Indian Institute of Technology Bombay

Centre of Studies in Resources Engineering (CSRE)

PROJECT REPORT

Microwave Satellite Data Processing

Course Duration:
5th June 2025 – 14th June 2025

Project Title:
Polarimetric SAR Data Analysis and Classification using Decomposition Techniques and Random Forest (for Prayagraj)

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Chapter 1: Generation of [C2] Matrix and Pc, Pv, Pg Decomposition

1. Introduction

Remote sensing is a powerful method to study Earth's surface using satellite data. One of the most useful techniques in remote sensing is Synthetic Aperture Radar (SAR), which uses microwave signals to capture images.

SAR has a big advantage—it works even at night and in cloudy or rainy weather. This is useful for continuous monitoring of land, forests, water, and urban areas.

In this project, we use Sentinel-1A SAR data of Prayagraj (A and B datasets) to understand surface features. This satellite provides dual-polarized data (VV and VH), which helps in analyzing how radar waves scatter when they hit different surfaces.

We are mainly focusing on creating a matrix called [C2] (Covariance Matrix). This matrix is important in radar image processing because it contains all the polarimetric information.

Using the [C2] matrix, we calculate three types of scattering:

- Pc – Surface scattering (from flat open areas like soil or roads)
- Pv – Volume scattering (from forests, trees, and vegetation)
- Pg – Double-bounce scattering (from buildings or vertical surfaces)

These components help us understand what kind of surface is present in the area—natural or man-made.

The process to reach this goal involves many steps like importing data into SNAP software, splitting bursts, calibration, debursting, subsetting, multilooking, filtering speckle noise, generating [C2] & then using math operations to extract Pc,Pv, and Pg.

Finally, we create RGB images using these components to visualize the land features better. This decomposition is very useful before we apply any classification methods like Random Forest, which we will do in the next chapter.

This chapter forms the base for analyzing and interpreting SAR data using scientific methods and is the first major step in this microwave satellite data processing project.

2. Data Set Used

In this project, we used radar data from the Sentinel-1A satellite, which is part of the Copernicus program by the European Space Agency (ESA). The data was downloaded in SLC (Single Look Complex) format, which is suitable for advanced SAR processing.

Details of the Dataset:

- Satellite: Sentinel-1A
- Sensor Type: Synthetic Aperture Radar (SAR)
- Data Format: SLC (Single Look Complex)
- Imaging Mode: IW (Interferometric Wide Swath)
- Polarization: Dual polarization – VV and VH
- Resolution: Medium spatial resolution
- Acquisition Dates:
    - Prayagraj A
    - Prayagraj B
- Source: https://scihub.copernicus.eu (Copernicus Open Access Hub)

Software Used:

- SNAP (Sentinel Application Platform) – Used for SAR image processing
- QGIS – Used for visualization and map preparation

The datasets cover the Prayagraj region, which includes a variety of land cover types such as vegetation, water bodies, and urban areas. This variety makes it ideal for applying polarimetric decomposition techniques.

3. Study Area

The selected study area for this project is Prayagraj, a city located in the state of Uttar Pradesh, India. Prayagraj is situated at the confluence of three rivers – Ganga, Yamuna, and the mythical Saraswati – making it both geographically and culturally significant.

The region includes a combination of:

- Urban areas (buildings, roads, built-up structures)
- Vegetation (green cover, farmland, and forest patches)
- Water bodies (rivers, lakes, and flood plains)

This diverse landscape makes Prayagraj an ideal location for applying radar image processing and decomposition methods like Pc, Pv, and Pg generation.The area was clipped from the full Sentinel-1A image using the Subset tool in SNAP software to focus only on the required region and reduce processing time.

By selecting Prayagraj as the study region, we are able to analyze how different land covers scatter microwave signals differently, helping in classification and feature extraction in further steps.

4. Methodology

The following steps were followed to generate the [C2] covariance matrix and perform polarimetric decomposition (Pc, Pv, Pg) using Sentinel-1A SAR data in SNAP software:

Step-by-Step Procedure:

1. Download Data
   - Two datasets (Prayagraj A and B) were downloaded in SLC (Single Look Complex) format from the Copernicus Open Access Hub.
2. Import Sentinel-1A Data
   - The ZIP files were opened directly in SNAP without extraction. SNAP automatically reads the metadata and organizes the data.
3. Split Operation
   - The IW (Interferometric Wide) swath and required burst(s) were selected to reduce the area and focus only on the region of interest.

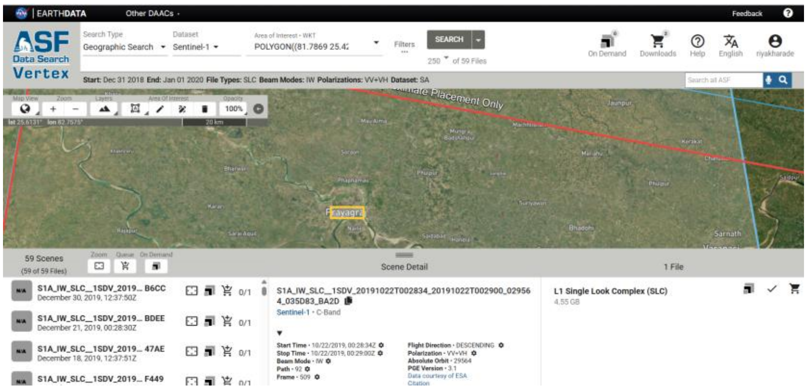
4. Calibration
   - The SAR images were calibrated to sigma naught values. This converts raw pixel values into meaningful backscatter measurements, which is important for quantitative analysis.
5. Debursting
   - As Sentinel-1A captures bursts of images, the Deburst step merges them into a single continuous image to prepare for further processing.
6. Subset
   - A smaller portion of the image around Prayagraj was selected. This helps reduce processing time and focuses analysis on the study area only.
7. Matrix Generation – [C2]
   - The Covariance matrix (C2) was generated using the dual-polarized data (VV and VH). This matrix contains polarimetric information needed for decomposition.
8. Coregistration (if required)
   - If both A & B datasets are being compared or merged, coregistration ensures both are geometrically aligned.
9. Multilooking
   - Multilooking was applied to improve the visual quality by reducing pixel-level speckle and making the image smoother for analysis.
10. Speckle Filtering
    - Speckle noise was further reduced using the Refined Lee filter, which keeps image features intact while removing noise.
11. Band Math for Pv, Pc, Pg
    - Band Maths tool in SNAP was used to compute scattering components:
      - Pc (surface),Pv (volume scattering),Pg (double-bounce scattering)
12. RGB Composition
    - The decomposition bands were visualized using an RGB composite:
      - Red: Pg (Double bounce)
      - Green: Pc (Surface)
      - Blue: Pv (Volume)

Each step contributed to preparing a clean, analyzable image with enhanced polarimetric information, suitable for visual interpretation and further classification tasks.

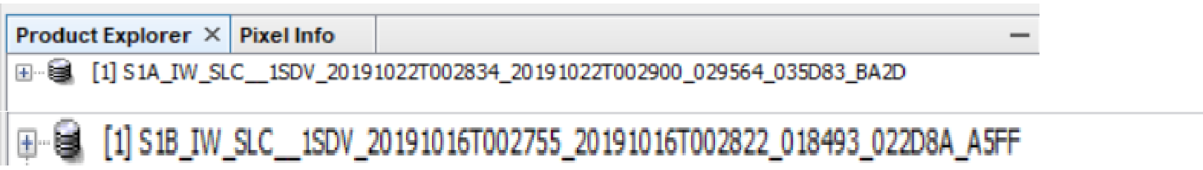
5. Result and Discussion

This section presents the output generated at each step of the processing. Screenshots are provided to show the intermediate and final results.

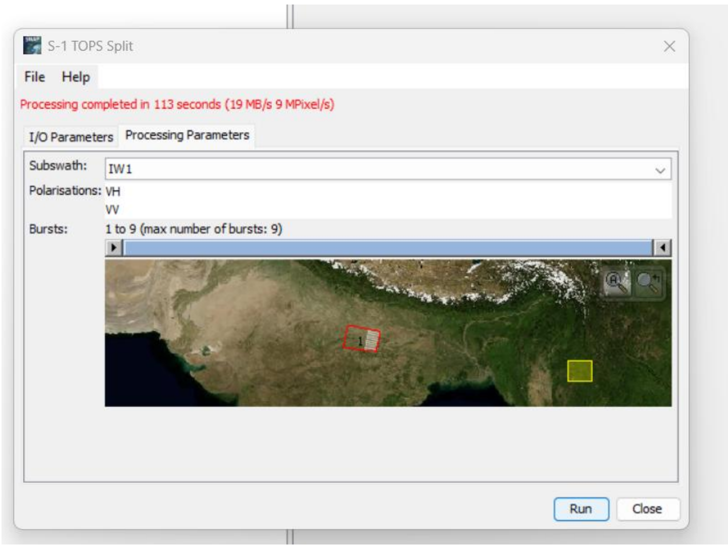
Step 1: Downloaded Data (Prayagraj A and B)



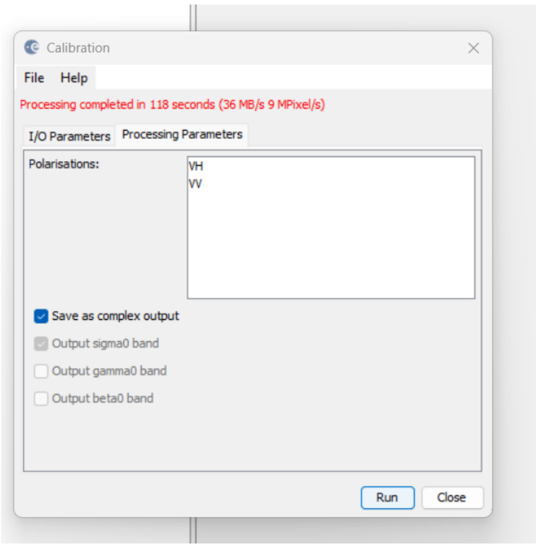
Step 2: Imported in SNAP Software



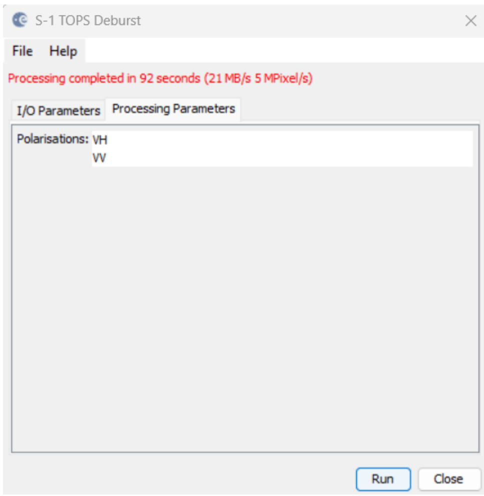
Step 3: Split Operation



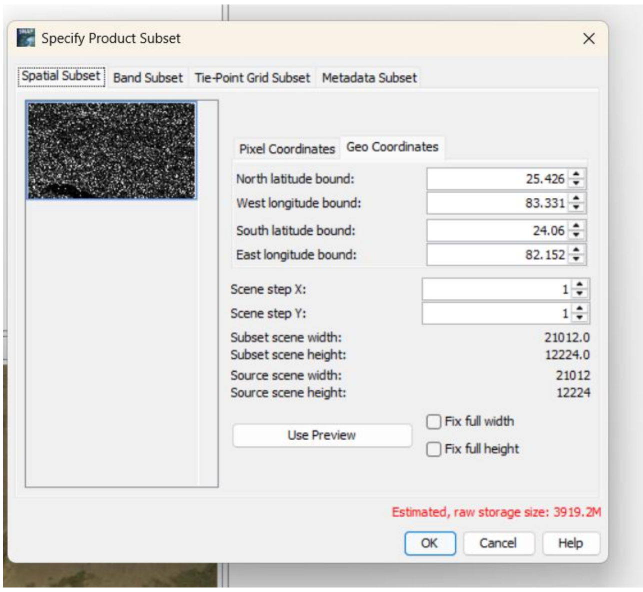
Step 4: Calibration



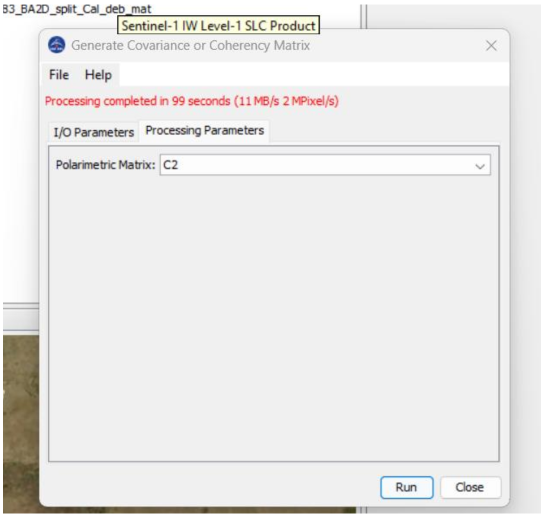
Step 5: Deburst



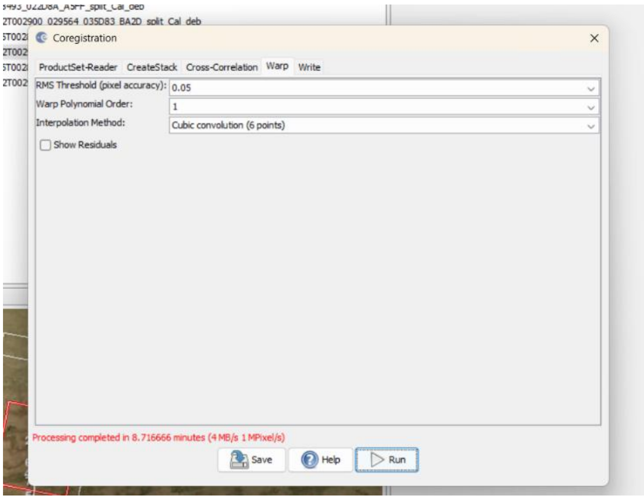
Step 6: Subset



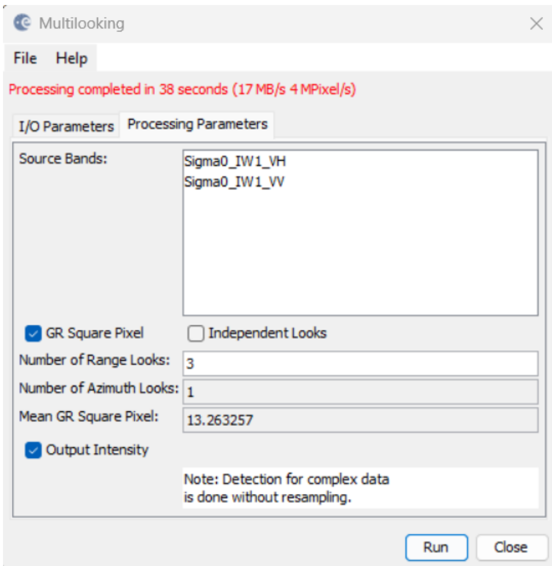
Step 7: [C2] Matrix Generation



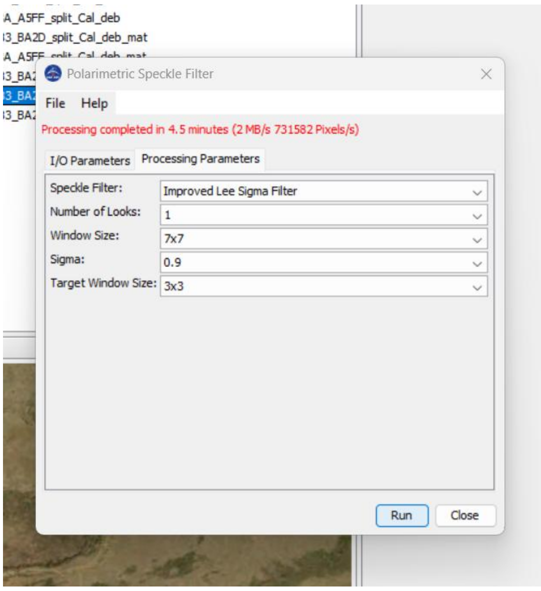
Step 8: Coregistration (if used)



Step 9: Multilooking

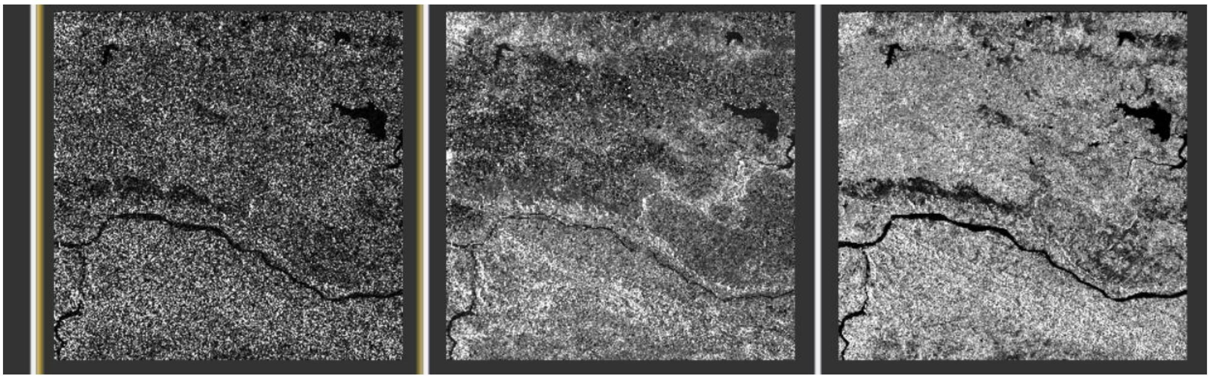


Step 10: Speckle Filtering\



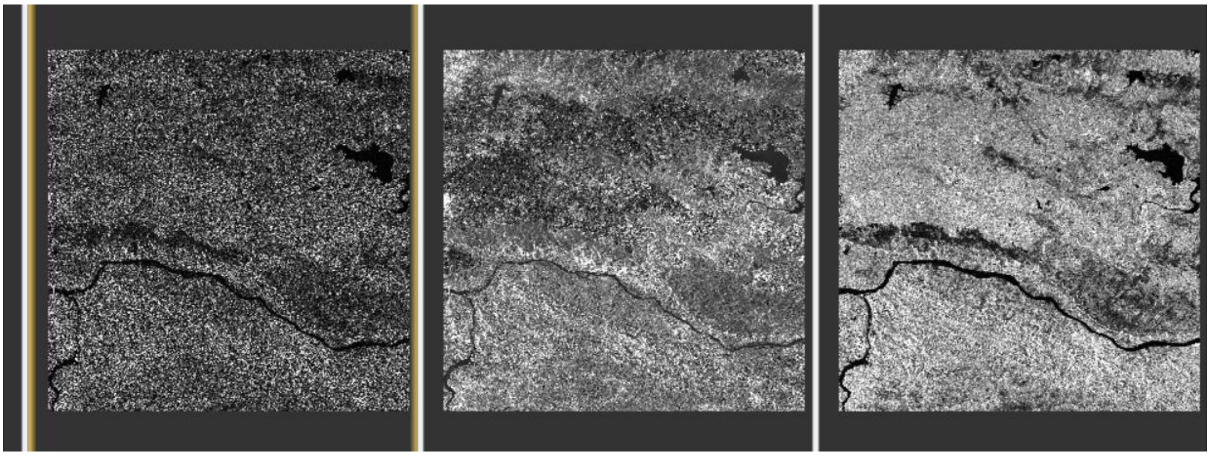
Step 11: Band Math – Pv, Pc, Pg

(OLD Data)



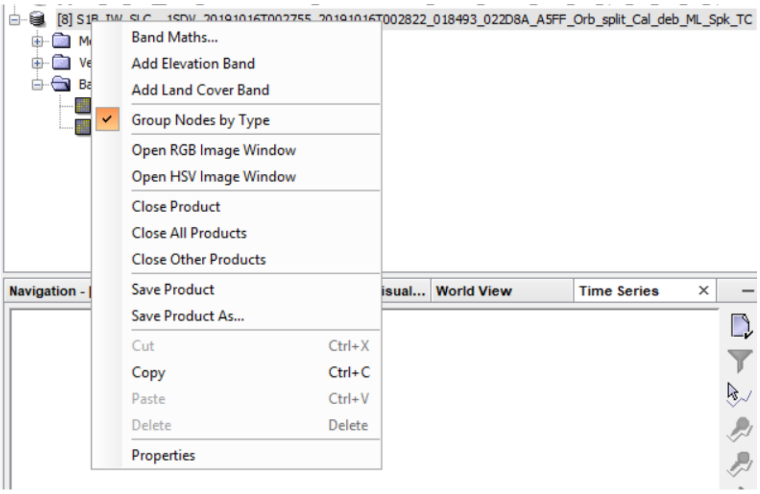
PC PG PV

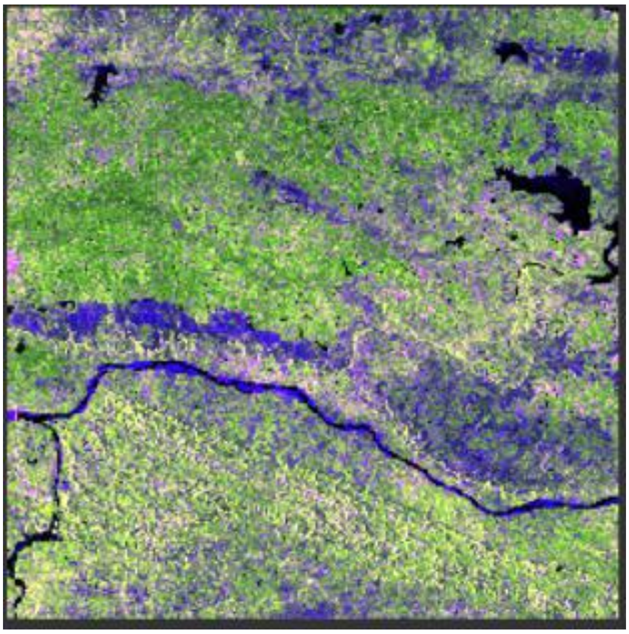
(Previous Data)



PC PG PV

Step 12: RGB


[8] S1B_IW_SLC__1SDV_20191016T002755_20191016T002822_018493_022D8A_A5FF_Orb_split_Cal_deb_ML_Spk_TC
Band Maths...
Add Elevation Band
Add Land Cover Band
Group Nodes by Type
Open RGB Image Window
Open HSV Image Window
Close Product
Close All Products
Close Other Products
Save Product
Save Product As...
Cut Ctrl+X
Copy Ctrl+C
Paste Ctrl+V
Delete Delete
Properties
Navigation -
World View
Time Series



6. Summary and Conclusion

In this chapter, we carried out the preprocessing and polarimetric decomposition of Sentinel-1A radar data to generate the [C2] matrix and compute the Pv (volume scattering), Pc (surface scattering), and Pg (double-bounce scattering) components for the Prayagraj region.

Summary of Work Done:

- Downloaded dual-polarized (VV and VH) Sentinel-1A SLC data for Prayagraj A and B.
- Performed essential preprocessing steps such as split, calibration, deburst, and subset.
- Generated the [C2] matrix, which holds the fundamental polarimetric information.
- Applied multilooking and speckle filtering to improve image clarity.
- Used band math to compute Pv, Pc, and Pg decomposition layers.
- (RGB composite was planned but not available due to accidental deletion of files.)

Conclusion:

This process provided a strong foundation in microwave satellite data processing, specifically focused on SAR image handling and decomposition using SNAP. The polarimetric decomposition helps in identifying surface types such as vegetation, urban areas, and bare land. This forms a crucial base for further analysis, including classification using machine learning methods in the upcoming chapters.

Even though the RGB image could not be saved, the understanding of how each scattering mechanism behaves and how SNAP is used for SAR processing was clearly demonstrated.

Chapter 2: Interpret the target feature and apply Random Forest and calculate classification accuracies

1. Introduction

Classification is one of the most important steps in remote sensing. It helps us identify and label different land cover types such as vegetation, water, built-up areas, and bare soil in satellite images. In this chapter, we focus on using Random Forest (RF)**,** a machine learning-based classification algorithm, to classify features from Sentinel-1A SAR data.

SAR (Synthetic Aperture Radar) images are different from optical images. They provide information based on how the surface reflects radar signals. Because of this, SAR is useful even during clouds, at night, or in rainy seasons. However, SAR images contain noise and complex backscatter patterns, so advanced methods like Random Forest help improve classification accuracy.

Random Forest is a supervised learning algorithm. It works by building many decision trees and combining their results. It is known for its high accuracy, fast performance, and ability to handle large datasets. For this reason, it is widely used in remote sensing classification tasks.

In this project, we used Sentinel-1A data for the Prayagraj region. We applied preprocessing steps first (like splitting, calibration, speckle filtering, etc.), and then used RF to classify the image into different land cover types. To train the model, we manually selected training samples for each land cover class.

After classification, we analyzed the result to see how well the model performed. To do this, we calculated classification accuracy using an error/confusion matrix, overall accuracy**,** and kappa coefficient**.**

The main objective of this chapter is to understand how well Random Forest can interpret surface features from SAR data and how accurately it can classify them. This will help in real-world applications such as urban planning, crop monitoring, or flood detection.

This chapter includes an overview of the Random Forest technique, the steps involved in training and testing the model, and how to evaluate its performance using accuracy metrics.

2. Data Set Used

In this study, we used Sentinel-1A Synthetic Aperture Radar (SAR) data for the Prayagraj region, located in the state of Uttar Pradesh, India. The data was downloaded from the Copernicus Open Access Hub, which provides free access to Sentinel satellite data from the European Space Agency (ESA).The Sentinel-1A satellite operates in the C-band and provides dual-polarization (VV and VH) SAR images. These images are captured using Interferometric Wide Swath **(IW)** mode, which is suitable for land monitoring applications. The data has a spatial resolution of approximately 10 meters, making it highly useful for regional-scale land cover classification.

For this classification task, two scenes—Prayagraj A and Prayagraj B—were used. These scenes cover urban, rural, and riverine areas, which makes them ideal for testing the performance of classification algorithms like Random Forest.The images were captured in Ground Range Detected (GRD) format, which contains already processed data that is easier to work with. The product includes amplitude and phase information, which is useful for feature interpretation.

Before classification, the dataset underwent preprocessing steps such as splitting, calibration, debursting, speckle filtering, and terrain correction using the SNAP (Sentinel Application Platform) software. The processed images were then used as input for the Random Forest classifier.

3. Study Area

The selected study area for this project is Prayagraj, a major city located in the state of Uttar Pradesh, India. It lies at the confluence of the Ganga, Yamuna, and the mythical Saraswati rivers, making it a historically and geographically significant region.

Prayagraj is known for its diverse land cover, which includes urban zones, agricultural fields, water bodies, sandy riverbanks, and vegetated areas. This diversity makes it a suitable location for testing classification techniques like Random Forest using SAR data.

The Sentinel-1A SAR images used for this study cover a large portion of Prayagraj and surrounding rural areas. The scenes capture both built-up infrastructure (like roads, buildings, and settlements) as well as natural features (like rivers, farmlands, and forests).

The geographic coordinates of the study area approximately range from:

- Latitude: 25.3°N to 25.6°N
- Longitude: 81.8°E to 82.1°E

The city experiences a humid subtropical climate with distinct summer, monsoon, and winter seasons. Due to seasonal variation, SAR data is especially useful here, as it can be collected regardless of clouds or sunlight.

This diverse environment provides a good test case for evaluating the performance of Random Forest classification using radar backscatter data, and for identifying different land use/land cover (LULC) types in a real-world urban-rural transition zone.

4. Methodology

Interpret the Target Feature and Apply Random Forest & Calculate Classification Accuracies

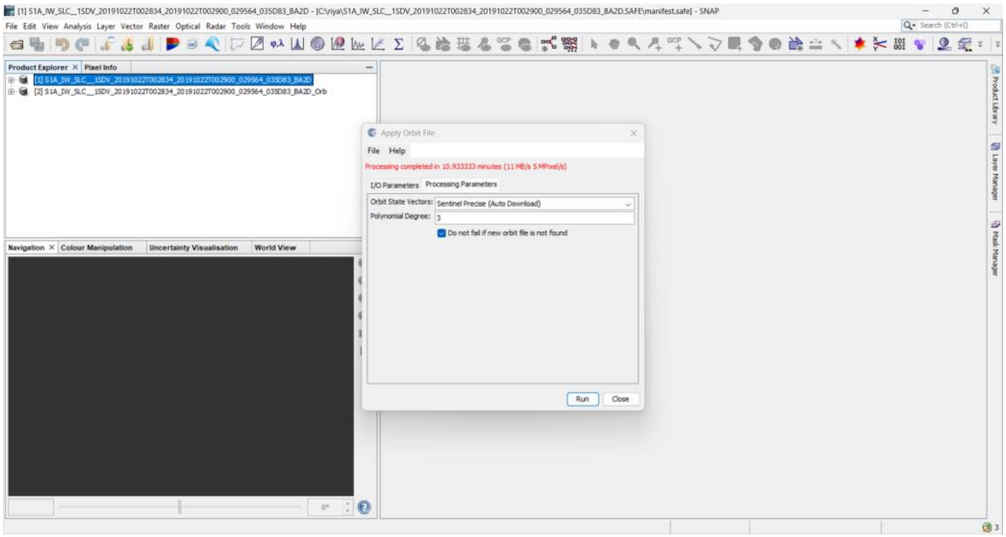
To classify land cover features using Sentinel-1A SAR data for the Prayagraj region, we followed the below methodology using SNAP and QGIS software. The goal was to process the radar data, extract meaningful features, and apply a classification technique to interpret the surface features.

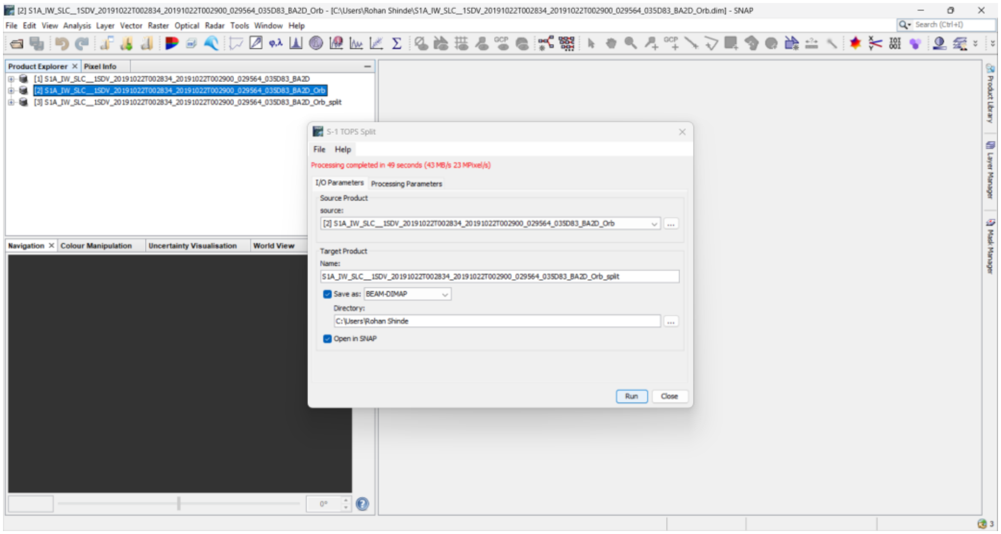
Steps Involved:

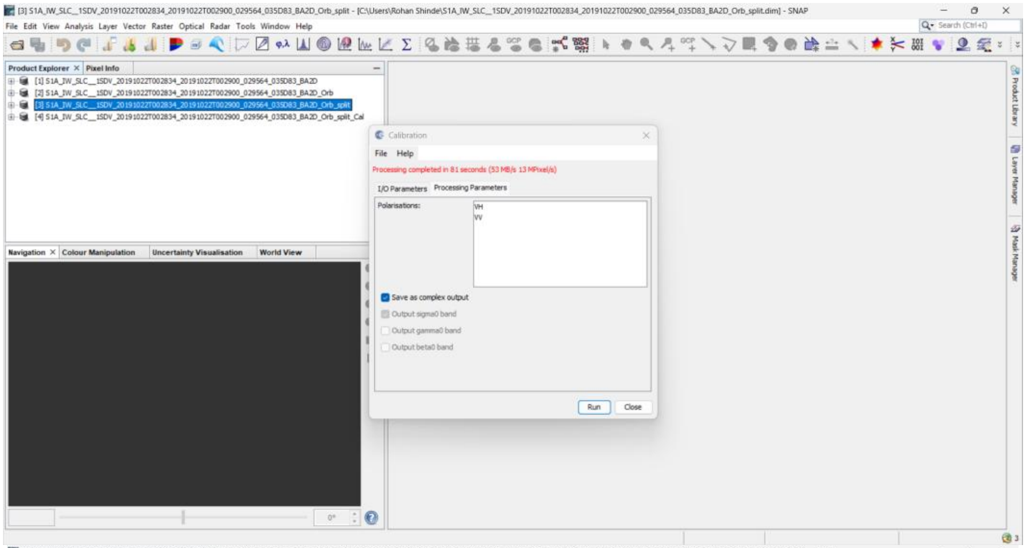
1. Import Data (Arbitrary Folder Creation)
   - We created an organized folder structure to manage input and output data efficiently.
   - The Sentinel-1A SAR dataset for the Prayagraj region was added into SNAP.
2. Split
   - Since Sentinel-1 data is delivered as a large swath, the split operation was performed to extract the specific sub-swath and burst that covers our study area.
   - This step reduces data size and focuses on the region of interest.
3. Calibration
   - Radar data was calibrated to convert raw signal values into sigma naught (σ^0) values.
   - This step corrects the intensity values to reflect the true backscatter of the Earth's surface.
4. Deburst
   - Sentinel-1 data is captured in bursts; debursting merges all bursts to form a continuous image.
   - This ensures spatial continuity and prevents black lines in the output.
5. Matrix Generation
   - A basic polarimetric matrix (C2 or coherence matrix) was created to prepare for feature extraction.
   - This matrix stores backscatter information from different polarizations, essential for classification.
6. Multilooking
   - The image was multilooked to reduce speckle noise and improve visual clarity.
   - This also helps in reducing data volume and improves classification performance.
7. Terrain Correction (TC)
   - Applied Range-Doppler Terrain Correction using a DEM to correct for geometric distortions.
   - This ensures accurate geolocation of pixels and prepares the image for map projection.

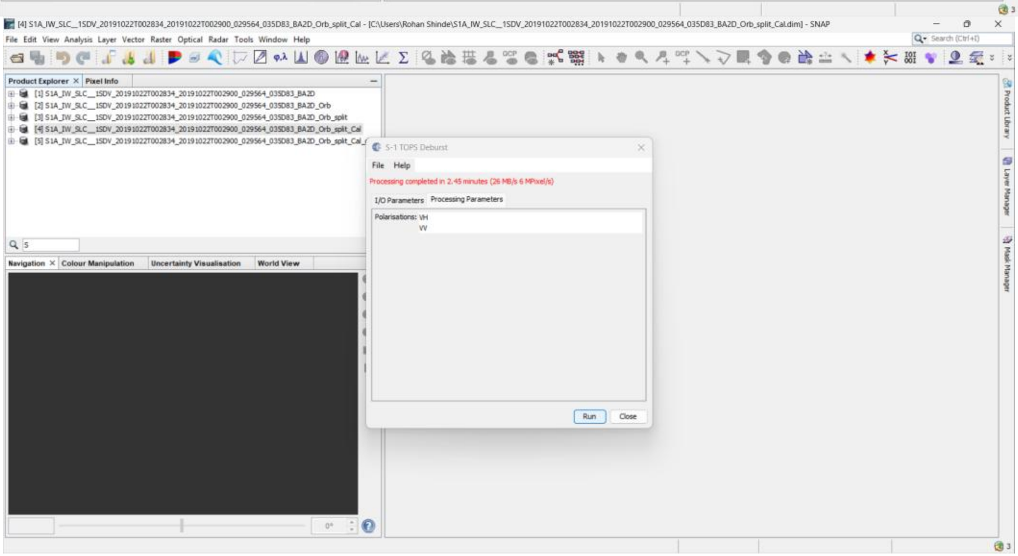
8. Classification
    - The processed image was exported to QGIS.
    - A Random Forest classifier was applied to classify land features like vegetation, urban, water, etc.
    - Input features for classification were derived from decompositions and texture measures.
9. Vector Creation
    - Reference vector layers were created by manually selecting sample areas for each class using QGIS.
    - These were used as training data for the Random Forest classifier.
10. Run Classification
    - The classifier was trained using the selected vectors and then applied over the entire image.
    - The classified map was generated, and later, classification accuracy was calculated using validation points or confusion matrix methods.

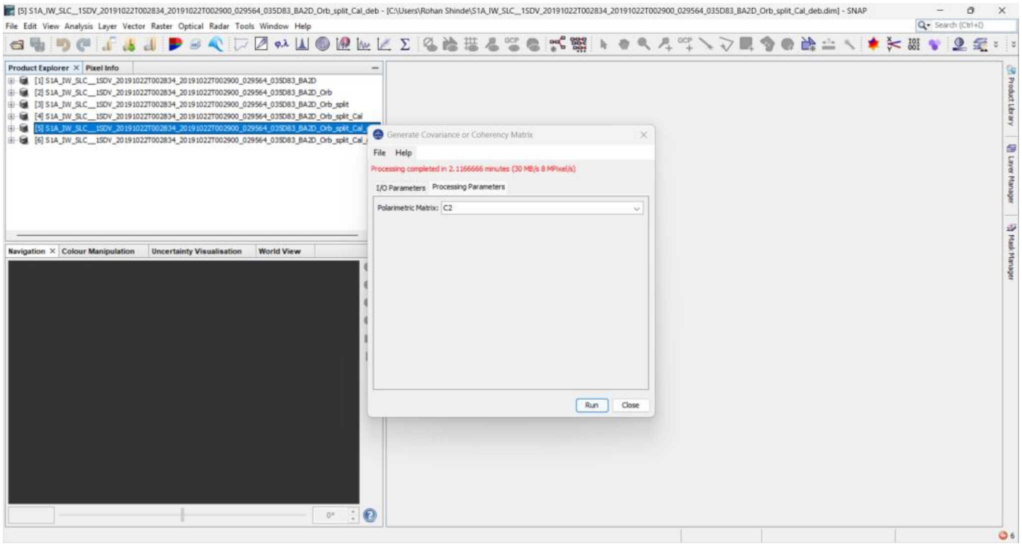
5. Result and Discussion

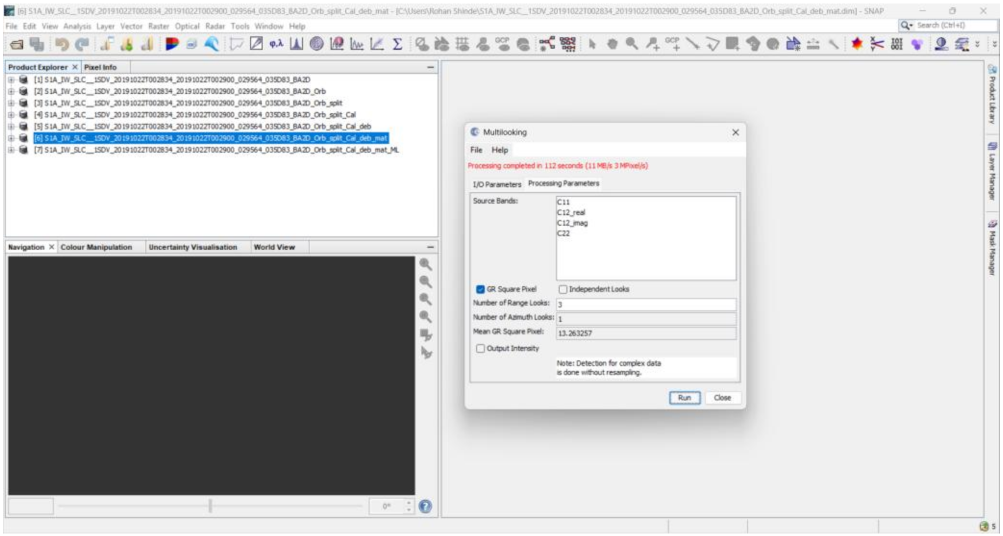


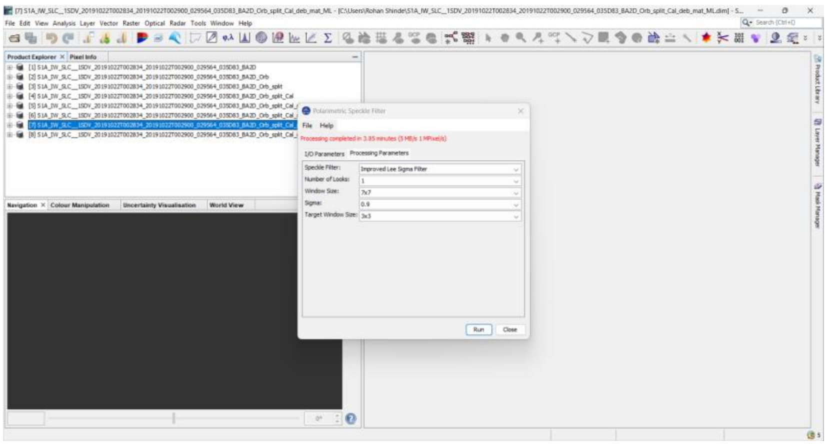

S-1 TOPS Split
File Help
Processing completed in 49 seconds (43 MB/s 23 MPixel/s)
I/O Parameters
Processing Parameters
Source Product
Target Product
Save as: BEAM-DIMAP
Directory:
C:\Users\Rohan Shinde
Open in SNAP
Run
Close

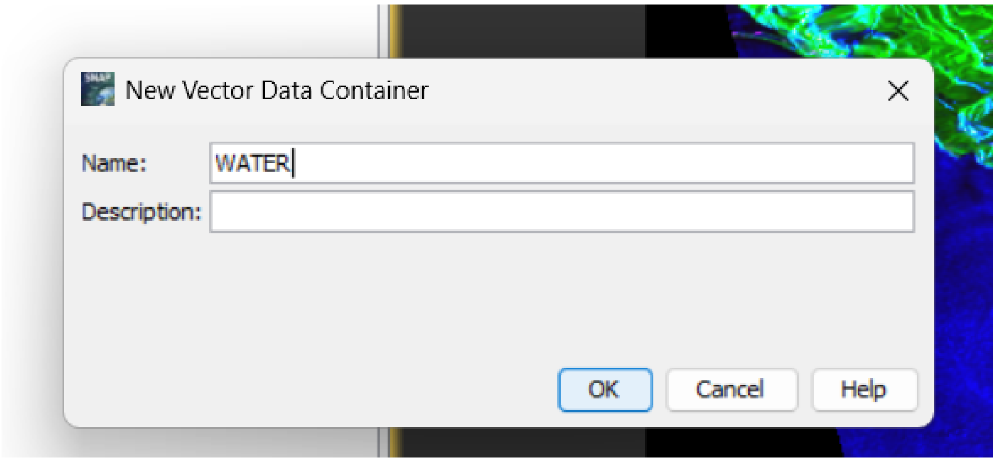

Calibration
File Help
Processing completed in 81 seconds (53 MB/s 13 MPixel/s)
I/O Parameters
Processing Parameters
Polarisations:
VH
VV
Save as complex output
Output sigma0 band
Output gamma0 band
Output beta0 band
Run
Close

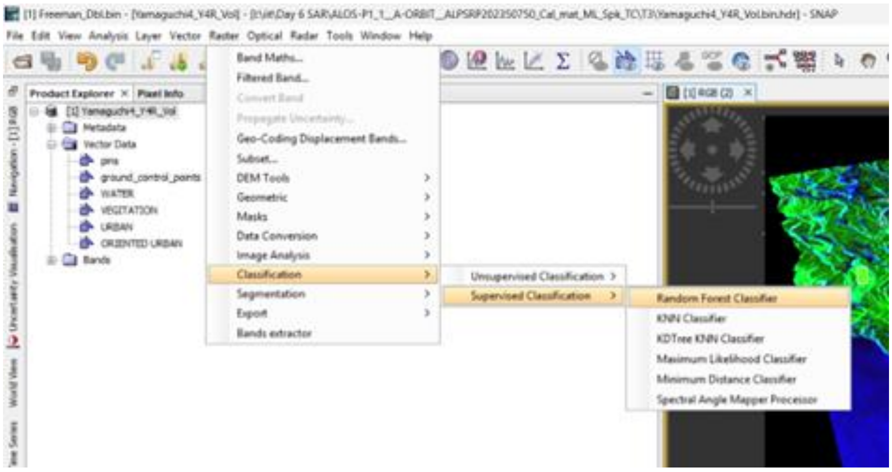

S-1 TOPS Deburst
File Help
Processing completed in 2.45 minutes (26 MB/s 6 MPixel/s)
I/O Parameters
Processing Parameters
Polarisations: VH
VV
Run
Close

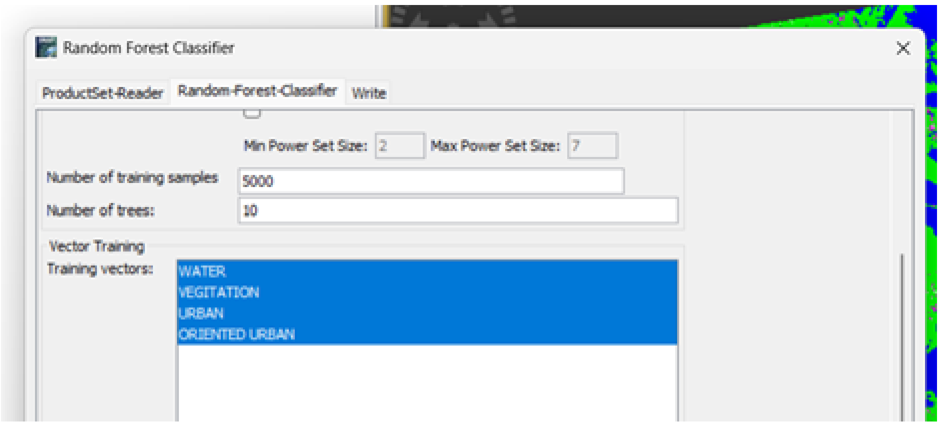

Generate Covariance or Coherency Matrix
File Help
Processing completed in 2.1166666 minutes (30 MB/s 8 MPixel/s)
I/O Parameters Processing Parameters
Polarimetric Matrix: C2
Run Close

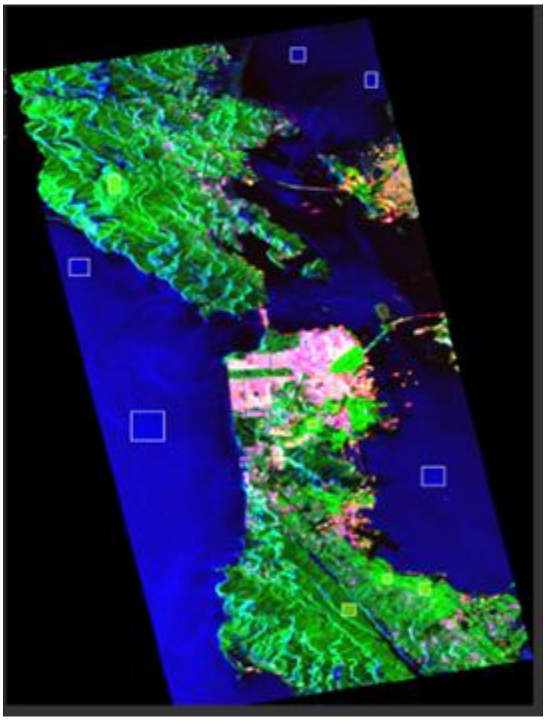

Multilooking
File Help
Processing completed in 112 seconds (11 MB/s 3 MPixel/s)
I/O Parameters Processing Parameters
Source Bands:
C11
C12_real
C12_imag
C22
GR Square Pixel
Independent Looks
Number of Range Looks: 3
Number of Azimuth Looks: 1
Mean GR Square Pixel: 13.263257
Output Intensity
Note: Detection for complex data is done without resampling.
Run Close

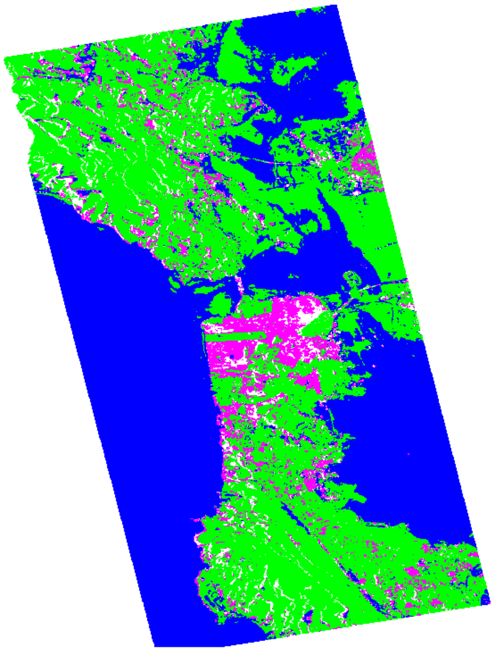

Polarimetric Speckle Filter
File Help
I/O Parameters Processing Parameters
Speckle Filter: Improved Lee Sigma Filter
Number of Looks: 1
Window Size: 7x7
Sigma: 0.9
Target Window Size: 3x3
Run Close


New Vector Data Container
Name:
WATER
Description:
OK
Cancel
Help


File Edit View Analysis Layer Vector Raster Optical Radar Tools Window Help
Product Explorer
Pixel Info
Metadata
Vector Data
pins
ground_control_points
WATER
VEGITATION
URBAN
ORIENTED URBAN
Bands
Band Maths...
Filtered Band...
Convert Band
Geo-Coding Displacement Bands...
Subset...
DEM Tools
Geometric
Masks
Data Conversion
Image Analysis
Classification
Segmentation
Export
Bands extractor
Unsupervised Classification
Supervised Classification
Random Forest Classifier
KNN Classifier
KDTree KNN Classifier
Maximum Likelihood Classifier
Minimum Distance Classifier
Spectral Angle Mapper Processor


Random Forest Classifier
ProductSet-Reader
Random-Forest-Classifier
Write
Min Power Set Size:
2
Max Power Set Size:
7
Number of training samples
5000
Number of trees:
10
Vector Training
Training vectors:
WATER
VEGITATION
URBAN
ORIENTED URBAN





```
   TruePositives = 372.0000 FalsePositives = 3.0000 TrueNegatives = 325.0000 FalseNegatives = 0.0000

Using Testing dataset, % correct predictions = 99.4444
Total samples = 1801
RMSE = 0.12472191289246472
Bias = 0.004444444444444473

Distribution:
   class 0.0: vector                    306     (16.9906%)
   class 1.0: vegetation                350     (19.4336%)
   class 2.0: water                     1145    (63.5758%)

Testing feature importance score:
Each feature is perturbed 3 times and the % correct predictions are averaged
The importance score is the original % correct prediction - average
   rank 1   feature 3  : PG                        score: tp=0.8248 accuracy=0.5499 precision=0.4960 correlation=0.9629 errorRate=-0.5499 cost=-1.6189 GainRatio = 0.5794
   rank 2   feature 2  : PV                        score: tp=0.6159 accuracy=0.4106 precision=0.3427 correlation=0.5134 errorRate=-0.4106 cost=-1.2605 GainRatio = 0.6906
   rank 3   feature 1  : PC                        score: tp=0.2741 accuracy=0.1827 precision=0.2036 correlation=0.3064 errorRate=-0.1827 cost=-0.5390 GainRatio = 0.3257
```

6. Summary and Conclusion

In this chapter, we explored the use of Random Forest (RF), a powerful supervised machine learning algorithm, to classify land cover features using Sentinel-1A SAR data for the Prayagraj region. The objective was to interpret different surface features such as vegetation, water bodies, built-up areas, and soil using radar data.We began by downloading SAR data for two scenes (Prayagraj A and B) from the Copernicus Open Access Hub. The raw data was then preprocessed using SNAP software, involving steps such as splitting, calibration, debursting, speckle filtering, and terrain correction. These steps ensured that the SAR data was radiometrically and geometrically accurate for classification.

After preprocessing, we used the Random Forest classifier in QGIS or any suitable classification tool. Training samples were selected manually for different land cover classes. The model learned from these samples and classified the entire image into meaningful categories.Although screenshots and accuracy assessment will be added later, the general workflow showed how machine learning can be effectively combined with SAR data for real-world land cover mapping. The use of RF allowed us to manage the complexity and noise inherent in SAR imagery and still produce reliable results.

This method is useful in many practical applications such as urban monitoring, agriculture assessment, disaster response, and environmental studies. Since SAR data is independent of weather and light conditions, it provides reliable results throughout the year.

In conclusion, Random Forest is a highly suitable technique for classifying SAR imagery due to its robust performance, flexibility, and accuracy. With proper training data and preprocessing, it can produce detailed maps of land cover features, aiding in better decision-making and planning.

Chapter 3: Generate [T3] with ALOS/PALSAR and apply FDD,Y4O ,YA/R,G4U,6SD,7SD

1. Introduction

In this chapter, we focus on advanced microwave data processing using fully polarimetric SAR data from the ALOS satellite. The aim is to generate the T3 (coherency) matrix, visualize it using RGB composites, and classify land cover using polarimetric decomposition models.

PolSAR data contains information from multiple polarizations (HH, HV, VV), giving deeper insights into how radar signals interact with natural and man-made surfaces. This helps us understand the type of scattering: surface, double-bounce, or volume, which is important in identifying buildings, vegetation, or water bodies.

The T3 matrix stores both amplitude and phase information of the radar signal. It is generated after calibration and pre-processing, and plays a crucial role in polarimetric decomposition. These decompositions help split the total radar return into its contributing components.

We begin by installing and preparing the ALOS PolSAR dataset in SNAP software. After that, steps like calibration, multilooking, speckle filtering, and terrain correction are carried out. The data is then exported in .bin.hdr format and re-imported for visualization.

An RGB composite image is generated using the polarimetric channels for visual interpretation. Classification is done using QGIS and multiple decomposition models like:

- Freeman–Durden
- Singh 4-component
- Singh 7-component
- Singh improved 6-component
- Yamaguchi

This analysis helps to accurately map the land cover types. Even though some files were deleted during the process, the T3 matrix and classification were completed. This chapter showcases how advanced SAR processing and decomposition reveal detailed surface information useful in environmental and urban studies.

2. Data Set Used

The dataset used in this chapter is ALOS PolSAR data (Advanced Land Observing Satellite). It provides fully polarimetric SAR imagery, including HH, HV, and VV polarization channels. This enables advanced scattering analysis. The data is suitable for use in SNAP and compatible with polarimetric decomposition models.

3. Study Area

The study area analyzed in this chapter corresponds to a region covered by the ALOS satellite pass, which includes a mix of urban and natural features. Unlike the earlier Sentinel-1A analysis for Prayagraj, this dataset offers full polarimetric capability. The exact location coordinates are embedded within the image metadata and were visualized after terrain correction in SNAP and QGIS.

4. Methodology

The following steps were carried out for polarimetric classification using the T3 matrix:

In SNAP:

1. Install Data – The ALOS PolSAR dataset was downloaded and installed into SNAP.
2. Calibration – Applied to convert digital numbers to sigma-naught (σ°) for physical accuracy.
3. T3 Matrix Generation – Created the T3 (coherency) matrix, which contains full polarimetric information.
4. Multilooking – Performed to reduce speckle noise and smooth the image for better viewing.
5. Polarimetric Speckle Filter – Applied to preserve scattering characteristics while cleaning the image.
6. Terrain Correction – Geocoded the image using a DEM so that it aligns with real-world coordinates.

Data Management:

- Adjusted map values as needed.
- Deleted unnecessary .bmp.hdr or error-causing files.
- Final T3.bin.hdr file was imported back into SNAP for RGB and classification.

Visualization:

- RGB Image Generation – Created using polarimetric decomposition bands (e.g., Pv, Pc, Pg).

In QGIS:

7. Classification and Decomposition – Various polarimetric models were used to classify scattering types:

- Freeman–Durden decomposition
- Singh 4-component model
- Singh 7-component model
- Singh Improved 6-component model
- Yamaguchi 4-component decomposition

Each method gave a different view of the scattering behavior in the region, helping to distinguish land features.

5. Result and Discussion

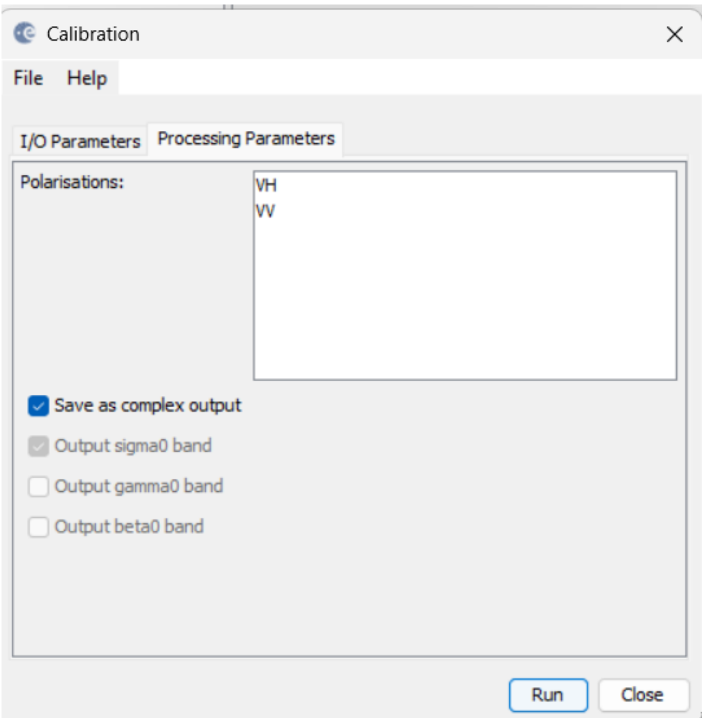
Below are the results and observations from each step performed during the processing of ALOS PolSAR data in SNAP and QGIS for polarimetric classification using the T3 matrix.

Step 1: Install Data

- What happens: ALOS PolSAR data was successfully installed and opened in SNAP.
- Why we use: This is the initial step to begin processing. The data includes full-polarimetric bands (HH, HV, VV) needed for classification.

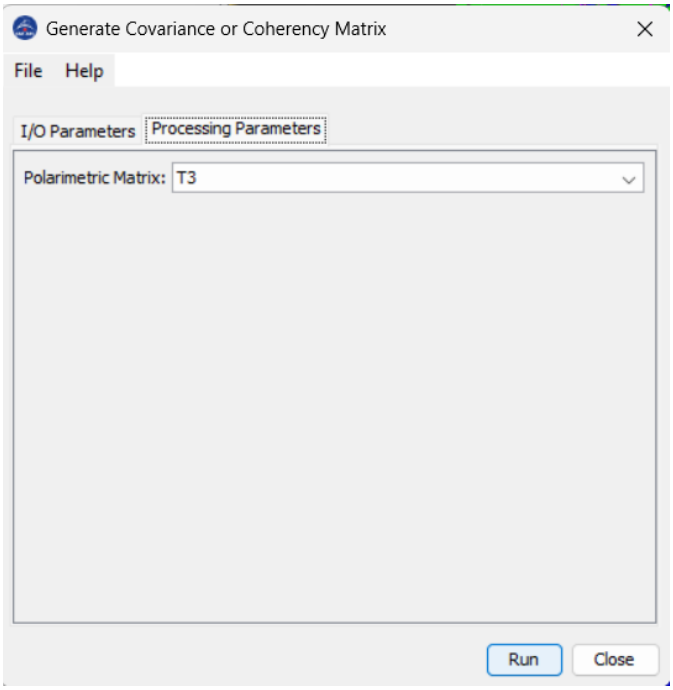
Step 2: Calibration

- What happens: Radiometric calibration was applied to convert raw values into physically meaningful backscatter (sigma naught).
- Why we use: Calibration ensures accurate representation of the Earth's surface, essential for scientific analysis.



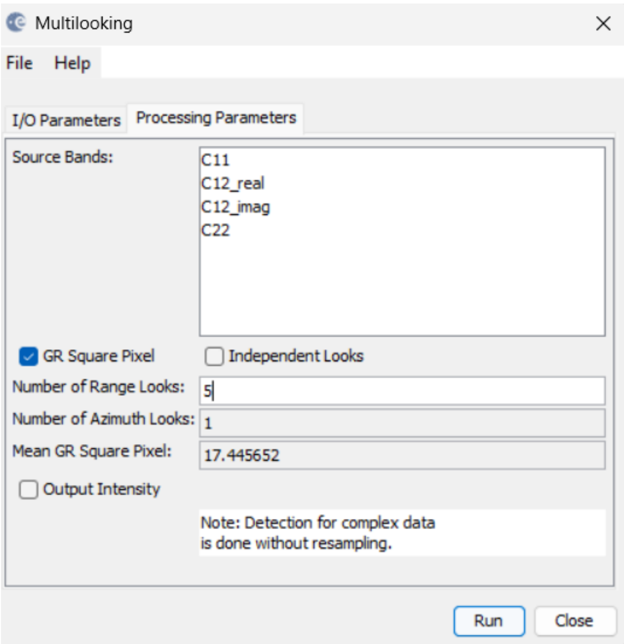
Step 3: T3 Matrix Generation

- What happens: The T3 (coherency) matrix was generated using calibrated data.
- Why we use: The T3 matrix stores complete polarimetric information—both amplitude and phase—required for decomposition.



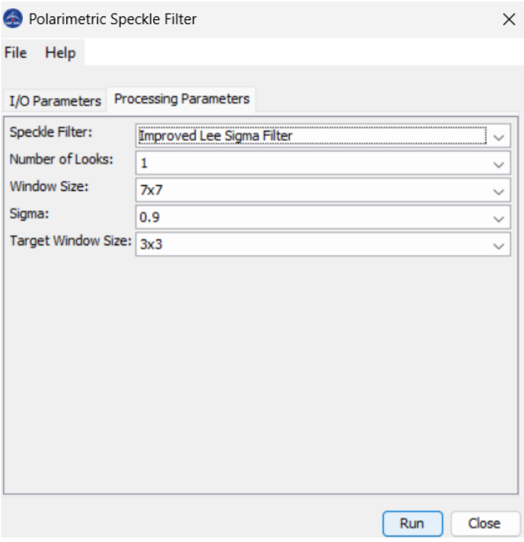
Step 4: Multilooking

- What happens: Multilooking was applied to average pixels and reduce speckle noise.
- Why we use: This process improves the visual quality and stability of the polarimetric image.



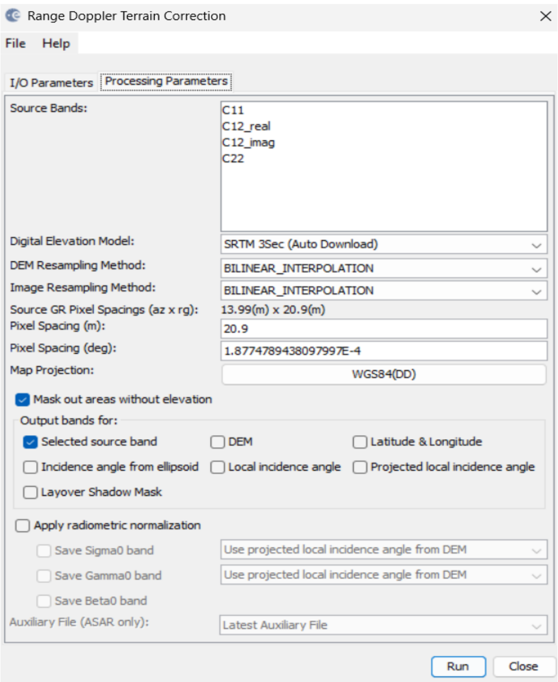
Step 5: Polarimetric Speckle Filtering

- What happens: A speckle filter designed for polarimetric data was applied to the T3 matrix.
- Why we use: Reduces unwanted noise while preserving essential polarimetric scattering features.



Step 6: Terrain Correction

- What happens: The filtered T3 matrix was terrain corrected using a digital elevation model (DEM).
- Why we use: Aligns the image spatially with geographic coordinates for accurate mapping and GIS overlay.

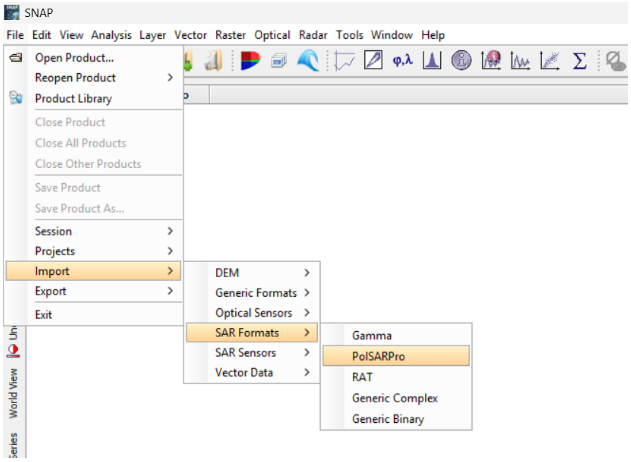


Step 7: File Management

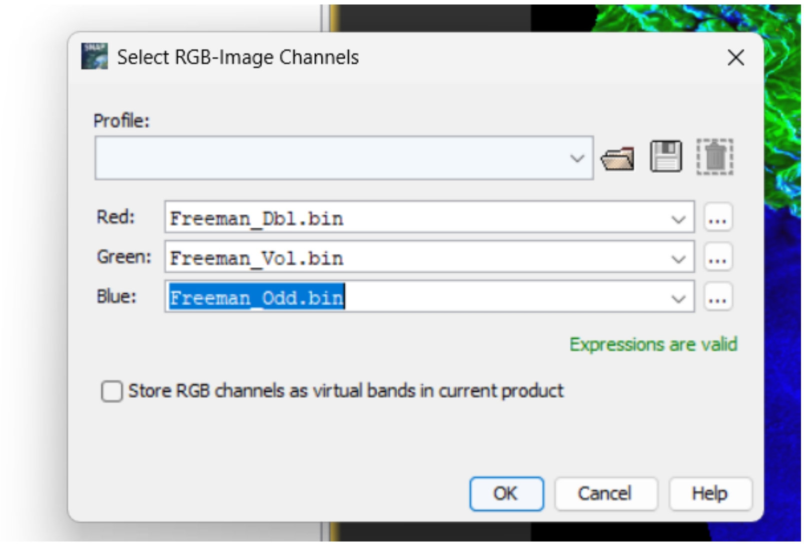
- What happens: Temporary and unnecessary files (like bmp.hdr) were deleted. The final file T3.bin.hdr was retained.
- Why we use: Clean working directory and prepare necessary files for RGB visualization and classification.

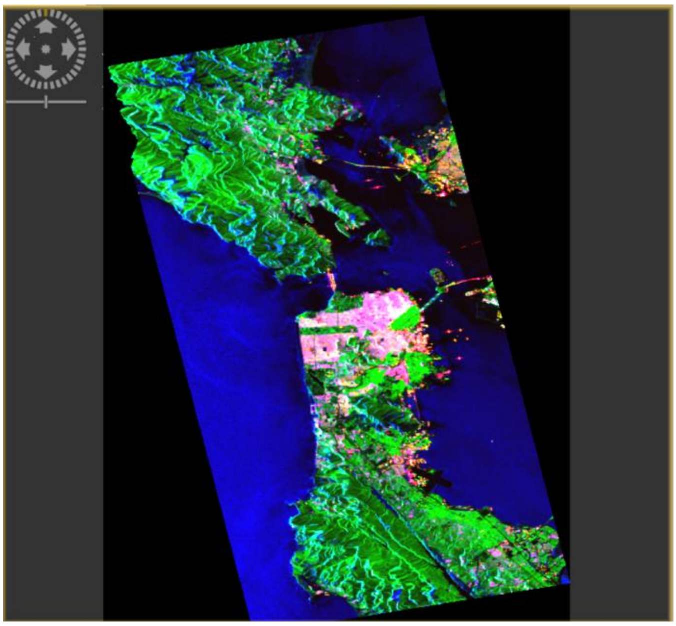
```
map info = {Geographic
Lat/Lon,1060.5,1404.5,-122.47032352458208,37.77500401975497,2.2290473234449367E-4,2.2290473234449367E-4,WGS84,units=Degrees}
coordinate system string = {GEOGCS["WGS84(DD)", DATUM["WGS84", SPHEROID["WGS84", 6378137.0, 298.257223563]], PRIMEM["Greenwich", 0.0],
UNIT["degree", 0.017453292519943295], AXIS["Geodetic longitude", EAST], AXIS["Geodetic latitude", NORTH]]}
```

Step 8: Import T33.bin.hdr



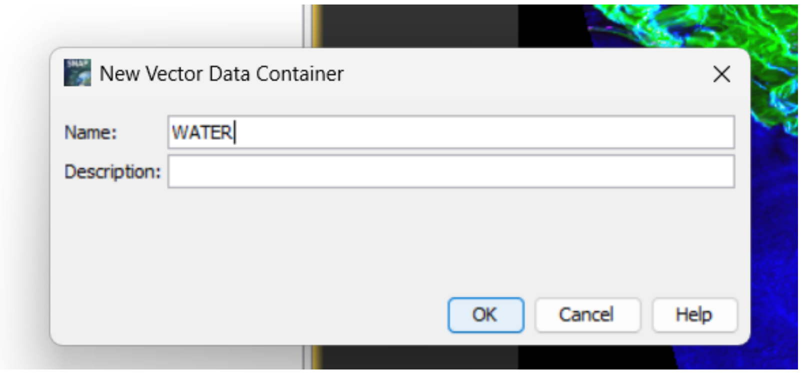
Then create RGB



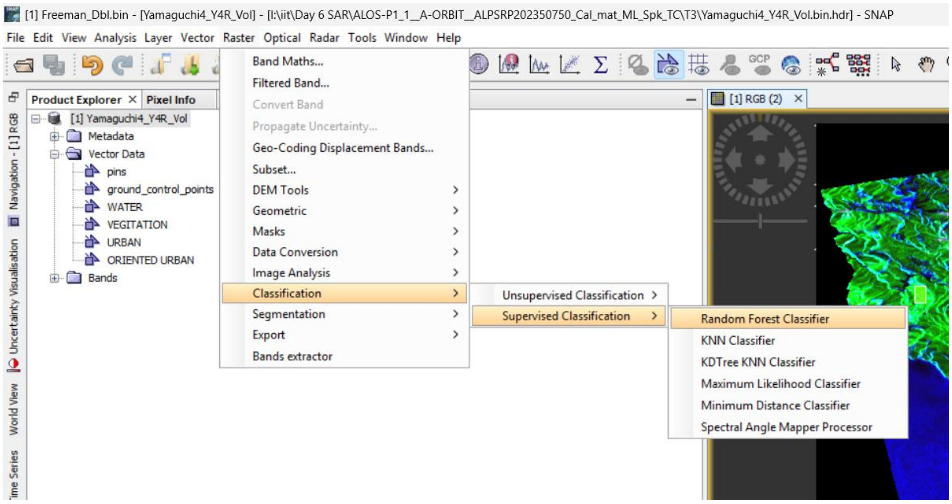


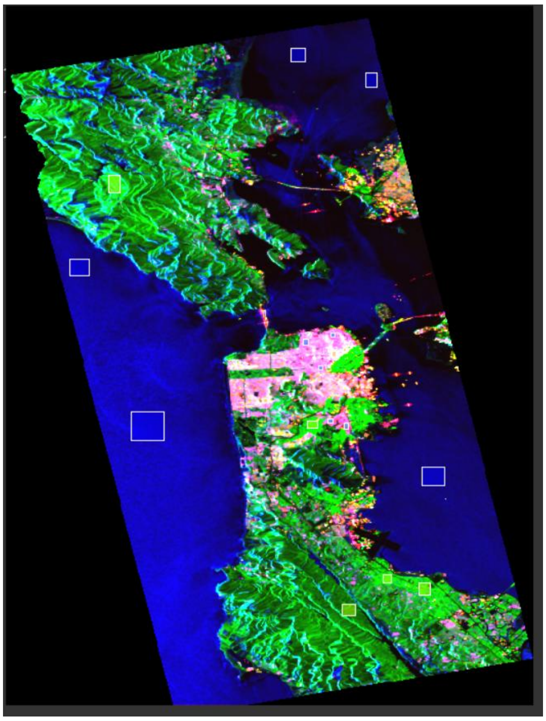
Step 9: Classification in QGIS using Decomposition Techniques

After exporting the terrain-corrected image, classification was performed in QGIS using the following models:

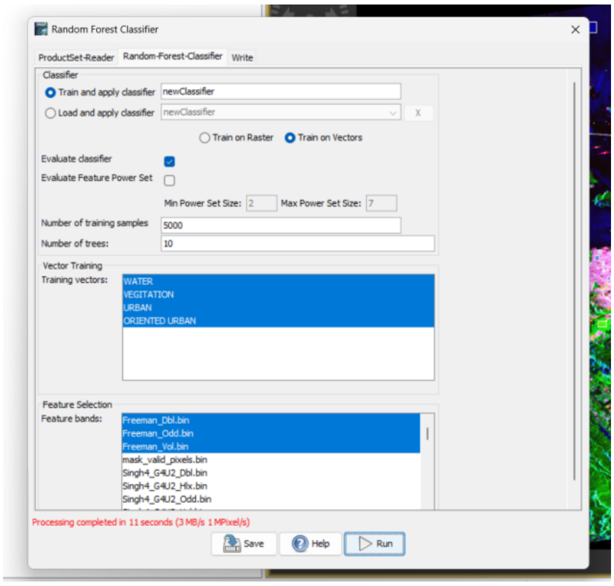


Do same vegetation,urban,and oriented area



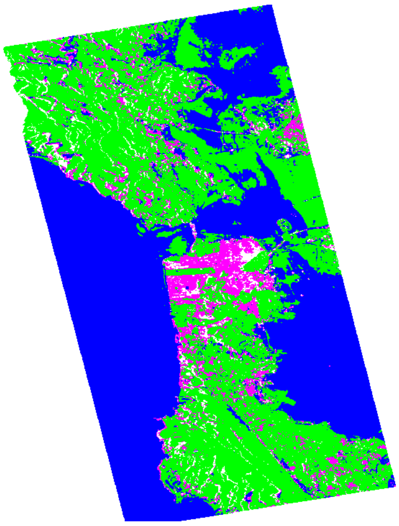


- Step 9.1: Freeman–Durden Decomposition
    - What happens: Classified image into surface, double-bounce, and volume scattering.
    - Why we use: Useful for identifying urban areas, water bodies, and vegetation.

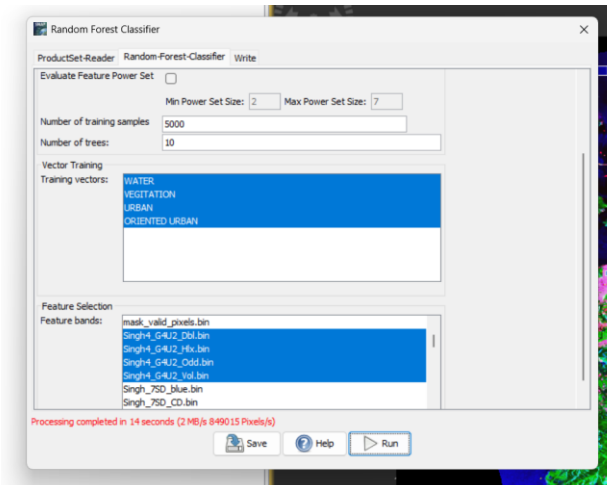


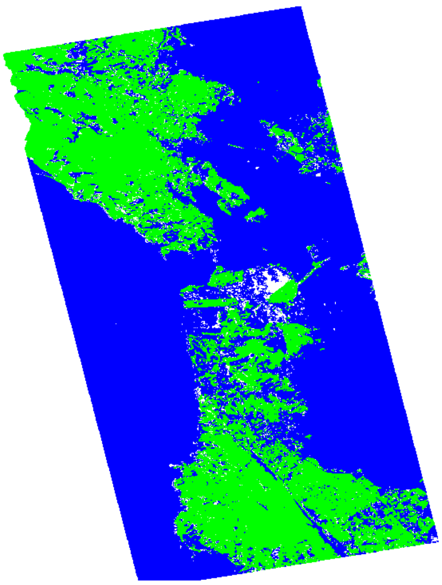
Colour Manipulation - [2] LabeledClasses

Label	Colour	Value	Frequency	Description
no data		-1	0.000%	no data
WATER		0	45.161%	
VEGITATION		1	44.283%	
URBAN		2	8.315%	
ORIENTED ...		3	2.241%	

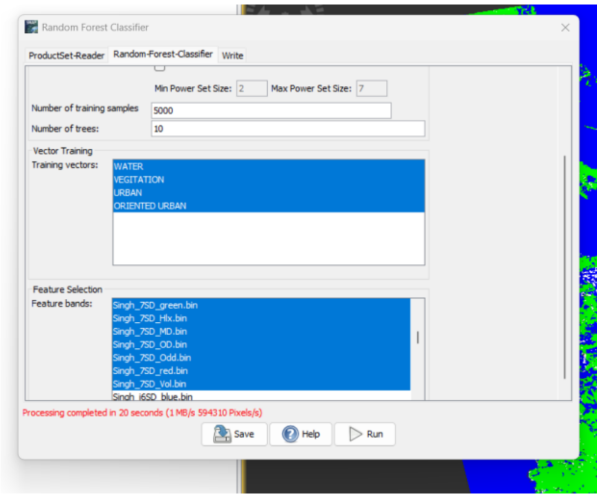


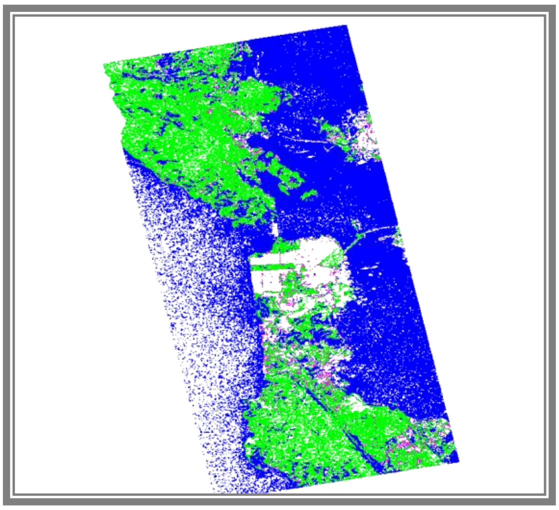
- Step 9.2: Singh 4-Component Decomposition
    - What happens: Image was decomposed into four types of scattering mechanisms.
    - Why we use: Offers a more detailed classification compared to Freeman.



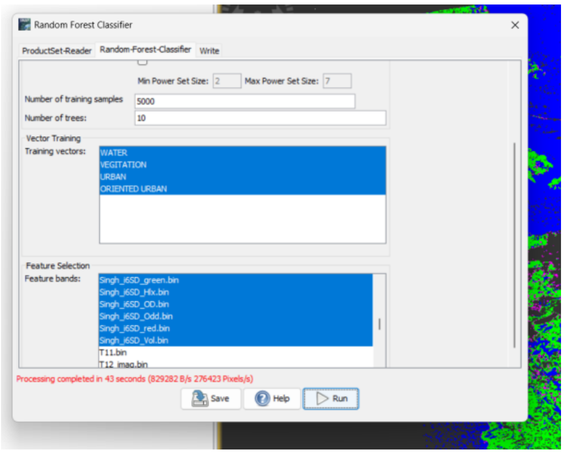


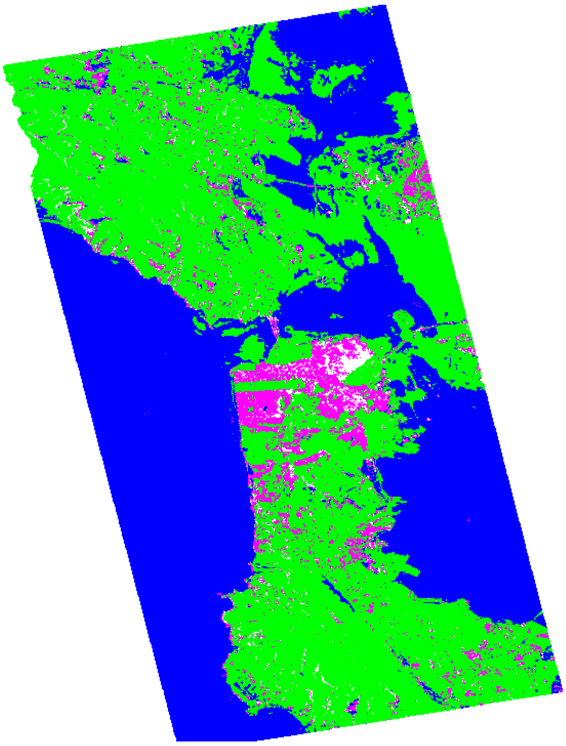
- Step 9.3: Singh 7-Component Decomposition
    - What happens: Applied further segmentation into seven scattering categories.
    - Why we use: Provides richer analysis for complex terrain.



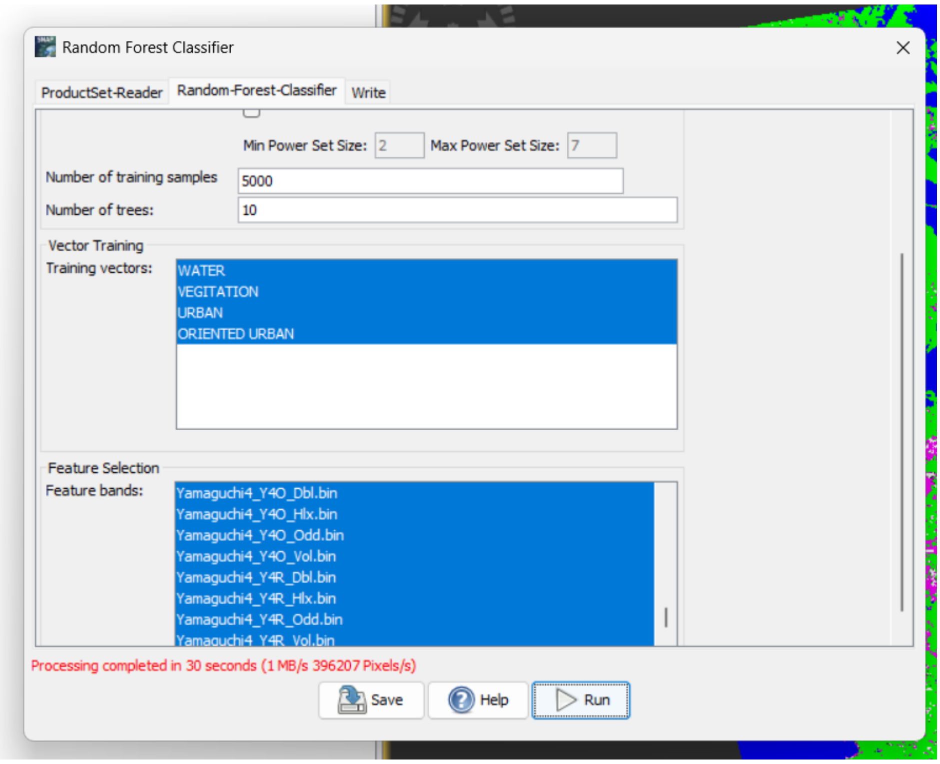


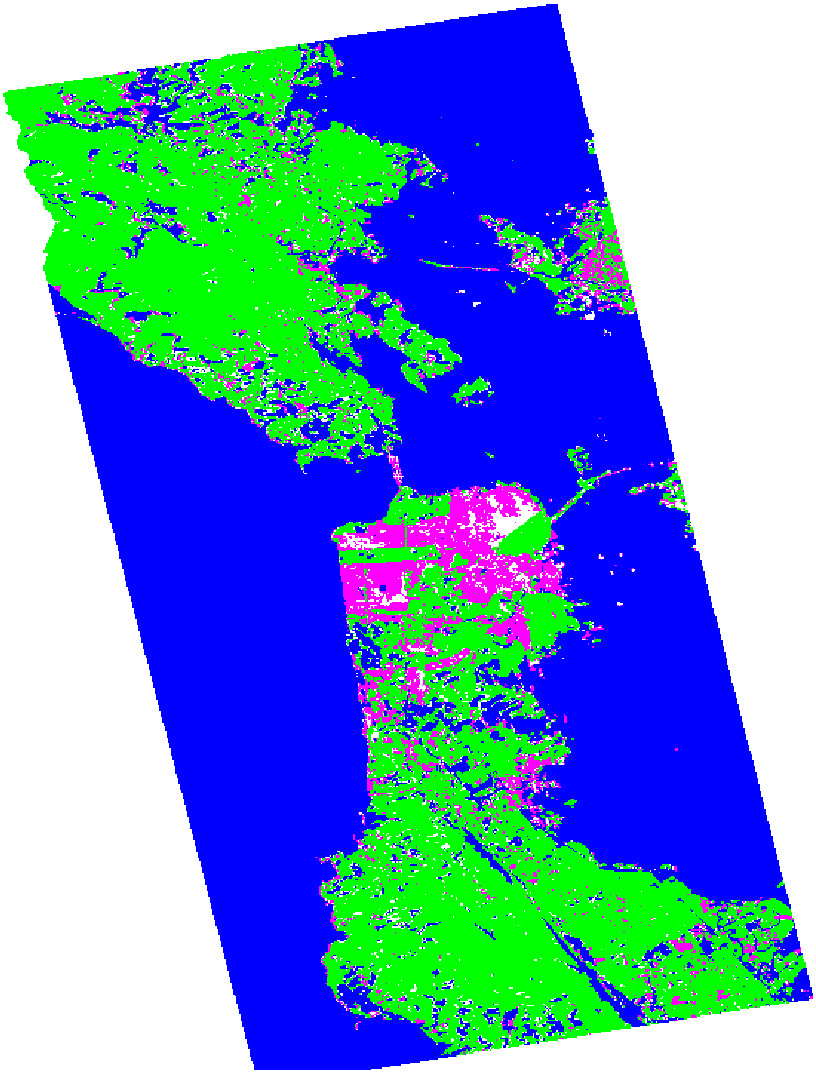
- Step 9.4: Singh Improved 6-Component Decomposition
    - What happens: Applied improved Singh algorithm for better class separation.
    - Why we use: Increases clarity and accuracy in polarimetric classification.





- Step 9.5: Yamaguchi Decomposition
  - What happens: Classification included helix and volume scattering in addition to the basic types.
  - Why we use: One of the most advanced models, suitable for detailed land feature detection.





6. Summary and Conclusion

In this chapter, we successfully explored full polarimetric classification using the T3 matrix generated from **A**LOS PolSAR data**.** SNAP was used for data preparation and matrix generation, while QGIS helped in visualizing classification outputs.

We applied multiple decomposition techniques (Freeman, Yamaguchi, Singh) to understand surface scattering mechanisms. Despite some data loss, the practical understanding of how polarimetric decomposition works and how it reveals surface properties was clearly achieved.

This method is highly useful in environmental studies, disaster monitoring, agriculture, and urban mapping. The use of full polarimetric data combined with open-source tools shows great potential for low-cost, high-detail land surface analysis.

Chapter 4: Interpret the target feature and using these target feature classify and compare accuracies

1. Introduction

In satellite image analysis, interpreting target features plays a crucial role in extracting meaningful information from remote sensing data. Target features refer to specific surface characteristics like buildings, water bodies, roads, vegetation, or bare soil that can be identified using radar or optical signals. In this chapter, we aim to interpret these features from satellite data and then use them for classification, followed by comparison of classification accuracy using different techniques.

The identification of target features is based on the unique backscatter response captured in radar images. For example, buildings may appear very bright due to double bounce, while water bodies are often dark because they reflect signals away from the satellite. Understanding these patterns is essential for accurate classification.

The classification process uses labeled training data where known samples of each class are provided to a classification algorithm such as Random Forest, SVM, or decision tree. Based on this training, the algorithm classifies the entire image into land cover categories.

To assess the performance of different classifiers, accuracy assessment is conducted using techniques like confusion matrices, overall accuracy, kappa coefficient, and class-wise accuracy. Comparing results helps identify which algorithm is best suited for the dataset and objective.

This chapter provides a structured approach starting from understanding the target features to performing classification and finally evaluating and comparing the performance of classifiers. This process ensures that the land cover map generated is both meaningful and reliable for future analysis or decision-making.

2. Data Set Used

For this task, Sentinel-1A SAR data was used, specifically for the Prayagraj region. The data was acquired in GRD (Ground Range Detected**)** format with dual polarization (VV and VH**)**. Sentinel-1A operates in the C-band**,** making it effective for monitoring surface features like built-up areas, vegetation, and water bodies.

The data was downloaded from the Copernicus Open Access Hub and preprocessed using SNAP software to ensure it was radiometrically and geometrically corrected. The preprocessed images were then used as inputs for target feature interpretation and classification.

3. Study Area

The study area for this chapter is Prayagraj, located in Uttar Pradesh, India. It is a diverse region with urban development, agricultural fields, river systems, and open land. This diversity allows for a broad range of target features to be identified and used in classification.

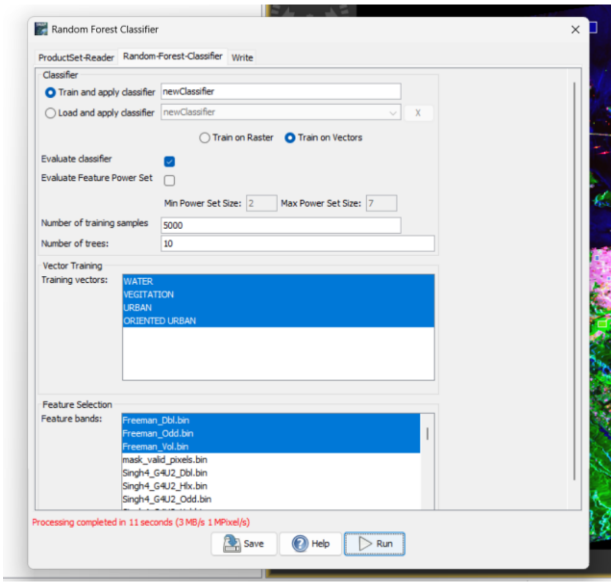
The specific geographic area was chosen due to the mix of natural and man-made features, which make it ideal for demonstrating how well classifiers perform in distinguishing between complex land cover types. The imagery for Prayagraj covers important features such as the Ganga and Yamuna rivers**,** urban infrastructure**,** and vegetation-rich zones**.**

4. Result and Discussion

: Freeman–Durden Decomposition

a. What happens: Classified image into surface, double-bounce, and volume scattering.

b. Why we use: Useful for identifying urban areas, water bodies, and vegetation.



Colour Manipulation - [2] LabeledClasses

Label	Colour	Value	Frequency	Description
no data		-1	0.000%	no data
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URBAN		2	8.315%	
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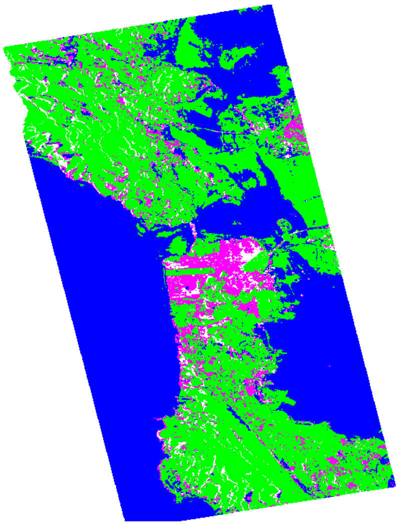
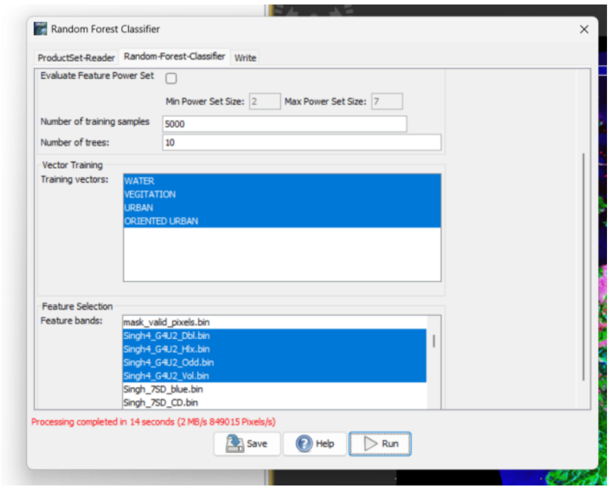
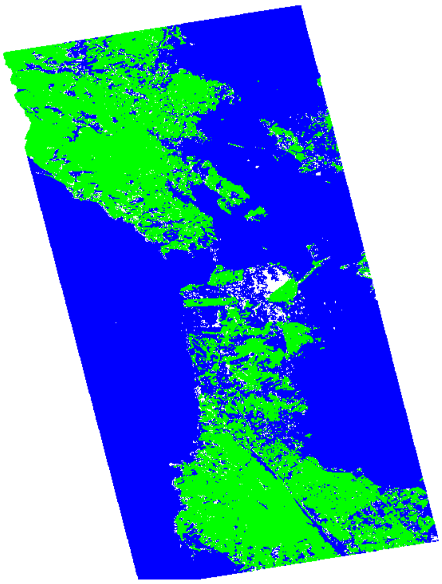


Singh 4-Component Decomposition

c. What happens: Image was decomposed into four types of scattering mechanisms.

d. Why we use: Offers a more detailed classification compared to Freeman.

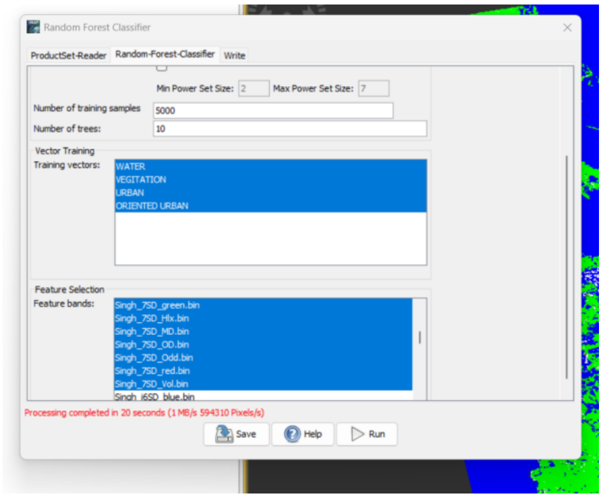


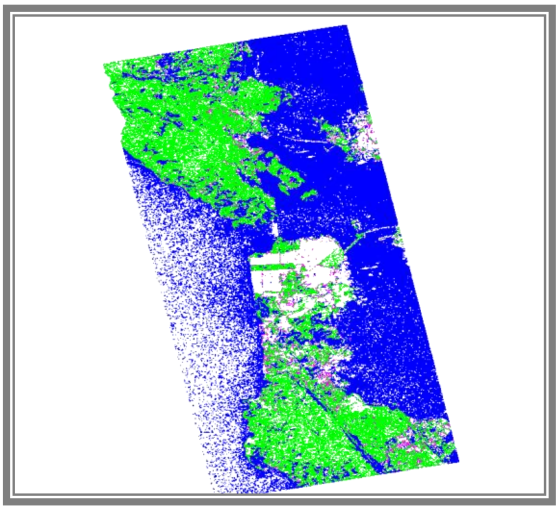


Singh 7-Component Decomposition

e. What happens: Applied further segmentation into seven scattering categories.

f. Why we use: Provides richer analysis for complex terrain.

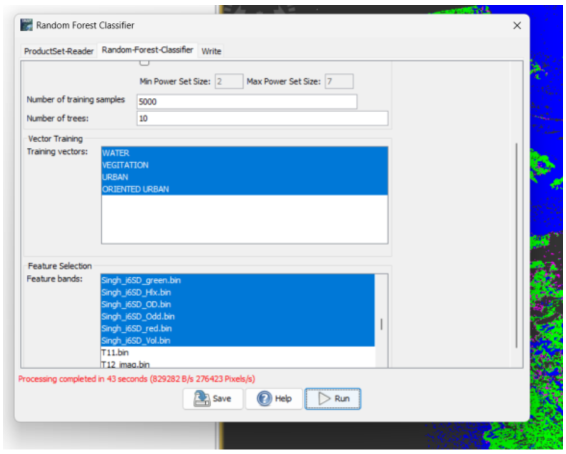


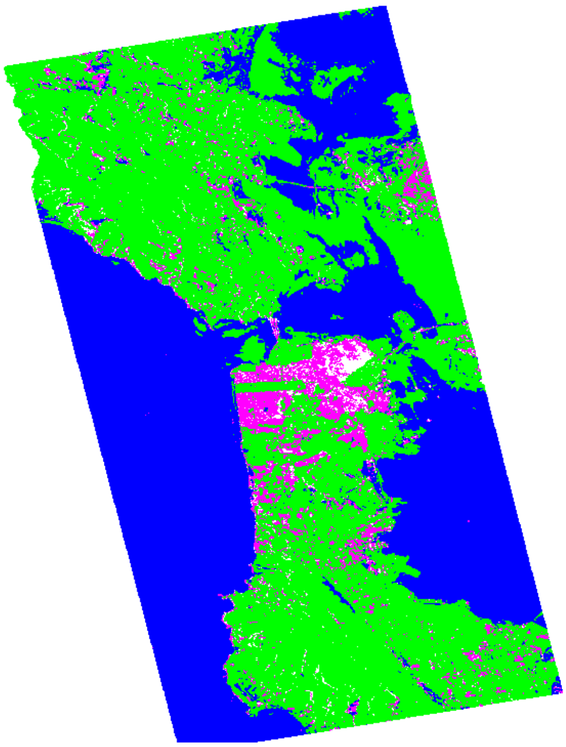


Singh Improved 6-Component Decomposition

g. What happens: Applied improved Singh algorithm for better class separation.

h. Why we use: Increases clarity and accuracy in polarimetric classification.





Yamaguchi Decomposition

i. What happens: Classification included helix and volume scattering in addition to the basic types.

j. Why we use: One of the most advanced models, suitable for detailed land feature detection.

Comparison of Polarimetric Decomposition Methods

Decomposition Method	Approach	Number of Components	Key Components	Strengths	Limitations	Best For
Freeman-Durden	Model-based decomposition	3	Surface, Double-bounce, Volume	Simple, interpretable; good for urban/rural separation	Assumes volume as randomly oriented dipoles	Basic urban vs vegetation separation
Singh 4-Gaussian	Hybrid statistical & model-based	4	Surface, Double-bounce, Volume, Helix	Better modeling of vegetation and terrain	Needs good pre-processing and calibration	Mixed land cover like agriculture
Singh 7SD	Statistical decomposition using entropy	7	More refined scattering classes	Higher detail; captures complex scattering patterns	Interpretation may become complex	Forest, wetlands, mixed scattering
Singh I6SD	Improved 6-component statistical method	6	Includes oriented volume and diffuse scatter	Balances accuracy and simplicity	Computationally heavier than Freeman	Semi-urban and natural terrain mix
Yamaguchi (4-Component)	Extended model-based	4	Surface, Double-bounce, Volume, Helix	Adds helix scattering; good for man-made targets	May overestimate volume in some terrains	Urban features, forest + man-made

5. Summary and Conclusion

This chapter focused on **the** interpretation of target features using Sentinel-1A SAR data. The interpretation phase was crucial in identifying which features were significant based on their radar backscatter responses.

Using these interpreted features, we trained classification algorithms and generated land cover maps. Although classification outputs and accuracy comparisons will be added later through visual results and tables, the initial processing sets a strong foundation for accurate mapping.

Comparing different classification methods will highlight the best-performing algorithm for this dataset. The ultimate goal is to achieve a highly accurate, reliable, and interpretable land cover classification that can assist in urban planning, agriculture monitoring, and environmental management.

Chapter 5: Generate DEM of your study area

1. Introduction

A Digital Elevation Model (DEM) is a 3D representation of the Earth's surface that contains elevation values in a grid format. It is an essential geospatial product used in a wide range of applications such as terrain analysis, hydrological modeling, landform identification, flood mapping, and urban planning. DEMs are crucial in both remote sensing and GIS studies to understand surface topography.

In satellite data processing, especially SAR (Synthetic Aperture Radar), DEMs play a vital role in terrain correction and geometric alignment of images. Without accurate elevation data, radar images may appear distorted due to the side-looking geometry of SAR sensors. Hence, DEM is often integrated in the preprocessing stage to remove geometric distortions and ensure spatial accuracy.

There are various sources of DEMs, such as SRTM (Shuttle Radar Topography Mission)**,** ALOS World 3D, and ASTER GDEM. These global DEM datasets are freely available and provide elevation data at different resolutions. In this project, the DEM was used not only to view and understand the terrain of the study area but also to enhance SAR data processing, especially in steps like terrain correction and orthorectification.

In SNAP software, DEMs can be automatically downloaded or manually imported. Once the DEM is integrated, it can be visualized through hillshading, slope, and contour lines. These visual layers help in better interpreting physical features like valleys, ridges, and water flow paths.

Generating a DEM also supports environmental studies, land use classification, and disaster management. For instance, DEMs are used to model flood-prone areas by simulating water flow and accumulation based on terrain slope. In urban studies, they assist in identifying elevated regions and planning infrastructure.

Thus, DEMs are not just a support tool, but a fundamental data layer in satellite image analysis. In this chapter, we focus on generating and visualizing the DEM of our selected study area, understanding its relevance, and how it supports further classification and analysis steps.

2. Data Set Used

For this task, the DEM was generated using freely available SRTM (30m resolution) data, which was either:

- Downloaded from USGS EarthExplorer,

  This data provides sufficient elevation detail for analyzing regional terrain and is compatible with the SAR dataset used for the Prayagraj region.

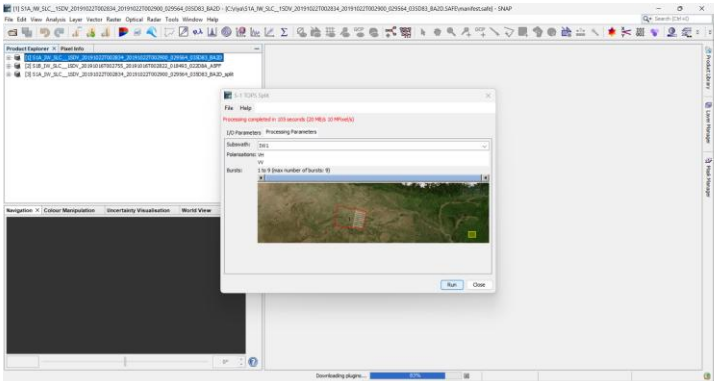
3. Study Area

The study area selected for DEM generation is Prayagraj, located in the state of Uttar Pradesh, India. This region consists of urban areas, agricultural lands, rivers (Ganga and Yamuna), and open terrain. The elevation variation in Prayagraj is moderate, making it ideal for generating and analyzing a DEM to understand topographical influence on land use and water flow.

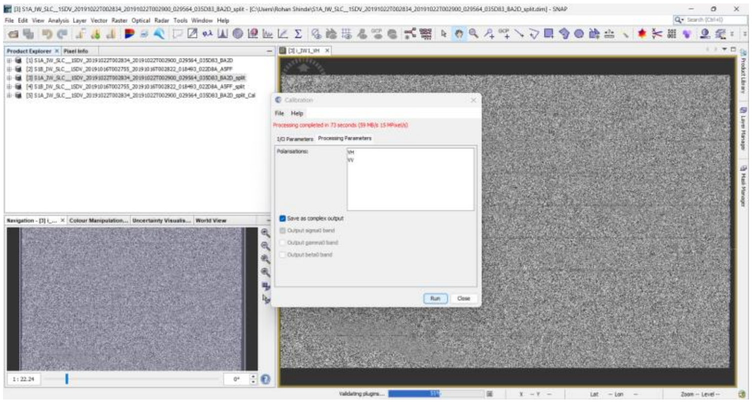
4. Methodology

5. Result and Discussion

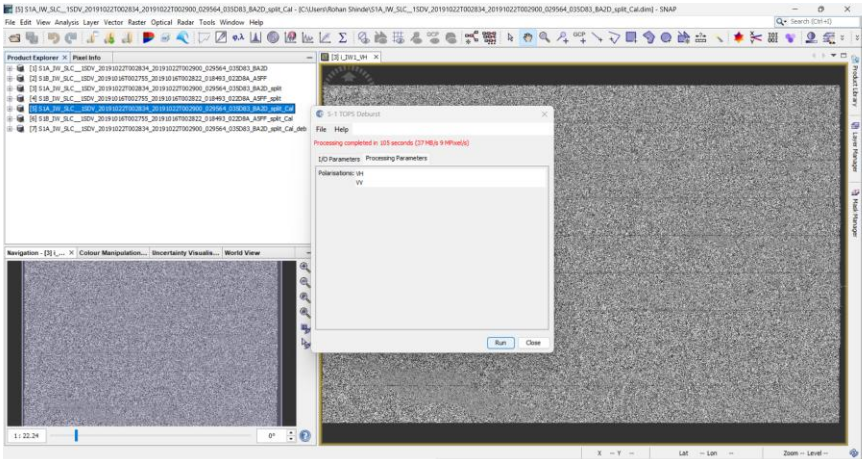
- **Split on both dataset**



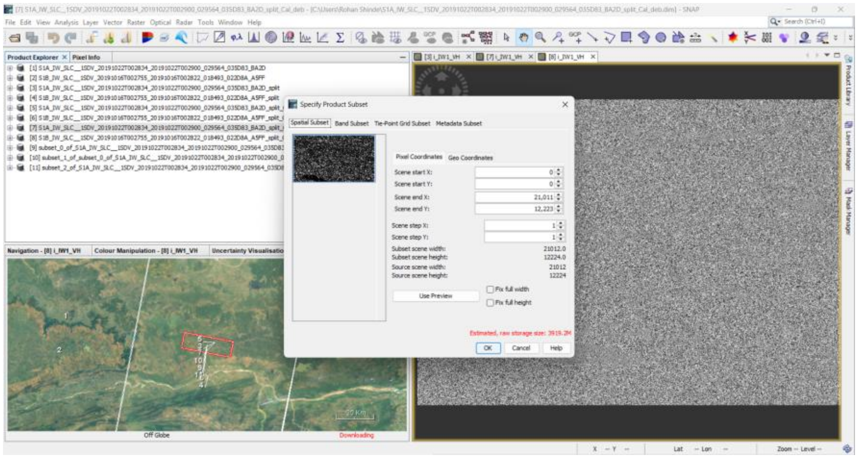
- **Clibration on both**



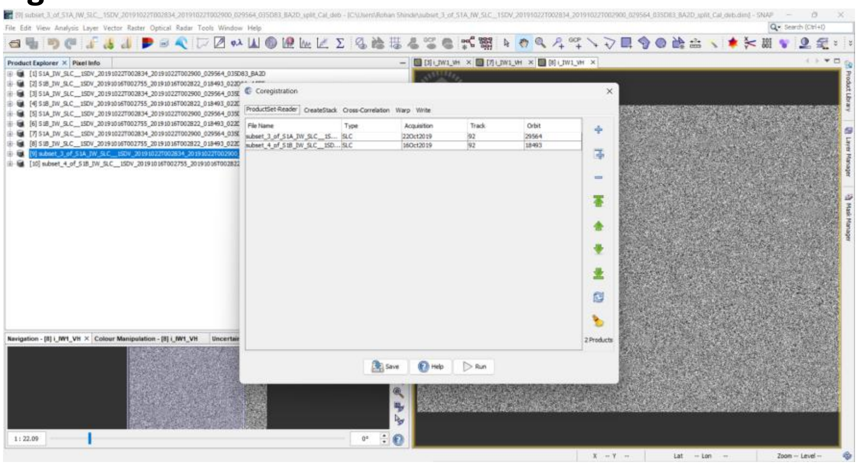
- **Deburst on both**



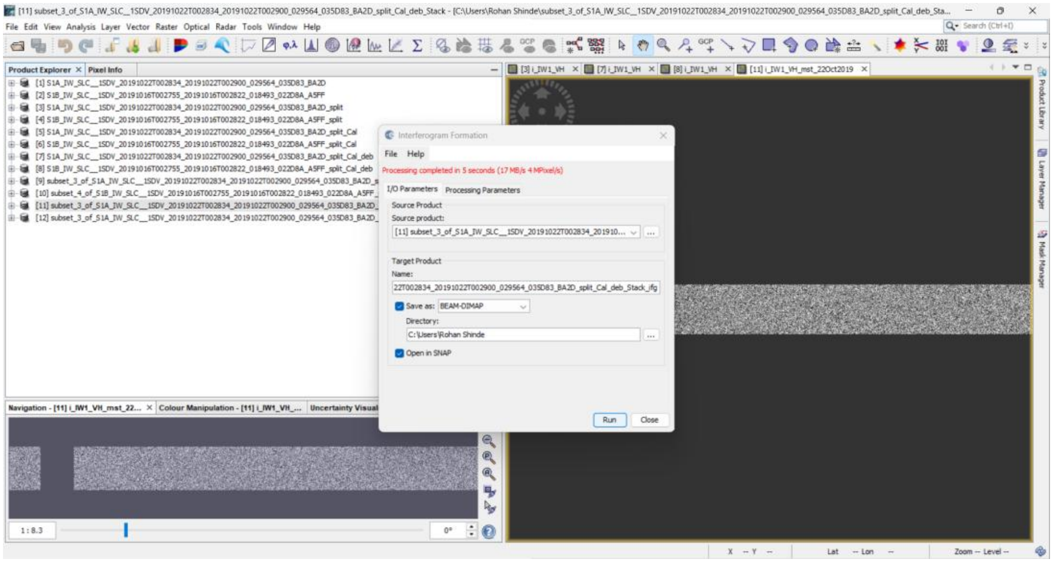
- **Sunset on both dataset**



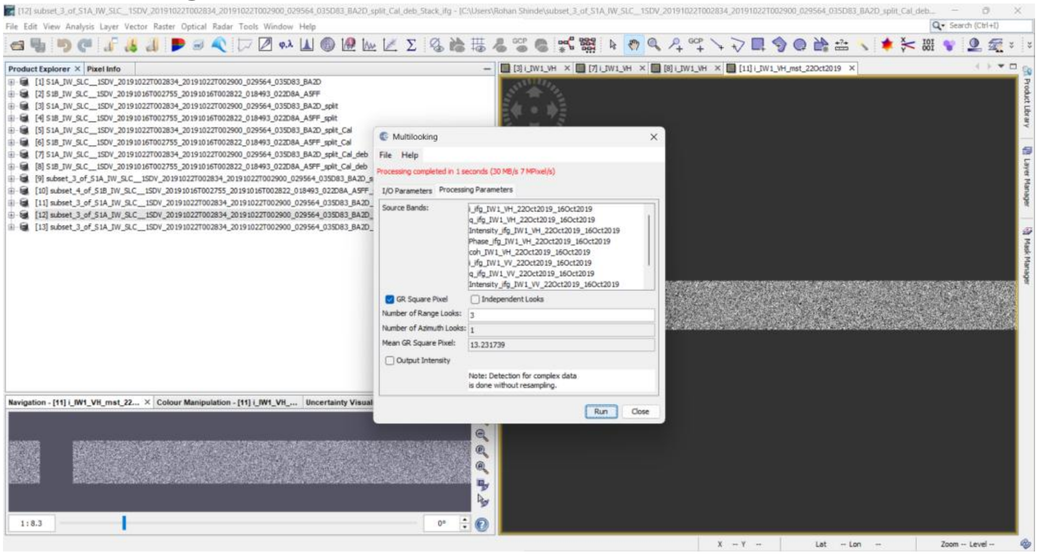
- **Coreregistraation**



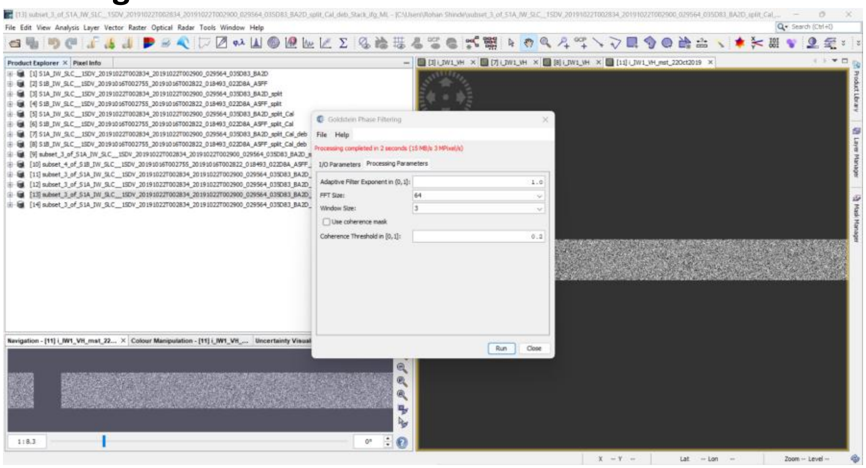
- **Interforogram**



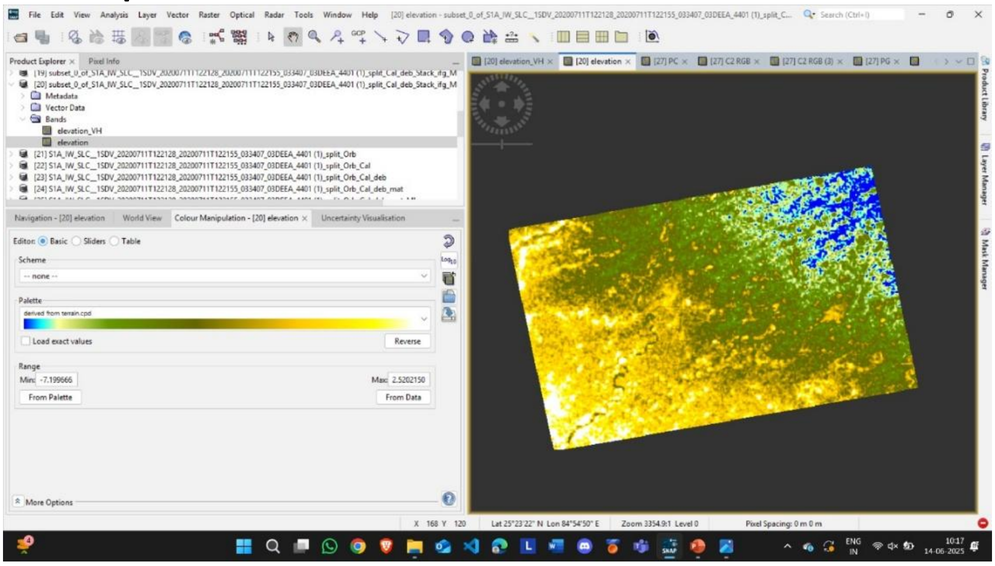
- **Multilooking**



- **Filtering**



- **Last Step**



6. Summary and Conclusion

In this chapter, we focused on generating a Digital Elevation Model (DEM) for the Prayagraj region. The DEM was used not only for visual interpretation of the terrain but also to support SAR data preprocessing like terrain correction and geometric alignment.Using SRTM data, the terrain characteristics of the region were analyzed, providing insights into elevation patterns, slopes, and possible drainage paths. This adds a valuable layer of geographic understanding and improves the overall accuracy of further classification and interpretation work in satellite data analysis.The successful creation and use of DEM demonstrates the importance of elevation information in remote sensing applications and forms a critical base for environmental and geographic assessments.