Remote Sensing 1: GEOG 4/585

Lecture 4.1.

Image classification 1

Johnny Ryan (he/him/his)
jryan4@uoregon.edu
Office hours: Monday 15:00-17:00
in 165 Condon Hall

Required reading:
Principles of Remote Sensing pp 280-306

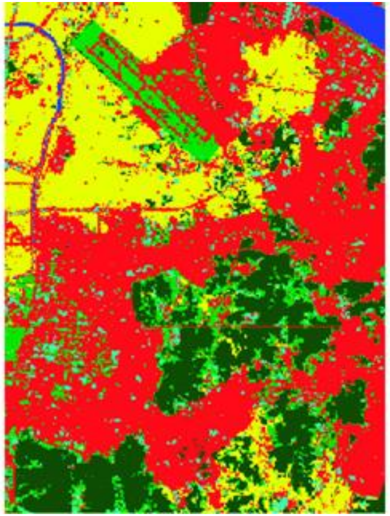
Overview

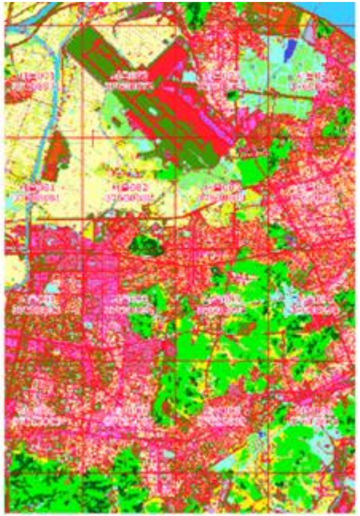
- Introduction to image classification
- Unsupervised classification
    - Algorithms
- Supervised classification
    - Process (e.g. collecting training data)
    - Algorithms
- Object-oriented vs. pixel-based approaches

Image classification

Process of sorting pixels into individual classes (categories of data)

The underlying assumption of image classification is that the spectral characteristics of a particular feature (i.e., a forest, corn field, road) will be relatively consistent throughout the image





Some terms

Spectral class: groups of pixels that are uniform with respect to their pixel values in several spectral bands

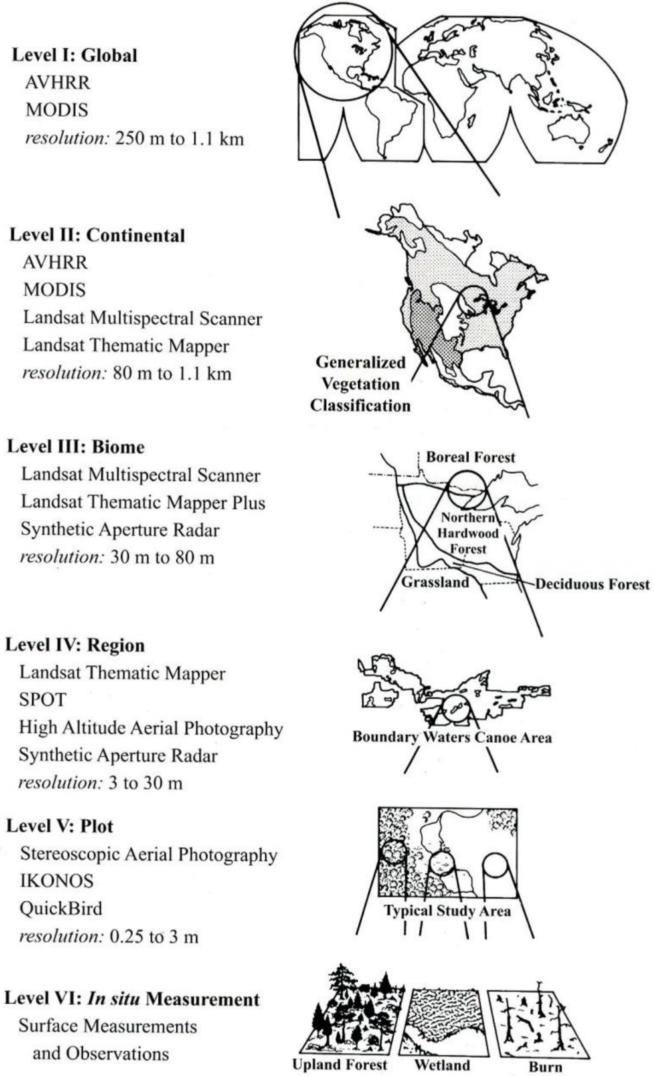
Land cover: categories of interest to users of the data (e.g., forest, sand, open water, buildings). Also known as informational classes.

Land use: refers to human use (e.g., commercial, residential, protected areas, abandoned lands)

- Often abstract/intangible
- Almost always requires high spatial resolution data

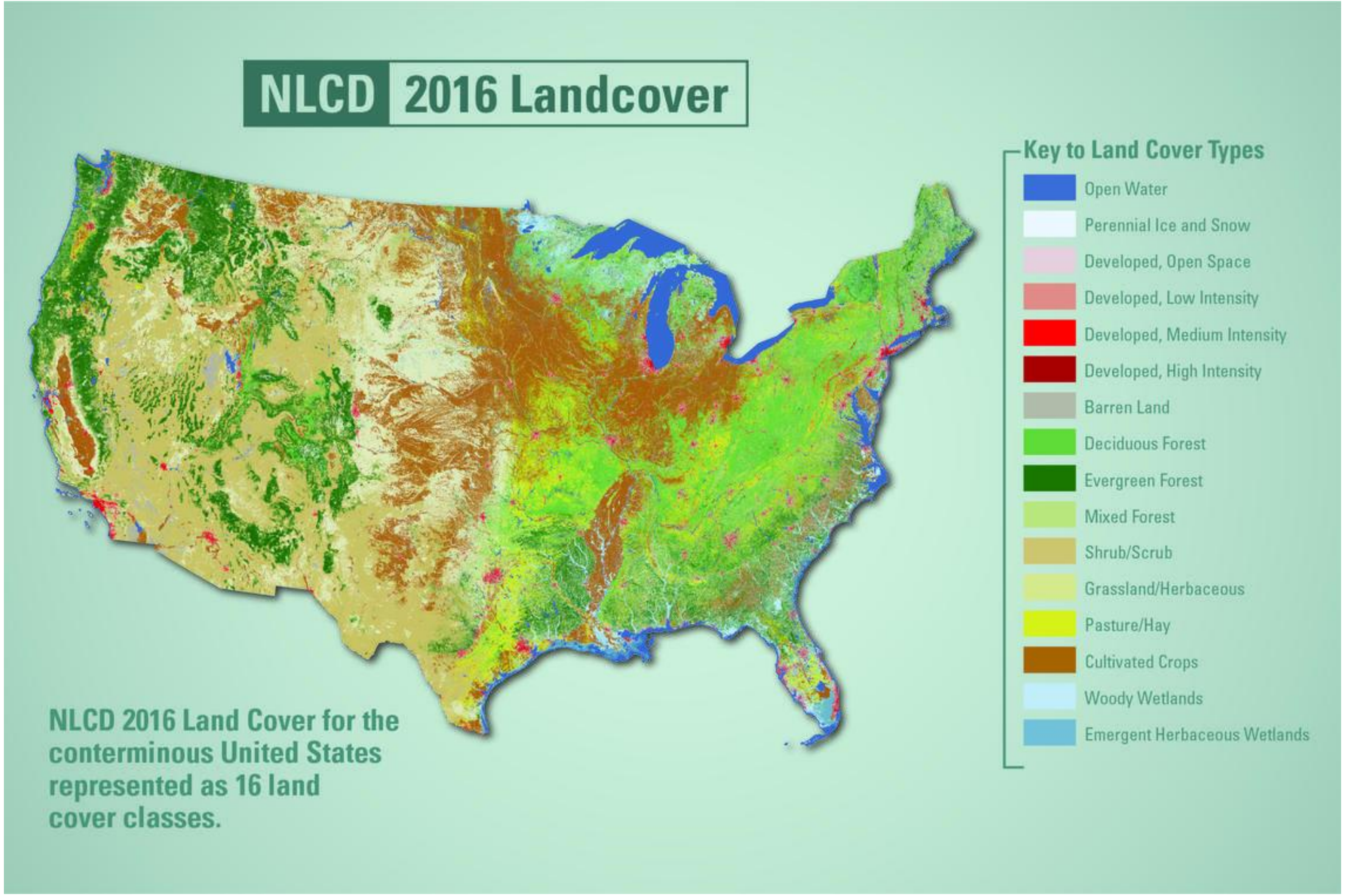
Remote sensing is much useful for mapping land cover, but deriving land use often involves deductive reasoning and can be less accurate

Classification scales



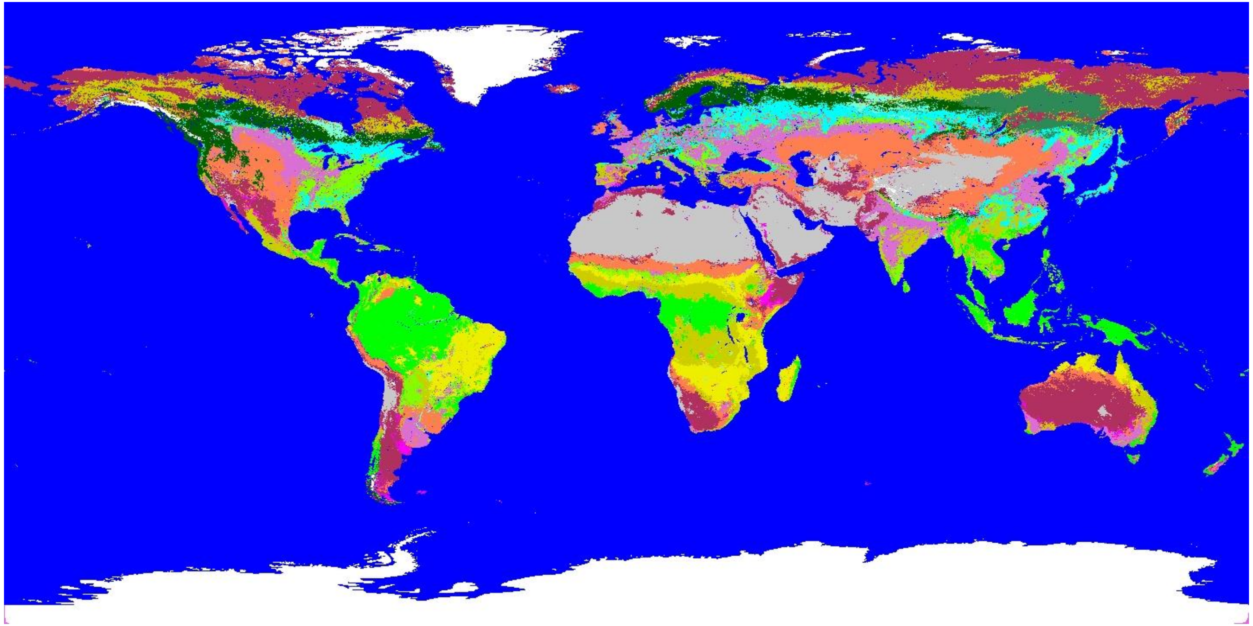
Sensor systems and resolutions useful for discriminating vegetation

USGS National Land Cover Database



- Landsat data
- 16 land cover classes
- Updated every 5 years
- 30 pixel resolution

MODIS Global Land Cover

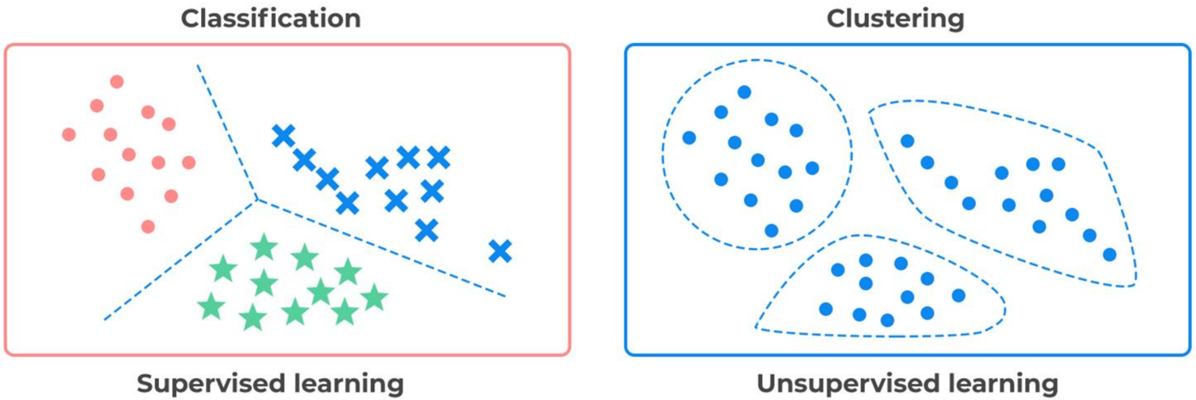


- MODIS-based land cover classifications (17 classes) made with “top down” approach:
- Created from suite of image processing and modeling algorithms applied to one year’s worth of MODIS imagery, including thermal infrared
- Not that accurate but entirely automated and can be produced annually

Two main approaches

- Unsupervised classification
  - Algorithm identifies groups of pixels that exhibit a similar spectral response
  - User assigns meaning to the resulting classes

- Supervised classification
  - Uses image pixels representing regions of known, homogenous surface composition (<u>training areas</u>) to classify unknown pixels
  - User assigns training areas



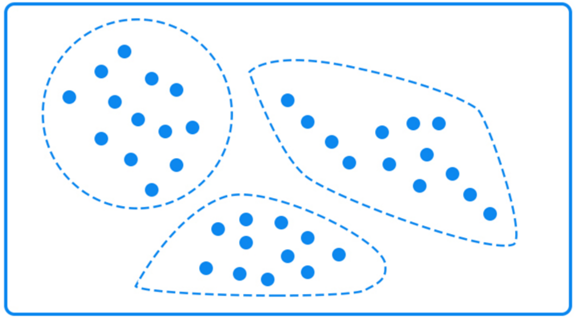
Unsupervised classification

- Land cover types within a scene are generally unknown (ground reference information lacking or surface features within the scene are not well defined).

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

- Then the computer re-labels and combines the spectral clusters into classes.

Clustering

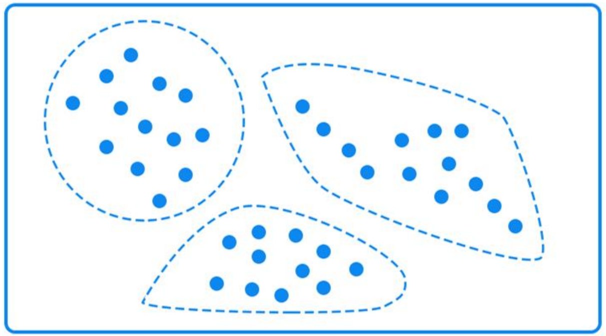


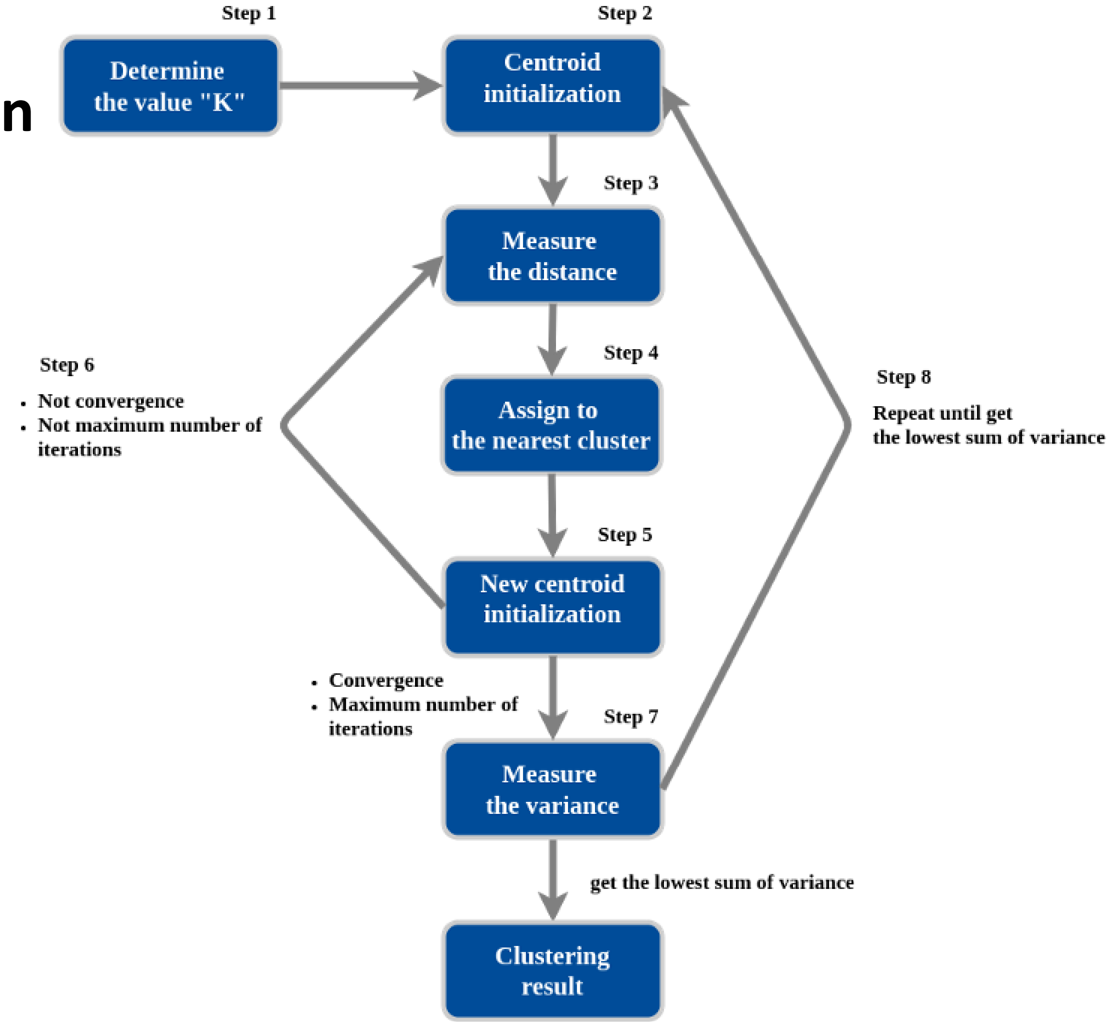
Unsupervised learning

Unsupervised classification algorithms

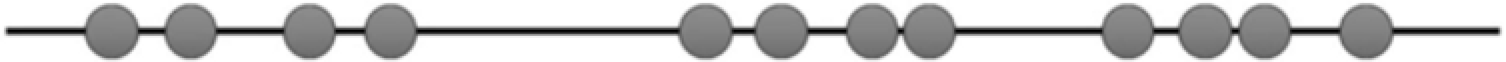
K-means clustering

<u>Goal</u>: assign each pixel to K clusters based on class means

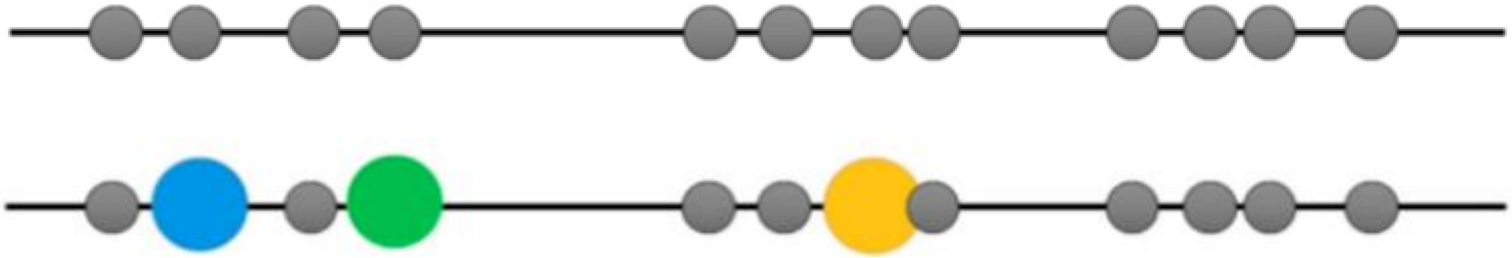




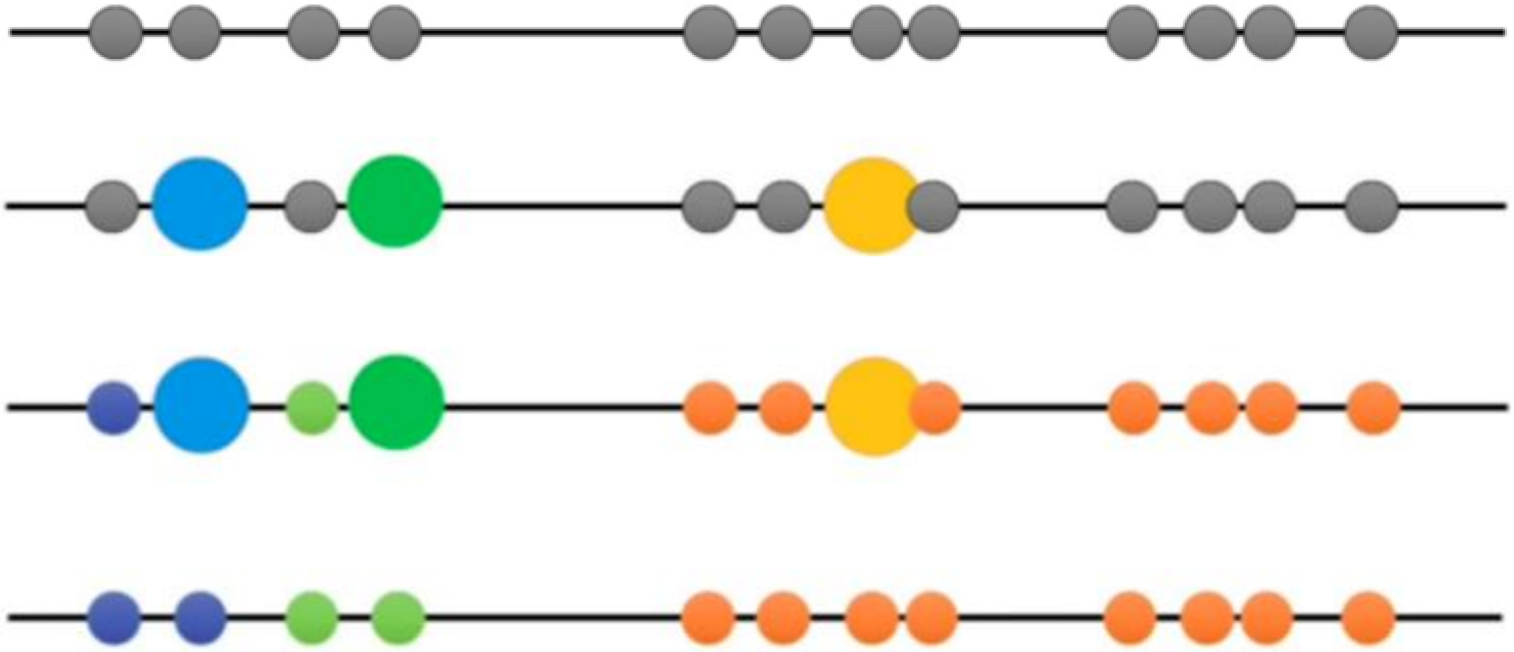
Step 1: Determine K



Step 2: Generate K random centroids

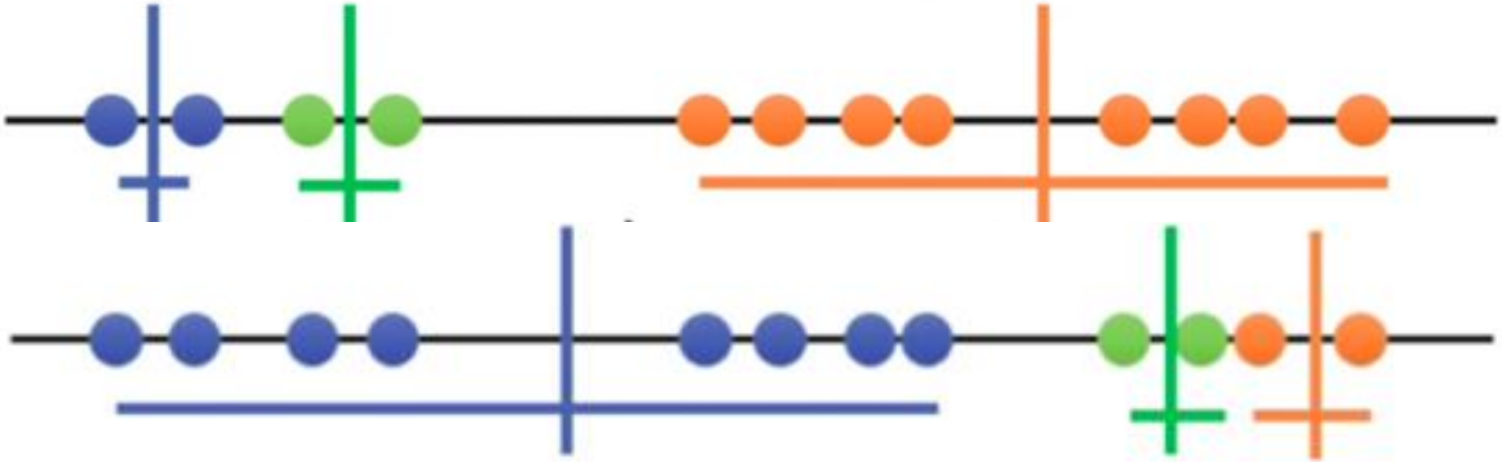


Step 3: Assign each pixel to random centroid

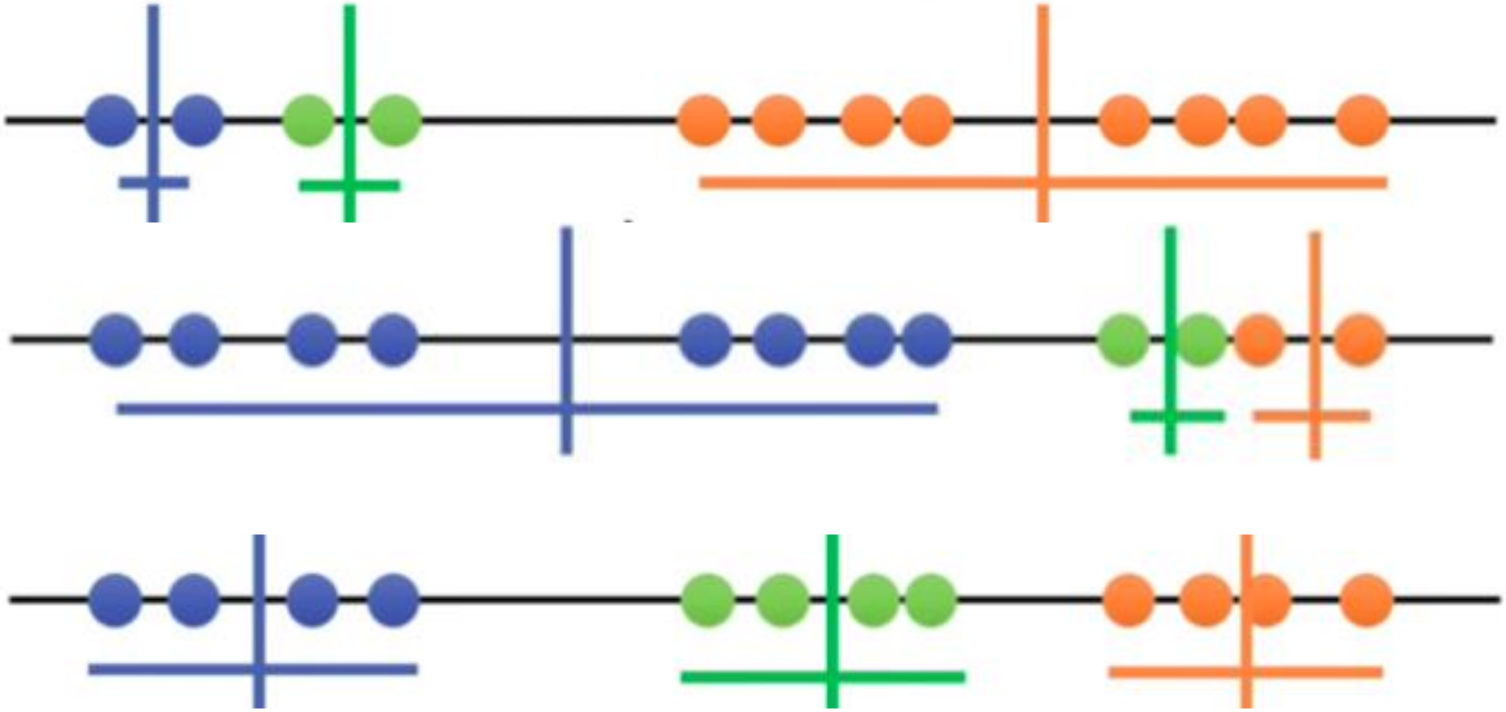


Step 4: Compute variance from cluster mean

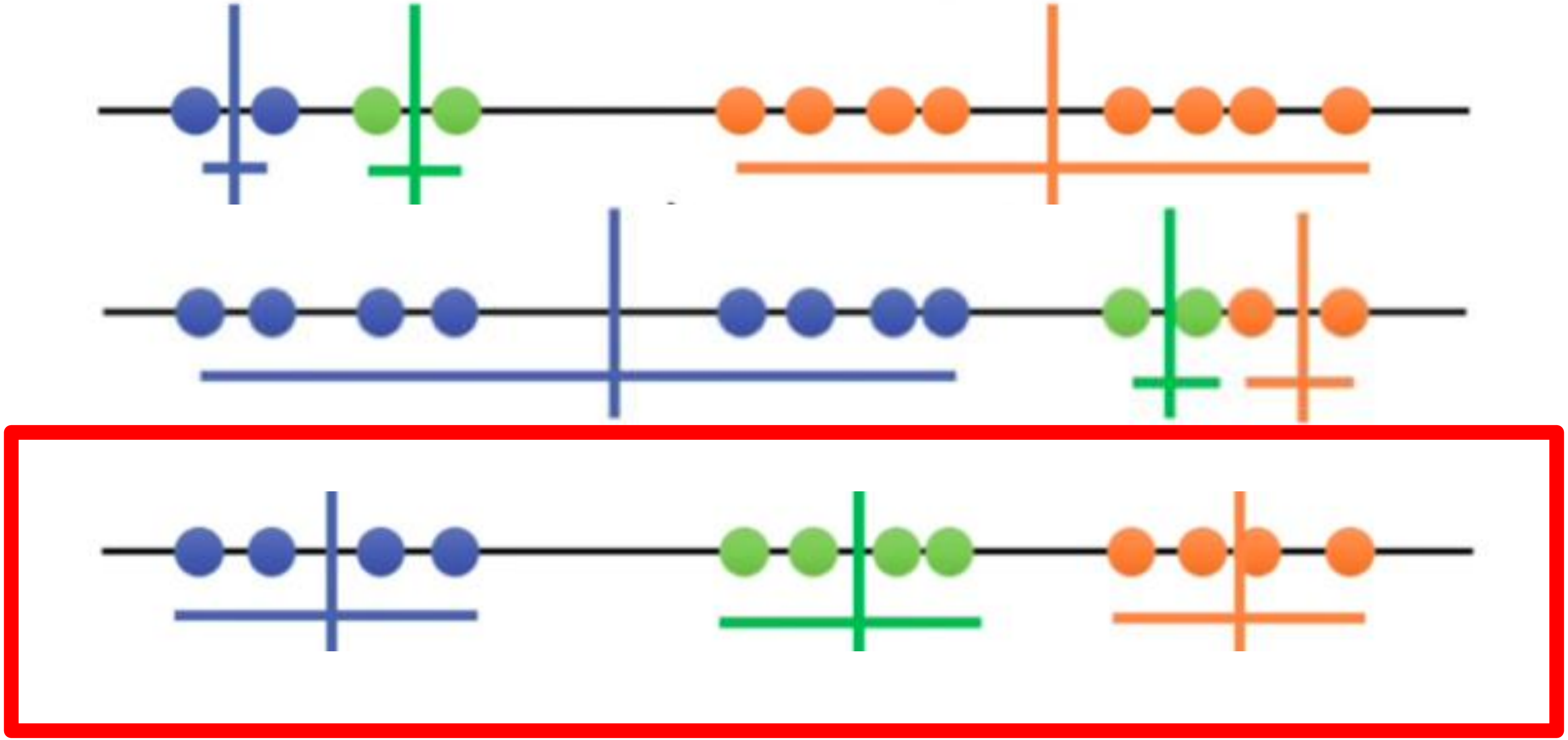
Step 5: Repeat steps 2 - 4



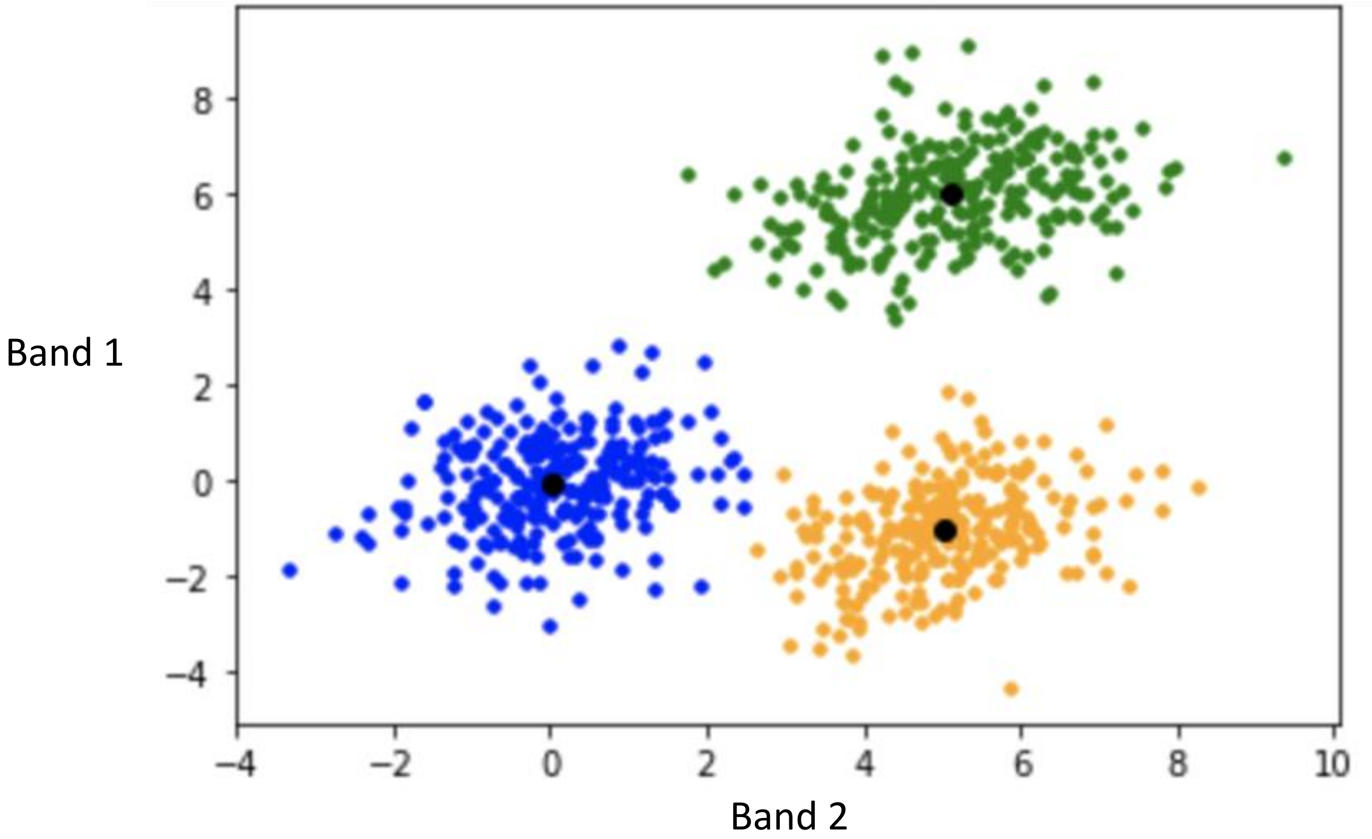
Step 5: Repeat steps 2 - 4



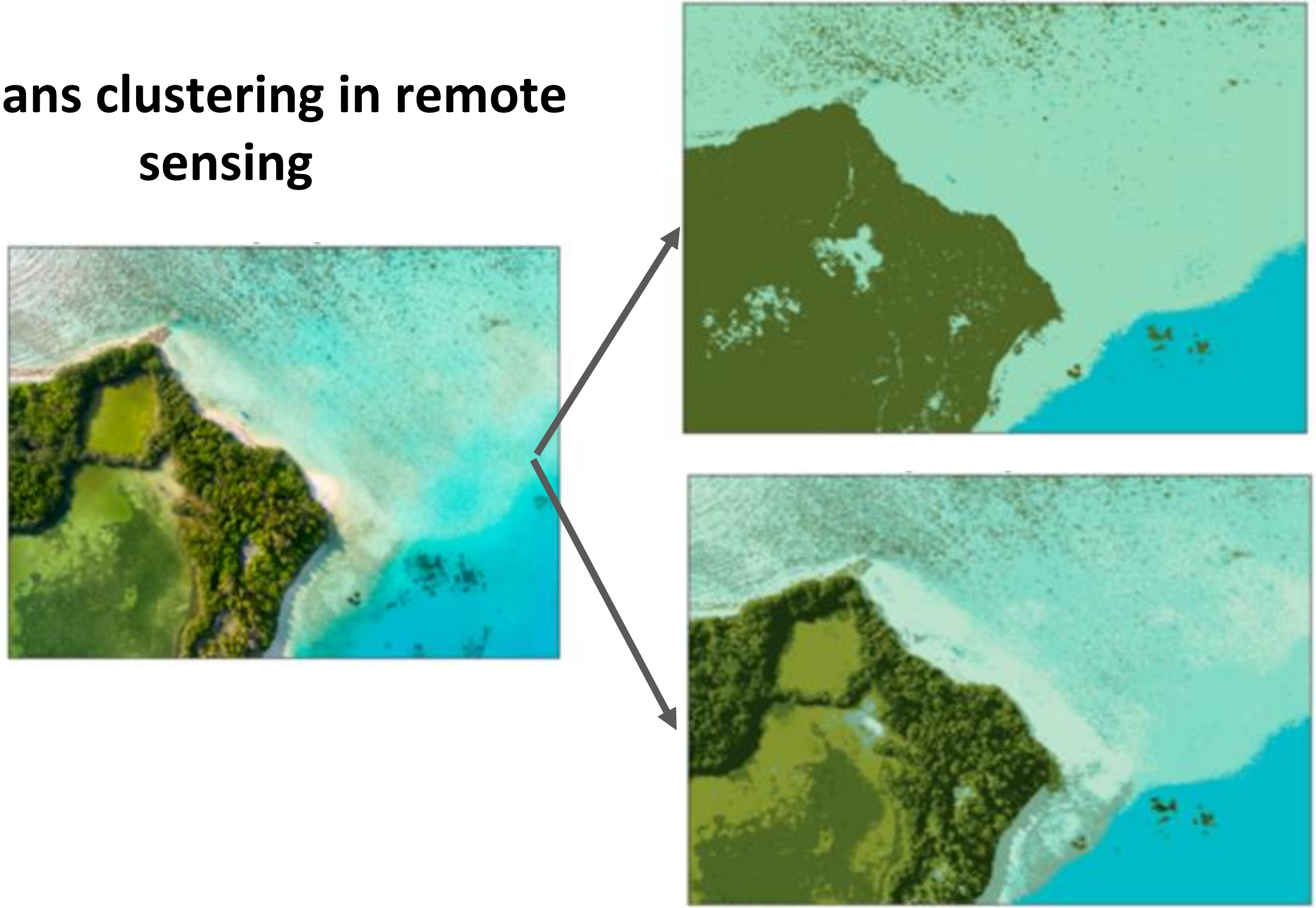
Step 6: Pick a winner



K means clustering in 2D



K means clustering in remote sensing



K=3

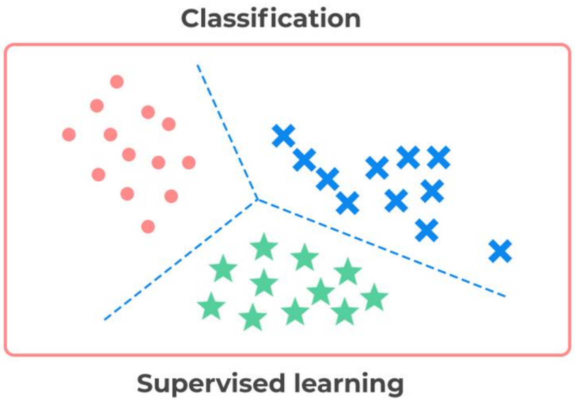
K=7

Supervised classification

- When we know the identity and location of some of the land cover types (e.g., urban, agriculture, or wetland) are known beforehand (a priori)

- User places a small portion of data into classes which are used to <u>train</u> an algorithm

- Algorithm computes multivariate statistical parameters (means, standard deviations, covariance matrices, correlation matrices, etc.) for each training site and groups pixels from rest of image(s) into similar classes.



Supervised classification algorithms

Many techniques exist including minimum distance, maximum likelihood, decision trees, etc.

General procedure:

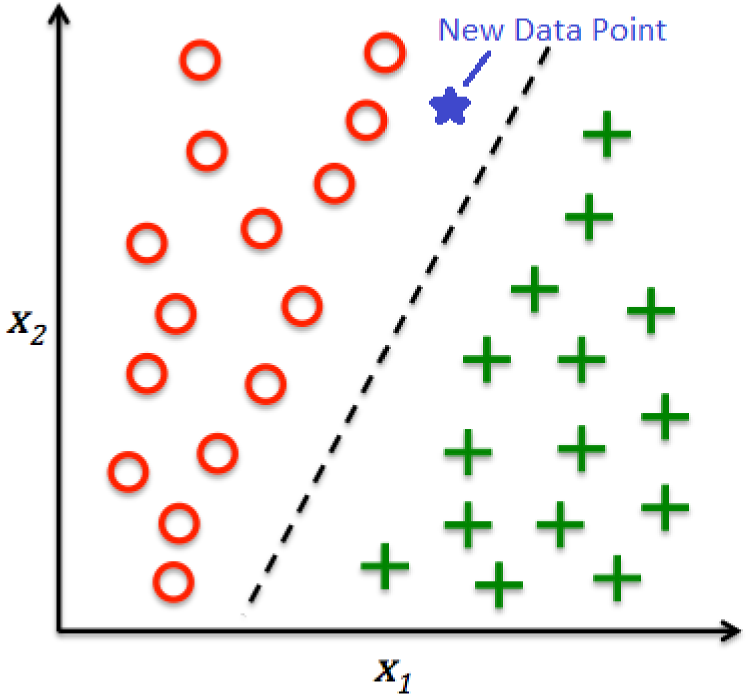
1) Define classes according to your objectives

1) Locate training sites

1) Extract training statistics

1) Train model

1) Classify

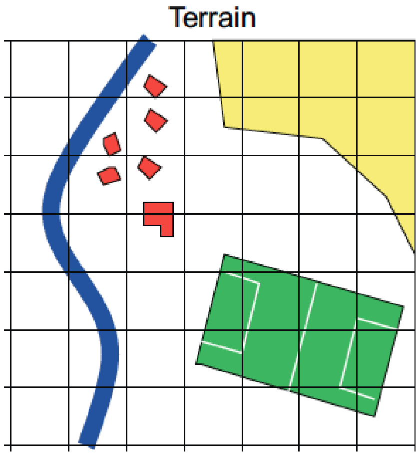


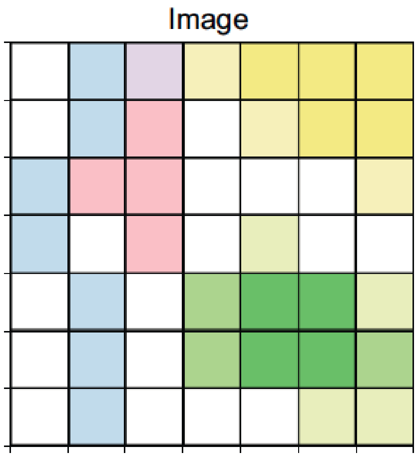
Step 1: Define classes

Defining classes is one of the most critical, and often overlooked steps

Critical questions:

- Land cover or land use or both?
- Resolution needed to capture these classes – is this data available for your purposes?
- How quickly do land cover/ land use change? (e.g., snow cover, crop growth…) What is the “shelf-life” of your classification product?
- Will a given classification scheme encompass all potential spectral variability?





Step 2: Select training sites

- Select training sites within the image that are representative of the land cover or land use classes of interest after the classification scheme is adopted.

    - The training data of most value is from a homogeneous environment

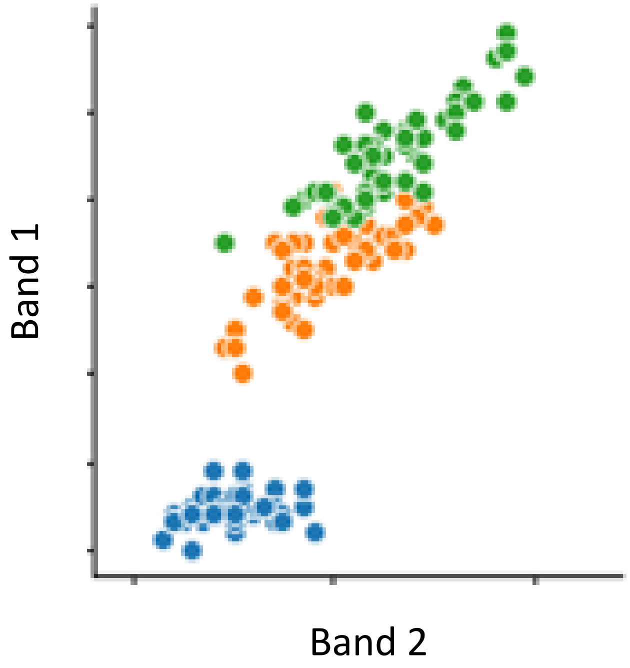
    - If your class is heterogeneous, try to capture some heterogeneity, within limits (if too variable new class)

Step 3: Select training sites continued

- There are a number of ways to collect the training site data, including:
    - Collection of in situ information such as forest type, height, percent canopy closure, ground cover, roofing material, water body, etc.
    - Use of external imagery, preferably with superior resolution
    - On-screen selection of polygonal training data…Regions of Interest (ROIs)

Step 3: Extract stats from training data

- Which bands (channels) are most effective in discriminating each class from all others?
- Avoid too many band correlations (e.g. green and red bands for vegetation are strongly correlated)
- Jeffries-Matusita (JM) distance calculates the separability of a pair of probability distributions
    - Ranges from 0 - 2.0, where 0 indicates identical signatures and 2.0 indicates completely different spectral signatures
    - Greater than 1.9 is good separability

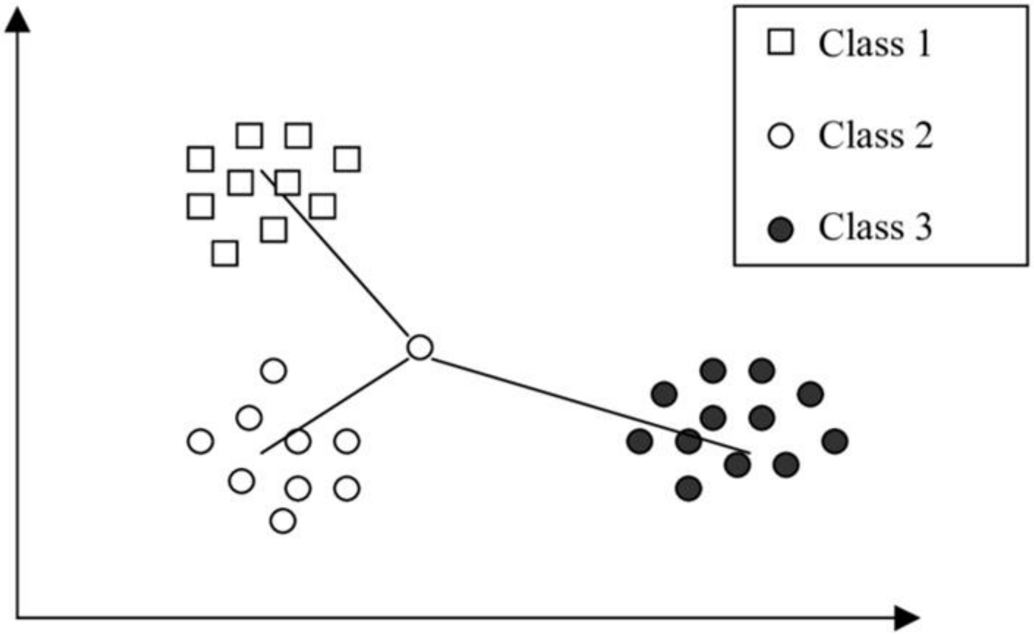


Step 4+5: Train models / classify image

- Several adopted classification algorithms exist:
  - Minimum distance
  - Parallelepiped
  - Maximum likelihood
  - K nearest neighbors
  - And many others…

Minimum distance to mean classification

- Computes Euclidean distance to the mean value of each class for each unlabeled pixel value.
- Assigns pixels to classes that are closest to mean



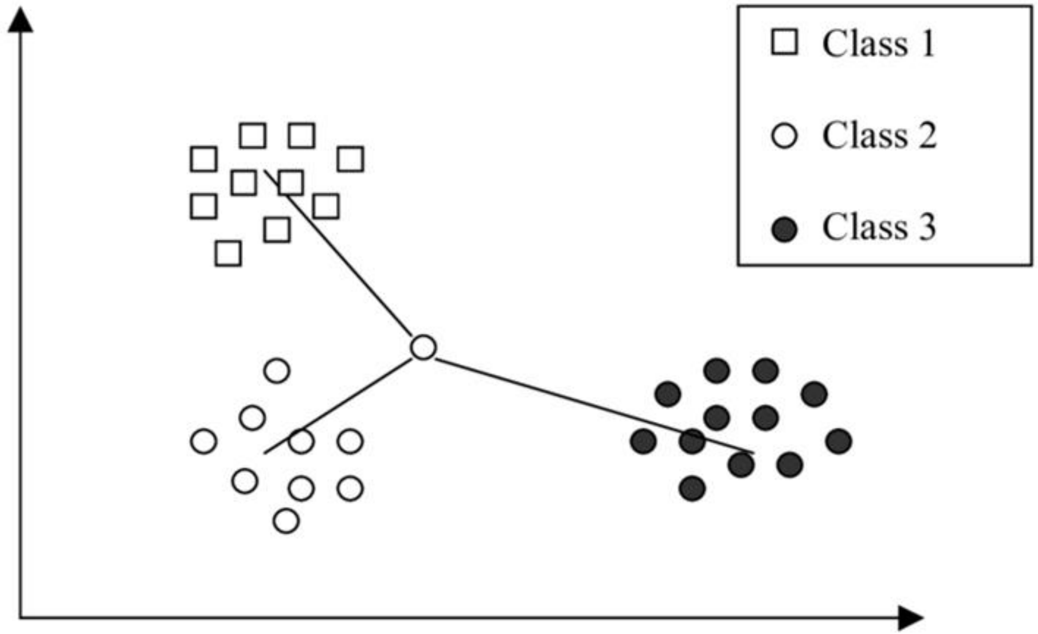
Minimum distance to mean classification

Advantages

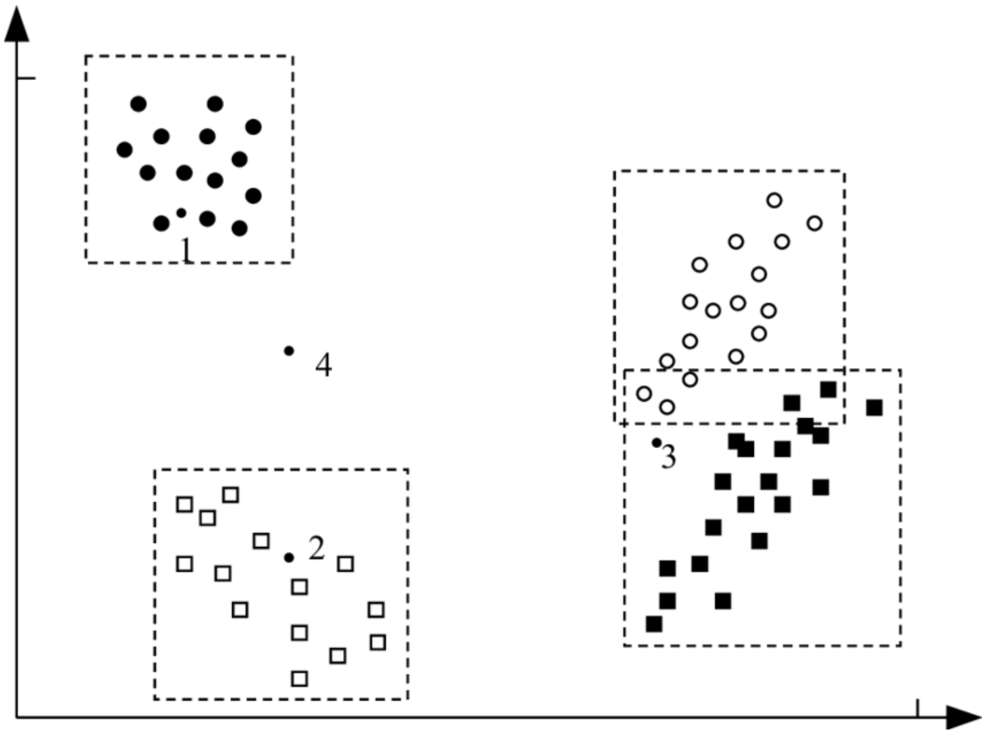
- Computational efficient
- Everything is classified

Disadvantages

- Does not take into account statistical differences between classes
- Does not take into account correlation between bands
    - i.e., treats all spectral differences as equally important

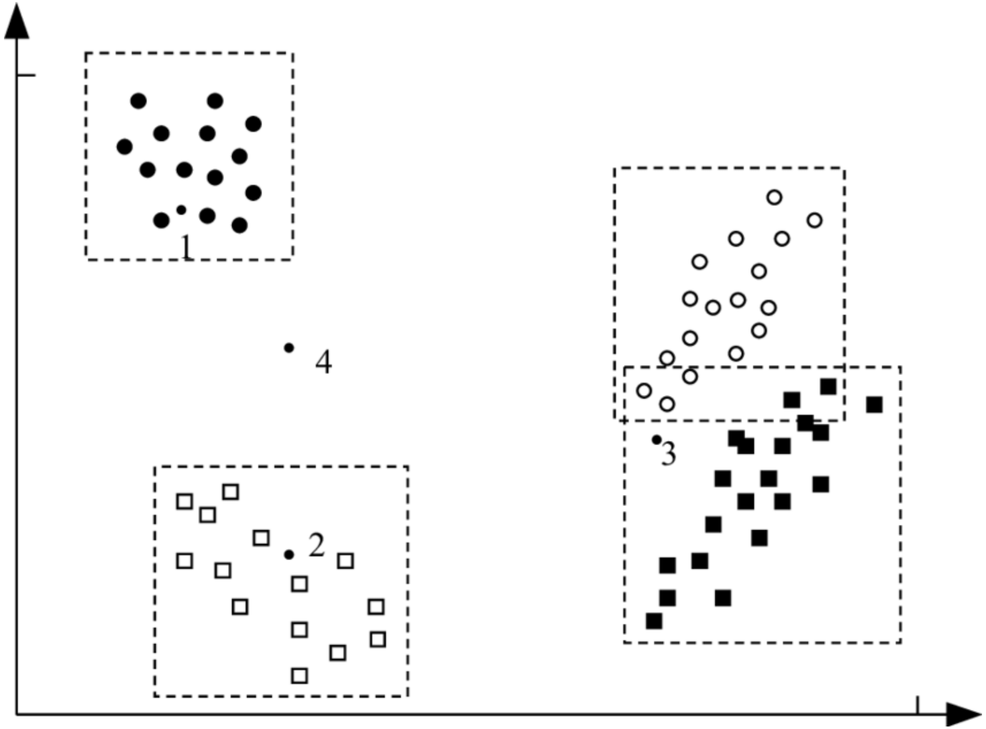


Parallelepiped (or box) classification



- A set of k-dimensional boxes, centered at the class mean vectors are placed in k-dimensional feature space
- The upper and lower limit of each parallelepiped is usually ±1 std dev
- If an unlabeled pixel lies within one of the boxes, it is assigned that class label
- A complication occurs if a pixel vector falls within two or more boxes.

Parallelepiped (or box) classification



Advantages

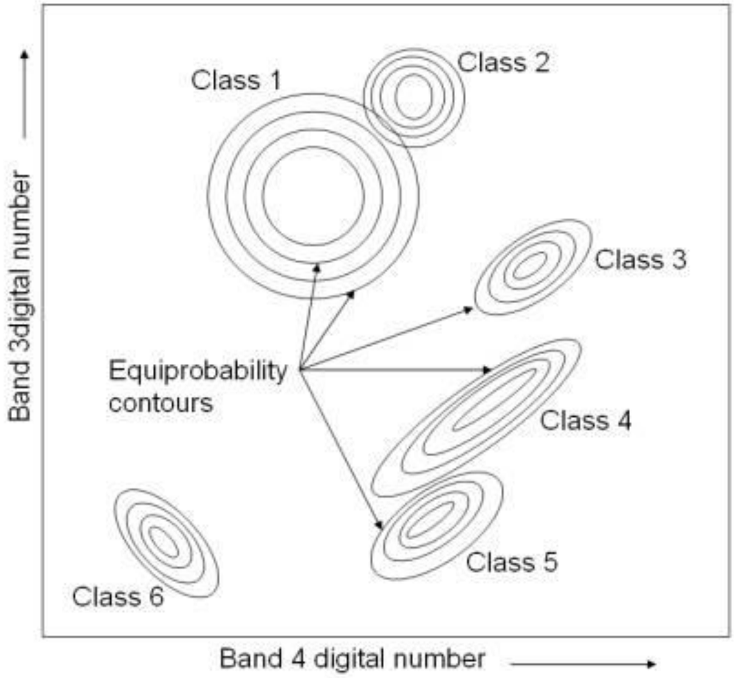
- Computationally efficient
- More realistic than Minimum Distance to Mean

Disadvantages

- Unclassified pixels
- Overlapping classes
  - Decision on a pixel's label must then be made with another algorithm, such as the nearest-mean
- Thresholds difficult to establish

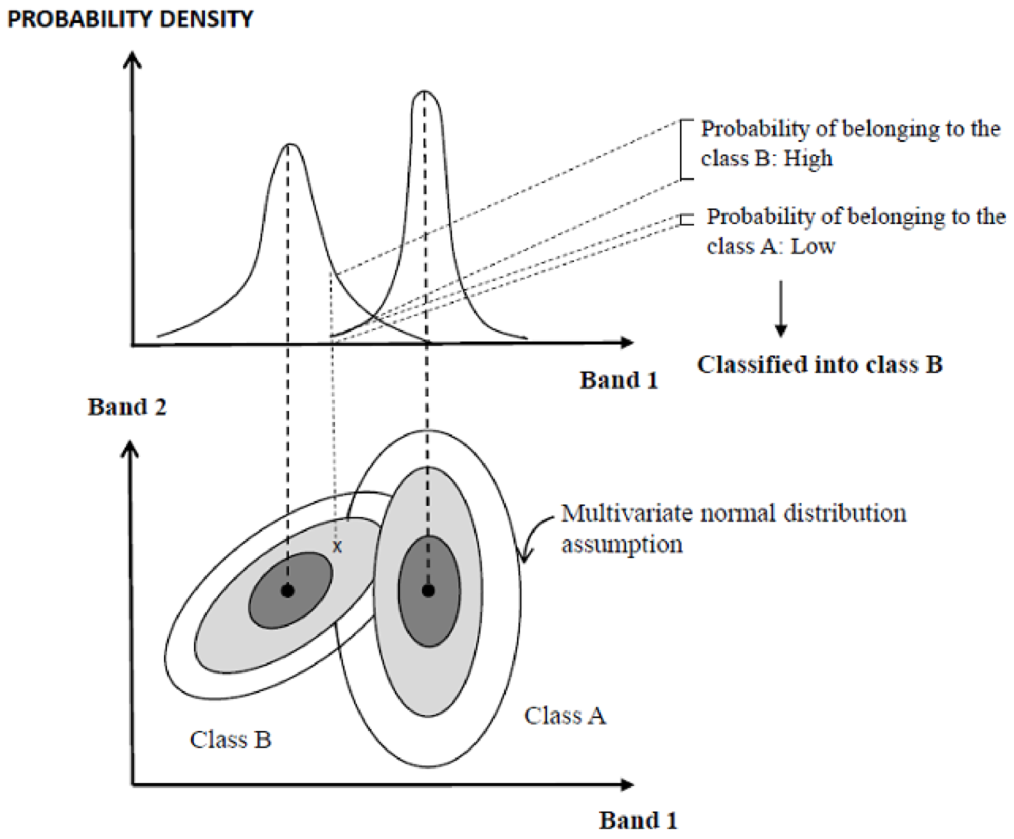
Maximum likelihood classification

- Assume that the training data for each class in each band are normally distributed (i.e. Gaussian).
- Compute the probability (likelihood) of an unlabeled pixel belonging to each class
- Assign pixel to class for which the probability of membership is highest
- One of the most widely used supervised classification algorithms



Maximum likelihood classification

- What happens when the probability density functions of two or more training classes overlap in feature space?
- Pixel X would be assigned to Class B because the probability of unknown measurement vector X is greater than Class A.



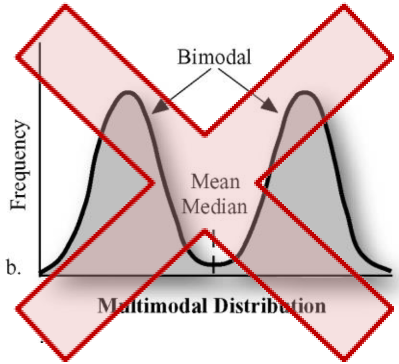
Maximum likelihood classification

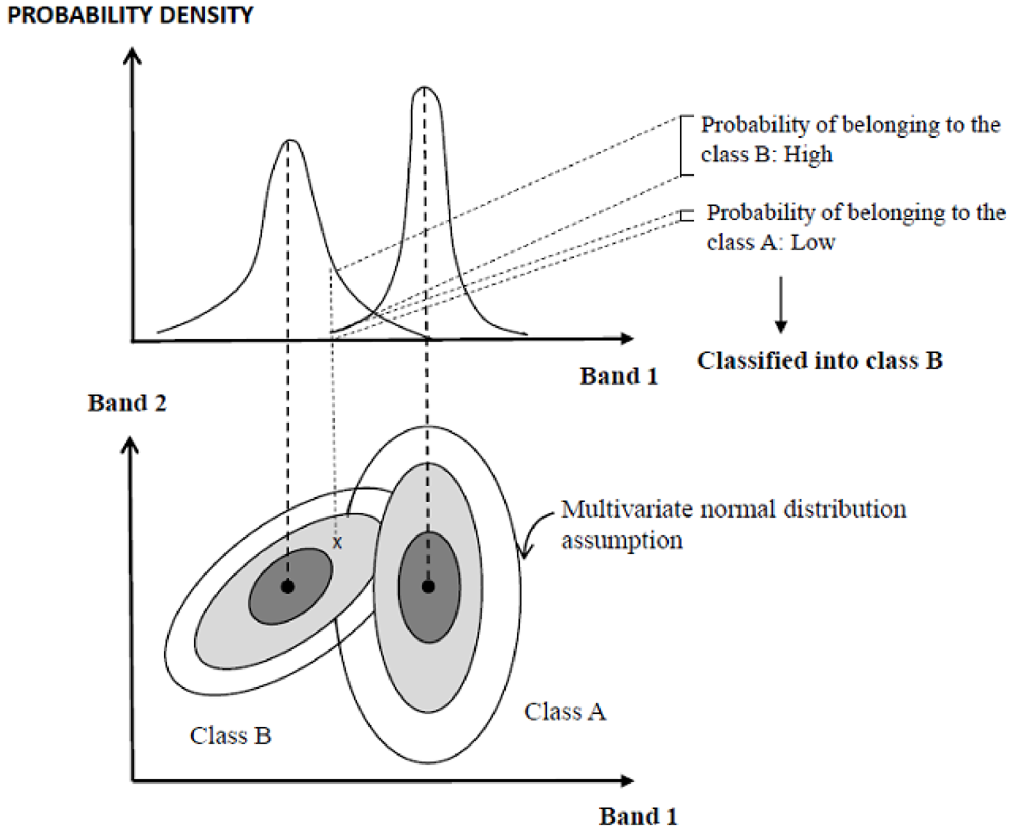
Advantages

- Everything is classified
- Robust for normally distributed data

Disadvantages

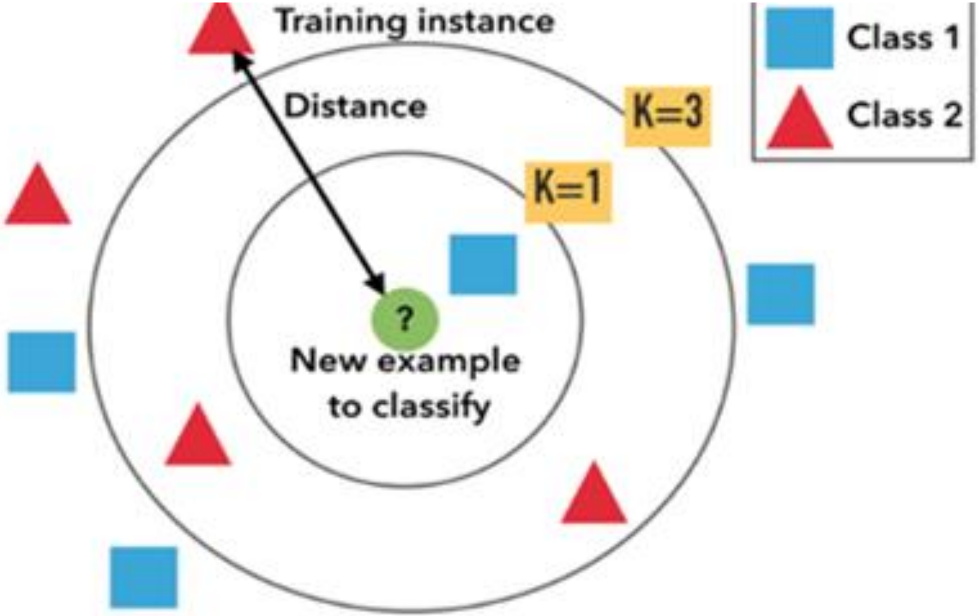
- Training data may not always be normally distributed





K nearest neighbors classification

- Choose the value of K i.e. the nearest data points.
- K can be any integer, usually odd number
- For each new data point, calculate the Euclidean distance to nearest K training values
- Assign class based on on most frequent class



K nearest neighbors classification

Advantages

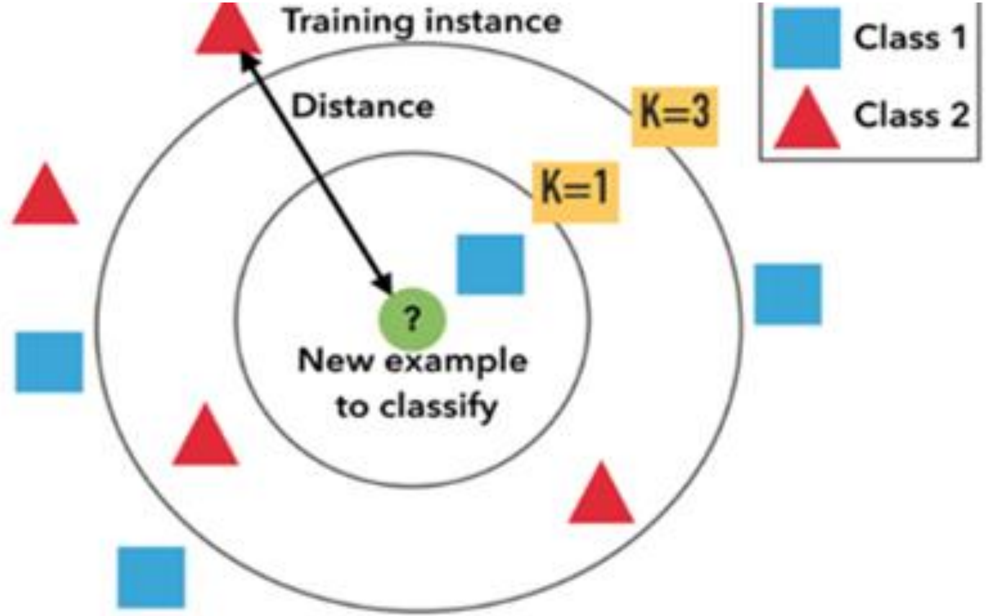
- Assumes nothing about the underlying data (termed “non-parametric”)

- Simple algorithm to understand and interpret

Disadvantages

- Computationally expensive algorithm because it stores all the training data

- Prediction can be slow in case of big N.



Supervised vs. unsupervised

Unsupervised

Pro

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

Con

- 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

Supervised

Pro

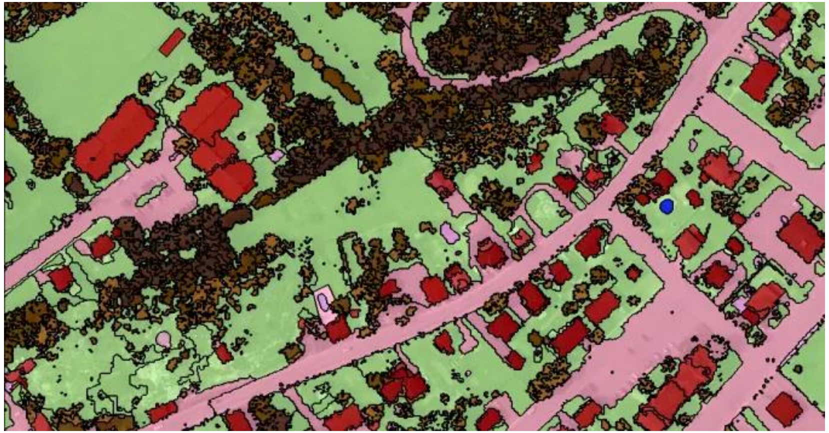
- Generates classes representing features on the ground
- Training areas are reusable (assuming they do not change)

Con

- 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)
- Difficulty and cost of selecting training sites

Object-oriented image analysis (OBIA)

- Traditional pixel-based image classification assigns a land cover class per pixel
- All pixels are the same size, same shape and don't have any concept of their neighbors
- OBIA segments an image into groups of pixels that have similar characteristics
- Apply a classification to <u>objects</u>, not pixels



OBIA segmentation

- Step 1: identify features or segments in imagery by grouping adjacent pixels together that have similar spectral characteristics

- Assign a label to every pixel in an image such that pixels with the same label share certain characteristics.

- Often use region-growing and watershed algorithms that take into account neighboring pixels

OBIA classification: color is not everything

Step 2: Apply supervised classification using:

- Spectral: mean value of spectral properties such as near-infrared, short-wave infrared, red, green, or blue.
- Shape: e.g. if you want to classify buildings, you can use a shape statistic such as “rectangular fit”.
- Texture: homogeneity of an object.
- Geographic context: objects have proximity and distance relationships between neighbors.

Object-based vs. pixel-based classification

- Object-based often outperforms pixel-based classification
- Especially useful for high resolution imagery
- Remove salt-and-pepper effects
- Distinguish between features that have similar spectral characteristics e.g lakes vs. rivers