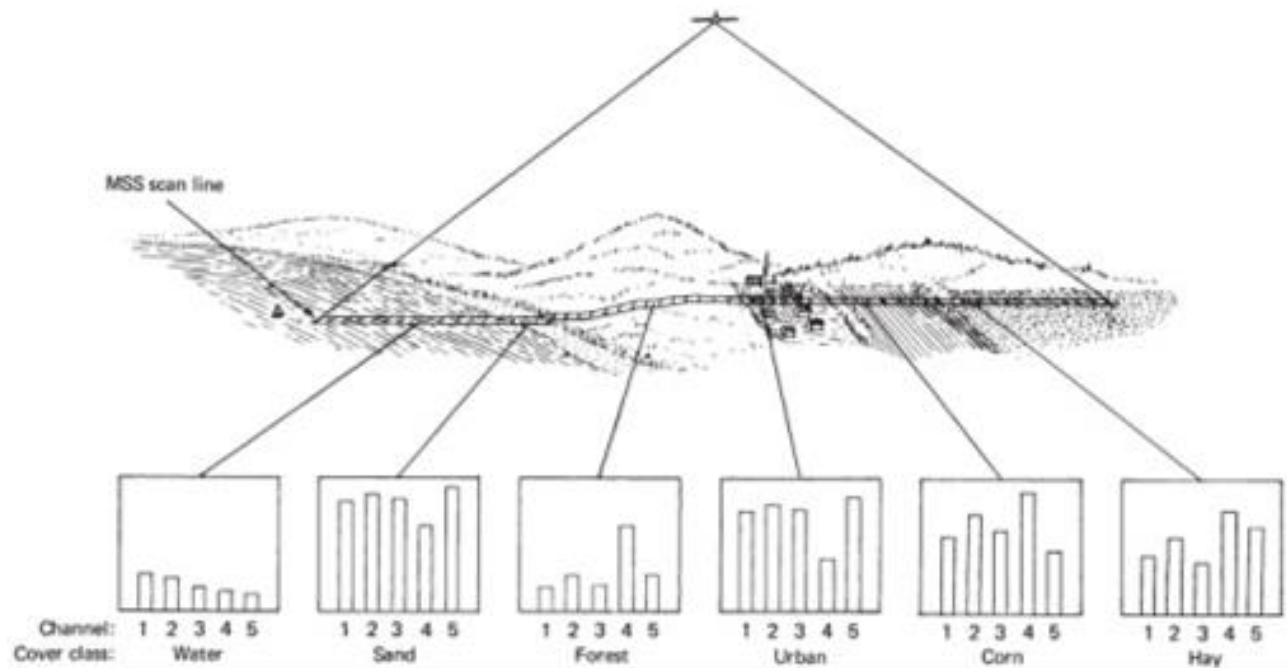


# Chapter 5: "Image Classification"

## Part 1 out of 3

### Introduction:

The overall objective of image classification procedures is to categorize all pixels on an image into land cover type in an automatic way,

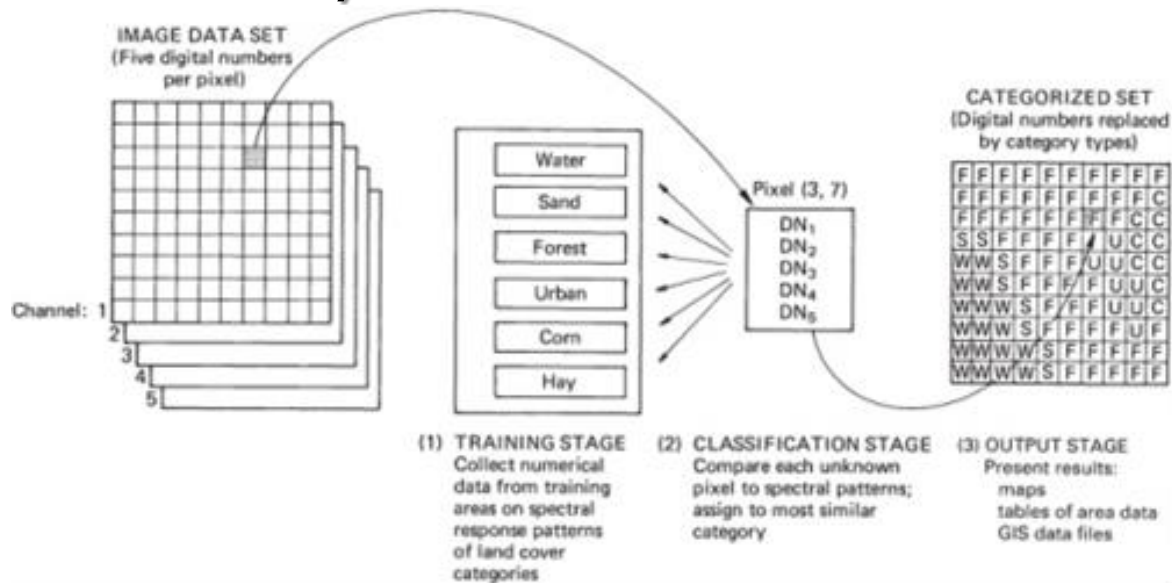


# Chapter 5: "Image Classification"

## Introduction: (continue)

We can approach image classification in 3-major approaches;

(1) pixel based classification that uses statistical values gathered from the image & reference data to classify pixels individually,



# *Chapter 5: “Image Classification”*

## *Introduction: (continue)*

*(2) object oriented classification that uses the shape & characteristics of objects as a base for the image classification, &*

*(3) by using artificial intelligence (AI) algorithms.*

*Number 2 & 3 approaches are outside the scope of this course despite the fact that AI can be used alone or as a complementary to the other approaches.*

# *Chapter 5: "Image Classification"*

## *Introduction: (continue)*

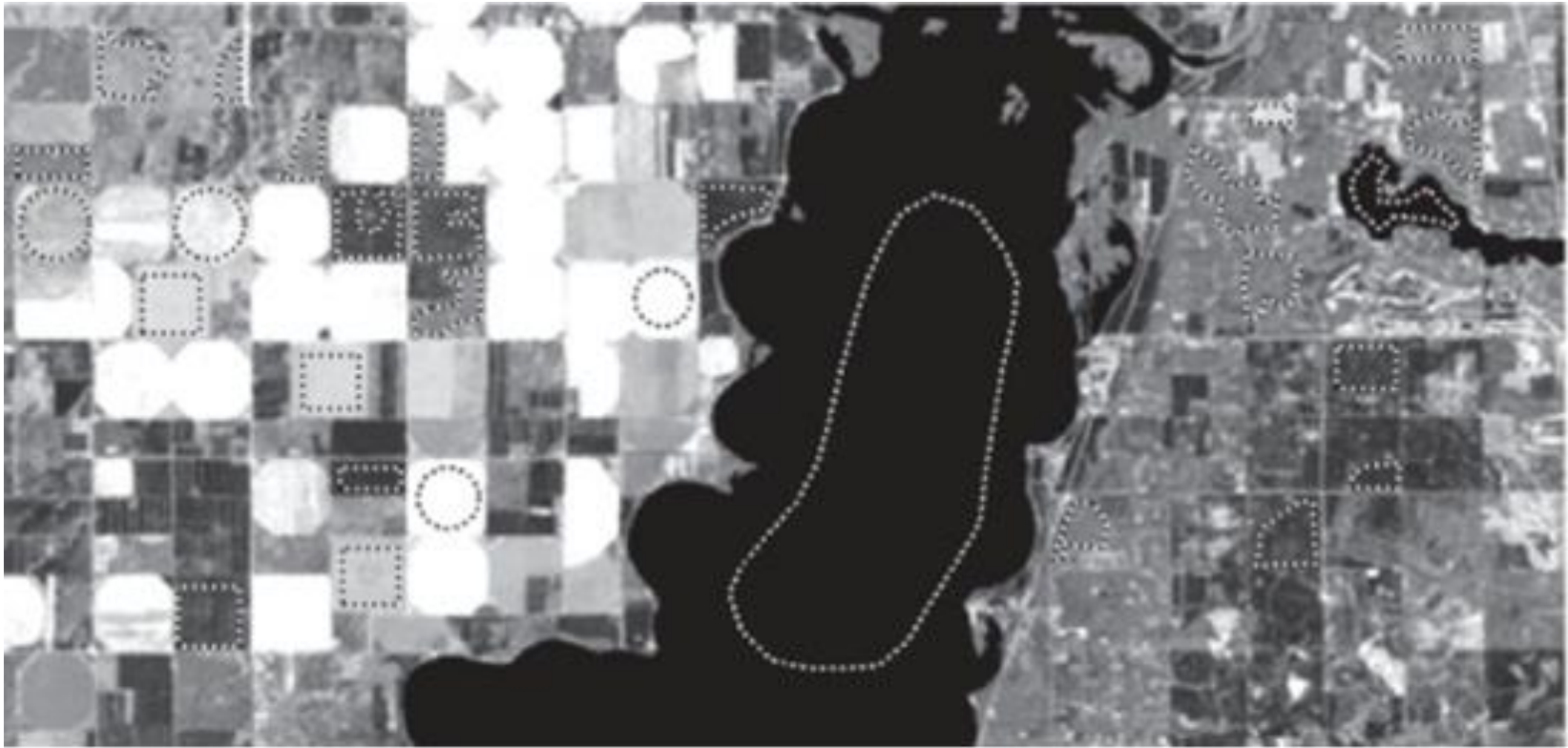
Correspondingly, there are 2-major approaches in pixel base image classification; (1) the supervised approach & (2) the unsupervised approach.

(1) In supervised approach, the analyst defines small areas on the image, called training sets that are representative of the land cover types on the ground with the aid of the reference data.

Base on individual values of the pixels & the measured statistical values of the training sets, such as the means & standard deviations, a computer algorithm will assign each pixel on the image to a land cover type.

# *Chapter 5: "Image Classification"*

## *Training Sets Selection: (continue)*



Author-prepared figure.

# *Chapter 5: "Image Classification"*

## *Introduction: (continue)*

*This approach is easy to understand, has fewer classes & fewer computations, & can be interrupted many times.*

*The main problem with this approach is that it depends to some extent on the analyst visual applets, which mean that it can miss some classes because the eyes of the analyst cannot discriminate between classes as good as a computer algorithm.*

# *Chapter 5: "Image Classification"*

## *Introduction: (continue)*

*(2) In the unsupervised approach the image is first clustered & then classified based on the statistical measures from these clusters.*

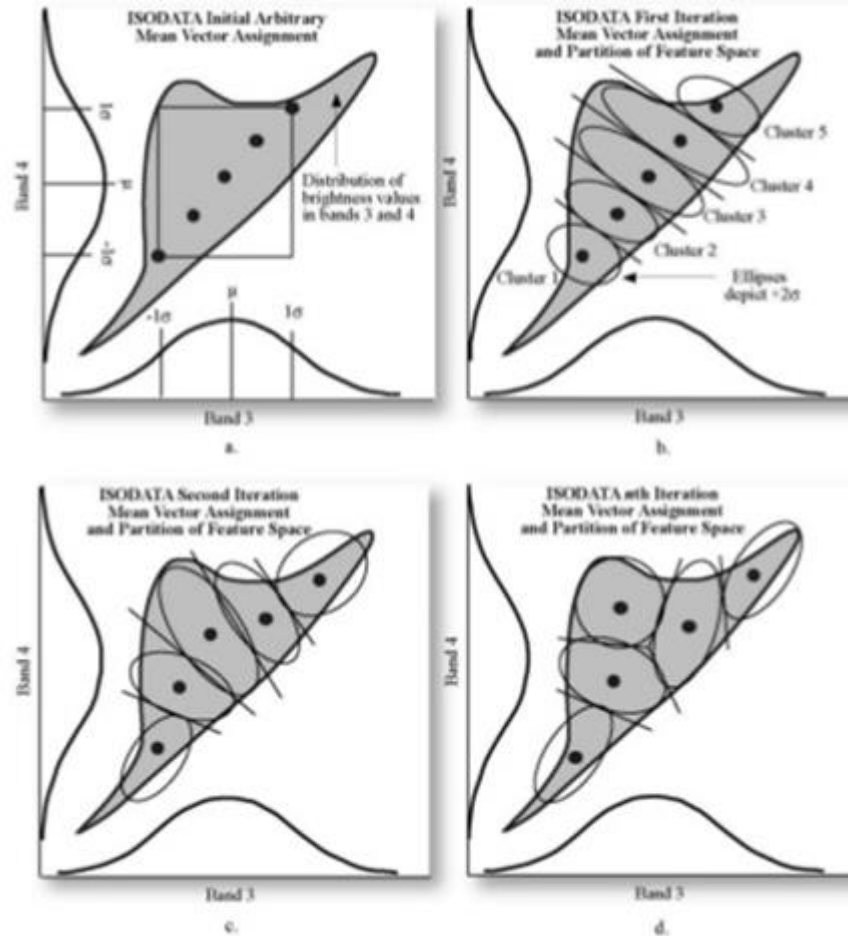
*Then the analyst has to connect between clusters & different land cover types based on the reference data.*

*This approach can represent spectral classes more faithfully & can be automated more effectively with the help of AI techniques.*

*The downside of this approach is that if it is not done properly it might create false classes that belong to more than one land cover type.*

# Chapter 5: "Image Classification"

## Introduction: (continue)



Digital Image Classification



# Chapter 5: "Image Classification"

## Introduction: (continue)

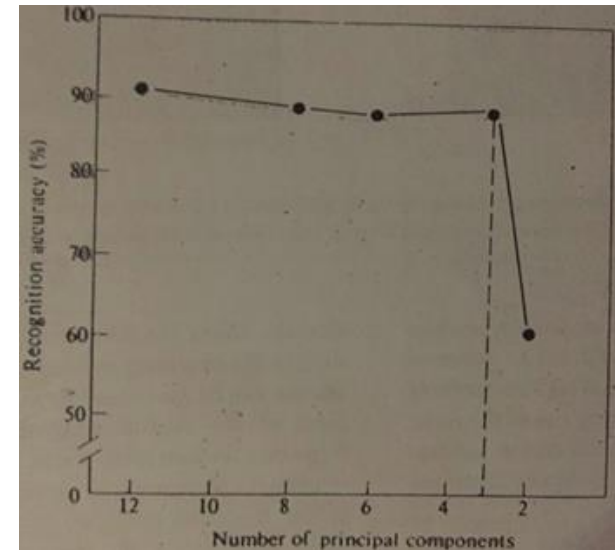
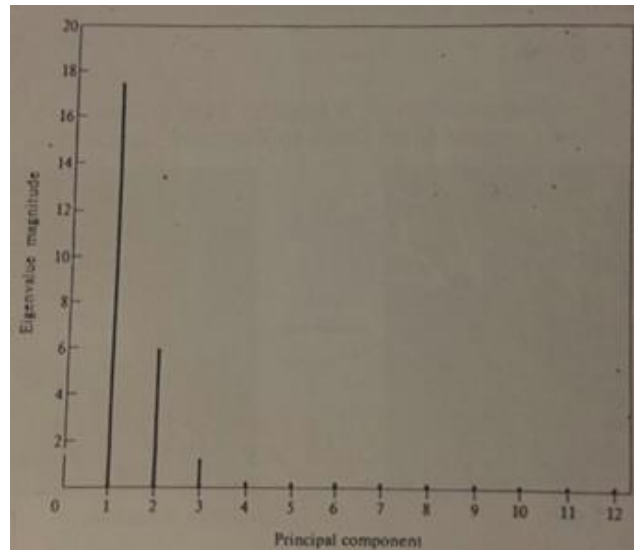


# Chapter 5: "Image Classification"

## Step Involved in Pixel Based Image Classification:

There is no single right way of doing pixel based image classification; however the following 7 steps are most likely to be involved in nearly all pixel based image classification;

1. Optionally, use PCA to reduce the number of bands without losing much of the spectral information.



# *Chapter 5: "Image Classification"*

## *Step Involved in Pixel Based Image Classification:*

- 2. Choose a classification approach, supervised or unsupervised, that is most suitable to the application on hand & apply all the necessary checks on the training classes & clusters to make sure that they are representative of the land cover types. If unsupervised approach is chosen, then it is more efficiently to connect all clusters to a land cover type at this stage.*
- 3. Derive all necessary statistical information from the training sets or clustered from step 2 above.*

# *Chapter 5: "Image Classification"*

## *Step Involved in PBI Classification: (continue)*

- 4. Classify the entire scene based on statistical values from step 3 above & the individual spectral values of each pixel on the scene using a reasonable classification algorithm.*
- 5. Group all training sets or clusters into information classes (land cover type).*
- 6. Edit & assess the classification accuracy.*
- 7. Optionally, smooth out the classified image to produce more accurate final classified image.*

*AI can play a great deal to improve the accuracy & flexibility of these classification steps. They can also automate some of these steps.*

# Chapter 5: "Image Classification"

## The Output Stage:

Spectral Class	Identity of Spectral Class	Corresponding Desired Information Category
<b>Possible Outcome 1</b>		
1	Water →	Water
2	Coniferous trees →	Coniferous trees
3	Deciduous trees →	Deciduous trees
4	Brushland →	Brushland
<b>Possible Outcome 2</b>		
1	Turbid water →	Water
2	Clear water →	
3	Sunlit conifers →	Coniferous trees
4	Shaded hillside conifers →	
5	Upland deciduous →	Deciduous trees
6	Lowland deciduous →	
7	Brushland →	Brushland
<b>Possible Outcome 3</b>		
1	Turbid water →	Water
2	Clear water →	
3	Coniferous trees →	Coniferous trees
4	Mixed coniferous/deciduous →	
5	Deciduous trees →	Deciduous trees
6	Deciduous/brushland →	
		Brushland

# *Chapter 5: "Image Classification"*

## *Selection of the Classification Algorithm:*

*There are many classification algorithms that use statistical information derived from the training set to categorize pixels into their appropriate classes. Three of these algorithms are discussed here;*

- (1) the minimum-distant-to-mean (MDM),*
- (2) the parallelepiped or the box classifier, &*
- (3) the maximum likelihood classifier (MLC).*

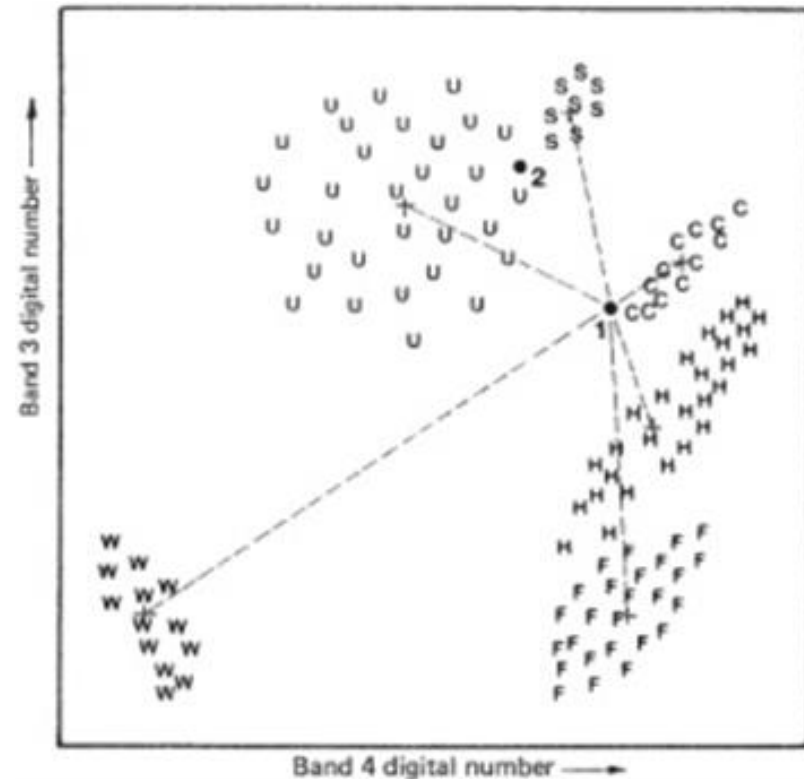
# Chapter 5: "Image Classification"

## Selection of the Classification Algorithm: (continue)

### (1) The MDM Classification Algorithm:

In this algorithm, a pixel of unknown identity may be classified by comparing the distances between the unknown pixel & each class mean.

Next, the unknown pixel is assigned to the closest class, the class with the minimum distant to this pixel.



# *Chapter 5: "Image Classification"*

## *Selection of the Classification Algorithm: (continue)*

### *(1) The MDM Classification Algorithm: (continue)*

*If a pixel is further than any mean by more than an analyst predefined distant then it well be classified as "unknown".*

*This algorithm is mathematically simple & computationally efficient. Nevertheless, it is insensitive to deferent degree of variance in the response data.*



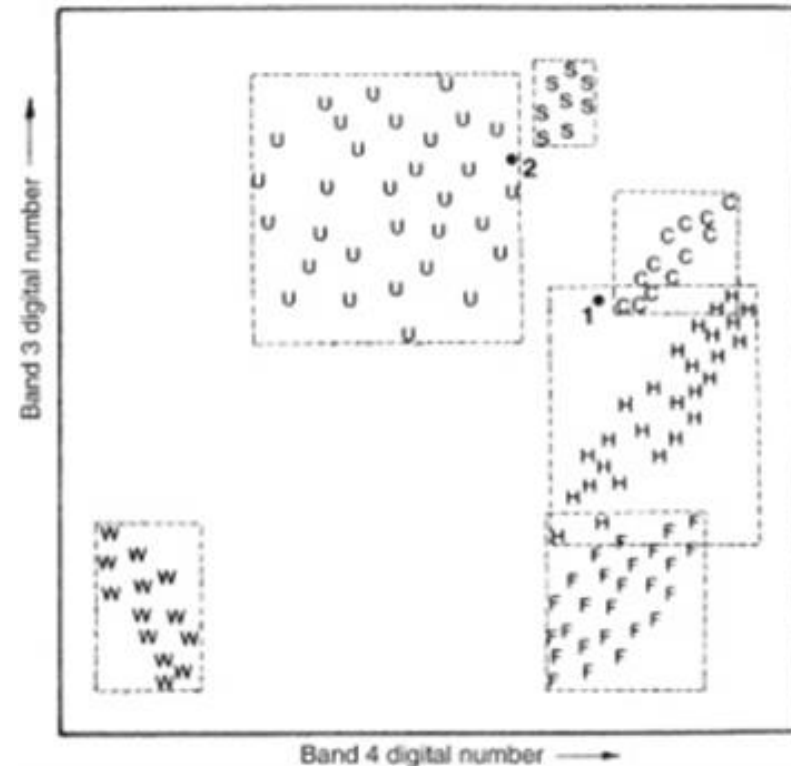
# Chapter 5: "Image Classification"

## Selection of the Classification Algorithm: (continue)

### (2) The Parallelepiped or the Box Classification Algorithm:

Sensitivity to category variance can be introduced by considering the range of values in each category training set.

This range may be defined by the highest & lowest digital number (DN) values, for each category, in each band. (other measured can be used).



# *Chapter 5: "Image Classification"*

## *Selection of the Classification Algorithm: (continue)*

### *(2) The Parallelepiped or the Box Classification : (continue)*

*An unknown pixel is classified according to category range in which it lies, or as unknown if it lies outside all ranges.*

*Pixels falling in overlapping areas of classes can be classified to any one of them.*

*This algorithm is very fast & very efficient. However, it has problems with overlapping areas. Moreover, classes with high variance can claim pixel falsely.*

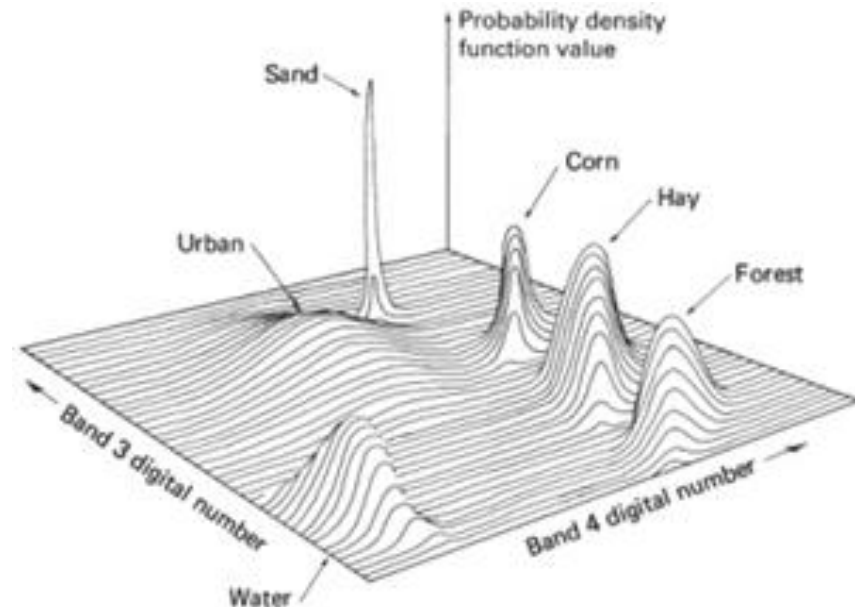
# Chapter 5: "Image Classification"

## Selection of the Classification Algorithm: (continue)

### (3) The ML Classification Algorithm:

The ML classification algorithm work well only if all of the training classes are normally distributed in all bands.

That means the distribution of every training class response pattern can be completely described by its means & its variance-covariance matrix.



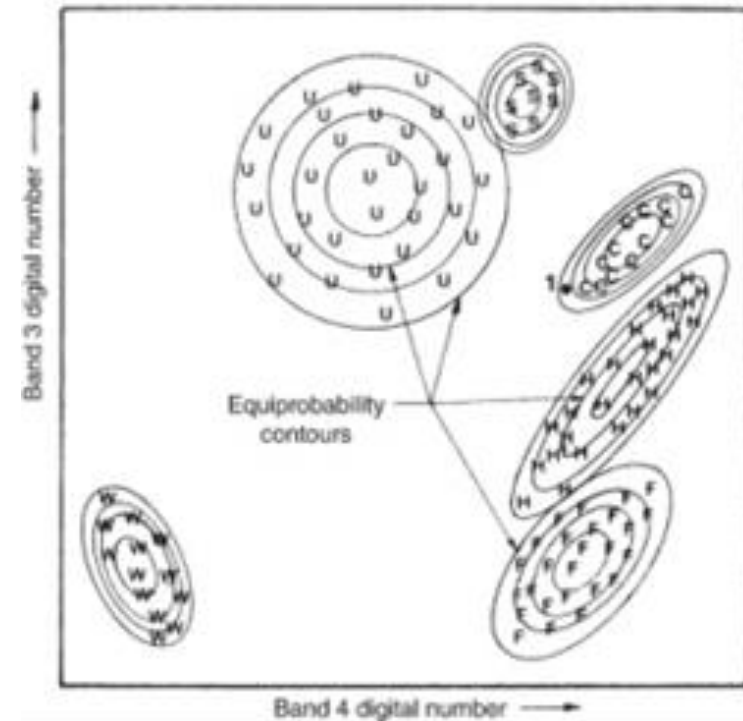
# Chapter 5: "Image Classification"

## Selection of the Classification Algorithm: (continue)

### (3) The ML Classification Algorithm: (continue)

When classifying an unknown pixel, the ML classification algorithm quantitatively evaluates the means & the variance-covariance matrix of each class spectral response patterns & computes the statistical probability of a given pixel being a member of every training class.

$$P(X|\omega_i) = \frac{1}{\sqrt{(2\pi)\sigma_i}} e^{-\frac{1}{2}\left(\frac{(X-\mu_i)^2}{\sigma_i^2}\right)}$$



# Chapter 5: "Image Classification"

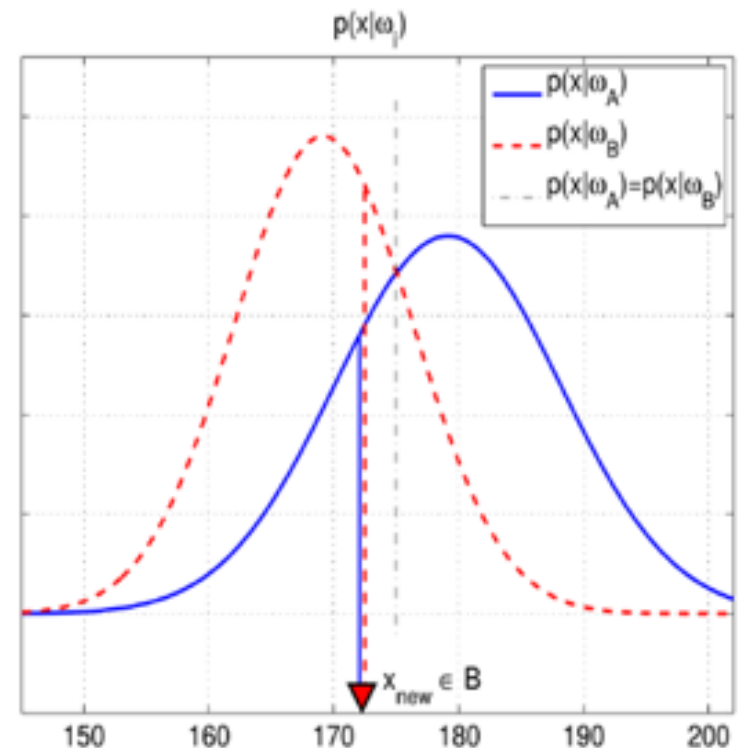
## Selection of the Classification Algorithm: (continue)

### (3) The ML Classification Algorithm: (continue)

Then this pixel would be assigned to the class with the highest probability value, (i.e., the most likely class).

$$P(X|\omega_j) \geq P(X|\omega_i), \text{ for all } j = 1, 2, \dots, k$$

If the probability values of all classes are below an analyst preset threshold value, a pixel will be classified as unknown.



# *Chapter 5: "Image Classification"*

## *Selection of the Classification Algorithm: (continue)*

### *(3) The ML Classification Algorithm: (continue)*

*The ML classification algorithm is one of the most accurate algorithms, if it is done properly; however, it has a lot of computation especially with large scene that has many classes.*

*Furthermore, this algorithm is sensitive to normal distribution of the classes.*

# *Chapter 5: "Image Classification"*

## *Part 2 out of 3*

### *Classification Accuracy Assessment:*

*Accuracy assessment involves comparing the results obtained from a digital classification algorithm to a known identity of land cover derived from reference data called test areas.*

*Contingency tables are often used, with randomly selected test areas. From these contingency tables, the categorical accuracies, the overall accuracy, the omission & commission errors, & kappa or khat indexes can also be measured.*

# Chapter 5: "Image Classification"

## Classification Accuracy Assessment: (continue)

### Contingency Tables;

- Overall accuracy =  
(# pixels correctly classified) / (total # of pixels in the testing sample).
- Producer's accuracy =  
(# of pixels correctly classified of a class) / (# ground reference pixels in this class).
- Omission Error: Excluding a pixel from a class when it should have been included (i.e., Omission error =  $1 - \text{Producer's accuracy}$ ).
- User's accuracy =  
(# of pixels correctly classified of a class) / (total # of pixels classified as of this class).



# *Chapter 5: "Image Classification"*

## *Classification Accuracy Assessment: (continue)*

### *Contingency Tables; (continue)*

- *Commission Error: Including a pixel in a class when it should have been excluded (i.e., commission error =  $1 - \text{User's accuracy}$ ).*
- *Average Accuracy = (sum of Procedure class accuracies) / number of classes.*
- *Minimum Class Accuracy: The lowest class accuracy noted in the classification.*
- *Kappa; an accuracy statistic that permits two or more contingency matrices to be compared.*

# Chapter 5: "Image Classification"

## Classification Accuracy Assessment: (continue)

The statistic adjusts overall accuracy to account for chance agreement, kappa can be calculated as following.

Use kappa to statistically test for agreement between two contingency matrices.

$$\hat{K} = \frac{N \sum_{i=1}^m D_{ij} - \sum_{i=1}^m R_i \cdot C_j}{N^2 - \sum_{i=1}^m R_i \cdot C_j}, \quad (4)$$

where:  $\hat{K}$  - Kappa-coefficient,  
 $N$  - total number of pixels,  
 $m$  - number of classes,  
 $\sum D_{ij}$  - total diagonal elements of an error matrix (the sum of correctly classified pixels in all images),  
 $R_i$  - total number of pixels in row  $i$ ,  
 $C_j$  - total number of pixels in column  $j$ .

# Chapter 5: "Image Classification"

## Classification Accuracy Assessment: (continue)

Example for accuracy assessment is presented in the table below;

Class	1	2	3	4	5	6	7	8	Total
1	<b>162</b>	2	20	0	1	0	2	0	187
2	1	<b>168</b>	13	0	0	0	8	0	190
3	6	4	<b>176</b>	0	0	0	7	0	193
4	0	0	4	<b>189</b>	0	0	4	0	197
5	0	1	0	0	<b>194</b>	1	3	0	199
6	0	0	0	0	0	<b>196</b>	0	3	199
7	1	7	2	0	2	1	<b>177</b>	3	193
8	0	0	0	0	0	1	2	<b>196</b>	199
Total	170	182	215	189	197	199	203	202	<b>1557</b>

<sup>a</sup>Overall accuracy = 92.11%; Kappa = 0.9115; 43 pixels unrecognized. Key to classes: 1 = green Tea; 2 = hazelnut; 3 = deciduous; 4 = coniferous; 5 = pasture; 6 = rock; 7 = agriculture; 8 = urban. A 50% threshold was applied to assign a pixel to one of the classes.

# Chapter 5: "Image Classification"

## Classification Accuracy Assessment: (continue)

From the Contingency Table above;

- Overall accuracy =  $[(162 + 168 + 176 + 189 + 194 + 196 + 177 + 196) / (1557)] * 100$   
 $= 93.6\%$
- Producer's accuracy for class 1 =  $162 / 170 = 0.95$
- Omission Error for class 1 =  $8 / 170 = 0.05$ ,  
It can also be found as  $= 1 - 0.95 = 0.05$
- User's accuracy for class 1 =  $162 / 187 = 0.87$
- Commission Error for class 1 =  $25 / 187 = 0.13$ ,  
It can also be found as  $= 1 - 0.87 = 0.13$

# Chapter 5: "Image Classification"

## Classification Accuracy Assessment: (continue)

From the Contingency Table above; (continue)

- To compute kappa we need to compute each part of the equation alone then compute kappa from these parts;
  - $N = 1557,$
  - $\sum Dij = 162 + 168 + 176 + 189 + 194 + 196 + 177 + 196) = 1458,$
  - $\sum Ri * Cj = (170 * 187) + (182 * 190) + \dots + (202 * 199) = 266432$
  - $kappa = [(1557 * 1458) - 266432] / [(1557 * 1557) - 266432] = 0.929,$   
or simply 92.9%.

TABLE 7.3 Error Matrix Resulting from Classifying Training Set Pixels

		Training Set Data (Known Cover Types) <sup>a</sup>						
		W	S	F	U	C	H	Row Total
Classification Data	W	480	0	5	0	0	0	485
	S	0	52	0	20	0	0	72
	F	0	0	313	40	0	0	353
	U	0	16	0	126	0	0	142
	C	0	0	0	38	342	79	459
	H	0	0	38	24	60	359	481
	Column total	480	68	356	248	402	438	1992
Producer's Accuracy								
W = 480/480 = 100%								
S = 052/068 = 76%								
F = 313/356 = 88%								
U = 126/248 = 51%								
C = 342/402 = 85%								
H = 359/438 = 82%								
User's Accuracy								
W = 480/485 = 99%								
S = 052/072 = 72%								
F = 313/353 = 87%								
U = 126/142 = 89%								
C = 342/459 = 74%								
H = 359/481 = 75%								
Overall accuracy = (480 + 52 + 313 + 126 + 342 + 359)/1992 = 84%								

<sup>a</sup>W, water; S, sand; F, forest; U, urban; C, corn; H, hay.

TABLE 7.4 Error Matrix Resulting from Classifying Randomly Sampled Test Pixels

		Reference Data <sup>a</sup>						
		W	S	F	U	C	H	Row Total
Classification Data	W	226	0	0	12	0	1	239
	S	0	216	0	92	1	0	309
	F	3	0	360	228	3	5	599
	U	2	108	2	397	8	4	521
	C	1	4	48	132	190	78	453
	H	1	0	19	84	36	219	359
	Column total	233	328	429	945	238	307	2480
Producer's Accuracy								
W = 226/233 = 97%								
S = 216/328 = 66%								
F = 360/429 = 84%								
U = 397/945 = 42%								
C = 190/238 = 80%								
H = 219/307 = 71%								
User's Accuracy								
W = 226/239 = 94%								
S = 216/309 = 70%								
F = 360/599 = 60%								
U = 397/521 = 76%								
C = 190/453 = 42%								
H = 219/359 = 61%								
Overall accuracy = (226 + 216 + 360 + 397 + 190 + 219)/2480 = 65%								

<sup>a</sup>W, water; S, sand; F, forest; U, urban; C, corn; H, hay.

# Chapter 5: "Image Classification"

## Classification Accuracy Assessment: (continue)

### Sample Size

Fitzpatrick-Lins (1981) suggests that the sample size  $N$  to be used to assess the accuracy of a land-use classification map be determined from the formula for the binomial probability theory:

$$N = \frac{Z^2(p)(q)}{E^2} \quad (\text{source: Jensen, 2011})$$

where  $p$  is the expected percent accuracy of the entire map,  $q = 100 - p$ ,  $E$  is the allowable error, and  $Z = 2$  from the standard normal deviate of 1.96 for the 95% two-sided confidence level.

With expected map accuracies of 85% and an acceptable error of 5%

$$N = \frac{2^2(85)(15)}{5^2} = \text{a minimum of 203 points.}$$

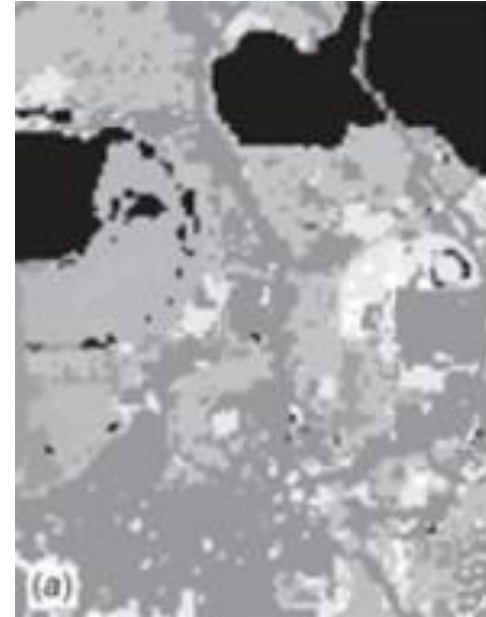
acceptable error of 10%

$$N = \frac{2^2(85)(15)}{10^2} = 51 \text{ points}$$

# Chapter 5: "Image Classification"

## *Post Classification Smoothing:*

*Classified data often manifest a salt & paper appearance due to the inherent spectral variability encountered by a classifier when applied on a pixel by pixel basis, like the image in (a).*



*It is often desirable to smooth the classified output to show only the dominant, presumably correct, classification identity.*

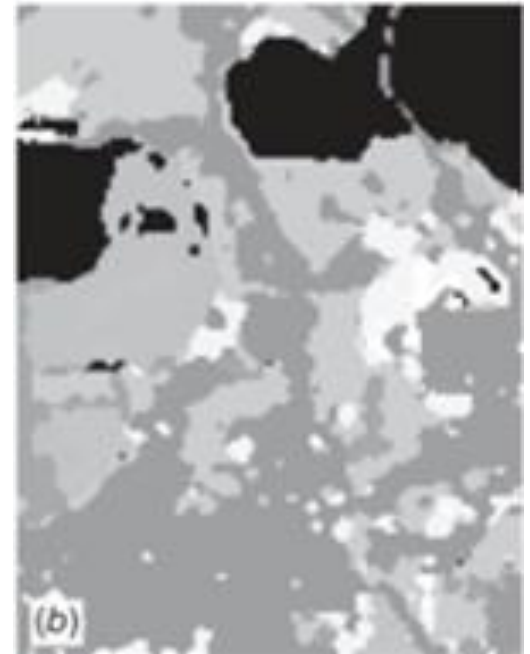


# Chapter 5: "Image Classification"

## *Post Classification Smoothing:*

The problem is that the output from an image classification process is an array of labeled pixel location not quantities.

One means of classification smoothing involves the application of a majority filter, where, a 3x3 moving window is run over the classified data set & the majority class within the window is assigned as the output class for the pixel at the center of the window.



The output image will be something similar to the image in (b).

# *Chapter 5: "Image Classification"*

## *Post Classification Smoothing: (continue)*

However, extra considerations should be taken when dealing with linear features such as roads & small rivers. In such cases special constraints must take place so that linear features will not be lost like to the image in (c).



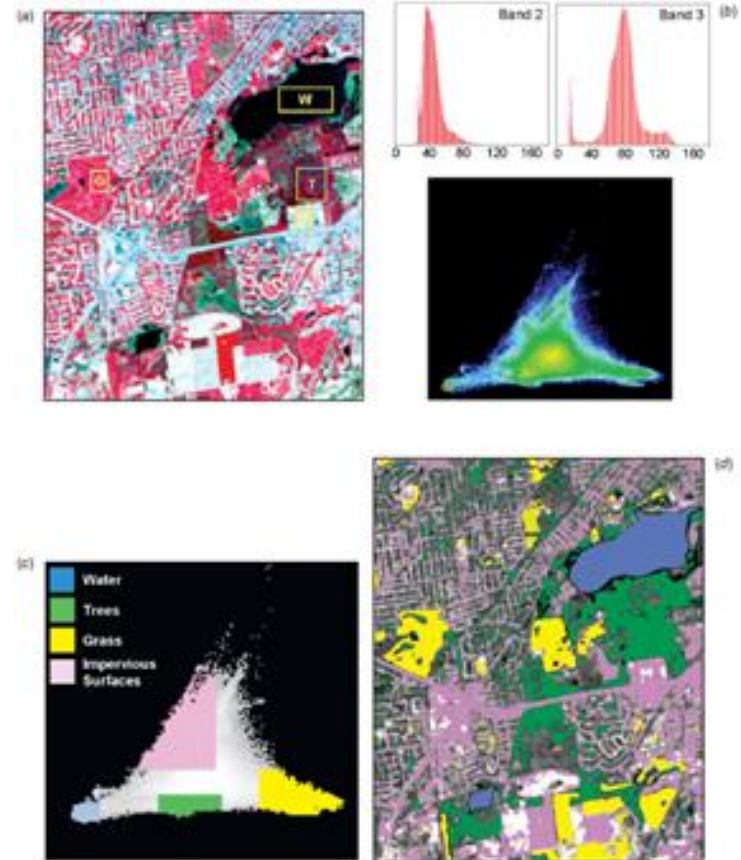
Artificial Intelligent programs, such as Artificial Neural Network or Fuzzy logic can be used very Effectively here.

# Chapter 5: "Image Classification"

## The Output Stage:

The value of any image classification is eventually dependent on the production of some kind of output products that effectively convey the interpreted information to its end users in a convenient & clear format.

There are three general formats that are commonly used to represent classified scene to end users. These are; (1) graphic or map products, (2) tabular of area statistics, & (3) digital data files & GIS.



# *Chapter 5: "Image Classification"*

## *Part 3 out of 3*

### *Training Sets Selection:*

The overall objective of the training process is to assemble sets of statistics that describe the spectral response pattern for each land cover type in the image.

Training effort, required in both supervised & unsupervised classifications, & is both science & art.

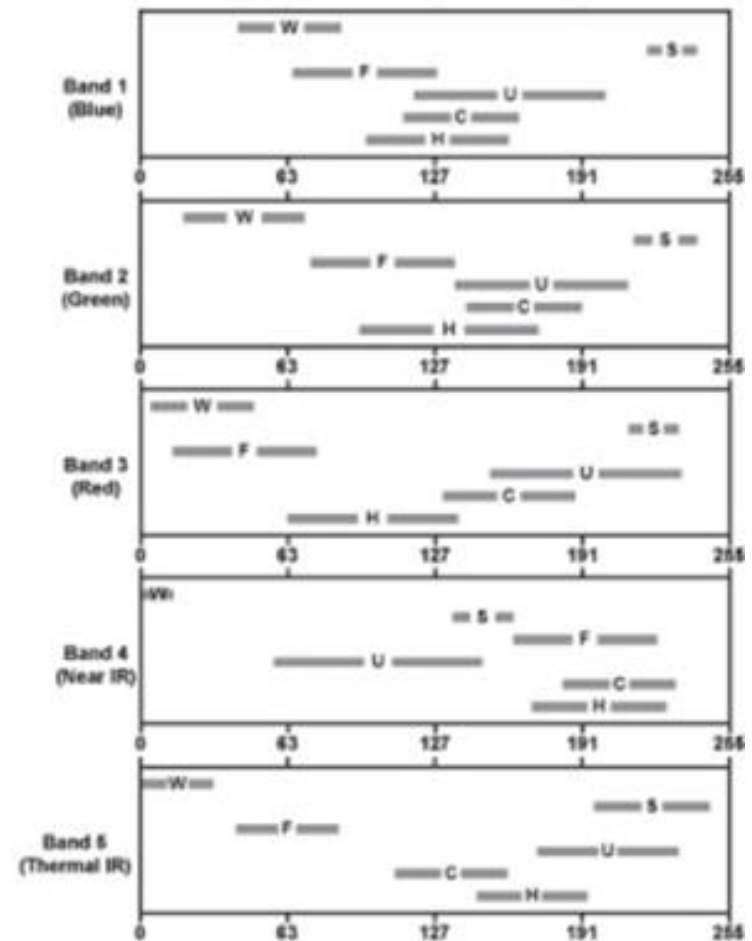
Training effort, requires a close interaction between the analyst & the image. The quality of the training process determines the success of the entire classification stage.

# Chapter 5: "Image Classification"

## Training Sets Selection: (continue)

Training data must be both representative & complete. This means that the analyst must develop training statistics for all spectral classes for each land cover type.

The quality of the data in each training set is assessed & the spectral separability between these training sets is studied.



# Chapter 5: "Image Classification"

## Training Sets Selection: (continue)

TABLE 7.1 Portion of a Divergence Matrix Used to Evaluate Pairwise Training Class Spectral Separability

Spectral Class <sup>a</sup>	W1	W2	W3	C1	C2	C3	C4	H1	H2 ...
W1	0								
W2	1185	0							
W3	1410	680	0						
C1	1997	2000	1910	0					
C2	1953	1890	1874	860	0				
C3	1980	1953	1930	1340	1353	0			
C4	1992	1997	2000	1700	1810	1749	0		
H1	2000	1839	1911	1410	1123	860	1712	0	
H2	1995	1967	1935	1563	1602	1197	1621	721	0
⋮	⋮								

<sup>a</sup>W, water; C, corn; H, hay.

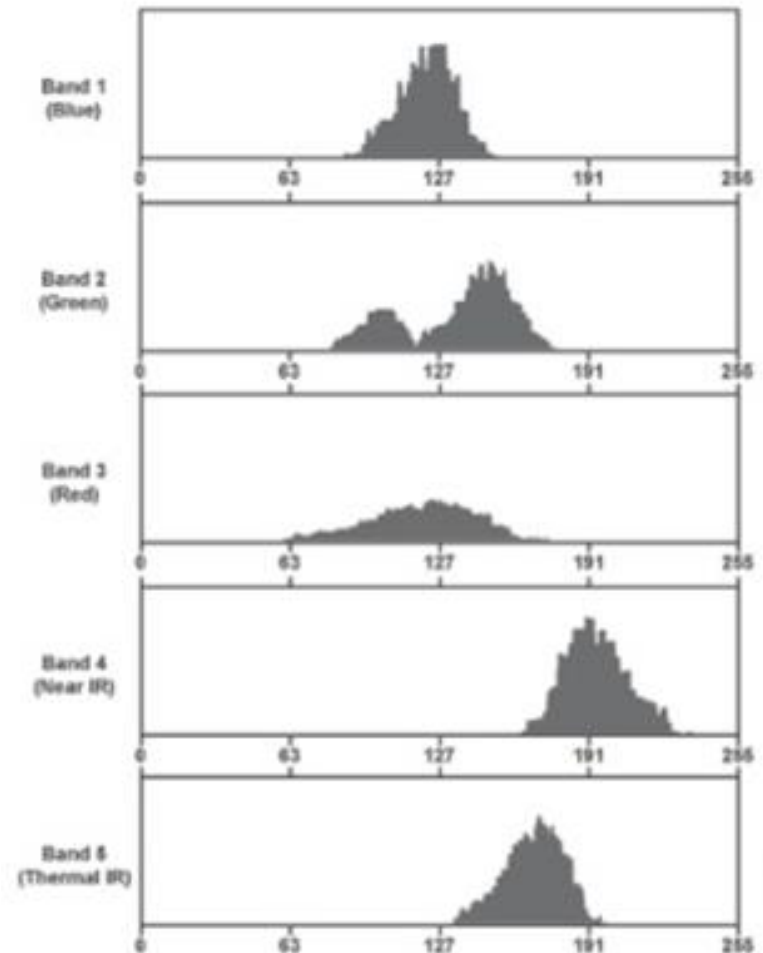
# Chapter 5: "Image Classification"

## Training Sets Selection: (continue)

The data in each training set must be normally distributed & spectrally pure.

Training sets that might be merged or deleted are identified.

The need to obtain additional training sets for poorly represented spectral classes is also addressed.



# *Chapter 5: "Image Classification"*

## *Training Sets Selection: (continue)*

*Training sets refinement process might involve one or more of the following of analyses;*

- 1. Graphical representation of the spectral response patterns.*
- 2. Quantitative expression of category representation.*
- 3. Self-classification of training sets data.*
- 4. Interactive preliminary classification.*
- 5. Representative sub-scene classification.*

*In general, the training set refinement process is normally an iterative procedure until they are sufficiently spectrally separable*



# *Chapter 5: “Image Classification”*

## *Artificial Intelligence in Image Classification:*

*Artificial Intelligence, (AI);*

*AI is the theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception & decision-making.*

*AI can come in a different methods & algorithms such as Artificial Neural Network, (ANN), or Fuzzy Logic.*

*ANN & Fuzzy Logic, can be used directly to classify a digital image or as a combined with other classification methods like Pixel Based & Object Based classification methods.*

# *Chapter 5: "Image Classification"*

## *Artificial Intelligence in Image Classification: (continue)*

*Artificial Neural Network, (ANN);*

*Artificial Neural Network is an information processing model that is inspired by the way biological nervous systems, such as the brain, process information.*

*ANN can come in a different methods & algorithms most of which will have an input layer, an out layer, & some other layers in-between.*

*Each layer in the ANN will have nodes that are connected to all nodes in the previous & next layers.*

# Chapter 5: "Image Classification"

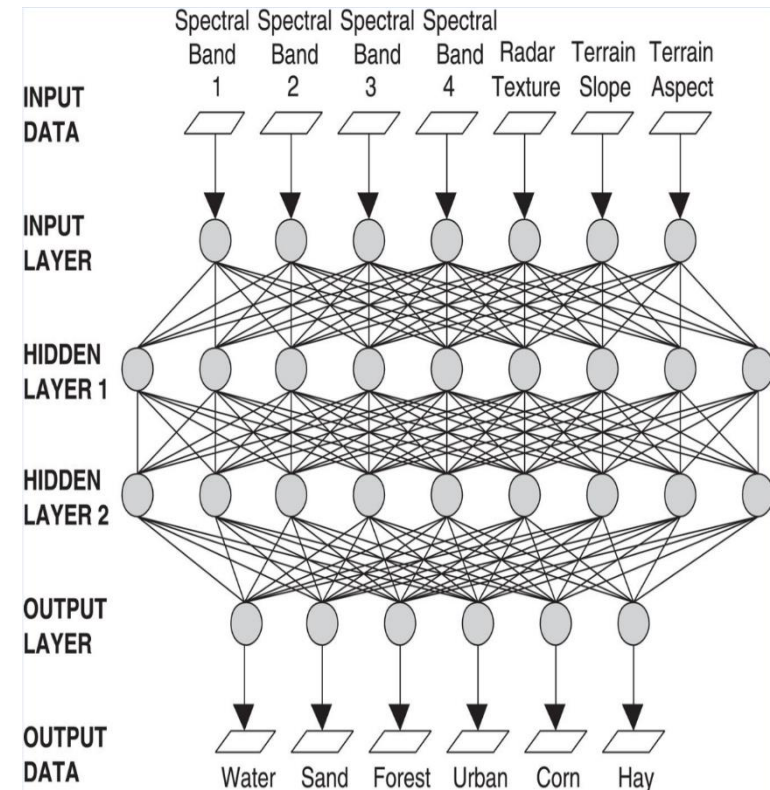
## Artificial Intelligence in Image Classification: (continue)

### Artificial Neural Network, (ANN); (continue)

Each node in the input layer is connected to one layer of data, (i.e. Blue band, green band, etc.).

Nodes in the output will show the result of the classification process.

Weights in the links between node in the ANN have to be adjusted with training data before it can be used effectively.



# *Chapter 5: "Image Classification"*

## *Artificial Intelligence in Image Classification: (continue)*

### *Fuzzy Logic;*

*Fuzzy logic, on the other hand, is an approach of computing based on "degrees of truth" rather than the usual "true or false" (1 or 0) Boolean logic.*

*Fuzzy logic can be used directly on the image,*

*Or it can be introduced to ML classifier to improve its accuracy by changing its design role from winner takes all to allow the use of uncertainty of the probability values to allow some interaction between classes that are closer to each other in nature.*

# *Chapter 5: “Image Classification”*

**That’s the end of Chapter 5**