

Exploring the spatial patterns of fire density in Southern Europe using Geographically Weighted Regression



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A B S T R A C T

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The spatial patterns of fire occurrence were analyzed in two regions of Southern Europe, focusing on the long-term factors that influence fire distribution. The relationship between fire occurrence and the physical and anthropogenic variables collected was investigated with Geographically Weighted Regression (GWR) and the results were compared with Ordinary Least Squares (OLS). Local patterns of the significant variables were explored and a strong spatial variability of their explanatory power was revealed. Climate (precipitation), livestock and land cover (shrubland) were found to be significant in both regions, although in particular areas and to different extents. Regarding model performance, GWR showed an improvement over OLS in both regions.

The investigation of the spatial variation in the importance of the main drivers over a broad study area, gives a valuable contribution to the improvement of fire management and prevention strategies, adjusted to the particular conditions of different areas.

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Introduction

Wildland fire is a widespread event that affects many regions of the world (Bowman et al., 2009; Dwyer, Pinnock, Gregoire, & Pereira, 2000; FAO, 2010; Flannigan, Krawchuk, de Groot, Wotton, & Gowman, 2009; Pechony & Shindell, 2010). Although the occurrence of fires largely depends on local factors, such as vegetation cover and land use (Dwyer et al., 2000; Sebastián-López, Salvador-Civil, Gonzalo-Jiménez, & San-Miguel-Ayanz, 2008), their impacts are evident also at global scale, when considering atmospheric emissions, land cover change or ecosystem functions and services (Carvalho et al., 2010; Pechony & Shindell, 2010; Sebastián-López et al., 2008). This global dimension of fires and the need to understand the complex interaction between factors that are not confined to a restricted geographical area, require the assessment of fire occurrence also at regional, continental or global scales (Chuvienco, Giglio, & Justice, 2008; Sá et al., 2011; Sebastián-López et al., 2008).

From a long-term perspective, fire occurrence is assessed considering the average conditions during a certain period of time, in relation to those factors which remain stable for at least one fire

season, such as topography and roads (Jappiot, Gonzalez-Olabarria, Lampin-Maillet, & Borgniet, 2009; San-Miguel-Ayanz et al., 2003). The long-term assessment is suitable to investigate the structural factors that affect the fire proneness of an area, assisting in the definition of prevention strategies and the allocation of fire resources prior to the start of the main fire season (Oliveira, Oehler, San-Miguel-Ayanz, Camia, & Pereira, 2012; San-Miguel-Ayanz et al., 2003).

At the European level, an extraordinary effort has been made in the last decades to compile reliable information on the fire events that affect many countries (Camia, Houston, & San-Miguel-Ayanz, 2010; San-Miguel-Ayanz et al., 2012), to assist in fire prevention and in support of policy-making. Statistics reveal that more than 80,000 fires occur on average a year in Europe, which burn over 500,000 ha of land (European Commission [EC], 2012) and cause extensive damage. The factors that influence fire occurrence differ among European countries and regions, as a result of the diversity of biogeographical features, the physical and anthropogenic conditions across the continent, and due to the fire prevention policies and fire suppression techniques applied at national or local levels (Ganteaume et al., 2013; Montiel & San-Miguel-Ayanz, 2009; Montiel-Molina, 2012; Roekaerts, 2002). Southern Europe, particularly the western countries, where Mediterranean-type climate and vegetation prevail, is the most affected region (Konstantinidis, Tsiourlis, & Galatsidas, 2005; San-Miguel-Ayanz & Camia, 2009; San-Miguel-Ayanz et al., 2009). Furthermore, these trends in fire

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occurrence are expected to be amplified due to ongoing land use and climatic changes, which could cause a substantial increase in the fire-proneness of certain areas and in fire severity, even where fires are currently less relevant (Flannigan et al., 2013; Flannigan, Krawchuk, de Groot, Wotton, & Gowman, 2009; Lindner et al., 2010; Moreira et al., 2011).

Understanding the spatial distribution of fires, its causes and impacts in relation to the specific characteristics of the places where they occur, is crucial for the implementation of efficient strategies of fire prevention and wildland management. The main purpose of this study is, therefore, to contribute to the investigation of the spatial patterns of fire distribution (number of fires) in Southern Europe and uncover the influence of the most important structural factors that drive fire occurrence in the region, with the following objectives:

- i) Analyze the spatial variability of fire occurrence in Southern Europe
- ii) Identify the main factors that influence fire occurrence across Southern European countries
- iii) Assess the consistency of the explanatory power of the variables throughout the study area, exploring the local and regional variations of their significance

Several methods exist to explore the interactions between spatial drivers and fire occurrence; regression methods have been widely used, such as linear and logistic regression (Chuvienco et al., 2010; Oliveira et al., 2012; Sebastián-López et al., 2008) and classification and regression trees (Amatulli, Rodrigues, Trombetti, & Lovreglio, 2006; Archibald, Roy, van Wilgen, & Scholes, 2009; Oliveira et al., 2012). These methods focus on the global picture and follow the assumption of spatial stationarity, which is often violated in real-world situations (Koutsias, Martínez-Fernández, & Allgöwer, 2010; Sá et al., 2011). In broad areas, the level of importance of the variables in explaining fire occurrence is, most likely, not homogeneous throughout the entire study domain (Archibald et al., 2009; Ganteaume et al., 2013). Previous studies suggest that fire assessment models can greatly benefit from the use of analytical methods that capture the spatial attributes of the phenomenon being studied (Koutsias, Martínez, Chuvienco, & Allgöwer, 2005; Koutsias et al., 2010; Kupfer & Farris, 2006; Sá et al., 2011). Geographically Weighted Regression (GWR) (Fotheringham, Brunson, & Charlton, 2002) has been applied in the investigation of fire activity at large scale, namely in Mediterranean Europe (Koutsias et al., 2005, 2010) and in sub-Saharan Africa (Sá et al., 2011). GWR allows for regression coefficients to vary for individual locations, capturing the effects of non-stationarity and revealing variations in the importance of the variables across the study area, focusing particularly on data analysis and interpretation, rather than prediction.

Considering the variety of fire data collection structures among countries and the difficulty in obtaining a robust model for the whole of Southern Europe, the study area was further divided in two regions, as described in the following section. OLS and GWR were applied separately in each region and the results compared. The resulting maps are expected to give an overview of the spatial patterns of fire occurrence and its main drivers throughout both regions, providing indications of the variations in the importance of the explanatory variables according to their spatial location.

Material and methods

Study area

This study was carried out for the countries of Southern Europe which are part of the European Forest Fire Information System

(EFFIS) network (Camia, Houston, & San-Miguel-Ayanz, 2010; San-Miguel-Ayanz et al., 2012) with a minimum period of data available (at least 6 years). In spite of the harmonized standards already in place, the data collection structures differ among countries (San-Miguel-Ayanz et al., 2012); country data is gathered by the national fire or civil protection services and the information collected depends, to a certain extent, on the resources available in the countries, which vary widely within the European territory. Thus, although European countries have been gathering fire data for several decades, an inclusive transnational coordination on data collection and harmonization is an ongoing effort. For this reason, and after an exploratory analysis of the data, the available countries were grouped in 2 regions: Southwestern Europe (SW Europe) and Southeastern Europe (SE Europe) (Fig. 1). Greece is usually considered part of Southwestern Europe, however our exploratory analysis showed that Greece evidenced similar patterns to the countries of Southeastern Europe regarding fire density and frequency, hence it was included in this region instead; for the same reason, the Balkan countries with available data were included in Southeastern Europe, despite the geographical gap. For France, only the southern provinces, where fire frequency is similar to the remaining countries, were included in Southwestern Europe.

Data collection and processing

Response variable

The probability of fire occurrence results from the joint combination of an ignition source and the conditions for fire to spread (Jappiot et al., 2009; Oliveira et al., 2012); to represent ignitions, we obtained the number of fires recorded in the European Fire Database for each country (Camia, Durrant-Houston, & San-Miguel-Ayanz, 2010; European Commission, 2012). This database compiles and harmonizes fire records from the participating countries since the 80's, the starting year varying according to country; for each individual fire event, specific information is added by the Forest Department and Civil Protection Services of the Member-States, such as the date of the fire, the type of land cover affected, the burned area size, and the administrative region where it occurred, usually a descriptive location at NUTS3 level (corresponding in most countries to the level of provinces), whereas accurate geo-referencing of the fires is lacking for the most part. The number of fires recorded was aggregated at NUTS3 level for each country, for the period 1996–2010 when available, or the longest time-series of the country (at least 6 years). In view of the geo-location uncertainty associated with the fire records, fire density (number of fires/area km²) was used as a proxy of fire ignition. The calculation of fire density follows a similar procedure to the one used by Oliveira et al. (2012), thus only a brief explanation is presented here.

The fire events with accurate geo-referencing available in the database, for several countries, were used for an exploratory analysis of the proportion of fires occurring in different land cover types, as defined by the Corine Land Cover 2000 map (EEA-ETC/TE, Joint Research Centre [JRC], 2002). From this analysis, the land cover types associated with fire occurrence were aggregated in 2 main categories: wildland and non-wildland areas. Wildland areas include those land cover categories where fires are more likely to occur due to their typical vegetation cover, such as forests, shrublands and grasslands. Non-wildland areas, on the other hand, are those land cover types where a proportion of the fires can occur (or at least start), although their conditions are not typically related to the occurrence of wildland fire, such as agro-forestry areas. The land cover categories with a negligible contribution to fire occurrence, such as water bodies and continuous urban surfaces, as well as areas with elevation above 2000 m, were excluded. It was found

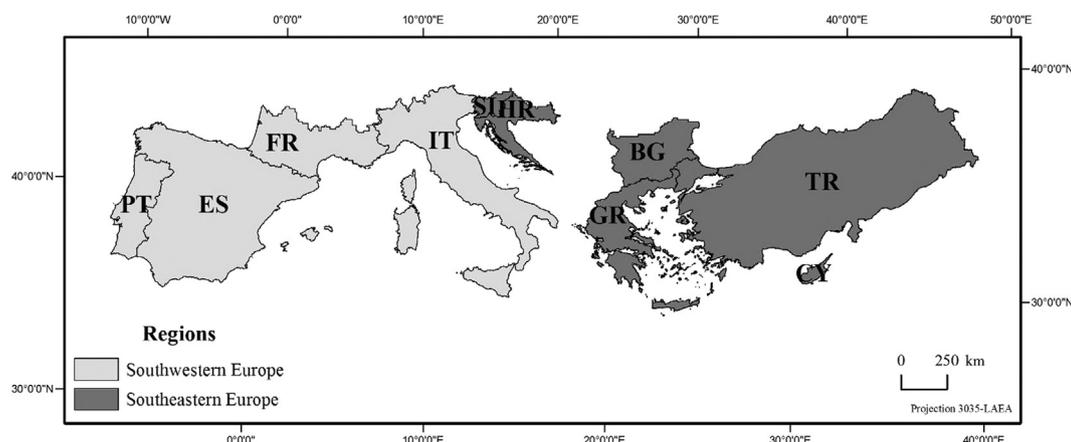


Fig. 1. Study area, with the countries grouped in 2 regions: Southwestern Europe–PT (Portugal), ES (Spain), FR (South France) and IT (Italy). Southeastern Europe–SI (Slovenia), HR (Croatia), BG (Bulgaria), GR (Greece), TR (Turkey) and CY (Cyprus). The missing countries in Southern Europe did not have data available matching the criteria defined.

that, in general, 65% of the fires occur in Wildland areas and 35% in Non-Wildland areas; these proportions were then used to transform the statistical-based data into a gridded format, by distributing 65% of the average number of fires per NUTS3 in each country in wildland areas and 35% in non-wildland areas. A reference grid available for Europe at 10 km, the selected spatial resolution (EEA, 2011), was superimposed and the number of points falling in each 10×10 km grid cell was counted. Fire density corresponds to the mean annual number of fires per unit area (km^2), adjusted by the fire domain, i.e., the land area of that grid cell where fires could potentially occur, corresponding to the wildland and non-wildland areas previously identified and excluding those land cover types (such as water bodies, bare rocks and urban areas, among others) where wildland fires are not present (Oliveira et al., 2012).

Diagnostic tests were applied to the data and evidence of dissimilar variances was found; a log-transformation was applied to the dependent variable to approximate the values to a normal distribution. Each log value was then subtracted from the mean value of the region, yielding a response variable that corresponds to a deviance in relation to the average of the corresponding region, as follows:

$$NF = nf - \text{reg}(nf)$$

With nf being the log of fire density of each cell and $\text{reg}(nf)$ the average log (fire density) for the corresponding region, either Southwestern or Southeastern Europe.

Explanatory variables

The explanatory variables were selected according to two main criteria: their potential relation with fire occurrence and their availability for a minimum period of time suitable for long-term analysis. Considering that nearly 95% of fires in the southern Mediterranean region result from human activity (e.g. Leone, Lovreglio, Martín, Martínez, & Vilar, 2009; Romero-Calcerrada, Barrio-Parra, Millington, & Novillo, 2010; San-Miguel-Ayanz & Camia, 2009), the human component is of major importance in the study area; both physical and anthropogenic variables were, thus, collected (Table 1) and transformed to a continuous scale at 10 km resolution; one value per grid cell was retrieved, using the reference grid.

Land cover. Land cover characterizes the distribution of land features related to nature, such as forests, water bodies or bare rocks, but also heterogeneous features that include the influence of

human activities, for example urbanized and crop areas, as represented by Corine Land Cover (Heymann, Steenmans, Croissille, & Bossard, 1994). This database is harmonized at European level and the classification incorporates as well human elements within its categories; bearing in mind the anthropogenic influence in fire activity in Southern Europe, and due to the lack of a harmonized fuel map at European level, land cover is here used as a surrogate for burnable vegetation types.

Previous studies have found an association between land cover and fire occurrence (e.g. Martínez, Vega-García, & Chuvieco, 2009; Oliveira et al., 2012; Syphard et al., 2008; Vilar, Woolford, Martell, & Martín, 2010). Certain land cover types are expected to have a positive correlation with fire occurrence, such as grassland, shrubland and forest; on the contrary, a high proportion of agricultural land is expected to have a negative association with fire occurrence (Carmo, Moreira, Casimiro, & Vaz, 2011; Moreira, Vaz, Catry, & Silva, 2009; Nunes et al., 2005; Oliveira, Moreira, Boca, San-Miguel-Ayanz, & Pereira, 2013). From the aggregation of Corine classes, six different variables were obtained, each corresponding to a specific aggregation of land cover or vegetation categories where wildland fires may occur (Table 1).

Topography. The topographic features affect the spatial patterns of vegetation, its composition and flammability, besides influencing the local climatic conditions (Syphard et al., 2008; Whelan, 1995). Elevation, slope and aspect were retrieved from the DEM at European level (Jarvis, Reuter, Nelson, & Guevara, 2008; Reuter, Nelson, & Jarvis, 2007) and transformed to classes, as shown in Table 1. The proportion of the different topographic classes in each grid cell was then retrieved. In total, 12 variables were obtained. Higher proportions of lower elevation and lower slope classes are expected to have a positive influence in fire occurrence, due to the presence of vegetation and the better accessibility of these areas to anthropogenic ignition agents (Moreira et al., 2009; Oliveira et al., 2013).

Climate. Temperature and precipitation are recognized as being strong determinants of fire occurrence, because they directly affect vegetation growth rates and moisture (e.g. Bowman et al., 2009; Bravo, Kunst, Grau, & Aráoz, 2010; Syphard et al., 2008; Vilar, Woolford, et al., 2010), thus influencing the likelihood of fire start and spread. Ensembles of daily gridded observational dataset from the E-OBS dataset (Haylock et al., 2008) were retrieved for the period 1995–2011. We selected this dataset due to its availability at European scale and because the time-series of the climatic variables matched the overall period of analysis of the fire data. Average

Table 1
Explanatory variables used in the model and their sources.

Variable type	Variable name	Code	Resolution/ scale	Source/reference	Description
Land Cover	Forest	forest	Raster 100 m	CLC 2000/2006 EEA-ETC/TE, JRC, 2002	Proportion of each land cover type in each grid cell. Forest = 23–25; Shrubland = 27–29; Grassland = 18, 26; Other natural areas = 21–22, 32–33; Agricultural areas = 12, 15–17, 19–20; WUI = 2
	Shrubland	shrub			
	Grassland	grass			
	Other natural areas	other_nat			
	Agricultural areas	agric			
	Wildland Urban Interface	wui			
Topographic	Elevation 0–500 m	elev0_500	Raster 100 m	DEM Europe Jarvis et al. 2008; Reuter et al. 2007	Proportion of each elevation class per grid cell
	Elevation 500–1000 m	elev500_1000			
	Elevation 1000–1500 m	elev1000_1500			
	Elevation above 1500 m	elev_ab1500			
	Slope 0–10%	slope0_10			Proportion of each slope class per grid cell
	Slope 10–20%	slope10_20			
	Slope 20–30%	slope20_30			
	Slope above 30%	slope_ab30			
	Aspect N (315–45 deg)	aspect_N			Proportion of each aspect class per grid cell
	Aspect E (45–135 deg)	aspect_E			
Aspect S (135–225 deg)	aspect_S				
Aspect W (225–315 deg)	aspect_W				
Climatic	Average maximum temperature June–October	tmax_fs	0.25 deg (28 km)	E-OBS 1995–2011 Haylock et al. 2008	Downscaled based on inverse distance weighted interpolation, assuming that the values of the closest stations are more alike than those that are farther apart.
	Average maximum temperature other months	tmax_nfs			
	Cumulative precipitation June–October	prec_fs			
	Cumulative precipitation other months	prec_nfs			
Infrastructure	Density highways	highway	1/100.000	TeleAtlas, 2007	Length/km ² - Level 00 Length/km ² - Levels 01–03
	Density main roads	main_road			
	Density local roads	local_road	Vector	Platts, 2006 (IET support, Petten)	Length/km ² - Levels 04–06 Length/km - transmission lines
	Density electric lines	electric			
Demographic	Average population density	popdens	100 m	Gallego, 2010 Gallego, Batista, Rocha, & Mubareka, 2011 Eurostat (TR)	Aggregated at 10 km based on average
	Intermediate urban areas	urban	1:3 million	Eurostat, GISCO 2001	Proportion of intermediate urban area in each grid cell
Livestock	Density of cattle	cattle	NUTS3	Eurostat regional statistics (agriculture), 2010	Average number of animals per km ² of the total agricultural land. Adjusted rate based on proportion of NUTS3 in each cell
	Density of goats	goat			
	Density of sheep	sheep			

maximum temperature and precipitation were the variables retrieved, at a resolution of 0.25° (approx. 28 km). Temperature and precipitation values were divided into two seasons: June–October and the remaining months. The June–October season (here called summer) represents the hottest and driest months in Southern Europe, when high values of precipitation are unusual but will have a negative influence in fire occurrence by increasing fuel moisture content, whereas temperatures are usually high and will reduce the moisture content of vegetation; on the other hand, precipitation in the other months (non-summer) is likely to favor vegetation growth and increase the availability of fine fuels, thus having a positive association with fire occurrence (Flannigan et al., 2013; Meyn, White, Buhk, & Jentsch, 2007; Oliveira et al., 2012; Pausas, 2004; Pereira, Trigo, Dacamara, Pereira, & Leite, 2005).

Infrastructure. Roads have been pointed out as influencing factors of fire occurrence (Cetry, Rego, Bação, & Moreira, 2009; Martínez et al., 2009; Oliveira et al., 2012; Romero-Calcerrada, Novillo, Millington, & Gomez-jimenez, 2008; Vilar, Woolford, et al., 2010), as it is associated with the accessibility of the area to human ignition agents. The road network data from Tele Atlas (Tele Atlas, 2007) was used to calculate road density, defined as road length per unit area. Density of power lines was also included, assuming

the possibility of electric discharges causing ignitions (European Commission, 2012; Vasilakos, Kalabokidis, Hatzopoulos, & Matsinos, 2008).

Demographic. The effect of demographic factors on fire occurrence can be two-fold: on the one hand, high population densities increase the possibility of human-caused ignitions; on the other hand, they also contribute to reduce fuel availability and change vegetation patterns, resulting in decreased fire occurrence (Archibald, Nickless, Govender, Scholes, & Lehsten, 2010; Bistinas et al., 2013; Sá et al., 2011). Population density per cell was, thus, included as a variable in the model.

The proportion of intermediate urban areas (EUROSTAT, 2001) in each cell was also retrieved, because it indicates areas of urban sprawl, adjacent to densely urbanized ones, with relatively high number of ignition agents (at least 50,000 people), good accessibility and an intermediate level of human activity.

Livestock. Livestock was disaggregated by type of animal, considering their diverse characteristics and based on results from previous studies. On the one hand, the abundance of goat and sheep was found to correlate with the absence of fire ignitions (Romero-Calcerrada et al., 2008; Sebastián-López et al., 2008), because these

species feed on grass and bushes and reduce the amount of vegetation available, particularly fine fuels. On the contrary, other studies have identified livestock density as being positively correlated to fire occurrence (Koutsias et al., 2010; Martínez et al., 2009; Oliveira et al., 2012), probably due to burning activities for pasture renovation. Data on cattle, sheep and goat, associated with outdoor farming activities and pasture management, were obtained as individual variables.

Methods

Collinearity among explanatory variables was assessed, in a first stage, by calculating the Pearson product–moment correlation. Correlation coefficients above 0.7 were used as a criterion to remove variables. Explanatory variables with a negligible relationship with the response variable were also removed. In a second stage, the variance inflation factor (VIF), which quantifies how much an estimated regression coefficient increases due to multicollinearity, was calculated for the remaining variables, using R Statistical Software (R Development Core Team, 2011). Only the explanatory variables with VIF values close to 1 were included. This procedure was applied to each region separately.

Geographically Weighted Regression. This method has been explained in detail by several authors (Fotheringham et al., 2002; Koutsias et al., 2010; Sá et al., 2011; Wang, Ni, & Tenhunen, 2005), thus only a brief description of its application to our dataset is presented here.

Relationships between fire density and the explanatory variables were derived for each region separately. GWR (version 3.0, Fotheringham et al., 2002) was applied to each region and a comparison with the performance of the Ordinary Least Squares (OLS) model was done. While OLS assumes stationarity and calculates the coefficients for the global model, GWR allows verifying if the relationships between the response variable and the explanatory variables vary in space, by calculating regression coefficients at each individual location (Fotheringham et al., 2002; Koutsias et al., 2010; Sá et al., 2011). These studies have shown the better performance of the GWR model in relation to OLS with fire occurrence and incidence data, thus the results presented are mainly to provide indication of the general influence of the explanatory variables over the region. The bandwidth, which is the distance radius around each observation point that comprises the observations to be used in the weighting matrix (Fotheringham et al., 2002), in this case a fixed distance since the grid cell values are equally spaced at 10 km, was obtained by minimizing the corrected Akaike information criterion (AICc) in each region. The local statistical significance of the coefficient estimates was assessed with a *t*-test and the distribution of the significant variables and the values of R^2 , which give indication of the model fit in each cell, were mapped using GIS tools. The level of importance of the variables, in explaining the distribution of the dependent variable, was obtained from the highest absolute *T*-value found in each cell.

To reduce the degree of dependency rate that results from the use of the same dataset to calibrate the model and control the family-wise error rate from the multiple hypotheses testing, the significance levels of *T*-values were adjusted using the formula provided by Byrne, Charlton, and Fotheringham (2009).

Spatial autocorrelation. Spatial autocorrelation was analyzed to determine whether the GWR model accounts for the spatial structure of the dependent variable and if it represents an improvement in relation to OLS, by showing a reduction in the spatial autocorrelation of the residuals (Koutsias et al., 2010; Sá et al., 2011).

The presence of spatial autocorrelation in the model residuals was tested by building semivariograms, which plot the semi-variance as a function of distance, and by analyzing clumping of model residuals.

Results

Fire density

Mean annual fire density varies largely among countries and regions in Southern Europe, as shown in Fig. 2, which represents the original values of fire density (non-transformed). The highest values are concentrated in northwest of Iberia, while the eastern part of Southeast region generally evidences lower values of fire density.

Explanatory variables

High correlation values were found between the explanatory variables of different categories and within the same category, particularly land cover, topography and climate. Some of the explanatory variables also showed low correlation with the dependent variable. From the initial set of 32 variables, 12 were selected for Southwestern Europe and 16 for Southeastern Europe (Fig. 3), based on the correlation with the response variable and the absence of collinearity with other predictors.

The explanatory variables selected were slightly different between the two regions; in Southwestern Europe, the wildland–urban interface (wui) was highly correlated to population density and temperature with slope, while in Southeastern Europe this was not observed, thus the latter model included a higher number of explanatory variables.

Global model of fire occurrence

The global model for Southwestern Europe explained 37% of the variance, while for Southeastern Europe this value was only 13% (Table 2). It is evident that the global models do not capture entirely the influence of the variables, particularly for Southeastern Europe where the adjusted R^2 value is very low.

The parameters estimates and *T* values provide, nevertheless, an overall indication of the most important variables and the direction of the association. For both regions, precipitation of the non-summer season showed the higher *T* values and a positive association, followed by topographic and livestock variables (Tables 3 and 4). In Southwestern Europe, slope 0–10% is the second most important variable, with a positive relationship, while in Southeastern Europe elevation 0–500 m shows the second highest *T* value, also with a positive direction. Cattle and goat density come next for Southwestern Europe, with a positive association, whereas for Southeastern Europe, goat density presents a negative relationship with the dependent variable.

GWR and local variations of variable influence

The results obtained with GWR showed a significant improvement in relation to OLS in both regions, although at different levels (Tables 5 and 6). For Southwestern Europe, the GWR model performs better than for Southeastern Europe, with the R^2 values reaching 82% and 47%, respectively.

The R^2 values show a dissimilar distribution within each region (Fig. 4). In SW Europe, the higher values are concentrated in the Western Iberian Peninsula and northwest Italy. The eastern part of Spain and northeast Italy show lower values, below 0.2.

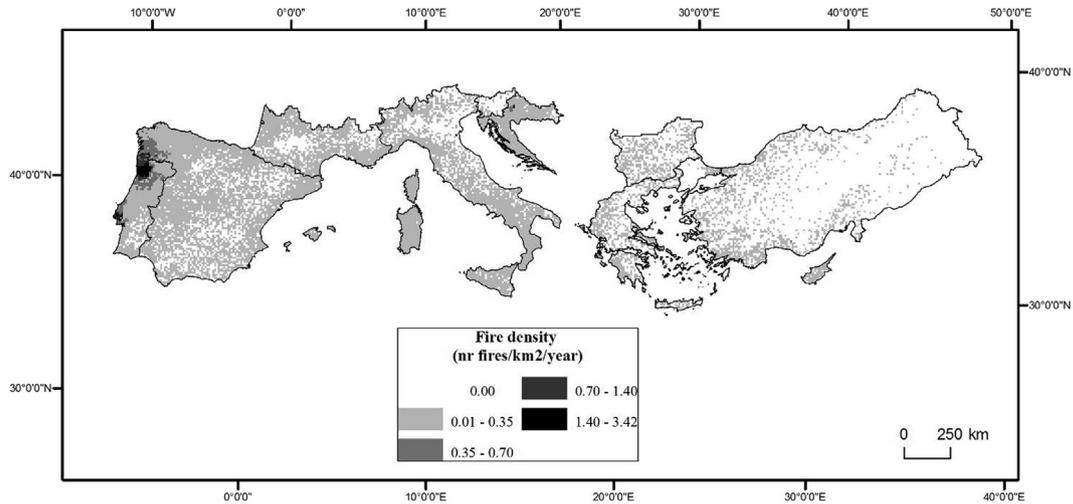


Fig. 2. Mean annual fire density in the study area (original values, before log transformation).

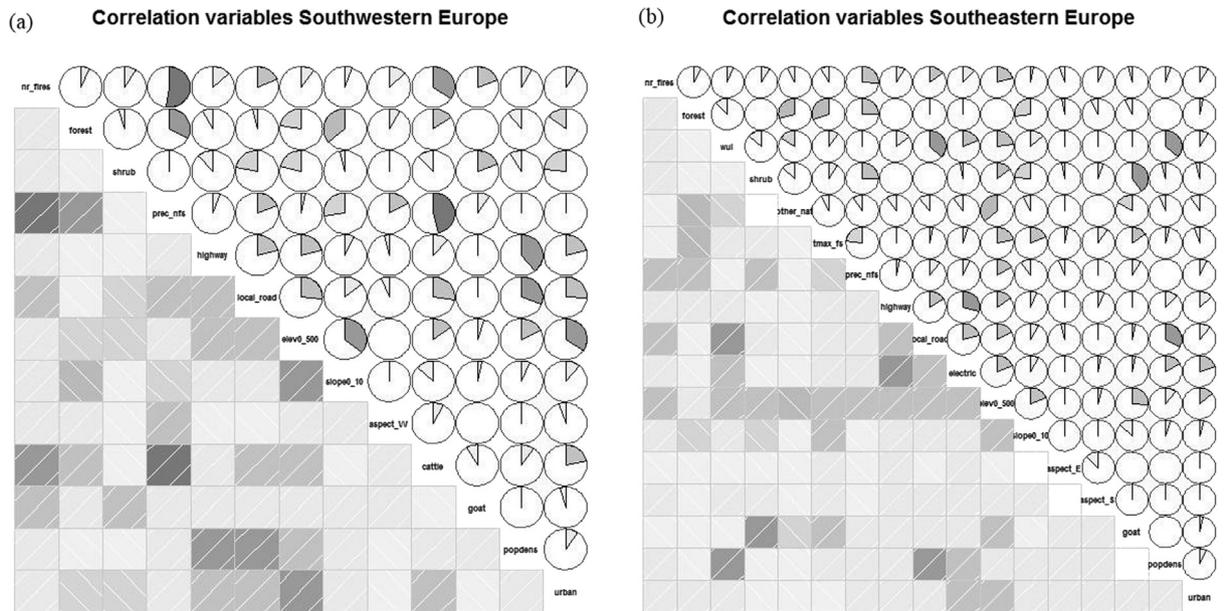


Fig. 3. Correlograms of the response variable and the explanatory variables in each region (SW Europe on top, SE Europe at the bottom). The position of the filled part of the pie graphs on the right shows the direction of the association: to the right is a positive association, to the left is negative. The squares on the left show the degree of correlation, darker shade means higher value (Wright, 2011).

In SE Europe, the spatial distribution of R^2 values show a general decreasing trend from West to East, with the Balkan countries showing the highest values, although below 0.5, and eastern Turkey the lowest R^2 . Cyprus shows higher values, similar to those found for the Balkan countries.

Table 2
Results of the OLS model for the two regions.

Parameters OLS	SW Europe	SE Europe
Nr observations	11,324	12,133
Residual sum of squares	17.663	2.270
Effective number of parameters	13	17
Sigma	0.040	0.040
Akaike information Criterion	-41,025	-69,682
Coefficient of determination	0.371	0.130
Adjusted r -square	0.370	0.129

Note: Sigma refers to the standard error of the estimate.

Table 3
Parameter estimates and VIF values of the OLS model for Southwestern Europe.

Variables	Estimate	Std error	T	VIF
Intercept	-0.152	0.004	-42.137	
forest	-0.10	0.002	-5.652	1.295
shrub	0.030	0.002	13.113	1.176
prec_nfs	0.000	0.000	51.729	1.544
highway	0.065	0.008	7.897	1.250
local_road	0.004	0.001	3.433	1.339
elev_500m	-0.005	0.001	-4.998	1.422
slope0_10perc	0.072	0.003	21.232	1.376
aspect_W	0.028	0.005	5.922	1.053
cattle	0.000	0.000	18.391	1.428
goat	0.000	0.000	18.361	1.083
popdens	0.000	0.000	2.729	1.284
urban	0.007	0.001	4.750	1.268

Table 4
Parameter estimates and VIF values of the OLS model for Southeastern Europe.

Variables	Estimate	Std error	T	VIF
Intercept	−0.006	0.002	−3.089	
forest	0.001	0.001	1.402	1.453
wui	−0.003	0.002	−1.411	1.394
shrub	0.006	0.001	7.139	1.399
other_nat	0.001	0.001	1.492	1.374
tmax_fs	0.000	0.000	−7.574	1.287
prec_nfs	0.000	0.000	20.059	1.261
highway	0.016	0.006	2.753	1.132
local_road	0.007	0.001	9.501	1.281
electric	0.007	0.001	6.019	1.195
elev0_500m	0.006	0.000	17.232	1.444
slope0_10perc	0.003	0.001	2.446	1.282
aspect_E	−0.003	0.001	−2.580	1.027
aspect_S	0.007	0.001	6.253	1.035
goat	0.000	0.000	−11.999	1.305
popdens	0.000	0.000	−0.412	1.230
urban	0.004	0.001	2.764	1.077

To assess the levels of significance, p -values were corrected according to the formula used by Byrne et al. (2009) and Sá et al. (2011), with $p = 0.000080$ and $p = 0.000247$ for SW and SE Europe respectively, for $\alpha = 0.05$. The number of significant variables, assessed with the corrected p -values, generally decreases from West to East in both regions, identical to the pattern verified for the levels of R^2 , with the western part showing a higher number of significant explanatory variables in relation to the remaining area, although some clusters can be found throughout the regions. The maximum number of significant variables in SW Europe is higher than for SE Europe, even though the latter included more explanatory variables in the model. In 67% of the area in SW Europe, no significant variable was found, 13% has 1 significant variable and 12% from 2 to 5 variables. In SE Europe, 50% of the region has no significant variable, 30% has 1 significant variable and 12% from 2 to 5 significant variables (Fig. 5).

Regarding the most important variables, non-summer precipitation, goat density and proportion of forest and shrubland appear in both regions as the most significant parameters in specific areas (Fig. 6). Goat density and precipitation together cover over 55% of the area in SW Europe where there is at least 1 significant variable, whereas in SE Europe this proportion increases to 66%. The influence of precipitation is mostly concentrated in Northern Portugal and East of Spain in SW Europe, and in SE Europe all over Greece and in the SW of Turkey. Goat density is more significant in NW Spain, Sardinia, in Italy and in central-south of Turkey.

In the northwest of the Iberian Peninsula (SW Europe), where higher values of R^2 were found, the effects of precipitation and goat density are particularly evident, both with a positive association with fire occurrence. Cattle and population density also appear locally as the most significant parameter in this region, covering, respectively, 15 and 12% of the area where there is at least 1 significant variable. In SE Europe, local roads cover 17% and highway 7% of the region. The proportion of shrubland covers around 5% and

Table 5
GWR parameters obtained for the two regions.

Parameters GWR	SW Europe	SE Europe
Nr observations	11,324	12,133
Bandwidth (in meters)	58,533	148,086
Residual sum of squares	4.731	1.373
Effective number of parameters	628	202
Sigma	0.040	0.040
Akaike information Criterion	−54,639	−75,404
Adjusted r -square	0.821	0.465

Table 6
ANOVA results with the comparison of OLS and GWR models for the two regions.

ANOVA	SW Europe	SE Europe
GWR improvement Mean Square	0.021	0.005
GWR residuals Mean Square	0.000	0.000
F-value (ANOVA)	47.537	42.116

7% of the area with significant variables in SW and SE Europe, respectively.

The direction of the association between fire density and the significant factors shows an interesting spatial variation; in SW Europe, goat density has a positive correlation with fire density, whereas in Turkey (SE Europe), some areas show goat density having a negative association with the dependent variable. Forest shows a negative relationship with fire density in both regions, whereas shrubland has a positive association.

Spatial autocorrelation

The spatial distribution of residuals for the OLS models reveals clustering, whereas for GWR the spatial pattern evidences a less structured distribution (Figs. 7 and 8). The semivariograms (Fig. 9) indicate spatial autocorrelation for the dependent variable up to 700 km lag, with the semivariance decreasing afterwards up to 1500 km, beyond which it increases again. The GWR model showed lower values of semivariance, as well as a flat semivariance line throughout most of the distance, up to 1500 km lag. This holds true particularly for SW Europe, while for SE Europe none of the models shows an effective decrease in the spatial autocorrelation of the residuals, although semivariance values for GWR are lower than for OLS.

Discussion

GWR and OLS performance

Fires occur throughout Southern Europe, although with strong spatial variability and under the influence of different factors. The application of a method that captures local variations in the influence of the explanatory variables revealed major improvements in relation to global models, when applied at broad scale. Our results suggest that GWR performs better than OLS in modeling fire occurrence overall, in spite of the different levels of model fit dependent on the area. These results agree with previous studies, which showed the potential of GWR for modeling fire occurrence at a large scale (Koutsias et al., 2010; Sá et al., 2011). GWR also seemed to deal better with spatial autocorrelation in the residuals, although the method does not address this issue directly (Koutsias et al., 2010). This means that the spatial patterns of the dependent variable could be explained by the spatial patterns observed in the explanatory variables included in the model (Dormann et al., 2007; Legendre & Legendre, 2012). The geographical discontinuities in Southeastern Europe, a region made of many islands, a convoluted coastline and spatial gaps, may partially explain the less powerful effect of GWR in addressing spatial autocorrelation. Nevertheless, GWR showed lower autocorrelation values in the residuals and a more random spatial distribution in both regions, in comparison to OLS.

Variable importance at global level

At a global level, OLS revealed the importance of the climatic variables in both regions, particularly non-summer precipitation, to

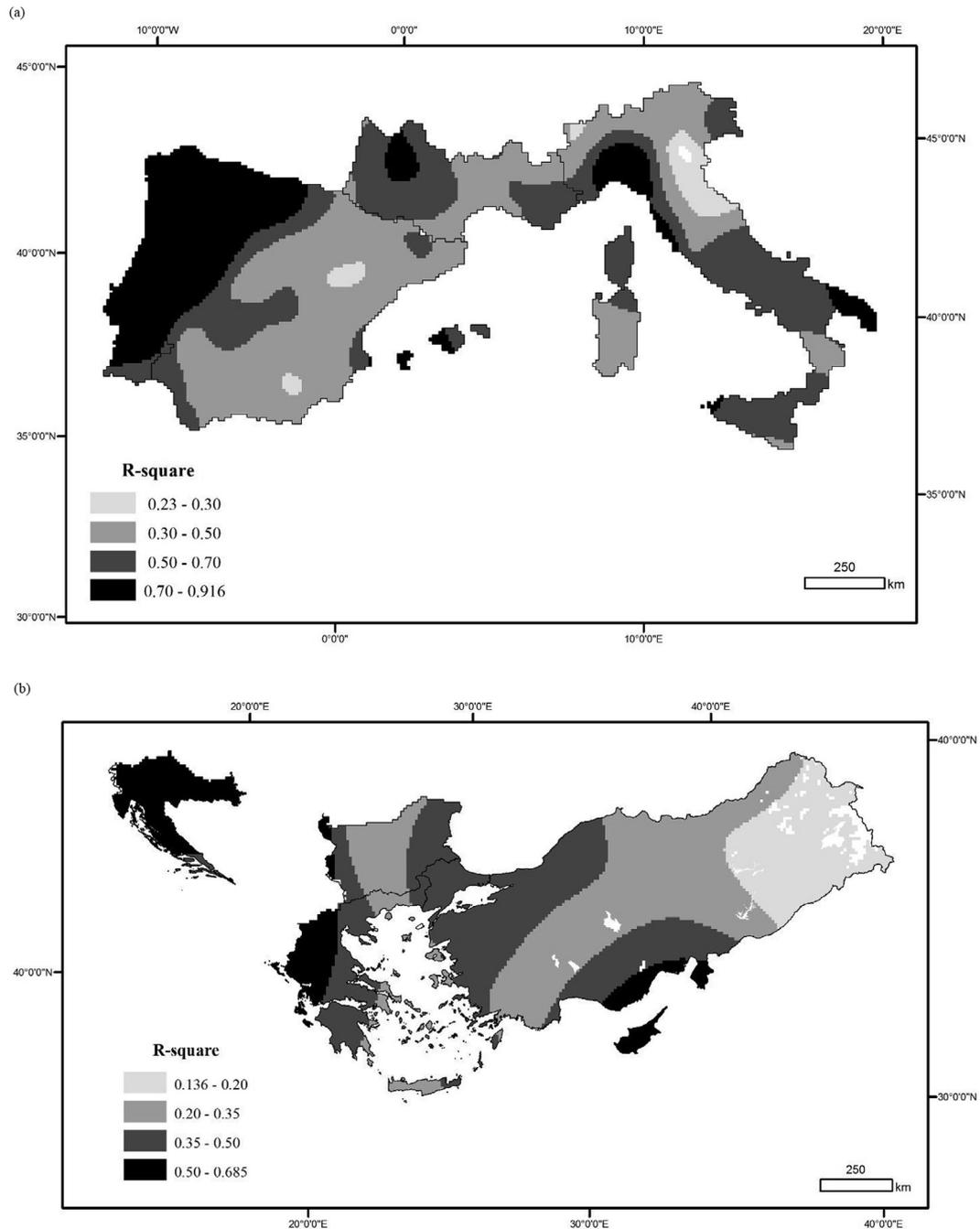


Fig. 4. Distribution of GWR local R^2 values in Southwestern Europe (a) and Southeastern Europe (b).

explain fire occurrence. The strong association between fire and precipitation has been previously indicated (Bravo et al., 2010; Carvalho et al., 2010; Cary et al., 2006; Drever, Drever, Messier, Bergeron, & Flannigan, 2008; Oliveira et al., 2012; San-Miguel-Ayaz, Moreno, & Camia, 2013). Our results suggest that precipitation in the winter months may contribute to the growth of vegetation and to an increase in fuel loads that will be available to burn in the dry season, as mentioned as well by Pausas (2004) and Moreno et al. (2011). The importance of the lower elevation and slope values is most likely related to the accessibility of the areas to ignition agents, indicating the contribution of anthropogenic variables for fire occurrence; other authors have also suggested a strong association between fire occurrence and human access to the

landscape (Conedera et al., 2011; Oliveira et al., 2013; Romero-Calcerrada et al., 2010).

The human influence on fires in Southern Europe is further confirmed by the significance of livestock variables; on one hand, the positive association of cattle and goat density verified in Southwestern Europe suggests the influence of agricultural activities in fire occurrence, possibly related to burning for pasture management, a relationship found as well in previous studies (Carmo et al., 2011; Ganteaume et al., 2013; Koutsias et al., 2010; Martínez et al., 2009; Nunes, 2012). In Southeastern Europe, on the other hand, the association with goat density is negative in particular areas in Turkey, possibly related to overgrazing by goats in this region, where grasslands are the most frequent land cover

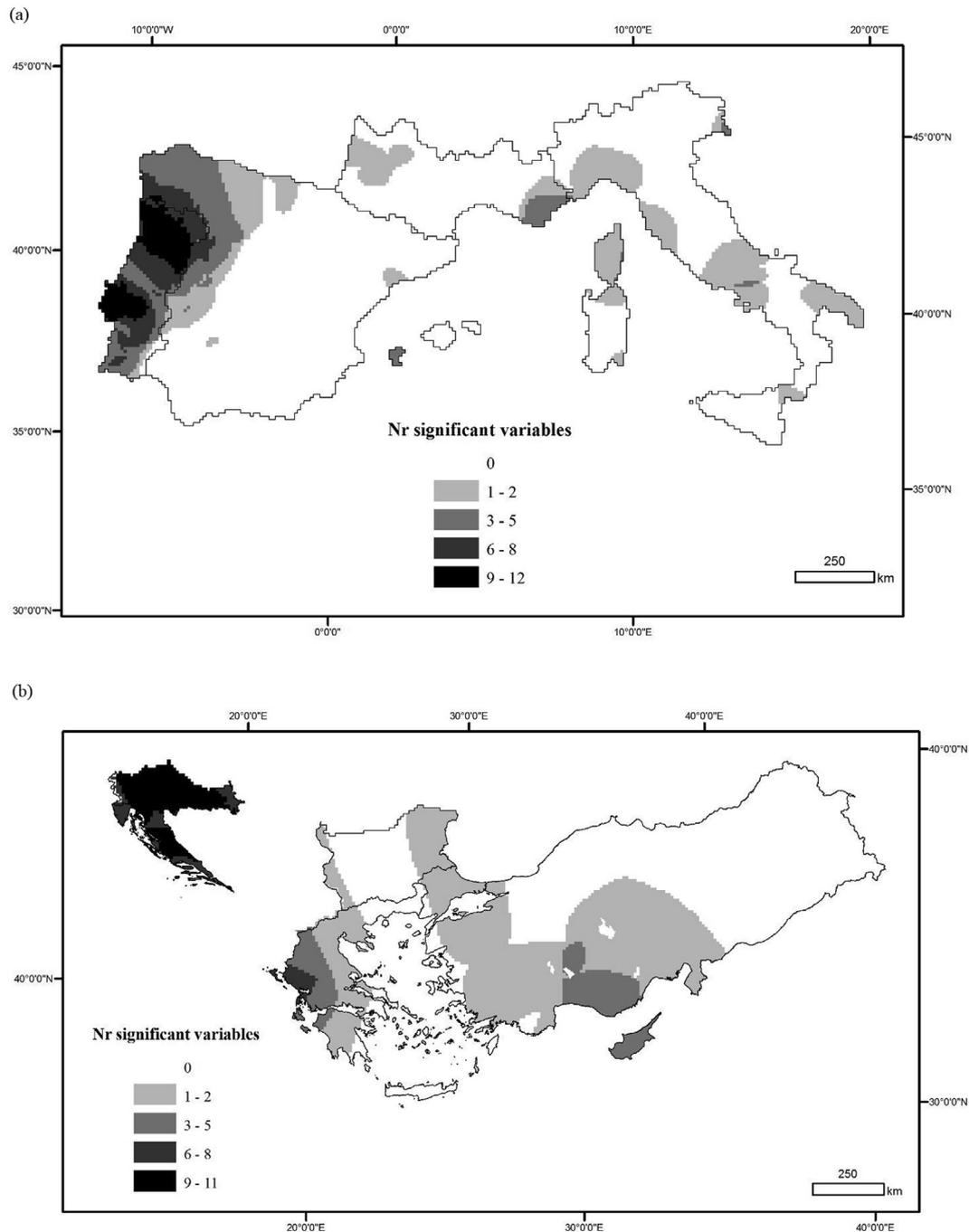


Fig. 5. Number of significant variables per cell in Southwestern Europe (a) and Southeastern Europe (b).

type (EEA, 2012; Roekaerts, 2002); the abundance of goats reduces the amount of fine fuels available to burn, similarly to what has been reported for other areas by Romero-Calcerrada et al. (2008) and Sebastián-López et al. (2008).

Local and regional variations in variable importance

The GWR model uncovered strong spatial variability in the explanatory power of the variables throughout the study area. The significance of the variables common to SW and SE Europe, namely non-summer precipitation, goat density and proportion of shrubland, varies within each region. These results confirm the influence of climatic, vegetation-related and human activities (agriculture)

on fire occurrence in different regions (Bowman et al., 2009), although at different extents. Besides the strong relationship of fire with precipitation and livestock activities, previously explained, shrubland has also been associated with fire and, in some studies, was considered more fire-prone than forests (Carmo et al., 2011; Mermoz, Kitzberger, & Veblen, 2005; Moreira et al., 2009; Nunes et al., 2005; Oliveira et al., 2013), thus the positive association with fire occurrence is somewhat expected.

In SW Europe, also population density was found to be significant in specific areas, evidencing the relevance of human-caused ignitions in this region, as pointed out as well by other authors (Leone et al., 2009; Nunes, 2012; Romero-Calcerrada et al., 2010; San-Miguel-Ayanz et al., 2013; Vilar, Nieto, et al., 2010).

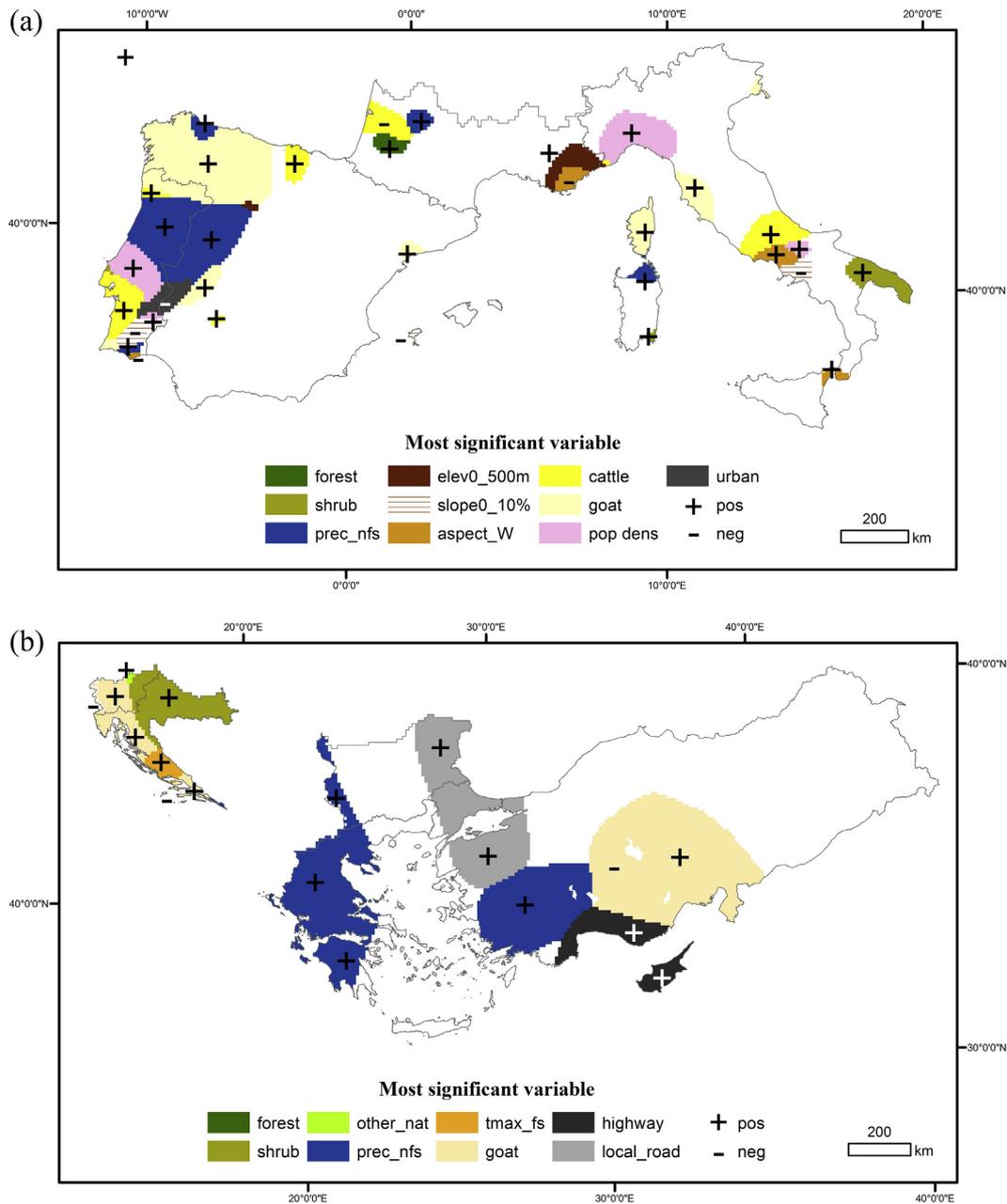


Fig. 6. The most significant variable in Southwestern Europe (a) and Southeastern Europe (b). The level of significance was retrieved by the highest absolute T value of the variables in each cell. The symbols show the positive (+) or negative (–) association with fire density.

In SE Europe, the significance of transportation infrastructure, namely local roads in the north of Turkey and highways in parts of southern Turkey and Cyprus, is a surprising result and difficult to explain. Highway density is rather low in the country and the values of fire density are also generally low in the area. As such, even a slight increase in roads density, which may represent an increase in accessibility, may correlate statistically to higher values of fire density.

Implications of country-specific conditions

Although long-term assessment of the spatial determinants of fire density implies the use of averaged values, it is clear that the results obtained partly reflect the influence of extreme fire seasons, occurred particularly in SW Europe during the study period.

Portugal is one of the most affected countries in this region (Carvalho et al., 2011; European Commission, 2012; San-Miguel-Ayanz et al., 2013) and the summer of 2003 and 2005 were particularly difficult with extensive damages, caused by several large fire events due to the extreme climatic conditions (Pereira et al., 2005; Trigo et al., 2006). Furthermore, since the dependent variable was derived from statistical databases compiled originally at national levels, data compatibility issues may arise, which hinder the application of a suitable model at a broad scale. The results of the model, whose performance favors particular areas, can partially be a result of the data idiosyncrasies, as for example, with Portugal having more fire events and more data available than the other countries. The availability of reliable and harmonized data at global level is, indeed, one of the limitations of broad-scale studies. Moreover, the GWR model showed, in both regions, large areas

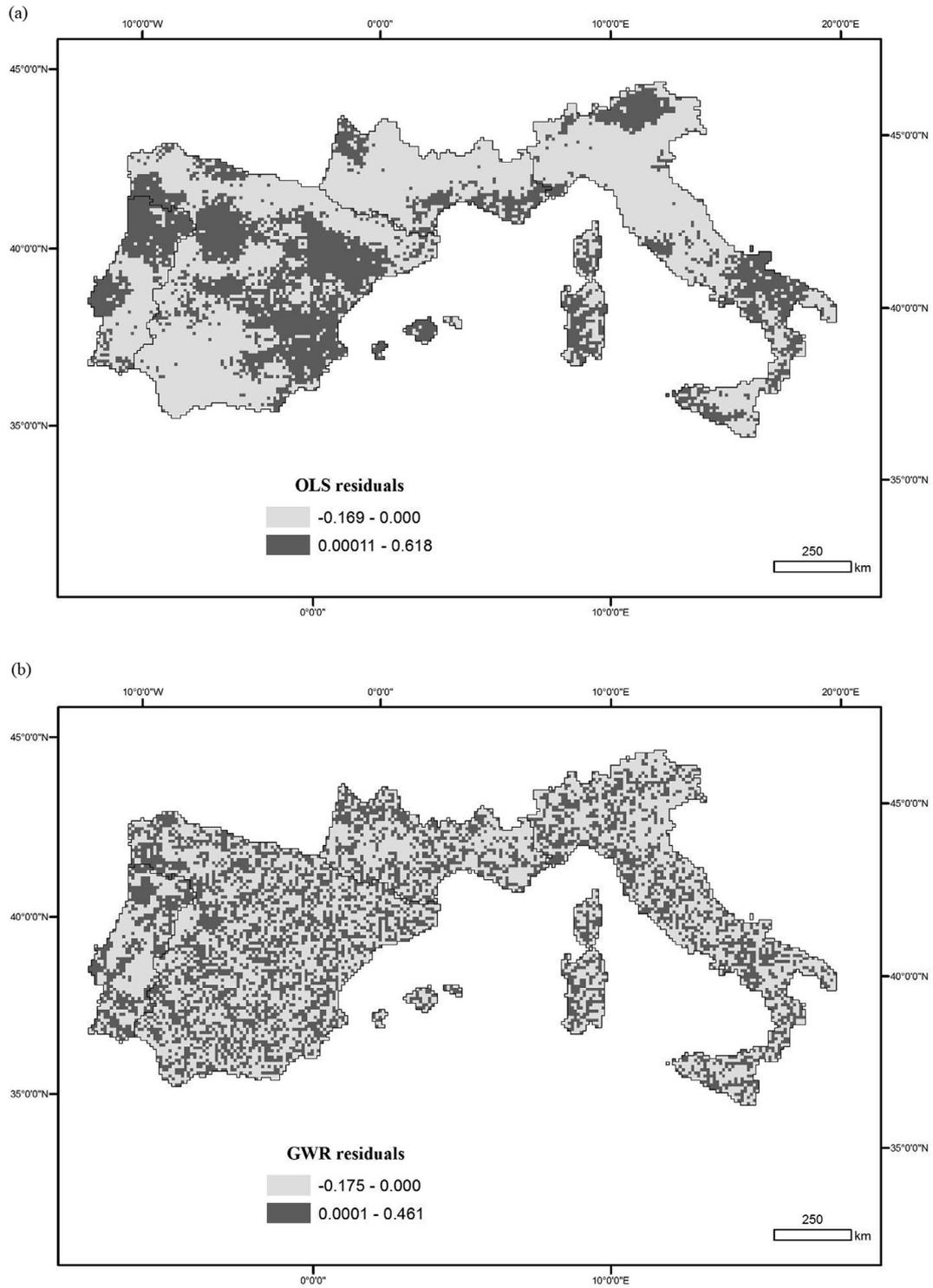


Fig. 7. Spatial patterns of residuals for the OLS model (a) and GWR (b) for Southwestern Europe.

where none of the explanatory variables was significant. These areas generally correspond to grid cells where fire density was low or null; in fact, the number of significant variables increases with increased values of fire density, which indicates a better fit of the model when fire data is more available. This also implies that, to explain fire occurrence patterns in the areas with low fire density, where the variables included didn't show a significant effect, other factors should be investigated and considered in the future, bearing

in mind that such variables, if too local, may not be available for a broad study area as the one used in this research.

Conclusion

This study intended to provide a better understanding of the spatial variability of long-term fire occurrence in Southern Europe, as well as the relative importance of the underlying factors. It had

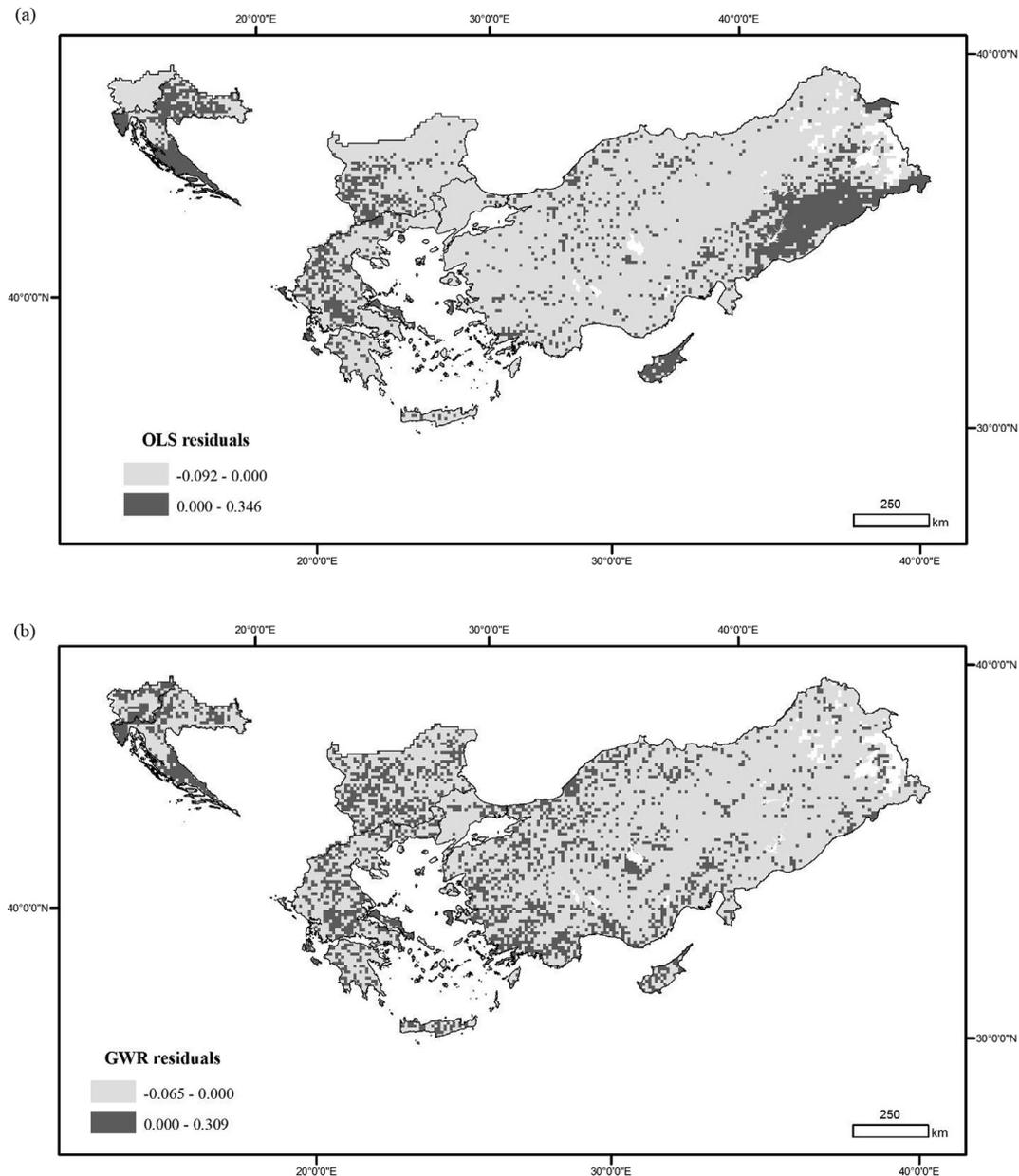


Fig. 8. Spatial patterns of residuals for the OLS model (a) and GWR (b) for Southeastern Europe.

also the purpose to contribute to the discussion around the feasibility and limitations of fire occurrence assessment at large scales, required by the transboundary nature of fire activity and its impacts. The use of Geographically Weighted Regression proved to be beneficial, as this method captured the spatial attributes of the phenomenon being studied and provided higher accuracy than the global model, while revealing the localized patterns derived from the influence of particular variables.

In spite of the difficulties in obtaining reliable data in a sufficient time-scale suitable for long-term analysis, this study is a contribution to the ongoing research on the drivers of fire occurrence in Southern Europe, showing the importance of the climatic variables, agricultural activities and land cover in several regions and countries.

These findings clearly indicate that precipitation patterns and land cover are paramount to explain the distribution of fire density in different parts of Southern Europe. In this context, and since climate cannot be controlled by man, the application of prevention

measures should focus on the management of vegetation, bearing in mind the influence of autumn and winter rainfall in fuel loads that will be available to burn in summer. Prescribed fires are a potential tool to reduce fire hazard by decreasing fuel loads before the driest season (Fernandes et al., 2013) and should receive further attention by fire managers.

Our results also show that, in these regions, the occurrence of fires is highly influenced by human activities. The importance of population density in Southwestern Europe, particularly in Central Portugal and NW Italy, indicate the need of increasing population awareness regarding their role on fire ignitions, as well as the implications of their actions for the protection of human and natural assets from fire. Public sensitization campaigns through the media and educational activities in schools, applied in a consistent way, are required to change human behavior. These campaigns, to be effective, must be adjusted to the particular cultural conditions and integrated in the educational system of each country and region.

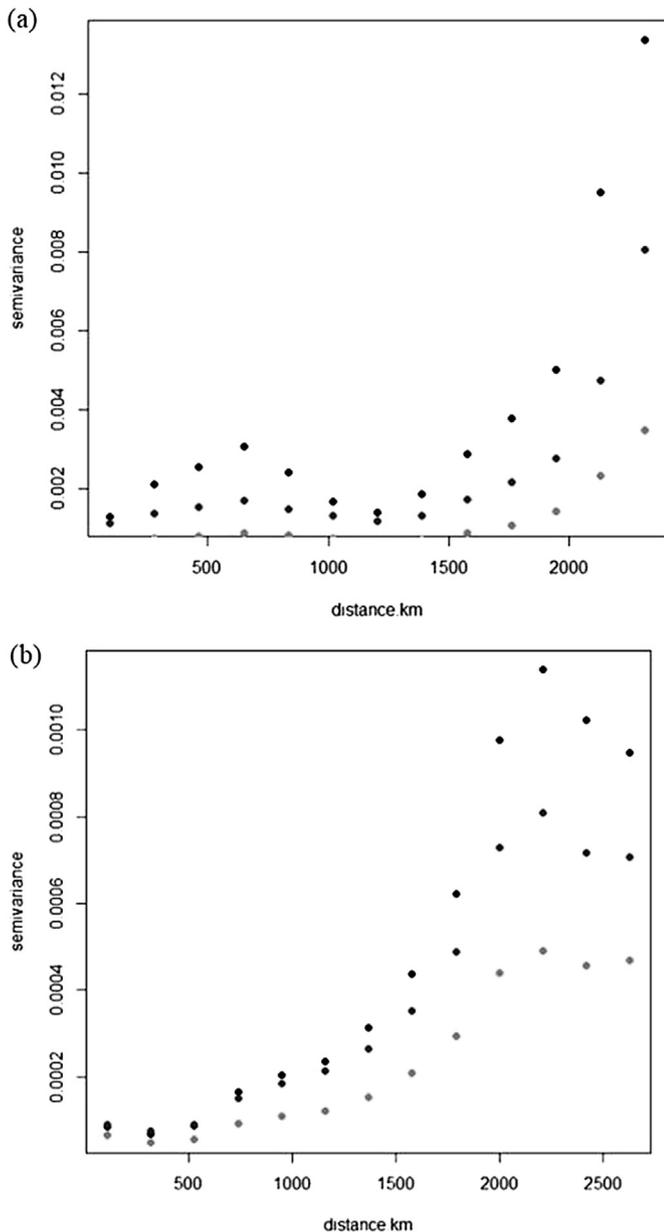


Fig. 9. Semivariance plotted as a function of distance (km) for the dependent variable (black) and the residuals of both models (OLS in dark gray, middle, and GWR in light gray, bottom), for Southwestern Europe (a) and Southeastern Europe (b). The values of the GWR residuals for Southwestern Europe were multiplied by two in order to be visible at this scale.

Agricultural activities were also evidenced as significant factors of fire density. The dichotomous effect of goat and cattle density in fire occurrence, as seen in different areas in both regions, is a rather interesting result; on one hand, the use of fire as a tool for pasture renewal may increase fire density, which means this practice should be prevented and monitored more strictly. On the other hand, the grazing provided by livestock (cattle, goats) is a valuable vegetation management tool; in fact, the use of goats as “land cleaners” (Nunes, 2012) for example, can assume an important role in decreasing fuel loads in less accessible areas, including in mountainous regions, where other practices are difficult to apply.

Despite the continuing research studies and their importance to the management of fire-prone areas, a comprehensive assessment of fire occurrence at the European level is not yet available. This study is an additional step towards this goal, by exploring the

spatial patterns of fire in a broad area, by identifying common and dissimilar features of fire distribution throughout the regions and by identifying the most significant factors of fire occurrence at local and regional levels, showing the possibility to adapt fire prevention strategies to the particular characteristics of the area.

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