CSIRO PUBLISHING

International Journal of Wildland Fire **2015**, *24*, 37–47
http://dx.doi.org/10.1071/WF14024

Location, timing and extent of wildfire vary by cause of ignition

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Abstract. The increasing extent of wildfires has prompted investigation into alternative fire management approaches to complement the traditional strategies of fire suppression and fuels manipulation. Wildfire prevention through ignition reduction is an approach with potential for success, but ignitions result from a variety of causes. If some ignition sources result in higher levels of area burned, then ignition prevention programmes could be optimised to target these distributions in space and time. We investigated the most common ignition causes in two southern California sub-regions, where humans are responsible for more than 95% of all fires, and asked whether these causes exhibited distinct spatial or intra-annual temporal patterns, or resulted in different extents of fire in 10–29-year periods, depending on sub-region. Different ignition causes had distinct spatial patterns and those that burned the most area tended to occur in autumn months. Both the number of fires and area burned varied according to cause of ignition, but the cause of the most numerous fires was not always the cause of the greatest area burned. In both sub-regions, power line ignitions were one of the top two causes of area burned: the other major causes were arson in one sub-region and power equipment in the other. Equipment use also caused the largest number of fires in both sub-regions. These results have important implications for understanding why, where and how ignitions are caused, and in turn, how to develop strategies to prioritise and focus fire prevention efforts. Fire extent has increased tremendously in southern California, and because most fires are caused by humans, ignition reduction offers a potentially powerful management strategy, especially if optimised to reflect the distinct spatial and temporal distributions in different ignition causes.

Received 22 February 2014, accepted 16 June 2014, published online 13 January 2015

Introduction

Recent increases in the size and extent of wildfires across the world (Bowman *et al.* 2009) are a major policy and management concern because of their ongoing and potentially escalating effects on ecological integrity (Pausas and Keeley 2009), and human lives and property (Price and Bradstock 2012; Syphard *et al.* 2012). Wildfire policy and management efforts have focussed largely on fire suppression and fuels management (e.g. Butry 2009). However, the growing fire problem has prompted investigation into alternative approaches for reducing fire hazard, such as hardening structures to make them more fire resilient (Gill 2005), land use planning (Syphard *et al.* 2012; 2013) and creating areas of defensible space immediately adjacent to structures in fire-prone areas (Cohen 2000; Winter *et al.* 2009, Syphard *et al.* 2014).

An additional option is to develop wildfire prevention efforts focussed on reducing fire ignitions (Prestemon *et al.* 2010; Gill *et al.* 2013). Simulation models suggest that ignition management, simulated through reduced ignition probability, can be more effective than fuels management in reducing area burned (Cary *et al.* 2009). However, we propose that beyond merely reducing ignitions, there may be value in targeting particular types of ignitions if certain sources play a larger role in area burned. In regions such as southern California and the Mediterranean basin, human-caused ignitions dominate over natural lightning ignitions, accounting for more than 95% of all fires (Syphard *et al.* 2007, 2008; Romero-Calcerrada *et al.* 2008). Human-caused fires derive from a variety of sources and these potentially vary spatially and temporally in ways that could affect the size and destructiveness of wildfires.

Most human-caused fires are unplanned and unintentional; for example, escaped campfires or debris burns, sparks from cars or equipment, children playing with fire or cigarette butts thrown out of car windows. However, arson – or incendiary – fires are intentionally set and represent fundamentally different behaviour. Ignition prevention programmes could take many forms depending on the target source of ignition. For example, some governmental or volunteer organisations devote time and resources to educating the public about the danger of accidental ignitions, law enforcement often targets arsonists and some public parks and forests are closed to recreational activities on days with extreme fire weather.

Prestemon *et al.* (2010) found that state expenditure on wildfire prevention programmes in Florida yielded net benefits economically and significantly reduced the number of preventable wildfires. However, the authors found spatial variation in the benefits of these programmes, potentially due to geographic differences in the type of prevention activity applied relative to the distribution and proportion of different preventable wildfire causes. It therefore stands to reason that if different causes of ignitions have distinct spatial or temporal distributions, ignition prevention programmes could be optimised to target these distributions in space, time or according to specific cause.

Recent investigations have demonstrated that ignition patterns are non-random and significantly influenced by a range of biophysical and anthropogenic factors (e.g. Cardille *et al.* 2001; Sturtevant and Cleland 2007; Syphard *et al.* 2008; Catry *et al.* 2009; Bar Massada *et al.* 2013; Sadasivuni *et al.* 2013), and that the distribution and drivers of lightning ignitions are quite different from those of anthropogenic ignitions (Reineking *et al.* 2010; Narayanaraj and Wimberly 2011). Other studies have also shown arson fires to be predictable in time and space (Prestemon and Butry 2005; Gonzalez-Olabarria *et al.* 2012; Penman *et al.* 2013). Distinct spatio–temporal signatures of different ignition sources have also been suggested through differences in spatial clustering (Genton *et al.* 2006).

Our objective in this study was to explore further distinctions among ignition causes – that is, beyond arson, accidental and lightning – to identify whether different ignition sources exhibit distinct spatial or intra-annual temporal patterns that result in disproportionate numbers of fires or area burned in two southern California sub-regions. Results demonstrating distinctive characteristics of ignition causes could benefit prevention programmes through the determination of why, where and when most ignitions occur, and which ignition causes are most important to target under varying circumstances.

We asked:

1. Do different ignition causes vary in terms of number of fires, and area and month burned?
2. Are different ignition causes explained by different drivers?
3. Are distinctive spatial patterns exhibited in different ignition causes?

Methods

Sub-regions

The two sub-regions included the Santa Monica Mountains in Ventura and Los Angeles counties and the western portion of San Diego County that falls within the South Coast Ecoregion in southern California, USA (Fig. 1). The San Diego study area did not include the land and ignitions from Military Base Camp Pendleton because of its unique ignition regime that is driven almost entirely by military training activities. Owing to a mediterranean climate, with mild, wet winters and long summer droughts, both areas are extremely fire prone and large, high-intensity wildfires driven by hot, dry Santa Ana winds are characteristic of their natural fire regimes (Keeley 2006). The areas are topographically and biologically diverse, and southern California is home to more threatened species than any other region in the mainland US. Although large areas of wildland vegetation remain in both areas, substantial population growth has resulted in massive expansion of the wildland–urban interface (WUI) (Hammer *et al.* 2007), which in turn has led to a surge in the number and areal extent of human-caused ignitions (Keeley *et al.* 1999). Escalating fire frequency threatens the

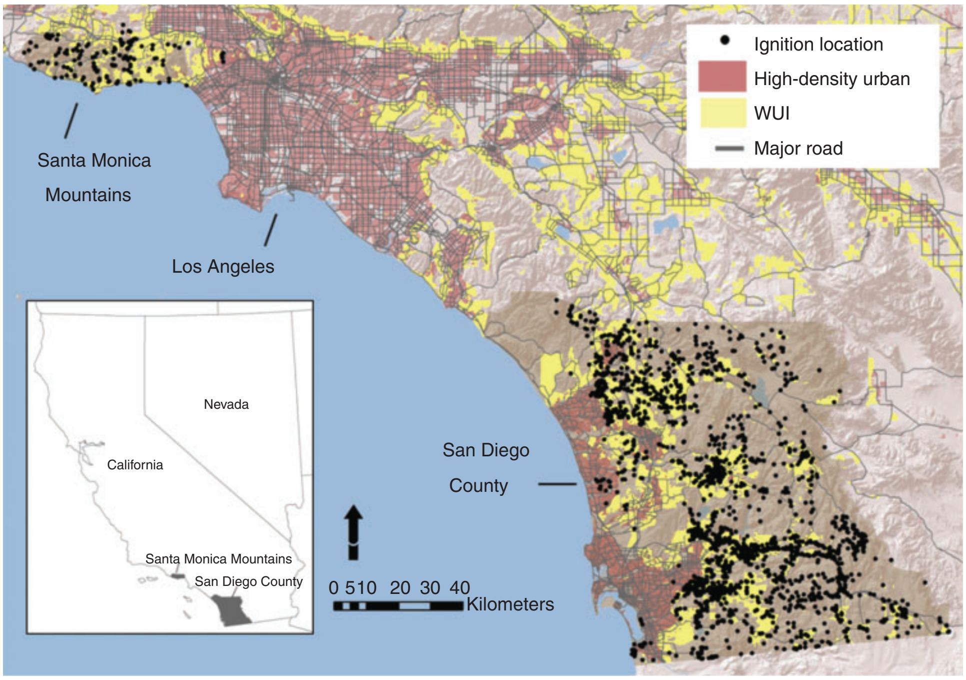

Fig. 1. The Santa Monica Mountains and San Diego County sub-regions in southern California. 'WUI' is the wildland–urban interface.

regions' biodiversity (Keeley *et al.* 2012) and human safety (Keeley *et al.* 2013). Southern California loses an average of 500 homes per year to wildfires (Cal Fire 2000). In both sub-regions, humans are responsible for more than 95% of all ignitions (Syphard *et al.* 2007).

Data

Ignition data

For San Diego County, we acquired all digital ignition data from the California Department of Forestry and Fire Protection (Cal Fire, Carl Palmer, pers. comm.). These data consisted of separate files for different agencies responsible for the fires, and we included those records from agencies that provided the source of ignition. To calculate statistics describing area burned, number of fires and month of ignition by cause, we used data from Cal Fire, the US Fish and Wildlife Service (FWS), and the US Forest Service (USFS) dating from 2000 to 2010, which included 3438 ignitions. Unlike other fire databases, these data had no minimum size limit. For all ignition data, we carefully reviewed the records to remove duplicates that were listed in more than one agency's database.

Owing to the spatial nature of the regression modelling and mapping analysis, we further restricted the San Diego ignition data to recent years when the spatial accuracy was more precise. For spatial analysis of Cal Fire data, we used ignition location data from 2006 to 2010 ($n = 1513$) as these were reported at the highest level of precision (precise to 5 *v.* 2 decimal digits, in earlier years). The precision of the FWS (2000–2010, $n = 372$) and USFS (2000–2010, $n = 535$) data matched the most recent Cal Fire data.

The ignition data for the Santa Monica Mountains included 248 coordinate points from 1982 to 2011 acquired from the National Park Service (NPS) fire records, assembled by Robert S. Taylor (pers. comm.). These data were compiled from the National Fire Plan Operations and Reporting System database, and the Department of Interior Wildland Fire Information Management database. Ignition locations were error checked, validated and corrected using the original paper 1202 forms and ancillary data on fire incidents, including historical orthophotos, satellite imagery and Burned Area Reflectance Classification imagery, as well as first-hand accounts by several long-time NPS personnel. The median estimated accuracy was 30 m, the mode was 10 m and the mean (286 m) was strongly affected by outliers.

Explanatory variable data

In a previous study in the Santa Monica Mountains, we identified several human and biophysical variables that were significant in explaining the spatial distribution of ignitions (Syphard *et al.* 2008). Here we considered the same terrain variables for both sub-regions, including elevation, slope gradient and a transformed slope aspect ('south-westness'),' all derived from 30-m US Geological Survey Digital Elevation Models. Terrain variables may explain ignition patterns through their influence on factors that affect flammability and spread, such as local climate, fuel moisture, vegetation composition and distribution, soil moisture and development, and relative humidity (Whelan 1995). Because human-caused ignitions frequently occur along transportation corridors (Stephens 2005), we also reused the US Topologically Integrated Geographic Encoding and Referencing system TIGER/line files (available at https://www.census.gov/geo/maps-data/data/tiger-line.html, verified 6 November 2014) to create interpolated maps of distance to roads, this time adding the San Diego sub-region.

Variables delineating climate, vegetation and human variables were updated from the Syphard *et al.* (2008) study to ensure data consistency between the two sub-regions, and in the case of human variables, to take advantage of better data availability. Maps of recent historical climate reflecting spatial variability in average conditions (averaged over 1970–1999) included mean January minimum temperature, mean July maximum temperature and mean annual precipitation using 800-m grids from the Parameter-elevation Regressions on Independent Slopes Model (PRISM Climate Group 2004). Broad-scale temperature and precipitation may be important predictors of ignition locations because climate trends are associated with factors such as fuel moisture or composition and productivity, which in turn can affect fuel accumulation or combustion (Whelan 1995). After performing a correlation analysis to check for multicollinearity, we eliminated January minimum temperature and annual precipitation from the analysis because they were correlated ($r > 0.6$) with several other variables. However, mean July maximum temperature was not correlated with the other variables in the analysis.

Because flammability and fire behaviour tend to vary according to vegetation type in southern California (Wells *et al.* 2004), we used the Calveg existing vegetation data (USDA Forest Service 2010), which covered the whole region. We stratified the vegetation classes into five general vegetation types that reflect physiognomic structure and broad differences in fire behaviour, including chaparral shrublands, coastal sage scrub, grass, forest and non-vegetated, which is typically urban and thus includes a mix of cover types, from impervious surface to grass and ornamental landscaping vegetation around homes.

Although fuel age and flammability are unrelated in extreme weather conditions in southern California (Moritz *et al.* 2004), we evaluated fuel age in this study as a potential predictor of ignition locations because our dataset included small fires that burned under a range of weather conditions. This was a variable we did not explore in previous research (Syphard *et al.* 2008). The majority of fires are stand replacing in southern California shrublands, so we calculated the age of the vegetation at every ignition point by subtracting the time of last fire from the year of the ignition event using fire perimeter maps from the California Department of Forestry and Fire Protection (Cal Fire 2013).

Finally, we used updated GIS data of all residential structures in each sub-region (from Syphard *et al.* 2012) to interpolate maps of housing density and distance of ignitions to structures. We used these variables in lieu of data delineating the WUI, which was important in Syphard *et al.* 2008, but correlated with our housing variables here ($r > 0.6$). Because most ignitions in this region are caused by humans, we expected the housing variables to delineate patterns where human activities, and thus fire ignitions, are concentrated.

Analysis

For both sub-regions, we divided the ignition data into groups representing the most common, major causes, which were listed as attributes of the spatial data. The major causes were the same for both regions, although a substantial number of wildfires were the result of escaped prescribed burns in the Santa Monica Mountains, so we retained this as an additional, separate group in that sub-region. In both regions, ~30% of fire ignition causes were labelled as 'unknown' or 'miscellaneous.' Because these were uninformative relative to our research questions, we excluded them from the analysis.

To evaluate the relative contribution of each ignition cause to the extent of fire in each sub-region, we plotted the proportion of number of fires and the area burned by those fires for all ignition types. We also evaluated the seasonal distribution of area burned by ignition cause by plotting the proportion of each cause's total area burned by the month when the ignitions of those fires occurred.

For both predictive mapping and evaluation of variable importance, we used the MaxEnt model (Phillips *et al.* 2006; Elith *et al.* 2011), which employs a machine learning algorithm to estimate distributions by minimising the relative entropy between probability densities through iterative contrasts among values of explanatory variables at locations where ignitions occurred *v.* locations that are randomly distributed across the sub-region. We chose the MaxEnt modelling approach because it was shown to be more suitable than other statistical methods for ignition modelling (Bar Massada *et al.* 2013); it has been successfully used to project fire risk to houses (Syphard *et al.* 2012, 2013); and it is one of the best-performing species distribution models, especially in cases with presence-only data and small sample sizes (Elith *et al.* 2006, Wisz *et al.* 2008). We developed separate MaxEnt models for all ignition types in both sub-regions.

For all models, we used the default random background sample of 10 000 points. These non-ignition points should not be considered true absence points because it is possible that an ignition could occur in these locations, but simply did not during the time frame of the study. Rather, these background points represent the full range of environmental variation across the sub-region from which we can thus distinguish the environmental conditions that characterise the ignition locations. We used hinge features, and linear and quadratic functions to produce smoother response curves that minimise over fitting of the model (Elith *et al.* 2011). The output of MaxEnt assigns a probability of ignition (from 0–1) to every cell in the map. This probability is based on logistic function of the MaxEnt raw values, which are exponential functions of the explanatory variables. MaxEnt estimates variable importance as a function of information gain resulting from every environmental variable throughout the model iterations. To assess the accuracy of the MaxEnt models, we used a bootstrapping procedure in which we ran the model 10 times, each with a random percentage of the ignition data (sampling with replacement) withheld for testing the model predictions. The results are presented as averages of the 10 replicate simulations.

We did not use fuel age as a predictor in the MaxEnt analysis because the software selects values of background points from static maps. Therefore, to evaluate the contribution of fuel age relative to other variables, and to determine whether relative variable importance was similar between two methodological approaches, we performed a hierarchical partitioning analysis (Chevan and Sutherland 1991) with the hier.part package in R (Walsh and Mac Nally 2008). Hierarchical partitioning evaluates all combinations of explanatory variables in a multiple regression framework and returns the unique, independent percent contribution of each variable to model fit. Because we had a binary dependent variable (ignition *v.* non-ignition), we used the binomial family and maximum likelihood goodness-of-fit measure to develop our models.

To perform the hierarchical partitioning, we generated random background points that were at least 250 m apart to minimise spatial autocorrelation (Dormann *et al.* 2007). We generated 10 000 points in San Diego County and 5089 points in the Santa Monica Mountains, which was the largest number possible while maintaining a 250-m separation distance. For all ignition and background points, we extracted values from our gridded maps of the explanatory variables. To assign a vegetation age to the random background points, we first recorded the proportion of ignitions that occurred in each year in each sub-region. Based on those proportions, we extracted vegetation age data for the background points from maps of time since last fire for every year. Because the hierarchical partitioning algorithm does not treat categorical variables, we converted the categorical vegetation map used for MaxEnt into a discrete binary variable representing grass or no grass. We chose grass as the vegetation type to model because the MaxEnt models showed a disproportionately large number of ignitions that occurred in that vegetation type, particularly in the Santa Monica Mountains.

Because some of the ignition cause groups had fewer than 20 observations, we only performed the hierarchical partitioning analysis for the full set of ignitions in the Santa Monica Mountains. Although MaxEnt has shown excellent predictive power at all sample sizes, even as small as 10 (Wisz *et al.* 2008), we also withdrew several ignition types from the MaxEnt analysis in the Santa Monica Mountains because of low sample size.

Results

There were no substantial differences in the number of fires by cause in the Santa Monica Mountains, although equipment fires were the most numerous (Fig. 2*a*). In contrast, most of the area burned in the Santa Monica Mountains resulted from arson and power line ignitions, with moderate area burned due to campfires and escaped prescribed fires. The most numerous fires occurred primarily in late spring from May through July, but most of the arson, power line and campfire ignitions that burned the majority of area occurred from August through November (Fig. 3*a*).

In San Diego County, equipment-caused fires were by far the most numerous, and these also accounted for most of the area burned, followed closely by the area burned by power line fires (Fig. 2*b*). Ignitions classified as equipment caused frequently resulted from exhaust or sparks from power saws or other equipment with gas or electrical motors, such as lawn mowers, trimmers or tractors. Most of the area burned by equipment use and power lines occurred in October, although a moderate extent of area burned was caused by power lines in July as well (Fig. 3*b*).

The analysis of variable importance in MaxEnt showed that the relative contribution of explanatory variables varied

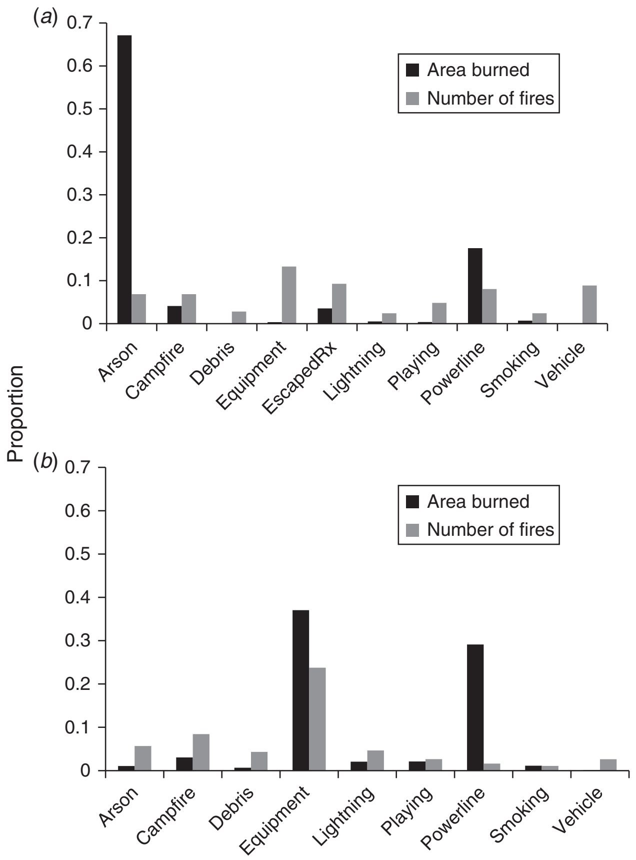

Fig. 2. Proportion of number of fires and area burned by cause of ignition in (*a*) the Santa Monica Mountains and (*b*) San Diego County. 'EscapedRX' means escaped prescribed fire.

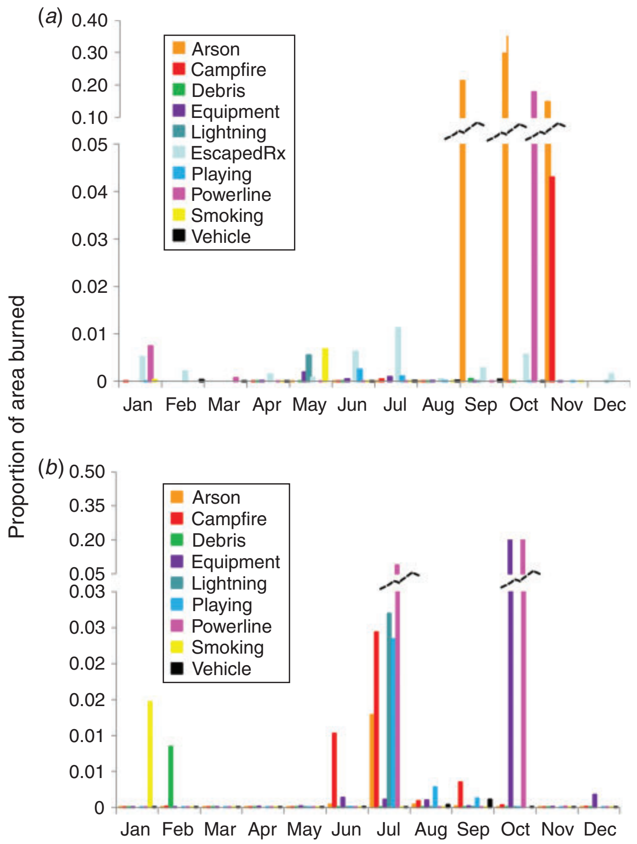

Fig. 3. Proportion of all area burned by ignition cause by month for (*a*) the Santa Monica Mountains and (*b*) San Diego County.

somewhat according to ignition source as well as by sub-region (Table 1). Overall, vegetation type was more important in the Santa Monica Mountains than in San Diego County, with grass being the most common vegetation type for all ignition causes. In San Diego, ignitions occurred most frequently in grass or forest vegetation types. Distance to roads and structure density were more predominant overall in explaining ignitions in San Diego County. In fact, distance to road contributed more than 50% to the model for all ignition sources except for campfire and lightning. In both sub-regions, ignitions were more likely to occur close to roads and structures, and at intermediate structure densities. The mean area under the curve (AUC) of receiver operating characteristic plots for the 10 replicate, bootstrapped models ranged from 0.90 to 0.97 for the Santa Monica Mountains and from 0.81 to 0.96 for San Diego County (Table 1). These AUCs indicated good overall ability of the models to discriminate between ignition and background locations.

The difference in relative contribution of explanatory variables between the sub-regions was not as apparent when all ignition data were modelled together using hierarchical partitioning (Fig. 4), although the hierarchical partitioning analysis of separate ignition cause groups in San Diego County showed similar rankings to the MaxEnt results (not shown). In the Santa Monica Mountains, more ignitions were explained by grass than in San Diego County, although vegetation age was not important in explaining ignition patterns in either sub-region.

Different sources of ignitions also had different spatial patterns, as seen through the predicted ignition probability maps (Figs 5, 6). In the Santa Monica Mountains (Fig. 5), campfires and playing-with-fire ignitions had high prediction probabilities in diffuse patterns throughout the sub-region with slightly higher probabilities along the perimeter. Power line ignitions had a more concentrated distribution along the perimeter of the sub-region and in all three the effect of topography is evident through the lines of high probability that trace the canyons leading into the mountains. The effect of roads on ignition probabilities for arson- and vehicle-caused fires is apparent through the linear features crossing the landscape, and the equipment-caused fires are mostly located near residential areas.

In San Diego County, lightning- and campfire-caused ignitions were predicted at highest probability in distinct patterns in the eastern part of the region, where the higher elevation conifer forests are distributed (Fig. 6). Road influence on the spatial pattern of ignition probabilities is clear in fires caused by arson, equipment use, playing with fire, smoking and vehicles, although arson fires show the highest probabilities in the western, high-density urban areas. The WUI, where housing density is low to intermediate is an apparent influence in most ignition maps as illustrated by comparison of Fig. 1 with Figs 4 and 5.

Table 1. Mean relative variable importance measured by percent contribution and AUC for 10 replicates of MaxEnt models for patterns of different ignition causes in the Santa Monica Mountains and San Diego County

	Distance to road	Distance to structure	Structure density	South-westness	July temperature	Elevation	Slope	Vegetation type	Mean AUC
Santa Monica Mountains									
Arson	37.8	12.9	6.2	6.3	5.5	1.5	14.1	15.6	0.96
Campground	12.4	21.8	10.1	16.4	9.4	8.5	11.4	10.0	0.90
Equipment	13.0	10.1	30.7	9.3	9.2	1.8	6.3	19.7	0.97
Playing	25.7	12.5	11.8	15.3	2.7	10.6	10.9	10.4	0.91
Powerline	20.3	6.3	19.4	7.1	19.8	7.8	4.3	15.0	0.94
Vehicle	47.5	4.4	5.2	12.0	3.4	9.4	5.5	12.5	0.96
San Diego County									
Arson	65.1	5.4	18.3	1.5	3.5	3.0	3.0	0.2	0.87
Campground	5.3	5.7	25.7	2.1	8.9	21.7	11.7	18.9	0.81
Debris	73.3	4.0	16.9	0.8	1.1	0.9	0.2	2.7	0.93
Equipment	72.0	0.5	20.9	0.5	3.8	1.5	0.6	0.3	0.87
Lightning	23.8	3.2	40.1	2.2	8.4	16.4	0.4	5.6	0.77
Playing	78.6	2.9	10.5	1.2	1.5	2.9	1.8	0.6	0.96
Powerline	49.0	4.0	20.0	0.1	1.4	3.3	2.2	1.7	0.96
Smoking	65.5	2.3	17.5	2.6	0.1	8.1	0.7	3.0	0.83
Vehicle	72.0	1.0	17.3	1.7	4.3	1.9	0.5	1.4	0.95

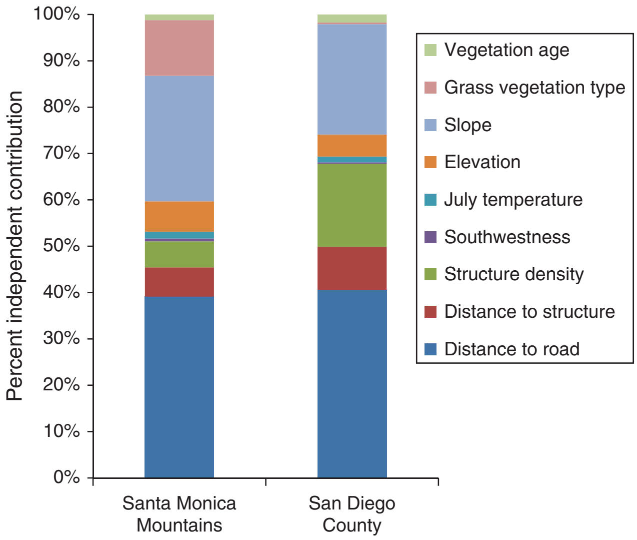

Fig. 4. Percent independent contribution of variables in hierarchical partitioning models explaining patterns of all ignitions in the Santa Monica Mountains and San Diego County.

Discussion

Fire extent and frequency have increased in recent decades in southern California (Keeley *et al.* 1999), and because most fires are caused by humans, ignition reduction offers a potentially powerful management strategy. The present study showed that in southern California, different causes of ignitions had distinctive spatial and temporal patterns, which resulted in varying numbers and extent of fires. This makes clear the point that certain causes of ignition have disproportionately high fire effects. As in previous modelling studies in the southern California region (Syphard *et al.* 2008), ignition locations in this study were generally concentrated in close proximity to human infrastructure, with some significant contributions from climate, terrain and vegetation (Table 1, Fig. 4). Despite these general similarities, however, this study showed that the relative importance in terms of number of ignitions and area burned, as well as factors that explained ignition patterns, varied by ignition cause. These variations in spatial patterns and importance of predictor variables have important implications for understanding why, where and how ignitions are generated in the region and in turn suggest avenues for developing strategies that would focus fire prevention efforts.

For both the Santa Monica Mountains and San Diego County, a major ignition source for area burned is power lines (Fig. 2). Power lines are recognised for causing large and destructive fires, not only in southern California (Keeley *et al.* 2012), but also in Australia (e.g. Cruz *et al.* 2012). One reason this is so important in southern California is that power line fires are concentrated in the autumn months (Fig. 3) and are associated with extreme winds known locally as Santa Ana winds, which contribute to extreme fire behaviour (Mitchell 2013). Santa Ana winds present a major challenge for utilities in the region because high-velocity gusts may cause power lines to fall or arc, conductors to clash or trees to come into contact with the lines. Power line-ignited fires may also become large when they are located in remote areas where access to the fire is difficult.

Aside from minimising vegetation under overhead conductors, options to reduce these ignitions have been controversial. Owing to a rash of lawsuits against utility companies (Keeley *et al.* 2012, box 13.2), some have responded by monitoring weather conditions and selectively turning off the power supply to high-risk areas under high wind conditions. However, this ‘solution’ is controversial because it carries with it other risks such as encouraging residents to use gas-powered generators, which can cause fires; and if a fire does occur, it disrupts communications and can threaten structure protection for

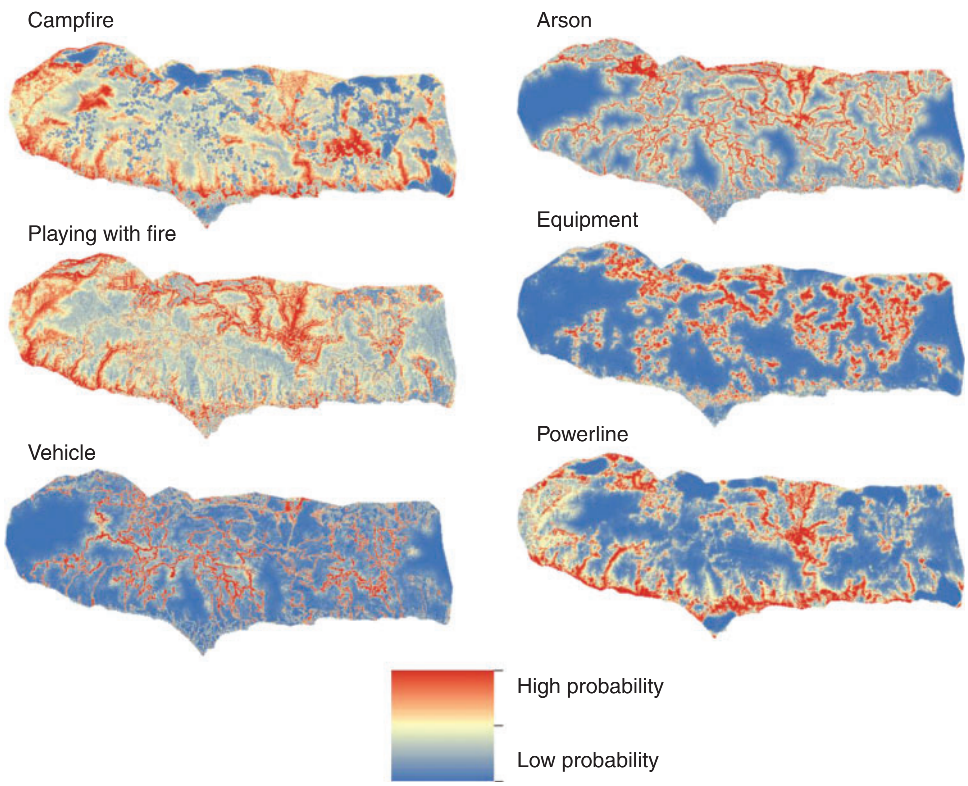

Fig. 5. Predicted probability of ignition (0–1.0) by major cause in the Santa Monica Mountains.

homes dependent on wells for their water source. It has been suggested that underground power lines in high-risk wind corridors could reduce such ignitions (Keeley *et al.* 2009), but this option is generally viewed as too costly by power companies. In Australia, however, underground power lines were recommended after the deadly Victoria fires in 2009, and some state regulations now require them under certain conditions (Victorian Bushfires Royal Commission 2010).

The other very important ignition source for area burned differed between the two regions. In the Santa Monica Mountains, arson fires were a major factor, and such ignitions are fundamentally different from other human ignition causes because they are intentional rather than accidental. Therefore, their location and timing are chosen. Miller (1968) noted a link between Santa Ana winds and crime in southern California, which would be consistent with large arson fires in the autumn months when the extreme fire hazard created by Santa Ana winds is widely noted in the media. Several comprehensive studies of arson ignitions have been conducted (Prestemon and Butry 2005; Thomas *et al.* 2011); but as these studies suggest, much more research needs to be carried out, as the behavioural patterns driving arson ignitions is complex and may be similar to other criminal activities. Further modelling of arson fires could therefore integrate theories from the criminology and social sciences into the development of explanatory variables. In fact, theories on accidents could also be used to create explanatory variables for unintentional human-caused ignitions.

Law enforcement has become quite strict in southern California, as arson is a felony. In fact, the arsonist convicted for starting the 2003 Old Fire in San Bernardino County, CA received the death penalty (http://articles.latimes.com/2013/jan/29/local/la-me-old-fire-sentencing-20130129, verified 13 August 2014). Information on the timing, drivers and spatial pattern of these ignitions, combined with more behavioural analyses, might help police organisations identify how to prevent these fires before they start. However, a potential pitfall of addressing arson fires is that, because arsonists want to cause fires, they might alter their behaviour to adapt to and avoid targeted management or enforcement activities. Nonetheless, research on other crimes suggests that criminal prevention efforts actually help reduce crime in neighbouring areas, rather than to simply move the criminal behaviour to untargeted locations (Weisburd *et al.* 2006).

The other ignition source associated with large area burned was equipment use in San Diego County. Although equipment use was one of the most numerous ignition causes in the Santa Monica Mountains, it did not result in extensive area burned. Across the state of California, equipment use is a common ignition cause and results in more than 1600 fires per year (Cal Fire 2011).

One challenge in trying to manage for equipment fires is that they encompass a wide range of activities that are collectively presented as ‘equipment caused’ in the fire records, making it impossible to pinpoint the type of equipment. Not surprisingly, most equipment-caused ignitions occur close to roads and within the WUI (Figs 5, 6). Because equipment use is such a common ignition source and is a potentially modifiable behaviour, this is one ignition source that should be a target for future

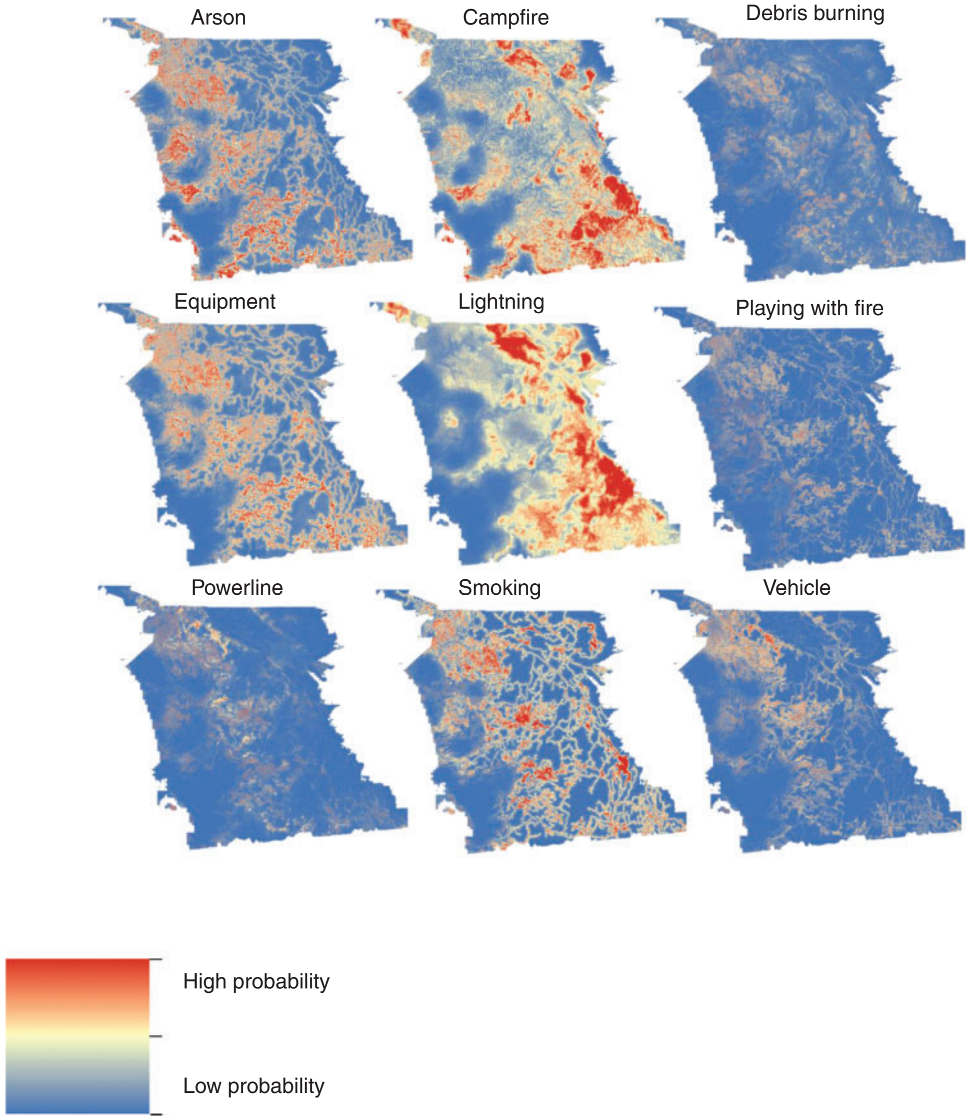

Fig. 6. Predicted probability of ignition (0–1.0) by major cause in San Diego County.

prevention actions. For example, strict ordinances on the use of certain types of equipment in and adjacent to wildland areas during red flag warning days could reduce the incidence of large catastrophic fires in the region. Further investigation into the types of equipment that cause most fires would also be useful in further refining how to best allocate resources for outreach materials.

In addition to the timing of different ignition causes in autumn months, another explanation for differences in number of fires and area burned is that certain ignition causes may exhibit distinct spatial patterns that correspond with locations of higher fire danger. For example, extreme wind patterns in the region follow predictable pathways, and the region's largest fires have historically occurred in those areas (Moritz *et al.* 2010). Therefore, an ignition that occurs along wind corridors during extreme fire weather and is also in a fairly inaccessible region may have a greater chance of developing into a large fire. In some places, these wind corridors are associated with repeated housing losses (Syphard *et al.* 2012).

One limitation in this analysis by ignition cause is that ~30% of ignitions were of unknown or miscellaneous cause in both sub-regions. These ignitions did contribute a substantial extent of fire burned, and it is difficult to develop targeted strategies for preventing these. Nevertheless, the proportion of known ignition causes is much higher in California than in many other regions, and is continuing to improve. Unknown fire causes is a worldwide problem, and many other regions or countries have substantially higher proportions of fires started by unknown causes (United Nations Economic Commission for Europe 2002). This uncertainty explains why some investigators lump human-caused ignitions together for study (e.g. Martínez *et al.* 2009). The importance of documenting fire causes is receiving increased recognition, however, and some studies are beginning to explain the complex social, environmental, economic and political controls that contribute to human-caused ignitions (Romero-Calcerrada *et al.* 2008; Meddour-Sahar *et al.* 2013).

Regardless of ignition cause, proximity to roads was consistently important in explaining ignition location. This relationship is highly consistent among studies of ignition patterns, including our previous study in the region (e.g. Sturtevant and Cleland 2007; Syphard *et al.* 2008; Narayanaraj and Wimberly 2012). One reason for this consistent relationship is that, in addition to the concentration of human activities that spark ignitions, vegetation may be more flammable along roads (Curt *et al.* 2007; Narayanaraj and Wimberly 2012). More research is needed, however, to understand how and why so many fires start along roads and whether any prevention strategies could be feasibly and effectively implemented. One idea would be to install barriers between roads and the wildland in fire-prone locations. However, this could be more costly than educational campaigns so a cost–benefit analysis would be highly beneficial.

Conclusion

Although it is generally understood that the primary causes and drivers of wildland fire ignitions vary over space and time (Stephens 2005), our results underline the importance of examining local trends in where, why and how ignitions occur. Even within two similar sub-regions in southern California, there were some differences in number and extent of fires by ignition cause, as well as the relative importance of the factors that explained their distribution. For example, the presence of grass explained a larger proportion of ignition distribution in the Santa Monica Mountains, whereas proximity to roads and structure density were more important in San Diego County. In regions where humans cause a substantial number of fire ignitions, it is important to recognise that not all ignitions have the same effect or spatio–temporal signature. Because each ignition cause represents a different type of behaviour, prevention programmes could allocate resources to target behaviours in proportion to their effect in time or space.

Despite local variation, broad-scale similarities within the study regions, such as the importance of power lines, timing of ignition in autumn, and proximity to roads and the WUI also suggest informative general patterns that may be useful when finer scale detail is unavailable. For example, given the overall importance of ignitions occurring close to human infrastructure, planners may want to consider that if housing development and roads continue to expand into the wildland, the distribution of ignitions may therefore also expand. Development of low-density, exurban housing may also lead to more homes being destroyed by fire (Syphard *et al.* 2013). Another consideration is that frequent fires and housing growth may lead to the expansion of highly flammable exotic grasses that can further increase the probability of ignitions (Keeley *et al.* 2012). Longer term management strategies may therefore benefit from future forecasts of ignition patterns relative to projections of housing growth or vegetation change.

Other management responses that could benefit both regions would be restrictions on equipment use and other activities that could start a fire during the Santa Ana wind season and greater patrol for arson during extreme weather conditions. Putting power lines underground and identifying strategies that could effectively reduce roadside ignitions are additional challenges that deserve serious consideration throughout the southern California region.

Acknowledgements

We are extremely grateful to Robert S. Taylor for providing ignitions data and insightful comments on the manuscript. We also thank the two reviewers and Associate Editor for their helpful suggestions. Any use of trade, product or firm names is for descriptive purposes only and does not imply endorsement by the US Government.

References

Bar Massada A, Syphard AD, Stewart SI, Radeloff VC (2013) Wildfire ignition-distribution modelling: a comparative study in the Huron–Manistee National Forest, Michigan, USA. *International Journal of Wildland Fire* **22**, 174–183. doi:10.1071/WF11178

Bowman DMJS, Balch JK, Artaxo P, Bond WJ, Carlson JM, Cochrane MA, D'Antonio CM, DeFries RS, Doyle JC, Harrison SP, Johnston FH, Keeley JE, Krawchuk MA, Kull CA, Marston JB, Moritz MA, Prentice IC, Roos CI, Scott AC, Swetnam TW, van der Werf GR, Pyne SJ (2009) Fire in the earth system. *Science* **324**, 481–484. doi:10.1126/SCIENCE.1163886

Butry D (2009) Fighting fire with fire: estimating the efficacy of wildfire mitigation programs using propensity scores. *Environmental and Ecological Statistics* **16**, 291–319. doi:10.1007/S10651-007-0083-3

Cal Fire (2000) 'Wildland fire hazard assessment: Final report on FEMA 1005–47.' California Division of Forestry and Fire Protection: Sacramento, CA.

Cal Fire (2011) Incident information. Available at http://cdfdata.fire.ca.gov/incidents/incidents_statsevents [Verified 12 May 2014]

Cal Fire (2013) Fire perimeters. Available at http://frap.fire.ca.gov/data/frapgisdata-sw-fireperimeters_download.php [Verified 9 December 2013]

Cardille JA, Ventura SJ, Turner MG (2001) Environmental and social factors influencing wildfires in the Upper Midwest, United States. *Ecological Applications* **11**, 111–127. doi:10.1890/1051-0761(2001)011[0111:EASFIW]2.0.CO;2

Cary GJ, Flannigan MD, Keane RE, Bradstock RA, Davies ID, Lenihan JM, Li C, Logan KA, Parsons RA (2009) Relative importance of fuel management, ignition management and weather for area burned: evidence from five landscape–fire–succession models. *International Journal of Wildland Fire* **18**, 147–156. doi:10.1071/WF07085

Catry FX, Rego FC, Bação F, Moreira F (2009) Modeling and mapping wildfire ignition risk in Portugal. *International Journal of Wildland Fire* **18**, 921–931. doi:10.1071/WF07123

Chevan A, Sutherland M (1991) Hierarchical partitioning. *The American Statistician* **45**, 90–96.

Cohen JD (2000) Home ignitability in the wildland–urban interface. *Journal of Forestry* **98**, 15–21.

Cruz MG, Sullivan AL, Gould JS, Sims NC, Bannister AJ, Hollis JJ, Hurley RJ (2012) Anatomy of a catastrophic wildfire: the Black Saturday Kilmore East fire in Victoria, Australia. *Forest Ecology and Management* **284**, 269–285.

Curt T, Ganteaume A, Alleaume S, Borgniet L, Chandioux O, Jappiot M, Lampin C, Martin W (2007) Vegetation flammability and ignition potential at road–forest interfaces (southern France). In '4th International Wildland Fire Conference 2007', May, Sevilla, Spain (CD-ROM). (Ministerio de Medio Ambiente: Madrid, Spain)

Dormann CF, McPherson JM, Araujo MB, Bivand R, Bolliger J, Carl G, Davies RG, Hirzel A, Jetz W, Kissling WD, Kuhn I, Ohlemuller R, Peres-Neto PR, Reineking B, Schroder B, Schurr FM, Wilson R (2007) Methods to account for spatial autocorrelation in the analysis of species distributional data: a review. *Ecography* **30**, 609–628. doi:10.1111/J.2007.0906-7590.05171.X

Elith J, Graham CH, Anderson RP, Dudik M, Ferrier S, Guisan A, Hijmans RJ, Huettmann F, Leathwick JR, Lehmann A, Li J, Lohmann LG, Loiselle BA, Manion G, Moritz C, Nakamura M, Nakazawa Y, Overton JM, Peterson AT, Phillips SJ, Richardson K, Scachetti-Pereira R, Schapire RE, Soberon J, Williams S, Wisz MS, Zimmermann NE (2006) Novel methods improve prediction of species' distributions from occurrence data. *Ecography* **29**, 129–151. doi:10.1111/J.2006.0906-7590.04596.X

Elith J, Phillips SJ, Hastie T, Dudík M, Chee YE, Yates CJ (2011) A statistical explanation of MaxEnt for ecologists. *Diversity & Distributions* **17**, 43–57. doi:10.1111/J.1472-4642.2010.00725.X

Genton MG, Butry DT, Gumpertz ML, Prestemon JP (2006) Spatio–temporal analysis of wildfire ignitions in the St Johns River Water Management District, Florida. *International Journal of Wildland Fire* **15**, 87–97. doi:10.1071/WF04034

Gill AM (2005) Landscape fires as social disasters: an overview of the bushfire problem. *Environmental Hazards* **6**, 65–80. doi:10.1016/J.HAZARDS.2005.10.005

Gill AM, Stephens SL, Cary GJ (2013) The worldwide 'wildfire' problem. *Ecological Applications* **23**, 438–454. doi:10.1890/10-2213.1

Gonzalez-Olabarria J, Brotons L, Gritten D, Tudela A, Angel Teres J (2012) Identifying location and causality of fire ignition hotspots in a Mediterranean region. *International Journal of Wildland Fire* **21**, 905–914. doi:10.1071/WF11039

Hammer RB, Radeloff VC, Fried JS, Stewart SI (2007) Wildland–urban interface housing growth during the 1990s in California, Oregon, and Washington. *International Journal of Wildland Fire* **16**, 255–265. doi:10.1071/WF05077

Keeley JE (2006) South coast bioregion. In 'Fire California's Ecosystems'. (Eds NG Sugihari, JW van Wagtendonk, KE Shaffer, J Fites-Kaufman, AE Thode) pp. 350–390. (University of California Press: Berkeley, CA)

Keeley JE, Fotheringham CJ, Morais M (1999) Reexamining fire suppression impacts on brushland fire regimes. *Science* **284**, 1829–1832. doi:10.1126/SCIENCE.284.5421.1829

Keeley JE, Safford HD, Fotheringham CJ, Franklin J, Moritz MA (2009) The 2007 southern California wildfires: lessons in complexity. *Journal of Forestry* **107**, 287–296.

Keeley JE, Bond WJ, Bradstock RA, Pausas JG, Rundel PW (2012) 'Fire in Mediterranean Ecosystems Ecology, Evolution and Management.' (Cambridge University Press: Cambridge, UK)

Keeley JE, Syphard AD, Fotheringham CJ (2013) The 2003 and 2007 Wildfires in Southern California. In 'Natural Disasters and Adaptation to Climate Change'. (Eds S Boulter, J Palutikof, DJ Karoly, D Guitart) pp. 42–52. (Cambridge University Press: Oxford, UK)

Martínez J, Vega-Garcia C, Chuvieco E (2009) Human-caused wildfire risk rating for prevention planning in Spain. *Journal of Environmental Management* **90**, 1241–1252. doi:10.1016/J.JENVMAN.2008.07.005

Meddour-Sahar O, Meddour R, Leone V, Lovreglio R, Derridj A (2013) Analysis of forest fires causes and their motivations in northern Algeria: the Delphi method. *Journal of Biogeosciences and Forestry* **6**(4), 247–254. doi:10.3832/IFOR0098-006

Miller WH (1968) Santa Ana winds and crime. *The Professional Geographer* **20**, 23–27. doi:10.1111/J.0033-0124.1968.00023.X

Mitchell JW (2013) Power line failures and catastrophic wildfires under extreme weather conditions. *Engineering Failure Analysis* **35**, 726–735. doi:10.1016/J.ENGFAILANAL.2013.07.006

Moritz MA, Keeley JE, Johnson EA, Schaffner AA (2004) Testing a basic assumption of shrubland fire management: how important is fuel age? *Frontiers in Ecology and the Environment* **2**, 67–72. doi:10.1890/1540-9295(2004)002[0067:TABAOS]2.0.CO;2

Moritz MA, Moody TJ, Krawchuk MA, Hughes M, Hall A (2010) Spatial variation in extreme winds predicts large wildfire locations in chaparral ecosystems. *Geophysical Research Letters* **37**, L04801. doi:10.1890/1540-9295(2004)002[0067:TABAOS]2.0.CO;2

Narayanaraj G, Wimberly MC (2011) Influences of forest roads on the spatial pattern of wildfire boundaries. *International Journal of Wildland Fire* **20**, 792–803. doi:10.1071/WF10032

Narayanaraj G, Wimberly MC (2012) Influences of forest roads on the spatial pattern of human- and lightning-caused wildfire ignitions. *Applied Geography.* **32**(2), 878–888. doi:10.1016/J.APGEOG.2011.09.004

Pausas JG, Keeley JE (2009) A burning story: the role of fire in the history of life. *Bioscience* **59**, 593–601. doi:10.1525/BIO.2009.59.7.10

Penman TD, Bradstock RA, Price O (2013) Modelling the determinants of ignition in the Sydney Basin, Australia: implications for future management. *International Journal of Wildland Fire* **22**, 469–478. doi:10.1071/WF12027

Phillips SJ, Anderson RP, Schapire RE (2006) Maximum entropy modeling of species geographic distributions. *Ecological Modelling* **190**, 231–259. doi:10.1016/J.ECOLMODEL.2005.03.026

Prestemon JP, Butry DT (2005) Time to burn: modeling wildland arson as an autoregressive crime function. *American Journal of Agricultural Economics* **87**, 756–770. doi:10.1111/J.1467-8276.2005.00760.X

Prestemon JP, Butry DT, Abt KL, Sutphen R (2010) Net benefits of wildfire prevention education efforts. *Forest Science* **56**, 181–192.

Price OF, Bradstock RA (2012) The influences of weather, terrain and land management on fire severity in the catastrophic 2009 fires in Victoria, Australia. *Journal of Environmental Management* **113**, 146–157. doi:10.1016/J.JENVMAN.2012.08.041

PRISM Climate Group (2004) PRISM climate data. Available at http://prism.oregonstate.edu [Verified 12 May 2014]

Reineking B, Weibel P, Conedera M, Bugmann H (2010) Environmental determinants of lightning- *v.* human-induced forest fire ignitions differ in a temperate mountain region of Switzerland. *International Journal of Wildland Fire* **19**, 541–557. doi:10.1071/WF08206

Romero-Calcerrada R, Novillo CJ, Millington JDA, Gomez-Jimenez I (2008) GIS analysis of spatial patterns of human-caused wildfire ignition risk in the SW of Madrid (Central Spain). *Landscape Ecology* **23**, 341–354. doi:10.1007/S10980-008-9190-2

Sadasivuni R, Cooke WH, Bhushan S (2013) Wildfire risk prediction in southeastern Mississippi using population interaction. *Ecological Modelling* **251**, 297–306. doi:10.1016/J.ECOLMODEL.2012.12.024

Stephens SL (2005) Forest fire causes and extent on United States forest service lands. *International Journal of Wildland Fire* **14**, 213–222. doi:10.1071/WF04006

Sturtevant BR, Cleland DT (2007) Human and biophysical factors influencing modern fire disturbance in northern Wisconsin. *International Journal of Wildland Fire* **16**, 398–413. doi:10.1071/WF06023

Syphard AD, Radeloff VC, Keeley JE, Hawbaker TJ, Clayton MK, Stewart SI, Hammer RB (2007) Human influence on California fire regimes. *Ecological Applications* **17**, 1388–1402. doi:10.1890/06-1128.1

Syphard AD, Radeloff VC, Keuler NS, Taylor RS, Hawbaker TJ, Stewart SI, Clayton MK (2008) Predicting spatial patterns of fire on a southern California landscape. *International Journal of Wildland Fire* **17**, 602–613. doi:10.1071/WF07087

Syphard AD, Keeley JE, Bar Massada A, Brennan TJ, Radeloff VC (2012) Housing arrangement and location determine the likelihood of housing loss due to wildfire. *PLoS ONE* **7**(3), e33954. doi:10.1371/JOURNAL.PONE.0033954

Syphard AD, Bar Massada A, Butsic V, Keeley JE (2013) Land use planning and wildfire: development policies influence future probability of housing joss. *PLoS ONE* **8**(8), e71708. doi:10.1371/JOURNAL.PONE.0071708

Syphard AD, Brennan TJ, Keeley JE (2014) The role of defensible space for residential structure protection during wildfires. *International Journal of Wildland Fire*, in press. doi:10.1071/WF13158

Thomas DS, Butry DT, Prestemon JP (2011) Enticing arsonists with broken windows and social disorder. *Fire Technology* **47**, 255–273. doi:10.1007/S10694-010-0145-1

United Nations Economic Commission for Europe (2002) Forest fire statistics. UNECE Timber Committee, United Nations, Report ECE/TIM/BULL/2002/4. Available at http://www.unece.org/forests/ff-stats.html [Verified 12 May 2014]

USDA Forest Service (2010) Vegetation classification and mapping. Available at http://www.fs.usda.gov/detail/r5/landmanagement/resourcemanagement/?cid=stelprdb5347192 [Verified 12 May 2014]

Victorian Bushfires Royal Commission (2010) Fire preparation, response and recovery. Final Report Volume II. (Parliament of Victoria: State of Victoria, Australia).

Walsh C, Mac Nally R (2008). hier.part: Hierarchical Partitioning. R package version 1.0–3. (R Foundation for Statistical Computing: Vienna, Austria)

Weisburd D, Wyckoff LA, Ready J, Eck JE, Hinkle JC, Gajewski F (2006) Does crime just move around the corner? A controlled study of spatial displacement and diffusion of crime control benefits. *Criminology* **44**, 549–592. doi:10.1111/J.1745-9125.2006.00057.X

Wells ML, O'Leary JF, Franklin J, Michaelson J, McKinsey DE (2004) Variations in a regional fire regime related to vegetation type in San Diego County, California (USA). *Landscape Ecology* **19**, 139–152. doi:10.1023/B:LAND.0000021713.81489.A7

Whelan RJ (1995) 'The Ecology of Fire.' (Cambridge University Press: Cambridge, UK)

Winter G, McCaffrey S, Vogt CA (2009) The role of community policies in defensible space compliance. *Forest Policy and Economics* **11**, 570–578. doi:10.1016/J.FORPOL.2009.07.004

Wisz MS, Hijmans RJ, Li J, Peterson AT, Graham CH, Guisan A (2008) Effect of sample size on the performance of species distribution models. *Diversity & Distributions* **14**, 763–773. doi:10.1111/J.1472-4642.2008.00482.X