METMA V International Workshop on Spatio-Temporal Modelling
Santiago de Compostela 30 Jun - 2 Jul 2010

UNIVERSITAT JAUME·I

Characterizing spatial-temporal forest fire patterns

Pablo Juan[1], Jorge Mateu [1] and C. Díaz-Avalos[2]

[1]Department of Mathematics, Campus Riu Sec, University Jaume I , E-12071 Castellon, Spain. Email: *mateu@mat.uji.es; juan@mat.uji.es*

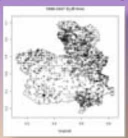
2Instituto de Investigaciones en Matemáticas Aplicadas y en Sistemas, Universidad Nacional Autónoma de México; zhangkalo@gmail.com

ABSTRACT

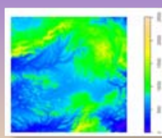
The spatial-temporal patterns of wildfire incidence and their relationship to various meteorological, geographical and geological variables is analyzed. Such relationships may be treated as components in separable point process models for wildfire activity. We show some of the techniques for the analysis of spatial point patterns that have become available due to recent developments in point process modelling software. These developments permit convenient exploratory data analysis, model fitting, and model assessment. The discussion of these techniques is conducted jointly with and in the context of some preliminary analyses of a collection of data sets which are of considerable interest in their own right. These data sets consist of the complete records of wildfires which occurred in Castilla La Mancha (a central Spanish region) during the years 1998-2007.

Introduction and data set

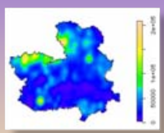
Spatial point pattern data occur frequently in a wide variety of scientific disciplines, including seismology, ecology, forestry, geography, spatial epidemiology, and material science, see e.g [2, 5]. For an overview of spatial point processes, we refer to [5, 9]. We analyze the spatio-temporal patterns produced by wildfire incidences in Castilla La Mancha, located in the middle of the Iberian peninsula, and occupying the greater part of the Submeseta Sur, the vast plain composing the southern part of the Meseta Central. The region is bordered by mountain landscapes: the southern slopes of Sistema Central in the north, Sistema Ibérico in the northeast, and Sierra Morena and Montes de Toledo in the south. Castilla La Mancha is the third largest of Spain's autonomous regions, with a surface area of 79463 square kilometres (30681 sq mi), representing 15.7% of the Spanish national territory. The total number of fires recorded in the study area during the period 1998-2007 is 8488. In addition to the locations of the fire centroids, we consider the following covariates and marks: (a) forest and vegetation types, (b) climatological characteristics (temperature, humidity,...), (c) altitude, slope and orientation, (d) type of wildfire, and (e) time of occurrence.

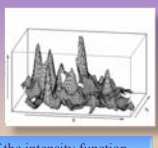


Wildfires in Castilla La Mancha in the period 1998-2007

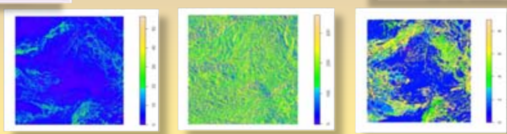


DEM image





Density estimation of the intensity function for the whole period 1998-2007



Covariates: Left: Slope; Middle: Orientation ; Right: Land use

Statistical methods

A convenient, and conventional, starting point for the analysis of a spatial point patterns is to test for complete spatial randomness (CSR), under which the data are a realization of homogeneous Poisson process. A homogeneous Poisson process is a point process which satisfies two conditions: the number of events in any planar region A follows a Poisson distribution with mean $\lambda|A|$ where $|\cdot|$ denotes area and λ is the intensity or mean number of events per unit area; and the numbers of events in disjoint regions are independent. It follows that, conditional on the number of events in any region A, the locations of the events form an independent random sample from the uniform distribution on A. With this, a regular pattern is one in which events are more evenly spaced throughout A than would be expected under CSR, and typically arises through some form of inhibitory dependence between events.

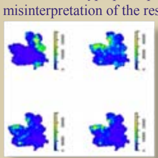
Conversely, an aggregated pattern is one in which events tend to occur in closely spaced groups. Informally, the first-order and second-order properties of a point process ([9]) can be described by the (first-order) intensity function $\lambda(x)$, which is the point process analogue of the mean function for a real-valued stochastic process, and the second-order intensity function $\lambda_2(x,y)$, which is analogous to the covariance function of a real-valued process. The pair correlation function is defined as $g(x, y) = \lambda_2(x,y)/\lambda(x)\lambda(y)$.

The process is stationary and isotropic if its statistical properties do not change under translation and rotation, respectively. If we now assume that the process is stationary and isotropic, the intensity function reduces to a constant, λ, equal to the expected number of events per unit area. In the nonstationary case, they are functions of the distance between points, or in the general case of the individual locations.

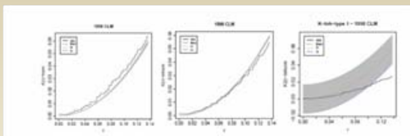
If the temporal argument is of interest, we may consider data in the form of a realization of a spatio-temporal point process within a finite spatio-temporal region. For many areas of application, a suitable point process model must be able to accommodate spatial and/or temporal inhomogeneity. In this setting, a natural starting point for analysis of spatio-temporal point process data is to investigate the nature of any stochastic interactions among the points of the process after adjusting for spatial and/or temporal inhomogeneity. [9] introduced the *K-function* as a tool for data-analysis. One of its advantages over the pair correlation function is that it can be interpreted as a scaled expectation of an observable quantity. Specifically, let $E(s)$ denote the expected number of further events within distance s of an arbitrary event. Then, $K(s)= \lambda^{-1}E(s)$. [3] extended to two dimensional processes a method for nonparametric estimation of the intensity function of an inhomogeneous Poisson process that had been proposed in the one-dimensional case by [4]. [6] extended [9] definition of a reduced second moment measure, or *K-function*, to include a class of nonstationary processes.

Results and Modeling forest fires

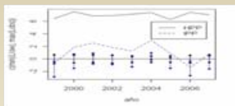
Forest fires can be regarded as spatio-temporal point patterns and thus space-time statistical tools can be of help in analyzing the behavior of fires ([6,8]). Additionally, forest fires represent a problem of considerable social importance worldwide. Investigation of the intensity is one of the first steps in analysing a point pattern. We are in particular interested in testing whether the point pattern intensity depends on a covariate, and thus we fit an inhomogeneous Poisson process model with an intensity function which is log-linear on an observed covariate.In order to model the dependence of a point pattern on a spatial covariat , there are several requirements. First, the covariate must be a quantity $Z(u)$ observable (in principle) at each location u in the window (e.g. altitude, slope, orientation). Such covariates may be continuous valued or factors (e.g. vegetation type). Second, the values $Z(x_i)$ of Z at each point of the data point pattern must be available. Thirdly, the values $Z(u)$ at some other points u in the window must be available. In addition to covariates there are other variables measured only at fire locations which are considered as marks. For example, fires are classified into two or more different types depending on the field size burned or on the cause starting the fire. In such cases, we may consider multitype point patterns The inhomogeneous *K-function* depends on the first-order intensity. Accounting for the degree of inhomogeneity may force a variation in the form of the *K-function*. Thus treatment of the homogeneous function may lead to misinterpretation of the results.



Forest fires with marks defining the four different types in Castilla La Mancha



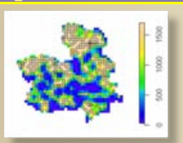
Left: Homogeneous K-function and envelopes under CSR for 1998; Middle: Inhomogeneous K-function for 1998; Right: Inhomogeneous K-function for 1998 and fire type 1



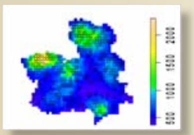
L-cross index 1998 to other year
HPP: homogeneous Poisson Process
IPP: Inhomogeneous Poisson Process

Having all the previous descriptive information at hand, we propose several spatial point process models, univariate and multivariate taking into account the corresponding covariates and marks.

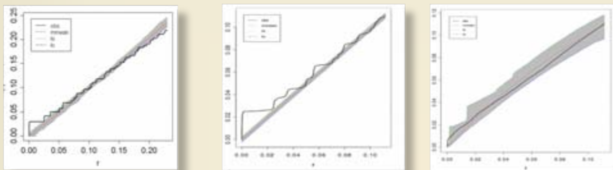
Spatial modeling



Area–Interaction 1998



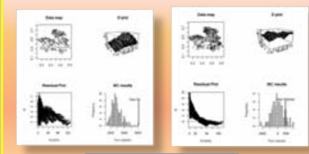
Strauss 1998



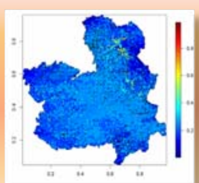
Different L-index modeled. Left: Inhomogeneous L-index 1998 (4 covariates trend);Middle: Inhomogeneous L-index 2002 (polynom trend); Right: Inhomogeneous Matern claster L-index 2007 (trend: x, y and 4 covariates

Space-time modeling

Previous to finally consider the space-time structure, we first test for separability and then we propose a model for the space-time first-order intensity function. Cox processes are very useful for modelling aggregated point patterns, in particular in the spatial case where the two main classes of models are log-Gaussian Cox processes and shot-noise Cox processes. For spatio-temporal point pattern data, spatio-temporal log-Gaussian Cox process models have recently found different applications. Here we study and apply spatio-temporal shot-noise Cox point process models in the line suggested by [8] to model the space-time first-order intensity function.



Space-time separatbility 1998 - 2003

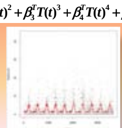


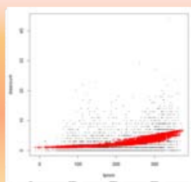
Spatial Intensity

$$\log\lambda_1(u)=c(\beta^{V,C,E})+\sum_{i=1}^{9}\beta_i^V 1[V(u)=i]+\sum_{i=1}^{9}\beta_j^C 1[C(u)=j]+\beta_1^E E(u)+\beta_2^E E(u)^2$$

and

$$\log\lambda_2(t)=\beta_0+\beta_1^S\cos(\eta_t t)+\beta_2^S\sin(\eta_t t)+\beta_3^S\cos(2\eta_t t)+\beta_4^S\sin(2\eta_t t)+\beta_1^T T(t)+\beta_2^T T(t)^2+\beta_3^T T(t)^3+\beta_4^T T(t)^4+\beta_5^T T(t)^5$$





Temporal Intensity (ºC*10)

References

1) Baddeley, A., Møller, J. and Waagepetersen, R. (2000). Non- and semi-parametric estimation of interaction in inhomogeneous point patterns. *Statistica Neerlandica,* **54**, 329-350.
2) Baddeley, A., Gregori, P., Mateu, J., Stoica, R. and Stoyan, D. (eds.) (2006). Case Studies in Spatial Point Process Modeling. *Springer Lecture Notes in Statistics,***185**, Springer-Verlag, New York.
3) Berman, M. and Diggle, P.J. (1989). Estimating weighted integrals of the second-order intensity of a spatial point process. *Journal of the Royal Statistical Society, Series B,* **51**, 81-92.
4) Diggle, P.J. (1985). A kernel method for smoothing point process data. Applied Statistics, **34**, 138-147.
5) Diggle, P.J. (2003). Statistical Analysis of Spatial Point Patterns. *Arnold*, London, 2nd edition.
6) Hering, A.S., Bell, C.L. and Genton, M.G. (2009). Modeling spatio-temporal wildfire ignition point patterns. *Environmental and Ecological Statistics,* **16**, 225-250.
7) Møller, J. and Waagepetersen, R.P. (2007). Modern statistics for spatial point processes (with discussion). *Scandinavian Journal of Statistics*, **34**, 643-711.
8) Møller, J. and Díaz-Avalos, C. (2010). Structured spatio-temporal shot-noise Cox point process models, with a view to modelling forest fires. *Scandinavian Journal of Statistics,* **37**, 2-15.
9) Ripley, B.D. (1976). The second-order analysis of stationary point processes. *Journal of Applied Probability,***13**, 256-266.