Paper Code: GIS 04

Image Classification

PG Diploma in RS & GIS

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Concept of Image Classification

This is the science of turning RS data into meaningful categories representing surface conditions or classes (i.e. feature extraction).

✓ Spectral pattern recognition:

procedures classification a pixel based on its pattern of radiance measurements in each band: more common and easy to use.

✓ Spatial pattern recognition:

Classification a pixel based on its relationship to surrounding pixels: more complex and difficult to implement.

✓ Temporal pattern recognition:

Looks at changes in pixels over time to assist in feature recognition.

Importance of Image Classification

- ✓ Multispectral classification is the process of sorting pixels into a finite number of individual classes or categories of data, based on their data file values. If a pixel satisfies a certain set of criteria, the pixel is assigned to the class that corresponds to that criteria.

- ✓ Multispectral classification may be performed using a variety of algorithms.

- ✓ Hard classification using supervise or unsupervised approaches.

- ✓ If natural boundaries are not clear then we will go for Classification using fuzzy logic

- ✓ If features are difficulty to identification then we will go hybrid approaches of classification, often involving use of ancillary information.

What is Digital Image Classification

- ✓ Grouping of similar pixels.
- ✓ Separating of dissimilar ones.
- ✓ Assigning class label to pixels.
- ✓ Resulting in manageable size of classes.

Classification method

- ✓ Manual(tone , texture, size, pattern etc)
- ✓ Computer assisted (digital image classification , based on tone or pixel values) or hard classification method.
- ✓ Stratified (hybrid or fuzzy classification)

Why Should Be Go for Digital Image classification?

- ✓ To translate continuous variability of image data into map patterns that provide meaning to the user.
- ✓ To obtain insight in the data with respect to ground cover and surface characteristics.
- ✓ To find anomalous patterns in the image data set.
- ✓ Cost and time efficient in the analyses of large data sets.
- ✓ Results can be reproduced (because of computer oriented, you can get as many as copy)
- ✓ More objective (based on some rule or algorithm) then visual interpretation.
- ✓ Effective analysis of complex multi band (spectral) interrelationship take into the account.

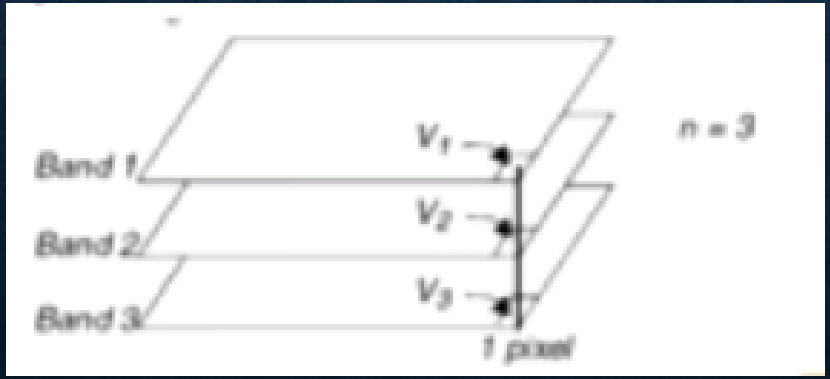
Dimensionality of Data

- ✓ Spectral dimensionality is determined by the number of sets (or Number of Bands) of values being used in a process.

- ✓ In image processing, each band of data is a set of values. An image with four band of data is a set of values. An image with four bands of data is said to be four-dimensional (Jansen, 1996)

Measurement vector

- ✓ The measurement vector of a pixel is the set of data file values for one pixel in all n bands.
- ✓ Measurement vector is equal to matrix value hear it V1*V2*V3



Mean Vector

- ✓ When the measurement vectors of several pixels are analyzed, a mean (and other statistical properties such as variance, Standard Deviation, Range or Percentage etc.) vector is often calculated.

- ✓ Hear, This is the vector of the means of the data file values in each band. It has n elements.

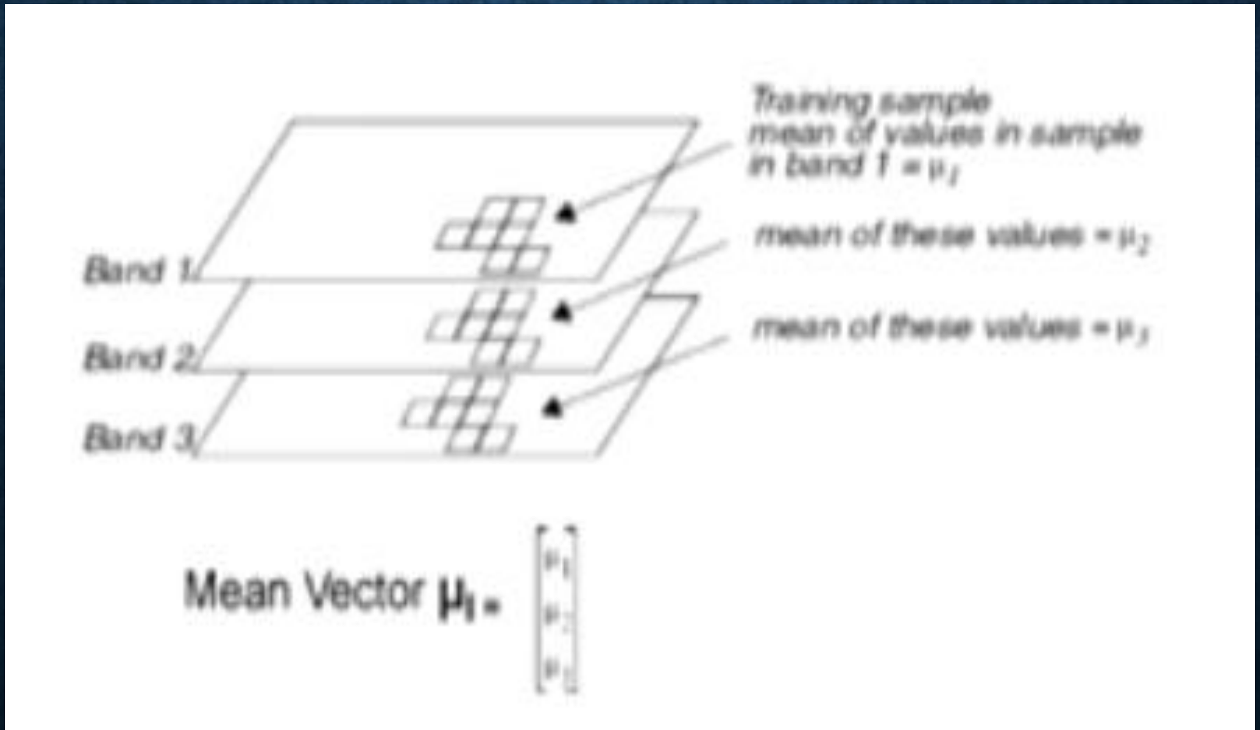
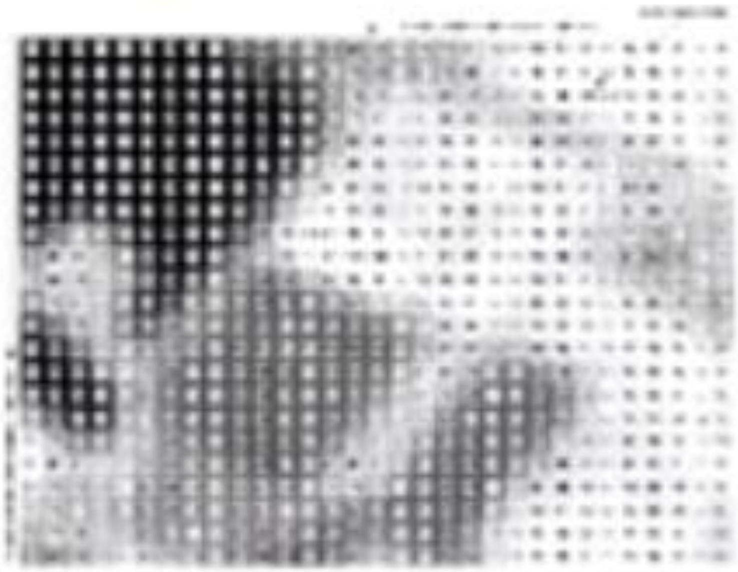
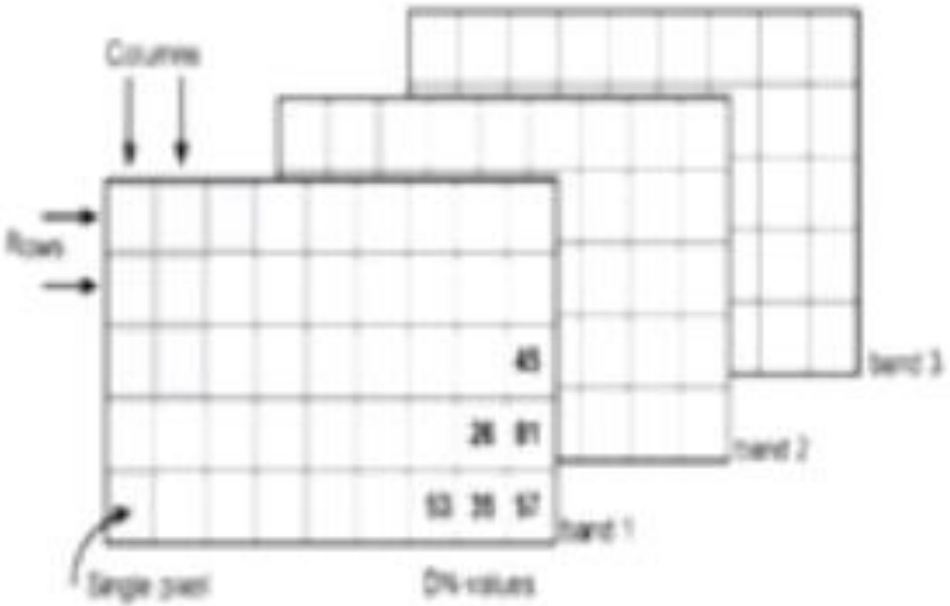


Image space



Single-band Image



Multi-band Image

- Image space (col,row)
- array of elements corresponding to reflected or emitted energy from IFOV
- spatial arrangement of the measurements of the reflected or emitted energy

Feature Space

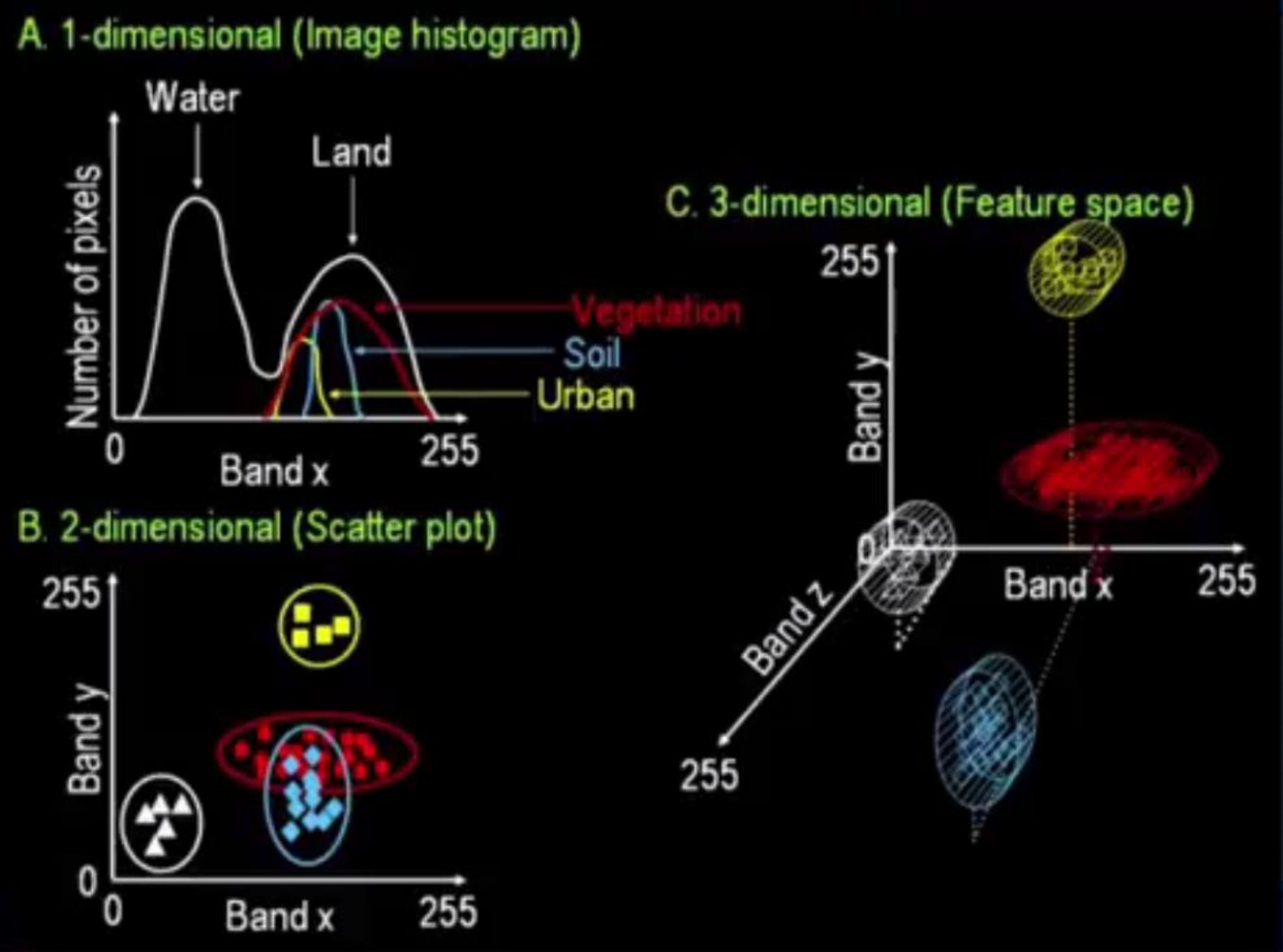
A feature space image is simply a graph of the data file values of one band of data against the values of another band.

ANALYZING PATTERNS IN MULTISPECTRAL DATA

PIXEL A: 34,25

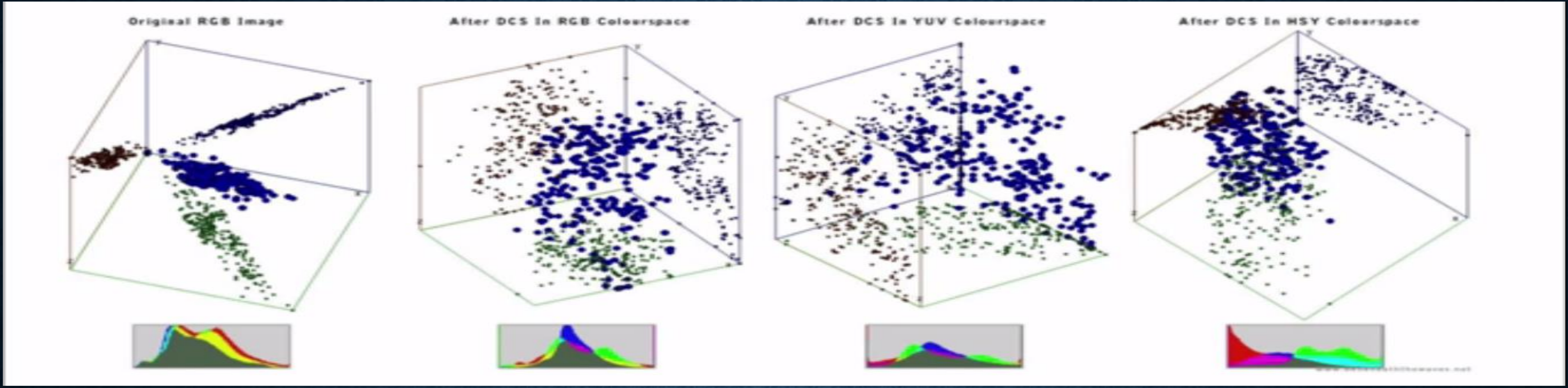
PIXEL B: 34,24

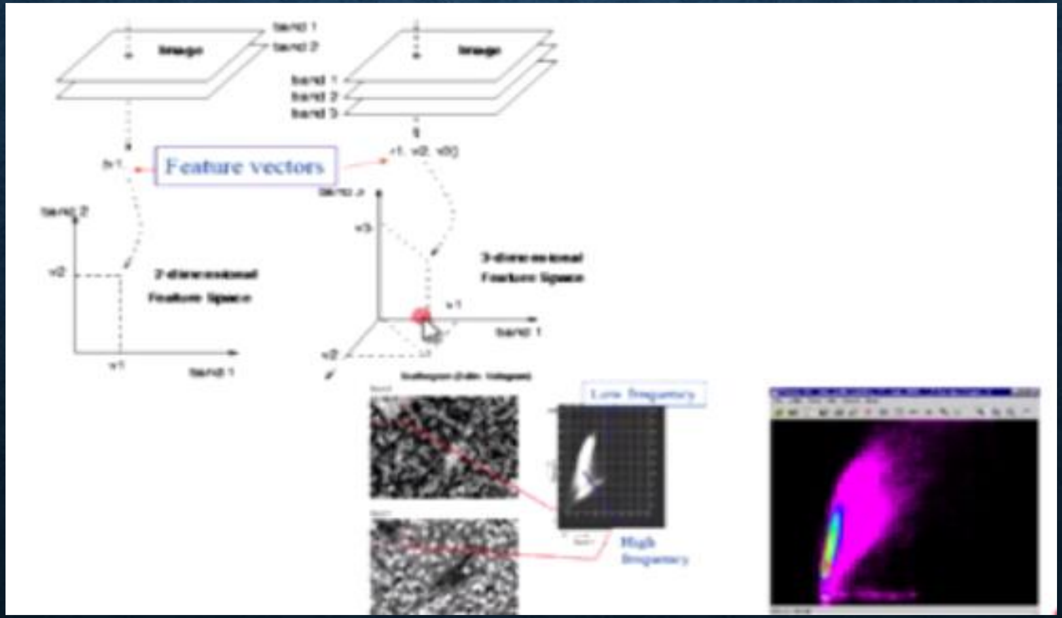
PIXEL C: 11,77



A. 1-dimensional (Image histogram)
Water
Land
Number of pixels
Vegetation
Soil
Urban
0
255
Band x
B. 2-dimensional (Scatter plot)
255
Band y
0
0
Band x
255
C. 3-dimensional (Feature space)
255
Band y
0
Band x
255
Band z
255

Feature Space Multi - Dimensional





Spectral Distance

- Euclidean Spectral distance is distance in n- dimensional spectral space. It is a number that allows two measurement vectors to be compared for similarity. The spectral distance between two pixels can be calculated as follows:

$$D = \sqrt{\sum_{i=1}^{n} (d_i - e_i)^2}$$

Where:

D = spectral distance

n = number of bands (dimensions)

i = a particular band

d_i = data file value of pixel d in band i

e_i = data file value of pixel e in band i

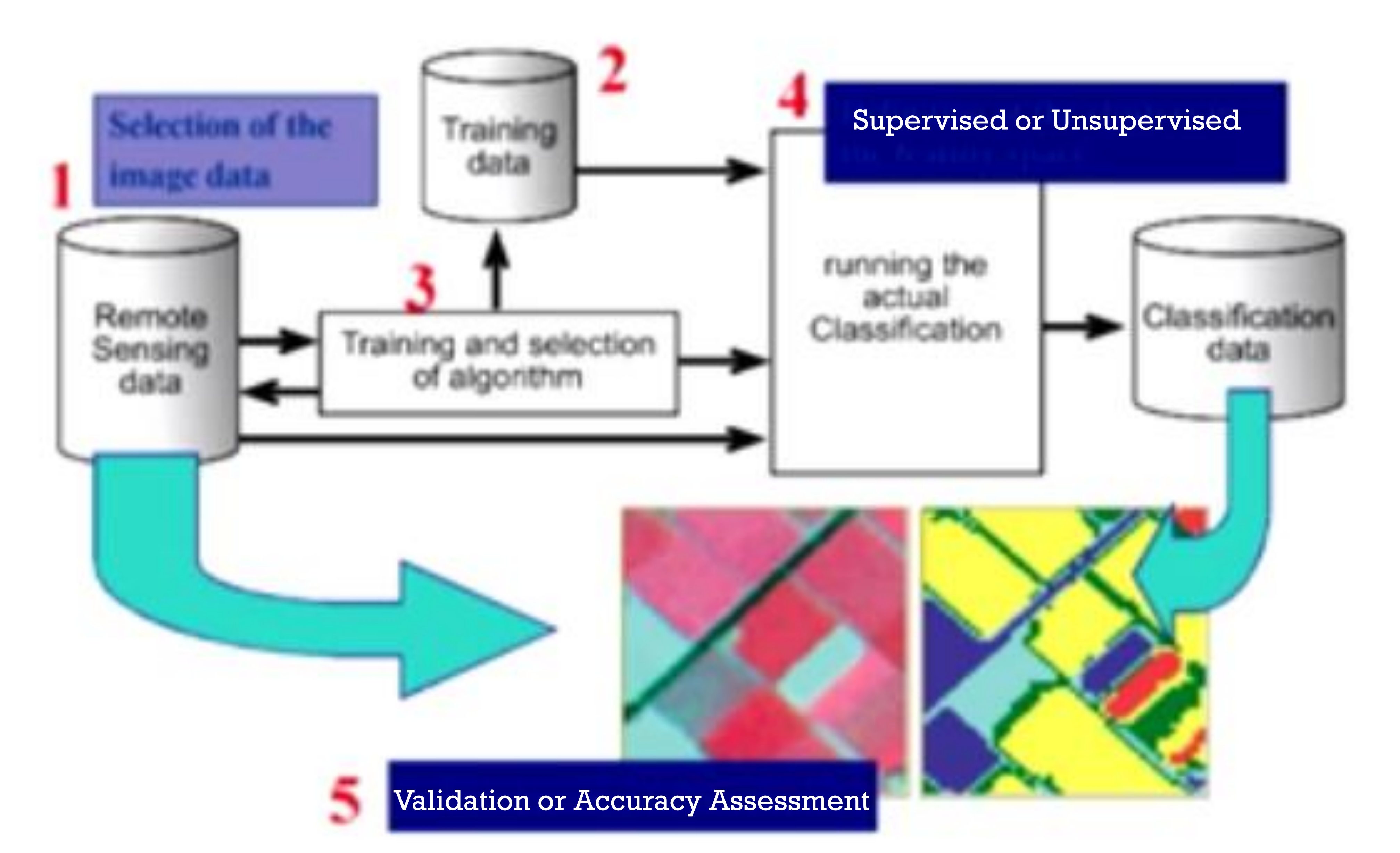
This is the equation for Euclidean distance—in two dimensions (when $n = 2$), it can be simplified to the Pythagorean Theorem ($c^2 = a^2 + b^2$), or in this case:

$D^2 = (d_i - e_i)^2 + (d_j - e_j)^2$

Purposes of Image Classification

- ✓ Geologic Terrains
- ✓ Mineral exploration
- ✓ Alteration mapping
- ✓ Land use and land cover (LULC)
- ✓ Vegetation types

Image Classification Process



Types of Classification

Unsupervised classification

- Aggregating into natural spectral groupings/clusters.
- No knowledge about "Thematic" land cover class.

Supervised classification

- Based on "Looks like most".
- Pixels categorization being "Supervised".
- Training sets/areas are used a numerical interpretation keys.

Supervised Classification

- ✓ The identity and location of some of the land cover types such as urban, agriculture, wetland are known a priori through a combination of field work and experience.
- ✓ The analyst attempts to locate specific sites in the remotely sensed data that represent homogenous examples of these known land cover types known as training sites.
- ✓ Multivariate statistical parameters are calculated for these training sites.
- ✓ Every pixel both inside and outside the training sites is evaluated and assigned to the class of which it has the highest likelihood of being a member.

Unsupervised Classification

- ✓ The identities of land cover types to be specified as classes within a scene are generally not known a priori because ground reference information is lacking or surface features within the scene are not well defined.

- ✓ The computer is required to group pixels with similar spectral characteristics into unique clusters according to some statistically determined criteria.

- ✓ Analyst then combine and relabels the spectral clusters into information classes.

Supervised VS Unsupervised Training

- ✓ In supervised training, it is important to have a set of desired classes in mind, and then create the appropriate signatures from the data.

- ✓ Supervised classification is usually appropriate when you want to identity relatively few classes, when you have selected training sites that can be verified with ground truth data or when you can identify distinct, homogeneous regions that represent each class.

- ✓ On the other hand, if you want the classes to be determined by spectral distinctions that are inherent in the data so that you can define the classes later, then the application is better suited to unsupervised training. Unsupervised training enables you to define many classes easily and identify classes that are not in contiguous easily recognized regions.

- ✓ Supervised classification uses image pixels representing regions of known, homogenous surface composition -- training areas -- to classify unknown pixels.

Supervised Classification

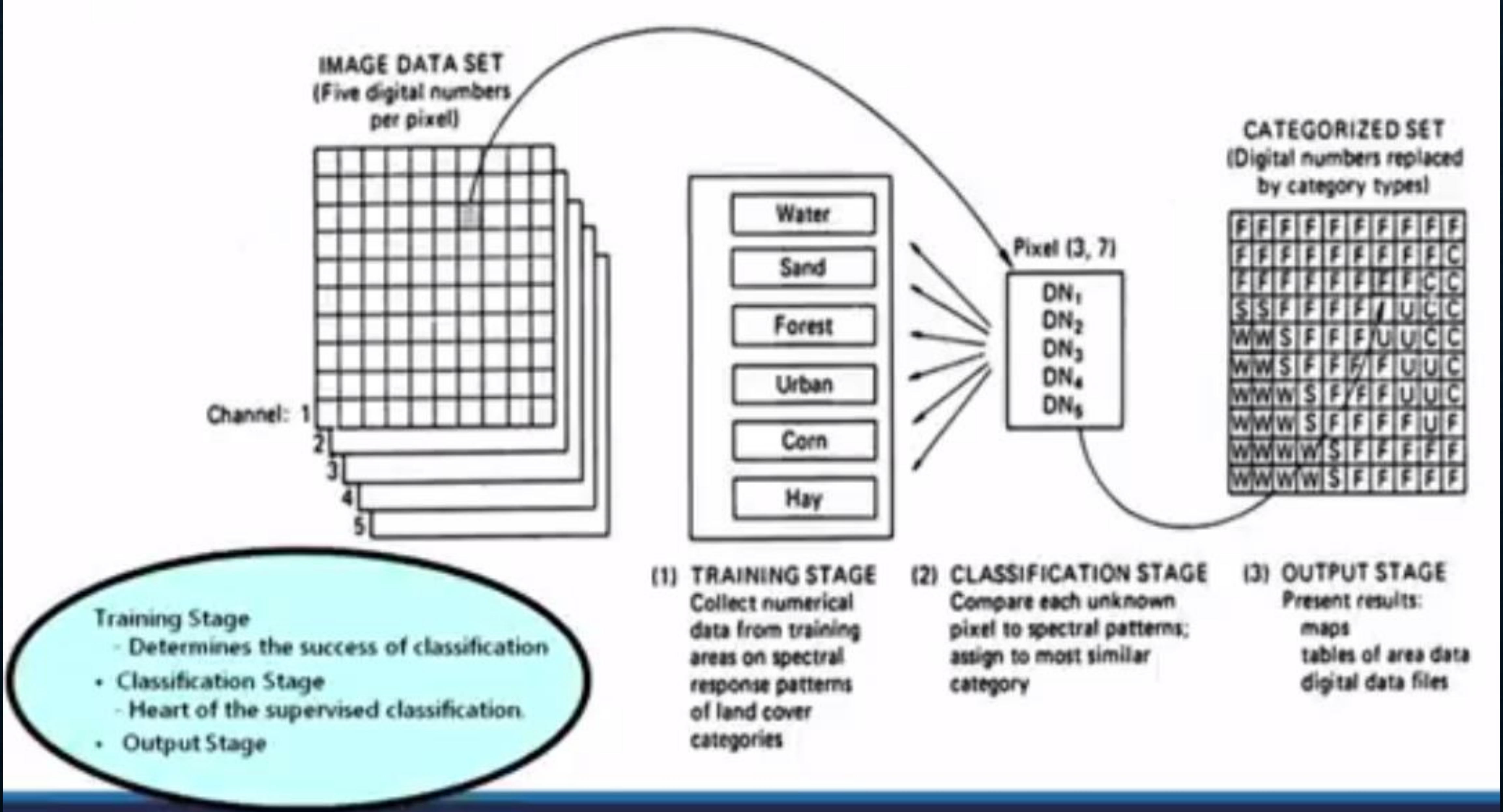
- ✓ In supervised training, you rely on your own pattern recognition skills and a priori knowledge of the data to help the system determine the stratification criteria (signatures) for data classification.

- ✓ To select reliable samples , you should know some information either spatial or spectral about the pixels that your want to classify.

Process of Supervised Classification

1) Determine a classification scheme
2) Create training areas
3) Generate training area signatures
4) Evaluate and refine signatures
5) Assign pixels to classes using a classifier (a.k.a., “decision rule”)

Basic Steps in Supervised Classification



1 | Determine Classification Scheme

1) Depends upon the purpose of the classification
2) Make the scheme as specific as resources and available reference data allow
3) You can always generalize your classification scheme to make it less specific; making it more specific involves starting over

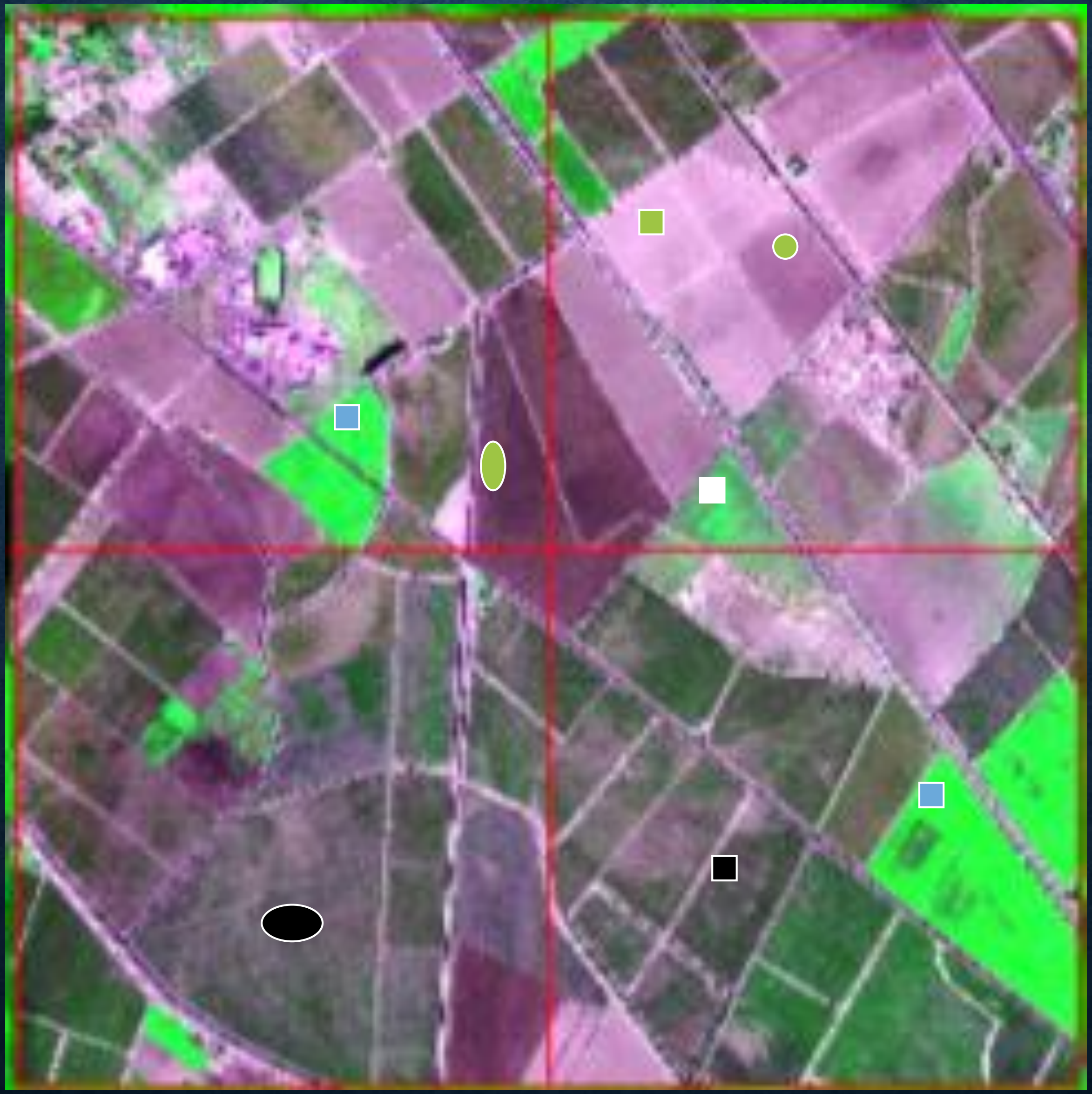
2 | Create Training Areas

1) Digitizing: drawing polygons around areas in the image
2) Seeding: “grows” areas based on spectral similarity to seed pixel
3) Using existing data: existing maps, field data (GPS, etc.), high-resolution imagery
4) Feature space image training areas

Training Area methods

Method	Advantages	Disadvantages
Digitizing	High degree of control; can incorporate additional imagery	May overestimate class variance; relatively time consuming
Seeding	Auto-assisted; fast	May underestimate class variance
Existing data	Precise map coordinates; represents known ground information	May overestimate class variance; data can be difficult & costly to collect

Digitizing



Selecting Training data

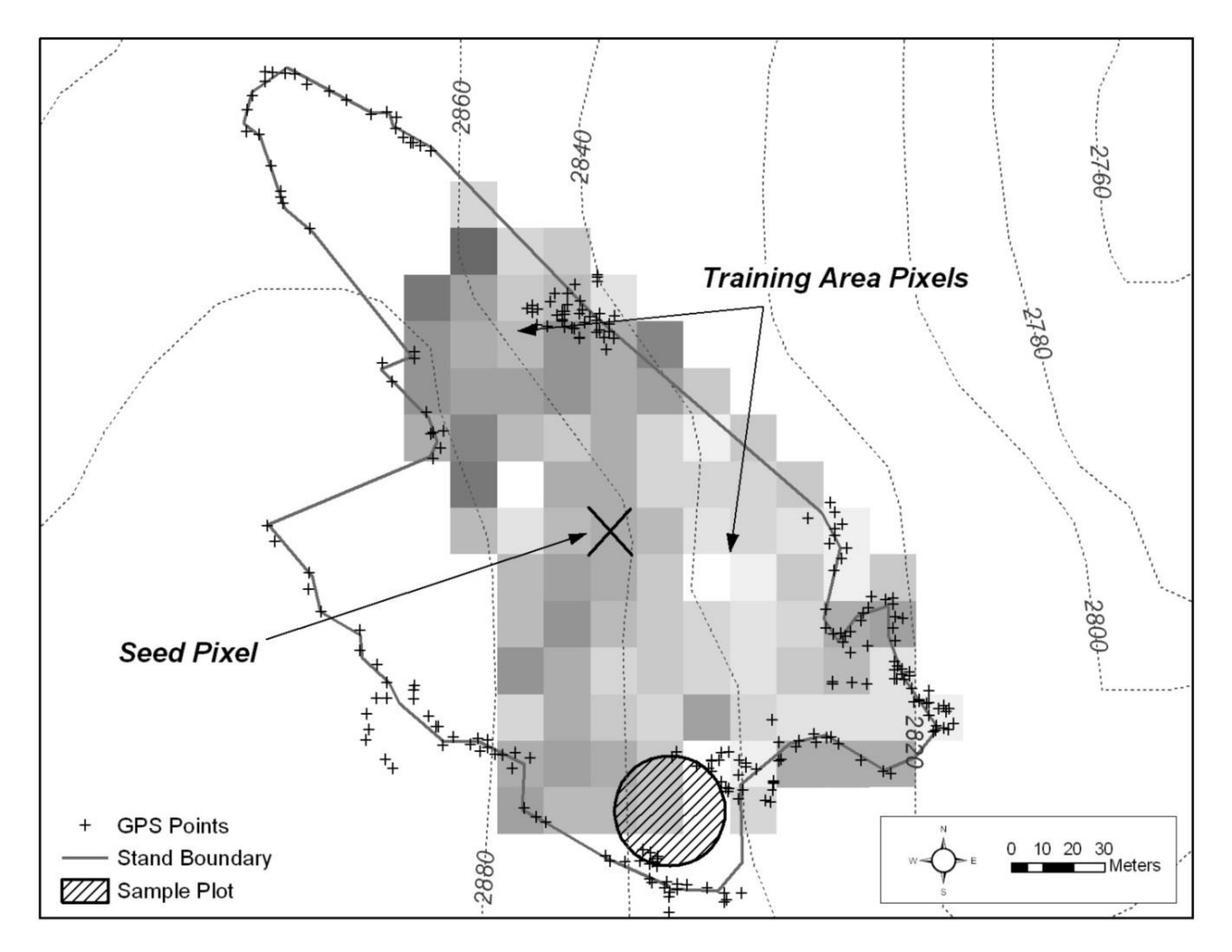
Rice

Cotton

Grass

Fallow

Seeding



2860
2840
2760
2780
2800
2820
2880
Training Area Pixels
Seed Pixel
GPS Points
Stand Boundary
Sample Plot
N
W
E
S
0 10 20 30
Meters

Training Areas “Best Practices”

1) Number of pixels > 100 per class
2) Individual training sites should be between 10 to 40 pixels
3) Sites should be dispersed throughout the image
4) Uniform and homogeneous sites

3 | Generate Training Areas Signatures

1) Signatures represent the collective spectral properties of all the training areas defined for a particular class
2) the most important step in supervised classification

Types of Signatures

1) Parametric : signature that is based on statistical parameters (e.g., mean) of the pixels that are in the training area (normal distribution assumption)
2) Non-parametric : signature that is not based on statistics, but on discrete objects (polygons or rectangles) in a feature space image

5 | Assign Pixels to Classes

1) Each pixel is independently compared to each signature relative to the selected classification criteria, or “decision rule”
2) Pixels that satisfy the criteria for a class signature are assigned to that class

Classification "Decision Rules"

1) Parametric: image is classified based on a statistical representation of the data derived from the training area signatures; all image pixels are classified
2) Parametric classifiers are "comprehensive"; they assign every pixel in an image to a class (regardless of how well that pixel fits into the classification scheme)
3) Non-parametric: pixels are classified as objects in feature space; only those pixels within the feature space object are classified

Supervised Classification

- ✓ Better for cases where validity of classification depends on a priori knowledge of the technician; already known what "types" you plan to classify.
- ✓ Conventional cover classes are recognized in the scene from prior knowledge or other map layers.
- ✓ Training sites are chosen for each of those classes.
- ✓ Each training site "class" results in a cloud of points in n-dimensional "measurement space" representing variability of different pixels spectral signatures in that class.

Training Samples & Feature Space Objects

- ✓ Training samples (also called samples) are sets of pixels that represent what is recognized as a discernible statistics from the sample pixels to create a parametric signature for the class.

Selecting Training Samples

- ✓ Training data for a class should be collected from homogeneous environment.

- ✓ If training data is being collected from n band >n pixels of training data is to be collected for each class.

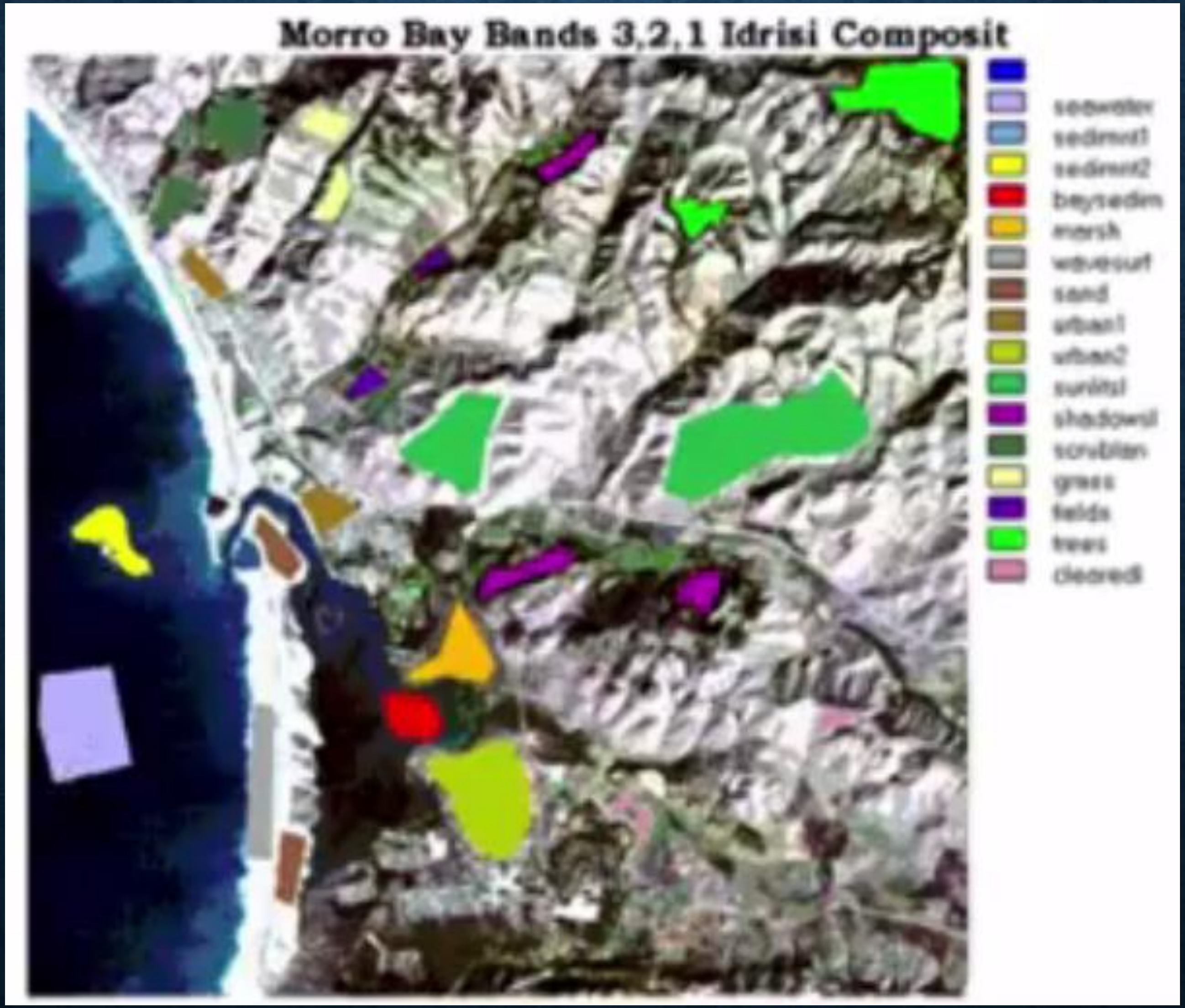
Selecting Training Samples

There are a number of ways to collect training site data

- ✓ Using a vector layer.
- ✓ Defining a polygon in the image.
- ✓ Using a class from a thematic raster layer from an image file of the same area (i.e., the result of an unsupervised classification).

Supervised Classification

Pre-chosen Training Sites of Known Cover Type



Advantages

- ✓ Generates informational classes representing features on the ground
- ✓ Training areas are reusable (assuming they do not change; e.g. roads)

Disadvantages

- ✓ Information classes may not match spectral classes

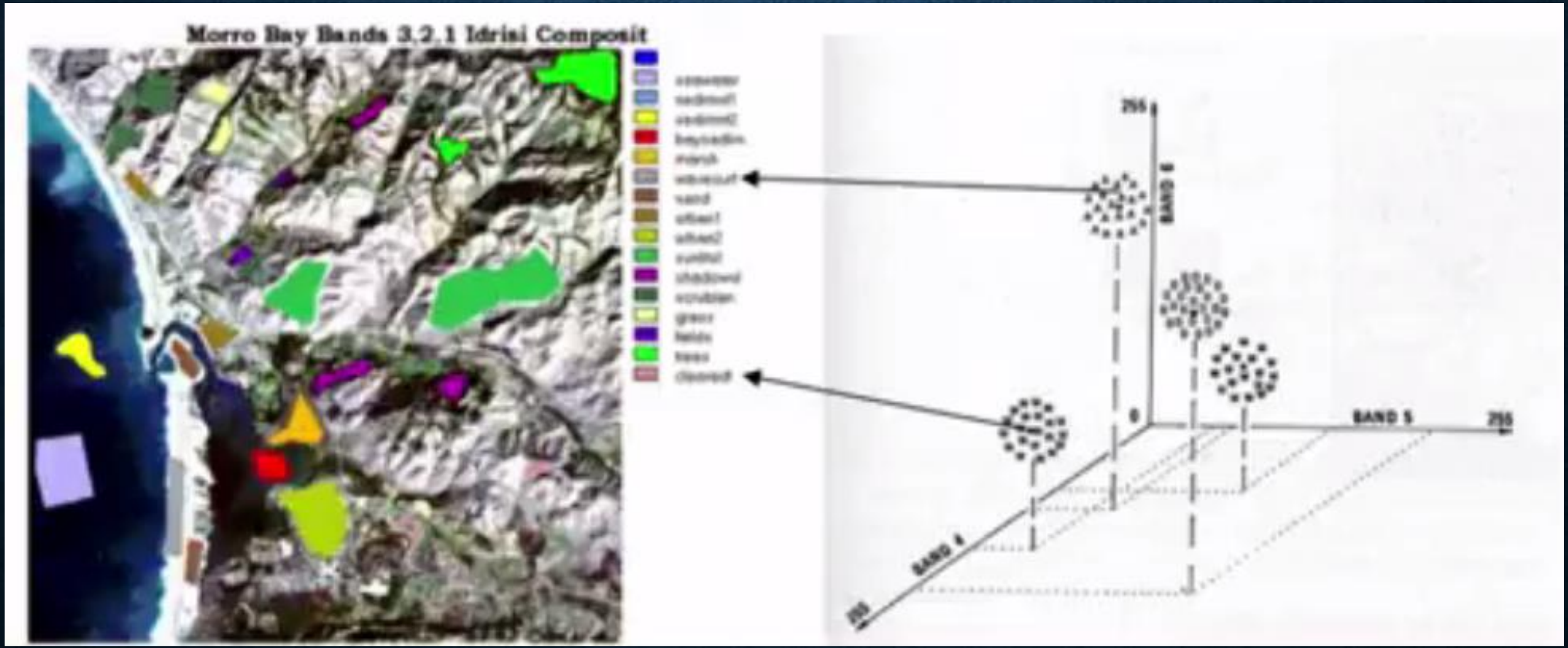
(e.g., a supervised classification of “forest” may mask the unique spectral properties of pine and oak stands that comprise that forest)

- ✓ Homogeneity of information classes varies
- ✓ Difficulty and cost of selecting training sites
- ✓ Training areas may not encompass unique spectral classes

Supervised Classification

- ✓ The next step is for the computer to assign each pixel to the spectral class is appears to belong to based on the DN’s of its constituent bands.

- ✓ Clustering algorithms look at “clouds” of pixels in spectral “measurement space” from training areas to determine which “cloud "a given non training pixel fall in.



Supervised Classification

Algorithms include:

- ❖ Minimum distance to means classification (Chain method)
- ❖ Gaussian Maximum Likelihood Classification.
- ❖ Parallelepiped Classification

- ✓ Each will give a slightly different result
- ✓ The simplest method is "Minimum Distance" in which a theoretical center point cloud is plotted, based on mean values, and an unknown point is assigned to the nearest of these. That point is then assigned that cover class.

Supervised Classification

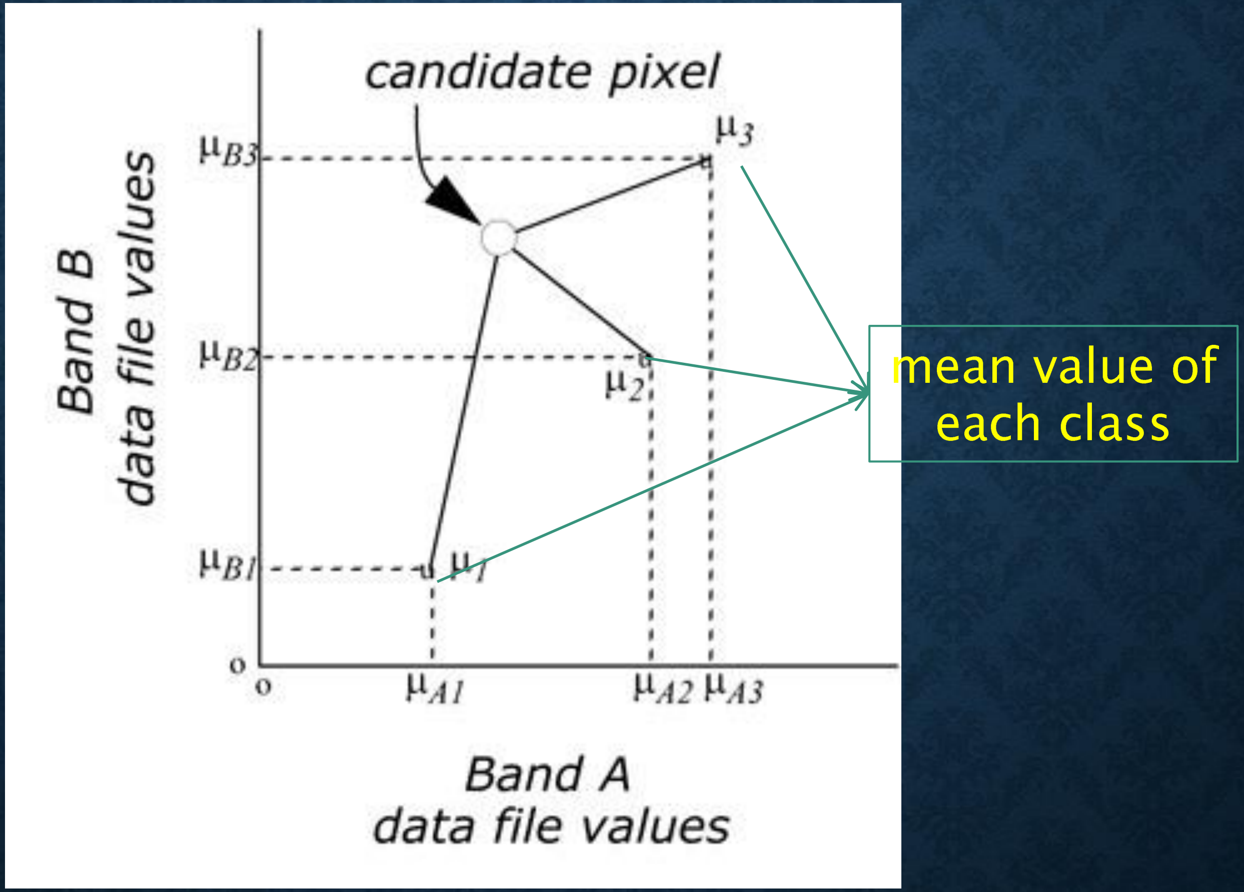
1. Minimum Distance to Mean/ Centroid Classifier/Euclidean
2. Parallelepiped Classifier/ Box Classifier
3. Maximum Likelihood/ Bayesian Classifier

1.Minimum Distance to Mean/ Centroid Classifier/Euclidean

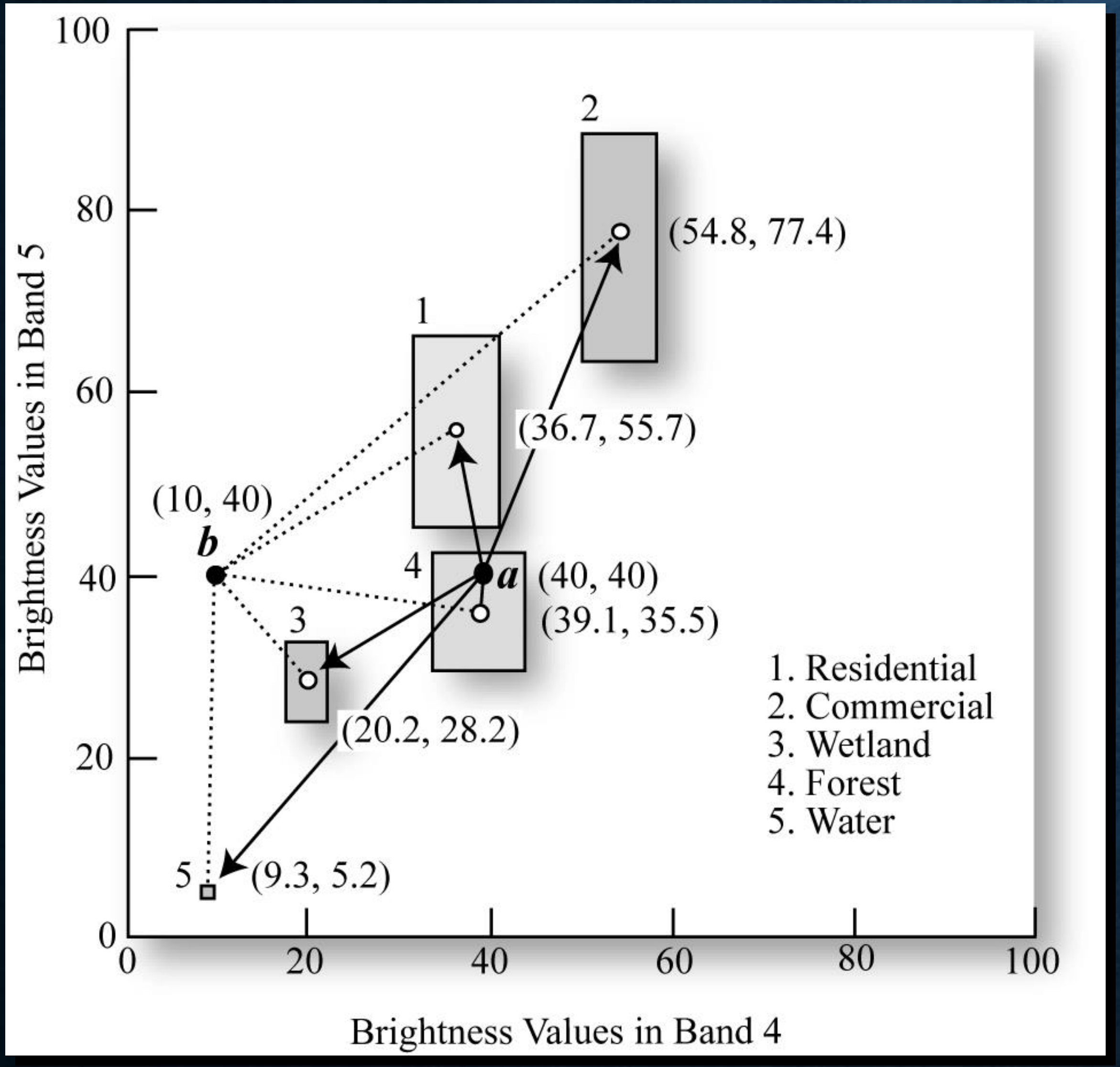
Minimum Distance Classifier

- ✓ Classifies pixels based on the spectral distance between the candidate pixel and the mean value of each signature (class) in each image band

Minimum Distance Classifier



Minimum Distance Classifier



- ✓ The vectors (*arrows*) represent the distance from candidate pixels *a* and *b* to the mean of all classes in a *minimum distance to means* classification algorithm

- ✓ Pixel a – Forest
- ✓ Pixel b - Wetland

Minimum Distance Classifier

Advantages:

- ✓ fast; no unclassified pixels
- ✓ Since every pixel is spectrally closer to either one sample mean or other so there are no unclassified pixels.
- ✓ Fastest after parallelepiped decision rule.

Disadvantages:

does not incorporate variability of signatures

- ✓ In most cases, a maximum likelihood classifier is a better choice
- ✓ This decision rule is computationally simple and commonly used.
- ✓ Any unknown pixel will definitely be assigned to one of any classes, there will be no unclassified pixel.
- ✓ Pixels which should be unclassified will become classified.
- ✓ Does not consider class variability.

SUPERVISED CLASSIFICATION

- ✓Feature space clusters
- ✓E.g. 2 channels of information
- ✓Are all clusters separate?

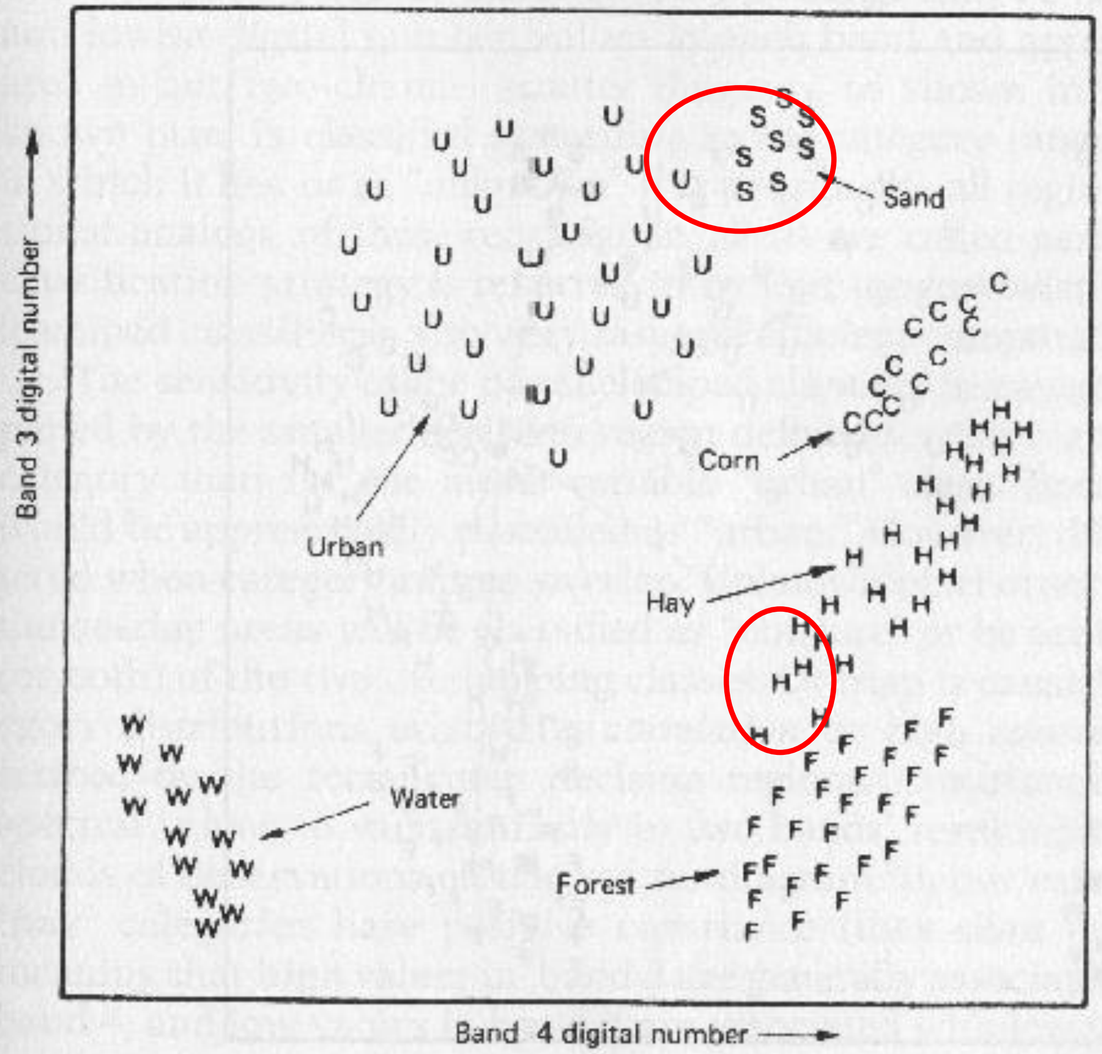


Figure 7.39 Pixel observations from selected training sites plotted on scatter diagram.

SUPERVISED CLASSIFICATION: MDM

- ✓Find closest cluster mean for each pixel
- ✓Simple and quick BUT what about points 1, 2?
- ✓i.e. MDM insensitive to variance of clusters
- ✓Can we improve?

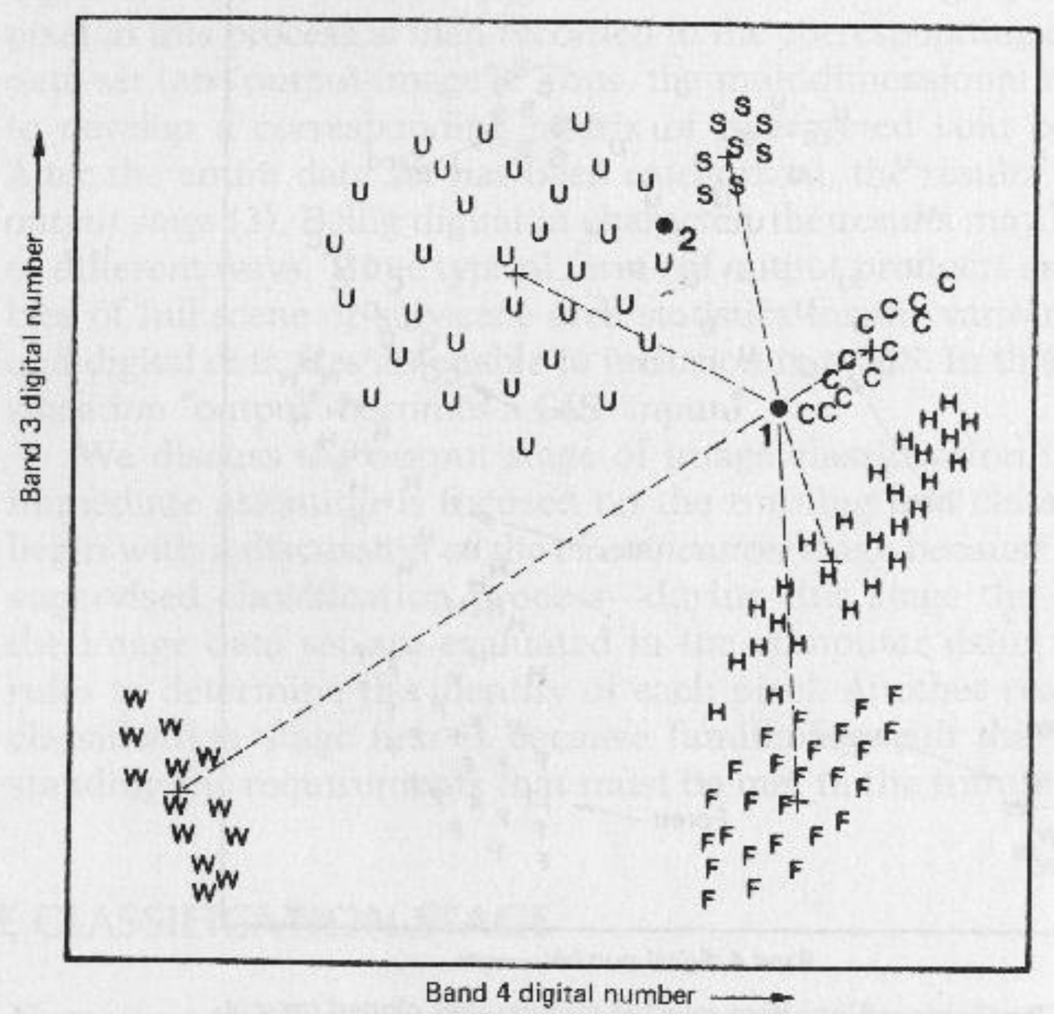
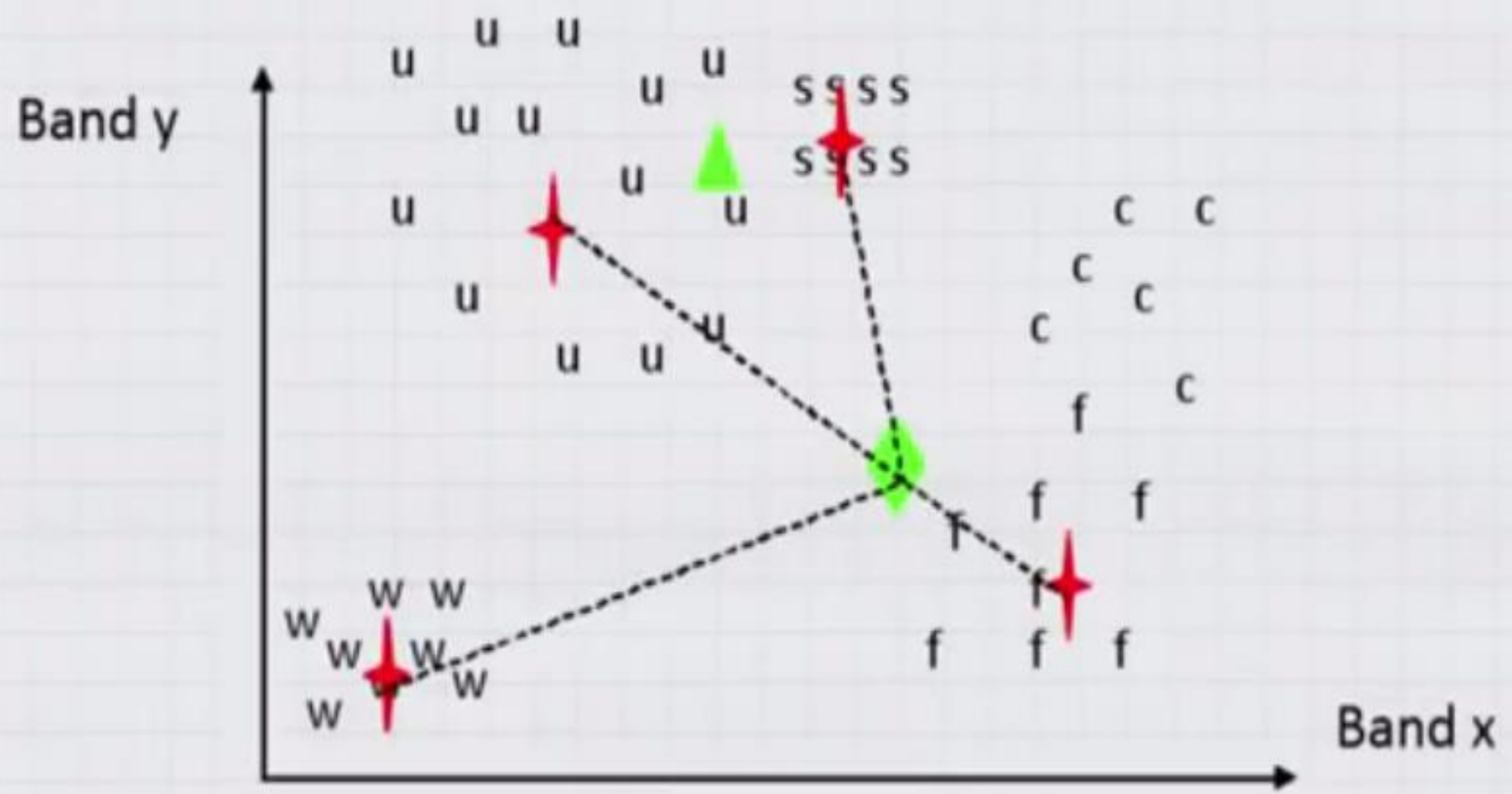


Figure 7.40 Minimum distance to means classification strategy.


Band y
Band x
u u
u u
u u
u u
u
u u
u
u
u
u u
s s s s
s s s s
c c
c
c
c
c
f
f f
f
f
f f f
w w
w
w w
w
w

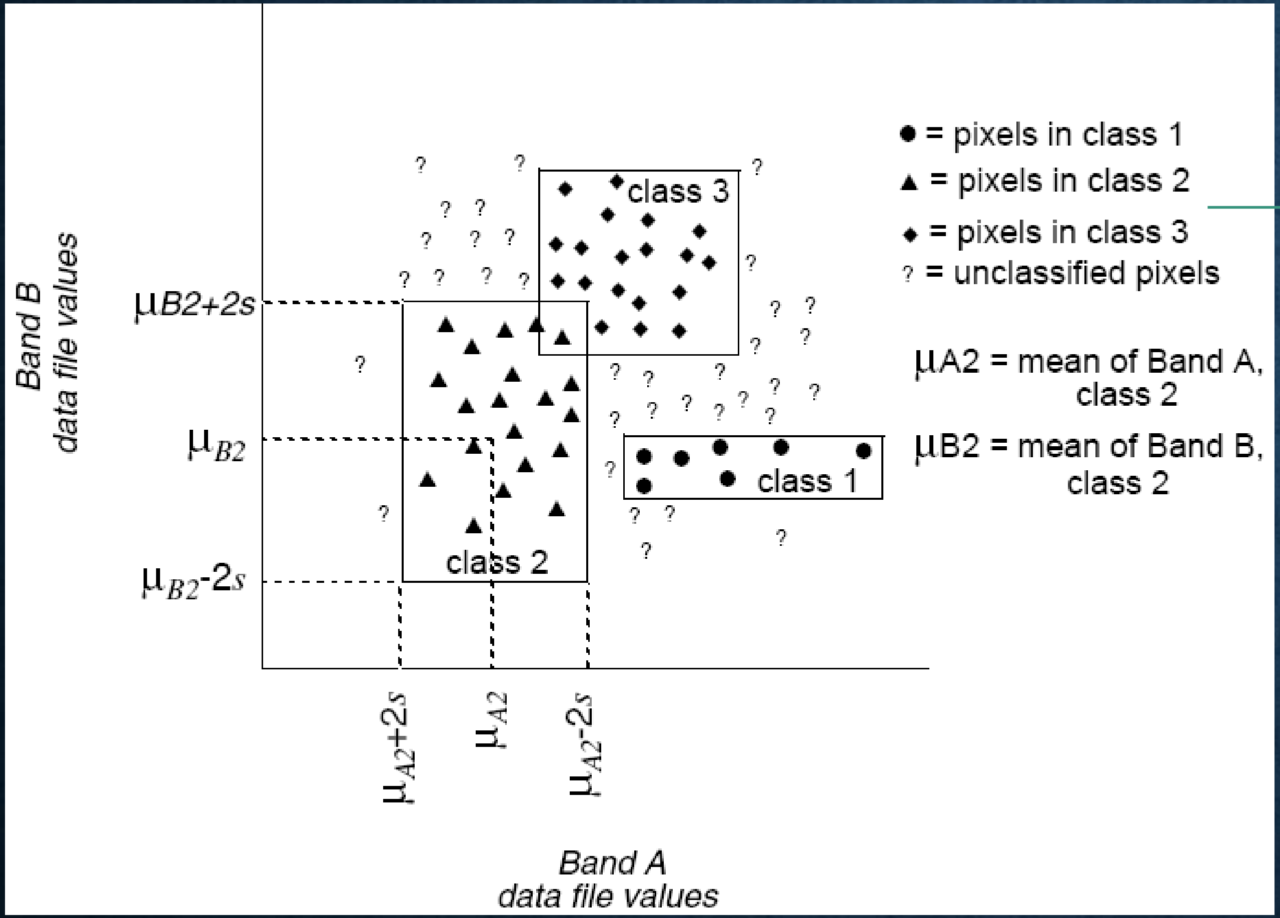
2.Parallelepiped Classifier/ Box Classifier

PARALLELEPIPED CLASSIFIER

- ✓ The pixels values are compared to upper and lower limits of each signature class (i.e., the min/max pixel values in each band, or the mean of each band +/- 2 standard deviations)
- ✓ In the parallelepiped decision rule, the data file values of the candidate pixel are compare to upper and lower limit, these limits can be either:

1. The minimum and maximum data file values of each band in the signature.
2. The mean of each band, plus and minus a number of standard deviation or
3. Any limits that you specify, based on your knowledge of the data and signature.
4. There are high and low limits for every signature in every band. When a pixels data file values are between the limits for every band in a signature, then the pixels is assigned to that signature's class.

PARALLELEPIPED CLASSIFIER

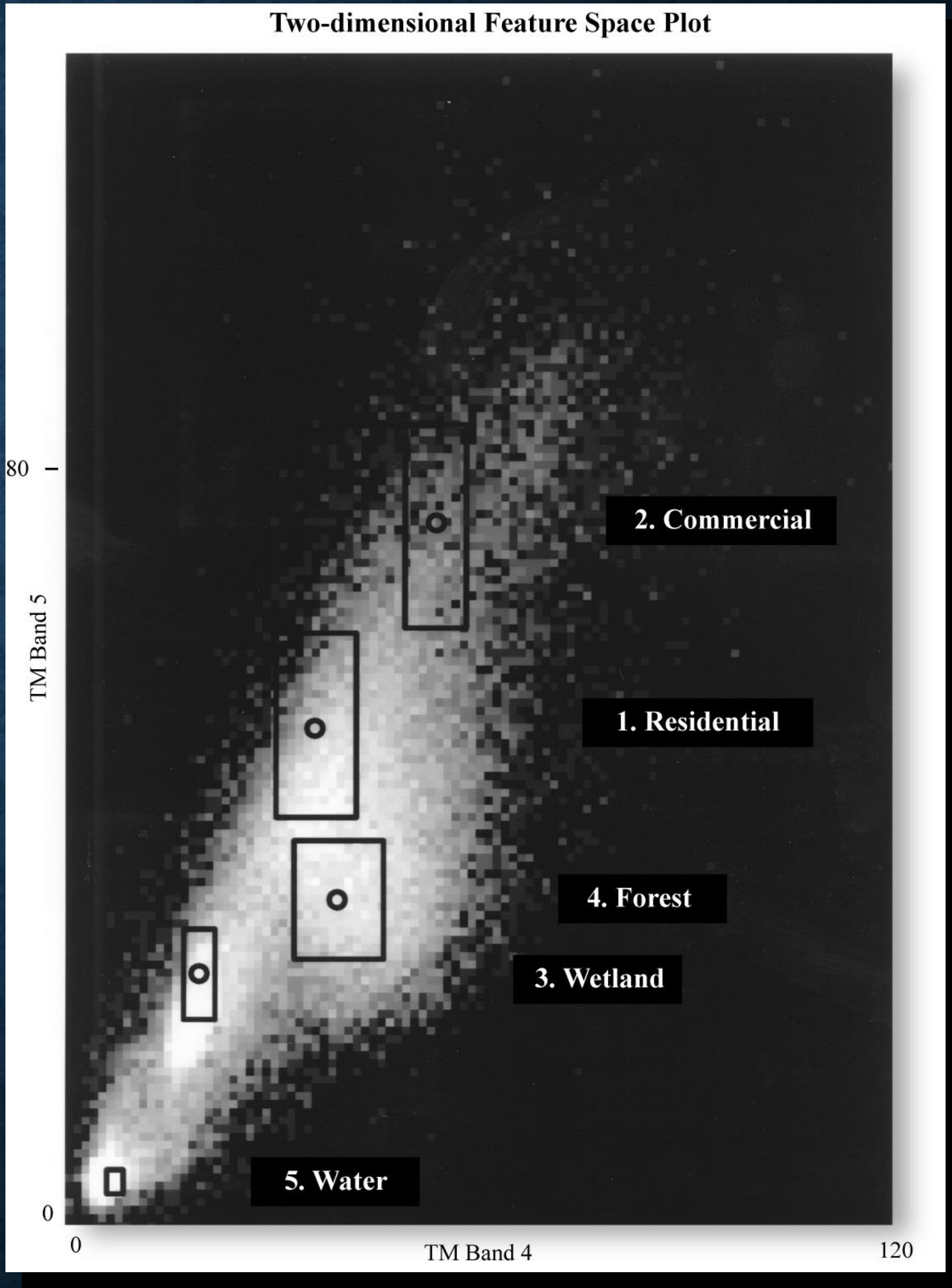


leave them unclassified or classify them using a parametric classifier

- If the pixel value lies above the low threshold and below the high threshold for all n bands evaluated, it is assigned to that class
- When an unknown pixel does not satisfy any of the criteria, it is assigned to an unclassified category
- We can visually see the two-dimensional box, but this could be extended to n dimensions.

PARALLELEPIPED CLASSIFIER

- ✓Landsat TM training statistics for five classes measured in bands 4 and 5 displayed as cospectral parallelepipeds.
- ✓The upper and lower limit of each parallelepiped is ±1s, superimposed on a feature space plot of bands 4 and 5.
- ✓Band 4: confusion between class 1 and 4
- ✓Band 5: confusion between class 3 and 4
- ✓Both band 4 and 5: separate all 5 classes at ±1s



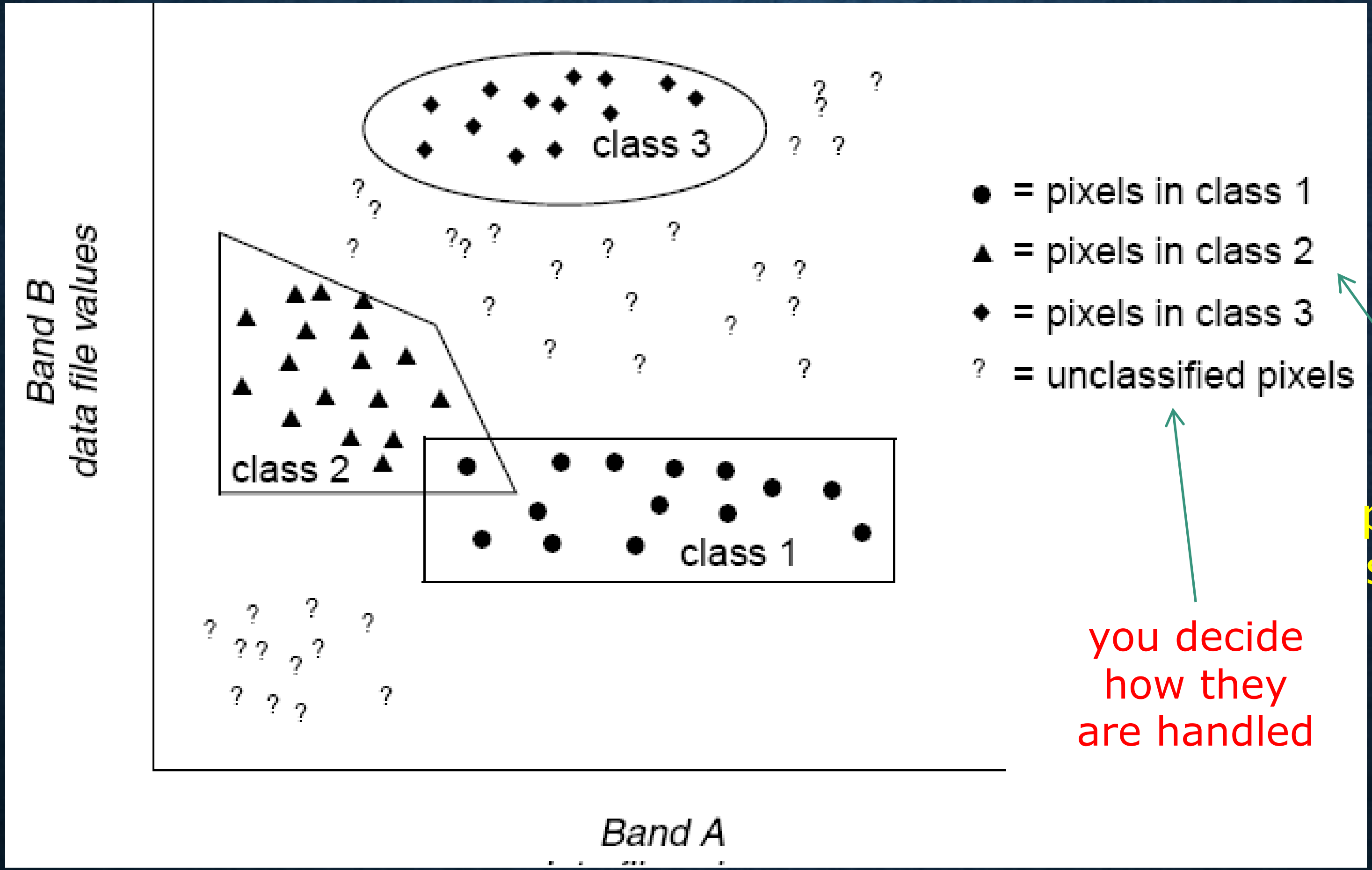
PARALLELEPIPED CLASSIFIER

- Advantages: fast; good for non-normal distributions; can limit classification to specific land cover
- Disadvantages: classes can include pixels spectrally distant from the signature mean; does not incorporate variability; not all pixels are classified; allows class overlap

FEATURE SPACE CLASSIFIER

- ✓Classifies pixels that fall within non-parametric signatures identified in the feature space image not used very often because it is difficult to accurately create and evaluate non-parametric signatures

FEATURE SPACE CLASSIFIER



non-parametric signatures

you decide how they are handled

FEATURE SPACE CLASSIFIER

Advantages:

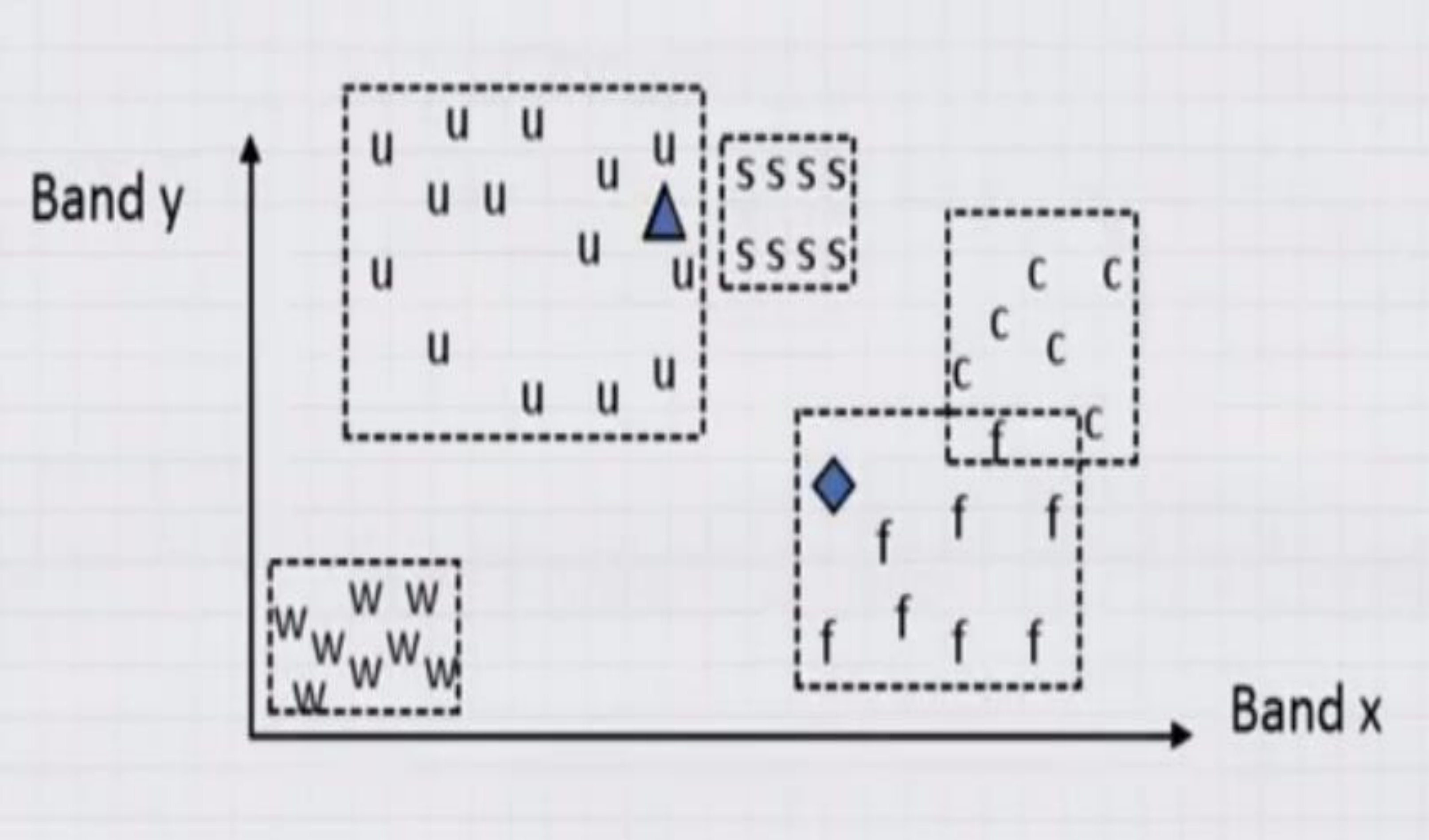
- ✓ good for non-normal distributions and multi-modal signatures (that include many land cover features)
- ✓ Fast and simple
- ✓ Give a broad classification thus narrow down the number of possible classes to which each pixel can be assigned before more time consuming calculations are made.
- ✓ Not dependent on normal distribution

Disadvantages:

- ✓ feature space images are difficult to interpret; allows class overlap.
- ✓ Since parallepied has corners pixels that are actual quite far, spectrally from the mean of the signature may be classified.

Supervised Classification: Parallelepiped (‘Box’)

- ✓ Assign Boundaries Around The Spread Of A Class In Feature Space I.E. Take Account of Variance
- ✓ Typically Use Minimum/Maximum Of DN In A Particular Class To Define Limits, Giving A Rectangle In 2D, Box In 3D (If We Have > 2 Bands) Etc.
- ✓ Pixels Outside Of These Regions Are Unclassified (Which Is Good Or Bad, Depending On What You Want!!)
- ✓ Problems If Class Regions Overlap Or If High Covariance Between Different Bands (Rectangular Box Shape Inappropriate)
- ✓ Can Modify Algorithm By Using Stepped Boundaries With A Series Of Rectangles To Partially Overcome Such Problems
- ✓ Simple And Fast Technique
- ✓ Takes Some Account Of Variations In The Variance Of Each Class



Band y
Band x
u u
u u
u u u
u u
u u
u u
u u u
ssss
ssss
c c
c c
c
c
f
f f f
f f f f
w w
w
w w w
w w
w

Supervised classification: parallelepiped

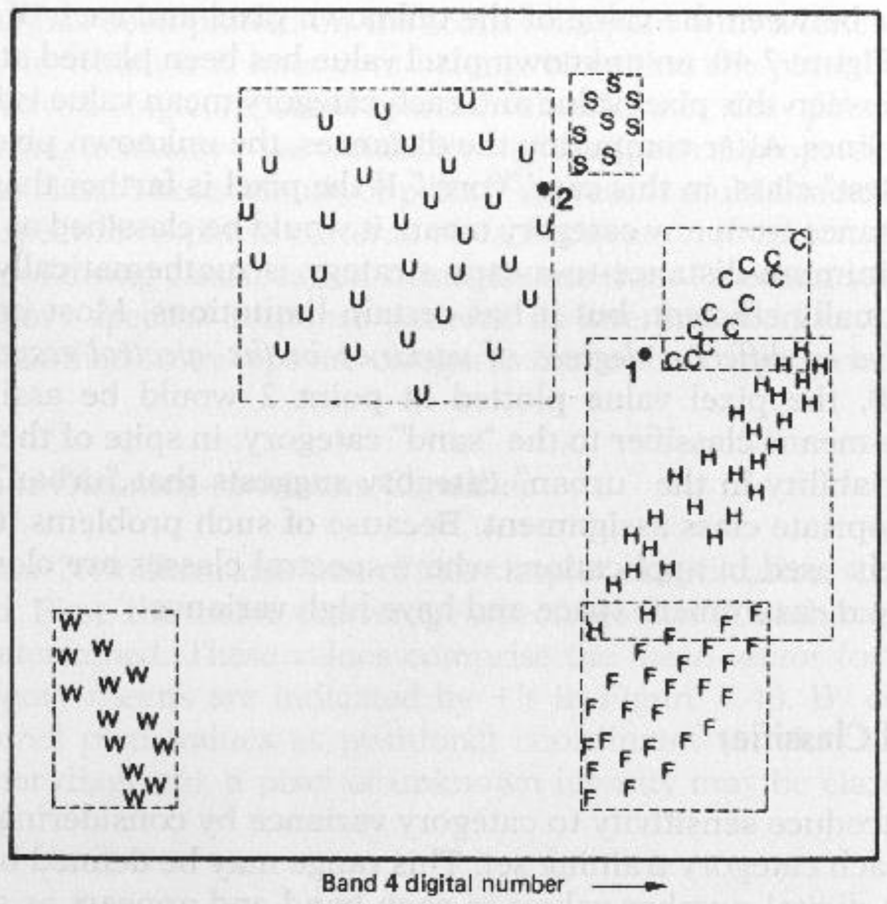


Figure 7.41 Parallelepiped classification strategy.

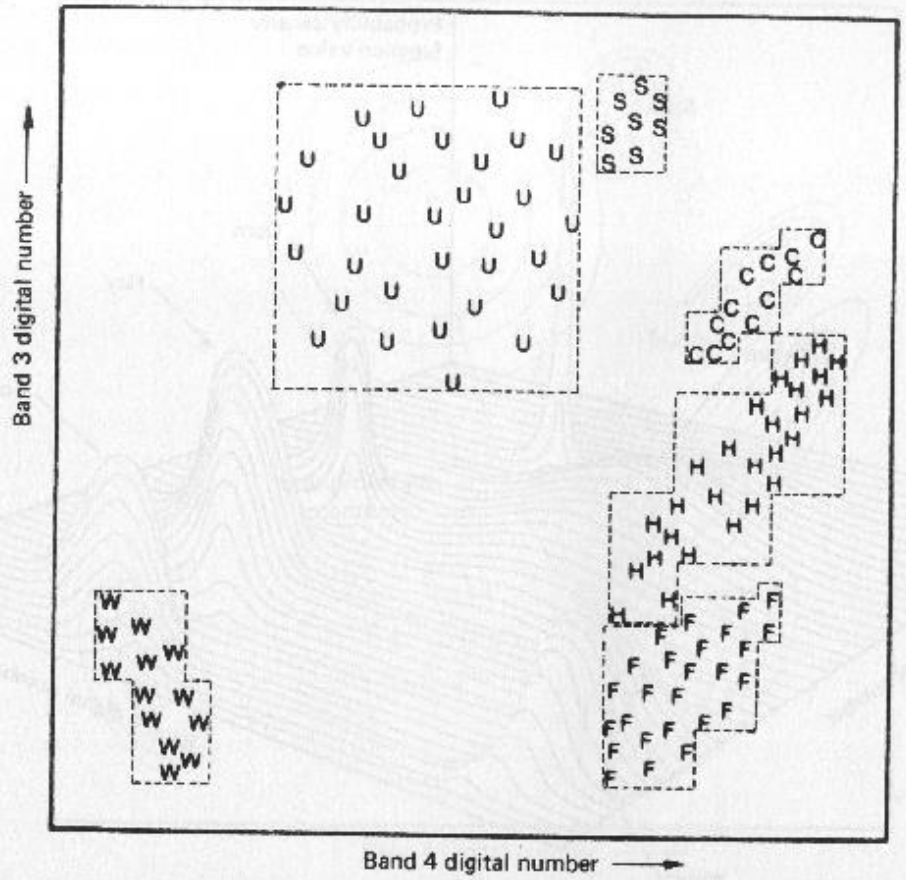
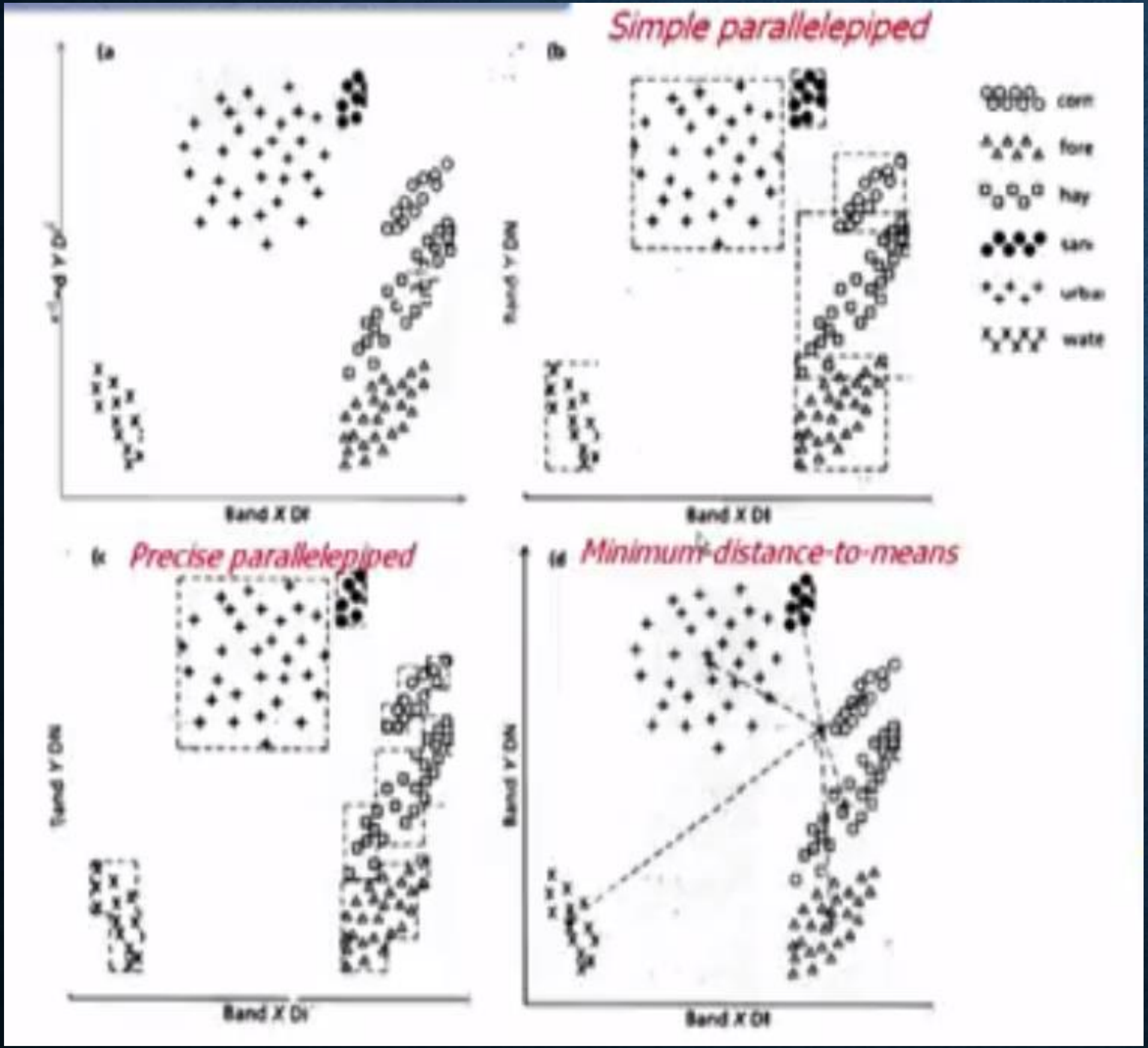


Figure 7.42 Parallelepiped classification strategy employing stepped decision region boundaries.

Simple boxes defined by min/max limits of each training class. But overlaps……..?

…so use stepped boxes

Supervised Classification



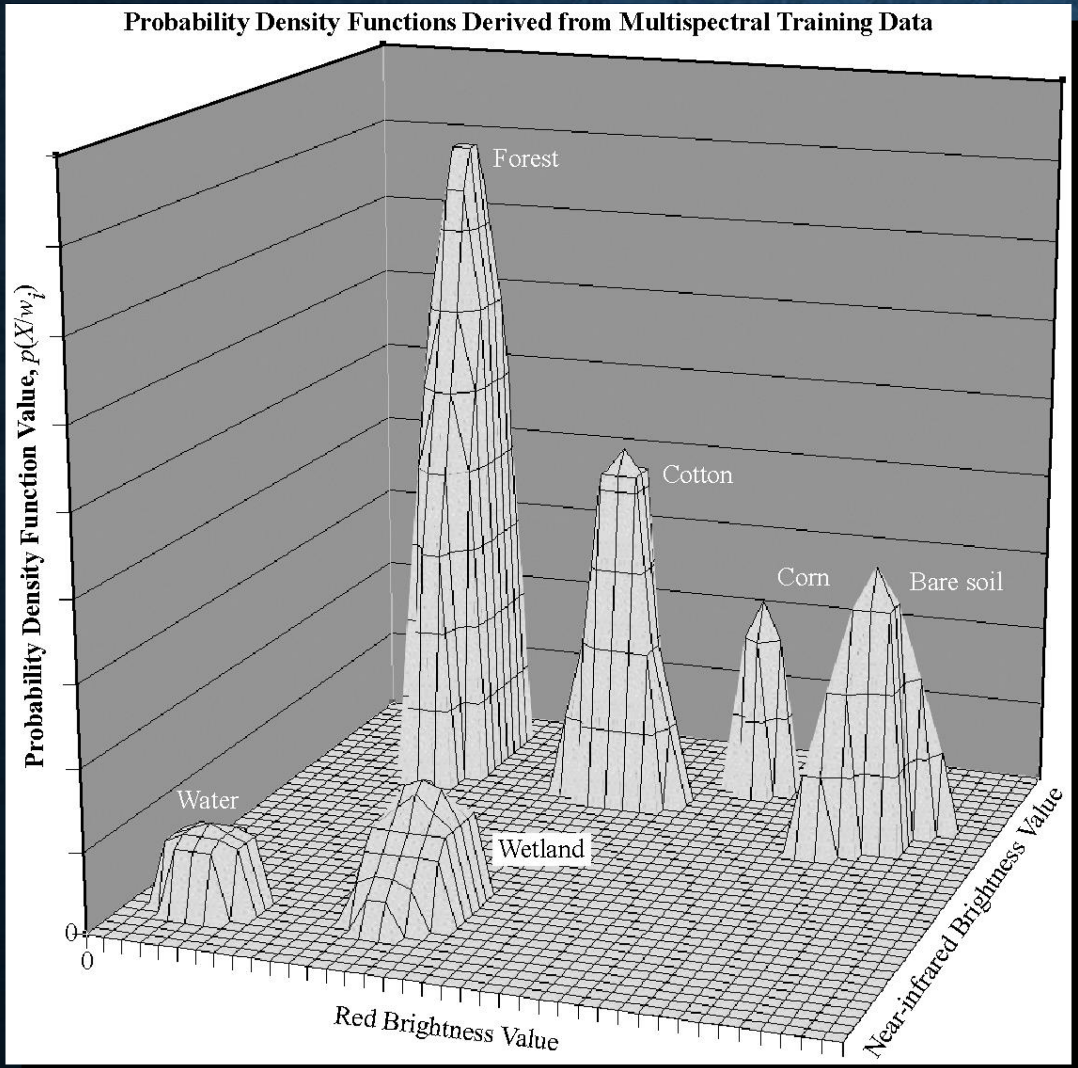
Different methods of spectral classification can be represented diagrammatically be reference to bivariate plots

3. Maximum Likelihood/ Bayesian Classifier

Maximum Likelihood Classifier

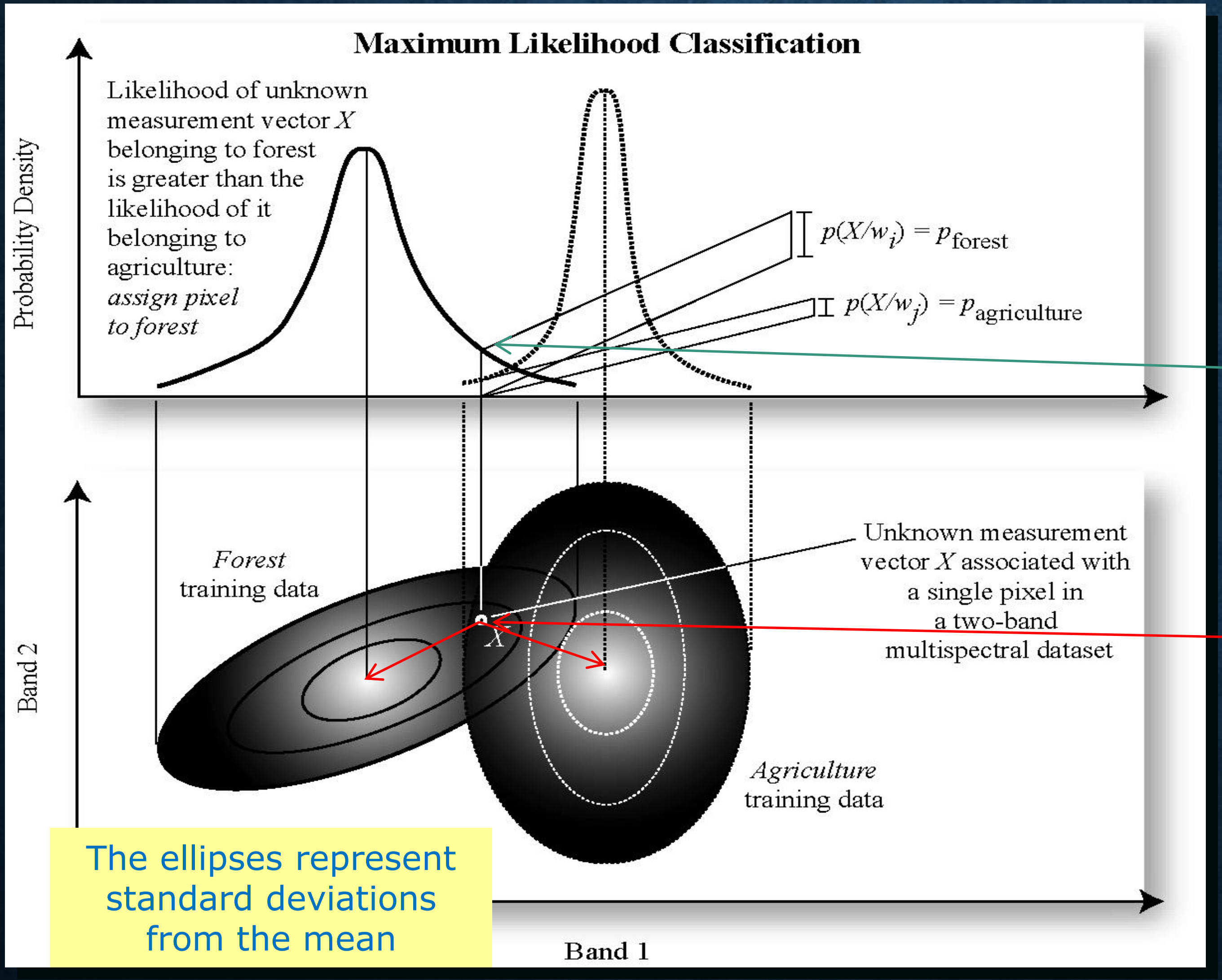
- ✓Classifies pixels based on the probability that a pixel falls within a certain class
- ✓If you know that the probabilities are not equal for all classes, you can specify weight factors
- ✓For example, if you know that a large percentage of a particular image area is forested, you may want to weight that class with a higher probability than other classes.
- ✓The maximum likelihood decision rule is abed on the probability that a pixel belongs to a particular class. The basic equation assumes that input bands have normal distribution.
- ✓If you have a knowledge that the probabilities are not equal for all classes, you can specify weight factors for particular classes.
- ✓This variation of the maximum likelihood decision rule is known as Bayesian decision rule.

Maximum Likelihood Classifier



- ✓ Probability of an unknown pixel being one of the classes
- ✓ If an unknown pixel has brightness values within the wetland region, it has a high probability of being wetland

Maximum Likelihood Classifier



pixel *X* would be assigned to forest because the probability is greater for forest than for agriculture.

Minimum distance classifier - Agriculture

Maximum Likelihood Classifier

Advantages:

- ✓ most accurate; considers variability.
  - ✓ The most accurate of the classification (if the input samples/ clusters have a normal distribution), because it takes the most variables into consideration.

Disadvantages:

- ✓ slow; relies heavily on normally distributed signatures
- ✓ An extensive equation that takes a long time to compute. The computation time increases with the number of input bands.
- ✓ Maximum likelihood is parametric, meaning that it relies heavily on a normal distribution of the data in each input band.
- ✓ Tends to overclassify signatures with relatively large values in the covariance matrix.

Supervised Classification: Gaussian Maximum Likelihood

- ✓Now we use probability rather than distance in feature space.
- ✓Which class is each pixel "most likely" to belong to??

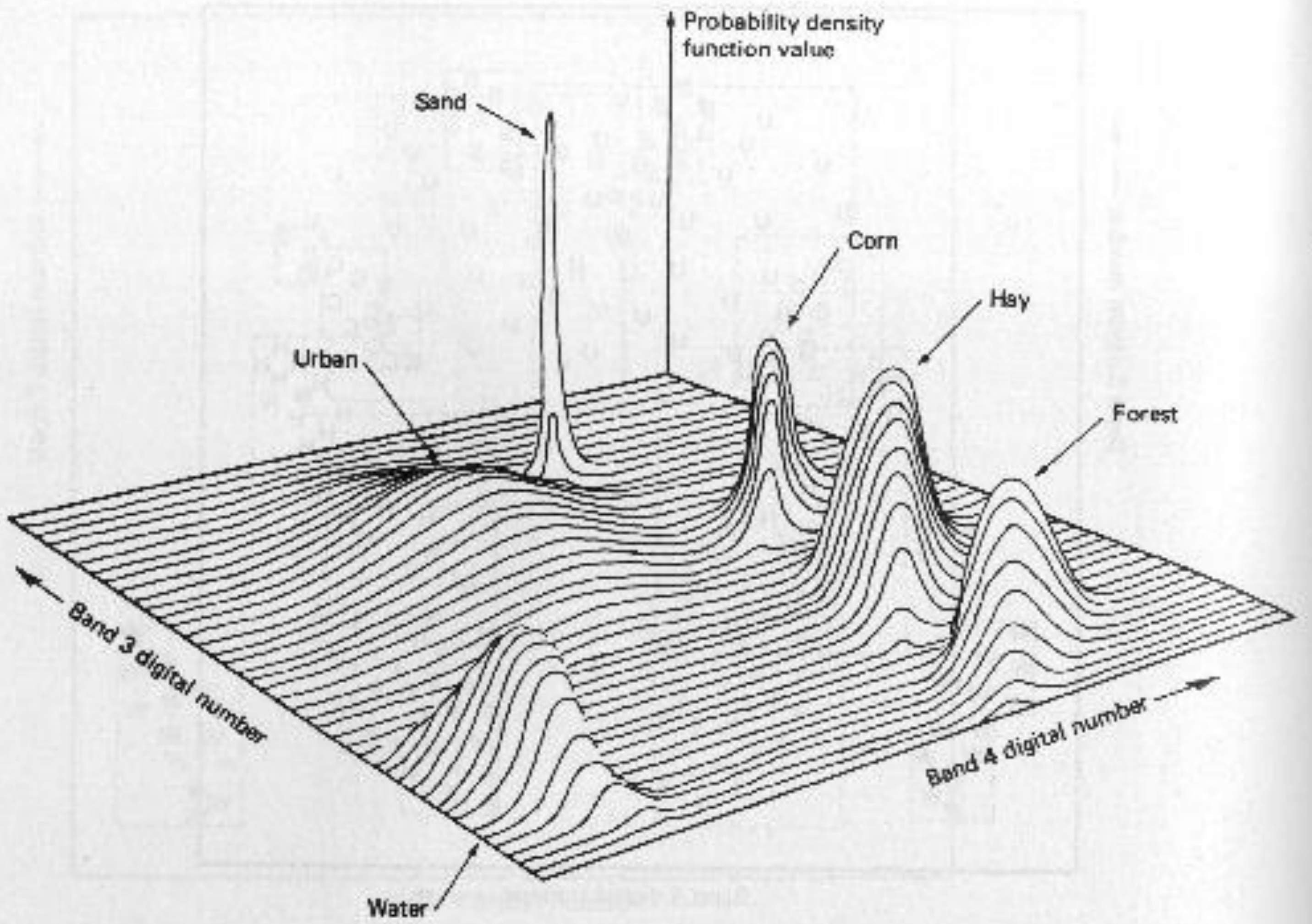
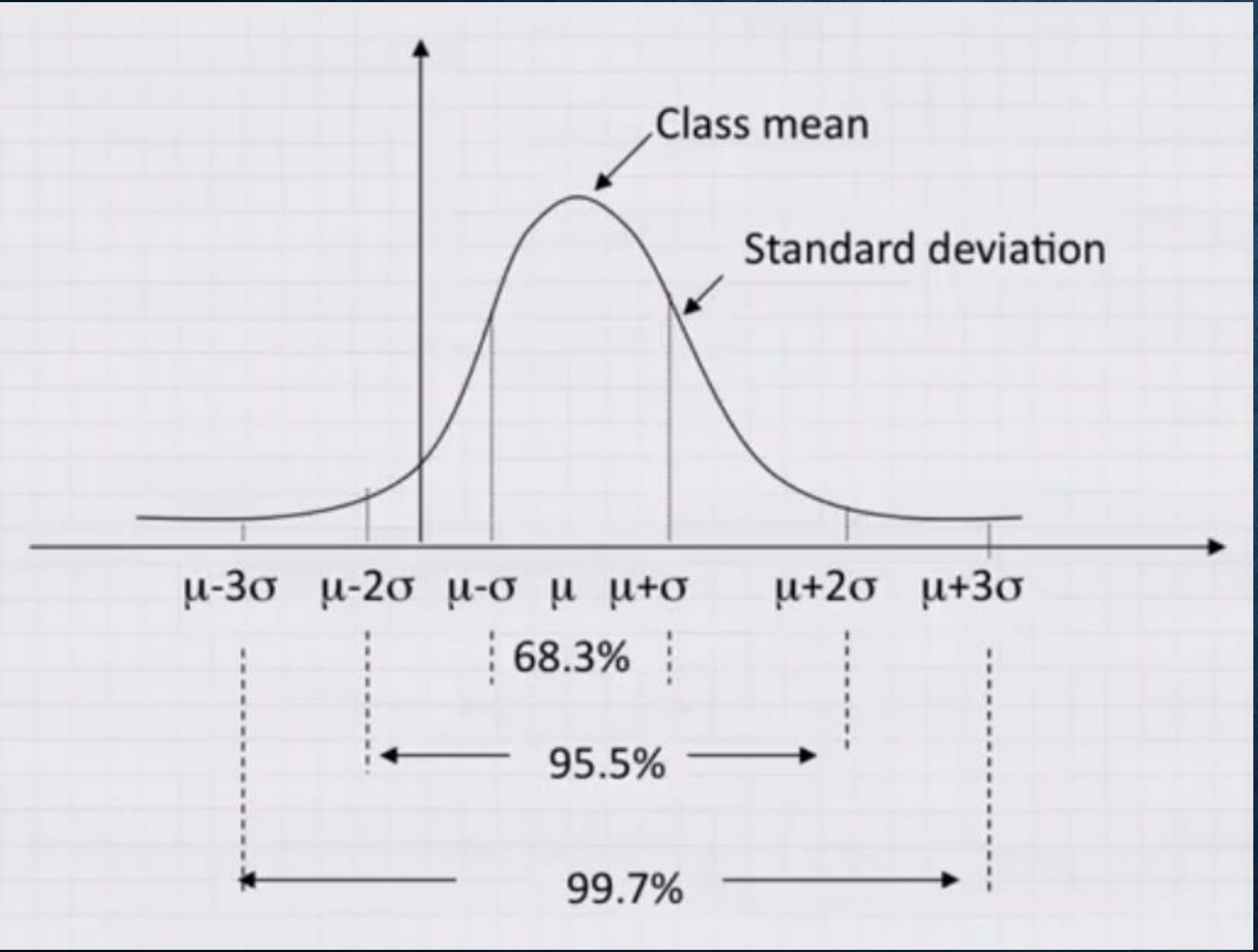
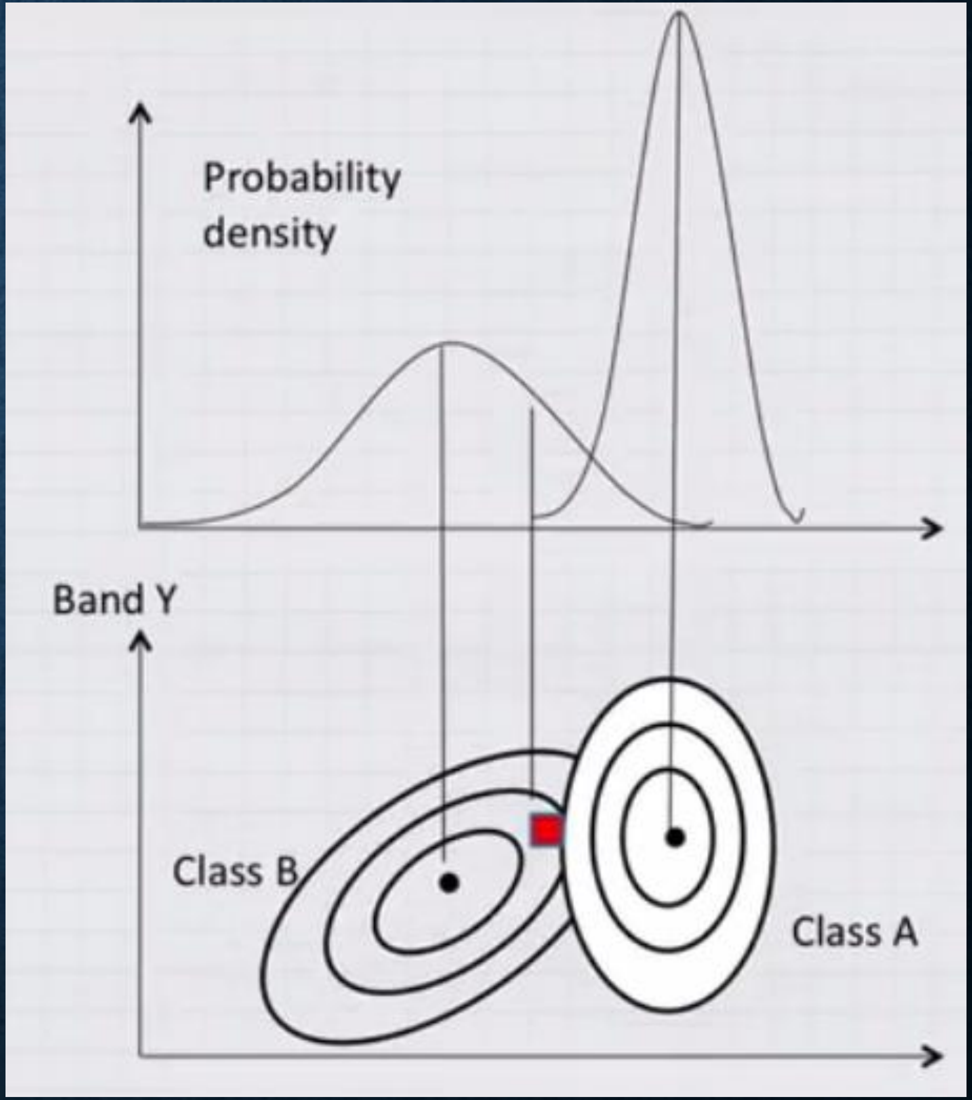


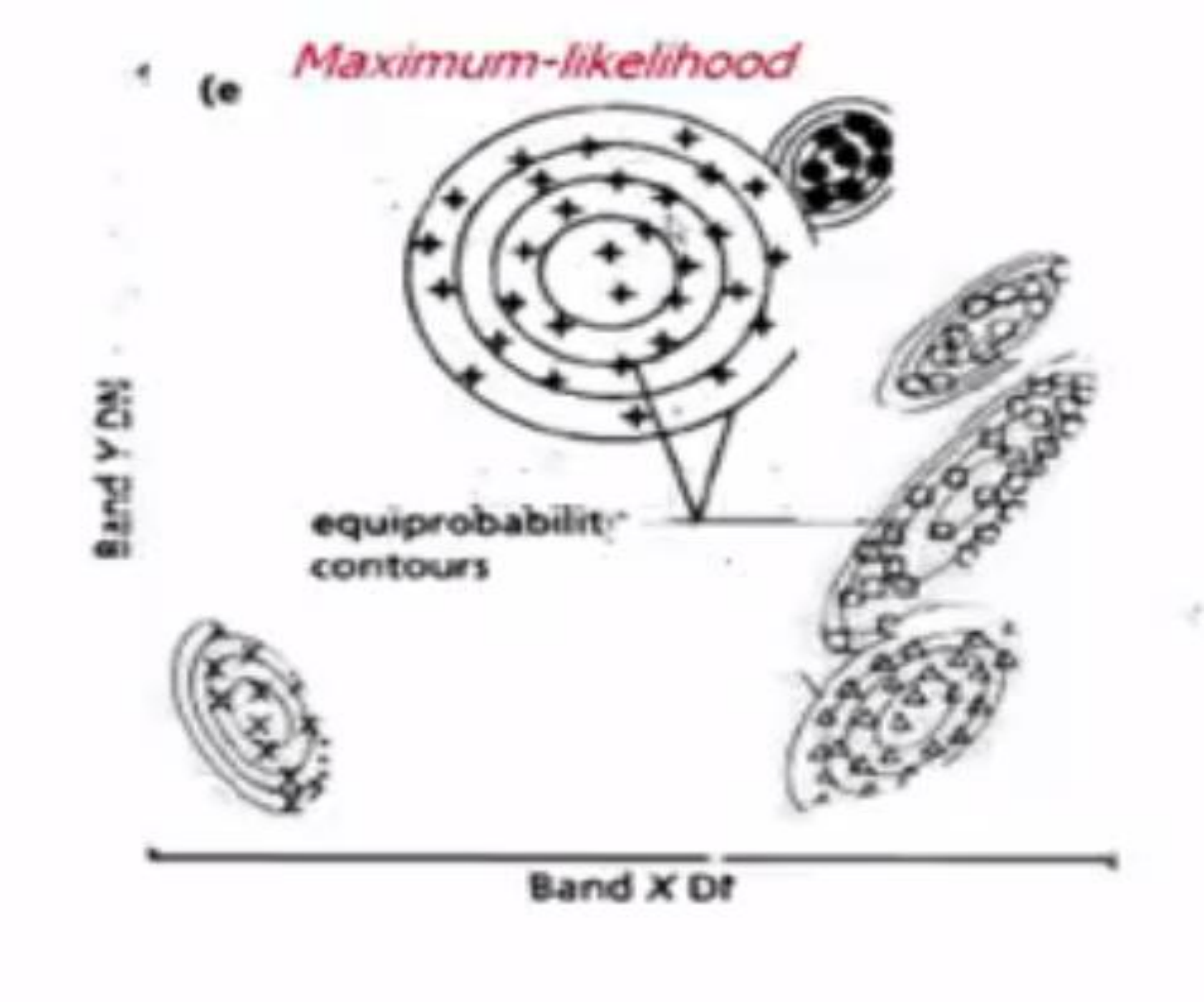
Figure 7.43 Probability density functions defined by a maximum likelihood classifier.

Supervised Classification: Gaussian Maximum Likelihood





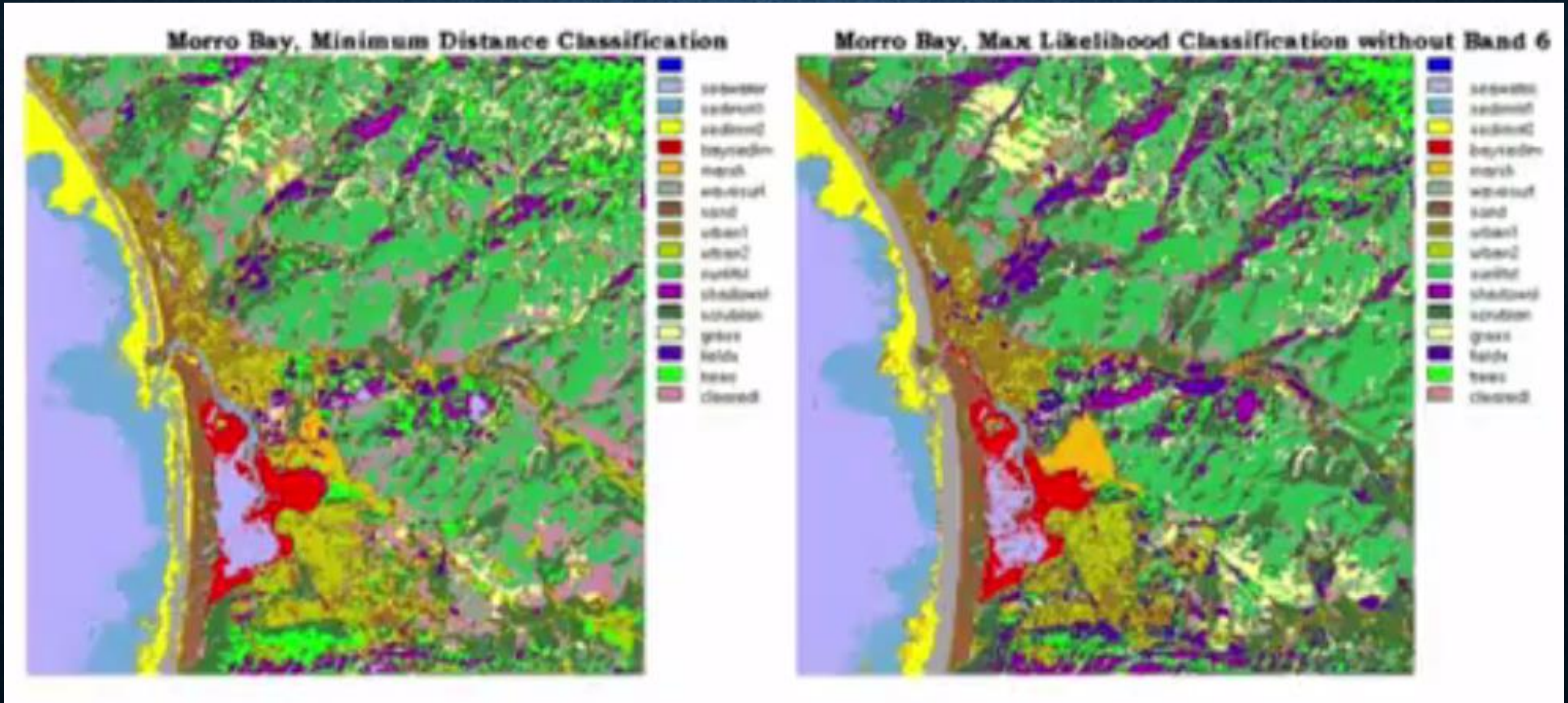
Supervised Classification



The contours express the probability that any point belongs toa particular class, which is the basis of the maximum likelihood method of classification.

Supervised Classification

Example of Two Classification



Unsupervised Classification

When access to domain knowledge or the experience of an analyst is missing, the data can still be analyzed by numerical exploration, whereby the data are grouped into subsets or ***clusters*** based on statistical similarity

Unsupervised Classification

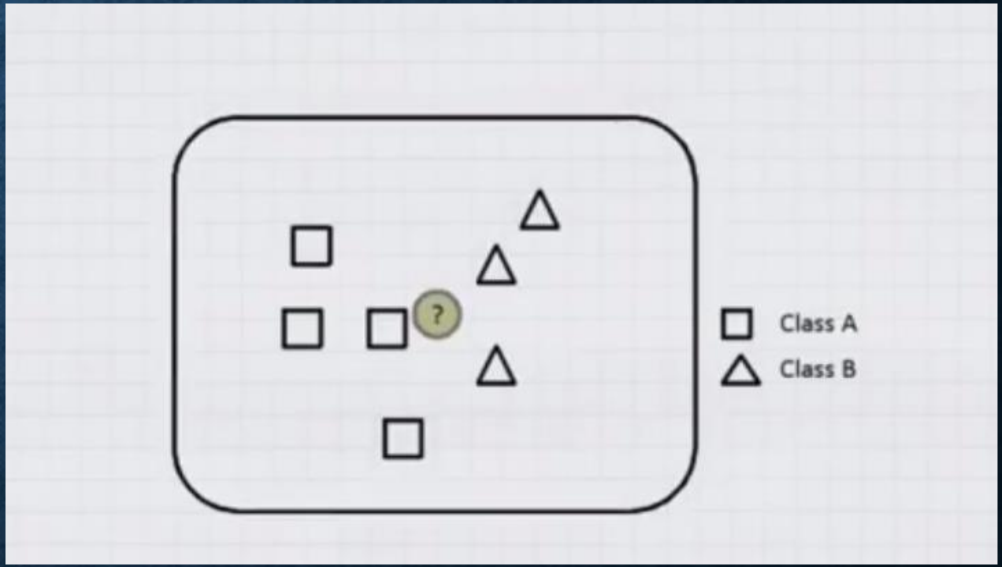
Unsupervised classification is also known as learning without teacher

- ✓ In the absence of reliable training data it is possible to understand the structure of the data using statistical methods such as *clustering algorithms*

- ✓ *Popular clustering algorithms are k-means and ISODATA*

Process of Unsupervised Classification

1. Determine a *general* classification scheme
2. Assign pixels to spectral classes (ISODATA)
3. Assign spectral classes to informational classes



Clustering Algorithms

All feature vectors are points in an L-dimensional space where L is the number of bands *(The letter K is reserved for the number of clusters!)*

- ✓ It is required to find which sets of feature vectors tend to form clusters
- ✓ ***Members of a cluster are more similar to each other than to members of another cluster – In other words, they possess low intra-cluster variability and high inter cluster variability***

Clustering algorithms

K-means

- ✓ Locate centers of seed clusters
- ✓ assign all pixels to the cluster with the closest mean vector
- ✓ revise mean vectors for each clusters
- ✓ reclassify the image
- ✓ iterative until there is no significant change

Iterative self-organizing data analysis (ISODATA)

Permit the number of clusters to change from on iteration to the next by

- ✓ Merging: distance some predefined minimum distance
- ✓ Splitting: standard deviation some predefined maximum distance
- ✓ Deleting: pixel number in a cluster some specified minimum number

K-Means

Iterative algorithm

- ✓ Number of clusters K is known by user
- ✓ Most popular clustering algorithm
- ✓ Initialize randomly K cluster mean vectors
- ✓ Assign each pixel to any of the K clusters based on minimum feature distance
- ✓ After all pixels are assigned to the K clusters, each cluster mean is recomputed.
- ✓ Iterate till cluster mean vectors stabilize

Process of Unsupervised Classification

1. Determine a *general* classification scheme
   - ✓ Depends upon the purpose of the classification
   - ✓ With unsupervised classification, the scheme does not need to be very specific

2. Assign pixels to spectral classes (ISODATA)
3. Assign spectral classes to informational classes

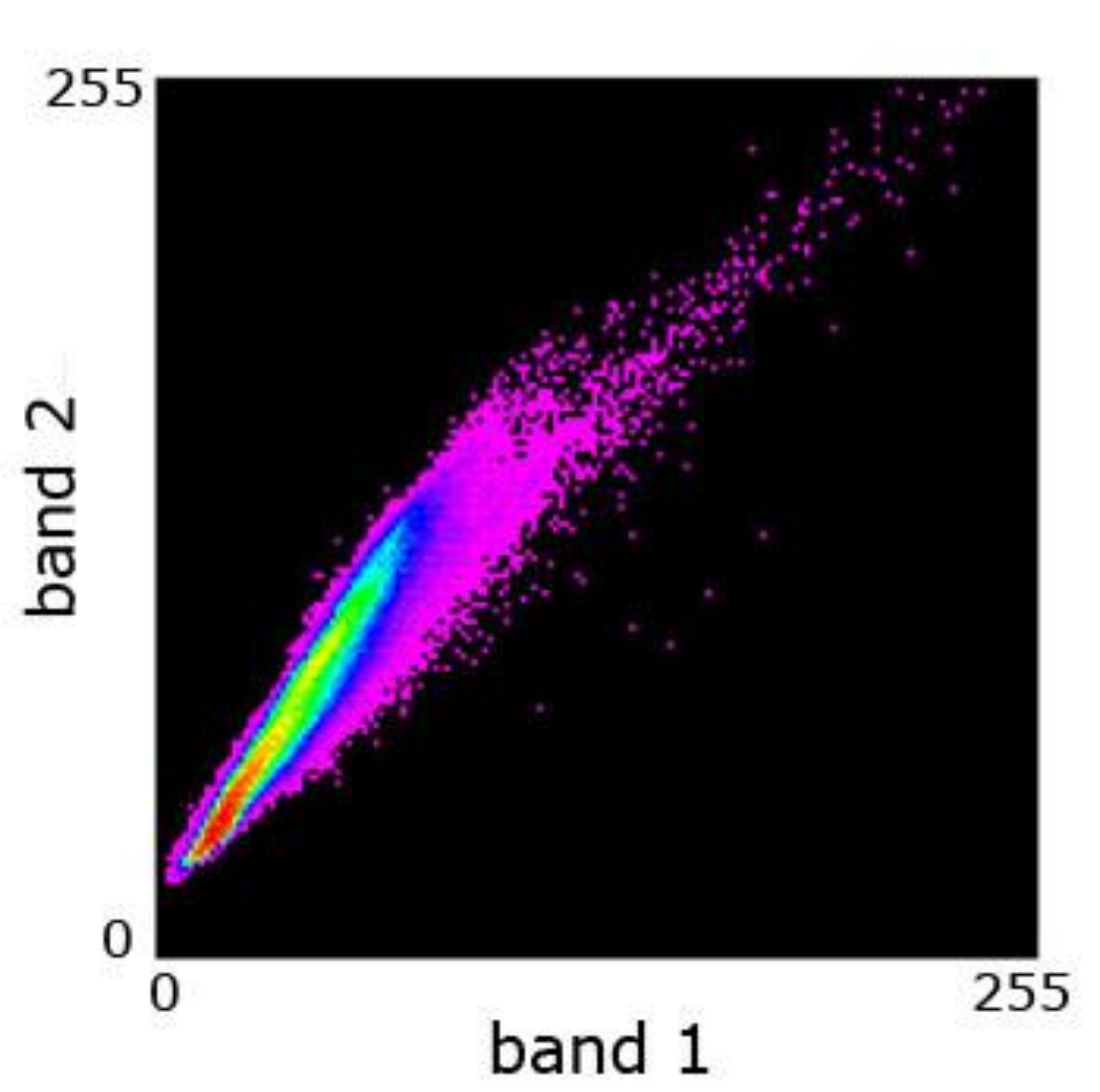
Process of Unsupervised Classification

1. Determine a *general* classification scheme
2. Assign pixels to spectral classes (ISODATA)
   - ✓ Group pixels into groups of similar values based on pixel value relationships in multi-dimensional feature space (clustering)
   - ✓ Iterative ISODATA technique is the most common
3. Assign spectral classes to informational classes

Feature Space

- ✓ Multi-dimensional relationship of the pixel values of multiple image bands across the radiometric range of the image
- ✓ Allows software to examine the statistical relationship between image bands

Feature Space Plot



- ✓ Feature space images represent two-dimensional plots of pixel values in two image bands (with 8-bit data, in a 255 by 255 feature space)
- ✓ The greater the frequency of unique pairs of values, the brighter the feature space
- ✓ Distribution of pixels within the spectral space at bright locations, correspond with important land-cover types

ISODATA

- ✓ "Iterative Self-Organizing Data Analysis Technique"
- ✓ Developed in biology in the 1960's by Ball and Hall
- ✓ See Tou and Gonzalez's classic "Pattern Recognition Principles" for an excellent exposition to clustering algorithms.
- ✓ Uses "spectral distance" between image pixels in feature space to classify pixels into a specified number of unique spectral groups (or "clusters")

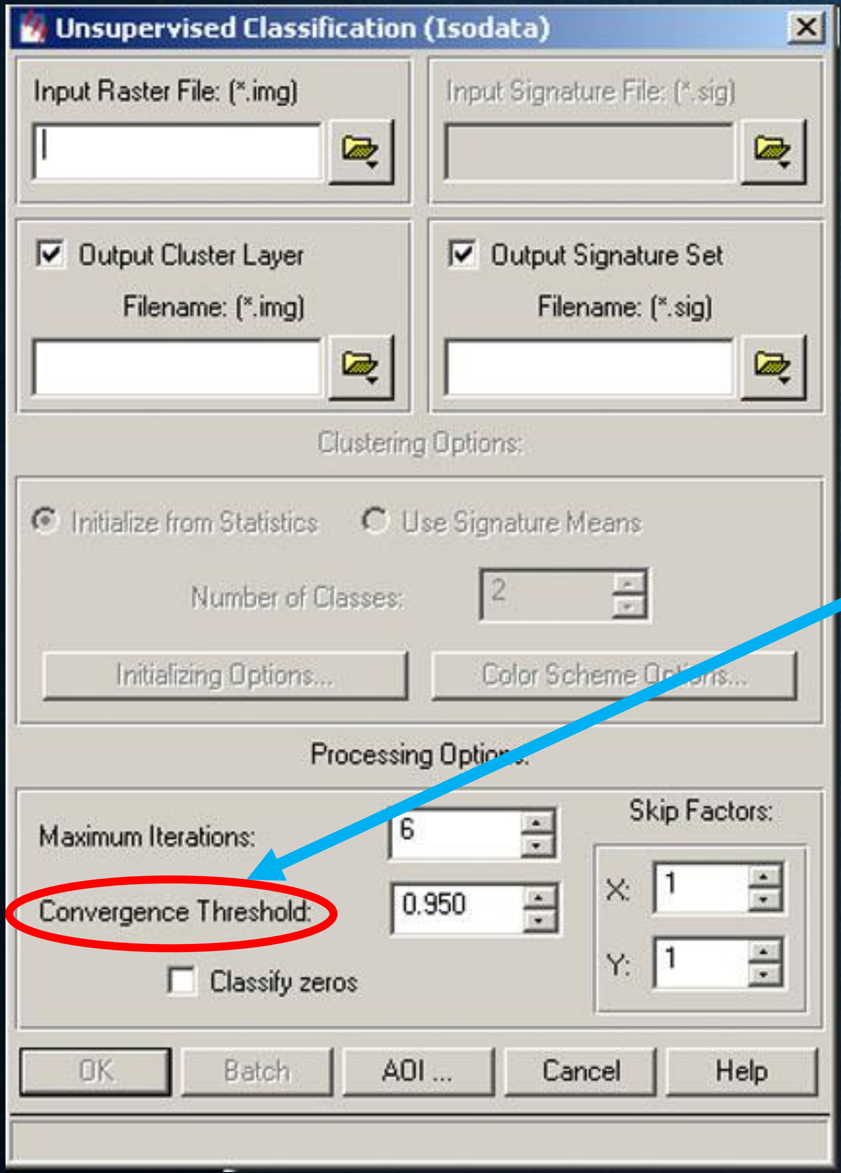
User specified parameters for ISODATA

Generalization of K-Means algorithm

Consists of many user-specified parameters

- ✓ Minimum size of cluster
- ✓ Maximum size of cluster
- ✓ Maximum intra-cluster variance
- ✓ Minimum separation between pairs of clusters
- ✓ Maximum number of clusters
- ✓ Minimum number of clusters
- ✓ Maximum number of iterations

ISODATA Parameters & Guidelines



- ***Number of clusters*:**

  10 to 15 per desired land cover class

- ***Convergence threshold*:**

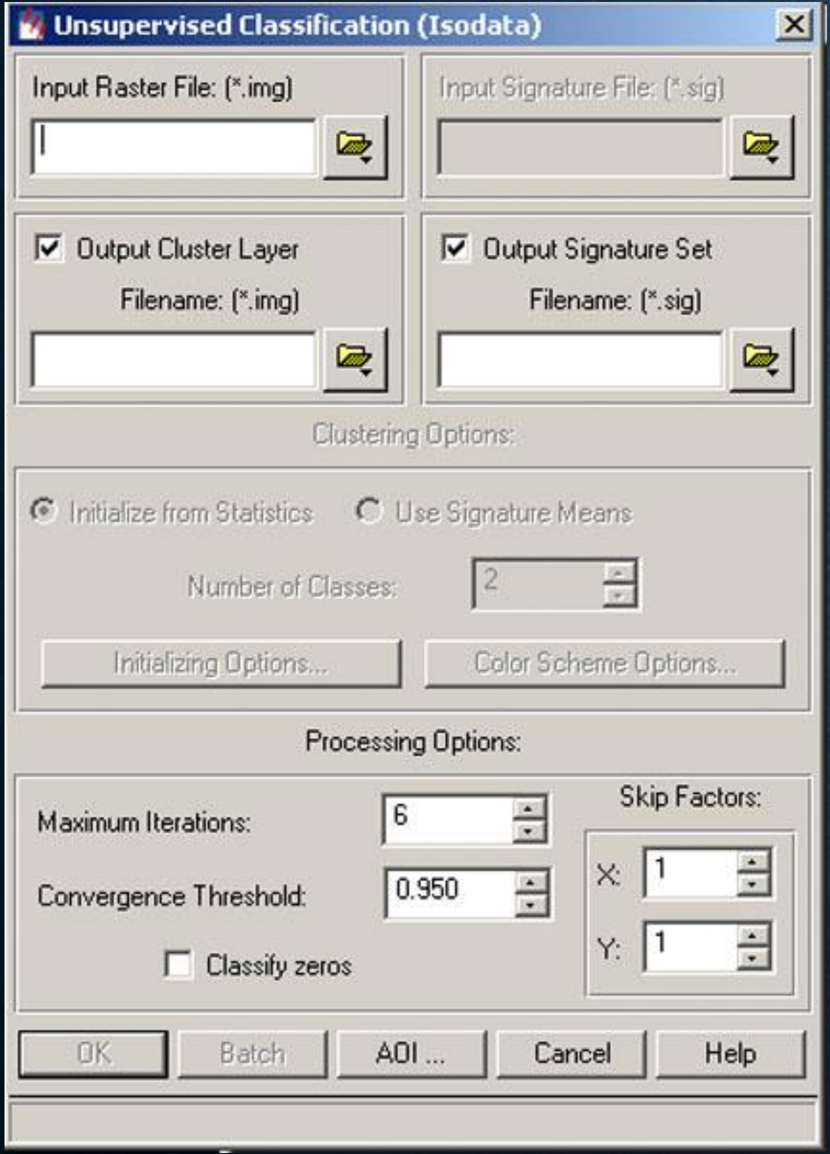
  percentage of pixels whose class values should not change between iterations; generally set to 95%

➢A convergence threshold of 0.95 indicates that processing will cease as soon as 95% or more of the pixels stay the same from one iteration to the next (or 5% or fewer pixels change)

➢Processing stops when the # of iterations or convergence threshold is reached (whichever comes first)

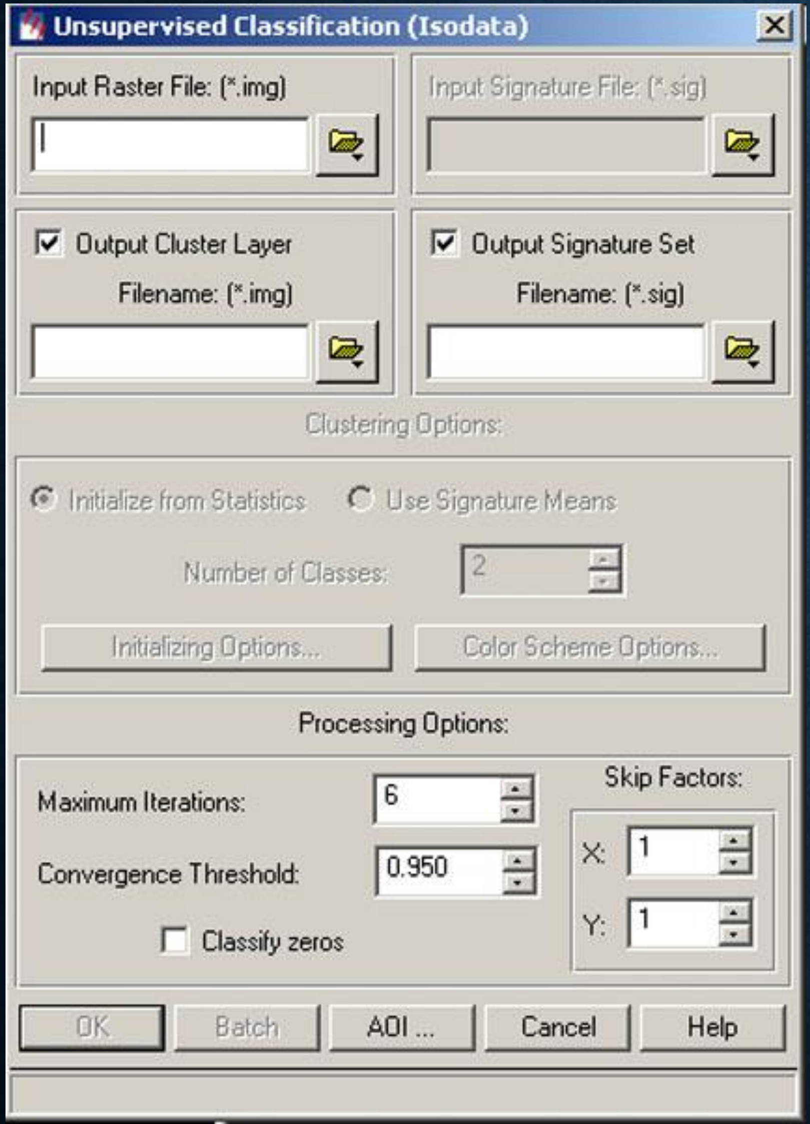
➢Should set “reasonable” parameters so that convergence is reached before iterations run out

ISODATA Parameters & Guidelines



- ✓ A convergence threshold of 95% indicates that processing will cease as soon as 95% or more of the pixels stay the same from one iteration to the next (or 5% or fewer pixels change)
- ✓ Processing stops when the # of iterations or convergence threshold is reached (whichever comes first)

ISODATA Parameters & Guidelines

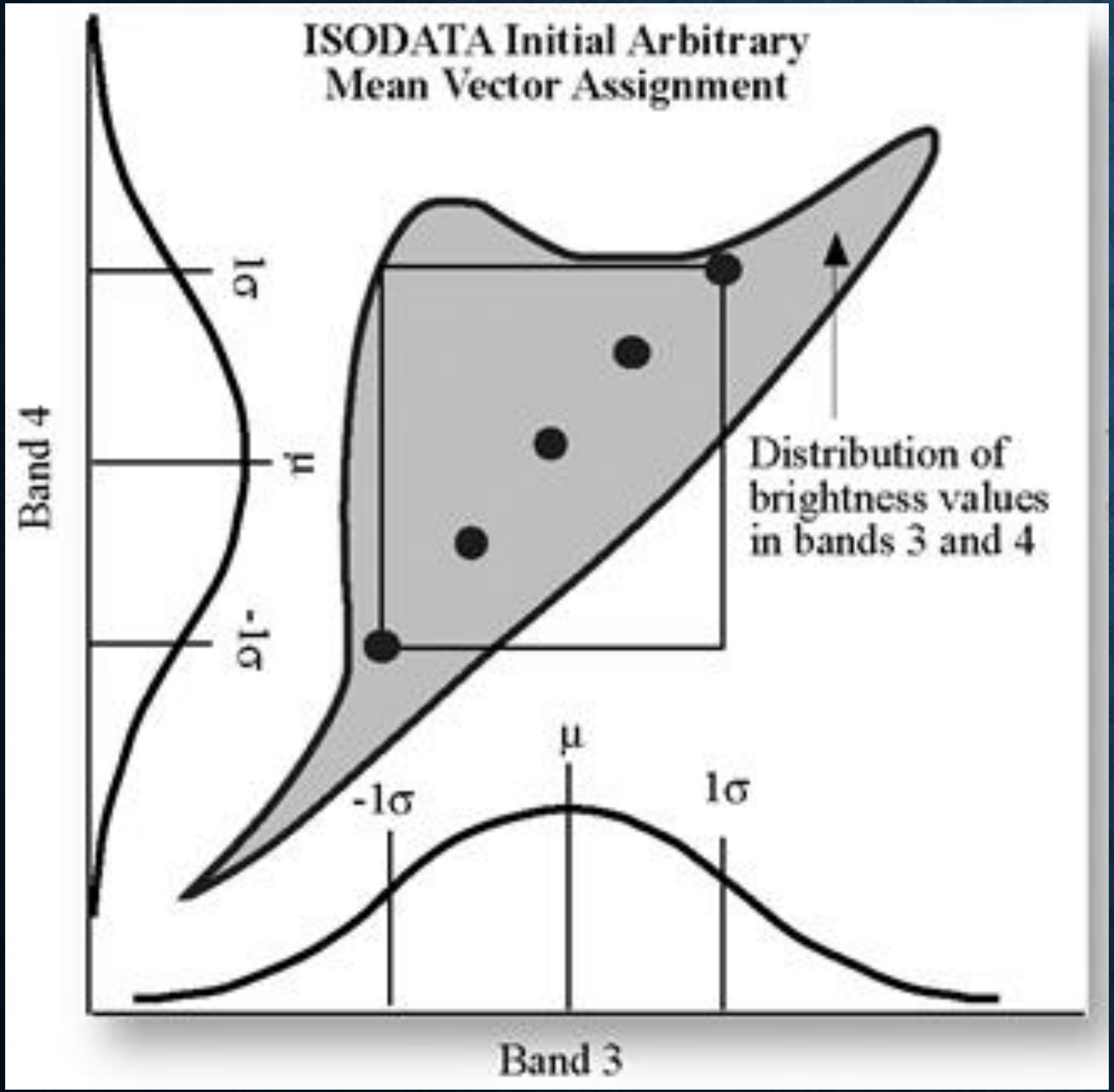


- ✓ *Maximum number of iterations:*

  ideally, the convergence threshold should be reached

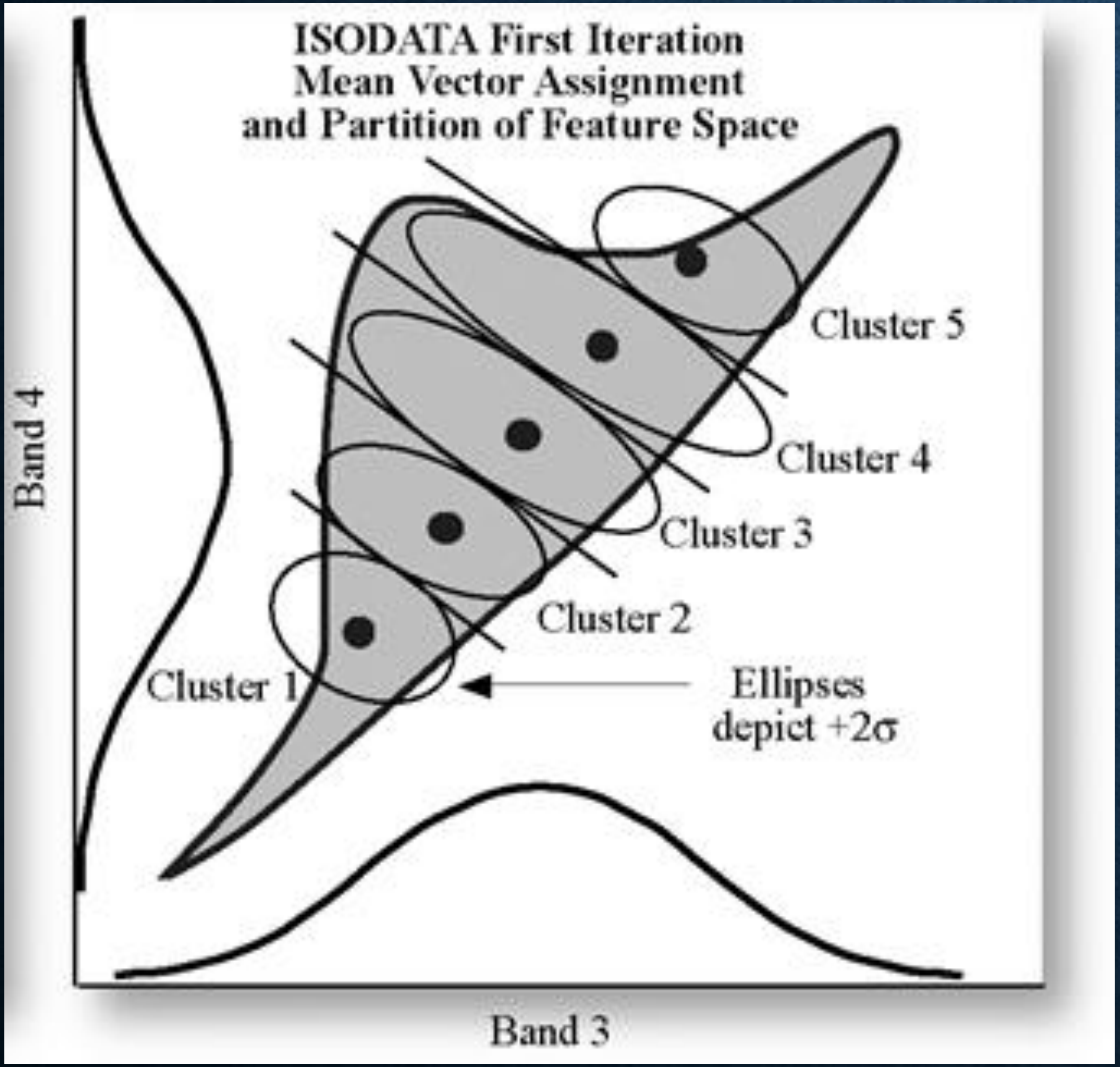
- ✓ Should set "reasonable" parameters so that convergence is reached before iterations run out

ISODATA: Step 01



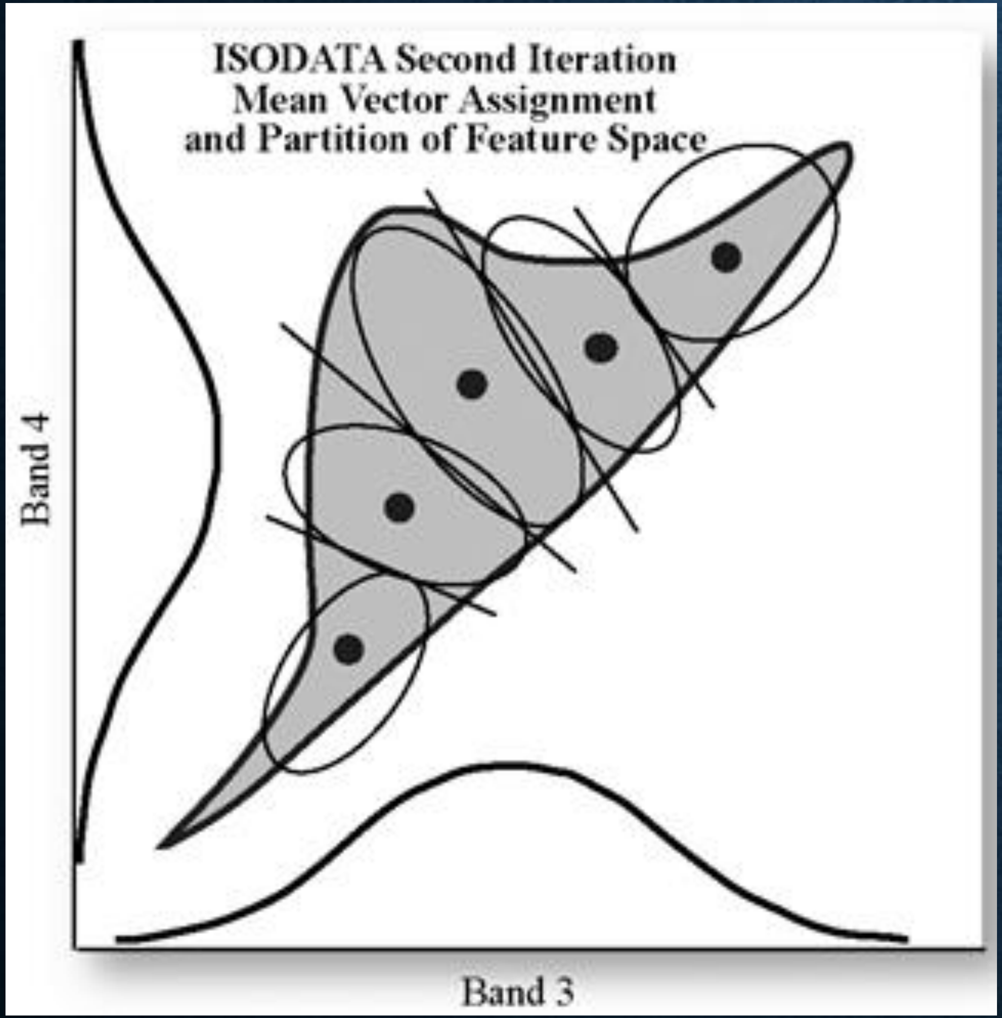
a) ISODATA initial distribution of five hypothetical mean vectors using +/- 1 standard deviation in both bands as beginning and ending points.

ISODATA: Step 02



b) In the first iteration, each candidate pixel is compared to each cluster mean and assigned to the cluster whose mean is closest

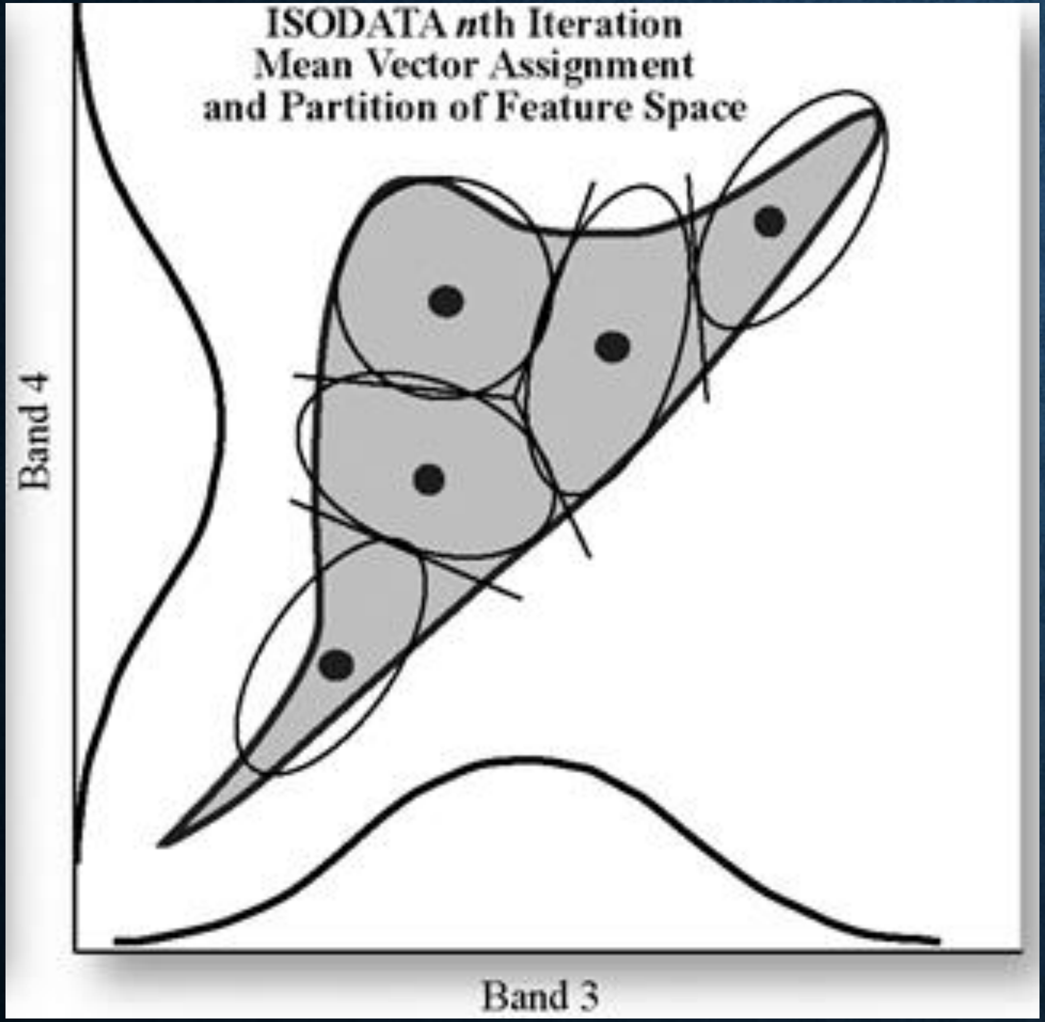
ISODATA: Step 03



c) During the second iteration, a new mean is calculated for each cluster based on the actual spectral locations of the pixels assigned to each cluster.

After the new cluster mean vectors are selected, every pixel in the scene is assigned to one of the new clusters

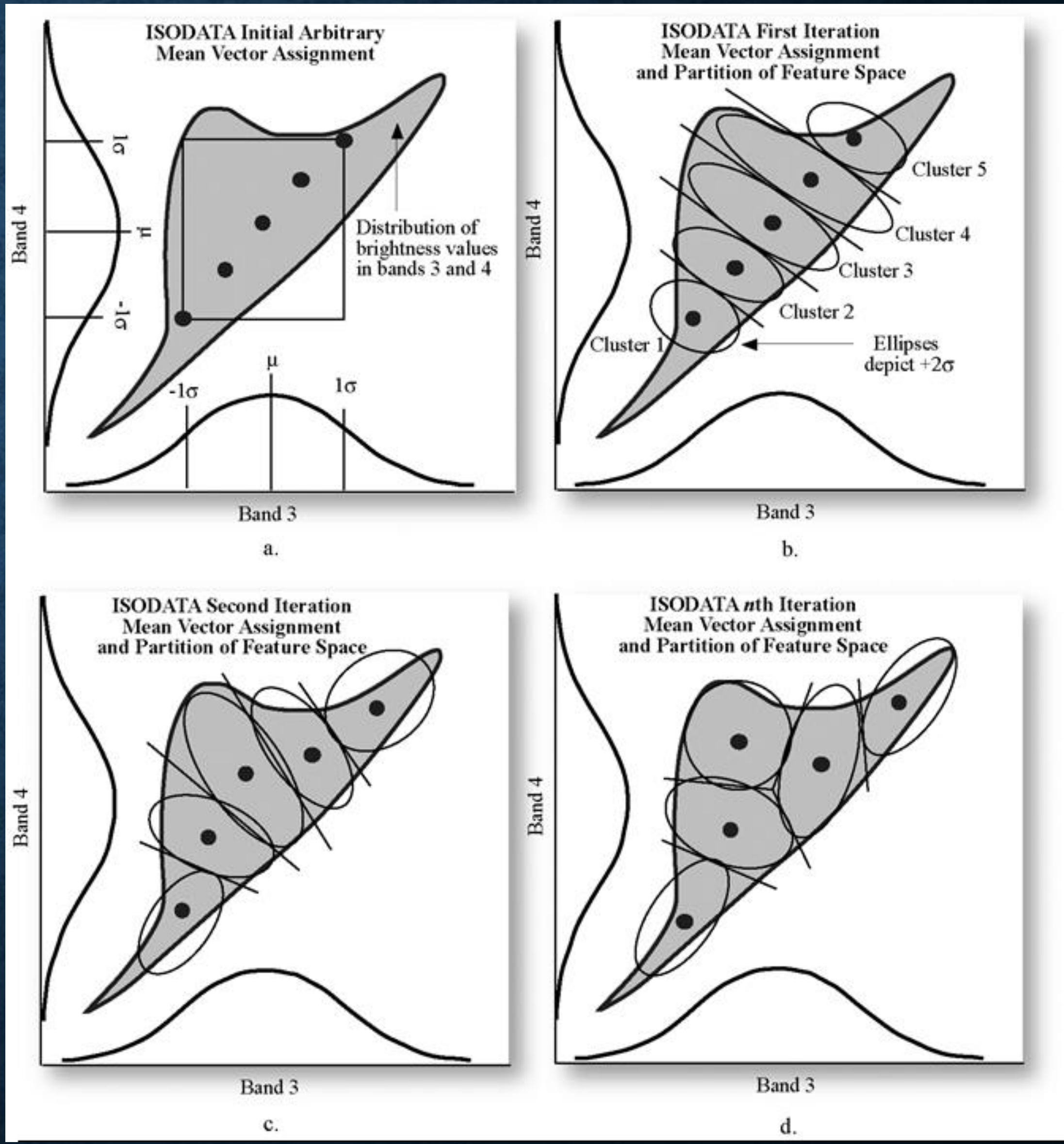
ISODATA: Step 04



d) This split-merge-assign process continues until there is little change in class assignment between iterations (the T threshold is reached) or the maximum number of iterations is reached (M)

ISODATA

- ✓ ISODATA iterations; pixels assigned to clusters with closest spectral mean; mean recalculated; pixels reassigned
- ✓ Continues until maximum iterations or convergence threshold reached.
- ✓ This is a simple, 2D illustration.
- ✓ Explain ISODATA iterations; pixels assigned to clusters with closest spectral mean; mean recalculated; pixels reassigned
- ✓ Continues until maximum iterations or convergence threshold reached



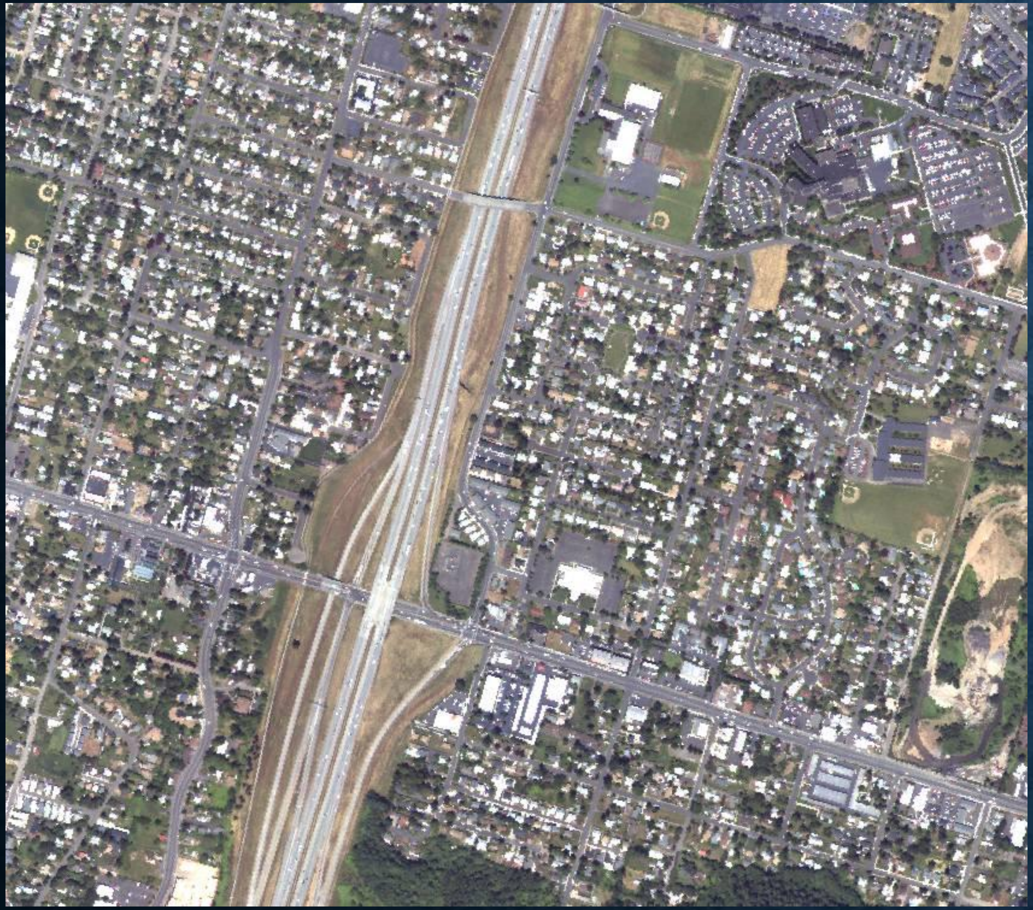
Process of Unsupervised Classification

1. Determine a *general* classification scheme
2. Assign pixels to spectral classes (ISODATA)

3. Assign spectral classes to informational classes

Once the spectral clusters in the image are identified, the analyst must assign them to the "informational" classes of the classification scheme (i.e., land cover)

Example: Image to be Classified



- ✓ Multiple clusters likely represent a single type of “feature” on the ground.
- ✓ Someone needs to assign a landcover class to all of these clusters; can be difficult and time consuming.

Advantages and Disadvantages of Unsupervised Classification?

Advantages

- ✓ No prior knowledge of the image area is required
- ✓ Human error is minimized
- ✓ Unique spectral classes are produced
- ✓ Relatively fast and easy to perform

Disadvantages

- ✓ Spectral classes do not represent features on the ground
- ✓ Does not consider spatial relationships in the data
- ✓ Can be very time consuming to interpret spectral classes
- ✓ Spectral properties vary over time, across images