Unsupervised Classification

Classification = simplification, mapping

The early promise of satellite imagery: (1970s-80s)

A. Rapid map updating

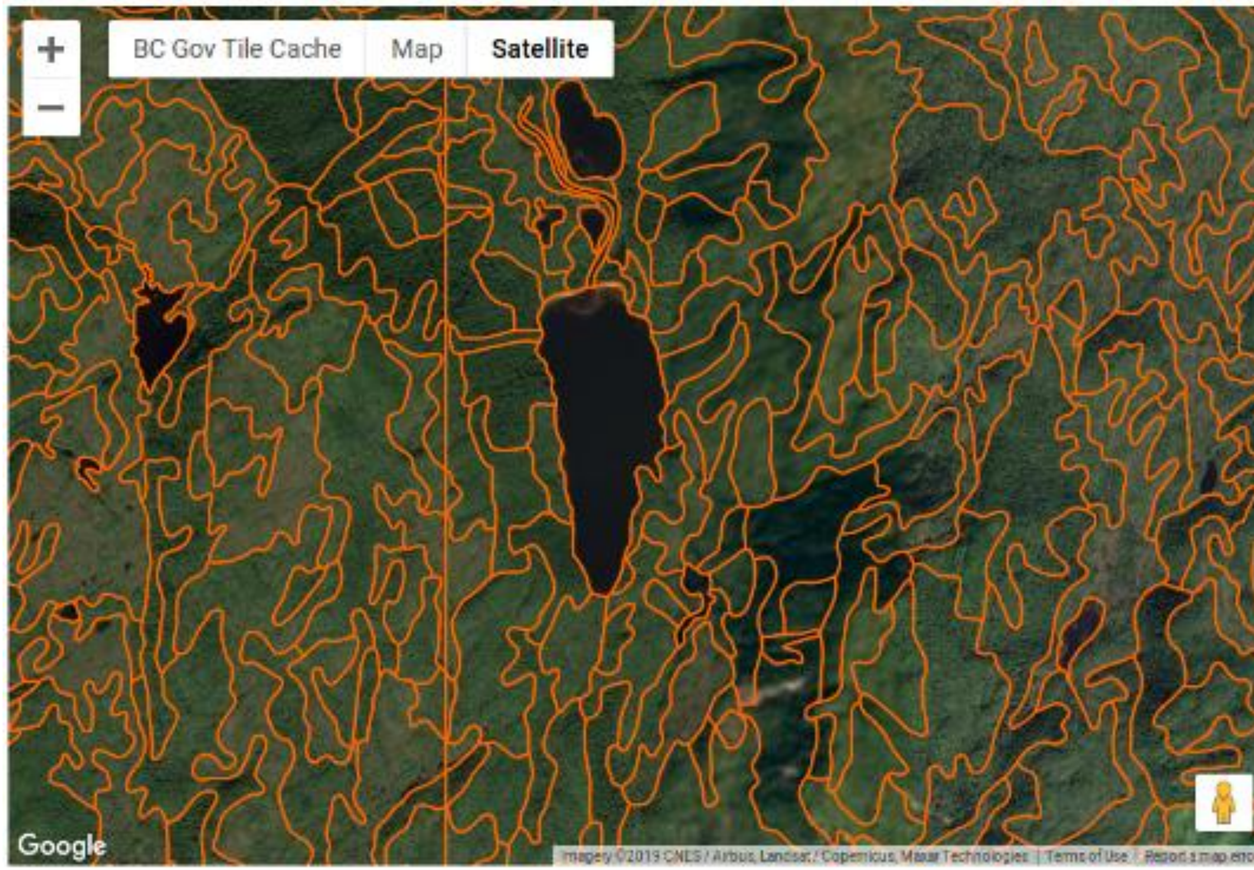
B. Automated mapping of ‘Land Cover’

- avoid manual digitizing … by use of <u>multispectral</u> band data

Manual digitizing (yawn …)

e.g. BC VRI (vegetation resource inventory)

BC TRIM data layers 7027 x 1:20,000 tiles



NTS 1:50,000 example

All federal NTS map Sheets (13,370) created from Air photos

Human interpretation / classification relies on attributes such as:
Shape, pattern, texture, shadows, size, association, **tone**, **colour**

Algorithms mostly use Digital Number (DN) =~digital version of tone/colour

Remote Sensing Classification

- Automated grouping of similar pixels using <u>multispectral</u> DNs
- Software developed following 1972 (Landsat 1)
- Digital alternative to manual mapping of Land Cover

Classified layer in the Virginia Urban Tree Canopy Mapper - http://www.utcmapper.frec.vt.edu

Land Use v Land Cover (LULC) e.g. parks

Sugarbowl-Grizzly Den

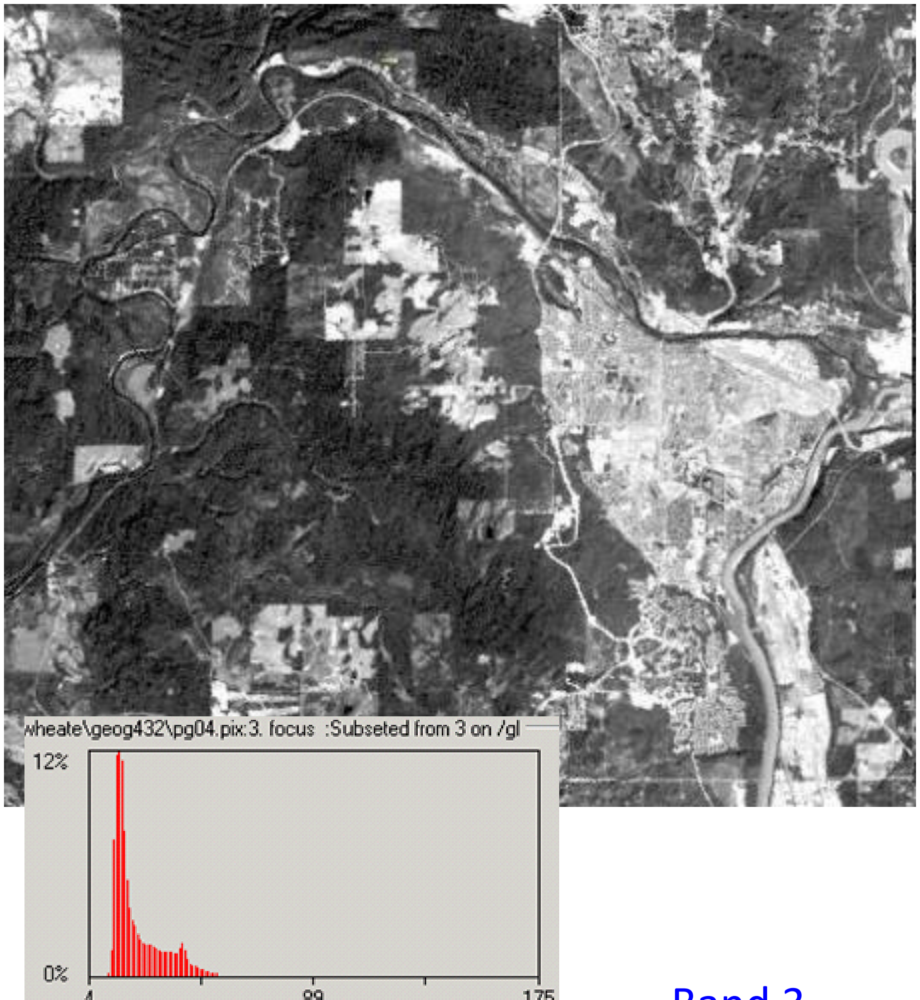
Bowron Lakes

Mt. Egmont / Taranaki, NZ

Can we use just one band to classify ?

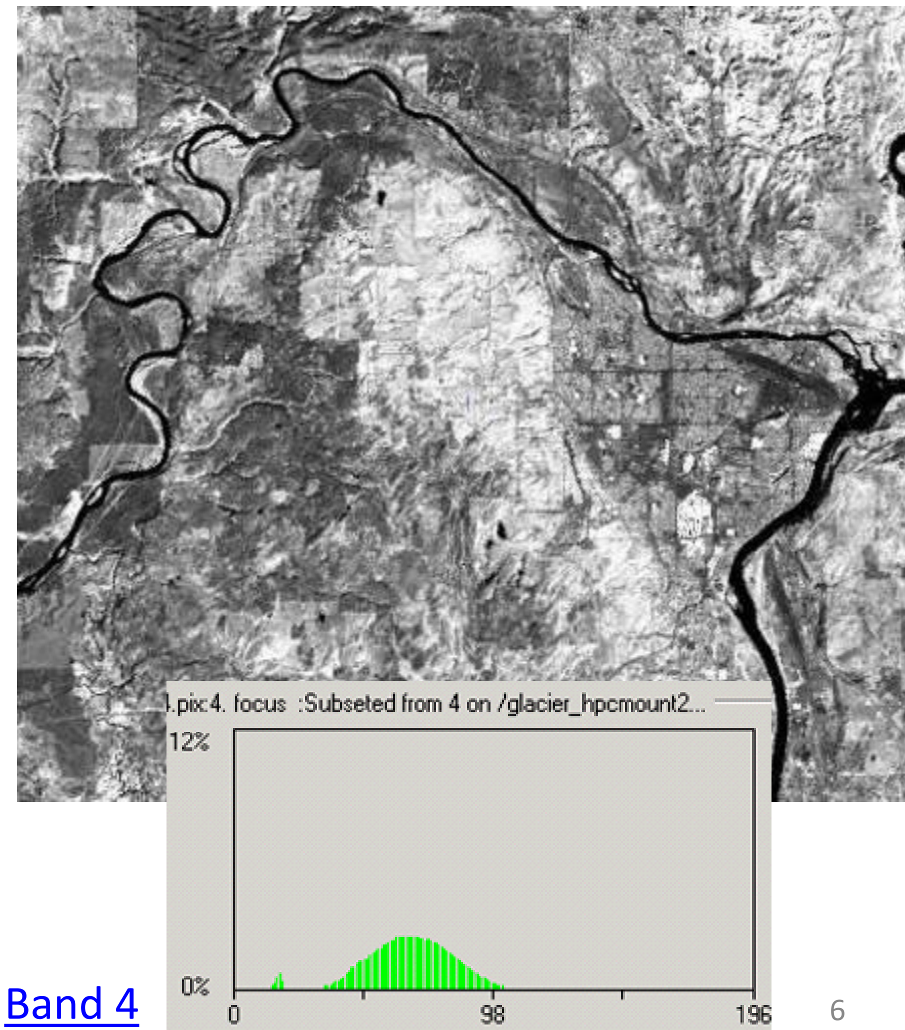
One image band could only be treated as a monochrome air photo (interpretation)

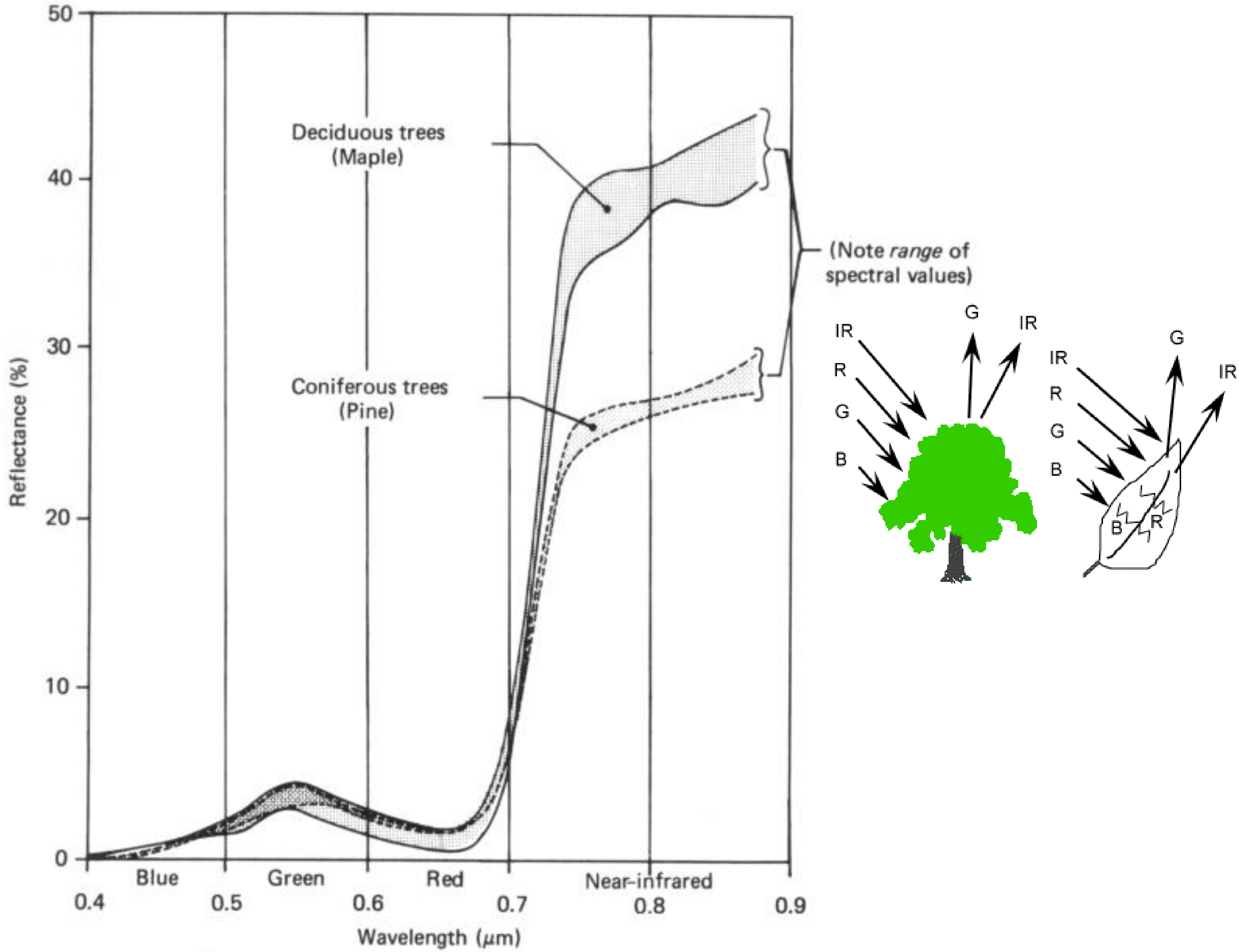
Digital Numbers from one band alone are rarely enough – features are not unique



Band 3

Band 4




50
40
30
20
10
0
Reflectance (%)
Deciduous trees
(Maple)
Coniferous trees
(Pine)
(Note *range* of
spectral values)
Blue
Green
Red
Near-infrared
0.4
0.5
0.6
0.7
0.8
0.9
Wavelength (μm)
IR
R
G
B
G
IR
IR
R
G
B
G
IR
B
R

Band / channel selection
TM: 1-7; OLI/TIRS 1-11
Thematic Mapper Operational Land Imager

Bands 1, 2, 3

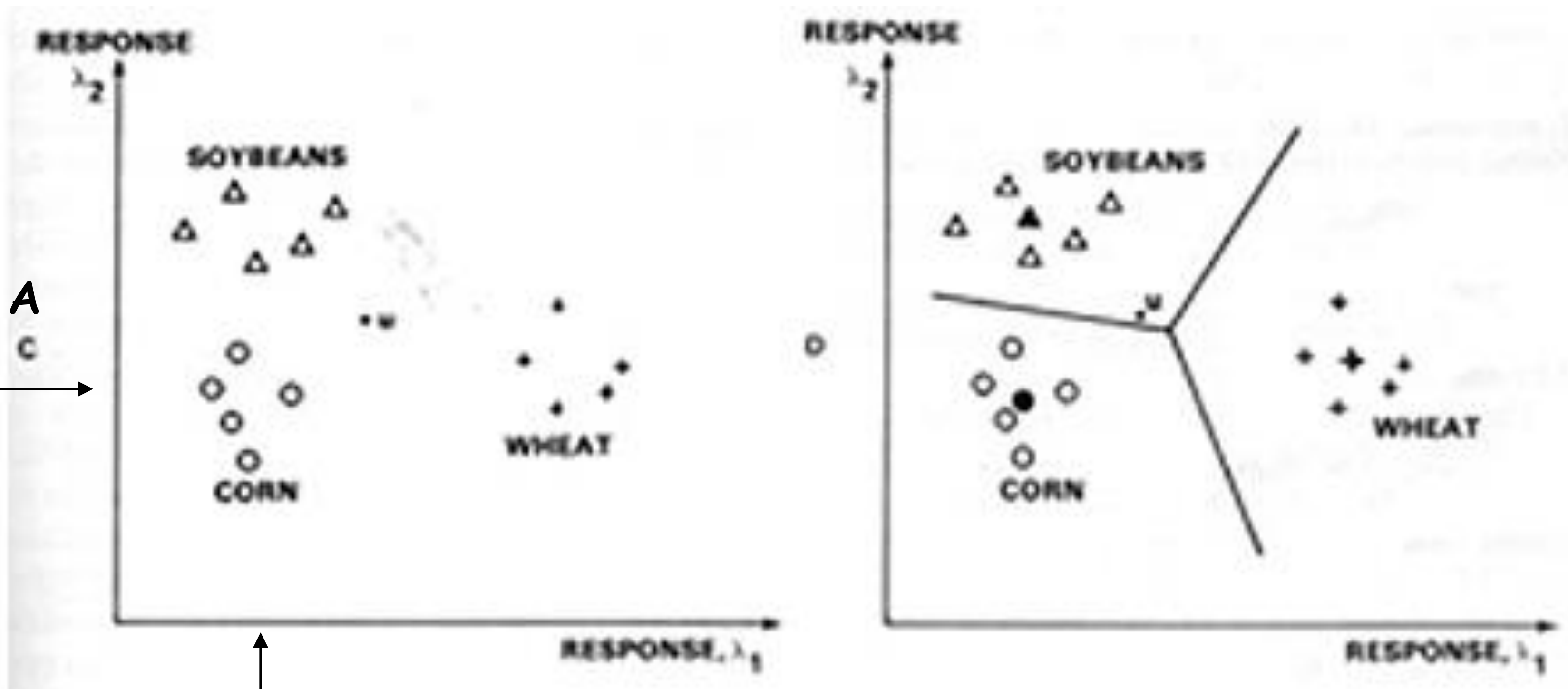
Band 5, 4, 3

Landsat TM has 7 bands: You would NOT select 3 visible bands to classify

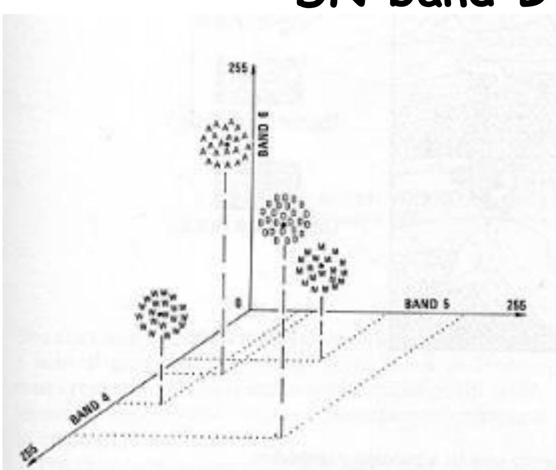
The visible bands are similar – and thus the composite is low in contrast

The role of multispectral sensing in classification

DN
Band A



DN band B



DNs in Band A are similar for Corn and Wheat
DNs in Band B are similar for Corn and Soybeans

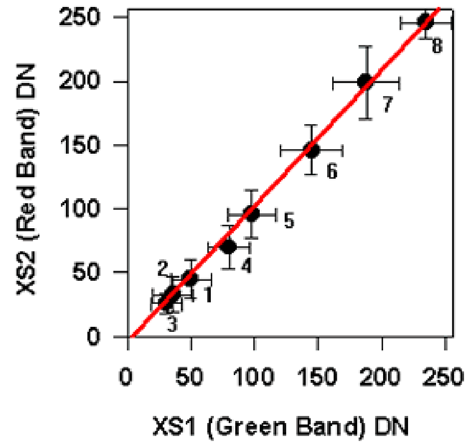
… but if we use both Bands A and B, then all 3 differ

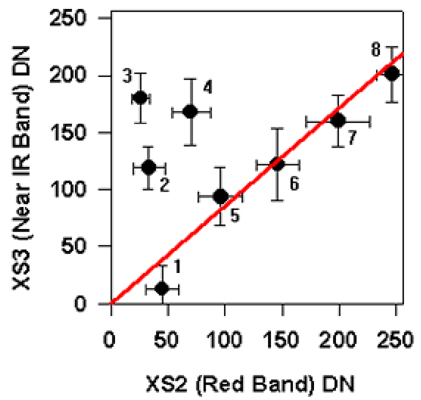
… Algorithms are ‘**per pixel**’ classifiers

band correlation coefficients and scatterplots

Example: PG Landsat data (r values between bands)

	TM1	2	3	4	5	6
TM1						
TM2	.97					
TM3	.96	.96				
TM4	.07	.16	.11			
TM5	.66	.72	.76	.46		
TM6	.77	.77	.81	.14	.80	
TM7	.83	.86	.90	.25	.93	.86





The Visible bands are highly correlated (similar) .. (r = .96 to .97)

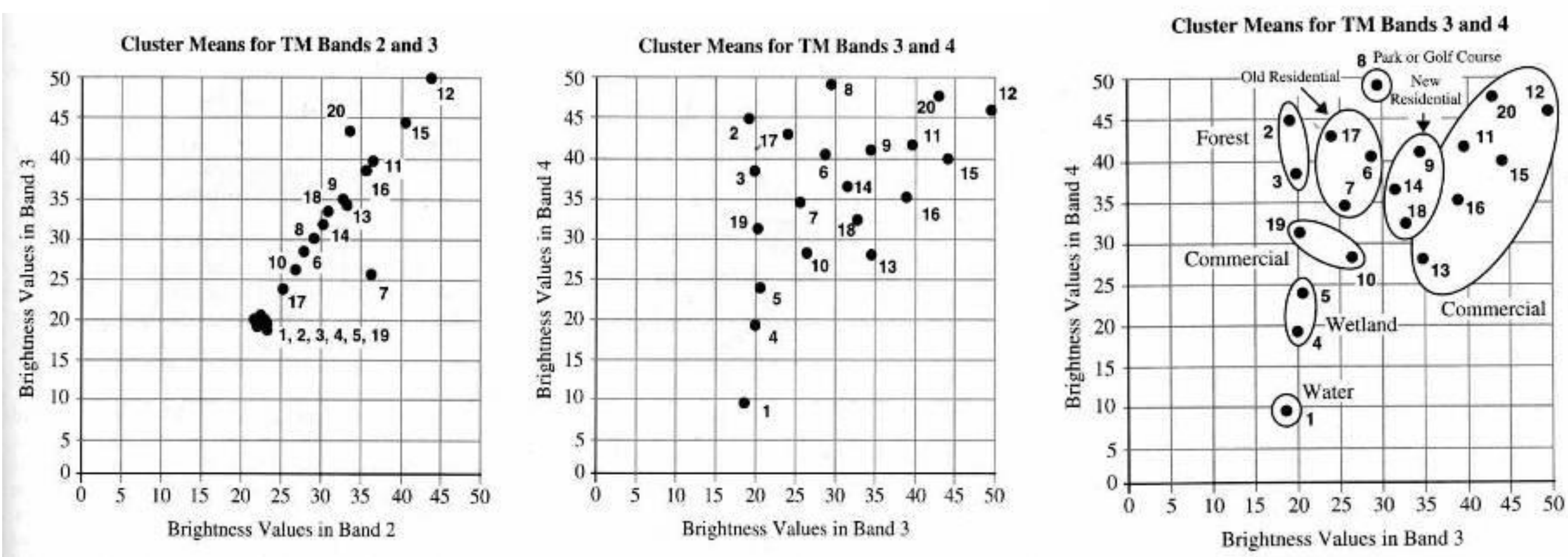
.. so also are bands 5 and 7 (r = .93)

band 4 (near-IR) is not very correlated with Visible or MIR (nor thermal)

Note: these values will vary for different environments e.g. urban, desert, forested

Unsupervised classification = 'clustering'

Example of Visible bands only (2,3) versus Visible and Near-IR



Two bands are shown for simplicity

Input bands selected – minimum 3 or 4 bands;

Note: you can only display 3 bands, but you can input many more

Classification: Band / Channel Selection

How to choose which ones to use:

1. Low correlation e.g. TM 3-4-5 or 2-4-7 (Visible-NIR-MIR)

2. Past experience, visual examination, logical thinking

3. Channels that separate the features we want to identify
(based on DNs / spectral curves / histograms)

4. Or simply just use them all ? … (except the thermal band)
- This can confuse the classifier and not find clusters

Unsupervised classification

Characteristics

-user initially needs little 'a priori' knowledge of area

-The software clusters pixels by natural DN groupings (based on similarity and contrast – 'natural breaks')

Steps

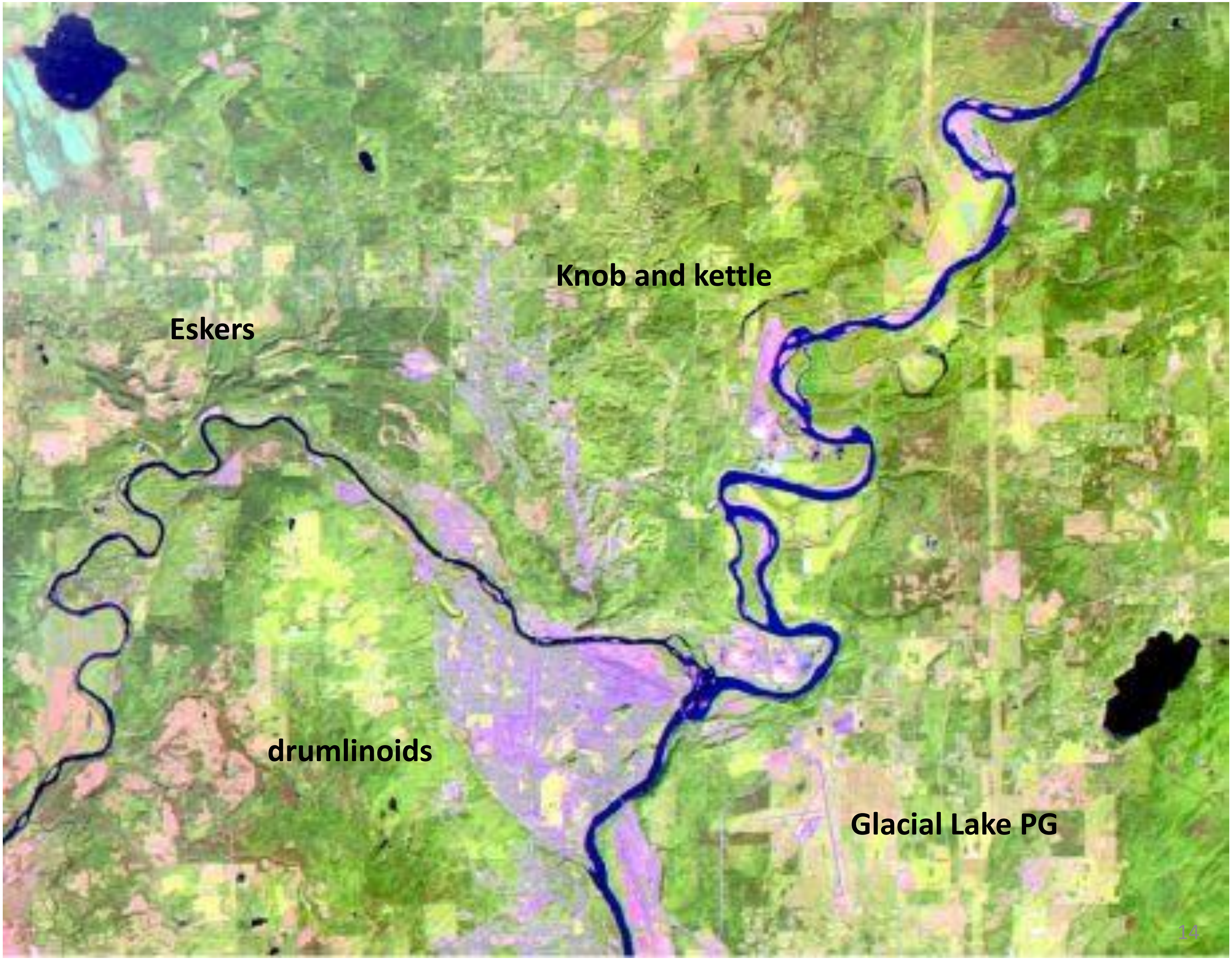
- determine how many classes / clusters

- determine which input bands / channels to use

- run classifier : K-means or Isodata

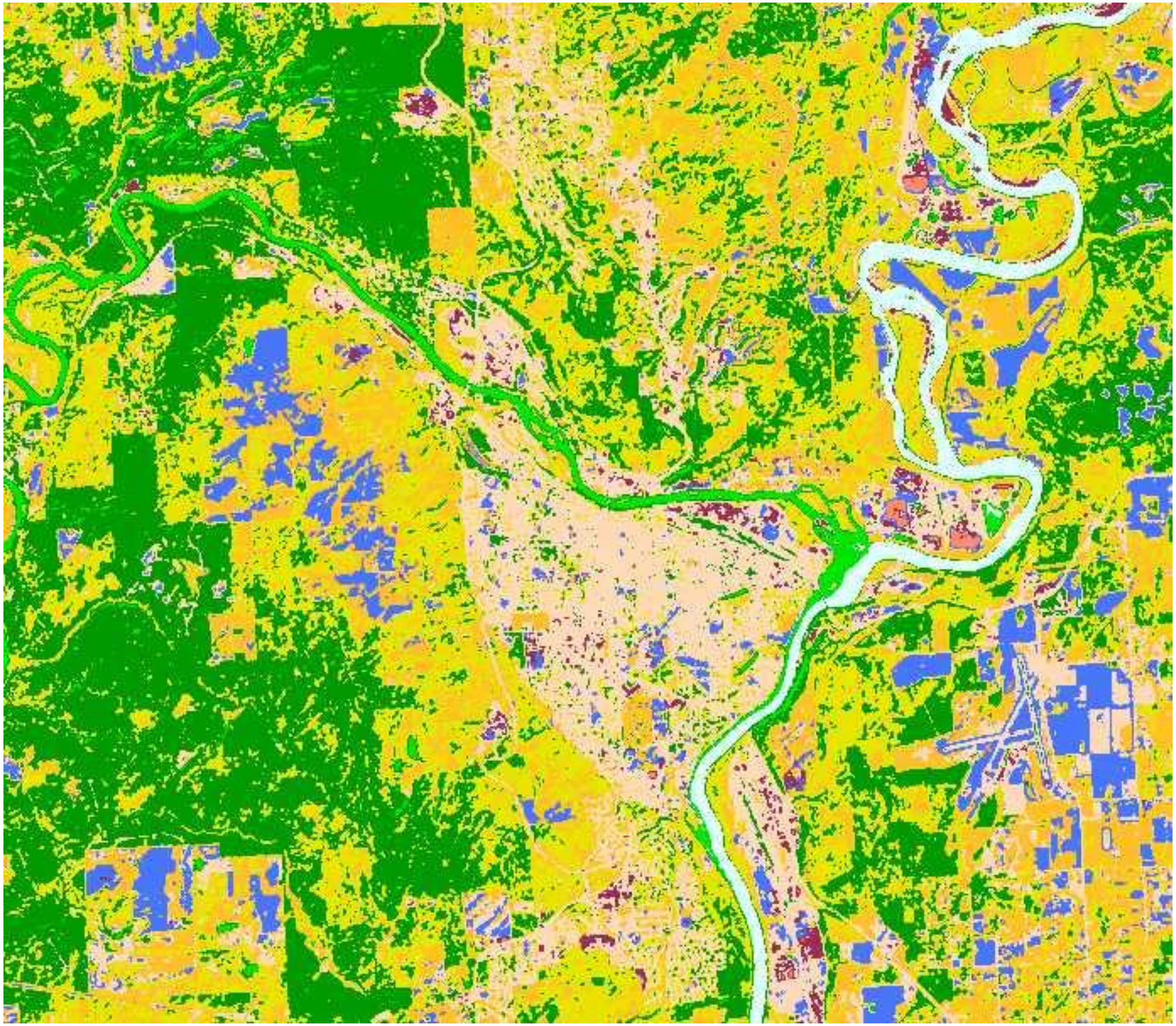
- Rerun with more clusters if needed

- assign names to classes (merge classes if needed)



Knob and kettle
Eskers
drumlinoids
Glacial Lake PG

Unsupervised result – 10 classes (clusters)



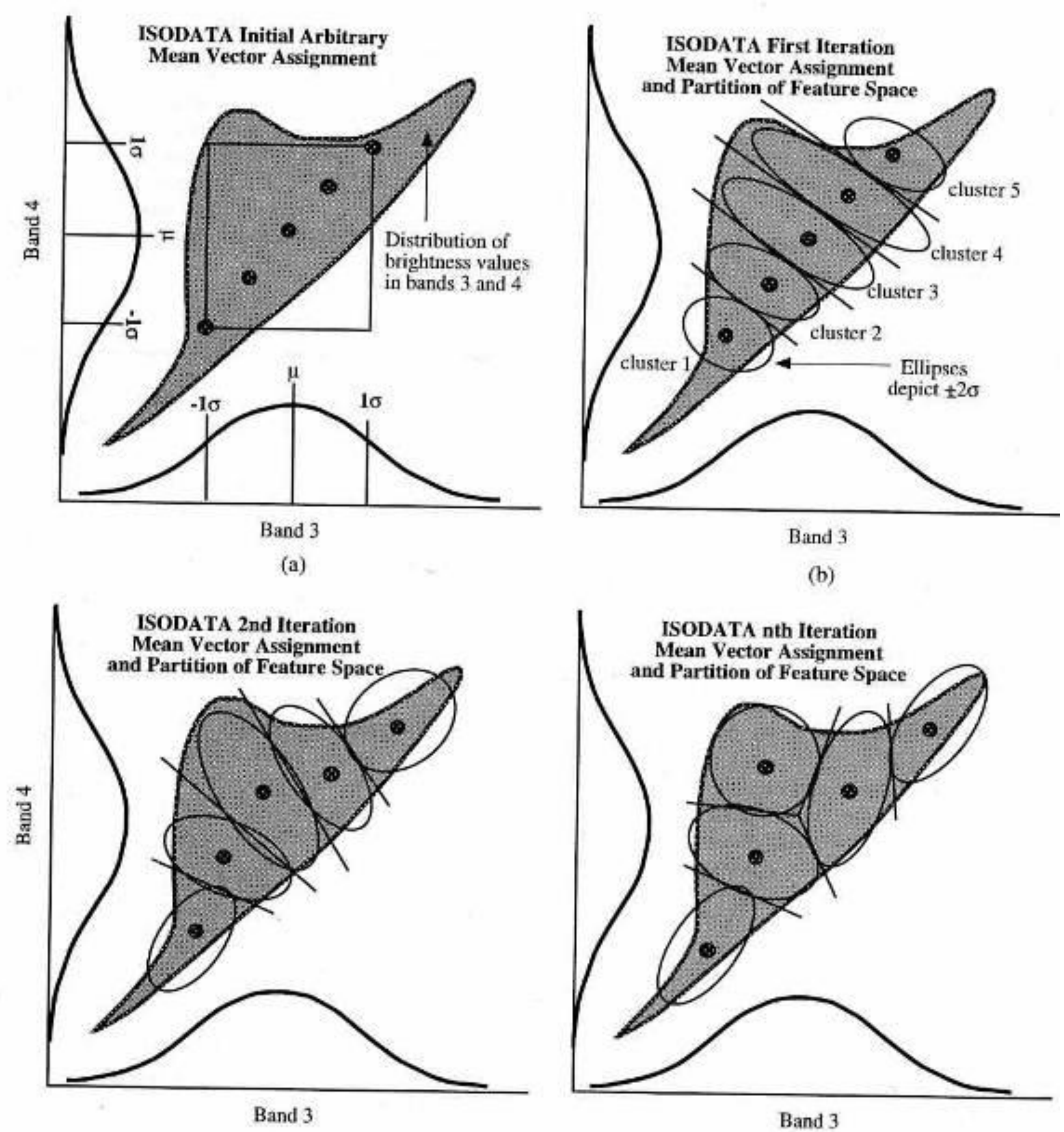
This is a new <u>channel</u> in your .pix file
- It's not a band

Colours are random

Note: urban classification is NOT often easy!

Unsupervised – how it works …. YIKES! (do we need to know this?)

- ❑ Algorithm starts with statistical seed points
- ❑ Assigns each pixel to the closest seed
- ❑ Calculates group mean …. in 'n-dimensional' space
- ❑ Re-assigns pixels to the closest group mean
- ❑ Re-calculates group mean
- ❑ Iterates (10 ?) until relatively little change and fixes groupings



unsupervised classification –algorithms and iterations

1. **K-means** minimises within cluster range of DNs

2. **Fuzzy K-means** enables mixed membership, based on distribution of the cluster

3. **Isodata** can also merge or split clusters, so the number of clusters is more flexible

classification report

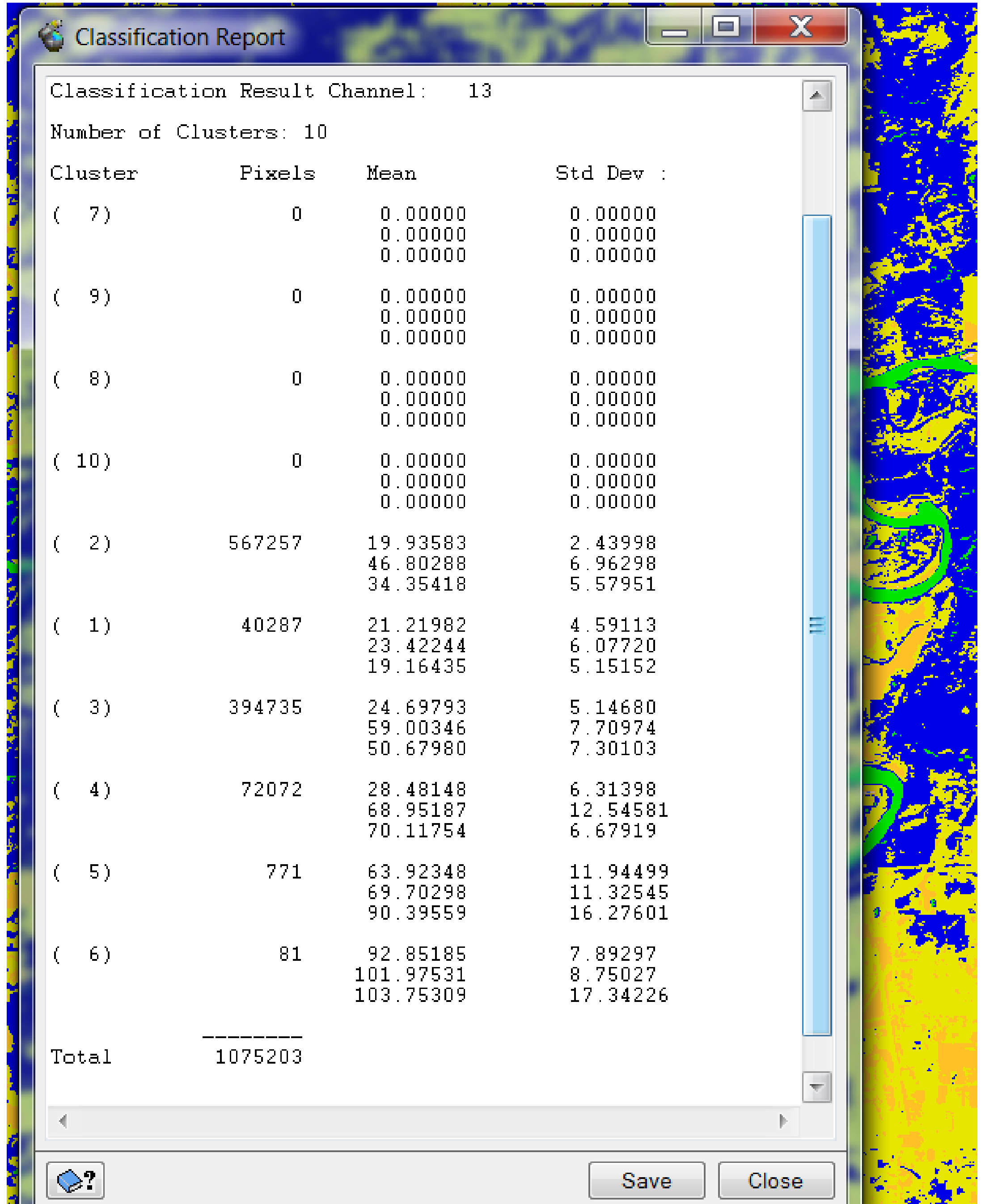
1 iteration

Note:

clusters with 0 pixels

DN values for bands 3,4,5 averages

Final step ..
Assigning names to clusters
(and merge some)



Classification Result Channel: 13

Number of Clusters: 10

Cluster	Pixels	Mean	Std Dev :
(7)	0	0.00000	0.00000
		0.00000	0.00000
		0.00000	0.00000
(9)	0	0.00000	0.00000
		0.00000	0.00000
		0.00000	0.00000
(8)	0	0.00000	0.00000
		0.00000	0.00000
		0.00000	0.00000
(10)	0	0.00000	0.00000
		0.00000	0.00000
		0.00000	0.00000
(2)	567257	19.93583	2.43998
		46.80288	6.96298
		34.35418	5.57951
(1)	40287	21.21982	4.59113
		23.42244	6.07720
		19.16435	5.15152
(3)	394735	24.69793	5.14680
		59.00346	7.70974
		50.67980	7.30103
(4)	72072	28.48148	6.31398
		68.95187	12.54581
		70.11754	6.67919
(5)	771	63.92348	11.94499
		69.70298	11.32545
		90.39559	16.27601
(6)	81	92.85185	7.89297
		101.97531	8.75027
		103.75309	17.34226

Total	1075203		

After 16 iterations and 16 classes/clusters

Classification Report

Classification Algorithm: Fuzzy K-Means Unsupervised
Classification Input Channels: 3,4,5
Classification Result Channel: 9

Number of Clusters: 16

Cluster	Pixels	Mean	Std Dev :
(2)	296774	23.24140	8.24662
		44.77742	8.91783
		32.44915	10.04080
(3)	292356	24.48324	7.14404
		67.65602	10.67916
		49.51679	9.53926
(4)	155525	24.75149	5.03961
		107.39487	18.20386
		74.22362	13.35878
(1)	135750	42.07941	13.08230
		26.82458	8.12628
		16.47926	11.00162
(5)	151100	42.87475	9.25817
		60.36603	13.13133
		89.47187	18.67191
(7)	86198	84.79987	12.60066
		59.46275	9.37685
		20.03181	14.03484
(8)	85354	122.33620	10.20878
		85.34046	8.68392
		19.40815	16.75611
(9)	79592	151.05591	9.22842
		105.45887	8.13428
		20.59924	20.61743
(10)	60789	175.72850	8.52307
		125.70449	8.00244
		25.36989	25.79001
(11)	55539	201.23238	7.64972
		142.52280	7.16980
		17.82207	16.81002
(12)	54187	225.29511	7.08180
		159.06710	6.45671
		16.18565	13.71707
(13)	56164	247.23974	6.06449
		172.45732	4.56608
		13.11189	7.50873
(14)	113965	254.84619	0.99330
		185.52277	4.41832
		12.44097	4.33174
(15)	51887	254.93781	0.76476
		202.95095	5.59141
		14.38227	7.67388
(16)	33140	254.99879	0.08035
		225.13265	8.29124
		13.28431	3.35810

Fuzzy classification – each pixel has potential membership in more than one cluster

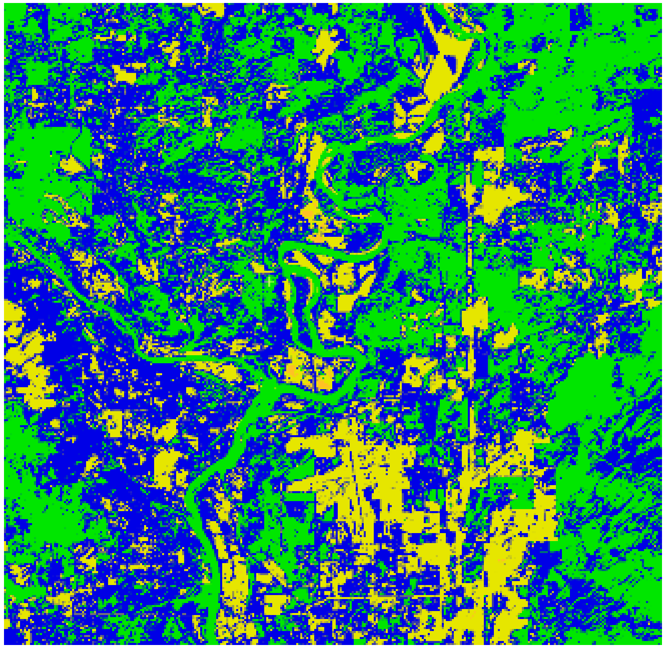
Merging and adding classes

Merging – if clusters are not really separate features; Clusters are merged if they overlap spatially or are similar spectrally.

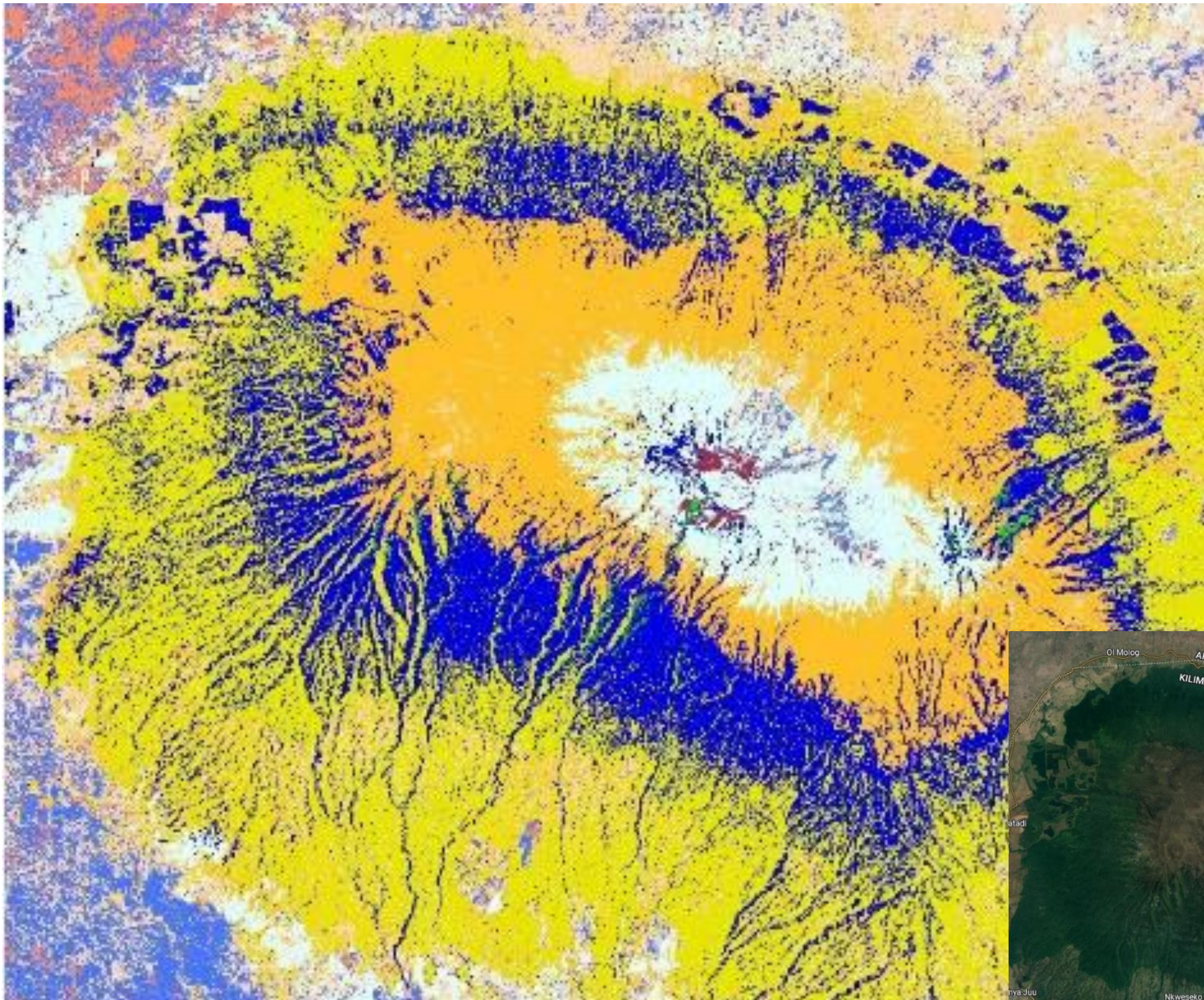
Splitting / adding

If one cluster covers too much area – run again with more clusters

Can generate many clusters, and then group merge later …



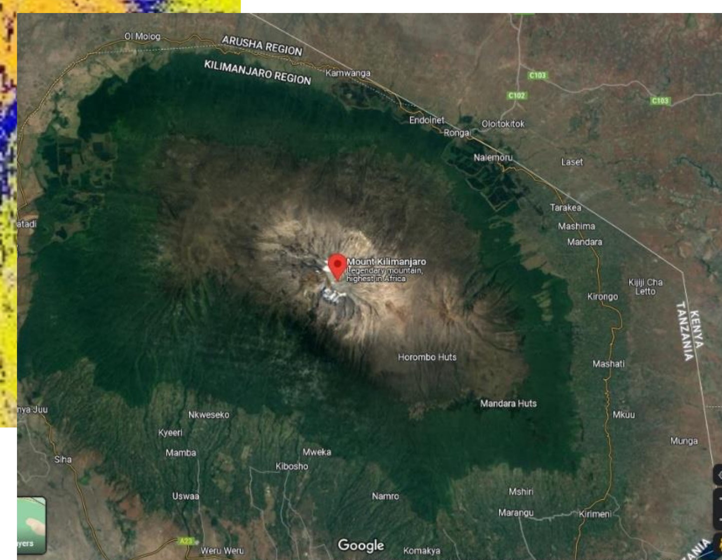
Mt. Kilimanjaro



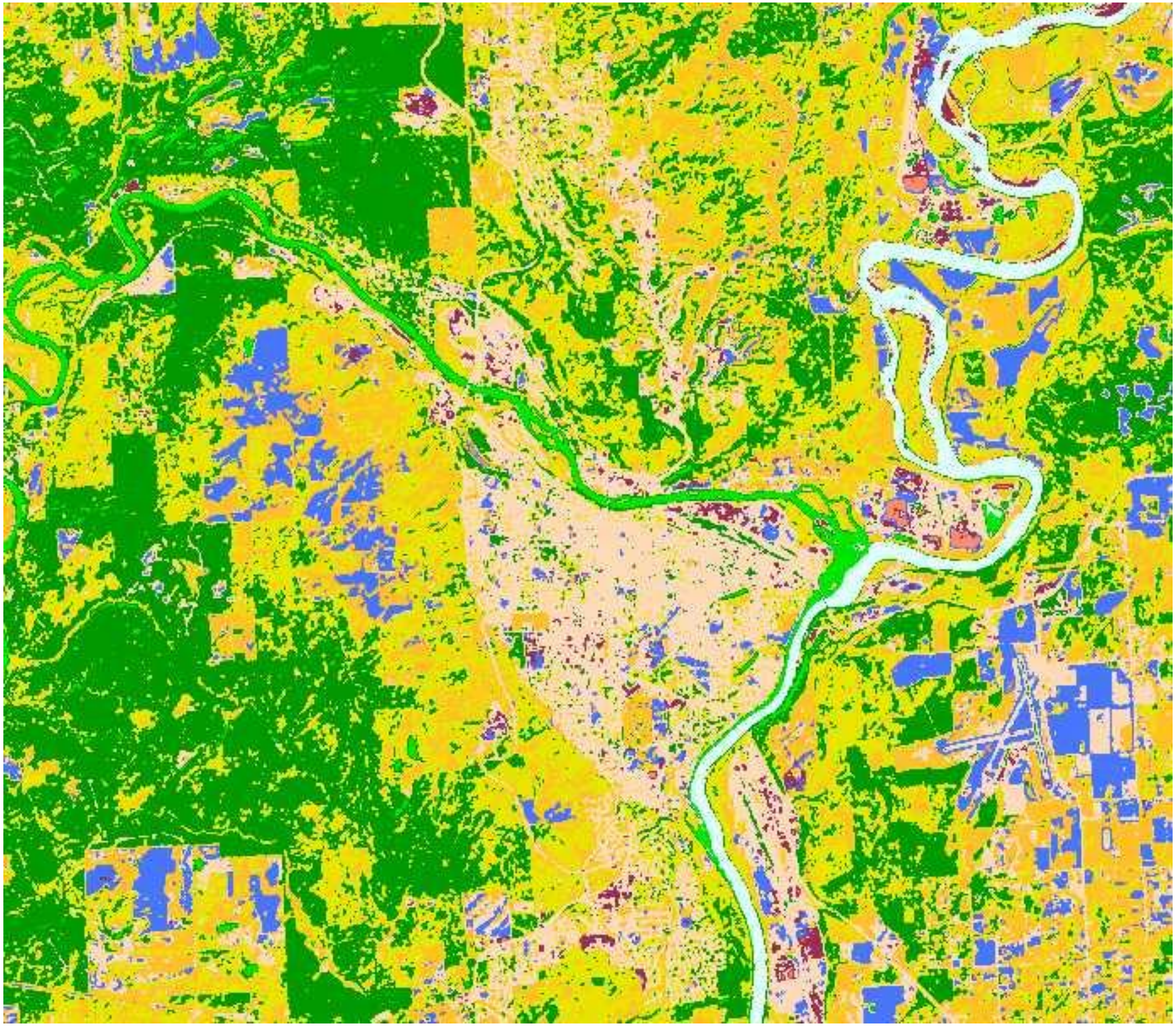
Classification **ALWAYS** produces a <u>'salt and pepper'</u> effect with isolated pixels

Due to :

- fine local DN variations
- '**per-pixel**' classifiers



reduced by Filters (GIS) / Sieve (Catalyst)



Filters can blur the result

Only PCI Catalyst (?) has SIEVE option

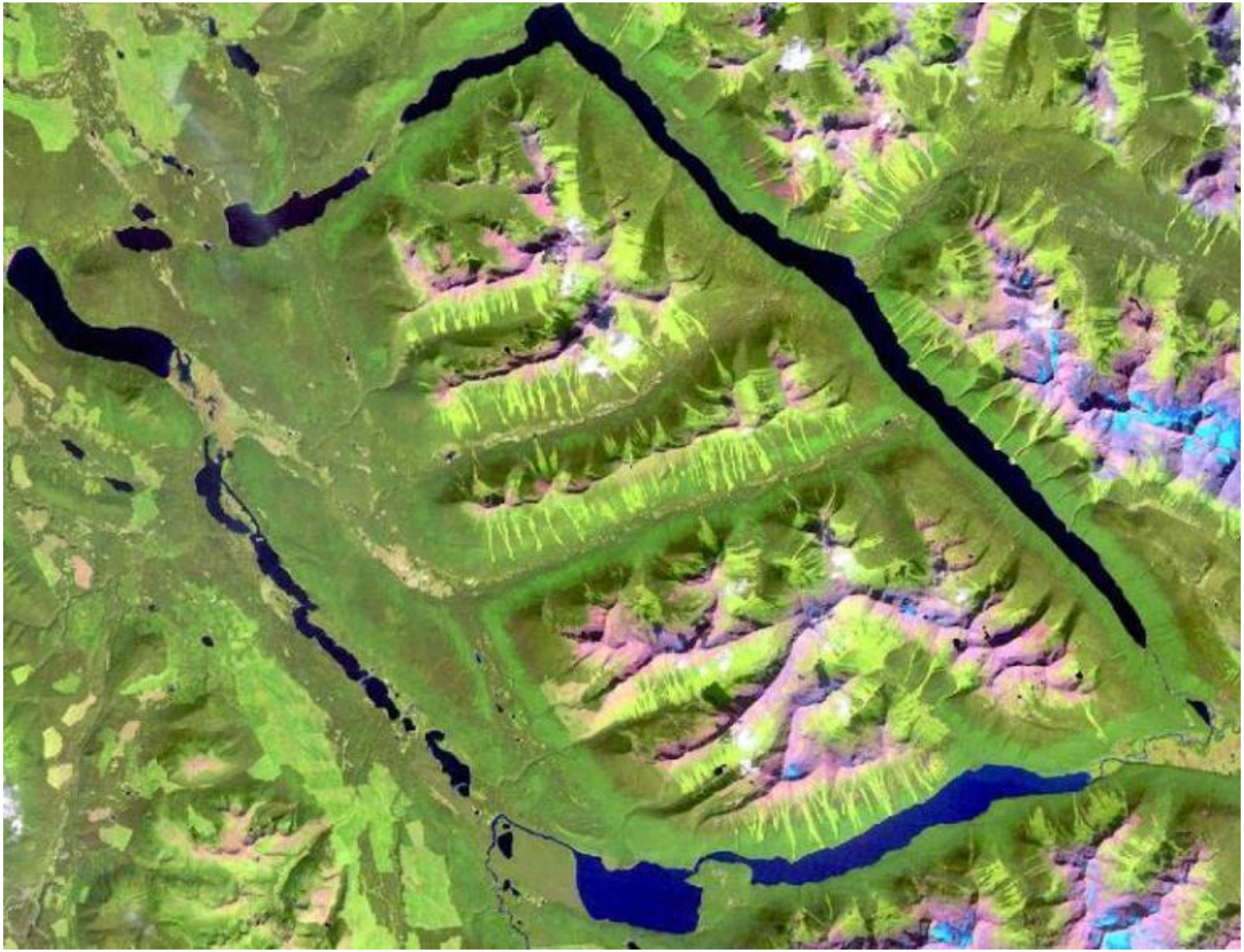
Minimum cluster :

GIS polygon:
1 ha ~ 11 pixels
Or 2 or 5 ha ?

Challenges in classification – why it doesn't always beat digitising

There are many spatial variations in reflectance (a range of DNs for a feature)

e.g. stand purity, understory, age/maturity, density, disease, sun angle, **topography**



Classes/clusters: water, bare rock, glaciers, deciduous, coniferous, shadow?, cutblocks, planted..

URBAN / HUMAN – mosaic of smaller features inside a 30 metre pixel

- amount of grass, types of material, roofing colour, weathering, sun angle (building shape)

Overall summary on classification

It is always complex – the classes and contrasts
There are many causes of spatial variations in reflectance
Most (natural) features are continuous, not discrete

Using only DNs:
Any land cover types have a range of values
Conversely, different cover types can look similar

Further complications for all images:

a. moisture (recent events)
b. edge (mixed) pixels
c. sun angle (illumination) – mid-morning

Textbook classification goal: ~ 85% accuracy
But even manual digitizing may not do any better