

The relationship between landscape patterns and human-caused fire occurrence in Spain

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Abstract

Aim of study: Human settlements and activities have completely modified landscape structure in the Mediterranean region. Vegetation patterns show the interactions between human activities and natural processes on the territory, and allow understanding historical ecological processes and socioeconomic factors. The arrangement of land uses in the rural landscape can be perceived as a proxy for human activities that often lead to the use, and escape, of fire, the most important disturbance in our forest landscapes. In this context, we tried to predict human-caused fire occurrence in a 5-year period by quantifying landscape patterns.

Area of study: This study analyses the Spanish territory included in the Iberian Peninsula and Balearic Islands (497,166 km²).

Material and methods: We evaluated spatial pattern applying a set of commonly used landscape ecology metrics to landscape windows of 10 × 10 sq km (4,751 units in the UTM grid) overlaid on the Forest Map of Spain, MFE200.

Main results: The best logistic regression model obtained included Shannon's Diversity Index, Mean Patch Edge and Mean Shape Index as explicative variables and the global percentage of correct predictions was 66.3%.

Research highlights: Our results suggested that the highest probability of fire occurrence at that time was associated with areas with a greater diversity of land uses and with more compact patches with fewer edges.

Key words: human-caused wildfires; landscape ecology; logistic regression.

Introduction

Landscape structure is the result of past and present interactions between human activities and natural processes (De Aranzabal *et al.*, 2008; Echeverría *et al.*, 2007; Löfman and Kouki, 2003; Naveh and Lieberman, 1994; Serra *et al.*, 2008). Variations in frequency, magnitude and extension of disturbances produce complex patterns in vegetation composition, age structure and patch size distribution over the landscape (Farina, 2006; Regato *et al.*, 1999; Saura, 2010). Thus, the spatial pattern of vegetation, usually assessed by different metrics, allows understanding historical ecological processes and socio-economic factors. Landscape composition and configuration metrics have been proved to be influenced by climate (Pickett and White, 1985),

forest pests and diseases (Hatala *et al.*, 2010; Romero *et al.*, 2007), land use changes (Ferraz *et al.*, 2009; Gallant *et al.*, 2003; Serra *et al.*, 2008), human settlements (Fuller, 2001), deforestation (Löfman and Kouki, 2003; Zhang and Guindon, 2005), the abandonment of traditional agrarian tasks (plowing, grazing and cutting) (De Aranzabal *et al.*, 2008) and fires: burned area and frequency (Chang *et al.*, 2007; Moreno, 2007; Naveh and Lieberman, 1994; Pickett and White, 1985).

In the Mediterranean environment, the landscape has long been modified by human influence (Pausas, 2006), becoming what we call a cultural landscape (Farina, 2006). Landscape patterns are created by direct human action through the design of boundaries between crops and natural vegetation, wildland-urban

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Abbreviations used: Landscape Metrics (Table 2), ANND (Average Nearest Neighbor Distance Index).

interfaces, presence of infrastructures, or indirectly by allowing the spread of disturbances, for instance. Hence, landscape metrics may be proposed as surrogate variables for human activities in our Mediterranean environment.

In the past, fire was the main tool used in cleaning and removal of forest residues, along with grazing and firewood extraction (Pausas, 1999; Torre Antón, 2010). In current times, fires are still linked to the persistence of traditional agrarian activities (Martínez *et al.*, 2009). Approximately 18,600 fires occur per year in Spain, and 96.2% are caused by people (MAGRAMA, 2010). About 75% of human-caused forest fires in Spain are related to the rural use of fire for vegetation management (MAGRAMA, 2010; Torre Antón, 2010). Fires are a human artefact emanating from the rural activities that shape the Mediterranean landscapes.

Consequently, the quantitative analysis of landscape structure becomes a relevant tool to make inferences on future fire occurrence. Among the studies that have dealt with fire occurrence in the literature, many have included geographic or spatial variables (*i.e.* Padilla and Vega-García, 2011) but only Henry and Yool (2004), Martínez *et al.* (2009) and Ortega *et al.* (2012) have included independent variables measuring landscape pattern. Henry and Yool (2004) calculated landscape metrics (area, shape and diversity indices) in remote sensing images (Landsat TM and SIR-C data) to relate landscape pattern with historical fire occurrence in National Saguaro Park (Arizona). Martínez *et al.* (2009) considered area, density and fragmentation indices (landscape and cropland fragmentation) with socio-economical and geographical variables to predict human-caused fire occurrence at the municipal scale in Spain. A recent study by Ortega *et al.* (2012) did analyze landscape structural factors (11 metrics) related to increased wildfire incidence in forest-agriculture interfaces within the SISPARES monitoring network (observation size 16 km²), finding that certain landscape configurations were more vulnerable (fire-prone) than others.

Building on these findings, we propose that some metrics may be more appropriate than others to characterize and identify fire-prone landscape traits at the national level. Thus, the aim of this paper is to evaluate specifically the relationship between landscape patterns and human-caused forest fire occurrence with a comprehensive array of landscape metrics, encompassing the wide range of compositions and configurations that can be found in Spain.

Material and methods

Study area

This study analyzes the Spanish territory included in the Iberian Peninsula and Balearic Islands (497,166 km²). Most of the study area is dominated by a Mediterranean climate, and only the Northern third has an Atlantic climate. These climatic zones and the complex topography combined with human socio-economical development over millennia have given way to a very uneven spatial distribution of the vegetation, combining the presence of medium-scale farming areas, areas with scarce natural vegetation cover (grasses, rangelands), extensive shrublands, park-like open forest structures (*dehesas*) with undergrowth and high forests of variable densities (EEA, 2007).

The main reference for the study of vegetation cover in Spain is the Forest Map of Spain by Ruiz de la Torre (1990) at 1:200,000 scale (digitized 1:50,000). It locates more than 5,500 species of trees, shrubs and grasses, collecting information about other land uses.

In order to fulfill the goals of this study and work at the considered scale (Peninsular Spain and Balearic Islands) it was necessary to reclassify the different plant species and land uses in manageable categories meaningful for risk analysis. The classification was designed according to the fuel models of Rothermel (1972) and species response to fire (Riaño *et al.*, 2001; Rothermel, 1972; Sturtevant and Cleland, 2007). Fig. 1 displays the vegetation classes used, defined in Table 1.

Independent variables: landscape metrics

To characterize the vegetal landscape pattern we selected 13 metrics related to the area, shape, fragmentation and diversity of the vegetation patches. All of them were indices commonly used in the scientific literature of fire landscape ecology (Forman, 1995; Frohn, 1998; Henry and Yool, 2004; Hernández-Stefanoni, 2005; Lloret *et al.*, 2002; Martínez *et al.*, 2009; McGarigal *et al.*, 2002; Ortega *et al.*, 2012; Romero-Calcerrada and Perry, 2004). Table 2 shows the selected indices, the group they belong to and a brief description about the information they convey (McGarigal *et al.*, 2002).

These 13 metrics were computed for the landscape units in Spain using Patch Analyst 4 (Elkie *et al.*, 1999)

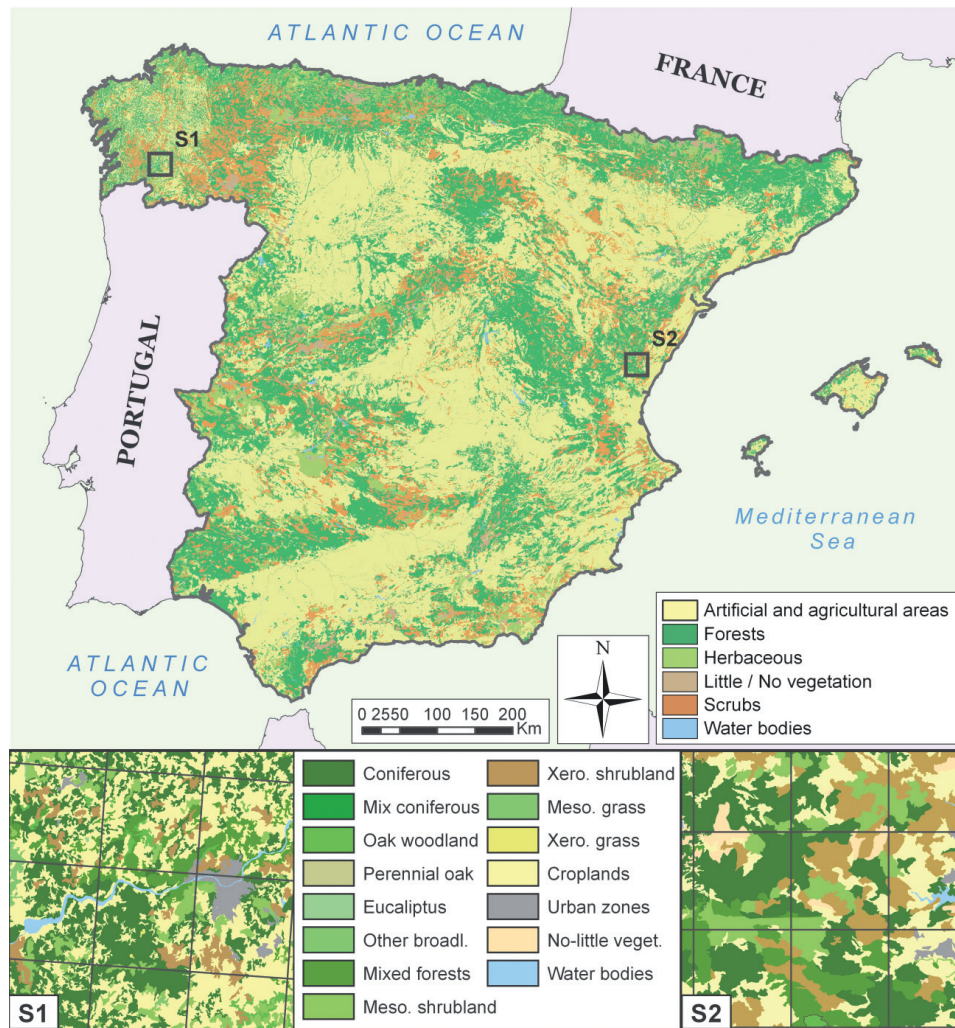


Figure 1. Forest Map of Spain with the classes used in the study grouped in six land uses. Zoom windows of 900 sq km, as examples of two forest landscapes in Atlantic (S1) and Mediterranean Spain (S2).

and ArcGis 9.3 (ESRI Inc., 2009). The landscape units corresponded to 10×10 sq km UTM grid cells used by the Ministry of Environment in Spain to record locations of fires in the reports (Fig. 2). Because these landscape units were not constant in area, it was not possible in principle to compare the values for each grid, since some metrics are sensitive to the size of the landscape unit (Saura, 2002). The original grid consisted of 5,278 cells, but some irregular cells on the coast-line and in the boundaries between UTM zones 29, 30 and 31 were excluded to obtain comparable landscape units (100 ± 25 km²). The resulting grid of 4,751 cells was set as the spatial base for calculation of the explanatory variables and for the analyses of the present study.

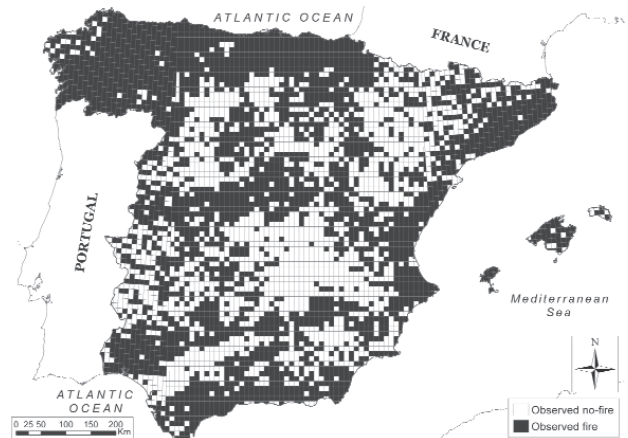


Figure 2. Human-caused forest fire occurrence in Spain, 1989-1993.

Table 1. Land use classes and fuel description. Classes for landscape metrics calculation

<i>Forest soil layer-driven fuels</i>	
Formations with woody plants taller than 7 m and corresponding to fuel models 7, 8, 9 and 10.	Conifers-FC (pinaceous, cupressaceous, mix of conifers and other conifers) Broadleaves-FB (oak woodland, perennial oak, beech forest, riparian forest, eucalypt forest, poplar stand, mix of broadleaves, other broadleaves) Mixed forest-FM
<i>Shrub-driven fuels</i>	
This group is composed by formations with woody plants shorter than 7 m, alone or under tree cover less than 30% fraction cover that correspond to Rothmel fuel models 4, 5 and 6	Xerophyllous shrubland-XS Mesophyllous shrubland-MS
<i>Grass-driven fuels</i>	
This group includes vegetal formations with natural herbaceous habitats (fuel models 1, 2 and 3) and ferns for their shade-tolerance preference and low height	Xerophyllous grassland-XG Mesophyllous grassland-MG
<i>Little/No-vegetation</i>	
Composed by open spaces with little or no vegetation such as beaches, dunes, sandy areas, nude land, bare rocks and sparsely vegetated and burned areas	Little/No-vegetation-NV
<i>Anthropic surface</i>	
High human influence areas. We separate urban fabric, industrial units, mines dumps and construction sites from herbaceous and woody agricultural plants	Artificial surface-AS Agricultural areas-AA
<i>Continental water</i>	
Contains any surface covered by water bodies or stream courses. It also includes those herbaceous or woody plants that grow in water	Continental Water-W

Dependent variable: fire occurrence

The fire history registry from 1983 to 2008 was provided by the Ministry of the Environment and Rural and Marine Affairs (MAGRAMA) in Spain. The fire reports routinely included information about the causes of the fires, dividing these into natural (lightning) and human-caused fires. This information could be easily summarized in number of fires per year for each 10×10 sq km UTM grid used by the Ministry to locate fires. According to our stated goal, only anthropogenic fires were selected for this study.

The dependent variable was the probability that at least one fire happened in the 5-year period between 1989 and 1993. Fire occurrence data in the historical reports (Fig. 2) was summed up for each 10×10 sq km UTM cell or landscape unit and coded as $Y = 1$ if at least one fire took place in the period and cell, or $Y = 0$ if otherwise.

This study period of 5 years was carefully chosen so that it chronologically followed the time span between the acquisitions of the ortophotos (1982-1986), the field work (up to 1989) and the date of creation of the Forest Map of Spain (MFE200, 1990). According to Chuvieco (1996), Viegas *et al.* (1999) and Vega-García and Chuvieco (2006), the reasonable period for updating dynamics in vegetation maps is around 4 or 5 years. More importantly, the years 1989 and 1994 were severe fire-years; a number of large fires occurred in those years (burning 426,468 and 437,635 ha respectively), and in between, fires burned slightly more (90,000-260,000) hectares than are burned nowadays (50,000-190,000 ha, MAGRAMA, 2010), reflecting worse conditions than at present, but conditions that could develop again in the future (Vega-García and Chuvieco, 2006). The number of occurrences, though, was very similar (12,913-20,811 in 1989-1993) to present numbers (10,932-25,492 in 2004-2008).

Table 2. Table of all landscape metrics considered in the study

Group	Abrev.	Description	Mean	Std. dev.	References where the variable or a similar factor were used
Density	PD	Patch Density	0.327	0.199	(Henry and Yool, 2004*; Lloret <i>et al.</i> , 2002; Martínez <i>et al.</i> , 2009*; Ortega <i>et al.</i> , 2008, 2012*)
Area	MPS	Mean Patch Size	5.188	7.721	(Henry and Yool, 2004*; Hernandez-Stefanoni, 2005; Lloret <i>et al.</i> , 2002; Ortega <i>et al.</i> , 2012*; Romero-Calcerrada and Perry, 2004)
	MedPS	Median Patch Size	1.341	6.804	(Martínez <i>et al.</i> , 2009*)
Shape	ED	Edge density	0.036	0.040	(Ortega <i>et al.</i> , 2012*)
	MPE	Mean Patch Edge	10.682	3.839	(Ortega <i>et al.</i> , 2012*)
	MSI	Mean Shape Index	1.967	0.276	(Henry and Yool, 2004*; Ortega <i>et al.</i> , 2012*)
	AWMSI	Area-Weighted Mean Shape Index	2.846	0.993	(Henry and Yool, 2004*)
	MPAR	Mean Perimeter-Area Ratio	0.162	1.314	(Henry and Yool, 2004*; Hernandez-Stefanoni, 2005; Ortega <i>et al.</i> , 2008)
Diversity	PR	Patch Richness	7.102	2.335	(Ortega <i>et al.</i> , 2012*)
	SHDI	Shannon's Diversity Index	1.114	0.502	(Henry and Yool, 2004*; Lloret <i>et al.</i> , 2002; Ortega <i>et al.</i> , 2012*; Romero-Calcerrada and Perry, 2004)
	SHEI	Shannon's Evenness Index	0.565	0.217	(Henry and Yool, 2004*)
	SIDI	Simpson's Diversity Index	0.534	0.231	
	SIEI	Simpson's Evenness Index	0.624	0.258	

* References which have used landscape metrics to predict forest fire occurrence.

During this study period (1989 to 1993), at least one human-caused forest fire occurred in 60.5% (2,876 cells) of the 4,751 observations in Spain, and no fire took place in 39.5% (1,875) of the landscape units. The landscapes for analysis were sufficiently large (100 sq km) and diverse to include all Table 1 classes under different spatial arrangements. Composition seemed influential but not determinant: for instance, out of 772 cells with > 90% forest cover, 544 had fires (71%), 228 had not (29%). Out of 667 cells with > 90% no-forest classes, there were 213 with fires (31%) vs 454 without fires (69%). 140 cells > 90% agriculture had fires. The only landscape with 40% water had experienced fire. The only two landscapes > 90% urban (Madrid) had fires in the study period.

Statistical analysis: logistic regression

Logistic regression has been frequently used to predict fire occurrence (Chuvieco *et al.*, 2009; Henry and Yool, 2004; Martell *et al.*, 1987; Martínez *et al.*, 2009;

Padilla and Vega-García, 2011; Stolle and Lambin, 2003; Vega-García *et al.*, 1995; Vilar del Hoyo *et al.*, 2008), and it was also chosen for this work.

Logistic regression models can estimate or predict the probability P that a dichotomous or binomial variable occurs or not, based on a more or less extensive list of independent variables related to the event studied (Equation [1]). Logistic regression requires fewer statistical assumptions than linear, being the main that independent variables are uncorrelated with each other.

$$P(y = 1/X) = \frac{\exp(\sum B_i X_i)}{1 + \exp(\sum B_i X_i)} \quad [1]$$

where P is the probability of an event happening (wild-fire), and X_i and B_i are the independent variables (the metrics computed in the landscape units) and the estimated coefficients of the model, respectively.

The cut-off point of the logistic function is usually set by default to 0.5 (the midpoint of the distribution). However, this value is arbitrary and depends on the model goals or the user interests (Jamnick and Beckett,

1987). The decision on the level of maximum likelihood involves usually predicting correctly both (Stolle and Lambin, 2003; Vega-García *et al.*, 1995).

The number of variables is important when dealing with logistic regression. A small number of variables introduced in any model make it simpler, and the appearance of high errors in the formulation or non-significant values is more likely. On the contrary, an excessive amount of variables reduces the residual errors but makes fitting the equation more difficult (Martínez *et al.*, 2009). A variable selection process was carried out before modeling the relationship between fires and landscape metrics, based on a Spearman's correlation analysis between all independent variables, most not-normally distributed. We grouped the variables according to their landscape feature typology (size, density, shape, diversity) and their Spearman correlation, calculated using SPSS 15 (SPSS Inc, 2006). Also, their individual capability to predict human-caused fires occurrence was tested by building one-variable models. Only uncorrelated variables from every metric group and with significant relationship to fire occurrence entered the model building process.

Model fit and validation

The database for analysis was divided randomly in two groups: 60% of cases were used to adjust the logistic regression function and the remaining 40% were reserved for validation. The overall fit of the model was evaluated by the -2LL value, the Nagelkerke R^2 , the Hosmer-Lemeshow test and the percentage correctly predicted in the classification table. In addition, the significance of the dependent variables was assessed using the Wald statistic and its statistical significance (p -value less than 0.05) (Hair, 1999; Silva and Barroso, 2004). The validation results were evaluated using the classification table and the Kappa statistic (Congalton and Green, 1999).

The adjustment method for the logistic regression model was the forward stepwise approach, more demanding than the backward stepwise approach, which proceeds by adding variables with statistical significance (p -value less than 0.05) one by one (Hair, 1999; Silva and Barroso, 2004).

In order to evaluate the spatial distribution of errors, we tested clustered or dispersed conditions of the over and underestimated errors (false alarms and missed

fires) with the Average Nearest Neighbor Distance Index (ANND) (Martínez *et al.*, 2009). This index examines the distances between the centroid points of the closest misclassified quadrants, and compares their distance mean with the expected mean distance that would occur for a random distribution. Expected R values for randomness should be close to one, within an interval ranging from 0 to 2.14.

Results

Results of the variable selection

The Spearman correlation values between variables are presented in the Appendix.

As should be expected, Mean Patch Size (MPS), Patch Density (PD) and Edge Density (ED) were strongly correlated. MPS was inversely correlated to ED and PD. Median Patch Size (MedPS) had a moderate correlation to MPE, but not to MPS and PD.

Regarding shape, the correlation between the Mean Shape Index (MSI) and the Area-Weighted Mean Shape Index (AWMSI) was moderate. Both have a similar behaviour, although MSI is more influenced by the area of the observation unit.

The low correlations of MedPS and Mean Perimeter-Area Ratio (MPAR) with the other metrics discouraged their grouping with any other landscape metrics.

All diversity metrics were highly correlated (r -values over 0.427 with Patch Richness and over 0.939 between Shannon and Simpson's Indices). Correlation between PR and SHEI and SIEI was low, but these indices showed good correlation with other diversity metrics. We included the five variables (PR, SHDI, SHEI, SIDI and SIEI) in the same group, and selected only one at a time for model building trials.

Thus, all metrics considered were classified into six groups (Table 3) depicting landscape patch size, patch density (fragmentation) and vegetation diversity, plus shape characteristics split into three groups.

Table 3. Uncorrelated groups of correlated metrics

Size	Density	Shape			Diversity
Group 1	Group 2	Group 3	Group 4	Group 5	Group 6
MPS	PD	AWMSI	ED	MPAR	SIDI
MedPS		MSI			SIEI
MPE					SHEI
					SHDI
					PR

Within each group, we selected the most significant variable in terms of individual prediction of the human-caused forest fires occurrence, if any. We also regarded previous use in the literature. The Shannon’s Diversity Index had been the most widely used metric in studies of landscape diversity (Henry and Yool, 2004; Lloret *et al.*, 2002; Ortega *et al.*, 2012; Romero-Calcerrada and Perry, 2004) and we wanted the results of this study to be comparable. Also, Shannon’s Diversity Index predictive capability in the one-variable models was the highest among all variables (Nagelkerke $R^2_{SHDI} = 0.141$). The selected metrics were four: Mean Patch Edge (MPE), Patch Density (PD), Mean Shape Index (MSI) and Shannon’s Diversity Index (SHDI).

These uncorrelated metrics best explained fire occurrence within their groups in the one-variable models built (Nagelkerke $R^2_{MPE} = 0.023$, $R^2_{PD} = 0.121$, $R^2_{MSI} = 0.052$, $R^2_{ED} = 0.111$, $R^2_{SHDI} = 0.154$). MPS, MedPS, MPAR and AWMSI showed low human-caused fire occurrence predictability in the univariate logistic regression analysis (Nagelkerke R^2 less than 0.007).

Results of the logistic regression

The best model included three variables: Shannon’s Diversity Index (SHDI), Mean Patch Edge (MPE) and Mean Shape Index (MSI), all significant with p -value less than 0.016. The p -value of the Hosmer-Lemeshow test was significant (p -value < 0.001), and the Nagelkerke R^2 was 0.224. Table 4 lists the estimated coefficients and variables of this model.

Table 4. Estimated coefficients and significance values of the best logistic regression model (p -values for the three variables < 0.001)

Variables	β	ET	Wald	Exp(β)
SHDI	1.431	0.085	280.966	4.181
MPE	-0.065	0.013	24.665	0.937
MSI	-0.221	0.092	5.796	0.801

Interpretation of the Wald statistic indicated that SHDI was the variable with greater weight in the adjusted model (Wald = 280.97), followed by MPE (Wald = 24.67) and MSI (Wald = 5.80). The analysis of $\exp(\beta)$ confirmed this since a unit increase of the Shannon Diversity Index increased by 418.1% the probability of forest fire occurrence, while the unit chance of the MPE meant a decrease of 93.7% and only 80.1% for the MSI. The analysis of signs of the β coefficients indicated that the highest probability of human-caused forest fire occurrence occurs with high values of the SHDI and with low values of MPE or MSI.

A classification table (Table 5) was used for evaluating the predictability of the model, comparing predicted and observed fire occurrence. The cut-off point applied was 0.61, which balanced the percentages of correct matches of the landscape units with fire ($Y = 1$) and no fire ($Y = 0$) occurrences. The overall percentage of correct predictions was 66.3%, 65.1% for no-fire and 67% for fire observations.

Results in the classification table (Table 5) for the validation data (40% of the initial data) were similar to those obtained with the model building dataset. The percentage of correctly predicted no-fire observations was 62.7% and the percentage of correctly predicted and observed fires was 68.6% (with an overall percentage of correct predictions of 66.3%).

Lastly, the fitted equation was used to map the correct human-caused forest fire occurrence predictions for the 10 × 10 sq km landscape units in the period 1989 to 1993 (Fig. 3a).

In general, the model identified landscape units with higher fire occurrence probability in Northwest areas and in the Mediterranean coast. Agricultural inland valleys with scarcer presence of natural vegetation presented a lesser likelihood of fire (Ebro, Guadalquivir). Both general spatial trends agreed with historical forest fire records from the Ministry of Environment in Spain (MAGRAMA). The spatial representation

Table 5. Classification table of logistic regression (cut-off point = 0.61)

Model building data				Validation data			
Observed	Predicted			Observed	Predicted		
	No-fire	Fire	Total		No-fire	Fire	Total
No-fire	742	397	1,139	No-fire	462	275	737
Fire	565	1,147	1,712	Fire	365	798	1,163
Total	1,307	1,544	2,851	Total	827	1,073	1,900

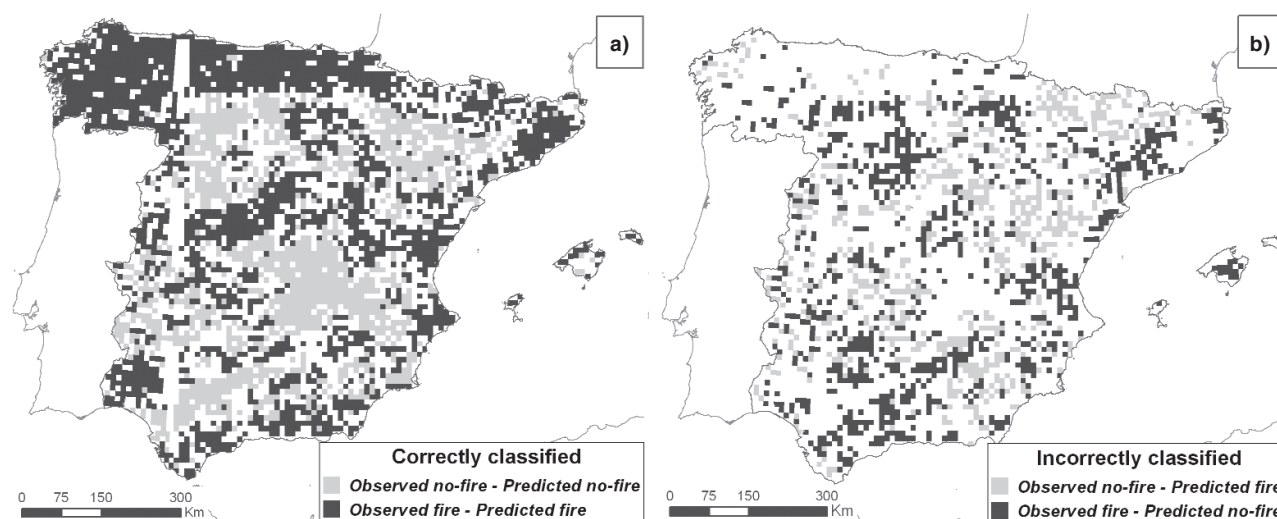


Figure 3. Correctly (a) and incorrectly (b) classified landscape units of human-caused forest fire occurrence.

(Fig. 3b) of misclassified predictions did not show a clear pattern indicative of a specific geographic trend (North/South, Atlantic/Mediterranean), but the $ANND_{OMISSION}$ z-score value was -9.647 and the $ANND_{COMMISSION}$ z-score value was -14.570 , both significant (p -value < 0.001). Overestimation errors (false alarms) were aggregated in locations with high diversity (mean SHDI 1.47), but lower than in the fire-prone areas correctly classified (1.50) and underestimation errors (missing fires) were aggregated in areas with greater diversity (0.76) than in the identified as no-fire-prone (0.58).

Discussion

The probabilistic relationship between landscape metrics and human-caused fire occurrence could be modelled and was found to be significant in Spain. These results agreed with previous studies that made use of landscape metrics as proxies for the impact of human activities on the territory (Echeverría *et al.*, 2007; Fuller, 2001; Löfman and Kouki, 2003; Ruiz-Mirazo *et al.*, 2012; Serra *et al.*, 2008).

The results of the classification table suggested a moderate predictive capability of the best model, with overall percentage correctly predicted of 66.3%. This value was almost identical to that obtained with the validation sample (66.3%), which indicated the model robustness. However, the low value of Nagelkerke R^2 (0.224) pointed at the fact that a large portion of the dependent variable variance was not explained by the

fitted model. This should be expected. We knew other environmental or socioeconomic factors affected human-caused fire occurrence (Díaz-Delgado *et al.*, 2004; Romero-Calcerrada *et al.*, 2008; Padilla and Vega-García, 2011; Sturtevant and Cleland, 2007), but it was not our purpose to evaluate those factors in this study.

The reduction in the number of variables to include in the fitting of the logistic regression allowed to respect the non-collinearity assumption and made the model more parsimonious. There were three significant variables in the model: Shannon's Diversity Index (SHDI), Mean Patch Edge (MPE) and Mean Shape Index (MSI), in line with the statement by Forman (1995) that two or three well-selected landscape metrics should be sufficient to answer specific questions on landscape processes.

These selected variables were also found significant in other studies. Henry and Yool (2004) determined that SHDI and MSI explained some of the variability of fire occurrence in Arizona from remote sensing images in a fusion of SIR-C and Landsat TM images. Other variables, such as MPAR and AWMSI, were significant in the analysis with Landsat TM images. SHDI and MPS were found to have significant effects on wildfire occurrence in the period 1985-1998 by Ortega *et al.* (2012). Fine-grained forest-agriculture mixtures and road density had significant effects in all periods (1974-2008) in their forest-agriculture interface landscapes. The study by Martínez *et al.* (2009) tested only three landscape metrics (Fragmentation using a 7×7 kernel on the Corine Land Cover 1990 grid reclassified into four classes, Patch Density and

MedPS) but only agricultural land fragmentation was selected for their model.

Landscape diversity was the main factor in predicting human-caused forest fires in this study. Our analysis concluded that in the 10×10 sq km units with greater landscape diversity the probability of human-caused forest fire occurrence was generally higher. Also, this likelihood of occurrence was greater in landscape units with fewer edges and with more compact patches. These characteristics are common in humanized environments (Badia-Perpinyà and Pallares-Barbera, 2006) because, for example, the sharing of edges between roads and agricultural areas (Martínez *et al.*, 2009).

The map obtained by applying the fitted equation (Fig. 3a) agreed with that of Martínez *et al.* (2009) at the municipal level. The areas with greater agreement between observed and predicted values in the model are given in the Atlantic North of Spain. It is in these areas where most of the human-caused fires occur in Spain, and consequently, there it is greater the consistency in the relationship of the fitted model between landscape structure and fire occurrence. The landscape configuration of the Atlantic zone is characterized by small and highly fragmented patches with high diversity of species, due mainly to a fractured topography, high rainfall and humidity (Fig. 1, S1). In the Northwest these landscape characteristics are associated with risk factors such as a traditional use of fire to obtain open areas for increasing pasture land and the low profit from forests by local people (Torre Antón, 2010). There is also agreement in the Mediterranean coast (Coastal Catalonia and the Baetic Ranges), a scenario of significant urban development linked to tourism and the influx of population in the summer overlaps with dry weather to increase fire risk levels (Vilar del Hoyo *et al.*, 2008). Most of the landscape units without fire occurrence in the period are plains with fertile deep soils where intensive agriculture is the most profitable economic activity: the Ebro and Guadalquivir river basins and the Meseta Central, where large extensions of croplands exist and natural vegetation is scarce.

Misclassified units (errors) were found scattered throughout the Spanish territory (Fig. 3b), but their distribution was locally aggregated. These clusters respond to the presence of local conditions that influence the occurrence or absence of fire, according to Martínez *et al.* (2009) and Padilla and Vega-García (2011). Martínez *et al.* (2009) found that landscape metrics showed comparatively lower significance compared to socio-economic changes in rural and urban areas and

traditional activities associated with fire, and the authors obtained better results in predicting overall fire occurrence in Spain (model building data: 85.4%, and validation: 76.2%) by including socio-economic factors in their model.

Results in previous studies indicate that it is not possible to have good wildfire predictions taking into account only landscape structure, but landscape pattern variables, and specifically diversity and shape, must be considered in fire occurrence models in Spain. It would be highly convenient to test these results at different scales, and with more recent fire data, once the Forest Map of Spain MFE50 (Andalucía not available yet) and MFE25 (expected 2017) are published.

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Appendix. Spearman's correlation matrix of all landscape metrics

	PD	MPS	MedPS	ED	MPE	MSI	AWMSI	MPAR	SHDI	SHEI	SIDI	SIEI	PR
PD	1												
MPS	-0.454	1											
MedPS	-0.175	0.849	1										
ED	0.415	-0.204	-0.077	1									
MPE	-0.569	0.728	0.583	-0.162	1								
MSI	0.114	-0.205	-0.189	0.176	0.253	1							
AWMSI	0.499	-0.353	-0.179	0.276	-0.112	0.493	1						
MPAR	0.005	-0.017	-0.014	0.003	-0.017	0.014	0.010	1					
SHDI	0.553	-0.481	-0.173	0.269	-0.333	-0.051	0.102	0.002	1				
SHEI	0.463	-0.479	-0.190	0.246	-0.245	-0.037	0.134	0.002	0.931	1			
SIDI	0.527	-0.490	-0.180	0.271	-0.293	-0.036	0.149	0.003	0.976	0.966	1		
SIEI	0.495	-0.485	-0.184	0.262	-0.258	-0.030	0.162	0.003	0.947	0.985	0.991	1	
PR	0.540	-0.476	-0.220	0.227	-0.456	0.007	0.122	0.006	0.735	0.473	0.633	0.541	1
