concerns and have been used to define spatial and temporal trends, determine causal factors and develop predictive models. The methods and results from the research are highly varied due to the range of environmental and human landscapes that they consider. The majority of fire occurrence research has been undertaken in North America and Europe. There has been very little specific fire occurrence research undertaken in Australia. This review considers the methods used for analysis, modelling and application of fire occurrence data in order to identify appropriate methods for undertaking such research in parts of Australia.

Fire occurrence analysis and modelling methods

Fire occurrence research has largely been undertaken to gain a better understanding of spatial and temporal factors influencing wildfire ignitions, and to develop models that can be used to predict the probability of ignition in different areas and at with different weather conditions.

Spatially based fire occurrence research is primarily concerned with the spatial distribution of ignitions in relation to geographic variables, such as terrain and human landscape features. This research relies on fire data with ignition point locations from multiple years and does not generally consider dynamic weather or time variables. A range of methodologies have been employed to determine spatial factors influencing fire occurrence. These include traditional statistical hypothesis tests (Cardille and Ventura 2001; Maingi and Henry 2007; Mercer and Prestemon 2005), linear (Donoghue and Main 1985) and logistic regression analysis (Cardille and Ventura 2001; Catry *et al.* 2009; Chou 1992; Kalabokidis *et al.* 2007; Krawchuk *et al.* 2006; Martinez *et al.* 2009; Pew and Larsen 2001; Prasad *et al.* 2008; Syphard *et al.* 2008; Vasconcelos *et al.* 2001), classification and regression trees (Amatulli *et al.* 2006) and Bayesian network methods (Dilts *et al.* 2009; Dlamini 2010). Some spatially based research has investigated the clustering of ignition points and have used *K*-function and *L*-function analyses to assess clustering and kernel density smoothing to provide graphical depictions (Genton *et al.* 2006; Hering *et al.* 2009; Podur *et al.* 2003; Turner 2009; Wang and Anderson 2010; Yang *et al.* 2007). A list containing the details of some published spatial fire occurrence research is presented in Table 1.

Temporally based fire occurrence research has been undertaken to model the probability of a fire occurrence, defined as one or more fires occurring within defined temporal and spatial limits. Temporal fire occurrence research has also been undertaken to estimate the number of ignitions that may occur on a particular day. These models mainly use dynamic weather and fire weather index variables. Some temporal fire occurrence analyses and models have been specifically undertaken to evaluate fire danger indices (e.g.: Andrews *et al.* 2003; Haines *et al.* 1983; Haines *et al.* 1970; Padilla and Vega-García 2011; Vasilakos *et al.* 2009; Viegas *et al.* 1999). These papers considered other metrics such as area burned and number of fires over a given size threshold and are used to select the most appropriate fire danger index for an area. Similarly other papers have compared fire occurrence with dynamic live and dead fuel moisture content (Chuvieco *et al.* 2009; Viegas *et al.* 1992). The influence of geographic variables has been minimised in most temporal fire occurrence papers by dividing the landscape up into relatively homogenous units and treating these individually.

Table 1. Examples of spatially based fire occurrence models and analyses.

Reference	Origin	Ignition type	Primary method	Significant factors
Donoghue and Main (1985)	Eastern USA	Anthropogenic	Linear regression analysis	Latitude, weather (rainfall), population density (non-urban) and number of legal prosecutions and convictions
Chou (1992)	Southern California, USA	Not specified	Logistic regression modelling	Topography, vegetation, temperature, precipitation, proximity to buildings and transport
Cardille and Ventura (2001)	Upper Midwest USA	All (97% anthropogenic)	Statistical analysis (two-sided Z tests)	land tenure
Cardille *et. al.* (2001)	Upper Midwest USA	All (96% anthropogenic)	Logistic regression analysis	Population and road density, precipitation and temperature
Pew and Larsen (2001)	Vancouver Island, Canada	Anthropogenic	Logistic regression modelling	Temperature, distance from towns, roads and rail, precipitation
Vasconcelos *et al.* (2001)	Central Portugal	Anthropogenic (arson)	Logistic regression and neural network modelling	Altitude, slope, distance from roads, agriculture and shrublands
		Anthropogenic (negligence)	Logistic regression and neural network modelling	Distance from roads, urban areas and shrublands, and aspect
Podur *et al.* (2003)	Ontario, Canada	Lightning	K-function	Localised dry weather and lightning-storm occurrence
Mercer and Prestemon (2005)	Florida, USA	Not specified	Statistical analysis (likelihood estimates)	Unemployment, poverty, number of police
Amatulli *et al.* (2006)	Southeast Italy	Not specified	Decision tree analysis	Land cover classification, average temperature of warmest and coldest months, slope and elevation
Genton *et al.* (2006)	Florida, USA	All (75% anthropogenic)	K-function	Clustering for lightning, arson and railroad fires
Krawchuk *et al*. (2006)	Alberta, Canada	Lightning	Logistic regression analysis	forest composition (species), fire history
Kalabokidis *et al.* (2007)	Northern Greece	Not specified	Logistic regression analysis	Vegetation cover, slope, elevation, density of livestock
Maingi & Henry (2007)	Kentucky, USA	Anthropogenic (mainly arson)	Statistical analysis (Kruskal–Wallis test, correlation)	Distance to roads and populated places, elevation and slope
Sturtevant and Cleland (2007)	Wisconsin, USA	Anthropogenic	Classification and regression tree analysis	Housing density, road density, percentage owner-occupied homes, distance to railroads, percentage of agriculture or grassland cover and relative forest flammability

Table 1. continued

Reference	Origin	Ignition type	Primary method	Significant factors
Yang *et al.* (2007)	Missouri, USA	Anthropogenic	K-function	Land tenure, distance to towns and roads, forest type and slope
Prasad *et al.* (2008)	Deccan Plateau, India	Not specified	Logistic regression analysis	Biomass density, average precipitation of the warmest quarter, amount of forest area, rural population density and mean annual temperature
Romero-Calcerrada *et al.* (2008)	Madrid region, Spain	Anthropogenic	Bayesian statistics (weights of evidence)	Proximity to urban areas and roads
Syphard *et al.* (2008)	California, USA	All (mainly anthropogenic)	Logistic regression modelling	Distance to development, roads and trails, vegetation type, density of wildland urban interface and average January minimum temperature
Yang *et al.* (2008)	Missouri, USA	Anthropogenic	Classification and regression tree modelling	Proximity to roads, land ownership and distance to towns
Catry *et al.* (2009)	Portugal	All (mainly anthropogenic)	Logistic regression modelling	Population density, followed by land cover type, elevation, and distance to roads
Dilts (2009)	Nevada, USA	Lightning	Bayesian modelling	Lightning strike density, topographic roughness
Martinez *et al*. (2009)	Spain	Anthropogenic	logistic regression analysis	Agricultural landscape fragmentation, agricultural abandonment and development processes
Dlamini (2010)	Swaziland	Not specified	Bayesian modelling	Land cover, together with elevation, mean annual rainfall and mean annual temperature
Duncan *et al.* (2010)	Florida, USA	Lightning	Statistical analysis (correlation)	Precipitation, lightning polarity and vegetation
Wang and Anderson (2010)	Alberta, Canada	Lightning	K-function	Presence of air mass type thunderstorms, and combination of topography and dominant coniferous species
		Anthropogenic	K-function	Areas where agriculture, forest and forest industries coexist

Many papers have considered the temporal probability of the occurrence of one or more fires (Table 2). The vast majority of papers have considered the probability of a fire occurrence at the daily scale. Some lightning fire occurrence models have considered the probability of a fire occurrence from a lightning strike (e.g.: Anderson 2002; Dowdy and Mills 2009; Wotton and Martell 2005). Daily fire occurrence has mostly been modelled using logistic regression (Andrews *et al.* 2003; Loftsgaarden and Andrews 1992; Martell *et al.* 1989; Martell *et al.* 1987; Padilla and Vega-García 2011; Preisler *et al.* 2004; Reineking *et al.* 2010; Vega Garcia *et al.* 1995; Vilar *et al.* 2010b; Wotton and Martell 2005). Other authors have used methods such as artificial neural networks (Vasconcelos *et al.* 2001; Vasilakos *et al.* 2009), classification and regression trees (Krusel *et al.* 1993; Sturtevant and Cleland 2007; Yang *et al.* 2008) and logistic generalised additive models (Vilar *et al.* 2010b). Some Canadian lightning fire occurrence papers (Anderson 2000; Anderson 2002; Kourtz and Todd 1991; Wotton 2004; Wotton and Martell 2005) have divided the occurrence process into phases relating to ignition from a lightning strike; smouldering combustion or possible slow flaming combustion; and detection and reporting. These papers have developed probability models for these phases and then combined them to give an overall estimate of lightning fire occurrence.

Some temporal fire occurrence papers have presented models that predict the number of fires occurring on a single day (Table 3). These have used a range of approaches, such as poisson regression (Cunningham and Martell 1973; Wotton *et al.* 2003), auto regressive meteorological modelling (Garcia Diez *et al.* 1999; Garcia Diez *et al.* 1994) and Baysesian modelling (Todd and Kourtz 1991). Preisler *et al.* (2004) estimated the number of fires within a region by suming the daily probability of fire occurrence within each square kilometre. Anderson (2002) estimated the number of daily fires in a region by summing modelled probabilities of individual lightning strikes. Wotton and Martell (2005) used logistic regression models to predict the probability that a lightning strike would cause a sustainable reported ignition and multiplied this by the number of lightning strikes in defined areas each day to predict the number of fires.

Table 2. Examples of temporal models and analyses of fire occurrence (probability of one or more fires on a given day).

Reference	Origin	Ignition type	Primary method	Significant factors
Haines *et al.* (1970)[1]	Northeast USA	Not specified	Linear regression analysis	Fine fuel spread index[2]
Cunningham and Martell (1973)	Ontario, Canada	Anthropogenic	Poisson regression	Fine Fuel Moisture Code[3]
Haines *et al.* (1983)[1]	Northeast USA	Not specified	Linear regression analysis	Initial Spread Index[3] and the Fosberg Fire Weather Index[4]
Martell *et al.* (1987)	Ontario, Canada	Anthropogenic	Logistic regression modelling	Fine Fuel Moisture Code[3], Build Up Index[3], Fire Weather Index[3]
Martell *et al.* (1989)	Ontario, Canada	Anthropogenic	Logistic regression modelling with periodic function	Fine Fuel Moisture Code[3] and day of the season
Kourtz and Todd (1991)	Quebec, Canada	Lightning	Expert systems analysis	Lightning activity, rainfall, fuel moisture content, duff depth, Drought Code[3], Duff Moisture Code[3], Initial Spread Index[3]
Krusel *et al.* (1993)[5]	Northwest Victoria, Australia	Not specified	Decision tree analysis	Meteorological variables (temperature, days since last rain, Keetch-Byram Drought Index [6], wind speed and relative humidity)
Vega Garcia *et al.* (1995)	Alberta, Canada	Anthropogenic	Logistic regression modelling	District, Build Up Index[3] and Initial Spread Index[3]
Andrews *et al.* (2003)[1]	Arizona, USA	All	Logistic regression modelling	Energy release component[7]
Preisler *et al.* (2004)[9]	Oregon, USA	All	Logistic regression modelling	Spatial location, day in year, elevation, 1000 hour fuel moisture[7], dry bulb temperature and state of weather[8]
Prestimon and Butry (2005)	Florida, USA	Anthropogenic (arson)	Poisson auto-regression	Recent fire activity[10], day of week, economic conditions, fire management actions
Albertson *et al.* (2009)	English Peak District, UK	Anthropogenic	Probit model	Fire in last week, rain, temperature, public holiday, day of the week and month
Chuvieco *et al.* (2009)[11]	Central Spain	All	Poisson auto-regression	Live fuel moisture
Vasilakos *et al.* (2009)[1]	Lesvos Island, Greece	all (mainly anthropogenic)	Neural network modelling	Rainfall, 10-hour fuel moisture content[7], month, relative humidity, elevation and day of the week

Table 2. continued

Reference	Origin	Ignition type	Primary method	Significant factors
Reineking *et al.* (2010)	Canton Ticino, Switzerland	Lightning	logistic regression analysis	Duff Moisture Code[3], Buildup Index[3] and LandClim Drought Index[12],
		Anthropogenic	logistic regression analysis	Angstroem[13] and Fosberg Fire Weather Index[4]
Vilar *et al.* (2010b)	Madrid region, Spain	Anthropogenic	Logistic regression modelling	Day of year, urban density, distance from roads and rail, elevation, maximum temperature
Padilla and Vega-García (2011)[1]	Spain	Anthropogenic	Logistic regression modelling	Weather indices (Fire Weather Index[3], Fine fuel moisture code[3] and 1000 hour fuel moisture[7]) and variables (maximum temperature and relative humidity), road density, distance from populations, and live fuel moisture content.

[1] Papers using fire occurrence for fire danger index evaluation.
[2] The fine fuel spread index is based on the moisture content of fast drying fuels and wind speed (Main 1969).
[3] Components of the Canadian Forest Fire Weather Index System (Van Wagner 1987).
[4] Based on temperature, humidity and wind speed (Fosberg 1978).
[5] Considered categorical criteria for fire activity, which included number of fires, area burned and resources deployed on a given day.
[6] From Keetch and Byram (1968).
[7] From the US National Fire Danger Rating System (Deeming *et al.* 1977).
[8] Categorical variable: clear, scattered clouds, broken clouds, overcast, raining or snowing and thunderstorm.
[9] Fire occurrence considered over a monthly scale.
[10] Binary variable related to the occurrence of other fires in the same district in the previous 11 days.
[11] Paper comparing fire occurrence with live fuel moisture content estimated from satellite imagery. The time period considered is eight days owing to the return cycle of the satellite.
[12] From Bugmann and Cramer (1998).
[13] Calculated from temperature and relative humidity, defined in Reineking *et al.* (2010).

Table 3. Examples of temporal models predicting the number of daily fires.

Reference	Origin	Ignition type	Modelling type	Model parameters
Haines *et al.* (1983)[1]	North-eastern USA	Not specified	Linear regression	Ignition Component[2]
Todd and Kourtz (1991)	Quebec, Canada	Anthropogenic	Bayesian	Wind speed, Fine Fuel Moisture Code[3] and Duff Moisture Code[3]
Garcia Diez *et al.* (1994)	Galicia, Spain	Not specified	Autoregressive	Atmospheric stability and saturation deficit level
Mandallaz and Ye (1997)	South Switzerland	All	Poisson regression	Region, day of week, recent fire history, relative humidity and ETP[4]
	South France	All	Poisson regression	ICONA[4], recent fire history and IP[4]
	North Italy	All	Poisson regression	Region, recent fire history, precipitation, humidity, wind speed and Fine Fuel Moisture Code[3]
	Portugal	All	Poisson regression	RN[4], IREPI[4] and recent fire history
Garcia Diez *et al.* (1999)	Galicia, Spain	Not specified	Autoregressive	Atmospheric stability and humidity
Anderson (2002)	Saskatchewan, Canada	Lightning	Physically based probabilistic	Number of lightning strikes, fuel moisture content, rainfall, forest type
Wotton *et al.* (2003)	Ontario, Canada	Anthropogenic	Poisson regression	Probability of sustained flaming, Fine Fuel Moisture Code[3], Duff Moisture Code[3], Drought Code[3]
Preisler *et al.* (2004)[6]	Oregon, USA	All	Sum of predicted occurrence in each grid	Spatial location, day in year, elevation, 1000h fuel moisture[2], dry bulb temperature and state of weather[5]
Wotton and Martell (2005)	Ontario, Canada	Lightning	Number of lightning strikes multiplied by the probability of a strike igniting a detectable fire	Number of lightning strikes, Sheltered Duff Moisture Code[7], Drought Code[3], Fine Fuel Moisture Code[3], percent positive lightning strikes, percent closed canopy fuels, timing of storm, drying phase, and rain occurrence
Wotton *et al.* (2010)	Canada	Anthropogenic	Poisson regression	Ecoregion, Fine Fuel Moisture Code[3], Duff Moisture Code[3], Drought Code[3], timing within season (by ignition cause) and time of season
		Lightning	Poisson regression	Ecoregion, Duff Moisture Code[3], Fine Fuel Moisture Code[3], Drought Code[3] and time of season

[1] Paper using number of fires per day for fire danger index evaluation.
[2] From the US National Fire Danger Rating System (Deeming *et al.* 1977).
[3] Components of the Canadian Forest Fire Weather Index System (Van Wagner 1987).
[4] Undefined and unreferenced Swiss (ETP), Spanish (ICONA), Portuguese (IP), Italian (IREPI) and French (RN) fire danger indices used by Mandallaz and Ye (1997).
[5] Categorical variable: clear, scattered clouds, broken clouds, overcast, raining or snowing and thunderstorm.
[6] Predicted the number of fires over a month.
[7] From Wotton *et al.* (2005).

Factors affecting fire occurrence

A large variety of factors have been found to affect fire occurrence and been used in prediction models (Tables 1-3). These depend on the types of ignition occurring in the locations considered and the variables that are available for testing. Many fire occurrence papers have considered lightning caused fires and anthropogenic fires separately as they are affected by distinctly different process and have different temporal and spatial distributions (Amatulli *et al.* 2007; Fujioka *et al.* 2008; Gill *et al.* 1987; Reineking *et al.* 2010; Vilar *et al.* 2010a; Wang and Anderson 2010; Wotton *et al.* 2010). Most papers have only considered fires from one of these ignition categories or have come from regions dominated by one type of ignition.

Lightning ignited fires require storms for ignition, particularly those with little or no precipitation. The occurrence of such storms has been linked with atmospheric conditions featuring low moisture and high instability (Dowdy and Mills 2009; Rorig and Ferguson 1999). Many lightning fire occurrence papers have used variables related to storm activity, such as storm occurrence (Podur *et al.* 2003), type of storm (Wang and Anderson 2010), lightning polarity (Anderson 2002; Duncan *et al.* 2010), lightning strike density (Dilts *et al.* 2009), and number of lightning strikes (Kourtz and Todd 1991; Wotton and Martell 2005). As lightning ignitions can smoulder for days before detection, some authors (e.g.: Cunningham and Martell 1976; Tithecott 1992; Wotton 2004; Wotton and Martell 2005) have specified that the occurrence and reporting ("arrival") of lightning fires be considered separately.

Some spatial analyses of lightning ignited fires have linked them with terrain features (e.g.: Dilts *et al.* 2009; Kilinc and Beringer 2007; McRae 1992; Vazquez and Moreno 1998) and areas with drier fuels (e.g.: Podur *et al.* 2003; Wotton and Martell 2005). Temporal lightning fire occurrence models and analyses have highlighted the importance of fuel moisture and rainfall for prediction. Many models have used indices within the Canadian Forest Fire Weather Index System (CFFWIS) (Van Wagner 1987), particularly the Duff Moisture Code (e.g.: Anderson 2002; Flannigan and Wotton 1991; Krawchuk *et al.* 2006; Podur *et al.* 2003; Reineking *et al.* 2010; Wotton 2004; Wotton and Martell 2005; Wotton *et al.* 2005), which is associated with the moisture content of deeper fuel layers. An Australian report (Dowdy and Mills 2009) that used the CFFWIS found the Fine Fuel Moisture Code provided the best indication of ignition from lightning, probably due to the general lack of duff in Australian forests and the warmer and drier climate. Fuel moisture related variables are less important in arid areas where they are more available for burning and ignition mechanisms have a greater influence on fire occurrence (Dilts *et al.* 2009). Krawchuk *et al.* (2006) found fuel variables related to species composition and fuel age to influence the inter-annual variation in lightning ignited fires. Fuel related variables have not been considered in other research, often because they have used areas with relatively homogenous vegetation.

The majority of spatial fire occurrence research has been conducted in areas dominated by anthropogenic ignitions. These have linked anthropogenic fire occurrence with a range of geographic variables (see Table 1) associated with population density (e.g.: Cardille *et al.* 2001; Catry *et al.* 2009; Donoghue and Main 1985; Mercer and Prestemon 2005; Prasad *et al.* 2008; Romero-Calcerrada *et al.* 2008; Sturtevant and Cleland 2007); proximity to roads, towns and infrastructure (e.g.: Catry *et al.* 2009; Chou *et al.* 1993; de Vasconcelos *et al.* 2001; Maingi and Henry 2007; Martinez *et al.* 2009; McRae 1995; Padilla and Vega-García 2011; Pew and Larsen 2001; Roman-Cuesta *et al.* 2009; Romero-Calcerrada *et al.* 2008; Syphard *et al.* 2008; Vega-Garcia *et al.* 1996; Vega Garcia *et al.* 1995; Vilar *et al.* 2010b) and land use variables (e.g.: Cardille and Ventura 2001; Padilla and Vega-García 2011; Romero-Calcerrada *et al.* 2008; Vasconcelos *et al.* 2001). Some spatially based investigations of anthropogenic fire occurrence have also identified socioeconomic variables, such as poverty and unemployment rates as having some influence (e.g.: Donoghue and Main 1985; Maingi and Henry 2007; Martinez *et al.* 2009; Mercer and Prestemon 2005; Sturtevant and Cleland 2007). Fuel variables have been considered in a few papers, mainly in terms of vegetation type (e.g.: Padilla and Vega-García 2011; Syphard *et al.* 2008; Vega-Garcia *et al.* 1996), but have been consistently found to be less significant than the human variables.

Temporal fire occurrence models considering anthropogenic ignitions assume that fire prevention measures, land use and socioeconomic variables remain constant during the data collection period (Martell *et al.* 1989; Todd and Kourtz 1991; Vilar *et al.* 2010b). Many of these models have linked fire occurrence to the moisture content of surface fuels, which has often been estimated with the Fine Fuel Moisture Code from the CFFWIS (Martell *et al.* 1989; Martell *et al.* 1987; Padilla and Vega-García 2011; Vega Garcia *et al.* 1995; Wotton 2004; Wotton *et al.* 2003). Some models have included variables associated with date (day of the year or season) to account for the distribution of fires occurring across the fire season (e.g.: Albertson *et al.* 2009; Martell *et al.* 1989; Preisler *et al.* 2004; Vilar *et al.* 2010b).

Some anthropogenic fire occurrence research has considered the influence of different ignition types. Martell et al. (1989) and Wotton et al. (2003) divided anthropogenic fires into two groups based on their annual distributions of occurrence. Vasconcelos *et al.* (2001) considered arson and negligent ignitions separately and found that they exhibited different spatial patterns. Separating arson ignitions from other anthropogenic ignitions in fire occurrence prediction would be worth pursuing as arson ignitions have been found to have distinct spatial trends related to accessibility (Maingi and Henry 2007; Prestemon and Butry 2006) and temporal trends associated with weekends and public holidays and recent fire activity (Beale and Jones 2011; Mandallaz and Ye 1997; Prestemon and Butry 2005).

Discussion

All fire occurrence research is based on fire records and requires data that spans multiple fire seasons. Fire incident databases maintained by fire agencies are the most common source of this data. Though occasionally, when these records are not available, archives of satellite images have been used for spatial fire occurrence research (e.g.: Dlamini 2010; Maingi and Henry 2007; Prasad *et al.* 2008). Research papers based on satellite data rely on the identification of fire scars, and it is unlikely that they would detect all fires, particularly smaller fires. While official fire agency records are a more reliable data source, there can be significant variability in the reporting standards kept by agencies (Andrews *et al.* 2003). The availability of fire records has restricted fire occurrence research in the past. Recent trends for increased data capture within fire agencies in many countries and advances in computer programs designed for data analysis and modelling have enabled more research to be undertaken in this field, as demonstrated by the large number of papers published last few years.

The critical data fields required for the fire observation components of fire occurrence data sets regard the time and location of a detected ignition. Detection time will usually be different to the ignition time depending on the source of the ignition. Accidental fires may be detected and reported within minutes of ignition. Lightning fires can smoulder for many days before they grow to a detectable size (Anderson 2000; Anderson 2002; Cunningham and Martell 1976; Kourtz and Todd 1991; Wotton and Martell 2005), although in Australia, the majority of lightning ignited fires have been found to be detected soon after ignition (Dowdy and Mills 2009). Detection time data is essential for developing temporal fire occurrence models for operational purposes. In the same way, ignition location coordinates are essential for all spatial fire occurrence analyses. Distinguishing between different ignition sources, particularly between anthropogenic and lightning caused ignitions, is beneficial for analysing fire occurrence data, as these are driven by different processes, as described earlier.

Spatial fire occurrence analysis requires geographic data encompassing terrain; vegetation and human factors (see Table 1 for examples). Human factors relate to land tenure, population and infrastructure. Predictor variables for these fields are either proximity measures, such as distance between an ignition and the nearest road or town, or the density measures. The determination of these variables is done in a geographic information system using the coordinates of each ignition point. Some spatial analyses have considered weather variables based on geographic interpolations of average annual or monthly values (e.g.: Dlamini 2010; Pew and Larsen 2001; Prasad *et al.* 2008).

Temporal fire occurrence research typically uses variables related to weather and weather indices (Tables 2 and 3). These may be spatially interpolated to give a better approximation of actual values at ignition points (e.g.: Wotton and Martell 2005). Some timing variables have been considered, such as Julian date, day of the season, day of the week and public holidays (e.g.: Albertson *et al.* 2009; Martell *et al.* 1989; Preisler *et al.* 2004; Reineking *et al.* 2010). Temporally based papers have included spatial variables by dividing the landscape into units and giving an average value for each spatial variable in each unit.

Fire occurrence research has always been applied to defined regions associated with management, environmental and political boundaries. This research has been undertaken in a variety of countries, with most papers originating from USA, Canada and Spain (Tables 1-3). Fire occurrence related papers originating from Australia have considered causal factors for lightning ignited fires (Dowdy and Mills 2009; McRae 1992) and the weather conditions on days of high fire activity in the Mallee region of Victoria (Krusel *et al.* 1993). No other papers have been published that investigate the spatial or temporal occurrence of fires in regions of Australia. Australia is likely to have different fire occurrence patterns to other countries because of its unique climate, vegetation and culture. Fire occurrence patterns are also likely to be highly variable across Australia for these reasons.

Some recently published papers have applied temporal fire occurrence models in climate change predictions (Albertson *et al.* 2010; Drever *et al.* 2009; Krawchuk *et al.* 2009; Podur and Wotton 2010; Wotton *et al.* 2003). These papers have generally applied simulated weather from climate change prediction models to regionally based fire occurrence models for the purpose of examining the effects of climate change on fire regimes. Papers considering regions in Canada (Drever *et al.* 2009; Krawchuk *et al.* 2009; Podur and Wotton 2010; Wotton *et al.* 2003) and the UK (Albertson *et al.* 2010) have indicated a general increase in the number of expected fires with varying regional effects. No such research has been undertaken in Australia, other than a recent paper concerned with large fire probability by Bradstock *et al.* (2009) who suggest significant increases in the occurrence of days suitable for large fires in the Sydney region. Developing Australian fire occurrence models will help facilitate better forecasting of the effects of climate change on the Australian fire environment.

Summary and recommendations

Wildfire occurrence research has been undertaken in many parts of the world to enhance knowledge of factors affecting the distribution of wildfire ignitions and develop predictive models. This type of research utilises historical fire data and has been undertaken at regional levels. A variety of analysis and modelling techniques have been applied to fire occurrence data, although logistic regression has been used in much of the spatially based research and for most models predicting the occurrence of one or more fires within defined spatial and temporal limits. Most papers have considered lightning and anthropogenic ignitions separately or have been undertaken in regions where there is one dominant ignition cause. These ignition types have been separated because they sources are driven by different processes and have different spatial and temporal distributions. Some studies have also considered arson and accidental anthropogenic ignition sources separately.

A large number of influential variables have been identified by fire occurrence research. These reflect the variety in climate, landscape and cultures in the regions where they have been undertaken. Generally anthropogenic ignitions have been found to be influenced by human geography variables related to proximity to and density of people and infrastructure, as well as occurrence of weekends and public holidays, and the moisture content of surface fuels. Lightning fire ignitions have been linked with storm activity, precipitation and the moisture content of heavier fuel layers.

Spatially based fire occurrence research has been used identify areas with high ignition risks, based on fire history and geographic associations. This information has been used in broader wildfire risk analyses and in fire management operations where it has aided the targeting of fuel treatments and the allocation of suppression resources. Temporally based studies have developed models predicting the probability of a fire occurrence day and the number of fires that could occur on a given day. These types of models allow fire managers to estimate the suppression load that an agency will face and plan resource availability and locations to address that load, thereby optimising suppression effectiveness.

While, there has been little fire occurrence related research undertaken in Australia, there is much to be gained by such work in the form of practical fire management application. Results from related research undertaken in other parts of the world are not readily transferrable to Australia, as the research is highly regional and Australia has unique fire environments. An Australian fire occurrence study would be able to investigate the utility of Australian fire danger indices, drought measures and fuel moisture models for predicting fire occurrence.

An Australian fire occurrence research project should initially investigate a case study area with desirable Australian attributes (e.g.: Eucalypt dominated vegetation). A suitable region would require comprehensive fire agency records and preferably have uniform vegetation, terrain and human geography. Records available for analysis would need to include a variety of types of data that can be aligned over a common time period and region. Table 4 outlines the variables that should be considered for Australian fire occurrence case studies. Data for the case study region should be used to investigate both spatial and temporal relationships within the case study region. Information on suspected ignition source will be critical to allow lightning and arson and other anthropogenic sources to be considered separately. Areas selected for further Australian case studies will also require high quality data to be available and should be selected from regions with contrasting features to the first, so that a variety of landscapes can be investigated. Data sets for case studies may be useful for other related analyses, such investigating large fire occurrence and initial attack success, if appropriate other data (e.g.: fire area data) is available.

Table 4. Variables to consider for Australian fire occurrence case studies

Variable type	Description	Importance
Fire occurrence	Coordinate location of ignition point, time of detection, suspected cause.	Essential
Standard weather variables	Standard Bureau of Meteorology weather station parameters (temperature, dew point, wind speed & direction, pressure, precipitation etc).	Essential, preferably gridded data to reflect conditions at ignition points in temporal study. Spatial averages desirable for spatial study.
Combined weather variables	Fire danger indices, drought indices and fuel moisture models (calculated from previous)	Essential for temporal study. Spatial averages desirable for spatial study.
Storm/ lightning occurrence	Lightning strike records, rainfall associated with storm events, atmospheric stability.	Highly desirable
Land cover and vegetation	Vegetation type, fire history, fuel hazard classification, curing etc.	Vegetation type essential. Fire history and fuel information highly desirable.
Land tenure and use	Categorised land ownership and/or management, type of agriculture etc.	Essential for spatial study.
Terrain	Elevation, aspect, slope etc.	Highly desirable
Population	Proximity to towns/ suburbs, population density	Essential (to have at least one type) for spatial study.
Infrastructure	Proximity to/ density of roads, tracks, fire trails, rail, industry etc.	Essential for spatial study.
Timing	Julian date, day of week, public/ school holiday.	Essential
Socio-economic	Wealth/ poverty indicators, crime rates etc.	Desirable for spatial study.
Fire area	Area of fire at initial attack and containment.	Useful for future related research (e.g. large fire occurrence, initial attack success).

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