Spatio-temporal analysis of wildfire patterns in Galicia (NW Spain) [1]

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Abstract: In this work some of the analysis and inference techniques developed recently for spatial point patterns are applied in order to analyze spatial patterns of wildfire ignitions recorded in Galicia (NW Spain) in the period 1999-2008.

Keywords: Spatial point process, intensity, stationarity, K-function, wildfire ignition point.

1. Introduction

Spatial point patterns arise in a wide variety of scientific contexts, including seismology, forestry, geography and epidemiology, (Diggle, 2003).
Wildfire is the most ubiquitous natural disturbance in the word and represents a problem of considerable social and environmental importance. In this work we analyze the spatio-temporal pattern of wildfire ignitions in Galicia (NW Spain), where arson fires are the main cause of forest destruction, in order to model and predict fire occurrence. Such information is of great value in elaborating fire prevention and fire fighting plans.

2. Materials and Methods

Data set:
In this study, the spatio-temporal pattern of wildfires recorded in Galicia during the period 1999-2008 is analyzed. Galicia is located in the North-West of the Iberian peninsula and has a surface area of 29,574 km^2 (11,419 sq mi), which 69% is covered by forests. The total number of fires recorded in the study area from 1999 to 2008 is 85,134. In addition to the spatial location and the date of occurrence of the ignition points, we consider two marks: cause (arson (82.5%), natural, negligence, reproduction and unknown cause) and the size of the burned area.

Statistical methods.
A spatial point process X is a stochastic model governing the locations of events $\{x_i; i=1,...,n\}$ in a bounded region $A \subset R^2$ (Diggle 2003). If the point process contains

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associated measures or marks, it is referred as a marked point process. A point process is characterized by the probability function $P\left(N\left(A\right)=N\right)$, where $N\left(A\right)=\#\left(x_i\in A\right)$, which is the probability of finding N events in the region A, and by its first and second order characteristics. The (first order) intensity, *λ(x)*, is the point process analogue to the mean function for a real-valued stochastic process. Second order characteristics describe the spatial structure of point processes and are based on the analysis of pairs of points. Although several second order characteristics have been developed to describe point patterns (Diggle, 2003), this work focuses on the analysis of the reduced second order moment measure or Ripley´s K-function. (Ripley, 1977), which expresses the expected number of events within a ball b(x,r) centred in an arbitrary event x. The point process is stationary and isotropic if its statistical properties do not change under translation and rotation, respectively. Under these conditions the intensity function is a constant λ, equal to the expected number of events per unit area. In the non-stationary case, the intensity depends on the individual locations.

The first step in the analysis of an observed spatial point pattern is to test the complete spatial randomness (CSR) hypothesis, under this assumption the data are a realization of a homogeneous Poisson process, which is characterized by two properties: (i) the expected number of events (fires) in a flat area (study area) $A\subset R^2$ of surface area |A| has Poisson distribution with mean λ|A|, and (ii) for n events {x_i, i=1,…,n} in A, these are a random sample of the uniform distribution in A. The constant λ in (i) is the intensity of the process. According to (ii), there are no interactions between events (Poisson). This property acts as a dividing hypothesis between regular and aggregated patterns.

In this work, the stationarity assumption was tested by the measure of inhomogeneity proposed by Comas *et at.* (2009):

$$\hat{S}=\int_A\left\|\hat{\lambda}-\hat{\lambda}\left(x\right)\right\|dx \tag{1}$$

where $\hat{\lambda}=N/A$ and $\hat{\lambda}\left(x\right)$ the non-parametric kernel estimator of the intensity (Diggle, 1985).

The second order structure of the observed patterns was characterized by the estimate of the inhomgeneous K-function proposed by Baddeley et al. 2000:

$$\hat{K}_{in\hom}\left(r\right)=\frac{1}{\left|A\right|}\sum_{x_i\in X\cap A}\sum_{x_j\in\left(X\cap A\right)\setminus\left\{x_i\right\}}\frac{I\left(\left\|x_i-x_j\right\|\le r\right)}{\hat{\lambda}\left(x_i\right)\hat{\lambda}\left(x_j\right)w_{ij}} \tag{2}$$

where w_{ij} is Ripley´s edge correction factor. Specifically, a Monte-Carlo test based on the inhomogeneous L-function $L_{in\hom}\left(r\right)=\sqrt{K_{in\hom}\left(r\right)/\pi}$ was applied to test the Poisson hypothesis, since it is easier to visualize dependence between points, as for a Poisson process $L_{inhom}(r)=r$.

The wildfires database is a spatial point process marked by cause and size of the burned area. Spatial interaction between events of two types occurs when different types of events are either closer or further apart than expected under independence. This hypothesis is tested applying a Monte Carlo test based on the inhomogeneous L-cross function. For ease of comparison the L-index (Genton et al. 2006), that enables presentation of the test for several pairs of patterns in a single plot, and its simulation envelopes were computed to analyze the spatial dependence between ignition points in pairs of sequential weeks.

3. Results

As described in section 2, the dataset contains the ignition points of wildfires reported in Galicia during the period 1999-2008, marked by cause and size of burned area. In this section we present some results of the analysis of wildfires recorded in the whole period and, for ease of interpretation, wildfires recorded in 2006.
In order to characterize the degree of inhomogeneity of the different patterns, the maximum value ($\hat{S}_{\max}$) of $\left\{\hat{S}_b^*, b=1,\ldots,B\right\}$, for B=20 realizations of a homogeneous Poisson process involving the same number of fires as the observed pattern, was compared with the empirical $\hat{S}$ for the original pattern. When $\hat{S} > \hat{S}_{\max}$, we reject the stationarity assumption. This test shows that all the patterns analyzed should be considered non-stationary, see results for fires classified by cause in table 1. The kernel intensity estimates for these patterns (figure 1) confirms the importance of arson fires in Galicia and shows that the South and South-West of the region are the most conflictive areas, expect for natural fires, which present higher intensity in the East.

	Fires	$\hat{S}_{obs}$	$\hat{S}_{\max}$
Arson	70223	41939.7	1667.0
Natural	887	526.6	101.0
Negligence	4224	1707.6	255.2
Reproduction	2574	2224.4	242.6
Unknown	7226	4844.7	423.7
Total	85134	48161.2	1707.8

Table 1: Stationariy test for wildfires recorded in 1999-2008.

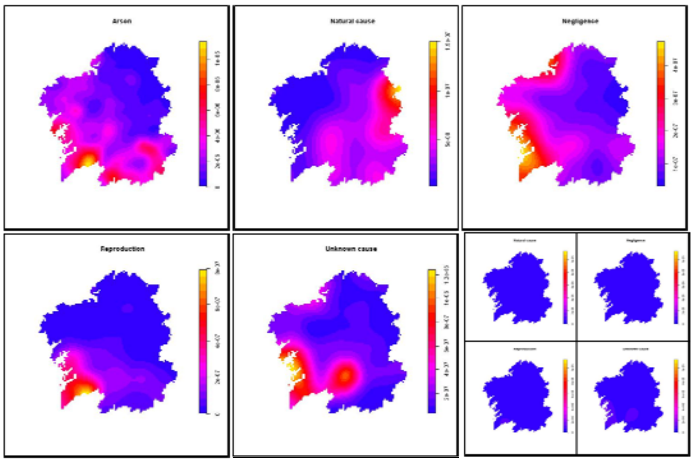

Figure 1: Kernel intensity estimate for wildfires by cause in Galicia 1999-2008. Bottom right: comparison between arson fires and rest of causes.

Independence L-tests applied to some spatial patterns of wildfires recorded in 2006 are shown in figure 2. Comparison of inhomogeneous L-tests (top left and middle) shows more evidence of aggregation for arson fires than for natural fires. The inhomogeneous

L-cross (top right) shows positive interaction between small and large fires up to 6 km. Finally, the L-index test shows positive spatial interaction between wildfires in consecutive weeks assuming both homogeneous and inhomogeneous patterns, although the evidence is higher for the homogeneous test.

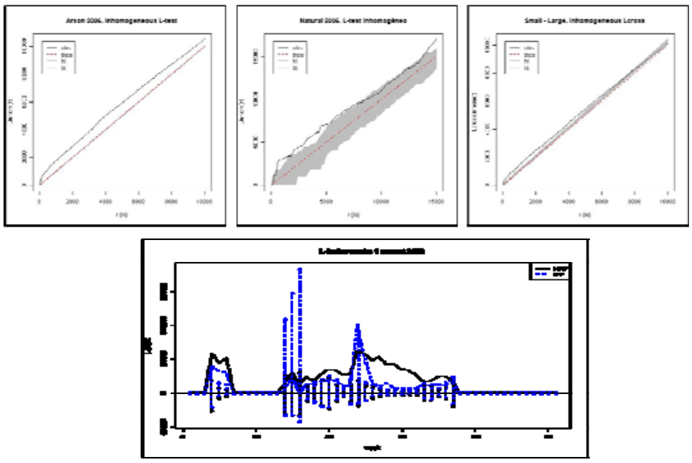

Figure 2: Second order analysis 2006. Top left: Inhomogeneous L-test arson fires; middle: inhomogeneous L-test natural fires; right: L-cross small-large fires. Bottom: L-index for consecutive weeks.

4. Concluding remarks

In this work we have seen the utility of spatial point processes in the analysis of wildfires.
Taking into account the results obtained, we propose to include meteorological and socioeconomic variables in order to fit an accurate spatial model. Finally, we propose to consider the spatio-temporal point pattern defined by spatial location and starting date of wildfires, test for separability and fit a spatio-temporal model.

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