Digital Image Classification

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Supervised Classification

- In this type of classification the image analyst "*supervises*" the **pixel categorization process** by specifying, to the computer **algorithm**, numerical descriptors of the various land cover types present in a it a scene.
- **Representative sample sites of known cover type**, called training areas, are used to compile a numerical "**interpretation key**" that describes the **spectral attributes for each feature type** of interest.
- **Each pixel** (*unknown*) in the data set is then **compared numerically to each category in the interpretation key** and labeled with the name of the category it "*looks most like*."
- The output image can be represented in the form of:
  - ✓ Thematic maps,
  - ✓ Tables of full scene or subscene area, and
  - ✓ Digital data files amenable to inclusion in a *GIS*.

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Process

- The **three basic steps** involved in a typical supervised classification procedure.
  1. Training Stage: the analyst identifies representative training areas and develops a numerical description of the spectral attributes of each land cover type of interest in the scene
  2. Classification Stage :each pixel in the image data set is categorized into the land cover class it most closely resembles. If the pixel is insufficiently similar to any training data set, it is usually labeled "unknown."
  3. Output Image: Final classified image
- The input data is a *multidimensional image matrix,* to develop a corresponding matrix of interpreted land cover category types.

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Methods

1. Minimum –distance to means classifier (Non –parametric)
2. Parallelepiped classifier (Non –parametric)
3. Maximum Likelihood classifier (Parametric)

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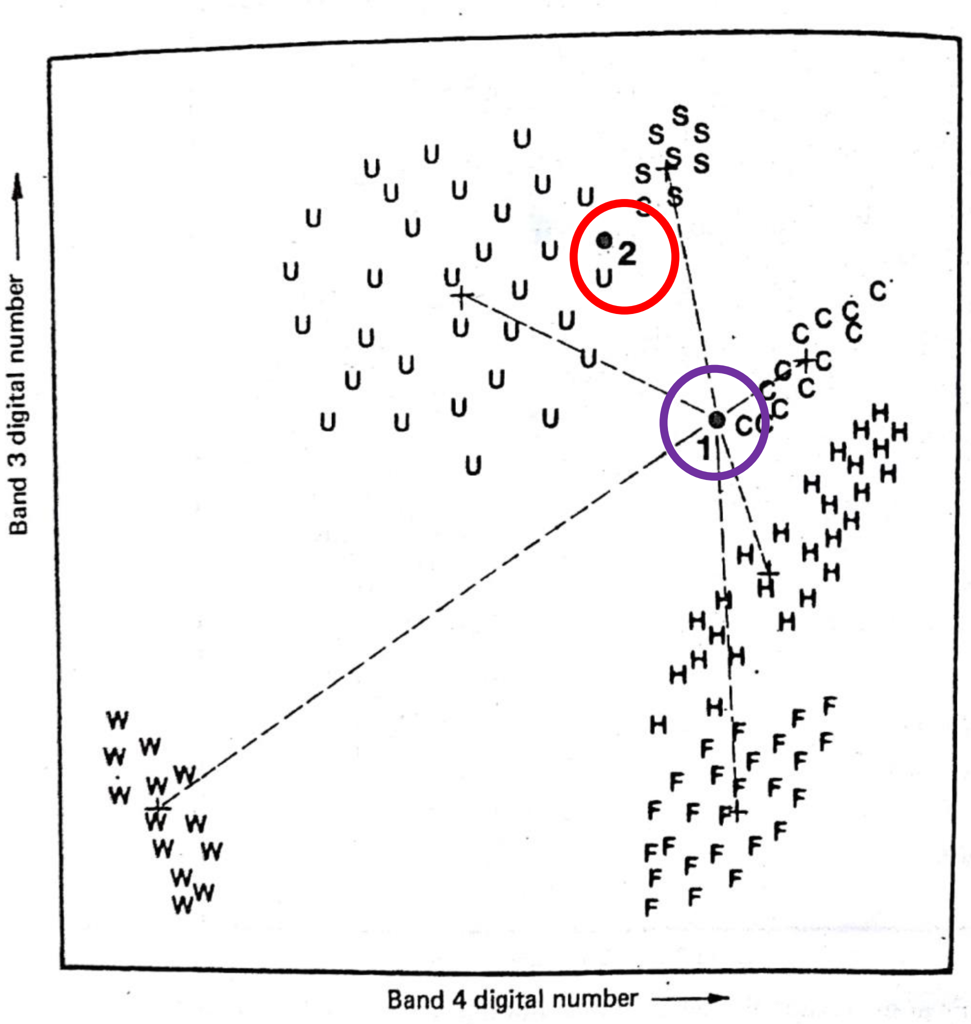
Minimum-Distance-to-Means Classifier

- First, the ***mean spectral value*** in **each band** for each scale is determined.
- These *values* comprise the ***mean* vector for each category**
- The **category means** are indicated by **+** in figure
- A *pixel* of *unknown identity* may be classified by computing the distance between the value of the unknown pixel and each of the category means.
- Unknown pixel value has been plotted at **point 1**.
- The distance between this pixel value and each category mean value is illustrated by the *dashed lines*.
- After computing the distances, the unknown pixel is assigned to the ***"closest" class***, in this case "***corn***."



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Minimum-Distance-to-Means Classifier

Advantages & Limitations

- If the **pixel is farther than** an *analyst defined distance* from any category mean, it would be classified as "**unknown**".
- The minimum-distance-to-means strategy is **mathematically simple** and **computationally efficient**.
- It is insensitive to **different degrees of variance** in the spectral response data.
- This classifier is *not widely used in applications* where spectral classes are
  - ✓ *close* to one another in the *measurement space* and
  - ✓ have *high variance*

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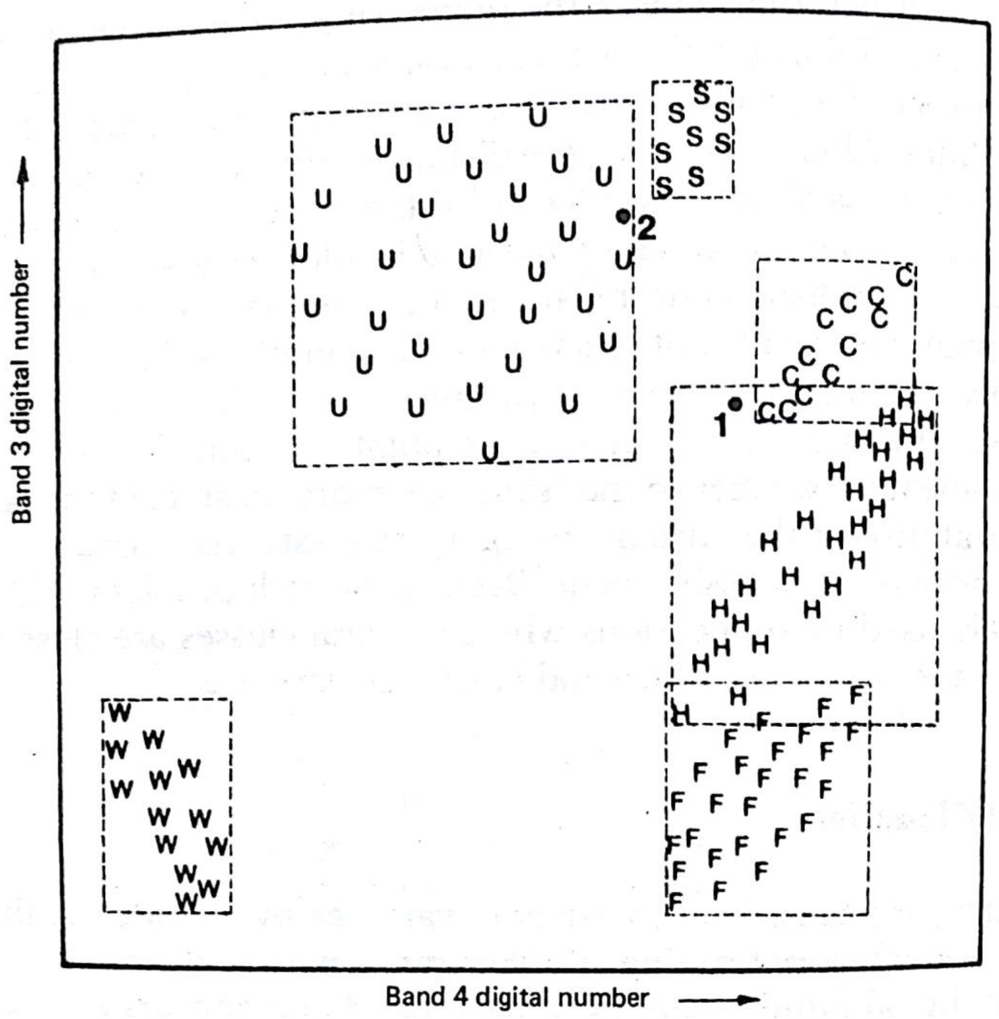
Parallelepiped Classifier

- We can introduce sensitivity to category ***variance*** by considering the *range* of values in each category training set.
- This range may be defined by the ***highest*** and ***lowest*** *digital number values in each band* and appears as a rectangular area.
- An *unknown pixel* is classified according to the **category range**, or **decision region**, in which it lies or as "*unknown*" if it lies *outside* all regions.
- The *multidimensional analogs of these rectangular areas* are called parallelepipeds, and this classification strategy is referred to the parallelepiped classifier.
- Smaller decision region is defined for the **highly repeatable** ***"sand"*** category
- *Larger decision region* is defined for the **more variable** *"urban"* class.
- Therefore, ***pixel 2*** would be appropriately classified as *"urban."*



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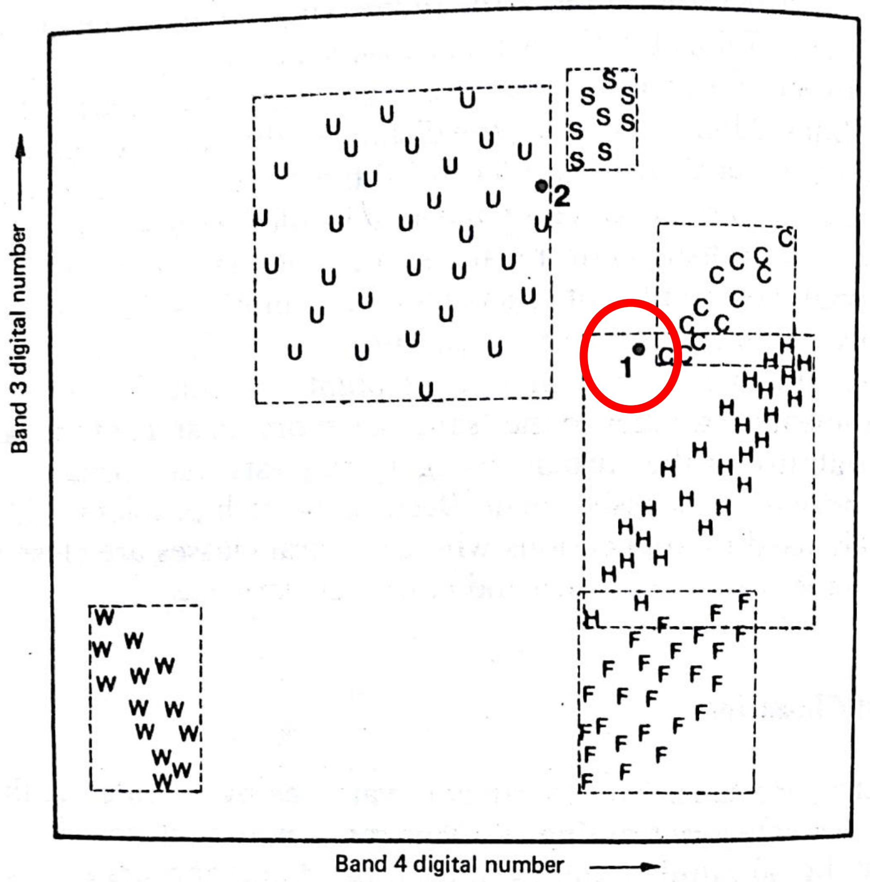
Parallelepiped Classifier…

- *Limitation* : When category ranges **overlap**.
- *Unknown pixel* observations that occur in the **overlap areas** will be classified as "*not sure*" or be arbitrarily placed in one (or both) of the two overlapping classes.
- Overlap is caused largely because category distributions exhibiting *correlation or high covariance* are poorly described by the rectangular decision regions.
- **Covariance** is the tendency of spectral values to *vary similarly in two bands*, resulting in elongated, **slanted clouds of observations** on the scatter diagram.
    - ✓ The "corn" and "hay" categories have ***positive*** covariance
    - ✓ "Water" has ***negative*** covariance
    - ✓ "Urban" class is ***highly variable***
- The classifier is insensitivity to covariance
- Therefore, ***pixel 1*** will be classified as "*hay*" instead of "*corn*."
- Unfortunately, *spectral response patterns* are frequently *highly correlated*



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Gaussian Maximum Likelihood Classifier

- The maximum likelihood classifier quantitatively evaluates both the **variance** and **covariance** of the category spectral response patterns when classifying unknown pixel.

- To do this, an **assumption** is made that *the distribution of the cloud of points forming the category training data is* **Gaussian** (*normally distributed*).

- Given these parameters, we may compute the statistical probability of a given pixel value being a member of a particular land cover class.

- The **probability density functions** are used to classify an unidentified pixel by computing the probability of the pixel value belonging to each category.

- After evaluating the probability in each category, the *pixel* would be assigned to the **most likely class** (***highest probability value***) or be labeled "*unknown*" if the *probability values* are all *below* a **threshold set** by the analyst.

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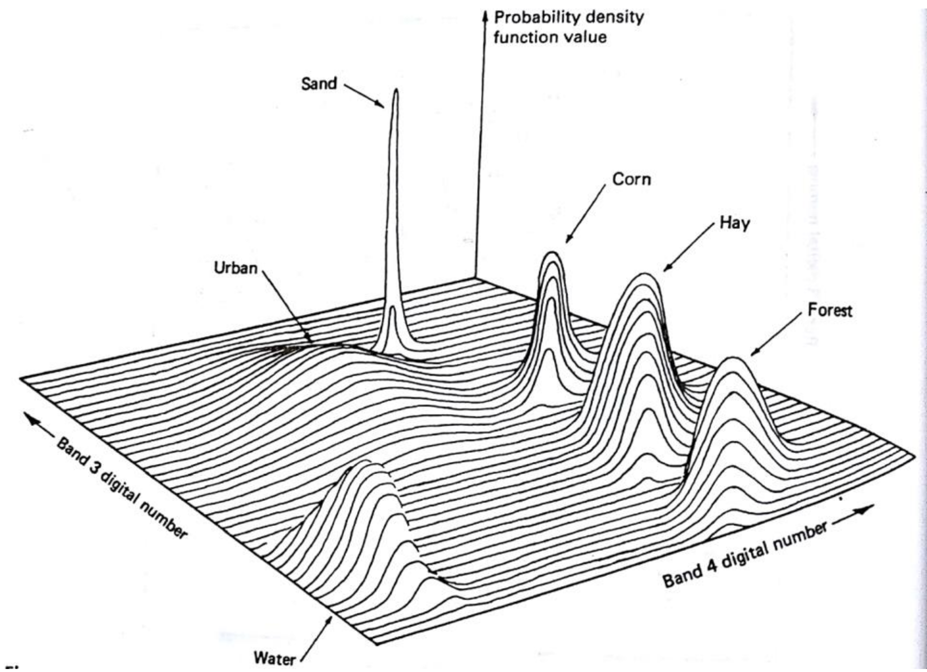
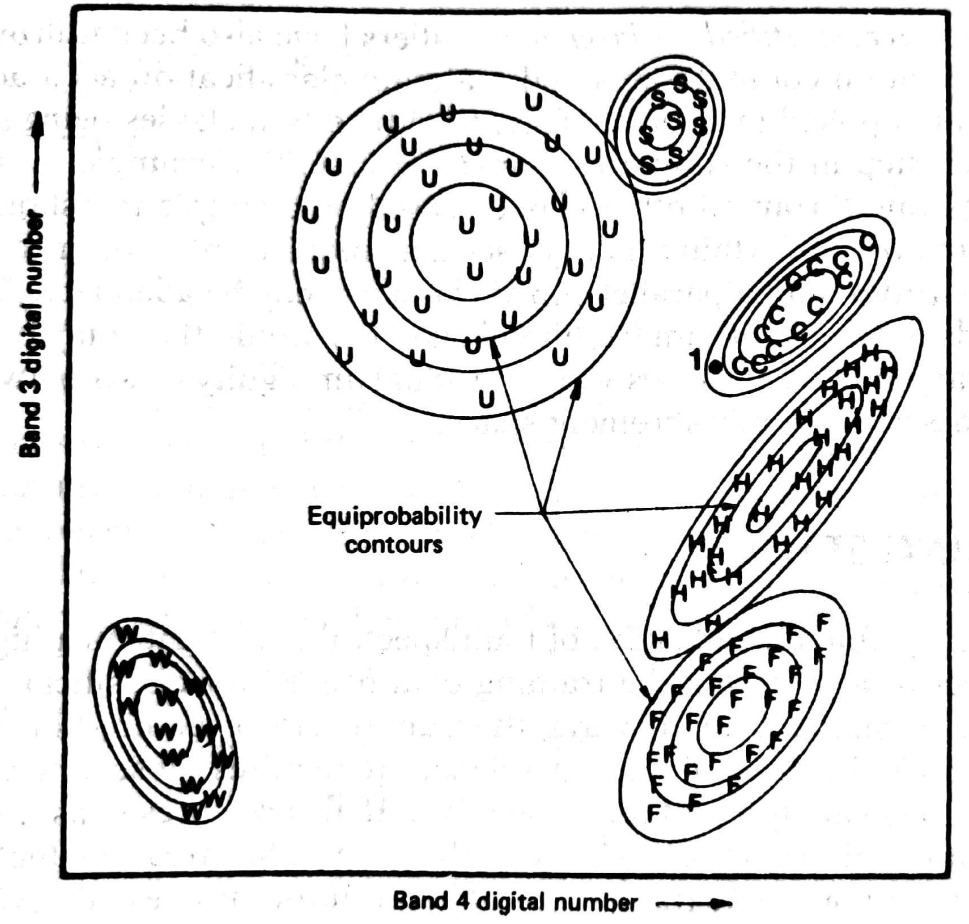


- ✓ Here, shows the probability values plotted in a three-dimensional graph.
- ✓ The **vertical axis** is associated with the **probability** of a pixel value being a member of one of the classes.
- ✓ The resulting **bell-shaped surfaces** are called **probability density functions.**

Gaussian Maximum Likelihood Classifier…

- In essence, the maximum likelihood classifier delineates ellipsoidal "**equiprobability contours**" in the scatter diagram.
- The shape of the equiprobability contours expresses the sensitivity of the likelihood classifier to covariance.
- It can be seen that *pixel 1* would be appropriately *assigned* to the "**corn**" category.
- The *principal drawback* of maximum likelihood classification is the **large number of computations** required to classify each pixel.
- Computationally ***slower technique***.
  - ✓ when either a *large number of spectral channels* are involved or
  - ✓ a large number of *spectral classes* must be differentiated.



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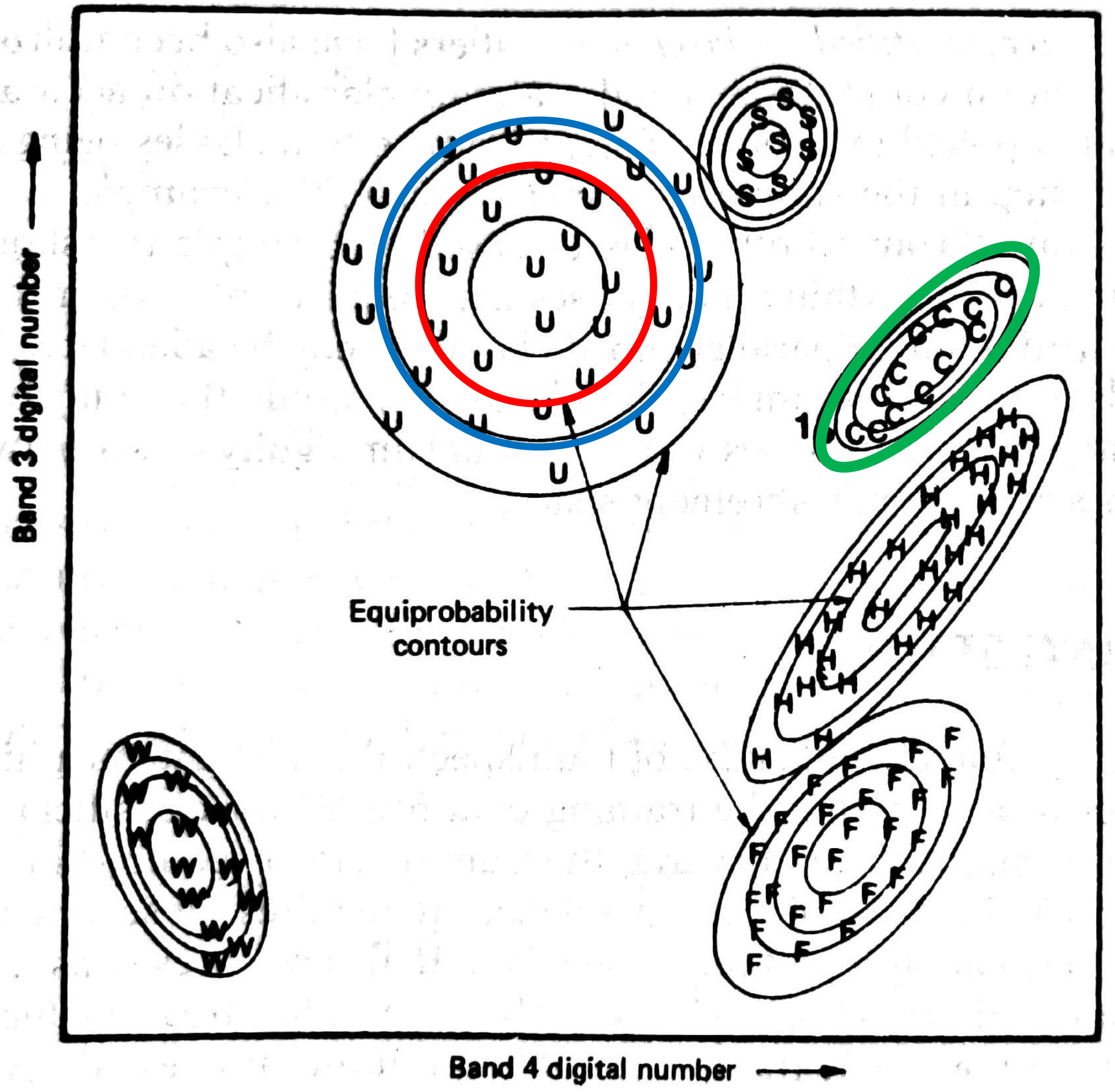

- Red circle: 0.8 for urban
- Blue circle: 0.6 for urban
- Probabilities of *pixel 1* for various categories:
  - ✓ Urban = 50 %
  - ✓ **Corn = 95%**
  - ✓ Hay = 73 %
  - ✓ Scrub = 56 %
  - ✓ Water = 2 %
  - ✓ Forest = 60 %
- Highest for "Corn"
- ***Therefore pixel is assigned to Corn class.***

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The Training Stage

- It requires substantial **reference data** and a **thorough knowledge of the geographic area** to which the data apply.
- The overall objective of the training process is to **assemble a set of statistics** that describe the spectral response pattern for each land cover type to be classified in an image.
- To yield acceptable classification results, **training data** must be both **representative** and **complete**.
- This means that the image analyst must **develop training statistics for all spectral classes constituting each information class to be discriminated by the classifier**.
- ***Dispersion of the sites*** throughout the scene *increases the chance that the training data will be representative* of all the variations in the cover types present in the scene.
- In practice, a minimum of from ***10n* to *100n*** *pixels* is used

where **n** is *total number of spectral bands* used in classification.

- Say n = 2, minimum pixels in each (land cover class) category should be 10*2 = 20
- This improves the estimation of the *mean vectors* and *covariance matrices* as the number of pixels in the training sets increases.
- The more pixels that can be used in training, the better the statistical representation of each spectral class.

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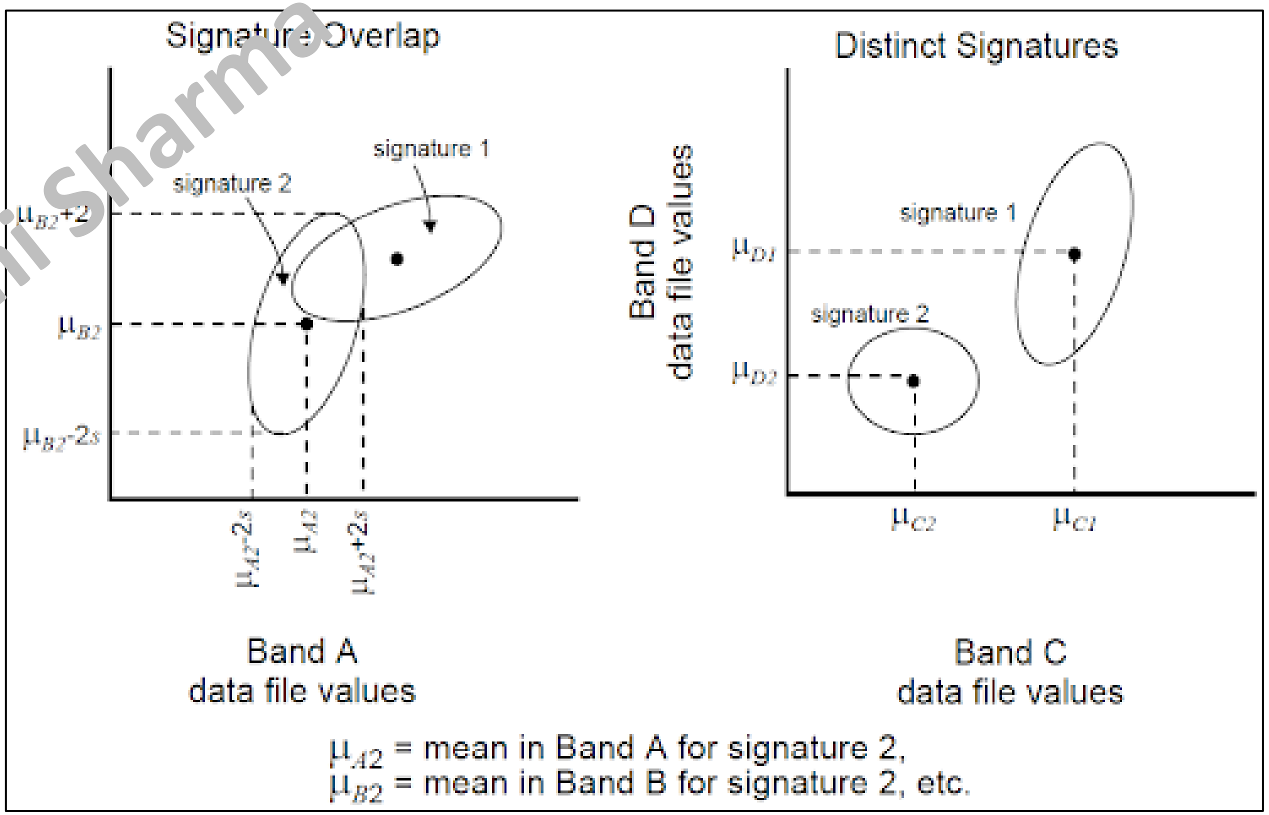
Evaluation of Signatures

- **Signature separability** is a *statistical measure* of distance between two signatures.
- Separability can be calculated for any combination of bands that is used in the classification
- It enables you **to rule out any bands** that are not useful in the results of the classification.
- Various methods:
  1. Euclidian Distance
  2. Divergence
  3. Transformed Divergence
  4. Jeffries-Matusita



Ellipse Evaluation of signatures

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