GEOG 357

LECTURE 5

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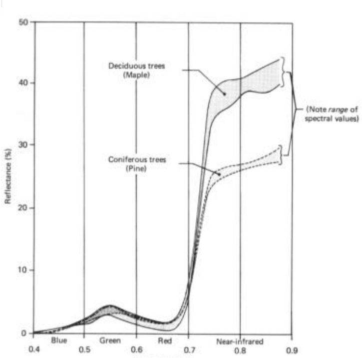
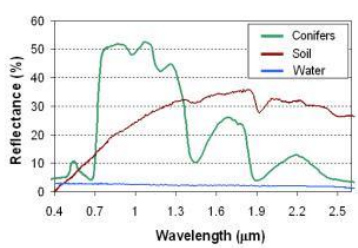
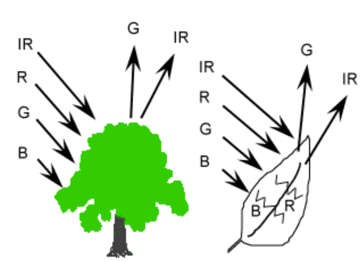
Remote Sensing







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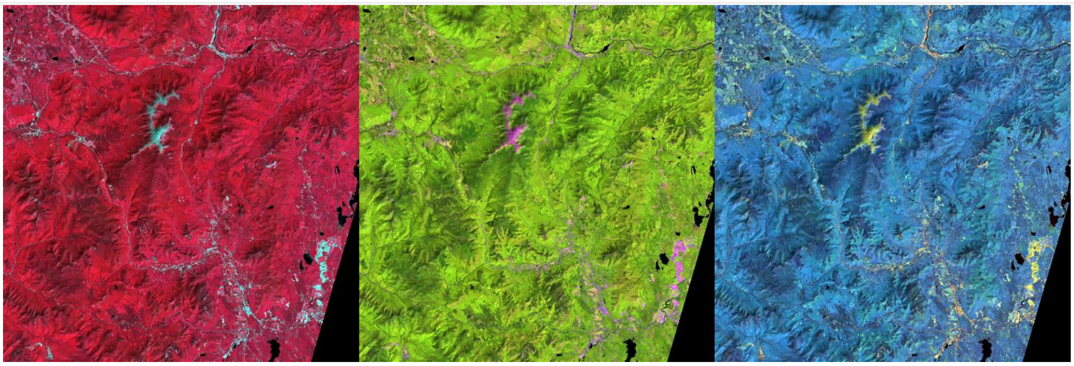
Remote Sensing



4, 3, 2 Combination   5, 4, 3 Combination   2, 5, 4 Combination

https://forestwatch.sr.unh.edu/imagery/aboutimagery.shtml

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Image Classification

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

- Rapid map updating
- Automated mapping of 'Land Cover' / Land use
  - no manual digitizing … use of multispectral band data

VRI (BC -vegetation resource inventory) is an. example of manual digitizing

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Image Classification

- Image classification is the process of assigning pixels to classes.
  - categorise and label groups of pixels within an image to create new information classes
  - follows specific rules on how the pixels are grouped or assigned
  - the classes form regions on an image
    - therefore, image classification is used to create thematic maps

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Image Classification

- Groupings are of similar pixels using multispectral DNs
- Software was developed following 1972 (Landsat 1)
- Served as a digital alternative to manual mapping of Land Cover

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

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Image Classification

- Land Use and Land Cover
  - Land cover refers to the surface cover on the ground
    - e.g. vegetation, urban infrastructure, water, bare soil
  - Land use refers to the purpose the land serves
    - e.g. recreation, wildlife habitat, or agriculture

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Land Use vs Land Cover (LULC) e.g. Parks

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






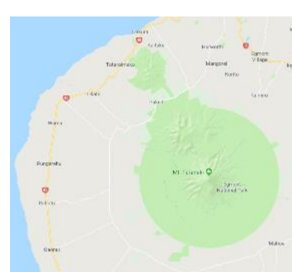

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Image Classification

- A simple form image classification is to consider each pixel individually and assign it to a class. This is referred to as point classification
- But…
  - It misses relationship between the pixel and its neighbors because each pixel is considered in isolation
  - E.g. human interpreter of air photos

- Manual interpretation: Features are classified by *simplification* which is a form of generalization

- Human interpretation / classification relies on attributes such as:
  - Shape, pattern, texture, shadows, size, association, **tone, colour**
  - Human eyes are not good at distinguishing between brightness of individual pixels but do well with groups of pixels
  - Digital Numbers from one band (e.g. an air photo) alone are rarely enough – features are not unique
- Algorithms mostly use Digital Number (DN) =~digital version of tone/colour

Image Classification

- More complex classification processes consider groups of pixels within the image as a means of using both textural and spectral information.
  - These are referred to as spatial or neighborhood classifiers

- An alternative way of categorization is based on technique

Image Classification

- The main types of image classification are supervised classification and unsupervised classification

  - Supervised classification requires the analyst to identify areas on the image that are known to belong to each category/class

  - Unsupervised classification, on the other hand, proceeds with only minimal interaction with the analyst in a search for natural groups of pixels present within the image.

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

- 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


Bands 1, 2, 3


Band 5, 4, 3

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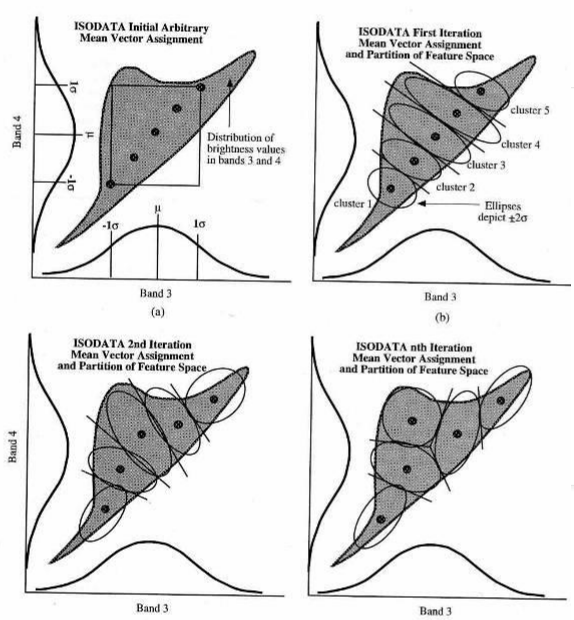
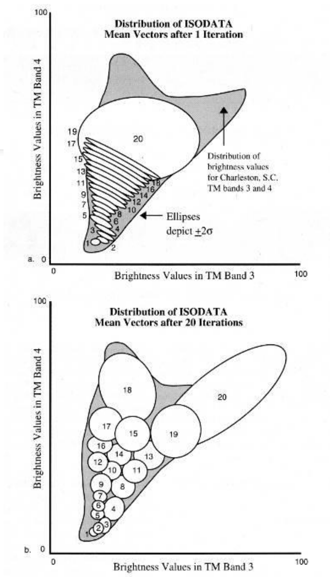
Unsupervised – how it works

- ❑ 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

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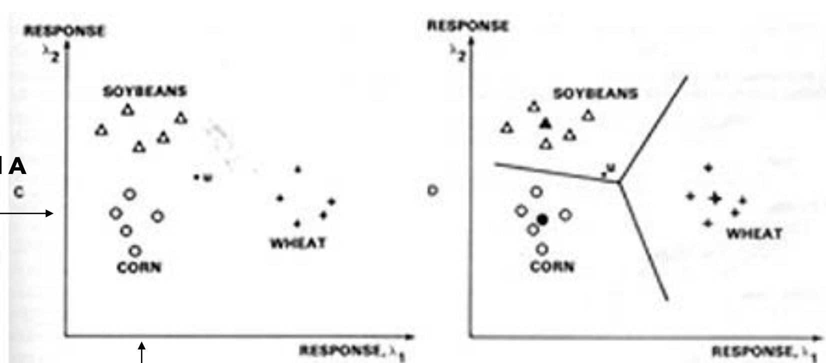
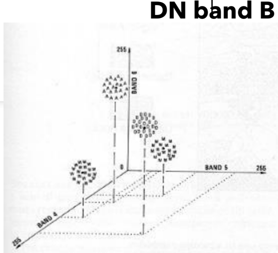
The role of <u>multispectral</u> sensing in classification

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

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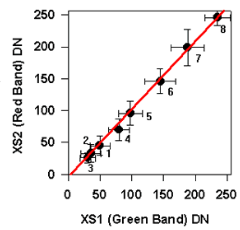
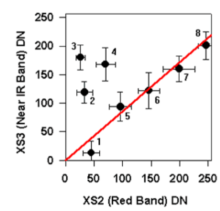
band correlation coefficients and scatterplots

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 17

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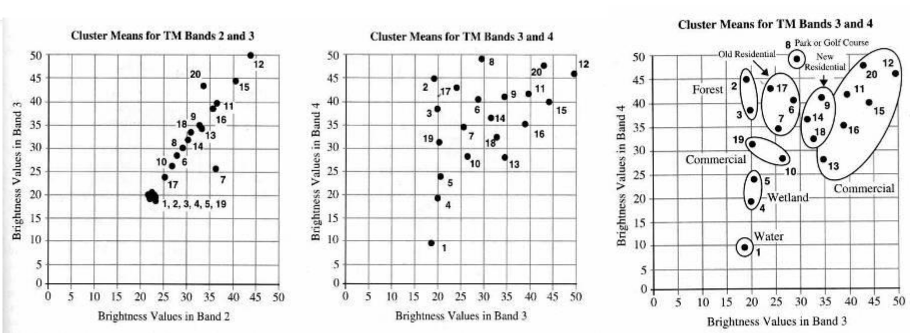
Unsupervised classification

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;

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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)

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Unsupervised classification

Characteristics

-user 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)

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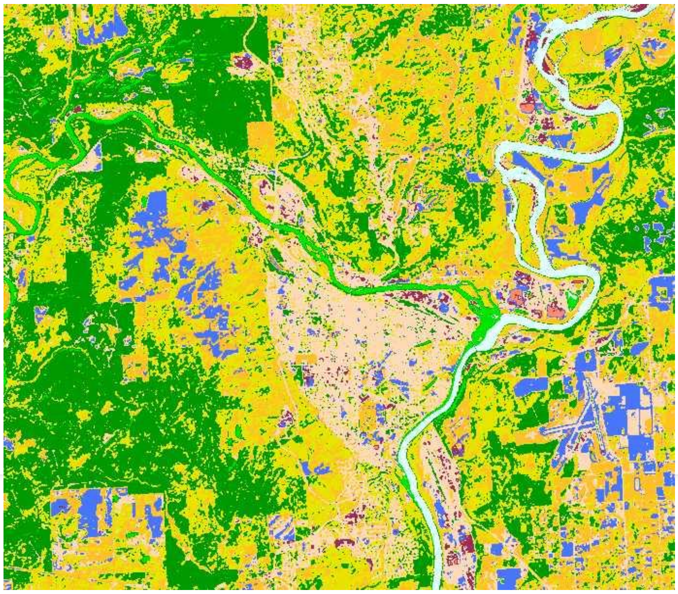
Unsupervised result – 10 classes (clusters)



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

Colours are random

Note: urban classification is NOT easy!

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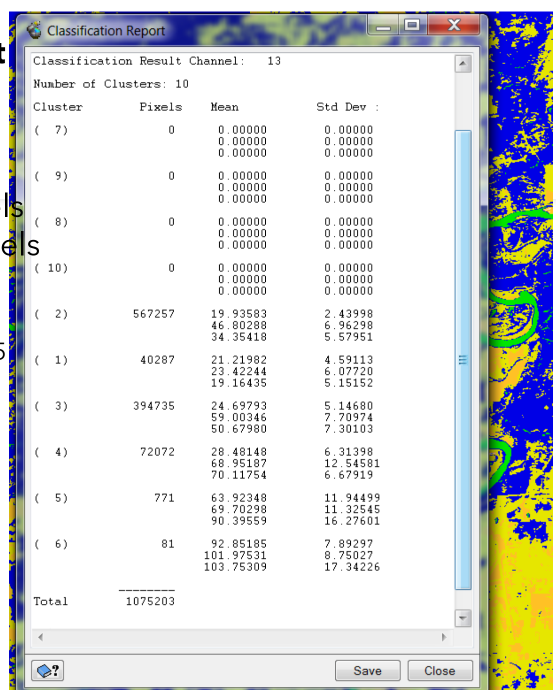
classification report
1 iteration

Note:
clusters with 0 pixels
Clusters with ### pixels

DN values for bands 3,4,5

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



Classification Report

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 46.80288 34.35418	2.43998 6.96298 5.57951
(1)	40287	21.21982 23.42244 19.16435	4.59113 6.07720 5.15152
(3)	394735	24.69793 59.00346 50.67980	5.14680 7.70974 7.30103
(4)	72072	28.48148 68.95187 70.11754	6.31398 12.54581 6.67919
(5)	771	63.92348 69.70298 90.39559	11.94499 11.32545 16.27601
(6)	81	92.85185 101.97531 103.75309	7.89297 8.75027 17.34226
Total	1075203		

Save Close

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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

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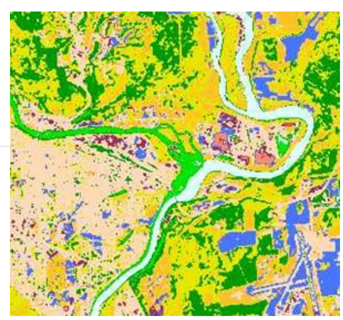
Merging and adding classes

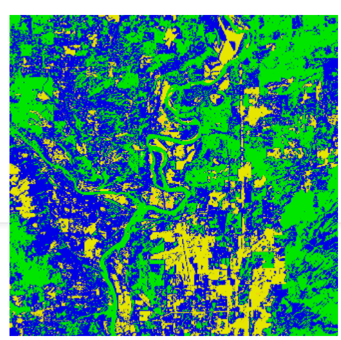
Merging – if clusters are not really separate features; Clusters are merged if they overlap spatially or are similar spectrally.



Splitting / adding

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

Can generate many clusters, and then group merge later …



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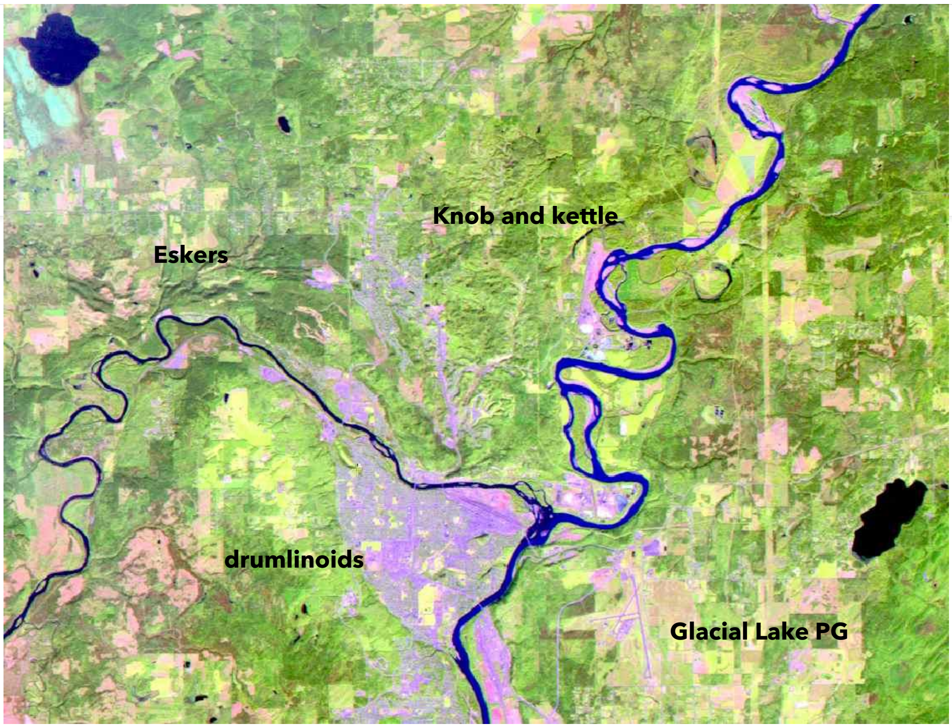

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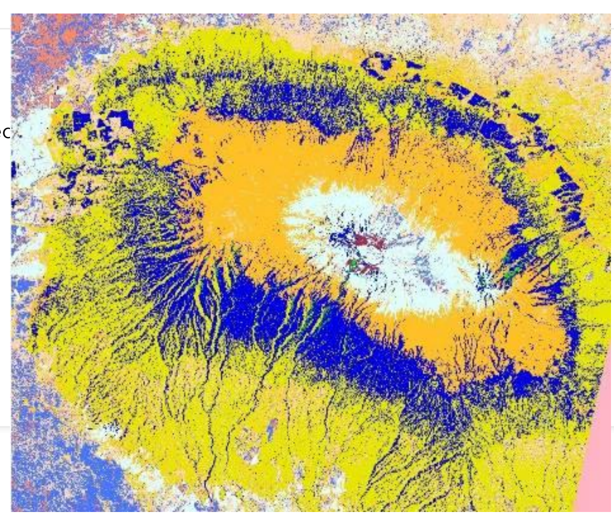
Sieve - filter

Mt. Kilimanjaro

Classification **ALWAYS** produces a 'salt and pepper' effect with isolated pixels

This is a result of

a. fine local variations in DNs and
b. b. using **'per-pixel'** classifiers



Minimum desirable cluster / GIS polygon – 1 ha ? … ~ 11 pixels ?

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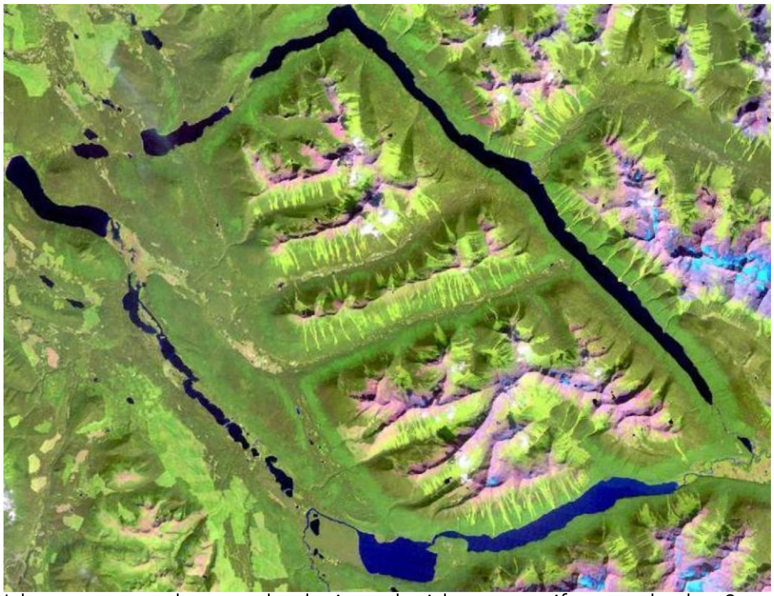
Challenges in classification – why it doesn't always beat digitising
There are many spatial variations in reflectance (a range of DNs for a feature)
e.g. stand purity, understory, age/maturity, density, disease, sun angle, **topography**



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

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There are many causes of spatial variations in reflectance (a range of DNs for a feature)
URBAN / HUMAN – mosaic of smaller features inside a 30 metre pixel
- amount of grass, types of material, roofing colour, weathering, sun angle (building shape)

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Classification….

It is always complex – the classes and their 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)

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

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