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RESEARCH ARTICLE

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Modelling spatial patterns and temporal trends of wildfires in Galicia (NW Spain)

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Abstract

Aim of study: The goal of this paper is to analyse the importance of the main contributing factors to the occurrence of wildfires.

Area of study: We employ data from the region of Galicia during 2001-2010; although the similarities shared between this area and other rural areas may allow extrapolation of the present results.

Material and Methods: The spatial dependence is analysed by using the Moran's I and LISA statistics. We also conduct an econometric analysis modelling both, the number of fires and the relative size of afflicted woodland area as dependent variables, which depend on the climatic, land cover variables, and socio-economic characteristics of the affected areas. Fixed effects and random effect models are estimated in order to control for the heterogeneity between the Forest Districts in Galicia.

Main results: Moran's I and LISA statistics show that there is spatial dependence in the occurrence of Galician wildfires. Econometrics models show that climatology, socioeconomic variables, and temporal trends are also important to study both, the number of wildfires and the burned-forest ratio.

Research highlights: We conclude that in addition to direct forest actions, other agricultural or social public plans, can help to reduce wildfires in rural areas or wildland-urban areas. Based on these conclusions, a number of guidelines are provided that may foster the development of better forest management policies in order to reduce the occurrence of wildfires.

Keywords: Cause-effect relationship; climatology; spatial and temporal indicators; fixed effects; random effects; socio-economic factors.

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Introduction

It is estimated that more than 1.3 million hectares of forest are destroyed by wildfires in Europe each year (FOREST EUROPE, UNECE & FAO, 2011). Spain is one of the five southern European countries with the highest level of damage caused by wildfires, with a yearly average of 19,705 wildfires from 1998 to 2007, affecting a total of 130,714 hectares (SECF, 2010). Within Spain, the case of Galicia is particularly relevant. While only representing 6% of national surface area, between 1991 and 2010 Galicia registered an approximate average of 46% of Spanish wildfires and 21% of the total burned surface area (Figure 1), according to MARM (2012) and the regional government

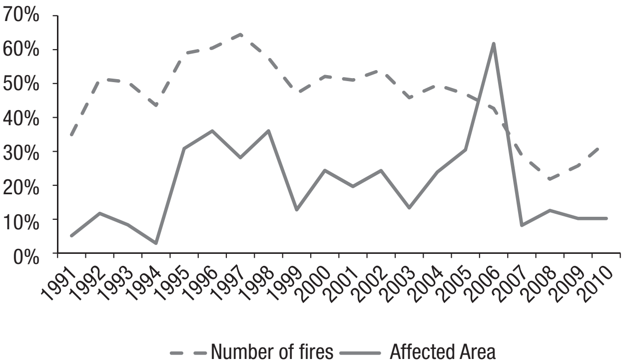

Figure 1. Galician wildfires with respect to the total number of Spanish wildfires (1991-2010).

(Xunta de Galicia, 2011). Given the geographical concentration of this problem, we limit our analysis to the wildfires occurring in this region, also due to the lack of comparable data for other Spanish regions. We believe, however, that the current paper may provide insights which are closely applicable to other European rural and wild land-urban areas.

According to data provided by the Galician Institute of Statistics (IGE, 2012a), since 2001 the number of wildfires reveals an upward trend until 2005, decreasing then in number. With regards to the affected surface area, this increased gradually from 2002 to 2006, but since then it has decreased considerably as well. It should be noted that the number of affected areas reach catastrophic levels during 2006. Furthermore, the evolution of wildfires throughout Galicia varies considerably in spatial and temporal terms. Geographically, and based on the data published by the IGE (2012a), wildfires affect more severely southern districts than northern districts of Galicia, both in terms of the number of fires and forestry area affected (Figure 2). Also, western districts are the area in which forestry lands are the most affected in relation to their surface area, while the southern districts record the highest numbers of wildfires.

The wildfire risk depends on several climatological, social or environmental factors, which could be modified by public policies at short or medium term. Nevertheless, decision-making is characterised by the presence of dynamic risk factors (Rogalski, 1999) [1].

In order to study wildfires in depth, it is necessary to be aware of the currentsituation of the agro-forestry areas in Galicia. Certain areas have scattered populations with a constant rural depopulation and continuing migration of young people to more highly populated areas (Marey *et al.*, 2007). In addition, the thinning out of the agro-forestry sector within the economy has been clear for some time now, as well as the reduction in employment in this sector. This has contributed to make much more difficult youth employment in the countryside, while at the same time, fewer farms use woodland areas to obtain productive resources (Vega, 2007; Sineiro, 2006). This trend has also caused forestry land to become increasingly neglected, allowing for an increase in the severity and spread of wildfires. Moreover, the structure of forest property is often very divided, with a high level of private property increasingly belonging to elderly people, making it more difficult to manage the lands correctly (Sineiro, 2006).

Galicia contains different climatic areas, resulting in an uneven availability of biomass that can be burnt (Martínez *et al.*, 1999). This makes it difficult to organise the prevention and extinguishing of wildfires. Taking these circumstances into account, together with the social and environmental impacts caused by wild-

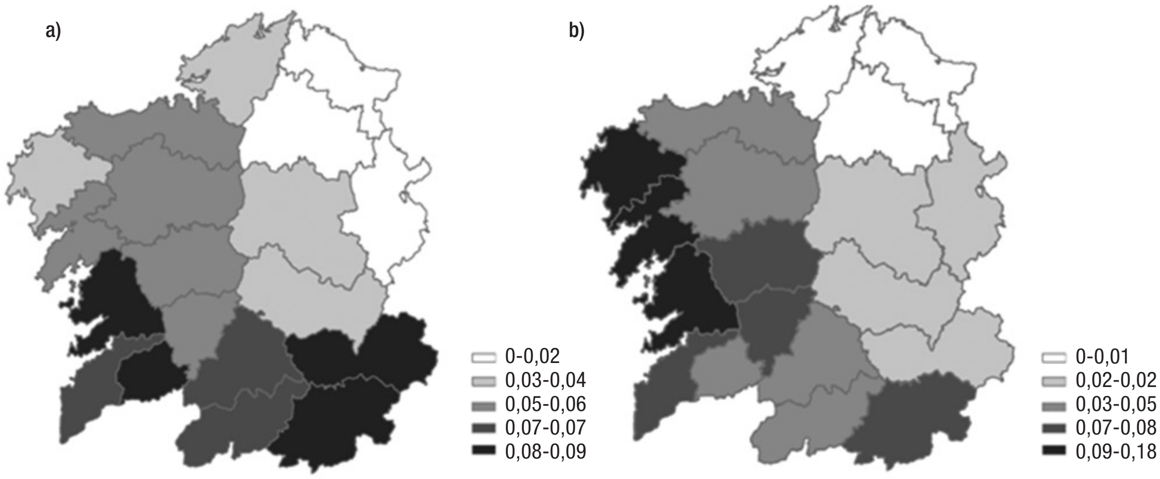

Figure 2. Geographic distribution of the occurrence of wildfires during 2001-2010. a) Representation of the number of wildfires per district with respect to the total number of Galician wildfires. b) Representation of the affected forestry area per district with respect to total affected area in Galicia.

[1] Following Molano *et al*. (2007) and Martínez *et al*. (2009), the causing factors of wildfires can be divided into two main categories: avoidable and unavoidable. Unavoidable causes are considered those that cannot be foreseen or dissuaded, whereas avoidable causes are those that can be prevented through individual actions or forestry policies. This implies that there are exogenous factors, which are uncontrollable, to which other endogenous factors must be added. In general, the unavoidable category contains natural phenomena, whilst the avoidable can be divided into three possible sub-categories: intentional, negligent and unknown causes. Avoidable causes represent almost all of the causes, although the majority of these are classified as unknown, showing that the causality of wildfires is not recorded reliably and depends heavily on the criteria of investigators (Pérez & Delgado, 1995; Molano *et al.,* 2007).

fires, over the last few years the government has prioritized the design of preventative policies, although most of its budget goes toward extinction activities. For these policies to work well, it is important to identify the factors that affect the occurrence of wildfires.

To this end, the proposed model must be simple, structured and easy to standardise so that it can be easily updated (King & MacGregor, 2000).

Until now, several methods have been used to identify wildfire risk factors. Some studies have used various explanatory variables in order to explain the reasons why some areas are more heavily affected than others, although they do not quantify the described relationships and/or support their arguments in a quantitative way (Lavorel *et al.*, 2007). However, other papers use techniques based on Geographic Information Systems (GIS), using probability risk models and linking variables to the forest environment. (Cabrera, 1989; Vilar *et al.*, 2008; Chuvieco *et al.*, 2009; Martínez *et al.*, 2009; Romero-Calcerrada *et al.*, 2010). GIS techniques are used in several models in which geographic and other statistical variables are included (Pew & Larsen, 2001; Vega-García & Chuvieco, 2006). Relevant geographic variables include the location of roads, and industrial or recreational areas, amongst other factors (Romero-Calcerrada *et al.*, 2010). Therefore, geographical implications in the occurrence of wildfires have also been widely studied. As a result, this study focuses on assessing the geographical differences in the occurrence of wildfires.

In some earlier work, researchers have studied the error term to identify geographical and temporal trends (Disdier & Head, 2008; Prestemon *et al.*, 2002; Jones, 1991; Moulton, 1986). Testing the error term allows the researcher to control for the unobservable factors across the different entities, implying that this research can be used to determine whether differences across entities are significant. Therefore, an econometric model with random effects (RE) or fixed effects (FE) can be developed in order to account for specific local effects.

Other papers explore the possible relationship between wildfires and a specific group of variables (Finney *et al.*, 2009), including forest management (Prestemon *et al.,* 2002; Butry, 2009; Wimberly *et al.*, 2009), meteorological variables (Aguado *et al.*, 2007), and socio-economic factors (Mercer & Prestemon, 2005). This research, as well as Prestemon *et al.* (2002), uses time series models to analyse temporal trends in wildfire risk. Other relevant research also includes socioeconomic variables such as income, machinery used, and/or number of livestock (Vilar *et al.*, 2008). Wildfire risk is also analysed from the perspective of the different phases in the duration of a fire, and the ignition, intensity or area affected are used as dependent variables (Genton *et al.*, 2006).

Several international studies analyze the problem of fires from a spatial context. For example, Prestemon *et al*. (2002) developed a model with fixed effects as to assess whether there is a spatial behavior in the occurrence of fires between administrative units from North Florida. Preisler *et al.* (2004) used temporal and spatial effects through a logistic regression to study the probability of fires in Oregon (USA) since 1970. Meanwhile, Brillinger *et al*. (2006) developed an empirical model for analyzing the evolution of fire risk. Their model contains both, FE and RE to analyze the fires occurrence in California (USA) during the years 2000-2003. Finally, Chen *et al.* (2014) also analyze the risks and causes of fires using spatial econometrics.

The aim of this study is to extend previous analyses using current data and taking into account the impact of socio-economic factors, land cover, and climatology using spatial analysis. Thus, econometric models have been developed to analyse the possible influence of socioeconomic factors on the risk of wildfires. The Ordinary Least Square (OLS) and econometric models for counted data are used to identify these socioeconomic factors. Random effects (RE) and Fixed Effects (FE) are also estimated to assess the presence of spatial patterns. Other methods, such as the Moran's I and LISA statistics, are included to determine whether wildfire occurrence shows spatial patterns. We expect the present results can help to improve public policy focussing on exploring spatial and temporal impacts on fire occurrence.

This research starts by explaining the data and methods used. In the next section, the results are described and discussed, and then it follows a section in which the main conclusions of the research are summarized and policy implications are provided.

Materials and methods

Data

Data have been gathered from 2001 to 2010. The most up-to-date data available from the 19 forest districts established by the Galician regional government were collected (Xunta de Galicia, 2011). Variability over time and between districts will be one of the desirable data properties (Cameron & Trivedi, 2009). Data have been grouped by forest districts in order to have a common geographical reference. Therefore, some variables had to be transformed prior to be included into the model by aggregating municipal data up to the district level. In the following analysis, the hectare is the unit used to measure the surface area.

The explanatory variables are shown in Table 1, and these can be grouped into seven main categories, including: the population structure, weather variables, territorial features, economic information, agroforestry situation, wildfire characteristics and time dummy variables. To avoid perfect multicollinearity in the econometric models, the dummy year for 2001 has been used as a baseline, and time effects are interpreted by using this year as a reference point. As several variables for different groups showed high correlations with each other, a limit of 70% was set for the value of the linear correlation coefficient. Furthermore, the variance inflation factor (VIF) was used to analyse the level of multicollinearity among the chosen variables (Neter *et al.*, 1983). The VIF had values lower than 2.16 for each variable and 3.70 for the set. These values indicate that multicollinearity is not a problem in the selected variables.

Table 1. Variables

Variable	Description	Data source	Mean	Standard Error	Min	Max
		WILDFIRES CHARACTERISTICS				
Number of wildfires	Number of wildfires per year in each district[1]	IGE	381.179	275.987	23.000	1,268.000
Ratio of burned-forest area	Affected area, in hectares, between the total forestry areas in each district	IGE	0.017	0.030	0.000	0.223
		CLIMATOLOGY				
Summer average rainfall	Annual average rainfall during the summer (l/m^2)	MeteoGalicia	43.217	19.821	13.55	120.917
Summer maximum temperature	Average maximum temperature, in Celsius, during the summer in each district	MeteoGalicia	22.946	2.663	16.747	30.367
		SOCIO-ECONOMIC VARIABLES				
		Territorial				
Ratio of protected areas	Total protected areas over the total Forest District area	MAGRAMA[2]	0.140	0.142	0.011	0.474
		Population				
People Density	People by hectare in each Forest District	IGE	1.049	1.163	0.104	5.081
		Agro-Forestry				
Ratio of equine stock	The ratio of equines in Forest District livestock	IGE	0.036	0.028	0.004	0.110
Ratio of natural pasture	Total natural pasture area over the District area	CORINE	0.113	0.074	0.006	0.294
Ratio of Pinus pinaster	Total Pinus pinaster area over the forested area by District	IFN3	0.390	0.201	0.044	0.831
		Economy				
Agricultural cooperatives	Number of cooperatives in each Forest District	IGE	18.158	13.627	2.000	49.000
		DUMMY VARIABLE				
Dummy year t[3]	Represents each individual year t		1.100	0.301	1.000	2.000

[1] Forest administrative entity determined by Xunta de Galicia (Xunta de Galicia, 2011).

[2] Ministry of Agriculture, Nature and Food Quality.

[3] t= (2002,…,2010).

Wildfires data were recorded from the Galician Forest Districts. On the other hand, meteorological data were recorded directly by the weather stations, and such data had to be linked and extrapolated to the District level. Finally, the agro-forestry data are mainly recorded by Geographic Information Systems (GIS). Thus, a shape-file with the Galician Forest Districts was designed adding the municipality limits obtained from the National Geographic Institute (IGN, 2011). To conclude, agro-forestry data were obtained cropping GIS information with the previous defined shape-file.

The data for the climatic variables were collected from MeteoGalicia (2012). The climate stations belonging to each district were geographically located. The average maximum temperature and rainfall recorded per month during the summer were collected[2]. The proportion of the protected areas in each district was also included to describe relevant territorial features. The protected areas were obtained from the MAGRAMA (2010). These data were provided by two maps containing the Community Interest Sites (CIS) and Special Protection Areas for Birds (SPAB). Thus, the GvSig software was used to compute the size of both protected areas by Forest District (GvSig, 2014). In this way, the ratio of protected areas is computed using the total protected area divided by total district area.

The density per hectare is used to describe the population structure. Therefore, the total population divided by the total Forest District area is used to calculate this variable. Both data were recorded from IGE (2012a) and municipality statistics. This density variable presents high correlations with the personal income, level of studies or employment rate. In order to avoid such multicollinearity problems, variables referring to personal income, education and employment rates had to be dropped from the final specification due to their high correlations among each other.

The Third Spanish National Forest Inventory (NFI3), the Corine Land Cover and the Livestock Census were the main sources to gather information about the agro-forestry situation (IGE, 2012b). Tree dominant tree species were recorded in order to describe the forest plantations. The forestry areas, in which the *Pinus pinaster* is the main specie, were calculated from the NFI3 (MAGRAMA, 2008) while the district-forested areas were recorded from IGE (2012b). Hence, the ratio of *Pinus pinaster* was included in order to describe the forestry structure. The natural pasture was obtained by accounting for the lands where this activity is recorded according to the Corine Land Cover database (European Environment Agency, 2010). The GvSig software was employed to calculate both the agricultural and forestry area (GvSig, 2014). The ratio of equines was also taken into account in order to describe the livestock structure, as in Barreal *et al.* (2011). This variable was considered given that previous literature related the presence of equines with land management and fuel treatments (Rigueiro *et al*., 2002). The percentage of equines represents 1% up to 11% of total livestock according to each Forest District data (IGE, 2012b). Although cattle are the main livestock in Galicia; equines usually graze in pasturelands or forest areas. The number of agricultural cooperatives is also included in the model. This variable can be a proxy for the dynamics of the rural areas. These data were collected from IGE (2012b). However, we should note that there are some years in which yearly data are missing, so that the series had to be completed with the closest data points available.

The wildfire variables were also obtained from the IGE (2012b). For the first six years, municipalities provided the data, then the burned area and the number of wildfires had to be aggregated by forest districts. The ratio of burned area was calculated using the total forest area provided by IGE (2012a). The GeoDa software was used to obtain the spatial statistics of the dependent variables (Anselin *et al.*, 2006; GeoDa, 2014). In order to create the final database, and conduct the estimation process, the Stata 10.1 software was used (Stata, 2010).

Methodology

Descriptive Spatial Analysis

Graphs and statistics are useful in order to identify the spatial patterns in Galician wildfires. The first one involves the representation of the data to identify the temporal trends and the heterogeneity between the Galician forest districts. Then, in case of existing temporal trends, these could be identified showing differences of each entity´s mean value. Another alternative is to represent the data for each year by a graph. The independent years could register more or less spatial differences.

The Moran's I statistic (Moran, 1948) was used for statistical analysis, as well as the Local Indicators of Spatial Association -LISA- (Anselin, 1995). With both statistics, the spatial dependence can be analysed using the autocorrelation coefficients between the Galician forest districts. The first statistics analyses the spatial

[2] In some cases, climatological data were not available for all of the time periods and/or forest districts. The unavailable data had to be supplemented with those from other forest districts according to the climatic areas established by Martínez *et al.* (1999).

heterogeneity of the sample. Meanwhile, the second focuses on the relationship between each geographic unit, identifying the clusters of study.

The Moran's I statistic takes into account the number of geographical areas (N); the analyzed areas (*j* and *i*); the study variable for each location (*y*); the mean of the variables of interest in all areas ($(\bar{y})$); and finally the weight matrix that describes the relationship between both locations ($W_{j,i}$). Then, the Moran's I statistic could be expressed by the Eq. (1).

$$I = \frac{N}{\sum_i \sum_j W_{ij}} * \frac{\sum_i \sum_j W_{ij}\left(y_i - \bar{y}\right)\left(y_j - \bar{y}\right)}{\sum_i \left(y_i - \bar{y}\right)^2} \qquad [1]$$

According to the definition of the weight matrix, the relations between close forest districts are included. Therefore, the closest neighbors to each polygon are identified with this matrix. Mathematically, the weight matrix could be expressed as Eq. (2), in which $\hat{w}_{ij}$ represents the spatial matrix of adjacent polygon (*j*), respect to the polygon that we are studying (*i*).

$$w_{ij} = \frac{\tilde{w}_{ij}}{\sum_j \tilde{w}_{ij}} \qquad [2]$$

The spatial relationships in this matrix can be used with different contiguity interpretations. In other words, if a regular grid is designed, the weight matrix could be constructed according to four spatial relationships: linear (Fig.3a), Rook (Fig.3b), Bishop (Fig.3c) and Queen (Fig.3d). These relations depend on the number and directions of spatial dependences that the researchers may find. In this research, the polygons are irregular, so the criterion with more spatial directions is selected (Moreno & Vayá, 2000), and as a consequence, the queen contiguity is chosen to analyze the spatial patterns. This contiguity can be used at several levels (Lesage & Kelley, 2009). This research analyzes the direct relationships between the closed forest districts in terms of fire occurrence.

The LISA statistics can be developed from the Moran's I statistics (Anselin, 1995). This is described in the Eq. (3) where z_i represents the normalized value of the selected variable in respect to the mean and J_i is all polygons (districts) next to *i*. Therefore, the LISA statistics analyzes the spatial patterns between each entity to the selected data. In other words, the spatial autocorrelation is individually analyzed.

$$I_i = \frac{z_i}{\sum_i z_i^2 / N} \sum_{j \in J_i} W_{ij} z_j \qquad [3]$$

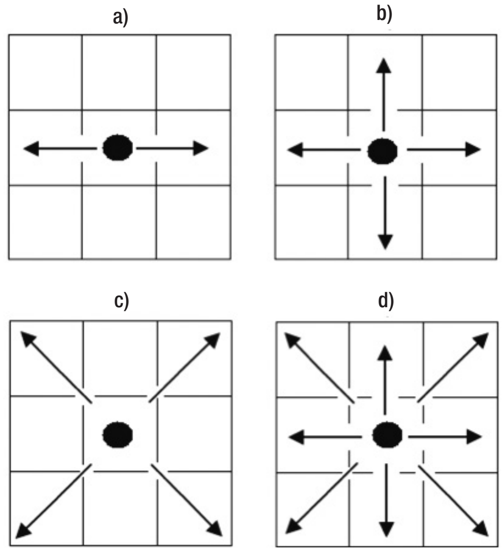

Figure 3. Types of contiguity for direct relations.

Econometric Analysis

In order to analyse the relationship between the previous variables and wildfires in Galicia, a baseline lineal regression estimated by OLS was used. In this baseline estimation the coefficients are controlled by the heterogeneity of each district through the Huber-White correction of standard errors (Cameron & Trivedi, 2009). Thus, the econometric model is presented by Eq. (4), in which the variables are arranged into a panel according to each district and their respective periods of time. In this equation, the subscripts "j, k, h" represent the type of variable, "i" is the forestry district, and "t" is the period.

$$Y_{it} = \beta_0 + \beta_j X_{jit} + \beta_k X_{kit} + \beta_h X_{hit} + \varepsilon_{it} \qquad [4]$$

With this common specification, two independent equations were estimated. The first model used the ratio of forest-burned area in each forest district as the dependent variable, and the second specification modelled the number of wildfires. The independent variables in both models include socio-economic factors represented by X_{jit}, (mainly population structure, territorial features, economic information and agroforestry data for each forest district), climatology represented by X_{kit} (including the variables of average maximum temperature and average monthly precipitation); and finally, the vector X_{hit} represents the dummy yearly indicators.

Using the Box-Cox test, the functional form of the Eq. (4) was selected. The Box-Cox test develops a transformed dependent variable represented by the Eq. (5), in which the residual (μ_{it}) assumes a normal distribution in order to estimate the parameters β and θ.

$$g\left(y_{it}\middle|\theta\right) \equiv \frac{y_{it}^{\theta}-1}{\theta} = X_{it}\beta_i + \mu_{it} \quad [5]$$

As such, if the estimation of θ is close to zero, then the best specification to be used would be the log-lineal model. However, if the respective statistics are significant and close to one, a lineal model should be used. Eq. (6) is then formulated according to the following specification.

$$Y_{it} = \beta_j X_{jit}^{\lambda} + \beta_k X_{kit}^{\lambda} + \gamma_h X_{hit} + \varepsilon_{it} \quad [6]$$

Since, the number of wildfires is a counted data variable, the Poisson Regression Model (PRM) shown on Eq. (7) is employed, with the specification earlier presented in Eq. (4):

$$E\left[y_{it}\middle|x_{it}\right] = \exp\left(\beta_0 + \beta_j X_{jit} + \beta_k X_{kit} + \beta_h X_{hit}\right) \quad [7]$$

Given that count data can exhibit overdispersion (Cameron & Trivedi, 2005), we need to assess whether this is present by estimating Eq. (8). Overdispersion implies that the variance depends on the mean plus square parameter (α^2). In this case if α=0, then the variance is equal to the mean and there is no overdispersion; and thus, the PRM can be a suitable model.

$$\mathrm{Var}\left(y_{it}\middle|\mathrm{x_{it}}\right) = \mathrm{E}\left(y_{it}\middle|\mathrm{x_{it}}\right) + \alpha^2 \mathrm{E}\left(y_{it}\middle|\mathrm{x_{it}}\right) \quad [8]$$

On the other hand, if the coefficient α is different from zero, then the number of wildfires should be estimated by a Negative Binomial Regression model (NBRM). This model is more general than the PRM and should prove to have a better goodness of fit in case of overdispersion (Cameron & Trivedi, 2009).

In order to interpret the coefficients of the previous model, the use of the Incidence Rate Ratio (IRR) is recommended as its results are easier to interpret (Long & Freese, 2001). As such, the IRR coefficients are estimated to directly quantify the values of the respective parameter estimates. This ratio is calculated by Eq. (9), in which the results can be analysed as a change in the probability of wildfire occurrence, when there is a change in the analysed independent variable, whenever the others parameters are constant.

$$IRR = \frac{E\left(y\middle|x, x_{it}+1\right)}{E\left(y\middle|x, x_{it}\right)} = e^{\beta} \quad [9]$$

In this setting, two different models could be used to analyse the error term: FE and RE. The FE represented by the Eq. (10) in which the error term (ε_{it}) of the Eq. (4) is broken into two parts: one fixed term (v_i) and another error term (τ_{it}).

$$Y_{it} = \beta_0 + \beta_j X_{jit} + \beta_k X_{kit} + \beta_h X_{hit} + v_i + \tau_{it} \quad [10]$$

In the following RE models, the previously fixed term (v_i) is now random. The specification of this model is equal to Eq. (10), but in this case the random term will have a mean of v_i and different variance from zero ($\mathrm{Var}(v_{it}) \neq 0$). These unobservable factors are used for the OLS model but also for the MRP (Eq. 11), or NBMR in case of overdispersion.

$$E\left[y_{it}\middle|x_{it}\right] = \exp\left(\beta_0 + \beta_j X_{jit} + \beta_k X_{kit} + \beta_h X_{hit} + v_{it}\right) \quad [11]$$

The Hausman test (H) is used to select between RE and FE models. The specification of this test is shown in Eq. (12) and analyzes the consistency of estimators for both models. The null hypothesis states that there is no correlation between the unique errors and the independent variables. This hypothesis is tested at the 5% significance level. If the null hypothesis is not rejected, then FE are selected over RE. Otherwise, RE should be used.

$$H = \left(\beta_{RE} - \beta_{FE}\right)' \left[Var\left(\beta_{RE}\right) - Var\left(\beta_{FE}\right)\right] \left(\beta_{RE} - \beta_{FE}\right) \; H \sim \chi_n^2 \quad [12]$$

Results

Spatial patterns and temporal trends analysis

The spatial patterns of the number of wildfires and burned-forest area ratio can be observed with graphical displays. The variation of the burned-forest area ratio by year is represented in the Figure 4a. In this graph the x-axis represents the Galician forest districts according to each number (Xunta de Galicia, 2011). Different values between the districts are recorded in all graphs; however its difference depends on the year. Another way to identify the existence of spatial patterns is by using the average of the burned-forest area ratio for the sample. This is included in the Figure 4b where the difference between districts can be observed. Also, the temporal trends are observed per year.

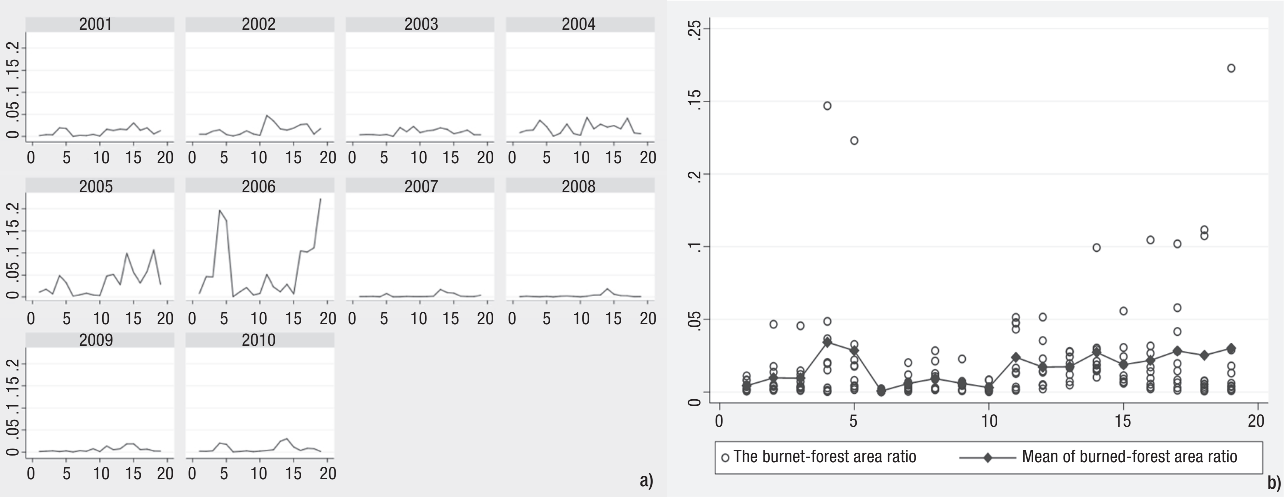

Figure 4. Graphical representation for variation of burned-forest area ratio in Galicia from 2001 to 2010. a) Data represented by year. b) Data recorded by year and the mean of each district.

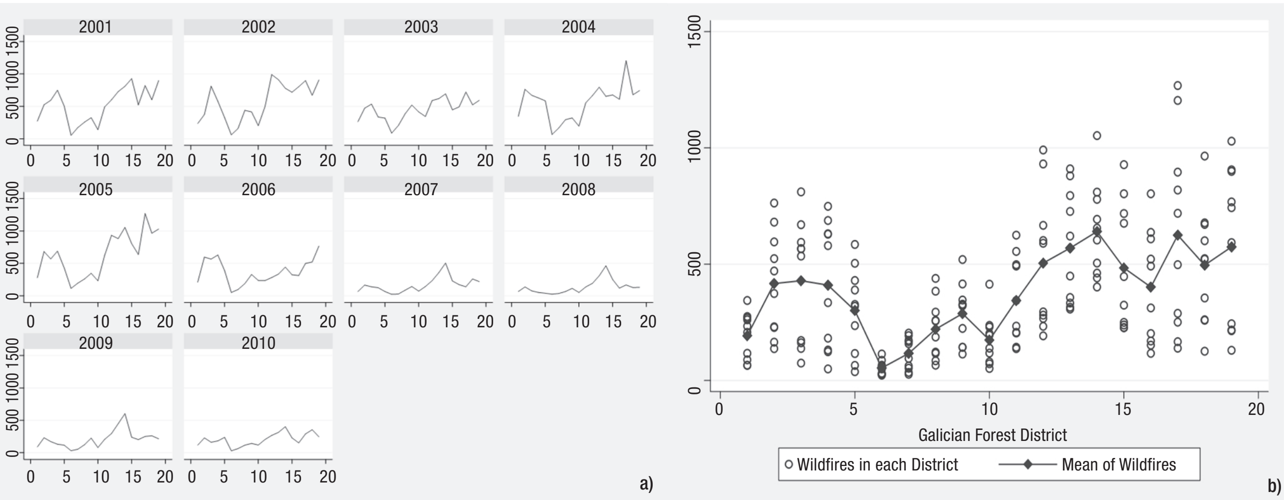

Figure 5. a) The number of wildfires represented by year in Galicia from 2001 to 2010. b) The number of wildfires recorded each year according to Galician Forest Districts from 2001 to 2010.

Figure 5a and Figure 5b describe the evolution of wildfires per year from 2001 to 2010. The spatial patterns can be identified in this graph. Figure 5b shows also spatial patterns in the mean of wildfires according to each district. Data show significant differences across years, therefore the number of wildfires contains also temporal effects.

A weight matrix should be constructed to develop the spatial statistics. As stated earlier, the direct Queen contiguity is selected to analyse the relationship between districts (Fig. 3d) and its histogram is represented in Figure 6. In this graph, it can be observed the lowest and highest contiguity between forest districts. Thus, Galician forest districts have at the minimum two influential neighbours and six as a maximum. This histogram also highlights a big number of districts with six entities around them. However, the biggest contiguity group has only three neighbours.

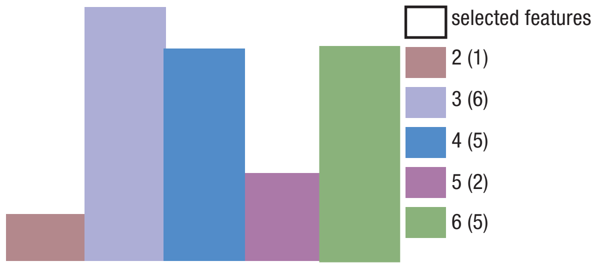

Figure 6. Histogram of contiguity according to Level 1 for Galician Forest District.

The Moran's I and LISA statistics are used to analyse the spatial patterns of wildfires and the yearly burned-forest area ratio in Galicia. Figure 7 reports the Moran's I statistic by year, and its average for the entire sample. It can be observed that Moran's I registers higher values for the number of wildfires than for the ratio of burned-forest area. Thus, more spatial autocorrelation is detected for the number of wildfires than for the ratio of burned-forest area. Also, in 2007 no spatial correlation is found for burned-forest area. This may be explained because in 2006 wildfires affected many areas (Molano *et al.*, 2007). This caused social alarm, therefore over the next year, the wildfires occurrence has been drastically reduced. Even the recorded data for the burned-forest area diminished a 97% in 2007 with respect to 2006.

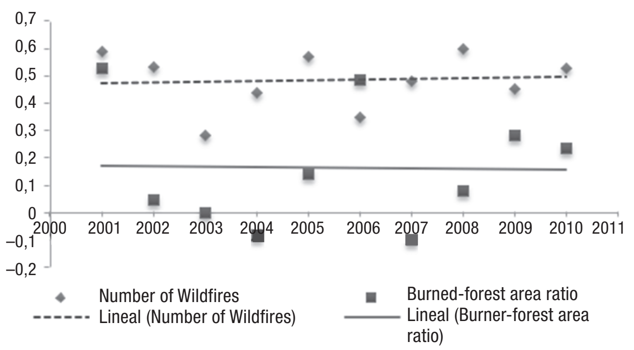

Figure 7. The Moran's I statistic for the burned-forest area ratio and the number of wildfires recorded in Galicia during 2001-2010.

The LISA statistic represents the various significant spatial patterns as follows (Anselin, 1995; Lesage & Kelley, 2009):

— High-High (H-H): a particular forest district and their neighborhoods have high values. This type of relationship is represented by the red color.

— High-Low (H-L): a particular forest district has high values and their neighborhoods have lower values. This type of relationship is represented by the pink color.

— Low-High (L-H): is similar to the previous category, but in this case the forest district has high values and their neighborhoods have lower values. This type of relationship is represented by the sky-blue color.

— Low-Low (L-L): the forest district and their neighborhoods have low values. This type of relationship is represented by the blue color.

The remaining values are represented by a grey color because these entities have a random relationship (Moreno & Vayá, 2000). Figure 8 represents the LISA statistics related to each dependent variable. The colored results are significant at the 5% level. Taking into account the burned-forest area ratio, the LISA statistics is represented in Figure 8. In each map the LISA statistic for each district is represented according to the relation with its neighborhoods. With this result, the Low-Low (L-L) relation is mainly recorded in the North of Galicia, although, this relationship was also recorded in the South for some particular years. However, the High-High (H-H) relationship occurs primarily in the South. Thus, Southern forest districts and their neighbourhoods record high values of burned-forest area ratio.

In order to analyze the number of wildfires, the LISA statistics are shown in Figure 9. In these maps the Low-Low (L-L) relationship could be observed in the Northeast districts. On the other hand, Higher-Higher (H-H) relations are recorded in the South and Southeast. Therefore, there is evidence of spatial patterns in the number of wildfires.

All previous graphs and statistics show the existence of relevant spatial patterns and temporal trends. Therefore, these should be included in the econometric model for both dependent variables. The temporal trends are included in the empirical models by using dummy variables for each year, considering 2001 as the baseline year. On the other hand, in order to correct for spatial patterns in the research, data are set according to a panel of forest districts and controlling the heterogeneity by district through standard errors correction. The spatial patterns are also analyzed using FE and RE models.

Econometric models results

Results for the burned-forest area

In order to specify the most suitable econometric model to analyse the evolution of the burned-forest area ratio, a Box-Cox test was estimated (Cameron & Trivedi, 2009), being its results reported in Table 2. A logarithmic model is used in accordance with the results obtained in the Box-Cox test. In other words, the statistics could not reject the logarithmic specification both for the dependent and independent variables.

Following the results displayed in Table 3, the estimation by OLS captures 69.04% of the variation of the burned forest area rate. Taking into account the F-statistic, we find that all parameters are jointly significant. As regards the choice between the use of FE

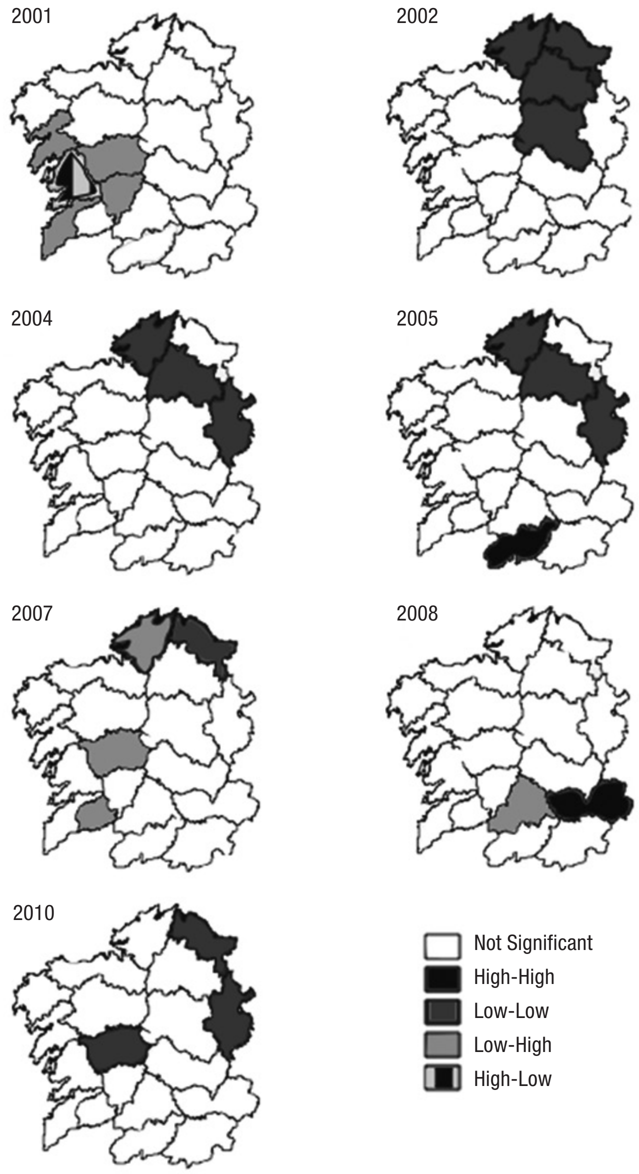

Figure 8. LISA statistic for the burned-forest area ratio in Galicia during 2001-2010.

Table 2. Box-Cox test for the regressions of the ratio of burned-forest area

Dependent Variable				Independent Variables			
Test H_0	Restricted log likelihood	LR Statistic chi^2	P-value (Prob > chi^2)	Test H_0	Restricted log likelihood	LR Statistic chi^2	P-value (Prob > chi^2)
$\Theta = -1$	360.932	742.700	0.000	$\lambda = -1$	445.396	9.150	0.002
$\Theta = 0$	732.266	0.030	0.859	$\lambda = 0$	449.422	1.100	0.295
$\Theta = 1$	448.330	567.900	0.000	$\lambda = 1$	448.330	3.280	0.070

and RE in the previous models, the Hausman test recommends the use of RE to estimate the burned-forest ratio model (Prob>chi2= 0.98).

The dummy variables determine significant effects over several years. A positive trend is identified from 2002 to 2006. The majority of dummy variables are

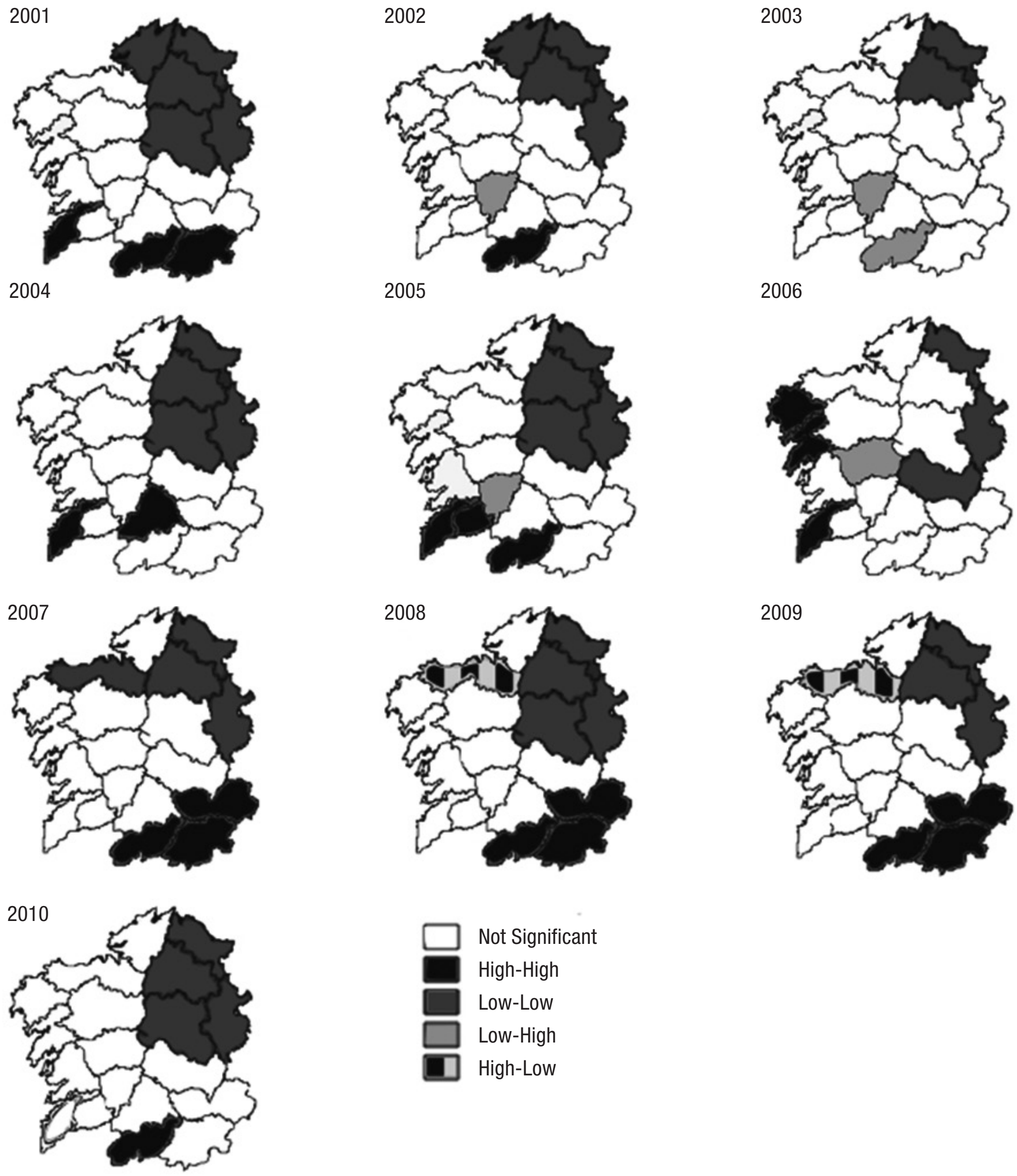

Figure 9. LISA statistic for the number of wildfires in Galicia during 2001-2010.

significant and positive with respect to the 2001 year. However, after 2006, the trend is clearly negative and significant for all years. These results are robust across the econometric selected models.

The climatological variables show in particular the importance of rainfall in order to reduce the burned-forest area ratio. This variable is significant carrying a negative effect in the causes of wildfire occurrence. Thus, the average effect of rainfall on burned-forest areas ratio is -0.643, when the precipitation changes by one unit over time and between districts. However, the maximum temperature has a positive effect, although this variable is not significant in order to predict the burned area. The small variability in this variable may be responsible for this finding.

In terms of socioeconomic variables, the ratio of the equines and the number of agricultural cooperatives have both a negative and significant effect on the burned-forest ratio area for the OLS and RE models. Their effects show that if the value changes over time and between districts by one unit, then the average effect of equine radio stock and the number of agricultural cooperatives over the burned-forest area will respectively decrease by a factor of -0.385 and -0.555.

On the other hand, the density of *Pinus pinaster* and the ratio of protected areas are positively related with this dependent variable. The coefficients are significant for the OLS and RE results. We also find that the ratio of natural pasture has no statistical impact on any of the econometric models.

Table 3. Econometric results for the regresions of burned-forest area

	OLS		OLS with FE		OLS with RE	
	Coef,	P>t	Coef,	P>t	Coef,	P>t
Dummy 2002	0.418 (0.195)	0.046	0.314 (0.248)	0.208	0.357 (0.246)	0.146
Dummy 2003	0.173 (0.270)	0.531	0.263 (0.253)	0.301	0.241 (0.249)	0.334
Dummy 2004	0.659 (0.1949	0.003	0.681 (0.245)	0.006	0.698 (0.243)	0.004
Dummy 2005	0.883 (0.179)	0.000	0.912 (0.263)	0.001	0.942 (0.256)	0.000
Dummy 2006	1.172 (0.291)	0.001	1.188 (0.267)	0.000	1.230 (0.259)	0.000
Dummy 2007	-1.037 (0.290)	0.002	-1.288 (0.271)	0.000	-1.126 (0.259)	0.000
Dummy 2008	-1.557 (0.227)	0.000	-1.827 (0.265)	0.000	-1.632 (0.251)	0.000
Dummy 2009	-0.738 (0.226)	0.004	-0.739 (0.371)	0.048	-0.731 (0.287)	0.011
Dummy 2010	-0.797 (0.248)	0.005	-0.751 (0.369)	0.044	-0.732 (0.277)	0.008
Summer average rainfall	-0.576 (0.130)	0.000	-0.720 (0.189)	0.000	-0.643 (0.176)	0.000
Summer maximum temperature	1.043 (0.970)	0.297	-0.749 (1.256)	0.552	-0.215 (1.051)	0.838
Ratio of natural pasture	0.119 (0.139)	0.405	0.000 (omitted)		0.084 (0.215)	0.695
People Density	0.344 (0.142)	0.026	-2.651 (2.405)	0.272	0.266 (0.258)	0.302
Ratio of Pinus pinaster	0.538 (0.239)	0.037	-5.369 (3.851)	0.165	0.611 (0.277)	0.027
Ratio of equine stock	-0.419 (0.203)	0.054	-0.182 (0.357)	0.612	-0.385 (0.192)	0.045
Ratio of protected areas	0.446 (0.173)	0.019	0.000 (omitted)		0.404 (0.208)	0.051
Agricultural cooperatives	-0.520 (0.141)	0.002	-0.901 (1.819)	0.621	-0.555 (0.253)	0.029
Intercept	-3.352 (3.256)	0.317	-4.353 (7.864)	0.581	0.819 (3.949)	0.836
Number of observations	190		190		190	
F Statistic	112.150					
Prob > F	0.000					
R2	0.690					

Table 4. Box-Cox test for the regression of number of wildfires

Dependent Variable				Independent Variables			
Test H_0	Restricted log likelihood	LR Statistic chi^2	P–value (Prob > chi^2)	Test H_0	Restricted log likelihood	LR Statistic chi^2	P–value (Prob > chi^2)
$\Theta = -1$	–1,368.202	417.560	0.000	$\lambda = -1$	–1,223.004	7.630	0.006
$\Theta = 0$	–1,163.885	8.930	0.003	$\lambda = 0$	–1,221.815	5.250	0.022
$\Theta = 1$	–1,225.002	131.170	0.000	$\lambda = 1$	–1,225.002	11.620	0.001

Results of the number of wildfires

For the purpose of determining the functional form for the regression of wildfires, the Box-Cox test does not provide conclusive evidence of the superiority of any functional form. However, in order to compare the number of wildfires with the regression of the burned-forest area ratio, the logarithmic model is selected. Also, this functional form is estimated to allow for comparability between all regressions.

Following the results displayed in Table 5, the estimation by OLS explains 78.60% of the variation of the

Table 5. Econometric results for the regressions of the number of wildfires

	OLS		**NBMR**		**NBMR with FE**		**NBMR with RE**	
	Coef,	**P>t**	**IRR**	**P>t**	**IRR**	**P>t**	**Coef,**	**P>t**
Dummy 2002	0.147 0.116	0.222	1.039 0.092	0.665	0.985 0.063	0.808	1.003 0.063	0.965
Dummy 2003	–0.006 0.147	0.968	1.004 0.110	0.970	0.950 0.068	0.474	0.956 0.065	0.502
Dummy 2004	0.067 0.104	0.526	1.077 0.085	0.351	1.088 0.066	0.165	1.088 0.066	0.160
Dummy 2005	–0.099 0.163	0.552	1.004 0.094	0.965	1.160 0.077	0.027	1.134 0.075	0.055
Dummy 2006	–0.894 0.164	0.000	0.602 0.071	0.000	0.674 0.053	0.000	0.653 0.049	0.000
Dummy 2007	–1.366 0.214	0.000	0.370 0.048	0.000	0.320 0.030	0.000	0.328 0.030	0.000
Dummy 2008	–2.155 0.201	0.000	0.223 0.027	0.000	0.218 0.023	0.000	0.227 0.022	0.000
Dummy 2009	–1.289 0.236	0.000	0.405 0.061	0.000	0.379 0.040	0.000	0.376 0.036	0.000
Dummy 2010	–1.625 0.187	0.000	0.333 0.042	0.000	0.365 0.036	0.000	0.345 0.032	0.000
Summer average rainfall	–0.430 0.120	0.002	0.990 0.002	0.000	0.994 0.001	0.000	0.994 0.001	0.000
Summer máximum temperature	1.696 0.726	0.031	1.022 0.039	0.576	0.972 0.015	0.074	0.981 0.014	0.189
Ratio of natural pasture	0.227 0.079	0.010	149.018 213.364	0.000	43.453 102.163	0.109	141.696 185.066	0.000
People Density	0.339 0.104	0.004	1.173 0.143	0.190	1.313 0.203	0.078	1.180 0.080	0.015
Ratio of Pinus pinaster	0.354 0.151	0.031	5.437 5.331	0.084	5.135 4.705	0.074	6.132 2.838	0.000
Ratio of equine specie	–0.201 0.161	0.227	0.005 0.022	0.257	0.035 0.085	0.163	0.004 0.008	0.007
Ratio of protected areas	0.253 0.116	0.042	3.276 2.068	0.060	4.334 5.060	0.209	4.072 2.538	0.024
Agricultural cooperatives	–0.110 0.118	0.363	1.012 0.009	0.167	1.010 0.013	0.421	1.015 0.008	0.052
Intercept	3.662 2.360	0.138	12,259.780 13,443.070	0.000	1,775.902 1,497.628	0.000	1,391.861 936.366	0.000
Number of observations	190		190		190		190	
F Statistic	107.240							
Prob > F	0.000							
R2	0.786							
Ovesdispersion Analysis								
Muhat			0.111 0.015	0.000				

number of wildfires. In addition, the parameters are all jointly statistically significant. In the OLS results, temporal trends are also identified. Until the year 2005, the coefficients are not significant; however, from this year onwards, all yearly dummies are significant and negative. Therefore, from 2005 onwards, the wildfire occurrence diminishes with respect to 2001. Taking into account the climatological variables, the rainfall carries a significant and negative effect on the number of wildfires (-0.430). On the opposite, the maximum temperature is significant and positively related to wildfire occurrence (1.696).

Some variables, such as the ratio of equines and the agricultural cooperatives do not have a significant relationship with the number of wildfires during 2001-2010, are not significant in the assessment of the wildfires using the OLS models. However, the rest of the socioeconomic variables, are significant and have positive effects over the wildfires occurrence.

The number of wildfires is modelled by count data models. Therefore, overdispersion should be studied in order to select the best econometric model. Taking into account the results of Table 3, the data show overdispersion, and hence, the NBMR is selected to estimate the number of wildfires. The Hausman test recommends the use of RE to estimate the number of fires by the NBMR (Prob.>chi2=1.00).

Analysing the effects of the yearly variables, temporal trends are found according to the NBMR results, both with FE or RE. In this way, since 2006, it is observable that the wildfire occurrence diminishes with respect 2001. However, the NBRM also detects a significant growth in wildfires in 2005 with respect to the baseline year. The OLS and NBMR models, with or without RE, demonstrate the presence of temporal trends in Galician wildfires.

Furthermore, the estimator of summer rainfall is significant and carries a negative effect on the number of wildfires (0.994). According to the estimation with RE, if this independent variable changes over time and between districts by one unit, then the average effect of the average summer rainfall over the number of wildfires is significant (0.944). Otherwise, the average of the maximum temperature during the summer is not significant to explain the wildfires according with the NBMR models.

In the NBMR models, the ratio of natural pasture, *Pinus pinaster* and protected areas are statically significant. The effects of these variables on wildfire occurrence are positive. By analysing the IRR, if the ratio of natural pasture, the ratio of *Pinus pinaster* and the ratio of protected areas per landowner show an increase by one unit, then the number of wildfires increases by a factor of 149.018, 5.437 and 3.276, respectively.

In addition, socioeconomic variables are significant in the NBRM with RE. Nevertheless, the remaining variables have different impacts on wildfire occurrence. The agricultural cooperatives and population density have a positive relationship with the occurrence of Galician wildfires. If these previous variables increase by one point, the rate of the number of wildfires would be expected to increase by a factor of 1.015 and 1.180, respectively, while holding all other variables constant. Furthermore, the ratio of equines has a negative relationship with wildfires occurrence.

The summer average rainfall is significant in order to predict the wildfires occurrence. This is explained by the absence of raining, given that this increases the wildfire risk. Nevertheless, the summer maximum temperature is only significant in the OLS results.

Discussion

Spatial patterns and temporal trends can be observed with graphical data representation. Furthermore, the spatial dependence of wildfires can also be determined by spatial statistics. Various econometric models are employed to assess the impact of socio-economic, climatic and geographical variables, as well temporal and spatial effects. Following the econometric models employed, and in particular those from RE models, the number of wildfires and the affected area ratio are estimated for each Galician forest districts in 2010. The estimations portrayed in Figure 10 show the actual data for both dependent variables and predictions. The data of these variables are distributed in quantiles and represent each district. In doing so, the geographical patterns of wildfire occurrence can be clearly differentiated in these maps. It is shown that the wildfire risk depends on the forest district; and as such, regulators should focus their forestry efforts on the areas in which the prediction of wildfires is higher. In other words, and for the area of study, public policy efforts should focus more closely on the southern rather than the northern districts.

In terms of the econometric results, it was found that the agro-forestry features are important factors given that the land cover is conditioned by this activity. The type of forest plantation, the livestock used in the farms or the land assigned to agricultural activity influences the wildfire occurrence. The ratio of equines is slo important in order to reduce the wildfire occurrence (Rigueiro *et al.*, 2002; Pasalodos *et al.*, 2009). This species grazes freely in the surrounding farm; fed mainly with grass, bushes or seeds; keeping the land cover cleaner. Thus, the wildfire risk diminishes where there are more equines than other livestock species. The presence of agricultural cooperatives also affects the wildfires occurrence. This happens because of the traditional agricultural management practices using fires. Nevertheless, the effect is the opposite for the burned area, because in general terms, the lands are better managed when the agricultural sector is more powerful in rural areas.

We also find that the *Pinus pinaster* ratio has a positive influence on the occurrence of wildfires, because this species is pyrophyte, with wildfires spreading more where *Pinus pinaster* are being planted. Protected areas could also be expected to have a negative relationship with wildfire occurrence; however the social rejection or ineffective protection measures could cause a positive influence. Furthermore, climatology variables condition the occurrence of wildfires, how they spread or the suppression efforts. Finally, the evolution of wildfires over time demonstrates high variability. This is the justifying reason why yearly dummy variables were included.

In general terms, the population density is important in order to predict the wildfire occurrence. However, in some of the empirical models, results are not conclusive. For example, in the OLS with RE, this variable is not significant when explaining the burned-forest area ratio. The same happens in the NBRM when analyzingthe wildfire number. In the remaining models, the population density is positively related to the occurrence of wildfires. This result is explained by the progressive migratory flow from the rural to urban areas. Then, the wild land-urban density around to main areas is increasing. In addition, the new residents are not involved in the agricultural sector and they are not involved with forest production (Barreiro & Hermosilla, 2013). This generates worst environmental conditions, causing an increase of wildfires (Herrero-Corral *et al.*, 2012). Public policies may supervise the surrounding environment of these areas and aware society to avoid wildfire occurrence.

The types of forest covers are represented by the ratio of *Pinus pinaster*. The results show a positive influence on both, the ratio of burned-forest area and wildfires number. These results are related with the species characteristics because these are more inflammable and the wildfires, when occurring, move faster than with other species. The preventive measures and supervision should also be incremented in these areas in order to avoid wildfires.

Unexpectedly, the protected areas influence positively the occurrence of wildfires. This result may show the general rejection towards having protected lands in rural areas. This result could also imply an inadequate public policy to manage these areas against wildfires (Carroll *et al.*, 2006). Therefore, the zooning of protection areas may be revised in order to identify the possible social and environmental factors that can be improved when reducing management conflicts. These improvements will imply lower wildfire occurrence if these factors are corrected.

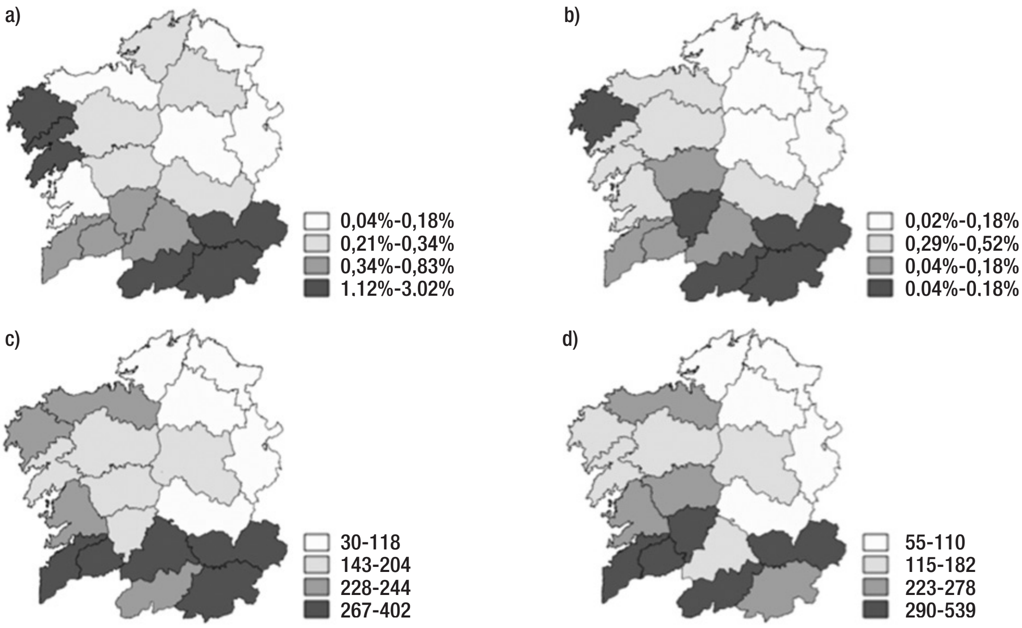

Figure 10. Estimation of wildfire occurrence in 2010. a) Actual ratio of burned area (%). b) Estimated rate of burned area (%). c) Actual number of wildfires. d) Estimated number of wildfires.

Conclusion

This research provides evidence characterizing the wildfire occurrence in the agricultural sector in relation to the climatic conditions, the forest cover, the social context, and time and spatial patterns. A relevant finding is that the forest species and the farming systems condition the wildfire risk. Hence, public policies may mitigate the factors that affect the wildfire risk. In this way, the presence of equines and extensive agricultural practices should be promoted in order to reduce the wildfire risk.

According to the main results, some guidelines could be developed as a reference for regional and local governments to help in the fight of wildfires. In particular, public policies could regulate the quality and quantity of woodland made available, as well as the plantation of different species. These regulatory agencies should also consider the geographical and spatial differences in the occurrence of wildfires in order to formulate better forest policies, and deal with possible "contagion" effects across districts.

Finally, we should remark that the current research has some limitations. In particular, additional variables would be desirable by employing more geographical disaggregated data, such as roads and infrastructures. Unfortunately, such data are not currently available, although, they are expected to be in the near future. In spite of that, many of the obtained conclusions could be applicable to other similar European areas, especially in depopulated rural areas. In particular, these main results could be implemented in the French Mediterranean basin (INSEE, 2015; PROMETHEE, 2015) and Portugal (INE, 2015), among others.

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