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Research article

Suppression resource decisions are the dominant influence on containment of Australian forest and grass fires

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ABSTRACT

Fire agencies aim to contain wildfires before they impact on life, property and infrastructure and to reduce the risk of damage to the environment. Despite the large cost of suppression, there are few data on the success of suppression efforts under varying weather, fuel and resource scenarios. We examined over 2200 forest and 4600 grass fires in New South Wales, Australia to determine the dominant influences on the containment of wildfires. A random forest modelling approach was used to analyse the effect of a range of human and environmental factors. The number of suppression resources per area of fire were the dominant influence on the containment of both forest and grass fires. As fire weather conditions worsened the probability of containment decreased across all fires and as fuel loads and slope increased the probability of containment decreased for forest fires. Environmental controls limit the effectiveness of wildfire management. However, results suggest investment in suppression resources and strategic fuel management will increase the probability of containment.

1. Introduction

Wildfires have caused significant loss of human lives and property and billions of dollars of economic losses across the globe (Gill et al., 2013). For example, destructive wildfires reported in the media in 2017 occurred in Spain, Portugal, South Africa, USA, Canada, Chile, New Zealand and Australia. The cost of impact can be reduced through fire management actions. Fire agencies deploy resources to suppress wildfires to protect life, property and infrastructure from impact by fire and reduce the risk of damage to the environment. Active suppression of fires can reduce the total area burnt (Cumming, 2005; DeWilde and Chapin, 2006) however, fires that escape initial attack can become large and costly to manage (Calkin et al., 2013; Gebert and Black, 2012). Therefore, it is important to know what factors influence the probability of containment of fires.

Environmental factors can have a strong influence on the probability of containment. Fuel type (Arienti et al., 2006; Hirsch et al., 2004), fuel load (McCarthy et al., 2012; Plucinski, 2012), weather conditions (Arienti et al., 2006; Plucinski, 2012, 2013) and slope (McCarthy et al., 2012) may influence the probability of containment. These factors are likely to be important because they all influence various aspects of fire behaviour - rate of spread, flame height, intensity and likelihood of spotting (Cruz et al., 2015). All these factors can influence fire containment difficulty. The faster a fire spreads, the larger its perimeter grows, requiring crews to establish a longer length of control line to contain the fire compared with a slower spreading fire (e.g. Parks, 1964; Weber et al., 2009). The higher the fire's intensity, the higher the flame height, the more likely spot fires will occur, and the less likely ground crews can extinguish the fire directly at the fire edge. The upper limit for direct attack of fires with hand tools is estimated to be 500 kW/m and for ground-based crews around 2000–4000 kW/m (Hirsch and Martell, 1996). Fire intensity also influences the rate of control line construction. For example, Loane and Gould (1986) found a machine crew (D6 dozer with tankers and 9 firefighters) constructed a control line at a maximum and constant rate up to 500 kW/m but this rate drops sharply to zero for intensities above 2000 kW/m. They found a similar pattern for hand crews with control line construction occurring at a constant rate until falling sharply to zero for intensities above 800 kW/m.

Decisions around suppression response are also known to influence the probability of containment. One of the key decisions is resource placement as resource response time (Arienti et al., 2006; Plucinski, 2012) and fire area when crews arrive at the fire (Arienti et al., 2006; McCarthy et al., 2012; Plucinski, 2012, 2013) can influence the probability of containment. A fast response time will lead to a smaller fire area when crews begin suppression operations which could be important when a fire is spreading rapidly. However, under conditions conducive to a low rate of spread, response time would be less

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influential as the fire size will change little over time. Another key decision is the number and type of resources to deploy to the fire as this relates to the rate of control line construction (Fried and Gilless, 1989; McCarthy et al., 2003). More resources can create a control line faster and for successful containment to occur the rate of construction needs to exceed the rate of fire perimeter growth (Weber et al., 2009).

There are few studies globally that have quantified the influence of various environmental and human factors on the probability of suppression. In Australia, existing studies have used limited datasets. These studies have considered suppression success in either forest (McCarthy et al., 2012; Plucinski, 2012) or grass (Plucinski, 2013) fires but have used a maximum of 334 fires. We aimed to conduct a comprehensive assessment of the factors affecting containment using a much larger data set (n = 6837) and a broader range of factors than has previously been attempted. No comprehensive data that contains all relevant factors was available, so we used data that is consistently available from fire incident reports plus weather, fuel load and topographic data. Specifically, we asked what is the relative importance of environmental and human factors in containing grass and forest fires at various time periods from when the first ground crews arrived at the fire. From the findings of previous studies, we hypothesise that:

1. Factors which influence fire behaviour – fuel, weather and topography - will be important in determining the probability of containment.
2. The number of resources and the response time will be important in determining the probability of containment.

2. Materials and methods

The study area was the state of New South Wales in Australia. The population is largely city based with over 60% of the population residing in the greater Sydney area (http://www.censusdata.abs.gov.au, accessed April 2017). Other high population centres are along the coastal fringe and nearby inland areas. Large areas of western New South Wales are sparsely populated (Collins et al., 2015). The natural vegetation of the study area (Fig. 1) is varied with *Eucalyptus* spp. dominant forests and woodlands in the coastal and mountainous hinterland areas (Keith, 2004). The climate in these areas ranges from temperate to moist subtropical and these forests can burn at very high intensities (Murphy et al., 2013). The dominant species in the semiarid woodlands in central and western New South Wales are *Eucalyptus, Casuarina, Acacia* and *Callitris* spp. (Keith, 2004). These woodlands burn infrequently at low to medium intensities (Murphy et al., 2013). Chenopod shrublands dominate the arid and semiarid regions of western New South Wales where rainfall or local soil moisture is too low to support tree-dominated vegetation (Keith, 2004). Chenopods typically burn as low intensity fires although fires are rare events (Murphy et al., 2013). The grasslands are predominately perennial tussock grasses (Keith, 2004) which burn as low intensity fires (Murphy et al., 2013). Agriculture areas cleared of natural vegetation are largely pasture and croplands which burn infrequently as low intensity grass fires (Murphy et al., 2013).

Fire and response data were taken from fire incident records held by the New South Wales Rural Fire Service who are responsible for the suppression of wildfires across approximately 95% of New South Wales, Australia. Only incident records contained in both the fire incident reporting system and incident management system were included in the study as both sets of data were used to confirm the reported information. Incidents where the time the first ground crews arrived at the fire was listed as 0 were removed as this is a default value for the incident reporting system i.e. the recorder may have failed to enter the actual value. Incidents where no tankers were tasked to the fire or where the fire incident report stated that ground crews delayed attacking the fire as the fire was either inaccessible or was not posing a threat to property were also removed. The study data included incident and response records from July 2005 to June 2013.

Predictor variables used in the study are defined in Table 1. The time the fire was contained was defined as the time when the fire is no longer spreading i.e. when the final fire area was reached. The response time refers only to when the first ground crews arrived at the fire. The peak number of firefighters and tankers at the incident was used as this is the only field available in the fire incident reporting system on the number of resources at the fire and the incident management system does not record the arrival and departure times of all resources over the duration of the fire. All firefighters and tankers tasked to the fire were assumed to be attempting to contain the fire as it was not possible to ascertain if some of these resources were used for other purposes such as property protection. Size/category of tankers, earth-moving machinery and aircraft despatched to the fire was not available. Earth-moving machinery only used to strengthen containment lines after the fire had been contained or to remove dangerous trees were not recorded as assisting in containing the fire. Aircraft only used to map the fire or to provide reconnaissance were not recorded as suppressing the fire. For analysis purposes, the peak number of tankers and firefighters were divided by the square root of the final fire area. This was done to enable comparison between fires and to scale the resources to the length of perimeter needing containment. The number of earth-moving machinery and aircraft used was converted to a binary factor as these resources were not used at every fire. Earth-moving machinery was used on 5% of grass fires and 24% of forest fires and aircraft used on 4% of grass fires and 27% of forest fires. Broad fuel type was either a grass or forest fire. Crop fires were included in grass fires and those classified as scrub or bush fires were included as forest fires.

The ignition cause was assigned to one of five cause types: deliberate, lightning, powerline, accidental and undetermined. Deliberate ignitions included arson and fires where it was suspected that they were intentionally lit. Powerline ignitions were due to fires starting because of powerlines clashing, arcing or vegetation or animals contacting the live parts of the network or breakage of wires, poles or other parts of the network. Accidental ignitions included all other human caused fires that were unintentionally started e.g. escapes from prescribed burns, camping or cooking fires, fires caused by equipment or machinery use or smoking. Undetermined cause fires included all fires where the fire cause was unknown or unreported.

The fuel load at the ignition point was estimated for forest fires using fire history databases (NSW Government unpublished data) to delineate the time since fire, the vegetation class based on Keith (2004) using vegetation data (Vegetation Classes of NSW ver. 3.03, http://data.environment.nsw.gov.au/dataset/vegetation-classes-of-nsw-version-3-03-200m-raster-david-a-keith-and-christopher-c-simpc0917, accessed April 2017) and fuel accumulation relationships (Gordon and Price, 2015; Watson et al., 2012). The grassland and forest fire danger indices combine ambient weather variables (temperature, relative humidity and wind speed) and fuel moisture (% curing for grass and drought factor for forest) to derive an index of the forward rate of spread and suppression difficulty of fires (Noble et al., 1980). For grass fires, the grassland fire danger index was calculated using 100% grass curing as there were no grass curing data available for the study.

Random forests were used to analyse the factors which influence the containment of fires (Breiman, 2001). Random forests are an ensemble learning technique, a random subset of the predictor variables are used to develop individual classification trees that are assigned a class vote, and then the predictions from all trees are combined using majority vote (Breiman, 2001). The model error is calculated by comparing the prediction of each tree with data held back during its development (out of bag samples) and then averaged over all observations (Cutler et al., 2007). Variable importance for a given variable is estimated by comparing increases in out of bag error when that variable is randomly permuted while all others remain unchanged (Cutler et al., 2007). Partial dependence plots provide a graphical representation of the marginal effect of a variable on the response and are developed for an

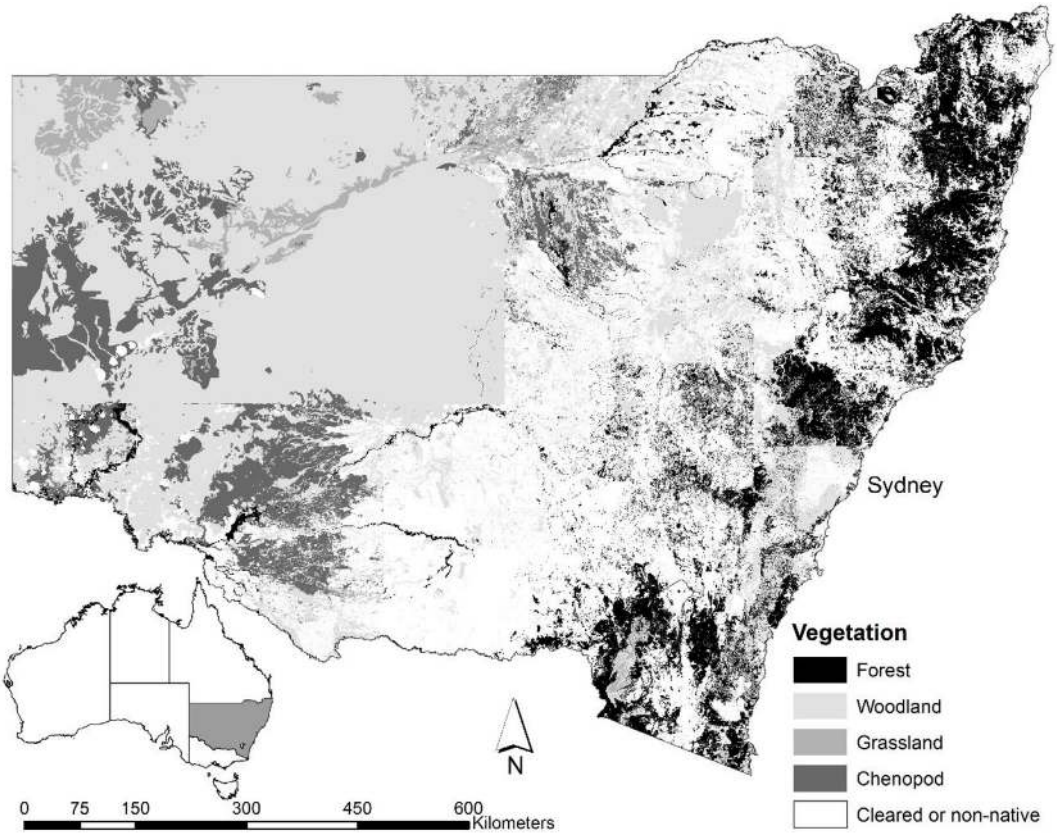

Fig. 1. Location of study area and predominant natural vegetation in New South Wales (source: National Vegetation Information System version 4.1; Department of the Environment and Energy, http://www.environment.gov.au/land/native-vegetation/national-vegetation-information-system/data-products).

Table 1
Variables used in the study.

Variable	Description
Response time	Time between when the fire was reported and ground crews arriving at the fire (min)
Containment time	Time between ground crews arriving at the fire and the fire contained (min)
Tpa	The peak number of tankers at the fire divided by the square root of the final fire area in hectares
FFpa	The peak number of firefighters at the fire divided by the square root of the final fire area
EMM	Was earth moving machinery used to contain the fire? (yes or no)
Aircraft	Was aircraft used to contain the fire? (yes or no)
Fuel load	The estimated forest fuel load (t/ha) at the point of ignition. Estimated from time since fire data and fuel accumulation curves.
Ignition cause	Deliberate, lightning, powerline, accidental or undetermined
Fire load	The number of uncontained fires in the management district when the fire started (see Fig. 2 for district boundaries)
Slope	The estimated slope at the point of ignition (°) Estimated from a 30-m digital elevation model obtained from Geoscience Australia (http://www.ga.gov.au/elvis/)
Temperature	Air temperature recorded at 1500 h on day of ignition (°) from the nearest available Bureau of Meteorology station
Relative humidity	Relative humidity recorded at 1500 h on day of ignition (%) from the nearest available Bureau of Meteorology station
Wind speed	Wind speed recorded at 1500 h on day of ignition (km/h) from the nearest available Bureau of Meteorology station
GFDI	Grassland Fire Danger Index at 1500 h on day of ignition. Calculated from equation in Noble et al., (1980).
FFDI	Forest Fire Danger Index at 1500 h on day of ignition. Calculated from equation in Noble et al., (1980).

individual predictor variable by fixing the values of this predictor and averaging the prediction function over all the combinations of observed values of the other variables in the model (Cutler et al., 2007).

Grass and forest fires were analysed separately, and a hierarchical order of models were developed to test the time to containment. The first model used all data (e.g. for forests) and tested whether containment was achieved within 2 h of ground crews arriving at the fire (binary 0 or 1). Then those fires that were not contained within 2 h were used as input to a model of containment between 2 and 4 h. This same process of using the fires not contained in the previous time period as the input was repeated for containment between 4 and 12 h and 12–24 h. The time periods beyond 2–4 h were not used for grass fires as there were too few records within these time periods to conduct an analysis. For each analysis, the data was randomly split into training (70%) and test (30%). The number of trees to grow and the number of variables randomly sampled at each split are random forest tuning parameters (Hastie et al., 2009). Therefore, ten-fold cross-validation was used on the training data for each time period to select the optimal settings for these parameters. The variable importance value (mean decrease in accuracy) was used to determine whether the variable should be included in the final model. Variable importance values close to zero indicate these variables contribute very little to the predictive accuracy of the forest and a negative variable importance value indicates that when this variable is randomly exchanged the predictive accuracy in the forest increases. Therefore, the variable with the lowest importance value was iteratively removed from the random forest

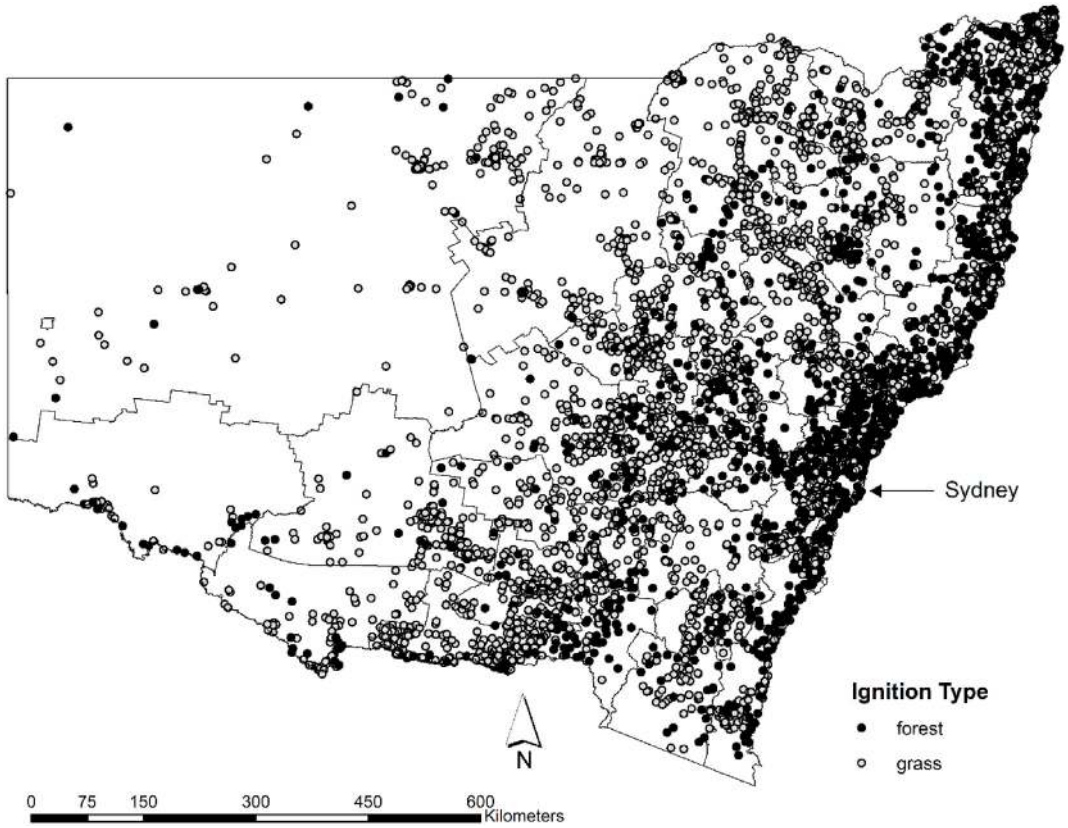

Fig. 2. Location of grass and forest ignitions in the study in relation to New South Wales Rural Fire Service district boundaries.

model until all variables had an importance values > 2 as measured by the mean decrease in accuracy (mda). The random forest model was developed using the training data and the accuracy of the resultant model was assessed using the test data.

All analyses were conducted using the R statistical package version 3.3.1 (R Core Team, 2016). The R package caret (Kuhn et al., 2017) was used for the cross-validation to determine the random forest settings. The random forest models were generated using the R package randomForest (Liaw and Wiener, 2002). The partial dependence plots were developed using the R package pdp (Greenwell, 2017). The model fit was measured by calculating the area under the curve (AUC) of the Receiver Operating Characteristic plot (Hanley and McNeil, 1982) using the R package pROC (Robin et al., 2011). AUC values range from 0 to 1 where 0.5 represents a completely random prediction, 0.5–0.6 = fail, 0.6–0.7 = poor, 0.7-0-8 = fair, 0.8–0.9 = good and 0.9–1 = excellent (Thuiller et al., 2003).

3. Results

A total of 2219 forest fires and 4618 grass fires (Fig. 2, Table 2) were available for the study. Most grass fires were contained within 2 h of ground crews arriving at the fire (95%) and only 1% of grass fires were not contained within 4 h. In contrast, 50% of forest fires were contained within 2 h and 13% were still uncontained after 24 h. The summary statistics of variables used in the modelling are included in Table S1.

Table 2
Summary of fires used in the study by containment time.

Containment Time	Fuel type	No. of fires	No. of fires contained	% Contained
< = 2 h	Forest	2219	1100	49.6
> 2 & < = 4 h	Forest	1119	370	33.1
> 4 & < = 12 h	Forest	749	291	38.7
> 12 & < = 24 h	Forest	459	171	37.3
< = 2 h	Grass	4618	4397	95.2
> 2 & < = 4 h	Grass	221	172	77.8

Ground crews on average took longer to arrive at the fire for forest fires compared to grass fires (35 min for forest, 23 min for grass), they took longer to contain the fire (762 min for forest, 52 min for grass) and the mean fire area was larger (183 ha for forest, 20 ha for grass). For both forest and grass fires the average response time (50 min for forest, 30 min for grass) and containment time (1078 min for forest, 73 min for grass) was highest for lightning caused fires (Table S2). The fire load was zero (i.e. no other fires were uncontained in the district when the fire started) for 74% of forest fires and 83% of grass fires.

3.1. Determinants of forest fires contained within 2 h

The most important variables for the random forest model for forest fires contained within 2 h of ground crews arriving at the fire were earth-moving machinery, aircraft and the number of tankers and fire-fighters per ha of fire (Fig. 3). Fuel load and slope were the next most important variables, followed by fire weather variables and response time (Fig. 3). Ignition cause had the lowest variable importance value (mda 3.5). Fire load was excluded from the final random forest model because it had a very low importance value (mda 1.8). For both earth-moving machinery and aircraft, a fire was less likely to be contained if these resources were working on the fire (Fig. 4). When these resources were used for forest fires, 20% of fires that used aircraft and 13% of fires that used earth-moving machinery were contained within 2 h whereas 60% of fires were contained within 2 h without using aircraft and 61% were contained without using earth moving machinery. The probability of containment of a forest fire increased as the number of tankers per ha of fire increase (Fig. 4) although the relationship flattens when > 4 tankers per ha of fire are present (Probability of containment (P) = 0.58). Similarly, for the number of fire fighters per ha of fire, the

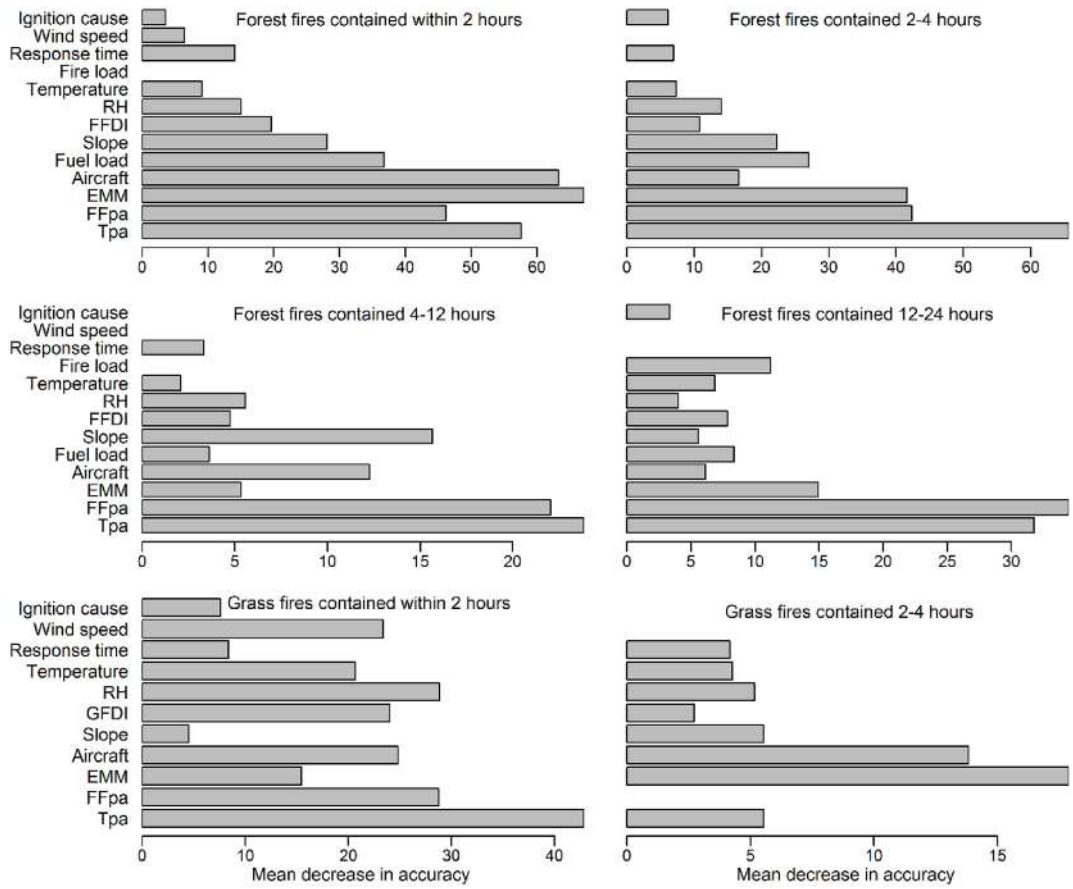

Fig. 3. Variable importance as measured by the mean decrease in accuracy in predictions of random forest models for containment time of forest and grass fires. RH = relative humidity, FFDI = forest fire danger index, GFDI = grassland fire danger index, EMM = earth-moving machinery, FFpa = number of firefighters per square root of the final fire area, Tpa = number of tankers per square root of final fire area.

probability of containment increased as the number of firefighters increased but the relationship flattens when the number of firefighters per ha of fire is > 5 (P = 0.53). A forest fire had a higher probability of containment within 2 h if the fuel load < 10 t/ha (P = 0.57) and slope < 8° (P = 0.50) compared to when the fuel load > 20 t/ha (P = 0.42) and slope > 15° (P = 0.42, Fig. 4). The partial response for forest fire danger index indicates the probability of containment increases when the index < 10 (Pmax = 0.53) and then flattens when the index > 10 (P = 0.48). Response time increases when response time < 25 min (Pmax = 0.52) and then flattens when the response time > 25 min (P = 0.47). There was only a 2% difference between the probability of containment for ignition causes (lightning P = 0.48, powerlines P = 0.50, Fig. 4).

The training error for the random forest model for forest fires contained within 2 h was 21.6% and the model had a good fit with an AUC of 0.87 (Table 3). The test set error rate was 22.1% and the model had a good fit for the test data with an AUC of 0.85 (Table 3).

3.2. Determinants of forest fires contained within 2–4 h

The most important variables for the random forest model for forest fires contained within 2–4 h of ground crews arriving at the fire were the number of tankers and firefighters per ha of fire and earth-moving machinery (Fig. 3). Fuel load and slope were the next most important variables (Fig. 3). Fire load and wind speed were excluded from the final random forest model because of negative variable importance values. The partial responses for the probability of containment within 2–4 h of ground crews arriving at the fire for each variable (Fig. S1) show similar relationships to the plots for probability of containment within 2 h (Fig. 4), but the probability of containment within 2–4 h was lower for each variable. For example, the maximum probability of containment for the 2–4 h time period for the number of tankers and firefighters per ha of fire was 0.49 and 0.44 compared with 0.59 and 0.54 for the within 2 h time period. The training error for the random forest model for forest fires contained within 2–4 h was 25.0% and the model had a good fit with an AUC of 0.82 (Table 3). The test error rate was 25.3% and the model had a good fit for the test data with an AUC of 0.81 (Table 3).

3.3. Determinants of forest fires contained within 4–12 h

The most important variables for the random forest model for forest fires contained within 4–12 h of ground crews arriving at the fire were the number of tankers and firefighters per ha of fire (Fig. 3). Wind speed, fire load and ignition cause were excluded from the final random forest model because of low variable importance values (mda 1.3, 1.4 and 1.6 respectively). The main difference in variable importance rankings for this containment time period compared to the previous time periods was that slope had a higher importance ranking (third most important for 4–12 h, sixth for within 2 h and fifth for 2–4 h) and fuel-load a lower importance ranking (eighth most important for 4–12 h, fifth for within 2 h and fourth for 2–4 h). The partial responses for the probability of containment within 4–12 h of ground crews arriving at the fire for each variable (Fig. S2) show similar relationships to the plots for probability of containment within 2 h (Fig. 4) but the probability of containment within 4–12 h was slightly lower for each variable. For example, the maximum probability of containment for the number of tankers and firefighters per ha of fire was 0.54 and 0.52 for

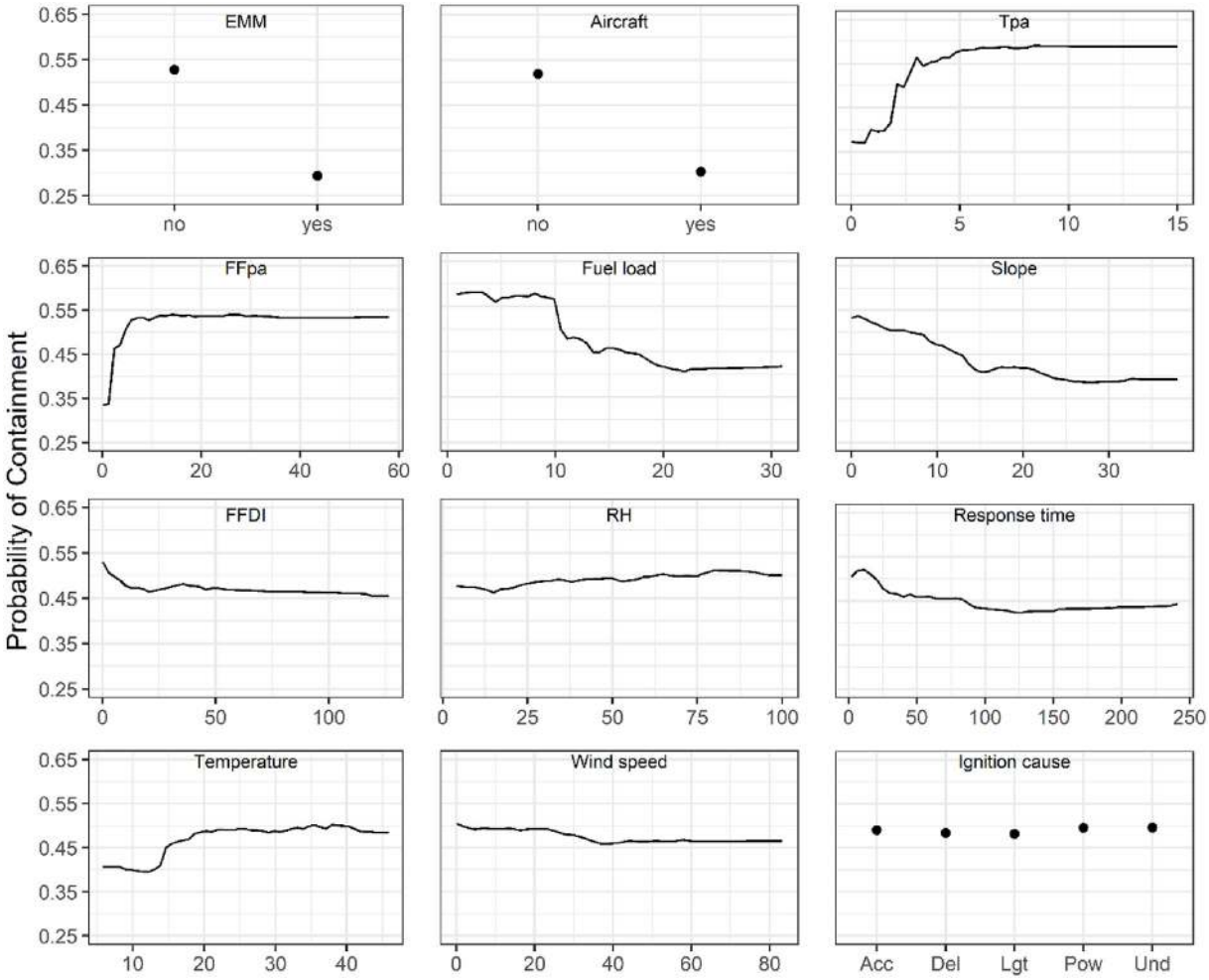

Fig. 4. Partial dependence plot for variables in the random forest model for containing forest fires within 2 h of ground crews arriving at the fire. Variables are ranked in order of importance. EMM = earth-moving machinery, Tpa = number of tankers per square root of final fire area, FFpa = the number of firefighters per square root of final fire area, FFDI = forest fire danger index, RH = relative humidity. Acc = accidental, Del = deliberate, Lgt = lightning, Pow = powerline, Und = undetermined.

the 4–12 h time period compared with 0.59 and 0.54 for the within 2 h time period. The training error for the random forest model for forest fires contained within 4–12 h was 28.6% and the model had a fair fit with an AUC of 0.78 (Table 3). The test set error rate was 22.7% and the model had a good fit for the test data with an AUC of 0.81 (Table 3).

3.4. Determinants of forest fires contained within 12–24 h

The most important variables for the random forest model for forest fires contained within 12–24 h of ground crews arriving at the fire were the number of firefighters and tankers per ha of fire (Fig. 3). In contrast to the previous time periods, fire load was included in the final random forest model and was the fourth most important variable in the model (Fig. 3). The partial response for the probability of containment within 12–24 h of ground crews arriving at the fire for fire load (Fig. S3) show a fire is less likely to be contained when 2 or more fires are uncontained in the district ($P \leq 0.31$) compared to when 1 ($P = 0.38$) or 0 ($P = 0.37$) other fires are uncontained in the district. Wind speed and response time were excluded from the final random forest model because of negative variable importance values. However, the results of this random forest model should not be relied upon as the training error for the model was 31.2% and the model had a fair fit with an AUC of 0.74 (Table 3). The test set error rate was 35.5% and the model had a poor fit for the test data with an AUC of 0.67 (Table 3).

3.5. Determinants of grass fires contained within 2 h

The most important variable for the random forest model for grass

Table 3
Random forest model number of variables used at each split, number of trees grown, training and test error rate and AUC for containment of forest and grass fires.

Containment Time	Fuel type	No. of variables	No. of trees	Training Error	Training AUC	Test error	Test AUC
< = 2 h	Forest	4	1000	21.6	0.87	22.1	0.85
> 2 & < = 4 h	Forest	2	2000	25.0	0.82	25.3	0.81
> 4 & < = 12 h	Forest	2	500	28.6	0.78	22.7	0.81
> 12 & < = 24 h	Forest	2	2000	31.2	0.74	35.5	0.67
< = 2 h	Grass	3	1000	4.76	0.86	4.91	0.87
> 2 & < = 4 h	Grass	2	1500	24.0	0.62	23.9	0.73

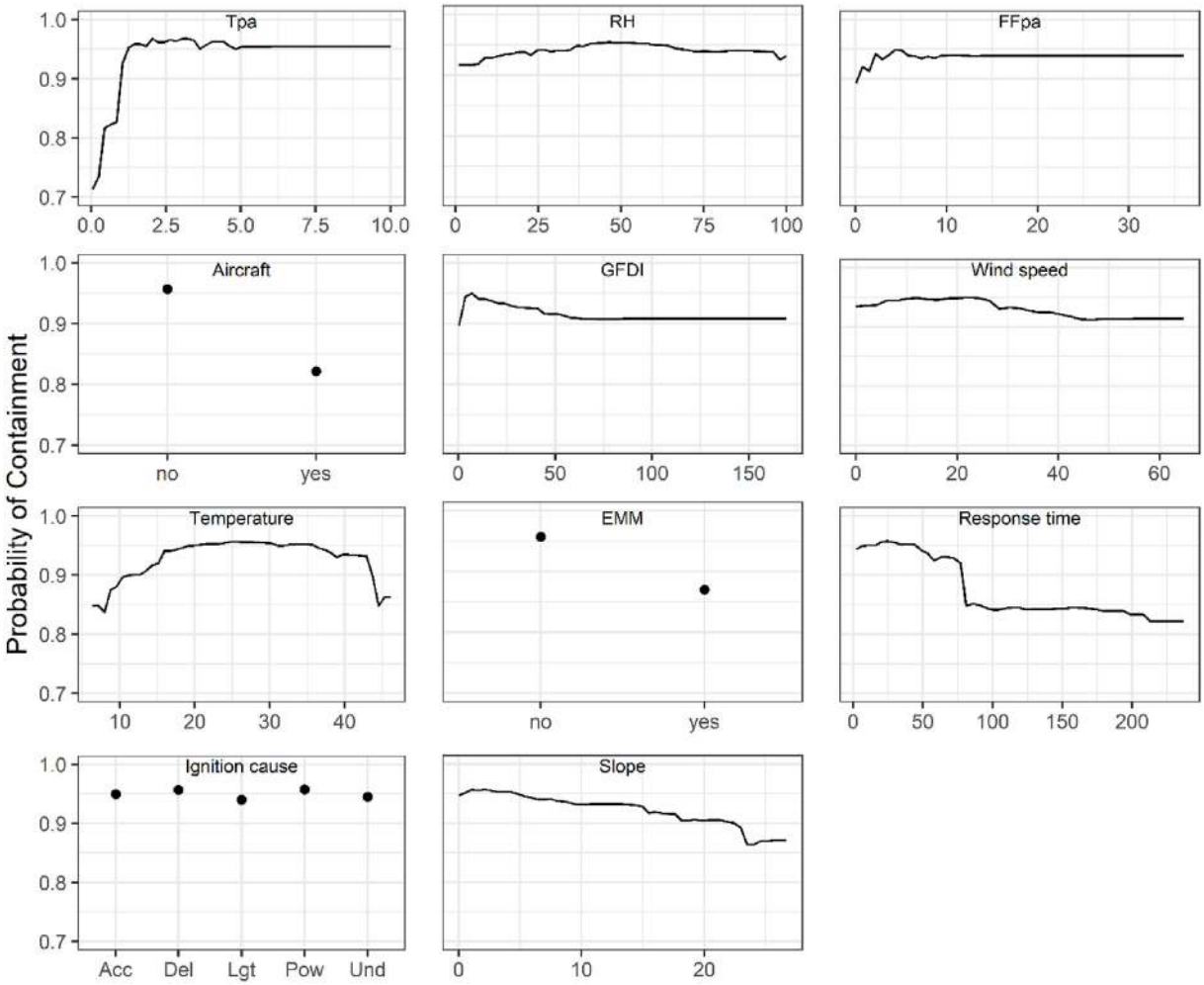

Fig. 5. Partial dependence plot for variables in the random forest model for containing grass fires within 2 h of ground crews arriving at the fire. Variables are ranked in order of importance. Tpa = number of tankers per square root of final fire area, RH = relative humidity, FFpa = the number of firefighters per square root of final fire area, GFDI = grassland fire danger index, EMM = earth-moving machinery, Acc = accidental, Del = deliberate, Lgt = lightning, Pow = powerline, Und = undetermined.

fires contained within 2 h of ground crews arriving at the fire were the number of tankers per ha of fire (Fig. 3). Weather variables, the number of fire fighters per ha of fire and aircraft were the next most important variables and slope had the lowest variable importance value (mda 4.5, Fig. 3). Fire load was excluded from the final random forest model because its importance value was negative. The partial responses for the probability of containment within 2 h of ground crews arriving at the fire show there is a high probability of containment of grass fires at both low and high values for each variable (Fig. 5). The probability of containment of grass fires increases as the number of tankers per ha of fire increase (Fig. 5) although the relationship flattens when > 2 tankers per ha of fire are present (P = 0.97). Like the results for forest fires, grass fires are less likely to be contained within 2 h if aircraft and earth-moving machinery are despatched to the fire. When these resources were used for grass fires, 72% of fires that used aircraft and 71% of fires that used earth-moving machinery were contained whereas 96% of fires were contained within 2 h without using aircraft and 97% were contained without using earth moving machinery. The training error for the random forest model for grass fires contained within 2 h was 4.76% and the model had a good fit with an AUC of 0.86 (Table 3). The test set error rate was 4.91% and the model had a good fit for the test data with an AUC of 0.87 (Table 3).

3.6. Determinants of grass fires contained within 2–4 h

The most important variables for the random forest model for grass fires contained within 2–4 h of ground crews arriving at the fire were earth-moving machinery and aircraft (Fig. 3). Fire load, ignition cause, wind speed, and the number of firefighters per ha of fire were excluded from the final random forest model because of negative variable importance values. The partial responses for the probability of containment within 2–4 h of ground crews arriving at the fire for each variable (Fig. S4) show similar relationships to the plots for probability of containment within 2 h (Fig. 5) but the probability of containment within 2–4 h was lower for each variable. For example, the maximum probability of containment for the 2–4 h time period for the number of tankers per ha of fire was 0.83 compared with 0.97 for the within 2 h time period. The results of this random forest model should not be relied upon as the training model AUC was poor (0.62) and the model had a fair fit for the test data with an AUC of 0.73 (Table 3).

4. Discussion

Human factors i.e. the number of resources per ha of fire, were the dominant influence on the containment of both forest and grass fires. Environment factors i.e. fuel load and slope had a strong influence on the probability of containment of forest fires and weather conditions

were also influential in containing both forest and grass fires. These results are similar to previous studies that found increasing crew size increased the probability of containment (Hirsch et al., 2004; McCarthy et al., 2012) and reduced average fire area (Penman et al., 2013b; Podur and Martell, 2007). The probability of containment of forest fires decreases as fuel load (McCarthy et al., 2012; Plucinski, 2012), slope (McCarthy et al., 2012) and fire weather severity increase (Arienti et al., 2006; Penman et al., 2013b; Plucinski, 2012). Slope and response have only a minor influence on the probability of containment of grass fires (Plucinski, 2013).

Unsurprisingly, the more resources available to control the fire, the more likely the fire will be contained. Grass fires are generally easily accessible to tankers and containment is achieved by directly applying water to the fire edge. If the fire spread is too fast or the flame height too high, then direct attack is made on the flanks of the fire, working from the rear to the head (Cheney and Sullivan, 2008; Luke and McArthur, 1978). The more resources available, the faster the fire will be contained. Forest fires may be directly attacked at the fire edge if it is safe and accessible to firefighters or contained by indirect attack which involves burning back from control lines to provide an effective barrier against the main fire (Fried and Fried, 1996; Luke and McArthur, 1978). Indirect attack cannot be achieved unless a suitable control line is established, hence the more crews available to prepare the control line and ensure the back burn is contained within the control line, the faster the fire will be contained.

Fires are successfully contained when the fire spread has been stopped, therefore factors which influence fire spread, fuel load, weather conditions and topography (Cruz et al., 2015) are also important factors influencing fire containment. Our results align with Tolhurst and McCarthy (2016) who characterised fires burning when the fire danger index < 50 as mostly fuel- and topography-dominated fires and fires burning when the fire danger index > 50 as mostly weather-dominated fires. In our study, fuel and topography were the dominant environmental variables in forest models with weather less important. However in our study, most (97%) forest fires occurred when the fire danger index < 50. In New South Wales, a fire danger index > 50 occurs on average only 1.9% days each year (calculated using 3pm weather data from the Bureau of Meteorology weather stations in NSW over a 30 year period from 1982 to 2013). Studies that focus on fires above FDI 50 find weather conditions are the strongest predictor of fire spread (e.g. Jin et al., 2014; Moritz et al., 2010; Price et al., 2015) and therefore we may expect suppression effectiveness to be more strongly linked to fire weather in these conditions.

Probability of containment was reduced for fires that used earth-moving machinery and aircraft however this seems counterintuitive as these resources are commonly used for rapid establishment of containment lines. However, the associated costs with these resources means that aircraft and earth-moving machinery are typically only used when firefighting conditions are difficult for ground crews to contain the fire due to the fast spread of the fire or difficulty in accessing the fire, or to protect people and property from the impact of fire (Plucinski et al., 2012). Therefore, these resources are usually only tasked to fires which are predetermined by fire managers as potentially being difficult to control or are at risk of impacting on houses. It is possible that for some of the fires in the study that used these resources, the time to containment would have been much greater if these resources were not available (Plucinski et al., 2012).

Response time had a limited influence on the probability of containment in contrast to previous studies (Arienti et al., 2006; Plucinski, 2012). Our study only included fires where ground crews were deployed immediately on notification of the fire whereas the other studies included all fires regardless of whether there was a delay in sending crews to the fire. The median and maximum response times in our study were 27 and 241 min for forest fires (Table S1), whereas the values were 29 and 89530 min in Arienti et al. (2006) and 40 and 690 min for ground crews and 60 and 1320 min for aircraft in Plucinski (2012). Plucinski (2012) only included fires where aircraft were used in the initial attack phase, so his data may be skewed to the more difficult fires to contain. The importance of response time is also dependent on the fire behaviour. A long response time on days when the fire weather conditions are benign is irrelevant as the fire would be spreading slowly with a low intensity and relatively small perimeter to contain when crews arrived. Likewise, a short response time when the fire weather conditions are extreme may also be irrelevant as the fire may have rapidly spread and be too intense for crews to contain at initial attack.

Containment of fires could be improved by modifying the number of resources available, the response time of these resources and/or the fuel load. Fire managers determine the number and type of resources deployed to a fire based on location of the fire, the values at risk, the likely fire behaviour and the total number of resources available. One way of increasing resources without large increase in costs is to shift resources around when there is a high likelihood of ignitions. The number of ignitions increase as the fire weather severity increases (Penman et al., 2013a; Plucinski, 2014) so it may be beneficial to move resources from areas where the fire danger index is low to areas where the fire danger index is higher, particularly on weekends and public holidays as these are the days when the highest number of human-caused ignitions occur (Albertson et al., 2009; Plucinski, 2014; Prestemon et al., 2012).

Resource response time can be improved by the early detection of fires and the strategic location of resources. The earlier a fire is reported and the more information that is known about the fire, including its precise location, accessibility to ground crews, size and fire behaviour, the more likely a fire will be contained at a small size (Martell, 2001). Investment in fire detection and monitoring systems e.g. fire towers, patrol aircraft, and ground-based, manned airborne-based, satellite-based and unmanned aerial vehicles remotely sensed systems (Hua and Shao, 2017; Yuan et al., 2015, 2017) can improve response times. Encouraging the public to report fires can also improve resource response time.

Fire managers can reduce the fuel load by clearing, grazing, slashing of grassy vegetation, mechanical treatments of forests and prescribed burning and reduce the probability of containment. Reducing the fuel load can facilitate fire suppression efforts by decreasing the rate of spread, flame height and intensity (Fernandes and Botelho, 2003). Although, this effect diminishes as the time since treatment and fire weather severity increases (e.g. Penman et al., 2013b; Price and Bradstock, 2010, 2012; Tolhurst and McCarthy, 2016) and simulation studies have shown that fuel management is less effective at reducing the area of moderate to high intensity unplanned fire and total area burned than efforts to prevent or quickly extinguish wildfire ignitions and year to year weather variability (Cary et al., 2009, 2017). To be effective, a fire must encounter a treated patch while in a fuel reduced state and under weather conditions that will allow suppression resources to contain the fire. In the Sydney basin, Price and Bradstock (2010) found that 22% of treated patches encountered a fire within 5 years of treatment and there was a 10% chance that the fire would stop in the treated patch. Therefore, like the strategic placement of resources, fuel reduction treatments should be targeted to areas where fire ignitions are predicted to occur. Human-caused ignitions are most likely to occur close to population centres and roads (e.g. Collins et al., 2015; Narayanaraj and Wimberly, 2012; Penman et al., 2013a; Syphard et al., 2008) which suggests that fuel treatments should be placed close to the urban interface (Gibbons et al., 2012; Penman et al., 2014). Lightning-caused ignitions are more likely to occur at high elevation sites away from population centres (e.g. Narayanaraj and Wimberly, 2012; Penman et al., 2013a; Wu et al., 2014). Targeting fuel treatments in these areas may be effective in improving the probability of fire containment provided that it is not across a broad area of the landscape given the relatively low fire encounter rates.

The resolution of the available data imposed some constraints on the study. Only the response time for the first crews that arrived at the fire was available, so it was not possible to adjust the number of

resources undertaking fire suppression based on when they arrived at the fire. It was also assumed all firefighters and tankers were actively engaged in fire suppression. For small fires, these limitations are likely to have had minimal impact on the results, however this may not be the case for large fires where additional resources may have taken some considerable time to arrive at the fire or crews are diverted to property protection. We tried to control for the variable number of resources available over time by dividing the resources by the square of fire area, but this does not completely solve the problem. These limitations could be overcome if resources were tracked using global positioning systems (GPS). If GPS tracking was available, then resource arrival and departure times and the type/category of resource is known but additional information on the tasks undertaken at the fire would still be needed. GPS tracking of aircraft has become increasingly available in recent years, but these are not generally tagged with what tasks the aircraft did at the fire e.g. water-bombing, reconnaissance, transporting firefighters and equipment, and when they were undertaking each task. Similarly, for tankers GPS tracking would need to identify when the crew were undertaking containment operations and when they were undertaking other tasks e.g. property protection, reconnaissance, mop up and patrol.

5. Conclusion

Our study demonstrated that resources per ha of fire and weather conditions were the most important factors influencing the probability of containment of grass fires and forest fires, these factors plus fuel load and slope for forest fires were the most important factors. Of these, only the number of resources available and fuel load can be modified by fire managers and the effectiveness of these management actions may be diminished by the encounter rate of fires and weather conditions. Targeting fuel treatments and locating resources to areas where fire ignitions are predicted to occur may be effective in improving the probability of fire containment. There are costs and benefits associated with increasing prevention and suppression resources that require further study. Improvements in response data collection, particularly the timing of resource arrival, the type/category of the resource and activities undertaken by the resource, is required to further assist managers in determining the appropriate level of response to despatch to fires and support cost effective use of resources.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.jenvman.2018.09.031.

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