CSIRO PUBLISHING

RESEARCH PAPER
https://doi.org/10.1071/WF22030

International Journal of WILDLAND FIRE
International Association of Wildland Fire

Non-parametric comparative analysis of the spatiotemporal pattern of human-caused and natural wildfires in Galicia

M. F. Marey-Pérez[A,*], Isabel Fuentes-Santos[B], Paula Saavera-Nieves[C] and Wenceslao González-Manteiga[C]

For full list of author affiliations and declarations see end of paper

*Correspondence to:
M. F. Marey-Pérez
PROePLA Research Group, Department of Crop Production and Engineering Projects, Universidade de Santiago de Compostela, Spain
Email: manuel.marey@usc.es

ABSTRACT

Background. Wildfire is a major environmental threat worldwide and climate change is expected to increase its severity. Galicia has suffered high wildfire incidence during the last decades, most wildfires being from arson, in contrast with the low rate of natural wildfires. **Aim.** This work aims to characterise the spatiotemporal dynamics of human-caused and natural fires in Galicia. **Methods.** We apply first- and second-order non-parametric inference to spatiotemporal wildfire point patterns. **Key results.** The distribution of natural wildfires remained stable over years, with high incidence in summer and in the eastern area of Galicia. Arson wildfires had aggregated patterns, with strong interaction between outbreaks and fires, and their distribution varied both over and within years, with high incidence shifting between the southern and western areas, and high hazard in early spring and late summer. Negligence wildfire patterns showed short-distance aggregation, but large-distance aggregation between outbreaks and fires; their spatial distribution also varied between and within years. **Conclusions.** Different models and covariates are required to predict the hazard from each wildfire type. Natural fires are linked to meteorological and environmental factors, whereas socioeconomic covariates are crucial in human-caused wildfires. **Implications.** These results are the basis for the future development of predictive spatiotemporal point process models for human-caused wildfires.

Keywords: inhomogeneous point processes, intensity function, non-parametric inference, smooth bootstrap, Spain wildfire, spatiotemporal interactions, wildfire hazard.

Received: 15 March 2022
Accepted: 22 November 2022
Published: 23 December 2022

Cite this:
Marey-Pérez MF *et al.* (2023)
International Journal of Wildland Fire
32(2), 178–194. doi:10.1071/WF22030

Introduction

Wildfire is a major environmental threat around the world that causes substantial natural damage and socioeconomic losses (Zhang *et al.* 2016; Costafreda-Aumedes *et al.* 2017; Bowd *et al.* 2019; Marrs *et al.* 2019; Pausas and Keeley 2021). In the southern European Union (EU) countries (Portugal, Spain, France, Italy and Greece), 48 600 forest fires burn on average 447 800 ha (1980–2015) every year, most of this area being burned by a small number (<15%) of large fires (San-Miguel-Ayanz *et al.* 2013). This high wildfire incidence in Mediterranean Europe can be attributed to climate, environmental and anthropogenic factors. On one hand, climate change has increased temperature and has reduced relative humidity. On the other hand, socioeconomic factors such as the abandonment of farms and rural areas have resulted in an unusual accumulation of forest fuels (Vilar del Hoyo *et al.* 2011; Aragó *et al.* 2016).

Unravelling wildfire patterns is crucial to understand fire behaviour and to develop prevention and mitigation strategies, as well as landscape restoration plans. The increasing availability of georeferenced wildfire data has enhanced the development of a prolific line of research focused on analysing the spatial distribution of wildfire and on identifying biotic and abiotic risk factors. Spatiotemporal cluster analysis has been proposed as a useful tool to address important scientific challenges such as characterising observed short-term clustering of ignition points, detecting changes in the spatial distribution of ignition points and understanding the causes of those changes, and measuring temporal variations in wildfire clusters (Prestemon *et al.* 2013). Clustering analysis applied to wildfire research has been conducted through the combination of classical statistics with GIS (Geographic Information System) tools (Rodrigues *et al.* 2019), and by spatiotemporal point process analysis and modelling (Serra *et al.* 2013; Wing and Long 2015; Aragó *et al.* 2016; Díaz-Avalos *et al.* 2016; Parente *et al.* 2016; Woo *et al.* 2017). In addition to the analysis of interactions between fire events, point process modelling also allows estimation of the effect of environmental and socioeconomic covariates on wildfire incidence, and the creation of fire hazard maps.

In the analysis of wildfires, we should distinguish between natural and human-caused fires, which, in addition to different origins, have different dynamics (González-Olabarria *et al.* 2015). Natural fires, mainly caused by lightning, tend to be concentrated in summer months, fostered by the high temperatures, low air humidity and, hence, low fuel moisture content (Pineda *et al.* 2014; Nampak *et al.* 2021; He *et al.* 2022). On the other hand, more than 90% of fires worldwide are directly or indirectly linked to intentional and unintentional human activities (Costafreda-Aumedes *et al.* 2017). The spatiotemporal dynamics of human-caused fires have been studied for a long time (Crosby 1954; Bruce 1963; Donoghue and Main 1985). Recent studies found that arson fires in the Iberian Peninsula have aggregated patterns (Costafreda-Aumedes *et al.* 2016) and analysed the biophysical and socioeconomic factors that favour the occurrence of arson and negligence fires (Rodrigues *et al.* 2016; Parente *et al.* 2018; Silva *et al.* 2019; Dupuy *et al.* 2020), reaching complementary conclusions. In particular, Rodrigues *et al.* (2016) identified changes in agricultural activity as the main driver of arson wildfires in Spain in the last decade of the 20th and the first decade of the 21st centuries; Dupuy *et al.* (2020) and Rodrigues *et al.* (2018) linked human-caused wildfires with climate change, while Silva *et al.* (2019) suggested that anthropogenic factors are the main cause that explains arson fires in the Iberian Peninsula.

Galicia (north-west Spain, Fig. 1 (left)) has suffered high wildfire incidence over several decades, although climate-related fire danger in this region is lower than in the Mediterranean and southern regions of Spain (Fig. 1, right). This is due to the fact that a large fraction, above 75%, of wildfires in Galicia are arson, 25% higher than the national rate (MAGRAMA 2016). The particular characteristics of wildfires in Galicia, and their severe environmental and socioeconomic consequences, have motivated of a large body of research with the aim of understanding fire dynamics, identifying fire risk drivers and predicting the occurrence of future events. Any progress in these research topics will contribute to improving the effectiveness of current fire prevention and suppression plans. Different studies have proposed the application of a wide variety of statistical analysis and modelling techniques. Boubeta *et al.* (2015) proposed a semiparametric time series model to predict the burned area in Galicia 1 week in advance. Boubeta *et al.* (2016, 2019) used area-level mixed effects models to predict the number of fires; the former showed good performance of Poisson mixed regression models and bootstrap techniques, and the latter incorporated time effects into these models. Wildfire occurrence and burned area have also been estimated through structured additive regression (STAR) that incorporates space- and time-varying covariates, as well as spatial and temporal correlations (Ríos-Pena *et al.* 2017, 2018). Non-parametric first- and

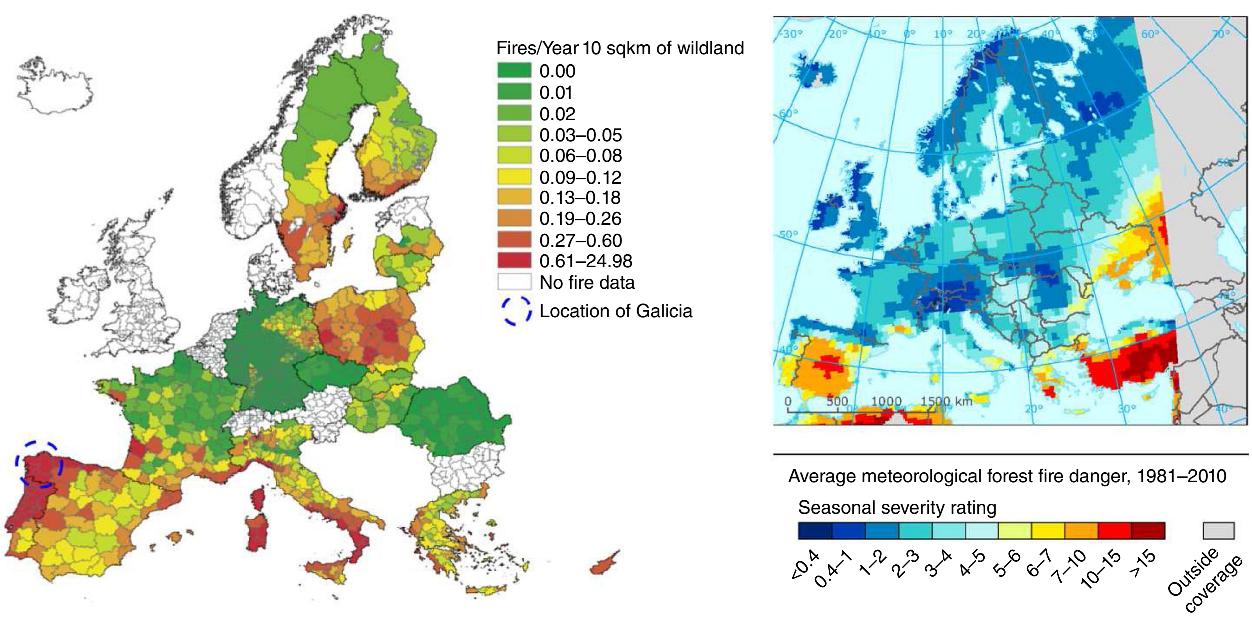

Fig. 1. Left: location of Galicia and annual mean intensity of wildfire in Europe. Source: Birot *et al.* (2009). Right: average climate-related forest fire danger in Europe (European Environmental Agency).

second-order analysis of spatial point processes was used to study the spatial distribution of wildfire activity in a forest district in Galicia by Fuentes-Santos *et al.* (2013). In parallel, some studies have developed new non-parametric inference techniques for spatial and spatiotemporal point processes and have used wildfire patterns in Galicia as case studies to illustrate their applicability. Fuentes-Santos *et al.* (2016) proposed a plug-in bandwidth selector for the kernel intensity estimator, which contributes to obtaining more accurate estimators for the spatial distribution of wildfires. The non-parametric first-order intensities comparison by Fuentes-Santos *et al.* (2017) can be used to test if fires with different causes have the same spatial distribution, whereas the log-ratio based separability test proposed by Fuentes-Santos *et al.* (2018) allows us to check if the spatial distribution of wildfires varies over time.

In the present work, we analyse a large dataset comprising the ignition points and time of occurrence of the wildfires recorded in Galicia during 16 years (1999–2014). We focused on comparing the patterns of natural, arson and negligence wildfires. Given that over 70% of wildfires in Galicia burn less than 1 ha, we analyse wildfires smaller (outbreaks) and larger (fires) than 1 ha burned separately. The novel non-parametric first-order inference techniques for spatial and spatiotemporal point processes introduced above were applied to describe the distribution of arson, negligence and natural wildfire patterns, and test for differences between years in order to identify a potential change point in wildfire patterns and between the spatial distributions of wildfire causes. We also applied Monte Carlo tests based on the inhomogeneous L-function (Baddeley *et al.* 2000), the inhomogeneous L-cross (Ripley 1981) and the spatiotemporal K-function (Fuentes-Santos *et al.* 2018) to test for interactions between fires.

Study area and dataset

Study area

Galicia, located in the north-west of the Iberian Peninsula (Fig. 1), has a surface area of 29 574 km^2, which represents 5.78% of the surface of Spain, and has a population of 2.7 million (5.84% of the Spanish population), which implies a mean population density of 94.1 inhabitants/km^2, close to the mean population density of Spain (Spanish Statistical Office (INE) 2019, https://www.ine.es/). Forests occupy 69% of the surface in Galicia, a large proportion in comparison with the Spanish average (55%, MAGRAMA 2019). Forested land in Galicia is mainly private (97%) and distributed among a large number of small landowners at an average rate of 2 ha/owner (Marey-Pérez *et al.* 2012). The forestry sector in Galicia generates 20 320 direct and 50 000 indirect jobs, and represents 3.5% of the regional gross domestic product (GDP) (XERA 2018). Indeed, Galicia, with an average income of EUR2652 million/year, is the major timber producer in Spain and the ninth in Europe (Balsa-Barreiro and Hermosilla 2013).

As we can see in Fig. 1 (left), Galicia is one of the regions with higher wildfire incidence in Europe (Comas *et al.* 2014; Álvarez-Díaz *et al.* 2015; Da Ponte *et al.* 2019) despite its relatively unfavourable fire weather conditions. In fact, Galicia suffered more than 255 000 forest fires between 1961 and 2014, with an estimated affected area of 1.83 million ha (Ríos-Pena *et al.* 2017).

Wildfire dataset

This work analyses the 104 000 wildfires recorded in Galicia from 1999 to 2014. Data were obtained from the Wildfire General Statistics available at the Spanish Government Data Portal (https://datos.gob.es/es/catalogo/e05068001-estadistica-general-de-incendios-forestales). The dataset comprises the spatial location and time of detection of each ignition point together with additional information about the source of ignition, suppression and damage caused by the wildfire. This work focuses on the burned area and the cause of fire. Although the Wildfire General Statistics provide wildfire records form 1983, the period 1983–1998 was discarded in this study after conducting a data quality control of the georeferenced information provided. Data quality control was conducted testing whether the spatial coordinates of each ignition point were within the reported municipality and type of land assigned to the event. Discrepancies found in the period 1999–2014 were corrected, assigning new coordinates to the event through the procedure detailed in Fuentes-Santos *et al.* (2013), and less than 10% of ignition points needed to be corrected.

Forest fires in Spain have been classified with five main causes: natural, arson, accidental or negligence (referred to as negligence hereafter), reproductions (reigniting fires) and unknown cause (MAGRAMA 2016). This work focuses on arson, negligence and natural wildfires. However, as in previous work (Fuentes-Santos *et al.* 2013), forest fires were also divided into these groups according to burned area (S), outbreaks ($S < 1$ ha), regular fires ($1 \leq S < 25$ ha) and large fires ($S \geq 25$ ha).

Non-parametric point processes analysis

Point processes are mathematical models that govern the occurrence of a random number of events in a bounded domain, $W \subset \mathbb{R}^d$ (with $\mathbb{R}^d$ being Euclidian space). If each event has any measure or mark associated with it, we have a marked point process. A multitype point process is a marked point process with categorical marks that define different point processes according with the type of event. Spatial point processes generate a random number of events

$\mathbf{X} = \{\mathbf{x_1}, \ldots, \mathbf{x_N}\}$ in a planar region $W \subset \mathbb{R}^2$ with area $|W| > 0$. Spatiotemporal point processes comprise the location and time of occurrence of a random number of events, $\boldsymbol{S} = \{(\mathbf{x_1}, \mathbf{t_1}), \ldots, (\mathbf{x_N}, \mathbf{t_N})\}$, irregularly placed in $W \times T \subset \mathbb{R}^2 \times \mathbb{R}^+$. Throughout this paper, point processes and patterns are denoted in bold capitals and events are denoted in bold.

The wildfires dataset introduced in the previous section, comprising the spatial location of the ignition points and date and time of detection of wildfires in Galicia, can be seen as a realisation of a spatiotemporal point process. Each event is marked by the cause of fire and its burned area.

Non-parametric inference techniques recently developed for first- and second-order analysis of spatial and spatiotemporal point processes allow us to answer important questions regarding the distribution and behaviour of different types of forest fires in Galicia. Kernel estimators of the first-order intensity functions (Diggle 1985; Fuentes-Santos *et al.* 2016; van Lieshout 2020) characterise the spatial distribution of arson and natural fires, and the non-parametric comparison of first-order intensities tests (Fuentes-Santos *et al.* 2017), for instance, whether arson and natural fires had the same spatial distribution or whether wildfire distribution varied over years. A first-order spatiotemporal separability test (Fuentes-Santos *et al.* 2018) checks whether the spatial distribution of wildfire patterns varies over time. Second-order characteristics, which analyse pairwise interactions between events, allow us to test if wildfire patterns are clustered, regular or random, i.e. whether a wildfire at a given location enhances (clustered) or inhibits (regular) wildfire occurrence in its neighbourhood. Second-order characteristics of multitype point processes allow us to analyse the relationship between different types of events. We can test, for instance, if arson outbreaks and fires appear closer or further apart than would be expected if they were independent.

First-order analysis

One of the main issues in the analysis of any observed pattern is estimating its first-order intensity function, $\lambda(\cdot)$, which determines the expected number of events per unit domain (Diggle 2013). In this work, we estimate the first-order intensity of the arson and natural fire patterns under study through kernel smoothing with full bandwidth matrix (Fuentes-Santos *et al.* 2016).

$$\hat{\lambda}_H(x) = p_H(x)^{-1}|H|^{-1/2}\sum_{i=1}^{N} k(H^{-1/2}(x - \mathbf{x_i})) \tag{1}$$

where $k(\cdot)$ is a bivariate Gaussian kernel, H is a positively defined bandwidth matrix and $|H|$ denotes the determinant of $H \cdot p_H(x) = \int_W |H|^{-1/2}k(H^{-1/2}(x - y))\mathrm{d}y$ is the edge-correction term that reduces the bias near the boundary of the observation domain W, and guarantees the consistency of the kernel estimator of the density of event locations, $\lambda_0(x) = \lambda(x)/m$ where $m = \int_W \lambda(x)\mathrm{d}x$ is the expected number of events in W. The bandwidth parameter, which determines the degree of smoothing of kernel estimators, is crucial for the performance of the kernel intensity estimation. Different bandwidth selectors, such as the mean nearest distance used in the seminar paper of Koutsias *et al.* (2004), have been used in the analysis of wildfire patterns. In the present work, bandwidth selection was conducted through the two-stage plug-in algorithm introduced by Fuentes-Santos *et al.* (2016), which minimises the bootstrap estimate of the AMISE (asymptotic mean integrated square error) of the kernel density of event locations. As can be seen in Fuentes-Santos *et al.* (2016), large bandwidths are obtained for small point patterns of natural wildfires, and small ones for large point patterns of arson wildfires.

Taking advantage of the consistency of the kernel density of event locations, Fuentes-Santos *et al.* (2017) proposed a formal test to compare the spatial distribution of two observed patterns. This test relies on the fact that two spatial point processes, $\mathbf{X_1}$ and $\mathbf{X_2}$, with the same spatial distribution have the same density of event locations. Thus, we can use an L_2 discrepancy measure to test the null hypothesis, $\mathcal{H}_0$: $\lambda_{01}(x) = \lambda_{02}(x) = \lambda_0(x)$, and define the test statistic

$$\hat{T} = \int_W (\hat{\lambda}_{01}(x) - \hat{\lambda}_{02}(x))^2\mathrm{d}x = \hat{\psi}_1 + \hat{\psi}_2 - (\hat{\psi}_{12} + \hat{\psi}_{21}) \tag{2}$$

where $\hat{\psi}_{ij}$ and $\hat{\psi}_i$ are estimators of $\psi_{ij} = \int_W \lambda_{0i}(x)\lambda_{0j}(x)\mathrm{d}x$ for $i, j = 1, 2$ and $\psi_i = \int_W \lambda_{0i}(x)^2\mathrm{d}x$, obtained by kernel smoothing with plug-in bandwidth (Chacón and Duong 2010). The test was calibrated through smooth bootstrap with $B = 200$ realisations of the null hypothesis. We use this procedure to compare the intensity of arson and natural wildfires and to test if the spatial distribution of each type of fire varied across years. This procedure is referred as the T-test hereafter.

Up to now, we have focused on the spatial distribution of wildfire, overlooking the temporal dimension. To fill this gap, we estimate the spatiotemporal intensity of the wildfire patterns under study by kernel smoothing, and apply the log-ratio based separability test proposed by Fuentes-Santos *et al.* (2018) to check whether the spatial distribution of wildfires varies over time. The kernel intensity estimator is given by

$$\hat{\lambda}_{H_s,h_t}(x, t) = p_{H_s,h_t}(x, t)^{-1}|H_s|^{-1/2}h_t^{-1} \sum_{i=1}^{N} k_s(H_s^{-1/2}(x - \mathbf{x_i}))k_t(h_t^{-1}(t - \mathbf{t_i})) \tag{3}$$

where $k_s(\cdot)$ and $k_t(\cdot)$ are bivariate and univariate Gaussian kernels, H_s is the two-dimensional bandwidth matrix for the spatial component, and h_t is the bandwidth for the temporal component. $p_{H_s,h_t}(x,t) = \int_T \int_W k_{s,H_s}(x-u)k_{t,h_t}(t-v)\mathrm{d}u\mathrm{d}v$ is the spatiotemporal edge-correction factor.

A spatiotemporal point process is first-order separable if its intensity can be expressed as the product of its spatial and temporal marginals: $\lambda(x,t) = \lambda_1(x)\lambda_2(t)$ and, consequently, the log-ratio between the spatiotemporal and spatial intensities, $\rho(x,t) = \log(\lambda(x,t)/\lambda_1(x))$, does not depend on the spatial locations x for any $t \in T$. Considering this property, Fuentes-Santos et al. (2018) proposed using a no-effect test to check the separability assumption. To implement the test, we first estimate $\rho(x,t)$ as the log-ratio of the kernel spatiotemporal (Eqn 3) and spatial (Eqn 1) intensity functions with diagonal bandwidth matrices selected by least-squares cross-validation. Once $\hat{\rho}(x,t)$ is obtained, we consider a regression problem with a response variable, $Y = \{y_i = \hat{\rho}(\mathbf{x_i}, \mathbf{t_i}), i = 1, \ldots, n\}$, that may depend on the spatial covariate $X = \{x_i = (x_{i1}, x_{i2}), i = 1, \ldots, n\}$ comprising the event locations, and we test for the effect of X on Y. Thus, following Bowman and Azzalini (1997), we check whether $E[Y|X] = \mu$ or $E[Y|X] = m(X)$ through the test statistic

$$F = \frac{(\mathrm{RSS}_0 - \mathrm{RSS}_1)/(\mathrm{df}_1 - \mathrm{df}_0)}{\mathrm{RSS}_1/\mathrm{df}_1} \tag{4}$$

where RSS_0 and RSS_1 are the residual sum of squares for non-parametric estimators of the null and alternative models, and df_0, df_1 denote their respective degrees of freedom. The test is calibrated through a permutation test, which relies on the fact that under $\mathcal{H}_0$, the pairing of any particular X and Y is completely random. This procedure is referred to as the F-test hereafter.

Second-order analysis

Once the spatial and spatiotemporal distribution of wildfire patterns are characterised, we apply Monte Carlo tests based on the spatial and spatiotemporal inhomogeneous K-functions to check for interaction between ignition points. The K-function of a homogeneous spatial point process is defined as $K(r) = \lambda^{-1}\mathbb{E}[N_0(r)]$ where $N_0(r)$ is the number of further events within distance r of an arbitrary event (Ripley 1977). Given that the homogeneity assumption can be very restrictive and unrealistic when dealing with real data, Baddeley et al. (2000) extended this function to the case of inhomogeneous point processes, $K_{\mathrm{inhom}}(r)$, and proposed an empirical estimator

$$\hat{K}_{\mathrm{inhom}}(r) = \frac{1}{|W|} \sum_{\mathbf{x_i}, \mathbf{x_j} \in \mathbf{X} \cap W}^{i \neq j} \frac{I(\|\mathbf{x_i} - \mathbf{x_j}\| \leq r)}{\hat{\lambda}(\mathbf{x_i})\hat{\lambda}(\mathbf{x_j})} \omega_{i,j}^{-1}; \quad 0 \leq r \leq r_{\max} \tag{5}$$

where $I(\cdot)$ is the indicator function, $r_{\max}$ is the maximum distance at which the function is evaluated, w_{ij} is Ripley's edge-corrector, and $\hat{\lambda}(x)$ is the kernel intensity estimator detailed in Eqn 1. The L-function (Besag 1977), defined as $L_{\mathrm{imhom}}(r) = \sqrt{K_{\mathrm{inhom}}(r)/\pi}$, is a transformation of the K-function widely used in practice. The inhomogeneous L-function of a spatial Poisson point process is $L_{\mathrm{inhom}}(r) = r$, where values below or above this threshold indicate, respectively, inhibition or clustering between events at distance r. This property suggests testing for interaction between events through a Monte Carlo test, which compares the L-function of the observed patterns, $\mathbf{X}$, with the upper and lower envelopes of $B-1$ realisations of the inhomogeneous spatial Poisson point process with the same first-order intensity as $\mathbf{X}$.

Spatial interactions between two types of fires, e.g. arson and natural fires in a given year, were tested through Monte Carlo tests based on the inhomogeneous L-cross function, which is the natural extension of the previous procedure to the multitype framework (Ripley 1981; Baddeley et al. 2015).

The Monte Carlo procedures introduced above test for spatial interaction in wildfire patterns overlooking the temporal lag between events. However, testing for spatiotemporal interaction, i.e. whether the occurrence of a wildfire increases or reduces the probability of new events in its neighbourhood during the next hours and days, is crucial for a proper analysis of fire behaviour. To address this issue, we applied a Monte Carlo test based on the spatiotemporal inhomogeneous K-function (Gabriel and Diggle 2009), as for a Poisson point process $K_{\mathrm{ST,inhom}}(r,t) = \pi r^2 t$, where larger and smaller values indicate clustering and inhibition, respectively. To implement the spatiotemporal K-test, we first obtained the empirical estimator of $K_{\mathrm{ST,inhom}}(r,t)$ as follows

$$\hat{K}_{\mathrm{ST,inhom}}(r,t) = \frac{1}{|W \times T|} \sum_{\mathbf{x_i}, \mathbf{x_j} \in W \, \mathbf{t_i}, \mathbf{t_j} \in T}^{i \neq j} \frac{I(\|\mathbf{x_i} - \mathbf{x_j}\| < r, |\mathbf{t_i} - \mathbf{t_j}| < t)}{\hat{\lambda}(\mathbf{x_i}, \mathbf{t_i})\hat{\lambda}(\mathbf{x_j}, \mathbf{t_j})} \omega_{i,j}^{-1} \quad 0 \leq r \leq r_{\max} \;\; 0 \leq t \leq t_{\max} \tag{6}$$

where $I(\cdot)$ is the indicator function, ω_{ij} is Ripley's spatiotemporal edge-corrector, $r_{\max}$, $t_{\max}$ are the maximum spatial and temporal distances at which the function is evaluated, and $\hat{\lambda}(x,t)$ is an estimator of the spatiotemporal first-order intensity function. Gabriel and Diggle (2009) assume first-order separability, i.e. they use a separable estimator of the spatiotemporal intensity, $\hat{\lambda}(x,t) = \hat{\lambda}_1(x)\hat{\lambda}_2(t)$, and attribute any non-separable effect to the second-order structure. We used separable or non-separable kernel intensity estimated in agreement with the results of the first-order separability test introduced in the previous section. As well as for the spatial framework, the Monte Carlo test compares the spatiotemporal K-function of the observed pattern, $\hat{K}_{\mathrm{ST,inhom}}(x,t)$, with upper and lower envelopes determined by Monte Carlo realisations of a spatiotemporal Poisson point process with the same intensity as the observed pattern. The maximum values r and t for which $\hat{K}_{ST,inhom}(x, t)$ falls above or below the envelopes determine the spatial and temporal interaction radius, respectively.

Software

The statistical analysis of the spatial and spatiotemporal wildfire patterns was conducted with the R statistical software (R Core Team 2018). The *Spatstat* package (Baddeley *et al.* 2015) was used for kernel intensity estimation and second-order analysis of spatial point patterns, whereas plug-in bandwidths were obtained with the help of the *ks* package (Duong 2018). The *kde.test* function in the *ks* package was adapted by Fuentes-Santos *et al.* (2017) to implement the L_2-test for comparison of first-order intensities. Kernel log-relative risk functions and their tolerance contours were estimated using the *sparr* package (Davies *et al.* 2018). Fuentes-Santos *et al.* (2018) extended some functions in the *sparr* package (Davies *et al.* 2018) to estimate the spatiotemporal intensity and log-ratio functions to implement the separability test with the help of the *sm* package (Bowman and Azzalini 2014).

Results

Exploratory analysis

Fig. 2 shows the number of wildfires and area burned by cause of fire and year (see Table A1 in Supplementary Appendix A for further details). The majority of wildfires recorded were arson (>80%), while the incidence of those caused by negligence (~3%)) and natural causes (~1%) was very small. The year 2006 registered a decrease in the number of wildfires in comparison with previous years but had the largest affected area, and we observed a significant reduction in the number of wildfires and affected area from 2007 onward. The correspondence analysis conducted as a preliminary analysis of wildfire behaviour identified 2006 as a change point, as we found association between arson fires and the years 1999–2006, and between negligence fires and 2007–2014 (see details in Supplementary Appendix A).

According to the official reports, a large proportion of the wildfires, 72.5%, burned less than 1 ha, and just 2% affected more than 25 ha. Although we do not see large differences between causes, arson wildfires have the lowest rate of events with less than 1 ha burned (see Supplementary Table A1). Taking into account these particular features of wildfire in Galicia, this work considers all events, not only

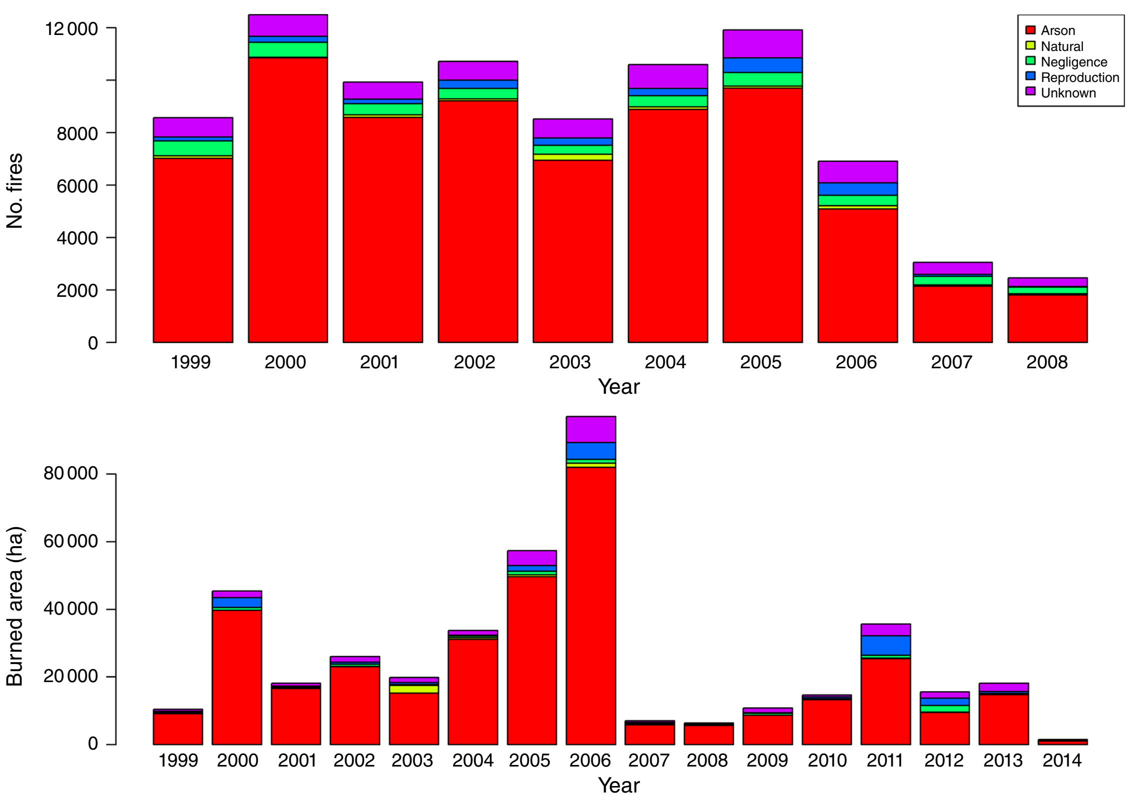

Fig. 2. Number of ignition points registered in Galicia from 1999 to 2014 (top); and burned area (bottom) by cause of fire.

those with more than 1 ha burned as is usual in wildfire research. Hereafter, 'wildfires' refers to all events, 'outbreaks' to wildfires with $S < 1$ ha, and 'fires' to those with $S \geq 1$ ha.

Spatial and spatiotemporal distribution of wildfire

We analysed the spatial and spatiotemporal distribution of arson, negligence and natural wildfires, distinguishing between outbreaks ($S < 1$ ha) and fires ($S \geq 1$ ha) when the size of the observed pattern was large enough. Given the large number of analyses conducted, detailed results for the spatial and spatiotemporal analyses are provided as Supplementary Appendices B and C, respectively.

The kernel intensity estimators of arson, negligence and natural wildfires shown in Figs 3–5 show clear differences in the spatial patterns of wildfire between the three causes. These differences were confirmed by the non-parametric comparison between intensity functions (T-test, P value < 0.005 for all years with more than 20 natural fires).

Now, we focus on testing for interannual variability in the spatial pattern of each cause of wildfire, and on testing for differences between outbreaks and fires for the two types of human-caused wildfires. The non-parametric test found that the spatial distribution of arson wildfires, outbreaks and fires varied across years (T-test, P value < 0.005). In particular, Fig. 3 suggests a trend with wildfire hotspots spreading from the south of Galicia, on the boundary with Portugal, to the west coast every 4 years. We also found differences (T-test, P value < 0.005) between the spatial patterns of outbreaks (Supplementary Fig. B1 in Supplementary Appendix B) and fires (Supplementary Fig. B2); for instance, in 2006, we observed a low intensity of outbreaks, but a high incidence of fires in the SE of Galicia.

The spatial distribution of wildfires caused by negligence, outbreaks and fires varied over years, although pairwise

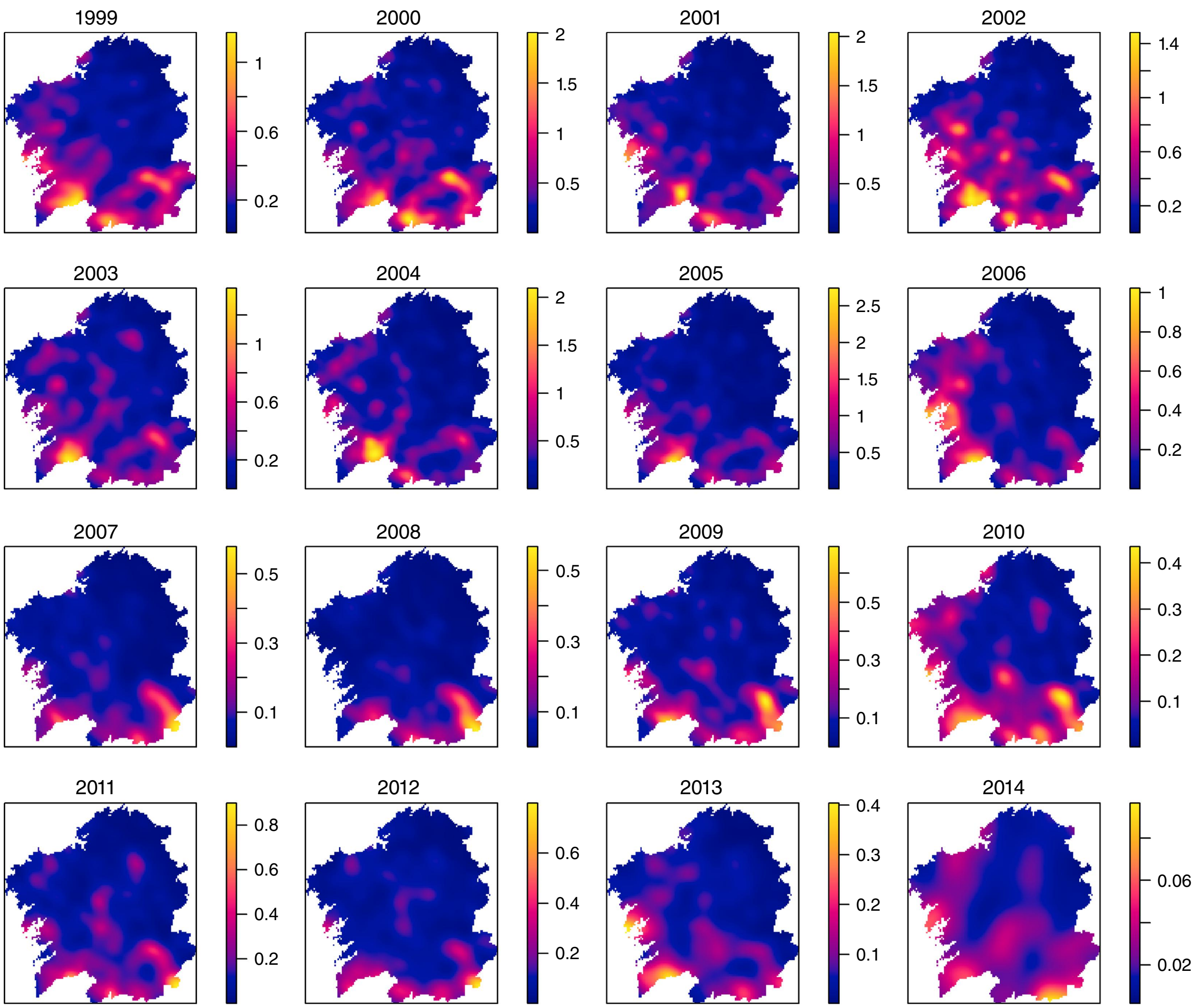

Fig. 3. First-order intensity estimator for the spatial patterns of arson wildfires by year (different scales).

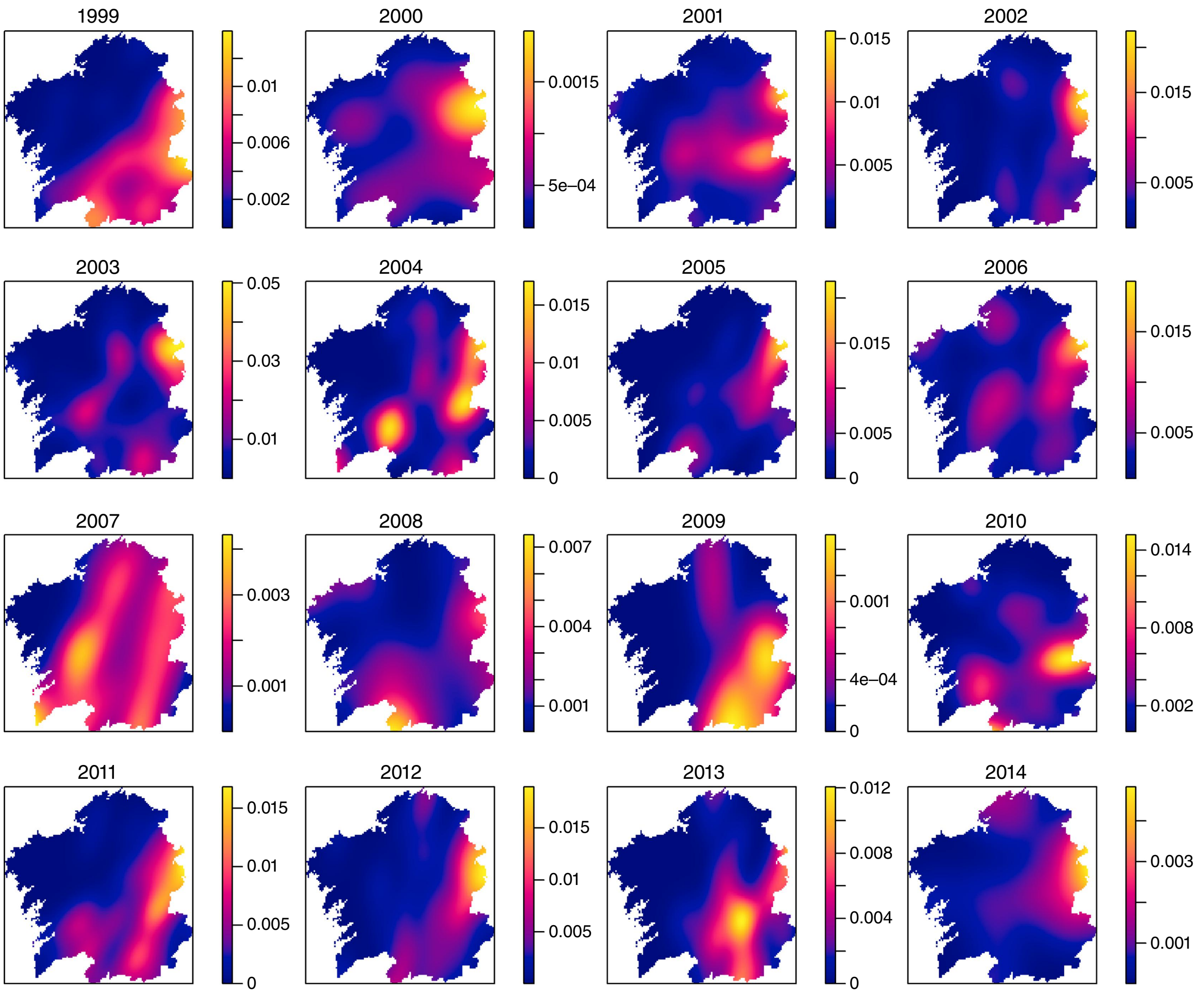

Fig. 5. First-order intensity estimator for the spatial patterns of natural wildfires by year (different scales).

comparison did not always report significant differences (see Table S3). Fig. 4 shows negligence fires occurred mainly in the Atlantic coastal area of Galicia, with high-incidence areas moving between the northern and southern coastal areas, and some hotspots in the inner region of Galicia. Comparison between outbreaks and fires found significant differences between them in 1999, 2000, 2002, 2003, 2007 and 2008. As observed for arson fires, the inner and southern areas tend to have larger fire than outbreak (details are given in Supplementary Table B2, Supplementary Figs B3, B4).

The spatial distribution of natural wildfires was more stable over years, with higher incidence in the east of Galicia (Fig. 5), although the non-parametric comparison detected differences between some pairs of years (Supplementary Table B3). Outbreaks and fires were not analysed separately owing to the small number of events observed.

Supplementary Appendix C shows the kernel estimator of the spatial and spatiotemporal intensities, and the temporal density of ignition points for arson, negligence and natural fires by year. As for the spatial distribution, we observed differences between the temporal patterns of human-caused and natural wildfire patterns. The temporal pattern of arson wildfires varied over years, early spring and late summer–autumn being the seasons with the highest fire incidence. Fires caused by negligence occurred mainly in spring and summer, but the highest-incidence period also varied over years. Finally, natural fires occurred mainly in summer. The spatiotemporal separability test rejects the null hypothesis for arson and negligence wildfires (F-test, P value < 0.005), i.e. the spatial distribution of wildfire varied over time, as can be seen in the spatiotemporal intensity estimators (see animations in Supplementary Appendix C). Although data sparseness and the small number of natural wildfires recorded each year do not allow the application of

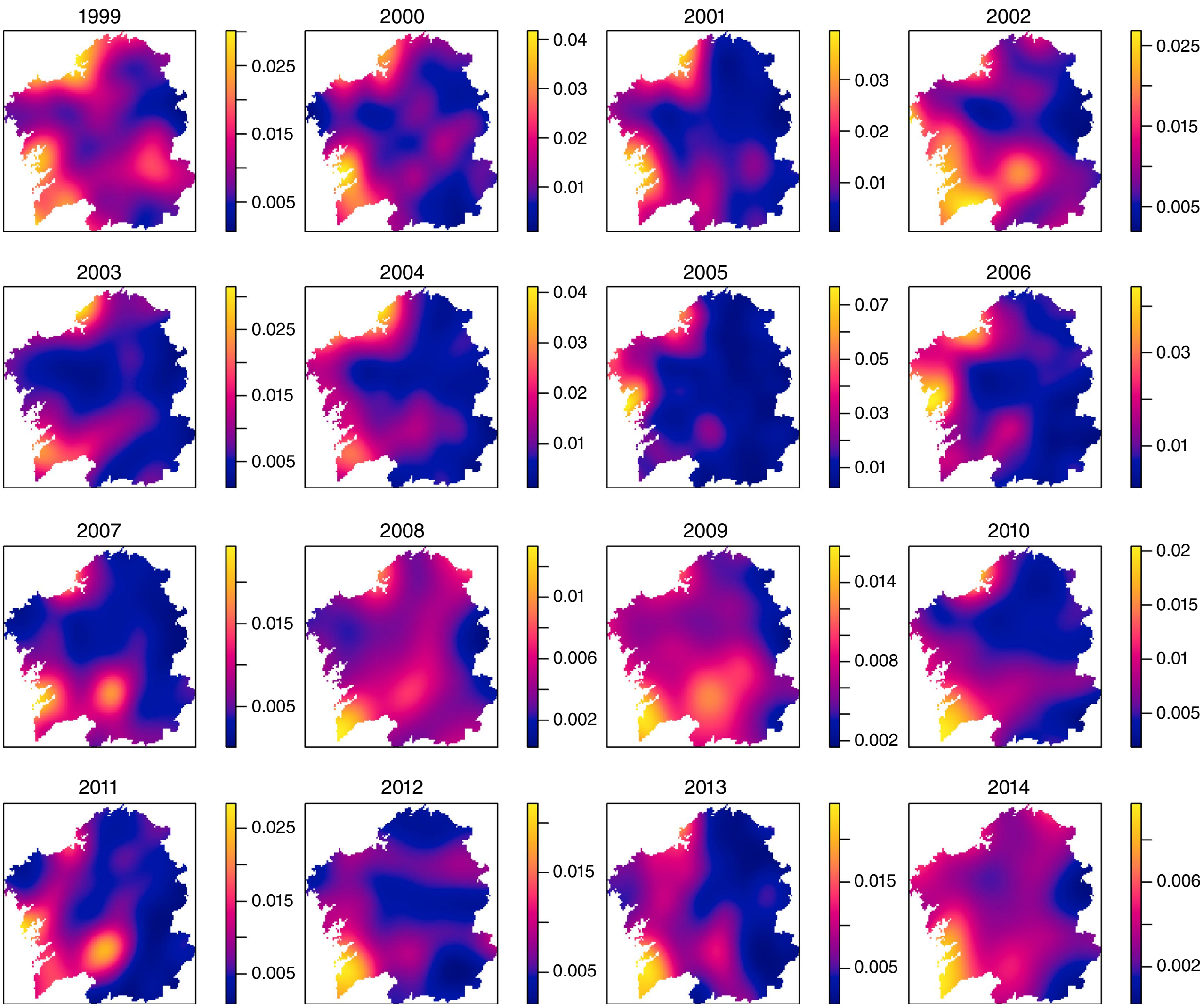

Fig. 4. First-order intensity estimator for the spatial patterns of negligence wildfires by year (different scales).

the separability test for these patterns, visual inspection of the kernel estimators of the spatiotemporal intensity suggests that their distribution also varied over time.

Spatial and spatiotemporal interaction between wildfires

Table 1 shows the maximum interaction rates found with the inhomogeneous L-tests for arson, negligence and natural wildfire patterns, and for interactions in the outbreak and fire patterns of the two types of human-caused fires. The inhomogeneous L-test detected clustering in the arson wildfire patterns for all years but 2007 with an interaction radius between 1 km in 2004 and 6 km in 2014, and inhibition at large distances (see Supplementary Fig. B4 in Supplementary Appendix B). We also found interactions between the outbreaks (Supplementary Fig. B6) and fires (Supplementary Fig. B7); as observed for the whole wildfire patterns, the interaction radius varied over years. The inhomogeneous L-cross test found evidence of positive interaction between arson outbreaks and fires (Table 2, Supplementary Fig. B8). Arson wildfires also show aggregation between arson events over years (Supplementary Fig. B17), i.e. a higher probability of arson fires in areas that recorded arson fires in previous years. In contrast, we did not find evidence of interactions between fires over sequential years (Supplementary Fig. B18).

The spatiotemporal inhomogeneous K-tests (Fig. 6), which test for interactions between events up to 15 km and 15 days after the occurrence of a given event, show that the probability of new wildfires in the neighbourhood of an observed event decreases over time. In this sense, except for 2009 and 2012, which had long-term aggregation up to 15 km, the interaction radius decreases with time. In particular, in 1999, 2005 and 2006, the spatiotemporal K-test detected long-term interaction up to 6–10 km, an

Table 1. Inhomogeneous L test, maximum aggregation radius between arson negligence and natural wildfires. Interactions between outbreaks ($S < 1$ ha) and fires ($S \geq 1$ ha) for arson and negligence.

	Arson			Negligence			Natural
	Wildfire	Outbreak	Fire	Wildfire	Outbreak	Fire	Wildfire
1999	4.24	3.94	2.27	0.45	0.00	0.00	0.00
2000	2.42	2.42	3.94	0.76	4.39	0.00	0.00
2001	1.67	4.09	1.36	0.61	0.00	0.00	1.5
2002	1.52	2.27	0.00	0.76	0.00	3.48	0.00
2003	3.33	3.18	0.61	0.61	0.00	0.00	0.00
2004	2.12	1.67	3.18	0.45	0.00	0.00	2.41
2005	2.42	4.24	4.70	0.76	1.97	0.00	0.00
2006	1.36	3.48	1.06	0.61	0.00	0.00	0.75
2007	0.45	1.52	0.00	1.52	0.00	0.00	0.00
2008	2.12	3.94	0.00	0.45	0.00	0.00	0.00
2009	5.00	0.00	3.64	0.30	0.00	0.00	0.00
2010	5.30	5.91	1.21	0.15	0.00	0.00	0.00
2011	1.52	4.70	0.76	0.00	0.00	0.00	0.00
2012	3.64	5.45	2.12	0.30	0.00	0.00	0.00
2013	2.73	0.91	1.67	0.76	0.00	0.00	0.00
2014	8.79	8.18	3.03	0.76	0.00	0.00	0.00

Table 2. Inhomogeneous L-cross, maximum aggregation radius between causes of wildfire (Ar: arson, Ng: negligence Nt: natural), and between outbreaks and fires (size) for arson and negligence wildfires.

	Cause			Size	
	Ar–Nt	Ar–Ng	Nt–Ng	Ar	Neg
1999	1.67	15.00	0.00	15.00	0.30
2000	0.15	13.18	0.00	15.00	8.18
2001	0.00	13.94	0.76	15.00	0.00
2002	1.82	15.00	4.55	15.00	15.00
2003	5.61	5.45	4.39	15.00	0.00
2004	0.76	15.00	0.00	15.00	3.18
2005	2.42	15.00	0.00	15.00	14.39
2006	1.67	15.00	0.00	15.00	8.33
2007	0.00	10.76	0.00	14.39	0.45
2008	0.00	9.24	1.06	15.00	0.00
2009	0.00	12.12	0.00	15.00	0.00
2010	0.00	15.00	0.00	15.00	5.45
2011	0.00	3.94	0.00	15.00	10.76
2012	3.64	15.00	0.30	15.00	15.00
2013	0.00	14.85	0.00	15.00	0.15
2014	4.09	11.82	0.00	15.00	0.00

interaction radius that reached 15 km within 2 days after an ignition. In other years, such as 2010 and 2013, the K-test found a shorter spatial and temporal aggregation radius, or even independence between ignition points, as found for 2007, in agreement with the findings of the spatial L-test. Similar results were found when testing for spatiotemporal interactions between arson fires (Fig. 7).

The inhomogeneous L-test found short-distance ($r < 1$ km) aggregation or even independence for wildfire events caused by negligence (see Supplementary Fig. B9). Positive interactions between outbreaks were found in 2002 and 2005 (Supplementary Fig. B10), and we only observed aggregation between fires caused by negligence in 2004 (Supplementary Fig. B11). The inhomogeneous L-cross test found evidence of positive interaction between outbreaks and fires caused by negligence for all years but 2001,2003, 2007 and 2014 (Table 2, Supplementary Fig. B12). Finally, we did not find evidence of interactions between negligence wildfires over sequential years (Supplementary Fig. B19). Data sparseness and the small sample size, particularly if we focus on negligence fires ($S < 1$ ha), advise against testing for spatiotemporal interactions.

For natural wildfires, the inhomogeneous L-test suggests aggregation at small distances in 2001, 2006 and 2009, and independence for the remaining years. The L-index tests suggests that the occurrence of natural fires over sequential years tended to be independent (Supplementary Fig. B20). As argued for the separability test, data sparseness and the

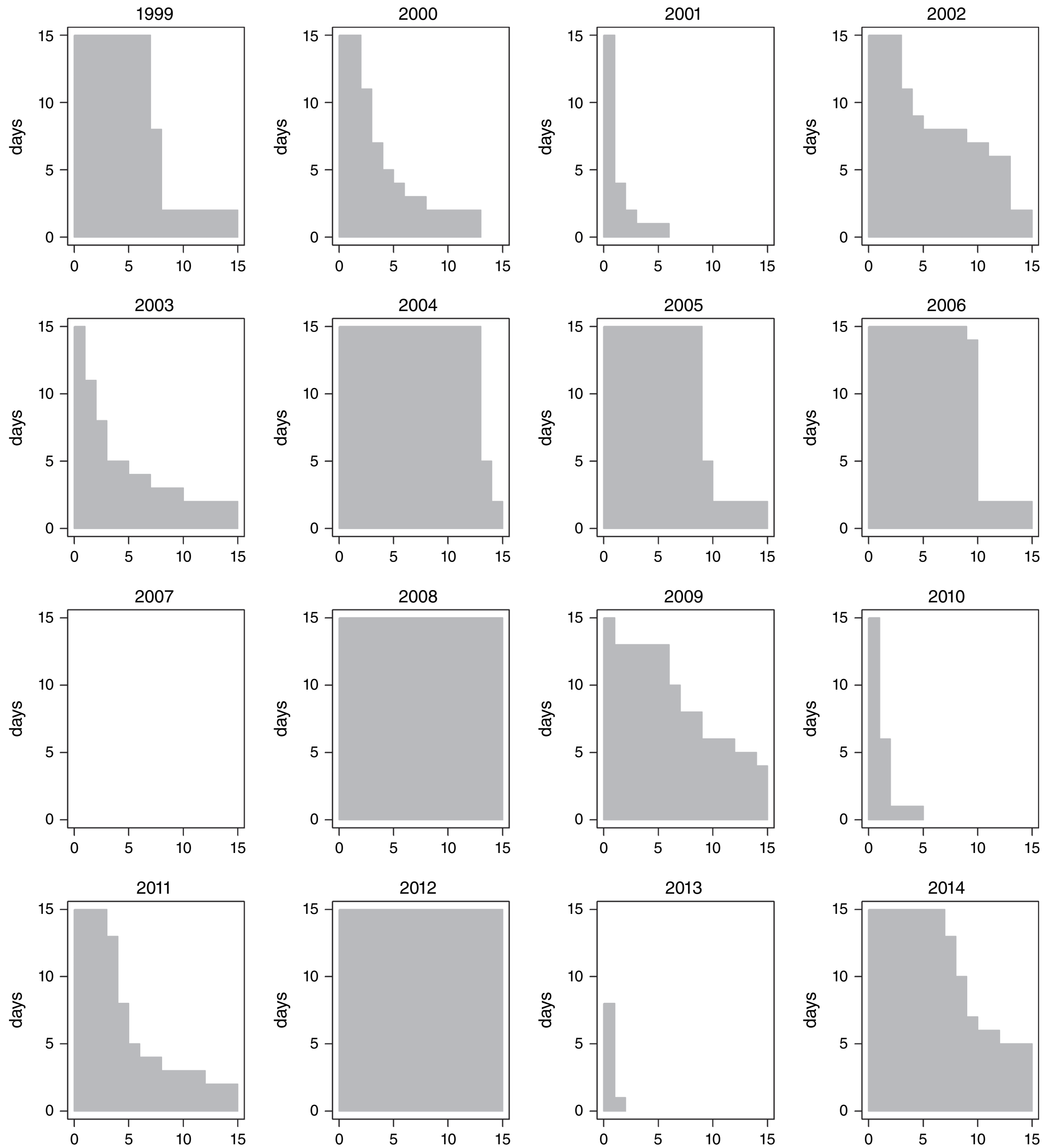

Fig. 6. Inhomogeneous spatiotemporal *K*-test for arson wildfires by year. In grey, the maximum spatial (*r*) and temporal (days) interaction ratios, i.e. the maximum values for which the observed inhomogeneous *K*-function is above the upper envelope for $B = 39$ realisations of a spatiotemporal Poisson point process with the same intensity as the observed pattern.

small number of events per year advise against testing for spatiotemporal interactions.

Searching for interaction between wildfire causes (Table 2), the inhomogeneous *L*-cross test did not find any spatial dependence between arson and natural wildfires at small distances, and detected inhibition between wildfires located more than 2 km apart in some years (Supplementary Fig. B14). Short-distance positive interactions were also found between natural and negligence wildfires (Supplementary Fig. B15), whereas the two types of human-cause fires showed mid- to large-distance aggregation (Supplementary Fig. B16). Note that these results

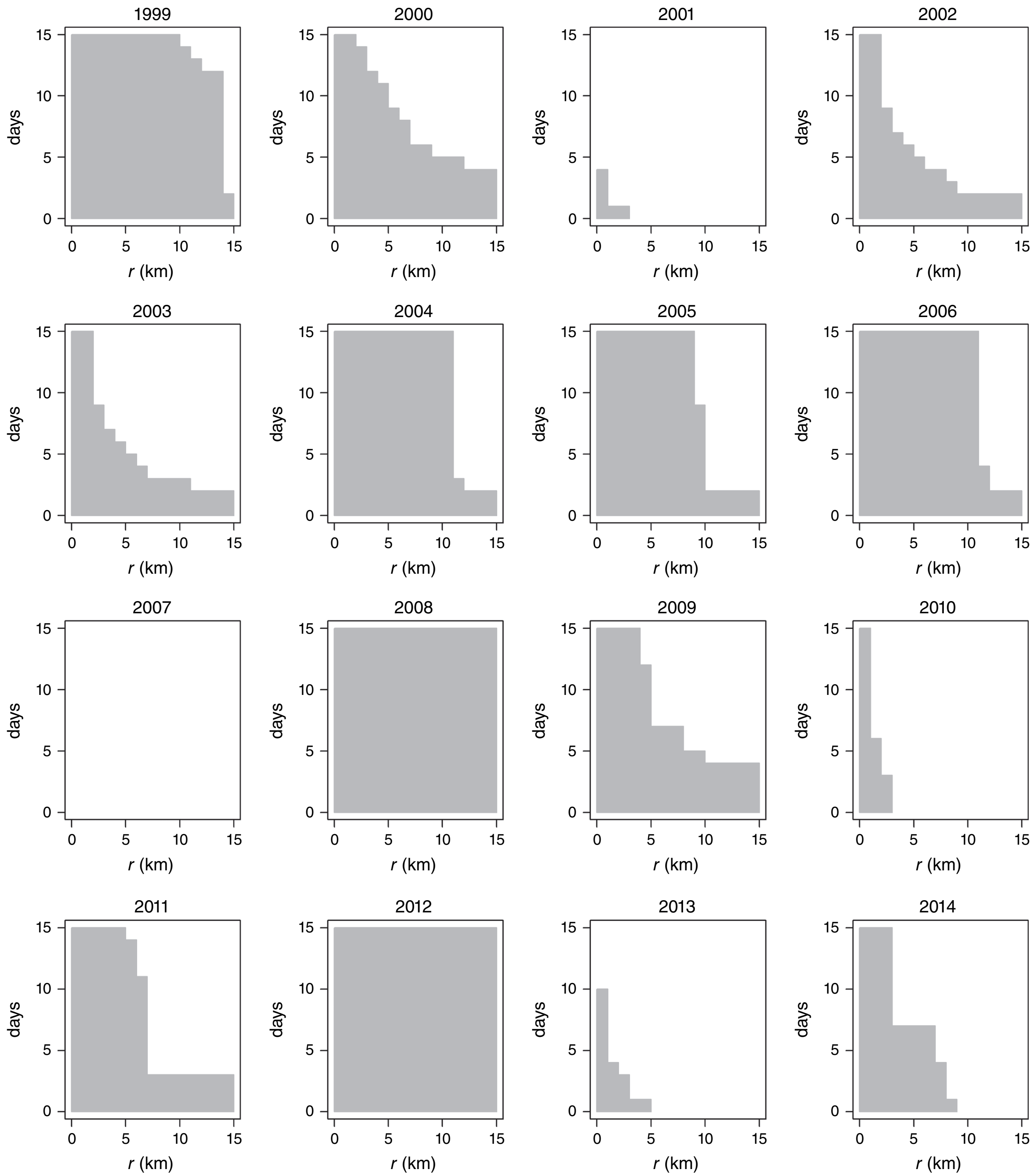

Fig. 7. Inhomogeneous spatiotemporal *K*-test for arson fires ($S > 1$ ha) by year. In grey, the maximum spatial (r) and temporal (days) interaction ratios, i.e. the maximum values for which the observed inhomogeneous *K*-function is above the upper envelope for $B = 39$ realisations of a spatiotemporal Poisson point process with the same intensity as the observed pattern.

should be regarded with caution given that the number of arson wildfires is much larger than the number of natural negligence wildfire events, i.e. we are dealing with highly unbalanced designs.

Discussion

Wildfire is a major environmental and socioeconomic problem in Galicia. In this work, we applied recently developed non-parametric inference techniques for spatial and spatiotemporal point processes to analyse the behaviour of forest fires recorded in Galicia from 1999 to 2014. Prior to delving deeper into the results of this study, it should be noted that Fig. 2 shows a decrease in the number of wildfires from 2007 onward; indeed, we observed a 67% reduction in wildfire incidence between the first half (9794 fires/year in 1999–2006) and the second half (3234 fires/year in 2007–2014) of the period under study. This decreasing trend has been attributed to the implementation of regional firefighting systems since the mid-1990s (Moreno *et al.* 2014; MAGRAMA 2016; Rodrigues *et al.* 2020). The burned area also decreased, from 35 000 ha/year in the first half to 17 500 ha/year in the second half. However, this reduction was lower than that of the number of fires, indicating an increase in the severity of wildfire (Dupuy *et al.* 2020; Moreno *et al.* 2021). Similar decreasing trends have been observed across Europe (Venäläinen *et al.* 2014; Krasovskii *et al.* 2016; MAGRAMA 2016; Vilar *et al.* 2016; Urbieta *et al.* 2019; Fernandez-Anez *et al.* 2021).

In spite of the observed reduction in wildfire incidence, the correspondence analysis highlights the continuous presence of arson fires during the whole period. Several works have reflected concern about the high incidence of arson fires in Galicia (Fuentes-Santos *et al.* 2013; Marey-Pérez *et al.* 2014; Álvarez-Díaz *et al.* 2015; Boubeta *et al.* 2015; Chas-Amil *et al.* 2015; Boubeta *et al.* 2016; Ríos-Pena *et al.* 2018; López-Rodríguez *et al.* 2021; Marey-Perez *et al.* 2021) and in Mediterranean Europe (Canepa and Drogo 2021; Palaiologou *et al.* 2021). In agreement with our observations, Vilar *et al.* (2016) found an increase in arson fires in the first decade of the 21st century in comparison with the last decade of the 20th century in Mediterranean Europe (Portugal, Spain, France and Italy), while the incidence of natural wildfires became negligible. Serra *et al.* (2013) found that human actions, either negligence or arson, are not only the main cause of wildfire in Catalonia (NE Spain) but also responsible for large fires, whereas natural fires tend to burn small areas.

Focusing on wildfire dynamics, we saw that arson, negligence and natural wildfires differ not only in number but also in their first- and second-order structure. Natural fires were concentrated in the summer months and their spatial distribution remained quite stable over the 16 years under study, the eastern area of Galicia being the most affected; this is a mountainous region with a high incidence of dry storms and a low population density (Pineda and Rigo 2017). Finally, evidence of interaction between natural wildfires was not found.

The spatial and temporal patterns of arson wildfires varied over years, with high-intensity areas shifting between the west coast and the southern area of Galicia, and higher wildfire incidence in early spring and late summer. In addition, the first-order separability tests found that the spatial distribution of arson fires also varied within years. In contrast with the independence found between natural fires, arson fires showed spatiotemporal clustering. These aggregated patterns, which indicate that the occurrence of an arson fire increased wildfire hazard in its neighbourhood for a few days after its detection, can be attributed to the behaviour of arsonists, who try to start a fire repeatedly in a given area until the meteorological conditions and lack of firefighting resources in the area allow fire spread. This hypothesis is supported by the strong aggregation found between small outbreaks and fires. On the other hand, the positive interaction between arson wildfires in subsequent years suggests that these fires are associated with long-term conflicts and socioeconomic conditions (López-Rodríguez *et al.* 2021; Marey-Perez *et al.* 2021). However, the lack of interannual aggregation between arson wildfires with more than 1 ha burned may be related to the long recovery time of burned forest. Similar clustered patterns were found in Portugal, with hotspots in the north-west of the country, on the boundary with Galicia (Tonini *et al.* 2017). As in Galicia, the majority of wildfires in Portugal are human-related and just a small proportion (~1%) have natural causes (Parente *et al.* 2018). Aragó *et al.* (2016) found that spatial interactions between human-caused wildfires in Castellón varied from inhibition to aggregation during the period 2001–2006.

Wildfires caused by negligence were concentrated in the Atlantic coastal area between 1999 and 2006, and mainly on the south coast of the region in the second half of the period under study. This type of forest fires has been linked with two main causes: agricultural and forestry activities, particularly the removal of unwanted or residual biomass (Lovreglio *et al.* 2010; Camia *et al.* 2013; Tedim *et al.* 2016), and an increase in the number of negligent wildfires in areas with high population density (Martínez *et al.* 2009; Vilar *et al.* 2010; Depicker *et al.* 2020; Pozo *et al.* 2022). Both origins explain the patterns observed in the present work. On one hand, the coastal area of Galicia has experienced a remarkable increase in agricultural activity in recent years, mainly in viticulture (Cachón *et al.* 2019) and horticulture (López-Iglesias 2019); grapevines (*Vitis vinífera*) and kiwifruit (*Actinidia deliciosa*) generate from 2 to 5 t/ha year of waste biomass (Mateus *et al.* 2021). This biomass is burned by farmers, resulting in a high wildfire hazard. On the other hand, Galicia can be described as a rural region suffering from high population loss (López-Penabad *et al.* 2022). However, a detailed analysis shows that the southwest (metropolitan area of Vigo) has registered a significant population increase (Otero-Varela and Paül 2022). This may imply an increase in outdoors activities, which are usually associated with a higher incidence of accidental and negligence wildfire (Chas-Amil *et al.* 2015; Calviño-Cancela and Cañizo-Novelle 2018; de Diego *et al.* 2021).

The differences found between the spatiotemporal dynamics of arson and natural fires may be associated with the factors that favour each type of fire, pointing out the need to use different covariates to model each type of fire. Natural wildfires, caused by lightning, are directly linked to meteorological conditions, orography and vegetation type (Fuentes-Santos *et al.* 2013; Jiménez-Ruano *et al.* 2019). However, although meteorological conditions play an important role in the spread of arson fires, these events are increased by socioeconomic factors such as distance to the wildland–urban interface (WUI), roads and railways (Álvarez-Díaz *et al.* 2015; Chas-Amil *et al.* 2015; Aragó *et al.* 2016; Zhang *et al.* 2016; Ruffault and Mouillot 2017; Calviño-Cancela and Cañizo-Novelle 2018). In fact, arson fires in Galicia have been attributed to conflicts about ownership and land use as well as rural abandonment (Marey-Pérez *et al.* 2014; Boubeta *et al.* 2015; Calviño-Cancela *et al.* 2016; Ríos-Pena *et al.* 2018; López-Rodríguez *et al.* 2021; Marey-Perez *et al.* 2021). In particular, Marey-Perez *et al.* (2021) recently showed an increase in the resilience to wildfire in those rural communities that have adapted their land management to fire. Along the same lines, Ferrara *et al.* (2019) found that territorial characteristics such as steep topography, depopulation and land abandonment, rural poverty, unemployment and restricted accessibility increase the incidence and severity of fires in Italy. Ruffault and Mouillot (2017) found that in Mediterranean Europe, where the majority of fires have anthropogenic origins, the spatial distribution of fire is mainly determined by human activities and settlements whereas the continuity and type of fuels drive fire spread and, consequently, the spatial distribution of large fires. In contrast with these findings, Zhang *et al.* (2016), who analysed wildfires detected by MODIS in south-eastern Australia, found that wildfire patterns are influenced by land cover, vegetation type and topography, whereas the impact of human-related factors is lower. It should be noted that although most fires in Australia are related to human activities, the MODIS database does not identify the cause of fires and has a bias towards natural wildfires, which does not allow a proper estimation of the actual dependence of wildfire on socioeconomic factors.

Point process models based on covariates have been applied to estimate wildfire incidence and burned area in the Mediterranean area of Spain (Serra *et al.* 2013; Aragó *et al.* 2016; Díaz-Avalos *et al.* 2016). Serra *et al.* (2013) used topography, meteorological conditions and distance to anthropic areas as covariates to model the spatial pattern of fires, finding a higher incidence of human-caused fires near cities and in forest areas, and a significant effect of aspect and land use on fire size. Aragó *et al.* (2016) and Díaz-Avalos *et al.* (2016) used land use, land cover and distance to roads to model the hazard of arson and natural fires and burned area in Castellón. Prior analyses of wildfires in Galicia have considered environmental and socioeconomic variables. Boubeta *et al.* (2015), who applied area-level Poisson models to estimate wildfire incidence at the forest district level, detected higher fire incidence in districts with small parcels and high scrub area in the application of this model to the wildfires recorded in 2007. Ríos-Pena *et al.* (2018) used meteorological variables to estimate wildfire incidence and burned area at the municipality level during the severe wave of wildfires episode in August 2006 using topographic and meteorological covariates. However, these models did not discriminate between arson and natural fires.

Conclusion

This work shows that non-parametric first- and second-order inference techniques for point processes are valuable tools to characterise the distribution of environmental or socioeconomic hazards. These techniques can be used to characterise wildfire dynamics in other regions, and also in other research areas, such as gun violence (Fuentes-Santos *et al.* 2021).

The long-term (1999–2014) spatiotemporal analysis of arson, negligence and natural wildfires in Galicia conducted in this work shows that they have different patterns, indicating that different models should be used to predict the hazard of each type of fire, and provides a characterisation of their dynamics. These results, in combination with the findings of prior work focused on modelling wildfire incidence (Boubeta *et al.* 2016, 2019; Ríos-Pena *et al.* 2018) and identifying socioeconomic risk factors (Marey-Pérez *et al.* 2014, 2021; López-Rodríguez *et al.* 2021) can be used as a starting point for the development of a predictive model for the hazard from arson fires, which is a priority in view of the high incidence and severity of these fires in Galicia. For this purpose, we can use a spatiotemporal point process model based on covariates (Serra *et al.* 2013; Aragó *et al.* 2016; Díaz-Avalos *et al.* 2016). However, the low spatial and temporal resolution of socioeconomic covariates has become an important limiting factor in advancing this line of research. We hope to make significant progress in the near future to cover this knowledge gap.

Supplementary material

Supplementary material is available online.

References

Álvarez-Díaz M, González-Gómez M, Otero-Giraldez MS (2015) Detecting the socioeconomic driving forces of the fire catastrophe in NW Spain. *European Journal of Forest Research* **134**(6), 1087–1094. doi:10.1007/s10342-015-0911-1

Aragó P, Juan P, Díaz-Avalos C, Salvador P (2016) Spatial point process modeling applied to the assessment of risk factors associated with forest wildfires incidence in Castellón, Spain. *European Journal of Forest Research* **135**(3), 451–464. doi:10.1007/s10342-016-0945-z

Baddeley A, Rubak E, Turner R (2015) 'Spatial point patterns: methodology and applications with R.' (Chapman and Hall/CRC)
Baddeley AJ, Møller J, Waagepetersen R (2000) Non- and semi-parametric estimation of interaction in inhomogeneous point patterns. *Statistica Neerlandica* **54**(3), 329–350. doi:10.1111/1467-9574.00144
Balsa-Barreiro J, Hermosilla T (2013) Socio-geographic analysis of the causes of the 2006s wildfires in Galicia (Spain). *Forest Systems* **22**(3), 497–509. doi:10.5424/fs/2013223-04165
Besag J (1977) Contribution to the discussion of Dr Ripley's paper. *Journal of the Royal Statistical Society, Series B (Methodological)* **39**(2), 193–195.
Birot Y, Rigolot E, Goldammer JG (2009) Conclusions. In 'Living with wildfires: what science can tell us. A contribution of the science-policy dialogue'. (Ed. Y Birot) pp. 79–82. (European Forest Institute: Joensuu, Finland) Available at https://efi.int/sites/default/files/files/publication-bank/2018/efi_discussion_paper_15.pdf
Boubeta M, Lombardía MJ, Marey-Pérez MF, Morales D (2015) Prediction of forest fires occurrences with area-level Poisson mixed models. *Journal of Environmental Management* **154**, 151–158. doi:10.1016/j.jenvman.2015.02.009
Boubeta M, Lombardía MJ, González-Manteiga W, Marey-Pérez MF (2016) Burned area prediction with semiparametric models. *International Journal of Wildland Fire* **25**(6), 669–678. doi:10.1071/WF15125
Boubeta M, Lombardía MJ, Marey-Pérez M, Morales D (2019) Poisson mixed models for predicting number of fires. *International Journal of Wildland Fire* **28**, 237–253. doi:10.1071/WF17037
Bowd EJ, Banks SC, Strong CL, Lindenmayer DB (2019) Long-term impacts of wildfire and logging on forest soils. *Nature Geoscience* **12**(2), 113–118. doi:10.1038/s41561-018-0294-2
Bowman AW, Azzalini A (1997) 'Applied Smoothing Techniques for Data Analysis: The Kernel Approach with S-Plus Illustrations'. Oxford Statistical Science Series 18. (Oxford University Press)
Bowman AW, Azzalini A (2014) 'R package sm: non-parametric smoothing methods (version 2.2-5.5).' (University of Glasgow, UK and Università di Padova: Italia)
Bruce D (1963) How many fires. *Fire Control Notes* **24**(2), 45–50.
Cachón DC, Crego ER, González NN, Camba PB (2019) Yeast diversity on grapes from Galicia, NW Spain: biogeographical patterns and the influence of the farming system: Macrowine 2018. *Oeno One* **53**(3), 573–587. doi:10.20870/oeno-one.2019.53.3.2379
Calviño-Cancela M, Cañizo-Novelle N (2018) Human dimensions of wildfires in NW Spain: causes, value of the burned vegetation and administrative measures. *PeerJ* **6**, e5657. doi:10.7717/peerj.5657
Calviño-Cancela M, Chas-Amil ML, García-Martínez ED, Touza J (2016) Wildfire risk associated with different vegetation types within and outside wildland–urban interfaces. *Forest Ecology and Management* **372**, 1–9. doi:10.1016/j.foreco.2016.04.002
Camia A, Durrunt HT, San-Miguel-Ayanz J (2013) Harmonized classification scheme of fire causes in the EU adopted for the European Fire Database of EFFIS. EUR 25923. Luxembourg (Luxembourg): Publications Office of the European Union. JRC80682. http://dx.doi.org/10.2788/86859
Canepa A, Drogo F (2021) Wildfire crime, apprehension and social vulnerability in Italy. *Forest Policy and Economics* **122**, 102330. doi:10.1016/j.forpol.2020.102330
Chacón JE, Duong T (2010) Multivariate plug-in bandwidth selection with unconstrained pilot bandwidth matrices. *Test* **19**(2), 375–398. doi:10.1007/s11749-009-0168-4
Chas-Amil ML, Prestemon JP, McClean CJ, Touza J (2015) Human-ignited wildfire patterns and responses to policy shifts. *Applied Geography* **56**, 164–176. doi:10.1016/j.apgeog.2014.11.025
Comas C, Costafreda-Aumedes S, Vega-García C (2014) Characterizing configurations of fire ignition points through spatiotemporal point processes. *Natural Hazards and Earth System Sciences Discussions* **2**(4), 2891–2911. doi:10.5194/nhessd-2-2891-2014
Costafreda-Aumedes S, Comas C, Vega-Garcia C (2016) Spatio-temporal configurations of human-caused fires in Spain through point patterns. *Forests* **7**(9), 185. doi:10.3390/f7090185
Costafreda-Aumedes S, Comas C, Vega-Garcia C (2017) Human-caused fire occurrence modelling in perspective: a review. *International Journal of Wildland Fire* **26**(12), 983–998. doi:10.1071/WF17026
Crosby JS (1954) Probability of fire occurrence can be predicted. USDA Forest Service, Central States Forest Experimental Station.
Da Ponte E, Costafreda-Aumedes S, Vega-Garcia C (2019) Lessons learned from arson wildfire incidence in reforestations and natural stands in Spain. *Forests* **10**(3), 229. doi:10.3390/f10030229
Davies TM, Marshall JC, Hazelton ML (2018) Tutorial on kernel estimation of continuous spatial and spatiotemporal relative risk. *Statistics in Medicine* **37**(7), 1191–1221. doi:10.1002/sim.7577
Depicker A, De Baets B, Baetens JM (2020) Wildfire ignition probability in Belgium. *Natural Hazards and Earth System Sciences* **20**(2), 363–376. doi:10.5194/nhess-20-363-2020
Díaz-Avalos C, Juan P, Serra-Saurina L (2016) Modeling fire size of wildfires in Castellon (Spain), using spatiotemporal marked point processes. *Forest Ecology and Management* **381**, 360–369. doi:10.1016/j.foreco.2016.09.013
de Diego J, Rúa A, Fernández M (2021) Vulnerability Variables and Their Effect on Wildfires in Galicia (Spain). A Panel Data Analysis. *Land* **10**, 1004. doi:10.3390/land10101004
Diggle P (1985) A kernel method for smoothing point process data. *Journal of the Royal Statistical Society. Series C (Applied Statistics)* **34**(2), 138–147. doi:10.2307/2347366
Diggle PJ (2013) 'Statistical analysis of spatial and spatio-temporal point patterns', 3rd edn. (CRC Press: Boca Raton, Florida)
Donoghue LR, Main WA (1985) Some factors influencing wildfire occurrence and measurement of fire prevention effectiveness. *Journal of Environmental Management* **20**(1), 87–96.
Duong T (2018) ks: Kernel smoothing. R package version 1.11.1. Available at https://CRAN.R-project.org/package=ks
Dupuy J-l, Fargeon H, Martin-StPaul N, Pimont F, Ruffault J, Guijarro M, Hernando C, Madrigal J, Fernandes P (2020) Climate change impact on future wildfire danger and activity in southern Europe: a review. *Annals of Forest Science* **77**(2), 35. doi:10.1007/s13595-020-00933-5
Fernandez-Anez N, Krasovskiy A, Müller M, Vacik H, Baetens J, Hukić E, Kapovic Solomun M, Atanassova I, Glushkova M, Bogunović I, *et al.* (2021) Current wildland fire patterns and challenges in Europe: a synthesis of national perspectives. *Air, Soil and Water Research* **14**, 11786221211028185. doi:10.1177/11786221211028185
Ferrara C, Salvati L, Corona P, Romano R, Marchi M (2019) The background context matters: Local-scale socioeconomic conditions and the spatial distribution of wildfires in Italy. *Science of the Total Environment* **654**, 43–52. doi:10.1016/j.scitotenv.2018.11.049
Fuentes-Santos I, Marey-Pérez MF, González-Manteiga W (2013) Forest fire spatial pattern analysis in Galicia (NW Spain). *Journal of Environmental Management* **128**, 30–42. doi:10.1016/j.jenvman.2013.04.020
Fuentes-Santos I, González-Manteiga W, Mateu J (2016) Consistent smooth bootstrap kernel intensity estimation for inhomogeneous spatial Poisson point processes. *Scandinavian Journal of Statistics* **43**(2), 416–435. doi:10.1111/sjos.12183
Fuentes-Santos I, González-Manteiga W, Mateu J (2017) A non-parametric test for the comparison of first-order structures of spatial point processes. *Spatial Statistics* **22**, 240–260. doi:10.1016/j.spasta.2017.02.007
Fuentes-Santos I, González-Manteiga W, Mateu J (2018) A first-order, ratio-based non-parametric separability test for spatiotemporal point processes. *Environmetrics* **29**(1), e2482. doi:10.1002/env.2482
Fuentes-Santos I, Gonzaléz-Manteiga W, Zubelli JP (2021) Non-parametric spatiotemporal analysis of violent crime. a case study in the Rio de Janeiro metropolitan area. *Spatial Statistics* **42**, 100431. doi:10.1016/j.spasta.2020.100431
Gabriel E, Diggle PJ (2009) Second-order analysis of inhomogeneous spatio-temporal point process data. *Statistica Neerlandica* **63**(1), 43–51. doi:10.1111/j.1467-9574.2008.00407.x
González-Olabarria JR, Mola-Yudego B, Coll L (2015) Different factors for different causes: analysis of the spatial aggregations of fire ignitions in Catalonia (Spain). *Risk analysis* **35**(7), 1197–1209. doi:10.1111/risa.12339
He J, Loboda TV, Chen D, French NHF (2022) Cloud-to-ground lightning and near-surface fire weather control wildfire occurrence in Arctic tundra. *Geophysical Research Letters* **49**(2), e2021GL096814. doi:10.1029/2021GL096814
Jiménez-Ruano A, Rodrigues Mimbrero M, Jolly WM, de la Riva Fernández J (2019) The role of short-term weather conditions in

temporal dynamics of fire regime features in mainland Spain. *Journal of Environmental Management* **241**, 575–586. doi:10.1016/j.jenvman.2018.09.107

Koutsias N, Kalabokidis KD, Allgöwer B (2004) Fire occurrence patterns at landscape level: beyond positional accuracy of ignition points with kernel density estimation methods. *Natural Resource Modeling* **17**(4), 359–375. doi:10.1111/j.1939-7445.2004.tb00141.x

Krasovskii A, Khabarov N, Migliavacca M, Kraxner F, Obersteiner M (2016) Regional aspects of modelling burned areas in Europe. *International Journal of Wildland Fire* **25**(8), 811–818. doi:10.1071/WF15012

López-Iglesias E (2019) The agricultural and agri-food sector in Galicia; assessment of changes since European integration, 1986-2016. *Revista Galega de Economía* **28**(3), 1–20. doi:10.15304/rge.28.3.6168

López-Penabad MC, Iglesias-Casal A, Rey-Ares L (2022) Proposal for a sustainable development index for rural municipalities. *Journal of Cleaner Production* **357**, 131876. doi:10.1016/j.jclepro.2022.131876

López-Rodríguez G, Rodríguez-Vicente V, Marey-Pérez MF (2021) Study of forest productivity in the occurrence of forest fires in Galicia (Spain). *Sustainability* **13**(15), 8472. doi:10.3390/su13158472

Lovreglio R, Leone V, Giaquinto P, Notarnicola A (2010) Wildfire cause analysis: four case-studies in southern Italy. *iForest - Biogeosciences and Forestry* **3**(1), 8–15. doi:10.3832/ifor0521-003

MAGRAMA (2016) Los incendios forestales en Espana. Decenio 2006–2015. (Coord. AL López-Santalla, M López-García). Ministerio de Agricultura, Pesca y Alimentación. Secretaría General Técnica. [In Spanish]

MAGRAMA (2019) Anuario de Estadística Forestal 2017. Ministerio de Agricultura Pesca y Alimentación. Secretaría General Técnica. [In Spanish]

Marey-Pérez MF, Rodríguez-Vicente V, Álvarez-López JC (2012) Practical application of multivariant analysis techniques to the forest management of active farmers in the northwest of Spain. *Small-scale Forestry* **11**(4), 453–476. doi:10.1007/s11842-012-9195-1

Marey-Pérez MF, Calvo-González A, Domínguez-Torres G (2014) Are the communal forest owners involved in the management of their lands? A qualitative analysis for the case of Galicia (Spain). *Bosque (Valdivia)* **35**(2), 207–215. doi:10.4067/S0717-92002014000200008

Marey-Perez M, Loureiro X, Corbelle-Rico EJ, Fernández-Filgueira C (2021) Different strategies for resilience to wildfires: the experience of collective land ownership in Galicia (northwest Spain). *Sustainability* **13**(9), 4761. doi:10.3390/su13094761

Marrs RH, Marsland E-L, Lingard R, Appleby PG, Piliposyan GT, Rose RJ, O'Reilly J, Milligan G, Allen KA, Alday JG, *et al.* (2019) Experimental evidence for sustained carbon sequestration in fire-managed, peat moorlands. *Nature Geoscience* **12**(2), 108–112. doi:10.1038/s41561-018-0266-6

Martínez J, Vega-Garcia C, Chuvieco E (2009) Human-caused wildfire risk rating for prevention planning in Spain. *Journal of Environmental Management* **90**(2), 1241–1252. doi:10.1016/j.jenvman.2008.07.005

Mateus S, Ferreira V, Sanches A, Resende P, Pinho C (2021) Determination of combustion kinetic data of some agricultural wastes from the Galicia-northern Portugal Euroregion. *Waste and Biomass Valorization* **12**(6), 3091–3107. doi:10.1007/s12649-020-01227-7

Moreno JM, Morales-Molino C, Torres I, Arianoutsou M (2021). Fire in Mediterranean pine forests: past, present and future. In 'Pines and their mixed forest ecosystems in the Mediterranean Basin'. (Eds G Ne'eman, Y Osem) pp. 421–456. (Springer)

Moreno MV, Conedera M, Chuvieco E, Pezzatti GB (2014) Fire regime changes and major driving forces in Spain from 1968 to 2010. *Environmental Science & Policy* **37**, 11–22. doi:10.1016/j.envsci.2013.08.005

Nampak H, Love P, Fox-Hughes P, Watson C, Aryal J, Harris RMB (2021) Characterizing spatial and temporal variability of lightning activity associated with wildfire over Tasmania, Australia. *Fire* **4**(1), 10. doi:10.3390/fire4010010

Otero-Varela A, Paül V (2022) The never-ending story of the metropolitan area of Vigo (Galicia, Spain). In 'International symposium: New metropolitan perspectives'. (Eds F Calabrò, L Della Spina, MJ Piñeira Mantiñán) pp. 946–956. (Springer) https://doi.org/10.1007/978-3-031-06825-6_90

Palaiologou P, Kalabokidis K, Troumbis A, Day MA, Nielsen-Pincus M, Ager AA (2021) Socio-ecological perceptions of wildfire management and effects in Greece. *Fire* **4**(2), 18. doi:10.3390/fire4020018

Parente J, Pereira MG, Tonini M (2016) Space-time clustering analysis of wildfires: The influence of dataset characteristics, fire prevention policy decisions, weather and climate. *Science of the Total Environment* **559**, 151–165. doi:10.1016/j.scitotenv.2016.03.129

Parente J, Pereira MG, Amraoui M, Tedim F (2018) Negligent and intentional fires in Portugal: Spatial distribution characterization. *Science of the Total Environment* **624**, 424–437. doi:10.1016/j.scitotenv.2017.12.013

Pausas JG, Keeley JE (2021) Wildfires and global change. *Frontiers in Ecology and the Environment* **19**(7), 387–395. doi:10.1002/fee.2359

Pineda N, Rigo T (2017) The rainfall factor in lightning-ignited wildfires in Catalonia. *Agricultural and Forest Meteorology* **239**, 249–263. doi:10.1016/j.agrformet.2017.03.016

Pineda N, Montanyà J, van der Velde OA (2014) Characteristics of lightning related to wildfire ignitions in Catalonia. *Atmospheric Research* **135–136**, 380–387. doi:10.1016/j.atmosres.2012.07.011

Pozo RA, Galleguillos M, González ME, Vásquez F, Arriagada R (2022) Assessing the socio-economic and land-cover drivers of wildfire activity and its spatiotemporal distribution in south-central Chile. *Science of the Total Environment* **810**, 152002. doi:10.1016/j.scitotenv.2021.152002

Prestemon JP, Hawbaker TJ, Bowden M, Carpenter J, Brooks MT, Abt KL, Sutphen R, Scranton S (2013) Wildfire ignitions: a review of the science and recommendations for empirical modeling. General Technical Reports SRS-GTR-171, 1–20. (USDA Forest Service, Southern Research Station: Asheville, NC)

R Core Team (2018) 'R: A Language and Environment for Statistical Computing.' (R Foundation for Statistical Computing: Vienna, Austria)

Ríos-Pena L, Kneib T, Cadarso-Suárez C, Marey-Pérez M (2017) Predicting the occurrence of wildfires with binary structured additive regression models. *Journal of Environmental Management* **187**, 154–165. doi:10.1016/j.jenvman.2016.11.044

Ríos-Pena L, Kneib T, Cadarso-Suárez C, Klein N, Marey-Pérez M (2018) Studying the occurrence and burnt area of wildfires using zero-one-inflated structured additive beta regression. *Environmental Modelling & Software* **110**, 107–118. doi:10.1016/j.envsoft.2018.03.008

Ripley BD (1977) Modelling spatial patterns. *Journal of the Royal Statistical Society: Series B (Methodological)* **39**, 172–192. doi:10.1111/j.2517-6161.1977.tb01615.x

Ripley BD (1981) 'Spatial statistics.' (Wiley: New York)

Rodrigues M, Jiménez A, de la Riva J (2016) Analysis of recent spatial–temporal evolution of human driving factors of wildfires in Spain. *Natural Hazards* **84**(3), 2049–2070. doi:10.1007/s11069-016-2533-4

Rodrigues M, Jiménez-Ruano A, Peña-Angulo D, De la Riva J (2018) A comprehensive spatial-temporal analysis of driving factors of human-caused wildfires in Spain using geographically weighted logistic regression. *Journal of Environmental Management* **225**, 177–192. doi:10.1016/j.jenvman.2018.07.098

Rodrigues M, Costafreda-Aumedes S, Comas C, Vega-García C (2019) Spatial stratification of wildfire drivers towards enhanced definition of large-fire regime zoning and fire seasons. *Science of the Total Environment* **689**, 634–644. doi:10.1016/j.scitotenv.2019.06.467

Rodrigues M, Jiménez-Ruano A, de la Riva J (2020) Fire regime dynamics in mainland Spain. part 1: Drivers of change. *Science of The Total Environment* **721**, 135841. doi:10.1016/j.scitotenv.2019.135841

Ruffault J, Mouillot F (2017) Contribution of human and biophysical factors to the spatial distribution of forest fire ignitions and large wildfires in a French Mediterranean region. *International Journal of Wildland Fire* **26**(6), 498–508. doi:10.1071/WF16181

San-Miguel-Ayanz J, Moreno JM, Camia A (2013) Analysis of large fires in European Mediterranean landscapes: lessons learned and perspectives. *Forest Ecology and Management* **294**, 11–22. doi:10.1016/j.foreco.2012.10.050

Serra L, Juan P, Varga D, Mateu J, Saez M (2013) Spatial pattern modelling of wildfires in Catalonia, Spain 2004–2008. *Environmental Modelling & Software* **40**, 235–244. doi:10.1016/j.envsoft.2012.09.014

Silva JMN, Moreno MV, Le Page Y, Oom D, Bistinas I, Pereira JMC (2019) Spatiotemporal trends of area burnt in the Iberian Peninsula, 1975–2013. *Regional Environmental Change* **19**(2), 515–527. doi:10.1007/s10113-018-1415-6

Tedim F, Leone V, Xanthopoulos G (2016) A wildfire risk management concept based on a social-ecological approach in the European Union: Fire Smart territory. *International Journal of Disaster Risk Reduction* **18**, 138–153. doi:10.1016/j.ijdrr.2016.06.005

Tonini M, Pereira MG, Parente J, Orozco CV (2017) Evolution of forest fires in Portugal: from spatio-temporal point events to smoothed density maps. *Natural Hazards* **85**(3), 1489–1510. doi:10.1007/s11069-016-2637-x

Urbieta IR, Franquesa M, Viedma O, Moreno JM (2019) Fire activity and burned forest lands decreased during the last three decades in Spain. *Annals of Forest Science* **76**(3), 90. doi:10.1007/s13595-019-0874-3

van Lieshout MNM (2020) Infill asymptotics and bandwidth selection for kernel estimators of spatial intensity functions. *Methodology and Computing in Applied Probability* **22**, 995–1008. doi:10.1007/s11009-019-09749-x

Venäläinen A, Korhonen N, Hyvärinen O, Koutsias N, Xystrakis F, Urbieta IR, Moreno JM (2014) Temporal variations and change in forest fire danger in Europe for 1960–2012. *Natural Hazards and Earth System Sciences* **14**(6), 1477–1490. doi:10.5194/nhess-14-1477-2014

Vilar L, Woolford DG, Martell DL, Martín MP (2010) A model for predicting human-caused wildfire occurrence in the region of Madrid, Spain. *International Journal of Wildland Fire* **19**(3), 325–337. doi:10.1071/WF09030

Vilar L, Camia A, San-Miguel-Ayanz J, Martín MP (2016) Modeling temporal changes in human-caused wildfires in Mediterranean Europe based on land use–land cover interfaces. *Forest Ecology and Management* **378**, 68–78. doi:10.1016/j.foreco.2016.07.020

Vilar del Hoyo LV, Isabel MPM, Vega FJM (2011) Logistic regression models for human-caused wildfire risk estimation: analysing the effect of the spatial accuracy in fire occurrence data. *European Journal of Forest Research* **130**(6), 983–996. doi:10.1007/s10342-011-0488-2

Wing MG, Long J (2015) A 25-year history of spatial and temporal trends in wildfire activity in Oregon and Washington, USA. *Modern Applied Science* **9**(3), . 117–132. doi:10.5539/mas.v9n3p117

Woo H, Chung W, Graham JM, Lee B (2017) Forest fire risk assessment using point process modelling of fire occurrence and Monte Carlo fire simulation. *International Journal of Wildland Fire* **26**(9), 789–805. doi:10.1071/WF17021

XERA (2018) La cadena forestal – madera en Galicia 2017. 2018, Axencia Galega da Industria Forestal. (Coord. J Picos) (Consellera de Economa e Industria, Universidade de Vigo)

Zhang Y, Lim S, Sharples JJ (2016) Modelling spatial patterns of wildfire occurrence in south-eastern Australia. *Geomatics, Natural Hazards and Risk* **7**(6), 1800–1815. doi:10.1080/19475705.2016.1155501

Data availability. Wildfire data used in this were obtained form the Wildfire Statistics dataset of the Wildfire General Statistics available at the Spanish Government Data Portal (https://datos.gob.es/es/catalogo/e05068001-estadistica-general-de-incendios-forestales).

Conflicts of interest. Thea authors declare no conflicts of interests.

Declaration of funding. This work was supported by Projects MTM2016-76969-P and PID2020-116587GB-I00 (AEI/FEDER, UE), and projects IN607B: Modalidad B – Grupos con potencial crecemento, GPC GI-1716 PROXECTOS E PLANIFICACIÓN (PROEPLA), 2018-PG078 (Ref. ED431B 2018/23) from the Galician Government (Xunta the Galicia).

Acknowledgements. We would like to acknowledge Luis Franco for his technical support in the access and pre-processing of wildfire data.

Author affiliations

[A]PROePLA Research Group, Department of Crop Production and Engineering Projects, Universidade de Santiago de Compostela, Spain.

[B]Marine Research Institute, Spanish National Research Council, Spain.

[C]Department of Statistics, Mathematical Analysis and Optimisation, University of Santiago de Compostela, Spain.