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LUÍS MÁRIO RIBEIRO

Spatial wildfire hazard patterns in the Eastern Mediterranean: perspectives from a harmonised approach

Andrea Trucchia*[1]; Giorgio Meschi[1]; Paolo Fiorucci[1]; Antonello Provenzale[2]; Marj Tonini[3]; Umberto Pernice[4,1]

[1] *CIMA Research Foundation, I-17100 Savona, Italy, {andrea.trucchia, giorgio.meschi, paolo.fiorucci}@cimafoundation.org*
[2] *Istituto di Geoscienze e Georisorse del CNR, Via Moruzzi 1, 56124 Pisa, Italy {antonello.provenzale@cnr.it}*
[3] *Institute of Earth Surface Dynamics, Faculty of Geosciences and Environment, University of Lausanne, CH-1015 Lausanne, Switzerland, {marj.tonini@unil.ch}*
[4] *University of Rome 'La Sapienza', Scuola di Ingegneria Aerospaziale, Via Salaria 851, 00138, Rome, Italy, {umberto.pernice@uniroma1.it}*

**Corresponding author*

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Abstract

Wildfires are a menace which is growing in intensity and spreading in range across all planet's ecosystems causing devastation on the environment, wildlife, human health, and infrastructure. Most of the damage caused by forest fires is related to extreme wildfire events (EWEs). To foster prevention activities, a thorough understanding of territorial features determining EWEs is crucial in Civil Protection and fire management activities. An approach which learns from past wildfire events providing susceptibility, intensity and hazard maps is presented. This mapping approach leads to the individuation of the main drivers of EWEs and in the zonation of the areas more prone to hazardous and impactful wildfire events. The case study where the mapping approach is applied encompasses thirteen countries of the Eastern Mediterranean and Southern Black Sea basins. The presented results focus on wildfire susceptibility. A Machine Learning approach is pursued, by adopting open data layers as both predisposing factors and past wildfire events.

1. Introduction

Fire trends from the '70s up to now show on the average a decrease in burned area and number of fires, after the large impacts of the '80s wildfire seasons, in most of the Southern European countries, as demonstrated by (Turco et al. 2016). This can be mainly considered as the results of increasing firefighting capacities and awareness thanks to improved forecasting. However, impacts of climate change, coupled with the drastic modifications in land use and socio-economic conditions, occurred in the same period, have triggered a potential increase in frequency, extent and severity of wildfires worldwide (Doerr and Santín, 2016). Wildfires are growing in intensity and spreading in range across all planet's ecosystems, causing devastation on the environment, wildlife, human health, and infrastructures (UNEP, 2022). In highly densely populated areas, recent studies indicate that most of the damage caused by forest fires is related to extreme wildfire events (EWEs) which represent less than 2% of the total number of fires (Catry et al., 2009; Tedim et al., 2013). Despite huge investments in fire suppression, firefighting activities cannot effectively cope with EWEs, even in cases of massive resource deployment (Fernandes et al., 2016).

The impacts of the recent and recurrent EWEs in the Mediterranean highlight that societies are facing an increasing fire risk due to the combination of climate conditions and landscape-scale accumulation of fuel because of the almost complete abandon of rural activities.

Recently, EWEs characterized the 2021 wildfire summer season, where Greece, Italy, Algeria and Turkey experienced a large number of severe wildfire events burning more than 630,000 ha (San-Miguel-Ayanz, 2022). The 2021 Algerian wildfires killed at least 90 people (ReliefWeb, 2021) resulting in the deadliest fires of the recent times after the EWEs in Portugal (2017) and in Mathi, Greece (2018).

It is evident that there is an urgent need to shift from suppression to prevention and risk mitigation in order to reduce such impacts. A limitation to this shift is represented by the absence of a collective and pervasive understanding of the conditions related with EWEs beyond both the sole cause of ignition and the effect of weather, which are the main uncontrollable aspects of EWEs. The fatalist approach which blames only ignition patterns and weather effects neglects that there is still plenty of room for knowledge improvement leading to the identification of priorities for effective wildfire prevention. Such knowledge begins with susceptibility, hazard and risk mapping, including the characterization of the exposed elements in terms of their value and vulnerability, and ultimately leads to the identification of the areas where EWEs can happen with more severe impacts.

To foster prevention activities, a thorough understanding of the features of the territory determining EWEs is of crucial help in Civil Protection and fire management activities. From a technological point of view, there is plenty of data, tools and models which can be applied to this issue.

A harmonized mapping methodology is needed to be applied at different scales. Synoptic time series of burned area a significant help to learn from the past, bringing useful knowledge to present wildfire management, determining the principal drivers of catastrophic wildfires. However, those time series may be not long enough locally to reach these goals. To circumvent this problem, a more vast and diverse area can be studied, to infer wildfire drivers in different climates, topographic and anthropogenic conditions. This is achieved using wildfire susceptibility, hazard, and risk maps, which can help decision makers and practitioners in wildfire management and long-term landscape management, strengthening proactive prevention activities adapted to local environmental and socio-economic contexts. The objective of such maps may range from the static assessment (hazard) to the dynamic one (danger).

This is in line with the recent IPAFF European program, which targets Western Balkans (Albania, Kosovo*[1], Montenegro, Serbia, North Macedonia, Bosnia-Herzegovina) and Turkey to empower capacities in forest fire risk assessment and mapping, considering static hazard and risk mapping across boundaries.

The Authors with the presented work continue a research framework started at the local level (Tonini et al., 2020) and recently expanded at the national scale (Trucchia et al., 2022). The described work is one of the first attempts (up to the Authors' knowledge), to model wildfire hazard at the supernational scale, where useful information can be drawn in view of cross-border wildfire management, supporting also the European Civil Protection Mechanism.

1.1. The proposed framework to wildfire hazard assessment and mapping

The proposed approach combines multi-source data gathering, model / expert-based processes and Machine Learning (ML) analyses.

This preliminary work, undertaken for a large set of countries in the Eastern Mediterranean and Southern Black Sea region, tries to get the most from the available global data sets, using only open data. The main steps are summarised below:

1. Susceptibility mapping - wildfire susceptibility is defined as the static probability of experiencing wildfire in a certain area, depending on the intrinsic characteristics of the terrain. This can be achieved with several approaches, ranging from the statistical hierarchical ones to the ML driven ones.
2. Intensity mapping - wildfire intensity is defined as the rate of heat energy released by the fire. At this stage, the areas where severe wildfires can develop owing to the fuel cover and other features of the terrain are detected. This can be done with expert-based classification of fuel cover or via empirical models.
3. Hazard mapping – wildfire hazard is the spatial distribution of the areas where a severe wildfire is likely to occur. This can be done merging the outputs of the two previous steps.

In this short abstract, the results obtained for Steps 1-2-3 are described.

[1] This designation is without prejudice to positions on status, and is in line with UNSCR 1244 and the ICJ Opinion on the Kosovo declaration of independence.

2. Materials and Methods

2.1. Study Area

The considered countries are the following: Italy, Slovenia, Croatia, Western Balkans (Albania, Bosnia and Herzegovina, North Macedonia, Montenegro, Kosovo* and Serbia), Greece, Cyprus, Bulgaria, and Turkey. They constitute a vast area (more than 1,600,000 km2) characterized by a high number of biogeographical regions: Mediterranean, Continental, Alpine, Anatolian, Pannonian, and Black Sea biogeographical region (European Environment Agency, 2002).

2.2. Methodology

The proposed methodology for susceptibility mapping is based on a ML model (Trucchia et al., 2022), structured as a classification task. It uses a Random Forest Classifier (RF) as an algorithm, to find a functional relation between the dependent variable (the label, that is, wildfire occurrences) and the independent variables (that is, the predisposing factors). As per the predisposing factors, geographic data (elevation, slope, aspect, land cover/fuel cover), climatic data (Köppen-Geiger climate classes, mean precipitation, mean temperature) and anthropogenic data (distance from settlements and crops) are considered. The input layers are summarised in Table 3. The main data source used for computing vegetation cover variables is CORINE Land Cover 2018 (CLC2018). The obtained raster, containing the CORINE code for the pixels, then has been processed to obtain the neighbouring vegetation variables, which express the vegetation continuity over the analysed landscape. Those extra variables are used to associate with any pixel information on the surrounding vegetation. This is useful to identify homogeneity in vegetation, or to spot the interface between two main vegetation covers. For any pixel, a Moore neighbourhood of order 2 (the 24 surrounding pixels) has been evaluated (see Figure 1). The frequency of appearance of the several vegetation types has been computed. For instance, in case of a pixel is totally surrounded by CLC2018 code “311”, that is, broadleaves, the variable “neighbouring_311” will be set to 1 while all the other "neighbouring_XXX" variables will be set to 0.

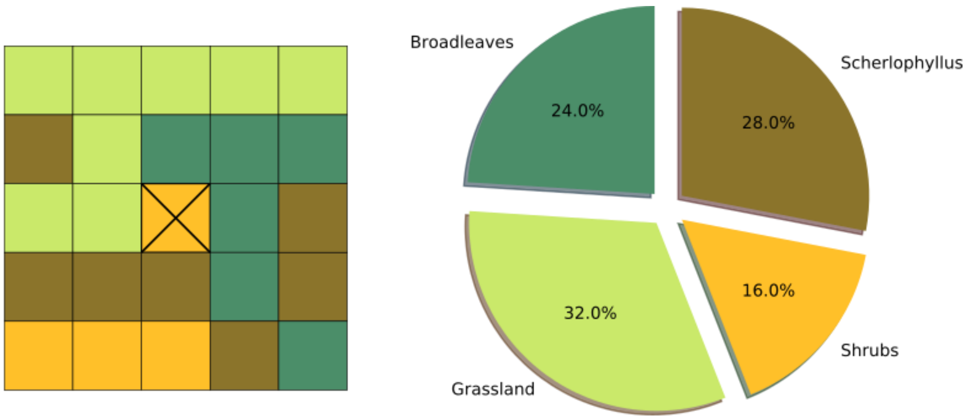

Figure 1- A representation of a Moore Neighbourhood and the obtained “neighbourhood percentages” of vegetation classes (vegetation continuity) is portrayed. Any other neighbour vegetation type not represented in the image is set to 0%.

As per the observed data, the EFFIS database of 10,118 burned polygons (more than 2,922,500 burned hectares), retrieved from 2008 to 2019 is considered.

All inputs and outputs are rescaled to the working resolution of 500m.

For any of the considered countries, 10% of their burned pixels is retrieved and their predisposing factors collected, as well as an equal number of non-burned pixels with their geoclimatic and anthropogenic factors. This allowed building a balanced dataset. The contribution of each country is merged in the total dataset. Such database was split between the training ones (75 percent of the entries) and the test ones (the remaining 25% of the database). The RF model has been trained on the training dataset and evaluated over the test pixel, to compute performance indicators. In this work, the Area under the ROC Curve (AUC) and the Mean Square Error (MSE) are considered and reported in Table 4.

The input features then are ranked by their relevance using the measure given by the Gini impurity to spot the main drivers of wildfire occurrence in the study area.

While the susceptibility layer raw values ranging from 0 to 1 have been used to compute the performance indicators, the values have been also aggregated into percentile classes (see Figure 2).

In order to have a layer accounting for wildfire intensity, the CLC2018 land cover has been processed aggregating the CLC2018 classes into four different intensity classes, as reported in Table 1.

Having for every pixel of the study area a class for potential intensity and a class for wildfire susceptibility, a simple expert-based contingency matrix for hazard assessment has been developed. Such matrix is reported in Table 2.

Table 1- Fire behaviour / fire intensity classification. Thanks to this classification a land cover map can be converted to a fire intensity map, to be used as input for the hazard mapping.

Intensity classes	Description	Vegetation cover
1	Surface fire – low intensity	crops, grasslands
2	Surface fire – medium intensity	broadleaves, agroforest
3	Surface fire – high intensity	Sclerophyllus, shrubs
4	Crown fires – very high intensity	Conifers, mixed forest

Table 2- The contingency matrix for the Hazard is portrayed. It combines the input classes of susceptibility (rows) and intensity (columns). Every entry of the matrix is the hazard level (from one to six: very low, low, medium, high, very high, extreme hazard) related to a specific combination of susceptibility and intensity levels.

Susceptibility / Fire Intensity	Low Intensity	Medium Int.	High Int.	Very High Int.
Low Susceptibility	1	2	3	4
Medium Susc.	2	3	4	5
High Susc.	3	4	5	6

3. Results

The first results for the susceptibility mapping of the study area are here listed. In Figure 2, the susceptibility distribution is portrayed after aggregating via percentile classes. In Figure 3, the Hazard Map for the reported area is portrayed.

The performance indicators are resumed in Table 4, with promising and consistent results for the AUC score.

Interesting insights are also given by the ranking of the predisposing factors in Table 5: the importance of vegetation continuity when compared to single pixel vegetation is an evident result of the analysis, with climatic and topographic classes which cannot be neglected for a good classification of the study area. This is in line with the more consolidated results from the recent work at the national scale in Italy (Trucchia et al., 2022).

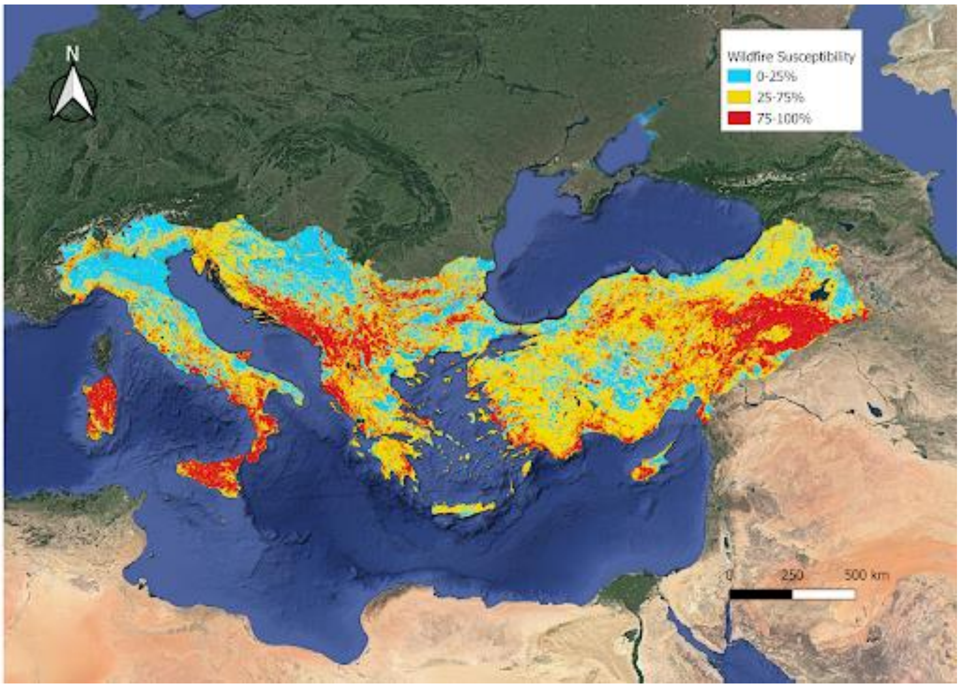

Figure 2: Susceptibility map of the study area, coloured by percentiles: 0-25% (low susceptibility), 25-75% (medium susceptibility), 75-100% (high susceptibility).

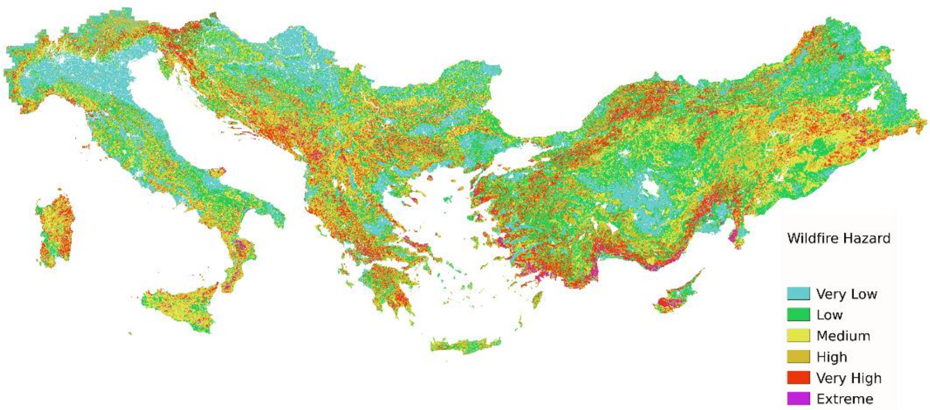

Figure 3: Wildfire Hazard map of the study area, coloured by the hazard classes of Table 2, taking as inputs the susceptibility classes (Figure 2) and the fire intensity category (Table 1)

4. Discussion and Conclusions

Promising results showing the most wildfire prone areas achieved through ML in step 1 supported the work in step 2 and 3 of the proposed approach. The susceptibility map produced at this stage of the implementation evidenced the importance of vegetation continuity in susceptibility assessment. At the scale of the presented analysis of course climatic information is a good asset for discriminating between different species of vegetation that belong to the same CORINE class. On the other hand, vegetation continuity covers at least two roles: firstly, high flammability fuels continuity is the main responsible of EWEs; secondly, continuity of native broadleaved forests may limit the propagation of EWEs. The adopted strategy for fire behaviour/intensity mapping and Hazard mapping are an example of how to make use of open data and informed decisions to perform hazard mapping at the supernational level. There exist of course plenty of different modelling choices, but the Authors tried to stick to the most straightforward one to highlight the solidity of the proposed framework. For instance, a modelling approach relying to worst-case scenarios for wind and moisture conditions could have been employed for intensity mapping (Trucchia et al. 2022 b). These preliminary results open the right path to restoration and adaptation strategies, fostering the objectives of EU Biodiversity Strategy for 2030. This initial susceptibility mapping is currently under refinement by implementing ad-hoc spatial validation procedures, and a more thorough factor importance analysis, with a special focus on the impact of the different vegetation types.

Table 3- Input data for the susceptibility mapping

Input data	Source	Description
CORINE land cover	Copernicus[2]	Land cover raster file of the Corine 2018 at 100 m resolution
Copernicus tree cover density (TCD)	Copernicus[3]	Density of the forestry areas at European level at100 m resolution
Digital Elevation Model (DEM)	JAXA's Global ALOS 3D World (Takaku et al. 2020)	Raster file related to the elevation in meter for the study area
Köppen-Geiger - climate	Open data repository (Beck et al. 2018)	Raster layer of the Köppen-Geiger climate classification at 1-km resolution
Mean Precipitation	ERA5 data (ECMWF reanalysis) of the 1991-2020 time window from Climate Change Knowledge Portal (CCKP) of World Bank Group [4]	Average of yearly accumulated precipitation [mm]
Mean Temperature		Average mean temperature [°C]
Burned areas	EFFIS[5]	Historical burned areas retrieved from EFFIS (data ranging from 2008 to 2019)

Table 4- Performance indicators of the training dataset for the susceptibility ML model.

AUC	MSE
0.77	0.192

Table 5- Importance ranking of the input factor of the ML model. Importance of factors belonging to same category have been summed up.

Predisposing Factor (feature)	Gini based Importance
Climate variables	0.279
Vegetation continuity (sum of all Gini importances)	0.265
Topography	0.235
Anthropic	0.141
Tree Cover Density	0.045
Vegetation (value for single pixel)	0.03

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