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Bayes Nets as a method for analysing the influence of management actions in fire planning

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Abstract. Wildfire can result in significant economic costs with inquiries following such events often recommending an increase in management effort to reduce the risk of future losses. Currently, there are no objective frameworks in which to assess the relative merits of management actions or the synergistic way in which the various combinations may act. We examine the value of Bayes Nets as a method for assessing the risk reduction from fire management practices using a case study from a forested landscape. Specifically, we consider the relative reduction in wildfire risk from investing in prescribed burning, initial or rapid attack and suppression. The Bayes Net was developed using existing datasets, a process model and expert opinion. We compared the results of the models with the recorded fire data for an 11-year period from 1997 to 2000 with the model successfully duplicating these data. Initial attack and suppression effort had the greatest effect on the distribution of the fire sizes for a season. Bayes Nets provide a holistic model for considering the effect of multiple fire management methods on the risk of wildfires. The methods could be further advanced by including the costs of management and conducting a formal decision analysis.

Additional keywords: Bayesian Belief Network, fire suppression, initial attack, prescribed burning, risk management.

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Introduction

Large fire can result in significant economic costs to forest managers and adjacent property owners (e.g. Butry *et al.* 2001; Prestemon *et al.* 2006). A wildfire that entered the city of Canberra, Australia, in January 2003 resulted in four deaths and losses of over AU$350 million, including the complete loss of 414 urban houses and 87 rural houses and extensive other losses (Ganewatta 2008). The Black Saturday fires that occurred in Victoria, Australia, in February 2009 resulted in the loss of over 2000 houses and 173 lives (Leonard *et al.* 2009). Large losses have been reported from wildfires elsewhere in Australia (e.g. Valent 1984), North America (e.g. Cohen 2000) and Europe (e.g. Lampin-Maillet *et al.* 2010).

Official inquiries following significant wildfires frequently recommend an increase in management effort to reduce the risk of future losses (e.g. Krusel and Petris 1992; McLeod 2003; Ellis *et al.* 2004). Most commonly, the recommendation is for an increase in the area treated annually by prescribed burning (Esplin *et al.* 2003; Anonymous 2008). Other strategies include increased investment in more aggressive fire-suppression methods, e.g. large aircraft, and methods to reduce the response time to ignition events. These options are complementary, probably synergistic, and have complex effects on fire behaviour, so that it is difficult to predict intuitively how fires will respond to any particular mix of management strategies. Land-management agencies need to deploy an optimum mix of strategies to reduce the risk of fires starting, spreading and reaching the wildland–urban interface, but to date, there has been no objective framework by which to judge the return on investment from these strategies. There have been studies of the effectiveness of prescribed burning (Boer *et al.* 2009; Price and Bradstock 2011) and initial attack (Plucinski *et al.* 2007), but studies that simultaneously compare several strategies and measure return on investment are lacking.

Bayesian Belief Networks or Bayes Nets (BN) are a statistical framework capable of analysing complex environmental relationships (Johnson *et al.* 2010). The networks are depicted as directed acyclic graphs with variables and their interactions represented by nodes and directed links (Nyberg *et al.* 2006). Nodes can represent predictor variables in relationships, management decisions or outcomes. Values for the predictor variables in the relationships are quantified through a series of conditional probability tables (CPTs). Outcomes of a BN are represented as likelihoods, which can then form the basis for risk analysis and management (Marcot *et al.* 2001). Bayes Nets have been applied in a wide range of fields including medical

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diagnosis (e.g. Lucas 2004), forensic science (e.g. Oatley and Ewart 2003), economic analysis (e.g. Ejsing *et al.* 2008) and water management (e.g. Said 2006). There are several texts that describe the mechanics and theory of BN in greater detail, which we refer readers to (e.g. Pearl 1986; Charniak 1991; Varis 1995; Korb and Nicholson 2004; Uusitalo 2007; Barton *et al.* 2008).

The process of developing a BN requires several key steps, which are described in detail by Marcot *et al.* (2006). Developing an influence diagram or causal web is the first step in the process. These figures consist of boxes and arrows showing relationships between the variables, with the arrows depicting the direction of influence. An initial BN is then created from the influence diagram with parent and child nodes, where parent nodes feed into child nodes. Each node is represented by one or several probability distributions, which form the CPT. If a node has no parent nodes, it is represented by a single distribution, but for all child nodes, there is a probability distribution for all combinations of the parent nodes (Uusitalo 2007). Data for the CPTs can come from a variety of sources. Parentless nodes generally represent environmental factors that can be measured or estimated from the study area of interest. Conditional probability tables for child nodes can be populated with data from empirical statistical models, process models and expert opinions where data are lacking (e.g. Johnson *et al.* 2010). Finally, once a BN is developed, it should undergo validation with field data to test the underlying assumptions and CPTs of the model (Marcot *et al.* 2006).

Bayes Nets have the potential to be valuable in determining the effect of a combination of management strategies on all stages of a fire from the probability of an ignition through to the ultimate fire size when the fire is contained. In this study, we examine the value of BNs as a method for assessing the relative reduction in wildfire risk in a fire management scenario using a case study from the Wollemi Wilderness Area, a forested landscape managed primarily for conservation. We focus on modelling how fire management influences the occurrence of large fires. Fire spread is known to be predominantly influenced by weather and fuel loads (McArthur 1966; Fernandes and Botelho 2003). In Australia, fire weather is often forecast using the Forest Fire Danger Index (FFDI), which captures the effects of recent rainfall and ambient temperature, humidity and wind speed. Fuel loads are determined by vegetation type and time since fire, which can include prescribed fire. In the case study, we combine a range of existing datasets and statistical models with expert opinion. We use the derived BN to test the effect of each of the three management actions on the annual risk of large or extreme fires (defined below).

Materials and methods

The case study was prepared for Wollemi National Park (WNP), a conservation reserve of ~489 000 ha (33°45′S, 150°30′E), ~100 km north-west of the Sydney central business district. WNP is a dissected mountain range that is contiguous with several other National Parks that form the Greater Blue Mountains World Heritage Area (GBMWHA – for further details see http://www.environment.nsw.gov.au/protectedareas/GreaterBlueMountainsWorldHeritageArea.htm, accessed July 2010). The majority of the park comprises dry sclerophyll open eucalypt forests on steep sandstone-shale terrain. Small pockets of rainforest, heath and grassland also occur throughout the park (NSW National Parks and Wildlife Service 2001). WNP is warmest in January (mean maximum temperature 31.7°C, mean minimum temperature 17.1°C) and coolest in July (mean maximum temperature 17.4°C, mean minimum temperature 3.8°C). Average annual rainfall is 642 mm, with the average wettest months being January and February (77 and 72.4 mm) and the driest month being August (36.4 mm) (Australian Bureau of Meteorology (BOM), http://www.bom.gov.au/climate/data/index.shtml, accessed August 2011 – station number 061086).

The NSW National Parks and Wildlife Service (NPWS, Department of Environment, Climate Change and Water) manages the park, and has a range of pro-active and reactive fire management strategies at their disposal. Chiefly, these are prescribed burning (to reduce fuels), Remote Area Fire Teams (RAFT, mobile firefighters who can be dropped into remote areas using a helicopter that also has water-bombing capabilities), and fire suppression potentially using large numbers of personnel, tankers and aircraft when available.

Statistical methods

Bayes Net models were developed to assess the reduction in risk of large or extreme fires by varying the levels of investment in fire management options. Specifically, the objective of the model was to determine which set of management actions minimised the risk of large and extreme fires (i.e. those greater than 1000 ha) in the landscape. The objective was chosen as it generally corresponds with the overall objectives of the park's fire management plan (NSW National Parks and Wildlife Service 2006). BN were chosen as the modelling method as they allow multiple forms of evidence to be included and the outcomes are presented as likelihoods or risks of occurrence, i.e. the outcomes can be related directly to the objective. We followed the guidelines for developing and updating BNs presented by Marcot *et al.* (2006). All BN analysis was undertaken in the *GeNIe* v.2.0 package (Decision Systems Laboratory, University of Pittsburgh, http://genie.sis.pitt.edu, accessed July 2011).

The first step in the development of the BN was the development of a conceptual framework of the fire process (Fig. 1). This model described the progression of a fire from an ignition through to the ultimate fire size, which is depicted by solid arrows in Fig. 1. Ignitions can be derived from either unplanned anthropogenic ignitions, commonly termed 'arson', or from lightning. We did not consider other ignition sources in this model as arson and lightning account for 87% of known fire ignitions. Other sources are more random, e.g. motor vehicle accidents and escaped camp fires, and cannot easily be modelled. Once ignited, fires can self-extinguish at a small size (<10 ha) and not require suppression. If a fire does not self-extinguish, it can then be treated through initial attack (IA) where resource deployments attempt to control the fire to less than 100 ha within the first day following ignition. Where IA is unsuccessful, the fire is then treated with different suppression methods. At each of these steps, the fire behaviour is influenced by fuel loads and weather.

The BN was then developed as a series of submodels for each of the processes described above. Submodels were developed

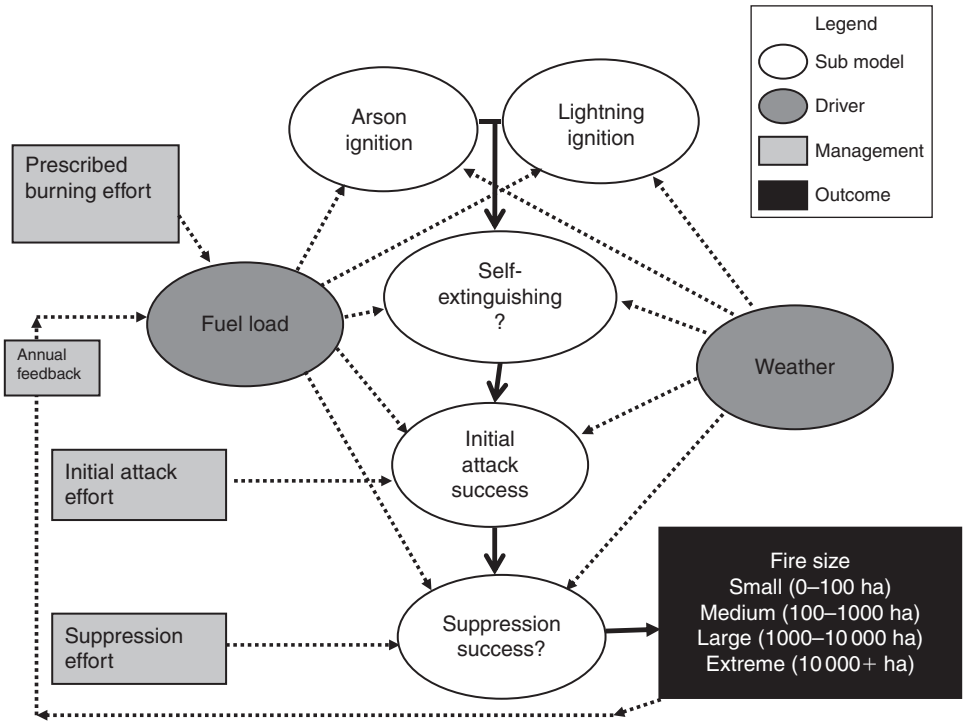

Fig. 1. Conceptual model describing the process for a fire event. Solid arrows represent the fire establishment and development and dashed arrows represent the links between the fire and the variables of influence. The direction of the arrows indicates the direction of influence.

from published literature, unpublished datasets and process-based models. Where possible, submodels were limited to three or more parent nodes (i.e. variables of influence) after Marcot *et al.* (2006), although this was not always possible. Early versions of the model were discussed with fire management experts and BN experts and revised accordingly.

Model structure

The BN structure is depicted in Fig. 2, with the nodes described in Table 1. This diagram depicts the nodes with arrows depicting the direction of influence on child nodes. Each node represents a CPT, which is populated with probability distributions as described above. There is a linear flow through the model representing the conceptual model described in Fig. 1. The model output or target node was termed 'fire size', which represents the probability of a fire event of a given size – no fire (<1 ha, true no-fire days or those ignitions that self-extinguish), small fire (1–100 ha), medium fire (100–1000 ha), large fire (1000–10 000 ha) and extreme fire (>10 000 ha). The target node can also be considered as the proportion of days per fire year on which a fire event of a given size can be expected to occur. The model does not allow for the consideration of multiple fires on one day; rather, it records the largest fire expected to occur under those conditions. We do not consider this to be a significant limitation as the fire size classes have been defined such that multiple fires of a smaller size category add little to the total area burnt and subsequent calculations.

Models for the probability of either an arson or lightning ignition were derived from long-term datasets from the GBMWHA (NSW National Parks and Wildlife Service, unpubl. data). Generalised additive models (GAMs) were used to determine the relationships between environmental variables, climatic variables and the probability of ignition, with the best models determined by the Akaike Information Criterion (Akaike 1973). In summary, the models were based on an 11-year dataset recording the dates and grid coordinates of ignitions for the WNP, with a total of 347 lightning ignitions and 161 arson ignitions. Lightning ignitions were compared with 10 000 recorded lightning strikes that did not result in an ignition. Arson ignitions were compared with 10 000 random points within the WNP. Both ignitions forms were more likely to occur in dry forest compared with other vegetation categories, in high to very high fuel loads on days with FFDI in the Very High category. Arson was most likely to occur within 1 km of a road, most commonly within the first 200 m (T. D. Penman, R. A. Bradstock and O. Price, unpubl. data). Outputs from the arson and lightning models were then combined into the ignition node with a count distribution derived from the distribution of number of ignitions per day in the ignitions dataset. Successful ignitions then flowed through to the self-extinguishment model. Self-extinguishment was considered to occur where fire-line intensity (a function of fuel load and FFDI (Gill *et al.* 1987)) was less than 85 kW m^{-1} based on the models presented by McCarthy and Cary (2002). If an ignition self-extinguished in this part of the model, it was classified as 'no fire', i.e. <1 ha.

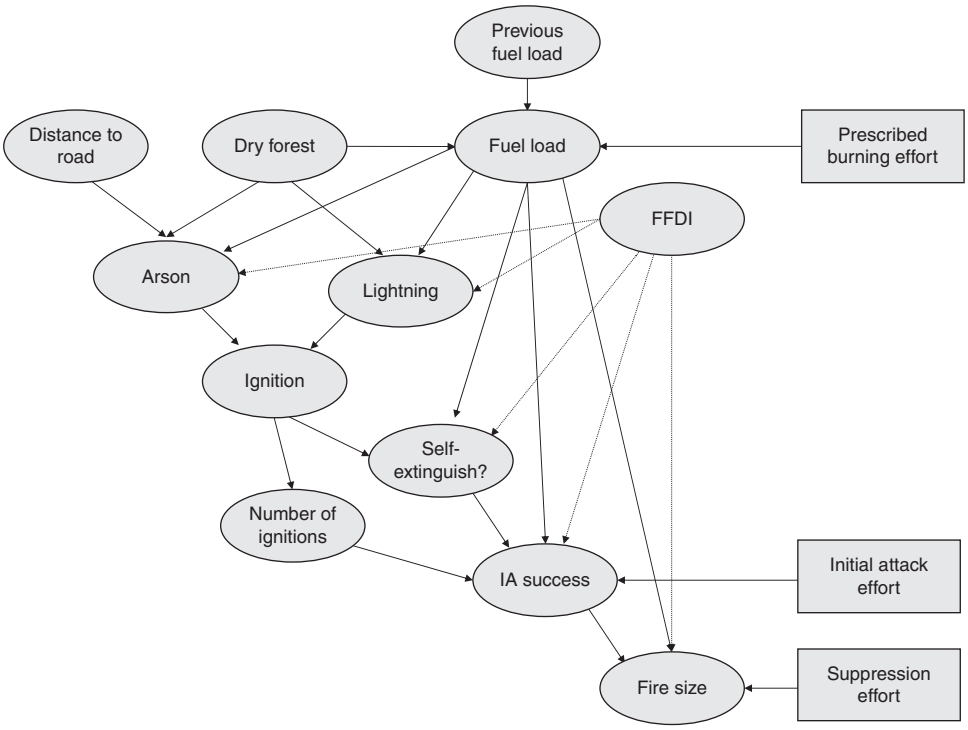

Fig. 2. Influence diagram for the management of fires in Wollemi National Park. Node descriptions appear in Table 1. (FFDI, Forest Fire Danger Index.)

Ignitions that did not self-extinguish were then assumed to be treated by an IA method. Three levels of IA were included in the model: (1) ground crews; (2) one RAFT (comprising one helicopter with water-bombing capabilities and a crew of 10 who are air-lifted into remote areas) plus ground crews; and (3) two RAFT plus ground crews. The probability of success of any IA was affected by the number of ignitions, fuel load, FFDI and the level of initial attack (after Plucinski *et al.* 2007). Initial attack was only considered successful if all ignitions were contained. Successful IA results in a small fire; unsuccessful IA resulted in the management response requiring the fire-suppression model.

Fire-suppression models considered the potential success of three levels of management effort on the maximum fire size. The levels considered were (1) zero suppression, where a fire is not suppressed and is allowed to run its natural course; (2) local resources, which can include some light aircraft and ground crews; and (3) optimum resources, where all feasibly obtainable resources are on-hand. As with the IA model, the ultimate fire size was affected by fuel load, FFDI and suppression effort, based on the models of Cary *et al.* (2009) and data presented by Boer *et al.* (2009). Prescribed burning effort is included within the model through its effect on fuel loads from the previous season (Fig. 1). In NSW, the timing of prescribed burning is guided by fuel accumulation and ecological attributes of different vegetation communities (Kenny *et al.* 2004). Based on these, prescribed burning within WNP would usually only be conducted in fuels more than 8 years old, which are represented by the high to extreme fuel categories (Table 1). When running the model over multiple seasons, fuels for the subsequent season are then influenced by the fire size distribution from the current season and fuels from the current season. Unlike prescribed burning, wildfire reduces fuels for all categories equally.

Conditional probability tables were populated with data where it was available and by experts for other components (see below). Values for all biophysical variables were calculated from data for the WNP for the period from 1997 through to 2007. These variables were fuel load (measured by time since fire), vegetation communities (dry forest *v.* wet forest) and distance to the nearest road. The values were the proportion of WNP that fell into each category.

Two expert workshops were run to populate CPTs relating to IA and suppression submodels. Expert opinion was necessary as there are insufficient data available on the relationship between these and the variables of interest for the study area. Workshops were run with staff from two government agencies with experience in fire suppression and IA methodologies in the Wollemi area. One agency was primarily a fire-suppression agency and the other was a land-management agency with responsibilities for fire management. Workshops were held separately to explicitly capture the differing opinions and experiences of each agency. Each workshop was held on a single day, with the two workshops held 2 weeks apart. There were five participants in the first workshop and seven in the second. All participants were required to have knowledge of the WNP and experience in fire suppression and IA methods described in the model.

At each workshop, participants were asked to assess the influence of weather (FFDI) and fuel loads (based on fuel categories defined by McCarthy *et al.* 2009) for varying scenarios of IA (number of ignitions crossed with IA effort) and suppression

Table 1. Nodes and states of the fire-management Bayes Net
NPWS, National Parks and Wildlife Service; WNP, Wollemi National Park; GBMWHA, Greater Blue Mountains World Heritage Area; RAFT, Remote Area Fire Teams. Websites cited in this table were last accessed in March 2010

Node	Description	States	Data source
FFDI	Forest Fire Danger Index, a commonly used measure of fire weather. See http://www.bom.gov.au/weather-services/bushfire/index.shtml for further details	Low, High, Very High, Severe, Extreme	Bureau of Meteorology
Fuel load	Measures based on the Victorian Department of Sustainability and Environment fuel classification presented in McCarthy *et al.* (2009) and field data from P. Watson (University of Wollongong)	Low, Moderate, High, Very High, Extreme	NSW NPWS fire mapping data for WNP
Distance to road	Distance (km) to the nearest mapped road	0–1 km, 1–3 km, more than 3 km	NSW NPWS road mapping for WNP
Dry forest	A coarse measure of vegetation community based on vegetation mapping for the region	Dry sclerophyll forest, other (includes wet sclerophyll forest, heath, rainforest)	NSW NPWS vegetation mapping for WNP
Number of ignitions	Number of ignitions regardless of the cause occurring on the day, based on recorded data for WNP	One to two, three to four, five to ten, more than ten	NSW NPWS fire database for WNP
Last fuel	Fuel loads of the previous season. See fuel load description above	Low, Moderate, High, Very High, Extreme	NSW NPWS fire mapping data for WNP
Arson	Probability of an arson ignition	Yes, No	Statistical model
Lightning	Probability of a lightning ignition	Yes, No	Statistical model
Ignition	Probability of an ignition by lightning or arson	Yes, No	Statistical model
Self-extinguishment	Probability of a fire self-extinguishing	Yes, No, No fire	Process model in McCarthy and Cary 2002
Initial attack success	Probability of the initial attack being successful at containing all ignitions to less than 100 ha	Yes, No, No fire	Expert opinion
Fire size	Maximum fire size achieved on a given day	Small (0–100 ha), Medium (100–1000 ha), Large (1000–10 000 ha), Extreme (10 000+ ha).	Expert opinion
Prescribed burning effort	Decision node representing the chosen level of prescribed burning effort for the season	0, 1% per annum, 5% per annum	Decision node
Initial attack effort	Decision node representing the chosen level of initial attack effort available for the season	Ground crew only, one RAFT team plus ground crew, two RAFT teams plus ground crew	Decision node
Suppression effort	Level of suppression effort available for the season	Zero, Constrained (local resources), Optimal	Decision node

(varying suppression effort). As this would have required probabilities for 375 scenarios, the number was reduced to capture the extreme and the mid-range scenarios, resulting in 135 scenarios. The participants were asked to provide an estimate of the probability using standardised terms taken from Pollack (2003), as described in Table 2. For each scenario, there was a discussion within the group and a consensus reached. In the discussion, participants were asked to draw on their fire-suppression experience, as well as the local knowledge of the area. This included consideration of natural fire breaks, e.g. cliffs and rivers, timing between ignitions and detection, accessibility to fires via road and aircraft and standard operating procedures of the organisations involved. No other expert groups were available that held the relevant experience in fire suppression and control and local knowledge required for the BN. At the end of each workshop, participants were shown how the model performed to ensure we had accurately captured their opinions.

Table 2. Probability terminology used within the expert workshops based on Pollack (2003) and the values that were subsequently entered into the conditional probability table (CPT)

Terminology	Pollack range	Probability value used
Extremely unlikely	<1%	0
Very unlikely	1–10%	0.05
Some chance or unlikely	10–33%	0.2
Medium chance	33–66%	0.5
Likely/probable	66–90%	0.75
Very likely	90–99%	0.95
Virtual certainty	>99%	1

Three versions of the model were then developed, with the first two representing the opinions of each agency and the third representing an average of the experts' opinions (hereafter the mean model). Although there is some debate over the best

methods to combine expert opinions (e.g. Morgan and Henrion 1990; Keith 1996), some argue that averaging expert opinions may be the best estimate of probability (e.g. Uusitalo 2007). The mean model was assessed by an independent reviewer to consider the model structure and CPT values (after Marcot *et al.* 2006), and no changes were required.

All three models were validated by comparing the predicted fire-size distribution with the actual size distribution of fires mapped within the park over an 11-year period from 1997 through to 2007 (NSW National Parks and Wildlife Service, unpubl. data). The BN model was run for each year consecutively within the period to produce a multiseason model with FFDI varying between years according to recorded data. Annual probability distributions for the FFDI values were derived from the annual distribution of daily maximum FFDIs recorded at three nearby BOM weather stations (Cessnock Station number 61260, Nullo Station number 62100, Richmond Station number 67033). Fire outputs from year t were then used to influence the fuel loads for year $t+1$ (see below). Climatic variables were based on recorded data for the region for the fire season, i.e. from July through to June. Fire size probability distributions from each year were multiplied by 365 days to get the number of days per year of each fire size and then these were summed for the 11-year period. Outputs from the BN could be compared with the annual distribution of the daily maximum fire sizes recorded by NSW NPWS for the study period. A Chi-square test compared the fire size distribution predicted by the model and the actual distribution recorded for realistic scenarios. Analyses were conducted in the R statistical package v.2.11.1 (R-Development Core Team 2007).

Four management scenarios were compared with the recorded data. These scenarios were considered by the expert workshops to be the best representation of current management practices in WNP. Scenarios were based on the combinations of prescribed burning, IA and suppression effort described below (see Table 1 for definitions):

(1) Prescribed burning effort: 1% of the landscape burnt per annum (pa);
(2) Initial attack effort: either ground crews or ground crews and one RAFT; and
(3) Suppression effort: either local resources or a mixed effort with 5% of fires with zero suppression, 60% local resources and 35% with optimal suppression effort.

Results

When an ignition occurred in the single-season model (i.e. with an average annual FFDI distribution), the probability of a fire not requiring suppression owing to self-extinguishment, or being controlled by IA, ranged from 0.493 to 0.959 (Table 2). The probability increased with an increase in prescribed burning effort, which was largely due to an increase in the probability of fires self-extinguishing before requiring an IA effort. For any ignition, the probability of self-extinguishment was 0.131 for zero prescribed burning, 0.138 for prescribed burning at 1% pa and 0.176 for prescribed burning at 5% pa. Expert opinion was not included in the self-extinguishment node, and therefore it was identical across the three models. Models based on the expert opinions were used to examine the success of the different IA methods (Table 2). The models from Agency A resulted in the probability of initial attack success (IAS) almost doubling when IA included a single RAFT compared with only ground crews and another small (0.03) increase when the second RAFT was added. In contrast, the models from Agency B suggested little advantage in using RAFT, with the addition of a single RAFT resulting in only a minor (0.001) increase in P_{IAS} and a further increase of only ~0.005 when a second RAFT was included.

The predicted annual probability of a large or extreme fire (hereafter $P_{\mathrm{L,E}}$) responded to IA and suppression effort, but prescribed burning (PB) had an extremely limited direct effect (Fig. 3). While holding IA and suppression effort constant, increasing PB from 0 to 5% pa resulted in less than a 5% decrease in $P_{\mathrm{L,E}}$. Patterns for the effectiveness of IA described above were reflected in the $P_{\mathrm{L,E}}$, with models from Agency A predicting large decreases in $P_{\mathrm{L,E}}$ with the addition of RAFT, but limited changed in the models from Agency B. Similar patterns were seen in suppression effort, with agency A predicting large changes in $P_{\mathrm{L,E}}$ from increasing suppression effort. Models from Agency A predicted 40–50% reduction in $P_{\mathrm{L,E}}$ when suppression effort changed from zero to local resources, and again when effort changed from local resources to optimum resources. In contrast, Agency B predicted less than 0.5% decrease in $P_{\mathrm{L,E}}$ when suppression effort changed from zero to local resources and a decrease of ~11% in $P_{\mathrm{L,E}}$ when effort changed from local resources to optimum resources (Fig. 3).

In the period from 1997 to 2007, the number of actual days when large or extreme fires occurred was 32. Results from the BN simulations for this period appear in Fig. 4 and Table 3. Patterns in the 11-year simulation reflect those described for the 'average conditions' models above. When compared with the actual distribution of maximum fire size per day, data from the mean expert model using ground resources for IA with either suppression scenario were the best fit with the actual data ($P = 0.642$ local resources, $P = 0.343$ mixed suppression) (Table 4; Fig. 4). Models using the opinions of Agency B had a similar fit for all four of the 'realistic' fire management scenarios ranging from $P = 0.026$ (ground IA, mixed suppression) through to $P = 0.087$ (one RAFT, local suppression resources). The mean model for RAFT was significantly different from the actual data from WNP ($P < 0.005$), as were all models of Agency A ($P < 0.001$) (Table 4).

Discussion

The study demonstrated that BNs have the potential to provide a holistic analysis of the primary fire management strategies. Owing to the complexity of fire management, most research to date has focussed on the direct effect of single management strategies. There are several studies that examine the effect of varying levels of prescribed burning on the extent of area burnt in a landscape (e.g. Bradstock *et al.* 2008; King *et al.* 2008; Boer *et al.* 2009; Cary *et al.* 2009). Similarly, there are several studies that examine the effectiveness of rapid initial attack in controlling ignition events (e.g. Hirsch and Martell 1996; Plucinski *et al.* 2007). To our knowledge, the current study is the first study

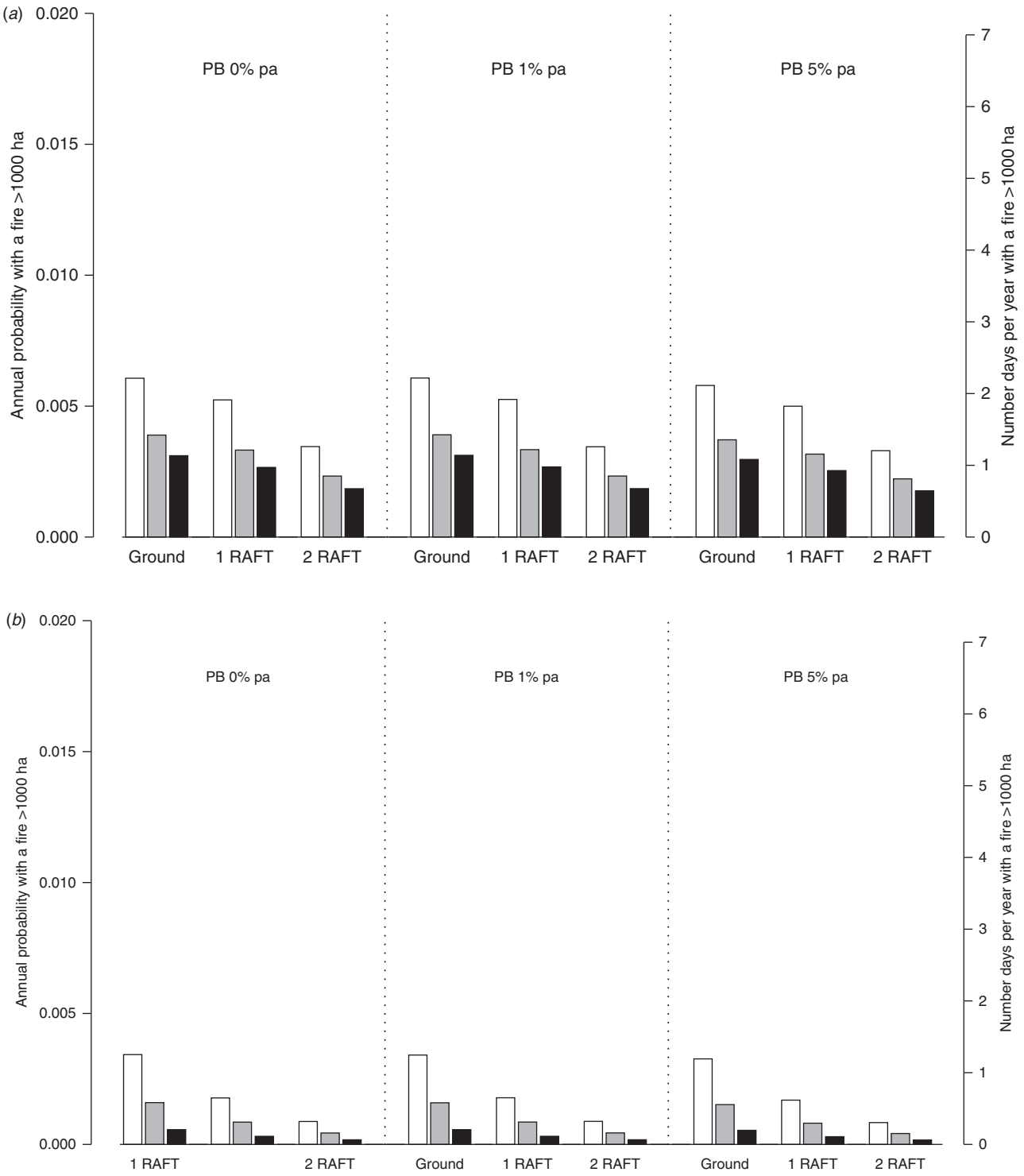

Fig. 3. Probability and number of days per year where a large or extreme fire is predicted to occur based on a single year of average conditions for varying levels of prescribed burning (PB), initial attack (IA) and suppression using (*a*) mean expert opinion; (*b*) agency A expert opinion; and (*c*) agency B expert opinion. White bars represent zero suppression, grey bars represent local suppression effort and black bars represent optimal suppression effort. (RAFT, remote area fire team.)

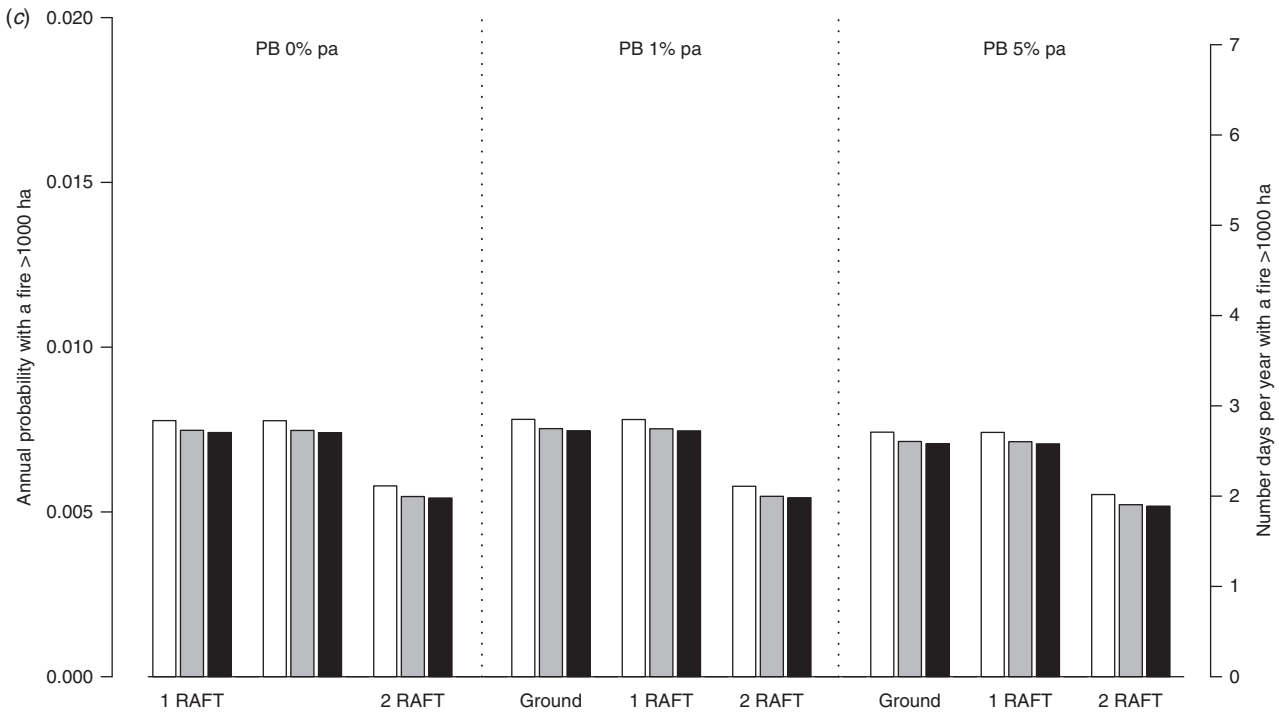

Fig. 3. (Continued)

to undertake an integrated analysis of several fire management techniques.

Probabilities generated through the expert workshops provided the greatest source of uncertainty in the model. All participants had valuable experience in fire management either within the WNP or in vegetation similar to the park. Uncertainties were related to the variation in agency opinions. Agency A appeared to overestimate their ability to control fires in both the IA and suppression phases of control, whereas the data suggest Agency B underestimated this ability. These differences could be related to the methods the two agencies used in attacking or suppressing fires. Agency A is a land-management agency that attempts to control fires within its boundaries and this was evident in the workshops. They believed they could either activate IA crews or, where they failed, create and control the fire boundaries under most weather and fuel combinations. In contrast, Agency B has a stronger focus on property protection, resulting in a primary objective of preventing a fire from affecting the wildland–urban interface (WUI). This was reflected in the results where Agency B had a limited range of FFDI values under which they would attempt any form of IA (aerial or ground) and would use large natural fire breaks (i.e. roads and rivers) to contain fires. These boundaries are rare within the WNP and this led to Agency B overestimating the number of extreme fire events.

Averaging the expert agency opinions resulted in a model that closely duplicated the recorded fire patterns within the WNP over an 11-year period. Methods for combining multiple opinions are still subject to debate in the literature as 'the fraction of experts who hold a given view is not proportional to the probability of that view being correct' (Keith 1996, p. 139). In the present study, we consider it unlikely that a truly average position of opinions would have been reached had we run a single workshop combining the two groups. There are different fire management paradigms between the organisations, and within a single workshop, it was expected that dominant personalities would have dictated proceedings, thereby biasing the results. Although this may have happened to a lesser extent within each group, the friendly and familiar nature of each workshop allowed more free-flowing discussion and debate. By validating the three models against data collected over an 11-year period, it is our opinion that the model derived from the average of the two expert opinions provided a realistic representation of the major drivers of the fire process in WNP as demonstrated by the model validation process.

Replicating fire patterns under existing management conditions allowed us to more confidently assess the predictions of the effects of varying management strategies on annual fire patterns. Our model suggests that increasing prescribed burning from 0 to 5% pa results in less than a 5% reduction on the annual $P_{L,E}$ while holding other management aspects constant. It is important to note that our approach to PB is comparable with random placement of fires, which is known to have a lesser effect than a strategic pattern (Loehle 2004; King *et al.* 2008). Increasing the level of effort for IA and suppression had a much greater effect on reducing the $P_{L,E}$ (Fig. 4). RAFTs resulted in a significant increase in the proportion of fires controlled during IA, which in turn reduced the risk of large or extreme fires.

Prescribed burning has a lower influence on the area burnt in comparison with other drivers such as suppression and weather,

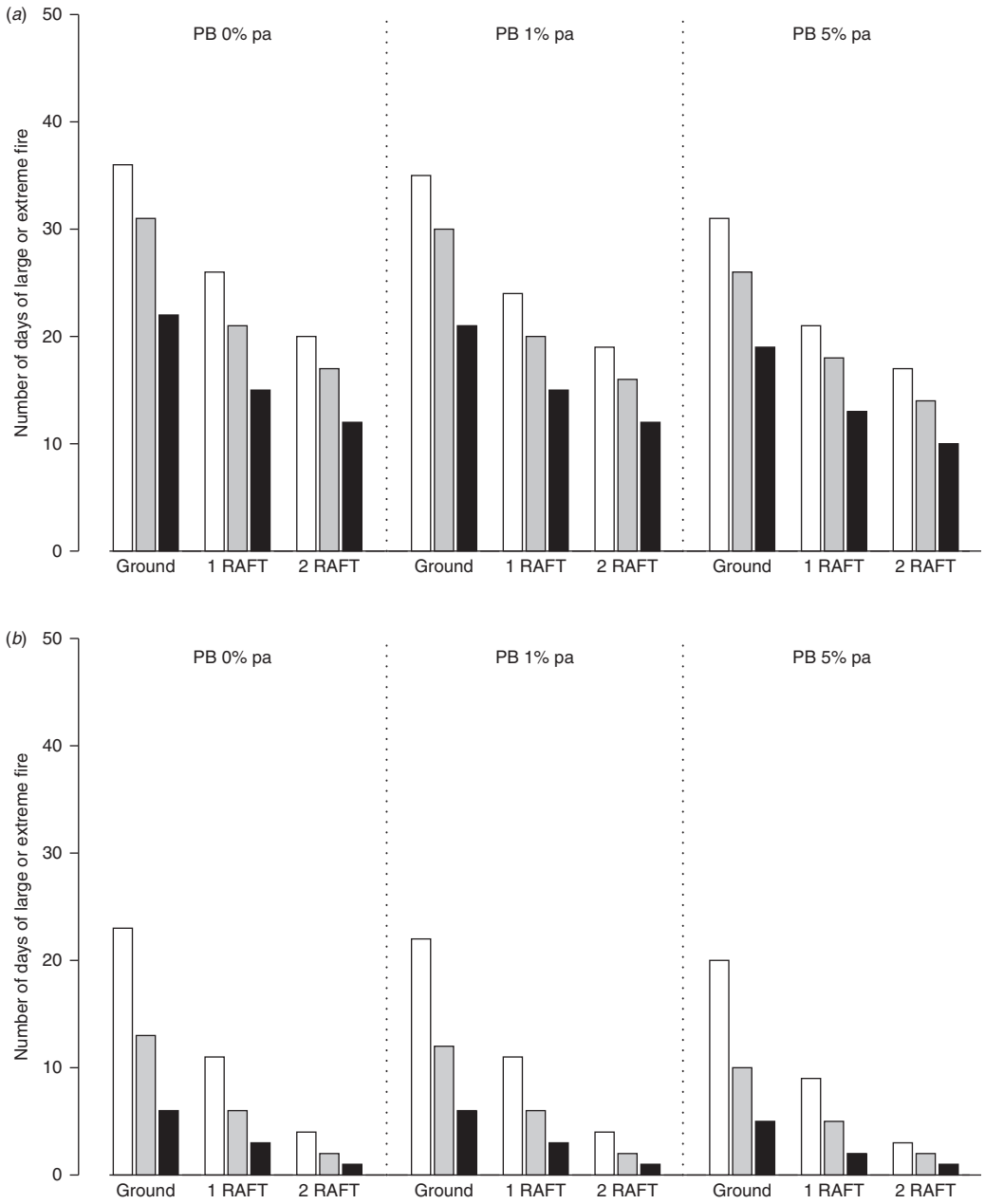

Fig. 4. Predicted number of days with large (1000–10 000 ha) or extreme (>10 000 ha) fires for the period from 1997 to 2007 using (*a*) mean expert opinion; (*b*) agency A expert opinion; and (*c*) agency B expert opinion. White bars represent zero suppression, grey bars represent local suppression effort and black bars represent optimal suppression effort. The actual recorded number of days of large or extreme fires was 32.

which is consistent with other studies in the same landscape (Cary *et al.* 2009; Price and Bradstock 2011). In the BN, the effect of prescribed fire was determined in two stages: (1) the direct effect on fuel hazard, and (2) through the effect of fuel hazard on the ability of management to control the fire through IA or suppression approaches. The analytical approach adopted is a very different approach to Price and Bradstock (2011), who used empirical data from fire-history mapping and Cary *et al.* (2009), who used established fire-spread models to simulate fire regimes. However, it is significant that all three approaches reach a similar conclusion that prescribed burning has limited effect on the extent of fire in the landscape.

The BN presented here could be parameterised for any fire-prone biome in the world as the underlying concepts remain the same. Regardless of geographic location, fire intensity is primarily a function of fuels and weather (McArthur 1966; Gill *et al.* 1987) and the probability of controlling a fire is a function of fire intensity (Hirsch and Martell 1996; Fernandes and Botelho 2003; Plucinski *et al.* 2007). Weather in the study is represented through FFDI, a value that combines air

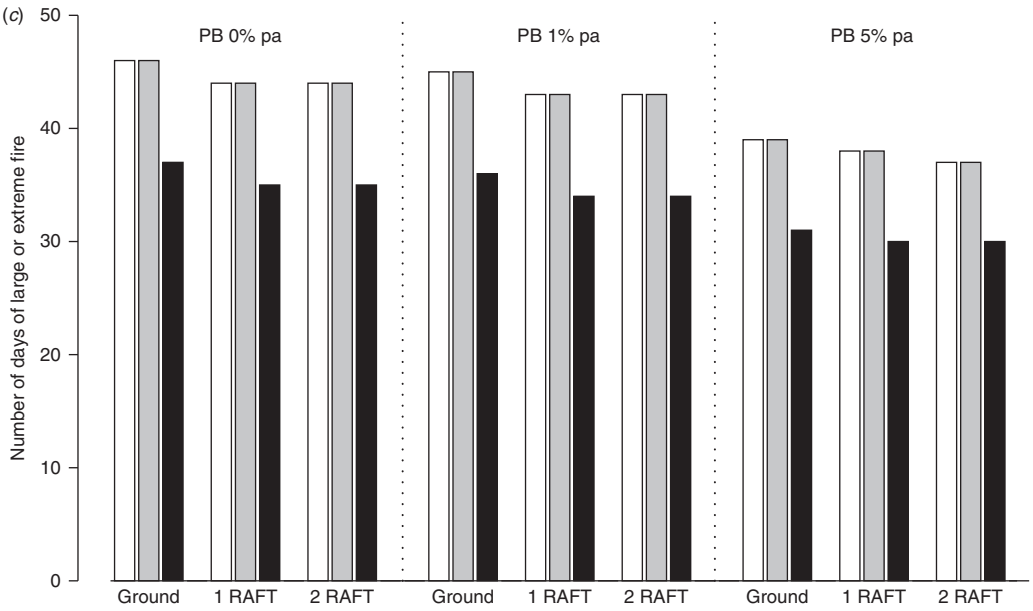

Fig. 4. (Continued)

Table 3. Chi-square comparisons between recorded fire distributions and potential 'real world' scenarios

Probabilities less than 0.05 represent the situation where the predicted data are significantly different from the actual data recorded in Wollemi National Park. Actual data for the study period were 146 days with only small fires, 31 days with medium fires, 21 days with large fires and 11 days with extreme fires. IA, initial attack; RAFT, Remote Area Fire Teams

Expert model	IA effort	Suppression effort	*P*
Mean model	Ground	Local resources	0.642
Mean model	Ground	Mixed effort	0.343
Agency B	RAFT1	Local resources	0.087
Agency B	Ground	Local resources	0.064
Agency B	RAFT1	Mixed effort	0.043
Agency B	Ground	Mixed effort	0.026
Mean model	RAFT1	Local resources	0.004
Mean model	RAFT1	Mixed effort	0.002
Agency A	Ground	Mixed effort	0.000
Agency A	RAFT1	Mixed effort	0.000
Agency A	Ground	Local resources	0.000
Agency A	RAFT1	Local resources	0.000

temperature, relative humidity, wind speed and both long- and short-term drought effects (McArthur 1967; Noble *et al.* 1980). Similar metrics are available for other regions (see Kaloudis *et al.* 2005 for a discussion of these) that could readily replace FFDI in the model. Fuels are represented by a series of five states from low to extreme as defined by McCarthy *et al.* (2009), which could be readily adapted for most systems. Some additional work would be needed to ensure the models for ignition are relevant to local conditions as regional variations in lightning ignition probabilities occur (Granström 1993; Larjavaara *et al.* 2004).

Table 4. Probability of fire being extinguished by self-extinguishment or initial attack (IA) based on a single year of average conditions for varying levels of prescribed burning (PB) and IA methods

RAFT, Remote Area Fire Teams; pa, per annum

PB effort	IA effort	Mean model	Agency A	Agency B
Zero	Ground	0.602	0.493	0.711
Zero	RAFT1	0.800	0.891	0.711
Zero	RAFT2	0.836	0.956	0.715
1% pa	Ground	0.603	0.497	0.710
1% pa	RAFT1	0.800	0.891	0.710
1% pa	RAFT2	0.836	0.957	0.714
5% pa	Ground	0.623	0.519	0.726
5% pa	RAFT1	0.811	0.897	0.726
5% pa	RAFT2	0.845	0.959	0.731

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