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Research article

Bayesian decision network modeling for environmental risk management: A wildfire case study

Trent D. Penman[a,*], Brett Cirulis[a], Bruce G. Marcot[b]

[a] School of Ecosystem and Forest Sciences, University of Melbourne, Victoria, Australia
[b] Pacific Northwest Research Station, USDA Forest Service, Portland, OR, USA

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ABSTRACT

Environmental decision-making requires an understanding of complex interacting systems across scales of space and time. A range of statistical methods, evaluation frameworks and modeling approaches have been applied for conducting structured environmental decision-making under uncertainty. Bayesian Decision Networks (BDNs) are a useful construct for addressing uncertainties in environmental decision-making. In this paper, we apply a BDN to decisions regarding fire management to evaluate the general efficacy and utility of the approach in resource and environmental decision-making. The study was undertaken in south-eastern Australia to examine decisions about prescribed burning rates and locations based on treatment and impact costs. Least-cost solutions were identified but are unlikely to be socially acceptable or practical within existing resources; however, the statistical approach allowed for the identification of alternative, more practical solutions. BDNs provided a transparent and effective method for a multi-criteria decision analysis of environmental management problems.

1. Introduction

Effective environmental decision-making requires an understanding of complex interacting systems across scales of space and time. Managers often are required to make decisions in the face of high uncertainty (Fackler and Pacifici, 2014; Thompson and Calkin, 2011) with limited budgets and multiple competing interests. There is increasing public pressure for environmental management agencies to quantify costs and benefits of decisions, yet there is little guidance on the best methods to achieve this.

A number of statistical methods, evaluation frameworks and modeling approaches have been applied for conducting structured environmental decision-making under uncertainty (e.g. Gregory et al., 2012; e.g. Soltani et al., 2017; Williams and Hooten, 2016). Environmental managers need to ensure that the method they adopt incorporates the utility or cost of the action and the impact of actions, and that a decision-advisory model captures the complexity of the system without losing predictive capacity. Adkison (2009) demonstrated that managers implementing simpler decision models outperformed those using overly complex decision models. It is therefore a delicate balance to achieve the necessary level of model simplicity without compromising the predictive capability and key interactions of the model.

Wildfire management is an area typically wrought with uncertainties. These uncertainties stem from the effects of both the wildfire and fire management on biological, social, cultural and economic values (Ager et al., 2015; Finney, 2005; Roloff et al., 2012; Tedim et al., 2016). Decisions made now need to account for the shifting fire regimes that we are already experiencing (Nolan et al., 2020) and predicted future regimes (Brown et al., 2004; Westerling and Bryant, 2008). Fuel treatments are used throughout the world to alter fuel loads in an attempt to reduce future fire impacts (Fernandes and Botelho, 2003). One of the more controversial approaches is prescribed fire (Penman et al., 2020) which is mainly used to protect people, property and infrastructure. Evidence suggests that prescribed burning regimes designed to reduce risk to people and property generally increase the extent of fire in the landscape (King et al., 2006; Price et al., 2015a) and a change in fire season (Penman et al., 2011a) which can impact negatively on environmental assets, such as biodiversity, water and carbon (Bradstock et al., 2012a; Fernández et al., 2006; Ooi et al., 2006).

Various applications of decision-science methods and tools have been developed for wildfire management. For example, Dunn et al. (2017) suggested a decision-support framework for large-fire management that includes consideration for financial, social, and ecological factors. Daniel et al. (2017) developed a stochastic, spatially-explicit

* Corresponding author. School of Ecosystem and Forest Sciences, University of Melbourne, 4 Water St, Creswick, Victoria, Australia.
E-mail address: trent.penman@unimelb.edu.au (T.D. Penman).

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Fig. 1. Location of the study area. Ignition locations were all within study bounding box.

state-and-transition simulation model for forest management planning that addresses timber harvest, wildfire, and climate change. Approaches to balancing tradeoffs among fire risk, management of fire-prone vegetation, and social costs in structured decision-theory frameworks have been suggested by Dunn et al. (2017), Roloff et al. (2012), Daniel et al. (2017) and others.

One construct that is useful for addressing uncertainties in environmental decision-making that can provide an intuitive and relatively simple structure is that of Bayesian decision networks (BDNs). Bayesian networks (BNs) are statistical tools that are ideal for risk analysis of complex environmental systems (Johnson et al., 2010; Kelly et al., 2013; Pollino et al., 2007; Sierra et al., 2018). BDNs are extensions of BNs that explicitly include decision structures and utility costs or benefits of those decisions weighted by outcome probabilities. BDNs have been successfully used in management of privately-owned forests (Ferguson et al., 2015), to assess adaptation strategy responses to sea-level rise (Catenacci and Giupponi, 2013), and other applications.

BNs have previously been applied to various aspects of fire management including modeling wildfire behaviour (Dlamini, 2010; Hanea et al., 2012; Penman et al., 2011b), response of vegetation (Liedloff (Liedloff and Smith, 2010), effects on wildlife (Hradsky et al., 2017), and impact on people and property (Cirulis et al., 2019; Papakosta and Straub, 2011; Penman et al., 2015a). However, the application of BDNs to explicitly evaluate expected values of wildfire management costs has seldom been applied to wildfire management.

In this paper, we apply a BDN approach to decision making around wildfire management. We present a real-world case of using BDNs to support prescribed burning decision management in southeast Australia, and then expand our findings to a broader application context. In doing so, we ask what is the value, general efficacy and utility of the BDN approach for further use in resource and environmental decision-making.

2. Materials and methods

2.1. Study area

The case study was set in the east central highlands of Victoria (~950,000ha) within and to the northeast of the city of Melbourne in south-eastern Australia (37.8136° S, 144.9631° E) (Fig. 1). The area is a complex mix of highly modified urban landscape, agricultural land (primarily pastures), softwood plantation and native forest. Most of the study area is within the Northern and Southern Fall Bioregions (Environment Australia, 2000). The native forest within these bioregions consists of many ecological vegetation classes as defined by Cheal (2010). In the Northern Fall Bioregion, the lower slopes are dominated by Herb-rich Foothill Forest and Shrubby Dry Forest. The plains and major river valleys consist mainly of Grassy and Valley Grassy Forest, whereas the upper slopes and plateau consist primarily of Montane Dry Woodland and Heathy Dry Forest (https://www.environment.vic.gov.au/Accessed May 2018). The Southern Fall Bioregion consists mainly of Shrubby Dry Forest and Damp Forest on the upper slopes, whereas the lower slopes are dominated by Wet Forest with patches of Cool Temperate Rainforest in protected gullies. Montane Forest occurs in the higher elevations (https://www.environment.vic.gov.au/, Accessed May 2018). The mean annual rainfall for the region varies between approximately 500 and 2000 mm (www.bom.gov.au, accessed July 2019).

The fire regime for the lower productivity areas in this region is characterised by infrequent low intensity surface fires in spring with medium to high intensity fires in late spring and summer. In the higher productivity tall eucalypt forest areas, the fire regime is characterised as very infrequent high-intensity crown fires in the summer *(Murphy et al., 2013)*. Wildfires were first recorded in 1927 and since then there have been 15–40 fires recorded per decade with a total of ~300 mapped wildfires. From this set, 103 large fires greater than 100ha occurred with

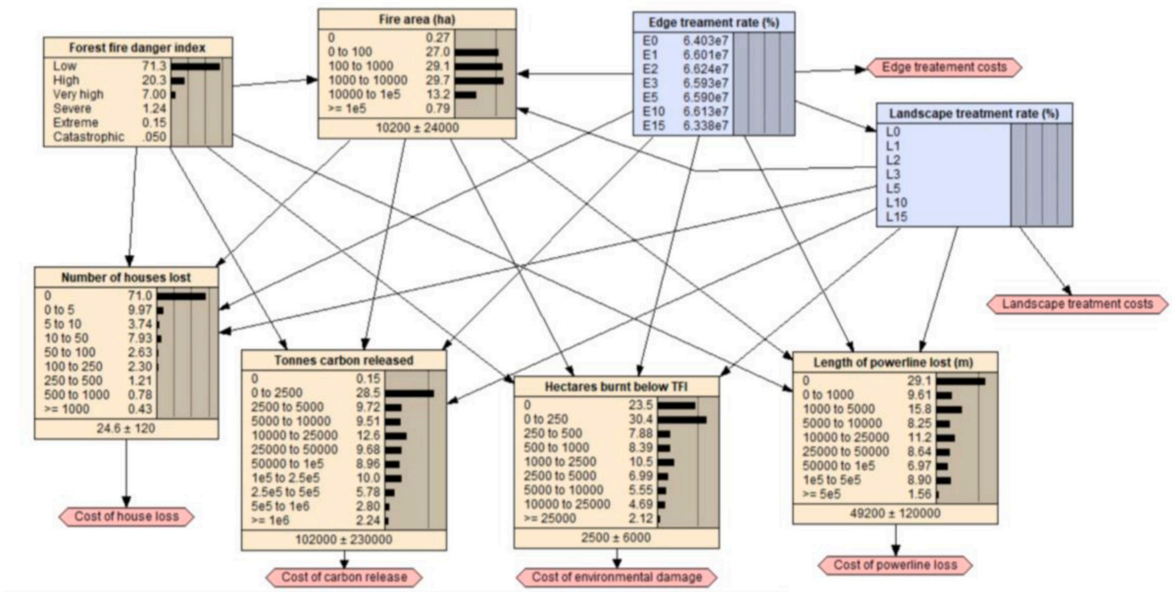

Fig. 2. Bayesian network for the analysis of fire management decisions. Blue boxes represent decision nodes, beige boxes represent stochastic nodes and pink hexagons represent the utility nodes. The numbers at the bottom of the boxes (nodes) for the continuous variables are expected values ± 1 standard deviation assuming Gaussian error distributions. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

a mean fire size of 28,181ha. The first recorded planned burn occurred in 1975 and prescribed burning has been conducted throughout the study area on an annual basis since 1975 with a total of 2180 burns recorded.

2.2. Bayesian decision network (BDN)

BNs are directed acyclic graphs with variables represented by nodes and arrows representing the directional and functional relationships between them (Pearl, 1986). Outputs of the model are expressed as probabilities, making them valuable in a risk management context (Marcot et al., 2001). Variables in a BN are typically represented by a conditional probability table (CPT) which contain the joint probability distributions representing combinations of conditions (Korb and Nicholson, 2011). Decision nodes in BDNs represent discrete actions that users can select to compare outcomes and utilities among competing approaches. BDNs can display the expected value of all utilities for each alternative decision, given the probability structure of the model. Expected values of each decision option allows managers to identify the relative cost and benefit of competing strategies. The structure of the BDN means they are far more flexible than other approaches such as decision trees as they allow for multiple decisions and values which can be scaled along different units of measure. Expected values of decisions are calculated through Bayesian learning algorithms.

We developed a BDN model to examine the trade-offs in prescribed burning strategies by varying effort in the landscape and at the interface among four assets considered in the study: houses and powerlines to represent human populations, as well as intact vegetation for carbon sequestration and biodiversity conservation to represent environmental values. The spatial resolution of the model is defined above for the study region and the temporal resolution is a single year, i.e. we estimate the annualized impact and treatment costs.

BN modeling methods of Marcot et al., (2006) and Chen and Pollino (2012) were used to develop the model. The primary steps used were to construct a conceptual model of the problem, develop influence diagrams to depict the relationships of variables within the conceptual model and finally populate all the conditional probability tables within the model and specify alternative decision actions and values of utilities.

We used a simple conceptual model based on previous BN studies of fire management (Cirulis et al., 2019; Penman et al., 2011b, 2014a). Fire weather and fire management (prescribed burning) affect the distribution of fire sizes. Fire weather, fire size and fire management then all affect the magnitude of the impact on each of the assets (utilities) of interest for each fire season. Costs are associated with the management decisions (treatments) and the impact on the assets.

Table 1
Data dictionary for the BDN. Descriptions for each node and the source of data used.

Node	Description	Source
FFDI	Proportion of the fire season where the maximum daily FFDI falls within each category	Australian Bureau of Meteorology Station 086282
Edge Treatment	Decision about the % of edge blocks treated per annum	NA
Landscape Treatment	Decision about the % of landscape blocks treated per annum	NA
Fire area	Distribution of fire size per season	PHOENIX simulation study
# houses lost	Distribution of the number of houses lost per season	PHOENIX simulation study
Tonnes carbon released	Distribution of the tonnes of carbon released per season	PHOENIX simulation study
Hectares burnt below TFI	Distribution of the number of hectares burnt below TFI per season	PHOENIX simulation study
Length of powerline lost	Distribution of the length of powerline lost per season	PHOENIX simulation study

We then created the full influence diagram from the conceptual model (Fig. 2). Two management decisions were included in the study: prescribed burning in either the landscape (hereafter *landscape*) or the interface zone (hereafter *edge*). We defined the edge as the area within 500m of an urban interface (Radeloff et al., 2005). We defined fire weather as the forest fire danger index (FFDI), which is a composite measure of temperature, relative humidity, wind speed and a long term drought factor (McArthur, 1967; Noble et al., 1980). We included two natural environment assets and two built environment assets in the BDN. Loss of environmental assets were the amount of carbon released per fire, and biodiversity impact was the area burnt below the estimated tolerable fire interval (TFI) per fire. TFI is defined as the time period

Table 2
Utility values for the house loss node. Upper estimates represent the mean + 1 standard deviation and the lower estimate is the mean - 1 standard deviation.

House loss category	Mean estimate	Upper estimate	Lower estimate
0	0	0	0
0 to 5	1,131,411	1,824,912	437,910
5 to 10	3,893,921	4,594,109	3,193,734
10 to 50	13,784,075	19,582,695	7,985,456
50 to 100	36,750,518	43,931,326	29,569,712
100 to 250	80,994,173	102,198,214	59,790,133
250 to 500	181,815,215	218,075,102	145,555,328
500 to 1000	362,675,073	433,465,303	291,884,843
≥1000	947,561,835	1,458,054,402	437,069,268

required for all plant species within a given community to reach reproductive maturity (Cheal, 2010; Kenny et al., 2004). Fires that occur below a TFI are expected to result in declines or localized extirpations of species (Keith, 1996). The loss of built environment assets is represented by the number of houses lost per fire and the length of powerlines lost per fire. In the BDN model, management decisions and all assets have associated utility nodes that represent estimated treatment and impact costs.

We then structured and parameterized the BDN (Fig. 2; see Table 1 for node definitions and data sources). A fire simulation study was undertaken using the Phoenix Rapidfire model (Tolhurst et al., 2008) to generate data to populate the CPTs for fire size and impact on assets. The study simulated fire behaviour under a range of weather conditions and generated fuel treatment scenarios. Full details of the Phoenix Rapidfire model and simulation parameters are presented in the Supplementary Material A. The final BDN can be found at www.abnms.org/bnrepo. Fire size and impact data are continuous nodes and each node was discretised on a semi log scale across the range of values for each node. Fire weather in the model was estimated using the six discrete categories in the FFDI – low, high, very high, severe, extreme and catastrophic. We calculated the maximum daily FFDI across the average fire season for the study area using data from Melbourne Airport automatic weather station (station 086282 – www.bom.gov.au accessed April 2018) and included days which fires have been recorded within a 200 km radius of the weather station. The proportional distribution of fire days in each of the six categories of FFDI was then used in the BN model to parameterize the prior probability distribution of states in the FFDI node.

We derived data for the utility nodes from a range of sources. We estimated costs of treatments using the equations of Penman et al. (2014a) which are a negative log-log relationship between area treated and cost per hectare. We calculated the average annual treatment cost for each of the simulated fuel treatment scenarios. Costs of house loss were estimated using the median property value for the suburb of Healesville (~$500K based on www.yourinvestmentpropertymag.com.au accessed November 2017). Replacement cost of powerlines was estimated at $120 per metre (www.energy.vic.gov.au/safety-and-emergencies/powerline-bushfire-safety-program/pb-report-indicative-costs-for-replacing-swer-lines. For the purposes of demonstrating our methods, we adopted a simple unit cost for powerlines ($120/m) rather than attempting to understand the economies of scale. Carbon released was calculated using Moore and Diaz (2015) who estimated a cost of $US 220 per tonne based on the potential impact on GDP. The value was then converted to $AUD 290 based on exchange rates in November 2018. There is no simple metric for translating TFI to economic metrics. We used a coarse value of $1000 per ha burnt below TFI based on the economic impact of major fires on environmental values (Stephenson, 2010).

Utility nodes require values for each category for the nodes to which they are associated. To estimate the values, we first calculated the impact costs per fire simulated. Data were then aggregated within each category for the loss node, e.g. the house loss utility values are presented in Table 2. We calculated the mean impact cost per category, as well as an upper and lower estimate. The upper and lower estimates are the mean plus or minus one standard deviation within each category.

2.3. Analysis

Model validation is vital to determining the confidence in the model performance and the data used to populate the model. Pitchforth and Mengersen (2013) highlight seven areas of validation for BNs. These methods have been designed for expert elicited BNs and as such are not all relevant to our study. The first six methods of validation focus on the model structure and discretization of nodes. Our model structure and methods for discretization has been developed based on nearly 10 years of research (Cirulis et al., 2019; Penman et al., 2011b, 2014a, 2015a) and therefore considered valid. We do however use quantitative methods to focus on the seventh attribute of Pitchforth and Mengersen (2013) namely predictive validity.

Two tests were used to examine the predictive validity of the model. Firstly, we looked at the accuracy of the model using k-fold cross classification. Data were separated into k approximately equal groups with k-1 groups allocated as training data and one group allocated as a testing set. The process is repeated k times so that all groups are used equally in

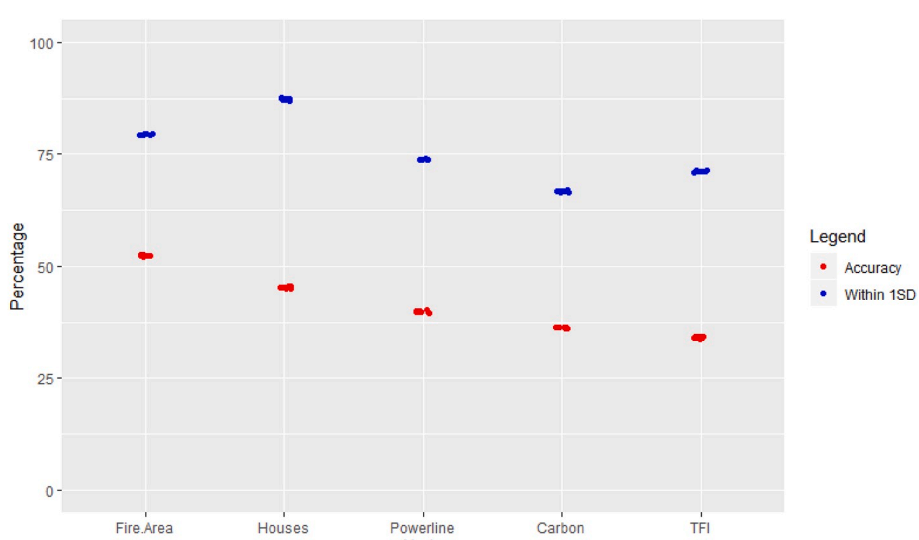

Fig. 3. Model performance using k-fold cross validation. Points represent the outcomes of the 10 folds tested.

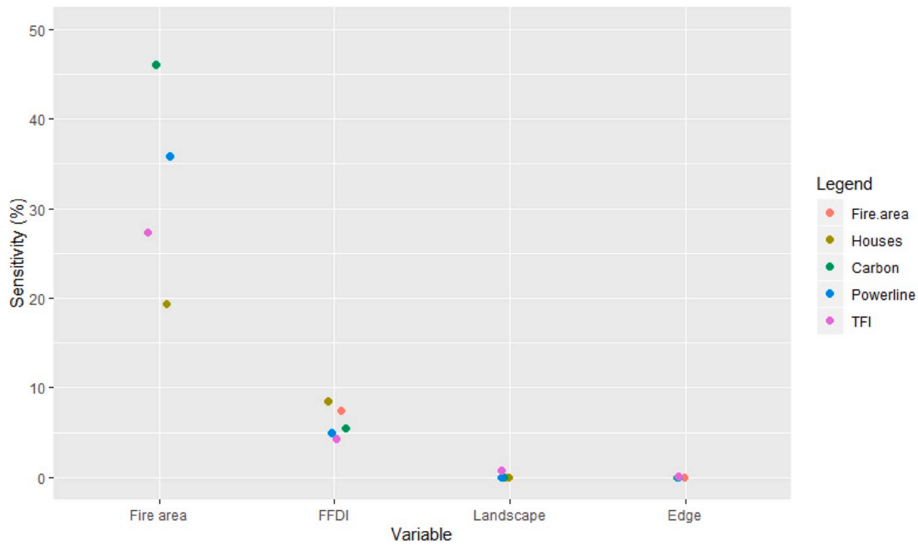

Fig. 4. Model sensitivity for the four asset types.

testing and training (Aguilera et al., 2011). In our study, we used a k value of 10 (Aguilera et al., 2010). We used the "Test with Cases" function in Netica to predict all output nodes (Fire area, House loss, Carbon Released, Area Burnt below TFI and Powerline Damage) based on known values of FFDI and the rates of Edge and Landscape Treatments. We recorded the accuracy (100 – classification error rate (%)) and the percentage of measured values within one standard deviation of the predicted value. Aguilera et al. (2011) argue the final model used for the analysis should be one with the most complete data set, as we have done. Our second method to examine predictive validity was to look at the sensitivity of findings for all output nodes. Netica has an inbuilt function which examines the extent to which changes in one variable affects the distribution in the variable of interest (Penman et al., 2014b).

To identify the effectiveness of management we undertook several analyses using the full BDN. Firstly, we examined how the interaction of the two prescribed burning treatments (landscape and edge) affected the risk to each of the assets individually. To do this we calculated the expected value of each of the assets given the management decisions and then normalised these on a scale of 0–1 to allow comparison between assets. Secondly, we calculated total costs of prescribed burning (treatment plus impact costs). This allowed for a ranking of the 25 combinations of landscape and edge treatments. Finally, to test the sensitivity of the ranking to the input cost data, we varied the utility values for each treatment and asset by taking the upper and lower estimate (e.g. Table 2) and calculated the revised ranking of the expected values for each combination of management decisions. Mean and 95% values for the ranks were then calculated and significant differences between treatments identified by non-overlapping confidence intervals which approximates significance of a *t*-test at $p = 0.05$ (Walshe et al., 2007).

3. Results

3.1. Model validity

Performance of the model varied across fire area and the assets (Fig. 3). Using k-fold cross validation, the predictive capacity of the model was relatively strong for predicting fire area and houses, but less accurate for the remaining assets. However, the proportion of values predicted within one standard deviation of the mean was >60% for all values.

Sensitivity analysis found all assets were most strongly influenced by fire area, followed by the FFDI (Fig. 4). Fire area and all assets were not sensitive to the changes in the edge or landscape treatments.

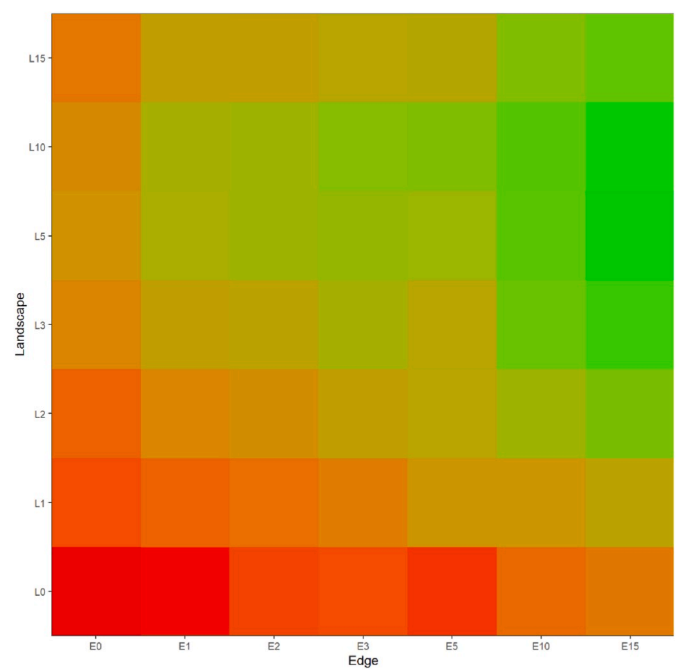

Fig. 5. Plot of the normalised expected values for fire area with green being the minimum and red being the maximum. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 3
Expected values derived from the Bayesian decision network (BDN) for fire area and the four assets per fire season. These values represent the range of expected values in the BDN definitions not the range of likely values of asset loss within the landscape. The minimum and maximum values are taken from the 49 decisions within the model. Values are used to assess the magnitude of difference (Figs. 4 and 5).

Asset	Minimum Expected	Maximum Expected
Fire area (ha)	9601	10,875
House loss (no. houses)	20.78	27.78
Powerline length loss (m)	46,138	53,022
Carbon released (metric tonnes)	96,539	109,252
Area burnt below TFI (ha)	411	3165

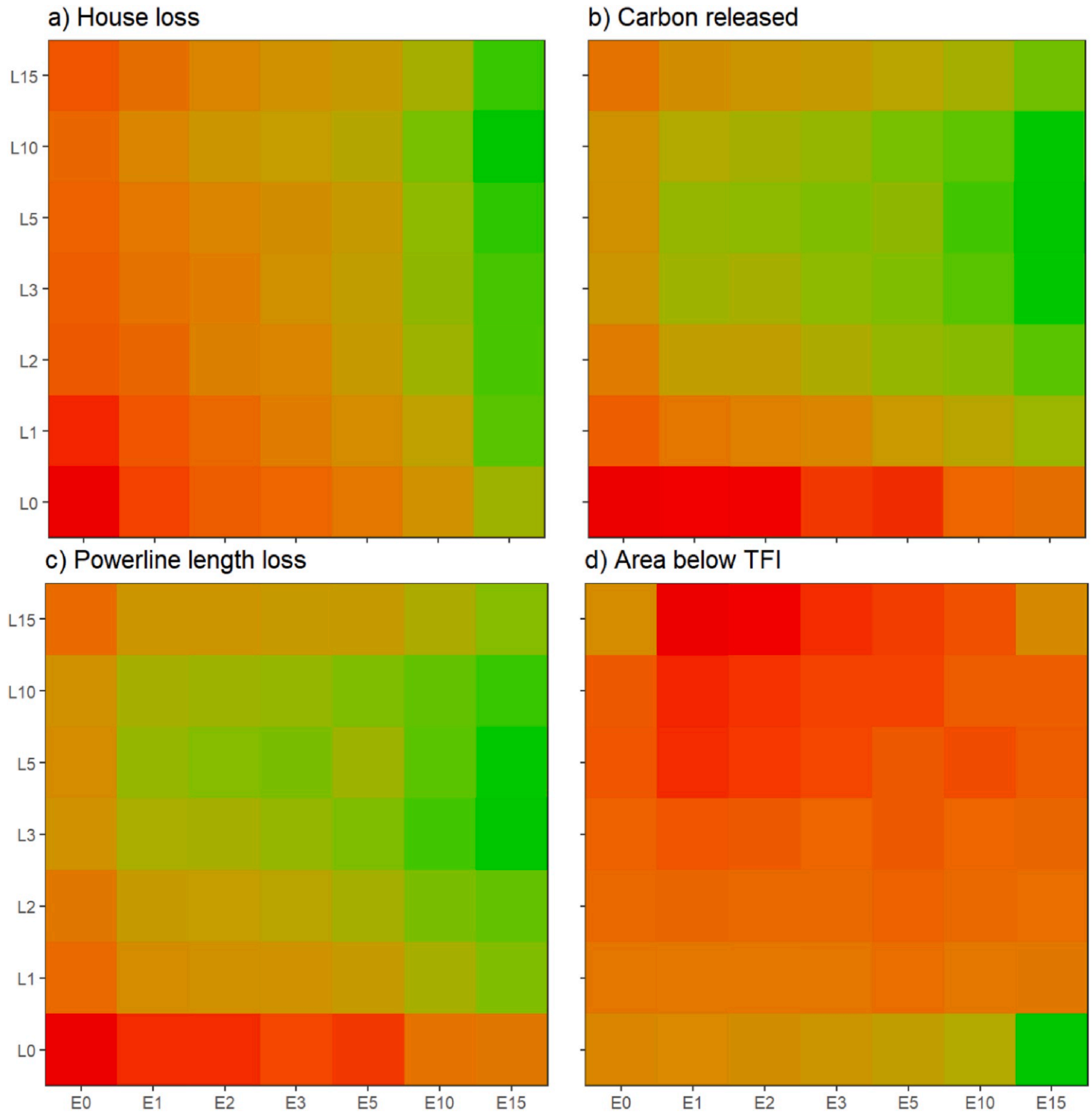

Fig. 6. Plot of the normalised expected values for a) house loss, b) carbon released, c) length of powerline lost and d) area burnt below TFI. Green represents the minimum risk and red represents the maximum risk. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

3.2. Risk to assets

Expected values per fire season for the five different risk metrics are presented in Table 3 There is a two to three-fold difference between the minimum and maximum values for each asset.

Asset loss values showed differing responses to the prescribed burning treatment combinations. Fire area (Fig. 5), powerline length and carbon released decreased strongly with increasing landscape treatments and showed only a minor reduction with increasing edge treatments (Fig. 6). Area burnt below TFI responded primarily to increasing landscape treatments with very limited effects of edge treatments. House loss decreased strongly with increasing edge treatments and showed only a minor reduction with increasing landscape treatments (Fig. 6).

Estimated costs (the expected values in the decision nodes) across all assets and treatments for the entire study area landscape considered ranged from $AUD 60.03 to 66.24 million per annum. The lowest total costs were seen in treatments with 15% of edges treated per annum and 0–3% of the landscape treated per annum. Treating landscapes with either 2 or 3% per annum and 0–5% of edges per annum were the least expensive treatment options. Landscape treatments of 15% with edge treatments between 1 and 10% were the most expensive treatment options. Decisions involving prescribed burning of the landscape at rates of 5% per annum or more were more expensive independent of edge treatment rates.

Annualized costs were correlated with the number of hectares burnt below TFI ($p < 0.001$, $r = 0.50$, $n = 49$). There were no significant correlations between annualized cost and the expected values for house loss ($p = 0.988$, $r = 0.002$, $n = 49$), powerline loss ($p = 0.955$, $r = -0.008$, $n = 49$) and carbon released ($p = 0.748$, $r = -0.047$, $n = 49$) (Fig. 8).

Rankings of treatments were sensitive to variations in the input cost values used (Fig. 9). Overall, the most and least cost-effective options had little variation in their rank. Edge treatments of 15% per annum and landscape treatments of 0–3% per annum were consistently within the lowest cost options. Similarly, landscape burning at levels above 5% per

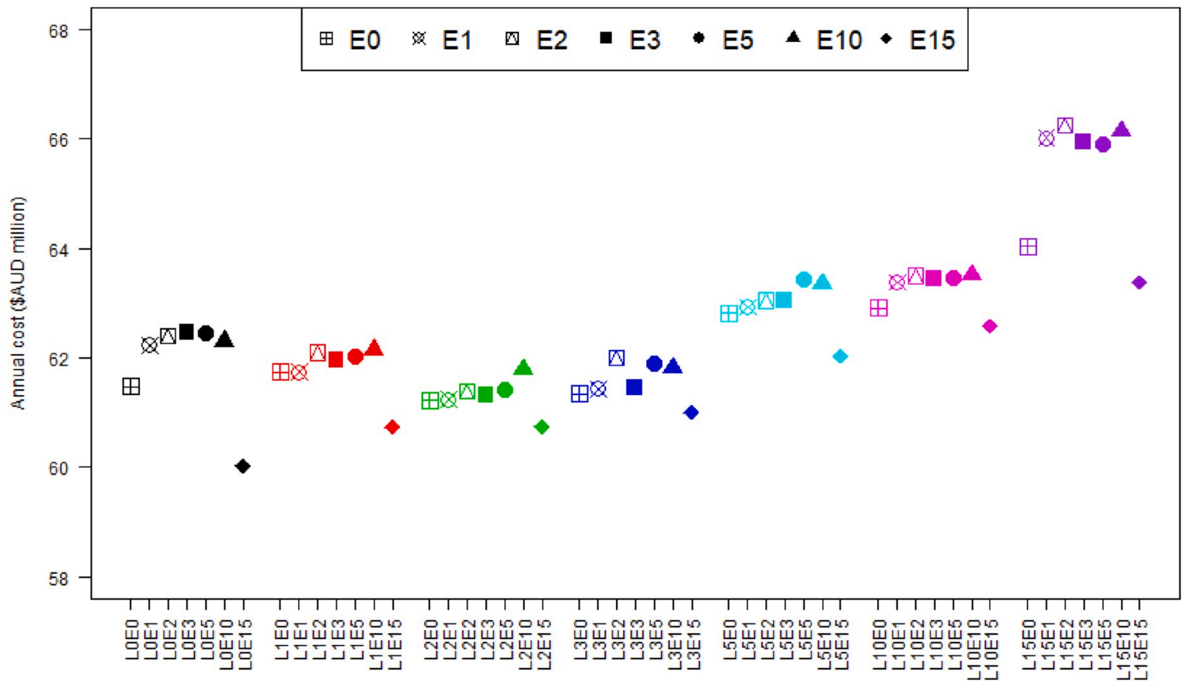

Fig. 7. Annualized cost per landscape and edge prescribed burn treatment options. Colours represent landscape treatment sets and symbols represent edge treatment sets as labelled on the x-axis. Labels represent the treatment rates for the landscape (L) and edge (E). For example, L2E5 represents prescribed burning at 2% of the landscape blocks per annum and 5% of the edge blocks per annum. See text for definitions of edge and landscape blocks. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

annum were consistently the most expensive options with the exception being the combinations including edge treatments of 15% per annum. Varying the cost of houses resulted in the greatest change in total cost (~30%) followed by carbon (~18%). In contrast, varying the prescribed burning, environmental and powerline costs resulted in a minor change to the total cost (<5%).

4. Discussion

BDNs were used to examine a key question in fire management – how much and where to undertake prescribed burning. Results showed that, when considering environmental and human assets, the most cost-effective approach is to treat up to 15% of the urban edge. However, where this is not socially acceptable, a range of landscape and edge combinations were possible with marginal increases in cost. The least desirable decisions were to burn 10–15% of the landscape annually. These results were robust to uncertainty in the data around costs of treatments and impacts.

We found that our BDN model provided a useful tool for environmental decision-making. We developed the BDN structure from empirical studies. The structure also combined complex simulation data sources simply and clearly for analyses. Explicitly adding decision and utility nodes to the basic network, to represent alternative fire management activities with associated cost and benefit outcomes, provided a flexible tool for determining lowest-cost alternatives. In that formulation, we found that best decisions were robust to reasonable variations in costs, which is new information for management. Our approach can be used as a general framework for risk-analysis evaluations of cost structures associated with wildfire control management in other ecosystems and locations (e.g. Fairbrother and Turnley, 2005; Melvin et al., 2017).

4.1. Implications for fire management

Fuel treatments around the urban interface have the greatest ability to reduce the risk of house loss compared to landscape treatments. Our results are consistent with a number of empirical and simulation studies that demonstrate this relationship (Ager et al., 2010; Gibbons et al., 2008; Penman et al., 2014a; Safford et al., 2009). Edge treatments that successfully reduce fire behaviour will reduce the risk of loss to those houses immediately adjacent to the treatment as there is a direct transfer of benefit (Penman et al., 2014a). Fuel treatments are only expected to modify fire behaviour if they encounter wildfires while in a fuel-reduced state (Price and Bradstock, 2010). Research has consistently found that any modification to fire behaviour is reduced under extreme fire weather conditions (Ager et al., 2010; Bradstock et al., 2010; Cochrane et al., 2012; Collins et al., 2013; Gibbons et al., 2008; Penman et al., 2014a; Price and Bradstock, 2012; Safford et al., 2009).

Edge treatments have limited value in reducing the risk to assets dispersed across the landscape, i.e. carbon, powerlines and area burnt below TFI. This is not surprising as edge treatments would not be expected to modify the likelihood or extent of landscape fires (Florec et al., 2019; Penman et al., 2014a). In contrast, landscape treatments altered the risk to these values. Risk to powerlines and carbon were both reduced as landscape treatments reduced the extent of fires and therefore the exposure of these assets to fire. The capacity of landscape fuel treatments to reduce fuels varies between environments (Boer et al., 2009; Loehle, 2004; Price et al., 2012, 2015b; Reinhardt et al., 2008). Empirical analysis from the study area suggests that 12 ha of landscape fuel treatment is required to reduce the annual extent of wildfire by one ha (Price et al., 2015b). In our study, there was only a small effect of landscape fuel treatments in altering fire size and risk to all assets. Increasing landscape fuel treatments resulted in increased environmental impacts, as measured by the area burnt below TFI. Fuel treatments increase the average annual extent of all fire in the landscape (King et al., 2006; Penman et al., 2011a) and consequently decrease the average time since fire. At treatment rates of 10% per annum, 70% of the landscape is less than 7 years since the last fire and below TFI for almost all vegetation communities. Subsequent wildfires are therefore likely to result in significant ecological impacts. Such rates of treatment are likely to breach ecological legislation for the study area – *Victorian Flora and Fauna Guarantee Act 1988* - which lists inappropriate fire regimes as a

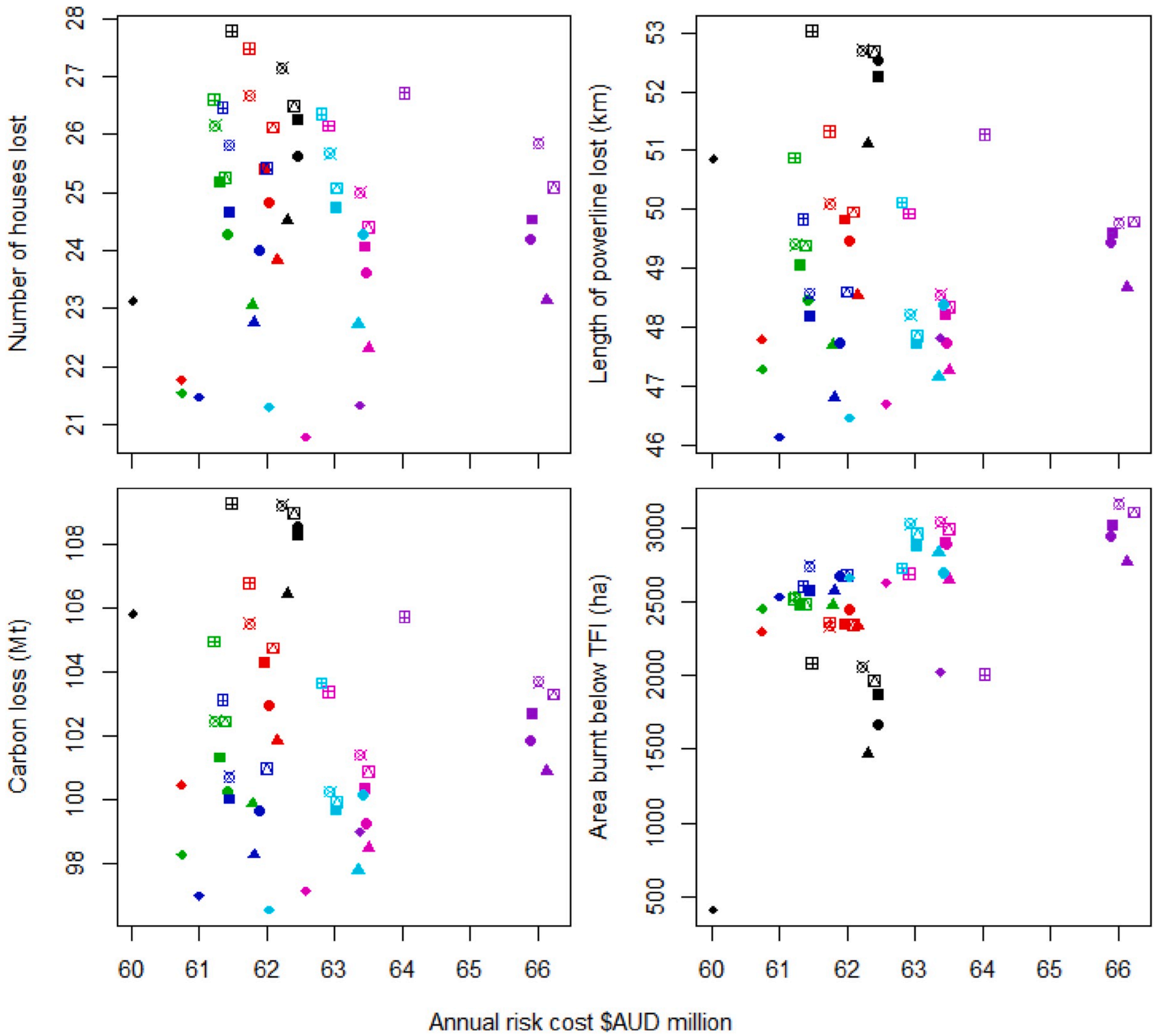

Fig. 8. Individual asset loss expected values vs annualized risk cost. Colours represent different landscape treatments and symbols different edge treatments and are all described in Fig. 7.

key threatening process, although impacts on the environment and legal mandates likely will vary in other ecosystems and locations.

The optimal decision in a statistical sense is unlikely to be implemented. The four lowest cost options all included high levels of edge treatments (15%), however such approaches may not be socially acceptable. Residents of the interface zone often move to these areas for the environmental values and many accept the risk from fire in order to maintain the social amenity (Daniel et al., 2003; Nelson et al., 2004), and fire behaviour in edge (wildland urban interface) locations likely vary among ecosystems and by effects of historic fire management (Ager et al., 2012; Dunn et al., 2017). Treatment costs in edge locations are significantly higher per ha than within landscape locations, and the community may prefer that these resources may be better allocated to other treatments (McGee et al., 2009; Walker et al., 2007) or other areas of governance such as disaster response, health and education (e.g. Healy and Malhotra, 2009).

A series of diverse alternatives were identified that were similar in cost, thereby allowing the decision makers to consider factors not within the model. All combinations of landscape (0–3% of treatable area burnt per annum) and edge (0–10% of treatable area burnt per annum) treatments have annual total cost values within 3% of each other. Within this subset, fire managers could select treatment rates within this range that were both logistically feasible when accounting for constraints such as weather and available resources (Bradstock et al., 1998) and socially acceptable without encountering significant increase in costs.

4.2. Value of BDNs in environmental decision making

The BDN provides significant value of the direct use of simulation models for decision making. The BDN readily combines data taken from multiple sources (Korb and Nicholson, 2011). For example, we combined the data with simulation model with empirical data from meteorological stations. In doing, so we were able to explicitly account for the likelihood of different weather scenarios in order to determine risk. Similarly, the simulation model does not account for the likelihood of an ignition on a given day. While a probabilistic model was used to select the most likely ignition locations (Clarke et al., 2019), these were held consistent across all weathers. Inclusion of the ignition likelihood function within the BDN overcame this issue and created a more realistic estimate of risk. Another advantage is that the model can be readily updated with new data in one or multiple nodes. Updating a single node in a BDN is relatively rapid (<1 h), whereas updating a simulation model can take days to weeks. Finally, the BDN approach would allow for a rapid assessment of the potential impact of climate change without having to re-simulate the data by simply changing the data distribution in the FFDI node. For these reasons and others outlined below, we argue that the BDN approach provides significant value beyond any simulation model.

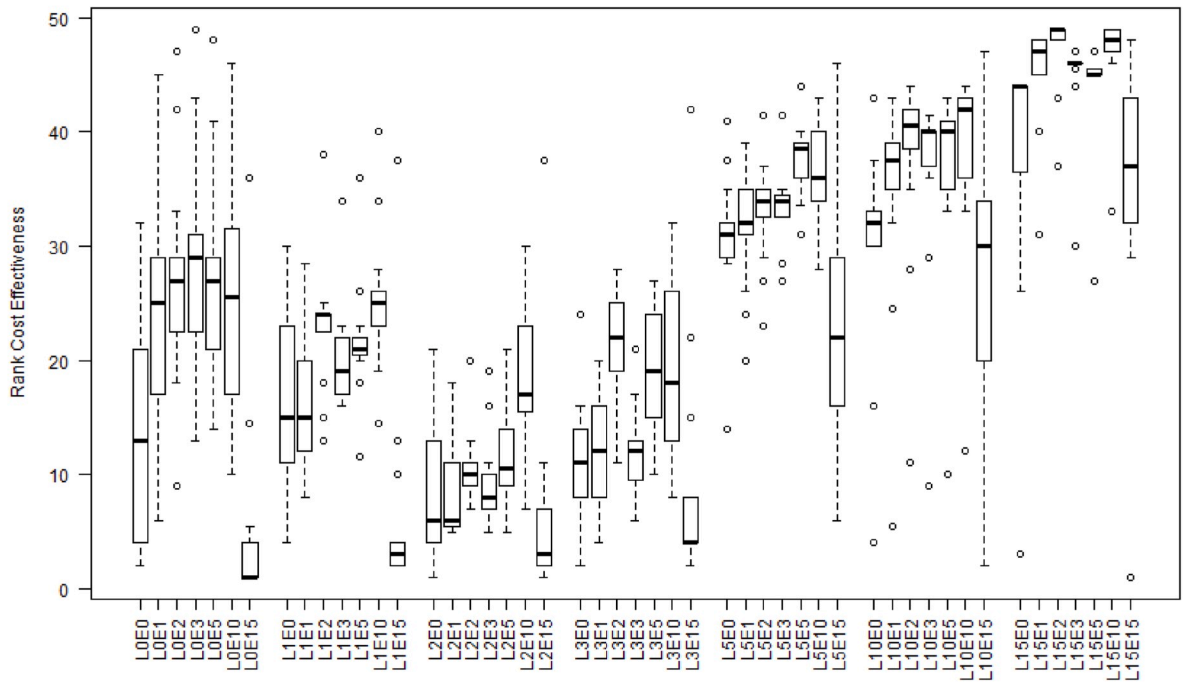

Fig. 9. Mean ranking of the cost effectiveness of the prescribed burning decision when varying the utility nodes up and down by one standard deviation. A rank of 1 denotes the lowest cost decision and 49 the highest cost decision. Each treatment and asset utility node was varied independently and the expected utility value recorded.

A major advantage of the BDN structure is the ability to include multiple utilities arranged on different scales, such as dollar value and number of structures affected, where the model then combines them into composite expected values. Different utility parameters also can be represented as costs with negative values, or benefits with positive values, and the model would calculate overall expected values accordingly. In this way, a BDN is a far more flexible framework than other decision-advisory constructs such as decision trees (Failing et al., 2004; Waring et al., 2011) in which only one form of utilities are generally denoted with only one unit of measure, such as monetary cost. Further, our BDN models were relatively simple but captured dependencies in a causal and logical network structure, again providing a more flexible and realistic framework than a purely hierarchical structure used in decision trees (Wotawa et al., 2010).

The BDN provides information on probabilities of potential outcomes and expected values of overall utilities (costs and benefits), which are key parameters used in structured decision-making and risk management (Borchers, 2005; Calkin et al., 2011), particularly in exploring the implications of alternative decisions, assumptions of fire management effectiveness, and uncertainty of costs and benefits. The BDN structure also allows for near-immediate analysis of the implications of the propagation of error (distributions of probability values among input variable states), best- and worst-case scenarios by specifying extremes of input variable states and alternative management decisions, showing calculated expected values of costs and benefits under each decision (Marcot and Penman, 2019). This allows not only for rapid decision making, but uncertainty analysis around those decisions. The tool also can be used to evaluate fire management risks at various spatial scales which is an important aspect of managing risk (Barbour et al., 2005), and in making explicit the implications of various sources and degrees of uncertainty which is a key dimension of wildfire management decision-making (Daniel et al., 2017; Thompson and Calkin, 2011). In general, our BDN modeling approach can be adapted to evaluation of risk in other aspects of resource and forest management, such as with land development (Ferguson et al., 2015) and effects of climate change (e.g. Borchers, 2005; Calkin et al., 2011; Catenacci and Giupponi, 2013).

4.3. Limitations

Our study demonstrates the utility of BDNs in a real-world example. Our results are consistent with the published fire risk literature (see above). The risk and loss distributions in our BDN were built on existing research methods (Penman and Cirulis, 2019), and the BDN provides a good relative evaluation of fire management decisions. It does not, however, specifically provide an accurate cost estimate of those decisions under our simplifying assumptions. Estimates of loss for the assets could be improved through a more nuanced economic analysis. For example, we used a median house price for the loss of houses which would be higher than the cost of rebuilding; however, it also does include additional costs to the householders during this time, such as rent, replacement of clothing, furniture, etc. In addition, the inclusion of a greater diversity of assets such as social amenity, recreation, roads or other infrastructures would alter the absolute cost but may not alter the relative order of those decisions.

The model presented here is a regional analysis that would provide useful insight for policy decisions around treatment rates over time. Our treatments were randomly allocated within each zone and increased risk reduction may be achieved by strategic placement of treatments. However, previous research suggests little difference in fire size, intensity and impact on assets between random and strategic treatments (Bradstock et al., 2012b). This study does not provide insight around where treatments should be placed nor does it identify which particular asset locations are most at risk, however this would be possible from these data and a revised Bayesian network.

5. Conclusion

BDNs provide a transparent and effective method for a multi-criteria decision analysis of environmental management problems. Developing the case study around a management decision typically wrought with uncertainties allowed us to demonstrate the utility of the approach. While we considered four asset types and two management decisions in this study, the method could easily accommodate an increase in the number of asset types and management decisions and can be calibrated to the assets and costs specific to other locations and conditions. The primary challenge will always be ensuring the data used to create and parameterize the model are of an appropriate scale (spatially and temporally) and have been rigorously collected.

Authorship contribution statement

Trent Penman: Study design, statistical analysis, writing. Brett Cirulis: Software, Formal analysis, Visualization, Writing - review & editing. Bruce Marcot: Studey design, statistical anlaysis, writing - review and editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary A

Fire simulation study.

The effect of fuel treatments on future fire behaviour was examined using the fire spread simulator PHOENIX RapidFire (hereafter PHOENIX) (Tolhurst et al., 2008) PHOENIX is routinely used within state agencies for eastern and southern Australia and these agencies consider the model to provide an adequate representation of fire behaviour in their jurisdiction (Bentley and Penman, 2017). PHOENIX simulates two dimensional fire growth over complex landscapes using Huygens' propagation principle of fire edge (Knight and Coleman, 1993). Two fire behaviour models are used to calculate rate of spread - a modified McArthur Mk5 forest fire behaviour model (McArthur, 1967; Noble et al., 1980) and a generalisation of the CSIRO southern grassland fire spread model (Cheney et al., 1998). PHOENIX also models discontinuous fire spread through ember propagation, transport and ignition (Chong et al., 2012; Saeedian et al., 2010). A number of other modules are also included. These include a fuel accumulation model to account for varying fuel loads across vegetation types within increasing time since fire and wind modification based on topographic variation and vegetation type based on the Wind Ninja program (http://www.firemodels.org/index.php/windninja-introduction - Accessed November 2011) We refer readers to Tolhurst et al. (2008) for more details on the model structure.

All data layers were provided by the Victorian Department of Environment, Land, Water and Planning (DELWP). A 30m resolution digital elevation model allowed PHOENIX to account for the influence of topography on fire behaviour. Fuel accumulation models for major vegetation types of the region have been developed to match a 30m fuel type map. Disruptions to fuels through streams and roads were represented by the estimated width on a 30m raster. Simulations were run by aggregating the data to 180m resolution cells to optimise model performance based on the recommendations by. For each cell, PHOENIX outputs fire ember density, convection, intensity and flame length.

Weather conditions have a significant influence on fire behaviour in all empirical fire behaviour models (Cruz et al., 2015). To account for the variation in daily weather, we selected a series of dates based on the McArthur Forest Fire Danger Index (FFDI) for the period from 1997 to 2015 from the nearby Melbourne Airport AWS station. FFDI is a composite measure that combines temperature, relative humidity and wind speed with a long term drying index to predict the difficulty of fire suppression (Noble et al., 1980). All six FFDI categories have been recorded in the region (low, high, very high, severe, extreme, catastrophic). Within each of these categories, three weather types were selected based on the predominant FFDI driver – strong wind, strong wind with an approximately 90° directional change or temperature. Three different days were chosen for each of these driver categories where available resulting in a total of 54 weather dates. Each weather stream contains hourly data on temperature, humidity, wind speed, wind direction, drought factor and curing. All weather streams covered a 24-h period beginning from midnight to allow the model to generate stable and realistic estimates of fuel moisture. Fuel loads were varied to represent a range of future fuel management scenarios. We focus solely on prescribed burning as the scale of the modeling is comparable to the scale of treatments and has been applied elsewhere (Penman et al., 2014a). PHOENIX estimates fuel loads using separate fuel accumulation curves for surface/near surface, elevated and bark fuels (Hines et al., 2010). These curves use a negative exponential growth function and vary between vegetation types. To simulate the effect of varying prescribed fire treatment rates in the landscape, a series of prescribed burning treatments were simulated over a period of 30 years (Penman et al., 2014a). The influence of wildfire on fuel loads was simulated by selecting a subset of actual wildfire sizes for a period of 30 years at a rate equivalent to the historical observed wildfire incidence rate in the case study landscapes (Bradstock et al., 2014). The treatable portion of each case study landscape was separated into management sized 'burn blocks' (data supplied by management agencies). Those near or adjacent to the urban interface were considered edge blocks and all remaining blacks considered landscape. A selection routine was then applied to the burn blocks, incorporating minimum fire intervals (5 years for edge, vegetation class-specific for landscape), simulated wildfire history and treatment target percentage (0, 1, 2, 3, 5, 10, 15 percent) for the edge and repeated for the landscape. This process was replicated 5 times to give a total of 245 simulated fire history layers (7 edge * 7 landscape * 5 replicates) for each case study landscape to be incorporated into the PHOENIX simulations. Ignition locations were selected using a probabilistic ignition model. An ignition probability was calculatedfor 10,000 random points within the study area based on an empirical model developed for similar forest types (Penman et al., 2015b). Ignition probability is modelled based on environmental factors (topography and productivity), and built environment factors (housing density and distance to the nearest road). The 1000 highest ignition probability locations were retained for use in the simulations. Each fire was ignited at 11am and propagated for up to 12 h unless the fire self-extinguished. Impacts on assets were calculated using loss functions for houses, human lives, roads and powerlines. The loss function for houses was the equation of Tolhurst and Chong (2011) where the probability of house loss is calculated using ember density, flame length and convection. House loss values are calculated per 180m cell and then multiplied by the number of houses in that cell to estimate the number of houses lost per 180m cell per fire. Little empirical data exist regarding the risk of loss for powerlines and we used a threshold of 10,000 kW/m to determine if powerlines within each 180m cell were considered lost for each fire. Carbon released per cell was calculated using Byrams fire intensity equation (Byram, 1959) to estimate the fuel consumed and this value was multiplied by 0.5 to estimate the carbon released. Area burnt under tolerable fire interval (TFI) was calculated using the ecological fire group (EFG) vegetation map provided by DELWP. Each EFG has a minimum TFI value. Fire history maps were used to estimate the area burnt below the minim TFI in each fire. We summed the number of houses lost, length of powerline lost, carbon released and area burnt below TFI for each fire to get a single measure of loss for each asset per fire.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2020.110735.

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