Analysis of recent spatial-temporal evolution of human driving factors of wildfires in Spain

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Abstract

Fire regimes are strongly dependent on human activities. Understanding the relative influence of human factors on wildfire is an important ongoing task especially in human-dominated landscapes such as the Mediterranean, where anthropogenic ignitions greatly surpass natural ignitions and human activities are modifying historical fire regimes. Most human drivers of wildfires have a temporal dimension, far beyond the appearance of change, and it is for this reason that we require an historical/temporal analytical perspective coupled to the spatial dimension.

In this paper, we investigate and analyze spatial-temporal changes in the contribution of major human factors influencing forest fire occurrence, using Spanish historical statistical fire data from 1988 to 2012. We hypothesize that the influence of socioeconomic drivers on wildfires has changed over this period. Our method is based on fitting yearly explanatory regression models – testing several scenarios of wildfire data aggregation – using logit and Poisson Generalized Linear Models to determine the significance thresholds of the covariates. We then conduct a trend analysis using the Mann-Kendall test to calculate and analyze possible trends in the explanatory power of human driving factors of wildfires. Finally, Geographically Weighted Regression Models are explored to examine potential spatial-temporal patterns. Our results suggest that some of the explanatory factors of logistic models do vary over time and that new explanatory factors might be considered (such as arson-related variables or climate factors), since some of the traditional ones seem to be losing significance in presence-absence models, opposite to fire frequency models. In particular, the Wildland-Agricultural Interface and Wildland-Urban Interface appear to be losing explanatory power regarding ignition probability, and Protected Areas is becoming less significant in fire frequency models. GWR models revealed that this temporal behavior is not stationary neither over space or time.

Keywords: trends; wildfire; GLM; GWR; human driving factors; occurrence

1. Introduction

Fire is no longer a significant part of the traditional systems of life; however, it remains strongly tied to human activity (Leone et al. 2009). Knowledge of the causes of forest fires and the main driving factors of ignition is an indispensable step towards effective fire prevention (Ganteaume et al. 2013). It is widely recognized that current fire regimes are changing as a result of environmental and climatic changes (Pausas and Keeley 2009) with increased fire frequency in several areas in the Mediterranean Region of Europe (Rodrigues et al., 2013). In Mediterranean-type ecosystems, several studies have indicated that these changes are mainly driven by fire suppression policies (Minnich 1983), climate (Pausas and Fernández-Muñoz 2012), and human activities (Bal et al. 2011). Human drivers mostly have a temporal dimension, which is why an historical/temporal perspective is often required (Zumbrunnen et al. 2011; Carmona et al. 2012). In Mediterranean Europe, increases in the number of fires have been detected in some countries, including Portugal and Spain (San-Miguel-Ayanz et al. 2012; Rodrigues et al. 2013). In addition, a recent work by Turco et al. (2016) suggests huge spatial and temporal variability in fire frequency trends specially in the case of Spain, where increasing and decreasing trends were detected depending on the analysis period and scale. This increase in wildfire frequency and variability, with its associated risks to the environment and society (Moreno et al. 2011; Moreno et al. 2014), calls for better understanding of the processes that control wildfire activity (Bar Massada et al. 2012).

In recent decades, major efforts have been made to determine the influence of climate change on natural hazards, and to develop models and tools to properly characterize and quantify changes in climatic patterns. For instance, Global Circulation Models can provide credible quantitative estimates of future climate change (Randall et al. 2007). In the particular case of wildfire hazard, most climate models are able to derive fire danger components and inputs, and thereby characterize a probable fire regime (Lynch et al. 2007; Chelli et al. 2014). In this regard, a big effort has been invested to explore and assess the influence of climate change on wildfire hazard. For example, several works such as Koutsias et al. (2013) or Harris et al. (2014), revealed long-term positive correlation between fire occurrence and air temperature and heat waves.

However, fire regimes are strongly dependent on human activities (Salis et al. 2013; Archibald et al. 2013). While physical processes involved in ignition and combustion are theoretically simple, understanding the relative influence of human factors in determining wildfire is an ongoing task (Mann et al. 2016). Due to the difficulty of predicting the peculiarities of human behavior, we face a high degree of uncertainty when modeling human-caused forest fires. However, it is clear that human-caused fires that occur repeatedly in a given geographical area are not simply reducible to individual personal factors, and thus subject to pure chance. They are usually the result of a spatial pattern, whose origin is in the interaction of environmental and socioeconomic conditions (Koutsias et al. 2016). This is particularly true in human-dominated landscapes such as Spain, where anthropogenic ignitions surpass natural ignitions, and humans interact to a large degree with the landscape, changing its flammability, and act as fire initiators or suppressors. In such cases, human influence may cause sudden changes in fire frequency, intensity and burned area size (Pezzatti et al. 2013). A first step is to identify all the factors linked to human activity, establishing their relative importance in space and time (Martínez et al. 2009; Martínez et al. 2013). According to Moreno et al. (2014), the number of fires over the past 50 years in Spain has increased, driven by climate and land use changes. However, this tendency has been recently reversed due to fire prevention and suppression policies. This highlights the influence of changes in the role of human activities as some of the major driving forces. For instance, changes in population density patterns – both rural and urban – and traditional activities have been linked to an increase in intentional fires. In this sense, several works have previously investigated the influence of human driving factors of wildfires in Spain. These works have explored in detail a wide range of human variables (Martínez et al. 2009; Chuvieco et al. 2010) and methods. Specifically, Generalised Linear Models (Vilar del Hoyo et al. 2008; Martínez et al. 2009; Moreno et al. 2014), machine learning methods (Vega-Garcia et al. 1996; Rodrigues and de la Riva 2014), and more spatial-explicit models like Geographically Weighted Regression (Martínez et al. 2013; Rodrigues et al. 2014) have previously been employed. However, all these approaches could be considered as stationary from a temporal point of view, since they are based on 'static' fire data information summarized or aggregated for a given time span. However, the influence of human drivers cannot be expected to be stationary. Zumbrunnen et al. (2012) stress the importance of dealing with the temporal dimension of human drivers of wildfires. Therefore, exploring temporal changes in socioeconomic or anthropogenic drivers of wildfire will enhance our understanding of both current and future patterns of fire ignition and thus help improve suppression and prevention policies.

The main goal of this paper is answering the following question. Do human drivers of wildfire vary over time and space? To do this, we investigate and analyze spatial-temporal fluctuations in the contribution of the major human factors of forest fire hazard (such as Wildland-Urban interface, Wildland-Agricultural interface, tracks, railways or protected areas) in Spain by fitting GLM and GWR models. We hypothesize that the influence of these socioeconomic drivers on wildfires has changed over this period.

2. Materials and methods

2.1. 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. Thus, the total area of the study region was around 498,000 km^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 settlement systems and population structure, productive sector, land use and land cover changes, or territory structure. The complexity of the socioeconomic conditions thus plays a determinant role in wildfire assessments, which is especially important when modeling human factors, since this complexity transfers into the relationships between socioeconomic variables and a natural phenomenon such as wildfire, making the assessment less straightforward.

2.2. Method overview

The proposed method aims to address spatial-temporal changes in the contribution of human explanatory factors to wildfires. The method is based on fitting yearly logistic and Poisson GLM (Generalized Linear Models) using historical fire data. These models allow determining the contribution of each covariate analyzing the Z-values of the beta coefficients. These models are fitted using three different temporal scales of aggregation of fire count data – 1, 3, and 5 years – in the period 1988-2012, obtained from the EGIF (General Statistics of Wildfires) database. The explanatory variables were constructed using data for different years within the analysis time span in order to reflect possible temporal or ongoing changes (both response and explanatory variables will be introduced and described later). Once models are fitted, trend detection – by means of the Mann-Kendall test – is applied to Z-values of beta coefficients, to determine to which extent their contribution varies over time.

Additionally, in order to search for underlying spatial patterns influencing temporal variations we model the spatial distribution of the explanatory factors using Geographically Weighted Regression (GWR) logit and Poisson models. We fitted separate models for 1990 and 2006 in the 5-year temporal scale, then mapping and comparing the significance ($p<0.05$) of each explanatory factor in both dates.

All the analysis were developed using the R statistical software (R Development Team Core 2013), packages *kendall* and *zyp* for trend analysis, and *glm* for model calibration; with the exception of GWR that was conducted using the software GWR v4.0.

2.3. Fire data and response variables

The dependent variable for both GLM and GWR models was built from the Spanish EGIF database using fire records from 1988 to 2012. The EGIF database is one of the oldest wildfire databases in Europe, beginning in 1968 (Vélez 2001). It is compiled by the Spanish Department of Defense Against Forest Fires

(ADCIF) in the Ministry of Agriculture, Food, and Environment (MAGRAMA) from forest fire statistical reports. Among other useful information relating to fire events, the reports include the starting point of each fire, recorded on a 10x10 km (Spanish Institute for Nature Conservation) reference grid used by firefighting crews for the approximate location of fire events. Note that this grid is used in this study as the spatial reference data unit, meaning that all data are obtained from or refer to it. Annual human-caused fire count data were retrieved from the EGIF database at grid level, spatializing fire records using the 10x10 grid. Figure 1 shows the annual fire occurrence of human-induced fire ignitions from 1988 to 2012.

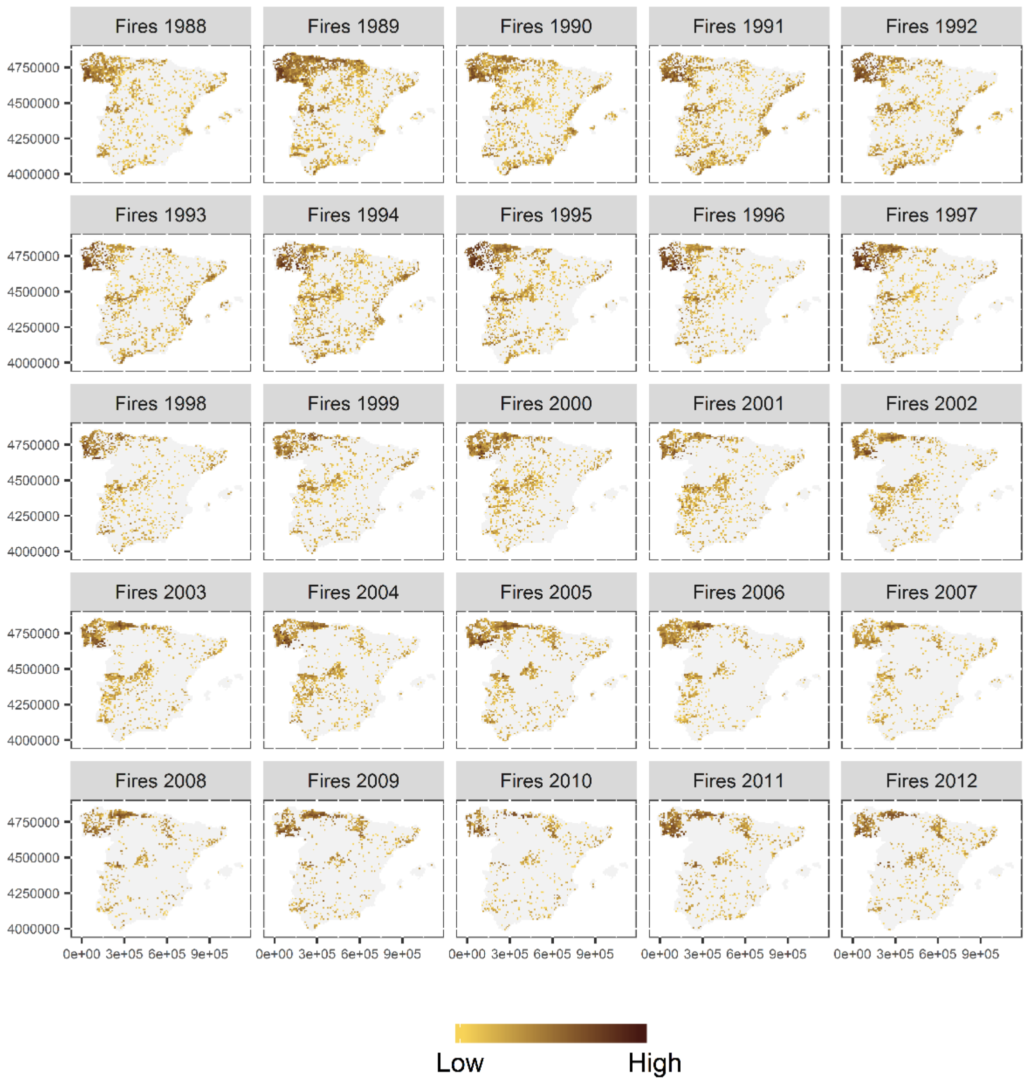

Figure 1. Spatial distribution of number of human-caused wildfires 1988-2012. Low 0 (light green), high 540 (dark brown). No fire displayed in light gray.

Two different response variables were constructed from these data for GLM models: fire counts were used as dependent variable in the Poisson models, and fire count data were also recoded into a binary presence (grid cells with at least 1 fire) or absence (no fire recorded) variable to construct the response variable for the logistic models.

In turn, three different temporal scales or aggregations – 1, 3, and 5 years – were explored to account for the effect of fire occurrence temporal (yearly) variability. The response variable used in the Poisson regression models was aggregated as the sum of fire counts using a time moving window procedure, so that data for 3 or 5 years were assigned to the central year of the window. As a consequence, the analysis time spans were reduced accordingly, to 1989-2011 and 1990-2010 for the 3 and 5 year aggregations, respectively. The response variable for the logistic regression model calibration was grouped in a similar way, but in this case as the maximum value instead of the sum. Thus, if at least 1 fire is recorded in one of the years, the grid is classified as fire-present and vice versa.

From these two sets of dependent variables, we are able to investigate driving factors of human-caused wildfires from two different perspectives. On the one hand, count data used in the Poisson models provide insights into factors relating to fire frequency, whereas presence/absence data are used to determine factors explaining fire occurrence regardless of frequency.

The dependent variable for GWR models was constructed following the same methodology and data. Due to the high computational demand of the GWR method, several assumptions had to be made: (i) only the 5-year temporal scale of fire data aggregation was considered; and (ii) only the years 1990 and 2006 were explored. These years were selected based on the reference dates of the Corine Land Cover (CLC) project since it is one of the main sources for the explanatory variables.

2.4. Human driving factors

The explanatory variables were selected and spatialized on the basis of the authors' experience with models at regional and national scales (Chuvieco et al. 2010; Chuvieco et al. 2012; Rodrigues et al. 2014; Rodrigues and de la Riva 2014). All these works have explored in detail human drivers of wildfires combining different temporal and spatial scales (national and regional), modelling tools (GLM and GWR), and data (statistical or spatial-explicit information). Specifically, driving factors and explanatory variables were selected on the basis of the studies by Rodrigues and de la Riva (2014) and Rodrigues et al. (2014), in which the main drivers of human causality in mainland Spain were identified. The explanatory variables were classified according to the typology of the affecting factor (Leone et al. 2003) as follows:

I. Factors related to socioeconomic changes
   - Human presence, population increase, and urban growth. Greater pressure on wildlands.
     - *Wildland-Urban Interface (WUI)*. Length of the boundary between populated and wildland areas inside the 10x10 km grid, obtained from CLC for 1990, 2000, and 2006.
     - *Demographic potential (DP)*. Demographic potential is an aggregate index related to the ultimate potential of the population. It reflects the demographic power of the nation and its ability to provide future population growth. The index was retrieved from Calvo and Pueyo (2008) for 1991, 2001, and 2006 at a spatial resolution of 5x5km, later rescaled (according to the average value) to the 10x10 km grid.

II. Factors related to traditional economic activities in rural areas
   - Agriculture. Use of fire to eliminate harvesting wastes and to clean cropland borders. These procedures are a potential source of ignition due to spread of fire to forest areas in the vicinity
     - *Wildland-Agricultural Interface (WAI)*. Length of the boundary between agricultural and wildland areas inside the 10x10 km grid, obtained from CLC for 1990, 2000, and 2006.

III. Factors which could cause fire mainly by accident or negligence
   - Electric lines. Possible cause of ignition by accident.
     - *Power lines (PWL)*. Length of the high-, medium-, and low-voltage transport network inside the 10x10 km grid forest area, obtained from the Numerical Cartographic Database 1:200,000 (BCN200). Power lines are spatialized for 1990, 2000, and 2006 using CLC data on forest area extent for each year.
   - Presence of roads, railways, and tracks and their accessibility. Increased human pressure on wildland.
     - *Railways (RR)*. Length of the railroad network (excluding the high-speed network) inside the 10x10 km grid, obtained from BCN200. Like power lines, railroads are spatialized for 1990, 2000, and 2006 using CLC data on forest area extent for each year.

- *Tracks (TRK)*. Length of forest tracks and paths inside the 10x10 km grid, obtained from BCN200. Tracks are also spatialized for 1990, 2000, and 2006 using CLC data on forest area extent for each year.

IV. Factors which could hamper fires

- Protected areas. Increasing concern about forest protection.
  - *Protected areas (PA)*. Delimitation of the area occupied by natural protected areas and the Natura 2000 network inside the 10x10 km grid. Protected areas are spatialized on a yearly basis using information about date of declaration available for each individual protected site.

All predictive variables were distributed in space using the 10x10 km reference grid. All the explanatory variables were constructed using data for 1990, 2000, and 2006 (except *Demographic potential*, which was retrieved for 1991, 2001, and 2006, and Protected *areas*, which was constructed separately for each year in the period 1988-2012). In this way, we were able to reflect the change over time of the explanatory factors due to socioeconomic shifts, in case they have occurred. To ensure consistency of results, a collinearity analysis of the explanatory variables was carried out; variables were found to be linearly independent.

2.5. Generalized Linear Models

GLM are an extension of linear models that can deal with non-normal distributions of the response variable, providing an alternative way to transform the response. The distributions used include those like Poisson, binomial, negative binomial, and gamma. In this study, Poisson and binomial distributions are used to model the relationship of human-induced fires and some of their major driving forces to subsequently explore temporal dynamics in the contribution and significance. These techniques have been traditionally employed in wildfire modelling. Examples of the application of these models to wildfire research can be found in Mann et al. (2016), Martínez et al. (2004a), Martínez et al. (2009), Syphard et al. (2008),Vasconcelos et al. (2001) or Zhang et al. (2016). Both regression methods were explored at three temporal scales (1-, 3-, and 5-year aggregation). Table 1 shows the correspondence between the data collection of the independent variables and data collection for the dependent variable, according to the time spans described in sections 2.3 and 2.4. Significance thresholds were retrieved yearly from each model subsequently used as inputs in trend detection.

Table1. Correspondence between data collection of independent variables and year of data collection for the dependent variable and regression model.

1988	**1989**	**1990**	**1991**	**1992**	**1993**	**1994**	**1995**	**1996**	**1997**	**1998**	**1999**	**2000**
WAI90	WAI90	WAI90	WAI90	WAI90	WAI90	WAI90	WAI00	WAI00	WAI00	WAI00	WAI00	WAI00
WUI90	WUI90	WUI90	WUI90	WUI90	WUI90	WUI90	WUI00	WUI00	WUI00	WUI00	WUI00	WUI00
DP91	DP91	DP91	DP91	DP91	DP91	DP91	DP91	DP01	DP01	DP01	DP01	DP01
TRK90	TRK90	TRK90	TRK90	TRK90	TRK90	TRK90	TRK00	TRK00	TRK00	TRK00	TRK00	TRK00
RR90	RR90	RR90	RR90	RR90	RR90	RR90	RR00	RR00	RR00	RR00	RR00	RR00
PWL90	PWL90	PWL90	PWL90	PWL90	PWL90	PWL90	PWL00	PWL00	PWL00	PWL00	PWL00	PWL00
PA88	PA89	PA90	PA91	PA92	PA93	PA94	PA95	PA96	PA97	PA98	PA99	PA00
2001	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**-**
WAI00	WAI00	WAI00	WAI06	WAI06	WAI06	WAI06	WAI06	WAI06	WAI06	WAI06	WAI06	-
WUI00	WUI00	WUI00	WUI06	WUI06	WUI06	WUI06	WUI06	WUI06	WUI06	WUI06	WUI06	-
DP01	DP01	DP01	DP06	DP06	DP06	DP06	DP06	DP06	DP06	DP06	DP06	-
TRK00	TRK00	TRK00	TRK06	TRK06	TRK06	TRK06	TRK06	TRK06	TRK06	TRK06	TRK06	-
RR00	RR00	RR00	RR06	RR06	RR06	RR06	RR06	RR06	RR06	RR06	RR06	-

PWL00	PWL00	PWL00	PWL06	PWL06	PWL06	PWL06	PWL06	PWL06	PWL06	PWL06	PWL06	-
PA01	PA02	PA03	PA04	PA05	PA06	PA07	PA08	PA09	PA10	PA11	PA12	-

2.6. Trend detection

Temporal trends were calculated using the Mann-Kendall test, a rank non-parametric test (Henry B. 1945; Kendall 1975), commonly used in environmental research, and suitable for detecting linear or non-linear trends in data time series (Hisdal et al. 2001; Wu et al. 2008). In this test, the null (H_0) and alternative hypotheses (H_1) are equal to the non-existence and existence, respectively, of a trend in the time series of the data. The magnitude of the change was subsequently assessed by means of Sen's slope (Sen 1968), a nonparametric alternative for estimating the median slope joining all possible pairs of observations.

The computational procedure for the Mann-Kendall test considers the time series of *n* data points and T_i and T_j as two subsets of data, where i = 1,2,3,…, n-1 and j = i+1, i+2, i+3, …, n. The data values are evaluated as a sorted time series. Each data value is compared with all subsequent data values. If a data value from a later time period is higher than a data value from an earlier time period, the statistic S (score) is incremented by 1. On the other hand, if the data value from a later time period is lower than a data value sampled earlier, S is decremented by 1. The net result of all such increments and decrements yields the final value of S (Drapela and Drapelova 2011).

Both the Mann-Kendall test and Sen's slope were applied to Z-values of beta coefficients from yearly logistic and Poisson GLM models at the three proposed temporal scales.

2.7. Model performance and influence of climate factors

To investigate the overall performance of GLM models and also the influence of biophysical factors, we fitted an alternative version of the 5-year logit and Poisson models including climate data (temperature and precipitation, 1970-2000) from the WorldClim version 2 database (Hijmans et al. 2005). WorldClim is a set of global climate layers (gridded climate data) available at several spatial resolutions, specifically developed for ecological modeling on GIS. Currently, Worlclim provides several datasets for different temporal scenarios (past, current, and future conditions).

Logit model performance was conducted using the Area Under de Receiver Operation Curve (AUC; Hanley and McNeil, 1982), whereas Poisson models are assessed in terms of RMSE.

A comparison of models with (Human-Climate) and without (Human-only) climate factors in terms of Area Under de Receiver Operation Curve and RMSE – for logit and Poisson models respectively – has been investigated to determine to which extent changes performance can be attributed to climate factors. Trend detection was not applied to these models.

2.8. Geographically Weighted Regression

GWR is a statistical technique for exploratory spatial data analysis developed within the framework of Local Spatial Models or Statistics. Local models could be inferred as the spatial disaggregation of global statistics whose main characteristic is the fact of being calibrated from a set of spatially limited samples and hence yielding local regression parameters estimates (Fotheringham et al. 2002). Therefore, GWR techniques extend the traditional use of global regression models, allowing calculation of local regression parameters. From a mathematical standpoint, a conventional GWR is described by the following equation:

$$y_i = \sum_k \beta_k \, (u_i, v_i) \; x_{k.i} + \varepsilon_i$$

where y_i , $x_{k,i}$ and ε_i are, respectively, dependent variable, k_{th} independent variable, and the Gaussian error at location i; (u_i,v_i) is the x-y coordinate of the i_{th} location; and coefficients β (u_i,v_i) are varying conditionals on the location.

Such modelling is likely to attain higher performance than traditional regression models, and reading the coefficients can lead to a new interpretation of the phenomena under study. However, GWR models are not just a simple local regression model like i.e. moving window regressions. In a moving window example, a region is drawn around a regression point and all the data points within this region (neighborhood) or window are then used to calibrate a model. This process is repeated over all the regression points obtaining as result a set of local regression statistics. However, in this example each point within the neighborhood is equally considered for regression purposes, no matter its distance to the target regression point. GWR overcomes this limitation by applying a distance weight pattern; hence, data points closer to the regression point are weighted more heavily in the local regression than data points farther away are. In addition to the regression coefficients, a GWR model calculates several useful statistical parameters to analyze the spatial behavior of each explanatory variable, such as the value of the Student t test, which is used to determine the level of significance. On the other hand, GLM approaches such as Geographically Weighted Logistic Regression (GWLR) and Geographically Weighted Poisson Regression (GWPR) have been incorporated to GWR to extend its functionality (Fotheringham et al. 2002; Nakaya et al. 2009). The GWR approach has been already explored in several works such as Koutsias et al. (2010); Martínez et al. (2013) or Rodrigues et al. (2014).

These two methodologies –GWLR and GWPR– are used in this study to complement the results from GLM. Several parameters have be accounted for when calibrating GWR models. Kernel shape and type, bandwidth selection and optimization parameters, or the local or global nature of the predictors (see Nakaya et al. (2009) for further details of both method and software). In this work, GWR model calibration was carried out using Fixed Gaussian Kernel bandwidth, optimized according to the value of AICc, considering all the predictors as local covariates.

3. Results

3.1. Generalized Linear Models

Results for logistic regression are a proxy for analyzing whether a fire is likely to occur. Figure 2 shows the temporal evolution of the significance level and sign (positive or negative) according to the observed Z-values for each temporal scale of analysis. A visual analysis of Figure 2 reveals some qualitative changes in the contribution of several driving factors, such as WAI, WUI, TRK, and PA, at different temporal scales. Most of the explanatory factors are significant right across the analyzed temporal span at any time scale, except for PA and TRK. PA switches its explanatory sense, whereas TRK losses significance towards the end of the study period. It is noteworthy that regardless of the considered time scale, PA changes its significance sign. However, this is more evident at the 5-year temporal scale being positive until 1995, negative since then until 2007, and mostly non-significant in the ending period. It also worth mention that WAI slightly loses explanatory power over time. For instance, looking at the 3- and 5-year scales, Z-values of WAI, which are higher than any other variable – although very close to WUI during early years – shrink to values close to DP’s and WUI’s. A similar behavior is observed in WUI. In turn, DP gains explanatory performance over time reaching WAI’s and WUI’s Z-values at the end of the analyzed time span.

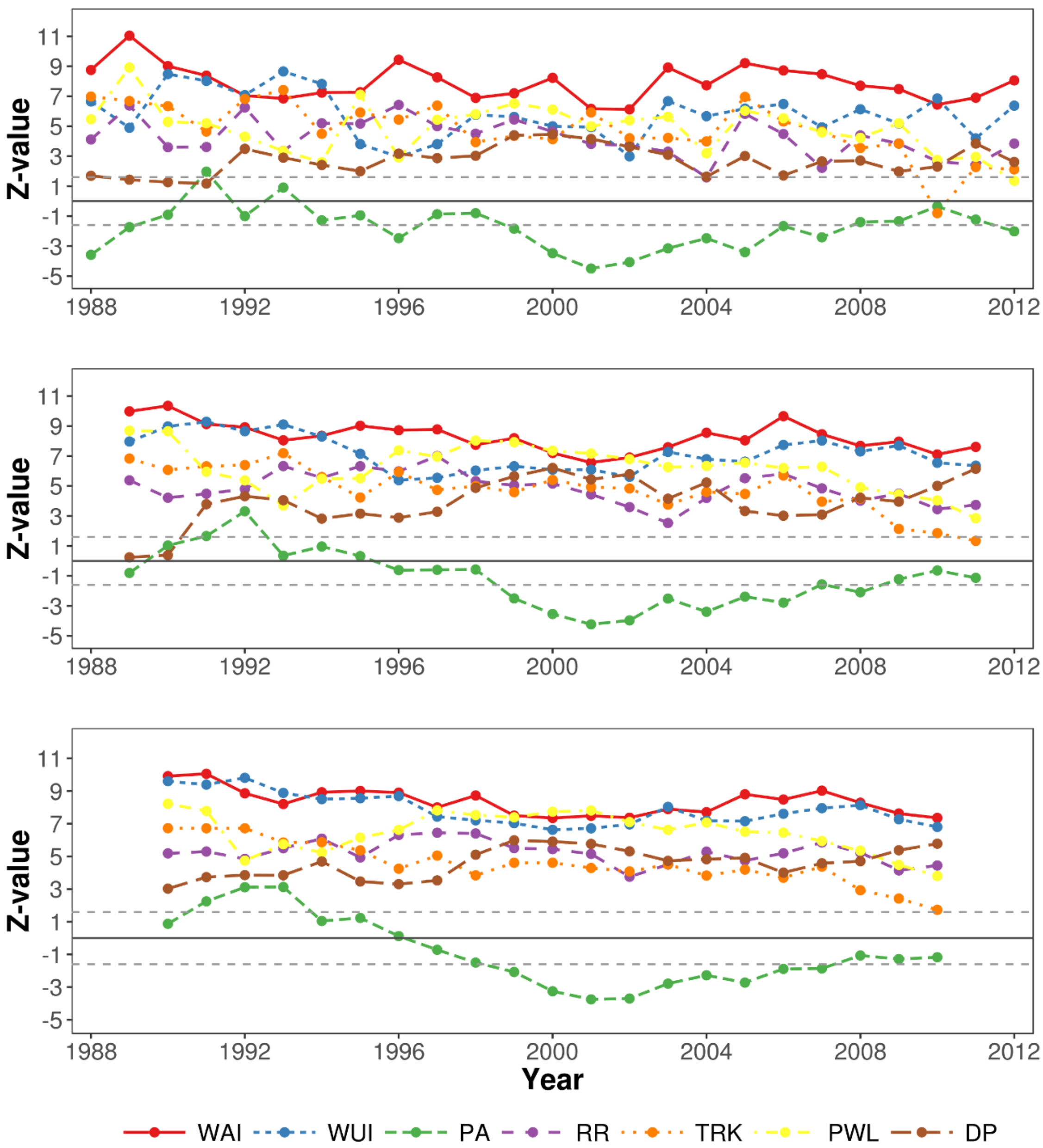

Figure 2. Temporal evolution of human driving factors. Z-values of beta coefficients for logistic regression. Dashed lines represent significance thresholds. From top to bottom, 1-, 3- and 5-year temporal aggregation scales.

This behavior is also supported by the results of the trend analysis (Table 2), which identifies significant (p-value<0.05) decreasing trends in TRK, and RR in the 1-year scale. In the 3-year scale, almost every explanatory factor shows a decreasing trend but DP, which shows the opposite and WUI with no significant trend detected. Looking at the 5-year scale, a similar behavior is observed. In this case, WAI shows a significant decreasing trend, same as WUI. RR's trend becomes not significant. DP shows an increasing trend at the 5-year temporal scale. According to Sen's slope, the strongest trends were detected for TRK and PA at the 5-year scale thus being the most variable factors in presence-absence models.

Table 2. Results of the trend detection procedure obtained for the logistic regression models at 1-, 3- and 5-year temporal aggregation scales. Areas shaded in light gray represent decreasing significant trends. Areas shaded in dark grey represent increasing significant trends. Significance threshold p<0.05.

	1-year			3-year			5-year		
	tau	**p-value**	**Sen**	**tau**	**p-value**	**Sen**	**tau**	**p-value**	**Sen**
WAI	-0.180	0.216	-0.044	-0.447	0.003	-0.084	-0.381	0.017	-0.085
WUI	-0.127	0.388	-0.059	-0.162	0.291	-0.067	-0.438	0.006	-0.117
DP	0.127	0.388	0.028	0.320	0.035	0.116	0.371	0.020	0.088
TRK	-0.560	0.000	-0.172	-0.668	0.000	-0.165	-0.762	0.000	-0.201
RR	-0.320	0.027	-0.093	-0.320	0.035	-0.071	-0.238	0.139	-0.042
PWL	-0.280	0.053	-0.100	-0.375	0.013	-0.140	-0.333	0.037	-0.102
PA	-0.080	0.591	-0.024	-0.352	0.020	-0.157	-0.362	0.024	-0.226

Results obtained for Poisson regression are an indicator of the relationship between fire frequency and the proposed covariates, i.e., the number of fires likely to occur. As in the case of logistic regression models, we can observe changes in the significance and contribution of some of the explanatory factors, such as TRK, RR, PA, and WUI. These changes have been detected both from visual analysis of Z-value plots (Figure 3) and trend detection analysis (Table 3). Same as in the logistic regression models TRK shows a negative and significant trend (p-value<0.05) at all temporal scales. At the 3-year scale, a significant decreasing trend has been detected in RR. The 5-year scale reveals positive trends in the case of PWL and PA, and a negative trend for WUI. Changes in TRK, RR, and WUI do not imply a loss of significance in their contribution to the models; however, the increasing trend detected in PA leads to a non-significant contribution for the latter years of the study period (from 2008 to 2010). PA shows a negative contribution in the first few years, which means that PA zones were related to low fire frequencies; however, the increase in PA Z-values leads to a loss of significance since they are slowly approaching zero. Finally, no trend has been identified in the case of WAI regardless of the temporal scale. This means that this covariate remains stable over time, while keeps being the most important driver of fire frequency.

Table 3. Results of the trend detection procedure obtained for the Poisson regression models at 1-, 3- and 5-year temporal aggregation scales. Areas shaded light gray represent decreasing significant trends; areas shaded dark gray represent increasing significant trends.

	1-year			3-year			5-year		
	tau	**p-value**	**Sen**	**tau**	**p-value**	**Sen**	**tau**	**p-value**	**Sen**
WAI	0.027	0.870	0.111	0.020	0.916	0.023	-0.067	0.695	-0.442
WUI	-0.160	0.272	-0.159	-0.225	0.139	-0.305	-0.324	0.043	-0.696
DP	-0.073	0.624	-0.132	-0.067	0.673	-0.192	-0.076	0.651	-0.383
TRK	-0.480	0.001	-1.007	-0.628	0.000	-1.957	-0.648	0.000	-2.071
RR	-0.220	0.129	-0.246	-0.375	0.013	-0.549	-0.400	0.012	-0.768
PWL	0.100	0.498	0.155	0.202	0.187	0.369	0.390	0.014	0.804
PA	0.253	0.080	0.602	0.289	0.057	1.187	0.343	0.032	1.390

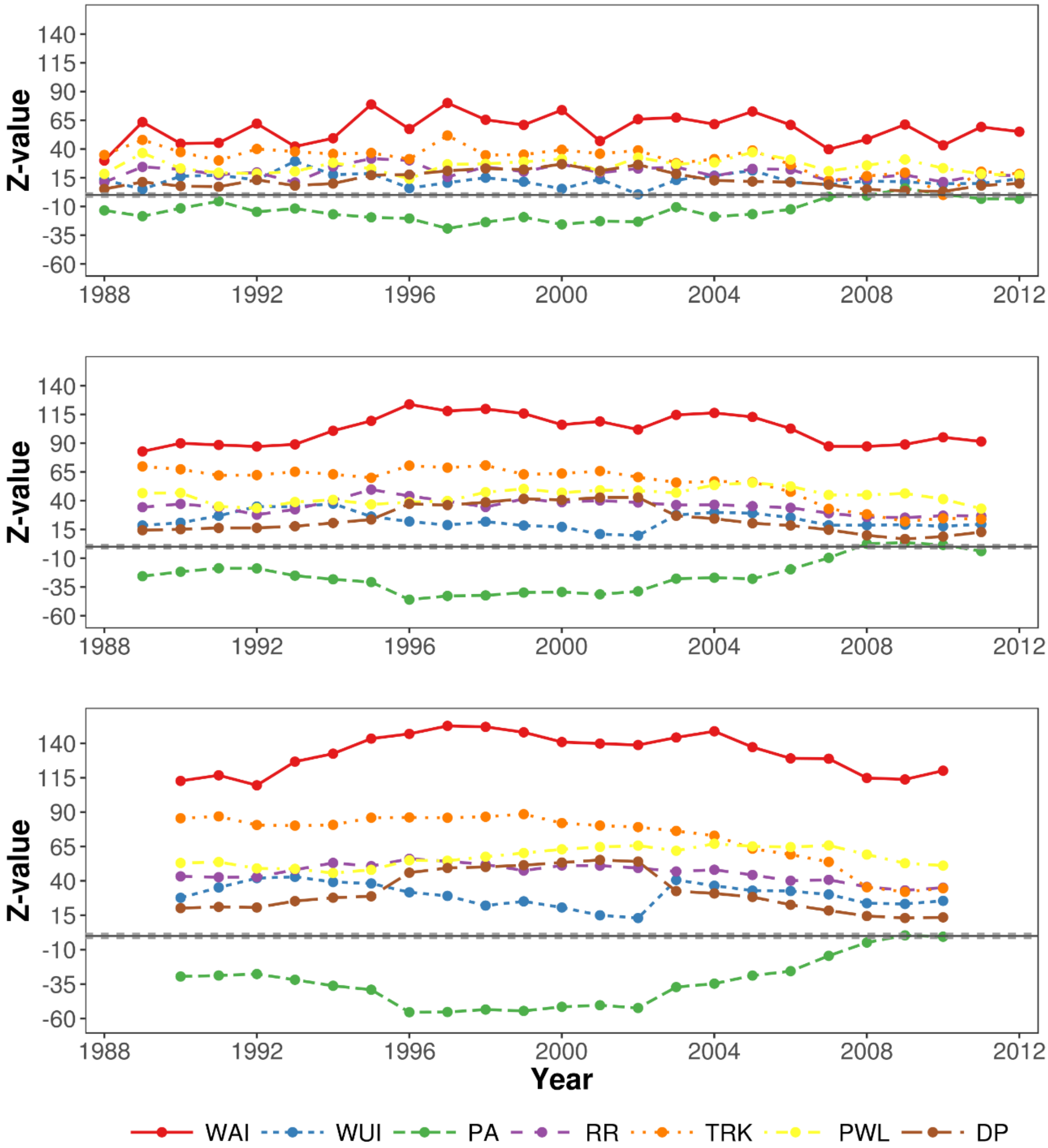

Figure 3. Temporal evolution of human driving factors. Z-values of beta coefficients for Poisson regression. From top to bottom, 1-, 3- and 5-year temporal aggregation scales.

3.2. GLM performance and influence of climate factors.

Figures 4 and 5 show the temporal evolution of model performance in the 5-year logistic and Poisson models, both for Human-only and Human-climate scenarios. From the visual inspection of these figures two different behaviors can be identified. Logistic models using only human covariates show a decreasing performance over time, starting from AUC values over 0.7 to values below 0.65. In turn, once we incorporate climate factors (Climate-Human), model performance increases compared to the Human-only scenario. What is more, the temporal evolution of AUC, although fluctuates over time, does not decrease as in the case of the Human scenario.

On the other hand, Poisson models, even though they show a considerable temporal variation of the RMSE, do not show a contrasting behavior between Human and Human-Climate scenarios. In this case, there is almost no difference between the two scenarios. This suggest that climate conditions has a less decisive influence in fire counts.

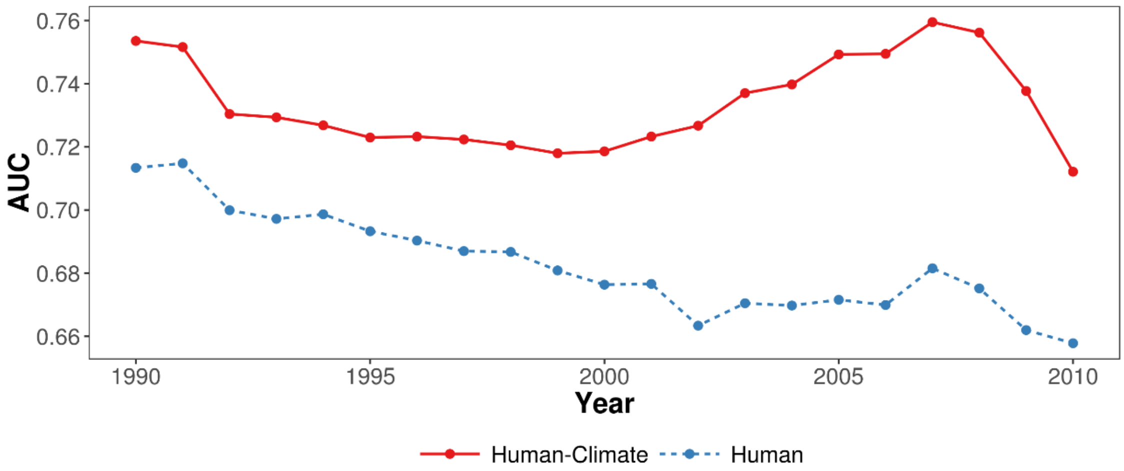

Figure 4. Temporal evolution of AUC values from Human-only and Human-Climate logistic models in the 5-year temporal scale.

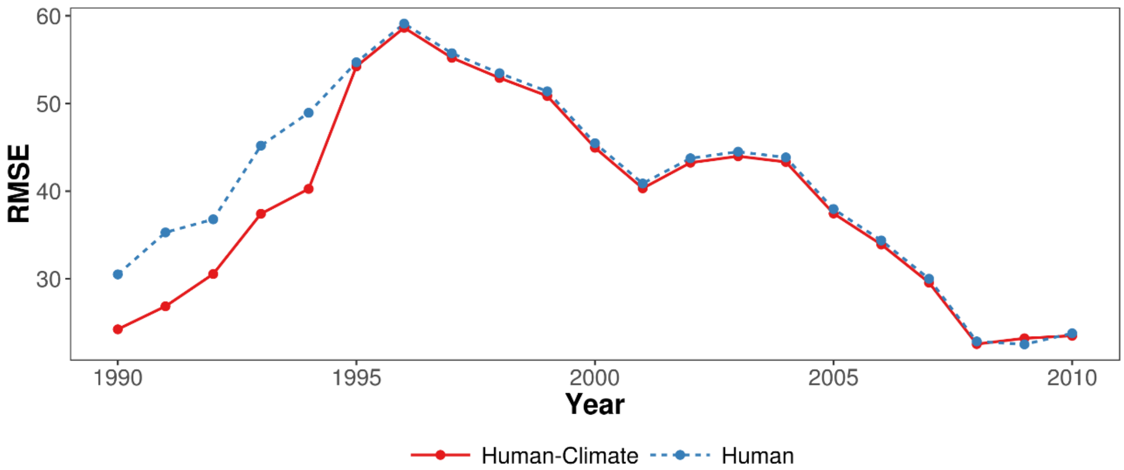

Figure 5. Temporal evolution of RMSE values from Human-only and Human-Climate Poisson models in the 5-year temporal scale.

3.3. Geographically Weighted Regression

Global –GLM– models provide insights into the overall behavior of wildfire drivers. To determine whether the detected trends and changes are spatially stationary or not, GWLR and GWPR models have been calibrated at the 5-year temporal scale for 1990 and 2006. As stated before, GWR models have been adjusted using the GWR 4.0 software. It should be noted that this application calculates the significance of the covariates using the Student's t distribution instead of the Z distribution although the interpretation of the results is similar. Table 4 and 5 summarizes the results for GWLR and GWPR models, respectively.

The increase over time of the optimal bandwidth size suggest that there is an underlying spatial change in the contribution of the explanatory factors. This increase, which has been observed in both GWLR (310 to 880 km) and GWPR (190 to 450 km) models, implies a reduction in the spatial variability of wildfire drivers.

The change in the contribution of each factor follows a pattern similar to the observed in GLM logit models, with WAI, WUI, TRK showing a decrease in their contribution to the probability of occurrence in the 5-year scale. However, the increase in DP's contribution detected in GLM logit is missing in GWLR models. This may occur because in GWR models we compare 1990 and 2006, and the increase in DP's significance strengthens in last years after 2006 (Figure 2). The decrease in PA is also observed in GWLR models. Same as GLM, PA starts from a positive contribution (the more protected the more affected) to become a deterrent factor in 2006.

Figure 6 shows the spatial distribution of changes from 1990 to 2006 in GWLR models. As can be seen, almost all covariates keep a similar spatial pattern in terms of explanatory sense and significance level. For instance, WAI, WUI, TRK and PWL are significant and positive all over the study region in both 1990 and 2006. The only factors that present a loss or gain of significance are DP and PA. DP losses significance in the southern area of Spain towards 2006, but is still significant in the main urban areas, i.e., from the central hinterlands –Madrid– and across the Mediterranean coast –Barcelona to Valencia. In turn, PA gains significance as a deterrent factor in all areas except the northeast region. However, if we look at the differences in t-values between 1990 and 2006 in GWLR (Figure 6 - right) we can observe that, regardless significance has changed or not, several areas within the study region are experiencing an increase or decrease in t-values. WAI and TRK increase their explanatory performance across the Mediterranean coast whereas the remaining territory shows the opposite. WUI is generally losing explanatory power except in the northwestern area of Galicia. DP's t-values are greater in 2006 in the central area (Madrid). RR's explanatory power is increasing all over the region. Finally, PWL' and PA's t-values are lower in 2006 than in 1990. Nevertheless, whereas this fact implies a loss of contribution in the case of PWL, it means that PA becomes significant and negative thus preventing fire occurrence.

A similar response has been detected in GWPR (Figure 7). However, fire frequency drivers show less spatial variation, at least regarding change of significance level. WAI, WUI, and RR are significant and positive all over the region. DP, TRK, and PWL show some small areas that exchange significance but are almost stationary. The greatest change is observed in PA which becomes significant and negative across the study region in 2006, acquiring significance in the eastern area of Spain. Same as GWLR, there are differences in t-values in GWPR. WAI and TRK present the same spatial pattern that GWLR, increasing t-values mainly in the Mediterranean coast. WUI losses explanatory performance all over the region. RR and PWL gain explanatory power in both coastal areas. Finally, PA's t-values decrease in the Mediterranean region, becoming significant and negative as stated previously.

Table 4. Summary of results for GLM logit and GWLR analysis. Significant threshold of t-values (p-<0.05) ±1.65. Areas shaded in light gray represent negative significant relationship. Areas shaded in dark gray represent positive significant relationship.

	GWR 1990			**GWR 2006**		
Bandwidth (km)	310			880		
t-values	**Median**	**Max**	**Min**	**Median**	**Max**	**Min**
WAI	6.825	10.004	4.508	6.622	8.362	5.496
WUI	7.942	9.203	3.969	5.803	5.987	5.649
DP	1.882	2.468	1.377	1.645	1.789	1.447
TRK	5.550	8.086	0.669	5.536	6.735	4.757
RR	4.027	4.750	2.377	4.820	5.149	4.416
PWL	7.205	8.420	4.361	5.801	6.068	5.357
PA	1.040	3.156	-1.283	-1.805	-1.453	-2.063

Table 5. Summary of results for GLM Poisson and GWPR analysis. Significant threshold of t-values (p-<0.05) ±1.65. Areas shaded in light gray represent negative significant relationship. Areas shaded in dark gray represent positive significant relationship.

	GWR 1990	**GWR 2006**
Bandwidth (km)	190	450

t-values	Median	Max	Min	Median	Max	Min
WAI	33.394	111.129	6.701	36.259	47.780	20.038
WUI	26.147	59.719	11.111	9.747	13.553	6.102
DP	12.037	99.781	0.317	5.254	8.529	2.228
TRK	37.871	82.092	-6.944	16.562	17.545	11.406
RR	18.118	27.558	-0.198	18.351	23.402	10.147
PWL	24.932	42.482	-6.173	24.418	26.269	16.027
PA	-5.260	3.799	-26.150	-5.052	-3.326	-7.360

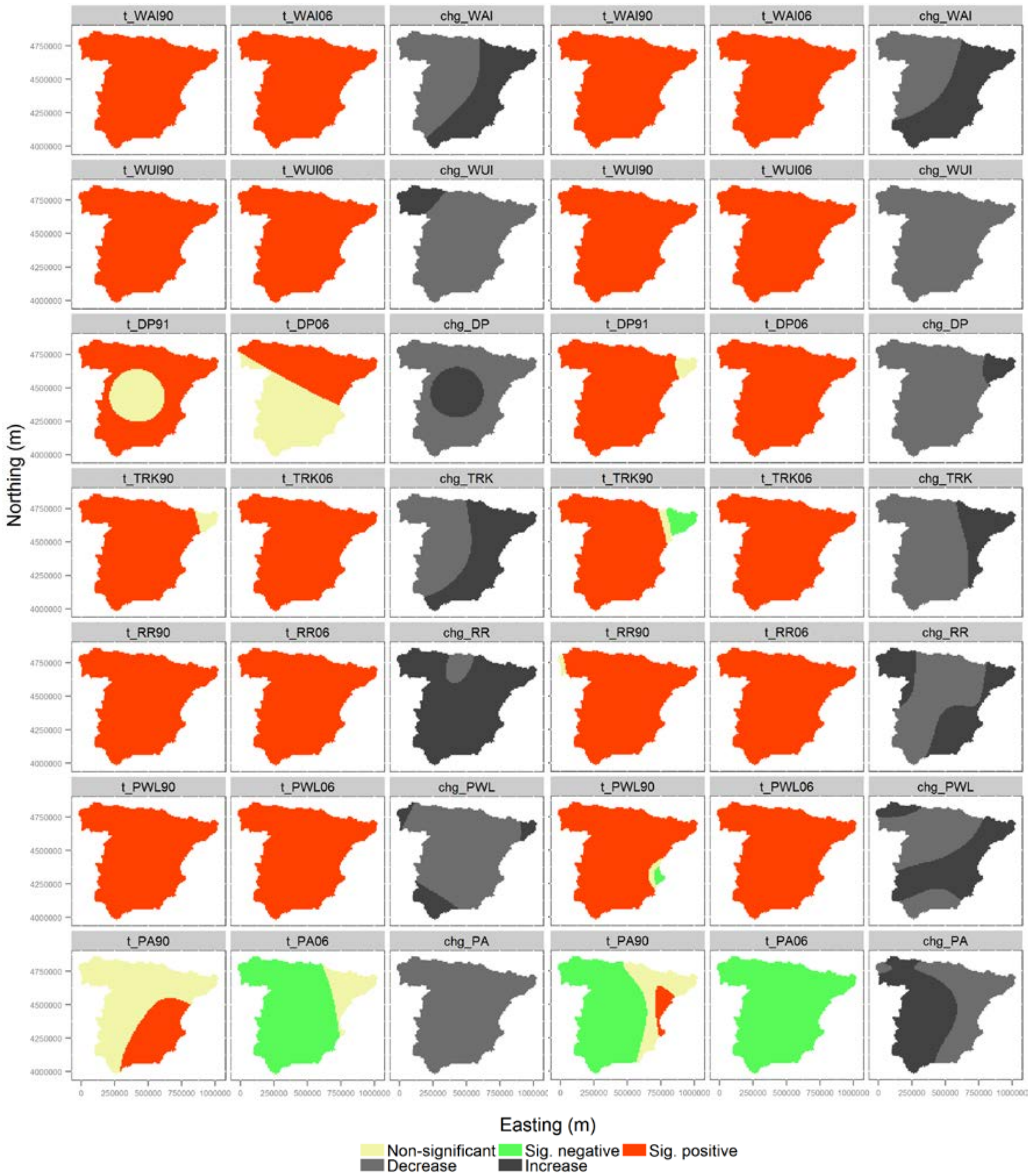

Figure 6. Spatial distribution of significance of explanatory factors in GWLR (first three columns on the left) and GWPR (last three columns on the right) models at the 5-year aggregation scale. Each 3-column map set is organized as follows: left, 1990; center, 2006; right, change 1990-2006.

4. Discussion

This paper analyzes the temporal and spatial evolution of several socioeconomic factors relating to human causality of forest fires using historical fire data, GLM and GWR techniques, and trend detection analysis. According to the results, the 5-year scale of fire occurrence aggregation seems the best choice to deal with spatiotemporal changes of fire drivers. This temporal scale allows detecting trends from a statistical standpoint besides ‘smoothing’ the temporal pattern of evolution so that changes can be visually addressed as well. Logistic regression is used as a proxy to determine the probability of a fire taking place, whereas Poisson models provide insights into the relationship between driving factors and fire frequency. Our results suggest that human driving factors of forest fires have shifted in explanatory power. Both trends in logistic and Poisson models revealed changes in some of the explanatory variables, although more evident in presence-absence models. Additionally, according to GWR models, the spatial pattern of explanatory performance of driving factors also varies over time in terms of significance and spatial dimension of the models.

GLM logistic regression models suggest a slight loss of significance of traditional explanatory factors, such as WAI and WUI (Figure 2) supported by findings from both GWLR. This is especially important, since agricultural activities have been identified among the most important factors triggering wildfires both in Spain and the European Mediterranean region (Rodrigues et al. 2014; Darques 2015). However, this behavior is not stationary across the study region. The WUI, usually considered the main factor relating to increased fire risk, and traditionally considered the main human ignition factor in the literature (Syphard et al. 2007; Martínez et al. 2009; Romero-Calcerrada et al. 2010; Galiana-Martin et al. 2011), also seems to lose explanatory power, with a significant decreasing trend in the 5-year regression model. However, WUI appears to be replaced by DP, which has increased its explanatory capacity over time according to GLM, although not detected in GWLR. In any case, the interpretation of DP in terms of explanatory sense is similar to WUI’s involving increased human pressure on wildlands. However, DP is linked on populated areas close to urban areas whereas WUI also considers rural settlements closer to forests (Leone et al. 2003). PA has switched its explanatory sense across the analyzed period. PA was related to increased fire occurrence probability during early years, becoming a deterrent factor from the mid-90s until 2007, suggesting increased environmental concern and awareness, but becoming non-significant at the end of the time series, although still with negative values.

To this overall variation of explanatory power, we should add that the loss of performance of logistic models in the 5-year temporal scale. The visual analysis of Figure 4 revealed an increase over time in the contribution of climate factors. The scenario considering only human covariates losses performance possibly because of the loss of explanatory power of WAI and WUI, whereas the Climate-Human models remain more stable and always with higher AUC values. In addition, Climate-Human models are consistently performing better than the Human ones.

This behavior can be understood in several ways. First, it could be concluded that the random component of fires associated with human activities is increasing. However, this is unlikely to be the case since human activities are governed by, or at least subject to, socioeconomic patterns (Romero-Calcerrada et al. 2010). On the other hand, it might be that biophysical factors (such as fuel moisture, topography, or climate) are becoming more significant and can thus no longer be excluded, or should be coupled to human factors to determine fire-prone areas when dealing with human-only fire occurrence. Nonetheless, it might be possible that new human explanatory factors are ruling fire occurrence.

According to figure 5, the Human-only model losses performance possibly because of the loss of explanatory power of WAI and WUI, whereas the Climate-Human model remains more stable. This finding might imply that fire prevention policies are achieving success, since the occurrence of forest fires seems to be less related to human activity and more determined by environmental conditions. In any case, climate and environmental drivers should be explored in greater depth using more accurate data from a temporal point of view, so that yearly climate data are retrieved.

An alternative possibility to explain the observed loss of significance of human driving factors is that maybe other socioeconomic factors are influencing wildfires. These could be accounted for by changes in the socioeconomic models or the establishment of new regulations and/or policies. Despite the increasing contribution of climate factors, AUC values are moderate (Hanley and McNeil 1982), which means there is still a proportion of fire ignition that remains unexplained. In this sense, deliberate fires – which have been increasingly reported since the early 1990s according to the EGIF database (Leone et al. 2009) – remain a source of uncertainty that might explain this. For instance, modeling deliberate fires would contribute to improving the contribution of human factors. The deliberate lighting of a fire or arson can be an action with multiple elements and purposes (Willis 2004) such as revenge or land cleaning. It is thus difficult to synthetize it in terms of explanatory variables, although there have been several proposals in the case of Spain (Martínez et al. 2004b). Variables related to arson have been found to be non-significant in structural or historical models (Chuvieco et al. 2010). However, perhaps they should be accounted for – or at least investigated – in this temporal context, given the observed temporal dynamics in some driving factors.

Temporal changes in human factors were also detected in the fire frequency regression analysis. However, in this case the temporal behavior was rather different. Poisson models do not show strong changes neither in model performance nor in the main drivers of wildfire. Opposite to logistic models, human drivers play a decisive role, whereas climate factors do not contribute to the explanation of overall fire frequency. The WAI remains the most important variable associated with the number of ignitions both in GLM and GWPR models, whereas PA seems to be losing significance, being a deterrent factor at the beginning of the analyzed period and becoming non-significant towards 2012. Therefore, considering the results from the logistic and Poisson models in the same picture, it seems that fire occurrence is becoming less dependent on human activities, while fire frequency is still strongly associated with agricultural activities (either by accident or negligence).

In the case of occurrence probability (logistic models), it seems quite clear that human driving factors are evolving over time. Socioeconomic changes during the last decades have driven changes in the structure of the Spanish rural landscape, increasing the complexity of the spatial distribution of the WAI and, accordingly, increasing wildfire probability (Ortega et al. 2012). Trends in fire regimes associated with socioeconomic factors have been identified in previous studies (Rodrigues et al. 2013; Pezzatti et al. 2013; Moreno et al. 2014), supporting our findings. In addition, in recent decades the European and Spanish authorities and governments have proposed and developed several initiatives and legislative procedures aiming to improve fire monitoring and prevention. Among other goals, fire suppression activities or environmental concern and awareness have been strongly supported. Some examples can be found in the *Plan of Priority Action Against Forest Fires* from 1988 (MAPA 1988a), encouraging monitoring and prevention activities by autonomous communities, as well as improvements to infrastructure; the royal decree for the regulation of compensation for the cost of fire suppression (MAPA 1988b), also in 1988; and the European regulations of 1992 (CEE 1992) and 1986 (CEE 1986) promoting prevention through sylviculture, and research into causes, awareness, and professional training. These policies could contribute to the explanation of the changes in human-caused driving factors. In this particular sense, fire prevention activities have been increasingly supported and funded during the last decade. Several initiatives such as the creation of teams for forest fire prevention, awareness campaigns or promoting the use of forest biomass (MAGRAMA 2012) have been promoted ever since 2002as a part of the Spanish Forestry Plan along with the Spanish Forest Strategy and the Forest Law.

Finally, GWR models revealed a certain degree of spatial variability. Again, changes are more important in the case of logistic models (GWLR) compared to Poisson ones (GWPR). This is not surprising, since it is well known that the explanatory factors of wildfires in Spain varies over space (Martínez et al. 2013; Rodrigues et al. 2014). Anyhow, spatial changes have been observed in both cases, being particularly interesting the loss of influence of WUI both in GWLR and GWPR. Similar to the global models (GLM), changes in the contribution of PA have been identified in GWLR. Besides the detected change in the spatial pattern of significance according to t-values, models appear to become local in recent years. The analysis of bandwidth size reveals an increase of the influence area in GWR models. This means that both GWLR and GWPR become 'more global' over time.

5. Conclusions and further work

In this paper, we investigate and analyze spatial-temporal changes in the significance and contribution of the major human factors of forest fire hazards using Spanish historical statistical data records from 1988 to 2012. Our results suggest that the human driving factors of wildfires have undergone significant shifts in their explanatory power in the case of occurrence probability, thus varying over time. However, according to Poisson models no significant changes have been observed. Consequently, fire frequency is still strongly associated with human drivers and with agricultural activities in particular (WAI).

Nonetheless, logistic regression models revealed a slight loss of significance of traditional explanatory factors. This was especially relevant in the case of the WAI, a variable that has traditionally been linked to forest fire occurrence in Spain, and the WUI, which is the most common driver in the literature. On the other hand, the influence of population density and accessibility (DP) appears to be increasing, so urban pressure on wildlands is a more influencing driver nowadays. Human factors still play a decisive role in fire occurrence but their overall performance seems to be decreasing over time. In addition, the overall loss of explanatory power of most of the driving factors indicates that biophysical factors (such as fuel moisture, topography, or climate) could be playing a more significant role today. Thus, they can no longer be excluded, but should be coupled to human factors to determine fire-prone areas or in conducting any kind of wildfire assessment. According to our results, fire occurrence is becoming less dependent on human activities, whereas fire frequency remains associated with agricultural activities (either by accident or negligence).

Our findings also open several new lines for future research. The analysis of the GWR models suggests a certain degree of spatial variability, which could imply that human driving factors vary both over space and time. Moreover, deeper insights into the temporal behavior of driving factors can be explored. Specifically, intra-annual – seasonal – variability might be investigated by splitting fire occurrence into summer and winter samples. Finally, the influence of fire size can also be included, isolating large fires so that fire triggering factors are analyzed separately. This is particularly interesting since most human-induced fires are smaller than 1 hectare. Driving factors might thus vary with fire size.

Acknowledgements

The Spanish Ministry of Education has financed this work: FPU grant 13/06618. We would also like to thank the reviewers for their valuable comments, which have undoubtedly helped to improve this work.

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