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Cost-Effective Prescribed Burning Solutions Vary Between Landscapes in Eastern Australia

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Fire management agencies undertake a range of fire management strategies in an attempt to reduce the risk posed by future wildfires. This can include fuel treatments (prescribed burning and mechanical removal), suppression and community engagement. However, no agency has an unlimited budget and numerically optimal solutions can rarely be implemented or may not even exist. Agencies are trying to quantify the extent to which their management actions reduce risk across multiple values in the most cost-effective manner. In this paper, we examine the cost-effectiveness of a range of prescribed burning strategies across multiple landscapes in south-eastern Australia. Landscapes considered include vegetated areas surrounding the cities of Hobart, Melbourne, Adelaide, Canberra, and Sydney. Using a simulation approach, we examine the potential range of fires that could occur in a region with varying levels of edge and landscape prescribed burning treatment regimes. Damages to assets are measured for houses, lives, transmission lines, carbon and ecological assets. Costs of treatments are estimated from published models and all data are analyzed using multi-criteria decision analysis. Cost-effectiveness of prescribed burning varies widely between regions. Variations primarily relate to the spatial configuration of assets and natural vegetation. Regions with continuous urban interface adjacent to continuous vegetation had the most cost-effective fuel treatment strategies. In contrast, those regions with fragmented vegetation and discontinuous interfaces demonstrated the lowest cost-effectiveness of treatments. Quantifying the extent to which fuel treatments can reduce the risk to assets is vital for determining the location and extent of treatments across a landscape.

Keywords: Bayes network (BN), fire simulation, wildfire (bushfire), risk, trade off analysis, cost-benefit

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INTRODUCTION

Wildfires are a natural disturbance in many ecosystems but when they encounter human settlements/infrastructure/communities they can have devastating consequences. Recent fires around the globe (e.g., Europe, USA, Chile and Australia,) have resulted in major losses of life, property, infrastructure and caused significant environmental changes (Bowman, 2018). These problems will be exacerbated under patterns of global change where expanding urban populations are increasingly moving into flammable parts of the landscape and fire regimes will shift in response to changing climates (Gill et al., 2013; Bowman and Moreira-Muñoz, 2019; Syphard and Keeley, 2019).

Prescribed burning is a form of fuel treatment: i.e., it aims to alter the quantity and structural complexity of fine fuel in a way that moderates the rate of spread and intensity of subsequent wildfires. An individual prescribed burn will be considered effective for the period in which consequent effects on rate of spread and intensity of subsequent fire are reduced compared to untreated fuels (e.g., Penman et al., 2007; Price and Bradstock, 2012). The effectiveness of prescribed burning is potentially a function of the dynamics of surface fine fuel loads which increase with time-since-fire until an equilibrium load is reached (e.g., Penman and York, 2010; Thomas et al., 2014). However, recent research has shown that these dynamics vary between regions and fuel strata. Variations in fuel and responses to prescribed fire will vary with environmental drivers such as climate and productivity (Dixon et al., 2018; McColl-Gausden and Penman, 2019; McColl-Gausden et al., 2019). Generally, the window of effectiveness of treatment has been shown to diminish as fire weather at the time of encounter by a wildfire increases in severity (Price and Bradstock, 2012; Collins et al., 2013; Tolhurst and McCarthy, 2016). Given that there are major variations in fire weather at regional scales, particularly the upper extreme, effectiveness of prescribed burning can be expected to vary as a coupled function of vegetation type (inherent fuel dynamics structure) and climate (potential fire weather).

Generally, the primary objective of prescribed burning is to reduce risks to human and natural assets via modifications to fire behavior, although prescribed burning can be undertaken to promote ecological assets or for cultural purposes (Penman et al., 2011). The degree to which prescribed burning can potentially alter fire behavior, constitutes an important but only partial element of the overall effectiveness in mitigating risk. Other factors in concert with changes to fire behavior caused by fuel treatments will affect risk. For example, the rates of treatment, spatial distribution of treatments and configuration of developments will alter the risk mitigation outcomes for people and property, of different prescribed burning strategies (Bradstock et al., 2012b; Penman et al., 2014; Thompson et al., 2017; Florec et al., 2019; Cirulis et al., 2020).

Fire and land managers are required to design prescribed burning strategies to protect a range of assets across the landscape. Prescribed fire is most commonly used to reduce the risk to assets that are vulnerable to exposure to high intensity fires, such as people, property and major infrastructure (Penman et al., 2011, 2020; Driscoll et al., 2016). Treatments have been used to offset carbon emissions in some environments (Russell-Smith, 2016) but may increase carbon emissions in others (Bradstock et al., 2012a). Many water supply catchments exist in naturally vegetated areas and are susceptible to fire (Smith et al., 2011; Langhans et al., 2016). Fuel treatments have been used to decrease the risk of reduction in water quality and quantity (Nyman et al., 2011; Smith et al., 2011). Inappropriate fire regimes can result in significant impacts on biodiversity, although ecological burns can be used to benefit some species (Gundale et al., 2005; Bentley and Penman, 2017).

Decisions around prescribed burning are therefore complex and require consideration of the costs of implementation and the impacts on assets of interest, although relatively few studies have attempted this approach. Results from such studies vary widely with some suggesting fuel treatments near houses are the most cost-effective strategy (Penman et al., 2014; Scott et al., 2016) and others suggesting landscape treatments are more cost-effective (Florec et al., 2019) for reducing cost. Optimal strategies for human and ecological values differed in some studies (Driscoll et al., 2016), but not others (Bentley and Penman, 2017). Most studies have focused on only one or two case study regions (Bradstock et al., 2012b; Thompson et al., 2013; Driscoll et al., 2016; Bentley and Penman, 2017; Florec et al., 2019; McFayden et al., 2019; Cirulis et al., 2020) making it difficult to generalize results. The performance of prescribed burning strategies needs to be systematically assessed in relation to these variations given the likely variation in potential effectiveness of prescribed burning in influencing fire behavior, along with differing configurations of assets and management values. Specifically, we need to determine if the risk mitigation potential of differing prescribed burning strategies is likely to be robust to such variations or if the optimum strategy (i.e., most cost-effective) varies widely according to biophysical and human context.

In this study, we aim to determine the cost effectiveness of prescribed fire treatments across multiple assets and multiple landscapes. These case studies are placed across a sub-continental gradient of biophysical (e.g., temperature and rainfall) and human variation (e.g., house density and land uses). We compare varying prescribed burning treatment rates in both landscape and edge treatments (i.e,. within 1 km of houses) across forested and woodland landscapes on SE Australia. Specifically, we ask:

1. What are the most cost-effective prescribed burning strategies/solutions across multiple landscapes and assets?
2. Do these solutions vary as a function of landscape context?

METHODS

Comparisons of treatment cost-effectiveness were conducted across 13 regions spanning the diversity of ecosystems in south-eastern Australia (**Figure 1**). Patterns of vegetation and fire regimes reflected variation in latitude (from temperate to sub-tropical), rainfall (from 250 mm in the semi-arid west to 1,500 mm in the coastal zone of the east) and altitude (the dividing range runs along the eastern coast up to an elevation of 2,000 meters above sea level. (Murphy et al., 2013). Case study regions were selected to cover the diversity of vegetation types, climates and built environments. Each case study was between 45 and 60 km rectangles with a dominant cover of native vegetation that can be treated with prescribed burning. A summary of each of the study areas appears in **Supplementary Material**.

To examine the cost-effectiveness of prescribed burning on landscape values we followed the methods of Cirulis et al. (2020). The approach required four main steps. Firstly, we prepared region specific data about weather, fire history and ignition locations. Secondly, wildfires were simulated across the full spectrum of historical weather and prescribed burning scenarios giving a broad range of outputs. Thirdly, the impact on five asset types was estimated for each fire. Finally, data

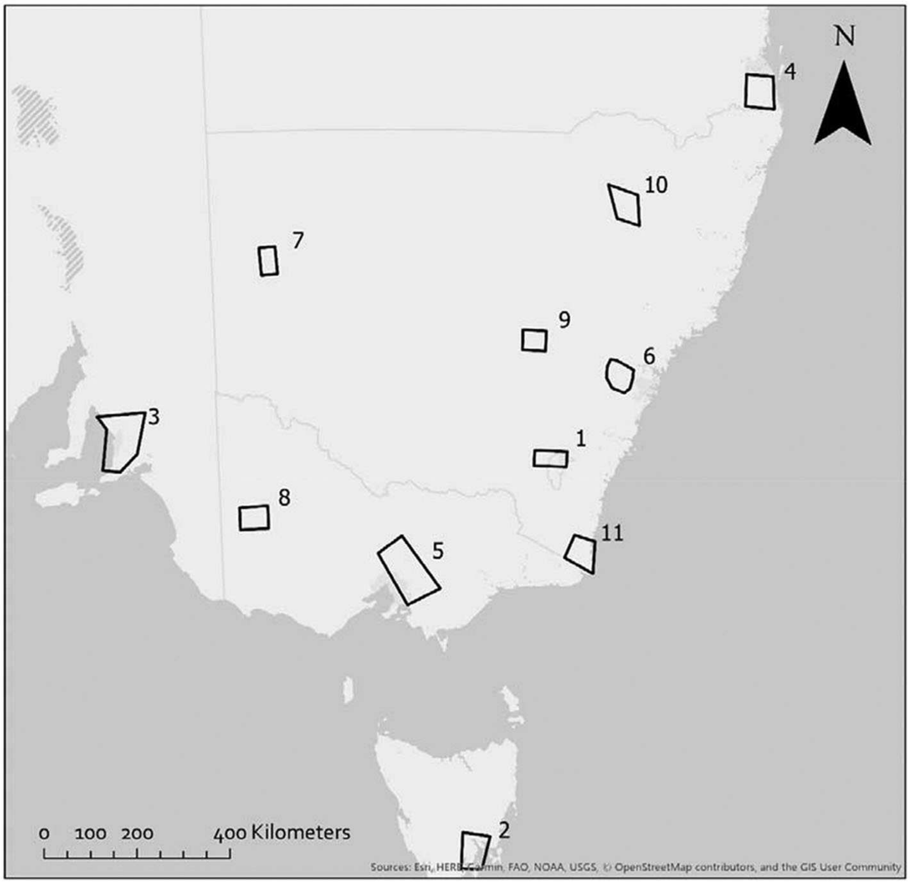

FIGURE 1 | Case study locations in south-eastern Australia. 1, ACT Canberra; 2, TAS Hobart; 3, SA Adelaide Hills; 4, South-eastern Queensland; 5, VIC Central Highlands; 6, NSW Blue Mountains; 7, NSW Broken Hill; 8, VIC Little Desert; 9, NSW SW Slopes; 10, NSW Nandewar; 11, NSW south-east corner.

were analyzed using a Bayesian Decision Network to estimate the cost-effectiveness of different prescribed burning strategies relative to a do-nothing approach. From this, the most cost-effective solution for each landscape was identified. The workflow is presented in **Figure 2** and described in more detail below.

Fire Simulation

Fire simulations were undertaken using PHOENIX RapidFire v4.0.0.7 (hereafter PHOENIX; Tolhurst et al., 2008)—the operational version of the software at the time of analysis. PHOENIX is used operationally by fire agencies in eastern and southern Australia (Bentley and Penman, 2017). Other fire behavior models are available, e.g., SPARK (Hilton et al., 2015), however the spatial datasets required for them are not available for all case study landscapes. Datasets for PHOENIX are available for all six states and territories included in the study. These datasets have been developed and tested by the relevant land and fire management agencies in each state.

Two-dimensional fire growth in PHOENIX is simulated using Huygens' propagation principle of fire edge (Knight and Coleman, 1993). Two fire behavior models are used to estimate rate of spread—a modified McArthur Mk5 forest fire behavior model (McArthur, 1967; Noble et al., 1980) and a generalization of the CSIRO southern grassland fire spread model (Cheney et al., 1998). PHOENIX produces outputs of ember density, convection, intensity and flame length for each 180 m cell affected by the simulation. PHOENIX is described more fully in a range of other studies (Tolhurst et al., 2008; Paterson and Chong, 2011; Tolhurst and Chong, 2011)

PHOENIX predicts fire behavior based on inputs of weather, ignition location, fire history, vegetation, fuel accumulation, topography and natural breaks in the landscape (rivers and roads that could slow or halt the spread of fire). Data on vegetation, fuel accumulation, topography and natural breaks were provided from the relevant state fire or land management agency.

Weather values were selected from the nearest Australian Bureau of Meteorology Automatic Weather Station (AWS) records for each region. Days were selected to capture variation in fire weather based on the forest fire danger index (FFDI)—a composite measure that combines temperature, relative humidity and wind speed with a long-term drying index to predict the difficulty of fire suppression (McArthur, 1967; Noble et al., 1980). Three primary drivers can influence the FFDI—(i) strong wind, (ii) strong wind with a significant directional change or (iii) high air temperature (Cirulis et al., 2020). Within each FFDI category, up to three different days were chosen for each of these

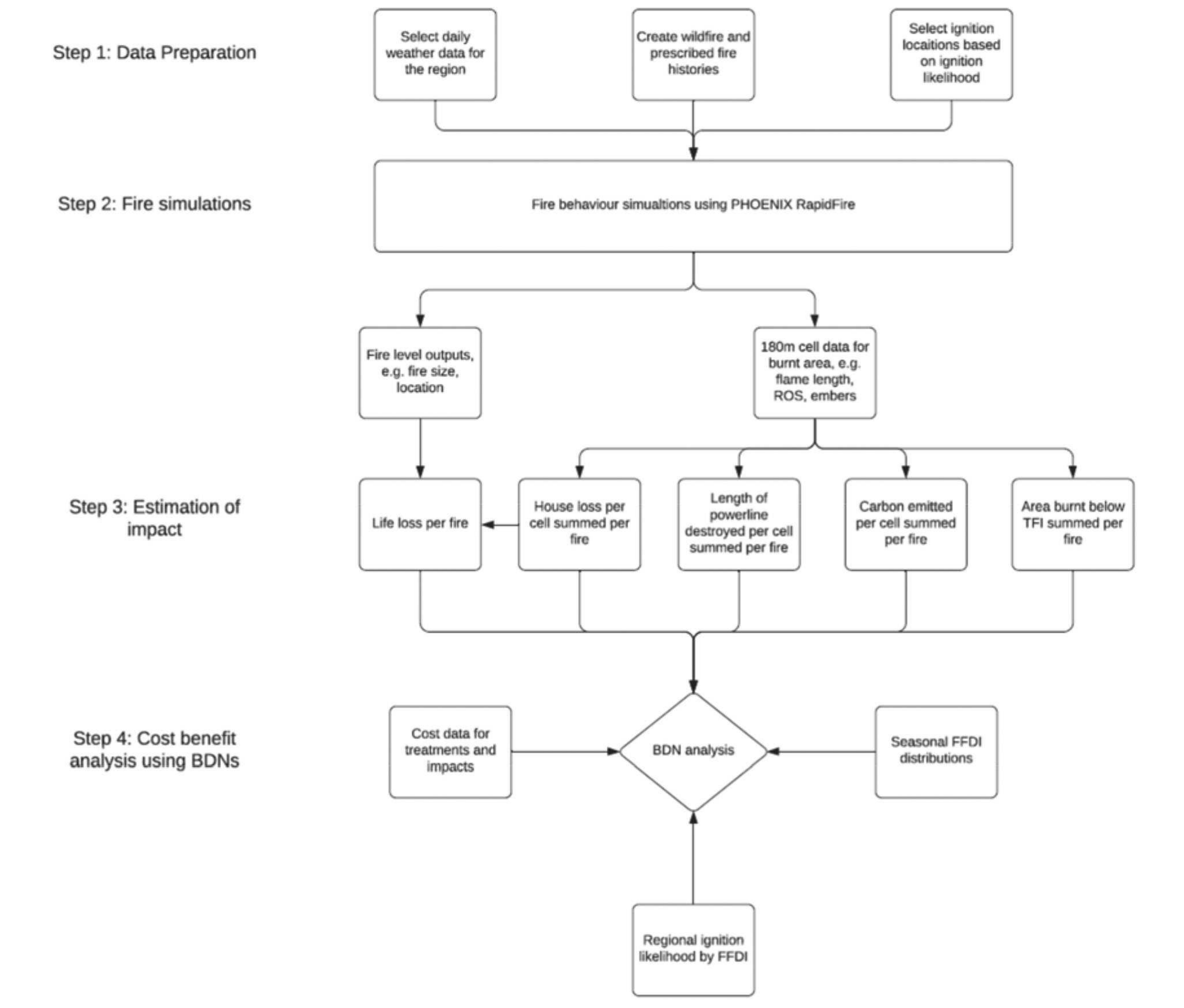

FIGURE 2 | Workflow for the study. ROS, rate of spread; BDN, Bayesian decision network; TFI, tolerable fire interval; FFDI, forest fire danger index.

FFDI drivers resulting in a maximum of 54 different weather streams, although this number was often smaller if there were not sufficient days that fit the selection criteria (**Table 1**). All weather streams covered a 24-h period beginning from midnight to allow the model to generate stable and realistic estimates of diurnal fluctuations in fuel moisture based on temperature and relative humidity (Tolhurst et al., 2008). Each weather stream contained hourly data for air temperature, relative humidity, wind speed, wind direction, drought factor and curing.

Fire histories were created to represent the different fuel management scenarios. Scenarios were based on the application of prescribed burning in the landscape (hereafter *landscape*) or the interface zone (hereafter *edge*)—within 500 m of an urban interface based on definitions of Radeloff et al. (2005). Within each of the landscape and edge zones we simulated seven levels (0, 1, 2, 3, 5, 10, and 15% per annum) of treatment and considered the 49 combinations resulting from the seven levels of landscape treatment and seven levels of edge treatment. We first generated a wildfire history using a random samping with replacement procedure. We firstly selected all wildfires within the case study landscape from the fire history geodatabase to create the available wildfires. Fires were randomly selected from the available wildfires to create an annual area burnt using a moving window target, based on the historic average annual area burnt as reported in Bradstock et al. (2014). After each season all fires were replaced in the available wildfires set and the process repeated for 30 years to create a wildfire history. Treatable vegetation in each case study landscape was divided into management sized "burn blocks" (data supplied by management agencies) and allocated to either edge or landscape treatments. Areas available as edge

TABLE 1 | Weather and ignition data summary for each case study landscape.

Region	Code	Bureau of meteorology station	Total weather streams	Total fires
ACT Canberra	ACT	Tuggeranong (70339)	39	686000
TAS Hobart	Hobart	Hobart Airport (94008)	26	539000
SA Adelaide Hills	Adelaide	Adelaide Airport (23034)	46	757000
South-eastern Queensland	SEQ	Amberley AMO (40004)	36	735000
VIC Central Highlands	VIC CH	Melbourne Airport (86282)	42	732338
NSW Blue Mountains	NSW BM	Richmond Airport (30161)	40	704000
NSW Broken Hill	NSW BH	Broken Hill Airport (47048)	40	686000
VIC Little Desert	VIC LD	Nhill Aerodrome (78015)	43	784000
NSW South Western Slopes	NSW SWS	Parkes Airport (65068)	41	646800
NSW Nandewar	NSW Nan	Tamworth Airport (55325)	44	686000
NSW South East Corner	NSW SEC	Merimbula Airport (69147)	30	539000

TABLE 2 | Area available for edge and landscape treatments in each case study landscape.

Region	Edge area (ha)	Landscape area (ha)
ACT Canberra	6,388	104780
TAS Hobart	84531.2	35855.86
SA Adelaide Hills	13307.2	7747.987
South-eastern Queensland	113495.9	48666.79
VIC Central Highlands	44408.86	181664.9
NSW Blue Mountains	24982.43	111890.7
NSW Broken Hill	5074.01	198791.1
VIC Little Desert	15830.31	115207.1
NSW South Western Slopes	20935.37	45115.2
NSW Nandewar	38391.65	152443.3
NSW South East Corner	72517.1	191476.1

or landscape blocks for each case study region are presented in **Table 2**. Prescribed burning treatments were simulated over a period of 20 years following the methods of Penman et al. (2014) which selects blocks for treatments based on time since fire—prescribed fire or wildfire. Blocks were considered available after 5 years for edge treatments, whereas in the landscape treatments ecological thresholds based on vegetation class were used. In creating a prescribed fire history, we first identified all blocks available for treatment. From this dataset we then randomly selected blocks until the desired treatment rate was achieved (± 0.1) or no more blocks were available. These steps were repeated to create a 20-year prescribed fire history for each level of landscape and edge treatments. Prescribed fire histories were then spatially merged with wildfire history to create a landscape fire history. The process was replicated 5 times for each of the 49 treatment combinations to give a total of 245 simulated fire history layers for each case study landscape.

Ignition locations were selected using a probabilistic model. Firstly, we generated 10,000 random points across the landscape. We then calculated the ignition probability for the random points based on an empirical model developed and tested across the study region (Clarke et al., 2019). From the 10,000 points, the 1,000 ignition points with the highest ignition probabilities were selected for use in the simulations. Individual fires were ignited at 1100 and allowed to propagate for up to 12 h, unless self-extinguished within this period. Fires were not simulated on successive days as the permutations were prohibitive and generally most area burned and damage from fires in these region occurs on a single day (Cunningham, 1984; Bradstock et al., 2009; Collins et al., 2016). Ignition points were randomly split into 5 groups of 200 ignitions. Each of these 200 ignitions was simulated for a single replicate of each weather category/driver combination and fuel treatment to reduce total simulation time.

Assessment of Fire Effects

The effect of fire on various assets was calculated for five management values: house loss, loss of human life, length of powerline damaged, quantity of carbon released and environmental impact measured by area burnt below minimum tolerable fire interval (TFI). Loss functions for house and life loss came from published sources (Tolhurst and Chong, 2011; Harris et al., 2012; Cirulis et al., 2020). Data for house locations were from Geocoded National Address File Database (https://www.psma.com.au/products/g-naf accessed 21 January 2019) which was combined with data from the Australian Bureau of Statistics to calculate the average number of people per household and therefore estimate population exposed to the fire. There are no published data on loss functions for power related assets. We used the intensity threshold value of 10,000 kW/m to determine damage to mapped powerlines (Cirulis et al., 2020). Carbon released was calculated from Byram's fire line intensity equation (Byram, 1959) using intensity and rate of spread values from PHOENIX to determine fuel consumed and multiplying by 0.5, the fraction of carbon in fuel (Roxburgh et al., 2006). This is a very coarse measure of carbon released but more specific could not be estimated from existing fire behavior models. Environmental impact was measured by the number of hectares area burnt by wildfire when the time since the last wildfire was less than the tolerable fire interval (TFI)—an ecological measure that considers the amount of time required between fires to maintain vegetation diversity (Kenny et al., 2004; Gosper et al., 2013). Area burnt below TFI was calculated from area burnt and existing TFI threshold mapping supplied by the management agencies.

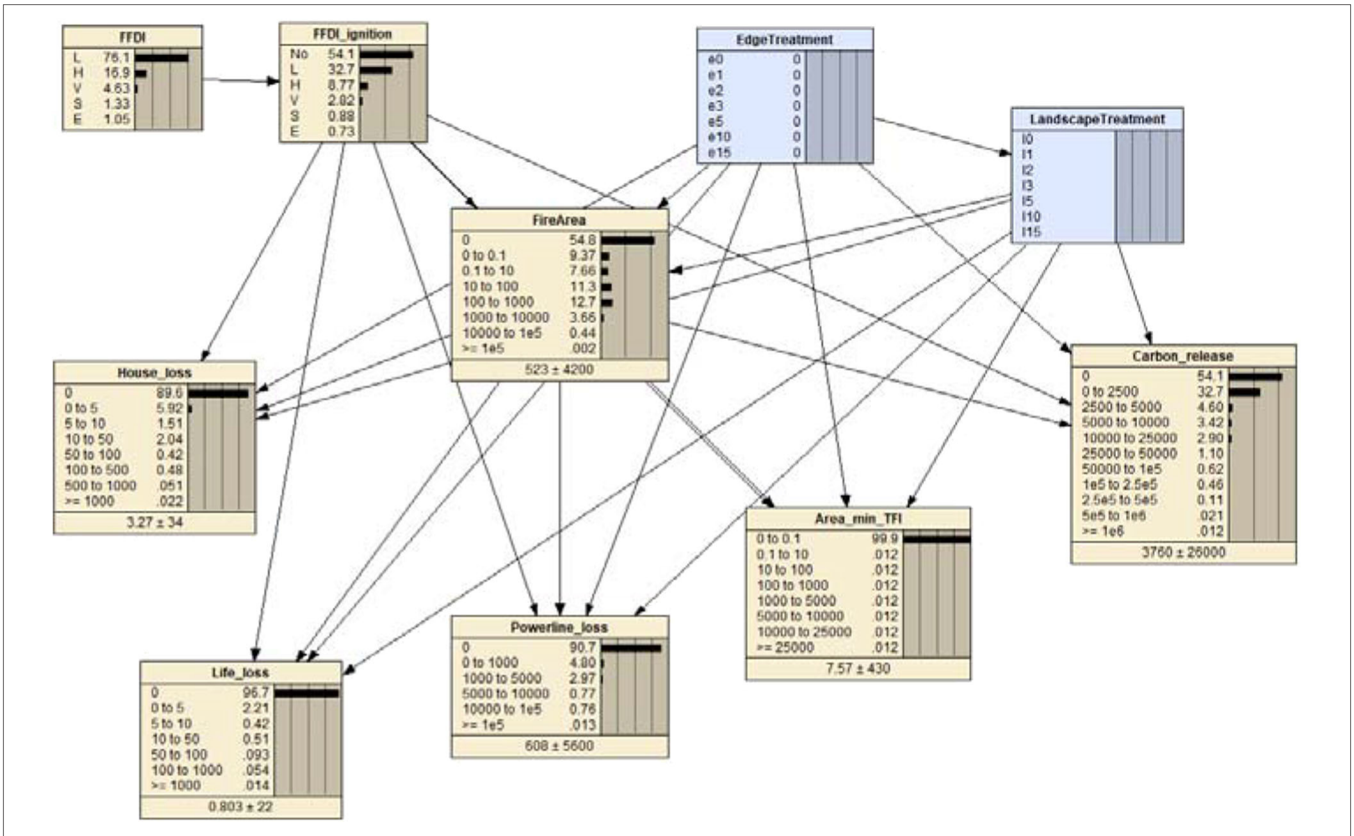

FIGURE 3 | The BDN structure (influence diagram) used in the study. Boxes represent nodes and the average distribution of values across all decisions. Bar plots represent the average distribution of values across all decisions. Numbers next to bars represent the probability of being in the given state. Values at the base of the boxes represent the expected values plus or minus one standard deviation.

Risk Estimation

A Bayesian Decision Network (BDN) model was used to examine prescribed burning effectiveness in altering risk. Bayesian networks (BNs) are statistical tools commonly used for risk analysis of complex environmental systems (Pollino et al., 2007; Johnson et al., 2010; Kelly et al., 2013; Sierra et al., 2018) as the outputs of the model are expressed as probabilities (Marcot et al., 2001). Variables ("nodes") contain the joint probability distributions representing combinations of conditions (Korb and Nicholson, 2011). BDNs are extensions of BNs that include decision structures and utility costs or benefits of those decisions. Decision nodes represent discrete actions to allow for the comparison of outcomes (e.g., costs) among competing approaches. Models can be used to identify the relative cost and benefit of competing strategies.

In developing the BDN model, we followed the BN modeling guidelines of Marcot et al. (2006) and Chen and Pollino (2012). The primary steps are:

1. Construct a conceptual model of the problem;
2. Develop influence diagrams that depict the relationships within the conceptual model;
3. Populate all the conditional probability tables within the model; and
4. Specify alternative decision actions and values of utilities.

We used the conceptual model and built on the influence diagram presented in Cirulis et al. (2020). Fire weather is represented by FFDI which influences the likelihood of ignitions given the FFDI (FFDI_ignition). Ignition FFDI and the rate of edge and landscape prescribed burning influence the distribution of fire sizes. All four of these factors then influence the distribution of loss for each asset type. Utility or cost nodes were added for treatments and assets to create the BDN. Utility nodes represent the cost (or benefit) associated with each a state in either a stochastic or decision node. To measure the cost of a decision, all utility node values are summed to provide a single value for each decision or combination of decisions allowing users to identify the best or best set of management strategies (Penman and Cirulis, 2020). The same structure was used for each case study with data specific to each case study (**Figure 3**).

Data for the conditional probability tables (CPTs) came from either empirical data or the PHOENIX simulation study. Fire weather was calculated using the maximum daily FFDI values across the fire season for the study area using data from the relevant weather stations to populate the FFDI node. The mean ignition probability was calculated for each FFDI category using the empirical model of Clarke et al. (2019) to create the distribution in the FFDI-ignitions node. Data for each of the fire size and each of the nodes representing fire impact on assetswere taken from the simulations for each case study (as described above). Each node was discretised on a semi-log scale in an iterative fashion to get a relatively even distribution across the non-zero values.

Data for the utility nodes were calculated from a variety of sources. Treatment costs were calculated using the equations in Penman et al. (2014) which had a log-log relationship between treatment size and cost per ha of treatment. Costs for individual burns in the simulated prescribed burn history were calculated and then average annual costs for the 20-year period calculated. Costs of house loss were estimated as $500,000 per house based on the estimates of median property values across the various study areas (based on www.yourinvestmentpropertymag.com.au accessed November 2017). We did not vary cost by region as this would prioritize areas with greater property values. Life loss was estimated as $4.2 million per life based on national standards (https://www.pmc.gov.au/sites/default/files/publications/Value_of_Statistical_Life_guidance_note.pdf, accessed November 2019), accessed November 2019). Cost of powerline replacement was estimated at $120 per meter (www.energy.vic.gov.au/safety-and-emergencies/powerline-bushfire-safety-program/pb-report-indicative-costs-for-replacing-swer-lines). We did not attempt to estimate the cost of loss of power as this requires detailed modeling of electricity networks, which is beyond the scope of the paper. Carbon released was calculated using the values of Hunt (2008) who estimated a cost of $AUD 61 per ton. There is no means of translating TFI into economic values, we used a coarse value of $1,000 per ha burnt below TFI based on the economic impact of major fires on environmental values (Stephenson, 2010).

The BDN was used to calculate the cost effectiveness of each treatment level accounting for the likelihood of weather and ignitions, as well as fire behavior. In this study, we focussed on the estimated cost for each asset by treatment, as well as the annualized risk cost per treatment. This value includes the cost of implementing the treatment(s) and the summed impact across all asset types. Cost effectiveness was measured as the difference between a given treatment and the "do nothing" approach with 0% edge and landscape treatment levels. Treatments were considered to have a positive effect if the annualized risk cost was less than the "do nothing" approach.

We undertook two analyses to determine if the ordering of prescribed burning approaches among case study landscapes were consistent. Firstly, we used Spearman rank correlations to compare the ranking of the 49 treatments between the case study landscapes. If a single solution existed, we would expect the ranking of treatments to be consistent with strong correlations between all case studies. Secondly, we undertook non-metric Multi-Dimensional Scaling (nMDS) using Bray-Curtis similarity index to look for groupings in the relative costs of treatments and impacts. Total costs were standardized on a scale of 0–1, with 0 representing the minimum cost for the case study region and 1 representing the maximum cost. This was done to remove the regional variations in the magnitude of the costs. nMDS will help identify regions with similar patterns in the cost data across treatments and impacts with less emphasis on the ordering. Results were plotted so that regions with similar cost profiles were positioned close together with the distance increasing as the differences increased.

RESULTS

Annualized risk cost ranged from $116,992 (NSW Broken Hill, L0E0) to $40,200,590 (VIC Central Highlands (L15E10) (**Figure 4**). Costs varied between the regions with consistently higher costs in the SA Adelaide Hills and VIC Central Highlands compared to all other case studies. Costs were lowest in NSW Broken Hill. The "do nothing" approach was the cheapest option in most case study regions with the exceptions being ACT Canberra, NSW Blue Mountains and TAS Hobart.

Increasing investment in treatment costs resulted in a reduction of risk and the cost of impact in all regions (**Figure 5**; **Supplementary B**). Edge treatments reduced the impact costs to a greater extent than landscape treatments where the cost of houses or lives were the primary components of the overall costs, the exceptions being VIC Central Highlands and NSW south-west Slopes. Landscape treatments had a small effect on impact costs, e.g., ACT Canberra and NSW Blue Mountains, or no meaningful effect, e.g., SA Adelaide Hills and TAS Hobart. A cost-effective solution only occurred where the reduction in impact costs was greater than the implementation cost. In both ACT Canberra and TAS Hobart, the increase in edge treatments to 10 or 15 % resulted in cost-effective solutions. However, adding any level of landscape treatment did not result in cost-effective solutions. Almost all treatments in the NSW Blue Mountains resulted in cost-effective solutions, although the edge treatments resulted in the greatest reduction in impact cost. The most cost-effective solution in this region consisted of edge treatments rates of 5% per annum or more combined with landscape treatment rates of 1–3% per annum. In all other regions, treatments did not reduce the risk of asset loss or the reduction was less than the treatment cost (**Figure 5**; **Supplementary B**).

Contributions to the total cost varied between regions, although some common patterns emerged (**Figure 6**; **Supplementary C**). Unsurprisingly, as treatment rates increased the contribution to total costs increased, reaching values as high as 80% of total risk costs in the ACT Canberra. The exception being SA Adelaide Hills where treatment costs were never more than 20% of total costs. Carbon, powerlines and environmental costs contributed to <10% of total costs in all regions except SA Adelaide Hills where environmental costs alone contributed approximately 25% of total costs. Cost of the impact on lives and houses combined represented the major asset impact cost, although the relative contribution varied. In most regions, the cost of life loss exceeded the cost of house loss, except in TAS Hobart where the reverse occurred.

There was no single cost-effective solution for prescribed burning that was common across all regions. Rank correlations of the treatment options indicated that a large group of regions with similar solutions (**Figure 7**). These were SA Adelaide Hills, ACT

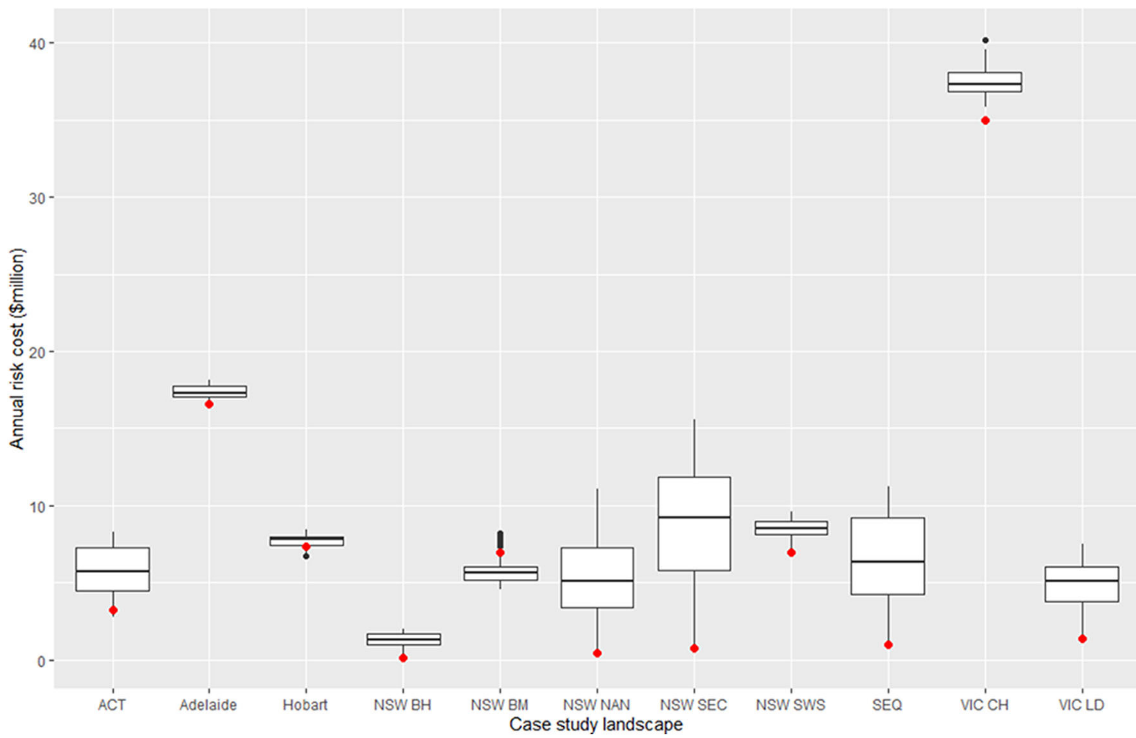

FIGURE 4 | Annualized risk cost across all values and treatments for the case study regions across all treatment rates. Red circle indicates the "do nothing" approach L0E0. See **Table 1** for case study codes.

Canberra, NSW Broken Hill, NSW Nandewar, NSW south-east corner, VIC Little Desert and VIC Central Highlands. Weaker relationships were seen between this group and the NSW south-west slopes and south-east Queensland. Ranking of treatments in TAS Hobart were not related to any region and NSW Blue Mountains showed negative correlations with most regions (**Figure 7**).

The nMDS analysis of the normalized cost data found different patterns (**Figure 8**). SE Queensland and the Blue Mountains were unique in their positions. Two broad groupings were identified. The first included areas from the semi-arid zone with ACT Canberra and the NSW south-east corner. In the second group were forested areas around three capital cities (Adelaide, Hobart and the Central Highlands which lies to the NE of Melbourne) and the NSW south-west slopes.

DISCUSSION

There was no "one size fits all" solution to prescribed burning when considering multiple assets. Edge treatments generally reduced impact costs to a greater extent than landscape treatments, but reductions in impact were not always equal to the treatment cost. Cost-effective solutions were only found in a quarter of the case study landscapes. There were three primary contributors to the total cost for all regions—treatments, houses and lives. Cost-effectiveness is likely to be driven by the spatial distribution of these assets within the landscape relative to the locations of treatments and the total value of assets within each case study landscape.

Treatment Effectiveness

Fire agencies around the world have increasingly adopted a risk management framework as no prescribed burning regime is expected to remove the risk to assets (Fernandes and Botelho, 2003; Hughes and Mercer, 2009; Penman et al., 2011; Thompson et al., 2013; Victorian DELWP, 2015). A significant residual risk to all assets remains regardless of treatment level which is consistent with previous studies (Stockmann et al., 2010; Bradstock et al., 2012b; Calkin et al., 2014; Florec et al., 2019). The treatments we simulated had only a limited influence on the size of fires in the case-study landscapes.

Landscape treatments were more likely to extend benefit to assets that occur in native vegetation within the study areas, e.g., powerlines, carbon and other environmental assets. Impact costs for these assets were correlated with fire size distributions and therefore the effectiveness of landscape treatments was likely to be related to the extent to which landscape fuel treatments reduce fire size and severity. This is a concept termed leverage: leverage potentially varies as a function of environmental variation (Loehle, 2004; Boer et al., 2009; Price et al., 2015). Only modest changes in the risk to the environmental assets were recorded across all study regions consistent with the fact that leverage is low or absent in most of these regions (Price et al., 2015).

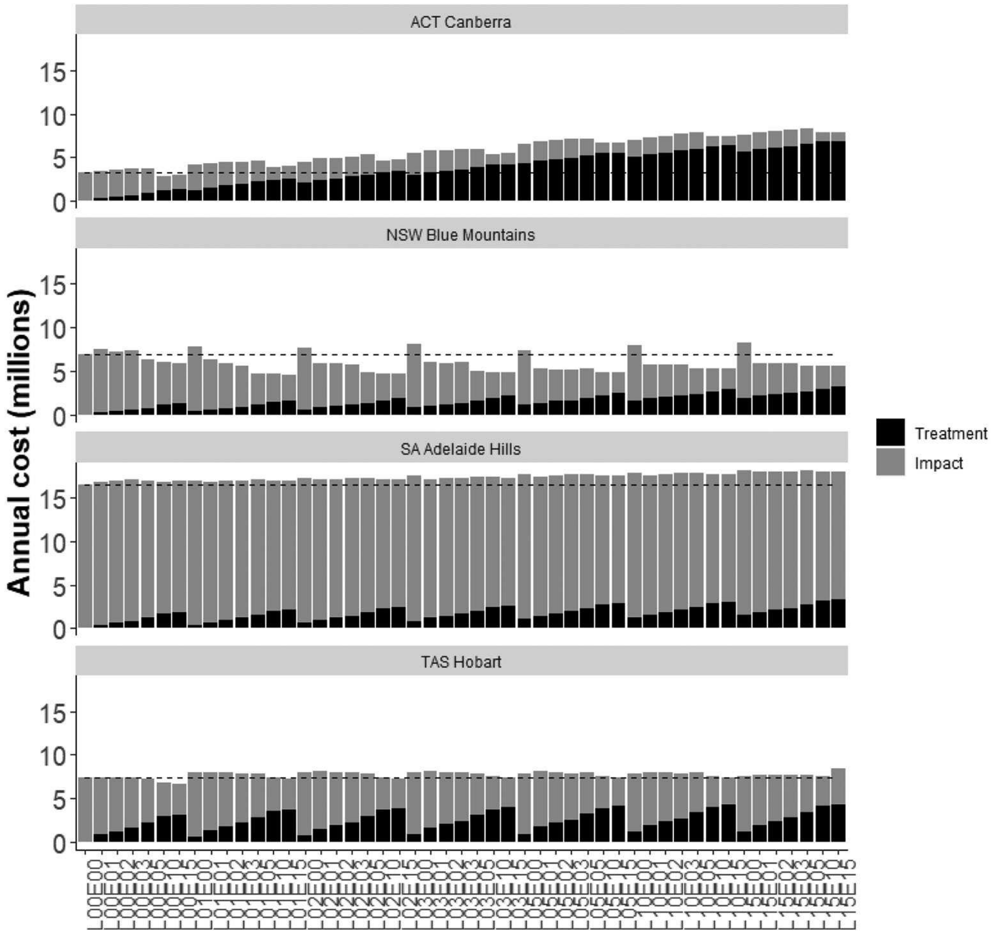

FIGURE 5 | Annualized risk costs for four case study regions across all treatment rates. The dashed line represents the do nothing approach—columns below this line are considered cost-effective. Treatment codes are presented as LXXEYY where XX represents the annual prescribed burning treatment rate in the landscape and YY the rate in the edge blocks.

Edge treatments were generally more effective at reducing risk compared with landscape treatments. This was consistent with a growing body on literature highlighting the ability of these treatments to reduce the risk of house and/or life loss (Safford et al., 2009; Ager et al., 2010; Gibbons et al., 2012; Penman et al., 2014; Florec et al., 2019). Results of these studies suggest that the effectiveness was due to the reduction in fire behavior immediately adjacent to the asset resulting in a direct transfer of benefit to houses and lives. Edge treatments did not alter landscape fire behavior and could not be expected to alter the risk to assets across the landscape such as environmental assets, roads and powerlines (Penman et al., 2014; Florec et al., 2019).

Cost-Effectiveness

Benefits of the treatments need to be offset by the cost of treatments, which were generally the greatest contributors to the overall cost estimation. In regions with low population densities (e.g., NSW Broken Hill, VIC Little Desert, NSW south-east corner), the treatment costs were 50–90% of the total costs. Edge treatments were generally more expensive as the risk of loss, should fires escape, is higher and therefore more resources and higher costs of treatment per hectare are required (Berry et al., 2006; Calkin and Gebert, 2006; Penman et al., 2014; Florec et al., 2019). In contrast, treating 1% of a landscape requires treatment of significantly more land than 1% of edge blocks.

Loss of houses and lives represent the greatest impact cost in case study areas with significant urban areas, e.g., NSW Blue Mountains, TAS Hobart, ACT Canberra, SA Adelaide Hills. These values are also the highest cost per unit in the study—$500K per house and $4.2 million per life. House and life loss were significantly correlated (Harris et al., 2012) as historically more than 60% of life loss during wildfires was associated with a residence (Blanchi et al., 2014). Single fires in these urban interface areas can result in large loss of houses (and at times lives) directly from the fire (Ahern and Chladhil, 1999; Blanchi et al., 2014) or indirectly through house to house transfer (Cohen and Stratton, 2008; Penman et al., 2018). In contrast, the contribution of houses and lives were relatively small in case studies with dispersed populations.

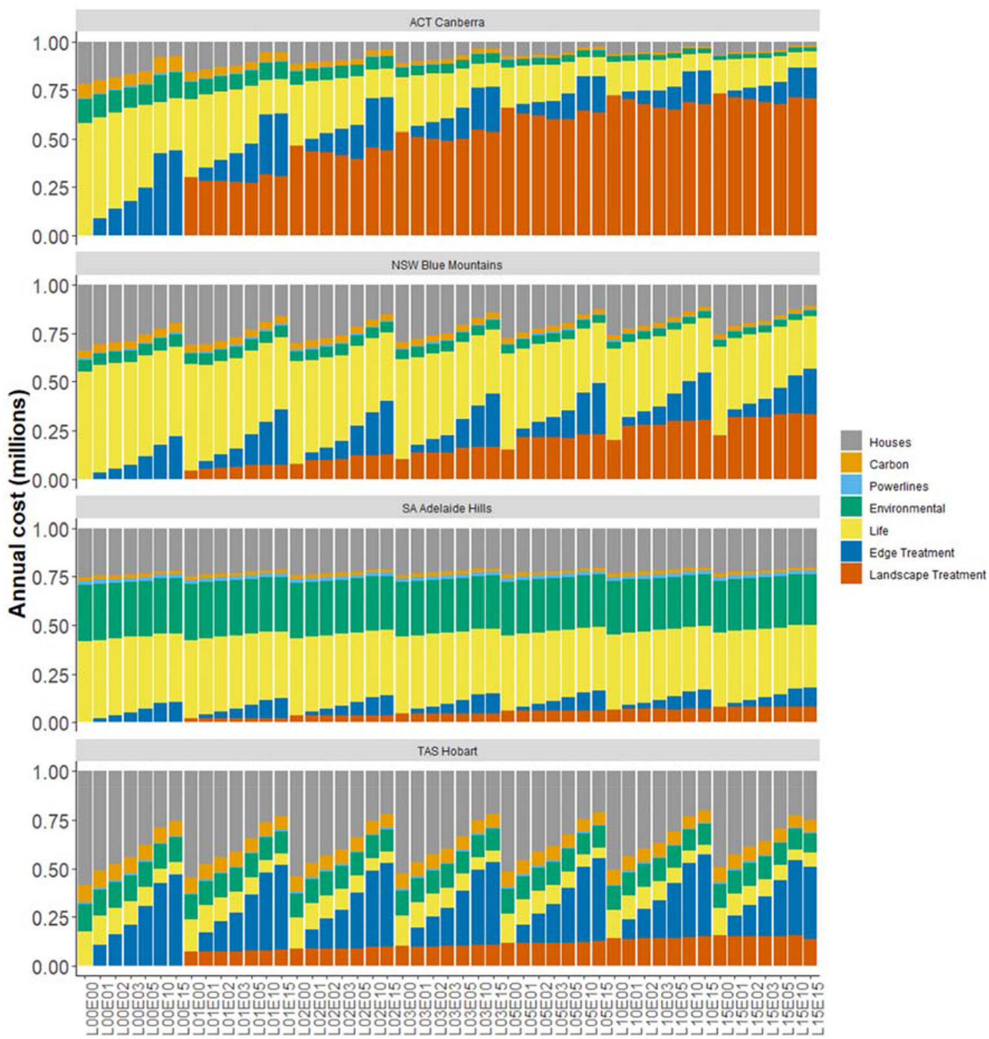

FIGURE 6 | Relative contribution of treatments and asset risk costs for four case study regions across all treatment rates. Treatment codes are presented as LXXEYY where XX represents the annual prescribed burning treatment rate in the landscape and YY the rate in the edge blocks.

Environmental costs were a key driver in other regions, e.g., VIC Central Highlands, NSW south-west Slopes. Few studies have considered environmental and human assets (Ager et al., 2016; Bentley and Penman, 2017) and rarely have they included a risk approach as done here (Milne et al., 2014). One of the key reasons for this gap in knowledge is that it is very difficult to estimate the economic value of environmental assets over complex landscapes (Fromm, 2000). Indeed, we used a coarse economic value of $1,000 per ha based on Stephenson (2010) who studied a relatively small number of large fires. Such an evaluation assumes that all fires are equal and all have negative impacts on the environment, which is not the case for ecosystems considered in this study (Bradstock R. et al., 2012). A true risk assessment should include the positive and negative effects of fire and account for them in a net value change framework (Finney, 2005). Ecological effects are a function of fire regimes rather than individual fires (Clarke, 2008; Enright et al., 2014) and could not be estimated from our fire simulation approach.

The cost of prescribed burning was rarely less than the reduction in risk cost for the values considered. Only in three case studies did we identify cost-effective solutions. These case studies differed in the optimal solution but were all near significant urban interfaces. Two of the case study landscapes had only one or two cost-effective solutions and only the NSW Blue Mountains had greater options with 40 of the 49 treatments providing cheaper alternatives to the "do nothing" approach. It is impossible to determine the reasons for this with a sample size of one. Regardless, the cheapest solution in the Blue Mountains was close to the current management strategy for the area (NSW RFS unpublished data).

Protection of life and property is the primary goal of fire managers around the world (Fernandes and Botelho, 2003; Penman et al., 2011) and cost may not be the optimal way to identify preferred approaches to achieve this goal. Loss of property and life can have significant flow on effects to communities. For example, the psychological effects of wildfires have been infrequently studied but the impact is extensive (Perry and Lindell, 1978; Morrissey and Reser, 2007; Papadatou et al., 2012). It may be desirable for fire agencies to spend more money than they save in order to decrease the impacts of wildfire on areas such as mental health and other measures of community wellbeing. A range of participatory approaches are available which can allow stakeholders to weight the various values in order to enhance decision making processes (Gregory et al., 2001; Kiker et al., 2005)

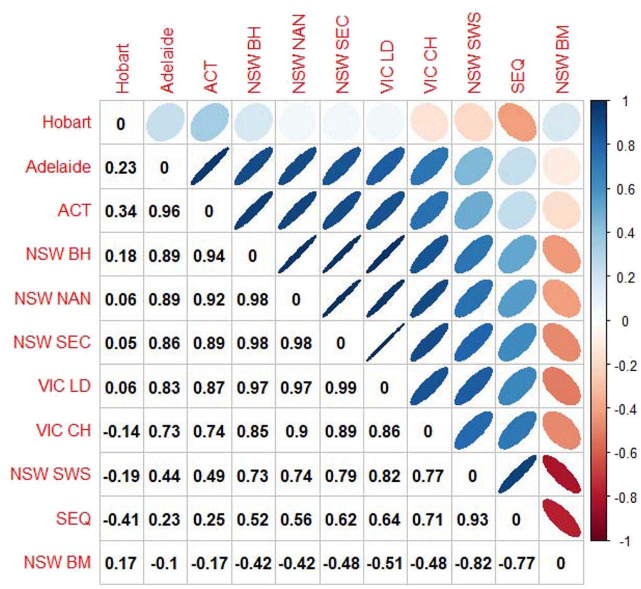

FIGURE 7 | Rank correlations of total cost across the 49 tested prescribed burning scenarios. Color of the ellipses depict the nature of the data, with blue representing positive relationships and red negative. Shape of the ellipses represent the nature of the fit, with thin ellipses representing a strong relationship whereas broad ellipses indicate greater uncertainty in the correlation. Upper right triangle represents the correlation coefficients. Case study codes appear in **Table 1**.

Model Limitations

Inclusion of a greater variety of values would increase the general applicability of the results. Our modeling approach considered five assets covering a range of values representing populations, infrastructure and the environment. There are a range of other values that could be included should the data become available. It is necessary for a value to have a spatial representation, a loss function to link to the fire behavior model outputs and a cost for any losses to be included in the modeling approach. Without all three of these, it is not possible to include in the overall analysis.

Dollar value was used in our study for comparisons between treatments and assets, however there are a range of other values that are not well represented in dollar terms. Non-market values such as biodiversity, mental health and community cohesion are difficult to place in an economic framework (Venn and Calkin, 2011; Milne et al., 2014). Furthermore, environmental, social and cultural benefits from treatments may not be realized for many years or decades (Burgess et al., 2005; Kalies and Yocom Kent, 2016), whereas negative impacts of fire are often realized immediately, e.g., loss of houses, or in the months following the fire, e.g., debris flows (Nyman et al., 2011).

Including smoke impacts on populations is likely to have significant consequences for future studies of this kind. Smoke from prescribed burns can result in mortality and respiratory illness in local populations (Bowman and Johnston, 2005; Weisshaupt et al., 2005; Broome et al., 2016). Similarly, smoke from wildfires can also increase mortality in populations (Borchers Arriagada et al., 2020). Modeling the impact of smoke

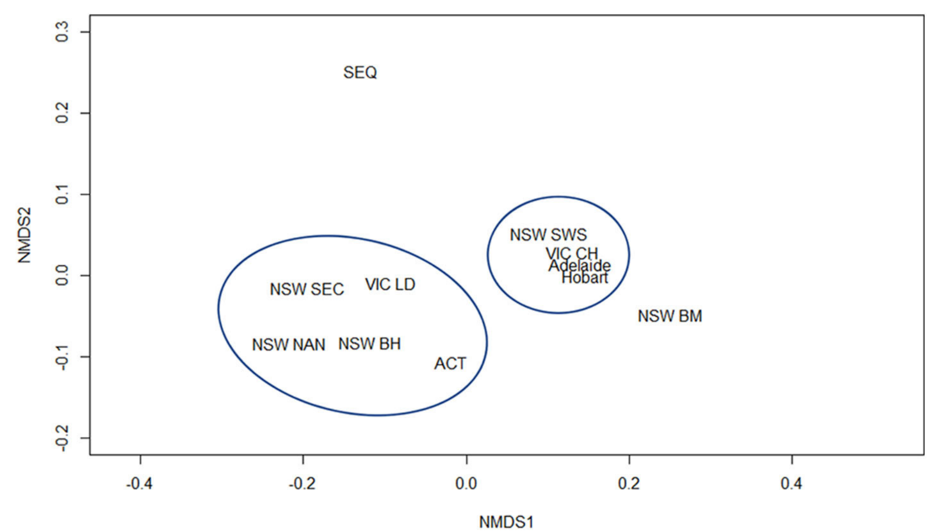

FIGURE 8 | Non-metric multidimensional scaling results of normalized cost data.

from fires requires an understanding of the rate of consumption of fuels and a three-dimensional smoke dispersal model (Wain et al., 2008) and was beyond the current study. Smoke from prescribed burning and wildfires can also impact on viticultural production with significant economic impacts expected in wine growing regions (Kennison et al., 2007, 2009). Inclusion of smoke in future modeling approaches would be prudent and an important priority.

Asset loss functions used were relatively simple but exclude actions of individuals. Loss functions were based on fire behavior and the distribution of assets, without accounting for human behavior. Individuals can significantly alter their risk to their property and the risk of life loss through their actions. The chance of a house surviving a wildfire can be increased 3–6 times if residents stay and defend (when it is safe to do so; Wilson and Ferguson, 1986; Ramsay et al., 1987; Blanchi and Leonard, 2008; Whittaker et al., 2012). These values can be enhanced by the property being well prepared for wildfire (Jakes et al., 2007; McCaffrey and Rhodes, 2009; McGee, 2011; Penman et al., 2013b, 2018). Similarly, mental preparedness for fires will reduce the risk of life loss during a fire (McGee and Russell, 2003; Paton et al., 2006; Morrissey and Reser, 2007; Eriksen and Prior, 2013; Prior and Eriksen, 2013). All these actions can affect individuals but cannot readily be included in the modeling process at this stage, as there are a wide range of factors affecting an individual's decision-making process.

Across the globe there has been significant investment in fire suppression (Loane and Gould, 1986; Calkin and Gebert, 2006; Milne et al., 2014; Thompson and Anderson, 2015), however our study did not explicitly include consideration of the role of past suppression in altering fuel loads. North American studies have found aggressive fire suppression strategies reduce the number and extent of wildfires in an area which results in an increase in landscape fuel load and subsequent wildfire size (e.g., Calkin et al., 2015). No such relationships have not been reported from Australia. In contrast, fuel responses vary according to vegetation type, productivity and climate (Thomas et al., 2014; McColl-Gausden and Penman, 2019; McColl-Gausden et al., 2019) with some systems having reduced fuel loads with increasing time since fire (Dixon et al., 2018; Zylstra, 2018) and others increasing (McCaw et al., 2002). The model used assumes an initial increase of fuels to a plateau and therefore does not assume an ongoing increase in landscape fuel hazard with an absence or reduction in fire.

We were not able to account for the interaction of prescribed burning with suppression. Prescribed burning was selected as it is one of the most widespread preventative strategy employed in Australia and elsewhere. One of the goals of prescribed burning is to reduce fire behavior in order to increase suppression effectiveness (Fernandes and Botelho, 2003; Penman et al., 2020). However, effectiveness of suppression is also influenced by the response time, fire size on arrival, number and type of resources deployed and the weather at the time of the fire (Hirsch and Martell, 1996; Hirsch et al., 1998; Finney et al., 2009; Plucinski, 2012). Coarse assessments of suppression effectiveness interactions with prescribed burning have given mixed results with some suggesting limited effects (Penman et al., 2013a) and others suggesting strong effects in ideal scenarios (Penman and Cirulis, 2020). Furthermore, few have been able to calculate the costs of suppression but acknowledge this is a significant component of fire agencies budgets (Gould, 1987; Butry et al., 2001; Calkin and Gebert, 2006; Snider et al., 2006). Therefore, it would be important to develop the capacity to include the interactive effects of suppression and prescribed burning in future cost-effectiveness studies.

CONCLUSION

There is no "one size fits all" solution to prescribed burning across landscapes. Environmental, human and societal challenges are likely to dictate ideal solutions. Based on current knowledge cost-effective prescribed burning solutions may be limited in scope, but this conclusion may change as some of the limitations noted above are overcome. Nonetheless, other factors such as social acceptability of treatments and wildfires may be greater determinants of treatment regions rather than cost alone.

DATA AVAILABILITY STATEMENT

The datasets generated for this study are available on request to the corresponding author.

AUTHOR CONTRIBUTIONS

All authors developed the approach through a series of workshops. BC ran the simulations and Bayesian Network analyses. TP undertook the analyses with feedback from all authors. TP wrote the manuscript and all authors contributed to the editing of the manuscript.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/ffgc.2020.00079/full#supplementary-material

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