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Modeling the Landscape Drivers of Fire Recurrence in Sardinia (Italy)

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Abstract Although recurrent fire events with very short return periods have the most dangerous effects on landscape degradation, only a few papers have explored the landscape ecological factors that drive the probability of fire recurrence. In this paper we apply a habitat suitability model for analyzing the spatial relationship between a selected set of landscape factors (mainly land use types) and fire recurrence in Sardinia (Italy) in the years 2005–2010. Our results point out that fire occurrence in already burned areas is lower than expected in natural and semi-natural land cover types, like forest and shrublands. To the contrary, like in all regions where human activity is the main source of fire ignitions, the probability of fire recurrence is higher at low altitudes and close to roads and to urban and agricultural land cover types, thus showing marked preference for those landscape factors denoting higher anthropogenic ignition risk.

Keywords Environmental niche factor analysis (ENFA) · Fire recurrence · Human impact · Land use · Ordination biplot

Introduction

In Mediterranean-type ecosystems, wildfires are a key disturbance that profoundly affects vegetation and landscapes (Moreira et al. 2011; Keeley et al. 2012). In this view, it is generally recognized that the most dangerous effects on ecosystem resilience are produced by recurrent fire events with very short return periods (Baeza and Vallejo 2008; Barbati et al. 2013).

Recurrent fires separated by short intervals notably tend to reduce the abundance of species that require long time intervals to recruit from seeds and to deplete resprouter bud banks (Schaffhauser et al. 2012). For example, some pine species, like *Pinus halepensis* or *P. pinaster*, show a low resilience to increased fire frequency. This is because if fires occur with a return interval shorter than the time needed for building a canopy seed bank in their serotinous cones, then pines will not regenerate and the resulting vegetation structure will be dominated by grasses and shrubs (Lloret et al. 2003; Kazanis and Arianoutsou 2004; Eugenio et al. 2006). Likewise, even in the case of some evergreen oaks that show vigorous resprouting after fire (as *Quercus suber* and *Q. ilex*), short fire intervals may reduce such ability, thus favoring the expansion of shrubland communities (Moreira et al. 2011).

In the Mediterranean Basin fire recurrence is well documented. In Corsica (France), some areas burned up to seven times between 1957 and 1997 (Mouillot et al. 2003). In central Spain, roughly 7 % of the total area burned in the years 1970–1990 burned twice (Vazquez and Moreno 2001), whereas in Catalonia more than 13 % of the total area burned during 1975–1998 reburned at least once (Diaz-Delgado et al. 2004). In Italy, 12 % of the forest area burned in 2006, reburned at least once in the following 3 years (Barbati et al. 2013).

It is usually assumed that wildfire recurrence results from a combination of environmental and human factors, like the presence of anthropogenic ignition sources, together with fuel availability and connectivity that favor fire spread (De Angelis et al. 2012; Barbati et al. 2013). However, in spite of the increased risk of future fires in previous burned areas across several Mediterranean

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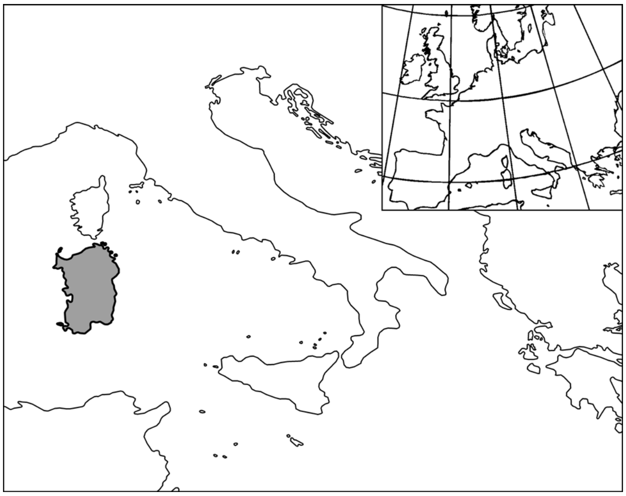

Fig. 1 Location of the study area

countries, only a handful of papers have explored the landscape drivers of fire recurrence (e.g., Lloret et al. 2002, 2003; Viedma et al. 2006; Roder et al. 2008; Loepfe et al. 2010; Barbati et al. 2013). Most of these authors point out to ecological mechanisms promoting post-fire fuel continuity through the establishment of highly connected patches of fire-prone secondary vegetation, or the increased amount of dead fuel, thus favoring future fire spread.

The aim of this study is thus to apply a habitat suitability modeling tool, originally developed in wildlife science, for analyzing the landscape factors affecting short-term fire recurrence in Sardinia (Italy) in the years 2005–2010. The paper is organized as follows: first, we describe the habitat suitability model used in this study. Next, the model is applied for analyzing the relationship between the spatial distribution of fires and a set of underlying environmental variables. Finally, the results are discussed and related to mechanisms that may cause fire recurrence in Sardinia.

Study Area

The island of Sardinia is located in the Mediterranean between 38°52′ and 41°15′N latitude and between 8°7′ and 9°49′E longitude, and covers roughly 24,000 km^2 (Fig. 1). Sardinia is largely granitic and is characterized by a complex physical geography with a prevalently hilly topography and high heterogeneity in geological and morphological features, which is reflected in the wide variety of biotopes and the high plant diversity of the island. According to the Italian checklist of vascular flora (Conti et al. 2005), roughly 10 % of the 2,407 island's plant species are endemic. The climate of Sardinia is mainly Mediterranean with hot and dry summers and mild and rainy winters. Average annual rainfall ranges from less than 500 mm in the coastal areas to more than 900 mm in the inner mountainous regions. Mean annual temperature ranges from 11 to 17 °C.

Like all Mediterranean islands, Sardinia has a very long history of human presence. Land cover in the coastal areas and the main alluvial plains is dominated by sclerophyllous shrublands and agriculture (mainly arable lands and permanent crops) that covers roughly 45 % of the island surface. Most cities of Sardinia are located along the coast. The inner and more temperate portions of the island are prevalently characterized by land cover types of lower human pressure, such as heterogeneous agricultural areas, shrublands, pastures, and forests. The principal forest formations include evergreen *Quercus ilex* and *Q. suber* forests. At higher elevations, these evergreen forests merge with broadleaved deciduous forests of *Q. pubescens*.

Data and Methods

In Sardinia, detailed records of individual fire scars have been kept by the Regional Forest Service (Corpo forestale e di vigilanza ambientale, CFVA) since 2005. Therefore, in this study, we used the digitized perimeters of all wildfires larger than 1,000 m^2 that occurred in Sardinia in the period 2005–2010, freely available in vector format at the GIS portal of Sardinia (www.sardegnageoportale.it). Fire scar perimeters were delineated in the field by the CFVA with a global positioning system (GPS), while very large fires were mapped with SPOT 5 satellite images followed by field validation with ground control points. Although the recording period is quite short, the dataset contains 17,327 burned patches, and the total surface burnt during 2005–2010 is ~110,000 ha, of which 5,460 ha reburned at least once in the following years. Fire size ranges over many orders of magnitude from 1,000 m^2 to >10 km^2, with the upper 1 % of the largest fires accounting for more than 50 % of the burned surface. Like most climate-driven processes, fire occurrence is strongly seasonal with more than 85 % of fires occurring between June and September and the peak of fire occurrence in July.

The burned areas were rasterized with a cell resolution of 50 m and used as input into the presence-only habitat suitability model for analyzing the distribution of wildfires in Sardinia. We used the Ecological Niche Factor Analysis (ENFA; Hirzel et al. 2002), an exploratory analysis tool developed for characterizing the ecological niche of a given species from a set of environmental variables measured at the locations it occupies. According to Hutchinson (1957), the ecological niche is defined as the hypervolume in the multidimensional space defined by the environmental variables where the species can potentially maintain a viable population. Although originally developed to describe the ecological requirements of a species, in this paper, we refer to the "niche" of wildfires in the same sense, as to the subset of conditions in multivariate ecological space, where wildfires are most likely to occur (De Angelis et al. 2012). The reason for using niche modeling tools for summarizing fire occurrence relies on the observation that wildfires can be considered as "herbivores" with variable preferences for different resources (i.e., vegetation or fuel types) under variable environmental conditions (Moreira et al. 2001; Bond and Keeley 2005).

ENFA quantifies the niche occupied by fires by comparing their distribution in multivariate ecological space with the distribution of the ecological variables in the entire region. The input data needed by ENFA consist of a set of quantitative raster maps describing the environmental conditions of the study area. Based on these maps, the environmental conditions of Sardinia are then compared with the conditions of all burned areas (dataset A in the remainder of this paper). In addition, to explore whether fire recurrence is favored by particular environmental conditions, we also applied ENFA to the subset of cells that burned at least twice in the years 2005–2010 (dataset B).

As input variables in ENFA, we used ten landscape factors, which are usually considered to affect fire occurrence (Nunes et al. 2005; Bajocco and Ricotta 2008; Moreira et al. 2011). These factors include altitude, distance from roads, and distance from the following eight land cover types: densely built up areas, sparsely built up areas, arable land, permanent crops, heterogeneous agricultural areas, natural grasslands and pastures, shrublands, and forests (Table 1). All land cover types were derived from CORINE land cover data updated for the reference year 2006 (ISPRA 2010), while the digital elevation model and the road network of Sardinia were downloaded from www.sardegnageoportale.it.

Because of the relative homogeneity and spatial continuity of fuel load within each class, the eight land cover types were considered adequate to study fire distribution at the landscape scale (Bajocco and Ricotta 2008). Bare soils, wetlands, and water bodies, regarded as non-combustible, were excluded from further analysis.

ENFA is basically an ordination method, like e.g. principal component analysis (Legendre and Legendre 1998) that searches for directions in the multivariate ecological space so that most of the available information is condensed into a hypervolume composed of a few relevant factors (Basille et al. 2008). However, unlike in principal component analysis, in ENFA, the resultant factors have an ecological meaning that defines different aspects of the ecological niche of fires (De Angelis et al. 2012). The first factor (the marginality) measures the deviation (either positive or negative) between the mean ecological conditions of the burned cells and the mean ecological conditions available on the entire study area. This factor is represented by the vector connecting the centroid of the distribution of burned cells with the centroid of all cells within the study area in multivariate ecological space (see Hirzel et al. 2002). The global system marginality usually ranges between 0 and 1 (although in extreme conditions the value can exceed one; Hirzel et al. 2002). If the burned cells were randomly distributed across the study area, then the expected marginality would be equal to zero, meaning that there is no difference between the ecological conditions of the reference area and the ecological conditions of the fire niche. The higher the marginality, the more the fire niche deviates from the average conditions of the reference area; in this case, the burned cells display increasingly different ecological features compared to the entire study area (Basille et al. 2008).

The remaining factors measure the so-called niche specialization. Once the marginality factor has been calculated, a specialization factor orthogonal to the vector of marginality can be extracted that maximizes the ratio between the variance of the ecological conditions of the entire reference area and the variance of the ecological conditions at fire locations. This procedure is repeated until all the system information has been explained (Hirzel et al. 2002). The specialization factors thus quantify how the niche width of fires differs from the global variance of

Table 1 Percent specialization explained by the marginality factor and the first (out of nine) specialization factors, and coefficient values of the input ecological variables

Ecological variables	Dataset A (all burned cells)		Dataset B (reburned cells)	
	Marginality (14 %)	Spec. 1 (18 %)	Marginality (12 %)	Spec. 1 (35 %)
Altitude	−0.152	−0.321	−0.189	−0.207
Distance from roads	−0.273	−0.241	−0.250	−0.127
Dist. from densely built up areas	−0.227	−0.148	−0.193	−0.144
Dist. from sparsely built up areas	−0.199	−0.138	−0.165	0.098
Dist. from arable land	−0.507	−0.324	−0.491	−0.592
Dist. from permanent crops	−0.446	0.773	−0.498	0.742
Dist. from heterogeneous agriculture	−0.323	−0.281	−0.253	−0.070
Dist. from grasslands and pastures	−0.069	0.012	−0.087	0.018
Dist. from shrublands	0.398	0.012	0.412	−0.018
Dist. from forests	0.291	−0.121	0.323	−0.040

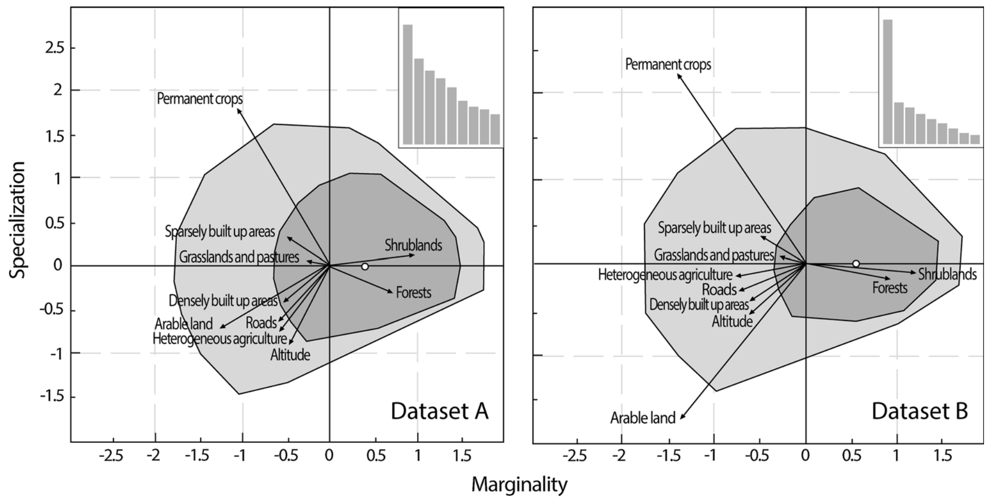

Fig. 2 ENFA biplot of the marginality factor (*X-axis*) and the first specialization factor (*Y-axis*) for datasets A and B. The *light* and *dark gray areas* correspond to the minimum convex hulls containing all background and focal cells, respectively. The centroid of the focal cells is represented by the *white circle*. The *arrows* represent the contributions of the input ecological variables to the axes of the biplot. For visualization purposes, the *arrows* are multiplied by an appropriate scaling factor, such that only differences between arrows are relevant. The *insets* show the amount of specialization associated to the nine specialization factors of each ENFA in arbitrary units. The amount of specialization associated to the first specialization axis is 18 % for dataset A and 35 % for dataset B

ecological variables. The global system specialization index ranges from one to infinity; the expected specialization for a random set of cells is equal to one, while increasingly higher values are related to increasing levels of specialization.

At the end, the first factor of the ENFA explains all the marginality and some part of the specialization. For instance, due to the deviation of the ecological niche of fires from the centroid of the ecological reference space, the higher the marginality of the fire niche, the higher the specialization associated to the marginality factor (Basille et al. 2008). The remaining factors explain the residual specialization in decreasing amounts (Hirzel et al. 2002). From an ecological viewpoint, ENFA thus quantifies different aspects of the ecological niche of fires: marginality summarizes the niche position of fires in ecological space, while specialization quantifies their niche width (De Angelis et al. 2012).

To visualize the results of ENFA, Basille et al. (2008) proposed to construct an ordination biplot (Legendre and Legendre 1998) in which the values of the burned and the background cells in ecological space are projected on the plane defined by the marginality axis and the first specialization axis (see Fig. 2). On the ENFA biplot, the environmental variables are represented by arrows, where the length of the arrows is related to the strength of the correlation between the corresponding environmental variable and the axes of the ENFA biplot. The longer the arrow, the higher the contribution of that variable to the definition of the axes of the ENFA biplot. Also, since the arrows point in the direction of maximum correlation with the axes of the ENFA biplot, the direction of the arrows is related to the contribution of the corresponding environmental variables to the marginality and the specialization axes of the ENFA.

ENFA is contained in the AdehabitatHS package for the R software available at http://cran.r-project.org/web/packages/adehabitatHS/ (Calenge 2006; R Core Team 2012). As the data used for modeling fire distribution are based solely on burned cells without taking into account the fire absences, ENFA belongs to the so-called "presence-only models". The reason for considering only burned cells is that, while burned areas are generally easy to identify, the absences are always uncertain (Rocchini et al. 2011). During the analyzed time period, fires may be absent from a given location, even though the environmental conditions are suitable for ignition, such that these "false" absences may significantly bias the analysis introducing a confounding effect when modeling the ecological niche of fires. For additional details on ENFA, see Hirzel et al. (2002) and Basille et al. (2008).

Results

The factor analysis of dataset A showed a marginality value of $M = 0.71$ and a global specialization of $S = 1.31$. This means that the average ecological conditions of all burned cells considerably differ from the mean ecological conditions of the reference area, whereas the niche width of fires is only moderately restrictive on the range of ecological conditions in which they occur. Compared to all burned cells, the subset of cells that burned at least twice in the years 2005–2010 (dataset B), showed a much higher deviation from the mean background ecological conditions of Sardinia ($M = 1.20$) being at the same time slightly more restrictive on the range of ecological conditions in which they occur ($S = 1.59$).

The coefficients of all ecological variables on the marginality factor and the first specialization factor of both datasets are shown in Table 1, while the ENFA biplots of dataset A and B are shown in Fig. 2. All coefficients range from −1 to +1. The higher the absolute value of a marginality coefficient, the further the fires depart from the mean ecological conditions of the reference area for this specific variable. Negative coefficients indicate preference for ecological values that are lower than the mean for the whole reference area, while positive coefficients indicate that fires prefer values that are lower than the background mean. For the specialization coefficients, only the absolute values are relevant, while their signs are arbitrary. High (absolute) values of the specialization coefficients indicate a restricted range of ecological conditions compared with the conditions of the reference area (De Angelis et al. 2012).

Although in ENFA there are potentially as many output factors as input variables, most of the system information is condensed into a few relevant factors. For dataset A, the marginality factor accounts for 14 % of specialization (100 % of marginality and 14 % of specialization; see Hirzel et al. 2002), while the first specialization factor accounts for 18 % of total specialization. For dataset B, the marginality factor accounts for 12 % of specialization, while the first specialization factor accounts for 35 % of total specialization. The remaining specialization is associated to the successive factors in decreasing amounts, as shown by the insets of Fig. 2.

As shown by the negative marginality coefficients in Table 1 and Fig. 2, fires occur preferentially at low altitudes and close to roads and to urban and agricultural land cover types. To the contrary, the average distance of burned cells from natural and semi-natural land cover types, like forest and shrublands, is higher than expected. The marginality coefficient associated to grasslands is very close to zero, meaning that there is only very low departure from the mean background conditions of the reference area for this specific variable.

The same pattern holds also for dataset B: fire recurrence occurs preferentially at low altitudes and close to roads and to urban and agricultural areas (mainly arable land and permanent crops) without any substantial difference with respect to dataset A. Also, for both datasets, the highest coefficients of the first specialization factor are related to the distances from permanent crops and arable lands, showing that fire distribution was mainly restricted on a limited range on these variables, with a mean shifted toward low distances. The remaining variables have only little effects on specialization.

Discussion: A Probabilistic Model for Fire Recurrence

In this paper, we used the ENFA (Hirzel et al. 2002) for summarizing the niche position and width of fire recurrence in Sardinia based on ten landscape factors that are generally thought to directly or indirectly affect fire occurrence. Fire patterns are influenced by a number of biotic, abiotic, and human drivers (Parisien and Moritz 2009). However, while a strong relationship between climate and fire is widely acknowledged with relatively less emphasis on other drivers (Flannigan and Harrington 1988; Flannigan et al. 2009; Wotton et al. 2010), in anthropogenic landscapes, where humans are the main source of ignitions, the climate-fire linkage may be less pronounced (Vazquez et al. 2002; Liu et al. 2012). In virtually all regions where humans influence fire incidence and vegetation cover (i.e., fuel characteristics), a high level of association between fire regimes and landscape attributes is observed. This relationship has been extensively documented in Mediterranean countries (e.g., Moreira et al. 2001, 2011; Nunes et al. 2005; Bajocco and Ricotta 2008; Catry et al. 2009), as well as in the Missouri Ozark Highlands (Yang et al. 2008) or the boreal forest ecosystems of Northeast China (Liu et al. 2012). In this framework, the rationale behind using landscape factors for modeling the fire niche is that such factors represent complex ecological indicators of human pressure, climate, topography, and fuel load; therefore, in human-dominated landscapes, the probability of fire occurrence will be usually affected by the nature and the spatial arrangement of the different landscape factors (Moreira et al. 2001, 2011; Nunes et al. 2005; Bajocco et al. 2010).

As pointed out by Hirzel et al. (2002), one reason for using ordination methods, like ENFA, is that ecological variables are typically not independent from each other. For example, cities and agricultural areas are generally located at lower altitudes where the road network is more developed and human impact is higher. On the other hand, the preferential location of more natural land cover types with higher fuel loads, like forests or shrublands, in more remote areas may cause longer time lags before fire detection and intervention, thus increasing fire size. Accordingly, ENFA is an appropriate method for condensing the information contained in a multivariate system of high dimensionality into a reduced set of ecologically relevant factors (De Angelis et al. 2012).

The interest in modeling fire recurrence resides in the observation that previously burned areas usually have higher probabilities of burning again compared to areas that were never burned (Moreira et al. 2011). This is in contrast to the fuel-age paradigm for which fuel reduction as a consequence of previous fires would also reduce the risk of future fires (Zedler and Seiger 2000).

Two main mechanisms were invoked to explain increased fire occurrence in already burned areas. On one hand, several authors observed a number of changes in fuel load and structure induced by previous fires that may favor repeated burning (for a detailed review see Moreira et al. 2011). For example, the low resilience to fire of some forest types may lead to the establishment of more fire-prone vegetation (Lloret et al. 2002, 2003; Acácio et al. 2009). A second explanation is that for some vegetation types (notably for shrublands), post-fire vegetation recovery is quite rapid, such that the post-fire fuel load often exceeds pre-fire amounts (Roder et al. 2008; Hernandez-Clemente et al. 2009). Also, in some cases, intense wildfires may give rise to a more continuous and homogeneous spatial distribution of fuel, thus favoring the spread of future fires (Viedma et al. 2006; Loepfe et al. 2010; van Leeuwen et al. 2010).

These positive feedbacks for which previous fires *determine* the conditions that will favor a new fire in a relatively short time period may be reinforced by the social perception of the low value of burned areas. This might potentially activate a spiral process for which frequent fires, altering the status quality of a given area or landscape, make it more prone to fire occurrence than less degraded ones (Bajocco et al. 2011; Moreira et al. 2011).

On the other hand, the results of our study point to a different mechanism, for which previous fires *are determined* by the same conditions that will potentially favor new fires in relatively short time period. For instance, like in all regions where human activity is the main source of fire ignitions, in Sardinia, fire occurrence is directly related to human impact (Nunes et al. 2005; Bajocco and Ricotta 2008; Catry et al. 2009; Moreira et al. 2010; Conedera et al. 2011; Ricotta et al. 2012), such that the burned cells are preferentially located closer than expected to those landscape factors where human presence is higher, like roads, urban settlements, and agricultural areas. The same holds for the cells that burned at least twice in the years 2005–2010, meaning that in Sardinia human impact is the main cause for fire occurrence (and recurrence). Unfortunately, the positional accuracy of the digitized fire scar perimeters is unknown. While this source of uncertainty may bias of our results, we believe that the causal mechanism driving fire recurrence is clear enough, even in the absence of a detailed analysis of data accuracy. For instance, the influence of human activities on the spatial distribution of fires has been already observed by several authors, and may vary from region to region as a function of local differences in anthropogenic impact on land cover (De la Cueva et al. 2006; Catry et al. 2009; Martinez et al. 2009; Carmo et al. 2011; Romero-Calcerrada et al. 2010). While in most regions high ignition risk is associated with human settlements and urban interfaces (Lampin-Maillet et al. 2010; Guglietta et al. 2011), in some areas higher probabilities of ignitions have been observed in connection to the use of fire for the management of pastures (Vazquez and Moreno 1998; Catry et al. 2009).

To sum up, irrespective of local differences in the spatial patterning of fires, the strong influence of human impact on fire occurrence implies that, in more fire-prone regions, the probability that a given area is burned twice in a relatively short time period is higher than in less fire-prone regions simply because of the higher anthropogenic ignition risk, without the need of invoking any a-posteriori mechanism for which previous fires induce the (biological) conditions favoring repeated burning. This is not to say that the positive effects of previous fires on the probability of burning again do not exist. However, our results suggest that, at least at this scale of analysis, these effects are not of very high relevance. Also, in the Mediterranean Basin, where most fires are of human origin, we cannot neglect the role of ignition patterns when considering the effects of previous fires on post-fire fuel load and structure, as these patterns ultimately determine the probability of fire occurrence in a given area. Is the proposed probabilistic model for fire recurrence a general model or do the processes that increase fire occurrence in already burned areas vary from region to region and with spatial scale? These are critical questions, and their answers may provide valuable insights into the spatial distribution of fire recurrence.

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