GEOG 892 - Geospatial Applications of Unmanned Aerial Systems (UAS)

Digital Image Classification
Land Use and Land Cover Assessment

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What is a raster image?

- A **digital image** or raster image or bitmapped image is a numeric representation of a two-dimensional image.

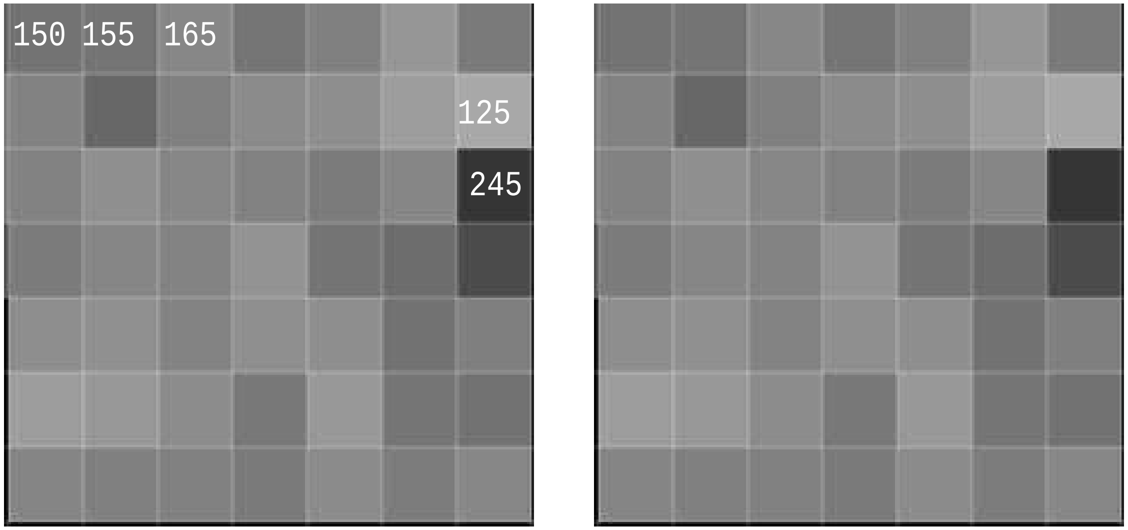

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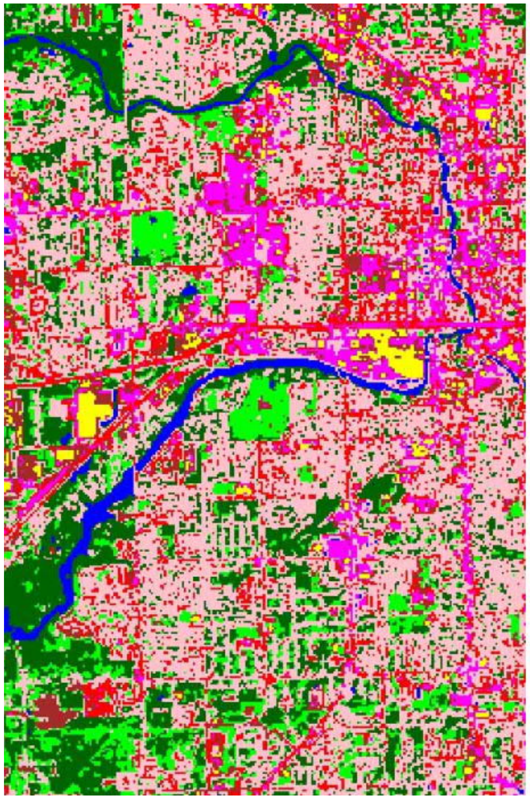
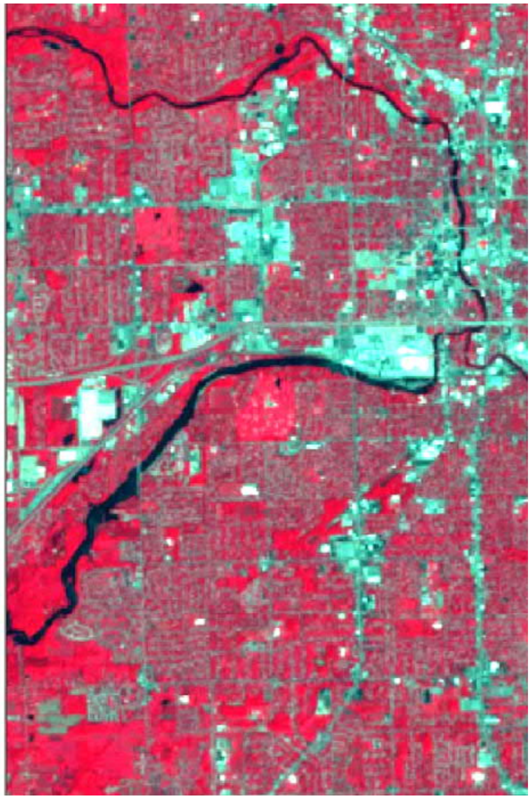
Image Classification

Is the process of categorizing each pixel in an image into one of several land cover classes.





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Suggested readings:

- https://gisgeography.com/image-classification-techniques-remote-sensing/

- https://earth.esa.int/landtraining09/D2L2_Caetano_Classification_Techniques.pdf

Image Classification

- Is an information extraction process (machine or automated interpretation) that involves the application of pattern recognition theory to multispectral images.
- It analyzes spectral properties of various surface features (e.g., crops) in a multiband image and sorts spectral data into spectrally similar categories by the use of predefined, numerical decision rules.

Image Classification

Is the process of categorizing each pixel in an image into one of several land cover classes.

The process utilize one or more of the following recognition types:

1. **Spectral pattern recognition:** When decision rules are based on spectral radiance characteristics of the scene.
2. **Spatial pattern recognition:** When decision rules are based on geometric characteristics of the scene (i.e. shape, size, patterns)
3. **Temporal pattern recognition:** uses time as an aid in feature identification
4. **Object-oriented classification:** involve combined use of both spectral and spatial recognition

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Image Classification

The process involves:

- Categorizing images into different surface materials or conditions
- Collection of spectral signatures for specific surface materials
  - Based upon spectral response
  - Assumes unique spectral signatures exist for land covers
- Trains the computer to recognize those spectral signatures
  - Statistical operation
  - No direct site or situation information
    - Does not rely on visual interpretation
  - Not necessarily more accurate or objective than visual interpretation
    - Someone has to decide the classes and whether signatures are accurate or not

Image Classification Process

- Signature extraction
  - Unsupervised classification using statistics or clustering algorithm
  - Supervised classification using training sites
  - Poor signatures lead to poor results
  - Possibly stratify broad classes first
- Classify the imagery
- Spatial filtering for GIS compatibility
- Accuracy assessment

- Difficulties
  - Signature not unique for given sensor characteristics
  - Signature too unique
    - Same cover type but with distinct differences
      - Soil moisture, surface material, atmospheric conditions
  - Mixed pixels
  - Signature extension issue (over space and time)

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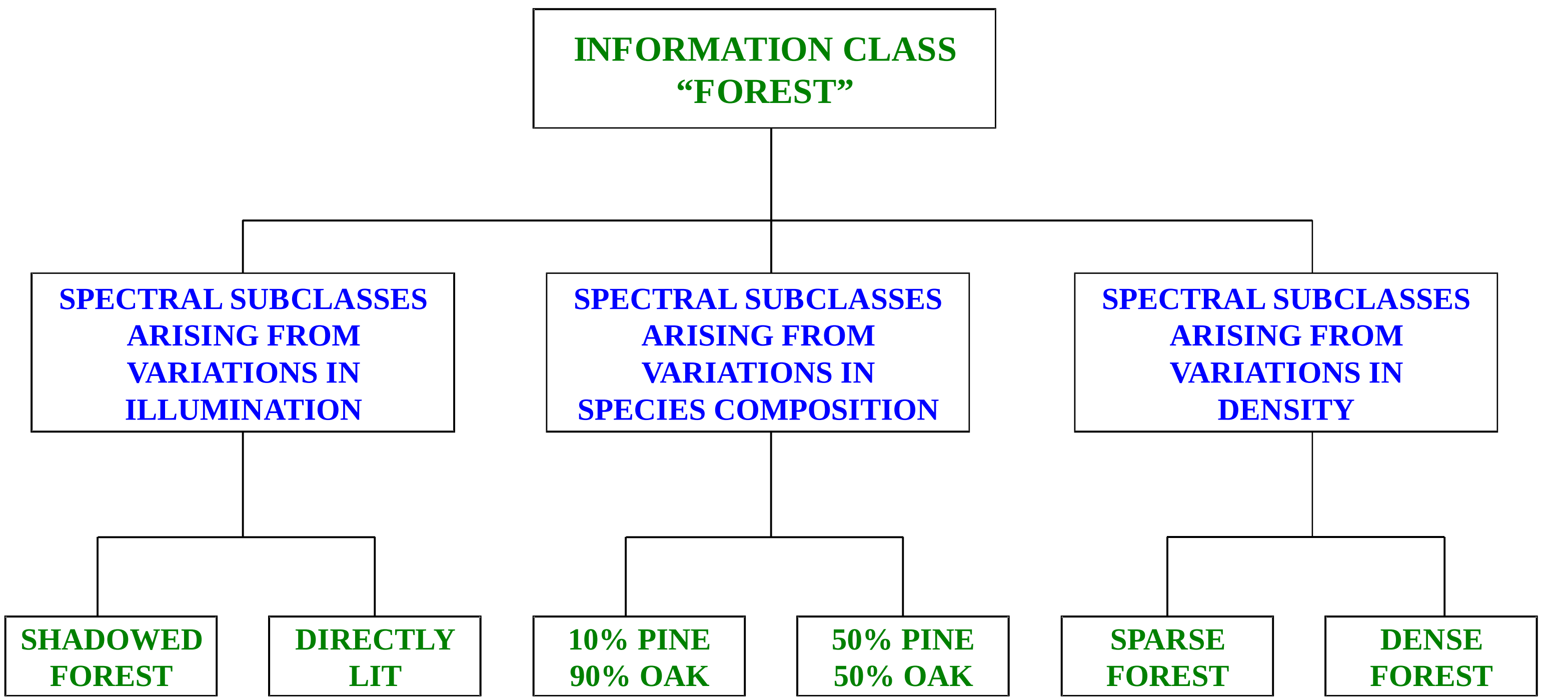
Spectral subclasses



Informational vs. Spectral Classes

- **Informational classes:**
  - Categories of interest to users – land use, water turbidity

classes, forest habitat types, geological units, chlorophyll types, soil organic matter content, depth of snow pack, sea surface temperature, etc…

  - Not directly recorded on a remotely sensed image!
- **Spectral classes:**
  - Groups of pixels that are uniform with respect to brightness values and patterns in their multiple spectral channels

The challenge is to derive quantitative connections between informational and spectral classes - rarely do we find discrete matches. Without a connection remote sensing may not be useful.

Classification Approaches:

A - Unsupervised Classification: uses an automatic clustering algorithm that analyzes the “unknown” pixels in the database and divide them into a number of spectrally distinct classes based upon their natural grouping or clusters

Steps: a - clustering or grouping

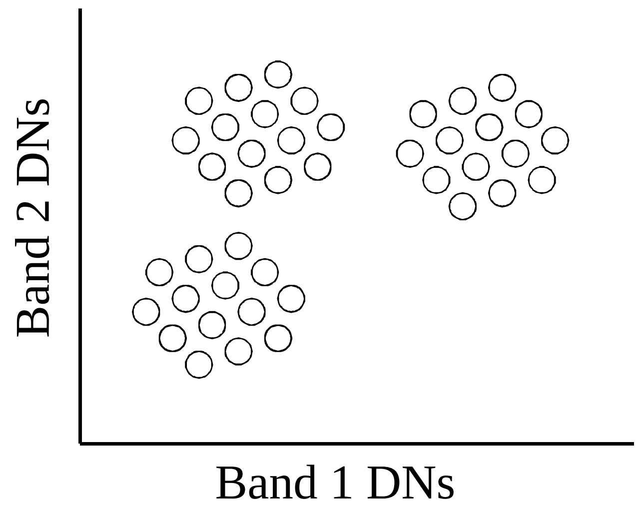
b - coloring

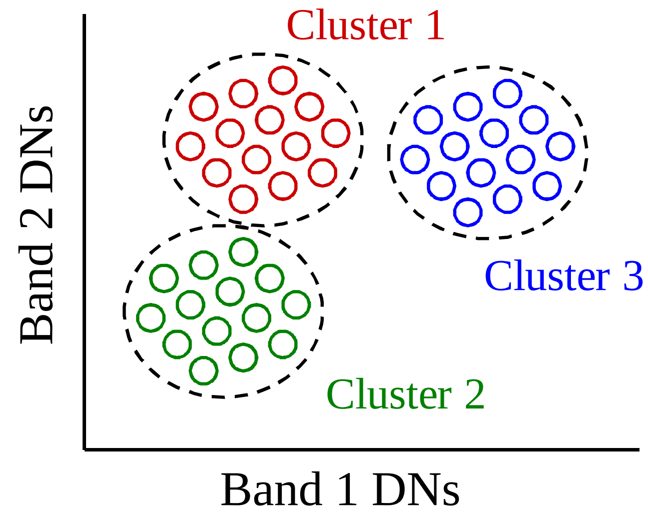
c - identification

Example:

Two-band data set (given)

Three spectral classes (analyst selection)





Sequential Clustering:

requires: - Maximum allowable number of spectral classes

- Maximum allowable distance to spectral class mean

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Classification Algorithms: Unsupervised

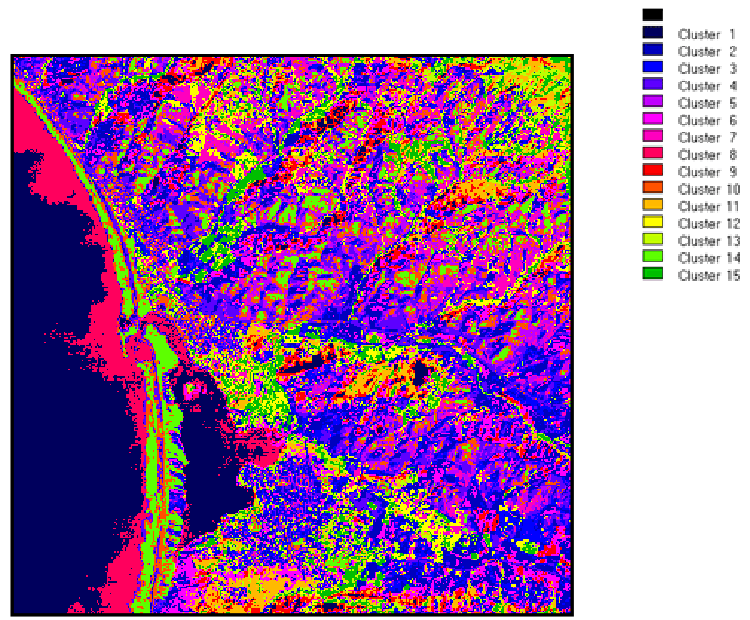
- User directs computer to categorize image into classes with similar statistical characteristics (clusters)
  - User specifies number of clusters
    - Minimum three times the number of land cover classes
      - e.g. 8 classes = minimum 24 clusters
    - May specify up to a couple of hundred clusters
    - Many clusters are insignificant or contain mixed pixels
  - Software package groups pixels
    - Similar spectral characteristics into unique clusters
  - Analyst then identifies the content of clusters and assigns classes (land cover)

Classification Algorithms: Unsupervised

- Iterative Self-Organizing Data Analysis Technique (ISODATA): uses the central values (means) of the spectral data clusters (defined by training data) to initially assign pixels to information categories, then iterates to alter the centroids based on distances
  - One of the most common
  - An iterative self-organizing classifier
- Process:
  1. User specifies the number of clusters
  2. Statistics are calculated on the dataset
  3. A set of N clusters is arbitrarily located in band space
  4. Pixels are then assigned to their nearest cluster location
  5. After all pixels are assigned, a new mean location is computed
  6. Steps 3 and 4 are iteratively repeated until there is no significant change in the output

Classification Algorithms: Unsupervised

- Common approach to unsupervised classification
- Do a classification with many classes (100-200)
- Examine results, group classes to form a limited number of final classes



Unsupervised Classification Advantages/Disadvantages

Pros:
+ no extensive prior knowledge of the region required
+ opportunities for human error minimized
+ unique classes are recognized as distinct units
+ logistically less cumbersome

Cons:
- natural groupings do not necessarily correspond nicely with desired information classes
- no control over the menu of classes and their specific id
- spectral properties of informational classes vary over time, relationships between information and spectral classes change - make it difficult to compare unsupervised classes from one image/date to another

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Supervised Classification

- The process of using samples of known informational classes (training sets) to classify pixels of unknown identity.
- Identification and delineation of training areas is key to successful implementation

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Supervised Classification:

- Basic strategy: To sample areas of known cover types to determine representative spectral values of each cover type.
- Training fields or spectral signatures:
  - Are established from homogeneous cover type areas
- Approaches:
  - Map digitizing - transfer photo information to base map (use table digitizer)
  - On-screen digitizing
  - Seed-pixel approach

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Image Classification Procedure

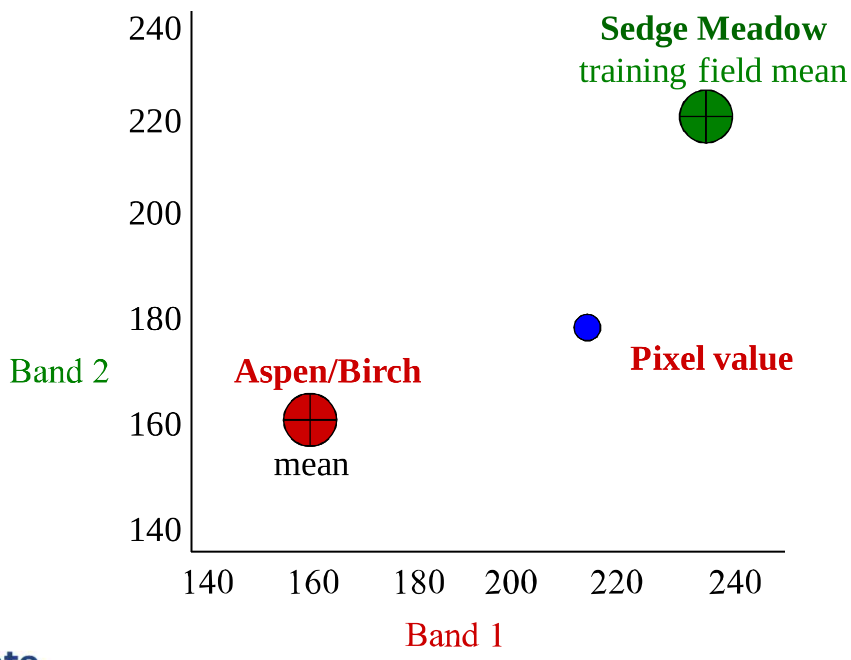
1. Training Class Selection
2. Generation of Statistical Parameters: To train the classification algorithm
   - class means
   - standard deviations
   - covariance matrices
   - correlation matrices

Image Classification Procedure

3. Data Classification: Assigning each pixel of the data to one of the training class
4. Evaluation and Refinement
5. Documentation: Maps and tabular summaries

Popular Simple Classifiers:

- Minimum Distance Classifer



- Advantage: simple and fast
- Disadvantage: relay on spectral means and not spectral variability

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Popular Simple Classifiers:

- Parallelpiped Classifier: Utilize spectral variability by using minimum and maximum values from each cover class
- Maximum Likelihood Classifier: Better classifier utilizes mean and covariance

Classification Algorithms: Supervised

- Supervised classification relies on user input to define cover-types in an image
  - Specific sites that represent homogeneous examples of known land cover types
  - Sources: ground truth, fine resolution images, or personal knowledge
- Areas are called training or calibration sites
  - Signatures are extracted to represent the spectral characteristics of that land cover type
  - Evaluated for separability
    - Signatures should allow the most accurate separation of land covers in an automated classification
- Additional sites are reserved as validation or "truth" sites used in the accuracy assessment process

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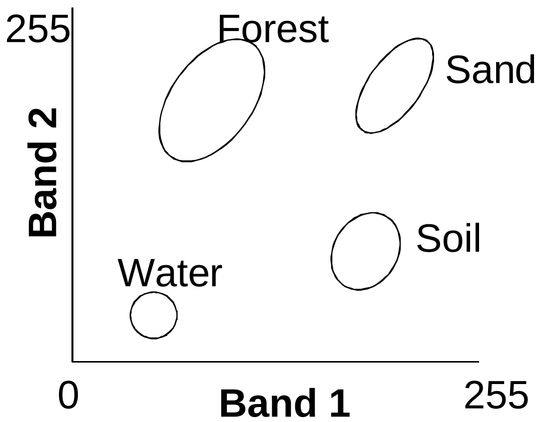
Classification Algorithms: Supervised

- Training sites are used to classify the entire image
  - Multiple classification algorithms exist
  - Maximum Likelihood is a very common one
- The Maximum Likelihood decision rule is based on probability and follows the general logic:
  - Estimates the mean and variance of each calibration class
  - Calculates the probability that any pixel belongs in a particular class
  - If the pixel, using all bands, has brightness values that lie within the forest region, it has a high probability of being forest
  - Highest (maximum) likely class wins



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Good Training Sets

- **# of pixels** - want to statistically characterize the spectral properties of an informational class (i.e. forest, crop, water), should have >= 100 pixels total for an informational class
- **location** - geographically dispersed, boundaries away from edge/mixed pixels
- **number of areas** - depends on number of information categories, 10 at a minimum, enough for accuracy assessment and incorporation of spectral subclasses
- **uniformity** - unimodal distributions, use training areas to characterize mean, variance, covariances - sometimes not easy due to spectral variation present

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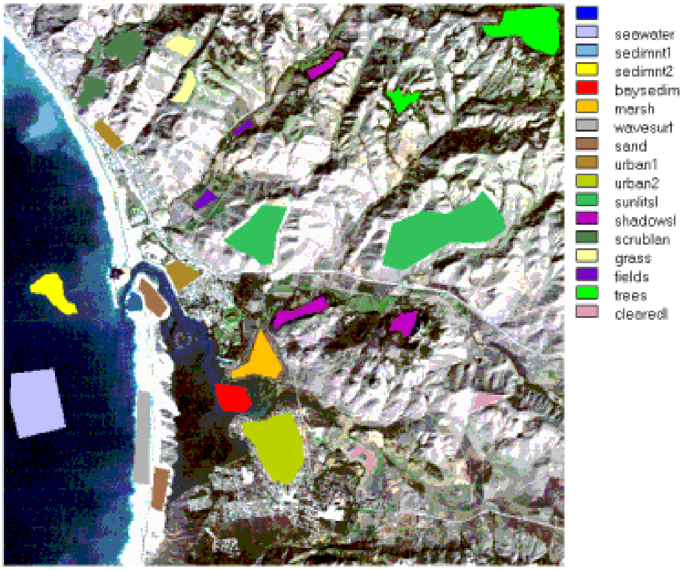
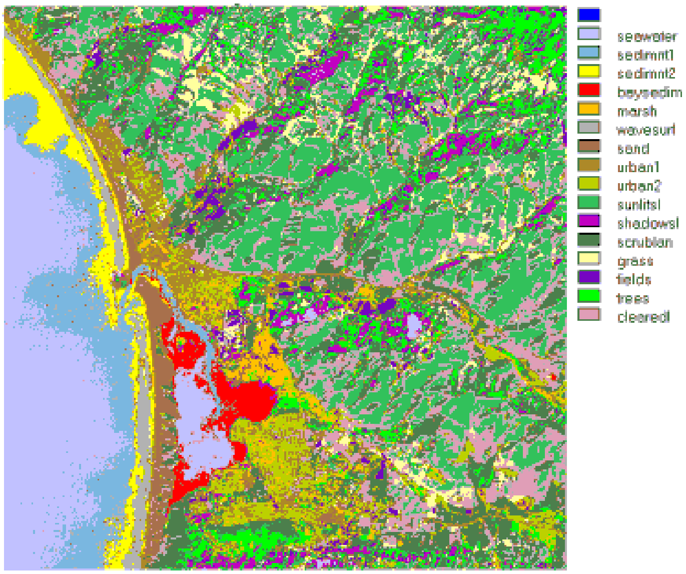
Classification Algorithms: Supervised





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Example on Land Use and Land Cover Classification using Supervised Classification

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Example: Waterfowl management unit:

Given:

Two cover types: cattail (CT) marsh, smartweed (SW) moist soil, Single band

Find:

Use maximum likelihood classifier to classify the following image:

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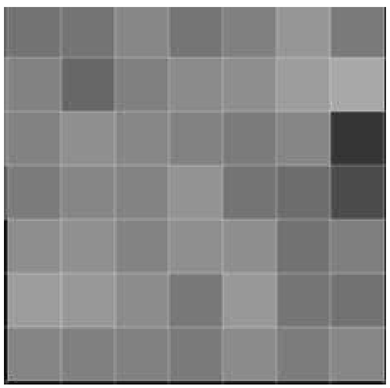
Example: Hypothetical Image



11	11	12	20	20	31	35	37	34	34
11	11	12	19	20	33	34	35	34	36
11	12	12	18	20	36	38	37	36	36
13	14	17	22	23	38	39	37	36	35
15	16	17	23	23	36	37	35	35	34
29	32	29	30	38	39	37	36	34	34
31	35	37	34	36	37	35	35	36	36
33	34	35	34	38	39	37	36	36	36
36	38	37	36	35	34	38	39	35	35
38	39	37	36	35	37	38	38	38	34

Formula for normal distribution (Likelihood Values)

$$f(x \mid \mu, \sigma^2) = \frac{1}{\sqrt{2\pi}\,\sigma} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right),$$

μ= Mean, σ = standard deviation X = spectral value

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Solution:

1. Calculate spectral values from cattail and smartweed training fields

	Mean Digital Value	Standard Deviation	Number of Pixels
Cattail (CT)	30	5	100
Smartweed (SW)	20	5	100

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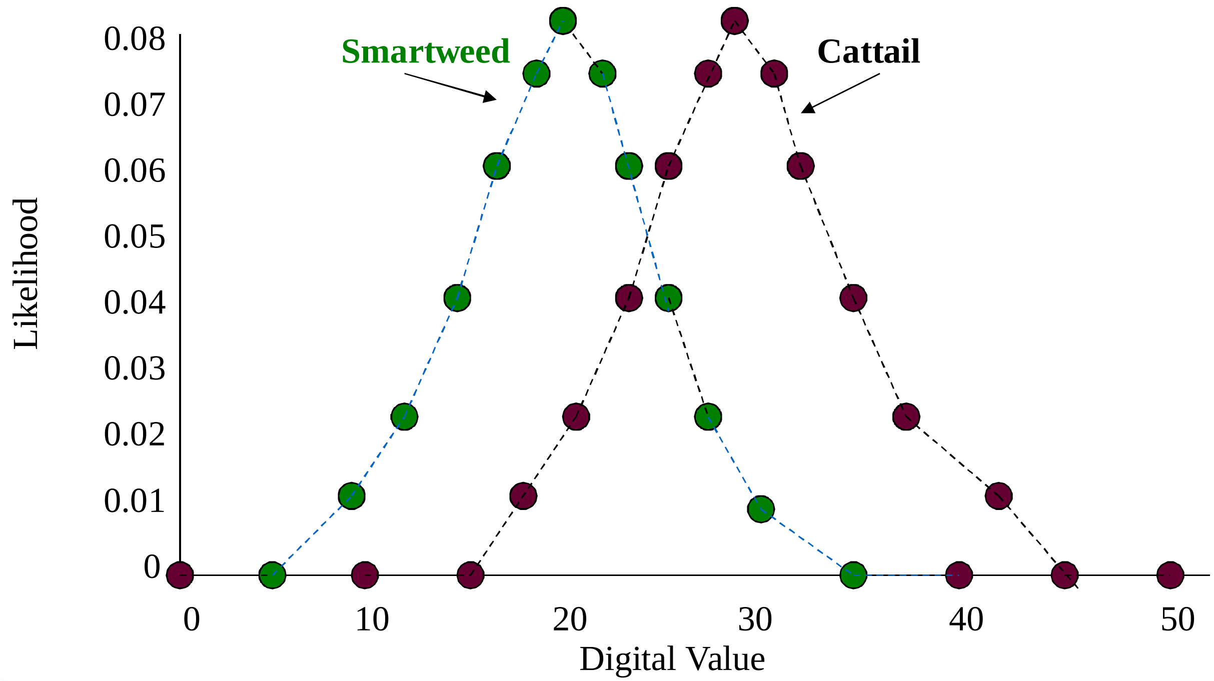
2. Compute the likelihood values for cattail using the normal distribution formula

Spectral Value	Likelihood
10	0.00003
15	0.0009
20	0.011
22	0.022
24	0.039
26	0.074
30	0.080
32	0.074
34	0.058
36	0.039
38	0.022
40	0.011
45	0.009
50	0.00003

3. Compute the same values for smartweed

4. Plot the two values to create likelihood curves



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5. Assign each candidate pixel to a cover class that had the highest likelihood

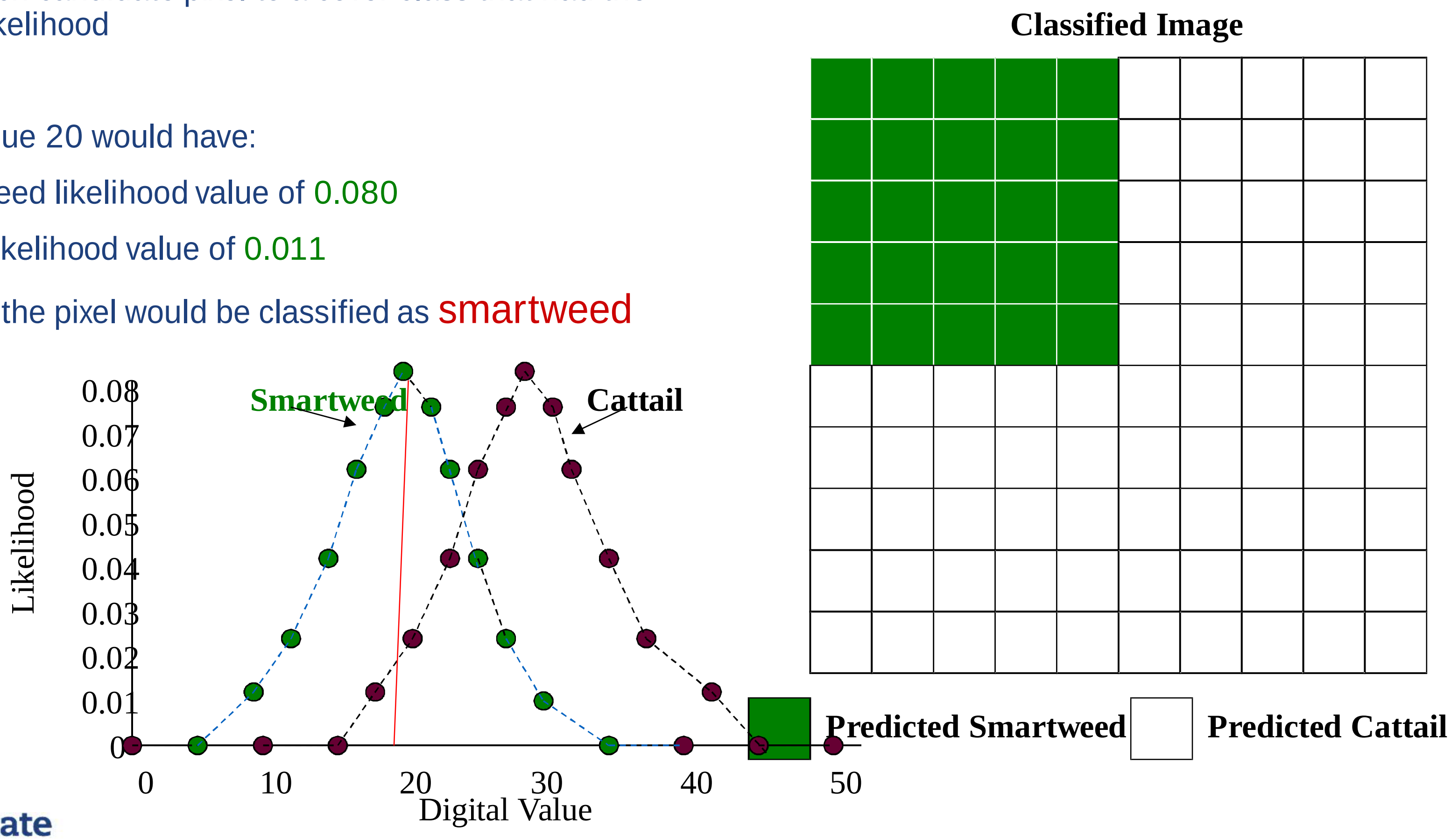
Example:

a pixel value 20 would have:

a smartweed likelihood value of 0.080

a cattail likelihood value of 0.011

Decision: the pixel would be classified as smartweed



Supervised Classification Advantages/Disadvantages

Pros:

- analyst controls the selected menu of informational classes or categories tailored for a specific purpose and geographic region
- tied to specific areas of known identity
- can evaluate results with additional training areas

Cons:

- analyst imposes a classification structure on the data (may not match the natural spectral clusters that exist)
- training data defined based on informational categories and not on spectral properties (may have important variation in forest)
- careful selection of training areas is time and labor intensive
- training areas may not encompass and subsequently represent special or unique categories that don’t fit the information classes

Methods to Improve Classification

- Pre-classification Image Segmentation
  - Segmenting study area/data prior to analysis
    - Each segment examined independently
    - GIS layers may provide segmentation not possible via remote sensing
  - e.g. vegetation vs. urban, watershed, administrative boundary, elevation, slope, soil type, historical land use/cover
- Post-classification sorting
  - Use GIS to finalize classes
    - e.g. Forest category 1 is class 13 above 350m and class 16 below 350m
- Change data input
  - Multitemporal
  - Multisensor
  - Hyperspectral
  - Context, texture
  - Ancillary data, GIS
  - Nested sampling
- Change processing
  - Better signatures
  - Change decision rule
    - Hierarchical
    - Neural networks
    - Artificial Intelligence
    - Expert systems
    - Fuzzy logic
    - Regression trees

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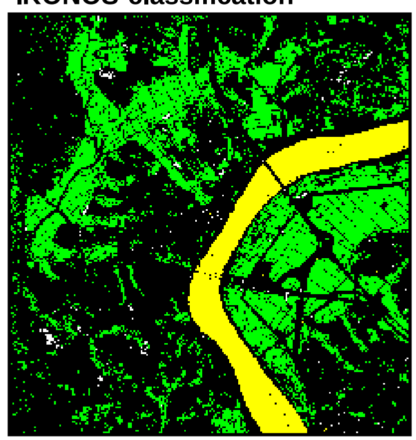
Spatial Resolution and Classification

Comparison of IKONOS false color composite and classification with Landsat. On the classification images, the river class is shown in yellow, rice fields in green, ponds in white. Each image is 5.5 km in width. Ponds were too small to be classified on the Landsat image

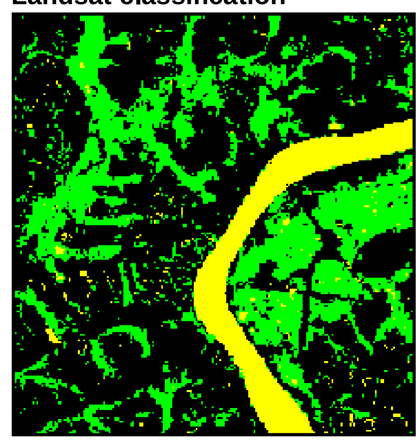
IKONOS image

Landsat image

IKONOS classification

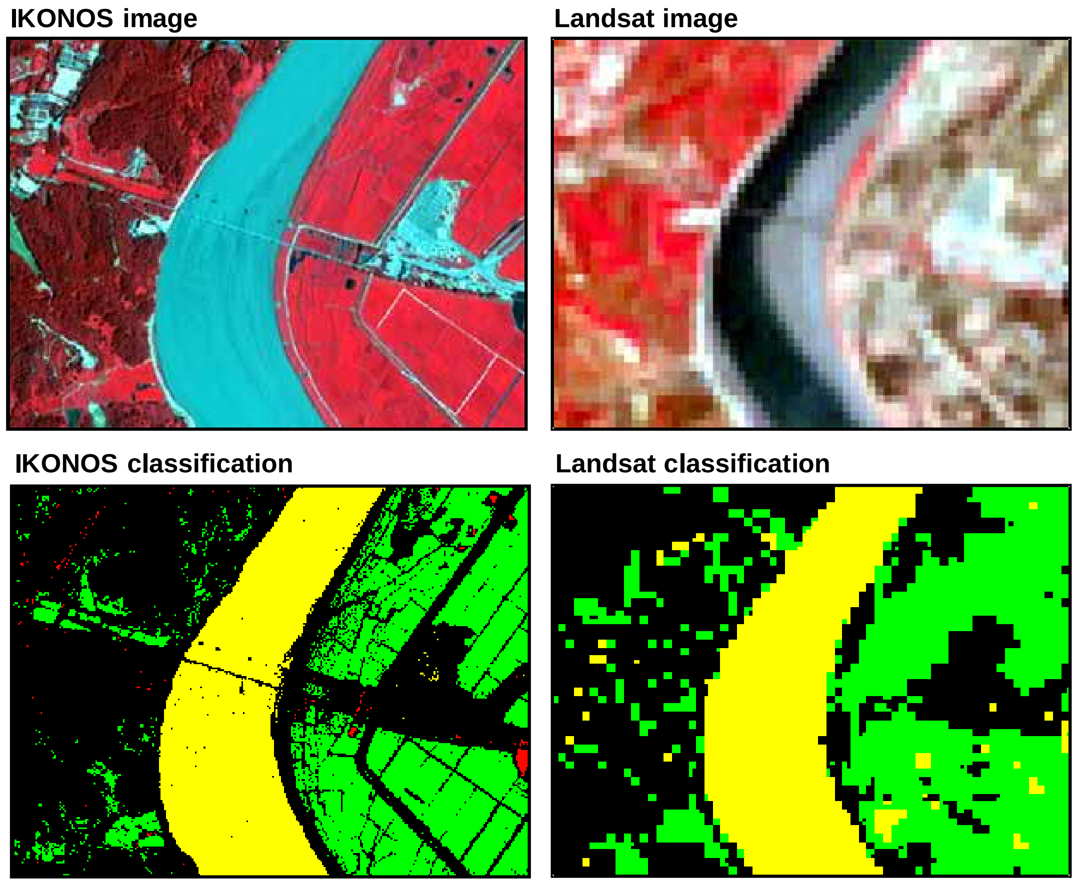


Landsat classification



Spatial Resolution and Classification

An enlarged subset of the images comparing an IKONOS false color composite and classification with Landsat. On the classification images, the river class is shown in yellow, rice fields in green, ponds in red.



Land Use and Land Cover Classification

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Land Use and Land Cover

- **Land Use**
  - What people do on the land surface
    - e.g. agriculture, urban, etc.
- **Land Cover**
  - The type of material present on the landscape
    - e.g., water, forest, etc.
- **Land Use/Land Cover image classification is used by:**
  - Governmental units involved in existing and future land use policy
    - Nuclear waste sites (transportation issues)
  - Global climate research and analysis
    - Carbon trading
  - Geographers and Economists use land-use patterns to understand economic systems
    - Land cover change patterns

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Land Use/Land Cover Classification

- State the nature of the land cover classification problem
  - Specify region
  - Determine classification scheme
- Select remote sensing data and begin ground truth
  - Select classification method
  - Define classes
- Classification scheme/definitions
  - Categories to define surface units
  - USGS for remote sensing
- Minimum Mapping Unit (mmu)
- Accuracy

LULC Classification Schemes

- Numerous classification schemes exist:
  - International Geosphere-Biosphere Program (IGBP) Land Cover Classification System
    - Commonly used for MODIS land-cover products.
  - United States Geological Survey Land Use/Land Cover Classification System for Use with Remote Sensor Data
    - Both general and detailed
  - American Planning Association Land-Based Classification System.
    - Oriented toward detailed land-use classification
    - Requires detailed ancillary data
  - U.S. Department of the Interior Fish & Wildlife Service "Classification of Wetlands and Deepwater Habitats of the Unites States"
    - Specialized
    - National Wetlands Inventory (NWI)

Classification Schemes

U.S. Geological Survey
Land Use/Land Cover Classification System
http://landcover.usgs.gov/pdf/anderson.pdf

- 9 levels at “Level 1”
  - Urban or built up
  - Agricultural Land
  - Rangeland
  - Forest Land
  - Water
  - Wetland
  - Barren Land
  - Tundra
  - Perennial Snow or Ice
- Can be subdivided further:

Level I	Level II	Level III
1. Urban or built-up	11. Residential	111. Single-family Units
		112. Multi-family Units
		113. Group Quarters
		114. Residential Hotels
		115. Mobile Home Parks
		116. Transient Lodging
		117. Other
	12. Commercial	121. ….

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Sources of Error in RS Process

- Acquisition
  - Sensor errors
  - Atmospheric conditions
- Data preprocessing
  - Geometric correction
  - Radiometric manipulation
- Data analysis
  - Interpretation
  - Classification
  - Generalization
- Data conversion
  - Raster to vector

Accuracy Assessment

- Accuracy assessment is important
  - For both visual and digital extraction
- Error reporting for both spatial and thematic content
  - Spatial data without accuracy of questionable value
  - Temporal differences often a constraint
  - Classification the most difficult to evaluate
    - Partly subjective
  - Accuracy should be a component of metadata
- Major difficulty is identification of ‘truth’
  - Truth data must be different from training sites

Accuracy Assessment

- High accuracy means that defined classes are consistently close to an accepted reference class
  - The most common reference sources are:
    - Visually recorded sites with a GPS and camera
    - Fine resolution imagery
  - Errors are present in any classification -- their sources are:
    - Misidentification of parcels
      - Shadow/water
    - Errors in georeferencing
    - Mixed pixels “mixels”
      - Field boundaries (resolution)
    - High landscape variability in an image
    - Quantity of categories chosen
      - Fewer classes incorporate more generalization

Accuracy Sampling Considerations

- It should be representative land cover
- It should be uniform
- It should be different from the training samples
- It should be more extensive that the training samples
- It should be randomly or semi-randomly selected
- Minimum of 50 sample per category (75-100 for large areas)

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- Overall accuracy = Total number of correctly classified pixels/Total number of reference pixels

- Producer's accuracy: When we say 84% of the forested area have been correctly identified as "forest"

= (Total number of correctly classified pixels)/(Total number of training set pixels for that category (the row total)) or *how well the statistics extracted from these areas can be used to classify the same areas!*

- user's accuracy : When user find only 60% of the areas identified as forest on the map are truly forest *or the probability that a pixel classified into a given category actually represents that category on the ground*

= (Total number of correctly classified pixels)/(Total number of pixels that were classified in that category (the column total))

Commission and Omission Errors

- Error of Inclusion (commission error): When including an area into category when it does not belong to that category.

- Error of Exclusion (omission error): When excluding an area from a category in which it truly does belong

- Every error is an omission from the correct category and a commission to a wrong category

➢ **Classification error matrices** compare, on category-by-category basis, the relationship between known reference data (ground truth) and the corresponding results of an automated classification.

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Producer's Accuracy

- Producers of a map are mainly concerned with how well the classification predictor captures what is actually on the ground. What site was omitted from a category? (Error of omission/exclusion.)
- Producer's Accuracy is computed by dividing the number of correctly classified pixels in each category by the number of test set pixels used for that category (the column total). This figure indicates how well the test set (training) pixels of the given cover type are classified.
- The Producer's Accuracy is complement of the Omission Error: Producer's Accuracy = 100%-Omission Error. It is also the number of reference sites classified accurately divided by the total number of reference sites for that class.

Producer's Accuracy

Users of a map are mainly concerned about:

- The likelihood that a pixel on the map correctly reflects what's on the ground.
- Was a site included erroneously in a category? (Error of commission/inclusion).
- For a given class, how many pixels are actually what the map says they are?

- User's Accuracy is computed by dividing the total number of correctly classified pixels in each category by the total number of pixels that were classified in that category (row total). This figure is a measure of commission error and indicates the probability that a pixel classified into a given category actually represents that category on the ground.
- The User's Accuracy is the accuracy from the point of view of a map user, not the map maker.

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Producer's Accuracy

- The User's accuracy essentially tells use how often the class on the map will actually be present on the ground. This is referred to as reliability.
- The User's Accuracy is complement of the Commission Error: User's Accuracy = 100%-Commission Error.

Accuracy Assessment

Error Matrix

Omissions error

Classified Image

Commissions error

Reference Image (training)

	Corn	Soy	Forest	Shrubs	Total Possible	omissions	Commissions	Mapping Accuracy
Corn	**25**	5	10	3	43	18/43=42%	7/32=22%	25/(25+18+7) = 50%**
Soy	2	**50**	6	5	63	13/63=21%	11/61=18%	50/50+13+11 = 68%
Forest	3	4	**60**	5	72	12/72=17%	18/78=23%	60/60+12+18 =67%
Shrubs	2	2	2	**100**	106	6/106=6%	13/113=12%	100/100+6+13 =84%
Total	32	61	78	113	**284**	** =25/(25+18+7) = 50%		

$$\text{Overall Classification Accuracy} = \frac{25 + 50 + 60 + 100}{284} = 83\%$$

omissions is non-diagonal row elements Commissions **is** non-diagonal column elements

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Accuracy Assessment

Class info	Producers Accuracy	User's Accuracy
Corn	25/43 = 58%	25/32 = 78%
Soy	50/63 = 79%	50/61= 82%
Forest	60/72 = 83%	60/78 = 77%
Shrubs	100/106 = 94%	100/113 = 88%

Overall Accuracy	25+50+60+100 / 284 = 83%

The **producer** may claim that 94% of the time an area that was shrubs on the ground was identified as such on the map.

The **user** may find only 88% of the time that the map says an area is shrubs will actually be shrubs on the ground

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