Image Processing and Analysis

Classification

- Bands of a single image are used to identify and separate spectral signatures of landscape features.

- Ordination and other statistical techniques are used to “cluster” pixels of similar spectral signatures in a theoretical space.

- The maximum likelihood classifier is most often used.

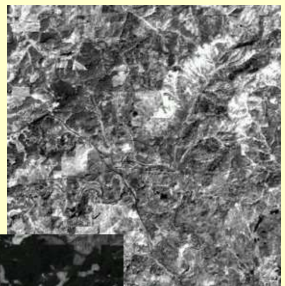
- Each cluster is then assigned to a category and applied to the image to create a classified image.

- The resulting classified image can now be used and interpreted as a map.

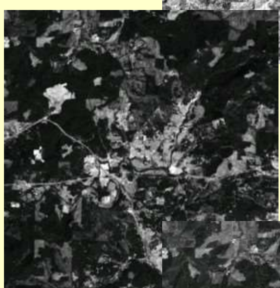
- *The resulting classified image will have errors!* Accuracy assessment is critical. Maps created by image classification should report an estimate of accuracy.

Image Processing and Analysis

3. Classification

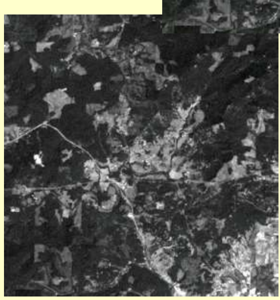


Band 4

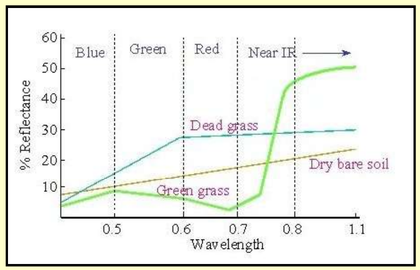


Band 3

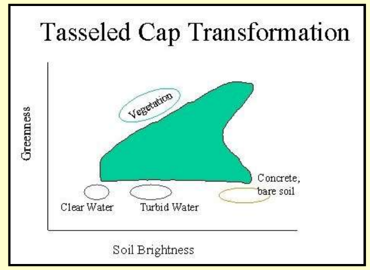
Band 2



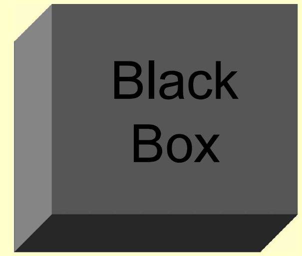
Band 1



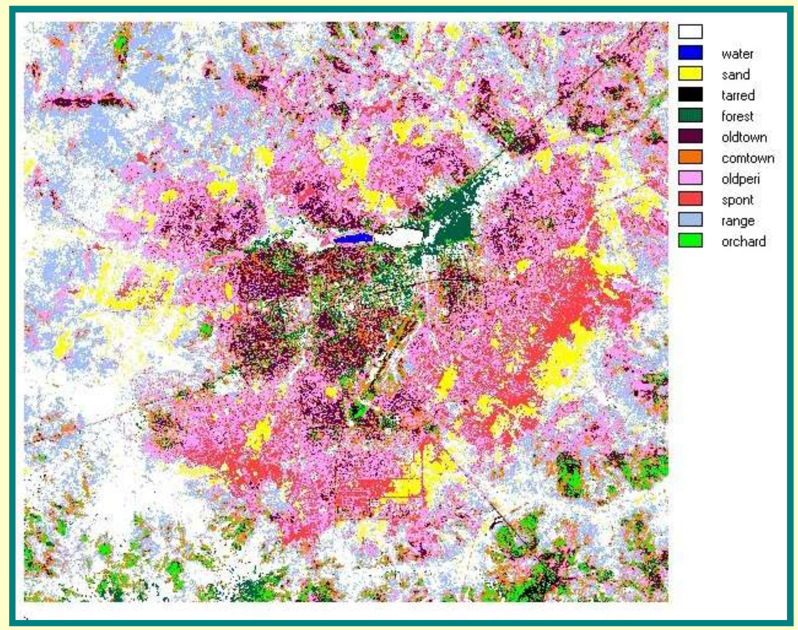
Spectral Signatures



Transformation / Clustering



Maximum Likelihood Classifier



Classified Image (Map)

Image Classification and Analysis (1/2)

- Introduction
- Sensors
- **Image analysis**
- Applications

<u>Aim</u> : to assign all pixels in the image to particular classes or themes

<u>2 classes</u> :

- information classes : categories of interest (water, forest)

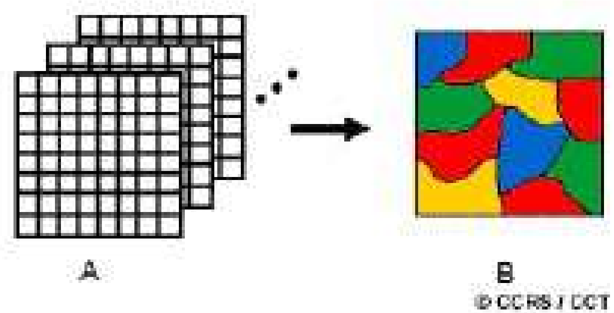
- spectral classes : group of uniform pixels (brightness)

<u>Objective</u> : to match the spectral classes to the information classes

<u>2 classification procedures</u> :

- Supervised classification

- Unsupervised classification



DIGITAL IMAGE CLASSIFICATION

It is the process of assigning pixels to classes. Usually each pixel is treated as an individual unit composed of values in several spectral bands.

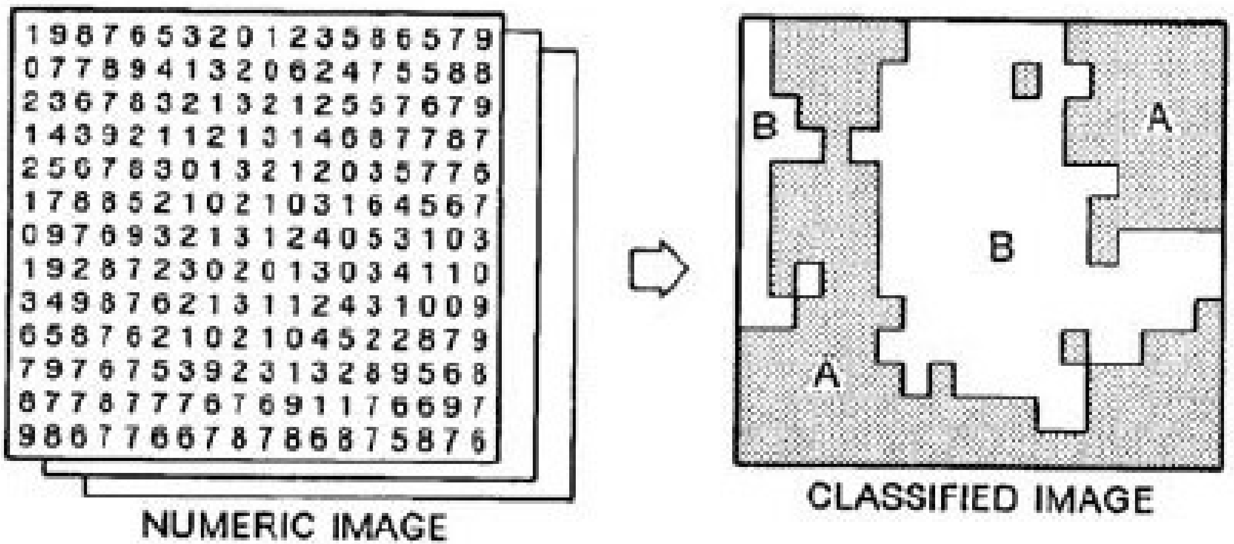


FIGURE 11.1. Numeric image and classified image. The classified image (right) is defined by examining the numeric image, then grouping together those pixels that have similar spectral values. Here class "A" is formed from bright pixels (values of 6, 7, 8, and 9), and class "B" is formed from dark pixels (values of 0, 1, 2, and 3). Usually there are many more classes and at least three or four spectral bands.

INFORMATIONAL CLASSES AND SPECTRAL CLASSES

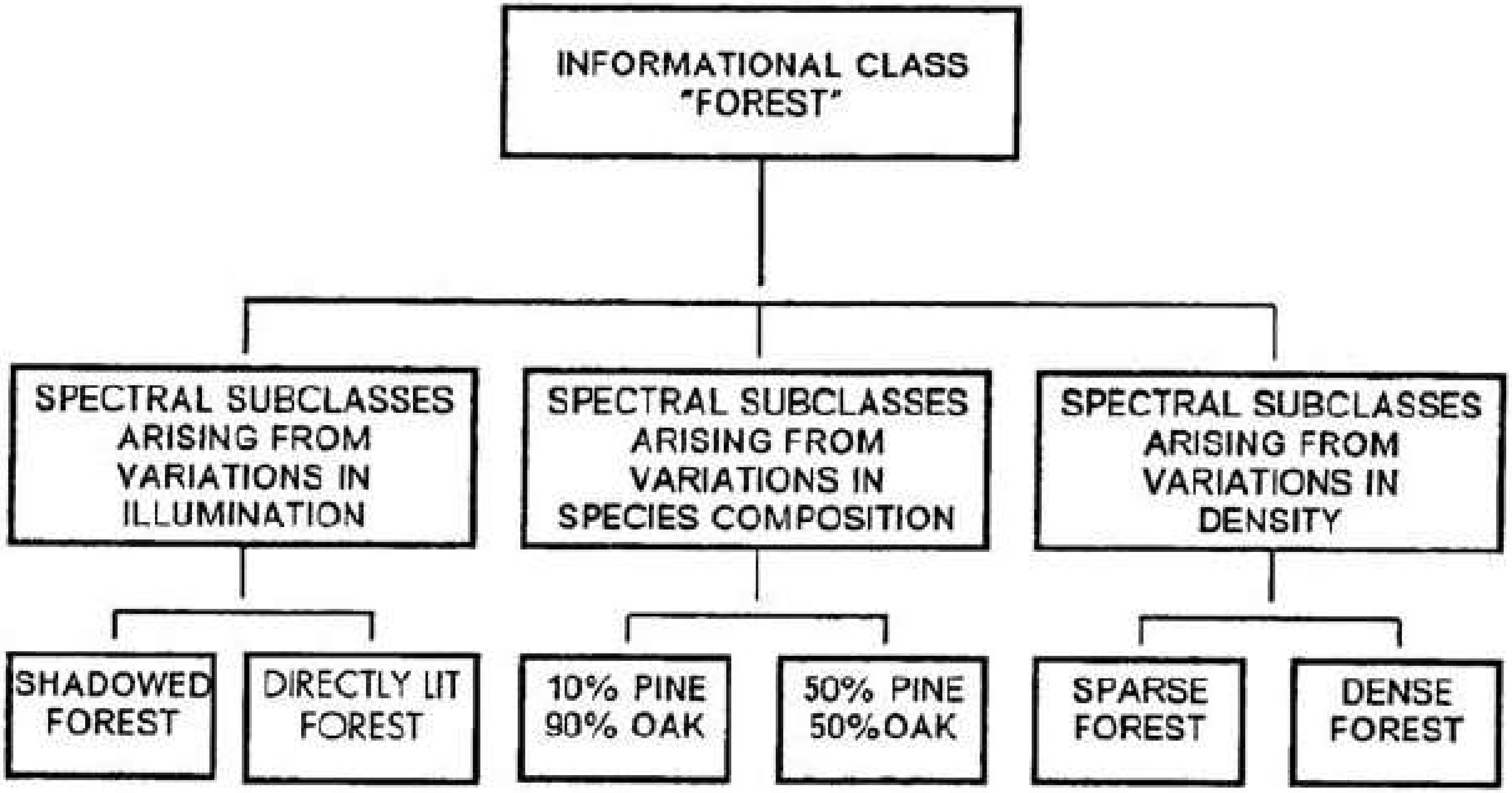


FIGURE 11.4. Spectral subclasses.

Image Classification

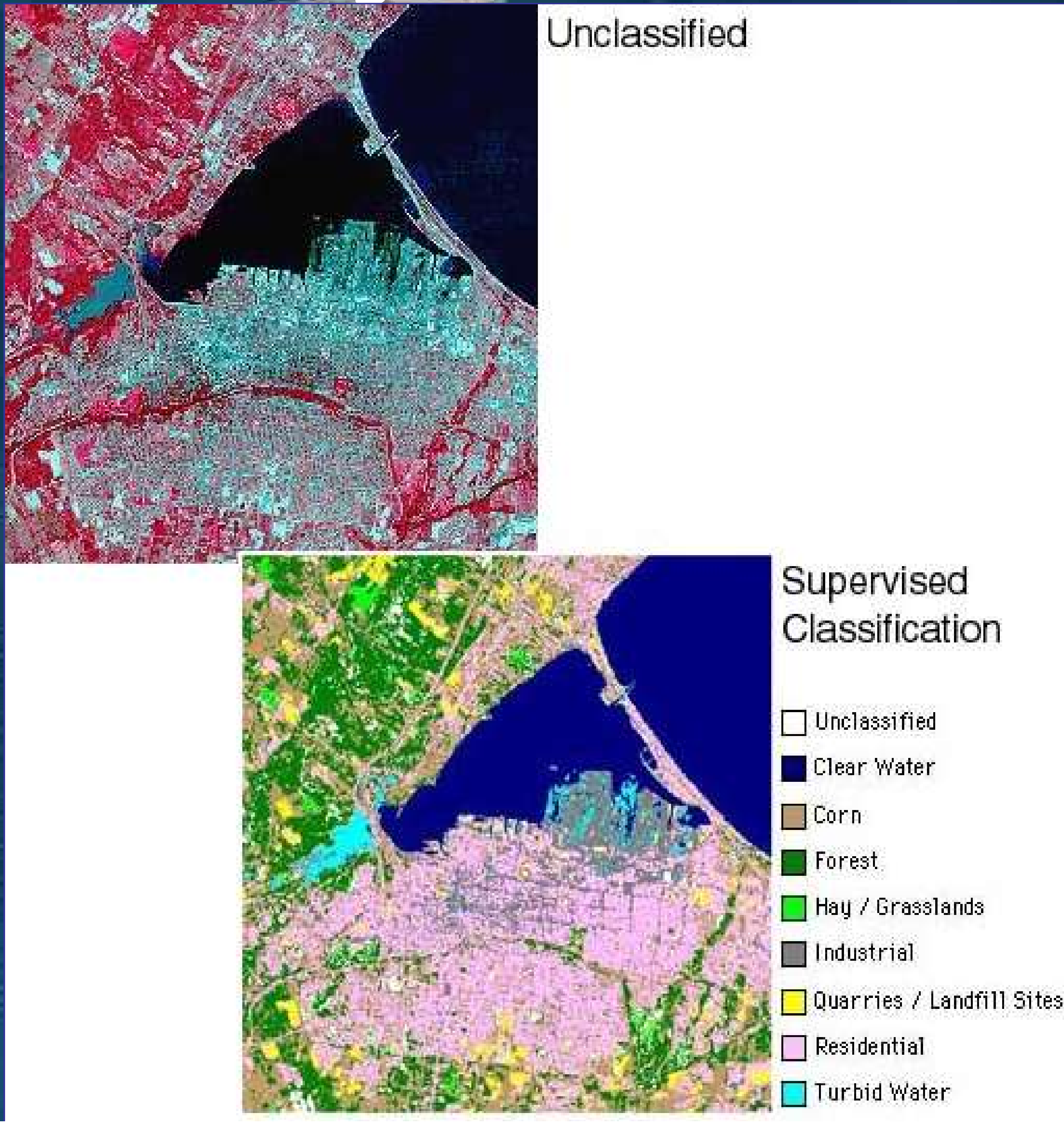
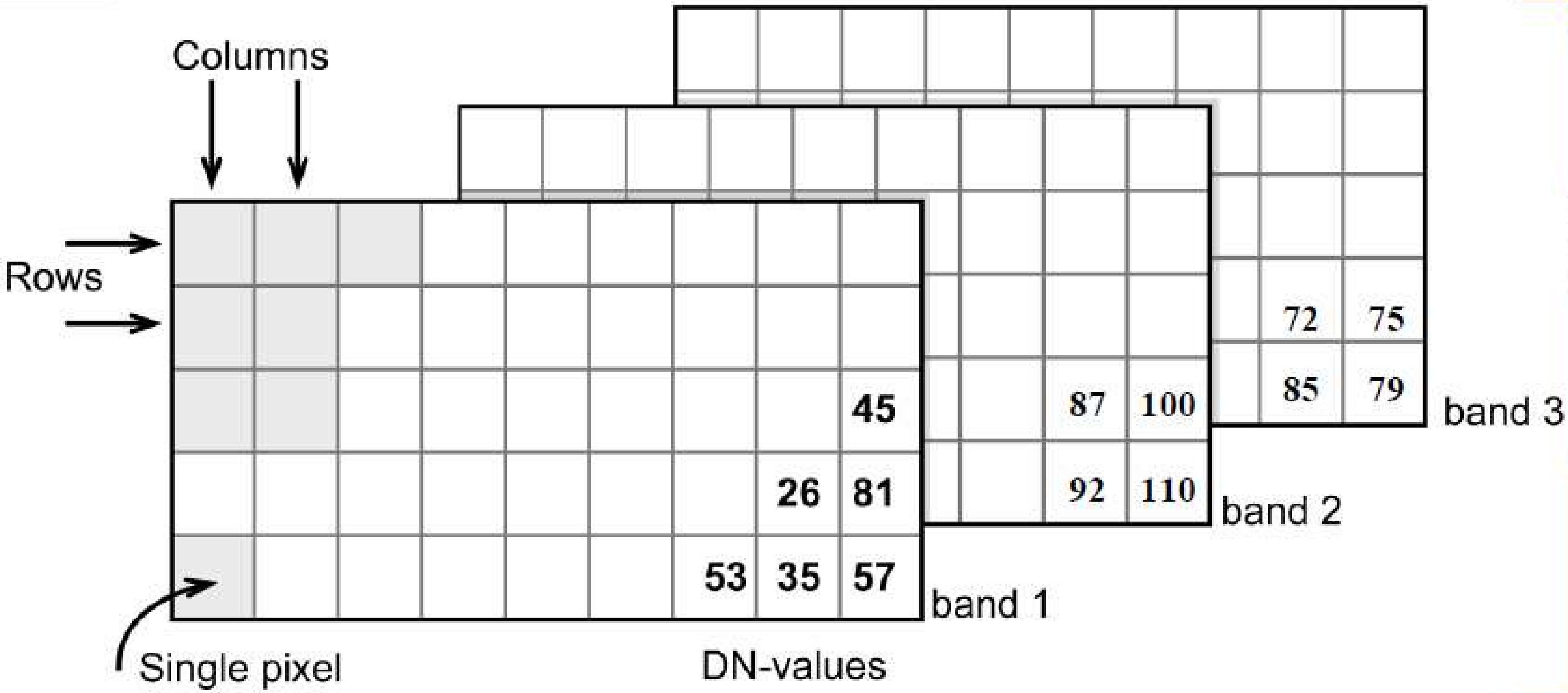
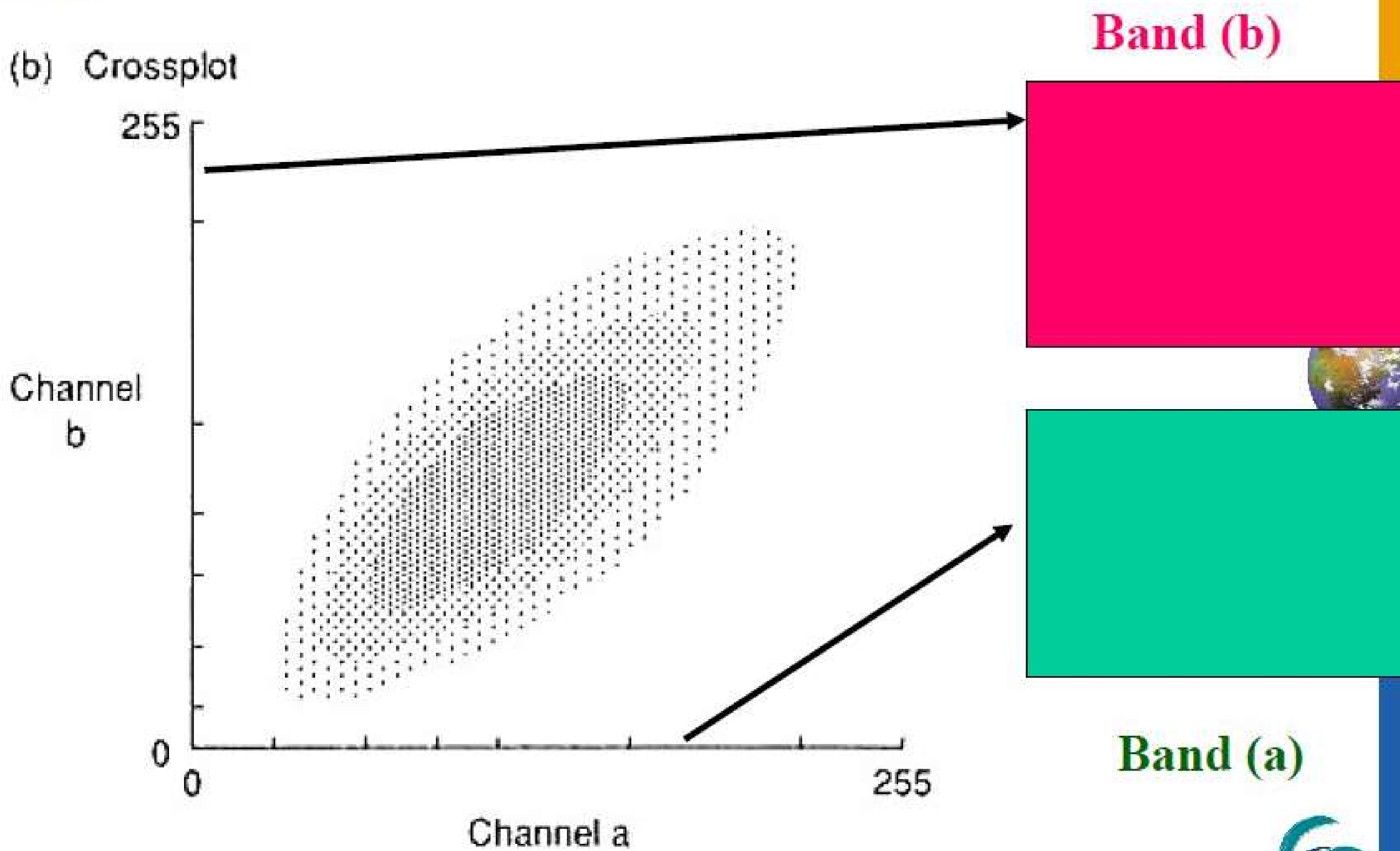


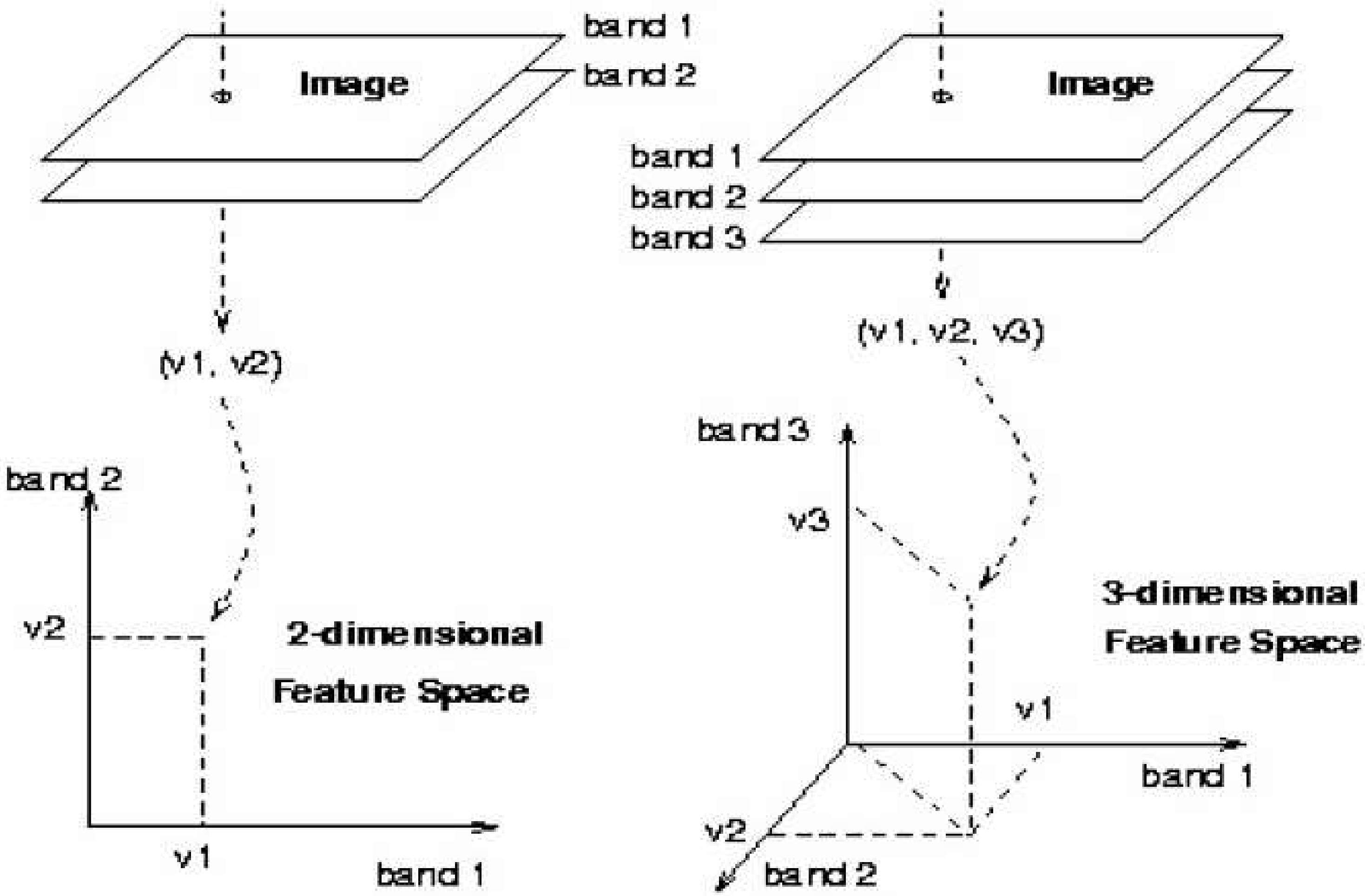
Image Space


Columns
Rows
45
26
81
53
35
57
87
100
92
110
72
75
85
79
band 1
band 2
band 3
Single pixel
DN-values

Spectral Scatter Plot



Feature Space



Supervised Classification

Is a classifier which requires a training sample for each class. Then based on how "close" each pixel to be classified is to each training sample

SUPERVISED CLASSIFICATION

It can be defined as the process of using samples (training data) of known identity to classify pixels of unknown identity.

SUPERVISED APPROACH

- Based on spectral groupings
- Incorporates prior knowledge
- Maximum user interaction

Supervised Classification:

1. Reference data
2. Representation and randomness
3. Pure pixels and variability
4. Informational and spectral classes

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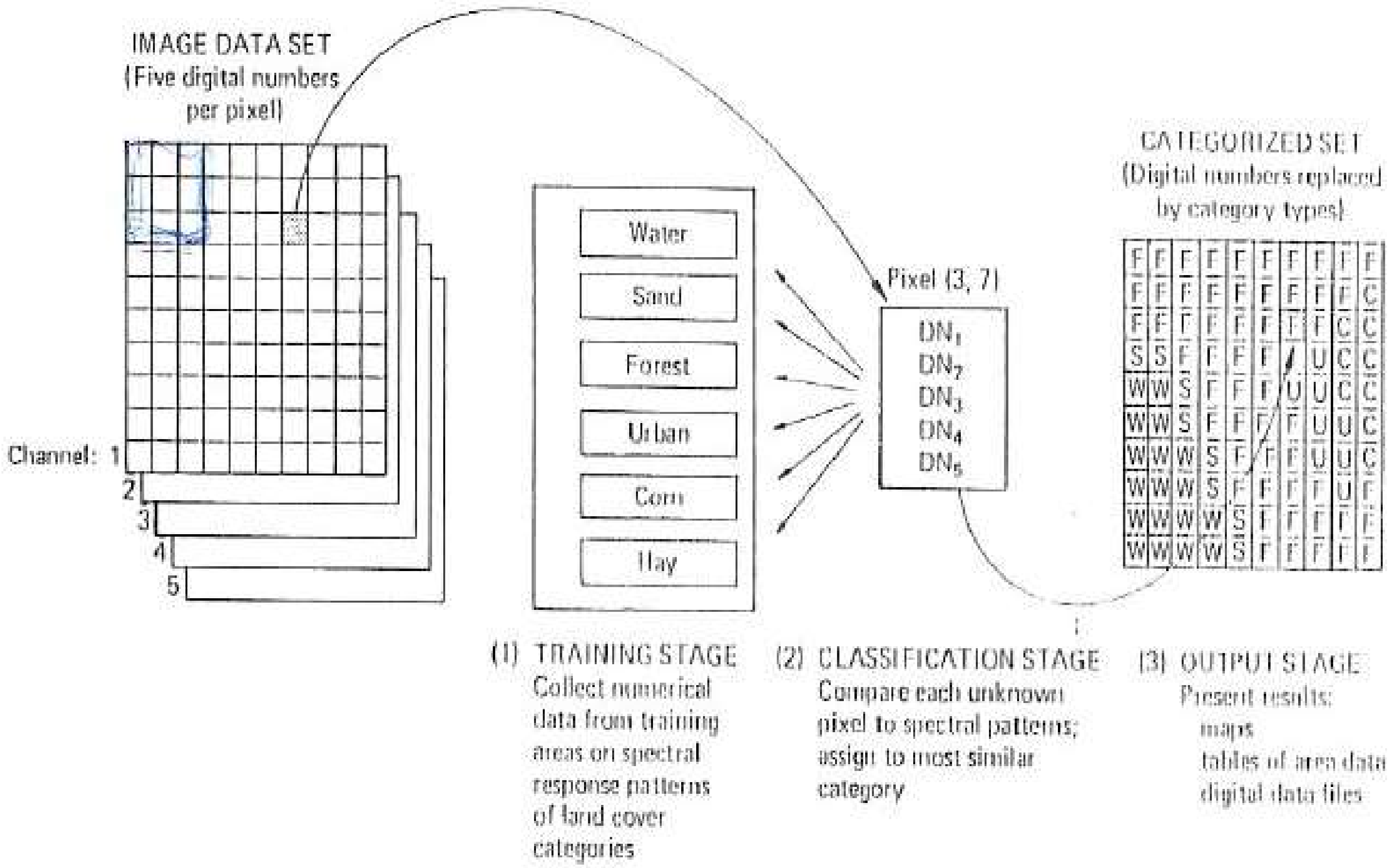
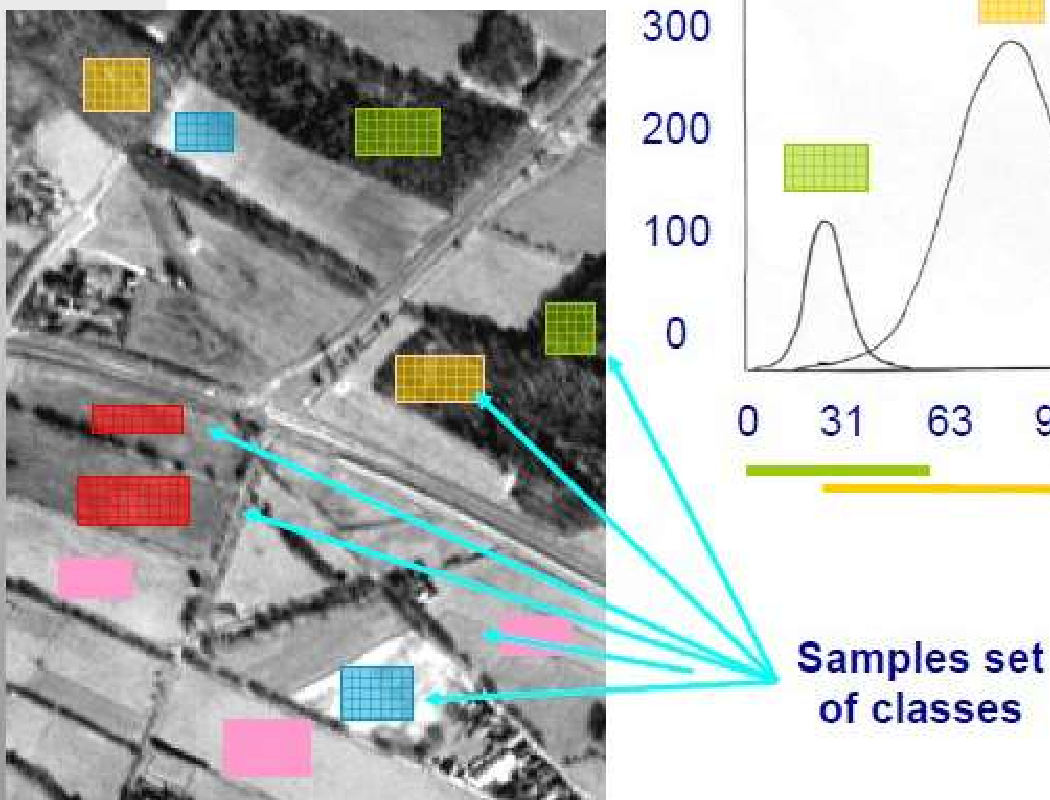
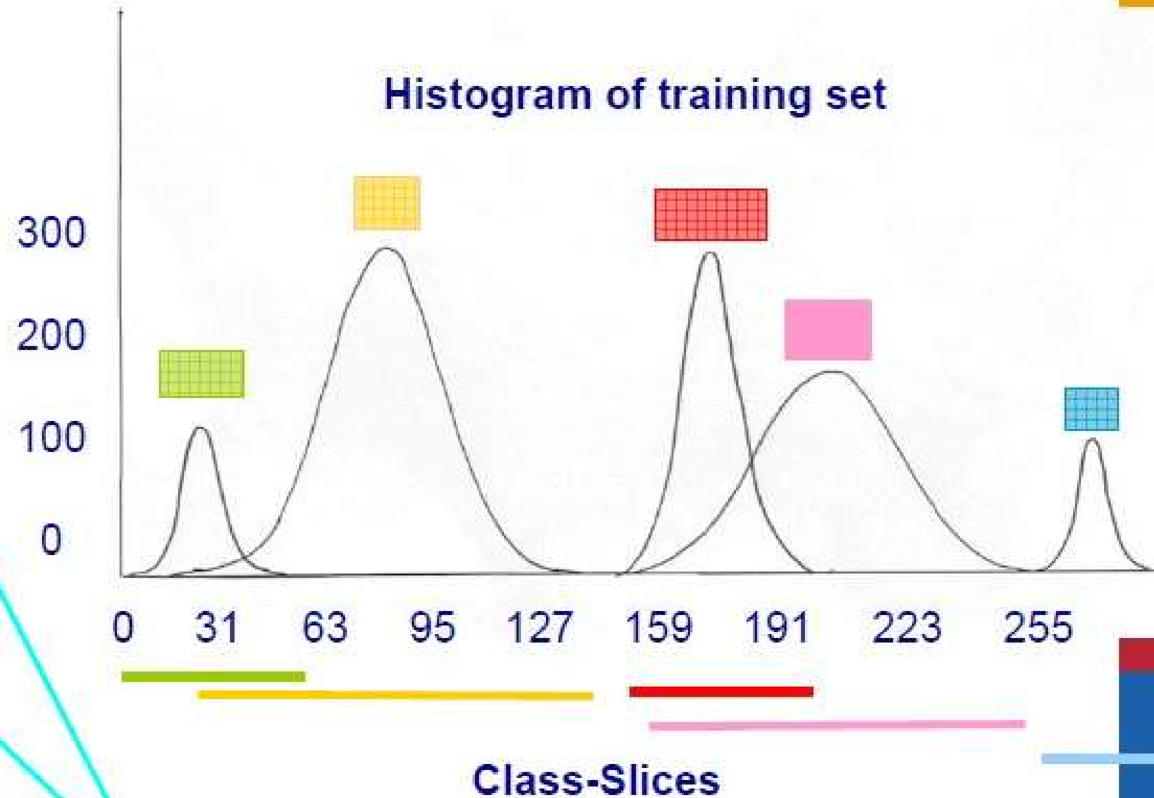


Basic steps in supervised classification.

Training samples

Ground-truth





In order to make the classifier work with thematic (instead of spectral) classes, some "*knowledge*" about the relationship between classes and feature vectors must be given.

Therefore, classifications methods are much more widely used, where the process is divided into **two phases: a training phase**, where the user "trains" the computer, by assigning for a limited number of pixels to what classes they belong in this particular image, followed by the **decision making phase**, where the computer assigns a class label to all (other) image pixels, by looking for each pixel to which of the trained classes this pixel is most similar.

During the training phase, the classes to be use are previously defined. About each class some "ground truth" is needed:

Guidelines for selecting training areas:

· **Training areas should be homogenous**. This can be tested by graphic histograms, numeric summaries, 2-band scatter plot for investigating separability of feature classes by pairs of bands, 3-D plot of 3-band feature space (if the softwareallows!).

· **One large 'uniform' training area per feature class is preferable** to several smaller training areas, though this must depend upon the degree of variability within each class from site to site, and degree of variability within individual site.

· **Easy to extract more than is needed**, and then examine site statistics before making decision.

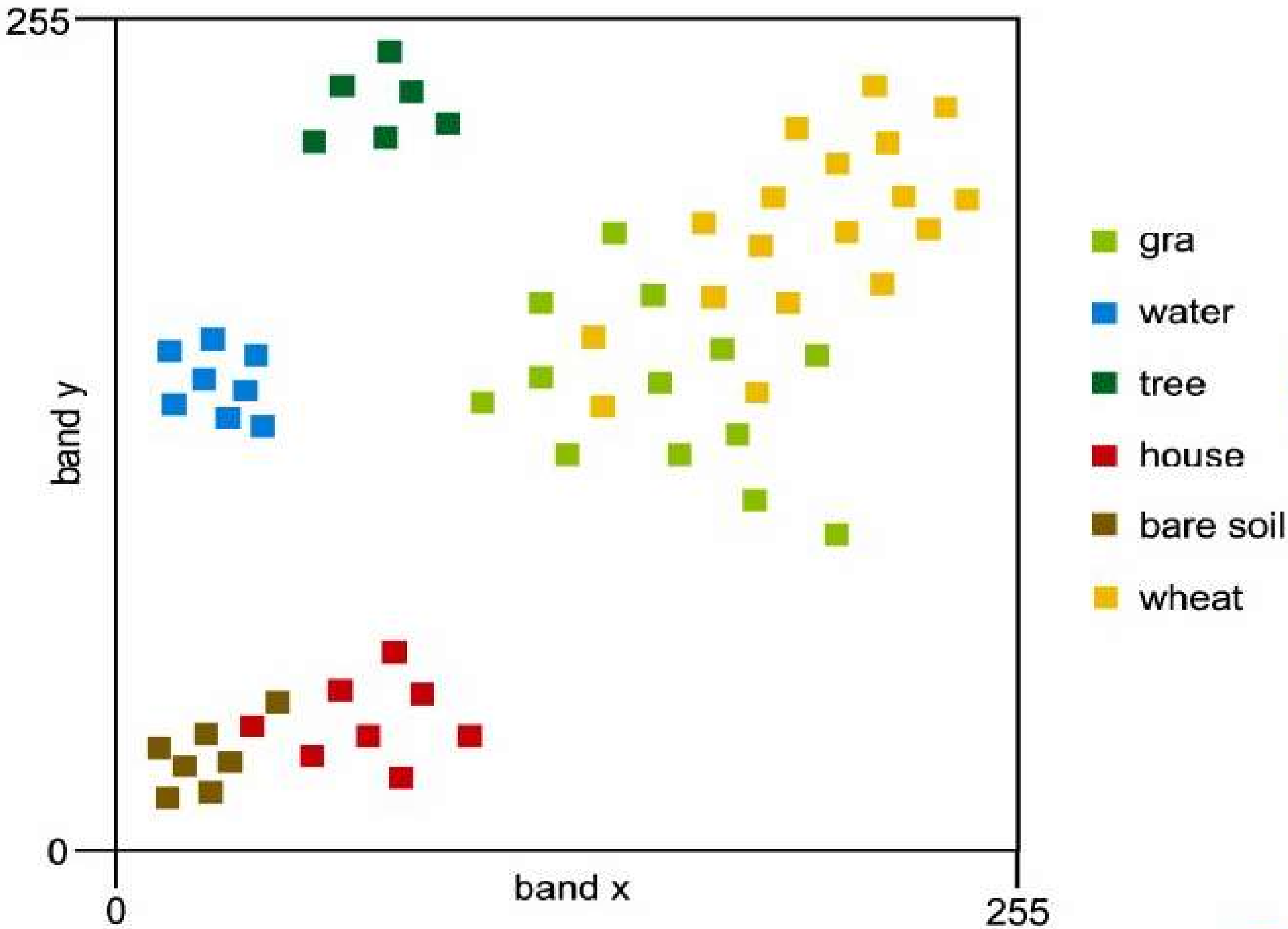
· **Each training area should be easily located in the image**: use a topographic map, nautical chart, or aerial photos to assist, though differential GPS observations may help.

· **If a smaller training area is necessary, then the minimum size is critical**. What should be the size of the training site?

· Note CCRS statement for MSS: individual training area should be minimum of **3 - 4 pixels East-West by 6 pixels North-South**.

· Others [e.g. Swain and Davis, IDRISI] state (10 x # bands used), e.g. area of 40 pixels if all four MSS bands used (or approx 6 pixels x 7 pixels).

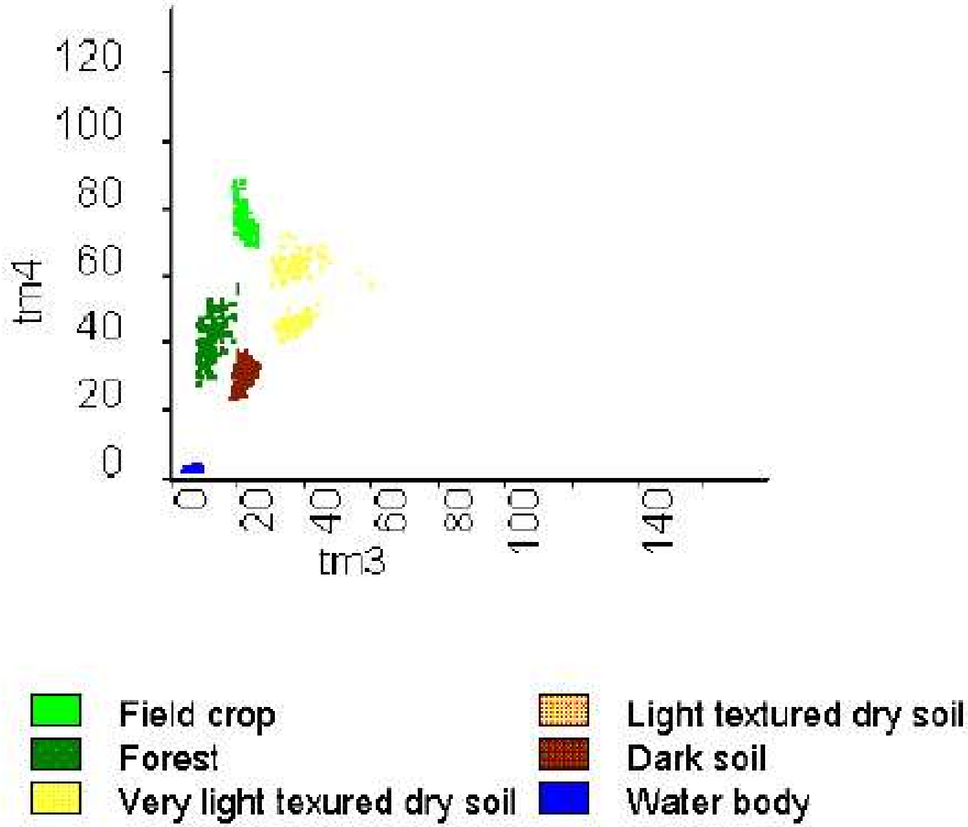
Feature Space



It is common to call the three bands as "*features*". The term features instead of bands is used because it is very usual to apply transformations to the image, prior to classification. They are called ***"****feature transformations*", their results ***"****derived features***"**. Examples are: Principal components,

In one pixel, the values in the (three) features can be regarded as components of a 3- dimensional vector, the feature vector. Such a vector can be plotted in a 3-dimensional space, called feature space. Pixels belonging to the same (land cover) class and having similar characteristics, end up near to each other in the feature space, regardless of how far they are from each other in the terrain and in the image. All pixels belonging to a certain class will (hopefully) form a cluster in the feature space.

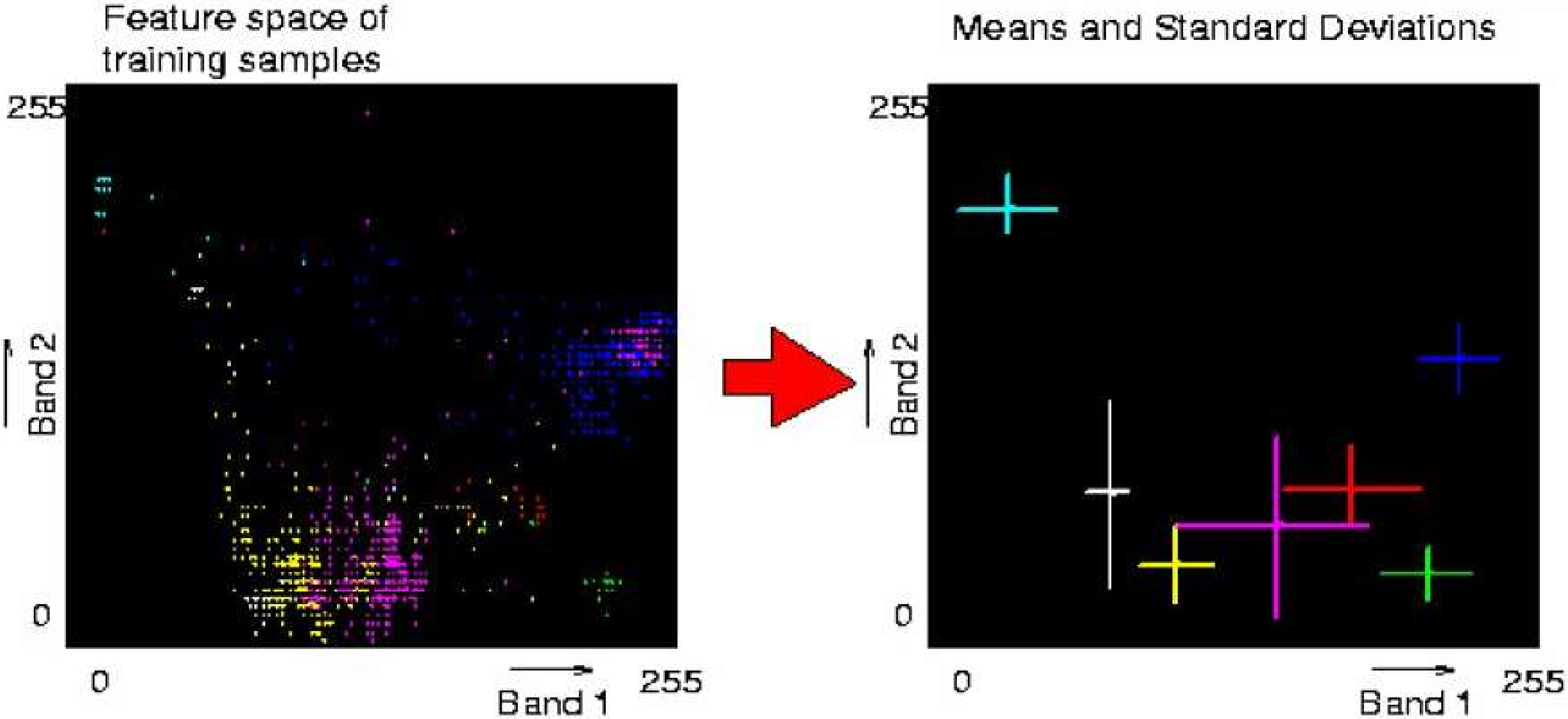
Training samples in a feature space



FEATURE SPACE

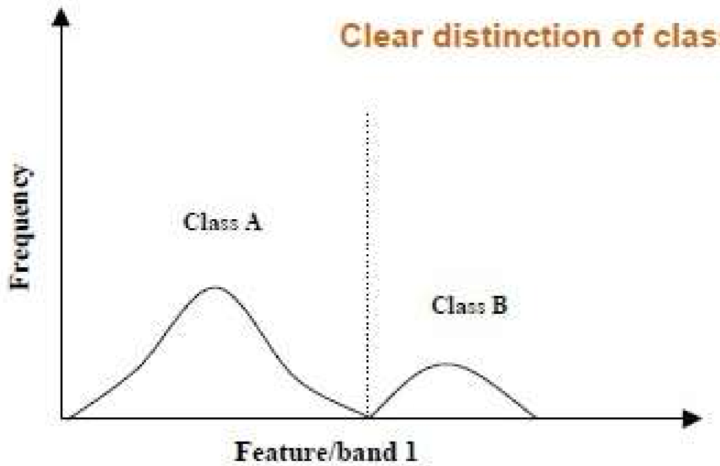
- two/three dimensional graph or scattered diagram
- formation of clusters of points representing DN values in two/three spectral bands
- each cluster of points corresponds to a certain cover type on ground

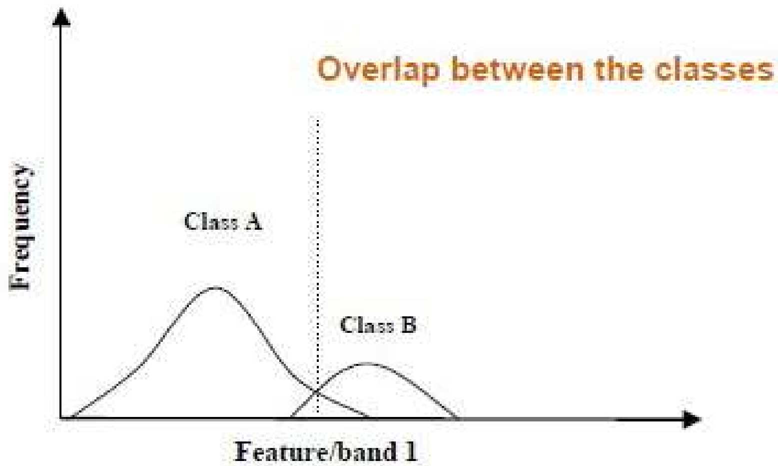
Statistics



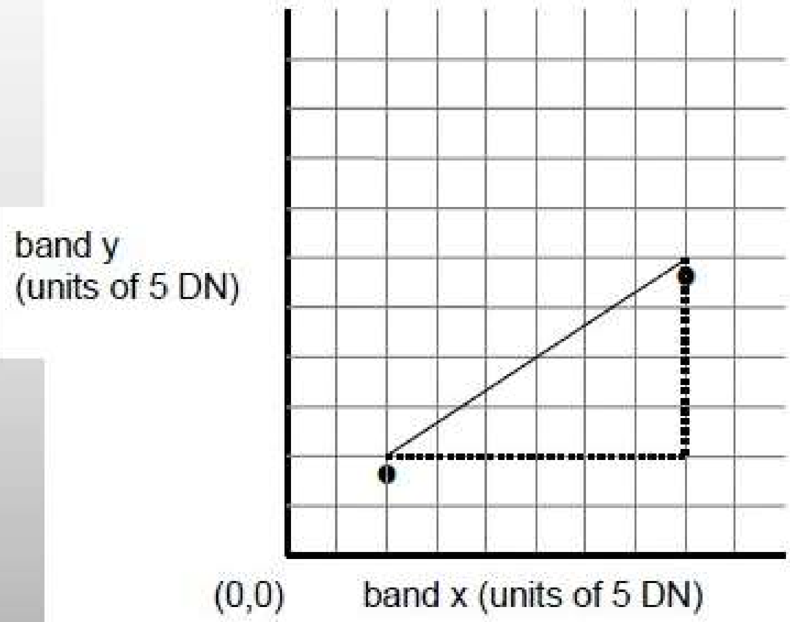
Collecting Class Statistics

Boundaries between clusters

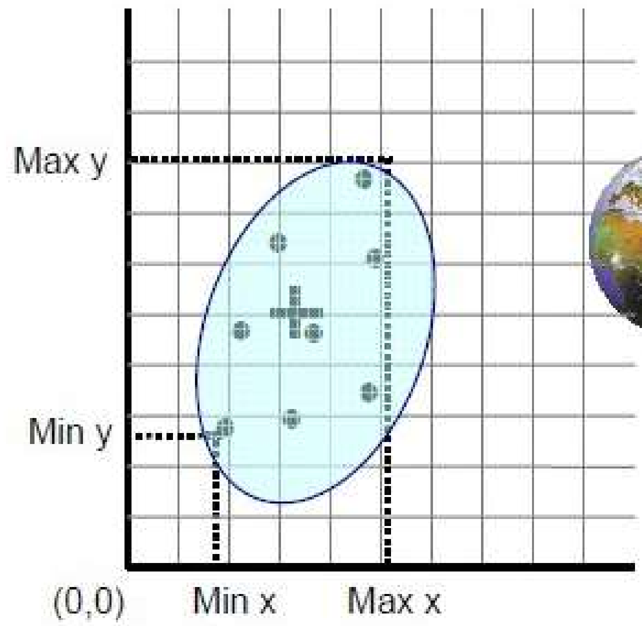




Distances and Clusters in Feature Space



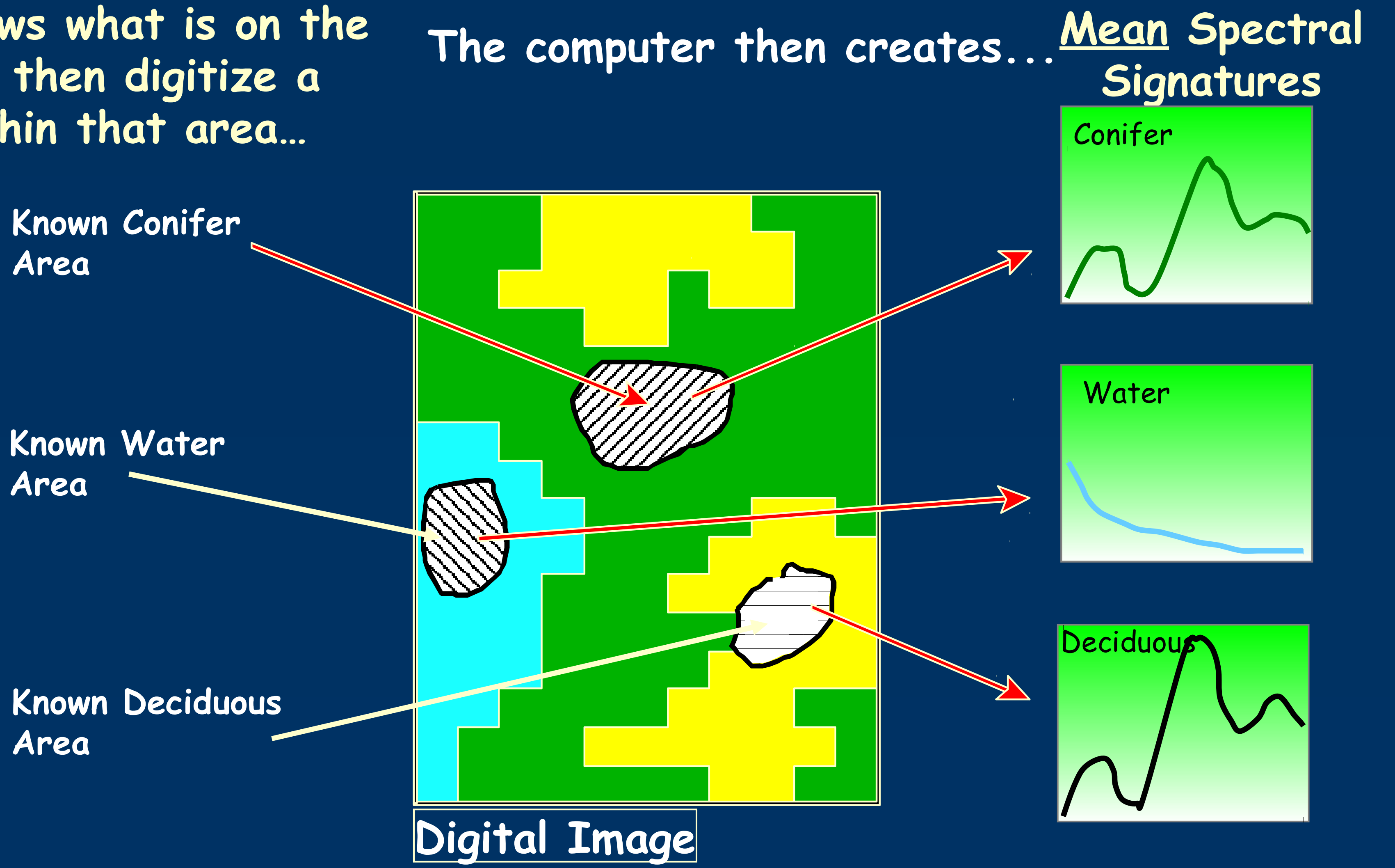
Euclidian distance



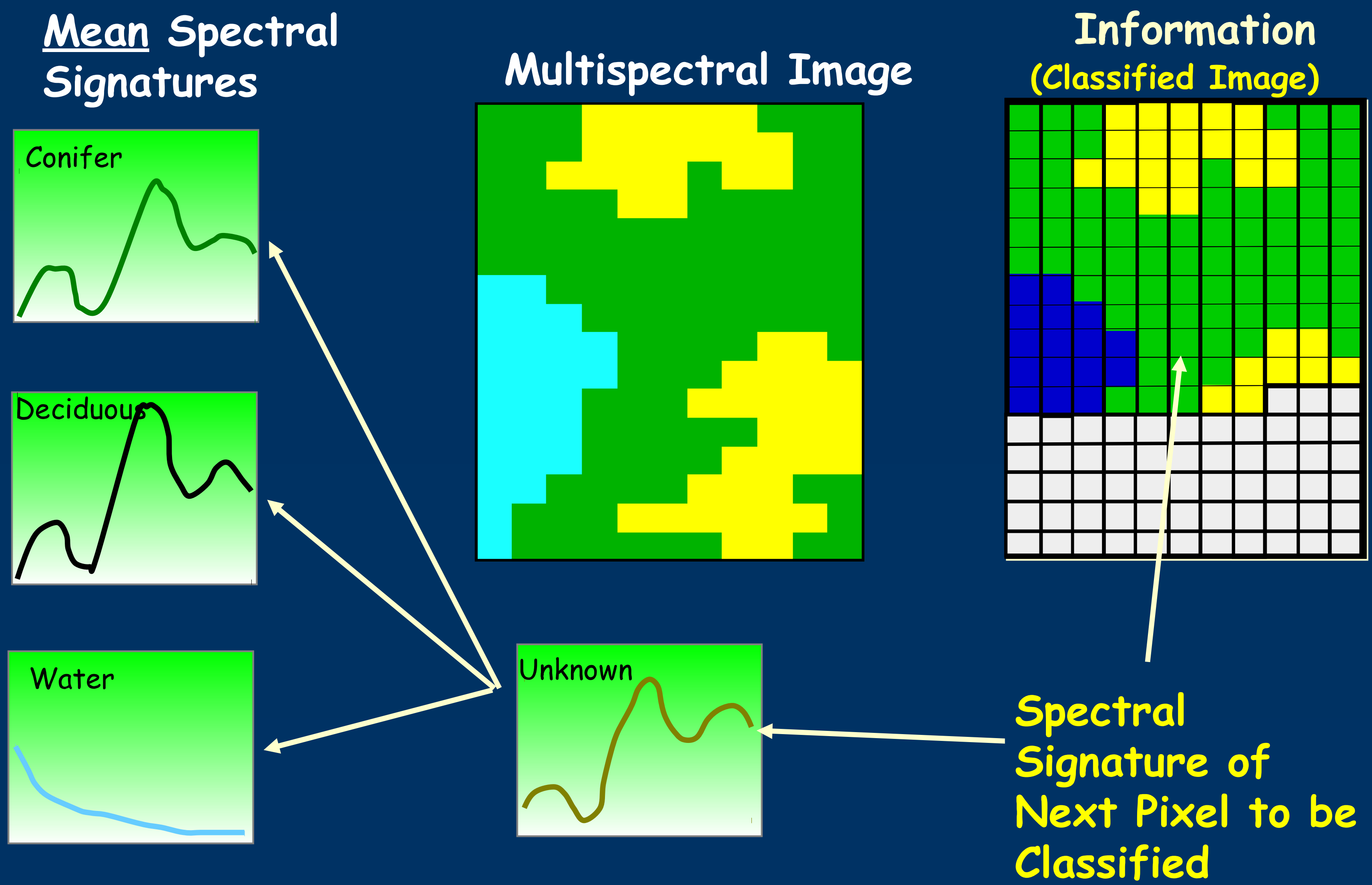
Cluster

Supervised Classification

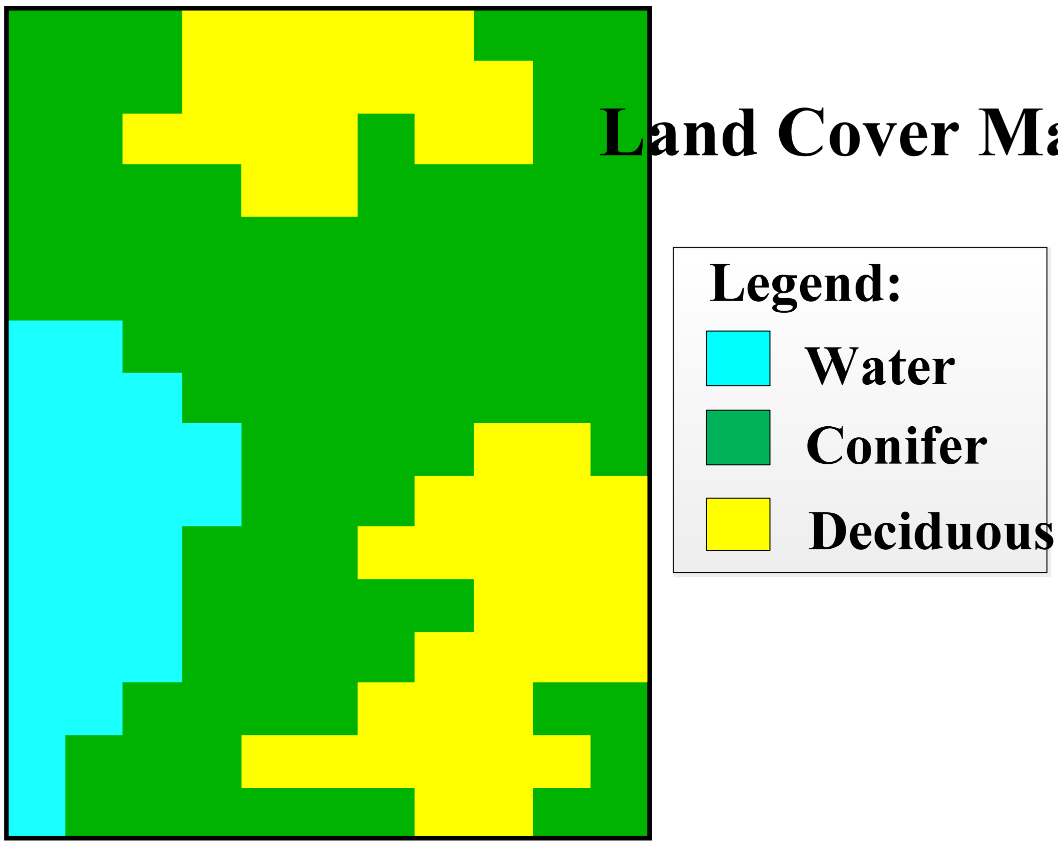
Supervised classification requires the analyst to select training areas where he/she knows what is on the ground and then digitize a polygon within that area…



Supervised Classification



The Result is Information--in this case a Land Cover map...



Unsupervised Classification

Cluster or Clustering

Is a classifier which does not compare pixels to be classified with training data. Rather, examine a large number of unknown data vectors and divided them into classes based on properties inherent to the data themselves.

UNSUPERVISED APPROACH

- Based on spectral groupings
- Considers only spectral distance measures
- Minimum user interaction
- Requires interpretation after classification

Unsupervised or Clustering

1. Questions:

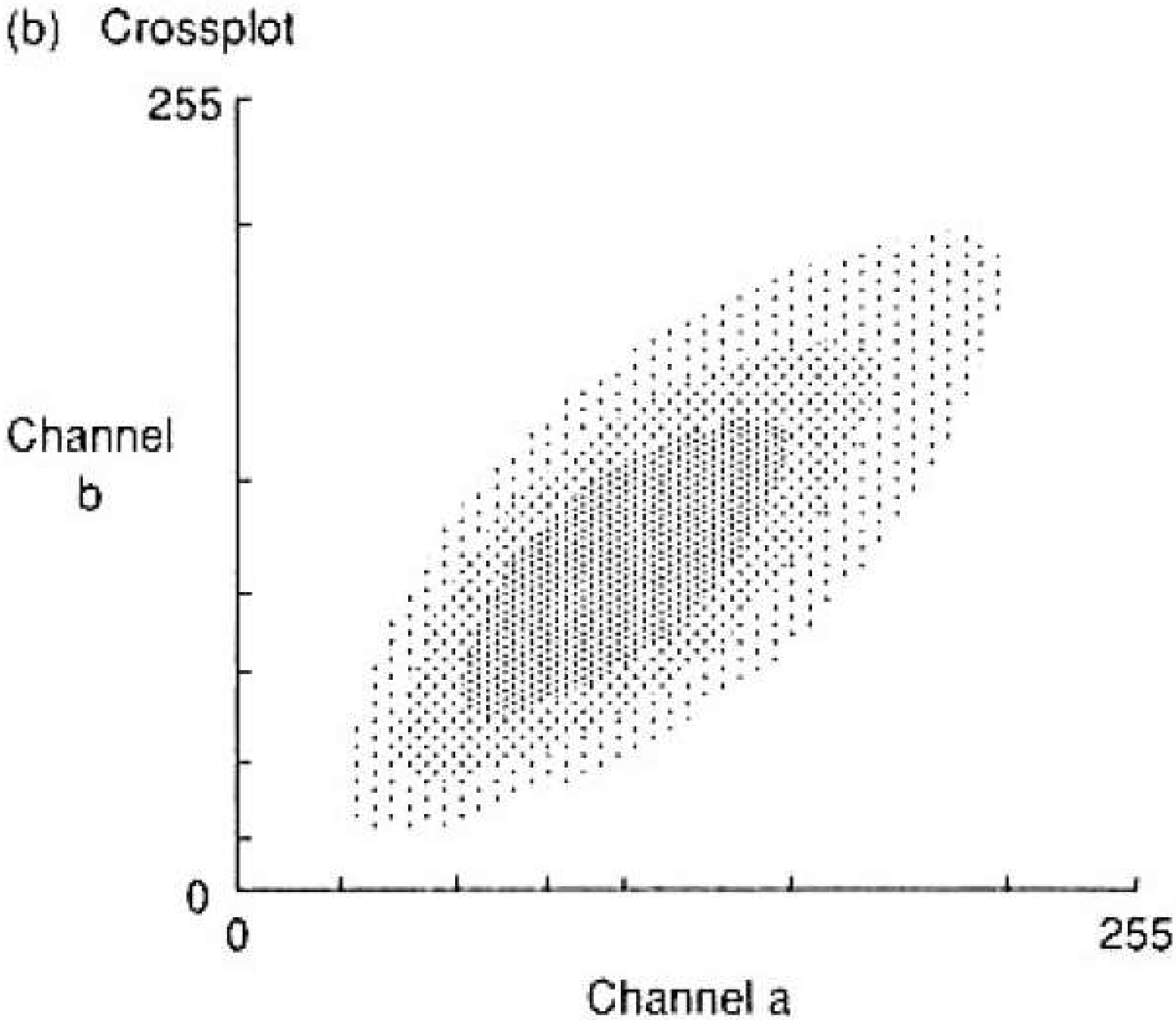
   a) Number of classes

   b) Number of bands

   c) Spectral Distance or radius in spectral space

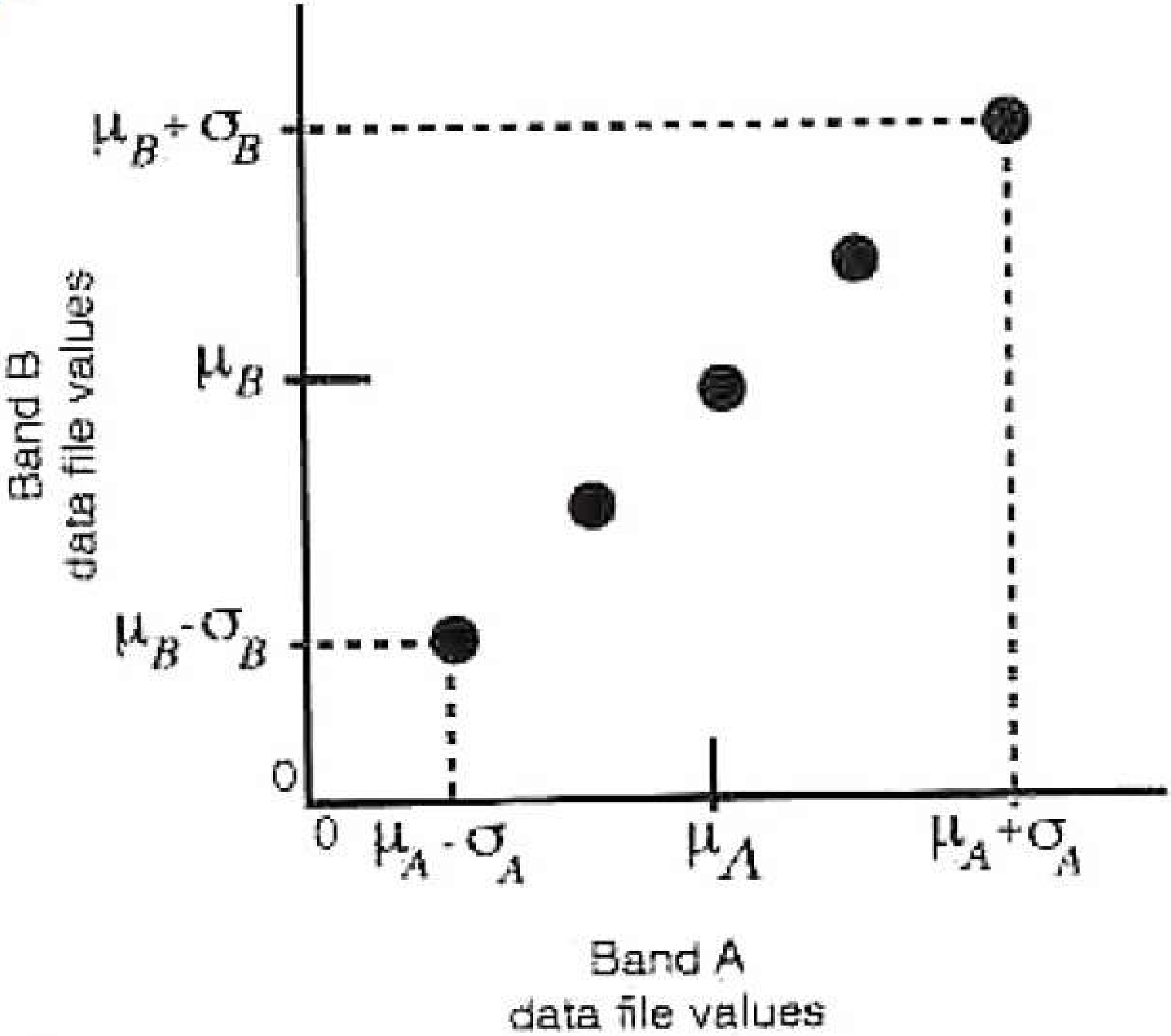
   d) Spectral space distance parameters when merging clusters

2. Spectral Plot of the whole image:

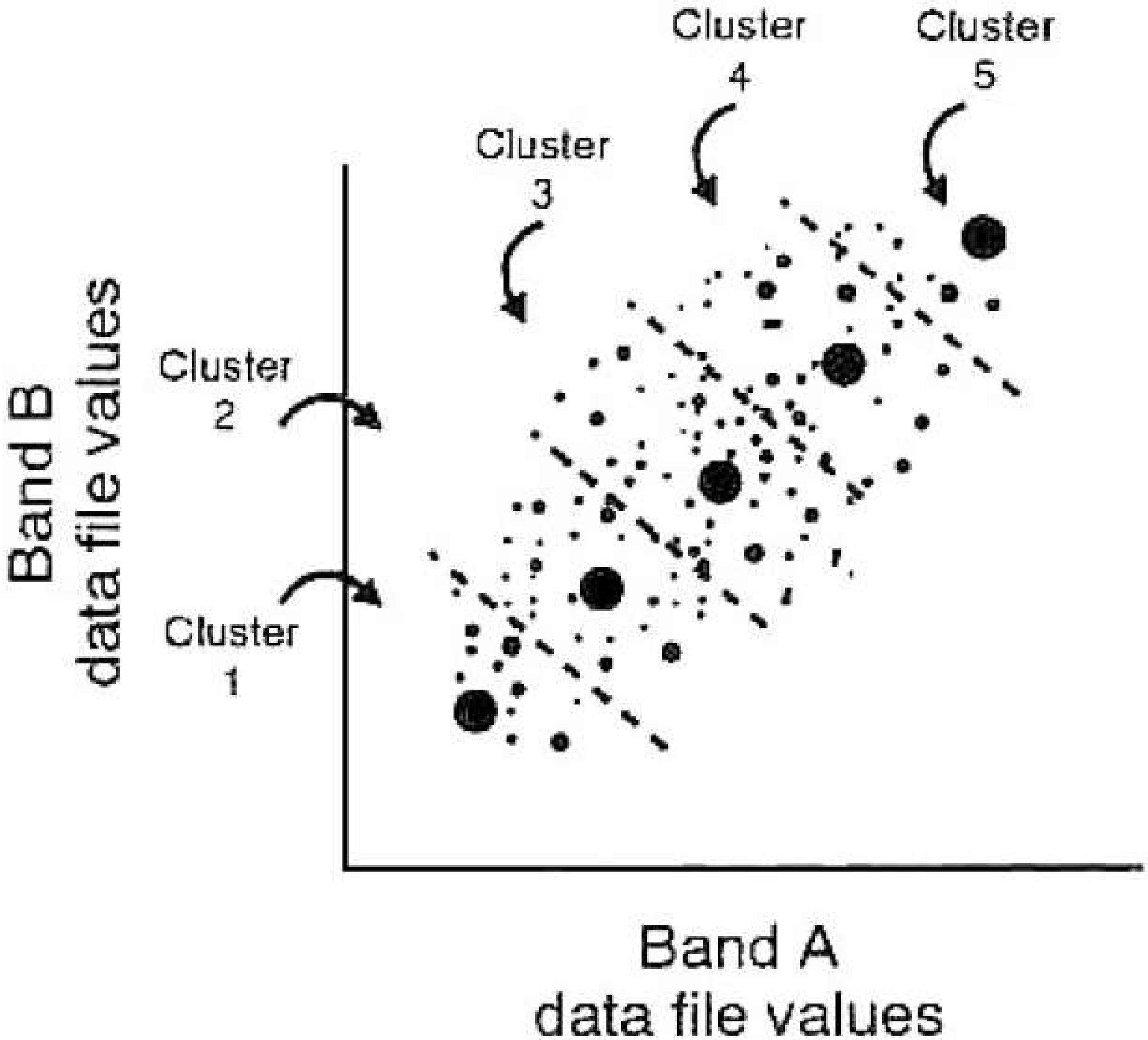


2005

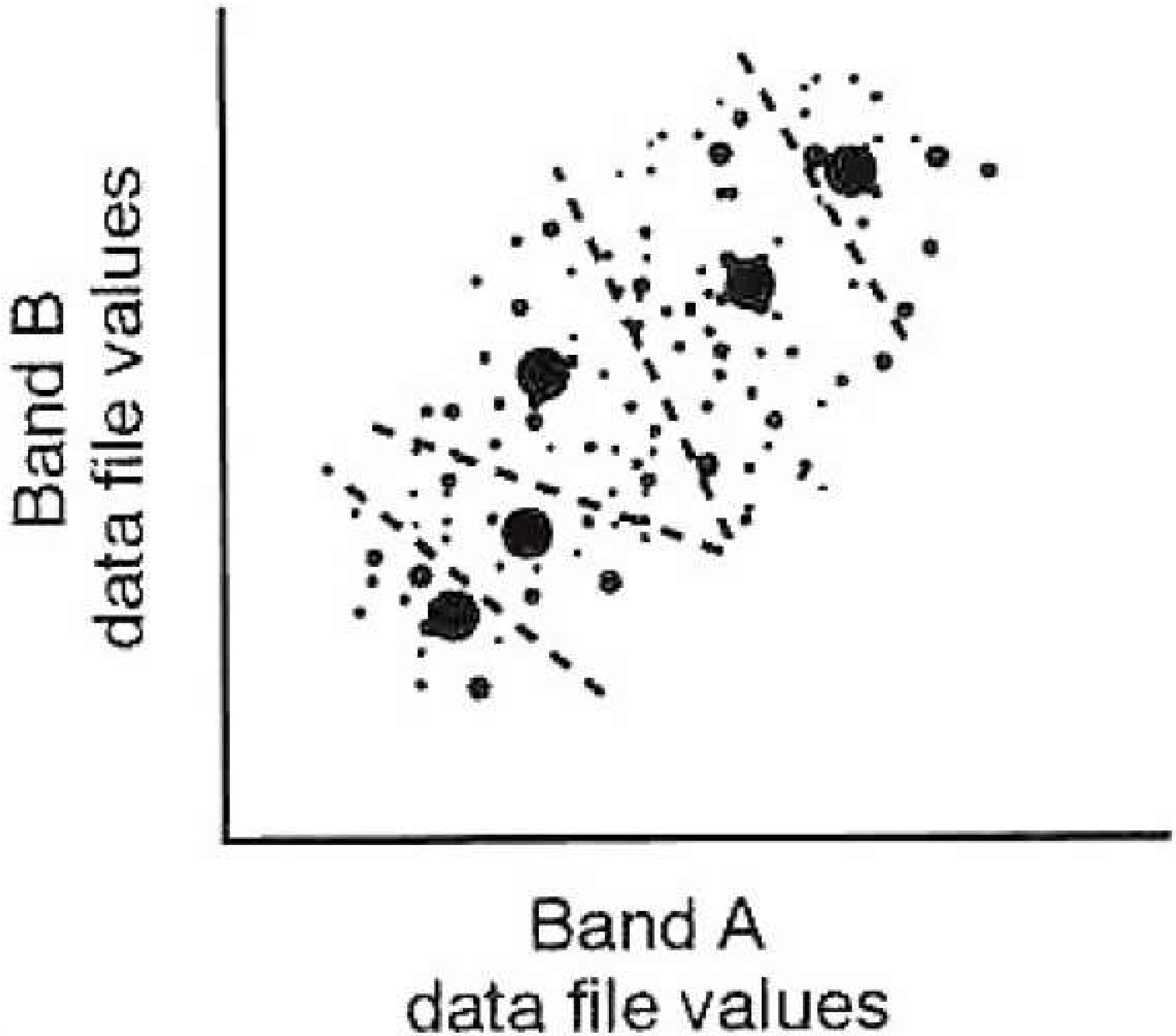
3. Initiate the classes centers:



4. Start separating (e.g. merging):



5. Iteration stage:



6. Define the statistics of the classes:

Mean

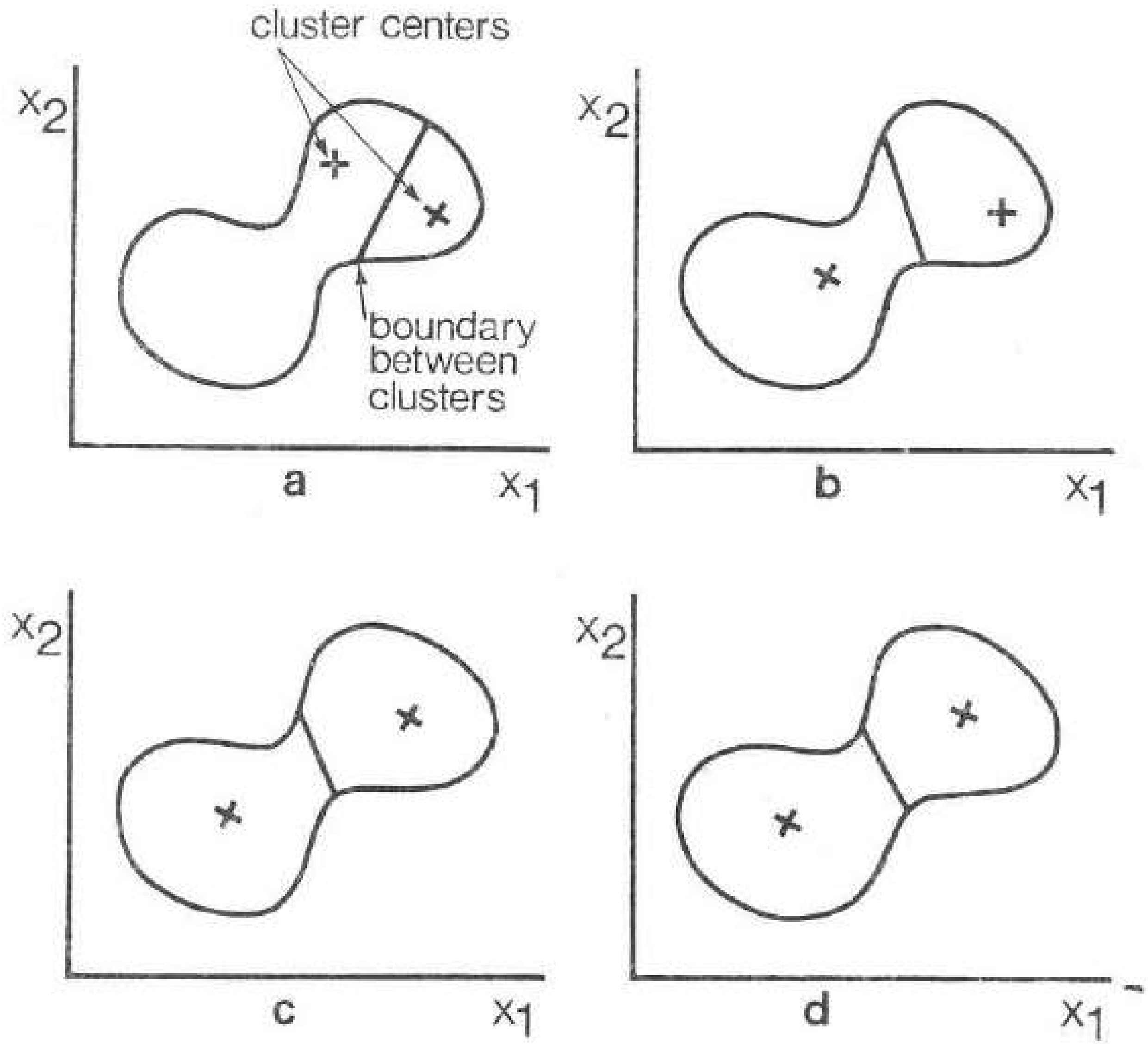
Variance

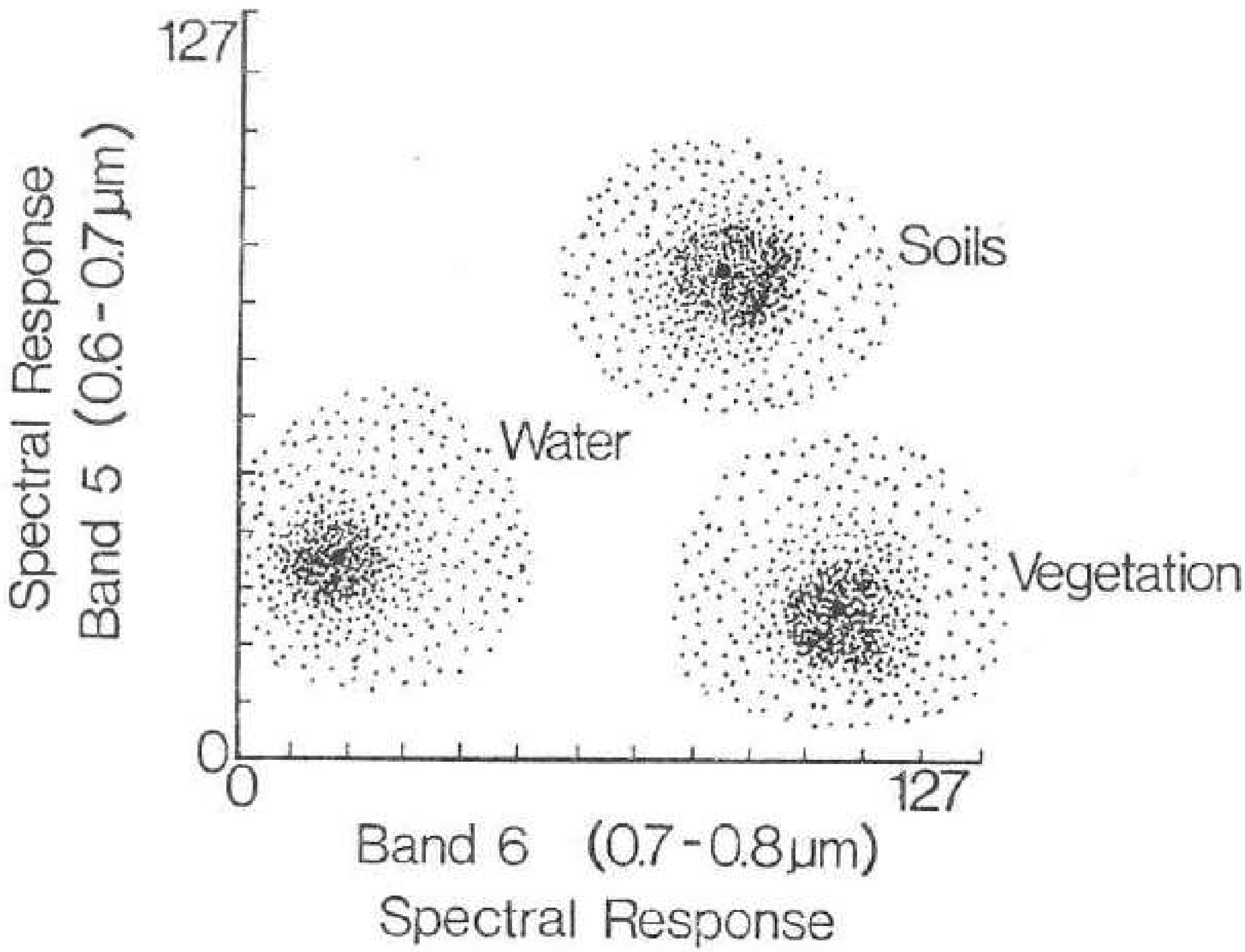
Standard deviation

Minimum

Maximum

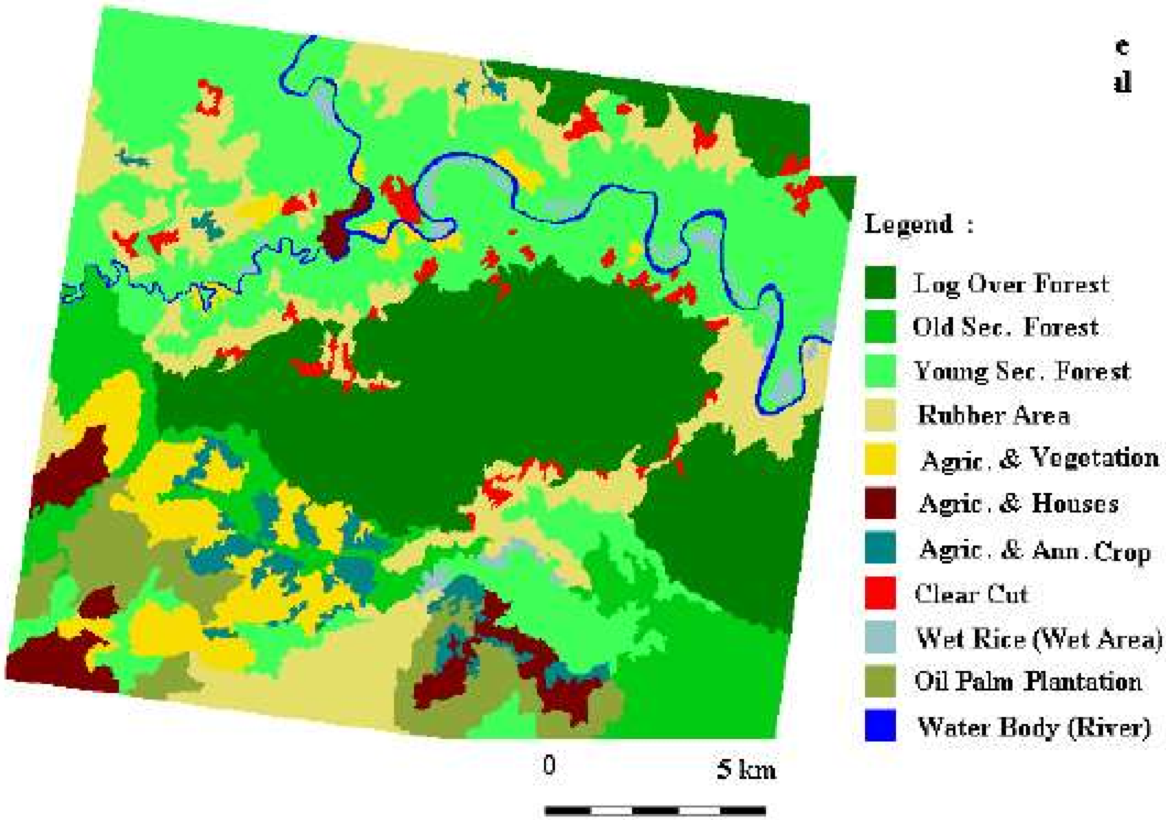
7. Finalizing the decision boundary:




127
0
Spectral Response
Band 5 (0.6 - 0.7 µm)
Soils
Water
Vegetation
0
127
Band 6 (0.7 - 0.8 µm)
Spectral Response

UNEP

8. Creating the classification map:



Un-Supervised Classification Input Parameters:

- ✓number of clusters
- ✓size of cluster
- ✓distance between the clusters
- ✓cluster elimination value (convergence threshold)

Unsupervised Classification Output

- cluster image
- distance or divergence measure between clusters
- cluster mean vector plots
- cluster histogram / feature space plots
- cluster variance-covariance matrices

Unsupervised Classification

- Identifies the natural groups (i.e., spectral classes) within multi-spectral data.
- Advantages
  - No prior knowledge is required
  - Human error is minimized
  - Unique classes are recognized
- Disadvantages
  - Spectral classes ≠ information classed
  - Additional labeling is required
  - Spectral properties vary over time, across images

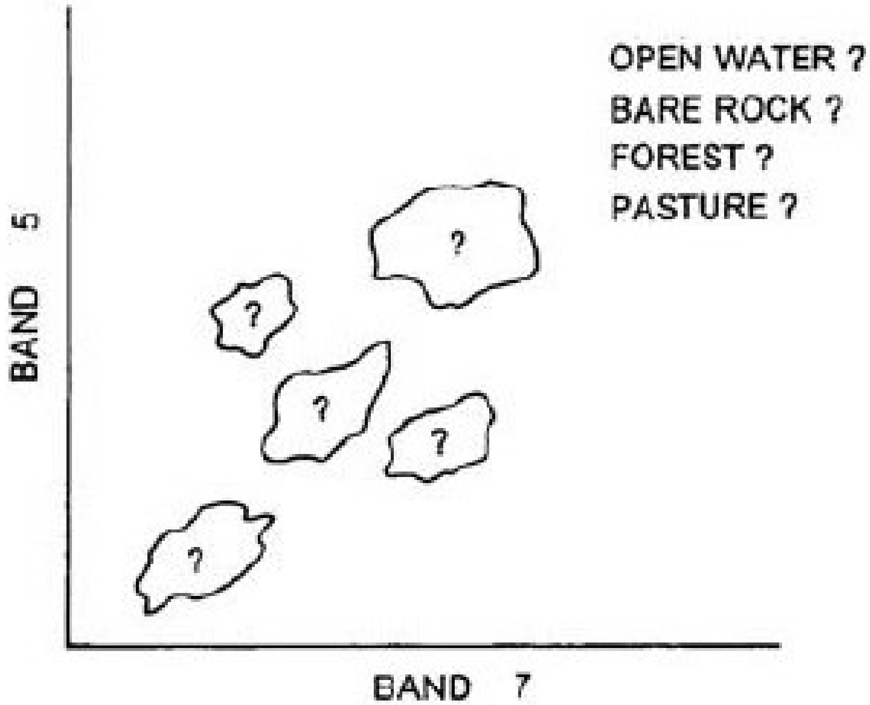


FIGURE 11.12. Assignment of spectral categories to image categories. Unsupervised classification defines the clusters defined schematically on the scatter diagram. The analyst must decide which, if any, match to the list of informational categories that form the object of the analysis.

Multi spectral image classification is used to extract thematic information from satellite images in a semi-automatic way.

Image classification are based on the theory about probabilities. Looking at a certain image pixel in M bands simultaneously, M values are observed at the same time.

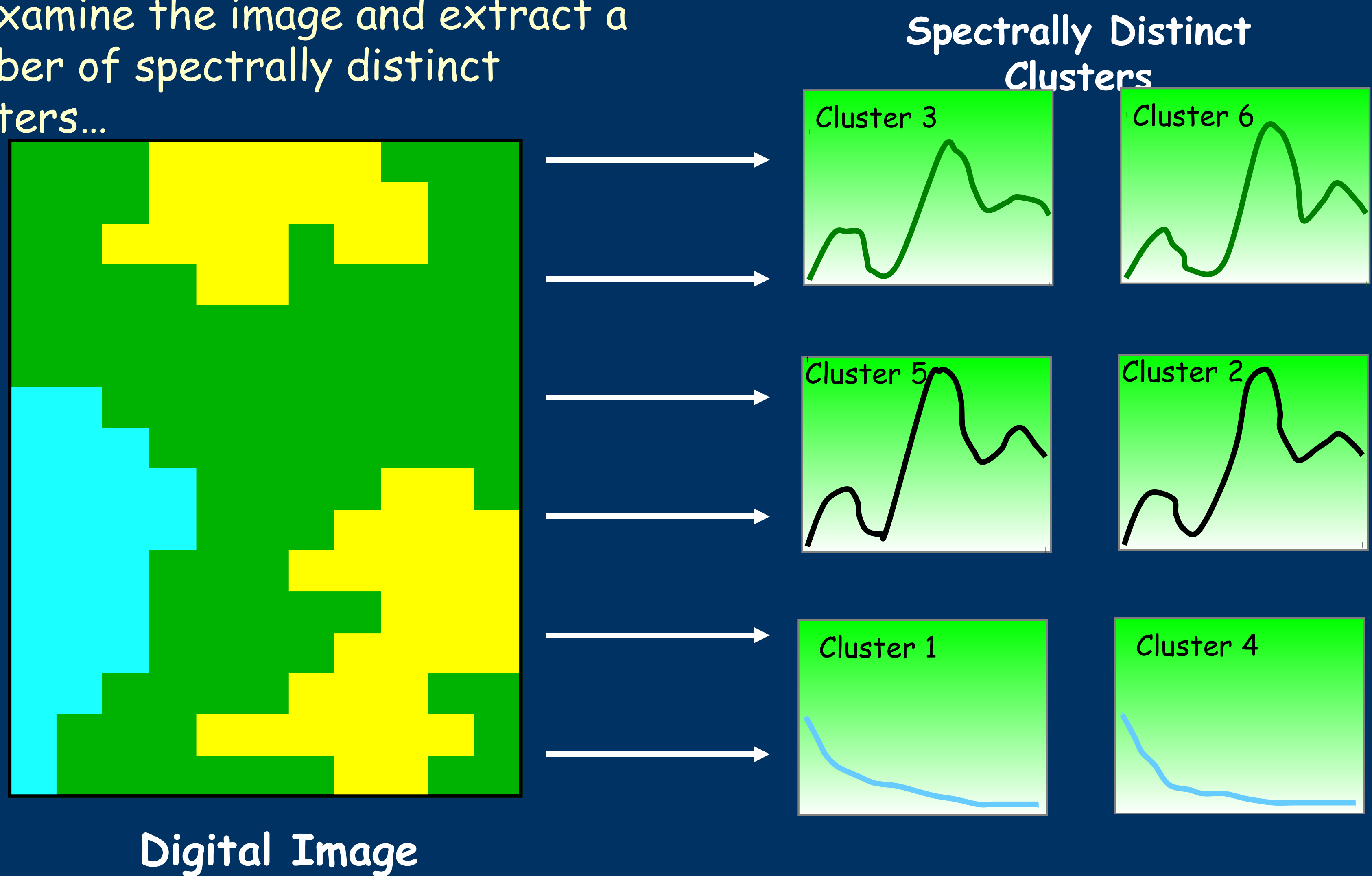
Using multi-spectral SPOT images, where M=3, three reflection values per pixel are given.

For instance, **(34, 25, 117) in one pixel, in another (34,24,119) and in a third (11, 77, 51).** These values found for 1 pixel in several bands are called feature vectors.

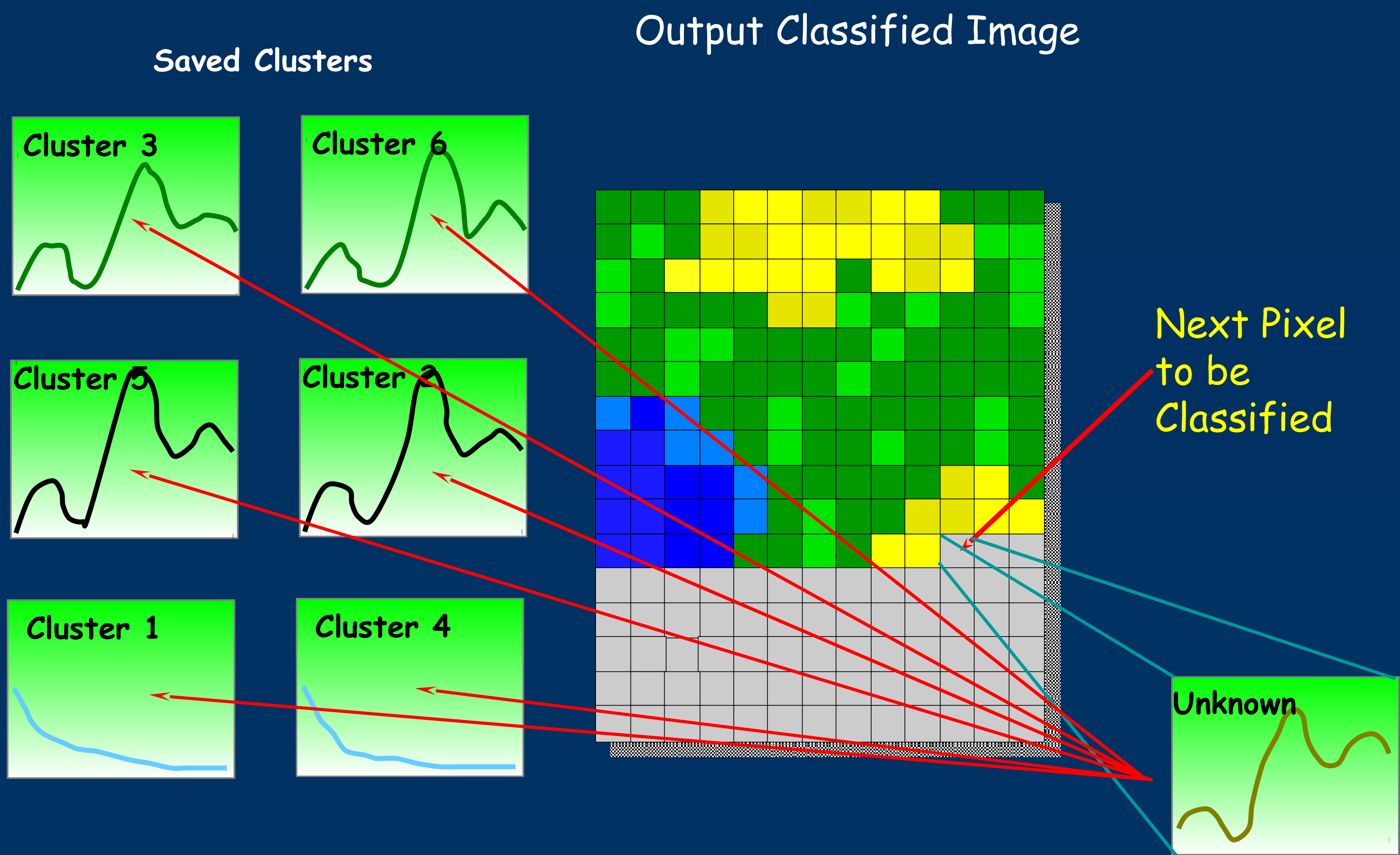
It can be recognized that the first two sets of values are quite similar and that the third is different from the other two. The first two probably belong to the same (land cover) class and the third belongs to another one.

Unsupervised Classification

The analyst requests the computer to examine the image and extract a number of spectrally distinct clusters…



Unsupervised Classification



Unsupervised Classification Procedures

- Generates spectral class signatures and assigns pixels to spectral classes iteratively (ISODATA).
- Maps spectral classes to information classes
- Regroups pixels into information classes

Unsupervised Classification

- Recall:

  In unsupervised classification, the spectral data imposes constraints on our interpretation

- How?

  Rather than defining training sets and carving out pieces of n-dimensional space, we define *no* classes before hand and instead use statistical approaches to divide the n-dimensional space into clusters with the *best separation*

- After the fact, we assign class names to those clusters

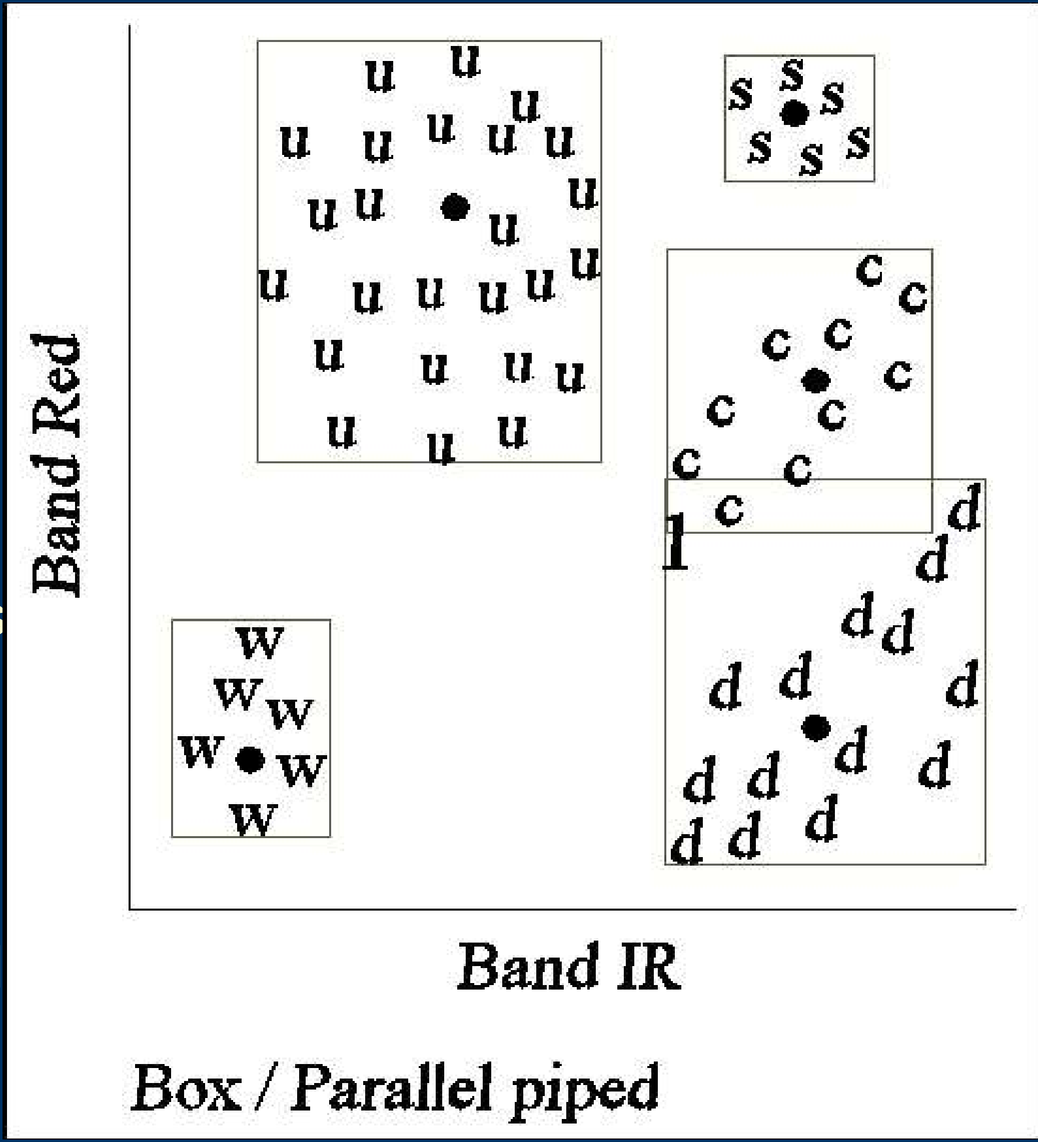
Supervised Classification

- Common Classifiers:
  - Parallelpiped/Box classifier
  - Minimum distance to mean
  - Maximum likelihood

Supervised Classification

- Parallelepiped/ Box Approach

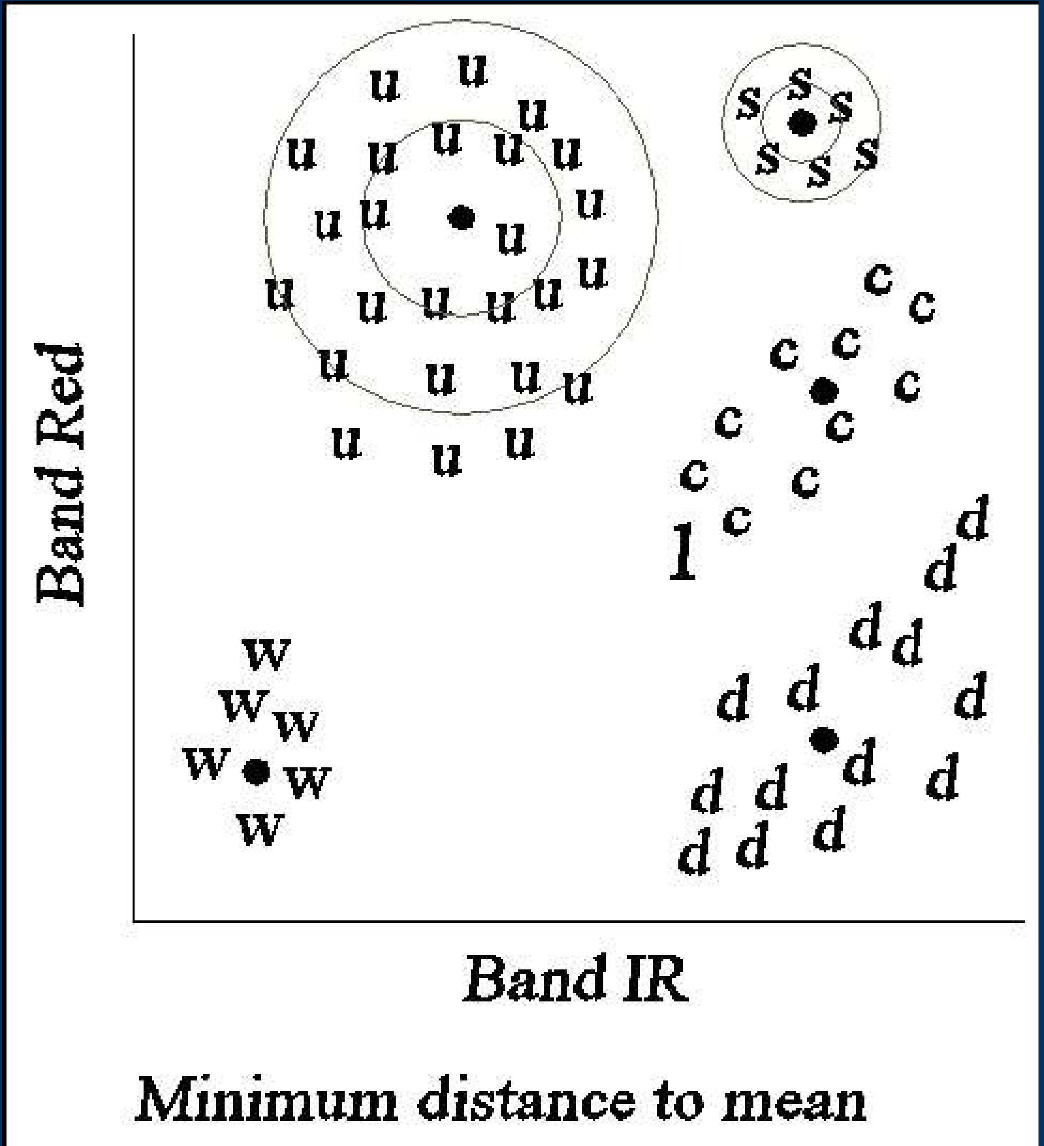
The Box classifier is the simplest classification method: In 2-D space, **rectangles are created** around the training feature vector for each class; in 3-Dimension they are actually boxes (blocks).
The position and sizes of the boxes can be exactly around the feature vectors (Min-Max method), or according to the **mean vector** (this will be at the center of a box) and the **standard deviations of the feature vector**, calculated separately per feature (this determines the size of the box in that dimension).



Supervised Classification: Statistical Approaches

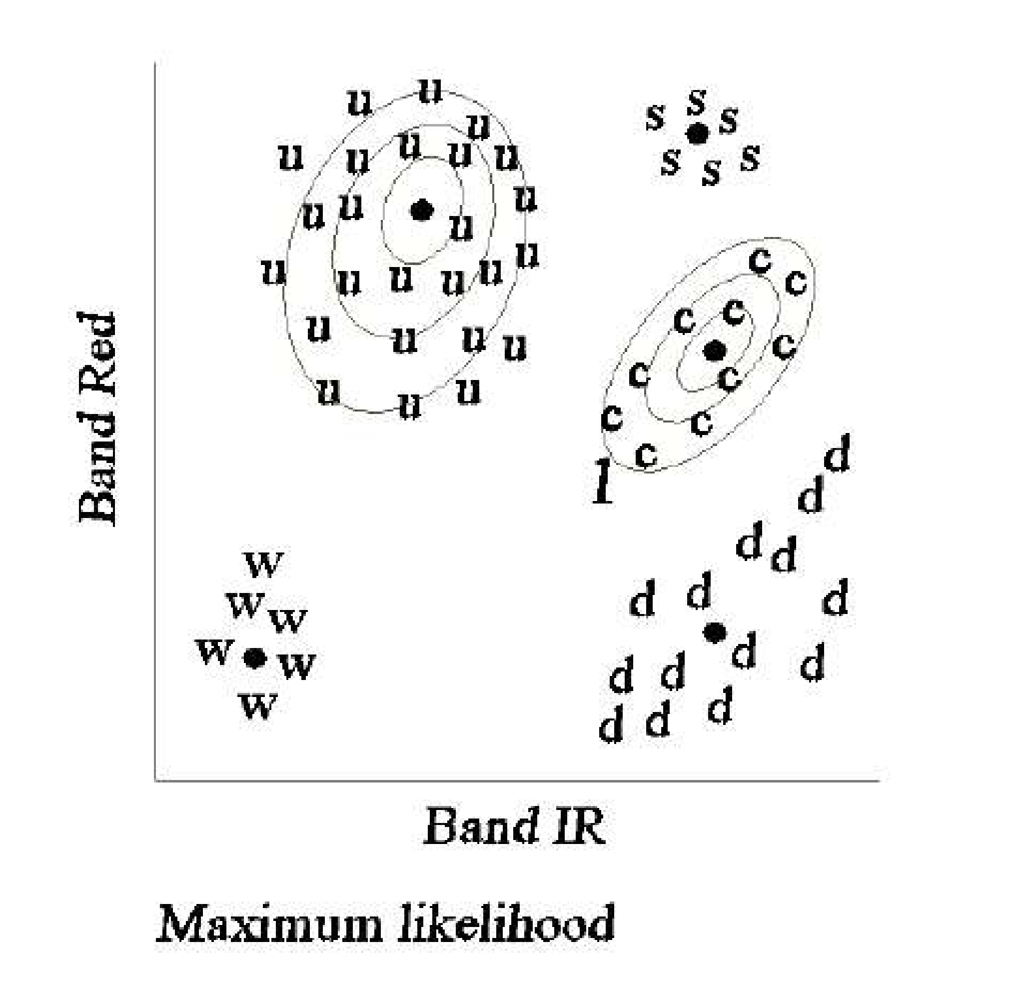
Minimum distance to mean

The Minimum Distance-to-mean classifier:
first calculates for each class the **mean vector** of the training feature vectors.
Then, the feature space is partitioned by giving to each feature vector the class label of the nearest mean vector, according to **Euclidean metric**.
Usually it is possible to specify a maximum distance threshold:



If the nearest mean is still further away than that threshold, it is assumed that none of the classes is similar enough and the result will be “**unknown**”

Gaussian Maximum Likelihood classifiers assume that the **feature vectors** of each class are (statistically) distributed according to a multivariate normal probability density function. The training samples are used to estimate the parameters of the distributions.



The boundaries between the different partitions in the feature space are placed where the decision changes from one class to another. They are called **decision boundaries**.

Supervised Classification

- Maximum likelihood
  - Pro:
    - Most sophisticated; achieves good separation of classes
  - Con:
    - Requires strong training set to accurately describe mean and covariance structure of classes

ADVANTAGES OF THE SUPERVISED CLASSIFICATION

- The analyst has control of a selected menu of informational categories tailored to a specific purpose and geographic region.

- It is tied to specific areas of known identity, called training areas.

- It is not necessary to match the spectral categories with the informational categories of interest.

- The operator may be able to detect serious errors in classification by examining how training data have been classified.

Classification: Critical Point

- LAND COVER not necessarily equivalent to LAND USE
  - We focus on what's there: LAND COVER
  - Many users are interested in how what's there is being used: LAND USE
- Example
  - Grass is land cover; pasture and recreational parks are *land uses* of grass