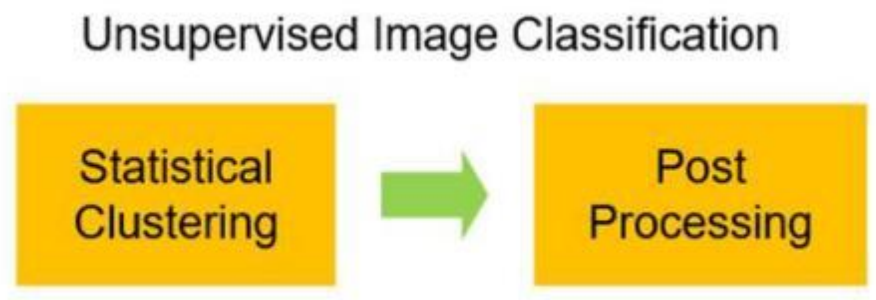
Supervised classification

Unsupervised classification is mainly clustering by the software

Supervised classification is more human-guided



Unsupervised classification: review

Characteristics

-user needs no 'a priori' knowledge of area (but it helps)

- software clusters pixels by natural DN groupings
 (based on similarity and contrast = ‘natural breaks’)

Steps

- determine input bands / channels

- determine how many classes / clusters

- run classifier : K-means or Isodata

- assign names to classes (merge classes if needed)

Supervised classification

Characteristics:

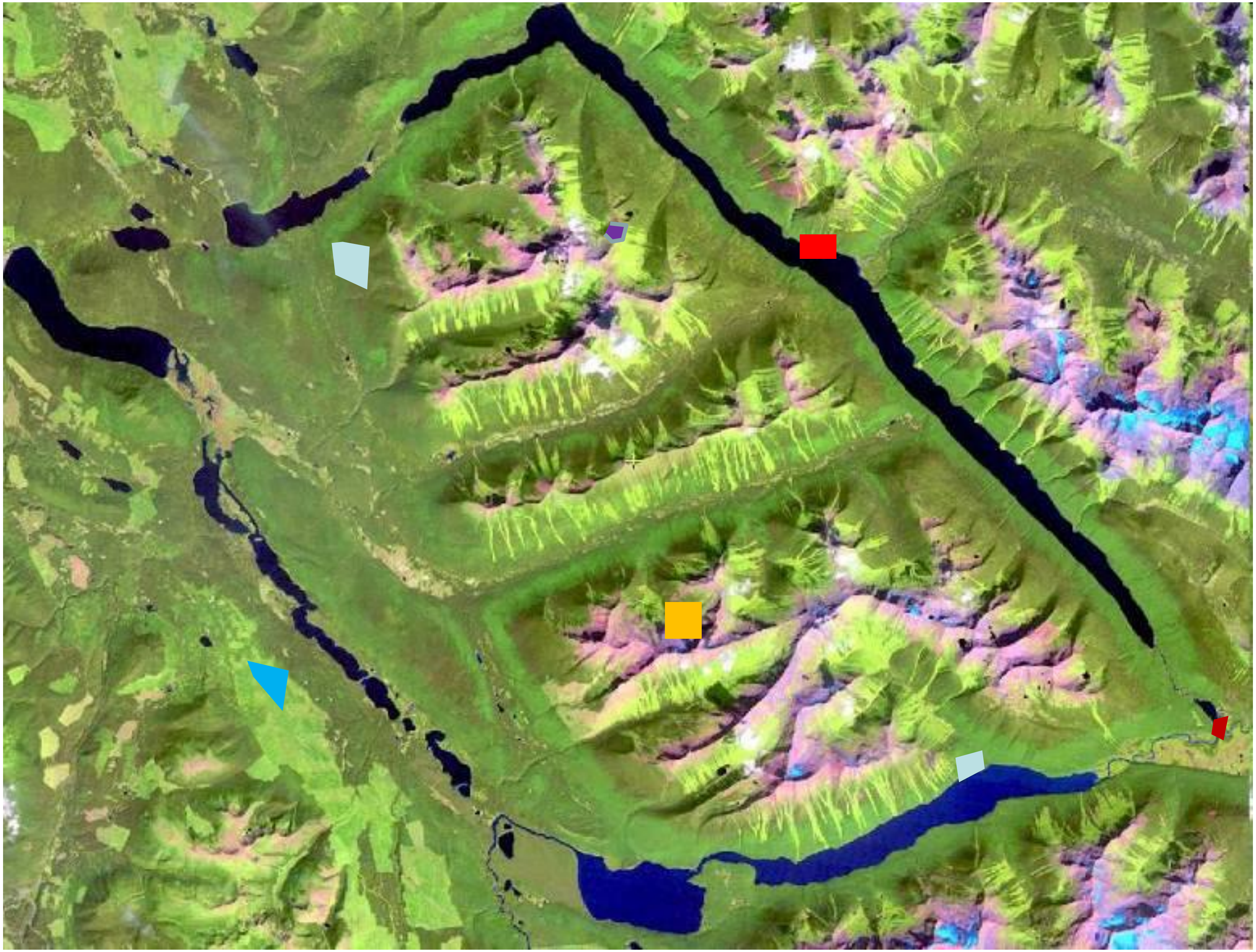
User has ' a priori' info: can identify homogenous known areas

Software groups the pixels according to these ‘training areas’

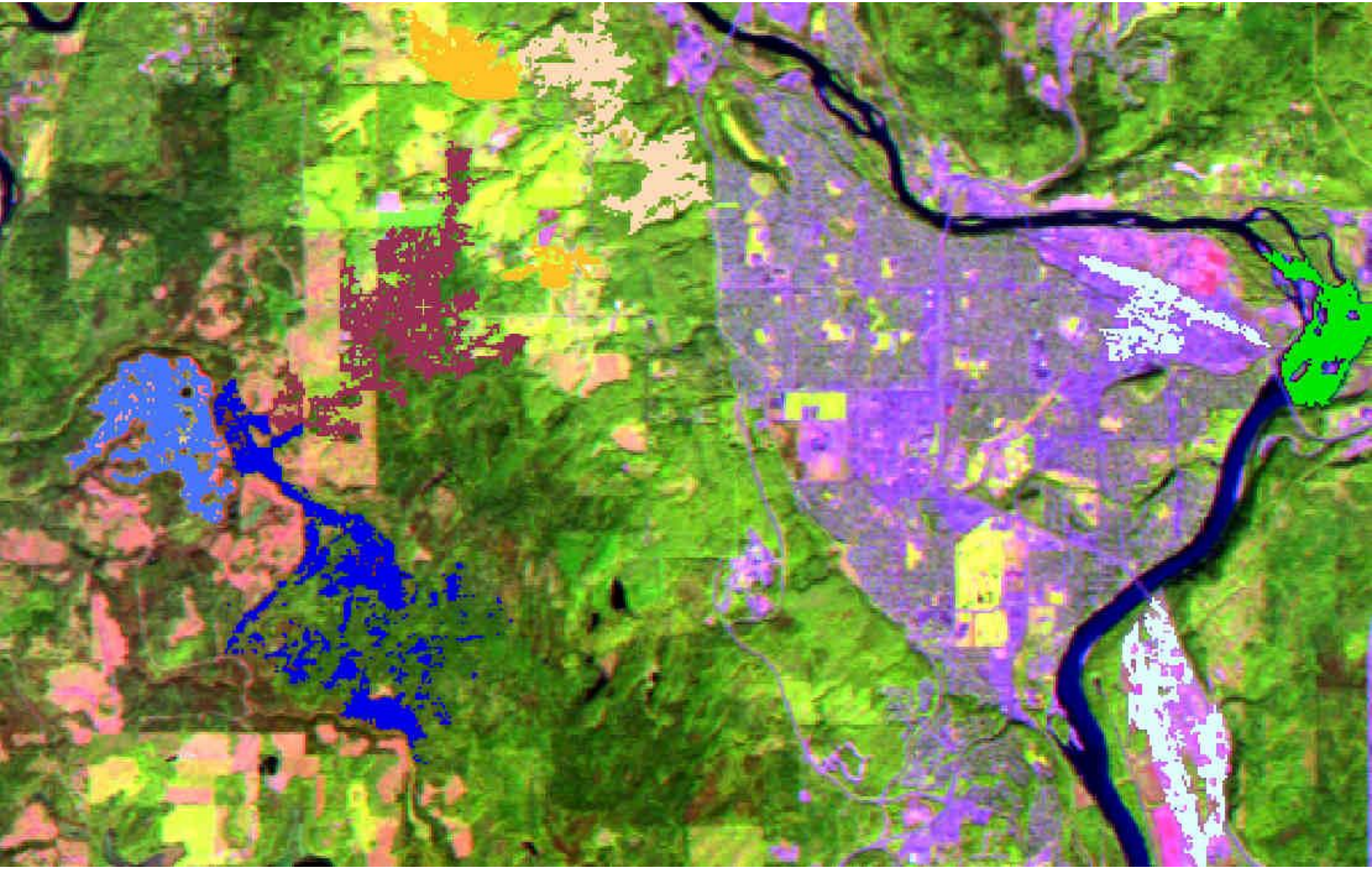
Steps

- determine input bands / channels
- identify ‘training areas’ for each class
- Check the statistics for separability
- run classifier: minimum distance / maximum likelihood
- Calculate accuracy

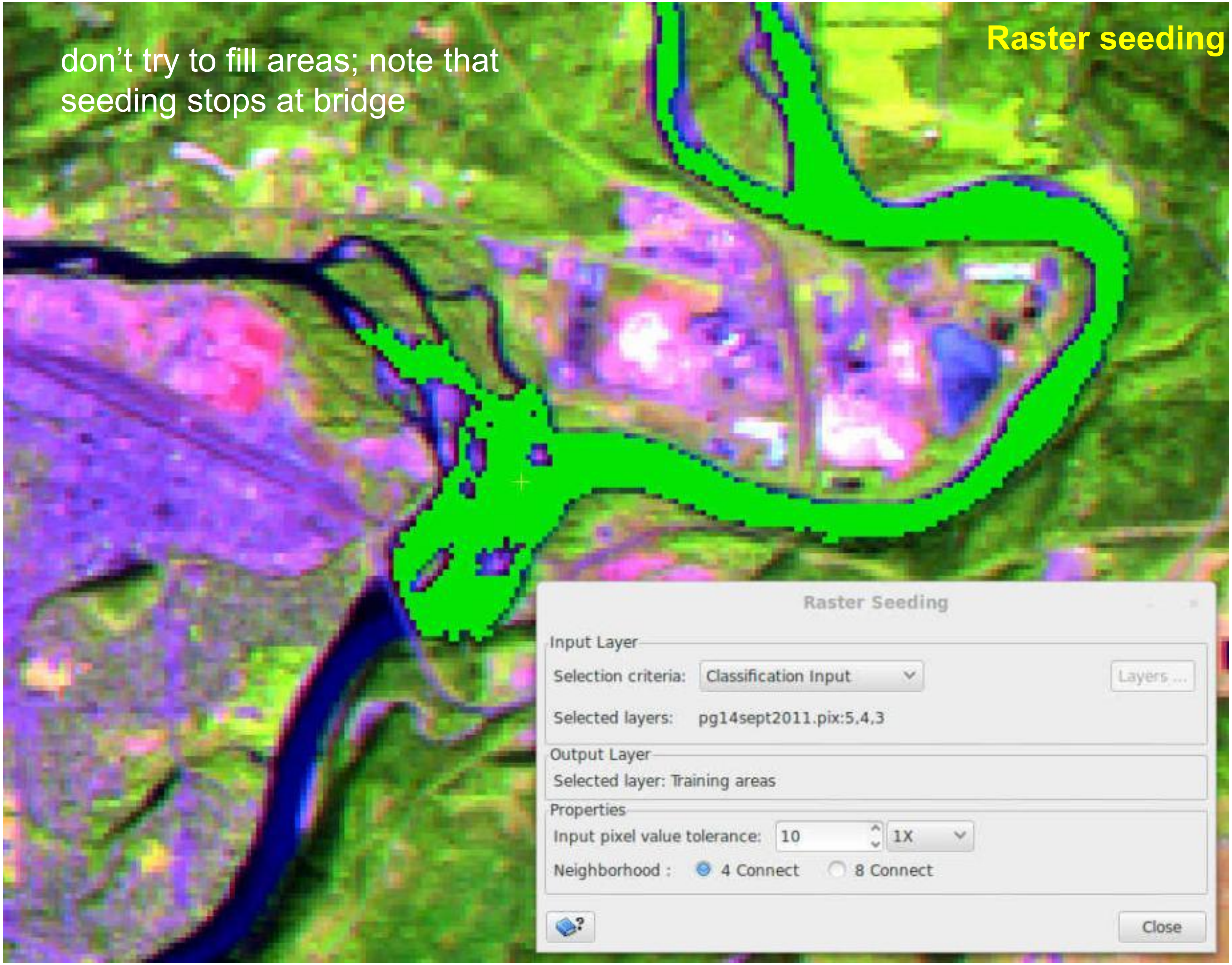
Creating training areas – digitizing polygons (in lieu of ground data)
Capture the range of DNs for a feature e.g. for water or for bare rock



Raster seeding – algorithm fills similar pixels from seeds, don't try to fill areas

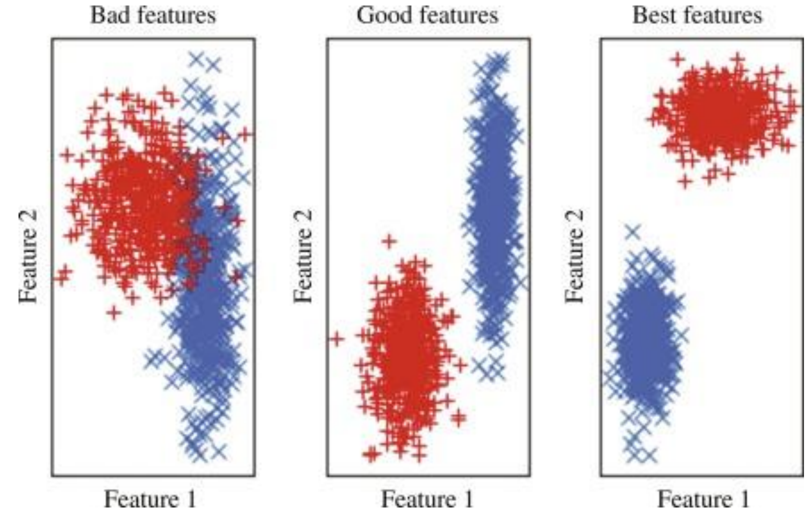


Size of seeded areas depends on 'tolerance' set – very different for 8 vs 16 bit data


Raster seeding
don't try to fill areas; note that seeding stops at bridge
Raster Seeding
Input Layer
Selection criteria: Classification Input
Layers ...
Selected layers: pg14sept2011.pix:5,4,3
Output Layer
Selected layer: Training areas
Properties
Input pixel value tolerance: 10 1X
Neighborhood : 4 Connect 8 Connect
Close

Supervised classification: separability

Create ground training sites per class
Create class signatures and
check for differences (separability)



Average DN by band and class

BAND:	1	2	3	4	5	6 (TH)	7	No. of Pixels
Class								
1. Seawater	57.4	16.0	12.0	5.6	3.4	112.0	1.5	2433
2. Sediments1	62.2	19.6	13.5	5.6	3.5	112.2	1.6	681
3. Sediments2	69.8	25.3	18.8	6.3	3.5	112.2	1.5	405
4. Bay Sediment	59.6	20.2	16.9	6.0	3.4	111.9	1.6	598
5. Marsh	61.6	22.8	27.2	42.0	37.3	117.9	14.9	861
6. Waves Surf	189.5	88.0	100.9	56.3	22.3	111.9	6.4	1001
7. Sand	90.6	41.8	54.2	43.9	86.3	121.3	52.8	812
8. Urban1	77.9	32.3	39.3	37.5	53.9	123.5	29.6	747
9. Urban2	68.0	27.0	32.7	36.3	52.9	125.7	27.7	2256
10. Sun Slope	75.9	31.7	40.8	43.5	107.2	126.5	51.4	5476
11. Shade Slope	51.8	15.6	13.8	15.6	14.0	109.8	5.6	976
12. Scrublands	66.0	24.8	29.0	27.5	58.4	114.3	29.4	1085
13. Grass	67.9	27.6	32.0	49.9	89.2	117.4	39.3	590
14. Fields	59.9	22.7	22.6	54.5	46.6	115.8	18.3	259
15. Trees	55.8	19.6	20.2	35.7	42.0	108.8	16.6	2048
16. Cleared	73.7	30.5	39.2	37.1	88.4	127.9	45.2	309

http://www.fas.org/irp/imint/docs/rst/Sect1/Sect1_17.html

Transformed Divergence - Battacharaya Distance measure

$0.0 < x < 1.0$ (poor separability)

$1.0 < x < 1.9$ (moderate separability)

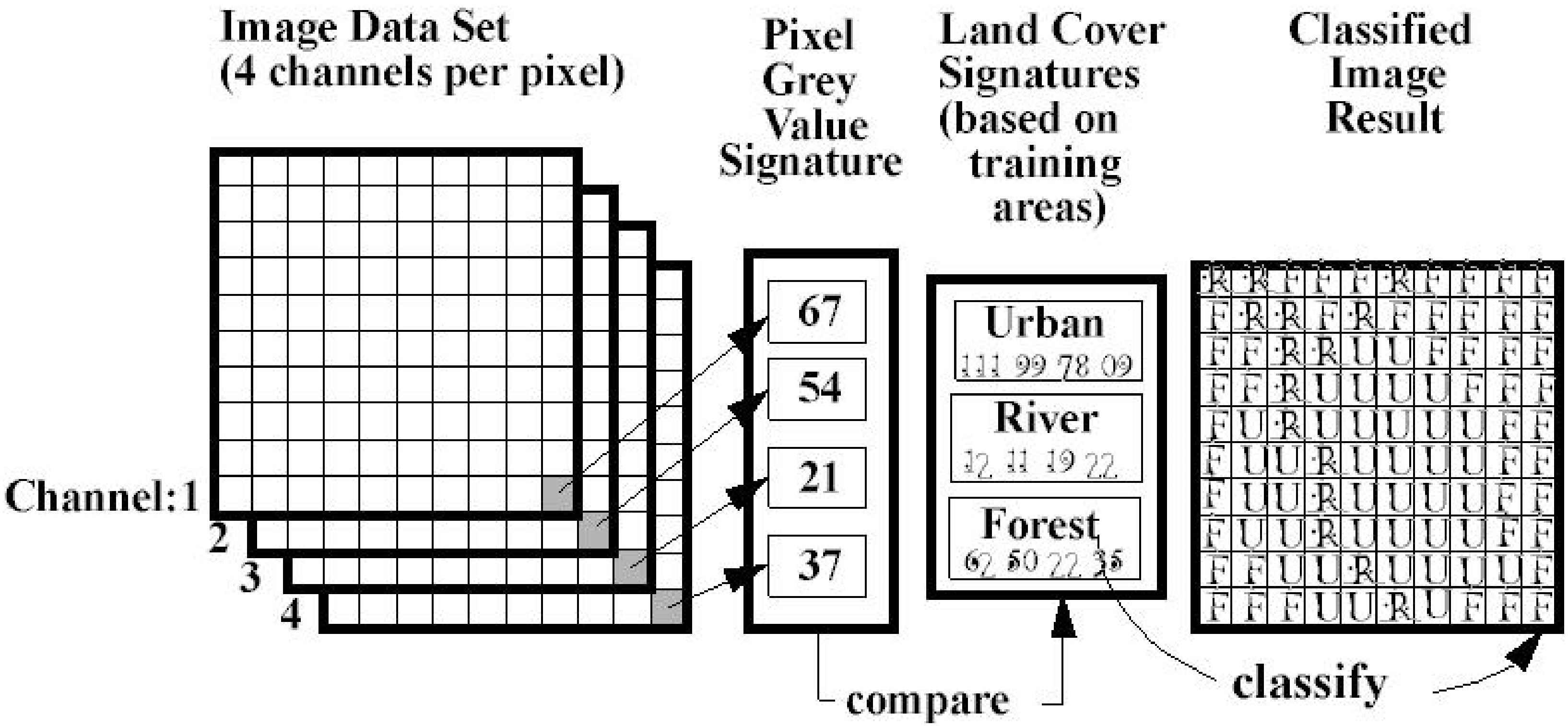
$1.9 < x < 2.0$ (good separability)

Poor separability ($0.0 < x$ 1.0) indicates that the two signatures are statistically close to each other. You have two options:

One signature can be discarded (suggested when the separability is closer to 0), or the two signatures can be merged using **Merge** option (suggested when the separability is closer to 1).

OK ? … ready to run the classifier

Supervised – class assignment



Per pixel classifiers

Supervised classification methods: a. Minimum distance

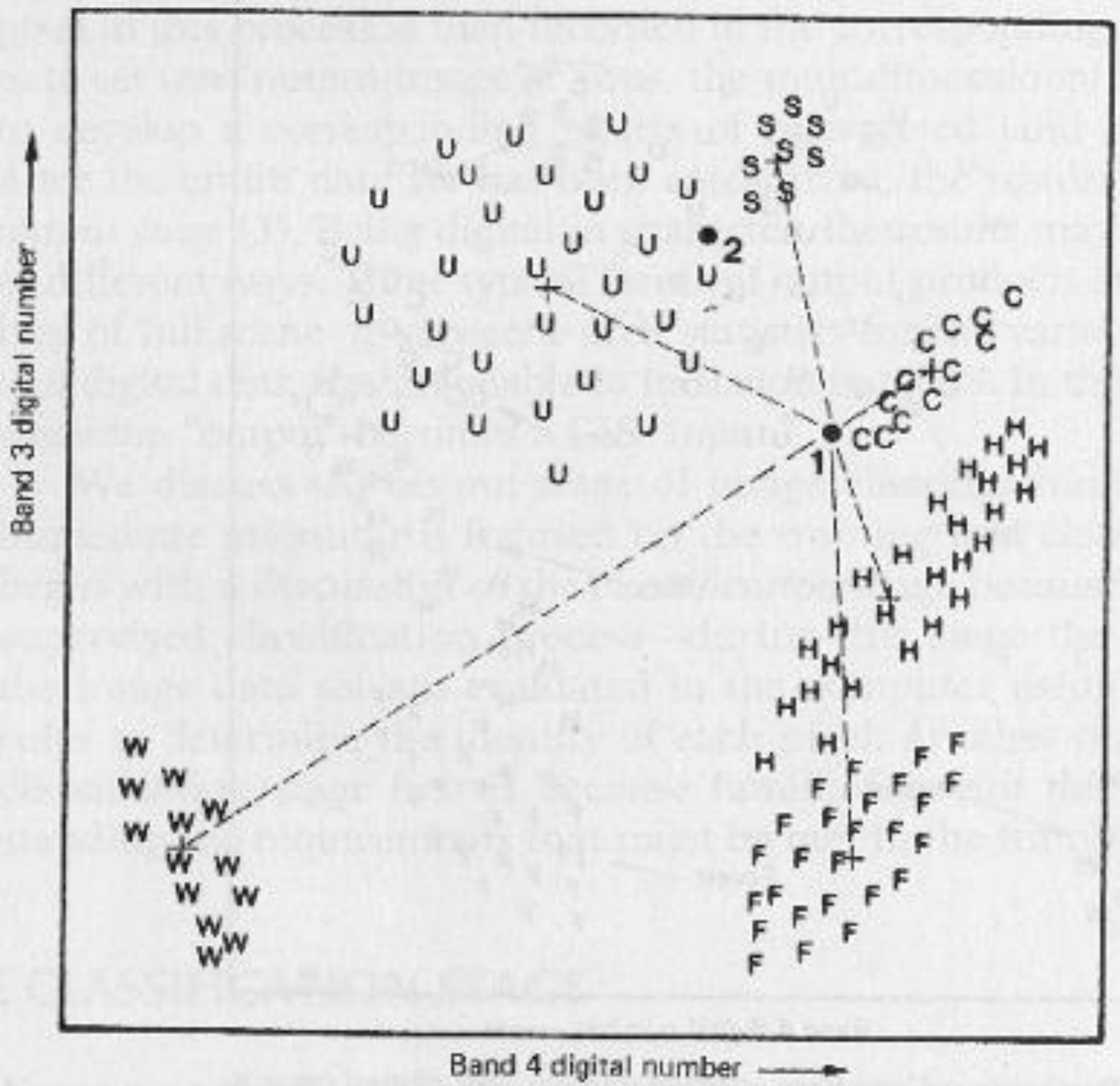


Figure 7.40 Minimum distance to means classification strategy.

This graphic is 2D

Letters indicate a training pixel

Think in n-dimensions:

The screen can only display 3 bands but a classifier can input many more

Supervised classification methods: b: Parallelepiped ??

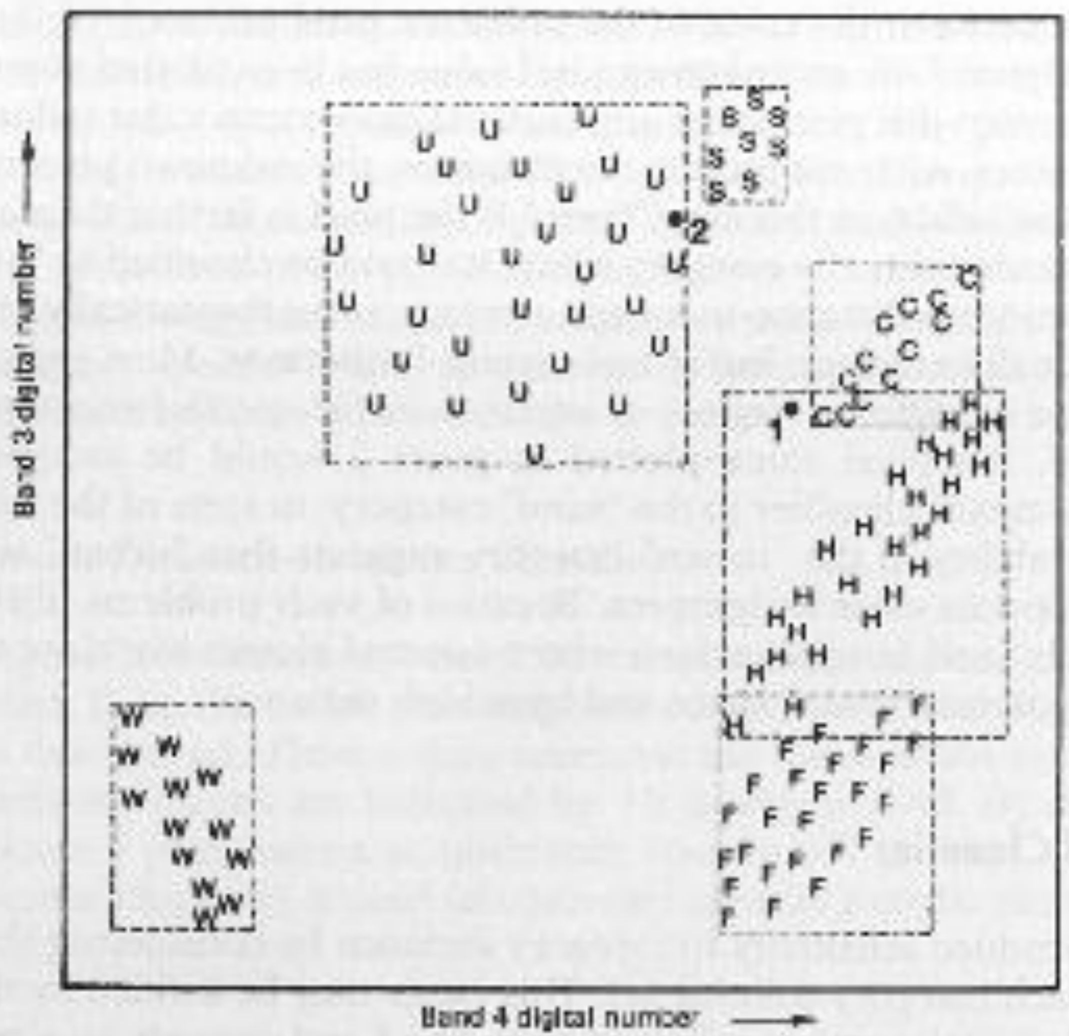
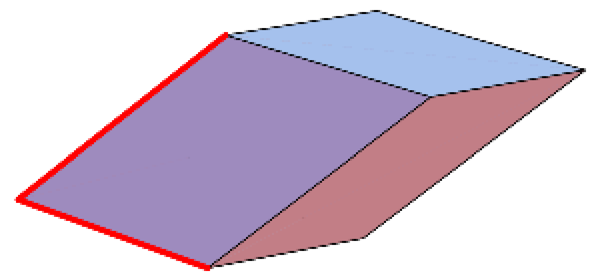


Figure 7.41 Parallelepiped classification strategy.

3D parallepiped



Less used due to overlap of training areas – conflict of assigning pixels to classes

Supervised classification methods c: Maximum likelihood

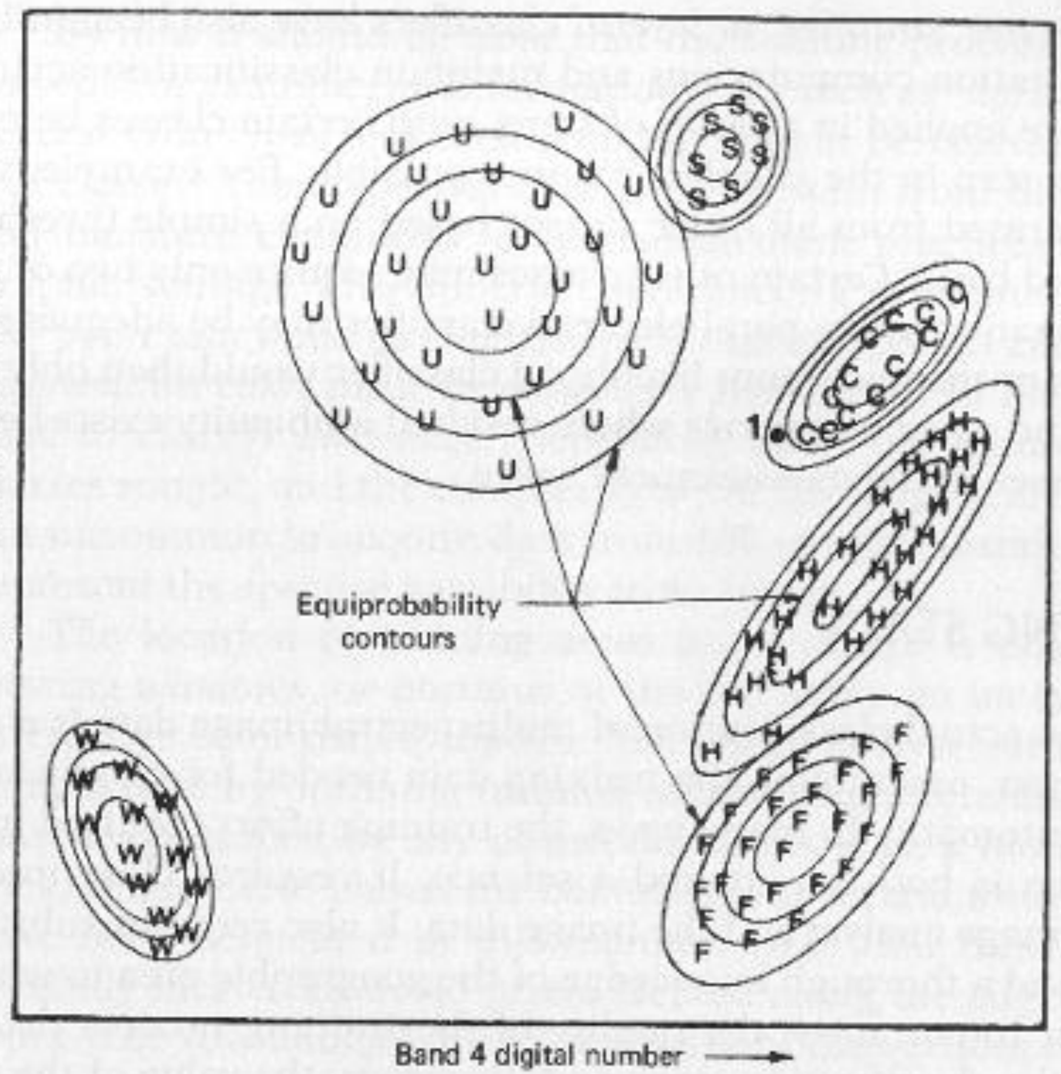


Figure 7.44 Equiprobability contours defined by a maximum likelihood classifier.

With or without null class

Supervised classification: how it works

Minimum distance: each pixel is assigned to the class whose mean is closest to data point (in n-dimensions)

Parallelepiped: Each pixel is assigned to the class whose range it falls in (overlap = double assignment)

Maximum Likelihood: each pixel is assigned to the class for which it has the highest probability, with or without 'null class'

Note: PCI catalyst will easily preview all options prior to running them

Merging and adding classes

Merging

a. if classes overlap spatially or b. are not distinguishable spectrally.

Splitting / adding: one class covers too much area

[Unsupervised: - run again with more clusters]

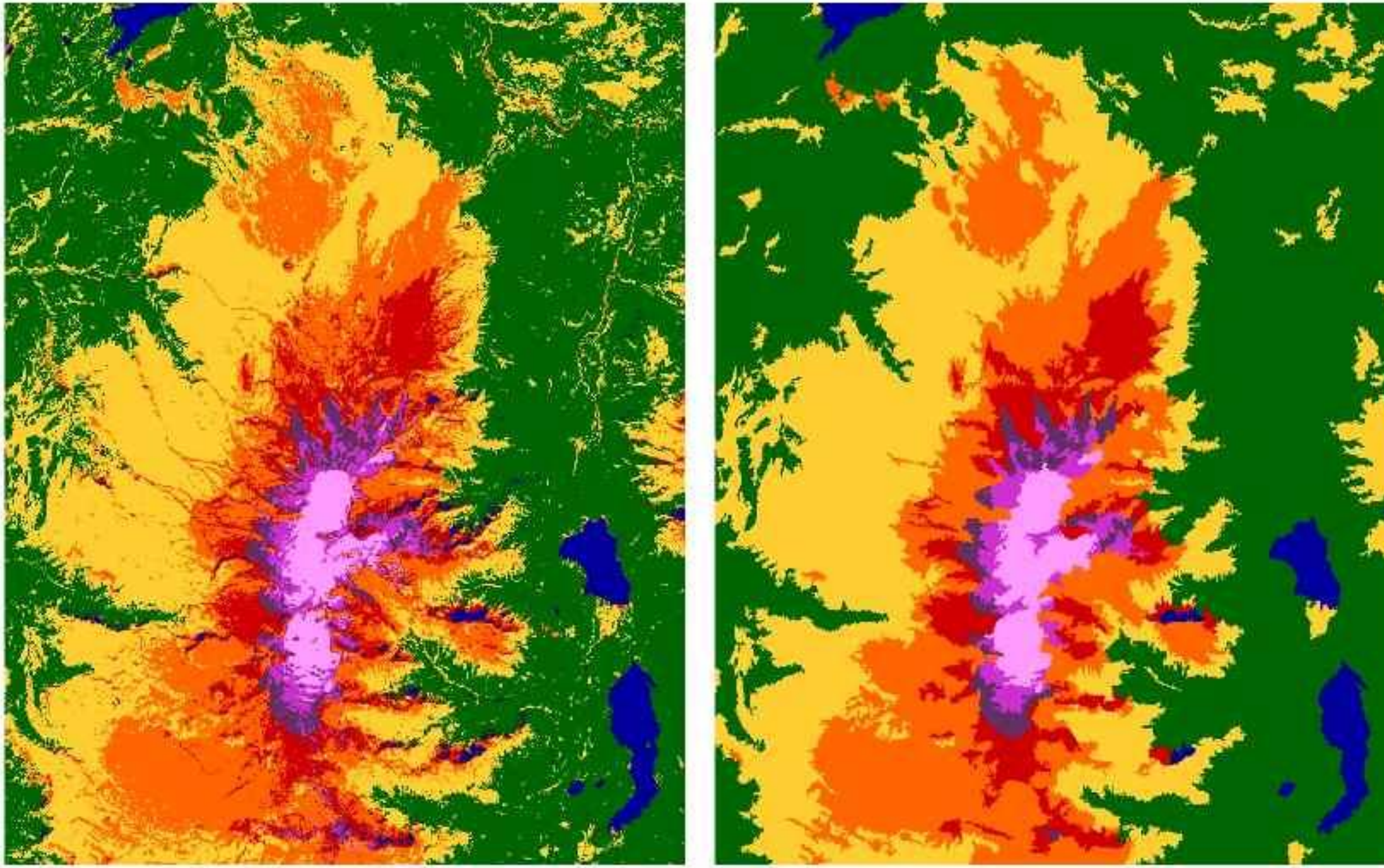
Supervised:– create new training class or delete some training areas

Areas are unclassed – create new training class

Post-classification steps

- **Check the display**
- **Merge / add classes**
- **Sieve / filter … to remove isolated pixels**
- **Accuracy assessment**
- Conversion of results to vectors – see lab 5

Mt. Edziza – classification and **sieve – removing isolated pixels**



- recognises connectivity of adjacent pixels in the same class
- special classes e.g. lakes or wetlands can be specified and preserved

Accuracy assessment

This requires knowing what is reality at some pixels (ground truthing), and how they were classified: more common with supervised classes. This generates a **'confusion matrix'**

		Reference test information					
	Class	Road	Building	Green	Bare	Row total	User's Accuracy
Remote sensing classification	Road	101	0	25	20	146	69.18%
	Building	0	128	0	17	145	88.28%
	Green	10	0	104	1	115	90.43%
	Bare	2	4	2	105	113	92.92%
	Column total	113	132	131	143	519	
	Producer's accuracy	89.38%	96.97%	79.39%	73.43%		

User's accuracy: based on classified pixels

Producer's accuracy: based on ground truth pixels

Overall accuracy = 84.4%, Kappa coefficient: 0.825. Kappa: a composite accuracy index:

- 0.7 = good; < 0.2 = no agreement

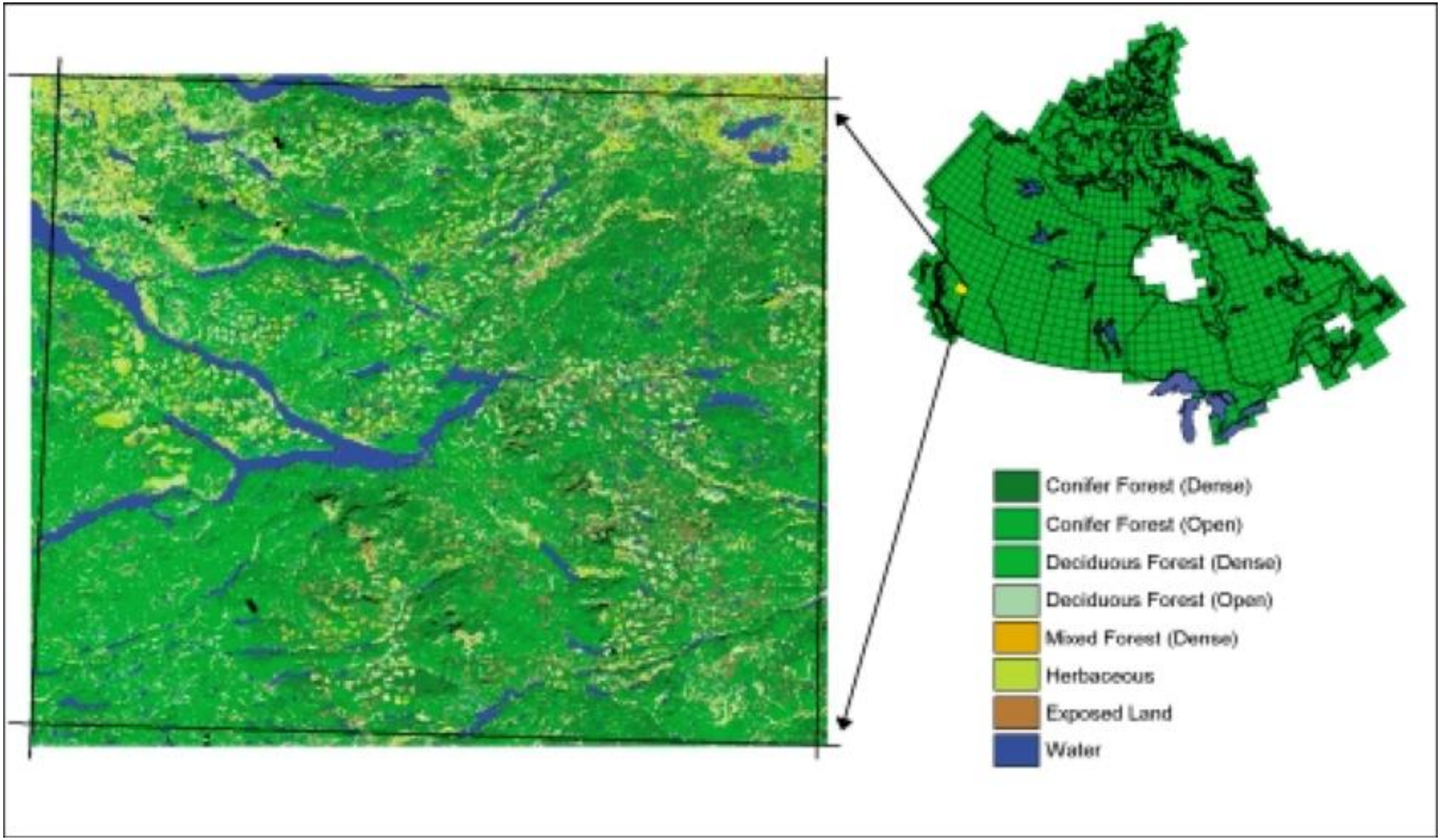
The diagonal represents pixels correctly classified
An off diagonal column element = an 'error of omission'
An off diagonal row element = 'error of commission'

http://www.gisdevelopment.net/application/nrm/overview/mma09_Mustapha.htm

EOSD Earth Observation for Sustainable Development of Forests

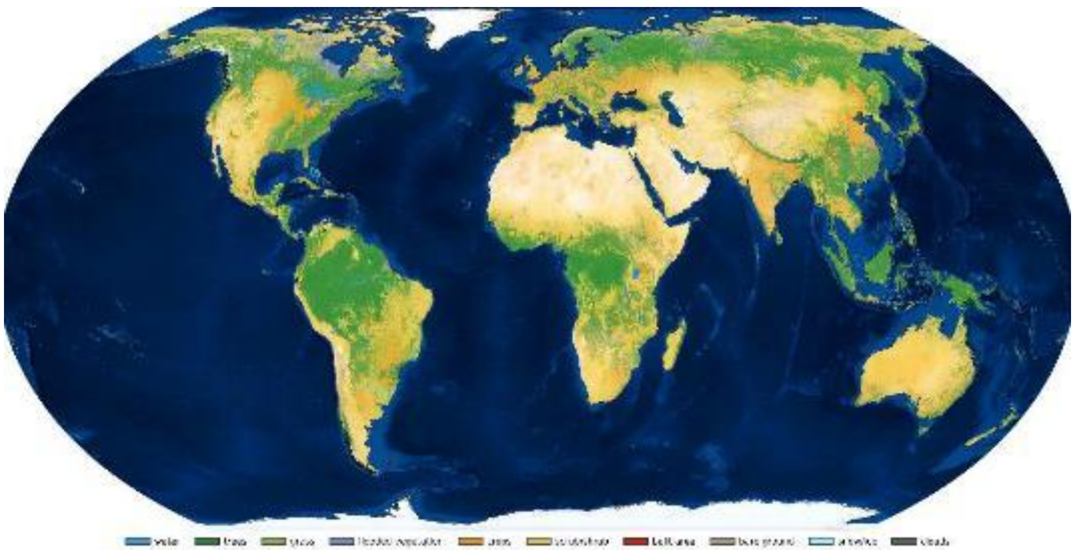
80% Canada mapped from Landsat 7 ~2000

- using supervised classification, 480 Landsat scenes, 630 1:250,000 map sheets



Global ESA Sentinel LULC classification 2017 -> 2025

https://www.arcgis.com/home/item.html?id=cfcb7609de5f478eb7666240902d4d3d
Global Viewer



Classification review

Unsupervised classification:
clustering into classes
identification of classes by user

Supervised classification:
training areas to 'train' the classification,
check the statistics of the classes created
check resulting coverage for errors and accuracy

Unsupervised	Supervised
Unknown classes beforehand	Pre-defined classes
Clusters may not match desired classes	Defined classes may not match natural classes
Desired clusters may be unidentifiable	Selected training areas may be inadequate
a posteriori' cluster identification time-consuming	'a priori' training is time consuming
Unexpected categories may be revealed	Only predefined classes will be found
Immediate execution, quick	Takes longer, but better directed

Classification summary

There are many articles on classification approaches:

- Input channel combinations (see the next lectures)

- Best algorithms - unsupervised and supervised

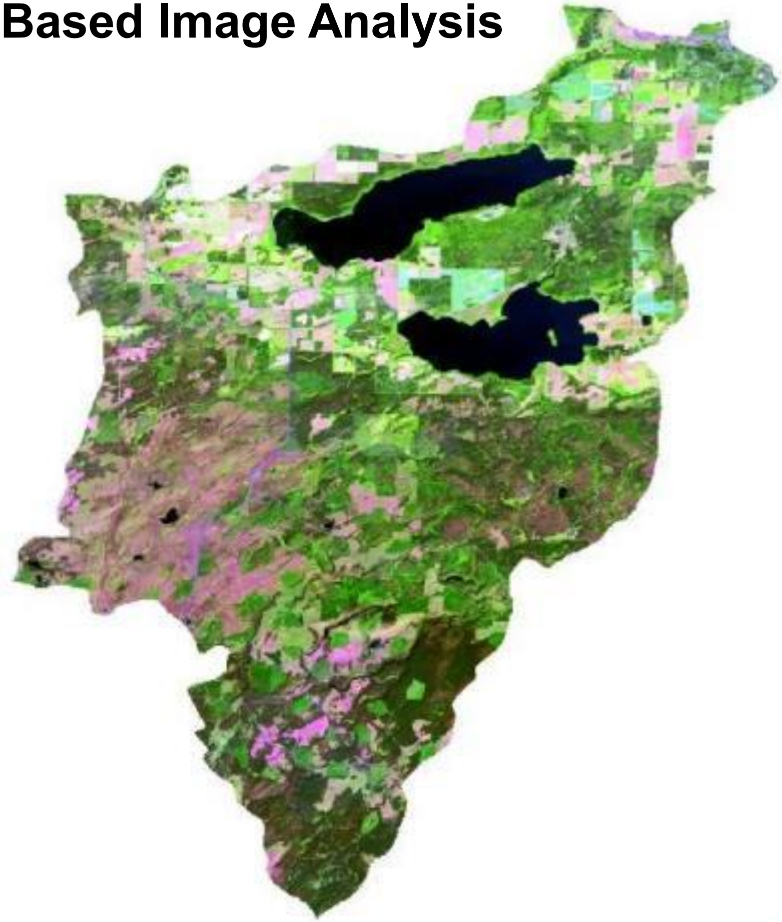
- New approaches e.g. include texture, shape etc.

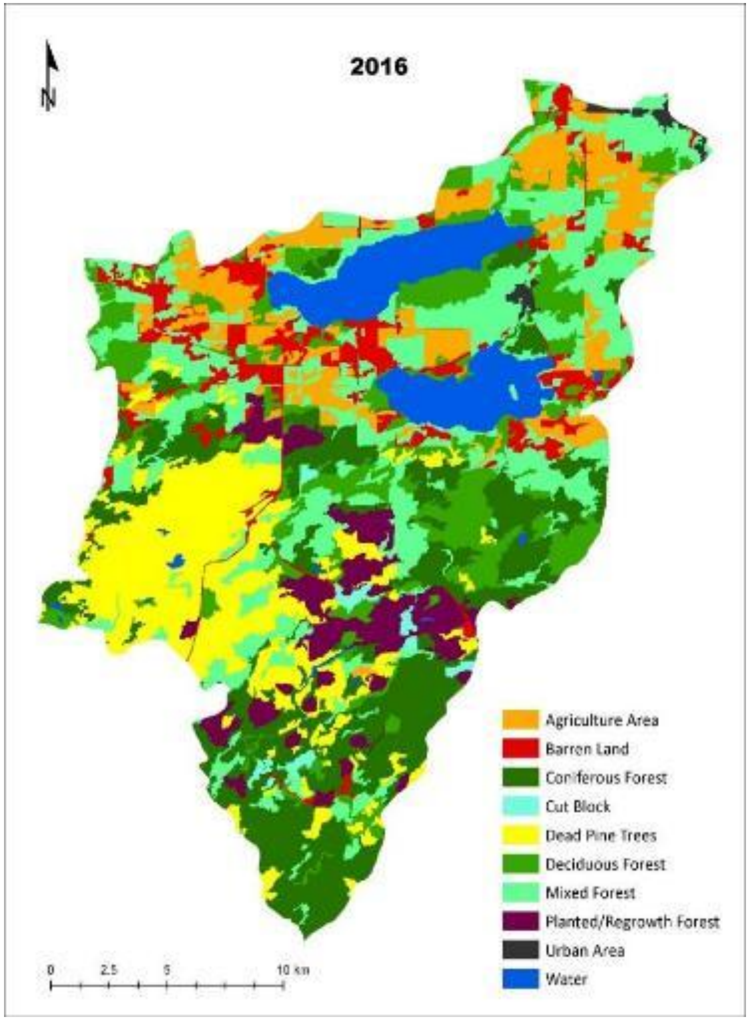
- Object based image analysis (not just pixel based)

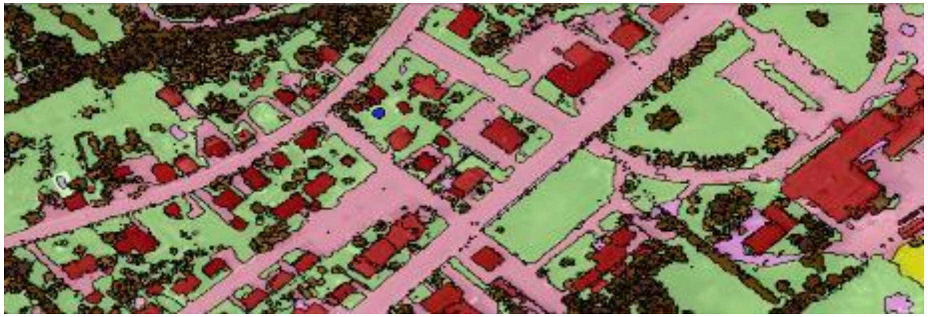
This started with eDefiniens software 2000, later adopted by PCI (2017), Esri, QGIS

‘biggest development in remote sensing software in this millennium’

Object Based Image Analysis

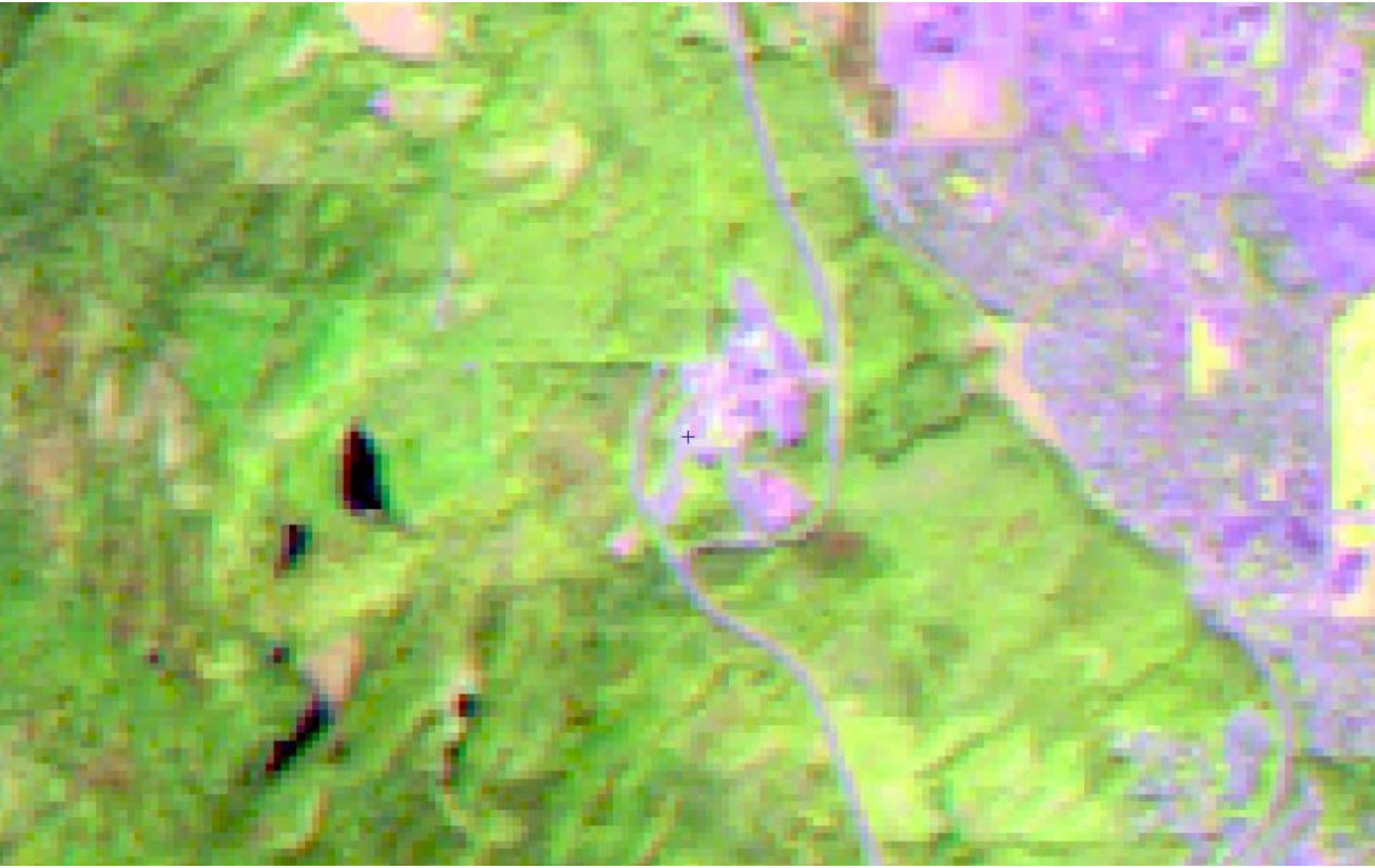






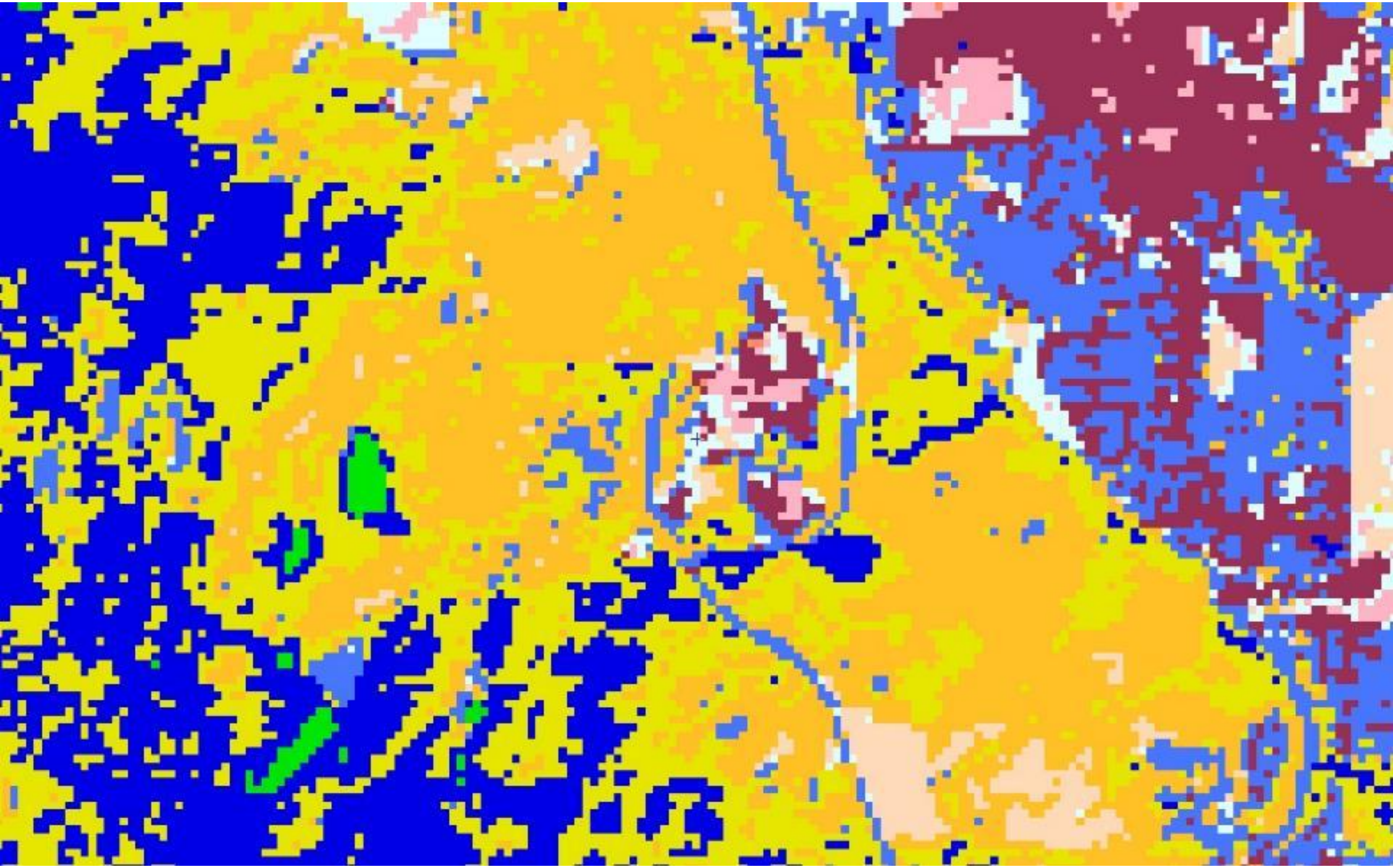
More complex than per-pixel classifiers; used in GEOG457/657 and by some graduate students – identifies objects or shapes first

PG 2013 - campus, Univ.Way / Tyner Blvd and Forests for the World / Shane Lake



See next slide showing limitation of ‘per pixel classifiers’ versus ‘OBIA’

Limitations of per-pixel classifiers e.g. road ‘staircase’ – may be addressed as an object



Note the ring of coniferous forest around Shane Lake .. could use machine learning rules