

Article

High-Resolution Burned Area Mapping Using Sentinel-2 Imagery and Robust Satellite Techniques

Roberto Colonna ¹, Carolina Filizzola ^{2,*}, Vita Elena Di Leo ¹, Iacopo Mancusi ¹, Mariano Lisi ¹ and Valerio Tramutoli ¹

¹ Department of Engineering (DIING), University of Basilicata (UNIBAS), via dell'Ateneo Lucano 10, 85100 Potenza, PZ, Italy; roberto.colonna@unibas.it (R.C.); dileovitaelena@gmail.com (V.E.D.L.); iacopo.mancusi@unibas.it (I.M.); mariano.lisi@unibas.it (M.L.); valerio.tramutoli@unibas.it (V.T.)

² Istituto di Metodologie Integrate per l'Osservazione della Terra (IMIOT), Consiglio Nazionale delle Ricerche (CNR), c/da S. Loja, 85050 Tito Scalo, PZ, Italy

* Correspondence: carolina.filizzola@cnr.it

Highlights

What are the main findings?

- The RST-based Sentinel-2 workflow mapped burned areas as small as 0.22 ha, with 97.85% of the mapped area confirmed as burned in the multi-source validation.
- The approach was effective over agricultural areas and mapped substantially more burned area (BA) than RSDI (+48%) and EFFIS (+143%) in the tested cases.

What are the implications of the main findings?

- Improved detection of small and agricultural burned areas can support more complete BA estimates for fire-emission modeling and carbon-budget assessments.
- The Google Earth Engine implementation enables repeated Sentinel-2 processing and provides a basis for timely BA updating and future near-real-time applications.

Abstract

High accuracy in burned area (BA) mapping is desirable for many fire-related applications. Most operational products are based on coarse-resolution satellite data with a final spatial resolution ranging from 250 m to 1000 m. The use of higher-resolution satellite data, such as that from the Multispectral Imager (MSI) on board Sentinel-2, is usually reserved for generating BA products only for specific countries and time periods. Moreover, BA algorithms are typically driven by fire detection products to minimize false identifications. The resulting accuracy of such BA products depends strongly on land cover, fire regime, and the reliability of the considered fire detection products. In this paper, we exploit the multitemporal Robust Satellite Technique (RST) to identify burned areas and implement a workflow based on Sentinel-2 images within Google Earth Engine. Test results from two complete region-wide experiments conducted under contrasting seasonal, phenological, and agricultural conditions showed that 97.85% of the mapped area was confirmed as burned within the adopted multi-source validation framework, with an area-based commission error of 1.38% and omission error of 0.60%. Missed detections documented by the Regional Spatial Data Infrastructure (RSDI) amounted to 10.60 ha, corresponding to approximately 0.9% of the burned area reported by RSDI over the tested periods. Polygon-level intercomparison with RSDI and the European Forest Fire Information System (EFFIS) yielded Intersection over Union (IoU) values of 0.69 and

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0.83, respectively. The proposed approach mapped larger burned areas than those reported by both RSDI (+48%) and EFFIS (+143%) as well.

Keywords: RST; Sentinel-2; multitemporal approach; burned areas; Google Earth Engine

1. Introduction

Accurately detecting burned areas (BA) is important for several fire-related applications [1,2], such as improving wildfire management strategies [3] and evaluating the impact of fires on biomes [4] and the climate [5]. For example, BA products are typically employed in fire-emission models, but variations in BA estimates can significantly impact emission uncertainties [6,7]. Indeed, although the magnitude and composition of estimated emissions are influenced by various components (e.g., BA, fuel loading, combustion characteristics, and emission factors), BA estimates are found to control the spatial and temporal distribution of such emissions [7].

In general, the accuracy of BA products depends on several factors, such as fire size, BA shape, and pixel size, particularly in the case of partially burned pixel area [8,9]. Additionally, even products with similar spatial resolutions may produce different results due to algorithm differences in the land cover maps used to mask non-burnable areas [10]. In fact, various country-, regional-, and global-scale BA databases [2,11] show different levels of accuracy [8,10,12]. While global BA appears to be in good agreement, significant discrepancies in the location and timing of fire activity are evident at smaller spatial and/or temporal scales [13].

Currently, the main operational BA datasets include the European Space Agency (ESA, Paris, France) BA products within the framework of the Fire-Climate Change Initiative (CCI) [14,15], the National Aeronautics and Space Administration (NASA, Washington, DC, USA) BA products within the Fire Information for Resource Management System (FIRMS) [16,17], the Rapid Damage Assessment (RDA) module of the European Forest Fire Information System (EFFIS) [18,19] and BA information over the EFFIS global extension, i.e., the Global Wildfire Information System (GWIS, <https://gwis.jrc.ec.europa.eu/>, accessed on 6 July 2026) [20].

Most of such operational products are based on coarse-resolution data, such as from the Moderate Resolution Imaging Spectroradiometer (MODIS) and the Visible Infrared Imaging Radiometer Suite (VIIRS). These products usually have spatial resolutions ranging from 250 m to 1000 m and an update frequency from daily to monthly [21]. Only some of them have been generated by integrating information at higher spatial resolution, such as from the Multispectral Imager (MSI) onboard Sentinel-2, in a systematic way (e.g., EFFIS since 2018) or over specific test areas and periods (e.g., ESA FireCCISFD20 [22] products over Sub-Saharan Africa for 2019), recognizing the importance of detecting small-size BAs. With respect to the operational products, the scientific literature focused on BA methodologies has a higher number of Sentinel-based algorithms (see [21] and references therein). The use of higher-resolution images is, indeed, highly desirable for evaluating fire-related aspects at the local or regional level, such as identifying areas susceptible to burning and annual trends [10]. Furthermore, generating BA maps from high-resolution satellite observations, like those from Sentinel-2, is one of the activities reported as part of the efforts to improve the Global Climate Observing System (GCOS) [23].

The accuracy of BA mapping also depends on the reliability of the methodology used. Operational products largely use BA algorithms driven by fire detection based on coarse-resolution data from VIIRS and MODIS to minimize false identifications (mainly when

they work on a global scale) (e.g., [14,15,24,25]). However, missing hotspot detections in such cases means missing BA identification. The authors of [8] report that the low number of MODIS active fires per km² within omitted burned areas is one of the primary causes of BA underestimation. These same authors point out that using VIIRS active fires instead of MODIS ones could theoretically increase accuracy thanks to VIIRS's higher sensitivity in detecting smaller and cooler fires. However, the coarse spatial resolution of the pixels used for mapping could not exhibit a spectral response that would allow for the identification of burned areas. Therefore, small areas may remain unidentified. Furthermore, the accuracy of this approach depends heavily on land cover and fire regime. For example, a high level of accuracy is achieved in boreal forests, which are characterized by large, long-lasting fires that are easier to detect. Meanwhile, a significant underestimation may be recorded in agricultural areas (see [8] and references therein).

Recent literature on operational products (e.g., [25] in the framework of the Copernicus Land Monitoring Service) and research from individual study groups (e.g., [26–29]) includes many examples of algorithms based on machine learning (ML) and its subset, deep learning (DL). DL-based algorithms have been shown to achieve high accuracy in mapping BA even in complex environments [21,30], but they require a large number of training samples [21]. The scarcity of labeled satellite datasets and data preprocessing are critical issues [30]. Conversely, more traditional ML techniques (e.g., Random Forest models) can yield results that are more easily interpretable, implementable, and less computationally expensive than DL. However, their accuracy depends heavily on training data, in terms of size and sample balance [21].

The use of Google Earth Engine (GEE) [31] is a further emerging element in the recent literature (e.g., [32–35]) as it is considered essential for improving analysis efficiency [2,3]. Around the turn of the millennium, indeed, there was an average fourfold increase in papers based on GEE, mainly due to its user-friendly interface and readily available remote sensing data [21].

In this paper, we adapt the multitemporal RST framework [36,37] to high-resolution BA mapping through a two-step workflow. This transfer is not straightforward because abrupt or persistent changes in the Normalized Burn Ratio (NBR) may also be produced by agricultural harvesting, land-cover transitions, or artificial surfaces; previously affected surfaces must be distinguished from newly burned areas; and statistically anomalous pixels identify reliable fire-related signals, but they do not delineate the complete burned perimeter on their own. Its main methodological distinction from many existing Sentinel-2 approaches is the use of multi-year, seasonally matched observations to construct local NBR and dNBR (i.e., the difference between NBRs) reference distribution for each pixel. Changes in NBR and dNBR are therefore evaluated relative to the expected behavior and natural variability of the same location, without requiring training samples or MODIS/VIIRS active-fire detections as inputs to the algorithm. To address the aforementioned challenges, the workflow combines two complementary RST-based indicators with different land-cover-dependent roles and introduces the Mid-Infrared Burn Index (MIRBI) as an additional spectral-consistency condition to reduce harvest-related false detections. It is based on two steps: i) identification of high-confidence seed pixels significantly affected by changes in NBR and dNBR through the RST-based anomaly indicators and MIRBI filtering; ii) spatial extension of these seed pixels through a dNBR-based region-growing procedure to map the complete burned area around the most robust detections. This approach leverages the high spatial resolution of Sentinel-2/MSI data and, in line with current trends in wildfire BA mapping [21], exploits the GEE's ability to manage multitemporal time series. Section 2 describes the approach and data, Section 3 reports the results, and Section 4 discusses the comparison with the official BA datasets and the limitations of the present regional test.

2. Data and Method

2.1. Data

2.1.1. Sentinel-2 Data

The Sentinel-2 mission consists of two identical satellites, designed to provide a high revisit frequency of five days at the equator. The two Sentinel-2 satellites are positioned 180° apart, in sun-synchronous orbits at a mean altitude of 786 km. Currently, the twin satellites are Sentinel-2B (S2B, launched in 2017) and Sentinel-2C (S2C, launched in 2024). The latter replaced Sentinel-2A (S2A, launched in 2015) in operation on 21 January 2025. Each satellite carries an MSI instrument that acquires data in 13 spectral bands: four bands at 10 m, six bands at 20 m, and three bands at 60 m spatial resolution [38]. Table 1 shows the MSI bands aboard all Sentinel-2 platforms and their main characteristics.

Table 1. MSI/Sentinel-2 bands and main characteristics [38]. Gray lines highlight the bands used in the paper.

Band Number	S2A		S2B		S2C		Spatial Resolution (m)
	Equivalent Wavelength (nm)	Bandwidth (nm)	Equivalent Wavelength (nm)	Bandwidth (nm)	Equivalent Wavelength (nm)	Bandwidth (nm)	
1	442.7	20	442.2	20	444.2	21	60
2	492.7	64	492.3	65	489	65	10
3	559.8	35	558.9	35	560.6	36	10
4	664.6	30	664.9	31	666.5	30	10
5	704.1	14	703.8	15	707.1	15	20
6	740.5	14	739.1	14	741.1	15	20
7	782.8	20	779.7	20	784.7	21	20
8	832.8	118	832.9	115	834.6	114	10
8a	864.7	20	864	20	865.6	20	20
9	945.1	20	943.2	20	947.2	20	60
10	1373.5	30	1376.9	30	1372.2	33	60
11	1613.7	88	1610.4	93	1612	89	20
12	2202.4	179	2185.7	181	2191.3	182	20

2.1.2. ESA WorldCover 10m v200

“ESA WorldCover 10 m 2021 v200” [39] provides the global land cover products for 2020 and 2021 with a resolution of 10 m. It was developed and validated in near-real time using Sentinel-1 and Sentinel-2 data. The product contains 11 land cover classes (see Table 2) and was generated in the framework of the ESA WorldCover project, which is part of the 5th Earth Observation Envelope Programme (EOEP-5) of the European Space Agency. It is available on GEE as the collection “ESA/WorldCover/v200”.

Within the workflow, WorldCover was not used as a general burnable/non-burnable mask: the “Tree cover” and “Shrubland” classes were used to identify pixels over which the additional $\otimes_{\text{dNBR}}$ detection pathway was enabled, whereas “Permanent water bodies” were excluded. The $\Delta\otimes_{\text{NBR}}$ pathway remained applicable to all other valid land pixels. Details are in Section 2.2.2.

Table 2. ESA WorldCover classes and corresponding values of the product.

Value	Description
10	Tree cover
20	Shrubland

30	Grassland
40	Cropland
50	Built-up
60	Bare/sparse vegetation
70	Snow and ice
80	Permanent water bodies
90	Herbaceous wetland
95	Mangroves
100	Moss and lichen

2.1.3. Validation Data

To validate RST-based BA products, we exploited different types of information, which are described below.

Fire perimeters from Regional Spatial Data Infrastructure (RSDI) [40]. This database includes areas demarcated by the State Forestry Corps from 2004 to 2016 and by the Forestry Carabinieri since 2017. These burned areas are primarily forests and pastures which, according to Article 10 of Law 353/2000 [41], must be included in the registry of fire-affected areas. Municipalities use such a registry on an annual basis to impose the restrictions provided for by law. Vector files can be downloaded from the RSDI website [40]. They include basic information, such as the date of the fire, the type of affected land cover (wooded, non-wooded, unclassified, or pasture), and the area of each polygon. The files for 2020 and 2024 have been downloaded. Tables S1 and S2 in the Supplementary Materials section provide an extract of such data related to the periods 9–12 April 2020 and 29 July–4 August 2024.

EFFIS BA products [18]. The product is derived from the daily processing of MODIS satellite imagery with a ground spatial resolution of 250 m, using an unsupervised procedure. It is based on a combination of band thresholds, the CORINE Land Cover, the active-fire product from MODIS and VIIRS, and the fire news application. Mapped burned scars are typically about 30 hectares in size or larger. However, smaller perimeters can be included (e.g., [10]). In fact, since 2018, Sentinel-2 information has been additionally used to map BAs smaller than 30 ha and to refine the perimeters mapped from MODIS 250 m imagery [18]. Data are available for European countries and some of their neighbors. Vector data can be downloaded after submitting a request form [42] and contain information about the affected area (size and land cover) as well as spatial (country, province, and municipality) and temporal information about the fire. However, the notes attached to the product specify that “start date and last update may not correspond to the date of ignition and extinction of the fire”. All of the data for April 2020, July and August 2024 have been downloaded. Table S3 in the Supplementary Materials section reports an extract of such data related to the period from 29 July to 15 August 2024 in the Basilicata region. No burned areas were recorded in Basilicata in April 2020.

FIRMS active fires [43]. The system mainly distributes active fire data from MODIS aboard the Aqua and Terra satellites (with 1 km spatial resolution), and VIIRS aboard Suomi-National Polar-orbiting Partnership (S-NPP), National Oceanic and Atmospheric Administration (NOAA)-20 and NOAA-21 (with 375 m spatial resolution). These data are globally available and can be downloaded in various formats. Shapefiles regarding the Basilicata region, from 7 to 12 April 2020 and from 29 July to 4 August 2024, have been downloaded for validation purposes.

RGB composites. We conducted a visual inspection of the RGB composites in natural colors ($R = B4 = 0.66 \mu\text{m}$, $G = B3 = 0.56 \mu\text{m}$, $B = B2 = 0.49 \mu\text{m}$) and false colors ($R = B12 = 2.2 \mu\text{m}$, $G = B8 = 0.83 \mu\text{m}$, $B = B4 = 0.66 \mu\text{m}$) from the pre- and post-event Sentinel-2 images to evaluate the presence of burned areas in the analyzed images as well as their absence in

previous overpasses. The presence of active fires at the time of the overpass confirmed not only that the burning occurred but also that it occurred between the pre- and post-event images. This was the primary validation approach because relying solely on official database comparisons would have produced unreliable results, mainly in terms of false positives. Examples of incompleteness and inaccuracy are reported in the following sections of the paper.

A major challenge in validating high-resolution BA products is the scarcity of exhaustive and sufficiently independent reference information, particularly for small or unreported fires. This issue is even more critical in the non-detected domain because an absence of an event in an administrative or satellite database does not demonstrate that all pixels classified as unburned are true negatives. At a spatial resolution of 10 m, a wall-to-wall map of Basilicata contains approximately 10^8 pixels, making exhaustive manual verification impractical.

Therefore, Basilicata was also selected because the RSDI administrative inventory provides a supplementary ground-based source in addition to the EFFIS BA perimeters and FIRMS active-fire detections. Although each of these sources may contain omissions or spatial inaccuracies, their combined use, together with multi-temporal Sentinel-2 visual interpretation, provides a more reliable validation framework than using any individual source separately. So, for validation, we adopted a multi-source reference framework and did not treat any single dataset as error-free ground truth. This procedure is nevertheless time-consuming, since each algorithm-derived polygon must be inspected individually on pre- and post-event natural- and false-color composites, and additional acquisitions must be examined whenever the timing or interpretation of the detected change remains uncertain.

2.2. Method

2.2.1. The RST Approach

The RST [36,37] is a multitemporal change detection approach. It identifies as “anomalous” any signal that significantly deviates from its normal behavior in specific places and times. It is based on the Absolutely Local Index of Change of the Environment (ALICE), defined as follows:

$$\otimes_V(x, y, t) = \frac{V(x, y, t) - \mu_V(x, y)}{\sigma_V(x, y)} \quad (1)$$

where $V(x, y, t)$ is the value of the V signal, measured at the place with coordinates (x, y) and at the time t . $\mu_V(x, y)$ and $\sigma_V(x, y)$ are the temporal mean and standard deviation, respectively, and represent the expected value and the normal variability of the signal $V(x, y, t)$ itself. Henceforth, we will refer to them as “reference fields”. They are computed based on a multi-year dataset $\tau(t)$ of cloud-free satellite records, which are collected under the same observational conditions (e.g., same platform, time of day, and period of the year) as the image to be processed.

It has been successfully applied to various fields, including volcanic (e.g., [44]), seismic (e.g., [45]), flood (e.g., [46]), landslide [47], and fire (e.g., [48,49]) risks, as well as in the context of Saharan dust (e.g., [50]), gas flaring (e.g., [51]), climate change-induced phenomena [52], and sea quality (e.g., [53]) monitoring. Its exportability to different geographic areas and satellite sensors has been widely tested in these applications.

2.2.2. RST-Based Approach for Burned Area Mapping

NBR and its multitemporal formulation, dNBR, have been widely used in various BA-based applications (see [2] and references therein). NBR [54] is the normalized difference between Near-Infrared (NIR) and Shortwave Infrared (SWIR) bands:

$$\text{NBR} = \frac{\text{NIR} - \text{SWIR}}{\text{NIR} + \text{SWIR}} \quad (2)$$

while dNBR is the difference in NBR between pre- and post-event images:

$$\text{dNBR} = \text{NBR}_{\text{pre-fire}} - \text{NBR}_{\text{post-fire}} \quad (3)$$

Several indices have been tested on different satellite data, and those based on NIR-SWIR bands have been found to be more effective than NIR-Red bands [2]. Some of these indices (e.g., NBR) were more effective at discriminating burned areas from clouds and shadows using Sentinel-2 data [55].

Therefore, in order to detect and map burned areas, two RST-based indices were implemented: $\otimes_{\text{NBR}}(x, y, t)$, whose temporal difference was subsequently used to derive $\Delta \otimes_{\text{NBR}}(x, y, t)$, and $\otimes_{\text{dNBR}}(x, y, t)$. In these formulations, $V(x, y, t)$ is represented by $\text{NBR}(x, y, t)$ and $\text{dNBR}(x, y, t)$, respectively, for each pixel centered at (x, y) in the Sentinel-2 image acquired on the target date t . For the $\text{dNBR}(x, y, t)$ index, which is given by $\text{NBR}(x, y, t_{\text{pre}}) - \text{NBR}(x, y, t)$, the t_{pre} observation is computed by using the temporally closest valid pixel available in the 15-day set of previous scenes.

The reference fields of the ALICE indices, μ and σ , were built using all valid cloud-free observations t' belonging to the reference set $\tau(t)$, defined as the union of: (i) observations acquired from 2017 to the year before the analyzed image within a ± 15 -day seasonal window around the target date t , and (ii) observations acquired in the year corresponding to the image to be analyzed during the 15 days preceding t . Mathematically, the acquisition time of the background observations can be expressed as follows:

$$t' \in \tau(t) = \{2017 - \text{PrecYear} \wedge [\text{DOY}(t) - 15, \text{DOY}(t) + 15]\} \cup \{\text{ImageYear} \wedge [\text{DOY}(t) - 15, t]\} \quad (4)$$

where PrecYear and ImageYear are, respectively, the year preceding and the year corresponding to the image to be analyzed. To compute the single $\text{dNBR}(x, y, t')$ values populating the background dNBR sample, each observation t' was paired with the closest valid previous observation available within the preceding 15 days.

Since burned surfaces are generally characterized by a decrease in NBR, the RST-NBR formulation was adapted (reversed in sign) to make NBR anomalies positive. Then, the ALICE index for NBR was defined as

$$\otimes_{\text{NBR}}(x, y, t) = \frac{\mu_{\text{NBR}}(x, y) - \text{NBR}(x, y, t)}{\sigma_{\text{NBR}}(x, y)} \quad (5)$$

where $\otimes_{\text{NBR}}(x, y, t)$ gives the local excess of the $\text{NBR}(x, y, t)$ signal compared to its historical mean value, $\mu_{\text{NBR}}(x, y)$, and weighted by its historical variability $\sigma_{\text{NBR}}(x, y)$, at the given location (x, y) and observation time t .

Accordingly, the ALICE index for dNBR was defined as

$$\otimes_{\text{dNBR}}(x, y, t) = \frac{\text{dNBR}(x, y, t) - \mu_{\text{dNBR}}(x, y)}{\sigma_{\text{dNBR}}(x, y)} \quad (6)$$

where $\mu_{\text{dNBR}}(x, y)$ and $\sigma_{\text{dNBR}}(x, y)$ represent the expected value and natural variability of dNBR, respectively. The $\otimes_{\text{dNBR}}$ formulation standardizes abrupt changes in NBR occurring between consecutive valid observations. A discrete transition generally produces a large dNBR value only for the image pair spanning the event; subsequent pairs compare two post-transition observations and therefore contribute little to the dNBR reference variability. Consequently, the dNBR reference distribution may remain comparatively narrow. This increases the capability of mapping newly burned surfaces, as well as abrupt non-fire changes, such as harvesting or changes over artificial surfaces. For this reason, $\otimes_{\text{dNBR}}$ was restricted to the ESA WorldCover tree-cover and shrubland

classes, where abrupt NBR decreases are less frequent and comparatively more likely to be fire-related. Within these classes, dNBR values greater than 0.5 were excluded from the reference sample to limit the influence of previous fire events.

A complementary indicator was derived from $\otimes_{\text{NBR}}$. To isolate newly developed low-NBR anomalies and progressively remove the contribution of changes already present in the previous valid acquisition, the temporal difference $\Delta\otimes_{\text{NBR}}(x,y,t)$ was computed as:

$$\Delta\otimes_{\text{NBR}}(x,y,t) = \otimes_{\text{NBR}}(x,y,t) - \otimes_{\text{NBR}}(x,y,t_{\text{pre}}) \quad (7)$$

with t_{pre} , again, computed by using the most recent pixels available among the previous 15-day scenes. The $\Delta\otimes_{\text{NBR}}$ indicator plays a complementary and more conservative role. Persistent changes, such as harvesting, may contribute several low-NBR observations to the NBR reference series until substantial vegetation recovery occurs. By contrast, the corresponding abrupt transition generally affects only one dNBR pair. Therefore, persistent or recurrent non-fire conditions are more strongly represented in the expected NBR variability, reducing the standardized response of $\Delta\otimes_{\text{NBR}}$ compared to $\otimes_{\text{dNBR}}$. Although this behavior helps to limit commission errors over cropland and other dynamic non-forest surfaces, it may also reduce the ability to detect weaker, fire-related changes in forest areas.

Accordingly, $\Delta\otimes_{\text{NBR}}$ was applied to all valid land pixels, while the more sensitive $\otimes_{\text{dNBR}}$ was additionally used only over tree cover and shrubland. Within these two classes, either indicator could identify a seed pixel, thereby reducing potential omissions; outside them, seed selection relied on the more conservative $\Delta\otimes_{\text{NBR}}$ alone. Since this was the first application, the thresholds adopted for $\otimes_{\text{dNBR}}$ and $\Delta\otimes_{\text{NBR}}$ were empirically selected through preliminary tests. This led us to adopt a threshold equal to 5 in both cases:

$$\otimes_{\text{dNBR}}(x,y,t) > 5; \quad \Delta\otimes_{\text{NBR}}(x,y,t) > 5 \quad (8)$$

One of the RST approach's main strengths is that the anomaly detection is based on local multitemporal reference fields, allowing recurrent spectral variations to be interpreted as part of the normal behavior for each pixel rather than as anomalous changes. This is particularly useful in agricultural areas during harvest time because when harvest-related spectral changes are already represented in the background sample, the method can distinguish recently harvested fields more effectively from burned areas. Nevertheless, crop rotation practices and interannual differences in climatic and phenological conditions may cause the harvesting date of specific fields to fall outside the ± 15 -day seasonal window used to build the reference fields. In such cases, a recently harvested field in the target image may lack a corresponding harvest signature in the background and may therefore be detected as anomalous. Therefore, to further reduce possible false detections, MIRBI was used as an additional spectral consistency condition:

$$\text{MIRBI}(x,y,t) = 10 \cdot \rho_{\text{B12}}(x,y,t) - 9.8 \cdot \rho_{\text{B11}}(x,y,t) + 2 \quad (9)$$

where ρ_{B11} and ρ_{B12} are the surface reflectance values measured in the Sentinel-2 SWIR Band 11 and Band 12, respectively. MIRBI is very sensitive to spectral changes caused by burning and, together with NBR, it helps to differentiate burned areas from harvested areas [56,57] and cloud cover [55]. Preliminary tests were also performed for MIRBI, and a threshold equal to 2 was adopted, consistent with previous applications reporting this value as an effective separability threshold between burned and harvested areas [57].

The suitability of this threshold was verified through a preliminary test carried out on ten agricultural fields located in northeastern Basilicata (southern Italy), selected because the landowners directly provided their harvesting dates and no harvesting events occurred, for the same fields, within the corresponding ± 15 -day seasonal windows in 2017, 2018 and 2019. The test was performed using Sentinel-2 images acquired in April 2020.

Under these conditions, the harvest signal observed in the 2020 target images was intentionally absent from the corresponding NBR reference fields, thus representing a conservative test for the proposed approach. As expected, $\Delta\otimes_{\text{NBR}}$ values largely exceeded the threshold of 5, producing potential false detections. Conversely, MIRBI values remained below the threshold of 2 for all pixels belonging to the investigated fields, confirming its usefulness as an additional condition to separate harvested fields from burned areas. An example is reported in Figure 1 for two agricultural fields harvested on 11 April 2020 and observed by Sentinel-2 on 12 April 2020.

Before (9 April 2020) and after (12 April 2020) harvesting: false-color RGB

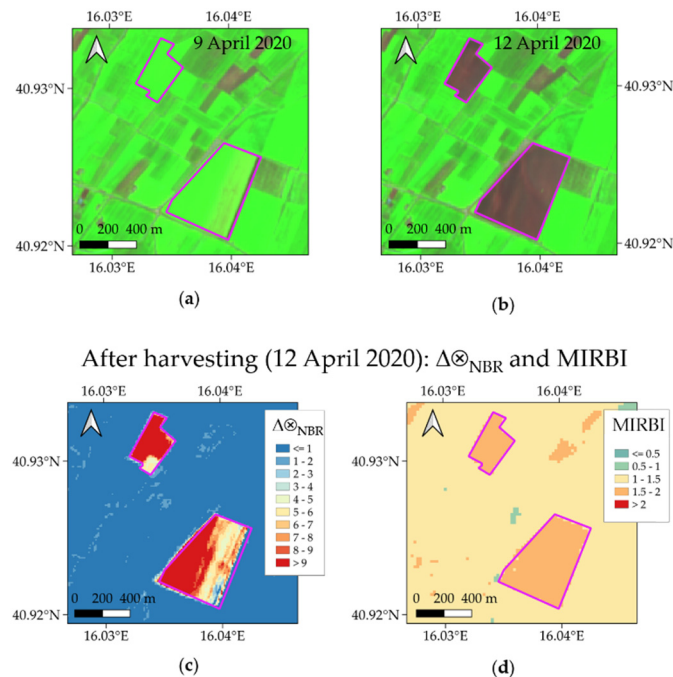


Figure 1. Example of two fields outlined in violet before (a) and after (b) harvesting, depicted using false-color RGB composites ($R = B12 = 2.2 \mu\text{m}$, $G = B8 = 0.83 \mu\text{m}$, $B = B4 = 0.66 \mu\text{m}$) of MSI/Sentinel-2 images. (c,d) report $\Delta\otimes_{\text{NBR}}$ and MIRBI over the same area, respectively, after harvesting (12 April 2020): values of $\Delta\otimes_{\text{NBR}}$ are quite high, while the MIRBI does not reach 2.

The preliminary BA seed mask was then defined by the following rule:

$$\text{Seed}(x, y, t) = [(\otimes_{\text{dNBR}}(x, y, t) > 5) \vee (\Delta\otimes_{\text{NBR}}(x, y, t) > 5)] \wedge [\text{MIRBI}(x, y, t) > 2] \quad (10)$$

This step was designed to select only seed pixels showing a strong, temporally coherent BA signal. These pixels were not intended to represent the complete burned perimeter, but rather to provide reliable starting points for the subsequent spatial extension of the burned area.

The final BA map was obtained by extending the seed pixels to neighboring pixels with a positive burn-related change. Specifically, pixels were included in the final BA class if they were spatially connected to at least one seed pixel and had a dNBR greater than 0.10 [58]. This threshold represents the lower boundary between the *unburned* class ($\text{dNBR} < 0.10$) and the first burned class (*low severity*) [58], thus providing a suitable lower limit for the binary burned/unburned discrimination adopted here. This region-growing step enabled the algorithm to recover the full burned perimeter around the most robust RST detections, while avoiding an unconstrained classification of all pixels with moderate dNBR values.

No fixed threshold was applied directly to NBR, which entered the seed-selection procedure through the standardized $\Delta\otimes_{\text{NBR}}$ anomaly. In qualitative terms, lowering the $\otimes_{\text{dNBR}}$, $\Delta\otimes_{\text{NBR}}$, or MIRBI thresholds makes seed selection more permissive and may reduce omission errors at the cost of increased commission errors, whereas increasing these thresholds has the opposite effect. Similarly, lowering the region-growing dNBR threshold expands the mapped perimeter into pixels characterized by weaker burn-related changes, while increasing it produces more conservative boundaries.

2.2.3. Implementation on Google Earth Engine

The proposed approach was implemented on the Google Earth Engine platform using Sentinel-2/MSI Level-2A surface reflectance data from the “COPERNICUS/S2_SR_HARMONIZED” collection. The analysis was carried out over the Basilicata region (southern Italy) by considering four Sentinel-2 Military Grid Reference System (MGRS) tiles covering the study area: “33TWE”, “33TWF”, “33TXE” and “33TXF”.

Cloud-contaminated pixels were masked using the Cloud Score+ product associated with the Sentinel-2 harmonized collection, specifically the cs_cdf quality-assessment band associated with each S2 pixel. Pixels with cs_cdf < 0.70 were excluded. Since, for BA detection, it is important to minimize residual contamination from thin clouds and haze, which can produce false positives, a slightly more conservative threshold than the values around 0.64–0.66 reported as balancing omission and commission errors was adopted [59–61]. To reduce residual cloud-edge effects, the cloud mask was spatially enlarged by 100 m. Pixels classified as water, snow, no data, or saturated/defective by the Sentinel-2 Scene Classification Layer were also excluded. In the final BA mapping step, water pixels were further buffered by 50 m to limit false detections along water boundaries. “Permanent water” pixels from the ESA land cover were excluded as well.

The reference fields were exported as intermediate GEE assets at 10 m spatial resolution. This pre-computation step was necessary to keep the subsequent processing within the computational limits of the platform and to make the workflow repeatable for different target dates. Although the procedure was parameterized to be applicable to all Sentinel-2 acquisitions, the present paper describes in some detail the products generated for 12 April 2020 and 4 August 2024.

For these target dates, the post-event Sentinel-2 observations were mosaicked tile by tile. The pre-event images used for dNBR computation were selected as the most recent valid observations available within the previous 15 days. The RST-based seed masks were then generated by applying the combined condition based on $\otimes_{\text{dNBR}}$, $\Delta\otimes_{\text{NBR}}$, and MIRBI. Finally, a spatially constrained region-growing procedure was applied starting from the seed pixels. Growth was allowed only through valid pixels with dNBR > 0.10, and the final binary burned-area products were exported at a 10 m spatial resolution in UTM zone 33N, preserving no-data values over clouds, water, invalid observations, and areas outside the study region.

2.3. Test Area and Experimental Periods

The approach proposed in this paper was tested over the area of the Basilicata region (southern Italy, Figure 2), for which fire perimeters are available via the RSDI platform [40]. Basilicata covers an area of around 10,000 km² and is a predominantly rural region characterized by extensive forests, semi-natural areas, and agricultural lands [62–64].

The latest ISPRA report [65] reveals a significant trend in Italian regions: only two regions, including Basilicata, have an increasing total area affected by wildfires. The estimated rate of increase in Basilicata is approximately 4.57 km² per year. The region suffers from fires throughout the year, but the fire season peaks in summer.

Two complete region-wide experiments were considered. As mentioned above, the first was based on the Sentinel-2 acquisition of 12 April 2020, and the second on the 4 August 2024 image. The latter was chosen because, according to the RSDI database, it contains the largest fires of the year that occurred on 1 August 2024 and that produced over 1000 hectares of burnt area (see Tables S2 and S3 in Supplementary Materials for details) and represented the summer fire-season conditions.

Two pre-event images (30 July and 1 August 2024) were used to compute the differential indices with 4 August 2024 as the target image. Both images were cloud-free, but the 30 July image was used to cover the northwestern part of the region, which was not covered by the overpass on 1 August 2024. Therefore, the testing period for northwestern Basilicata was the temporal range 30 July–4 August 2024; for the remaining areas, the testing period was 1–4 August 2024.

Figure 2 shows the test area (the Basilicata region) and the spatial coverage of the images used to compute the indices, with the target image being 4 August 2024.

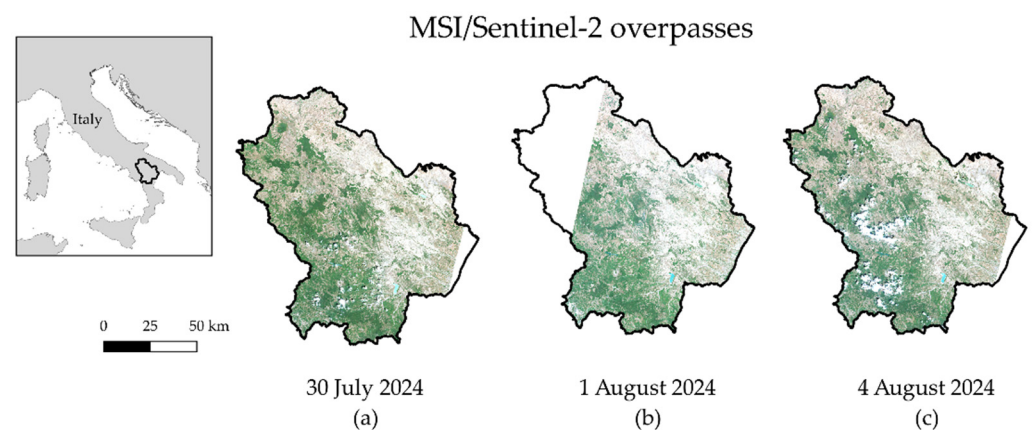


Figure 2. Test area (the Basilicata region) and spatial coverage of the Sentinel-2 images used in the work for the target image of 4 August 2024. 30 July 2024 (a) and 1 August 2024 (b) were used as the pre-event images, while 4 August 2024 (c) was used as the post-event image. Similar observational conditions occurred in the case of 12 April 2020 as the target image. Therefore, 7 and 9 April 2020 have been used as the pre-event images.

The 12 April 2020 image was chosen in order to include a different set of fire events under markedly different seasonal, phenological, and agricultural conditions. The inclusion of the April 2020 case therefore allowed the complete workflow to be evaluated under both interannual and seasonal conditions substantially different from those of the August 2024 experiment. Similar to the August case, different testing periods were considered for the northwestern part of Basilicata (7–12 April 2020) and the remaining areas (9–12 April 2020).

3. Results

3.1. Validation of the RST-Based BA Product

The RST-based BA products were tested in the Basilicata region using the MSI/Sentinel-2 images of 12 April 2020 and 4 August 2024. The raster products were converted to a vector format, yielding more than 300 polygons. Each of them was visually evaluated and, where appropriate, grouped together into clusters (“zones” hereafter) for easier validation. The letter “A” in the zone name refers to the April image and “B” refers to the August image. The decision on whether or not to group them together was based on the proximity and shape of

the visible burned areas in the Sentinel-2 images. If there was any doubt, different zones were created, as this had no effect on the total BA detected. A total of 177 zones were considered.

All zones were evaluated by visualizing RGB composites in true or false colors and by comparing pre- and post-event images. To perform this visual assessment, we employed not only the images used to compute the indices (e.g., Figure 2 for the August image), but also other pre- and post-event images from a broader time period. This approach was necessary to determine if the detected burn scar was actually related to the time period between the pre- and post-event images used to compute the indices or if the burning had occurred earlier. For this purpose, the Copernicus browser [66] was exploited. In cases of uncertainty, the zone was assigned to the “uncertain BA” category. Conversely, zones that burned during the expected period were assigned to the “true BA” category, while false detections were assigned to the “false BA” category. Details about the validation results for each zone are reported in the Supplementary Material (Tables S4 and S5).

The classification into “true BA”, “false BA”, and “uncertain BA” was derived from the multi-source validation framework described in Section 2.1.3, which integrates RSDI, EFFIS, FIRMS, and multi-temporal Sentinel-2 evidence. Taking the ESA WorldCover land-cover classification into account, the validated areas were stratified by land cover class, and the results are summarized in Table 3.

Table 3. Validation results over the test area and periods. For each category, the total BA is reported in column 8. From columns 2 to 7, the burned area per land cover (according to the ESA product classes) is reported.

BA Validation Results (Category)	Tree Cover [ha] (*)	Shrubland [ha] (*)	Grassland [ha] (*)	Cropland [ha] (*)	Built-Up [ha] (*)	Bare/Sparse Vegetation [ha] (*)	Total [ha] (**)
True BA	644.04 (36.47%)	18.03 (1.02%)	405.57 (22.97%)	690.61 (39.11%)	7.44 (0.42%)	0.21 (0.01%)	1765.90 (97.85%)
False BA	3.14 (12.72%)	0.15 (0.59%)	3.24 (13.14%)	1.69 (6.86%)	15.86 (64.31%)	0.59 (2.39%)	24.66 (1.37%)
Uncertain BA	7.73 (54.30%)	0.45 (3.14%)	1.17 (8.20%)	4.19 (29.48%)	0.69 (4.85%)	0.004 (0.03%)	14.23 (0.79%)

(*) percentage within each validation category; (**) percentage respect to the total detected BA.

Figure 3 provides a synthetic overview of the validation results as a percentage of the total RST-based mapped area. The results are strongly dominated by the “true BA” class: 1765.90 ha were visually confirmed as burned areas, corresponding to 97.85% of the mapped area. Conversely, false and uncertain detections accounted for only 24.66 ha (1.37%) and 14.23 ha (0.79%), respectively.

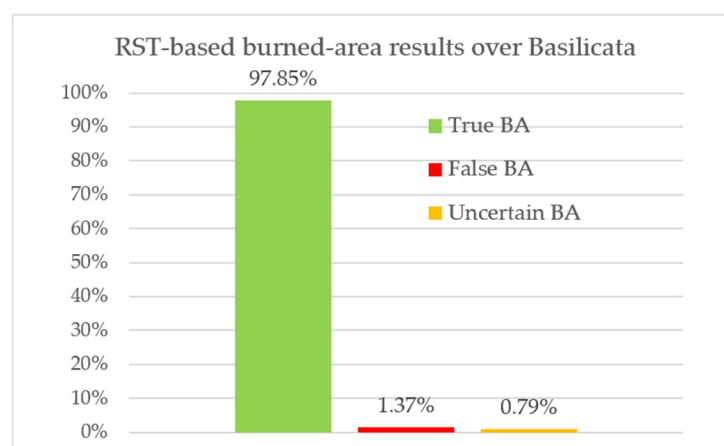


Figure 3. Validation summary of the RST-based BA product over the Basilicata test area and periods. Bars report the percentage of the total mapped area assigned to “true BA”, “false BA”, and “uncertain BA”; labels indicate area in percentage values.

The dominance of the “true BA” class is also evident in the land-cover distribution. Confirmed burned areas primarily affected “cropland” (~39%), “tree cover” (~36%), and “grassland” (~23%). Identifications corresponding to “shrubland” and “bare/sparse vegetation” together represent about 1%. Regarding “built-up” areas in the “true BA” category, the analysis showed that they consist of MSI/Sentinel-2 pixels containing a mixture of burned areas and human-made structures, such as roads and buildings. The “uncertain BA” category is represented by a very small percentage of possible burned areas, most of which correspond to “tree cover”. It should be noted that some zones in the “uncertain” category are actually burned areas, because the “uncertainty” only concerns the exact time of the burning event, which may have occurred before the study period.

With regard to the assessment of empirically selected RST thresholds, two additional configurations were processed for the 4 August 2024 case. In the first configuration, both $\otimes_{\text{dNBR}}$ and $\Delta\otimes_{\text{NBR}}$ were set to 4, while in the second they were both set to 6. MIRBI = 2 and the region-growing condition $\text{dNBR} > 0.10$ were kept unchanged. The resulting outputs were compared to the baseline configuration, based on thresholds equal to 5, in terms of total area classified by the algorithm and spatial differences.

The baseline configuration, with both RST anomaly thresholds set to 5, classified a total area of 1756.72 ha as potential BA. Lowering both thresholds to 4 resulted in a classified area of 1872.17 ha, corresponding to a +7% increase relative to the baseline. Conversely, increasing both thresholds to 6 produced a classified area of 1596.42 ha, corresponding to a 9% decrease (Table 4).

Table 4. Sensitivity of the total area classified as potential BA to variations in the ALICE-index thresholds.

$\otimes_{\text{dNBR}}$	$\Delta\otimes_{\text{NBR}}$	MIRBI	Growing dNBR	Total Classified Area [ha]	Change From Baseline
4	4	2.0	0.10	1872.17	+7%
5	5	2.0	0.10	1756.72	—
6	6	2.0	0.10	1596.42	−9%

These results indicate that the mapped area varied in the expected direction—expanding under the more permissive configuration and contracting under the more restrictive one—but remained within $\pm 10\%$ of the baseline in both cases. This suggests that the overall area estimate is moderately robust to a one-unit simultaneous variation in the two RST anomaly thresholds.

3.2. Comparison with Official BA Products

The validated RST-based product was then compared to the ground-based administrative RSDI database and the satellite-based EFFIS product to characterize similarities and differences in detected events, mapped BA extent, and perimeter delineation. As clarified above, this analysis was intended as a product intercomparison, and neither official dataset was treated as a definitive ground-truth source. As summarized in Table 5, the proposed approach mapped 1765.90 ha of burned areas, compared to the 1196.63 ha (+48%) reported by RSDI and the 727 ha (+143%) mapped by EFFIS. The minimum mapped area was smaller for the RST-based product as well, confirming its ability to identify small burned scars.

Table 5. Overview of the BA mapped by the RST-based product in comparison with that recorded by official BA products over the same area (Basilicata region) and periods used in the RST-based computation of differential indices.

BA Product	BA Minimum Size [ha]	Total BA [ha]
RST-based	0.22	1765.90
RSDI	0.40	1196.63
EFFIS/Basilicata	9	727

To test the EFFIS capability of mapping small areas, we also downloaded and checked the burned scar dimensions for a 2-month period in the summer (1 July–31 August 2024) in Basilicata, finding a minimum EFFIS burned area size of 2 ha.

The potential of the RST-based product is not only related to mapping small burned scars, but also to relatively large events that are not reported in the official datasets. A relevant example is a burned area of about 196 ha, in the municipality of Lavello, which the RST-based product mapped but which was missed in the EFFIS and RSDI databases. False-color Sentinel-2 composites clearly show the burn scar, and FIRMS/VIIRS active-fire detections confirm the occurrence of fire activity in the area (see Figure 4).

RSDI/EFFIS missed event (Lavello, 196.4 hectares)

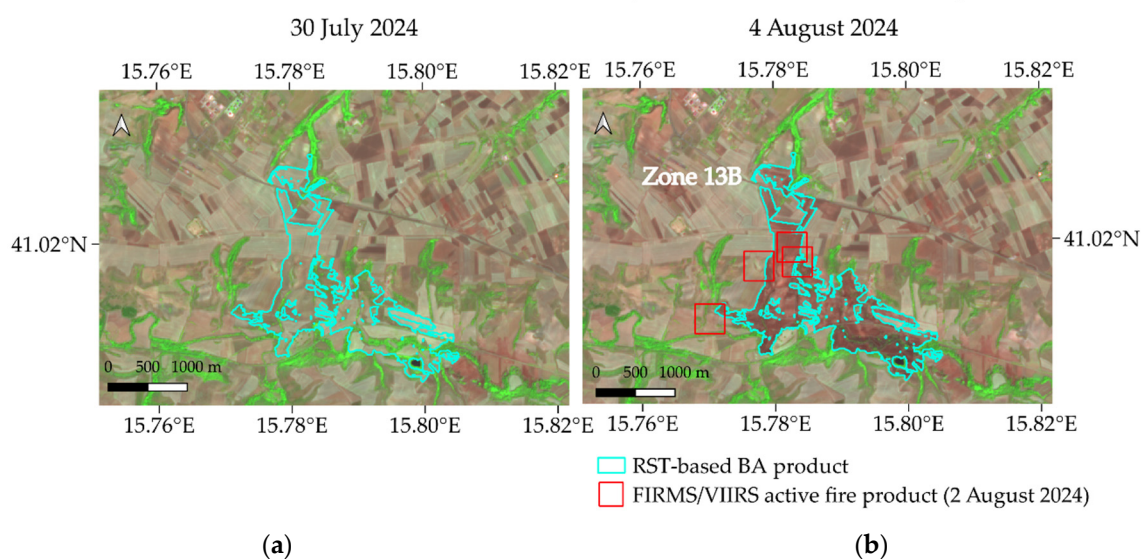


Figure 4. Burned scar covering about 196 hectares, mapped only by the RST-based product. RGB composites in false colors of (a) the pre-event MSI/Sentinel-2 image (30 July 2024) and (b) the post-event MSI/Sentinel-2 image (4 August 2024), where the fire scar is represented by the darker brown tones. Active fires detected by FIRMS over VIIRS overpasses confirm the occurrence of a fire at least on 2 August 2024.

The available evidence does not allow us to determine the exact cause of either omission. However, the RSDI omission is likely related to the predominantly agricultural composition of the scar (about 133 ha of cropland), as the regional registry primarily targets forested areas and pasture for administrative purposes. For EFFIS, possible contributing factors include the fragmented agricultural configuration of the scar, the operational mapping scale, land cover constraints, and the absence of a sufficiently strong or persistent trigger in the inputs used by the operational workflow.

Considering the fire scars reported in the official databases, the RST-based methodology mapped 11 out of 17 RSDI fire scars and all six EFFIS fire perimeters. The

missed RSDI scars correspond to very small areas, amounting to 10.60 ha in total, or 0.9% of the total burned area reported for the test periods in the RSDI database. Details on the mapped fire scars are reported in Table 6.

Table 6. Burned areas commonly detected by the RST-based approach and by RSDI and/or EFFIS databases. Further details are in Tables S1–S5 in Supplementary Materials.

Municipality	RSDI Database			EFFIS/Basilicata Database			RST-Based Database		
	RSDI Id(s)	Fire Date	Area [ha]	EFFIS Id	Initial Date	Final Date	Area [ha]	Zone Id	Area [ha]
Ruoti	1568 4733 6225	10 April 2020	1.18					25A	2.71
Melfi	4956 5309	30 July 2024	4.94					26B	4.18
Accettura	2666 3259	31 July 2024	167.96	235848	31 July 2024	2 August 2024	181	90B	138.35 (167.86 considering multi-temporal observations)
Accettura				236200	31 July 2024	2 August 2024	9	91B	7.99
Vaglio di Basilicata	868 2718	1 August 2024	189.06					1B	198.63
Filiano	1517 2155 3320	1 August 2024	236.16					2B	264.43
Barile	675 1178 3249	1 August 2024	114.26	236204	2 August 2024	2 August 2024	108	6B	109.84
Melfi	1179 1312 2580 3487	1 August 2024	346.80	236202	1 August 2024	3 August 2024	326	8B	320.85
Melfi	31 407 2965 5658	1 August 2024	162.25 (79.82 in Basilicata)	236206	1 August 2024	2 August 2024	144 (77 in Basilicata)	16B	74.06
Ripacandida	2935 4124	2 August 2024	5.03					36B	7.39
Melfi	3311 5545 5671	3 August 2024	14.67					20B	20.36
Castronuovo di Sant'Andrea	2105 4969 6173	3 August 2024	26.14	236207	3 August 2024	3 August 2024	26	79B	27.96

The most significant difference in the BA extension was recorded among the three products for the Accettura fire on 31 July 2024. A focused analysis of this fire scar revealed that the EFFIS product (181 hectares) more accurately delineated the area than the RSDI product (167.96 hectares). The RST-based product (138.35 hectares) delimited the perimeter of the commonly detected area in good agreement with the EFFIS product, but one large area remained undetected mainly due to the cloud mask applied to the RST product on 4 August. An additional area (less than 10 ha) can be partially detected on the 1 August image because the fire started on 31/07/2024, and about 23 ha on the 6 August image, recovering the cloudy area of 4 August. Processing such satellite observations

allowed us to create a merged RST-based product with a total area of 167.86 hectares (Figure 5).

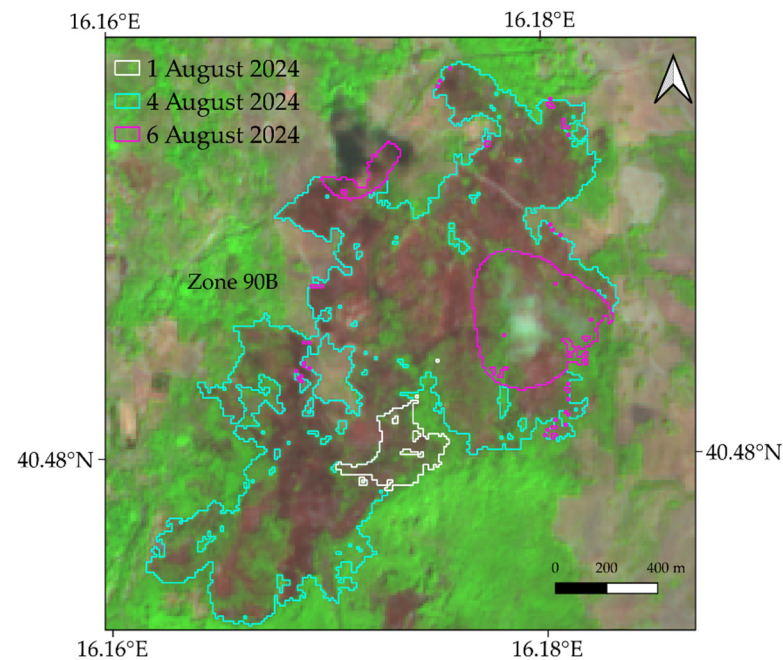


Figure 5. Cyan lines identify the burned area mapped on the 4 August 2024 Sentinel-2 image. About 6 hectares (white lines) can be mapped after the 1 August image processing because the fire started on 31 July 2024; about 23 ha (magenta lines) after the 6 August image processing, recovering the area covered by clouds on 4 August. The total affected area is finally 167.86 ha.

Based on the above results, the following are considered:

- True positives (TP) = true BA category (1765.90 ha);
- False positives (FP) = false BA category (24.66 ha);
- False negatives (FN) = areas of events recorded in official databases that were not identified at all by the algorithm (10.60 ha);
- Basilicata area = 999199.1 ha;
- Uncertain = 14.23 ha;
- True negatives (TN) = $2 \times \text{Basilicata area} - (\text{uncertain} + \text{TP} + \text{FP} + \text{FN})$.

The following standard metrics were computed:

- Commission error (CE) = 1.38%;
- Omission error (OE) = 0.60% (details on OE per land cover class can be found in the Supplementary Materials, Table S6);
- Sensitivity (or true positive rate) = 99.40%;
- F1-score = 99.01%;
- Balanced accuracy = 99.70%.

For common detections, a correlation analysis was performed to compare the BA estimates provided by the RST-based product and those reported by the official datasets. The comparison returned an R^2 of 0.98 for EFFIS and an R^2 of 0.99 for RSDI, indicating a strong linear relationship between the burned area estimates of commonly detected fire scars (Figure 6).

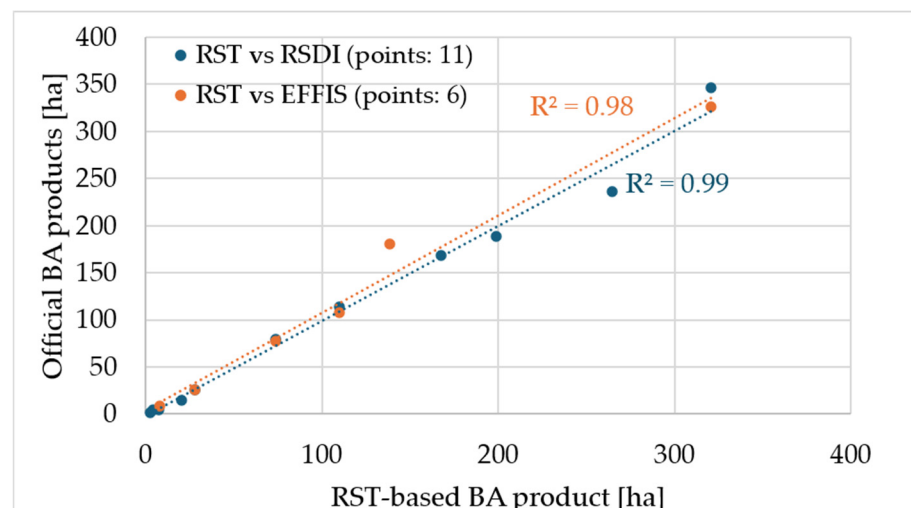


Figure 6. Correlation between BA (in hectares) mapped by RST-based products and official BA products related to commonly detected fire scars. For the Accettura fire of July–August 2024, the merged RST-based product shown in Figure 5 has been considered.

To measure the spatial boundary agreement between the RST-based product and the official database products, a polygon-level spatial intercomparison was also performed. It yielded an Intersection over Union (IoU) of 0.69 for the comparison with RSDI, and a corresponding value of 0.83 for EFFIS, highlighting a stronger agreement with the satellite-based EFFIS product, but in general a moderate-to-high agreement with these reference products. The complete spatial-overlap metrics are reported in Table 7.

Table 7. Polygon-level spatial agreement between the RST-based burned-area product and RSDI/EFFIS for commonly detected fire scars.

Reference Product	Municipality	Event ID	RST Area [ha]	Reference Area [ha]	Intersection [ha]	IoU
RSDI	Ruoti	25A	2.71	1.18	1.04	0.36
	Melfi	26B	4.18	4.94	3.76	0.70
	Accettura	90B	167.86	167.96	133.80	0.66
	Vaglio di Basilicata	1B	198.63	189.06	165.81	0.75
	Filiano	2B	264.43	236.16	192.50	0.62
	Barile	6B	109.84	114.26	100.04	0.81
	Melfi	8B	320.85	346.80	272.01	0.69
	Melfi	16B	74.06	79.82	69.86	0.83
	Ripacandida	36B	7.39	5.032	4.20	0.51
	Melfi	20B	20.36	14.666	10.17	0.41
	Castronuovo di Sant'Andrea	79B	27.96	26.143	24.11	0.80
RSDI pooled			1198.27	1186.02	977.30	0.69
EFFIS	Accettura	90B	167.86	181	157.18	0.82
	Accettura	91B	7.99	9	6.99	0.70
	Barile	6B	109.84	108	101.59	0.87
	Melfi	8B	320.85	326	294.17	0.83
	Melfi	16B	74.06	77	68.34	0.83
	Castronuovo di Sant'Andrea	79B	27.96	26	24.06	0.80
EFFIS pooled			708.56	727	652.33	0.83

However, the corresponding RST-based areas appear to better follow the actual burned scars visible in the post-event Sentinel-2 imagery than the ground-based RSDI perimeters. Figure 7 illustrates this with an example of a fire that occurred in the municipality of Filiano on 1 August 2024. For this fire, IoU is 0.62. However, the RST-based product not only better outlines the visible burned scar, but also detects additional nearby burned areas that are not included in the RSDI database. The RST-based product identifies an additional 28 hectares in the area flagged as “zone 2B”, and about 9 ha in the “zone 3B”, as compared to RSDI. Moreover, another correctly identified burned scar (“zone 4B”) is visible on the same scene, which is not included in the RSDI database. No EFFIS detection was recorded for this event.

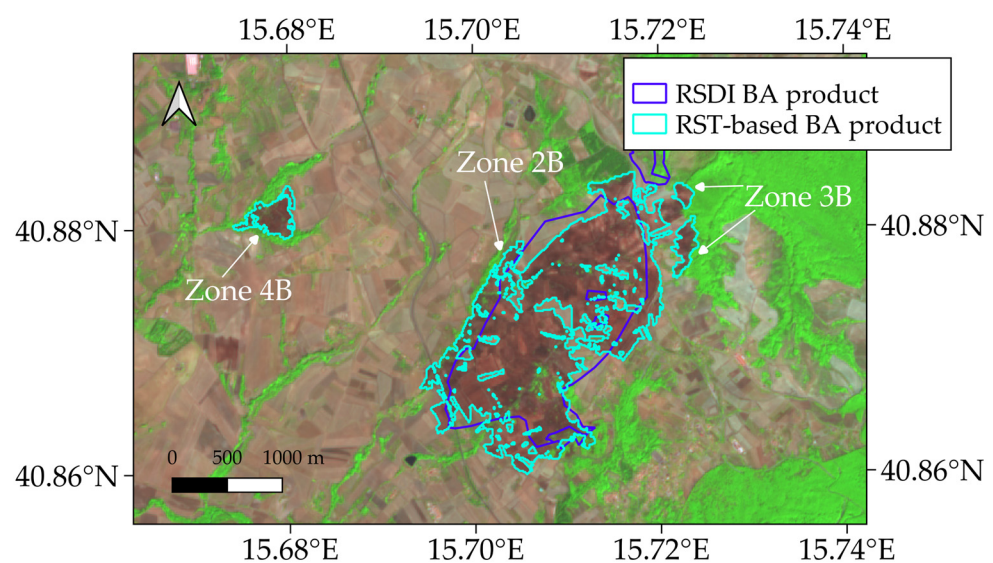


Figure 7. BA products from the RSDI database (blue color) and RST-based approach (cyan) concerning the fire that occurred in Filiano on 1 August 2024. The RGB composite in false colors, used as a background, highlights (dark brown areas) the burned scars. “Zone 2B” of the RST-based product roughly corresponds to the RSDI BA product (IoU is 0.62), but it better delineates the burned scar. “Zone 3B” is probably an additional area of the same fire event. “Zone 4B” is another independent fire scar, unregistered in the RSDI database. No corresponding burned scar was recorded in the EFFIS database.

Figure 8 shows the large fire that occurred in the municipality of Melfi on 1 August 2024. For this event, the EFFIS and RST-based products mapped comparable burned areas, equal to 326 ha and 320.8 ha, respectively, with an IoU of 0.83. This result confirms the high level of agreement among satellite-based products for large common fire scars. The RSDI product mapped a slightly larger burned area of 346.8 ha (IoU of 0.69 with the RST-based product).

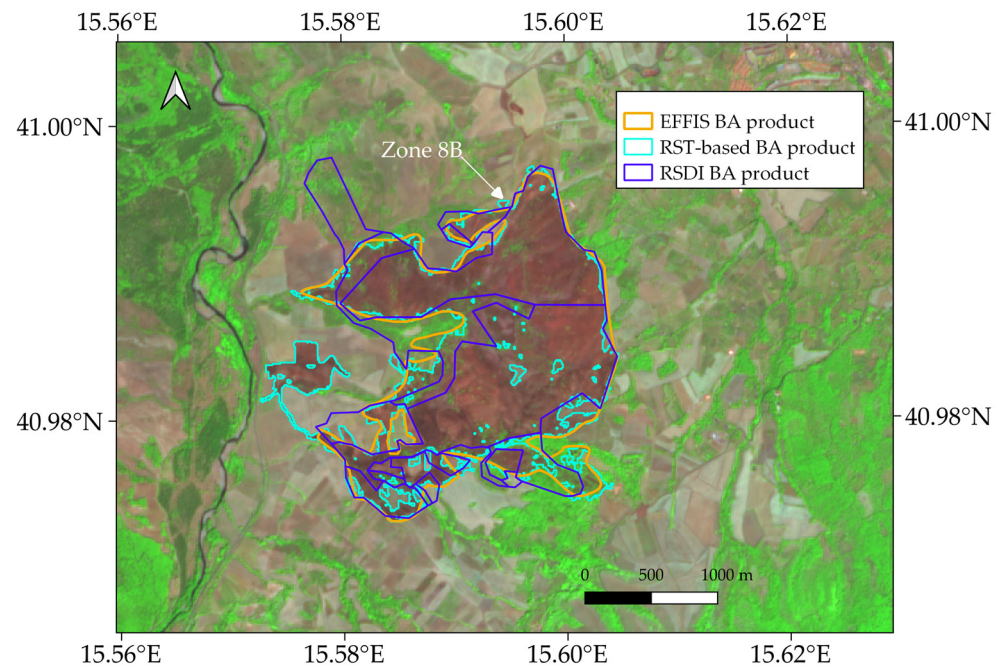


Figure 8. BA products from RSDI (blue color), EFFIS (orange color), and RST-based (cyan) BA products concerning the fire that occurred in Melfi on 1 August 2024. The RGB composite in false colors, used as background, highlights (dark brown areas) the burned scars. Both EFFIS- and RST-based products delineate fire scars better than the RSDI fire perimeter.

A comparison by land cover class was also performed. To facilitate an immediate comparison with our results, the EFFIS and RSDI vectorial fire areas were classified according to the ESA land cover. The results are in Table 8. It is worth noting that some small areas are included in the non-vegetated classes (“built-up” and “permanent water bodies”) for such products as well.

Table 8. RST-based, EFFIS and RSDI areas per land cover class, according to the ESA land cover product.

BA Product	Tree Cover [ha]	Shrubland [ha]	Grassland [ha]	Cropland [ha]	Built-Up [ha]	Bare/Sparse Vegetation [ha]	Permanent Water Bodies [ha]
RST-based	644.04 (36.47%)	18.03 (1.02%)	405.57 (22.97%)	690.61 (39.11%)	7.44 (0.42%)	0.21 (0.01%)	-
EFFIS/Basilicata	469.62 (64.57%)	6.90 (0.95%)	148.38 (20.40%)	100.75 (13.85%)	1.07 (0.15%)	0.60 (0.08%)	0.01 (0.001%)
RSDI	580.54 (48.51%)	9.44 (0.79%)	310.12 (25.92%)	292.17 (24.42%)	3.88 (0.32%)	0.47 (0.04%)	0.01 (0.001%)

The three products agree on the percentage of the “grassland” (in the range 20 ÷ 26%), “shrubland” (around 1%), and “bare/sparse vegetation” (less than 0.1%) classes. On the contrary, greater differences are recorded in the “tree cover” (from ~36 to ~65%) and “cropland” (from ~14 to ~39%) classes. The smaller percentage of “cropland” in the RSDI database was expected, as it mainly records fires that affect forested areas and pasture. Routine stubble burning is not usually recorded. Conversely, it is less clear why there are no EFFIS maps over even extensive burned areas such as the one corresponding to the

RST-based zone 13 (Figure 4), which consists of approximately 133 hectares of “cropland” and an additional 63 hectares of other land covers.

It should be highlighted that the inaccuracy of fire perimeters in ground-based databases (see Figures 7 and 8, for example), as well as the incompleteness of both ground- and satellite-based databases in mapping fire-affected areas of any size and land cover (e.g., Figures 4 and 7), led us to validate our results using a multi-source assessment, combining official databases, pre- and post-event Sentinel-2 visual interpretation, and FIRMS active-fire detections, as described in the “Validation data” section. This approach was necessary to distinguish actual omission/commission errors and explains the detailed and long validation effort carried out over the selected regional test case.

4. Discussion

Results from the Basilicata test area show that the proposed RST-based approach can combine high sensitivity with low commission and omission errors. This outcome is mainly related to the two-step structure of the algorithm. The RST-based indices are used to identify only the most reliable burned-area pixels, while the subsequent dNBR-based region-growing procedure allows the burned perimeter to be spatially extended around these robust detections. In this way, the method avoids an unconstrained dNBR fixed thresholding, which is known to produce omission/commission errors [67–69].

This aspect is particularly relevant for Mediterranean landscapes, where fire scars may affect very heterogeneous land covers and where small or fragmented burned areas can be missed by products based on coarser spatial resolutions or on active-fire detections. In this regard, a recent study [70] has shown that more than 90% of active fires detected using Sentinel-2 are missed by MODIS and VIIRS products because they are too small or characterized by a weak thermal signal for coarse-resolution sensors. In most cases, they omit fires corresponding to small agricultural burning. Conversely, the previously presented results indicate that the proposed approach is effective over agricultural areas, which represent a large fraction of the confirmed burned surfaces. This is an important point not only because cropland fires may be underrepresented in official products or administrative databases, but also because BA estimates are a key input for fire-emission models and carbon-budget assessments. Thus, improving the detection of agricultural or, in general, small burned areas may contribute to a more accurate characterization of fire-related greenhouse-gas emissions [70,71].

However, the comparison with RSDI and EFFIS should not be interpreted only as a direct accuracy ranking among products, since these datasets are produced with different objectives and procedures. In the case of RSDI, fire perimeters are derived from ground-based delineations carried out by the competent authorities for administrative purposes. Therefore, perimeter inaccuracies may occasionally occur due to practical factors, such as the need to simplify boundaries in narrow or inaccessible areas, the possible inclusion of unburned patches within the mapped perimeter, or the difficulty of recognizing low-severity burned patches several days after the event. Under these circumstances, satellite-based mapping may provide a more spatially detailed estimate of the actually burned surface, especially when high-resolution post-event imagery is available.

In the case of EFFIS, discrepancies may be partly related to differences in timing, mapping scale, perimeter generalization, or land-cover classes considered relevant by the operational product. Nevertheless, the absence of EFFIS detections over some clearly visible burned scars, including relatively large areas such as the 196 ha event in Lavello, suggests that omission errors still occur, even for fire scars that an operational, satellite-based product would be expected to identify. For this reason, no individual dataset was adopted as definitive ground truth. The validation instead relied on the convergence of RSDI, EFFIS, FIRMS, and multi-temporal Sentinel-2 evidence, while explicitly

acknowledging both the limited independence of the Sentinel-2 visual interpretation and the possible omissions or boundary inaccuracies affecting the external datasets.

One limitation of the proposed implementation is its dependence on the availability of cloud-free observations before and after the event. The adopted masking strategy was intentionally conservative, in order to reduce commission errors due to clouds, haze, water bodies, and cloud-edge effects. However, this choice may locally generate omission errors where the burned scar is partially masked in the target image. In an operational framework, this issue could be mitigated by applying the procedure sequentially to the following Sentinel-2 acquisitions, as shown in the case of the Accettura fire (Figure 5), allowing areas masked on a given date to be mapped as soon as valid observations become available.

Although false identifications accounted for only about 1% of the total BA detected by the RST-based approach, they were analyzed further. As shown in Table 3, most false BAs were associated with the “built-up” land cover class. These detections were mainly related to buildings or solar/photovoltaic panels showing anomalous SWIR channel signals between pre- and post-event images. Figure 9 shows some examples over an urban area (Figure 9a–c) and a terrain with photovoltaic panels (Figure 9d–f). The false-color RGB composites of the post-event MSI/Sentinel-2 image (4 August 2024) show the anomalous SWIR reflectance compared to the pre-event image (1 August 2024).

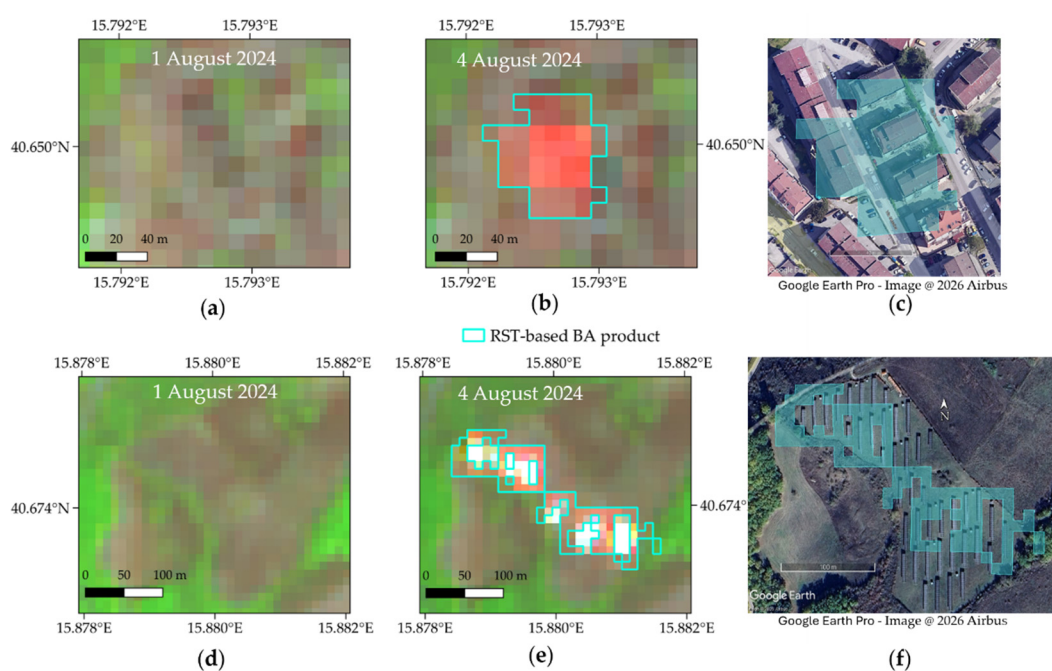


Figure 9. Examples of false BA identifications in correspondence with anomalous high values of SWIR signal in an urban area (top images, zone 34B in Table S5) and photovoltaic panels (bottom images, zone 43B in Table S5). RGB composites in false colors highlight high SWIR reflectance. Panels (a,d) show the pre-event image used for differential indices; panels (b,e) show the post-event image; in panels (c,f), the BA detected (cyan-colored area) is overlaid on satellite imagery acquired from Google Earth Pro (© [2026] Google, [Airbus]). Google Imagery is reproduced here for academic illustration and non-commercial research purposes in accordance with Google Geo Guidelines; original copyrights remain with their respective owners.

Disturbances over Sentinel-2 images caused by rooftops, solar panels, and photovoltaic stations are well known in the literature (see, for example, [72]). This effect is particularly prone to being generated by both the specific surface conditions (smooth and flat) and the observational conditions that produce specular reflection [72]. Since

burning can occur in areas such as urban green spaces or terrains with photovoltaic panels, the proposed approach does not exclude these land-cover classes a priori, accepting a very small percentage of false positives. Nevertheless, when a more conservative product is required, an additional land cover filter could be applied to exclude these types of land cover. In the present analysis, filtering out the “built-up” class would leave the amount of true burned areas almost unchanged (1758.46 hectares), corresponding to 98.75% of all detected areas. The percentages of “uncertain BA” and “false BA” would decrease to 0.76% and 0.49%, respectively. Another approach, though less immediate, could involve carrying out additional tests that exploit the increased reflectance in many bands compared to the pre-event image when roofs and photovoltaic panels are present. Figure 10 clearly shows the differences in spectral signatures of the roof and photovoltaic panels in Figure 9 compared to those of a fire over the same image.

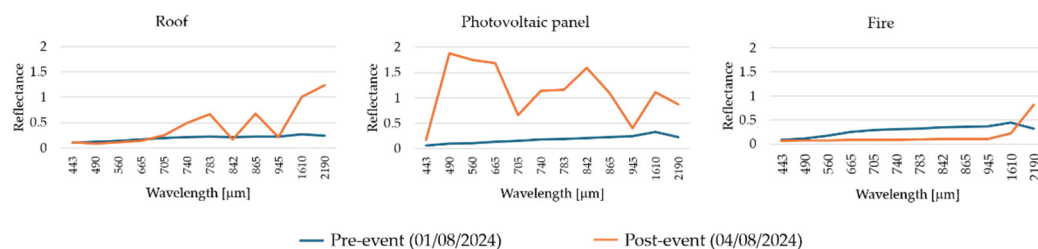


Figure 10. Spectral signatures from MSI/Sentinel-2A (level: L2A, tile: T33TWF) acquired on 1 August 2024 (blue lines) and 4 August 2024 (orange lines) in correspondence with a roof (lon: 15.79270E, lat: 40.6499329N, see Figure 9c), a photovoltaic panel (lon: 15.8807263E, lat: 40.6736678N, see Figure 9f), and a fire (lon: 15.924790E, lat: 40.9761069N).

The complete application of the workflow to the August 2024 and April 2020 cases indicates that the procedure can be repeated under contrasting seasonal, phenological, and fire occurrence conditions. Therefore, the second experiment provides an initial assessment of temporal and seasonal robustness beyond the single acquisition originally considered. However, since both experiments were conducted in Basilicata, these results should not be interpreted as a complete demonstration of geographic transferability.

Similarly, the GEE implementation provides the technical basis for repeatedly processing successive Sentinel-2 acquisitions, but operational near-real-time performance, including data availability and processing latency, was not explicitly evaluated in this study. Cross-regional validation and dedicated operational testing are therefore still required before broader claims regarding geographic exportability and near-real-time use can be made. However, the results obtained here suggest that combining the RST-based seed detection, MIRBI-based spectral consistency checking, and dNBR-based spatial extension with the potential exportability of RST represents a promising strategy for high-resolution BA mapping in complex Mediterranean environments.

5. Conclusions

This paper presented an approach to identifying burned areas that differs from many existing methods. Rather than relying on training samples or MODIS/VIIRS active-fire products, this approach uses multi-year, seasonally matched observations to create a local reference distribution for each pixel. Leveraging the high spatial resolution of the MSI/Sentinel-2 and the potential of the RST methodology, a two-step procedure was designed as follows: first, RST-based NBR and dNBR anomalies were used to identify reliable BA seed pixels; then, a dNBR-based spatial extension was applied to recover the full burned perimeter around these robust detections. The integration of MIRBI as an

additional spectral consistency condition helped to reduce possible confusion between burned and harvested areas.

The methodology was tested considering the Basilicata region, in southern Italy, and described in detail for the Sentinel-2 images acquired on 12 April 2020 and 4 August 2024. In such cases, the fires considered were those occurring between these target images and the previous valid Sentinel-2 observations, i.e., 7–12 April 2020 and 30 July–4 August 2024 for northern Basilicata, 9–12 April 2020 and 1–4 August 2024 for the remaining part of the region. The validation results showed that the proposed product correctly identified 1765.90 ha of burned areas, corresponding to 97.85% of the total mapped area.

Validation of the RST BA products, based on integrating RSDI, EFFIS, FIRMS and multi-temporal Sentinel-2 evidence, showed high sensitivity (99.40%), as well as low CE (1.38%) and OE (0.60%). The main residual source of false detections was associated with built-up surfaces, especially rooftops, solar panels, and photovoltaic installations producing anomalous SWIR responses. However, these cases represented only a small fraction of the mapped area, and the optional use of a built-up exclusion mask or additional multi-spectral tests would further reduce false positives when a more conservative product is required.

For commonly detected events, the RST-based products showed strong agreement with the official datasets. The R^2 values were 0.99 and 0.98 in the comparison with RSDI and EFFIS, respectively. Polygon-level intercomparison also showed substantial spatial overlap, with IoU values of 0.69 and 0.83, respectively. Overall, the burned area mapped by the approach presented in this paper was larger than that reported by both RSDI (+48%) and EFFIS (+143%) over the same test area and periods. It included several burned scars not recorded in the official products, mainly over forest and agricultural land. Results also showed the capability of identifying very small burned areas—0.22 hectares—compared with a minimum of 0.4 ha identified by RSDI and a minimum of 9 ha identified by EFFIS, and a better perimeter demarcation of the RST-based product. The results achieved on agricultural lands and small burned areas are particularly relevant because those fires may be underrepresented in administrative or operational datasets and because BA estimates are a key input for fire-emission modeling and carbon-budget assessments.

Although the workflow was evaluated through two temporally and seasonally contrasting experiments, both were conducted in Basilicata; therefore, the present study does not demonstrate geographic transferability. However, the large number of Sentinel-2 pixels analyzed over the regional test area, together with the intrinsic exportability of the RST framework to different geographic areas and satellite sensors, indicates a strong potential for applying the proposed workflow to other regions and satellite data sources. In terms of implementation, the workflow developed in GEE was designed to be repeatable over different Sentinel-2 acquisitions and to potentially map burned areas in near real time. Future developments of this work include applications over other geographic areas, fire seasons, and land-cover contexts to further assess its operational use and transferability. Nevertheless, the results indicate that the proposed RST-based approach can provide accurate, spatially detailed, and sensitive burned-area maps, supporting both fire management activities and broader applications related to environmental monitoring, fire emissions, and climate-impact assessments.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/rs18203494/s1>. An additional file contains details about validation information and results. Individual files are also available with figures containing RGB composites.

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Abbreviations

The following abbreviations are used in this manuscript:

ALICE	Absolutely Local Index of Change of the Environment
BA	Burned area
CCI	Climate Change Initiative
CE	Commission Error
DL	Deep Learning
dNBR	Differenced Normalized Burn Ratio
EFFIS	European Forest Fire Information System
ESA	European Space Agency
FNs	False Negatives
FPs	False Positives
FIRMS	Fire Information for Resource Management System
GCOS	Global Climate Observing System
GEE	Google Earth Engine
GWIS	Global Wildfire Information System
IoU	Intersection over Union
MGRS	Military Grid Reference System
MIRBI	Mid-Infrared Burn Index
ML	Machine Learning
MODIS	Moderate Resolution Imaging Spectroradiometer
MSI	Multispectral Imager
NASA	National Aeronautics and Space Administration
NBR	Normalized Burn Ratio
NIR	Near-Infrared
NOAA	National Oceanic and Atmospheric Administration
OE	Omission Error
RDA	Rapid Damage Assessment
RSDI	Regional Spatial Data Infrastructure
RST	Robust Satellite Techniques
RU	Reference unit
S2	Sentinel-2
S2A	Sentinel-2A
S2B	Sentinel-2B
S2C	Sentinel-2C
S-NPP	Suomi-National Polar-orbiting Partnership
SWIR	Shortwave Infrared
TNs	True negatives
TPs	True positives
VIIRS	Visible Infrared Imaging Radiometer Suite

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