

## An empirical wildfire risk analysis: the probability of a fire spreading to the urban interface in Sydney, Australia

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**Abstract.** We present a method and case study to predict and map the likelihood of wildfires spreading to the urban interface through statistical analysis of past fire patterns using 15 000 lines from 677 fires with known ignition points and date and random potential end points on the urban interface of Sydney, Australia. A binomial regression approach was used to model whether the fire burnt to the end point of the lines as a function of measures of distance, fuel, weather and barriers to spread. Fire weather had the strongest influence on burning likelihood followed by the percentage of the line that was forested, distance and time since last fire. Fuel treatments would substantially reduce risk from fires starting 1–4 km away from the interface. The model captured 90% of variation in burning with 98% predictive accuracy on test data and was not affected by spatial autocorrelation. We apply the method to map fire risk in Sydney and discuss how the method could be expanded to estimate total risk (from ignition to impact on assets). The method has considerable promise for predicting risk, especially as a complement to simulation methods.

**Additional keywords:** risk assessment, risk mapping, wildland–urban interface.

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### Introduction

Wildfires are a recurring natural hazard in south-eastern Australia, as in many regions globally (Bowman *et al.* 2011). There have been several events causing significant loss of life and property in Australia in recent decades (McAneney *et al.* 2009; Cruz *et al.* 2012). Quantitative estimates of the risk of loss of assets are required to implement an evidence-based approach to wildfire management (Penman *et al.* 2011; Price and Bradstock 2013a; Thompson *et al.* 2013). A formal understanding of risk can not only improve prediction of the probability of asset loss but also contribute to the development of formal cost–benefit analysis of a range of risk-reduction strategies. Such insights are required to improve planning of mitigation strategies such as fuel treatments, the location of firefighting resources and residential developments.

Operational risk measures are often limited to weather warnings (e.g. the Fire Danger Index in Australia or Fire Weather Index in Canada (McArthur 1967; Taylor and Alexander 2006)), but these consider all assets to have the same risk irrespective of wind direction, the type or amount of fuel or their location in the landscape with respect to topography and barriers to fuel spread. Recent advances in simulation techniques have allowed the development of quantified risk maps, most commonly in the USA (Ager *et al.* 2013), but also in

Australia (Atkinson *et al.* 2010; Tolhurst *et al.* 2013) and Europe (Salis *et al.* 2013). Simulators have the advantage that they implicitly account for the distribution of fuel amount and continuity and topography. However, simulation methods necessarily use a large number of assumptions, the most important of which is that the underlying fire behaviour model developed under a narrow range of controlled conditions is applicable to wildfires. Studies that compare predictions of fire shapes, sizes and rates of spread produced by simulators against actual fires generally find only moderate accuracy (Fujioka 2002; Duff *et al.* 2012; Duff *et al.* 2013; Metcalf and Price 2013; Filippi *et al.* 2014), partly because the fire-spread models used for simulation tend to underpredict rate of spread under severe weather conditions (McCaw 2008; Cruz and Alexander 2013).

Empirical research has been conducted into many aspects of fire risk, including the effectiveness of fuel reduction for limiting fire severity, and spread (Thompson *et al.* 2007; Price and Bradstock 2010, 2012), the contribution of house construction, the surrounding environment and the power of the fire to house loss (Gibbons *et al.* 2012; Harris *et al.* 2012; Syphard *et al.* 2012; Price and Bradstock 2013a), the likelihood of ignition (Penman *et al.* 2013), the distance travelled by fires (Price and Bradstock 2013b) and the number of fires experienced at the wildland–urban interface (WUI) (Haight *et al.* 2004). However,

there has been little research into the likelihood of fires spreading from their ignition point to the WUI (Price and Bradstock 2013b).

In the present study, we developed an empirical approach for estimating the likelihood that a fire will affect any location in the WUI, based on its point of origin in the landscape and a range of potential determinants. The method matched each fire ignition point with a series of randomly selected receiver points located at the WUI, which may or may not have burned in the fire, and analysed the probability of burning the receiver point as a function of the determinants measured along the straight line between ignition and receiver locations. The determinants were considered in five separate themes (groups of variables) reflecting distance, weather (either raw weather variables or fire weather indices), topography and fuel. We hypothesised that the themes would have strong, independent influences on the likelihood of burning because each has been found to influence particular aspects of fire behaviour (Bradstock *et al.* 2009; Bradstock *et al.* 2010; Price and Bradstock 2010). The method was applied to 677 fires that occurred in the surrounds of Sydney, Australia, between 1985 and 2008. The derived model was then applied to map the risk of fires spreading to the WUI across the Sydney region. Although the main aim was to derive a new approach for quantification of risk, the study also provides insights into the influence of weather, fuel and topography in driving fire spread. Hence, the results can be used to infer the levels of risk reduction that may result from differing fuel treatment strategies.

## Methods and materials

### Study area

The study area was the WUI around the city of Sydney and its hinterland. Sydney is a city of ~5 million people, situated largely on a coastal lowland plain, surrounded by dissected sandstone tablelands. The native vegetation in the tablelands is largely intact and is dominated by a diverse dry sclerophyll eucalypt forest (Keith 2004), with a total area of ~20 000 km<sup>2</sup>, much of which is protected in National Parks. The climate is warm and temperate, and the rainfall total of 1200 mm is evenly distributed through the year (Bureau of Meteorology data, available at <http://www.bom.gov.au>, accessed 5 May 2015). Approximately 5% of the forest is burnt by unplanned fires each year, and another 1% is burnt by prescribed fires (Price and Bradstock 2011). Other flammable vegetation types (grasslands, shrublands and woodlands) are minor components and mostly further from Sydney than the forests. Urban development abuts the forest around the edge of the city and there are fingers of development into the tablelands. There are also many forested patches within the city, usually associated with steep and rugged drainage lines. The WUI in the Sydney region has a length of ~7000 km (O. Price, R. Borah, R. Bradstock, T. Penman, unpubl. data).

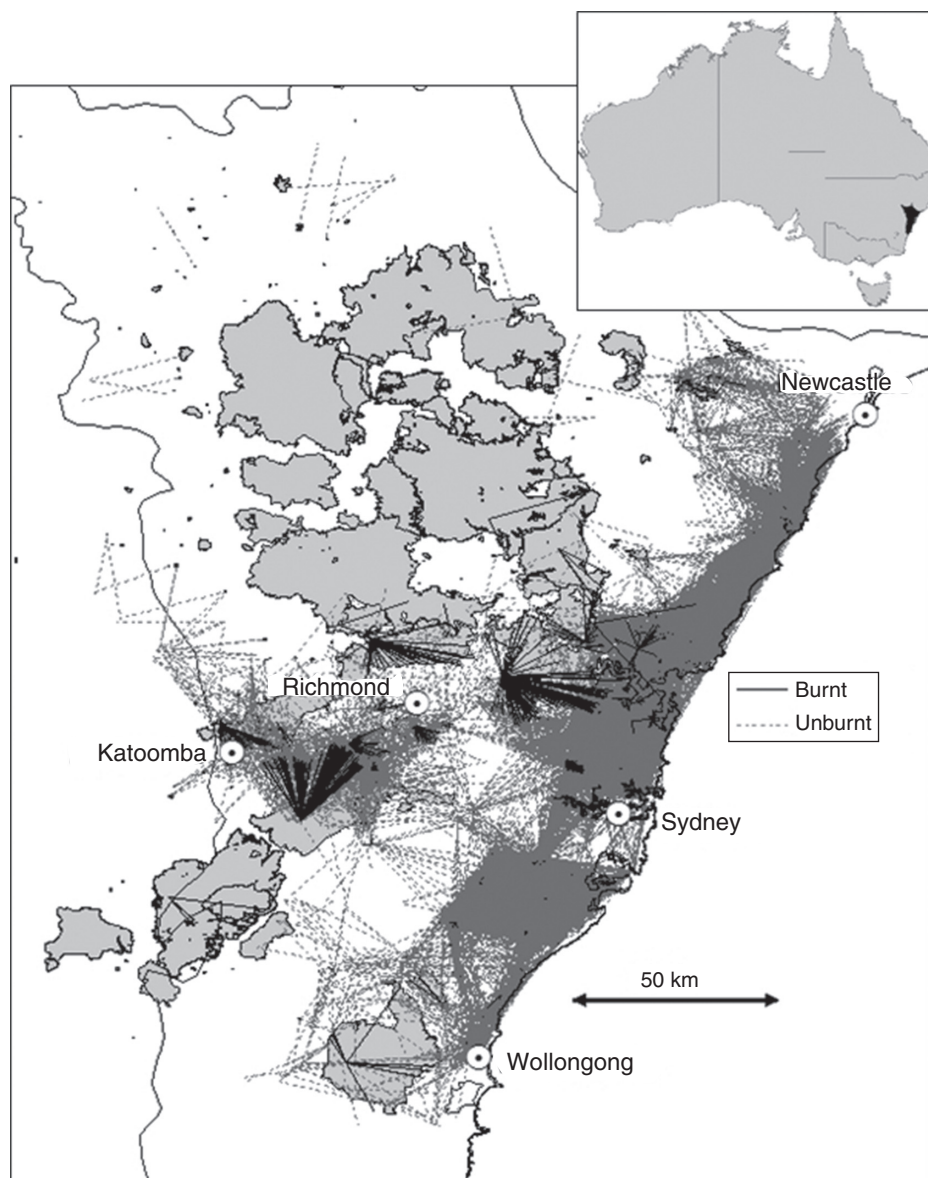
### Data and sample

The data consisted of all 667 fires from the fire history database for the Sydney region from the period 1985–2008 (New South Wales Office of Environment and Heritage, unpubl. data) for which the ignition location, date and final perimeter were

known. These were the ignition points. Receiver points were census mesh blocks located in the WUI and classified as either interface or intermix according to the classification of Radeloff *et al.* (2005). Mesh blocks are the smallest statistical unit used by the Australian Bureau of Statistics. They vary in area depending on population density, but the median area in our study region is 3.4 ha containing a mean of 27 properties. Radeloff *et al.* (2005) defines intermix and interface blocks as those where the house unit density is at least 6.17 km<sup>-2</sup>. Intermix blocks have at least 50% vegetation cover, whereas interface blocks have less than 50% vegetation cover but are within 2.4 km of a block of vegetation of at least 5 km<sup>2</sup>. For the Sydney study area, there are 22 000 interface and 4400 intermix blocks from a total of 70 000. All 1.7 million combinations of the 677 ignition points and 26 000 receiver points were considered. A sample for analysis was created by selecting all of the pairs where the receiver was burnt ( $n = 945$ ), and a random selection of 15 000 of the unburnt pairs (i.e. where an ignition failed to result in a fire reaching any given receiver point). The response variable in this study was whether or not the fire reached the receiver point (0 or 1).

For all of the selected pairs (Fig. 1), a Geographic Information System (GIS) was used to calculate a set of predictor variables describing the weather at the time of the fire, distance, topography and the fuel array along the direct line between the ignition and receiver (Table 1). Daily weather data for each ignition were derived from a 10-km gridded product (Clarke *et al.* 2013) from a regional climate simulation using the Weather Research and Forecasting (WRF) model (Evans and McCabe 2010), forced by a reanalysis dataset (Kalnay *et al.* 1996). This output has greater than 90% accuracy when compared with station observations for fire weather indices (Clarke *et al.* 2013). These hind-cast modelled variables consisted of daily 1500 hours values of the McArthur Forest Fire Danger Index (FFDI), wind maximum speed (and direction), minimum relative humidity, maximum temperature, rainfall and drought indices. FFDI incorporates effects of short-term drought (the Drought Factor) and ambient weather. We converted FFDI to a drought-independent index by removing the drought factor component from the index (referred to as FFDI\_df1), because it has been found that considering drought and ambient weather separately improved prediction of fire activity (Bradstock *et al.* 2009). Two alternative measures of dryness were considered. The Keetch–Byram Drought Index (KBDI) is a measure of soil moisture deficit (Finkele *et al.* 2006), which may affect fuel moisture (Luke and McArthur 1977; Viegas *et al.* 2001). The Drought Factor (DF) incorporates KBDI, but includes an additional term for recent rainfall, intended to predict dead fuel moisture (McArthur 1967). Biophysical variables were measured along the straight line between each ignition point and the centroid of the selected receiver mesh block. These were: the proportion of native vegetation cover and forest cover, the mean value of elevation, slope, aspect, topographic position, topographic roughness and time-since-fire and the total width of disruptions (roads and rivers).

The vegetation measures were obtained from the combined vegetation map of NSW (Keith 2004). Topographic measures were derived from a 30-m resolution digital elevation model (from Geoscience Australia, available at <http://www.ga.gov.au>, accessed 5 May 2015). Topographic position was defined as the



**Fig. 1.** The study area, fires and derived lines used in the study. The insert shows the Sydney Basin bioregion in the context of Australia.

mean of elevation expressed as a percentage of the range between the local (500-m radius) minimum and maximum: 0=valley bottom, 100=hill top. Topographic roughness was the standard deviation of all elevation values along the line. Time-since-fire values were obtained from a fire history database for NSW (Office of Environment and Heritage, unpubl. data). Disruptions were identified from 1:25 000 digital topographic layers from Geoscience Australia. Roads and watercourses of different types were assigned standard width values according to Australian Standard AS2482–1989 (Interchange of Geographic Data, available at <http://infostore.saiglobal.com/>, accessed 5 May 2015), and the sum of the widths of the features crossed by the line between ignition and receiver was calculated. The individual widths ranged from 5 to 60 m for

roads (5 m = track, 60 m = freeway) and from 5 to 30 m for watercourses (5 m = mainly dry watercourse, 30 m = braided river).

#### *Statistical modelling*

The sample was divided into training and testing sets by randomly selecting two-thirds and one-third of the data respectively. Statistical models of the likelihood that an ignition would burn a receiver point were developed using binomial (or logistic) regression (McCullagh and Nelder 1983). Initially, each predictor was fitted separately. Then the predictors were divided into five themes (distance, raw weather variables, fire weather indices, topography and fuels) and models were developed for

**Table 1. Predictor variables used in the analysis**

The % deviance column is the percentage of null deviance captured by the variable when fitted alone to a binomial regression model of burning the receiver. Note that for categorical variables no median or range is given

Theme	Variable name	Description	Median	Range	% of deviance
Distance	Log Dist	Natural log of distance between ignition and receiver (m)	15 490	23–25 000	18.79
	Disruption	Sum of road, rail and watercourse widths along line (m)	9.3	0–45	7.12
	Bearing	Bearing between ignition and receiver (octants)			10.41
Fire weather	FFDI	Forest Fire Danger Index	5	0–63	41.51
	FFDI_dfl	FFDI with Drought Factor component removed	0.74	0.10–6.9	43.09
	DF	Drought Factor	7.6	0.2–10	11.54
	KBDI	Keetch–Byram Drought Index	52	0–179	20.96
Raw weather	Rainfall (2 days)	Rainfall on day and previous day (mm)	0.2	0–75	13.25
	RH	Relative humidity (%)	51	8–69	37.41
	Tmax	Maximum temperature on day (°C)	24	12–43	27.42
	Wspeed	Maximum wind speed on day (km h <sup>-1</sup> )	20	1–57	3.26
	Wdir	Predominant wind direction on day (octants)			31.73
	Westwind	Wind was from W octant			28.88
	Wind angle	Angle between wind direction and line (degrees)	84	0–180	5.46
	TP	Topographic position (0 = valley, 100 = hill top)	50	0–98	3.59
Topography	Elevation	Mean elevation along the line (m)	72	–1–1069	13.30
	Alt_std	Standard deviation of elevation along line (m)	37	0–303	0.08
	Aspect	Topographic aspect in four classes (N, S, E, W)			0.77
	Alt_change	Difference in elevation between ignition and receiver	75	–891–165	8.62
	Slope	Mean of all slope values (degrees)	6.5	0–27	9.21
Fuel	ForestP	Percentage of line length mapped as forest	48.3	0–100	32.92
	VegPC	Percentage of line length mapped as native vegetation	55	0–100	17.26
	Tsf	Mean time since fire along line (years)	27	0–41	1.32
Spatial	SLRV	Spatially lagged response variable: distance-weighted mean of burning	0.001	0–0.93	29.7

each theme to compare the absolute and relative contribution of each theme with the prediction of burning likelihood. For each theme, all possible combinations of predictor variables were tested and the best model and all supported alternatives were identified using model selection techniques (Burnham and Anderson 2002). At this stage, non-linearity in the responses was tested by fitting the log-transformation of each of the selected predictors, retaining them if they reduced Akaike's Information Criterion (AIC). A final set of candidate predictors was obtained from the best models in each theme, and the best model and supported alternatives for this final set were developed in the same way: fitting all possible combinations. Finally, all the two-way interactions between variables in the best model were evaluated and retained if they reduced AIC. To account for the much larger number of unburnt cases in the sample, they were given a weight of 0.04 in all analyses. The accuracy of the final model was tested by comparing predictions with the retained, test data.

Because the data consisted of multiple potential receiver points for each fire, there was considerable potential for spatial autocorrelation and pseudoreplication in these data. We addressed this first by inclusion of a spatially lagged response variable (the mean of the response for all receivers other than the test one, weighted by distance) as a predictor in the modelling process. Second, we applied Moran's test for spatial autocorrelation for the response variable, with the location for each case being the receiver point. All analyses were conducted using *R* statistical software (R Core Development Team 2013).

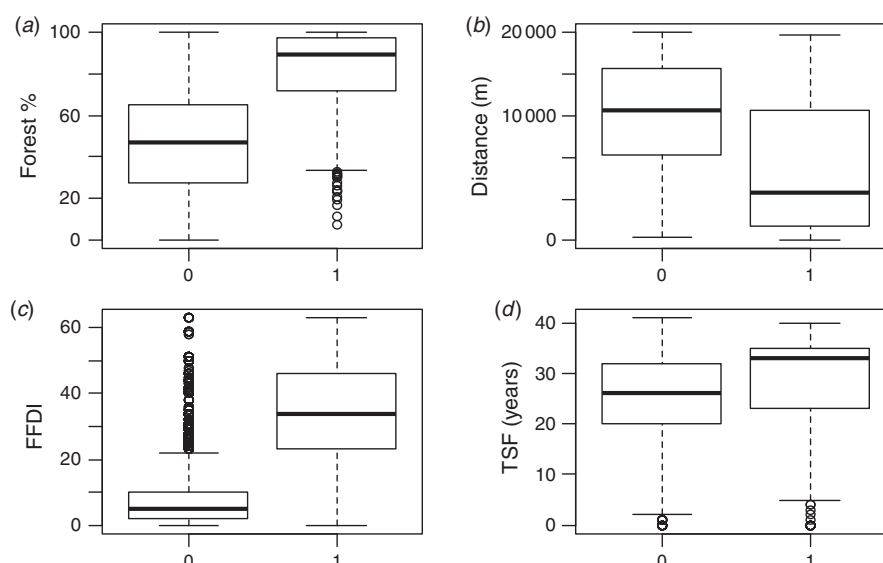
### Risk mapping

The final model was applied to create a map of the likelihood of fire spreading to each interface and intermix mesh block. A set of 20 random potential ignition points was created around each block (constrained so that four points were in each of five distance classes with minimum thresholds of 400 m, 1.1 km, 3.0 km, 8.1 km and 22.0 km). A line was generated between each of these points and the receiver block, the values of the model predictors calculated along the line, using time-since-fire calculated for June 2012, and for the 99.9th percentile value of gridded daily FFDI value for the block (the worst expected every 3 years based on the downscaled WRF daily weather data, mean 37.2). The mean model value for the 20 lines was calculated for each block.

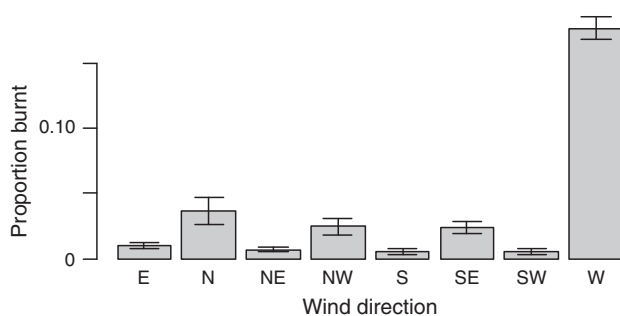
### Results

Receivers that burned were close to ignitions, had a higher forest percentage, were associated with a higher FFDI and slightly higher time-since-fire compared with receivers that did not burn (Fig. 2). Receivers were ~10 times more likely to burn under the influence of a prevailing west wind compared with most other wind directions (Fig. 3).

Most of the predictors yielded a significant relationship with burning the receiver (Table 1) when fitted individually, and of these, the fire weather variables (FFDI or FFDI\_dfl) were the strongest, both capturing >40% of null deviance in burning. Relative humidity, wind direction and the percentage of forest captured >30% of null deviance, and several other raw weather



**Fig. 2.** Box and whisker plots for burnt and unburnt cases for four predictor variables: percentage forests along line, distance, Forest Fire Danger Index (FFDI) and time-since-fire (TSF).



**Fig. 3.** Proportion of lines burnt in each wind direction class.

measures as well as distance and the spatially lagged response variable captured >20%. Among the themes, the best model was provided by fire weather, comprising FFDI\_dfl and KBDI, which captured 46% of null deviance (Table 2). This theme was followed closely by the raw weather theme (44%) and fuel theme (41%), with the distance and topography themes capturing lower amounts of deviance (33 and 26%).

The best combined model for the likelihood of burning the receivers contained positive effects of FFDI\_dfl, KBDI, forest percentage, west wind and time-since-fire and there was an interaction between distance and forest percentage (Table 3). The likelihood of burning was predicted to be very high for ignitions <1000 m from the receiver, but dropped rapidly above this threshold (Fig. 4a). The effect of fire weather was to increase this threshold distance (3000 m under severe cf. 1000 m under low fire weather indices) and to decrease the slope so that there is considerable likelihood of burning at distances above 5000 m under severe weather. The percentage forest effect was similar, increasing the threshold and flattening the curve (Fig. 4b). The west wind and time-since-fire effects acted in much the same way, but with lower magnitude, increasing the threshold by ~500 m in the presence of west

wind or when comparing 20-year-old fuels with 1-year-old (Fig. 4c and 4d). No topographic variables were included in the model. The spatially lagged response variable was not selected in the model, but its inclusion was a supported alternative (Table 2) whereas the burnt values were weakly but significantly spatially autocorrelated ( $I = 0.044$ ,  $P < 0.001$ ). Thus, spatial autocorrelation was not a serious consideration in this analysis.

The best model captured 91% of null deviance, an area under the curve of 0.995 and correctly predicted the outcome in the retained test data with 98% accuracy (comprising a 16.0% omission and 1.0% commission rate using a cut-off value of 0.96 predicted probability of burning).

The risk map showed that parts of the study area were directly connected to large expanses of forest had the highest risk (Fig. 5), as expected. Intermix blocks had substantially higher risk than interface (median 0.73 cf. 0.60), and at the 99.9th percentile fire weather, the majority of fires igniting within 20 km around intermix fires were predicted to impact on them (Fig. 6).

## Discussion

This empirical method produced a very accurate model of the risk of fires spreading to the urban interface. The relationships identified in this study conformed to our hypothesis that several fundamentally different determinants had strong influences on the likelihood of fire reaching the urban interface. Distance, fire weather and the proportion of forest were particularly strong predictors. Weather had the strongest influence (weather variables were ranked one and two in terms of the percentage of deviance captured by individual variables and by variable themes). The greater influence of weather compared with fuel is in agreement with many other studies of fire behaviour that find weather to be the most important factor determining the spread and size of fires (Bessie and Johnson 1995; Arienti *et al.* 2006;

**Table 2. Results of the model building process showing the selected model for each predictor theme and the final best models**

The % deviance column is the percentage of null deviance captured by the model. The column *Alternatives* shows alternative formulations with an Akaike's Information Criterion (AIC) value within 2 of the selected model

Theme	Variable	% deviance	AIC	Alternatives
Distance	Log Dist + Disruption + Bearing	33.2	423.93	None
Fire weather	Ffdi_dfl + KbdI	46.4	333.1	None
Raw weather	Rainfall + Rh + Tmax + Westwind	44.4	348.5	Several
Topography	Tp + Elevation + Alt_Std + Alt_change + Slope + Aspect	26.2	482.72	–Aspect, –Alt_change
Fuel	Forestp + Tsf + Sparse	40.6	392.9	None
Final model	Log_dist × Forestp + Ffdi_dfl + KbdI + Tsf + Westwind	90.9	54.91	+SLRV

**Table 3. Estimate table for the final model predicting the probability of the receiver burning, showing coefficients and probability level for each predictor variable in the final model**

‘:’ indicates an interaction term. See Table 1 for a description of the variables

Variable	Estimate	s.e.	z value	P
(Intercept)	58.658	10.552	5.559	0.000
logdist	–9.118	1.393	–6.547	0.000
forestp	–0.402	0.119	–3.373	0.001
kbdi	0.041	0.008	5.028	0.000
tsf	0.117	0.029	4.011	0.000
ffdi_dfl	0.931	0.247	3.768	0.000
Westwind	2.253	0.784	2.875	0.004
forestp : logdist	0.064	0.014	4.463	0.000

Bradstock *et al.* 2010; Price and Bradstock 2011). The only variable theme missing from the final model was topography, which is surprising because slope, aspect and topography are known to influence many aspects of fire behaviour, including severity (Thompson and Spies 2009; Price and Bradstock 2012) and spread (McArthur 1967; Price and Bradstock 2010). The absence of topography in the models is probably due to the co-occurrence of intact forest and steep slopes (tree clearance has occurred predominantly on flatter ground).

Fire weather was effectively represented by independent inclusion of dryness and the ambient weather in the final model. This presumably reflects fundamental differences in the influences of these components (Bradstock *et al.* 2009). Of the drought measures, the KBDI was superior to the DF. The inclusion of KBDI as an assumed indicator of stored moisture presumably reflects a more important role in fire spread for fuel elements with longer drying times than fine surface fuels (e.g. live fuels; Caccamo *et al.* 2012).

The time-since-fire effect suggests that fuel treatment would reduce fire risk. However, a high level of treatment would have to be applied to keep the mean fuel age substantially below the current median value of 27 years.

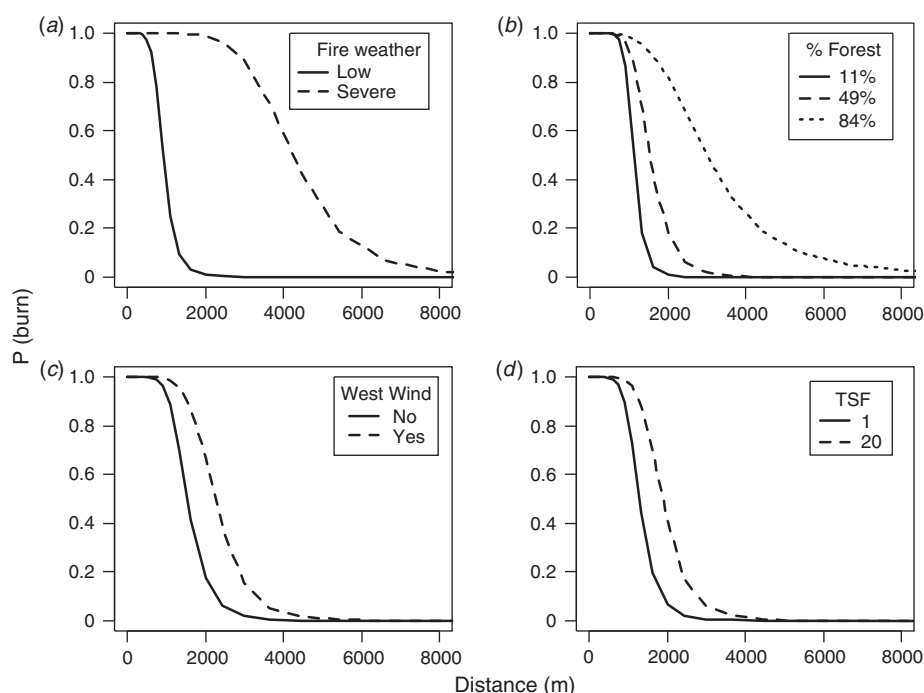
Previous studies have found that treatment concentrated close to the assets is more effective for protection than treatments that are more distant (Schoennagel *et al.* 2009; Price and Bradstock 2010). Low fuel age (via fuel treatment) would be expected to reduce fire severity (Bradstock *et al.* 2010) and rate of spread (McArthur 1967; McCaw *et al.* 2012), therefore making it more likely that the fire would be slowed before reaching the receiver and more favourable for suppression.

However, it should be noted that fuel age becomes less effective as fire weather becomes more severe (Price and Bradstock 2012), and none of the fires occurred in the upper range of fire weather in Sydney (maximum FFDI in the sample was 63, whereas the maximum experienced in Sydney is 96, (Lucas 2010)).

The weak effect of wind direction in the final model reflected the relationship between wind direction and FFDI. The highest FFDI occurs in west winds, such that the median FFDI under NW, W or SW winds was 16 and for all other directions was 3. The additional effect of westerly winds that was not captured by FFDI may reflect imperfection of FFDI as an index of fire weather or because there are other factors making spread from the west more risky.

It was surprising that the disruption measure was not present in the final model. This was because the presence of percentage forest in the model prevented the inclusion of disruption, even though the correlation between them was low ( $r = 0.013$ ). The measure of disruption used here is simply the sum of the estimated widths of roads and rivers along the line, and may not be a very good measure of the width of barriers in the path of the fire. For example, the width of the widest barrier may be a better measure of disruption.

The risk map (Fig. 5) appeared to highlight all areas on the periphery of Sydney as having high risk. However, the detail includes the demarcation of hotspots of very high risk where settlements are flanked by forest on two sides (such as near Katoomba) and where protection by water yields low risk (coast north of Sydney). The values are also moderated by recent burns, and forest exposure to the east (rather than west), but these effects are not obvious in the map. This map is a prediction of the likelihood of a fire reaching each census block should a fire occur in the surrounds, but the risk assessment would be improved by combining it with a spatial model of ignition likelihood, such as that of Penman *et al.* (2013). Further improvement would be gained if the prediction could include the likely intensity (or severity) of fires should they reach the census block and consequential house loss. For example, fire severity been found to be reduced in recently burnt areas (Bradstock *et al.* 2010; Price and Bradstock 2012) so the effects of prescribed burning on reducing intensity in addition to its effect on spread could be addressed by adding a severity component to the risk estimation. Empirically derived and spatially explicit models of these factors have been developed for fires in Australia (Bradstock *et al.* 2010; Price and Bradstock 2012, 2013a) so the potential exists to derive a more complete



**Fig. 4.** Predictions from the final model showing the relationship between the probability of the receiver burning ( $P(\text{burn})$ ) with distance and (a) fire weather; (b) percentage forest; (c) westerly wind; and (d) time since fire. In (a), the low fire weather index was defined with  $\text{ffdi\_dfl} = 0.28$  and Keetch–Byram Drought Index (KBDI) = 6 and the severe was defined with  $\text{ffdi\_dfl} = 6.5$  and KBDI = 130. In (b), the three lines are for the quartile values of forest percentage. In (d), TSF stands for time since fire. In each plot, the variables that are not displayed were held constant: FFDI\_dfl and KBDI were set at 1.3 and 60 respectively to give a fire weather of moderate, Tsf = 10 years, wind was not westerly, and percentage forest was set to 49% (median value).

fire risk map giving the probability of ignition, spread and house loss.

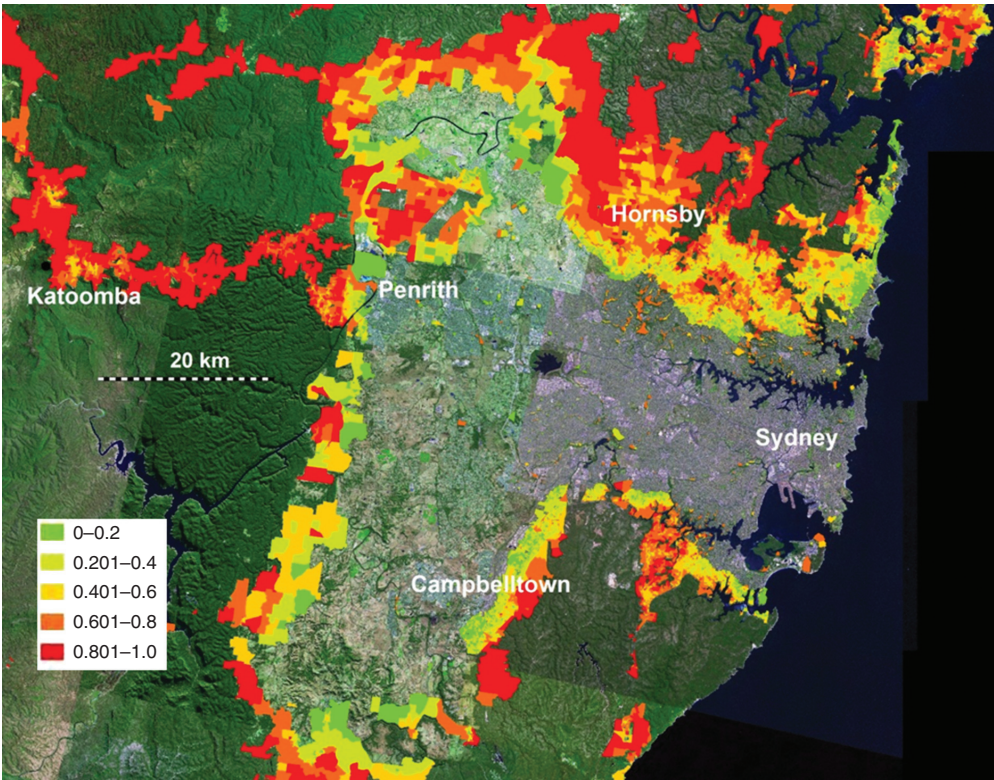
With 98% accuracy for discriminating locations on the WUI that will or will not burn in any particular fire, this empirical method has potential for broad application as a fire risk tool. In addition to the risk mapping mentioned above, there are two other applications: to plan responses to a new ignition and to evaluate the likely risk reduction from fuel treatments. Given that a fire has occurred, it would be possible to automate the evaluation of the model by analysing the straight lines between the ignition point and all WUI mesh blocks in the risk region. Forecast weather could be used for the FFDI value, while all of the other required variables are readily available from vegetation and topographic mapping and fire history databases. Because time-since-fire was a predictor in this model, it can be used to predict the risk reduction achievable from different levels and spatial arrangements of prescribed fire and other fuel treatments.

Modelling of fire risk at the interface using fire simulators is dependent on many assumptions about the drivers of fire spread (Atkinson *et al.* 2010; Ager *et al.* 2013; Salis *et al.* 2013; Tolhurst *et al.* 2013). Although the empirical method presented here has limitations (see below), it is based on analyses of real fire patterns and is probabilistic. This method is useful for mapping fire risk and comparing the risk reduction strategies, either as an alternative or a complement to simulation approaches. The main limitations of our approach reflect the

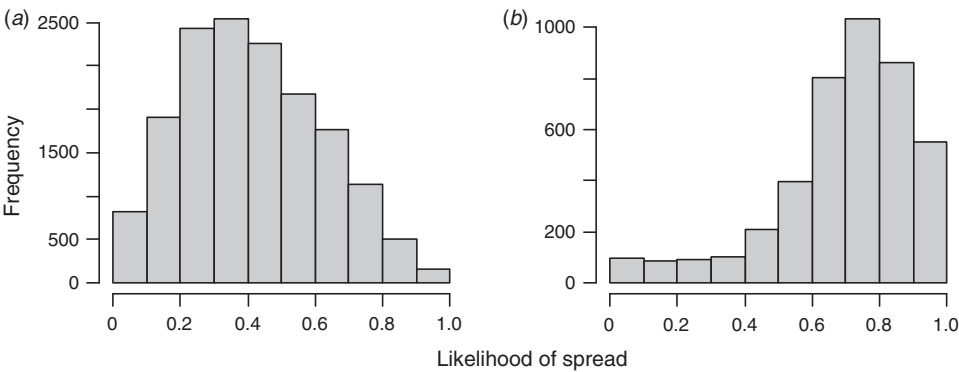
simplification of complex fire behaviour that is implicitly involved. First, we used maximum FFDI on the day of ignition although many of the fires in these data burned over many days. For example, some destructive fires have had their major impact on the second day after ignition. Second, fires do not spread linearly and are able to burn around obstacles. This was not accounted for in our method. Third, the method treated all parts of the line between ignition and receiver as equally important because it used mean values along the line. However, it may be that fuel and topography near to the receiver are more important because there are fewer available paths for the fire when it is close to the receiver than when it is distant. This is one of the main reasons that several studies have found that fuel treatments close to assets are more effective in protection of those assets than those in the broader landscape (Price and Bradstock 2010; Penman *et al.* 2014). Lastly, the spatial risk estimation could be improved if the 99.9th percentile FFDI values were calculated for days in each wind direction rather than for all days to better capture the higher fire danger present in westerly winds compared with others.

In spite of these limitations, the model was accurate and the method could be further developed for predicting fire risk elsewhere. Although the detail of the actual model presented here is specific only to Sydney, the general approach is widely applicable. Further refinements to the method, as discussed, may improve the scope for wider application.





**Fig. 5.** Risk map for the Sydney region showing the probability of extant fires spreading to each census block (only interface and intermix blocks). The background is a true-colour satellite image showing the urban areas in grey, peri-urban in speckled green and grey and forest (in green) surrounding the centre.



**Fig. 6.** Distribution of likelihood values in the risk map for (a) interface, and (b) intermix blocks.

**Conclusions**

This empirical method for estimation fire risk at the WUI had a high level of predictive accuracy and can be applied at fine spatial resolution. It can be combined with other empirical analyses to produce a comprehensive risk map (probability of fires starting, spreading and impacting on assets). It has some advantages over simulation modelling in that it is empirical (based on actual fire events) and probabilistic. There are also some limitations in the way it represents actual fire patterns and so we recommend its use

a complement to simulation modelling and with appropriate consideration of limitations and potential biases.

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Borah conducted the GIS analysis; Trent Penman contributed to method development and writing.

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