Spatio-temporal modelling of fires in Sicily

Nicoletta D'Angelo[1], Alessandro Albano[1,2], Andrea Gilardi[3], Giada Adelfio[1]

1. Department of Economics, Business, and Statistics, University of Palermo, Italy
2. Sustainable Mobility Center (Centro Nazionale per la Mobilità Sostenibile—CNMS)
3. MOX - Department of Mathematics, Politecnico di Milano, Milano, Italy
nicoletta.dangelo@unipa.it

Abstract. Sicily encountered a growing challenge of wildfires in 2023, necessitating a thorough investigation into their spatio-temporal dynamics. Our study addresses this concern by applying a Poisson separable spatio-temporal point process model. We prove that the spatial occurrence of fires is influenced by human activities, altitude, and slope, while the temporal one is mainly due to environmental variables, including temperature, wind speed, surface pressure, and total precipitation.

Keywords: fires, point processes, spatial analysis, intensity estimation

1 Introduction

Sicily has faced a sudden increase in fires, driven primarily by human-induced factors such as arson. Wildfires pose a significant threat to ecosystems, settlements, and economic activities, necessitating a comprehensive understanding of their dynamics. This paper advocates for point process methodology as a powerful analytical framework to unravel the spatial and temporal patterns of Sicilian wildfires in 2023.

Few papers have studied the relationships between environmental, climatic, and anthropogenic factors contributing to wildfires. Therefore, our study employs the fitting of a Poisson separable spatio-temporal point process model, incorporating covariates like land usage, altitude, slope, temperature, precipitation, surface pressure, and wind speed to comprehensively analyze wildfire patterns.

Considering the growing intrusion of human activities into natural landscapes, our primary emphasis is on quantifying the impact of various land uses on fire occurrences. In particular, the purely spatial regression model reveals the specific contributions of land usage categories while controlling for other environmental covariates.

The structure of the paper is as follows. Section 2 presents the data. Section 3 provides an overview of spatio-temporal point processes and the model employed in the paper, while Section 4 illustrates the actual model fitting through the spatial and temporal intensity estimation. Section 5 is devoted to conclusions.

2 Data

To conduct our analysis, we rely on data obtained from the Fire Information for Resource Management System (FIRMS) platform, accessible for download at the following URL: https://firms.modaps.eosdis.nasa.gov/download/. This source provides near real-time active fire locations to natural resource managers.

In particular, `Longitude` and `Latitude` will be used as spatial coordinates of our point pattern, while `Acq_Date` and `Acq_Time` will be combined in a unique variable serving as the time occurrence of the fire, with the smallest detail as the hour occurrence within a day.

Figure 1 compares fire counts that occurred in Italy and Sicily in 2023. It

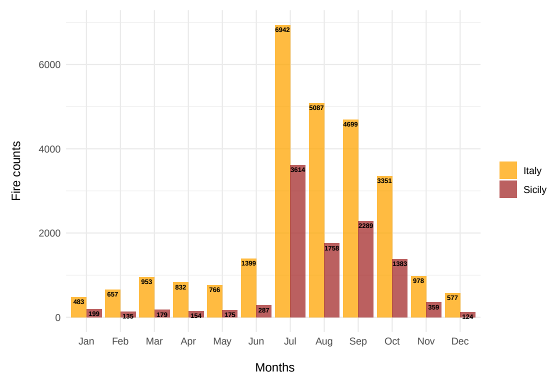

Fig. 1: Barplot comparing the number of fires that occurred in the whole country (yellow bars) and just in the Sicily region (red bars).

is evident that the summer months, from July to October, stand out as critical periods with the highest number of fires. Specifically, July emerges as the most challenging month, recording a total of 8,842 wildfires in Italy, of which 3,814 occurred exclusively in Sicily. Then, Figure 2 shows the spatial distribution of Sicilian fires in 2023, notably indicating clusters, particularly in the western regions.

Land use data come from https://land.copernicus.eu/en/cart-downloads. In particular, we use the macro land usage classification, whose categories are Artificial surfaces (5%), Agricultural areas (68%), Forest and semi-natural areas (26%), and Water bodies (1%).

Regarding other spatial covariates, we downloaded the Digital Elevation Model (DEM) data for the Sicily region from the webpage[1] of the National Institute of Geophysics and Vulcanology [6]. Starting from the DEM of the whole country, we selected the tiles belonging to the Sicily region and combined them to obtain a unique raster object at 10m resolution that represents the altitude in

[1] URL: https://tinitaly.pi.ingv.it/Download_Area1_1.html. Last access: Nov. 2023.

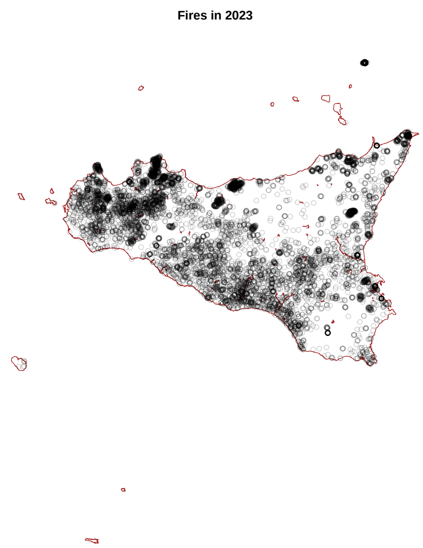

Fig. 2: Spatial distribution of fires recorded in the Sicily region during 2023.

the area of interest. Then, we used Horn's formula [5] through the GDAL DEM utility command-line tool [4] to derive a slope covariate from the DEM data.

Finally, Copernicus ERA5 data contains many environmental covariates that were downloaded from https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-land?tab=overview. All of them are obtained in a 38×34 spatial grid and hourly for each day of the year. The values are averaged daily over the whole year to match the temporal resolution of fire data.

3 Modelling

We consider a spatio-temporal point process with no multiple points as a random countable subset X of $\mathbb{R}^2 \times \mathbb{R}$, where a point $(u, t) \in X$ corresponds to an event at $u \in \mathbb{R}^2$ occurring at time $t \in \mathbb{R}$. A typical realisation of a spatio-temporal point process X on $\mathbb{R}^2 \times \mathbb{R}$ is a finite set $\{(u_i, t_i)\}_{i=1}^{n}$ of distinct points within a bounded spatio-temporal region $W \times T \subset \mathbb{R}^2 \times \mathbb{R}$, with area $|W| > 0$ and length $|T| > 0$, where $n \geq 0$ is not fixed in advance.

The intensity function describes the rate at which the events occur in the given spatio-temporal region, representing the point process analogues of the mean function of a real-valued process. We assume that this intensity function $\lambda(u, t)$ is separable [3], therefore given by the product

$$\lambda(u, t) = \lambda(u)\lambda(t)$$

where $\lambda(u)$ and $\lambda(t)$ are non-negative functions on W and T, respectively, depending on the characteristics of each application.

The spatial model has a linear predictor that includes a non-parametric term for the spatial coordinates and parametric expression for the spatial covariates, as follows:

$$\lambda(u) = \exp(f(u) + \boldsymbol{\theta}_1 Z_{land\_use}(u) + \theta_2 Z_{elev}(u) + \theta_3 Z_{slope}(u)). \quad (1)$$

Here, $f(\cdot)$ is a nonparametric function for $u \in W$, estimated through thin plate regression splines [7] with 30 knots.

The temporal model chosen comes with a linear predictor that includes a non-parametric term for temporal coordinates and parametric expression for the temporal covariates, as follows:

$$\lambda(t) = \exp(f(t) + \beta_1 Z_{v10}(t) + \beta_2 Z_{stl2}(t) + \beta_3 Z_{sp}(t) + \beta_4 Z_{tp}(t)), \quad (2)$$

with $f(\cdot)$ a nonparametric function for $t \in T$, estimated through penalized regression basis splines [8] with 50 knots. The set of terporal covariates $\mathbf{Z}(t) = \{Z_{v10}(t), Z_{stl2}(t), Z_{sp}(t), Z_{tp}(t)\}$ represents the daily maxima of the *wind speed from South*, the *temperature*, the *surface pressure*, and the *total precipitation.*

4 Results

Table 1 presents the results from the fitted spatial Poisson model in equation (1), which investigates the influence of various factors on fire occurrence. Notably, all land use types represent categories of the *land use* variable, with *Artificial surfaces* serving as the baseline. Also, note that the elevation has been converted from meters to kilometres to obtain estimated coefficients of the same magnitude as the others.

	Estimate	**Std. Error**	**z value**	**p value**
Intercept	-15.129	0.040	-376.580	$< 1 \times 10^{-3}$
Agricultural areas	-0.286	0.040	-7.179	$< 1 \times 10^{-3}$
Forest and semi-natural areas	-0.540	0.046	-11.727	$< 1 \times 10^{-3}$
Wetlands and water bodies	-0.595	0.154	-3.870	$< 1 \times 10^{-3}$
Elevation	1.675	0.040	42.320	$< 1 \times 10^{-3}$
Slope	0.006	0.001	4.768	$< 1 \times 10^{-3}$

Table 1: Estimated coefficients of the fitted spatial model in equation (1).

Agricultural areas exhibit a significant negative parameter, indicating a notable decrease in intensity compared to artificial surfaces. Forest and semi-natural areas also show a negative effect, with a higher magnitude than agricultural areas. Wetlands and water bodies display a significant negative parameter, albeit with a wider confidence interval, likely due to the sparse coverage of such land types in Sicily. Elevation and slope both exhibit a significant positive effect, indicating that higher elevations and steeper slopes are associated with higher wildfire intensity. Attempts to assess the significance of ERA5 spatio-temporal covariates averaged over time did not show an influence on the overall spatial occurrence of fires and were excluded from the model, possibly due to their coarse grid compared to elevation and slope representations.

Table 2 outlines the outcomes of the temporal Poisson model in equation (2), examining the relationship between environmental variables and fire counts. A detailed breakdown follows.

	Estimate	**Std. Error**	**z value**	**p value**
Intercept	77.314	5.471	14.133	$< 1 \times 10^{-3}$
Wind speed from South	0.232	0.008	30.426	$< 1 \times 10^{-3}$
Temperature	0.440	0.024	18.672	$< 1 \times 10^{-3}$
Surface pressure	-0.001	0.000	-16.251	$< 1 \times 10^{-3}$
Total precipitation	-14.848	2.266	-6.553	$< 1 \times 10^{-3}$

Table 2: Estimated coefficients of the fitted temporal model in equation (2).

In order to fit this model, the ERA5 environmental spatio-temporal covariates have been averaged with respect to the spatial components, making them purely temporal covariates. Moreover, the results of the models fitted with the daily means of such covariates have been compared to those containing the daily maxima, and the latter yielded better fitting.

Wind speed from the South is positively correlated with increased fire counts, emphasizing the role of African winds. Temperature shows a significant positive relationship, while higher atmospheric pressure is associated with lower fire counts. Precipitation has a substantial negative effect, indicating fewer fire counts with increased daily precipitation, showcasing its mitigating effect. The analysis of smooth terms reveals a complex temporal pattern influencing fire counts, suggesting the importance of time in understanding residual variability not accounted for by environmental factors.

5 Conclusions

The analysis of fire occurrences in Sicily during 2023 conducted in this paper emphasizes the role of human activities, particularly artificial surfaces, in increasing the probability of fires. Climatic conditions such as wind speed from the south and higher temperatures contribute to elevated fire risks, while surface pressure and total precipitation act as mitigating factors. Terrain characteristics, including elevation and slope, play a significant role in shaping the spatial distribution of fires. Note that some of the residual unexplained variability could be linked to arson, which is a man-driven input. For this reason, it can not be easily accounted for in a statistical model. Future work includes the assessment of separability assumption, as well as exploring more complex models, like the log-Gaussian Cox processes, multitype Poisson models, and local ones [2].

Fundings

The research work of Nicoletta D'Angelo and Giada Adelfio was supported by the Mobilità e Formazione Internazionali - Miur INT project "Sviluppo di metodologie per processi di punto spazio-temporali marcati funzionali per la previsione probabilistica dei terremoti" and the European Union - NextGenerationEU, in the framework of the GRINS -Growing Resilient, INclusive and Sustainable project (GRINS PE00000018 – CUP C93C22005270001). Andrea Gilardi acknowledges the support by MUR, grant Dipartimento di Eccellenza 2023-2027. His research work is funded by the European Union - NextGenerationEU, in the framework of the GRINS - Growing Resilient, INclusive and Sustainable project (GRINS PE00000018 – CUP D43C22003110001). The research work of Alessandro Albano has been partially supported by the European Union - NextGenerationEU - National Sustainable Mobility Center CN00000023, Italian Ministry of University and Research Decree n. 1033— 17/06/2022, Spoke 2, CUP B73C2200076000 and Targeted Research Funds 2024 (FFR 2024) of the University of Palermo (Italy). The views and opinions expressed are solely those of the authors and do not necessarily reflect those of the European Union, nor can the European Union be held responsible for them.

References

1. Daley, D. J., Vere-Jones, D. (2007) An Introduction to the Theory of Point Processes. Volume II: General Theory and Structure. Springer-Verlag, New York, second edition.
2. D'Angelo, N., Adelfio, G., and Mateu, J. (2023) Locally weighted minimum contrast estimation for spatio-temporal log-Gaussian Cox processes. Computational Statistics & Data Analysis, 180, 107679. ISSN: 0167-9473. doi: https://doi.org/10.1016/j.csda.2022.107679.
3. Diggle, P. J., & Ribeiro, P. J. Jr. (2013) Statistical Analysis of Spatial and Spatio-Temporal Point Patterns. CRC Press.
4. GDAL/OGR contributors. (2023) GDAL/OGR Geospatial Data Abstraction software Library. Open Source Geospatial Foundation. https://gdal.org. doi: 10.5281/zenodo.5884351.
5. Horn, B.KP. (1981) Hill shading and the reflectance map. Proceedings of the IEEE, 69(1), 14–47. IEEE.
6. Tarquini, S., Isola, I., Favalli, M, Battistini, A., and Dotta, G. (2023) TINITALY, a digital elevation model of Italy with a 10 meters cell size. Istituto Nazionale di Geofisica e Vulcanologia (INGV). Edition 1.1. https://doi.org/10.13127/tinitaly/1.1.
7. Wood, S. (2003) Thin plate regression splines. Journal of the Royal Statistical Society: Series B (Statistical Methodology), 65(1), 95-114. doi: https://doi.org/10.1111/1467-9868.00374.
8. Wood, S. (2017) Generalized Additive Models: An Introduction with R. Chapman and Hall/CRC, 2nd edition. ISBN: 978-1-138-94918-5.