



Quantifying post-fire vegetation loss and trace gas emissions from the July 2025 Çeşme wildfire using Sentinel-2 and Sentinel-5P

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Abstract

Aegean and Mediterranean countries have been experiencing many forest fires which caused extensive ecological damage and posed significant risks to habitants in recent years due to extreme temperature anomalies. Post-fire analyses are essential for rapidly assessing wildfire impacts and informing future mitigation strategies. This study investigates the effects of the Çeşme wildfire in İzmir, Türkiye, which began on July 2, 2025, and lasted four days, using Sentinel-2 and Sentinel-5P satellite imagery. Changes in vegetation conditions were examined using normalized difference moisture index (NDMI), normalized burn ratio index (NBR), normalized difference vegetation index (NDVI), and green chlorophyll vegetation index on the Google Earth Engine cloud-based platform. Burned area extent was quantified using differenced normalized burn ratio (dNBR) while changes of nitrogen dioxide (NO₂) and carbon monoxide (CO) gases were extracted from Sentinel-5P TROPOspheric Monitoring Instrument satellite data. The study results demonstrated that 96.21 km² was burned around Çeşme. The statistical relationships of NBR with NDMI and NDVI were lower after the fire. The average NDVI decreased from 0.39 to 0.25 and the average NBR decreased from 0.19 to 0.09, indicating the damage caused by the fire to the vegetation. The study findings highlighted the huge amount of forest destroyed due to wildfire. It has been shown that NO₂ and CO gases were released into the atmosphere at high rates during the wildfire. The study represents a powerful application of spatial information science in disaster management through the integration of various remote sensing indicators.

Keywords Air quality · Burn severity · Forest fire · Post-fire assessment · Remote sensing · Wildfire monitoring

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1 Introduction

Aegean and Mediterranean regions have experienced increasing wildfire frequency in recent years [1]. Increased temperature fluctuations due to global climate change have exacerbated wildfires worldwide in recent years [2, 3]. Additionally, drought and anthropogenic land use contribute significantly to the rising incidence of forest fires [4]. Wildfires affect ecosystem balance and have serious impacts on the carbon cycle, biodiversity, soil, and water regimes [5]. In addition, forest fires not only disrupt fauna and flora but also prevent water infiltration into the soil and increase surface runoff, leading to a loss of nutrients and organic matter from the soil [6]. Moreover, toxic and greenhouse gases such as carbon monoxide (CO), nitrogen dioxide (NO₂), and methane (CH₄) are released into the atmosphere due to wildfires which degrade regional air quality and intensify climate change through enhanced greenhouse effects [7]. Thus, inhabitants in forests are negatively affected by the gases released into the atmosphere and the destroyed nature. For this reason, the risk estimates and damage caused by forest fires should be analysed with rapid methods, and the damage they cause to the ecosystem and local inhabitants should be revealed so that the necessary precautions can be taken. Although wildfires cause severe ecological damage, post-fire rainfall can facilitate natural regeneration processes [8].

Remote sensing (RS) provides reliable and rapid monitoring of forest fires by enabling comparison of pre- and post-fire conditions, and objective analysis of environmental variables such as vegetation loss, soil moisture loss, and air pollution [9]. This allows both fire management and ecosystem rehabilitation processes to be conducted more effectively based on scientific data. Fire assessments based on field observations are often limited because they do not adequately reflect the spatial and temporal dynamics of wildfires [10, 11]. Moreover, recent studies have demonstrated the crucial importance of spectral RS indices derived from RS data in detecting fire damage and determining the fire severity. Thus, spectral indices such as normalized difference vegetation index (NDVI), normalized burn ratio (NBR), green chlorophyll vegetation index (GCVI), normalized difference moisture index (NDMI), soil moisture index (SMI), and land surface temperature (LST) are widely applied to quantify fire severity and changes in vegetation, soil moisture, and surface temperature.

Looking at some recent studies conducted using remote sensing methods, NBR, NDMI, NDVI, enhanced vegetation index (EVI), and soil-adjust vegetation index (SAVI) spectral RS indices were calculated using Sentinel-2, moderate resolution imaging spectroradiometer (MODIS) and Landsat-8 to detect a wildfire in Brazil [12]. They found that lower-resolution MODIS data performed best, demonstrating that

remote sensing can effectively detect forest fire damage. In addition, effects of some forest fires in Gujarat, India were analysed, using NDVI, LST and NBR spectral RS indices which were calculated from high-resolution Sentinel-2 and MODIS satellite images on the Google Earth Engine platform [13]. The study demonstrated a successful monitoring of fire damage assessment is possible using spectral RS indices. Moreover, post-fire burn severity was analysed using the difference normalized burn ratio (dNBR) and difference normalized difference vegetation index (dNDVI) derived from Sentinel-2 and Landsat-8 imagery in Google Earth Engine (GEE) [14]. Their study demonstrated that severity analyses calculated from both Sentinel-2 and Landsat-8 were at acceptable levels. Furthermore, the burn severity of a forest fire was analysed that started on July 7, 2015, near the villages of Montán and Caudiel in the Comunidad Valenciana, western Spain, using NDVI and NBR spectral indices calculated from Sentinel-2 RS data [15]. They noted that NDVI and NBR indices performed well in distinguishing damaged areas according to their severity levels, demonstrating that Sentinel-2 NDVI and NBR are a reliable for burn severity determination in areas with low vegetation cover. In recent years, machine learning (ML) approaches combined with satellite data have also improved wildfire detection and analysis of its effects [16]. Fire severity and wildfire impacts were detected in Capilla del Monte in Punilla Valley of Argentina by [17] using dNBR, combined with machine learning classifiers such as random forest (RF) and support vector machine (SVM). The study demonstrated ML classification methods are successful predictors for estimation of burnt areas. Furthermore, the effects of NO₂ and CO gases on the air quality because of the wildfire that occurred in the Southwestern Türkiye, especially in Antalya and Muğla in 2021, were examined by [18], using Sentinel-5P the TROPOspheric Monitoring Instrument (TROPOMI) data. The study found that wildfires negatively affected air quality, with significant increases in CO and NO₂ concentrations during the fire period.

The Mediterranean basin is one of the most vulnerable regions to wildfires due to long summer droughts, low humidity, and dense forest coverage [19]. Türkiye also has been frequently exposed to large-scale fires in recent years due to increasing heat waves, the intensity of tourist activities, and the expansion of forest-settlement interactions. The 160 km coastal-inland corridor spanning Türkiye's Mediterranean, Aegean, and Marmara regions is the most vulnerable to forest fires, and 58% of the fires in the country have occurred in this sensitive area [20]. According to the forest fire history records in Turkey between 2013 and 2020, the highest number of forest fires was recorded in 2013 with 3679 cases [21]. Moreover, forest fires occurred in many areas of Türkiye's Mediterranean region in 2021, and in

Bodrum, a tourist district, approximately 17,600 hectares of forest were affected by the wildfire [22]. A total of 291 wildfires covering 202,361 hectares in 2021 in Türkiye were brought to the public attention and [23], analysed dNBR values using Sentinel-2 satellite imagery to assess the severity of 30 major wildfires affecting more than 100 hectares in 2021 in Türkiye. In addition, the total area affected by the forest fires that occurred in Çanakkale in July and August 2023 is 79.1 km² [24].

A review of the literature on forest fire studies in the Aegean Region and across Turkey reveals a gap in studies integrating spectral indices with Sentinel-5P TROPOMI air quality data. Furthermore, the use of the GCVI index, the inclusion of ERA5 temperature data, and the supplementation of CHIRPS precipitation data in this study fill a gap in the literature regarding integrated analysis. Additionally, analyses with integrated data in high fire risk regions such as the Aegean are critical for both disaster management and environmental planning. Thus, the main objective of the study is to assess the environmental and atmospheric impacts of recent Çeşme forest fire that began on July 2, 2025, in Ildır neighbourhood, through the integration of Sentinel-2 and Sentinel-5P TROPOMI remote sensing satellite data on the GEE cloud-based platform. The Çeşme fire started in agricultural land but it spread to forest areas and surrounding settlements due to the strong winds. The spectral RS indices such as NDVI, NDMI, NBR and GCVI were calculated using Sentinel-2 dataset while atmospheric gas concentrations NO₂ and CO derived from Sentinel-5P TROPOMI. NDVI is an important index for distinguishing healthy plants, while NDMI is used to determine the moisture content and dryness of plants before the wildfire. In addition, GCVI is better at detecting subtle changes in very dense forests where NDVI might not be able to show a difference. Thus, the effects of fire are analysed in this study using the integration of these indices. This study is among the first to evaluate wildfire impacts in Türkiye's Aegean Region by integrating Sentinel-2 spectral indices with Sentinel-5P atmospheric gas data, supplemented by meteorological datasets. The results of the study will show the areas affected by the fire and how much gases in the atmosphere changed during the forest fire. Also, the findings will inform fire risk management, guide post-fire rehabilitation, support climate adaptation policies, and strengthen ecosystem resilience while reducing economic losses in tourism and residential areas. Furthermore, it can help to future studies for creating high-risk areas in the region, optimize fire management plans, and effectively manage rehabilitation processes. This can increase ecosystem resilience in the long term and help reduce economic losses by protecting tourism and residential areas in the region.

2 Materials and methods

2.1 Study area (SA)

The study area (SA) is located on the Çeşme, Urla and Karaburun Peninsula in the west of Izmir province, Türkiye as latitude 38° 18' N and longitude 26° 28' E. The total study area is shown in Fig. 1 and, it covers 169.21 km² which consist of 134.58 km² forest areas. Çeşme is a well-known tourist destination on the Aegean coast for its Mediterranean climate, annual average temperature ranges between 16 and 18 °C, while annual precipitation varies from 600 to 1000 mm, with hot, dry summers and mild, wet winters [25]. Vegetation cover in Izmir consists of fertile agricultural lands, Mediterranean forests and shrublands like maquis and phrygana [26]. The Karaburun and Alacati peninsulas, which cover our study area, contain Mediterranean red pine, Calabrian pine (*Pinus brutia*) and oak forests.

2.2 Datasets

Sentinel-2 satellite images are provided by Copernicus European Space Agency (ESA) program, and they were selected for three different periods: August 2024 (pre-fire), June 2025 (pre-fire), and August 2025 (post-fire). Time range of selected Sentinel-2 satellite images were between 1st and 30th August in 2024 and in 2025 as well as 1st and 30th June 2025. The spatial resolution of Sentinel-2 data is 10 m and the satellite revisits less than 5 days [27]. The cloud coverage of Sentinel-2 images was chosen less than 20%. In addition, Sentinel-5P TROPOMI satellite measures at different wavelengths such as ultraviolet (UV), visible, near-infrared (NIR), and shortwave infrared (SWIR) were used to monitor changes in air quality parameters due to wildfire [28]. The satellite images have 7 km × 3.5 km spatial resolution, and the satellite was launched on 13 October 2017. The Sentinel-5P TROPOMI data were obtained for the pre-fire period (29 June–1 July 2025) and post-fire period (2–4 July 2025) to extract nitrogen dioxide (NO₂) and carbon monoxide (CO) gases. ERA5 temperature data (0.1° resolution) and Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) precipitation data (0.05° resolution) were used to supplement meteorological conditions. The average precipitation and temperature data for pre and post fire are shown in Fig. 2. Moreover, the ERA5 is produced by the Copernicus Climate Change Service (C3S), and it has 0.1° × 0.1° spatial resolution, which is approximately 9 km × 9 km at the equator and 'temperature_2m' band of ERA5 used to obtain average temperature data [29, 30]. In addition, the monthly mean precipitation data was obtained from CHIRPS which has an 0.05° × 0.05° degree spatial resolution [31]. According to Fig. 2, June 2025 had the lowest mean

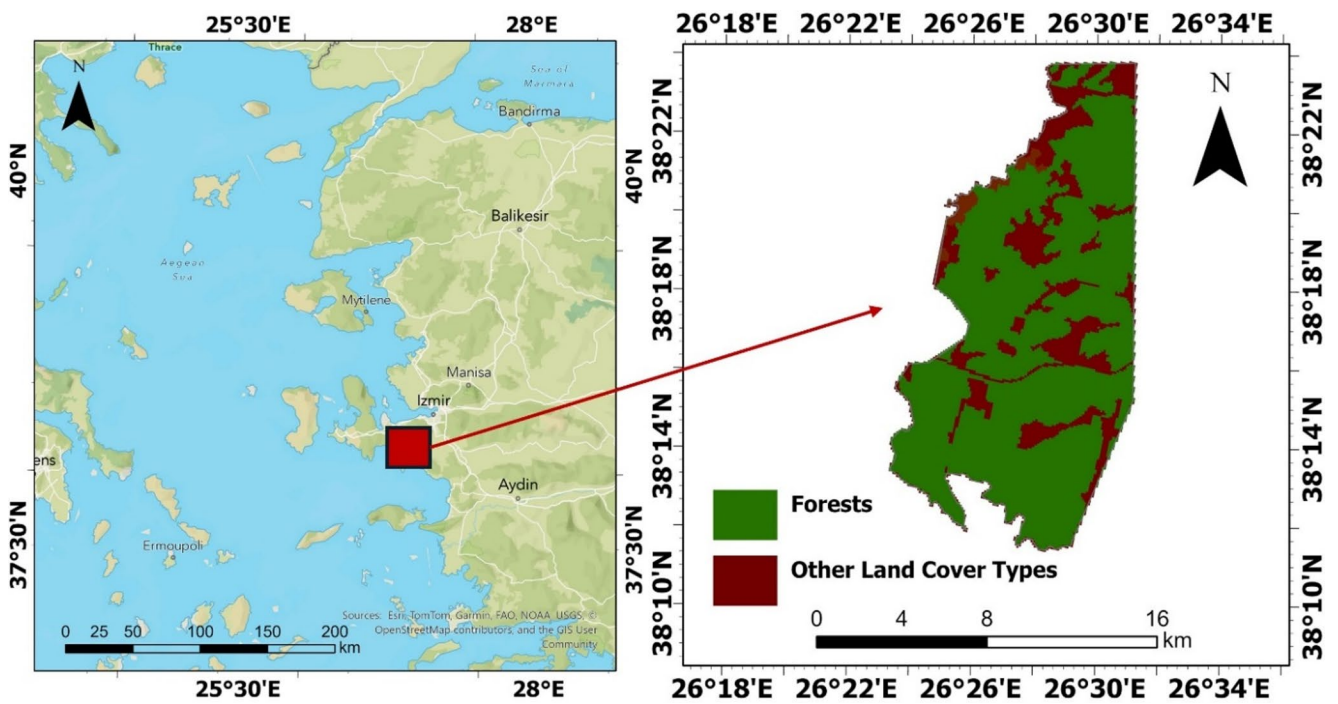


Fig. 1 Location of the study area in Türkiye (left), study area and its forest map (right)

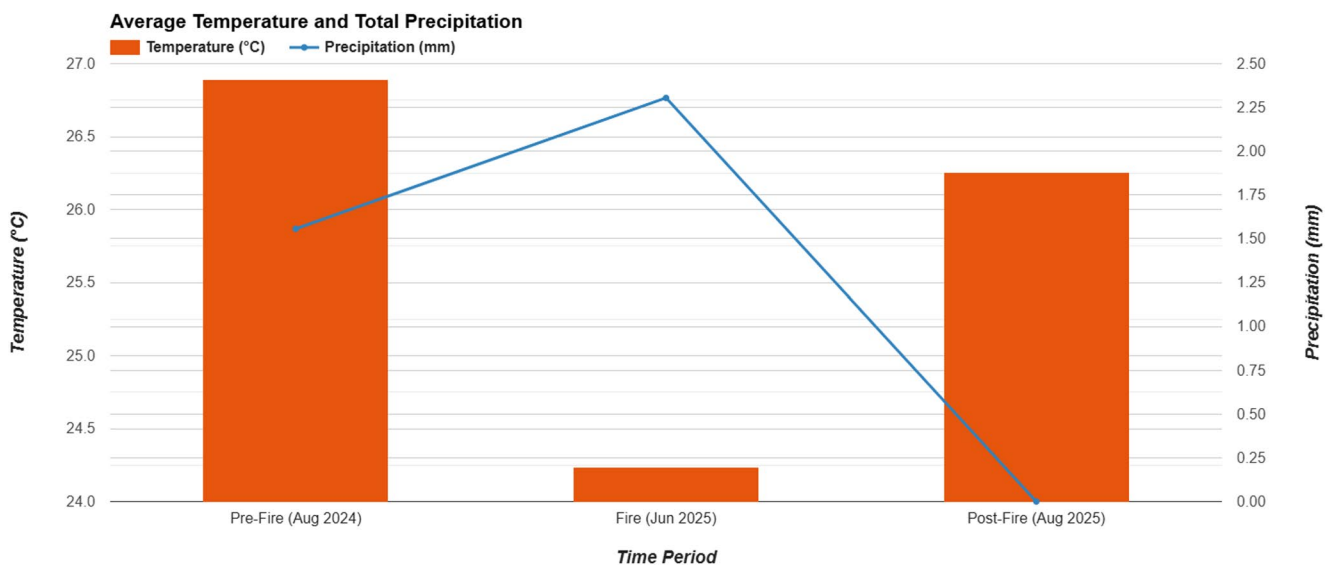


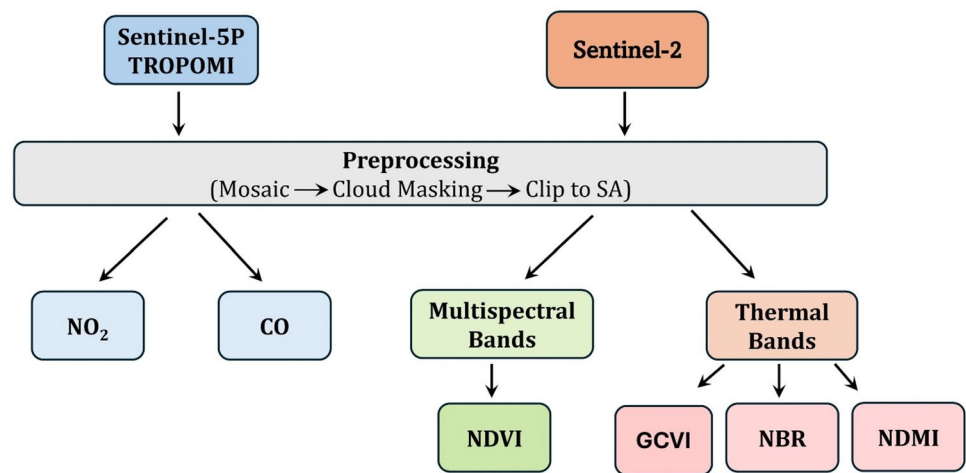
Fig. 2 Average temperature and precipitation graphs of study area by pre and post fire periods

temperature while the mean precipitation was the highest in June 2025. Also, the highest mean temperature was in August 2024 while the lowest precipitation was in August 2025 after the fire. On the other hand, there were no precipitation after the wildfire.

2.3 Methodology

Preprocessing and spectral index calculations were conducted on Google Earth Engine (GEE) which gives an

opportunity to deal with a huge amount of satellite dataset for different environmental issues [32]. The basic methodology steps are shown in Fig. 3 as a flowchart. Cloud masking was applied, and mosaicked images were clipped to the study area, with average pixel values extracted.

Fig. 3 Flowchart of the methodology steps

2.3.1 Calculation of normalized difference vegetation index (NDVI)

The NDVI is a spectral remote sensing index for discrimination of soil and vegetation cover and NDVI values > 0.2 were considered indicative of vegetation cover [33]. The NDVI is found using the red and near-infrared bands of the Sentinel-2 dataset using the formula provided in Eq. (1) [34].

$$\text{NDVI} = (\text{NIR} - \text{R}) / (\text{NIR} + \text{R}) \quad (1)$$

where NIR is the near-infrared band and R represents the red band of Sentinel-2 satellite while NDVI is vegetation density in the study area.

2.3.2 Normalized burn ratio index (NBR)

The NBR detects burned areas by contrasting reflectance between healthy and fire-affected vegetation in the SWIR interval of the electromagnetic spectrum [35]. NBR is calculated using short-wave infrared and near infrared band of the satellite data using formula that is given in Eq. (2) [36].

$$\text{NBR} = (\text{NIR} - \text{SWIR}_2) / (\text{NIR} + \text{SWIR}_2) \quad (2)$$

Where NIR is the near-infrared band of the satellite and SWIR_2 is the short-wave infrared band of the satellite that has 2.11–2.29 μm wavelength whereas NBR is the normalized burn ratio index.

2.3.3 Normalized difference moisture index (NDMI)

The NDMI quantifies plant moisture content, ranging from – 1 to 1. NDMI is calculated using near infrared and short-wave infrared bands of Sentinel-2 satellite images, and it was calculated by a formula that is given in Eq. (3) [37].

$$\text{NDMI} = (\text{NIR} - \text{SWIR}_1) / (\text{NIR} + \text{SWIR}_1) \quad (3)$$

Where NIR represents the near-infrared band of Sentinel-2 satellite, SWIR_1 is a first shortwave infrared band of the satellite image, and its wavelength is between 1.57 and 1.65 μm .

2.3.4 Green chlorophyll vegetation index (GCVI)

The GCVI estimates chlorophyll content using the ratio of NIR to green reflectance, and it was calculated by a formula that is given in Eq. (4) [38].

$$\text{GCVI} = \frac{\text{NIR}}{\text{G}} - 1 \quad (4)$$

Where NIR is the near-infrared band of the satellite data and G is the green band of the satellite while GCVI is the green chlorophyll vegetation index.

2.3.5 Estimation of burned areas and statistical validations

Burned areas were detected using the differenced Normalized Burn Ratio (dNBR) that was found by [39], and were calculated as the difference between pre-fire in August 2024 and post-fire in August 2025 NBR values. dNBR also gives an understanding about burn severity levels of burned areas. Correlation coefficients (r) of relationships between NDVI, NBR and NDMI spectral indices before and after the wildfire were calculated using 19,679 spatially distributed pixel samples, generated via fishnet grids to minimize sampling bias. The statistical analyses were done by Statistica v13 (TIBCO Software Inc.).

2.3.6 Extraction of air quality parameters

NO₂ and CO concentrations were extracted from Sentinel-5P TROPOMI data using GEE using the bands *NO2_column_number_density* and *CO_column_number_density*. The Sentinel 5P TROPOMI has a push broom scanner for observation of ultraviolet, visible, near infrared and short-wave infrared intervals of the electromagnetic spectrum [40]. Only pixels with valid quality assurance flags were retained, and mean values of NO₂ and CO were calculated for pre- and post-fire periods.

3 Results

3.1 Temporal dynamics of vegetation indices

The vegetation indices across Cesme before and after the fire event show a concerning pattern. NDVI values increased from 0.34 in August 2024 to 0.39 in June 2025. Since this is also a seasonal shift from late summer to late spring, this outcome is likely due to seasonal variation. However, NDVI dropped to 0.25 in August 2025, indicating significant vegetation loss attributable to both seasonal variation and the

fire event, with the fire impact dominating, as the seasonal variation is shown to be negligible compared to the previous year. The standard deviation of 0.19 indicates notable spatial variability in vegetation after the fire (Fig. 4).

The NBR decreased from 0.20 in August 2024 to 0.09 in August 2025, reflecting burned vegetation and exposure of bare soil or ash, as NBR is sensitive to reduced NIR and increased SWIR reflectance. This outcome suggests that there has been burned vegetation in the area in question during this timestep, since this index is specifically designed to capture areas affected by fire. This is because this index marks areas with low reflectance in NIR band and high in SWIR band, which would result in low NBR values. This would likely suggest bare soil has been exposed or there are areas covered with ash and other burned materials.

The NDMI also declined markedly after the fire, from -0.02 in June 2025 to -0.16 in August 2025, indicating reduced water retention in burned areas. The first shift is seemingly connected to seasonal variation, but the second shift both represents the seasonal variation and the fire's effect on the moisture content. This is because not only there has been a fire hazard in the region and burned areas cannot retain moisture effectively, but also shows there is a change of season from late spring to late summer, which would affect the moisture content directly.

The GCVI showed similar declines, dropping from 2.01 in August 2024 to 1.49 in August 2025, reflecting reduced chlorophyll content due to fire damage. The general trend agrees to what was expected, the seasonal variation also should be considered. It seems that while moving from August to June has caused a reduction of 0.09, both fire and seasonal change from June 2025 to August 2025 has caused the chlorophyll content to drop 0.43 units, which is significant compared to the first seasonal 0.09.

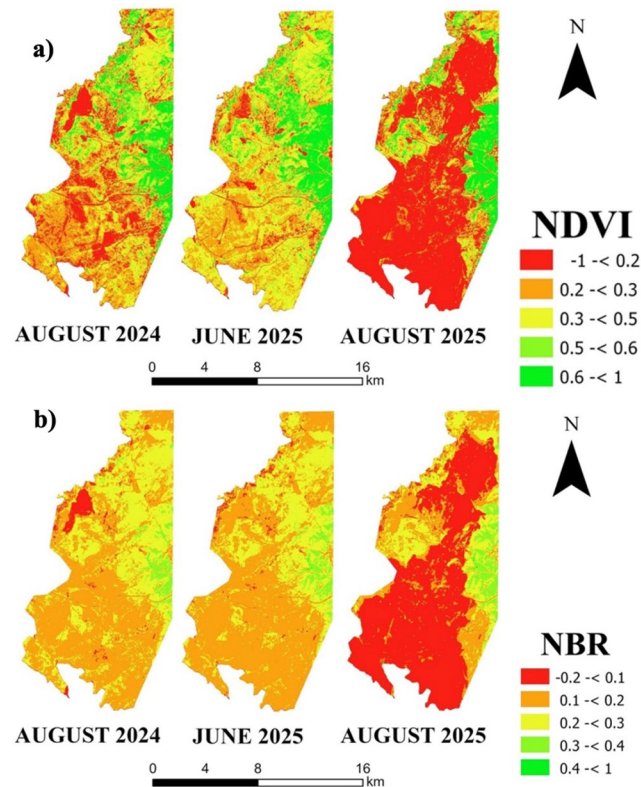


Fig. 4 **a** NDVI (up) and **b** NBR (down) maps of the study area. Pre-fire periods (August 2024 and June 2025) show moderate to high vegetation density, while post-fire (August 2025) data reveal extensive vegetation loss

3.2 Spatial distribution of vegetation and moisture indices

The NDVI patterns in Fig. 4 provide evidence of vegetation decline and it shows the drastic change the region went through as the result of the fire incident. During the pre-fire period in both August 2024 and June 2025, the region is showing a combination of both moderate and dense vegetation cover, which gives a general idea of how seasonal variation in the region would present itself through the NDVI distribution. However, after the fire, most of the land had NDVI < 0.2, indicating minimal or no healthy vegetation cover. Looking at how the index is calculated, this means in this case, NIR and red band reflectance are nearly equal, which indicates the absence of green vegetation cover and the presence of exposed soil or severely damaged vegetation.

Based on the seasonal variation between the previous time steps, the condition in August 2025 is evidence of how much of an effect the fire had on both the vegetation cover and its health. It should be clarified that NDVI values of between 0.3 and 0.6 typically represent moderately vegetated landscapes, as it happens when NIR reflectance is notably higher than the red reflectance which would indicate healthy vegetation. The map shows that the vegetation cover went through a significant collapse in most of the region, and the only part that remained reasonably vegetated after the fire incident was mostly eastern parts of Cesme. The presence of patches with between 0.3 and 0.5 suggest there have been areas that remained reasonably vegetated, though it was a very small percentage of the landscape.

The pre fire NBR patterns show most of the area have been covered with healthy vegetation, with NBR values mostly varying between 0.1 and 0.3. Based on how this index is calculated, this would happen when NIR is slightly greater than SWIR reflectance, which suggest the pre fire landscape has been mostly covered with moderately dry vegetation which also is affected by the fact that the time steps are both in the dry season, late summer and late spring. When it comes to the post fire event though, the region is

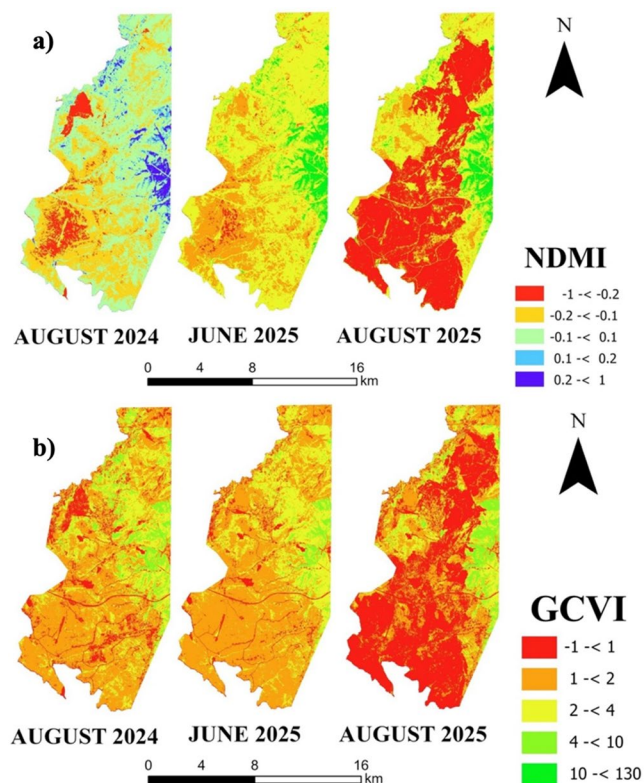


Fig. 5 **a** The NDVI (up) and **b** GCVI (down) maps of the study area. By August 2025, NDVI values became strongly negative (-1 to -0.2), especially in eastern regions, which indicates severe damage to the vegetation cover. GCVI maps show stable chlorophyll distributions pre fire, but post fire values drop substantially (-1 to 2) in the same eastern areas, which confirms loss of healthy vegetation

mostly covered with areas with NBR between -0.2 and 0.1. Based on the index itself, it means that SWIR is equal or greater than NIR, which would suggest bare soil or burned vegetation with minimal vegetation cover left. This output points out to moderate to severely burned areas as the result of the fire incident.

The NDMI values pre fire in both time steps are good indication of the seasonal shift before the fire incident (Fig. 5). It seems that during this seasonal shift between August 2025 and June 2025, a large area changed from NDMI value of 0.1 or less has changed into -0.1 or less. This means during this transition, SWIR reflectance became greater than the NIR reflectance, which indicates loss of vegetation. The figure also shows that after the fire incident, most of the area has the NDMI values of between -1 and -0.2, which translates to extremely dry or non-vegetated surfaces with minimal moisture content. This would suggest that the fire is mostly to blame for the reduction of this index, but also there is a minimal seasonal aspect to this as well. The figure also shows patches of vegetated moisture after the fire incidents, which suggest proximity to water sources in the region.

Moving on to GCVI, the results point out to a minimal seasonal variation in this index compared to other indices. Before the fire incident, most of the area has been covered by GCVI value of between 1 and 2. Based on how the index is calculated, this point to the fact that during the pre-fire period in the region, there has been strong evidence of high chlorophyll which mostly means healthy and green vegetation, as NIR has shown greater values than the green band reflectance. This however changed after the fire, when the vast majority of the landscape was covered with GCVI values of -1 to 1. This in turn is evidence of NIR reflectance to be way greater than the green reflectance, which means the green reflectance has collapsed due to the fire and bare soil and ash have been exposed. The interesting pattern of all the outputs show that the fire's affect has shown consistency in the region, with different intensities across different indexes. This points out to the practicality of using multi-spectral remote sensing as a tool to track fires' aftermath in Cesme.

3.3 Inter index correlations analysis and statistical aspect

The spectral analysis has shown strong evidence of consistency between the indices based on the previous results. This section examines the statistical associations among indices to better understand their interconnections. In order to do that, a correlation analysis has been performed to evaluate the strength of linear dependencies among the variables (Fig. 6). There is a strong linear correlation between

NBR, NDVI, and NDMI before fire incident (between 0.64 and 0.86), which suggest that healthy vegetation cover was predictable through vegetation density, health, and moisture across the region. From a remote sensing point of view, this happens because healthy vegetations have a certain signature when it comes to reflectance. Healthy vegetation absorbs red, reflects NIR, and shows moderate SWIR reflectance, producing strong correlations among NDVI, NBR, and NDMI.

After the fire incident however, it can be seen that the correlation has declined sharply ($r=0.24$ to 0.28), and the scatter plots cannot resemble a unique structured pattern anymore. This output compliments the previous results and expands on how the fire incident destroyed the natural interconnections between the vegetation health, density, and moisture. This is a direct result of the fact that previously vegetated and now burned areas like bare soil or ash now have a completely different spectral signature and

would not follow the previous order when it comes to the spectral reflectance. For example, white ash would reflect light strongly across all wavelengths, and black ash would absorb nearly all of them, and exposed soil would act differently based on the minerals it contains. This is now evident through the fact that the spectral indices would not resemble the same dependence structure as the pre fire incident, and the pre existing structure would no longer be valid. The one exception to this would be NDVI-NDVI correlation, with post fire value of 0.79, but this is likely because both indices have uniformly collapsed across the entire burned area in Cesme.

3.4 Fire severity assessment

The burn severity map (Fig. 7) illustrates the spatial distribution of burned areas derived from dNBR. The figure is showing the varied nature of the fire after path in Cesme,

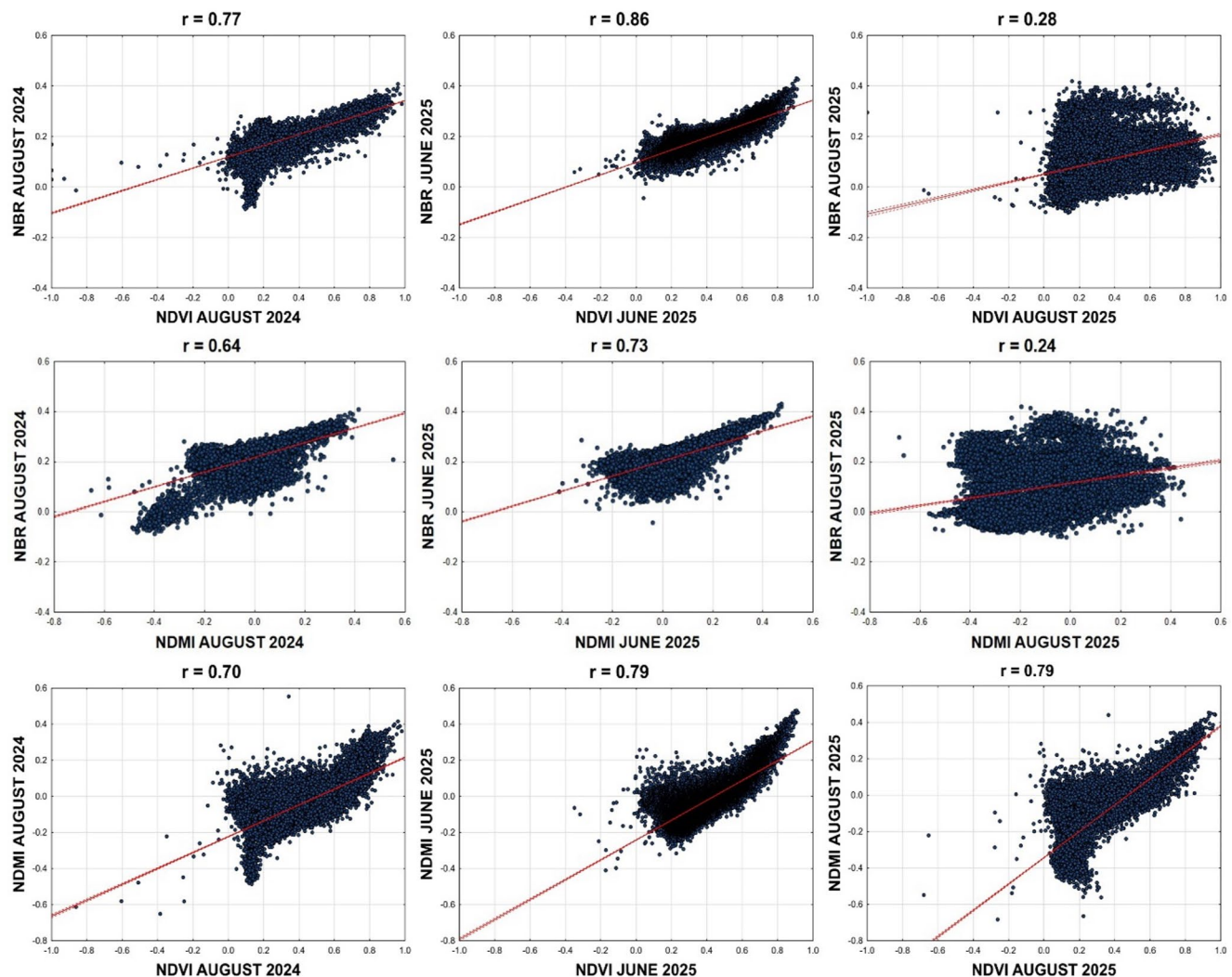


Fig. 6 Statistical relationship between spectral remote sensing indices ($p \leq 0.05$). Pre fire periods (August 2024 and June 2025) showed strong positive correlations, indicating consistent vegetation responses, while the post fire patterns fail to capture a defined structure in the data (August 2025)

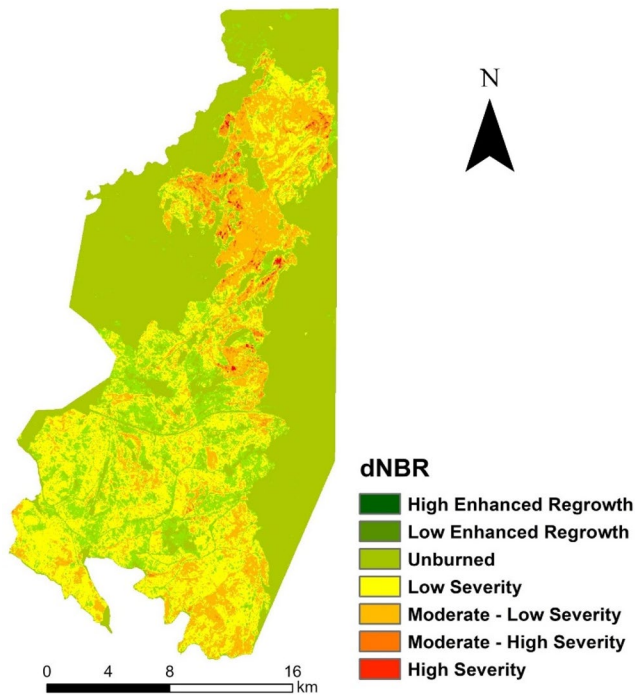


Fig. 7 dNBR map showing spatial variation in fire severity across the study area. Categories range from Unburned to High Severity

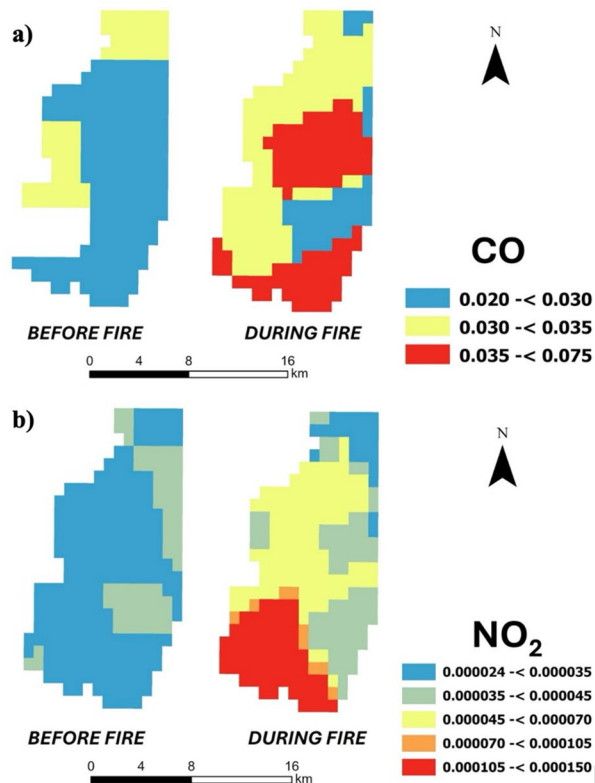


Fig. 8 a Carbon monoxide (CO) and b nitrogen dioxide (NO₂) distribution (mol/m₂) before and after the wildfire. This figure shows changes in atmospheric pollutant concentrations which were likely a result of the fire activity

which is an indication of how different areas have responded to the fire incident. Patches of severe damage highlight the need for further investigation into land cover vulnerability and human activity influences. As this is a remote sensing-based analysis, this again points out to the exposure of bare soil or ash, which is effectively captured by the sensors. Based on the reflectance analysis, high-severity burns correspond to reduced NIR and increased SWIR reflectance, while low-severity areas show only minor spectral changes, resulting in lower dNBR values.

3.5 Atmospheric impacts

The CO concentrations shifted markedly between pre- and post-fire periods. Before the fire, the CO has shown a uniform and low values across the region, which are mostly below 0.030 mol/m². After the fire incident however, there is a sudden increase in CO data (Fig. 8). Based on the results, not only the entire region has experienced a significant increase in CO values, but also there are major hotspots of burned areas showing CO being between 0.035 and 0.075 that showcase areas mostly affected by the fire. These hotspots are mostly in the central and southern regions of the study area, which seems to compliment the maps presented in Figs. 4 and 5. This would also help to raise confidence in the satellite measurements, as different datasets seems to complement each other.

The NO₂ values tell a similar story, with slightly different distribution across the region. Before the fire, the region has shown a minimal distribution of NO₂ with values mostly between 0.000024 and 0.000045 mol/m². This changed after the fire incident, with new values being mostly between 0.000045 and 0.000150, which is significant compared to the pre fire condition. This also shows resemblance with other datasets, showcasing the central and southern areas was mostly affected by the fire. Looking at both maps, the spatial scale illustrates the extent of atmospheric impact during the fire.

4 Discussion

The impacts of a wildfire in Cesme, Izmir, located on the Aegean Sea coast, were investigated using Sentinel-2 and Sentinel-5P RS data on the cloud-based GEE platform. Changes in vegetation cover and plant moisture were assessed using NDVI, NBR, NDMI, and GCVI, alongside NO₂ and CO concentrations. Sentinel-2 images superior performance in detecting burned areas compared to Landsat, even during active fire events [41]. Most studies in the literature have also investigated post-fire events using certain indices because of their better performance [42–45],

Table 1 Mean values and standard deviations of vegetation indices before and after the fire

Mean values	NDVI	SD	NBR	SD	NDMI	SD	GCVI	SD
August 2024	0.34	0.18	0.20	0.05	− 0.07	0.11	2.01	1.22
June 2025	0.39	0.17	0.19	0.05	− 0.02	0.11	1.92	0.91
August 2025	0.25	0.19	0.09	0.11	− 0.16	0.18	1.49	1.24

However, the integration of air quality parameters with spectral indices, supported by CHIRPS precipitation data, provides a novel perspective for wildfire studies in the Mediterranean basin.

The study results showed a significant change in vegetation index is observed in August 2025 respect to the period pre-event in August 2024 and June 2025. NDVI values declined markedly in August 2025, reflecting damaged and unhealthy vegetation. NDVI was also calculated from hyperspectral images as a determinant for forest health analysis [46]. The pixels corresponding to the burned areas are delineated by NBR with low NBR values which ranging from -0.2 to (0.1) . At the same pixels, the corresponding NDVI values ranged between -1 and (0.2) . As confirmation of the burned area identification is the NDMI and GCVI calculation. Their lowest pixels are observed in the area in which both the NDVI and NBR pixels are low too. Similar to our findings, NDVI and NBR spectral indices were used to detect burn severity of wildfire by [47] in Madeira Island. The results showed significant decreases in mean NDVI and NBR after the fire. In addition, the statistical reference mean values in Table 1 quantify the sudden change of the values between the June 2025 and August 2025. The mean value of the NDVI saw a decrease of approximately 36% from June 2025 to August 2025. A reduction of roughly 53% was recorded for the mean NBR value. Furthermore, the NDMI mean had a highly significant decrease from -0.02 to -0.16 , reflecting severe vegetation stress caused by the wildfire, alongside a 23% reduction for the GCVI. In addition, negative NDMI values such as -0.07 and -0.02 in August 2024 and June 2025 indicate pre-existing water stress, which may have facilitated fire spread. The effects of NDVI and NDMI were examined on forest fire risk by [48] and found that low NDMI causes water stress and increases the risk of wildfires, and that there is a high correlation between fire risk and NDMI. This massive decreasing of spectral indices is due to a strong event that must have caused it as a wildfire and supports the effectiveness of these indices in quantitatively reflecting the severity of fire damage.

In August 2024 the linear correlation between the NDVI and NBR was robust with a $r = 0.77$. In June 2025 this correlation increased becoming 0.86, showing a very strong linear correlation linked to the presence of a healthy vegetation. By August 2025, correlation declined to 0.28, signifying a weak relationship between NDVI and NBR due to fire-induced vegetation loss. This decrease in correlation

between NDVI and NBR after the wildfire can be explained by the fact that the mean NBR ratio decreased more than the mean NDVI ratio because it was also indicated that NBR is less sensitive than NDVI in characterizing post-fire vegetation recovery [49, 50]. A similar correlation between the NDMI and NBR dropped to $r = 0.24$ in August 2025, whereas June 2025 exhibited stronger vegetation and moisture due to milder temperatures. June can be expected to have more vibrant vegetation and humidity due to the lack of intense heat. The high correlation coefficients in June may be due to the lack of intense heat in June 2025, and the region may have more vibrant vegetation and humidity. The ERA5 temperature and CHIRPS precipitation data in Fig. 2 also support this conclusion, as the temperatures were low and precipitation was high in June 2025. However, the fact that it is the summer months and rainfall is low in the region during June and August indicates that rain has little effect on the fire. Despite the low rainfall, the moisture that plants retain in June, as seen in NDMI data, may have an effect. In both above week correlations in August 2025, the lower r values are attributable to a severe vegetative stress or extreme drought, or as in this case to a wildfire event. The precipitation and temperature data graph by CHIRPS in Fig. 2 indicating there was almost no precipitation in August 2025. In addition, NDMI is sensitive to vegetation moisture content and can capture moisture differences, while NBR predominantly reflects the presence of burned and charred surfaces [51]. Therefore, the two indices respond to different post-fire surface conditions, leading to a significant decrease in their linear relationship after wildfire.

Furthermore, the weakening of correlation coefficients between the indices after the fire indicates that the fire impact was spatially heterogeneous and that vegetation components were affected at different levels. Moreover, all correlations showed significant decrease after the wildfire, but NDVI-NDMI correlation remained relatively strong ($r = 0.79$) after the fire in August 2025, compared to August 2024, suggesting that some vegetation species continued to utilize available soil moisture. This indicates that some species that have adapted to the conditions that occurred after the fire continue to use the water available in the soil and that re-greening may occur in the future. Additionally, forest regeneration dynamics were analysed using Landsat RS data and a strong positive postfire Pearson's correlation were found between NDVI and NDMI as $r = 0.94$ [52].

The presence of CO and NO₂ demonstrated the existence of a fire. A notable increase of both the pollutants is reported in Fig. 7. The concentration of CO increased notably in some pixels in which the values before the fire event was about 0.02–0.025 mol/m₂. After the fire their concentrations arrived to 0.035 to 0.075 mol/m₂. This substantial elevation of CO concentrations means that a big amount of biomass burned. A similar trend has been registered to the NO₂ concentrations. The pixels that before the fire reached a concentration of 0.000024–0.000035 mol/m₂, then passed to 0.000105–0.000150 mol/m₂. The thermal product of NO₂ typical of the fire heat produced this NO₂ high concentration. In comparison with other studies, [53], reported a significant increase in NO₂ values obtained from Sentinel 5P following the largest fire in the history of the Czech Republic. Moreover, CO is an air pollutant emitted during the combustion of organic matter, including biomass combustion, and [54], reported that tropospheric CO column density values increased after the outbreak of the Gangneung Wildfire, South Korea.

According to a report published by the Aegean Forest Foundation [55] (<https://www.egeorman.org.tr>) on August 28, 2025, the large forest fires that broke out in Izmir in 2025 affected approximately 30,000 hectares, and the report states that approximately 90% or more of these fires were caused by human factors. In addition, it was also mentioned in the report that 9389 hectares, or 93.89 km² burnt in the Ildir Çeşme wildfire. Similar to their report, our study estimated burned areas as 96.21 km² by dNBR index, which represents approximately 56.9% of the study area. Moreover [56], determined the burned area as 93.85 km² in Çeşme wildfire by pre- and post-fire NBR analysis from Sentinel 2 data. Their results indicated similar burn severity levels like this study. In another recent study by [57], the burned areas were estimated at 99.85 km² using dNBR from Sentinel-2. In addition, it was also found by [58], that high slope did not change the fire severity rate by examining the relationship between slope and dNBR.

In summary, the study demonstrated that the fire of July 2, 2025, in the Çeşme, İzmir region negatively affected the air quality and a significant amount of vegetation was affected by the wildfire. Also, significant declines in NDVI, NDMI, NBR, and GCVI in August 2025, combined with rising CO and NO₂ concentrations, highlight the severity of the fire event in the study area. Moreover, the lack of ground data limits the comprehensiveness of the study results obtained but the results highlighted the need to integrate multiple remote sensing indices and environmental data to comprehensive observation of fire severity and post-fire ecosystem responses under heterogeneous fire impacts and drought conditions in the Mediterranean basin. This study demonstrated significant environmental impacts from the July

2025 Çeşme wildfire. However, Sentinel-2 and Sentinel-5P data may not capture micro-scale heterogeneity, and long-term recovery was not assessed. Furthermore, the study only examined post-fire recovery over a short time frame, and long-term ecosystem changes were not observed.

5 Conclusion

This study analysed the environmental impacts of the July 2, 2025, wildfire in Çeşme, İzmir, using Sentinel-2 and Sentinel-5P data. The results demonstrated that the wildfire caused widespread vegetation damage and significant decrease in air quality, as evidenced by elevated CO and NO₂ concentrations. In addition, spectral RS indices such as NDVI, NBR, NDMI, and GCVI effectively reflected vegetation stress and burn severity, while precipitation and temperature data provided additional context for pre- and post-fire conditions. The dNBR severity levels demonstrated that the fire generally occurred at low to moderate intensity levels. Burned areas were estimated as 96.21 km² using dNBR. This research demonstrates that multi-index remote sensing offers a more robust indicator of vegetation stress than univariate analysis by synthesizing spectral indices such as NDVI, NBR, NDMI, and GCVI, particularly in the sensitive ecosystems of the Mediterranean basin. The study re-emphasizes the serious ecological impacts of forest fires in the Mediterranean basin and provides insights relevant to forest policy and management. Moreover, this investigation represents the first comprehensive assessment of burned area extent in this region, providing a baseline for future studies on regeneration dynamics and long-term land cover change. Future studies should incorporate topographic factors, wind and broader climatic dynamics, and apply advanced models such as machine learning to improve fire impact assessments.

Author contributions All authors contributed to the study conception and design of the paper. Furkan Yilgan analysed remote sensing datasets using GEE platform with the relevant statistics calculations as well as wrote the first draft of the manuscript. Duygu Biyikli helped for writing the manuscript and interpretation of the results. Marsia Sanità helped for discussion of the results. Nasim Sadra wrote results part of the manuscript and interpreting the results. Guluzar Yigit contributed for determination of the study area with design of the methodology. Eva Savina Malinverni supported study with her academic knowledge. Sedat Dogan contributed with his academic experience to finalize the article and better interpret the results. All authors read and approved the final version of the manuscript.

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Declarations

Conflict of interest The authors have no relevant financial or non-financial interests to disclose.

Ethical approval All authors have read, understood, and have complied as applicable with the statement on “Ethical responsibilities of Authors” as found in the Instructions for Authors.

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