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A multi-scale approach for modeling fire occurrence probability using satellite data and classification trees: A case study in a mountainous Mediterranean region

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Abstract

Fires constitute one major ecological disturbance which influences the natural cycle of vegetation succession and the structure and function of ecosystems. There is no single natural scale at which ecological phenomena are completely understood and thus the capacity to handle scale is beneficial to methodological frameworks for analyzing and monitoring ecosystems. Although satellite imagery has been widely applied for the assessment of fire related topics, there are few studies that consider fire at several spatial scales simultaneously. This research explores the relationships between fire occurrence and several families of environmental factors at different spatial observation scales by means of classification and regression tree models. Predictors accounting for vegetation status (estimated by spectral indices derived from Landsat imagery), fire history, topography, accessibility and vegetation types were included in the models of fire occurrence probability. We defined four scales of analysis by identifying four meaningful thresholds related to fire sizes in the study site. Sampling methodology was based on random points and the power-law distribution describing the local fire regime. The observation scale drastically affected tree size, and therefore the achieved level of detail, and the most explanatory variables in the trees. As a general trend, trees considering all the variables showed a spectral index ruling the most explicative split. According to the comparison of the four pre-determined analysis scales, we propose the existence of three eventual organization levels: landscape patch or ecosystem level, local level and the basic level, the most heterogeneous and complex scale. Rules with three levels of complexity and applicability for management were defined in the tree models: (i) the repeated critical thresholds (predictor values across which fire characteristics change rapidly), (ii) the meaningful final probability classes and (iii) the trees themselves.

Keywords: Fire risk; Ecological hierarchy theory; Static models; Power-law distribution; Fire history; Observation levels

1. Introduction

The five Mediterranean-climate regions of the world occupy less than 5% of the Earth's surface, yet sustain about 20% of the world total vascular plant species (Cowling et al., 1996) and are considered to be biodiversity "hot-spots". In the Mediterranean Basin, natural and human-caused fires have driven landscape change for thousands of years (Trabaud et al., 1993), constituting one major ecological disturbance which influences the natural cycle of vegetation and the structure and function of ecosystems (Koutsias & Karteris, 2000).

Although fire alters ecosystem and biogeochemical processes at multiple scales (Rollings et al., 2004), most empirical research on the ecological effects of fire has been conducted at the stand level, and then conclusions are often extrapolated to broader scales (McKenzie et al., 2000). However, this kind of generalization is rarely ideal because natural systems show characteristic variability on a range of spatial and temporal scales (Levin, 1992). Indeed, landscape pattern and biodiversity arise through positive feedbacks on short time scales and local spatial scales and are stabilized by negative feedbacks on longer time scales and broader spatial scales (Levin, 2000). Therefore,

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by focusing on a single scale an observer imposes a perceptual bias, or filter, through which the system is viewed, so that investigation of one single organizational level or scale will necessarily lead to the neglect of crucial causal links (Reuter et al., 2005). Thus, the capacity to handle scale is beneficial to methodological frameworks for analyzing and monitoring ecosystems. This issue is closely linked with ecological Hierarchy Theory (Allen & Starr, 1982) which suggests that self-organized systems, such as ecosystems, are structured over discrete ranges of scale and that organization abruptly shifts with changes in scale (Allen & Holling, 2002). The highest levels in the hierarchy operate at a slower rate and they control the behaviour at the lowest levels. Furthermore, the assessment of the organizational levels of a given system should depend on the research questions and available tools, which are essential for subsequent data analysis (Levin, 1992; Suárez-Seoane & Baudry, 2002).

Numerous studies have examined the effect of spatial scale on remote sensing land-cover classification (e.g., Irons et al., 1985; Ju et al., 2005; Raptis et al., 2003). Much of this work concentrates on the effect of pixel size on classification accuracy, and it is only recently that studies have followed a multi-spatial-scale approach on remotely sensed data when assessing important vegetation features, such as pattern of change (Hayes & Cohen, 2007), biophysical parameters (Asner et al., 2003; Cheng et al., 2006; Houborg et al., 2007; McCabe & Wood, 2006; Widlowski et al., 2006) or forest fragmentation (Millington et al., 2003). Although imagery has been widely applied for the assessment of fire related topics at local (Chuvieco et al., 2004; Jia et al., 2006; López García & Caselles, 1991), regional (Collins et al., 2007; Díaz-Delgado & Pons, 2001) and global scales (Grégoire et al., 2003; Justice et al., 2002), there are not many ecological studies that consider fire at several spatial scales simultaneously. Exceptions include Chuvieco (1999), who applied several landscape metrics to Landsat and AVHRR images, before and after a fire event, to measure changes in the spatial mosaic across scales. Besides that, LANDFIRE, a fire risk assessment project for the U.S., follows a multi-scale approach to generate intermediate-resolution data of vegetation and fire fuel characteristics (Moisen et al., 2003).

Relationships between fire occurrence and environmental factors are often non-parametric and involve complex interactions, especially when humans play an important role in its dynamics. Because of this complexity, common linear and parametric models that try to explain fire occurrence with associated environmental variables often do not provide good model fits. An alternative are Classification and Regression Trees (CART) (Breiman et al., 1984), non-parametric statistical methods with the ability to capture hierarchical and nonlinear relationships and expose interactions among predictor variables (De'ath & Fabricius, 2000; Kelly & Meentemeyer, 2002) in an intuitive and easy way (Vayssières et al., 2000). Therefore, they are appropriate methods for analyzing complex, non-linear relationships between fire and associated environmental factors at different spatial scales. To date, they have not been used in that capacity, but they have been successfully used with remotely sensed data for vegetation characterization (Brown De Colstoun et al., 2003; Franklin et al., 2000; Friedl & Brodley, 1997; Hansen et al., 2002; Lawrence & Wright, 2001; Rogan et al., 2003; Tadesse et al., 2005), and modeling fire effects and pattern (Collins et al., 2007; Finney et al., 2005; McKenzie et al., 2000; Sá et al., 2003).

The main goal of this study is to understand how the relationships between fire occurrence and different families of environmental factors vary at different spatial observation scales. Previously, we modeled fire risk in the same study zone at a single-scale approach (Lozano et al., 2007). Here we aim to explore the importance of the observation scale on the results and the opportunities of CART, a technique that can provide valuable information about non-linear relationships among the environmental factors. Complementarily, the study aims (i) to develop spatial models of fire occurrence at different observation levels using remote sensing applications and digital maps, (ii) to assess the ability of CART based models for the identification of significant thresholds in predictors values and relationships between environmental variables and (iii) to identify eventual organization levels in the landscape.

2. Data and methods

2.1. Study site

Our study area is comprised by the Natural Park of Lago de Sanabria y Alrededores, in north-western Spain (Fig. 1), covering about 23,000 ha. The landscape has a heterogeneous and patchy pattern as a consequence of a history of fire events and human activities (cattle rising). At elevations range from 950 to 1,300 m, where most of the local population lives, vegetation pattern is characterized by woodlots (dominated by *Quercus pyrenaica*), mixed shrubland (*Erica* spp., *Genista* spp.) and riparian communities. However, at higher elevations where topography is steep, the landscape matrix is composed of a fire-adapted heathland (dominated by *Erica australis* and *Calluna vulgaris*). Mountainous grasslands are also present as patches within the matrix.

The frequency of fire is identified as the main problem for wildlife managers, especially during early spring (mid-late March) and summer (July to late September). Ignition is mainly (about 90%, Gutierrez, pers. com.) related to local population, who has been using fire to manage vegetation for centuries. Although the Park was declared a protected area in 1990, and legal regulations explicitly ban this kind of practice, fire recurrence has not decreased (Consejería de Medio Ambiente de la Junta de Castilla y León, 2002).

2.2. Satellite data and fire scar maps

One Landsat image was acquired for each year throughout the period 1991–2002 covering the whole Natural Park. When cloud cover allowed, images were taken in September in order to consider the majority of the burning season and to avoid bad solar illumination conditions in autumn (acquisition time was 10.40 am). When this was not possible, we selected the latest suitable image sensed during the summer. We undertook geometric (Pala & Pons, 1995; mean spatial error was 20.1 m

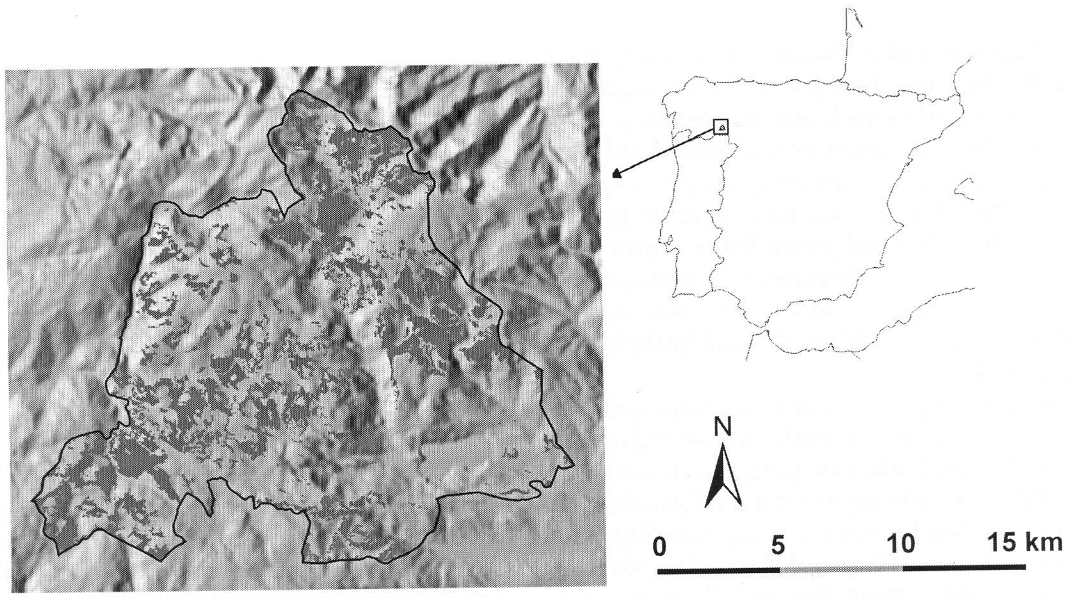

Fig. 1. Location of study site showing illumination model and heathland vegetation patches (landscape matrix and most the fire-prone unit).

for the Landsat TM images and 11.8 m for the ETM+images), radiometric (Moran et al., 1992), atmospheric (Chavez, 1996) and topographic (C-correction method; Riaño et al., 2003; Teillet et al., 1982) corrections to the images and then normalized the time-series using pseudo-invariant scene features (Hall et al., 1991). This enabled the comparison of pixel values in both time and space. Maps of burned areas were derived from Landsat imagery by means of the differenced Normalized Burned Ratio (dNBR index; Key & Benson, 1999) for the study period (1992–2002). The minimum surface for detection was established in 5 ha. Maps yielded an overall accuracy of 88.39%, a commission error of 10.09% and an omission error of 14.37%.

2.3. Variables

Fire occurrence was the binary response variable to be modeled. Maps of burned areas for the period 1992–2002 were used as the data source. The local population decides where and when to burn on the base of vegetation status (biomass, height, moisture, structure, etc.) and the physical features and accessibility of a given location. We captured these factors in thirty-three predictor variables (Table 1) and separated these variables into two groups, static and dynamic landscape features at the temporal study scale (a decade).

The first group included topography, accessibility and vegetation types. Elevation, slope, Heat Load Index and Annual Solar Radiation (McCune & Keon, 2002) were derived from a 30 m resolution DEM (generated from a digital cartography of 10 m of equidistance between isolines). To account for subpixel variations, standard deviation and variation coefficient of the elevation were calculated using a 5 m resolution DEM available for the study zone. This DEM was developed following a stereo-matching technique using 25 cm spatial resolution aerial photographs obtained in 2004. The model is reliable, as was concluded by a validation assessment with field data, and has been already used successfully in other environmental studies (Prieto, pers. com.). We used the distance to the nearest path, village or isolated building as an estimation of site accessibility. Although vegetation biomass and features change among years and within each year, vegetation types change at a different

Table 1
Thirty-three environmental predictors used to model fire occurrence

Code	Predictor description
Static landscape variables at the considered temporal scale (yearly)	
DEM	Elevation (m)
SLOPE	Slope (degrees)
DEM_SD	Inner pixel standard deviation of the elevation derived from a 5 m DEM
DEM_CV	Inner pixel variation coefficient of the elevation derived from a 5 m DEM
ASR	Annual Solar Radiation (MJ/(cm^2 · year))
HEAT	Heat Load Index (no unit)
DIS_VIL	Distance to the nearest village (m)
DIS_PATH	Distance to the nearest path (m)
DIS_BUILD	Distance to the nearest isolated building (m)
HEATH	Frequency (0 to 1) of heathland (dominated by *Erica* spp.) in a 7 × 7 kernel
SHRUB	Frequency (0 to 1) of mixed shrublands (dominated by *Cytisus scoparius* and *Genista* spp.) in a 7 × 7 kernel
YOU_FOR	Frequency (0 to 1) of young forest (dominated by *Q. pyrenaica*) in a 7 × 7 kernel
Dynamic landscape variables at the considered temporal scale (yearly)	
LAST_FIRE	Number of years since the last fire event for the last three years
NBR1-4	NBR (Normalized Burned Ratio) index values of the four previous years
NDMI1-4	NDMI (Normalized Difference Moisture Index) index value of the four previous years
NDVI1-4	NDVI (Normalized Difference Vegetation Index) index value of the four previous years
TCW1-4	TCW (Tasseled Cap Wetness) index value of the four previous years
TCG1-4	TCG (Tasseled Cap Greenness) index value of the four previous years

All spectral indices were multiplied by 100.

temporal scale, typically several decades, in the study zone (Calvo et al., 2002). We created integrated maps of vegetation types from detailed habitat maps (Junta de Castilla y León, 2002), reclassifying original classes into less detailed and more meaningful classes for the current purpose. Using those maps, the frequency of the three classes most affected by fire (heathland, mixed shrublands and young forests), were measured in the surroundings of a given pixel as a context variable within a kernel of 7×7 pixels. Kernel size was decided according to the minimum fire scar size detected by the burned areas cartography (5 ha).

The second group of variables included landscape variables that were dynamic at the study time range: spectral indices and recent fire occurrence history. The followed approach was based on the concept that the monitoring of vegetation status during the four previous years to a fire event can help to estimate fire risk. The length of this period was decided according to (i) the rapid vegetation recovery after fire due to high water availability (about 2,000 mm) and the presence of fire-adapted species (Lozano et al., 2005), (ii) the high occurrence and recurrence that exhibit the fire regime (36% of the Natural Park was burned in 1992–2002, and 20% of these sites were burned more than once), as well as a short fire-free period of three to five years (Lozano et al., in press), (iii) the knowledge of local wildfire managers (Guitiérrez, pers. com,) and (iv) previous modeling efforts in the study site (Lozano et al., 2007). We calculated several widely-used spectral indices in order to account for the yearly changing vegetation characteristics using Landsat imagery: Normalized Difference Vegetation Index or NDVI (Rouse et al., 1973), Normalized Difference Moisture Index or NDMI (Jin & Sader, 2005; Wilson & Sader, 2002), Normalized Burn Ratio or NBR (Key & Benson, 1999) and Tasseled Cap Greenness or TCG and Wetness or TCW (Crist & Cicone, 1984). These indices have already been applied successfully in the study site for fire occurrence modeling (Lozano et al., 2007). The accuracy of the constructed models depended on the included indices (NBR and TCW yielded the best results), suggesting that they add slightly different information to the static model of fire probability about several vegetation properties such as health, structure, biomass or moisture content. Although fire risk is closely related with weather and vegetation status at a given time, it is also strongly linked with fire history (Pyne, 1995; Whelan, 1995). Therefore, using the burned areas maps, a new variable was derived accounting for the fire history during the last three years (the period elapsed between the first year with available data, 1992, and the initial assessment year, 1995) before a fire occurred.

2.4. Scales

The relationships between fire occurrence and environmental factors were assessed at four different scales of observation, which were defined by means of the identification of four thresholds related to fire sizes (Table 2) that are meaningful for the local fire regime. These thresholds are also linked with the vegetation, topography and human-related features of the study site, because these are critical factors affecting fire scars sizes.

Table 2
Definition and features of the observation scales

Scale definition	Variables resolution (m)	Area (ha)		Sampling size
		T	R	
Basic (Landsat and DEM)	30	0.1	0.09	7700
Limit for definition of very small fires	90	1.0	0.81	1150
Detection limit of burned areas maps	210	5.0	4.40	266
Limit definition of severe fire events	540	30.0	29.16	52

The initial area of fire scar used as threshold (*T*) for scales definition and their corresponding pixel size and final area (*R*) are detailed. Total sample size is also shown (75% used for models development, 12.5% for inner validation and 12.5% for independent validation).

Initially, all predictors were rasterized with a resolution of 30 m to match the Landsat imagery. This resolution defined the finest scale, accounting for the most detailed spatial characteristics. Other study scales were set to be multiples of the basic resolution in order to allow raster operations. The second scale (90 m-grain) was related to very small fires, which are very frequent and cause little damage. Several countries in Europe commonly use 1 ha as the minimum fire scar size for the consideration of a given fire event in official statistics (European Communities, 2006), and a 90 m pixel is roughly equivalent to 1 ha (0.81 ha). The third scale (210 m-grain or 4.4 ha) corresponded to the minimum detection limit in the fire scars maps (5 ha), because these were used as data source for the response variable (fire occurrence). Finally, in order to account for large fire events, we defined the fourth scale (540 m-grain or 29.6 ha). Since the consideration of a large fire event is relative and depends on both landscape characteristics and fire regime of a given site, we used the threshold (30 ha) defined by the Regional Government for the identification of large fires (Junta de Castilla y León, 1999).

Response and predictor variables were resampled from the initial (30 m) to the coarser resolutions based on an average strategy. Since the response variable was binary, we considered a given pixel as burned (1) if at least 60% of the initial resolution (30 m) pixels were burned, and non-burned (0) if no more than 40% of the initial resolution pixels were burned.

2.5. Sampling method

For development and validation of models, a spatial database was created by means of a sampling methodology based on random points. Since fire patterns may change between years, we undertook multi-temporal sampling on scars burned in the period 1995–2002 (initial year was determined by the first available Landsat image–1991–for the calculation of the spectral indices corresponding to the four years previous to the events). Every year was equally represented in the database. Half of the sampling points was not burned in this period whereas the other half was burned. Two subsets were defined within the database according to the considered years: (i) 1995–1999 data for model development (75% of the data) and inner validation (12.5%) (ii) 2000–2002 for independent validation (12.5% of the data) to test the predictive capabilities of the models (on years not considered in their development). Points were located throughout the study area, excluding lakes and other water bodies.

The wildfire regime encompasses the frequency and magnitude of wildfires that occur in a region. Frequency–area probability usually follows a power-law (Malamud et al., 1998, 2005; Minnich, 1983; Ricotta et al., 2001) or "heavy-tailed" (Cumming, 2001; Reed & McKelvey, 2002) distribution over different fire regimes. The power-law is a scale-invariant statistical distribution (Newman, 2005), where the probability of a certain value occurring is raised to some power of the value (Eqs. (1) and (2)). Moreover, studies based on the ecological Hierarchy Theory, that describes self-organized systems, have identified power-law distributions as useful tools when identifying organizational levels in such systems (Feagin, 2005; Gardner, 1998; O'Neill et al., 1991).

$$f(A_B) = \beta A_B^{-\alpha} \tag{1}$$

$$\log(f(A_B)) = \log(\beta) - \alpha\log(A_B) \tag{2}$$

where A_B is the burned area, $f(A_B)$ is the frequency of fire events (in "unit" bins with A_B burned area), and α and β are constants. In Eq. (2), derived from Eq. (1), α determines the slope of the line and can be considered as the constant ruling the distribution (Newman, 2005), whereas β determines the frequency of fire events with very small area. Since power-law distributions are meaningful when (i) characterizing fire regimes, (ii) dealing across scales and (iii) identifying levels in self-organized systems, we defined sampling size by means of a power-law function, that shares the same α with the function describing the fire regime in the study site. For that aim, we derived the power-law function using the 347 fires that occurred in the study period (1992–2002). The other constant, β, was calculated to fit the scarce number of available observations at the coarser observation scale (540 m-grain). Table 2 shows final sampling size at each scale.

2.6. Data analysis

Classification and regression trees (CART), also known as recursive partitioning regression (Breiman et al., 1984), recursively divide the response variable into increasingly homogeneous subsets based on critical thresholds of the predictor variables (Kelly & Meentemeyer, 2002). To evaluate the relationship between the predictor variables and fire occurrence probability we used a classification tree analysis at each of the four scales. We selected the Gini index criterion of impurity for node splitting (Breiman et al., 1984; Zambon et al., 2006), assuming equal class prior probabilities and equal classification error costs for the burned and unburned classes. Final trees were pruned using the 1-S.E. rule (Breiman et al., 1984) calculated from a 10-fold cross-validation. Three different trees were developed for each observation scale, using respectively (i) the "static" predictors at the temporal scale of the study, (ii) the "dynamic" predictors and (iii) all of them (Table 1). We used the obtained trees to create maps of fire occurrence probability for each year for the period 1995 to 2002.

An important characteristic of CART models is the identification of meaningful thresholds for predictor variables that may have strong influence on the response variable (Kelly & Meentemeyer, 2002). Therefore, we looked for repeated thresholds of predictor variables at different scales. Moreover, classes identified in the trees with high or low probability of fire occurrence are valuable for fire risk characterization and management. Thus, we focused on final classes with low or high probability of fire occurrence, which we will call meaningful final classes in the next paragraphs.

Finally, we undertook a validation analysis using the data subsets for inner and independent analysis to test the consistency of the results. Thus, we calculated the probability errors yielded by the trees and the identified meaningful classes. Concerning the repeated thresholds, three parameters were calculated: (i) percentage of dataset observations with a higher value than the threshold, (ii) the mean observed probability of points where predictor value is higher and (iii) lower than the threshold.

3. Results

3.1. Tree models

The observation scale, and hence the number of observations included in the development of the trees, drastically affected

Table 3
Final tree models features

Scale	n	Predictor Variables	N. V.	N. T. N.	E. D. (%)	E. D. by each predictor (%)
30 m	5770	Static	9	12	18	HEATH (5), HEAT (4), ASR(2), DIS_BUILD (2), DIS_VIL(1), DEM_CV(1), SLOPE (1), DEM (1), DEM_SD(1)
		Dynamic	8	10	15	TCW1 (6), NDVI1(1), NDVI3(2), TCW2 (1), TCG1 (1), TCG2 (2), NBR2 (1), TCW3 (1)
		All	9	13	21	TCW1 (6), HEAT (4), NDVI1(1), DIS_PATH (1), HEATH (4), DIS_VIL (2), ASR(1), TCG2 (1), DIS_BUILD(1)
90 m	860	Static	3	4	12	SLOPE (6), HEATH (3), HEAT(3)
		Dynamic	3	4	17	NDVI1 (11), TCW1 (2), TCG2(4)
		All	4	5	21	NDVI1 (11), DIS_BUILD (4), TCW1(3), HEAT (3)
210 m	200	Static	1	2	7	SHRUB (7)
		Dynamic^	1	2	11	NDVI1 (11)
		All^	1	2	11	NDVI1 (11)
540 m	38	Static*	1	2	37	SLOPE (37)
		Dynamic	–	–	–	–
		All*	1	2	37	SLOPE (37)

* and ^ trees are respectively equal.
Number of observations used for their development (n), number of variables (N. V.) and terminal nodes (N. T. N.) in the final tree, percentage of the initial data deviance explained by the model (E. D.) and by each variable (E. D. by each predictor) are shown for static, dynamic and global models.

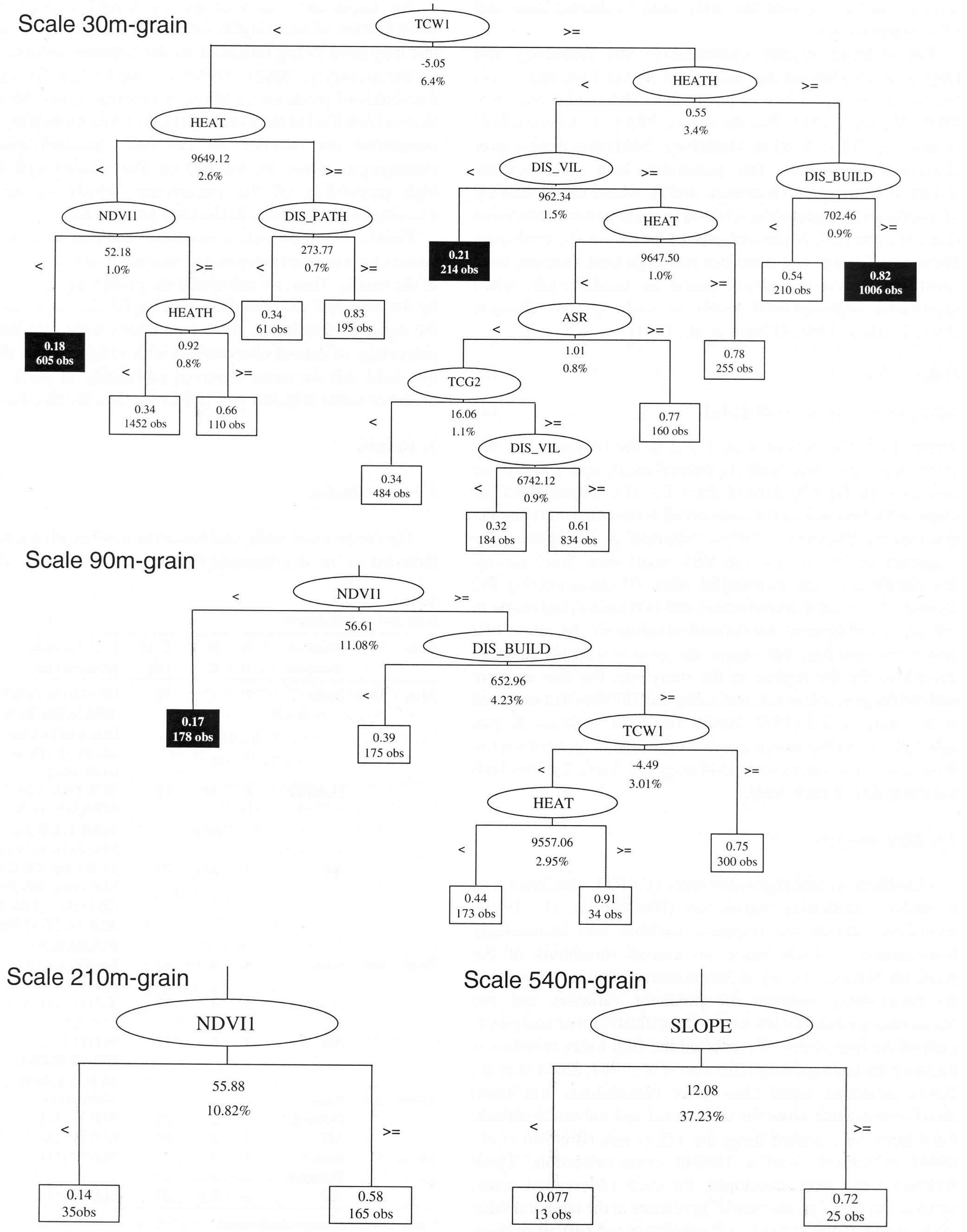

Fig. 2. Classification tree models of fire occurrence probability. They were developed for the full dataset at the four defined scales of observation. Ovals and squares represent non-terminal and terminal nodes, respectively. Within the ovals, variable ruling the split is shown (see Table 1 for abbreviations meaning), and values beneath them indicate the corresponding defining threshold value and the percentage of the total initial deviance that the split explains. The values inside the squares are the predicted probabilities (means) of fire occurrence, and the amount of observations included in the class. Filled boxes correspond to the meaningful classes identified within the tree.

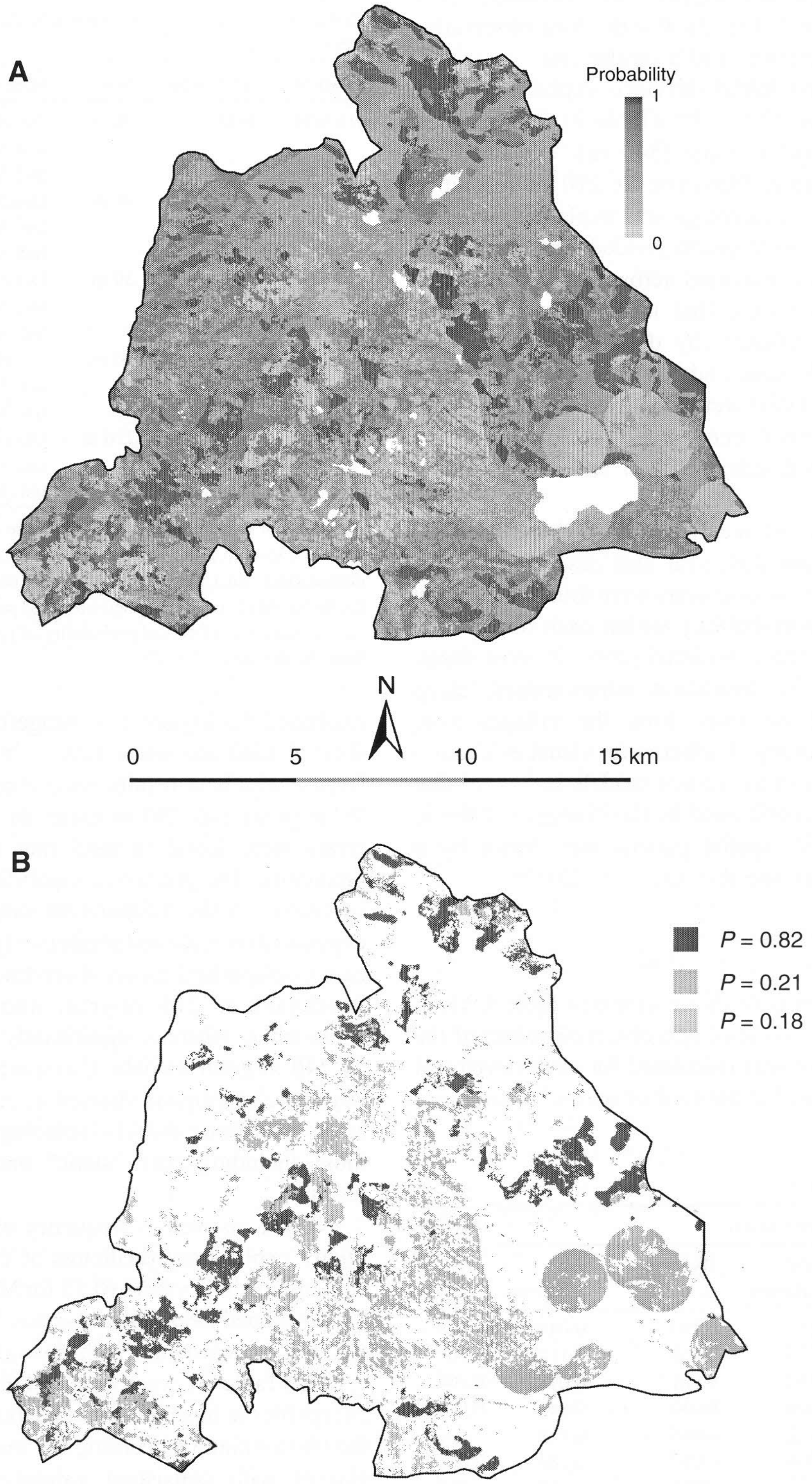

Fig. 3. Output map of predicted probability of fire occurrence for 1998. Map A was derived from the tree developed at the finest observation scale (30 m) including all the environmental predictors. Pixels with null probability are colored in white and those with $P=1$ in black. Map B exhibits only the spatial location of the meaningful final classes identified by the validation analysis within that spatial model.

tree size, measured as the number of terminal nodes (Table 3). Thus, basic scale trees were developed with 5,770 observations (from 30 m data) and had about 10 terminal nodes, whereas the coarser scales (540 m-grain, 210 m-grain) trees only had two. Tree size determined the number of defined classes. For the coarsest scale (540 m-grain), considering only the "dynamic" variables, cross-validation results showed that minimum error rate was yielded by the tree with no splits and, therefore, it was not developed. As expected, bigger trees included more predictor variables (Table 3, Fig. 2). For the four observation levels, the three developed trees had a similar size.

The proportions of the initial deviance explained by the CART models varied from 7 to 37% (Table 3). The smallest tree, obtained at the coarsest scale (540 m), explained the biggest deviance proportion. However, at 210 m resolution scale, the lowest deviance percentage was explained, whereas finer scales (90 m-grain, 30 m-grain) yielded similar intermediate results. There were differences across scales concerning the most explanatory variables, that is to say, the variable explaining the greatest variance (by definition, the variable ruling the first split). Only slope and NDVI index value for the year before the event (NDVI1) were identified as such at more than one scale. As a general trend, trees considering all the variables showed a spectral index (NDVI1 and TCW1) ruling the main split.

Maps of probability of fire occurrence (Fig. 3) were derived from the obtained trees for each year and observation scale. Although some differences among years were found, the spatial pattern of fire occurrence probability within each observation scale was similar for all the considered years. In most cases, zones mostly covered by heathland communities, steep topography and located far away from the villages were identified as at risk of burning. Furthermore, visual evaluation of the temporal evolution of the spatial models suggested that this pattern was strongly conditioned by the existence of fire in the previous year. Similar spatial pattern was drawn by a previous study in the study site (Lozano et al., 2007).

3.2. Validation analysis

Results of the validation analysis are shown in Table 4. Mean error (difference between predicted and observed value) of the fire occurrence probability was calculated for each developed tree. Although trees obtained at the coarser scale (540 m-grain) explained the highest percentage of initial deviance (Table 3), they yielded the worst results in the validation assessment. Conversely, best results were obtained by trees developed at 90 m-grain and 210 m-grain. In general terms, the smallest errors were found in trees that considered only "dynamic" predictors. The predictive capabilities of the models, assessed by means of the independent validation dataset, were highly dependent on scale and predictors types (Table 4). In most of the cases, comparison across observational scales identified models developed at 210 m-grain and 90 m-grain as the best approaches, whereas significantly worst results were yielded by 540 m-grain models. Unexpectedly models including only "dynamic" predictors showed in general terms similar or lower errors than those models including all the variables. However, those including only "static" predictors obtained the worst results.

Table 4
Results of the validation analysis

Scale	Validation set	*n*	Tree models			Average
			Static predictors	Dynamic predictors	All predictors	
30 m	Inner	1930	0.155	0.103	0.041	0.098
	Independent	1930	0.154	0.059	0.114	0.109
	Average		0.155	0.081	0.078	0.104
90 m	Inner	290	0.068	0.030	0.049	0.049
	Independent	290	0.112	0.044	0.126	0.094
	Average		0.090	0.037	0.088	0.072
210 m	Inner	66	0.133	0.065	0.065	0.088
	Independent	66	0.108	0.016	0.016	0.047
	Average		0.121	0.041	0.041	0.067
540 m	Inner	14	0.188	–	0.188	0.188
	Independent	14	0.355	–	0.355	0.355
	Average		0.272	–	0.272	0.272

Errors (absolute difference between predicted and observed value) were calculated for each validation point and the mean for each tree was then computed. The corresponding observation scale, validation set and number of considered observations are also shown. As summary statistics, the averages across validation sets and tree models are displayed.

Table 5
Probabilities of fire recurrence related to the repeated thresholds identified in the trees

Predictor	Threshold	Scale	Dataset	% (>T)	P(<T)	P(>T)
HEATH	0.55	30 m	Develop.	29	0.43	0.68
			Inn. Val.	31	0.44	0.63
			Ind. Val.	32	0.41	0.69
		90 m	Develop.	29	0.44	0.64
			Inn. Val.	29	0.43	0.68
			Ind. Val.	31	0.38	0.77
NDVI1	56	30 m	Develop.	81	0.30	0.56
			Inn. Val.	79	0.30	0.55
			Ind. Val.	82	0.28	0.55
		90 m	Develop.	81	0.16	0.58
			Inn. Val.	80	0.17	0.58
			Ind. Val.	82	0.49	0.56
		210 m	Develop.	82	0.17	0.57
			Inn. Val.	86	0.33	0.53
			Ind. Val.	83	0.18	0.54

Three datasets were used to calculate the probabilities: the tree development dataset (Develop.), the inner validation dataset (Inn. Val.) and the independent dataset (Ind. Val.). Percentage of dataset observations with a higher value than the threshold (% (>*T*)) and their observed probability (*P*(>*T*)) are also shown, as well as the mean observed probability of points where predictor value is lower than the threshold (*P*<(*T*)).

NDVI1, as well as frequency of heathland (HEATH), were highly explanatory predictors at the finer scales, and yielded similar threshold values (0.55 for NDVI1 and 56 for HEATH) in the developed trees at those scales. These threshold values were tested for consistency with the validation datasets. Consistent results (Table 5) were obtained for all the considered cases, except for the independent validation of the NDVI1 threshold at the 90 m-grain. Concerning the meaningful final classes, eight classes with consistent validation results were identified (Table 6), four at the finer scale (30 m-grain) and four at the 90 m-grain.

4. Discussion

4.1. Scale and models of fire occurrence probability

Significant differences between the trees were found depending on the observation scale, as was already reported by other

Table 6
Meaningful final classes ($P<0.3$ or $P>0.7$) identified by the tree models with consistent validation results

Scale	Dev. dataset	Class defining predictors	T. P.	In. V.	Ind. V.	F. 1998
30 m	Dynamic	TCW1, NDVI1	0.17	0.18	0.12	6.32
	All	TCW1, HEAT, NDVI1	0.18	0.19	0.20	12.81
		TCW1, HEATH, DIS_VIL	0.21	0.24	0.19	4.90
		TCW1, HEATH, DIS_BUILD	0.82	0.77	0.74	8.07
90 m	Static	SLOPE, HEATH	0.72	0.73	0.76	13.57
	Dynamic	NDVI1	0.17	0.22	0.21	24.39
		NDVI1, TCW1, TCG2	0.80	0.77	0.79	13.83
	All	NDVI1	0.17	0.22	0.21	24.39

The development database of the model (Dev. Dataset), the probability outlined by the tree model (T. P.), the mean probability obtained by points in the inner validation (In. V.) and the independent validation (Ind. V.) datasets are shown. As an example, the last column presents the frequency of each class (F. 1998), expressed as percentage, for the 1998 model (Fig. 3).

authors (for example, Millington et al. (2003) demonstrated the spatial dependence of several landscape metrics when studying the deforestation process with satellite imagery). Trees developed at finer spatial scales were more complex with regard to the number of splits and predictor variables, probably because heterogeneity is higher at those scales. Moreover, composition, variable interactions and explicative capabilities of the trees changed across scales. In general terms, models that included "dynamic" predictors had better predictive capabilities regardless of the applied observation level.

Slope and NDVI1 (NDVI index value for the year before the event) were the most repeated variables at high variance splits, such as the primary node of trees. Slope, a structural factor, was frequently included in the models regardless of the study scales, although, at local levels, solar insolation variables were more meaningful for fire risk assessment. Previous modeling efforts of fire occurrence in the study site (Lozano et al., 2007) identified slope and the spectral indices as highly explicative predictors and, to a lower extent, the frequency of heathland and variables related to accessibility. Similarly, these environmental variables were also highly explanatory in models constructed at the finest scale (30 m-grain). The uniqueness of the most represented predictors can be tested by assessing the surrogates splits (a splitting rule that closely mimics the action of a primary split). In this case, several spectral indices (NDMI1, NBR1, TCW1) were identified as possible substitutes of NDVI1, suggesting the suitability of different variables for the definition of the tree splits, which might allow for greater flexibility with data obtained by other sensors.

4.2. Scale and organization levels

The definition of the observation scales, based on meaningful fire scars sizes for the local fire regime and fire policy, has allowed exploring the organizational levels with regard to fire occurrence in the studied Natural Park. However, in areas where the fire size distribution is different, such as boreal zones or where another fire policy is undertaken (prescribed fires, fire suppression, etc), it would be advisable to redefine the scales according to the local characteristics.

According to the comparison of the four pre-determined analysis scales, we propose the existence of three eventual organization levels: (i) landscape patch or ecosystem level corresponding to the broadest resolution (540 m-grain), (ii) local level related to 90 m-grain and 210 m-grain and (iii) basic level (30 m-grain). Nevertheless, further research considering a greater range of spatial scales should be undertaken towards an in-depth understanding of the spatial organization levels of fire occurrence probability in the landscape. At the landscape patch level, topography, expressed in the model as slope, is the main variable explaining fire occurrence. This result is in agreement with the Hierarchy Theory premises, which establishes that the highest levels are ruled by variables that change at a slower rate and provide a context for the lower levels (Allen & Starr, 1982). It is remarkable that the high patchiness of the landscape posed challenges for vegetation characterization by means of spectral indices at this observation scale. Although the validation results (especially those yielded by the independent validation) were the worst, the percentage of the initial deviance explained by the models was the highest. This is likely to happen because of the greatly decreased variability among observations at this scale, due to the spatial averaging. This disagreement might be also caused by the low number of observation used for the CART models development, that was constrained by the availability of points considered as burned at that scale for the study period. Small sampling sizes are a concern, but there are examples in the literature of similar studies based on a low number of observations that obtained good results (Feldesman, 2002). For this type of situations, the new statistical method known as the Breiman Cutler classification (based on the CART approach) could be helpful, since on top of being robust to overfitting, it is probably not necessary to have a separate accuracy assessment data set (Lawrence et al., 2006).

Trees developed at 90 m-grain and 210 m-grain scales characterized a level of organization corresponding to intra-patches elements. Trees developed at this observation scale yielded the best validation results and included mainly predictors related to spectral indices, which accounted for biomass, and, indirectly, fire history. At this level, trees considering only "dynamic" predictors explained a similar percentage of the initial deviance than those including all predictors and, unlike the regional scale, "dynamic" predictors (i.e. NDVI1) were the most explicative, as far as the global deviance reduction is concerned. This performance is mainly based on the identification of areas with low probability of fire occurrence because of a lack of biomass to be burned as a consequence of (i) a recent fire event or (ii) the vegetation pattern (non or scarcely vegetated).

At the basic level (30 m resolution predictors), which has not necessarily an ecological meaning in itself, the spatial heterogeneity and complexity are greater. This led to (i) more detailed models including all the available predictor groups (topography, accessibility, structural vegetation type and spectral indices) and (ii) worst predictive capabilities than the models developed at the landscape scales (210 m-grain and 90 m-grain). In this sense, Rollings et al. (2004) found that topography, infrared reflectance and mean annual precipitation were the most significant variables when modeling fire intervals and severity at a local scale with CART. This is in agreement with our results and reinforces the need of several predictor types when explaining fire-related processes at this scale.

4.3. Model applications for fire risk management

Our results show that CART was a valid statistical approach for modelling fire occurrence, offering products that can be applied by managers. Thus, rules with three levels of complexity and applicability for management were defined in the tree models: (i) the repeated critical thresholds, (ii) the meaningful final probability classes and (iii) the trees themselves. Firstly, the repeated critical thresholds (predictor values defining splits in several trees) are linked to significant changes of fire occurrence probability. They can enhance our understanding of the discontinuous behaviour of ecological systems concerning the fire risk, which is an important issue for fire managers (McKenzie et al., 2000). Secondly, the meaningful final probability classes were valuable as simple, easily-applicable hierarchical rules identifying fire prone or non-prone areas. This helps with the design of fire prevention operations, saving money and human-resources and improving their results. These classes also help in the understanding of relationships between fire occurrence and environmental predictors, as was also concluded by McKenzie et al. (2000) when analysing fire frequency with CART methods. Finally, the trees themselves can be used to derive maps of fire occurrence probability, which are of great interest for fire managers and, indirectly, for the whole community involved in managing biodiversity and ecosystems. Maps of fire occurrence probability were derived in a previous study for the study site following a single-scale approach based on logistic regression (Lozano et al., 2007). The definition of strong, non-realistic spatial discontinuities when predicting fire risk is a weakness of CART-based maps when compared to those obtained by the logistic regression analysis.

The results of this research support the assertion that multi-scale, integrated assessments based on the principles of ecological theories provide an avenue for successful implementation of fire and ecosystem management (Hann & Bunnell, 2001). However, further studies are needed to gain insight of the validity of the proposed organization levels and the management rules derived from the models.

5. Conclusions

CART was a valid methodology for modeling the probability of fire occurrence at four different scales of observation. According to the comparison of the four pre-determined analysis scales and the premises of the ecological Hierarchy Theory, we propose the existence of three eventual organization levels: (i) a landscape patch scale, where fire occurrence pattern is driven by a topographic variable (slope) (ii) an intra-patch or local level, where the vegetation biomass and the recent fire history, expressed by means of the spectral indices, best explained the fire occurrence probability and (iii) the basic scale, the most heterogeneous and complex level, where all the predictor types are needed to model the fire occurrence. Moreover, rules with three levels of complexity and applicability for management were defined in the tree models: repeated critical thresholds, meaningful final probability classes and the tree itself.

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