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Quantification of inter-regional differences in risk mitigation from prescribed burning across multiple management values

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Abstract

Fire agencies are moving towards planning systems based on risk assessment; however, knowledge of the most effective way to quantify changes in risk to key values by application of prescribed fire is generally lacking. We present a quantification and inter-regional comparison of how risk to management values responds to variations in prescribed burning treatment rate. Fire simulations were run using the PHOENIX RapidFire fire behaviour simulator for two case study landscapes in interface zones in Tasmania and the Australian Capital Territory (ACT), Australia. A Bayesian network approach used these data to explore the influence of treatment and weather on risk from wildfire. Area burnt, length of powerline damaged and length of road damaged responded more strongly to treatment in the ACT than in Tasmania, whereas treatment mitigated house loss and life loss more strongly in Tasmania than the ACT. The effect of prescribed burning treatment rate on area burnt below minimum tolerable fire interval was similar in each case study landscape. Our study shows that the effectiveness of prescribed burning at mitigating area burnt by wildfire and other key values varies considerably across landscapes and values.

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Key words

Wildfire, bushfire, wildland fire, trends, climate change

Suggested running head

Quantifying prescribed fire risk mitigation

21 **Abstract**

22 Fire agencies are moving toward planning systems based on risk assessment, however knowledge
23 of the most effective way to quantify changes in risk to key values by application of prescribed fire
24 is generally lacking. We present a quantification and inter-regional comparison of how risk to
25 management values responds to variations in prescribed burning treatment rate. Fire simulations
26 were run using the PHOENIX RapidFire fire behaviour simulator for two case study landscapes in
27 interface zones in Tasmania and the Australian Capital Territory (ACT), Australia. A Bayesian
28 Network approach used these data to explore the influence of treatment and weather on risk from
29 wildfire. Area burnt, length of powerline damaged and length of road damaged responded more
30 strongly to treatment in the ACT than in Tasmania, while treatment mitigated house loss and life
31 loss more strongly in Tasmania than the ACT. The effect of prescribed burning treatment rate on
32 area burnt below minimum tolerable fire interval was similar in each case study landscape. Our
33 study shows that the effectiveness of prescribed burning at mitigating area burnt by wildfire and
34 other key values varies considerably across landscapes and values.

35

36 **Summary for non-specialist**

37 We use fire behaviour simulations and Bayesian Networks to estimate the risk mitigation effects of
38 prescribed burning for area burnt, house loss, life loss, length of powerline and road damaged, and
39 area burnt below minimum tolerable fire interval. Our methods can be used to quantify and
40 compare risk across regions.

41

42

43 **Introduction**

44 Fire management consists of a range of activities across the planning, response and recovery
45 phases, which are undertaken to manage the economic, social and environmental risks from wildfire
46 (Bradstock and Gill 2001; Gill et al. 2013). A pre-eminent priority of fire management is risk to life
47 and property e.g. the 2018 Greece fires which at the time of writing resulted in the loss of 91 lives
48 and damaged over 2,000 houses (Kantouris and Nellas 2018). Wildfires can also have impacts on
49 mental health and community wellbeing (Jakes and Sturtevant 2013; Eisenman et al. 2015),
50 infrastructure and economic productivity (Nielsen-Pincus et al. 2014) and a wide range of
51 environmental values including biodiversity and soil, water and air quality (Bradstock 2008;
52 Sawyer et al. 2017; Smith et al. 2011; Williamson et al. 2016).

53 Prescribed burning is used in fire management to reduce risks from wildfire by directly modifying
54 fuel properties through the application of fire under moderate weather conditions (Penman et al.
55 2011a; Burrows and McCaw 2013). The effects of different types of prescribed burning strategies
56 (e.g. spatial configurations, treatment rates) in altering wildfire characteristics such as area burned
57 have been partially explored (Fernandes & Botelho 2003; Boer et al. 2009; Price et al. 2015a,
58 2015b; Salis et al. 2018). However, further work is needed to quantify the differential effects of
59 prescribed burning on risk reduction across a wide range of management values, given the diversity
60 of values affected by wildfire and the potential for conflicting effects (e.g. asset protection and
61 biodiversity conservation; Driscoll et al. 2010; Penman et al. 2011a). Quantification of inter-
62 regional differences in prescribed burning effectiveness would support the efficient allocation of
63 resources within and between regions.

64 Fire behaviour simulation models provide a methodology for investigating alternative prescribed
65 burning strategies and other fire management decisions (Finney 2005; Cary et al. 2016). These
66 simulators apply models of fire behaviour to environmental determinants such as vegetation type
67 and condition, terrain and weather to estimate key fire properties such as intensity, rate of spread
68 and flame height in a spatially explicit manner. These fire properties can then be used as input to

69 estimate risk to multiple management values (Ager et al. 2010; Thompson et al. 2011; Salis et al.
70 2013; Driscoll et al. 2016). By applying estimates of likelihood and cost to simulations, cost
71 effectiveness of alternative management strategies can be compared and evaluated (Penman et al.
72 2014a; Thompson et al. 2015). Bayesian Networks (BNs) offer a probabilistic methodology for
73 evaluating the sensitivity of risk and the benefits or costs of a given decision or strategy (Johnson et
74 al. 2010; Kelly et al. 2013; Pollino et al. 2007).

75 While there have been diverse studies (e.g. King et al. 2006; Ager et al. 2010; Barros et al. 2017)
76 that have used simulations to estimate changes in risk in response to differing strategies (i.e.
77 variations in treatment rate and pattern), studies that systematically explore the way in which
78 response of risk to treatment may vary across ecosystems are lacking. Such lack of knowledge is
79 critical because policy and operational choices concerning the efficacy of treatment in risk
80 mitigation need to account for biophysical and human context and its fundamental effects on fire
81 regimes and risk. For example, King et al. (2013) showed that the response of number of wildfires
82 and the area burned by them, to differing rates of prescribed burning, was estimated to differ
83 substantially between arid and cool temperate ecosystems in Australia. Differing cities will have
84 differing levels of exposure and vulnerability of people and property to wildfires according to
85 legacies of development patterns and other biophysical constraints (Bradstock et al. 2012; Penman
86 et al. 2014a; Alcasena et al. 2018). Thus, response of risk to treatment may be expected to differ
87 considerably, due to such variations.

88 In this study we estimate how the effects of differing rates of treatment on risk are likely to vary in
89 two peri-urban landscapes in south-eastern Australia. These case studies, situated on western edges
90 of the small sized cities of Canberra and Hobart, exhibit both similarities and some differences that
91 encapsulate much of the context for the risk mitigation and management problem in relatively
92 densely populated urban centres across southern Australia. Both have experienced major wildfires
93 in the last 50 years that have resulted in significant losses of lives and property (Fromm et al. 2006;
94 Henley 2013; Hyde 2013). Both are situated adjacent to mountainous terrain, covered by fire-prone

95 eucalypt-dominated forest and woodlands. Both have also experienced varying degrees of
96 population growth and urban expansion, though in this regard Canberra has grown more rapidly and
97 recently (www.abs.gov.au, accessed 11 May 2018). Is there a common response of risk to treatment
98 or do fundamentally different responses emerge as a function of differences in key human and
99 environmental influences? The answer to this question will determine the extent to which novel
100 solutions for risk mitigation via prescribed burning need to be derived to suit local context. We
101 specifically tested the following hypotheses:

- 102 • the biophysical and human properties of fire-prone landscapes influence the effectiveness of
103 prescribed burning at wildfire risk mitigation, resulting in regional differences in the
104 response to treatment rate and
- 105 • the risk reduction afforded by a given prescribed burning rate differs between key
106 management values.

107

108

109 **Methods**

110 *Study area*

111 Two case study landscapes were chosen in the ACT and Tasmania, both with a substantial Wildland
112 Urban Interface (WUI) and history of large fires resulting in significant house loss. Both case study
113 landscapes were approximately 200,000 ha, which corresponds with the upper end of the size
114 distribution of wildfires in local ecosystems. The ACT case study landscape stretched from the
115 capital Canberra in the east to the Brindabella Ranges in the west (Figure 1), with a population of
116 approximately 420,000 (www.abs.gov.au, accessed 11 May 2018). The area contains a mixture of
117 native forest, agricultural land and urban areas. Major vegetation types within forested areas are dry
118 and wet sclerophyll forest, dominated by *Eucalyptus* spp., and in high altitude areas, subalpine
119 woodland forest. Mean annual rainfall ranges from 615 mm at Canberra airport to 1051 mm at Mt

120 Ginini in the ranges to the south of the study area (www.bom.gov.au, accessed 11 May 2018).

121 Mean summer daily maximum temperatures are 27.1 °C at Canberra Airport and 19.2 °C at Mt

122 Ginini.

123 The Tasmania landscape was centred on the capital city, Hobart (Figure 1). As with the ACT

124 landscape, the study area included a relatively small population (circa. 222,000 in the Greater

125 Hobart Area; www.abs.gov.au, accessed 11 May 2018), forests and agricultural areas. Major

126 vegetation types within forested areas are dry and wet sclerophyll forest. Mean annual rainfall

127 ranges from 614 mm at Hobart to 897 mm at Mt Kunanyi in the Wellington Range to the west of

128 Hobart (www.bom.gov.au, accessed 11 May 2018). Mean summer daily maximum temperatures are

129 21.3 °C in Hobart and 12.8 °C at Mt Kunanyi.

130 Both case study landscapes were part of the Eucalypt forest (temperate) fire regime niche, a

131 relatively high productivity niche characterised by infrequent low-intensity litter fires in spring and

132 medium-intensity shrub fires in spring and summer (Murphy et al. 2013). Typically fire intensity

133 ranges from 1,000-5,000 kW m⁻¹, although under extreme weather conditions crown fires can occur

134 and fire intensity may reach 10,000-50,000 kW m⁻¹. Fires typically recur every 5-20 years, although

135 the interval between fires can be as long as 20-100 years (Murphy et al. 2013). From 2009 to 2014

136 an annual average of 1.85% of the ACT was treated with prescribed burning (ACT Government

137 2014). In Tasmania between the 2008-2009 and 2012-2013 fire seasons, prescribed fire was applied

138 to an average of 0.66% of treatable land, ranging from 0.29% to 1.58% (Richards et al. 2014).

139

140 *Fire behaviour simulations*

141 The effect of prescribed fire fuel treatment scenarios on future fire behaviour was examined using

142 the fire characterisation and fire spread simulator PHOENIX RapidFire v4.0.0.7 (hereafter

143 PHOENIX; Tolhurst et al. 2008). PHOENIX was selected as it used operationally by agencies in all

144 the states of eastern and southern Australia (Bentley and Penman 2017). Huygens' propagation

145 principle of fire edge (Knight and Coleman 1993) is used in PHOENIX to simulate two
146 dimensional fire growth over complex landscapes. Rate of spread is calculated by one of two fire
147 behaviour models - a modified McArthur Mk5 forest fire behaviour model (McArthur 1967; Noble
148 et al. 1980) and a generalisation of the CSIRO southern grassland fire spread model (Cheney et al.
149 1998).

150 PHOENIX uses a range of other modules including fuel accumulation models to account for
151 varying fuel loads with increasing time since fire based on fuel type, wind modification based on
152 topographic variation based on the Wind Ninja program ([www.firemodels.org/index.php/windninja-](http://www.firemodels.org/index.php/windninja-introduction)
153 [introduction](http://www.firemodels.org/index.php/windninja-introduction), accessed November 2011) and fire spotting (via ember propagation, spread and spot-
154 fire ignition; Saeedian et al. 2010). We refer readers to Tolhurst et al. (2008) for more details on the
155 model structure. A 30 m resolution digital elevation model was included to allow PHOENIX to
156 account for the influence of topography on fire behaviour. Fuel accumulation models for major
157 vegetation types of the case study landscape were provided by the relevant agencies in both ACT
158 and Tasmania; ACT Parks and Conservation and the NSW Rural Fire Service for the ACT study
159 region and the Department of Primary Industries, Parks, Water and Environment (DPIPWE) for the
160 Tasmania study region. Disruptions to fuels through streams and roads were represented by the
161 estimated width on a 30 m raster and were also provided by the relevant agencies. All simulations
162 were run using 180 m resolution grid cells to optimise model performance based on the
163 recommendations by Tolhurst et al. (2008). PHOENIX was run in 'batch' mode with a modified
164 output format that included the following metrics for each cell within each fire: ember density,
165 convection, intensity and flame length.

166

167 *Model input data*

168 A series of daily weather datasets was selected from Automatic Weather Station (AWS) records
169 based on the Forest Fire Danger Index (FFDI) from 1994 to 2015; these datasets represent the

170 distribution in regional weather conditions affecting fire behavior in the case study areas. We used
171 the Hobart AWS station (Bureau of Meteorology (BOM) site no. 94929) for the Tasmanian
172 simulations and the Tuggeranong AWS station (BOM site no. 070339) for the ACT simulations.
173 FFDI is a composite measure that combines temperature, relative humidity and wind speed with a
174 long term drying index to predict the difficulty of fire suppression (McArthur 1967; Noble et al.
175 1980). Five of the six FFDI categories have been recorded in each case study landscape (Low-
176 Moderate, High, Very High, Severe, Extreme). To capture variability in weather, three weather
177 types were selected within each of these categories based on the predominant FFDI driver – i)
178 strong wind, ii) strong wind with a significant directional change or iii) high air temperature. Up to
179 three different days were chosen for each of these FFDI drivers, which when combined with
180 available observations within each FFDI category resulted in 34 weather dates for the ACT case
181 study landscape and 26 for the Tasmania landscape. Each weather stream contained hourly data for
182 air temperature, relative humidity, wind speed, wind direction, drought factor and curing. All
183 weather streams covered a 24-hour period beginning from midnight to allow the model to generate
184 stable and realistic estimates of fuel moisture based on temperature and relative humidity (Tolhurst
185 et al. 2008).

186 Fuel loads were varied to represent a range of past fuel management scenarios. PHOENIX estimates
187 fuel loads using separate fuel accumulation curves for combined surface/near surface, elevated and
188 bark fuels (Hines et al. 2010). These curves use a negative exponential growth function and vary
189 between vegetation types (Watson 2011). To capture the effect of varying prescribed fire treatment
190 rates in the landscape, a series of prescribed burning treatments were simulated over a period of 20
191 years (Penman et al. 2014a). The influence of wildfire on fuel loads was simulated by selecting a
192 subset of actual wildfire sizes for a period of 30 years at a rate equivalent to the historical observed
193 wildfire incidence rate in the case study landscapes (Bradstock et al. 2014). The treatable portion of
194 each case study landscape was separated into management sized ‘burn blocks’. These burn blocks
195 were a combination of historic prescribed fire boundaries and future planned burns. In the ACT

196 study region, the data were provided by ACT Parks and Conservation and the NSW Office of
197 Environment and Heritage (on behalf of ACT Parks and Conservation). In the Tasmania study
198 region, the data were provided by DPIPWE. A selection routine incorporating wildfire history,
199 treatment percentage (0, 1, 2, 3, 5 and 10 percent) and minimum burn intervals was then applied to
200 the burn blocks iteratively over 20 a year period. For burn blocks classified as edge, a minimum
201 burn interval of 5 years was used as it reflects what is feasible to achieve by the agencies whilst still
202 allowing fuels to recover sufficiently. For landscape blocks, the minimum burn interval is the
203 minimum tolerable fire interval for the majority of the vegetation type within each block. This
204 process was replicated 5 times to give a total of 30 simulated fire history layers for each case study
205 landscape to be incorporated into the PHOENIX simulations.

206 Ignition locations were selected using a probabilistic approach. Ten thousand random points were
207 generated within each study area. An ignition probability was calculated for each point based on an
208 empirical model developed for similar forest types (Penman et al. 2015). In the model, ignition
209 probability is a function of environmental factors (such as topography and productivity) and built
210 environment factors (such as housing density and distance to the nearest road). From the 10,000
211 random points, 1,000 ignition points with the highest ignition probabilities were selected for use in
212 the simulations. Individual fires were ignited at 11am and propagated for 12 hours, unless self-
213 extinguished within this period. To minimise ignition location bias and reduce total simulation time,
214 the 1,000 ignition points were randomly split into 5 groups of 200 ignitions. Each of these 200
215 ignitions was simulated for a single replicate of each weather category/driver combination (n=14
216 for ACT, n=11 for Tasmania) and fuel treatment (n=6), resulting in 98,000 fires in the ACT case
217 study landscape and 77,000 fires in the Tasmania case study landscape.

218

219 *Impact estimation*

220 Area burnt was a direct output from the fire behaviour simulations. Effectiveness of prescribed
221 burning at mitigating wildfire impacts was assessed on five values: house loss, loss of human life,
222 length of powerline damaged, length of road damaged and area burnt below minimum tolerable fire
223 interval (TFI). TFI is an ecological measure used in conservation management that considers the
224 amount of time between fires required for native vegetation to reproduce such that vegetation
225 diversity can be maintained (Department of Environment and Sustainability 2012). Area burnt
226 below TFI was calculated from area burnt and existing TFI mapping supplied by the management
227 agencies, and impacts on other values were calculated using loss functions. The probability of
228 house loss was calculated as a function of ember density, flame length and convection as presented
229 in (Tolhurst and Chong 2011). House loss was calculated per 180 m cell and then multiplied by the
230 number of houses in that cell to estimate the number of houses lost per fire. House locations were
231 derived from authoritative national location data (PSMA 2016). Statistical loss of human life was
232 based on house loss (using the house loss function), the number of houses exposed (using
233 simulation output) and the number of people exposed to fire (Harris et al. 2012). Mesh block data
234 from the Australian Bureau of Statistics was used to calculate the average number of people per
235 household in each block. These data were then combined with the house location dataset to give the
236 total number of people exposed to fire. Due to a lack of empirical data regarding the risk of damage
237 to roads and powerlines, we used a simple threshold of 10,000 kW/m to determine if roads or
238 powerlines within each 180 m cell were considered damaged by fire. The effects of fire are largely
239 associated with infrastructure such as signs and road closures, rather than damage to the road
240 surface itself. Locations of roads and powerlines were provided by ACT Parks, Tasmanian
241 Department of Primary industries, Parks, Water and Environment and Conservation and the NSW
242 Rural Fire Service.

243

244 *Risk estimation*

BNs are directed acyclic graphs with variables represented by nodes and the directional relationships between the nodes represented by arrows. In the BN developed for this study, two primary node types were used; stochastic nodes and decision nodes. Stochastic nodes are random variables represented by a conditional probability table which contain the joint probability distributions for the variable (Korb and Nocholson 2011). Decision nodes represent discrete decisions that can be made by users and when used in a BN, these are referred to as Bayesian Decision Networks (BDNs). The probability distributions and associated uncertainty for the stochastic nodes, together with the selected discrete values of the decision nodes, are propagated throughout the network and outputs are presented as likelihoods.

In this study, a BDN was used to evaluate prescribed burning effectiveness in mitigating risk. Broadly we followed the recommended methods for developing Bayesian Networks of Marcot et al. (2006) and Chen and Pollino (2012). The primary steps used were to construct a conceptual model of the problem, develop influence diagrams to depict the relationships of the conceptual model and finally populate all the conditional probability tables within the model. A simple conceptual model (Figure 2) was developed based on previous BN studies of fire management (Penman et al. 2011*b*; Penman et al 2014*b*). In the model, fire weather and fire management affect the distribution of fire sizes. Fire weather, fire size and fire management then all affect the extent of loss for a value of interest. The conceptual model was then used to create the influence diagram which included the full set of management decisions and values (Figure 3).

Data for the conditional probability tables (CPTs) in the Bayesian Network were derived from the simulation study for the case study landscapes. Data generated in the fire simulations were used to estimate the probability distributions in the CPTs for each of the fire size and value impact nodes. At each node continuous data were discretised on a log scale across the range of values in an iterative fashion to get a relatively even distribution across the non-zero values. Fire weather in the model was quantified using FFDI. For each FFDI category, we calculated the average maximum daily FFDI across the average fire season for the study area using data from the same weather

271 stations used to run PHOENIX. These values were then classified into fire days and days without
272 fire, where a fire day was defined as a day on which fire was recorded within a 200 km radius of the
273 weather station. The proportional distribution of fire days in each of the five categories of FFDI was
274 then used in the Bayesian Network.

275 The Bayesian Network was used to estimate the risk to each value at each treatment level from the
276 simulation-derived distributions of data. The resultant risks provide a basis for comparison between
277 regions that explicitly incorporates the observed frequency of fire weather conditions in each case
278 study landscape. Risk values were the expected node likelihoods for area burnt, house loss, life loss,
279 length of powerline damaged, length of road damaged and area burnt below TFI for each of the six
280 prescribed burning treatment rates. Risk values were also estimated in relation to expected node
281 likelihoods with no treatment, to allow for comparison of the relative change in risk at different
282 prescribed burning treatment rates across both case study landscapes.

283

284 **Results**

285 *Impact estimation*

286 Unplanned fires were considerably larger in the Tasmania case study landscape than in the ACT
287 case study landscape (Figure 4; see Supplementary Material for similar plots for each management
288 value). Although each landscape had a large range of area burnt for any given FFDI category and
289 treatment rate, maximum area burnt integrated across all weather categories was 1.5-2.1 times
290 bigger in Tasmania than in the ACT, depending on the treatment rate (Tables 1 and 2). The
291 magnitude of differences was greater for mean area burnt (2.7-5.9 times bigger in Tasmania) and
292 greater still for median area burnt (14.7-24 times bigger in Tasmania). Mean and maximum house
293 loss was greater in Tasmania than ACT, but median house loss results were low (0-2) in each
294 landscape. Median life loss (0) and mean life loss (1-4) were also similar in each landscape, but
295 maximum life loss was considerably greater in the ACT up to 5% treatment rates, but higher in

296 Tasmania (149 lives lost) than the ACT (35 lives lost) at 10% treatment rates. For length of
297 powerline damaged, length of road damaged and area burnt below minimum TFI, mean and
298 maximum impacts were much higher in Tasmania than the ACT. Overall, area burnt declined with
299 increasing treatment rate. However, in both landscapes, easing fire weather conditions by a single
300 FFDI category usually resulted in a greater reduction in median, 3rd quartile and maximum area
301 burnt than increasing the treatment rate from 0 to 10% (Figure 4). As with area burnt, there was a
302 decrease in house loss, life loss and length of powerline and road damaged as treatment increased,
303 while area burnt below minimum TFI increased with increasing treatment rate.

304

305 *Risk estimation*

306 The effect of increasing treatment rate was preserved after adjusting for the relative frequency of
307 fire weather conditions in each landscape i.e. the risk of substantial area burnt and significant house
308 loss, life loss and length of road and powerline damaged declined with increasing rate of treatment,
309 whereas increased treatment resulted in greater areas burnt below minimum TFI (Figure 5). Risks
310 were uniformly greater in Tasmania than in the ACT, regardless of value or treatment rate. With no
311 treatment, expected area burnt was 669 ha in Tasmania and 54 ha in the ACT. This decreased to
312 539 ha and 25 ha respectively at a treatment rate of 10%. As treatment rate increased from 0 to 10%
313 in Tasmania, expected house loss declined from 4.4 to 2.3 and expected life loss declined from 0.8
314 to 0.6. Risk of house loss and life loss were almost constant across all treatment levels in the ACT
315 (about 0.2), however prescribed burning effects were apparent when relative risk was examined (see
316 below). Expected length of powerline damaged in Tasmania decreased from 434 m to 297 m as
317 treatment increased from 0 to 10%. The equivalent figures for expected length of road damaged
318 were 7.6 km and 5.4 km. In the ACT, expected lengths of powerline and road damaged with no
319 treatment (44 m and 605 m respectively) were substantially larger than at the maximum treatment
320 rate of 10% (26 m and 285 m respectively). In both landscapes, increasing treatment from 0 to 10%

321 led to steady increases in expected area burnt below minimum TFI, with the exception of an
322 increase from 5% to 10% in treatment rate the ACT, which resulted in a slight decline from 5.6 ha
323 to 5.5 ha.

324 Prescribed burning led to much greater relative reductions in area burnt in the ACT (12-54%) than
325 in Tasmania (2-19%; Figure 6). There were also greater relative reductions in risk in the ACT for
326 length of powerline damaged (13-41%) and length of road damaged (11-53%) compared to
327 Tasmania (4-32% and 5-29% respectively). At up to 5% treatment rates, the relative effect of
328 prescribed burning on area burnt below TFI was greater in the ACT (7-14% increases) than in
329 Tasmania (2-9% increases), but at a treatment level of 10% this trend reversed, with a relative
330 increase in risk in Tasmania of 14% and in the ACT of 12%. In contrast, at all treatment rates there
331 was a greater relative reduction in the risk of house loss (9-49%) and life loss (8-24%) in Tasmania
332 than in the ACT (4-24% and 4-18% respectively). It was generally not possible to achieve a 50%
333 reduction in risk in either case study landscape. Exceptions were area burnt (54%) and length of
334 road damaged (53%) in the ACT at 10% treatment rates, while house loss in Tasmania was almost
335 halved (49% reduction) at 10% treatment rates.

336

337 **Discussion**

338 Relationships between prescribed burning treatment rates, area burnt and risk reduction supported
339 our hypotheses and largely conformed to previous findings (King et al. 2006; Bradstock et al.
340 2012). Prescribed burning led to a reduction in area burnt and risk of asset loss, but an increase in
341 area burnt below minimum TFI. Weather, however, had a consistently greater effect than prescribed
342 burning on area burnt and related risks, also in line with previous simulation studies (Cary et al.
343 2009; Penman et al. 2013) and empirical studies (Price and Bradstock 2010; 2012 and others).
344 Furlaud et al.'s (2017) findings that implementable treatment plans (corresponding to our treatment
345 rates of 1-5%) would only have a small effect on fire extent across Tasmania, are comparable to our

findings of relatively low reduction in area burnt from prescribed burning in the State's south-east. However, while Furlaud et al. (2017) did not investigate house loss, we found that the risk for this value could be halved at 10% treatment rates. Bradstock et al. (2012) found that treatment rates of 7-10% were required in order to halve risk to people and property in Sydney, a region whose vegetation and climate more closely resembles the ACT than Tasmania. Penman et al. (2014) found that halving the risk of high intensity fires reaching houses in Sydney was possible at rates of 10% if treatment was exclusively in the WUI, but that the same rate of treatment, when confined to landscape burns, achieved a reduction of just 19%. We found that in the ACT reductions in risk of 50% or more were possible for area burnt and length of road damaged, but that house loss and life loss did not respond as strongly to a maximum treatment rate of 10%. However, in our simulations treatment was distributed across both landscape and interface zones. Possibly, higher levels of risk reduction to assets within the WUI in this landscape could be achieved if treatments were concentrated near the interface (Penman et al. 2013; Kennedy and Johnson 2014). Importantly, current treatment rates in both landscapes are well below 5% and a treatment rate of 10% is not currently likely to be achievable due to various constraints such as budgets, resource limitations and available days suitable for prescribed burning (e.g. Clarke et al. (in press)). Overall, the effectiveness of prescribed burning at mitigating area burnt by wildfire and other key values varied considerably across landscapes and values: i.e. a given rate of prescribed burning did not deliver the same degree of risk mitigation for all values, and the results differed between study landscapes.

Although the Tasmania and ACT case study landscapes share many similarities in fire regime, climate and vegetation type, there are considerable differences in the risk profiles. These may be driven by variations in fuel load, terrain, fuel accumulation and asset arrangement in the landscape. The proportion of forest in ACT and Tasmania is similar (48% and 54%; ESCAVI 2003), but the mean proportion of forest in ACT census blocks (1.6%) is considerably lower than in Tasmania (17%) (Australian Bureau of Statistics, 2011 Census). Populated areas are thus around ten times more forested in Tasmania than in the ACT. Overall fire size showed little response to treatment

level in the Tasmanian case study landscape but a strong response in the ACT landscape. This contrasted with the house loss results, where Tasmania showed a strong response to prescribed burning. A possible explanation for this is that the house loss metric factors in fire intensity, convection and ember attack. Given the terrain, forest type and proximity of housing to vegetation in the Tasmania case study landscape, house loss there may be more driven by flame contact, radiant heat and short-range spotting (Cruz et al. 2012) than in the ACT landscape. This is supported by the fact that values with intensity-driven loss functions like length of powerline and road damaged showed very similar responses to treatment level as area burnt in both the ACT and Tasmania. These results demonstrate the importance of considering the interplay between multiple fire properties and the arrangement of assets throughout the landscape, rather than simpler measures such as fire presence/absence and fire intensity.

The effect of treatment level on the ecological value of area burnt below minimum TFI was consistent between case study areas but unlike the other values, increases with treatment percentage. The reason for this is that although the prescribed burning selection routine was constrained to not burn below the minimum TFI, increased treatment places more of the landscape at risk of being burnt by the next wildfire before the minimum TFI. The simulation results reflect this in both the ACT and Tasmania case study landscapes up to treatment rates of 3%. However, beyond 3% in both landscapes, the effect of prescribed burning is dampened by the fact that wildfire size is also decreasing, thus burning less area below minimum TFI. In the ACT case study landscape, it is evident from the area burnt results that wildfire size is reduced sufficiently to result in a decrease in area burnt below minimum TFI under 5% and 10% treatment rates. The response of this indicator of ecological values provides a basis for understanding trade-offs between management objectives such as biodiversity conservation and reduction of risk to life and property (e.g. Bentley and Penman 2017).

Whilst the simulation methodology was consistently applied to both case study landscapes, a number of caveats and limitations apply to both our study design and the PHOENIX RapidFire

398 simulator. There are a range of additional management strategies to reduce wildfire risk that we did
399 not consider, such as manual fuel removal, suppression, fuel breaks, asset construction
400 characteristics and general community preparedness. Although some of these strategies can be
401 simulated in PHOENIX, their current implementation within the simulator does not accurately
402 address the complexities of real world situations (Penman et al. 2013). Nevertheless, one study
403 found that increasing fuel treatment led to only marginal increases in containment success due to
404 suppression (Penman et al. 2013). Although rapid gains continue to be made in the development of
405 simulations (Duff et al. 2018), the primary focus of this study was to analyse the effect of fuel
406 treatment on wildfire risk. The prescribed burning assignment routine, although based on actual
407 management burn blocks, operated randomly within edge and landscape zones. While random
408 assignment of fire treatment has been shown to decrease fire size in past studies (Bradstock et al.
409 2012; Price et al. 2015), other studies have shown that management decisions and the application of
410 prescribed burning close to assets can further reduce the risk to assets (Finney 2001; Finney *et al.*
411 2007; Bentley and Penman 2017; Penman *et al.* 2014*b*). Fuel load within each burn block in this
412 study was also considered to be reset to its lowest value in PHOENIX for surface, elevated and bark
413 fuels. In reality, prescribed burning is performed in mild fire weather resulting in a mosaic of fire
414 severity within each burn block, which will yield varying post-fire fuel properties, fire behaviour
415 and impacts (Penman et al. 2007; Loschiavo et al. 2017; McCarthy et al. 2017). Furthermore, post
416 fire fuel accumulation within PHOENIX is assumed to be follow an Olson curve (Olson 1963), i.e.
417 a negative exponential growth equation. Although surface fuel accumulation can be reliably
418 represented by an Olson curve, the suitability of an Olson curve for elevated and bark fuels is largely
419 untested (e.g. Duff et al. 2012; Dalgleish et al. 2015). Further, although state agencies have invested
420 in developing curves specifically for local vegetation types (e.g. Watson 2011), it is not clear how
421 consistent these estimates are between case study landscapes.

422 The risk trade-offs presented here reflect the methodologies used for estimation of impacts: life and
423 property loss, length of powerline and road damaged, and area burnt below TFI. Overall risk

424 estimates should therefore be interpreted in light of known or potential weaknesses in these models,
425 such as the use of a single fire intensity threshold alone to determine the length of powerline and
426 road damaged or knowledge gaps concerning tolerable fire intervals. However, the use of loss
427 functions to characterise wildfire impacts on various values is essentially modular, allowing for
428 their revision or replacement as improvements and alternatives become available. The methodology
429 also allows for the introduction of new values (e.g. other environmental and health values) as loss
430 functions are developed. Integration over the entire distribution of fire weather likelihood at a given
431 location provides a better estimate of risk than methods limited to specific fire weather categories
432 (e.g. Ager et al. 2010; Salis et al. 2016; Furlaud et al. 2017; Alcasena et al. 2018), but our method
433 still allows for the interrogation of these results along those lines. Weather inputs can be adjusted to
434 reflect new observations or projected changes in fire weather conditions due to climate change
435 (Clarke and Evans 2018).

436 We have developed a methodology for quantifying risk as a function of prescribed burning. The
437 method incorporates inherent differences between landscapes in weather, fuel, asset arrangement
438 and ignition patterns, and a Bayesian Network to that provides a quantitative basis for assessing
439 risks to multiple management values. These features allow for formal comparisons between both
440 landscapes and values. While we have applied this methodology to two fire-prone case study
441 landscapes, future studies could expand this to a more comprehensive selection of fire-prone areas
442 in Australia and elsewhere, exploring the influence of variation in climate, population and land use
443 on prescribed burning effectiveness. Such a systematic investigation could explore the reasons why
444 risk does not always respond linearly to prescribed burning and why there may be diminishing
445 returns in response to increasing treatment rates. Further studies could also utilise the Bayesian
446 Network framework to incorporate information about economic costs and climate change impacts
447 and investigate trade-offs between different management options (Driscoll et al. 2016).

448

449

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455

456

457 **Figure captions**

458 Figure 1 Study area location. Fire behaviour simulations were carried out for two case study
459 landscapes in south-eastern Australia, Tasmania (left) and the Australian Capital Territory (ACT;
460 right).

461 Figure 2 Conceptual model for the analysis of fire management decisions, used to formulate
462 influence diagrams for Bayesian Network model of risk mitigation from prescribed burning.

463 Figure 3 Example influence diagram for Bayesian Network model of risk mitigation from
464 prescribed burning. Data is for the Tasmania case study landscape with no treatment.

465 Figure 4 Fire behaviour simulation output for area burnt in ACT (top) and Tasmania (bottom) case
466 study landscapes. Each panel shows the distribution of area burnt at different treatment rates within
467 a given fire weather category. Each category includes FFDI values driven primarily by temperature,
468 wind speed and wind direction change. For all boxplots, lower and upper whiskers span the 95%
469 interval, lower and upper hinges show first and third quartile, central line shows median and notch
470 shows 95% confidence interval of median. Similar plots for each management value are shown in
471 Supplementary Figures 1-10.

472 Figure 5 Influence of prescribed burning and weather on risk for area burnt and five key
473 management values in the ACT (cross) and Tasmania (circle) case study landscapes. For each
474 treatment level, the Bayesian Network incorporates all weather streams and adjusts impacts to
475 reflect the proportional distribution of fire days within the five fire weather categories in each case
476 study landscape.

477 Figure 6 Influence of prescribed burning and weather on relative risk for area burnt and five key
478 management values in the ACT (cross) and Tasmania (circle) case study landscapes. For each
479 treatment level, the Bayesian Network incorporates all weather streams and adjusts impacts to
480 reflect the proportional distribution of fire days within the five fire weather categories in each case
481 study landscape. Relative risk is defined as the change in risk due to treatment, with a value of 1
482 representing no treatment. Note the Y axis scale is different for area burnt below TFI.

483

484 **Supplementary material**

485 Supplementary Figure 1 Impact estimation for house loss in Tasmania case study landscape. Each
486 panel shows the distribution of house loss at different treatment rates within a given fire weather
487 category. Each category includes FFDI values driven primarily by temperature, wind speed and
488 wind direction change.

489 Supplementary Figure 2. As for Supp Fig 1, but for life loss.

490 Supplementary Figure 3. As for Supp Fig 1, but for length of powerline damaged.

491 Supplementary Figure 4. As for Supp Fig 1, but for length of road damaged.

492 Supplementary Figure 5. As for Supp Fig 1, but for area burnt below minimum tolerable fire
493 interval (TFI).

494 Supplementary Figure 6. Impact estimation for house loss in ACT case study landscape. Each panel
495 shows the distribution of house loss at different treatment rates within a given fire weather category.
496 Each category includes FFDI values driven primarily by temperature, wind speed and wind
497 direction change.

498 Supplementary Figure 7. As for Supp Fig 6, but for life loss.

499 Supplementary Figure 8. As for Supp Fig 6, but for length of powerline damaged.

500 Supplementary Figure 9. As for Supp Fig 6, but for length of road damaged.

501 Supplementary Figure 10. As for Supp Fig 6, but for area burnt below minimum tolerable fire
502 interval (TFI).

503

504

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Figure 1 Study area location. Fire behaviour simulations were carried out for two case study landscapes in south-eastern Australia, Tasmania (left) and the Australian Capital Territory (ACT; right).

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760 Figure 2 Conceptual model for the analysis of fire management decisions, used to formulate
 761 influence diagrams for Bayesian Network model of risk mitigation from prescribed burning.

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764 Figure 3 Example influence diagram for Bayesian Network model of risk mitigation from
 765 prescribed burning. Data is for the Tasmania case study landscape with no treatment.

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769 Figure 4 Fire behaviour simulation output for area burnt in ACT (top) and Tasmania (bottom) case
 770 study landscapes. Each panel shows the distribution of area burnt at different treatment rates within
 771 a given fire weather category. Each category includes FFDI values driven primarily by temperature,
 772 wind speed and wind direction change. For all boxplots, lower and upper whiskers span the 95%
 773 interval, lower and upper hinges show first and third quartile, central line shows median and notch
 774 shows 95% confidence interval of median. Similar plots for each management value are shown in
 775 Supplementary Figures 1-10.

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778 Figure 5 Influence of prescribed burning and weather on risk for area burnt and five key
 779 management values in the ACT (cross) and Tasmania (circle) case study landscapes. For each
 780 treatment level, the Bayesian Network incorporates all weather streams and adjusts impacts to
 781 reflect the proportional distribution of fire days within the five fire weather categories in each case
 782 study landscape.

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786 Figure 6 Influence of prescribed burning and weather on relative risk for area burnt and five key
 787 management values in the ACT (cross) and Tasmania (circle) case study landscapes. For each
 788 treatment level, the Bayesian Network incorporates all weather streams and adjusts impacts to
 789 reflect the proportional distribution of fire days within the five fire weather categories in each case
 790 study landscape. Relative risk is defined as the change in risk due to treatment, with a value of 1
 791 representing no treatment. Note the Y axis scale is different for area burnt below TFI.

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793 **Table 1**
794 Summary of the distributions of area burnt and estimated impacts on management values from fire
795 behaviour simulations for the ACT case study landscape (prior to Bayesian Network analysis). Data
796 is summarised across all weather scenarios.
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		<i>Treatment rate per annum</i>					
<i>Impact</i>		<i>0%</i>	<i>1%</i>	<i>2%</i>	<i>3%</i>	<i>5%</i>	<i>10%</i>
Area burnt (ha)	Max	74,930	72,269	70,836	60,198	64,205	48,490
	Mean	3,055	2,568	2,112	1,784	1,402	1,066
	Median	113	98	77	67	54	35
	SD	6,861	5,889	5,129	4,380	3,787	3,168
House loss (No.)	Max	1,026	1,042	1,019	1,020	972	191
	Mean	10	8	7	6	4	1
	Median	0	0	0	0	0	0
	SD	74	66	59	58	45	7
Life loss (No.)	Max	1,018	921	952	915	731	35
	Mean	3	2	2	2	1	0
	Median	0	0	0	0	0	0
	SD	28	24	19	21	14	1
Length of powerline damaged(m)	Max	79,840	74,170	67,430	61,290	61,990	62,220
	Mean	1,730	1,412	1,130	939	776	623
	Median	0	0	0	0	0	0
	SD	4,784	4,061	3,456	2,987	2,694	2,483
Length of road damaged (m)	Max	753,290	697,470	566,680	558,580	421,290	459,310
	Mean	33,320	27,607	21,969	18,737	14,342	10,985
	Median	1,170	1,010	780	640	460	240
	SD	72,896	60,460	48,207	41,367	33,641	28,308
Area burnt below minimum TFI (ha)	Max	943	905	1,274	1,297	1,864	1,975
	Mean	4	13	19	21	24	19
	Median	0	0	0	0	0	0
	SD	30	52	79	87	106	89

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Table 2
Summary of the distributions of area burnt and estimated impacts on management values from fire behaviour simulations for the Tasmania case study landscape (prior to Bayesian Network analysis).

		<i>Treatment rate per annum</i>					
<i>Impact</i>		<i>0%</i>	<i>1%</i>	<i>2%</i>	<i>3%</i>	<i>5%</i>	<i>10%</i>
Area burnt (ha)	Max	109,288	111,254	107,527	108,006	105,726	101,064
	Mean	8,110	7,904	7,659	7,480	7,071	6,322
	Median	1,660	1,545	1,449	1,352	1,175	839
	SD	14,097	13,890	13,582	13,417	12,931	12,137
House loss (No.)	Max	6,453	8,372	5,304	3,889	3,337	2,920
	Mean	117	100	88	78	64	40
	Median	2	2	2	2	1	1
	SD	386	340	290	250	211	135
Life loss (No.)	Max	423	674	357	242	176	149
	Mean	4	3	3	2	2	1
	Median	0	0	0	0	0	0
	SD	19	17	13	11	9	5
Length of powerline damaged (m)	Max	223,190	223,300	219,480	221,860	217,260	218,300
	Mean	5,413	5,022	4,729	4,518	3,927	3,171
	Median	0	0	0	0	0	0
	SD	14,958	14,070	13,634	13,263	11,953	10,484
Length of road damaged (m)	Max	2,271,430	2,285,050	2,226,220	2,232,940	2,139,070	1,971,240
	Mean	126,944	119,689	113,817	109,119	99,131	84,111
	Median	11,510	9,945	8,590	7,850	5,780	3,210
	SD	266,549	254,721	244,038	236,393	219,701	196,388
Area burnt below minimum TFI (ha)	Max	5,849	5,860	6,468	6,572	7,420	7,922
	Mean	255	263	280	292	302	320
	Median	30	31	31	32	30	26
	SD	551	569	610	631	676	735