Cover typing

Changes in land cover

- Changes in land cover can indicate:
  - Habitat loss
  - Deforestation
  - Ecological succession
- Monitoring land cover change requires first that we have land cover maps
  - Thematic = interpreted
- Cover type maps are not recorded, they are constructed

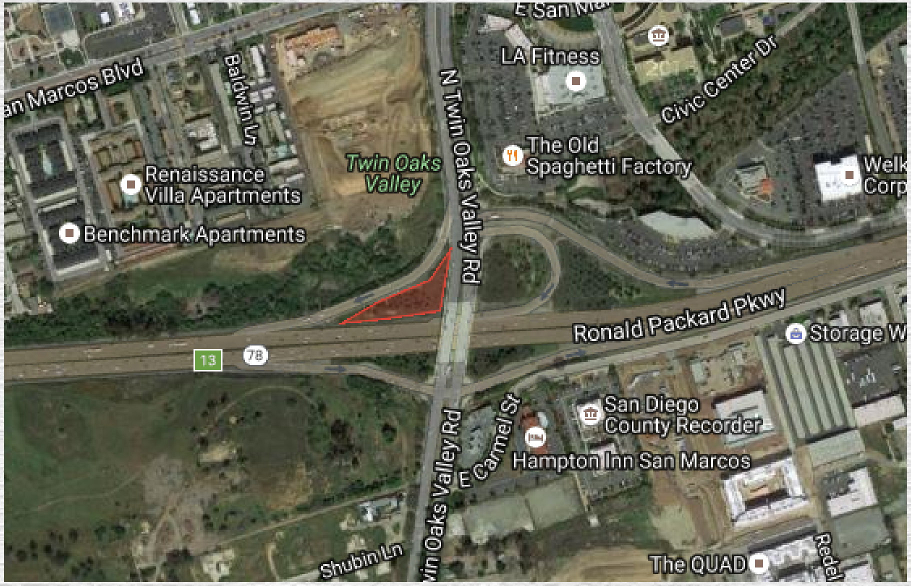
Making cover type maps

- Many different ways to do this
  - Manual method
    - GPS, field-based mapping
    - Manual interpretation, digitizing
  - Automated methods
    - Unsupervised classification
    - Supervised classification
- Each has strengths and weaknesses

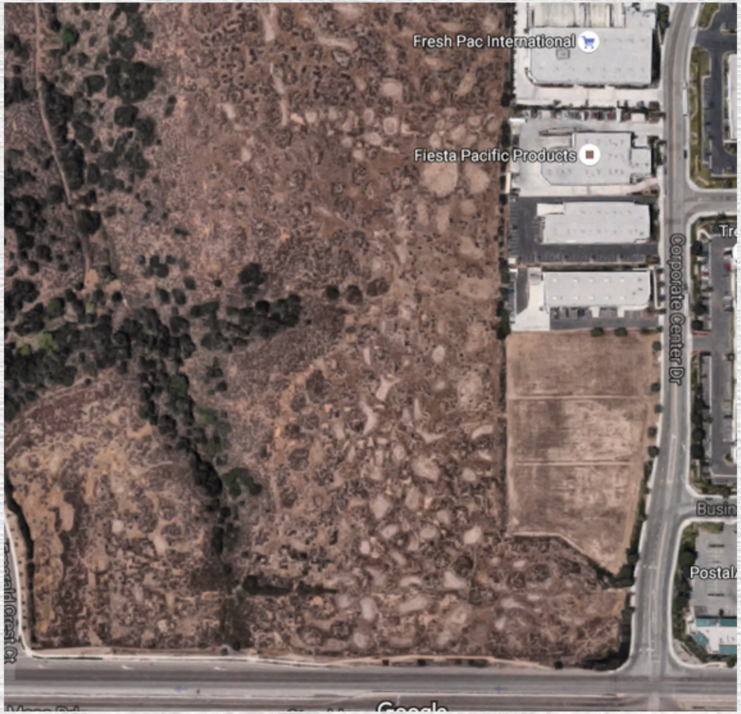
Manual cover typing

- Observe an image, distinguish cover types, manually draw polygons around areas of each cover type
- Advantages
  - We're good pattern recognizers
  - Can use both properties of individual pixels (color) and of collections of pixels (texture, pattern) easily
  - Good, well-trained analysts can be highly accurate
- Disadvantages
  - Labor intensive → expensive
  - Need high-resolution imagery → expensive
  - Slow → instant obsolescence, gets worse over time
  - Subjective → inter-observer variation
  - Need to pick a minimum mapping unit (MMU)

MMU – small features can be ecologically important



Riparian areas



Vernal pools

Need high-resolution imagery for manual interpretation

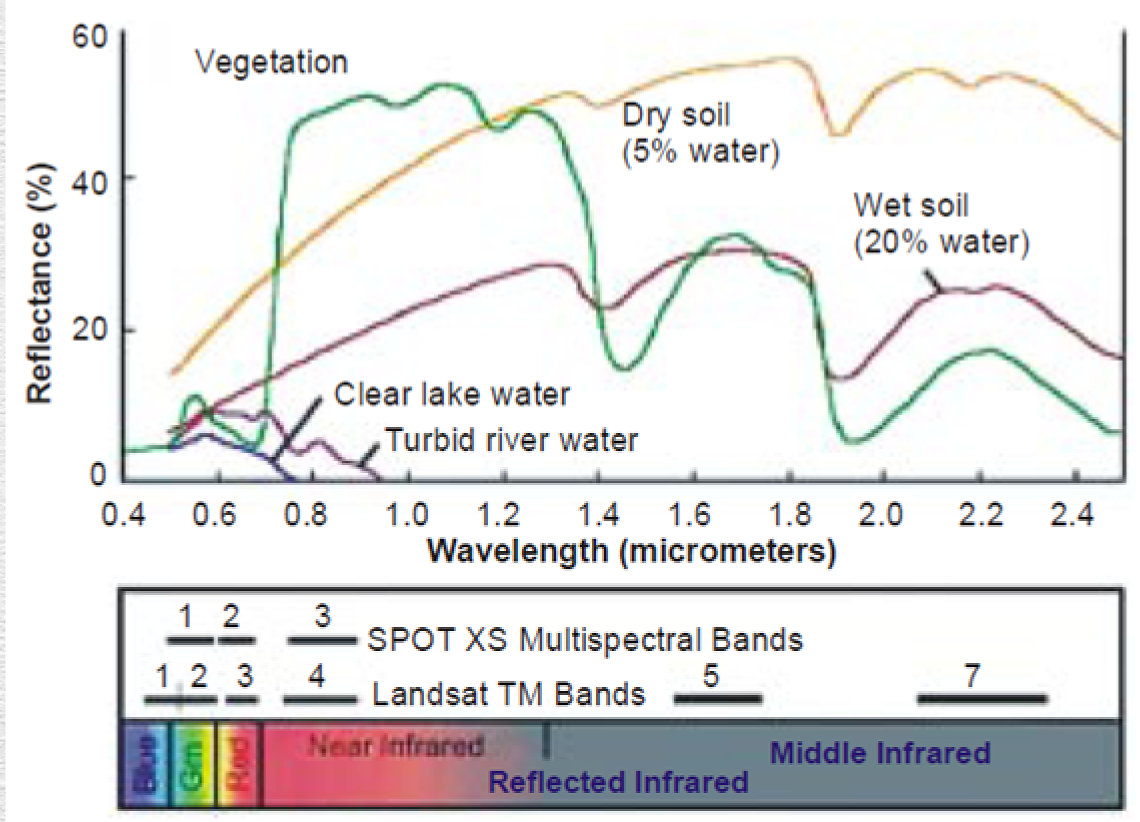
- For manual interpretation, there's no such thing as a resolution that's too high – more detail the better
- High resolution = more pixels = larger file sizes
- Currently, the best satellite images have about 0.3 - 4 m pixel sizes
- Most are 15 m, 30 m, or higher – difficult to use for fine-grained interpretation of features (public domain images are generally coarser resolution)
- Aerial photos (scanned prints, or digital sensors) are often better, but less readily available

Automated approaches

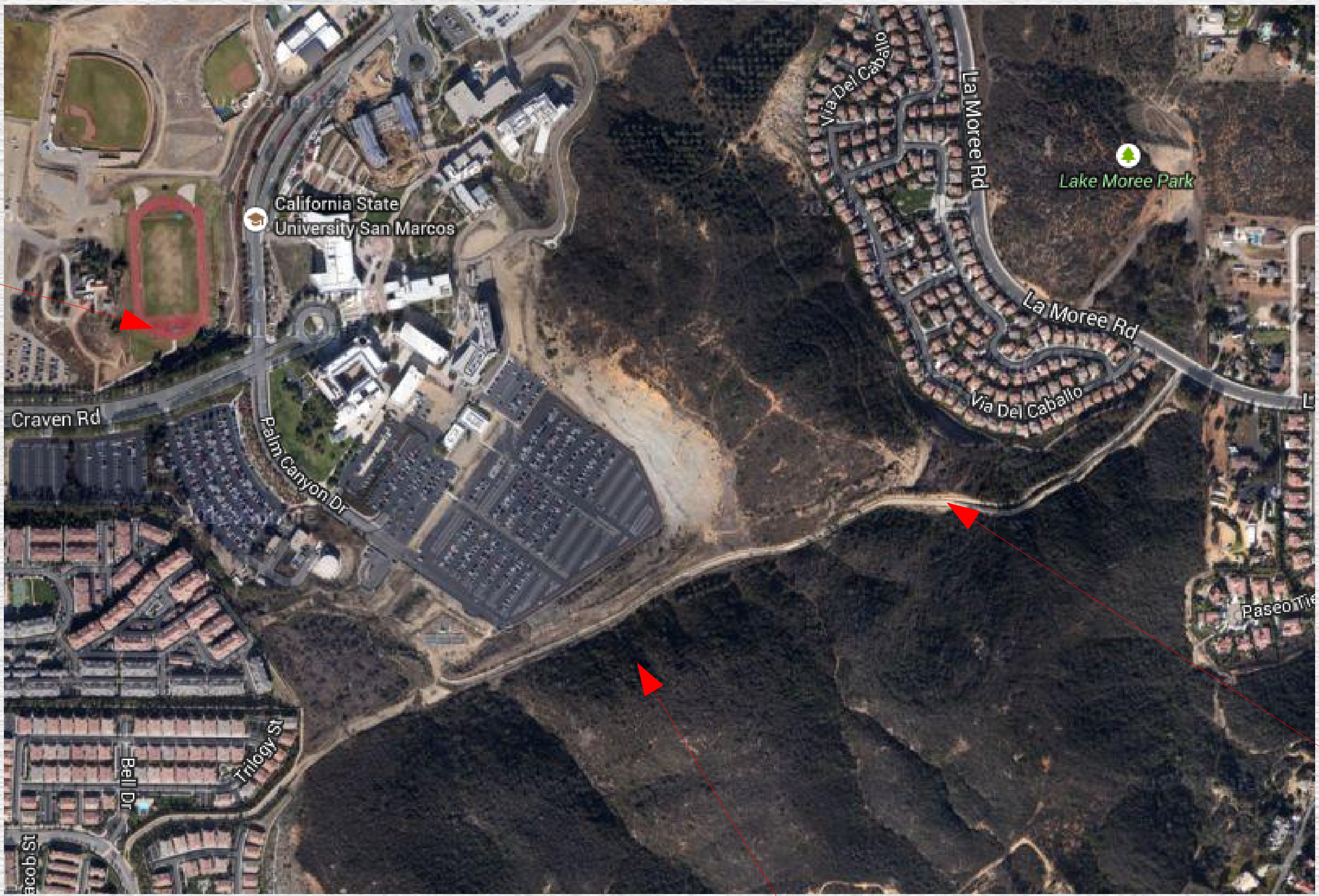
- Pixels are classified into cover types using a formula or algorithm
- Classification can be **supervised** (guided) or **unsupervised**
- Advantages
  - Fast → an entire map can be classified at once
  - Objective → no inter-observer variation
- Disadvantages
  - Pixel-based approaches only use the pixel-level **spectral signature** of cover types, which may not be distinct between cover types
  - Resolution issues (too big, too small)
  - Different classification approaches yield different results – which to use?

Spectral signatures of cover types

- The profile of reflectance across a range of wavelengths is called a “spectral signature”
- If two cover types differ in at least one band, they can be separated



153, 84, 77

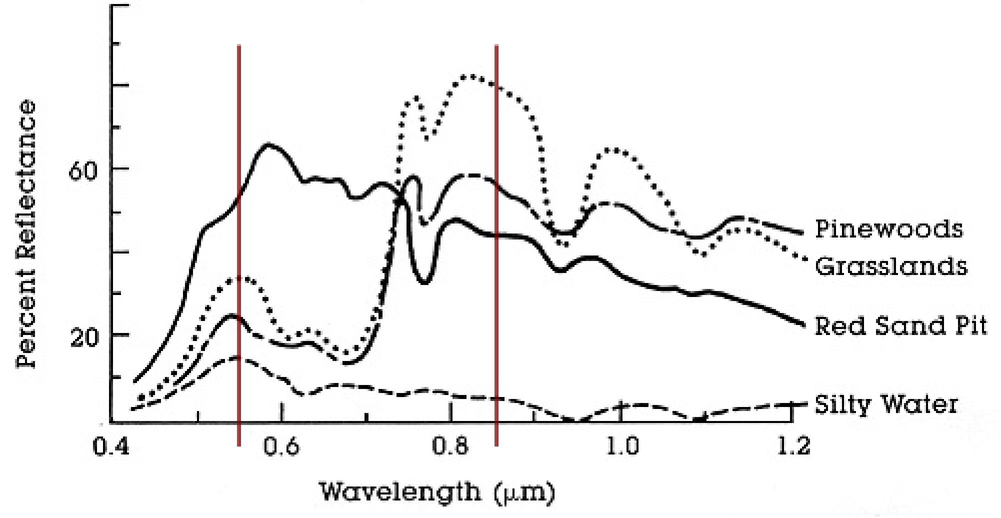


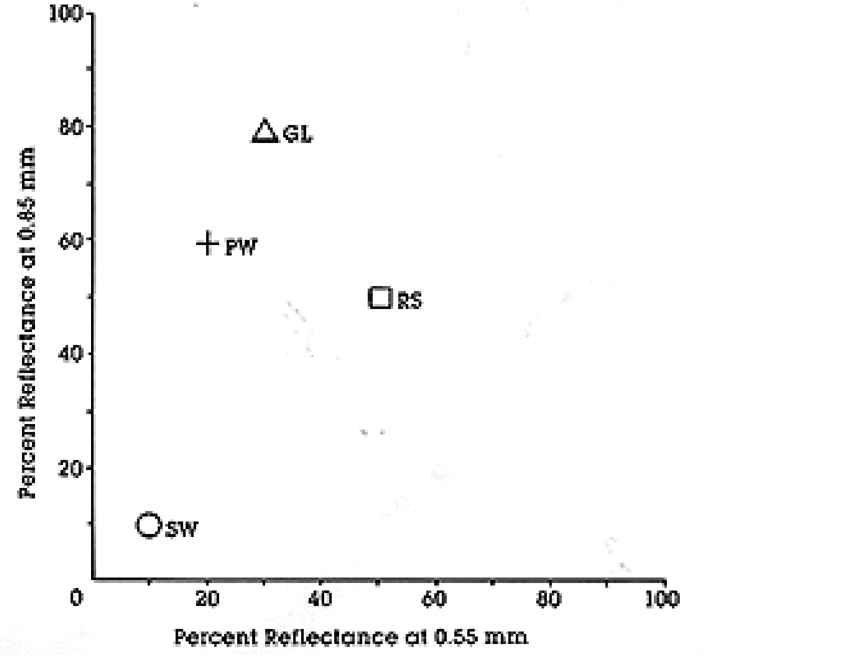
214, 193, 171

RGB values are a spectral signature for visible light, using three bands

22, 26, 35

Cover type	Percent reflectance at 0.55 μm	Percent reflectance at 0.85 μm
Pinewoods	19	59
Grasslands	31	80
Red sand pit	51	47
Silty water	10	9



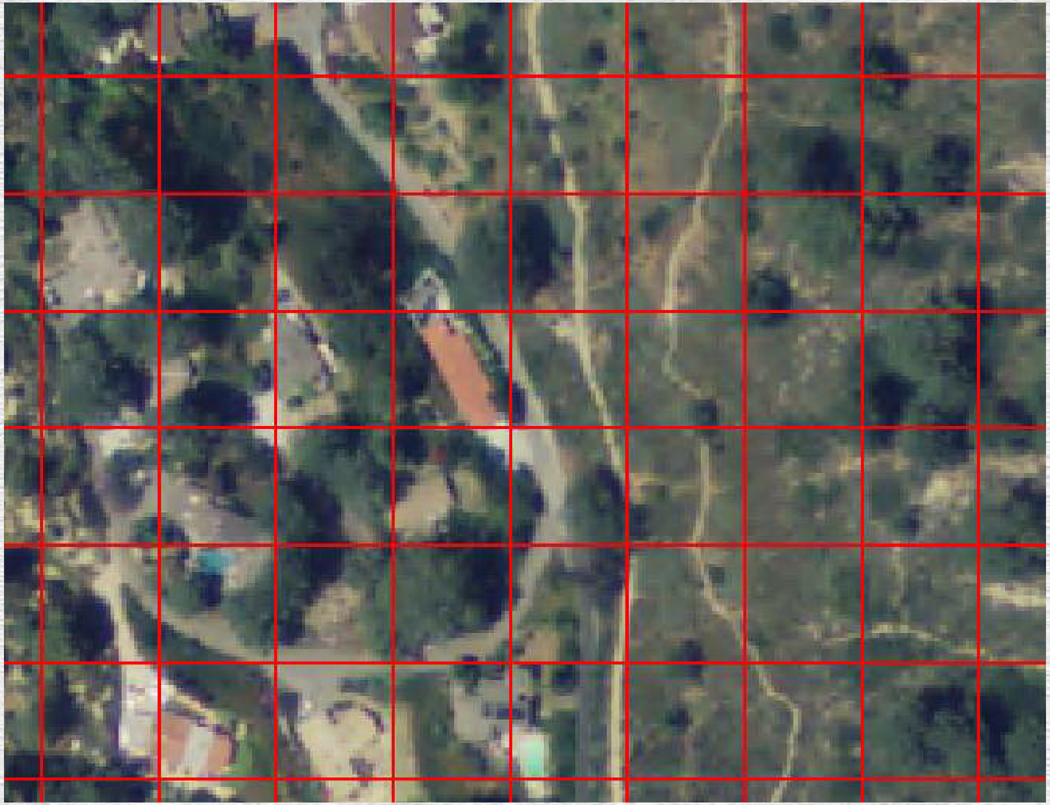


Spectral signatures based on two bands for four cover types

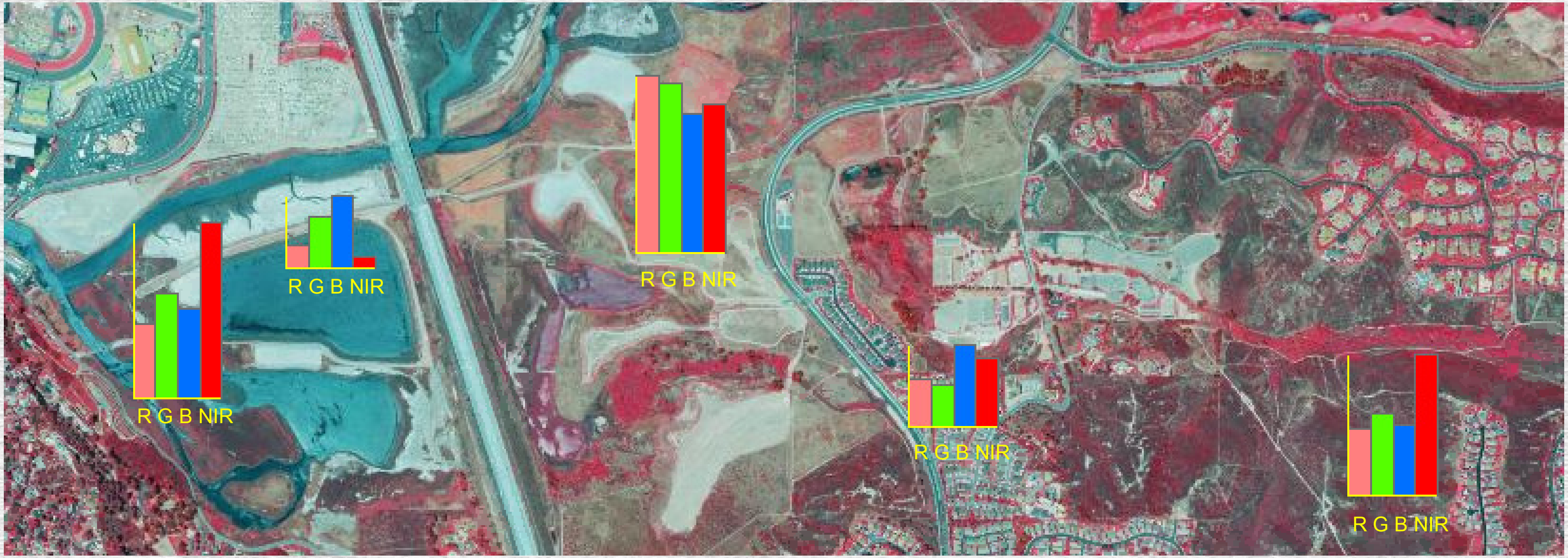
Is LandSat too coarse?

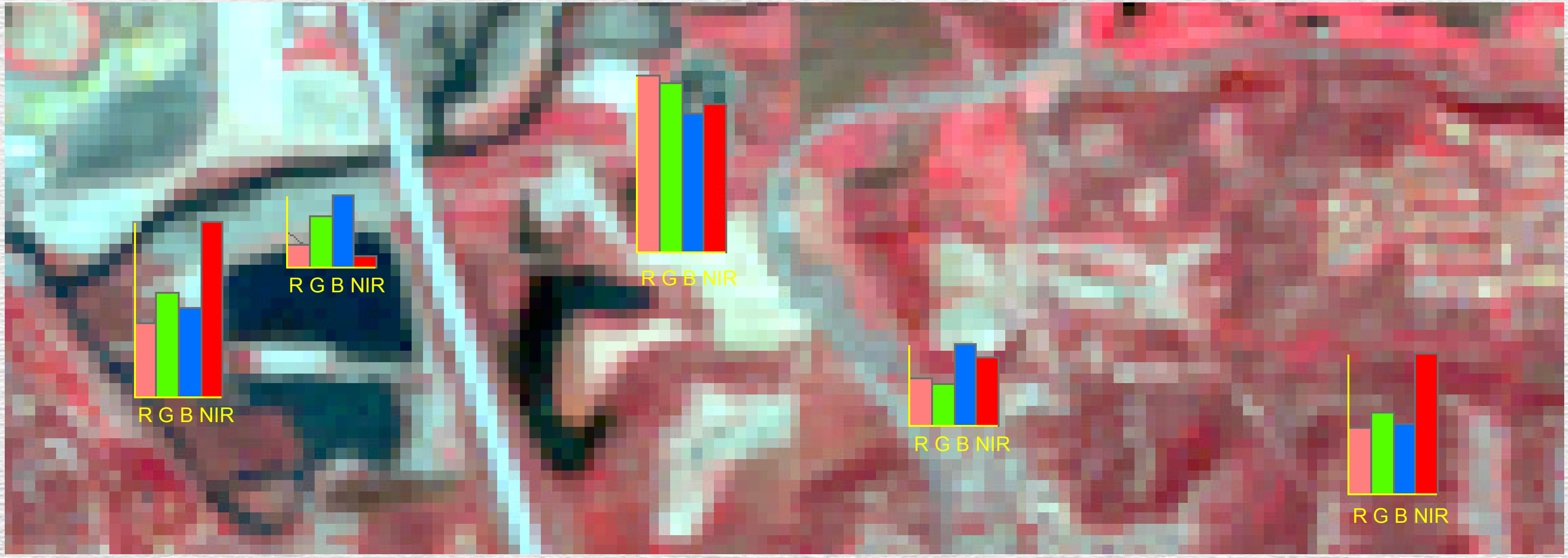
- LandSat has IR bands, which is good
- For manual image interpretation, though, the higher resolution the better
  - In imagery, or any raster data, resolution is pixel size
  - Smaller the pixels, higher the resolution → finer detail can be seen
- This is not the case for cover typing with spectral signatures

Types, rather than individual features



LandSat pixels are too big to identify fine detail,
but they are better at integrating the spectral information from a cover *type*


R G B NIR
R G B NIR
R G B NIR
R G B NIR
R G B NIR

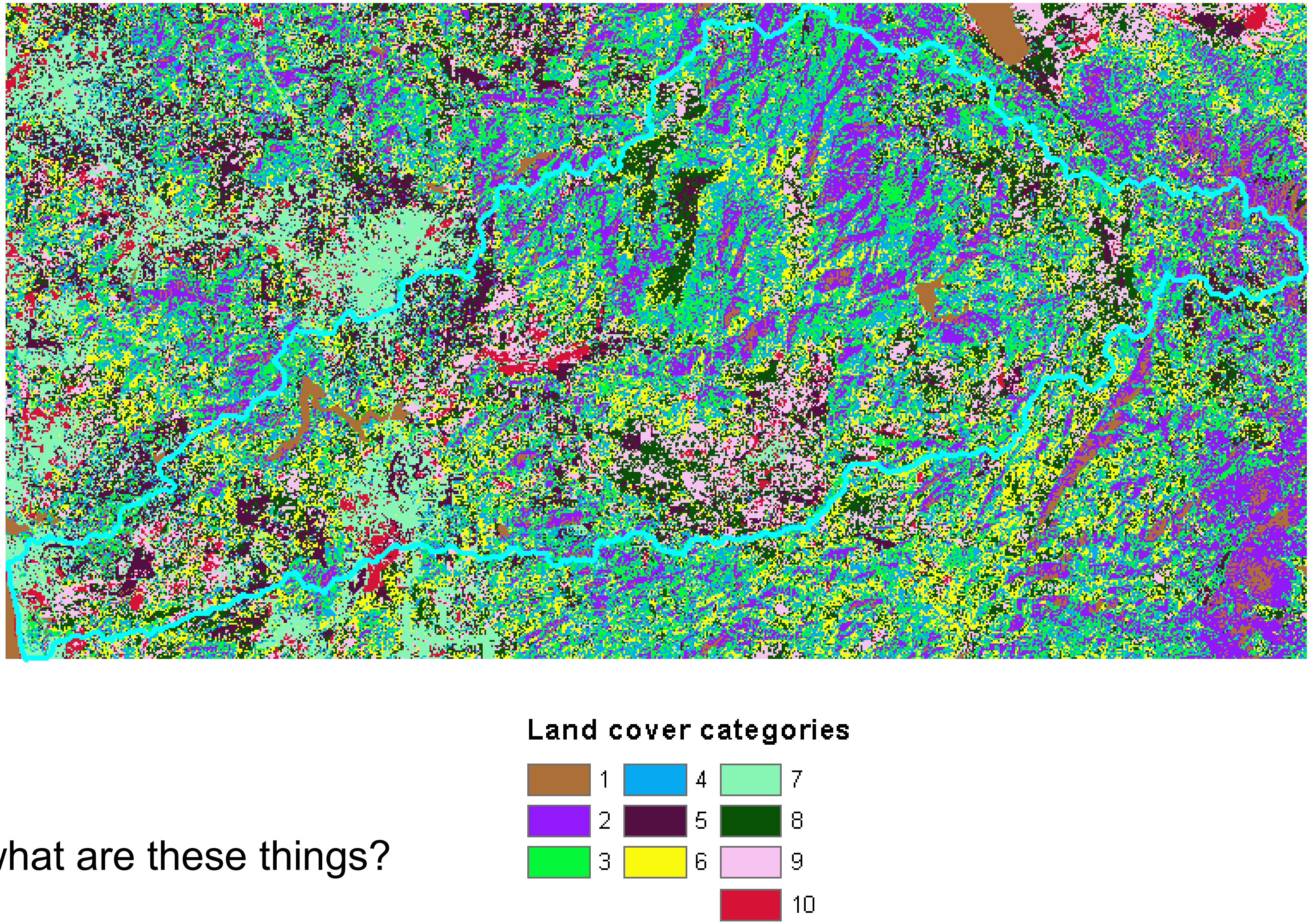

R G B NIR
R G B NIR
R G B NIR
R G B NIR
R G B NIR

Unsupervised classification

- Based on a search for natural breaks in the spectral data
  - Expected that pixels with the same cover type will tend to have similar spectral signatures
  - Groupings of similar values should indicate different cover types
  - Find the most discrete groups possible – lots of difference between, little variability within
  - Once the groups are found, the band means of all the pixels assigned to the groups become the group’s spectral signature
- The identity of the cover types have to be determined after the groups are found
- The most commonly used approaches are various types of cluster analyses

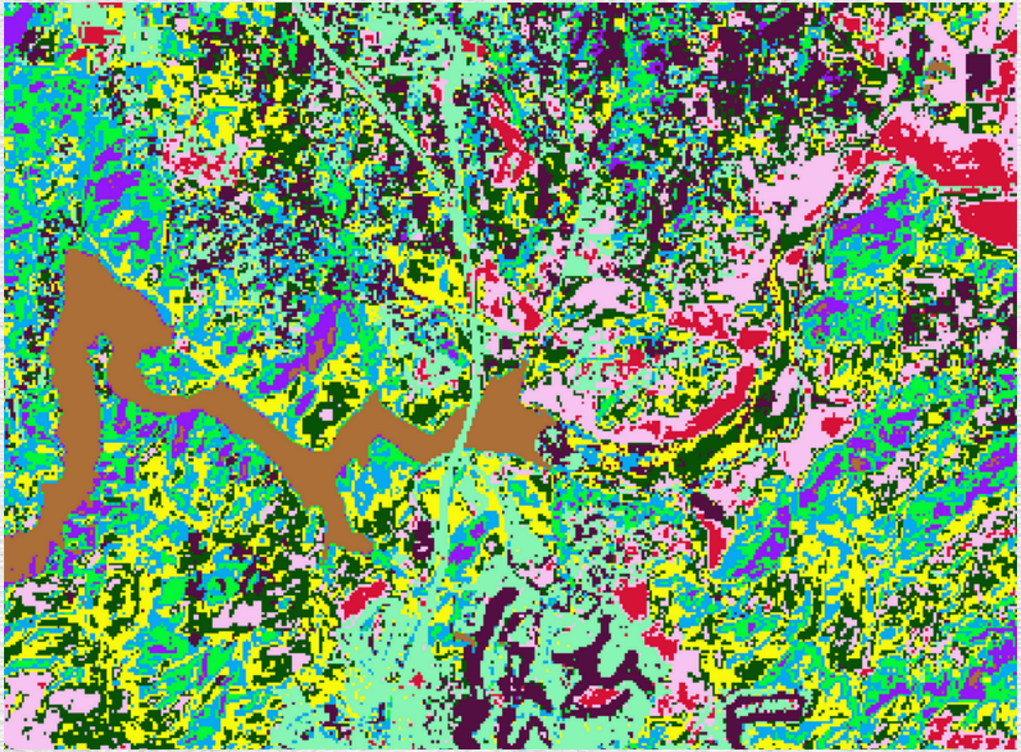
Example: SDRP land cover in 1984

- 6 bands (1-5, 7)
- 10 classes
  - Need to specify number of classes, but not what kinds of vegetation they represent
  - Based on finding means that best separate groups
- Pixels are assigned to the group whose mean spectral signature they're closest to



Problem: what are these things?

Identify what the clusters are



Can use high resolution imagery, visits to the site

Supervised classification

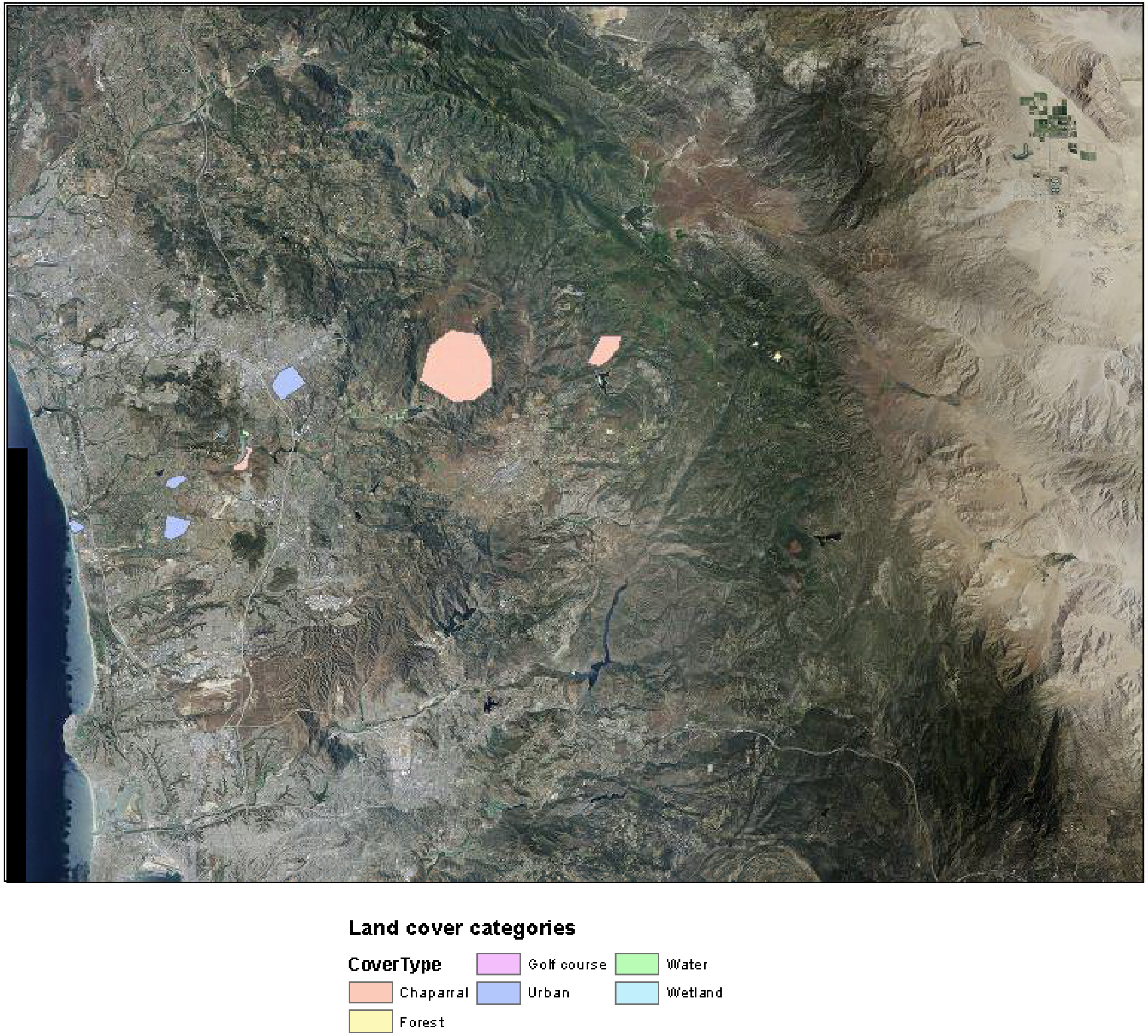
- Cover types are specified in advance, and samples of training data with known cover type are collected
- A spectral signature is derived from the samples for each cover type
- Unknown pixels are compared against the spectral signatures, and are assigned to the cover type whose signature is closest to their own band values
- There are many different approaches
  - Cluster analyses
  - Discriminant function analysis (DFA)
  - Classification and regression trees (CART)

Developing training data

- Want a representative sample of all the cover types you wish to delineate
- Identify locations of known cover type
  - Can be points within, or polygons drawn around, known cover types on a map
  - Can come from field sampling – stand in a known cover type with a GPS, record the location and the cover type
- The band data from the pixels within the training data cover types are then averaged
  - Mean for each band
  - Collectively, the means across all the bands used is the spectral signature for the cover type
  - Each cover type has its own signature

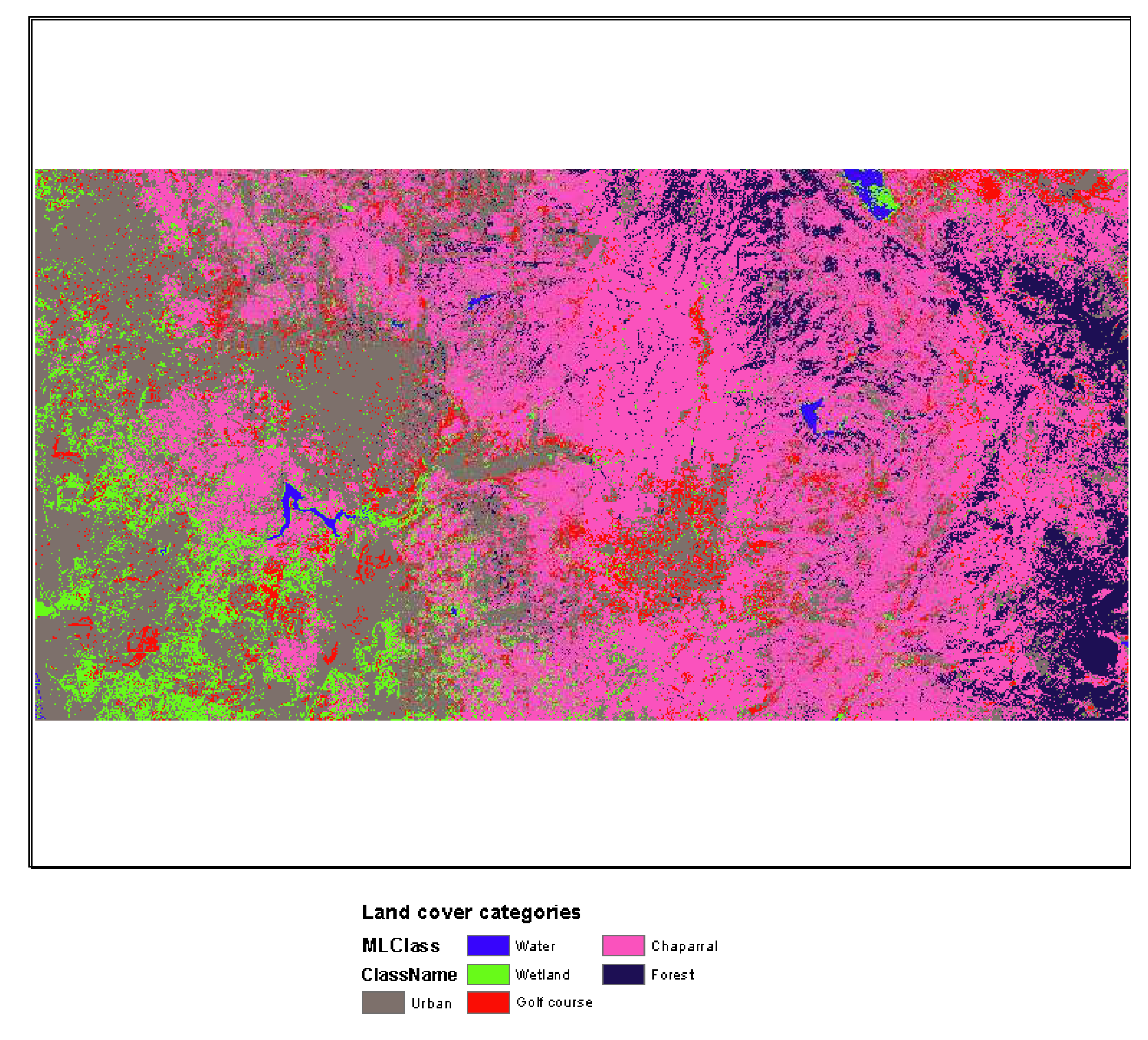
Training data

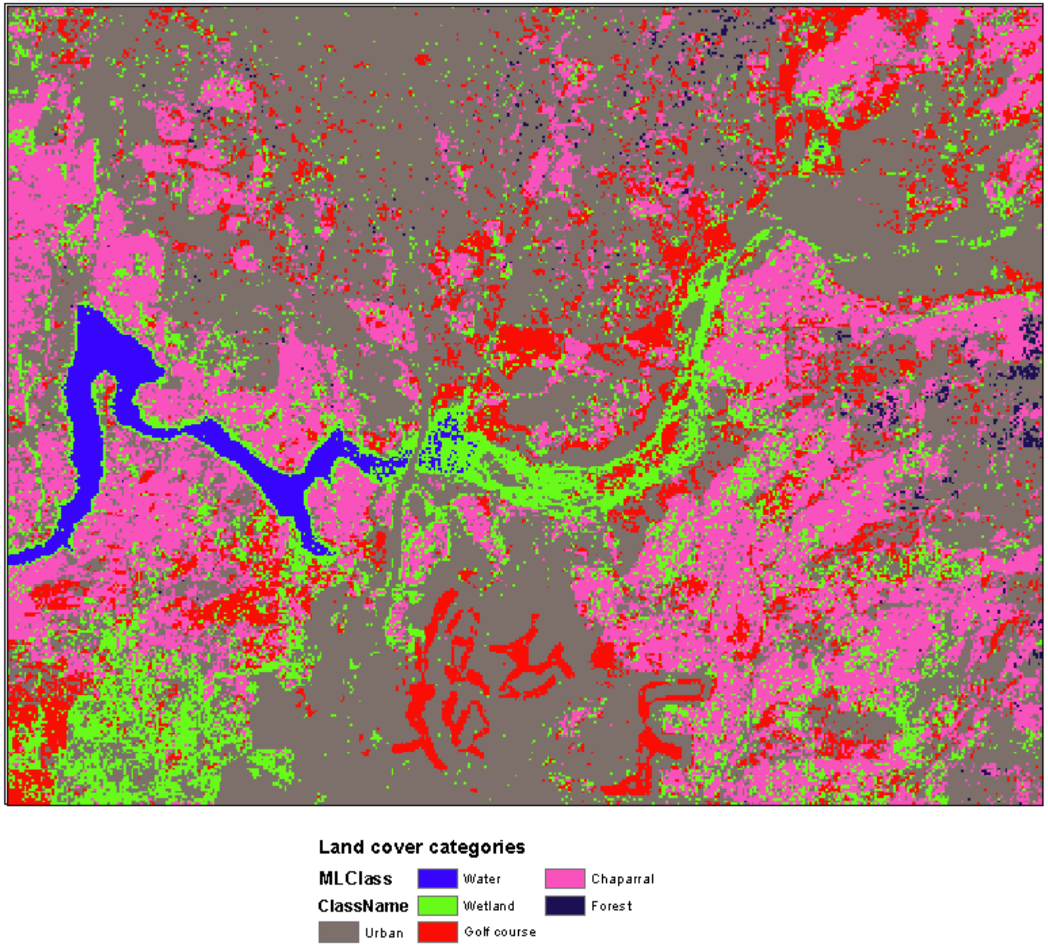
- Polygons drawn over known cover types
- Pixels within each polygon used to derive spectral signatures



Classified map

- Each pixel's band values are compared to every cover type spectral signature
- Each pixel is then assigned to the cover type its band values are closest to




Land cover categories
MLClass
ClassName
Water
Wetland
Urban
Golf course
Chaparral
Forest

Sources of classification error

- For supervised classification, pixels are mis-classified because:
  - Cover types are left out of the training set
  - Spectral signatures are not discrete = overlap in the band values for different cover types
- For unsupervised classification, pixels are mis-classified because:
  - A cover type is heterogeneous, such that the clusters that form split cover types apart
  - If too few categories are used, cover types are lumped together
  - Finds clusters that have distinct spectral signatures, but functionally important cover types may not differ enough in spectral signature to be distinguished
- For both, the resolution of the data may be mismatched to the scale at which the cover types vary
  - Need homogeneity within cover types, but big differences between → complete separation of the distributions of the spectral data

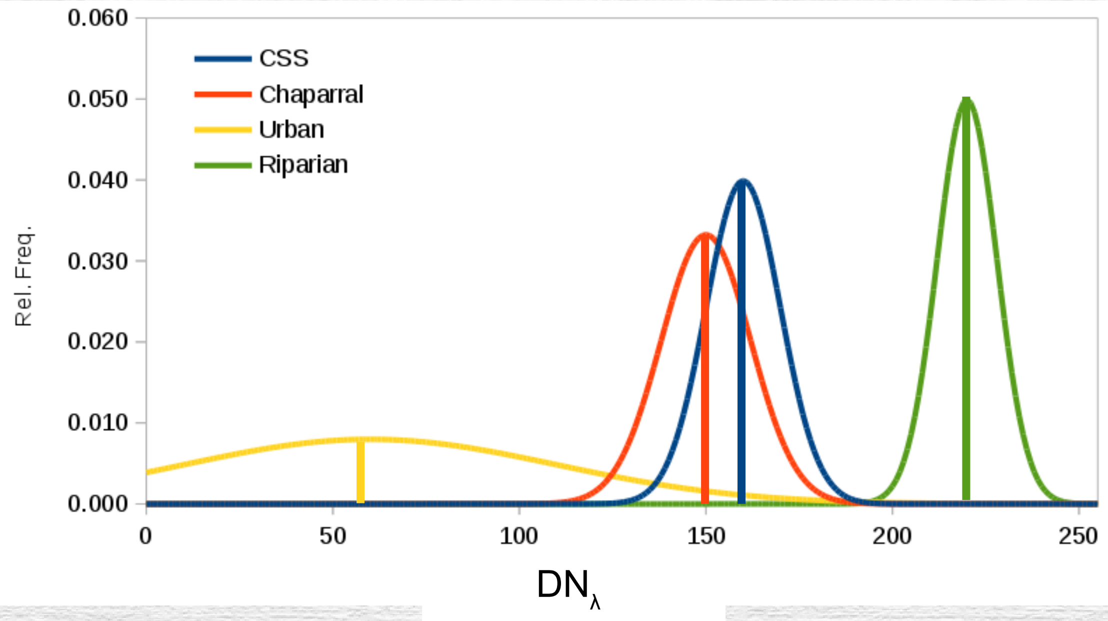
Discrete signatures, or not

Simple example – one band

Curves are distributions of reflectances for each cover type, vertical lines are means

Any pixel that's closest to its own mean will be correctly classified

CSS and chaparral have very similar distributions, will be mis-classified as one another frequently



What about urban? Will it ever be mis-classified as CSS and chaparral? Will CSS or chaparral ever be mis-classified as urban?

Which cover type should be correctly classified all the time?

Resolution of data and heterogeneous cover types

Zoomed to pixel level

Would reducing the pixel size help this time?

Classification errors: what to do...

- Several possibilities...
  - Clean up the maps – absorb single isolated pixels into the cover type surrouning them
  - Add more categories – maybe more than one urban type
  - Use “auxiliary data” = data other than the spectral signatures, such as elevation, aspect (direction a slope is facing), soil type, etc.
  - Try a different (usually bigger) pixel size, combine more than one pixel size
  - Use patterns across multiple pixels – take into account the sorts of things we do automatically when we interpret an image (texture)
  - Try a different season – golf courses and native grasslands look more similar in the wet season than the dry season in our region, so dry-season images may work better (can even use difference maps)