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Using a statistical model of past wildfire spread to quantify and map risk to assets and prioritise fuel treatments

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Abstract

We present a method to quantify and map the probability of fires impacting assets in a wildfire prone region, by extending a statistical fire spread model developed on historical fire patterns in the Sydney region, Australia. The new method calculates the mean probability of fire spreading along random sample lines around a set of assets, weights the risk according to ignition probability and also calculates the reduction in risk that fuel removal in treatment blocks would achieve. We have developed an R package WildfireRisk to implement the analysis and demonstrate it with two case studies in forested eastern Australia.

The risk of a fire spreading to an asset was highest in the heavily forested parts of each case study, but when weighted for ignition probability, the areas of highest risk shifted to the Wildland Urban Interface. Similarly, when ignition probability and the distribution of assets was taken into account, the highest priorities for treatment was strongly focussed on blocks next to the Wildland Urban Interface.

This method is objective, fast to implement and based on the behaviour of real historical fires. We recommend its use in wildfire risk planning, as an adjunct to more heuristic methods and simulations.

Brief Summary

We present a statistical method to quantify and map wildfire risk to assets and the risk reduction gained by removing fuel from treatment blocks, based on fire spread patterns in historical fires. Risk to assets was highest in areas with high forest cover, but risk reduction was highest in treatment blocks at the Wildland Urban Interface.

Introduction

Efficient mitigation of the risk from wildfires to human assets such as houses requires knowledge of the level of risk, how it varies spatially and how effective mitigation measures will be (Mell *et al.* 2010) in order to determine priorities and expenditure. . Currently in Australia (and elsewhere in the world) official wildfire risk assessments are crude, usually a combination of a map of flammable vegetation and a distance rule. For example, in New South Wales (Australia) houses that are within 100 m of forest or heathland vegetation are classified as 'bushfire prone' (RFS 2006), while in California, hazard rankings are derived from a combination of fuel type and mean inter-fire interval (Syphard *et al.* 2012). There have been a number of scientific studies that nuance this approach but they are essentially combining static risk layers describing the conjunction of fuels assets (Lein and Stump 2009; Herrero-Corral *et al.* 2012; Sirca *et al.* 2017). These approaches overlook the spatial distribution of ignitions and the fact that fire spreads from an ignition point through a matrix of fuels toward an asset. Whether the asset is impacted depends on its distance from the ignition, the spatial arrangement of the fuels, the topography and the weather. Simply examining the situation immediately around an asset does not give comprehensive risk estimation.

It is possible to estimate this more nuanced information, either through fire simulation or by analysis of historical fire behaviour. Fire simulations have been used extensively by researchers and fire management agencies for a variety of purposes, including risk mapping, operational fire spread forecasting and cost-benefit analysis. Risk mapping for human assets has been undertaken in many countries using several simulators. In Australia, Phoenix Rapidfire (Tolhurst *et al.* 2008) is the most common tool (Tolhurst *et al.* 2013), though others have been used (Atkinson *et al.* 2010). Phoenix

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uses several underlying fire behaviour models to predict fire rate of spread, chosen for different vegetation or fuel types. The most relevant for wildfire risk is the McArthur model (McArthur 1967), which predicts rate of spread and intensity as a function of surface fuel loads, recent drought, ambient weather and slope. It was developed from observations of prescribed fires mostly lit in open forests near Canberra. In most of the world outside Australia, a variety of simulators that implement the Rothermel (1972) fire spread model have been used. For example, in Italy (Salis *et al.* 2013), Spain (Alcasena *et al.* 2016), Israel (Carmel *et al.* 2009), Greece (Mitsopoulos *et al.* 2015) and the USA (Bar Massada *et al.* 2009; Ager *et al.* 2013; Ager *et al.* 2016; Scott *et al.* 2017). The simulators most commonly used are Farsite (Finney 2001) or one of its derivatives. Only some of these studies account for variation in weather and only some incorporate non-random spatial ignition patterns (Bar Massada *et al.* (2009); Ager *et al.* (2013); Tolhurst *et al.* (2013) and Mitsopoulos *et al.* (2015) do not). Simulation studies have not been applied to prioritise specific areas for fuel treatment, though there are current research projects aiming to do so.

The main advantage that simulators have over other potential methods for risk estimation is that they incorporate landscape variation in risk, for example the effect of one area having higher fuel loads than another or being protected by a wide river. However, simulators have several drawbacks when applied to risk mapping, the most important being:

1) The underlying fire spread models are usually developed from a limited set of fires under mild weather conditions. Thus, for example the McArthur model is known to significantly underestimate rate of spread in severe fire weather (McCaw 2008; Cheney *et al.* 2012), and to poorly represent the effects of vertical fuel distribution on fire behaviour (Cheney *et al.* 2012; Zylstra *et al.* 2016) and the complex influence of topography on fire behaviour (Price and Bradstock 2012; Sharples *et al.* 2012).

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2) The commonly used simulators do not incorporate complex and stochastic fire behaviour such as spotting and lateral spread (or fire-channelling (Sharples *et al.* 2012)), although some apply 'work arounds' to estimate these phenomena.
3) The commonly used simulators have been found to have only moderate accuracy in predicting the dynamics and final outcome of fires (Fujioka 2002; Filippi *et al.* 2014).
4) The simulation approach typically requires the 'experimental' ignition of thousands of fires in different places and in different weather conditions. Using simulators to prioritise fuel treatment blocks also requires a method to re-run the experiment with each treatment block treated. This is time consuming for the analyst.

In contrast, a range of alternative empirical methods for quantifying wildfire risk do not suffer from these problems, though they potentially have others. Here, empirical method refers to any procedure used to draw inferences from information about how fires have actually behaved in a given study area, and quantify risk on this basis. The simplest approach is to use fire frequency derived from historical fire perimeter mapping as a map of risk. The main drawback of this approach is that it assumes that an area that has not recorded a fire in the past has zero chance of experiencing one in the future, and for this reason it is rarely used for risk mapping. Statistical analysis of the drivers of fire frequency can fill in these gaps (Arganaraz *et al.* 2017), but even then they cannot measure the effect of weather or fuel amounts on fire occurrence because fire frequency is aggregated over decades whereas the weather and fuel loads will vary over that period.

One alternative empirical approach is to undertake statistical analysis of the spread pattern of individual fires as a function of weather, fuel and topography. The resultant statistical model can be used to predict whether a fire igniting at any particular place in the study area will reach an asset. In this study we apply the empirical method of Price *et al.* (2015) to two contrasting Australian case studies: The Hills district on the edge of Sydney and the Australian Capital Territory (Figure 1). The model is based on a linear function of distance, fire weather, time-since-fire and proportion of

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forest. Here, this method is combined with a spatial layer of ignition density calculated from historical fires, to estimate which areas in the study area are at most risk from wildfire. The method is then extended to estimate where intervention to reduce fuel loads is likely to be most effective. The main advantage of the method compared to simulations is that it is directly informed by the spread of real fires in real urban interface situations. The main disadvantage is that the method employs a highly simplified depiction of weather (it uses the worst weather for a day) and fuel distribution (it uses the mean proportion of forest along a line between a possible ignition point and a location for which risk is being estimated). Thus, for example, the model treats a fuel break such as a wide highway only as a reduction in the mean proportion of forest along a line between ignition and receiver location, which will be trivial for a long line.

Methods

The empirical model

The empirical risk model of Price et al (2015) was developed by creating lines between the ignition points of known historical fires in the Sydney region and many potential receiver locations, and calculating the values of the predictors along each line. The receiver locations were the centres of wildland urban interface census blocks, census blocks being defined by the Australian Bureau of Statistics as their smallest reportable spatial units (median area 3.4 ha). Interface blocks were identified using the method of Radeloff et al (2005) as those blocks that exceed a certain housing density and have >50% native vegetation, or else are within 2.5 km of a 500 ha block of native vegetation. Generalized linear modelling was then used to relate the probability that a fire would spread from ignition to receiver (interface census block) to given predictor variables. A range of candidate weather, fuel and topographical predictors were investigated, and a preferred model identified using AIC. The chosen model included predictors for distance to ignition point, proportion of forest along the line between ignition and receiver, mean time since fire along the line, soil

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dryness (KBDI), FFDI (with the drought component removed), and an indicator variable for whether the wind was from the west. The equation is shown in Table 1.

Applying the model to risk analysis

The Price et al (2015) study used the model to map the risk of that a fire igniting in the surrounds of any interface census block would spread to reach that block (Figure 2). The method involved creating 20 lines, of varying lengths, radiating out from the centre of each census block; calculating the probability of fire spread along each line based on the risk equation; and taking the average probability of spread among the 20 lines.

This value was a true measure of risk because it was the probability that a fire would spread to a receiver location from an ignition in the nearby landscape under certain conditions. However, it was not a complete measure of risk because it did not take into account the probability of ignition, but rather assumed that a fire has started already. There have been several studies that used statistical methods to map the distribution of ignition probability, including in Australia (Penman *et al.* 2013) and the USA (Syphard and Keeley 2015). These highlight important roles of weather, fuel type and population (either population density or distance to roads). Ignition probability map values can be combined with the fire spread probabilities to determine the combined probability of fire starting and spreading from any point in the landscape to any other, given specified weather and underlying maps of the drivers of ignition and fire spread. In this study, we extend the method of Price *et al.* (2015) by a) increasing the sampling intensity from 20 lines around each census block to 80; and b) estimating ignition probability for each line.

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Applying the model to prioritise fuel treatment blocks

Fuel treatment blocks are the base unit for applying prescribed burns, meaning they are a mappable set of units where a burn will usually treat the entirety of a block. The mean risk value of the sample lines that pass through a treatment block is an estimate of the probability that a fire within the block will spread to any asset. The degree of protection that would be provided by treating blocks can be calculated for each treatment block by setting time since fire to zero for the portion of each line within the block. The mean probability of fire spread along the lines can then be recalculated to give a treated risk value. The empirical model uses a mean time-since-fire value for the entire line, so depending on the current time-since-fire and the proportion of the line within the treatment block, the new risk calculation will be somewhat lower than the current risk but rarely will it reduce to zero.

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The treatment blocks vary in the amount of protection they provide to assets both because of their position relative to the assets but also in proportion to the number of assets protected. The number of sample lines passing through a block can be used to weight the risk measures to prioritise blocks that offer more protection. Likewise, treatment blocks can be weighted by the ignition probability of the lines passing through them. There are many metrics that can be calculated using this general method, but for this study we define six measures that together describe the risk and risk reduction associated with treatment blocks:

i) Current Risk is the mean probability of spread for sample lines passing through a block;

ii) Weighted Current Risk is Current Risk multiplied by the number of sample lines and mean ignition probability;

iii) Treated Risk is the mean probability of spread for sample lines in a block if it had a time since fire value of zero years;

iv) Weighted Treated Risk is Treated Risk multiplied by the number of sample lines and mean ignition probability;

v) Risk Reduction is Current Risk minus Treatment Risk; and

vi) Weighted Risk Reduction is the proportional difference between Weighted Current Risk and Weighted Treated Risk.

WildfireRisk: An R package for estimating wildfire risk and prioritising treatments

In this study we introduce the WildfireRisk package for R (R Core Team (2018)) and apply it to two case studies from New South Wales (NSW), one in The Hills District, on the northern fringes of Sydney and one in the Australian Capital Territory (Figure 1).

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Five data layers need to be loaded into R: i) Treatment blocks – a polygon layer; ii) Assets – a point layer (can be actual asset locations or centroids of census blocks); iii) Forest cover raster (cell values: 1 for present, 0 for absent); iv) Time-since-fire raster (cell values: years); v) An ignition raster with values ranging from 0 to 1.

In addition, the values of five constants must be set: i) FFDI (e.g. the 99.9th value for the study area); ii) KBDI; iii) the number of sample lines; iv) the distance interval to sample raster values along the line; v) line lengths.

Once the layers are imported and the constants defined, the complete risk calculation takes six steps. The outputs from these steps are spatial datasets that can be converted to desired formats (such as shapefiles). The package and documentation are available for download at https://github.com/mbedward/WildfireRisk/tree/0.1.15. An example script for one of our case studies is provided in the appendix to this paper.

The Hills District case study

The Hills District is an area of 40,061 ha on the north-western edge of the city of Sydney (Figure 2a), comprising as one of the 63 Bushfire Management Districts in NSW under the Rural Fires Act (1997).

It comprises the towns of Baulkham Hills, Rouse Hill and Castle Hill in the south and extends 30 km north through largely forested hills to the Hawkesbury River, which is at least 200 m wide and tidal in this stretch. The last major fire was the 2002 Baulkham Hills fire that burnt most of the forested northern section and destroyed dozens of houses. Bushfire risk planning is coordinated through the Hills Bush Fire Management Committee and the assets used for this analysis were 731 points and small polygons defined by the committee for the current Hills Bushfire Risk Management Plan (Anon 2010), and comprising mostly residential and some infrastructure areas (Figure 2a). Most of the area is under private ownership, with only 520 ha of managed conservation land. Consequently most of the area has no history of prescribed burning and there was no available set of treatment blocks. Instead, we created treatment blocks as a grid of polygons with 500 x 500 m cells (25 ha), extending 5 km outside the Hills District boundary. Cells with no forest were removed, leaving a total of 2748 cells. Forest extent was extracted from the NSW vegetation map (Keith 2004): 61% of the study region is forested (Figure 2c). Time-since-fire was calculated from historical fire boundaries provided by the Office of Environment and Heritage (OEH, unpublished data) with some prescribed burn boundaries on private land provided by the Rural Fire Service (RFS unpublished data). Time-since-fire was <= 5 years for 14% of the study area (mostly due to several large prescribed burns in the 2015/16 season) and was <= 10 year for 17% (Figure 2d). For ignition probability, we used a raster layer derived from Penman *et al.* (2013) (Figure 2e). For fire weather we used a single value for FFDI of 50 and KBDI of 100 for the whole study area. This is approximately the 99.5th percentile of FFDI for the Richmond weather station and 92nd percentile for KBDI.

ACT case study

The Australian Capital Territory (ACT, area 235,700 ha) comprises the national capital (Canberra, population 196,000) and surrounds. There is no defined set of assets for the ACT, so we used the 2011 Australian Bureau of Statistics census mesh blocks (as in Price *et al.* (2015)), of which there

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were 6707 with a median area of 3.5 ha (Figure 3a). The treatment blocks comprised a combination of predefined management blocks mapped by ACT Parks and Wildlife Service that cover some of the ACT, together with the footprint of historical prescribed burns (those > 1 ha), to produce 861 blocks (Figure 3b). Approximately 60% of the ACT is forested, including almost the entire western and southern sections. The urban areas are much less forested but there are large forested reserves (Figure 3c). In December 2003, several fires started in the mountains 25 km to west of Canberra and spread to the western suburbs, destroying > 400 houses and killing four people (Doogan 2006). To account for distant fire ignitions, we included a 20 km buffer around the ACT. A vegetation/fuel map defining 24 types mapped at 30 m resolution was provided by ACT Parks and Conservation Service, which we used to determine forested areas (any forest or woodland vegetation type). A spatial fire history database was provided by ACT Parks and Conservation Service (supplemented by Office of Environment and Heritage (unpublished data) for the buffer around the ACT. Since the 2003 fires, there have been 90 fires, and all of them have been very small (largest 320 ha). The database includes 570 prescribed burns. There was very little prescribed burning prior to the 2003 fire (mean 0.1% of the forest area per year 1970-1999), but there has been a marked increase since then (0.96% per year). Time since fire is typically 14 years in areas to the west and south of Canberra but much longer most of the suburbs and the area to the east of Canberra (Figure 3c). There are only small pockets with more recent burning, much of this in the bushland around the inner suburbs.

The fire history data were used to calculate a normalised ignition density grid, using a kernel density function with 2 km radius , and to give more emphasis to larger fires (that had a higher chance of impact), the function was weighted by the square root of the area of each fire, (Figure 3e). For fire weather we used a single value for FFDI of 50 and KBDI of 100 for the whole study area. This represents the 99.5th percentile of FFDI for Canberra airport and 92nd percentile for KBDI.

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Results

The Hills

For the Hills, asset risk was highest in the forested northern part, where the probability of a fire reaching an asset under fire weather conditions set for the analysis was 0.8-0.9 (Figure 4a). In the southern urban part, risk was lower (<0.6), though this was still relatively high and is a consequence of the strong influence of long time-since-fire, distance and the high chosen value of FFDI on the probability. The results were similar when weighted by ignition probability because it varied little across the study area (Figure 4b).

The number of lines passing through each treatment block increased from north to south due to asset density (Figure 4c). Current Risk (mean risk for the lines passing through each treatment block) showed a similar pattern to the risk for assets. In contrast, Weighted Current Risk (risk weighted by ignition likelihood and the number of lines in each block) was highest in the interface areas to the south and south west (Figure 4d). This change was predominantly because of the high number of lines in the interface areas. Risk Reduction (the risk reduction from treating the block) showed a range of values from 0 to 6.5% (Figure 5), which means a residual risk range from 93.5% to 100%. The largest reduction was in areas that are currently long unburnt. For Weighted Risk Reduction the spatial pattern was very similar to Weighted Current Risk, which is concentrated in those areas on the interface with many assets close to each treatment block (Figure 4e).

ACT

Assets (census blocks) were most densely concentrated around the city of Canberra (Figure 6a). Asset risk was highest in completely forested census blocks, which were mostly in the southern, western and eastern extremes of the ACT, some of which recorded a mean probability >0.95 that a fire in the vicinity would spread to reach the centre of the block (Figure 6b). In the suburban centre

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of Canberra, some of the census blocks had probabilities ~0.7, typically those located near to forested areas within the city. Southern suburbs had lower values, mostly because these areas are surrounded by grasslands with low forest cover. The ignition weighted asset risk was strongly weighted toward the more forested suburbs within the city (this mapped by census block in Figure 10 and amalgamated to suburbs in Figure 6c). The forested census blocks at the extremes of the ACT had low values (< 0.1) because ignition density is low in these areas. By contrast, ignition density is highest in the suburbs, and this combined with relatively high forest cover in the central suburbs led them to have the highest overall risk.

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As with The Hills, Current Risk showed a similar pattern to the risk for assets. However, the number of sample lines in treatment blocks was highest in the treatment blocks within the suburbs, because they are in close proximity to many census blocks (Figure 6d). Hence, Weighted Current Risk for treatment blocks was highest in the forested tracts within the suburbs and low in the completely forested areas to the west (Figure 6e).

Treating blocks tended to yield a small reduction in risk, with most blocks having values < 1% (Figure 5, 6f). Generally, the spatial pattern of risk reduction (Weighted Risk Reduction) was similar to the pattern of Weighted Current Risk. The largest mean risk reduction was in the forested areas where risk could be reduced to up to 11%. Risk reduction tended to further re-inforce the priority of treating the bushland patches within the city.

Discussion

This empirical method produces an objective comparison of wildfire risk for locations across a large study area quickly and easily. In our study areas the computation took 2 hours on a Windows laptop computer with Intel i7 processor, once the five required spatial layers had been assembled. To date, simulation methods have not matched either this speed or ease of application. This difference would be particularly advantageous if the risk assessment is to be conducted frequently or by non-experts (e.g. regional fire agency offices).

In both study areas, the highest risk to assets tended to be in the forested rural areas, but the highest risk in treatment blocks when weighted by ignition and the number of assets protected tended to be exactly at the Wildland Urban Interface. This will always be the case because this is where large numbers of assets co-exist with forest fuel. Previous studies have concluded that fuel treatments are more effective near the assets, due to the modest and transitory effect that fuel treatment has on fire behaviour (Price and Bradstock 2012; Penman *et al.* 2014), but they have not explicitly highlighted the role of asset density on the value of treatment. In the ACT the dominance of the Wildland Urban Interface (Radeloff *et al.* 2005) in the risk profile was even more marked because the ignition density was far higher there than in the rural areas. This is a common feature of Wildland Urban Interface areas (Syphard *et al.* 2008; Ganteaume *et al.* 2013; Price and Bradstock 2013). The reason that it was not so apparent in The Hills is because the ignition model used there did not show a strong spatial pattern.

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The risk reduction achieved by treating any individual block was small: the largest was an 11% reduction in the probability of a fire reaching an asset, and a median value < 1%. This is because in our method reducing fuel in one treatment block does not impose a barrier to spread, but rather reduces the mean time since fire value along the sample line. This may be close to reality since most empirical studies of fuel treatments find they are not a complete barrier (Price and Bradstock 2010; Syphard *et al.* 2011). Since a fuel treatment program will involve treating many blocks, the total risk reduction will be much greater than it is for a single block. We did not compare the effects of treating sets of blocks in this study, but this is an obvious avenue for further development of the method and could be incorporated into the WildfireRisk package relatively easily. Another application would be to quantify and compare the variation in risk that an ignition along the electricity transmission network would spread to assets.

Most other attempts to comprehensively map wildfire risk involve simulation of thousands of individual fires (Salis *et al.* 2013; Soto *et al.* 2013; Whitman *et al.* 2013; Mitsopoulos *et al.* 2015; Ager *et al.* 2016; Scott *et al.* 2017). In order to compare treatment blocks, the process has to be repeated with fuel removed from each block in turn, which could potentially involve many millions of simulations for study regions such as ours. Other attempts to prioritise treatment priority only consider the risk factors in the immediately around the houses and not the probability of spread from elsewhere (Elia *et al.* 2014).

The actual results differ from simulation simply because of the assumptions made. Some simulators do not include spotting and so will halt spread at narrow roads or other fuel breaks. Phoenix does include spotting but the evidence behind the mechanism is not comprehensive. We conducted an informal comparison between our asset risk map for The Hills and one generated by the Phoenix simulator (Rural Fire Service, unpublished), and found broad agreement in the patterns. The main difference was that Phoenix produced low risk values for areas close to the Hawkesbury River because the likelihood of wildfires crossing the river was low. Our method does not explicitly incorporate such fuel disruptions and so may be considered less realistic. However, a fire has crossed the Hawkesbury River in the past, and destroyed houses as a consequence (the Mt Hall fire, 26th December 2001).

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There are a number of limitations to our approach. As explained in the introduction, the method considers the spread of fire along a single line so does not explicitly account for the effects of disruptions such as major roads. In reality, fires may stop, go around or spot over such features, and no method can easily capture the full range of possibilities. Simulation methods have an advantage in that they will spread around obstacles, although simulations suffer from other problems as discussed in the introduction.

In our statistical model, time-since-fire had a linear effect on the risk of spread, which is unlikely to be correct because fuel accumulate following an asymptotic relationship with maximum values reached after 7-15 years (Price and Bradstock 2012; Thomas *et al.* 2014).

Our method does not account for the fact that more distant fires will be larger should they reach the assets than would close fires, and so they will affect more assets (Leavesley *et al.* 2017). This tends to bias the risk estimation toward areas close to the assets. This issue could be addressed by adding a correction factor for the width of fires as a function of distance, estimated by examining the shapes of historical fires.

A more general issue is suitability of the statistical for each study region. In our study we used a model developed for the greater Sydney region, which was appropriate for the Hills District, but it would be better to develop a model specific to each region. In the ACT, grass or grassy woodlands are more common fuel types, but we assumed that grassland was un-burnable which is clearly not correct. Our use of the point estimates of the regression coefficients also does not account for uncertainty in the model. We are currently adapting the WildfireRisk package to allow other, user-specified and flexible fire spread functions instead of the function in Price *et al.* (2015). This would be particularly useful for using the package outside Australia.

Given that the method has these limitations, we recommend that this method be used as only one component in a final risk planning process. Simulations or risk models derived by generalising simulation (for example into a Bayesian network (Penman *et al.* 2015; Papakosta *et al.* 2017)) are a useful complement for the empirical method. Also, local knowledge is required to interpret or modify these results. For example, experienced fire managers might know about common fire-paths, differences among ignitions in the level of risk posed, or fuel patterns not well described in the vegetation map.

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Table 1: Estimate table for the empirical risk model in Price *et al.* (2015), predicting the probability of the receiver burning, showing coefficients and probability level for each predictor variable in the final model. ":" indicates an interaction term.

Variable	Estimate	Std. Error	z value	P
(Intercept)	58.658	10.552	5.559	0.000
Log(distance to ignition)	-9.118	1.393	-6.547	0.000
Proportion of Forest	-0.402	0.119	-3.373	0.001
KBDI	0.041	0.008	5.028	0.000
Time since fire	0.117	0.029	4.011	0.000
FFDI (with Drought Factor set to 1)	0.931	0.247	3.768	0.000
Westwind (is wind direction $>225^{o}$ & $<315^{o}$?)	2.253	0.784	2.875	0.004
Forest:log(distance)	0.064	0.014	4.463	0.000

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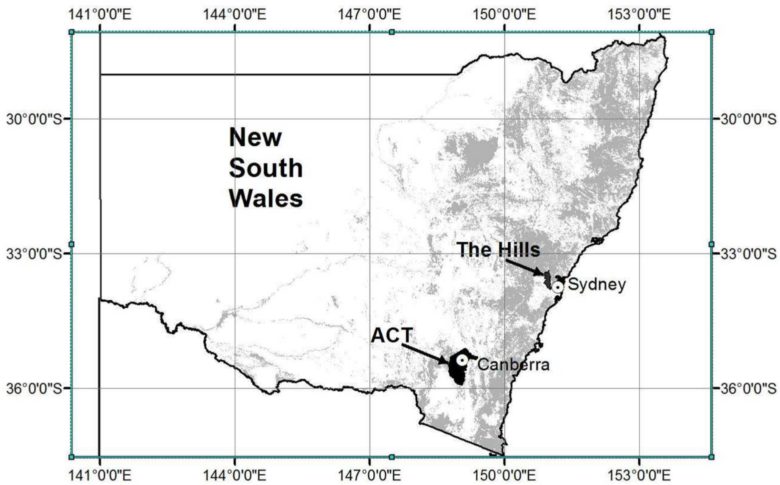

Figure 1 A map of New South Wales showing the two case studies in black and forests in grey (source New South Wales vegetation map (Keith 2004)).

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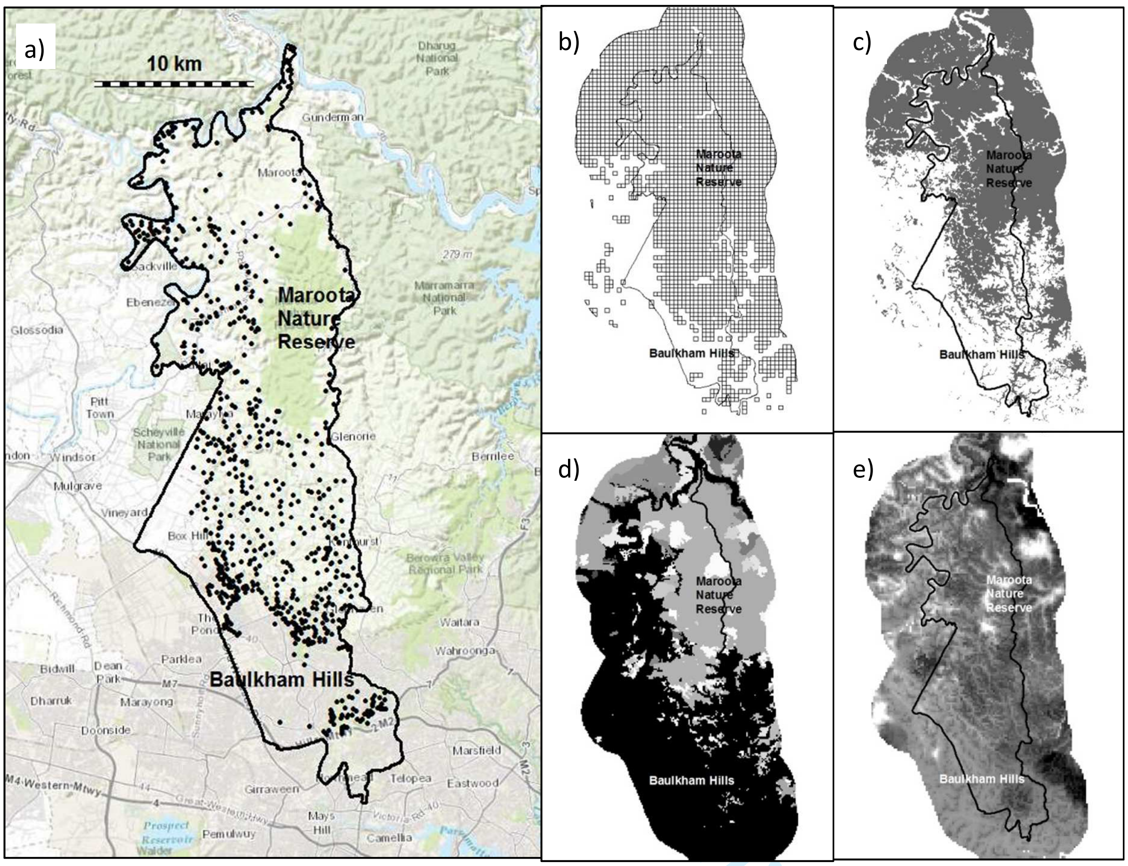

Figure 2: Context for The Hills case study: a) topography and centres of census blocks; b) treatment blocks; c) forest cover (0 or 1); d) time since fire (black = 47 years); e) ignition density.

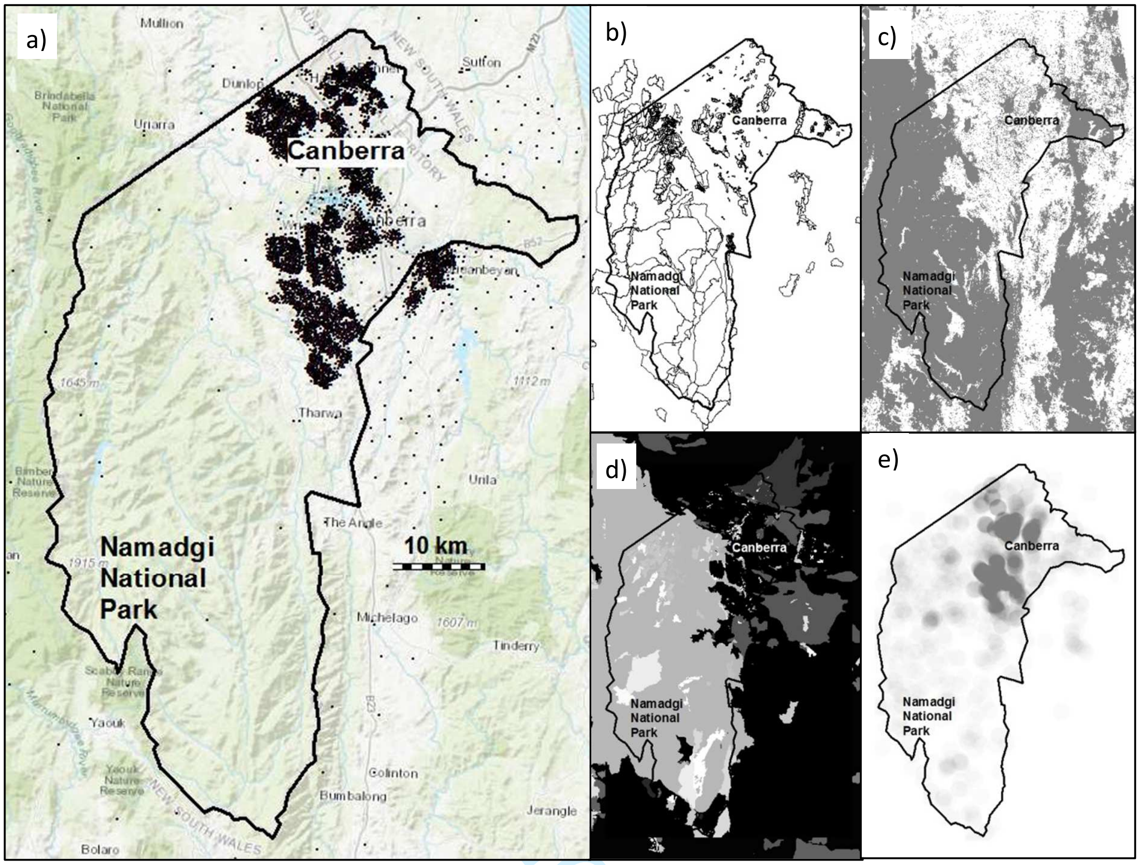

Figure 3: Context for the ACT case study: a) topography and centres of census blocks; b) treatment blocks; c) forest cover (0 or 1); d) time since fire (black = 47 years); e) ignition density.

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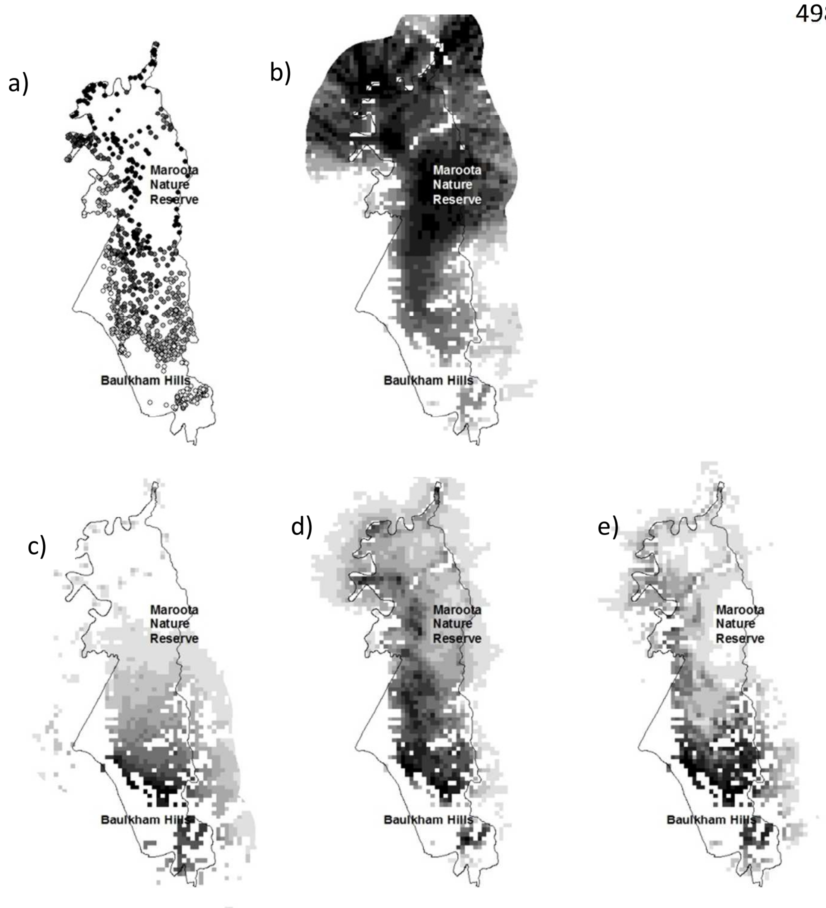

Figure 4: Results for The Hills case study: a) mean risk of fires reaching assets; c) current risk that fires from treatment blocks will reach assets; c) number of scan lines in treatment blocks; d) risk from treatment blocks weighted by ignition and number of scan lines; e) risk reduction in treatment blocks, weighted by ignition and number of scan lines.

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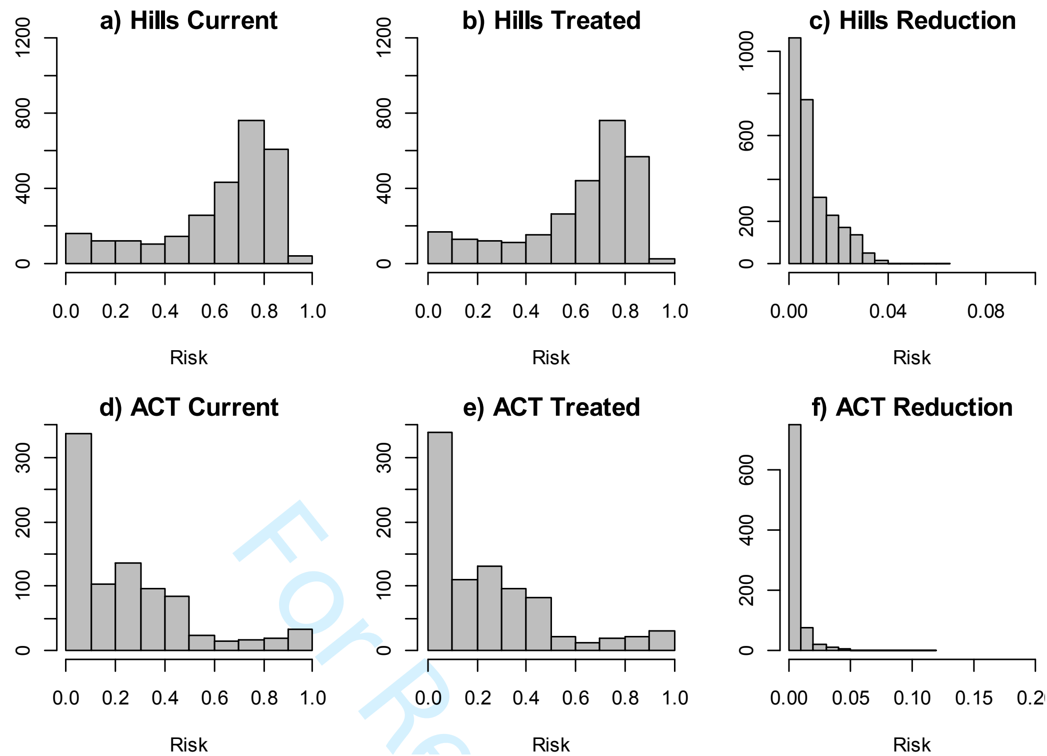

Figure 5. The distribution of mean risk values in the fuel treatment blocks (a-c for the Hills and e-f for the ACT): a and d) Current; b and e) Treated (if the time-since-fire in the block was zero) and c and f) the reduction (current – treated).

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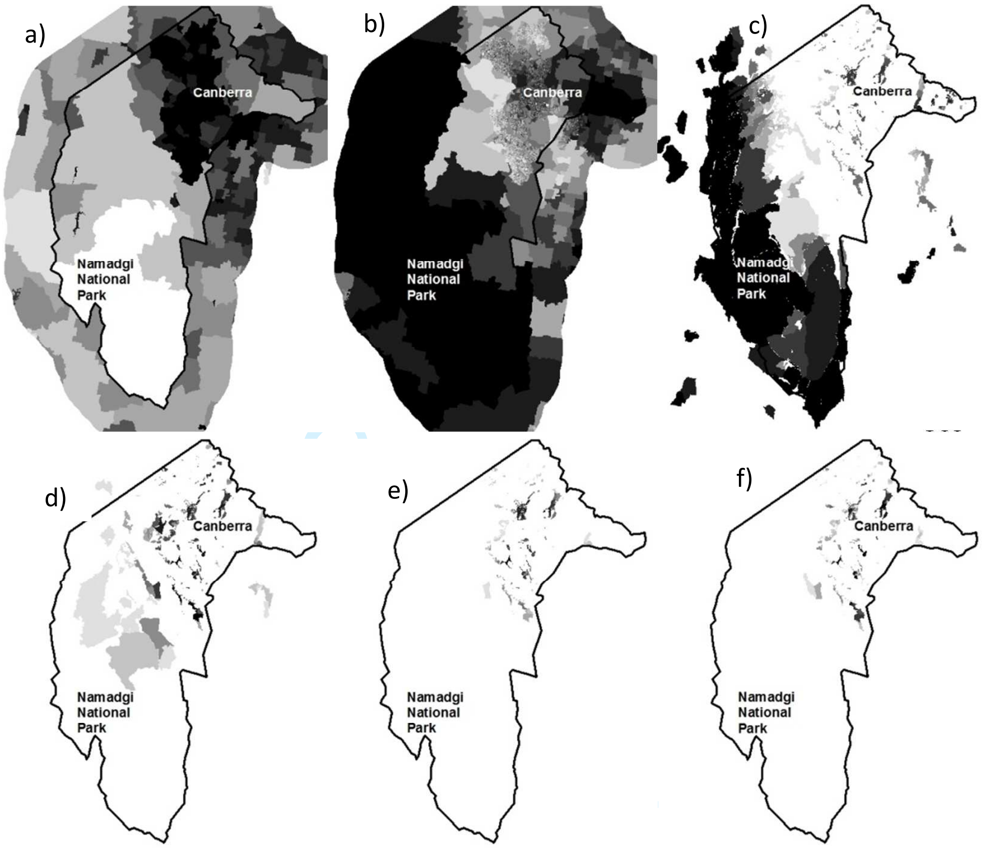

Figure 6: Results for the ACT case study: a) asset density (population); b) mean risk of fires reaching assets (census blocks); c) current risk that fires from treatment blocks will reach assets; d) number of scan lines in treatment blocks; e) risk from treatment blocks weighted by ignition and number of scan lines; f) risk reduction in treatment blocks, weighted by ignition and number of scan lines.

Appendix

```
# Example code for WildfireRisk package applied to data for The Hills District
#Several packages must also be installed for WildfireRisk to work.
library(raster)
library(sf)
library(dplyr)
library(dbplyr)
library(foreign)
library(WildfireRisk)

#Read in the feature data. Assets can be a shapefile or table with point coordinates. NB coordinates
must be in columns 1 and 2 (x then y)
setwd("c:/wollongong/projects/nsw_risk/hills/gis")
assets<-read.csv("hills_assets_56m.csv")
treatblocks <- st_read("hills_fish_buff.shp")

#read in raster layers
tsf<-readAll(raster("hillstslf17c/hdr.adf"))
forest<-readAll(raster("hills_for/hdr.adf"))
ignition<-readAll(raster("hills_igplus/hdr.adf"))

#Function to set random sample line lengths
len_fun <- function(n) rexp(n, 1 / 4000)

#create sample lines
sampelines<-make_scan_lines(assets,80,len_fun,crs = tsf)


#Calculate risk for lines
assetlinerisk<-calculate_risk(samplelines,tsf,forest,sample.spacing=100)
#Save the calculated line risk to avoid having to repeat, or to use it in another function
st_write(censlinerisk,"hills_r_line_risk.shp",delete_layer=TRUE)
assetrisk<-summarize_location_risk(assetlinerisk,quantiles=c(0.25,0.95))
st_write(censrisk,"hills_r_asset_risk.shp",delete_layer=TRUE)

#get the ignition probs at each line start point
ignition.loc <- summarize_location_nbrhood(samplelines,ignition)
st_write(ignition.loc,"hills_r_assets_ig.shp",delete_layer=TRUE)

#Calculate risk for treatment blocks
blockrisk <- summarize_block_risk(assetlinerisk, treatblocks)
#This is the block risk product, written to a shapefile
st_write(blockrisk,"hills_r_fishnet_riskb.shp",delete_layer=TRUE)

#Recalculate block risk if they are treated
blockrisktreat<-treat_blocks(blockrisk,assetlinerisk)
st_write(blockrisktreat,"hills_r_fishnet_risktreat.shp",delete_layer=TRUE)

#Save the results to a file
treatdat<-select(blockrisktreat,ID,ptreat_mean)
write.csv(treatdat,"Blocktreat.csv")
```

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