HW01. Homework on MODIS/AQUA data- Vegetation

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After that I download “MOD021KM.A2018095.1005.061.2018095224532.hdf” from the laads website https://ladsweb.modaps.eosdis.nasa.gov/search/. A MODIS image at 1-km resolution over south of Italy.

And after Performing data quality check:

RefSB:

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

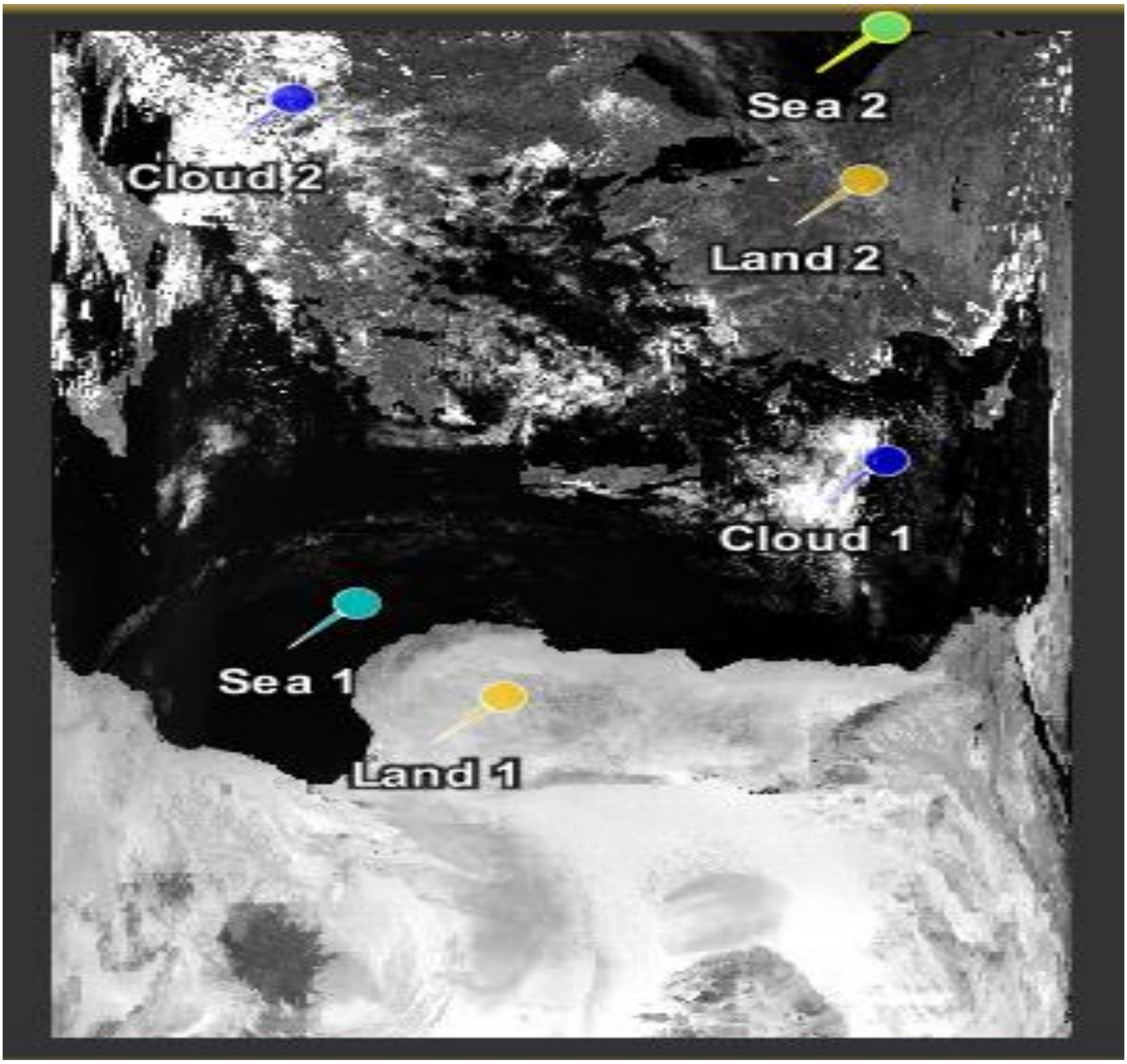
bad: None

Emissive:

ok : 20, 21, 22, 23, 24, 25, 27, 28, 29, 30, 31, 32, 33, 34, 35

bad: 36

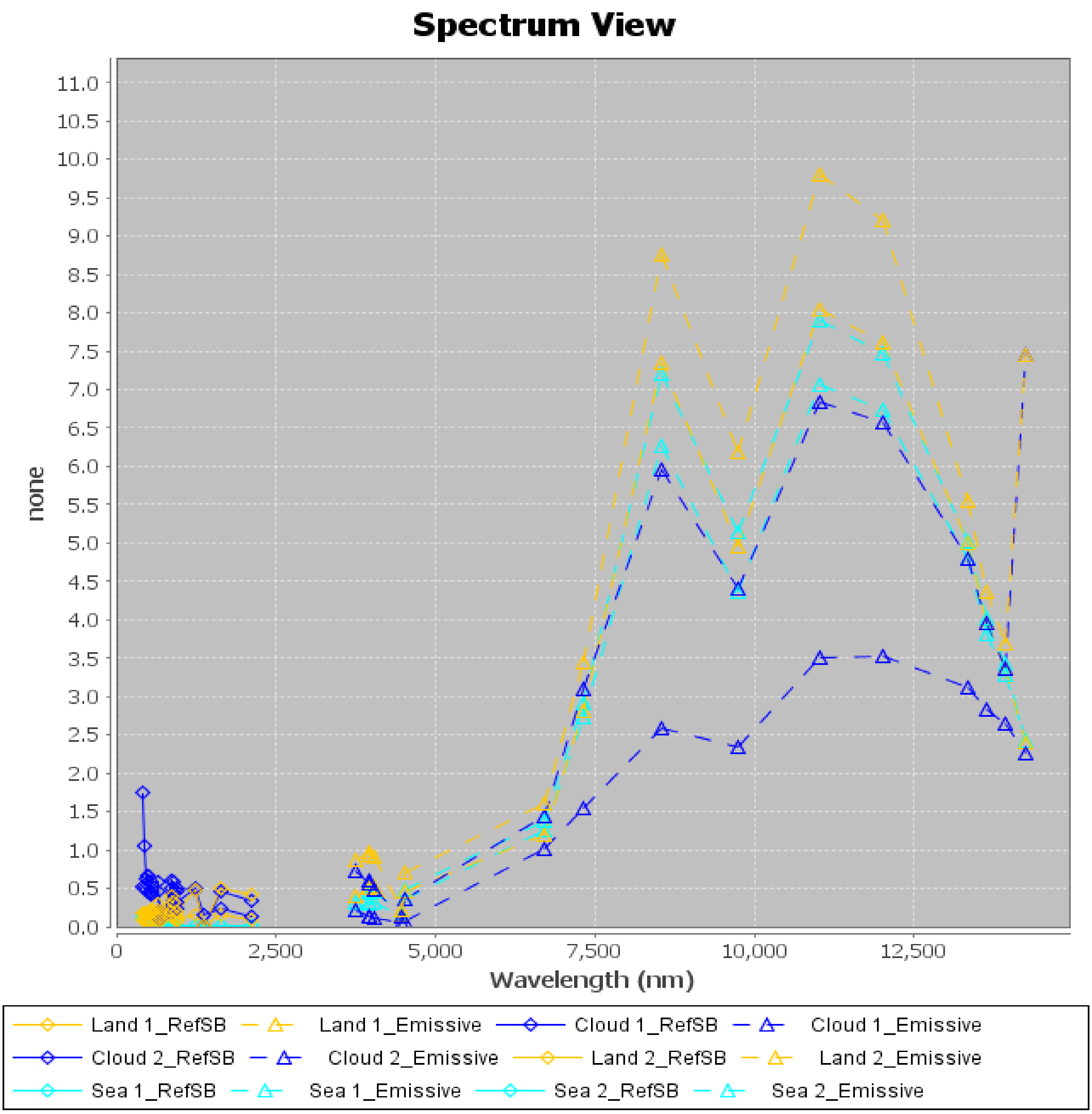
I create 6 pins, 2 for each of Land, Cloud and Sea.



HW01. Homework on MODIS/AQUA data- Vegetation

Umberto Junior Mele 388371

And this is the Spectrum for this Pins:



It’s interesting to notice that for low wavelength less than 2000 nm, the Clouds has higher values than lands and seas, while when the wavelength is between 8000 to 12500 nm we have the lands is higher than clouds and seas!!!

HW01. Homework on MODIS/AQUA data- Vegetation

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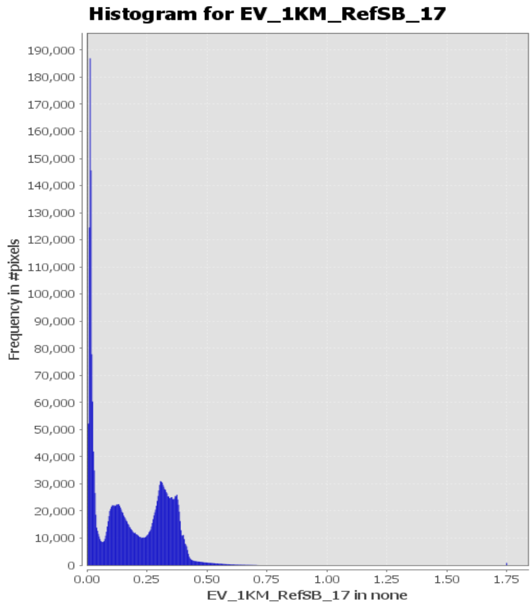
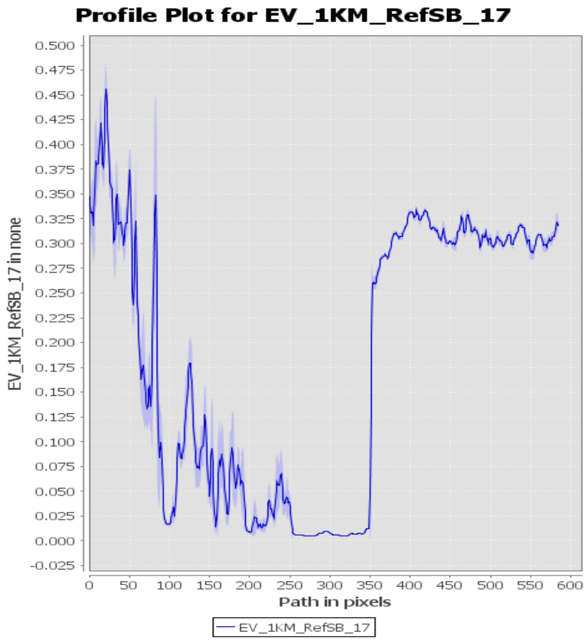
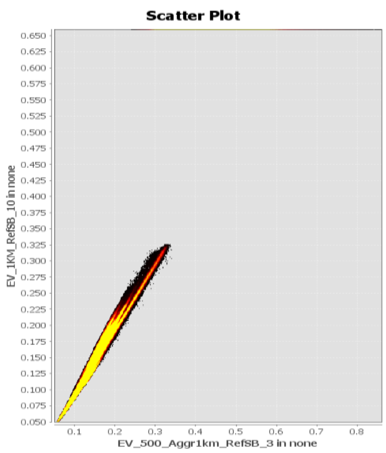
The histogram of the image of wavelength 905 nm is giving, how we sow in the spectrogram, white color for the cloud, less white for the lands and dark for seas.

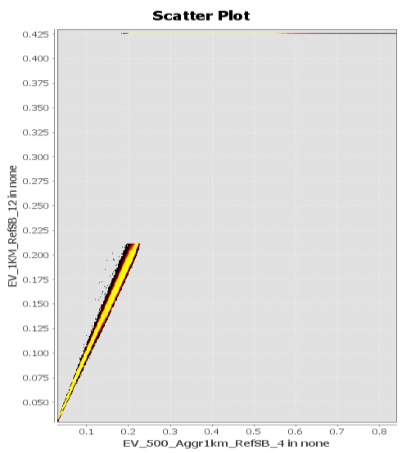
And, the Profile plot confirm High rough values for clouds (since the cloud have absorption), low values for Sea and medium values for lands.

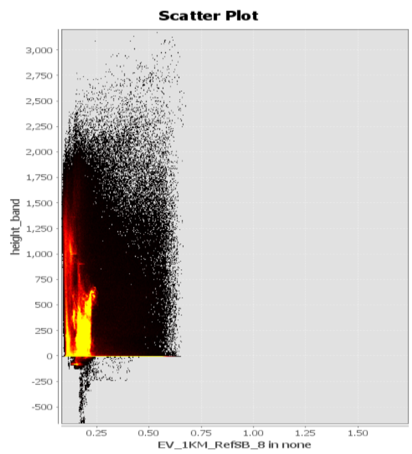




So, the next task to be performed is to display channel data correlation of the whole image and of a selected ROI (Region of Interest).





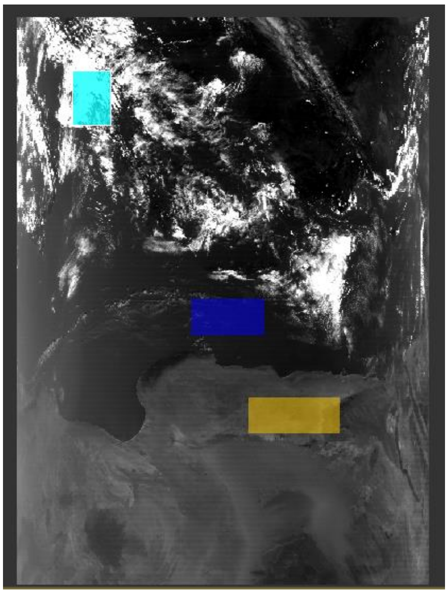


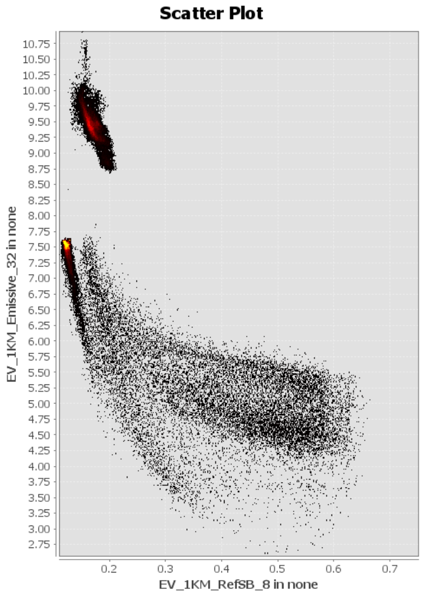
In the whole image scatter plot is clear that bands with similar wavelength like 3 and 10 (469 nm and 488 nm), 4 and 12 (555 nm and 547 nm). Have clearly high correlation, while bands far from each other no.

HW01. Homework on MODIS/AQUA data- Vegetation

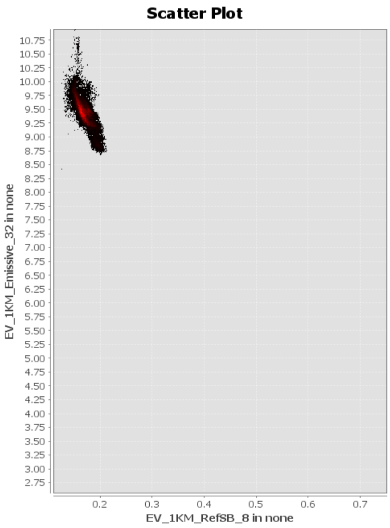
Umberto Junior Mele 388371

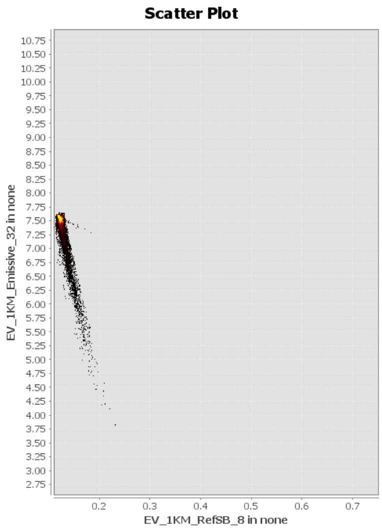
Next step is to see the correlation in a given ROI, for this reason I create three polygons to analyze sea, land and cloud; looking it for band 8 (412 nm) and band 32 (12020 nm) where we have seen more differences in the spectrum plot!

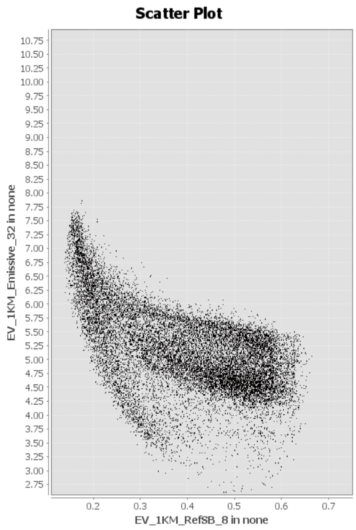




And dividing each polygon using ROI filter, we have the scatter plot for land, sea and cloud (in order).







And is interesting to note how land and sea are clearly distinguishable, whereas the clouds are not following a Normal distribution, since the phenomenon of absorption we have many noise in that pixels.

HW01. Homework on MODIS/AQUA data- Vegetation

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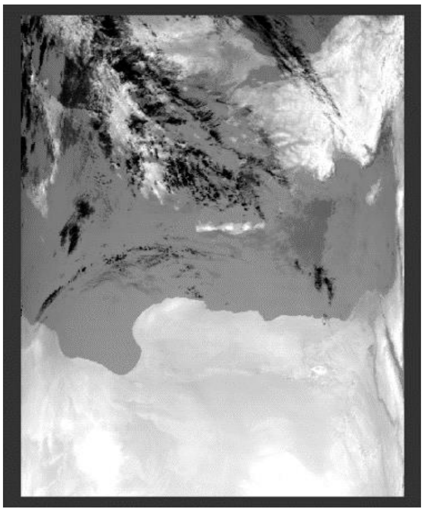
Principal Component Analysis

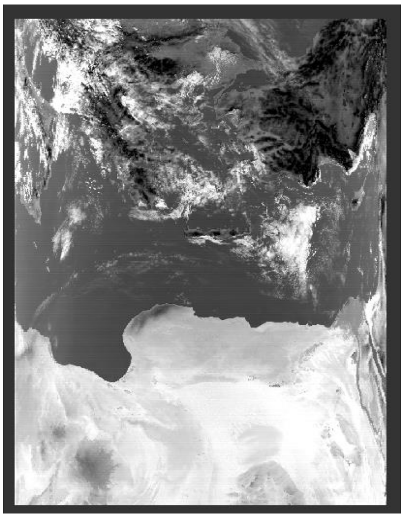
I made a PCA on all bands for 7 output components, this are the results excluding band 3 that is full of noise:

1

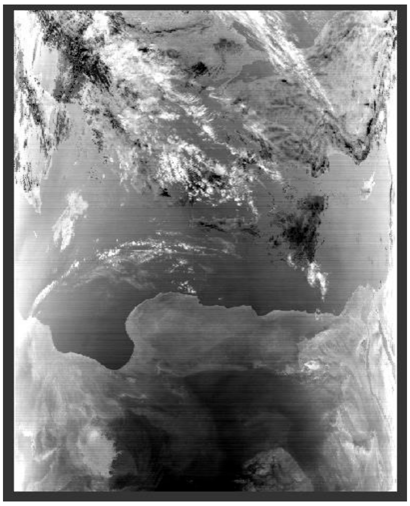
2



4

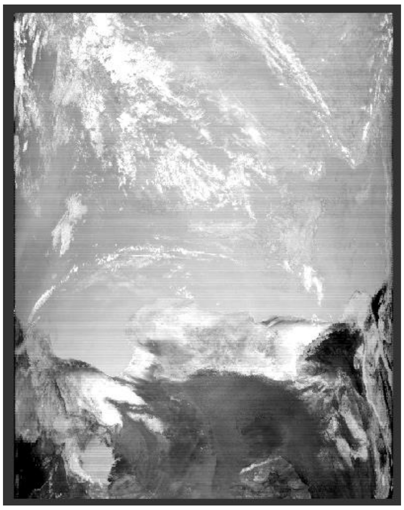


5



6

7



We can see from these images that just components 1, 2, 4 and 5 have good information the rest is noisy and less clear.

HW01. Homework on MODIS/AQUA data- Vegetation

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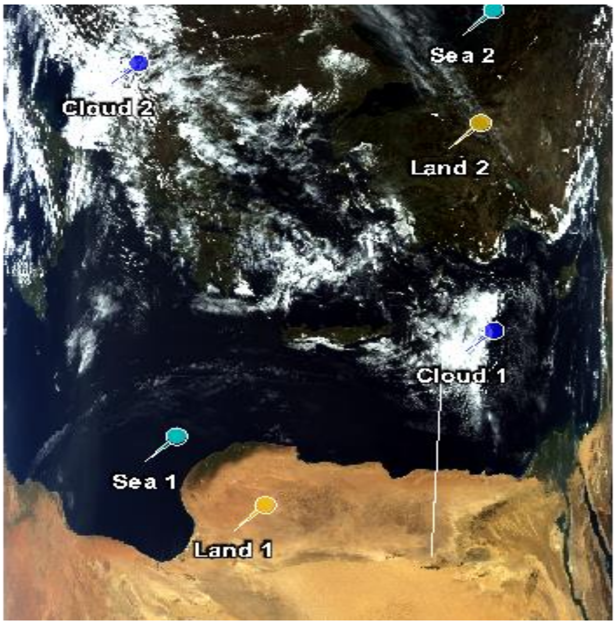
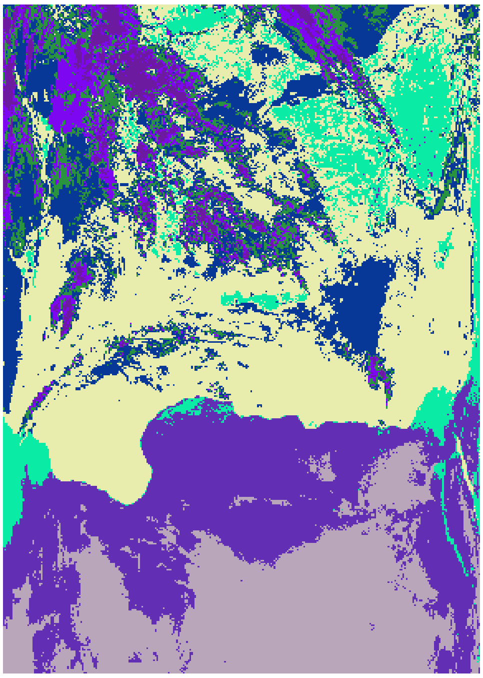
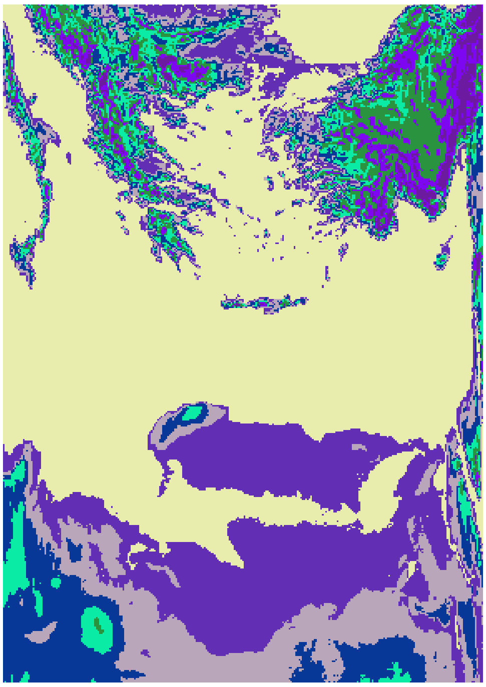
Unsupervised Classification

Next step, is to perform an unsupervised method like K-means, to cluster data in the best group.

First case I used only band 8 and 36 and 5-means algorithm, while in the second one I used PCA data and a 8-means algorithm:







Is interesting to note how the machine learning algorithm learns quite well the cluster of green land, while the second one is full of noise and we can find many errors…

HW01. Homework on MODIS/AQUA data- Vegetation

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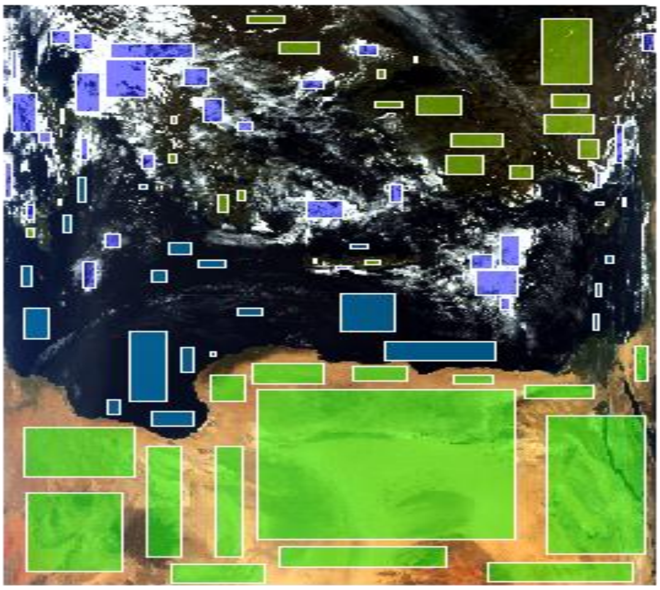
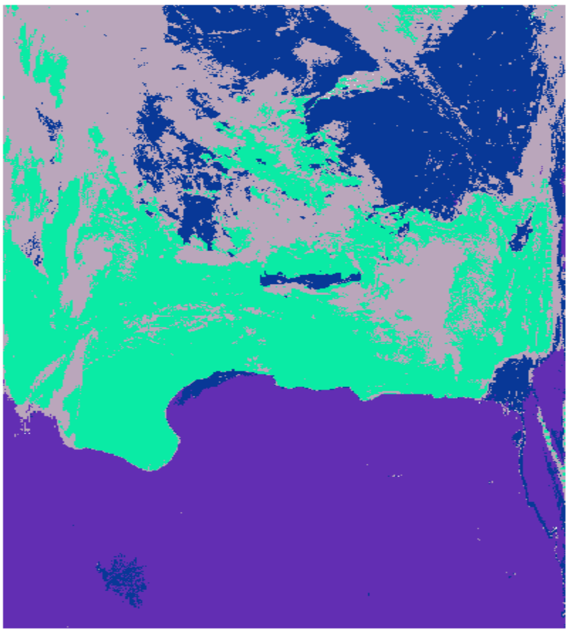
Supervised Classification

Afterwards, I implement MLE supervised classifier and Random Forest to this labelled data:

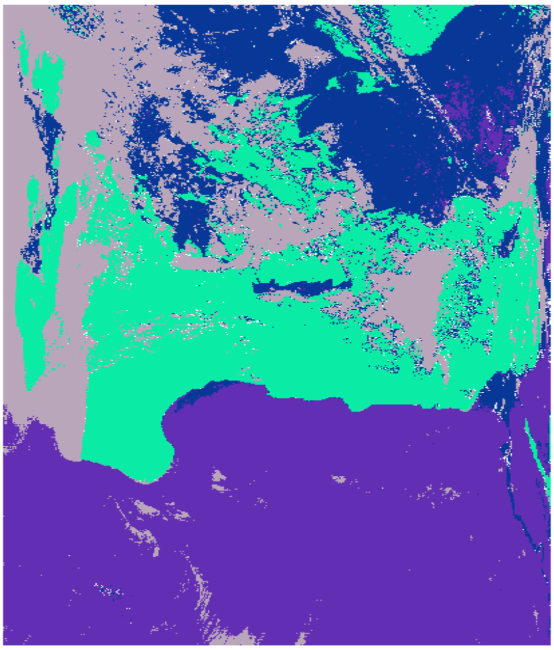
1) Green land
2) Desert land
3) Cloud
4) Sea



MLE



Random Forest



The accuracy now is improved, as expected, and green area is quite well predicted also when is not in the train data, like as on the Nile area.

HW01. Homework on MODIS/AQUA data- Vegetation

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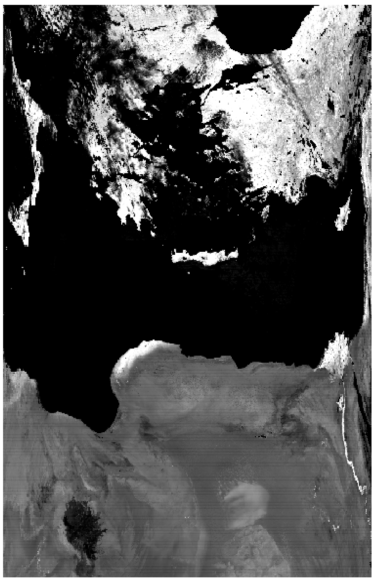
NDVI (Normalized Difference vegetation index)

The **normalized difference vegetation index** (**NDVI**) is a simple graphical indicator that can be used to analyse remote sensing measurements, typically, but not necessarily, from a space platform, and assess whether the target being observed contains live green vegetation or not.

$$NDVI = \frac{Nir - Red}{(Nir + Red)}$$

I used for RED the band 1 with 645 nm wavelength and for NIR band 5 with 1240 nm wavelength



Clearly the brightness areas are those where we have vegetation, like in Turkey, the Greece, in Italy and close to the Nile. The accuracy is high!

HW01. Homework on MODIS/AQUA data- Vegetation

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SAVI (Soil-adjusted vegetation index)

Empirically derived NDVI products have been shown to be unstable, varying with soil colour, soil moisture, and saturation effects from high density vegetation. The index is a transformation technique that minimizes soil brightness influences from spectral vegetation indices involving red and near-infrared (NIR) wavelengths.

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

Whit the same bands of NDVI case and with L = 0.5 this are the result

Where we can see that the effects of lands are reduced from the one that we have seen previously, whereas the vegetation has better valuation.

HW01. Homework on MODIS/AQUA data- Vegetation

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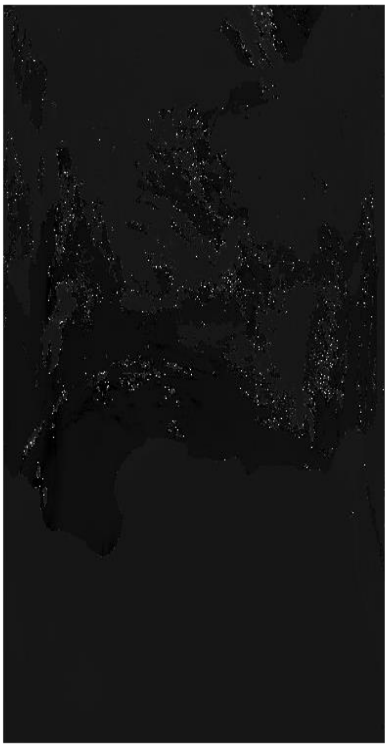
ARVI (Atmospherically Resistant Vegetation Index)

The resistance of the **ARVI** to atmospheric effects (in comparison to the NDVI) is accomplished by a self-correction process for the atmospheric effect on the red channel.
This is done using the difference in the radiance between the blue and the red channels to correct the radiance in the red channel.
Compared to the red band, the blue band is much more easily scattered by the atmosphere particles. This explains why the sky is usually perceived as being blue.
Thus, the ARVI index takes advantage of the different scattering responses from the blue and red band to retrieve information regarding the atmosphere opacity.
Simulations using radiative transfer computations on arithmetic and natural surface spectra, for various atmospheric conditions, show that ARVI has a similar dynamic range to the NDVI, but is, on average, four times less sensitive to atmospheric effects than the NDVI.

$$ARVI = \frac{IR_{factor} * NIR - RB}{IR_{factor} * NIR + RB}$$

Where: $RB = \left(Red_{factor} * Red\right) - gamma * (Blue_{factor} * Blue - Red_{factor} * Red)$



I don’t understand clearly why I have this last plot, probably all the pixel values are close to 0 so few once are not zero