Applied Geography 56 (2015) 164–176

Contents lists available at ScienceDirect

Applied Geography

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

Human-ignited wildfire patterns and responses to policy shifts

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ARTICLE INFO

Article history:
Available online 18 December 2014

Keywords:
Wildfire risk
Spatial distribution
Urban development pressure
Deliberate-caused fires
Wildland–urban interface

ABSTRACT

Development of efficient forest wildfire policies requires an understanding of the underlying reasons behind forest fire occurrences. Globally, there is a close relationship between forest wildfires and human activities; most wildfires are human events due to negligence (e.g., agricultural burning escapes) and deliberate actions (e.g., vandalism, pyromania, revenge, land use change attempts). We model the risk of wildfire as a function of the spatial pattern of urban development and the abandonment/intensity of agricultural and forestry activities, while controlling for biophysical and climatic factors. We use a count data approach to model deliberately set fires in Galicia, N.W. Spain, where wildfire is a significant threat to forest ecosystems, with nearly 100,000 wildfires recorded during a thirteen-year period (1999–2011). The spatial units of analysis are more than 3600 parishes. Data for the human influences are derived from fine-resolution maps of wildland–urban interface (WUI), housing spatial arrangements, road density, forest ownership, and vegetation type. We found wildfire risk to be higher where there are human populations and development/urbanisation pressure, as well as in unattended forest areas due to both rural exodus and a fragmented forest ownership structure that complicates the profitability of forestry practices. To better help direct management efforts, parameter estimates from our model were used to predict wildfire counts under alternative scenarios that account for variation across space on future land-use conditions. Policies that incentivize cooperative forest management and that constrain urban development in wildlands at hotspot fire locations are shown to reduce wildfire risk. Our results highlight the need for spatially targeted fire management strategies.

Introduction

Forestlands are increasingly exposed to multiple disturbances such as those associated with wildfires, storms, or pest outbreaks which can cause important losses to biodiversity and the provision of valuable ecosystem services (Holmes, Prestemon, & Abt, 2008). In Europe over the period 1990–2012, the average annual number of wildfires was 81,000, burning about 530,000 ha forest area. In the Mediterranean region, in countries such as Spain and Portugal where human-caused fires dominate, the data are of particular concern for policy makers: from 1990 to 2012, there has been an annual average of 18,000 and 23,000 forest fires, burning about 123,000 and 140,000 ha annually, respectively (European Commission, 2013). Figures of this magnitude highlight the need to reduce wildfires as an issue of major public concern, and justify targeted fire management strategies aimed at the underlying socioeconomic drivers.

The literature on the causes of wildfires accepts the significant role of human behaviour in increasing the risk of fires through: land use (Badia, Serra, & Modugno, 2011; Catry, Rego, Baçao, & Moreira, 2009); population density (Marques et al. 2011; Sebastián-López, Salvador-Civil, Gonzalo-Jiménez, & SanMiguel-Ayanz, 2008); road densities (Narayanaraj & Wimberly, 2012); forest land tenure (Cardille, Ventura, & Turner, 2001; Padilla & Vega-García, 2011); labour market opportunities (Martínez, Vega-García, & Chuvieco, 2009; Prestemon & Butry, 2005; Prestemon, Chas-Amil, Touza, & Goodrick, 2012). Moreover, the spatial pattern of wildfire risk is also receiving increasing attention, as fires are rarely randomly distributed across landscapes, i.e., they are often concentrated in certain locations (Genton, Butry, Gumpertz, & Prestemon, 2006; Hering, Bell, & Genton, 2009; Kwak et al. 2012). Consequently, many studies assert that only by taking into account the spatial arrangement of fires and their socioeconomic drivers, will it be possible to substantially advance in the understanding of this risk across landscapes and help direct management efforts (Prestemon

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http://dx.doi.org/10.1016/j.apgeog.2014.11.025
0143-6228/

& Butry, 2005; Syphard et al. 2007). This is because human factors, as those mentioned above, are themselves also spatially structured. Therefore, the predictive ability of any wildfire risk model may be limited without accounting for the heterogeneous distribution of these socioeconomic factors across the landscape. Spatial and spatio-temporal clusters of wildfires may also be manifested through copycat or serial firesetting behaviour, i.e., fires ignitions that have the potential for cascading effects in nearby areas (serial) or distant areas (copycat) (Prestemon et al. 2012). Therefore, the analysis of fire management strategies to minimise fire risk should include spatial targeting measures, in contrast to the spatial insensitivity of general prescriptions across regions/nations that may result from non-spatially based research on fires.

Here, we model the wildfire risk at a fine (local) spatial scale, focussing on the effects that human population, urban development patterns, and the abandonment/intensity of agricultural and forestry activities have on the probability of wildfire occurrence. In addition, to better understand this risk and to guide policy assessments, we use parameter estimates from our models to predict wildfire counts under various future scenarios that evaluate changing land-use conditions across the study area.

Our focus is on addressing the spatial heterogeneity of the incidence of wildfires and their underlying human related drivers, taking as a case study the region of Galicia in northwestern Spain. In this region, deliberately-caused fires expose the territory to an unusual fire regime with extreme fire frequency, in spite of the fact that climatic conditions would not generally favour wildfire occurrence (Vázquez de la Cueva et al., 2006). Nearly all wildfires in the region are human-caused; approximately 82% are set with illegal intent typically labelled “arson”, and only 5% are either ignited accidentally or through negligence[1] (Chas-Amil, Touza, & Prestemon, 2010). These intentionally caused wildfires may be related to pyromania, revenge, resentment against forestry policies, attempts to increase land value, or even to the use of fire in agricultural/livestock activities in cases where the responsible person does not undertake the necessary precautions established by law and has not obtained the corresponding burn permit. More than 30% of annual forest fires in Spain are located in Galicia, reaching values as high as 50% in some years, even though the region represents only 6% of Spanish territory. Previous research that modelled fire risk at the national level for Spain has been hampered by poor statistical fit of their models for the region of Galicia, because the high fire occurrence in this region creates a spatial imbalance in Spanish-scale wildfire models (Martínez et al. 2009; Padilla & Vega-García, 2011). We therefore seek to extend this literature by focussing on Galician biophysical, climatic and socioeconomic conditions, using data derived from fine-resolution maps, estimating count data models to improve existing understanding of the high vulnerability to wildfire events in this area of Spain.

We also develop further previous work, which has found higher wildfire intensity in wildland–urban interface (WUI) areas (Chas-Amil, Touza, & García-Martínez, 2013; Herrero-Corral, Jappiot, Bouillon, & Long-Fournel, 2012; Lampin-Maillet et al. 2010). WUI areas are increasing worldwide predominantly due to (i) urbanized spaces colonizing forested areas and (ii) forestland that is colonizing rural areas due to the rural population exodus (e.g., Hammer, Radeloff, Fried, & Stewart, 2007; Montiel & Herrero, 2010; Theobald & Romme, 2007). This work illustrates how these factors that influence on WUI expansion also affect wildfire risk. Thus, we found that fire counts are higher where there are higher human populations and development/urbanisation pressure, as well as in unmanaged forest areas, due to both rural exodus with the consequent expansion of shrublands in abandoned land, and a fragmented forest ownership structure that complicates the profitability of forestry practices.

Our investigation is organized around three key questions. First, what is the spatial distribution pattern of wildfire risk? Second, how do human factors explain the spatial pattern of (mostly deliberate) wildfire ignitions? Finally, how might wildfire occurrence change with higher proportions of cooperatively managed forest and with future expansion of urban uses?

Materials and methods

Study area

Galicia is located on the western edge of Europe. Its ancient mountains, with an average elevation of 508 m, characterize the territory. In winter, the climate is characterised by Atlantic storms, which leave heavy rains and winds predominantly from the southwest, while in Summer northeast winds bring mainly dry weather. The annual mean temperature is 13 °C, with remarkable differences between the coastal and continental temperatures; at the same elevation, in summer (winter), temperatures are on the order of 2° higher (5° lower) in the continental part. Thus, the lowest temperatures can be observed in the interior, where the highest mountains are located, with average minimum temperatures around 5 °C. Summers are warm, particularly in the southeast of the area, with maximum temperatures exceeding 30 °C. Annual rainfall ranges between 1600 and 1900 mm at the coast on the southwest of the region, while the interior is drier, with rainfall oscillating between 800 and 1000 mm (Lorenzo, Iglesias, Taboada, & Gómez-Gesteira M, 2010).

Forests cover nearly 70% of its territory, and approximately 67% of this forestland is wooded. *Pinus pinaster* (28%), *Quercus robur* (13%), *Eucalyptus globulus* (12%) and *Quercus pyrenaica* (7%) are the main species in monospecific stands. Mixed stands are very heterogeneous but are dominated by *P. pinaster* and the introduced exotic, *Eucalyptus globulus*. In fact, more than half of the total wooded-land is covered by these two species. Other tree species, such as *Pinus sylvestris*, *Pinus radiata* and *Castanea sativa* are less common. Publicly owned forestlands are negligible (around 1%), and private lands can either be owned by a single individual or collectively, where ownership is shared by a group of individuals in the same community. Individual private ownership represents 68% of the forestland, while 30% is under collective private ownership. Collective ownership forest holdings average 221 ha, while individual property plots average between 1.5 and 2 ha (GEPC, 2006).

We opted for parishes as the geographical unit for the analysis because they are the smallest administrative unit that divides the territory and are compatible with the scale of all of our datasets. Parishes are an important social division in Galicia given that population is highly dispersed. There are 3780 parishes, with a mean size of 779 ha and a standard deviation of 664 ha. Specifying the parish as the spatial unit of inference for our analysis also has the advantage that socioeconomic characteristics are likely to be homogeneous within these small geographical areas. In order to focus on the interactions between human presence and forest fires, we excluded the following parishes: two islands, two with no population, and fifteen that have no forestland.

Dataset development

Dependent variable

The wildfire data cover a 13-year series of reported fire events (1999–2011) with a total of 99,923 reported forest fires burning

[1] The remaining is explained by lightning (1%), unspecified (unknown) reasons (9%), and reproduced (reignited) fires (3%).

387,522 ha. These data were obtained from the National Forest Fires Database (EGIF), compiled by the Spanish Forest Service and the Rural Affairs Department of the Regional Government. Wildfire reports include area burned, date and estimated time of ignition, weather conditions, fire location, causes, and fire fighting measures applied. From the wildfires in the database, we assembled a dataset of total counts of reported wildfires for each of the Galician parishes during the 13-year span covered by our analysis.

Explanatory variables

We consider a number of societal factors that may influence human-ignited wildfires, focussing on human population, development pressures and agricultural and forestry land-use activities. Overall, the variables selected have been associated with fire risk because they: may affect fuel characteristics; segregate the landscape affecting forest fragmentation; determine the accessibility to forests; and capture important land-use social conflict aspects (Arndt, Vacik, Koch, Arpaci, & Gossow, 2013; Carmo, Moreira, Casimiro, & Vaz, 2011; Catry et al. 2009; Martínez et al. 2009; Mercer & Prestemon, 2005; Moreira, Vaz, Catry, & Silva, 2009; Narayanaraj & Wimberly, 2012). Moreover, our modelling controls for explanatory variables related to topographic and climatic conditions. Slope and elevation are often used to explain fire occurrence due to their influence in local climate, vegetation types, distribution of fuels, and accessibility (e.g., Carmo et al. 2011; Prestemon et al. 2013). Similarly, meteorological variables are widely accepted to have important influences on wildfire occurrence (Viegas, Bovio, Ferreira, Nosenzo, & Sol, 2000). In the study area, where human-caused forest fires are dominant, it is expected that the best time for intentional firesetting is on dry, warm, and calm wind days, with favourable fuel flammability conditions that make ignition more successful (Prestemon et al. 2012). Dummy variables indexing historical (1991–1998) wildfire activity were also included in the modelling to capture potential persistent wildfire risk over the long-run, indicating that there are factors not easily measurable, such as the presence of serial or copycat firesetters who reside in the vicinity of hotspot parishes (Prestemon et al. 2012). The selection of explanatory variables is summarised in Table 1 along with a review of such in the literature.

The sources and mapping process used in developing the explanatory variables are as follows.

(i) *Agriculture, forestland cover and forest ownership*: This information was obtained from the Third Spanish Forest Inventory cartography (1:50,000) for Galicia, covering the period 1997 and 1998. These maps describe the boundaries enclosing a patch (i.e., area under a single cover category) and provide a detailed description of forest species cover. This inventory distinguishes between land with tree crown cover, or equivalent stocking level, of at least 5% (wooded land) and of less than 5% (other wooded land). We derived information on dominant forest vegetation, depending on whether the forest is comprised mainly of conifers, eucalyptus, or other broad-leaved species. Area of forest plantations is defined as a subset of forest consisting primarily of conifers and eucalyptus species. Forest ownership status was included, distinguishing between individual private ownership and communal ownership parcels.

(ii) *Population density* was calculated as the mean of a parish's population during the study period, divided by its geographical area. Population data were obtained from the Spanish Statistical Institute (INE).

(iii) *Rural exodus* was estimated as the level of reduction in the parish's population from 1999 to 2011. We calculated the compound annual growth rate of the population for all parishes, and used this rate in absolute terms for those parishes in which there was a reduction in the population.

(iv) *Unemployment data* were collected from the Public Employment Service at the municipality level and assigned to all parishes belonging to the municipality. The unemployment rate was calculated over total population, obtained from municipal administrative records, because data on the size of the economically active population are not available at the municipality level.

(v) *Road density* was computed based on the road network obtained from the National Topographic Base 1:25,000 (BTN25) (©Spanish Geographic Institute).

(vi) *Wildland-urban interface (WUI)* was defined as the intersection of the forest area and/or forest influence areas (up to 400 m from forestland) with a buffer of 50 m around buildings, where bush clearing is compulsory by law.[2] The number of hectares under WUI per parish was obtained from Chas-Amil et al. (2013), expressed in our analysis as the proportion of total parish area occupied by the WUI.

(vii) *Spatial arrangement of buildings* was obtained from Chas-Amil et al. (2013) which distinguished between isolated-dispersed, and densely clustered building areas. Densely clustered building structure locations are defined as those with clusters of 8–155 buildings located less than 50 m apart. Note that about 47% of the WUI in the case study region and 60% of the buildings fall under this category.

(viii) *Topographic variables* were calculated using the Spatial Analyst extension to ArcGIS® 9.3.1 by ESRI to derive the slope, elevation, aspect, and curvature based on a 10 m spatial resolution digital elevation model (DEM) (1:5000 scale), developed by SITGA. For each parish, we calculated the slope in percentage (maximum, mean, minimum, and range) and elevation in meters (mean and range). Aspect, defined as the slope direction, was processed considering its circular scale (0–360°); by dividing the aspect cells values into 8 intervals of 45° (N, NE, E, SE, S, SW, W or NW) and flat. Curvature of the surface represents the variation in elevation around a cell, showing the relief characteristics. It indicates if the topographical surface is concave (negative), convex (positive) or flat (zero). We divided the curvature distribution among low (from -0.25 to 0.25), medium (from $-0.5/0.25$ to -0.25–0.5), high (from $-0.75/0.5$ to $-0.5/0.75$), and extreme curvature (<0.75 or >0.75). Our dataset includes the area of each parish that corresponds to each interval defined above for aspect and curvature.

(ix) *Meteorological information* on mean annual temperature (maximum, mean, and minimum) and mean annual precipitation by parish were extracted from the Digital Climatic Atlas of the Iberian Peninsula (Ninyerola, Pons, & Roure, 2005), with a spatial resolution of 200 m. This atlas is spatially interpolated from meteorological stations and data reported for more than 20 years.

(x) *Number of fires by parish in the years prior to the study period* (i.e., 1991–1998)[3] was included in the model through three dummy variables that take into account: if the number of fires has been between 10 and 20; between 20 and 30; or more than 30.

[2] Law 3/2007 of April 9, 2007, addressing the issues of wildfire prevention and suppression, as modified by Law 7/2012 of June 28, 2012.

[3] Available data on reported fire ignitions prior to 1991 have no location information, and therefore could not be used for this study.

Table 1
Independent variables considered for modelling forest fire occurrence.

Variables	Data source	Description	Units	Some references where similar variable is used
Land cover				
Agriculture land	Third Spanish Forest Inventory cartography (1:50,000). MARM.	Area of agricultural land	ha	Badia et al. (2011), Catry et al. (2009), Kalabokidis, Koutsias, Konstantinidis, and Vasilakos (2007), Martínez et al. (2009), Sebastián-López et al. (2008), Sturtevant and Cleland (2007), Vasconcelos et al. (2001)
Forest area: - Wooded forestland - Non wooded forestland	Third Spanish Forest Inventory cartography (1:50,000). MARM.	Area with tree crown cover, or equivalent stocking level of: - higher than 5% - lower than 5%	ha	Catry et al. (2009), González and Pukkala (2007), Magnussen and Taylor (2012), Martínez et al. (2009), Prasad, Badarinath, and Eaturu (2008), Sturtevant and Cleland (2007), Vasconcelos et al. (2001), Verdú et al. (2012)
Broadleaves area	Third Spanish Forest Inventory cartography (1:50,000). MARM.	Area dominated by broadleaves	ha	Badia et al. (2011), Calef, McGuire and Chapin (2008), González and Pukkala (2007), Kalabokidis et al. (2007), Reineking et al (2010), Syphard et al. (2007), Verdú et al. (2012)
Forest plantations	Third Spanish Forest Inventory cartography (1:50,000). MARM.	Area of planted forest consisting primarily of introduced species.	ha	Reineking et al (2010), Sturtevant and Cleland (2007)
Forest land tenure: Single private ownership Communal private ownership	Third Spanish Forest Inventory cartography (1:50,000). MARM.	Area	ha	Cardille et al. (2001), Martínez et al. (2009), Padilla and Vega-García (2011)
Human factors				
Population density	Nomenclator (INE)	Mean of parish's population in the period divided by parish area	Hab/ha	Brosofske, Cleland and Saunders (2007), Cardille et al. (2001), Catry et al. (2009), Magnussen and Taylor (2012), Mercer and Prestemon (2005), Miranda, Sturtevant, Stewart, and Hammer (2012), Narayanaraj and Wimberly (2012), Padilla and Vega-García (2011), Prasad et al. (2008), Sebastián-López et al. (2008), Sturtevant and Cleland (2007), Syphard et al. (2007)
Rural exodus	Nomenclator (INE)	Compound annual growth rate of the population in absolute terms for those parishes in which there was a reduction in the population.	%	Martínez et al. (2009), Sturtevant and Cleland (2007)
Unemployment rate	Population Census (2001) Municipal data	Mean rate	%	Butry and Prestemon (2005), Martínez et al. (2009), Mercer and Prestemon (2005), Oliveira et al. (2012), Prestemon and Butry (2005), Prestemon et al. (2012), Prestemon and Butry (2008), Sebastián-López et al. (2008)
Road density: Highways Conventional roads, Rural roads	Base Topográfica Nacional (BTN25) (1: 25,000)	m of roads included in the parish divided by parish area	m/m^2	Brosofske et al. (2007), Cardille et al. (2001), Martínez et al. (2009), Narayanaraj and Wimberly (2012), Oliveira et al. (2012), Padilla and Vega-García (2011), Sebastián-López et al. (2008), Sturtevant and Cleland (2007), Syphard et al. (2007), Syphard et al. (2008), Vilar, Woolford, Martell, and Martín (2010)
Wildland-urban interface	Chas-Amil et al. (2013)	Area	ha	Martínez et al. (2009), Narayanaraj and Wimberly (2012), Syphard et al. (2008), Vilar et al. (2010)
Dense built area	Chas-Amil et al. (2013)	Areas with clusters of 8–155 buildings located less than 50 m apart	ha	Miranda et al. (2012), Oliveira et al. (2012), Sturtevant and Cleland (2007)
Topographic variables				
Slope	10 m Digital Elevation Model (1:5000). SITGA.	Mean, minimum, maximum and standard deviation of the parish slope.	%	Badia et al. (2011), Calef et al. (2008), González and Pukkala (2007), Kalabokidis et al. (2007), Narayanaraj and Wimberly (2012), Padilla and Vega-García (2011), Prasad et al. (2008), Sebastián-López et al. (2008), Syphard et al. (2008), Vasconcelos et al. (2001), Verdú et al. (2012)
Aspect	10 m Digital Elevation Model (1:5000). SITGA.	Area in each interval of 45° (N, NE, E, SE, S, SW, W or NW) and flat	ha	Calef et al. (2008), González and Pukkala (2007), Kalabokidis et al. (2007), Oliveira et al. (2012), Padilla and Vega-García (2011), Prasad et al. (2008), Sebastián-López et al. (2008), Syphard et al. (2008), Vasconcelos et al. (2001)
Elevation	10 m Digital Elevation Model (1:5000). SITGA.	Mean and range elevation observed in the parish.	m	Brosofske et al. (2007), Catry et al. (2009), González and Pukkala (2007), Kalabokidis et al. (2007), Marques et al. (2011), Narayanaraj and Wimberly (2012), Padilla and Vega-García (2011), Prasad et al. (2008), Sebastián-López et al. (2008), Syphard et al. (2008), Vasconcelos et al. (2001), Verdú et al. (2012), Vilar et al. (2010)

(*continued on next page*)

Table 1 (*continued*)

Variables	Data source	Description	Units	Some references where similar variable is used
Curvature	10 m Digital Elevation Model (1:5000). SITGA.	Area in each curvature class: Low (0.2–0.25) Medium (0.5/0.25–0.-0.25–0.5) High (0.75/0.5–0.5/0.75) Extreme (<0.75 or >0.75)	ha	Narayanaraj and Wimberly (2012), Prasad et al. (2008)
Meteorological variables				
Temperature	Digital Climatic Atlas of the Iberian Peninsula- spatial resolution 200 m (Ninyerola et al. 2005). Monthly data.	Annual mean, maximum, mininum	°C	Alberston et al. (2010), Badia et al. (2011), Calef et al. (2008), Cardille et al. (2001), Kalabokidis et al. (2007), Magnussen and Taylor (2012), Miranda et al. (2012), Narayanaraj and Wimberly (2012), Oliveira et al. (2012), Padilla and Vega-García (2011), Pew and Larsen (2001), Prasad et al. (2008), Prestemon et al. (2012), Syphard et al. (2008), Verdú et al. (2012), Vilar et al. (2010)
Precipitation	Digital Climatic Atlas of the Iberian Peninsula- spatial resolution 200 m (Ninyerola et al. 2005). Monthly data.	Annual mean	l/m^2	Alberston et al. (2010), Badia et al. (2011), Brosofske et al. (2007), Calef et al. (2008), Cardille et al. (2001), Kalabokidis et al. (2007), Magnussen and Taylor (2012), Miranda et al. (2012), Narayanaraj and Wimberly (2012), Oliveira et al. (2012), Padilla and Vega-García (2011), Pew and Larsen (2001), Plucinski et al. (2014), Prasad et al. (2008), Prestemon et al. (2012), Sturtevant and Cleland (2007), Verdú et al. (2012), Vilar et al. (2010)

In addition to the above factors, it is important to include a parish-level *exposure to risk* variable in the fire occurrence prediction model. The number of hectares under forestland was taken as a good measure of an exposure variable.

Modelling approach

Question 1: what is the spatial distribution of wildfires?

To investigate if the distribution of wildfire occurrence is spatially clustered, we calculated global and local measures of spatial association using Global Moran's I statistics (Anselin, 1995), and the Getis and Ord (1992) Gi* statistics allow hotspot analysis. The Global Moran Index ranges from −1 to 1, taking a value approaching to zero when there is a random spatial pattern. A positive (negative) value for Moran's I indicates that parishes have neighbouring parishes with a similarly (dissimilarly) aggregated number of fires over the studied period. For statistical hypothesis testing, Moran's I values are transformed to *z*-scores, with a *z*-score near zero indicating no apparent clustering, and a positive (negative) value indicating clustering of parishes with a high (low) fire incidence risk rate.

Getis-Ord Gi* identifies whether a local pattern of forest fire occurrence for a given parish and its neighbours is different from what is generally observed across the whole study area. It computes a *z*-statistic by comparing the proximity-weighted sum of total fires at a particular parish to the sum across the entire sample in order to identify areas of more intense clustering of high (low) forest fire occurrence. A positive high (low negative *z*-score) *z*-score (p-value < 0.10) indicates areas of unusual high (low) risk indicating likely "hot spot" ("cold spot") areas across the region. A *z*-score near zero (p-value > 0.10) indicates no apparent spatial clustering. To summarize the spatial relation between parishes, we used a binary matrix of spatial weights considering polygon queen contiguity. The calculation of Global Moran's I and Gi* statistics was conducted using the Hot-Spot analysis function in ArcGIS 10.1.

Question 2: how does human presence explain the spatial pattern of (mostly deliberately-caused) wildfires?

This study models the number of fire events per parish during the 13-year study period. Unlike logit and probit approaches (e.g., Alberston, Aylen, Cavan, & McMorrow, 2010; Chang et al. 2013; Martínez et al., 2009; Padilla & Vega-García, 2011), which are based on the idea of a threshold-crossing latent probability of a fire variable with a modelled dependent variable binary counterpart, count data approaches assume a dependent variable resulting from an underlying discrete probability distribution. The expected number of wildfires per parish i, $E[y_i|x_i] = \mu_i$ is linked to the explanatory variables using a log-linear relationship, and the parish's forest area, F_i as an exposure variable:

$$\log(\mu_i) = \log(F_i) + \sum_{k=0}^{K} \beta_k x_{ik}$$

where the x_{ik}'s represent the explanatory variables and the β_k's are the estimable coefficients representing the effects of the covariates. Poisson regression is often the first choice for modelling count data, but recent research indicates that fire ignition data are likely to be overdispersed (e.g., Kwak et al. 2012; Plucinski, McCaw, Gould, & Wotton, 2014). Our wildfire data has an obvious signal of overdispersion, with an average number of forest fires per parish of 26.4 and variance of 1376.9. The existence of overdispersion causes an underestimation of the real variance, yielding attenuated standard errors and inefficient though unbiased parameter estimates (Cameron & Trivedi, 2005). Rather than constrain our model estimates to the mean-variance equality assumption, we assume that our dependent variable stems from a negative binomial data distribution (i.e., a Poisson gamma mixture), which requires estimation of an overdispersion parameter in addition to the conditional mean. Thus, the negative binomial regression relaxes the assumption that the mean of fire frequency equals the variance by adding an error term to the expected wildfire frequency (μ_i) such that

$$\log(\mu_i) = \log(F_i) + \sum_{k=0}^{K} \beta_k x_{ik} + \varepsilon_i$$

where ε is assumed to be independent of the covariates and follows a gamma distribution with mean one and variance α. We estimate a Generalised Linear Model (GLM) NB2 negative binomial specification, with a log-link function, which allows the mean to differ from the variance

$$Var(y_i) = \mu_i + \alpha\mu_i^2$$

Here, α is used as a measure of dispersion. If the value of this overdispersion parameter is zero, then $\alpha = 0$, the NB2 collapses to the Poisson model, producing the equidispersion property. The Langrange multiplier test and boundary likelihood ratio test (Hilbe, 2011) were used to support the appropriateness of using the negative binomial regression as opposed to a Poisson model. The Tukey-Pregibon link test (Hilbe, 2011) for generalized linear models was used to check if the logarithmic link function assumed was adequate.

In order to make our estimation robust to heteroskedasticity and any spatial correlation due to wildfire data from locations close to each other having more similar values than those farther apart, we utilize cluster-robust standard errors with clusters defined over municipalities (i.e., 313 clusters) (Cameron & Trivedi, 2005; Hilbe, 2011). We estimate our models using STATA® 11.2.

Correlation between variables in Table 1 was assessed, and a correlation limit of 0.5 was used for those variables included in the model. The AIC (Akaike Information Criterion) and pseudo-R^2 (ρ^2) were used to assess if dropping individual variables that were not statistically significant (p-value > 0.1) had a significant effect on the model fit. For instance, aspect and curvature were found to be statistically insignificant in a preliminary estimate and were therefore omitted from the final set of explanatory variables. The square, square root, and logarithmic terms of the variables were investigated for possible inclusion in the model using a multivariable fractional polynomials approach (Royston & Ambler, 1998). Summary statistics of the dependent, exposure, and explanatory variables included in the model are presented in Table 2. The Anscombe and Pearson residuals were used to evaluate the presence of unusual observations (outliers), and the presence of spatial autocorrelation. If spatial autocorrelation still exists in the residuals of an econometric model of spatial data, the independence and identically distributed assumption of the residuals is violated, compromising inference. It causes standard errors to be artificially low, and coefficients may appear significant when they are not (i.e., inflates type I errors) (Anselin, 2002; Dormann et al. 2007). The presence of residual spatial autocorrelation was examined using correlogram plots of the residuals, which measure the similarity of the residuals between observations as a function of geographical distances between the observations. Finally, note that extreme outliers, defined as parishes with more than 118 fires (three times the interquartile range) in either of the last two decades, were excluded. The final dataset contains 96% of the initial observations.

Question 3: how does wildfire occurrence change as a result of the effect of cooperative forest management and future expansion of urban uses?

We estimated the magnitude of change in fire counts that might result from future changes in urbanisation pressures (i.e., expansion of the WUI) and in forest ownership arrangements (i.e., promoting joint management of individually owned small parcels). We used parameter estimates from the negative binomial model to simulate the effects of plausible scenarios. From these analyses we derived the total predicted change in wildfires in the region and the effects of the changes on the spatial arrangement of wildfire occurrences. This allows us a more complete understanding of the underlying socioeconomic processes that produce wildfires, enlightening the effects of factors that are under the control of policy planners and/or controlled by people. For example, municipal, regional, or national policies may govern how land is used—encouraging or discouraging building houses at specific locations which may alter the prevalence of WUI conditions in parishes. Similarly, sustainable forest management might be favoured or discouraged by subsidies related to afforestation and restoration measures, or by ordinances (e.g., Galician Forestry Law 7/2012, June 28, 2012) that affect the importance of forestry land use in relation to other land uses in the region and may determine the level of silviculture practices, or the lack of them, and therefore the availability of fuel.

The scenarios considered are as follows:

(A) Expanded use of joint management of forest parcels through associations of single private owners. In this scenario we simulate that a policy to incentivize jointly/cooperative management will affect 25% of the forest under single private ownership in each parish. This effect was modelled through the corresponding increase in the variable communal forestlands, as each cooperative of single private owners are expected to “act” as a management unit, and therefore become comparable to communal forest management.

(B) Expansion of the proportion of land classified as WUI. Here, we conducted several versions of this simulated expansion. (1) An increase by 20% in the proportion of WUI areas in all parishes. This simulation provides us with a general appreciation of the effects of WUI land use on overall wildfire activity in the region. (2) The same simulation as in (1) but taking into account that such increases in the WUI are expected to be associated with changes in other socioeconomic variables: building density, conventional road densities, and local/rural road densities. To generate changes in each of these other variables, which were found to be significantly and positively correlated with WUI,[4] we estimated simple linear regressions of each of the variables against a constant and the proportion of WUI in the parish. The parameters estimated from these regressions were used to predict new levels of each of these variables, and these new levels were included in the prediction of wildfire counts given the WUI expansion (e.g., Ahn, 1996). (3) An increase by 20% in the proportion of WUI areas only in those parishes identified as hotspot areas taking into account also changes in the significantly correlated variables for those hotspot parishes where the WUI is assumed to increase. In order to be consistent with the previous simulation, correlated variables were the same as above, even though, rural exodus and agriculture, both positively correlated with WUI, met the criteria to have been included in this numerical analysis. This scenario allows us to identify the potential wildfire consequences of a continued increasing trend of the WUI in places most vulnerable to fires, as hotspot parishes were defined as those with high fire incidence that are surrounded by parishes with high fire risk as well. Following the results of the hotspot analysis, this scenario implies changes in simulated drivers in 596 parishes.

In all sensitivity analyses, the simulated number of wildfires is compared with the expected number of fires when the perturbed variables are set at their unperturbed (observed) values. The significance of simulated changes in wildfire is done with bootstrapping (1000 iterations). Bootstraps are performed with iterated random sampling with replacement of an equal number of observations as included in the original model estimate. Within each of the 1000 iterations, the estimated model parameters are used to predict the count of wildfire in each parish, with and without the simulated change. In the prediction step, outlier parishes are included.

[4] These variables had a correlation coefficient with the WUI of 0.3 or higher.

Table 2
Descriptive statistics for dependent and independent variables.

Variables (units)/Description	Statistics			
	Mean	Std. Dev.	Min.	Max.
Total fires per parish	21.41	23.31	0	117
Deliberately-caused fires per parish	17.09	20.23	0	111
Area forest (ha) Total forest area per parish	512.42	538.65	1.58	6538.35
Parish agriculture (%) Proportion of agricultural land in relation to parish area	34.32	19.40	0.00	99.26
Non wood forest (%) Proportion of non wood–forest in relation to parish forest area	27.21	25.60	0.00	100.00
Broadleaves area (%) Proportion of broadleaves area (no eucalyptus) as dominant forest vegetation in relation to parish forest area	24.81	23.11	0.00	100.00
Plantations dummy 1/0 if parish has/has no area of forest plantations consisting primarily of introduced species.	0.49	0.50	0	1.00
Communal forest (%) Proportion of communal private land ownership in relation to parish forest area	18.89	26.66	0.00	99.99
Population density (persons/ha) Mean of parish's population in the period divided by parish area.	1.07	4.52	0.01	106.04
Rural exodus (%) Mean % reduction in population in absolute terms from 1999 to 2011.	1.73	3.13	0.00	100.00
Unemployment rate (%) Annual mean of the unemployment rate by municipality.	8.40	2.24	3.1	20.4
Highway density (m/m^2)	0.00006	0.0002	0.00	0.003
Conventional road density (m/m^2)	0.0009	0.0007	0.00	0.009
Rural road density (m/m^2) m of each type of roads in the parish divided by parish area.	0.002	0.001	0.00	0.008
WUI (%) Proportion of Wildland–Urban Interface in relation to parish area.	10.14	8.57	0.00	90.59
Dense built area (%) Proportion of total built area in dense population category in relation to total parish area.	0.41	0.38	0.00	5.98
Slope range (%) Maximum - minimum slope of the parish.	68.40	20.99	1.92	99.99
Elevation mean (m) Mean elevation of the parish.	442.85	256.59	4.27	1572.62
Mean temperature (°C) Mean in the Summer months (June–September)	17.55	1.10	13.87	20.96
Mean precipitation (l/m^2) Mean in the Summer months (June–September)	52.85	9.74	21.79	107.25
Fires30 dummy 1 if wildfires higher than 30 in previous years (1991–1998).	0.19	0.39	0	1
Fires2030 dummy 1 if wildfires between 20 and 30 in previous years (1991–1998).	0.11	0.32	0	1
Fires1020 dummy 1 if wildfires between 10 and 20 in previous years (1991–1998).	0.20	0.40	0	1

Results

Question 1: what is the spatial distribution of wildfire occurrence?

A parish level map of the 13-year total number of reported wildfires (Fig. 1) illustrates that most fires occur along the Atlantic coast and in the south-eastern part of the region. The global Moran's Index for wildfire occurrence over the entire study area was 0.476, indicating the presence of a statistically significant positive spatial autocorrelation among fire rates (z-score = 49.916, p-value < 0.0001).

Fig. 2 illustrates the results of the Gi* statistics. Hotspots are mainly concentrated in the Atlantic coast, while another large cluster is located in the South, near the border with Portugal and other Spanish region. Coldspots are mostly located in the interior rural areas.

Question 2: how does human presence impact wildfire risk?

Table 3 presents the results of the negative binomial regressions for total fires and for deliberately caused fires. For total fires, the overdispersion parameter was found to be significantly different from zero, suggesting the appropriateness of the negative binomial specification relative to the Poisson. In addition, the Langrange multiplier test (LM value = 1,703,993.9, p-value < 0.000) and boundary likelihood ratio test (LR = 25,238.296, p-value < 0.000) both rejected the null hypothesis of no overdispersion. The majority of the explanatory variables are statistically different from zero at stronger than 1%, and the model has a reasonable overall statistical fit, as indicated by the ρ^2 statistic. The negative binomial model estimated for deliberately caused fires presents very similar results (Table 3), which is expected, given that nearly all fires in the region are intentionally-caused.

The marginal effects on the expected wildfire frequency in a parish with mean predictor values when one of its predictors changes for all the parishes are also reported in Table 3. For the continuous variables, we estimate the elasticities. For dummy variables, these values show the proportional change in wildfire frequency when there is a discrete change in the dummy variable from zero to one.

The relationship identified between human population density and wildfire occurrence is positive, as is the relationship between densely built area and wildfires; a 1% increase in the proportion of densely built area increases wildfire counts by over 0.15%.

The unemployment rate has a significant (10%) positive effect on the count of wildfires. Similarly, rural exodus has a positive effect on wildfire occurrences. The three measures of road densities (highways, conventional and rural/local roads) are each positive contributors to wildfire counts. Among the different types of roads, the density of rural/local roads has a greater contribution to wildfires, with an estimated increase in the number of fires by nearly 0.21% per 1% increase in density.

In relation to land use variables, we found that wildfire counts are related statistically to agricultural activities: the greater the share of agriculture in the parish, the higher the frequency of wildfires. A quadratic relationship is indicated, with the number of wildfires increasing at an increasing rate with respect to agricultural area. A positive relationship is observed for the percentage of non-wooded forestland: a 1% increase in the proportion of non-wooded forest has an increase in the number of wildfire occurrences by 0.13%. Non-wooded land is heavily vegetated with shrubs, whose fine fuels may serve as ideal ignition media. Tree plantation is negatively related to wildfire counts. The share of the parish's forest occupied by broadleaf species reduces the number of fires, but at a decreasing rate, and at locations where the proportion of broadleaf forest is relatively high fire risk increases. Forest ownership also has an impact on the count of wildfires. Communal private forestlands are negatively related to wildfire counts. Dummy variables indexing historical (1991–1998) wildfire activity in each parish indicate a positive relationship with the count of wildfires during the study period. The effect is larger for higher historical rates of wildfires. If there is a discrete change in the dummy fire 30 from zero to one (i.e., equal to 1 if the count of wildfires in the parish is higher than 30 in previous period 1991–98), the increase in the expected fire occurrences would be of 39%. This result highlights the importance of recognizing high historical rates of wildfires in the models, potentially accounting for the existence in the parish of one or more persons with an atypically high propensity to ignite multiple fires (e.g., Prestemon et al. 2012).

We found a negative association between fire incidence and the average slope in the parish and a positive association with the mean elevation. Mean temperature and mean precipitation in the summer months (June–September) showed positive and negative relationships to wildfire counts, respectively, even though, mean precipitation is not significant for deliberately-caused fires.

The correlogram plot in Fig. 3 shows that there is a small degree of spatial autocorrelation still present in the model's residuals. The negative binomial model's residuals display limited spatial autocorrelation up to 20 km.

Question 3: how does wildfire frequency change due to spatially heterogeneous changes in socioeconomic pressures?

The sensitivity analyses we conducted to evaluate the effects of changes in policy relevant variables on the total number of fires all show statistically significant effects of changes on the number of wildfires (Table 4). All changes are statistically different from zero at the 1% significance-level. Increasing the share of forests managed communally by 25% among current individually owned private forestlands would be expected to reduce the total wildfires from 104,563 to 97,663, a reduction of 6.6% (Fig. 4).

Changes in the WUI share in all parishes have a positive influence on the expected number of wildfires, but accounting also for expected changes in significantly correlated variables enlarges the effect of WUI expansion. Increasing the observed share of land classified as WUI by 20% in all parishes would be expected to increase the number of wildfires by nearly 1400 (Table 4). Fig. 5 shows that such an increase in the expected number of fires would be clustered in the Atlantic part of the region, in the parishes surrounding the main cities. Increasing the share of WUI by the same percentage but also changing the proportion of dense built area, local/rural road density, and conventional road density in ways demonstrated by their sample correlations as well, would be expected to yield a statistically significant additional 4607 wildfires (Table 4), and larger effects in a greater number of parishes (Fig. 6). Moreover, results show that a similar simulation for only hotspot

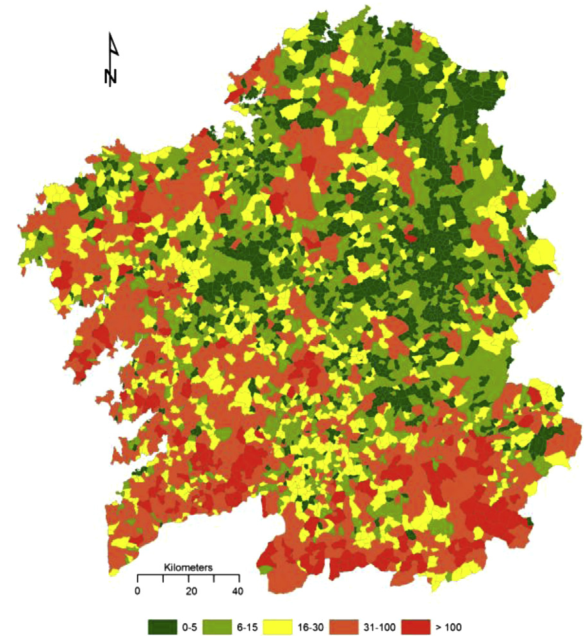

Fig. 1. Total 13-year (1999–2011) counts of reported wildfires in Galicia at parish level.

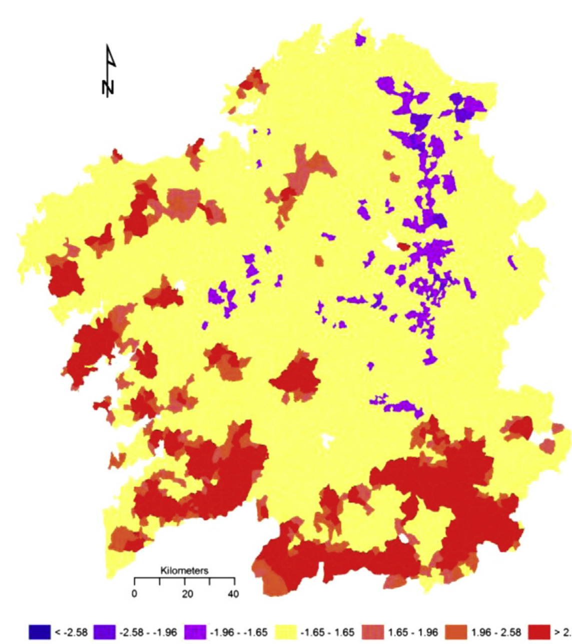

Fig. 2. *Z* scores from Gi* for spatial correlation of the total number of wildfires in each parish in Galicia. Observations from orange to red indicate "hot spots" with clustering of parishes with high fire counts while observations in blue indicate "cold spots" with clustering of parishes with low number of forest fires. Areas in yellow indicate no significant clustering of high or low total number of fires. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 3
Estimated coefficients, standard errors, and significance levels of independent variables using negative binomial estimation, and marginal effects estimates of independent variables (elasticities estimates for continuous variables, and one-unit change of dummies from 0 to 1).

Variable	Total fires			Deliberately caused fires		
	Coef. (Std. Err.)	*p*-value	Marginal effects	Coef. (Std. Err.)	*p*-value	Marginal effects
Constant	−9.994*** (0.752)	0.000		−11.011*** (0.848)	0.000	
Parish agriculture	0.735* (0.417)	0.078	0.255	1.017** (0.477)	0.033	0.353
Parish agriculture^2	1.498*** (0.488)	0.002	0.237	1.251** (0.557)	0.025	0.198
Non-wood forest	0.487*** (0.108)	0.000	0.129	0.615*** (0.119)	0.000	0.162
Broadleaves area	−1.013*** (0.290)	0.000	−0.254	−1.081*** (0.325)	0.001	−0.271
Broadleaves area^2	1.524*** (0.353)	0.000	0.178	1.708*** (0.387)	0.000	0.200
Plantations dummy	−0.190*** (0.040)	0.000	−3.141	−0.175*** (0.439)	0.000	−3.141
Communal forest	−0.382*** (0.097)	0.000	−0.069	−0.503*** (0.110)	0.000	−0.091
Population density	0.039*** (0.005)	0.000	0.042	0.037*** (0.005)	0.000	0.039
Rural exodus	0.007*** (0.002)	0.007	0.012	0.101*** (0.003)	0.005	0.017
Unemployment rate	0.026* (0.015)	0.086	0.220	0.033* (0.017)	0.052	0.277
Highway density	320.749*** (83.456)	0.000	0.020	302.007*** (92.987)	0.001	0.019
Conventional road density	107.811*** (34.043)	0.002	0.103	103.121*** (39.056)	0.008	0.099
Rural road density	84.144*** (18.919)	0.000	0.207	92.280*** (21.671)	0.000	0.227
WUI	0.627*** (0.255)	0.014	0.063	0.465 (0.287)	0.106	0.047
Dense built area	36.218*** (5.651)	0.000	0.150	36.169*** (6.502)	0.000	0.150
Slope range	−0.004*** (0.001)	0.000	−0.298	−0.006*** (0.001)	0.000	−0.417
Elevation mean	0.0008*** (0.0001)	0.000	0.364	0.0011*** (0.0002)	0.000	0.509
Mean temperature	0.313*** (0.038)	0.000	5.500	0.335*** (0.043)	0.000	5.881
Mean precipitation	−0.006** (0.003)	0.037	−0.324	−0.003 (0.003)	0.304	−0.171
Fires30 dummy	1.209*** (0.050)	0.000	39.269	1.344*** (0.057)	0.000	39.269
Fires2030 dummy	0.956*** (0.054)	0.000	30.380	1.072*** (0.059)	0.000	30.380
Fires1020 dummy	0.578*** (0.043)	0.000	14.028	0.639*** (0.049)	0.000	14.028
Sample size	3629			3629		
Alpha	0.4865	0.000		0.5911	0.000	
(1/df) Deviance	1.1235			1.1430		
AIC	7.4113			6.9991		
Restricted log-likelihood (constant only)	−15,067.76			−14,137.52		
Log-likelihood at convergence	−13,424.85			−12,676.99		
ρ^2	0.109			0.103		

Note: Standard errors in parentheses. Asterisks indicate that the parameter estimate is significantly different from zero at the 10% (*), 5% (**), or 1% (***) level.

parishes would be expected to yield a statistically significant additional 1554 wildfires (Table 4). This means that limiting the WUI expansion in these locations would generate a reduction on average of 2.26 fires per parish. The nature of the correlated variables included in the simulation means that wildfire risk effect from such an expansion is more apparent in the more populated WUI hotspots near the coast and less apparent in those hotspots in the south-east, which have lower urbanisation pressures (Fig. 7).

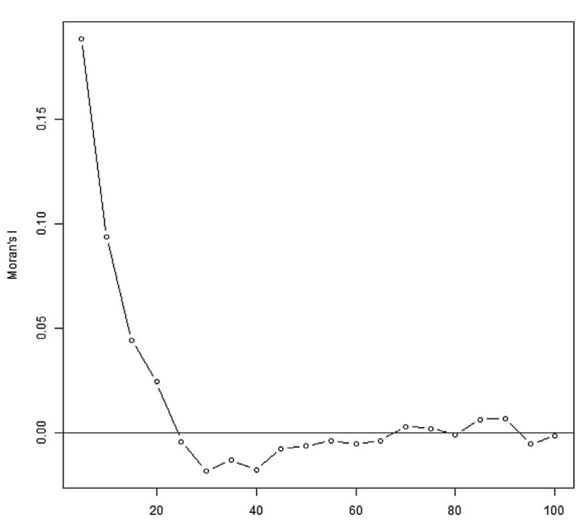

Fig. 3. Correlogram plot of residuals from negative binomial estimated model of wildfire frequency.

Discussion and conclusions

Our results show that wildfire occurrence at the parish level is positively spatially clustered; "hotspots" and "coldspots" are widespread in the region. Hotspots, mainly in the south and west, represent both locations of rapid urban growth in the surroundings of the most populated areas, as well as areas of abundant shrublands, and high rural exodus. Many hotspots in the west are found in proximity to Galicia's most populated locations, in particular surrounding the biggest cities (A Coruña, Ourense, Pontevedra, Santiago, and Vigo), which have experienced rapid urban development in the last few decades (Precedo, Míguez, & Fernández, 2008). While hotspots occurring in southern parishes are characterised by higher elevation (mean value over 800 m), higher proportions of shrublands in forestlands (mean value 54%) and greater rates of population decline (−2.1%/yr) than other hotspot parishes. Coldspots in the north and east interior parishes are associated with the lowest levels of population density of the region and with lower accessibility compared to the hotspots.

Consistent with this, the count data analysis derived from fine-resolution maps reveals that wildfire occurrence in Galicia is tightly connected not just to biophysical variables but also, critically, to multiple measures of human presence and human activities. More people living on and using landscapes generally leads to higher wildfire occurrence. However, similarly to Catry et al. (2009), the marginal effect of population density was found to be much smaller than the role of road densities, as these modulate human presence and uses of the landscape, representing forest accessibility. Among

Table 4
Sensitivity analysis on total fires.

	Number of observations	Average fires per parish	Total fires, all parishes combined	Simulated change in total fires	Implied percent change in total fires
Base expected fires	3763	27.79	104,563		
Increase the share of "jointly managed" individually owned private forests by 25%	3763	25.95	97,663	−6900***	−6.60
Increase the share of WUI by 20% for all parishes	3763	28.16	105,960	1397***	1.34
Increase share of WUI by 20% for all parishes and also imputed changes in correlated variables	3763	28.55	107,431	4607***	4.41
Increase share of WUI by 20% for hotspot parishes and also imputed changes in correlated variables	3763	28.28	106,419	1554***	1.49

Note: *** indicates statistically different from zero at 1% significance, based on confidence bounds generated by 1000 bootstrapped iterations.

the different types of roads, the density of rural/local roads has the highest influence on wildfire occurrence because these roads connect peri-urban areas, are often more proximate to flammable fuels, and give access to forested areas (Oliveira, Oehlera, San-Miguel-Ayanz, Camia, & Pereira, 2012). Moreover, parishes with densely clustered housing that capture the peri-urban interface have more wildfires. These areas where urban and rural activities are juxtaposed may have higher urbanisation pressure on wildland. The marginal effect of the variable measuring building density indicates that how human populations are spatially distributed matters more for wildfire occurrence than do the absolute levels of those populations.

Our results provide a picture of the effects of agricultural and land abandonment in Galicia. The unemployment rate, often used as a proxy for labour market conditions and potential social conflicts (e.g., Martínez et al. 2009; Oliveira et al. 2012), is only weakly related to wildfire occurrence in Galicia. A similar result was also shown in Prestemon et al. (2012). However, rural exodus, often a consequence of this unemployment, leads to unattended land and hence to an increase in available wildfire fuels, and therefore to more successful wildfire ignitions. Nevertheless, it is questionable whether this process increases wildfire probability compared to a situation of intense agriculture/livestock land use. According to prior research (e.g., Catry et al. 2009; Verdú, Salas, & Vega-García, 2012), agricultural lands are associated generally with higher rates of wildfires. There may be an ongoing culture of firesetting as a managerial tool related to agricultural and livestock activities in the studied area (e.g., Ganteaume et al. 2013; Vélez, 2002). In addition the effects of rural exodus and abandonment may be behind the non-linear effect on wildfires occurrences of the proportion of broadleaves in the landscape. This is because even though broadleaves, mainly oaks, have been exploited in Galicia in the past, they are now hardly used in forestry activities and their high presence is commonly associated to unattended forestlands and little silvicultural activity (Díaz-Maroto & Vila-Lameiro, 2008). Thus, the colonisation of abandoned fields by natural vegetation simplifies the traditional agriculture landscape mosaic and at the same time increases fuel loads if left unattended (e.g., Ganteaume et al. 2013). In an area such as Galicia, where frequent fires favour the expansion of shrubland communities or the persistence of regenerating forests with a shrubland-type physiognomy (Moreira et al. 2011), this effect increases the risk of wildfire.

Unattended forestlands and high numbers of fire occurrences are also associated here with an ownership pattern of individual

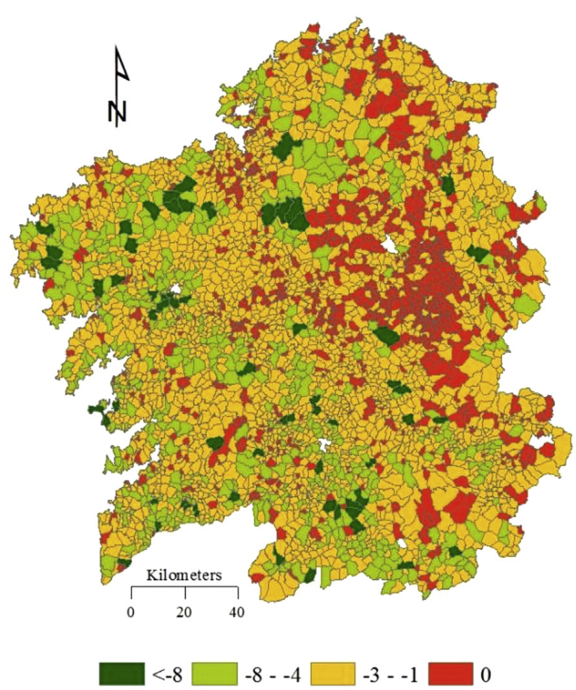

Fig. 4. Simulated changes in the total number of reported wildfires (1999–2011) by parish, given a 25% increase in the proportion of privately owned forests managed jointly.

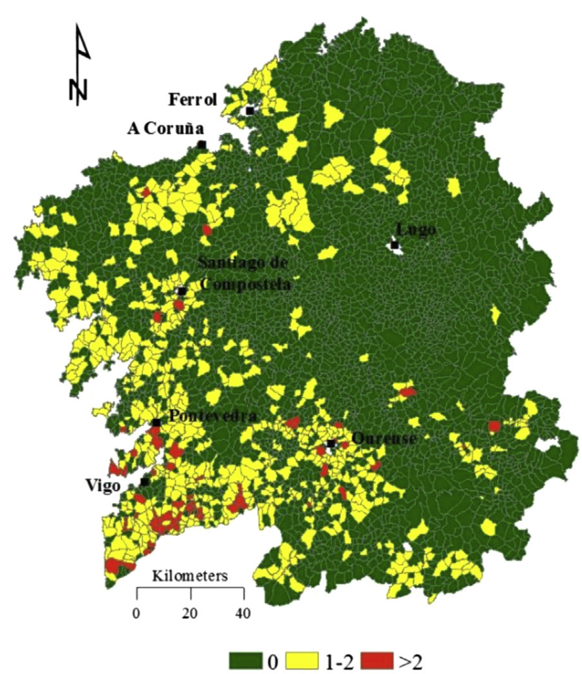

Fig. 5. Simulated changes in the total number of reported wildfires (1999–2011) by parish, given a 20% increase in the proportion of WUI for all parishes.

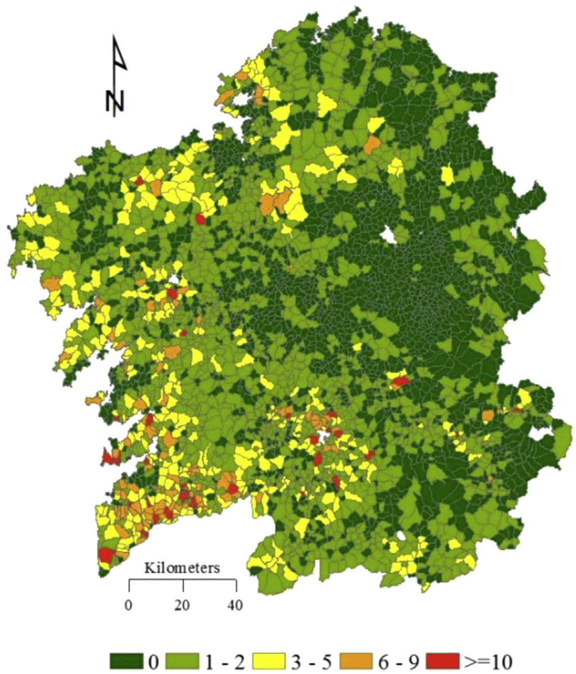

Fig. 6. Simulated changes in the total number of reported wildfires (1999–2011) by parish, given a 20% increase in the proportion of WUI and also imputed changes in correlated variables.

private holdings, whose typical size is too small to support many forestry practices. Moreover, coefficients on dummy variables measuring wildfire occurrences in the years previous to our period of inference indicate that coldspots and hotspots are temporally persistent. Persistent hotspots, therefore, might be targeted with higher levels of wildfire prevention education activities (e.g., Prestemon, Butry, Abt, & Sutphen, 2010), which can increase fire prevention awareness particularly among land managers in Galicia. Promotion of appropriate incentives for fuels management and sustainable forestry practices may also yield success. These policies could potentially have payoffs in terms of lowering overall damages and wildfire suppression spending in the region.

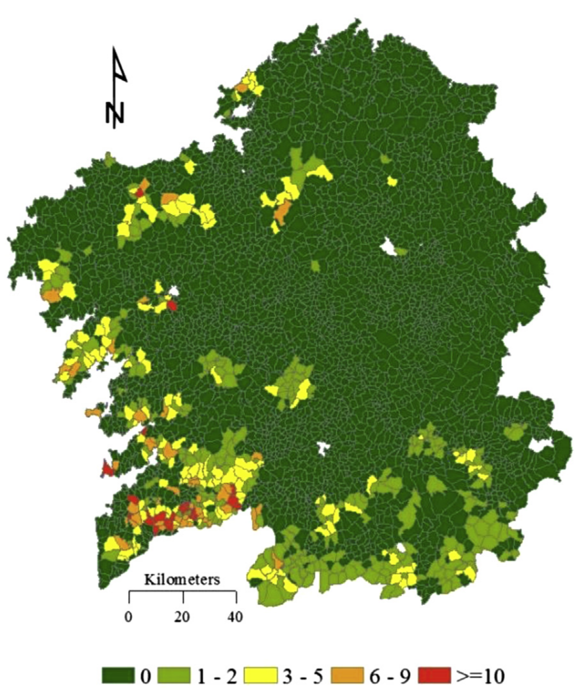

Fig. 7. Simulated changes in the total number of reported wildfires (1999–2011) by parish, given a 20% increase in the proportion of WUI in hotspot parishes and also imputed changes in correlated variables.

Our findings on slope and elevation variables are in concordance with other studies in similar regions of Portugal. As Catry et al. (2009) showed, at higher elevations, fire ignitions are more likely, probably as a consequence of pastoral burns; and Marques et al. (2011) found a higher proportion of burned areas in such upland locations. In addition, high-elevation areas are more likely to be characterised by larger proportions of non-wood forest areas (shrubland). We contend that the slope variable captures the more limited accessibility of steep forestlands, as well as the net effects of the types of vegetation and climatic conditions found in parish forests. Similarly, meteorological variables suggest higher counts of wildfires occur when warmer and drier conditions are favourable to fire spread, as has been found in other studies (Oliveira et al. 2012; Prestemon et al. 2012).

Our statistical simulation of changes in policy variables shows that homogeneous variation in land use conditions across the region generates heterogeneous effects in parishes. This highlights the suitability of spatially targeted fire management strategies, which would focus on those areas where higher benefits in wildfire risk reduction are expected. For example, incentives to jointly manage small single private holdings seem to have higher effects on fire risk in the west and south, where wildfire hotspots predominate. Therefore, promoting cooperative management of forest holdings would have many potential benefits for landowners, including economies of scale in forestry practices and the provision of a variety of ecosystem services (GEPC, 2006; Touza, Perrings, & Chas-Amil, 2010). Our study reveals an added potential benefit of cooperative management: reducing the overall rate of wildfires.

Additionally, although studies focused on many parts of North America have indicated the exacerbating role that building in wildland areas plays in terms of wildfire damages and suppression costs (e.g., Gude, Jone, Rasker, & Greenwood, 2013; Syphard, Keeley, Massada, Brennan, & Radeloff, 2012), few studies have shown this for European locations. Our simulations show that this WUI expansion, when linked to changes in WUI-correlated variables such as density of building clusters and roads, can lead to large increases in wildfire activity in some areas, to the potential detriment of the WUI's human occupants and for fire management budgets. It therefore follows that policies that limit the expansion of WUI areas in Galicia could potentially result in a significantly lower number of wildfires, mainly occurring in hotspot areas, and particular at the cluster of hotspot parishes in the west, which have had a rapid urban expansion in the last decades (Precedo et al. 2008).

Although our modelling uncovers a range of variables that appear to be influential on wildfire, our checks for spatial autocorrelation in model residuals also suggest that we may be missing explanatory variables. Residual spatial autocorrelation results in estimation inefficiencies, affecting tests of statistical significances. However, one “cure” for spatially autocorrelated residuals, spatial aggregation, carries with it another set of potential statistical distortions, including aggregation bias. Spatial resolution therefore represents modelling trade-offs. In our case, the parish level of the study has the benefit of providing potentially greater insights to the finer resolution variation of wildfires across Galicia.

Acknowledgements

This research was funded in part by Ministerio de Economía y Competitividad (ECO2012-39098-C06-05). The Spanish Ministry of

Agriculture, Food and Environment (MAGRAMA), and the Rural Affairs Department (Xunta de Galicia) provided the wildfire database. We thank E. García-Martínez for his technical support. The first draft of this paper was written when M.L. Chas-Amil was visiting the Environment Department at the University of York (UK). She gratefully acknowledges their hospitality.

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