Predicting spatial patterns of fire on a southern California landscape

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Abstract. Humans influence the frequency and spatial pattern of fire and contribute to altered fire regimes, but fuel loading is often the only factor considered when planning management activities to reduce fire hazard. Understanding both the human and biophysical landscape characteristics that explain how fire patterns vary should help to identify where fire is most likely to threaten values at risk. We used human and biophysical explanatory variables to model and map the spatial patterns of both fire ignitions and fire frequency in the Santa Monica Mountains, a human-dominated southern California landscape. Most fires in the study area are caused by humans, and our results showed that fire ignition patterns were strongly influenced by human variables. In particular, ignitions were most likely to occur close to roads, trails, and housing development but were also related to vegetation type. In contrast, biophysical variables related to climate and terrain (January temperature, transformed aspect, elevation, and slope) explained most of the variation in fire frequency. Although most ignitions occur close to human infrastructure, fires were more likely to spread when located farther from urban development. How far fires spread was ultimately related to biophysical variables, and the largest fires in southern California occurred as a function of wind speed, topography, and vegetation type. Overlaying predictive maps of fire ignitions and fire frequency may be useful for identifying high-risk areas that can be targeted for fire management actions.

Additional keywords: fire frequency, fire ignitions, generalised linear model, predictive mapping, wildland–urban interface.

Introduction

Altered fire regimes threaten ecosystem structure and function, create hazards for people, and increase fire suppression costs (Calkin *et al*. 2005; Stephens 2005; Steele *et al*. 2006). In the United States, fire regimes have been altered both through fuel accumulation due to fire suppression and from the dramatic increase in the number of human-caused ignitions in fire-prone areas, particularly the wildland–urban interface (WUI) (Keeley and Fotheringham 2003), which is the contact zone where human development abuts and intermingles with undeveloped vegetation (Radeloff *et al*. 2005). The convergence of these trends has resulted in substantial federal funding, and social and political pressure, to decrease fire hazard by reducing fuel loads (USDA and USDI 2001; NPS 2005).

Although fuel buildup creates conditions favourable for intense, large-scale fires (Pyne *et al*. 1996; Allen *et al*. 2002), human population growth contributes to increased ignitions and fire frequency (Keeley *et al*. 1999; Rundel and King 2001; Radeloff *et al*. 2005; Syphard *et al*. 2007*a*). Information on fuel loading is often the only factor considered when planning management activities to reduce fire hazard (Dickson *et al*. 2006).

In some forests, widespread fuel reduction methods, such as landscape-scale prescribed fire, can be beneficial for restoring natural disturbance regimes (Miller and Urban 2000; Scheller *et al*. 2005). However, in regions where human ignitions have increased fire frequency beyond its natural range of variability, widespread prescribed fire can be ecologically damaging to native plant communities (Keeley and Fotheringham 2003).

Also, management strategies based solely on fuel as a risk factor can become needlessly expensive if fuel treatments are placed in locations where fire hazard to humans is of little concern (G. Aplet and B. Wilmer, http://www.tws.org/OurIssues/Wildfire/CFPZ/index.cfm, accessed 11 August 2008). Considering that fire regimes vary among vegetation types and that humans impact fire regimes in different ways, there is growing awareness that fire management should be adapted to both the human and ecological landscape characteristics that vary from region to region (Odion *et al*. 2004; Halsey 2005; Badia-Perpinya and Pallares-Barbera 2006). With better understanding of regional context, fuels treatments can be prioritised and strategically placed in areas where fire is most likely to threaten values
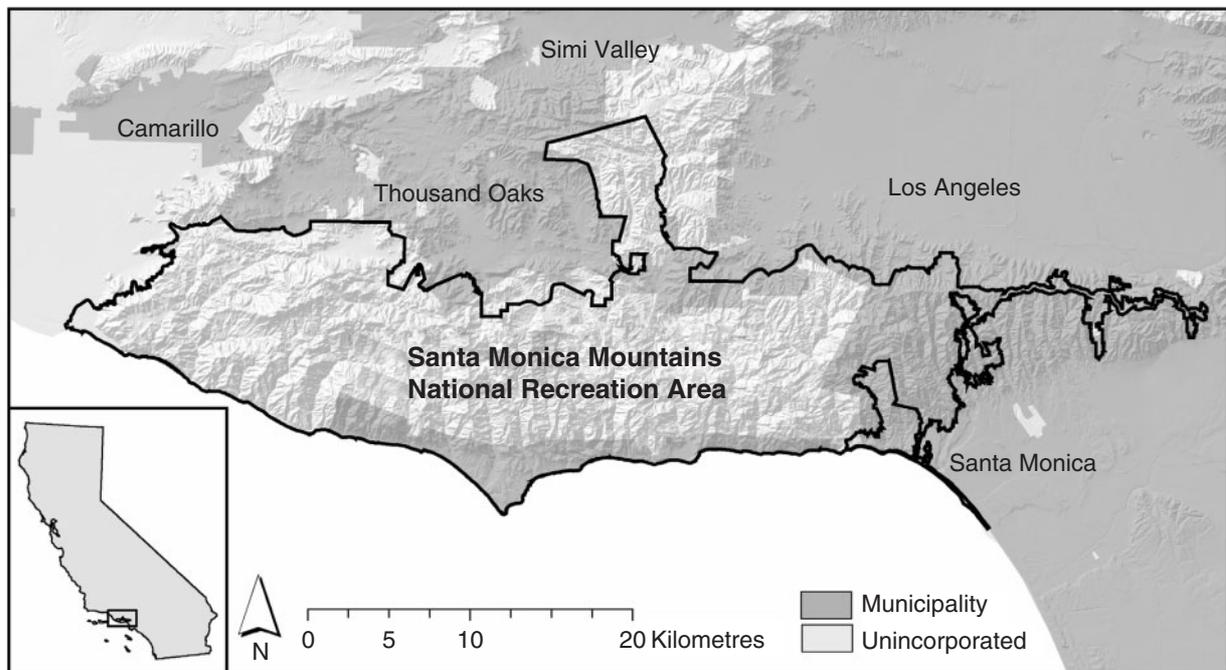
Fig. 1.   The Santa Monica Mountains National Recreation Area, California, USA.

at risk or where placement will minimise ecological impacts (Halsey 2005; Dickson *et al*. 2006).

To identify the best locations for strategically placed fuels treatments, it is first necessary to understand how and why fire patterns vary across landscapes (DellaSala *et al*. 2004). Fire behaviour is largely a physical phenomenon, as illustrated by the fire environment triangle that places fire as a function of weather, fuels, and topography (Countryman 1972). Therefore, many fire risk and probability assessments have focussed on biophysical and climate variables (e.g. Bradstock *et al*. 1998; Fried *et al*. 1999; Diaz-Avalos *et al*. 2001; Rollins *et al*. 2002; Preisler *et al*. 2004), and several models and methods have been used to predict fire behaviour within different fuels types and from weather condition inputs (Burgan and Rothermel 1984; Forestry Canada Fire Danger Group 1992). Models that predict the probability of lightning ignitions have also been useful for identifying places where fires are likely to occur (Larjavaara *et al*. 2005; Wotton and Martell 2005). Although these biophysical approaches are critical for understanding fire patterns and behaviour, it is also important to understand the human influence on the frequency and spatial pattern of fire to help identify where fire risk is highest on a landscape, especially in places where fire regimes have been altered (Pyne 2001; DellaSala *et al*. 2004; Haight *et al*. 2004).

Human effects on the spatial distribution of fire have been accounted for in recent efforts to map or model fire risk. Most of these studies focussed on fire ignition points (i.e. the spatial location of fire's origin) (e.g. Pew and Larsen 2001; Badia-Perpinya and Pallares-Barbera 2006; Dickson *et al*. 2006; Yang *et al*. 2007), but fire risk probability has also been mapped using fire occurrence data (i.e. any location that burned regardless of point of origin) (e.g. Chou 1992; Chou *et al*. 1993). One problem is that fire patterns depend on both ignition locations and

fire spread, but these are not necessarily determined by the same factors (Dickson *et al*. 2006; Syphard *et al*. 2007*a*, 2007*b*). For example, ignitions may or may not occur in fuel types that are highly flammable.

Our objective for the present research was to use a combination of biophysical and human explanatory variables to produce spatially explicit statistical models and maps predicting patterns of fire ignitions and fire frequency in a human-dominated southern California landscape. Most fires in the region result from human ignition sources (Keeley 1982; NPS 2005), so we expected proximity to human infrastructure to most strongly influence fire ignition patterns because the human activities that are likely to lead to ignitions are concentrated in or near these locations. The rate of spread for the largest fires in southern California is largely determined by wind speed, topography, and vegetation type (Keeley 2000). Therefore, we also expected the distribution of biophysical variables to be important predictors of fire frequency.

Methods

Study area

The Santa Monica Mountains National Recreation Area (hereafter referred to as the Santa Monica Mountains) encompasses ∼60 000 ha of Mediterranean-type habitat, characterised by steep, coastal mountains that form the southernmost range in the Transverse Ranges of southern California (Fig. 1). Slightly more than half of the land in the mountains is in public ownership (including the National Park Service), and much of the privately owned land remains undeveloped. However, the Santa Monica Mountains include a substantial amount of WUI and have been experiencing increased development pressure due to their proximity to the Los Angeles metropolitan region, which is

Table 1.   Variables analysed in the regression models explaining fire ignitions and fire frequency in the Santa Monica Mountains, CA
WUI, wildland–urban interface

Variable	Resolution	Source	Description or range
Dependent variables			
Ignition points	Point	National Park Service	$n = 126$, V $= 67$, from 1981 to 2003
Fire frequency	10 m	National Park Service fire perimeters	0 to 9, from 1925 to 2003
Explanatory variables			
Human			
Distance to development	10 m	Syphard *et al.* 2005	Mean Euclidean distance
Level of development	500-m buffer	Syphard *et al.* 2005	None (0); low (0.01–0.33); intermediate (0.34–0.66); high (0.67–1.0)
Distance to WUI	10 m	Radeloff *et al.* 2005	Mean Euclidean distance
Level of WUI	500-m buffer	Radeloff *et al.* 2005	None (0); low (0.01–0.33); intermediate (0.34–0.66); high (0.67–1.0)
Distance to roads	10 m	US Census Bureau TIGER/Line files	Mean Euclidean distance
Distance to trails	10 m	National Park Service	Mean Euclidean distance
Biophysical			
January temperature	1 km	J. Michaelson (Franklin 1998)	Interpolated by kriging
Elevation	30 m	USGS Digital Elevation Model (DEM)	
Slope gradient	30 m	Derived from DEM	
South-westness	30 m	Derived from DEM	$SW = (con(aspect(<dem>) == -12, 201,(cos(((aspect(<dem>) - 255) \, div \, deg) + 1) * 100)))$
Vegetation type	30 m	J. Franklin, J. J. Swenson and D. Shaari, pers. comm., 1997	Coastal sage scrub; northern mixed chaparral; chamise chaparral; non-native grass; oak woodland; riparian; other (less flammable vegetation such as salt marshes, agriculture, or urban)

home to more than 17 million people (Rundel and King 2001). The region that includes the study area is biologically rich, with ~1000 plant species, 50 mammal species, 400 bird species, and 35 species of reptiles and amphibians (NPS 2005). The region is also home to more than 20 federal or state-listed threatened or endangered animals and plants and another 46 animal and 11 plant species listed as species of concern (NPS 2002). The primary vegetation types are chaparral (e.g. *Ceanothus* spp. or *Adenostoma fasciculatum*, ~60%); coastal sage scrub vegetation (e.g. *Salvia* spp. or *Artemisia californica*, ~25%); exotic grass (~5%); oak woodland (~5%); and riparian vegetation (~5%).

Fire is a natural process in southern California Mediterranean-type ecosystems, and many of the region's native species are resilient to a range of fire frequencies (Zedler 1995). However, explosive population growth in the region has increased ignitions to the point that fire frequency exceeds its natural range of variability in many areas (Keeley *et al.* 1999). Repeated fires in short succession can also exceed the resilience of native species, and some shrublands have type-converted to exotic annual grasses under high fire frequencies (Zedler *et al.* 1983; Haidinger and Keeley 1993; Jacobsen *et al.* 2007). In the last 75 years, humans have been responsible for 98% of the fires in the Santa Monica Mountains, and some areas have burned up to 10 times (NPS 2005). Chaparral-dominated shrublands are typified by high-intensity, stand-replacing fires that are difficult or impossible to suppress under severe, high-wind weather conditions (Keeley 2000). Therefore, considering that fire frequency has increased despite aggressive fire suppression efforts, the most recent fire management plan in the Santa Monica Mountains recommends against using prescribed fire to reduce fuel across the entire

landscape (NPS 2005). Instead, the National Park Service (NPS) recommends strategically positioned fuels treatment in areas with high fire hazard near the WUI.

Data description

Dependent variables – fire ignitions and frequency

The ignition data included 126 coordinate points acquired from the NPS fire records from 1981 to 2003 (Table 1, Fig. 2). Ignition locations were entered into the Shared Applications Computer System (SACS) at the National Interagency Fire Center (NIFC) in Boise, ID, and then converted into a Geographic Information System (GIS) database. The median accuracy of the ignition locations was 100 m.

Fire perimeter polygons originally reported by NPS and County Fire Departments were compiled by the California Department of Forestry–Fire and Resource Assessment Program (CDF-FRAP) into a GIS database (http://frap.cdf.ca.gov/data/frapgisdata/select.asp, accessed 8 August 2008). Although this database generally provides the most complete digital record of fire perimeters in California, the fire record was incomplete, with a minimum mapping unit of 4.04 ha (10 acres). Therefore, the NPS staff at the Santa Monica Mountains updated this database to include additional smaller fires (less than 1 ha), which resulted in a fire frequency map that delineated overlapping fire perimeter boundaries from 1925 to 2003. Within this database, more than 75% of the fires occurred within the last 20 years. Although the average area burned also increased over time, the fire size distribution has remained generally stable, with a slight decline (Table 1, Fig. 2).

Fig. 2. Map showing proximity of ignition points (1981–2003) to roads and development in the Santa Monica Mountains, CA.

Using these boundaries, we created a continuous grid surface reflecting the number of fires that occurred during those 78 years for each cell. From this fire frequency grid, we randomly selected 1000 points to relate number of fires to the explanatory variables. We selected 1000 data points as our sample size because we wanted to use as many points as possible given the practical limitations of our statistical models. To ensure that the sample size was large enough to adequately represent the study area, we performed χ^2 goodness of fit tests to compare the true distribution of fire frequency (14 million points) with the distribution of fire frequency in our sample size of 1000, and we found no significant difference between them.

Explanatory variables – human

Human-caused ignitions frequently occur along transportation corridors and other areas where human activity is concentrated (Keeley and Fotheringham 2003; Stephens 2005). The ignition data points from the Santa Monica Mountains also appeared to be close to roads and development on a map (Fig. 2). Therefore, our explanatory human variables included distance to development, roads, trails, and WUI (Table 1, Fig. 2). We included trails because they provide a means of human access to otherwise undeveloped areas in the parks and protected areas. We created the map of development through airphoto interpretation and onscreen digitising of development evident on 1 : 12 000 at 1-m resolution digital orthorectified quarter quadrangles (DOQQs) from the US Geological Survey (USGS) for 2000. 'Development' included any part of the landscape with houses or other buildings, in addition to golf courses. We used 2000 US Topologically Integrated Geographic Encoding and Referencing system TIGER/Line files (US Census 2000) for our road data, and the NPS provided the GIS map of trails.

The interactions between human activities and natural dynamics tend to be spatially concentrated at the WUI, which

has received national attention because housing developments and human lives are vulnerable to fire in these locations and because human ignitions are believed to be most common there (Rundel and King 2001; USDA and USDI 2001). Our WUI map was created as part of a nationwide mapping project that produced fine-scale maps of the conterminous United States (Radeloff *et al.* 2005; http://www.silvis.forest. wisc.edu/silvis.asp, accessed 8 August 2008). These data were created based on the definition of WUI published in the Federal Register (USDA and USDI 2001) using housing density data obtained from the US Census and land cover data obtained from the USGS National Land Cover Dataset (at 30-m resolution).

Explanatory variables – biophysical

From a biophysical perspective, the expression of fire on a landscape is a function of its fire environment, including the climate, terrain, and fuels in a region (Pyne *et al.* 1996). Therefore, spatially explicit models that simulate fire behaviour use input measurements of elevation, slope, aspect, weather, and vegetation (Anderson 1982; Andrews *et al.* 2005). Likewise, we selected climate and terrain-derived variables, as well as vegetation type, as potential biophysical explanatory variables (Table 1, Fig. 2). The biophysical factors that influence fire ignitions and fire spread may produce multiple direct and indirect effects on the fire regime (Whelan 1995). For example, slope angle affects soil moisture and development, which in turn affects vegetation distribution and composition, and thus fuel characteristics and flammability (Franklin 1995). At the same time, slope produces a direct physical effect on active fire fronts because the flames are closer to the ground, and fires typically burn faster in an upslope direction (Whelan 1995). We expected that the spatial variability and distribution of these influential biophysical variables across the landscape would provide substantial explanatory power to

predict and map where fire ignitions and fire frequency were likely to occur.

Our terrain variables included elevation, percentage slope, and transformed slope aspect ('south-westness'). These topographic factors explain variation in local climate, provide natural firebreaks, and indirectly influence factors such as fuel moisture, vegetation distribution, and relative humidity (Whelan 1995). We scaled aspect to an index of 'south-westness' using a cosine transformation because the index better distinguished xeric exposures (high index values) from mesic exposures (low index values) (Franklin *et al.* 2000).

Because we were not simulating annual fire behaviour or weather, we used spatially interpolated climate variables (mean annual precipitation, average January minimum temperature and average July maximum temperature), which were more appropriate for the broad spatial and temporal scale of our study. Moisture and temperature affect vegetation productivity and rate of fuel accumulation as well as soil moisture, rate of combustion, and rate of spread (Whelan 1995). We evaluated both January minimum and July maximum temperatures because these represented upper and lower limits, both of which would therefore maximise the distribution of variability in temperature gradients and plant species distributions across the landscape (Franklin 1998). Annual precipitation had high correlation with other variables and was removed from the analysis. The temperature data layers were developed as a 1-km^2 gridded surface that was interpolated from climate station data, elevation, and a digital elevation model. The surfaces were interpolated using universal and ordinary kriging (Franklin 1998).

Several sophisticated systems have been developed to create fuels models to use in fire behaviour prediction (e.g. Forestry Canada Fire Danger Group 1992). However, only three of the thirteen standard fuel models used in the United States (by the National Forest Fire Laboratory) are considered applicable to chaparral shrublands (Anderson 1982). In southern California shrublands, the fire regime is strongly differentiated according to broadly defined, structurally similar vegetation types, and fire tends to behave uniformly within those types (Wells *et al.* 2004). Therefore, instead of using fuel types as predictor variables, we used a generalised map of vegetation types, created through a classification of 30-m Landsat Thematic Mapper (TM) data (J. Franklin *et al.*, pers. comm., 1997).

The fact that post-fire age (and thus fuel buildup) is a less critical factor in California chaparral than in some other vegetation types is an important additional consideration. Fire spread in North American coniferous forest areas is strongly affected by post-fire age, with younger stands having lower fuel loads and lower rates of fire spread. In contrast, post-fire age has relatively little effect on the spread of fires in California chaparral, particularly during high wind conditions (Moritz 2003). Owing to rapid post-fire fuel accumulation, chaparral and coastal sage shrublands can burn at high intensities at young ages (Radtke *et al.* 1982). Therefore, we assumed that post-fire age would not strongly influence temporal patterns of fire frequency in the Santa Monica Mountains as strongly as it would in other regions, and therefore we did not include it as a variable in our analysis. Some studies in forested regions have considered post-fire age and temporal autocorrelation when explaining fire frequency (e.g. Reed *et al.* 1998; Preisler *et al.* 2004).

Data manipulation

Because we expected fire to occur close to human infrastructure, we created continuous surfaces reflecting mean Euclidean distances to all of the human explanatory variables, and we used these distances in our models. To obtain better precision in our Euclidean distance calculations, we resampled all of our grids to a 10-m resolution and used those for overlay and extraction of data to relate the explanatory variables to fire ignitions and frequency. Because fire frequency and area burned also tend to be highest at intermediate levels of human activity and are a function of the spatial pattern of development and fuels (Keeley 2005; Syphard *et al.* 2007*a*), we created 500-m buffers around all point locations and calculated the proportion of development and WUI within those areas (total extent = 78 ha). We chose this buffer size because the dense nature of chaparral makes it difficult for humans to traverse far into the vegetation (Halsey 2005); therefore, we assumed that human influence would not exceed 500 m. The proportions were then classified into four arbitrary categories: none (0), low (0.01–0.33), intermediate (0.34–0.66), and high (0.67–1.0) (Table 1). We used the Spatial Analyst Extension of *ArcGIS*, in addition to *ArcInfo Workstation*, for our GIS analysis and data processing.

Modelling approaches

Fire ignitions

To predict the estimated probability, *P*, of a cell, i, in the study area experiencing an ignition, we developed a multiple logistic regression model. For logistic regression, if we let P_i be the probability of an ignition in cell i, and x_{ji} be the value of the jth covariate in cell i, the logistic regression model is:

$$P_i = \exp(\beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \ldots + \beta_n x_{ni})/ \\ (1 + \exp(\beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \ldots + \beta_n x_{ni}))$$

where β_0 is a constant and β_n are regression coefficients for the human and biophysical explanatory variables, x_{ni}. To determine whether the explanatory variables affected the ignition locations differently than what would be expected by chance, we also generated a random sample of 700 control points in the study area. Therefore, our model predicted the probability that ignitions would occur disproportionately as a function of multiple landscape characteristics compared with 700 randomly selected available locations within the study area. We chose 700 control points because we wanted to sample enough points to adequately capture the variability in the predictors across the entire landscape without substantially decreasing the ratio of ones to zeros. Our ratio (1 : 5.5) was similar to that of Brillinger *et al.* (2003) (1 : 4).

We first developed univariate logistic regression models for all of the explanatory variables because we wanted to evaluate their independent influence on the response variables and to determine the values and direction (i.e. positive or negative) of the coefficients independently of their interactions with other variables. The *P* values for these models were Bonferroni-corrected to account for the large number of tests performed. Next, we developed a multiple logistic regression model using the R statistical package (R Development Core Team 2005). We selected the final model through a backwards elimination process using the Akaike Information Criterion (AIC)

(Venables and Ripley 1999). Significance of effects was determined using the likelihood ratio test.

To ensure that there were no collinearity problems, we implemented a collinearity diagnostic procedure, the variance inflation factor (VIF), to ensure low correlation (VIF lower than 10) between the variables in the multiple regression model (Belsey *et al*. 1980). Because July maximum temperature was correlated with other variables, we removed this variable and refitted the multiple regression models. We also plotted semi-variograms of the models' deviance residuals to ensure there was no evidence of spatial autocorrelation. For all of our models, we evaluated the variables for non-linear relationships with the response through graphical checks and by fitting the models with quadratic terms included and determining whether those terms were significant.

To evaluate the performance of the multiple logistic regression model, we used a leave-one-out cross-validation approach (Lachenbruch 1967; Bautista *et al*. 1999). The procedure was to drop a single data point (i.e. an ignition), fit the model without it, and then calculate the predicted probability of an ignition at that point. This was repeated for every point. We then performed a receiver operating characteristic (ROC) analysis to determine the optimal probability cutoff for predicting that an ignition would occur. Based on this prediction rule, we were able to compare the yes–no ignition prediction with whether an ignition actually occurred, and estimate the sensitivity (fraction of true positive), specificity (fraction of false positive), and overall predictive ability of the fitted model (Fielding and Bell 1997).

The overall area under the curve (AUC) reflected the overall probability that, when we drew one ignition and one non-ignition point at random, our prediction rule correctly identified them. AUC values vary from 0.5 (no apparent accuracy) to 1.0 (perfect accuracy), but the interpretation of what is considered high or low predictive ability is subjective and can vary according to sample size, with lower sample sizes resulting in lower evaluations of model accuracy (Hernandez *et al*. 2006).

Fire frequency

Instead of using logistic regression, we used Poisson univariate and multiple regressions to develop the fire frequency models because they were appropriate for count data (Agresti 1996). For Poisson regression, if N_i is the number of fires observed in cell i, and x_{ji}, β_0 and β_n are as above, the model is:

$$N_i = \exp(\beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \ldots + \beta_n x_{ni})$$

As with the ignition multiple regression models, we developed univariate regression models for all of the explanatory variables because we wanted to evaluate their independent influence on the response variable, and adjusted the *P* values using the Bonferroni correction. For our multiple Poisson regression analysis, we again used a backwards stepwise elimination procedure based on the AIC to select the final model.

Although no spatial autocorrelation was present in the ignition data, we refitted the Poisson multiple regression model with allowance for a spatial exponential correlation between the deviance residuals owing to significant spatial autocorrelation in the fire frequency data (Littell *et al*. 1996). We fitted this model using the *GLIMMIX* macro of *SAS* Software (PROC GLIMMIX 2005).

To evaluate the performance of our multiple Poisson regression model, we randomly selected 300 independent observations in the study area. To determine how closely the observed and predicted values agreed in relative terms, we calculated Pearson's correlation coefficient. We also calculated the root mean square error (RMSE) and average error, which illustrate the discrepancy between the observed and predicted values (Potts and Elith 2006).

Predictive mapping

To convert our models into predictive map surfaces, we applied the formulae from the multiple Poisson and multiple logistic regression models to the entire study area using the predicted coefficients and the GIS map layers of the significant explanatory variables. Because logistic regression uses a prespecified number of control points, the intercept for the logistic regression is meaningless. However, we were able to adjust the intercept, and thereby map meaningful predicted probabilities, by using the ratio of control to experimental points (Preisler *et al*. 2004). We used the formulae from the Poisson model to predict and map fire frequency.

Owing to the difference in scales of fire ignition and fire frequency maps (probability of ignition *v*. predicted number of fires), we reclassified both maps into five equal-interval categories using the GIS and then summed these derived maps to generate a new map. This combined map was beneficial for identifying areas where ignitions and fire frequency were either both high or both low; however, intermediate values on the combined map did not differentiate between areas of high ignitions and low fire frequency and areas of high fire frequency and low ignitions. Therefore, we created a second map that reflected the differences in the predicted map surfaces.

Results

Fire ignitions

All of the human variables were significant ($P \leq 0.05$) in explaining fire ignitions in the univariate models except for distance to WUI after the Bonferroni adjustment (Table 2, Fig. 3). Ignitions were negatively related to all the distance variables and occurred closer to human infrastructure than the randomly selected points (Table 2). Although logistic regression coefficients can only be interpreted with respect to the intercept for categorical variables, the univariate models did indicate that fewer ignitions occurred when there was no development within a surrounding 500-m buffer, and more ignitions occurred with low or high proportions of nearby development. Similarly, fewer ignitions occurred when there was no WUI in the buffer, and more occurred with higher proportions of WUI. In addition to the human variables, the pattern of ignitions was also significantly related to slope and vegetation type, with ignitions being negatively related to slope.

When all of the variables were evaluated in the multiple logistic regression analysis, the final model for fire ignitions retained most of the human variables (distance to development, distance to roads, distance to trails, and level of WUI) as well as January minimum temperature and vegetation type (Table 3). The final model was highly significant at $P < 0.0001$.

Table 2.   Univariate regression results for all variables explaining fire ignitions and fire frequency in the Santa Monica Mountains, CA
WUI, wildland–urban interface

Explanatory variable	Fire ignitions			Fire frequency		
	Coefficient	s.e.	*P* value	Coefficient	s.e.	*P* value
Distance development	−0.001201	0.000258	<0.0001	0.000131	0.000043	0.0026
Distance WUI	−0.000298	0.000137	0.0183	0.000065	0.000045	0.1513
Distance roads	−0.002635	0.000637	<0.0001	0.000097	0.000059	0.1028
Distance trail	−0.001785	0.0007	0.0045	−0.00002	0.000073	0.7837
January	−0.00012	0.000115	0.2964	0.000194	0.000057	0.0007
South-westness	0.002373	0.001392	0.0869	0.000334	0.00012	0.0055
Slope	−0.039957	0.009359	<0.0001	0.001927	0.00092	0.0364
Elevation	−0.000414	0.000169	0.0132	0.000079	0.000044	0.0726
Level of development						
None (0)	−2.3706[A]	0.2012	0.0002	1.2394	0.3444	<0.0001
Low (0–0.33)	0.9784	0.2349		1.1649	0.3426	
Intermediate (0.34–0.66)	0.6127	0.3972		0.9595	0.3338	
High (0.67–0.1)	0.9843	0.8158		−0.2587[A]	0.3604	
Level of WUI						
None (0)	−2.3302[A]	0.2095	<0.0001	0.07604	0.05809	0.5728
Low (0–0.33)	1.174	0.2704		0.03285	0.04838	
Intermediate (0.34–0.66)	0.8506	0.3119		0.01377	0.04237	
High (0.67–0.1)	0.4861	0.285		0.8651[A]	0.08816	
Vegetation type						
Coastal sage scrub	−1.39872[A]	0.17656	<0.0001	−0.02177	0.6849	0.3812
Northern mixed chaparral	−0.99918	0.24968		−0.00314	0.06824	
Chamise chaparral	0.01242	0.58624		−0.09035	0.1025	
Non-native grass	0.3001	0.3657		−0.05593	0.0823	
Other	0.19474	0.30509		−0.099	0.08529	
Oak woodland	0.64495	0.46368		−0.1134	0.09551	
Riparian	0.41789	0.69965		0.9235[A]	0.1039	

[A]Intercept of the model; the coefficients of the categorical variables (level of development and WUI, and vegetation type) are relative to the value of the intercept.

The map surface generated by applying the formula and coefficients of the final model to the original GIS maps showed the distribution of predicted ignition probabilities across the study area (Fig. 4). The spatial pattern of those areas predicted as having the highest likelihood of ignition reflected the influence of development, WUI, and roads, as seen through their similar distributions (Fig. 2).

The leave-one-out cross-validation of the final multiple logistic model resulted in an AUC of 0.71. An AUC of 0.71 indicates that, although our ability to predict is not perfect, our model performs considerably better than chance, and thus provides useful and novel information about the properties of the locations where ignitions are likely to occur. Our maximum sensitivity (true positive fraction) and specificity (false positive) occurred at a cutoff of 0.16, which yielded sensitivity = 0.685, and specificity = 0.667 (Fig. 4). In other words, if the model predicts a probability of ignition of 0.16 or more, we predict an ignition, otherwise we predict no ignition.

Fire frequency

Unlike the univariate models for fire ignitions, there were more biophysical variables than human variables that were significant ($P \leq 0.05$) in explaining fire frequency (Table 2, Fig. 3). Specifically, January minimum temperature, south-westness, slope, and elevation all had a positive influence on fire frequency. However, elevation, slope, and south-westness were not considered significant with the Bonferroni adjustment. Whereas distance to development negatively influenced the likelihood of ignition, it had a significant positive influence on fire frequency, so that fires were more likely to burn farther away from development. Fire frequency was also significantly related to level of development, but the influence was opposite that for fire ignitions in that fires were more likely to occur in none, low, and intermediate levels than in high levels of development.

Except for distance to development, all of the variables that were significant in the non-adjusted univariate models were also retained in the final model for fire frequency (Table 3). This model was also highly significant at $P < 0.0001$. The spatial pattern of predicted fire frequency on the map generated from the final regression model showed a strong influence of level of development and reflected the influence of the 500-m buffers (Fig. 4). The influence of January temperature was also visually apparent in the predictions, with more fires occurring along the coast where the temperature is generally warmer. The areas predicted to experience the most fires roughly corresponded to the fire history map (Fig. 2).

The evaluation of our multiple Poisson regression fire frequency model with the independent dataset showed that we predicted the number of fires correctly 40% of the time,
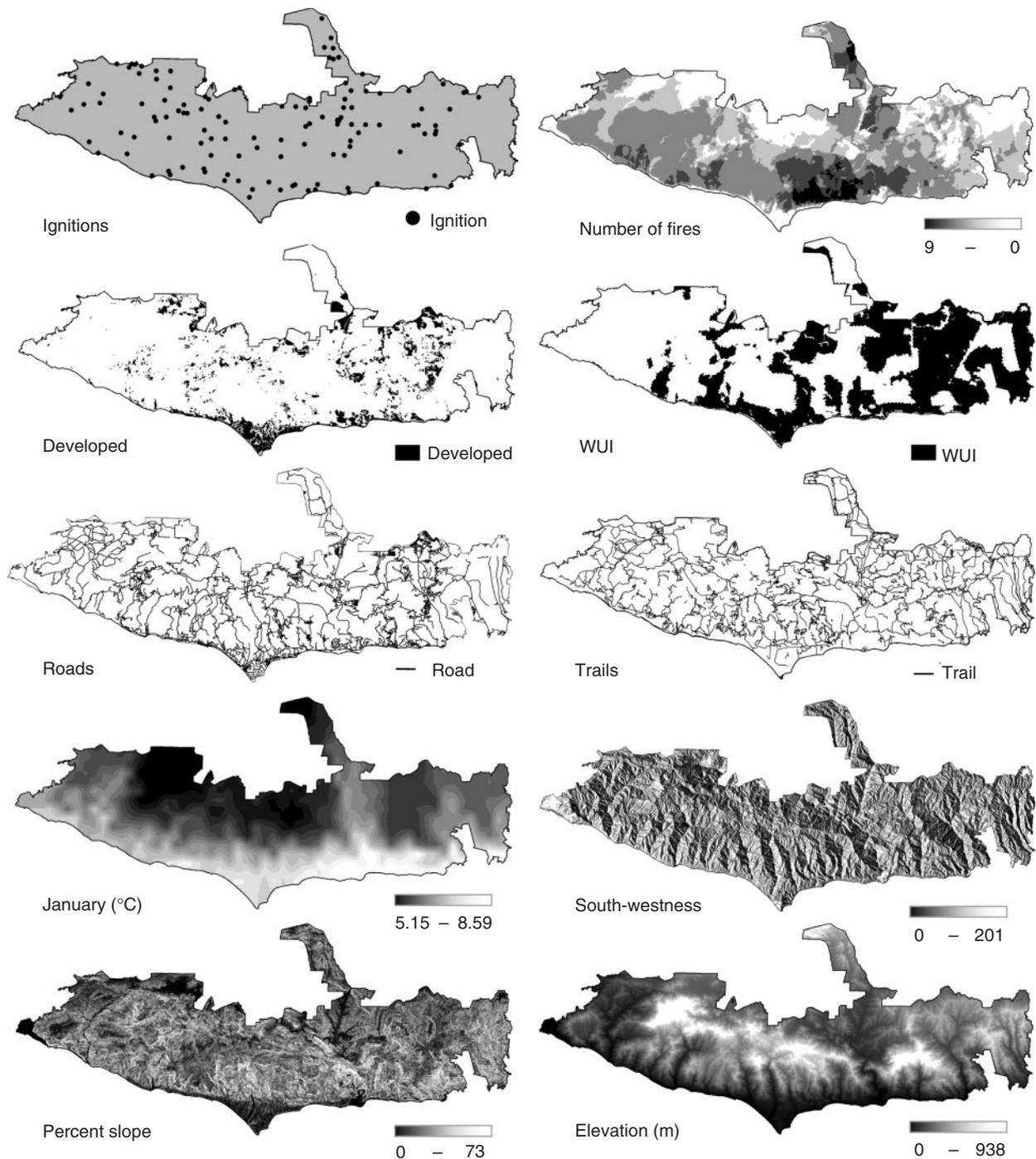
Fig. 3. Maps of variables used for regression models and predictive mapping of the Santa Monica Mountains, CA. Dependent variables included ignitions and number of fires; independent variables included developed, wildland–urban interface (WUI), roads, trails, mean January minimum temperature, south-westness, percentage slope, and elevation. Vegetation map not shown. The WUI is the area where houses meet or intermingle with undeveloped wildland vegetation, based on the definition in the Federal Register.

80% were within one fire of being correct, and 95% were within two. The Pearson's correlation coefficient was 0.490, the RMSE was 1.219. These statistics indicate that the model's performance was fair, but the positive error shows that we tended to underestimate fire frequency.

The combined map showed that, although some areas had a high potential for both fire ignition and frequency, not all areas with high potential for ignition were likely to experience many fires. In some of the most remote portions in the interior of the landscape, both fire ignition probability and fire frequency were

predicted to be low. Along the coast and through some of the more developed canyons in the interior, however, both ignitions and frequency were predicted to be higher (Fig. 4).

Discussion

As we expected, humans significantly influenced the spatial pattern of ignitions, which were located in close proximity to all measures of human infrastructure included in our univariate

Table 3.   Variables retained in the multiple regression models explaining fire ignitions and fire frequency in the Santa Monica Mountains, CA
WUI, wildland–urban interface

Model	Explanatory variable	*P* value
Ignitions	Distance development	<0.0001
	Distance roads	0.002
	Vegetation type	0.002
	Level of WUI	0.011
	January	0.016
	Distance trails	0.08
	Full model	<0.0001
Fire frequency	Level of development	<0.0001
	January	<0.0001
	South-westness	0.005
	Elevation	0.036
	Slope	0.045
	Full model	<0.0001

models and were most strongly related to distance to development and roads in the multivariate models. Previous research showed that fire frequency and area burned were highest at intermediate levels of human activity; however, at lower and higher levels of human activity, fire activity was lower (Keeley 2005; Syphard *et al.* 2007a, 2007b). In the present study, ignitions were more likely to occur with consistently larger proportions of both development and WUI within 500-m buffers. However, the spatial extent of these buffers may not have captured the intermediate effects that were apparent through the landscape and county scales used in the other studies. Slope, vegetation type, and January temperature were also significantly related to ignitions, which may in part reflect the fact that fire ignition success is conditional on factors such as fuel moisture content and stand structure (Tanskanen *et al.* 2005).

Considering that humans start most fires in the Santa Monica Mountains and that human activities are concentrated around roads and developed areas, these results are not surprising. Yet, statistically modelling these human relationships and their interactions with biophysical variables is necessary for more precisely explaining and mapping the parts of the landscape that are most likely to ignite. Although other regions may not experience the same proportion of human ignitions as southern California, human-caused ignitions along transportation corridors have been documented broadly (Stephens 2005), and the significance of our results underscores the importance of considering more than just fuel loads in fire risk assessments. The WUI is not just the area with the highest concentration of human
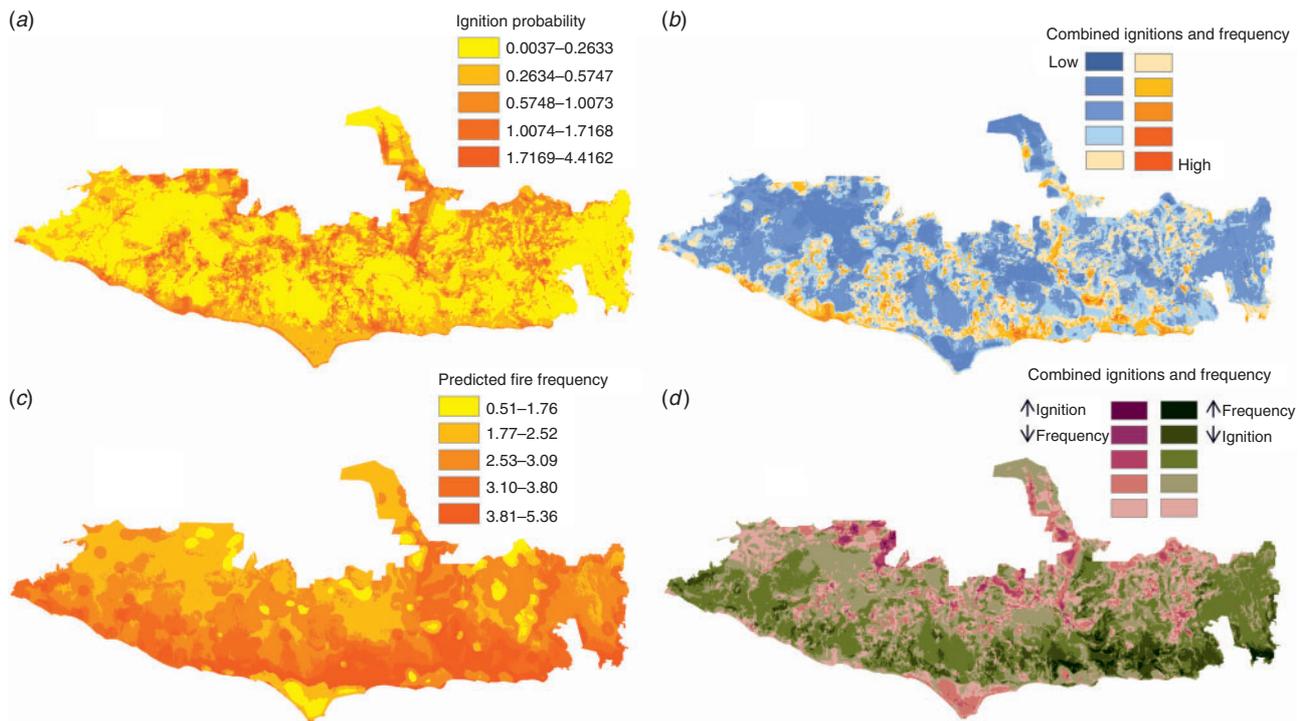

Fig. 4.   Maps showing predicted probability of ignition (*a*), predicted fire frequency (*b*), overlay and sum of the classified ignition and fire frequency maps (*c*), and the distribution of differences between predicted ignition probabilities and predicted fire frequency (*d*) developed from multiple regression models in the Santa Monica Mountains, CA.

values at risk; it is also the area where humans are most likely to put these valuable assets at risk by starting fires, intentionally or not.

Although ignition locations were primarily related to the distribution of human activities, fire frequency was mainly determined by biophysical variables, which was expected because fire spread is ultimately a function of vegetation characteristics, climate, and terrain (Pyne *et al*. 1996). Fire frequency was significantly related to two human variables, but more fires occurred with longer distances to development and with lower proportions of development within buffers. Although this result seems surprising given the location of ignitions, one likely reason that fires burned more frequently when they were farther from human infrastructure is that there is typically more continuous vegetation in remote areas. Therefore, fires would not be interrupted by fragmented fuels that characterise urban areas. Also, there are lower concentrations of fire suppression resources outside urban areas (Calkin *et al*. 2005), so fires will be able to consistently burn longer and grow larger when they spread beyond their ignition source into more remote regions. This means that, although fires start closer to roads or development, the areas that actually burn most frequently are the non-urban regions where fire spreads after ignition.

A possible shortcoming in our fire frequency models was that the human explanatory variables only represented the contemporary time period, but the fire frequency data spanned a period of 78 years (although more than 75% of the fires in the record occurred within the last 20 years). Despite this temporal mismatch, our results were consistent with previous research in California that showed that, whereas human variables are the best predictors for the number of fires that start, biophysical variables are better at explaining the variation in area burned (Syphard *et al*. 2007*a*). Therefore, the most important predictors for the fire frequency models were the biophysical variables that remained constant over the temporal extent of the fire frequency data.

Although it would have been ideal to incorporate temporally extensive human variables in our multiple regression analysis, adding these data would have likely only improved the fit of our models, particularly because human development patterns have high spatial autocorrelation, particularly in the Santa Monica Mountains (Syphard *et al*. 2007*b*). Historic housing data were most likely distributed in the exact same locations as the contemporary housing data that we used in our analysis because houses persist over time. Nevertheless, the fair performance of our fire frequency models may have been improved if we had had access to temporally extensive data for the human variables.

The fact that the variables that best predicted fire ignitions differed from those that best predicted fire frequency explains why the spatial patterns in the predictive maps of ignitions and frequency were somewhat different from one another. Nevertheless, there were regions in the interior of the landscape where fire ignitions and fire frequency were predicted to be very low. Therefore, although fires spread away from ignition sources and burn more frequently outside urban areas, there are also even more remote areas that burn with much less frequency. However, some of the coastal areas and interior canyons are more likely to experience greater numbers of ignitions and more frequent fire. The coastal areas tend to be warmer and dryer than the more remote interior regions of the landscape, which makes them more conducive to fire. These regions also have gentler slopes and are more favourable for housing development and human activity.

From a management perspective, overlaying the two predictive maps is useful because the resulting combined map can identify areas that are not only at a high risk for experiencing an ignition, but also where those ignitions are likely to initiate into a full, spreading fire. Areas where high predicted ignition probability coincides with high predicted fire frequency can then be targeted for fire management actions, such as fuel reduction. The Santa Monica Mountains fire management plan has outlined additional criteria, including socioeconomic variables and other resources at risk, to further the decision-making process for identifying potential strategic fuel modification locations (NPS 2005). These additional criteria are important for ensuring that treatments are not placed in low-hazard areas where protection is not needed.

The present and other studies have determined that fire ignition locations, as well as areas where frequent fires occur, can be statistically modelled using readily measurable sets of social, biological, and physical features (e.g. Keeley *et al*. 1999; Cardille *et al*. 2001; Pew and Larsen 2001; Prestemon *et al*. 2002; Mercer and Prestemon 2005). Therefore, the approach used here can be used in other landscapes to refine the strategic placement of fuels treatments and to better anticipate where fires are most likely to occur. To adapt these methods to other regions, scientists and managers should be aware that the relative influence of human or biophysical variables is likely to vary according to region, temporal or spatial scale of analysis, and type of human activity. Therefore, the choice of predictor variables should be relevant to the primary characteristics driving each region's fire regime.

References

Agresti A (1996) 'An Introduction to Categorical Data Analysis.' 1st edn. (Wiley: New York)

Allen CD, Savage M, Falk DA, Suckling KF, Swetnam TW, Schulke T, Stacey PB, Morgan P, Hoffman M, Klingel JT (2002) Ecological restoration of south-western ponderosa pine ecosystems: a broad perspective. *Ecological Applications* **12**, 1418–1433. doi:10.1890/1051-0761(2002)012[1418:EROSPP]2.0.CO;2

Anderson HE (1982) Aids to determining fuel models for estimating fire behavior. USDA Forest Service, Intermountain Research Station, General Technical Report INT-167. (Ogden, UT)

Andrews PL, Bevins CD, Seli RC (2005) BehavePlus Fire Modeling System, version 3.0: user's guide. USDA Forest Service, Rocky Mountain Research Station, General Technical Report RMRS-GTR-106WWW Revised. (Ogden, UT)

Badia-Perpinya A, Pallares-Barbera M (2006) Spatial distribution of ignitions in Mediterranean periurban and rural areas: the case of Catalonia. *International Journal of Wildland Fire* **15**, 187–196. doi:10.1071/WF04008

Bautista D, Arana E, Marti-Bonmati L, Paredes R (1999) Validation of logistic regression models in small samples. *Journal of Clinical Epidemiology* **52**, 237–241. doi:10.1016/S0895-4356(98)00165-6

Belsey D, Kuh E, Welsch RE (Eds) (1980) 'Regression Diagnostics: Identifying Influential Observations and Sources of Collinearity.' (Wiley Sons: New York)

Bradstock RA, Gill AM, Kenny BJ, Scott J (1998) Bushfire risk at the urban interface estimated from historical weather records: consequences for the use of prescribed fire in the Sydney region of south-eastern Australia. *Journal of Environmental Management* **52**, 259–271. doi:10.1006/JEMA.1997.0177

Brillinger DR, Preisler HK, Benoit JW (2003) Risk assessment: a forest fire example. In 'Science and Statistics: a Festschrift for Terry Speed'. (Ed. DR Goldstein) pp. 177–196. (Institute of Mathematical Statistics: Beachwood, OH)

Burgan RE, Rothermel RC (1984) BEHAVE: fire prediction and fuel modelling system – FUEL subsystem. USDA Forest Service, Intermountain Research Station, General Technical Report INT-167. (Ogden, UT)

Calkin DE, Gebert KM, Jones JG, Neilson RP (2005) Forest Service large fire area burned and suppression expenditure trends, 1970–2002. *Journal of Forestry* **103**, 179–183.

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

Chou YH (1992) Spatial autocorrelation and weighting functions in the distribution of wildland fires. *International Journal of Wildland Fire* **2**, 169–176. doi:10.1071/WF9920169

Chou YH, Minnich RA, Chase RA (1993) Mapping probability of fire occurrence in San Jacinto Mountains, California, USA. *Environmental Management* **17**, 129–140. doi:10.1007/BF02393801

Countryman CM (1972) The fire environment concept. USDA Forest Service, Pacific Southwest Forest and Range Experiment Station, General Technical Report PSW-7. (Berkeley, CA)

DellaSala DA, Williams JE, Williams CD, Franklin JF (2004) Beyond smoke and mirrors: a synthesis of fire policy and science. *Conservation Biology* **18**, 976–986. doi:10.1111/J.1523-1739.2004.00529.X

Diaz-Avalos C, Peterson DL, Alvarado E, Ferguson SA, Besag JE (2001) Space–time modelling of lightning-caused ignitions in the Blue Mountains, Oregon. *Canadian Journal of Forest Research* **31**, 1579–1593. doi:10.1139/CJFR-31-9-1579

Dickson BG, Prather JW, Xu Y, Hampton HM, Aumack EN, Sisk TD (2006) Mapping the probability of large fire occurrence in northern Arizona, USA. *Landscape Ecology* **21**, 747–761. doi:10.1007/S10980-005-5475-X

Fielding AH, Bell JF (1997) A review of methods for the assessment of prediction errors in conservation presence/absence models. *Environmental Conservation* **24**, 38–49. doi:10.1017/S0376892997000088

Forestry Canada Fire Danger Group (1992) Development and structure of the Canadian Forest Fire Behaviour Prediction System. Forestry Canada, Science and Sustainable Development Directorate, Report ST-X-3. (Ottawa, ON)

Franklin J (1998) Predicting the distribution of shrub species in Southern California from climate and terrain-derived variables. *Journal of Vegetation Science* **9**, 733–748. doi:10.2307/3237291

Franklin J, McCullough P, Gray C (2000) Terrain variables used for predictive mapping of vegetation communities in Southern California. In 'Terrain Analysis: Principles and Applications'. (Eds J Wilson, J Gallant) pp. 331–353. (Wiley: New York)

Fried JS, Winter G, Gilless JK (1999) Assessing the benefits of reducing fire risk in the wildland–urban interface: a contingent valuation approach. *International Journal of Wildland Fire* **9**, 9–20. doi:10.1071/WF99002

Haidinger TL, Keeley JE (1993) Role of high fire frequency in destruction of mixed chaparral. *Madrono* **40**, 141–147.

Haight RG, Cleland DT, Hammer RB, Radeloff VC, Rupp TS (2004) Assessing fire risk in the wildland–urban interface. *Journal of Forestry* **104**, 41–48.

Halsey RW (2005) 'Fire, Chaparral, and Survival in Southern California.' (Sunbelt Publications: San Diego, CA)

Hernandez PA, Graham CH, Master LL, Albert DL (2006) The effect of sample size and species characteristics on performance of different species distribution models. *Ecography* **29**, 773–785. doi:10.1111/J.0906-7590.2006.04700.X

Jacobsen AL, Pratt RB, Ewers FW, Davis SD (2007) Cavitation resistance among twenty-six chaparral species of southern California. *Ecological Monographs* **77**, 99–115. doi:10.1890/05-1879

Keeley JE (1982) Distribution of lightning and man-caused wildfires in California. In 'Proceedings of the International Symposium on the Dynamics and Management of Mediterranean-type Ecosystems', 22–26 June 1981, San Diego, CA. (Eds CE Conrad, WC Oechel) USDA Forest Service, Pacific Southwest Forest and Range Experiment Station, General Technical Report PSW 58, pp. 431–437. (Berkeley, CA).

Keeley JE (2000) Chaparral. In 'North American Terrestrial Vegetation'. (Eds MG Barbour, WD Billings) pp. 202–253. (Cambridge University Press: Cambridge, MA)

Keeley JE (2005) Fire history of the San Francisco East Bay region and implications for landscape patterns. *International Journal of Wildland Fire* **14**, 285–296. doi:10.1071/WF05003

Keeley JE, Fotheringham CJ (2003) Impact of past, present, and future fire regimes on North American Mediterranean shrublands. In 'Fire and Climatic Change in Temperate Ecosystems of the Western Americas'. (Eds TT Veblen, WL Baker, G Montenegro, TW Swetnam) pp. 218–262. (Springer-Verlag: New York)

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

Lachenbruch PA (1967) An almost unbiased method for the probability of misclassification in discriminant analysis. *Biometrics* **23**, 639–645. doi:10.2307/2528418

Larjavaara M, Pennanen J, Tuomi TJ (2005) Lightning that ignites forest fires in Finland. *Agricultural and Forest Meteorology* **132**, 171–180. doi:10.1016/J.AGRFORMET.2005.07.005

Littell RC, Milliken GA, Stroup WW, Wolfinger RD (1996) 'SAS System for Mixed Models.' (SAS Institute Inc.: Cary, NC)

Mercer DE, Prestemon JP (2005) Comparing production function models for wildfire risk analysis in the wildland–urban interface. *Forest Policy and Economics* **7**, 782–795. doi:10.1016/J.FORPOL.2005.03.003

Miller C, Urban DL (2000) Modeling the effects of fire management alternatives on mixed-conifer forests in the Sierra Nevada. *Ecological Applications* **10**, 85–94.

Moritz MA (2003) Spatiotemporal analysis of controls on shrubland fire regimes: age dependency and fire hazard. *Ecology* **84**, 351–361. doi:10.1890/0012-9658(2003)084[0351:SAOCOS]2.0.CO;2

National Park Service (2002) Final general management plan and environmental impact statement, Vol. 1 of 2. USDI, National Park Service. (Thousand Oaks, CA)

National Park Service (2005) Final environmental impact statement for a fire management plan, Santa Monica Mountains National Recreation Area. USDI, National Park Service. (Thousand Oaks, CA)

Odion DC, Frost EJ, Strittholt JR, Jiang H, DellaSalla DA, Moritz MA (2004) Patterns of fire severity and forest conditions in the western Klamath Mountains, north-western California. *Conservation Biology* **18**, 927–936. doi:10.1111/J.1523-1739.2004.00493.X

Pew KL, Larsen CPS (2001) GIS analysis of spatial and temporal patterns of human-caused wildfires in the temperate rainforest of Vancouver Island, Canada. *Forest Ecology and Management* **140**, 1–18. doi:10.1016/S0378-1127(00)00271-1

Potts JP, Elith J (2006) Comparing species abundance models. *Ecological Modelling* **199**, 153–163. doi:10.1016/J.ECOLMODEL.2006.05.025

Preisler HK, Brillinger DR, Burgan RE, Benoit JW (2004) Probability-based models for estimation of wildfire risk. *International Journal of Wildland Fire* **13**, 133–142. doi:10.1071/WF02061

Prestemon JP, Pye JM, Butry DT, Holmes TP, Mercer DE (2002) Understanding broadscale wildfire risks in a human-dominated landscape. *Forest Science* **48**, 685–693.

PROC GLIMMIX (2005) '*SAS/STAT* Software, version 9.1.3 of the SAS System for Unix.' (SAS Institute Inc.: Cary, NC)

Pyne SJ (2001) 'Fire in America.' (Princeton University Press: Princeton, NJ)

Pyne SJ, Andrews PL, Laven RD (1996) 'Introduction to Wildland Fire.' (Wiley: New York)

R Development Core Team (2005) R: a language and environment for statistical computing. (R Foundation for Statistical Computing: Vienna, Austria) Available at http://www.R-project.org [Verified 11 August 2008]

Radeloff VC, Hammer RB, Stewart SI, Fried JS, Holcomb SS, McKeefry JF (2005) The wildland–urban interface in the United States. *Ecological Applications* **15**, 799–805. doi:10.1890/04-1413

Radtke KWH, Arndt AM, Wakimoto RH (1982). Fire history of the Santa Monica Mountains. (Eds CE Conrad, WC Oechel) USDA Forest Service, Pacific Southwest Forest and Range Experiment Station, General Technical Report PSW-58, pp. 438–443. (Berkeley, CA)

Reed WJ, Larsen CPS, Johnson EA, MacDonald GM (1998) Estimation of temporal variations in historical fire frequency from time-since-fire map data. *Forest Science* **44**, 465–475.

Rollins MG, Morgan P, Swetnam T (2002) Landscape-scale controls over 20th century fire occurrence in two large Rocky Mountain (USA) wilderness areas. *Landscape Ecology* **17**, 539–557. doi:10.1023/A:1021584519109

Rundel PW, King JA (2001) Ecosystem processes and dynamics in the urban/wildland interface of Southern California. *Journal of Mediterranean Ecology* **2**, 209–219.

Scheller RM, Mladenoff DM, Crow TR, Sickley TA (2005) Simulating the effects of fire reintroduction versus continued fire absence on forest composition and landscape structure in the Boundary Waters Canoe Area, northern Minnesota, USA. *Ecosystems* **8**, 396–411. doi:10.1007/S10021-003-0087-2

Steele BM, Reddy SK, Keane RE (2006) A methodology for assessing the departure of current plant communities from historical conditions over large landscapes. *Ecological Modelling* **199**, 53–63. doi:10.1016/J.ECOLMODEL.2006.06.016

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

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

Syphard AD, Clarke KC, Franklin J (2007*b*) Simulating fire frequency and urban growth in southern California coastal shrublands. *Landscape Ecology* **22**, 431–445. doi:10.1007/S10980-006-9025-Y

Tanskanen H, Venäläinen A, Puttonen P, Granström A (2005) Impact of stand structure on surface fire ignition potential in *Picea abies* and *Pinus sylvestris* forests in southern Finland. *Canadian Journal of Forest Research* **35**, 410–420. doi:10.1139/X04-188

US Census (2000) 'Census 2000 TIGER/Line Files [machine-readable data files].' (US Census Bureau: Washington, DC)

USDA, USDI (2001) Urban–wildland interface communities within vicinity of Federal lands that are at high risk from wildfire. *Federal Register* **66**, 751–777.

Venables WN, Ripley BD (1999) 'Modern Applied Statistics with S-Plus.' 3rd edn. (Springer: New York)

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)

Wotton BM, Martell DL (2005) A lightning fire occurrence model for Ontario. *Canadian Journal of Forest Research* **35**, 1389–1401. doi:10.1139/X05-071

Yang J, He HS, Shifley SR, Gustafson EJ (2007) Spatial patterns of modern period human-caused fire occurrence in the Missouri Ozark Highlands. *Forest Science* **53**, 1–15.

Zedler PH (1995) Plant life history and dynamic specialization in the chaparral/coastal sage scrub flora in southern California. In 'Ecology and Biogeography of Mediterranean Ecosystems in Chile, California, and Australia'. (Eds MTK Arroyo, PA Zedler, MD Fox) pp. 89–115. (Springer-Verlag: New York)

Zedler PH, Clayton RG, McMaster GS (1983) Vegetation change in response to extreme events: the effect of a short interval between fires in California chaparral and coastal scrub. *Ecology* **64**, 809–818. doi:10.2307/1937204