Journal of Environmental Management 235 (2019) 34–41

Contents lists available at ScienceDirect

Journal of Environmental Management

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

Research article

# Developing and testing models of the drivers of anthropogenic and lightning-caused wildfire ignitions in south-eastern Australia

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ARTICLE INFO

*Keywords:*
Wildfire
Ignition
Bushfire
Risk
Modelling

ABSTRACT

Considerable investments are made in managing fire risk to human assets, including a growing use of fire behaviour simulation tools to allocate expenditure. Understanding fire risk requires estimation of the likelihood of ignition, spread of the fire and impact on assets. The ability to estimate and predict risk requires both the development of ignition likelihood models and the evaluation of these models in novel environments. We developed models for natural and anthropogenic ignitions in the south-eastern Australian state of Victoria incorporating variables relating to fire weather, terrain and the built environment. Fire weather conditions had a consistently positive effect on the likelihood of ignition, although they contributed much more to lightning (57%) and power transmission (55%) ignitions than the 7 other modelled causes (8–32%). The built environment played an important role in driving anthropogenic ignitions. Housing density was the most important variable in most models and proximity to roads had a consistently positive effect. In contrast, the best model for lightning ignitions included a positive relationship with primary productivity, as represented by annual rainfall. These patterns are broadly consistent with previous ignition modelling studies. The models developed for Victoria were tested in the neighbouring fire prone states of South Australia and Tasmania. The anthropogenic ignition model performed well in South Australia (AUC = 0.969) and Tasmania (AUC = 0.848), whereas the natural ignition model only performed well in South Australia (AUC = 0.972; Tasmania AUC = 0.612). Model performance may have been impaired by much lower lightning ignition rates in South Australia and Tasmania than in Victoria. This study shows that the spatial likelihood of ignition can be reliably predicted based on readily available meteorological and biophysical data. Furthermore, the strong performance of anthropogenic and natural ignition models in novel environments suggests there are some universal drivers of ignition likelihood across south-eastern Australia.

## 1. Introduction

Wildfire incidence is driven by four key phenomena, or 'switches', all of which need to be on for fire to occur – biomass, fuel moisture, ignitions and weather (Archibald et al., 2009; Bradstock, 2010). Studies that examine the determinants of area burned or burn probabilities rarely distinguish between the individual effects of each of the limiting "switches" (Salvador et al., 2005; Price and Bradstock, 2011; Fontaine et al., 2012). Weather has been found to be the key determinant of the extent of area burned in both empirical and simulation studies (e.g. Cary et al., 2009; Penman et al., 2013b; Bradstock et al., 2014). However, there is evidence that ignitions and fuels are greater drivers than climate of spatial patterns of burn probabilities (e.g. Parisien et al., 2010; Pausas and Paula, 2012; Yocom Kent et al., 2017). It is therefore important to understand spatial and temporal variations in ignitions in order to predict risk to environmental and human assets and apply targeted management strategies (Finney, 2005; Vasilakos et al., 2007; Bar Massada et al., 2013).

Simulation modelling is a cost- and time-effective way of studying the relationships between fire regimes, climate vegetation and fire management (Keane et al., 2004). Researchers and management agencies use these tools to quantify the potential impacts of fire management strategies, such as prescribed burning, on risk reduction (Keane et al., 2013; Cary et al., 2016). Ignition likelihood is generally

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https://doi.org/10.1016/j.jenvman.2019.01.055
Received 6 June 2018; Received in revised form 7 January 2019; Accepted 17 January 2019
Available online 19 January 2019
0301-4797/ 

poorly considered in these tools. Some simulation studies have applied random or evenly distributed ignition patterns (Finney, 2007; Ager et al., 2014a; Penman et al., 2014) while others have used historic ignition density in the study area as a surrogate for ignition likelihood (e.g. Bradstock et al., 2012; King et al., 2013; Salis et al., 2015; Kalabokidis et al., 2016). Few studies have used empirically derived ignition likelihood for use in the simulation models (e.g. Bentley and Penman, 2017; Alcasena et al., 2017).

Spatial variation in ignition likelihoods has been reported (e.g. Parisien and Moritz, 2009; Reineking et al., 2010; Mundo et al., 2013), although some patterns are consistent. For example, anthropogenic fires are generally concentrated near areas of high population and human infrastructure such as roads (Syphard et al., 2008; Collins et al., 2015; Costafreda-Aumedes et al., 2017), while lightning-caused fires are more prevalent along ridges and in older fuels (Bar Massada et al., 2013; Penman et al., 2013a). Local variation in the natural and built environment is therefore expected to affect the spatial distribution of ignitions within and between landscapes. Despite similarities in the broad drivers of spatiotemporal ignition patterns, there has been little attempt to assess the ability of empirical ignition models to predict ignition likelihood outside the landscapes used for model development. Understanding the drivers of specific ignition types is also important because area burnt and fire impacts vary by ignition cause (Syphard and Keeley, 2015; Collins et al., 2016).

Here we examine the influence of environmental and anthropogenic factors on the likelihood of ignition in the State of Victoria, south-eastern Australia (Fig. 1). Historically fires in this State have resulted in the largest loss of human life and assets for Australia (Blanchi et al., 2010, 2014; Haynes et al., 2010). The 2009 Black Saturday bushfires resulted in the death of 173 people, the loss of more than 2000 houses and an estimated economic cost of $AUS4.2 billion (Leonard et al., 2009; Blanchi et al., 2010; Whittaker et al., 2013). Victoria has a diverse range of ecosystems including alpine shrublands and tall wet forests in the north-east of the state, dry forests in the coastal zone through to woodlands and the semi-arid communities in the west of the state (Cheal, 2010). These vegetation communities reflect the variation in topography, climate and weather patterns. Most of the human population and infrastructure is located in the urban centres of Melbourne, Geelong, Ballarat and Bendigo. Given the wide variation in both the natural and human environment of Victoria, the likelihood of ignition is also expected to vary widely. We test the Victorian models on ignition patterns in the adjacent States of South Australia and Tasmania to determine the generality of relationships between environmental and human factors, and ignition likelihood. Tasmania and South Australia are also fire prone, with their own history of large fires (e.g. the Ash Wednesday fires of 1983 and the 2016 Tasmanian fires). However, these states have substantial differences in climate, terrain, ecosystems and population density and are hence good candidates for testing whether ignition models developed for Victoria can be applied to a broader geographic range.

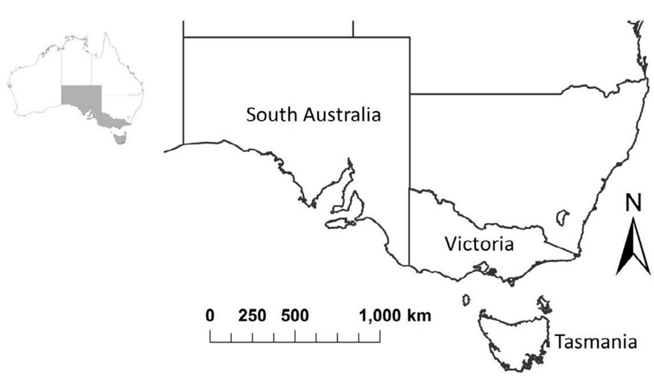


**Fig. 1.** Study area location. Wildfire ignition models were developed in Victoria and tested in South Australia and Tasmania.

By undertaking both model development and validation we specifically tested the following hypotheses:

- fire weather influences the likelihood of ignition for all ignition types;
- the likelihood of ignitions caused by humans increases near the built environment;
- the likelihood of lightning-caused ignitions will increase in areas of native vegetation with time since fire (i.e. in older fuels), on ridges and at higher elevation, and
- ignition models developed in one landscape have skill in other landscapes.

## 2. Methods

### 2.1. Study areas

Ignition models were developed for the State of Victoria in south-eastern Australia (Fig. 1). Victoria is the second most populous State in Australia, with a population of 5.9 million, most of whom live in Melbourne (4.5 million; www.abs.gov.au, accessed 5 April 2018). There has been extensive clearing of native vegetation for agriculture and human settlement with about 46% of the original extent of native vegetation remaining. More than 80% of this is protected in National Parks and Nature Reserves. There is considerable variation in the climate across Victoria. In the north-west average annual rainfall is approximately 300 mm, while in the south-east average annual rainfall ranges from 1000 to 1500 mm. Similarly, average daily maximum summer temperatures range from 33 °C in the north-west to 24 °C in the south-east (www.bom.gov.au, accessed 5 April 2018).

Ignition models were evaluated in the States of South Australia and Tasmania, which are to the north-west and south of Victoria respectively (Fig. 1). South Australia has a population of 1.7 million, with circa 80% located in the capital city of Adelaide. In the arid north, which covers almost 90% of the State, native vegetation is largely intact but has been degraded from pastoral use (Environment Protection Authority South Australia, 2013). The climate is highly variable, with rainfall below 300 mm across much of the State and ranging from 400 to 1000 mm for most coastal areas. Average daily summer maximum temperatures range from over 36 °C in the north to 24 °C on some parts of the coast (www.bom.gov.au, accessed 5 April 2018). The mountainous island State of Tasmania has a population of 500,000, with circa 40% residing in its capital, Hobart. Around a quarter of the State's native vegetation has been cleared (Resource Planning and Development Commission, 2003). The climate is relatively wet, with most of the east receiving between 600 and 1000 mm annual rainfall, and western regions receiving 1500–3000 mm. Average daily maximum summer temperatures range from 15 to 18 °C throughout much of the State and coastal areas to below 9 °C in some mountainous regions (www.bom.gov.au, accessed 5 April 2018). A wide range of fire regime niches are represented in South Australia, Tasmania and Victoria (Murphy et al., 2013).

### 2.2. Data compilation

Ignition point locations and dates for the years 1997–2009 (n = 48,355) were supplied by the Victorian Country Fire Authority (CFA) and the former Department of Sustainability and Environment (currently the Department of Environment, Land, Water and Planning; DELWP). Ignition causes were classified by these agencies into nine types; arson, arson caused by minors, lightning strike, accidental, accidental relating to buildings/infrastructure, accidental relating to machinery/vehicles, escaped fire from prescribed burning ignition, power transmission lines, and unknown/uncertain (Table 1, Fig. 2). For the statistical analysis, a set of 260,000 random points were generated

**Table 1**
The number and percentage of occurrences of the nine ignition types in Victoria (1997–2009), South Australia (2013–2015) and Tasmania (1998–2016).

| Ignition Type | % of all ignitions | | |
|---|---|---|---|
| | Victoria | South Australia | Tasmania |
| Accidental | 7.0 | 0.9 | 8.3 |
| Arson | 26.4 | 3.3 | 37.5 |
| Arson (child) | 1.0 | | 1.5 |
| Building | 0.4 | 1.3 | 0.3 |
| Escaped fire | 19.8 | 9.6 | 12.6 |
| Lightning | 11.0 | 2.9 | 1.4 |
| Machinery | 8.0 | 3.5 | 4.9 |
| Power Transmission | 0.1 | 1.0 | |
| Unknown | 26.4 | 77.4 | 33.5 |
| Total | 100 | 100 | 100 |

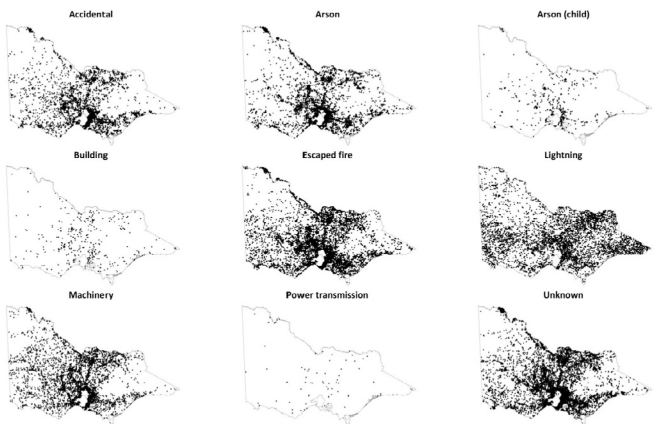


**Fig. 2.** Spatial patterns for the nine wildfire ignition types in Victoria.

across the State from a uniform distribution. A random date was assigned to each of the points using only those dates that fell within the expected fire season.

For each ignition and random point we examined a series of variables relating to both natural and built environments (summarised in Table 2). Elevation was extracted from a 9 s (~25 m) resolution digital elevation model (DEM). Slope, Topographic Position Index (TPI) and aspect relative to north-west were calculated from the same DEM. Positive TPI values represent ridges, negative TPI values represent valleys and values near zero represent plains and areas of constant slope. Time since fire (TSF) is a measure of potential fuel accumulation and was calculated from fire history maps developed by state agencies since 1970 (www.data.vic.gov.au, accessed 5 April 2018). TSF was set to 40 years for ignitions in areas without previously mapped fires. Housing density was defined as the number of properties within a 2 km radius using address locations sourced from the Victorian Government. Distance to the nearest mapped road and watercourse was calculated from data supplied by the Victorian Government. Mean annual rainfall (1960–1990) was sourced from Worldclim v1.4, a 0.01° resolution gridded climate dataset (Hijmans et al., 2005). Ecological vegetation communities sourced from Victorian Government mapping were classified into ten major vegetation types: cleared, grassland, woodland, mallee, heathland, wetland, shrubland, dry forest, wet forest and rainforest. Geology was not included in the analysis, as soils were not expected to affect ignition likelihood independently of vegetation and topographic factors. All variables except rainfall were sampled to a 25 m grid.

The Forest Fire Danger Index (FFDI) is a measure of fire weather conditions and the associated difficulty in fire suppression based on a combination of temperature, humidity, wind speed and recent drying (Luke and McArthur, 1978; Noble et al., 1980). Estimation of FFDI was done for the ignition date or the date assigned to random sampling locations. Estimates were based on data from the nearest Bureau of Meteorology weather station containing a complete set of measurements. All weather data were drawn from stations no more than 60 km from the ignition and random points, giving a reasonable representation of the FFDI value at the target point. FFDI, distance to water, distance to road and housing density were log transformed for modelling purposes due to skewness.

### 2.3. Ignition model development

To model fire ignitions we used Maxent (Phillips et al., 2006), a species distribution modelling approach based on the maximum entropy algorithm. Maxent iteratively contrasts environmental and anthropogenic predictor values at occurrence locations (i.e. ignition points) with those of a large background sample of random locations taken across the study area (Elith et al., 2011). This method performs well compared to other modelling techniques and has been previously used in ignition modelling (Bar Massada et al., 2013; Renard et al., 2012). Observed ignition points were treated as "presence" data and random points as "pseudo-absence" data. Analyses were conducted separately for each ignition type across Victoria to determine whether the drivers varied between them. Models were prepared using a two-step approach. In the first step, all variables were included in the analysis. In the second step, the model was re-run using only variables that contributed > 5% of the variation in the first model, to increase parsimony. We only reported the results of the second step of the process for clarity. All analyses were conducted in the R-statistical software (R-Development Core Team, 2011) in conjunction with the dismo package (Hijmans et al., 2014). The area under the curve (AUC) of the receiver operating characteristic (ROC) plot was used to measure each model's prediction accuracy (Hanley and McNeil, 1982). For each analysis, 15% of the historical and random datasets was withheld for model performance testing. We reported the contribution of each variable to the model, which sums to 100% and is not the same as proportion of variance explained.

### 2.4. Ignition model evaluation

A similar approach to the initial model development was undertaken for model evaluation in South Australia and Tasmania. Known ignition points in South Australia for the period 2013 to 2015 (n = 5506) were compiled from datasets held by the South Australian Department of Environment, Water and Natural Resources. Known ignition points in Tasmania for the period 1998 to 2016 (n = 33,420) were compiled from datasets held by the Tasmania Fire Service. Values for each of the final model variables from Section 2.3 (annual rainfall, FFDI, housing density, distance to road) were calculated for each point. Using the models for anthropogenic and natural ignitions developed in Section 2.3, we then calculated ignition probability for both actual ignition points as well as an equivalent number of random points across the landscape. The AUC of the ROC plot was used to assess the prediction accuracy of the Victorian models for South Australia and Tasmania. We also compared the distribution of these two modelled probabilities using a one sided *t*-test ($H_0$: modelled ignition probability for actual points is less than or equal to that of random points) and confidence intervals (Walshe et al., 2007).

## 3. Results

Regional variation was observed in the spatial distribution of ignitions, both between and within ignition types (Fig. 2). The spatial patterns of arson and accidental anthropogenic ignitions were similar, with ignition points clustered around Melbourne and surrounding areas, in the State's centre. In contrast, lightning ignitions were more uniformly distributed about the state, although there were still areas of

**Table 2**
Environmental and anthropogenic variables used as predictors for model development in Victoria. Table shows information, source and predicted effect on ignition likelihood for each variable. TSF (time since fire), EVC (Ecological Vegetation Community), DEM (digital elevation model), TPI (topographic position index, combines slope position and landform category), FFDI (Forest Fire Danger Index), DSE (Department of Sustainability and Environment, Victorian Government), CFA (Country Fire Authority, Victoria), BOM (Bureau of Meteorology).

| Variable | Details | Source | Predicted effect on ignition likelihood |
|---|---|---|---|
| TSF (yrs) | Derived from fire history maps | DSE, CFA | Positive. Increase in fuel load with time since fire may result in increased ignition likelihood. |
| Vegetation type | Derived from EVC mapping | DSE | Mixed. Vegetation types vary in their flammability varies which may influence ignition likelihood. |
| Distance to mapped watercourse (km) | Calculated from watercourse locations | DSE | Positive. Fuel moisture near drainage lines is expected to be higher; decreasing fuel moisture with distance from watercourse may increase ignition likelihood. |
| Elevation (m) | Calculated from 25 m DEM | Geoscience Australia | Positive. Lightning strikes are more frequent at higher elevation, which may increase lightning ignition likelihood. |
| TPI | Calculated from 25 m DEM | Geoscience Australia | Mixed. Lightning is more likely on ridges which may increase ignition likelihood. Fuel moisture is higher in gullies, which may decrease ignition likelihood with respect to slopes and ridges. |
| Slope (degrees) | Calculated from 25 m DEM | Geoscience Australia | Mixed. Fires are more likely to spread on intermediate slopes than on flat or very steep slopes, which may influence the likelihood of an ignition resulting in a sustained fire. |
| Aspect (degrees) | Calculated from 25 m DEM, relative to north-west | Geoscience Australia | Mixed. Fuel moisture is expected to be lower on sites exposed to the north-west, which may increase ignition likelihood. |
| FFDI | Calculated from BOM data from nearest rainfall station | BOM | Positive. Increasing FFDI is associated with lower fuel moisture and fire weather conditions conducive to fire spread, which may increase the likelihood of an ignition and the likelihood of an ignition resulting in a sustained fire. |
| Rainfall (mm) | Mean annual rainfall (1960–1990) | Worldclim v1.4 | Mixed. Increasing rainfall is associated with increased fuel mass, which may increase the likelihood of an ignition resulting in a sustained fire. |
| Housing density (houses/km$^2$) | Calculated from vector files of address locations | DSE | Positive. Increased housing density is associated with increased population, which may increase the likelihood of arson ignition. |
| Distance to mapped road (km) | Calculated from vector files of roads | DSE | Negative. Lower distance to road may increase the likelihood of arson ignitions near roads. |

**Table 3**
Mean and range in values of predictor variables used in model development in Victoria. Values of predictor variables used in the final model are shown for South Australia and Tasmania. Vegetation type is categorical and is excluded (see Table 4). TPI (Topographic Position Index), FFDI (Forest Fire Danger Index), TSF (time since fire).

| Predictor | Mean (Range) | | |
|---|---|---|---|
| | Victoria | South Australia | Tasmania |
| TPI | 0.6 (−150.8–207.6) | | |
| Slope (°) | 4.0 (0–44.7) | | |
| Aspect (°) | 84.9 (0–180) | | |
| Elevation (m) | 199.3 (-14–1670.6) | | |
| Rainfall (mm) | 751 (262–1970) | 543 (251–1111) | 849 (483–2959) |
| Log (FFDI) | 2.5 (0.0–6.1) | 2.4 (0.1–4.8) | 1.7 (0.1–4.5) |
| TSF (years) | 38.4 (1–40) | | |
| Log (Distance to water) (km) | 5.0 (0–10.8) | | |
| Log (Distance to road) (km) | 2.7 (0–9.3) | 2.8 (0–7.3) | 2.8 (0–7.6) |
| Log (Housing density) (km$^{-2}$) | 3.3 (0–7.9) | 3.1 (0–7.3) | 4.3 (0–8.5) |

high and low concentrations. There was considerable variation about state-wide mean values of the predictor variables, especially slope, elevation, rainfall, FFDI and housing density (Table 3). There were also contrasting patterns of ignition prevalence across vegetation types (Table 4).

### 3.1. Ignition model development

Of the 11 variables examined, only FFDI, housing density, distance to mapped roads, rainfall and vegetation type contributed at least 5% of the variation in the first model and were therefore included in the final model. There was a positive relationship between FFDI and ignition likelihood for every ignition type (Fig. 3). FFDI contributed the most to models for lightning (56.5%), power transmission lines (55.4%) and machinery ignitions (31.6%), and the least to the arson ignition models (7.5%; Table 5 and Fig. 3).

Anthropogenic ignitions were influenced strongly by the built environment. There was a negative relationship between distance to mapped roads and ignition likelihood for all ignition types (a higher likelihood of ignition closer to roads). Distance to mapped roads contributed 20% to the lightning model, but had a relatively small effect

**Table 4**
Distribution of the nine ignition types in Victoria across the major vegetation types.

| Code | Vegetation Type (proportional cover) | Ignition Type | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Accidental | Arson | Arson (child) | Building | Escaped fire | Lightning | Machinery | Power transmission | Unknown |
| 0 | Cleared (0.54) | 2267 | 9930 | 400 | 138 | 6221 | 2273 | 2769 | 28 | 9418 |
| 1 | Grassland (0.29) | 639 | 1665 | 53 | 24 | 2064 | 1913 | 659 | 26 | 2022 |
| 2 | Woodland (0.03) | 191 | 380 | 20 | 8 | 379 | 192 | 160 | 1 | 473 |
| 3 | Mallee (0.02) | 4 | 7 | 1 | 0 | 8 | 32 | 2 | 0 | 10 |
| 4 | Heathland (0.01) | 17 | 53 | 0 | 0 | 45 | 81 | 9 | 0 | 39 |
| 5 | Wetland (0.0) | 3 | 16 | 1 | 0 | 12 | 6 | 7 | 0 | 27 |
| 6 | Shrubland (0.01) | 5 | 19 | 0 | 2 | 23 | 48 | 10 | 0 | 25 |
| 7 | Dry Forest (0.06) | 165 | 481 | 10 | 16 | 646 | 581 | 190 | 4 | 572 |
| 8 | Wet Forest (0.02) | 18 | 45 | 0 | 2 | 123 | 172 | 28 | 0 | 69 |
| 9 | Rainforest (0.0) | 0 | 0 | 0 | 0 | 2 | 3 | 0 | 0 | 0 |

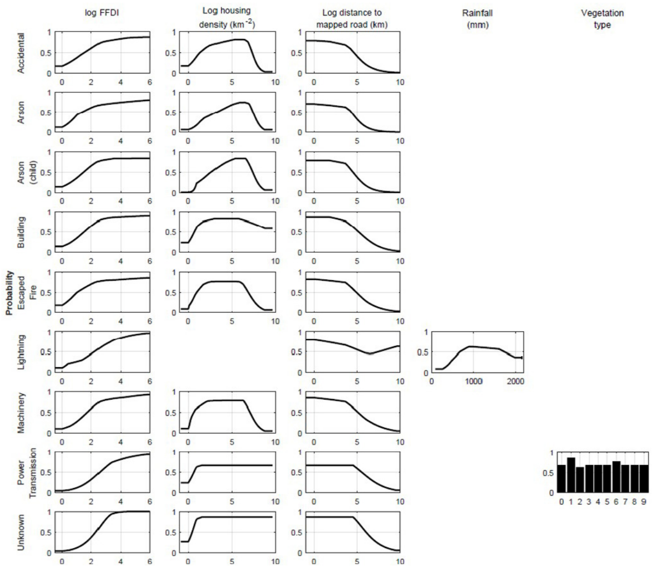


**Fig. 3.** Maxent response curves for the nine ignition types in Victoria. Models were initially run with 11 variables (see Table 2), and then re-run using only variables that contributed > 5% of the variation. FFDI (Forest Fire Danger Index). Vegetation codes are shown in Table 4. See Table 5 for summarised Maxent results.

(i.e. a 17% decline in the likelihood of lightning ignitions, compared to > 70% for each anthropogenic ignition type; Fig. 3 and Table 5). Housing density influenced the likelihood of ignition for all ignition types except lightning, and contributed the most to models for arson (69.6%) and child arson (68.7%; Table 5). The likelihood of ignition increased steadily with increasing housing density and then declined steeply at very high housing densities for all ignition types except power transmissions, which remained stable. Because model predictions of individual anthropogenic causes were highly correlated, they were reclassified for the purposes of evaluation into a single anthropogenic category (the maximum likelihood from all human causes, including unknown ignitions).

Rainfall was included in the model for lightning ignitions, as a positive influence on ignition likelihood up to about 940 mm, and moderately negative influence thereafter (Fig. 3). Power transmission ignitions were influenced by vegetation type, whereby ignitions were more likely in grasslands than any other vegetation type (Fig. 3). There was strong discrimination on held out data in each analysis, with < 0.05 difference in AUC values between test and training datasets (Table 5). Four of nine test AUC values indicated model performance was strong (AUC > 0.9), with three of the remaining five values at the upper end of moderate (AUC > 0.88).

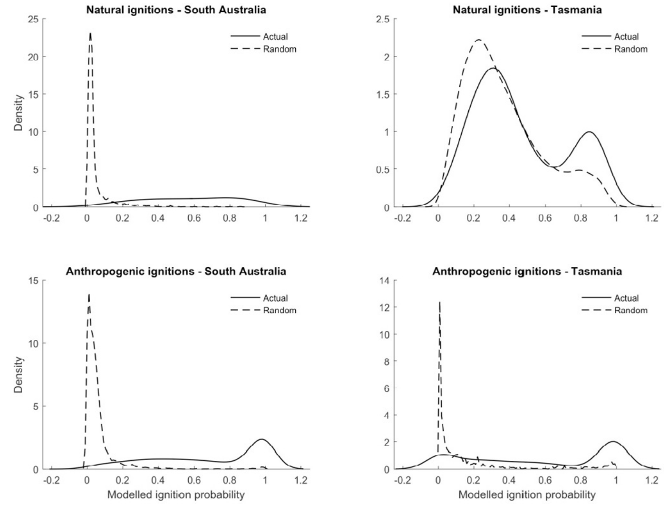


**Fig. 4.** Modelled probability of natural and anthropogenic ignitions in South Australia and Tasmania for actual ignition points and random points.

### *3.2. Ignition model evaluation*

The vast majority of ignitions were anthropogenic in both South Australia (97%) and Tasmania (99%; Table 1). There were 157 lightning ignitions recorded in South Australia and 472 in Tasmania. As with Victoria, there was large variation about mean values of predictor variables in South Australia and Tasmania (Table 3). Overall South Australia is considerably drier than Victoria while Tasmania is considerably wetter. Tasmania has lower overall FFDI values and greater housing density than both Victoria and South Australia. There was a clear distinction between modelled probabilities at actual and random points for anthropogenic ignitions in both States, but only in South Australia for natural ignitions (Fig. 4). Values at random points were strongly skewed towards low probability, whereas values at actual ignition points were skewed towards high probability, suggesting model skill. In contrast, the modelled probabilities at actual and random points overlapped considerably for natural ignitions in Tasmania (Fig. 4). Both sets of points had probabilities skewed towards zero, although there was a clear secondary peak at high probability for actual points that was not present at random points, which may indicate model skill. The AUC values indicated model performance was strong for both ignition types in South Australia, but only for anthropogenic ignitions in Tasmania (Table 6). Mean modelled ignition probability was significantly greater ($p < 0.05$) at actual points than random points for both ignition types and both States (Table 6). However, the difference between the two means was much smaller for natural ignitions in Tasmania (0.10) than the other three models (0.47–0.61), consistent with AUC values and graphical interpretations.

**Table 5**
Summarised Maxent results for the nine ignition types in Victoria. Area under the curve (AUC) shows the fit of the model for training and test data. % contribution to model adds to 100 and is not the same as proportion of variance explained.

| Ignition type | AUC values | | % contribution to model | | | | |
|---|---|---|---|---|---|---|---|
| | AUC (training) | AUC (test) | FFDI | Housing density | Distance to mapped road | Rainfall | Vegetation type |
| Accidental | 0.913 | 0.919 | 18.1 | 44.9 | 37 | | |
| Arson | 0.937 | 0.938 | 7.5 | 69.6 | 22.9 | | |
| Arson (child) | 0.965 | 0.967 | 12.9 | 68.7 | 18.4 | | |
| Building | 0.909 | 0.887 | 28.6 | 36.3 | 35.1 | | |
| Escaped fire | 0.890 | 0.897 | 14.8 | 46.6 | 38.7 | | |
| Lightning | 0.797 | 0.793 | 56.5 | | 20 | 23.5 | |
| Machinery | 0.894 | 0.889 | 31.6 | 33.1 | 35.3 | | |
| Power transmission | 0.899 | 0.846 | 55.4 | 21.6 | 13.8 | | 9.3 |
| Unknown | 0.910 | 0.911 | 13.3 | 46.3 | 40.4 | | |

**Table 6**
Model evaluation results in South Australia and Tasmania. CI = 95% confidence interval for mean modelled ignition probability at actual and random ignition points using a one sample *t*-test, p = p value for one sided *t*-test for equality of modelled mean ignition probability.

| Ignition type | Region | AUC | CI(Actual) | CI(Random) | p |
|---|---|---|---|---|---|
| Natural | SA | 0.972 | 0.510–0.526 | 0.049–0.054 | < 0.0001 |
| Natural | Tas | 0.612 | 0.442–0.486 | 0.362–0.369 | < 0.0001 |
| Anthropogenic | SA | 0.969 | 0.668–0.685 | 0.060–0.066 | < 0.0001 |
| Anthropogenic | Tas | 0.848 | 0.560–0.569 | 0.086–0.091 | < 0.0001 |

## 4. Discussion and conclusions

### 4.1. Ignition model development

The relationships we found for natural and anthropogenic ignitions largely support the hypotheses based on previous research (e.g. Penman et al., 2013a; Ager et al., 2014b; Costafreda-Aumedes et al., 2017 and references therein). Fire weather, as represented by FFDI, was a positive influence on ignition likelihood irrespective of the cause of ignition. However, FFDI contributed much more to the models for lightning-caused ignitions than to arson and other human-related accidental ignition types. As hypothesised, anthropogenic ignitions (e.g. arson and accidental) were more likely near roads and densely populated regions (e.g. Faivre et al., 2014; Collins et al., 2015). Consistent with Abt et al. (2015), there were strong similarities between different anthropogenic ignition types in the response to key drivers, although we found that ignitions from powerlines and unknown sources did not show the same decrease in likelihood at very high housing densities. Contrary to our hypothesis lightning ignitions were not found to be strongly influenced by TSF, topography or elevation.

#### 4.1.1. Effects of fire weather

The greatest impacts of fire happen under the worst fire weather conditions (Blanchi et al., 2010, 2014). Given that FFDI incorporates temperature, relative humidity, wind and an index of fuel moisture (albeit a relatively weak one, Drought Factor; Resco de Dios et al., 2015), it is not clear whether the influence of fire weather on ignition likelihood is due to drier fuels igniting more easily, or the effects of hot, windy conditions on the rate of fire spread and other aspects of fire behaviour. Ignitions may occur at low FFDI values, but self-extinguish due to unfavourable fire weather conditions before they are detected. Our analysis does not distinguish between these competing mechanisms and FFDI may influence ignitions through some combination of the two. Nevertheless, fires that potentially ignite and self-extinguish under mild weather conditions would not be a serious target for ignition management given their negligible contribution to the overall extent of burnt area in the landscape. Fire weather (FFDI) contributed far more to models for the prediction of lightning (56.5%) and powerline (55.4%) ignitions than to arson (7.5%) and accidental ignitions (18.1%; Table 5). This has important implications for future fire risk (see 4.4 below).

#### 4.1.2. Other variables

Time since fire (TSF) was predicted to be an important driver of lightning ignitions. Given the increased frequency of lightning during the late afternoon (Christian et al., 2003), lightning strikes may not lead to wildfire if the fire cannot sustain itself under the milder weather conditions present overnight. However, logs and other heavy fuels can sustain burning under such conditions and are more abundant in long unburnt areas (Lindenmayer et al., 1999; Hély et al., 2000), suggesting an increased probability of a fire sustaining itself with increasing TSF. However, TSF was not a factor in final models for any ignition type (Table 5). This could be because TSF is less suitable as a proxy for fuel amount in areas with highly diverse vegetation such as Victoria. Further, while accumulation of surface fuels may follow the Olson curve (Olson, 1963), other fuels important for fire behaviour may not, e.g. grasses and shrubs (Clarke and Knox, 2002; McCaw et al., 2002; Duff et al., 2012). It was not possible to estimate the impacts of fuel moisture or grass curing on ignition likelihood, the implicit inclusion of Drought Factor in FFDI notwithstanding (Section 4.1).

Elevation and topography were also hypothesised to be key drivers of lightning ignitions, in particular via higher likelihood on ridges and with increased elevation (Penman et al., 2013a). However, as with TSF, elevation and topography did not contribute substantially to final models of lightning ignition (Table 5). It may be that TSF, elevation or topography effects were only apparent at a regional level within Victoria. Regional variation in topography and population density could have driven similar variation in lightning activity across the State. Alpine areas may be a suitable place to detect topographic position effects on lightning ignitions, given their rugged terrain and abundance of high ridge tops close to deep valleys. Elevation effects on lightning ignitions may be related to urban development patterns, in that there may be less development in higher and more rugged sites, resulting in more native vegetation cover with its higher capacity to sustain fire (Penman et al., 2013a).

Overall our results were comparable to a recent study of lightning ignitions in Victoria, which detected a larger range of influences on ignitions (n = 10; Read et al., 2018). FFDI, rainfall and distance to road were the most important variables in our study, while maximum temperature, maximum FFDI, rainfall and 3pm relative humidity were the four most important predictors in Read et al. (2018). Read et al. (2018) did not consider distance to road or other non-climate predictors, but did include atmospheric instability and upper atmospheric humidity, which are known to influence lightning.

### 4.2. Ignition model evaluation

The ignition models developed for Victoria performed well in the neighbouring states of Tasmania and South Australia, clearly distinguishing areas and times (i.e. daily fire weather conditions) of low and high ignition likelihood. The success of these models in replicating anthropogenic ignition likelihood and, in South Australia, natural ignition likelihood, comes despite significant differences between these states in climate, vegetation and urban settlements. This suggests that, particularly for anthropogenic causes, fire weather conditions, population density and proximity to roads may be universal factors in driving wildfire ignition.

Factors that may limit the applicability of these ignition models include a lack of overlap in the environmental space between case study regions as well as data limitations (Parisien and Moritz, 2009). Poor model performance for natural ignitions in Tasmania may relate to the relatively high rainfall and relatively low FFDI there compared to Victoria, where the lightning ignition model was developed. Further, the recorded frequency of lightning-caused ignitions in both Tasmania (1.4%) and South Australia (2.9%) is well below that of Victoria (11.0%). While this may reflect differences in climate and other underlying drivers of lightning, it is possible that there are some deficiencies in the classification of ignition causes in the underlying datasets for Tasmania and South Australia, which would affect the model performance. Poor model performance in Tasmania may also be due to factors that were not found to be most important in the Victorian model, such as TSF, elevation and topography.

### 4.3. Future implications

Fire weather is an important driver of ignition likelihood, particularly for lightning ignitions and powerlines, which are responsible for the vast majority of area burnt and damage in Victoria and elsewhere (Dowdy and Mills, 2011; Collins et al., 2016). Given the potential increase in the incidence of severe fire weather conditions predicted in this region with climate change (Cai et al., 2009; Hasson et al., 2009; Clarke and Evans, 2018), as well as an increased frequency of lightning strikes (Price and Rind, 1994; Krause et al., 2014), there is a high potential for the rate of powerline and lightning ignitions to increase in the future, along with the corresponding extent of area burnt and house loss. Studies of regional variation in ignition factors could be combined with climate change impacts on regional weather patterns to allow for predictions of ignition likelihood at this scale.

In conclusion, fire weather conditions, housing density and proximity to roads are key drivers of anthropogenic and lightning-caused wildfire ignitions in Victoria, and models incorporating these drivers perform well in the neighbouring fire prone states of South Australia and Tasmania. Building models of the drivers of ignition likelihood from readily available meteorological and biophysical data is an important step towards a more comprehensive bushfire risk assessment, which would deepen our understanding of regional to continental scale controls on fire and fire regimes. Such an assessment could also facilitate mapping of the wildfire likelihood and extent, for both current conditions as well as those projected under climate change (Parisien and Moritz, 2009).

## Acknowledgements

Thank you to Jill Galluci from DELWP, Simeon Telfer from DEWNR and David van Geytenbeek from Tasmania Fire Service for providing data. Funding was provided by the Australian Attorney-General's Department through the National Emergency Management Projects Program. Funding for TP was provided by the NSW Rural Fire Service. An earlier version of this manuscript appeared as an appendix to a funding agency report as a requirement of the funding agency.

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