**CHARACTERIZING FOREST FIRES PATTERNS IN PORTUGAL**

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**Introduction**

In Portugal, forest fires are a relevant public policy issue due to the significant economical, social and ecological damage they cause. The vast majority of forest fires in Portugal result in a very small burned areas. However, some forest fires go out of control causing large damages and are these fires that have more significant economic, social and ecological impacts, requiring more priority in terms of fire prevention and suppression.

Forest fires can be regarded as spatio-temporal point patterns and thus space-time statistical tools can be of help in analyzing the behaviour of fires. The aim of this work is to model the location of forest fires in Portugal by a log-Gaussian Cox process. The approach taken is to view the data as arising from a time series of spatial point processes, where a dynamic model describes the temporal evolution in a latent space.

**Data**

The point pattern under investigation consists of satellite imagery records of 6295 forest fires larger than 100 hectares, observed in Portugal during the years 1975 through 2005 (53 years), acquired annually after the end of the summer fire season. The data, fire locations at each year, should be treated as a spatio-temporal point process, discrete in time and continuous in space.

Figure 1 shows how the forest fires are distributed spatially, the majority of the forest fires occurred in the north of Portugal.

![Figure 1: Forest fires location](image)

**Model**

The data is modeled as a dynamic spatio-temporal log-Gaussian Cox process (Reis, 2008). Conditional on a spatially and temporally Gaussian field, observations, X, are assumed to arise from a nonhomogeneous Poisson process with random intensity function \( \lambda(t) \). The likelihood is expressed as

\[
L(x|\lambda) = \exp \left( -\sum_{s=1}^{n} \int f(x_s, t_s) \lambda(s, t) \right) \prod_{i=1}^{n} \lambda(s_i, t_i),
\]

where

- \( s \) are the spatial coordinates (latitude and longitude) of the centroids of recorded fires,
- \( t \) is the year of occurrence,
- \( n \) is the number of forest fires observed in each year \( t \),
- \( \mathcal{O} \subset \mathbb{R}^2 \) is the observation region in space (Portugal).

The intensity function \( \lambda(s, t) \) is defined as

\[
\log(\lambda(s, t)) = \beta_0 + \phi(s, t),
\]

where \( \phi(s, t) \) is a Gaussian process stationary and isotropic on space and autoregressive and stationary on time

\[
\phi(s, t) = \eta\phi(s, t-1) + W(s, t) \\
W(s, t) \sim \mathcal{N}(0, \sigma^2/\rho_0) \\
t = 2, \ldots, T
\]

and

\[
\phi(s, 1) \sim \mathcal{N}(0, \sigma^2/\rho_0),
\]

where

- \( |\eta| < 1 \) is the coefficient of the first order autoregressive dynamics (the temporal correlation parameter),
- \( \rho_0 \) is the exponential correlation function with scale parameter \( \sigma > 0 \). A purely spatial correlation function since we are assuming that \( W(s, t) \) is iid over time and the spatio-temporal covariance function is

\[
Cov(W(s, t), W(s', t')) = \begin{cases} 
0 & \text{if } t \neq t' \\
\sigma^2/\rho_0 & \text{if } t = t'
\end{cases}
\]

for \( s \neq s' \)

where \( h = |s - s'| \in \mathbb{R} \) is the Euclidean spatial distance.

The likelihood (1) is analytically intractable because it requires the integral of the intensity function. Therefore it is important to find methods to approximate this likelihood.

One possibility is the Stochastic Partial Differential Equation (SPDE) approach introduced by Lindgren et al. (2011). The SPDE approach uses a finite element representation to define the Gaussian random field as a linear combination of a basis function, defined on a triangular mesh of the domain, and a Gaussian weights, to which a Markovian structure can be given (Simpson et al., 2011). This approach approximates the Gaussian linear combination of a basis function, defined on a triangular mesh of the domain, and a Gaussian weights, (2011). The SPDE approach uses a finite element representation to define the Gaussian random field as a space-time Gaussian Markov random field, \( W(s, t) \), with local neighbourhood and sparse precision matrix.

So, replacing in our model \( W \) to which a Markovian structure can be given (Simpson et al., 2011). This approach approximate the Gaussian linear combination of a basis function, defined on a triangular mesh of the domain, and a Gaussian weights, (2011). The SPDE approach uses a finite element representation to define the Gaussian random field as a space-time Gaussian Markov random field, \( W(s, t) \), with local neighbourhood and sparse precision matrix.

\[
\mathbb{Q}^2 = \tau Q \odot Q^2
\]

where

- \( Q \) is the precision matrix of the temporal autoregressive process of order 1, \( t \) is a \( T \)-dimensional matrix with zero entries outside the diagonal and first off-diagonals,
- \( \mathbb{Q}^2 \) is the precision matrix of the spatial process obtained from the SPDE representation, a \( r \)-dimensional matrix (with \( r \) equal to the number of vertices of the domain triangulation) which does not change in time.

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**Results**

The first step is to define a triangulation mesh of the region \( D \) (Portugal) that covers the space in a regular way. It was applied the Delaunay triangulation to divide Portugal into 715 triangles that gave rise to 421 vertices (Figure 2) with a maximal edge length of 25 \( \text{km} \).

![Figure 2: Delaunay Triangulation of Portugal](image)

**Further Work**

In this work we only present a modeling strategy based on the SPDE approach. In our ongoing research, we intend to explore this model to include covariates with spatial and temporal support. Also of interest is the possibility of using a more complex covariance function, since preliminary studies show evidence that occurrence of forest fires in space and time have a dependence more complex than the structure implemented. We intend to model not only the location of the forest fires but also the burned area, i.e. a spatio-temporal marked point process. Further, we want to explore methods to analyze residuals and validate our fire risk maps.

**References**


