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Discussions

Characterizing configurations of fire ignition points through spatiotemporal point processes

C. Comas[1], S. Costafreda-Aumedes[2], and C. Vega-Garcia[2]

[1]Department of Mathematics, University of Lleida, Agrotecnio Centre, Spain
[2]Department of Agriculture and Forest Engineering, University of Lleida, Spain

Correspondence to: C. Comas (carles.comas@matematica.udl.cat)

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Abstract

Human-caused forest fires are usually regarded as unpredictable but often exhibit trends towards clustering in certain locations and periods. Characterizing such configurations is crucial for understanding spatiotemporal fire dynamics and implementing

5 preventive actions. Our objectives were to analyse the spatiotemporal point configuration and to test for spatiotemporal interaction. We characterized the spatiotemporal structure of 984 fire ignition points in a study area of Galicia, Spain, during 2007–2011 by the K-Ripley's function. Our results suggest the presence of spatiotemporal structures for time lags of less than two years and ignition point distances in the range

10 0–12 km. Ignition centre points at time lags of less than 100 days are aggregated for any inter-event distance. This cluster structure loses strength as the time lag increases, and at time lags of more than 365 days this cluster structure is not significant for any lag distance. Our results also suggest spatiotemporal interdependencies at time lags of less than 100 days and inter-event distances of less than 10 km. At time lags of up

15 to 365 days spatiotemporal components are independent for any point distance. These results suggest that risk conditions occur locally and are short-lived in this study area.

1 Introduction

Human-caused forest fires accounted for more than 95 % of all wildfires occurred in Spain in the last ten years (2002–2011) and burned an annual average area of

20 120 000 ha (MAGRAMA, 2012). These fires were not randomly distributed: the ignition points showed broadly identifiable spatial and temporal patterns (Moreno et al., 2011; Padilla and Vega-Garcia, 2011; Juan et al., 2012; Díaz-Avalos et al., 2013). For instance, fire starts occurred most often near roads (see among others Badia-Perpinya and Pallares-Barbera, 2006; MAGRAMA, 2012), near urban– and cropland–forest in-

25 terfaces (Martínez et al., 2009; Moreno et al., 2011) and in areas with an extensive presence of shrubs or conifers (Torre-Antón, 2010; Verdú et al., 2012). Fire starts also

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showed clustered temporal structures due to the seasonal distribution of the risk of ignitions (Prestemon et al., 2012).

Because the number of wildfires can vary widely between locations and time spans, the characterization of spatiotemporal patterns of fire ignition can provide important information for optimizing resource allocation in strategic firefighting (Genton et al., 2006; Carmel et al., 2009) and generally inform forest and fire policies (Chas-Amil et al., 2010). These strategies usually focus on the control of potential multiple-fire days or large forest fires in areas and periods with high risk of fire (Martell, 2007; Gonzalez-Olabarria et al., 2012). Because of budgetary restrictions and rising firefighting costs, it is usually impossible to maintain sufficient resources to cope with all potential multiple-fire days or potential large fires (Alonso-Betanzos et al., 2003). In fact, under extreme weather conditions, available firefighting resources may be overloaded beyond suppression capacity. In these cases, the ability to anticipate high-risk wildfire events and take preventive actions, or to pre-position firefighting resources in advance, can reduce the damages and optimize the use of the suppression resources (Boychuk and Martell, 1988; Genton et al., 2006).

Several previous studies have focused on the spatial and/or temporal distribution of wildland fires. For instance, Prestemon and Butry (2005) and Padilla and Vega-Garcia (2011) identified the most significant spatial variables for analysing human-caused fire occurrence using non-spatially explicit models (autoregressive Poisson and logit processes). Other studies have focused on spatially explicit models to explain patterns of fire occurrence using, for instance, geographically weighted regression (de la Riva et al., 2004), ignition density estimates (Amatulli et al., 2007) or Ripley's K function (Turner, 2009; Juan et al., 2012). A statistically significant positive autocorrelation of fire counts per parish in Galicia, Spain, has been found by Chas-Amil et al. (2012). A few studies have focused on the temporal pattern of fire ignitions. For instance, Gralewicz et al. (2011) found temporal aggregations using temporal trajectory metrics of wildfire ignition densities, while Tanskanen and Venäläinen (2008) found temporal aggregations when analysing the fire weather indices of summer fire ignitions in Fin-

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land. Prestemon et al. (2012) time series fire occurrence models included temporal and and spatiotemporal lags lasting up to 2–3 days.

All these previous studies found spatial and temporal aggregation patterns between fire start events, though none of them considered the spatiotemporal interdependencies (spatiotemporal structures).

Wildfire occurrences have also been analysed as points placed within a spatiotemporal region using point process statistical tools. These tools include, for instance, analysis of inhomogeneous spatiotemporal structures of wildfire ignitions (Hering et al., 2009), modelling of fire locations by spatiotemporal Cox point processes (Møller and Díaz-Avalos, 2010), and spatiotemporal analysis of fire ignition points combined with geographical and environmental variables (Juan et al., 2012). Here we consider inhomogeneous spatiotemporal point processes to analyse the point pattern configuration of fire ignition points of a data set in Galicia, Spain. This approach was taken because of the apparent inhomogeneous structure of this spatiotemporal point pattern. The analysis of these spatiotemporal point configurations may be valuable for interpreting the spatiotemporal dependencies of fire ignitions points in order to understand wildfire dynamics and to predict ignition points over time periods spanning several years.

The main aims of this study were to analyse the spatiotemporal structure of fire starts for a data set located in Galicia (Spain) and to characterize the related interaction between the spatial and temporal components. To this end, we applied the inhomogeneous spatiotemporal counterpart version of Ripley's K function proposed by Gabriel and Diggle (2009) to analyse this spatiotemporal configuration.

2 Materials and methods

2.1 Study area

The study area is a square region of 30 km × 30 km located in southwest Galicia, Spain, and bounded by UTM coordinates [532450, 4665950] and [562450, 4695950] within

the *Galicia litoral meridional y montañas occidentales* ecoregion (as defined in Garcia del Barrio et al., 2001, see Fig. 1). Galicia is the Spanish region most affected by wildfires, with more than 80 % classified as intentional, but with only 9 % classified as unknown-caused, one of the lowest rates in Spain (Chas-Amil et al., 2010). Wildfires usually aggregate on the Atlantic coast and in the south (Chas-Amil et al., 2012), where the study area is placed. The study area is representative of conditions in this high-risk Spanish ecoregion and provides a reasonable number of points for obtaining robust estimators of summary statistics to study the spatiotemporal dynamics of fire ignition. The climate in the region is coastal Atlantic, with a mean annual precipitation of 1200 mm that peaks in autumn–winter and a mean annual temperature of 14.5 °C. These conditions favor the rapid growth of vegetation in spring, mainly composed in natural conditions of Euro-Siberian broadleaved tree species (*Quercus robur L.*, *Quercus pyrenaica Willd.*) and grasses. Forests have been highly fragmented by human activities over time, and livestock production is currently an important economic activity that maintains traditional uses of fire in a fine-grain landscape mosaic in which many agricultural plots are abandoned. Highly productive forest covers 35 % of the land area and the main species are fire-prone *Pinus pinaster Ait.* and *Eucalyptus globulus Labill.*, which are demanded by pulp and plywood markets. Forest land is privately owned (98 %), with two-thirds of the area in very small units of 0.3 ha average size, and one-third in collective private properties around 230 ha (Chas-Amil, 2007). These and other structural risk factors have been proposed to explain why Galicia is the Spanish region with the highest number of human-caused forest fires (99 %) (Vázquez and Moreno, 1998). From 2002 to 2011, of the 67 910 human-caused fires that occurred in Galicia, 5013 started in our study area. Fires take place mainly in two time periods, late winter (February–April) and summer (August–September), and they are linked to socioeconomic activities and traditional agricultural-cattle-related use of fire, but also to a wide and complex mix of social motivations categorized in up to forty classes in fire statistics (Chas-Amil et al., 2010). Arson may be triggered by malice, vengeance, vandalism, thrill-seeking behaviour, pyromania, ownership conflicts, hunting or pastoral

rights, protest against policies, land use changes, political motivations and many other drivers (Chas-Amil et al., 2010; Prestemon et al., 2012).

2.2 Fire data

Our data set involved historical records of daily human-caused forest fire occurrences in an ecoregion of Galicia during the period 2007–2011. This data set was provided by the Spanish Forest Service of the Ministry of Environment and Rural and Marine Affairs (MAGRAMA). The period of study was restricted to five years due to data availability, but this period was considered appropriate because it is approximately the usual time framework for fire prevention planning in Spain. Moreover, the unusual weather, fuel and human risk conditions in August 2006 (1900 fires set in just 12 days), affecting impenetrable forest with low accessibility and close to human habitations, forced a turning point in forest and fire fighting policies in Galicia already in 2007 (Chas-Amil, 2007). The spatiotemporal point pattern consisted of 984 fire ignition points located in a square area of 30 km × 30 km for the five years, with 110 ignitions in 2007, 138 in 2008, 216 in 2009, 247 in 2010 and 273 in 2011.

2.3 Spatiotemporal statistics

To analyse the spatiotemporal structure of inhomogeneous point patterns representing ignition point fires, we used the spatiotemporal counterpart version of Ripley's K function proposed by Gabriel and Diggle (2009). For a review about space-time point processes see Illian et al. (2008). Consider a stationary and anisotropic spatiotemporal point process Φ on $\Re^2 \times \Re$ whose elements form a countable set $S_i = (X_i, t_i)$, for $i = 1, \ldots, n$ and $X_i = (x_i, y_i) \in \Re^2$ and $t_i \in \Re$ in a bounded region $M = W \times T$. Loosely speaking, this M region contains all the ignition fires for a given planar region W for a time interval $T \in [T_0, T_1]$. Now the point pattern should be assumed as a set of points in a continuous tridimensional space. Strictly speaking, the inhomogeneous spatiotemporal Ripley's K function proposed by Gabriel and Diggle (2009) assumes that the point

pattern under analysis is second-order intensity reweighted stationary and isotropic or, in other words, it assumes a weaker form of stationarity and therefore relaxes the hypothesis of homogeneity. This function is defined by the authors as (see also, Møller and Ghorbani, 2012)

$$K_{st}(u,v) = 2\pi \int_{-v}^{v} \int_{0}^{u} g(u',v')u'\mathrm{d}u'\mathrm{d}v', \tag{1}$$

where u and v are the spatial distance and the time interval to be tested, and $g(u,v)$ is a spatiotemporal counterpart version of the pair correlation function (see, for instance, Illian et al., 2008). Loosely speaking, (1) is the expected number of further points in a spatiotemporal region delimited by a cylinder whose bottom surface area is centred at an arbitrary point of Φ with radius u and height $2v$. Note that Gabriel and Diggle (2009) also proposed a version of Eq. (1) in which only future events are considered. For any inhomogeneous Poisson process with spatiotemporal intensity function bounded away from zero, $K_{st}(u,v) = 2\pi u^2 v$, and hence $K_{st}(u,v) - 2\pi u^2 v$ can be considered a measure for detecting spatiotemporal point dependences (Gabriel and Diggle, 2009). Values of $K_{st}(u,v) - 2\pi u^2 v < 0$ will indicate regularity, while $K_{st}(u,v) - 2\pi u^2 v > 0$ will suggest spatiotemporal clustering. Moreover, $K_{st}(u,v)$ can also be used to detect absence of spatiotemporal interaction. In particular, separability of $K_{st}(u,v)$ into purely spatial and temporal components, $K_{st}(u,v) = K_s(u)K_t(v)$, suggests absence of spatiotemporal dependency (Diggle et al., 1995). The lack of spatiotemporal interaction indicates that ignition point locations and ignition times are independent, i.e. there is no correlation between where a fire happens and when it happens. However, in real life one may expect these two components to be correlated, so the time occurrence of a fire will depend on the spatial location. From the theoretical definition of Eq. (1), an edge-

corrected estimator of this function can be defined via (Gabriel et al., 2013)

$$\hat{K}_{st}(u,v) = \frac{1}{|W \times T|} \sum_{i=1}^{n} \sum_{j \neq i}^{n} \frac{1}{\omega_{ij} v_{ij}} \frac{I(u_{ij} \leq u) I(|t_j - t_i| \leq v)}{\hat{\lambda}(S_i)\hat{\lambda}(S_j)}, \tag{2}$$

where n is the total number of points in M, $u_{ij} = \|X_i - X_j\|$, $I(\cdot)$ is the indicator function
where $I(F) = 1$ if F is true and $I(F) = 0$ otherwise, $|W \times T|$ denotes the volume of this
region and $\hat{\lambda}(\cdot)$ is an estimator of the spatiotemporal intensity function at the location
S_i (say) or, in other words, an estimator of expected number of points per unit volume
at this exact location. To correct spatial edge effects we use Ripley's factor ω_{ij} (Ripley,
1976) and to deal with time-edge effects we consider v_{ij}. It is equal to 1 if both ends
of the interval of length $2|t_j - t_i|$ centred at t_j lie between T and $1/2$ otherwise (Gabriel
et al., 2013).

To obtain an estimator of the spatiotemporal intensity function we adopt the prag-
matic working assumption that first-order effects (i.e. the intensity function) are sepa-
rable from the space and the time domain, as suggested by Gabriel and Diggle (2009),
i.e.

$$\lambda(X,t) = m(X)\mu(t), \tag{3}$$

and thus any non-separable effects can be considered as second-order effects (i.e.
related to the variance of the process) rather than first-order effects. From Eq. (3) we
can estimate $\lambda(\cdot)$ as

$$\hat{\lambda}(X,t) = \hat{m}(X)\hat{\mu}(t). \tag{4}$$

We used a Gaussian kernel-based estimator for $m(X)$ (Silverman, 1986; Baddeley
et al., 2000), with bandwidth to visually fit the empirical point pattern. Initially, we used
a kernel bandwidth chosen to minimize the estimated mean-square error of $\hat{m}(X)$, as
suggested in Berman and Diggle (1989). However, the resulting bandwidth generated

very sharp intensity surfaces, promoting the presence of very high-intensity values or very low-intensity ones (zero values). To avoid zero-intensity values we used a slightly larger value of bandwidth than that obtained by Berman and Diggle's optimization, while visually fitting the empirical point pattern. The time intensity, $\mu(t)$, is estimated using a restricted cubic spline regression (Harrell, 2001). We used a spline regression because it is a smooth, flexible curve that makes no strict mathematical assumption on the shape of this intensity while providing a robust intensity estimator for this data set. In particular, we used 6 knots at the 5th, 23rd, 41st, 59th, 77th and 99th percentiles of these five years to provide a flexible parametric model (Harrell, 2001, p. 23). Notice that suitable estimates of $m(X)$ and $\mu(t)$ in Eq. (3) will depend on the characteristics of each application. For instance, Gabriel and Diggle (2009) used a kernel-based estimator for the spatial intensity and a parametric log-linear model for $\mu(t)$.

To test for evidence of spatiotemporal clustering or regular structures, we follow common practice by comparing the estimator $\hat{K}_{st}(u, v)$ with estimates obtained for simulations under a suitable null hypothesis. Here the null hypothesis is that the underlying point process is an inhomogeneous Poisson process, and therefore the empirical spatiotemporal pattern is compared with a spatiotemporal Poisson process with point intensity Eq. (4), based on a Monte Carlo test. We simulate 199 spatiotemporal point patterns under this null hypothesis and for each one an estimator of Eq. (1) is obtained. This set of functions is then compared with the resulting estimator for the empirical data under analysis. Under this test, we reject the null hypothesis (spatiotemporal point independence) if the resulting estimator of this function lays outside the fifth-largest and/or fifth-smallest envelope values obtained from the set of simulated functions (Eq. 2), with an exact significance level of $\alpha = 2 \times 5/(199 + 1) = 0.05$. A similar approach is used to test for spatiotemporal interaction. In this case, the comparison is between the data and simulations based on random permutation of the spatial locations, X_i, holding the time, t_i, fixed.

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All the spatiotemporal statistical analyses were computed using the *stpp* statistical package (Gabriel et al., 2013) for the *R* statistical environment (R Development Core Team, 2007).

3   Results

Figure 2a shows the spatial positions of the 984 ignition points from 2007 to 2011 in the study area. Visual inspection of this point pattern highlights that the point structure is clearly inhomogeneous, with areas of high point intensity followed by areas of low point intensity. This figure also highlights the presence of point clusters, suggesting that these events can be aggregated in space and time.

The resulting Gaussian kernel-based estimator for the space intensity $m(X)$ (see Fig. 2b) confirms the presence of this inhomogeneous structure for the empirical point pattern. Moreover, the estimator of the time intensity of ignition fires is shown in Fig. 2c together with the number of ignition points per day for the five years of study, highlighting that the number of ignition points for this period of time apparently follows a cyclic structure that repeats itself annually. Changes in the number and percentile positions of knots do not significantly affect the resulting parametric model for this data set.

Figure 3a shows $\hat{K}_{st}(u,v) - 2\pi u^2 v$ for times lags of less than $T_1/2 = 730$ days (two years) and a maximum spatial interval of around 12 km. We used these maximum time and space intervals to avoid edge effects that are probably not corrected by the mathematical assumptions made here. Figure 3b shows a more detailed view for this estimator under the time domain. These figures suggest the presence of spatiotemporal structures for time lags of less than two years and ignition point distances in the range [0, 12] km. Clustered point configurations are apparent for time lags of less than 100 days (3 months) and inter-ignition point distances of less than 12 km. Under time lags of up to 100 days and large inter-event distances (> 5 km), $\hat{K}_{st}(u,v) - 2\pi u^2 v < 0$, thereby suggesting regularity.

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Let us now test whether these departures of $\hat{K}_{\text{st}}(u, v) - 2\pi u^2 v$ from 0 are significant. Figure 4 shows $\hat{K}_{\text{st}}(u, v) - 2\pi u^2 v$ for time lags $v = 30$ days, 100 days (around three months), 180 days (6 months), 365 days (12 months), 540 days (18 months) and 730 days (24 months), together with the resulting fifth-largest and fifth-smallest envelope values based on 199 inhomogeneous Poisson point randomizations with intensity (Eq. 4). There is evidence that ignition points at time lags of less than 100 days are aggregated for any inter-event distance. Moreover, this cluster structure loses strength as the time lag increases. In fact, for a time lag of less than 180 days this clustered configuration is only significant for lag distances of less than 4 km; for time lags of more than 365 days this cluster structure is not significant for any lag distance, suggesting that ignition points are independent up to that time interval and for any inter-point distance. Similarly, Fig. 5 shows $\hat{K}_{\text{st}}(u, v) - 2\pi u^2 v$ for the same time lags as in Fig. 4, together with the resulting fifth-largest and fifth-smallest envelope values based on 199 simulations assuming random permutation of the spatial locations, X_i, holding the time, t_i, fixed. This finding highlights the presence of spatiotemporal interaction at time lags of less than 100 days (three months) and inter-event distances of less than 10 km. Moreover, these spatiotemporal interdependencies lose strength as the time lag increases; at the time lag of 180 days these dependencies are only observable for inter-ignition point distances of less than 4 km. For time lags greater than 365 days and any inter-event distance, the spatial and temporal components are independent, suggesting that with respect to an arbitrary ignition point, the time occurrence of a new fire start within the next 365 days will be only related to the spatial position.

4 Discussion

The spatiotemporal analysis of human-caused fire ignition points in a study area located in Galicia (Spain) suggests the presence of spatiotemporal structures for time lags of less than two years and ignition point distances in the range 0–12 km. This result is in full agreement with the findings of other authors who have also detected spa-

tiotemporal structures (see for instance Marey-Perez et al., 2010; Juan et al., 2012). In particular, ignition points at time lags of less than 100 days are aggregated for any inter-event distance. This structure suggests the presence of local fire risk factors (< 12 km) with a short interval prevalence (< 100 days), which may promote this aggregated spatiotemporal configuration. Moreover, this cluster structure loses strength as the time lag increases, and at time lags of between 540 and 730 days it is not significant for any lag distance. This indicates that at a seasonal level (for a time lag of less of, say, six months) the persistence of these risk factors is very local (< 4 km). In fact, this lack of spatiotemporal structure for large lag intervals seems to suggest that in this area there are no persistent risk factors that are repeated on an annual basis, such as ongoing local social conflicts (i.e. for hunting rights), cyclic traditional agricultural practices (Barreal et al., 2011) or long-term serial firesetters as suggested by Chas-Amil et al. (2012), but there may be on a short-term basis. However, caution should be used in this context as the database for analysis only allowed dependencies up to 730 days to be explored. Risk factors linked to shrub-burning cycles, for instance, generally take place in Galicia over periods longer than 18–24 months (J. Ramírez, personal communication, 2013).

Regarding the short range of inter-ignition point distances, results are in agreement with the fragmented land mosaic structure of the area. Martínez et al. (2009) found agricultural fragmentation to be a factor of human risk, as higher density of plots and properties increase likelihood of conflicts, negligence and use of fire to eliminate vegetation and residues and to reclaim abandoned lands.

The results allow for the proposition by Chas-Amil et al. (2012) about the possible influence of serial firesetters on the clustered spatial pattern in Galicia, but given the range 0–12 km adopted to avoid edge effects conditions, the influence of copycat firesetters in distant locations could not be accounted for. This influence of window frame size (30 km × 30 km) on the results remains to be explored in future research.

5 Conclusions

We conclude that fire ignition points are correlated (aggregated) for short inter-event distances (< 12 km) and short time lags (< 1 year). Moreover, the spatiotemporal inter-dependencies found for short time lags (< 182 days) suggest that the occurrence of any fire will depend on where and when others happen. This finding suggests that factors ruling fire starts are likely to be variable on a yearly basis. Fire ignitions in the study area respond to biophysical (i.e. weather, fuels, topography, fragmentation) and complex socioeconomic factors (i.e. forest property, population, weekends, law enforcement and arrests) (Prestemon et al., 2012). Thus, fire occurrence modelling schemas should rely more on these annually variable risk factors than on more persistent ones. And in fact, fire occurrence modelling based on biophysical and socioeconomic variables should be approached using techniques that allow such spatial and temporal dependencies to be incorporated, especially if the goal is to predict wildfire occurrences with high temporal and spatial resolution.

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Spatiotemporal characterization of fire ignitions

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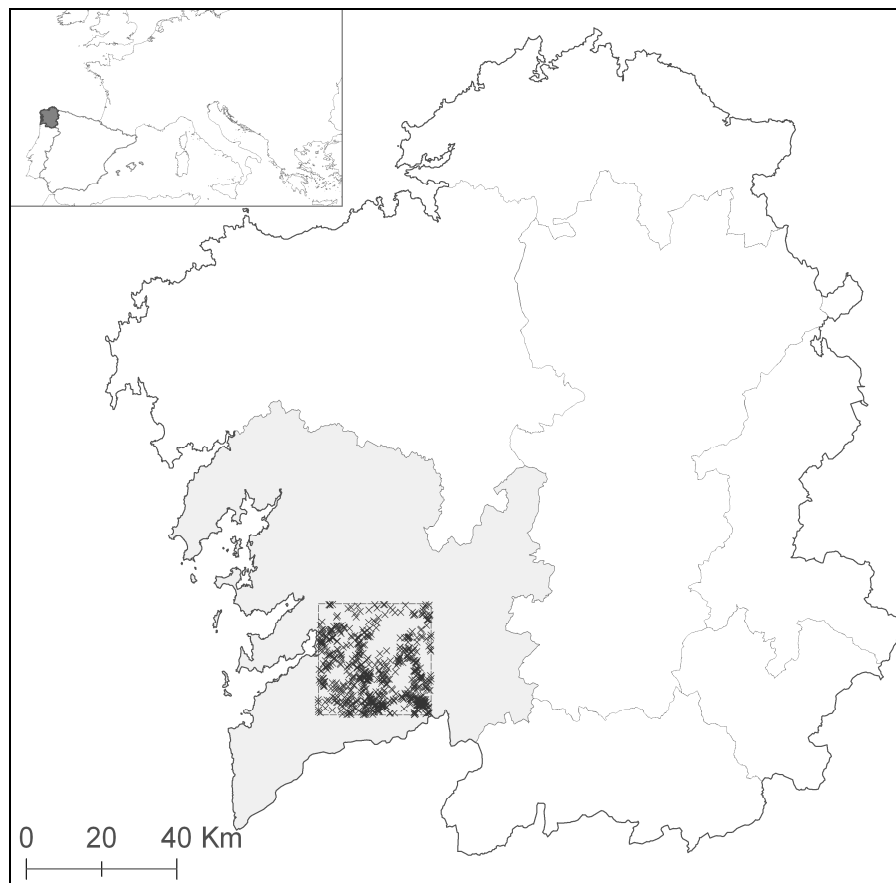
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Fig. 1. Location of the study area together with 984 ignition points in Galicia located inside the *Galicia litoral meridional y montañas occidentales* ecoregion (in grey).
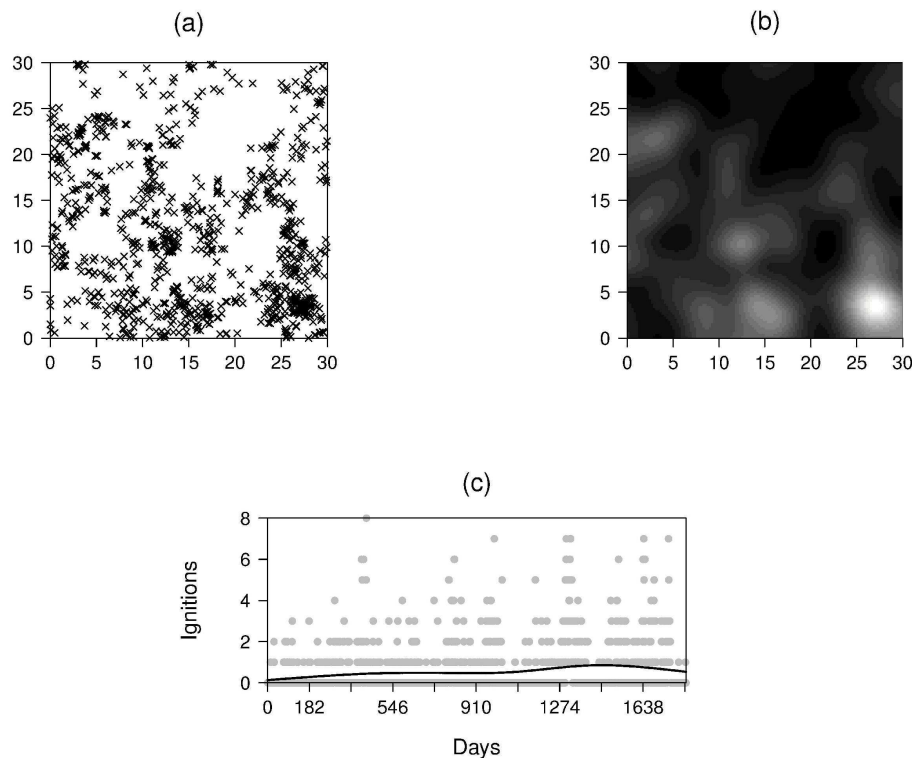
Fig. 2. (a) Spatial positions of the 984 ignition points from 2007 to 2011 in the study area; **(b)** resulting Gaussian kernel-based estimator for the space intensity $m(X)$, where white colours are areas of high point intensity; and **(c)** number of ignition points per day for the five years of study compared with fitted regression curve.

(a) **(b)**
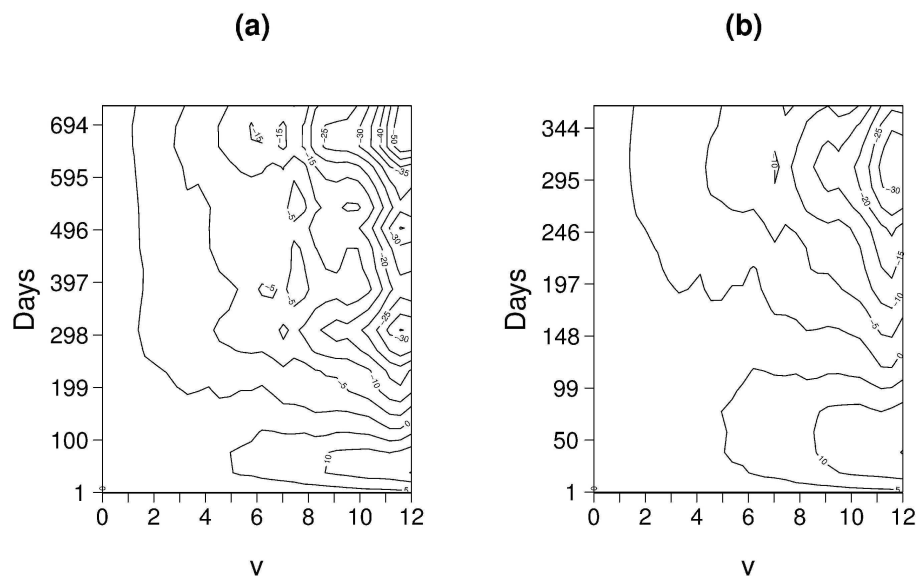
Fig. 3. Values of $\hat{K}_{st}(u,v) - 2\pi u^2 v$ for the point pattern and time evolution shown in Fig. 1 for times lags of less than **(a)** 730 days and **(b)** 365 days; u distances are given in km.
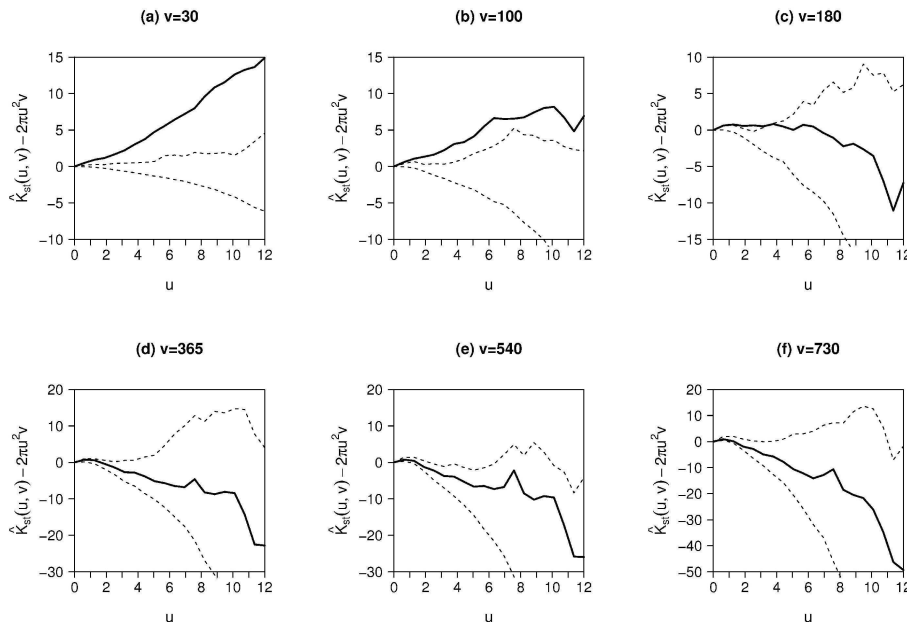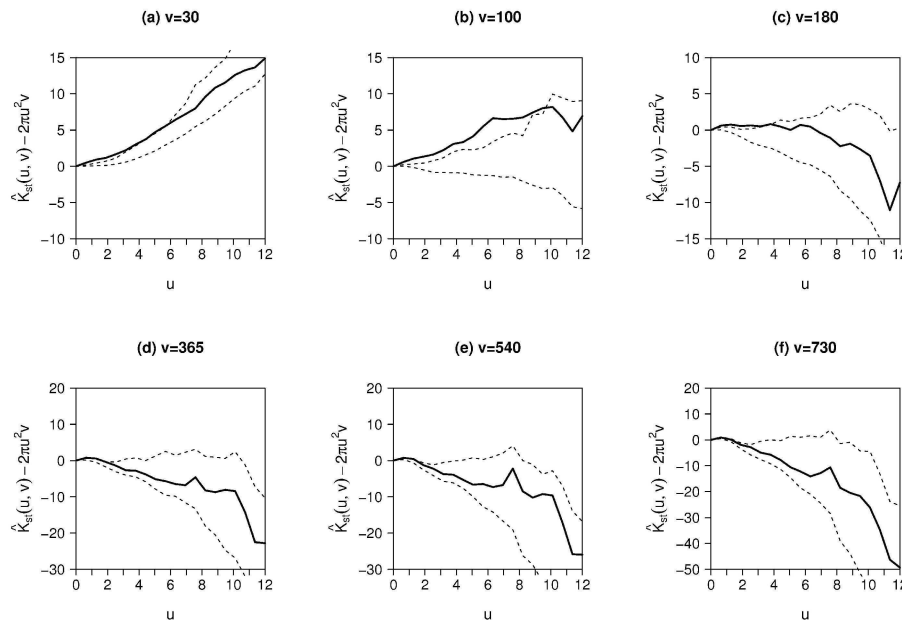
Fig. 4. Values of $\hat{K}_{st}(u,v) - 2\pi u^2 v$ for time lags v (black lines) for the point pattern and time evolution shown in Fig. 1, together with the fifth-largest and fifth-smallest envelope values (dashed lines) based on 199 inhomogeneous Poisson configurations with point intensity (Eq. 4); u distances are given in km.

Fig. 5. Values of $\hat{K}_{st}(u,v) - 2\pi u^2 v$ for time lags v (black lines) for the point pattern and time evolution shown in Fig. 1 together with the fifth-largest and fifth-smallest envelope values (dashed lines) based on 199 random permutations of the spatial locations, X_i, holding the time, t_i, fixed; u distances are given in km.