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A Multivariate Approach for Mapping Fire Ignition Risk: The Example of the National Park of Cilento (Southern Italy)

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Abstract Recent advances in fire management led landscape managers to adopt an integrated fire fighting strategy in which fire suppression is supported by prevention actions and by knowledge of local fire history and ecology. In this framework, an accurate evaluation of fire ignition risk and its environmental drivers constitutes a basic step toward the optimization of fire management measures. In this paper, we propose a multivariate method for identifying and spatially portraying fire ignition risk across a complex and heterogeneous landscape such as the National Park of Cilento, Vallo di Diano, and Alburni (southern Italy). The proposed approach consists first in calculating the fire selectivity of several landscape features that are usually related to fire ignition, such as land cover or topography. Next, the fire selectivity values of single landscape features are combined with multivariate segmentation tools. The resulting fire risk map may constitute a valuable tool for optimizing fire prevention strategies and for efficiently allocating fire fighting resources.

Keywords Cluster analysis · Fire selectivity · Land cover · Landscape features · Segmentation · Topography

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Introduction

Every year more than 45,000 wildfires occur in Mediterranean Europe (European Commission 2011) leading to very high costs of fire prevention and fighting. Several studies demonstrated that wildfires do not occur randomly across the landscape (Moreira et al. 2001; Nunes et al. 2005; Bajocco and Ricotta 2008), but their frequency, intensity, and distribution are controlled and determined by the coinciding of basic conditions, such as fire-prone land-use and vegetation types (fuel), favorable climatic conditions (meteorology) and ignition energy provided by lightning or humans (Krawchuk et al. 2009; Bajocco et al. 2010). In the Mediterranean basin, the anthropogenic component exerts a direct control on fuel type (i.e., land cover) and ignition energy, thus affecting fire incidence patterns. On the other hand, the variability of climate and fuel conditions in space and time play an important role in determining fuel flammability and fire behavior through the landscape (Ricotta and Di Vito 2014). In this view, fire is considered 'selective' and can be regarded as acting like an 'herbivore' that positively (or negatively) selects different resources (Nunes et al. 2005; Bajocco and Ricotta 2008).

Recent advances in fire management led landscape managers to move away from a traditional fire fighting approach in which the main effort is concentrated on fire suppression, toward an integrated strategy in which fire suppression is supported by prevention actions and by knowledge of local fire history and ecology (Swetnam et al. 1999; Bergeron et al. 2002; Silva et al. 2010; Conedera et al. 2011). In this view, understanding and predicting the patterns of fire risk (i.e., 'the chance of fire starting, as determined by the presence and activity of causative agents', NWCG 2012) plays an essential role for improving the effectiveness of fire prevention, detection, and fire-fighting resource allocation (Conedera et al. 2011; Moreira et al. 2011). To this end, fire risk maps have become widely used in many countries (Bonazountas et al. 2005). These maps generally represent the spatial pattern of fire ignition risk by integrating fuel models and vegetation types with local fire history (Keane et al. 2001; Riano et al. 2002; Chuvieco et al. 2004; Hessburg et al. 2007; Jolly 2007; Conedera et al. 2011). Given the importance of fire risk maps for landscape management and control policies, in this work we propose a multivariate method for identifying and spatially portraying areas most prone to fire ignition in the National Park of Cilento, Vallo di Diano, and Alburni (southern Italy). The proposed method consists first in estimating the fire selectivity of selected landscape features that are usually considered relevant in relation to fire ignition, such as land cover or topography, and then in combining the fire selectivity values of single landscape features with multivariate segmentation tools. The resulting fire risk map can then be used for fire management planning and efficiently allocating fire fighting means and resources.

Study Area

The National Park of Cilento, Vallo di Diano, and Alburni (hereafter National Park of Cilento) is located close to the city of Salerno in Campania (southern Italy) between 39°59′ and 40°34′N and 14°54′ and 15°37′E, making up a total area of roughly 181,000 ha (Fig. 1). The Park is characterized by a prevalently hilly topography and high heterogeneity in geological and morphological features resulting in a wide variety of habitats and a rich floristic diversity (Moggi 2001). The coastal area is characterized by a typical Mediterranean climate. The inner areas up to 1899 m a.s.l. have more temperate climatic features with cooler and more humid weather conditions. Average annual rainfall ranges from less than 980 mm to roughly 1900 mm in the inner mountainous regions. Mean annual temperatures range from 10 to 18 °C. Land cover along the coast is dominated by sclerophyllous shrubs, *Quercus ilex* forests, and agriculture (mainly olive trees, vineyards, and chestnuts). At higher elevations the vegetation ranges from mixed forests of deciduous oaks to *Fagus sylvatica* forests and grasslands.

Data

Fire Database

Information on the fire history of the National Park of Cilento for the years 2000–2013 was extracted from the database of the Regional Forest Service of Campania and is assumed to be complete and reliable down to the smallest fires. For each fire record the database includes some basic characteristics, such as the date of ignition, the geographic coordinates (UTM) of the ignition point and a field estimate of the burned area. The dataset contains 2274 wildfire records, while the total area burned during 2000–2013 is approximately 13,751 ha. Fire size ranges from 0.01 to >700 ha, with 2044 fires that are less than 10 ha in size

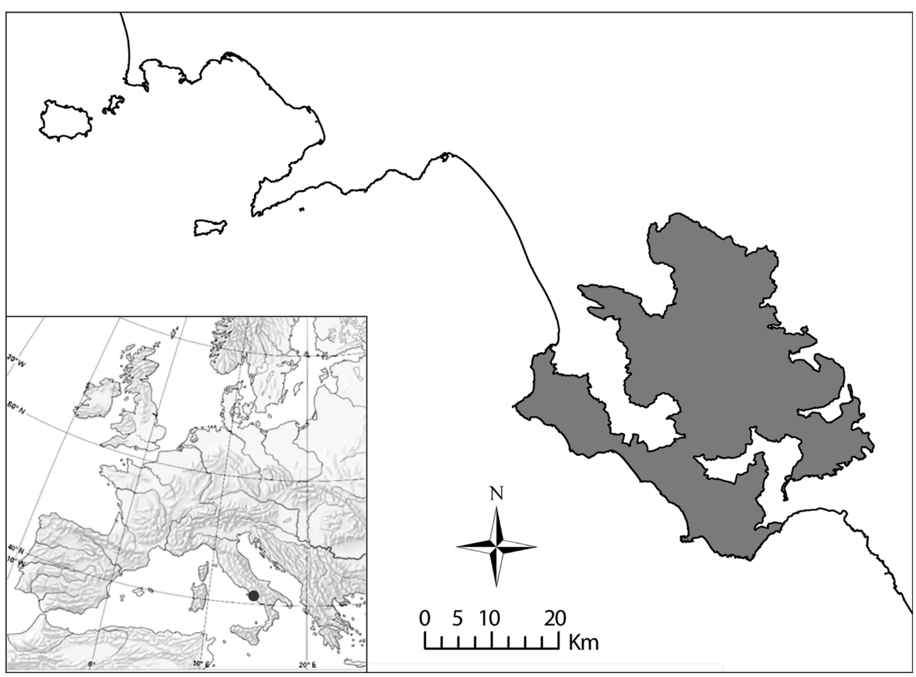

Fig. 1 Location of the National Park of Cilento

and only 16 fires that are larger than 100 ha. While these large fires represent less than 1 % of total records, they account for roughly 27 % of the total area burned in Cilento from 2000 to 2013. Like in most Mediterranean regions, fire occurrence is strongly seasonal with more than 70 % of fires occurring between July and September and a peak of fires in August.

Landscape Features

Based on previous literature, expert knowledge and data availability, we selected five landscape features (elevation, aspect, slope, land units, and land cover) that are thought to influence fire ignition risk in the study area (Table 1). Elevation, aspect, and slope were derived from the regional elevation model of Campania (cell size 20 × 20 m). The land cover map of the National Park of Cilento (scale 1:25,000) was derived by visual interpretation of digital orthophotos of the years 2004–2005 and field surveys.

The land unit map (scale 1:25,000) reduces the natural heterogeneity of the landscape to land units with a certain degree of homogeneity in terms of some basic environmental physical features, such as climate, lithology, and morphology (Blasi et al. 2000; Bailey 2009). Such features contribute to soil formation and to the distribution of vegetation and land cover. Topography directly affects fire risk by reducing ignitions in areas that are difficult to access. Indirectly, topography also affects fire risk by creating different climatic conditions, which influence air temperature and fuel moisture, as well as the distribution of vegetation and land cover (Heyerdahl et al. 2001; Mermoz et al. 2005). In turn, vegetation and land cover play a key role for fire ignition, as human impact (i.e., the presence of ignition sources), together with fuel load, structure, and spatial continuity ultimately depend on these landscape features (Moreira et al. 2001, 2009; Bajocco and Ricotta 2008).

Methods

Selectivity Analysis

The contribution of each landscape feature to fire risk was assessed by testing its selectivity with respect to fire ignitions. Some authors (Nunes et al. 2005; Bajocco and Ricotta 2008; Pezzatti et al. 2009) have suggested that fire may be considered like an 'herbivore' exerting variable pressure on different land cover or vegetation types as a function of their differential fuel load. In this sense, fire is considered selective when fuels are burnt disproportionately to their availability (Moreira et al. 2001; Nunes et al. 2005). In order to perform the selectivity analysis, each landscape feature was treated as a different GIS layer. Bare soils, water bodies and all non-burnable surfaces were excluded from the analysis. All topographic features were divided into a variable number of equal-sized intervals ranging from seven to nine (Table 1). First, the ignition points were overlaid on the selected landscape feature and the number of fires within each category (i.e., land cover type, land unit, or topographic interval) was computed. For each category, we next computed a summary statistic of fire selectivity originally developed for summarizing resource selection by animals (Manly et al. 1993) as the relative proportion of fires in a given category divided by the relative area of that category in the study site. This 'selectivity ratio' σ takes values in the range $[0, \infty]$; values larger than 1 denote categories where ignitions occur more frequently than would be expected by chance alone; values lower than one denote areas where ignition is less frequent than expected (Nunes et al. 2005; Bajocco and Ricotta 2008). Each landscape feature was then rasterized with a pixel resolution of 20 × 20 m and the selectivity values were assigned to all pixels of the corresponding categories.

Table 1 Description of the landscape features used in this study

Landscape features	No. of classes	Description
Elevation	7	6 Classes of 250 m each from 0 to 1500 m and 1 class >1500 m
Aspect	9	8 Classes of 45° each (N, NE, E, SE, S, SW,W, NW) and flat terrain
Slope	7	5 Classes of 8° each from 1 to 40°; 1 class >40° and flat terrain
Land cover	17	Urban areas; arable land; mixed agriculture; vineyards; olive groves; pastures; natural grasslands; coniferous forests and plantations; shrublands on abandoned agriculture and pastures; transitional woodland-shrub (after fire or clear-cut); riparian vegetation; maquis; sclerophyllous oak forests; deciduous oak forests; chestnut coppices; chestnut orchards; broad-leaved deciduous forests
Land units	7	Coastal plains; holocenic alluvial plains; coastal terraces; coastal carbonate massif of Mt. Bulgheria; interior hills on clay flysch; interior hills on marly flysch; Pre-Apenninic carbonate massifs of the Alburni–Cervati range and Picentini Mts

Data Segmentation

The fire selectivity values of single landscape features were then combined into a single fire risk layer with multivariate segmentation tools. As the spatial distributions of the selectivity values within single landscape features are not fully independent of each other, to reduce the amount of redundant information and noise, we first performed a principal component analysis (PCA) on the selectivity data. PCA is a well-known ordination technique that undertakes a linear transformation of a multivariate set of numerical variables to create a new set of variables with the new ordination axes (i.e., principal components) that are uncorrelated and are ordered in terms of the amount of variance explained in the original data. In this manner, the first principal components account for most of the variance of the original dataset, while the remaining components will usually contain most residual noise (Chavez and Kwarteng 1989; Ricotta et al. 1999). In this paper, the first three principal components, accounting for 87 % of the total system variance, were retained for further analysis.

The first three principal components were then used for segmenting the territory of the National Park of Cilento into homogeneous objects in terms of fire behavior. The segmentation process was conducted using the Definiens eCognition software (Definiens Imaging, Germany) with scale parameter = 200, shape criterion = 0.5 and compactness = 0.5. Individual pixels were sequentially merged into larger objects (segments) with the aim of minimizing the internal heterogeneity of the resulting objects with regard to their numerical and textural properties. The numerical parameters for the segmentation process, which drive the size and shape of the resulting objects, were empirically determined by the operator based on trial-and-error and on the visual interpretation of the results.

Cluster Analysis

To identify groups of segments with similar fire behavior, we performed a hierarchical cluster analysis on the mean values of the three principal components of each segment using the Euclidean distance and the average linkage between groups criterion (UPGMA; Legendre and Legendre 1998). The clustering procedure produced the dendrogram of Fig. 2 in which three distinct groups of segments were detected.

To determine the level of fire risk associated to the three clusters of segments, we computed the selectivity ratio σ of each cluster as the ratio between the relative proportion of fires in a given cluster and the relative area of that cluster in the study site. The statistical significance of the selectivity values was then assessed using a randomization procedure in which all ignition points that occurred in the study area during the period 2000–2013 were randomly reassigned to the different clusters such that the probability of assignment of each fire to a given cluster of segments was kept equal to the relative extent of that cluster. The null hypothesis is that fires occur randomly across the landscape, so that the relative abundance of fire ignitions in a given cluster should be proportional to the relative abundance of that cluster within the study area. The actual number of fires in each cluster was then compared with the results of 9999 random simulations. For each cluster, P values (two-tailed test) were computed as the proportion of random values that were as extreme or more extreme than the actual values.

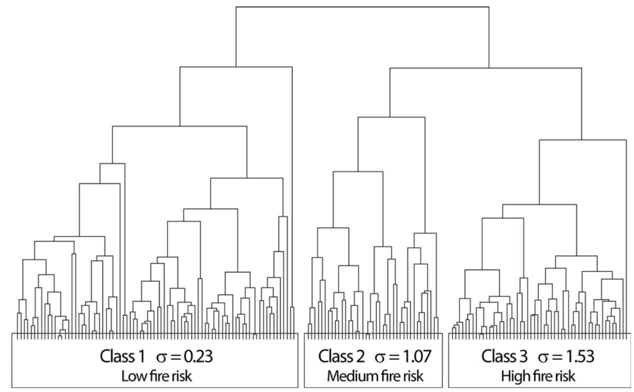

Fig. 2 Results of the hierarchical cluster analysis on the mean values of the first three principal components for each landscape segment. The *boxes* represent three classes of increasing fire risk from *left* to *right*; σ = selectivity ratio

Results

The results of our selectivity analysis for the landscape characteristics considered are summarized in Tables 2 and 3. Values of $\sigma > 1$, denoting higher than expected fire incidence, were prevalently associated to land cover classes of high human impact, such as urban areas, mixed agriculture, olive groves, chestnut orchards, conifer plantations, or pastures. Fire incidence was also overrepresented in the natural and seminatural land cover classes located in the Mediterranean portion of the study area, such as sclerophyllous forests and shrublands (maquis). In contrast, values of $\sigma < 1$, denoting lower than expected fire incidence, were mainly associated to more mesophilous vegetation types, such as riparian vegetation and broadleaved deciduous forests, and to high-quality agricultural classes, such as vineyards (Table 2). Unlike in other Mediterranean areas (e.g., Bajocco and Ricotta 2008), arable lands are not greatly affected by fires, such that $\sigma < 1$. The low selectivity value is probably due to the

Table 2 Results of the fire selectivity analysis for the land cover types and the land units used in this study

Classes	Area (ha)	Number of ignition points	Selectivity index σ
Land cover types			
Urban areas	2595	44	1.32
Arable land	4821	49	0.79
Mixed agriculture	11,250	196	1.36
Vineyards	141	0	0.00
Olive groves	18,880	319	1.32
Pastures	33,286	684	1.61
Natural grasslands	4442	19	0.33
Coniferous forests and plantations	2555	51	1.56
Shrublands on abandoned agriculture and pastures	8608	120	1.09
Transitional woodland-shrub (after fire or clear-cut)	1823	40	1.71
Riparian vegetation	1531	11	0.56
Maquis	4914	73	1.16
Sclerophyllous oak forests	18,200	294	1.26
Deciduous oak forests	23,150	143	0.48
Chestnut coppices	6109	64	0.82
Chestnut orchards	4477	87	1.52
Broad-leaved deciduous forests	30,880	80	0.20
Land units			
Coastal plains	878	34	3.03
Holocenic alluvial plains	7799	121	1.21
Coastal terraces	2194	56	1.99
Coastal carbonate massif of Mt. Bulgheria	3245	98	2.36
Interior hills on clay flysch	44,892	495	0.86
Interior hills on marly flysch	55,002	1218	1.73
Pre-Apenninic carbonate massifs of the Alburni–cervati range and Picentini Mts.	63,652	252	0.31

importance of arable lands for the economy of the region, which leads to a reduced number of ignitions in this landscape class.

Fire ignitions are clearly underrepresented in the interior hills on clay flysch and in the pre-Apenninic structures of the Alburni–Cervati range and the Picentini Mts., whereas their frequency is higher than expected in all coastal land units and in the interior hills on marly flysch (Table 2). The topographical distribution of fires clearly shows that fire incidence is overrepresented at lower altitudes (0–250 m) and on south-facing slopes, whereas fires ignite less than expected at higher altitudes (>750 m) and on north-facing slopes. Likewise, fires ignite less frequently on steep slopes (>40°), being more frequent on more level areas (Table 3).

The segmentation of the first three principal components identified 173 objects with a minimum size of 87 ha (2175 pixels). These objects were then grouped into 3 main clusters. According to the values of the selectivity ratio σ these clusters correspond to three classes of increasing fire risk: low ($\sigma = 0.23$; $P < 0.01$) medium ($\sigma = 1.07$; not significant at $P = 0.05$), and high ($\sigma = 1.53$; $P < 0.01$). Finally, the results of the cluster analysis were spatially represented in a map of fire ignition risk (Fig. 3), which shows the spatial distribution of the three risk classes in the National Park of Cilento and identifies areas more prone to fire ignition.

Discussion

Given the relevance of ignition risk for fire management policies, in this paper we proposed a simple and flexible method for assessing areas of high ignition risk across a complex and heterogeneous landscape, such as the National Park of Cilento. The method combines the selectivity ratios of selected landscape features that are thought to drive fire ignition in the study area into one single fire risk map by means of image segmentation and clustering procedures. While multivariate segmentation methods are generally used for object-based image classification

Table 3 Results of the fire selectivity analysis for the topographic variables used in this study

Classes	Area (ha)	Number of ignition points	Selectivity index σ
Elevation (m)			
0–250	32,810	926	2.21
250–500	40,180	496	0.96
500–750	39,190	555	1.11
750–1000	29,630	245	0.65
1000–1250	23,370	46	0.15
1250–1500	10,200	5	0.04
>1500	2282	1	0.03
Aspect			
Flat terrain	2311	80	2.70
N	20,654	96	0.36
NE	21,153	222	0.82
E	16,520	229	1.08
SE	19,670	296	1.18
S	22,760	495	1.70
SW	30,280	365	0.94
W	24,300	270	0.87
NW	19,974	221	0.86
Slope (°)			
Flat terrain	2311	80	2.70
1–8	29,130	338	0.91
8–16	55,818	674	0.94
16–24	42,090	599	1.11
24–32	26,610	382	1.12
32–40	15,340	188	0.96
>40	6363	13	0.16

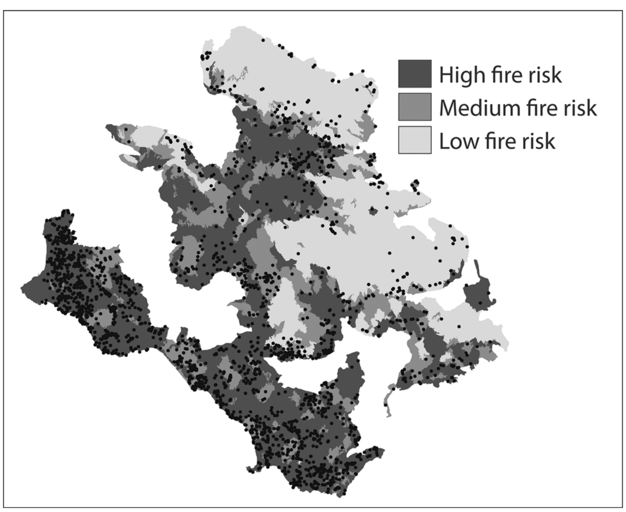

Fig. 3 Fire risk map of the National Park of Cilento. The fire risk classes correspond to the three main clusters in Fig. 2

(Blaschke 2010), in our framework, segmentation represents a basic tool for partitioning the study area into a set of homogeneous regions in terms of fire ignition.

The main advantage of our proposal consists in its generality, which provides fire managers with a great flexibility in selecting the appropriate landscape features. This selection can be done based both on data availability and on the strength of the relationship between available landscape features and fire ignitions. However, as fire occurrence is driven by complex non-linear interactions between natural and anthropogenic forces (Conedera et al. 2011), we recommend the use of some data reduction method, such as principal component analysis, to reduce the degree of correlation among the selectivity values of single landscape features. Furthermore, the explained variance of the principal components may help the practitioner in deciding how many components to include in the subsequent steps.

According to our results, the study area can be divided into three classes of increasing fire risk. Class 1 covers roughly 33 % of the study area and is characterized by a selectivity ratio $\sigma < 1$. This class is mainly located in the mountain areas where human impact is generally low and the climatic conditions are less favorable to ignition. In this class, the landscape is mainly composed of natural and semi-natural land use classes with dominance of deciduous oak forests (14 % of this fire risk class is covered by deciduous oaks), pastures (22 %), broad-leaved deciduous forests (42 %), and natural grasslands (7 %). Notably, this fire risk class hosts 79 % of all broad-leaved deciduous forests in the study area and 90 % of the natural grasslands.

On the other hand, Class 3, which is the class with the highest fire risk ($\sigma > 1$; 46 % of the study area) is mainly located in the interior hills on marly flysch and along the coast were human pressure is highest especially during the fire season, due to the increasing popularity of summer tourism in the region. This class is mainly dominated by olive groves (17 % of this fire risk class), sclerophyllous oak forests (17 %) and mixed agriculture (9 %). In addition, this class hosts 73 % of all urban areas found in the National Park of Cilento, 74 % of maquis and 67 % of conifer forests.

The class of intermediate fire risk is characterized by a selectivity ratio that does not significantly differ from random, and represents a transition between Class 1 and Class 3. Ecologically, Class 2 is more tightly related to the class of highest fire risk, as shown by the clustering tree in Fig. 2. It is mainly located in the inner regions on clay soils and at medium altitudes where human pressure is less intense than along the coast. Land cover in Class 2 is characterized by a lower amount of olive groves (12 % in Class 2 vs. 17 % in Class 3), Sclerophyllous oak forests (11 vs. 17 %), and mixed agriculture (6 vs. 9 %), and by a higher amount of pastures (20 vs. 16 %) and broad-leaved deciduous forests (10 vs. 3 %).

Our results are in agreement with previous studies on fire risk in southern Europe. A number of authors, such as Bajocco et al. (2010), De Angelis et al. (2012), Oliveira et al. (2012), or Pausas and Fernández-Muñoz (2012) have emphasized the combined effect of climate, fuel load and human pressure in driving the coarse-scale spatial distribution of fire occurrence in Mediterranean Europe. In this view, like in all regions where humans influence fire incidence and vegetation cover, fire occurrence at the landscape scale will be affected to a large extent by the nature of the different land cover types (e.g., Bajocco and Ricotta 2008; Catry et al. 2009; Moreira et al. 2011). Accordingly, the proposed approach for developing a map of fire ignition risk may effectively support landscape managers in planning valuable fire fighting and prevention strategies: it should provide guidance for optimizing the location of detection systems and fire fighting resources, for the regulation of hazardous activities in areas of increased fire risk, and for adapting fuel management activities (i.e., silvicultural treatments or prescribed burning) to the mapped risk scenarios.

As a cautionary note, local fire hot spots, which are typically related to the presence of punctual ignition sources (such as specific silvicultural practices, localized pastoral activity, railways, etc.) are usually not considered for building the general landscape-scale models of fire risk (Conedera et al. 2011). Nonetheless, such punctual deviations from the mapped distribution of fire risk can be easily identified by local experts and thus incorporated within more efficient fire prevention strategies.

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