Unsupervised Classification

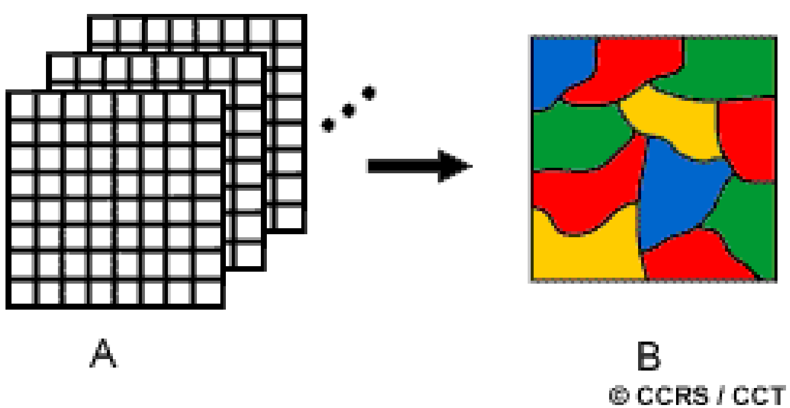
Classification = simplification, mapping

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

A. Rapid map updating

B. Automated mapping of ‘Land Cover’

- avoid manual digitizing … by classifying multispectral band data



We don’t need a million different pixels
They can be grouped into ‘n’ classes

Manual digitizing (yawn …)

e.g. BC VRI (vegetation resource inventory)

BC TRIM data layers

7027 x 1:20,000 tiles

Digitising required for single band (Pan) imagery e.g b/w photography

NTS 1:50,000 example

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

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

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

Remote Sensing Classification

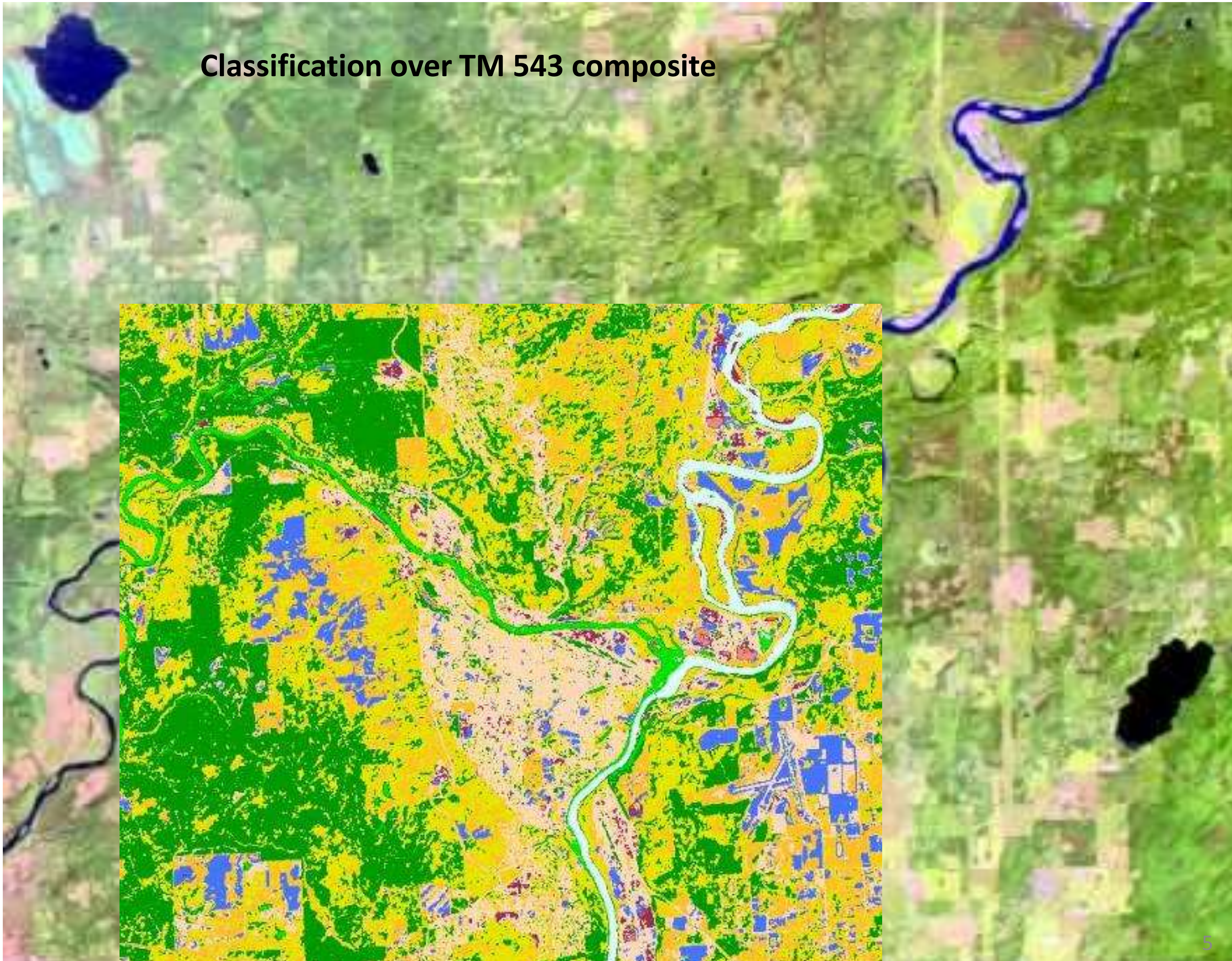
- Automated grouping of similar pixels using <u>multispectral</u> DNs
- Software was developed following 1972 (Landsat 1)
- Digital alternative to manual mapping of Land Cover

Information Classes Derived from an ISODATA Unsupervised Classification Using 10 Iterations and 10 Mean Vectors of an Area Near North Inlet, SC

a. Color composite of HyMap data.

c. Classification map derived from

Classification over TM 543 composite

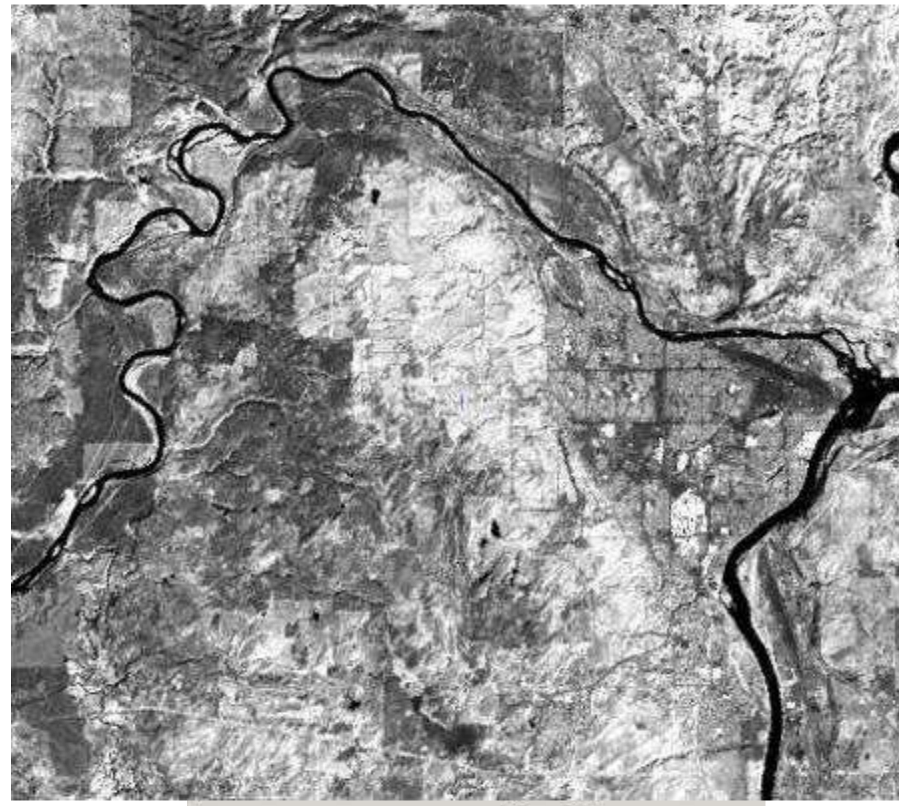


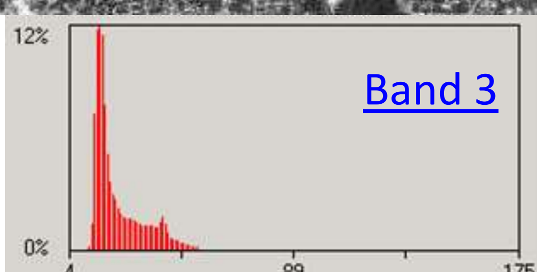
Land Use v Land Cover (LULC) e.g. parks

Sugarbowl-Grizzly Den **Bowron Lakes** **Mt. Egmont / Taranaki, NZ**

Can we use just one band to classify ?

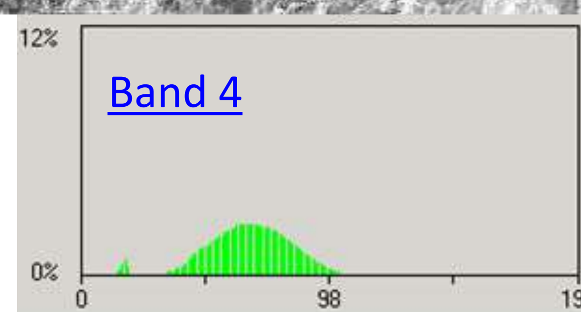
One image band could be treated as a monochrome air photo (as in interpretation)
Digital Numbers from one band alone are rarely enough – features are not unique

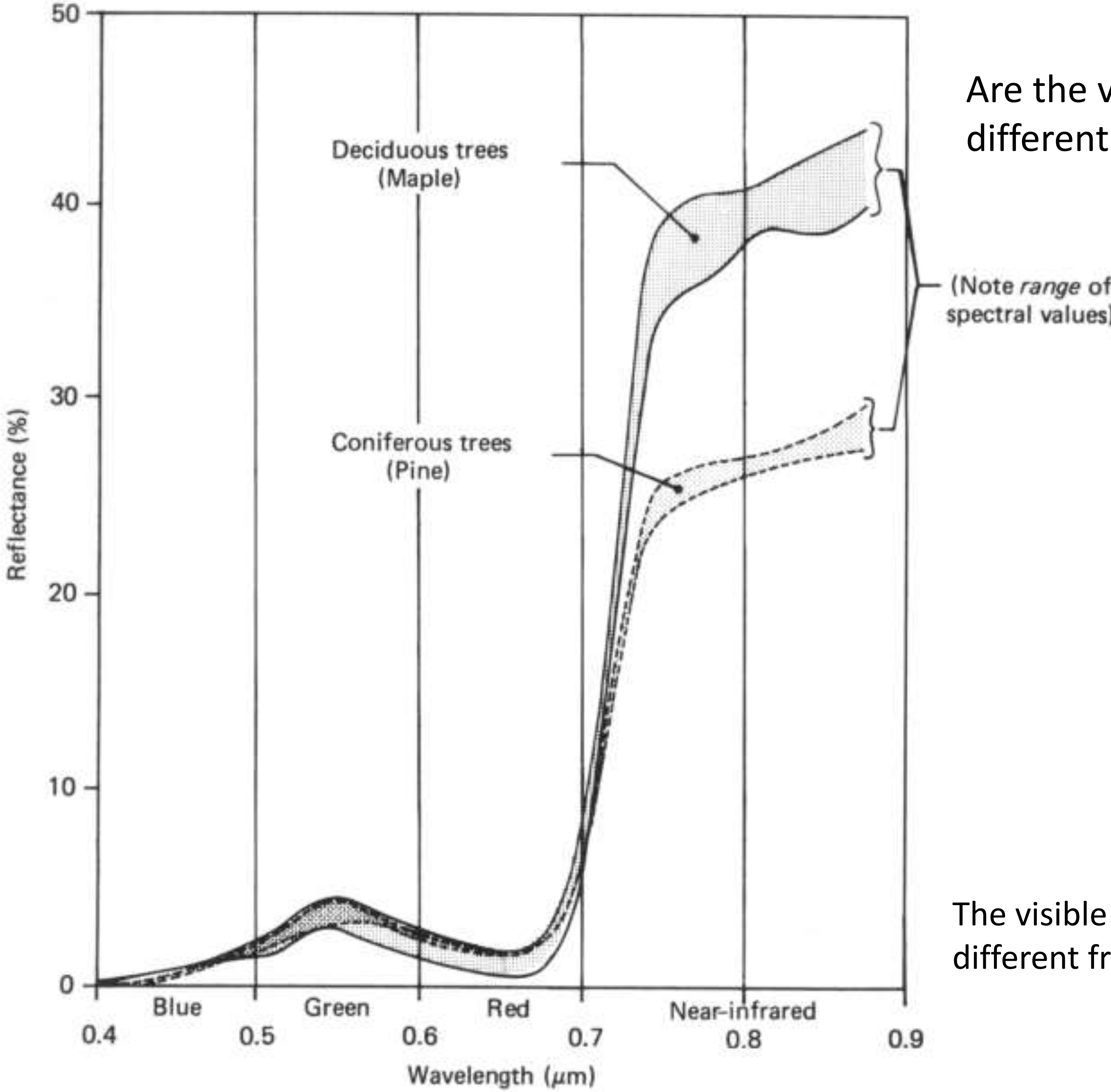




Landsat TM

Water is almost unique in IR bands (low DNs)





Are the vegetation types different enough in IR ?

The visible bands are not too different from each other

Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS)

Reference

Barsi, J.A.; Lee, K.; Kvaran, G.; Markham, B.L.; Pedelty, J.A. The Spectral Response of the Landsat-8 Operational Land Imager. *Remote Sens.* **2014**, *6*, 10232-10251
doi:10.3390/rs61010232

Band	Wavelength	Useful for mapping
Band 1 – Coastal Aerosol	0.435 - 0.451	Coastal and aerosol studies
Band 2 – Blue	0.452 - 0.512	Bathymetric mapping, distinguishing soil from vegetation, and deciduous from coniferous vegetation
Band 3 - Green	0.533 - 0.590	Emphasizes peak vegetation, which is useful for assessing plant vigor
Band 4 - Red	0.636 - 0.673	Discriminates vegetation slopes
Band 5 - Near Infrared (NIR)	0.851 - 0.879	Emphasizes biomass content and shorelines
Band 6 - Short-wave Infrared (SWIR) 1	1.566 - 1.651	Discriminates moisture content of soil and vegetation; penetrates thin clouds
Band 7 - Short-wave Infrared (SWIR) 2	2.107 - 2.294	Improved moisture content of soil and vegetation and thin cloud penetration
Band 8 - Panchromatic	0.503 - 0.676	15 meter resolution, sharper image definition
Band 9 – Cirrus	1.363 - 1.384	Improved detection of cirrus cloud contamination
Band 10 – TIRS 1	10.60 – 11.19	100 meter resolution, thermal mapping and estimated soil moisture
Band 11 – TIRS 2	11.50 - 12.51	100 meter resolution, Improved thermal mapping and estimated soil moisture

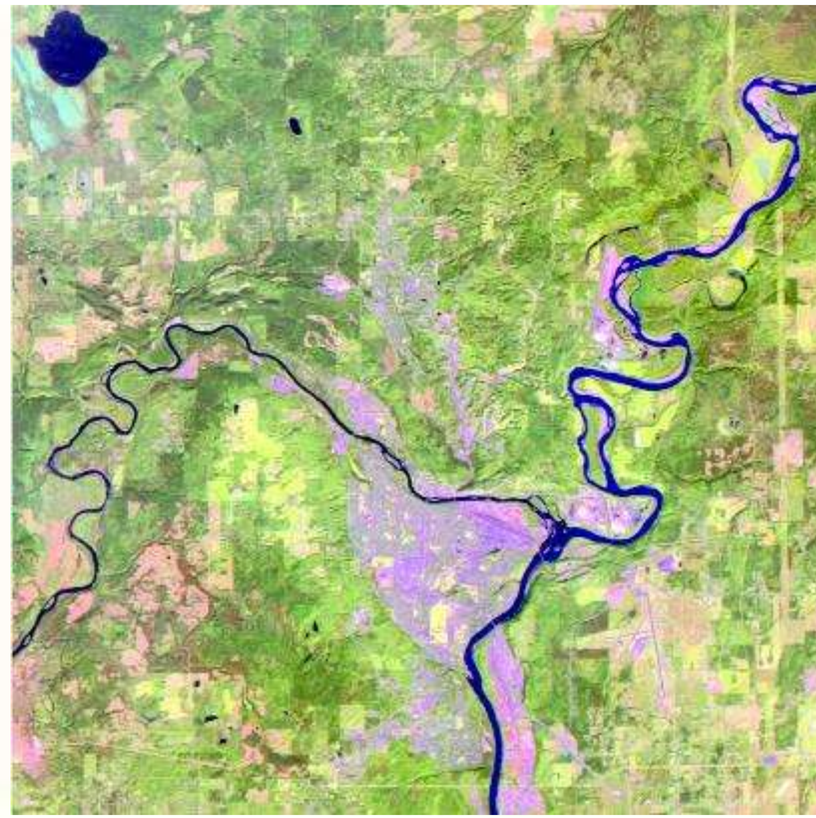
Landsat 4-5 Thematic Mapper (TM) and Landsat 7 Enhanced Thematic Mapper Plus (ETM+)

Band	Wavelength	Useful for mapping
Band 1 - Blue	0.45 - 0.52	Bathymetric mapping, distinguishing soil from vegetation, and deciduous from coniferous vegetation
Band 2 - Green	0.52 - 0.60	Emphasizes peak vegetation, which is useful for assessing plant vigor
Band 3 - Red	0.63 - 0.69	Discriminates vegetation slopes
Band 4 - Near Infrared	0.77 - 0.90	Emphasizes biomass content and shorelines
Band 5 - Short-wave Infrared	1.55 - 1.75	Discriminates moisture content of soil and vegetation; penetrates thin clouds
Band 6 - Thermal Infrared	10.40 - 12.50	Thermal mapping and estimated soil moisture
Band 7 - Short-wave Infrared	2.09 - 2.35	Hydrothermally altered rocks associated with mineral deposits
Band 8 - Panchromatic (Landsat 7 only)	0.52 - 0.90	15 meter resolution, sharper image definition

Band / channel selection

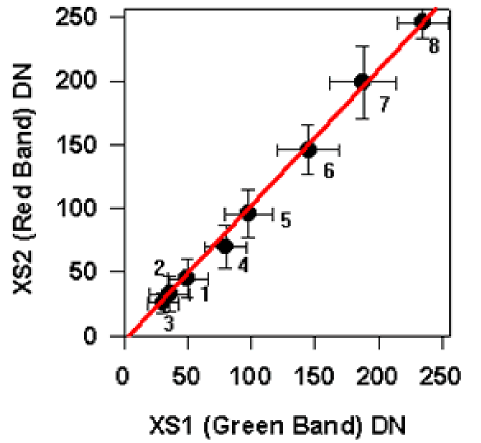
e.g. Thematic Mapper TM: 1-7 or

Operational Land Imager OLI 1-9; (TIRS 10-11)



Landsat TM has 7 bands: You would NOT select 3 visible bands to classify
The visible bands are similar – so the composite is low in contrast (left)

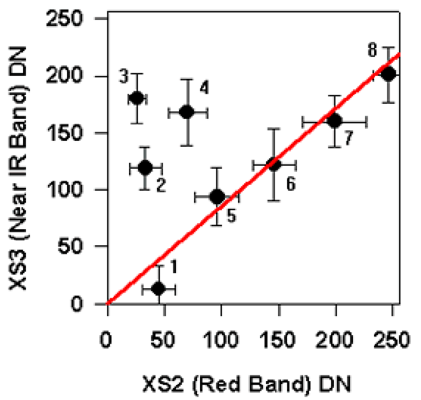
band correlation coefficients and scatterplots



Example: PG Landsat data

Correlation: (r values between bands)

	TM1	2	3	4	5	6
TM1						
TM2	.97					
TM3	.96	.96				
TM4	.07	.16	.11			
TM5	.66	.72	.76	.64		
TM6	.77	.77	.81	.14	.80	
TM7	.83	.86	.90	.40	.93	.86



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

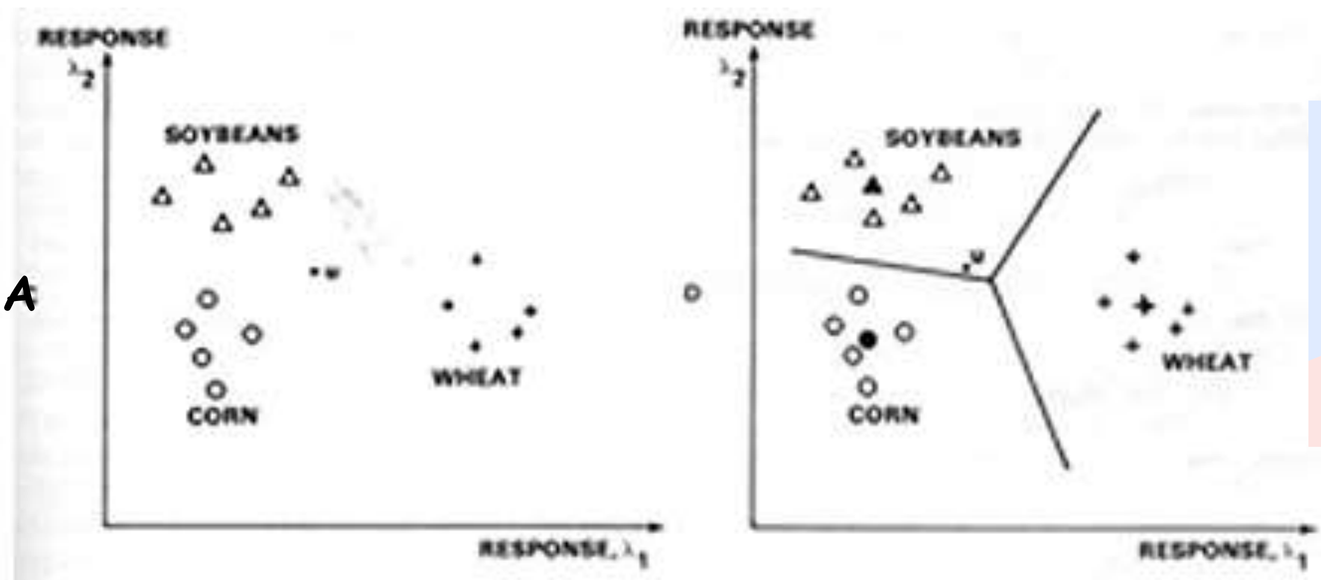
.. so also are bands 5 and 7 (r = .93)

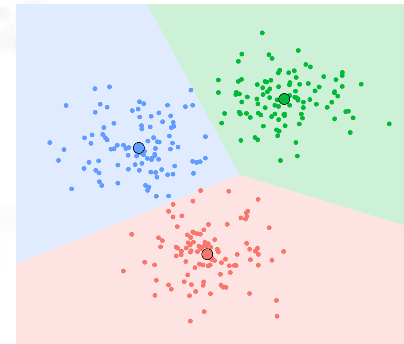
band 4 (near-IR) is not very correlated with Visible or SWIR (nor thermal)

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

The role of multispectral sensing in classification
(fuzzy textbook figure)

DN
Band A





DN band B

The value of multiple bands

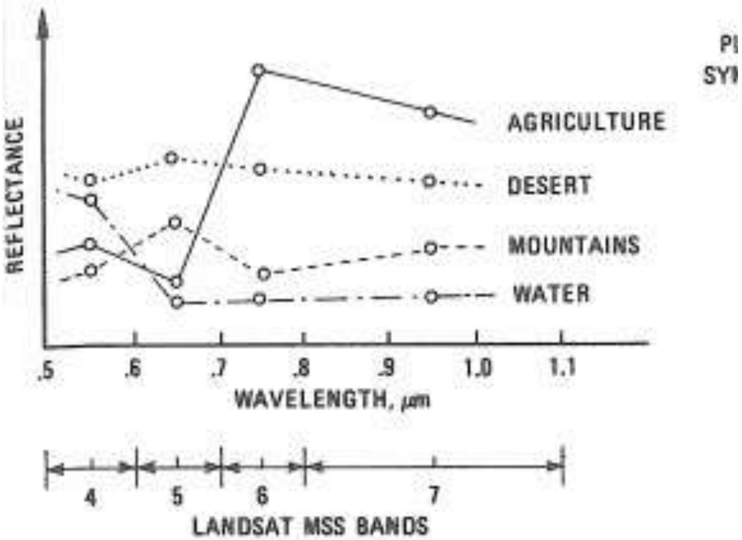
DNs in Band A are similar for corn and wheat

DNs in Band B are similar for corn and soybeans

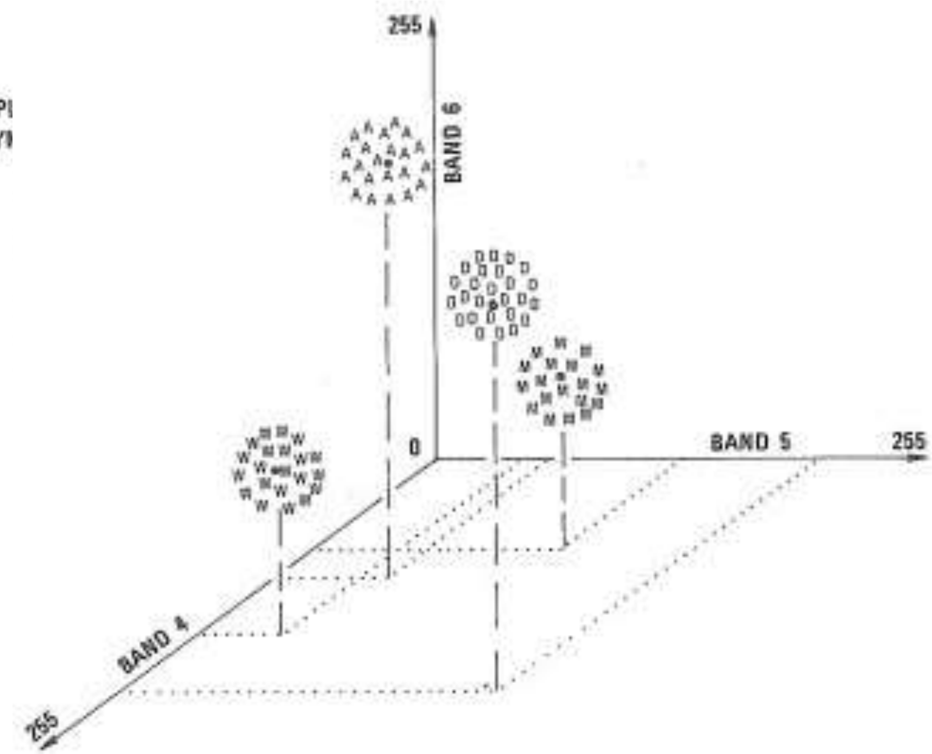
… but if we use both Bands A and B, then all 3 differ

4 land cover types - spectral reflectance

'3D' scatter plots



A. SPECTRAL REFLECTANCE CURVES FOR MAJOR TERRAIN TYPES.

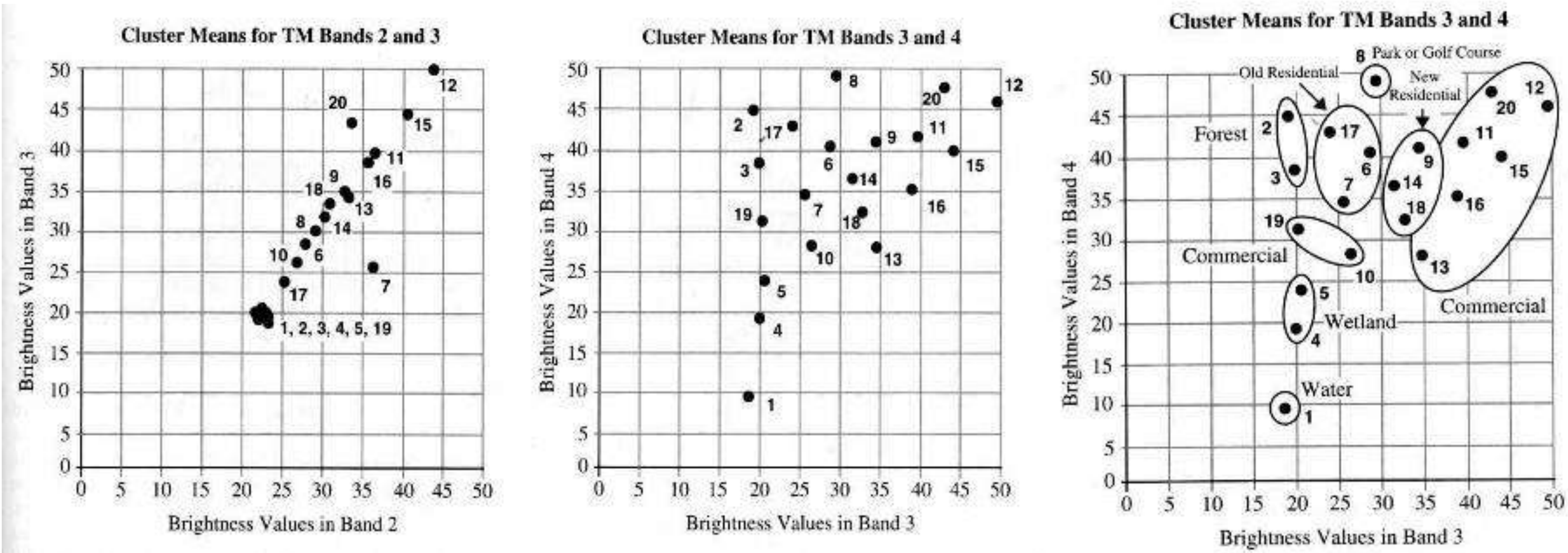


B. THREE–DIMENSIONAL CLUSTER DIAGRAM FOR CLASSIFICATION.

… Algorithms are '**per pixel**' classifiers

Unsupervised classification = 'clustering'

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



Two bands are shown for simplicity

Input bands selected – minimum 3+ bands;

Note: you can only display 3 bands, but you can input **more than** 3 (no limit)

… but the classifier can be constrained with too many inputs

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)

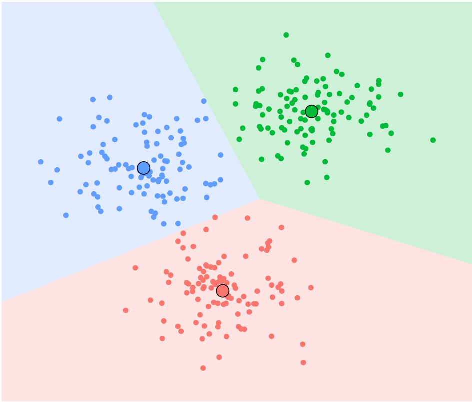
2. Past experience, visual examination, logical thinking

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

Background



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

- the software clusters pixels by natural DN groupings
  based on similarity and contrast ~ 'natural breaks'

e.g. 1000 x 1000 pixel area = 1 million pixels, many are alike

Steps

- determine how many classes / clusters

- determine which input bands / channels to use

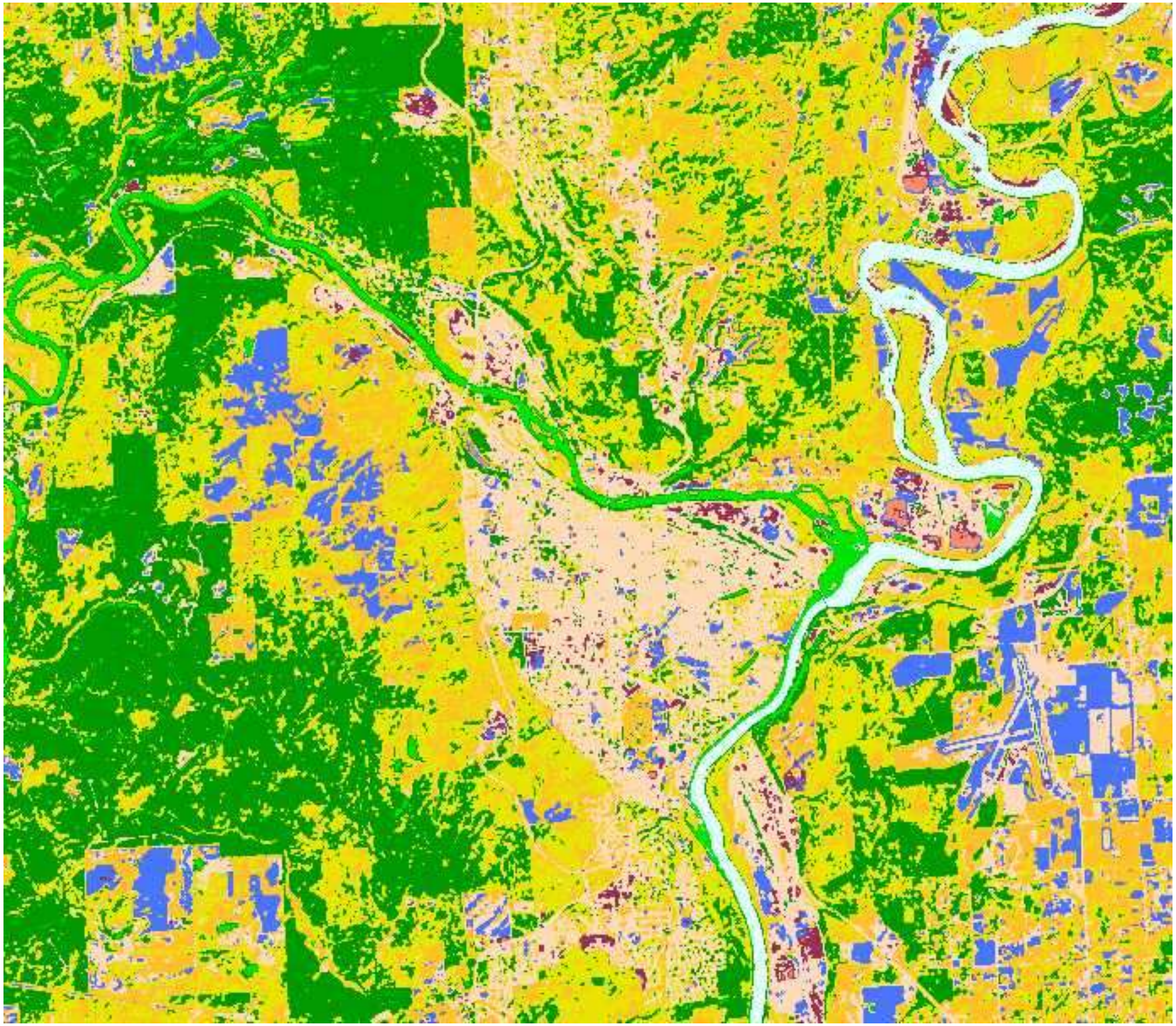
- run classifier : K-means or Isodata

- Rerun with more clusters if needed

- assign names to classes (merge classes if needed)


Knob and kettle
Eskers
Fields
Beetle blocks
drumlinoids
Glacial Lake PG

Unsupervised result – 10 classes (clusters)



This is a new <u>channel</u> in your .pix file

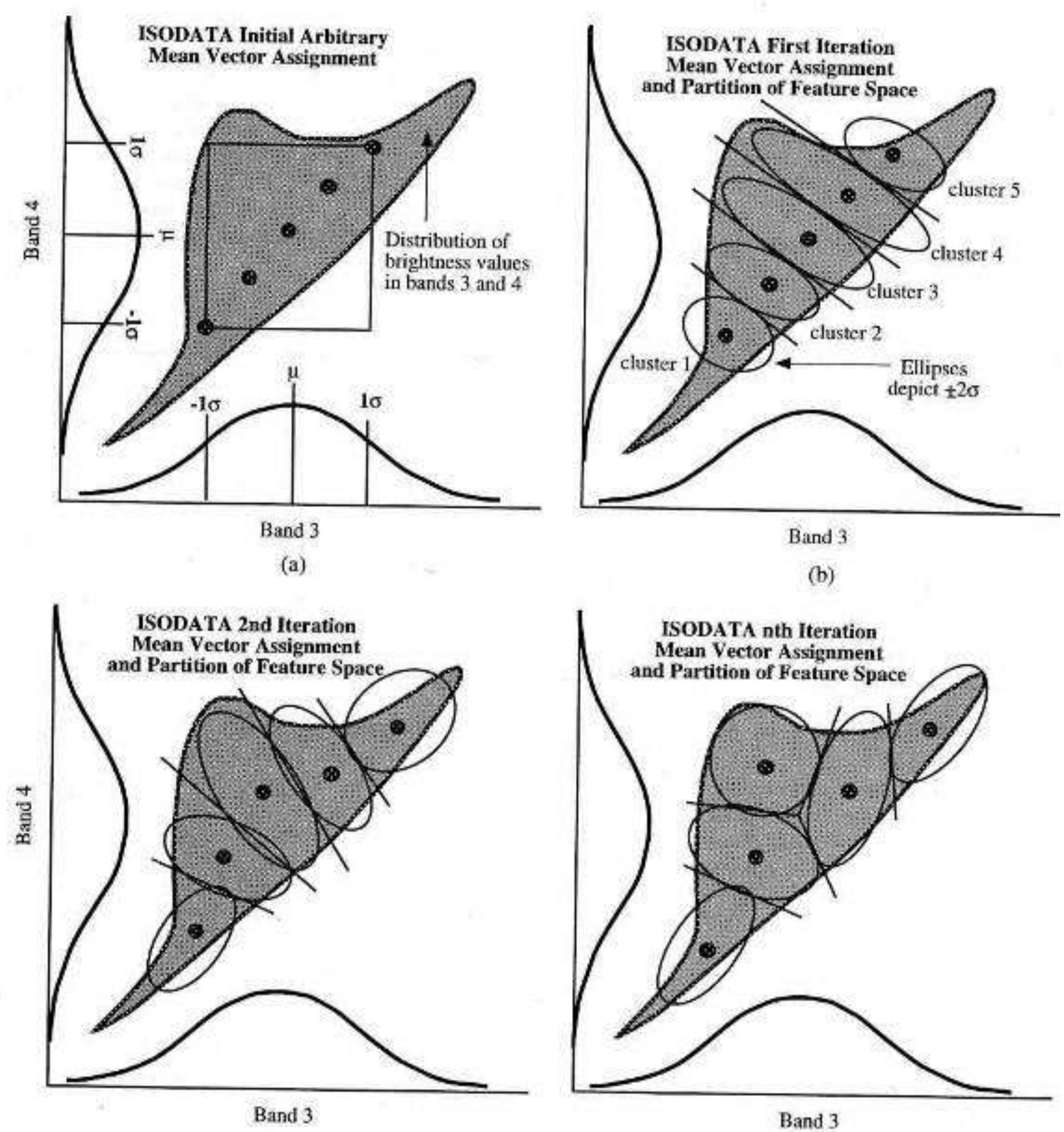
- it's not a band

Colours are random

Note: urban classification is often NOT 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

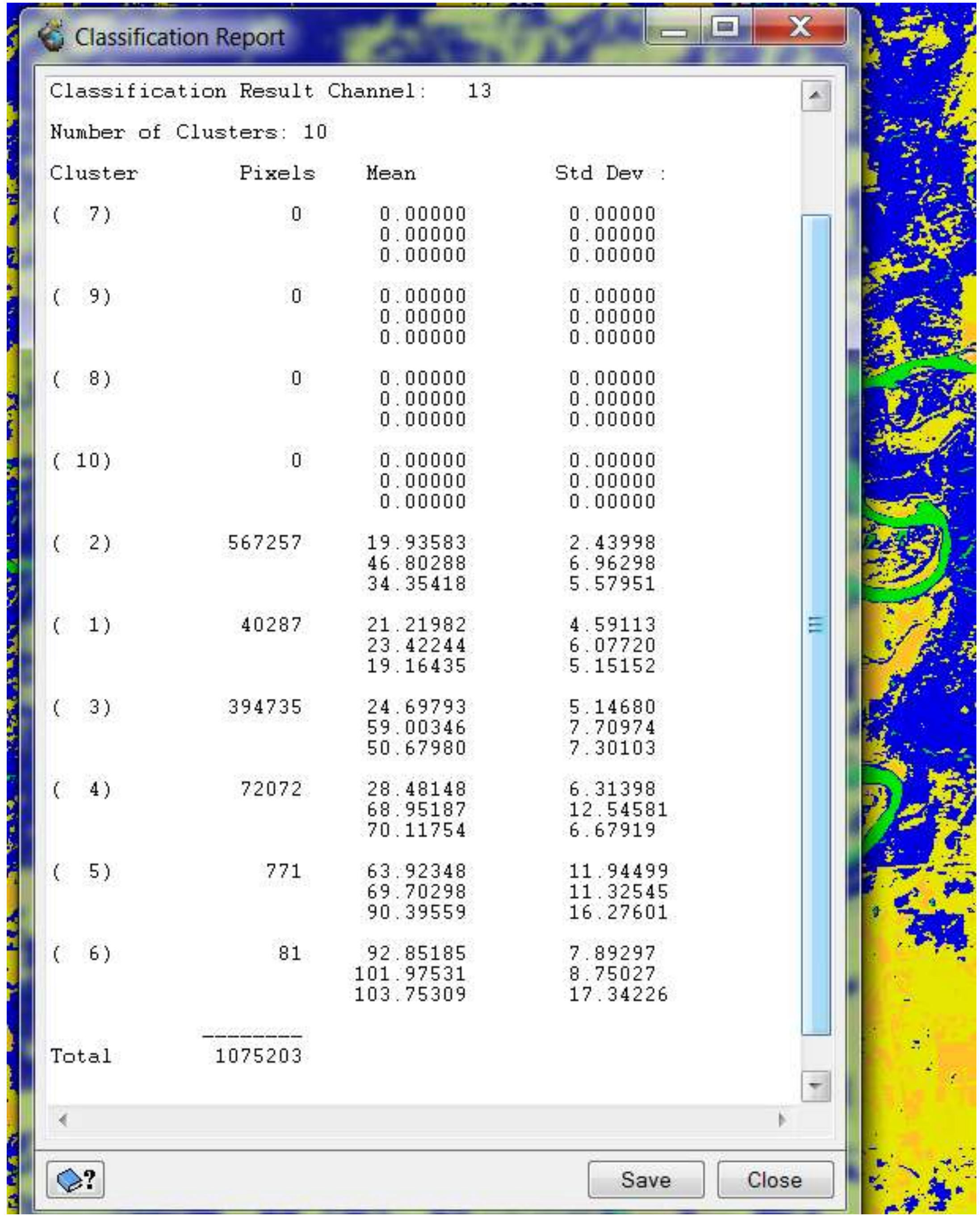


classification report
1 iteration

Note:
clusters with 0 pixels

DN values for bands 3,4,5 averages .. Distribution is 1-2 dimensional

Final step will be Assigning names to clusters (and maybe 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

Unsupervised classification –algorithms and iterations
(PCI .. Fuzzy K-means is less common in GIS software)

1. K-means minimises within cluster range of DNs

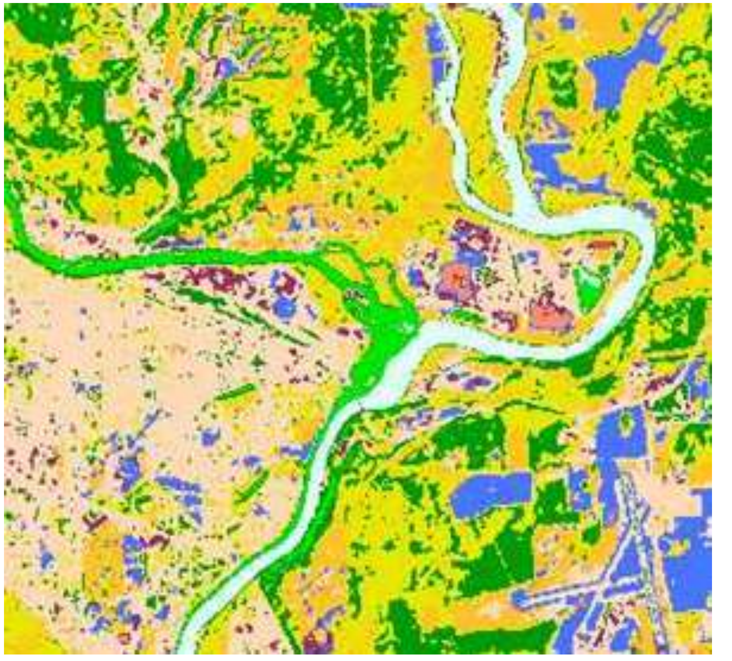
2. Fuzzy K-means enables mixed membership, based on distribution of the clusters

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

The ISODATA algorithm is similar to the k-means algorithm with the difference that **the ISODATA algorithm allows for different number of clusters while the k-means assumes that the number of clusters is known** *a priori*. The prime objective of the k-means algorithm is to minimize the within cluster variability.

Merging and adding classes

Merging – if clusters are not really separate features; Clusters are merged if they overlap spatially or are similar spectrally. *(visually examine image)*



Splitting / adding

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

Can also generate many clusters, and then group merge later …

One ploy is to make many clusters (e.g. 50-100 and plan to merge)

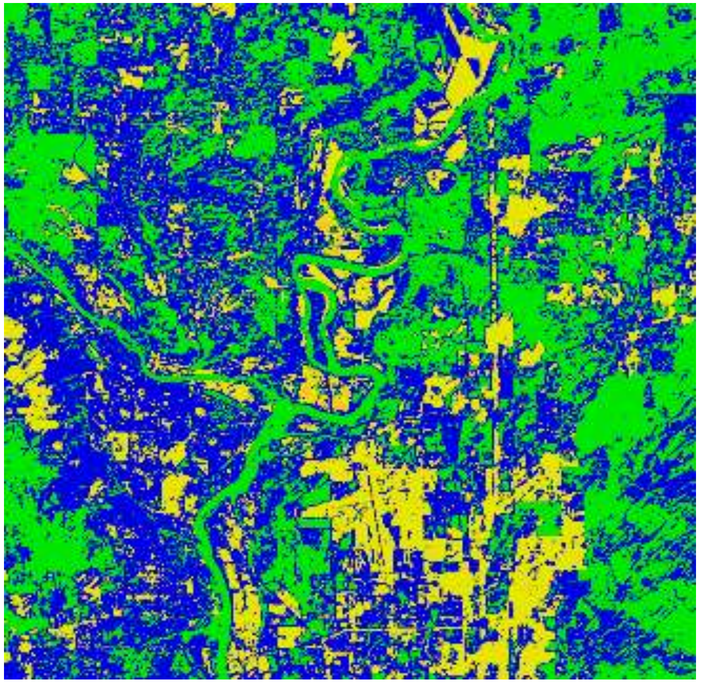
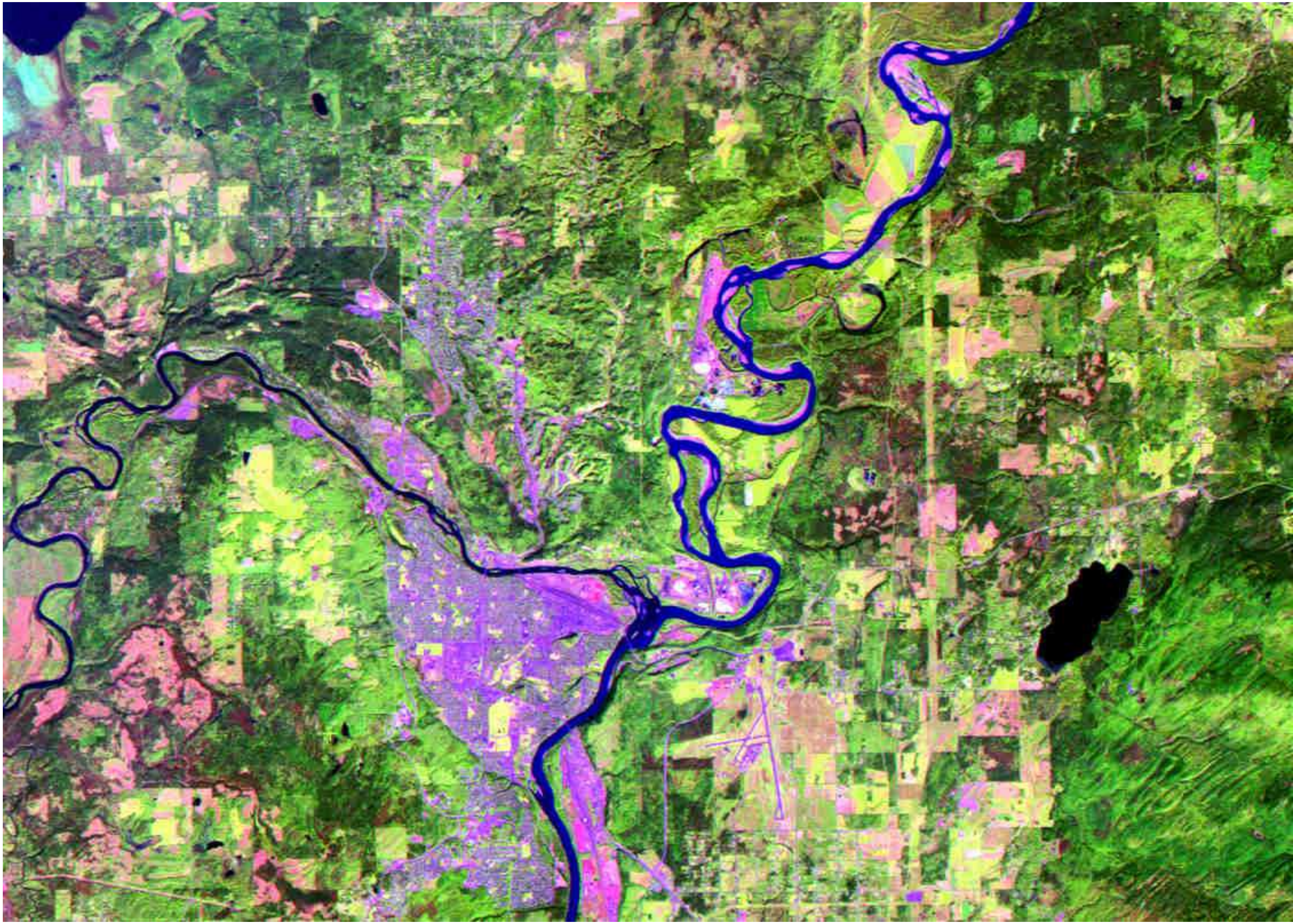
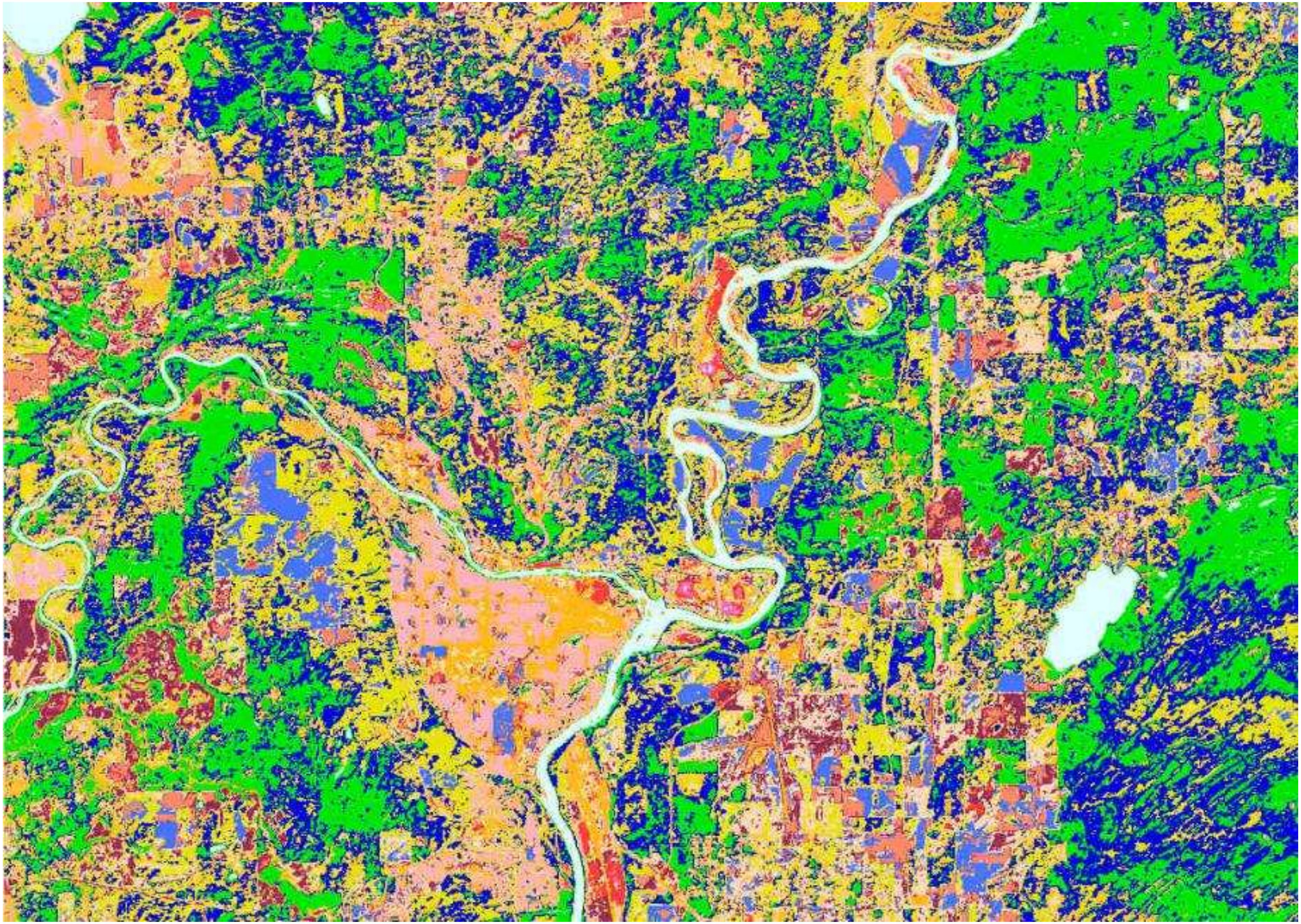
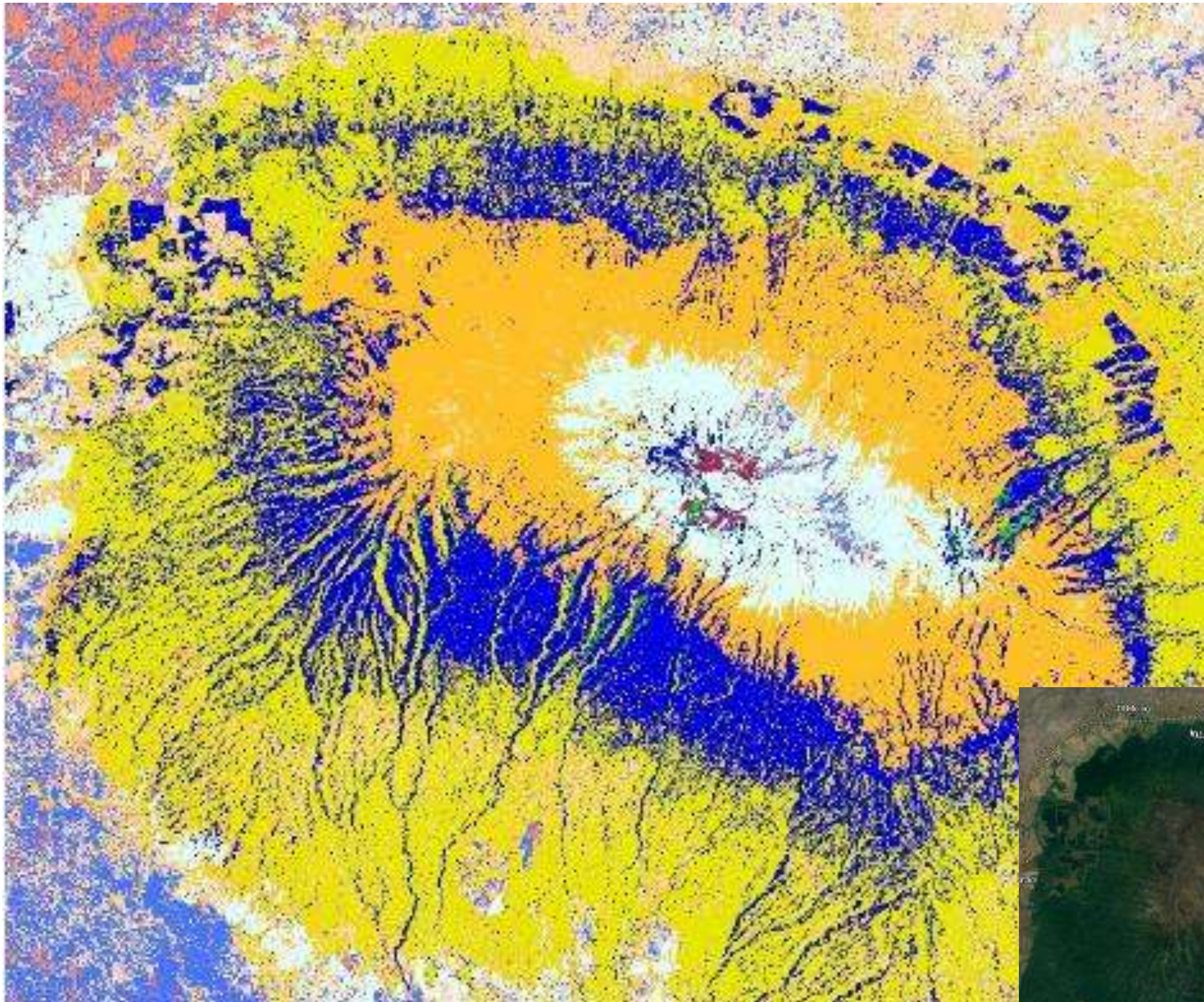


Image- TM 543



Isodata



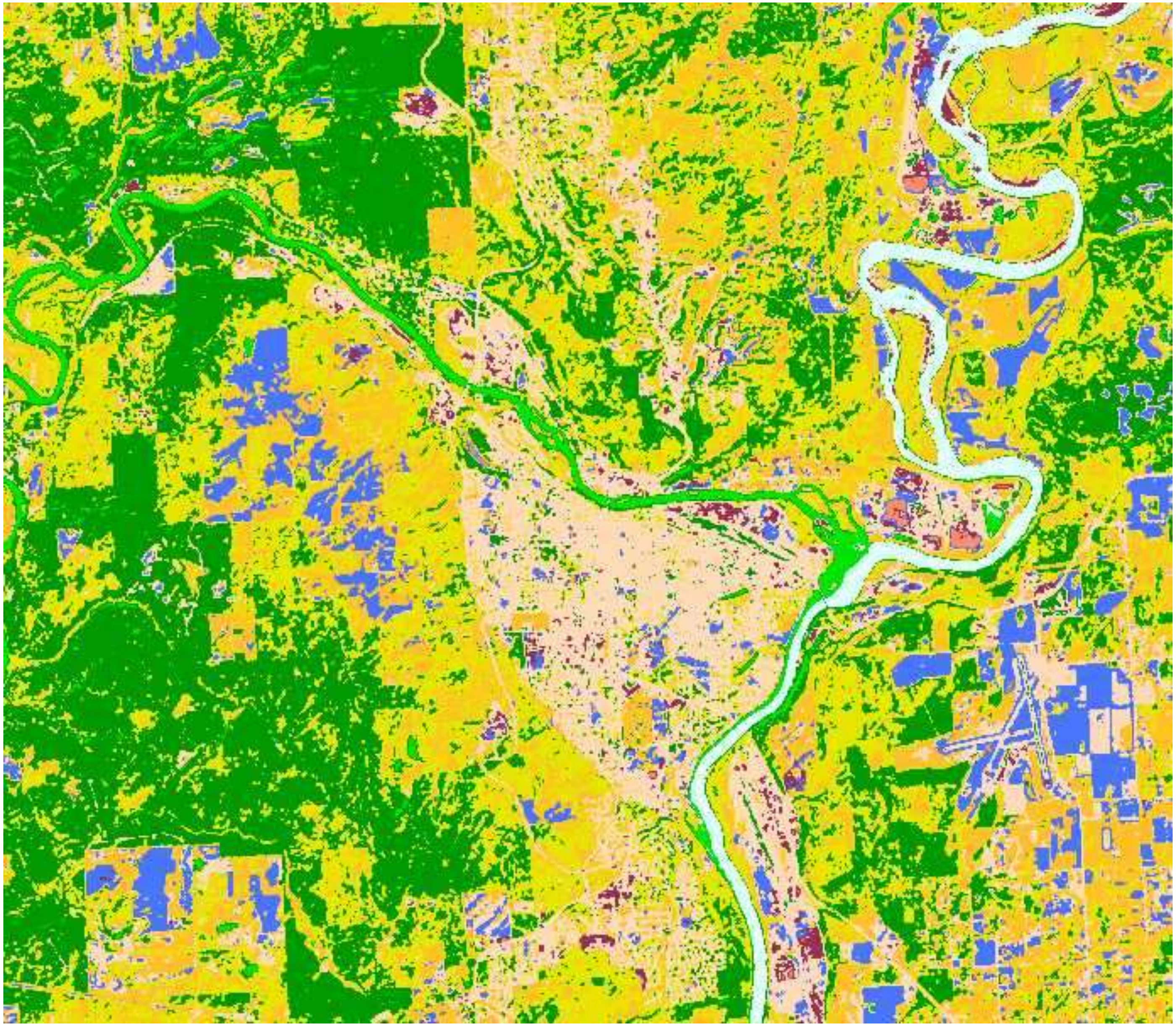


Classification **ALWAYS** produces a <u>'salt and pepper'</u> effect with isolated pixels

Due to :
- fine local DN variations
- **'per-pixel'** classifiers

Mt. Kilimanjaro

reduced by Filters or Sieve tool



Modal Filters

1 1 1

1 2 1

1 1 1

replace centre pixel in 3x3 window with mode value (= 1 here)

SIEVE

Merges isolated pixels into adjacent class

Minimum cluster = ?

GIS polygon:

1 ha (100x100m) = 10,000

Pixel = 30x30m (900m^2)

~ 11 pixels

Or use 2 or 5 ha ?

Challenges in classification – range of DN values

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

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

Challenges in classification (why it doesn't always beat digitizing)
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, cutblocks, regrown

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 appear similar

Further complications for all images:

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

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