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Fire management now and in the future: Will today's solutions still apply tomorrow?

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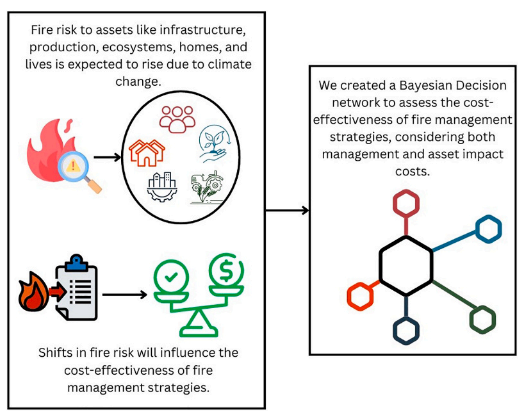
HIGHLIGHTS

- Fire regimes are intensifying with climate change.
- This increases risk to human and environmental assets.
- Wildfire management will become less cost-effective considering climate change.
- Decision support tools, can help managers prioritise cost-effective fire management strategies.

GRAPHICAL ABSTRACT



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ABSTRACT

Climate change and fire management actions are the two key drivers of fire regime changes now and into the future. The predicted effects of these drivers vary between regions and global climate projections; however, it is expected that fire regimes globally are likely to intensify. Increased wildfire extent, frequency and severity mean impacts to people, property, infrastructure, production and the environment are also likely to increase under worsening climate conditions. Fire management programs aim to reduce the influence of worsening climatic conditions on wildfires and risk to assets now and into the future However, given the pace of changes to fire regimes, trade-offs between assets are increasingly likely. Therefore, understanding the cost-effectiveness of fire management in the form of both fuel management and suppression is critical for managers to make informed decisions regarding resource allocation. We develop and test a Bayesian Decision Network (BDN) incorporating data from ~1200 fire regime simulations capturing 16 management strategies across six regions and six climate models. We quantify the effects of management and climate on fire size and risk to environmental, infrastructure, and production assets, as well as people and property. We calculate the overall cost-effectiveness of the management scenario based on the cost of implementing the program and the subsequent cost of impacts caused by wildfires. We found that costs increased under future climate conditions for all management scenarios in most regions. Despite some regional variation in the cost-effectiveness of management scenarios we were able to

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identify key scenarios which consistently had high cost-effectiveness. These were combinations of prescribed burning and suppression. Importantly, the model clearly demonstrates the risk of a do-nothing approach and highlights that action is needed to prevent high impacts now and into the future and to reduce the overall costs of wildfires.

1. Introduction

Fire regimes are intensifying around the world in response to climatic changes, resulting in increasing damage to human and environmental values (Collins et al., 2021; Filkov et al., 2020; Halofsky et al., 2020; Johnston et al., 2021). Fire risk, as measured by the outcomes of fire, weighted by probabilities of those outcomes occurring, is a key factor driving fuel management and suppression decisions (Borchers, 2005; Calkin et al., 2011). Appropriate management activities, and the magnitude of impacts from these activities, are highly variable across systems and time periods, leading to variable degrees in uncertainty around management outcomes (Burrows, 2008; Burrows and McCaw, 2013; Clarke et al., 2022; Di Virgilio et al., 2020). Identifying optimal fire management decisions in the face of uncertainty is complicated, particularly when managers seek to meet multiple objectives. For instance, previous research on identifying optimal fire management practices has focused on reducing impacts to biodiversity (Giljohann et al., 2015), forest thinning to restore resilience of dry western U.S. forests (North et al., 2021), using fire management to maintain community diversity (Richards et al., 1999), and other considerations.

Fire risk has the potential to increase dramatically over the next 50 years due to combined effects of past and recent forest management activities, and changing climate (Clarke and Evans, 2019; De Groot et al., 2013; Kelly et al., 2023; Matthews et al., 2015). Designing fire management programs which account for the uncertainty in climate futures, as well as the uncertainty in risks to ecosystem services, production, infrastructure, and people and property, is critical for achieving effective management of these assets. Moreover, fire managers are increasingly expected to evaluate their management programs against the costs of implementation and their effectiveness long-term (Aparício et al., 2022; Clarke et al., 2023). Balancing outcomes across such a broad range of management objectives and accounting for changing impacts with climate is a key challenge in fire management (Driscoll et al., 2016; Ferguson et al., 2015; Williams et al., 2017), particularly in land-use administrations operating under multiple-use regulations and mandates.

One tool used to evaluate probabilities and uncertainties of fire occurrences and impacts is Bayesian causal networks (Carriger et al., 2021; Dlamini, 2010; Hanea et al., 2012; Papakosta et al., 2017). Hradsky et al. (2017) used Bayesian networks to evaluate the effects of fire history on faunal distributions and risks to species post-fire. Additionally, Bayesian networks have been used to assess impacts of fire on property (Papakosta and Straub, 2011; Zwirglmaier et al., 2013) and to evaluate the effectiveness of multiple fire management procedures on wildfire risk (Penman et al., 2011b). Bayesian decision networks are a useful extension on this approach and can be used to evaluate the potential economic costs and outcomes of multiple fire management decisions (Penman et al., 2020a). Bayesian decision networks (BDNs) extend the causal network structure by explicitly incorporating decision options and utility (cost, benefit) outcomes (Ben-Gal, 2007; Taylor, 2023). Using this approach, BDNs quantify the consequences of alternative decision pathways as expected values of the combinations of utility factors, weighted by the probability and uncertainty within the network (Ferguson et al., 2015; Johnson et al., 2023; Taylor, 2023).

Here, we build and apply a BDN to provide a comprehensive modelling framework for analysing the potential risks of fire management scenarios on multiple outcomes. Specifically, we examine annual area burnt and the subsequent impact of area burnt on human life and property, environmental services, infrastructure, agriculture and production industries. We demonstrate use of the model for analysing conditions in six landscapes across Victoria, southeastern Australia. Fire management in Victoria is critical for addressing changing fire conditions (Keenan and Nitschke, 2016; Leonard et al., 2016) and managers in the state seek novel approaches for testing and evaluating the cost-effectiveness of their management programs. Simulated fire regimes over 50 years, under six climate projections, and considering 16 fire management scenarios were used to populate the model. Using this combination of data we seek to:

1) Quantify and interpret the implications of the uncertainty in fire regime outcomes and impacts with fire management accounting for changes in climate, and
2) Estimate management regime cost-effectiveness under current and future climates within each landscape.

2. Methods

2.1. Study area

We examined six case study landscapes within the state of Victoria (Fig. 1) all of which are approximately 1.2 million hectares in size. Victoria has suffered several major fire events in these forests over the last two decades. For example, the Black Saturday fires of February 2009 burnt approximately 350,000 ha (Cameron et al., 2009) and the 2019/2020 Black Summer fires, which burnt almost 19 million hectares, destroyed 300 houses and took >33 lives (Filkov et al., 2020). The economic impacts of the Black summer fires were estimated to reach 4.6 Billion AUD (SGS Economics and Planning, 2020). Environmental conditions in Victoria vary widely across the state, with average annual rainfall ranging from ~300 mm and average annual temperatures of 27–30 °C in the drier north-west, up to ~1500 mm of rainfall and temperatures of 18–24 °C in the wetter south-east portion of the state (http://www.bom.gov.au/, accessed 31st July 2024). Whereas Victoria is highly modified, the landscapes tested here cover much of the remnant native vegetation which accounts for ~46 % of the state (Fig. 1). Much of the remnant vegetation consists of fire-prone *Eucalyptus* forests typical of the region (Baker et al., 2019), with pockets of shrub and grasslands.

2.2. Bayesian network model structure

We used Bayesian networks as the modelling framework. Bayesian networks are structured as directed acyclic graphs that depict logical and causal links among variables (Pearl, 1986), with calculations of posterior probabilities for user-specified outcome states. The calculations use Bayes' Theorem (Niedermayer, 2008) and the network expresses the propagation of probabilities among the linked variables (termed nodes) making the framework useful for natural resource management accounting for uncertainty (Grêt-Regamey et al., 2013). The states of the variables are expressed with conditional probability tables. Bayesian *decision* networks (BDNs) are a variant that explicitly includes decision and utility nodes for evaluating potential benefits or costs. We populated the BDN with data on the costs of each management decision (Marshall et al., 2023) and of simulated damage to ecological and social values (Penman et al., 2014; Penman and Cirulis, 2020). Using the BDN we estimate the overall utility of each management scenario based on costs versus benefits.

We used the modelling methods of Marcot et al. (2006) and Chen and Pollino (2012) to develop the full Bayesian network structure from our conceptual model (Fig. 2) in the program Netica (norsys.com) and to parameterize the conditional probability tables (CPTs) using results from case-file databases generated through fire regime simulations. Conditional probability tables quantify the relationships between the nodes in a network by representing the probability of a state occurring in a child node based on the states in the parent nodes. We used the expectation maximization (EM) algorithm (Dlamini, 2011), a convergent log-likelihood function, in Netica to establish the CPT values. We based our model structure and discretization on nearly 15 years of research on wildfire impacts in the state (Cirulis et al., 2020; Penman et al., 2020a; Penman et al., 2011a, 2011b).

We incorporated 15 assets as outcomes in the BDN, representing four environmental service assets, four infrastructure assets, five production assets, and a life and property asset, (Table S1). The four environmental service assets included carbon released (in tonnes per year), the total area burnt below the minimum tolerable fire interval (TFI) over the simulation period, the proportion of water catchments burnt per year and mean annual erosion rate per year (Fig. S1). TFI is defined as the time required for plant species within a given community to reach reproductive maturity (Cheal, 2010). Fires that occur below a TFI are expected to result in declines or localized extirpations of species. The four infrastructure assets were measured as impacts to roads and powerlines in kilometres per year and the predicted loss of individual buildings, power stations and bridges per year. The five production assets included loss of crops, horticulture, livestock, plantations and vineyards (Fig. S1). Life and house loss were measured as the total losses per year in these two values. Summary nodes for each asset group were added to help simplify the otherwise over-complex probability tables in the network (Table S1; Fig. S1). The ranges of state values in the summary nodes were based on the range of the data in each asset group.

In the BDN model, management decisions also have associated utility nodes that represent costs of each treatment option. All assets except bridges and power stations also have utility nodes which characterise the impact costs. Bridges and power stations were excluded from the calculation of utility as we did not have accurate cost data for this asset and where cost data was available it was regionally variable.

To create the BDN structure, we first developed a general influence diagram denoting the major categories of covariates and response variables (Fig. 2). We used a simple conceptual model extending from previous studies of fire management (Cirulis et al., 2020; Penman et al., 2011b; Penman et al., 2020b) while accounting for climate change and associated factors. We expanded on this conceptual model in our final influence diagram and specified discrete durations of time projections as "epochs" (Fig. S1). The climate change model used and the epoch (hereafter, considered together as the "climate scenario"), combined with the fire management strategies in the model to determine the distribution of fire sizes. Therefore, the climate scenarios and fire management strategies influence the magnitude of the impact on each of the utilities of interest. The management decisions included in the model were to conduct prescribed burning, mechanical treatments, strategic fuel breaks, and suppression.

2.3. Data sources

We structured and parameterized the BDN using fire regime simulation data produced in the spatially explicit fire regime modelling framework FROST (Penman et al., 2015). FROST combines a fire event simulator, PHOENIX RapidFire (Tolhurst et al., 2008), with models of ignition likelihood (Clarke et al., 2019), fuel trajectories (McColl-Gausden et al., 2020), and climate projections (Olson et al., 2016) to model fire regimes over several years or decades. Fires were simulated over 50 years for each epoch of time (current and future climate) and six climate models for each of the six landscapes. We generated simulation outputs across 16 management scenarios (Table 1) resulting in ~1200 simulations, each with 50 replicates. For each landscape this amounted to ~10,000 rows of data which were used to populate the CPTs for fire size and impact on assets, using the EM algorithm mentioned above. Greater details of the FROST model and simulation parameters are presented in Supplementary Material B.

We defined the utility nodes as the total cost per year of implementing a management scenario in each landscape, given a particular climate model. Data to establish the values in the utility nodes were derived from a range of sources. We estimated the cost of management scenarios using the models produced in Marshall et al. (2023) to determine the utility values of each management strategy used i.e. the cost per hectare of prescribed burning, suppression, mulching and strategic fuel breaks. We estimated costs of asset impacts using a range of data sources (Table S1) applied for each unit impacted in the FROST simulations, totalled over the year and averaged across years for annual estimates of impact costs. For instance, we estimated the cost of

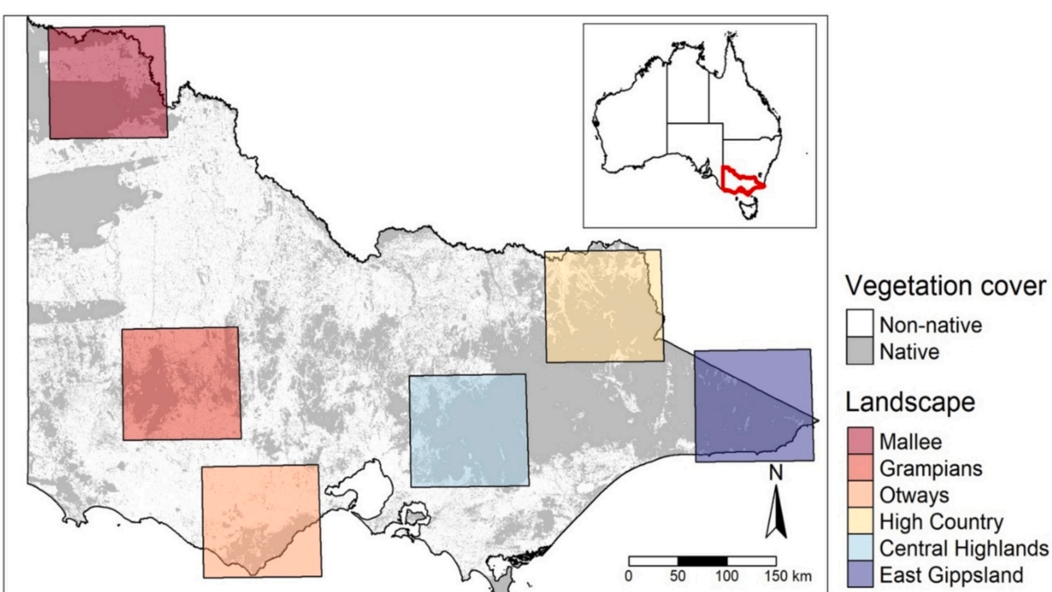

Fig. 1. Map showing the distribution of study sites across Victoria (shown in the Site legend) and the vegetation cover across the state of Victoria where grey indicates native vegetation and white shows non-native vegetation. The inset map displays the location of Victoria relative to the rest of mainland Australia.

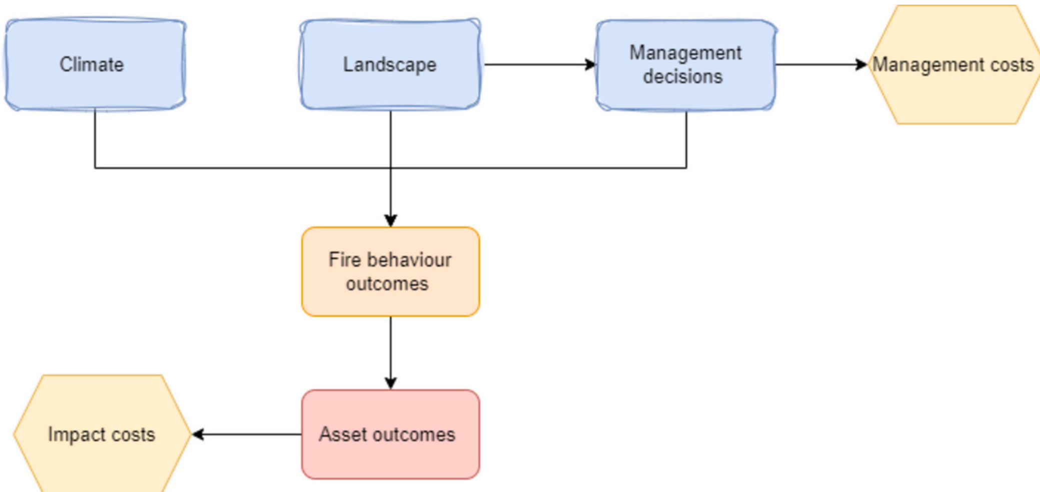

Fig. 2. Conceptual model showing how climate, landscape, and management decisions influence fire regime outcomes and risk to assets. The yellow boxes show the utility nodes, and the blue boxes show the decision nodes.

Table 1
Summary of management categories and scenarios tested, and the acronym codes used to represent these management regimes in subsequent figures and text. See Supplementary materials B for the methods used for each management scenario. All fuel treatments were conducted in native vegetation on public land managed by DEECA (Fig. S2). Strategic fuel breaks and mulching were implemented in existing locations used by DEECA (Figs. S3–S4).

Management category	Scenario	Code
No management	No management	No Mgt.
Suppression	No fuel management + suppression	NMLS
Prescribed burning	1 % prescribed burning	PB1
	5 % prescribed burning	PB5
	Strategic fuel rotations - Prescribed burning using strategic rotations (based on DEECA yearly rotations for when fuel load is high) at 3 %	SFR
Suppression & prescribed burning	PB1 + suppression	PB1S
	PB5 + suppression	PB5S
	SFRSFR + suppression	SFRS
Mulching, suppression, & prescribed burning	Mulching + suppression	MLS
	Mulching + PB1 + suppression	MLPB1S
	Mulching + SFR + suppression	MLSFRS
Strategic fuel breaks, suppression, & prescribed burning	Strategic fuel breaks + suppression	SFBPS
	Strategic fuel breaks + PB1 + suppression	SFBPB1S
	Strategic fuel breaks + SFR + suppression	SFBSFRS
All management categories	Non-burn fuel treatments + PB1 + suppression	NBTPB1S
	Non-burn fuel treatments + SFR + suppression	NBTSFRS

replacing powerlines at AU$120 per meter, multiplied by the total length of roads (in meters) impacted each year in the fire simulation (www.energy.vic.gov.au/safety-and-emergencies/powerline-bushfire-safety-program/pb-report-indicative-costs-for-replacing-swer-lines). We then averaged this value across years and over replicates to get the average cost impact to powerlines of a management scenario and climate scenario in each landscape.

2.4. Model calibration and validation

Model calibration is used to determine the percent of model predictions that match known outcomes in a case-file database (Marcot et al., 2006). We calibrated the model as initially parameterized before validation. We assessed calibration accuracy as error rates in the classification (confusion) tables (Marcot, 2012) to determine the degree to which the model incorrectly predicted the known outcomes from the data we used to parameterize the CPTs. We then evaluated model validity as the degree of accuracy of simulation outcomes as compared with other outcome results. That is, model validation determines the degree to which a model correctly predicts outcomes for cases not used to structure or parameterize the model (Boxell, 2015; Fushiki, 2011). Validation is vital to determining the confidence in the model performance and hence the applicability of the model to new situations. We used a k-fold cross-validation approach, which entailed partitioning each of our six simulated casefile databases (one for each landscape) into k subsets, parameterizing the model using 1–1/k case files and testing it against each 1/k subset of cases. We used a k = 5 following guidelines of Marcot and Hanea (2021) as our model contained independent variable structures for multiple outcome nodes. We used the *dismo* package in R (version 1.3–14; Hijmans et al., 2023) to generate the folds, and then used *RNetica* (version 7.1; Almond, 2024) to conduct the cross-validation analyses by running Netica's in-built functions to learn the CPTs with the EM algorithm, and to test the cases in each test set for classification accuracy and error rate against the simulated data.

2.5. Analysis of expected costs and risks

We used the calibrated model to analyse the effectiveness of management scenarios under each climate scenario for all six landscapes. We ran Netica's test with cases function and extracted the expected utilities under each combination of decisions. The ranges of values of the expected utilities of each management decision reflect the variations among the climate scenarios. We calculated the percent change in expected utility between current and future climate for each management scenario in each landscape and ranked the management decisions within each climate scenario and landscape based on costs. Each case in the casefile was assigned a rank between one and 16 for each landscape, with one being the most cost-effective strategy and 16 being the least cost-effective strategy. We present the cost ranking across all landscapes for current and future climates. We summarised and plotted all data in the R statistical programming language (version 4.4.1; R Core Team, 2022).

3. Results

3.1. Model structure

The model consisted of a total of 18 variables (15 asset nodes, plus area burnt and exposure of people and property), four summary nodes and six decision nodes (Fig. S1). Each landscape had its own model variant resulting in variation in the size of the models. The landscape specific models differed slightly in the number of nodes, links, and probability table values, by including only those asset variables present in each landscape. Overall, the models each consisted of 43 to 47 nodes, including the same six decision nodes and 14–15 utility nodes, four summary nodes and three intermediary nodes. The latter nodes consisted of variables such as area burnt, people and houses exposed, for which we do not directly measure utility, but which influence the utility of the asset variable. The landscape models contain between 73 and 77 links, and 32,563 to 32,613 unconditional (prior) and conditional probability values.

3.2. Model cross-validation and calibration

The calibrated models had overall classification error rates of 35–41 % depending on the landscape. Error rates of individual asset outcomes, however, ranged between 2 and 80 % depending on the landscape (Fig. 3). For example, in the Central Highlands, the asset with the lowest error rate of 13 % in both the cross-validation testing and the calibrated model was the amount of carbon released. In the same landscape, the lives lost node had the highest mean error rate of 67 % in the cross-validation and 66 % in the calibration testing (Fig. 3).

Across most landscapes, except East Gippsland and High Country, the annual number of houses and people lost had consistently high error rates. The Mallee had the highest error rates for house loss with mean values of 76 % percent in both the cross validation and calibration tests. These error rates probably reflect the high variation in the spatial distribution and density of assets in this landscape, the spatial patterns in fire occurrence, and the inter-annual variability of impacts to people and property across management scenarios. Across all landscapes, the estimated life and house loss values tended to be very low, meaning that the models are attempting to predict a very narrow range of values with high inter-annual variability (i.e. in some years it was zero). Conversely, the consistently low impacts to people (usually zero or close to zero) in East Gippsland and High Country resulted in low error rates for the number of people lost in both the cross-validation and calibration tests (Fig. 3).

Generally, for area burnt, biodiversity loss, as well as most of the environmental, infrastructure and production measures, the cross validation and calibration error rates were low (<50 %) in most landscapes (Fig. 3). Additionally, the variation in error rates across k-folds was

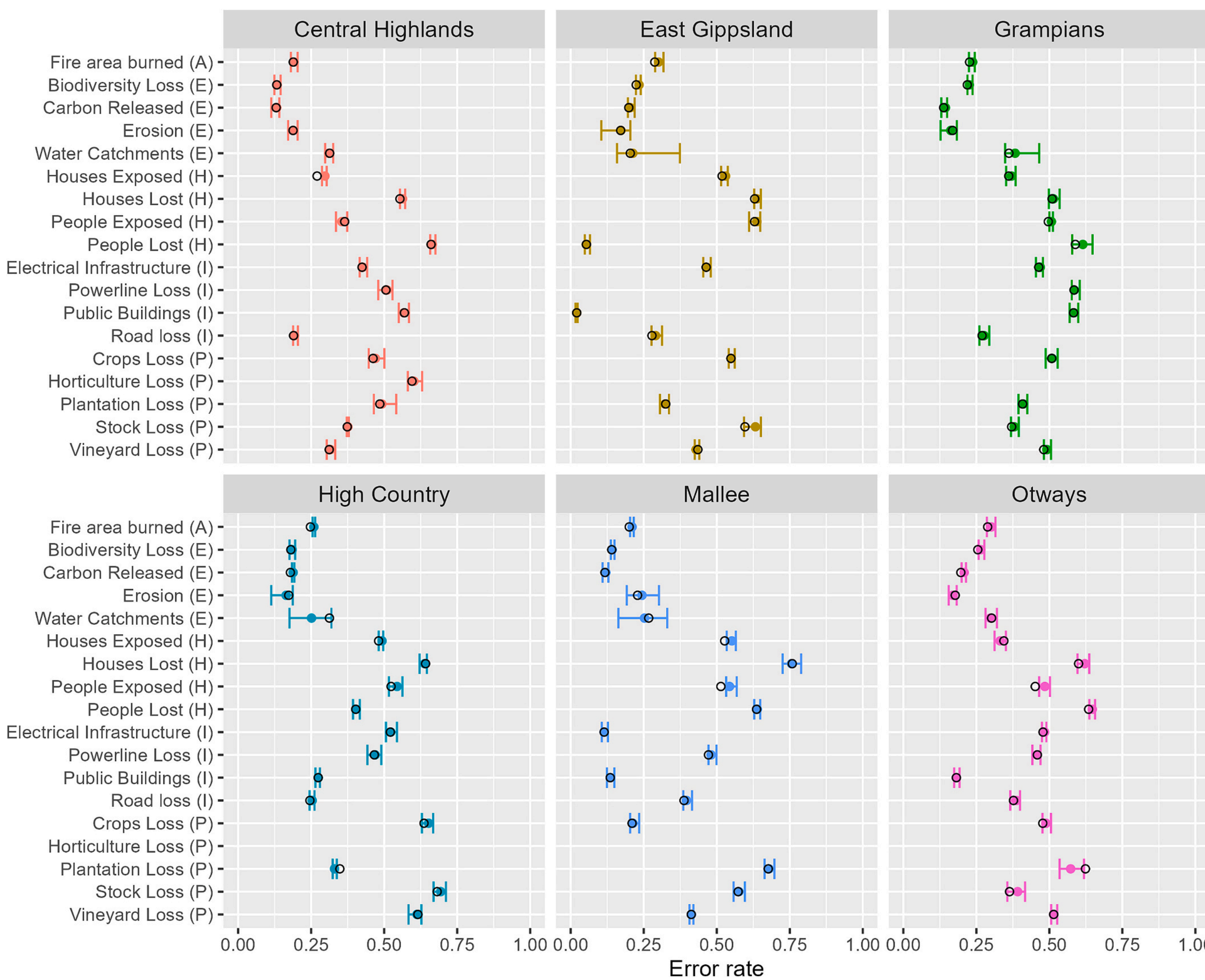

Fig. 3. The test with cases error rates for each of the asset nodes (y-axis). Asset nodes have been grouped into their sub-models; Area burnt (A), environmental assets (E), life and property (H), infrastructure assets (I), and production assets (P). Testing error rates for the cross-validation are shown as solid-coloured points of the mean error rate across k-folds and error bars showing the minimum and maximum values across k-folds. The mean error rate for each asset in the calibrated model using the test with cases function is shown as a black circle.

small except for the water catchment nodes in East Gippsland, High Country and the Mallee.

3.3. Analysis of management costs and risks

Across all six landscapes, annual area burnt increased under future climate conditions. Climate-limited regions, such as Central Highlands, East Gippsland and the Otways, increased the most by up to 60 % in some replicates (Fig. S5). The costs of management scenarios varied significantly among landscapes depending on the assets located within those landscapes, the fire regime patterns, and the climate model. However, on average across climate models, the costs of management were higher under future climate conditions in most landscapes (Fig. 4). The increase in costs under future conditions aligns with emerging research suggesting that worsening weather conditions will make it difficult to implement fuel management treatments and reduce their effectiveness (Baijnath-Rodino et al., 2022; Clarke et al., 2022), thus resulting in greater impacts to assets. Despite consistent increases in costs under future conditions across most landscapes, there was variation across climate models in how much the costs of each management scenario shifted (Figs. S6 – S11). This results in a wide range of percent change values for each management scenario (Fig. 4). The exception to this was in the Grampians landscape where approximately half of the management scenarios were cheaper under future conditions (Fig. 4). This suggests that within Grampians both the costs of management and the costs of impacts under these management scenarios were cheaper when future climate conditions were used.

Consistencies in the rankings of strategies occurred despite variation in the absolute cost values for each landscape (Fig. 5). The three most cost-effective strategies across all landscapes were the PB1S, PB5S, and the MLS strategies which represent prescribed burning treatments plus suppression and mulching plus suppression. The high cost-effectiveness of these scenarios highlights the importance of combining both fuel management and suppression i.e. neither strategy on its own is likely to achieve the desired outcome. The no-management scenario was ranked the least cost-effective strategy on average across landscapes and climate models (Fig. 5). This outcome was generally consistent between landscapes and climates. However, many of the other management regimes varied widely between landscapes and climates, resulting in a wide range of rankings. For example, the Strategic Fuel Break (SFB) scenario has significant variation in rankings under both current and future conditions both within and between landscapes (Figs. 5; S12). In the Otways for example, this scenario was ranked as one of the most expensive (high ranking) and least expensive (low ranking) management regimes depending on the specific climate model used (Fig. S12). Similarly, in the Mallee under current climate the SFBS scenario had a wide range of rankings, depending on the climate model and across replicates, but was consistently ranked lower under future conditions i.e. it was more cost-effective under future conditions than in other landscapes (Fig. S12; Table 2).

Climate was an important driver in management strategy rankings. Between current and future climate models the ranking of scenarios shifted significantly in some regions (Table 2). For example, in High Country the MLPB1S scenario was less costly under current climate models than future climate models. As a result, on average this scenario ranked seven under current climate and ten under future climate (Table 2; Fig. S12). Similar trends were seen across landscapes highlighting that some strategies that are cost-effective in a landscape now may not have longevity under future conditions, or strategies that currently are not very cost-effective could become significantly more so in future climates. That said, we found that for Central Highlands, High Country and the Mallee the two most cost-effective scenarios (PB1S and PB5S) were consistent between current and future climates. The other three regions also had these scenarios ranked in the top two depending on climate (Table 2).

4. Discussion

Decision support tools for fire management are critical for addressing the increasing risks posed by wildfires under changing climates. Specifically, managers seek tools that help to quantify the trades-offs in cost-effectiveness between management scenarios and landscapes (Clarke et al., 2023; Penman et al., 2020b). Here, we use one such decision support framework, Bayesian Decision Networks (BDNs), to identify

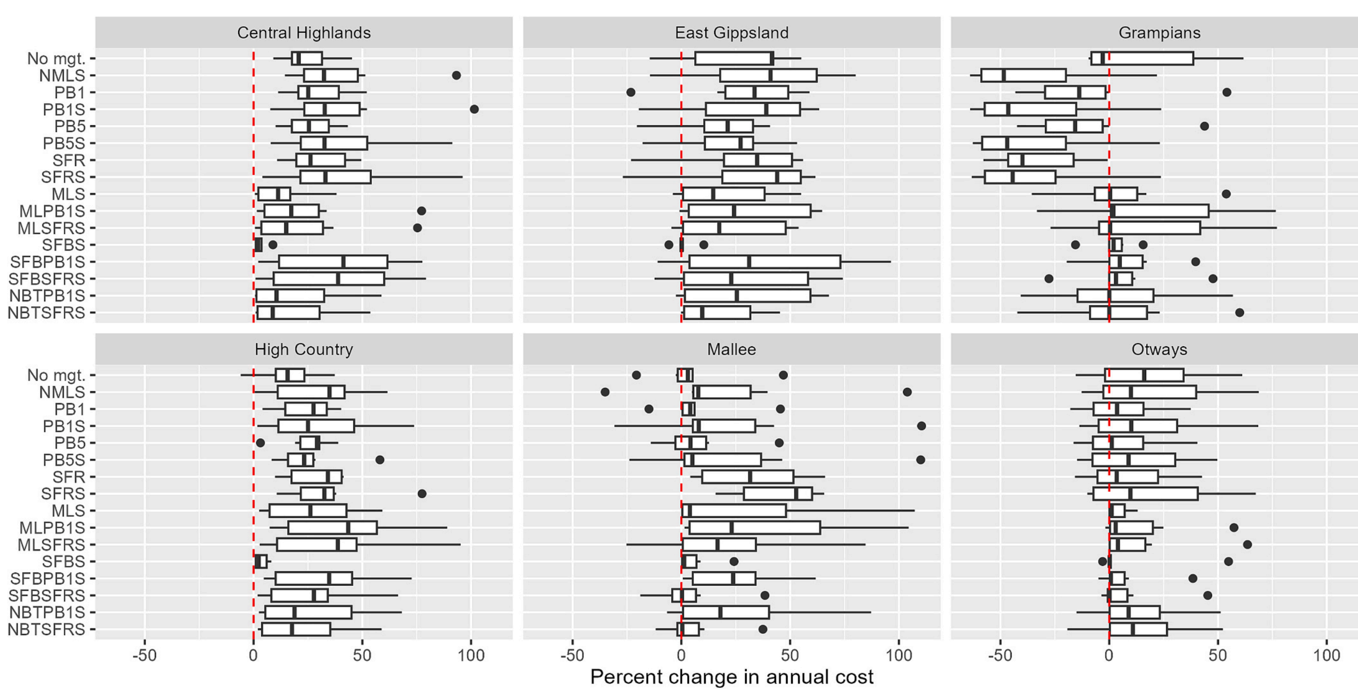

Fig. 4. Percent change in cost (x-axis) between current and future climate for each management regime (y-axis). The red line indicates zero change in costs. Positive values are an increase in cost under future conditions and negative values are decreases in costs under future conditions.

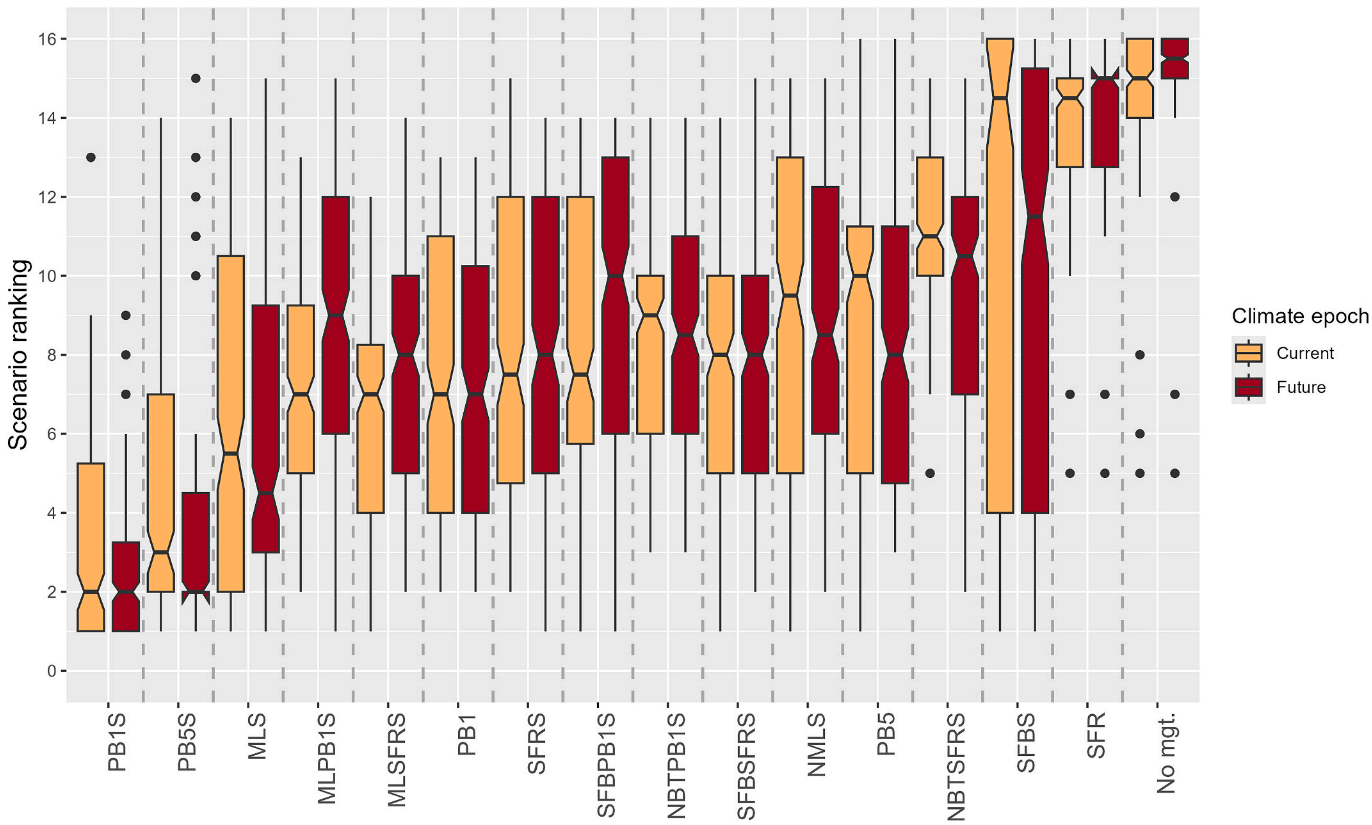

Fig. 5. Boxplots showing the range of scenario rankings for each management scenario under current (orange) and future (red) climates across all landscapes. Scenarios have been ranked between one (most cost-effective) and 16 (least cost-effective; y-axis). The variation shown in each boxplots shows the range of rankings across all landscapes, and climate models i.e. some scenarios were cost-effective in some landscapes or climate models (i.e. have a low ranking) but were not cost-effective in others (i.e. have a high ranking), resulting in a wide range of rankings shown in the boxplots.

Table 2
Ranking of scenarios for each region in order from most cost-effective (rank 1) to least cost-effective (rank 16). Ranks were averaged across climate models and replicates for current and future climate. Rankings under future conditions are shown in parentheses if they differed from current climate. Where no scenario is shown in parentheses the scenario was ranked the same across both current and future climates.

Landscapes	Central highlands	East Gippsland	Grampians	High country	Mallee	Otways
Rank 1	PB1S	NMLS (SFRS)	MLS (PB5S)	PB1S	PB1S	PB1S (PB5S)
Rank 2	PB5S	SFRS (PB1S)	SFBS (PB1S)	PB5S	PB5S	PB5S (PB1S)
Rank 3	SFBSFRS (MLS)	PB1S (NMLS)	MLSFRS (MLS)	PB1	MLS (SFBS)	MLS
Rank 4	MLS (NBTPB1S)	SFBPB1S (MLS)	MLPB1S (SFBS)	SFRS (PB5)	SFBS (MLS)	SFBS
Rank 5	PB1 (MLSFRS)	MLPB1S (SFBPB1S)	SFBSFRS (PB5)	PB5 (SFRS)	SFRS (PB1)	PB5
Rank 6	SFBPB1S (NBTSFRS)	SFBSFRS (MLPB1S)	PB5S (PB1)	MLSFRS (SFBSFRS)	NMLS	PB1
Rank 7	PB5 (MLPB1S)	NBTPB1S (SFBSFRS)	NBTSFRS (MLSFRS)	MLPB1S (SFBPB1S)	MLPB1S (SFBSFRS)	NMLS
Rank 8	MLSFRS (PB1)	MLS (NBTPB1S)	SFBPB1S (NMLS)	SFBPB1S (MLSFRS)	NBTPB1S (PB5)	SFRS
Rank 9	NBTPB1S (PB5)	MLSFRS	PB1S (MLPB1S)	SFBSFRS (NBTPB1S)	PB1 (NBTSFRS)	MLPB1S
Rank 10	MLPB1S (SFBSFRS)	SFR (NBTSFRS)	NBTPB1S (NBTSFRS)	NBTPB1S (MLPB1S)	MLSFRS	MLSFRS
Rank 11	NBTSFRS (SFBPB1S)	PB1	PB5 (NBTPB1S)	NMLS	PB5 (NBTPB1S)	NBTPB1S (SFBPB1S)
Rank 12	SFRS	PB5S (SFR)	PB1 (SFBSFRS)	NBTSFRS	NBTSFRS (SFRS)	NBTSFRS (SFBSFRS)
Rank 13	NMLS	NBTSFRS (PB5S)	NMLS (SFRS)	SFR	SFBSFRS (SFBPB1S)	SFBSFRS (NBTPB1S)
Rank 14	SFR (SFBS)	No mgt.	SFRS (SFBPB1S)	MLS	SFBPB1S (MLPB1S)	SFBPB1S (NBTSFRS)
Rank 15	No mgt. (SFR)	PB5	No mgt. (SFR)	No mgt.	SFR (No mgt.)	SFR
Rank 16	SFBS (No mgt.)	SFBS	SFR (No mgt.)	SFBS	No mgt. (SFR)	No mgt.

cost-effective management solutions across six landscapes of south-eastern Australia under current and future climates. While there was some regional variation in costs, driven by the spatial shifts in fire occurrence and therefore impacts over time, we found that costs generally increased under a future climate. This concurs with previous research and is driven by an increase in the size and frequency of fires resulting in high costs of management as well as greater costs from impacts to assets (Bradstock et al., 2010; Collins et al., 2021, 2022; Di Virgilio et al., 2020; Johnston et al., 2021).

The only landscape for which some management strategies became more cost-effective under future conditions was the Grampians (Fig. 4). This is likely due in part to the reductions in fuel continuity expected within the landscape under future conditions. The Grampians has a mix of high fuel ecosystems (e.g. mixed forests) and fuel limited ecosystems (e.g. dry heathlands; DELWP, 2021; McColl-Gausden et al., 2022; Murphy and Timbal, 2008; Nolan et al., 2021). Under current conditions, fire risk in most of the landscape is driven by fuel continuity, so where fuel loads are high and fuel is well connected there is a higher likelihood of large fires (McColl-Gausden et al., 2022; B. F. Murphy and Timbal, 2008). The future conditions modelled here cover a range of both hotter and drier, and hotter and wetter climates (Evans et al., 2014; Olson et al., 2016). Hotter and drier conditions in particular have the potential to reduce productivity and therefore fuel load in some ecosystems e.g. mixed forests, making these parts of the landscape more fuel limited (Bradstock, 2010; McColl-Gausden et al., 2020). This could contribute towards a reduction in fire size because there is less fuel and reduced fuel continuity within which fires can spread (Clarke et al., 2020). Reduced fuel loads make suppressing fires easier and increases the likelihood of early containment (Collins et al., 2018; Marshall et al., 2022; Plucinski, 2012; Wotton et al., 2017). Additionally, prescribed burns have more leverage on the landscape scale because the same sized treatments under future conditions lead to more continuous patches of low fuel load vegetation (Duff et al., 2019; Penman et al., 2011a; Price et al., 2015). Therefore, a reduction of fuel load in the Grampians under future conditions would explain the improved cost-effectiveness of management strategies in this landscape. However, these costs could also be underestimates since we do not account for changes in costs over time associated with inflation or increased difficulty to implement management due to other economic drivers. For example, it is likely that with increased frequency of natural disasters and disruptions to supply chains, the value of assets and the costs of management are likely to increase in the future (Kotz et al., 2024).

In all other landscapes, the costs of each management scenario increased under future scenarios due to worsening climatic conditions. Hotter-drier conditions mean that more of the fuel in these landscapes is available to burn. Since some of these landscapes are high fuel load areas, with highly connected vegetation, drier conditions can result in increased fuel continuity and larger fires overall. For example, in climate-limited systems, such as the Central Highlands, East Gippsland and the Otways, we observed significant increases in fire size under future scenarios which also shifted the cost-effectiveness of each management scenario over time.

4.1. Cost-effectiveness of fire management

We observed some consistencies in the rankings of management scenarios, despite variations in cost between landscapes and climate. The no-management scenario was generally the least cost-effective management scenario out of the 16 tested in most landscapes. This reflects the significantly higher impact costs associated with a do-nothing approach both now and as conditions worsen (Abatzoglou et al., 2018; Ellis et al., 2022; Jones et al., 2022; Williams et al., 2009). Importantly all costs in the do-nothing approach are related to the loss of assets, i.e. there are no costs associated with the management actions themselves. Therefore, in this scenario the increase in costs is entirely attributed to the increased impacts on a variety of asset types. These findings concur with previous research showing that a do-nothing approach generally results in the highest costs to a range of assets (Penman et al., 2020b). Furthermore, these findings do not support assertions that a do-nothing approach will eventually decrease fire risk (Lindenmayer and Zylstra, 2024; Zylstra et al., 2022), and doing so could be costly to a range of assets. The fuel model used in this study (McColl-Gausden et al., 2020) is consistent with the point-based predictions of the aforementioned studies with a peak followed by a decline in fuel structures. However, these studies only focus on single fire recovery and point based changes in flammability. They do not account for landscape fire behaviour, spatial distribution of fuels, fire regimes or the over-riding effect of fire weather on fire behaviour (Bowman et al., 2021; Collins et al., 2021; Furlaud et al., 2021; Tran et al., 2020), which our study does.

Some scenarios, such as the SFB scenario, varied in rankings across landscapes and climate models, whereas other scenarios were consistently ranked low i.e. had high cost-effectiveness. For example, prescribed burning and mulching in combination with suppression were consistently estimated to be cost-effective strategies across all regions. Comparatively, SFBs generally ranked only in the top five under current conditions, except in the Grampians where they were cost-effective under current and future conditions. These trends largely reflect the shift in fire weather and the spatial distribution of risk under future conditions, meaning some treatments are more or less likely to interact with fire. These findings are consistent with previous research and with managers' current approaches, which tend to combine fuel management techniques and active suppression efforts (Bonebrake et al., 2014; Burrows and McCaw, 2013; Cary et al., 2009; Marshall et al., 2024; Wollstein et al., 2022). The only region for which suppression alone emerged as a cost-effective strategy was East Gippsland (Table 2), however, this was not cost-effective under future conditions. This likely reflects that we used the fire history up to the end of the Black Summer fire season in 2019/20 as the preceding fire history for determining fuel load at the start of the simulation periods. Since much of East Gippsland was burnt in these fires (Filkov et al., 2020; Ward et al., 2020), fuel load was very low at the start of the simulations. Under current climate, when fire weather conditions were more moderate, this fuel load reduction had enough leverage to reduce most fire risks through suppression alone. However, given we are already observing more extreme fire weather conditions that do not reflect those in the modelled current climate, this strategy is unlikely to be as cost-effective in reality (Clarke et al., 2022; Páscoa et al., 2022).

Previous research suggests that an over-investment in preparedness and response to fires in Australia could be reducing the overall cost-effectiveness of management programs (Ashe et al., 2009, 2012). While this was not apparent in some of our management scenarios, the order of ranking of our management scenarios highlights that increased investment in more management strategies (e.g. combining many approaches to treat more of the landscape) did not necessarily reduce impacts or increase cost-effectiveness. For example, the PB5S scenario was not as cost-effective as the PB1S scenario due to the high ecological impacts of burning a greater proportion of the landscape (Boer et al., 2009; Doherty et al., 2024; Pastro et al., 2011; Santos et al., 2022). Therefore, the BDN captures some of the key trade-offs among the asset impacts that ecological managers are increasingly required to consider when designing their management programs (Driscoll et al., 2010, 2016). Managers likely still need to consider where and when management actions are applied in the future, and how these programs account for the spatial and inter-annual variability in fire risk (Dimopoulou and Giannikos, 2001; Price et al., 2015; Thomson et al., 2020; Williams et al., 2017).

4.2. Using the model for adaptive management under climate change

The model could help fire managers develop proactive solutions or scenarios for future testing as an adaptive management tool, particularly in the school of Decision-Theoretic Adaptive Resource Management (DT-ARM; McFadden et al., 2011). The BDN provides insights into the utility trade-offs for assets in environmental services, infrastructure, production, people and property between different management scenarios, climates and landscapes. The ranking of these scenarios could help prioritisation of state funding towards specific management practices, such as prescribed burning, or investment in additional testing of the spatial distribution of fuel management. Alternatively at a more local scale, it may assist managers in determining which sets of fuel management strategies are best suited for their landscape and help them identify which combinations of management strategies warrant further testing or require additional data. For example, the variation in ranking of the SFBS scenario reflects a wide range of outcomes between landscapes, climate models and asset impacts. Further, in an adaptive management context, results of monitoring outcomes can be used to further update and improve the decision-management utility outcomes of the BDN model.

Strategic fuel breaks are increasingly being used across all the landscapes tested, but their implementation is currently based on the historic patterns of fire and the ease with which they can be built in certain locations (Bar Massada et al., 2011; Shinneman et al., 2018;

Syphard et al., 2011). Similarly, mechanical treatments such as mulching are increasingly being used to modify fuels when prescribed burns cannot be implemented, i.e. in vegetation too wet to burn or when weather conditions prohibit burning (Jeanneau et al., 2021; Pickering et al., 2022). Optimising the location of strategic fuel breaks or other fuel management efforts to account for future fire regimes could improve the cost-effectiveness of these treatments under future conditions (Dimopoulou and Giannikos, 2001; Shinneman et al., 2012; Williams et al., 2017). Incorporating additional data and building on the framework presented here could help managers achieve some of these goals. This would improve the capacity of the BDN to predict outcomes for specific values, and importantly will reduce the error associated with these predictions for certain assets, making it easier for managers to assess the trade-offs of different management programs.

Error rates for some values, particularly life and property, were high across most landscapes (Fig. 3). This is largely due to the high inter-annual variability and spatial variation in the impacts caused by fires in both the model and reality (Blanchi et al., 2012, 2014; Filkov et al., 2020; Gill, 2005). No houses or lives were lost in most years, reflecting the spatial and environmental drivers required to align for house loss to occur (Calkin et al., 2023; Duff and Penman, 2021; Gibbons et al., 2012; Penman et al., 2019; Price et al., 2021). The value in a Bayesian approach, and BDNs in particular, is that the uncertainty across cases is represented and propagated throughout the system. With increasingly unknown future fire regimes under changing climate, quantifying uncertainty and accounting for it in a decision-making process, is a critical goal of fire managers (Borchers, 2005; Johnson et al., 2023; Thompson and Calkin, 2011). There are outputs from the BDN with greater richness not used in this study that could be used to better inform land management decisions if required. For example, the distribution of values within a node can be used to assess whether a strategy reaches a minimum acceptable risk value. The BDN developed and tested here will enable fire managers in Victoria, and potentially further afield, to explore a range of possible outcomes from management while accounting for the uncertainty in future fire regimes caused by landscape and climatic drivers.

4.3. Utility of the modelling framework for other applications

Our modelling approach focused on fire management but also has wide application across multiple risk and natural hazard management disciplines. For example, other work has utilised BDNs to explore implications of managing coastal marsh habitats of at-risk wildlife species (Stantial et al., 2024), prescribed burning of sugar cane (Price et al., 2018) and much more. Additional future application of this modelling approach within fire risk and other natural hazard fields could utilise a participatory approach within the network whereby managers weight the utility values according to their key priorities i.e. houses and lives versus biodiversity impacts, thereby improving model performance (Chenery et al., 2020). Testing management actions under an adaptive management approach is critical for making more informed future decisions about fire and for designing fire management programs that are fit for purpose under a changing climate (Prichard et al., 2021; Reilly et al., 2021)

4.4. Limitations

Error rates within the BDN reflect the real-world inter-annual variability in asset impacts, but there are also introduced errors within the model that could be addressed in future research or with additional data. For example, the simulation model used to generate the data, FROST, is populated using a series of separate models for ignition likelihood, fuels and suppression (Clarke et al., 2019; Marshall et al., 2022; McColl-Gausden et al., 2020). While all these models are peer-reviewed, the simulations and therefore the BDN, necessarily inherits any errors and limitations associated with these modelling approaches. Additionally, the fire simulator central to this exercise, PHOENIX Rapidfire, is only one method in a suite of available fire spread models and modelling frameworks (Cruz, 2021; McArthur, 1967; Miller et al., 2015; Tolhurst et al., 2008). Future research should explore the variability of management effectiveness between rate-of-spread models which function differently among dissimilar vegetation types. Here we only explore management scenarios on public land managed by DEECA despite some management occurring in non-native vegetation and on private land. This was largely due to the lack of publicly available data on these treatments. However, future research should attempt to fill this gap by examining the role of fuel management on private land for reducing fire risk to assets. Some limitations in the simulation framework include the implementation approach for SFBs and areas with mulching treatments (Supplementary materials B). As these features were implemented as static changes to the disturbance and fuel layers, except for the prescribed burns adjacent to strategic fuel breaks, the simulations do not include repeated treatments within these scenarios over time. Comparatively, the prescribed burning scenarios involve repeated treatments. This has two potential consequences on the results; 1) the cost of management is lower than is likely in reality because strategic fuel breaks would need to be maintained, and mulched areas would eventually need to be retreated, and 2) the effect of these treatments on fire regimes may not reflect their true value. For example, in the case of strategic fuel breaks we model them as static changes in fuel (with repeated prescribed burning either side of the break) but do not incorporate their utility as a feature of suppression efforts (Kornakova and March, 2017; Penman et al., 2019; Syphard et al., 2011, 2014). This was not modelled because strategic fuel breaks are often used during suppression for managing fires that run for multiple days (campaign fires) which are not possible to simulate in PHOENIX currently (Tolhurst et al., 2008), although emerging fire simulation tools and research could solve this problem for future iterations (Miller et al., 2015). Moreover, these management strategies have an additional ecological cost that is not accounted for here, i.e. the impacts of implementation and maintenance activities on species and habitats.

These are modelling limitations that could be addressed in future and subsequent versions of this tool can include the updated simulations to reevaluate cost-effectiveness for these strategies. Despite these limitations, the results presented here still align broadly with what is expected of these treatments, the costs of which are an economy of scale (Marshall et al., 2023). Moreover, the cost effectiveness of SFBs and mulching likely reflects reality since these treatments are not currently being applied at a great enough extent across any of the landscapes tested to be as cost-effective as prescribed burning. The inability to model campaign fires could also result in under-estimates of fire size in some regions. For example, East Gippsland, which is a climate limited system, is characterised by infrequent but high intensity, large overnight fires (Murphy et al., 2013). Therefore, excluding overnight fires likely means some of the largest fires that occur in reality are not being accounted for here.

Future research should also endeavour to improve the costs estimates for impacts and management over time. Here, we assume costs remain the same over the simulation period, which does not account for inflation in the costs of assets or the increasing costs of management e.g. increased personnel costs. Additionally, we do not account for the loss of assets in one part of the landscape in subsequent simulation years i.e. the spatial distribution of assets is static throughout the simulations meaning the impact costs incurred could be consistently higher than is likely in reality. Fine scale mapping of assets is a key knowledge gap in determining cost-effectiveness of fire management strategies. Accounting for the spatial and temporal variation in asset impacts due to human behaviour and settlement patterns, regulation (Haghani et al., 2024; Mockrin et al., 2020) and other natural hazards risk should be addressed in future research and decision support tools.

5. Conclusions

The unique combination of fire regime simulations and Bayesian Decision Network modelling utilised here provides insights into the cost-effectiveness of fire management pathways under changing climatic conditions. This approach highlights that while there is some variation between landscapes and climate models, there are clear winners and losers in terms of the cost-effectiveness of management strategies. It is clear from these results that a do-nothing approach will not prevent wildfire impacts on values such as environmental services, production, infrastructure, or people and property. This was consistent under both current and future climates. We also found that highly intensive management activities are not necessarily the most cost-effective management solution due to the increased environmental costs of such programs. Despite some limitations in the tool presented here it could provide fire management agencies, who are charged with a mandate to manage wildfire risk and protect people and property, with a decision support system that gives them insights into their adaptive management programs. Such tools are helpful for quantifying uncertainties and incorporating new data as it emerges, ultimately to enable new scenario development and to help prioritise proactive solutions now and under rapidly changing conditions.

CRediT authorship contribution statement

Erica Marshall: Writing – review & editing, Writing – original draft, Visualization, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Bruce G. Marcot:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Formal analysis, Conceptualization. **Kate Parkins:** Writing – review & editing, Investigation, Funding acquisition, Data curation, Conceptualization. **Trent D. Penman:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

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Declaration of competing interest

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2024.177863.

Data availability

Data will be made available on request.

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