National Fire Danger Rating System Probabilistic Framework Project

Final Report for Year 1

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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 the first 12 months of activity:

a) A new “consequence-based” fire danger rating system has been developed. 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 to generate spatially explicit surfaces of the probability of property loss. The system has the ability to represent the probability of property loss at 10 Km spatial resolution and daily time-step;

c) An initial evaluation of the key components and processes of the BN framework has been performed.

In the next stage of the project (i.e., Year 2), the BN framework will be applied to one or two case study regions in south-eastern Australia. The study regions will be selected after consultation with relevant end users in New South Wales, Victoria and Australian Capital Territory.

2. Purpose

The purpose of this document is to describe the activities and results of the first 12 months (i.e., from the 1st of November 2011 to the 31st of October 2012) of the National Emergency Management Projects (NEMP) sponsored National Fire Danger Rating System – Probabilistic Framework Project.

3. Background: Fire danger rating systems and Bayesian networks

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), 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'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., based on Forest Fire Danger Index, FFDI) and grassland (based on Grassland Fire Danger Index, GFDI) fuel types (McArthur, 1966; NSW Rural Fire Service). FFDI and GFDI are divided into six categories (i.e., low, high, very high, severe, extreme and catastrophic) representing increasing levels of fire severity and potential impact on property (McArthur, 1966; Noble et al., 1980; Sharples et al., 2009; Bradstock and Gill, 2001). However, these indices only account for weather parameters (i.e., rainfall, temperature, relative humidity, and

wind speed) and do not consider other environmental and human variables (e.g., spatially varying fuel load, fuel type, terrain characteristics, house density) which can have a significant influence on fire behaviour and, consequently, on the impact of fire on human communities (McArthur, 1966; Noble et al., 1980; San-Miguel-Ayanz et al., 2003; Maingi and Henry, 2007; Archibald et al., 2008; Sharples et al., 2009; Price and Bradstock, 2010).Therefore, in order to more effectively assess fire danger, it is necessary to develop a more robust “consequence-based” modelling framework able to integrate a wider range of variables and link their complex interactions to the probability of property loss.

Bayesian Networks (BN) represent 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 (Penman et al., 2011). 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 result, 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.

4. Project objectives

The objectives of the first 12 months of the project were:

Objective 1: Construction of an initial BN framework for the implementation of a "consequence-based" fire danger rating system.

The required characteristics of the modelling framework are:
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;
b) Capacity to adequately predict the probability of property loss due to fire;
c) Ability to generate spatially-explicit surfaces at 10km spatial resolution (i.e., 10Km grid cell) and daily time-step representing the probability of property loss.

Objective 2: Initial assessment and test parameterisation of the key processes of the Bayesian network framework.

5. Objective 1- Bayesian network: a spatially explicit approach

5.1. Background

Bayesian Networks are modelling tools capable of capturing the probabilistic relationship between variables. BNs are based on the Bayes' rule which can be expressed as:

$$P(b \mid a) = \frac{P(a \mid b) * P(b)}{P(a)} \qquad \text{(i)}$$

Where P(a) is the probability of *a*, and P(a | b) is the probability of *a* given that *b* has occurred.

BNs are based on graphical models called influence diagrams (Figure 1). These diagrams consist of nodes (i.e., variables) and linkages (i.e., causal relationships), with the linkages depicting the direction of influence (Korb and Nicholson, 2004). When two nodes are connected through a linkage, the causal node is called parent node and the other is called child node (Figure 1). Nodes without parents represent input variables.

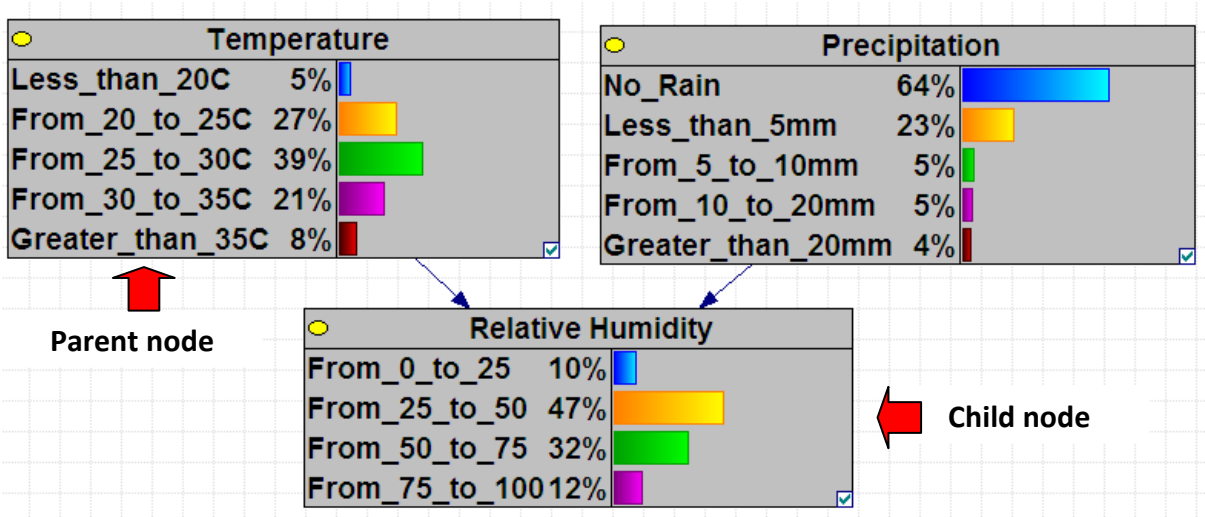

Figure 1. Example of Bayesian network consisting of 2 parent nodes (i.e., temperature and precipitation) connected to one child node (relative humidity)

Each node (i.e., variable) has a series of discrete states. For example, the variable "Temperature" could be less than 20℃, in the 20-25℃ range, in the 25-30℃ range, in the 30-35℃ range or greater than 35℃ (Figure 1). Finally, for each node, a conditional probability table (CPT) is constructed (Figure 2). CPTs contain the joint probability distribution of each node (i.e., variable) in the BN. If a node has no parent nodes, CPT is represented by a single distribution (Penman et al., 2011). For all child nodes, the CPT contains the probabilities of the node being in state X given the states of the parent nodes (Uusitalo 2007).

Data for the CPTs can come from a variety of sources. CPTs of parentless nodes can be measured or estimated using existing evidences from the study area (e.g., GIS layers). Conditional probability tables for child nodes can be populated with data from empirical statistical models, process models and expert opinions where data are lacking (e.g. Johnson et al. 2010).

a)

Less_than_20C	0.053804119
From_20_to_25C	0.26607818
From_25_to_30C	0.38629676
From_30_to_35C	0.20891131
Greater_than_35	0.084909626

b)

Temperature	Less_than_20C	From_20_to_25C	From_25_to_30C	From_30_to_35C	Greater_than_35
From_0_to_25	0.25	0	0	0.25	0.5
From_25_to_50	0.25	0.5	0.625	0.5625	0.5
From_50_to_75	0.25	0.16666667	0.375	0.1875	0
From_75_to_100	0.25	0.33333333	0	0	0

Figure 2. Conditional probability tables (CPT) of a (a) parent and (b) child node.

When the CPT values of a given node (i.e., variable) are updated with new evidences (e.g., new information from existing data), this information will propagate through the network of causal relationships and the CPTs of the child nodes will change according to (i).

5.2. Bayesian network development and structure

The first step in the construction of the BN for this project was the development of a conceptual framework of the fire process. A general description of the conceptual framework will be provided first. Each component (i.e., sub-model) of the BN framework will be then analysed separately.

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).

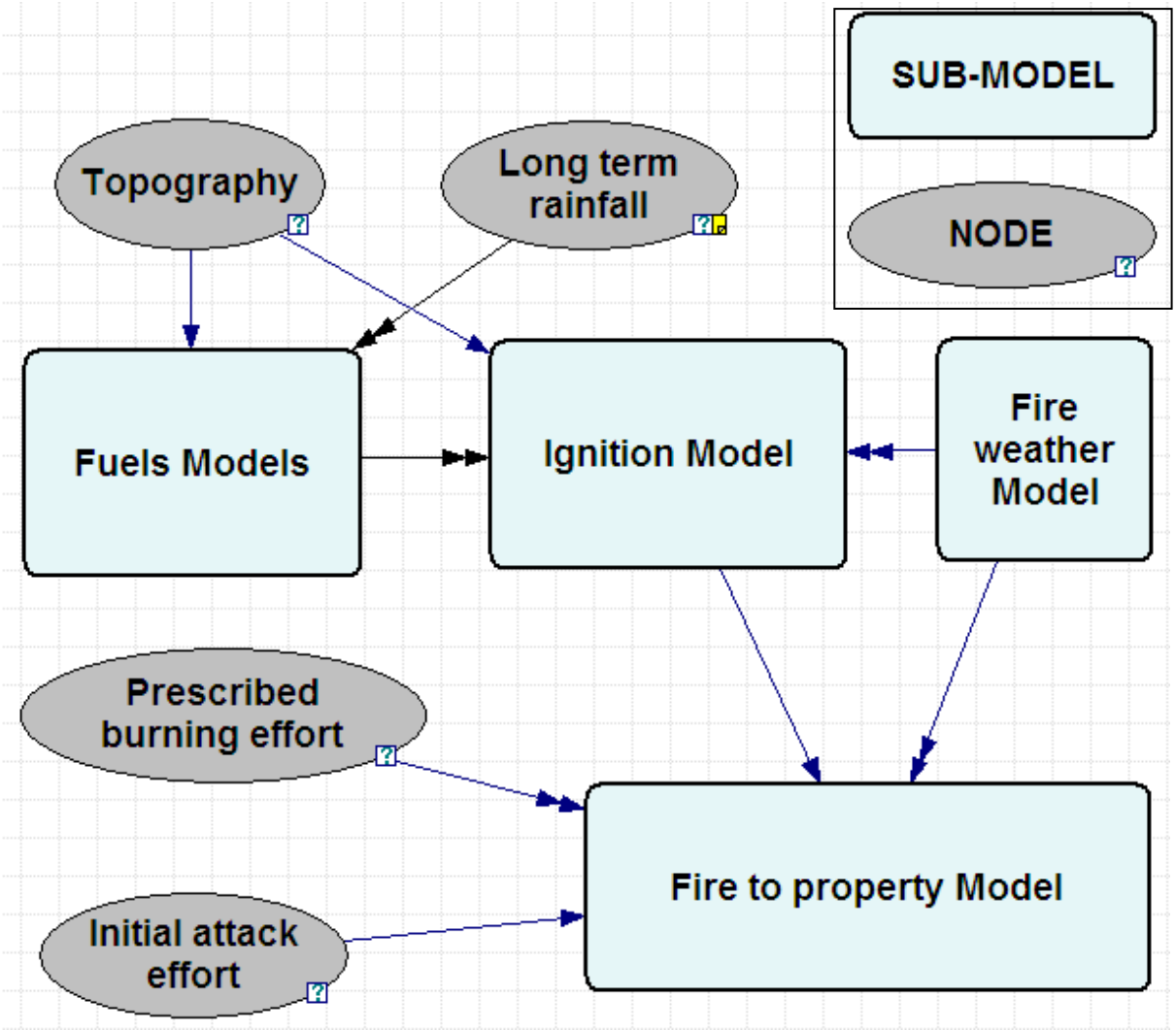

Figure 3. Conceptual framework of the Bayesian network developed to predict the probability of property loss from fire. The direction of the arrows indicates the direction of influence. Node descriptions appear in Table 1. See text and Figure 4, 5, 6 and 7 for the description of the sub-models.

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.

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

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
Elevation	Elevation (m) relative to sea level	0-300 m; 300-800m; greater than 800m
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

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

The '*Fuels models'* (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.

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.

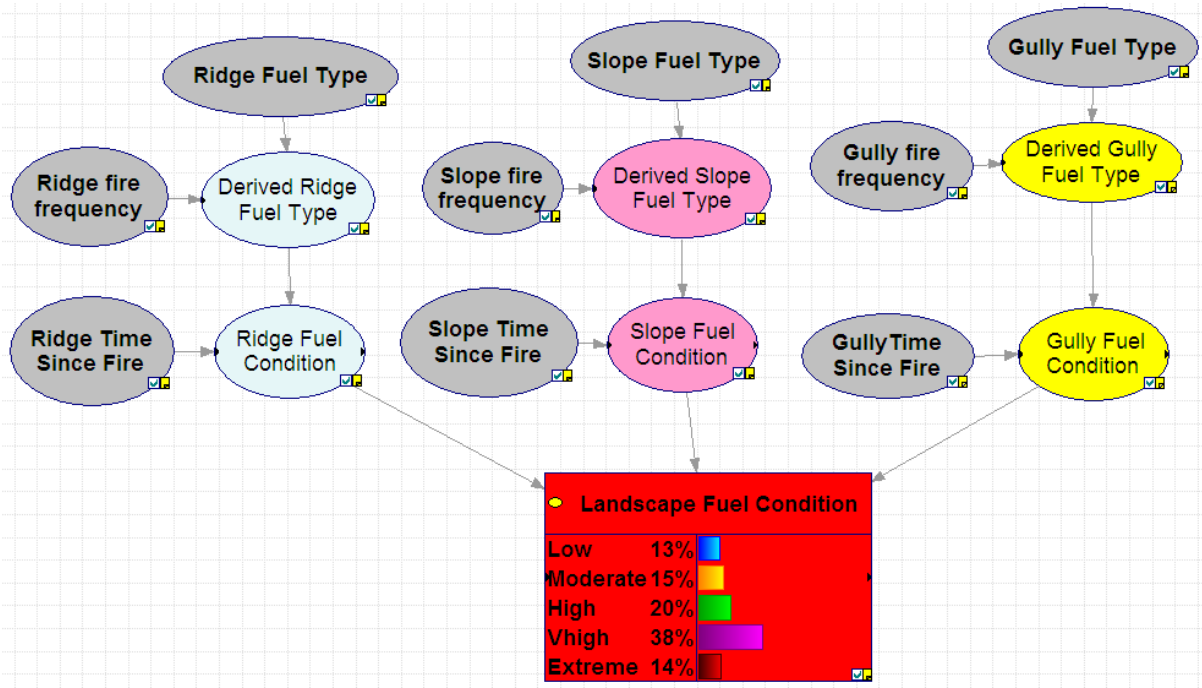

Figure 4. Structure of the '*Fuels Model*' of the Bayesian network. The input variables (i.e., parentless nodes) are in light grey and the model output (i.e., Landscape Fuel Condition) is in red. Parentless nodes description appears in Table 1. '*Long Term Rainfall*' is also an input to this submodel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

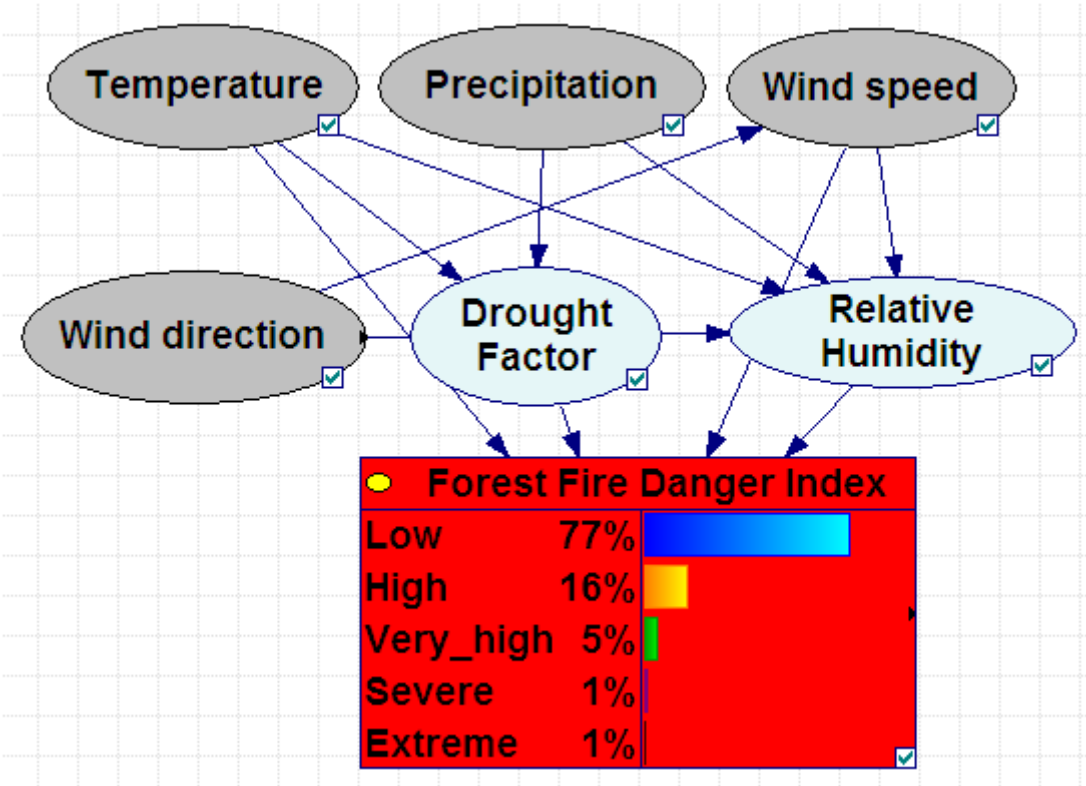

Figure 5. Structure of the '*Fire Weather Model*' of the Bayesian network. The input variables (i.e., parentless nodes) are in light grey and the model output (i.e., Forest Fire Danger Index, *FFDI*) is in red. Parentless nodes description appears in Table 1.

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 road', 'Elevation' 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). Arson and anthropogenic ignitions were more likely to occur in vegetation closer to roads and with increased housing density. Lightning ignitions were more likely to occur further from roads and human populations, reflecting the low population density in the high elevation sites within the study area. All ignition types had increased probabilities as fire weather increased. These models were then used to derive the relevant CPTs.

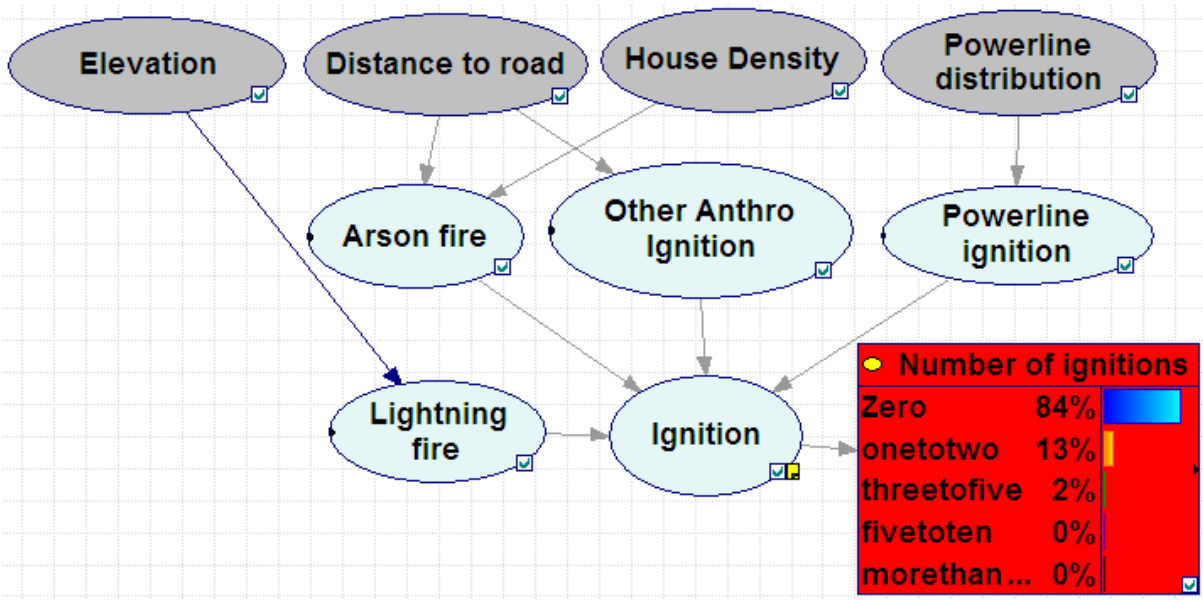

Figure 6. Structure of the '*Ignition Model'* of the Bayesian network. The input variables (i.e., parentless nodes) are in light grey and the model outputs (i.e., Number of ignitions) is in red. The outputs of '*Fire weather model*' and '*Fuels model*' are also input (see Figure 3) to the '*Ignition 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', Table 1) and spatially varying landscape characteristics (i.e., *Region*) (Figure 7).

Once an ignition has occurred, it may self-extinguish or continue to grow relative to the wind direction. Ignitions are more likely to self-extinguish in areas not covered by Dry Sclerophyll forest ('Vegetation@ignition', Figure 7). 'Vegetation@ignition', 'Prescribed burning effort', 'Initial attack effort', 'Region', '*Ignition model*', and '*Fire weather model*' influence the probability of a fire to self-extinguish ('Self-Extinguish?' node in Figure 7).

Finally, the sub-model '*Exposure Model*' (Figure 7) predicts the probability of fire having an intensity of 'zero', 'suppressible' (<4000kW) or 'unsuppressable' (>4000kW) at WUI as a function of 'Prescribed burning effort', 'Region', weather (i.e., wind direction and FFDI) and 'Distance to WUI' (Table 1). Fires > 4000kW are considered beyond the limit or fire suppression equipment (Gill and Stephens 2009) and therefore the risk of house loss is very high. Fires <4000kW are within the limits of suppression and therefore the risk of exposure is high, however the risk of loss is lower. Threshold values for each of these will be determined through the case studies proposed for Year 2. 'Distance to WUI' measure the distribution of six classes of distance to WUI across eight direction classes (Table 1 and Appendix A). Fires are more likely to travel different distances downwind as compared to upwind or perpendicular to the wind. Therefore, the probability of property loss increases when distances to WUI along the dominant wind direction are small. 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).

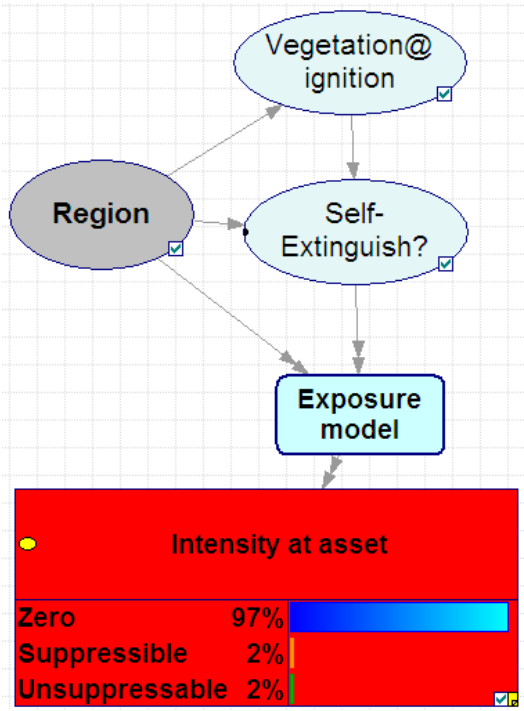

Figure 7. Structure of the '*Fire to property Model*' of the Bayesian network. The input variables (i.e., parentless nodes) are in light grey and the model outputs (i.e., Intensity at asset) is in red. 'Wind direction', 'Prescribed burning effort', 'Initial attack effort' and the outputs of '*Fire weather 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.

5.3. Geographic Information System (GIS) and Bayesian Network integration

In order to generate continuous surfaces representing the probability of property loss (see Section 4) it was necessary to apply the BN framework in a spatially explicit manner. This requirement could only be achieved integrating the modelling framework with spatially varying information about the environmental factors (e.g., fuel type and load, distance to road, house density). Geographic Information System (GIS) data have the capacity to incorporate the complexities of spatial dimension within such analyses. As a consequence, a spatial-modelling approach was developed to link the BN framework to GIS and model the probability of property loss in a spatially-explicit manner.

In particular, the aim was to produce daily (i.e., 1 day time-step) gridded surfaces of probability of property loss at 100km^2 spatial resolution (i.e., 10 km grid cells). This

aim was achieved through a two steps modelling approach which linked BN parentless nodes (i.e., input variables. See Section 5.2) to spatial information stored in GIS format (Figure 8). The two processing steps will be described separately.

Step 1: Spatial information extraction

The parentless nodes (i.e., input variables) of the BN were initialized using evidences provided by spatially explicit datasets (Figure 8a-c). For example, the vegetation map was used to provide the conditional probability tables of ridge, slope and gully fuel type nodes (Figure 4) with evidences on the distribution of dry sclerophyll forest, wet sclerophyll forest, heath, grassy woodland and cleared.

For each parentless node, the values in the CPTs were calculated using evidences extracted from spatial data within areas of 100km^2. First, a grid of cells at 10km resolution is used to define the spatial extent of analysis (Figure 8a). Within each 10 km cell (Figure 8b), the percentage cover of all the "states" of the variable of interest is calculated (Figure 8b). In the example in Figure 8a-c, a vegetation map is used to update the CPT of the '*Ridge Fuel Type*' node. In the cell in Figure 8b, 16% of the area is covered by Wet Sclerophyll forest, 62% by Dry Sclerophyll forest, 20% by Heath and 2% by Grassy Woodland. The CPT of the '*Ridge Fuel Type*' node (Figure 8c) is finally updated using the "spatially-explicit" evidences previously extracted (Figure 8b).

This process is applied to each cell of the 10km grid, and for each parentless node (i.e., input variable) of the BN framework. At the end of this process, for each single grid cell, the evidences of all the states of all the parentless nodes (i.e., variables) of the BN framework are updated.

Using this approach, predictions of the probability of property loss can be efficiently generated at daily time-step. On each day of simulation, only dynamic input variables (e.g., weather) need to be updated, whilst more static variables (e.g., topography, fuel type) will remain unchanged.

Moreover, this modelling approach is flexible as it allows extracting spatial information at different resolution. The size of the cells in the grid can be increased or decreased in order to extract spatial evidences from larger or smaller areas.

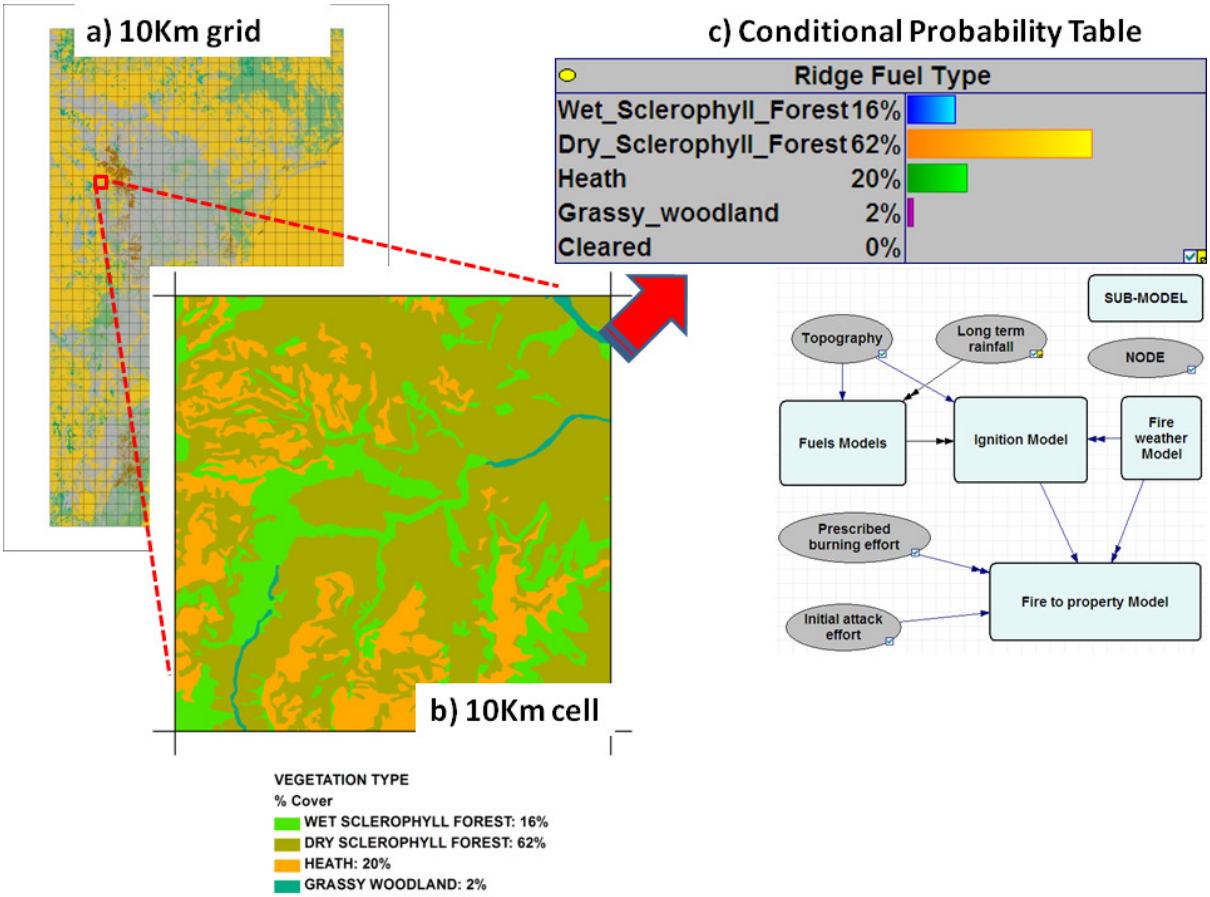

Figure 8. Schematic of 'Step 1' of the Bayesian Network–Geographic Information System integration procedure.

Step 2: Probability of property loss calculation

For each cell in the 10 Km grid, the evidences in the CPTs (Figure 9a) provided by the spatially explicit datasets (Figure 8a-c) are propagated through the BN to calculate the probability of property loss (Figure 9a). The output of each single cell is then saved into a geo-referenced grid with the same cell size (Figure 9b). The final output is therefore a gridded surface representing the spatial distribution of the probability of property loss at 10 km resolution (Figure 9b).

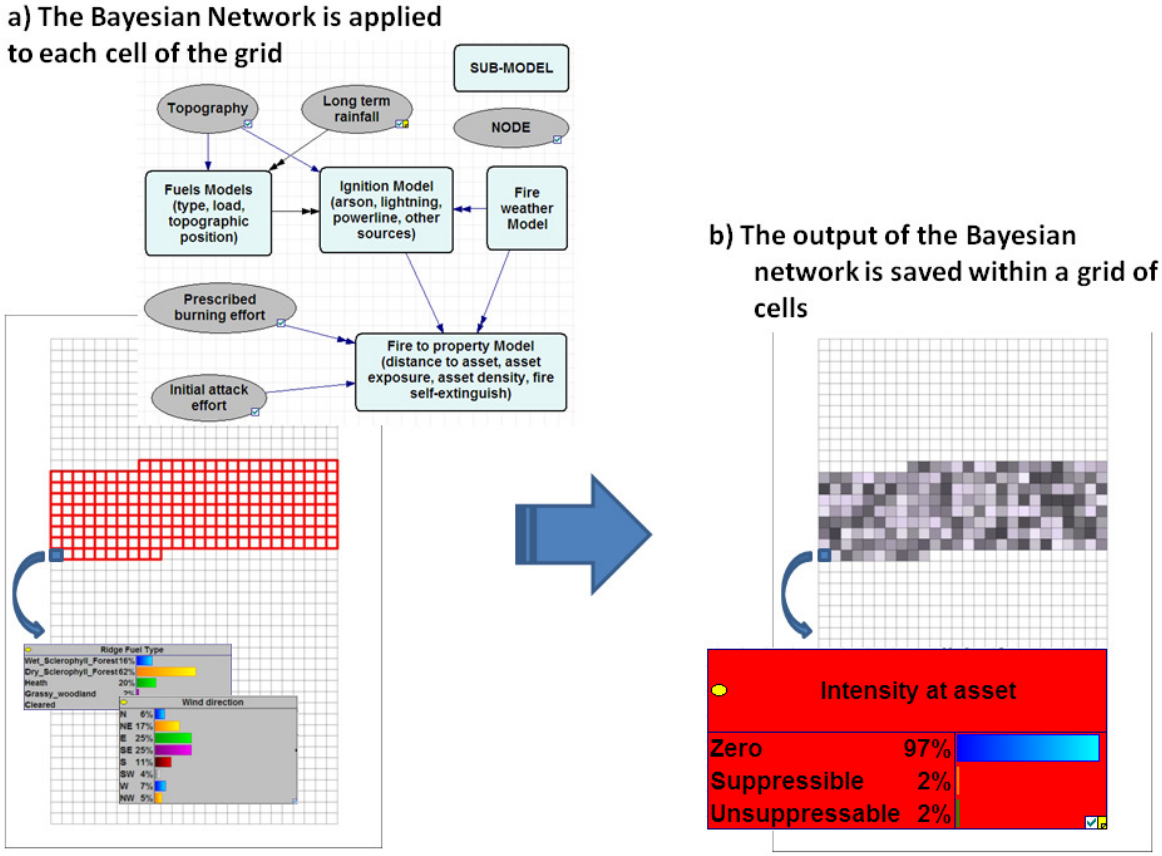

Figure 9. Schematic of 'Step 2' of the Bayesian Network–Geographic Information System integration procedure.

5.4. Outcomes

A new "consequence-based" fire danger rating system has been developed. 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 approach was used as the basis for the modelling framework because BNs are suitable for representing complex interactions among multiple variables and processes. This modelling framework is potentially more suitable than FFDI to assess fire danger because it accounts for the causal relationships between larger numbers of environmental variables.

The BN framework has been successfully integrated with GIS to generate spatially explicit surfaces of the probability of property loss. The input variables of BN were linked to information stored in GIS layers to account for spatially varying

environmental variables. The system has the ability to represent the probability of property loss at 10 Km spatial resolution and daily time-step.

The first project objective has been therefore successfully achieved within the expected delivery date.

6. Objective 2- Bayesian network framework assessment

6.1. Initial model evaluation

In order to perform a preliminary evaluation of the modelling approach, the BN framework was applied to a study area using historical records. The specific aims of this retrospective analysis were to:

a) Initial test of the different model components and parameterisation of its key processes;

b) Planning of a retrospective study for preliminary assessment of the accuracy of the model.

6.2. Spatial and temporal domain of analysis

The analysis focused on the Sydney Basin Bioregion in south-eastern Australia (Figure 10). A number of fires have occurred in recent years within this region affecting properties (e.g., Bradstock et al., 2009). In particular, two major fire seasons occurred in 2001/02 and 2002/03 burning over 500,000 ha of land and resulting in several residential and commercial properties damaged or lost (NSW RFS *unpublished data*). Our analysis specifically targeted these two fire seasons to assess the performance of the BN framework under condition of higher fire danger. Moreover, fire seasons when fires had a more limited impact on properties were also considered (i.e., 2000/01 and 2003/04) for comparison purposes.

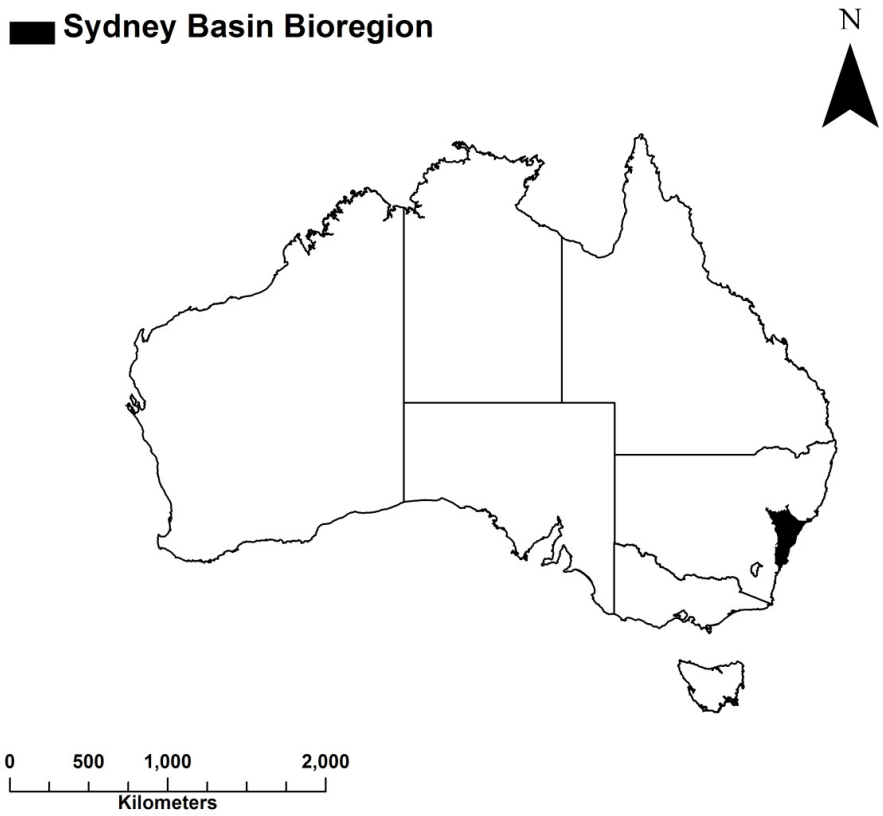

Figure 10. Location of the Sydney Basin Bioregion

6.3. Data and methods

A large set of spatial data was acquired to extract the spatial information required by the BN framework (see Section 5.3). GIS layers were acquired from a variety of sources (Table 2).

The spatial resolution of all input data was finer than the project requirement (i.e., 10km). The temporal resolution of the input data varied markedly. Daily weather data (e.g., wind, rainfall, temperature) were necessary to model daily variations in fire weather patterns during fire season (October-February) in the years of interest. Annual fire history records were required to account for inter-annual changes in fire frequency and time since fire. Other data were static throughout the time-period of analysis (e.g., elevation).

GIS layers required extensive pre-processing before implementation in the BN framework. Specifically, spatial data had to be pre-processed (e.g., geo-referencing and format conversion), transformed (e.g., overlay operations) and reclassified to

provide the input variables of the BN with the necessary spatial evidences (Figure 11).

Upon completion of data pre-processing, the BN framework was integrated with the GIS layers following the approach described in Section 5.3 to generate grids representing the distribution of the probability of property loss due to fire. The integration is based on programming codes developed in Python and Java languages.

Table 2. List of the parentless nodes of the Bayesian network framework and data source used for their processing.

NSW, New South Wales; NPWS, National Parks and Wildlife Service; DLPI, Department of Land and Property Information. See 'Appendix A' for details about the GIS methods used to create the spatial data required.

Node	Data source
Topography	NSW DLPI
Distance to Road	NSW DLPI
House density	NSW DLPI
Powerline	NSW DLPI
Region	N/A
Distance to WUI	Derived from Keith (2004) and NSW DLPI
Gully Fuel Type	Keith (2004)
Slope Fuel Type	Keith (2004)
Ridge Fuel Type	Keith (2004)
Prescribed burning effort	N/A
Initial attack effort	N/A
Long term rainfall	Bureau of meteorology
Ridge Fire Frequency	NSW NPWS fire history data
Ridge Time Since Fire	NSW NPWS fire history data
Slope Fire Frequency	NSW NPWS fire history data
Slope Time Since Fire	NSW NPWS fire history data
Gully Fire Frequency	NSW NPWS fire history data
Gully Time Since Fire	NSW NPWS fire history data
Wind direction	Bureau of meteorology
Temperature	Bureau of meteorology
Precipitation	Bureau of meteorology
Wind Speed	Bureau of meteorology
Ignition	NSW NPWS fire history data

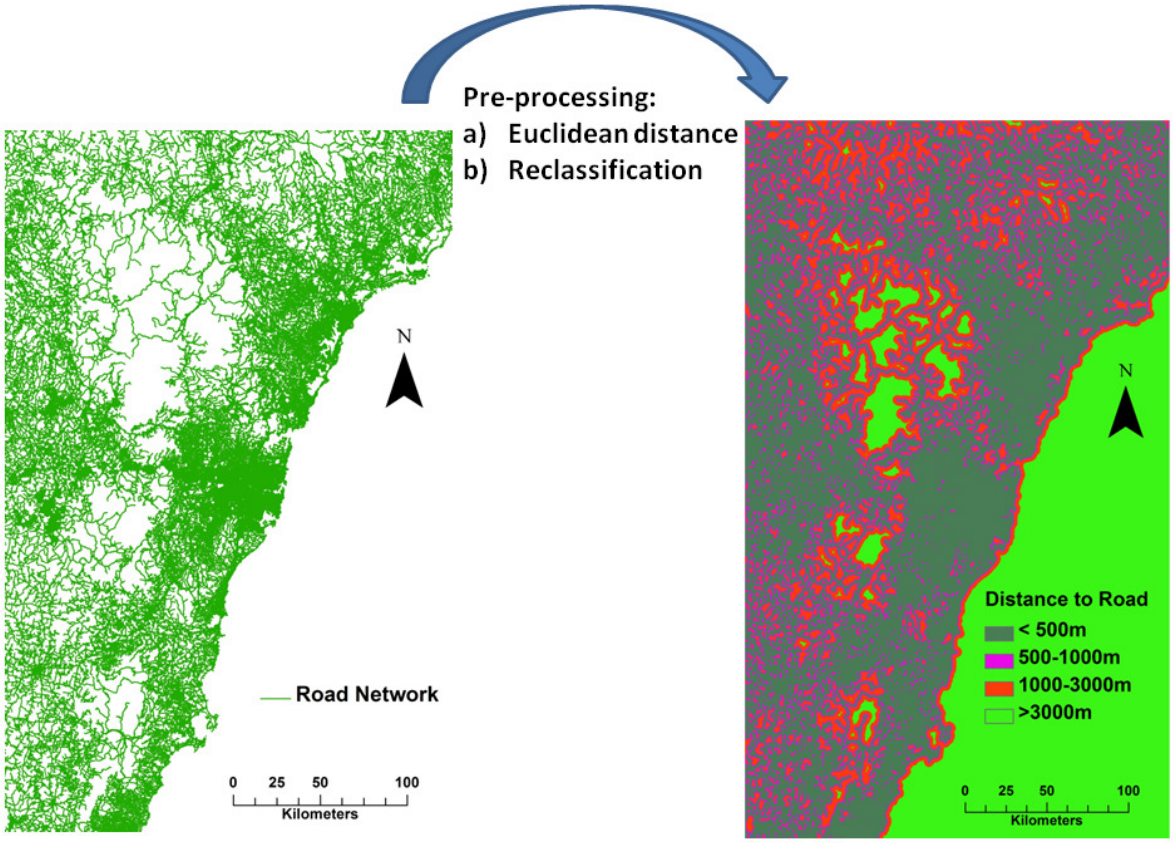

Figure 11. Example of GIS pre-processing operations. In this example, Euclidean distances are calculated for each feature of the road network GIS layer. The output is reclassified into four categories (i.e., <500m, 500m-1000m, 1000-3000m and >3000m) representing the four states of the '*Distance to Road*' node of the Bayesian network framework.

6.4. Outcomes

The outcomes of the retrospective analysis provided important insights into the overall performance of the BN modelling approach. In particular the results were useful to:

1. Refine the structure of the BN framework. The BN framework was improved by redesigning specific sub-models (Table 1; Figure 3, 4, 5, 6 and 7). In particular, the '*Ignition model*' and '*Fire to property model*' have been improved to account for the influence of elevation on the probability of ignition and the interaction between dominant wind direction, WUI exposure and distance to WUI (Section 5.2);

2. Refine the number and type of input variables used in the modelling framework. A number of nodes were modified and/or added to the BN framework. In particular, the node “WUI exposure” was combined with the node “Distance to WUI”. This change allowed to more efficiently model the interaction between wind direction, exposure of WUI and distance to WUI (Section 5.2, Table 1and Appendix A). Moreover, the node ‘Elevated’ (Figure 6) was added to model the probability of ignition from lightning in the ‘*Ignition model*’;

3. Test the programming codes. Several tests were conducted to assess the functionality of the programming codes used in the operations described in Section 5.3. The tests aimed at (i) locating and fixing potential errors and failures in the codes, and (ii) assessing the flow and functionality of the connections among the processing steps described in Section 5.3. In particular, output values generated using the programming codes were validated against outputs generated through interface-based software packages (i.e., Graphycal Network Interface (Genie), http://genie.sis.pitt.edu/about.html).

4. Evaluate and optimize the BN model processing speed. The programming codes required to integrate GIS layers and BN framework (Figure 8 and 9) were subject to several testings and modifications aiming at improving the BN model processing speed. Initial versions of the BN model required up to 20 minutes to produce an output (i.e., 10 km grid). In its final version, the BN model is capable to generate an output in 62 seconds (tested on a computer equipped with Intel(R) Core(TM)2 Duo CPU, 2.66GHz, 3.23 GB RAM);

5. Provide a working prototype that can be evaluated for validity and operational effectiveness during the next stage (i.e., Year 2) of the project using historical data. In Year 2, the accuracy of the model output will be tested against actual events of property loss to provide indications on the potential of the BN framework proposed as fire danger rating system.

7. Conclusion

The activities and outcomes achieved during the first 12 months of the NEMP sponsored National Fire Danger Rating System – Probabilistic Framework project have been discussed.

A Bayesian network framework was applied to develop a new “consequence-based” fire danger rating system. This framework is capable of predicting the probability of property loss from fire through the integration of a wide range of environmental variables and key processes governing fire behaviour. This framework can be linked to GIS and applied in a spatially-explicit manner to generate continuous surfaces representing the distribution of the probability of property loss across the landscape. This activity was completed within the expected finish date, June 30th 2012.

An initial assessment of the BN framework has been conducted. The BN framework was improved by redesigning selected nodes and models. The different programming codes required for integrating GIS layers and BN framework were tested and improved. The processing speed of the model has been improved. Finally, a retrospective analysis has been planned to test the model against historical records of property loss (i.e., in Year 2). The initial assessment was completed within the expected finish date, October 31st 2012.

In the next stage of the project, the performance of the BN framework will be assessed using historical records of property loss. This analysis will provide useful insights into the overall model accuracy. Moreover, the BN framework will be applied to one or two case study regions in south-eastern Australia. The study regions will be selected after consultation with relevant end users in New South Wales, Victoria and Australian Capital Territory.

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APPENDIX A

This section provides a brief description of the GIS processing steps applied to create the spatial data required to feed the parentless nodes (Table 1):

Topography: First, the distance (scaled from 0 to 100) above the lowest local point within a 1,000m x 1,000m sample window was calculated. Then, pixels with values <25, >25 and <75, and >75 were classified as gully, slope and ridge, respectively;

Distance to Road: The grid representing the Euclidean distance (m) to nearest mapped road was reclassified according to the classes in Table 1;

Elevation: reclassification of the digital elevation model according to the classes in Table 1;

House density: First, the density of properties within a two kilometre radius was calculated. Then, the grid was reclassified according to the classes in Table 1;

Powerline: Binary layer (1 and 0) representing the presence (1) or absence (0) of powerline

Region: Classification of the study area in three macro-regions (i.e., Blue Mountains, Hornsby and Woronora). These regions represent the north, south and western areas of the study area. Each the regions have different mixes of topography, vegetation, climate and wildland urban interface. Regions are described more fully in Bradstock et al. (2012).

Distance to WUI: First, the WUI was defined by overlaying vegetation (Keith, 2004) and cadastral map. This approach allowed erasing parcels or part of parcels containing wildland features (e.g., natural vegetation). Then, for each point within a 1,000m x 1,000m sample window, the distance to the nearest WUI along bearing lines (from 0° to 360°) was reclassified in <1Km, 1-2.5 Km, 2.5-5 Km, 5-10 Km, 10-20 Km and >20 Km. Finally, the distribution (i.e., count) of the six distance classes across eight direction classes (i.e., N, NE, E, SE, S, SW, W and NW; Table 1) was calculated;

Gully, Slope and Ridge fuel type: Based on the reclassification of Keith (2004);

Prescribed burning effort and Initial attack: N/A. These variables are not calculated based on spatial data, but are defined by the user;

Long term rainfall: First, a grid representing the distribution of long term (1960-2012) average precipitation from October of year x-1 to September of year x was created. Finally, the grid was classified according to the classes in Table 1;

Gully, Slope and Ridge fire frequency: Using digital fire history records, the number of fire events in the last 30 years was mapped and classified according to the classes in Table 1;

Gully, Slope and Ridge time since fire: Using digital fire history records, the time (number of years) since last fire was mapped and reclassified according to the classes in Table 1;

Wind direction, temperature and precipitation: Based on the reclassification of gridded data acquired from the Bureau of Metereology.