Applied Geography 48 (2014) 52–63

Contents lists available at ScienceDirect

Applied Geography

journal homepage: www.elsevier.com/locate/apgeog

Modeling the spatial variation of the explanatory factors of human-caused wildfires in Spain using geographically weighted logistic regression

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Keywords:
Fire risk
Human causality
Forest fires
GWR
Logistic regression
GIS modeling

A B S T R A C T

Forest fires are one of the main factors transforming landscapes and natural environments in a wide variety of ecosystems. The impacts of fire occur both on a global scale, with increasing emissions of greenhouse gases, and on a local scale, with land degradation, biodiversity loss, property damage, and loss of human lives. Improvements and innovations in fire risk assessment contribute to reducing these impacts. This study analyzes the spatial variation in the explanatory factors of human-caused wildfires in continental Spain using logistic regression techniques within the framework of geographically weighted regression models (GWR). GWR methods are used to model the varying spatial relationships between human-caused wildfires and their explanatory variables. Our results suggest that high fire occurrence rates are mainly linked to wildland–agricultural interfaces and wildland–urban interfaces. The mapping of explanatory factors also evidences the importance of other variables of linear deployment such as power lines, railroads, and forestry tracks. Finally, the GWLR model gives an improved calculation of the probabilities of wildfire occurrence, both in terms of accuracy and goodness of fit, compared to global regression models.

Introduction

Forest fires are an important factor in landscape transformation, vegetation succession, land degradation, and air quality. Although fire has been traditionally used as a land management tool, and many ecosystems are well adapted to fire cycles, recent changes in weather and social factors relating to wildfire could be modifying the historical fire regimes (Gonzalez, Neilson, Lenihan, & Drapek, 2010; San-Miguel Ayanz et al., 2012), possibly resulting in undesired effects. Indeed, the influence of climate change on an increase in fire frequency and intensity has been reported in several ecosystems (Kasischke & Turetsky, 2006; Westerling, Hidalgo, Cayan, & Swetnam, 2006). Climatic projections suggest worse conditions in future decades in tropical and boreal regions (Flannigan, Logan, Amiro, Skinner, & Stocks, 2005). In addition to these global effects, wildfires also have relevant local effects which are commonly associated with the frequency and intensity of fires, often implying soil loss and land degradation, loss of lives or biodiversity, and damage to property and infrastructure (Omi, 2005). On the other hand, human beings have a great impact on fire regimes because they alter ignition frequency and fuel fragmentation and suppress fires (Guyette, Muzika, & Dey, 2002). The dynamics of fire regimes in southern Europe are mainly related to human factors. In fact, humans are responsible for more than 95% of the fires in this region (San-Miguel Ayanz & Camiá, 2009). In the case of Spain, nearly 90% of wildfires are related to an anthropogenic source (Chuvieco et al., 2012; Martinez, Vega-Garcia, & Chuvieco, 2009). It is thus clear that human factors play an important role in fire ignition. Furthermore, determining the explanatory factors facilitates the development of future wildfire scenarios in the context of climate change. Therefore, a better comprehension of the local driving forces of fire ignition and of predicting where fires are likely to start are core elements in designing strategies to mitigate wildfire initiation and to identify areas at risk (Finney, 2005). In recent years, several methods for wildfire risk assessment have been developed using different methodological schemes, variables, and scales (Martínez-Vega, Echevarría, Ibarra, Echeverría, & Rodrigues, 2012). Without being exhaustive, some of the more recent efforts have included those by Amatulli, Rodrigues, Trombetti, and Lovreglio (2006), Chuvieco et al. (2010, 2012), Cooke et al. (2007), Loboda (2009),

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0143-6228/$ – see front matter
http://dx.doi.org/10.1016/j.apgeog.2014.01.011

Martínez, Chuvieco, and Koutsias (2013), Martinez et al. (2009), Padilla and Vega-Garcia (2011), and Romero-Calcerrada, Barrio-Parra, Millington, and Novillo (2010). Similar efforts have been invested in modeling fire occurrence (see Plucinksi, 2011 for an exhaustive review) and, particularly, to human-caused ignition (Martinez et al., 2009, 2013; Padilla & Vega-Garcia, 2011). The analysis of human factors in forest fires is widely recognized as critical for fire risk estimation (Kalabokidis, Gatzojannis, & Galatsidas, 2002; Martínez, Chuvieco, & Martín, 2004), however the literature on this topic is scarce and mainly site-specific (Krawchuk et al., 2009; Le Page, Oom, Silva, Jönsson, & Pereira, 2010; Martinez et al., 2009), perhaps due to the complexity of predicting human behavior, both in space and time. Currently, most fire risk models in use are based on physical parameters such as weather data or fuel moisture content – there is no global forest fire risk system that includes the human factors operationally, although some consider it in their components (San-Miguel Ayanz & Camiá, 2009). However, over recent years, the role of human factors in fire behavior modeling has been increasing, and several models now include an anthropogenic component in their assessments (Chuvieco et al., 2010, 2012; Loepfe, Martinez-Vilalta, & Piñol, 2011).

Additionally, the fit of statistical models of risk estimation, previously discussed for different regions of the Iberian Peninsula by Chuvieco et al. (2010), shows that the explanatory factors vary spatially in their significance and contribution. This finding is also supported by Padilla and Vega-Garcia (2011), who reported the existence of high spatial variation in the relationships between explanatory variables and historical human-caused fire occurrences. Accordingly, the use of global regression methods over wide areas, such as here, could be inappropriate due to the application of stationary coefficients over the whole study area, possibly masking local interactions with the explanatory factors. Hence, to better understand the causes of wildfires, the spatial variation of the human factors associated with wildfires must be properly analyzed. To overcome this limitation, in the present paper we use geographically weighted regression techniques (GWR) (Fotheringham, Brunsdon, & Charlton, 2002), which allow us to incorporate in the models the spatial variation of the explanatory variables, in a way similar to Martínez and Koutsias (2013) but focusing exclusively in the human influence on wildfire ignitions. Examples of the application of GWR to a number of subjects are found in Cardozo, García-Palomares, and Gutiérrez (2012), Chalkias et al. (2013), Chi, Grigsby-Toussaint, Bradford, and Choi (2013), Li, Heap, Potter, and Daniell (2011), Lu, Charlton, and Fotheringhama (2011), Tu (2011), Su and Zhang (2012), Wang, Zhang, and Li (2013) and Xiao et al. (2013); GWR is applied specifically to the occurrence of forest fires in Chuvieco et al. (2012), Koutsias, Chuvieco, and Allgöwer (2005), Martínez and Koutsias (2011), Martinez et al. (2013), and Rodrigues and de la Riva (2012). In this context, we apply binary logistic regression, commonly used for probabilistic explanation of human-caused occurrence (Chuvieco et al., 2010; Martínez, Chuvieco, et al., 2004; Vasconcelos, Silva, Tomé, Alvim, & Pereira, 2001; Vega-Garcia, Woodard, Titus, Adamowicz, & Lee, 1995), but within the framework of GWR models.

Therefore, the aim of this paper was to model and analyze, using GWLR techniques, the spatial variation in the human factors associated with forest fires. Our hypothesis is that the explanatory factors for human wildfires are not-stationary, rather their relationship with fires changes significantly over the space. The fit of GWLR models (geographically weighted logistic regression) required the statistical analysis and spatialization both of the historical occurrence (in the period 1988–2007) and of a large number of explanatory variables, selected based on experience of models at regional and national scales (Chuvieco et al., 2010; Martinez et al., 2009; Vilar del Hoyo, Martín Isabel, & Martínez Vega, 2008). Ignition data was retrieved from the General Statistics of Wildfires database (EGIF), one of the oldest 'complete' wildfire databases in Europe, beginning in 1968 (Vélez, 2001). The EGIF database registers information about several parameters related with fire ignition such as location, cause, date, size or affected vegetation. The explanatory variables were derived from spatial datasets and statistical data obtained from official data sources of the Spanish Government, later explained in detail. Model adjustment was carried out using a random sample of 60% of the ignition data, reserving the remaining 40% for the validation process. Additionally, an alternative validation sample constructed from the occurrence in the period 2008–2011 was used in the validation process to test the predictive capacity of the model.

This work was developed within the framework of the FIRE-GLOBE project (www.fireglobe.es, Chuvieco et al., 2011, 2012). In following sections, we describe the method used for modeling the spatial variation of the explanatory factors, the main results of the application of the methodology to peninsular Spain, the degree of fit of the model, and the results of the validation process. A comparison of the performance of GWR and global models, and of our work and similar studies is also conducted. Finally, we present our conclusions and suggestions for further research.

Materials and methods

The methodology for modeling human causality in forest fires is based on GWLR techniques. Specifically, we used the GWR 3.0 software developed by the NCG (Fotheringham et al., 2002). Like global logistic regression models (GLR), GWLR are statistical models that provide insights into the relationship between a qualitative dependent variable, dichotomous in our case, and one or more independent explanatory variables, whether qualitative or quantitative. Therefore, its development requires on the one hand a binary dependent variable, in this case the high/low occurrence of fires, and secondly a set of predictor variables, which are listed below. Fig. 1 shows a schematic of the workflow followed for modeling human causality.

Overview of GWLR

GWR techniques extend the traditional use of global regression models, allowing calculation of local regression parameters. Taking as a starting point the typical equation of the logistic regression:

$$y_i = \frac{e^{(\beta_0+\beta_1 x_{1i}+\cdots+\beta_k x_{ki})}}{1+e^{(\beta_0+\beta_1 x_{1i}+\cdots+\beta_k x_{ki})}} \tag{1}$$

the mathematical expression of its geographically weighted version is:

$$y_{(u_i,v_i)} = \frac{e^{(\beta_0(u_i,v_i)+\beta_1(u_i,v_i)x_{1i}+\cdots+\beta_k(u_{ki},v_{ki})x_{ki})}}{1+e^{(\beta_0(u_i,v_i)+\beta_1(u_i,v_i)x_{1i}+\cdots+\beta_k(u_{ki},v_{ki})x_{ki})}} \tag{2}$$

where (u_i,v_i) are the location coordinates in space of point i.

Accordingly, the use of GWLR models allows one to obtain regression coefficients whose values vary spatially, thus obtaining a different set of regression coefficients for each location in the study area. To do this, a regression model is adjusted for each point and its nearest neighbors. The influence of the points in this neighborhood varies according to the distance to the central point (Fotheringham et al., 2002). The optimum distance threshold (also known as the bandwidth) or the optimum number of neighbors is determined in two ways: by minimizing the square of the residuals (cross-Validation, Cleveland, 1979) or by minimizing the Akaike Information Criterion (AIC, adapted for GWR by Hurvich, Simonoff, & Tsai, 1998).

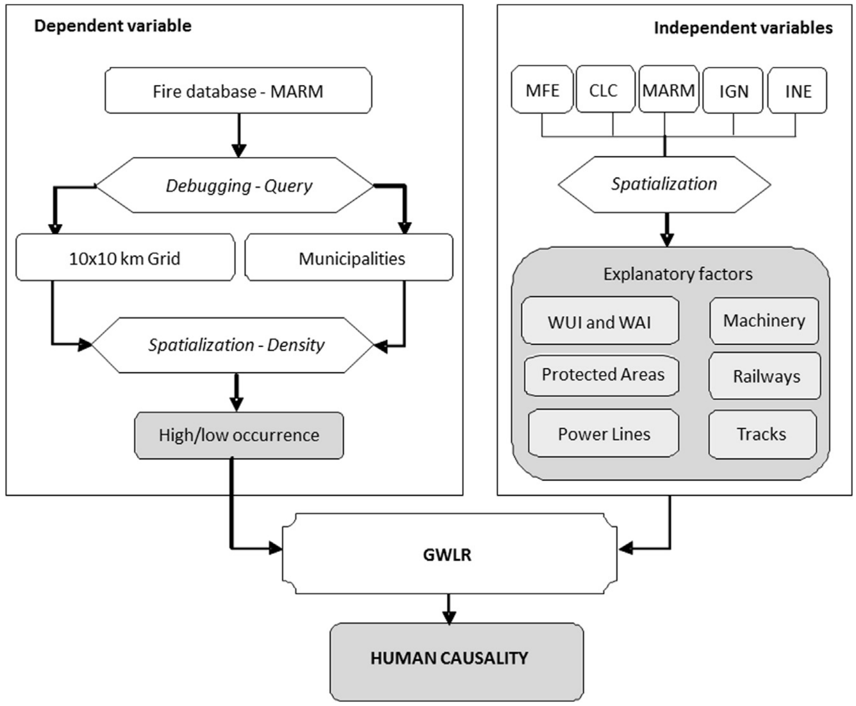

Fig. 1. Workflow followed for human causality modeling.

In addition to the regression coefficients, the GWLR model calculates several useful statistical parameters to analyze each of the explanatory variables, such as the value of the Student *t* test (used to determine the level of significance) and the local R^2 value (i.e., the R^2 value of the resulting model at the point where the value is referenced and its neighbors), among others. However, GWLR does not allow estimation of regression coefficients in locations where there is no observation. In order to overcome this limitation and apply the model to the entire area of study, the regression coefficients are interpolated using the Local Polynomial Interpolation method in ArcGIS 10.1 (1st order polynomial and exponential kernel function), thus preserving the original values of locations with observations and hence the internal consistency of the model.

In this work, a GWLR model was adjusted using a random sample of 60% (3582 points) of the total sample, reserving the remaining 40% (2408 points) for the validation process. Model calibration was carried out using Adaptive Kernel to select the bandwidth, optimized according to the value of AIC. In this case, the optimum number of neighbors was 914.

Study area

The study area covers the whole of peninsular Spain excluding the Balearic and Canary Islands and the autonomous cities of Ceuta and Melilla, as some parameters needed to develop the methodology were not available in those areas. Thus the total area of the study region was around 498 000 km^2. Further, the study region was restricted to forested areas; consequently, urban areas and agricultural and inland water zones were excluded from the assessment and no data are detailed or shown on the maps (Fig. 2). Spain is very biophysically diverse, presenting a wide variety of climatic, topographic, and environmental conditions. This diversity also appears when discussing socioeconomic conditions, in terms of population systems and population structure, productive sector, or territory structure. The complexity of the socioeconomic conditions thus plays a determinant role, which is especially important when modeling human factors, since this complexity is transferred to the relationships between socioeconomic variables and a natural phenomenon such as wildfires, making assessment less straightforward.

Dependent variable

The dependent variable was created on a conceptual framework which assumed that there were no true cases of fire absence. In ignition data, most or all of the fire occurrences are accounted for, which may make it seem as if all other locations in the landscape have no fires. In this context, most previous attempts at fire occurrence modeling had used background subsets of “no occurrence” during the analyzed time span, considering them to be true

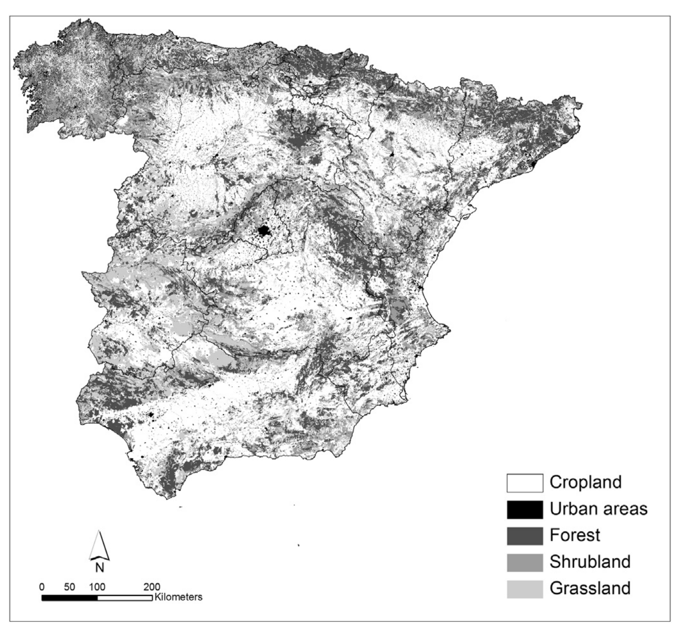

Fig. 2. Study area and land use distribution.

cases of fire absence (e.g., Chuvieco et al., 2010; Padilla & Vega-Garcia, 2011). However, the fact that these areas did not experience an ignition event during the temporal span of the data set does not mean that they could not feasibly support an ignition event in the future, or that they never ignited in the past (Bar Massada, Syphard, Stewart, & Radeloff, 2012). In line with this reasoning, the dependent variable – high/low wildfire occurrence – is constructed from the EGIF database, 1988–2007, compiled by the Ministry of Environment, Rural, and Marine Affairs (MARM) using forest fire reports from the various autonomous regions (Moreno, Malamud, & Chuvieco, 2011). Among other useful information relating to fire events, these reports include data regarding the starting location point of each fire. This position is recorded on the basis of a reference 10 × 10 km grid, used by firefighting services for approximate location of fire events, and the municipality origin of the ignition. The ignition location procedure is based in the method developed by de la Riva, Pérez-Cabello, Lana-Renault, and Koutsias (2004). This method is widely recognized and has been used in many wildfire assessment research works in the Spanish territory such as Amatulli, Peréz-Cabello, and de la Riva (2007) or Chuvieco et al. (2010). The method proposes a multi-step procedure which successively refines and decreases the potential location area of the ignition points. Firstly it starts in the 10 × 10 grid with a potential location area of 100 km^2. Then this area is decreased by intersecting with the municipality boundaries. Finally, the location area is restricted to the forest perimeter – since the ignition location of every wildfire is expected to be in the forest area – to determine the final potential location area. This process leads to a significantly smaller area where the ignition points are then randomly distributed. After cleaning and treatment of the database, human-caused fires over 5 ha in size were selected (8727 fires) and spatialized by the random assignment of each fire to its respective combination of grid/municipality, restricted to forested areas. This allowed us to calculate fire density maps with a spatial resolution of 1 × 1 km by overlapping the ignition points cloud and a 1 × 1 km UTM grid (which perfectly fits the 10 × 10 grid). It should be noted that in this study density values were calculated only in locations where at least one fire event was recorded (7873 cells). These density values were divided into high (1) and low occurrence (0) by separating the sample into tertiles. We considered the third tertile (sample above the 66th percentile or 1.83 fires/km^2) as high occurrence, and the first tertile (sample below the 33rd percentile or 1.00 fires/km^2) as low occurrence, discarding the second tertile from the analysis.

Independent variables

As stated previously, the explanatory variables were selected on the basis of experience of models at regional and national scale (Chuvieco et al., 2010; Martinez et al., 2009; Vilar del Hoyo et al., 2008). Thus, the explanatory variables were classified according to the typology of the affecting factor (Leone, Martínez, Vega-García, Allgöwer, & Lovreglio, 2003; Martínez, Martínez-Vega, & Martín, 2004), as follows:

1. Factors related to socioeconomic transformation.
   1.1. Abandonment of traditional activities in wildland/rural areas. Accumulation of forest fuel.
      1.1.1. ***People employed in the primary sector.*** Obtained at the municipal level from the Agricultural Census 1999 of the Spanish Statistics Institute (INE).
   1.2. Abandonment of traditional activities in wildland/rural areas especially in privately owned forests with no prospect of economic profit. Little or no interest in forest conservation.
      1.2.1. ***Forestry area in public utility.*** Delimitation of the area occupied by forestry areas included in the public utility catalog.
   1.3. Increasing use of forest as a recreational resource. More frequent visits to forests.
      1.3.1. ***Tracks.*** Area occupied by the buffer 200 m either side of the forestry track network. Obtained from BCN200.
   1.4. Human presence, population increase and urban growth. Increased pressure on wildlands
      1.4.1. ***Wildland–Urban Interface (WUI).*** Area occupied by the buffer 200 m from the line of contact to the forest area. Constructed from the Spanish Forestry Map 1:200,000 (MFE200).
      1.4.2. ***Changes in demographic*** *potential, 1991–2006* (Calvo & Pueyo, 2008). Variation rate between the demographic potential in 1991 and 2006.
2. Factors related to traditional economic activities in rural areas.
   2.1. Aged rural population. Traditional management methods.
      2.1.1. ***Percentage of owners of holdings aged over 55 years.*** Obtained at the municipal level from the Agricultural Census 1999 of the Spanish Statistics Institute (INE).
   2.2. Agriculture. Use of fire to clear harvesting waste, cleaning along borders of cropland.
      2.2.1. ***Wildland–agricultural interface (WAI).*** Area occupied by the buffer 200 m from the line of contact to the forest area. Constructed from the Spanish Forestry Map 1:200,000 (MFE200).
   2.3. Cattle grazing. Possible fire to maintain herbaceous vegetation.
      2.3.1. ***Extensive livestock.*** Obtained at municipal level from the Agricultural Census 1999 of the Spanish Statistics Institute (INE).
      2.3.2. ***Wildland-grassland interface (WGI).*** Area occupied by the buffer 200 m from the line of contact to the forest area. Constructed from the Spanish Forestry Map 1:200,000 (MFE200).
3. Factors that could cause fire mainly by accident or negligence.
   3.1. Electric lines. Possible cause of ignition by accident.
      3.1.1. ***Power lines.*** Area occupied by the buffer 50 m either side of the high, medium, and low voltage power network. Obtained from BCN200.
   3.2. Engines and machines working in or close to forested areas possible cause of ignition by accident or negligence.
      3.2.1. ***Density of agricultural machinery (DAM).*** Obtained at municipal level from the Agricultural Census 1999 of the Spanish Statistics Institute (INE).
   3.3. Existence of roads, railroads, tracks, and accessibility. Greater human pressure on wildland.
      3.3.1. ***Railroads.*** Area occupied by the buffer 200 m either side of the railroad network (excluding the high-speed network). Obtained from a digital cartographic database (BCN200).
      3.3.2. ***Tracks.***
      3.3.3. Changes in demographic potential 1991–2006.
4. Factors that could help prevent fires.
   4.1. Protected area. Increasing concern about forest protection.
      4.1.1. ***Protected areas.*** Delimitation of the area occupied by protected natural areas and the *Natura 2000* network.
5. Factors that generate conflicts, and which could lead to intentional starting of fire and/or facilitating its spread.
   5.1. Changes from forest use. Possible cause of arson.
      5.1.1. ***Changes in land cover.*** Loss or increase of area covered by forest or semi-natural regions.

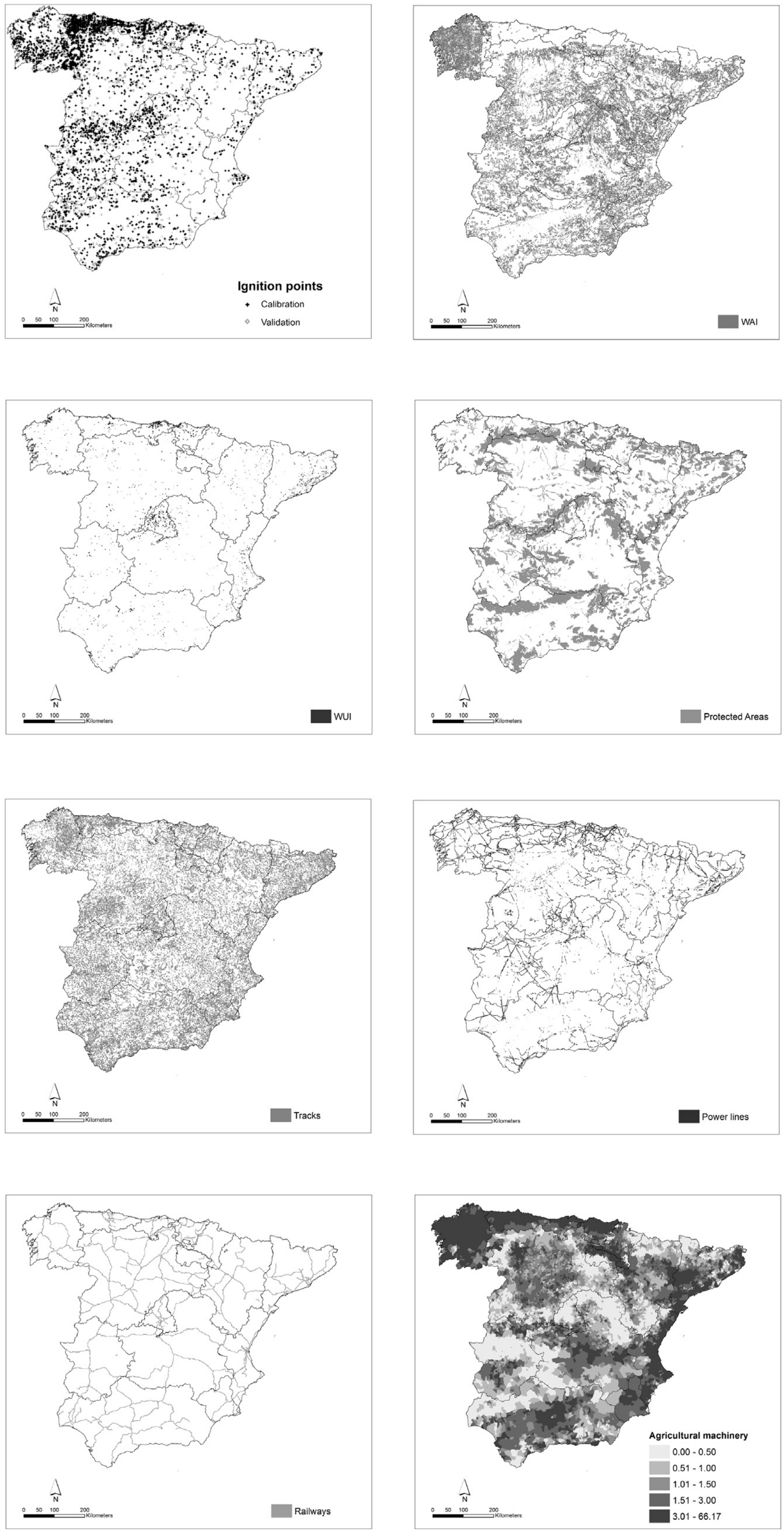

Fig. 3. Variables considered in the GWLR model.

Obtained from the Corine Land Cover 1990 and 2006 maps.

5.2. Fire industry. Fire started to gain income, work, payment or subsidies from fire prevention or fighting and in restoration of land affected by fire.

5.2.1. ***Unemployment rate.*** Obtained for municipal level in 2007 from the population and housing census 2001 (updated to 2007) of the Spanish Statistics Institute (INE).

All the predictive variables, as well as the dependent variable, were spatialized at a resolution of 1 × 1 km (see Fig. 3). To ensure consistency of results, we conducted an analysis of collinearity in the explanatory variables using the non-parametric Spearman's Rho correlation index. No collinear variables were found (Table 1). To determine the variables that would eventually be included in the model, we set a preliminary GWLR model including all the considered variables. From this first model, we discarded those variables that were not significant by Student's t test ($p < 0.05$), or its explanatory sense was not consistent with what would be expected based on experience and expert opinion. The variables used for adjustment of the final model were WAI, WUI, protected areas, power lines, railroads, tracks, and DAM.

Model validation

The model validation procedure was conducted using firstly the local R^2 values obtained during the calibration of the model. The local R^2 values allow a first assessment of the degree of fit of the GWLR model. Secondly, we present the percentage of success in the classification of the points and the calculation of the degree of agreement using Cohen's Kappa. The Kappa value is calculated for two different validation samples: the first with 40% of the total sample for 1988–2007 and the second constructed from the fire events recorded for 2008–2011, to test the predictive capacity of the model. The latter was spatialized using the same process and thresholds for the classification of the occurrence as for the period 1988–2007.

Results and discussion

The main results obtained from modeling human causality in forest fires were the regression coefficients of the explanatory variables, the spatial variation in the significance level of these variables, and the probability of wildfire occurrence. The results of the validation are also presented in this section.

Spatial variation of probability of ignition and its driving factors

Fig. 4 shows the map of interpolated regression coefficients associated with the explanatory variables. As can be seen, the values of these coefficients vary spatially as a result of the adjustment by GWLR. At this point, it should be noted that these values are not directly related to a greater or lesser weight in the model but to the units of measurement of the predictive variables. However, the maps of regression coefficients are a first approximation to the measurement of the spatial variation of the explanatory factors. To determine the degree of participation of the variables in the model, the significance thresholds should be taken as reference, mapped in Fig. 5. These thresholds are not only linked to the degree of participation of the independent variables in the model, but also provide information about their explanatory sense. Accordingly, the higher the significance threshold (and therefore the higher the value of the Student t test, regardless of its sign), the greater the participation of the variable in the model. On the other hand, positive values of significance imply a direct relationship between the explanatory variable and human causality or, which is the same, the higher the value of the variable the higher the probability of occurrence, and vice versa. In the opposite case, i.e., Student's t values below 0, we find an inverse relationship between the values of the explanatory variables and the occurrence, the probability being lower the greater the value of the variable. For a correct interpretation of these results, it is important to recall that the mapped values of significance thresholds represent a value obtained locally with a sample composed of the point where the value is assigned and represented on the map, plus its 914 closest neighbors, and not only at the represented point.

A more detailed analysis of the cartography, shown in Fig. 6, reveals that the greatest burden in the model falls on the explanatory variable WAI. Contrary to the other variables, which do not exceed the threshold of $p < 0.25$ in some parts of the study region, WAI is significant with $p < 0.05$ in almost all locations which means that it has a relevant contribution in the whole Spanish territory. To this must be added the fact that the explanatory sense of the WAI is always positive. This outstanding contribution could be related to the large-scale socioeconomic changes in recent decades which have driven shifts in the structure of Spanish rural landscape, increasing the complexity of the spatial distribution of the WAI and, accordingly, increasing wildfire frequency. It should also be noted that the WAI is an area of intense competition between agricultural and forestry activities. In some cases this competence may turn into conflicts of interest that result in aggressive practices such as the use of fire for clearing forests and pasture establishment. This,

Table 1
Results from the colinearity analysis. Spearman's Rho rank correlation index.

	WUI	WAI	WGI	MUP	PA	VARPOT	LUC	UR	PS	OWN55	DAM	EXTLIVS	PWL	RAIL	TRACKS
WUI	1.00	0.05	0.03	−0.06	−0.04	0.12	0.01	−0.03	−0.16	0.01	0.06	0.00	0.14	0.15	0.07
WAI	0.05	1.00	−0.31	−0.29	−0.18	0.26	−0.04	−0.09	−0.09	0.13	0.06	−0.30	0.03	−0.02	0.01
WGI	0.03	−0.31	1.00	0.16	0.04	−0.20	−0.02	0.00	0.12	−0.14	0.06	0.25	0.03	0.05	0.07
MUP	−0.06	−0.29	0.16	1.00	0.14	−0.15	0.02	−0.08	0.11	−0.15	−0.04	0.09	−0.03	−0.05	−0.08
PA	−0.04	−0.18	0.04	0.14	1.00	0.02	0.02	0.07	0.06	−0.05	−0.18	−0.05	−0.05	0.00	−0.05
VARPOT	0.12	0.26	−0.20	−0.15	0.02	1.00	−0.03	−0.08	−0.40	0.02	−0.21	−0.29	0.05	0.01	−0.02
LUC	0.01	−0.04	−0.02	0.02	0.02	−0.03	1.00	−0.07	0.03	0.04	0.04	0.02	0.02	−0.01	−0.03
UR	−0.03	−0.09	0.00	−0.08	0.07	−0.08	−0.07	1.00	−0.26	0.09	−0.26	0.04	−0.05	0.02	−0.02
PS	−0.16	−0.09	0.12	0.11	0.06	−0.40	0.03	−0.26	1.00	−0.26	0.12	0.15	−0.12	−0.15	−0.06
OWN55	0.01	0.13	−0.14	−0.15	−0.05	0.02	0.04	0.09	−0.26	1.00	−0.18	−0.34	0.05	0.02	−0.03
DAM	0.06	0.06	0.06	−0.04	−0.18	−0.21	0.04	−0.26	0.12	−0.18	1.00	0.38	0.10	0.03	0.15
EXTLIVS	0.00	−0.30	0.25	0.09	−0.05	−0.29	0.02	0.04	0.15	−0.34	0.38	1.00	0.03	0.03	0.12
PWL	0.14	0.03	0.03	−0.03	−0.05	0.05	0.02	−0.05	−0.12	0.05	0.10	0.03	1.00	0.15	0.07
RAIL	0.15	−0.02	0.05	−0.05	0.00	0.01	−0.01	0.02	−0.15	0.02	0.03	0.03	0.15	1.00	0.09
TRACKS	0.07	0.01	0.07	−0.08	−0.05	−0.02	−0.03	−0.02	−0.06	−0.03	0.15	0.12	0.07	0.09	1.00

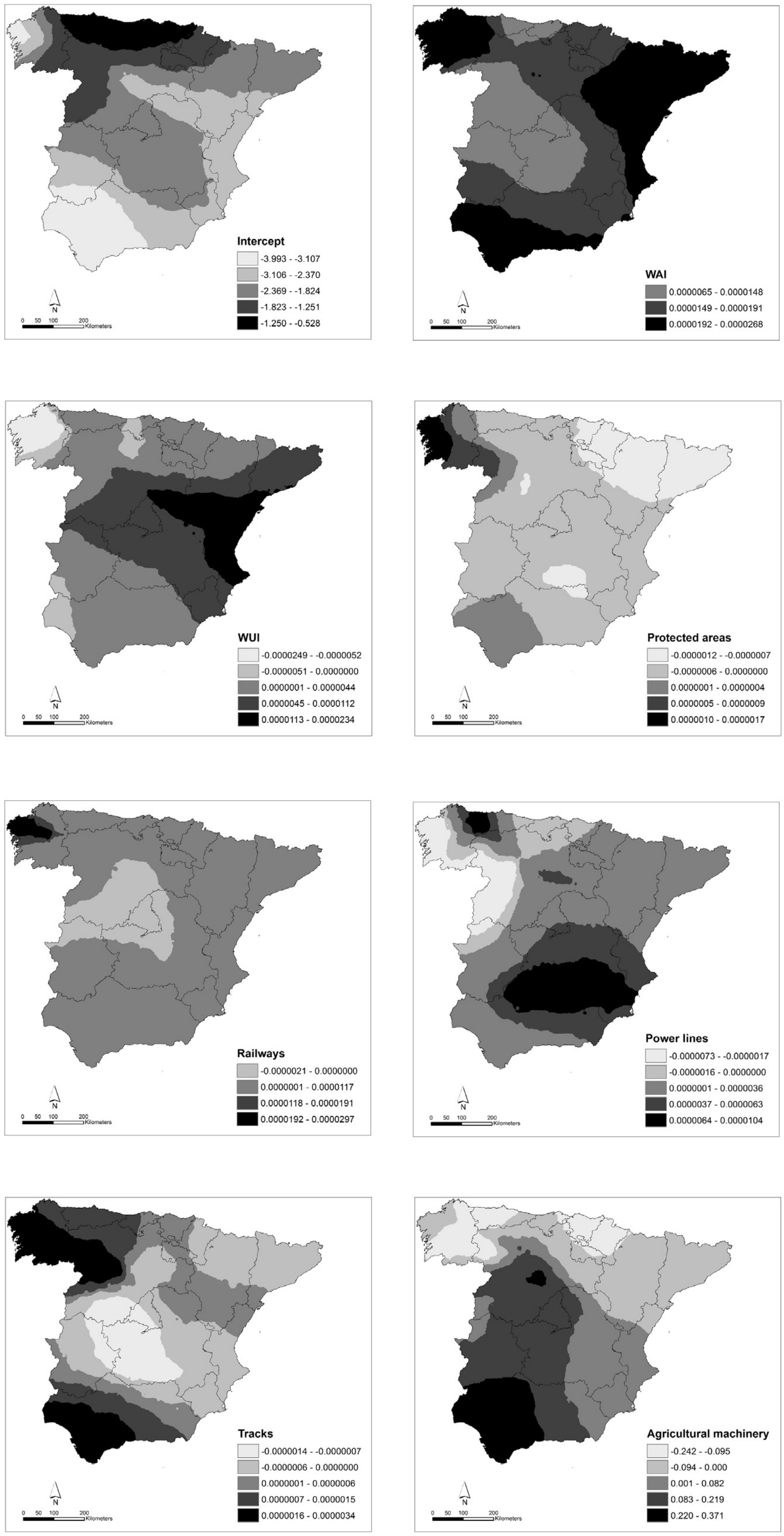

Fig. 4. Regression coefficients for the explanatory variables in the GWLR model.

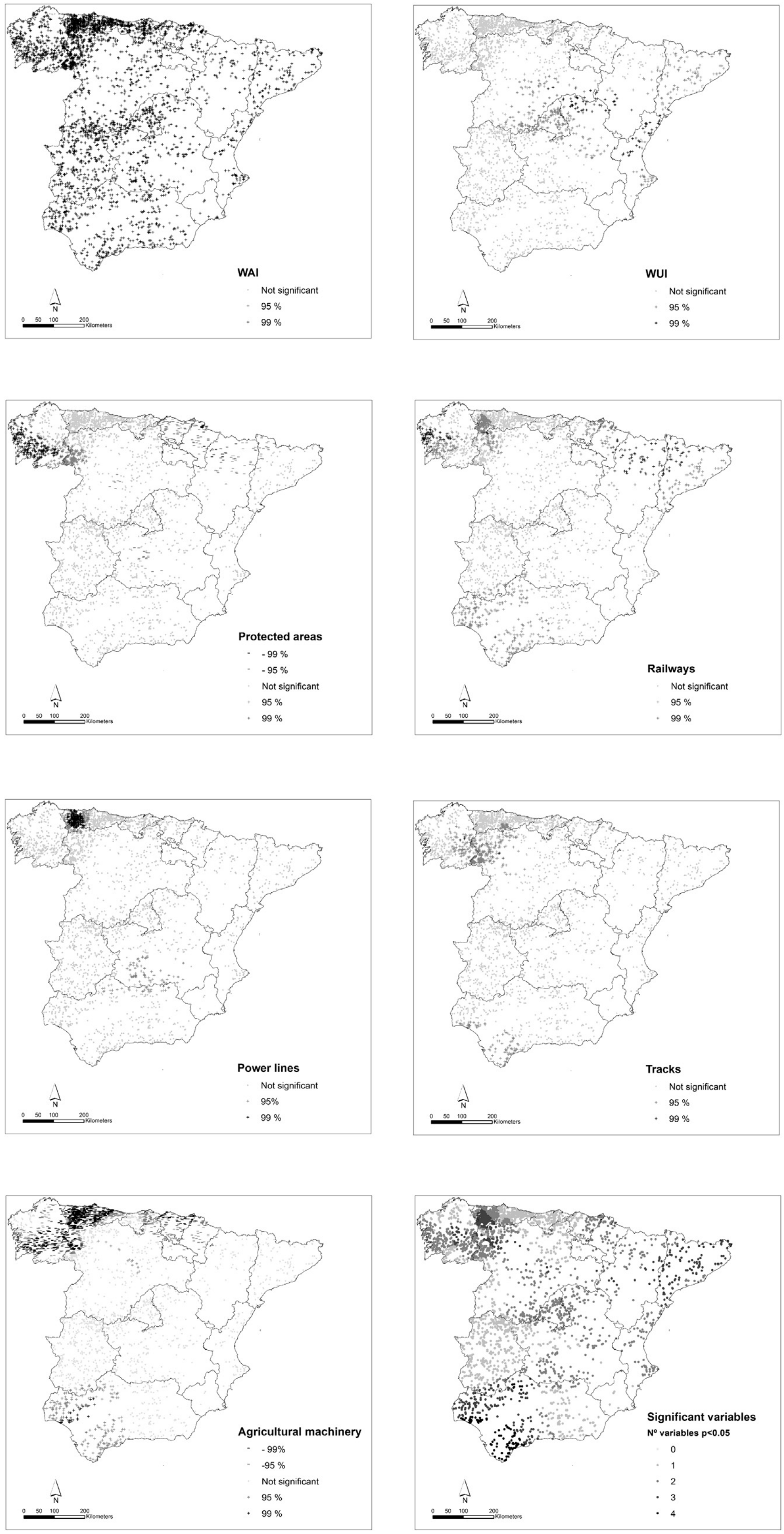

Fig. 5. Significance thresholds of the explanatory variables according to Student's *t* in the GWLR model.

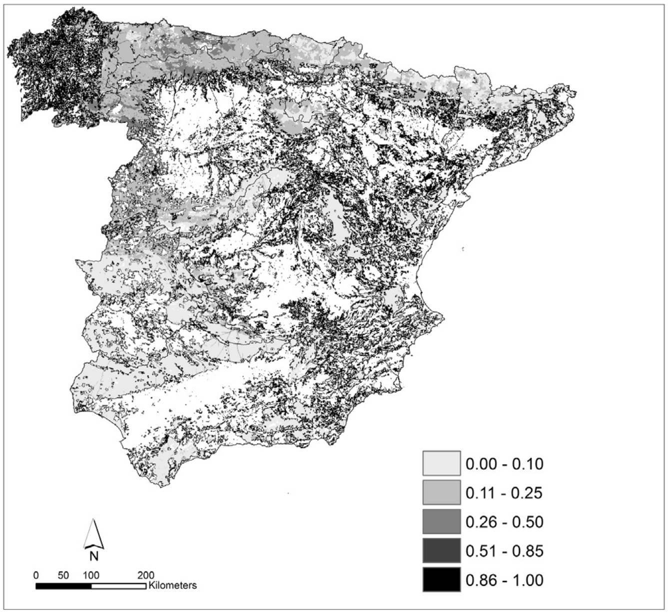

Fig. 6. Probability of wildfire occurrence related to human causality.

jointly with the scarcity of forestry works, makes WAI areas an important source of forest fire occurrence (Ortega, Saura, González-Ávila, Gómez, & Elena-Rosselló, 2012). Also noteworthy is the contribution to the explanation of the occurrence of the WUI, which plays an important role in the sites located in the imaginary triangle formed by the center of the Iberian Peninsula (Madrid) and the Mediterranean coast (especially the stretch Valencia–Barcelona). The intense growth of urban areas can be considered a general trend nationwide, but it has been particularly intense in this area, leading to an increased human pressure on wildlands. In addition, the WUI are regions marked by their highly scattered system of settlements, a situation that is a potential source of wildfire ignition particularly in those areas with the highest levels of urbanization. That is the case of the metropolitan rings of Madrid, Barcelona and, to a lesser extent, Valencia and the rest of Mediterranean coast, due to the higher intensity of touristic uses (Galiana-Martín, 2012). Then, in order of highest significance, the linear variables appear corresponding to the communication network and accessibility (railroads, power lines, and forest tracks). The railroads, like the WAI, have a positive explanatory sense in all locations though the regression coefficients seem not to vary over the study area. In the case of power lines and forest tracks, although most of their locations are not significant (with $p < 0.25$), they also have a positive explanatory sense. DAM is expected to have a positive explanatory sense in all locations of the sample, but appears with a negative sign in the northwest area corresponding to Cantabria and Galicia. Finally, the protected areas participate in the model as a deterrent agent, lowering the fire occurrence in most of the country, and occurring with a positive sign only in some locations of the northwestern peninsula. In addition to the significance thresholds, Fig. 4 also shows the mapping of the number of significant variables with $p < 0.05$. As can be seen, there is always at least one significant variable in the threshold, and it is most common to find two or more significant variables.

Finally, we present the probability map of occurrence relating to human causality (Fig. 6). Based on this figure, the highest values of probability are associated with the WAI, especially in the northwest and on the borders of mountain areas. In the central area and along the Mediterranean coast there are also high probability values mainly associated with the WUI. These two variables, as already seen above, have the highest explanatory load in the model according to Student's t values, both being interfaces significant to more than $p < 0.05$, in some locations reaching more than 99%. The mapping also evidences the importance of the explanatory variables with linear deployment, such as power lines, railroads, and forest tracks.

Model performance

The average local R^2 obtained from the calibration sample yielded a value of 0.7, ranging between 0.19 and 0.85. As seen in Fig. 7, the minimum values of R^2 were located on the Cantabrian coast, mainly in the principality of Asturias. The presence of such low values is due mainly to the absence of WAI and WUI, which have virtually no spatial representation in this region. To try to correct these values, we considered different predictive variables that could explain the occurrence in this area. Specifically, several models were adjusted to include variables such as extensive livestock and WGI. In the case of extensive livestock, the contribution in the models was not significant, so it was eventually rejected. In the case of WGI, despite it being significant at $p < 0.05$, its explanatory sense was negative, so this was considered inconsistent and the variable was also rejected. Regarding the percentage of correctly classified points, Table 2 shows the classification for the two periods examined. In the period 1988–2007, the overall percentage of success was 87% with a Kappa value of 0.73. In turn, the overall success obtained using the 2008–2011 sample was 78% with a Kappa value of 0.49. The reason for the lower success rate in the second validation sample is that the model underestimates the actual occurrence of the period, possibly because the shortest period of data collection distorts the classification of the density of high or low occurrence due to a lower number of registered fire events.

On the other hand, the GWLR model shows a little performance improvement when compared to its GLR version in terms of accuracy (Kappa), relative goodness of fit (AIC), and residuals. The GLR was adjusted and validated with the same sample as in GWLR but using two different sets of explanatory variables. A first GLR model was developed using the same variables, which resulted significant according to the GWLR model, and a second model was calibrated

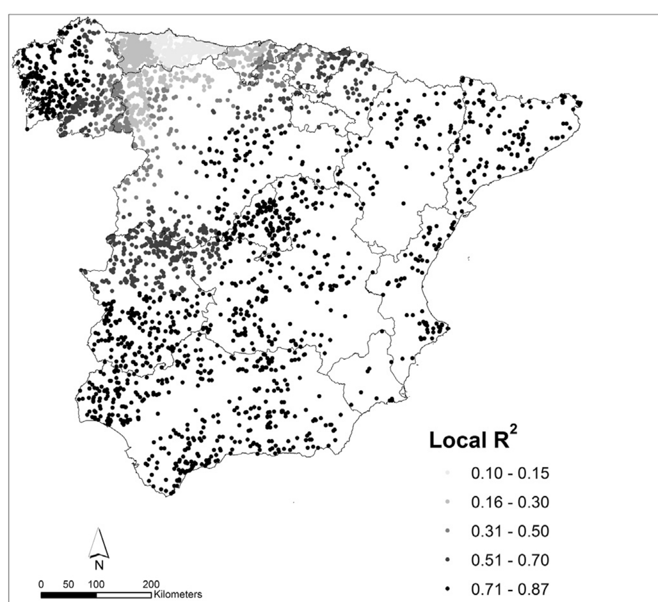

Fig. 7. Local R^2 values.

Table 2
Successfully classified points. Top, period 1988–2007. Bottom, period 2008–2011.

% Observed	High	Low	% Marginal
1988–2007	**% Predicted**		
High	31.4	11.5	42.9
Low	1.5	55.5	57.1
% Marginal	33.0	67.0	100.0
2008–2011	**% Predicted**		
High	17.8	21.0	38.8
Low	0.1	61.1	61.2
% Marginal	17.9	82.1	100.0

following a step-forward procedure to select the explanatory variables. This gave the significant variables WAI, WUI, railroads, forest tracks, and the percentage of owners of holdings aged over 55 years. Table 3 summarizes the comparison of the models.

As has been stated before, the GWLR model shows a small improvement compared to the global models in terms of accuracy and AIC. However, analysis of the residuals through the overall value of the sum and mean of residuals in mismatching locations reveals that the GWLR has lower residual values and, accordingly, a better model adjustment. In any case, GWR techniques are not design just for improve model performance; rather it is focused on exploring significant spatial varying relationships among the explanatory factors (Fotheringham et al., 2002).

Comparison with other studies

This section compares the results of the current paper with similar studies, specifically Martinez et al. (2013) and Chuvieco et al. (2010). These works were selected for comparison as they were used as background references for our study.

Martinez et al. (2013) calculated the probability of human-caused wildfire occurrence for the entire Spanish territory (excluding the Autonomous Region of Navarra due to a lack of data) at municipality level. The probability model was developed using GWR techniques for the period 1983–2007. Chuvieco et al. (2010) presented a framework for wildfire risk estimation by integrating several parameters, one of which was the probability of human-caused forest fires occurrence. The calculation was also conducted using logistic regression, though in this case with a spatial resolution of 1 × 1 km and for the period 1990–2004. In contrast to Martinez et al. (2013) and our study, in Chuvieco et al. (2010) the model was restricted to four Spanish regions considered representative of wildfires in Spanish Mediterranean environments (the Community of Madrid, the Community of Valencia, the Province of Huelva, and Aragon). The comparison is summarized in Table 4.

The method followed in Chuvieco et al. (2010) is similar to that of the current study, except for our use of geographically weighted regression techniques. In consequence, the results are also similar in terms of explanatory variables (WUI, WAI, protected areas, power lines, and forest tracks). In contrast, however, the overall percentage of agreement of the model is considerably higher in the current study. On the other hand, despite the fact that the results in Martinez et al. (2013) refer to municipalities, there are some commonalities, such as the use of GWLR or the high explanatory power of WAI. Regarding the percentage of success, the overall performance in this paper is higher (87% and 78.4% for the current study and Martinez et al., 2013, respectively), possibly due to the way in which the regression variables have been constructed. Martinez et al. (2013) proposes the municipality as reference spatial unit and therefore both method and results are developed on this basis, which may lead to potential inaccuracies. We believe that our result can be considered a relative improvement, since it provides a better spatial representation of the probability of ignition and better accuracy in the prediction.

Table 3
Comparison of GWRL and GLR models.

	GWLR	GLR with GWLR variables	GLR step-forward
AIC	2426	2623	2611
Kappa value	0.726	0.715	0.714
Sum of Res	248.2	268.0	268.3
Mean of Res	0.79	0.82	0.82
Stdev of Res	0.11	0.10	0.10

Conclusions and further research

Determining which model type to use for occurrence-distribution modeling is important because the outcomes may

Table 4
Comparison with other studies. Light gray represents explanatory variables common to the current study and Chuvieco et al. (2010) and dark gray the current study and Martinez et al. (2013).

	Martinez et al. (2013)	Chuvieco et al. (2010)				Current study
		Madrid	Valencia	Huelva	Aragón	
Model accuracy	78.4%	70.6%	68.4%	84.4%	86.8%	87.0%
Period	1983-2007	1990-2004				1988-2007
WAI	X	-	-	-	X	X
WUI	-	X	-	-	-	X
Protected areas	-	X	-	-	-	X
Railroads	-	-	-	-	-	X
Tracks	-	-	-	X	-	X
DAM	-	-	-	-	-	X
Power lines	-	-	-	-	X	X
Land use change	-	-	-	X	X	-
% Forest area	X	-	-	-	-	-
Rural exodus 1950-1991	X	-	-	-	-	-
Forest area with less management	X	-	-	-	-	-
Mean annual precipitation	X	-	-	-	-	-
Mean summer temperature	X	-	-	-	-	-
Decrease in agricultural area	X	-	-	-	-	-
CORINE 243 category	X	-	-	-	-	-
Demographic potential	X	-	X	X	-	-

have direct management implications. GWLR techniques have showed a high predictive potential for human-caused wildfire occurrence modeling, surpassing classical regression techniques like global logistic regression and allowing the detection of non-stationary relationships between dependent and predictive variables.

The use of GWR techniques applied to LR models has also corroborated the existence of spatial variation in the explanatory factors associated with human causality in wildfires. In addition, the validation of the results confirms that both the method used and the products obtained are consistent and sufficiently robust. However, the model still can be improved in some ways. As an example, in some areas – especially the northwest of Spain (Asturias) – there are certain mismatches, making it necessary to introduce additional independent variables for a better explanation of wildfire occurrence, specifically in relation to fires in grass and bush from February to March. On the other hand, comparison of the GWR and GLR models shows a small improvement in the accuracy, possibly due to the use of GWR techniques. This improvement is also supported by the comparison with Chuvieco et al. (2010).

Regarding the explanatory factors, as in most human-dominated landscapes where anthropogenic ignitions surpass natural ignitions, in peninsular Spain, both human accessibility (forestry tracks) and population density (WUI) are likely to be strong predictors of ignition risk (Bar Massada et al., 2012; Galiana-Martin, Herrero, & Solana, 2011). However, although these factors make an important contribution in the study, other explanatory factors more related to agricultural activities and forest management also influence wildfire occurrence. More specifically, these involve the use of fire in cleanup of harvest wastes and crop boundaries (WAI), negligence and accidents due to engines and machines working close to the forest areas (DAM), and forestry protection policies (protected areas). Nonetheless, whereas DAM, CDP, WAI, and WUI are factors related to an increased ignition probability, the presence of protected intervenes in the opposite way, i.e., by decreasing ignition likelihood, because it is directly linked with the protection and conservation of landscape. However, the WAI appears to be the most important factor related to fire ignition in Spain, its participation in the model surpassing even the WUI, and being strongly related over the whole study area. We believe this to be especially relevant, considering that the existence of areas of WUI is usually the main factor related to increased fire risk, and is traditionally considered the main human ignition factor in the literature (Galiana-Martin et al., 2011; Martinez et al., 2009; Romero-Calcerrada et al., 2010; Syphard et al., 2007; Vilar del Hoyo et al., 2008).

In future research, we will explore new predictors as well as new methods for spatialization (distance to the interface, density maps and so on). In addition, we will consider the temporal dimension in fire risk assessment with the aim of developing dynamic models.

Acknowledgements

This work was financed by the National I + D Plan of the Spanish Ministry of Science and Innovation: FPI grant BES-2009-023728. The research was conducted within the framework of the FIRE-GLOBE project: *Analysis of fire risk scenarios at the national and global scales*, CGL2008-01083/CLI.

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