On the Mapping of Burned Areas and Burn Severity Using Self Organizing Map and Sentinel-2 Data

R. Lasaponara, A. M. Proto, A. Aromando, G. Cardettini, V. Varela, and M. Danese

Abstract—**In this letter, we propose an approach based on the use of Sentinel-2 spectral indices and self-organizing map (SOM) to automatically map burned areas and burned severity. These analyses were performed on a test area in Chania, located in Crete, affected by a fire (around 200 ha) that occurred from July 13, 2018 to July 28, 2018. The investigated area is characterized by heterogeneous land cover types made up of natural and agricultural lands. To identify different levels of fire severity without using fixed thresholds, we applied SOM to the three spectral indices normalized difference vegetation index (NDVI), normalized burn ratio (NBR), and burned area index for sentinel (BAIS) used to enhance burned areas. This is a particular critical issue because fixed threshold values are generally not suitable for fragmented landscapes, vegetation types, and geographic regions different from those for which they were devised. To cope with this issue, the methodological approach herein proposed is based on three steps: 1) indices computation; 2) maps of the difference of the three indices computed using the data acquired from prefire and postfire occurrences; and 3) unsupervised classification obtained processing all the difference maps using the SOM. The obtained results were validated using an independent data set, which showed high correlation with satellite-based fire severity.**

Index Terms—**Burned areas, burned severity, remote sensing, self-organizing map (SOM), Sentinel-2.**

I. Introduction

WILDFIRES are considered as one of the most important causes of degradation [1] being that they induce significant alterations not only on the vegetation cover but also on fauna, soil, and atmosphere, thus producing high direct and indirect damage including economic ones.

Significant efforts have been addressed from the major national and international space agencies to monitoring forest fires from space so that several open products are currently made available by NASA and ESA (see http://www.esa.int/About_Us/ESRIN/World_fire_maps_now_available_online_in_near-real_time). These products are mainly related to global active fires and burned areas. Today, fire is one of the most important focal issues of Copernicus program (see european forest fire information system (EFFIS) products [2]), which aims at supporting EU member states through the use of satellites for risk monitoring including fire mainly in terms of active fire mapping and the rapid assessment of burned areas and burned severity. Burned severity is a qualitative indicator of the effects of fire on ecosystems whether it affects the forest floor, canopy, and so on. The effects of fires on soil, plants, landscape, and ecosystems depend on many factors, such as fire frequency and plant resistance. Assessing and mapping burn severity is important for monitoring positive and negative [3], [4] fire effects to model and evaluate postfire dynamic and to estimate the ability of vegetation to recover after fire (generally indicated as fire-resilience). In an operational context, burn severity estimation is critical to short-term mitigation and rehabilitation treatments. Traditional methods of recording fire severity involve expensive and time-consuming field surveys, and the use of satellite remote sensing can help in overcoming these drawbacks. Earth observation (EO) technologies can enable advanced performance and new operational applications specifically addressed to security and risk. In particular, Copernicus Program and Sentinel missions have been devised specifically for supporting risk monitoring and offer advanced satellite data free of charge (as Sentinel-2 [5]) that can suitably support forest fire monitoring from risk estimation to damage quantification. Nevertheless, the Sentinel data pose several challenges related to the processing, analysis, and interpretation of the data that need to be tackled by the scientific community in order to ensure reliability and operational applicability.

In this letter, we propose an approach based on the use of Sentinel-2 spectral indices and self-organizing map (SOM) to automatically map burned areas and burn severity. The methodology herein proposed is applied to a fire occurred from July 13, 2018 to July 28, 2018 in Chania, Crete, Greece, affecting both agricultural land and natural vegetated areas. Strong winds were stoking the blaze, making it difficult for firefighting crews to contain the flames (from Greek Fire Brigade Report [6]). According to Corine land cover 2012, the investigated area is characterized by the presence of heterogeneous land cover types made up of natural vegetation as woodland and sclerophyll Mediterranean Evergreen forest, natural, and agricultural areas. To identify different levels of fire severity without using fixed thresholds, burned areas and severity were enhanced using spectral indices and further

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classified using SOM. This is a particular critical issue because fixed thresholds are generally not suitable for fragmented landscapes and inadequate for vegetation types and geographic regions different from those for which they were devised. The results obtained from Sentinel-2 were validated using an independent data set.

II. Methodological Approach

There are many indices that can be derived from the satellite data for burn severity estimation but, still today, their automatic or semiautomatic classification is an open issue. These methods are a part of Geo-visual Analytics and also used for image analysis with different techniques coming from disciplines, such as geographic information science, exploratory data analysis [7], and visual data mining of geospatial information [8]. The aim is to combine the human visual ability to discover patterns [9] and the computer processing ability to analyze and extract patterns in a huge quantity of complex data.

In this letter, the SOM [10] was used. It is mainly a multiparametric tool for dimensionality reduction and classification, and in this case, it demonstrated to be very useful for the categorization of burned severity classes. It lies in an unsupervised learning algorithm developed inside a neural network architecture. The first part of SOM is a recursive and competitive training process. Through it, the best matching units (BMUs) constituting the neural network are chosen, and the vectors of the analyzed data set are associated with them by considering both the value of attributes and the distances between them. The second part is a mapping process. BMUs are organized in a 2-D lattice. The closer the SOM cells are, the more they show similar behavior and spatial proximity.

III. Study Cases

The analyses were performed on a fire occurred in the Chania municipality, located in Crete, Greece, in which a fire between July 23, 2018 and July 28, 2018 affected 200 ha.

Sentinel-2 images analyzed has an extent of 427 × 261 (= 111447) pixels that have three attributes associated with each of them: the variation computed between postoccurrence and preoccurrence of three vegetation indices normalized difference vegetation index (NDVI), normalized burn ratio (NBR), and burned area index for sentinel (BAIS) shown in Fig. 1 and defined in formulas (1)–(3)

$$NDVI = \frac{B8 - B4}{B8 + B4} \tag{1}$$

$$NBR = \frac{\mathrm{B8} - \mathrm{B12}}{\mathrm{NB8} + \mathrm{B12}} \tag{2}$$

$$BAIS = \left(1 - \frac{\sqrt{B6 + B7 + B8A}}{B4}\right) * \left(\frac{B12 - B8A}{\sqrt{B12 + B8A}} + 1\right) \tag{3}$$

where B4 B06, B7, B8A, and B12 are the Sentinel-2 spectral channels used for the index computation

For this letter, SOM classification was based on the use of all the three indices 1–3.

Totally, there are 334 341 information (T in Table I) to analyze. SOM was performed with the V-analytics software [11].

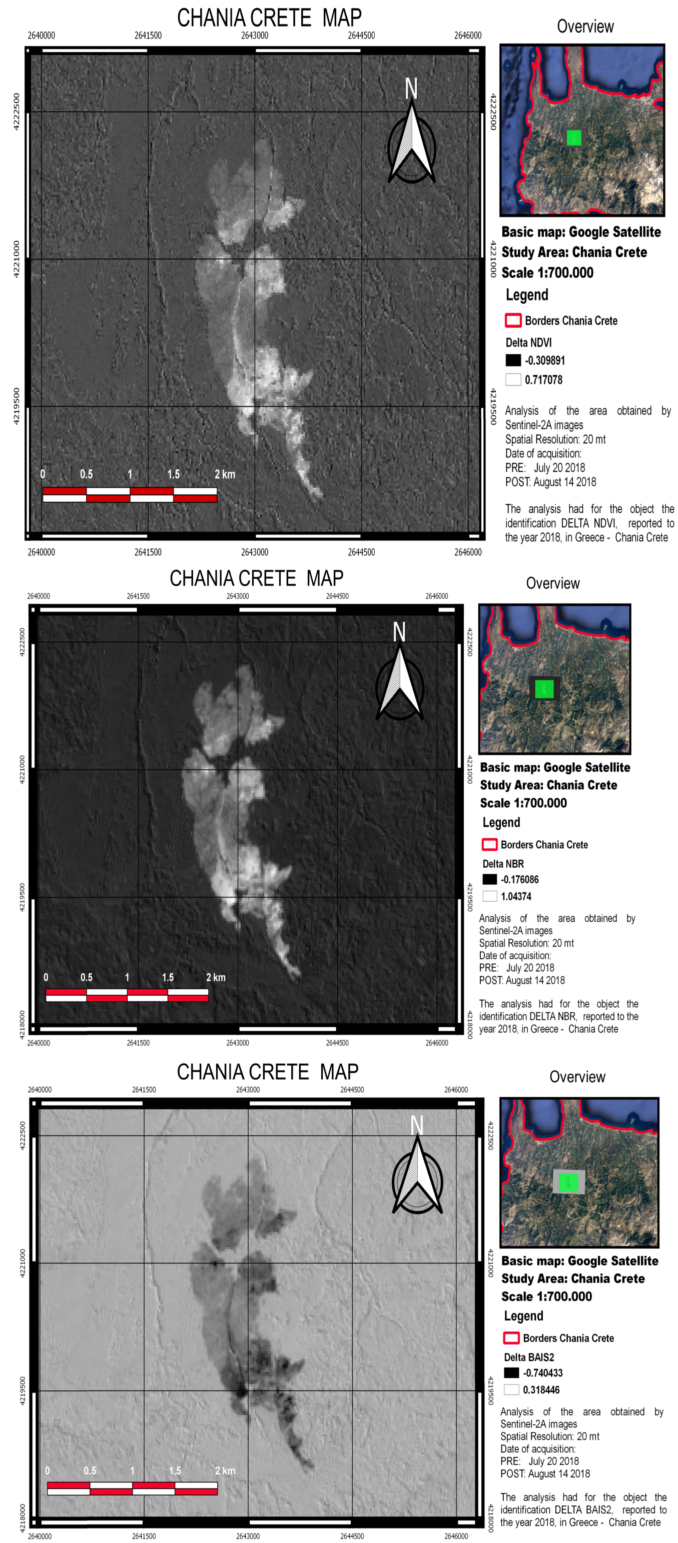

Fig. 1. Study area location along with the difference in (Top) NDVI, (Middle) NBR, and (Bottom) BAIS maps computed as prefire and postfire occurrences.

First, the Vesanto [12] expression [in formula (4)] was used to determine the optimal SOM size

$$S = 5 \cdot \sqrt{N}. \tag{4}$$

While for the SOM shape, the recommendation [13], [14] to use an asymmetrical SOM shape was followed. In particular,

TABLE I
SAMPLE SIZE AND SOM DIMENSIONS

R	C	A	N	T	S	S_a	S_b
427	261	3	111447	334341	1669	29	58

R = rows, C = columns, A = attributes, N = R x C, T = R x C x A.

TABLE II
BURNT SEVERITY CLASSES, SOM DIMENSIONS, AND BURNT AREAS DETECTED

SOM sides	SOM cells with different burnt severity (row x - column y)	Number of classes obtained	Burnt areas (Ha)
13x6	5-1, 5-2, 5-3, 6-1, 6-2, 6-3	6	167.12
11x5	2-1, 3-1, 4-1, 5-2, 5-1	5	170.68
10x4	1-1, 1-2, 1-3, 1-4	4	152.72

the shorter side (Sa) should be at least half of the longer side (Sb).

Consequently, the following expressions were used:

$$Sa = \sqrt{\frac{S}{2}} \quad Sb = 2 \cdot Sa. \tag{5}$$

The SOM sizes found with expression (5) (see Table I) were used first to perform SOM and identify burned areas. In order to obtain fire severity categorization inside the burned areas, we iteratively reduced the SOM size and, consequently, the burn severity classes. Finally, three SOM sizes (13 $\times$ 6, 11 $\times$ 5, and 10 $\times$ 4) were chosen as final candidates (see Table II) because under a lattice of 10 $\times$ 4 elements, the classification is no more effective being that the burned areas are not well extracted.

IV. RESULTS

The SOM colors found in the three results enabled us to effectively visualize the classification system of burned areas and burn severity via node clusters so that burned areas and burn severity levels are easily identified and interpreted according to their hot spot locations. Actually, the SOM cell colors are a way to group data, in our case pixels, according to their values and their spatial proximity. In other words, large distance in values is automatically assigned to different colors and clusters. The interpretation of the output of the SOM classification (based on all the three indices 1–3) was made mainly on the use of NBR because it is the most commonly used index for burn categorization.

We found that burned areas and burn severity with similar hot spot values have automatically similar colors on the grid nodes and have a small distance in the pixel values. By comparing the SOM outputs with the extension of the known burned area and burn severity available from both the Fire Brigade report (150 ha, plus areas damaged by heat even if not directly affected by fire) and the EFFIS website (200 ha) [5], we found that with SOM classifications, the best result is given by the 13 $\times$ 6 lattice (see Fig. 2). Here, we gave a severity level to the different SOM classes found by considering dNBR mean that is the most commonly

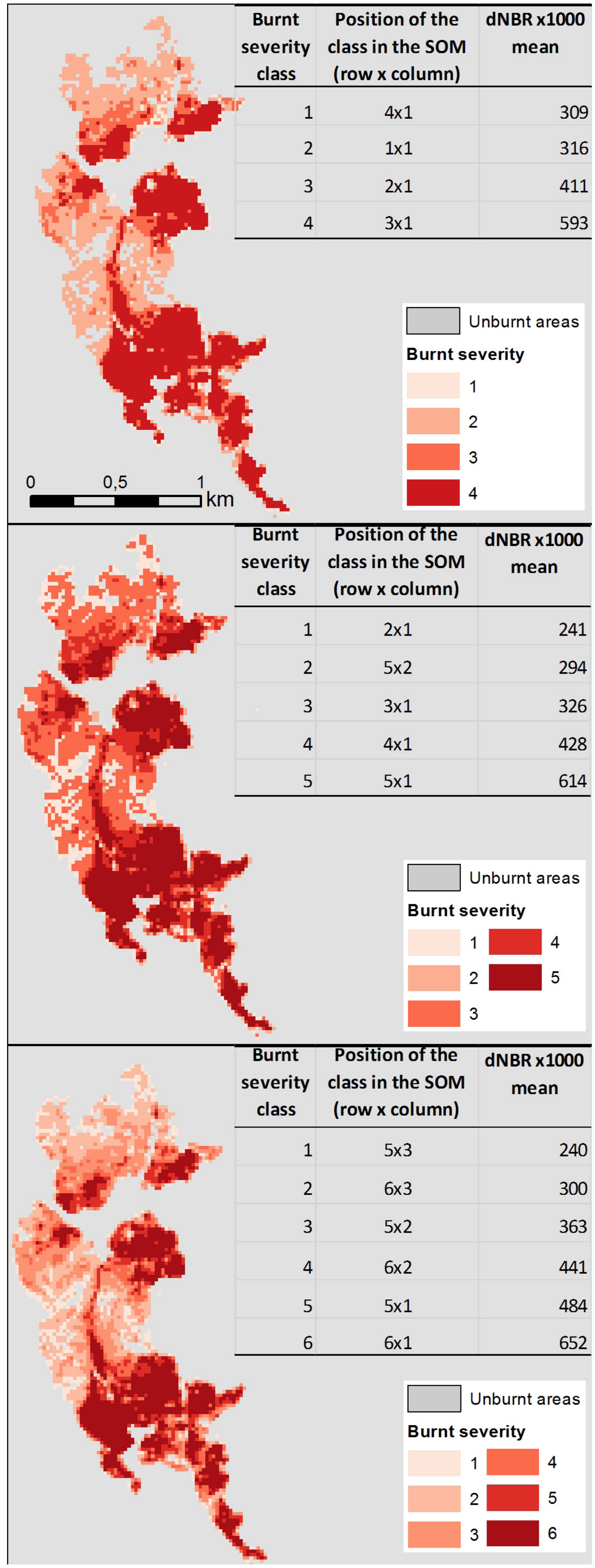

Fig. 2. Fire severity classes and corresponding dNBR mean for the three best SOM classifications found.

TABLE III
Δ NBR BURN SEVERITY USGS CATEGORIES [4]

ΔNBR	Burn Severity
0.1 to 0.27	Low-severity burn
0.27 to 0.44	Moderate-low severity burn
0.44 to 0.66	Moderate-high severity burn
> 0.66	High-severity burn

adopted for fire severity categorization compared with other vegetation indices. Table III lists the United States Geological Survey (USGS) burn categorization based on the dNBR values. To characterize the burn severity level, we found six clusters (plus one unburnt) coherent with the traditional assumption of fire severity as listed from (2) to (7).

The number of classes and, in turn, the different levels of burn severity were based on the following "guideline," defined considering a quantification of the direct impact of fire.

1) *Unburnt Areas* (*No Change*): Unchanged surfaces, i.e., fire unaffected areas.
2) *Burn Severity* 1 (*Very Low*): Areas of surface fire occurred with very little change in cover and little mortality of the structural dominant vegetation.
3) *Burn Severity* 2 (*Low*): Areas of surface fire occurred with little change in cover and little mortality of the structural dominant vegetation.
4) *Burn Severity* 3 (*Moderate*): The area exhibits a mixture of effects ranging from unchanged to high severity within the scale of one pixel.
5) *Burn Severity* 4 (*High*): The area exhibits a mixture of effects ranging from moderate to high severity within the scale of one pixel.
6) *Burn Severity* 5 (*Very High*): Vegetation has high to 100% mortality.
7) *Burn Severity* 6 (*Extreme*): Soil burn severity assessment with the characteristics of high severity, including heavy white ash deposition indicating the loss of substantial levels of organic matter and loose unstructured soil.

According to the report of Fire Brigade, the fire propagated into areas with rough topography, burning mainly grassland and forest land, also causing damage to crops and honeybees. The type of burned vegetation reported in the Fire Brigade report was mainly forested area 80 ha, grassland 50 ha, agriculture 20 ha, plus additional areas made up of crops and agricultural lands not directed affected by fire, but severely damaged by heat released by combustion. Fig. 3 (top) shows the Corine land cover for the fire affected area. The levels of burn severity we adopted are based on the consideration that they have to provide a qualitative measure of the immediate effects of fire on the ecosystem. Therefore, the diverse burn severity levels are related to the effect of fire on plants and specifically "to the extent of mortality and survival of plant and animal life both aboveground and belowground and to

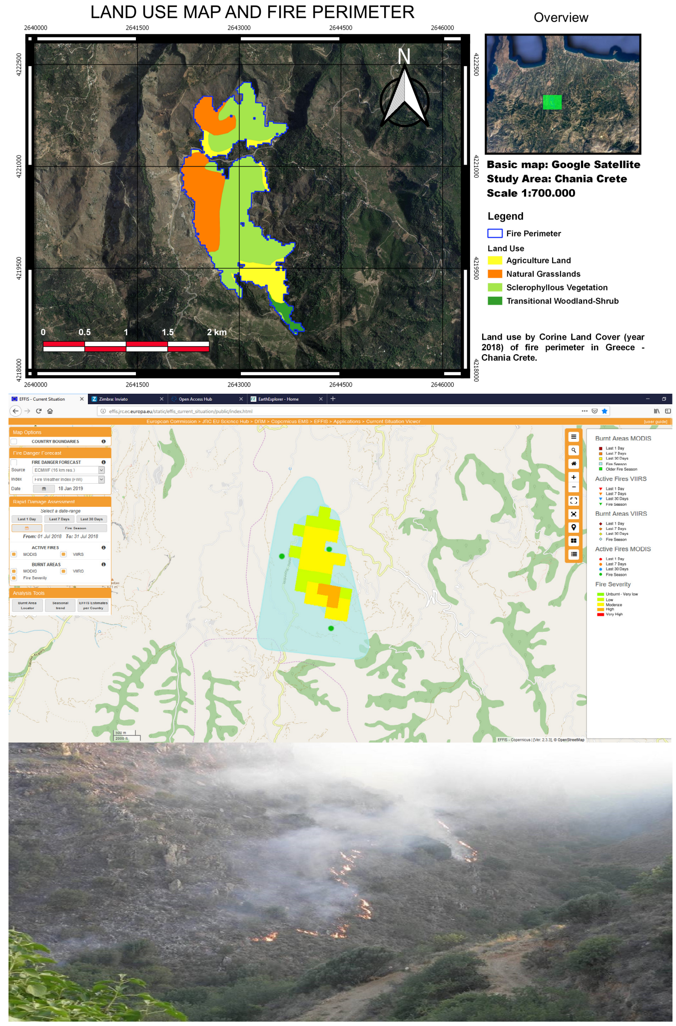

Fig. 3. (Top) Land use as obtained from the Corine land use–land cover map. (Middle) Burned severity as obtained from the Modis data in the EFFIS [2] system (available free of charge online). (Bottom) Aerial photographs of burning area as obtained from media and Fire Brigade report.

loss of organic matter" [15]. These effects are dependent on intensity and residence and determined by the heat released aboveground and belowground [15]. The diverse levels of burn severity herein defined are characterized for each class by a dNBR average whose meaning is consistent for the different land cover types: from a visual comparison between Fig. 2 (bottom) and Fig. 3 (top), it is clear that the highest fire severity levels were mainly found in forest lands, shown in Fig. 3 (top) in green colors and corresponding to transitional woodland shrubs and sclerophyllous vegetation according to the Corine land cover. As a whole, the levels of burn severity herein adopted are not only coherent with the USGS categorization (listed in Table III) but also they may be considered as a "refined identification" of burn severity based on the USGS. This "refined categorization" is necessary for many reasons, and above all, it is driven by the scale of mapping, linked, in our case, to the pixel size. The outputs from the satellite were successfully compared with the independent validation data set made up of the following.

1) Corine land cover to assess the meaning of each class and this is consistent for the different land cover types affected by the fire. Fire severity levels were mainly

found in the areas with denser vegetation as forest and agricultural lands.

2) EFFIS burn severity map 250 m (Sentinel 10–20 m).
3) Fire Brigade report, aerial photographs, and in situ analysis to assess that, actually, the dNBR values reflect the meaning of the burn severity classes (see [4] and references therein).

The comparison between the satellite-based results and the independent data sets and analysis confirmed that the different classes of fire severity actually correspond to the areas affected by the fire at different levels. Actually, we have to consider that burn severity is: 1) related to the effect of fire [15] that can be very different even in homogenous areas with similar vegetation cover and 2) strongly dependent on local effects (previous forest treatments, slope, aspect, elevation, specific conditions of fuels, and so on) and meteorological conditions.

For these reasons, burn severity levels usually consider the various percentages of burned severity in order to cope with the presence of complex mixture of effects [15]. Therefore, burn severity mapping is also strongly linked to the pixel size, which obviously provides indication related to an average of all the targets therein present. For this reason, the categorization available in EFFIS, made using MODIS with a pixel size at 250 m, roughly fits the burn severity herein obtained using the Sentinel-2 data with a pixel size at 10 and 20 m. Of course, to deeper investigate the scale effects/constrains, additional analyses are needed using multiscale, multisensor data set.

V. Conclusion

This letter illustrates the potential for Sentinel-2 for burned area mapping and for the characterization of burn severity using the SOM approach. The results from the classification were validated on the basis of independent analysis conducted in the investigated area and shown in Fig. 3. The novelty of our approach is the automatic identification of burn severity obtained using the following three steps: 1) computation of NDVI, NBR, and BAIS indices and their difference from cloud-free images acquired before and after the fire occurrence; 2) maps of difference of these three indices computed as postfire and prefire occurrences; and 3) unsupervised classification obtained processing all the difference maps (NDVI, NBR, and BAIS) using the SOM. One of the most important advantages of our approach compared with the traditional ones is that both burned areas and the different levels of burn severity can be identified automatically and without using fixed threshold values. Further studies will be carried out to make our approach more statistically robust.

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