Bushfire simulation and suppression probability weighting for strategic bushfire planning

Simeon D. Telfer
Department of Environment and Water, Adelaide, South Australia, Australia,
simeon.telfer@sa.gov.au

Introduction

Decisions on how to best manage effects of bushfires are the subject of discussion, debate and even controversy. One decision that can be agreed upon by most policy makers and fire practitioners is that doing nothing is not an option. Land managers and fire agencies have social, ecological and political drivers to minimise the negative impacts of fire on people and the environment. While large budgets are invested in fuel management and suppression operations, there are limits to the increasing effectiveness of these activities (Penman *et al.* 2014). Decision makers in fire and land management agencies require analysis of fire trends and tools to assess the effectiveness of prevention, mitigation and suppression of fires. Models of fire risk and interventions can be useful in assessing risk treatment options. Most decision makers understand that models of complex processes, while helpful, will never be perfect. In this study, the utility for decision makers of several different techniques is compared.

Multi-factor GIS risk analysis techniques

Numerous approaches to modelling fire risk have been developed, each with underlying assumptions which have implications for the utility to decision makers (Finney 2005; Taylor and Wallace 2011; Alexander and Cruz 2013). Static grid analysis techniques in Geographic Information Systems (GIS) are used to guide risk analysis and fire planning around Australia and the world (Hawkes and Beck 1997; Daniel 2003; Beck and Simpson 2007; Taylor and Wallace 2011). Commonly known as the Wildfire Threat Analysis (WTA) and Bushfire Risk Analysis Model (BRAM), these layered approaches use various indices to combine risk factors. Models of this form are useful in understanding some of the factors influencing bushfire risk. Decision makers use them for prepositioning resources, fuel mitigation planning and strategic relative risk assessment.

There are significant limitations in these approaches included the subjective combination of factors and static fire behaviour calculations (Tolhurst *et al.* 2008; Miller and Ager 2013). The requirement for risk factors such as ignition likelihood, high fire behaviour and high value assets to all be located in the same grid cell in order for the cell to be designated high risk leads to over and under estimations of risk (Atkinson *et al.* 2010).

Strategic Risk Analysis using fire simulators

Fire simulators have become a common tool for assessing risk from bushfires (Tolhurst *et al.* 2006; Ager *et al.* 2010; Finney *et al.* 2011; Department of Environment Primary Industries 2013; Duff *et al.* 2014; Penman *et al.* 2014). The use of simulators overcomes one of the primary drawbacks of GIS threat analysis techniques, namely the dynamic component of fire weather and subsequent fire behaviour. The uses of gridded ignition coupled with a fire simulator and dynamic weather inputs has been widely incorporated into strategic fire planning and analysis in

Australia (Department of Environment Primary Industries 2013; State Fire Management Council 2014). As well as simulating fire dynamically, the ignition grid approach has the advantage of covering almost all of the landscape with a simulated fire, and therefore a useful indication of the fire behaviour across the entire landscape (Bar Massada *et al.* 2011).

The Victorian and Tasmanian approaches both assume each individual ignition location is equally likely to occur and start a fire. However, numerous studies have shown that ignition patterns show strong spatial variability (Penman *et al.* 2013; Collins *et al.* 2015; Read *et al.* 2018). Ignition location strongly influences outcomes of simulations due to the likelihood of ignition and also the ease of suppression of the ignition (Bar Massada *et al.* 2011). Weighting ignition locations has been undertaken in several studies (Bar Massada *et al.* 2011; Bentley and Penman 2017). These approaches use an ignition probability weighting to ignite more simulated fires in areas of high ignition probability and fewer fires in low probability regions.

Probability modelling in wildfire risk analysis

A large number of studies look at the probability of various wildfire factors (Brillinger *et al.* 2006; Bar Massada *et al.* 2011; Finney *et al.* 2011; Penman *et al.* 2011; Penman *et al.* 2013; Plucinski 2013; Rodrigues *et al.* 2014; Read *et al.* 2018). Suppression (or initial attack success) models attempt to model the ability of firefighting resources to contain a fire before causing damage to assets or become too large to contain in a reasonable time period (Hirsch *et al.* 1998; Plucinski 2013). These models are used for preparedness and operational decision making. Penman *et al.* (2011) describe an initial attack Bayesian Network (BN) model as part of a larger model which focussed on remote area firefighting ground crews.

Combining a suppression probability model with dynamic fire simulator presents another option of improving accuracy and confidence for decision makers in fire simulators compared to dynamic suppression models (Cruz *et al.* 2012; Duff *et al.* 2014; Duff *et al.* 2016).

This study examines two approaches to combine suppression models with simulations and assess the usefulness to decision makers. This study uses two approaches to modelling bushfire risk to assets, compares the results of these models, and surveys fire planners to test the ease of comprehension and usefulness of each approach to strategic fire planning. The first model uses a threat analysis approach (BRAM) to determining ignition likelihood to weight fire simulation outputs. The second uses a BN probability model of initial suppression efficacy to weight fire simulation ignitions and the fire behaviour outputs of the simulator.

Methods

This study looked at the Mount Lofty Ranges and Fleurieu Peninsula in South Australia. Geographic datasets used in this study were sourced from the South Australian Department of Environment and Water (DEW) and the South Australian Country Fire Service (CFS). Input datasets include digital elevation model (DEM), vegetation mapping, road network, aircraft priority response zones, fire station locations and soil characteristics. ArcMap Desktop v.10.2 and Spatial Analyst extension were used for all GIS analyses in this study. These data were processed using GIS to derive slope, distance to road and distance to fire station layers for use in both BRAM and BN models. 95 and 99.5 percentile days were calculated from the maximum FFDI for each day using hourly observations from Bureau of Meteorology (BoM) automatic weather stations for the previous 10 years. Representative geographic areas were assigned 99.5 and 95 percentile which was used in the suppression probability and fire simulation models.

The suppression component of the Bushfire Risk Assessment Model for SA (BRAM-SA) was used to calculate the probability of suppression of an ignition within 4 hours. This probability was derived from combining a suppression index and suppression probability calculator (Plucinski 2009). Table 1 provides a summary of the inputs used to calculate the index. Each factor was accumulated giving a maximum possible index score of 9. Areas of grassland with no slope had one point removed as they were considered particularly easy to access for suppression.

Table 1. Suppression access index factors

Score	Factor	Score	Factor
1	Distance to road > 100m	1	Stringybark fuels
2	Distance to road > 200m	1	Outside Aircraft PRZ
1	Slope > 10deg	1	Distance to Fire Station > 35km
2	Slope > 20deg	1	High Rockiness Soil Type
1	Shrubby understorey	-1	Grass with no slope

This index was then further classified into 4 categories based on number of suppression inhibiting factors and availability of aircraft. The fire containment guide (Plucinski 2009) and associated calculator were used to derive probability of suppression success for each of the 4 classes for a range FFDIs based on derived assumptions as shown in Table 2. Low flammability fuel types with no modelled probability were assigned a high probability of success (.99).

Table 2. Suppression factor and response time assumptions used in suppression calculations

Suppression Factors	Ground response Time (mins)	Aircraft response Time (mins)
0-2 factors + PRZ	20	10
3-9 factors + PRZ	60	10
0-2 factors + SRZ	30	45
3-9 factors + SRZ	60	45

A Bayesian Network (BN) model was developed in *GeNIe* v.2.0 (Decision Systems Laboratory, University of Pittsburgh, http://genie.sis.pitt.edu, accessed 2014) for the probability of suppression failure, and therefore spread as simulated by a dynamic fire simulator. The initial model structure was developed during the workshop with fire planners in DEW and initial values for conditional probability tables (CPT) were derived from expert elicitation. The CPT were updated using the PC learning algorithm in *GeNIe* by incorporating ignition data from the CFS for the period of 2005 to 2015 which was geographically intersected with predictor variables in GIS. FFDI was obtained for the ignition date from the most representative station using the regions described above. Suppression was considered effective if the final fire size was less than 10ha in forest and less than 100ha in grass. Figure 1 depicts the structure of BN for suppression. Each node of the model represent a CPT with arrows indicating the direction of influence.

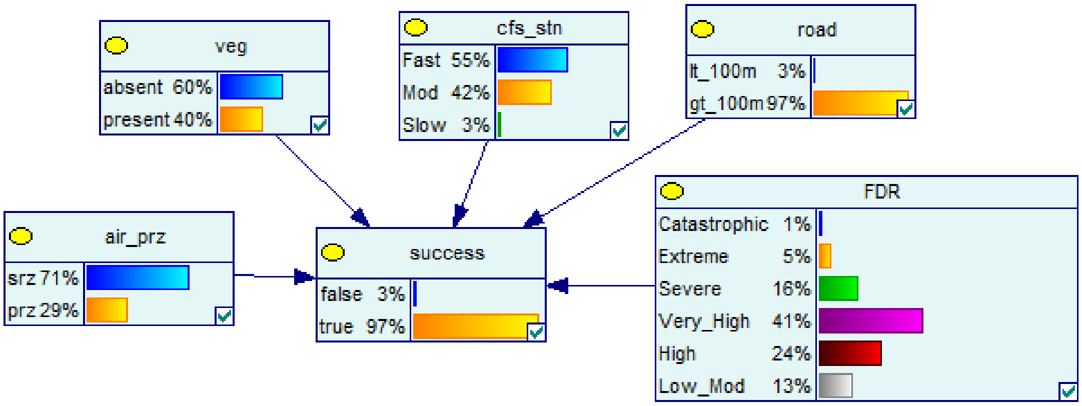


Figure 1. Bayesian Network suppression model with including histogram of variables from 10 years of ignition data

The CPT for successful suppression was used to create a probability layer for the 95th and 99.5th FFDI percentiles in ArcMap. Geographic data used in the creation of probability layer was the same as the BRAM-SA suppression model with the exception of FFDI. FFDI percentile data was sourced from BoM Atmospheric high-resolution Regional Reanalysis for Australia (BARRA) data. Figure 2 shows the suppression probability outputs of both the BRAM and BN models for the 99.5 percentile weather conditions.

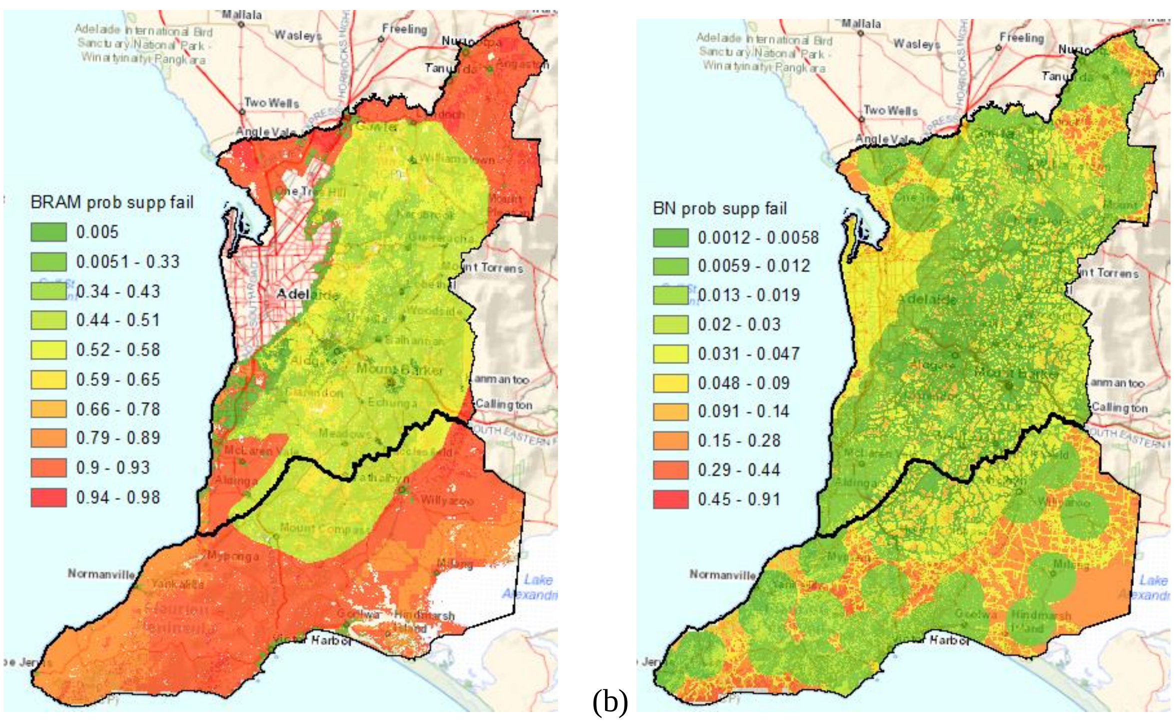
(a) 

Figure 2. Suppression probability maps for 99.5 percentile maximum daily FFDI. (a) BRAM probability of suppression failure (b) Bayesian Network (BN) model probability of suppression failure

Bushfire behaviour, spread and impacts were modelled using PHOENIX RapidFIRE v4.3 (Tolhurst et al. 2008). Inputs to simulation were the same datasets used by DEW for operational fire simulation. They include fuel type, DEM, fire history, fire disruptions (e.g road, streams), and topographic wind modifiers. The fuel types have corresponding fuel accumulation curves based on the time since last fire. Bushfires were simulated from a regular grid of points with 1km horizontal separation using weather data for the day that had the closest maximum FFDI to the 95 and 99.5 percentile FFDI. Points mapped as “no fuel” in the DEW Phoenix fuel map were adjusted spatially by up to 1 km or excluded if no fuel was within 1km of the original point location. Ignitions were simulated to start at 12:00 and run for 6 hours. The resulting fire spread and behaviour outputs were collated and used to produce a burn frequency, asset impact and ignition impact maps. This same series of maps were then produced with the outputs weighted by the suppression probability of both BRAM and BN models.

The maps and products were presented to decision makers in a planning meeting for Fleurieu Peninsula south of Adelaide. The workshop participants had each model explained to them and compared the resulting maps. At the end of the workshop they were asked about their understanding of each model and their perceptions of the usefulness for strategic fire management planning.

Results and discussion

Maps of suppression probability were produced for both the BRAM and BN models (Figure 2). The resulting map from the BRAM model is the inverse of the suppression success probability, whereas the BN model calculates the probability of suppression failure. The colour ramp of each model was calculated using natural break (Jenks) method and are not equivalent. This makes direct comparison of the probabilities difficult. The BRAM output probability for 99.5 percentile day was heavily skewed towards suppression failure, while BN was more evenly distributed, with slight skew to suppression success. Some observations can be made between models if the range of probabilities are considered as relative within the output bounds of each model. In this case the relative patterns of risk can be analysed and treatment effectiveness can be prioritised. The influence of the effectiveness of the treatments to suppression probability will still be heavily influenced by actual probability scores though.

The BRAM model shows the strong influence of the categorical nature of the model. This is particularly evident with the primary aircraft response zone which was included as a factor that increased suppression potential and in the probability calculator. Whilst the suitability of this approach is difficult to measure empirically, it may be assessed through subjective analysis of bushfire planners.

The results of discussion about the utility of the modelling approach revealed that most of the planners found the concept of suppression weighted ignition difficult to understand. When the concepts were more clearly understood there was agreement that the general approach is useful. Whilst the number of factors included in the BRAM suppression analysis seemed to give it more credibility, the arbitrary nature of combining input variables led to a level of confusion and mistrust in the outputs. Conversely, the BN model was questioned as it didn’t incorporate factors that some planners considered important. Overall, the majority of planners agreed that the BN model was more dependable than the theoretical BRAM model of suppression as the probabilities were derived from empirical data which was shown to be correlated with input variables. While the probability calculator used in BRAM was derived from empirical data, the approach used to combine suppression inhibiting factors in an arbitrary way and assigning meaning to those combination without evidence led to questions raised of the validity of the outputs.

There were differing opinions of the usefulness of testing the influence of input variables in GeNIe software. The BN model was considered an advantage in decision making, due to the finer variation in probability and the influence of the inputs on overall probability.

The planners all agreed that using weighted Phoenix simulation was more useful for decision making than the current approach of subjective risk assessment.

Conclusion

Both methods of assessing suppression probability were considered useful in improving bushfire simulations for strategic planning. The BRAM weighted simulation outputs were limited in usefulness by assumptions made in categorisation of variables and the arbitrary assignment of effects to those categories. The BN model was fairly simplistic and possibly lacked some predictive power due to the low quality input data. However the effects of changes to input variables were transparent to decision makers, who found it useful for guiding strategic planning.

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