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NATIONAL FIRE DANGER RATING SYSTEM PROBABILISTIC FRAMEWORK PROJECT

Final report year three

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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 5km spatial resolution.

In year two, a “consequence-based” system (developed in Year 1) was refined and applied in two case study regions: the Sydney Basin, and the Victorian East Central Risk Landscape. The BN framework was successfully integrated with GIS facilities 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 (>4000kWm^{-1}, hereafter unsuppressible fires). Overall, the model indicated that the highest risk areas may potentially be identified by accounting for not only fire weather, but also fuels, the distribution of property, plus features inherent in the landscape that influenced fire spread.

The objective for the third stage of the project was to develop and test an operational application of the daily fire danger rating Bayesian Network model for two case study areas - Sydney Basin and the East Central Risk Landscape in Victoria. In this report, we present the results of the operational application of the model, quantify sensitivities of the model and finally we make recommendations for the future of the modelling approach.

We developed a prototype Fire Danger Rating (FDR) website for updating fire risk in real-time (30-60 seconds per case study). Maps are generated through use of landscape data and additional daily 3pm weather data downloaded from the Bureau of Meteorology. Across the 2014/15 season spatial variation was seen between the predictions from the FDR and that of FFDI. It is important to note that these variations exist despite the fact FFDI is an input into the model influencing ignition probability, fire spread and fire intensity. One of the main reasons for these differences is that FFDI only accounts for weather and does not consider topography, fuels, spatial arrangement of assets or the directionality of the wind.

The sensitivity analysis suggested that the model is performing well relative to expectations. Logical relationships and coarse scale patterns are holding true. The results indicate strong reliance on the empirical analysis of ignition probabilities in the landscape. FFDI was found to be the input node that required the greatest accuracy.

A number of recommendations were made by state agencies during an end of study review of the project. These included expanding the FDR website to new landscapes, with particular interest in assessing the model for grassland environments. In addition, the group thought the model had considerable capacity for longer term planning of fuel treatments, accounting for changing human patterns and future climates.

Overall, the project has succeeded in delivering a spatially-explicit framework capable of generating daily maps representing the distribution of the probability of property loss at 5km spatial resolution.

2 Purpose

The purpose of this document is to describe the activities and results of the third stage of the National Fire Danger Rating System – Probabilistic Framework Project. This project is funded by the Attorney-General's Department.

3 Background: Fire danger rating systems and Bayesian network

Fire danger rating systems have been developed in many fire-prone regions globally. These rating systems function primarily as a tool for assisting management authorities in a variety of fire management activities such as assessing the potential for fire occurrence and issuing fire warnings (Sharples et al., 2009). Traditionally, fire danger rating systems combine different environmental variables that affect fire behaviour, such as: weather data (e.g. temperature, relative humidity, wind speed and direction); terrain properties (e.g. slope and aspect); and fuel characteristics (e.g. type and load) (Burgan et al., 1998, Leblon et al., 2001, Matthews, 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 (Canadian Forestry Service, 1984).

In Australia the McArthur Fire Danger Rating System has been widely used since its formulation in the 1960s. This rating system assesses the potential for fires to ignite and spread, the difficulty of suppression, and the potential impact of fires on the community (i.e. property), in forest (i.e. Forest Fire Danger Index, FFDI) in grasslands (Grassland Fire Danger Index, GFDI) and different fuel types (McArthur, 1967). In this system, FFDI and GFDI are divided into six categories (i.e. low-moderate, high, very high, severe, extreme and catastrophic) representing increasing levels of fire severity and potential damage to property (McArthur, 1967, Noble et al., 1980, Bradstock and Gill, 2001, Sharples et al., 2009). However, the indices' 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 efficiently assess fire danger, it is necessary to develop a more robust “consequence-based” modelling framework that is 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, with 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 of predicting the probability of property loss due to fire. Indeed in Year 1 of the project, we demonstrated the potential for the approach through a pilot study and then extended this with two case studies covering daily risk for a 20 year period (1990-2010).

Research conducted in year two of the project provided baseline information valuable for understanding patterns of fire in NSW and Victoria. In year two, a "consequence-based" system (developed in Year 1) was refined and applied in two case study regions: the Sydney Basin, and the Victorian East Central Risk Landscape. The BN framework was successfully integrated with GIS facilities 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 (>4000k^{Wm-1}, hereafter unsuppressible fires). Overall, the model indicated that the highest risk areas may potentially be identified by accounting for not only fire weather, but also fuels, the distribution of property, plus features inherent in the landscape that influenced fire spread.

Data for the networks came from a variety of sources. Empirical modelling of human ignitions (both accidental and arson) and lightning ignitions for Sydney and the state of Victoria has been undertaken to support the application of the BN model in each case study. Two simulation studies have been undertaken using Phoenix Rapidfire to generate data regarding fire size and travel distances under a range of fire weather and fuel treatment scenarios (see Penman et al., 2014 for data for the Sydney Basin study). The results were then used to populate the BN model used to generate predictions of likelihood of unsuppressible fires reaching the urban interface.

The predictions derived from the BN model indicated that the probability of unsuppressible fires reaching the urban interface was most strongly influenced by weather conditions. In addition, the BN predictions indicated that such probabilities were 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 the incorporation of these elements into the BN framework exhibit considerable variation at fine temporal and spatial scales. Therefore, the probabilistic BN framework was considered to have the capacity to derive more carefully targeted 'fine-grained' warnings of potential property loss.

4 Project objectives

In the first two stages of the project we constructed an initial BN framework for the implementation of a "consequence-based" fire danger rating system and tested it for two case study regions. The resulting models were parameterised for the Sydney Basin (New South Wales) and for the East Central Risk Landscape (Victoria) and tested against real data at a daily time step for 20 years. These results were reported in the previous annual report for the project.

The objective for the third stage of the project was to develop and test an operational application of the daily fire danger rating Bayesian Network model for two case study areas - Sydney Basin and the East Central Risk Landscape in Victoria. In addition, we undertook a sensitivity analysis of the model to guide future model development.

In this report, we present the results of the operational application of the model (Section 5). We then describe the results of the sensitivity analysis (Section 6) and finally we make recommendations for the future of the modelling approach (Section 7).

5 Operational application

In this section, we briefly outline the model domain, the operational application model through a website, the architecture of the site and the results of the website.

5.1 Model Domain

FDR BN models for each of the study areas are described in detail in previous reports and therefore only a brief overview is presented here. A conceptual model of the network is presented below in Figure 1. 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 being exposed to an unsuppressible fire is a function of the distance from the ignition to the interface and the fire weather.

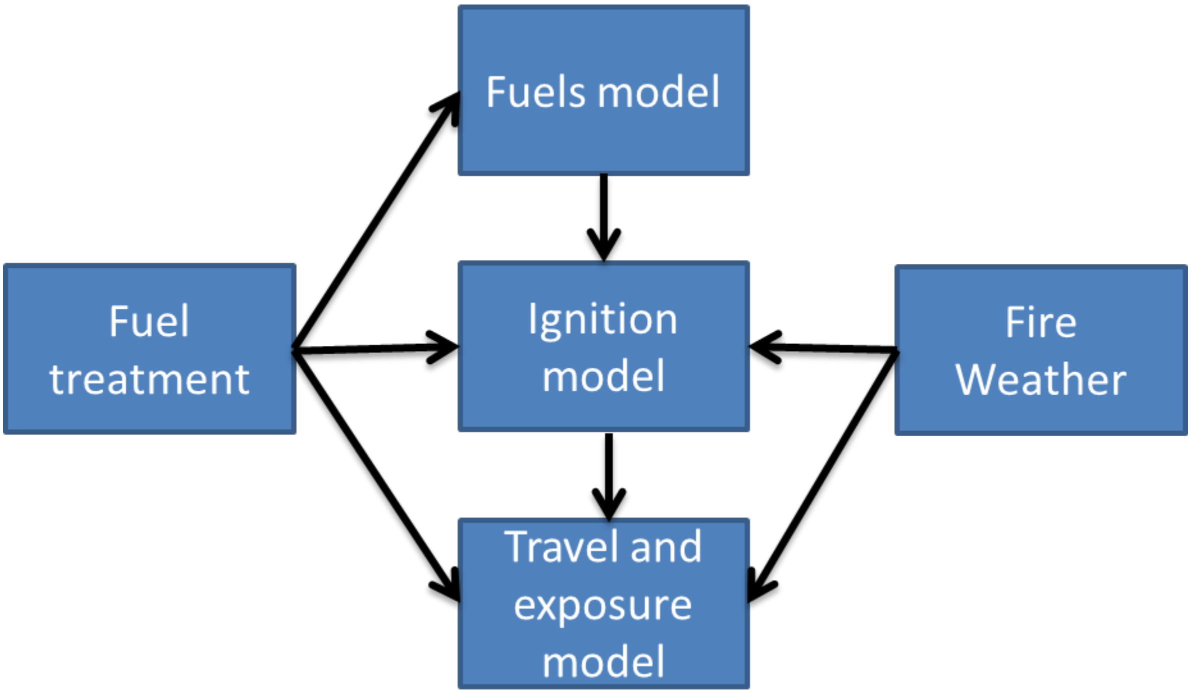


Figure 1: A conceptual model of the Bayesian Network model

The full BN models estimate the daily probability of an fire igniting and impacting upon property at an unsuppressible intensity (>4000kWm^{-1}) (Gill and Stephens, 2009). A full list of the nodes in the BN and their descriptions is presented in Appendix A. Predictions for the model are made for a 5km grid across each of the study areas. Unique values are calculated for each 5 x 5 km grid cell on a daily basis. Each cell is considered partially independent of other cells as the BN is not spatially connected across cells. Predicted probabilities of the BN are considered independent however, we undertake post-processing of the final output to overcome this issue. In short, the post-processing estimates risk over a weather dependent neighbourhood of cells, with the neighbourhood size increasing with FFDI (see report for year 2 for details).

5.2 Data inputs

Two broad data types are used in the BN model for the FDR. The first type is data that are embedded in the BN and are identical for all cells in the respective study areas. This includes the relationships for the probability of ignition and fire spread which have been derived from empirical or simulation analysis of data. The second type of data is those that vary between cells and may also vary between days. These data are hereafter referred to as input nodes in the model, as they are nodes in the BN that require unique inputs.

Data for the input nodes are probability distributions that replace a node's Conditional Probability Tables (CPTs). There is a CPT for each node that contains the joint probability distributions for the variable (Korb and Nicholson, 2011). Root nodes occur at the top of the model and are not influenced by other variables in the model. These nodes have a conditional probability table containing a single probability for each state in that node. Child nodes are variables that are influenced by one or more variables (parent nodes). These nodes have a conditional probability table that represents the probability of a given state in the child node given the state(s) in the parent node(s). For any given cell in a raster the CPTs are generated from the distributions that apply in that cell. For example, the distribution over all three topographies that exist in the given 5km x 5km cell in the grid are calculated, and then entered as the CPT for topography. The list of input nodes and the data source used in the model is presented in Table 2.

Inputs for the majority of nodes were based on static values for the entire season for both models. This meant that a single calculation of each variable was made for each cell and these data stored prior to the operationalization of the model. The exceptions were forest fire danger index (FFDI) and wind direction at 3pm. Both of these were sourced daily from the Bureau of Meteorology.

Table 1. Input nodes in the model and the source data for East Central Risk Landscape (ECRL) and Sydney Basin. DELWP= Victorian Department of Land, Water and Planning, NSW RFS = New South Wales Rural Fire Service, BOM = Australian Bureau of Meteorology. See Appendix A for a full description of the nodes.

Input node	Source ECRL	Source Sydney
House density (HouseDens)	Calculated from DELWP asset layer	Calculated from Land Planning Information cadastral layer
Vegetation at ignition (IgFuel)	Developed from Ecological Vegetation Class layer	Developed from Keith (2004) vegetation layer
Distance to road (D2RD)	Calculated from road layer provided by DELWP	Calculated from road layer provided by NSW RFS
Elevation (Elevation)	Geoscience 9 sec digital elevation model	Geoscience 9 sec digital elevation model
Topography (Topography)	Derived from Geoscience 9 sec digital elevation model	Derived from Geoscience 9 sec digital elevation model
Region (Region)	NA	Spatial location reflecting different fire behaviours see Penman et al. (2014)
PB effort (PBEffort)	Assessment of fuel age in surrounding 20 x 20km based on DELWP fire history layer	Assessment of fuel age in surrounding 20 x 20km based on NSW RFS fire history layer
Ridge/Slopes/Gully fuel type (Ridge_/Slopes_/Gully_Fuel_Type)	Developed from Ecological Vegetation Class layer	Developed from Keith (2004) vegetation layer
Ridge/Slopes/Gully time since last fire (Ridge_/Slopes_/Gully_TSF)	Derived from DELWP fire history layer and Geoscience 9 sec digital elevation model	Derived from NSW RFS fire history layer and Geoscience 9 sec digital elevation model
Powerline distribution (Powerline_distribution)	Occurrence of high voltage powerlines sourced from DELWP	Occurrence of high voltage powerlines sourced from NSW RFS
Distance to asset on each cardinal bearing (W,X,Y,Z) (W/X/Y/Zdist2asset)	Calculation based on DELWP asset layer and definitions of interface of Radeloff et al. (2005)	Calculation based on Land Planning Information cadastral layer and definitions of interface of Radeloff et al. (2005)
FFDI (FFDI)	BOM 3 pm FFDI	BOM 3 pm FFDI
Wind direction (wind_dir)	BOM 3pm wind direction	BOM 3pm wind direction

5.3 Website development

The Fire Danger Rating (FDR) website is a prototype website designed to test the feasibility of a national rating system for fire risk that is capable of being updated in real-time. Ultimately, the maps are generated by combining the static and dynamic input data into the FDR BN. The website has been created to depict risk on a daily basis at a 5km resolution. The website uses Bureau of Meteorology (BOM) data through an RSS feed and updates the model, assuming that all other variables are static within a given year. The program downloads the 3pm predicted FFDI and wind direction, updates the BN, makes a prediction and projects the predictions onto Google Maps. An example prediction for the Sydney Basin is shown in Figure 2 and an example projection for the East Central Risk Landscape is shown in Figure 3. Once the program has run once, it checks three times per minute for updates in the weather data and updates the output accordingly.

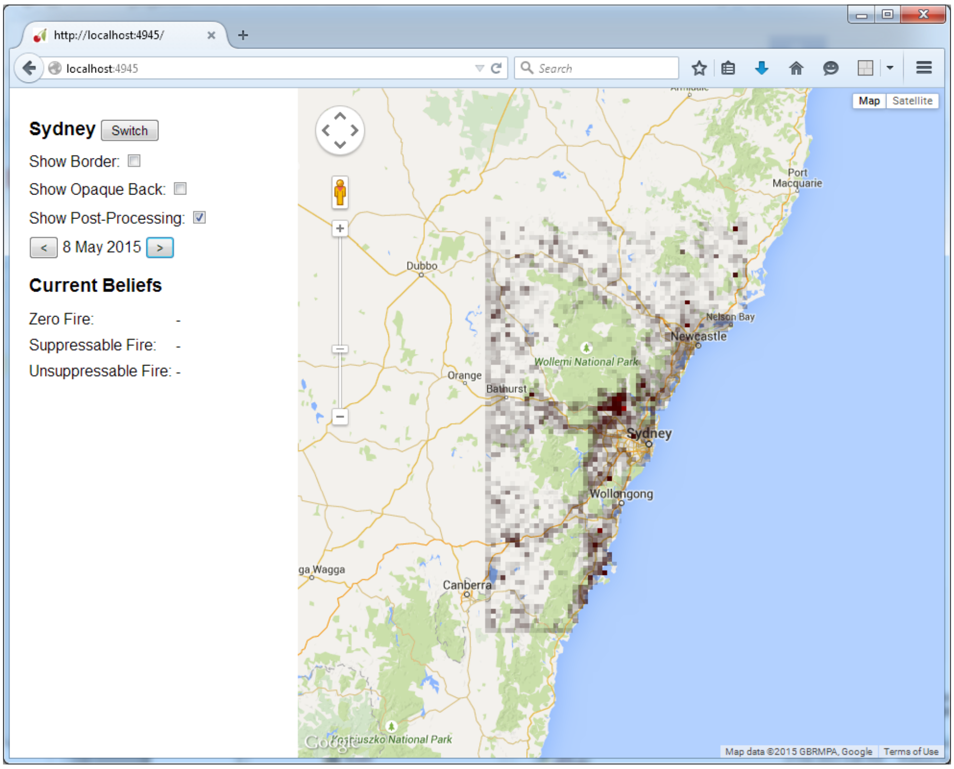


Figure 2: Example of the interface for Sydney, after data has been processed for the day

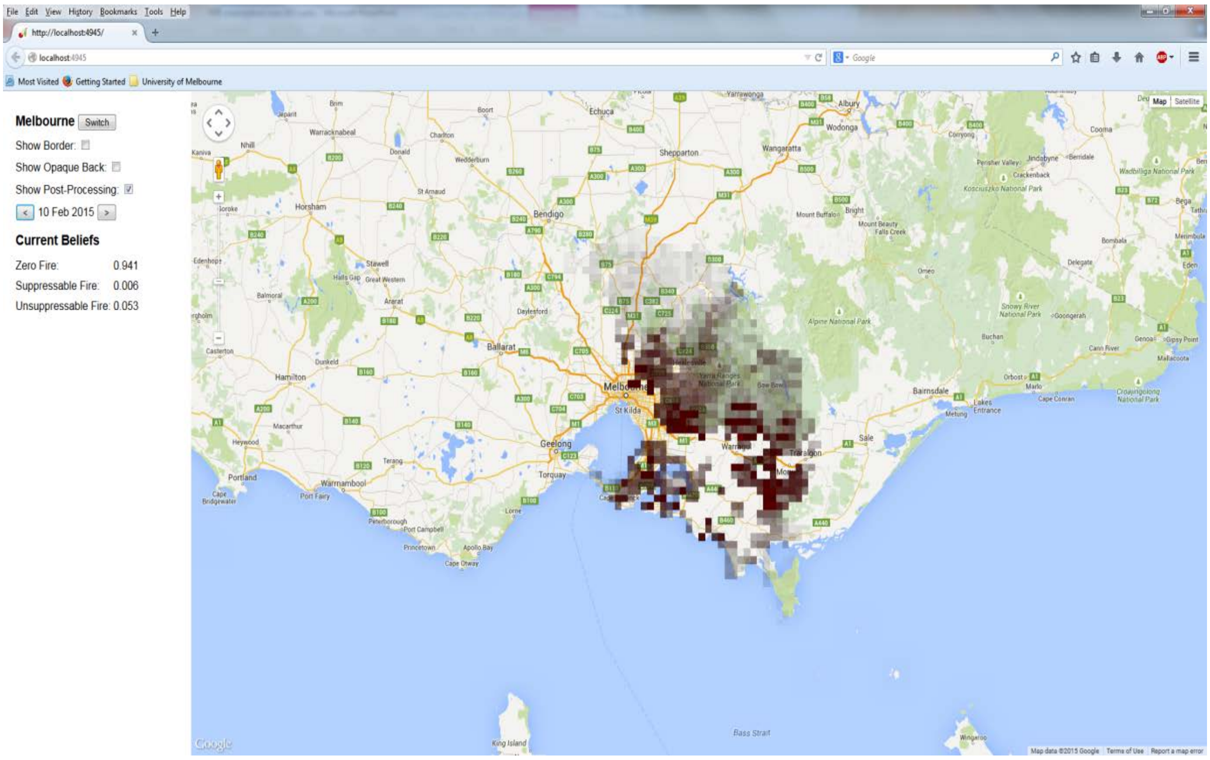


Figure 3. Example of the interface for the East Central Risk Landscape.

5.4 Architecture of the website

The site consists of a Python backend (which processes the input data with the BNs and generates the fire danger maps) and browser-based front-end.

5.4.1 Backend

The Python backend uses the CherryPy web framework. This allows the site to be organised as a Python class, with class methods corresponding to pages that are delivered to the browser. The main web server is located in 'firedangerserver.py'.

All the main data processing for the software is contained within the 'location.py' file. This file contains generic methods for processing the input data using the BNs in a given location. It also contains location-specific information needed to run the processing for both Sydney and Melbourne. (The organisation for a production system would be different.)

The 'location.py' file also contains the implementation for the pre-processing functions of the static data. To run (and re-run) these functions, call the 'process_input_layers.py' file from the command line (assuming layerDir in settings.py points to the correct fdr_layers directory). Pre-processing can be slow, so each step is commented out by default. It is recommended that only one step be uncommented and run at a time.

The main server can be run by calling 'firedangerserver.py'. This file also contains a scheduling thread that will periodically download data and then process that data using the BNs. The scheduling thread will also monitor the output directories and, if the output files for a particular day go missing or if new input data is detected, will regenerate the maps for that day. This can be used to re-run processing, or run processing anew on new data.

5.4.2 Frontend

The frontend is written in HTML, CSS and Javascript. jQuery is used a lightweight UI and AJAX framework, and Google Maps is used for the mapping interface. An example of the front end is shown in Figure 2. The user is able to switch between Sydney and Melbourne, as well as moving back and forth to particular days. In addition, the user can hover over parts of the map to get more information about the probabilities of no fire, suppressible fire (<4000kWm^{-1}) and unsuppressible fire.

5.5 Operational testing

The model was run over the 2014/15 on a standard laptop. The time taken for updating per day ranges between 30 and 60 seconds for each landscape, with an average time of 42 seconds. Due to the timing of the project, only part of the season was run live. For the remainder of the season, an additional program was developed to retrospectively predict the FDR values for new data. This functionality will also allow for the system to be tested retrospectively for other time periods or in other study areas.

Outputs from the daily analysis for the 2014/15 fire season are supplied with this report in PDF format. Presented in the file is prediction from the FDR adjacent to the 3pm FFDI. Examples from both the Sydney Basin and East Central Risk Landscape study regions are provided below (Figure 4 - Figure 7). Lower risk areas (projected in white, see Figure 4) suggest the probability of a fire starting, spreading and impacting on the urban interface is low. Higher risk areas (projected in green, see Figure 5) suggest the probability of a fire starting, spreading and affecting the interface is high.

Across the season variations were seen between the predictions from the FDR and that of FFDI. It is important to note that these variations exist despite the fact FFDI is an input into the model influencing ignition probability, fire spread and fire intensity. One of the main reasons for these differences is that FFDI only accounts for weather and does not consider fuels, spatial arrangement of assets or the directionality of the wind.

During the 2014/15 fire season, no fires impacted on property in either study area which limited analysis.

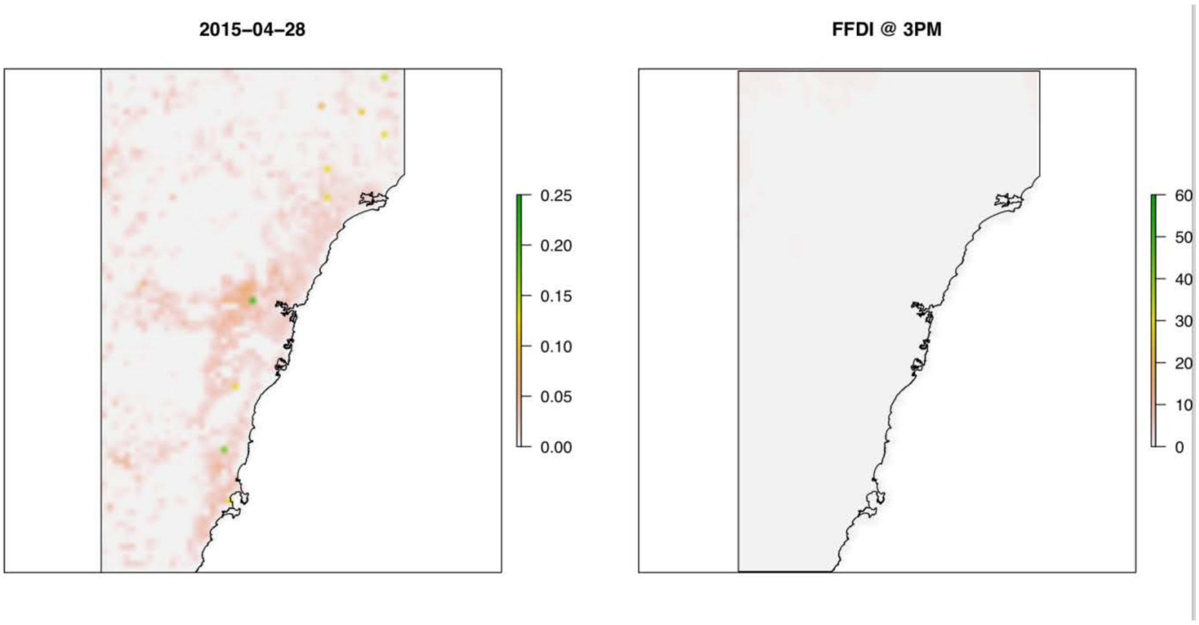


Figure 4. Example projection for the 28th of Aril 2015, for the Sydney Basin region.

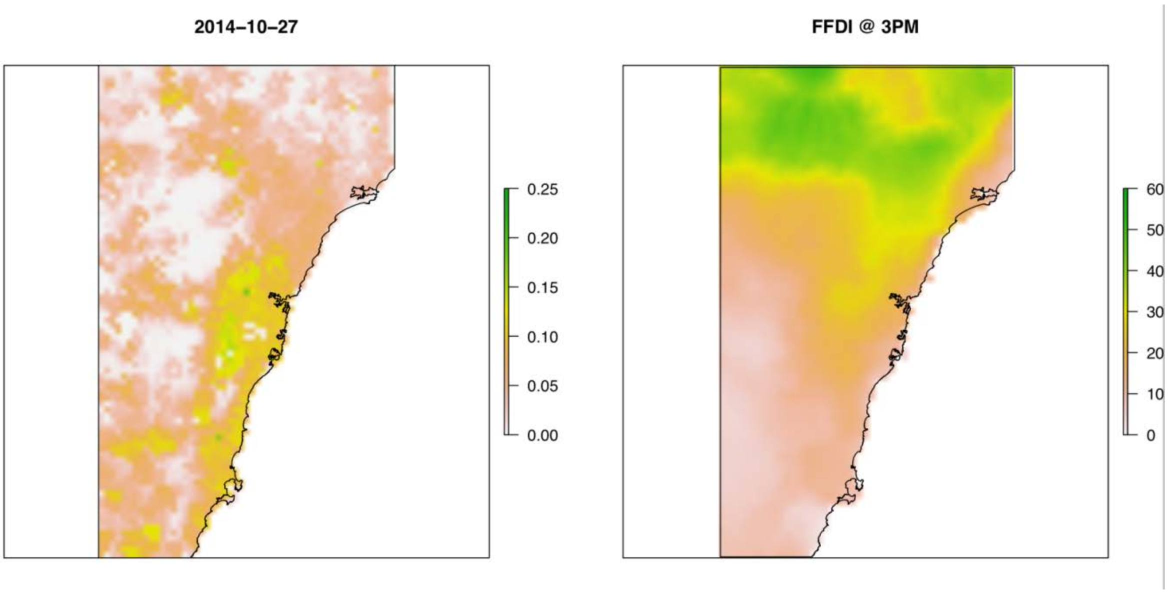


Figure 5. Example projection for the 27th of November 2014, for the Sydney Basin region.

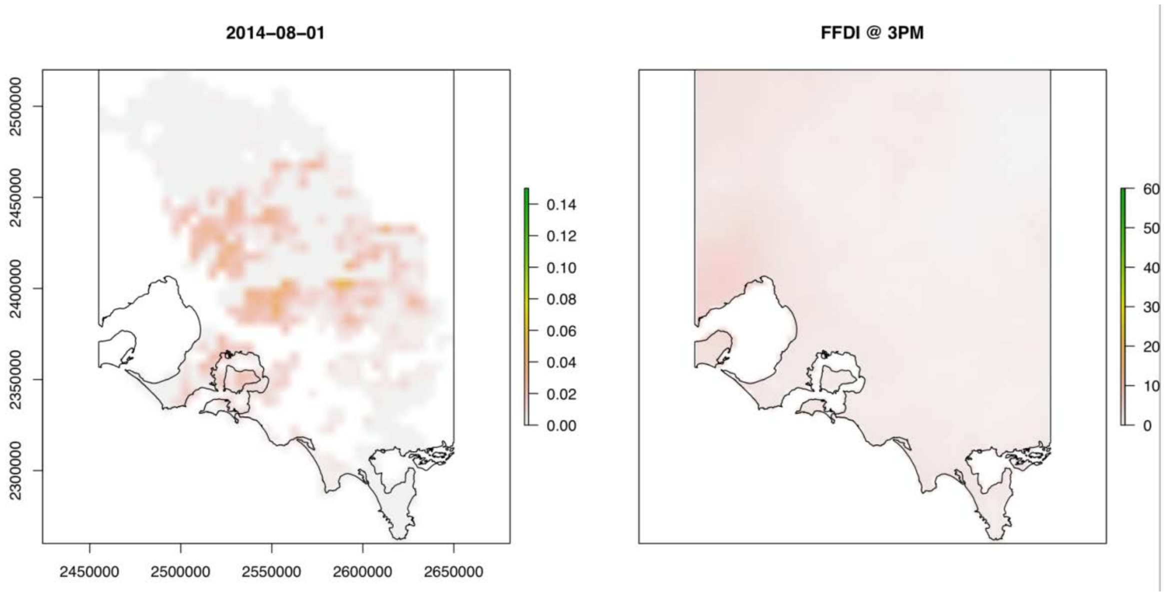


Figure 6. Example projection for the 1st of August 2014, for the East Central Risk Landscape case study region

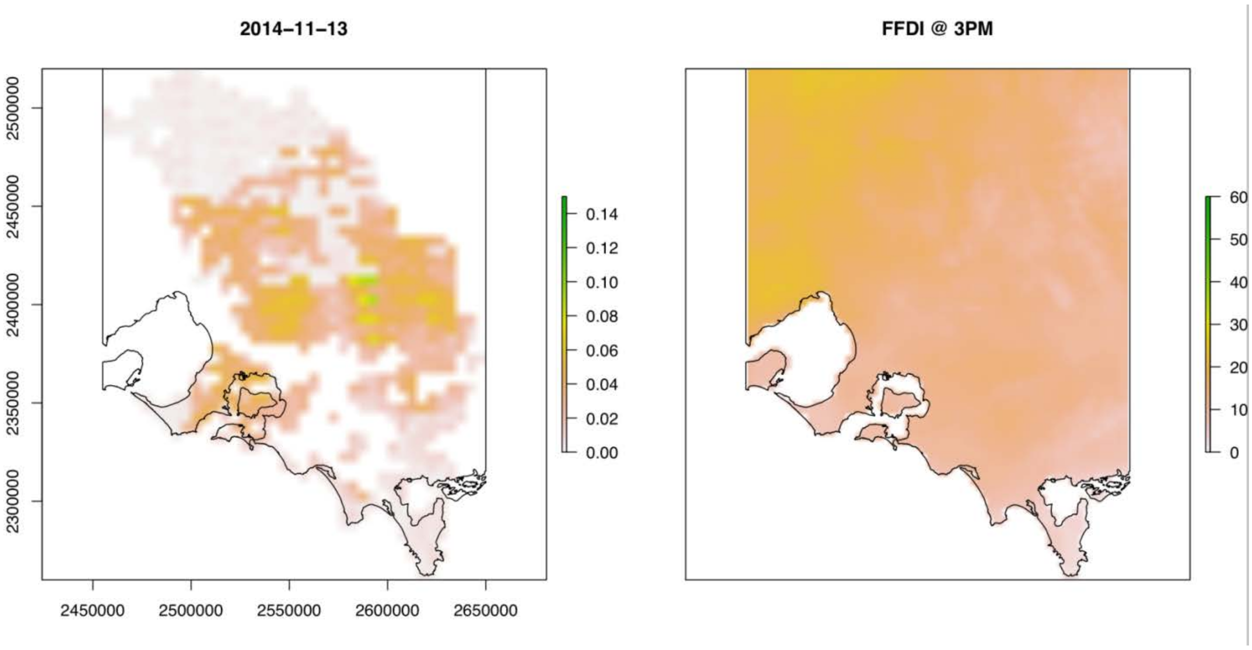


Figure 7. Example projection for the 13th of November 2013, for the East Central Risk Landscape case study region.

6 Sensitivity analysis

Two different sensitivity analyses were undertaken to examine the sensitivity of the model to the structure and the input nodes of the model. Sensitivity to findings is a bottom up approach across the entire network which determines which variables have the greatest influence in the output node. Sensitivity to parameters is a top down examination of the influence of the input nodes on the output node. Combining these two approaches allows us to determine which variables are most important in the model prediction and which input nodes we require the greatest confidence in.

6.1 Sensitivity to findings

In the BN field, a 'sensitivity to findings' analysis identifies what information can be learnt about a variable (the target variable) if further information is discovered about other variables (evidence or findings variables). This type of analysis assumes that such evidence does *not* include changes to the relationships between the variables in the network. The target variable can be any node – whether a root, intermediate or leaf node – and the same applies to the evidence variables. Evidence is never entered into the network, instead distributions are entered which is equivalent to adding likelihood evidence on the node when it has a uniform CPT. Hence, a sensitivity to findings analysis will provide information regarding which nodes are most influential, important or informative in terms of the final output. Mutual information between the intensity at the asset (the output node) and all other variables in the network as provided in Figure 8 for Sydney and Figure 9 for East Central Risk Landscape.

In sensitivity to findings analyses, it is expected that nodes that are *closer* to the target (i.e. having smaller numbers of arcs in the path) are more informative, unless other nodes happen to be particularly significant. Indeed we found these results for both study areas with the intensity and asset-reached variables in each cardinal directional ranking highly (z_int,y_int, x_int, w_int). However, the self-extinguish node (*selfext*) and the two ignition related nodes (*Number_of_ignitions* and *P_ignit*) also rank very highly in the model. This result is particularly important as these nodes are several steps removed from the output node. We have a high degree of certainty in these nodes as data for these nodes have been derived from empirical models developed in the Sydney Basin for the last 20 years, and in the East Central for the last 10 years. It can also be seen that Forest Fire Danger Index (FFDI) is ranked lower than might be expected intuitively (Figure 8; Figure 9). FFDI is one of the parent nodes appearing at the top of the model and is therefore more removed, hence given a lower ranking. However it should be noted that FFDI influences all processes in the model including ignition and fire spread which the model is sensitive to.

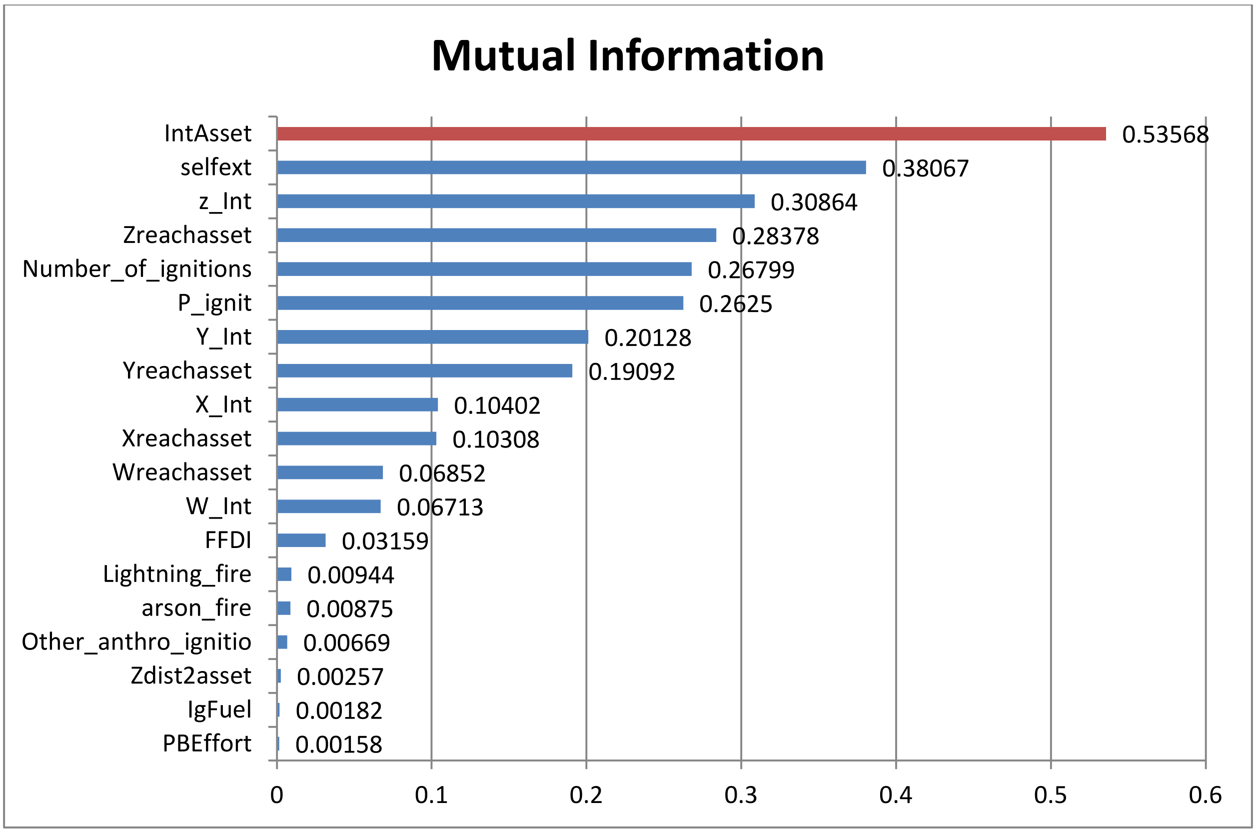


Figure 8: (Sydney Basin) Sensitivity to findings in the existing network (top 20 nodes out of 44)

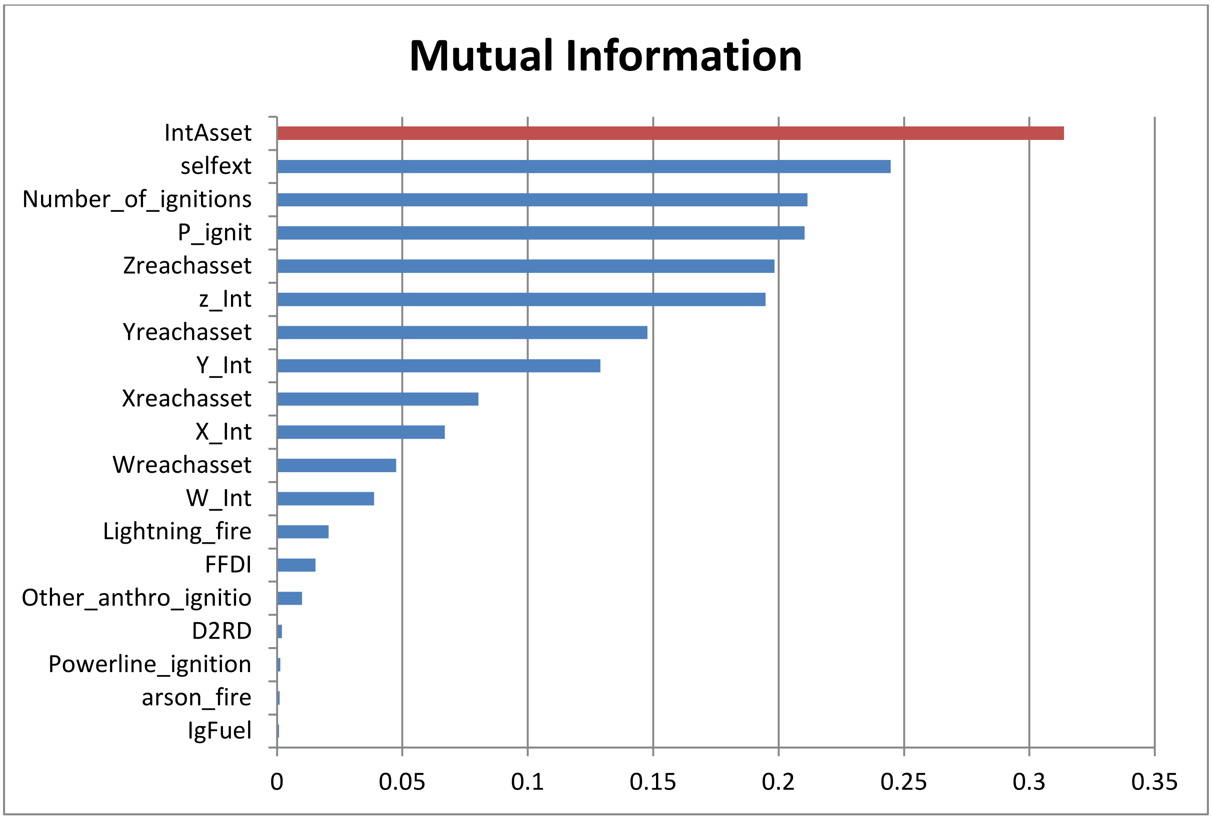


Figure 9: East Central Risk Landscape - Sensitivity to findings in the existing network (top 20 nodes out of 44)

6.2 Sensitivity to Parameters

A 'sensitivity to parameters' analysis was also conducted which involves varying the CPT parameters within the model. This type of analysis can be useful for a number of reasons. Firstly, it allows the identification of which CPT parameters have the greatest influence on the model conclusions. In turn, this identifies which parameters require the highest level of confidence in the input data and for which parameters accuracy is less critical.

A variance-based sensitivity analysis (VBSA) was used to explore the model outputs sensitivity to CPT parameters. Full details of this approach are beyond the scope of this report, however in short, a VBSA method explores how the variance over the range of inputs of a model (i.e. CPT parameters) affects the variance of the output (i.e. beliefs). This analysis has been restricted to consider uncertainties across the input nodes. The parameters in the analysis are given as the centre points of normal distributions (truncated to between 0 and 1) that have a standard deviation of 0.5 (that is, *half* the probability interval).

Figure 10 and 11 show the results of the analysis for Sydney Basin and East Central Risk Landscape. Numbers on this graphic are sensitivity indices with the First Order column describing the effect of a node in isolation from other nodes, while the Total Order column is describing the effect of a node when it is varying in conjunction with other variables. Higher numbers indicate higher sensitivity. Results presented here are approximate as the approach is a simulation approach to sensitivity.

Node	First Order	Total Order
FFDI	1.014543119	1.558723577
IgFuel	0.355288737	0.422519673
Ridge_TSF	0.328048297	0.765280735
Elevation	0.321878932	0.387677778
PBEffort	0.172667417	0.422726399
D2RD	0.151721644	0.417583295
Region	0.139727262	0.435966686
Topography	0.10653892	0.179798243
Gully_TSF	0.068332747	0.340173661
Powerline_distribution	0.065430037	0.095075521
wind_dir	0.037397436	0.314402435
Slopes_TSF	0.03696028	0.204036915
HouseDens	0.033285666	0.18301862

Figure 10: Sydney Basin - Sensitivity to the root input nodes

Node	First Order	Total Order
FFDI	1.388120304	2.309422701
D2RD	0.875420839	1.35279544
HouseDens	0.843919452	1.26767448
IgFuel	0.559645145	1.466849033
Elevation	0.543735152	0.747513929
PBEffort	0.218764006	0.88005945
Region	0.173280955	0.277515101
wind_dir	0.162199476	1.482606421
Powerline_distribution	0.154117468	0.284733596

Figure 11: East Central Risk Landscape - Sensitivity to the root input nodes

In both regions, the results of the model were most sensitive to changes in FFDI when considering both the first order and total order values. This result is to be expected but supports the functionality of the model. A large range of studies have highlighted the pivotal role FFDI plays in predicting fire extent and impact on assets (Bradstock et al., 2009, Cary et al., 2009, Blanchi et al., 2010, Gibbons et al., 2012, Price and Bradstock, 2013, Blanchi et al., 2014, Penman et al., 2015).

There was variance in the secondary influences between the two study areas. In the Sydney Basin model, the model was also sensitive to values which relate to fuel loads, in particular ridge time since fire (Ridge_TSF) is particularly significant. In contrast, the East Central Risk Landscape model was sensitive to values for the built environment- (distance to road (D2RD) and house density (HouseDens)), fuel type at the ignition point (IgFuel) and wind direction (wind_dir). These results probably reflect the fact that the eastern portion of the East Central Risk Landscape study area is primarily forested areas with few roads and houses, except on the western fringe which would primarily be exposed to fires under easterly winds (an uncommon occurrence in this landscape). This pattern doesn't hold in the western and southern parts of the study areas, where assets are likely to be exposed to fires from most directions. In contrast, assets in Sydney Basin are exposed in most compass directions for many ignition points.

6.3 Conclusions of the sensitivity analysis

It is vital to ensure the inputs in any model are rigorously collected and judiciously used. Overall, the sensitivity analysis suggests that the model is performing well relative to expectations. Logical relationships and coarse scale patterns are holding true. The results indicate strong reliance on the empirical analysis of ignition probabilities in the landscape. Further work to refine these models will be valuable, if new data become available. Simulation study results were less critical but still important. FFDI was found to be the input node that required the greatest accuracy. In our study, FFDI was taken as a single value for 3pm based on forecast information. This could be improved by better understanding the accuracy of these forecasts and including these uncertainty values into the model. This would be possible by comparing forecast information with observations at BOM stations.

7 Recommendations for future applications

On June 12th 2015 a workshop was held with representatives from the Victorian Department of Environment, Land, Water and People (DELWP), the New South Wales Rural Fire Service (RFS) and Victorian Country Fire Association (CFA). The model was presented and discussed in detail, with representatives having the opportunity to provide feedback on both the model and the web based tool to determine its limitations and value. The suitability of the model was discussed and opportunities for future developments were outlined.

Presented below is a summary of the outcomes from the workshop and directions for future development.

1. **Testing the models applicability to other areas.**
   The model could be tested in other study locations to determine the applicability of existing platforms to accurately predict risk in new locations. We would expect predictive accuracy to be highest for those areas that have similar environmental conditions to the two case study landscapes. Models should not be applied outside forested systems as they have not been developed for these environments (see point 2).
2. **The system, as it currently stands, is heavily focused on forested areas**.
   Analysis of ignition data and simulation studies in the project has focused on two heavily forested regions. Attempting to develop the model for one or more grassland regions would provide insight as to the suitability of this model for application at the state and national level.
3. **An examination of the potential to integrate the BN model (or aspects thereof) with the National Fire Danger Rating Project.**
   Aims of this project and the national fire danger rating project are converging. The models developed in this study broadly cover the areas identified as being important by the national fire danger rating project. One key area missing from the current BN that is required in the National Fire Danger Rating Project is suppression. While not explicitly included in the FDR model used here, this is a feasible (and useful) addition to the model. Different suppression techniques could be easily added through the models of Plucinski (Plucinski, 2012, Plucinski et al., 2012) and Penman et al. (2013). Preliminary testing suggests this is feasible and relatively accurate.
4. **Consideration of evaluating risk assessments of different management approaches.**
   The model presented here was developed for a daily assessment of fire risk to people and property. The fuel layers can easily be altered to include various fuel management approaches. Using the BN model in an annualised format would allow users to assess changes in risk as a result of fuel management (Penman et al., 2014, Penman et al., 2015), or changing patterns of urban development. Such information would provide management agencies with a quantitative assessment of alternate fuel strategies. Furthermore, this analysis could incorporate current and future climate scenarios will be important to effectively calculate future risk (and changes in the level of risk) in different landscapes.

8 Conclusion

Over the three years of the study we have demonstrated the value of the BN approach for predicting fire risk to people and property at interface. The project has taken static BNs to a spatial application which has ultimately been used through a web interface to predict daily risk values at the interface. These steps have required considerable analysis of data through empirical and simulation studies which in themselves have presented new research findings.

The underlying philosophy of the approach is that patterns of fire behaviour and risk are relatively predictable when the uncertainty is explicitly considered. Our BN approach does not seek to remove the need for fire behaviour simulation, rather it builds on fire simulation studies to rapidly evaluate risk and highlight areas of potential concern. Comparisons between the BN approach and the burn probability approach (Wei et al., 2008, Parisien et al., 2010, Cochrane et al., 2012) that has been widely applied in Australia through management agencies would be valuable in developing a comprehensive national fire danger rating system.

One of the major hurdles that will need to be addressed in the application of our proposed system is the interpretation of risk values. Our model predicts the risk of an unsuppressible fire at the interface on a scale of 0 to 1. These values are predictions across the probability of a fire igniting, spreading and impacting at an intensity >4000kWm^{-1}. Due to the complexity of these relationships and the interactions between the model components, these values should not be considered an absolute risk value, i.e. 0.1 does not necessarily equal a 10% risk. Therefore, the challenge is determining threshold values of concerns. Existing research in this project can be used to inform that debate, however decisions will need to be made by managers as to when actions are triggered. Given the potential implications of an incorrect decision, determining the appropriate threshold values will require careful consideration and debate.

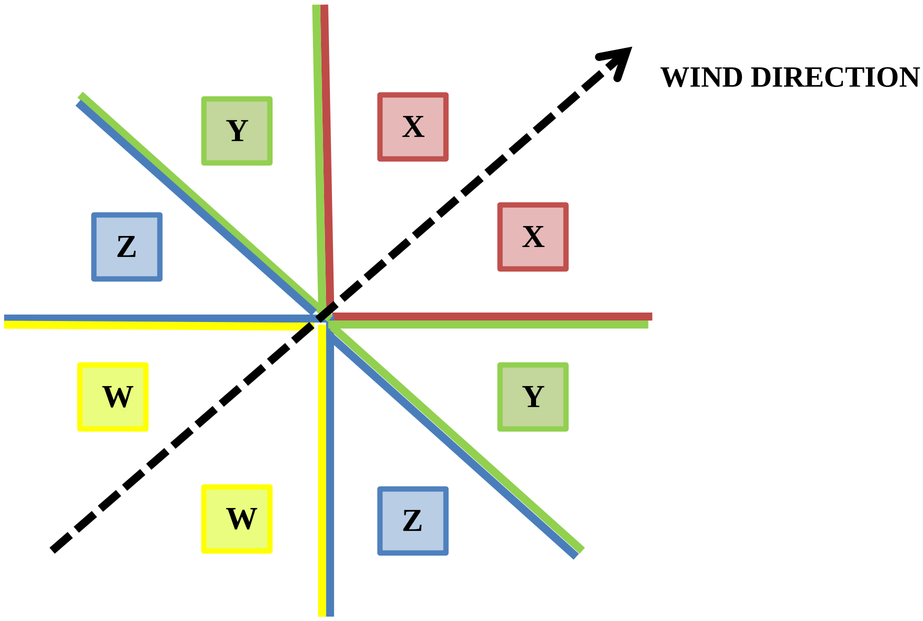
The overall aim of the three year project was to test whether a risk based approach to fire danger rating systems was possible, which we have demonstrated to be true. Models presented here are readily updatable and are a starting point for the development of a more comprehensive system. The question as to whether this is the best system remains subject to debate. To answer this question satisfactorily would require a quantitative comparison of all available candidate models. The final answer may indeed be an ensemble modelling approach.

9 Appendix A: Input nodes in the model, node descriptions and source data.

Node name in BN	Node description	Source of the input data
arson_fire	The probability of a fire starting from arson	Empirical analysis
D2RD	The distance from mapped road	Static spatial data
Elevation	Elevation above sea level	Static spatial data
FFDI	Forest Fire Danger Index	BOM dynamic data
Gully_Fuel_Condition	The fuel condition in the gully	Static spatial data
Gully_Fuel_Type	The fuel type in the gully	Static spatial data
Gully_TSF	Number of years since there was last a fire in the gully	Static spatial data
HouseDens	The density of housing	Static spatial data
IgFuel	The presence of dry forest (or not) at the point of ignition.	Static spatial data
IntAsset	The intensity of fire at assets	Simulation analysis
Landscape_Fuel_Condition_	This node is averaged across each cell for the ridge, slope or gully	Static spatial data
Lightning_fire	Probability of a fire being caused by lightning	Empirical analysis
Number_of_ignitions	The total number of ignitions	Empirical analysis
Other_anthro_ignition	The probability of accidental anthropogenic ignitions.	Empirical analysis
P_ignit	Probability of total ignitions	Empirical analysis
PBEffort	Prescribed burning effort	Empirical analysis
Powerline_distribution	Presence of powerlines	Static spatial data
Powerline_ignition	The probability of an ignition caused by a powerline	Empirical analysis
Region	Sydney only, three broad fire landscapes were identified. This node identifies which landscape values are to be used.	Static spatial data
Ridge_Fuel_Condition	The fuel condition at the ridge	Static spatial data
Ridge_Fuel_Type	The fuel type at the ridge	Static spatial data
Ridge_TSF	Number of years since there was last a fire at the ridge	Static spatial data
selfext	Probability that a fire will self-extinguish	Empirical analysis
Slope_Fuel_Condition	The fuel condition on the slope	Static spatial data
Slopes_Fuel_Type	The fuel type on the slope	Static spatial data
Slopes_TSF	The number of years since there was last a fire on the slope	Static spatial data
Topography	Ridge, slope and gully.	Static spatial data
W_Int	This node identifies the fire intensity at a given distance in the 'W' direction (see Figure 1).	Simulation analysis with static spatial data

Node name in BN	Node description	Source data
Wbearing	Projected bearing. This node defines the direction, i.e. the compass bearings for 'W' direction (see Figure 12	Simulation analysis
Wdist2asset	This node represents the distance from potential ignition point to mapped assets in the 'W' direction (see Figure 12).	Simulation analysis with static spatial data
wind_dir	This node represents wind direction	BOM dynamic data
Wreachasset	Probability of a fire moving from the ignition point to an asset in the 'W' direction (see Figure 12).	Simulation analysis with static spatial data
X_Int	This node identifies the fire intensity at a given distance in the 'X' direction.	Simulation analysis with static spatial data
Xbearing	Projected bearing. This node defines the direction, i.e. the compass bearings for 'W' direction (see diagram below).	Simulation analysis with static spatial data
Xdist2asset	This node represents the distance from potential ignition point to mapped assets in the 'X' direction.	Simulation analysis with static spatial data
Xreachasset	Probability of a fire moving from the ignition point to an asset in the 'X' direction.	Simulation analysis with static spatial data
Y_Int	This node identifies the fire intensity at a given distance in the 'W' direction.	Simulation analysis with static spatial data
Ybearing	Projected bearing. This node defines the direction, i.e. the compass bearings for 'Y' direction (see diagram below).	Simulation analysis with static spatial data
Ydist2asset	This node represents the distance from potential ignition point to mapped assets in the 'Y' direction.	Simulation analysis with static spatial data
Yreachasset	Probability of a fire moving from the ignition point to an asset in the 'Y' direction.	Simulation analysis with static spatial data
z_Int	This node identifies the fire intensity at a given distance in the 'Z' direction.	Simulation analysis with static spatial data
Zbearing	Projected bearing. This node defines the direction, i.e. the compass bearings for 'Z' direction (see diagram below).	Simulation analysis with static spatial data
Zdist2asset	This node represents the distance from potential ignition point to mapped assets in the 'Z' direction.	Simulation analysis with static spatial data
Zreachasset	Probability of a fire moving from the ignition point to an asset in the 'Z' direction.	Simulation analysis with static spatial data

a)



b)

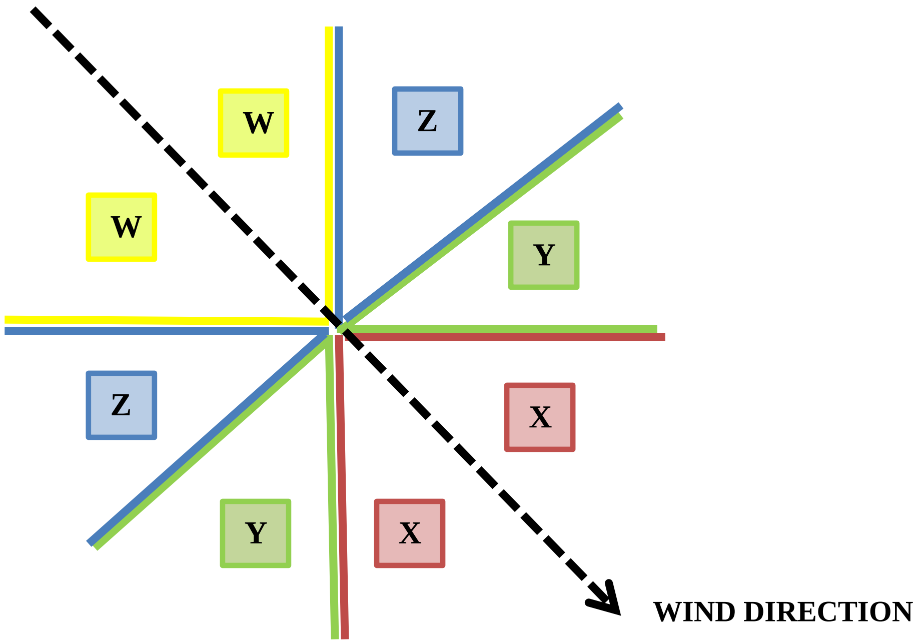


Figure 12: A diagrammatic explanation of wind direction and the use of "X, "Y", "Z", and "W" directions for a) a SW wind and b) NW wind. The X direction is the 45 degrees either side of the primary wind axis (in black). The Y direction is 45 to 90 degrees from the primary axis, Z direction is 90 to 135 degrees and the W direction is 135 to 180 degrees from the primary axis.

10 Reference List:

ARCHIBALD, S., ROY, D. P., VAN WILGEN, B. W. & SCHOLES, R. J. 2009. What limits fire? An examination of drivers of burnt area in Southern Africa. *Global Change Biology,* 15**,** 613-630.

BLANCHI, R., LEONARD, J., HAYNES, K., OPIE, K., JAMES, M. & OLIVEIRA, F. D. D. 2014. Environmental circumstances surrounding bushfire fatalities in Australia 1901–2011. *Environmental Science & Policy,* 37**,** 192-203.

BLANCHI, R., LUCAS, C., LEONARD, J. & FINKELE, K. 2010. Meteorological conditions and wildfire-related houseloss in Australia. *International Journal of Wildland Fire,* 19**,** 914-926.

BRADSTOCK, R. A., COHN, J. S., GILL, A. M., BEDWARD, M. & LUCAS, C. 2009. Prediction of the probability of large fires in the Sydney region of south-eastern Australia using fire weather. *International Journal of Wildland Fire,* 18**,** 932-943.

BRADSTOCK, R. A. & GILL, A. M. 2001. Living with fire and biodiversity at the urban edge: in search of a sustainable solution to the human protection problem in southern Australia. *Journal of Mediterranean Ecology,* 2**,** 179-195.

BURGAN, R., KLAVER, R. & KLAVER, J. 1998. Fuel Models and Fire Potential From Satellite and Surface Observations. *International Journal of Wildland Fire,* 8**,** 159-170.

CARY, G. J., FLANNIGAN, M. D., KEANE, R. E., BRADSTOCK, R. A., DAVIES, I. D., LENIHAN, J. M., LI, C., LOGAN, K. A. & PARSONS, R. A. 2009. Relative importance of fuel management, ignition management and weather for area burned: Evidence from five landscape-fire-succession models. *International Journal of Wildland Fire,* 18**,** 147-156.

COCHRANE, M. A., MORAN, C. J., WIMBERLY, M. C., BAER, A. D., FINNEY, M. A., BECKENDORF, K. L., EIDENSHINK, J. & ZHU, Z. 2012. Estimation of wildfire size and risk changes due to fuels treatments. *International Journal of Wildland Fire,* 21**,** 357-367.

DEEMING, J. E., LANCASTER, P. Y., FOSBERG, M. A., FURMAN, W. R. & SCHROEDER, M. J. 1972. The National Fire-Danger Rating System. Research Paper RM-84. USDA Forest Service, Rocky Mountain Forest and Range Experiment Statio.

GIBBONS, P., VAN BOMMEL, L., GILL, A. M., CARY, G. J., DRISCOLL, D. A., BRADSTOCK, R. A., KNIGHT, E., MORITZ, M. A., STEPHENS, S. L. & LINDENMAYER, D. B. 2012. Land Management Practices Associated with House Loss in Wildfires. *PLoS ONE,* 7**,** e29212.

GILL, A. M. & STEPHENS, S. L. 2009. Scientific and social challenges for the management of fire-prone wildland–urban interfaces. *Environmental Research Letters,* 4**,** 034014.

JOHNSON, S., MENGERSEN, K., DE WAAL, A., MARNEWICK, K., CILLIERS, D., HOUSER, A. M. & BOAST, L. 2010. Modelling cheetah relocation success in southern Africa using an Iterative Bayesian Network Development Cycle. *Ecological Modelling,* 221**,** 641-651.

KORB, K. B. & NICHOLSON, A. E. 2011. *Bayesian Artificial Intelligence. Computer Science and Data Analysis. Second Edition,* Boca Raton, CRC/Chapman Hall.

LEBLON, B., ALEXANDER, M., CHEN, J. & WHITE, S. 2001. Monitoring fire danger of northern boreal forests with NOAA-AVHRR NDVI images. *International Journal of Remote Sensing,* 22**,** 2839-2846.

MAINGI, J. K. & HENRY, M. C. 2007. Factors influencing wildfire occurrence and distribution in eastern Kentucky, USA. *International Journal of Wildland Fire,* 16**,** 23-33.

MARCOT, B. G., HOLTHAUSEN, R. S., RAPHAEL, M. G., ROWLAND, M. M. & WISDOM, M. J. 2001. Using Bayesian belief networks to evaluate fish and wildlife population viability under land management alternatives from an environmental impact statement. *Forest Ecology and Management,* 153**,** 29-42.

MATTHEWS, S. 2009. A comparison of fire danger rating systems for use in forests. *Australian Meteorological and Oceanographic Journal,* 58**,** 41.

MCARTHUR, A. G. 1967. Fire behaviour in eucalypt forest. Canberra: Australian Forestry and Timber Bureau, Leaflet No. 107

NOBLE, I. R., BARY, G. A. V. & GILL, A. M. 1980. Mcarthurs Fire Danger Meters Expressed as Equations. *Australian Journal of Ecology,* 5**,** 201-204.

NYBERG, J. B., MARCOT, B. G. & SULYMA, R. 2006. Using Bayesian belief networks in adaptive management. *Canadian Journal of Forest Research,* 36**,** 3104-3116.

PARISIEN, M.-A., MILLER, C., AGER, A. & FINNEY, M. 2010. Use of artificial landscapes to isolate controls on burn probability. *Landscape Ecology,* 25**,** 79-93.

PENMAN, T. D., BEUKERS, M., KAVANAGH, R. P. & DOHERTY, M. 2011. Are long-unburnt eucalypt forest patches important for the conservation of plant species diversity? *Applied Vegetation Science,* 14**,** 172-180.

PENMAN, T. D., BRADSTOCK, R. A. & PRICE, O. F. 2014. Reducing wildfire risk to urban developments: Simulation of cost-effective fuel treatment solutions in south eastern Australia. *Environmental Modelling & Software,* 52**,** 166-175.

PENMAN, T. D., COLLINS, L., PRICE, O. F., BRADSTOCK, R. A., METCALF, S. & CHONG, D. M. O. 2013. Examining the relative effects of fire weather, suppression and fuel treatment on fire behaviour – A simulation study. *Journal of Environmental Management,* 131**,** 325-333.

PENMAN, T. D., NICHOLSON, A. E., BRADSTOCK, R. A., COLLINS, L., PENMAN, S. H. & PRICE, O. F. 2015. Reducing the risk of house loss due to wildfires. *Environmental Modelling & Software,* 67**,** 12-25.

PLUCINSKI, M. P. 2012. Factors Affecting Containment Area and Time of Australian Forest Fires Featuring Aerial Suppression. *Forest Science,* 58**,** 390-398.

PLUCINSKI, M. P., MCCARTHY, G. J., HOLLIS, J. J. & GOULD, J. S. 2012. The effect of aerial suppression on the containment time of Australian wildfires estimated by fire management personnel. *International Journal of Wildland Fire,* 21**,** 219-229.

PRICE, O. & BRADSTOCK, R. 2013. Landscape Scale Influences of Forest Area and Housing Density on House Loss in the 2009 Victorian Bushfires. *PLoS ONE,* 8**,** e73421.

PRICE, O. F. & BRADSTOCK, R. A. 2010. The effect of fuel age on the spread of fire in sclerophyll forest in the Sydney region of Australia. *International Journal of Wildland Fire,* 19**,** 35-45.

RADELOFF, V. C., HAMMER, R. B., STEWART, S. I., FRIED, J. S., HOLOCOMB, S. S. & MCKEEFRY, J. F. 2005. The wildland-urban interface in the United States. *Ecological Applications,* 15**,** 799-805.

SAN-MIGUEL-AYANZ, J., CARLSON, J., ALEXANDER, M., TOLHURST, K., MORGAN, G., SNEEUWJAGT, R. & DUDLEY, M. 2003. Current methods to assess fire danger potential. *Wildland Fire Danger Estimation and Mapping. The Role of Remote Sensing Data. World Scientific Publishing, Singapore***,** 21-61.

SERVICE, C. F. 1984. Tables for the Canadian Forest Fire Weather Index System. *Forestry Technical Report 25: 4th edition. .* Canadian Forestry Service.

SHARPLES, J. J., MCRAE, R. H. D., WEBER, R. O. & GILL, A. M. 2009. A simple index for assessing fire danger rating. *Environmental Modelling & Software,* 24**,** 764-774.

WEI, Y., RIDEOUT, D. & KIRSCH, A. 2008. An optimization model for locating fuel treatments across a landscape to reduce expected fire losses. *Canadian Journal of Forest Research-Revue Canadienne De Recherche Forestiere,* 38**,** 868-877.