

Fire Severity and Vegetation Recovery Determination Using GEE and Sentinel-2: The Case of Peschici Fire

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Abstract. We propose an accurate and rapid methodology for the extraction of spatio-temporal fire features using Sentinel 2 products and the Google Earth Engine (GEE) platform. All Sentinel 2 images available in the GEE platform were clipped using the fire area mask and then the NBR, NDVI. dNBR and RdNBR indices were derived. The differential values of NBR, NDVI, dNBR and RdNBR were obtained by calculating the difference of the index values between two temporally adjacent images. The use of all available images in GEE restricted the time of occurrence of the images 5 days, excluding cloud-covered images and shortening the processing time of each satellite image. The results obtained showed that the proposed methodology allows for the rapid and accurate identification and classification of burnt areas, and also allows for the efficient and accurate extraction of the spatio-temporal characteristics of post-fire vegetation recovery. The results obtained can be used to implement targeted post-fire vegetation restoration practices.

Keywords: forest fire · remote sensing · GEE · GIS

1 Introduction

The factors that define the rate of vegetation regeneration after a fire are many and their complete identification is difficult. These factors are related to the characteristics of the fire environmental conditions and the characteristics of the plant species. Fire severity levels, topography (elevation, slope and orientation), post-fire climate and vegetation cover class are the most commonly used in estimates of regeneration [1]. Several studies have revealed that the influence of environmental factors on regeneration can vary between vegetation types [2].

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O. Gervasi et al. (Eds.): ICCSA 2023 Workshops, LNCS 14112, pp. 220–231, 2023.
https://doi.org/10.1007/978-3-031-37129-5_19

Fire intensity represents the energy released during a fire. Topography, fuel type and condition, moisture content and chemical composition, and wind are the decisive factors in determining fire intensity. Therefore, fire intensity and fire duration take on opposite meanings in the presence of a given amount of fast-burning fuel. Consequently, high intensity fire with a low residence time may not be severe and may have low plant mortality. In contrast, low-intensity fires may damage the soil more than vegetation during combustion, e.g. burning litter or peat produce long-lasting heating resulting in increased severity. The vulnerability of vegetation to fire and post-fire responses are related to a set of characteristics that characterize each individual vegetation type. Remote sensing is often used in the monitoring of post-fire vegetation [1]. Indices derived from spectral bands have been widely used to estimate fire severity remotely [3, 4]. Fire causes changes in the spectral behavior of vegetation [5, 6]. Reflectance in the mid-infrared, which is sensitive to the water content of soil and vegetation, increases after fire, while in the near-infrared region the decline in reflectance occurs due to the fall in chlorophyll content of living vegetation.

Remote sensing is often used in the monitoring of post-fire vegetation [7, 8]. Indices derived from spectral bands have been widely used to estimate fire severity remotely. Fire causes changes in the spectral behavior of vegetation. Reflectance in the mid-infrared, which is sensitive to the water content of soil and vegetation, increases after fire, while in the near-infrared region the decline in reflectance occurs due to the fall in chlorophyll content of living vegetation.

Satellite earth observation is widely used to detect burnt areas [4, 9–12]. Satellite detection of burnt areas is commonly based on the detection of the effects of fire on the reflectance of vegetation. The increasing availability of medium spatial resolution sensors such as Landsat-OLI (30 m) or Sentinel-2 Multi Spectral Instrument (MSI) (10 m) can also overcome the limitations of lower resolution sensors in detecting smaller fires. In addition to improving fire detection and response times, there is also a need to improve the delineation, assessment and post-event monitoring of affected areas. Such post-event analysis can then be brought within the framework of strategies and policies for fire prevention, prediction, mitigation and response. The use of satellite imagery allows for accurate post-event delineation of fire extent and makes it possible to

- identify and estimate smaller areas affected by fires;
- avoid ground surveys in difficult areas to determine the location and extent of fires;
- use additional data in conjunction with satellite imagery to better assess, monitor and respond to fire-affected areas and communities;
- monitor environmental recovery, especially in relation to agricultural and forest areas.

To assess fire severity and vegetation regeneration using time series, several methodologies have been proposed, the most common being to monitor the state of vegetation from spectral indices. Among the most widely used indices are the Normalized Difference Vegetation Index (NDVI) [13–15]. Some studies have successfully applied NDVI, due to the relationship between the amount of vegetation consumed and fire intensity. In addition, specific indices have been developed that record the effects of fires with greater spectral contrast, such as the Normalized Burn Ratio (NBR). We propose an accurate and efficient framework for the extraction of spatio-temporal fire features using Sentinel 2 products and the Google Earth Engine (GEE) platform. All Sentinel 2 images available

in the GEE platform were clipped using the fire area mask and then the NBR, NDVI and RdNBR indices were derived.

The Google Earth Engine (GEE) platform infrastructure allows for the production of complex geospatial products on various geographical and temporal scales, cloud-based processing and access to the platform, algorithms for classification and data processing [16–19].

There are still few works in the literature that have seen the application of GEE for monitoring fire severity and burnt areas [16, 20, 21].

Sentinel-2 is due to its innovative spectral properties, including red-edge bands suitable for characterizing chlorophyll content, which provide the means to create new indices for mapping fire severity [22, 23], is a useful source for monitoring burnt areas. Several previous studies have assessed forest fires using the normalized burn ratio (NBR). The NBR, in fact, exploits the near-infrared (NIR) and shortwave infrared (SWIR) regions of the electromagnetic spectrum [24] which makes it suitable for detecting fires in vegetation because changes in the NIR usually represent changes in photosynthetically active vegetation, which is reduced by fire, while changes in the SWIR reflect moisture content [25]. Indeed, fire causes a sharp contrast between NIR and SWIR recordings [26]. Furthermore, previous studies have used NBR variants, among which the differenced normalized burn ratio (dNBR) is commonly applied. The dNBR is a bi-temporal image differentiation performed on pre- and post-fire NBR images [5] to distinguish burn severity levels. The dNBR based on fire category has become a practical reference for obtaining information on burn severity [4, 27].

In this preliminary study, we present a rapid method for monitoring burnt forest areas and estimating post-fire vegetative recovery, using the NBR, dNBR, RdNBR and NDVI indices derived from Sentinel-2 within the GEE framework.

2 Material and Method

2.1 Study Area

The methodology was applied to the study of the fire of 24 July 2017, the area affected is approximately 3 km^2 and is located between the municipalities of Peschici and Vieste, in the province of Foggia. This area is a typical Mediterranean ecomosaic in which the driest periods are contextual with the hottest periods of the year [28, 29] Two pre-fire and immediate post-fire satellite images totally devoid of cloud cover were used to calculate the dNBR.

For an estimate of vegetation recovery following the fire, the NDVI was calculated for the entire available historical series (2016–2021). A map of the vegetation cover of the burnt areas was generated from the Nature Map (2013) in vector format (Fig. 1). The vegetation species affected by the fire mainly concern coniferous plantations, and to a lesser extent we find orchards, olive groves and agricultural areas. The topographic variables (altitude, slope and aspect) were generated from the DEM mosaic for the fire, resampled at a resolution of 20 m and projected in the WGS84 UTM 33N reference system. The average altitude is about 180 m above sea level, the area affected by the fire has fairly steep slopes, ranging from 0 to 15° in most of the area, accompanied by slopes with slightly milder slopes. The exposure of the slopes, takes into account the

ability of the land to benefit from sunlight, in relation to its orientation with respect to the four cardinal points and the possible presence of mountains in the surroundings, or to suffer negative phenomena such as exposure to winds, which would be detrimental to cultivation. It is possible to divide the burnt area into two parts, one in which the vegetation is predominantly wooded and the prevailing exposure is from the east and south, while in the other part the prevailing exposure of the burnt area is from the east and north (Fig. 1).

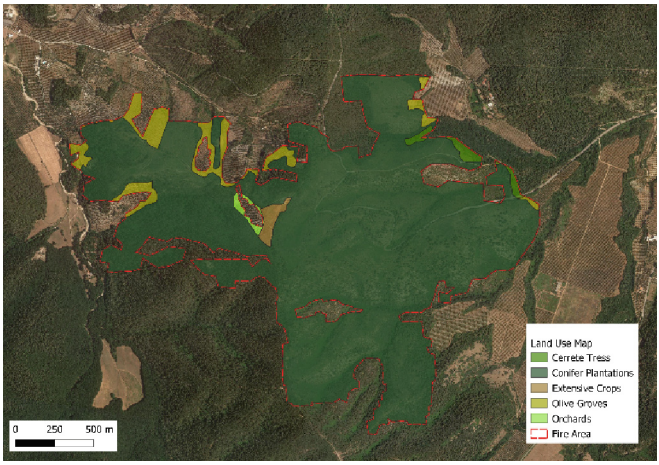

Fig. 1. Fire area and land use.

2.2 Methodology

The objective of the research is to implement an automatic procedure (tool) capable, starting from the processing of satellite images, of perimeter fires in a rapid and expeditious manner (i.e. as close as possible to the event) and to calculate severity indices that allow the mapping of first-order impacts (i.e. immediately after the event and second-order impacts (years after the event). The GEE software is the tool used for all data processing and spatial analyses. In particular, for the management of satellite images, which allows you to download satellite images and to pre- and post-process them. Images from the Sentinel-2 satellite were used to assess the severity of the fire.

The first analysis focused on estimating the fire severity of the entire burned area, through the calculation of the dNBR and RdNBR indices. The fire shows a very high severity (Fig. 2), with the presence of dNBR and RdNBR values higher than 1, in wooded areas. Subsequently, the severity was calculated in the years following the fire (from 2018 to 2021). During this pre-processing stage, proper masking of extremely dark pixels that do not represent burned-out areas plays a key role in reducing the generation of false positives, as well as reducing the computational effort.

After having identified and bounded the burned area and estimated the fire severity, we proceeded with the calculation of the NDVI index for the estimation of post-fire vegetative recovery.

3 Results and Discussions

3.1 Fire Severity Impact Assessment

As a consequence of a fire, vegetation shows a series of changes in the electromagnetic spectrum due to the effect of fire on chlorophyll. Fire destroys vegetation and, in many cases, leaves the ground bare, charring the roots of trees and also altering soil moisture.

This reduction in chlorophyll results in an increase in the visible region of the electromagnetic spectrum and a decrease in the near-infrared region [3, 30, 31]. There are many spectral indices used for the identification of burnt areas and the estimation of fire severity, among these the NBR (Normalized Burn Ratio) is one of the most widely used. This index combines near infrared and mid-infrared information and has been used extensively for the discrimination of burnt areas in the Mediterranean. The difference between the two pre/post-fire times allows us to estimate the dNBR, which in GEE has been reclassified from 0 to 1 based on the severity value (Fig. 2). The dNBR range values are fundamentally site-specific, no fixed thresholds are applied, but are classified according to the severity of the event by applying clustering algorithms to objectively assign fire severity classes to dNBRs based on an iterative breakdown of the data [32].

In this study, six classes of dNBR and RdNBR were selected: unburned; very low, low, moderate, high and very high.[33]. The dNBR shows the absolute value of change, while the RdNBR is a relative index which allows a certain independence from the conditions of the vegetation before the fire. Some studies have found that RdNBR is more accurate than dNBR [24] while others have found that RdNBR does not improve fire severity estimation and have shown similar correlations between the two indices and fire data field [33].

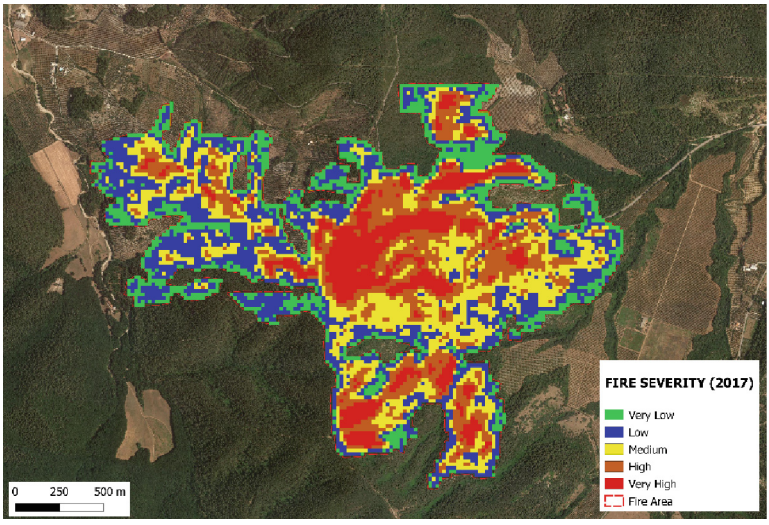

Fig. 2. Fire Severity of the fire of 07/24/2021.

Furthermore, several studies show that the RdNBR index is more sensitive to vegetation mortality and the dNBR to the severity of soil burn [34, 35]. The dNBR index, being linked to the variation of the NBR values calculated before and after the event, provides a measure of the effects of the fire and can therefore be used to characterize the degree of fire severity. The dNBR and RdNBR indices relating to the period of the event were first calculated and subsequently it was calculated over a period of 4 years (2017–2021). After the fire, we observe a mosaic of areas with different degrees of fire severity and this heterogeneity determines important implications in ecosystem recovery and land use possibilities (Fig. 2).

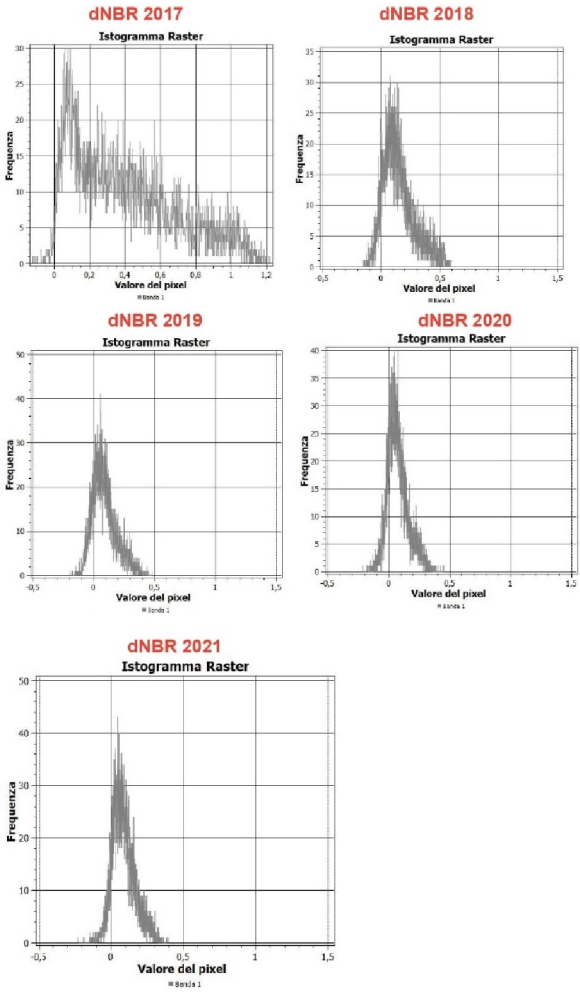

Fig. 3. Fire severity histograms for 2017 to 2021.

The fire shows a very high severity (Fig. 2), with dNBR and RdNBR values above 1 in the wooded areas. Subsequently, the severity was calculated in the years following the fire (from 2018 to 2021). Figure 3 shows the histograms with the fire severity values in the years following the event, what can be seen is that already starting from the year following the event, the severity values decrease significantly. In order to better photograph the evolution and impact of the fire in the affected area, the dNBR values calculated in the years following the event were compared with the dNBR value calculated immediately after the fire along 6 representative profiles. What emerges by analyzing the six profiles is a drastic decrease in the impact of the fire in the following years. The dNBR values significantly decrease going from severity values greater than 0.8 with peaks of 1.2 in 2017 to values of 0.4 the year following the event and values close to the non-burned threshold of 0.1 in 2021.

While the dNBR algorithm measures the absolute change between the pre- and post-fire images, the RdNBR algorithm determines burn severity based on the pre-fire reflectance and calculates the relative change caused by the fire. Similarly, to the processing listed previously for dNBR, the RdNBR value was calculated along the 6 profiles, also in this case, a fire behavior similar to dNBR emerges, with very high values, in some areas even higher than 1, which decrease in the following years.

The comparison of vegetation classes, RdNBR and dNBR showed, therefore, similar patterns of pixels classified as burnt.

3.2 Recovery Estimation

The spectral indices help to identify the state of the vegetation along the time series thanks to the improvement of the sensitivity of the different spectral bands. One of the most used indices is the Normalized Difference Vegetation Index, which is calculated by combining the near infrared (NIR) and red (R) bands, it is particularly useful for monitoring plant regeneration after fires.

Following the estimation of the impacts of the first order fire through the estimation of the fire severity and the perimeter of the burned area, a historical analysis of the vegetational state of the burned area was carried out through the use of NDVI. Specifically, an estimate was made of the state of the vegetation before the fire (June 2016–2017) and after the fire (June 2018–2021). Finally, the values of the dNBR pixels were compared with those of the historical series of NDVI, to verify how the vegetation responded to different degrees of severity. What can be seen in most of the studied area, even by carrying out a visual analysis with Google Earth orthophotos, is a change in the vegetation following the fire. Specifically, before the event the vegetation present belonged to the class of conifers, following the fire (year 2017) the vegetation was extensively damaged, in fact the effects of the fire on the shrubs are also evident in 2019, where the foliage of the plants remained standing still show the signs of the fire. Where the shrubs have been completely or almost totally destroyed, in the following years the vegetation present is mainly herbaceous (Fig. 4).

Comparing two images where the pre-fire vegetative cover is made up of coniferous forests, the fire has not completely destroyed this part of the forest, in fact the burned part of the forest, after a decrease in the NDVI index immediately following the event,

shows a slow vegetative recovery of the same vegetation typology, as shown by the slight increase of NDVI in the following years (Fig. 5).

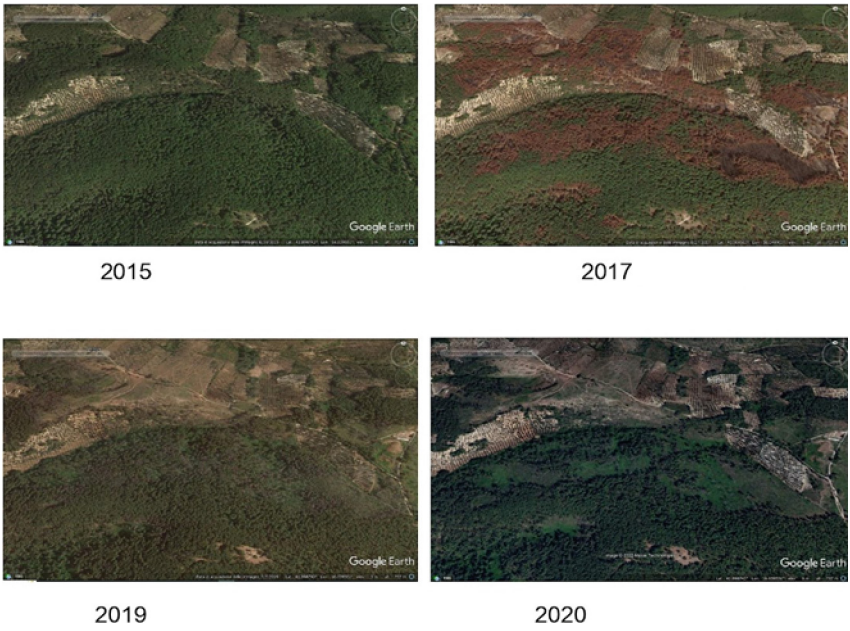

Fig. 4. Detail of the burnt area: pre-fire, during and post-fire images.

On the contrary, in an area of the forest completely destroyed by the fire, there was a drastic decrease in 2018 (following the fire) and a rapid rise in the index values which correspond to those of a meadow. In fact, in this part of the forest, following the fire, the trees were totally destroyed and/or removed following the fire, leaving space for the growth of bushes and meadows. This change of vegetation cover from woods to meadows is confirmed by the values of the historical series of NDVI which are higher following the fire than those pre-event in the same pixel. Comparing the areas in which the vegetation is composed of meadows and pastures, what emerges is a similar behavior of the NDVI both in non-burned areas and in areas affected by the fire with a severity greater than 1. This indicates the very of shrubs and meadows, so as not to highlight the presence of the fire starting as early as the following year. In areas covered by grass, the effects of fire are strongly influenced by the water content: if it decreases, dNBR and RdNBR increase because the fire resistance of the vegetation is lower. The dNBR values are also determined by the water content but in two opposite aspects: the residence time of the fire and the heat transferred to the ground. In fact, with the increase in water content, the duration of the fire increases while the amount of heat transferred to the ground decreases. The very high severity values in the meadows is probably due to the higher humidity of the same which, consequently, increases the duration of the fire.

It is interesting to note that the presence of shrubs mixed with grass compared to the presence of shrubs alone in a wooded area. This difference is fundamental in

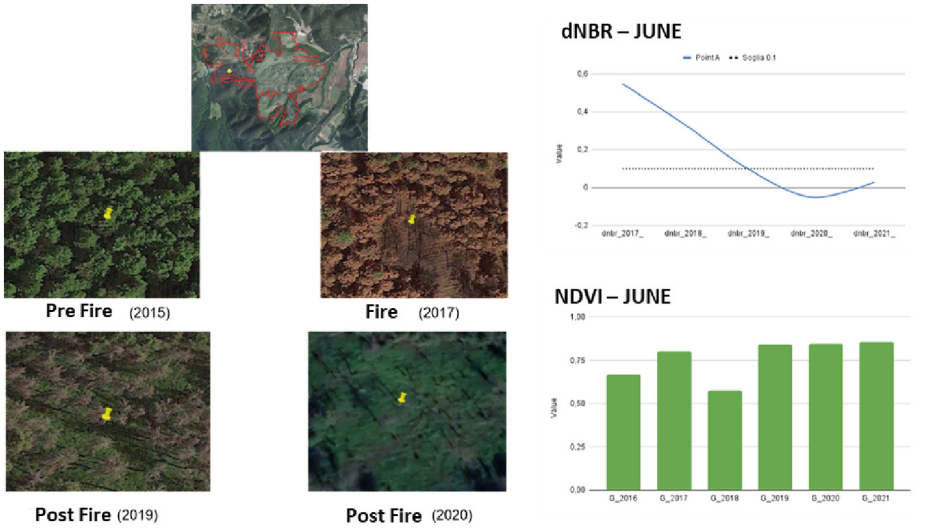

Fig. 5. Fire area pixel detail, pre-, during and post-fire images with dNBR trend curve and NDVI historical series of the considered pixel.

understanding fire behavior, because due to the presence of tall grass the fuel load, added to the load of shrubs, increases the fire in terms of intensity and duration. However, the presence of grass mixed with shrubs increases the moisture content and reduces the likelihood of the fire reaching a high severity in this type of vegetation, contrary to what happens in the presence of dry shrubs. Remote sensing-based analysis of fire severity is an essential tool for assessing ecosystems in general at different spatial scales. Behavior varies within each vegetation class. In particular, the dNBR index in conifer plantations is more severe than in the other vegetation classes present in the area; in fact, the presence of shrubs (in this case conifers) causes the fire duration to increase.

4 Conclusions

The paper further demonstrates that the use of satellite data in activities related to the development, implementation and pre-operational management of systems for remote monitoring and mapping of forest and interface fires is very useful. In the scientific field, algorithms and forecasting models based on Earth observation technologies have been developed with the aim of obtaining, at different spatial and temporal resolution, information on parameters concerning the estimation of fire severity and vegetative recovery.

Therefore, the activities carried out in this paper were aimed at implementing a monitoring model with pre-operational purposes in order to carry out a correct perimeter of the effects of first and second order fire. For proper forest management, accurate identification and mapping of burnt areas is necessary, but field monitoring is complex and expensive, and not always accurate. With ready-to-use satellite data freely accessible in cloud-based Google Earth Engine (GEE), monitoring first- and second-order fire

effects is much faster and cheaper. The results of this study demonstrate the great potential of Sentinel-2 satellite data and the use of GEE.

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