Land Cover mapping with Neural Network

Microwaves project second part
University of Rome Tor Vergata, 2022-2023

Author: Davide Savini (0310795)

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Introduction

SNAP and Neumapper

In this report, a Land-Cover Classification of an area that includes Sassari, a city of Sardinia (Italy), is performed through an artificial neural network (ANN) built on the Neumapper software [1]. This project involves LC classification in two cases: one as image data acquired with Sentinel-2 and another with a multitemporal image acquired with Sentinel-1. Initially, the SNAP (Science Toolbox Exploitation Platform) software [2] is used to show and process the images to be input to the neural network. As the next step, it's used Neumapper that is software that implements, in the same environment, the various stages of the generation of an ANN for automatic pixel-based image classification:

- Definition of the network topology;
- Generation of training data;
- Training of the network;
- Classification of an image using the trained network.

This software has a simple and intuitive interface that permits separate handling of networks, pattern sets, and images, enabling multi-image network training, and classification of multiple images using the very same trained network.

Chapter 1

Land Cover mapping

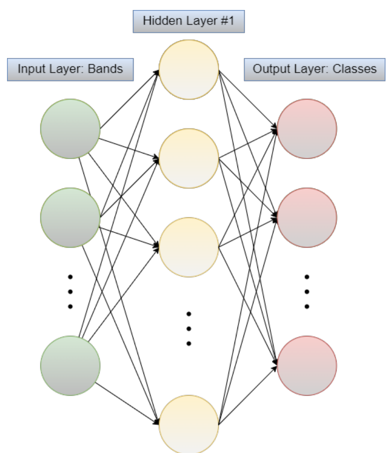

Figure 1.1: *ANN architecture*

Land Cover (LC) maps provide information about the land surface coverage and its variations. This means that we have a dynamic variable representing the interactions between socioeconomic activities and environmental changes. Traditional approaches require geographic studies, surveys for LC characterization and mapping, and multidisciplinary dataset management. Vice versa, Remote Sensing technologies produce global information within a short time frame. This characteristic makes it useful for visualizing, analyzing, and monitoring the dynamics of the LC. The goal of the project is to perform a classification of the selected area into three classes: Natural soil (forests, bare soil, cropland, parks. . .), Built-up, and Water. To do this classification, the artificial neural network (ANN) approach is a suitable way. In this project, we used Multi-Layer Perceptron (MLP) from Neumapper, which is useful for LC problems that can be described as a Supervised classification and/or as a Pixel-based classification [3]. For any try, the architecture of ANN (Fig. 1.1) is built with bands as input (one perceptron (or neuron) for each band), one hidden layer of 48/64 perceptrons, and classes as output (one perceptron for each class).

1.1 Download Data

To download data we used Copernicus [4], which is a European program that provides free satellite and in-situ information. In particular, we talk about Sentinel Missions which are ESA missions developed within the Copernicus program. It's a constellation (Fig 1.2) of different satellites that are composed of radar and multispectral sensors for monitoring land, water, and atmosphere. From this mission, we focus on Sentinel-2 (Fig. 1.3) and Sentinel-1 (Fig. 1.4).

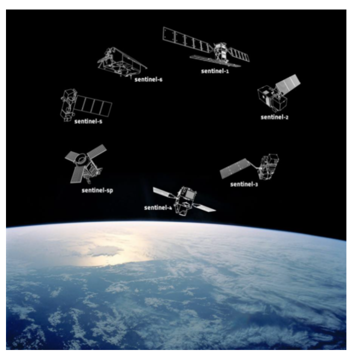

Figure 1.2: *Sentinel Constellation*

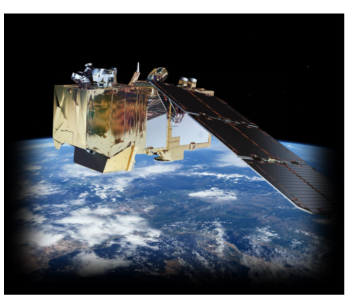

Figure 1.3: *Sentinel-2*

Figure 1.4: *Sentinel-1*

Chapter 2

Sentinel-2

Sentinel-2 satellites are twin satellites placed in the same orbit, phased at 180° to each other. They have a combined revisit time of 5 days with Multispectral images (12 bands) acquired in the visible and infrared; a Spatial resolution that depends on the acquisition band (10, 20, or 60 m); they are used for Land monitoring, emergency management, security, climate change, marine services. Before starting the overall steps it is good to say that to have a Natural color composition (RGB) we have to choose bands in the following way:

- Red → Band 4
- Green → Band 3
- Blue → Band 2

2.1 Sassari, download data: Sentinel-2

As I said in the introduction, the area of interest is Sassari, a city in the North-West of Sardinia (Italy). I chose it because it's a complex scene, where several features can be extracted. Using Copernicus I downloaded the image data of the interest area, in particular, the capture is done from Sentinel-2 at 10:16 AM on April 26, 2023 (Fig. 2.1). It can be seen the image data, using SNAP, shown in band B8A (Fig. 2.2) and in RGB (2.3).

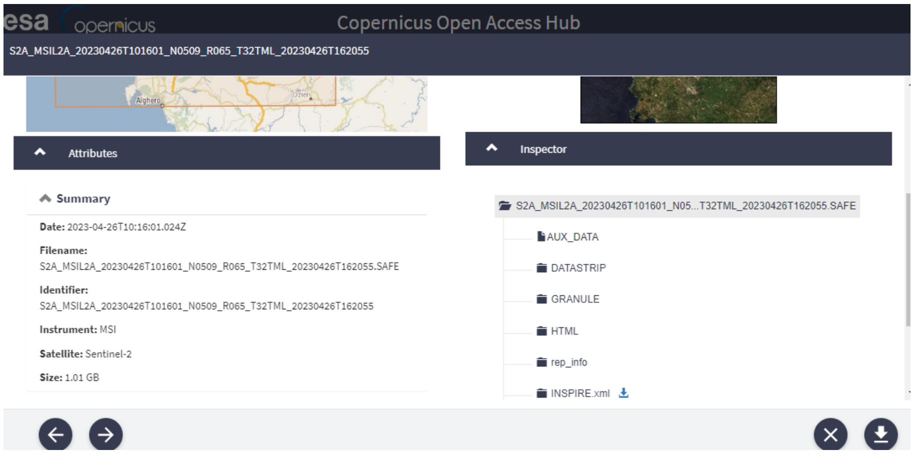

Figure 2.1: *Copernicus: Sentinel-2 download data*

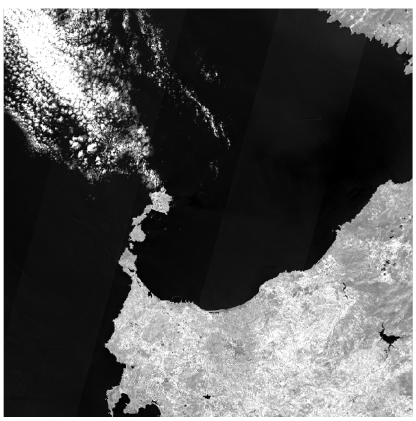

Figure 2.2: *North-West of Sardinia captured at 10:16 AM on April 26, 2023, from Sentinel-2 in band B8A*

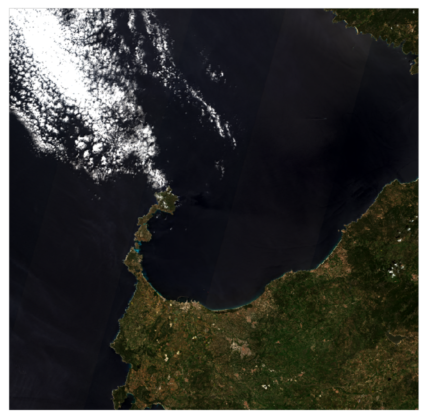

Figure 2.3: *North-West of Sardinia captured at 10:16 AM on April 26, 2023, from Sentinel-2 in RGB*

2.2 SNAP-Sentinel-2: Subset and Resampling

From this image, I selected an area with Sassari and I did a subset (Fig. 2.4) that is the image I worked with. The area can be seen in band B12 in Fig. 2.5 and with RGB composite in Fig. 2.6.

The subset is done considering only the 12 Acquisition bands. After this, I did a Resampling considering the band B2 (band at 10m of spatial resolution) as reference band from source product. It can be seen the subset image in band B12 (Fig. 2.7) and its RGB composite in Fig. 2.8. After

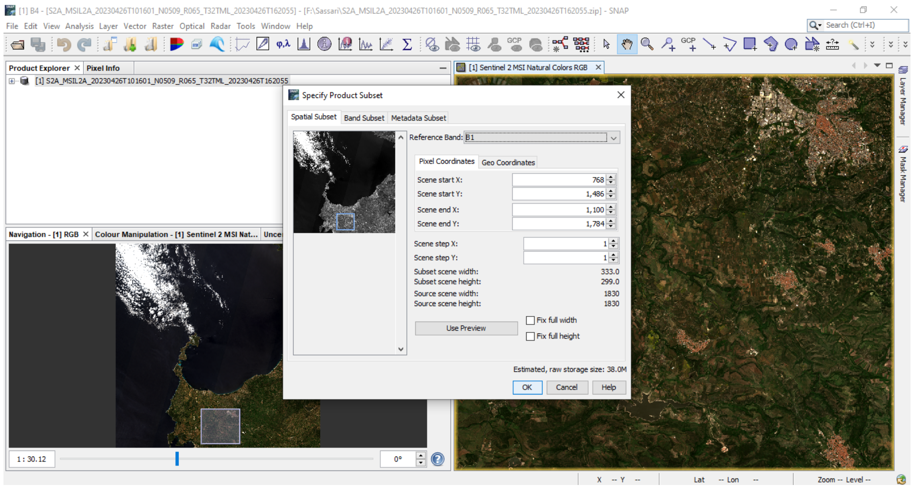

Figure 2.4: *SNAP subset*

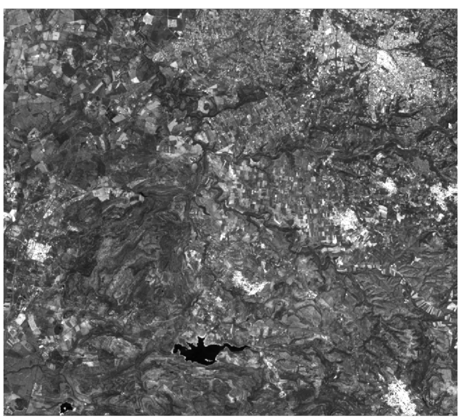

Figure 2.5: *Subset shown in band B12*

Figure 2.6: *Subset shown in RGB*

the RGB composite, I exported the subset File from SNAP in a GeoTIFF format for Neumapper's purpose.

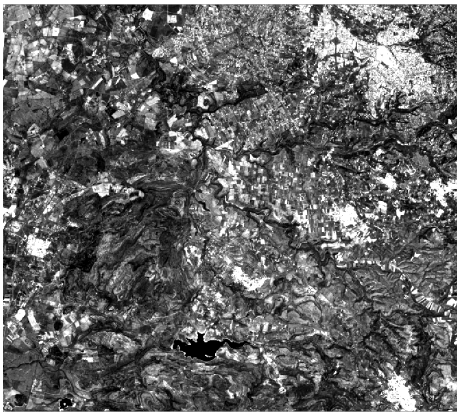

Figure 2.7: *Subset resampled shown in band B12*

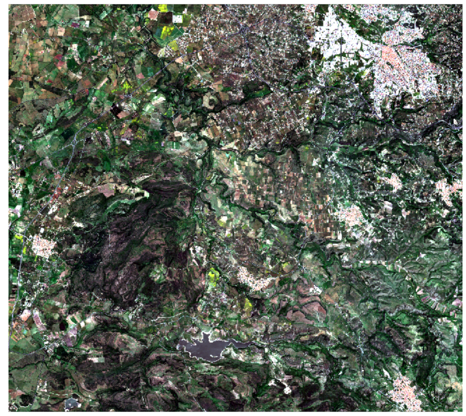

Figure 2.8: *Subset resampled shown in RGB*

2.3 Neumapper Sentinel-2, Land Cover classification

In the first step, I opened with Neumapper the RGB image exported in the previous report section and I started to create a dataset selecting pixels on the image (example in Fig 2.9). The used rule to build a dataset in this project is:

- Training 80 %;
- Test 20 % (example of neumapper interface in Fig 2.10).

As I said at the beginning of the first chapter, the classes for classification are:

- Natural soil (forests, bare soil, cropland, parks. . .);
- Built-up;
- Water.

I made several tries, initially, I did a particular try with a training/test of 1000/200 pixels; then I rebuilt the dataset using 5000/1000 pixels. After I obtained some acceptable classification results, I tried to create a dataset larger (around 10000/2000 pixels for training/test) to find an improvement in my classification. In overall cases, I also tuned the hyperparameters model to improve the classification, in particular changing the learning-rate hyperparameter with the following values: 0.1, 0.5, 0.05, 0.005, and 0.0005.

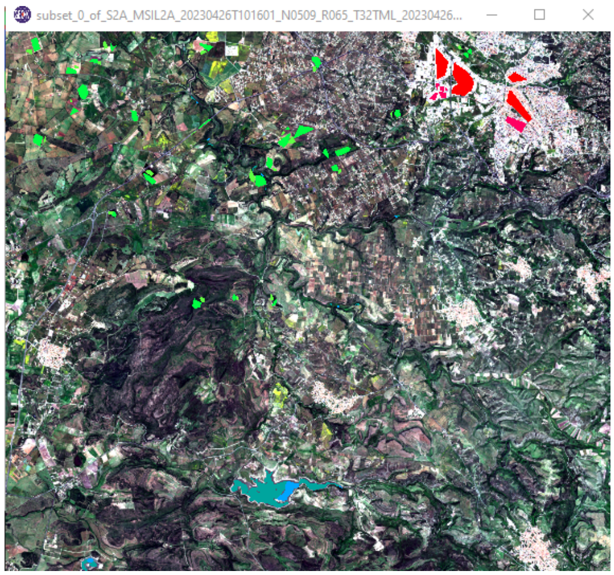

Figure 2.9: *(Example) Neumapper: collection of Pixels on the RGB image*

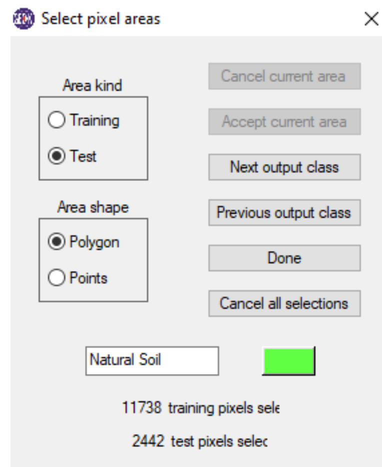

Figure 2.10: *(Example) Neumapper: interface of collect pixels*

2.3.1 Neumapper: S2A - 1st try

Dataset with a training/test of 1000/200 pixels, I tried a classification using five classes (I added roads and bare soil as extra classes to vegetation, water, and built-up (2.11)) instead of the required three.

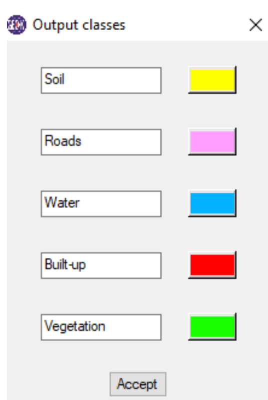

Figure 2.11: *Neumapper: Output classes*

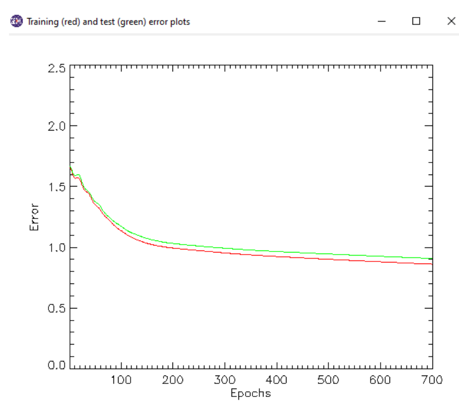

Figure 2.12: *Neumapper: Learning curves (red for training and green for test), 700 epochs*

I chose a learning rate equal to 0.01 and I run the ANN two times, one with 700 epochs (Fig. 2.12 and Fig. 2.13) and one with 500 epochs (Fig. 2.14). I have shown the results of ANN classification by observing the Learning curves (training in red and test in green), the original RGB image, and the classified image. The classification in both cases seems good except for roads where pixels are so less to build a good dataset. In this area, there are only thin rivers that are also covered by vegetation which means they are difficult to classify as water. A good observation is that in the case of 700 epochs, the ANN learned better and classified better. Regarding learning curves, they decreased and achieved the plateau as expected. A reason that they didn't reach error values lower than 0.5 is because of the road problem.

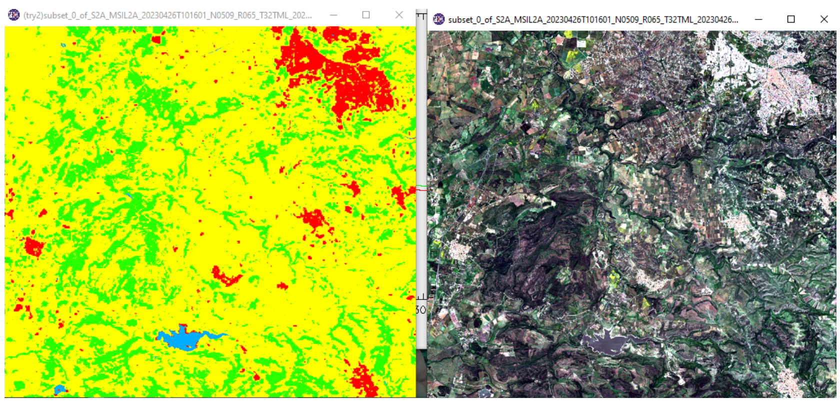

Figure 2.13: *Neumapper: Classification (700 epochs) vs Sentinel-2 RGB image*

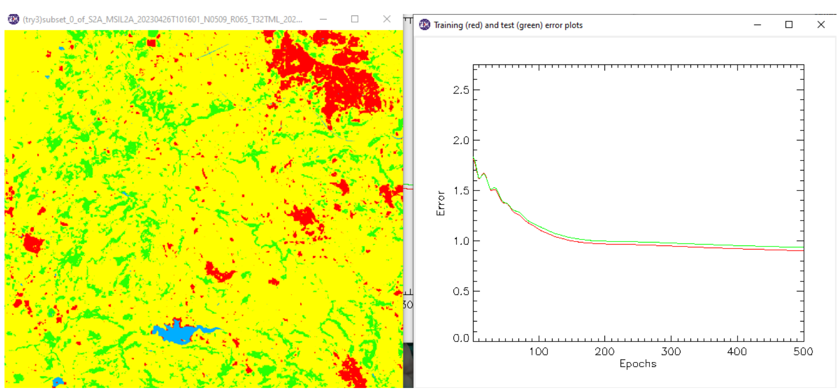

Figure 2.14: *Neumapper: Classification and Learning curves, 500 epochs*

2.3.2 Neumapper: S2A - 2nd try

Dataset with a training/test of 5000/1000 pixels, now using the required classification with the three classes (natural soil, water, and built-up (Fig. 2.15)). For the ANN, I chose a learning rate equal to 0.005 and epochs equal to 700. I had an acceptable result except for the larger roads and some "black fields" that are classified as water. A good observation is where there is a high backscattering from the sand around the two lakes and from the bare rocks on the top of the mountains (small parts) that are classified as built-up (Fig. 2.16). In this case, the learning curves (Fig. 2.17) have a smaller error, lower than 0.5, although training and test are a little bit far from each other (around 0.1 difference).

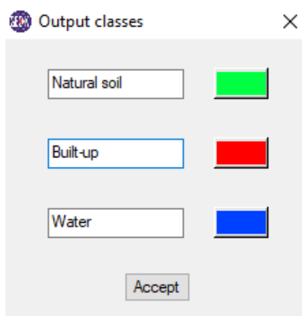

Figure 2.15: *Neumapper: Output classes*

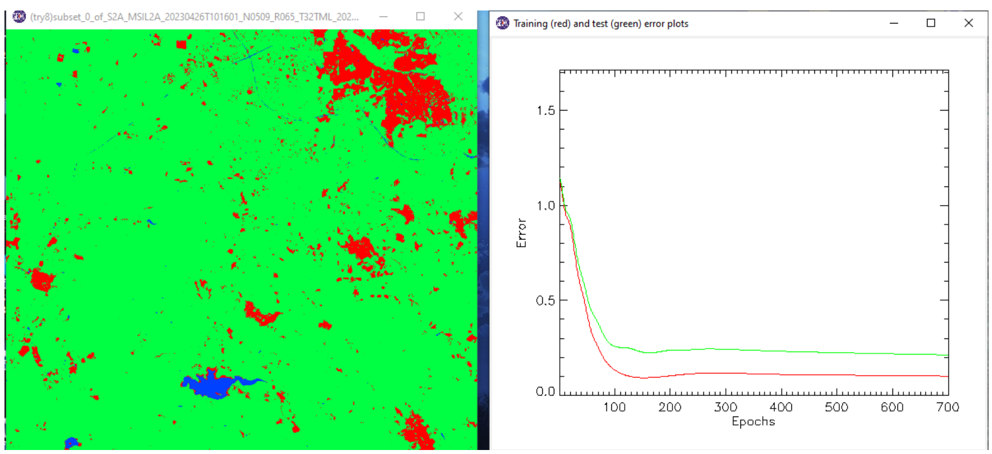

Figure 2.16: *Neumapper: Classification and Learning curves*

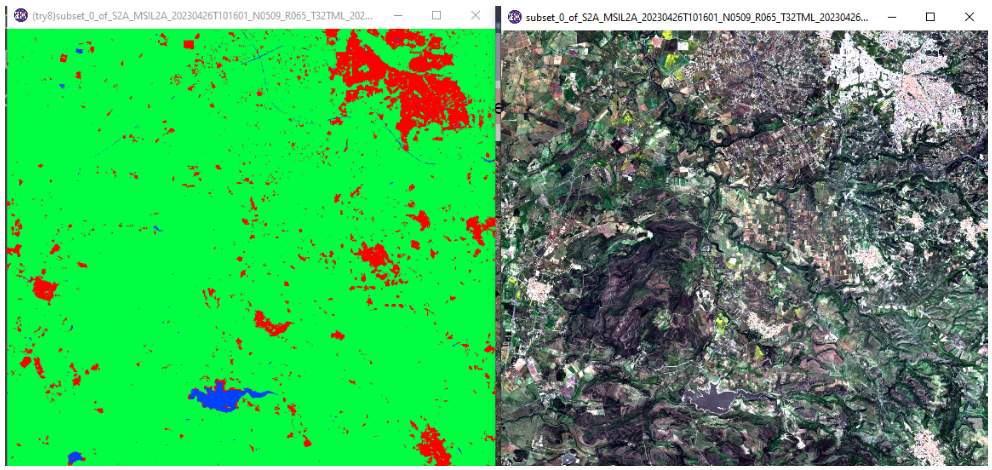

Figure 2.17: *Neumapper: Classification vs Sentinel-2 RGB image*

2.3.3 Neumapper: S2A - 3rd try

Dataset with a training/test of 10000/2000 pixels, still with the three classes. For the ANN, I did some experiments choosing several learning rates equal to: 0.10, 0.05, 0.005 (1000 and 1500 epochs), and 0.0005 (1500 epochs).

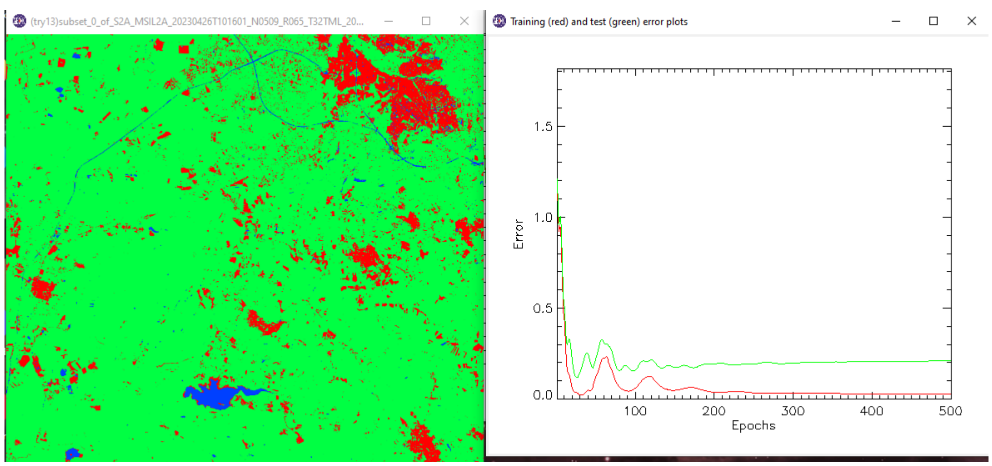

Figure 2.18: *Neumapper: Classification and Learning curves, learning rate 0.10 and 500 epochs*

After all of these experiments, on this 3rd try, the better classification with this dataset is done when I ran the ANN with a learning rate and epochs equal to 0.005 and 1500 respectively.

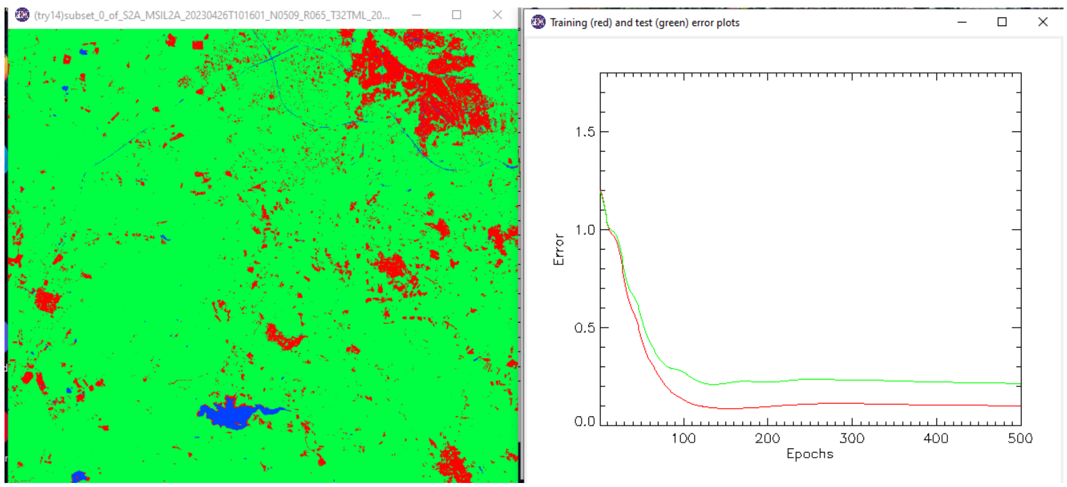

Figure 2.19: *Neumapper: Classification and Learning curves, learning rate 0.05 and 500 epochs*

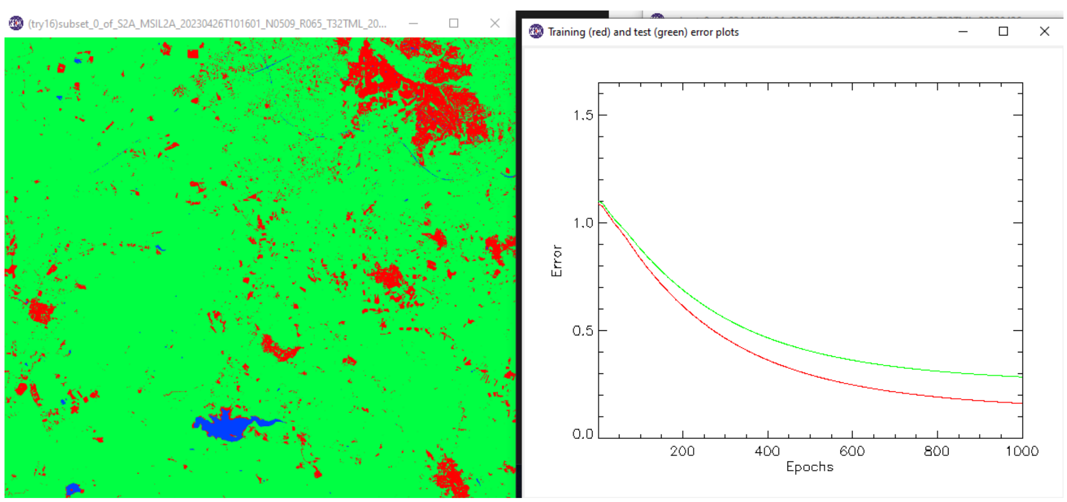

Figure 2.20: *Neumapper: Classification and Learning curves, learning rate 0.005 and 1000 epochs*

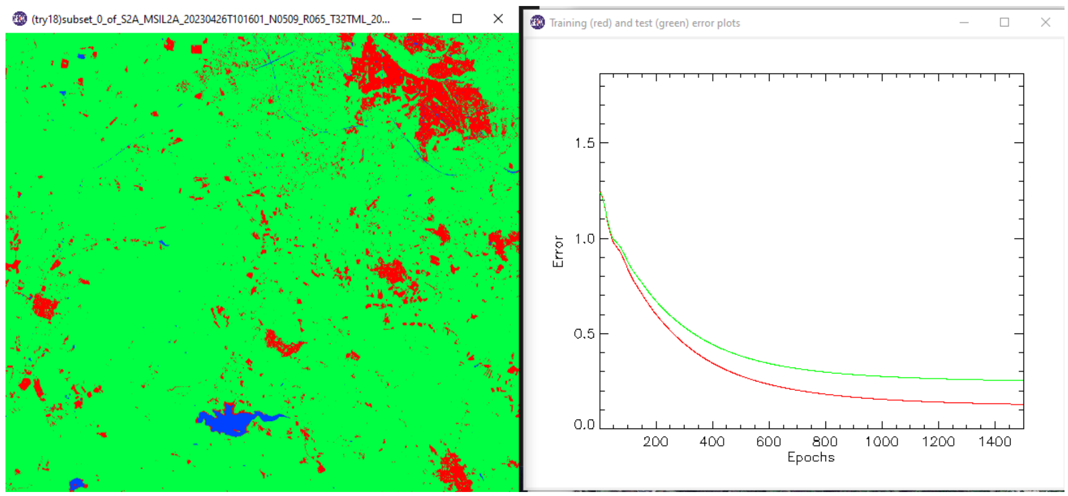

Figure 2.21: *Neumapper: Classification and Learning curves, learning rate 0.005 and 1500 epochs*

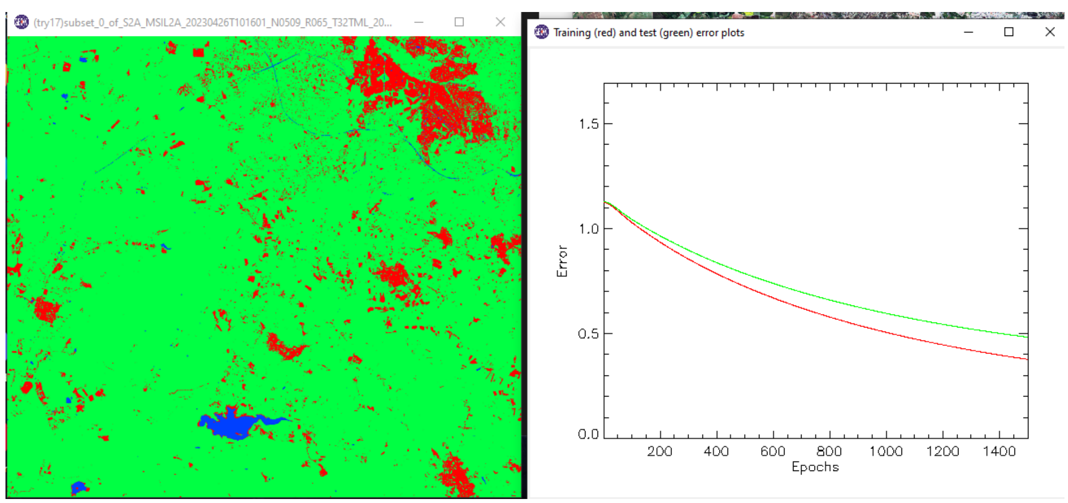

Figure 2.22: *Neumapper: Classification and Learning curves, learning rate 0.0005 and 1500 epochs*

Chapter 3

Sentinel-1

Sentinel-1 is a constellation of two identical radar imagery satellites in the same orbit. They used dual polarisation and they have very short revisit times; C-band synthetic aperture radar imaging operating in four exclusive imaging modes; a different resolution (down to 5 m) and coverage (up to 400 km); they are used for Ice monitoring, oil spills and ships monitoring, marine winds and waves, agriculture, deforestation, land deformation, emergency management.

3.1 Sassari, download data: Sentinel-1

As for Sentinel-2, I downloaded image data thanks to Copernicus (Fig. 3.1). For Sentinel-1, I used two images, one captured at 17:22 AM on January 21, 2023 (Fig. 3.2), and the other image captured at 17:22 AM on June 26, 2023 (Fig. 3.3). I did this to make a multi-temporal image acquired over the same area with Sentinel-1. As the next step, a subset of images to have a similar subset of Sentinel-2 is done (the area around Sassari).

3.2 SNAP-Sentinel-1: Pre-processing operations

For Sentinel-1 there are some pre-processing operations that are to be done with SNAP before using the image bands as input for ANN Neumapper to have the classification of the acquired area. First of all, I had to do a subset for both cases trying to choose the same Geographic Coordinates; to do this in an easy way I used Wicket, a lightweight Javascript library [5] to find the Geo. Coordinates just selecting the interested area on a Geographic World map. After the subset, for each of the two images, the pre-processing

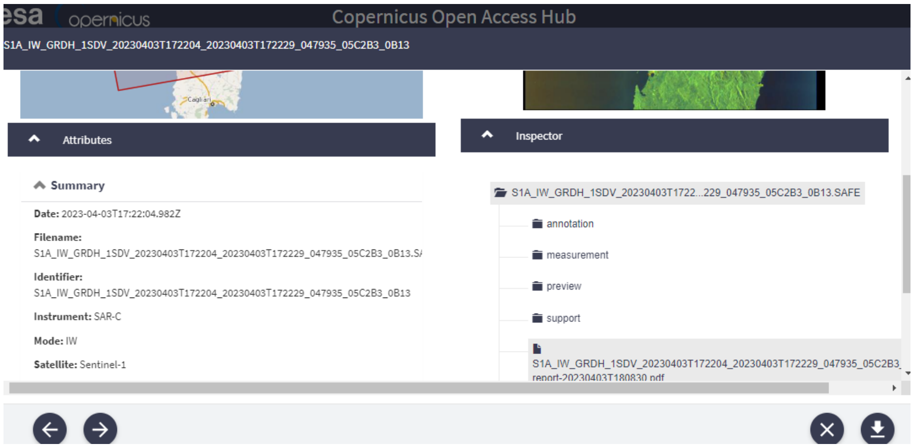

Figure 3.1: *Copernicus: Sentinel-1 download data*

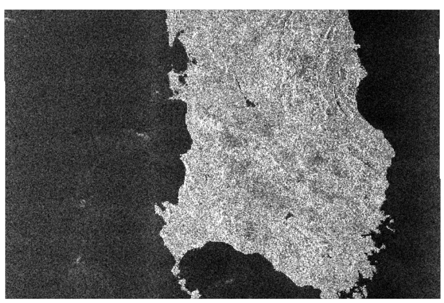

Figure 3.2: *Sardinia captured at 17:22 AM on January 21, 2023, from Sentinel-1 in band Amplitude VH*

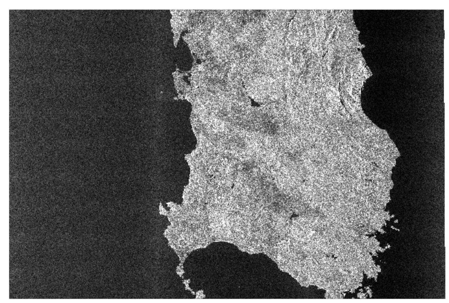

Figure 3.3: *Sardinia captured at 17:22 AM on June 26, 2023, from Sentinel-1 in band Amplitude VH*

operations are Speckle filter, Calibration, and Terrain Correction (Fig. 3.6 and Fig. 3.7); then the Stack of the two processed images to have the multi-temporal image acquired over the same area, and as the final step the Conversation to dB (it can be done before the Stack).

These steps can be seen and processed in SNAP by doing a chain with the tool Graph Builder. I did it step-by-step because of limited hardware resources, but it can be seen in the overall steps on the Graph Builder chain

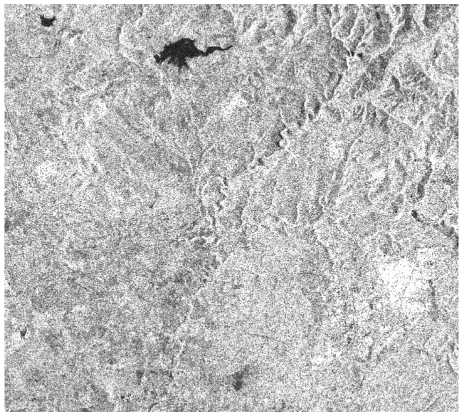

Figure 3.4: *Subset of Sardinia captured at 17:22 AM on January 21, 2023, from Sentinel-1 in band Amplitude VH*

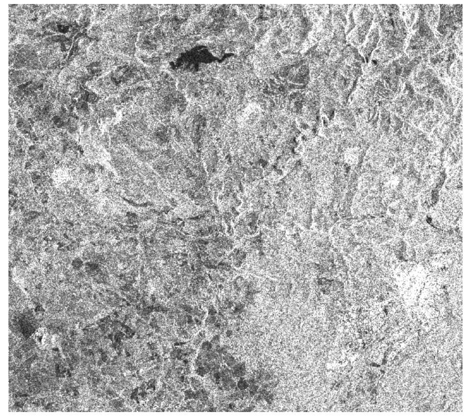

Figure 3.5: *Subset of Sardinia captured at 17:22 AM on June 26, 2023, from Sentinel-1 in band Amplitude VH*

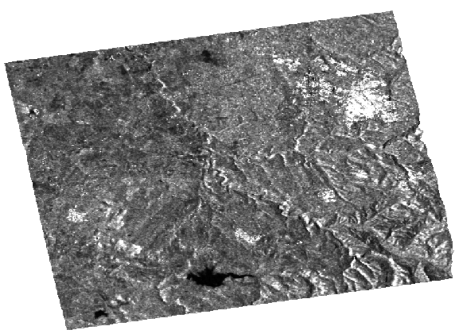

Figure 3.6: *Terrain Corrected, Calibrated and Speckle filtered subset of Sardinia captured on January 21, 2023, in band Amplitude VH*

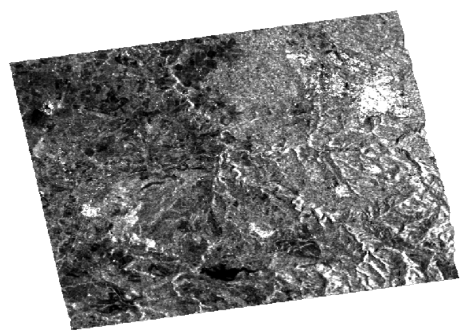

Figure 3.7: *Terrain Corrected, Calibrated and Speckle filtered subset of Sardinia captured on June 26, 2023, in band Amplitude VH*

that I made in Fig. 3.8. In the upper single chain (Stack-Master), there are all steps for the acquired area on January 21 meanwhile the bottom single chain (Stack-Slave) is for the acquired area on June 26. After the Stack and Conversion to dB, I did another subset to have a "squared" image avoiding the "empty part" that Neumapper doesn't like to process (Fig. 3.9 and Fig.

3.10); in this way, after RGB composite, I exported the image as GeoTIFF format so it's ready for the ANN.

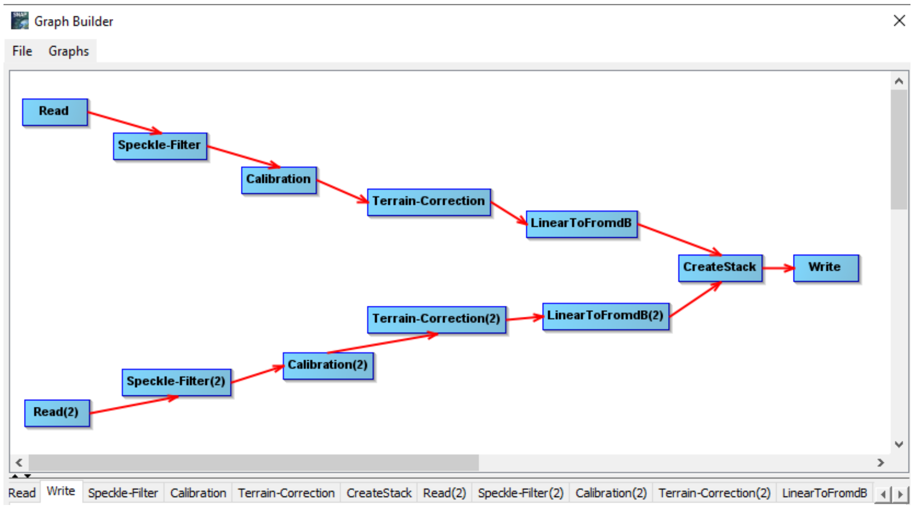

Figure 3.8: *SNAP: Graph Builder chain*

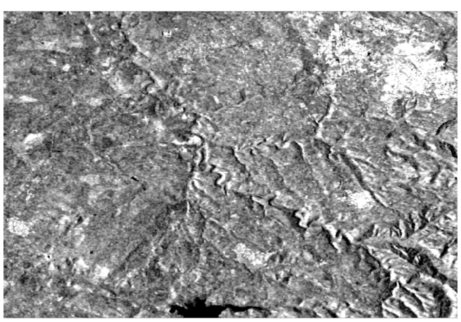

Figure 3.9: *Stack-dB-subset of master (January 21, 2023) in band VV*

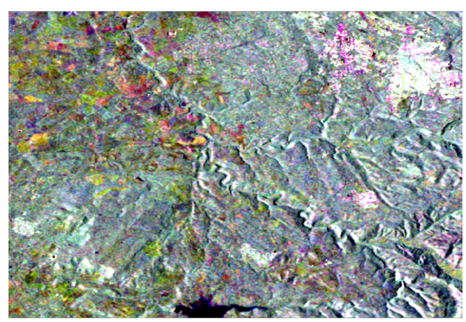

Figure 3.10: *Stack-dB-subset with RGB composite*

3.3 Neumapper Sentinel-1, Land Cover classification

The first step is to open the image on Neumapper and it must be done the Create texture bands of the image and choosing some Texture measures (a step that requires some minutes to be finished). I chose Texture measures: Contrast, Homogeneity, and Mean. After this, the image is ready for building the dataset (training and test of 80% and 20% respectively); from now the steps are the same as Neumapper Sentinel-2, Land Cover classification.

3.3.1 Neumapper: S1A - 1st try

Dataset with a training/test around 6000/1200 pixels, using the required classification with the three classes (natural soil, water, and built-up (Fig. 3.12)). For the ANN, I chose a learning rate equal to 0.05 and 0.005 and epochs equal to 500 in both cases. The result in both cases is acceptable for Natural soil and buildings; in the case of the ANN trained with a learning rate equal to 0.05 (Fig. 3.13) I had a good classification of lake water and also of some thin rivers (in particular the one that passes through the middle of the image) that I wasn't able to classify with Sentinel-2; in case of learning rate equal to 0.005 (Fig. 3.14) I had a curious classification of natural soil mixed water inside the lake that could be algae/vegetation inside it. The learning curves have an error of around 0.5 and training and test have a difference of around 0.1 after achieving the plateau.

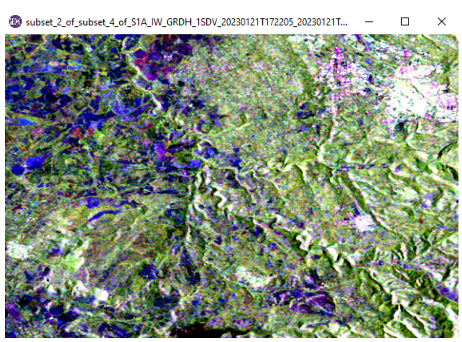

Figure 3.11: *Neumapper: RGB image*

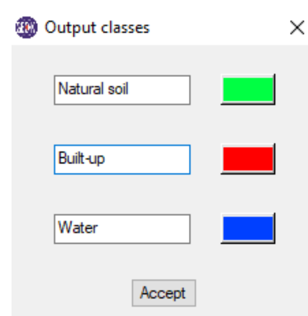

Figure 3.12: *Neumapper: Output classes*

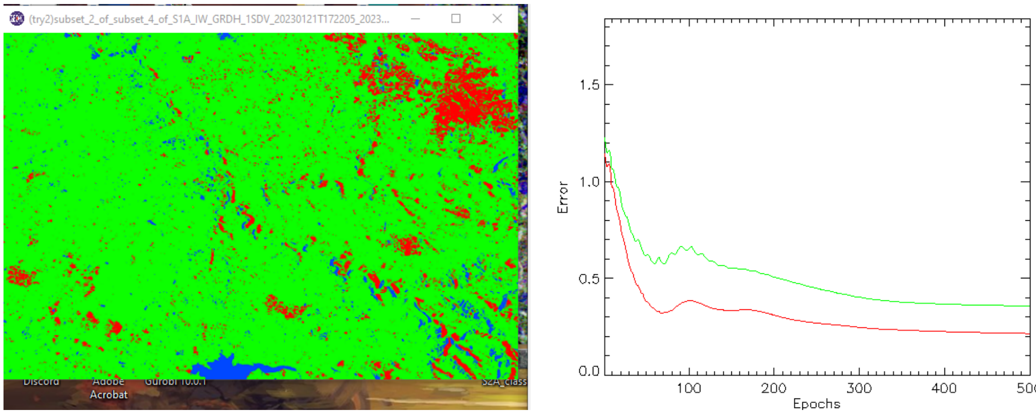

Figure 3.13: *Neumapper: Classification and Learning curves, learning rate 0.05 and 500 epochs*

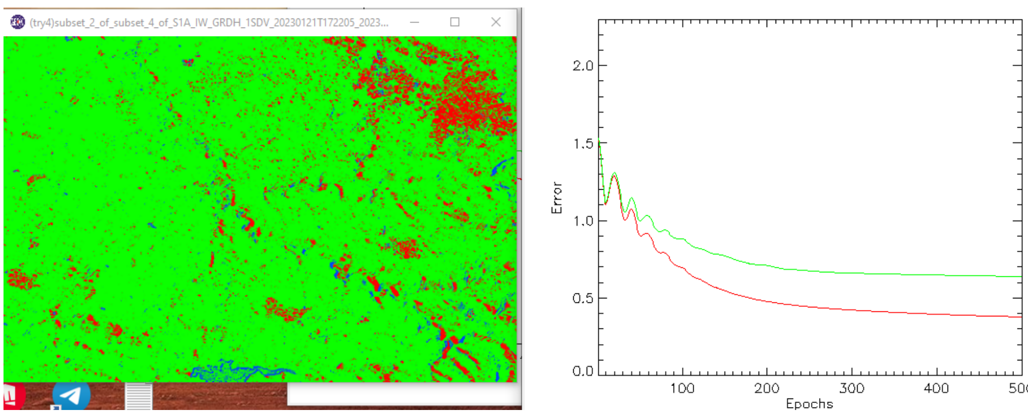

Figure 3.14: *Neumapper: Classification and Learning curves, learning rate 0.005 and 500 epochs*

3.3.2 Neumapper: S1A - 2nd try

Dataset with a training/test around 14000/2800 pixels, using the same previous three classes. The used learning rate is 0.005 with 500 epochs. Also, in this case, a good observation is that some "black fields" are classified as water; the thin rivers are not classified; where there is a high backscattering from the bare rocks on the top of the mountains and "white fields", there is a classification as built-up.

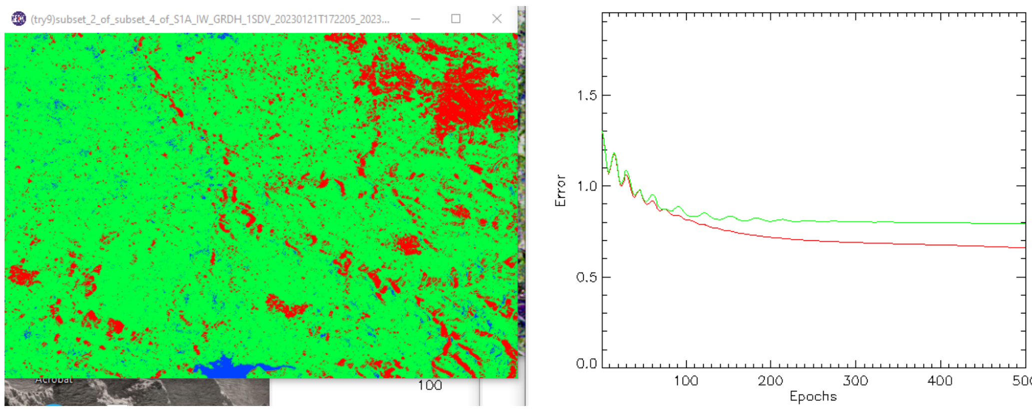

Figure 3.15: *Neumapper: Classification and Learning curves, learning rate 0.005 and 500 epochs*

3.4 Conclusion

I had a better generic classification in Sentinel-2 and better learning curves trend but, thanks to Sentinel-1, I was able to detect and classify thin rivers that are covered by trees and vegetation, and also a curious classification of natural soil mixed water inside the lake that could be algae/vegetation at its bottom.

Bibliography

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