Assessment of Vegetation Damage Due to the 2017 Split Fire in Croatia Using Sentinel-2 Imagery and Remote Sensing Techniques

Alessio De Luca *

* *Artificial Intelligence for Science and Technology, Università degli Studi di Milano-Bicocca, ID: 919790 (email: a.deluca63@campus.unimib.it)*

Abstract: This study investigates the impact of the 2017 wildfire near Split, Croatia, on vegetation using remote sensing techniques. Leveraging Sentinel-2 satellite data, we analyzed pre- and post-fire conditions to assess the extent of vegetation loss and recovery. Key indices, such as the Normalized Difference Vegetation Index (NDVI) and Normalized Burn Ratio (NBR), were employed to quantify vegetation health and burn severity. Additionally, RGB imagery was used for visual inspection, and unsupervised clustering was conducted to identify distinct areas affected by the fire. The findings provide valuable insights into the environmental consequences of wildfires and the utility of remote sensing for monitoring ecosystem recovery.

Keywords: Remote Sensing, Sentinel-2, Wildfire, Vegetation, NDVI, NBR, Unsupervised Clustering, Split Fire 2017, Google Earth Engine, Environmental Monitoring

1. INTRODUCTION TO THE SPLIT FIRE OF 2017

In July 2017, a massive wildfire broke out near Split, Croatia, one of the largest urban areas along the Adriatic coast. The fire started on July 17, 2017, and rapidly spread due to strong winds and dry conditions, which are typical during the summer months in the Mediterranean region. The fire burned for several days, causing widespread damage to both natural and urban areas. The blaze affected approximately 4,500 hectares of land, including forests, agricultural fields, and residential areas.

The cause of the fire was believed to be a combination of natural and human factors, including high temperatures, low humidity, and potential human negligence. The fire threatened several villages, leading to the evacuation of residents and tourists. Firefighters, along with the Croatian military and international assistance, eventually managed to contain the fire after several days of intense effort. Despite their work, the fire caused significant environmental damage, destroying large areas of vegetation and leaving a lasting impact on the local ecosystem.

This tragic event is a reminder of the increasing frequency and intensity of wildfires in Mediterranean regions, likely aggravated by climate change. These events underscore the importance of monitoring and managing affected areas to assess the environmental damage and aid in recovery efforts. Remote sensing techniques, such as those utilized in this study, provide valuable tools for this purpose, enabling large-scale analysis of affected areas over time.

2. REMOTE SENSING AND SENTINEL-2 OVERVIEW

Remote sensing is a powerful method for collecting information about the Earth's surface without direct physical contact. This is achieved through the use of satellites, aircraft, or drones that capture data in the form of images or other sensor readings. Remote sensing is extensively used in environmental monitoring, agriculture, forestry, urban planning, and disaster management, among other fields. It allows for the observation of large and often inaccessible areas, providing critical data for understanding and managing Earth's natural resources and environmental changes.

One of the key tools in remote sensing is satellite imagery, and among the many satellites available, the Sentinel-2 mission, part of the European Union's Copernicus Program, stands out for its high-resolution optical imagery. The Sentinel-2 mission consists of two identical satellites, Sentinel-2A and Sentinel-2B, launched by the European Space Agency (ESA) in 2015 and 2017, respectively. A third satellite, Sentinel-2C, has been released on September 2024. These satellites provide continuous coverage of the Earth's surface, capturing images with a spatial resolution of up to 10 meters and revisiting the same location every five days, which is crucial for monitoring dynamic environmental phenomena like wildfires.

Sentinel-2, shown in Fig. 1, carries a multispectral instrument (MSI) that captures data in 13 spectral bands, ranging from visible to shortwave infrared. These bands allow for detailed analysis of various Earth surface features, including vegetation, water bodies, and urban areas. The spectral bands are divided as follows:

Visible Bands (10m resolution):

Band 2 (Blue, 490 nm)

Band 3 (Green, 560 nm)

Band 4 (Red, 665 nm)

Near-Infrared Bands (10m resolution):

Band 8 (NIR, 842 nm)

Red-Edge Bands (20m resolution):

Band 5 (705 nm)

Band 6 (740 nm)

Band 7 (783 nm)

Shortwave Infrared Bands (20m resolution):

Band 11 (SWIR, 1,610 nm)

Band 12 (SWIR, 2,190 nm)

Atmospheric Correction Bands (60m resolution):

Band 1 (Coastal aerosol, 443 nm)

Band 9 (Water vapor, 940 nm)

Band 10 (Cirrus, 1,375 nm)

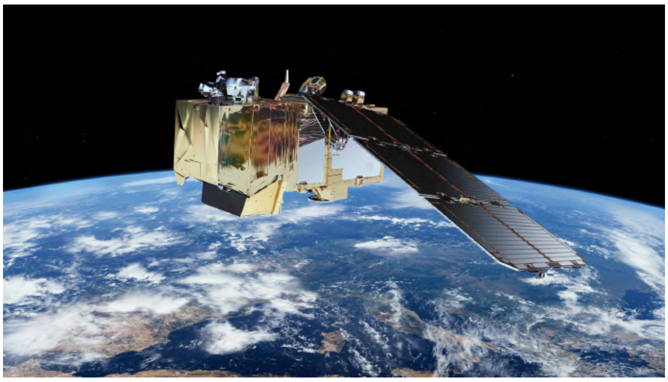

Fig. 1. Image of the Sentinel-2 satellite.

The wide range of bands enables the analysis of vegetation health, water content, soil properties, and atmospheric conditions. In wildfire studies, the Near-Infrared (NIR) and Shortwave Infrared (SWIR) bands are particularly useful for assessing burn severity and vegetation recovery, as they are sensitive to changes in vegetation structure and moisture content.

In this project, Sentinel-2 data is processed using Google Earth Engine, a cloud-based platform that allows for efficient analysis of large geospatial datasets. Through the use of indices like NDVI, which highlights healthy vegetation, and NBR, which emphasizes burned areas, we can assess the impact of the Split fire on the local ecosystem. Unsupervised clustering further aids in identifying distinct patterns within the affected regions, providing a comprehensive view of the fire's aftermath and the subsequent regeneration process.

3. DATA COLLECTION

The first step of the work was to select an area of interest and the images to work with. The Area of Interest (AOI) was defined by a point near Split,Croatia, which was near the epicenter of the Wildfire (coordinates: 16.563798, 43.496451). As for the Satellite Images, we decided to collect 3 of them, in particular: Pre-Fire Image, dated 2017-07-07, During-Fire Image, dated 2017-07-17, and Post-Fire Image, dated 2017-08-06. The reason we selected 3 images was to be able to make a comparison of the evolution of the ground as the Wildfire spread out. The imagery was sourced from the COPERNICUS/S2_SR_HARMONIZED collection and saved in TIFF format.

A TIFF (Tagged Image File Format) image is a high-quality, flexible image file format widely used in photography, publishing, and geographic information systems (GIS). It supports lossless compression, meaning it retains all image data without loss of quality, making it ideal for detailed images and extensive post-processing. TIFF files can store multiple layers or pages, handle various color depths (grayscale, RGB, CMYK), and are often used in professional environments where image fidelity is crucial. In our case, we can save images with the bands we want to select: for this project, we decided to import bands 2, 3, and 4 to visualize images in RGB. Two additional bands were imported, B8 and B12, allowing for the calculation of indices for better visualization.

Sentinel-2 indices are mathematical combinations of different spectral bands that help highlight specific features of the Earth's surface. These indices are crucial for monitoring vegetation health, water content, burn severity, and other environmental factors. They are calculated using specific band ratios or differences and are available on platforms like Sentinel Hub, where you can directly apply them to satellite imagery.

NDVI (Normalized Difference Vegetation Index)

NDVI is one of the most commonly used indices for assessing vegetation health and density. It uses the difference between the near-infrared (NIR) and red bands, capitalizing on the fact that healthy vegetation reflects more NIR light and absorbs more red light.

The formula for NDVI is:

$$\mathrm{NDVI} = \frac{\mathrm{B8} - \mathrm{B4}}{\mathrm{B8} + \mathrm{B4}} \tag{1}$$

Where:
B8 is the Near-Infrared (NIR) band.
B4 is the Red band.

NDVI values range from -1 to $+1$, where higher values indicate healthier vegetation. It is widely used in agriculture, forestry, and environmental monitoring to assess plant health, monitor crop conditions, and detect changes in vegetation over time.

NBR (Normalized Burn Ratio)

NBR is used to assess burn severity in forest fires by comparing pre- and post-fire satellite imagery. It relies on the contrast between the NIR and shortwave infrared (SWIR) bands, as burned areas typically reflect less NIR and more SWIR light.

The formula for NBR is:

$$\mathrm{NBR} = \frac{\mathrm{B8} - \mathrm{B12}}{\mathrm{B8} + \mathrm{B12}} \tag{2}$$

Where:

B8 is the Near-Infrared (NIR) band.

B12 is the Shortwave Infrared (SWIR) band.

NBR values help distinguish between burned and unburned areas and can also be used to monitor vegetation recovery after a fire. It is a valuable tool in disaster management and ecological studies.

Using these indices, we can enhance our analysis and better understand the environmental conditions captured by Sentinel-2 imagery.

4. IMAGES VISUALIZATION AND CONSIDERATIONS

4.1 RGB Images analysis

The first images we analyzed were in RGB format. By examining Fig. 2 to Fig. 4 from top to bottom, it becomes quite clear how the wildfire evolved and the extent of the damage it caused. In the first image, the entire area appears green, with no noticeable signs of fire damage. However, in the second and third images, which were taken during and after the fire, the active fire is visible with smoke rising, and the extent of the damage from the fire is evident. Comparing the pre-fire and post-fire images provides a clear visualization of the wildfire's devastating impact on the vegetation. What was once green is now burnt and transformed into dark brown and black patches. This contrast not only illustrates the severe damage but also highlights the vast scale of the wildfire. Notably, on the left side of each image, you can see Split, which is nearly as large as the burned area, further emphasizing the scale of the disaster.

Fig. 2. RGB image pre wildfire.

Fig. 3. RGB image during wildfire.

Fig. 4. RGB image post wildfire.

4.2 NDVI Index Analysis

The second set of images we examined were NDVI images. These images provide a different perspective on the wildfire's impact by highlighting the health of vegetation. In the NDVI images, healthy vegetation is represented by high values, appearing in bright green, while burned or damaged areas show lower values, which are depicted in shades of orange to red. In the initial NDVI image, the area appears uniformly green and yellow, indicating robust vegetation with no visible damage. In contrast, the subsequent images, captured during and after the fire, reveal a dramatic shift. The green areas are now replaced by large red patches, corresponding to lower NDVI values, showcasing the extensive damage. The NDVI images clearly illustrate the severe reduction in vegetation health, with the burned areas contrasted against the surviving green patches.

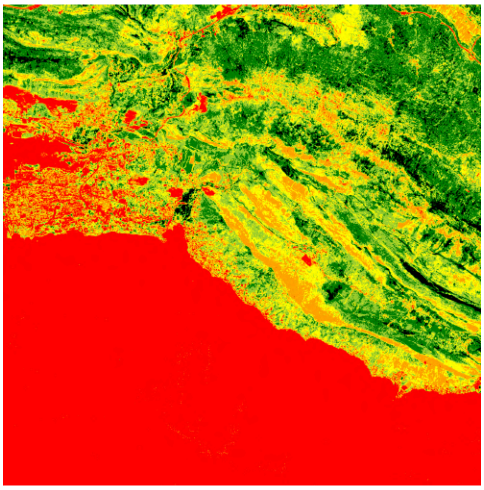

Fig. 5. NDVI image pre wildfire.

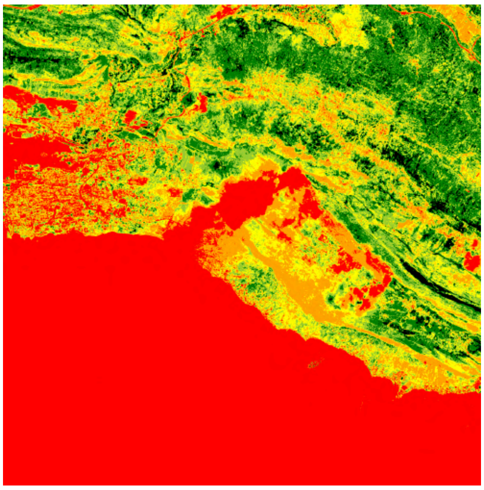

Fig. 6. NDVI image during wildfire.

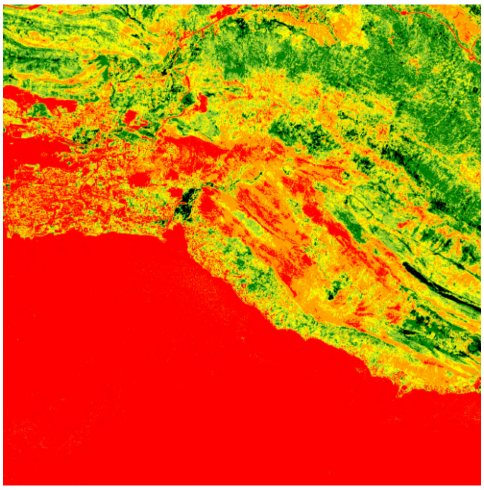

Fig. 7. NDVI image post wildfire.

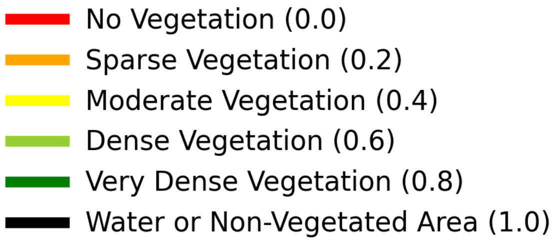

Fig. 8. NDVI index legend.

To further illustrate the changes in NDVI values, Fig. 9 highlights the differences between pre- and post-fire images. In this comparison, blue areas indicate a decrease in NDVI values, red areas show an increase, and white areas represent no change. The map reveals extensive dark blue regions, which precisely correspond to areas where the vegetation has burned. This visual representation clearly demonstrates the significant loss in vegetation health across the affected areas.

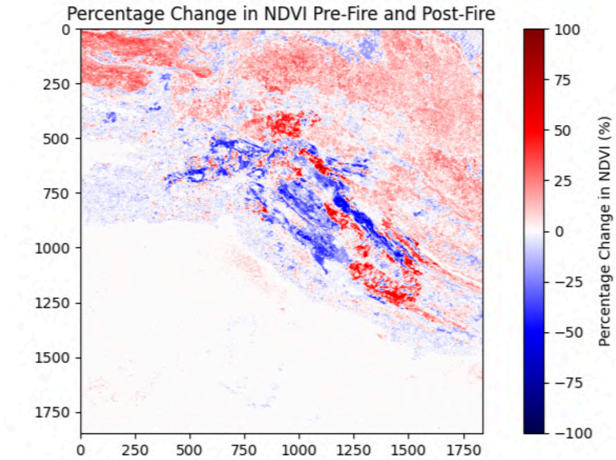

Fig. 9. Difference between NDVI index pre and post fire.

4.3 NBR Index Analysis

Continuing with our analysis, the third set of images we reviewed were NBR images. These images help us identify fire-affected areas by showing the contrast between burned and unburned regions. In the pre-fire NBR image, the landscape shows mostly gray areas, indicating no recent fire activity. However, in the images taken during and after the fire, a large black area becomes visible, contrasting significantly with the pre-fire image. This blackened region highlights the extent of the burn, revealing how extensive the wildfire's impact was. The clear difference between the pre-fire and post-fire NBR images effectively illustrates the scale and severity of the wildfire.

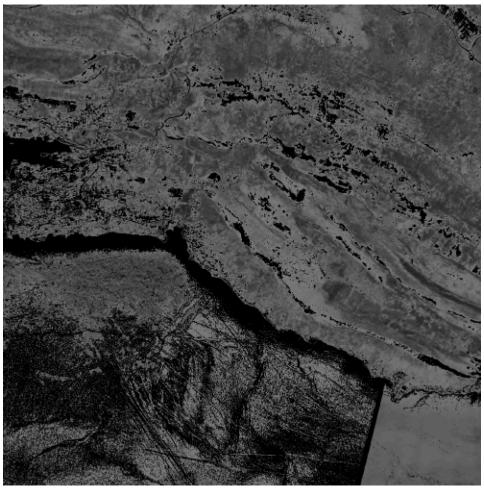

Fig. 10. NBR image pre wildfire.

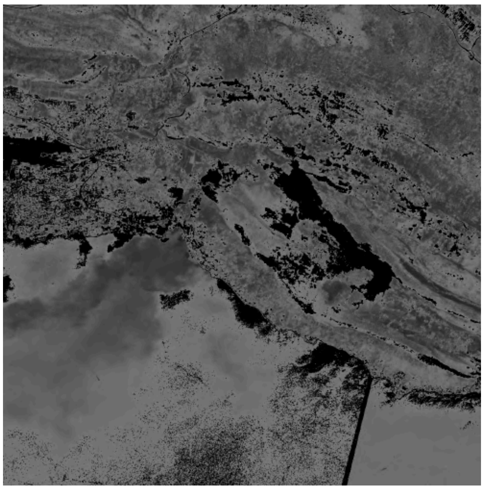

Fig. 11. NBR image during wildfire.

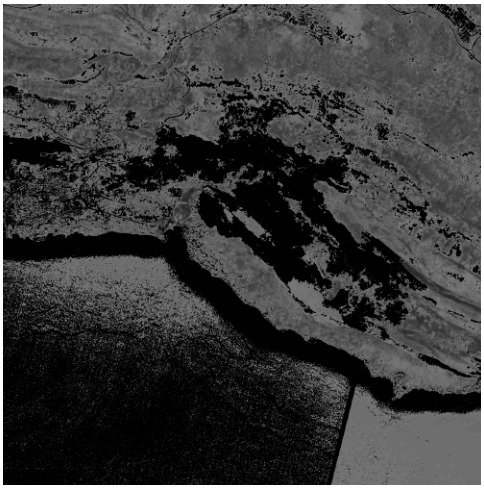

Fig. 12. NBR image post wildfire.

Fig. 13 image offers a clear visualization of the changes in the NBR index before and after the fire. The blue areas in the image indicate regions where vegetation has been burned, providing a clear depiction of the fire's impact. It is important to note that the sea regions should be disregarded, as they are not the focus of this study and may exhibit anomalous index values.

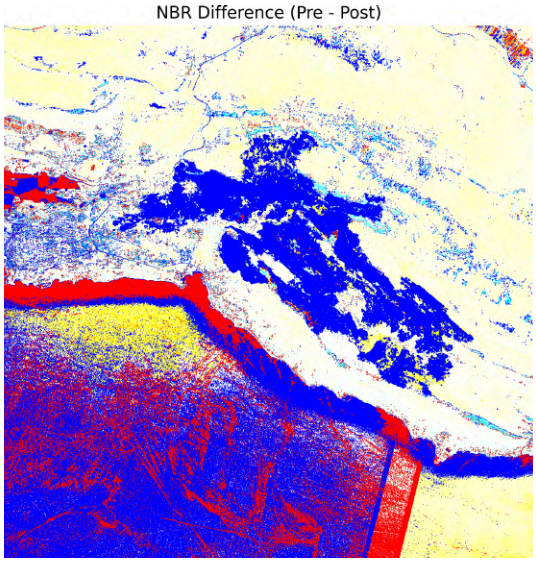

Fig. 13. Difference between NBR index pre and post fire.

5. UNSUPERVISED CLUSTERING

Unsupervised clustering in remote sensing, particularly using Google Earth Engine (GEE), is a powerful technique for analyzing large sets of geospatial data without requiring labeled training samples. This approach leverages algorithms to group data points into clusters based on their similarities, allowing researchers to identify patterns and structures within the data.

In GEE, the *ee.Clusterer* package is central to performing unsupervised classification. This package encompasses a variety of clustering algorithms derived from the Weka machine learning library, which are designed to handle different types of clustering tasks. These algorithms operate without predefined class labels, making them ideal for exploring and analyzing spatial datasets where the structure of the data is not known in advance.

The typical workflow for clustering in GEE involves several steps. First, a dataset with numerical features is assembled. These features can be derived from satellite imagery, where each pixel or feature point contains multiple spectral bands or indices. Next, a clusterer is instantiated, and its parameters are configured according to the specific requirements of the analysis. The clusterer is then trained using a sample of the dataset, enabling it to identify patterns and group similar data points into clusters. Once trained, the clusterer can be applied to the entire image or feature collection, assigning cluster IDs to each pixel or feature. The final step is to label the clusters, providing meaningful interpretations for the identified groupings.

Google Earth Engine supports several clustering algorithms, each with its own strengths and use cases:

K-Means Clustering: This algorithm partitions data into a predefined number of clusters by iteratively assigning data points to the nearest cluster centroid and updating the centroid positions. It is simple and effective but requires specifying the number of clusters in advance.

Cascade K-Means: An extension of K-Means, Cascade K-Means can handle varying numbers of clusters and includes a process to automatically determine the optimal number of clusters. It iterates through a range of cluster numbers, adjusting as needed to improve clustering results.

Learning Vector Quantization (LVQ): This algorithm uses a supervised approach to refine cluster boundaries, although it can be adapted for unsupervised use. LVQ adjusts cluster centers based on learning rates and epochs, allowing for more nuanced clustering of complex datasets.

X-Means Clustering: X-Means extends K-Means by dynamically adjusting the number of clusters. It uses model selection criteria to decide on the optimal number of clusters, making it suitable for datasets where the number of clusters is not known beforehand.

5.1 Results analysis

In our analysis of different clustering methods for remote sensing imagery, we tested four techniques: K-Means, Cascade K-Means, Learning Vector Quantization (LVQ), and X-Means. Each method was applied to both pre-fire and post-fire images.

Starting with K-Means, we set the number of clusters to 4, targeting specific features like water, vegetation, and burnt areas. The pre-fire image clustering did not yield interpretable results, likely due to the absence of burnt areas at that stage. However, the post-fire clustering performed much better, accurately identifying water in green and burnt areas in pink, while yellow and brown represented other landscape features.

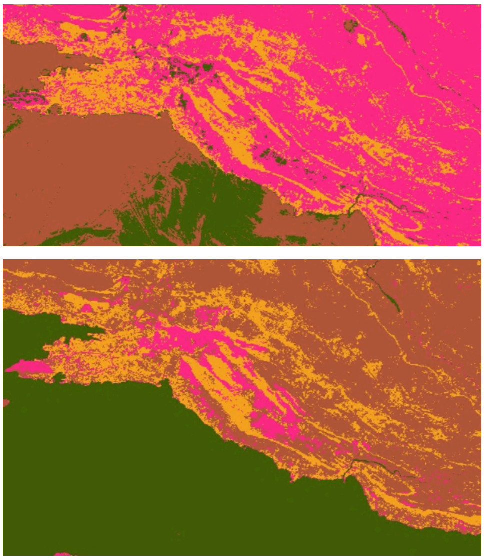

Fig. 14. K-Means clustering visualization.

Cascade K-Means was configured to search for the optimal number of clusters between 5 and 7, ultimately selecting 5 clusters as the best fit. This method performed well, especially in the post-fire image, where it successfully highlighted the burnt area in yellow.

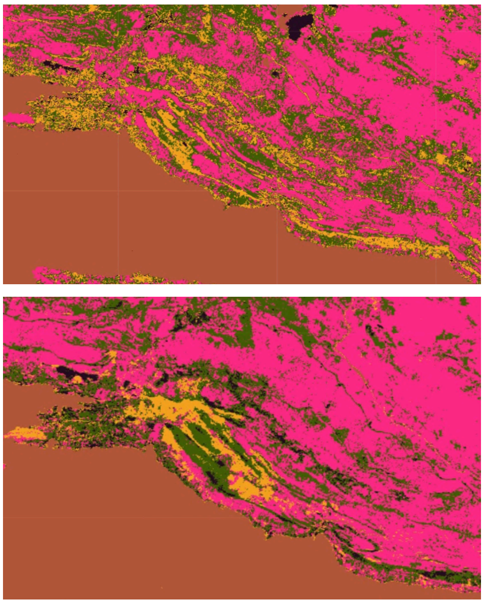

Fig. 15. Cascade K-Means clustering visualization.

LVQ was tested using the following parameters: 4 clusters, a learning rate of 0.5, 1000 epochs, and normalized input data. This method performed consistently well in both pre-fire and post-fire images. In the post-fire image, LVQ clearly delineated the wildfire area, showing its effectiveness in identifying burnt regions.

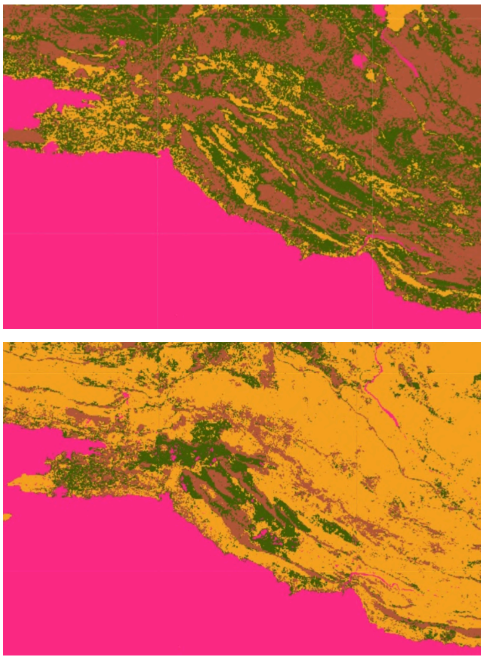

Fig. 16. LVQ clustering visualization.

Finally, X-Means was tested with parameters allowing for 2 to 8 clusters and other fine-tuned settings. While this method did not perform as well overall, it did manage to highlight the wildfire area in the post-fire image.

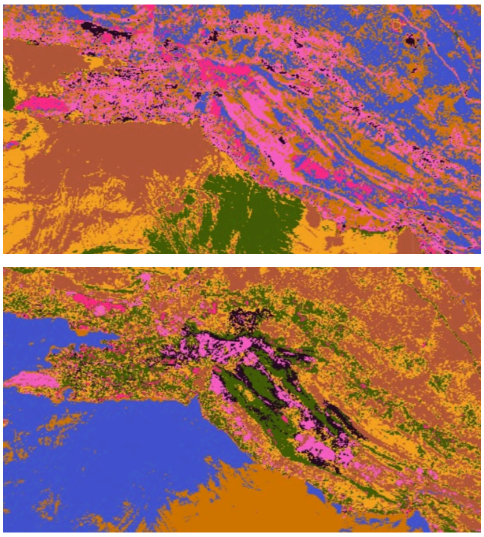

Fig. 17. X-Means clustering visualization.

Overall, each clustering method provided valuable insights, with LVQ, K-Means and Cascade K-Means standing out as particularly effective for identifying wildfire-affected areas.

6. CONCLUSIONS

This study demonstrates the value of Sentinel-2 imagery and remote sensing techniques for assessing vegetation damage from wildfires. By utilizing NDVI and NBR indices, we were able to effectively capture the extent of the 2017 Split Fire's impact on the local ecosystem. These indices provided clear visualizations of vegetation loss and burn severity.

In addition, the application of unsupervised clustering methods—K-Means, Cascade K-Means, and LVQ—proved effective in identifying fire-affected areas. Each method successfully highlighted the burned regions, with LVQ and Cascade K-Means standing out for their precise delineation of wildfire damage. X-Means, while useful, performed less effectively compared to the other methods.

Overall, the integration of remote sensing and clustering techniques provides a powerful approach for monitoring and managing wildfire damage. These tools offer critical insights that can support environmental recovery efforts and inform future disaster management strategies.

References

1. N. C. A. Y. Jin, A. N. Wilkinson, and B. J. Smith, "Assessment of Wildfire Impacts on Vegetation Using Remote Sensing Data," International Journal of Remote Sensing, vol. 41, no. 8, pp. 3145-3168, 2020.
2. D. D. Chen, M. R. Epting, and J. A. Rogan, "Remote Sensing of Post-Fire Vegetation Recovery: A Review," Remote Sensing of Environment, vol. 237, p. 111593, 2020.
3. G. K. R. M. Xu, P. Du, and S. Li, "Using Sentinel-2 Data to Assess Wildfire Damage in Mediterranean Ecosystems," Remote Sensing, vol. 10, no. 3, p. 456, 2018.
4. A. K. G. K. Kamal, N. Khanna, and P. K. Sharma, "Analyzing Wildfire Severity with NDVI and NBR Indices from Sentinel-2 Imagery," Environmental Monitoring and Assessment, vol. 193, no. 8, pp. 1-13, 2021.
5. E. A. J. Smith, and P. D. Jones, "Application of Google Earth Engine for Large-Scale Fire Damage Assessment," Journal of Applied Earth Observation and Geoinformation, vol. 95, p. 102263, 2021.
6. M. I. Gonzalez, and R. G. Lee, "Unsupervised Clustering in Remote Sensing for Environmental Monitoring," IEEE Transactions on Geoscience and Remote Sensing, vol. 58, no. 5, pp. 3210-3224, 2020.