

The use of Random Forest classifier for the mapping of burnt areas based on satellite Sentinel-1 and Sentinel-2 data

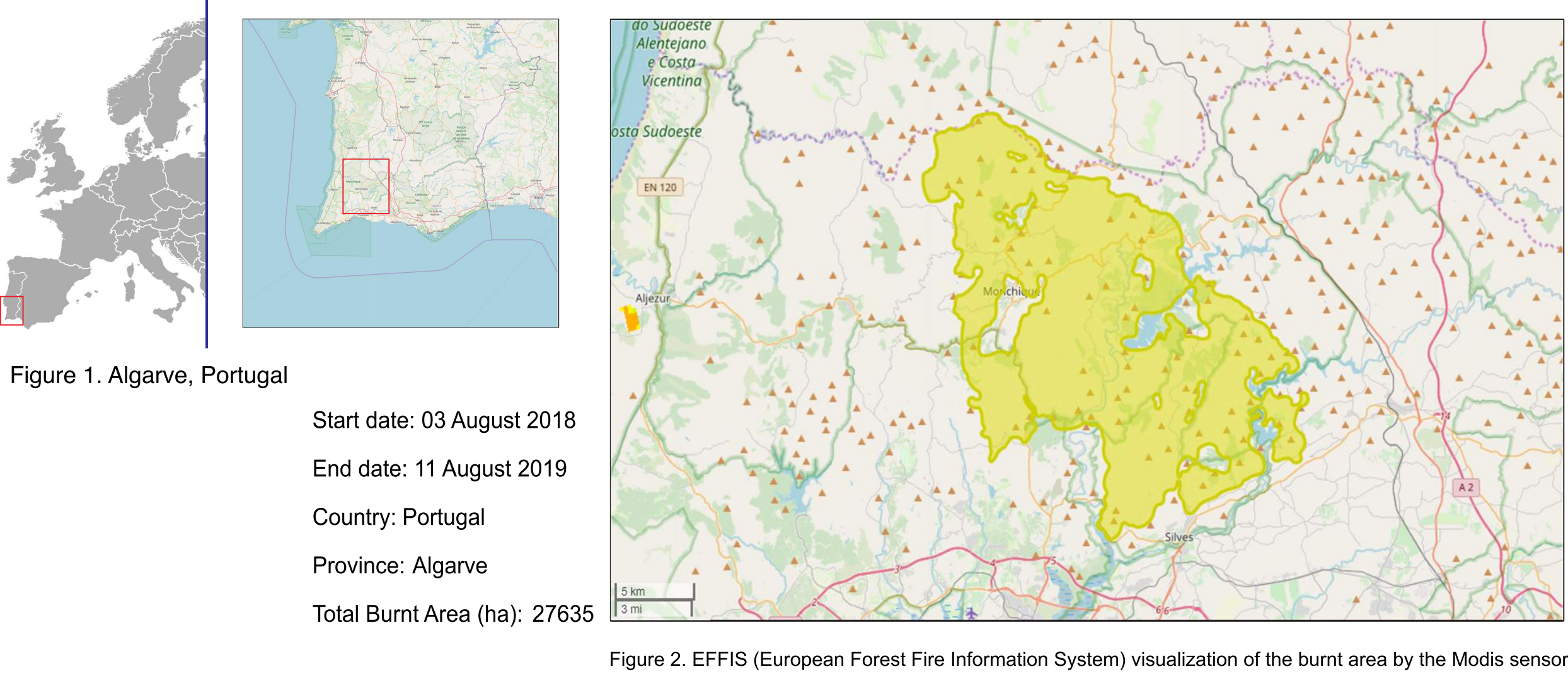
Carmen Fattore^{1,2} , Rosa Lasaponara¹

¹ University of Basilicata – DICEM - Department of European and Mediterranean Cultures, Environment, and Cultural Heritage, Via Lanera, 75100, Matera, Italy
² Institute of Methodologies for Environmental Analysis, Italian Research Council, C.da S. Loja, Tito Scalco, 85050 Potenza, Italy

Introduction

Forest fires in Portugal have become a serious environmental problem in recent years. According to the Annual Report 2017 drawn up by EFFIS (European Forest Fire Information System), the number of fires that occurred was around 21002 for a burned area of about 540630 ha; in 2018 the burned areas decreased, but 37436 hectares have been affected however.

In this paper, the study area is located in southern Portugal, particularly in the Algarve region. The event took place in August 2018, it damaged the town of Monchique and burned down about 27,000 ha. The satellite data used for this case study are the optical images and SAR images (respectively Sentinel 2 and Sentinel 1 of the ESA Copernicus program), which have different resolutions, to better understand how the two sensors return different information based on the processing of the data.



Materials and Methods

The characterization of fire severity [1] and the identification and mapping of the surfaces affected by fire is based on the recognition of the spectral response of the burnt vegetation, that is different from the response of the unburnt surface. In this case we used vegetation spectral indexes such as NDVI (Normalized Difference Vegetation Index), the NIR-SWIR index to estimate the water content of vegetation, as the fire causes a strong decrease in the content of humidity of plants and soil, so as to obtain the subdivision of it in the different classes of risk.

We also use other indexes such as NBR (Normalized Burn Ratio), concerning the NIR reflection pattern with an increase in infrared reflection, the BAI (Burned Area Index) which has a higher sensitivity to distinguish the burned areas from everything different such as bare soils, areas not very vegetated or areas with various ground covering; this let us underline the signal of the burned areas, allowing us a satisfactory and accurate classification.

A comparison was made between the limits values of the normalized combustion ratio (dNBR) and the normalized differential vegetation index (dNDVI) (from pre- and post-fire images). However, dNBR can present problems in areas with low pre-fire vegetation cover, where the absolute change between pre-fire and post-fire NBR is not significant, so we applied an additional RBR index (Relativized Burn Ratio)[2], in which the relativized version of the gravity of the fire is advantageous for our classification[3].

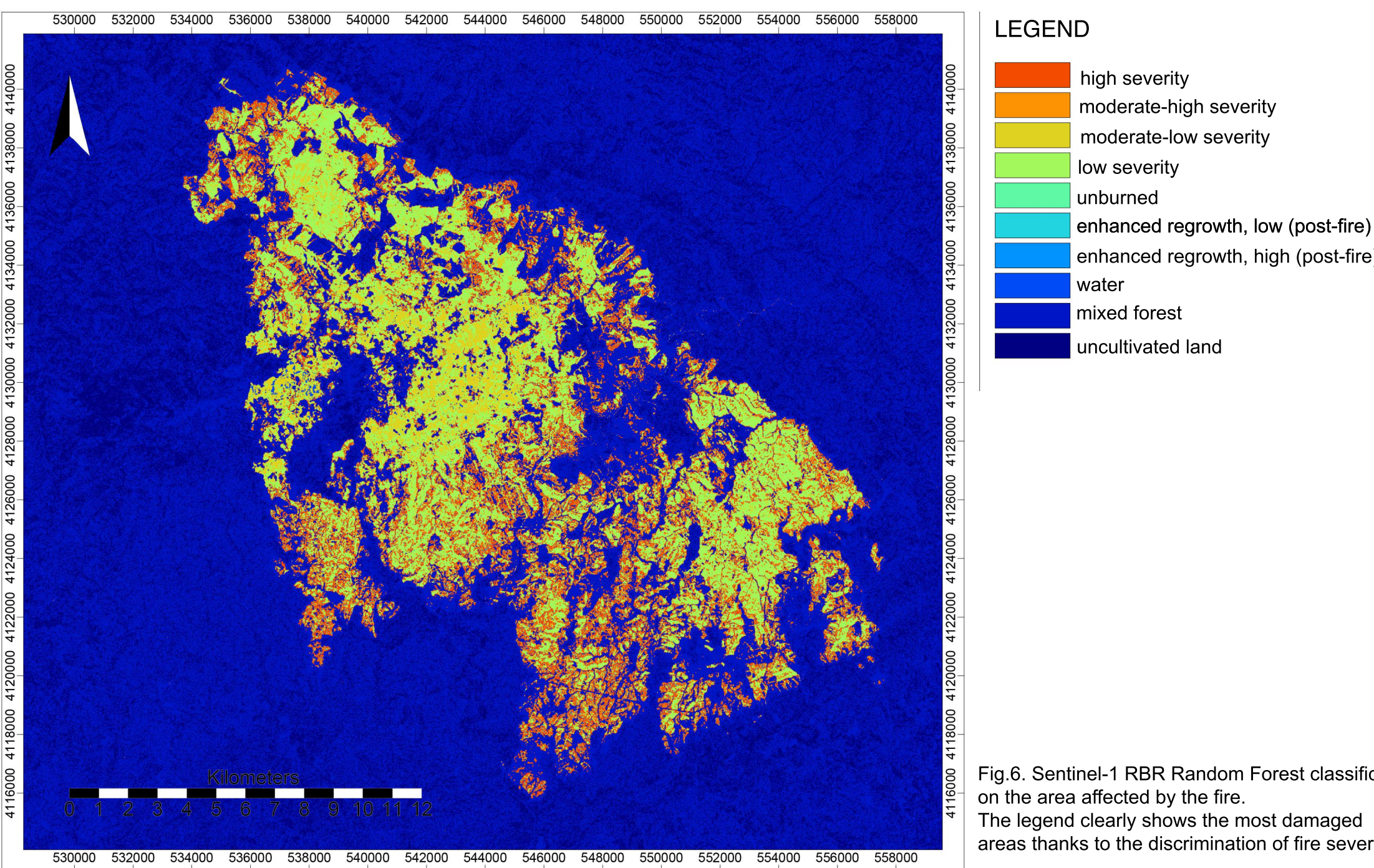
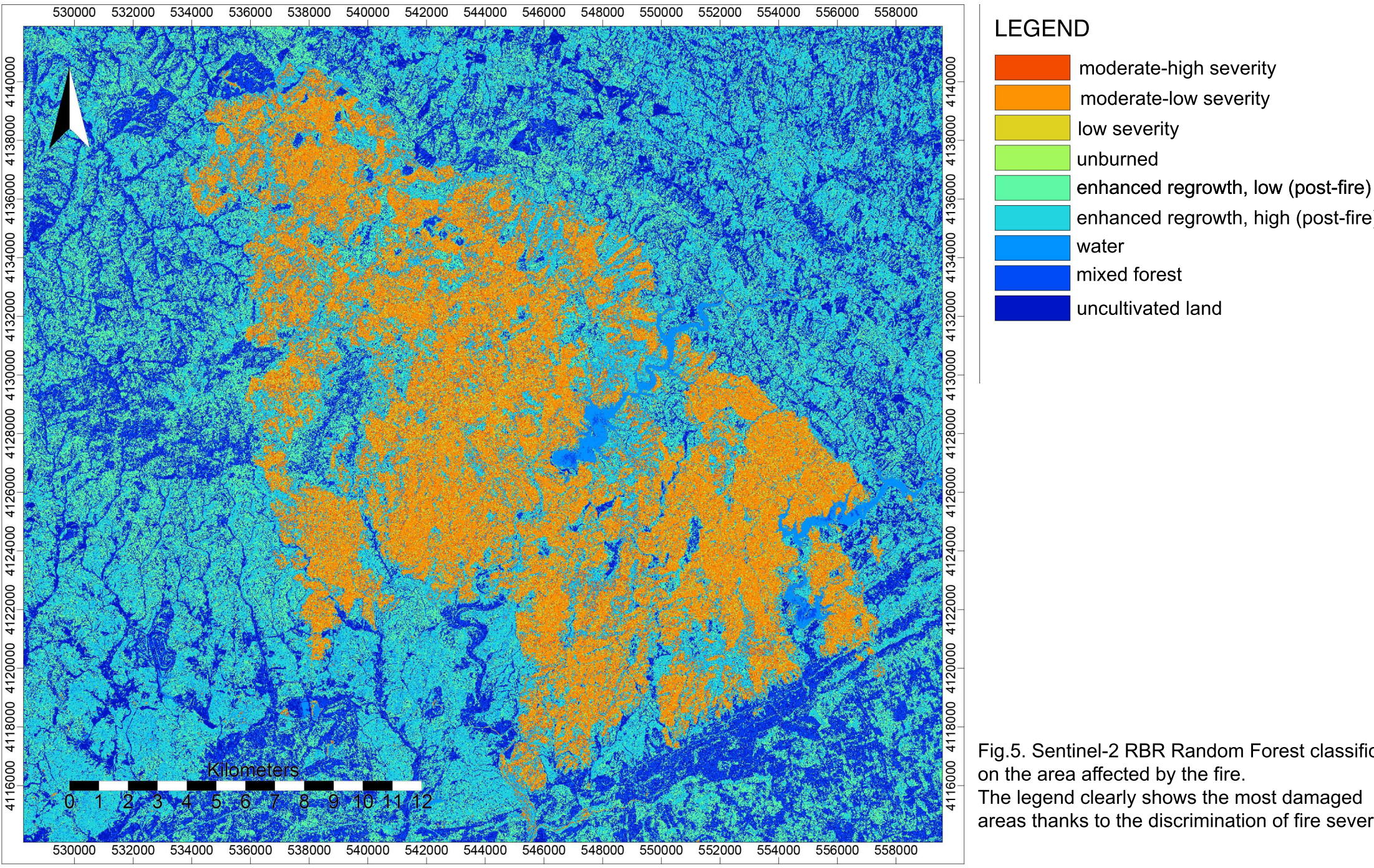
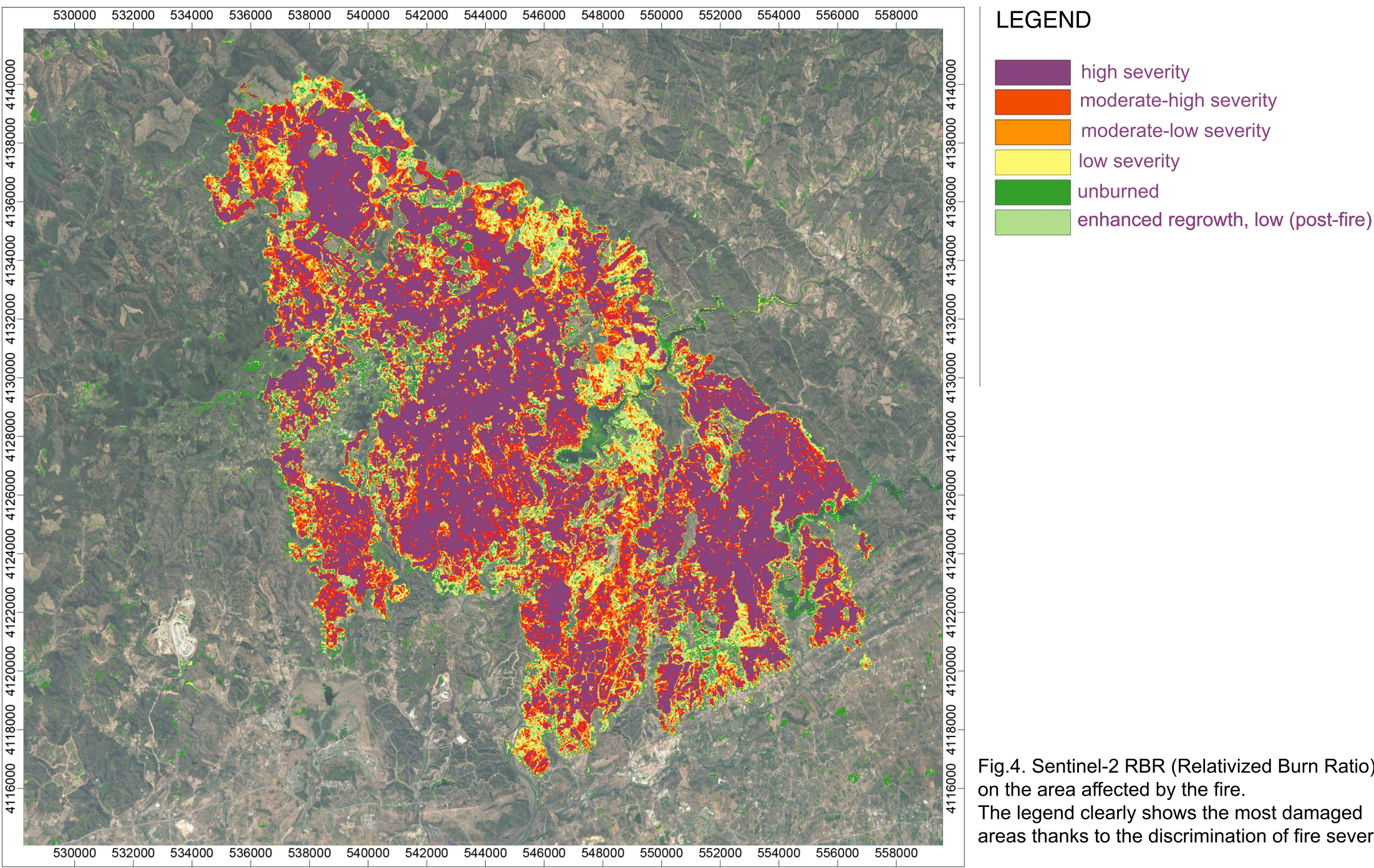
On the latter, new Machine Learning techniques were being applied, with a particular attention to the Random Forest[4], a special classifier formed by a set of simple classifiers represented as independent and identically distributed random element. This procedure allows us to obtain better classification accuracy. It is important to carefully choose the attributes to be provided to the Random Forest as they must be as significant as possible. Our features are determined by the results of the mapping of the burned area from which, thanks to the RBR (Relativized Burn Ratio), we obtained the different levels of fire severity; these levels are catalogued by the United States Geological Survey (USGS), which proposed a classification table to interpret the severity of burns.

Conclusions

The spectral indexes return information about the valuation of the risks, fire and burn severity, characterizing the entity of the damage, but they are not adequate for greater discrimination of the burnt areas and of the damaged they went through, instead the classification supervised by the classifier Random Forest returns us a level of fire severity more accurate, allowing us to extract precise information for the evaluation of post-fire damage.

Severity Level	dNBR Range (scaled by 10 ³)	dNBR Range (not scaled)
Enhanced Regrowth, high (post-fire)	-500 to -251	-0.500 to -0.251
Enhanced Regrowth, low (post-fire)	-250 to -101	-0.250 to -0.101
Unburned	-100 to +99	-0.100 to +0.99
Low Severity	+100 to +269	+0.100 to +0.269
Moderate-low Severity	+270 to +439	+0.270 to +0.439
Moderate-high Severity	+440 to +659	+0.440 to +0.659
High Severity	+660 to +1300	+0.660 to +1.300

Figure 3. The United States Geological Survey (USGS) has drafted a classification table to interpret the burn severity (dNBR). Credits: UN-SPYDER Knowledge Portal



References

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- [4] Phan Thanh Noi, Martin Kappas, Comparison of Random Forest, k-Nearest Neighbor, and Support Vector Machine Classifiers for Land Cover Classification Using Sentinel-2 Imagery, MDPI, Article in Sensors, December 2017