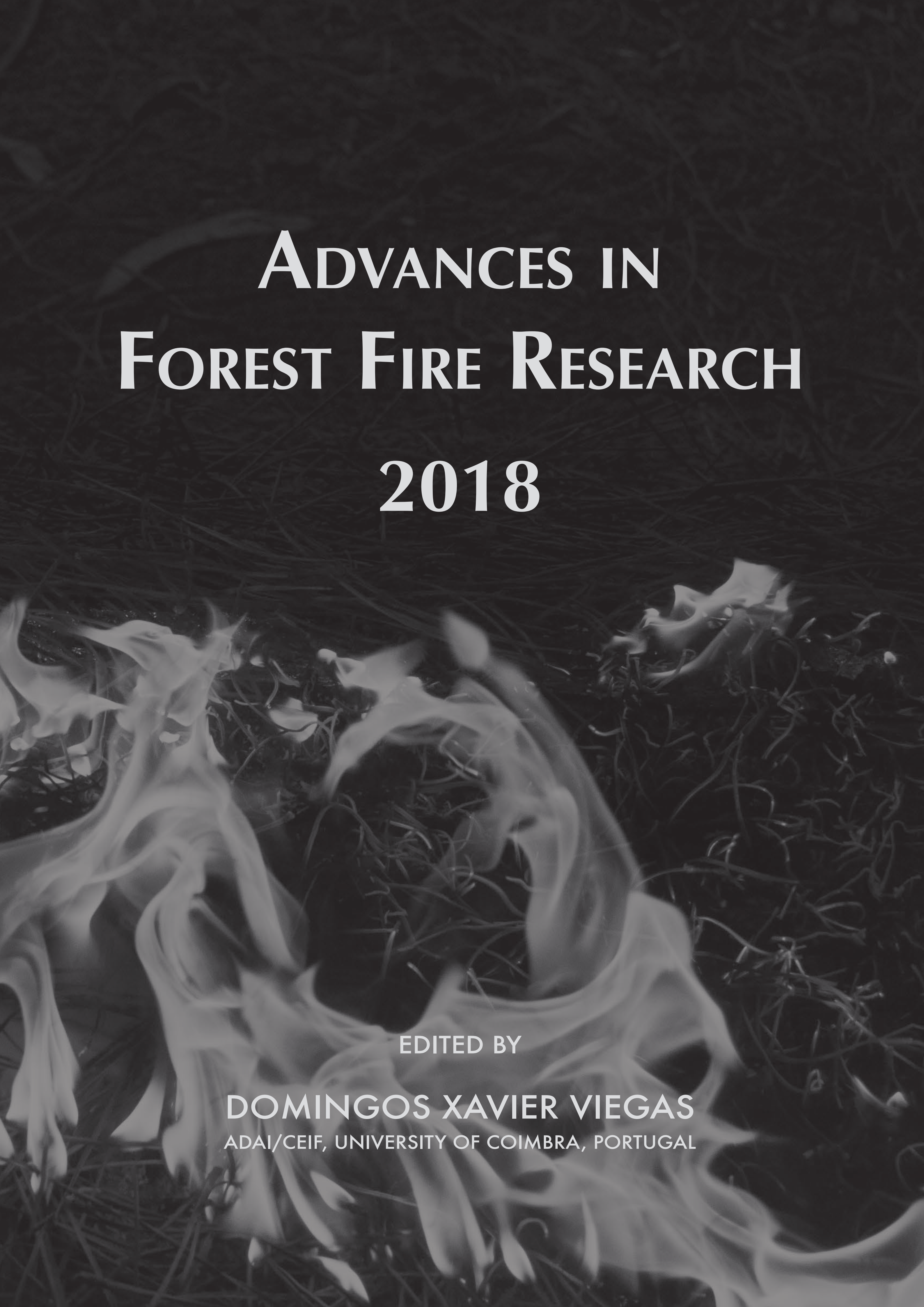

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Identifying pyroregions by means of Self Organizing Maps and hierarchical clustering algorithms in mainland Spain

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Abstract

Defining pyro-regions, i.e., of homogenous zones of fire activity, is an on-going task in Spain with few case studies in the literature. Their characterisation and understanding is a crucial step towards improving forest fire management and prevention. It is widely agreed that fire activity is non-stationary. Several works already report temporal dynamics in fire frequency and burned area. In this work we propose a spatial-temporal approach to define pyro-regions considering both structural and temporal fire behaviour using historical fire records from the EGIF database. A combination of Self Organizing Maps (SOM) and hierarchical clustering is applied to time series (1974-2015) of fire regime features: number/burned area of summer fires, number/burned area of large fires (>500 ha), number/burned area of natural fires, number/burned area of winter fires and number of small fires (<1 ha). The structural component of fire activity is computed as the average value whereas the temporal evolution is addressed by means of Sen's slope.

Prior to cluster analysis, fire features were submitted to Principal Component Analysis with Varimax rotation. Eigenvalues were then pre-classified using SOM. Subsequently, hierarchical clustering was applied to SOM outputs. We obtained a set of 4 structural clusters relating to increased number of fires; low fire incidence, slightly linked to winter season; large and natural fires; and moderate impact of human-related large fires mainly. The process was repeated using Sen's slope to build the dynamic component, ultimately characterised by: highly dynamic winter with increased in summer frequency; increased summer burned area and natural fires; and small fires; and no trend.

Keywords: forest fires, pyro-regions, Sen's Slope, SOM, hierarchical clustering, Spain

1. Introduction

Forest fires are a highly complex phenomenon affecting most ecosystems worldwide. Fire is known as a natural process responsible for the evolution of wild communities, but nowadays it has been altered, with potential undesired effects on vegetation structure, composition and ecosystemic functions. Fire activity is controlled by multiple factors such as climate, fuel, physiography and human activity. Humans influence fire incidence acting as both initiators and suppressors, increasing the complexity of the phenomena. Thus, understanding fire regime's components and behaviour (both temporal and spatial) may improve our current knowledge. Mapping fire regimes may contribute enhancing fire planning or risk assessment; as well as diminishing undesired ecological impacts (Morgan *et al.* 2001). In this sense, one of the most promising lines of study lies in the definition and characterization fire regime itself. Fire regime is usually described using several quantifiable parameters such as affected area, fire frequency, cause, seasonality, fire size, etc. (Boulanger *et al.* 2014). Currently, there still is an open debate on the definition of the concept itself, with slight variations depending on the scale of analysis, the length of the study period or the available information.

Several attempts to define fire regimes from different approaches are already found in the literature. Without being exhaustive we find some analyses using remote sensing data (Chuvieco *et al.* 2008) or climate information (Boulanger *et al.* 2013, 2014; DaCamara *et al.* 2014). Others employ fire weather danger indexes coupled to fuel and environmental conditions (Perera and Cui 2010). Despite of the success in the characterisation of fire regime, most works still rely on existent zoning schemes to spatialize their boundaries and extent: administrative units (Pereira *et al.* 2015), ecoregions (Malamud *et al.* 2005; Kasischke and Turetsky 2006; Perera and Cui 2010; Mori and Johnson 2013) or a combination of both (Wotton *et al.* 2010).

In the case of Spain, examples of fire regime zoning are really scarce, with Moreno and Chuvieco (2013) as the most representative effort. We find other examples in Vázquez de La Cueva *et al.* (2006) and more recently in Montiel Molina and Galiana-Martín (2016). These approaches are mostly based on cluster analysis, the most used and well-known zoning approach. They are a flexible multivariate technique with different available implementations, widely used to analyse ignition points distribution (Wang and Anderson 2010; Serra *et al.* 2013; Pereira *et al.* 2015; Parente *et al.* 2016) or occurrence large fire linked to synoptic climatology (Rasilla *et al.* 2010). Nevertheless, all of them provide a static picture of fire regime, i.e., disregarding the evolution of fire features over time and space. For this reason, a temporal perspective is extremely necessary.

In this work we propose and exemplify a method to outline homogenous fire regime zones (the so-called pyroregions) in mainland Spain. We combine average information of fire features with their temporal evolution (trend detection) during the study period (1974-2015). The method is based on PCA and Self Organizing Maps coupled to hierarchical clustering. Such combination of methods is applied to the averaged values of fire features and their respective trends, separately. By doing so we are able to discriminate static and dynamic pyroregions.

2. Materials and methods

2.1. Study area

The study area encompasses the whole mainland Spain covering a surface of around 498,000 km^2. Climate distribution in the region allows to differentiate two regions: Mediterranean and Oceanic. The first one is characterized by high annual thermal amplitude with hot-summer in the inner region and milder conditions towards the coast. Precipitation is irregularly distributed both in terms of time and space, with maximums peaking in autumn and spring. In addition, the driest areas are located in the southeast region and the Ebro Valley (inner Mediterranean region). On the other hand, Oceanic climate is notable by milder temperature values during summer-winter with high precipitation values regularly distributed throughout the year (average values over 1,000 mm) with maximum during winter. From the biogeographical point of view, the Oceanic area is covered by diverse types of vegetation from deciduous to evergreen oak woodlands (*Quercus robur*, *Fraximus excelsior* or *Fagus sylvatica*) and large areas of scrubland and grassland, as well as areas with afforestation of fast-growing species such as *Pinus radiata* and *Eucaliptus globulus*. The Mediterranean vegetation coexists with complex mosaics of agricultural systems and plant communities, such as sclerophyllous and evergreen vegetation. Oak (*Quercus ilex*) and pine (mainly *Pinus halepensis,* the most widespread of the species introduced by afforestation) forest, and thermophilous scrubland, dominate the region. In addition, altitudinal belts exist within the highest ridges such as the Pyrenees along the French border or Sierra Nevada on the southern Mediterranean coast, being home to a large variety of tree species which are common in central Europe (deciduous species, beech, oak, and some mountain pines: *Pinus uncinata, Pinus sylvestris*).

2.2. Fire data

Fire records in the period 1974-201 5 were collected from the General Wildfire Statistics (EGIF). Selected fire records were on a 10x10 km UTM reference grid. Then, fire frequency, total burned area (ha), ignition date and source were extracted from the database. Is it important to note, that only those grids with at least a 25% of forest cover were retained for analysis. Therefore, 3,308 out of 5200 grids were finally considered in the analyses.

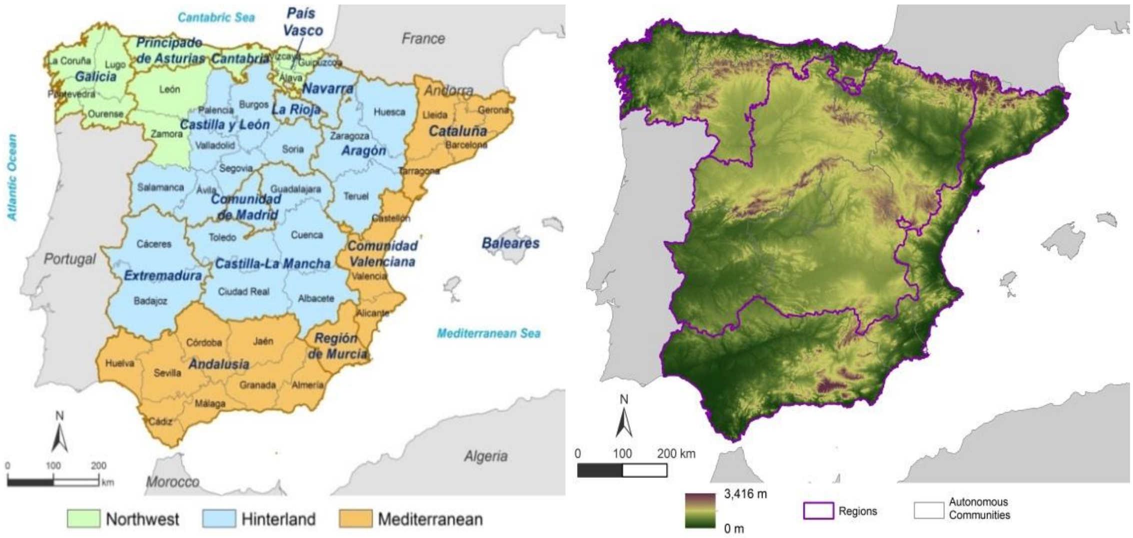

Figure 1 - Spatial distribution of the three regions (Northwest, Hinterland and Mediterranean) also NUTS3 and NUTS2 units in mainland Spain (left) and digital elevation model (right)

Two fire seasons were defined with the aim of differentiating the intra-annual peaks of fire activity (August and March). So, annual fire data were split into spring – summer season (S), from April to September; and autumn-winter season (W) from October to March. From all available fire information, we computed 9 fire features: number of fires and burned area during summer (NS-BAS), summer frequency and burnt area of large fires –above 500 ha– (N500, B500), summer frequency and burnt area of natural fires (NL-BL), number of fires and burnt area during winter (NW-BAW) and total number of small fires (N <1 ha).

2.3. Temporal evolution of fire features

In order to account for the temporal dimension of fire activity during the analyzed time span we estimated the magnitude of the temporal change using Sen’s slope (Sen 1968) test. This allows to outline fire zones according to the temporal behavior of fire features rather than address the average ‘structural’ pattern alone.

2.4. Environmental and human factors

To characterize the final pyroregions we used data related with environmental and human factors. Temperature and precipitation data in the period 1974-2010 were extracted from MOTEDAS (González-Hidalgo *et al.* 2015) and MOPREDAS (González-Hidalgo *et al.* 2011) datasets (Figure 3). Additionally, forest communities were derived from the Forest Map of Spain. Finally, the Human Pressure Index (Figure 2) was calculated according to Jiménez-Ruano *et al.* (2017).

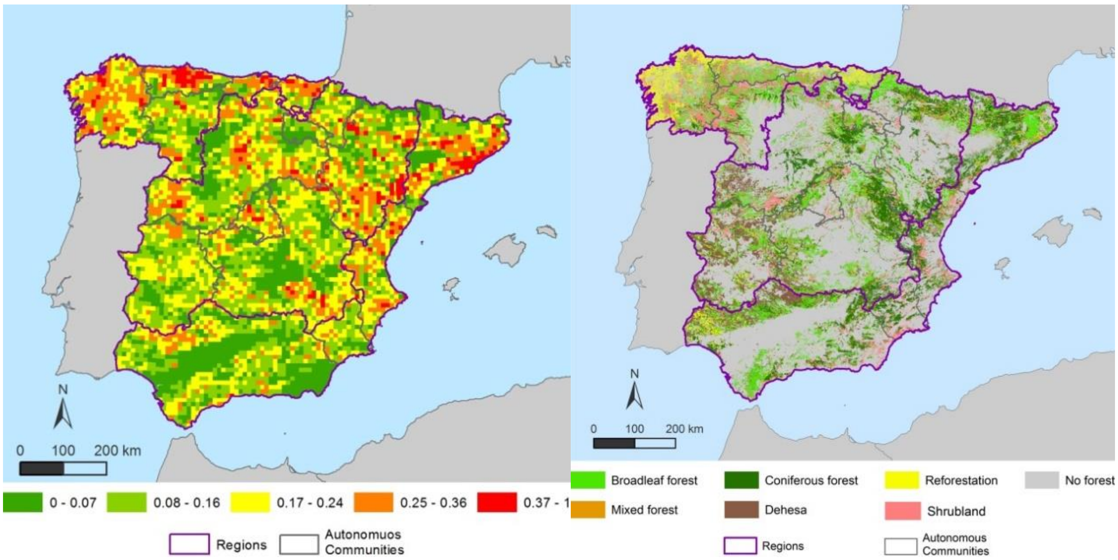

Figure 2 - Spatial distribution of the Human Pressure Index (left) and main forest formations from National Forest Map (right).

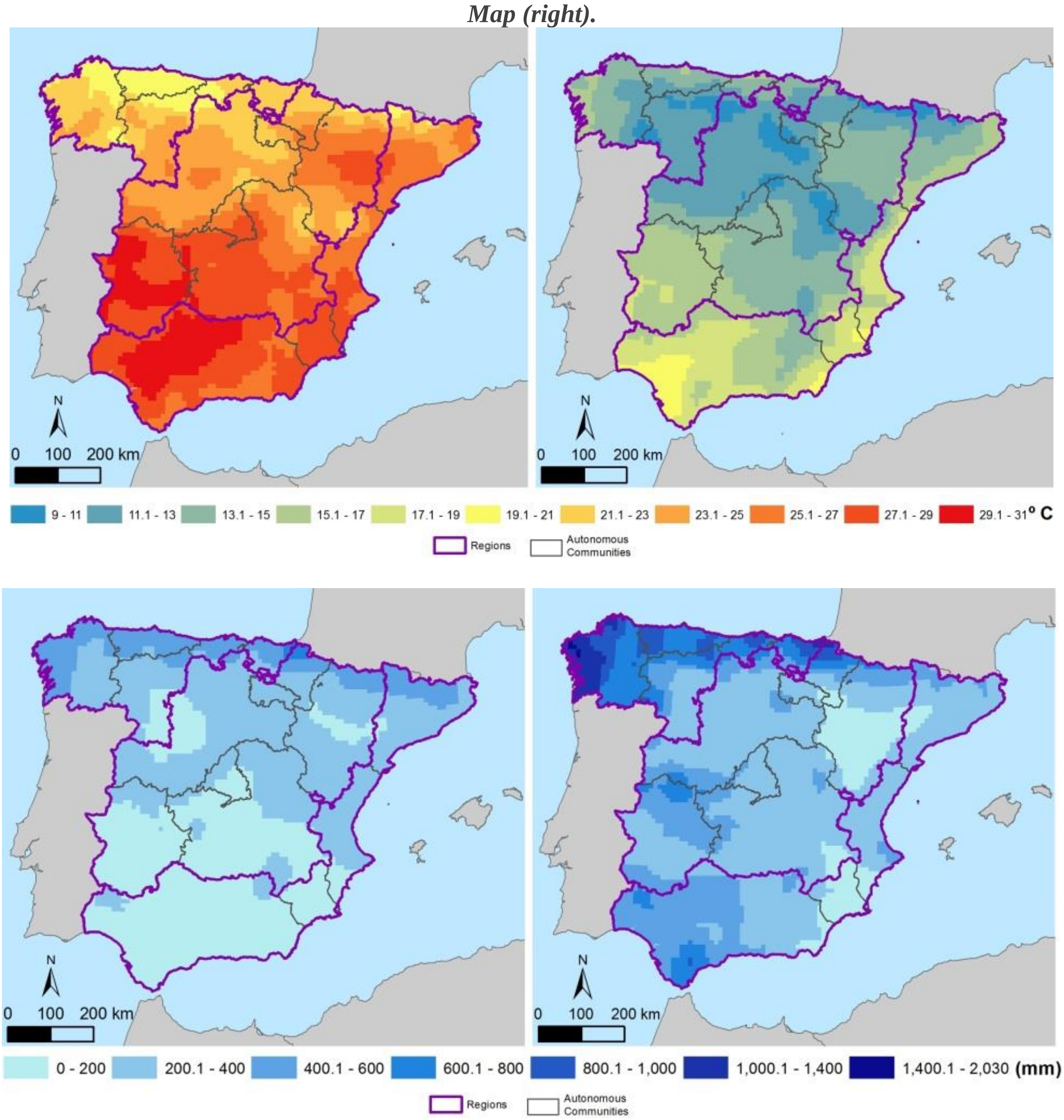

Figure 3 - Climate factors. Top-left, average summer temperature; top-right, average winter temperature; bottom-left, summer mean annual precipitation; bottom-left, winter mean annual precipitation

2.5. Principal Component Analysis and Varimax rotation

Prior to submit fire data to cluster analysis, a PCA with varimax rotation was applied to reduce the amount of information. All fire features (both structural and dynamic) were scaled before applying PCA. Principal Components (PC) were selected according to the Kaiser Criterion, i.e., only those PC with standard deviation over 1 were retained.

2.6. Clustering overview

The objective of clustering analysis is grouping objects into categories such that objects within one cluster share more in common with one another than they do with the objects of other clusters (Gore 2000). Many clustering algorithms do exist. The most basic variants resort to data partition and minimizing the distance between points of a same group from another assigned as center. Among all the clustering methods, we selected hierarchical clustering coupled to Self-Organizing Maps to delineate our pyroregions.

The purpose of hierarchical clustering is determinate the best clustering scheme from different results obtained. It is proceeded with the application of various combinations of number of clusters, distance measures and clustering methods. This algorithm routinely produce a series of solutions ranging from *n* clusters to a solutions with only one cluster present (Charrad *et al.* 2014). It requires a dissimilarity measure (or distance) and an agglomeration criterion. Many distances area available (Manhattan, Euclidean, etc.) as well as several agglomeration methods (Ward, single, centroid, etc.). In our case, we employed all methods available in the *NbClust* function from RStudio, the Canberra distance and the Ward D2 method (Murtagh and Legendre 2014), which minimizes the total within-cluster variance and the dissimilarities are squared before cluster updating.

SOM is a neural-network algorithm that implements an orderly mapping whose main strength lies in converting complex and non-linear relationships between high-dimensional data (Kohonen 1998). In other words, it compresses information while keeping topological and metric relationships of the input data. The algorithm consists of a two-dimensional model of regular grid of nodes, where some data are associated with each node. In each iteration, the SOM algorithm computes all the models to best describe the domain of the observations. The idea is to group the similar models that are closer to each other in the grid than the more dissimilar ones.

As aforementioned the cluster approach was applied both to 'structural' and 'dynamic' components, thus 2 sets of cluster were obtained. In a final step we overlay all clusters (structural and dynamic) to into the final pyroregions.

3. Results

Figures 4 and 6 show the spatial distribution of the structural (4) and dynamic (3) clusters, and their description, respectively. First structural cluster characterises by high fire activity but no large fires; it extends across the Northwest region. In turn, cluster 2 comprises areas of moderate winter activity, in the remaining territory. Cluster 3 brings together summer large fires (>500 ha) caused by lightning. This cluster covers mostly mountain ranges. Finally, cluster 4 brings together medium-size human-caused fires.

Dynamic clusters depict a different behaviour. Tendencies were grouped into clusters 1 and 3. In the first case, winter trends and the increase in summer small fires are grouped in cluster 1. Geographically, these trends are located in the north-western end, some locations of the inland mountain ranges and few spots of the Mediterranean basin. Remaining trends depict an increase in overall area burned during summer and decreased incidence of natural fires (Table 1), occupying an area that mainly extends over the northern and northwest hinterlands.

When combining both cluster approaches into a single product we obtain a final set of 8 pyroregions (Figures 5 and 6). Generally speaking, three main groups of pyroregions can be distinguished: (1) those experiencing increase in the fire activity, especially small fires; (2) regions with no noticeable trend; and (3) those characterised by increased summer burnt area and lightning-triggered wildfires.

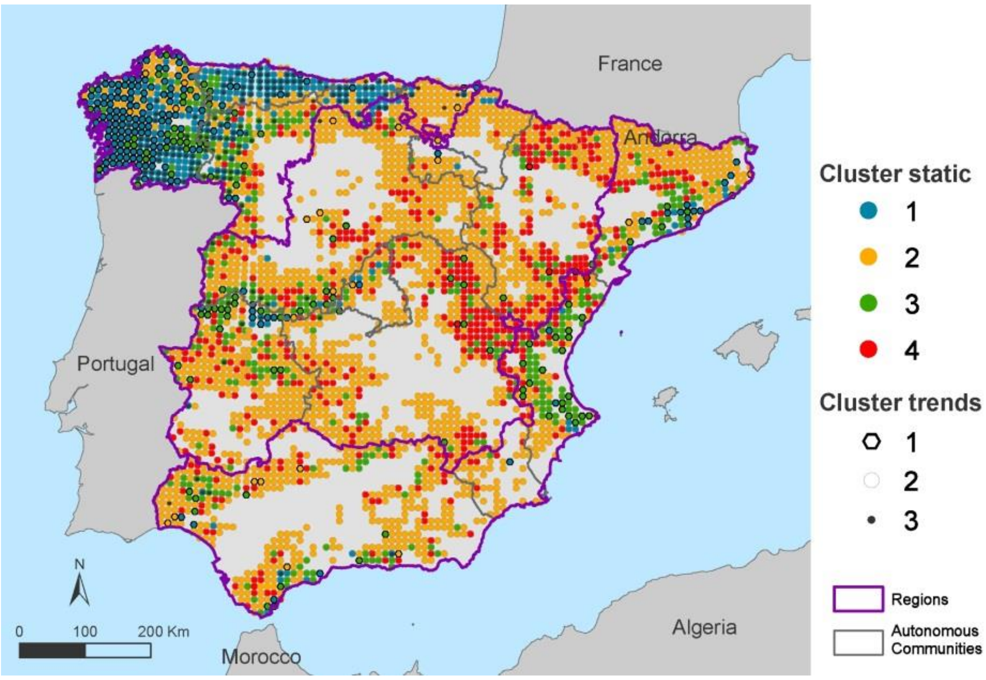

***Figure 4** - Spatial distribution of the clusters structural (colour codes) and dynamic (shape codes).*

***Table 1** - PCA-Varimax eigenvectors of the first two components of static (fire features averages) and the first three components for trends in fire features*

	Fire features	NS	BAS	N500	B500	NL	BL	NW	BAW	N <1ha
Static	PC1	**0.526**	0.148				-0.152	**0.526**	0.328	**0.529**
	PC2		**-0.508**	-0.436	**-0.581**	-0.212	-0.408			
Trends	PC1	**0.534**	-0.271					**0.512**	0.262	**0.557**
	PC2					**-0.702**	**-0.705**			
	PC3		**0.674**					0.230	**0.672**	-0.203

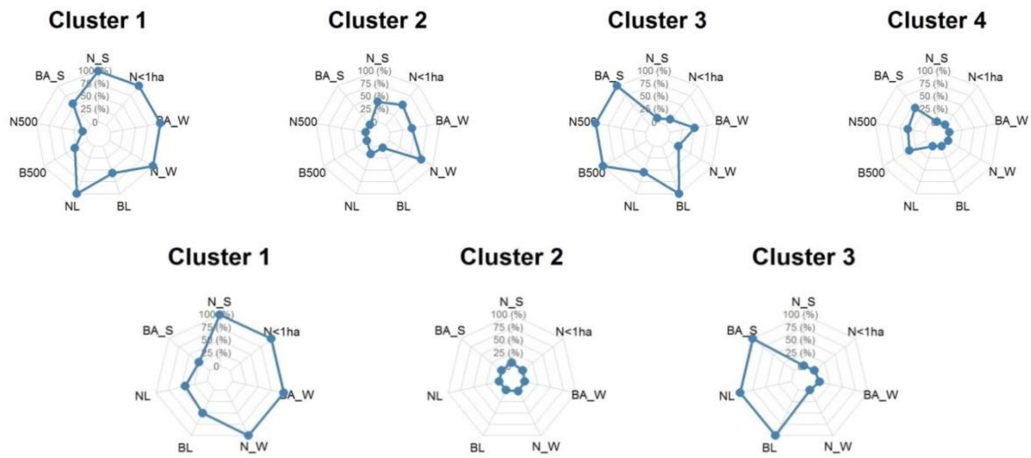

***Figure 5** - Description of the contribution percentage for each fire feature in each cluster static (four on the top) and in each cluster of trends (three on the bottom)*

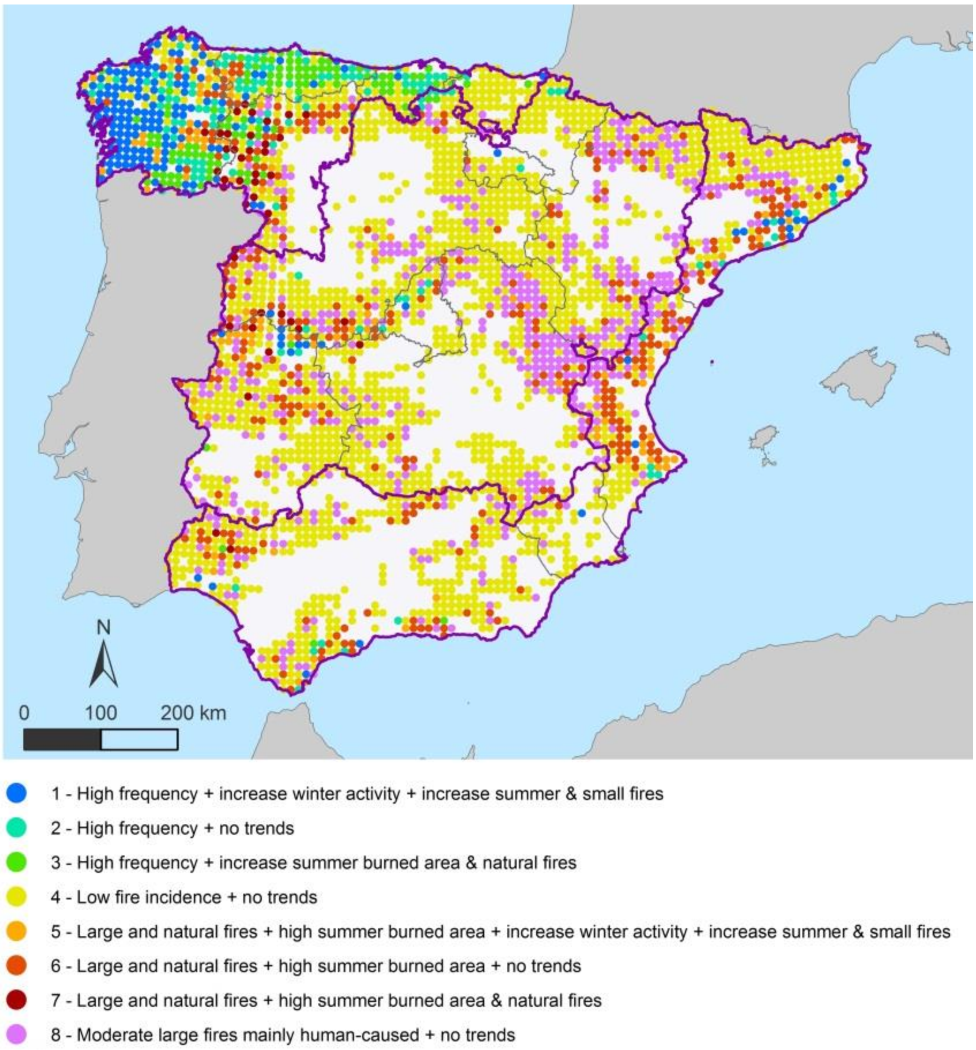

Figure 6 - Spatial distribution of the final pyroregions

The most relevant pyroregion in terms of spatial extent is 4 (55.1%), characterized by a low fire incidence without trends. Secondly, pyroregion 8, covering 16.4% of the territory, is represented by medium-sized fires mainly anthropogenic. With a 10.2% of the study area, pyroregion 6 combines large and natural fires with an increase in summer burned area. Pyroregion 1 (5.4% area) is mainly located in the Northwest region. It shows a high fire frequency linked to winter dynamics, as well as an increase in summer and small fires. Remaining pyroregions account for just over 1% and less than 4% individually. In summary, they would reach roughly 11.6% of the territory. These are characterized by a high frequency with no trends (2), or with an increase in summer burnt area and natural fires (3). In addition, large fires with an increase in summer-winter activity and small fires (5) and large fires associated with an increase in summer burnt area and natural fires (7).

3.1. Characterization of pyroregions based on environmental and human variables

The inclusion of climate-and-human variables enables deeper insights into the characterisation of the pyroregion (Figure 7):

Pyroregion 1: small winter fires and increased summer fire activity. It covers conifer and reforested communities with large rainfall and moderate warm winters and low human pressure.

Pyroregion 2: low fire activity in areas with moderate rainfall, temperate winters and summers.

Pyroregion 3: increasing winter fire incidence in shrubland communities linked to increased human pressure, large precipitation and moderate temperatures.

Pyroregion 4: low fire activity in isolated warm regions with conifer and mixed forest.

Pyroregion 5: low fire activity increasing during summer. It covers warm and dry regions with a variety of forest communities. Low human pressure.

Pyroregion 6: large natural fires with moderate-low human pressure, high temperature and low rainfall; affecting the whole spectrum of forest communities.

Pyroregion 7: very low fire activity in shrubland communities.

Pyroregion 8: natural fires in warm and dry locations affecting tree communities.

4. Discussion

The proposed methodology enabled identifying 8 pyroregions providing a more complete picture than previous attempts. We took a step further, not only by bringing in the dynamic component of fire incidence but digging into more sophisticated zoning techniques. Our contribution further deepens into fire features while complementing them with their main trends such as the rise in summer and winter activity or the increase in small fires.

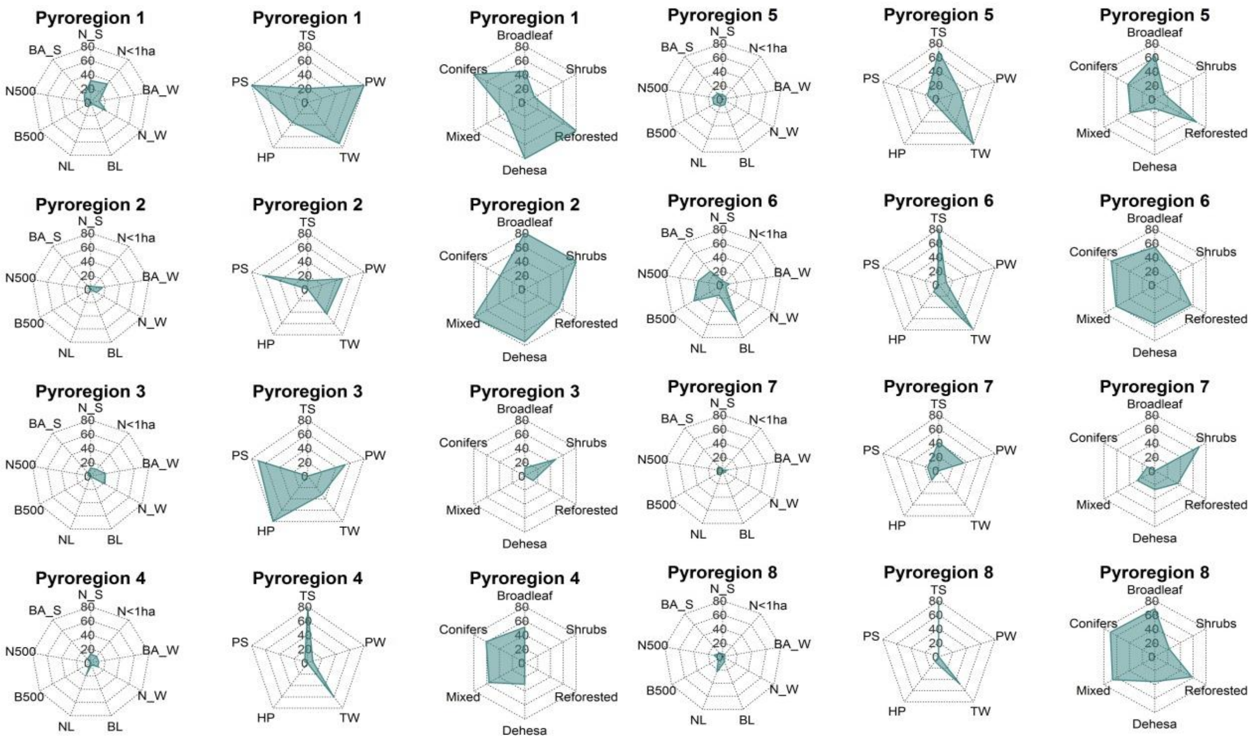

Figure 7 - Pyroregion description. Left column, fire features; center, environmental and human drivers; right, forest communities.

When combining the resulting pyroregions with climatic and human factors, we deliver deeper insights into what factors may be driving fire regimes. Our findings suggest coincidence between temporal clusters of increased fire activity (except for natural fires) dominated by pine woodland and reforestation communities (Vázquez *et al.* 2015). In many areas of Spain, plantations for timber harvesting and pine tree forests were promoted over the last decades (Pausas *et al.* 2004). This factor is known to increase flammability in the event of favourable weather conditions (Shakesby 2011).

Regarding climatic factors, fire-prone conditions along the Mediterranean coast seem to promote larger human-cause fires, especially during summer. However, the correspondence of climate with trend clusters is not clear. In this sense, the human impact (represented here as the combination of the length of wildland-urban and wildland-agricultural, WUI-WAI interfaces and demographic potential) seems to be more closely related with fire activity (Rodrigues and de la Riva 2014).

5. Conclusions

In this work we propose a pyrogeographical characterization of fire behaviour using averaged of fire features and their main temporal trends in mainland Spain. We submitted fire data in the period 1974-2015 to PCA and cluster analysis.

Our findings suggest 8 different pyroregions in mainland Spain, depicting by three structural fire regimes (high fire frequency, large-natural fires and medium size human-cause wildfires) and two main trends (overall increase in fire activity) and decrease in the incidence of natural fires. The implications of the delimited pyroregions play a crucial role in better understanding fire regimes in a broad context, not only in terms of their structural patterns but also of its main trends. Moreover, assessing the environmental and human conditions in the proposed pyroregions improved our understanding of the underlying drivers of fire regimes.

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