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Exploring spatial patterns and drivers of forest fires in Portugal (1980–2014)

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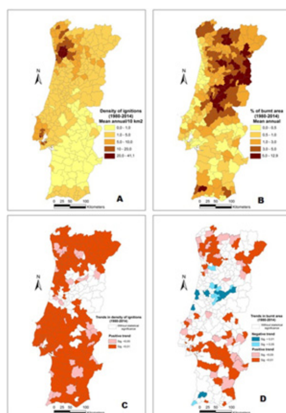
HIGHLIGHTS

- Wildfires are irregularly distributed in Portugal, both in ignitions and burnt area.
- In 80% of the municipality's ignition density reveal a positive trend since the 80s.
- Geographically Weighted Regression was used to identify relevant municipal drivers of fires.
- Topography and population density were significant factors in municipal ignitions.
- Topography and uncultivated land were significant factors in municipal burnt area.

GRAPHICAL ABSTRACT



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ABSTRACT

Information on the spatial incidence of fire ignition density and burnt area, trends and drivers of wildfires is vitally important in providing support for environmental and civil protection policies, designing appropriate prevention measures and allocating firefighting resources. The key objectives of this study were to analyse the geographical incidence and temporal trends for wildfires, as well as the main drivers of fire ignition and burnt area in Portugal on a municipal level. The results show that fires are not distributed uniformly throughout Portuguese territory, both in terms of ignition density and burnt area. One spot in the north-western area is well defined, covering 10% of the municipalities where more than one third of the total fire ignitions are concentrated. In >80% of Portuguese municipalities, ignition density has registered a positive trend since the 1980s. With regard to burnt area, 60% of the municipalities had a nil annual trend, 35% showed a positive trend and 5%, located mainly in the central region, revealed negative trends. Geographically weighted regression proved more efficient in identifying the most relevant physical and anthropogenic drivers of municipal wildfires in comparison with simple linear regression models. Topography, density of population, land cover and livestock were found to be significant in both ignition density and burnt area, although considerable variations were observed in municipal explanatory power.

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1. Introduction

Fire has been an important element in ecosystem dynamics (Pausas and Ramon-Vallejo, 1999; San-Miguel-Ayanz et al., 2012, Nunes et al., 2014) and a tool used by humans for many thousands of years. It therefore plays an important role in certain forest ecosystems and species evolution (Terradas, 1996), especially in the Mediterranean basin but also in other Mediterranean-type areas of the world (Naveh, 1975; Gill et al., 1981; Keeley and Keeley, 1988; Ganteaume et al., 2013, Ganteaume and Jappiot, 2013). According to the European Commission (2010), between 1980 and 2009 fires burnt an average of approximately 480,000 ha of land per year in this region alone, with an annual average of 50,000 occurrences. Portugal has the highest ignition density and relative burnt area of all southern European countries. Consequently, wildfires rank top of all European forest problems (Barbati et al., 2010), affecting landscape, vegetation, soils and air quality (DeBano et al., 1998; Cerdà, 1998; Certini, 2005; Cerdà and Lasanta, 2005; Miranda et al., 2008; Catry et al., 2010; Malkinson et al., 2011; Silva et al., 2011; Novara et al., 2013; Bodí et al., 2014).

A better knowledge of the spatial patterns and temporal trends in fire occurrences is crucial to understanding their driving forces and the resulting environmental and socio-economic impacts, and for planning appropriate fire prevention strategies, land use and ecological goals (Martínez et al., 2009; Miranda et al., 2012; San-Miguel-Ayanz et al., 2012; Rodrigues et al., 2013). Understanding the underlying processes affecting spatial and temporal trends in wildfire patterns is also crucial to projecting future wildfire risks (Miranda et al., 2012).

Numerous studies have therefore been carried out to identify the spatial-temporal patterns and drivers behind occurrences of fire (Preisler et al., 2004; Catry et al., 2007; Syphard et al., 2007; Chas-Amil et al., 2010; Nunes, 2012; Miranda et al., 2012; Ganteaume et al., 2013; Ganteaume and Jappiot, 2013; Martínez-Fernández et al., 2013; Zhang et al., 2013; Oliveira et al., 2014; Rodrigues et al., 2014). Combined statistics are commonly used in wildfire occurrence modelling to analyse fire occurrence patterns for several factors (e.g. ignition density, total number of fires, total and mean burnt area) on various spatio-temporal and aggregation scales (e.g. from local to global, community to country, and short- to long-term) (De la Riva et al., 2004; Koutsias et al., 2004; Amatulli et al., 2007; Martínez et al., 2009; Oliveira et al., 2014; Rodrigues et al., 2014). With regard to fire occurrence modelling, different statistical and regression modelling techniques have been used on different temporal and spatial scales. Several studies, in particular those using classical linear regression modelling, assume that the model parameters are valid and homogeneous for the whole study area or that the model structure is spatially stationary (e.g. Syphard et al., 2007; Chuvieco et al., 2010; Vilar et al., 2010, Kwak et al., 2012; Nunes et al., 2014).

Nevertheless, global regression methods may be inadequate for large geographical areas such as the Portuguese territory, due to the use of stationary coefficients for the whole study area, probably masking local interactions within the explanatory factors. When modelling fire densities, several authors (Koutsias et al., 2005, 2010; Oliveira et al., 2014) observed that the explanatory power of classical linear regression increased considerably after varying relationships were assumed instead of constant ones, using Geographically Weighted Regression (GWR). In fact, GWR improves the predictive performance of classical linear regression by considering regression as a spatial non-stationary process. GWR is a technique which specifically includes the spatial component in regression procedures, not only capturing the spatial variability of wildfire driving factors but also determining and quantifying their contribution and errors (Rodrigues et al., 2014). Several authors have therefore used this regression procedure in wildfire analysis (Koutsias et al., 2005; Chuvieco et al., 2012; Martínez-Fernández and Koutsias, 2011; Rodrigues and de la Riva, 2012; Martínez-Fernández et al., 2013; Oliveira et al., 2014; Rodrigues et al., 2014).

Taking the above perspectives into consideration, the main objectives of this study were: (i) to analyse the spatial patterns and temporal trends of fire frequency (fire ignition density and burnt area size, in percentage), on a municipal level; (ii) to identify the most critical drivers of wildfires, by comparing the performance of classical linear regression and GWR modelling; (iii) to explore spatially varying relationships between the biophysical and human causes associated with wildfires, on a municipal level in Portugal.

In fact, information on spatial incidence, trends and the main municipal driving factors of wildfires is vitally important in supporting environmental and civil protection policies, designing appropriate prevention measures and allocating firefighting resources more effectively, as well as providing insights into achieving a more sustainable coexistence with wildfires.

2. Material and methods

2.1. Main characteristics of study area

Mainland Portugal is located in the Iberian Peninsula in the extreme southwest of continental Europe and covers an area of 89,015 km^2. It is composed of 278 municipalities (Fig. 1). In general, the climate is Mediterranean, with warm, dry summers and cool, wet winters: almost all the precipitation falls between October and April. However, the country is also characterized by heavy precipitation and sharp temperature gradients, driven by the latitude as well as its complex terrain and proximity to the Atlantic Ocean. The average annual precipitation ranges from over 2500 mm in the central and north-west mountains to 500 mm yr^{-1} in the southernmost regions. This pattern is reversed for the mean annual temperature, with the highest figures recorded in the Alentejo (Central and Lower Alentejo, i.e. Portalegre, Évora and Beja) and Algarve (Faro) regions, and the lowest in the northernmost territories. With the exception of the north-west region, the whole territory has a reasonably long dry season, lasting three to five months and increasing from north to south and from coastal to inland Portugal.

The physical environment varies greatly between northern and southern Portugal. This variation is largely explained by the different physiographic characteristics (Fig. 1A): most of the mountains in the country lie north of the River Tejo, where the landscape is more rugged and intersected by deep valleys. The highest mountain range is the Serra de Estrela, which runs from the north-east to the south-west of central Portugal, reaching a maximum height of 1993 m. In these mountains, as in the north-west ranges, the average annual precipitation exceeds 2000 mm. The southern part of mainland Portugal has different physiographic characteristics; is mainly characterized by the vast flat or rolling terrain of the pediplain where the average altitude is around 200–300 m. The São Mamede mountain ridge, the highest in the Alentejo region with an altitude of over 1000 m, lies in the extreme north-east. In contrast, in the far south, the landscape is dominated by the two main Algarve mountain ranges, Monchique in the west and Caldeirão in the east.

Major social and economic changes have affected the entire Portuguese territory, mainly in the last five decades. During the period 1960–2011, the population declined in 65% of the Portuguese municipalities, with figures varying from 71% to 0.2%, whilst 35% recorded an increase of 0.3% to 675%. The northern and central inland municipalities, as well as those in the southern region, were the most affected by depopulation, leading to the abandonment of agricultural lands and a reduction in the size of herds and the amount of forest fuels consumed by grazing and gathering firewood (Rego, 1992; Moreira et al., 2011; Nunes, 2012). Mass emigration to other European countries and to coastal areas within Portugal explains this declining population and the parallel trend of an aging population. In contrast, the population in the coastal municipalities increased during the same period and these areas nowadays have the highest concentrations, densities and urban populations, as well as younger residents (Bandeira et al., 2014). Approximately 2/3 of the Portuguese population is concentrated in the urban and suburban areas of the coastal regions, mainly in the metropolitan areas of Lisbon and Porto (Fig. 1B).

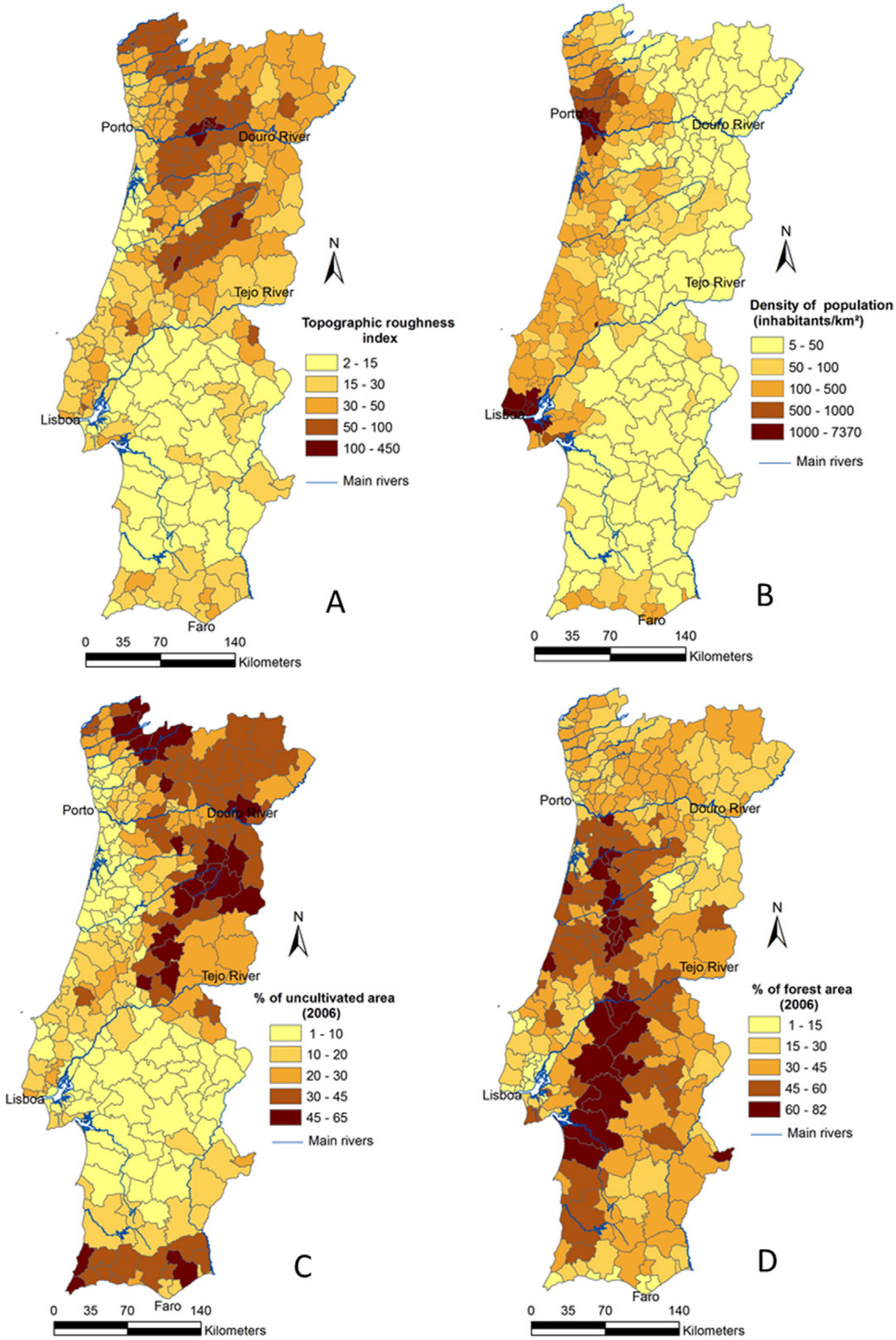

Fig. 1. Study area and distribution by municipality of the topographic roughness index (A), population density (2001/11) (B), percentage of uncultivated area (C) and percentage of forest area (D).

According to Agrarian Recognition and Management Service statistics (SROA, 1970), in the middle of the last century agricultural land represented about half the total area of mainland Portugal. Five decades later, the same land use only represented about 17% of the total area, meaning that >2/3 of the agricultural land had been converted into agro-forestry systems and pastures, or abandoned to the natural process of ecological succession, thus becoming shrubland and woodland, or forest plantations (CORINE land cover, 2006). Consequently, uncultivated land, which has more than doubled in size in recent decades, is covered largely by vegetation that is very prone to fire, such grass, shrubs and other light vegetation. Uncultivated lands register high spatial variability, representing 1% to 65% of the total municipal surface area (Fig. 1C). Forest area, which occupies around 1/3 of the Portuguese territory, is composed of woodland, 55% of which is classified as highly inflammable (mostly *Eucalyptus globulus* and *Pinus pinaster*) and mainly located in the centre and north of Portugal. *Quercus rotundifolia* and *Quercus suber* represent around 40% of the national forest land and predominate in the south of Portugal in the so-called “montado”, in association with silvopastoral practices (Fig. 1D) (AFN, 2010).

2.2. Forest fire variables

The forest fire database was compiled using data from the National Institute for Nature Conservation and Forestry (ICNF), the Portuguese Government Forestry Service. The extensive data set consists of relevant information on each fire event in mainland Portugal within the study period 1980–2014, including the ignition date, duration, location of outbreak and total burnt area. In order to compare occurrences of fires and burnt areas among municipalities, a density index (the number of fire ignitions per 10 km^2) for annual fire ignitions and the percentage of burnt area (the proportion of burnt area in relation to the total municipal area) were established to reduce the bias involved in comparing the absolute number of fires and burnt area per municipality, since the size of the latter varies widely in Portugal (the smallest municipality is 17.5 km^2 and the largest 580 km^2) (Table 1). Spatial autocorrelation analysis was carried out using Moran's Index (Moran, 1950) to evaluate the degree of spatial autocorrelation in the fire data for the Portuguese municipalities during the study period, indicating the tendency of data to cluster or disperse.

2.3. Test trend procedures (ignition density and burnt area at municipal level)

Temporal trends for fire ignition density and burnt areas during the period 1980–2014 were analysed. The trends were assessed using the Spearman's Rho (SR) correlation, which is a non-parametric statistical test with uniform power for linear and non-linear trends. The Spearman Rho is usually used to verify the absence of trends (Dahmen and Hall, 1990; Tonkaz et al., 2007). In this test, the null hypothesis (H0) is that all the data in the time series is independent and identically distributed, whilst the alternative hypothesis (H1) is that increasing or decreasing trends exist (Yue et al., 2002). Statistical significance was assessed to p-value less than or equal to 0.05.

Table 1
Forest fire and explanatory variables used at municipal level.

Forest fires	Source
Density of ignitions (10 km^2) (1980–2014)	Portuguese Government Forest Service (INCF)
% of burnt area per municipality (1980–2014)[a]	
Explanatory variables	**Source**
Topographic roughness index[c]	Portuguese Environment Agency
Average annual precipitation, 1971–2000 (in mm)	National Institute of Meteorology
Average annual temperature, 1971–2000 (in mm)	National Institute of Meteorology
Density of population, 2001/11[b,c]	Statistics Portugal
Aging index, 2001/11[b,c]	Statistics Portugal
Total number of farmers, 1999/09[b]	Statistics Portugal
Variation in unemployment rate, 2001/11[b,c]	Statistics Portugal
Percentage of agricultural area, 2006[c]	National forest inventory (ICNF)
Percentage of forest area, 2006[c]	National forest inventory (ICNF)
Percentage of uncultivated area, 2006[c]	National forest inventory (ICNF)
Density of small livestock, 1999/09[b,c]	Statistics Portugal
Density cattle livestock, 1999/09[b,c]	Statistics Portugal
Number of plots per farm, 1999/09[b]	Statistics Portugal
Road density (km/km^2), 2010	Statistics Portugal

[a] Burning of agricultural and forest fuels, including renewal of pastureland.
[b] Average value based on Census results (1999–2009 or 2001–2011).
[c] Variables considered in the statistical analysis at municipal level.

2.4. Selection of explanatory variables

In order to understand the factors influencing the incidence of wildfires and certain types of causality, a list of exploratory variables was drawn up, based on physical and demographic characteristics, changes in land use and land cover, and economic structure at municipal level. The statistical variables were compiled from the Census, whereas spatial variables such as average annual precipitation, land use and other factors were obtained from digital maps provided by national bodies. A simple topographic roughness index was also calculated for each municipality, based on the relationship between its hypsometric variation and the square root of its surface area. Pearson correlation coefficients were calculated to assess possible collinearity among the variables, thus enabling several variables to be discarded, since their probable effects on fire ignition density and burnt area could be explained by other more appropriate physical, ecological or human variables. A correlation coefficient threshold between predictor variables of $|r| > 0.7$ ($p < 0.05$) was considered an appropriate indicator for the point where collinearity begins to severely distort model estimation and subsequent prediction (Dormann et al., 2013). As a result, only the variables identified in Table 1 were considered in the statistical analysis at municipal level.

2.5. Simple linear regression (SLR) vs geographically weighted regression (GWR) to model relationships between dependent and exploratory variables

Simple linear regression and geographically weighted regression were used to identify the most important factors involved in fire ignition and burnt area. Simple linear regression is a statistical method that describes the relationships between two quantitative variables, modelled as a stationary spatial process. GWR is a statistical technique that allows variations in relationships between predictors and outcome variable over space to be measured within a single modelling framework (Fotheringham et al., 2002).

The GWR model can be expressed as:

$$y_i = \beta_0(u_i, v_i) + \sum_{j=1}^{k} \beta_j(u_i, v_i)x_{ij} + \varepsilon_i$$

where y_i is the value of the outcome variable at the coordinate location i where (u_i, v_i) denotes the coordinates of i, β_0 and β_j represents the local estimated intercept and effect of variable j for location i, respectively.

Determining the size of the neighbourhood region (bandwidth calibration) is a key step since regression output will vary considerably according to this parameter value. Two different approaches for bandwidth calibration are therefore available in any GWR model: (i) fixed kernel, which specifies an equal distance threshold for each regression point; and (ii) adaptive kernel, which specifies the number of neighbours to be considered for each regression point. In the first case, the number of neighbours will probably vary from one regression point to another according to the spatial point pattern. Conversely, the adaptive kernel changes the distance threshold to fit the number of data points. In general, fixed kernels should be appropriate in a scenario where the point cloud is regularly distributed over space and the adaptive approach is more suitable for spatially clustered patterns. Finally, the optimum distance bandwidth value or optimum number of neighbours can be determined in two ways: by minimizing the square of the residuals (Cleveland, 1979) or by minimizing the Akaike Information Criterion (AIC) (Hurvich et al., 1998; Wang et al., 2005; Kupfer and Farris, 2007).

In this study, we used an adaptive kernel type and selected an optimal bandwidth by minimizing both the square of the residuals and the corrected Akaike information criterion (AICc). Many regression models were calculated using different numbers of neighbours, and AICc statistics were compared to assess the goodness-of-fit for each model. On the basis of the AICc scores, the number of neighbours selected was 20. In itself, the value of the AICc for a given data set has no meaning, but becomes interesting when compared to the AICc of a series of models specified a priori (Mazerolle, 2004). It is simply a way of ranking the models, and the model with the lowest AICc is classified as the "best" out of all the models specified for the data analysed (Mazerolle, 2004; Snipes and Taylor, 2014). Comparing the GWR AICc value to the simple regression AICc value is one way of assessing the benefits of moving from a global to a local regression model (GWR) (Desktop, ArcGis, 10.1, ESRI). Thus, AIC is largely used in the biological sciences, specifically in the environmental and marine and watershed sciences.

For the purpose of this paper, the GWR geoprocessing tool in ArcGIS software (10.1, ESRI) was used to compute the results for the global and municipal regression models. All the maps were also generated using ArcGIS software (ArcGIS, ESRI).

3. Results

3.1. Spatial incidence of wildfires at municipal level

In Portugal, fires are not distributed uniformly throughout the territory and vary greatly, both in terms of the annual ignition density and percentage of burnt area (Fig. 2). With regard to forest fire ignitions, the Portuguese mainland can be roughly divided into the south and north regions, separated by the River Tejo (Fig. 2A). Higher fire ignition densities prevail north of the River Tejo and a very high number of fires, totalling up to 20 occurrences/10 km^2 y^{-1}, are concentrated in specific geographical areas.

One cluster in the northern coastal area is well defined, covering 10% of the Portuguese municipalities in which more than one third of the total fire ignitions are concentrated. Apart from the Portuguese north-western region, which has the highest incidence of wildfires, another group further to the south, including the most of the municipalities in the Lisbon Metropolitan region, also registers a very high number of ignitions every year. The municipalities south of the River Tejo emerge as having the lowest ignition density, with the exception of some located in the Setúbal Peninsula and the Algarve region. These spatial clustered patterns are confirmed by the results of the global Moran's Index, showing a significant positive spatial autocorrelation (Moran's $I = 1.1163$; z-score: 39.3065; $p < 0.0000$).

Spatially, the largest burnt areas are found in the municipalities of central inland Portugal, covering the vast majority of the highland territories of the central region mountain range. In these areas the mean annual burnt area amounts to >5% of the total municipality surface (Fig. 2B). However, other territories also reveal a high proportion of burned spots, including municipalities in the Viana do Castelo, Vila Real, Viseu and Castelo Branco districts. In southern Portugal, three other municipalities (Monchique, Lagos and Tavira) can be identified as the most affected by fire. The global Moran's Index for burnt area was 0.4381 (z-score: 0.000831; $p < 0.0000$), also indicating the presence of a statistically significant positive spatial autocorrelation in mainland municipalities.

3.2. Trends in density of ignitions and burnt area at municipal level

The Fig. 3 maps and Table 2 summarize the degree of significance of the trend detected for ignition density and percentage of burnt area using the Spearman rho correlation coefficient. According to the results ignition density has increased in 80% of the Portuguese municipalities during the period studied, revealing a positive trend with at least a 0.05 significance level. Moreover, a large percentage of municipalities (around 70%) display a very strong positive trend, statistically significant at 0.01 level, indicating that several areas in Portugal have experienced a significant increase in the annual number of fires since the early 1980s. Spatially, the northernmost areas, together with the Lisbon and Alentejo regions, are the most severely affected. Conversely, most of

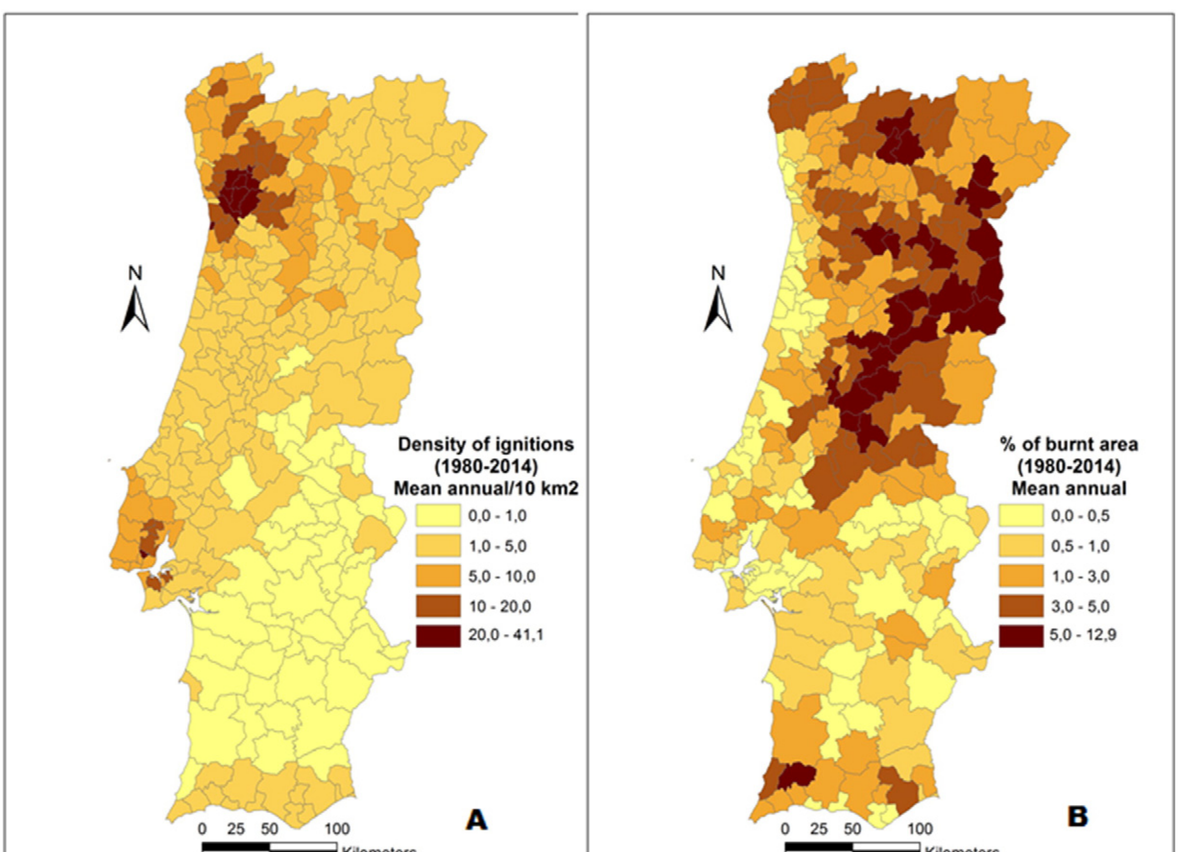

Fig. 2. Spatial incidence of fire ignition density (A) and percentage of burnt area (B) at municipal level.

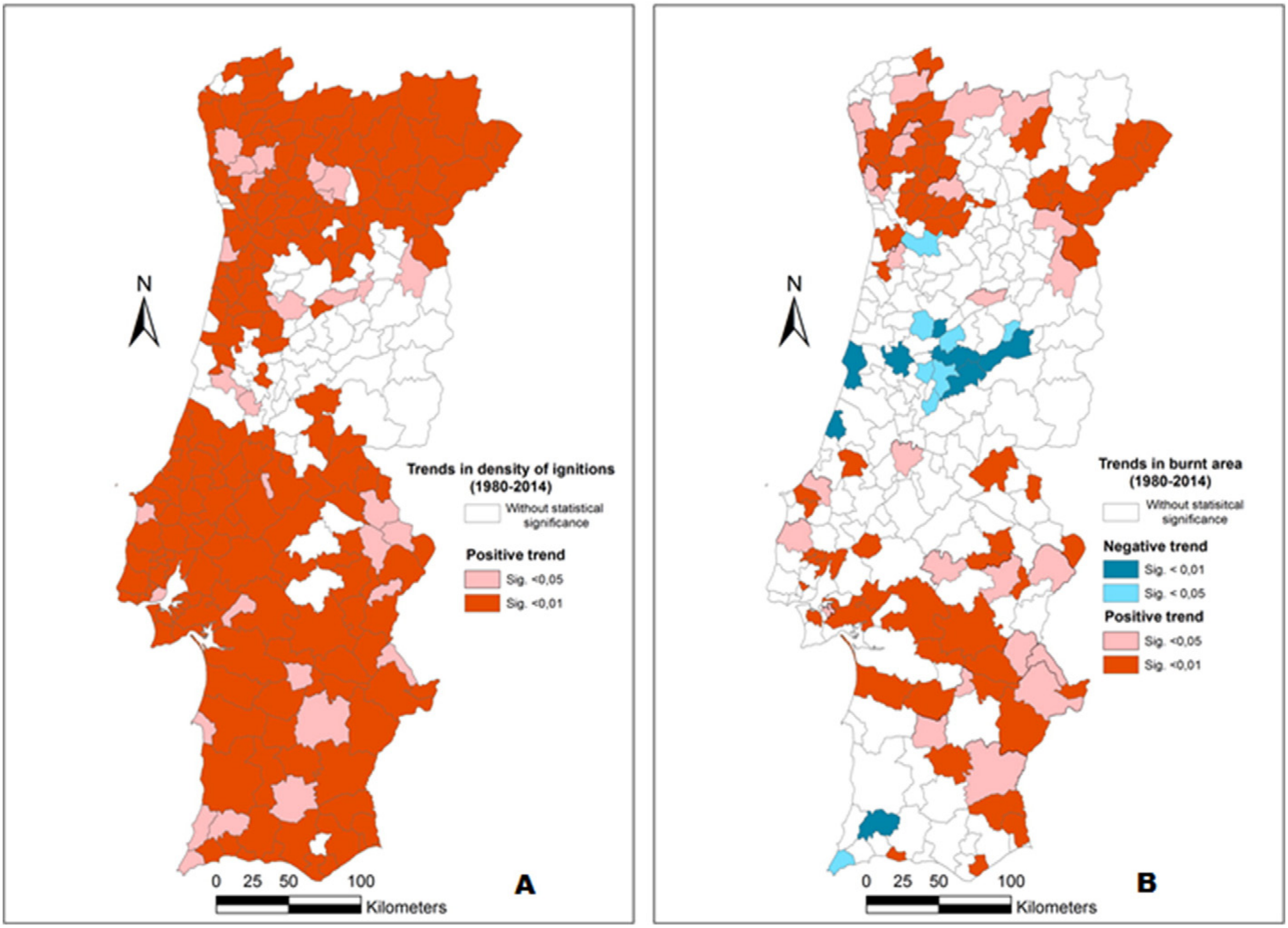

Fig. 3. Trends for ignition density (A) and % of burnt area (B) at municipal level, 1980–2014.

the municipalities located in the centre of Portugal reveal a nil trend for ignition density during the period analysed (Fig. 3A).

With regard to burnt area, 60% of the municipalities reveal a nil annual trend, whilst 35% revealed a positive trend when the Spearman rho correlation coefficient was applied (Fig. 3B). These trends were most significant in the northernmost region, particularly in the north-western and north-eastern areas. In the Alentejo region most of the municipalities also show a positive burnt area trend. Negative trends predominated in only 5% of the municipalities, located mainly in the central region of Portugal. In seven municipalities a very strong negative trend, statistically significant at 0.01 level, was detected. The other nine counties had also a statistically significant negative trend, at 0.05 level.

3.3. Wildfires and major driving forces: simple linear regression (SLR) vs geographically weighted regression (GWR)

In attempting to interpret the influence of physical and socio-economic characteristics on wildfires (ignition density and percentage of burnt area) at national level, certain differentiated features can be observed in Tables 3 and 4, as a result of applying SLR and GWR.

Table 3 systematizes the exploratory variables which correlated best with fire ignition density by applying SLR. The highest positive correlations detected were between ignition density and variation in unemployment rates registered in the last decade (R^2 adjusted: 0.13), population density (R^2: 0.12), and topographic roughness index (R^2: 0.05). The aging index (R^2: 0.17), density of small livestock (R^2: 0.12) and percentage of forest area (R^2: 0.05) presented a significant negative relationship. Despite these significant statistical correlations (p-value < 0.001), the coefficient of determination R^2 (in %) shows a very weak fit in the relationship, since the respective values range from 5% to 17%.

Conversely, the results obtained by applying GWR show a significant improvement in the degree of relationship between the dependent and each exploratory variable. In the case of fire ignition density, the overall R^2 increased to values ranging from 0.68 to 0.76 (Table 3), showing a high predictive potential for socioecological forest ignition incidence modelling.

In relation to the burnt area (Table 4), the percentage of uncultivated area emerges with the best positive correlation (R^2: 0.52). The other variables presented very low associations when simple linear correlations were applied: positive with regard to the topographic roughness index and the aging index and negative for density of population, percentage of agricultural area and density of livestock. The respective values range from R^2: 0.05 to R^2: 0.21. The results of R^2 obtained by GWR vary from 0.57 (density of livestock) to 0.70 (% of agricultural area). In fact, the GWR results greatly surpass the SLR, the classical

Table 2
Ignition density and % of burnt area trends (values in parentheses are in %).

		Negative trend		Positive trend	
	ns	0.05	0.01	0.05	0.01
Density of ignitions	55 (19.8)	–	–	30 (10.8)	193 (69.4)
% of burnt area	167 (60.1)	8 (2.9)	8 (2.9)	28 (10.1)	67 (24.1)

ns: without statistical significance; significant at 0.05 and 0.01 level.

Table 3
Coefficients of determination resulting from the application of SLR and GWR between fire ignitions density and the selected exploratory variables.

Fire ignitions density	Topographic roughness index	Density of population	Aging index	Variation in unemployment rate	% of forest area	Density of small livestock
SLR adjusted R^2	(+) 0.05**	(+) 0.12**	(−) 0.17**	(+) 0.13**	(−) 0.05**	(−) 0.12**
AICc	1772.3	1751.3	1734.8	1746.8	1771.7	1751.7
GWR adjusted R^2	0.76	0.74	0.70	0.73	0.68	0.76
AICc	1451.9	1473.9	1515.7	1482.6	1500.7	1446.8
Res. squares	1593.8	1746.9	1923.7	1680.3	2288.1	1556.6

(+) positive correlation; (−) negative correlation.
** Significant at 0.01 level.

regression technique, and enable nonstationary relationships between dependent and predictive variables to be detected. The AICc scores obtained for both methods also indicate that GWR techniques are the most economical for the data analysed.

3.4. Wildfires and major driving forces: mapping the results of municipal relationships using GWR

Fig. 4 shows the municipal coefficients produced by GWR for fire ignition distribution and the explanatory variables. Spatial mapping of the municipal R^2 shows the presence of spatial non-stationarity relationships between dependent and explanatory variables and a significant spatial variation in the proportion of variance explained by the municipal GWR models. As an example, the global R^2 obtained from the relationship between density of ignitions and density of population yielded a value of R^2: 0.74, whereas at municipal level the values ranged from 0.00 to 0.81 (Table 5), with the highest values for R^2 located in southern Portugal and in the centre of the northern region. The proportion of variance explained by the other explanatory variables varies from <0.1 to a maximum of 0.88 for density of small livestock, 0.76 for the topographic roughness index and aging index, 0.66 for variation in the unemployment rate and 0.50 for percentage of agricultural land.

The municipal R^2 values were mapped on the basis of relationships between burnt areas and the exploratory variables also demonstrate significant differences in the proportion of variance explained by GWR. A visual analysis reveals that the topographic roughness index and percentage of agricultural land have the highest local predicted values (0.90 and 0.85 respectively), while uncultivated land (registering a positive correlation with burnt area) includes the highest number of municipalities in the final class, where the coefficient of variability explained by this variable is over 60% (Fig. 5).

When considering the two most important variables together (multivariate models), namely the topographic roughness index and density of population, the predictive power for the spatial density of ignitions only changed slightly, whereas the residuals decreased significantly (Table 6). However, at municipal scale substantial improvements in GWR R^2 can be observed in Fig. 6(A), where the two combined predictive variables explain the large degree of variance in fire ignition density (between 60% and 90%) in over one third of the Portuguese municipalities. In relation to the burnt area, the combination of the topographic roughness index and the percentage of uncultivated area increased to 0.83 showing a significant improvement in municipal GWR, corroborated by the decrease in the AICc scores and residual values (Table 6). The mapping of municipal R^2 also demonstrates the importance of these two explanatory variables, since around half of the municipalities were included in the final class, where the variance ranged from 60% to 91% (Fig. 6B).

However, although these two variables make an important contribution, both in terms of spatial ignition density and burnt area, in some municipalities the performance of the model is very low, meaning that it is necessary to include additional explanatory variables for a better explanation of the occurrences and extent of wildfires.

4. Discussion

4.1. Spatial incidence and trends in wildfires at municipal/regional level

The results of this study show the uneven distribution of wildfires, both in terms of ignition density and burnt area, among the municipalities in mainland Portugal. The results obtained also suggest an overall positive trend for ignition density since the 1980s. This tendency agrees with the results obtained by Rodrigues et al. (2013) in their analysis of fire trends in Southern European countries, which found that Portugal and Spain had greatest number of provinces with a significant upward trend in the number of fires.

With regard to the burnt area percentage, significant differences were observed in temporal trends. Although the burnt area percentage has clearly increased in many Portuguese municipalities during the period analysed, some of them, particularly those located in the central region of the country, show a negative trend for the annual area affected by fire. In searching for general explanations correlated with the application of specific measures in these municipalities, it is very difficult to explain the decline in burnt area, since the measures are identical to those applied in other municipalities which show the reverse, i.e. an increase in burnt area. This trend may be the result of the many recurrent large fires that occurred at the beginning of the study period, which significantly reduced the burnable fuels, particularly forest fuels. As Niklasson and Granström (2000) note, temporal and spatial fire patterns may be modified as subsequent fires interact with characteristics of the landscape that can alter susceptibility to fire in burnt areas and their surroundings. In some cases, a fire may have a negative effect on future burning due to the lack of fuel during the early post-fire period. However, the explanations for this trend require further research.

These results also suggest that burnt area trends should be analysed carefully and further analyses should be performed to check this phenomenon. Moreover, the temporal trends for both variables need to be assessed with alternative tests, such as the Mann-Kendall test, in order to increase the robustness of the results.

Table 4
Coefficients of determination resulting from the application of SLR and GWR between burnt area and the selected exploratory variables.

% of burnt area	Topographic roughness index	Density of population	Aging index	% of agricultural area	% of uncultivated area	Density cattle livestock
SLR adjusted R^2	(+) 0.15**	(−) 0.05**	(+) 0.17**	(−) 0.21**	(+) 0.52**	(−) 0.11**
AICc	1169.0	1200.8	1161.7	1148	1009.2	1182.4
GWR adjusted R^2	0.69	0.61	0.63	0.70	0.68	0.57
AICc	948.4	1009.6	988.8	939.1	955.5	1038.0
Res. squares	267.4	336.8	307.6	248.8	274.6	374.0

(+) positive correlation; (−) negative correlation.
** Significant at 0.01 level.

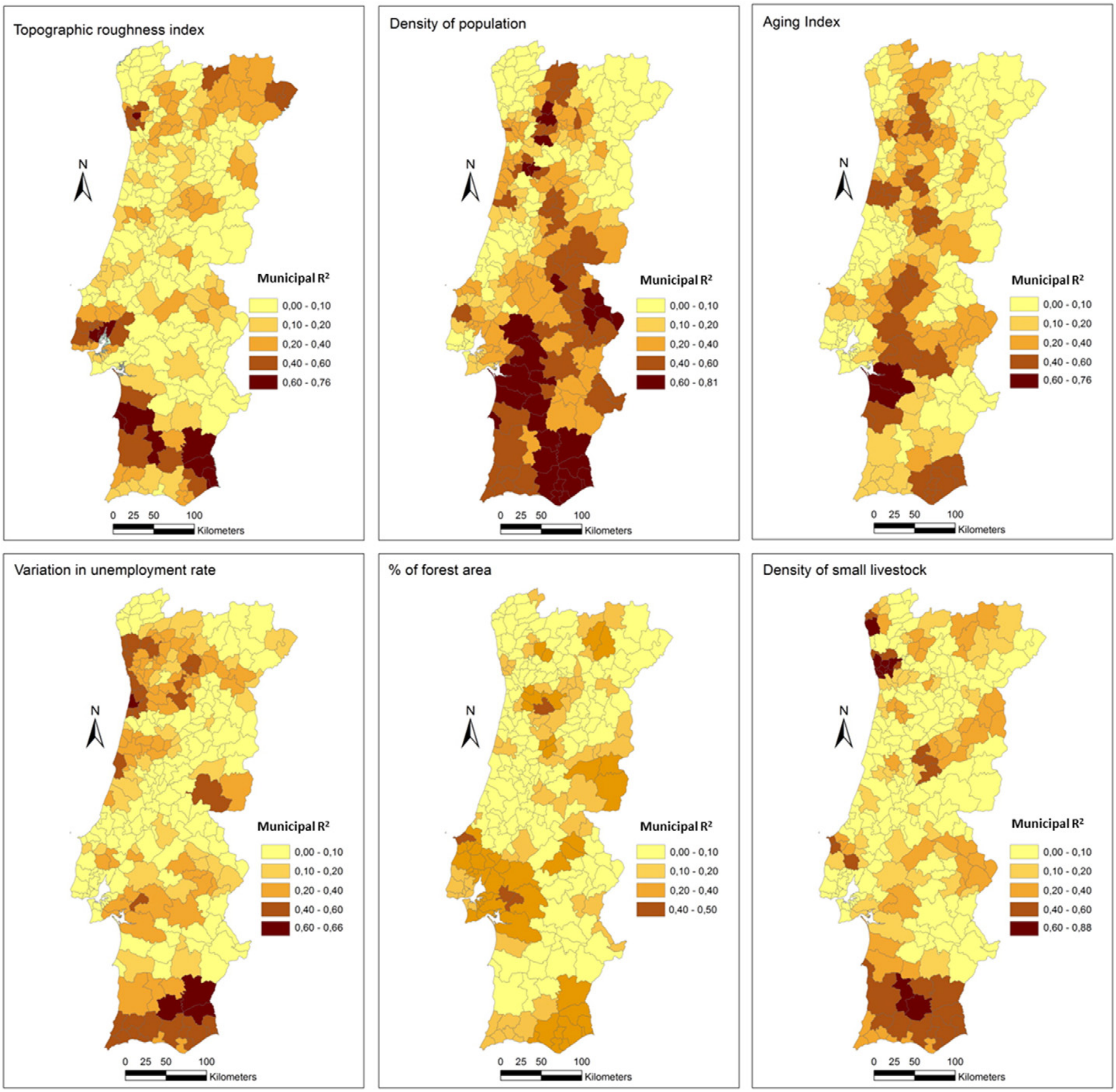

Fig. 4. Distribution of municipal R^2 results from the application of GWR between fire ignition density and the explanatory variables.

Table 5
Descriptive statistics for GWR municipal R^2.

Fire ignitions density ($n = 278$)	Topographic roughness index	Density of population	Aging index	Variation in unemployment rate	% of forest area	Density of small livestock
Maximum	0.76	0.81	0.76	0.66	0.50	0.86
Mean	0.16	0.27	0.18	0.17	0.11	0.16
Minimum	0.00	0.00	0.00	0.00	0.00	0.00
Stand. deviation	0.18	0.22	0.16	0.17	0.17	0.18

% of burnt area	Topographic roughness index	Density of population	Aging index	% of agricultural area	% of uncultivated area	Density cattle livestock
Maximum	0.89	0.53	0.70	0.85	0.79	0.65
Mean	0.20	0.14	0.16	0.27	0.38	0.11
Minimum	0.00	0.00	0.00	0.00	0.00	0.00
Stand. deviation	0.21	0.12	0.17	0.20	0.21	0.13

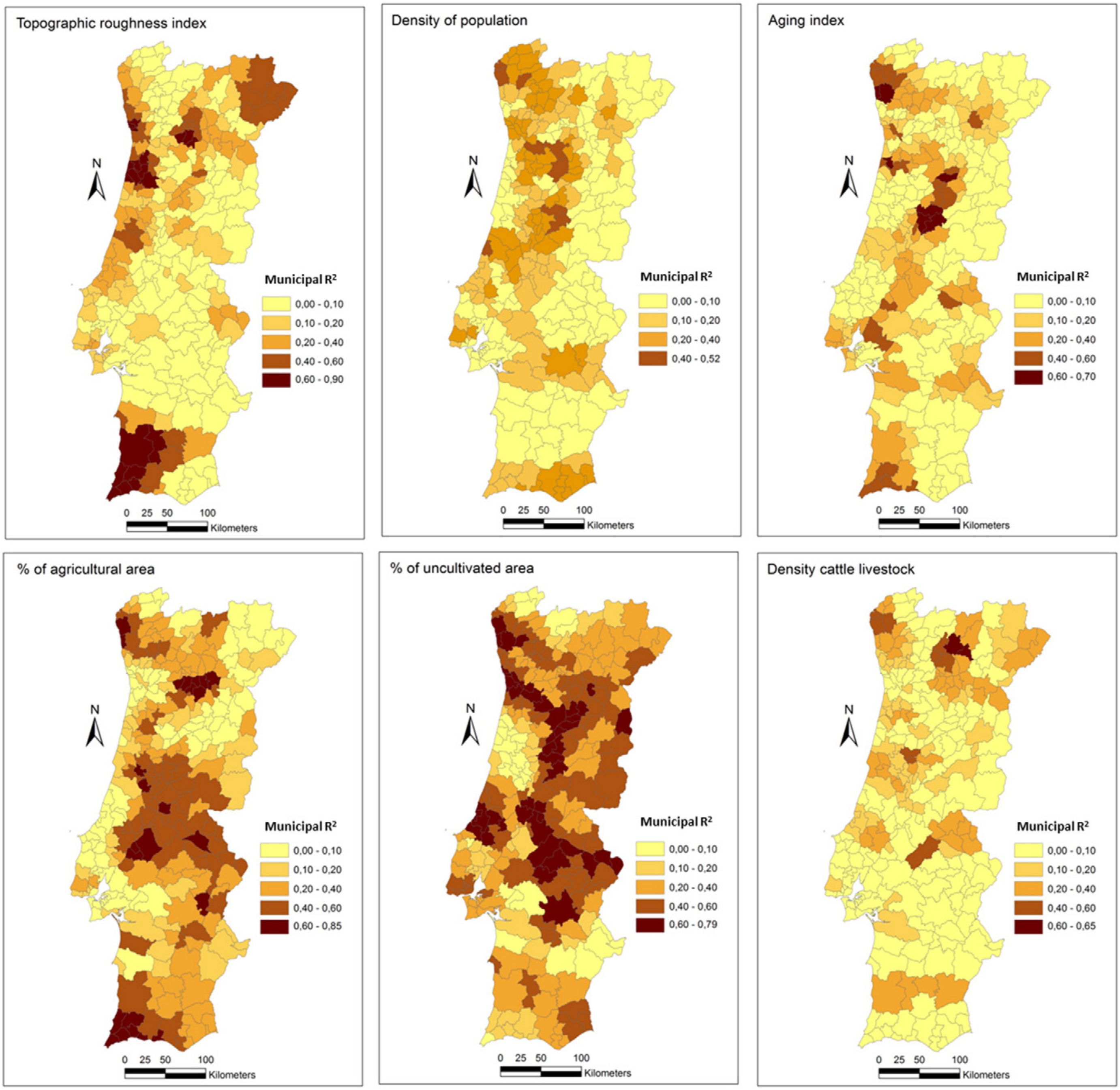

Fig. 5. Distribution of municipal R^2 results from the application of GWR between burnt area and the explanatory variables.

Table 6
Coefficients of determination resulting from the application of multiple linear regression (MLR) and GWR between ignition density, topographic roughness index and density of population, and between burnt area, topographic roughness index and percentage of uncultivated area.

	Fire ignitions density Vs Top. rough. index + Dens. pop.	% of burnt area Vs Top. rough. index + % of uncul. area
MLR adjusted R^2	0.18	0.52
AICc	1731.9	1008.04
GWR adjusted R^2	0.77	0.83
AICc	1473.2	819.86
Res. squares	1335.6	126.64

4.2. Major driving forces for wildfires on a municipal/regional scale

The spatial incidence and increase in outbreaks of fire are related to several factors. In general, ignition was significantly higher in the more urban and suburban municipalities of Portugal than the more rural areas. The Portuguese coastal areas, especially those north of Lisbon, have the highest population density and a complex mix of land-use types, especially in the urban-forest interfaces where agricultural areas or industrial land border on forests, which may explain the large number of ignitions and their positive trends. Our results agree with several studies which also found a significant relationship between population density and the occurrence of fires in the Mediterranean region (Piñol et al., 1998; Martínez et al., 2009; Romero-Calcerrada et al., 2008; Badia et al., 2011; Padilla and Vega-García, 2011; Ganteaume et al.,

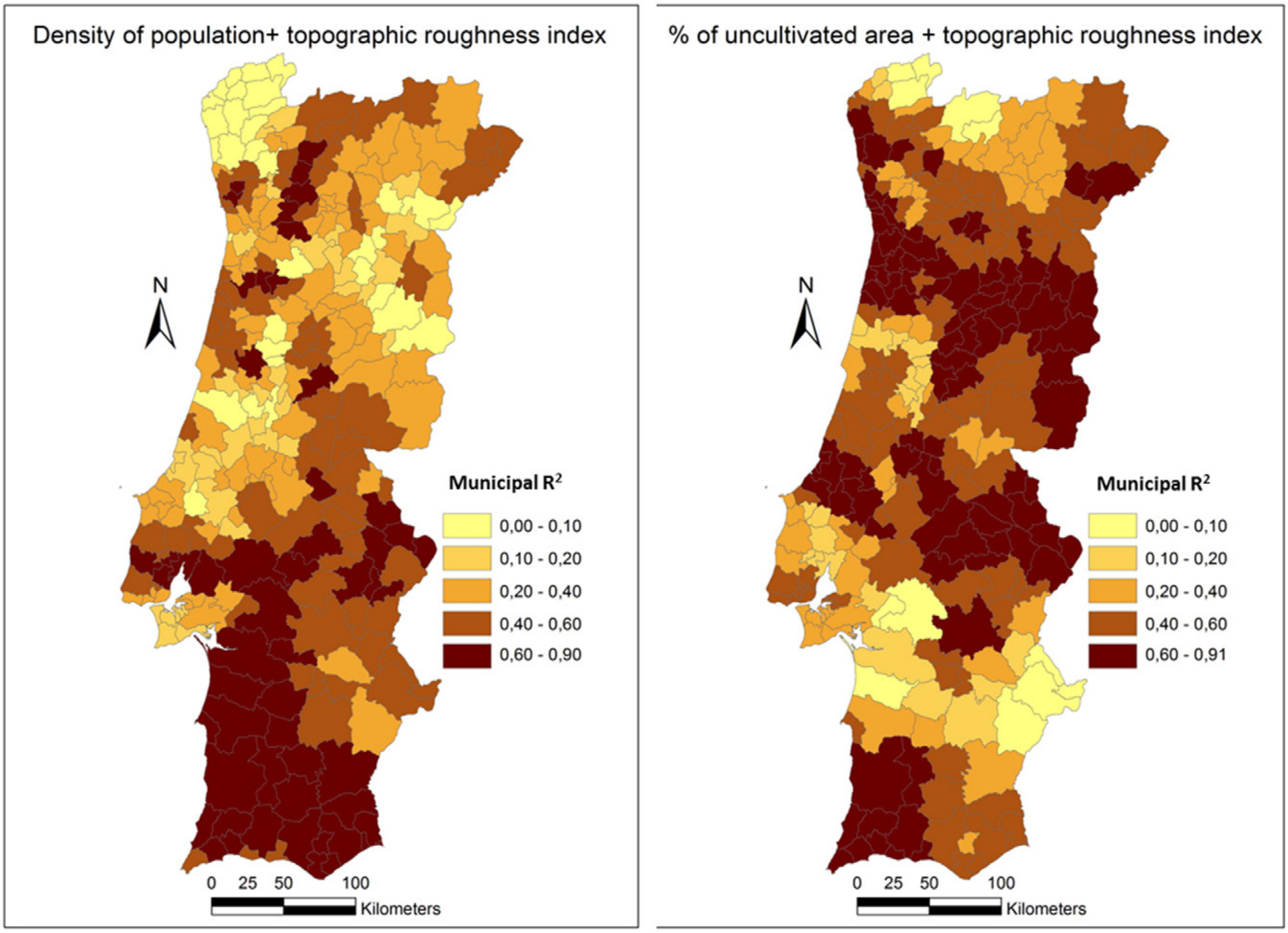

Fig. 6. Distribution of municipal R^2 results from the application of GWR between fire ignition density and burnt area and two explanatory variables (A: fire ignition density vs population density and topographic roughness index; B: % of burnt area vs percentage of uncultivated area and topographic roughness index).

2013; Ganteaume and Jappiot, 2013). Ganteaume et al. (2013), Ganteaume and Jappiot (2013) consider that in densely populated Mediterranean regions the impact of anthropogenic pressure on fire regimes reflects the expansion of the wildland-urban interface landscape and the increasing demand for recreational facilities in wildland areas.

The varying unemployment rate in the previous decade also emerges as a significant factor in explaining the spatial variability in density of ignitions, confirming the idea of various authors (Bertrand and Baird, 1975; Leone and Vita, 1982; Martínez et al., 2009; Oliveira et al., 2012) who have identified economic difficulties as a possible reason for increasing conflicts that result in more deliberate fires.

Socioecological causes also act together to create the conditions for a greater incidence of burnt areas in certain regions of Portugal. Since the second half of the last century, agricultural abandonment, as a consequence of demographic changes (the population exodus from rural areas to European countries and to coastal cities, and the aging population), has led to a marked increase in uncultivated land, which is covered mainly by shrubs, grass and other light vegetation that is very prone to fire. Several studies have confirmed that shrub is one of the land cover types most affected by fire (Nunes et al., 2005; Sebastián-López et al., 2008; Catry et al., 2009; Moreira et al., 2009; Bajocco and Ricotta, 2008; Nunes, 2012; Carmo et al., 2011; Oliveira et al., 2012; Ganteaume et al., 2013; Oliveira et al., 2014), mainly due a combination of two factors: the higher rate at which fire spreads and the fact that it is considered a lower firefighting priority (based on the assumption that shrub is the least valuable land cover due to the low economic value of restoration, valued at around 250 € per hectare, according Oehler et al., 2012). The exclusion of fires from forest management and the unmanaged accumulation of large quantities of fuel and has also contributed to a dramatic increase in the magnitude and frequency of wildfires (Carvalho et al., 2002; Moreno, 1998; Moreno and Oechel, 1995; Moreira et al., 2011).

Topography is another factor that positively affects both burnt areas and ignition density on a municipal scale in Portugal. In several studies (Dickson et al., 2006; Sebastián-López et al., 2008; Badia et al., 2011; Nunes, 2012; Padilla and Vega-García, 2011; Narayanaraj and Wimberly, 2012; Martínez-Fernández et al., 2013) variables associated with topography (e.g. elevation and slope) have been correlated with fires, although some of the results are contradictory. Narayanaraj and Wimberly (2012), for example, detected a negative association between elevation and slope and fires caused by humans in a mountain area of Washington State. Dickson et al. (2006), analysing the incidence of major fires occurring between 1986 and 2000 in the southwestern U.S., verify that the probability of occurrence was greatest in areas of high topographic roughness and lower road density.

In general, shrub is a common type of land cover on steeper slopes, where fire spreads at a faster rate (Rothermel, 1983). Moreover, the delay in detecting fires, difficulties in gaining access to the sites where fires tend to start and spatial continuity of susceptible vegetation cover explain the significant influence of topography on burnt incidence. In these latitudes, the topographic roughness index showed strong positive correlations with mean annual precipitation (r: 0.816, p-value < 0.000) and negative associations with average annual temperature (r: −0.830) (Nunes et al., 2014), meaning that the higher average annual precipitation and the lower average annual temperatures recorded in the more mountainous areas increase productivity and generate higher fuel loads in shrubland. The accumulation of fuel biomass could be one reason why farmers, negligently or intentionally, start fires in order to control the spread of shrubs and facilitate farming and the regeneration of forage (De la Riva and Perez-Cabello, 2005).

The aging index correlates negatively with ignition density and positively with the burnt area percentage, meaning that the largest burnt area occurs in the regions most seriously affected by the rural exodus (fewer people living in, and using, the countryside) where land abandonment seems to be more significant. Martínez-Fernández et al. (2013) also found, for the NW of Spain (Galicia), the region most severely affected by fire, a strong positive relationship with the aging agricultural population variable, since in this region older people are more accustomed to using fire as an agricultural technique (Vélez, 2009).

At the municipal level, agriculture, forestry and grazing seems to reduce fire ignitions and burnt area, suggesting that the survival of traditional Mediterranean silvopasture activities reduces the incidence and impact of wildfires. However, some previous research (e.g., Catry et al., 2009; Verdú et al., 2012) has found that agricultural land is generally associated with higher wildfire rates. The results also indicate that livestock grazing has a negative impact on the level of fuel due to removal of vegetation, and the grinding of fine fuels by animal hoofs (Nader et al., 2007; Diamond et al., 2009), meaning fewer wildfires and burnt areas. Nevertheless, several authors found positive correlations (Leone et al., 2009; Koutsias et al., 2010; Moreira et al., 2011). For example, Moreira et al. (2011) confirm that in the Cantabrian Mountains and north coast of Spain there are fires are frequently used to create, maintain, or regrow pasture for livestock.

4.3. The performance of GWR modelling in comparison with classical linear regression

The results obtained by using the GWR method showed a high predictive potential for environmental and man-made wildfire occurrence modelling that greatly surpasses simple regression techniques. The improved performance of GWR in comparison with SLR models is demonstrated by the significantly higher R^2 values and lower AICc scores. This study produced results similar to previous GWR models applied to wildfire data (Martínez-Veja et al., 2012; Martínez-Fernández et al., 2013; Oliveira et al., 2014; Rodrigues et al., 2014) in which GWR was shown to be a significant improvement on global regression techniques. In analysing the long-term factors that influence fire distribution in two Mediterranean regions, Oliveira et al. (2014) found an improvement in GWR in comparison to OLS (Ordinary Least Squares) ranging from 37% to 82% and 13% to 47% in south-western and south-eastern Europe respectively.

The use of GWR also corroborated the existence of spatial variations in the predictive variable, enabling nonstationary relationships between dependent and explanatory factors to be detected. In fact, an additional advantage of the GWR method was the ability to explore spatial variability in relationships between wildfires and explanatory variables by mapping the variation in local parameter coefficients.

Despite offering many advantages, GWR should be used with some caution. The size of the kernel bandwidth should be carefully selected, due to its significant impact on the outcome of the GWR analysis. In general, increasingly smaller bandwidths result in parameter estimates that are highly localized and have a large degree of variance, whereas increasingly larger bandwidths tend towards the normal global regression estimates. Attention should be also paid to possible collinearity in the municipal regression coefficients, which may limit interpretation of their distributional patterns (Wheeler and Tiefelsdorf, 2005).

5. Conclusion and further research

Understanding the spatial variations, trends and driving forces behind wildfires in Portugal on a municipal/regional level can assist in the design of appropriate prevention measures and improve the effectiveness of fire prevention, as well as provide support for environmental and civil protection policies such as the allocation of firefighting resources.

In fact, there is a geographical gradient associated with both fire ignition and burnt area that is significantly related to population density, topography and land cover. As the topography cannot be controlled, the management options for reducing wildfires must address the root causes of fires associated with human and land-use factors which influence the management of agricultural, forest and shrubland fuels.

Although the identification of these factors represents an important contribution provided by this study, other explanatory factors should be integrated into future research, such as the role of human action in fire ignition, since the majority of fires are directly or indirectly caused by human activities (involuntary or deliberate actions), and other variables related to agricultural activities and forest management that also influence wildfire occurrence.

Moreover, the influence of the future climate in the Mediterranean region should not be forgotten, since climate change projections indicate longer dry, hot summers and more frequent and intense extreme weather events, leading to larger and more frequent fires, with severe consequences for Portuguese terrestrial ecosystems. In addition to exploring new predictors, future research should test new data modelling procedures in order to capture the true relationship between the variables in question more efficiently.

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