Analyzing Wildfires and their Socio-economic Factors in Sardinia

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Abstract

In the last decades, wildfire hazards have increased to dangerous levels, becoming the focus of debate among policymakers both at the local and national levels. This paper proposes a Spatio-temporal approach to study the determinants of fire size distributions taking Sardinia as a case study in the time span 1998-2009. Special attention is devoted to socio-economic factors of local communities where wildfires occurred. The main finding of this study is that the proportion of public lands in a given municipality tends to mitigate the extent of the burned area. In addition, communities with a higher percentage of people employed in the primary sector are less likely to experience large burned extents.
Keywords: wildfires; burned area; Sardinia; Spatio-temporal model; INLA

1 Introduction

A wildfire is an uncontrolled combustion of vegetation which, in contrast with other fires, has a particular spreading speed, size, unpredictable behaviour and difficulty to be stopped due to its ability to overcome artificial or natural fire breaks such as roads or rivers ([25]). They may occur both in the countryside or in uninhabited regions. Their ignition cause, their physical properties, how they are affected by the weather or the kind of combustible material burned are some typical attributes to characterize them ([14]). In particular, wildfires are a part of the broader concept "forest fires" which, in addition to wildfires, includes any ignition occurred in a forest or a wild land area. Recently, in the Mediterranean countries and specially in coastal regions, wildfires have become one of the main environmental problems causing direct damage to humans and structures as well as significant economic and ecological damage ([32],[23]). Actually, they have been considered as one of the most relevant causes of forest destruction in Mediterranean countries and some studies indicate that in the latest future there will be an increase in wildfire events due to changes in climate and land management ([5],[22],[30]).
Frequently, wildfires have been analysed focusing on the number of wildfires, giving information about the probability of occurrence as well as determining the effect of some covariates on the trend in the intensity of fire location. However, it is also of high interest the analysis of the burned area. Burnt area is a very important topic to be analysed. Previous works present the analysis of wildfires using the burned area as a mark not as the main characteristic of the study ([11]). Indeed, this is a key element for people working on fires because not only it is important to know its position but also the number of hectares burned. In this framework, there are many ways for studying wildfires. For instance it can be analyzed as a spatial point pattern ([9],[10],[20],[33] and [37]) or through modeling the size of fires ([2]) or the relative risk of the big fires ([38]). Lately a large variety of complex statistical models can be fitted routinely to complex data sets, in particular wildfires, as a result of widely accessible high-level statistical software, such as R ([28]). In particular, all analyses have been carried out using the R freeware statistical software (version 4.1.0) and the R-INLA package. The main objective of this project is to analyse and model the phenomenon of burned areas in Sardinia and, in particular, to study the role played by socio-economic factors. More specifically it can be split up in two main goals; to analyse the patterns produced by wildfire incidents focusing on their extension and their distribution across space-time and to analyse the impact of socio-economic factors on the size of burned areas.

2 Data setting

2.1 Study area

The study area is Sardinia which is a region located in the Mediterranean Basin (see Figure 1). In particular, it is the second largest island in the Mediterranean Sea with a surface area of 23,821 square kilometres. Fire risk is highly important in the Mediterranean region because of its marked seasonality. In general, we can speak about a summer period with high temperatures and low relative humidity combined with episodes of hot and dry winds which are typical of these regions ([3], [6]). Such factors create the perfect setting for the occurrence of large fires. In particular, in the case of Sardinia, the climate consists of mild rainy winters, dry hot summers and a remarkable water deficit from May until September which still make easier the occurrence of wildfires and difficult the tasks of the fire-fightings to suppress and mitigate large fires occurrence and their associated impacts ([7]).

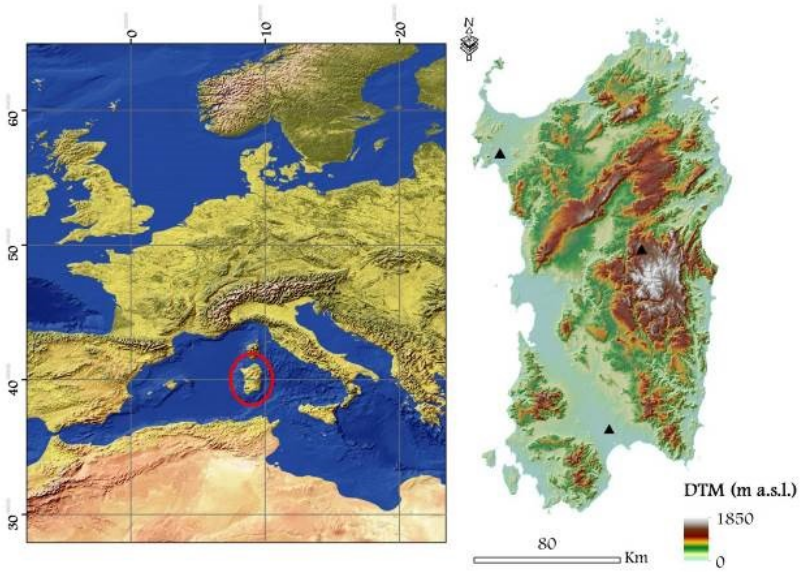

Figure 1: Sardinian location. The figure on the right shows the elevation map (as derived by the 10m DTM - Digital Elevation Model - of Sardinia). The weather stations used in this study are represented by the black triangles.

2.2 Data

The data used throughout this work are those fires occurred in Sardinia from 1995 to 2009. Within the study period, we analysed all events occurred from

June to September, being fires ignited from October to May relatively few in number and very small in size. In particular, we considered only those fires with burned areas bigger than ten hectares discarding those small wildfires that, even if they represent more than 75% of all the wildfires occurred during the period under study, they burn only very few hectares. The total number of fires recorded in the analysis is 2,808. Our dataset includes, for each fire, the coordinates of its origin, the starting time and some covariates related to the location where the wildfire occurred. In addition, the ending time of the fire, the affected hectares, the geological characteristics about the point of ignition, the type of the burned hectares and the perimeter of the fire are also recorded. Other than the information at the locations of the fire centroids, several covariates are considered at the municipality level.

Table 1 and Table 2 show the summary statistics of all the covariates used in the model. They distinguish between those considered at the wildfire level and those at the municipality level, respectively. It is worth noting that the model includes all the covariates shown in these two tables but then we will only show the results of those which are statistically significant[1].

[1] Full results are available upon request.

TABLE 1: Summary statistics (at the wildfire level)

	mean	s.d.
$Elevation$	252.21	217.38
$Slope$	4.04	4.23
$Orientation1$	0.171	0.376
$Orientation2$	0.307	0.461
$Orientation3$	0.338	0.473
$Temperature$	30.45	3.19
$Diff.of.Temperature$	0.336	2.12
RH	63.23	8.70
$Drought$	15.57	13.38
$Windspeed$	16.98	6.17
$Dist.Anthr$	757.33	656.44

TABLE 2: Summary statistics (at the municipality level)

	mean	s.d.
Public lands	0.085	0.178
Social capital	22.15	6.387
Primary sector	0.135	0.077
Tertiary sector	0.593	0.084
Density of population	0.79	1.57
Small municipalities	0.129	0.335
June	0.215	0.411
July	0.420	0.494
August	0.252	0.434
September	0.113	0.317
Weekend	0.344	0.475

Regarding variables at the wildfire level it is very important to take into account topographic variables (elevation, slope and orientation) as they not only affect fuel and its availability for combustion [26], but also the weather, inducing diverse local wind conditions, which include slope and valley winds. In fact, [12] topographic variables are relatively more important predictors of severe fire occurrence, than either climate or weather variables. Slope is the steepness or degree of incline of a surface. In this article, the slope for a particular location is computed as the maximum rate of change in elevation between the location and its surroundings. Slope is expressed in degrees, indicating the angle of curvature of the surface. The variable orientation represents the orientation of the slope and it is measured clockwise in degrees from 0 to 360. In this paper we have used "Orientation1" for indicating the north-facing, "Orientation2" for the east-facing and "Orientation3", the south facing. So, west-orientation is the reference group. Finally, elevation are the number of meters above sea level. As climatic variables we consider the temperature at the location of the wildfire registered at the moment the wildfire started and 7 days before of the occurrence of the wildfire. Then, in the model we consider both, the temperature registered at the moment the wildfire started and also the difference between this temperature and the one registered one week before in order to see if an increase or decrease

of temperature contribute to the occurrence of big wildfires. Drought represents the number of days without raining before the occurrence of the wildfire and RH is the relative humidity compute at the wildfire location. The proximity to anthropic areas can be considered a factor explaining not only the incidence of fires in the intentional fires and arson category, but also why natural cause fires do not occur. This variable is compute taking into account the distance from the ignition point to the nearest point with anthropological activity. Regarding variables at the municipality level we mainly consider socio-economic variables. First, public land is a very important variable in the context of Sardinia as it represents how the land is administrated throughout the population. In particular, in this paper we consider this variable as the percentage of common lands occupied by public lands. Second, social capital represents the number of graduates. Then, we also consider the number of people dedicated to the primary and tertiary sector. In addition, they are also considered the density of population at the municipality level, the variable called "small municipalities", which is a dichotomous variable being 1 when the municipality is smaller than 1000 inhabitants and 0 otherwise. Finally, temporal variables are also included, the month of occurrence, taking into account September as the reference month and the weekend which is a variable constructed also as a dichotomous variable as its value is 1 when the wildfire occurs during the weekend and 0 otherwise.

3 Methods

3.1 Statistical framework

Spatio-temporal data can be idealized as realizations of a stochastic process indexed by a spatial and a temporal dimension

$$\mathrm{Y}\,(\mathrm{s},\mathrm{t}) \equiv \{\mathrm{y}(\mathrm{s},\mathrm{t})|(\mathrm{s},\mathrm{t}) \in \mathrm{D} \times \mathrm{T} \in \mathbb{R}^2 \times \mathbb{R}\} \tag{1}$$

where D is a (fixed) subset of $\mathbb{R}^2$ and T is a temporal subset of $\mathbb{R}$. The data can then be represented by a collection of observations $\mathrm{y} = \{\mathrm{y}\,(\mathrm{s}_1, \mathrm{t}_1)\,, \ldots, \mathrm{y}\,(\mathrm{s}_\mathrm{n}, \mathrm{t}_\mathrm{n})\}$, where the set $(s_1, ..., s_n)$ indicates the spatial locations, at which the measurements are taken, and $(t_1, ..., t_n)$ the temporal instants.
In our case we assume separability in the sense that we model the spatial correlation by the Matérn spatial covariance function and the temporal correlation using a random walk model of order 1 (RW1).

3.2 The model

Methods presented in this work are included in the theory of point processes. In particular, we analysed the spatio-temporal pattern observed in wildfires occurred in Sardinia taking into account the burned area as a dependent variable. Assuming that the subscript i (t=1,...,2808) denotes the point where the wildfire occurred, j (j=1,..377) the municipality at the wildfire belong and t (t=1995,...,2009)

is the time when they started, it is possible to specify a spatio-temporal mixed model by means of a linear predictor([18]) of the form:

$$\eta_{ijt}(m_j) = \beta_0 + \sum_{\alpha} \beta_\alpha z_{\alpha,it} + \sum_{\kappa} \beta_\kappa z_{\kappa,jt} + S_j + \tau_t \tag{2}$$

where β_0 is a scalar which represents the intercept, β_α are the coefficients which quantify the effect of some covariates $z_{\alpha,it}$ on the response at the wildfire level and β_κ are the coefficients which quantify the effect of the some covariates $z_{\kappa,jt}$ on the response at the municipality level. In addition, two random effects are also introduced: (i) spatial dependence, S_j and (ii) temporal dependence, τ_t.

Specifically we specified a spatio-temporal log-Gaussian Cox process (LGCP) model which is a flexible class of spatial point process models that have been successfully used for modelling spatial or spatio-temporal point processes in realistic and relevant applications. In particular, these processes are hierarchical Poisson processes, are characterised by a random-intensity function modelled as the expression $log(\lambda(s)) = Z(s)$, where Z(s) is a Gaussian random field and fit naturally within the Bayesian hierarchical modelling framework.

3.3 Statistical inference

3.3.1 SPDE approach

Standard methods to fit Cox processes have a high computational cost and those methods which use Markov chains by Monte Carlo methods (MCMC) are very difficult to fit this problem. Expert programming skills are required and can be very time-consuming both to tune and to run so that, fitting complex models can easily become computationally prohibitive. Using a Bayesian approach, we provide a modern model fitting methodology for complex spatial point pattern data. This approach is based on the integrated nested Laplace Approximation (INLA), which speeds up parameter estimation substantially so that Cox processes can be fitted within feasible time.

Assuming separability we need to define the Matérn spatial covariance function which controls the spatial correlation at distance $\|h\| = \|s_i - s_j\|$ and this covariance is given by

$$M\left(h \mid \nu, \kappa\right) = \frac{2^{1-\nu}}{\Gamma\left(\nu\right)} (\kappa \left\|h\right\|)^{\nu} \mathrm{K}_{\nu}(\kappa \left\|h\right\|) \tag{3}$$

where K_ν is a modified Bessel function of the second kind and $\kappa > 0$ is a spatial scale parameter whose inverse, $1/\kappa$, is sometimes referred to as a correlation length. The smoothness parameter $\nu > 0$ defines the Hausdorff dimension and the differentiability of the sample paths ([16]).
Using the expression defined in (3), when $\nu + d/2$ is an integer, a computationally efficient piecewise linear representation can be constructed by using a different representation of the Matérn field

$x(s)$, namely as the stationary solution to the stochastic partial differential equation (SPDE) ([35])

$$(\kappa^2 - \triangle)^{\alpha/2} x(s) = W(s) \tag{4}$$

a $\alpha = \nu + d/2$ is an integer, $\triangle = \sum_{i=1}^{d} \frac{\partial^2}{\partial s_i^2}$ is the Laplacian operator and $W(s)$ is spatial white noise.

Then, the basic idea is that, from a Gaussian Field (GF) with Matérn spatial covariance function, we use a stochastic partial differential equation (SPDE) approach to transform the initial Gaussian Field to a Gaussian Markov Random Field (GMRF), which is discretely indexed and has very good computational properties ([21]). The idea is to construct a finite representation of a Matérn field by using a linear combination of basis functions defined in a triangulation of a given domain D (see Figure 2). This representation gives rise to the SPDE approach given by (4), a link between the GF and the GMRF which allows replacement of the spatio-temporal covariance function and the dense covariance matrix of a GF with a neighbourhood structure and a sparse precision matrix, respectively, typical elements that define a GMRF.

In particular the SPDE approach consists in defining the continuously indexed Matérn GF X(s) as a discrete indexed GMRF by means of a basis function representation defined on a triangulation of the domain D,

$$\mathrm{X}(\mathrm{s}) = \sum_{\mathrm{l}=1}^{\mathrm{n}} \varphi_{\mathrm{l}}(\mathrm{s})\omega_{\mathrm{l}} \tag{5}$$

where n is the total number of vertices in the triangulation, $\{\varphi_{\mathrm{l}}(\mathrm{s})\}$ is the set of basis function and $\{\omega_{\mathrm{l}}\}$ are zero-mean Gaussian distributed weights. The basis functions are not random, but rather are chosen to be piecewise linear on each triangle

$$\varphi_{\mathrm{l}}(\mathrm{s}) = \begin{cases} 1 & \text{at vertix l} \\ 0 & \text{elsewhere} \end{cases} \tag{6}$$

The key is to calculate the weights $\{\omega_{\mathrm{l}}\}$, which reports on the value of the spatial field at each vertex of the triangle. The values inside the triangle will be determined by linear interpolation ([35]).
Thus, the expression (5) defines an explicit link between the Gaussian field X(s) and the Gaussian Markov random field, and it is defined by the Gaussian weights $\{\omega_l\}$ that can be given by a Markovian structure.
The temporal dependence (on t) is assumed smoothed function, in particular RW1 ([29]). Thus, RW1 for the Gaussian vector $x = (x_1, \ldots, x_n)$ is constructed assuming independent increments

$$\triangle x_i = x_i - x_{i-1} \sim N(0, \tau^{-1}) \tag{7}$$

The density for x is derived from its $n-1$ increments as

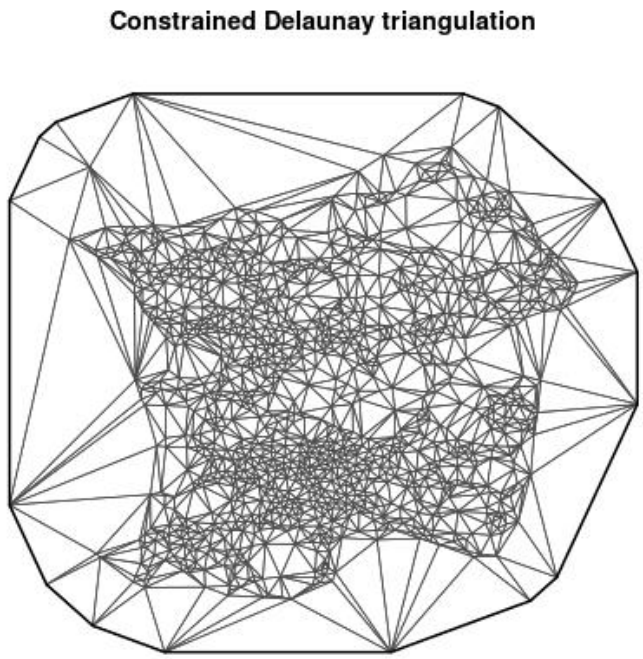

Figure 2: Triangulation of the case study

$$\pi\left(x \mid \tau\right) \propto \tau^{(n-1)/2} exp\left\{-\frac{\tau}{2}\sum\left(\triangle x_i\right)^2\right\} = \tau^{(n-1)/2} exp\left\{-\frac{1}{2}x^T Q x\right\} \qquad (8)$$

where $Q = \tau R$ and R is the structure matrix reflecting the neighbourhood structure of the model ([29]).

4 Results

The results of the estimated model are shown in Table 3 which only shows those statistically significant covariates. On the one hand, we can observe those covariates which contribute to increasing the number of burned areas. The main factors which have a positive effect are: small municipalities (0.8110), June-July-August (0.3905 - 0.4639 - 0.1872) compared to September, the weekend (0.1242), the density of the population (0.0644), the wind speed (0.0325) and

the temperature (0.0478). These results indicate that large forest fires in terms of the amount of burned area occur in municipalities with less than 1,000 inhabitants, mainly during the weekends of June, July and August, in areas with high density of population and when the wind speed and the temperature take high values. In addition, regarding the temperature, it is also observed that an increase in temperature compared to the previous week, contribute to an even greater effect in the occurrence of wildfires (0.0659). On the other hand, we can see that public lands (-0.7212), social capital (-0.0492) and relative humidity (-0.0100) help decrease the burned area. Thus, public lands are protective territories in the sense of occurrence of fires. Moreover, looking at the random effects, one observes that the temporal effect has a small impact and instead, the values of the spatial component show that there is an important spatial dependence. These results mean that there are differences in how wildfires are distributed throughout the territory while this distribution does not vary a lot along the time span.

TABLE 3: Results of estimating the model
(dependent variable = *Burned Area*; $N = 2,808$)

	$Mean\ (sd)$
$Intercept$	-6.4865 (0.5604)
— **Fixed effects**	
$fuelSands - Rocks$	2.0007 (0.8750)
$Weekend$	0.1242 (0.0457)
$Temperature$	0.0478 (0.0124)
$Diff.Temperature$	0.0659 (0.0164)
RH	-0.0100 (0.0029)
$WindSpeed$	0.0325 (0.0042)
$Dist.AnthropicAreas$	0.0001 (0.0000)
$June$	0.3905 (0.0858)
$July$	0.4639 (0.0845)
$August$	0.1872 (0.0894)
$Public\ lands$	-0.7212 (0.1818)
$Social\ capital$	-0.0492 (0.0069)
$Density\ Population$	0.0644 (0.0196)
$Small\ municipalities$	0.8110 (0.0888)
— **Random effects**	
$Spatial\ effect$	1.8470 (0.0932)
$Temporal\ effect$	0.0065 (0.0046)
DIC	-22064.20
$Effective\ number\ of\ parameters$	657.86
CPO	-3.4708

The table only collects the significant covariates

5 Discussion

The main finding of this study is that the proportion of public lands in a given municipality tends to mitigate the extent of the burned area. In addition, communities with a higher percentage of social capital are less likely to experience large burned extents. These results agree with the literature ([4], [8] and [19]) and agrees with what foresters, State Agencies, Fire Departments, and civic leaders support. Residents have to be considered as members that can diminish fire risk and educational activities to raise awareness of the dangers of fires, adopting special but cheap and easy measures have to be promoted.

There is a growing body of literature on the importance of proper wildfire mitigation planning ([24], [13], [1] and [36]). Likewise, and in the same direction, a study focuses on the need for all organizations with competencies in this area to work in the same direction ([15]).

On the other hand, our data shows that small municipalities are more likely to be associated with larger burned areas, probably due to their lack of resources or preparedness. This result continues to support the idea of the need to mobilize and sensitize society about the wildfires problem and the need for investment in tools allowing them to know the risks to which they may be exposed. In this line, there are other studies interested in the spatial distribution of wildfires and in the need to do good planning of their occurrence to improve their management and to be able to apply instruments that integrate work and fire processes decision making from different sectors ([17]).

Regarding the moment of occurrence, September is the month with the lowest probability of having large burned areas. This result may be associated with a drop in temperature compared to the other analysed months which are June, July and August. In particular, among the summer months, July is the month more likely to develop large fires in terms of the burned area. In this sense, and as it is reported in the literature, this is the warmest month with the lowest values of rainfall and so it becomes very susceptible to intense and large fire events [31].

In addition, large burned areas are more frequent during the weekends. This finding is in accordance with other studies that have found that big wildfires are mainly caused by human actions either by negligence and accidents or by intention or arson ([34]); over 95 % of the fires in Europe are due to human causes. During the weekends, and considering we are only analysing the summer months, there is a greater concentration of population which may lead to a probability rise of wildfires occurrence.

Analyzing the burned area as a dependent variable, both spatial and temporal variability is observed although the latter takes smaller values than the former. This could be understood because as there are only analysed the summer months, the pattern of wildfires that occur during this time period follows an essentially stationary behaviour. However, their distribution varies throughout the territory and seems that their occurrence depends on the land use and the typology of the land's property.

Thus, this work confirms that it is worth investing in programs that make people aware of being proactive in the protection of the territory against fires. This means that looking at the results, every resident of rural wildland-urban interface areas at risk should know to defend their properties, their lives from wildfire and realize that their activities contribute to a firefighting safer job as well. In addition, these results can contribute to improving fire management policies, leading to an increase in investments in social capital and to being aware of the importance of public lands as they are a factor that can help mitigate the occurrence of fires.

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