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NATIONAL FIRE DANGER RATING SYSTEM PROBABALISTIC FRAMEWORK PROJECT

Final report year two

T.D Penman, M. Bedward and R.A Bradstock
Centre for Environmental Risk Management of Bushfires, University of Wollongong

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Cover: A bushfire looms over a town. Photo by CFA Communities and Communication.

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1. Executive summary

The objective of the Probabilistic Framework Project is to develop a new consequence-based fire danger rating system able to integrate a wide range of variables and link their complex interactions to the probability of property loss. The project aims at delivering a spatially-explicit framework capable of generating daily maps representing the distribution of the probability of property loss at 10Km spatial resolution.

The Probabilistic Framework Project has yielded the following achievements during its second year:

a) A new "consequence-based" system (developed in year 1) has been refined and applied in two case study regions (Sydney basin; Victorian Central East Risk Landscape) . This system integrates a large range of environmental variables (e.g., fuel type, topography, house density, weather) and fundamental processes (e.g., fire ignition and propagation) governing fire behaviour to predict the probability of property loss from fire. A Bayesian network (BN) approach was used as the basis for the modelling framework;

b) The BN framework has been successfully integrated with GIS facilities using newly developed specialist software to generate spatially explicit predictions of the probability of a fire spreading to and reaching the urban interface and then burning there at high intensity. Such predicted probabilities provide an index of the probability of property loss. The BN framework has the ability to generate predictions of these probabilities at varying spatial scales. Results for 5 and 10 Km grids at a daily time-step are presented here for the Sydney basin. Results for a 10 km grid only are presented for the Victorian case study;

c) For both case studies there was model predictions and fire history data over a 20 year period (1990 to 2010). Median predicted probabilities of fires reaching the interface and burning there at high intensity correspond with recorded instances of large fires that affected interfaces in this period. Model predictions over-predicted relatively high probability events compared with observed data. This result was consistent with the effects of suppression that were not accounted for in the model. Model predictions based on dates of large or destructive fires (Sydney case study only, 2000 to 2010 data) produced higher probabilities than a randomly based sample, consistent with the effects of more severe weather on days of large and/or destructive fire activity. Effects of differing grid resolution (Sydney only) were small. The model predictions showed greater spatial variation and resolution than modelled estimates of FFDI only. Overall, use of the model indicated that highest risk areas may potentially be identified by accounting not only for fire weather, but also fuels, the distribution of property, plus features inherent in the landscape that affect fire spread.

d) Statistical modelling of human (accidental and arson) and lightning ignitions for the State of Victoria was done to support application of the BN model to the Victorian case study landscape.

Accidental ignitions in the Central East Risk Landscape were predicted by the FFDI, house density and distance to road, whereas arson ignitions were a function of human development – namely distance to road and the density of houses. Lightning ignitions were predicted by FFDI, house density, distance to road an elevation. In all cases, preferred models were complex and non-linear. A broader set of models for the entire state of Victoria, along with a description of the methodology, are presented in the Appendix

e) A simulation study was undertaken using the Phoenix Rapidfire to generate data regarding fire size and travel distance under various fire weather and fuel treatment scenarios for the Victorian case study. . Fire size increased with FFDI and decreased with increased prescribed burning effort. Weather had the strongest effect on fire size with prescribed burning effort having a smaller effect within these bounds. Distance travelled was strongly correlated with fire size. The results were then used to populate the BN model used to generate predictions of likelihood of high intensity fires reaching the interface.

f) The predictions derived from the BN model, and associated fire spread simulations indicate that the probability of fires of reaching the interface and burning there at high intensity are most strongly influenced by weather conditions. In addition the BN predictions indicate that such probabilities are highly sensitive to ignition and fire spread information, as conditioned by the totality of weather, terrain and fuel variations. Predictions of risk as derived through incorporation of these elements in the BN framework will exhibit considerable variation at fine temporal and spatial scales. Such variation is more nuanced that that derived from models of fire weather alone. This indicates that the probabilistic BN framework has the potential to be used to derive more carefully targeted “fine-grained” warnings of potential property loss. The results derived from the BN also indicated that predictions will be sensitive to fire suppression activity. This element of management is poorly dealt with in current fire spread simulation models. Improvement in the capacity to model suppression is therefore an important research priority.

2. Purpose

The purpose of this document is to describe the activities conducted and the results achieved during the second contract (i.e., from February 2013 to June 2014) of the Attorney-General's Department National Fire Danger Rating System – Probabilistic Framework Project.

3. Background: Fire danger rating systems and Bayesian network

Fire danger rating systems have been developed in many fire-prone regions around the world to assist authorities in a variety of fire management activities such as assessing the potential for fires and issuing fire warning (Sharples et al., 2009). Traditionally, these systems combine different environmental variables affecting fire behaviour, such as weather data (e.g., temperature, relative humidity, wind speed and direction), terrain properties (e.g., slope and aspects) and fuel characteristics (e.g., type and load) (Leblon et al., 2001; Burgan et al., 1998; Mathews et al., 2009), into numerical fire danger indices (San-Miguel-Ayanz et al., 2003). Such indices are designed to provide a quantifiable measure of the potential for fires to ignite, spread and be suppressed (Noble et al., 1980). Examples of fire danger indices include the National Fire Danger Rating System in the USA (Deeming et al., 1972), and the Canadian Forest Fire Danger Rating System in Canada (van Wagner and Pickett, 1985).

In Australia, the McArthur's Fire Danger Rating System has been widely used since its formulation in the 1960s to assess the potential for fires to ignite and spread, the difficulty of suppressing fires and their potential impact on the community (i.e., property) in forest (i.e., Forest Fire Danger Index, FFDI) and grassland (Grassland Fire Danger Index, GFDI) fuel types (McArthur, 1967). FFDI and GFDI are divided into six categories (i.e., low, high, very high, severe, extreme and catastrophic) representing increasing levels of fire severity, difficulty of suppression and potential damage to property (McArthur, 1967; Noble et al., 1980; Sharples et al., 2009; Bradstock and Gill, 2001). However, the index calculation is based only on weather parameters (i.e., rainfall, temperature, relative humidity, and wind speed) and does not account for other environmental and human variables (e.g., spatially varying distribution of fuel load, fuel type, terrain characteristics, house density, wildland/urban interface, and road network) which can have a significant influence on fire behaviour and, consequently, on the impact of fire on human communities (McArthur, 1967; Noble et al., 1980; San-Miguel-Ayanz et al., 2003; Maingi and Henry, 2007; Archibald et al., 2009; Sharples et al., 2009; Price and Bradstock, 2010).Therefore, in order to more effectively assess fire danger, it is necessary to develop a robust "consequence-based" modelling framework able to integrate a wider range of variables and link their complex network of interactions to the probability of property loss or damage.

Bayesian Belief Networks or Bayes Nets (BN) are a statistical framework capable of analysing complex environmental relationships (Johnson et al., 2010; Penman et al., 2011). The networks are depicted as directed acyclic graphs with variables and their interactions represented by nodes and directed links (Nyberg et al., 2006). Nodes can represent predictor variables in relationships, management decisions or outcomes. Directed links can be constructed to represent simple or complex influences among nodes. Values for the predictor variables in the relationships are quantified through a series of conditional probability tables (CPTs). These probability tables can be defined using a wide range of data, ranging from expert knowledge to predictions from complex process models. Outcomes of a BN are represented as probabilities, which can then form the basis for risk-analysis and management (Marcot et al., 2001).

As a consequence, a BN modelling approach is highly suited to the task of representing complex interactions among multiple processes and it has been selected to develop a new “consequence-based” fire danger rating system capable to predict the probability of property loss due to fire. Indeed in year 1 of the project, we demonstrated the potential for the approach.

4. Project objectives

In the first 12 months of the project we constructed an initial BN framework for the implementation of a “consequence-based” fire danger rating system. The main characteristics of the modelling framework were:

a) Ability to integrate a wide range of variables (e.g., weather, terrain, fuel, house density, proximity to urban interface) and represent fundamental processes (i.e., complex interactions among variables) that govern the behaviour of fire and their impact on human communities;

b) Capacity to adequately predict the probability of property loss due to fire at 10km spatial resolution (i.e., 10Km grid cell) and daily time-step; and

c) Ability for integration with Geographic Information System (GIS) data and production of spatially-explicit surfaces (i.e., 10km grid cell) representing the probability of property loss.

The resulting model was parameterised for the Sydney Basin and tested coarsely against real data. These results were reported in the previous annual report for the project.

The objective for the second stage of the project was to develop and test a daily fire danger rating Bayesian Network model for two case study areas - Sydney Basin and the central east risk landscape in Victoria. Models were tested against a 20 year time series from 1991 to 2010. As the Sydney Basin model was developed in year 1 of the project, no additional model parameterisation was necessary. However, for the Victorian case study no data were available and data needed to be analysed to allow for the model parameterisation. Two main studies were required – an ignition probability model and a fire behaviour simulation.

In this report, we present the results of the ignition probability model and the fire behaviour simulation study (section 5). We then describe the resulting Bayesian Network Model, the methods for integration with the GIS data (section 6) and finally the results of the 20 year study for each of the case study regions (section 7).

5. Data analysis for the Victorian model

5.1. Ignition analysis

i. Overview

An analysis of ignition probabilities was required for the Central East Risk Landscape of Victoria. However given the data provided it was prudent to undertake a broader study on ignition probability in Victoria. A draft manuscript outlining this work is presented in Appendix A. This section outlines the results relevant to the Central East analysis.

ii. Methods

Fire history data (ignition point locations and mapped fire boundaries) were compiled from comprehensive datasets held by the Country Fire Authority (CFA) and the Department of Sustainability and Environment (DSE), spanning 12 years from 1997 to 2009. Ignition causes were categorised into 9 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. For the study area, there were 1463 accidental ignitions, 7847 arson, 263 arson by a child, 4469 escaped fires, 1232 by lightning, 1155 started by machinery and 6738 from an unknown cause. The study focused on accidental, arson and lightning ignitions. All ignition types are considered in the full study in Appendix A.

A range of environmental and anthropogenic-related factors that were hypothesised as potential predictor variables of ignitions were included in the analysis (Table 1). Positive topographic position index (TPI) values represent locations that are higher than the average of their surroundings (i.e. ridges), negative values represent locations that are lower than their surroundings (i.e. valleys), and values near zero represent either flat areas or areas of constant slope (Weiss 2001). TPI, slope and aspect relative to north-west were calculated across the study area based on a 9-s (25m resolution) digital elevation model. Time since fire (TSF, an indicator of potential fuel accumulation) was calculated using fire history mapping that has been undertaken by state government authorities since 1970. For ignition point locations where no previous fires had been mapped, TSF was set as 40 years as fire mapping before this time is unreliable. Tenure density was measured by calculating the number of properties within a 2-km radius using address locations provided by the Victorian Government. Ecological vegetation communities (EVCs) were categorised into 9 broad vegetation types; grassland, woodland, mallee, heathland, wetland, shrubland, dry forest, wet forest, rainforest. Geology was excluded from the analysis, as there was no expectation that soils would influence ignitions, independently of vegetation and topographic effects.

Table 1 Details of the environmental and anthropogenic predictor variables used in model development, including the predicted effect of each variable on ignition probabilities. TSF (time since fire), DEM (digital elevation model, 25m resolution), 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
TSF (yrs)	Derived from fire history mapping	DSE, CFA
Vegetation Type	Derived from Ecological Vegetation Community mapping	DSE
Distance to mapped watercourse (kms)	Calculated from vector files of watercourse locations	DSE
Elevation (m)	Calculated from DEM	Geoscience Australia
Topographic Position Index	Calculated from DEM	Geoscience Australia
Slope (degrees)	Calculated from DEM	Geoscience Australia
Aspect (degrees)	Calculated from DEM, relative to north-west	Geoscience Australia
Log(FFDI)	Calculated from BOM data from nearest rainfall station	BOM
Rainfall (mm)	Mean annual rainfall	BOM
Tenure density (no. houses/2kms)	Calculated from vector files of address locations	DSE
Distance to mapped road (kms)	Calculated from vector files of roads	DSE

The forest fire danger index (FFDI) is a measure of fire weather and the associated probability of the destruction of property based on a combination of temperature, humidity, rainfall, average wind speed and longer term drying (Noble *et al.* 1980; Bradstock *et al.* 2009). FFDI was calculated for the day of the ignition or the date assigned to the random sampling locations (see below) from the nearest Bureau of Meteorology weather station that recorded all the required measurements. All weather stations were within 60 km of the ignition or random point location, which is likely to sufficiently represent the FFDI value at the target point. Given that FFDI is on an exponential scale, we took the natural log of FFDI for the analysis.

Data were analysed using the maximum entropy algorithm (hereafter Maxent) that has been used to model fire ignitions (Parisien and Moritz 2009; Renard *et al.* 2013). Maxent is a robust method for presence only data that performs well in comparison to other modelling techniques (Phillips *et al.* 2006; Elith *et al.* 2011; Bar Massada *et al.* 2013; Renard *et al.* 2013). 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).

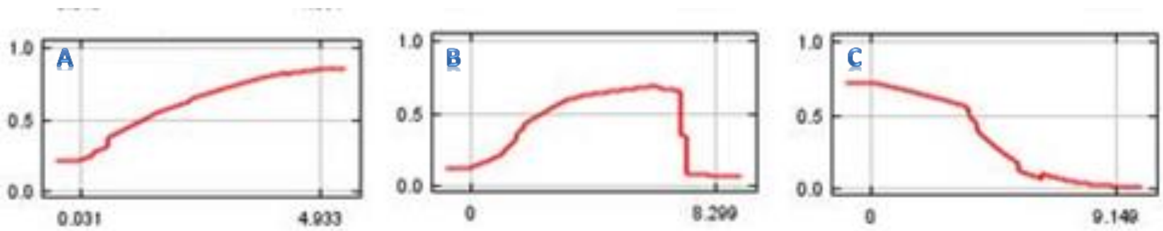
Separate analyses were undertaken for each ignition type. In each analysis, predictor values for each ignition point and random sampling point (i.e. background data) were obtained using the stack and extract functions of the raster and dismo packages in R v 3.0.0 (R Development Core Team 2011) and combined to create the dataset for the analysis. We used the Maxent function in the dismo package R which uses the Java MaxEnt species distribution model software (http://www.cs.princeton.edu/~schapire/maxent/). From the results for each model, a subset of variables were selected that contributed >5% explanation of the variance before repeating the Maxent analysis, in order to increase parsimony in the model. The results reported refer to the Maxent results for each sub-model. The response curves from the model output show the marginal effect of changing one variable only, whereas the model may take advantage of sets of variables changing together.

In each analysis, 15% of the dataset was withheld and used for testing model performance. The area under the curve (AUC) of the receiver operating characteristic (ROC) plot was used to assess prediction accuracy of each model (Hanley and McNeil 1982). AUC values range from 0.5 to 1, where 0.5 is equivalent to a completely random prediction and 1 implies perfect prediction. Model performance is considered poor for AUC values between 0.5 and 0.7; moderate for AUC values between 0.7 and 0.9 and strong for AUC values larger than 0.9 (McCune and Grace 2002). The difference between the AUC values of the training and test datasets provides a measure of how well the model (based on the training dataset) predicts ignition locations for data not used in model development (i.e. the test dataset).

iii. Results

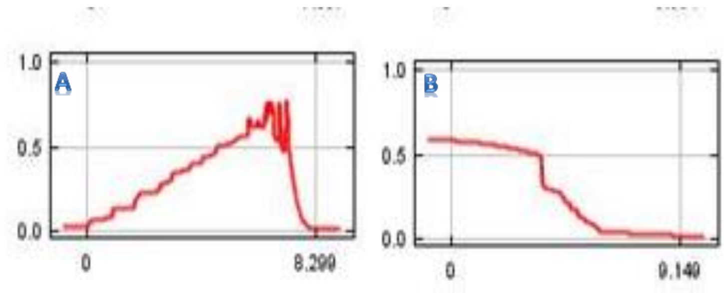
Accidental ignitions in the Central East Risk Landscape were predicted by the FFDI, house density and distance to road (Figure 1). As the FFDI increased the probability of ignition increased exponentially. The probability of an accidental ignition increased with housing density however this rapidly decreases above a threshold value of approximately 1.5-2 houses per hectare. Probability of an accidental ignition decreases with distance from a road with the majority of accidental ignitions occurring within 150 metres of a mapped road.

Figure 1: Probability of an accidental ignition as a function of a) log of the forest fire danger index; b) log number of houses in a 2km radius; c) log distance to the nearest road



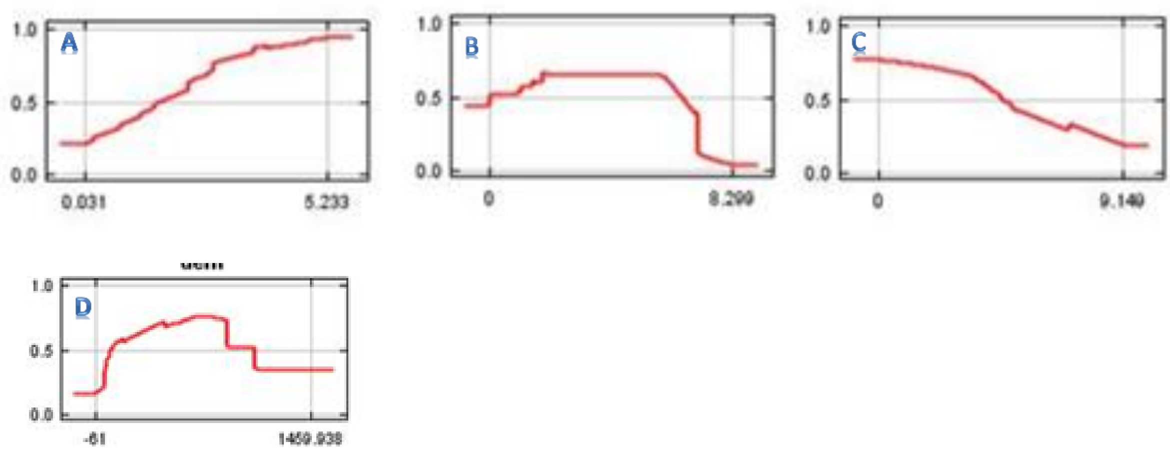
Arson ignitions in the Central East risk landscape were a function of human development – namely distance to road and the density of houses (Figure 2). The probability of an arson ignition increases with housing density however this rapidly decreases above a threshold value of approximately 1.5 houses per hectare. Probability of an arson ignition decreases with distance from a road with the majority of arson ignitions occurring within 150 metres of a mapped road.

Figure 2: Probability of an arson ignition as a function of a) log number of houses in a 2km radius; b) log distance to the nearest road



Lightning ignitions in the Central East Risk Landscape were predicted by the FFDI, house density, distance to road an elevation (Figure 3). As the FFDI increased the probability of ignition increased exponentially. The probability of a lightning ignition increased with housing density however this rapidly decreases above a threshold value of approximately 1.5-2 houses per hectare. Probability of a lightning ignition decreases with distance from a road. Lightning ignitions were more commonly reported at elevations from seas level up to approximately 1000 m a.s.l. These effects partially reflect the co-location of houses and developments with certain topographic features such as ridges, as well as the fact that more ignitions are likely to have been attributed to lightning in areas where houses are sparse.

Figure 3: Probability of a lightning ignition as a function of a) log of the forest fire danger index; b) log number of houses in a 2km radius; c) log distance to the nearest road and d) elevation above sea level



5.2. Fire simulation modelling

i. Methods

A simulation study was undertaken using the Phoenix Rapidfire model (Tolhurst *et al.*, 2008) to generate data regarding fire size and behaviour under various fire weather and fuel treatment scenarios. Phoenix simulates the two dimensional growth of fires in landscapes, including point-scale estimates of rate of spread and fire intensity. Surface fire behaviour within Phoenix is based on a generalisation of the CSIRO southern grassland fire spread model (Cheney and Sullivan, 1997;

Cheney *et al.*, 1998) and a modified version of the McArthur Mk5 forest fire behaviour model (McArthur, 1967; Noble *et al.*, 1980). Phoenix uses a range of additional models (for more detail see Tolhurst *et al.* (2008)), including fuel accumulation models to account for varying fuel loads within increasing time since fire, wind modification based on topographic variation and vegetation type based on the Wind Ninja program (http://www.firemodels.org/index.php/windninja-introduction - Accessed November 2011) and fire spotting (via ember propagation, spread and spot-fire ignition (Saeedian *et al.*, 2010). A 30m resolution digital elevation model was used to estimate the influence of topography on fire behaviour, though simulated fire behaviour parameters such as rate of spread, intensity and ember density were estimated for 180m grid cells (Tolhurst *et al.* (2008).

A series of fire history scenarios were constructed to simulate prescribed fire treatment levels over a 30 year period. Each of the three study areas were divided into realistic treatment blocks typically bounded by roads or drainage lines. For each of the study areas, five replicate histories of five levels of prescribed burning (PB) effort (0, 1, 2, 5, and 10% per annum) were generated for a thirty year period. Blocks were randomly sampled for treatment until the treatment level was within 0.05% of the target burn level. Bradstock et al. (2012) found random versus strategically targeted treatments had little effect on resultant wildfire size, intensity and impact on the urban interface. We modelled wildfires on the basis of temporal patterns of weather associated with recorded wildfires for the region. This was done using a ten year moving window. Annual area burnt by wildfire was calculated over a ten year window to reflect temporal patterns of wildfires in the region. Wildfires were randomly selected from the fire history database until the threshold value was crossed, with the threshold being the average area burnt by wildfires in the previous 10 years adjusted for the reduction as a result of prescribed fire. Prescribed fire and wildfire histories were combined to develop 20 (four prescribed burning levels x five replicates) fire history layers for inclusion in the Phoenix model.

The maximum daily value of the McArthur Forest Fire Danger Index (FFDI, Noble et al. 1980) was estimated for a period of 40 years at various Australian Bureau of Meteorology weather stations within the study area. Temperature, relative humidity, wind speed, wind direction, precipitation, cloud cover and curing, beginning at midnight on each day were used to estimate hourly changes to FFDI and maximum FFDI for the day. Curing was included, even though the bulk of vegetation represented in the study was forest, because patches of grass are occasionally encountered by spreading fires. From this time series, daily maximum FFDI was classified into six categories – Low 0-12, High 12-25, Very High 25-50, Severe 50-75, Extreme 75-100 and Catastrophic. Five replicate days were drawn at random from each category for use in simulations within each of the six categories. We only considered data from those days on which fires are known to have occurred and from this data we only considered either the first day or the maximum FFDI day for a fire. The first day was included as this represents conditions which fires could ignite and spread. Maximum FFDI days represent the worst conditions for a fire and are likely to represent the greatest growth of the fire (Bradstock *et al.*, 2009). Fires were not simulated on successive days as the permutations became prohibitive and most area burned in fires occurs on one day (Cunningham, 1984; Bradstock *et al.*, 2009).There were no consistent data relating to curing or cloud cover, so for all FFDI classes we assumed maximum curing (i.e. a worst case scenario) and 0% cloud cover.

A total of 2 000 ignitions were generated in the study area and randomly assigned to one of the 30 weather streams. Each ignition was then run for the 25 fire history scenarios. This resulted in a total of 500 000 simulated fires

Fires were started at 1000 hours to allow the model to calculate meaningful fuel moisture values and then allowed to run up until 2330, unless they self-extinguished.

ii. Results

A total of 500 000 fires were simulated in the study. Fire sizes ranged from less than one hectare up to 297585 hectares. Fire size increased with FFDI ($p<0.001$) and decreased with increased prescribed burning effort ($p<0.001$). Weather had the strongest effect on fire size (Figure 4) with prescribed burning effort having a smaller effect within these bounds (Figure 5 - Figure 10). Distance travelled was strongly correlated with fire size and for this reason we only present the fire size data here.

Figure 4: Fire size values under a PB effort of 2% per annum with increasing FFDI. Values presented are means with the error bars representing 95% confidence intervals.

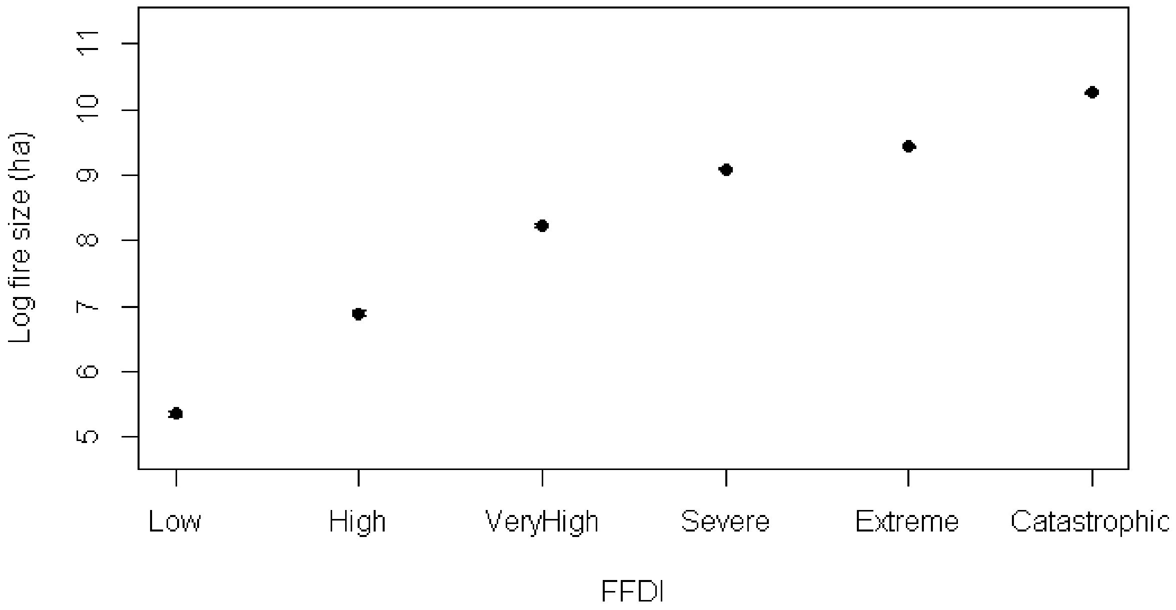


Figure 5: Fire size values under low FFDI (0-12.5) for increasing PB effort. Values presented are means with the error bars representing 95% confidence intervals.

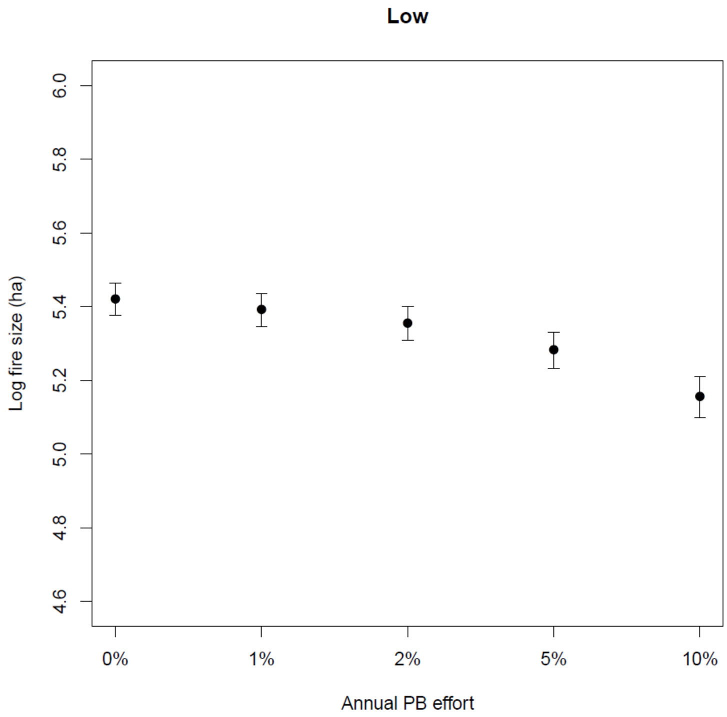


Figure 6: Fire size values under high FFDI (12.5-25) for increasing PB effort. Values presented are means with the error bars representing 95% confidence intervals.

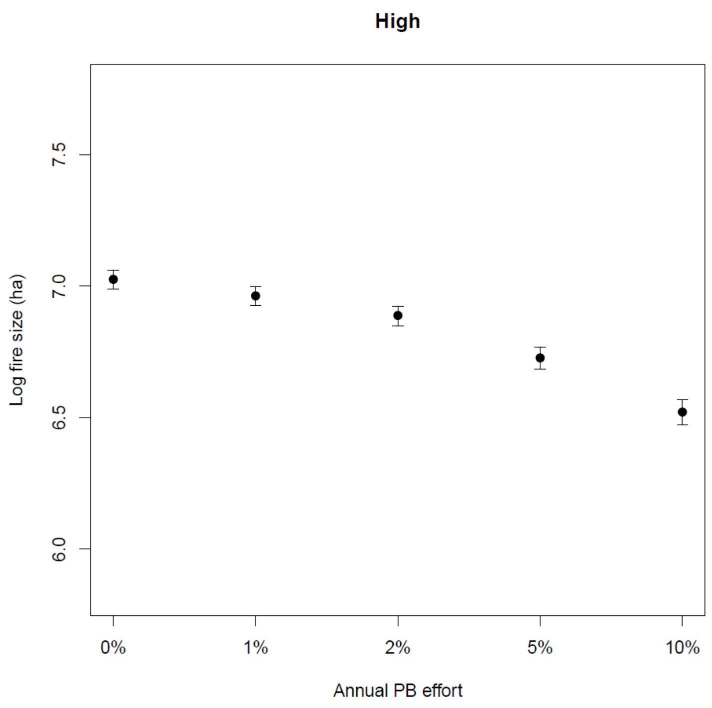


Figure 7: Fire size values under very high FFDI (25-50) for increasing PB effort. Values presented are means with the error bars representing 95% confidence intervals.

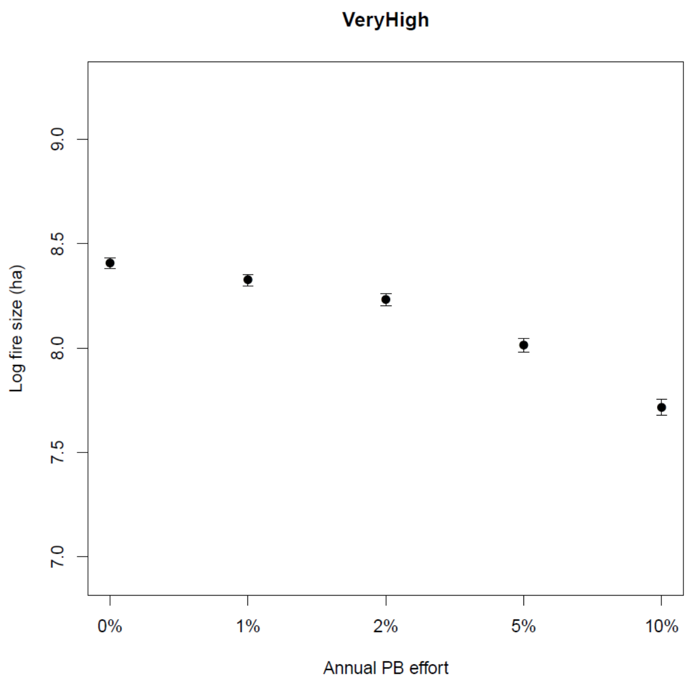


Figure 8: Fire size values under severe FFDI (50-75) for increasing PB effort. Values presented are means with the error bars representing 95% confidence intervals.

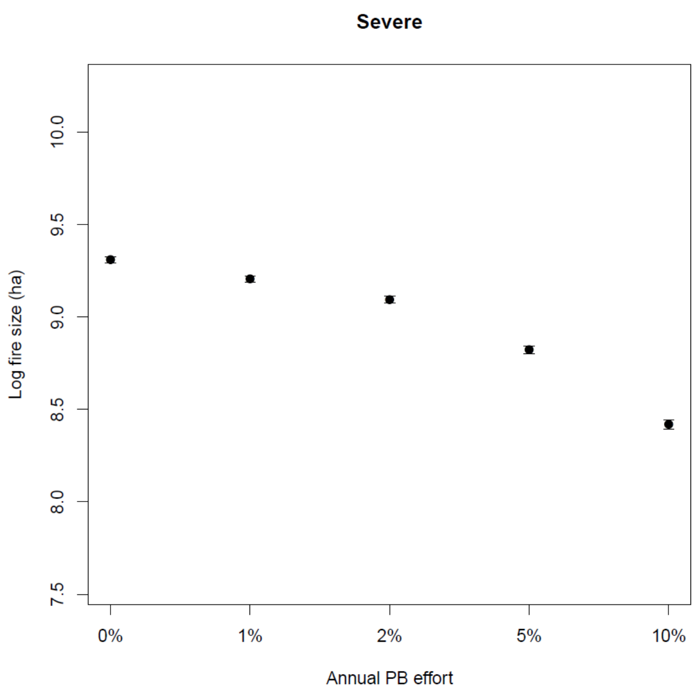


Figure 9: Fire size values under extreme FFDI (75-100) for increasing PB effort. Values presented are means with the error bars representing 95% confidence intervals.

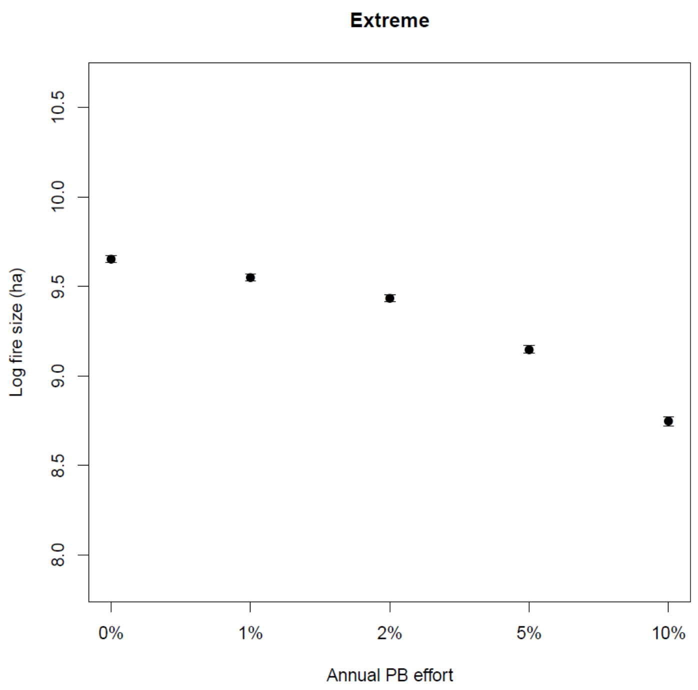
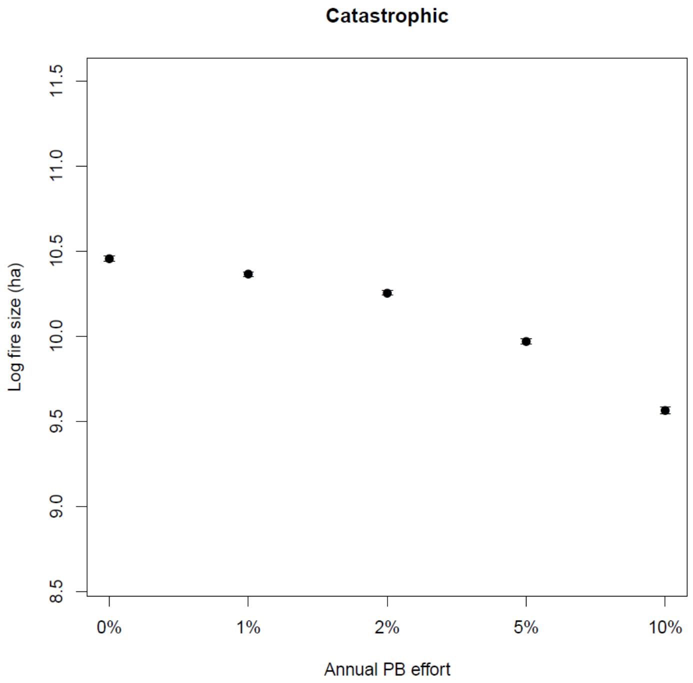


Figure 10: Fire size values under catastrophic FFDI (>100) for increasing PB effort. Values presented are means with the error bars representing 95% confidence intervals.

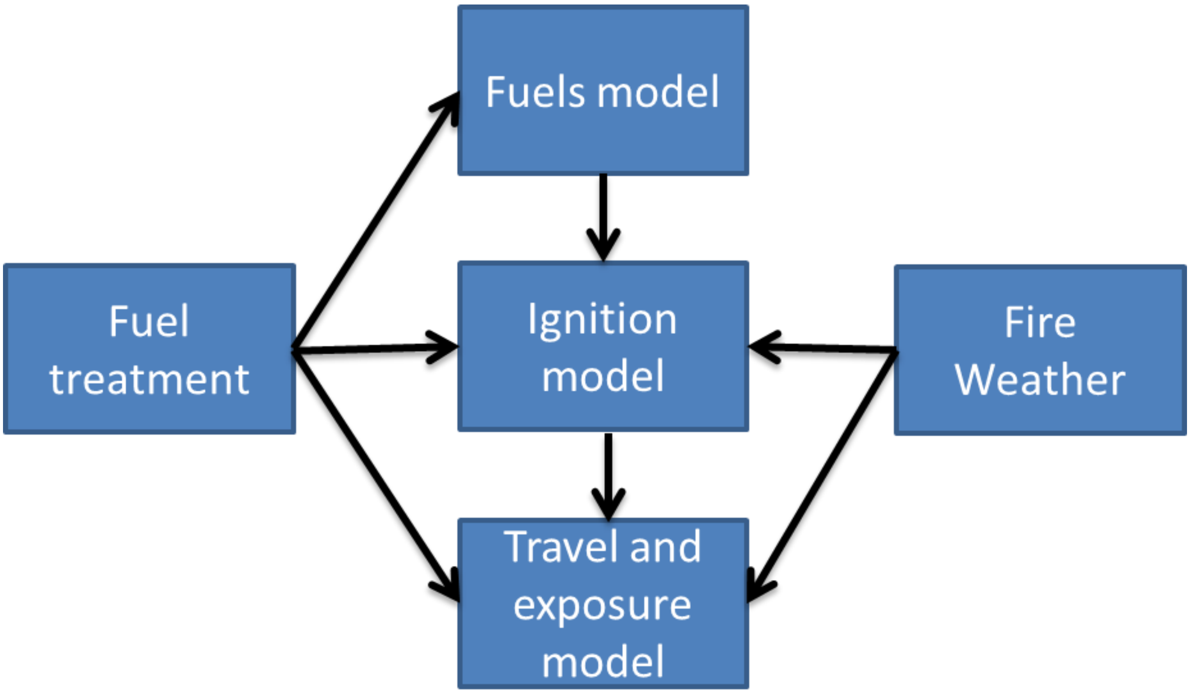


6. Bayesian Network Model

In this section we briefly describe the model and describe variations on the initial model.

A conceptual model of the network is presented below in Figure 11. In the model, fuels in the landscape are controlled by fuel treatments. Ignition probabilities are a function of fuels, fuel treatment and fire weather. If an ignition occurs, the distance the fire travels is a function of fuel treatment and weather. The probability an interface is exposed is then a function of the distance from the ignition to the interface and the fire weather. The Bayesian Network Model was described in detail in the report for year 1. This section of the report is included as Appendix B for reference.

Figure 11: A conceptual model of the Bayesian Network model



In year 2 the model was moved from the Genie software package to Hugin. The reason for this was that GeNie is a freeware package and therefore there are no guarantees for ongoing support or availability of this package. This was considered to be a significant risk if the project were to expand.

No changes to the Sydney model have been made since the report at the end of year 1.

Only minor variations were required to parameterise the Victorian model. Firstly, we included an additional prescribed burning category of 2% per annum to allow for greater accuracy in the prediction of distance travelled by a fire. Secondly, the predictors for the ignition probabilities as described above varied from the Sydney model and the model was adjusted to reflect this. For example, the influence of fuel age on ignition was removed as none of the ignition models for the Central East Risk Landscape were related to time since fire. Models for all ignition types were simplified and no additional variables were added.

Significant improvements were required for the integration of the Bayesian Network with the spatial datasets. This was necessary for the validation as we tested the model against 20 years of daily data. The new system was developed not only for validation but also with a view of streamlining the operationalization proposed for year 3 of the project. The system consists of three interacting components: a controller implemented in the R statistical computing environment (R Development Core Team 2011), the Bayesian Network model implemented in Hugin and accessed via the Hugin Java API, and a model driver implemented in the Scala programming language (Odersky et al., 2010) which links the controller to the model.

The controller contains a description of each of the input nodes of the Bayesian Network, including links to the spatial data sources (rasters, shapefiles, data tables) from which values for each node will be drawn and specific functions to sample those sources when required. For time-invariant nodes (e.g. topographic variables) the controller only needs to sample data sources once and cache the resulting data, while for other nodes (e.g. weather variables) it samples specific data layers for each year or day of the time series. The controller also contains a depiction of the study area represented as a vector grid of square cells for which model predictions will be generated. For each day of the modelling time sequence, the controller updates the data for all input nodes across all grid cells, passes the resulting data set to the model driver for processing, receives model predictions from the driver and outputs these as raster layers.

The model driver is responsible for taking data from the controller and, for each grid cell in the study area, loading values into the conditional probability tables of the Bayesian Network model and then running the model to generate a prediction. The predictions for all grid cells are then passed back to the controller. The principal reasons for working with a model driver, rather than the controller interacting with the Hugin API directly, were speed of processing and flexibility. Generating predictions from a complex Bayesian network is a computationally intensive procedure which must be carried out for a large number of grid cells for each day of a 20 year period. The driver makes this possible by running multiple copies of the Bayesian Network concurrently on multi-processor hardware, optimally distributing the grid cells across these copies, and compiling the resulting predictions into a single output dataset. The driver also allows data and results to be exchanged with the controller in more flexible and reliable formats, rather than having to work with the limited formats supported by the Hugin software. Finally the driver decouples the Bayesian Network from the controller, allowing for the possibility of creating different versions of the controller (e.g. as an ArcGIS extension or a web-based service).

7. Model testing

Model testing examined the predictive capacity of the models for daily data covering the period from 1 January 1990 through to 31 December 2010.

Data were prepared for each study region. Environmental and fire history data for the Sydney case study were provided by the NSW Rural Fire Service. These data were provided by the Victorian Department of Environment and Primary Industries for the Central East Risk Landscape. Meteorological data for both study sites were purchased from the Australian Bureau of Meteorology under a research users licenses.

A 10km output grid was used for both study regions. All data were summarised to provide distributions within each grid cell as inputs to the Bayesian Network model. In the case of Sydney, we also tested a 5km output grid as a preliminary examination of the sensitivity of the model to cell size.

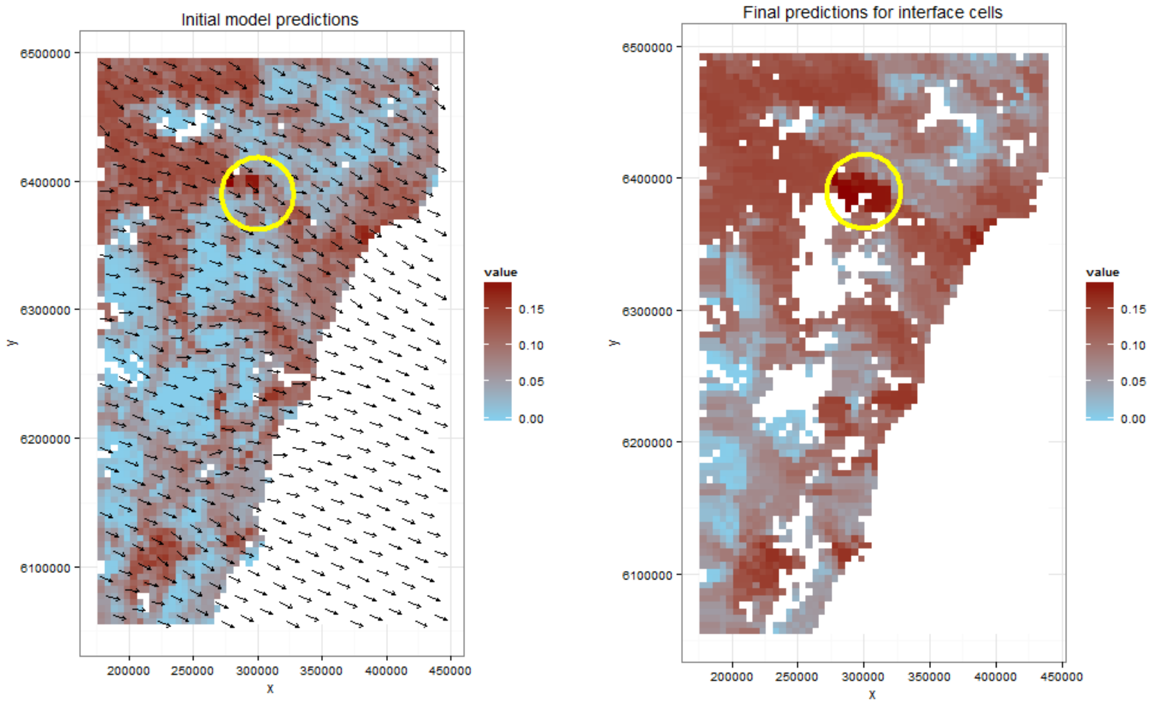
Outputs from the model testing were daily grids predicting the probability of a fire starting in a cell and travelling and burning at high intensity at the interface (i.e. fire intensity > 4,000 kW/m). This does not represent the total probability of exposure of the interface within a cell, as fires that reach the interface in any particular cell may spread from ignitions in neighbouring cells. In order to address this issue, a secondary filter was applied to the data. Once the initial model runs were complete we then used an upwind scanning procedure to identify the maximum risk an interface may be exposed to. The scanning angle was fixed as 45 degrees either side of the primary wind angle. Scanning distance was a function of the predicted maximum FFDI based on the values in Table 2.

Table 2: Scanning distances for the post processing of the data

FFDI	Scanning distance (km)
Low	3.5
High	10
Very high	16
Severe	25
Extreme	43
Catastrophic	50

Figure 12 illustrates the scanning procedure for a single day of the study period (Sydney 5km grid resolution). The yellow circle in the two figures highlights an area where individual cell probabilities were markedly increased by up-wind scanning, with the median probability of a fire spreading to and burning at high intensity at the interface going from 0.06 in the initial model output to 0.13 in the final layer.

Figure 12: an initial model output for single day in the study period, with arrows indicating wind direction, together with the final layer after adjusting cell probabilities of fires reaching and burning at high intensity at the interface, by up-wind scanning. The yellow circle highlights an area of change (see text for details).



Results for the Sydney Model

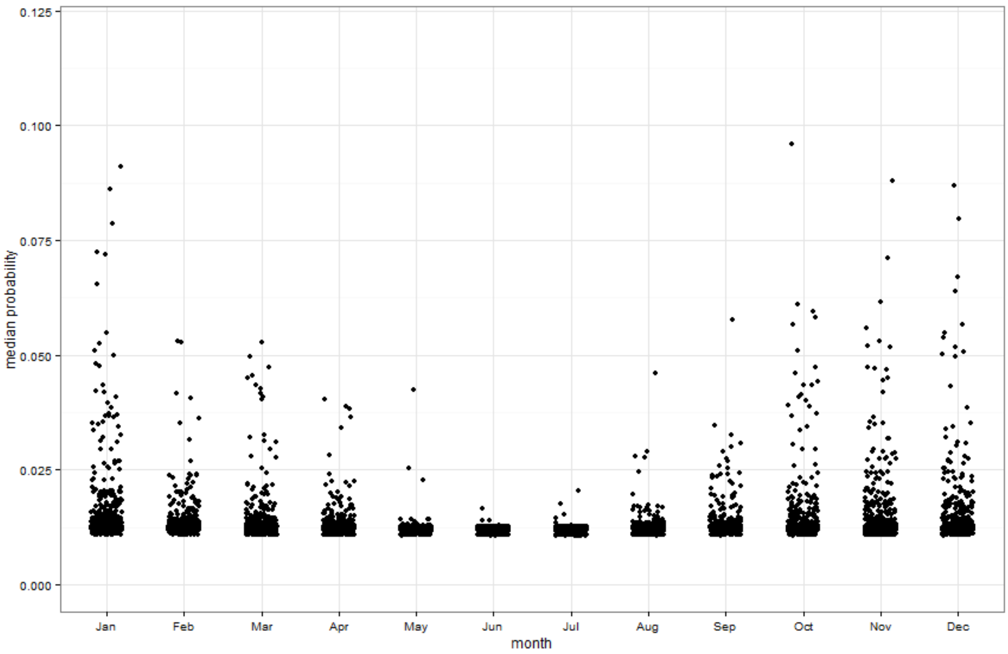
The median predicted probability of a fire spreading to and burning at high intensity at the interface was estimated for all cells containing an interface, for each day of the 20 year study period. The strong seasonal pattern evident in these values reflected the influence of FFDI (Figure 13). Effects of differing grid resolution (i.e. 10 km versus 5 km) were small. There was strong correspondence between model predictions and fire history (Figure 14). The sequence of daily median probability values, as estimated by the model, for the study period is overlaid with vertical lines indicating the actual start dates of large fires (10,000 ha or more) which contacted the interface at some stage (identified by analysis of fire perimeter mapping provided by the NSW Office of Environment and Heritage). There was good correspondence between the estimates of high probability of fires reaching the interface and burning there at high intensity and recorded days with large fires, though the number of estimates of relatively high probability exceeded the recorded occurrences. This may in part reflect effects of successful suppression in the historical data. On some days with potential for large fires, rapid early suppression may have prevented fires from reaching their potential. Effects of differing grid resolution (i.e. 10 km versus 5 km) for these data were also small.

The relationship was examined (Figure 15) between median estimated daily probability values of high intensity fires spreading to the interface for dates during the study period where: actual recorded fires of 1000ha started and reached the interface, and ; house loss or damage was recorded. A background sample of median model estimates for 100 dates, randomly selected outside of the critical event dates was also derived. Estimates were made for the period in which house loss data were available (2000-2010).

The results (Figure 15)show that the predicted median probability of a fire reaching the interface and burning there at high intensity was considerably higher when estimated for the dates of origin of both categories of significant recorded fires, than for the random sample of dates. This reflected the influence of more severe weather on the significant dates compared with that which occurred on dates in the random sample. Median predicted probability of a fire reaching the interface and burning there at high intensity was higher for the sample of dates when house loss occurred than for the sample of dates on which large fires originated. Again, this may reflect the influence of more severe weather on dates associated with house loss. Effects of grid resolution were small, with slightly higher median probabilities predicted for the 5 km grid compared with the 10 km grid (Figure 15).

Figure 13: median daily probabilities of fires reaching and burning at high intensity at the interface for cells, in the Sydney basin, containing an interface, for the 20 year study period (1990 to 2010) aggregated by month

(a) Sydney 10km grid resolution



(b) Sydney 5km grid resolution

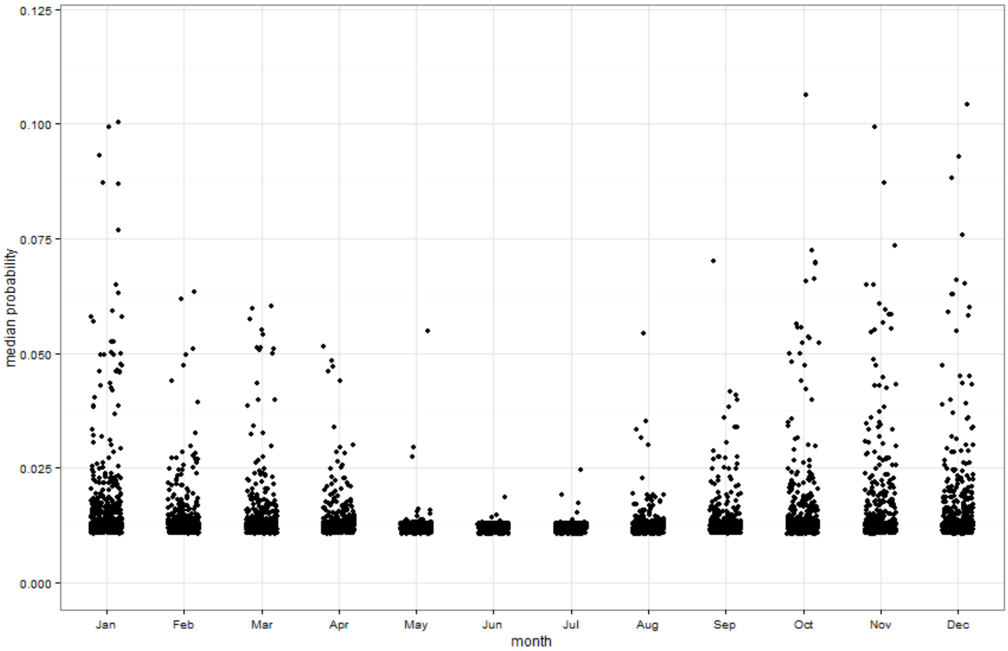
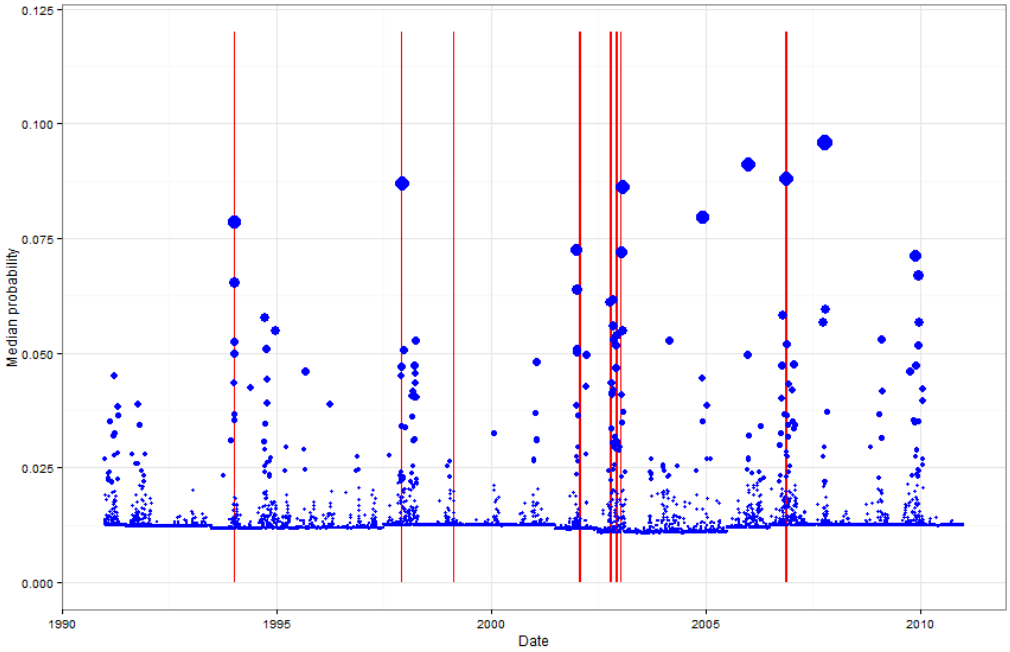


Figure 14: median daily probabilities of fires reaching and burning at high intensity at the interface for cells, in the Sydney basin, containing an interface, for the study period (1990 to 2010) with the dates of significant fires indicated by vertical lines. Dot size is proportional to probability value at aid clarity.

(a) Sydney 10km grid resolution



(b) Sydney 5km grid resolution

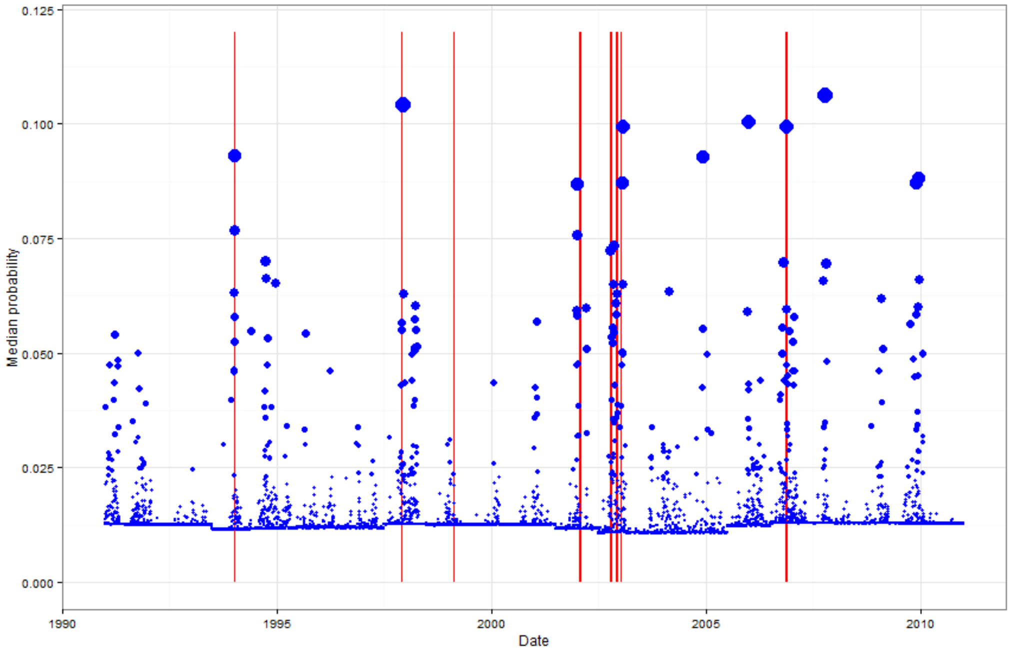
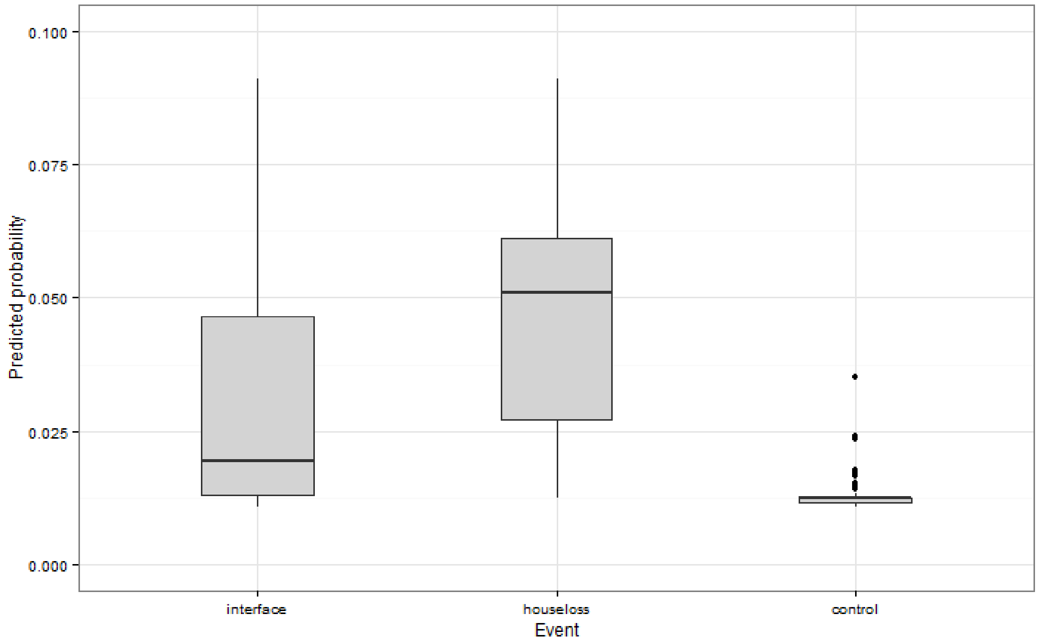
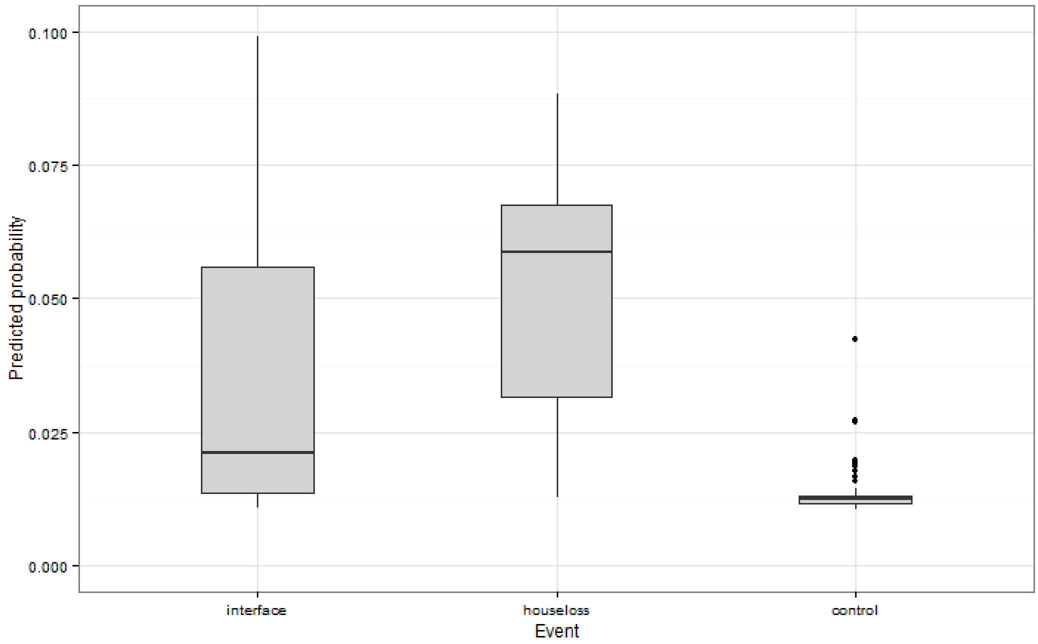


Figure 15: comparison of model predictions of fires reaching and burning at high intensity at the interface for cells, in the Sydney basin, containing an interface (median daily probabilities), for start dates of fires which are known to have progressed to the interface (left hand box); dates for which house loss or damage was recorded (middle box); and 100 randomly selected dates (right hand box). Boxes represent the middle two quartiles of values with the median value indicated by the horizontal line.

(a) Sydney 10km grid resolution



(b) Sydney 5km grid resolution



The model showed greater spatial variation and resolution in the prediction of fires reaching and burning at high intensity at the interface than estimated FFDI. This effect was consistent across the spectrum of FFDI values from Low (Figure 16) to Extreme (Figure 17). These results show that areas of highest risk areas may potentially be identified by accounting not only for fire weather, but also fuels and the distribution of property, along with other features inherent in the landscape that affect fire spread.

Figure 16: comparison of the spatial pattern of FFDI values and model predictions of fires reaching and burning at high intensity at the interface on a Low FFDI day

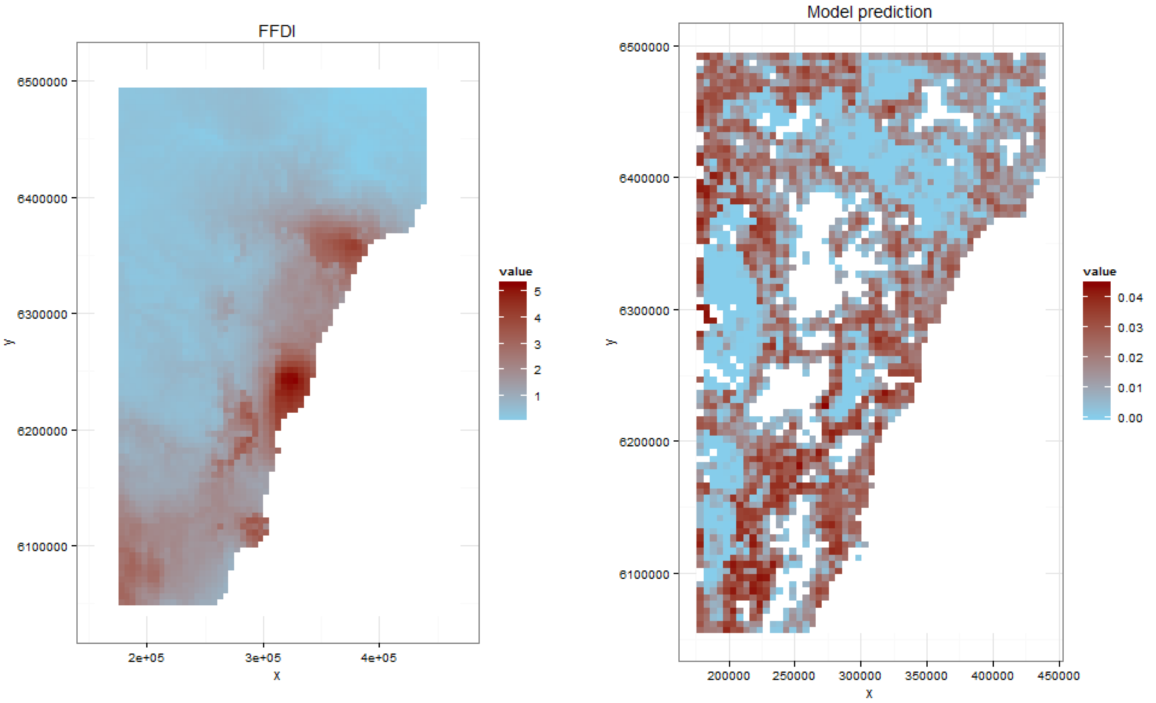
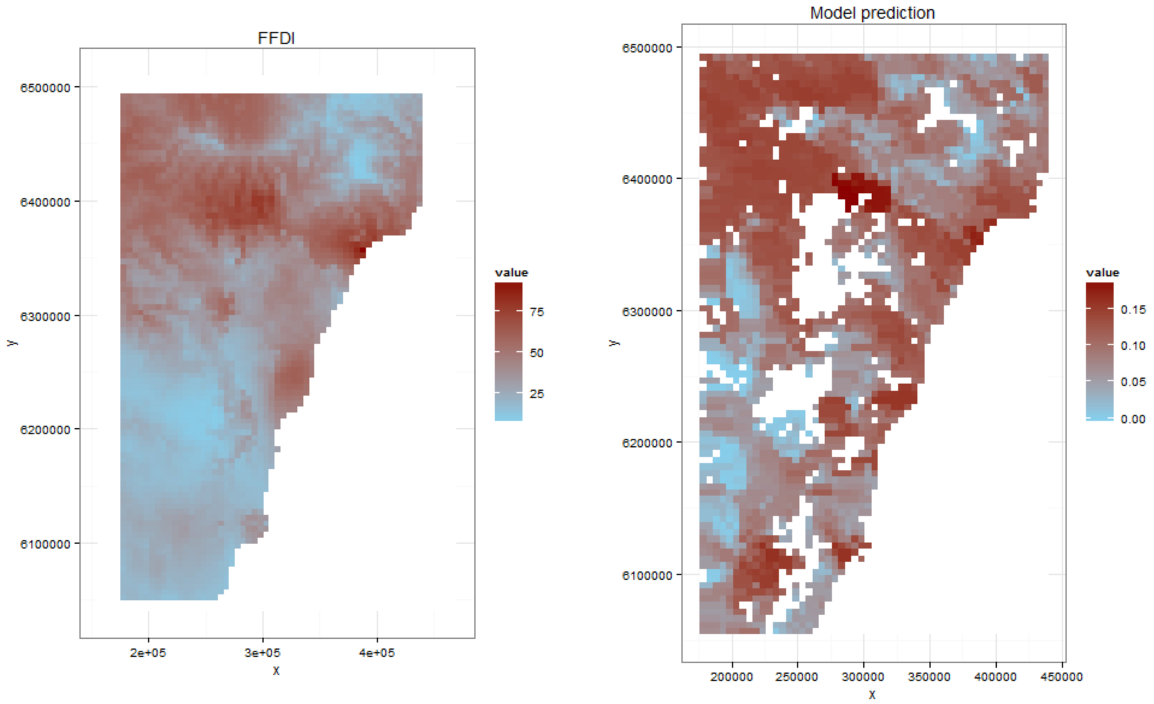


Figure 17: comparison of the spatial pattern of FFDI values and model predictions of fires reaching and burning at high intensity at the interface on an Extreme day



Results for the Victorian Central East Risk Landscape

The median predicted probability over all interface grid cells was calculated for each day of the 20 year study period. Similar to the Sydney study area, the strong seasonal pattern evident in these values reflected the influence of FFDI (Figure 18).

Figure 19 shows the correspondence between model predictions and fire history. The sequence of daily median probability values for the study period is overlaid with vertical lines indicating the start dates of fires (1000 ha or more) which spread to the interface (identified by analysis of fire perimeter mapping provided by Victorian Department of Environment and Primary Industries). As with the Sydney case study, there was good correspondence between modelled estimates and actual occurrences of large fires, and general over-prediction of the instances with relatively high probability of fires spreading to the interface and burning there at high intensity.

Figure 20 shows the distribution of estimated median daily probability values for dates of fires of 1000ha or more that reached the interface compared to a background sample of 100 randomly selected, non-fire dates. As with the Sydney case study, the estimate probability for dates with large fires exceeded that generated for the random sample of dates. This probably also reflects the influence of more severe fire weather associated with the past incidence of large fires in the Victorian case study area.

Figure 18: median daily probabilities of fires reaching and burning at high intensity at the interface for cells containing an interface, Victorian Central East Risk Landscape, for the 20 year study period (1990 to 2010) aggregated by month

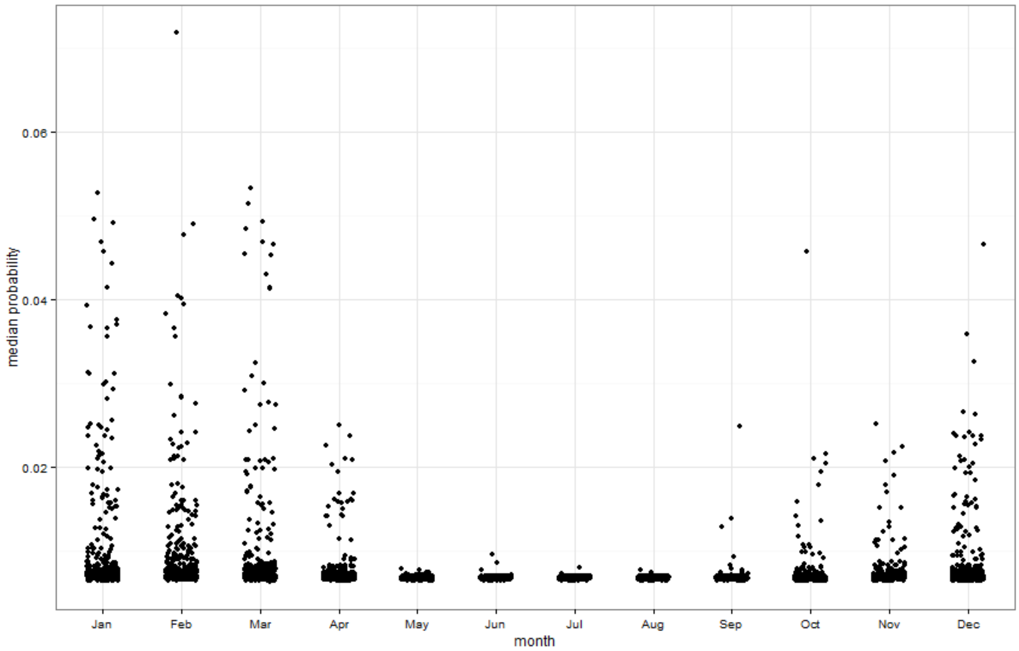


Figure 19: median daily probabilities of fires reaching and burning at high intensity at the interface for cells, in the Victorian Central East Risk Landscape, containing an interface for the study period (1990 to 2010) with the dates of significant fires indicated by vertical lines. Dot size is proportional to probability value at aid clarity.

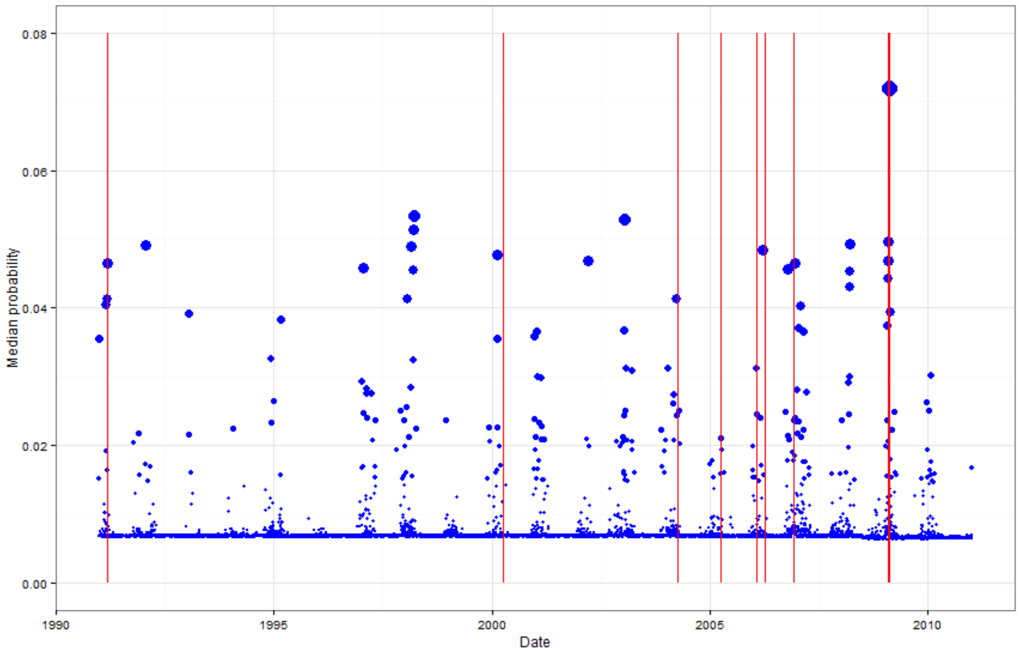
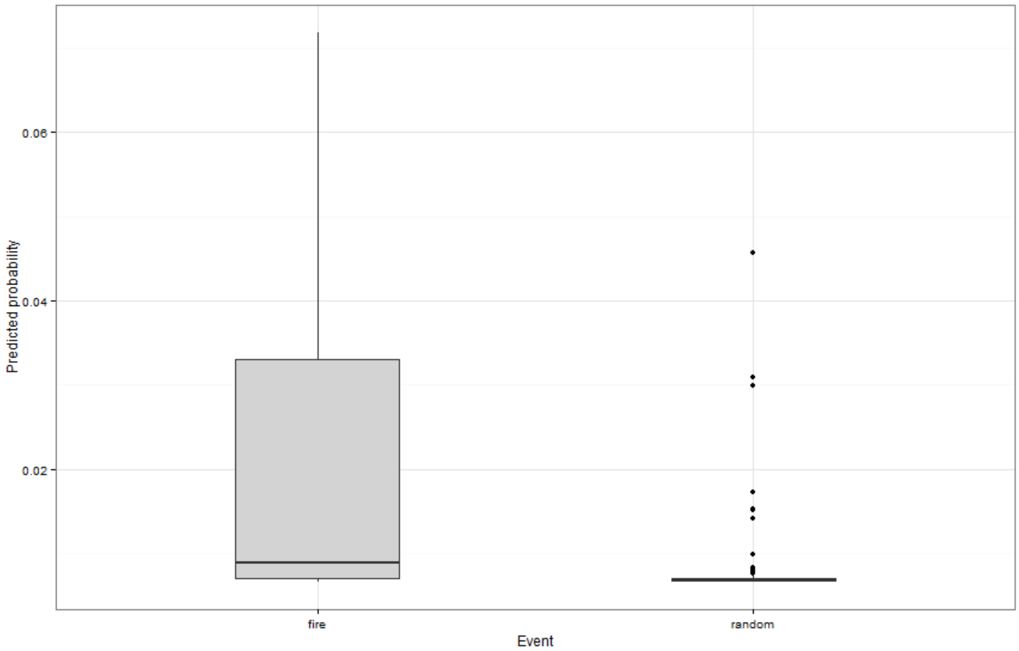


Figure 20: comparison of model predictions of fires reaching and burning at high intensity at the interface for cells, in the Victorian Central East Risk Landscape, containing an interface (median daily probabilities), for start dates of fires which are known to have progressed to the interface (left hand box) and 100 randomly selected dates (right hand box). Boxes represent the middle two quartiles of values with the median value indicated by the horizontal line.



8. Discussion and conclusions

Research conducted in the second year of the project has not only provided baseline information valuable for understanding patterns of fire in NSW and Victoria, but has demonstrated that the use of a Bayesian Network model has potential for predicting risk to properties posed by fire on a daily time step. The results demonstrate that an understanding of the full range of processes that determine the spread of fire from the location of an ignition to the point of potential impact on property will have a substantial effect on estimation of potential risk of loss. Insights into such processes, and their use in an appropriate modelling framework, can produce spatially explicit indices of risk that are more detailed and potentially more incisive and insightful than a fine-scale spatial predictions of FFDI. Thus there is great potential to use the BN modelling approach to refine and target warnings and risk estimation in a more effective way in the future.

An empirical basis for understanding ignition probabilities in the two case study areas is a major output of this research. These studies represent some of the first attempts to comprehensively model a range of ignition types across large geographic areas and relate them to the key drivers (Penman et al. 2013; Appendix A). Previous work in this area has generally focused on fire behaviour models or past ignition locations. The results of the empirical model results allow for enhanced prediction of ignition risk in new areas and under changing climates and patterns of human activity.

Temporal patterns in the median probability of fire reaching the interface and burning there at high intensity were consistent with information recorded in corresponding fire seasons for the two study areas with peaks in the spring/summer for NSW and summer/autumn for Victoria. The predicted probabilities corresponded well with known periods of exposure from large fires (i.e. recorder fires reaching the interface) in both study areas. There were a greater number of days when predicted median probabilities were high, but no exposure was recorded. This may have occurred due to an absence of ignitions on these days, or due to the success of suppression resources if ignitions did occur. Alternatively, fires may have occurred but impacted on the interface but at a much smaller size than 10000 ha. Scrutiny of the correspondence between the modelled predictions and consequences of a greater range of actual fire sizes will be carried out in the future. Regardless, it is more important to minimise false negatives (failing to predict risk when it does occur) than false positives (predicting risk when it doesn't occur). In this sense the performance of the Bayes Net modelling approach is promising.

The model demonstrated spatial variation within the case study regions at a scale useful for management. Our model predicted risk as a function of weather, fuels and the built environment and this is reflected in the differences between the predictions of FFDI and risk (Figure 16; Figure 17). These differences would allow for more localised warnings and information to residents, rather than broad scale warnings over fire districts. Furthermore, the predictions may allow fire management agencies to position resources more efficiently to reduce response times and increase the probability of initial attack success.

Sensitivity of risk to major drivers.

The Bayes Net modelling approach, and associated fire spread modelling using Phoenix Rapidfire, has provided several major insights into the sensitivity of risk of loss to major drivers of fire activity across landscapes.

First, the results illustrate the fundamental importance of incorporation of ignition and fire spread effects into the prediction of risk of loss, compared with indices based solely on weather. Such insights are encapsulated in Figure 17, which illustrates the finer grain of predictive capacity resulting from use of the BN model in the Sydney basin compared with spatial predictions of FFDI. The comparison of median probability of occurrence of high intensity fire at the interface on days in which large fires were known to occur (Figures 14, 19), also reinforces the importance of the influence of ignitions along with other external management influences such as suppression . Arguably, suppression may have accounted for the bulk of the over prediction of relatively high probability events produced by the model. Current simulation tools such as Phoenix Rapidfire have relatively limited capacity to predict suppression. These early results indicate that an investment in improving suppression modelling capacity may have significant benefits in terms of prediction of risk of loss.

Secondly, fire spread modelling, as illustrated here for the Victorian case study and previously for the Sydney region (Penman et al. 2014) indicated that weather was the most influential determinant of area burned and potential fire travel distance. Fuel treatment via prescribed burning also influenced area burned and fire travel distance but to a lesser degree than weather. Improvements in the modelling and prediction of weather, particularly at relatively fine-scale spatial and temporal resolution are therefore likely to offer scope for fundamental improvements in predicting risk of loss, via improved fire behaviour predictions.

Thirdly, weather, as represented by FFDI has a major effect on ignitions as shown in the Victorian case study and in published analyses for the Sydney basin (Penman et al. 2013). Such effects compound the importance of weather via effects on ignitions in providing a more nuanced understanding of risk at relatively fine spatial and temporal scales (Figure 16) and the general effects on fire spread. This reinforces the need to improve the accuracy and precision of weather modelling and prediction.

Future directions

Values presented in the models are indicators of relative risk because they do not encompass all influences that will determine the absolute probability of destruction. Nonetheless the model encompasses most of the critical elements involved in determining whether a potentially destructive fire is likely to reach the interface with property. As shown, such an estimation has the potential to give much greater insight into the landscape-level variation in potential loss of property than spatial estimates of the fire danger index. A period of testing is required to determine thresholds in the type of probability values produced by the model for management responses. In part, this will be addressed in the proposed program of work for year 3 of the project. However, the 20 year testing has found there is clearly a level of residual risk that forms the baseline (Figure 13; Figure 14; Figure 18) and risk could be measured as deviations from this value.

There is still considerable work to be done in the third year of the project. Firstly, the model will be operationalized for the two case study regions and tested in real time scenarios for a fire season. The tool will be developed as a web based application that interacts with Bureau of Meteorology, NSW Rural Fire Service and Victorian Department of Environment and Primary Industries. Secondly, a sensitivity analysis of the model should be undertaken to determine which components of the model the results are most responsive too and ensuring that data in these components are sound. Finally, a workshop will be run with end users following the fire season for feedback on the model and the web based tool to determine its limitations and value, to identify future model development.

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10. Appendices

Appendix A – Ignition probability draft manuscript.

NB this manuscript is in draft form

Modelling the drivers of ignition across Victoria, Australia

R. Gibson[1,2], T.D. Penman[1], R.A. Bradstock[1]

1. Centre for Environmental Risk Management of Bushfires, Institute of Conservation Biology and Environmental Management, University of Wollongong, NSW 2522, Australia

2. Corresponding author: Email tpenman@uow.edu.au, Phone +61 2 4298 1232

ABSTRACT

1 Introduction

Understanding spatial patterns of ignitions is required in order to detect areas of high ignition risk and apply targeted management strategies (Finney 2005; Vasilakos *et al.* 2007; Bar Massada *et al.* 2013). Fire danger rating models, such as the McArthur Forest Fire Danger Index (FFDI), a commonly used fire danger rating system for temperate, forested regions of Australia (Luke and McArthur 1978; Noble *et al.* 1980), are largely based on the influence of ambient weather conditions on the rate of fire spread (Catchpole 2002; Plucinski 2003; Blanchi *et al.* 2010). Such models do not include a specific ignition component and therefore assume that fires have equal probability of ignition in all conditions and locations.

While fire weather may have an overriding influence on fire extent and severity in many ecosystems (Bradstock *et al.* 2009; Parisien and Moritz 2009; Bradstock 2010; Moritz *et al.* 2010), Parisien *et al.*

(2010) found that ignitions were one of the main drivers of the spatial patterns of burn probabilities across the landscape, along with fuel dynamics (i.e. biomass accumulation with time since last fire and fuel moisture). In regions where the determinants of ignitions have been examined, large spatial variation has been reported in ignition probabilities (Parisien and Moritz 2009; Reineking *et al.* 2010; Bar Massada *et al.* 2013; Mundo *et al.* 2013; Penman *et al.* 2013). Fires ignited by arson tend to be highly clustered around population centres and human infrastructure such as roads (Syphard *et al.* 2008; Mundo *et al.* 2013; Penman *et al.* 2013); while fires ignited by lightning are more likely to occur in older fuels and on ridges (Bar Massada *et al.* 2013; Penman *et al.* 2013). Local variation in factors such as fuel characteristics, topography, climate and human population densities and infrastructure is therefore expected to influence the spatial distribution of ignitions.

Climate change is predicted to result in an increase in the number of days with elevated fire danger indices across much of southern Australia, which is likely to drive an increase in the size and severity of bushfires (Hennessy *et al.* 2006; Enright *et al.* 2012). However, an increased incidence of severe fire weather may also be expected to directly cause an increase in the frequency of ignitions, as sparks from various sources (e.g. engines, power transmission lines) have a greater chance of igniting a fire under hot, dry and windy conditions. In addition, increased temperatures associated with global warming is predicted to cause an increase in the frequency of lightning activity (Price and Rind 1994). However, such effects of climate change may not be expected to increase ignition probabilities in a uniform manner across the landscape, due to interactions with local variation in fuel dynamics, topography and other environmental factors. Understanding the relative influence of ambient weather conditions compared to anthropogenic and environmental factors on the spatial variation in ignition probability would provide insight into potential changes in ignition probabilities that may be expected with climate change.

The state of Victoria in south eastern Australia is one of the most fire-prone regions in the world with a history of devastating fire events that have resulted in the loss of human life and assets (refs). For example, the Black Saturday bushfires in 2009 resulted in 173 people being killed and the overall economic cost was estimated to be $AUS4.2 billion (refs). Victoria contains a diversity of bioregions from the Victorian Alps, highlands and midland ranges, to the Riverina, mallee and coastal plains. While many ecological communities across Victoria have the capacity to regenerate and persist after fire, some systems are sensitive to high severity or high frequency fire regimes (e.g. Mountain Ash forests and cool temperate rainforests; (Lindenmayer *et al.* 2011; Worley 2012). Given the range of vegetation communities, topography, climate and weather patterns and the distribution of human population and infrastructure, the probability of ignition is expected to vary widely across Victoria.

This study aims to examine regional variation in the influence of environmental and anthropogenic factors on the probability of ignition. In particular, we considered the relative influence of fire weather compared to other potential drivers of ignitions. We also aimed to determine the effect of scale on determining drivers of ignitions, by comparing state and regional analyses. This study also provided the opportunity to examine the generality of relationships between environmental factors and ignition risk that have been previously reported for other regions. Based on the outcomes of previous research in other regions, we tested the following hypotheses:

1. fire weather has a strong influence on the risk of ignition, irrespective of ignition type (Penman *et al.* 2013) refs).
2. the probability of ignitions caused by humans will be higher closer to the built environment (e.g. (Yang *et al.* 2007; Mundo *et al.* 2013; Penman *et al.* 2013)
3. the probability of ignitions caused by lightning will be higher in areas of native vegetation with older fuels (i.e. greater time since fire), at higher elevation and on ridges (Nash and Johnson 1996; Penman *et al.* 2013).

4. there will be a high degree of spatial variability at a regional scale in the drivers of ignition risk.

2 Methods

2.1 Study area

The study area encompasses the state of Victoria in south eastern Australia (Figure 21). The state is divided into 7 land management units by the Victorian Department of Environment and Primary Industries. Boundaries of these units are based on water catchments, fire history, bioregions and administrative zones. The city of Melbourne has an estimated population size of 4.24 million, the second largest population centre in Australia. A further 1.38 million people reside across regional and rural Victoria, in varying densities (www.abs.gov.au, accessed 16 July 2013). Extensive clearing of native vegetation has occurred across the state for agriculture and human settlement. Approximately 46% of the original extent of native vegetation remains, with the majority (>80%) protected in national parks and nature reserves. There are approximately 300 ecological vegetation communities (EVCs) across Victoria that are assigned to simplified native vegetation groups including grasslands, woodlands, shrublands, dry forests, wet forest, mallee, heathlands, wetland, and rainforest (DSE 2004). Across the region, average annual rainfall exhibits large variation. For example, in the Mallee and Murray Goulburn region (north west) average annual rainfall is approximately 300mm, while in the Alpine & Greater Gippsland region (south east), average annual rainfall ranges from 1000-1600mm. Similarly, average daily maximum summer temperatures range from 33°C in the Mallee and Murray Goulburn region to 24°C in some parts of the Alpine & Greater Gippsland region (www.bom.gov.au, accessed 16 July 2013).

2. 2 Data compilation

Fire history data (ignition point locations and mapped fire boundaries) was compiled from comprehensive datasets held by the Country Fire Authority (CFA) and the Department of Sustainability and Environment (DSE), spanning 12 years from 1997 to 2009. Ignition causes were categorised into 9 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. The number and distribution of each ignition type within each BRL region across Victoria is presented in Table 3 and Figure 21. The comprehensive ignitions database used in this study provides a unique opportunity to examine drivers of different anthropogenic ignition types (i.e. the separation of arson from accidental human-related causes of ignitions).

A range of environmental and anthropogenic-related factors that were hypothesised as potential predictor variables of ignitions were included in the analysis (Table 1). Positive topographic position index (TPI) values represent locations that are higher than the average of their surroundings (i.e. ridges), negative values represent locations that are lower than their surroundings (i.e. valleys), and values near zero represent either flat areas or areas of constant slope (Weiss 2001). TPI, slope and aspect relative to north-west were calculated across the study area based on a 9-s (25m resolution) digital elevation model. Time since fire (TSF, an indicator of potential fuel accumulation) was calculated using fire history mapping that has been undertaken by state government authorities since 1970. For ignition point locations where no previous fires had been mapped, TSF was set as 40 years as fire mapping before this time is unreliable. Tenure density was measured by calculating the number of properties within a 2-km radius using address locations provided by the Victorian Government. Ecological vegetation communities (EVCs) were categorised into 9 broad vegetation types; grassland, woodland, mallee, heathland, wetland, shrubland, dry forest, wet forest, rainforest.

Geology was excluded from the analysis, as there was no expectation that soils would influence ignition risk, independently from effects of vegetation and topographic factors.

The forest fire danger index (FFDI) is a measure of fire weather and the associated probability of the destruction of property based on a combination of temperature, humidity, rainfall, average wind speed and longer term drying (Noble *et al.* 1980; Bradstock *et al.* 2009). FFDI was calculated for the day of the ignition or the date assigned to the random sampling locations (see below) from the nearest Bureau of Meteorology weather station that recorded all the required measurements. All weather stations were within 60 km of the ignition or random point location, which is likely to sufficiently represent the FFDI value at the target point. Given that FFDI is on an exponential scale, we took the natural log of FFDI for the analysis.

2. 3 Modelling ignition distributions

Maxent (Phillips *et al.* 2006) is a species distribution modelling technique using the maximum entropy algorithm that has been used to model fire ignitions (Parisien and Moritz 2009; Renard *et al.* 2013). While various methods have been used in ignition modelling, Maxent is a robust method for presence only data that performs well in comparison to other modelling techniques (Phillips *et al.* 2006; Elith *et al.* 2011; Bar Massada *et al.* 2013; Renard *et al.* 2013). 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).

Separate analyses were undertaken for each ignition type within each BRL region as well as for the whole of Victoria. In each analysis, predictor values for each ignition point and random sampling point (i.e. background data) were obtained using the stack and extract functions of the raster and dismo packages in R v 3.0.0 (R Development Core Team 2011) and combined to create the dataset for the analysis. We used the Maxent function in the dismo package R which uses the java MaxEnt species distribution model software (http://www.cs.princeton.edu/~schapire/maxent/). From the results for each model, a subset of variables were selected that contributed >5% explanation of the variance before repeating the Maxent analysis, in order to increase parsimony in the model. The results reported refer to the Maxent results for each sub-model. The response curves from the model output show the marginal effect of changing one variable only, whereas the model may take advantage of sets of variables changing together.

In each analysis, 15% of the dataset was withheld and used for testing model performance. The area under the curve (AUC) of the receiver operating characteristic (ROC) plot was used to assess prediction accuracy of each model (Hanley and McNeil 1982). AUC values range from 0.5 to 1, where 0.5 is equivalent to a completely random prediction and 1 implies perfect prediction. Model performance is considered poor for AUC values between 0.5 and 0.7; moderate for AUC values between 0.7 and 0.9 and strong for AUC values larger than 0.9 (McCune and Grace 2002). The difference between the AUC values of the training and test datasets provides a measure of how well the model (based on the training dataset) predicts ignition locations for data not used in model development (i.e. the test dataset).

3 Results

There was regional variation in the distribution of ignitions, both within and between ignition types (Figure 23). Arson and accidental anthropogenic ignition types displayed a similar spatial pattern with a concentration of ignition points around the central portion of the state. By contrast, lightning ignitions were relatively more uniform in distribution across the state, though still exhibited some areas of high and low concentrations. Regional variation occurred in the mean values of predictor variables, particularly for slope, elevation, rainfall, FFDI and tenure density (Table 5).

In the Victoria-wide analyses, FFDI was included in the model for each ignition type, whereby the probability of ignition increased with increasing FFDI values (Figure 24). The highest percentage contribution of FFDI occurred in the models of lightning (54.4%), power transmission lines (56%) and machinery ignitions (30.4%), while the lowest contribution of FFDI occurred in the models of arson ignitions (7.9%; Table 7 and Figure 24). Distance to mapped roads influenced the probability of ignition for all ignition types, whereby there was a higher probability of ignition closer to roads. Although distance to mapped roads contributed 21.2% to the model of lightning, the magnitude of the effect was relatively minor (i.e. a 20% decline in the probability of lightning ignitions, compared to >75% for all anthropogenic ignition types; Fig. 4; Table 7). Tenure density influenced the probability of ignition for each ignition type, except for lightning. The highest percentage contribution occurred for ignitions caused by arson (60.4%) and child arson (59.1%; Table 7). The probability of ignition consistently increased with increasing tenure density, and showed a steep decline at very high tenure densities in all cases except for power transmission ignitions, which remained steady. Rainfall was included in the model of lightning ignitions, whereby the probability of ignition increased with increasing rainfall. In addition, power transmission ignitions were influenced by vegetation type, whereby a higher number of ignitions occurred in grasslands compared to any other vegetation type (Figure 24). In each analysis, there was strong discrimination on held out data, with <0.08 difference in AUC values between the test and training datasets (Table 7). The AUC values indicated model performance was strong in the majority of cases (i.e. AUC > 0.9).

In the analyses of ignition probabilities across BRL regions, the results are largely congruent with state-wide results. However, some regional differences were apparent for some ignition types. Rainfall was included in a number of regional models of anthropogenic ignition types, in contrast to each corresponding state-wide model. In most cases, the probability of ignition declined with increasing rainfall (Fig. 8, Fig. 10; Table 5). However, the opposite trend occurred in BRL 5 and 6 (i.e. the probability of ignition increased with increasing rainfall). Rainfall was excluded from some regional models of lightning, in contrast to the state-wide model of lightning (i.e. BRL 2, 3 and 4; Fig. 9). Time since fire was included in the models of accidental, arson and lightning ignitions in the Alpine & Greater Gippsland region (BRL1), but the percentage contribution to each model was relatively minor (7.2%, 3%, 12.6%; Table 5). For arson and lightning ignitions, there was a sharp increase in ignition probability of approximately 30% within 5 years since the last fire (Fig. 6 and 9; Table 7). Time since fire was not included in the models for any other ignition type in any other BRL region.

Elevation contributed to the model of accidental ignitions in the Alpine and North East and Murray Mallee and Goulburn regions (BRL 2 and 5; Fig. 5; Table 7). In both cases, the probability of accidental ignitions declined with increasing elevation. In the Alpine and Greater Gippsland region (BRL1), elevation contributed to the models of arson and machinery ignitions (Fig. 6 and 10; Table 7), where the probability of accidental ignitions declined with increasing elevation. Elevation also contributed to the models of machinery and escaped fire ignitions in the West Central region (BRL7), but the effect on the probability of ignitions increased with increasing elevation (i.e. opposite to the anthropogenic ignitions in other regions). Elevation contributed to the models of lightning ignitions in the East Central (BRL4) and West Central regions (BRL7; Fig 9; Table 7), where the probability of ignition increased with increasing elevation.

Topographic position (TPI) was only included in the model of lightning ignitions in the Alpine and North East region (BRL 2; Fig. 9; Table 7), where the probability of ignition increased with increasing values of the topographic position index (i.e. ridges). Distance to mapped watercourse was only included in the model of accidental ignitions in the Murray Mallee and Goulburn region (BRL 5; Fig. 5; Table 7), where there was a decline in the probability of ignition with increasing distance to watercourses. Vegetation type was only included in the model of lightning ignitions in the Alpine and Greater Gippsland, and the Barwon Otway regions (BRL 1 and 3; Fig. 9; Table 7). In both cases, no lightning ignitions occurred in mallee vegetation, due to the absence of this vegetation type in these BRL regions (Figure 22). However, lightning ignitions also tended to be lower in cleared areas in both regions, and in wet forest in the Barwon Otway region (BRL 3).

4 Discussion

The results largely conform to the predictions based on previous research in other regions. Fire weather consistently influenced ignition probability; FFDI was included in each model, regardless of ignition type. However, FFDI had a far greater percentage contribution to the models of lightning ignitions compared to arson, and other human-related, accidental ignition types. Human-related ignition types (e.g. arson and accidental ignitions) were more likely to occur close to densely populated areas and mapped roads, as predicted. The nature of these relationships were consistent for both the state and regional scale analyses. However, in contrast to predictions, lightning ignitions were not consistently influenced by TSF, elevation or topography, as detected in previous studies. Spatial variation in the drivers of ignition probabilities was detected at a regional scale, though in most cases, the percentage contribution of the additional variables to the models was relatively minor.

4. 1 Effects of fire weather

Under severe fire weather conditions, fires ignite more easily from sparks associated with accidental, human-related sources which, under milder weather conditions, would normally not start a fire. However, the effects of hot, windy conditions on the rate of fire spread may be the mechanism driving the apparent effect FFDI on the probability of ignitions. Fires may still ignite under lower FFDI values, but self-extinguish before detection due to a lack of fire weather conditions. The analysis of FFDI on ignition probability cannot distinguish between these competing mechanisms, though the effect of FFDI on ignitions may be driven by a combination of both processes. Regardless, fires that potentially ignite and self-extinguish under mild weather conditions do not significantly contribute to the extent of burnt area in the landscape, and therefore, would not be an important consideration for targeting ignition management actions.

Fire weather (FFDI) had a far greater percentage contribution to state and regional models of lightning (41.6-78.5%) compared to arson (0-12%) and accidental ignitions (8.7-18.4%; Table 7). In Victoria, fires ignited by lightning account for 90% of the total area burnt by all fires, but only 30% of the number of ignitions (Dowdy and Mills 2011). Given the potential increase in the incidence of severe fire weather conditions predicted in this region with climate change (Hennessy *et al.* 2006; Enright *et al.* 2012) , as well as an increased frequency of lightning strikes (Price and Rind 1994), there is a high potential for the rate of lightning ignitions to increase in the future, along with the corresponding extent of area burnt.

4. 2 Regional variation

Drivers of lightning ignitions showed the highest degree of spatial variation at a regional scale, compared to all other ignition types. Time since fire was expected to be a key driver of lightning ignitions, because lightning activity is more frequent during the late afternoon hours (Christian *et al.*

2003). Therefore, for a lightning strike to result in a wildfire, the fire will often need to sustain itself overnight under more mild weather conditions. Heavy fuels, such as logs, continue to burn under mild weather conditions and are more abundant in long unburnt sites (Lindenmayer *et al.* 1999; Hély *et al.* 2000), thereby increasing the probability that a fire will sustain itself with TSF. However, TSF was only detected as a minor contributing factor to the model of lightning ignitions for the Alpine and Greater Gippsland region (BRL 1; Table 7).

Elevation and topography were also predicted to have a strong influence on the probability of lightning ignitions, but only contributed a small percentage to the models of lightning ignition for 3 of the 7 BRL regions. There was a higher probability of lightning ignitions on ridges (i.e. higher TPI) in the Alpine and North East region (BRL 2; Table 7) and with increased elevation in the East Central and West Central regions (BRL 4 and 7; Table 7). The nature of these relationships, where they occurred, was consistent with previous studies. The high degree of regional variation in drivers of lightning ignitions likely reflects the distribution patterns for topography and population densities. The rugged terrain of the Alpine landscape, which dominates BRL 2, has more examples of high ridge tops in close proximity to deep valleys. Therefore, there would be a greater chance of detecting an effect of topographic position on the probability of lightning ignitions compared to environments with more even topography. The East and West Central regions contain the highest population densities in Victoria. As such, the effect of elevation on lightning ignitions may be a function of urban development patterns, as higher elevation sites may be more rugged and less suitable for development, and therefore, would have a greater cover of native vegetation with a higher capacity to carry fire.

The regional variation detected in this study highlights the effect of scale in determining spatial patterns in the drivers of ignition probabilities. While wildfire is an abiotic ecological process, it can be considered analogous to biological organisms; both are strongly regulated by environmental factors. Like the distribution of species, site-specific factors such as topography and fuel structure, will be more important for the occurrence of fire at a fine, local scale whereas climate-related factors will prevail at the broader regional scale (Pearson *et al.* 2004). As such, a finer resolution of analysis (e.g. a comparison between different vegetation types within each BRL region), may be expected to characterise ignition probabilities as driven by a different set of variables than may be detected at the broader state and regional scales. For example, vegetation types in which fire propagation is limited by fuel biomass and connectivity may be expected to exhibit a stronger influence of TSF on ignition probabilities compared to vegetation types in which fire propagation is limited by fuel moisture. Further research would be required to quantify the effect of local environmental conditions compared to the broader regional scales. Such knowledge would be beneficial in directing appropriate ignition management actions at a local scale.

4. 3 Future implications

The results indicate that fire weather is an important driver of ignition probability, particularly for lightning ignitions, which account for the vast majority of area burnt in Victoria. The rate of all types of ignitions has the potential to increase in the future, given the predicted effects of climate change on the incidence of fire weather in this region. Refined predictions of effects of climate change on weather patterns at a regional scale in the future may be used in conjunction with the results of the regional variation in the additional factors that contribute to the models of ignitions, to allow for more accurate predictions of ignition probabilities.

The results of this study could be used to develop spatial predictions of ignition risk by geographically projecting the modelled determinants of ignitions. This would allow the ability to assess the generality and spatial transferability of the models. Furthermore, such predictive models of the potential distribution of ignition risk would provide the ability to detect areas where ignitions are highly probable but have not recently been observed (e.g. (Parisien and Moritz 2009), which may assist in targeting ignition management actions. In addition, models of the determinants of ignition probabilities could contribute towards building a comprehensive predictive bushfire risk assessment that includes a specific ignition component. Such assessments are needed to refine our understanding of controls on fire and fire regimes at broad spatial scales (regional to continental) while allowing mapping of the likelihood and potential spatial extent of wildfire under both current and future climate scenarios (Parisien and Moritz 2009).

5 Acknowledgements

6 Figures

Figure 21 Location of the study area and BRL risk land management groups

Figure 22 The variation in the relative proportion of vegetation types across BRL regions. BRL 1 (Alpine & Greater Gippsland), BRL 2 (Alpine and North East), BRL 3 (Barwon Otway), BRL 4 (East Central), BRL 5 (Mallee & Murray Goulburn), BRL 6 (South West), BRL 7 (West Central).

Figure 23 The distribution of each ignition type across each BRL land risk management group. Ignition types are: a. accidental, b. arson, c. arson (child), d. lightning, e. escaped fire, f. building, g. machinery, h. power transmission lines, i. unknown.

Figure 24 Response curves of maxent output for each ignition type across Victoria.

Figures 5-11 Regional variation in the response curves of maxent output for each ignition type.

Figure 21

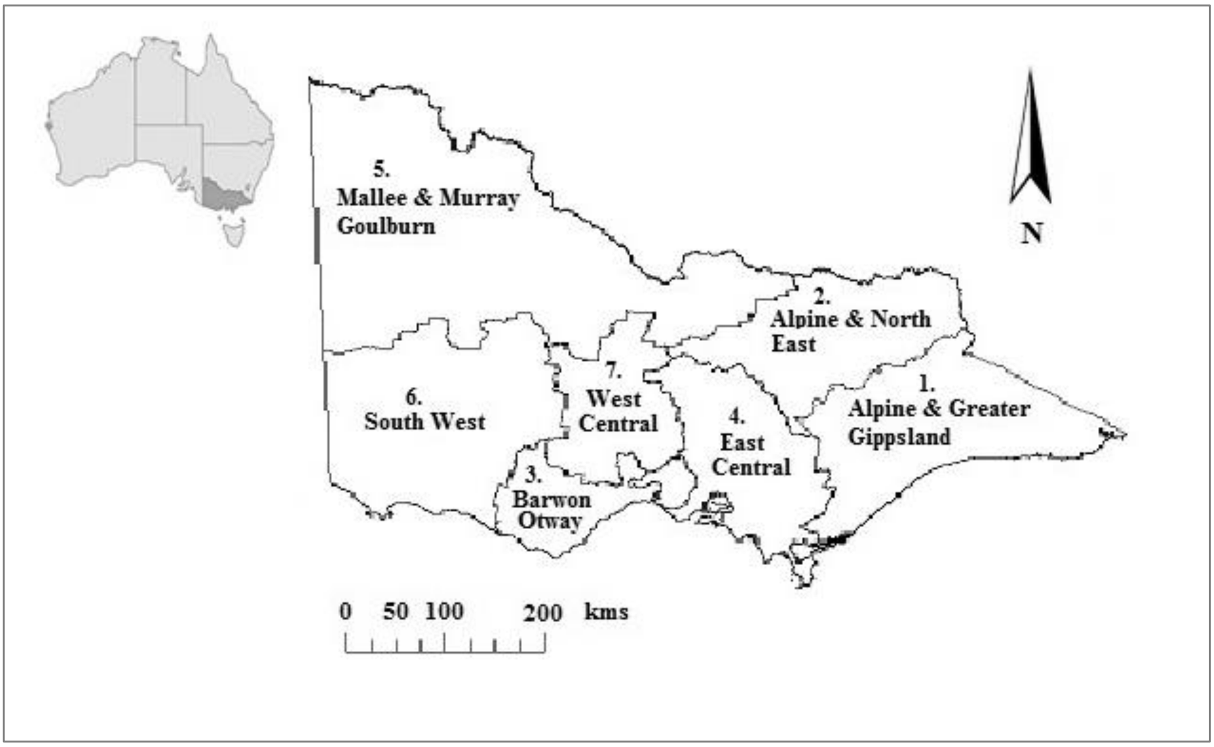


Figure 22

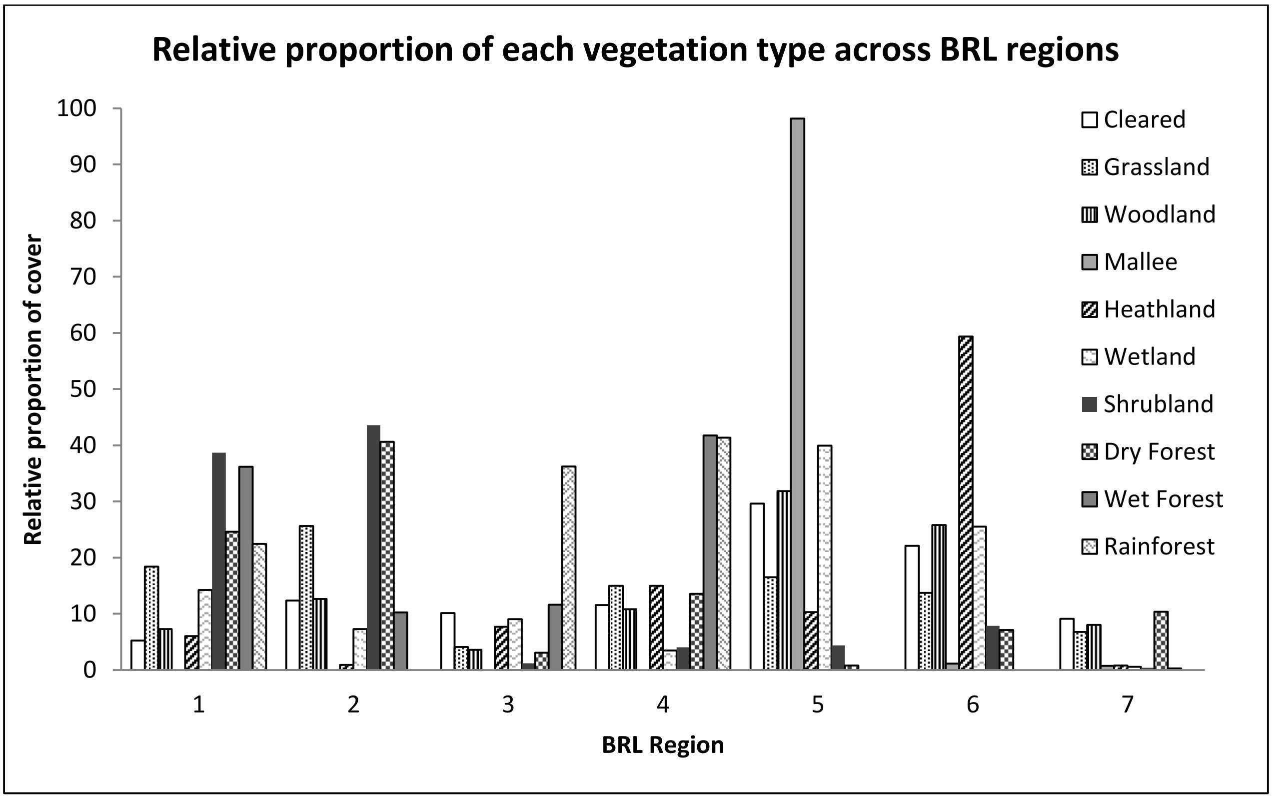
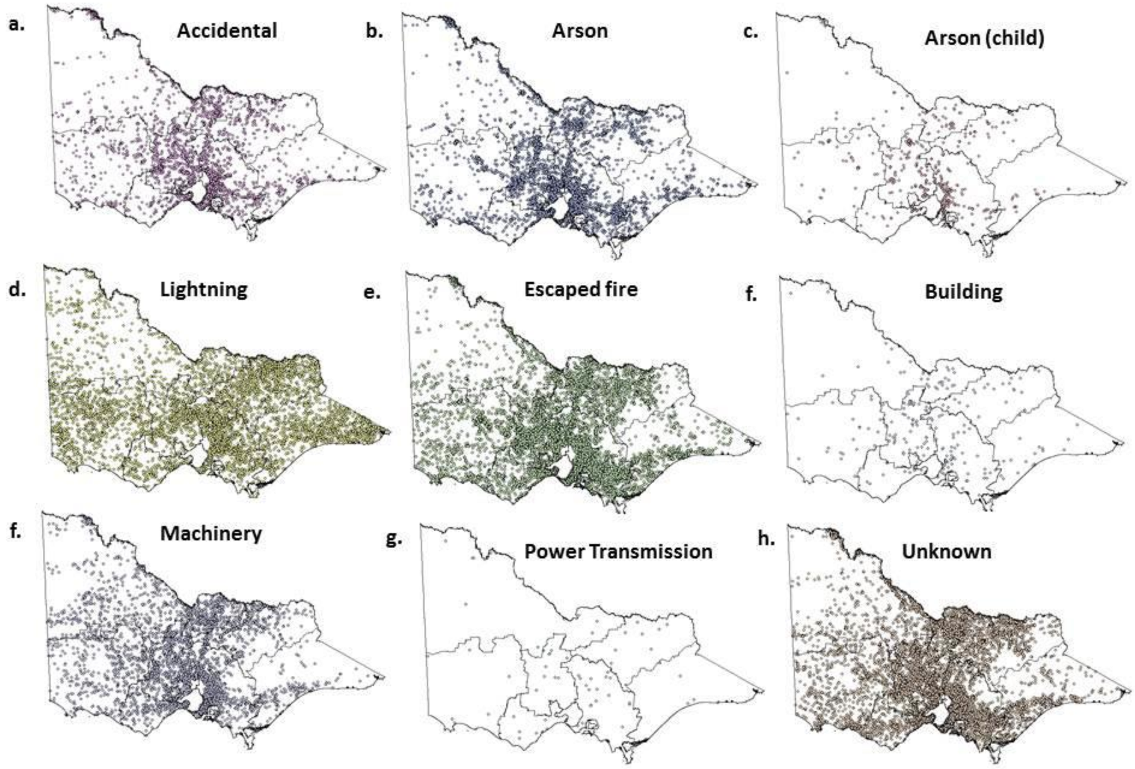


Figure 23



a.
Accidental
b.
Arson
c.
Arson (child)
d.
Lightning
e.
Escaped fire
f.
Building
f.
Machinery
g.
Power Transmission
h.
Unknown

Figure 24

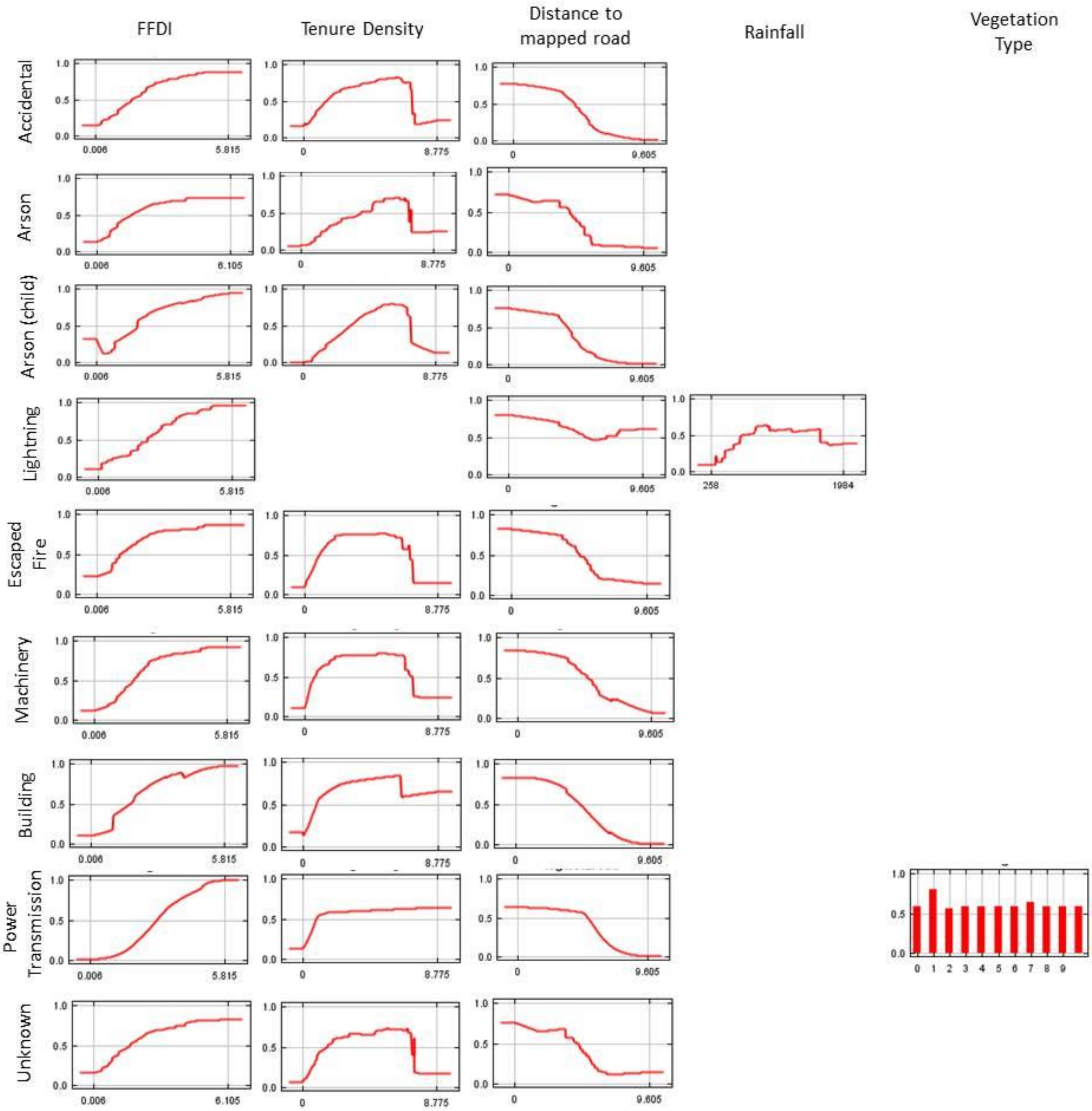
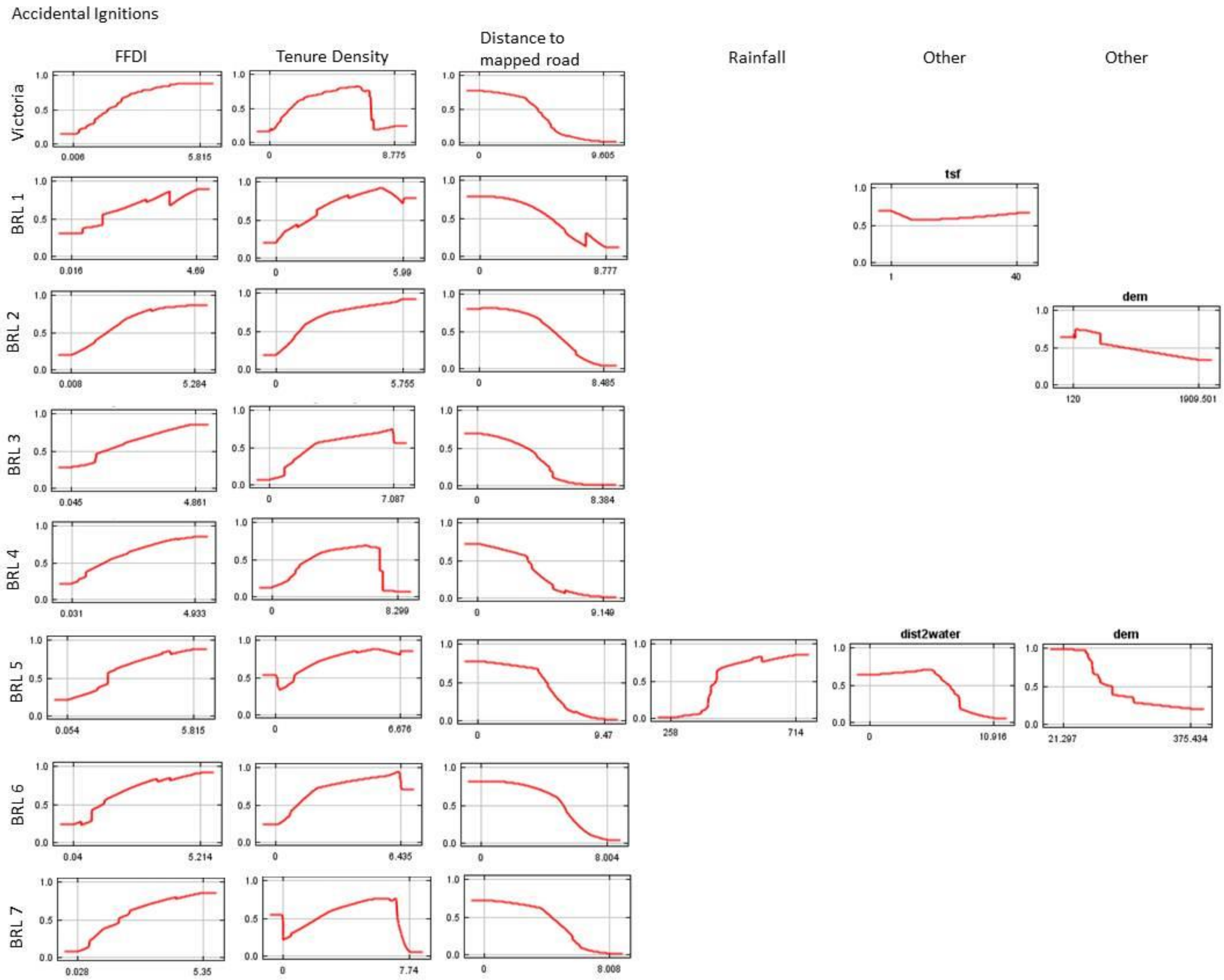
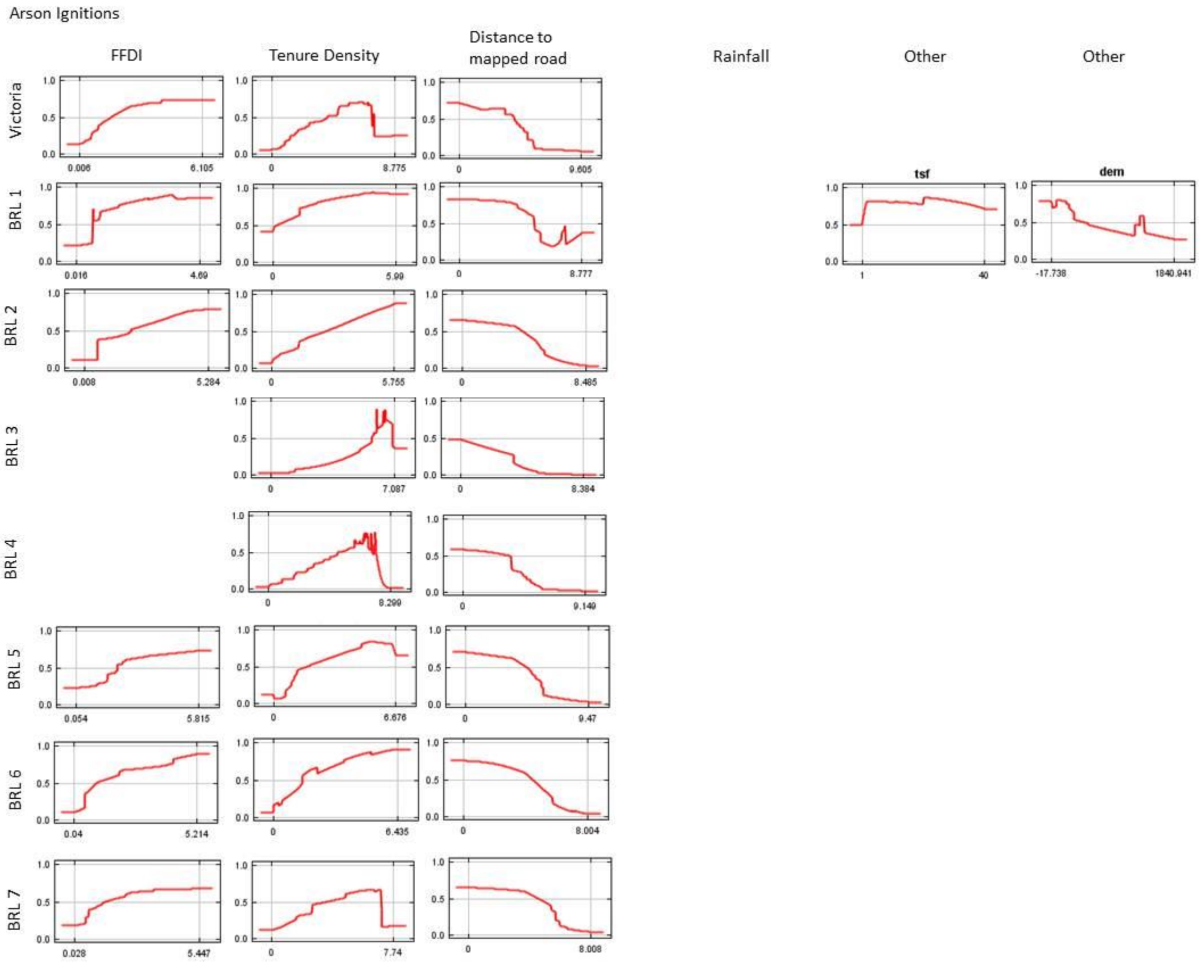

FFDI
Tenure Density
Distance to mapped road
Rainfall
Vegetation Type
Accidental
Arson
Arson (child)
Lightning
Escaped Fire
Machinery
Building
Power Transmission
Unknown

Figure 25



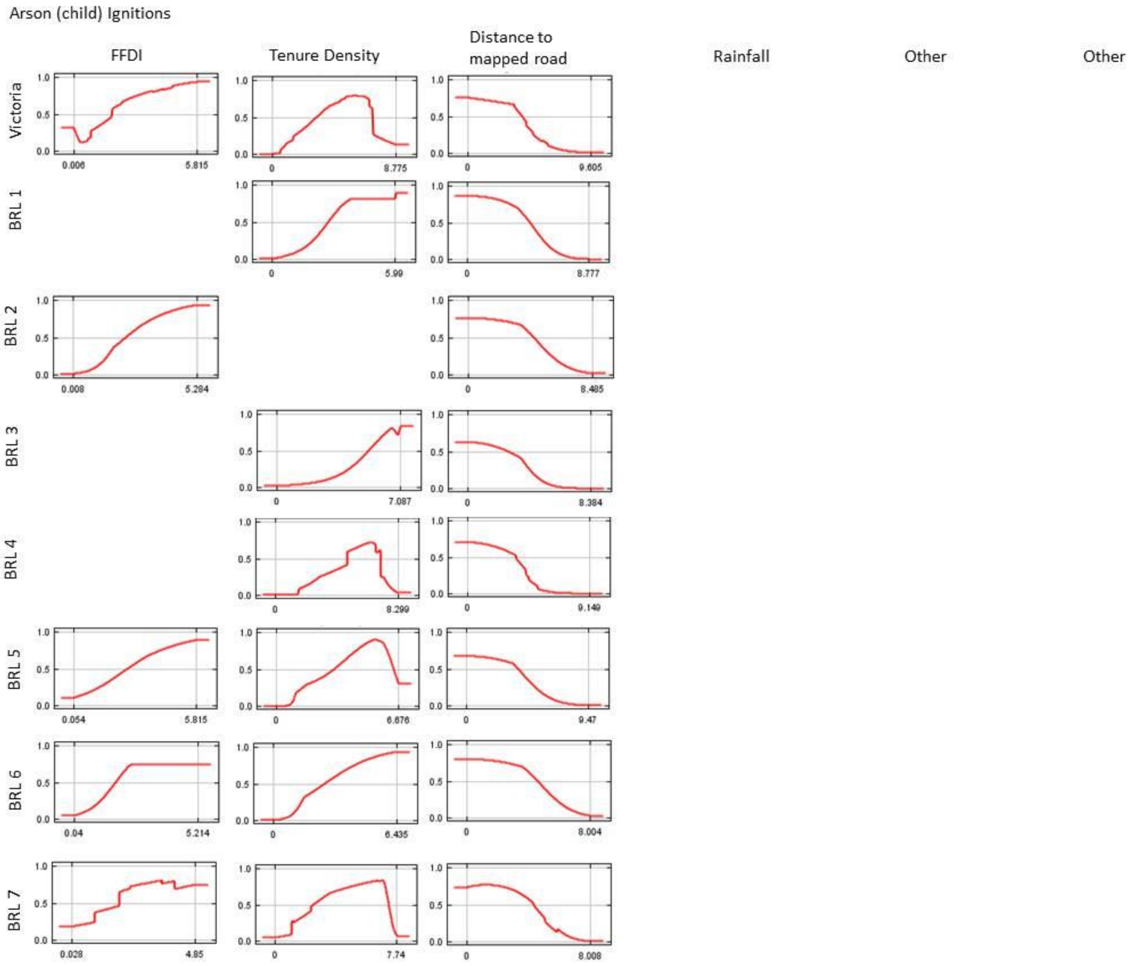
Accidental Ignitions
FFDI
Tenure Density
Distance to mapped road
Rainfall
Other
Other
Victoria
BRL 1
BRL 2
BRL 3
BRL 4
BRL 5
BRL 6
BRL 7
tsf
dem
dist2water
dem

Figure 26



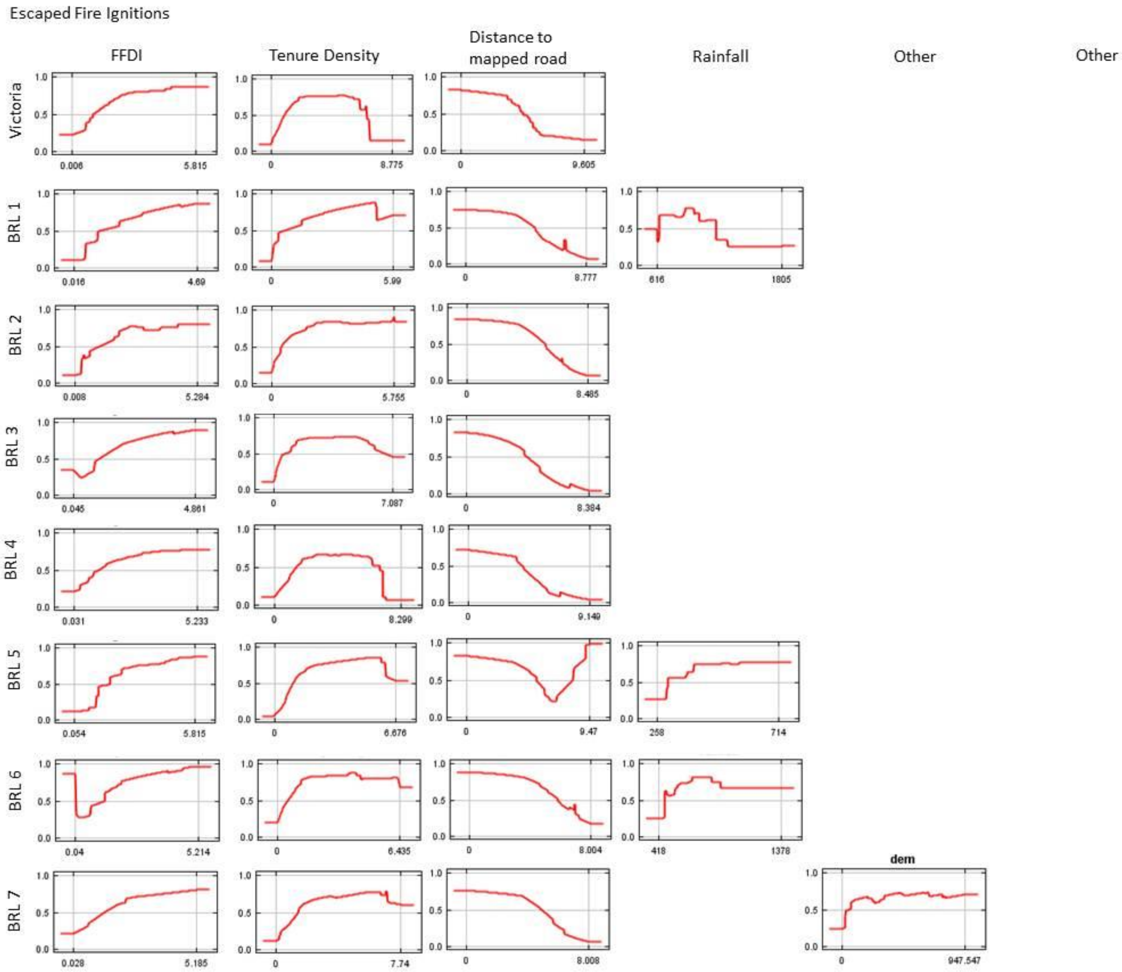
Arson Ignitions
FFDI
Tenure Density
Distance to mapped road
Rainfall
Other
Other
Victoria
BRL 1
BRL 2
BRL 3
BRL 4
BRL 5
BRL 6
BRL 7
tsf
dem

Figure 27



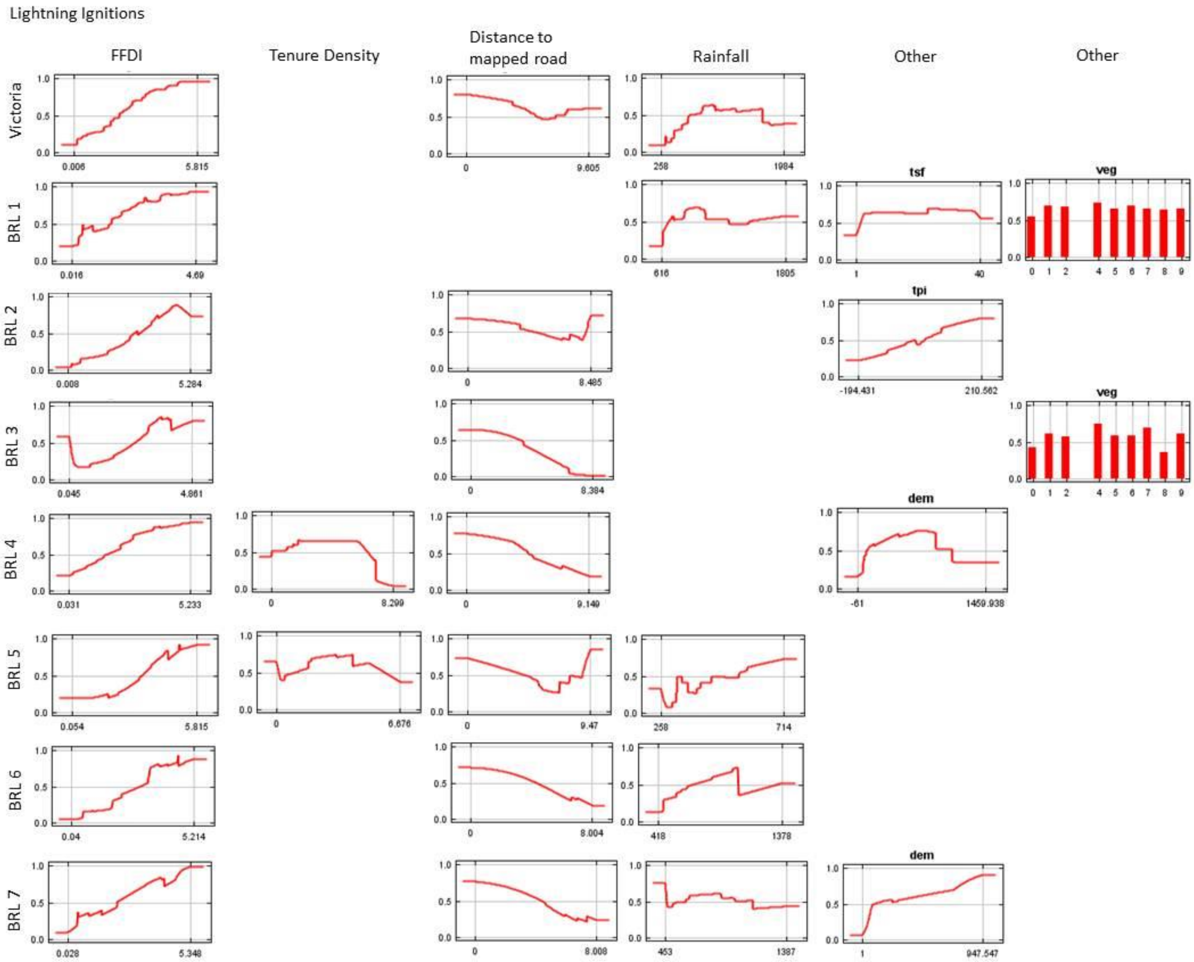
Arson (child) Ignitions
FFDI
Tenure Density
Distance to mapped road
Rainfall
Other
Other
Victoria
BRL 1
BRL 2
BRL 3
BRL 4
BRL 5
BRL 6
BRL 7

Figure 28



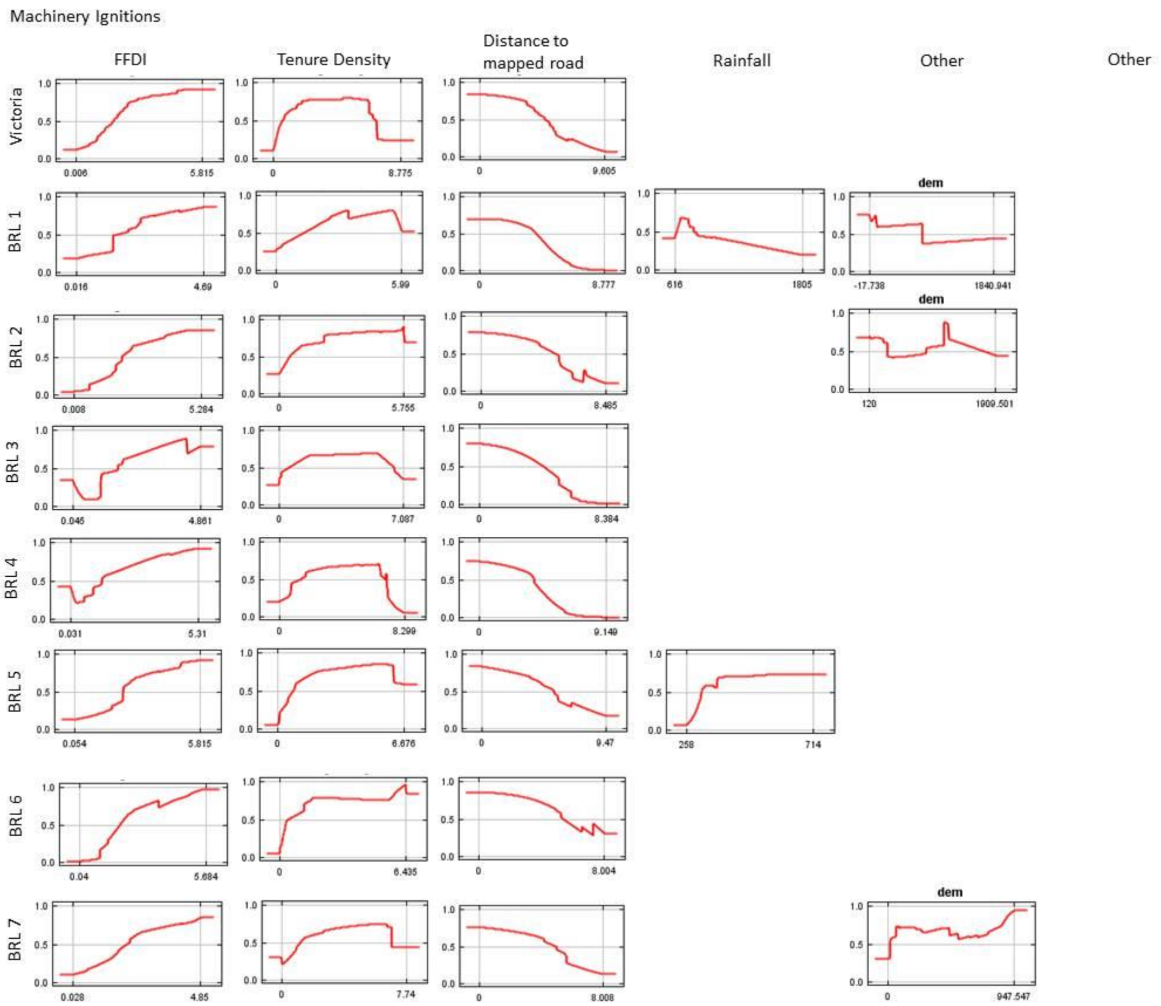
Escaped Fire Ignitions
FFDI
Tenure Density
Distance to mapped road
Rainfall
Other
Other
Victoria
BRL 1
BRL 2
BRL 3
BRL 4
BRL 5
BRL 6
BRL 7
dem

Figure 29



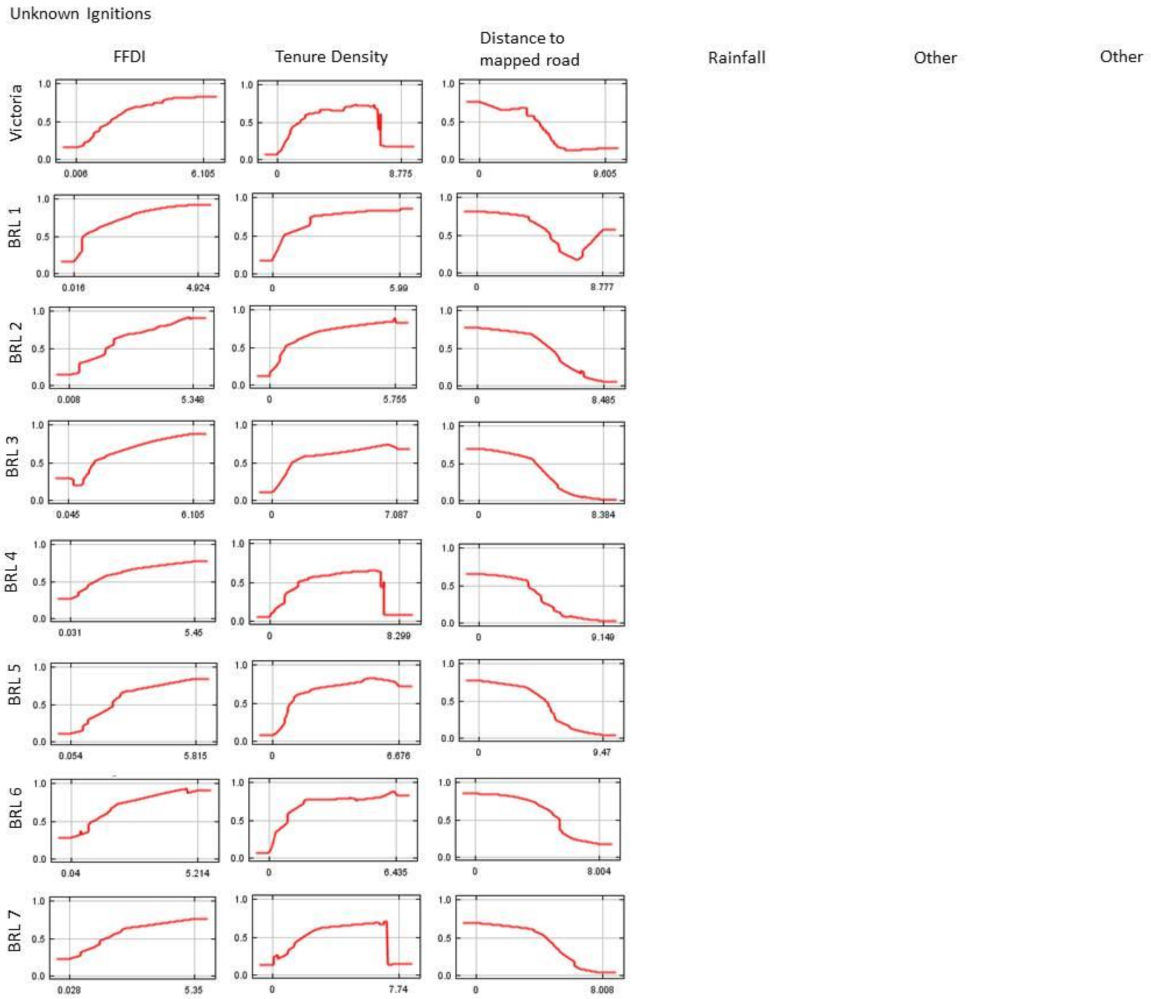
Lightning Ignitions
FFDI
Tenure Density
Distance to mapped road
Rainfall
Other
Other
Victoria
BRL 1
BRL 2
BRL 3
BRL 4
BRL 5
BRL 6
BRL 7
tsf
veg
tpi
veg
dem
dem

Figure 30



Machinery Ignitions
FFDI
Tenure Density
Distance to mapped road
Rainfall
Other
Other
Victoria
BRL 1
BRL 2
BRL 3
BRL 4
BRL 5
BRL 6
BRL 7
dem

Figure 31


Unknown Ignitions
FFDI
Tenure Density
Distance to mapped road
Rainfall
Other
Other
Victoria
BRL 1
BRL 2
BRL 3
BRL 4
BRL 5
BRL 6
BRL 7

7 Tables

Table 3 The number of ignitions within each category, across each BRL region and combined across Victoria (1997-2009). Accidental ignitions associated with buildings and power transmission lines were only examined at the state wide level due to small sample sizes within each BRL region; BRL 1 (Alpine & Greater Gippsland), BRL 2 (Alpine and North East), BRL 3 (Barwon Otway), BRL 4 (East Central), BRL 5 (Mallee & Murray Goulburn), BRL 6 (South West), BRL 7 (West Central).

Ignition Type	No. of Ignitions in each region							
	BRL1	**BRL2**	**BRL3**	**BRL4**	**BRL5**	**BRL6**	**BRL7**	**Victoria**
Accidental	199	359	421	1463	907	350	855	4554
Arson	640	936	1599	7847	2021	863	5568	19474
Arson (child)	23	51	42	263	96	65	179	719
Building	-	-	-	-	-	-	-	242
Escaped fire	819	1126	696	4469	1590	1114	2387	12201
Lightning	1113	1273	244	1232	816	1004	563	6245
Machinery	161	532	355	1155	1182	558	1064	5007
Power transmission	-	-	-	-	-	-	-	73
Unknown	748	1357	1086	6738	2712	1158	4155	17954

Table 4 Details of the environmental and anthropogenic predictor variables used in model development, including the predicted effect of each variable on ignition probabilities. TSF (time since fire), DEM (digital elevation model, 25m resolution), 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
TSF (yrs)	Derived from fire history mapping	DSE, CFA	Fuel loads increase with time since fire, which may results in an increased probability of ignition
Vegetation Type	Derived from Ecological Vegetation Community mapping	DSE	Flammability varies between vegetation types and is expected to influence the probability of ignition accordingly
Distance to mapped watercourse (kms)	Calculated from vector files of watercourse locations	DSE	Fuel moisture likely to be higher closer to drainage lines, therefore the probability of ignitions may increase with distance from watercourses.
Elevation (m)	Calculated from DEM	Geoscience Australia	Lightning strikes occur more frequently at higher elevation sites, increasing the probability of lightning ignitions.
Topographic Position Index	Calculated from DEM	Geoscience Australia	Lightning more likely on ridges. Fuel moisture higher in gullies, therefore ignitions higher on ridges and upper slopes

Slope (degrees)	Calculated from DEM	Geoscience Australia	Fires on flat and very steep slopes are less likely to spread than those on intermediate slopes
Aspect (degrees)	Calculated from DEM, relative to north-west	Geoscience Australia	Fuel moisture lower on sites exposed to the north-west, therefore ignitions more likely in these areas
Log(FFDI)	Calculated from BOM data from nearest rainfall station	BOM	Fire weather conditions may increase the risk of an ignition resulting in a sustained fire
Rainfall (mm)	Mean annual rainfall (based on what? 30 years centred on 1990)	BOM	Increased rainfall promotes increased fuel mass, increasing the probability of an ignition resulting in a sustained fire
Tenure density (no. houses/2kms)	Calculated from vector files of address locations	DSE	Increased housing density reflects increased population, increasing the probability of arson ignition
Distance to mapped road (kms)	Calculated from vector files of roads	DSE	Increased probability of arson ignitions closer to roads.

Table 5 Regional variation in mean values of each variable used in model development. Vegetation type, a categorical variable, is excluded. FFDI (Forest Fire Danger Index), TSF (time since fire), BRL 1 (Alpine & Greater Gippsland), BRL 2 (Alpine and North East), BRL 3 (Barwon Otway), BRL 4 (East Central), BRL 5 (Mallee & Murray Goulburn), BRL 6 (South West), BRL 7 (West Central).

BRL Region	TPI	Slope	Aspect	Elevation	Rainfall	log(FFDI)	TSF	Distance to water	Distance to mapped road	log(Tenure density)
1	0.2652	11.14	90.98	415.41	929.9	1.472	28.89	4.34	5.609	0.527
2	0.05	11.49	85.34	506.8	996.7	1.756	31.71	4.336	5.519	0.618

3	0.089	4.325	87.97	149.886	821.8	1.499	37.43	5.332	5.376	1.216
4	0.277	8.695	88.1	305	1084	1.507	38.28	4.419	4.87	1.654
5	0.015	2.108	88.53	105.8	421.2	2.554	38.79	5.986	5.506	0.609
6	-0.001	3.454	88.86	194.46	661.5	1.835	37.79	5.393	5.458	0.684
7	0.0383	3.96	90.55	336	697.1	1.966	37.07	4.841	4.993	1.719

Table 6 The number of ignitions across Victoria across vegetation types (1997-2009).

Code	Vegetation Type	Ignition Type								
		Accidental	**Arson**	**Arson (child)**	**Building**	**Escaped fire**	**Lightning**	**Machinery**	**Power transmission**	**Unknown**
0	Cleared	3213	15644	590	171	7943	2740	3661	35	13635
1	Grassland	848	2463	79	34	2720	2203	835	29	2756
2	Woodland	227	463	25	9	459	232	195	2	585
3	Mallee	8	11	2	0	20	50	7	0	21
4	Heathland	26	140	3	4	85	100	20	0	94
5	Wetland	10	32	2	0	17	10	11	1	38
6	Shrubland	7	38	0	2	35	54	12	0	35
7	Dry Forest	195	618	18	19	786	657	233	5	708
8	Wet Forest	20	65	0	3	133	196	32	1	81
9	Rainforest	0	0	0	0	3	3	1	0	1

Table 7 Summary of Maxent results for each ignition type within each region. Area under the curve (AUC) of training and test data demonstrate the fit of the model.

		AUC values		% contribution of each variable								
Ignition type	Region	**AUC - training**	**AUC - test**	**FFDI**	**Tenure density**	**Distance to mapped road**	**Rainfall**	**TSF**	**Elevation**	**Topographic position**	**Distance to mapped watercourse**	**Vegetation type**
Accidental	Victoria	0.915	0.918	18.3	42	39.7						
	BRL1	0.87	0.919	13	48.8	31		7.2				
	BRL2	0.916	0.91	18.4	47.6	28.5			5.5			
	BRL3	0.956	0.967	8.7	41.4	49.9						
	BRL4	0.913	0.911	11.6	41	47.4						
	BRL5	0.939	0.914	9.5	36.2	28.7	12.5		6.3		6.8	
	BRL6	0.89	0.906	17.7	44.3	38						
	BRL7	0.887	0.885	18.2	32.4	49.4						
Arson	Victoria	0.94	0.941	7.9	60.4	31.7						
	BRL1	0.914	0.895	12	37.2	39.6		3	8.3			
	BRL2	0.931	0.942	9.5	63.8	26.7						
	BRL3	0.969	0.972		68.3	31.7						
	BRL4	0.914	0.917		64.8	35.2						
	BRL5	0.939	0.931	5.4	69.7	24.9						

	BRL6	0.919	0.915	8.2	56.4	35.4						
	BRL7	0.869	0.872	6.3	61	32.6						
Arson (child)	Victoria	0.968	0.967	12.6	59.1	28.3						
	BRL1	0.966	0.996		74.5	25.5						
	BRL2	0.906	0.939	53.1		46.9						
	BRL3	0.977	0.924		78.8	21.2						
	BRL4	0.964	0.942		69.2	30.8						
	BRL5	0.982	0.987	6.3	82.1	11.6						
	BRL6	0.978	0.964	12.1	78.2	9.7						
	BRL7	0.939	0.956	13.7	52.9	33.4						
Lightning	Victoria	0.806	0.794	54.4		21.2	24.4					
	BRL1	0.788	0.786	64.6			16	12.6				6.9
	BRL2	0.793	0.763	78.5		11.7				9.8		
	BRL3	0.85	0.852	48		43.4						8.6
	BRL4	0.84	0.822	55.9	6.5	29.3			8.3			
	BRL5	0.839	0.817	42.9	13.7	25.3	18.1					
	BRL6	0.83	0.82	71.7		20.2	8.1					
	BRL7	0.82	0.852	41.6		42.9	9.1		6.4			
Escaped fire	Victoria	0.892	0.897	14.7	42.3	43						

	BRL1	0.9	0.819	16.5	47.8	29.4	6.3		
	BRL2	0.88	0.865	15.7	43.5	40.8			
	BRL3	0.896	0.89	20.3	15.6	64.2			
	BRL4	0.863	0.868	13.6	35.4	51			
	BRL5	0.919	0.913	8.3	60.6	26.1	5		
	BRL6	0.882	0.886	21.2	35.3	37.6	5.9		
	BRL7	0.847	0.844	15.7	31.8	44.8			7.7
Machinery	Victoria	0.897	0.887	30.4	28.2	41.4			
	BRL1	0.938	0.878	18.7	25.8	33.1	16.1		6.3
	BRL2	0.917	0.932	33	18.8	34.2			
	BRL3	0.905	0.916	36.4	7.3	56.3			
	BRL4	0.89	0.907	21.8	22.7	55.5			
	BRL5	0.892	0.898	20.3	44.9	30.3	4.5		
	BRL6	0.879	0.873	42.4	26.7	30.8			
	BRL7	0.86	0.848	34.1	18.4	41.3			6.3
Unknown	Victoria	0.913	0.915	13.4	40.3	46.4			
	BRL1	0.890	0.887	12.7	44.7	42.8			
	BRL2	0.897	0.896	22.6	41.8	35.6			
	BRL3	0.916	0.911	13.8	31.3	54.9			

	BRL4	0.874	0.883	8.9	38.6	52.5	
	BRL5	0.914	0.903	8.6	61.5	30	
	BRL6	0.893	0.893	17.3	38.1	44.6	
	BRL7	0.852	0.852	11.5	34.3	54.1	
Building	Victoria	0.913	0.897	26.9	32.8	40.3	
Power transmission	Victoria	0.915	0.843	56	20.4	16.3	7.3

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Appendix B – Description of the model as appears in the report at the end of year 1

Conceptual framework

The conceptual framework of the BN model is illustrated in Figure 3. This model determines the probability of a fire ignition to result in property loss. Fire ignitions can occur as a consequence of arson, lightning, powerline faults/failures and other unplanned anthropogenic sources. Once ignited, the model determines the probability of a fire to self-extinguish. If the ignition is successful and the initial attack operations are unsuccessful, then the model determines the probability of the fire to propagate and reach properties (Figure 3). This probability is influenced by the distance to properties, the spatial arrangement and exposure of the urban/wildland interface and fire weather condition. The final output of the model provides an estimation of the probability of property loss (Figure 3).

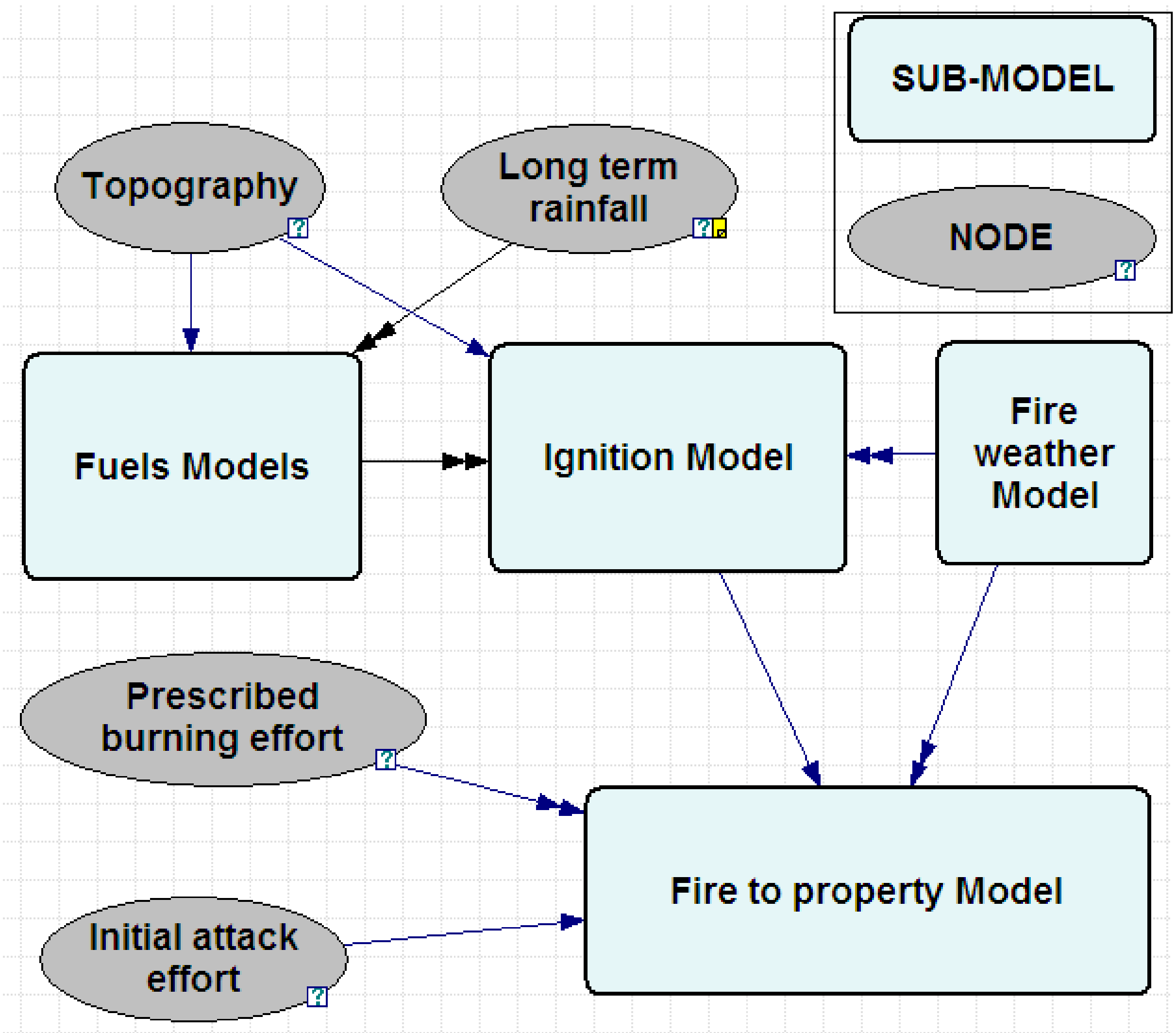

Figure 3. Conceptual framework of the Bayesian network developed to predict the probability of property loss from fire. The direction of the arrows indicates the direction of influence. Node descriptions appear in Table 1. See text and Figure 4, 5, 6 and 7 for the description of the sub-models.

Bayesian network structure

The BN consists of 46 nodes connected through 91 linkages and has been compiled using GeNIe v.2.0 package (Decision Systems Laboratory University of Pittsburgh, http://genie.sis.pitt.edu/, accessed August 2012). The BN includes 23 parentless nodes which represent the set of input variables required to calculate the CPTs of all the child nodes and determine the probability of property loss. The methodology used to derive the evidences of the CPTs of the parentless nodes is described in Section 6.1. Name, description and states of all the parentless nodes are provided in Table 1.

Node	Description	State
Topography	Terrain characteristics	Ridge, Slope, Gully
Distance to Road	Distance (m) to nearest mapped road (including fire trails)	<500, 500-1000, 1000-3000, >3000
House density	House density within 2km radius	0, 0-5, 5-20, >20
Powerline	Absence/presence of powerline	YES, NO
Region	Landscape characteristics	Blue Mountains, Hornsby, Woronora
Distance to WUI	Distance to wildland/urban interface (WUI). Distances were calculated along eight directions (i.e., N, 337.5-22.5; NE, 22.5-67.5; E, 67.5-112.5; SE, 112.5-157.5; S, 157.5-202.5; SW, 202.5-247.5; W, 247.5-292.5; NW, 292.5-337.5) and classified into six classes (i.e., <1km, 1-2.5km, 2.5-5km, 5-10km, 10-20km, >20km).	48 states resulting from the combination of eight direction and 6 distance classes
Gully Fuel Type	Type of fuel in Gully areas	Wet Sclerophyll Forest, Dry Sclerophyll Forest, Heath, Grassy woodland, Cleared
Slope Fuel Type	Type of fuel in Slope areas	Wet Sclerophyll Forest, Dry Sclerophyll Forest, Heath, Grassy woodland, Cleared
Ridge Fuel Type	Type of fuel in Ridge areas	Wet Sclerophyll Forest, Dry Sclerophyll Forest, Heath, Grassy woodland, Cleared
Prescribed burning effort	Chosen level of prescribed burning effort for the season	0, 1, 5, 10
Initial attack effort	Chosen level of initial attack effort available for the season	None, Ground, Air and ground, RAFT
Long term rainfall	12-month precipitation anomaly	< -10% long term average, >-10% and <10% long term average, >10% long term average
Ridge Fire Frequency	Fire frequency (events in the last 30 years) in Ridge areas	0, 1-2, 3-4, >4
Ridge Time Since Fire	Time Since Fire (years) in Ridge areas	1-3, 3-6, 6-9, 9-15, >15
Slope Fire Frequency	Fire frequency (events in the last 30 years) in Slope areas	0, 1-2, 3-4, >4
Slope Time Since Fire	Time Since Fire (years) in Slope areas	1-3, 3-6, 6-9, 9-15, >15
Gully Fire Frequency	Fire frequency (events in the last 30 years) in Gully areas	0, 1-2, 3-4, >4
Gully Time Since Fire	Time Since Fire (years) in Gully areas	1-3, 3-6, 6-9, 9-15, >15
Wind direction	Wind direction (degree)	North, North-East, East, South-East, South, South-West, West, North-West
Temperature	Max temperature (°C)	<20, 20-25, 25-30, 30-35, >35
Precipitation	Precipitation (mm)	0, 0-5, 5-10, 10-20, >20

Table 1. Name, description and states of all the parentless nodes of the Bayesian network framework.

The BN is divided into four sub-models: ‘*Fuels model*’, ‘*Fire weather model*’, ‘*Ignition model*’ and ‘*Fire to property model*’ (Figure 3).

The ‘*Fuels model*’ (Figure 3 and 4) accounts for the fuel arrangement and links it to the potential for fire to ignite and to spread. This model is based on previous research on fuel accumulation and arrangement in Australia (e.g., Keith, 2004; Hines et al., 2010; Watson et al. 2011). This model accounts for the distribution of five fuel types (i.e., wet sclerophyll forest, dry sclerophyll forest, grassy woodland, heath and cleared areas) across three distinct topographic features (i.e., ridge, gully and slope) as a function of time since fire, fire frequency and long term rainfall anomaly (which is one of the parent nodes of 'Derived Ridge/Slope/Gully Fuel Type' and 'Ridge/Slope/Gully Fuel Condition'; Figure 4). Fuels tend to follow a negative exponential increase with time since fire (e.g., Conroy 1993; Penman and York 2010). Fire frequency was included to account for the structural changes that can result from frequent fire in some ecosystems (e.g., Cary and Morrison 1995; Keith 1996;Watson et al. 2004). The long term drought anomaly accounts for the slower rate of fuel accumulation that occurs in drier periods (e.g. Penman and York 2010). The stratification across topographic features and fuel types allows accounting for variations in treatment and differing rates of fuel accumulation across the landscape. The output node (i.e., Landscape fuel condition) has five states (Low, Moderate, High, Very High and Extreme). These five states correspond to the levels described in Hines et al. (2010), and feed into the '*Ignition model*' and '*Fire to property model*'. The proportion of each topographic position in the landscape is used to go from the fuel distribution for ridges, slopes and gullies to the landscape fuel condition.

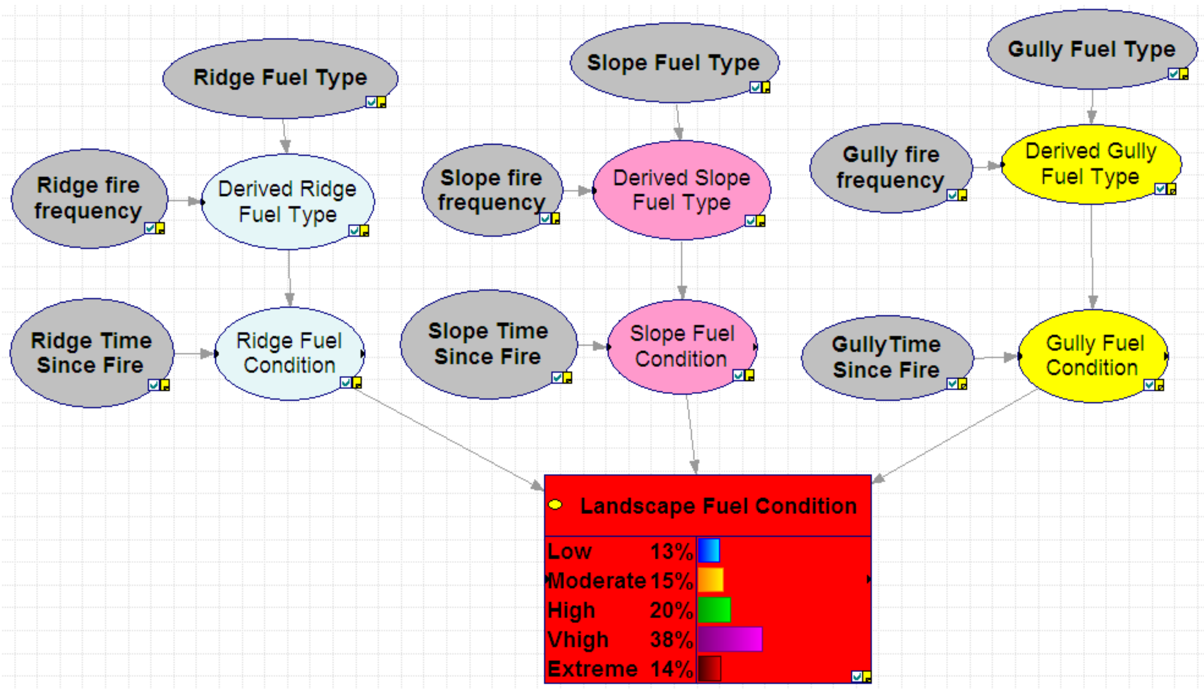

Figure 4. Structure of the '*Fuels Model*' of the Bayesian network. The input variables (i.e., parentless nodes) are in light grey and the model output (i.e., Landscape Fuel Condition) is in red. Parentless nodes description appears in Table 1. '*Long Term Rainfall*' is also an input to this submodel as shown in Figure 3.

The '*Fire weather model'* (Figure 3 and 5) is used to estimate the Forest Fire Danger Index (FFDI) based on key input weather variables (i.e., wind speed, wind direction, temperature and rainfall). FFDI is classified into five categories (i.e., low, high, very high, severe and extreme) and provides a "weather-based" indication of the potential for fire to ignite and spread. The network structure and CPTs for fire weather were learnt using an expectation maximisation algorithm (Korb and Nicholson 2011) from data collected at the Richmond BOM station for the period from 1970 through to 2010. FFDI was calculated from the equations in Noble et al. (1980). FFDI represents a key node used as input in both "*Ignition model*" and "*Fire to property model*". Relative humidity could be predicted from temperature, wind speed and precipitation. The model allows for the relative humidity value to be insert directly or learnt using this relationship if the data are not available for any reason.

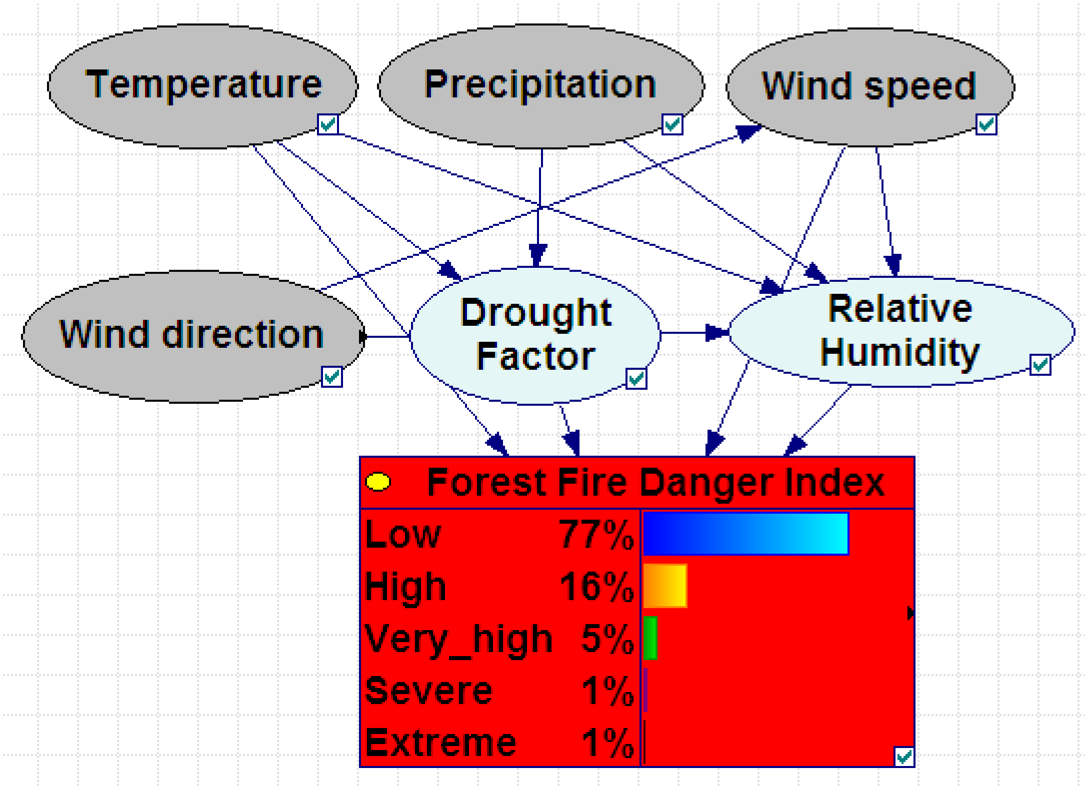

Figure 5. Structure of the '*Fire Weather Model*' of the Bayesian network. The input variables (i.e., parentless nodes) are in light grey and the model output (i.e., Forest Fire Danger Index, *FFDI*) is in red. Parentless nodes description appears in Table 1.

The '*Ignition model'* (Figure 3 and 6) estimates the probability of fire ignition. This model integrates fire weather (i.e., '*FFDI*') and fuel availability (i.e., '*Landscape fuel condition*') information generated through the '*Fire weather model*' and '*Fuels model*' with three variables affecting the probability of ignition: house density, distance to nearest road and powerline distribution. These variables are combined to estimate the probability of ignition due to arson, powerline faults/failures, lightning and other anthropogenic causes. Finally, the different fire ignition probabilities are combined to estimate the overall probability and number of fire ignitions (Figure 6).The underlying logic of this model is that proximity to road network, elevated house density and presence of powerline increase the probability of fire ignition under condition of high fuel availability and severe fire weather. Relationships and probabilities used in this model are based on the results of an empirical anlaysis of ignition probabilities within the Sydney Basin (Penman et al., in press). These models were then used to derive the relevant CPTs.

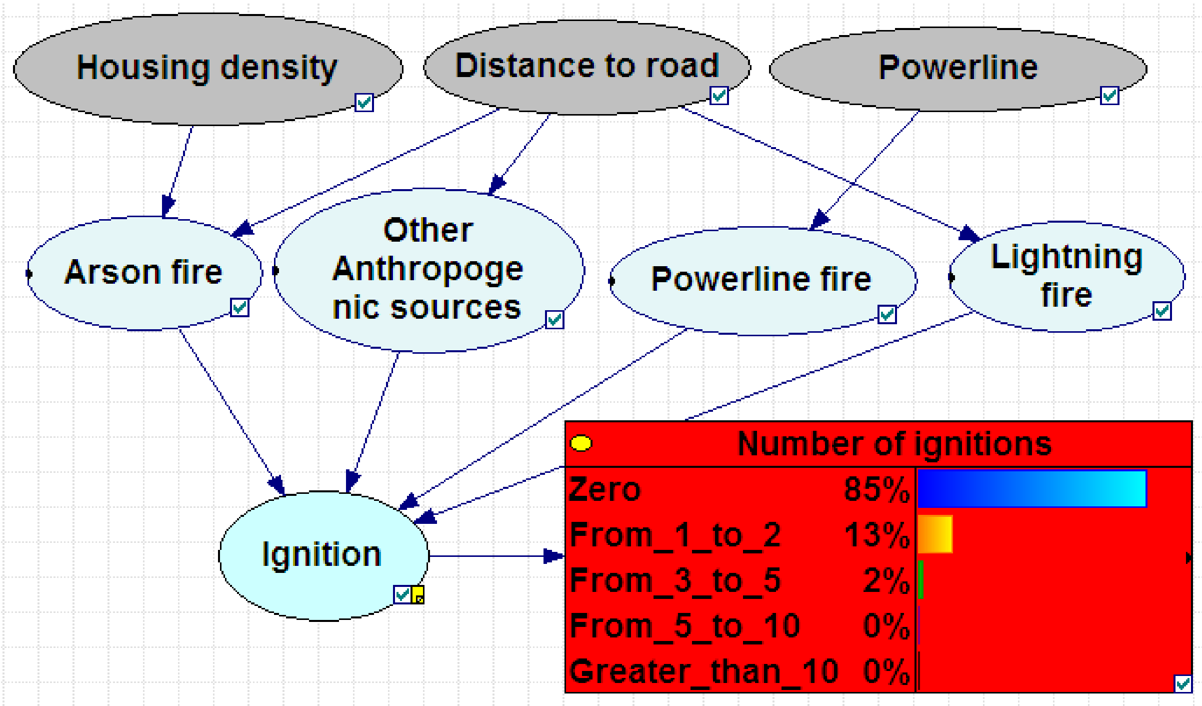

Figure 6. Structure of the '*Ignition Model'* of the Bayesian network. The input variables (i.e., parentless nodes) are in light grey and the model outputs (i.e., Number of ignitions) is in red. The outputs of '*Fire weather model*' and '*Fuels model*' are also input (see Figure 3) to the '*Ignition model*' and are not represented in this schematic. Parentless nodes description appears in Table 1.

The '*Fire to property model'* (Figure 3 and 7) accounts for the process of fire spread and provides an estimation of the probability of property loss from fire. This is achieved by combining wind direction, 'Prescribed burning effort', 'Initial attack effort' , '*Fire weather model*' and '*Ignition model*' outputs (i.e., *FFDI* and *Number of ignition*, respectively) with information about the spatial arrangement of properties (i.e., 'Distance to WUI') and spatially varying landscape characteristics (i.e., *Region*) (Figure 7). 'Prescribed burning effort', 'Initial attack effort' influence the probability of a fire to self-extinguish ('Self-Extinguish?' node in Figure 7). Once an ignition has occurred, it may self-extinguish or continue to grow relative to the wind direction. The model predicts the probability of a fire travelling a given distance on bearings relative to the wind as a function of fuels, weather and region. Finally, the model predicts the probability of fire having an intensity of 'zero', 'suppressible' (<4000kW)or 'uncontrollable' (>4000kW) at WUI as a function of distance from ignition, fuels, weather and distribution of the distance from WUI across all directions ('Distance to WUI'; Figure 7). Fires are more likely to travel different distances downwind as compared to upwind or parallel to the wind. Relationships and probabilities used in this model are based on a simulation study (Penman *et al. in review*) conducted in Phoenix Rapidfire (Tolhurst *et al.* 2008).

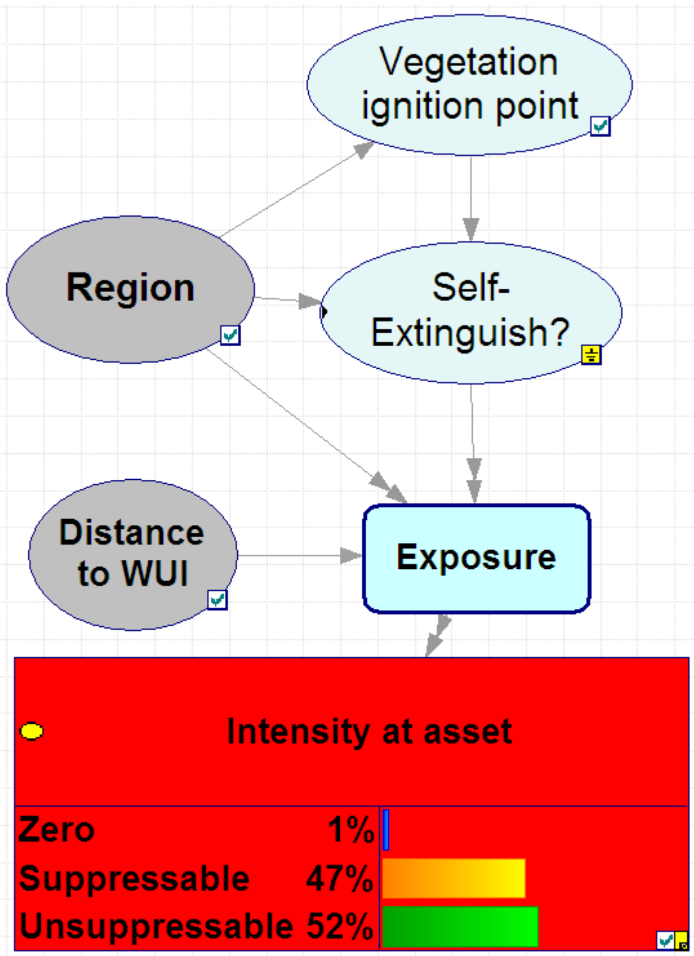

Figure 7. Structure of the '*Fire to property Model*' of the Bayesian network. The input variables (i.e., parentless nodes) are in light grey and the model outputs (i.e., Intensity at asset) is in red. 'Wind direction', 'Prescribed burning effort', 'Initial attack effort' and the outputs of '*Fire weather model*' and '*Ignition model*' are also input (see Figure 3) to the '*Fire to property model'* and are not represented in this schematic. Parentless nodes description appears in Table 1.