Exploiting Medium-Resolution Sentinel Data in Google Earth Engine for Burned Area Reflectance Classification

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Abstract. To analyze and forecast changes triggered by a fire in a natural ecosystem, it is critical to look into the extent of specific traceable physical indicators, such as fire intensity, fire severity, and burn severity. Previous research has shown that Earth observation data plays an important role in quickly assessing burnt regions. Despite several technological constraints, especially related to geospatial and temporal resolution, these data enable the development of burned area reflectance categorization maps with a strong correlation with ground-truth fire severity. Thus, this research is aimed at investigating the damages induced by fire in two Apulian municipalities (Bitonto and Vico del Gargano) by exploiting the potentialities of Sentinel images. To accomplish this purpose, a custom JavaScript code was created in the Google Earth Engine environment to calculate two indices: the Delta Normalized Burn Ratio (dNBR) and the Relativized Burn Ratio (RBR). The resulting thematic maps' accuracy was assessed using both the ground truth given by the European Forest Fire Information System (EFFIS) and those obtained by applying a photointerpretation technique. Both indices performed well in extracting burnt regions using the two ground-truth datasets, even though EFFIS perimeters had low-quality categorization, indicating poor data accuracy. Nonetheless, in both situations, RBR outperformed dNBR, and hence may be suggested as a reliable method for swiftly quantifying burnt zones. Finally, the Javascript code could be easily transferred to handle data from multiple research zones based on geographical location and size. Google Earth Engine appears to be a feasible option for storing and processing a large amount of geospatial big data.

Keywords: Burn Severity · Delta Normalized Burn Ratio (dNBR) · Relativized Burn Ratio (RBR) · European Forest Fire Information System (EFFIS) · Copernicus Program

1 Introduction

Natural and built environments have always been affected by fires. To some researchers, such as Stephen Pyne [1], fire is an important natural process that regenerates and boosts biodiversity, contradicting the common conviction that all fires are negative. By

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releasing nutrients into the soil, controlled burns can allow certain plants to thrive [2, 3]. Additionally, sometimes they may prevent invasive species from growing by enabling their native counterparts to flourish [4, 5]. However, large forests can be destroyed due to wildfires, resulting in the loss of habitats and the extinction of several organisms found therein [6, 7]. These flames also destroy houses and infrastructure, and they could bring huge suffering to those who live nearby, socially and economically [8, 9]. This implies that uncontrolled bushfires should be monitored so that intervention measures happen at the right time.

To properly plan and execute maintenance and restoration strategies, accurate data is essential for evaluating and monitoring the extent and severity of fire damage in real-time whenever possible [10]. Initially, such data was primarily collected through ground-based methods, which often imposed limitations on the scope and reliability of assessments. However, recent advancements in remote sensing technologies have overcome these constraints, revolutionizing the ability to gather critical data on a global scale. Transitioning from field measurements to remote sensing and modeling introduces various challenges in assessing burn severity. Within remote sensing, a range of data types, including optical, RADAR, LiDAR, and methodologies for evaluating burned areas, exists [11]. Among them, multispectral missions provide a continuous stream of images that allow for monitoring the location and behavior of fires, as well as the assessment of burn severity and post-fire impacts on vegetation and ecosystems [11]. These images are typically used to generate a burn severity map of conditions on the ground, which can be referred to as the Burned Area Reflectance Classification (BARC). There appears to be a reasonably good correlation between these BARC classification categories and field assessments of fire severity [12, 13]. However, since these assessments must be conducted shortly after the fire, it is not always possible to avoid cloud cover and ensure clear skies. Beyond this limit, three additional primary challenges need to be addressed:

i) developing and implementing the optimal classification approach to generate a BARC map;
ii) detecting the most adequate satellite images in terms of spatial, temporal and spectral resolution; and,
iii) selecting an appropriate geospatial big data handling platform.

Addressing the first issue involves testing various classification methods to generate a reliable BARC map. Typically, index-based methods are preferred as they facilitate the swift extraction of land use/cover categories and comparison of multi-temporal outcomes [14–17]. In this regard, both the Normalized Burn Ratio (NBR) and delta NBR (dNBR) indices are considered the gold standard for producing BARC products [18] due to their promising results, which are highly correlated with field measurements of burn severity. However, in the field validation of BARC maps, [12] found dNBR to be no more accurate than NBR. In 2014, a new metrics was introduced to estimate the fire severity: the Relativized Burn Ratio (RBR) [19].

Performance indices are closely correlated with the spatial and spectral resolution of satellite images [20]. Indeed, higher resolution leads to a better ability to accurately delineate the boundaries of areas affected by fire events and extract the damages caused by them on both natural and built ecosystems. Nevertheless, it is important to find a good compromise between spatial and temporal resolution. Ideally, to optimize monitoring

policies, high spatial and temporal resolutions are required. However, these variables are inversely proportional, meaning that increasing one implies reducing the other [21]. The Sentinel-2 mission, launched by the European Space Agency (ESA) in 2015 and comprising two twin satellites (Sentinel-2A and Sentinel-2B), offers a viable solution to address this challenge. It is characterized by thirteen spectral bands, with four bands at a resolution of 10 m, six bands at 20 m, and three bands at 60 m. Its temporal resolution is approximately 10 days (or 5 days if images collected by both Sentinel-2A and Sentinel-2B are considered). Because of these features, it could provide a good opportunity to assess the changes that occur in a specific area subjected to a hazard event [22–24].

To meet this purpose, a change detection analysis should be performed by selecting a proper algorithm. These methods are commonly grouped into two main categories: i) bi-temporal change detection and ii) temporal trajectory analysis [25]. The former is based on the direct comparison between the information extracted from multi-source data, bringing them into a uniform model. Conversely, the latter processes a large amount of long-time series of remotely sensed images. A bi-temporal change detection approach is preferred when only two images gathered before and after the event are needed [26–28].

However, to monitor the status of an event, a huge amount of geospatial data should be handled. As a result, standalone software is no longer convenient to speed up data acquisition and processing phases. To overcome such a limitation, the cloud-based platform, Google Earth Engine (GEE), developed by Google in 2017 to store and manage geospatial big data, could be adopted. Indeed, it is characterized by an integrated catalogue, updated daily with free and open-source data provided by different sources, and hundreds of processors running customized scripts in parallel [29, 30]. Through an Application Programming Interface (API), any IT-skilled user can consult the integrated data, both in raw and pre-processed formats, as well as program a proper JavaScript or Python code defined to meet specific requirements [31].

As a result, this research aims to investigate the changes in Bitonto and Vico del Gargano (Puglia region) in 2021 following two small wildfire events. To achieve this goal, the potential of processing medium-resolution Sentinel-2 images pre and post-event in the Google Earth Engine (GEE) environment were explored. This involved implementing a proprietary JavaScript code to compute the dNBR and RBR indices. The accuracy of the resulting thematic maps was statistically analyzed by comparing them with both the ground truth provided by the European Forest Fire Information System (EFFIS) and the results obtained through photointerpretation techniques.

2 Material and Methods

This section outlines the methodology adopted to achieve the research objectives. As depicted in Fig. 1, the approach can be broken down into six main steps:

i) analysis of wildfire events to delineate test areas physical boundaries and determine dates;
ii) selection of Sentinel-2 satellite images and creation of a geodatabase;
iii) pre-processing analysis of the selected images to correct atmospheric interference and remove clouds, when necessary;
iv) application of an index-based classification method by computing the NBR index;

v) change detection analysis using a bi-temporal approach (dNBR); and,
vi) validation of resulting thematic maps through statistical assessment of their accuracy.

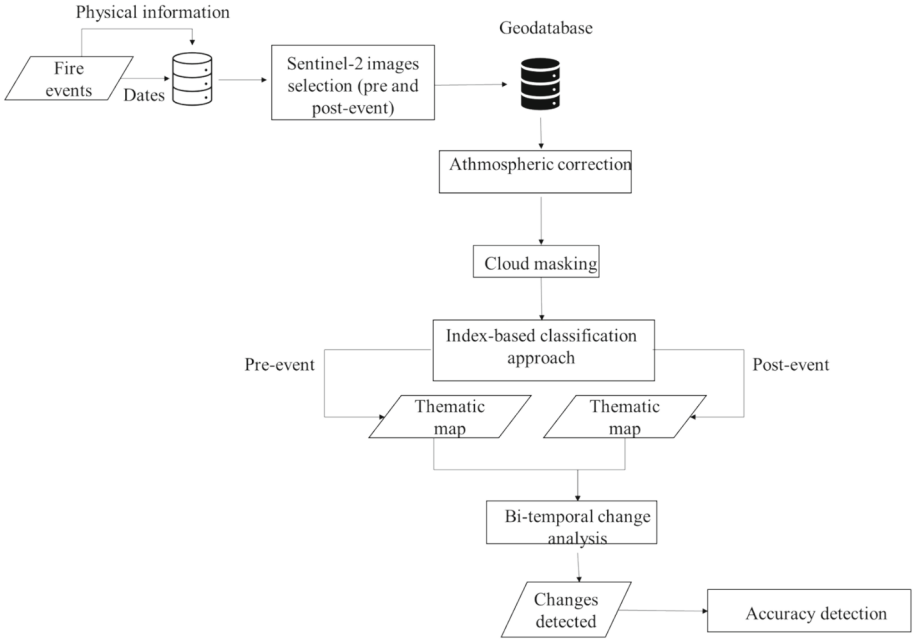

Fig. 1. Operative workflow to investigate the damages caused by a wildfire event from the medium-resolution Sentinel-2 images.

After investigating the major wildfire events in the Puglia region, Bitonto and Vico del Gargano were chosen as pilot sites to test the entire analysis. Accordingly, Sentinel-2 data corresponding to these areas were selected from the data catalogue integrated into the GEE environment and pre-processed to eliminate atmospheric influences and cloud cover. The resultant images were then processed in GEE using a custom JavaScript code, and the index-based method was applied, specifically estimating NBR and dNBR. Finally, the damages sustained by the pilot sites were examined through bi-temporal change detection analysis. The accuracy of the final outcomes was statistically evaluated by comparing them with both EFFIS data and ground truth obtained through photointerpretation. The procedure was performed on the two pilot sites separately. Each phase of the procedure is detailed in the following paragraphs.

2.1 Study Area and Input Data

The operational workflow outlined above was tested on two study areas, Vico del Gargano and Bitonto, located in the Puglia region, as they experienced small wildfire events in 2021.

Vico del Gargano, situated in Foggia province, is a municipality within the Gargano National Park and the Gargano Mountain Community. Covering 110.4 km2 in the north-eastern part of the Gargano promontory, it is a key area within the Gargano National Park, hosting a significant portion of the Umbra Forest. Its terrain varies from sea level to 782 m, encompassing sub-mountainous forests, coastal beaches, and Aleppo pine forests. The coastline is adorned with olive groves, citrus orchards, and terraced landscapes. The region features karstic geology, with numerous caves, including marine ones.

Bitonto, located in the metropolitan city of Bari in Puglia, spans over 170 km2, stretching from the Murgia highlands to within 2 km of the Adriatic Sea. The town is situated on the first step of the Murgia plateau at 118 m a.s.l., with its lowest point at 102 m a.s.l. The municipal terrain ranges from a minimum elevation of 39 m a.s.l. in the northern coastal area to a maximum of 491 m a.s.l. in the hilly southern region, resulting in an altimetric range of 452 m. Bitonto's municipal territory includes the Alta Murgia National Park and the Lama Balice, established in 2007 as a regional park on the outskirts of the historic city center. The terrain is characterized by Bari limestone and bitontina dolomite, used extensively in local construction.

The fire events in these pilot sites were identified by examining the EFFIS database (https://effis.jrc.ec.europa.eu/). EFFIS, developed in collaboration with the European Commission (EC) services (Directorate General Environment and the Joint Research Centre) and the relevant fire services in the countries (forest fires and civil protection services), provides both real-time and time series information on forest fires at the European level [32]. It encompasses the entire fire cycle, from pre-fire conditions to post-fire damage analysis (Fig. 2) [33]. Specifically, the system identifies vulnerable areas and elements at risk prior to a fire event, gathers data on burn areas such as perimeters during the event, and ultimately evaluates the damages, erosion, and emissions following a wildfire. It makes available all data about wildfires that happened after 2000.

EFFIS fire danger products are generated by computing the Canadian Fire Weather Index (FWI) based on data provided by two meteorological forecast models, conducted by Météo-France and the Deutsche Wetter Dienst (DWD) [32]. Conversely, near-real-time applications such as active fire detection and rapid damage assessment are derived from the daily processing of MODIS satellite images at a spatial resolution of 250 m, aboard the NASA TERRA and AQUA satellites, for detecting hot spots (active fires) and mapping burnt areas. In 2019, thanks to the introduction of Sentinel-2 outcomes, EFFIS resolution was significantly improved in terms of spatial accuracy. Now, it can indeed capture and describe burnt areas with a minimum size of 5 hectares, whereas previously it could only detect areas as small as 40 hectares [34]. More information about EFFI system and products are in [32–34].

Table 1 reports the EFFIS data events occurring at the test locations and the area of the regions burned by these fires. Date events were then utilized to identify Sentinel-2 images suitable for examining the observed phenomenon in more detail, while the shapefiles of the burnt areas, illustrated in Fig. 3, were subsequently employed to validate the methodology developed in this research. Since the accuracy of this database was unknown, the accuracy of the implemented methodology was also evaluated by selecting appropriate samples through the interpretation of Sentinel-2 images (Fig. 3). The validation procedure is explained in further detail in Sect. 2.4.

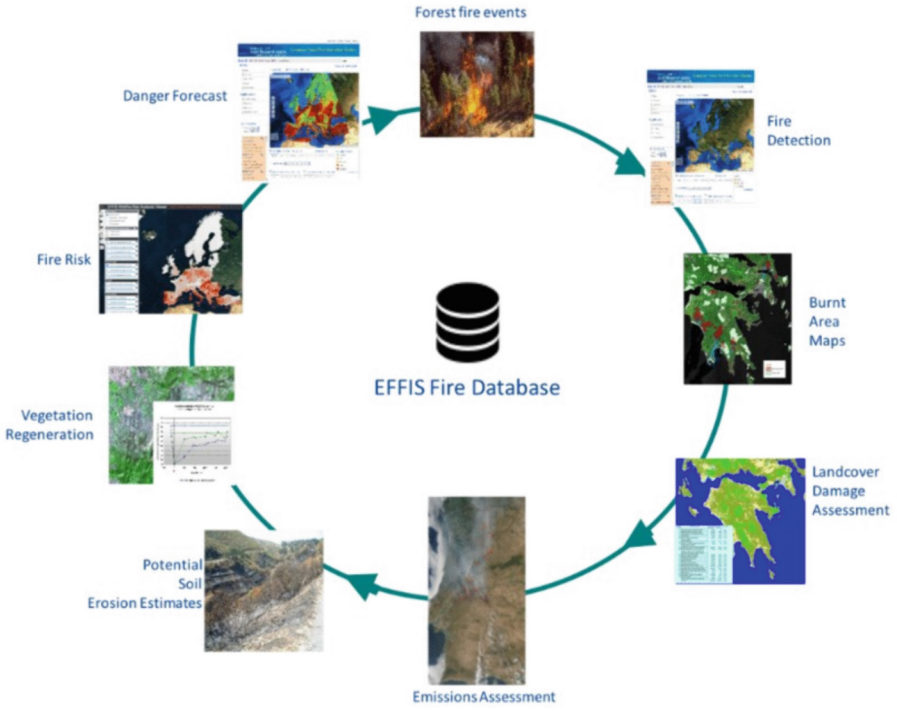

Fig. 2. Description of EFFIS products (source: [33])

Table 1. Wildfires events parameters provided by EFFIS dataset.

City	Municipality	Burned area (ha)	Date (dd/mm/yyyy)
Foggia	Vico del Gargano	116	13/07/2021
Bari	Bitonto	154	05/08/2021

Four Sentinel-2 images were selected for each study area: two acquired before the fire event and the remain two after it. It was decided to pick up four images to minimize the potential errors due to the clouds and their shadows. These images were retrieved directly from the GEE data catalogue by defining the boundaries of the test sites and setting temporal range and cloud cover percentage thresholds lower than 5. Table 2 provides further details on the temporal range used to identify the images before and after wildfire events addressing the requirements above-mentioned. Potential useful data were subsequently visually investigated to clean out those ones characterized by a low sun angle and a mismatched phenology between pre- and post-fire conditions, as suggested by [35–37].

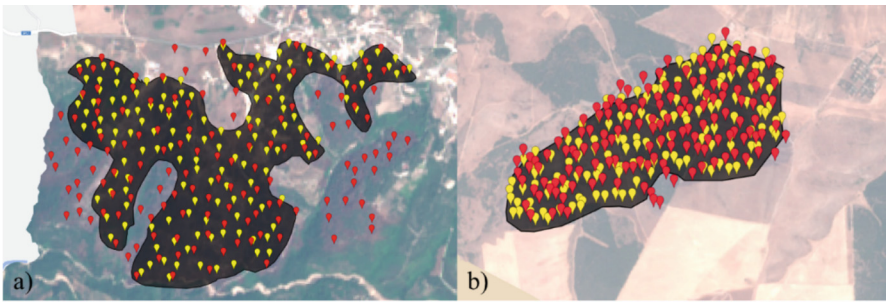

Fig. 3. EFFIS perimeters of the burned areas of Vico del Gargano (a) and Bitonto (b), respectively. Yellow and red points are the samples extracted from EFFIS data and Sentinel 2 images using photointerpretation, respectively. (Color figure online)

Table 2. Temporal range set in GEE data catalogue to select Sentinel-2 images with a cloud cover percentage lower than 5.

Municipality	Pre-fire range (dd/mm/yyyy)	Post-fire range (dd/mm/yyyy)
Vico del Gargano	06/07/2021–11/07/2021	21/07/2021–23/07/2021
Bitonto	28/07/2021–02/08/2021	10/08/2021–11/08/2021

As a result, the resultant radiometrically and atmospherically corrected images provided in the Universal Transverse Mercator (UTM) projection and the World Geodetic System (WGS84) datum, were imported in the GEE API.

2.2 Preprocessing Analysis

The collected images underwent preprocessing. Given their satisfactory geometric accuracy, further orthorectification was deemed unnecessary. However, clouds and their corresponding shadows were masked using the Sentinel-2 Correction (Sen2Cor) algorithm [38] where needed.

Sen2Cor produces an internal map characterized by 12 classes, including thin cirrus, cloud shadows, defective pixels, no data and clouds. This map helps differentiate cloudy pixels from clear ones, enabling the removal of the former to ensure clean processing in subsequent phases.

2.3 Severity Metrics

The resulting pre-processed images were subsequently handled to compute the NBR burn severity metrics, developed by Key and Benson within the Joint NPS-USGS National Burn Severity Mapping Project in 2005, for extracting fire information from Landsat satellite images [39]. This index relies on the combination of NearInfraRed (NIR) and Short Wavelength InfraRed (SWIR) bands (Eq. 1) and, recently, has been adapted for

use with Sentinel-2 data [40]. By differencing its pre and post-fire values pixel by pixel, the dNBR was obtained (Eq. 2) enabling the rapid estimation of fire damage over large areas.

$$NBR = \frac{(NIR - SWIR)}{(NIR + SWIR)} \tag{1}$$

$$dNBR = (NBR_{pre-fire} - NBR_{post-fire}) \text{ x } 1000 \tag{2}$$

A dNBR value approaching zero indicates minimal changes in the surveyed area, whereas values further from zero suggest more significant changes. Following the recommendations of the Fire Effects Inventory and Monitoring Protocol [26], dNBR values were categorized into seven groups: High Severity, Moderate-high Severity, Moderate-low Severity, Low Severity, Unburned, Enhanced Regrowth – Low, Enhanced Regrowth – High. High severity areas are those that underwent substantial alterations post-fire, such as extensive tree mortality, significant consumption of ground fuels, and limited post-fire regeneration. Low-severity areas experienced lower mortality rates, minimal fuel consumption, and higher levels of regeneration.

Lastly, the RBR index, introduced by [19], was estimated using Eq. 3:

$$RBR = \frac{(dNBR)}{(NBR_{pre-fire} + 0.01)} \tag{3}$$

RBR is calculated by dividing the dNBR index by the NBR calculated from the images captured before the fire events, plus 0.01. This coefficient ensures that the index will never reach zero or infinity, thereby preventing failure. Also in this case, RBR values were discriminated into seven levels of severity: High Severity, Moderate-high Severity, Moderate-low Severity, Low Severity, Unburned, Enhanced Regrowth – Low, Enhanced Regrowth – High.

2.4 Validation

The samples identified using EFFIS data and Sentinel-2 images through photointerpretation were utilized to statistically estimate the accuracy of NBR and DNBR. Specifically, Overall Accuracy (OA) and Kappa coefficient (K) were calculated. OA measures the accuracy of the entire resulting burn severity maps without specifying the different classes related to the level of damage. However, it assigns greater weight to the class with a larger number of samples [41]. In contrast, K assesses the performance of each classification individually, making it preferable for comparing different classification maps [42].

2.5 GEE Code

The GEE data catalogue was consulted to select the optimal Sentinel-2 images required to fulfill the research objectives. As mentioned earlier, the catalogue contains both raw and pre-processed data; however, in this instance, raw format was preferred. The process was designed to merge the information provided by one image acquired before the fire

event and one after it, with specific parameters and temporal range set to select the images to be processed, as previously specified. These variables can be easily modified in the code to accommodate user requirements.

Subsequently, the selected images were imported into the API, and a custom JavaScript code was implemented to pre-process them, as detailed in Sect. 2.2, and then to estimate the NBR, dNBR and RBR indices, as described in paragraph 2.3. Finally, the resulting thematic maps underwent statistical validation through the development of a specific code aimed at evaluating the overall accuracy and K coefficient, as outlined in Sect. 2.4. This code was designed for easy application to various geographical locations, wildfire extents, and timeframes.

3 Results and Discussion

This research aims to assess the damages caused by wildfire events in Bitonto and Vico del Gargano, two municipalities located in the Puglia region, in 2021, by leveraging the potential of Sentinel-2 medium-resolution satellite images and GEE. To achieve this, a custom JavaScript code was developed and implemented in the GEE API to collect the necessary data for storage and analysis in subsequent steps, eliminating the need for additional platforms or standalone software. Indeed, as demonstrated by [29, 31], GEE proves to be an optimal tool for expediting procedures by saving both data collection and processing time. Indeed, it features an integrated data catalogue that consolidates all open-source and freely available data, eliminating the need to consult other platforms or download these layers separately. The data catalogue communicates directly with the API, allowing each layer to be imported into the script editor seamlessly without additional steps. Furthermore, it takes advantage of hundreds of processors that work in parallel, significantly reducing processing time. However, it is not a user-friendly platform, and as a result, only IT-skilled operators are able to implement correct and customized scripts tailored to meet users' needs [43]. Nevertheless, following the programming phase, the developed scripts can be easily adapted to process multi-source data and layers covering different geographical areas. This allows for minimizing the time required to extend the analysis to larger and diverse regions in order to monitor the damages triggered by a significant number of wildfire events. This feature is particularly compelling as it enables the monitoring of fire severity in regions lacking a dedicated program for mapping fire damages, similar to EFFIS, which provides information concerning the entire fire cycle, from pre-fire conditions to post-fire damage analysis (Fig. 2) [33], since 2000. However, EFFIS data resolution was not sufficient to discriminate elements smaller than 40 hectares until 2019, when a resolution of 5 hectares was achieved.

Such a dataset was used to list events that occurred recently in Bitonto and Vico del Gargano [32–34]. Consequently, it was employed to identify the timeframe under investigation (Table 1) and to provide ground truths (Fig. 3), although the accuracy of the data is not known beforehand. For that reason, the implemented GEE-based approach was validated using the Ground Control Points (GCPs) provided by EFFIS and those ones extracted manually by photointerpretation (Fig. 3).

For what above, GEE was selected to compute NBR, dNBR and RBR indices which are commonly defined as the gold standard to produce a BARC map and classify the

burn severity [12, 18]. The NBR index was estimated using Eq. 1, as suggested by [39, 40], on Sentinel-2 images captured both before and after the fire events. Subsequently, the dNBR index was calculated using Eq. 2 [18], while the RBR was derived from Eq. 3 [19].

dNBR and RBR resulting maps, reported in Fig. 4 and Fig. 5, delineate the varying levels of fire severity for both pilot sites. Specifically, RBR and dNBR values were grouped into seven classes in accordance with the recommendations of the Fire Effects Inventory and Monitoring Protocol [26]: High Severity, Moderate-high Severity, Moderate-low Severity, Low Severity, Unburned, Enhanced Regrowth – Low, Enhanced Regrowth – High. Both maps utilized a graduated color-scale, ranging from dark green to violet, to illustrate these classes. Dark green indicates areas experiencing highly enhanced regrowth, while violet signifies regions affected by high fire severity. Halfway colors were employed for the intermediate severity groups.

Figure 4 reveals that both dNBR and RBR maps, derived from the satellite images covering Vico del Gargano, extract the same number of pixels related to burnt areas. While most classes show comparable outcomes, there is a discrepancy in the high severity group. Indeed, RBR underestimates the pixels associated with this group, as evidenced by the absence of violet pixels in this map. Similarly, the yellow pixels representing areas characterized by "low severity" damages are fewer in the RBR map, as they are commonly classified as "unburned zones".

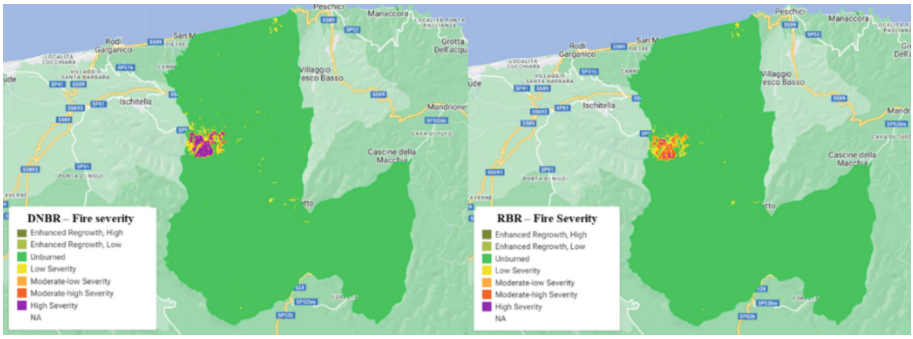

Fig. 4. Fire severity maps of Vico del Gargano. Such maps were produced from dNBR (on the left) and RBR (on the right) values.

While the thematic maps highlight these spatial variances among the maps derived from the two applied classification indices, they do not allow for a quantitative appreciation of such differences. Therefore, to quantify the differences for each specific class obtained by dNBR and RBR maps, the area expressed in hectares, corresponding percentage value, and the number of pixels involved are reported in Table 3. This table converts the spatial differences highlighted in Fig. 4 into numerical values.

By comparing such values, it is evident that both maps' outcomes are comparable albeit RBR underestimated fire severity, indeed, any pixels have been classified as high severity level (0 versus 871). Similarly, the pixels associated with the unburned zones are higher than those ones identified by dNBR (161069 versus 160011).

Table 3. Burnt area information related to the study area of Vico del Gargano extracted from dNBR and RBR maps.

Severity level	DNBR			RBR		
	Area (ha)	%	Pixel	Area (ha)	%	Pixel
High Severity	34.84	0.53	871	0	0	0
Moderate-high Severity	25.24	0.38	631	32.32	0.49	808
Moderate-low Severity	37.24	0.56	931	48.96	0.74	1224
Low Severity	106.52	1.61	2663	81.2	1.23	2030
Unburned	6400.44	96.89	160011	6442.76	97.54	161069
Enhanced Regrowth, Low	1.28	0.02	32	0.32	0	8
Enhanced Regrowth, High	0	0	0	0	0	0

Table 4. Burnt area information related to the study area of Bitonto extracted from dNBR and RBR maps.

Severity level	DNBR			RBR		
	Area (ha)	%	Pixel	Area (ha)	%	Pixel
High Severity	0.24	0	6	0	0	0
Moderate-high Severity	4.64	0.05	116	1.56	0.02	39
Moderate-low Severity	30.56	0.3	764	30.16	0.3	754
Low Severity	170.72	1.67	4268	126.76	1.24	3169
Unburned	9936.32	97.47	248408	9959.2	97.69	248980
Enhanced Regrowth, Low	51.24	0.5	1281	75.52	0.74	1888
Enhanced Regrowth, High	1	0.01	25	1.52	0.01	38

Figure 5 reports dNBR and RBR maps covering Bitonto. Similar to the previous case, the RBR map shows lower values than dNBR map. Upon comparison of the two maps, it's evident that the pixels associated with the moderate-high severity level class are fewer in the RBR map, and the unburned region appears to be larger.

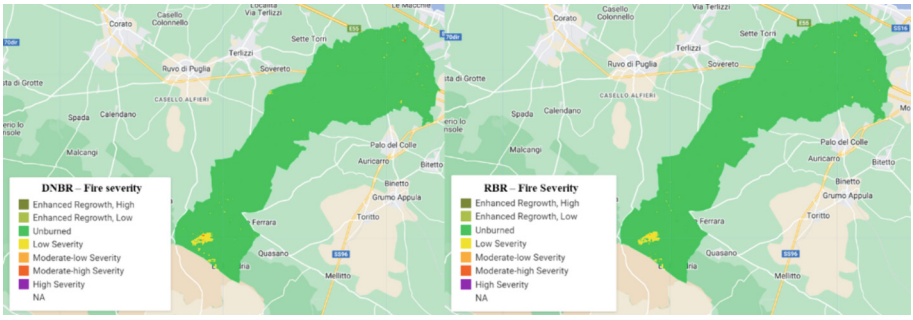

Fig. 5. Fire severity maps of Bitonto. Such maps were produced from dNBR (on the left) and RBR (on the right) values.

The area, the corresponding percentage value and the number of pixels involved are detailed in Table 4. Despite the fire severity level in Bitonto being lower than that in Vico del Gargano, the trends of dNBR and RBR are similar in both cases. Specifically, RBR consistently shows lower values than dNBR. For example, the high severity group is represented by 6 and 0 pixels in dNBR and RBR maps, respectively, while the unburned zones encompass 248408 and 248980 pixels in dNBR and RBR maps, respectively. This performance is in line with what detected by previous researchers [19] since RBR was developed to investigate the changes due Indeed, dNBR is better suited to explore regions covered by dense vegetation, whereas RBR is suitable for extracting information even in areas where pre-fire vegetation cover is low or discontinuous. This versatility is interesting since it allows for exploring urban areas too. Moreover, although Parks et al., (2014) [19] demonstrate that RBR has better correspondence to field-based burn severity measurements and a higher classification accuracy compared to dNBR, there is no universally optimal index for detecting fire severity levels. The choice depends on the specific areas of application and the objectives being measured.

To determine which fire severity metric is best suited for the specific features of the geographical area under investigation, the resulting classification maps were validated using GCPs extracted from both EFFIS data and those identified through photointerpretation. Since the samples' accuracy is unknown their OA and K coefficients were estimated. The outcomes of this analysis for the two pilot sites are detailed in Table 5. Both ground-truth datasets seem to be robust since their OA and K are higher than 0.90 and 0.80, respectively, for the study areas. Furthermore, their performance is similar in both cases, indicating that the samples' accuracy is independent of geographical conditions. As a result, estimating classification maps accuracy based on EFFIS or photointerpreted data yields similar outputs. The OA of dNBR and RBR derived maps are 0.91 and 0.93 for Vico del Gargano and 0.93 and 0.95 for Bitonto, respectively. Hence, both classification charts are consistent with fire severity damages and suitable for investigating the damages due to wildfire events. Nevertheless, in this case study, RBR performed better than dNBR even though their outcomes are pretty similar.

Table 5. Validation parameters (OA: Overall accuracy, K: Kappa coefficient)

	Vico del Gargano		Bitonto	
	OA	K	OA	K
Photointerpretation	0.98	0.96	0.99	0.98
EFFIS	0.91	0.81	0.92	0.83

4 Conclusion

The primary objective of this research is to assess the damages incurred by Vico del Gargano and Bitonto in the Puglia region following two wildfire events, utilizing medium-resolution satellite images provided by ESA's Sentinel-2 and Google Earth

Engine (GEE), a cloud-based platform developed by Google in 2017 for managing geospatial big data. To achieve this objective, the index-based classification method was employed by calculating the dNBR and RBR indices, recognized as the standard for estimating fire severity levels from satellite imagery. Consequently, seven classes were utilized to categorize the fire severity levels in line with the Fire Effects Inventory and Monitoring Protocol, and the quantity of pixels and the area involved were assessed and quantified for each class.

Through comparison of the classification results, it was observed that dNBR and RBR exhibit similar trends, which are consistent with the ground truth dataset. As such, both indices can be considered robust for fulfilling the research objectives, although RBR demonstrates superior performance in both cases. This discrepancy is primarily attributed to the geographical conditions of the pilot sites, as mentioned earlier, emphasizing that there is no universally applicable index due to variations in vegetation type and density.

Furthermore, Google Earth Engine emerges as the optimal tool for implementing custom scripts tailored to address users' specific requirements, offering a versatile platform that can be easily adapted to process multi-source data spanning various timeframes and geographical regions.

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