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Multi-scale evaluation of the environmental controls on burn probability in a southern Sierra Nevada landscape

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Abstract. We examined the scale-dependent relationship between spatial fire likelihood or burn probability (BP) and some key environmental controls in the southern Sierra Nevada, California, USA. Continuous BP estimates were generated using a fire simulation model. The correspondence between BP (dependent variable) and elevation, ignition density, fuels and aspect was evaluated at incrementally increasing spatial scales to assess the importance of these explanatory variables in explaining BP. Results indicate the statistical relationship between BP and explanatory variables fluctuates across spatial scales, as does the influence of explanatory variables. However, because of high covariance among these variables, it was necessary to control for their shared contribution in order to extract their 'unique' contribution to BP. At the finest scale, fuels and elevation exerted the most influence on BP, whereas at broader scales, fuels and aspect were most influential. Results also showed that the influence of some variables tended to mask the true effect of seemingly less important variables. For example, the relationship between ignition density and BP was negative until we controlled for elevation, which led to a more meaningful relationship where BP increased with ignition density. This study demonstrates the value of a multi-scale approach for identifying and characterising mechanistic controls on BP that can often be blurred by strong but correlative relationships.

Additional keywords: fire regime, fuels, ignitions, spatial scale, topography.

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Introduction

Mapping the likelihood of fire is becoming an important aspect of strategic land management planning in fire-prone landscapes (Finney 2005). However, the reliability of fire likelihood estimates depends on our understanding of and ability to model the influence of environmental conditions on fire ignition and spread. Controls on fire regimes have often been described as top-down – the weather- or climate-related factors that exert an influence across a large area – and bottom-up – those whose influence is site-specific, such as topography (Heyerdahl *et al.* 2001; Kellogg *et al.* 2008). Although this framework is conceptually useful, strong interactions among top-down and bottom-up controls can blur the distinction between them (Peters *et al.* 2004; Parisien *et al.* 2010). For example, topography affects patterns of ignitions, weather and flammable vegetation (i.e. fuels), thereby obscuring the relationship between fire likelihood and the environment. Anthropogenic factors, which influence the number, timing and locations of ignitions, as well as fuel structure and composition, can further blur these relationships (Fry and Stephens 2006; Martell and Sun 2008). As a result of this complexity, nonlinear fire–environment relationships appear to be the norm rather than the exception (Kasischke *et al.* 2002), further impeding our ability to isolate the specific role of a given environmental factor (Carmel *et al.* 2009).

The strength and polarity of fire–environment linkages may vary as a function of the spatial scale of study (Falk *et al.* 2007). That is, a fire–environment relationship observed at one spatial scale may not hold at another (Parisien and Moritz 2009). This phenomenon, termed 'scale effect', is quite common in ecology (e.g. Weiher and Howe 2003; Wu 2004), highlighting the need to analyse ecological systems at multiple scales. For example, Randin *et al.* (2009) found that models using fine-resolution data predicted significantly greater habitat persistence than models using coarse-resolution data. Convincing examples of the scale effect also have been recently reported in studies of fire regimes. For instance, Cyr *et al.* (2007) showed that fire frequency in the eastern boreal forest of North America was related to slope aspect at some spatial scales, but not at others. Studies in the western USA (McKenzie *et al.* 2006) and

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in boreal Canada (Podur *et al*. 2002) illustrate scale domains at which fire patterns are aggregated and others at which they are regular or relatively random. Similarly, relationships to fuels and weather inferred from cumulative fire size distributions (Moritz *et al*. 2005; Boer *et al*. 2008) suggest different controlling mechanisms for small and large fires (Ricotta *et al*. 2001). Although these studies have firmly established that controls on fire are scale-dependent, pinpointing the true environmental drivers of fire regimes has proved a difficult task. Furthermore, these drivers are highly site specific and can be expected to vary by region (Littell *et al*. 2009).

A common challenge in studying the spatial relationship between fire and its environment is obtaining a sufficient number of reliable fire observations, which rarely span more than a century (e.g. Kasischke *et al*. 2002; Rollins *et al*. 2002). However, recent advances in landscape fire simulation modelling offer new possibilities to study fire–environment relationships and, thus, maximise the value of field observations and fire history atlases (Miller *et al*. 2008; Ager *et al*. 2010). High-resolution burn probability (BP) maps can be generated by explicitly simulating the ignition and spread of a very large number of fires, whose parameters are derived from historical fire observations. These outputs not only help circumvent the problems related to relative sparseness of the historical data but also allow a spatially continuous comparison of BP with environmental factors of interest.

Our central purpose was to evaluate the relationship between BP and some of its key environmental controls in a mountainous landscape of the southern Sierra Nevada, California, USA, at multiple spatial scales. Four environmental variables known to affect patterns in BP were selected for the multi-scale analysis: elevation, vegetation (i.e. fuels), ignitions and aspect. Although by no means exhaustive, these factors were selected because they are commonly related to spatial fire patterns in mountainous areas in the published literature. For example, fire regimes are often associated with different elevation-based vegetation types (Tande 1979; Mermoz *et al*. 2005). Lightning density, which generally experiences spatial variation in mountainous areas, has also been related to fire activity (Wierzchowski *et al*. 2002; Lutz *et al*. 2009). Fire activity in rugged terrain varies significantly as a function of aspect (Heyerdahl *et al*. 2001; Rollins *et al*. 2002), because it affects patterns in fuels (vegetation composition and structure) and fuel moisture.

We examined multiple spatial scales using a data aggregation technique called ‘moving window analysis’ (e.g. Bebi *et al*. 2003; Manley *et al*. 2009), in which all pixels within a circular moving window are averaged and assigned to the centre pixel. We define ‘spatial scale’ as a given moving window size; changes in the size of the moving window correspond to changes in spatial scale. We expect the strength of the relationship between fire and a given environmental factor (i.e. explanatory variable) to fluctuate according to the spatial scale of observation and that there is a scale at which each relationship is maximised. To examine our expectations, we used a suite of analyses with increasing complexity in terms of explanatory variable inclusion to isolate variable influences at each scale. However, because of strong covariance among environmental factors, determining relationships between BP and a given environmental factor is difficult. Therefore, another objective of this study involved analysing and controlling for covariance among the explanatory variables to gain a better idea of the more direct (i.e. mechanistic) influences of environmental controls on fire likelihood and the scales at which they operate (cf. Pausas and Austin 2001).

Materials and methods

Study area

The 572 170-ha study area in the southern Sierra Nevada, California, USA is primarily managed by the USDA Forest

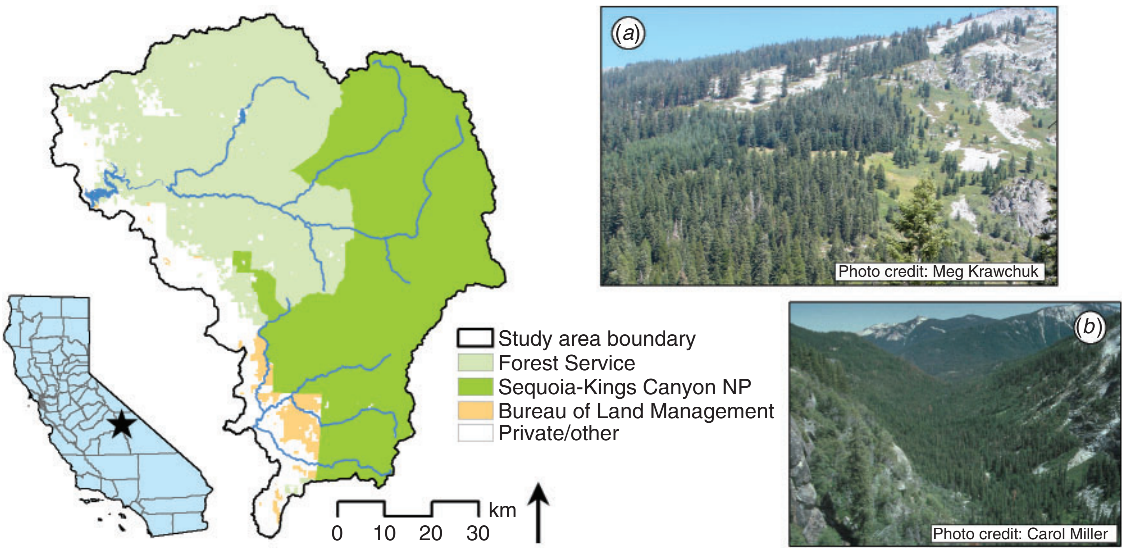

Fig. 1. Map of the study area in the Southern Sierra Nevada and its land management types (left). The study area is characterised by sharp topographic and vegetation gradients of variable patchiness. The upper picture (*a*) shows a vegetated upper-elevation landscape of coniferous forest, shrubland, grassland and exposed rock, whereas the lower picture (*b*) shows a conifer-dominated valley.

Service and the National Park Service (Fig. 1). Elevation ranges from 212 to 4297 m and generally increases from west to east; the easternmost boundary is particularly rugged. The main mountain range is north–south oriented and is dissected by large, steep canyons, numerous smaller canyons and glacially carved valleys at upper elevations. The area experiences a Mediterranean climate, where there is virtually no rain during the summer, except for occasional thunderstorms. The temperature is highly variable among high-elevation (cooler) and low-elevation (warmer) areas. Across the study area, the average maximum and minimum monthly temperatures range from 1.0 to 25.5°C and −8.0 to 11.5°C respectively. Average annual precipitation ranges from 37 to 155 cm (Daly *et al*. 2002); total precipitation and the proportion of this that falls as snow generally increase with elevation.

The natural vegetation at the lowest elevations, typified by hot, dry summers, is a mosaic of grassland, oak woodland and chaparral shrubland. As elevation increases, the vegetation transitions into pure ponderosa pine (*Pinus ponderosa* Dougl.) stands, then to mixed conifer forest (ponderosa pine, sugar pine (*P. lambertiana* Dougl.), white fir (*Abies concolor* (Gord. And Glend.) Lindl. ex Hildebr.), incense cedar (*Calocedrus decurrens* Torr.)), then to a higher-elevation zone dominated by red fir (*Abies magnifica* A. Murr.) and lodgepole pine (*Pinus contorta* (Grev. & Balf.) Engelm.). At upper elevations, where the growing season is much shorter, the vegetation consists of open subalpine forests and alpine environments dominated by sparse low vegetation (i.e. alpine grassland and shrubland, stunted trees). Discontinuities in vegetation (i.e. natural fuel breaks) generally increase with elevation.

Fire type and frequency generally vary with vegetation throughout the study area. Typically, grasslands and woodlands experience surface fires, chaparral experiences crown fires, and the conifer belt experiences a mix of non-lethal surface fires and, under suitable weather and fuel conditions, lethal surface fires and stand-replacing crown fires (Collins and Stephens 2010). Prior to Euro-American settlement, the fire interval throughout most of the Sierra Nevada was thought to be less than 20 years on average for the area extending from the foothills through the mixed conifer belt and approximately 26 years for the higher elevation red fir zone (McKelvey *et al*. 1996). The chaparral at the lower elevations may have had longer fire intervals of 50–60 years (Keeley *et al*. 2005). Fire frequency has decreased significantly since Euro-American settlement, largely due to successful fire suppression practices and possibly the cessation of Native American burning (van Wagtendonk and Fites-Kaufman 2006). The lengthening of fire-free intervals has altered forest structure, composition and fuel continuity and, consequently, modified fire behaviour (Kilgore and Taylor 1979; Stephens *et al*. 2009).

The fire season of the study area typically runs from mid-May to mid-October. However, fire season length generally decreases as elevation increases. Lightning density increases with elevation, but high elevation areas typically do not experience many fire ignitions because fuels are sparse (van Wagtendonk and Cayan 2008). Virtually all human-caused ignitions are aggressively suppressed; the majority of these occur in the lower elevations. In contrast, relative to Forest Service and private lands, a high proportion (~52% from 1980 to 2004) of lightning ignitions is not suppressed within the national park (NPS 2004).

The BP model

We used a customised version of the FlamMap model (Finney 2006), called Randig, to generate a BP grid for the study area. Randig simulates the ignition and spread of a very large number of fires and counts how many times each pixel burns, thereby providing an estimate of the relative likelihood of burning. Randig uses the minimum travel time algorithm (Finney 2002) to simulate fire growth. The model does not account for changes in fuels due to vegetation succession and, thus, estimates BP for a static landscape. Randig differs from FlamMap by allowing for non-random (i.e. spatially patterned) ignitions and variable wind directions and wind speeds. Hence, Randig combines probabilistic components of fire regimes, such as spatial ignitions and changing winds, with deterministic fire growth. Its inputs, as detailed below, can be categorised as either spatial or aspatial.

Only large fires (≥50 ha) of lightning origin were used to parameterise the model. Although they represent a fraction of the total fires, fires ≥50 ha are responsible for most of area burned (94.2%) in our study area. As such, considering only large fires for parameterisation represented a sensible 'shortcut' with minimal effect on the resulting BP patterns (Finney 2005). In addition, we considered only lightning-ignited fires because our focus was on natural fire–environment relationships. All spatial inputs extended 13 km beyond the study area boundary to minimise edge effects. The original fuels and topographic inputs had a 30-m resolution but were resampled to a 100-m pixel size to increase computation speed. In this study, 50 000 ignitions were simulated to produce a BP grid. We determined that this number of ignitions restricts the pixel-wise relative BP difference among runs to less than 2%.

Spatial BP inputs: fuels, topography and ignitions

The fuels data are comprised of five raster grids describing the type and structure of flammable vegetation: the fire behaviour fuel model (Scott and Burgan 2005), percentage canopy cover, crown base height, crown bulk density and stand height. The fire behaviour fuel model (hereafter referred to as the 'fuel model') is a classification that describes predicted fire behaviour (e.g. rate of spread, flame length) (Rothermel 1972); canopy cover is necessary for calculating the reduction factors for the wind's effect on fire spread rates and direction; and crown base height, crown bulk density and stand height are used in crown fire behaviour calculations (Finney 2006). The fuel model grid, created from aerial photographs, satellite images and disturbance history, was obtained from the Wildland Fire Decision Support System (see http://wfdss.usgs.gov/, accessed 3 August 2011). The WFDSS data source was recommended by experts familiar with the study area (Bernie Bahro, USDA Forest Service (retired) and Anne Birkholz, National Park Service, pers. comm.). Topographic inputs (elevation, slope and aspect) were created from a digital elevation model obtained from the US Geological Survey using standard GIS methodology.

An ignition probability density grid was created from the locations of large (≥50-ha) lightning-caused fires observed during the fire season (June–October) from 1970 to 2007. We used these observations ($n = 76$) as the dependent variable in a classification and regression tree (CART). CART requires 'absence' data in addition to 'presence' observations, so we used 76 randomly placed points that did not share the same pixel as our 76 fire observations to serve as pseudo-absences. Model predictions were used to generate a generalised and spatially continuous grid of the relative probability of ignitions that adequately described recent history of ignition patterns of the study area (cf. van Wagtendonk and Cayan 2008). The independent variables in the CART model were vegetation type (i.e. a generalised LANDFIRE vegetation map) (Rollins 2009) and elevation. Other variables, such as solar radiation, might also affect ignition probabilities, but exploratory analysis between ignitions and solar radiation showed no relationship.

Aspatial BP inputs: fire duration, fuel moisture and wind

The duration of each simulated fire was drawn from a frequency distribution of the number days that fires have burned in our study area. Fires in this region can burn for months, but they achieve significant growth only during a few 'spread-event days' (cf. Parisien *et al.* 2005) that generally correspond to dry, hot and windy weather conditions. We created this frequency distribution using MODIS satellite fire detection data (USDA Forest Service 2008), a subdaily record of fire activity at a 1-km^2 spatial resolution. Using MODIS fire detection data for fires greater than 50 ha that occurred between 2001 and 2007 within 75 km of the study area ($n = 71$ fires), we generated daily fire progression maps. The fine temporal resolution of these data compensate for their somewhat coarse spatial resolution, providing an objective and reliable means of detecting significant growth in large fires. We defined a spread-event day as follows:

$$\sqrt{a_i} \Bigg/ \sum_{i=1}^{n} \sqrt{a_i} \times 100\% \geq 5\% \qquad (1)$$

where a_i represents the daily area burned for a given fire (a surrogate for the daily spread rate), n is the last day of burning and the summation term is the sum of all a_i. The square root transformation of area burned accounts for the nonlinear (power function) expansion of fire size with time. The 5% threshold was selected through trial-and-error and captures the major spread of fires we've analysed. The resulting distribution of spread-event days had a decaying form ranging from 1 to 11 days, which we smoothed according to a logistic function. Therefore, this analysis identified specific dates that experienced substantial fire growth, which were then used to select fuel moisture values and wind data for our simulations (below).

Moisture values of live fuels (herbaceous and woody) and of 1-, 10- and 100-h time lag dead fuels (Cohen and Deeming 1985) were estimated using historical weather data from days identified as spread-event days. Randig does not allow for the adjustment or conditioning of fuel moisture values based on aspect, elevation and previous-day weather, so fuel moisture values were held constant across the landscape. To derive fuel moisture values, weather observations (temperature, relative humidity and precipitation) from three remote automated weather stations (RAWS) and the FireFamily Plus program (Bradshaw and McCormick 2000) were used to compute daily fuel moisture values for each station. Daily fuel moisture values were extracted for each spread-event day and averaged across the three stations; the median of the daily averages was used for the fire simulations.

We created a frequency distribution of wind speed and wind direction from which Randig randomly drew values for each spread-event day of each simulated fire. Therefore, wind speed and wind direction changed daily for multi-day fires (each day represents 8 h of simulated fire growth). Wind speed and wind direction are coupled in the frequency distribution, therefore avoiding non-existent combinations of speed and direction. We used a single RAWS (Park Ridge) to generate the frequency distribution, as this station is most representative of wind conditions in the study area (Dave Bartlett, National Park Service, pers. comm.).

Validation of simulated BP

To assess the ability of Randig to depict the spatial patterns in BP, we quantified the correspondence between the simulated BP and historical (1900–2007) fire frequencies (CDF 2007). To this end, we produced a Spearman rank-correlation between simulated BP and number of times burned for ~10 000 random pixels (excluding nonfuels). To account for the higher fire suppression on private lands, we conducted two comparisons: one including and one excluding private land. Although this type of validation is informative, there are several reasons we expected differences between simulated BP and historical fire frequencies. First, simulated BP is a point-in-time estimate reflecting the year in which the fuel information is valid, whereas historical fire frequency manifests over time during which vegetation changes due to disturbance and succession. Furthermore, the simulated BP in our study is intended to reflect natural fire–environment processes and does not account for fire suppression and human-caused ignitions that have influenced the historical fire record.

Data analysis: explanatory variables

Our analysis considered four explanatory variables to assess the environmental controls on BP: elevation (ELEV), potential spread rate (PSR), ignition density (IGN) and 'southwestness' (SW) (cf. Franklin 2002) (Fig. 2). All four variables were spatial so we could evaluate their spatial correspondence to BP. Initially, we explored the relationship between BP and several other variables: slope, solar radiation, heat load index, nonfuel percentage, nonfuel patch density, nonfuel patch aggregation and the coefficient of variation of elevation. However, many of these variables were redundant in that they measured very similar characteristics and were similar in their relationship to BP. For example, southwestness, heat load index and solar radiation all measure insolation and were highly correlated with each other and similarly correlated with BP. Variables that were difficult to interpret across multiple spatial scales (e.g. nonfuel patch density), or displayed little to no relationship with BP (e.g. slope), were subsequently dropped.

The ELEV and IGN exploratory variables were identical to the Randig inputs (Fig. 2), whereas the PSR and SW variables are interpretations of fuels and aspect respectively. The PSR variable is a continuous characterisation of the categorical fuel model grid. PSR was created by calculating the maximum heading rate of spread, which describes the speed at which fire moves through a pixel, for each fuel model under a given set of

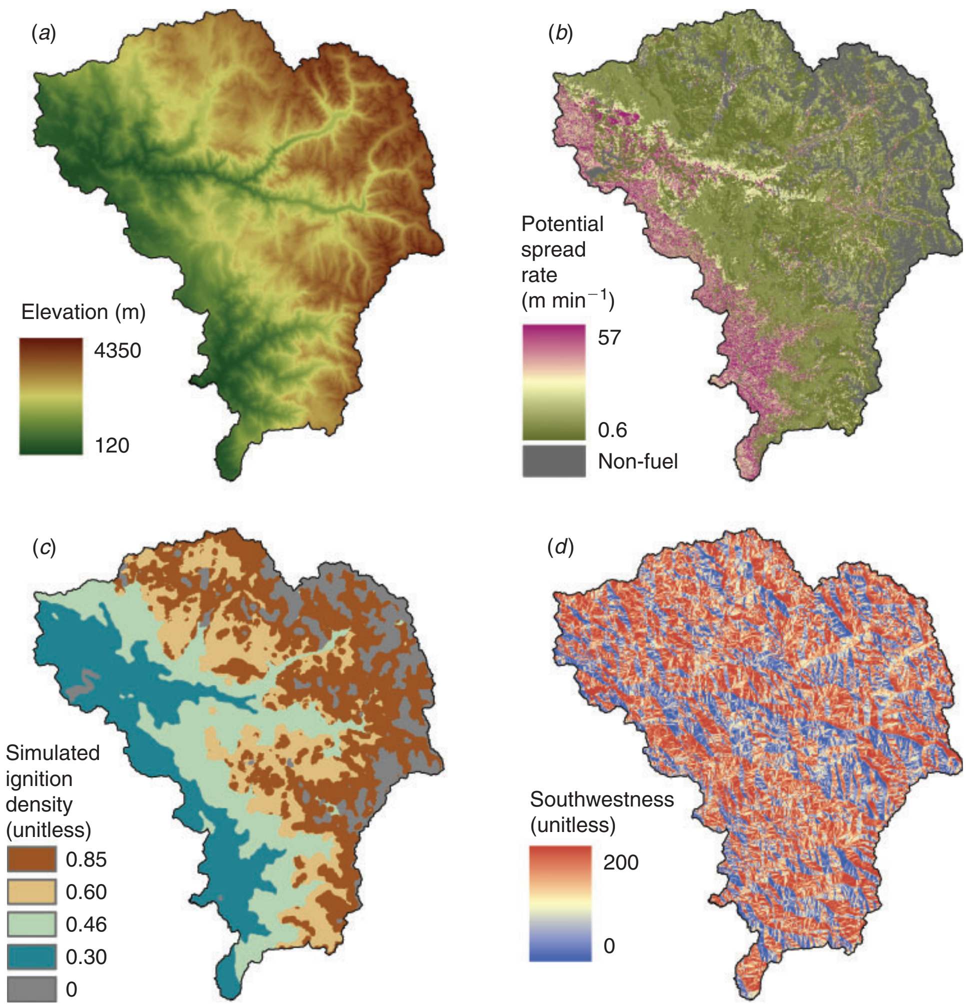

Fig. 2. The four exploratory variables used to explain burn probability: (*a*) elevation; (*b*) potential spread rate; (*c*) simulated ignition density; and (*d*) southwestness.

wind conditions, fuel moisture conditions and flat topography. Inputs were the fuel moisture values calculated using RAWS data for the spread-event days identified through the MODIS analysis (described above) and a wind speed of 8.1 km h^{-1} (the median wind speed for all spread-event days). The SW variable is a proxy for insolation (Franklin 2002); it is a continuous index for which south-west aspects have highest values (200) and north-east aspects have lowest values (0).

For each of the four explanatory variables, moving window surfaces were created for 42 window sizes, ranging from 100 to 100 000 ha (window radii from 564 to 17 841 m) and incrementing 100 ha at smaller sizes and 5000 ha at larger sizes. Specifically, for each 1-ha pixel of the study area, the mean value of each explanatory variable was computed within a circular window (i.e. neighbourhood) corresponding to each of the 42 window sizes (Fig. 3). These window sizes were chosen through exploratory analyses and comparison to other studies (Cyr *et al*. 2007, Falk *et al*. 2007). Raw pixel level data (1 ha) were also considered one of the scales in these analyses, resulting in 43 spatial scales. To relate BP to the explanatory variables at each scale, we randomly sampled ~10 000 burnable pixels (i.e. excluding non-fuels) and, at each of these pixels, we extracted the BP value and those values of the four explanatory variables at each spatial scale. Note that we analysed the relationship between the explanatory variables at each scale to the pixel-level BP; the BP grid did not undergo the moving window analysis.

Analysis of scale-dependent environmental controls on BP

The details of the scaling analyses are presented in Table 1. The functional relationship between BP and each explanatory variable was described at three spatial scales: 100, 5000 and 50 000 ha (radii of 564, 3990 and 12 600 m respectively). To allow a flexible depiction of the relationship, a self-fitting generalised additive model (GAM) was fit to the data with the *mgcv* package (Wood 2008) in the *R* statistical program (R Development Core Team 2007), which provides functions for generalised additive modelling and generalised additive mixed modelling. We defined the data distribution as the

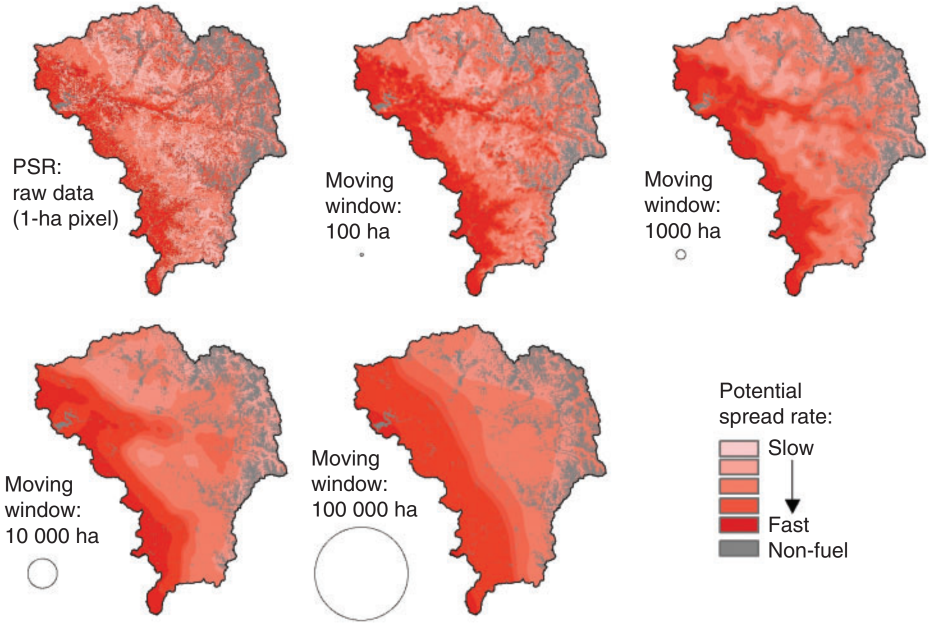

Fig. 3. Illustration of the moving window concept: the raw (1-ha pixel) potential spread rate (PSR) grid and the resulting moving window grids at the 100-, 1000-, 10 000- and 100 000-ha scales. The circles to the left of each moving window grid illustrate the size of the moving window, where all pixels within the window are averaged and assigned to the centre pixel.

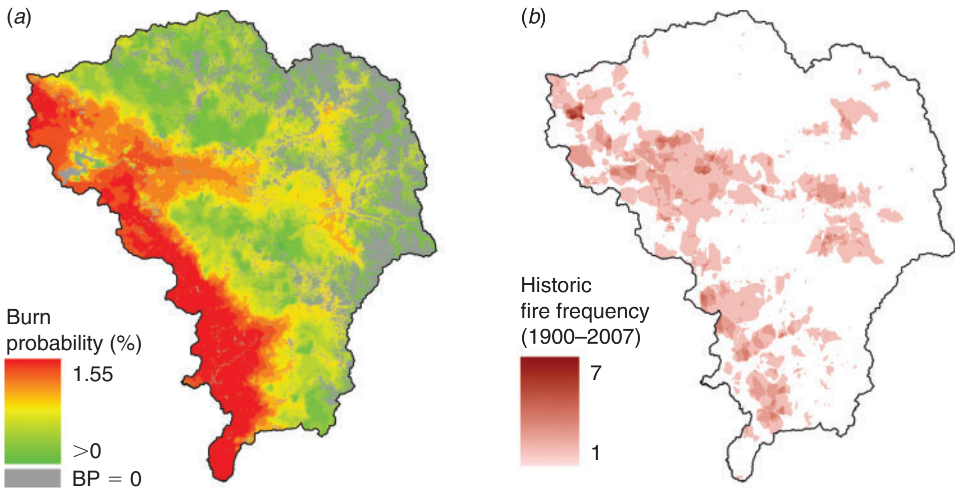

Fig. 4. The burn probability for the study area estimated using (*a*) the Randig model, and (*b*) the historical record of fire frequency from 1900 to 2007.

'binomial' family. To limit the wiggliness in the relationship, the fit of the GAM was constrained (gamma = 1.5 in *mgcv*). These parameters were applied to every self-fitting GAM within this study.

The spatial structure (i.e. autocorrelation) of each explanatory variable was described using autocorrelograms. The correlation values were squared to provide a measure of variance explained (R^2) that is analogous to the deviance explained (DE) produced in the remaining analyses described below. Unlike the approach taken in other analyses, the autocorrelograms did not include all the pixels within the entire circular neighbourhood for each spatial scale, but instead, included only pixels found in concentric rings so that the spatial dependence could be evaluated independently at each scale.

GAMs of BP (dependent variable) were built to measure DE by each explanatory variable at each scale. The results of this and the subsequent analysis were described using scalograms. We then increased the complexity of the models by building a GAM of BP using each pair of explanatory variables. However, because ecological variables often covary, it was useful to

Table 1. Description of the suite of analyses performed to evaluate the effects of the four explanatory variables (elevation (ELEV), ignitions (IGN), potential spread rate (PSR) and southwestness (SW)) on burn probability (BP) at spatial scale *s*

A spatial scale represents a circular window centred on each sampling location in which values of exploratory variables were averaged.
Note: previously stated definitions of equation terms are not repeated

Measurement	Analysis details	Results
Relationship between BP and each exploratory variable	$\mathrm{BP} = f(\mu(x1)_s)$ BP, burn probability value at a sampling location f, smoothing term used in a generalised additive model (GAM) $\mu(x1)_s$, mean value of exploratory variable $x1$ at scale s	Predicted (GAM) BP response curves at the following scales: 100, 5000 and 50 000 ha (Fig. 5)
Spatial structure of exploratory variables	$r_{x1(i)\cdot x1(h)} = \dfrac{Cov(x1_i, x1_h)}{\sqrt{Var(x1)_i \cdot Var(x1)_h}}$ $r_{x1(i)\cdot x1(h)}$, autocorrelation between values at sampling location i and interval distance h $Cov(x1_i, x1_h)$, covariance of $x1$ between samples at i and those at h $Var(x1)_i$ and $Var(x1)_h$: variance of $x1$ between samples at i and those at h	Autocorrelograms (Fig. 6) Note: the $r_{x1(i)\cdot x1(h)}$ values were squared to be interpreted as 'variance explained'
Correspondence between BP and each exploratory variable	$\mathrm{BP} = f(\mu(x1)_s)$ The DE[A] was extracted for the GAM built at each scale s ($\mathrm{DE}_{\mathrm{BP}x1(s)}$)	Scalograms of $\mathrm{DE}_{\mathrm{BP}x1(s)}$ (Fig. 6)
Correspondence between BP and each pair of exploratory variables	$\mathrm{BP} = f_1(\mu(x1)_s) + f_2(\mu(x2)_s)$ The DE was extracted for the GAM built at each scale s ($\mathrm{DE}_{\mathrm{total}(s)}$)	Scalograms of $\mathrm{DE}_{\mathrm{total}(s)}$: the combined effect of both variables (Fig. 7)
Information unique to each variable within pairs of exploratory variables	$\mathrm{BP} - \mu(x2)_s = f(\mu(x1)_s)$ where $\mu(x2)_s$ is an offset term The DE unique to variable $x1$ was extracted at each scale s ($\mathrm{DE}_{x1\|x2(s)}$)	Scalograms of $\mathrm{DE}_{x1\|x2(s)}$: the effect of $x1$ when controlling for effect of variable $x2$ (Fig. 7)
Information shared between exploratory variables in terms of their relationship to BP	$\mathrm{DE}_{\mathrm{shared}(s)} = \mathrm{DE}_{\mathrm{total}(s)} - (\mathrm{DE}_{x1\|x2(s)} + \mathrm{DE}_{x2\|x1(s)})$	Scalograms of $\mathrm{DE}_{\mathrm{shared}(s)}$: the DE that is not unique to either variable (Fig. 7)
Contributions of exploratory variables on BP in a model using all variables	$\mathrm{BP} = f_1(\mu(\mathrm{ELEV})_s) + f_2(\mu(\mathrm{PSR})_s) + f_3(\mu(\mathrm{IGN})_s) + f_4(\mu(\mathrm{SW})_s)$ Contributions consist of the percentage of sum of Chi-square values for each model terms (i.e. exploratory variables)	Total DE of the GAM model; scalograms of the relative importance of each variable in the model (Fig. 8)
Same as previous, but controlling for the effect of ELEV	$\mathrm{BP} - \mu(\mathrm{ELEV})_s = f_1(\mu(\mathrm{PSR})_s) + f_2(\mu(\mathrm{IGN})_s) + f_3(\mu(\mathrm{SW})_s)$ where $\mu(\mathrm{ELEV})_s$ is an offset term	Total additional (i.e. non-ELEV) DE of the GAM model; scalograms of the relative importance of each non-offset variable in the model (Fig. 8)

[A]DE is the deviance explained (1 – model deviance/null deviance).

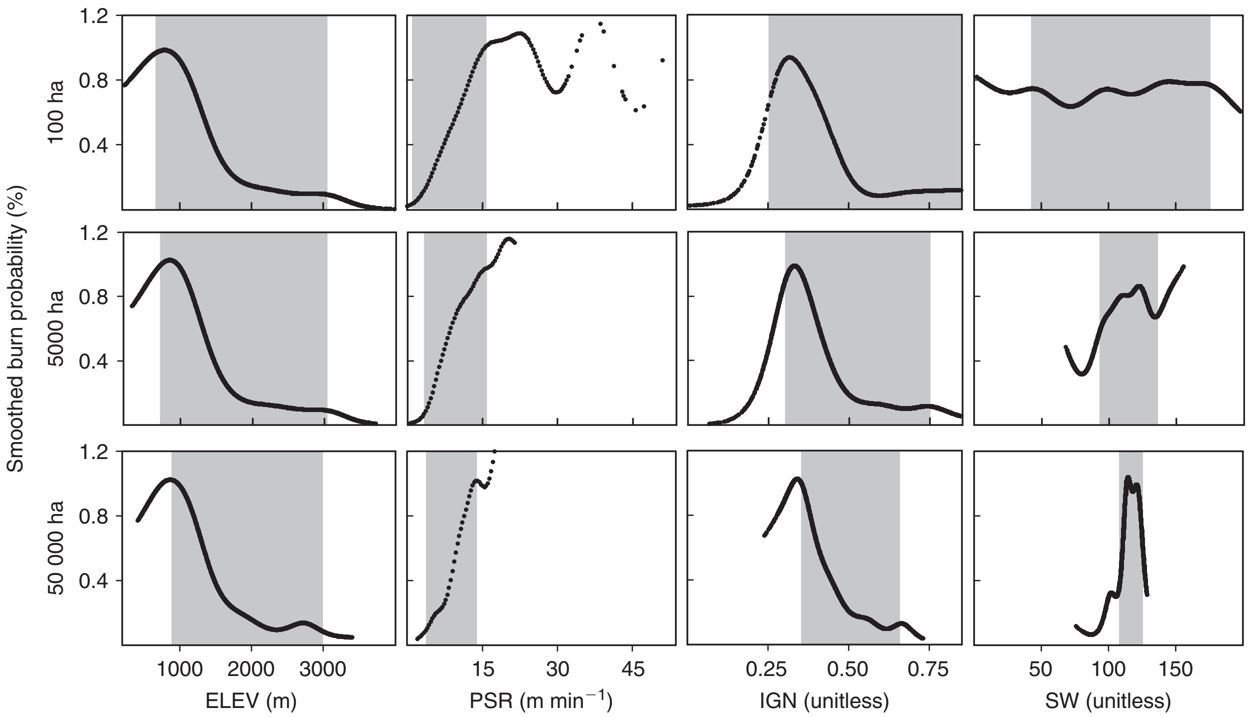

Fig. 5. The relationship between burn probability and each of the four explanatory variables modelled using generalized additive models for three spatial scales (100, 5000 and 50 000 ha). The shaded background represents the middle 80th percentile of the values for each exploratory variable (lowest 10th and highest 90th percentile not shaded).

partition the DE into the fraction that is shared between the two explanatory variables and the fraction that is unique to each variable. The deviance unique to an explanatory variable (e.g. $x1$) was obtained by using the other explanatory variable (e.g. $x2$) as an offset term in the GAM, which effectively controlled for the effect of variable $x2$. To use $x2$ as an offset term, we forced the GAM to first model BP as a function of $x2$, and then modelled the residuals of this relationship as a function of $x1$. The deviance shared among the pair of predictors was obtained by subtracting the sum of the two predictors' unique contributions from the total DE. Evaluations of pairs including the IGN variable were not performed at the smallest (i.e. pixel) scale because the ignition CART model resulted in only four discrete ignition density values (Fig. 2), which are too few for GAM fitting; this was no longer a limitation as the scale increased because the moving window approach essentially created continuous IGN values.

To measure the relative contribution of each explanatory variable when all four variables were used to predict BP, GAMs of BP including all variables were built at all scales except the single pixel. The relative contribution of variables was defined as the percentage of the sum of Chi-square values attributed to each variable. Because ELEV has such an overarching effect on the landscape characteristics of the study area, we controlled for its influence by including it as an offset term in a parallel set of models. For simplicity, no interaction terms among variables were included in these models. Given the large number of possible combinations, it was not feasible to extract the shared and unique fractions of DE in this analysis.

Results

Burn probability

Simulated BP in our study area ranged from 0 to 1.55% (Fig. 4*a*). BP values should be interpreted as a relative probability whereby a pixel with 1% BP burned twice as often as a pixel with a value of 0.5%. A broad south-west to north-east decreasing trend in BP corresponded to an increase in elevation, a pattern also reflected in the map of historical fire occurrence from 1900–2007 (CDF 2007) (Fig. 4*b*). The Spearman rank-correlation of simulated BP to historical fire frequency was 0.50; this correspondence increased somewhat ($R = 0.56$) when private lands, which experience the greatest degree of human influence, were excluded.

Analysis of scale-dependent environmental controls on BP

The relationships between BP and each explanatory variable, except SW, were relatively similar among the three scales we examined (Fig. 5). Although these relationships were strongly non-linear, they were fairly monotonic where the bulk of the observations lie (i.e. excluding the values smaller and larger than the 10th and 90th percentiles respectively). The relationship between BP and ELEV was generally negative: as ELEV increased, BP decreased. The relationship between BP and PSR was positive, as expected. Further, as the density of ignitions increased (IGN), BP decreased. This is counterintuitive and suggests that the true relationship may be masked by one or more covariates. The BP–SW relationship was unstable

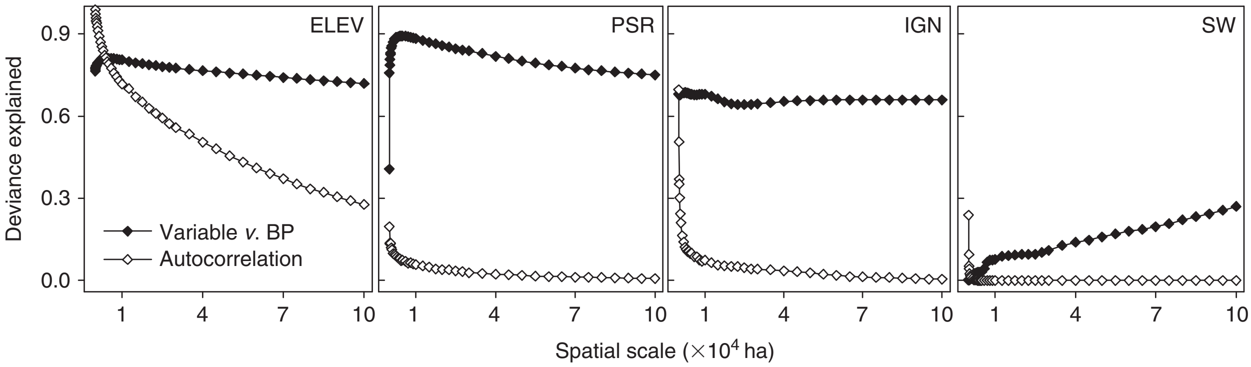

Fig. 6. The cross-scale correspondence, expressed as deviance explained, in burn probability as a function of each of the following variables: elevation (ELEV), ignitions (IGN), potential spread rate (PSR) and southwestness (SW) (black diamonds) and the autocorrelation (squared) of each variable (autocorrelogram, white diamonds).

among the three scales, becoming more unimodal as the spatial scale increased.

The autocorrelograms show varying degrees of spatial structure in the four explanatory variables (Fig. 6). ELEV and IGN were the most strongly autocorrelated, but the autocorrelation in IGN dropped off more rapidly than that of ELEV as a function of increasing spatial scale. PSR and SW were weakly autocorrelated; indeed, SW had virtually no spatial autocorrelation beyond the 500-ha scale.

In simple GAM models of BP using one explanatory variable, the DE by ELEV, PSR and IGN was fairly high (DE > 0.6) at most spatial scales. The DE by SW never exceeded 0.3 at any scale (Fig. 6). The maximum DE by ELEV (5000 ha), PSR (5000 ha) and IGN (2500 ha) occurred at somewhat moderate spatial scales, whereas the maximum DE by SW was presumably at a scale larger than our largest window size of 100 000 ha. The maximum DE of ELEV and PSR appear to occur at approximately the same scale as the inflection points of their respective autocorrelograms (Fig. 6).

Adding a second explanatory variable to a simple GAM of BP increased the DE, but not always substantially, suggesting that there is considerable covariance among some explanatory variables (Fig. 7). The shared DE by the ELEV-PSR, ELEV-IGN and IGN-PSR pairs of explanatory variables was moderate to high (DE > 0.4) at most scales. Indeed, the shared DE by variable pairs involving ELEV, IGN and PSR, almost always exceeded that of the simple sum of unique contributions. Despite this strong covariance, each variable did uniquely explain some deviance in the models. The highest unique contributions for ELEV, IGN and PSR occurred in the 1- to 20 000-ha range of scales; however, these values fluctuated as a function of the explanatory variable pairs. There was little shared DE by variable pairs involving SW.

Except at the broadest scales (>∼50 000 ha), the GAMs incorporating all four explanatory variables performed only marginally better with respect to DE than those models using pairs of explanatory variables (Fig. 8). These larger models explained 80.2–91.4% of the deviance, with the best-performing model at the 3500-ha scale (however, models at the 2000- to 12 500-ha scales all had DE ≥ 91.0%). As in the previous analysis, the relative contribution of each variable fluctuated among scales. The DE by ELEV was greatest at the 100-ha scale. The DE by PSR was greater than any other variable at all scales, increasing from the 100- to 4500-ha scale and then decreasing at broader scales. The DE by IGN was low to negligible compared to ELEV and PSR at all scales. The DE by SW was relatively low at all but the broadest scales (≥50 000 ha).

In models using ELEV as an offset term, the remaining three explanatory variables provided an additional 28.1–42.3% of DE compared to that of a simple BP–ELEV model, peaking at the 2000-ha scale (Fig. 8). PSR was still dominant at each scale in the ELEV-offset models. The IGN variable, which contributed marginally to DE in the no-offset models, was relatively important once we controlled for ELEV. Controlling for the effect of ELEV thus appeared to uncover the IGN variable's positive relationship to BP (Fig. 9), which is a more logical relationship. There was a small decrease in the relative importance of SW at scales broader than ∼50 000 ha once we controlled for ELEV.

Discussion

Our results support the claims that environmental controls on fire likelihood are scale dependent (Cyr *et al*. 2007; Falk *et al*. 2007; Beverly *et al*. 2009). Some environmental factors, such as elevation and fuels, exerted their strongest influence at fine to moderate spatial scales (1–10 000 ha), whereas the influence of aspect was generally more pronounced at broader scales (>50 000 ha). The scale at which the influence of ignitions was greatest was highly dependent on the complexity of the analysis. In the models using one or two environmental factors, the influence of ignitions was highest at relatively fine scales (≤2500 ha), but in the analyses using all factors, its influence was strongest at much broader scales (≥40 000 ha). We noted that throughout the suite of analyses performed here, in very few instances did the scale defined by the raw data (e.g. 1-ha pixel-based analysis) correspond to the scale that yielded the highest importance.

The model of BP using the four explanatory variables suggests that, at the finest scales, fuels and elevation are the most important controls on BP and that aspect and ignitions have a negligible effect. In contrast, at broader scales, it is fuels and aspect that could be interpreted as having the strongest influence. Therefore, it is conceivable that different grid resolutions

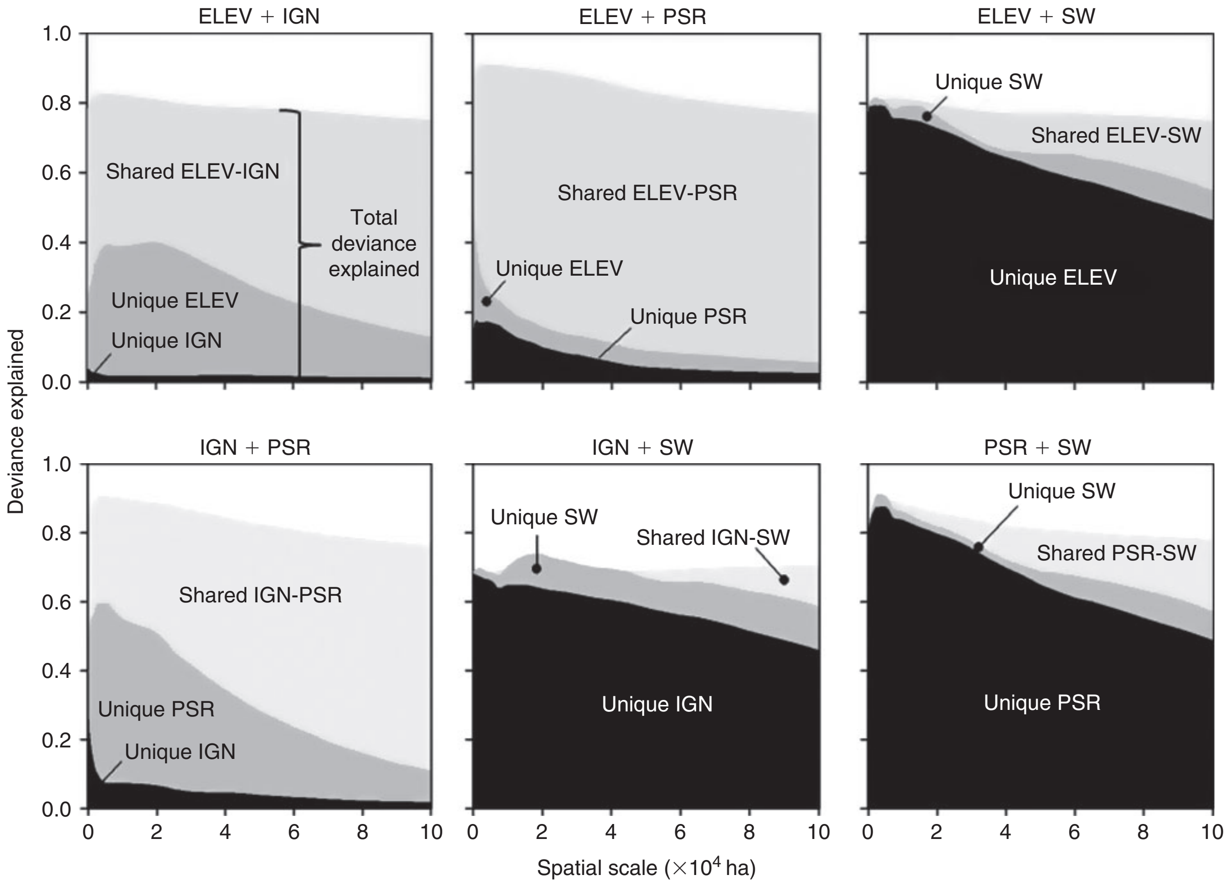

Fig. 7. The cross-scale unique and shared contributions (expressed as deviance explained (DE)) of elevation (ELEV), ignitions (IGN), potential spread rate (PSR) and southwestness (SW), when each combination of two of these variables are used to predict burn probability in a general additive model. The vertical distance of each colour at each scale represents the DE of that particular variable at each scale. The plot area represented by each colour is additive; therefore, the sum of unique and shared contributions represent the total DE by each variable pair.

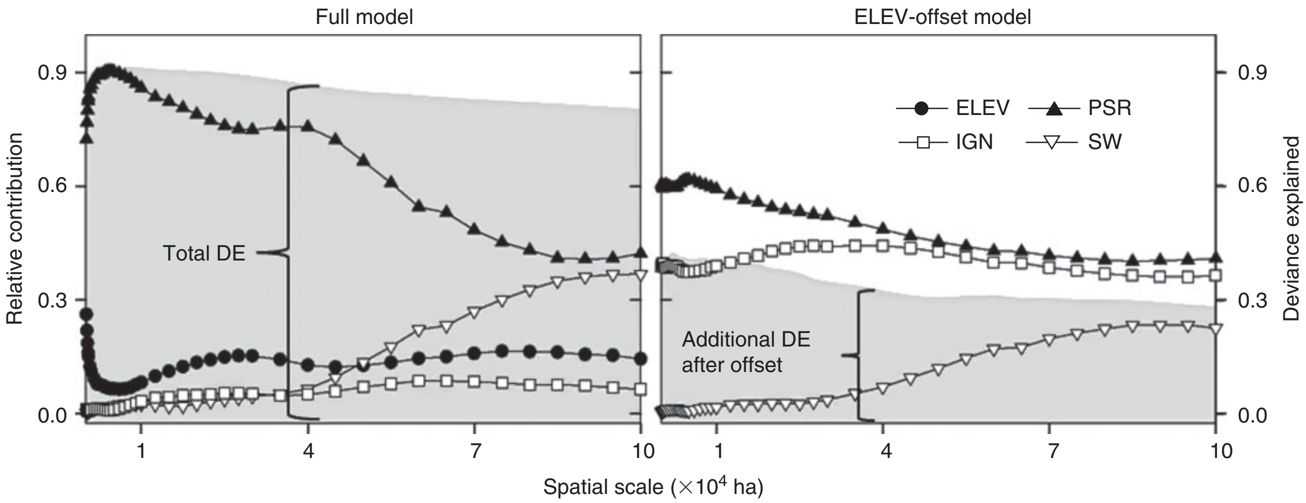

Fig. 8. Multi-scale results of the multivariate GAMs in explaining burn probability. The 'dots' depict the relative contribution of each explanatory variable at each scale and the grey background shows the total deviance explained by the models at each scale. The relative importance represents the percentage of the total Chi-square contribution from each variable (calculated separately for models with and without the offset term). The left panel shows full models with no offset term; the right panel shows full models using ELEV as an offset term.

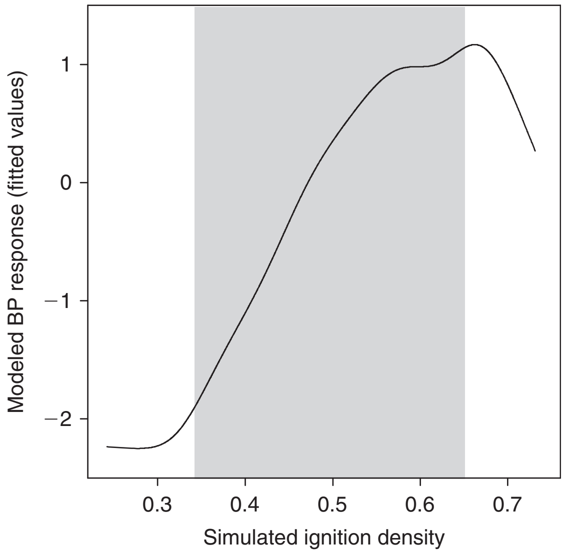

Fig. 9. Fitted function of the IGN predictor variable of a generalized additive model (GAM) of burn probability when elevation (ELEV) is used as an offset term (see Table 1). This GAM is at the 40 000-ha scale, which is the scale at which IGN had the largest relative contribution (Fig. 7). The shaded background represents the middle 80th percentile of IGN values (lowest 10th and highest 90th percentile not shaded).

could lead to slightly different conclusions about the association between fire activity and environmental covariates. That is, the simple act of using the data in its raw form, with a particular grain size (resolution) and extent (study area size), is an implicit use of a single spatial scale. In arbitrarily selecting a single spatial scale of study from a continuum of meaningful scales, 'the observer imposes a perceptual bias, a filter through which the system is viewed' (Levin 1992). In light of these concerns, recent studies of fire–environment relationships have examined the potential effect of spatial scale selection before initiating the main analysis of their study (e.g. Archibald *et al*. 2009; Balshi *et al*. 2009).

The mechanisms generating the scale dependence in BP–environment relationships are due predominantly to the fact that fire spread is a contagious process that forcibly induces spatial dependency with its environment. Our results support claims that fire patterns are better predicted at broader scales (i.e. a larger than the pixel size) by virtue of incorporating 'neighbourhood' information (Chou *et al*. 1993). The probability that an individual pixel will burn is highly contingent upon whether or not the neighbouring pixel burns, and this spatial dependence can be more important than the fine scale information that might get lost when increasing the scale (grain) of observation (Turner *et al*. 1989). If we consider the models using all explanatory variables to be the most realistic, the spatial scale with the greatest explanatory power occurred at the 2000–3500-ha range. This range of scales is comparable to the mean fire size from our simulations (~3700 ha), suggesting a potential link between fire size distribution and the scale at which this system is best studied, the so-called 'characteristic scale' (Urban *et al*. 1987).

The covariance among environmental factors (i.e. shared information) is an important consideration when analysing and interpreting ecological systems. In our study, elevation, fuels (PSR) and ignitions were moderately to highly correlated (0.4–0.9) at most scales. This covariance introduced counterintuitive relationships (e.g. BP *v*. ignition density) and complicated interpretation of the relative importance of each explanatory variable. For example, in the model of BP as a function of elevation and fuels (PSR), the shared contribution of these two variables far outweighed their unique contributions. These issues are further complicated because the covariance between environmental factors is scale dependent (i.e. the covariance changes with scale). Although we were able to identify and tease apart some of these complex relationships, more complex statistical treatment may be useful for future analyses (Borcard *et al*. 1992).

Our results further suggest that variables that correlate well with fire likelihood, but exert a largely indirect influence, can inhibit our understanding of the factors directly responsible for fire ignition and spread of wildfire (i.e. mechanistic controls) (cf. Austin 1980). For example, topography, which appears to have a pervasive effect on fire regimes in many mountain landscapes (Kellogg *et al*. 2008; Stambaugh and Guyette 2008; Viedma 2008), mainly affects fire regimes via its effects on fuel moisture, fire season length, ignition patterns, fuel type and fuel configuration. For example, Rollins *et al*. (2002) showed that in the moisture-limited south-western USA, wildfires were more frequent on north-east slopes, where fuels are more continuous, whereas in the northern Rocky Mountains, USA, where fuels are not limiting, wildfires were more frequent on the drier western and south-western slopes. This illustrates that, although the relationship between fire activity and aspect was strong, it is not aspect *per se* that promotes or limits fire, but rather the coincidence of spatially continuous biomass and fire-conducive fuel moisture conditions. Similarly, in our study area, the effect of fuels and ignition patterns could only be uncovered by statistically controlling for elevation. This is particularly obvious with ignitions, as the relationship between BP and ignition density suggests the nonsensical conclusion that fire likelihood decreases as ignition density increases. However, once we controlled for elevation and the effect of other environmental factors was considered, the relationship between ignitions and fire likelihood became ecologically meaningful.

Despite our effort to provide realistic inputs for fire likelihood estimations, some simplifying assumptions were necessary due to software limitations or information gaps. For example, we would expect wind to spatially vary across the study area, because rugged topography can cause local shifts in wind direction and speed, notably in deep canyons. Furthermore, we would expect fuel moisture values to spatially vary as a function of aspect and elevation. Although spatial variability in both wind and fuel moisture plays a major role in fire activity in the Sierra Nevada, we assumed their general effect was homogeneous due to Randig's limitations. The omission of this variability may affect the resulting BP patterns, the relative importance of the explanatory variables, and the scaling relationships. Specifically, BP patterns would have likely exhibited more fine-scale variation, particularly in areas of rugged terrain, had we been able to include spatial variability in winds and fuel moisture. Furthermore, fuels may have exerted less of an influence and aspect may have had more of an influence, particularly at finer scales (i.e. the scales exhibiting the most topographic variability). Further caution may be warranted due to discrepancies in modelled *v.* observed fire behaviour (Cruz and Alexander 2010).

Despite the modelling assumptions and limitations, our BP estimates appear representative of current landscape conditions. We attribute this apparent success of the model to thoughtful parameterization and the sophistication of the FlamMap fire spread algorithm. Indeed, in comparison to previous studies of fire likelihood (e.g. Ager *et al*. 2007, 2010; Parisien *et al*. 2007; Beverly *et al*. 2009), the inputs and settings used in this study are the most detailed and complex to date. For example, using MODIS fire detection data to provide estimates of fire duration variability and using variable weather conditions (wind speed and direction) from actual spread-event days allowed us to simulate a more realistic envelope of the fire environment. We also incorporated a non-random ignition pattern, knowing that ignitions vary with fuel type (Krawchuk *et al*. 2006) and elevation (van Wagtendonk and Cayan 2008). The implications of incorporating as much natural variability as possible are not trivial, as formal assessments in artificial landscapes have shown that including variable inputs in fire simulation models produce more realistic fire patterns (Lertzman *et al*. 1998).

Conclusion

The need to better understand scaling effects on biota and ecological processes has been recognised for decades (Wiens 1989; Levin 1992), but requires more thorough investigation in disturbance ecology (Beever *et al*. 2006; McKenzie *et al*. 2006). The present study reinforces the observation that topology, or neighbourhood, may hold information that is more relevant to controls on fire regimes than that of the scale defined by the raw data (e.g. pixel-based analyses) (Cyr *et al*. 2007). Indeed, the simple act of using the data in its raw form, with a particular grain size and extent, is an implicit use of a single scale. In this study area, our results suggest that scales of ~2000–3500 ha are most relevant for analysing fire likelihood.

Our results further indicate that covariance among environmental controls may overwhelm some fire–environment responses. As a result, identification of the characteristic scale (Urban *et al*. 1987) (or range of scales) of study, and the causative effect of these controls on fire regimes, may be blurred. Controlling for these interactions can clarify the spatial scales and environmental variables that more directly influence fire regimes, which is particularly relevant because of current efforts for mitigating fire risk through fuel and ignitions management (Brown *et al*. 2004; Schoennagel *et al*. 2009). These results provide a necessary step towards a more mechanistic understanding of fire probability at a landscape level. We encourage similar examinations of other study areas with different landscape characteristics to shed further light on the problem of scaling and controls of fire regimes.

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