Earth Observation and Data Analysis
Homework 1

Submitted by:
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1. Checking channel image quality

- Emissive channels:

  OK: 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35
  Noisy/failures/strips: 36

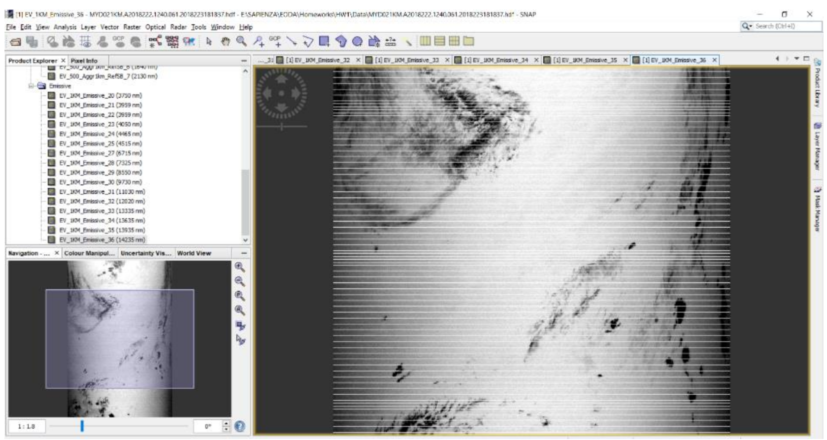

Fig 1.1. Strips found on emissive channel 36

- Reflective channels:

  OK: 1, 2, 3, 4, 5, 7, 8, 9, 10, 11, 12, 13lo, 13hi, 14lo, 14hi, 15, 16, 17, 18, 19, 26
  Noisy/failures/strips: 6

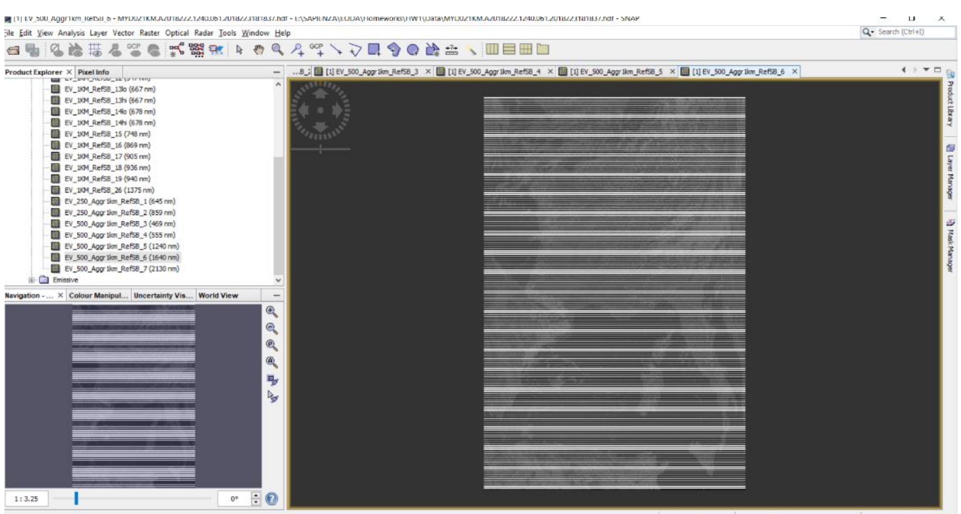

Fig 1.2. Strips found on reflective channel 6

2. Data analysis by spectrum, histogram and profile tools

To perform the spectrum analysis, three different locations were pinned on the map on interesting locations (sea, clouds, and land) as follows:

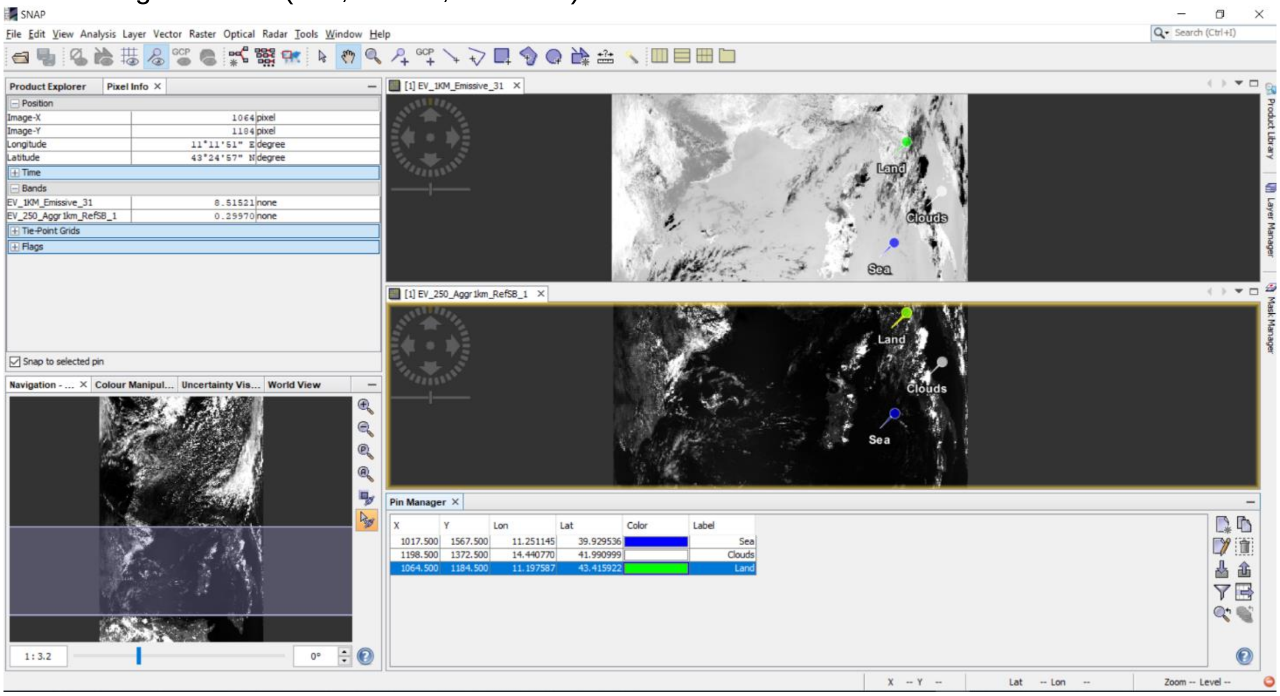

Fig 2.1. Pins created over band images

<u>Sea:</u> at the sea
<u>Clouds:</u> Montazzoli, Province of Chieti, Italy (Land with Clouds)
<u>Land:</u> Poggibonsi, Province of Siena, Italy (Land)

2.1 Spectrum

We performed a spectrum analysis of all the three pinned locations for both emissive and reflective channels. The graph is shown on the following figure:

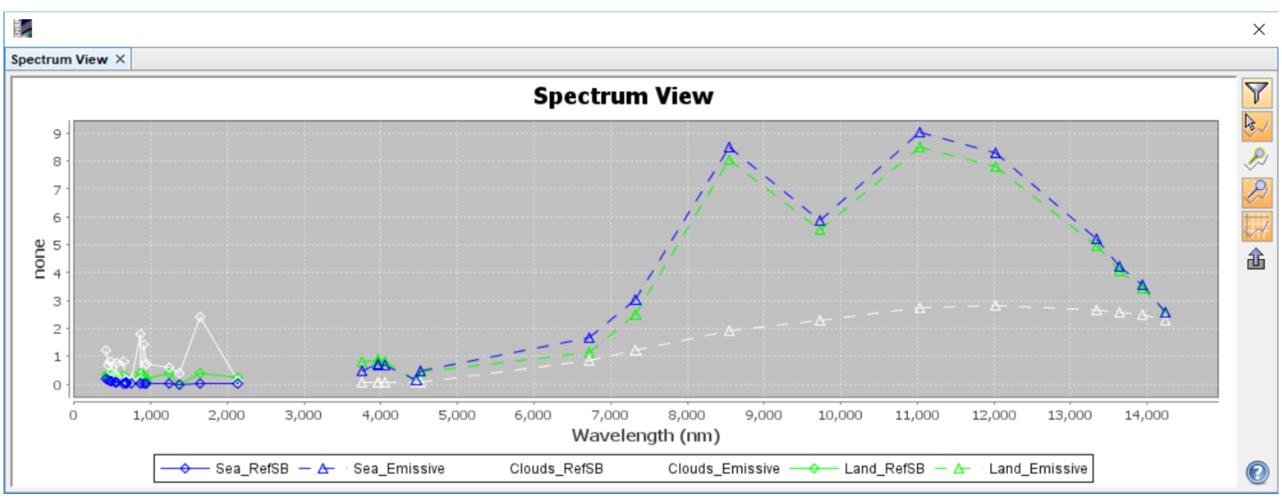

Fig 2.2. Spectrum plot for

Results:

The pin labeled “Clouds” has higher amplitude of electro-magnetic waves in reflective band due to presence of clouds. Similarly, the pin labeled “Sea” has the highest amplitude in emissive band since water is a strong infrared absorber and has a correspondingly high emissivity.

2.2 Histogram

Reflective Band 1 (645 nm):

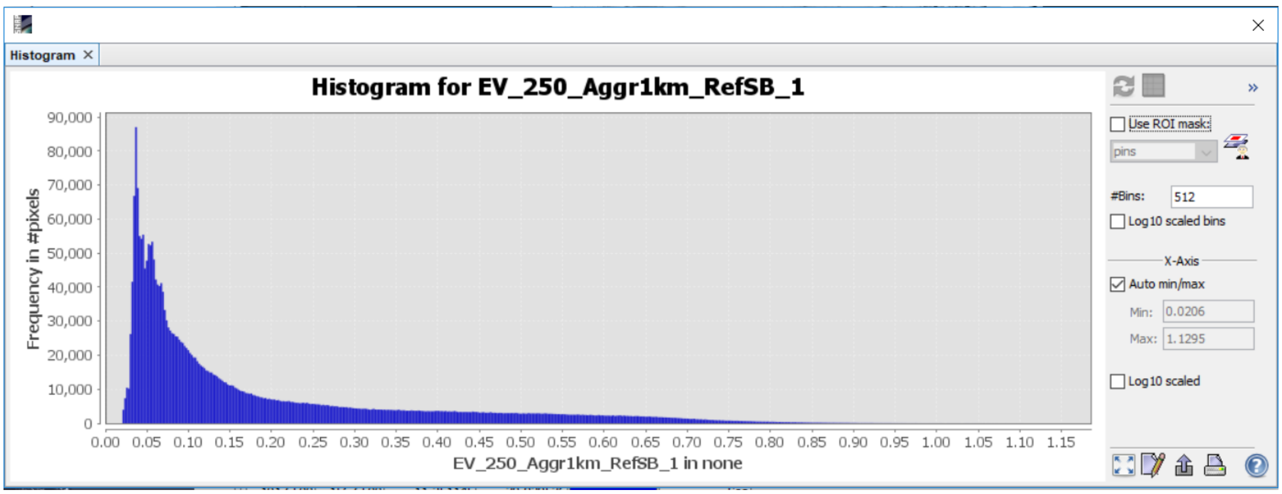

Fig 2.2. Histogram plot of Reflective Band 1

The highest frequency observation is at around 0.035 and no observations were recorded for values greater than 0.90.

Reflective Band 31 (11030 nm):

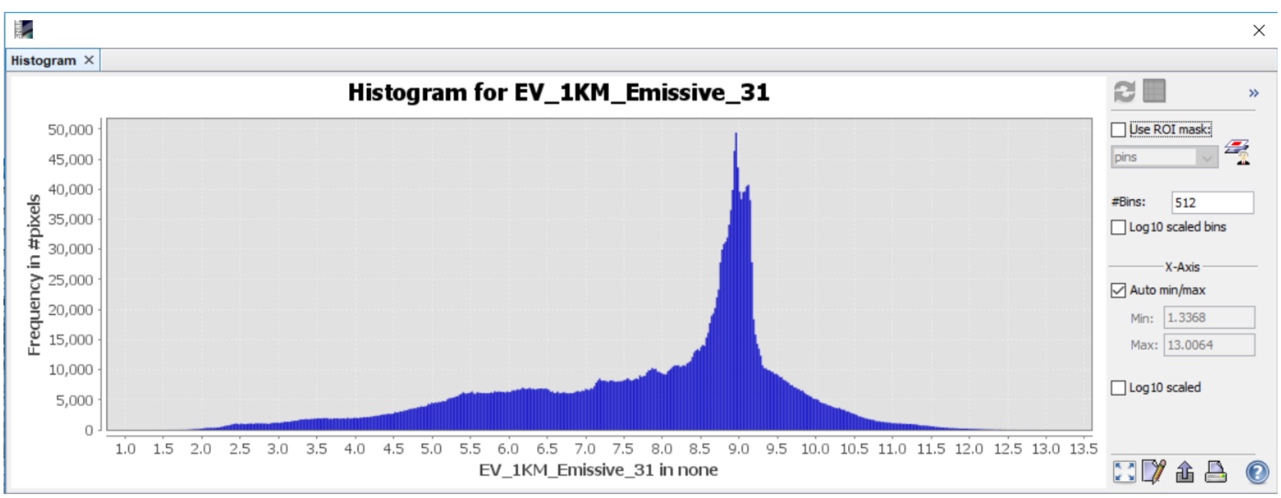

Fig 2.3. Histogram plot of Emissive Band 31

The highest frequency observation is at around 8.95 and no observations were recorded for values greater than 12.5 and lower than 1.5.

2.3 Profile

The following is the profile plot among the three pins labeled by “Sea”, “Clouds”, and “Land”:

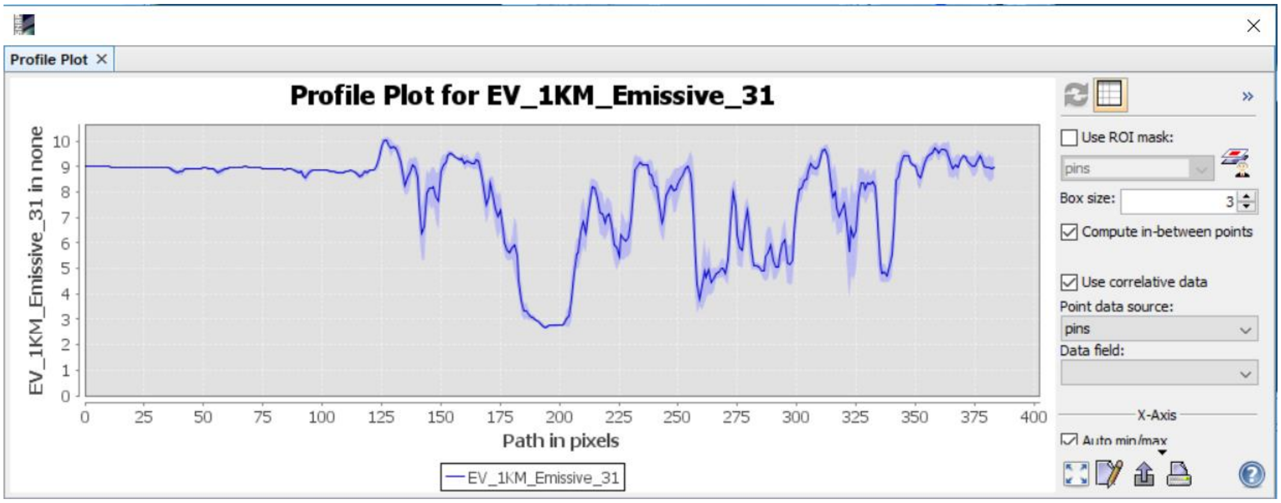

Fig 2.4. Profile plot among “Sea”, “Clouds”, and “Land”

3. Channel data correlation by whole image

To analyze the correlation over the whole image, we decided to use a scatter plot between bands Ref 1 and Em 31. The following is the resulting plot:

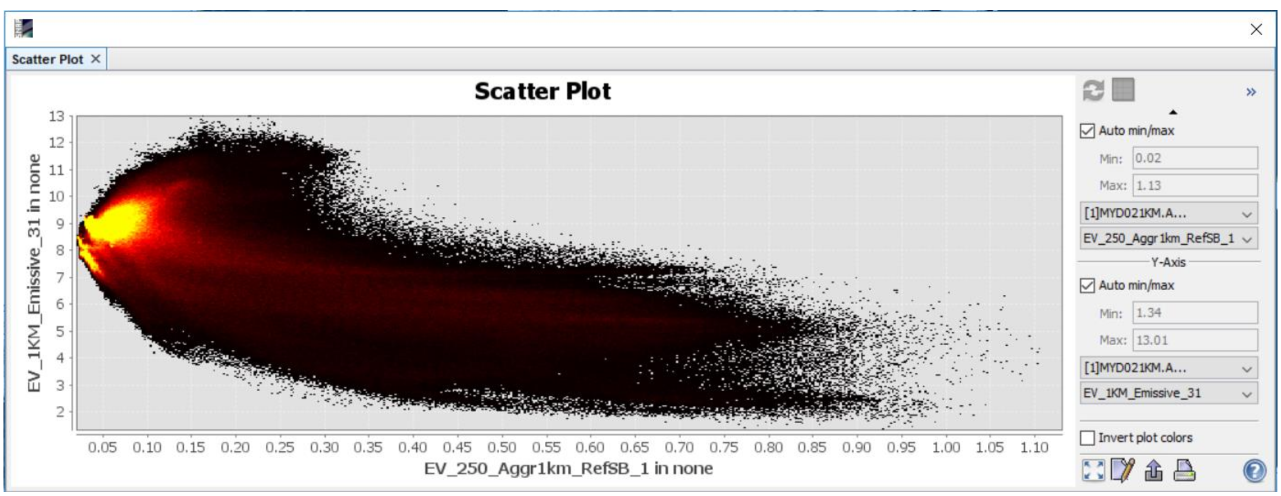

Fig 3.1. Scatter plot between Band Ref 1 and Em 31

The plot shows that the two channel bands are negatively correlated as a decreasing line could be down over the scatter plot.

4. Channel data correlation of ROI (region of interest)

We choose the above cloud region as ROI using a geometry (rectangle) as visible on the following figure:

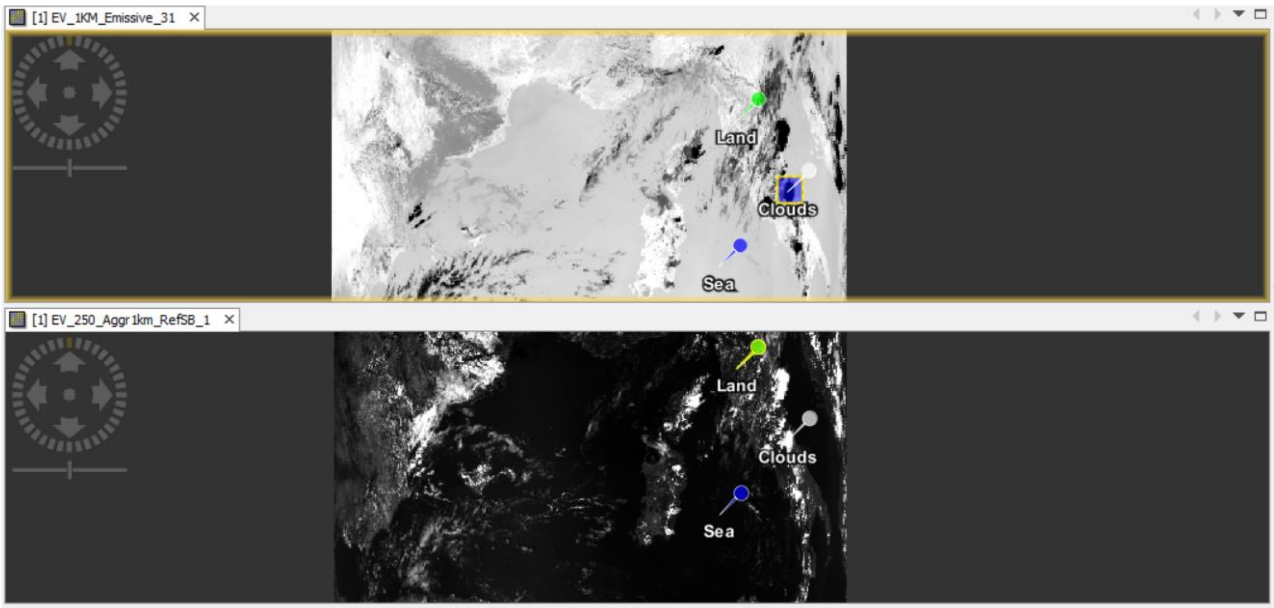

Fig 4.1. Selected ROI (Region Of Interest)

We then made a scatter plot limited on a Region Of Interest (Cloud Region) in order to perform once again the data correlation between bands Ref 1 and Em 31. The following figure shows the output plot:

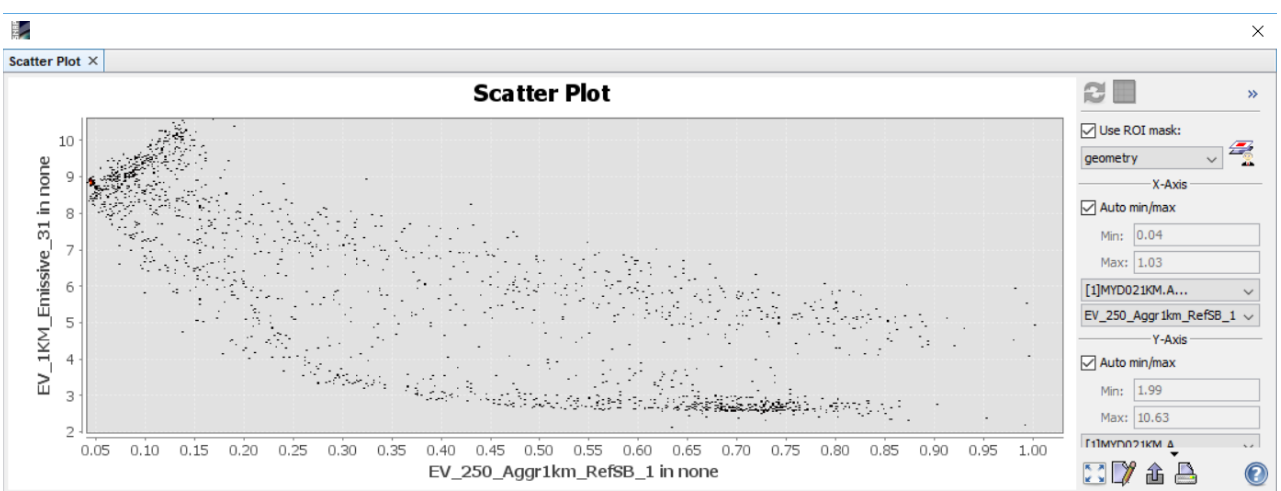

Fig 4.1 Scatter plot between Band Ref 1 and Em 31 (Region of Interest)

As before, the two channel bands appear to be negatively correlated in the selected ROI (Region Of Interest).

5. Principal component analysis

We performed Principal component analysis on the first seven reflective bands using the SNAP toolbox. The following figures illustrate the analysis that has was performed:

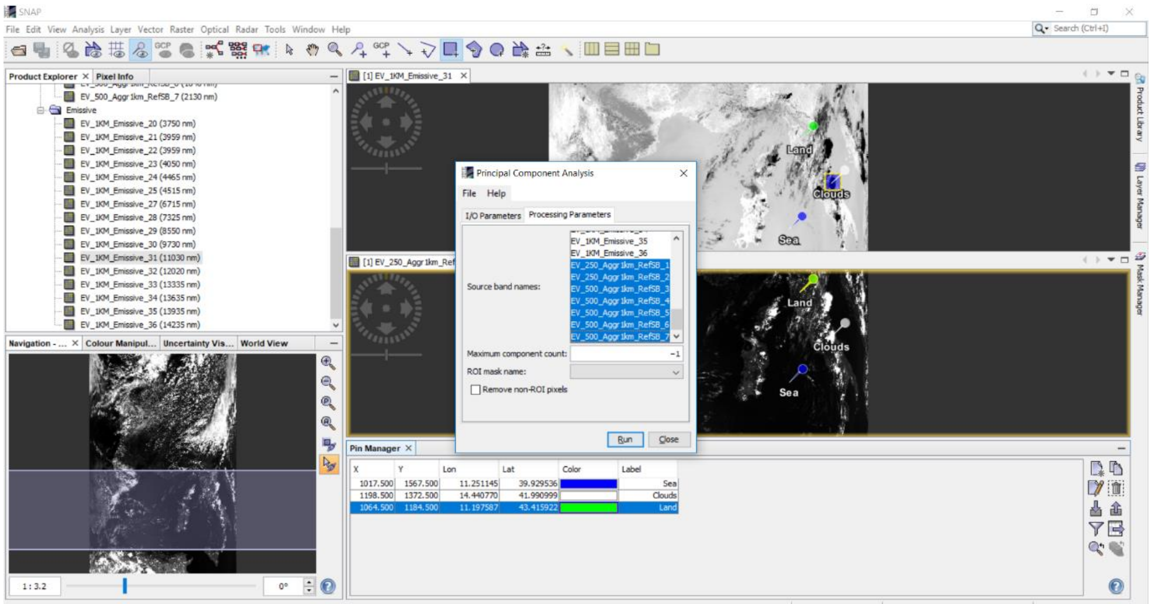

Fig 5.1 SNAP PCA tool options

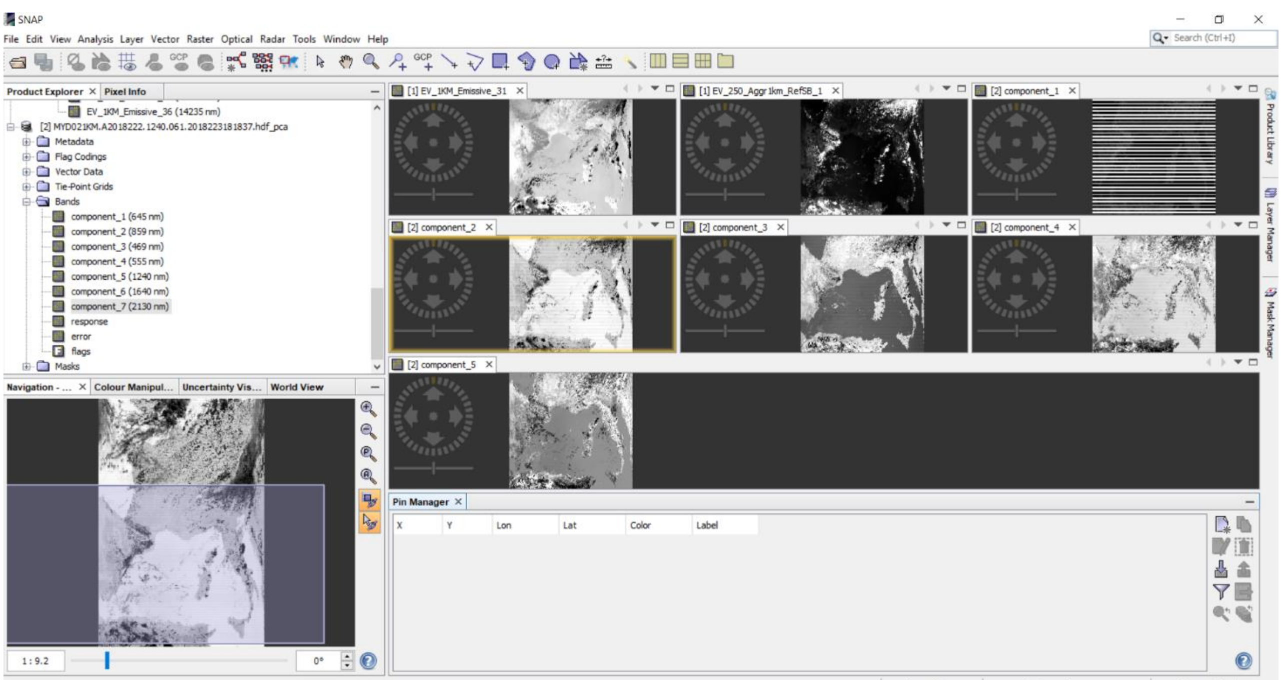

Fig 5.2 SNAP PCA tool results for 7 bands

Results:

- PCs 2, 3 and 5: carry most of the information
- While PCs 1 and 4: approximate noise features

6. Unsupervised classification with 3 classes (Sea, Land and Cloud)

An unsupervised K-means cluster analysis was performed with number of cluster set to 3 and number of iterations 30. Multiple trails were conducted with random selection of bands as feature sets but no interesting results were obtained. Performing the clustering operation on all the bands, we obtained a good result that correctly classified desired land, sea, and cloud features.

Results:

Bands used: All

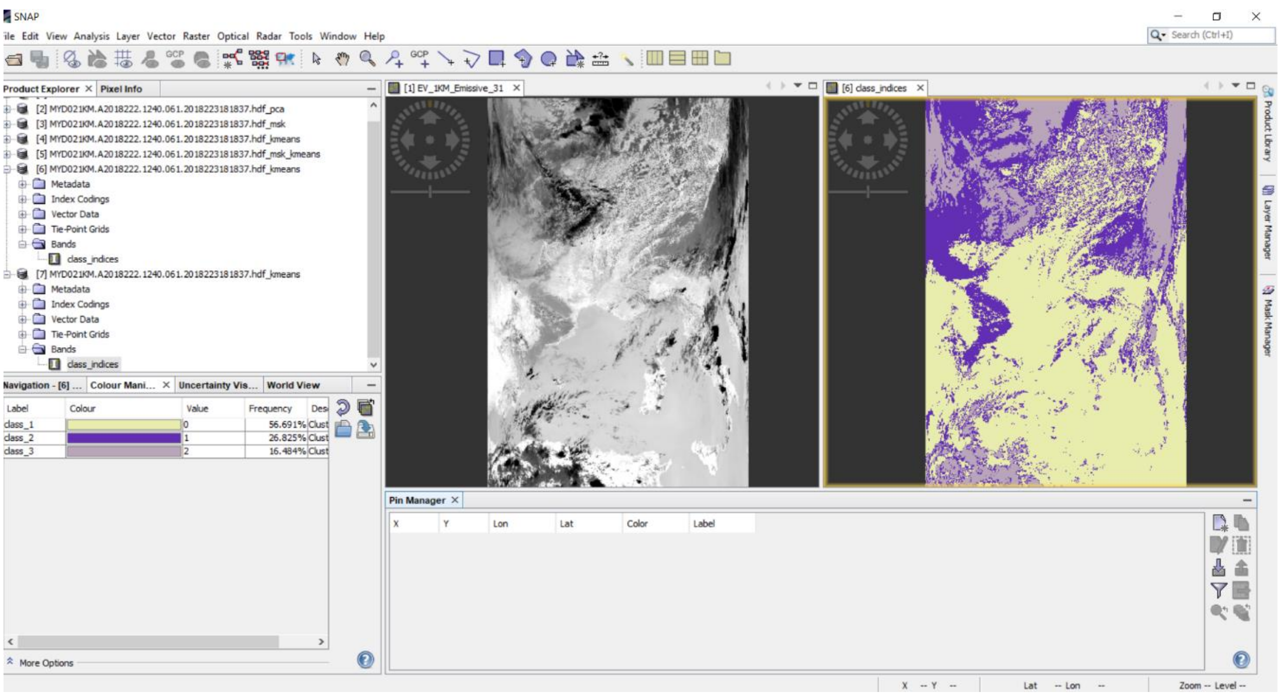

Fig 6.1 Result for unsupervised K-means classification using SNAP toolbox

The SNAP tool approximatively classified sea (yellow), land (violet) and cloud (grey) section into different clusters as we can visibly examine the correctness of the result

7. Supervised classification with 3 classes (sea, land and cloud)

We started by converting the *hdf* file into *BEAM-DIMAP* format, then we created an RBG visible composite image using three reflective bands.

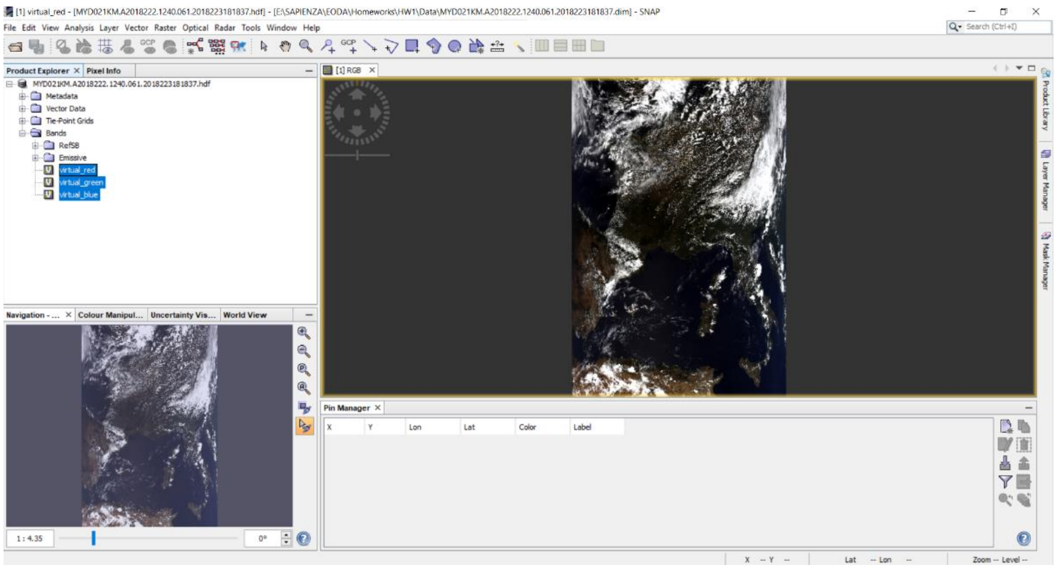

Fig 7.1 RGB visual composite

Subsequently, we created three vector data containers representing the following three classes: sea, land and clouds. We used drawing tools to sample sections for all three classes from the visible composite image. Supervised classification was performed using Maximum Likelihood Classifier across the whole area.

Results:

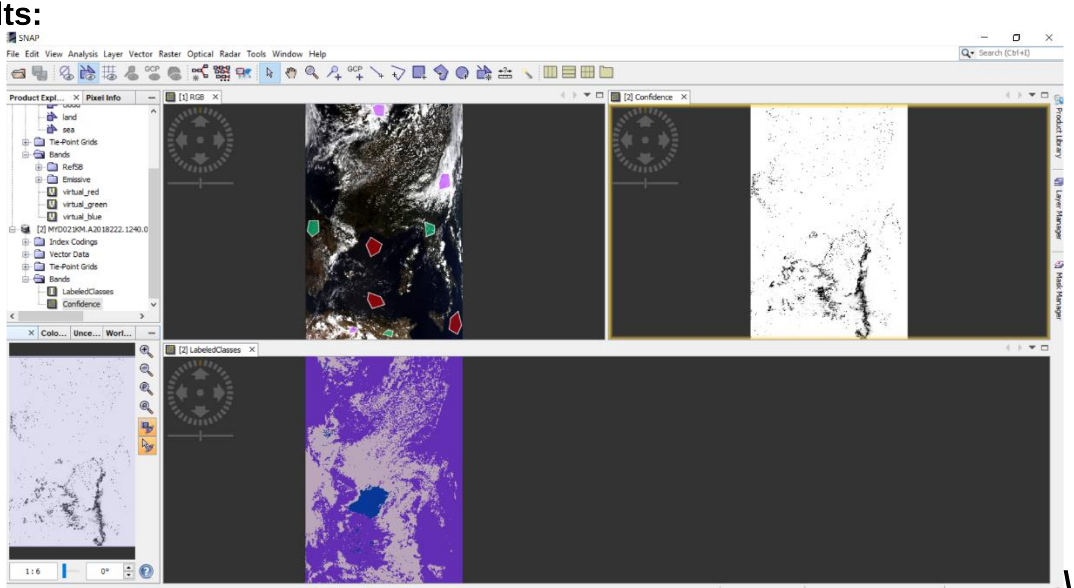

Fig 7.2 Class labelled vector geometries and corresponding results using Supervised Learning

The classifier seem to have classified well enough the three classes: land (grey), clouds (purple) and sea (blue) section. Supervised classification was not quite accurate due to the lack of lightness on the initial image.

8. Vegetation Index using SNAP processing tools

8.1. Normalized Difference Vegetation Index (NDVI)

NDVI is one of the simplest indicator used to analyze remote sensing measurements for live green vegetation in the observed land mass. Normalized Difference Vegetation Index (NDVI) quantifies vegetation by measuring the difference between *near-infrared* (strongly reflected by the vegetation) and *red light* (absorbed by the vegetation).

$$\mathrm{NDVI} = \frac{NIR - Red}{NIR + Red}$$

8.2. Soil-adjusted vegetation index (SAVI)

SAVI is an improvement over NDVI in terms that it accounts for the differential red and near-infrared extinction through the vegetation canopy. SAVI minimizes soil brightness influences from spectral vegetation indices involving red and near-infrared (NIR) wavelengths.

$$\mathrm{SAVI} = \frac{(1 + L)(NIR - Red)}{NIR + Red + L}$$

Here, **L** is a canopy background adjustment factor. An **L** value of 0.5 in reflectance space was found to minimize soil brightness variations and eliminate the need for additional calibration for different soils. The transformation was found to nearly eliminate soil-induced variations in vegetation indices.

8.3. Ratio Vegetation Index (RVI)

RVI is the simplest vegetation index with the assumption that ratio of **Red** to **NIR** is proportional to healthy vegetation.

$$\mathrm{RVI} = \frac{Red}{NIR}$$

Following are our observations for NDVI, SAVI and RVI obtained using SNAP's inbuilt processing tools to distinguish vegetation.

Results:

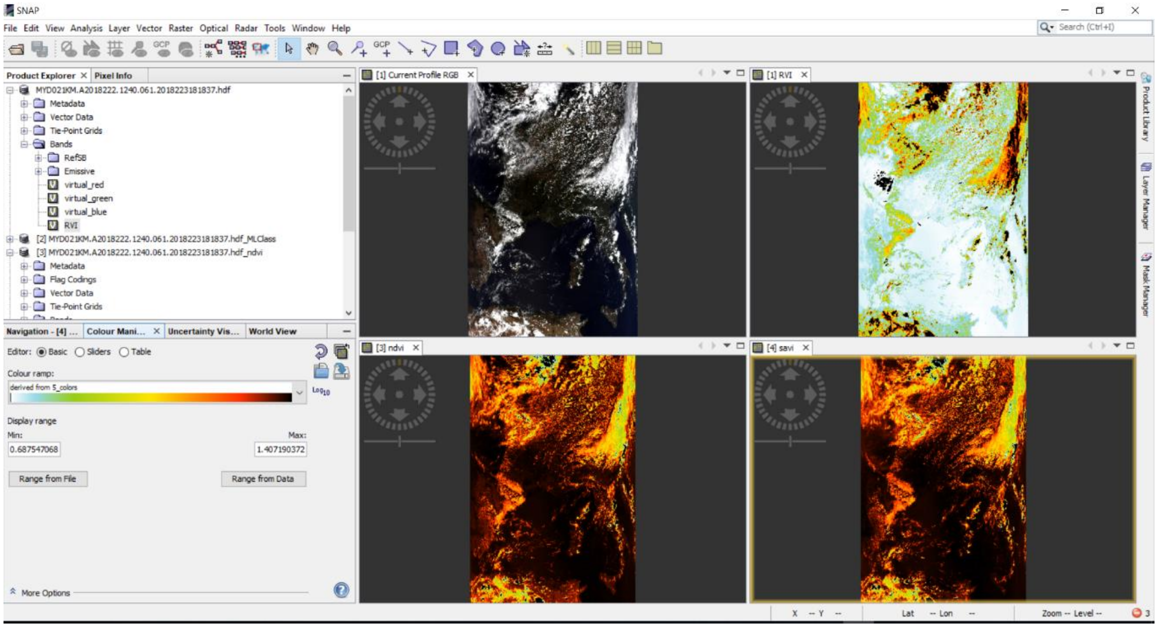

Fig 8.1 Visual comparison of RVI, SAVI and NDVI vegetation index results

As we can visualize notice, RVI projects high degree of contrast between vegetations with darker segments representing clouds and barren desert against much brighter vegetation segments in the Tunisian shorelines and mainland Italy.

9. Unsupervised classification using VI index

We performed unsupervised classification over the SAVI band and observed slightly better results compared to classification using RGB visible bands (with a lighter image the results would have been surely far better)

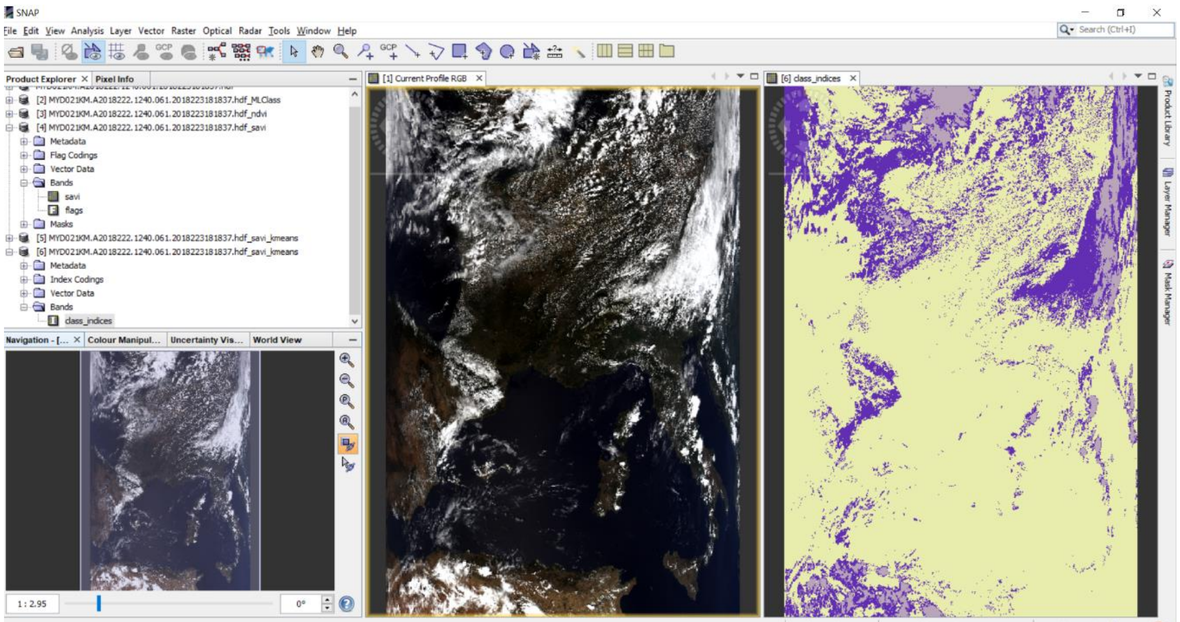

Fig 9.1 Unsupervised classification of using RVI index band

The classifier accurately distinguished the land (purple), sea (yellow) and clouds(gray) for whole band.

10. Qualitative analysis of VI index over interested area in winter

We used SAVI algorithm to detect vegetation over Tunisia for two datasets assimilated one in summer (March 2019) and another in winter (December 2018). We set common visualization scale for the both VI bands.

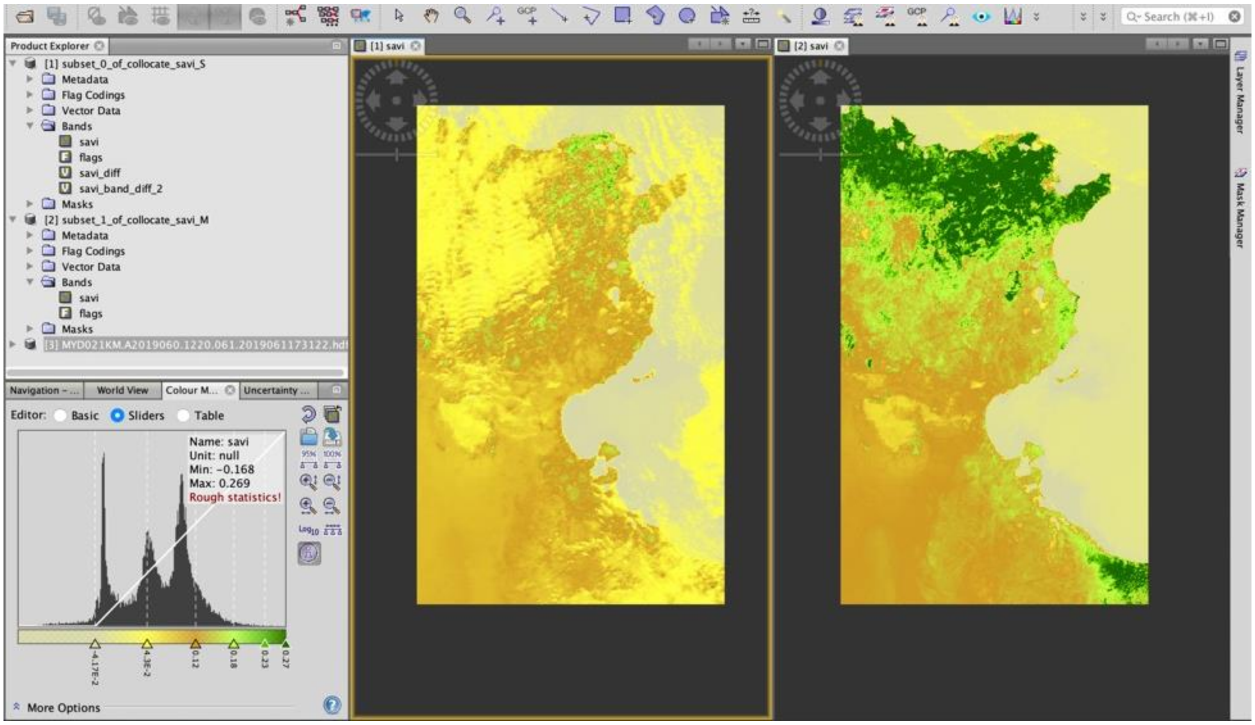

Fig 10.1 Qualitative comparison of vegetation index in summer and winter using SAVI index

It was clearly observed that the vegetation is widespread across norther Mediterranean shore line in summer but barely existing in winter. However we see no change in vegetation in southern region which is occupied by Saharan desert.

11. Quantitative change detection of vegetation coverage in summer and winter

In this section, we used band-math tool to compute the difference between SAVI index to quantitatively check the difference in vegetation index for two seasons and the results obtained corroborated our qualitative analysis in previous section summarizing the difference of vegetation in the northern shoreline.

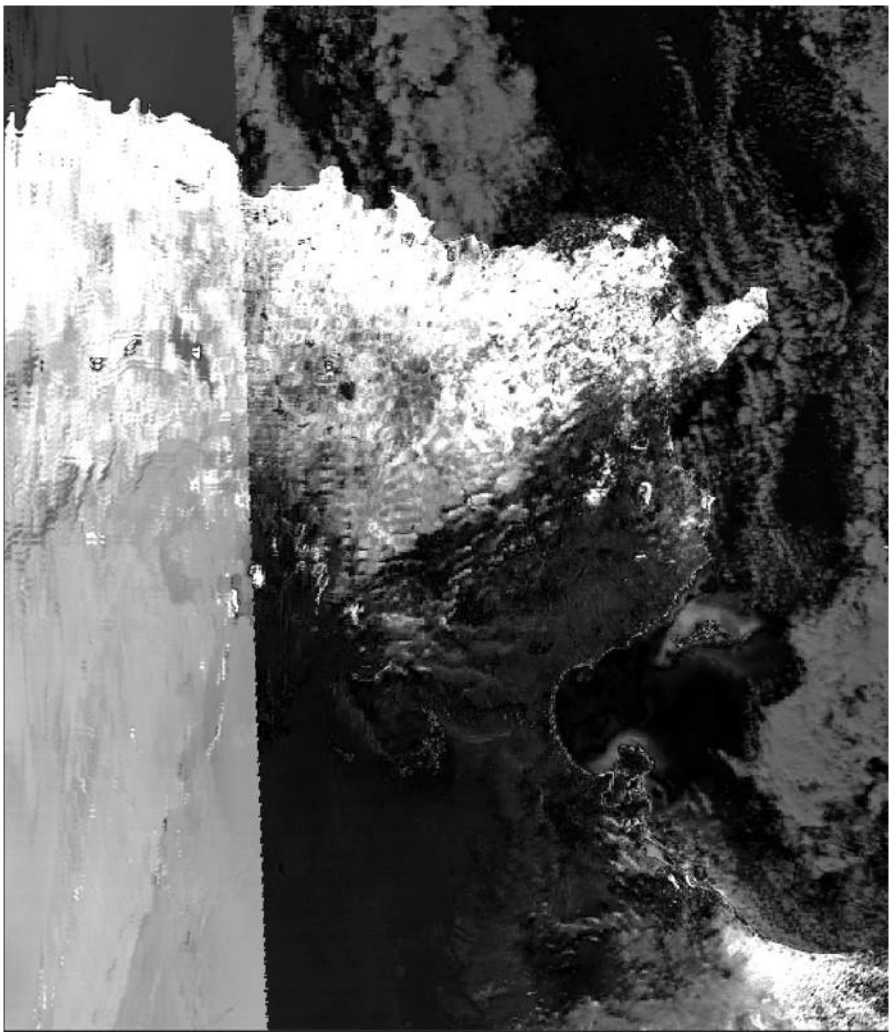

Fig 11.1 Qualitative analysis of change in vegetation