LAB 3: SUPERVISED and UNSUPERVISED IMAGE CLASSIFICATION

NOTE: This lab exercise is lengthy and meant to be conducted over the next two+ weeks. **This Lab is DUE on March 18th**

BACKGROUND

The classification of land cover, and to a certain degree of land use, is a common type of thematic mapping task that is often performed using satellite image data. The idea is to create one layer of thematic (categorical) information from many layers of spectral data. Users are interested in themes or categories that can be displayed in map or image space. Classification algorithms are used to extract the features of interest from multi-dimensional statistical distributions, i.e., from feature space.

In supervised classification the human analyst, normally with some knowledge of the scene and possibly knowing the spatial, textural and spectral characteristics of the desired classes, selects training pixels within the image, in order to develop representative spectral signatures for each information class. Whereas in unsupervised classification the human analyst lets the computer group pixels into like classes and then the analyst labels those classes. In both cases successful classification requires experience and experimentation. Analysts with a sound understanding of the physical scene characteristics (e.g., absorption, reflectance, atmospheric effects, illumination conditions), and the statistical structure of the data and the assumptions of different classifiers, can effectively classify an image. At the end of a typical classification project a final thematic map is created.

OVERVIEW

The objective of this exercise is to expose you to both supervised and unsupervised classification techniques, how they can be used to explore and classify multi-spectral data, and to show how to evaluate classification results. Since a "quality" classification takes much time and experience, the processing has been simplified for the purpose of this exercise.

In the first part of the lab you will use six Landsat Thematic Mapper bands to create spectral signatures for a *supervised classification* from the 2001 Landsat TM scene. You will query pixel values in all six TM bands to develop a basic understanding of the spectral characteristics of some landscape types. You will learn to use the IMAGINE "Area Of Interest" tools to digitize training site polygons. Next, you will explore some techniques for evaluating and modifying the signatures you have created. To finish Part 1, you will apply a maximum likelihood classifier to all pixels in the image. The second part of the lab will be using unsupervised classification to classify the 1994 Landsat TM scene. In both cases you will be classifying the images into four landcover categories, urban, vegetation, water, and soil.

DATA REQUIREMENTS

You will need several images for this lab. All digital data sets you should already have (the names may be different, but you should have already created these images):

`1994_corrected.img`	Subset of a 6-band Landsat TM scene, from August 23, 1994 that shows the metro D.C. area including portions outside of the beltway that has been geometrically registered to the 2001 Landsat image.
`2001_sub.img`	The subset of the 2001 6-band Landsat ETM scene, from August 2, 2001 that covers only the metro D.C. area, including portions outside of the beltway. The area covered and spatial location should be approximately the same as the 1994 Landsat TM image used.
`Ikonos_dc.img`	An April 1, 2000, IKONOS 4 band multispectral image of a portion of downtown DC

PROCEDURES

1. Supervised Classification - Selecting Training Samples on a TM Image
Training samples are sets of pixels selected by the user as part of the supervised image classification process. They are chosen to represent the spectral signatures of land cover types. The signatures are then used to "train" the classifier. In IMAGINE the easiest way to extract training samples for parametric signatures is using the Area of Interest Tool:

(a) Entering the boundaries of training sites ("**A**reas **O**f **I**nterest" or **AOI**) representing specific land cover types, by digitizing polygons over a displayed image.

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You will generate training statistics for four landcover types and evaluate them using the Signature Editor.

1. urban, 2.vegetation, 3.water, 4. soil.

Part 1: Exploratory Analysis

For any type of image classification, it is essential to familiarize yourself with the image data, maps, and the features to be classified. For the purpose of this lab, you are provided with a high resolution IKONOS image and two lower resolution Landsat Images. .

- From the Add Views 

button, select Display two views.

- In View #1 on the left display the false color composite (`2001_sub.img`, **True Color**, R=4, G=3, B=2, **Fit to Frame**).
- In View # 2 display `Ikonos_dc.img.img`, **True Color**, R=4, G=3, B=2, **Fit to Frame**.

- To Geo-link the Viewers: click on the 

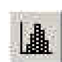
button.

Now you will learn about the different land-cover classes and how they relate to the imagery. The idea is to identify what each class looks like in your `2001_sub.img`. You will use the high resolution image as a guide, so that you can determine the four different classes that you will be mapping, and therefore the best areas to be used for signature collection.

- Select the 

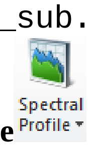
button. If all images are linked, the inquire cursor should come up in all three of the viewers.
- Use this tool to identify different land cover types from the high resolution, in different areas until you feel confident in recognizing them on the image. Soil may be a hard one to map as there is very little soil in both the high resolution and the Landsat TM scene.

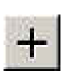
Next you will learn about the general properties of the TM subset, and about some basic spectral characteristics of the land cover types you want to classify. First analyze the histograms and statistics of the actual TM image:

- Making sure the correct Viewer number is selected, # 1 (`2001_sub.img`) select the  button tool bar, click on the **Image Info** icon.
- Look the summary **statistics,** and **histograms** for all **layers**.  

You should be able to ascertain whether the spectral response patterns of your class cover types are different enough to ensure a decent classification output. This will become more evident when we use the Signature Editor later.

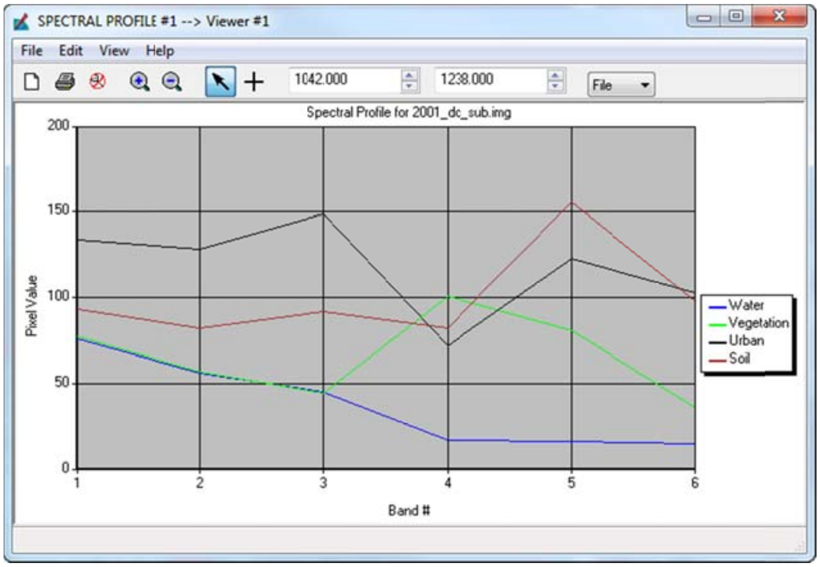
With the Viewers still geo-linked, in make sure Viewer #1 is highlighted (`2001_sub.img`):

- Click on **Multispectral** Tab on the main toolbar, select **Spectral Profile** 

button and select **Spectral Pofile**.
- Use the Inquire Cursor to locate a pixel that seems representative for a specific class (e.g. urban).
-  In the **SPECTRAL PROFILE** Viewer, click on the **Create New Profile Point** icon, and digitize a point at the selected pixel location in the TM image Viewer (`2001_sub.img`).
- Repeat this process for each of the four land cover classes (***urban*** (buildings and roads)***, vegetation, water and soil),*** to generate four profile lines (the six bands are on the x-axis, the pixel DNs on the y-axis). If you can't find a soil landcover area within the immediate metro area covered by the ***<u>Make sure you do this all at once and print the graph or take a screen shot so you have this to</u>***

turn in. Also you can write down the digital numbers of the spectral profiles (make sure you have each band and each point) and turn them in.

Hint:
If you pick a plot that you don't like, use **Edit/ Delete Plots**..., and select the plot row to be removed.
If you want to change the **colors and the names** of the plots to make them easier to identify, select **Edit/ Chart Legend**, and right-mouse click on the color patch and/or the name to change it. Your chart should look like the one below:



Written Assignment Part 1:

1. List the pixel values in each of the six bands for the four points selected in the plots, or print the graph. From the spectral profiles, which bands do you think would be most useful to discriminate the 4 classes and why?

- `Close the Inquire Cursor and Spectral Profile windows.`

Part 2: Training

You will now select areas that correspond to your four landcover types.

- Display the image `2001_sub.img` in **True Color**, with **Layers to Colors** assigned `R=4, G=3, B=2` in your first Viewer (you can clear the other if it is still open).

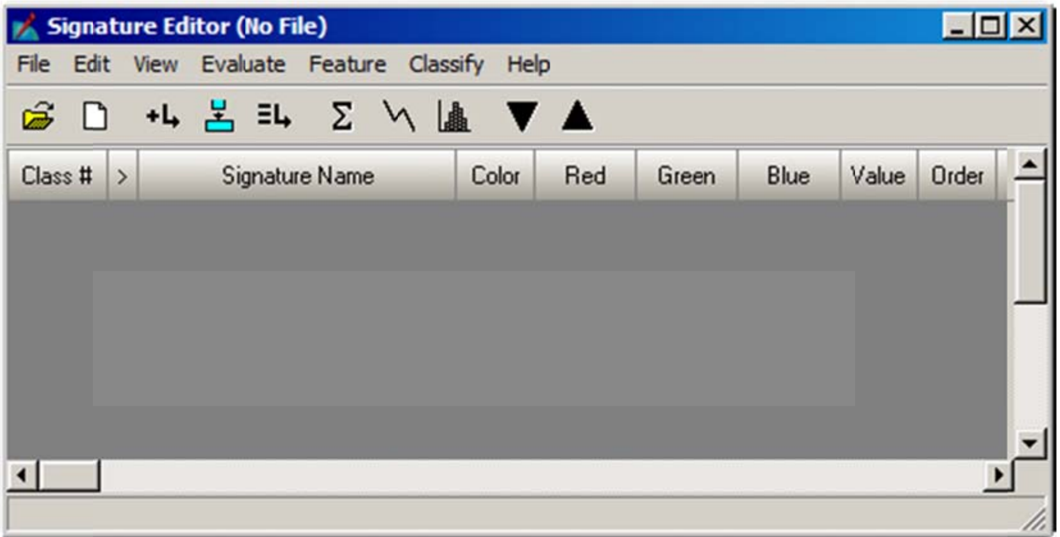
You will now use the AOI tools and the Signature Editor on this image to create spectral signatures:

- In the main icon panel click on Raster

- Select Supervised 

, and then **Signature Editor...**

  The box below should now be displayed:

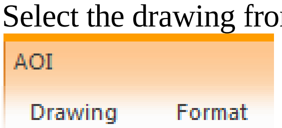


- Move the Signature Editor window so that you can see the image

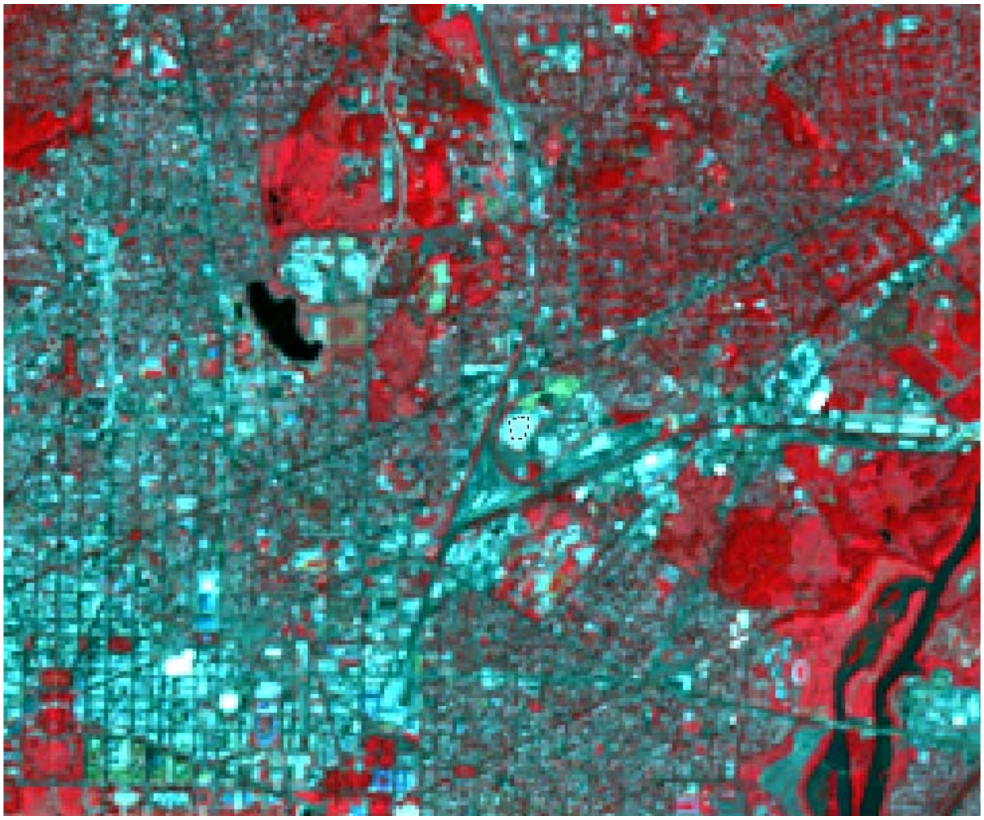
Note:
When you start creating signatures make sure that you frequently save them to a file (**File, Save As**)..

Note:
When you re-start the signature for a new session you will need to re-link the image and therefore your previous AOI's. To do this select all your signatures, select View/ Image AOI. You will need to click within your `2001_sub.img` viewer. If all your AOI's are not added you will need to select them individually and repeat the procedure.

You will first outline a few training sites for each class, first by digitizing polygons:

- Select the drawing from the main icon panel
- 

- Select the drawing tool that looks like this 
  - This is the polygon drawing tool and allows you to select and draw areas any size you want.
- Draw a polygon in an area that is covered by one of the classes. These polygons will be used to train the supervised classification. Below is a polygon drawn for the ***urban*** class that is a good size and in a representative area.



Whilst the polygon is selected, you will add this signature to the Signature Editor.

-  Click the **Create new signature from AOI** button to create a new signature from the chosen pixels.

You will see the signatures appear in the CellArray.

- Add a descriptive name for each signature (like *urban1*, *urban2*) and choose a distinct color for each class (for example, black = ***urban,*** green **=** ***vegetation,*** and use different hues to discriminate between the signatures of the same cover type).

The names and colors you enter here will be automatically used for display during signature evaluation, and for the final classified image.

Below is an example from the AOI drawn above, plus some other ones that I drew:

Hint:
The Red, Green, and Blue represent the values used to create the color you see in the Color column in the boxes above. This has **nothing** to do with the spectral values of the pixels you selected. You see that the count is 34, 55, and 52. This means that the AOIs I drew had 34, 55, and 52 pixels in each of them.

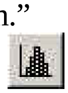
Select at least four signatures for each of the land cover classes, select training sites from different areas.

Written Assignment Part 2:

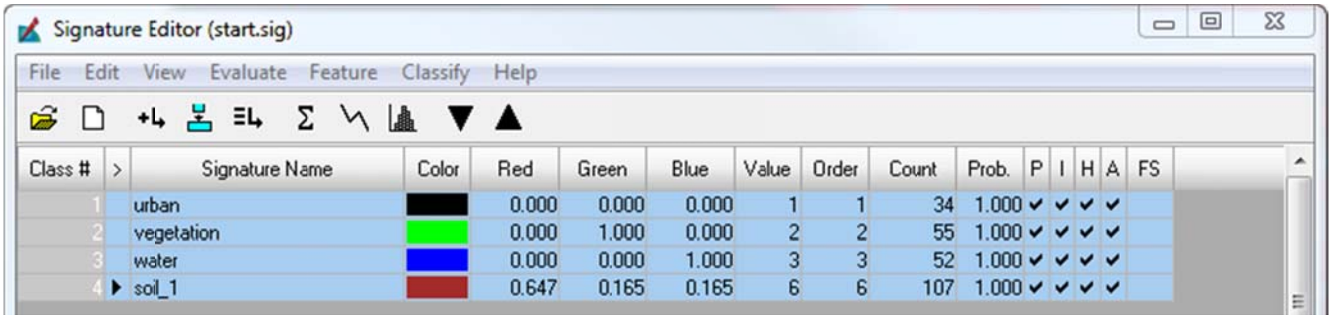
1. What statistical values do you need to know to ensure that these classes are separable?
2. What classes were polygons hardest to draw for, which was the easiest?

Part 3: Signature Evaluation

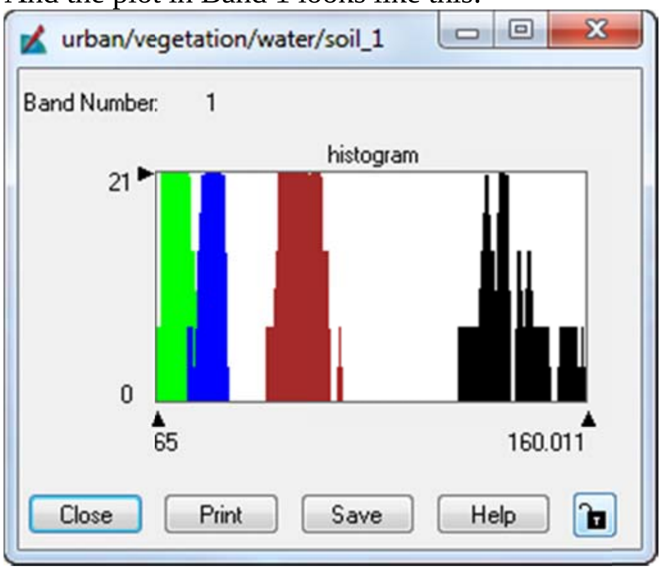
Now you will modify your signatures (merge, delete, redo, add new) so that each of the signatures uniquely characterize each class (hopefully no overlap between classes!). Training is a highly iterative process. IMAGINE provides more tools to create, evaluate and modify signatures than you will want to use here. The most intuitive will be signature **histograms** and **ellipses**. You will also examine the contingency matrix for the classified training sites, statistical separability measurements, and an "image alarm."

1.  In the **Signature Editor**, click on the **histogram** icon.
2. In the Histogram Plot Control Panel, check on **All Selected Signatures** and **All Bands** radio buttons.
3. In the CellArray of the Signature Editor select one or more signatures (by left-clicking on a class, or shift+left click to add classes), then click **Plot...**
4. Rearrange the windows (there will be six, one for each band) to view all histograms simultaneously and examine your signatures.

The signature editor should look similar to the own below, however you should have more signatures for each of the classes:



And the plot in Band 1 looks like this:

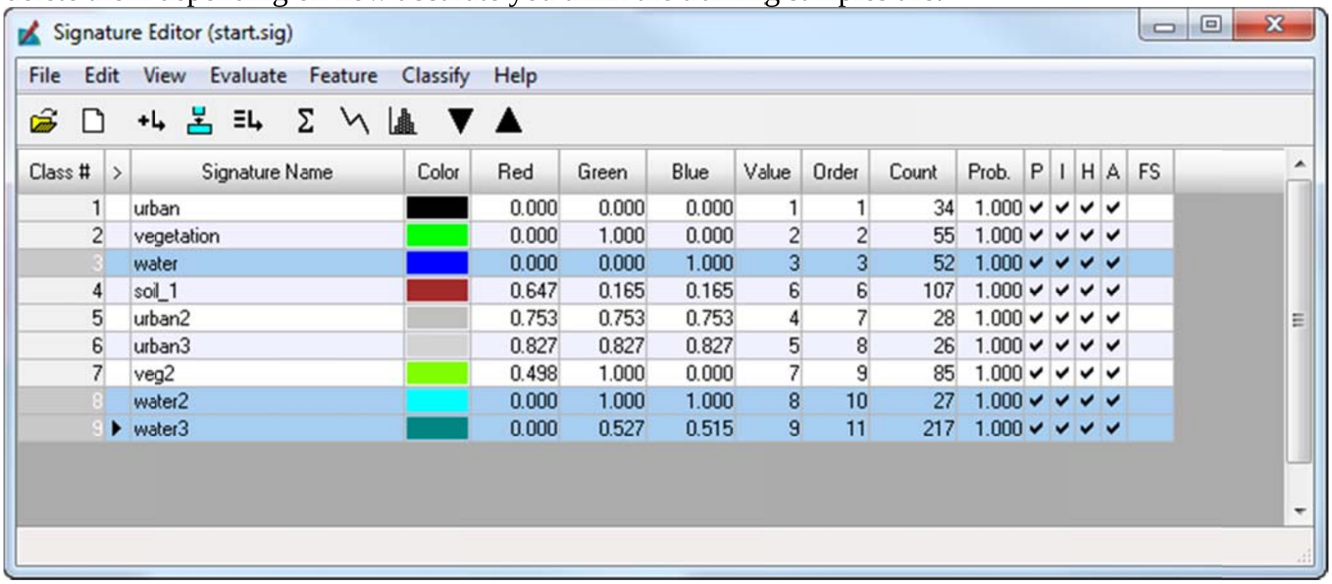


Also, Make sure to examine each of the classes individually. By this I mean to run the same process on all four of the signatures that you selected in the above. This will allow you to determine how similar your training sites are.

<u>Written Assignment Part 3</u>:

1. Examine your signature histograms and briefly describe their compactness, normality, overlap.
2. Are the histograms distinct between your cover-types?
3. If the histograms overlap, what does this suggest about your signatures and how can this be improved?
4. If the histograms do not overlap, what does this suggest about your signatures? Is this always good?

Your signature editor should look something like the one below with the exception that there might be more signatures for each of the classes. Through the instructions below you will reduce the signatures from multiple ones per class into only one per class. You can either merge them together, keep them as a second training for the decision rule (i.e., a very bright urban or a darker, mixed urban training class) or delete them depending on how accurate you think the training samples are:



Class #	>	Signature Name	Color	Red	Green	Blue	Value	Order	Count	Prob.	P	I	H	A	FS
1		urban		0.000	0.000	0.000	1	1	34	1.000	✓	✓	✓	✓	
2		vegetation		0.000	1.000	0.000	2	2	55	1.000	✓	✓	✓	✓	
3		water		0.000	0.000	1.000	3	3	52	1.000	✓	✓	✓	✓	
4		soil_1		0.647	0.165	0.165	6	6	107	1.000	✓	✓	✓	✓	
5		urban2		0.753	0.753	0.753	4	7	28	1.000	✓	✓	✓	✓	
6		urban3		0.827	0.827	0.827	5	8	26	1.000	✓	✓	✓	✓	
7		veg2		0.498	1.000	0.000	7	9	85	1.000	✓	✓	✓	✓	
8		water2		0.000	1.000	1.000	8	10	27	1.000	✓	✓	✓	✓	
9	▶	water3		0.000	0.527	0.515	9	11	217	1.000	✓	✓	✓	✓	

You will not keep any signatures with less than 15 pixels (these are too small to generalize a large area of cover), or that do not have an X in the column labeled "I" (for an invertible covariance matrix)- signature merging may help!

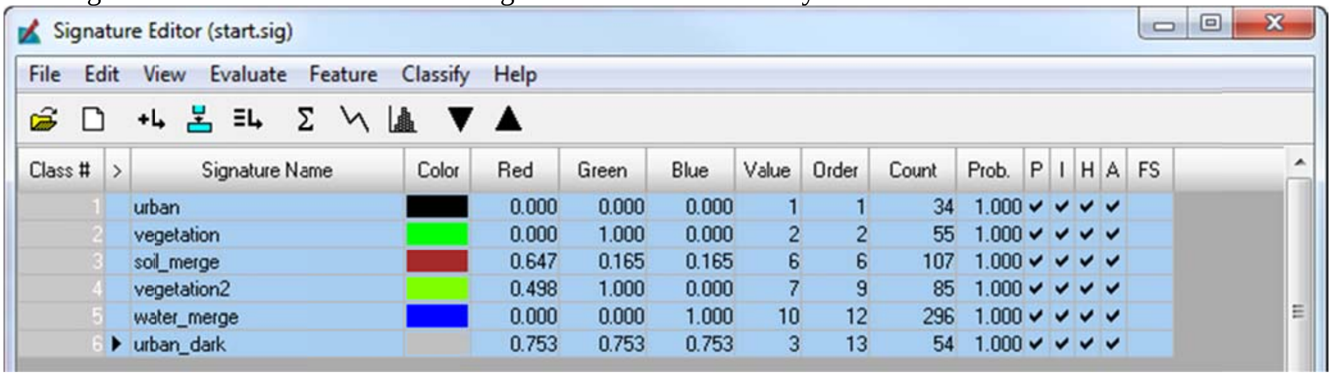
Hint:
To delete a class, select the row and right-click to choose delete selection.

You can also **merge** a signature instead of deleting especially if it small.

Note:
Use **MERGE** if you consider the signatures to have originated from the same cover type. To check this before you merge, look at the histograms. If the histograms overlap almost exactly, then they are the same cover type and you can merge. Be careful that you do not merge different signatures (i.e. a bright urban and a darker urban training class) as you may cause overlap between the cover types.

- Drag or shift-left click under **Class #** you want to merge and highlight them in blue. Then select the click **Edit/ Merge**  button. This will merge the two signatures together.
- Enter a descriptive name for the merged signature and choose a color.
- Delete any of the classes that you have decided to merge as these classes are now part of the new merged class. Remember it is right click, delete. Make sure you only have one row highlighted as you will delete all of the rows that are highlighted.
- Continue merging and/or deleting until you have consolidated at least <u>**one, possibly two**</u> useful signatures for each class.

Your signature editor should look something like the one below once you are done with this section:



Signature Editor (start.sig)

File Edit View Evaluate Feature Classify Help

Class #	>	Signature Name	Color	Red	Green	Blue	Value	Order	Count	Prob.	P	I	H	A	FS
1		urban		0.000	0.000	0.000	1	1	34	1.000	✔	✔	✔	✔	
2		vegetation		0.000	1.000	0.000	2	2	55	1.000	✔	✔	✔	✔	
3		soil_merge		0.647	0.165	0.165	6	6	107	1.000	✔	✔	✔	✔	
4		vegetation2		0.498	1.000	0.000	7	9	85	1.000	✔	✔	✔	✔	
5		water_merge		0.000	0.000	1.000	10	12	296	1.000	✔	✔	✔	✔	
6	▶	urban_dark		0.753	0.753	0.753	3	13	54	1.000	✔	✔	✔	✔	

Hint:

You can check whether you merged the correct signatures, since general signature information is stored for each class. Highlight the row, and select **View/ Comments.** You can also use this dialog box to enter any additional comments that you think may be useful.

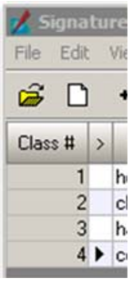
- In the Histogram dialog box select **File/ Save/ Close.**
- Look at the **Statistics** and **Mean Plots** that are also available for signature evaluation.

 .

Below is the mean plots for the signatures above.

Hint:

The little arrow shown below can be moved between rows to get the statistics for each band. Use the Univariate mean to answer the question below.



Written Assignment Part 3 (continued):

1. How many land cover classes did you use? How many pixels were utilized as training data and what are the mean DN values for each class in each band?

Now you will analyze your signatures in "feature space." Feature space images are similar to scatterplots. The pixel values of two bands are plotted against each other, and color is used to add a third dimension to the graph. Hot colors (red to white) are the peaks of these "pseudo-3D"-histograms.

- In the Signature Editor, left-click on **Feature/Create** and select **Feature Space Layers...**
- Use the 6-band TM image (`2001_sub.img`) as input file, **OK**.
- Make sure the Output Root Name goes to your file folder.

This will generate scatter plots of the 6-band combinations. Please display the following band combinations in the three images similar to below 1_2= b1:b2, 3_4=b3:b4, 4_6=b4:b7

- Fit the feature space images to the viewers. To do this, right click in the viewer and select fit image to window

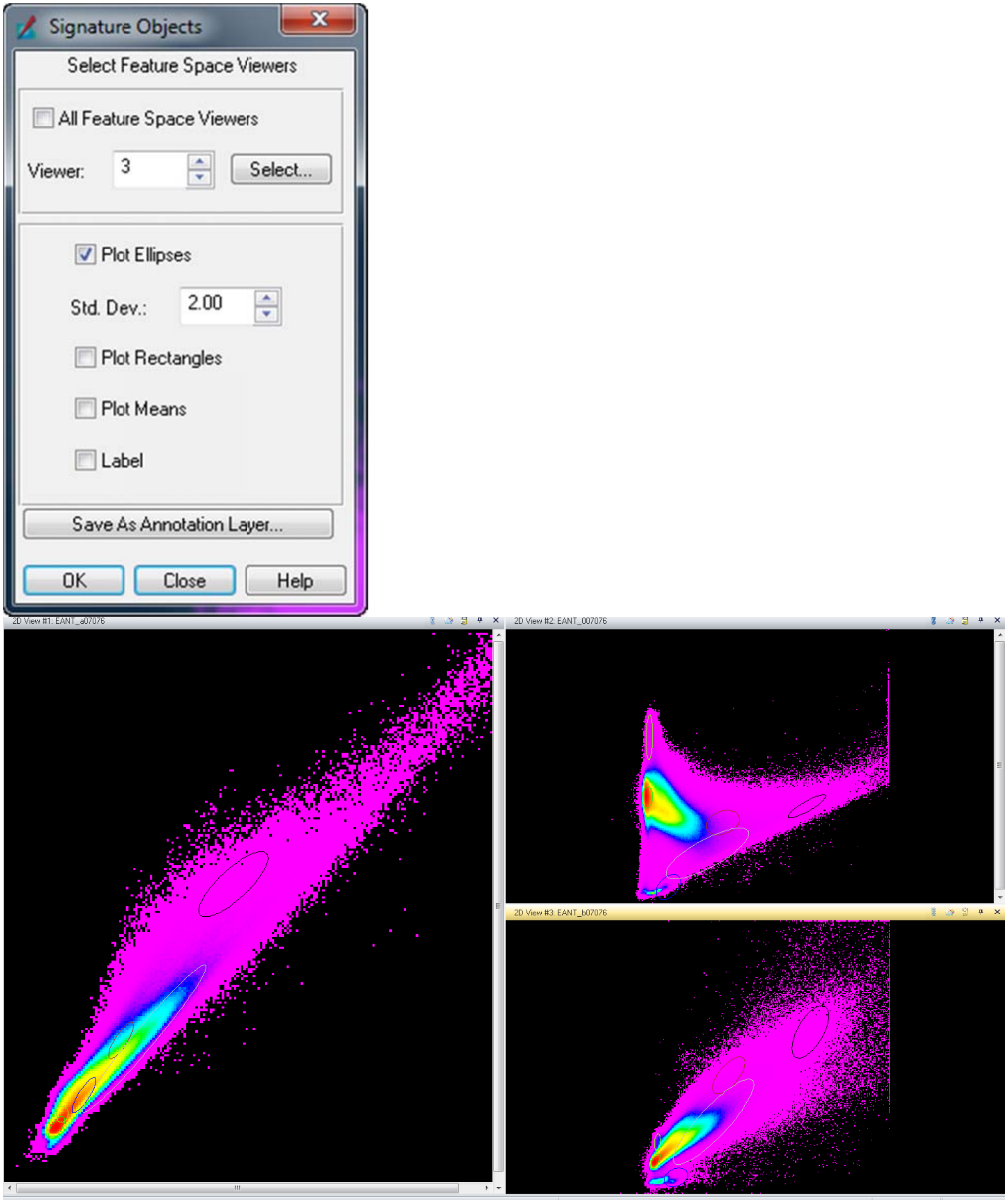
We will plot signature ellipses on these scatter plots:

- Select **Feature/Objects...**
- In the Cell Array select one or more signatures.
- Make sure all of the classes are highlighted in blue.
- Check on **Plot Ellipses, `2 Std.Dev.`, Labels**,

Ellipses and signature names will be displayed in feature space in the colors you selected.

Note:

If the "All Feature Space Viewers" does not always work, **Select...** the Viewers individually.
To create the images below I had to select Viewer #1, Viewer #2, and Viewer #3 individually.



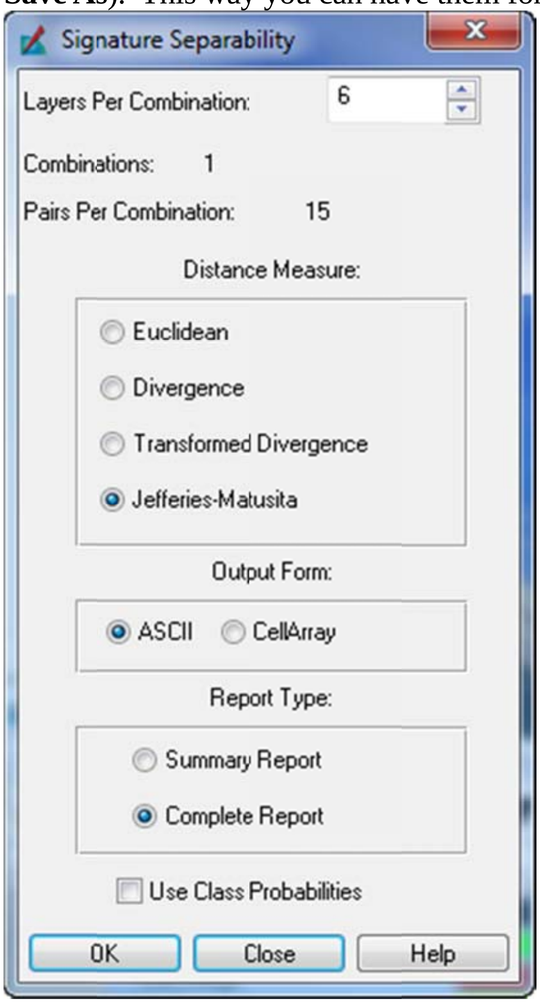
- Check the ellipses off and plot **Rectangles** and **Means.**

Written Assignment Part 3 (continued):

2. With ellipse graphs for four classes, list the two class signatures, which have the least overlap when analyzing each of three combinations of feature space images.

Now explore more quantitative ways to evaluate the homogeneity or representatives of your training areas and the separability of your signatures. First, use "Transformed Divergence" or "Jeffries-Matusita" to measure the separability of signatures, and to determine which features (bands) are most useful for discriminating classes. Both are measures of distances in multi-dimensional normal distribution and therefore, suitable for assessing signatures that will be used for parametric classifiers.

- In the Signature Editor, select all signatures (highlight them in blue), left-click **Evaluate, Separability...**
- Enter **6** layers, check **ASCII Output form**, click on the measure you want reported (pick one), **OK**
- Print the reports (an Editor window opens, and you can **Print**). Also, save them as text files (**File, Save As**). This way you can have them for later. YOU WILL NEED TO TURN THESE IN.



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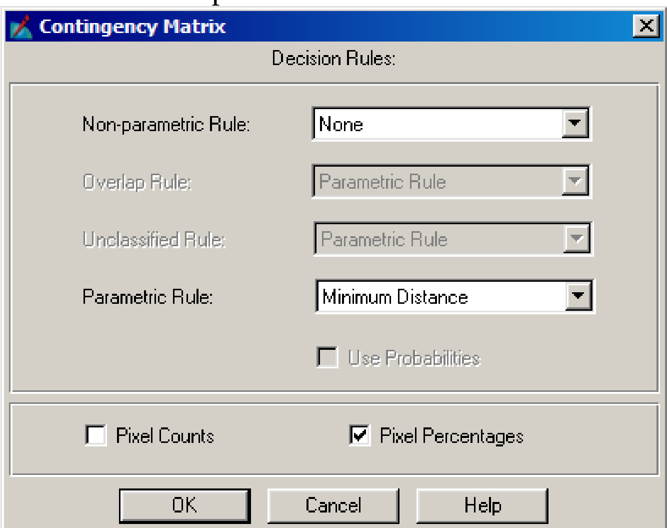
Next, perform a quick classification of just the training sites and then analyze the contingency matrix:

- **Close** the feature space Viewers.
- In the Signature Editor, select all signatures (left-drag in first column) and make sure they are all highlighted in blue.
- Left-hold **Evaluate, Contingency...**
- Use **`minimum distance`** as **Parametric Rule**, check the pixel percentages box, **OK**.
- Print the report and save it to a text file. YOU WILL NEED TO TURN THIS IN.

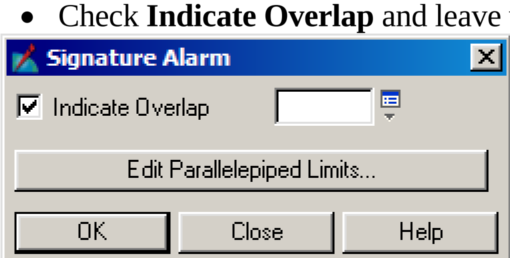


Finally, use "Image Alarm" to highlight all pixels in the image that are estimated to belong to a class using a parallelepiped decision rule.

- To ensure that you can identify the classes from the original image, change the color patches for each of your signatures (these need to be distinguishable from colors in the scene).

Hint:
You can restore the original color combination through **Edit/Colors/Approximate True Colors..**

- In signature editor, left-click **View/ Image Alarm...**, **Edit Parallelepiped Limits...**
- **Set...** either minimum/maximum limits for all bands, or use 2 standard deviations. (This function allows you to cut off the tail ends of the histograms that might cause confusion between the classes).
- Check **Indicate Overlap** and leave white as color to highlight signature overlap, **OK**.



<u>Written Assignment Part 3 (continued)</u>:

3. How accurately were the pixels in your signatures assigned to the four land cover classes?
4. Did most of the pixels classified in the "quick alarm" appear to correspond to the areas you expected?

5. Were there areas missed in the alarm, or many areas overlapping? What may have caused this and what do you need to do in order to rectify these problems?
6. What classes if any did overlap appear to occur? Did you miss any areas or land cover types?

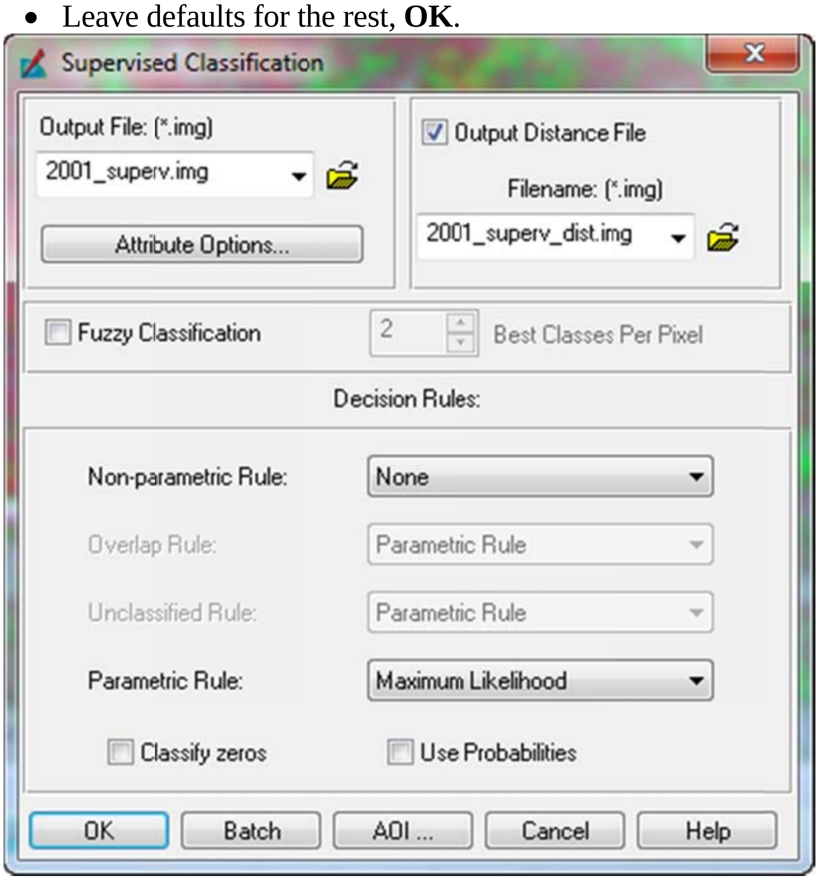
Part 4: Supervised Classification

You will now use your signatures to run a supervised classification with a "minimum distance to mean" decision rule:

- From the Signature Editor, select **Classify/ Supervised**.

Note:
This dialog box can also be access from the **Raster Main Icon/ Supervised Classification...**

- Name the output image: `2001_superv.img.`
- Check the distance box, and enter `2001_superv_dist.img.`
- **As Parametric Rule** specify **`Maximum likelihood.`**
- Leave defaults for the rest, **OK**.



Examine your `2001_superv.img` in a Viewer, but remember that it is a categorized data layer and the DN value range is limited to k+1, where k = number if training classes.
Examine your `2001_superv_dist.img.`

Written Assignment Part 4:

1. How accurately do you think the pixels in your signatures that you assigned to the four land cover classes are? Which class did you have the most problems with?
2. What does the distance image show you? How does this relate to the signatures you have created?
3. What is the difference between your `2001_superv.img` and the Image Alarm? Why is it different? Did this improve the classification?
4. Based on the accuracy of your visual interpretation of the final image, and the information extracted from the distance image what additional steps, or iterative processes would you want to go through?

Create a subdirectory `lab3-report`, copy the classified images created in Part 4 to it. Print your ASCII reports created in signature evaluation in Part 3. Hand in the printouts and your answers to the written assignments. Make sure you list your data files on your lab write-up.

UNSUPERVISED IMAGE CLASSIFICATION

BACKGROUND

Unsupervised classification refers to the process of classifying remotely sensed images into a finite number of clusters. A cluster is a grouping of pixel vectors in spectral-radiometric feature space that satisfy a certain set of criteria such as statistical separability from other clusters. Image pixels are assigned to clusters based on the pixels' spectral similarity and minimum spectral distance from other clusters in feature space.
Unsupervised classification is semi-automated, in the sense that relatively little user input is required during clustering. ERDAS Imagine™ uses a clustering algorithm called ISODATA. The algorithm consists of the following steps: (1) user defines variables (i.e. number of iterations, number of clusters); (2) algorithm groups pixels into clusters; (3) user accepts or modifies of clusters, and (4) user assigns appropriate cluster names. The assignment of cluster names requires that the user be familiar with the area of interest from personal experience or from interpretation of ancillary data, e.g. aerial photographs. If too few clusters are generated, a complex cluster can be broken down into several clusters called "cluster-busting" (sometimes with multiple pass approach.) If too many clusters are generated, several clusters can be grouped into a single cluster.

OVERVIEW

In this lab you will perform an unsupervised classification on the six-band TM subscene from 1994. IMAGINE uses an iterative, self organizing clustering routine (ISODATA) to identify a user-specified number of clusters (i.e., spectral classes with the corresponding statistics). You will use these cluster statistics as signatures in a maximum likelihood classification. Then you will submit the output of the classification to a thresholding routine in order to test and refine the classification. Finally, you will assign thematic class labels to the output of the classification.

PROCEDURES

1. Training by Clustering

Use ISODATA to automatically generate training statistics for 36 classes for the six-band subset (i.e., the 36 clusters identified by the clustering algorithm).

Left-click **Raster, Classifier, Unsupervised Classification...** 

Unsuperivised Classification

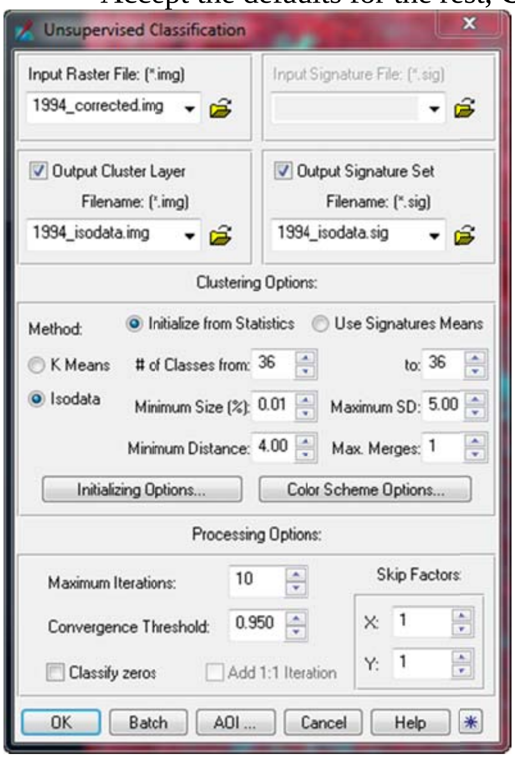
In the ISODATA menu specify `1994_corrected.img` as the **Input Raster File.**

Enter `1994_isodata.img` as name for the **Output Cluster Layer** and `1994_isodata.sig` as name for the **Output Signature Set.**

Make sure that both output types are checked on.

Enter `36` for **Number of Classes**.

Accept the defaults for the rest, **OK.**



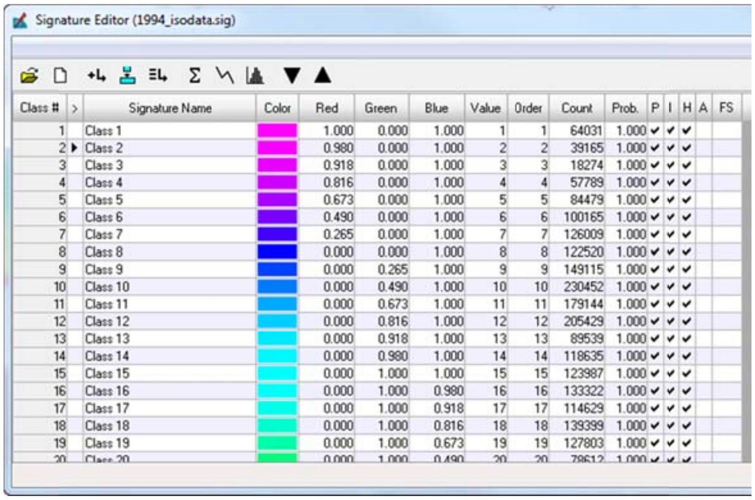
2. Signature Evaluation

Evaluate the signatures:

Raster, Supervised, Signature Editor, File, Open... (the `.SIG` file just created using ISODATA).

Left-click **Edit, Colors, Levels Slice**

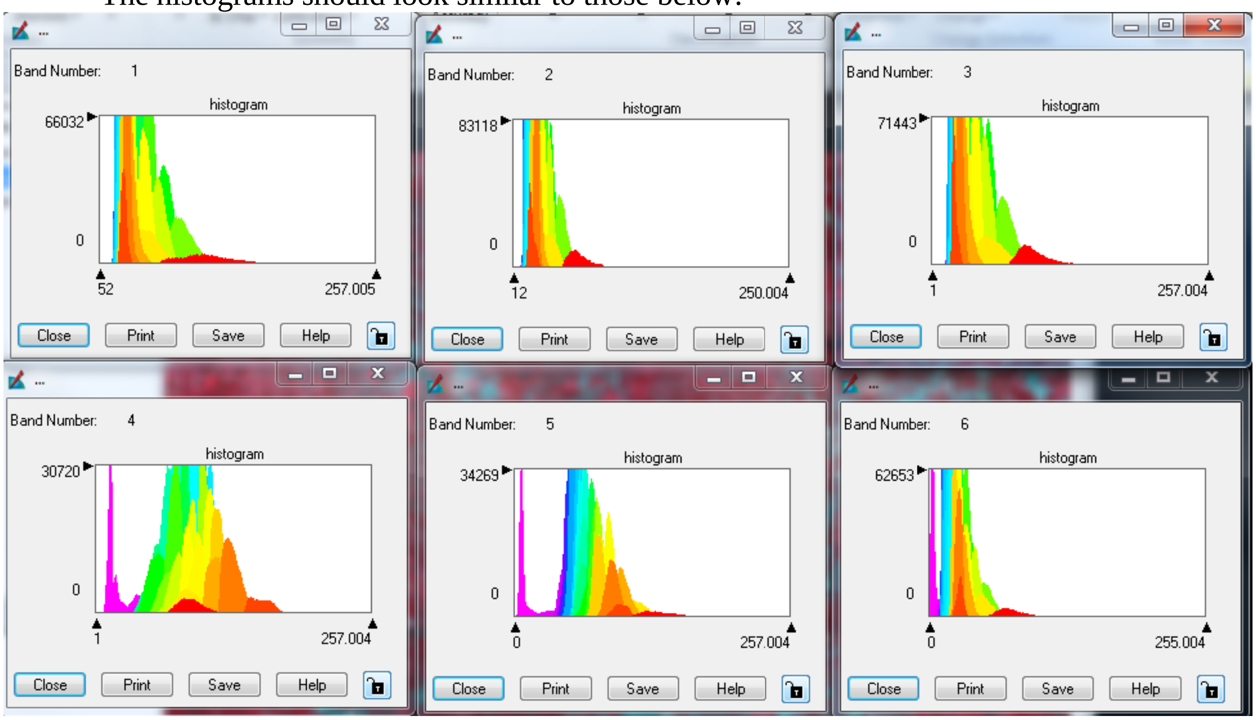
The signature editor should look similar to the one below:



Signature Editor (1994_isodata.sig)

Class #	>	Signature Name	Color	Red	Green	Blue	Value	Order	Count	Prob.	P	I	H	A	FS
1		Class 1		1.000	0.000	1.000	1	1	64031	1.000	✔	✔	✔		
2	▶	Class 2		0.980	0.000	1.000	2	2	39165	1.000	✔	✔	✔		
3		Class 3		0.918	0.000	1.000	3	3	18274	1.000	✔	✔	✔		
4		Class 4		0.816	0.000	1.000	4	4	57789	1.000	✔	✔	✔		
5		Class 5		0.673	0.000	1.000	5	5	84479	1.000	✔	✔	✔		
6		Class 6		0.490	0.000	1.000	6	6	100165	1.000	✔	✔	✔		
7		Class 7		0.265	0.000	1.000	7	7	126009	1.000	✔	✔	✔		
8		Class 8		0.000	0.000	1.000	8	8	122520	1.000	✔	✔	✔		
9		Class 9		0.000	0.265	1.000	9	9	149115	1.000	✔	✔	✔		
10		Class 10		0.000	0.490	1.000	10	10	230452	1.000	✔	✔	✔		
11		Class 11		0.000	0.673	1.000	11	11	179144	1.000	✔	✔	✔		
12		Class 12		0.000	0.816	1.000	12	12	205429	1.000	✔	✔	✔		
13		Class 13		0.000	0.918	1.000	13	13	89539	1.000	✔	✔	✔		
14		Class 14		0.000	0.980	1.000	14	14	118635	1.000	✔	✔	✔		
15		Class 15		0.000	1.000	1.000	15	15	123987	1.000	✔	✔	✔		
16		Class 16		0.000	1.000	0.980	16	16	133322	1.000	✔	✔	✔		
17		Class 17		0.000	1.000	0.918	17	17	114629	1.000	✔	✔	✔		
18		Class 18		0.000	1.000	0.816	18	18	139399	1.000	✔	✔	✔		
19		Class 19		0.000	1.000	0.673	19	19	127803	1.000	✔	✔	✔		
20		Class 20		0.000	1.000	0.490	20	20	79612	1.000	✔	✔	✔		

Then select all of the signatures using **shift and left click** and dragging all the way down.
Then click **View, Histograms, All Selected Signatures**, All Bands, **Plot...**
The histograms should look similar to those below:



Create a report to evaluate the separability of the signatures using the Jefferies-Matusita measure.

Left-click **Evaluate, Separability,** Jefferies-Matusita, **OK**.

Save the Separability reports as a text file in your working directory. Enter `sep_jm_isodata.txt` as name for the Jefferies-Matusita report.

Leave the Signature Editor open. You will need it for the following section.

Contingency analysis cannot be performed, since there are no "AOIs" for these training statistics. Instead of doing an "Image Alarm," examine the preliminary thematic raster layer created by the clustering algorithm in unsupervised classification.

In the View #1 display the six-band TM image.

Add another view, and display the "cluster map" in Pseudo Color.

File, Open, Raster layer, select `1994_isodata.img`.

Click **Raster Options**, Display as **Pseudo Color**, Clear Display, **OK**.

Link the two Viewers 

In the "cluster-map" Viewer:

Start **Inquire Cursor** 

Right-click **in the Contents View on the** `1994_isodata.img.`

Select **Display Attribute Table**

The Attribute Table should appear at the bottom of the screen.

Use the Inquire cursor to explore the relationship between your new clusters and the image.

<u>Written Assignment - Part 5:</u>

1) Compare the signatures created in this lab with those created in your supervised approach.
   a) Briefly discuss the similarities.
   b) Briefly discuss the differences.

3. Maximum Likelihood Classification

Classify the six-band TM image into a digital raster map with 36 classes, based on the statistics file generated for 36 clusters in ISODATA.

Left-click **Raster, Supervised, Supervised Classification**

Input Raster File is `1994_corrected.img`, **Input Signature File** the `.SIG` file from ISODATA unsupervised classification.

Enter `1994_unsuperv.img` as name for the **Output Classified File**.

Check on **Distance File.**

Enter `1994_unsup_distance.img` as name for the distance file.

Choose `Maximum Likelihood` as the parametric classification decision rule.

Accept defaults for other settings, press **OK**, and keep the file with the classified image.

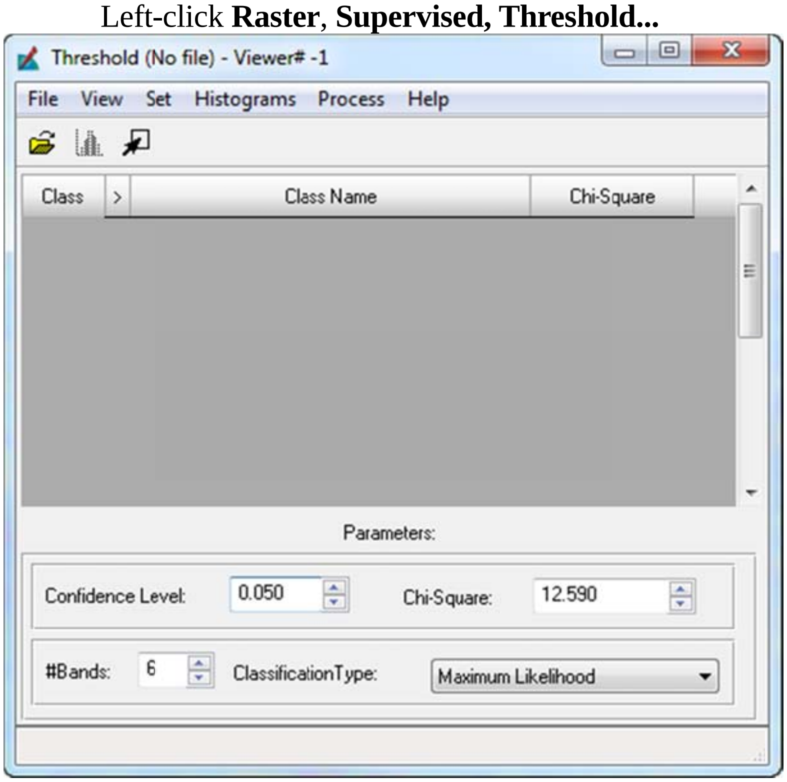
4. Thresholding

Assuming a multidimensional normal distribution, maximum likelihood classifiers use the determinant of the covariance matrix and the mean vector of each class, to calculate the probabilities that a pixel falls into each of the classes. The pixel is then assigned to the class with the highest associated probability. This means that the spectral classes are identified by regions of higher probability values on the probability surface. These regions in multispectral space may be surrounded by lower probability regions, where pixels have an almost equal chance of belonging to adjacent classes. This situation can lead to poor classification results. Therefore, thresholding routines can be applied, which specify probability thresholds below which pixels will not be assigned to any class.

Examine and modify the classification based on the distance file which has been created during the classification. Each value in the distance file is the Chi-square distance between a pixel in the input image file and the mean of the spectral class to which it was assigned. In the distance file, pixels with high values are more likely to be incorrectly classified, since the distance from the pixel to the signature mean is larger.

You can <u>interactively</u> set thresholds for excluding pixels that were erroneously assigned to a spectral class, based on their distance from the class mean. In case you want to use the <u>numeric input</u> option, you first need to check whether the signatures used for the classification approximate normal distributions in every band. If yes, the confidence level (α) of the Chi-Square distribution can be used to set the threshold distance.

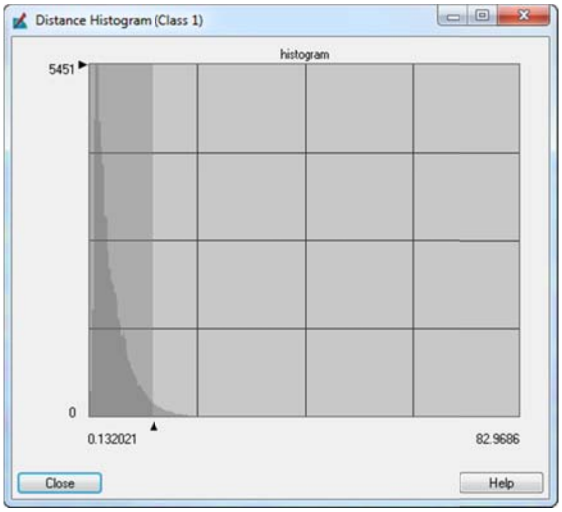
Display the classified image `1994_unsuperv.img`
Left-click **Raster**, **Supervised, Threshold...**

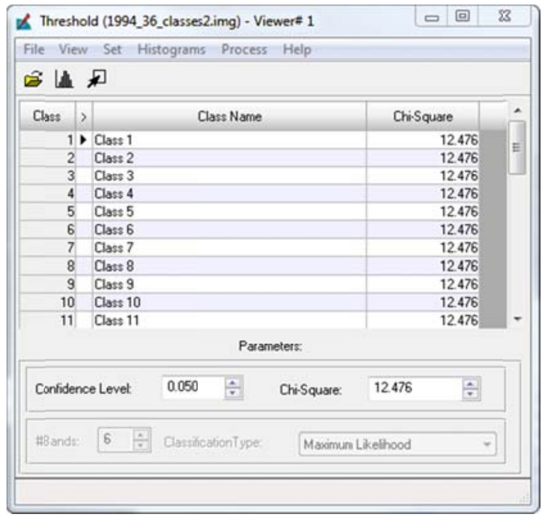


Left-click **File, Open**. A Dialogue box should open asking for a classified image and the corresponding distance file, select your files and then **OK**.
Left-hold **View, Select Viewer...**(Select the viewer with the `1994_unsuperv.img`)
Left Click, **Set, All…,**
Left Click**, Histograms, Compute...**,

Left Click, **Histograms, View...**

In the histogram graph that appears, you can drag the little, black wedge along the x-axis to adjust the distance from the class mean. Or, since you used ISODATA to generate signatures set a confidence level (e.g. 0.05) for all within the **Threshold** window. As you move around the black arrow in the Histogram view, the Confidence Level should move in the Threshold Window. Below are the Histogram View and the Threshold window.





Process, To Viewer to see the results immediately (that is pixels beyond the threshold will be left unclassified and appear as black).

Process, To File... to save the thresholding as a new image, where pixels outside of your designated thresholds will be assigned a zero value (they are thresholded out). Enter `1994_thresholded.img` as name for the output file name.

Display the thresholded image:

Right click on the `1994_thresholded.img` in the Contents Window and Select **Display Attribute Table** and note the number of “unclassified” pixel using this threshold value.

<u>**Written Assignment – Part 6:**</u>

2. How many pixels were above the threshold at confidence level $\alpha = 0.05$?

5. Class Labeling

Finally, you are ready to assign land cover class labels to the "cluster classes."

Display the 6 Band TM image:

True Color (`4 3 2`), Clear Display, Fit to Frame.

In the same Viewer display your classified image `1994 unsuperv.img`:

Pseudo Color, do ***NOT*** Clear Display, Fit to Frame

In another View, display the 6band TM.

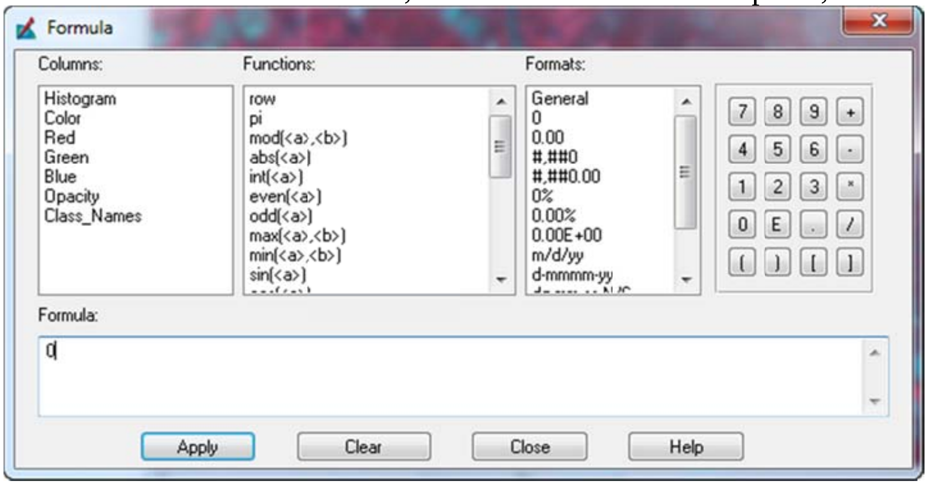
Next, **Right Click** on the classified image `1994 unsuperv.img` in the Contents Panel

Select Display Attribute Table

Right Click on `Opacity`

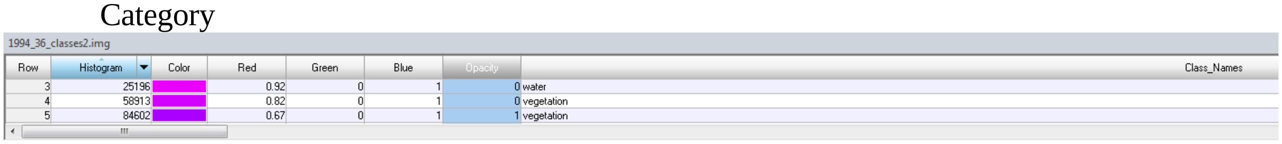
Click **Formula…**,

In the **Formula** window, click on 0 on the numbers panel, and click **Apply**.



Opacity is now 0 for all classes. Entering a 1 in the opacity column for any class will display the class over the image. Switch individual classes on or off (turning them between 1 & 0), determine the corresponding land cover and enter the class names in the Class_Names. Attempt to determine cluster labels by:

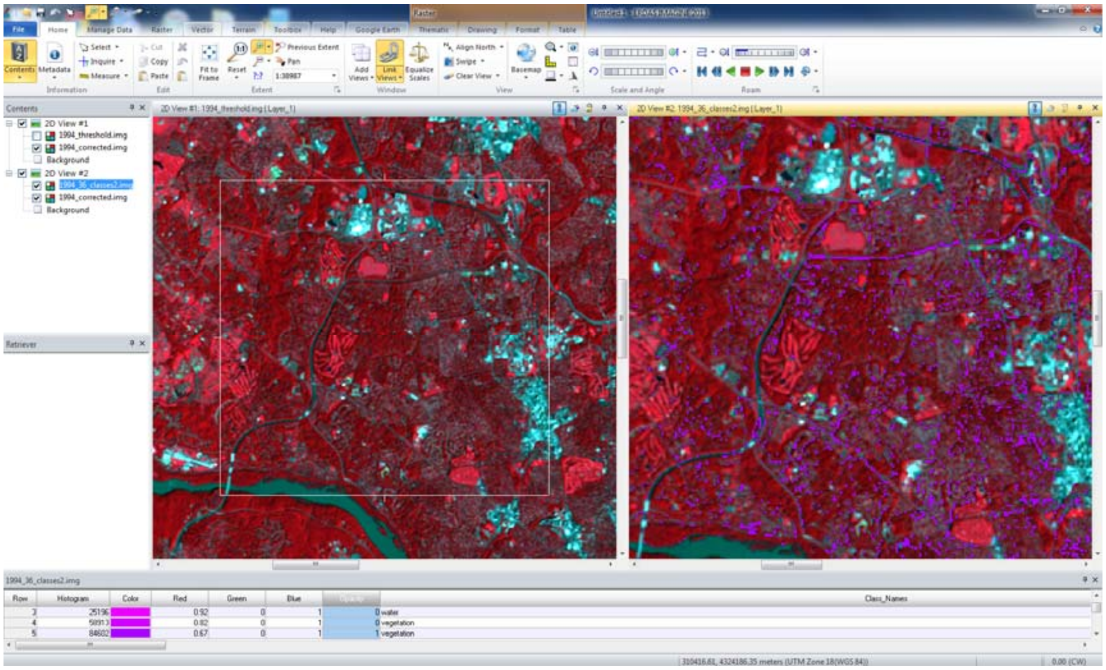
a. Assessing the location of pixels of a given class relative to the false-color image; or
b. Incorporating your general knowledge of the area in the image
c. Then write in one of the four classes, urban, vegetation, soil, or water in the Class_Names Category



1994_36_classes2.img

Row	Histogram	Color	Red	Green	Blue	Opacity	Class_Names
3	25196		0.92	0	1	0	water
4	58913		0.82	0	1	0	vegetation
5	84602		0.67	0	1	1	vegetation

Your setup should be something like this:



Set all opacities back to `1` before you quit!

When all clusters are assigned to one of the following four land cover classes: 1) Water, 2) Urban, 3) vegetation, or 4) soil.

<u>**Written Assignment - Part 7**</u>**:**

3) Which land cover types were the most separable and easiest to identify when labeling the unsupervised cluster classes?
4) Which land cover types were the most commonly confused, suggesting that they may not be spectrally separable?
5) Which methodology, supervised or unsupervised, do you think was the easiest to do? Which one do you think was more accurate?

Indicate your work directory in your written report and make sure that the following files are in that directory: `1994_isodata.img`, 1994`_isodata.sig`, `sep_jm.txt`, 1994`_unsuperv.img`, 1994`_unsuperv_distance.img`, and 1994`_thresholded.img`. Make sure you do this correctly as you will use all of the files created in this lab in the next lab as well.