HOMEWORK II

PREPARED BY

NAME SURNAME : ONAT BİNGÖL

STUDENT NUMBER : 010180617

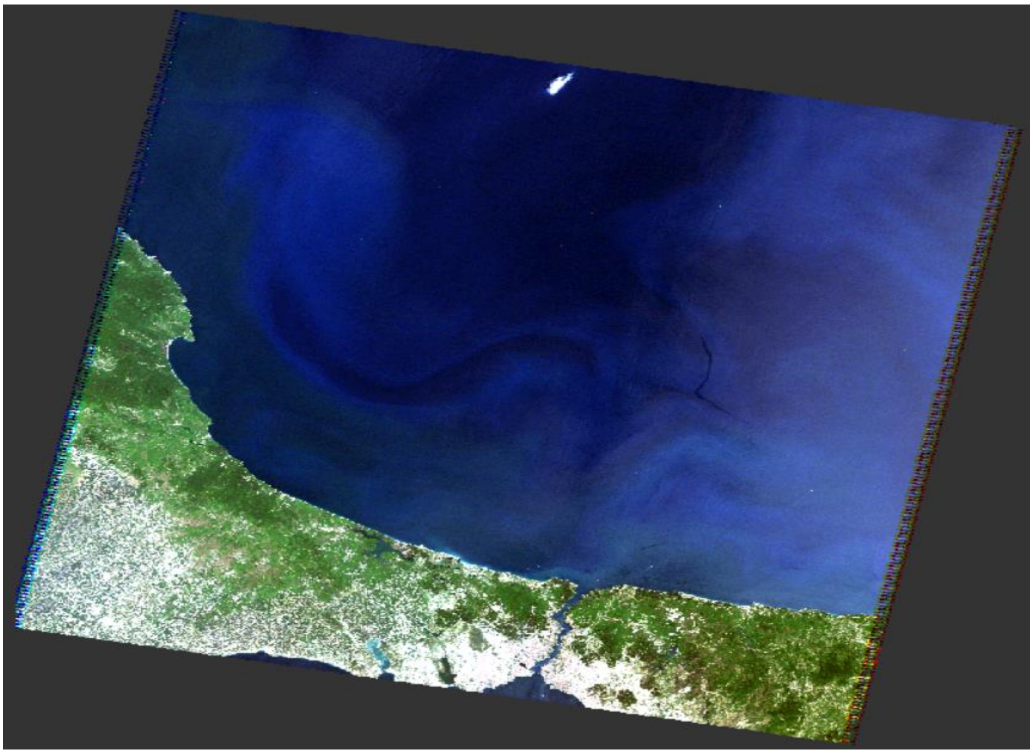
DUE DATE : 22/03/2023

COURSE NAME : REMOTE SENSING II

LECTURER : ASSOC.PROF. ESRA ERTEN

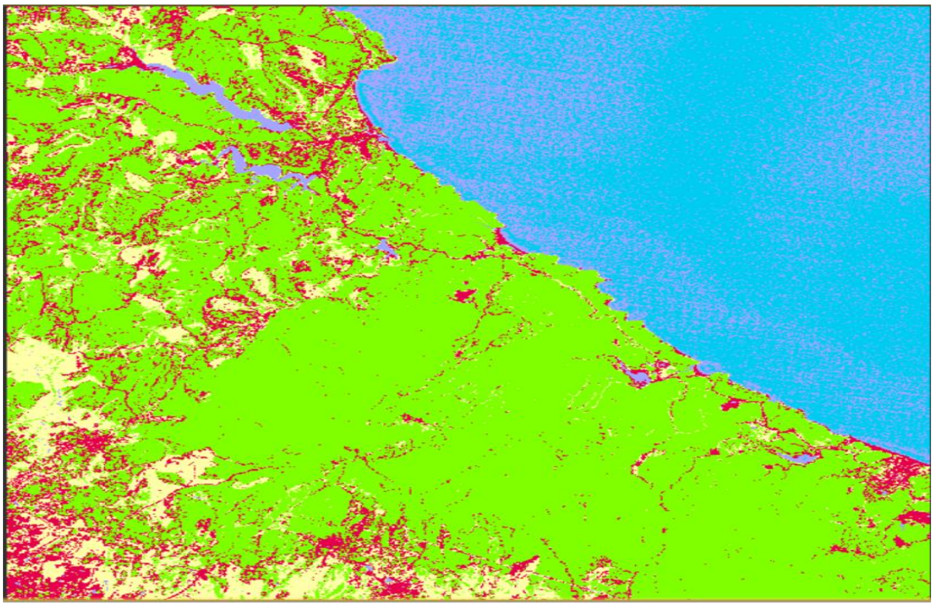
The purpose of this assignment is to make geometric and radiometric corrections on an uncorrected image using the methods taught, using the SNAP applications.

Data Set Attribute	***Attribute Value***	***Data Set Attribute***	***Attribute Value***
Satellite ID	Landast 5	Image acquisition date and time	2007/06/06
Sensor ID	TM	Image Path number	180
Image Scene ID	LT51800312005157MTI00	Image Row number	031
Image Product ID	LT05_L1TP_180031_20050606_20200902_02_T1	Image quality	9
Sun elevation	63.29149694	Sun azimuth	128.65785632
Land Cloud Cover	1.00	Scene Cloud Cover	1.00
Corner Upper Left Latitude	42.70394	Corner Upper Left Longitude	28.24930
Corner Upper Right Latitude	42.38177	Corner Upper Right Longitude	30.45888
Corner Lower Left Latitude	41.12716	Corner Lower Left Longitude	27.75566
Corner Lower Right Latitude	40.81262	Corner Lower Right Longitude	29.91411
Corner Upper Left Lat DMS	42°42'14.18"N	Corner Upper Left Long DMS	28°14'57.48"E
Corner Upper Right Lat DMS	42°22'54.37"N	Corner Upper Right Long DMS	30°27'31.97"E
Corner Lower Left Lat DMS	41°07'37.78"N	Corner Lower Left Long DMS	27°45'20.38"E
Corner Lower Right Lat DMS	40°48'45.43"N	Corner Lower Right Long DMS	29°54'50.80"E



UNSUPERVISED IMAGE CLASSIFICATION

The five primary Corine Level 1 LULC classes were used to label each generated spectral class (cluster), and the colors were assigned using the RGB codes provided in the Corine table. The part for color processing was utilized for this. Eventually, the K. Means Cluster Classification RGB edited output image is shown in the figure below, and the new table image was shown in the first table below by including 20 cluster RGB codes for the agricultural, forest, urban, and water classes.

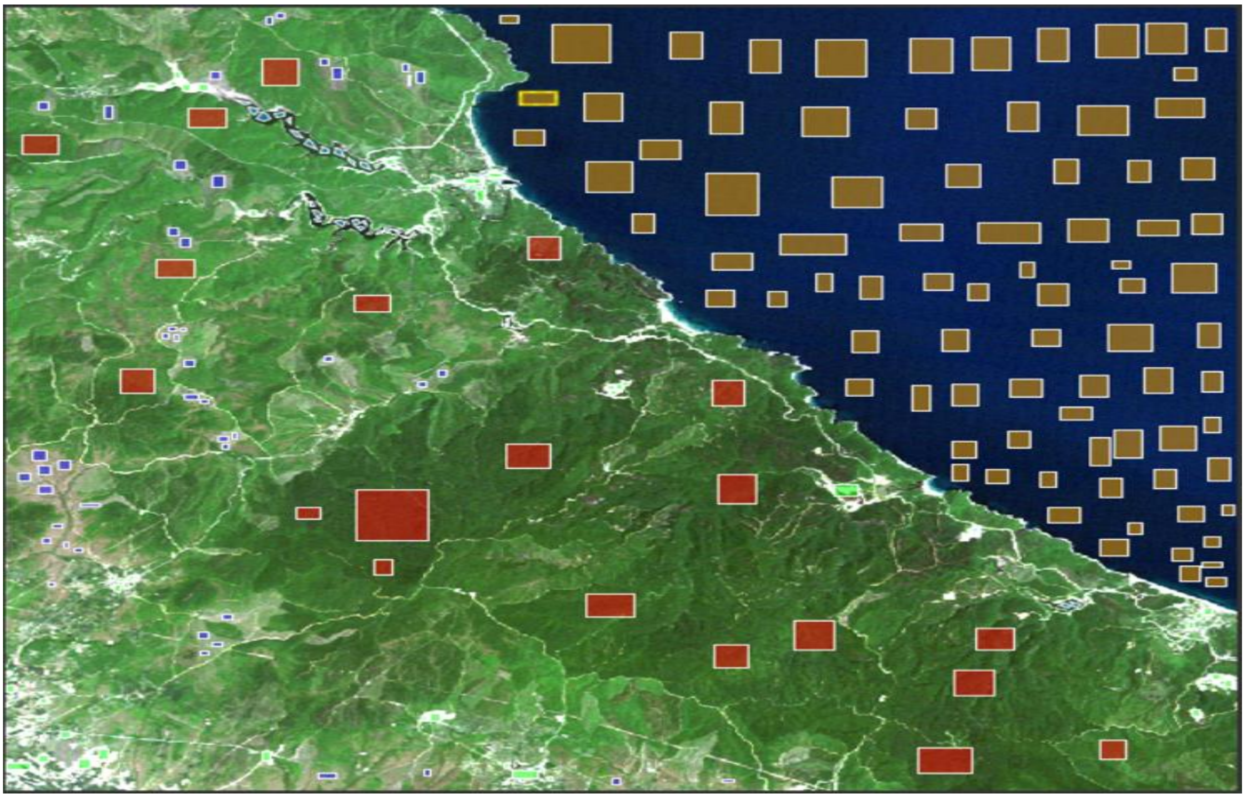


Label	Colour	Value	Frequency	Description
Forest		0	10.340%	Cluster 1
Wet Lands		1	9.638%	Cluster 2
Forest		2	8.255%	Cluster 3
Forest		3	8.278%	Cluster 4
Water Bodies		4	7.446%	Cluster 5
Water Bodies		5	7.932%	Cluster 6
Water Bodies		6	6.921%	Cluster 7
Forest		7	6.787%	Cluster 8
Road		8	6.352%	Cluster 9
Forest		9	6.378%	Cluster 10
Agricultural ...		10	4.992%	Cluster 11
Forest		11	4.341%	Cluster 12
Forest		12	3.832%	Cluster 13
Agricultural ...		13	3.873%	Cluster 14
Road		14	1.587%	Cluster 15
Forest		15	1.478%	Cluster 16
Road		16	0.643%	Cluster 17
Wet Lands		17	0.408%	Cluster 18
Wet Lands		18	0.324%	Cluster 19
Urban Areas		19	0.197%	Cluster 20

SUPERVISED IMAGE CLASSIFICATION (MAXIMUM LIKELIHOOD ALGORITHM)

By finding training sites for known targets and extrapolating their spectral signatures to areas of unknown targets, supervised image classification is a technique for identifying spectrally comparable regions on an image. At its basis is the idea of segmenting the spectral domain into chunks that can be combined with the ground cover classes relevant to a particular application. Supervised image classification was done in this stage. The Maximum Likelihood technique was utilized as a supervised classifier in accordance with the assignment's requirements. Data collection for the training sample was done first. Finally, spectral pictures of the chosen training fields were displayed for spectral analysis. The categorization stage was completed lastly.Training Sample Data Collection

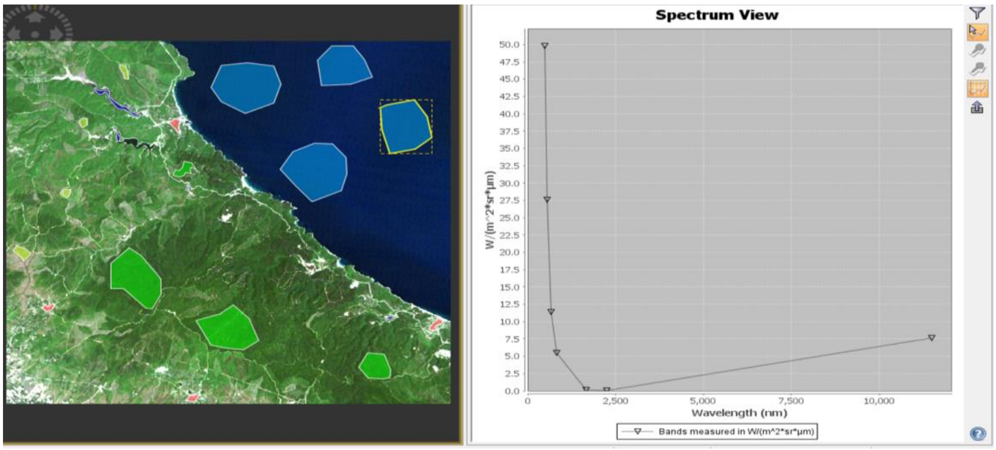
Each field received its own unique vector data container throughout the phase of gathering training sample data. For the most part, green square shapes were made for forests, blue square forms for water bodies, red square forms for water bodies, and orange circles for agricultural areas.

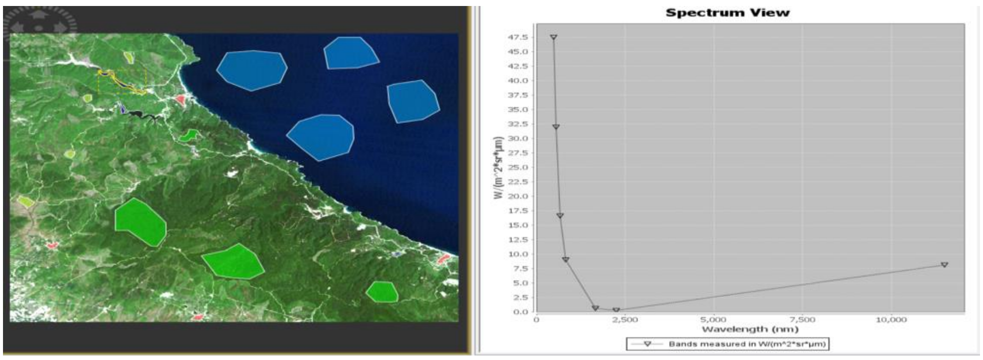


Spectral Analysis of the Training Areas Chosen

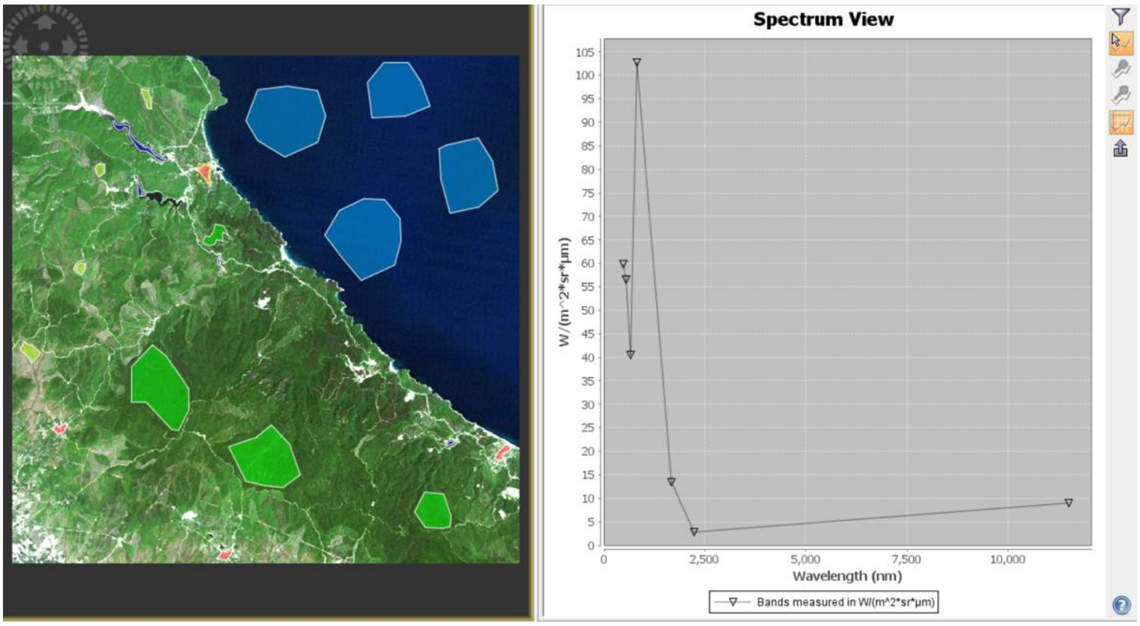
To pinpoint specific areas and check whether the classes were accurate, the spectrum view was employed. As a result, two general and detailed spectrum images were created for each area and are shown below. These images are based on the spectrum reflection of each pixel on which the cursor is moved.For water bodies;

From the region depicted in this Picture , a training data sample was chosen, and a spectrum picture was obtained. The frequency range of the spectrum image is between 500 and 12000, or across a span of 11500. This spectrum image shows a dramatic reduction of roughly 1800 nm from the beginning point to the region. The spectrum chart's dropping point has a tiny upward slope at the end. The spectrum view of the training data shows that it was used as an example for the water area.

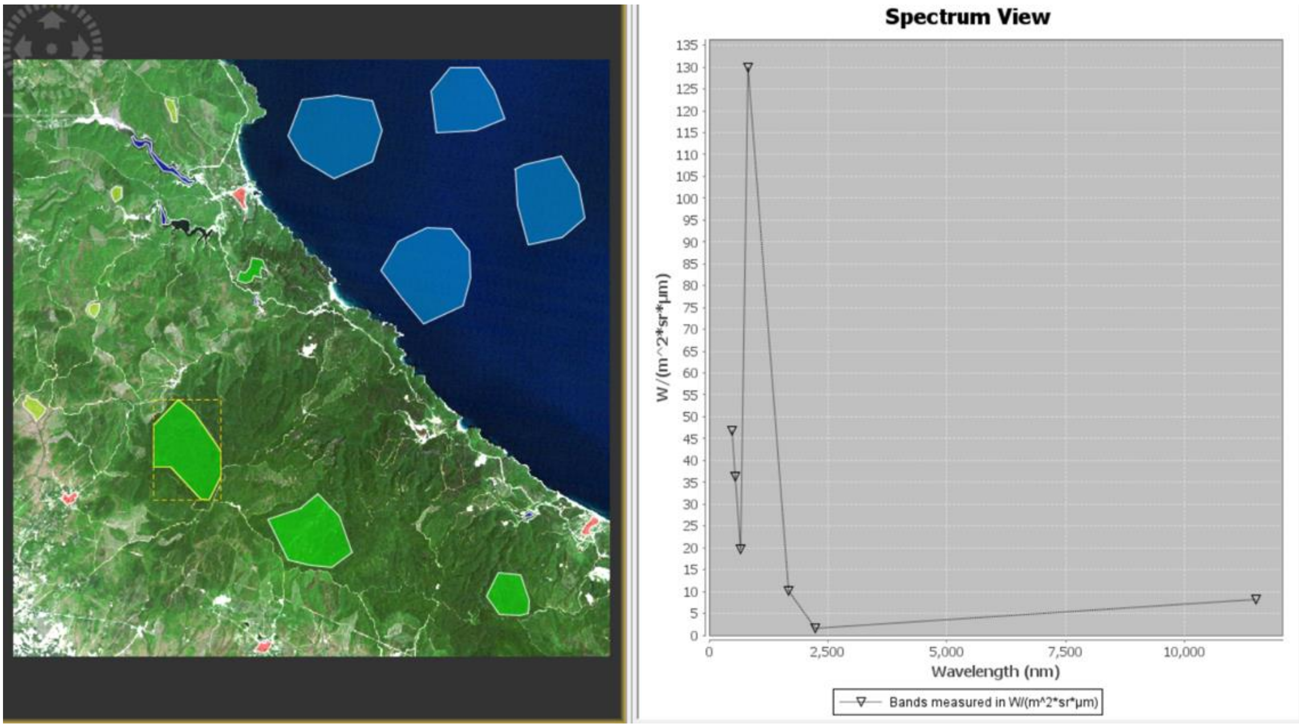




They are components of a variety of urban coverings, including roadways and buildings. For the example of artificial field training data, this image is displayed. The frequency range of the spectrum image is from 500 to 12000, or a span of about 11500. The spectrum view fell to a wavelength of roughly 2000 nm and then gradually climbed. This demonstrated that the chosen vector area is a part of the man-made surface.

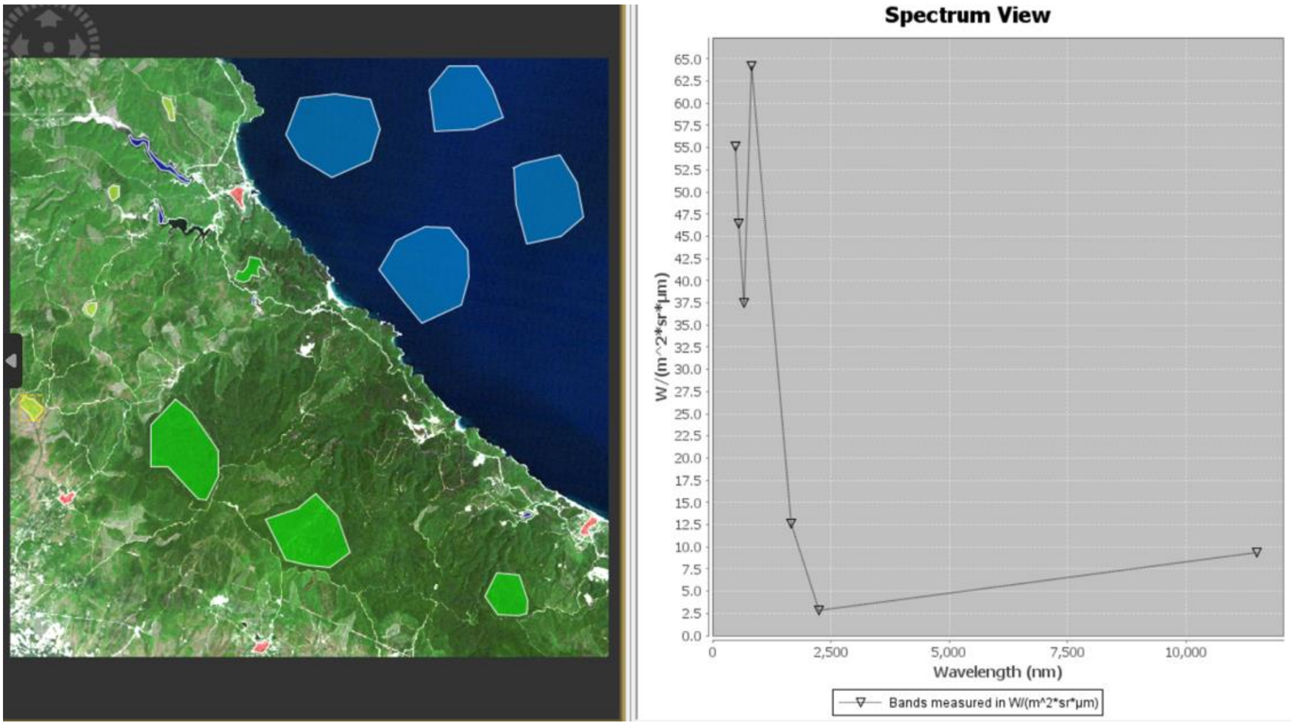


This image displays the training data example's spectrum taken from a forest and other semi-natural settings. Upon examining the figure, it is clear that the range has a peak between 900 and 1150 nm in frequency. This demonstrates that the woodland region is responsible for the abruptly rising and decreasing spectrum image.



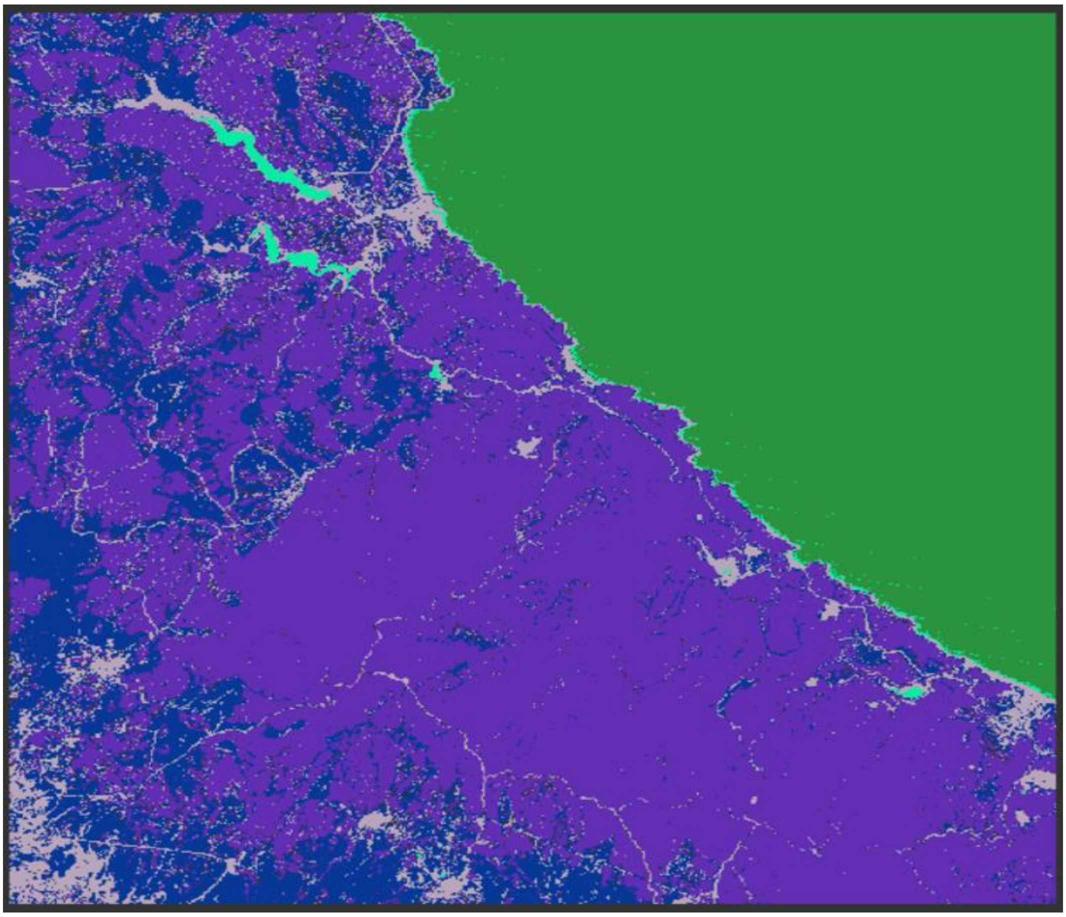
For agricultural areas;

The spectrum view of the training sample data that was chosen from the agricultural area is shown in this image. As with earlier data samples, the frequency range of this spectrum is roughly500 to 1200 nm, or a span of 11500. After a brief peak, the spectrum clearly declines before softly descending. This demonstrated the accuracy of the training data sample for the agricultural area.

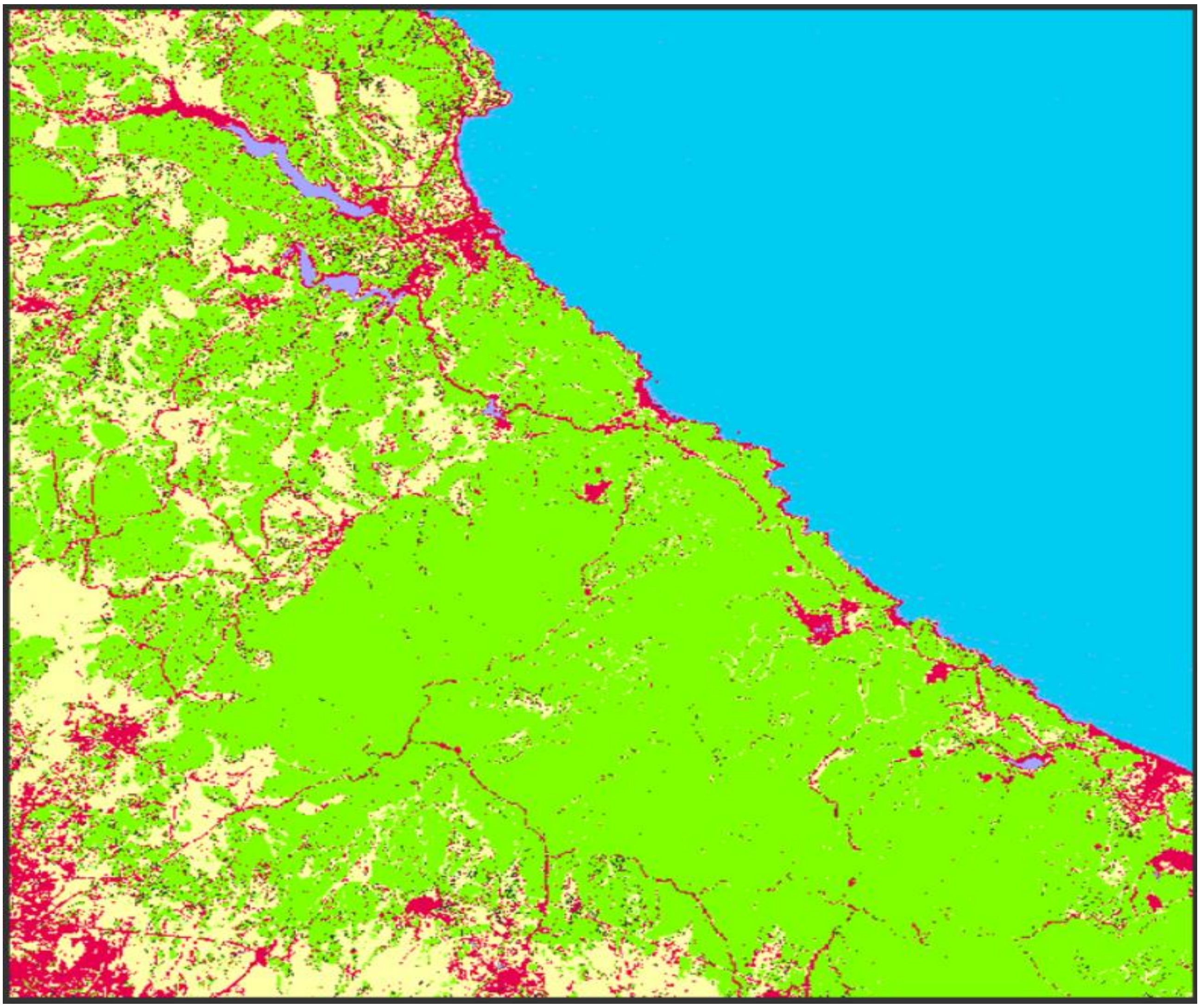


CLASSIFICATION

The Maximum Likelihood Classifier, which places a pixel into the appropriate class based on its likelihood, is one of the most popular classification techniques. The likelihood is used to define the posterior probability of a pixel belonging to a specific class. TIR Band (radiance 6) was not utilized during the Supervised Classification as it was during the prior classification. As a consequence of the classification, the SNAP software organized the classes' colors in accordance with the hues listed in level 1 of the CORINE classification system.



Label	Colour	Value	Frequency	Description
no data		-1	0.000%	no data
Forest		0	45.790%	
art_surf		1	6.308%	
Agr_Surf		2	15.201%	
wet lands		3	0.596%	
Water Bodies		4	32.106%	



Label	Colour	Value	Frequency	Description
Water Bodies		4	32.106%	
Forest		0	45.790%	
wet lands		3	0.596%	
art_surf		1	6.308%	
Agr_Surf		2	15.201%	
no data		-1	0.000%	no data

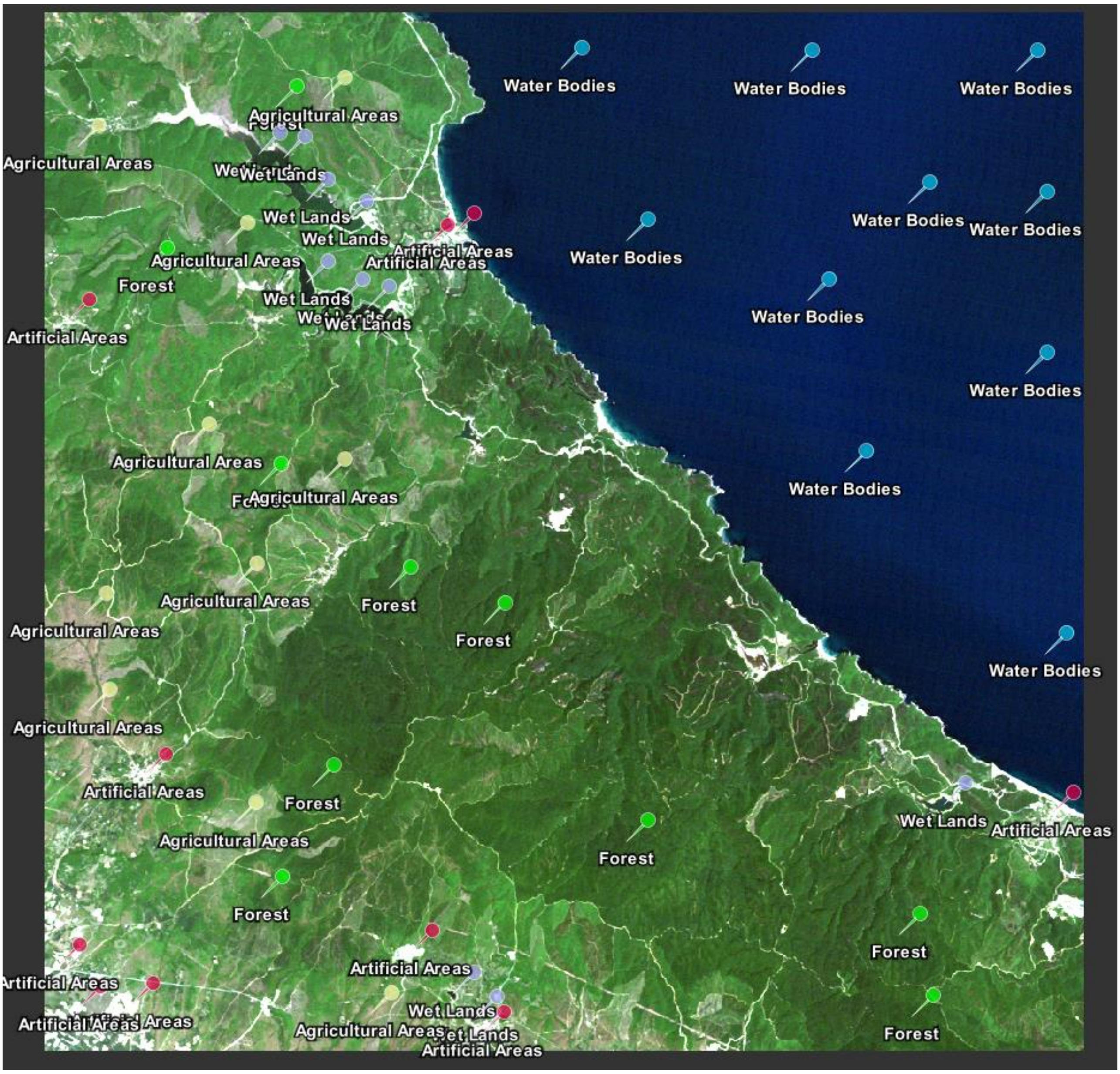
CLASSIFICATION ACCURACY ASSESSMENT

10 test points were chosen for each of the four classes in order to assess and evaluate the classification's correctness. 50 pins in total were chosen. This table displays an image that was captured from the SNAP program and displays the characteristics of these pins. To avoid confusion and represent the urban fabric, the labels A for agricultural regions, F for forest and semi-natural areas, W for water bodies, and U for artificial surfaces were chosen.

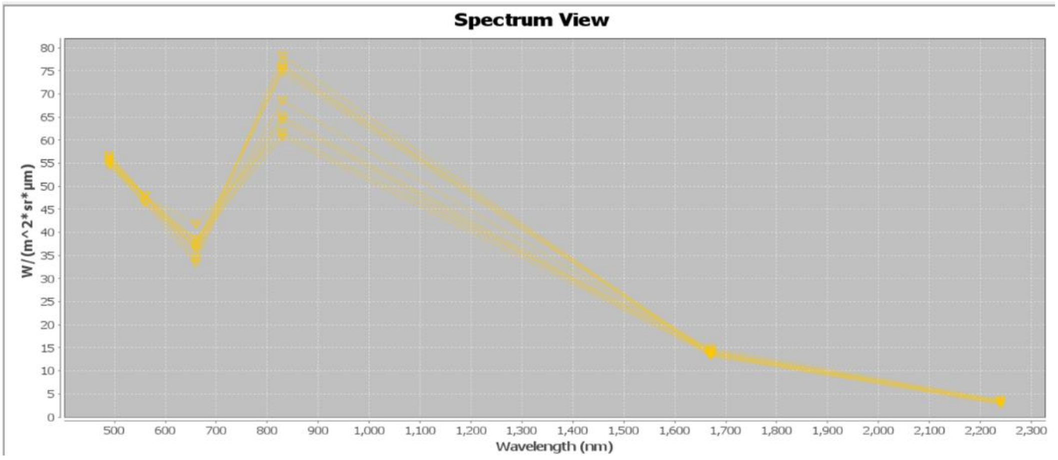
Image under the pin tables shows the positions of the total 50 pins on the RGB image.

Pin Manager

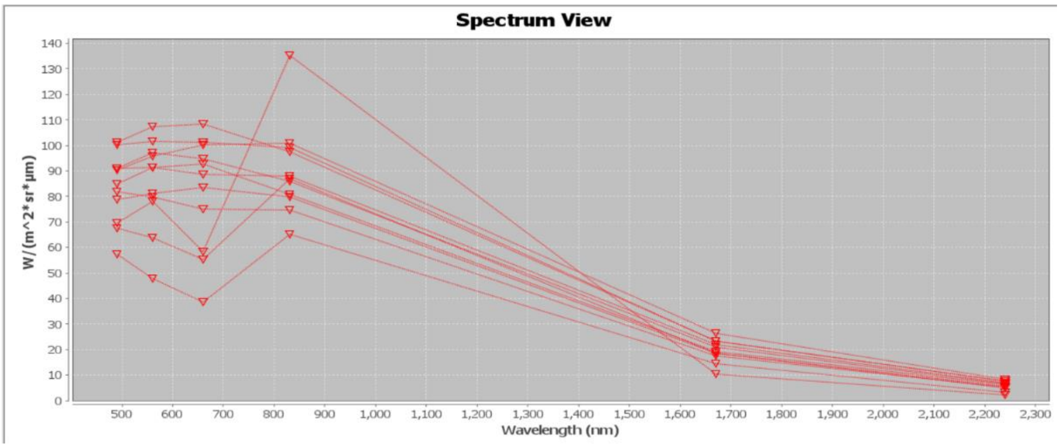
X	Y	Lon	Lat	Color	Label
496.500	54.684	28.131495	41.677551		Water Bodies
718.500	57.500	28.211478	41.675975		Water Bodies
936.500	57.500	28.290030	41.675120		Water Bodies
832.500	184.500	28.251891	41.641225		Water Bodies
945.500	193.500	28.292538	41.638343		Water Bodies
560.500	220.500	28.153758	41.632524		Water Bodies
735.500	277.500	28.216485	41.616476		Water Bodies
945.500	348.500	28.291702	41.596470		Water Bodies
771.500	443.500	28.228594	41.571492		Water Bodies
964.500	618.500	28.297080	41.523452		Water Bodies
222.500	91.500	28.032595	41.668534		Forest
97.500	247.500	27.986911	41.626782		Forest
206.500	455.500	28.025271	41.570242		Forest
331.500	555.500	28.069797	41.542815		Forest
422.500	589.500	28.102366	41.533320		Forest
257.500	746.500	28.042357	41.491455		Forest
560.500	799.500	28.150979	41.476098		Forest
208.500	853.500	28.024294	41.462704		Forest
823.500	889.500	28.244991	41.450799		Forest
835.500	968.500	28.248890	41.429410		Forest
205.500	136.500	28.026277	41.656431	Green (0,255,0)	Wet Lands
229.500	140.500	28.034906	41.655273		Wet Lands
252.500	181.500	28.043012	41.644121		Wet Lands
289.500	202.500	28.056246	41.638326		Wet Lands
252.500	260.500	28.042668	41.622777		Wet Lands
285.500	278.500	28.054471	41.617806		Wet Lands
311.500	284.500	28.063805	41.616099		Wet Lands
866.500	763.500	28.261091	41.484671		Wet Lands
392.500	946.500	28.089961	41.436970		Wet Lands
414.500	969.500	28.097755	41.430681		Wet Lands
393.500	214.500	28.093647	41.634733		Artificial Areas
367.500	225.500	28.084234	41.631850		Artificial Areas
21.500	297.500	27.959344	41.613505		Artificial Areas
95.500	735.500	27.984189	41.494940		Artificial Areas
970.500	772.500	28.298406	41.481824		Artificial Areas
352.500	905.500	28.075783	41.448183		Artificial Areas
12.500	919.500	27.953633	41.445477		Artificial Areas
83.500	956.500	27.978978	41.435266		Artificial Areas
32.500	959.500	27.960655	41.434610		Artificial Areas
421.500	984.500	28.100199	41.426604		Artificial Areas
268.500	83.500	28.049205	41.670545		Agricultural A...
31.500	129.500	27.963620	41.658865		Agricultural A...
174.500	223.500	28.014740	41.633025		Agricultural A...
137.500	417.500	28.000605	41.580728		Agricultural A...
268.500	451.500	28.047594	41.571122		Agricultural A...
183.500	551.500	28.016590	41.544379		Agricultural A...
38.500	580.500	27.964326	41.536992		Agricultural A...
41.500	673.500	27.965032	41.511856		Agricultural A...
182.500	782.500	28.015254	41.481970		Agricultural A...
313.500	965.500	28.061514	41.432102		Agricultural A...



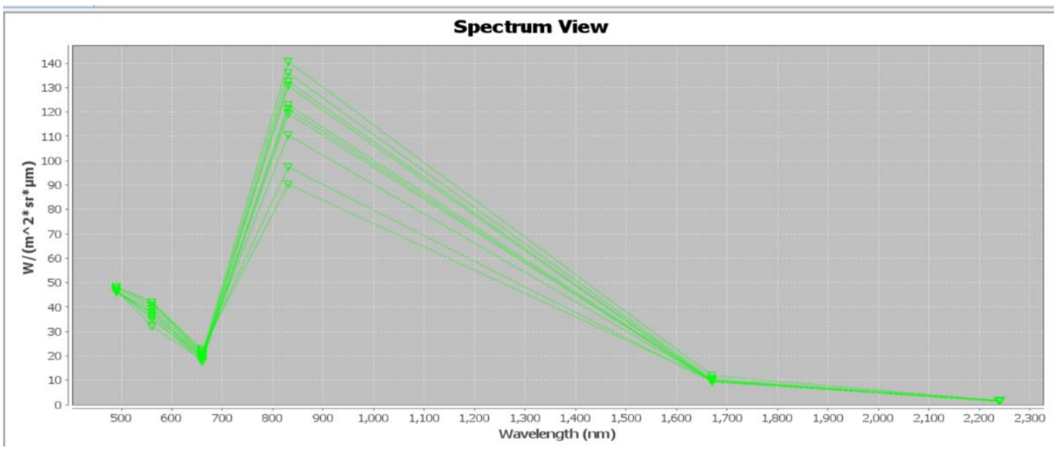
Spectrum views of diffrent earth classes.



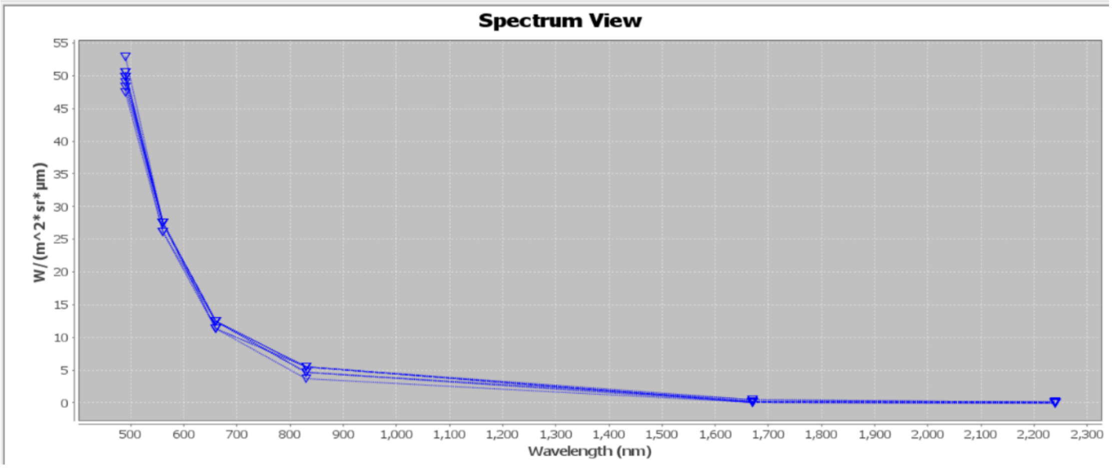
Agricultural Areas Spectrum Views



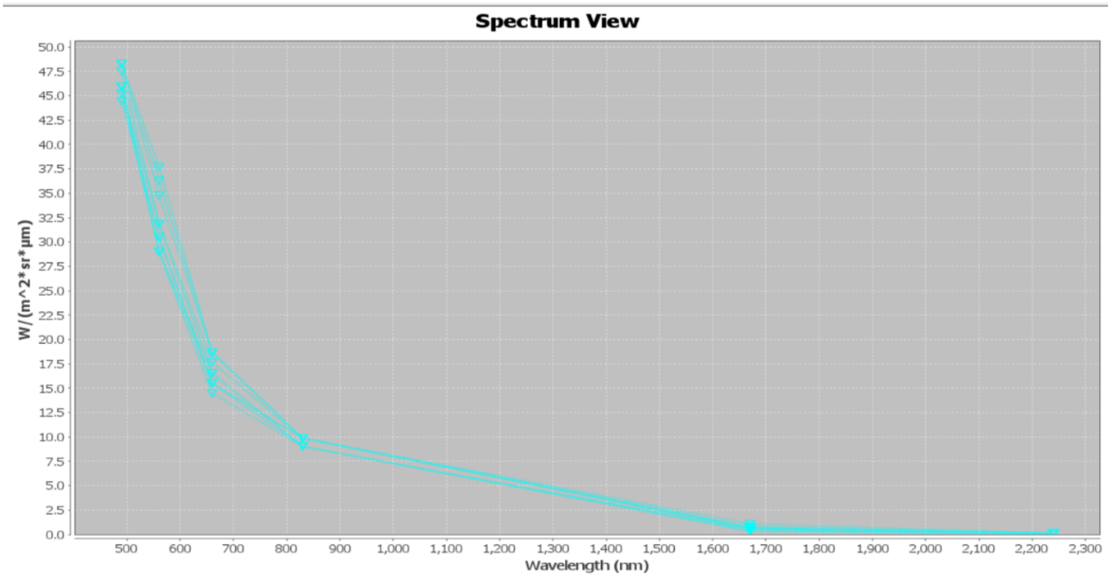
Artificial Areas Spectrum Views



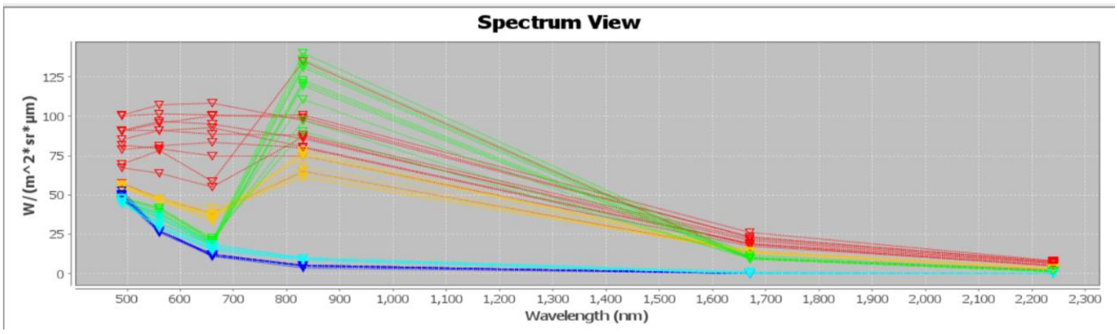
Forest Spectrum Views



Water Body Spectrum Views



Wetlands Spectrum Views



All Spectrum Views

Pins were imported into Google Earth as.kmz files after being saved as pins. The setting of the date was taken into consideration in this phase. This phase is crucial because Google Earth has a comprehensive image library that includes satellite, airplane, 3D, and Street View photographs. The visual interpretation came first.

The Unsupervised Image Classification pins are then opened, as seen in the upper image. The Supervised Image Classification pins are opened in the following phase, as shown in the image below. It can be shown that the K-Meas Cluster analysis is quite effective at classifying images for the water area. When the pins in the RGB image were compared to the information from Google Earth, it was determined that they had been positioned correctly.

Supervised

Unsupervised

Pins were tossed on RGB and their placement was verified by comparing the data to that from Google Earth. Pins on Google Earth data are therefore regarded as reference data. Pins were verified to make sure they were in the right places in both supervised and unsupervised photos. The incorrectly placed pins are seen in the photographs below.

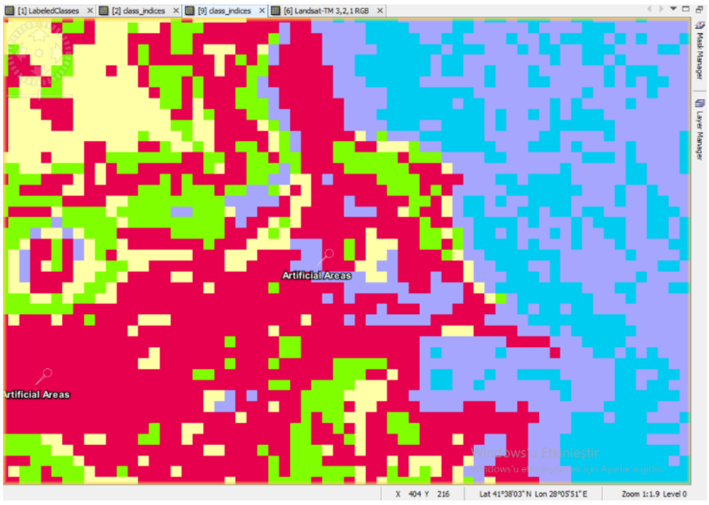


Image that unsupervised by checked one by one and there is only one error on artificial area pin. Pin is on wet land.

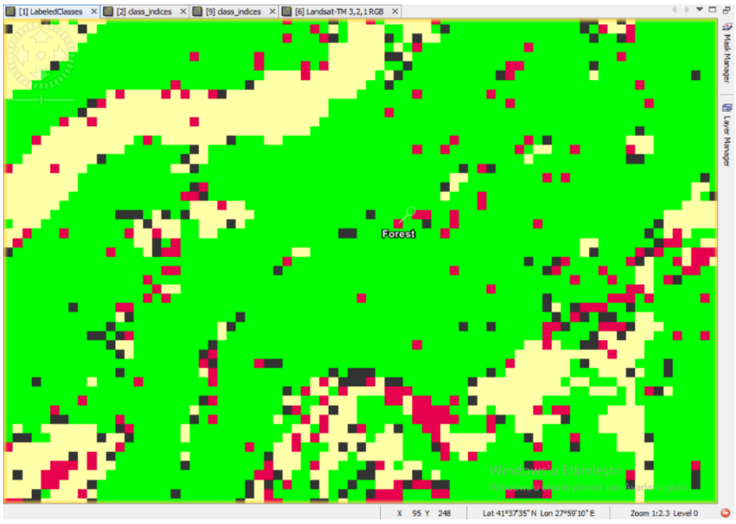


Image that supervised by checked one by one and there is only one error on Forest pin. Pin is on artificial area.

MAIN CLASS ACCURACY ERRORS

	FOR SUPERVISED IMAGE CLASSIFICATION						
Unknown class type test data class type		SUPERVISED IMAGE DATA					
	Classes	Water	Wet Land	Forest	Agriculture	Artificial	∑
	Water	10	0	0	0	0	10
	Wet Land	0	10	0	0	0	10
	Forest	0	0	9	0	0	9
	Agriculture	0	0	0	10	0	1
	Artificial	0	0	1	0	10	11
	∑	10	10	10	10	10	50

Total Accuracy = (10+10+10+10+9)/50 = **%98**

User Accuracy;

For water bodies = 10/10 = %100

For forest = 10/10 = %100

For agriculture = 10/10 = %100

For artificial = 9/10 = %90

Producer Accuracy;

For water bodies = 10/10 = %100

For forest = 9/10 = %90

For agriculture = 10/10 = %100

For artificial = 10/10 = %100

KAPPA ACCURACY = [50*(10+10+10+10+9)-(10*10+10*10+10*9+10*110)]/[50^2-10*10+10*10+10*9+10*10] = **0.95**

	FOR UNSUPERVISED IMAGE CLASSIFICATION						
Unknown class type test data class type		UNSUPERVISED IMAGE DATA					
	Classes	Water	Wet Land	Forest	Agriculture	Artificial	∑
	Water	10	0	0	0	0	10
	Wet Land	0	10	0	0	1	11
	Forest	0	0	10	0	0	10
	Agriculture	0	0	0	10	0	10
	Artificial	0	0	0	0	9	9
	∑	10	10	10	10	10	50

Total Accuracy = (10+10+10+10+9)/50 = **%98**

User Accuracy;

For water bodies = 10/10 = %100

For forest = 10/10 = %100

For agriculture = 10/10 = %100

For artificial = 9/10 = %90

Producer Accuracy;

For water bodies = 10/10 = %100

For forest = 9/10 = %90

For agriculture = 10/10 = %100

For artificial = 10/10 = %100

KAPPA ACCURACY = [50*(10+10+10+10+9)-(10*10+10*10+10*9+10*110)]/[50^2-10*10+10*10+10*9+10*10] = **0.95**

COMPARISON of UNSUPERVISED and SUPERVISED IMAGE CLASSIFICATIONS

The research area has a complex structure when looked at in its whole. As the area corresponding to each satellite pixel, from which the image is acquired, is large and the resolution is low, there are multiple land features that are interwoven with one another. Two categorization investigations were hampered by this circumstance, and inaccurate results were the result.

When comparing the outcomes of these two classification methods, supervised classification shows forest regions more clearly. It is observed that artificial fields produce more accurate results in unsupervised categorization. Artificial areas, however, did not seem to be accurate in any classification type. This is due to the fact that, as was indicated at the outset, each pixel has a sizable real area and that adjacent pixels represent various terrain characteristics. For instance, if pixels are located in an area with trees surrounding a building, both the urban area and the greenery can be visible in that pixel.