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## **Driving factors of fire density can spatially vary at the local scale in SE France**

Running head title: Spatial variation of fire density driving factors at local scale

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### **Abstract**

Southeastern France is the most wildfire prone region of the country. To identify the main driving factors of fire density (defined as the number of fires per hectare) at the local scale (cluster of communities which are homogeneous in terms of land cover, climate and WUI) and to assess their spatial variation at this scale, the fire density was investigated in the département Bouches du Rhône using georeferenced fire ignitions. To assess relationships between fire density and explanatory factors, statistical analyses and spatial evaluation were performed on each clusters taking into account climate conditions, topography, land cover, Wildland-Urban Interface (defined as a buffer of 100 m around housing located at less than 200 m from natural vegetation), minor road and population densities as well as fire density as dependent variable. High fire density was mainly related to high proportion of WUI in the study area. The proportion of natural vegetation and steep slope were also among the most important drivers of fire density. Depending on the cluster, some biophysical factors can in turn enhance or mitigate fire density but coolest and wettest climate conditions related to highest elevations as well as low housing density always mitigated fire density. This work showed that, at the local scale, the identification of fire density driving factors could improve fire prevention as they can better be targeted.

### **Short general summary**

Spatial relationships between fire density and biophysical and human-related factors were found in the study area, pointing to WUI as the principal driver of fire density but at a smaller scale, some of these factors spatially varied. A better understanding of their influence on fire density will help to improve fire prevention at a fine scale.

### **Introduction**

Wildfires have been an important disturbance in the Mediterranean region for thousands of years and, more recently, fire risk has become a more and more serious concern, especially in the Wildland-Urban Interface (WUI) where the stakes are the greatest. Since the past decades, WUIs have expanded in many Mediterranean countries, leading to an increase in the fire

ignition as population and human infrastructure facilities are disseminated throughout the forested zones, especially in the vicinity of large cities and tourist resorts (Viegas *et al.* 2003). This trend is also due to afforestation of abandoned agricultural lands located close to settlements (Galiana-Martin *et al.* 2011). In these areas, most fires are human-caused and human development as well as activity patterns (both starting and putting out fires) are increasingly overriding the biophysical factors that historically controlled fire regimes (Syphard *et al.* 2007a). Thus in these places, human-related factors such as housing density, population density or road networks have all been identified as important influences in the spatial distribution of wildfires (Maingi and Henry 2007; Sturtevant and Cleland 2007; Calef *et al.* 2008; Catry *et al.* 2009; Grala and Cooke 2010) while their relationships might vary in space (Koutsias *et al.* 2010). However, apart from the human component, specific traits of vegetation, topography, and meteorology are considered critical variables in fire ignition, spread and behavior in the Mediterranean Basin (Catry *et al.* 2009; Koutsias *et al.* 2012).

Numerous works evaluating the relationships between fire metrics and a large range of explanatory factors (mostly socio-environmental factors such as land cover or climate and human factors such as population density) have been carried out at different spatial scales such as the global scale (Chuvieco *et al.* 2008; Chuvieco and Justice 2010; Ganteaume *et al.* 2012), national scale (Vazquez and Moreno 1998; Catry *et al.* 2008; Martinez *et al.* 2009, Thompson *et al.* 2011; Verdu *et al.* 2012), regional scale (Syphard *et al.* 2007b, Koutsias *et al.* 2002, 2012; Miranda *et al.* 2012; Ganteaume and Jappiot 2012, 2013) or ecoregions (Padilla and Vega-García 2011), local scale (Badya-Perpinyá *et al.* 2006, Romero-Calcerrada *et al.* 2008; Syphard *et al.* 2007b, 2008), and even at several spatial scales (Lozano *et al.* 2008).

Southeastern France, which is characterized by Mediterranean climate conditions, is the most wildfire prone region of the country. Previous studies carried out at the regional scale (Ganteaume and Jappiot 2012, 2013) showed that this region accounted for 55% of the total number of fires in 2010, and fire ignition as well as burned area varied spatially within this region for the small as for the large fires. However, the spatial variation of the fire density, defined as the number of fires per surface area unit (hectare) and which is one of the fire characteristics commonly grouped under the general term of fire regime (Morgan *et al.* 2001; Stocks *et al.* 2003), has not been investigated at a fine scale yet. As already noted by Martinez *et al.* (2009), the use of a density index reduces the bias of comparing the absolute number of fires per municipality, since they have a wide range of sizes. Moreover, at the regional level in SE France, the spatial variation of the fire patterns influenced by anthropogenic and environmental factors has been highlighted in previous works (Ganteaume and Jappiot 2012, 2013), as has the need for further analyses at a smaller scale which better takes into account the environment of fire ignitions.

To fill this gap, the current work focuses on two fine spatial scales: (i) an administrative district of SE France (called “département”) and (ii) the different subsections identified within this section (clusters of communities). As stated by Padilla and Vega-García (2011), refining the spatial resolution of the work can help to take into account the spatial variation of fire metrics over a large study area; the spatial patterns of fire being better integrated. In this framework, the first aim of this work was to identify the main driving factors of fire density (predictor variables) at the two fine scales previously identified. Another aim of this work was

to assess whether the relationships between underlying drivers and ignition density varied within these scales using both a statistical descriptive analysis (multivariate analysis) and a spatial approach (hereafter named spatial analysis). This latter was identified by Díaz-Delgado *et al.* (2004) to lead to a better understanding of the processes underlying spatial trends and of the relative importance of variables involved in wildfire patterns. Accomplishing these objectives will help improving fire prevention at fine scale and, consequently, improve the local fire risk management.

## Material and methods

### Study area

The study area was the département Bouches du Rhône (Northwestern coordinates: 43.655°N, 5.495°E; Southeastern coordinates: 43.832°N, 5.672°E; total area: 508 700 ha), one of 15 administrative districts composing the Southeastern part of France (Fig 1). This département is among the areas most affected by wildfires (54 fires year<sup>-1</sup> and 1247.3 hectares burned per year in the 2000-2010 period according to the regional forest fire database Prométhée). The main fuel types of the study area, located mostly on limestone-derived soils, are *Pinus halepensis* forests (Quézel 2000) and mixed pine-oak (*Quercus ilex* and *Q. pubescens*) forests (respectively 42% and 18% of the forest stands; database of Inventaire National Forestier), often the pre-forest vegetation type before oak forests (Quézel and Barbéro 1992). Shrublands, called “garrigue” on limestone-derived soils, are another dominant fuel type in the study area (43% of the natural vegetation; database of Inventaire National Forestier) that corresponds to the predominant successional stage after woodland degradation (Barbéro *et al.* 1998). Wildfires occur frequently in the whole area and overall, the study area is a mosaic of all the previously mentioned types of natural vegetation and of agricultural areas. The Southwestern part of the département Bouches du Rhône is occupied by a large wetland area and by irrigated crops like rice paddies corresponding to the Rhône’s delta.

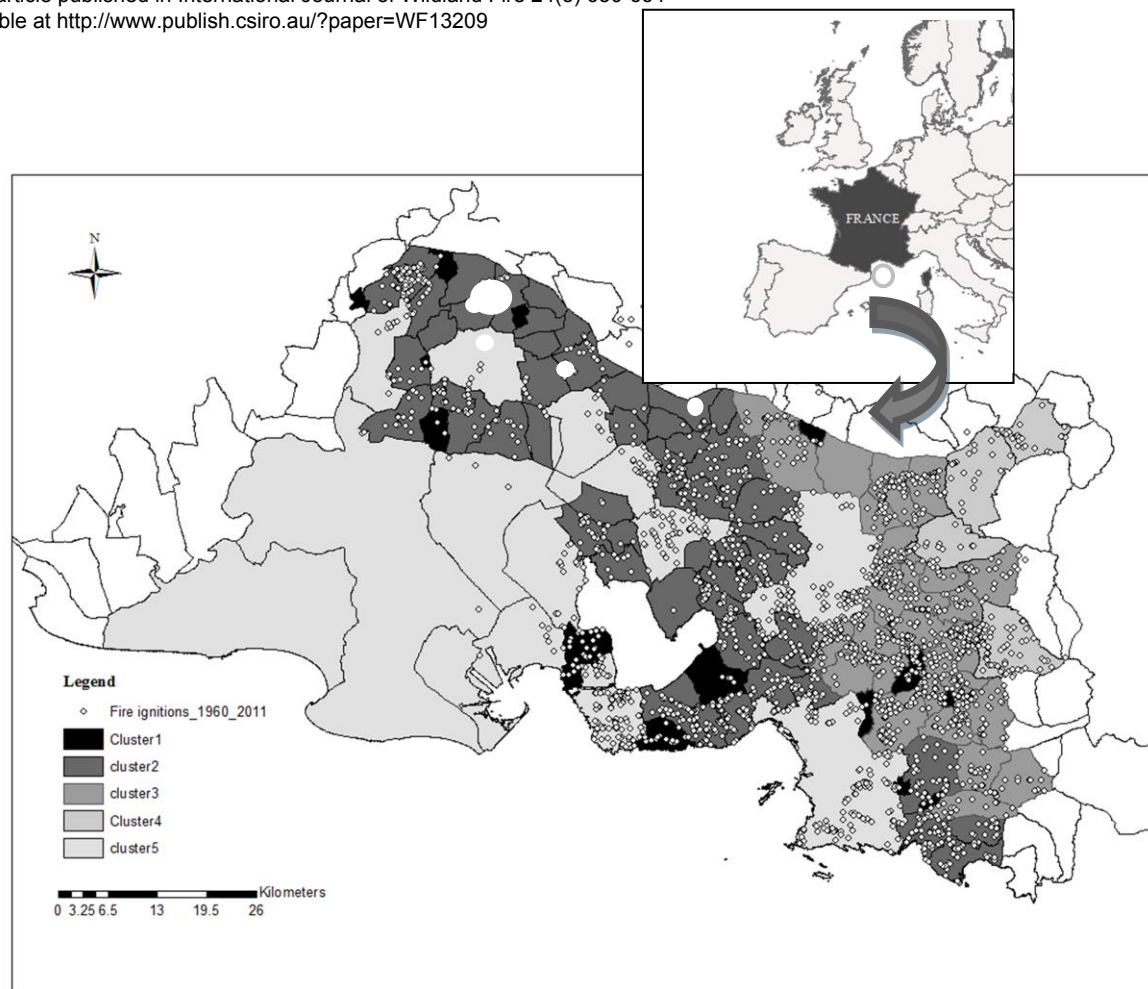
The Mediterranean climate prevailing in the study area is characterized by short and wet winter periods and by prolonged hot and dry summer periods, with strong drying wind (called Mistral) which favours fire incidence (Ruiz de la Torre 1999). The mean maximum temperature ranged from 9.8°C to 13.2°C in winter and from 27.9°C to 30.6°C in summer. Mean annual precipitation ranged from 472 mm to 820 mm (Météo France database). In general, topography is not very rough and the altitude ranges from sea level to 1038 m.

The total population of the study area is estimated to about 2 000 550 inhabitants, with a density of 388 inhabitants per km<sup>2</sup>, most concentrated around big cities like Marseilles. Initially the finer scale used in this work was the community (Local Administrative Unit 2 according to Eurostat<sup>1</sup>), which was defined as a city and its outskirts. The study area is composed of 119 communities (Fig. 1) among which 107 have been affected by wildfires since 1960; however, in order to get as many fire ignitions as required for the analyses, homogeneous geographical

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<sup>1</sup> <http://epp.eurostat.ec.europa.eu>

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**Fig. 1** Map of the study area (Département Bouches du Rhône) in Southeastern France showing the five clusters of communities and the fire ignition points (BD Carto®).

areas, defined as “cluster of communities”, were identified in the study area according to climate and land cover variables as well as to the proportion of WUI.

### *Data description*

Dependent variables: We compiled the georeferenced forest fire database of the French Forest Office (ONF) that records since 1960 all the georeferenced forest fires with a burned area larger than 1 ha in Southeastern France. In total, 2557 georeferenced fire ignitions were recorded between 1960 and 2011 in the département Bouches du Rhône (Fig. 1). Fire densities, calculated in each community, were taken into account as dependent variables in the analyses. For the statistical analyses, mean fire density was calculated in each cluster, as the number of fire ignitions divided by the vegetation area in the cluster, and for the multivariate analysis, this variable was classified in three groups: high (14.89 - 89.05 fires ha<sup>-1</sup>), medium (4.69 - 14.89 fires ha<sup>-1</sup>), and low (0 - 4.69 fires ha<sup>-1</sup>) fire density. For the spatial approach, fire density was calculated, in each cluster, as the number of fire ignitions divided by the area occupied by each explanatory factor.

### Explanatory factors (recorded in each community):

➤ Climate conditions: climate factors such as precipitation and temperature, which were important in the models of Cardille *et al.* (2001), were often not significant in other studies (García-Díez *et al.* 1999; Padilla and Vega-García 2011; Miranda *et al.* 2012; Ganteaume and Jappiot 2012) likely because they operate on a broader scale. Thus, the climate factors used in this work were derived from the bioclimatic index of Vennetier (2007) which combined several climate and topographic variables (elevation, exposure, mean annual temperature, mean annual precipitation, mean summer precipitation, number of dry months and number of cold months, distance to the sea). This index, previously coded in nine classes, has been re-coded into four classes used as proxy variables for climate conditions, from warm and dry conditions to cooler and wetter conditions as defined in Vennetier (2007): (i) coastal, (ii) intermediate, (iii) inland and (iv) relief (Fig. 2a). These data were given in percentage of the total community area.

➤ Topography: The topographic factors were generated from a 1:25 000 digital terrain model from the National Geographic Institute using geographical information systems (*ArcGIS 10*). Three types factors were thus derived:

(i) Elevation was coded in five classes in the spatial analysis (Fig. 2b) and the mean elevation in each community was used in the statistical analyses. In the département Bouches du Rhône, the topographic elevation gradient increases from the South-West to the North-East.

(ii) Slope was coded in four classes in the spatial analysis (Fig 2c) and the maximum slope was used in the statistical analyses.

(iii) Exposure to the dominant wind (Mistral, blowing from the North-West) was coded in three classes in the spatial analysis (Windward: 270° to 360°, leeward: 90° to 180°, and intermediate: 0° to 90° and 180° to 270°). This factor was derived from the direction of the descending slope and from the maximum variation rate of the values obtained in each pixel compared to the neighbouring pixels (Fig. 2d). Only the proportion of area exposed to the dominant wind in each community was used in the statistical analyses.

➤ **Land cover:** We used Corine Land Cover maps from 2006 at a 1:100 000 scale. In the spatial analysis, land-cover categories were simplified into 3 thematic classes by reclassifying the original categories: “Natural vegetation” (merging the different classes of fuels corresponding to forests, shrublands and pastures), “Agriculture” and “Others”. The latter merged the urban and other artificialized areas (such as dump areas, mines, communication networks, industrial areas) where fire ignitions can occur, but did not take into account wetlands or water bodies (Fig. 2e). Each land cover type was given in percentage of the total community area.

➤ **Socio-economic factors:** Mean population density (number of inhabitant per ha per community; INSEE 2011) was used in the statistical analyses, however, as this variable was not available as a spatial layer, housing density (calculation of the number of housing per ha) was used as a proxy of population density in the spatial approach of the results. This variable was coded in four classes extracted from BD TOPO® 2009 and was calculated by the Kernel density method in *ArcGis 10* (Fig. 2f).

➤ **Wildland-Urban Interfaces areas** were defined as a buffer of 100 m around housing located at less than 200 m from natural vegetation (Lampin-Maillet *et al.* 2010)(Fig. 2g).

➤ **Network density:** The spatial data related to all types of networks (electric lines, railways, main roads, and minor roads in  $\text{km ha}^{-1}$ ) were extracted from BD TOPO® 2009. A buffer of 50 m around the network, which corresponded to the area where the maximum fire density occurred (Romero-Calcerrada *et al.* 2008), was calculated around each type of network in order to have the corresponding network area. This calculation was done using the command ‘Distance’ in the *ArcGIS* software, which computes the Euclidian distance from each point to its closest road. The ignition frequency occurring along each type of network was calculated in order to highlight the type of network that concentrated most fire ignitions. Minor road network showed the highest fire occurrence (78% of ignitions occurred within the minor network buffer) compared to the other types of networks. Thus, in the spatial analysis we only focused on minor roads (Fig. 2h).

### *Data Analysis*

The identification of homogeneous clusters of communities according to descriptive factors (climate conditions, land covers and WUI in each community) was performed using Hierarchical Cluster Analysis (R 2.11-1, ADE-4 1.5-1 package). This analysis allowed the 119 communities to be grouped into five homogeneous clusters of communities according to these factors (Fig. 1 and tab. 1).

Partial least squares (PLS) regression analysis was used to examine the influence of the explanatory variables on fire density ( $\times 1000$ ), quoted “FD”, in the whole study area as well as in each cluster (in each case, the sample was the communities belonging to the whole study area or to each cluster). This analysis can be used as an exploratory analysis tool to select suitable predictor variables. Because of the too small number of communities, PLS regression was not performed on cluster 4. The dependent variable (FD) was normalized using a logarithmic transformation ( $\text{Ln}(\text{FD} + 1)$ ) prior to calculations and the explanatory variables were centred and scaled to unit variance to give all variables of the same relative importance. The significance of components for the models was determined by uncertainty tests carried

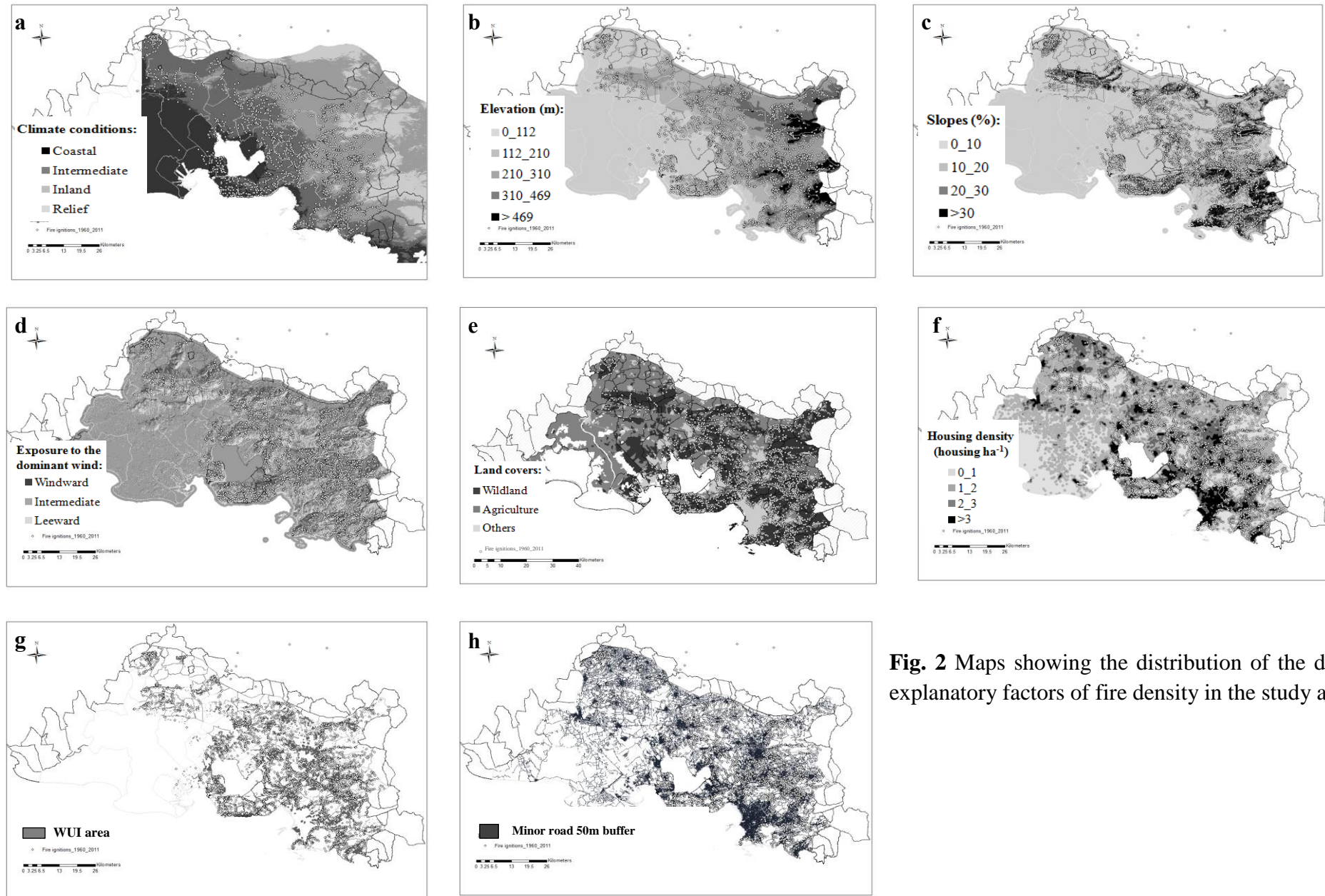
out within a full cross-validation. PLS was carried out using Statgraphics Centurion XV software. Then, using R statistical packages, a bootstrap procedure (bootsize=1000) was performed on the set of variables that presented the highest regression coefficients to rebuild the model, followed by a backwards elimination process until all predictor variables in the model were significant with  $P$  values  $< 0.05$ .

Co-inertia analysis (Dolédec and Chessel 1994) is fitted when the dataset is comprised of a large number of variables compared with a small number of data, and avoids the problems of co-linearity between variables. In the present work, this analysis was performed on the dependent variables (high, medium and low fire density) and on the explanatory factors (climate, land-cover, WUI, network density, topographic, socio-economic variables) to examine associations between these two types of data. The complete matrix of data was transferred to the statistical package under R 2.11-1 (R Development Core Team 2005) then analysed using the ADE-4 1.5-1 package (Thioulouse *et al.* 1997). The first step of this multivariate analysis (Ter Braak and Schaffers 2004) was to conduct a correspondence analysis on the dependent variables, then a principal component analysis on the explanatory factors. A factorial plane was thus created and enabled a new ordination of each data set. The statistical significance of each effect or combination of effects has been tested using the Monte-Carlo permutation test with 1000 permutations using the “randtest” in the ‘coin’ package on R.

The analysis of spatial fire patterns (called spatial analysis in this work), here fire density, studying the spatial relation according to different explanatory factors, was performed in order to identify the socio-environmental variables that are important determinants of the spatial distribution of fire density. All spatial analysis and cartographic production were made with the previously commented fire metrics, as well as with the explanatory factors using geographical information systems (*Arc Gis 10*). We used the Spatial Analyst Extension of *ArcGIS*, for our GIS analysis and data processing. The spatial relationships between fire density and explanatory variables were assessed through the spatial distribution of the fire ignition. In order to decrease the uncertainty of the location of fire ignitions (accuracy at  $\pm 10$  m), the layer of fire ignitions was, at first, converted in raster with a 10 m resolution in order to combine it to the other raster spatial data. Then this layer was transformed in point density using the Kernel density method in order to have continuous data on the whole study area.

The resolution of the statistical analyses was the community as data is available for each community whereas spatial data, which is continuous in the study area, is available at different resolutions according to the spatial explanatory variables. Analyzing the spatial fire density was thus performed taking into account these spatial resolutions.





**Fig. 2** Maps showing the distribution of the different explanatory factors of fire density in the study area.

## Results

### *Spatial distribution of fire density at the different fine scales*

The fire density obtained using the Kernel method in the whole study area showed an increase along a West-East gradient with values up to 0.052 ignitions per hectare (Fig. 3). Regarding fire density cluster by cluster, clusters 2 and 3 presented the highest fire densities (up to 0.055 and 0.048 ignitions per hectare respectively) and cluster 4 the lowest values (up to 0.023 ignitions per hectare). Higher fire densities were located in the Southern part of the clusters 1 and 4, in the centre of cluster 3 and in the East of cluster 5 whereas, in cluster 2, fire density was quite homogeneous in the whole area (Fig. 3).

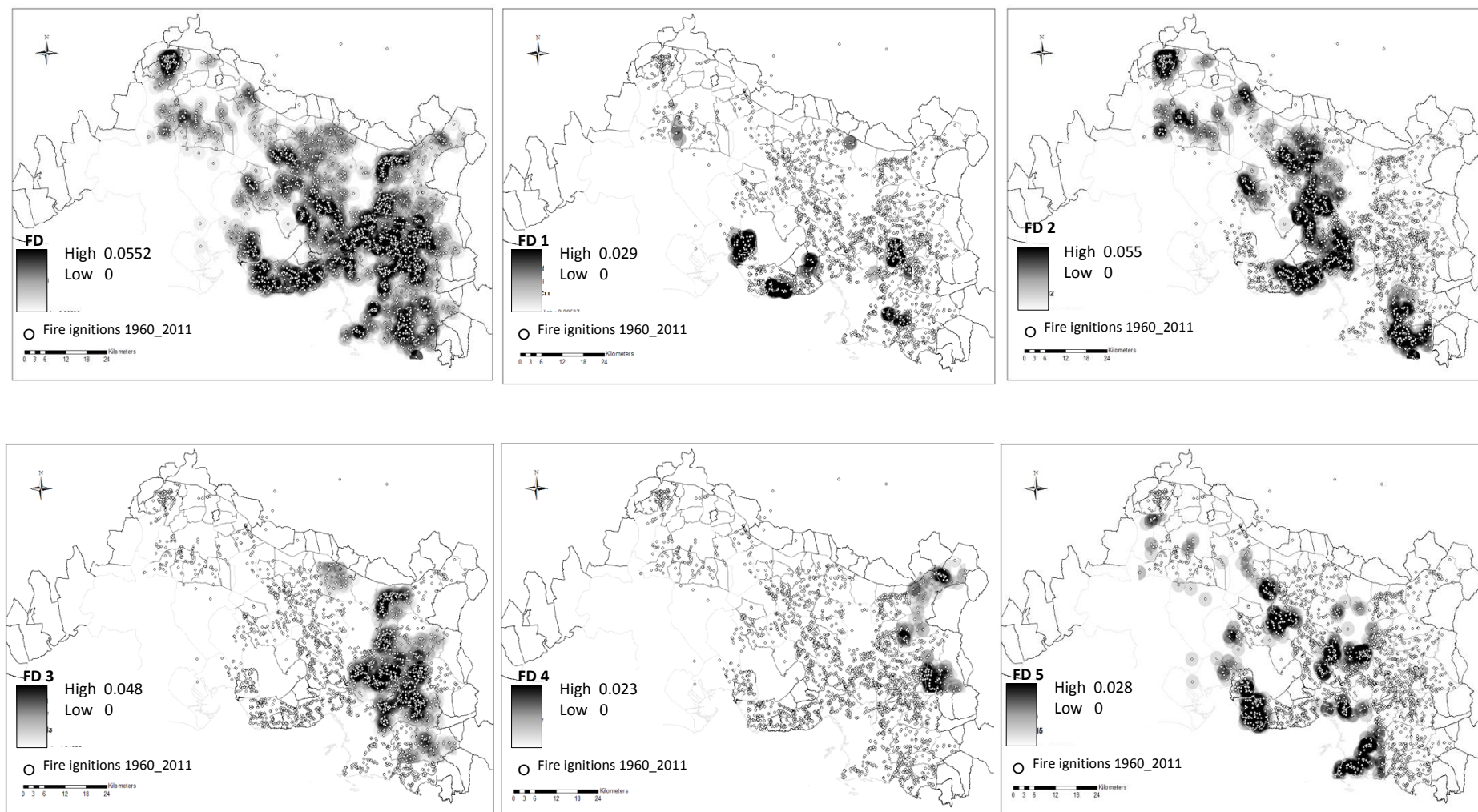
### *Characterization of the main explanatory factors of fire density*

At the level of the entire study area, results of the Partial Least Squares regressions, including the dataset of explanatory variables (climate conditions, land covers, WUI, minor road and population densities, mean elevation, maximum slope and exposure to dominant wind), showed that fire density was enhanced by population and minor road densities, WUI, topographic variables (all of them), land covers “natural” and “others” as well as the climate condition “intermediate” (2 components,  $p < 0.0001$ ,  $r^2 = 0.49$ ). On the contrary, fire density was mitigated by the climate condition “relief” and the land cover “agriculture” (Fig. 4). After the bootstrap procedure, only the explanatory variables climate condition “relief”, WUI (both highly significant), land cover “agriculture”, population density and the three topographic variables remained significant predictors of the fire density (Tab. 2).

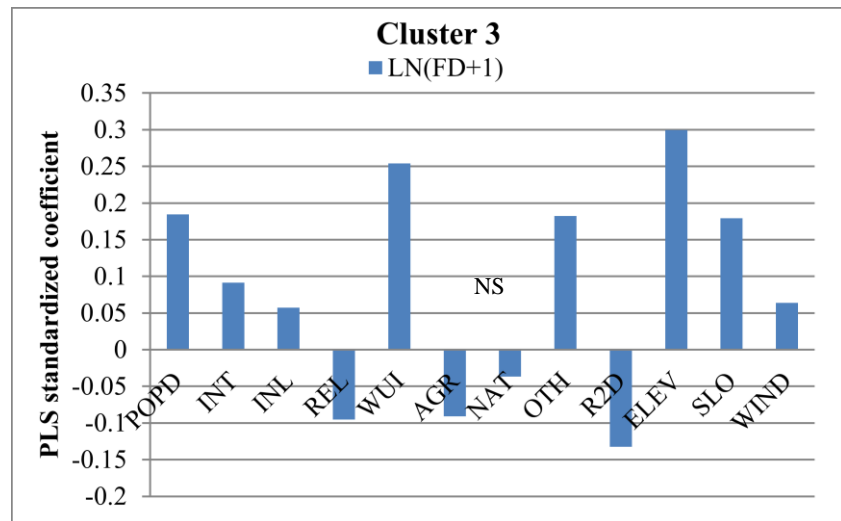
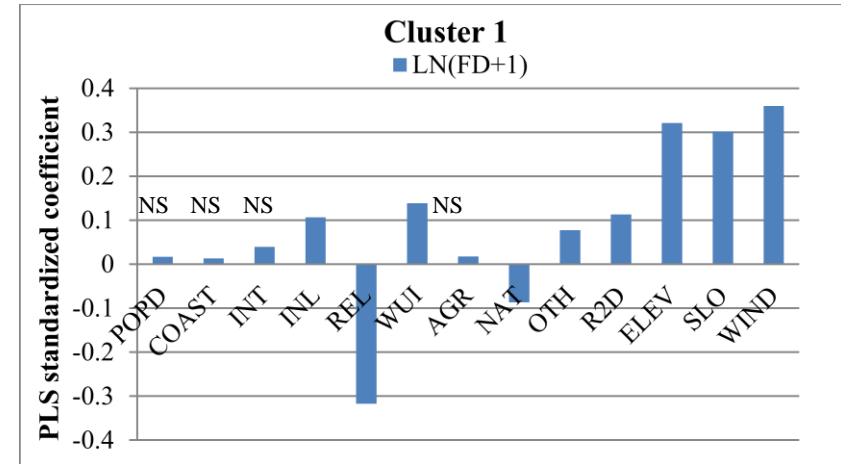
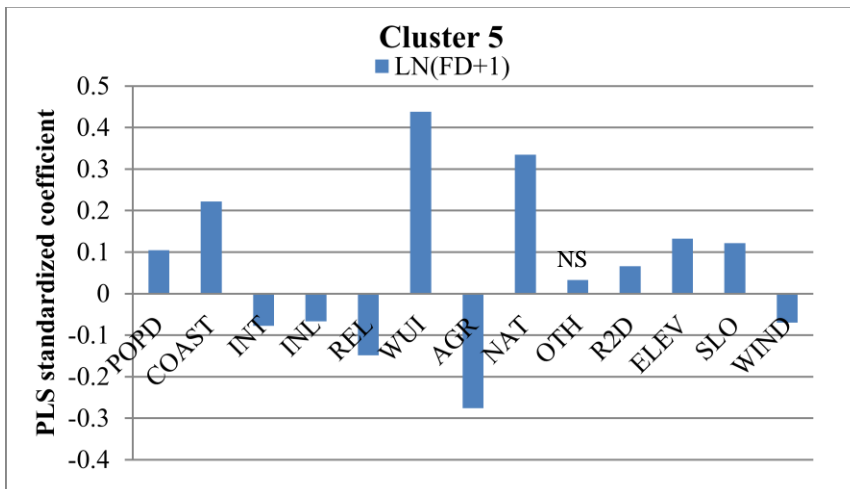
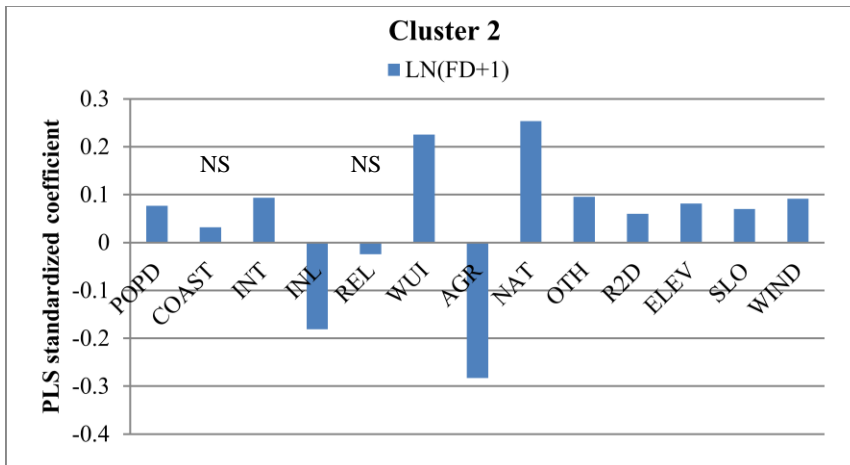
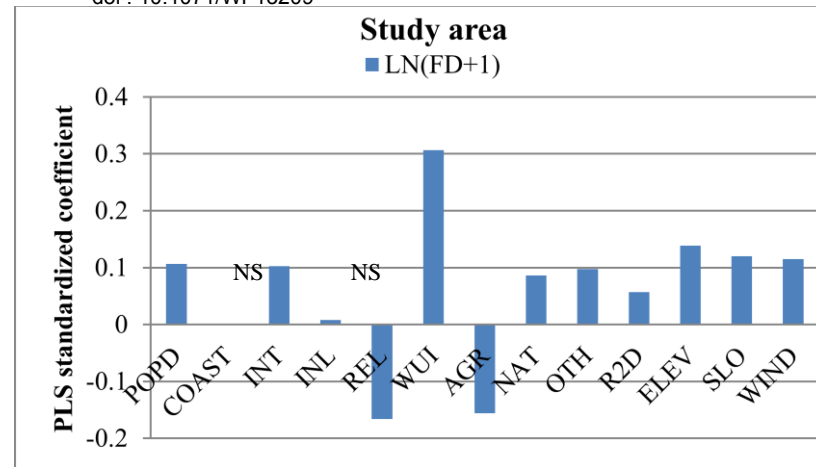
At the cluster level, results of the regression analysis, including the dataset of explanatory variables according to the fire density, showed that fire density was significantly correlated to most explanatory variables always mitigated by the land cover “agriculture” and, according to the cluster, either mitigated or enhanced by climate conditions “relief” and “inland” as well as by minor road density (Fig. 4). After the bootstrap procedure, only one explanatory variable remained a significant predictor of the fire density in clusters 1 and 5: exposure to dominant wind (cluster 1) and WUI (cluster 5). The variables WUI, land cover (all the classes), population density and the climate condition “inland” remained significant in cluster 2 whereas population density, WUI, land cover “others”, slope and elevation were significant predictors in cluster 3 (in this cluster, the climate condition “coastal” has not been taken into account in the analysis because cluster 3 does not contain any coastal community) (Tab. 2). This analysis was not carried out on cluster 4 because of the too small sample (four communities).

### *Revealing the relationships between explanatory factors and fire density*

At the level of the study area, the spatial approach showed that fire density was among the lowest in the agricultural areas (0.0026 fires ha<sup>-1</sup>) whereas it was highest in the “natural” areas (0.0091 fires ha<sup>-1</sup>) even if this land cover represents only 36% of the study area. “Relief” was the only significant climate condition correlated to fire density (Tab. 2), however, fire density values were not high in this “climate” class. Although WUI areas only represented 15% of the territory, fire density was highest (0.014 fires ha<sup>-1</sup>) in these areas.



**Fig. 3** Maps showing the fire density (FD: number of ignitions per ha) calculated by the kernel density method in the whole study area (FD) and in the five clusters of communities (FD1, FD2, FD3, FD4, FD5).



**Fig. 4** Predictor variables resulting from a Partial Least Squares (PLS) regression analysis carried out with the fire density (FD log-transformed and x 1000): POPD: population density, COAST: coastal climate conditions, INT: intermediate climate conditions, INL: inland climate conditions, REL: relief climate conditions, WUI: wildland-urban interface, AGR: agriculture land cover, NAT: natural vegetation land cover, OTH: other land covers, R2D: minor road density, ELEV: elevation, SLO: slope, WIND: exposure to dominant wind, NS: non-significant variable.



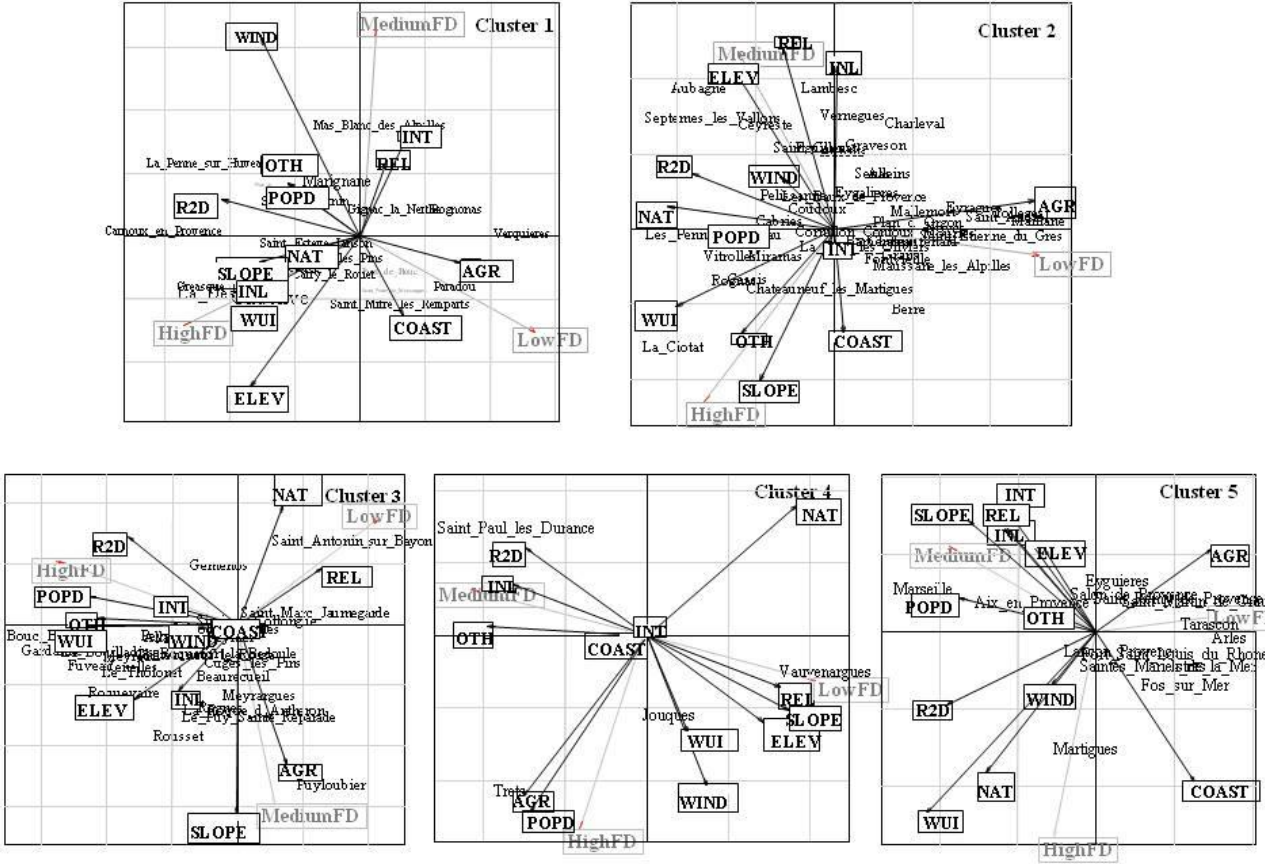
Regarding the topographic variables, fire densities were highest in areas presenting medium slopes ( $0.012 \text{ fires ha}^{-1}$ ), at lowest elevation ( $0.01 \text{ fires ha}^{-1}$ ) and in windward areas ( $0.008 \text{ fires ha}^{-1}$ ). Regarding the socio-economic factors, fire density was highest in dense housing areas (2 to 3 housing  $\text{ha}^{-1}$ ). Minor road network, whose area represented 31% of the study area, presented a mean fire density of  $0.009 \text{ fire ha}^{-1}$ .

In each cluster of communities, the link between the different explanatory factors and the fire density was investigated using multivariate analysis (co-inertia analysis) and spatial analysis (Tab. 3). In cluster 1, results obtained using co-inertia analysis showed that high proportions of WUI, of the climate condition “inland”, and to a lesser extent, of natural vegetation, as well as steep slopes and high elevations, were linked to high fire density (Fig. 5). This result was confirmed by the spatial approach (Fig. 6). For low fire density, both types of analysis identified the high proportion of agricultural lands and the low population/housing density as mitigating factors. Besides, spatial analysis highlighted the proportion of the climate condition “intermediate”, low and higher elevations and low slopes as mitigating factors of fire density. Low proportions of the land cover “others” and low network density were also linked to low fire density according to co-inertia analysis.

In cluster 2, the results obtained using co-inertia analysis showed that high proportions of the land cover “others” (here the urban areas where fires are concentrated around), of the climate condition “coastal”, of WUI as well as steep slopes were linked to high fire density (Fig. 5). Spatial analysis also identified high proportion of WUI and steep slope as linked to high fire density but added to these factors the high proportion of natural vegetation (Fig. 6). For low fire density, both types of analysis identified the high proportion of agricultural lands and low population/housing density as mitigating factors. Besides, spatial analysis highlighted the proportion of the climate condition “coastal” and low slopes, as mitigating factors of fire density. Low proportions of the land cover “natural” and of areas exposed to dominant wind as well as low network density were linked to low fire density according to co-inertia analysis.

In cluster 3, the results obtained using co-inertia analysis showed that high proportions of the land cover “others” and of WUI and to a lesser extent, of the climate condition “intermediate”, as well as high population and network densities, were linked to high fire density (Fig. 5). Except for the land cover “others”, this result was confirmed by spatial analysis which also added medium elevations and slopes, natural vegetation as well as exposure to dominant wind to the factors linked to high fire density (Fig. 6). For low fire density, both analyses identified the proportion of the climate condition “relief” as a mitigating factor. Besides, spatial analysis also highlighted higher elevation and low housing density as linked to low fire density whereas low proportion of the climate condition “inland” and low elevations were linked to low fire density according to co-inertia analysis.

In cluster 4, results obtained using co-inertia analysis were highly significant (randtest,  $p < 0.001$ ) in spite of the small sample. They showed that high proportion of agricultural lands, high population density as well as low proportion of the land cover “natural” were linked to high fire density (Fig. 5). This result was confirmed by spatial analysis which also added the high proportion of WUI to the factors linked to high fire density (Fig. 6). For low



**Fig. 5** Identification of the explanatory variables (in black with box) of fire density (in grey) in the five clusters by means of co-inertia analysis: FD log-transformed and x 1000): POPD: population density, COAST: coastal climate conditions, INT: intermediate climate conditions, INL: inland climate conditions, REL: relief climate conditions, WUI: wildland-urban interface, AGR: agriculture land cover, NAT: natural vegetation land cover, OTH: other land covers, R2D: minor road density, ELEV: elevation, SLO: slope, WIND: exposure to dominant wind. In lower case: communities composing each cluster.

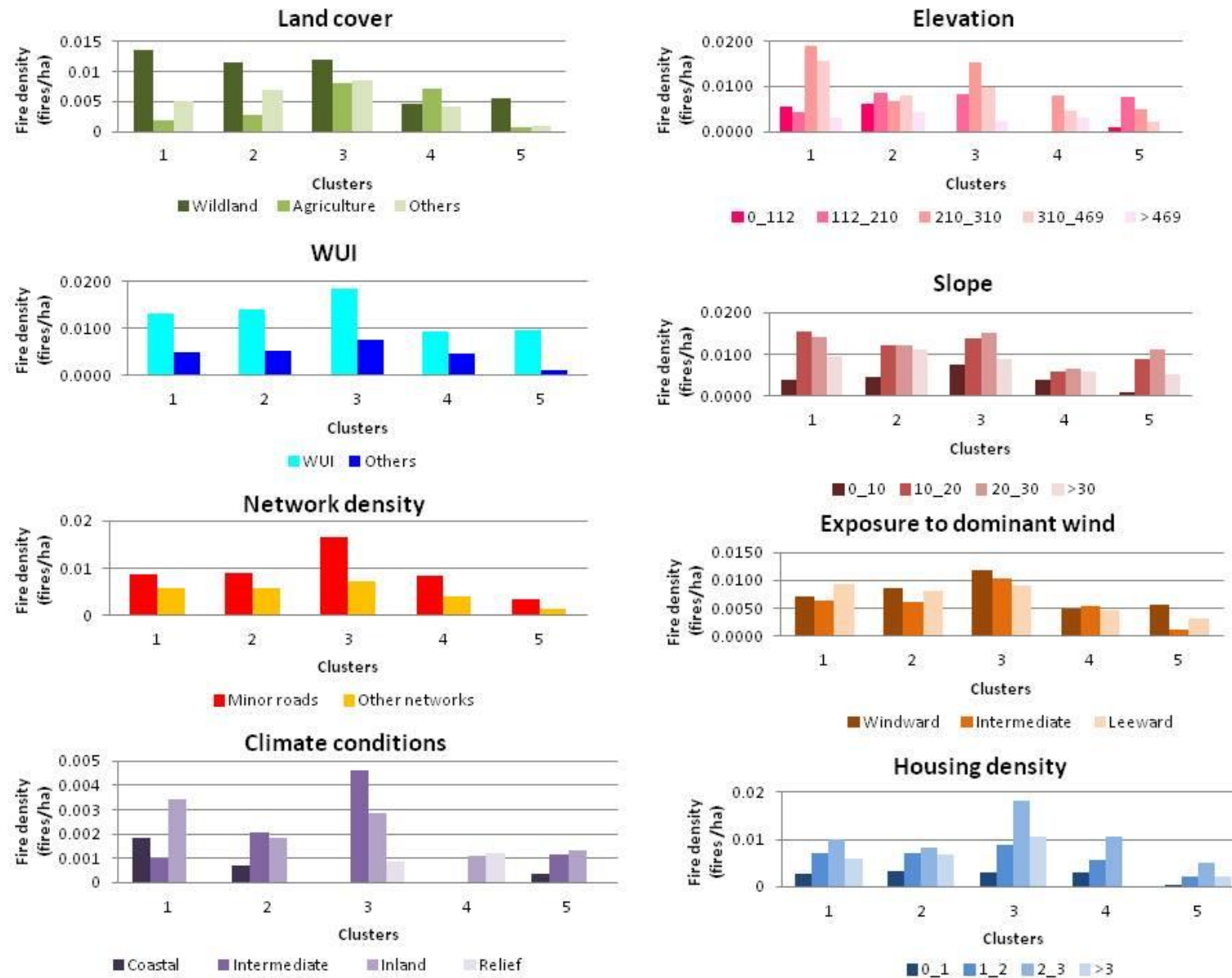
fire density, this latter analysis identified higher elevation and low housing density as mitigating factors whereas high proportion of the climate condition “relief” as well as high elevations and steep slopes were linked to low fire density according to co-inertia analysis.

In cluster 5, results obtained using co-inertia analysis showed that high proportions of natural vegetation and of WUI as well as of areas exposed to the dominant wind were linked to high fire density (Fig. 5). Spatial analysis identified medium elevations and slopes as enhancing factors of fire density (Fig. 6). For low fire density, both analyses identified the proportion of agricultural lands as a mitigating factor. Besides, spatial analysis also highlighted the proportions of the land cover “others” and of the climate condition “coastal”, low slopes, low and higher elevations and low housing density as mitigating factors of fire density. Low network density was also linked to low fire density according to co-inertia analysis.

## Discussion

In the study area, fire density increased along a gradient from the West to the East and it varied at the finer scale (cluster of communities). The low fire density recorded in the Western part of the study area could be explained by the large flat area of marshes and irrigated crops which are not favourable to fire ignition. At the level of the study area, the climate condition “relief” and the land cover “agriculture” mitigated fire density contrary to population density, topographic variables (all of them) and especially WUI. This latter variable strongly enhanced fire density even if the WUI area represented only 15% of the study area (from 4% to 35% according to the cluster) and its influence on fire metrics has been already highlighted in several works (Prestemon *et al.* 2002; Romero-Calcerrada *et al.* 2008; Badia-Perpinyà and Pallares-Barbera 2006). In areas where most fires are human-caused, ignitions are often more frequent along transportation networks (Vega-García *et al.* 1995; Abhineet *et al.* 1996; Thompson 2000; Cardille *et al.* 2001; Vasconcelos *et al.* 2001; Keeley and Fotheringham 2003; Stephens 2005). Several works showed that these networks should be an important descriptor of the effect of human population (Vasconcelos *et al.* 2001; Cardille *et al.* 2001; Chou *et al.* 1993; Romero-Calcerrada *et al.* 2008; Badia-Perpinyà and Pallares-Barbera 2006; Dickson *et al.* 2006). However, depending on the authors, population and road densities were either positively (Cardille *et al.* 2001; Keeley *et al.* 1999) or negatively (Mercer and Prestemon 2005) correlated to fire; some authors also found no correlation between these variables (Prestemon *et al.* 2002; Ganteaume and Jappiot 2012). As Syphard *et al.* (2007a) already showed, we found that the minor road density was not a significant predictor of fire density (since roads are narrow and linear features, the influence of this variable may not be detected at the scale used in this work) in contrast of the population density. Catry *et al.* (2009) also found that population density was among the main driving factors of fire occurrence in Portugal.

At finer scale (cluster of communities), a spatial variation of the driving factors of fire density has been highlighted and the proportion of WUI in the cluster was one of the most important factor positively linked to high fire density (except in cluster 4) as previously found at the scale of the study area. However, according to the regression analysis, WUI was not a significant variable in cluster 1 (despite it was positively linked to high fire density



**Fig. 6** Fire density in the five clusters of communities according to the different explanatory factors using a spatial approach.



according to both multivariate and spatial analyses) which could be explained by the lower proportions of WUI in this cluster as well as in cluster 4 (respectively 6 and 4% of the study area). This result agreed with several works which showed that the influence of WUI on fire metrics varied spatially (Keeley *et al.* 1999; Cardille *et al.* 2001; Prestemon *et al.* 2002; Syphard *et al.* 2007a).

Topographic variables were significant predictors of fire density only in two clusters (in cluster 3, elevation and slope enhanced fire density, so was the exposure to dominant wind in cluster 1). Moreover, exposition to dominant wind was linked to high fire density in cluster 3 according to the spatial analysis as well as in cluster 5 according to both co-inertia and spatial analyses. Usually, wind appeared to be an important factor, as highlighted in the Southwestern part of the USA and in southern California (Cohen and Miller 1978; Schoennagel *et al.* 2004; Keeley 2004) but this variable was often related to the burned area. On the whole, medium and steep slopes were linked to high or medium fire density, which agreed with the work of Syphard *et al.* (2008) and Lampin-Maillet *et al.* (2010), and spatial analysis revealed that medium to high elevations were also linked to high fire density in clusters 1 and 3. In Portugal, Catry *et al.* (2009) found that higher fire occurrence at high elevation (from 500 to 1000 m) was linked to renovation of pastures for livestock; however this explanation did not fit with our context as the natural vegetation in clusters 1 and 3 was only forests not pastures. In most clusters, higher elevations, corresponding to “mountainous” areas, were not favorable to fire density and low slopes, mostly corresponding to agricultural or wetland areas, also mitigated fire density. In contrast, Badia-Perpinyá and Pallares-Barbera (2006) found that fires were mostly situated in easily accessible areas on gentle slopes in some part of Catalonia (Spain) and other authors (Vega-García *et al.* 2008; Padilla and Vega-García 2011) showed trends suggesting that more ignitions were likely to occur in low elevation areas.

At the cluster level, after the bootstrap procedure, climate conditions were significant predictors of fire density only in cluster 2 in which “inland” mitigated fire density. Before this procedure, “relief”, characterized by the coolest and wettest climate conditions, significantly mitigated fire density in the other clusters. Both multivariate and spatial analyses showed that this climate variable was also positively linked to high fire density in cluster 1 and that the climate variable “relief” was positively linked to low fire density in cluster 3. Syphard *et al.* (2008) noted that coastal areas in Southern California which were warmer and dryer than remote interior regions were more conducive to fire; however, in our work, different climate conditions could enhance fire density according to the cluster: warm and dry climate conditions (“intermediate”), conducive to fire ignition, were positively linked to high fire density in cluster 3 but cool and wet climate conditions (“inland”) did the same in cluster 1, likely increasing the fuel load. Indeed, for this latter cluster, high fire density was also linked to high elevation and steep slopes, often corresponding to the climate condition “inland”. However, the coolest and wettest conditions (relief), which are not favourable to fire ignition, were linked to low fire density in the most “mountainous” areas (clusters 3 and 4).

The land cover classes were significant predictors of fire density only in cluster 2 in which the proportions of land covers “natural vegetation” and “others” enhanced fire density in contrast of the proportion of agricultural land. However, the proportion of natural vegetation was positively linked to high fire density in cluster 1 and 5 according to both

multivariate and spatial analyses. This result agreed with Syphard *et al.* (2008) who showed that, usually, the vegetation type is related to ignition. In cluster 3, only the land cover “others” (mostly corresponding to the urban areas) enhanced fire density, indicating that fires were concentrated around urban areas; this significant variable was also associated to population density in this cluster. Our analyses also revealed that the proportion of agricultural land was negatively linked to high fire density in clusters 1, 2 and 5 and positively linked in cluster 4 in contrast of the proportion of natural vegetation. This result agreed with several works, carried out in Mediterranean countries or in the upper Midwest of the USA, which showed a tendency of fire to occur on or near non-forested areas (Cardille and Ventura 2001; Badia-Perpinyá and Pallares-Barbera 2006; Catry *et al.* 2009). Indeed, this behavior was probably due to the relative ease of igniting non-forest fuels, which could be agricultural residues. However, the impact of agriculture on fire can differ in the literature; for instance, Chuvieco and Justice (2010) showed that crops were negatively correlated to fire density but Martinez *et al.* (2009) found that, in Spain, agricultural variables entailed an increase in fire ignition due to sparks emitted by engines or stubble burning, given that most agricultural practices in this country imply frequent use of fire. This could be the case in cluster 4 where the fire was related to agricultural areas.

Regarding socio-economic variables, minor road density was not a significant predictor of fire density regardless of the cluster but, according to multivariate analysis, this variable was linked to high fire density at least in cluster 3. In the literature, most works did not detail the type of transportation network as we did in the current study but they showed that human-caused fires were more likely to occur in areas of high road density improving access to remote forested locations (Swetnam 1990; Cardille *et al.* 2001; DellaSala and Frost 2001), and near those roads (Chou *et al.* 1993). Population density significantly enhanced fire density in clusters 2 and 3 and this variable was also linked to high fire density in cluster 4 according to multivariate and spatial analyses. It is worth noting that low housing density, often corresponding to agricultural areas, was linked to low fire density regardless of the cluster, and that medium housing density was linked to high fire density (especially in clusters 3 and 4) as previously found by Syphard *et al.* (2007a). Usually, the distribution of fires is influenced by such human-related factors (Martinez *et al.* 2009; Vega-Garcia *et al.* 1995, Thompson 2000; Vasconcelos *et al.* 2001; Syphard *et al.* 2008) and these factors have been identified as influencing the spatial distribution of wildfires in places where people tend to start most fires (Cardille *et al.* 2001; Maingi and Henry 2007; Sturtevant and Cleland 2007; Syphard *et al.* 2007a; Calef *et al.* 2008; Catry *et al.* 2009; Grala and Cooke 2010). However, Badia-Perpinyá and Pallares-Barbera (2006) showed that, according to the population density, the influence of roads on ignition varied; this factor did not influence the spatial distribution of ignitions in areas with sparse population.

## Conclusions

There were significant relationships between fire density and biophysical and human-related factors in the study area. The spatial distribution of high fire density at this scale was clearly related to a combination of abiotic, biotic, and human factors: no single factor or factor type dominates in this area. At a finer scale (cluster of communities), there was also a spatial variation of fire density. The main explanatory variable in the different analyses pointed to

WUI as the principal factor enhancing fire density regardless of the scale. Hence, better fire prevention must target WUIs in the whole study area with land use planning taking into account the lessening of sprawling development of WUIs. Moreover, controls of the implementation of the mandatory brush-clearing should be reinforced in these areas. Sometimes, this variable was associated with population/housing density (clusters 2 and 3) so people awareness should also be reinforced in these areas as well. Indeed, humans are altering both spatial and temporal pattern of fire regime and the fire risk is a function of the spatial arrangement of housing development and fuels (Syphard *et al.* 2007a; Lampin-Maillet *et al.* 2011). In cluster 4 only, agricultural practices seemed to enhance fire density; thus, reinforcing farmer awareness, especially regarding the practice of residues burnings, would help improve fire prevention in this area. Depending on the geographical location, climate conditions and topography parameters can enhance (inland, steep slopes, high elevations, exposure to dominant wind) or mitigate (relief, low slopes, low and higher elevations) fire density, often associated with the natural vegetation factor. In the study area, and probably at a finer scale, most fires are intentional, arsonists selecting the right place at the right moment regarding meteorological conditions to set fires. However, these climate conditions will be changing in the future according to the global change; areas in altitude presenting cool and wet conditions becoming warmer and dryer. This change, combined with the change in land use, will play on the spatial variation of fire density. With this perspective, more management of fire risk and of fire prevention planning will be needed for instance in the elevated part of the study area which are currently less at risk.

The different analyses we used mostly gave similar or complementary results and the insights they provided allowed better understanding of the influence of these explanatory factors on fire density at fine scale. As already noted by Syphard *et al.* (2009), the fine scale spatial analysis of relationships between people and fires may help identify areas where increases in fire metrics will threaten valuable areas.

In further works, the temporal variation of the driving factors of fire density as well as the driving factors of the burned area have to be checked at fine scale in the framework of the global change. Moreover, as several authors pointed out that economic difficulties may promote conflicts manifested by the increase in intentional fires (Martinez *et al.* 2009; Ganteaume and Jappiot 2012), socio-economic factors such as the unemployment rate should be added to the analyses if they are available in the requested format.

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**Table 1 : Characteristics of each cluster of communities according to the descriptive variables (proportions of climate conditions, WUI and land covers)**

		CLUSTER 1	CLUSTER 2	CLUSTER 3	CLUSTER 4	CLUSTER 5
CLIMATE CONDITIONS	Coastal	High	High	None	None	High
	Intermediate	High	High	Medium	None	High
	Inland	High	Medium	High	Low	Medium
	Relief	Medium	Low	High	High	Low
WUI	WUI	High	Medium	Medium	Low	Medium
LAND COVERS	Agriculture	High	High	Medium	Medium	High
	Natural vegetation	High	High	High	High	Medium
	Others	High	Medium	Medium	Low	High



**Table 2: Regression coefficients and p-values (\*: 0.05, \*\*:0.01, \*\*\*:0.001) of the significant explanatory variables (PLS model with 2 components with bootstrap procedure)**

Percentile	0.1th	1th	5th	95th	99th	99.9th	P-value
<b>Study area</b>							
Population density	-0.067	-0.0261	0.0147	0.224	0.2606	0.2834	*
% Relief	-0.3876	-0.3563	-0.3126	-0.0965	-0.0617	-0.018	***
% WUI	0.2003	0.2335	0.2613	0.4377	0.4645	0.5193	***
% Agricultural land	-0.4248	-0.3576	-0.3131	-0.0814	-0.0292	0.0267	**
Elevation	-0.0788	-0.0228	0.02	0.2829	0.3313	0.375	*
Slope	-0.055	-0.023	0.0155	0.2032	0.2361	0.2599	*
Exposure to dominant wind	-0.0585	-0.0322	0.0207	0.2592	0.3028	0.3498	*
<b>Cluster 1</b>							
Exposure to dominant wind	-0.2932	-0.1108	0.0376	0.5937	0.7134	0.8275	*
<b>Cluster 2</b>							
Population density	-0.0513	-0.0281	0.0073	0.1468	0.1805	0.2138	*
% Inland	-0.4669	-0.3541	-0.3013	-0.0541	-0.0114	0.022	**
%WUI	0.0532	0.0938	0.1341	0.3341	0.3806	0.4281	***
% Agricultural land	-0.4394	-0.4117	-0.3786	-0.242	-0.2022	-0.1726	***
% Natural vegetation	0.1027	0.1604	0.1963	0.3435	0.3697	0.3954	***
% land cover "Others"	-0.0499	-0.0143	0.0229	0.2029	0.2392	0.2606	*
<b>Cluster 3</b>							
Population density	0.014	0.0715	0.1339	0.2959	0.3326	0.3824	***
%WUI	0.0625	0.162	0.2113	0.4577	0.5387	0.6841	***
% land cover "Others"	-0.0344	0.0332	0.0881	0.2822	0.3106	0.3489	**
Elevation	0.0862	0.1416	0.219	0.4745	0.5642	0.6597	***
Slope	-0.0471	-0.0097	0.0712	0.2833	0.318	0.3579	*
<b>Cluster 5</b>							

%WUI	-0.284	-0.0852	0.1247	0.9374	1.1072	1.4485	*
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**Table 3 : Factors enhancing and mitigating fire density at the local scale obtained using co-inertia analysis and spatial analysis (FD: fire density; in bold, factors that matched in both analyses)**

	Combination of factors enhancing FD (co-inertia analysis)	Factors enhancing FD (spatial analysis)	Combination of factors mitigating FD (co-inertia analysis)	Factors mitigating FD (spatial analysis)
Cluster 1	High values of: % <b>WUI</b> , % <b>Inland</b> , <b>slope</b> , % <b>Natural</b> Low values of: % Intermediate, % Relief	% <b>WUI</b> , % <b>Inland</b> , <b>medium and high slope</b> , high elevation, % <b>Natural</b>	High values of: % <b>Agriculture</b> and % Coastal Low values of: % Others, <b>population</b> and minor road <b>densities</b>	% <b>Agriculture</b> , % intermediate, low and higher elevation, low slope, <b>low housing density</b>
Cluster 2	High values of: % <b>WUI</b> , % Others, <b>slope</b>	% <b>WUI</b> , <b>medium and high slope</b> , % Natural	High values of: % <b>Agriculture</b> Low values of: <b>population</b> and minor road <b>densities</b> , exposure to dominant wind, % Natural	% <b>Agriculture</b> , % Coastal, low slope, <b>low housing density</b>
Cluster 3	High values of: % <b>WUI</b> , % <b>Intermediate</b> , % Others, <b>Minor road &amp; population density</b>	% <b>WUI</b> , medium elevation, medium slope, <b>high minor road density &amp; medium housing density</b> , % Natural, % <b>Intermediate</b> , exposure to dominant wind	High values of: % <b>Relief</b> , % Natural Low values of: elevation, % Inland	% <b>Relief</b> , higher elevation, low housing density
Cluster 4	High values of: % <b>Agriculture</b> , <b>population density</b> Low values of: % Natural	% WUI, % <b>Agriculture</b> , <b>medium housing density</b>	High values of: % Relief, <b>elevation</b> , slope Low values of: % Intermediate, minor road density	<b>higher elevation</b> , low housing density
Cluster 5	High values of: % <b>WUI</b> , %	% <b>WUI</b> , % <b>Natural</b> , high	High values of: % <b>Agriculture</b>	% <b>Agriculture</b> , % Others, %

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<b>Natural, exposure to dominant wind</b>	<b>slope, exposure to dominant wind</b>	Low values of: minor road density	Coastal, low and higher elevation, low slope, low housing density,
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