HACETTEPE UNIVERSITY
DEPARTMENT OF
GEOMATICS ENGINEERING

GMT446 - Microwave Sensing Systems

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21905024

CONTENTS

Introduction

Forest fires are one of the events that can lead to environmental issues globally, threatening ecosystems. Damages caused by fires are associated with factors such as loss of vegetation, habitat destruction, and atmospheric pollution. These fires can impact biodiversity, alter atmospheric conditions, and harm water sources. Moreover, fires pose threats to agricultural areas and settlements, resulting in economic losses and long-term environmental effects. In this context, evaluating and accurately mapping the impacts of forest fires is crucial. This study will discuss the situation assessment of a forest fire in the Attica Region of Greece, and techniques identified for comparing data will be addressed.

Within the scope of the project, the focus has been on the use of dual-polarimetric and quad-polarimetric Synthetic Aperture Radar (SAR) remote sensing data. In this context, the utilization of SENTINEL-1 satellite Level-1 GRD data provides a robust tool for analyzing the pre- and post-fire conditions and determining the extent of damage. SENTINEL-1 data stands out as a source with high resolution, frequency, and advantages in radar technology. These data can track surface changes with high precision, making them a powerful tool, especially in identifying areas affected by events such as forest fires.

This study aims to analyze the effects of a specific forest fire event using SENTINEL-1 satellite data before and after the incident, and to present statistical, graphically and mathematical comparisons for pre- and post-fire conditions. The information gathered will provide a crucial foundation for developing intervention strategies for forest fires and protecting natural ecosystems.

The forest fire to be examined in the study took place on Tuesday, August (11.56 local time) in the forest area near the Kleiston Monastery on Mount Parnitha in the Attica Region of Greece. The forest fire study area is approximately 493000000 square meters.

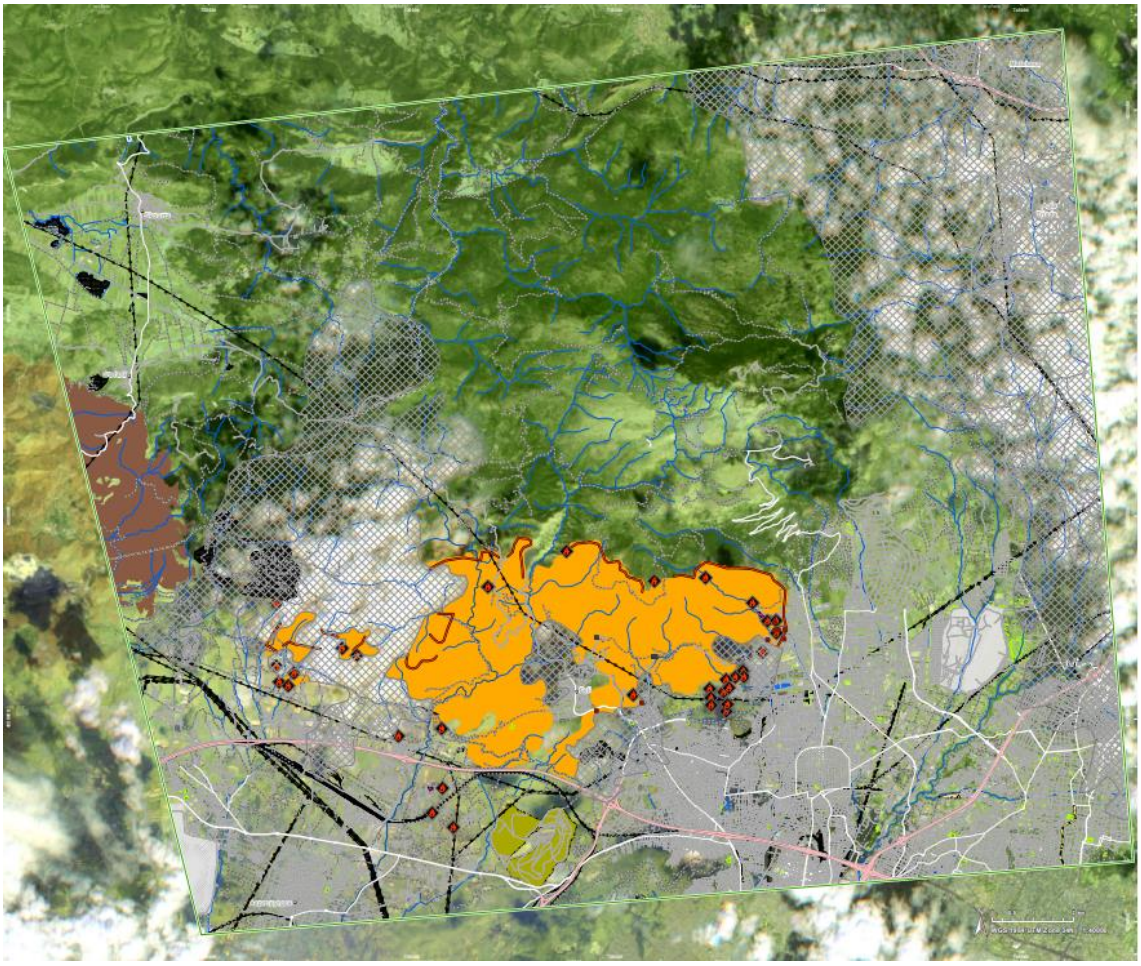
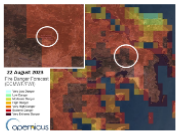


Figure 1: Wildfire Area

Activation

Timeline



22/08 - Fire Danger

Fire danger from *Extreme danger* to *Very Extreme Danger* within the area of Parnitha mountain, according to the Fire Danger Forecast (EFFIS)

22/08 (08:56) - Event description

On Tuesday of 22 August (11.56 local time) a wildfire started in a forest area near the monastery of Kleiston on Parnitha mountain in Attica Region. The fire has led to the destruction of houses and vehicles in suburb of Fyli (Source: GreekReporter.com)

23/08 (08:36) - Activation start

On the 23 August 2023 at 08:36 UTC, the General secretariat for Civil protection of Greece triggered Copernicus EMS Rapid Mapping service to cover the fire event affecting the Parnitha mountain. Copernicus EMS Rapid Mapping was requested to provide initial rough estimation, fire extent and daily monitoring emergency mapping.

23/08 - First production plan

Sentinel-2 satellite imagery was acquired on the 23rd of August on the affected area. The production of a delineation map started immediately after satellite data reception.

23/08 (20:27) - First Delineation Product - Delivery

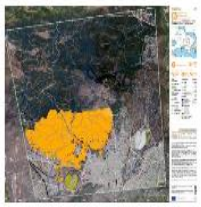
Analysis of a Sentinel 2A/B image 16.6 m / 3027.6 ha burned.

24/08 (18:39) Delineation Monitoring 01 Product - Delivery

Analysis of a GeoEye image 2.0 m / 5741.6 ha burned.

25/08 (21:03) Delineation Monitoring 02 Product - Delivery

Analysis of a GeoEye image 2.0 m / 6105.8 ha burned.



28/08 (18:13) Delineation Monitoring 03 Product - Delivery

Analysis of a GeoEye image 2.0 m / 6193.1 ha burned.

Wildfire Timeline

Methods

The forest fire to be examined in the study took place on Tuesday, August (11.56 local time) in the forest area near the Kleiston Monastery on Mount Parnitha in the Attica Region of Greece. The forest fire study area is approximately 493000000 square meters.

Within the scope of the project, SENTINEL-1 Level-1 GRD data was downloaded from the Copernicus DataSpace section for the fire date of 22/08/2023 morning UTC. The selected data covers the period pre (20.08.2023) and post (13.09.2023) when the fire started. Compatibility was determined by examining satellite features for pre-fire and post-fire data.

Beginning date time:	Completion time from ascending node:	Cycle number:	Datatake id:
2023-08-20T04:31:56.853Z	2341287	300	393833
Ending date time:	**Instrument configuration id:**	**Instrument short name:**	**Operational mode:**
2023-08-20T04:32:21.852Z	7	SAR	IW
Orbit direction:	**Orbit number:**	**Origin:**	**Platform serial identifier:**
DESCENDING	49954	ESA	A
Platform short name:	**Polarisation channels:**	**Processing center:**	**Processing date:**
SENTINEL-1	VV&VH	Production Service-SERCO	2023-08-20T05:07:08.959937+00:00
Processing level:	**Processor name:**	**Processor version:**	**Product class:**
LEVEL1	Sentinel-1 IPF	003.61	S
Product composition:	**Product type:**	**Relative orbit number:**	**Segment start time:**
Slice	IW_GRDH_1S	7	2023-08-20T04:22:18.152000+00:00

Beginning date time:	Completion time from ascending node:	Cycle number:	Datatake id:
2023-09-13T04:31:57.828Z	2341283	302	396898
Ending date time:	**Instrument configuration id:**	**Instrument short name:**	**Operational mode:**
2023-09-13T04:32:22.826Z	7	SAR	IW
Orbit direction:	**Orbit number:**	**Origin:**	**Platform serial identifier:**
DESCENDING	50304	ESA	A
Platform short name:	**Polarisation channels:**	**Processing center:**	**Processing date:**
SENTINEL-1	VV&VH	Production Service-SERCO	2023-09-13T05:08:46.412688+00:00
Processing level:	**Processor name:**	**Processor version:**	**Product class:**
LEVEL1	Sentinel-1 IPF	003.61	S
Product composition:	**Product type:**	**Relative orbit number:**	**Segment start time:**
Slice	IW_GRDH_1S	7	2023-09-13T04:22:19.126000+00:00

Figure 2: Satellite information of data before (left image) and after (right image) wildfire date

You can observe the compatibility of the Sentinel data acquired for both dates in the shared image in Figure 2.

The downloaded data is being prepared for pre-processing using the SNAP (Sentinel Application Platform) application. SNAP is a free and open-source software platform developed for processing and analyzing Sentinel satellite data. This platform provides a user-friendly tool, particularly designed for researchers, experts, and environmental professionals working with Sentinel-1, Sentinel-2, and other satellite data.

This application was used within the scope of the project for the implementation of pre-processing stages, as well as for Change Detection Analysis and Classification.

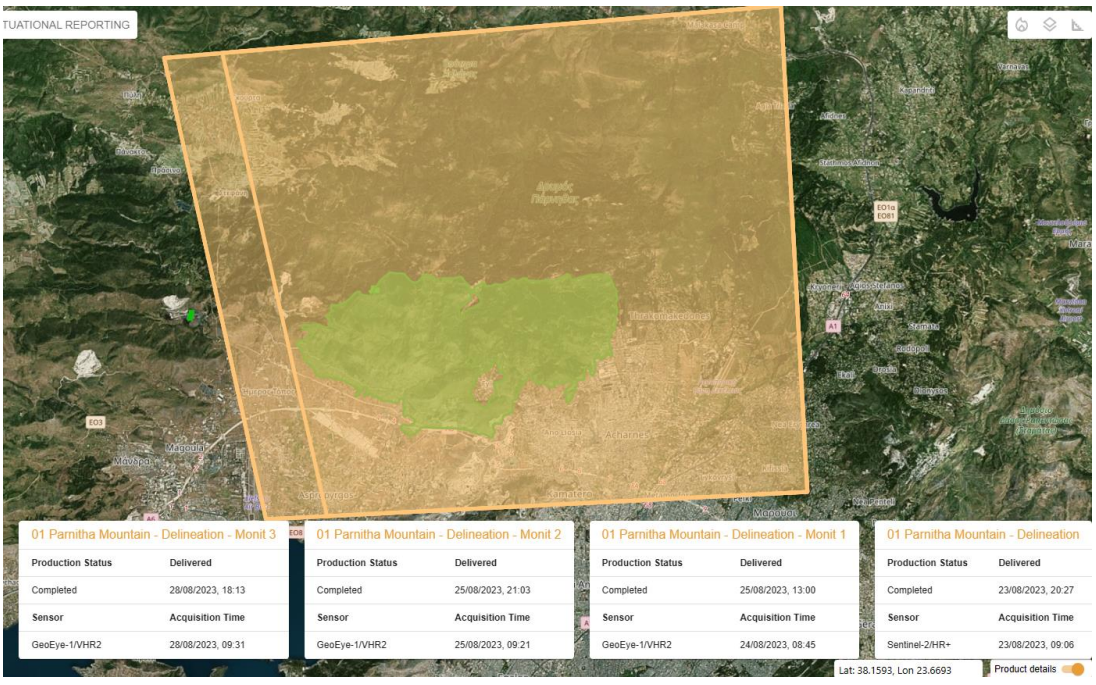
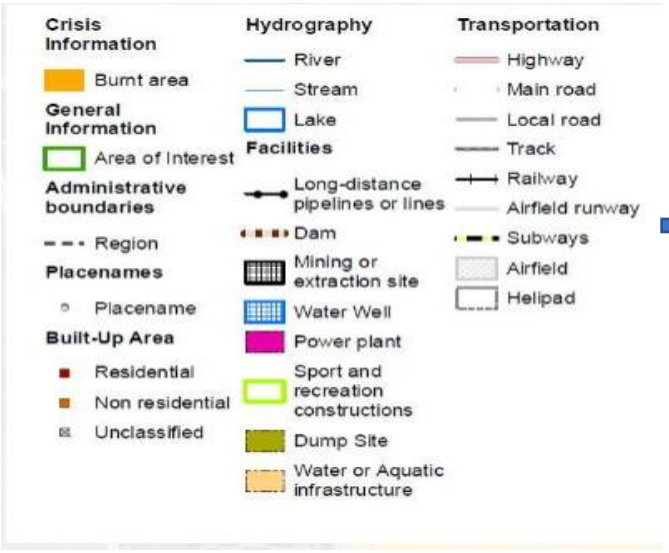


Figure 3: Wildfire Area and Burned Areas

As seen in Figure 3, there are fire-related data taken on four different dates. These are, respectively, “Delivery: 23/08/2023, 20:27”, “Delivery: 25/08/2023, 13:00”, “Delivery: 25/08/2023, 21:03” and “Delivery: 28/ 08/2023, 18:13”. The orange area seen in Figure 2 shows the fire area in a comprehensive manner. In addition, the green area within this area represents the area burned in the wildfire.



Attica Region is a region where forest fires are frequently seen due to its geographical location and climate characteristics.

As seen in Legend 1, you can see areas affected by fire in the geographic area.

Legend 1

Firstly, the source of the downloaded SENTINEL-1 data is the European Space Agency (ESA). The Sentinel-1 satellite is a series of satellites developed and operated by ESA within the Copernicus program.

In this study, if we were to represent the technical specifications of the data sources used for the Sentinel-1 satellite, it can be stated that the SAR (Sentinel-1 Synthetic Aperture Radar) sensor type was used, and it is part of the Sentinel-1 satellite platform. The coordinate system used is WGS84 (World Geodetic System 1984), a geographic coordinate system. The data is provided in the file format of Level-1 GRDH (Ground Range Detected High-Resolution), which is a Sentinel-1 data product format.

The file type used is the SNAP standard I/O file (BEAM-DIMAP format) (.dim). This format, a combination of the terms BEAM (Basic Envisat Advanced SAR Toolbox) and DIMAP (Digital Image MAP), is a standard format for storing and processing SAR (Synthetic Aperture Radar) data, such as Sentinel-1. The BEAM-DIMAP format is commonly used for organizing, storing, and sharing SAR data.

The "Swath" used in this study is "IW" (Interferometric Wide Swath). The expression "IW" represents a wide swath width, enabling the simultaneous scanning of a large area and facilitating interferometric analyses. For polarization, both VV (Vertical-Vertical) and VH (Vertical-Horizontal) have been utilized. "VV" polarization denotes the vertical propagation and reflection of radar waves, while "VH" polarization indicates vertical propagation and horizontal reflection. The orbit direction for the downloaded data on both dates is "Descending," signifying that the Sentinel-1 satellite moves in the direction of descent when scanning the Earth. The descending orbit involves the satellite moving from north to south, providing crucial insights into how the observed area changes in the Earth's coordinate system.

After the data was downloaded, the pre-processing procedure was performed using the previously mentioned SNAP application. Pre-processing encompasses data preparation for more advanced analysis methods such as change detection analysis. For SENTINEL-1 data, pre-processing involves calibrating and organizing raw data. These processes correct atmospheric effects, standardize the data set by balancing sensor characteristics, and rectify geometric distortions. Radiometric and geometric corrections are crucial for accurate geographic positioning and comparison. Additionally, mitigating topographic effects enables obtaining more precise results, especially in areas with high slopes. Processed data is now ready for change analysis in the wildfire areas within our study area. The workflow summarizing the applied steps can be seen in Figure 4.

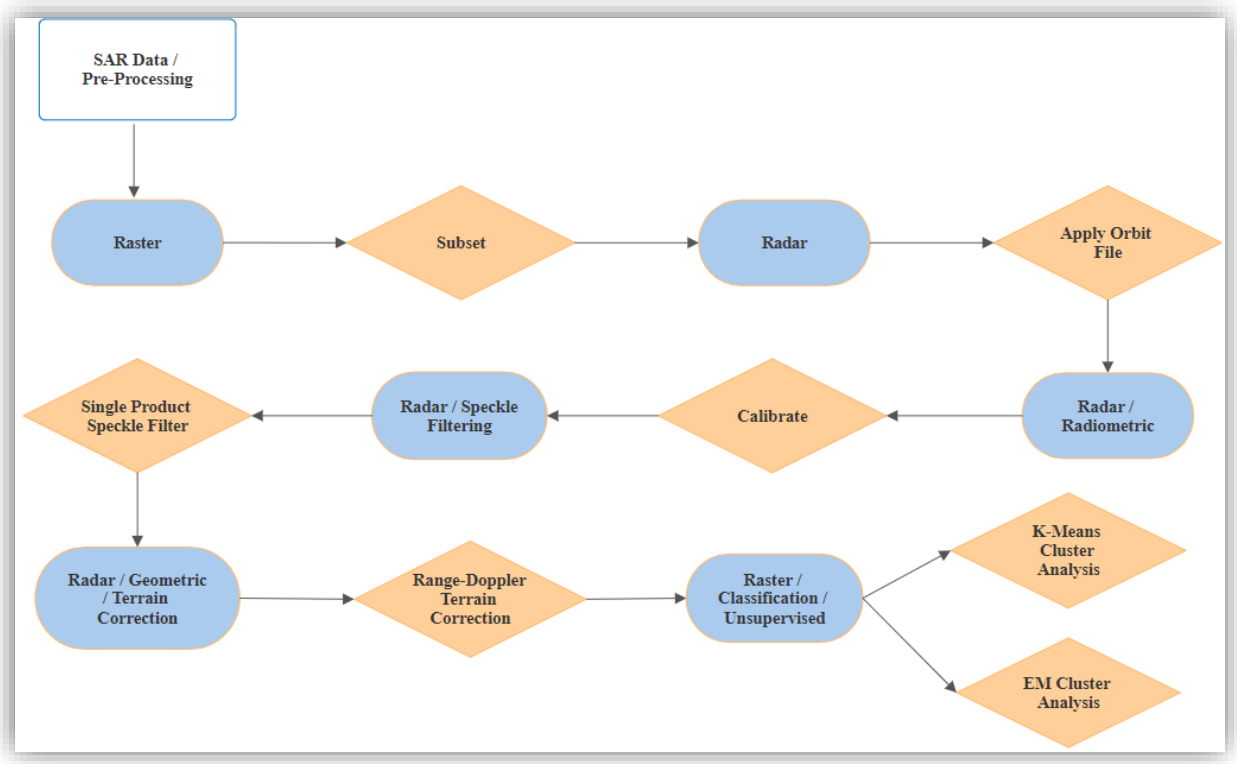


Figure 4: Workflow Pre-Processing

Within the scope of the project, a Classification method was employed for analysis. Unsupervised classification is a method of automatically grouping data by identifying patterns and similarities within the dataset. As seen in Figure 4, two different algorithms were used with the Unsupervised method: K-Means cluster and EM cluster algorithms. The K-Means algorithm is utilized to separate the data into clusters by defining a specific number of cluster centers. Each data point is assigned to the nearest cluster center, and the algorithm operates by iteratively updating these centers. The EM Cluster algorithm separates the data into clusters using a two-stage process. In the "Expectation (E)" stage, probabilities of data points belonging to specific clusters are calculated. In the "Maximization (M)" stage, cluster centers and covariance matrices are updated using these probabilities.

Before classification, the VV and VH bands were converted to dB using the linear to/from dB command. The reason for converting to dB is to better understand and interpret the radiometric values in the dataset. Subsequently, the VV and VH bands were taken in the algorithms as VVdB and VHdB, and also taken binarily as VVdB - VHdB.

The acquired bands are planned to be used for change analysis through methods such as addition, subtraction, and region-based operations for pre- and post-date data. Additionally, histograms and statistical tables of these bands can be extracted to perform change analysis using these methods.

Within the scope of the project, in addition to the SNAP application mentioned for pre-processing, the use of the ERDAS Imagine application is also planned. ERDAS Imagine provides powerful tools such as radiometric transformations, band math operations, and image processing functions. It has a user-friendly interface for performing complex processes like change analysis. Therefore, it is planned to use the ERDAS Imagine application in addition to the analyses in SNAP.

Results

In this section, the classified versions of pre- and post-fire data using K-Means and EM Cluster algorithms will be analyzed and interpreted. Firstly, the SENTINEL-1 data for both pre- and post-fire periods were classified using the VV and VH bands with two algorithms. Figure 5 displays these classified bands.

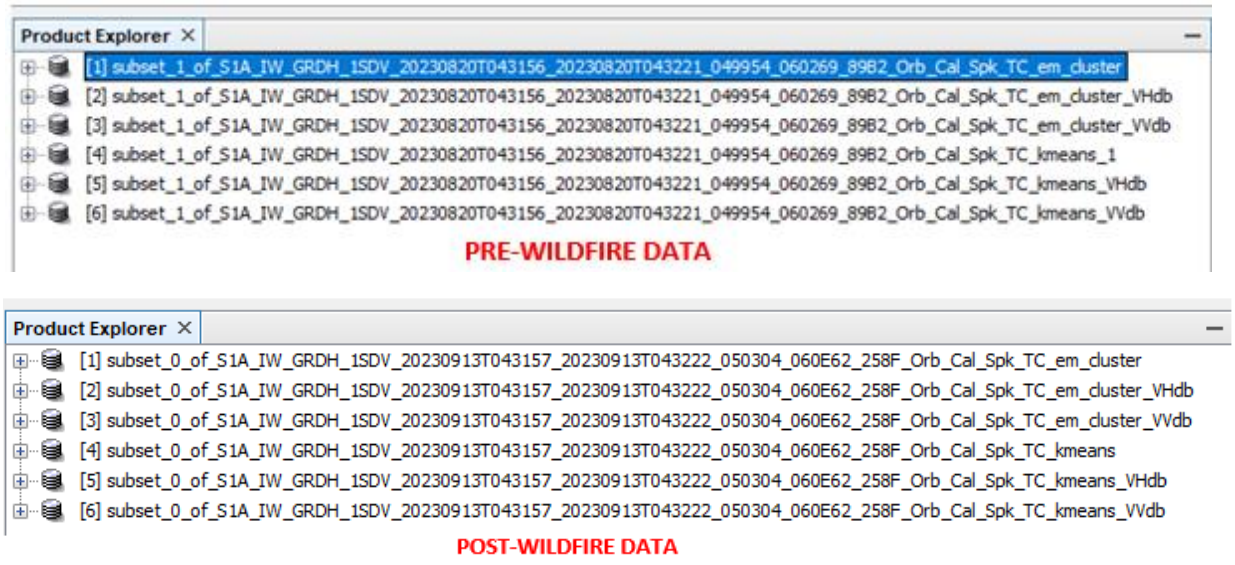


Figure 5: Classified Files of Pre- And Post-Wildfire Data

As seen in Figure 5, all files for both algorithms are available. The 'em_cluster' and 'kmeans' files contain a combination of both VVdB and VHdB polarizations (VV_dB+VH_dB).

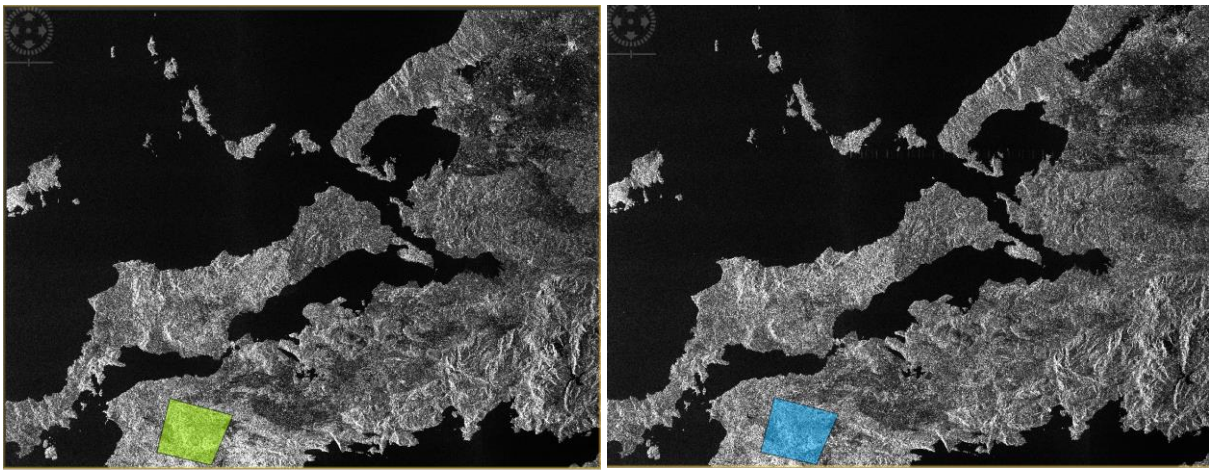


Figure 6: Wildfire Area Pre-Date and Post-Date

As seen in Figure 6, the image given in the SNAP application represents the work area. On the first data downloaded from ESA's website, the "Shapefile" file downloaded from the field information provided in the project was imported into the program environment.

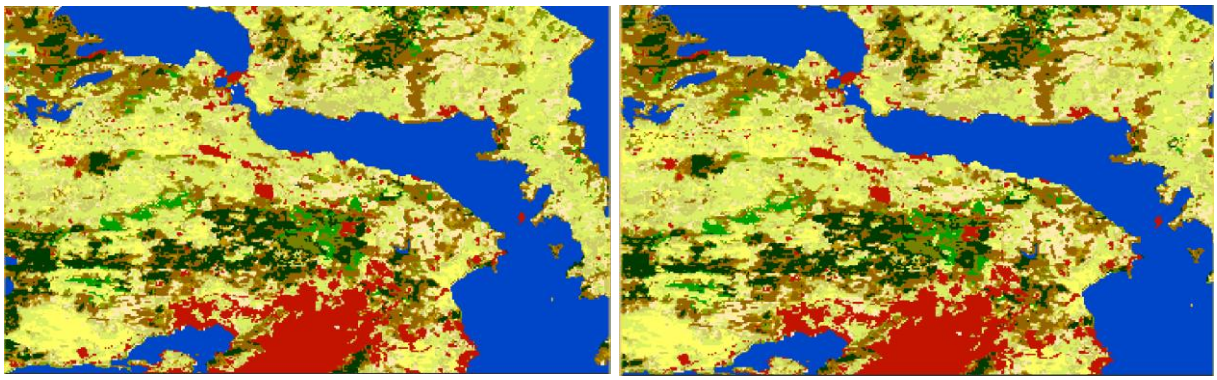


Figure 7: Land Cover Classification of Pre- (left one) and Post-Fire (right one) Data

Land_cover_globcover has been specifically extracted to detect land cover and land use in a particular geographic region after geometric and radiometric corrections. This dataset is specifically extracted for detecting the land cover and land use of the geographical region of the study area. These data are shown in Figure7.

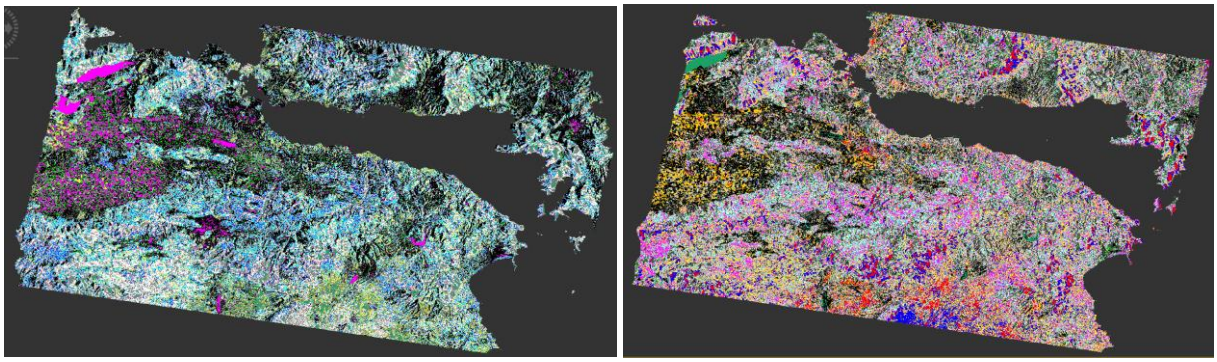


*Figure 8: Pre (Left Side) and Post (Right Side) Wild Fire İmages Classified with The **EM Cluster** Algorithm*

The band colors of the images classified with the EM Cluster algorithm, which you see in Figure 8, were chosen to be the same color. Thus, analyzes will be easier. The image you see in Figure 8 includes both VVdB and VHdB polarizations (VV_dB+VH_dB).

!!! Classification colors are set to be the same for all classified bands to be shared from now on.!!!

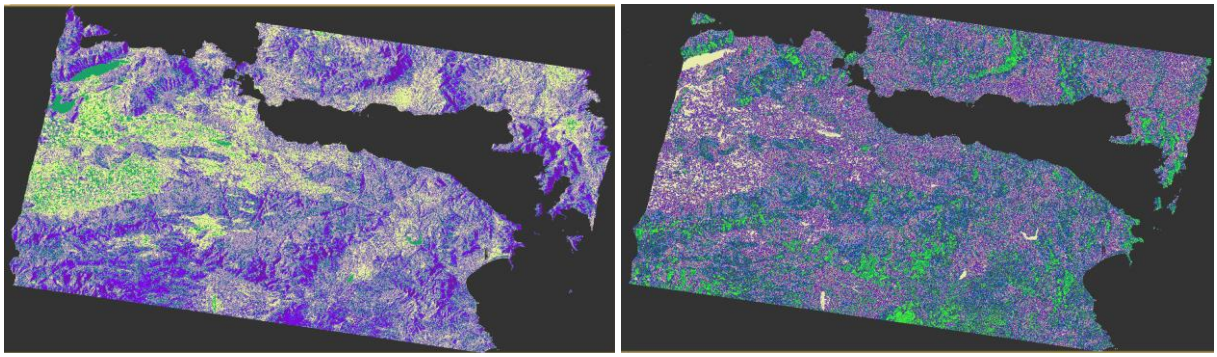


*Figure 9: Pre (Left Side) and Post (Right Side) Wild Fire İmages Classified with The **EM Cluster (VHdB)***

In the image shown in Figure 9, for pre- and post-forest fire data, only the VH (dB) band was classified with the EM Cluster algorithm. The reason why the bands are taken in separate polarizations is that they can be analyzed easily by performing operations such as subtraction and division.

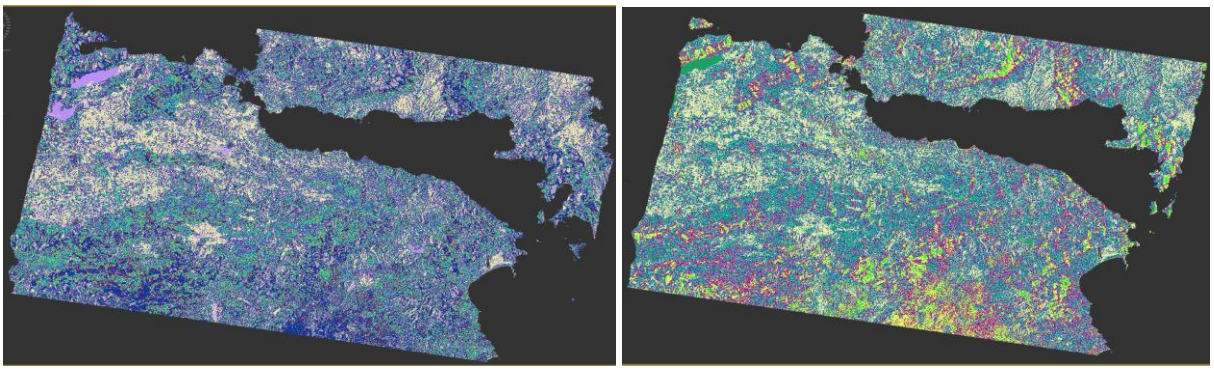


*Figure 10: Pre (Left Side) and Post (Right Side) Wild Fire İmages Classified with The **EM Cluster (VVdB)***

In the image shown in Figure 10, for pre- and post-forest fire data, only the VV (dB) band was classified with the EM Cluster algorithm. The reason why the bands are taken in separate polarizations is that they can be analyzed easily by performing operations such as subtraction and division.

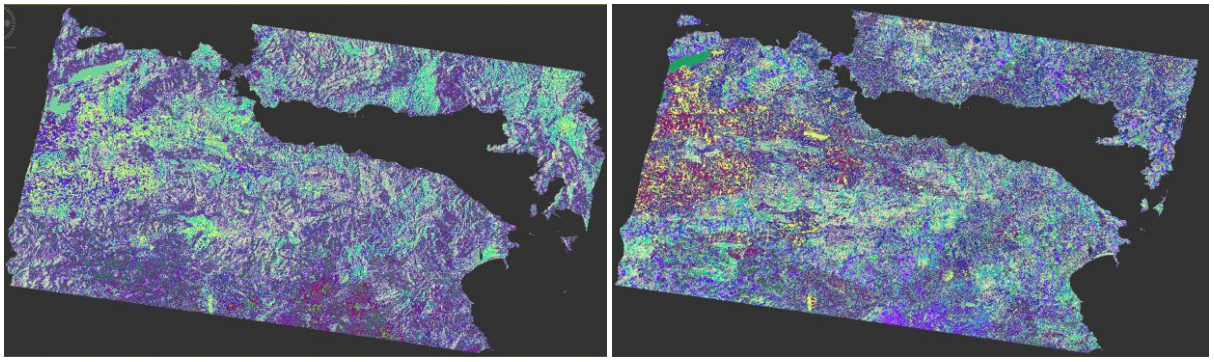


*Figure 11: Pre (Left Side) and Post (Right Side) Wild Fire İmages Classified with The **K-Means** Algorithm*

The band colors of the images classified with the K-Means algorithm, which you see in Figure 8, were chosen to be the same color. Thus, analyzes will be easier. The image you see in Figure 8 includes both VVdB and VHdB polarizations (VV_dB+VH_dB).

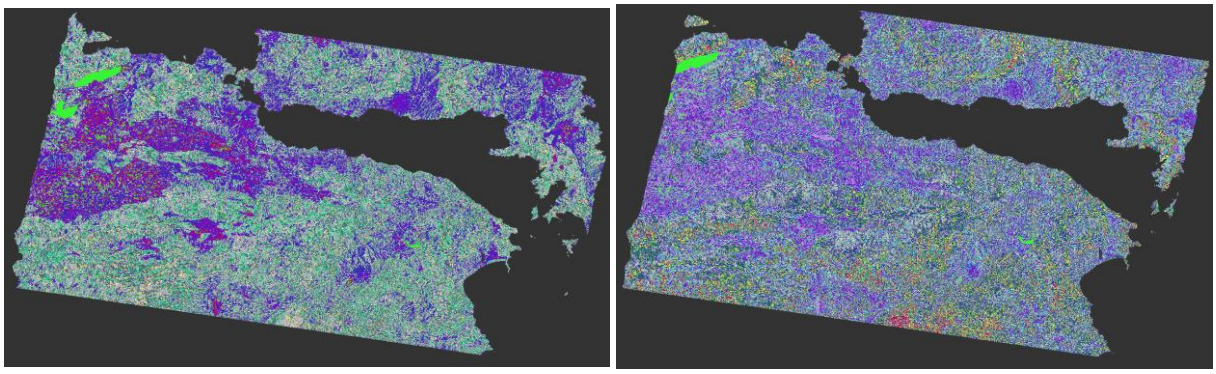


*Figure 12: Pre (Left Side) and Post (Right Side) Wild Fire İmages Classified with The **K-Means (VHdB)***

In the image shown in Figure 9, for pre- and post-forest fire data, only the VH (dB) band was classified with the K-Means algorithm. The reason why the bands are taken in separate polarizations is that they can be analyzed easily by performing operations such as subtraction and division.

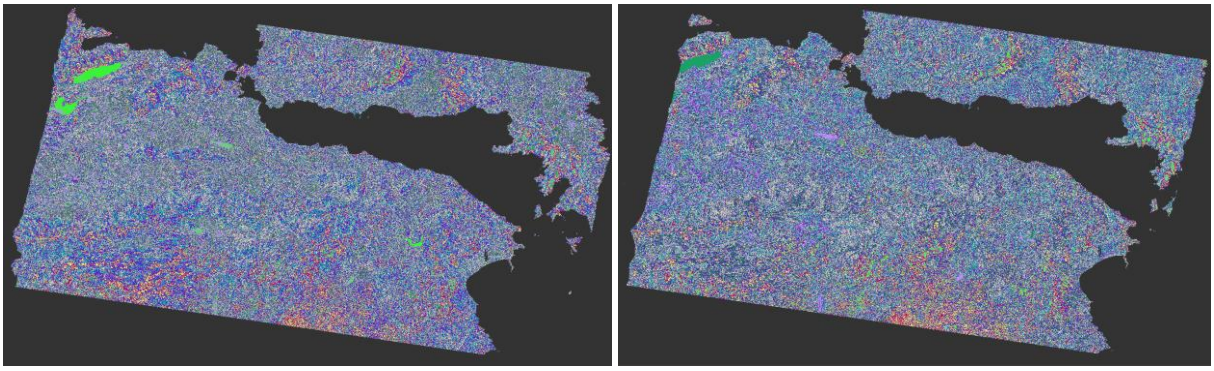


*Figure 13: Pre (Left Side) and Post (Right Side) Wild Fire İmages Classified with The **K-Means (VVdB)***

In the image shown in Figure 9, for pre- and post-forest fire data, only the VV (dB) band was classified with the K-Means algorithm. The reason why the bands are taken in separate polarizations is that they can be analyzed easily by performing operations such as subtraction and division.

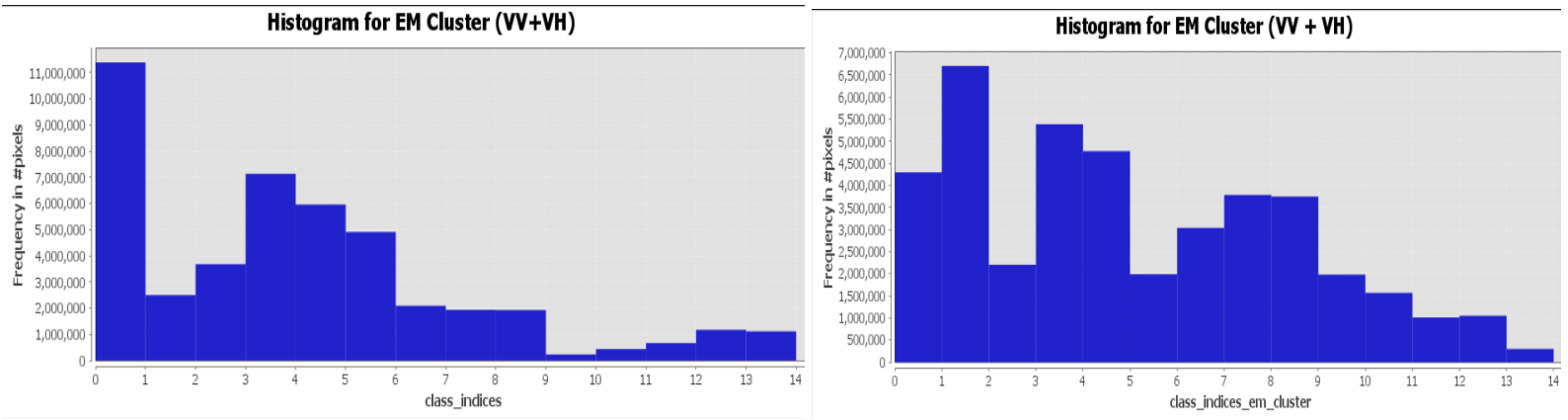


Figure 14: Histogram for Pre (left side) and Post (right side) Wildfire in EM Cluster

The contents seen in Figure 14 are histograms of the images in Figure 8.

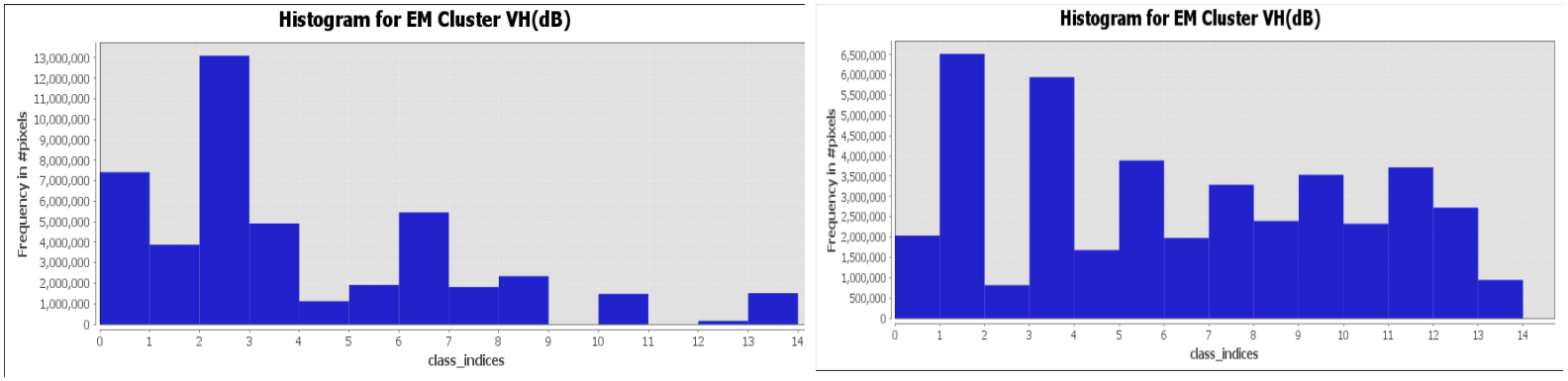


Figure 15: Histogram for Pre (left side) and Post (right side) Wildfire in EM Cluster VH

The contents seen in Figure 15 are histograms of the images in Figure 9.

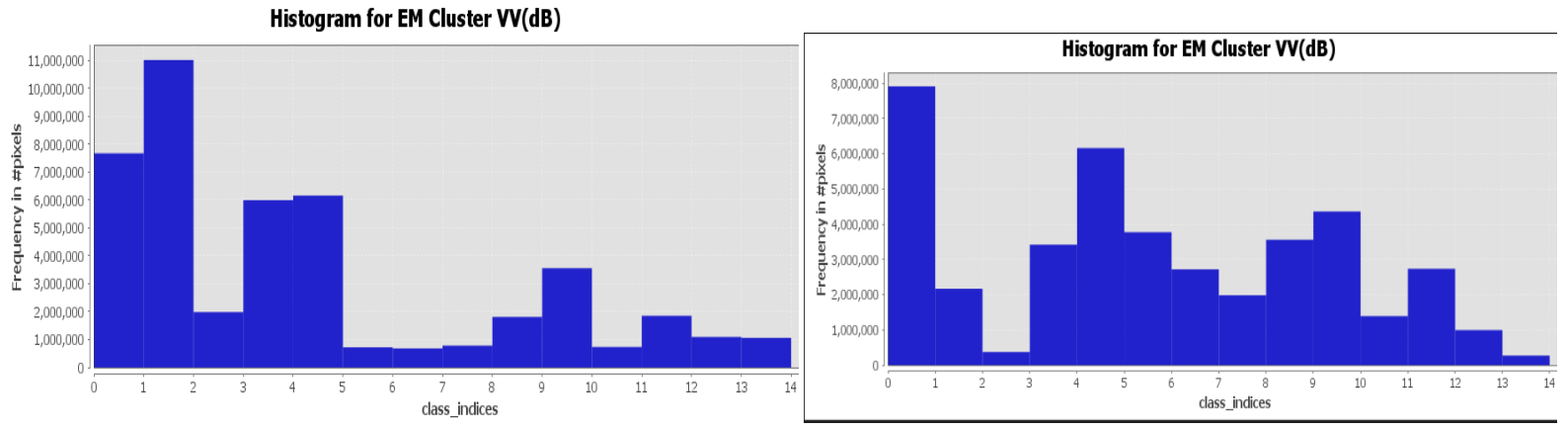


Figure 16: Histogram for Pre (left side) and Post (right side) Wildfire in EM Cluster VV

The contents seen in Figure 16 are histograms of the images in Figure 10.

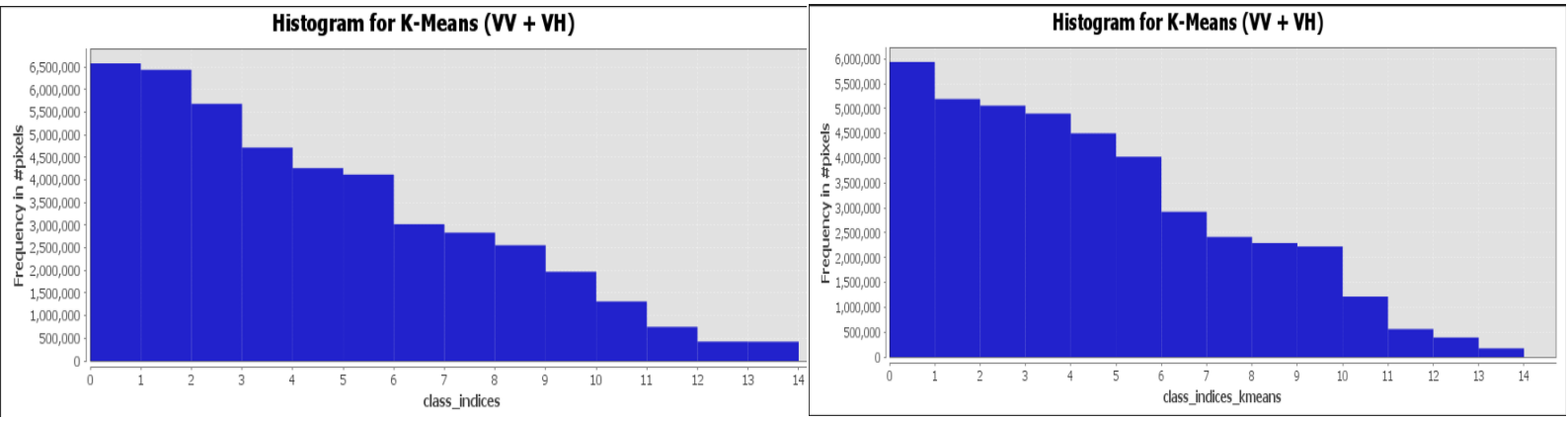


Figure 17: Histogram for Pre (left side) and Post (right side) Wildfire in K-Means

The contents seen in Figure 17 are histograms of the images in Figure 11.

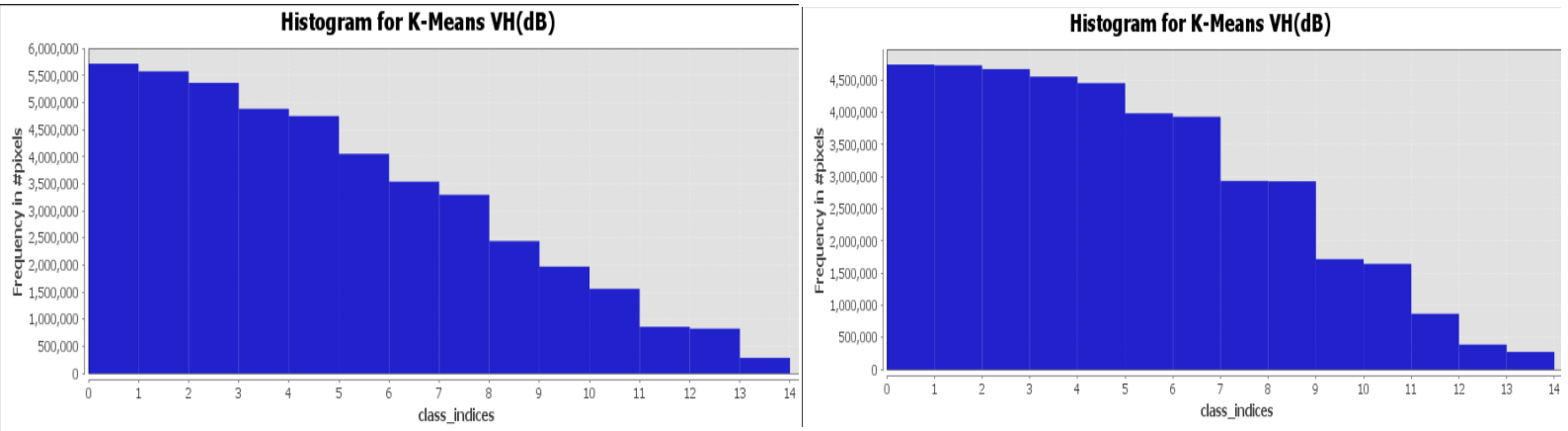


Figure 18: Histogram for Pre (left side) and Post (right side) Wildfire in K-Means VH

The contents seen in Figure 18 are histograms of the images in Figure 12.

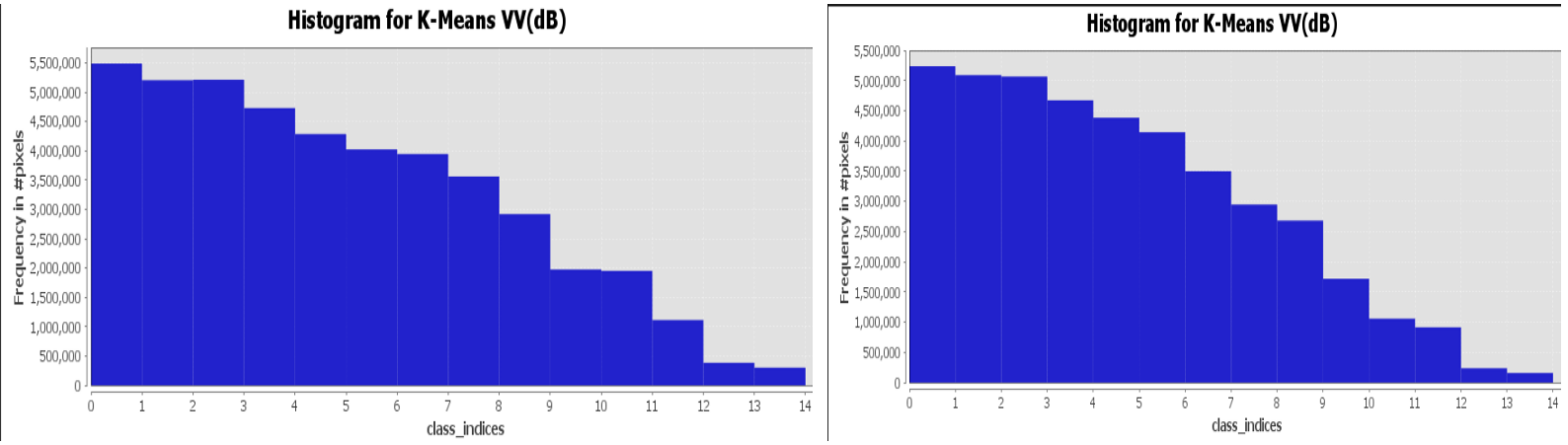
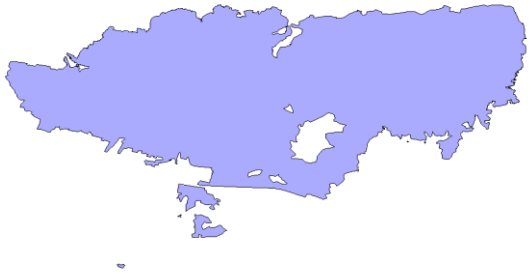


Figure 19: Histogram for Pre (left side) and Post (right side) Wildfire in K-Means VV

The contents seen in Figure 19 are histograms of the images in Figure 13.

Figure 20: Total Area of Forest Fire (Left Side) and Burned Area Approx (Right Side)

In Figure 20, the study area for the wildfire is given as approximately 492.71 square kilometers (~493000000 square meters), and the burned area within the study area is approximately 67.01 square kilometers (~67000000 square meters).



Record	obj_desc	det_method	notation	dmg_src_id	area
1	Forest Fire	Photo-interpretation	Burnt area	5	1.92661445305
2	Forest Fire	Photo-interpretation	Burnt area	5	0.33288184997
3	Forest Fire	Photo-interpretation	Burnt area	5	39.43157191790
4	Forest Fire	Photo-interpretation	Burnt area	5	54.61724087790
5	Forest Fire	Photo-interpretation	Burnt area	5	6009.07806836000
6	Forest Fire	Photo-interpretation	Burnt area	5	0.07289216914
7	Forest Fire	Photo-interpretation	Burnt area	5	0.13196693082
8	Forest Fire	Photo-interpretation	Burnt area	5	0.07342032907
9	Forest Fire	Photo-interpretation	Burnt area	5	0.11290324876

Figure 21: Burnt area calculation in ERDAS Imagine

As you can see in Figure 21, the calculation of burnt forest areas in the study area was made in the ERDAS Imagine application.

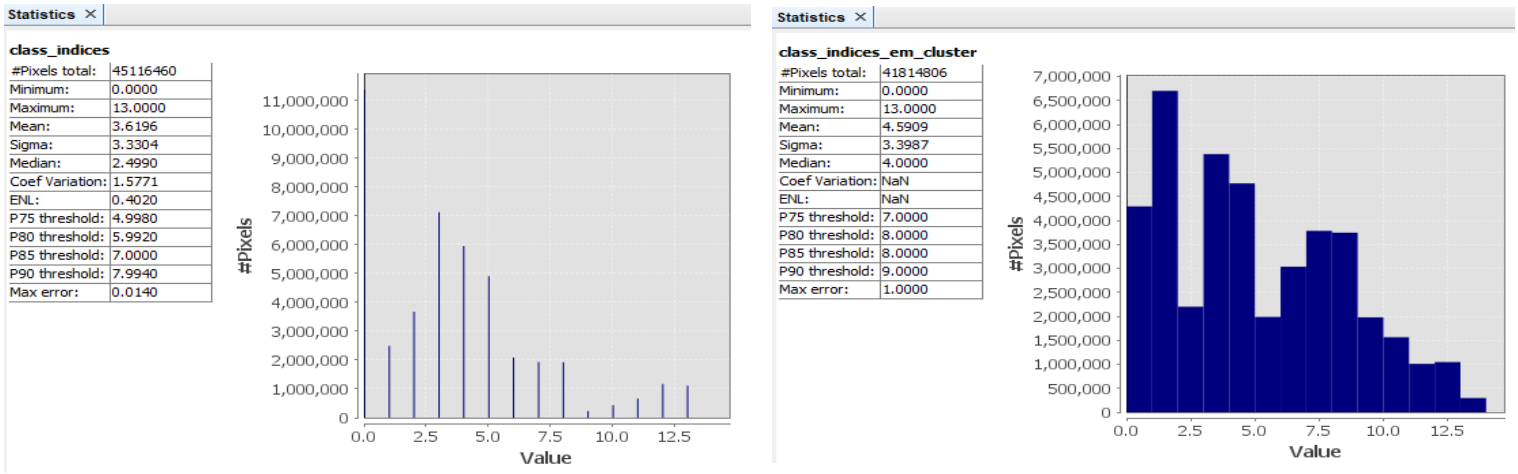


Figure 22: Statistics for Pre (left side) and Post (right side) Wildfire in EM Cluster (VV + VH)

The contents seen in Figure 22 are statistics of the images in Figure 8.

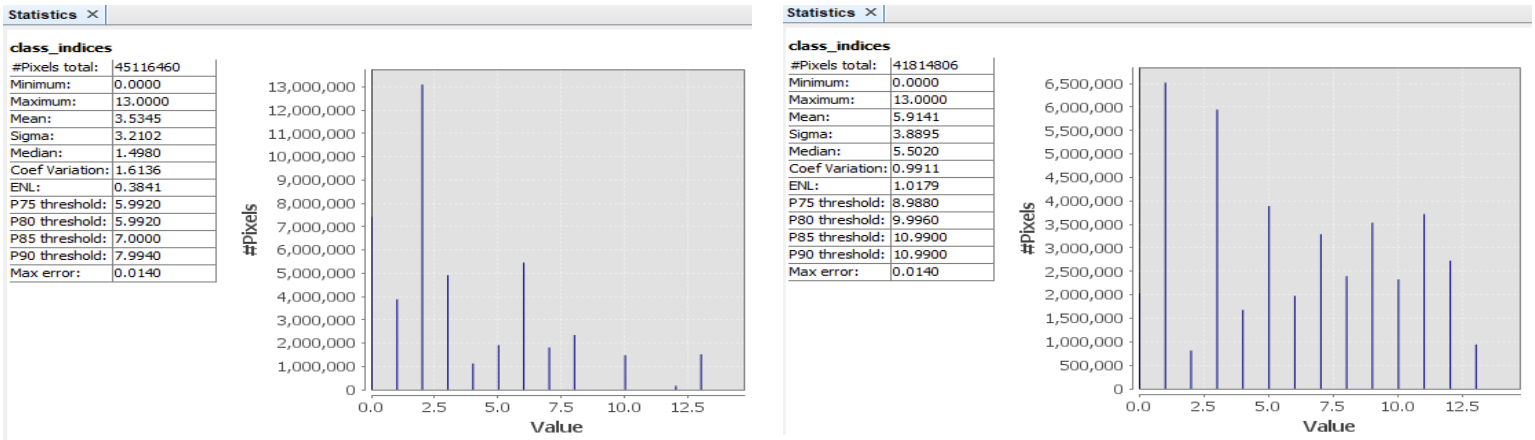


Figure 23: Statistics for Pre (left side) and Post (right side) Wildfire in EM Cluster VH

The contents seen in Figure 23 are statistics of the images in Figure 9.

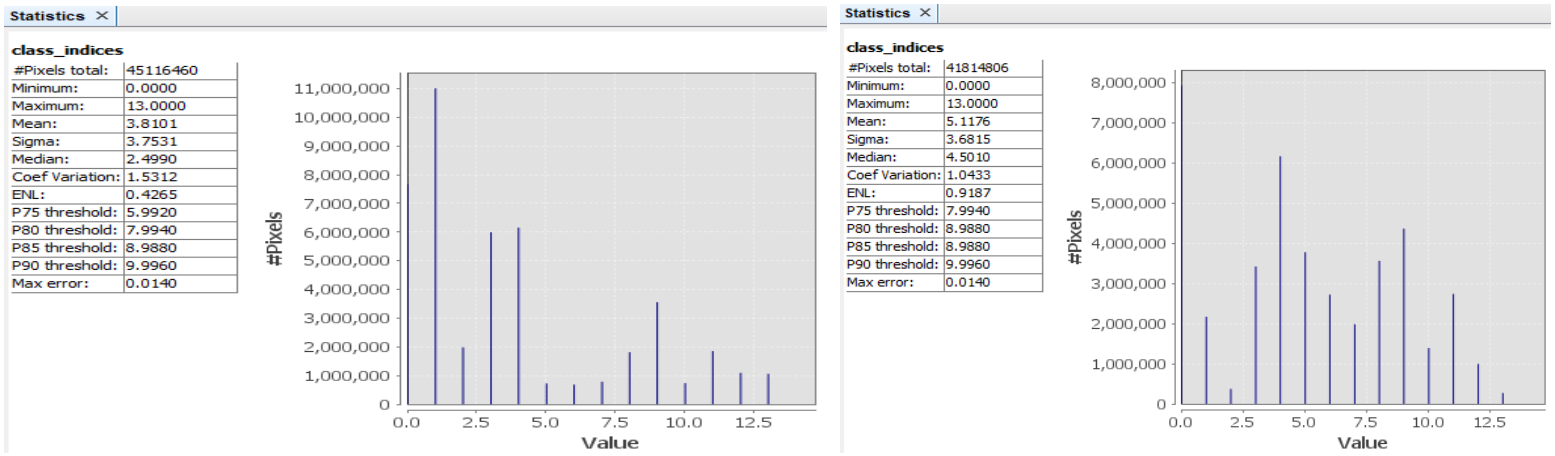


Figure 24: Statistics for Pre (left side) and Post (right side) Wildfire in EM Cluster VV

The contents seen in Figure 24 are statistics of the images in Figure 10.

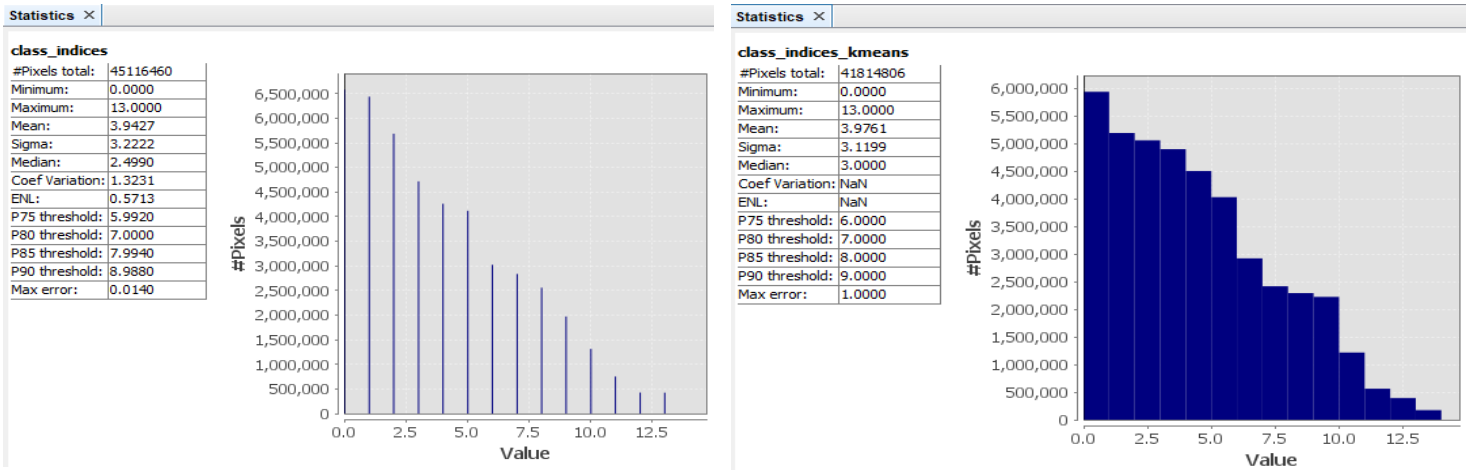


Figure 25: Statistics for Pre (left side) and Post (right side) Wildfire in K-Mean (VV + VH)

The contents seen in Figure 23 are statistics of the images in Figure 11.

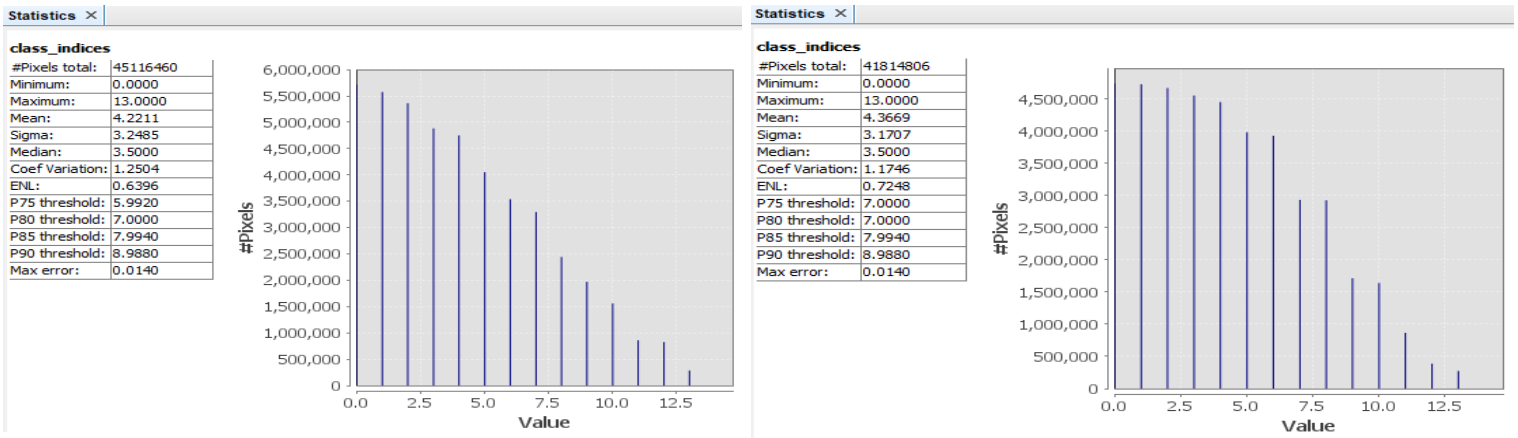


Figure 26: Statistics for Pre (left side) and Post (right side) Wildfire in K-Mean VH

The contents seen in Figure 26 are statistics of the images in Figure 12.

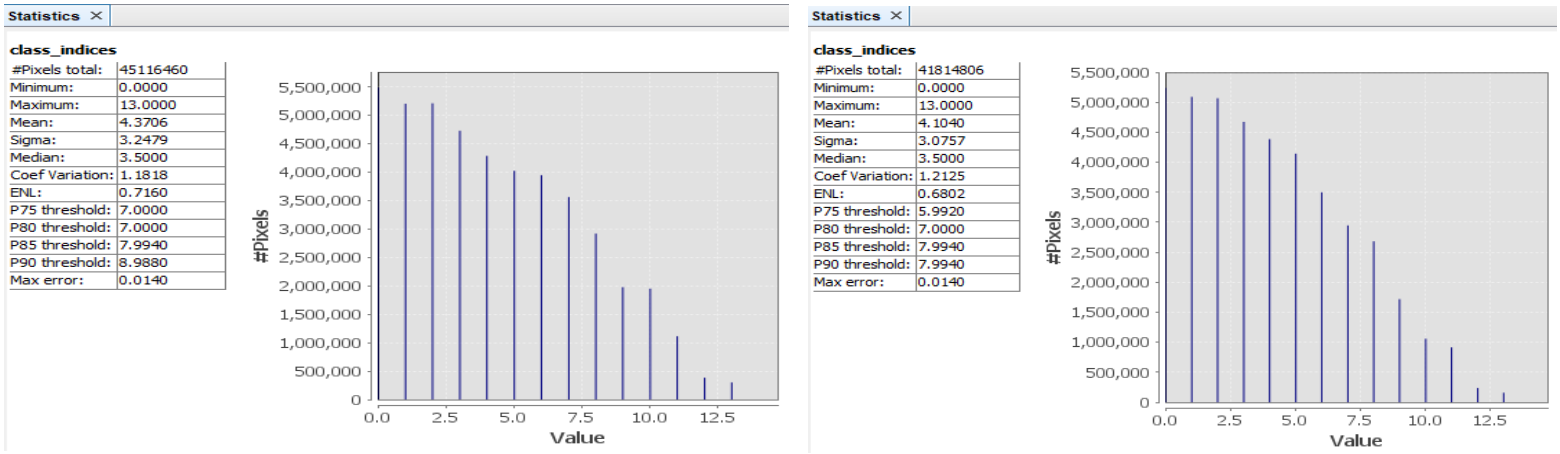


Figure 27: Statistics for Pre (left side) and Post (right side) Wildfire in K-Mean VV

The contents seen in Figure 27 are statistics of the images in Figure 13.

Discussion

Firstly, interpretations of the output shared in the "Results" section will be provided, focusing on the histogram analyses. Bands created using unsupervised classification with K-means and EM Cluster algorithms have segmented the areas into classes. The numbers on the x-axis of the histograms represent the classes, while those on the y-axis represent pixel intensity. In the pre-fire histograms, a generally low-intensity and homogeneous distribution is observed, whereas a significant increase and change occur after the fire. This increase reflects the intensity of surface changes in the areas affected by the fire. We can assume that this post-fire increase and change indicate high values in the satellite's backscatter measurements. The loss of vegetation due to the fire may expose more of the soil surface, leading to a stronger reflection of the satellite signal. In this case, an increase in backscatter values is expected in the areas affected by the fire. Therefore, pixel intensity is higher in the classes in the fire-affected regions.

For instance, if we take a look at all the data between Figure 14 and 19, we observe that there is no change in some classes, while others exhibit a high pixel intensity. The areas with no change are those without a fire, and when examining classes with pixel intensity, we find that pre-fire pixel intensities are low, while post-fire pixel intensities are high. Moreover, in the histogram of VH (Vertical-Horizontal) polarized data, a more pronounced shift is evident, indicating that changes in post-fire areas are more emphasized.

In the project, VV (Vertical-Vertical) and VH (Vertical-Horizontal) polarizations have been studied. Based on my research and analyses, if I were to provide information, VV polarization measures the reflection characteristics of microwaves in the horizontal plane, whereas VH combines reflections in the vertical and horizontal planes. VV is generally capable of detecting vegetation cover and surface deformations more sensitively. On the other hand, VH can provide a more distinct contrast, especially regarding surface changes and structural features. The combined use of these two modes is an advantage for a more comprehensive understanding of different changes on the surface. According to my research, for fire risk assessment, VV polarization tends to yield good results, especially in wet conditions, while VH polarization is generally more successful in overall outcomes.

When examining the statistics in Figures 22-27, we observe an increase in post-fire statistics (pixel total, mean, sigma, median). Thermal effects may contribute to the stronger reflection of radar signals after a fire due to the increased surface temperature and heat distribution. Therefore, the increase in post-fire statistics may indicate that the satellite observations more distinctly detect the effects of the fire and sensitively respond to surface changes.

According to the articles shared in the reference, the statement is as follows: "Validation results indicated that VH polarization data provided reliable fire intensity predictions with an overall accuracy of 82.3% (kc = 0.78) under dry conditions. Although VH polarization yielded the most reliable prediction results in both dry and average conditions among dry and wet images, VV polarization data achieved the best results under wet conditions. According to our analysis, NORM models outperformed STAND models, particularly in the average between wet and dry/wet images." A commonality with this project is the emphasis on the ability of VH polarization to identify surface changes and its potential to detect fire effects more reliably.

Conclusion

Thanks to the methodology of the project, I gained the ability to implement remote sensing techniques and polarimetry pre-processing. It helped me better understand SENTINEL-1 data and the Unsupervised classification method, specifically the K-Mean and EM Cluster algorithms, guiding me on when to use them in different stages. The image classification and statistical analysis stages provided detailed insights into data analysis and feature extraction. The comparison of VH and VV polarizations helped me understand how to effectively utilize these different data types. Additionally, interpreting the results obtained in the project was beneficial for enhancing analytical thinking and problem-solving skills in various applications. The project also allowed me to establish interactive relationships with various units to explore and implement potential restoration strategies after evaluating the impact of fires.

Institutions such as forestry management, emergency management, environmental protection agencies, remote sensing experts, city planning departments, and insurance companies can benefit from using this data to monitor, assess, and develop appropriate strategies for the impacts of fires. These analyses play a crucial role in making informed decisions in areas such as environmental risk management, infrastructure planning, and sustainable management of natural resources.

ALL DATA AVAILABLE IN DRIVE LINKS

https://drive.google.com/file/d/1wuGFXuX3ghSfb3-y9zTbD76i1PxujFU2/view?usp=sharing

https://drive.google.com/file/d/1_hKtCXF77serhi3s3irKkwemPNC0XDLV/view?usp=sharing

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