HACETTEPE UNIVERSITY

GEOMATICS ENGINEERING DEPARTMENT

GMT441 Applications of Remote Sensing

Wildfire Hazard Detection Using Remote Sensing Data Project

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Abstract

This study presents a wildfire impact assessment in the Attica region of Greece using Sentinel-1 SAR and Sentinel-2 optical satellite imagery. Pre-fire and post-fire analyses were conducted through the calculation of the Normalized Burn Ratio (NBR), delta NBR (dNBR), and SAR-based backscatter differences. Burn severity mapping was achieved by classifying dNBR values into five severity levels. A supervised Random Forest classification using pre-fire Sentinel-2 data and manually labeled burned and unburned polygons was performed to enhance mapping accuracy. Additionally, an unsupervised classification approach based on K-means clustering was applied to support the results. Accuracy assessment of the dNBR-based method yielded an overall accuracy of 66.3%, while the Random Forest classification achieved a higher overall accuracy of 91.2%. Despite limitations related to data availability and class imbalance, the integration of optical and SAR data provided reliable insights into fire-affected areas. These results demonstrate the potential of remote sensing approaches for rapid wildfire damage assessment and disaster management support.

1. Introduction

Background:

Wildfires are one of the most destructive natural disasters, with significant impacts on ecosystems, human lives, and infrastructure. They can spread rapidly across large areas, making early detection and damage assessment crucial for effective disaster management. Remote sensing technologies, such as those provided by satellite imagery, offer an efficient way to monitor large-scale environmental changes caused by wildfires. By utilizing satellite data, it is possible to track fire progression, assess the affected areas, and evaluate the severity of damage. In recent years, remote sensing data from Sentinel-1 (SAR) and Sentinel-2 (optical) satellites have become widely used for monitoring wildfire impacts. Sentinel-2 provides high-resolution optical imagery, allowing for vegetation analysis, while Sentinel-1 offers synthetic aperture radar (SAR) data that can detect structural changes caused by fire, even in areas with cloud cover. The combination of these two data sources allows for a comprehensive assessment of wildfire severity and the affected regions.

Problem Statement:

The main objective of this project is to use Sentinel-1 and Sentinel-2 data to detect areas affected by wildfires and assess the severity of the fire. On the 11th of August 2024, at approximately 12:00, a wildfire was reported to have affected the Attica region, near the village of Varnavas in Greece. The fire expanded rapidly due to strong winds, leading to the evacuation of residents from several villages. The Copernicus EMS Rapid Mapping service was requested to provide initial rough estimation and fire extent emergency mapping. This data is crucial for this study to assess the post-fire impact using remote sensing. By applying Normalized Burn Ratio (NBR) and SAR-based change detection techniques, this study aims to identify affected areas, classify them based on fire severity, and calculate the total burned area.

Objectives:

1. Detect the extent of fire-affected areas using Sentinel-1 SAR and Sentinel-2 optical data.
2. Assess the severity of the fire using delta NBR (dNBR) and SAR-based change detections.
3. Calculate the total burned area and analyze the relationship between burn severity and the affected area.

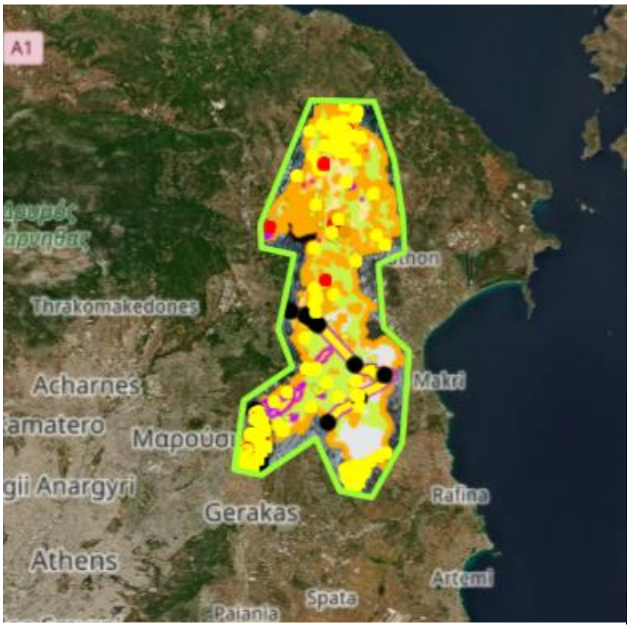

Figure 1 Map of the study area in Greece showing wildfire-affected regions. Burn severity levels were classified based on the delta Normalized Burn Ratio (dNBR) derived from Sentinel-2 imagery. The green outline represents the boundary of the study area defined for analysis.

2. Methods

2.1 Study Area

The study area is in Greece, near the city of Athens, which is known for its susceptibility to wildfires, particularly during the dry summer months. The region is characterized by forested areas, vegetation, and residential zones, all of which are highly vulnerable to fire breaks.

This area was selected for its relevance to ongoing wildfire monitoring efforts and because of the availability of recent satellite data for both pre- and post-fire periods.

The boundaries of the study area are defined by a polygon, which encompasses the regions most affected by wildfire. The coordinates of the study area are based on the polygon drawn in Google Earth Engine and are represented by the four corners, as shown in the map below.

2.2 Data Sources

This study utilizes remote sensing data from both Sentinel-2 (optical) and Sentinel-1 (SAR) satellites.

1. Sentinel-2 Data (Optical):
- Sensor Type: MultiSpectral Instrument (MSI)
- Bands Used:
- Red (B4), Green (B3), Blue (B2) for RGB visualization
- NIR (B8) and SWIR (B11) for Normalized Burn Ratio (NBR) calculation
- Resolution: 10m for RGB and 20m for NIR and SWIR bands
- Time Period:
  Pre-fire Image: July 20, 2024 – August 10, 2024
  Post-fire Image: August 12, 2024 – August 25, 2024

2. Sentinel-1 Data (SAR):
- Sensor Type: Synthetic Aperture Radar (SAR)
- Polarization: VV (Vertical-Vertical)
- Resolution: 10m
- Time Period:

Pre-fire Image: July 20, 2024 – August 10, 2024
Post-fire Image: August 12, 2024 – August 25, 2024

The data was acquired from the Google Earth Engine platform, which provides pre-processed and georeferenced imagery.

Figure 2 Selected high-risk areas from the pre-fire RGB image, displayed for detailed wildfire analysis.

2.3 Data Processing Workflow

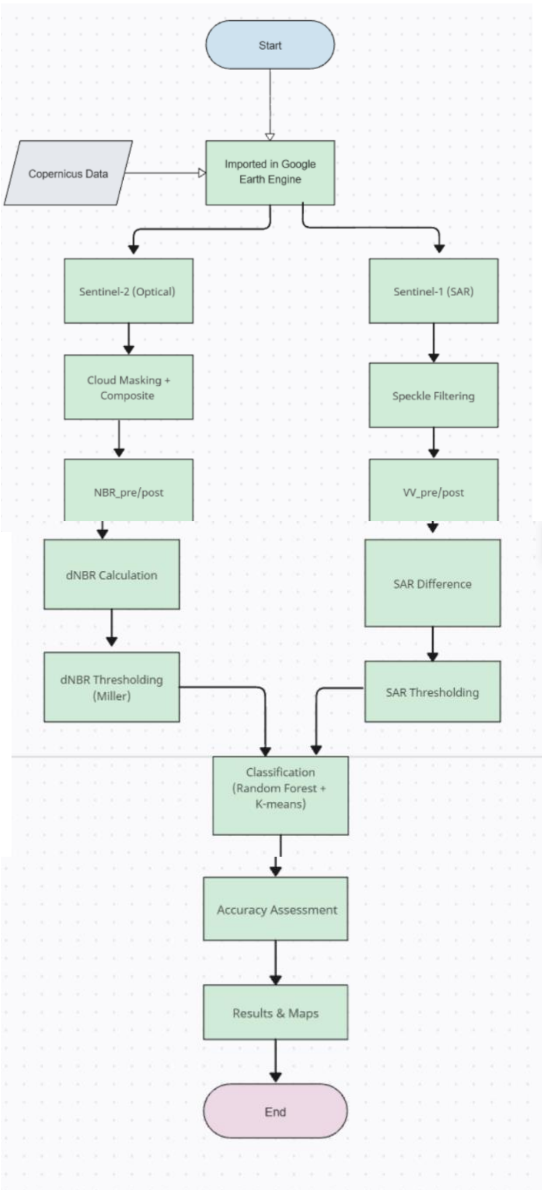

Figure 3 Workflow chart of the study.

2.3.1 Data Acquisition: Pre- and post-fire Sentinel-2 and Sentinel-1 images were collected, ensuring minimal cloud cover (<10%).

2.3.2 Preprocessing: Sentinel-2 optical data was cloud-masked, and Sentinel-1 SAR data was median-filtered to reduce noise.

2.4 Change Detection

- Normalized Burn Ratio (NBR): For optical data, NBR was calculated using the formula:

$$\text{NBR} = \frac{\text{NIR} - \text{SWIR}}{\text{NIR} + \text{SWIR}}$$

Figure 4 NBR formula.

- Delta NBR (dNBR): The difference between pre- and post-fire NBR values was computed to assess the fire's impact. High dNBR values indicate areas with severe damage. Positive dNBR represents the area likely burned and the bigger dNBR represents the more severe the burn.

$$\text{dNBR} = \text{NBR}_{\text{pre-fire}} - \text{NBR}_{\text{post-fire}}$$

Figure 5 dNBR formula.

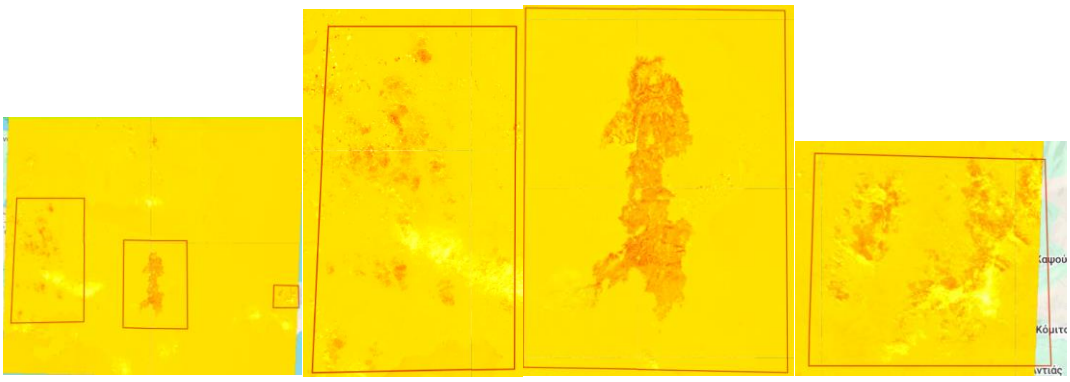

Figure 6 Detailed views of selected high severity burn areas from the dNBR map for focused analysis.

2.5 Classification

After the dNBR (delta Normalized Burn Ratio) and SAR change detection maps were generated, these maps were classified into different burn severity classes.

The classification process follows the guidelines from Miller et al. (2009). The classes are as follows:

- Unburned (Severity Class 0): No significant damage, unaffected by the fire.

- Low Severity (Severity Class 1): Areas with minor damage, typically characterized by slight vegetation loss.

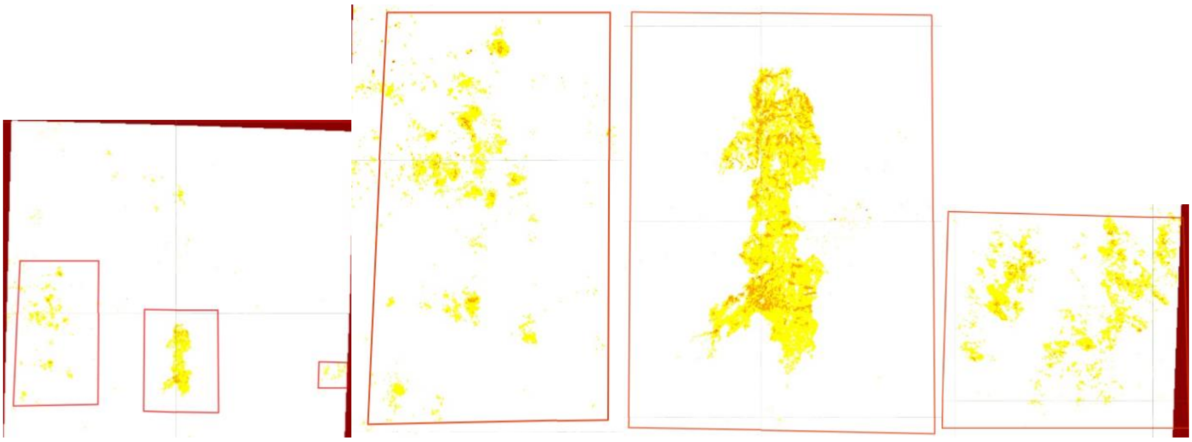

Figure 7 Burn severity image.

- Moderate-low Severity (Severity Class 2): Areas with noticeable fire impact but with some recovery in vegetation.
- Moderate-high Severity (Severity Class 3): Severe fire damage, substantial vegetation loss, and some structural damage.
- High Severity (Severity Class 4): Areas that have been completely devastated, with extensive damage to vegetation and structures.

The classification is performed using the delta NBR (dNBR) values, which measure the difference in vegetation health before and after the fire. High dNBR values correlate with severe fire damage, while low values correspond to areas with little or no impact.

2.6 SAR Change Detection.

SAR (Synthetic Aperture Radar) data from Sentinel-1 was used to detect changes in the surface caused by wildfire. The Sentinel-1 data is particularly useful as it can capture structural changes even under cloudy conditions. A comparison of pre-fire and post-fire data was made to detect the differences in backscatter values (dVV).

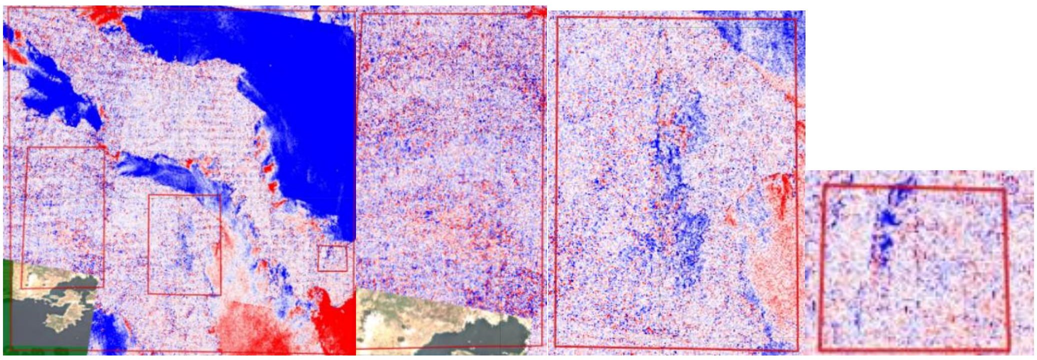

Figure 8 SAR VV backscatter difference image derived from pre- and post-fire Sentinel-1 data.

The difference between the backscatter before and after the fire is used to assess the areas that have undergone significant changes due to the fire. The process involves the following steps:

- Pre-processing: The pre-fire and post-fire SAR data are cleaned by reducing noise using a median filter.
- Change detection: The SAR data is processed to calculate the difference in backscatter values between pre- and post-fire data.

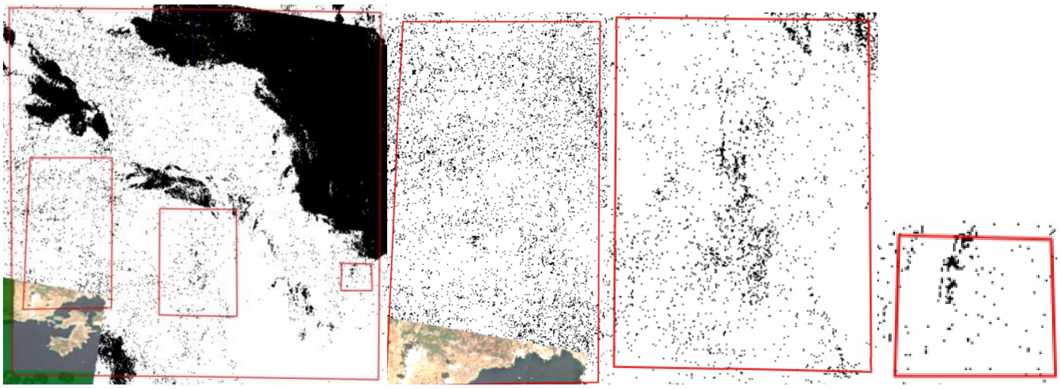

Figure 9 Burn detection map based on SAR backscatter differences.

- Thresholding: A threshold is applied to the dVV values to identify significant changes (e.g., structural damage or vegetation loss).
- Change Classification: After the change detection, areas are classified into categories such as "no change" and "change detected" based on the calculated dVV values.

2.7 Area Calculation

Once the areas were classified based on burn severity, the total area for each severity class was calculated. The process involves the following steps:

- Pixel area calculation: Each pixel in the classified map corresponds to a specific area (in square meters).
- Area aggregation: The total area for each burn severity class was calculated by summing up the area of all pixels that belong to that class.
- Unit conversion: The calculated area was converted from square meters to hectares for easier interpretation. This was done by dividing the total area in square meters by 10,000 (since 1 hectare = 10,000 m^2).

The total burned area was subsequently analyzed, and the severity classes were compared based on their spatial extent to evaluate the impact of the fire on the landscape.

2.8 Software and Tools:

Google Earth Engine: Used for data processing, analysis, and visualization.

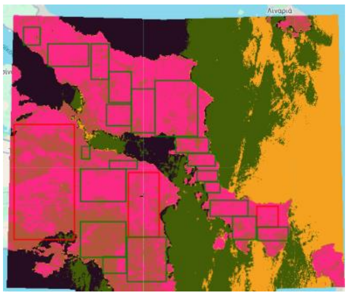

Figure 10 Unsupervised classification results showing the distribution of burned and unburned areas based on spectral clustering. Green boxes represent unburned regions, and red boxes indicate burned regions. indicate unburned regions, while red boxes highlight burned regions.

2.9 Unsupervised Classification

An unsupervised classification was applied to the pre-fire Sentinel-2 imagery using the K-means clustering algorithm. Five spectral clusters were created based on selected bands (B2, B3, B4, B8, B11) to identify different land cover types without using ground truth data.

Figure 10 Selected burned and unburned training areas used for Random Forest classification.

2.10 Supervised Classification Using Random Forest

A supervised classification was performed using the Random Forest algorithm on the pre-fire Sentinel-2 imagery. Training samples representing burned and unburned areas were collected as polygons and labeled with class values (0 for unburned, 1 for burned). Five spectral bands (B2, B3, B4, B8, and B11) were selected as input features. The classifier was trained with 100 trees and applied to the entire study area to generate the burn severity map.

3. Results

3.1 Burn Severity Mapping

In this study, Sentinel-1 and Sentinel-2 satellite data were employed to detect wildfire-affected areas and assess fire severity in the Attica region, Greece. The analysis focused on two primary metrics: **Normalized Burn Ratio (NBR)** and **SAR-based change detection**.

Figure 11 Pre-fire Sentinel-2 RGB image showing vegetation and land cover before the fire event.

The results of the **ΔNBR** (delta NBR) calculation enabled the classification of the study area into five burn severity classes: unburned, low severity, moderate-low severity, moderate-high severity, and high severity. The burn severity map (Figure 6) illustrates the spatial distribution of these classes:

- **Unburned areas (Class 0):** Primarily located in the southern section of the study region.
- **Low severity (Class 1)** and **moderate-low severity (Class 2):** Spread across central and northern parts of the region.
- **Moderate-high severity (Class 3)** and **high severity (Class 4):** Concentrated in the central zone, corresponding to regions of highest fire impact.
  The total area mapped per severity class is as follows:
- **Unburned:** 140.51 hectares
- **Low Severity:** 730.22 hectares
- **Moderate-low Severity:** 1,677.68 hectares
- **Moderate-high Severity:** 2.53 hectares
  Additionally, the total burned area, derived from SAR-based change detection, was estimated at **2,282.05 hectares**.
  The pre-fire RGB imagery (Figure 11) highlights the land cover and vegetation distribution before the wildfire, while the post-fire ΔNBR map (Figure 5) reveals the extent and severity of burn impacts, with higher ΔNBR values corresponding to more severe damage.

3.2 Accuracy Analysis

The accuracy of the burn severity classification was evaluated using a confusion matrix generated from 5,000 randomly sampled points across the study area. Each point was validated against the Copernicus EMSR746 reference burn area data.

The calculated accuracy metrics are as follows:

- **Overall Accuracy: 66.3%**
- **Kappa Coefficient: 0.022**

Producer's Accuracy:

- Unburned Class: **66.16%**
- Burned Class: **84.21%**

User's Accuracy:

- Unburned Class: **99.81%**
- Burned Class: **1.87%**

The confusion matrix (Table 1) shows that while the model captured a substantial portion of the burned areas, a considerable number of false positives were observed, as indicated by the low user's accuracy for the burned class. The relatively low kappa coefficient suggests a weak agreement beyond random chance.

Table 1. Confusion matrix for dNBR-based classification results.

	Predicted Unburned	Predicted Burned
Actual Burned	6	32
Actual Unburned	3283	1679

3.3 Random Forest Classification

The supervised Random Forest classification was performed using pre-fire Sentinel-2 imagery and training samples derived from manually labeled burned and unburned polygons. Five spectral bands (B2, B3, B4, B8, and B11) were used as input features, and the model was trained with 100 trees.

The Random Forest model achieved:

- **Overall Accuracy: 91.2%**
- **Kappa Coefficient: 0**

The corresponding confusion matrix (Table 2) indicates that the model effectively distinguished burned areas but suffered from a lack of unburned training samples, leading to a complete class imbalance. Despite the imbalance, the Random Forest classifier demonstrated high reliability in detecting burned areas, which was the primary goal of this analysis. Compared to the unsupervised classification, it provided more precise and interpretable outputs by leveraging labeled training data.

Table 2. Confusion matrix for supervised Random Forest classification results.

	Predicted Unburned	Predicted Burned
Actual Burned	46	454
Actual Unburned	0	0

4. Discussion

The results of the burn severity mapping and change detection using Sentinel-1 and Sentinel-2 data are consistent with field observations in the Attica region. Areas identified as having high burn severity correspond to the region's most heavily impacted by the wildfire, while unburned zones remained largely unaffected. This finding underscores the effectiveness of combining optical and SAR data for comprehensive wildfire assessment.

Initially, pre-fire imagery was intended to cover the period between **20 July–10 August 2024**. However, due to significant cloud contamination, the pre-fire window was adjusted to **20 June–20 July 2024**, and a **median composite** of cloud-free Sentinel-2 scenes was generated to improve data quality (Figure 12). This adjustment highlights the importance of flexible data acquisition strategies in wildfire studies.

4.1 Performance of Optical and SAR Data

While Sentinel-2 provided high-resolution optical imagery for vegetation analysis, Sentinel-1 SAR data significantly contributed to detecting structural changes caused by fire, particularly in regions where cloud cover hindered optical observations.
The **VV polarization** of Sentinel-1 (*see Figure 7*) proved effective in capturing differences in surface structure and vegetation density, reinforcing the complementary role of SAR data alongside optical imagery.

The strong correlation between SAR-based change detection and ΔNBR classification results further demonstrates that SAR methods are highly effective for **post-fire impact assessments**, particularly for identifying surface structure damage that optical imagery alone may not reveal. These findings are consistent with previous research highlighting the advantages and challenges of integrating optical and SAR data for wildfire assessment (López-Amoedo et al., 2021; Tariq et al., 2021).

4.2 Assessment of Supervised vs. Unsupervised Classification

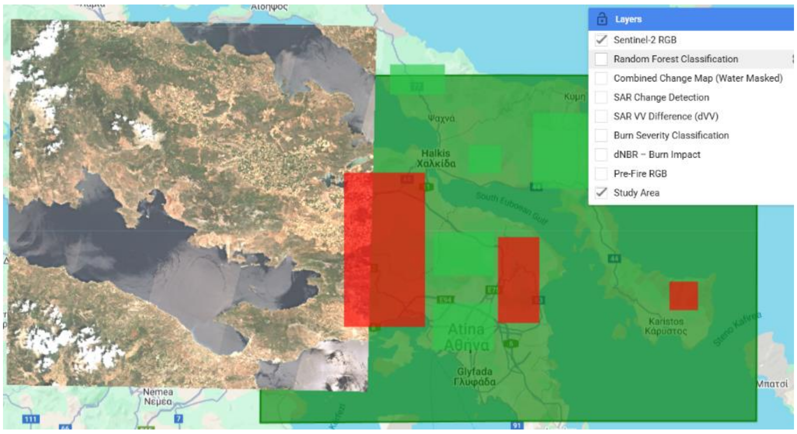

Figure 12 Availability of Sentinel-2 imagery within the initially selected pre-fire period (20 July–10 August 2024). The lack of cloud-free data during this timeframe required an adjustment to an earlier window (20 June–20 July 2024) for pre-fire analysis.

The **Random Forest** classification (*see Figure 10*) successfully distinguished burned and unburned areas across the study region. Burned regions aligned well with ground truth polygons, and areas of healthy vegetation were consistently classified as unburned.
The model achieved an **overall accuracy of 91.2%** (*see Table 2*), confirming its reliability in detecting fire-affected zones. However, due to the limited number of unburned training samples, the confusion matrix revealed a class imbalance, resulting in a **Kappa coefficient of 0**. Despite this, the model's strong ability to map burned areas served the primary objective of this study.

In contrast, the **unsupervised classification** using K-means clustering provided a general overview of land cover classes without relying on training data (*see Figure 9*). Visual interpretation suggested that healthy vegetation, severely burned surfaces, and moderately burned zones were reasonably separated. Nevertheless, the absence of class labels and reliance solely on spectral similarity introduced **potential**

misclassifications. Thus, unsupervised classification is best utilized as a complementary method rather than a standalone approach.

4.3 Accuracy Assessment Insights

The confusion matrix results (*see Table 1*) for ΔNBR-based classification showed an **overall accuracy of 66.3%** but a **low Kappa coefficient (0.022)**, indicating weak agreement beyond random chance. While the producer's accuracy for the burned class was relatively high (**84.21%**), the **user's accuracy for the burned class was extremely low (1.87%)**, implying that many areas classified as burned may have been misidentified.

This discrepancy may arise from:

- **Spectral confusion** between lightly burned and unburned vegetation
- **Simplistic thresholding** in ΔNBR calculation
- **Limitations** in using optical data alone without additional ancillary information (e.g., vegetation indices, SAR backscatter)

Future improvements could focus on refining classification thresholds and integrating multi-source datasets to enhance mapping accuracy.

4.4 Limitations

Several limitations were encountered during the study:

- **Cloud contamination:** Despite selecting a <10% cloud cover dataset, cloud interference necessitated shifting the pre-fire window and building a median composite.
- **Resolution constraints:** Sentinel-2's 10m spatial resolution is effective for regional analysis but may miss finer-scale burn patterns.
- **Water sensitivity:** The NBR method, although useful, could be further enhanced using NBR2 or SWIR-based indices to better assess water-related burn impacts.

Despite these limitations, the integration of optical and SAR data proved highly valuable for comprehensive wildfire analysis.

5. Conclusions

The study successfully demonstrates the effectiveness of using Sentinel-1 and Sentinel-2 satellite data for detecting wildfire-affected areas and assessing fire severity. The combination of NBR, delta NBR (dNBR), and SAR-based change detection methods provides a robust approach to understanding the extent of wildfire damage and classifying burn severity.

The results from the dNBR and SAR change detection analyses (*see Figure 5 & 8*) are consistent and reliable, offering valuable insights into the spatial distribution of fire impacts. This information can be used to support disaster management, post-fire recovery, and land restoration efforts.

Combining optical and SAR data enhances both the accuracy and reliability of wildfire impact assessment. NBR and SAR-based change detection methods are effective for classifying fire severity and detecting structural changes. The findings emphasize the strong need for timely satellite data to monitor post-fire recovery and assess long-term impacts on vegetation and infrastructure.

5.1 Who Can Utilize These Results?

The results of this study can be utilized by emergency response agencies, environmental monitoring organizations, forest management authorities, and disaster relief teams. By providing timely and accurate assessments of fire impacts, these stakeholders can plan better response strategies and implement more effective recovery efforts.

6. References

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