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Applying Binary Structured Additive Regression (STAR) for predicting wildfire in Galicia, Spain

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Abstract

Studies on causes and dynamics of wildfires make an important contribution to environmental. In the north of Spain, Galicia is one of the areas in which wildfires are the main cause of forest destruction. The main aim of this work is to model geographical and environmental effects on the risk of wildfires in Galicia using flexible regression techniques based on Structured Additive Regression (STAR) models. This methodology represents a new contribution to the classical logistic Generalized Linear Models (GLM) and Generalized Additive Models (GAM), commonly used in this environmental context. Their advantage lies on the flexibility of including spatial and temporal covariates, jointly with the other continuous covariates information. Moreover, these models generate maps of both structured and the unstructured effects, and they plotted separately. Working at spatial scales with a voxel resolution level of 1Km x 1Km per day, with the possibility of mapping the predictions in a color range, the binary STAR model represents an important tool for planning and management for the prevention of wildfires. Also, this statistical tool can accelerate the progress of fire behavior models that can be very useful for developing plans of prevention and firefighting.

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Keywords: Wildfire, Structured Additive Regression, STAR models, voxel.

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1. Introduction

Recently, wildfires have become a common occurrence especially in Mediterranean Europe [2, 3, 4]. Most of the studies have mentioned the importance of geographic area effect on the risk assessment of wildfires. There are several regression models to study this effect. For example in Greece [5], a logistic regression model is fitted through using a Geographic Information system to study the wildfires risks in the peninsula of Sithonia. Furthermore, in Spain [2] the relationship between landscape structure and the pastoral wildfires recorded between 1988 and 2000 is studied in Nature Park, Andalusia. Also, in Sierra de Gredos [6], they applied a Generalized Linear Model (GLM) by bootstrapping between the years 1975-90 which identifies hot spots on wildfire sequences. In Italy [8], spatial clustering and a space-time scan statistic method were used to study wildfires during six years in Tuscany region. In Israel [9] by means of logistic regression with GIS is applied to a database between 1944 and 1982.

In this paper, we use a Structured Additive Regression (STAR) model to study the geographical effects on the risk assessment of wildfires using flexible regression techniques to capture the effect of the spatial and temporal covariates.

2. Study area

Galicia has the sixth greatest absolute forest area among regions of Spain; with more than 1,424,094 ha of forest wooded representing 51% of Galician land covers [10]. Also Galicia is the ninth in Europe timber forest in terms of production [11]. The Galician forest sector generates annual revenues of 2,259,000,000 € creating 26,000 direct jobs and 50,000 indirect jobs [12].Wildfires in Galicia are an important problem not only for forest sector but also for environmental issues. [13, 14].

The increasing numbers of households close to forests cause an increasing severity which is the main problem of wildfires in Galicia. There were 251,106 wildfires recorded in this area since the year 1961 (when the wildfires statistics are started), until December 2013 [15]. These fires swept an area of 1,830,330 ha, equivalent to 65% of the total area of Galicia and more 100% of total wooded forest area. Wildfires mainly affect rural municipalities located in the South of the region having low population densities and regressive demographic dynamics due to both low birth rates and an ageing population [11, 3, 4]. From a meteorological perspective, Galicia is a part of the area of Spain called “Green Spain” with climate Atlantic, but nevertheless in summer air circulation is highly variable and has very dry periods.

3. Methodology

As compared to classical regression models, structured additive regression models [17, 18] replace the linear predictor by a structured additive predictor

$$\eta \coloneqq \gamma_0 + f_1(x_1) + \cdots + f_q(x_q) + \gamma_1 u_1 + \cdots + \gamma_p u_p = f_1(x_1) + \cdots + f_q(x_q) + \gamma' u \quad (1)$$

where we can replace linear effects $\gamma_j x_j$ by functions $f_j(x_j)$. These functions can be of different types depending on the different types of covariates x_j, thus the predictor is able to model the nonlinear effects of continuous variables or time scales and it can handle spatial information or specific unit.

We consider a data base with 362,625 observations on wildfires in Galicia in the first half of August 2006. The spatial component consists of 30.685 cells come from dividing the study area with a grid of 1km x 1km associating each of the grid values of climate variables, resulting in Binary Structured Additive Distributional Regression Model. This model is expressed as follows,

$$logit(P_k) = log\left(\frac{P_k}{1-P_k}\right) = \beta_0 + f_1(altitud) + f_2(ta_{media}) + f_3(hr) + f_4(pp) + f_{str}(cdconc) + f_{no-str}(cdconc) \quad (2)$$

Where k is the index of the set of voxels on the study area and period, therefore P_k denote the probability of ignition in the voxel k given the observed covariates set for each voxel. The selected model contains an intercept β_0. The f_i terms are smoothed functions that describe the nonlinear relationship between the explanatory variables and logit probability of the response variable, these functions have been estimated using Bayesian cubic P-splines of second-order with 20 interior knots. f_{str} is estimated using Markov Random Fields and f_{no-str} using i.i.d. Gaussian Random Effects.

The results obtained are shown in Fig. 1, where the covariate altitude (Fig.1a) presents a sharp decline in the occurrence of forest fires as it increases its value; this is due to that in the period considered in this study, most of the fires occurred in coastal areas where the altitudes tended to be low. The covariate average daily temperature (ta_media) (Fig. 1b) has an increasing effect over all, more pronounced at low temperatures below 20 °C to function. From this temperature, the occurrence of fire for temperatures between 20 and 28 °C is stabilized, showing from 28 °C, a not so drastic as at low temperatures (<20 °C) increasing effect. The effect of the covariate daily average relative humidity (hr) (Fig. 1c) is increasing for low values up to about 30%, where this effect becomes more pronounced and decreasing for high values of relative humidity (around 75%). The increments of the relative humidity are associated with a decrease in wildfire occurrence. The effect of the covariate daily precipitation (pp) (Fig. 1d) has a virtually linear decreasing effect. The credible bands for higher values than 5 l/m2 become wider, so again, we should not over-interpret the effects due to the uncertainty of these results.

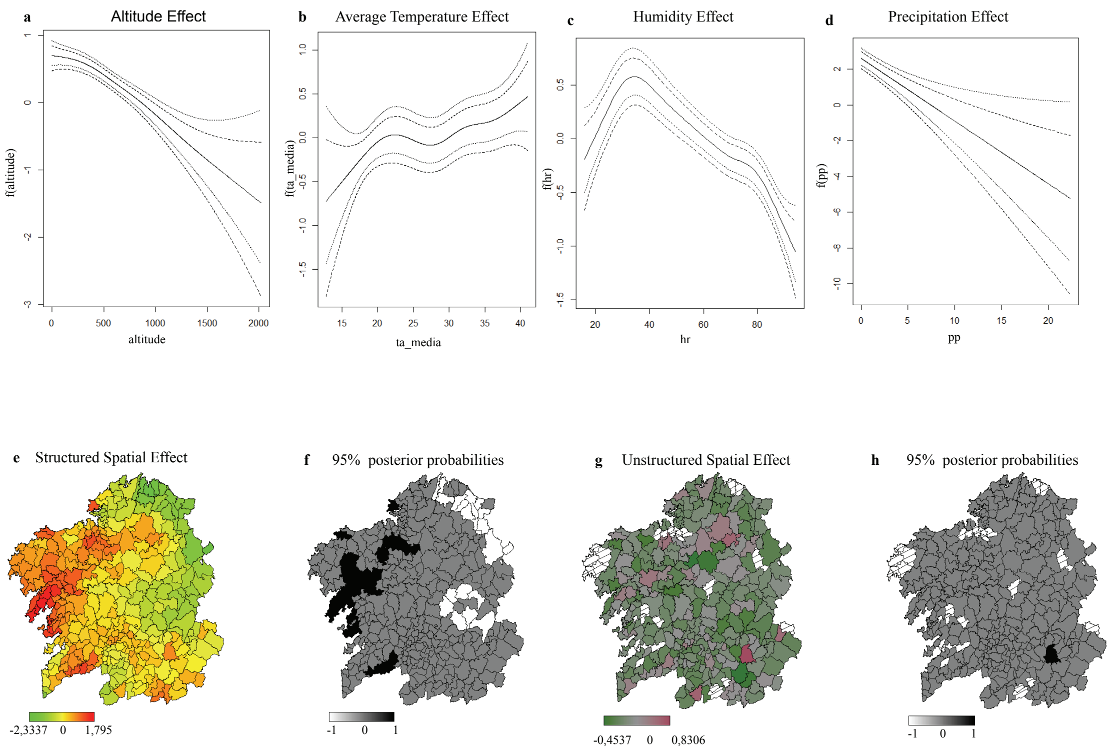

Fig. 1. Posterior mean estimates of centred nonlinear effects together with pointwise 80% and 95% credible intervals and posterior mean estimates to the 95% credible interval of spatial structured and unstructured effects, centred around zero. Note that axes and legend of sub figures have different ranges to enhance visibility of estimated effects.

Structured spatial effects (Fig. 1e) describe a trend of increased occurrence of wildfires in the west and south against a minor occurrence in the north and east Galician. Unstructured spatial effects (Fig. 2f) are not significant except one district "Chandrexa de Queixa", which requires a more detailed analysis on the cause of wildfires this district which is quite different from the districts of their environment and the rest of Galicia.

4. Conclusions

STAR models can overcome the limitations of other methods applied until now to understand a complex phenomenon such as the ignition of wildfires. This is due to the ability to introduce a spatial component model as a factor, which permits a better interpretation by visualization of structured spatial effects on regional level. The flexibility of these models allows the incorporation of new recorded covariates which will improve the prevention and calculation of wildfire risks.

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