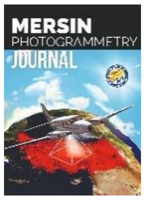
Mersin Photogrammetry Journal

https://dergipark.org.tr/en/pub/mephoj

E-ISSN 2687-654X



Beyond dNBR: Exploring Alternative Satellite Indices for Post-Fire Damage Assessment in Turkish Forests

Zeynep Kiraz [1], Bahadir Kulavuz [1], Tolga Bakirman [*1], Bulent Bayram [1]

[1]*Yildiz Technical University, Department of Geomatics Engineering, Türkiye*

Cite this study: Kiraz, Z., Kulavuz, B., Bakirman, T. & Bayram, B. (2025). Beyond dNBR: Exploring Alternative Satellite Indices for Post-Fire Damage Assessment in Turkish Forests. Mersin Photogrammetry Journal, 2025, 7(2), 52-62.

https://doi.org/10.53093/mephoj.1628753

Keywords
Forest Fire
Burn Severity
Sentinel-2
Google Earth Engine
dNBR

Research Article
Received:28.01.2025
Revised:26.06.2025
Accepted:01.07.2025
Published:01.12.2025

Abstract

Difference Normalised Burn Ratio (dNBR) is used as a reliable reference index since it has accepted thresholds for determining fire severity. However, the use of the dNBR index is limited if pre-fire data cannot be obtained due to weather and other conditions. This situation necessitates the development of alternative indices that are calculated only with post-fire satellite imagery. This study was conducted on forest fires in Mersin, Izmir and Mugla provinces of Turkey while aiming to evaluate the effectiveness of alternative indices to the dNBR index, which is widely used in determining ecosystem damage and fire severity after forest fires. Using Sentinel-2 satellite data operated by the European Space Agency (ESA), the study analysed the performance of the NDVI, NDMI, NBR, MSAVI, EVI and BAIS2 indices calculated using only post-fire data against the dNBR index calculated from pre- and post-fire imagery. The main methods used in this study include data processing and analyses performed on the Google Earth Engine (GEE) platform and comparisons made on the QGIS platform. In this study, the extent to which these alternative indices can be effective in accurately and reliably assessing post-fire ecosystem damage was investigated. The results of the analyses showed that the NBR and BAIS2 indices have the highest accuracy in detecting post-fire ecosystem damage. While both indices produced results close to the dNBR index, MSAVI and EVI were found to be effective in monitoring vegetation changes but insufficient in determining fire severity. In conclusion, BAIS2 and NBR provide strong alternatives to dNBR in analyses based on post-fire data, while the other indices used in the study are considered as complementary tools.

1. Introduction

Forest fires are among the most frequently encountered natural disasters, causing significant economic losses and severe degradation of forest ecosystems. Each year, approximately 450 million hectares of land are affected by fires resulting from both anthropogenic activities and natural causes [1]. Due to its climatic characteristics and dense vegetation cover, Turkey is considered one of the most vulnerable countries to forest fires. In particular, rising temperatures and prolonged droughts during the summer months substantially increase the risk of wildfires, leading to frequent fire incidents across the country driven by both natural and human-induced factors. According to the 2022 statistics of the General Directorate of Forestry, a total of 2,160 forest fires occurred in Turkey within that year alone, resulting in damage to approximately 12,799 hectares of forested land [2]. These fires not only threaten ecosystem integrity and biodiversity but also cause major economic losses, environmental degradation, and social disruption.

The increasing frequency and intensity of forest fires are directly linked to climate change, highlighting the importance of developing effective strategies for the sustainable management of natural resources. In this context, timely detection of fire-affected areas allows rapid and accurate planning of post-fire rehabilitation efforts. Since the 1970s, satellite imagery has become a widely adopted and routine tool for monitoring fire activity at the operational scale [3]. With the continuous advancement of satellite technologies, tools such as remote sensing (RS) and geographic information systems (GIS) have become indispensable for mapping fire-affected areas [2]. Through these technologies, the environmental impact of wildfires can be quantified, enabling the numerical assessment of short-term changes in soil and vegetation conditions [4]. Among the most commonly used spectral indices for this purpose are the Normalized Burn Ratio (NBR) and the Differenced Normalized Burn Ratio (dNBR).

The dNBR, in particular, is recognized for its high accuracy and standardized threshold values, and is considered especially suitable for assessing fire severity in dry Mediterranean climates [5]. Further studies have shown that the dNBR is able to better represent the spatial distribution of forest fire severity compared to the NBR [6, 7, 8]. However, a key limitation of dNBR is its reliance on both pre-fire and post-fire satellite imagery, which restricts its applicability in areas where pre-fire data are unavailable [9]. To overcome this limitation, the present study aims to evaluate the effectiveness of alternative spectral indices that can be derived solely from post-fire satellite imagery.

The research focuses on wildfire-affected areas in the Turkish provinces of Mersin, İzmir, and Muğla. Using Sentinel-2 satellite imagery processed through the Google Earth Engine (GEE) platform, six different indices namely NDVI, NDMI, NBR, MSAVI, EVI, and BAIS2 were calculated and comparatively analyzed with dNBR using QGIS software. This approach seeks to assess the potential of these post-fire indices as viable alternatives to dNBR and to contribute to the development of more flexible and accessible methods for evaluating fire severity.

2. Material and Method

2.1. Study Areas

Analysis was conducted on three different regions (İzmir, Muğla and Mersin) to compare the consistency and accuracy of the indices in different geographical conditions and ecosystems. The reason for choosing regions with large fires is that larger fire areas provide a more accurate and comprehensive assessment of the performance of the indices in determining fire severity and ecosystem damage. Since large-scale fires may involve different severity levels and various ecosystem responses, the reliability and effectiveness of each index were evaluated.The first study area is a fire area that occurred on 14 August 2020 in Bayraklı district of Izmir, where 1609 hectares of land was damaged. The region is characterised by a vegetation cover consisting of maquis and red pine forests typical of the Mediterranean climate. These features constitute a valuable research area in terms of examining post-fire ecosystem dynamics and vegetation responses and allow analyses of the performance of different indices in determining fire severity and ecosystem destruction.

The second study area encompasses a large-scale fire that occurred in Muğla on 12 August 2021, affecting 10,366 hectares of land. The fact that the fire spread over an extensive area and exhibited a range of severity levels provides a robust foundation for evaluating the consistency and accuracy of the indices. Furthermore, the Muğla region broadens the scope of the study by enabling the analysis of various ecosystem types.

The third study area is the fire event that occurred on 8 September 2022 in the Büyükeceli neighbourhood of the Gülnar district in Mersin, affecting an area of 2780 hectares.

2.2. Sentinel-2 Satellite Imagery and the Role of Spectral Bands in Fire Monitoring

Sentinel-2 satellite imagery consists of multispectral optical data provided through the Copernicus Program, operated by the European Space Agency (ESA). These data play a crucial role in observing and analyzing global environmental changes. They are widely employed in many fields, including forest fires, vegetation health, water resource management, land-use change, and ecosystem dynamics. Sentinel-2 satellites offer 13 spectral bands with 10 m, 20 m, and 60 m spatial resolution, enabling high-precision measurements of reflectance across various wavelengths [10]. This capability facilitates detailed analyses of numerous environmental factors, making Sentinel-2 particularly valuable for detecting and assessing post-fire ecosystem damage.

In this study, Sentinel-2 Level-2A products are used since they provide atmospherically corrected surface reflectance values, thereby enabling more accurate and reliable analysis. Atmospheric correction minimizes reflectance errors in vegetation and land assessments, allowing for a more precise detection of changes in vegetation cover before and after a fire. Sentinel-2 data can be accessed free of charge through platforms such as the Copernicus Open Access Hub and Google Earth Engine. These platforms offer a convenient infrastructure for time-series studies and spatial analyses, allowing researchers to quickly retrieve and examine high-resolution data covering extensive geographic regions. The total of 13 spectral bands measure reflectance at different wavelengths with high accuracy, enabling a broad range of applications. Shortwave infrared (SWIR), near-infrared (NIR), and red bands (Red) are particularly critical for calculating indices such as NDVI, NDMI, EVI, MSAVI, NBR, dNBR, and BAIS2, which help analyze variations in ecosystem structure, vegetation health, and moisture levels before and after fires.

2.3. Google Earth Engine (GEE) Platform and Processing Sentinel-2 L2A Data

Google Earth Engine (GEE) is a platform that enables rapid analysis of satellite imagery and vector data on a cloud-based infrastructure at a global scale [11]. By providing direct access to numerous datasets such as Sentinel-2, Landsat, and MODIS, GEE plays a crucial role in monitoring environmental changes, managing disasters, and assessing natural resources. Its support for both Python and JavaScript allows for interactive map-based applications as well as more extensive analyses within a single environment. Moreover, automated processes like cloud masking, projection transformations, and mosaicking streamline data preparation.

In this study, Sentinel-2 L2A satellite data were processed and analyzed through GEE. These L2A data, which offer atmospherically corrected surface reflectance values, serve as a key data source for tracking forest fires and ecosystem changes [12]. GEE enables the rapid and efficient processing of this information, allowing comparisons of pre- and post-fire vegetation changes. Within the scope of this research, various indices such as NDVI, NDMI, EVI, MSAVI, NBR, dNBR, and BAIS2 were computed to detect and evaluate fire severity. Implemented via JavaScript, these indices were visualized in real time using GEE's mapping tools, thus facilitating quick and accurate analysis of fire effects and ecosystem responses.

2.4. Data Acquisition and Preprocessing

In the İzmir study area, Sentinel-2 Level-2A images covering the pre-fire (31 July 2020–14 August 2020) and post-fire (14–20 August 2020) periods were obtained in Google Earth Engine with a <10 % cloud-cover filter. For NBR/dNBR calculations, only the B8 (NIR) and B12 (SWIR-2) bands were used; seasonal mean composites of these bands were generated, and "NBR_pre" and "NBR_post" maps were derived via normalized difference, with their difference computed as the "dNBR" layer. The dNBR map was visualized with a 'white–yellow–orange–red–darkred' palette over the range −1 to +1, while the post-fire natural-color composite was displayed using B4–B3–B2 bands. Next, only burned areas were clipped in QGIS and final map styling was applied; finally, both the İzmir dNBR and post-fire composite maps were reprojected to UTM Zone 35 N (EPSG:32635) at 10 m resolution and exported at high resolution.

This İzmir workflow illustrates that the same processing steps were applied to all other indices and study areas employed in this research (Fig. 1). The used co de and the resulting exported image is shown in Fig. 2.

Load Sentinel-2 L2A Collection in GEE
↓
Apply Cloud Filter (<10% cloud cover)
↓
Filter Pre-Fire & Post-Fire Dates
↓
Select Bands according to index formula
↓
Compute Mean Composites
↓
Calculate Index_pre & Index_post or only Index_post
↓
Compute differenced index if applicable
↓
Visualize index or differenced index and Post-Fire RGB
↓
Reproject outputs to UTM Zone 35N at 10 m resolution
↓
Export images to Google Drive via Export.image.toDrive
↓
Clip the burn mask in QGIS & apply final styling

Figure 1. Flowchart summarizing the preprocessing and export steps in GEE

Figure 2. JavaScript snippet showing the GEE workflow for deriving dNBR from Sentinel-2 L2A images in the İzmir study area.

2.5. DeepLabV3+: Deep Learning Based Image Segmentation Model

In this study, the DeepLabV3+ model, which was pre-trained within the scope of the International 2549-Poland-NCBR-TUBITAK Project (Project No: 122N254) 'Intelligent Management and Sustainable Use of Forests', was used to detect burnt areas in Sentinel-2 satellite images after the fire. The model was trained on a dataset developed using Sentinel-2 satellite imagery, focusing on forest fires that occurred in Türkiye between 2020 and 2024. The dataset comprises 71 satellite images with varying spatial dimensions (Fig. 3). For the annotation process, GEE was utilized. During preprocessing, the images were divided into 128×128 pixel patches, resulting in a total of 1,691 image tiles. Of these, 80% were allocated for training and 20% for testing. On the test dataset, DeepLabv3+ achieved accuracy metrics of 0.8824 (accuracy), 0.8114 (IoU), 0.8958 (F1-score), 0.8578 (precision), and 0.9375 (recall).

This artificial intelligence based segmentation model produced binary output as separated burnt and unburnt areas (Fig. 4). Based on the segmentation results, the fire indices calculated on the GEE platform were cropped over the burnt areas. This method increased the accuracy of the analyses by ensuring that index calculations are performed only in fire-affected areas.

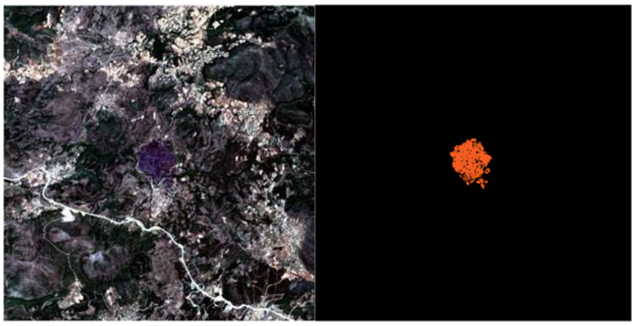


Figure 3. A sample from the dataset: Sentinel-2 image patch (left), Burned area mask (right)

DeepLabV3+ is an advanced deep learning model developed by Google Research and widely used for semantic image segmentation. The model includes structural improvements compared to previous DeepLab versions, especially to enable more precise detection of object boundaries. Its main components include Atrous Convolution, Atrous Spatial Pyramid Pooling (ASPP) and encoder-decoder structure. Atrous convolution collects information from a large area while maintaining the size of the feature map. The ASPP module captures multi-scale features using convolution layers with different dilation ratios, allowing the model to better detect objects of different sizes. The encoder part enriches the features extracted from the image with ASPP, while the decoder part uses this information to accurately restore the segmentation result.

2.6. Indices Used in This Study

2.6.1. Normalized Burn Ratio (NBR)

NBR is a commonly used remote sensing index for monitoring the effects of forest fires and other disasters. The Normalized Burn Ratio is derived from near-infrared (NIR) and shortwave infrared (SWIR) bands via specific mathematical formulas. Prior to a fire, healthy vegetation generally shows high reflectance in the NIR region and low reflectance in SWIR 2 [14]. Post-fire damage leads to decreased NIR reflectance and increased SWIR 2 reflectance. This spectral contrast is crucial for tracking fire-related impacts. NBR values range from −1 to +1: healthy vegetation typically exhibits high NBR, whereas burned areas display lower values. NBR also allows for precise monitoring of ecological changes by comparing pre- and post-fire imagery, making it a powerful tool for classifying fire severity and mapping damage.

$$\boldsymbol{NBR} = \frac{\boldsymbol{NIR(B08)} - \boldsymbol{SWIR\,2(B12)}}{\boldsymbol{NIR(B08)} + \boldsymbol{SWIR\,2(B12)}} \quad (\mathbf{2.2})$$

2.6.2. Differenced Normalized Burn Ratio (dNBR)

Currently, one of the most frequently used methods for determining forest fire severity is the dNBR [13]. This approach calculates the difference between pre-fire and post-fire NBR values to classify vegetation damage. In this study, dNBR (Equation 2.1) was selected as the reference index due to its widely recognized threshold values in the literature [9]. Positive dNBR values indicate burned areas and the extent of fire impact, while near-zero or negative values represent unburned or minimally affected regions.

$$\boldsymbol{dNBR} = \boldsymbol{NBR_{PreFire}} - \boldsymbol{NBR_{PostFire}} \qquad (\mathbf{2.1})$$

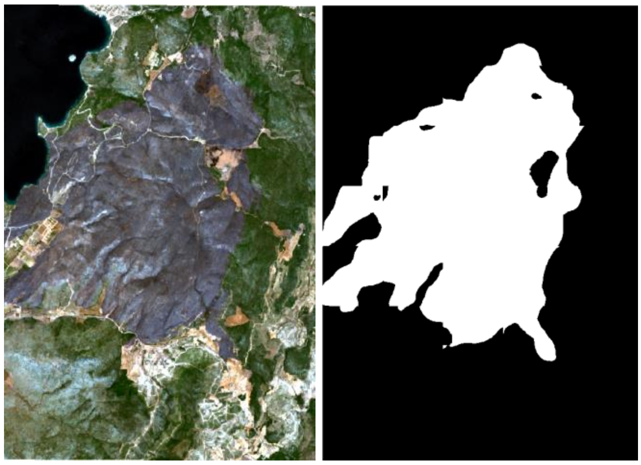


Figure 4. (a)Izmir Region post-fire image, (b)Izmir Region segmentation result

Damage levels are determined based on fire severity categories that are widely recognized in the literature (Table 1). These categories enable precise monitoring of post-fire ecosystem changes and allow for the accurate classification of fire severity [9]. Based on these categories, post-fire vegetation changes are visualized through thematic maps that reflect the severity and impact of the fire.

Table 1. Fire severity categories [9]

dNBR	Fire Severity (FS)
–500 to –251	Enhanced regrowth, high
–250 to –101	Enhanced regrowth, low
–100 to +99	Nonburnt
+100 to +269	Low severity
+270 to +439	Moderate-low severity
+440 to +659	Moderate-high severity
+660 to +1300	High severity

2.6.3. Normalized Difference Vegetation Index (NDVI)

Developed by Rouse Jr. et al. (1974), NDVI assesses the health and density of vegetation using the difference between red and NIR bands [15, 16, 17]. Healthy vegetation strongly absorbs red light while reflecting high amounts of NIR. Conversely, unhealthy or sparse vegetation reflects less NIR. NDVI values range from −1 to +1, with negative values indicating water, soil, or burned areas, and positive values signifying healthy vegetation [17]. NDVI effectively highlights the contrast between vegetation and underlying soil. NDVI difference analysis can be applied to evaluate vegetation changes before and after a fire and determine fire severity. In this research, NDVI (Equation 2.3) was calculated from Sentinel-2 imagery on the GEE platform to track post-fire ecosystem changes.

$$NDVI = \frac{NIR(B08) - RED(B04)}{NIR(B08) + RED(B04)} \quad (2.3)$$

2.6.4. Normalized Difference Moisture Index (NDMI)

NDMI measures the water content in vegetation by examining differences between NIR and SWIR 1 bands. While SWIR 1 reflects changes in leaf water content and mesophyll structure, NIR represents leaf internal structure and dry matter content. Subtracting these two bands isolates water content more accurately. NDMI values range from −1 to +1, with higher values found in areas with sufficient water or no water stress [17]. It also serves as an indicator of drought and fuel levels in areas prone to wildfires [26]. After wildfires, vegetation water loss is a key marker of ecosystem damage, and NDMI's pre- and post-fire difference can help identify affected regions and fire severity. Hence, NDMI (Equation 2.4) is a vital tool for closely monitoring changes in post-fire vegetation.

$$NDMI = \frac{NIR(B08) - SWIR\,1(B11)}{NIR(B08) + SWIR\,1(B11)} \quad (2.4)$$

2.6.5. Modified Soil-Adjusted Vegetation Index (MSAVI)

MSAVI is used to detect changes in vegetation, particularly by minimizing the influence of soil on vegetation health. This index is based on reflectance values from the red and NIR spectral bands and is calculated using the following equation (Equation 2.5) [18].

$$MSAVI = \frac{(2\,x\,NIR + 1) - \sqrt{(2\,x\,NIR + 1)^2 - 8\,x\,(NIR - RED)}}{2} \quad (2.5)$$

MSAVI has proven more accurate in monitoring vegetation in arid regions where soil-vegetation mixing is high [19, 20]. Its effectiveness in tracking plant health, water stress, and vegetation degradation under such conditions underscores its importance in environmental assessments.

2.6.6. Enhanced Vegetation Index (EVI)

EVI is designed to enhance the vegetation signal in areas with high biomass by reducing atmospheric effects and separating soil background signals. It uses a blue band to correct atmospheric noise more accurately compared to NDVI. EVI relies on the differences in reflectance from red and NIR bands and often yields better results in snowy conditions, as EVI increases instead of decreasing during snowfall events. Recognized as a standard product in MODIS sensors, EVI is widely applied due to its capacity to eliminate atmospheric noise [21].

$$EVI = G\,x\,\frac{(NIR - RED)}{(NIR + C_1\,x\,RED - C_2\,x\,BLUE + L)} \quad (2.6)$$

- G: Gain factor (usually 2.5)
- C_1: Coefficient used to correct for aerosol effect in the red band (usually 6)
- C_2: Coefficient used to correct for aerosol effect in the blue band (usually 7.5)
- L: Canopy background correction (usually 1)

2.6.7. Burn Area Index for Sentinel-2 (BAIS2)

BAIS2 (Burn Area Index for Sentinel-2) is an adaptation of the traditional Burn Area Index (BAI) for Sentinel-2 data. It leverages the broad range of visible, red-edge, NIR, and SWIR bands in Sentinel-2 imagery to detect fire damage more precisely [22, 23]. This index is particularly effective in monitoring and identifying post-fire ecosystem changes, as it can accurately measure the environmental impact of fires. BAIS2 values range from -1 to 1 for burned areas, and between 1 and 6 for active fires. These values can vary with fire severity and can be calibrated with specific threshold values [24]. Its sensitivity to different fire intensities and areas affected makes BAIS2 a valuable tool for detecting burn scars and classifying fire zones, thereby enabling close tracking of wildfire impacts.

$$BAIS2 = \left(1 - \left(\frac{B_{06} \times B_{07} \times B_{8A}}{B_{04}}\right)^{0.5}\right) \times \left(\frac{B_{12} - B_{8A}}{(B_{12} + B_{8A})^{0.5}} + 1\right) \quad (2.7)$$

- B4: Red
- B6: Red Edge 2
- B7: Red Edge 3
- B8A: Narrow Near Infrared (Narrow NIR)
- B12: Short-Wave Infrared 2 (SWIR-2)

3. Results

The detection of burnt areas in Sentinel-2 satellite images after the fire was carried out using the pre-trained DeepLabV3+ model described in Section 2.4. This artificial intelligence-based segmentation model separated burned and unburned areas by producing a binary output, thus enabling the calculation of fire indices on the GEE platform focused only on the burnt areas in the study regions covering Izmir, Mugla, and Mersin, which were cropped using QGIS. In this process, seven different indices detailed in Section 2.5 were calculated on the cropped areas and compared with the dNBR index as a reference. Based on the post-fire Sentinel-2 imagery, the potential of these indices as alternatives to dNBR in determining fire severity and ecosystem destruction was evaluated. The obtained results were visualized in the QGIS platform using colour palettes defined according to fire severity classes; high fire severity was represented by dark red, while decreasing severity was illustrated with red, orange, and yellow tones. Unburned areas were represented with colours ranging from light green (healthier vegetation) to dark green (less healthy vegetation), depending on the vitality of the plants. This visualization method enabled a clearer interpretation of the spatial distribution of post-fire ecosystem changes and contributed to making the results more understandable. The fire, pre-fire, and post-fire dates for the studied regions are summarized in Table 2, while the geographical locations of the study areas are shown in Fig. 5.

Table 2: Fire Timeline Information for Study Regions

Province	Pre-Fire Date	Fire Date	Post-Fire Date
Izmir	31 July 2020	14 August 2020	20 August 2020
Mugla	9 May 2021	12 August 2021	27 August 2021
Mersin	31 August 2022	8 September 2022	25 September 2022

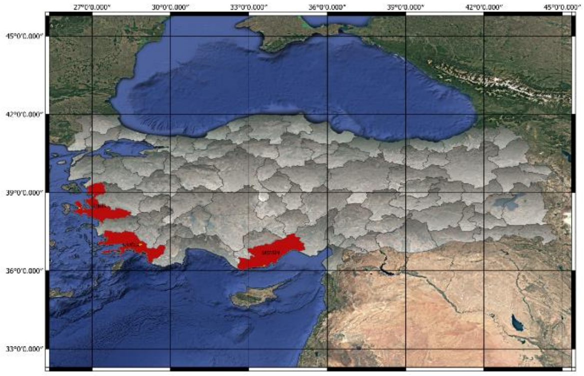


Figure 5. Study areas distribution

3.1. Izmir Region Use-Case

In the studies conducted for the İzmir region, all indices used in the analysis were calculated using the Sentinel-2 satellite image dated 20 August 2020, while the dNBR index was calculated by comparing this image with the pre-fire image dated 31 July 2020. The resulting dNBR output was classified on the QGIS platform based on the threshold values defined in Section 2.5 and visualized using a color scheme representing different levels of fire severity. This output, used as the reference image (Fig. 6), was then compared with the other six indices analyzed in the study to provide a comprehensive evaluation.

Fire severity categories specified in Table 1 are categorised from 0 to 6 respectively. According to Table 3, BAIS2 and NBR indices are the most reliable alternatives when compared to dNBR, which is accepted as the reference index, in the fire severity analysis in Izmir region. These two indices produced values very close to dNBR, especially in medium and high severity burnt areas, and stood out with their intraclass consistency. NDMI can be considered as a noteworthy alternative, especially in severely burnt areas, giving results that are largely compatible with dNBR. While NDVI and EVI showed high deviations in low and moderate fire areas, they produced results closer to dNBR in severe fire areas. MSAVI, on the other hand, significantly underestimates dNBR in severely burnt areas, indicating that it is an index that should be carefully considered when analysing such areas. In general, the BAIS2, NBR and NDMI indices produced the closest results to dNBR in assessing fire severity, while the other indices exhibited different trends in low- and moderate-severity fire areas and may over- or under-estimate. These findings provide an important basis for determining the reliability of alternative indices in studies where dNBR is taken as a reference and for analysing the effects of forest fires on the ecosystem more comprehensively.

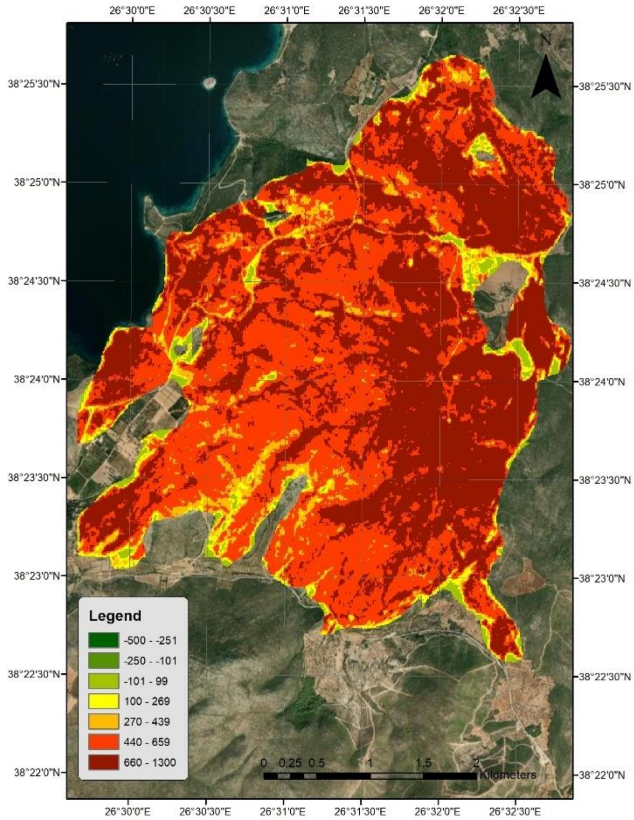


Figure 6. Results of dNBR index application to Izmir Region

Table 3: Burnt Area Values by FS Classes in Izmir Region

Value	dNBR (ha)	BAIS2 (ha)	NBR (ha)	NDVI (ha)	NDMI (ha)	EVI (ha)	MSAVI (ha)
0	0	0,04	0	6,09	1,91	0	5,68
1	0,02	3,03	5,74	20,47	4,29	1,17	13,51
2	35,35	37,17	28,48	34,68	44,43	39,73	18,94
3	51,12	46,42	42,13	25,42	41,81	24,58	48,53
4	111,76	111,74	112,14	97,12	87,46	77,57	109,35
5	654,62	650,11	660,93	657,88	669,96	565,14	534,23
6	681,49	685,85	684,94	692,7	684,5	826,17	804,12

According to the deviation percentages in Table 4, BAIS2 and NBR stand out as the most reliable alternative indices in all categories with the lowest deviation rates compared to dNBR. In category 3, BAIS2 and NBR exhibit low deviation rates, while MSAVI is also a remarkable alternative. In Category 4, BAIS2 and NBR show the lowest deviations, while MSAVI can also be considered as a reliable alternative for this category. In Category 5, NDVI is a strong alternative, showing the lowest deviation, while BAIS2 and NBR produced results very close to dNBR in this category. In Category 6, NDMI exhibited the lowest bias and together with BAIS2 and NBR were reliable alternatives for severely burnt areas. In contrast, EVI and MSAVI were not considered as alternatives to dNBR, exhibiting higher deviation rates in all categories. Overall, BAIS2 and NBR stood out as the most reliable indices, producing results close to dNBR in all four categories.

Table 4. Deviation Percentages for Izmir Region

FS	BAIS2	NBR	NDVI	NDMI	EVI	MSAVI
3	-9.19%	-17.59%	-50.27%	-18.21%	-51.92%	-5.07%
4	-0.02%	0.34%	-13.10%	-21.74%	-30.59%	-2.16%
5	-0.69%	0.96%	0.50%	2.34%	-13.67%	-18.39%
6	0.64%	0.51%	1.64%	0.44%	21.23%	17.99%

3.2. Mugla Region Use-Case

In the second study area, Muğla, all indices used in the analysis were calculated using the post-fire satellite image dated 27 August 2021. The dNBR index, on the other hand, was calculated using the pre-fire image dated 9 May 2021. The resulting dNBR output (Fig. 7) was classified on the QGIS platform and visualized according to fire severity levels. This output, used as the reference image, was then compared with the other indices examined in the study and analyzed accordingly.

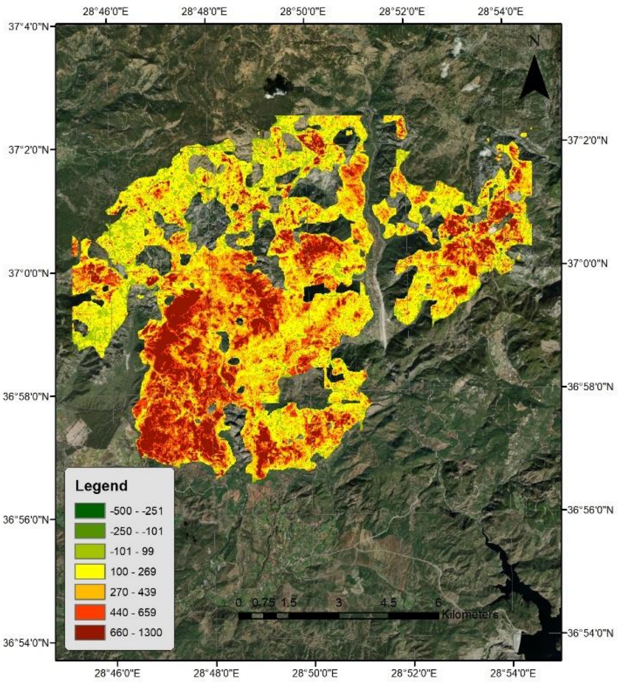


Figure 7. Results of dNBR index application to Mugla Region

In the post-fire burnt area analysis in Muğla region, it was determined that NBR and BAIS2 indices produced the closest results to the reference index dNBR and had low deviation rates, especially in categories 3, 5 and 6 (Table 5). While NBR is a reliable alternative with low deviation in category 3, it has a higher deviation in category 4 and should be evaluated carefully. BAIS2 produced the closest results to dNBR in category 5, and although it performed consistently in category 6, it exhibited larger deviations in category 4. Although NDVI showed low deviation in category 3, moderate deviation in category 4 and higher deviation in category 5, it performed better in category 6 and can be considered as an alternative index in high fire severity areas. NDMI agreed with dNBR with relatively low deviation in categories 5 and 6, but showed higher deviation in category 4. MSAVI produced results relatively close to dNBR in categories 3 and 6, but showed a significant deviation in category 5, indicating that it should be used with caution and supplemented with other indices. EVI, on the other hand, showed significant deviations in all categories, especially in categories 3 and 6, indicating that it cannot be considered as an alternative index to dNBR. In conclusion, NBR and BAIS2 stand out as the most reliable alternatives in certain categories, while NDVI and NDMI show that they can be a potential alternative for some burnt area severity levels, but MSAVI and EVI perform inconsistently and should be considered carefully in post-fire severity assessments.

Table 5. Burnt Area Values by FS Classes in Mugla Region

FS	dNBR (ha)	NBR (ha)	BAIS2 (ha)	NDVI (ha)	NDMI (ha)	MSAVI (ha)	EVI (ha)
0	0,13	0,09	0,19	2,16	0	0	0
1	1,16	81,26	19,82	149,78	65,93	21,52	4,59
2	640,81	362,93	660,86	144,75	532,88	606	258,53
3	2159,52	2222,29	2101,11	2191,96	2067,34	2181,17	2843,36
4	1945,54	2105,12	1824,03	1968,31	1855,25	2096,1	1484,57
5	1279,44	1240,44	1392,32	1531,59	1475,99	1095,97	1358,34
6	1002,75	1012	1025,8	1035,58	1026,74	1023,37	1074,74

According to Table 6, the indices that produced the closest results to dNBR in the burnt area analysis in Muğla region were generally NBR and BAIS2. In Category 3, BAIS2 and MSAVI stand out with low deviation percentages. In Category 4, NDVI and BAIS2 produced the closest results to dNBR with low deviation percentages. In Category 5, BAIS2 and NBR produced the closest value to dNBR, while NDVI and NDMI showed larger deviation percentages. In Category 6, BAIS2, NBR stand out as reliable alternatives with the lowest deviation percentages. However, EVI stands out in this category with a higher deviation percentage. In general, NBR and BAIS2 indices stand out as the indices that produce the closest results to dNBR in Muğla region, while NDMI and NDVI can be considered as alternatives by showing low deviation percentages in certain categories. However, EVI should be carefully evaluated in fire severity analyses due to its high deviation percentages.

Table 6. Deviation Percentages for Mugla Region

FS	NBR	BAIS2	NDVI	NDMI	MSAVI	EVI
3	2,91%	-2,70%	1,50%	-4,27%	1,00%	31,67%
4	8,20%	-6,25%	1,17%	-4,64%	7,74%	-23,69%
5	-3,05%	8,82%	19,71%	15,36%	-14,34%	6,17%
6	0,92%	2,30%	3,27%	2,39%	2,06%	7,18%

3.3. Mersin Region Use-Case

In Mersin, which was selected as the third study region, the calculations of all indices used in the study were performed using the post-fire satellite image dated 25 September 2022. The dNBR index, on the other hand, was calculated by comparing the pre-fire image dated 31 August 2022 with the post-fire image. The resulting dNBR output (Fig. 8) was classified on the QGIS platform and visualized according to fire severity levels. This output, used as the reference image, was analyzed by comparing it with the other six indices evaluated in the study.

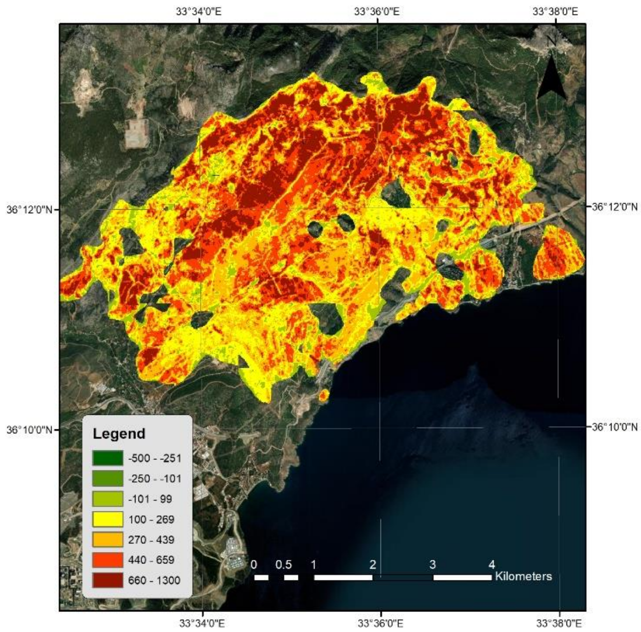


Figure 8. Results of dNBR index application to Mersin Region

In the analysis of post-fire burnt areas for Mersin, it was found that BAIS2 and NBR indices produced the closest results to the reference values with low deviation rates in general (Table 7). In Category 3, BAIS2 and NDVI produced values close to dNBR, while NDMI and MSAVI showed larger differences. In Category 4, NBR and EVI produced estimates close to dNBR, NDMI showed a larger percentage deviation, while MSAVI produced estimates that differed from dNBR by a significant margin. In Category 5, BAIS2, NBR and NDMI produce estimates closer to the dNBR, while NDVI, EVI and MSAVI show quite high differences and are not considered as alternatives to the dNBR index. In category 6, BAIS2, NBR were considered reliable alternatives and produced results very close to dNBR, while NDVI showed a larger difference and EVI and MSAVI produced more inconsistent estimates. Overall, BAIS2 and NBR produced results closest to the dNBR index, NDVI and NDMI produced estimates close to the dNBR index in certain categories but with significant differences in others, while EVI and MSAVI showed large deviations compared to dNBR results and are not recommended for use alone in post-fire ecosystem assessments. This analysis provides an important basis for determining the reliability of alternative indices in studies using dNBR as a reference index.

Table 7. Burnt Area Values by FS Classes in Mersin Region

FS	dNBR (ha)	BAIS2 (ha)	NBR (ha)	NDVI (ha)	NDMI (ha)	EVI (ha)	MSAVI (ha)
0	0	0,13	0,05	7,6	0	0	0
1	0,01	4,48	3,64	48,44	6,46	7,47	3,91
2	165,55	142,05	162,58	78,9	113,96	160,95	222,05
3	524,1	560,97	511,98	541,49	484,53	583,14	665,86
4	767,51	708,57	764,24	671,15	865,2	740,59	350,91
5	683,53	719,62	685,9	730,11	687,47	457,64	871,98
6	390,02	394,9	402,33	453,03	373,1	580,93	416,01

As a result of analysing Table 8, it was determined that the NBR index gave the best results with the lowest deviation percentages in all categories, but the second best index varied by category. In particular, BAIS2 produced the best result in category 6, which represents the most severely burnt areas, indicating that this index may be an alternative to dNBR. BAIS2 produced the closest estimates to dNBR in categories 3 and 5 and NBR produced the closest estimates to dNBR in category 4, but NDMI and MSAVI produced inconsistent estimates with high deviation percentages in some categories. In general, NBR and BAIS2 indices stand out as the most reliable alternatives in Mersin region, while NDVI and NDMI produced estimates close to dNBR in certain categories, but EVI and MSAVI showed larger deviations and were identified as indices that should be considered with caution. These findings suggest that NBR and BAIS2 offer strong alternatives for assessing post-fire ecosystem damage.

Table 8. Deviation Percentages for Mersin Region

Value	BAIS2	NBR	NDVI	NDMI	EVI	MSAVI
3	7,04%	-2,31%	3,32%	-7,55%	11,27%	27,05%
4	-7,68%	-0,43%	-12,55%	12,73%	-3,51%	-54,28%
5	5,28%	0,35%	6,81%	0,58%	-33,05%	27,57%
6	1,25%	3,16%	16,16%	-4,34%	48,95%	6,66%

4. Discussion

The results were also evaluated using Insersection over Union (IoU) accuracy metric for area based overlaps. IoU analyses provide crucial insights into the effectiveness of alternative indices compared to the widely used dNBR index in assessing post-fire ecosystem damage. The evaluation of six alternative spectral indices (NDVI, NDMI, NBR, MSAVI, EVI, and BAIS2) across three study regions (Izmir, Mugla, and Mersin) highlights the relative reliability of each index in different fire severity classes. The calculation is based on dNBR-derived classes, which are treated as ground truth.

The IoU values for Izmir indicate that BAIS2 and NBR show relatively high agreement with dNBR in categories 5 and 6, where fire severity is greater (Table 9). However, in lower severity classes (3 and 4), deviations are more noticeable. NDMI also provides moderate consistency, particularly in high-severity burn areas where moisture depletion is critical. NDVI, EVI, and MSAVI exhibit significant deviations, particularly in lower severity classes, making them less reliable for capturing fire-induced damage comprehensively.

Table 9. IoU results for İzmir Region

IZMIR				
FS	**3**	**4**	**5**	**6**
BAIS2	0.25767772	0.26995852	0.54092262	0.6371212
EVI	0.17874218	0.14265386	0.46577253	0.54292259
MSAVI	0.1462727	0.0548314	0.36591573	0.38947815
NBR	0.24381412	0.2729397	0.52398322	0.61767039
NDMI	0.22693686	0.21840592	0.44360869	0.53894829
NDVI	0.1525406	0.05164772	0.3669312	0.38889843

In the Mugla region (Table 10), BAIS2 and NBR provide moderate agreement with dNBR in categories 3 and 6, but they show greater deviations in category 4. NDMI and MSAVI also present relatively lower deviations in categories 3 and 6. However, NDVI and EVI display high variations, particularly in categories 5 and 6, indicating that they do not perform well in high-severity fire areas.

Table 10. IoU results for Muğla Region

MUGLA				
FS	**3**	**4**	**5**	**6**
BAIS2	0.38081981	0.30220467	0.34104975	0.57900677
EVI	0.45271239	0.25316386	0.27634928	0.51235368
MSAVI	0.39752221	0.30657451	0.23831493	0.51577404
NBR	0.38135935	0.2836906	0.3085935	0.57452778
NDMI	0.3814803	0.29911781	0.30865095	0.51107157
NDVI	0.35979076	0.25210745	0.19002523	0.35397625

In Mersin (Table 11), BAIS2 and NBR again demonstrate relatively higher agreement with dNBR in categories 5 and 6. However, deviations increase in lower severity categories. NDMI shows moderate agreement in categories 4 and 5, while NDVI and MSAVI present higher deviations, especially in category 6. EVI exhibits the least consistency across all categories.

Table 11. IoU results for Mersin Region

MERSIN				
FS	**3**	**4**	**5**	**6**
BAIS2	0.32790346	0.32118677	0.32967289	0.43507747
EVI	0.34631477	0.27899383	0.27173975	0.35743629
MSAVI	0.27228988	0.23397968	0.27590456	0.36393257
NBR	0.2670308	0.30176391	0.33089773	0.44462749
NDMI	0.18561436	0.30220702	0.30910152	0.40615407
NDVI	0.143227815	0.190399	0.186685248	0.101493966

Across all three study regions, the IoU results indicate that BAIS2 and NBR provide relatively better agreement with dNBR in high-severity fire areas, while NDMI, although showing moderate agreement in some cases, is not consistently reliable. NDVI, EVI, and MSAVI tend to exhibit significant deviations, especially in lower-severity classes; this makes them less suitable as standalone fire-severity indicators. The root of this poor performance lies in the fact that each index is calculated using spectral bands that are affected to varying degrees by the complex atmospheric and surface conditions present after a fire. EVI uses the blue band to reduce aerosol and atmospheric noise compared to NDVI and performs better when it comes to shadowing and saturation; nevertheless, the thin smoke and aerosol particles that rise after a fire still disrupt blue-band reflectance and increase the error margin, substantially lowering EVI's overlap with dNBR in low- and moderate-severity burn classes [25]. MSAVI, which aims to minimize soil influence, is undermined immediately after a fire because the char residue and bare soil that accumulate on the surface create a mixed spectral signal that weakens its soil-correction mechanism, making it difficult to distinguish vegetation from burned areas in low-cover environments. NDVI, which relies solely on the red and near-infrared bands, cannot achieve clear spectral separation in post-fire conditions due to the presence of dry grass, charred plant debris, and aerosol reflections; therefore, NDVI's IoU values with dNBR remain quite low in lower-severity regions such as FS = 3 and FS = 4. Consequently, the spectral-band limitations of these indices, along with their sensitivity to soil and aerosol effects and the atmospheric noise generated after a fire, prevent them from consistently producing reliable results within dNBR-referenced regional severity classifications.

5. Conclussion

The main objective of this study is to evaluate the effectiveness of alternative indices to the widely used dNBR index for determining ecosystem damage after forest fires. Using only post-fire satellite data, the study examined how effectively six different indices such as NDVI, NDMI, NBR, MSAVI, EVI and BAIS2 can determine post-fire ecosystem destruction. Analyses for Mersin, Muğla and İzmir regions show that NBR and BAIS2 indices give the closest results to dNBR index in determining post-fire ecosystem damage. In Izmir, NBR and BAIS2 highlighted the areas under the influence of fire most clearly, while in Mugla and Mersin, these indices accurately detected post-fire ecosystem destruction. After these two indices, NDMI provides supportive results in the detection of severe burn areas as it targets moisture loss in plant tissue. Although plant-orientated indices such as NDVI, EVI and MSAVI were able to map burned areas at a basic level, they were not found to be as effective as other indices in terms of detailed grading of fire damage. Therefore, BAIS2 and NBR stand out as the closest alternative indices to dNBR for all three regions. While these indices offer high accuracy in monitoring post-fire ecosystem destruction and determining fire severity, indices such as MSAVI can be considered as alternatives by providing complementary information. Future studies suggest that indices such as BAIS2 and NBR should be used more widely, while indices such as MSAVI can be used as alternatives, and that these indices can be important tools for post-fire ecosystem restoration and biodiversity conservation in different geographical regions.

The findings suggest that NBR and BAIS2, as the indices that produce the closest results to the dNBR reference index in analysing post-fire burnt areas, are considered as reliable and strong alternatives for the three study regions of İzmir, Muğla and Mersin. These two indices have an important potential in determining ecosystem destruction by providing results close to dNBR in the detection and classification of burnt areas according to their severity. In the Izmir region, BAIS2 and NBR showed high agreement, especially in the classification of low, moderate, severe and very severe burnt areas, while in the Muğla region, BAIS2 stood out as a strong alternative for severely burnt areas. In the Mersin region, the NBR produced results close to the dNBR in all categories. These findings reveal that the use of NBR and BAIS2 in both local and general scale fire analysis studies is valuable from a practical and scientific point of view. However, the differences in the performance of other indices on a category basis indicate that the use of these indices should be more cautious. In particular, it was observed that indices such as NDVI, NDMI and MSAVI exhibited lower performance in low and moderate severity burnt areas, but gave results close to dNBR in some categories, especially in severe and very severe burnt areas. This situation emphasises that the use of a single index in post-fire damage analyses may be limited and the importance of supporting the indices with more than one method according to the situation.

Acknowledgement

This study was supported by the Scientific and Technological Research Council of Turkey (TUBITAK) ARDEB 2549 (NCBR) Grant No: 122N254. The authors declare the utilization of AI-assisted technologies to enhance the readability and linguistic quality of the manuscript.

Author contributions

Zeynep Kiraz: Conceptualization, Writing-Original draft preparation, Methodology, Validation, Software. **Bahadir Kulavuz:** Data curation, Software, Validation. **Tolga Bakirman:** Validation,Visualization, Investigation, Writing-Reviewing and Editing. **Bulent Bayram:** Investigation, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

References

1. Bowman, D.M., Kolden, C.A., Abatzoglou, J.T., Johnston, F.H., Werf, G.R. & Flannigan M. (2020). Vegetation fires in the Anthropocene. Nature Reviews Earth & Environment, 1, pages 500–515. https://doi.org/10.1038/s43017-020-0085-3
2. Bıçakcı, C., & Yıldız, S. S. (2024). Google Earth Engine ve Coğrafi Bilgi Sistemleri Kullanarak Orman Yangını Şiddetinin Belirlenmesinde Farklı İndekslerin Karşılaştırılması: 2023 Hatay-Belen Yangını Örneği. Osmaniye Korkut Ata Üniversitesi Fen Bilimleri Enstitüsü Dergisi, 7(2), 708-719. https://doi.org/10.47495/okufbed.1404480
3. Chuvieco, E. et al. Historical background and current developments for mapping burned area from satellite Earth observation. Remote Sens. Environ. 225, 45–64 (2019). https://doi.org/10.1016/j.rse.2019.02.013
4. dos Santos, S. M. B., Bento-Gonçalves, A., Franca-Rocha, W., & Baptista, G. (2020). Assessment of burned forest area severity and postfire regrowth in Chapada Diamantina National Park (Bahia, Brazil) using dNBR and RdNBR spectral indices. Geosciences, 10(3), 106. https://doi.org/10.3390/geosciences10030106
5. Miller, J. D., & Thode, A. E. (2007). Quantifying burn severity in a heterogeneous landscape with a relative version of the delta Normalized Burn Ratio (RdNBR). Remote Sensing of Environment, 109(1), 66–80. https://doi.org/10.1016/j.rse.2006.12.006
6. Van Wagtendonk, J.W.; Root, R.R.; Key, C.H. Comparison of AVIRIS and Landsat ETM+ detection capabilities for burn severity. Remote Sens. Environ. 2004, 92, 397–408. https://doi.org/10.1016/j.rse.2003.12.015
7. TAN Liuxia, ZENG Yongnian, ZHENG Zhong. An adaptability analysis of remote sensing indices in evaluating fire severity[J]. Remote Sensing for Natural Resources, 2016, (2): 84-90. https://doi.org/10.6046/gtzyyg.2016.02.14
8. Han, A., Qing, S., Bao, Y., Na, L., Bao, Y., Liu, X., Zhang, J., & Wang, C. (2021). Short-term effects of fire severity on vegetation based on Sentinel-2 satellite data. Sustainability, 13(1), 432. https://doi.org/10.3390/su13010432
9. Key, C. H., & Benson, N. C. (2006). Landscape assessment (LA). In: Lutes, Duncan C.; Keane, Robert E.; Caratti, John F.; Key, Carl H.; Benson, Nathan C.; Sutherland, Steve; Gangi, Larry J. 2006. FIREMON: Fire effects monitoring and inventory system. Gen. Tech. Rep. RMRS-GTR-164-CD. Fort Collins, CO: US Department of Agriculture, Forest Service, Rocky Mountain Research Station. p. LA-1-55, 164. https://doi.org/10.2737/RMRS-GTR-164
10. Sinergise Ltd. (n.d.). Sentinel-2 L2A data documentation. Sentinel Hub. Retrieved April 20, 2025, from https://docs.sentinel-hub.com/api/latest/data/sentinel-2-l2a/
11. Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone.

Remote Sensing of Environment, 202, 18–27. https://doi.org/10.1016/j.rse.2017.06.031

12. Baş, N.: Introducing a Learning Tool (QSVI): A QGIS Plugin for Computing Vegetation, Chlorophyll, and Thermal Indices with Remote Sensing Images, Geosci. Instrum. Method. Data Syst. Discuss. [preprint], https://doi.org/10.5194/gi-2024-8, in review, 2025.
13. Chen, X., Vogelmann, J. E., Rollins, M., Ohlen, D., Key, C. H., Yang, L., Huang, C., & Shi, H. (2011). Detecting post-fire burn severity and vegetation recovery using multitemporal remote sensing spectral indices and field-collected composite burn index data in a ponderosa pine forest. International Journal of Remote Sensing, 32(23), 7905–7927. https://doi.org/10.1080/01431161.2010.524678
14. Chen, D., Loboda, T. V., & Hall, J. V. (2020). A systematic evaluation of influence of image selection process on remote sensing-based burn severity indices in North American boreal forest and tundra ecosystems. ISPRS Journal of Photogrammetry and Remote Sensing, 159, 63–77. https://doi.org/10.1016/j.isprsjprs.2019.11.011
15. Rouse, J.W., Jr.; Haas, R.H.; Schell, J.A.; Deering, D.W. Monitoring the Vernal Advancement and Retrogradation (Green Wave Effect) of Natural Vegetation; Texas A & M University, Remote Sensing Center: College Station, TX, USA, 1973.
16. Huang, S., Tang, L., Hupy, J. P., Wang, Y., & Shao, G. (2021). A commentary review on the use of normalized difference vegetation index (NDVI) in the era of popular remote sensing. Journal of Forestry Research, 32(1), 1–6. https://doi.org/10.1007/s11676-020-01155-1
17. Strashok, O., Ziemiańska, M., & Strashok, V. (2022). Evaluation and correlation of Sentinel-2 NDVI and NDMI in Kyiv (2017–2021). Journal of Ecological Engineering, 23(9), 212–218. https://doi.org/10.12911/22998993/151884
18. Qi, J., Chehbouni, A., Huete, A. R., Kerr, Y. H., & Sorooshian, S. (1994). A modified soil adjusted vegetation index. Remote Sensing of Environment, 48(2), 119–126. https://doi.org/10.1016/0034-4257(94)90134-1
19. Lamaamri, M., Lghabi, N., Ghazi, A., El Harchaoui, N., Adnan, M. S. G., & Islam, M. S. (2023). Evaluation of desertification in the Middle Moulouya Basin (North-East Morocco) using Sentinel-2 images and spectral index techniques. Earth Systems and Environment, 7, 473–492. https://doi.org/10.1007/s41748-022-00327-9
20. Li, Q., Zhang, C., Shen, Y., Jia, W., & Li, J. (2016). Quantitative assessment of the relative roles of climate change and human activities in desertification processes on the Qinghai-Tibet Plateau based on net primary productivity. CATENA, 147, 789–796. https://doi.org/10.1016/j.catena.2016.09.005
21. Rodriguez, P. S., Schwantes, A. M., Gonzalez, A., & Fortin, M.-J. (2024). Monitoring changes in the Enhanced Vegetation Index to inform the management of forests. Remote Sensing, 16(16), 2919. https://doi.org/10.3390/rs16162919
22. Filipponi, F. (2018). BAIS2: Burned Area Index for Sentinel-2. Proceedings of the 2nd International Electronic Conference on Remote Sensing, 2(7), 364. https://doi.org/10.3390/ecrs-2-05177
23. Deshpande, M. V., Pillai, D., & Jain, M. (2022). Agricultural burned area detection using an integrated approach utilizing multi spectral instrument based fire and vegetation indices from Sentinel-2 satellite. MethodsX, 9, 101741. https://doi.org/10.1016/j.mex.2022.101741
24. Alcaras, E., Costantino, D., Guastaferro, F., Parente, C., & Pepe, M. (2022). Normalized Burn Ratio Plus (NBR+): A new index for Sentinel-2 imagery. Remote Sensing, 14(7), 1727. https://doi.org/10.3390/rs14071727
25. Miura, T., Huete, A. R., Yoshioka, H., & Holben, B. N. (2001). An error and sensitivity analysis of atmospheric resistant vegetation indices derived from dark target-based atmospheric correction. Remote Sensing of Environment, 78(3), 284–298. https://doi.org/10.1016/S0034-4257(01)00223-1