REMOTE SENSING DAY I

PREPARED BY

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DUE DATE : 20/06/2023

COURSE NAME : GEOMATICS PROJECT III

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Evaluation of the Pleiades Satellite Image (Visual/Digital)

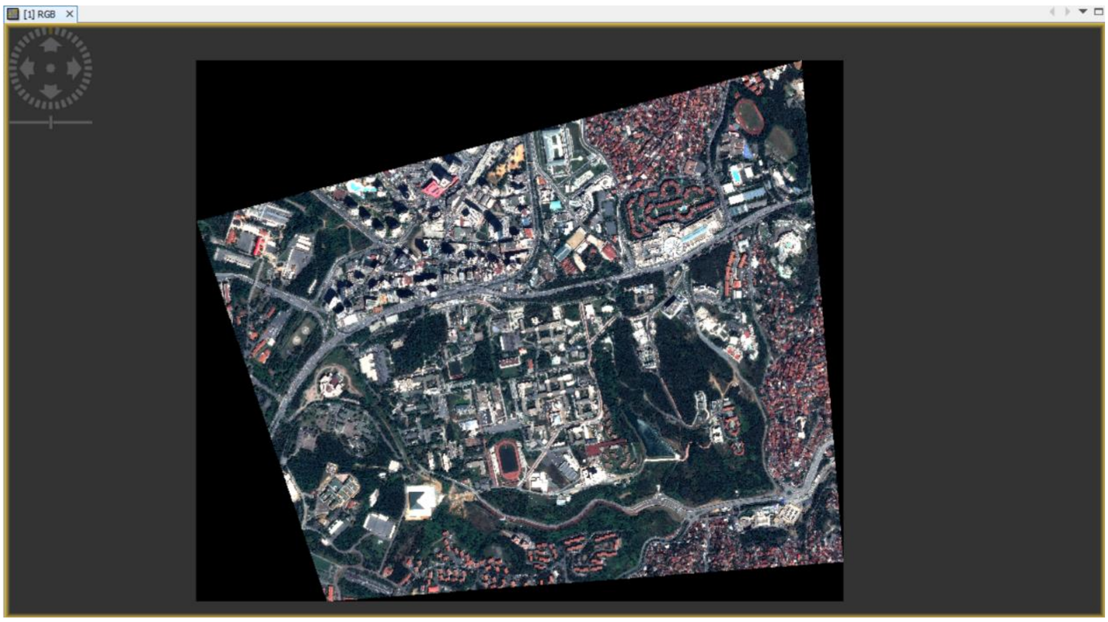
Start the visual study by first importing the Pleiades satellite picture of the ITU Ayazaa campus into the SNAP application. It's crucial to keep in mind that the assessments performed at this point are more subjective and lack universal objective values. We have four photos available for the four bands, which are known as "Red, Green, Blue, and Near-Infrared." The features found in each band of an image can be subjected to various studies. We can see that our location contains four different sorts of land cover features when we look at photographs for each of the four bands: roads, artificial areas, open spaces with little to no vegetation, and forests. Since the SNAP program cannot read the metafiles of Pleiades data, manually modify the metafiles of the Pleiades image spectral bands. The required settings for this step are outlined below.

Band 1 (Red) 600 – 720 nm: Band wavelength: 660; Bandwidth: 120

Band 2 (Green) 490 – 610nm: Band wavelength: 550; Bandwidth: 120

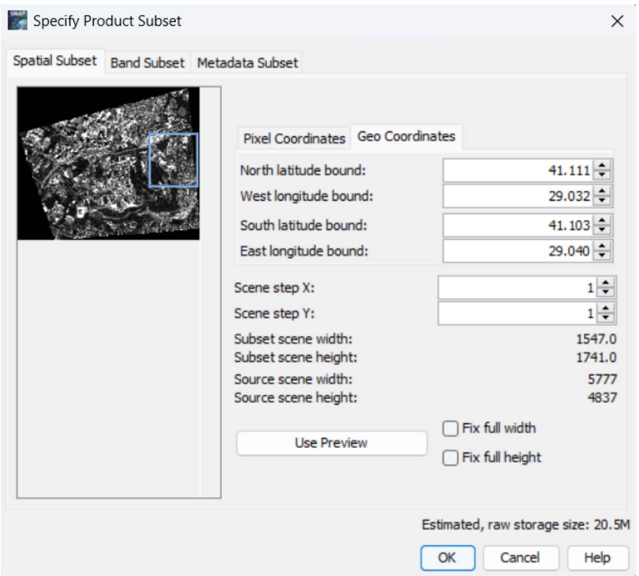
Band 3 (Blue) 430 – 550 nm: Band wavelength: 490; Bandwidth: 120

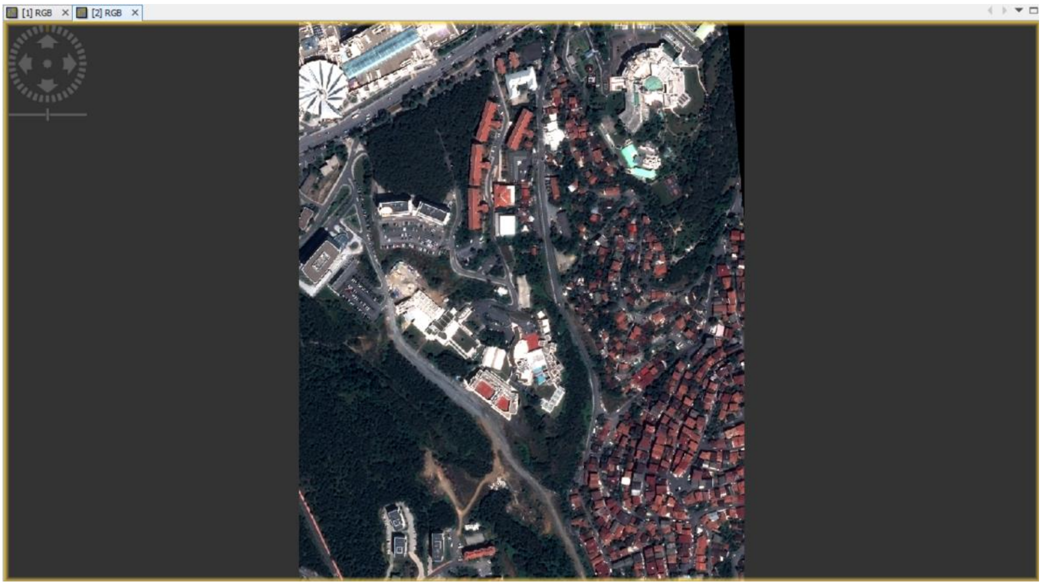
Band 4 (NIR) 750 – 950 nm: Band wavelength: 850; Bandwidth: 200

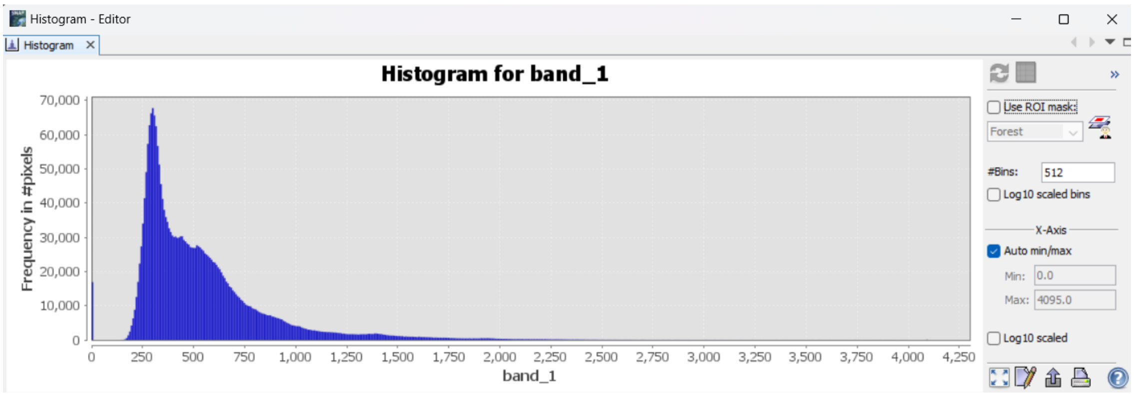


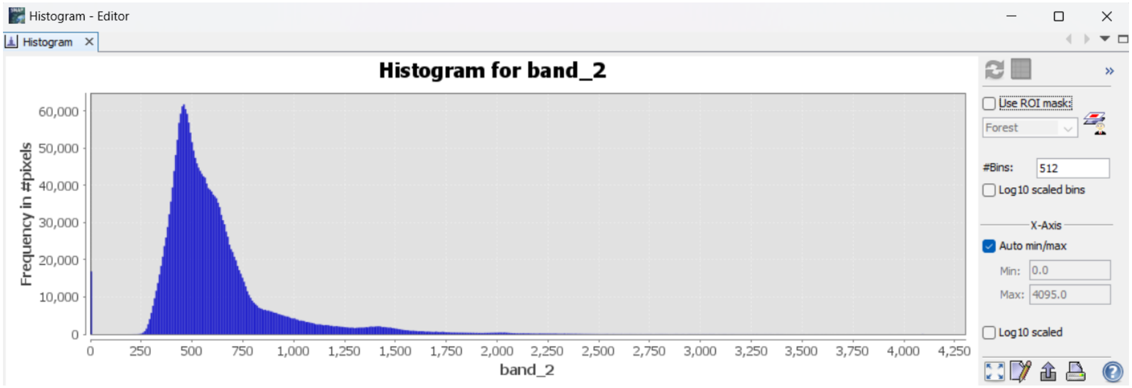
Subsetting the Image

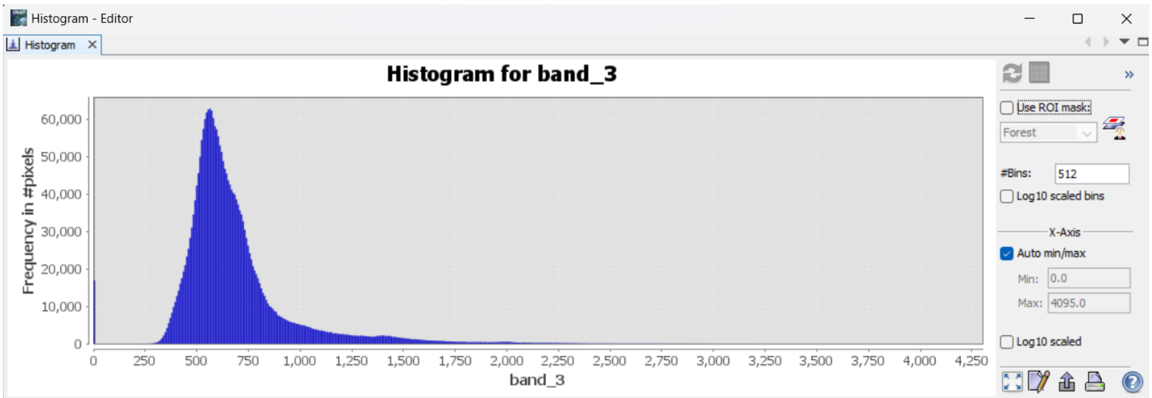
After this Evaluation of the Pleiades satellite image step, our image was subset according to the geo coordinates specified below within the frame of the land area of group 26. The output of the process is shown in the image just below the settings.






Histogram - Editor
Histogram
Histogram for band_1
Frequency in #pixels
band_1
Use ROI mask:
Forest
#Bins: 512
Log10 scaled bins
X-Axis
Auto min/max
Min: 0.0
Max: 4095.0
Log10 scaled


Histogram - Editor
Histogram
Histogram for band_2
Frequency in #pixels
band_2
Use ROI mask:
Forest
#Bins: 512
Log10 scaled bins
X-Axis
Auto min/max
Min: 0.0
Max: 4095.0
Log10 scaled


Histogram - Editor
Histogram
Histogram for band_3
Frequency in #pixels
band_3
Use ROI mask:
Forest
#Bins: 512
Log10 scaled bins
X-Axis
Auto min/max
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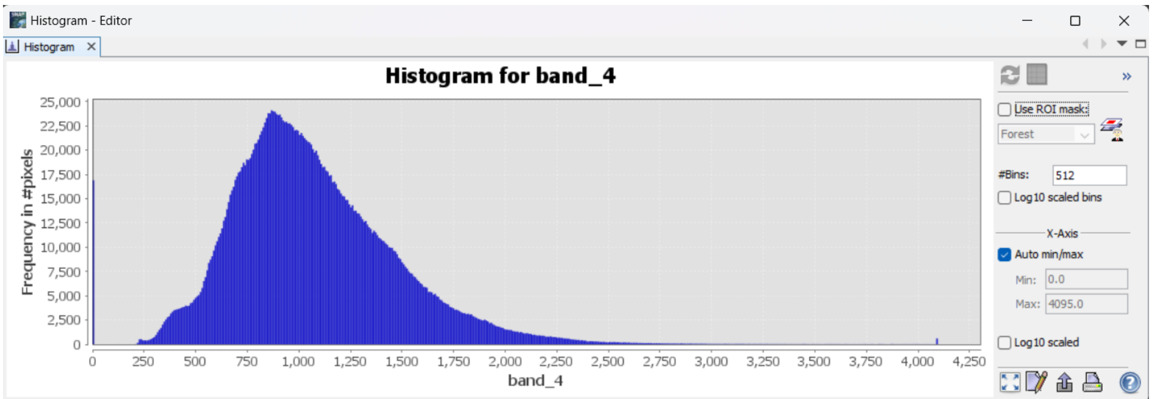
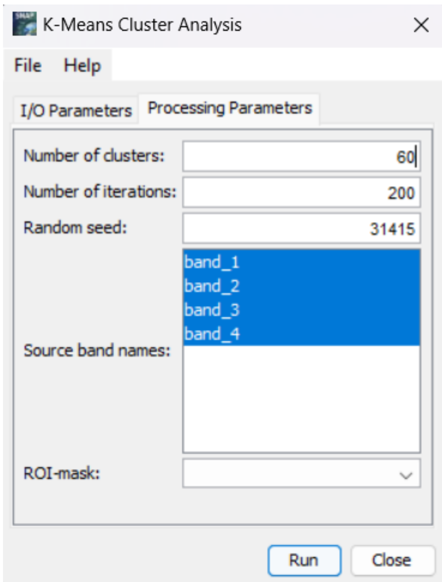
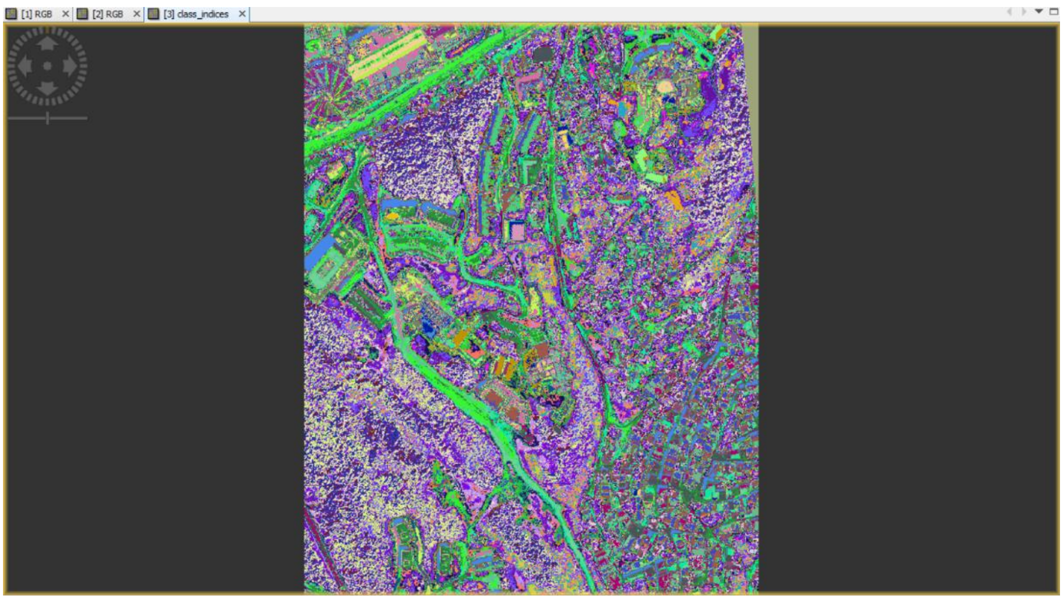
Max: 4095.0
Log10 scaled

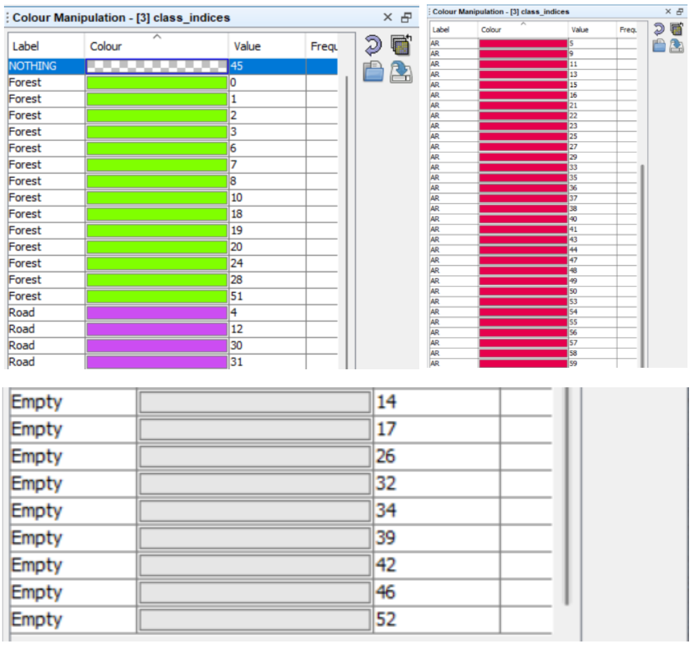

Histogram - Editor
Histogram
Histogram for band_4
Frequency in #pixels
band_4
Use ROI mask:
Forest
#Bins: 512
Log10 scaled bins
X-Axis
Auto min/max
Min: 0.0
Max: 4095.0
Log10 scaled

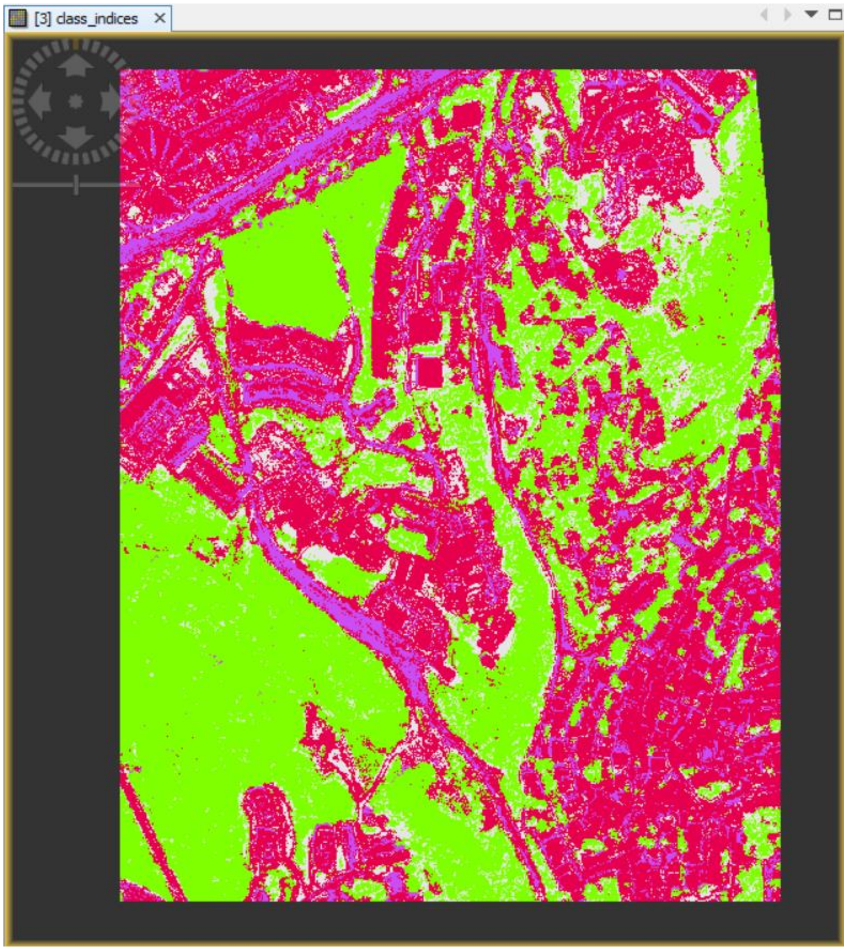
Unsupervised Classification

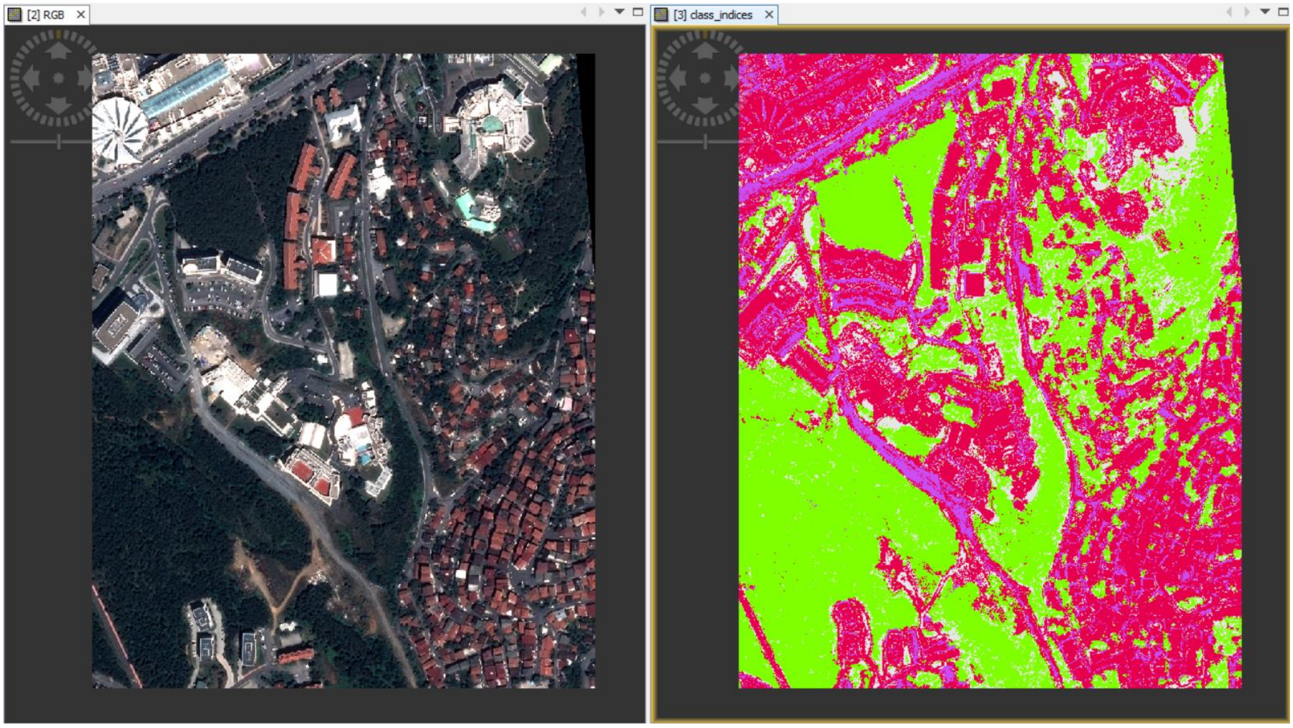
The unsupervised image classification process was carried out using K-Means Cluster Analysis. There are four classes that need to be taken into account. These are roads, artificial areas, open spaces with little to no vegetation, and forests, as in the Supervised Classification. Sixty class numbers were initially selected, and they were later gathered into four primary classes. For the arrangements, we used the Corine land cover legend. The output images that were produced are shown below.






Colour Manipulation - [3] class_indices
Label
Colour
Value
Frequ
NOTHING 45
Forest 0
Forest 1
Forest 2
Forest 3
Forest 6
Forest 7
Forest 8
Forest 10
Forest 18
Forest 19
Forest 20
Forest 24
Forest 28
Forest 51
Road 4
Road 12
Road 30
Road 31
Empty 14
Empty 17
Empty 26
Empty 32
Empty 34
Empty 39
Empty 42
Empty 46
Empty 52

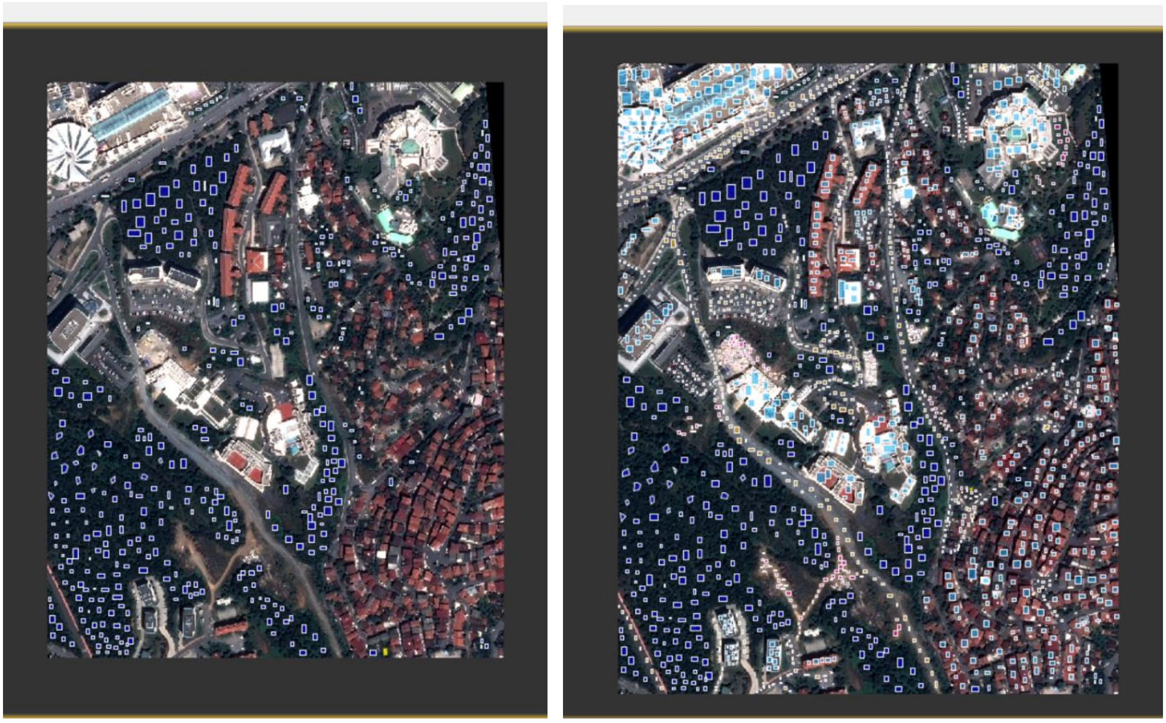

[3] class_indices

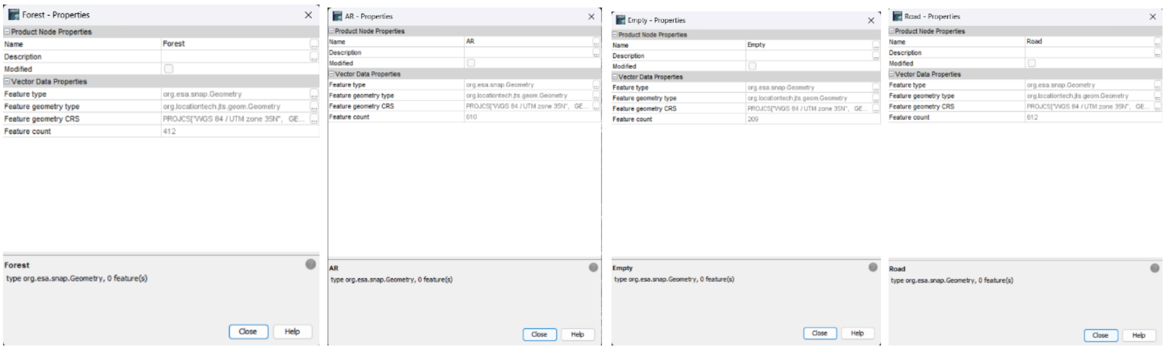


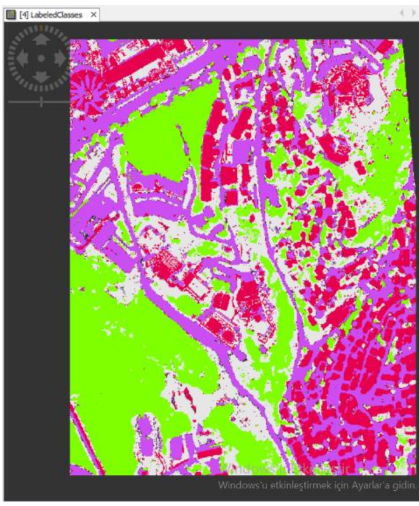
When we look at our RGB and unsupervised image, we can say that a large part of our area consists of forests and settlements. In general, when we look at the classification map, we can see that my daughter and green colors are dominant. These green colors represent forests and red colors represent artificial areas.

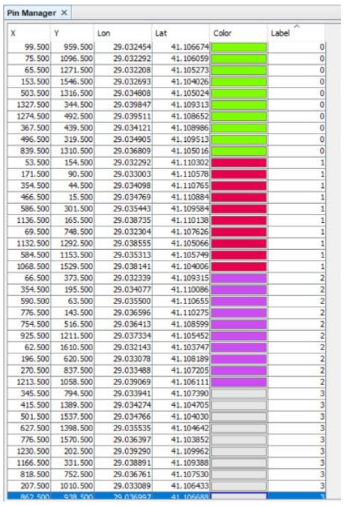
Supervised Classification

One of the most popular classification techniques is the maximum likelihood classifier, which assigns the correct class to the pixel with the highest likelihood. The likelihood is the post-hoc likelihood that a pixel belongs to a particular class. The Pleiades dataset is subjected to the Maximum Likelihood technique with the aid of training sample data gathering. Land use Land cover classes (LULC) were selected from as roads, artificial areas, open spaces with little to no vegetation and forests. The criteria of picking training sites with at least 200 points was applied for this level.

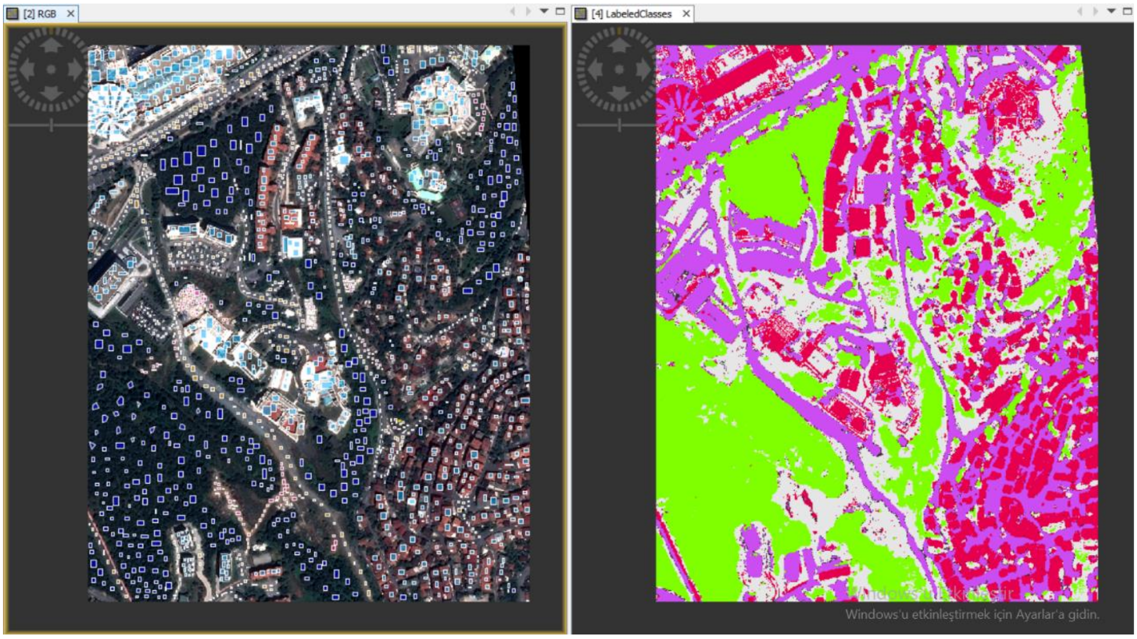







Pin Manager

X	Y	Lon	Lat	Color	Label
99.500	959.500	29.032454	41.106674		0
75.500	1096.500	29.032292	41.106059		0
65.500	1271.500	29.032208	41.105273		0
153.500	1546.500	29.032693	41.104026		0
503.500	1316.500	29.034808	41.105024		0
1327.500	344.500	29.039847	41.109313		0
1274.500	492.500	29.039511	41.108652		0
367.500	439.500	29.034121	41.108986		0
496.500	319.500	29.034905	41.109513		0
839.500	1310.500	29.036809	41.105016		0
53.500	154.500	29.032292	41.110302		1
171.500	90.500	29.033003	41.110578		1
354.500	44.500	29.034098	41.110765		1
466.500	15.500	29.034769	41.110884		1
586.500	301.500	29.035443	41.109584		1
1136.500	165.500	29.038735	41.110138		1
69.500	748.500	29.032304	41.107626		1
1132.500	1292.500	29.038555	41.105066		1
584.500	1153.500	29.035313	41.105749		1
1068.500	1529.500	29.038141	41.104006		1
66.500	373.500	29.032339	41.109315		2
354.500	195.500	29.034077	41.110086		2
590.500	63.500	29.035500	41.110655		2
776.500	143.500	29.036596	41.110275		2
754.500	516.500	29.036413	41.108599		2
925.500	1211.500	29.037334	41.105452		2
62.500	1610.500	29.032143	41.103747		2
196.500	620.500	29.033078	41.108189		2
270.500	837.500	29.033488	41.107205		2
1213.500	1058.500	29.039069	41.106111		2
345.500	794.500	29.033941	41.107390		3
415.500	1389.500	29.034274	41.104705		3
501.500	1537.500	29.034766	41.104030		3
627.500	1398.500	29.035535	41.104642		3
776.500	1570.500	29.036397	41.103852		3
1230.500	202.500	29.039290	41.109962		3
1166.500	331.500	29.038891	41.109388		3
818.500	752.500	29.036761	41.107530		3
207.500	1010.500	29.033089	41.106433		3
862.500	938.500	29.036997	41.106688		3

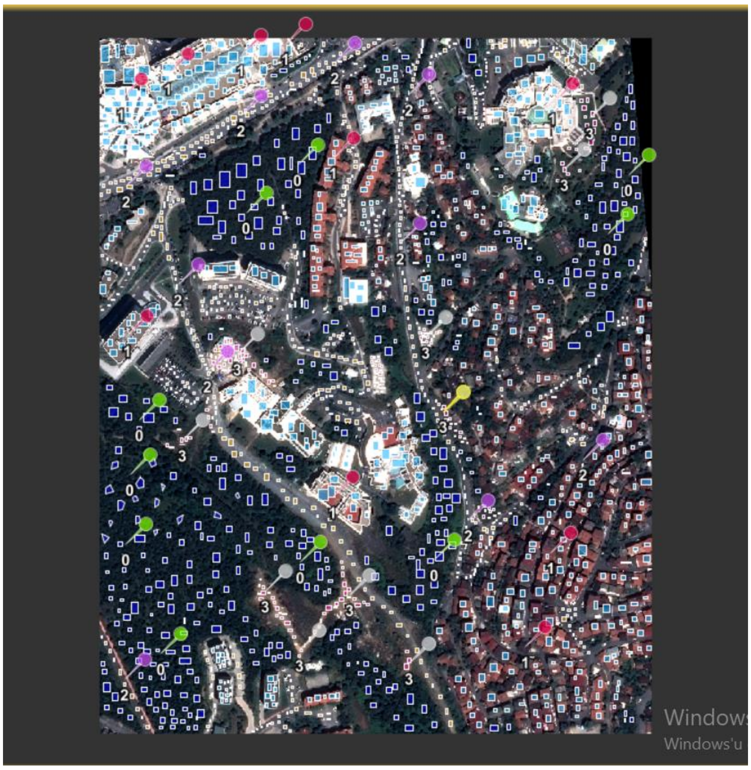


When we put the supervised classification image side by side with RGB and examine it, the features on the map are generally distinguishable, but the artificial area has perceived some of it as roads. It performed a more accurate classification in areas with forest and empty soil. This may be because there are less factors affecting the reflection in those regions. For example, things like the building material of the car on the road can increase the probability and the amount of wrong classification.

When comparing the two classification methods, the 'Unsupervised Classification' execution initially allows us to comprehend items in a certain area that have comparable properties. This approach creates a foundation for investigating these places in greater depth and strengthening our understanding of them. On the other hand, 'Supervised Classification' includes categorizing an image using reference data or prepared classification labels. It includes building a training dataset with areas comprising sample pixels from various classes within the image with known classification labels. For training reasons, many examples of classes like buildings, trees, and water in a picture are compiled and used. For supervised classification to be successful, the training dataset must be carefully and precisely constructed.

In general, when comparing the two categories, supervised classification outperforms unsupervised classification in terms of interpretability, accuracy, and consistency if the training data is provided precisely and carefully.

Accuracy Assessment



To evaluate the classifications and their positional correctness across all classes, we conducted a correctness Analysis as the final step of our study. We examined the RGB image with accurate colors combined with the Unsupervised Classified image and the Supervised Classified image by using pins implemented using SNAP programs. After closely examining the results, we found that the mistake rates and numerical quantities of errors were the same in the Supervised Classified and Unsupervised Classified photos. These results support the achievement of a high level of accuracy in our classifications and the subsequent classification analysis.

Sütun1	waterbodies	forest	agricultur	artificial surfac	total	user accurac
waterbodies	10	0	0	0	10	1
forest	0	8	2	0	10	0.8
agriculture	0	0	10	0	10	1
artificial surface	0	0	2	8	10	0.80
total	10	8	14	8	40	
producer accuracy	1	1	0.71	1.00		
overall accuracy	1.85					
kappa statistic	0.87					
a	b					
36	400					

Supervised Classification Accuracy : %87

Sütun1	waterbodies	forest	agricultur	artificial surfac	total	user accurac
waterbodies	10	0	0	0	10	1
forest	0	10	0	0	10	1
agriculture	0	2	7	1	10	0.7
artificial surface	0	0	0	10	10	1.00
total	10	12	7	11	40	
producer accuracy	1	0.83333333	1.00	0.91		
overall accuracy	1.88					
kappa statistic	0.90					
a	b					
37	400					

Unsupervised Classification Accuracy : %90