AESB2440: Geostatistics & Remote Sensing

Lecture 8: Terrain Classification

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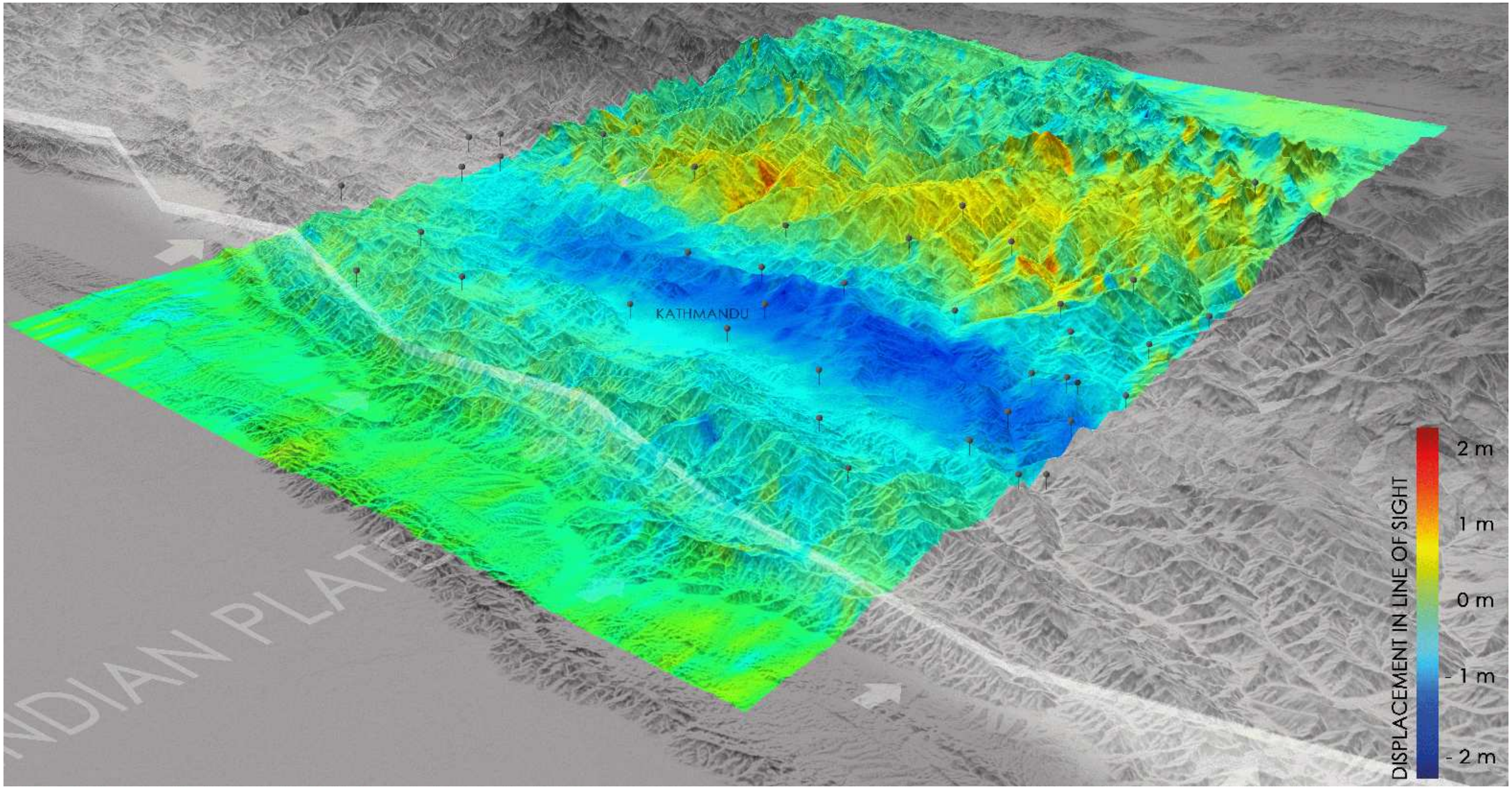
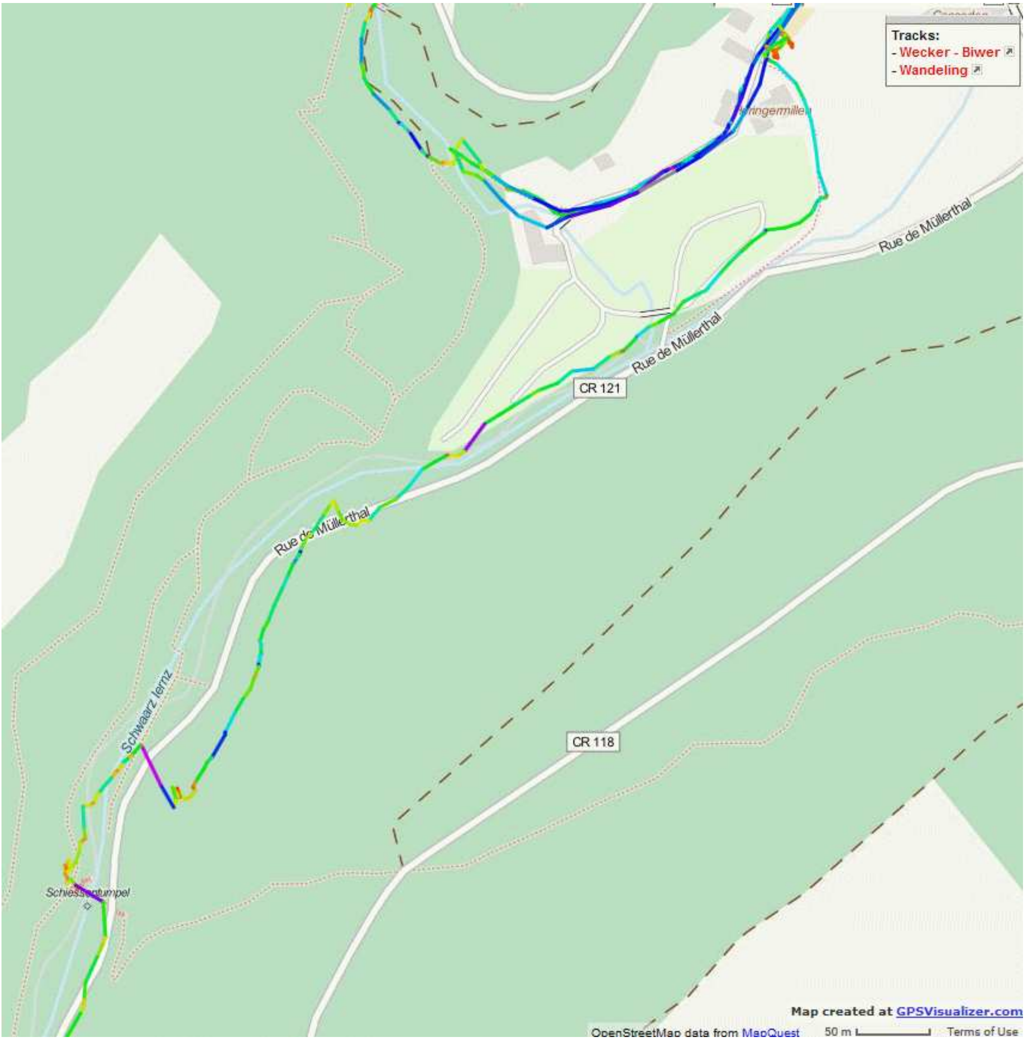
Update on height Mt. Everest



Source http://www.esa.int/spaceinimages/Images/2015/04/Nepal_earthquake_displacement

GNSS/GPS Experiment



Contents - Classification

Data with multiple bands

Feature Space

Supervised and unsupervised classification

Supervised: Closest Distance, SAM, Maximum Likelihood

Unsupervised: K-Means clustering

Validation of classification results

References

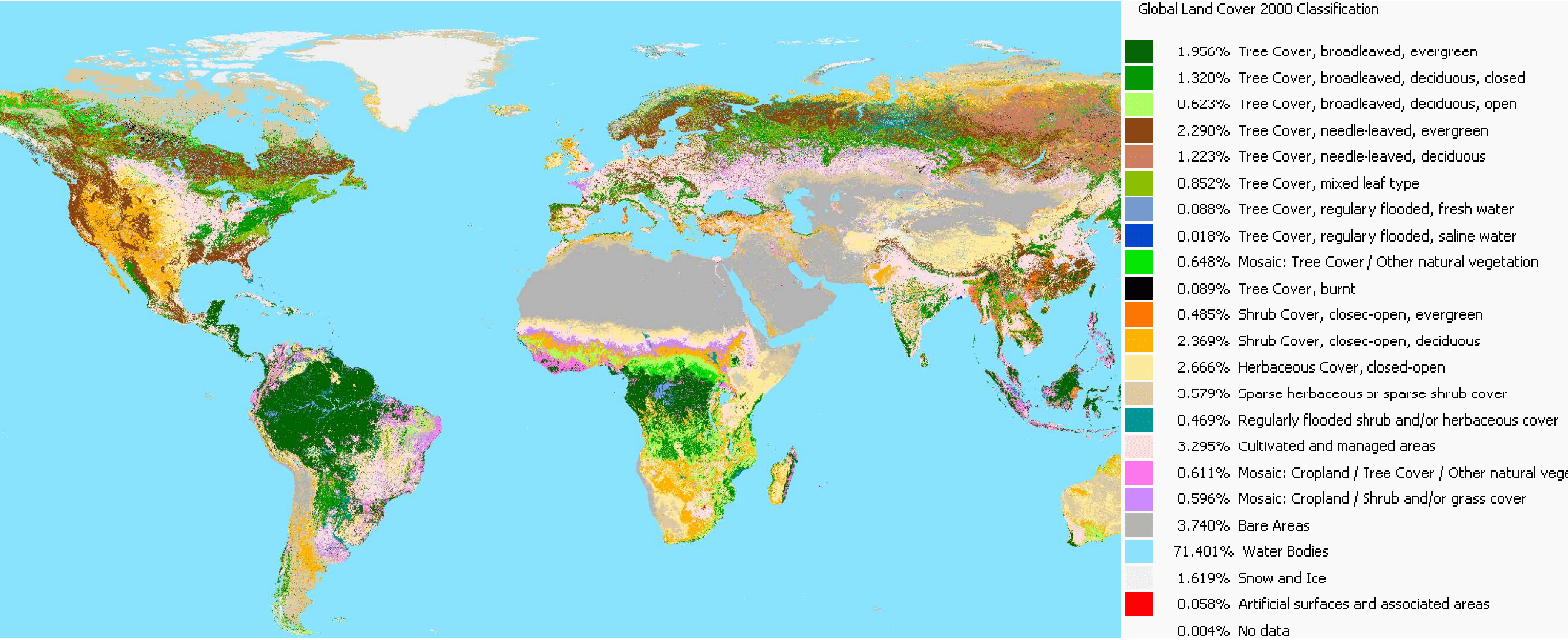
Available via Blackboard

Reduced Convex Hulls: A Geometric Approach to Support Vector Machines,
Sergios Theodoridis and Michael Mavroforakis,
IEEE Signal Processing Magazine, 119, May 2007

A Review of Assessing the Accuracy of Classifications of Remotely Sensed Data,
Russell G. Congalton,
Remote Sensing of the Environment 37:35-46 (1991)

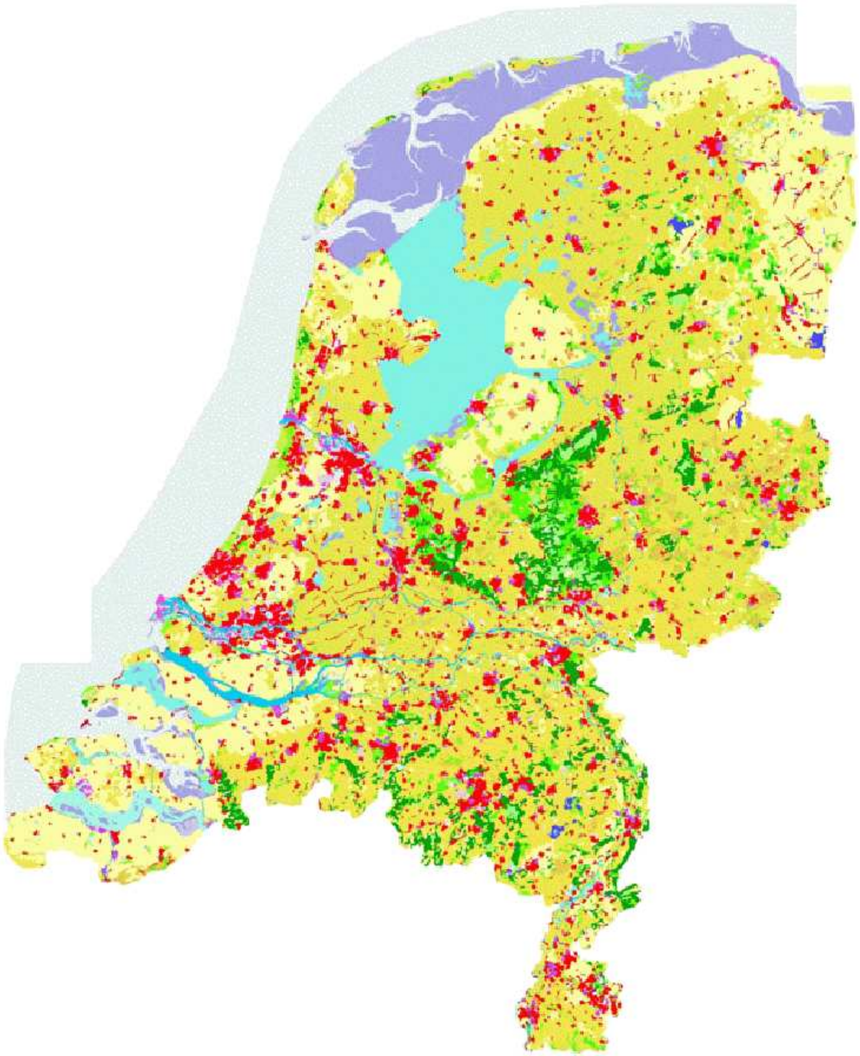
A. Goal and Principle of Classification

Earth surface classification



Source http://www.usna.edu/Users/oceano/pguth/website/so262/global_landcover.htm

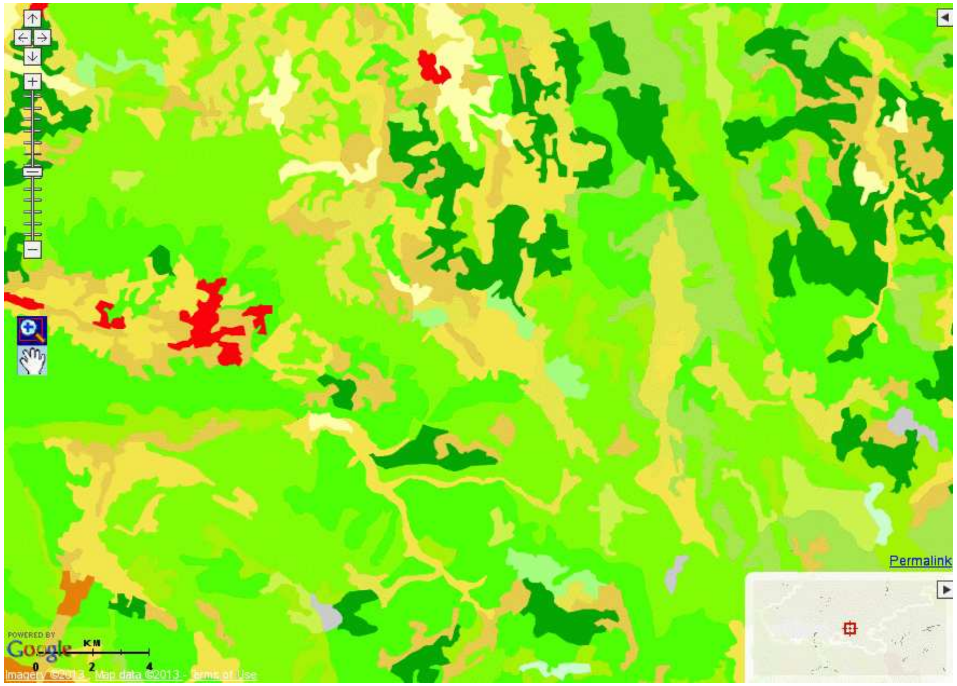
Land cover classification



- 11. Urban fabric
- 12. Industrial, commercial and transport units
- 13. Mine, dump and construction sites
- 14. Artificial, non-agricultural vegetated areas
- 21. Arable land
- 22. Permanent crops
- 23. Pastures
- 24. Heterogeneous agricultural areas
- 31. Forests
- 32. Scrub and/or herbaceous vegetation associations
- 33. Open spaces with little or no vegetation
- 41. Inland wetlands
- 42. Maritime wetlands
- 51. Inland waters
- 52. Marine waters

http://www.eea.europa.eu/data-and-maps/data/corine-land-cover-2000-clc2000-100-m-version-12-2009

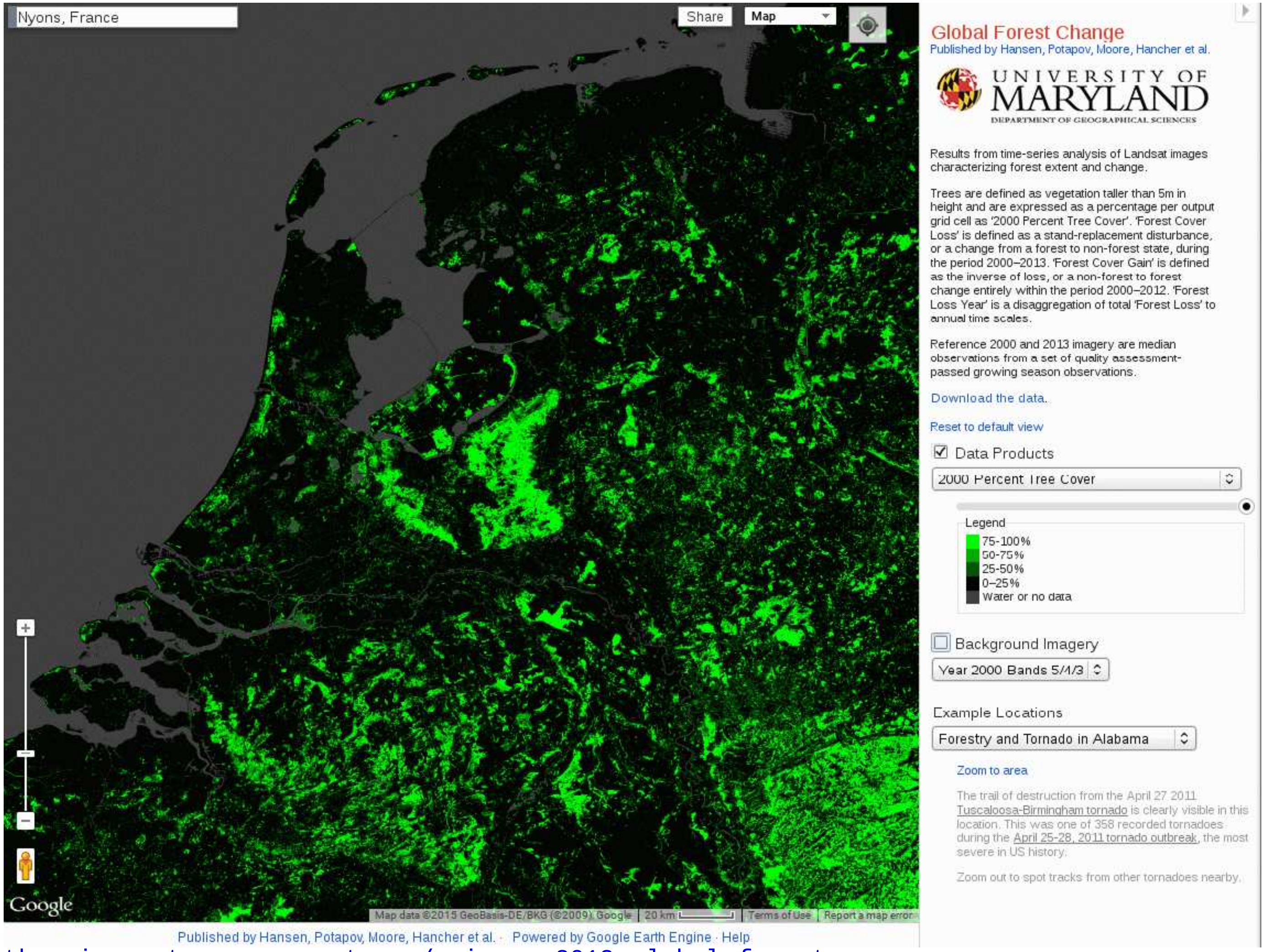
Vesc, Google + Land Cover



Red: Urban
Green: Natural areas: Forests, Meadows & Shrubs,
Yellow/Brown: Agricultural areas
Purple: Swamps

http://sd1878-2.sivit.org/

Global Forest Change



Source http://earthenginepartners.appspot.com/science-2013-global-forest

Landsat bands

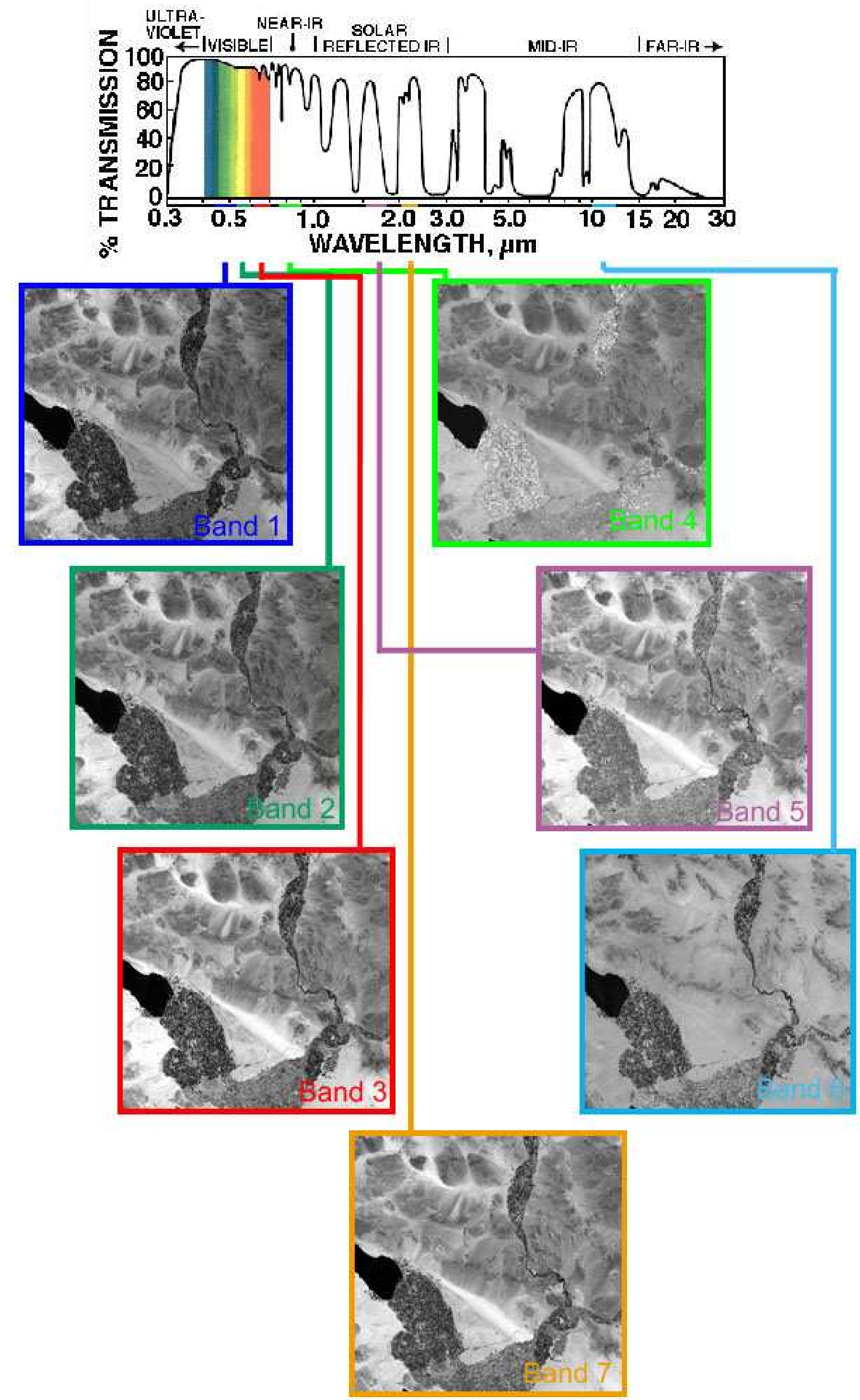
Landsat 7, spectral bands

Band	**Wavelength***	**Spectral Response**
1	0.45-0.52	Blue-Green
2	0.52-0.60	Green
3	0.63-0.69	Red
4	0.76-0.90	Near IR
5	1.55-1.75	Mid-IR
6	10.40-12.50	Thermal IR
7	2.08-2.35	Mid-IR

*: in micrometer, ($1\mu m = 10^{-6} m$)

IR: Infrared

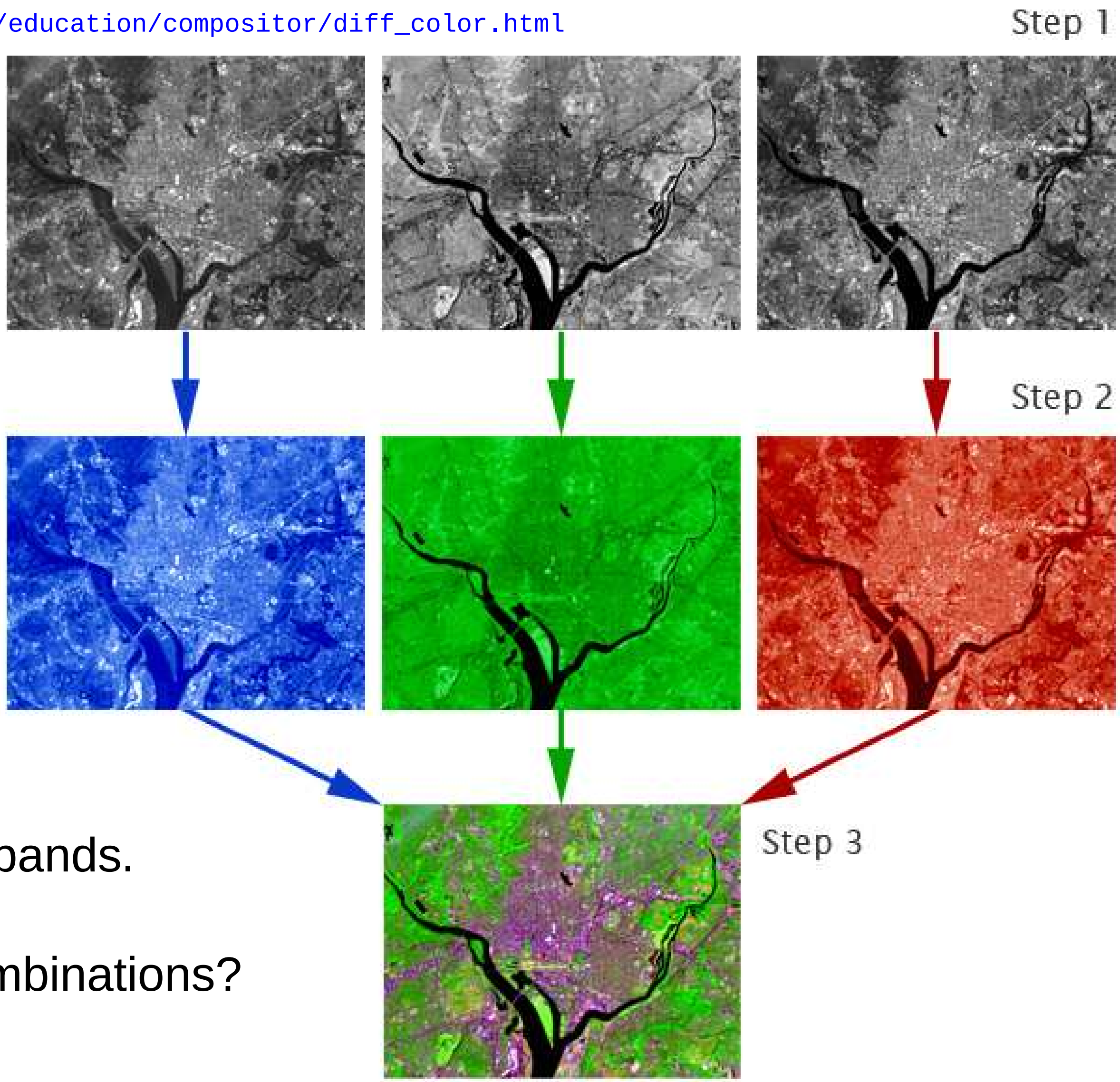
http://landsat.gsfc.nasa.gov/education/compositor/invisible_light.html



Electromagnetic Spectrum Image from Virtual Hawaii.

Landsat false color image

Source http://landsat.gsfc.nasa.gov/education/compositor/diff_color.html



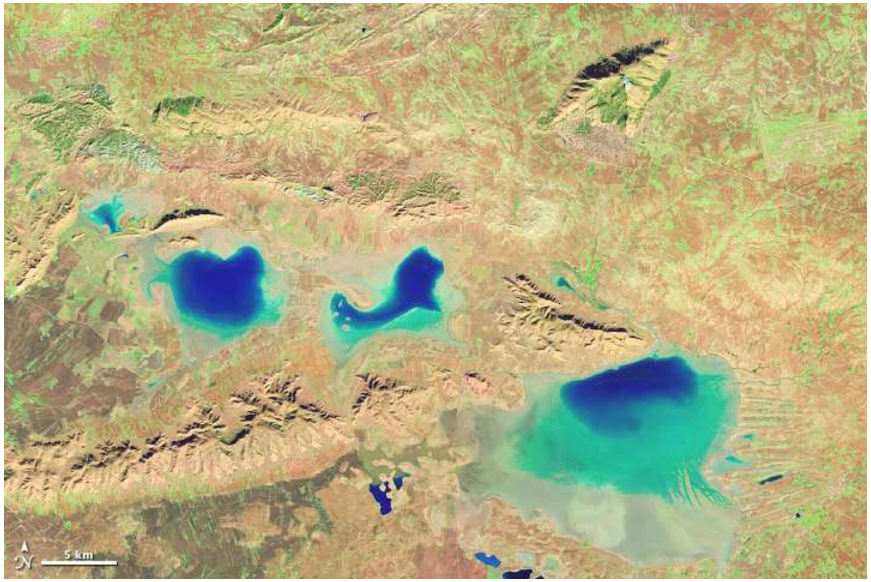
Many combinations of 3 bands.

Question. How many combinations?

Source http://landsat.gsfc.nasa.gov/education/compositor/color_comp.html

Band combinations and land cover

Different band combinations highlight different landcover



Near infrared light → red,
red light → green,
green light → blue
highlights vegetation

Shortwave infrared → red,
infrared → green
visible green → blue
highlights sediment rich water and
saturated soil

Source http://earthobservatory.nasa.gov/Features/FalseColor/page6.php

Landsat's Feature space

Artificial piece of Landsat data:

Location	Band 1	Band 2	Band 3	Band 4	Band 5	Band 6	Band 7
52.0 N 7.0 E	0.9	0.8	0.8	0.6	0.5	0.7	0.9
52.1 N 7.0 E	0.7	0.6	0.4	0.8	0.7	0.3	0.5
52.2 N 7.0 E	0.8	0.7	0.5	0.5	0.6	0.3	0.7
52.3 N 7.0 E	0.9	0.9	0.8	0.3	0.9	0.1	0.2
52.4 N 7.0 E	0.7	0.8	0.9	0.8	0.4	0.2	0.8

The properties of each pixel are described by a 7 dimensional vector.

Feature Space: 7D space (in this case) of all possible band combinations.

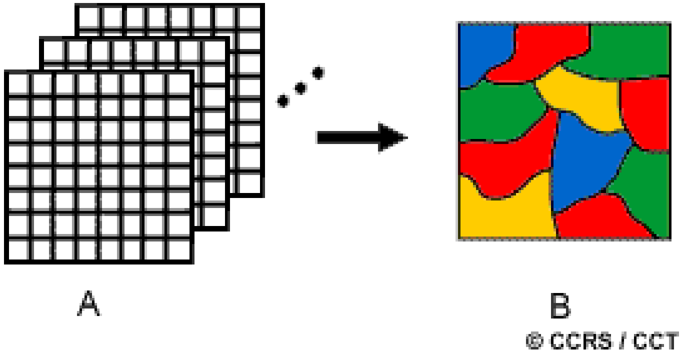
Class signature: "Part of the feature space where class members live"

Example

For the class Rock only certain band values are possible.

Classification

(Composite) image classification:
Assigning (composite) pixels to classes.



A. Input

- Grid of pixel locations
  (Think of Lat/LON pixels)
- Per location: $k(=7)$ bands.

B. Output

Subdivision of the locations in p classes.

Classes typically correspond to physically or thematically interpretable entities.

Class examples:

- Forest, pine forest
- Urban area, highway, road
- Water, river, floodplain
- Mountains, rock, granite rock

http://www.nrcan.gc.ca/earth-sciences/geography-boundary/remote-sensing/fundamentals/1920

Classification & Feature Space

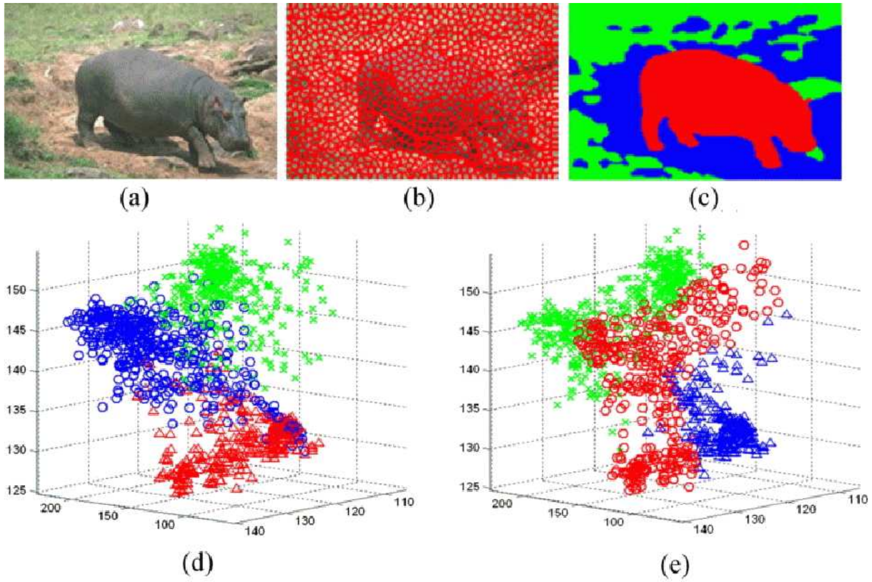
Most common way of classification:

Divide the (e.g. 7D) feature space in parts,
with each part corresponding to a target class.

Question. Possible exceptional scenario?

Feature Space, color image

Color is parameterized by 3 values (RGB, HSV,...)



For image classification:

- Determine for each pixel p_i its 3 color values, e.g. (r_i, g_i, b_i)
- Add point (r_i, g_i, b_i) to 3D RGB space.
- Divide 3D RGB space into components corresponding to suitable image classes.

Source: R. Huang, N. Sang, D. Luo, Q. Tang, Image segmentation via coherent clustering in Lab color space, Pattern Recognition Letters, 32(7), 1 May 2011, Pages 891-902

B. Supervised Classification

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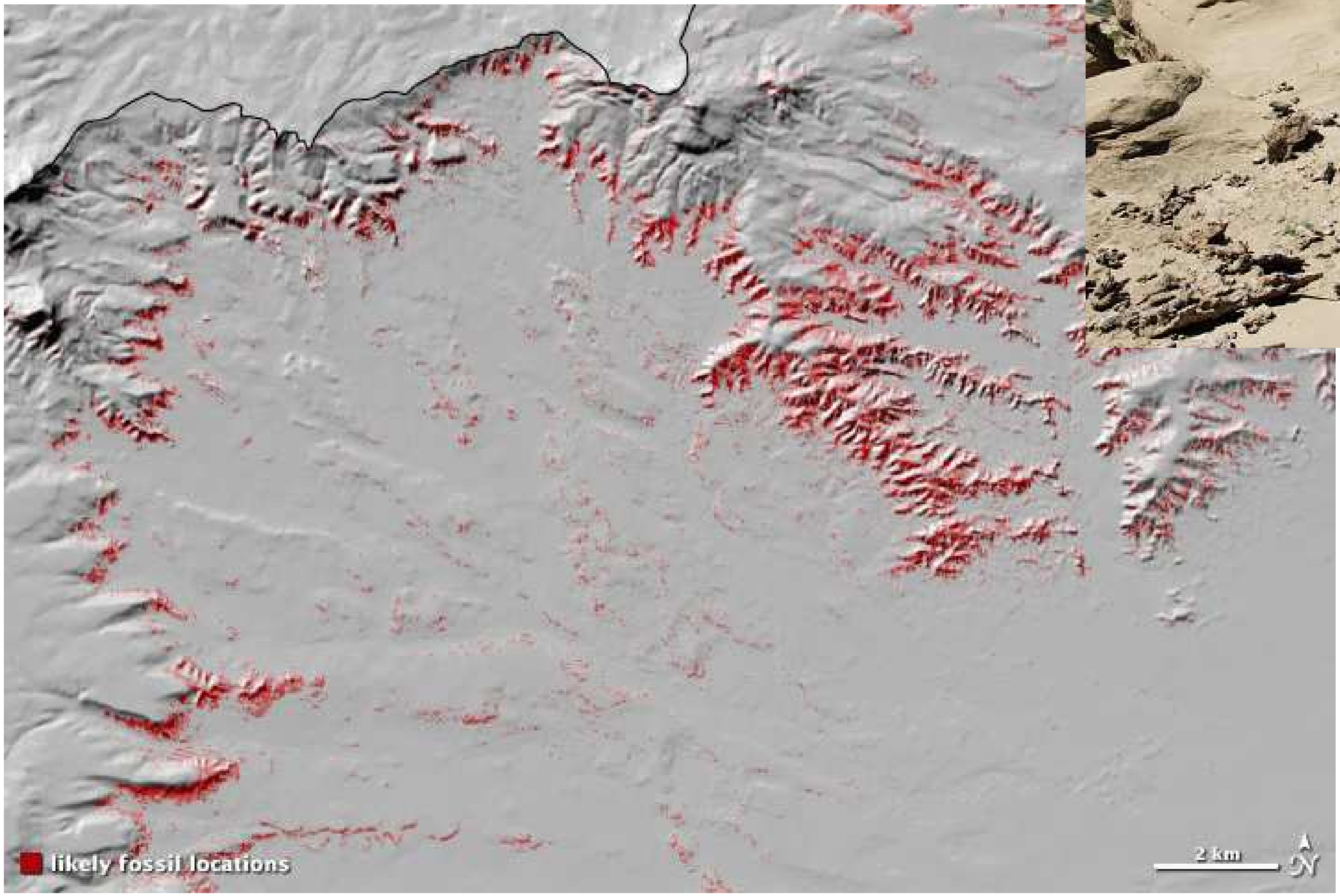
Fossil Hunting



http://earthobservatory.nasa.gov/IOTD/view.php?id=79613&src=eoa-iotd

Supervised Classification

Required: training data
$\Rightarrow$ Class membership is known for some of the pixels.

1) Use training data to derive statistics/signatures of each target class.

2) Use a rule to decide to which class a new pixel belongs to

Example methods

- Decision tree
- Minimum Distance Classification
- Maximum Likelihood Cl.
- Support Vector Machines
- Spectral Angle Mapping

Getting Training Data

A. Field work

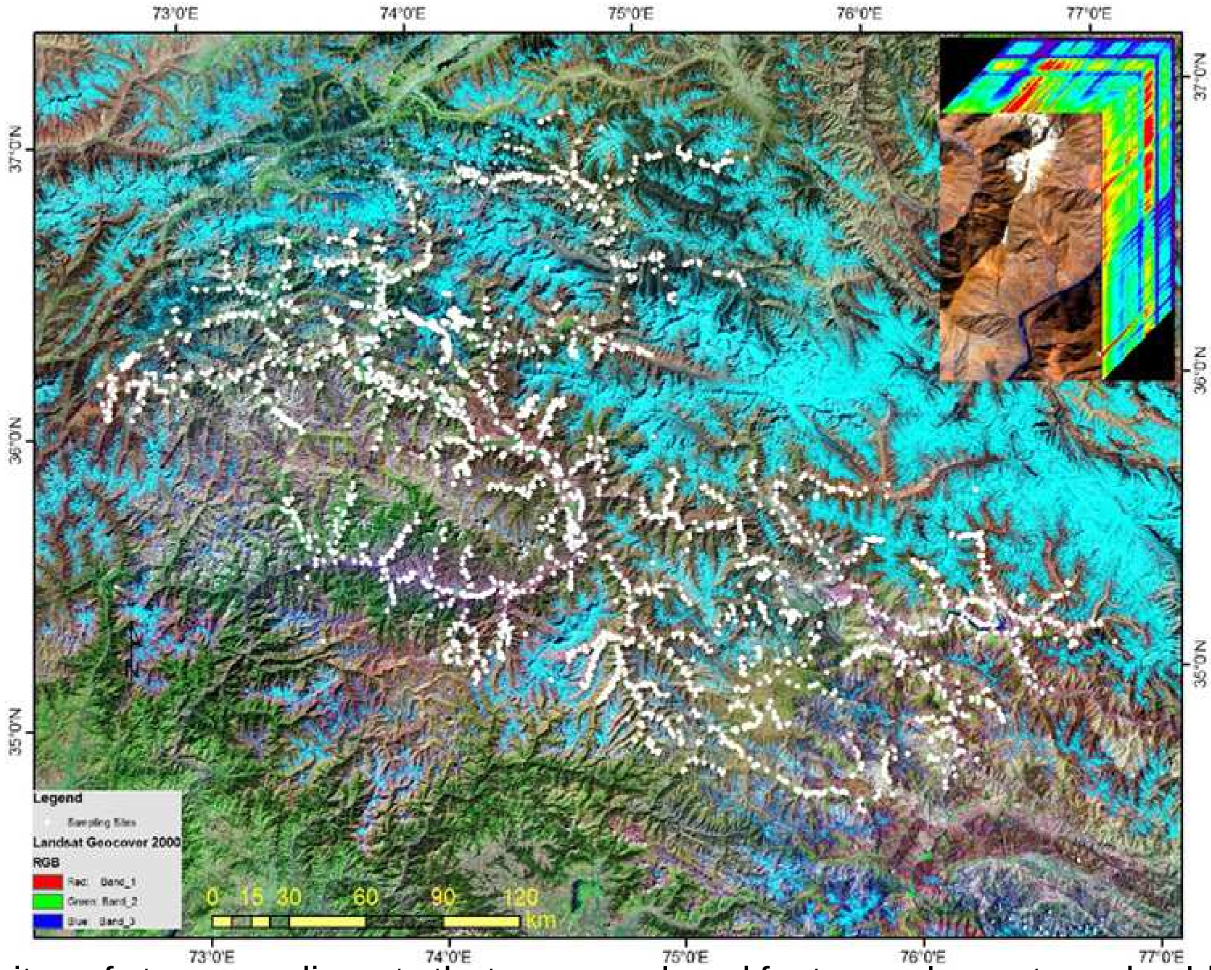
In situ measurements

B. By human operator

Judging e.g. Landsat data from screen.

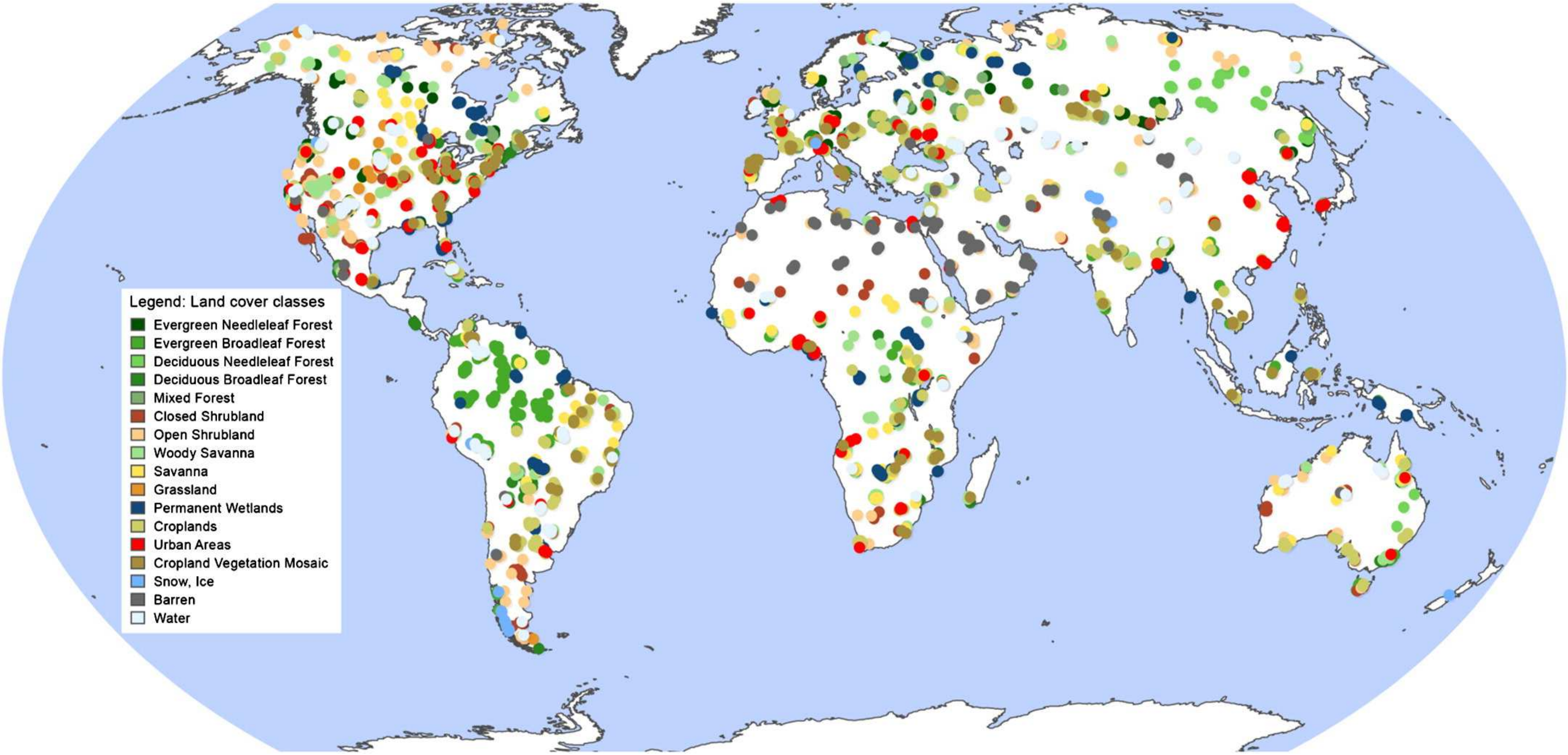
http://www.tankonyvtar.hu/hu/tartalom/tamop425/0027_BGD3/ch01s02.html

Looking for gold



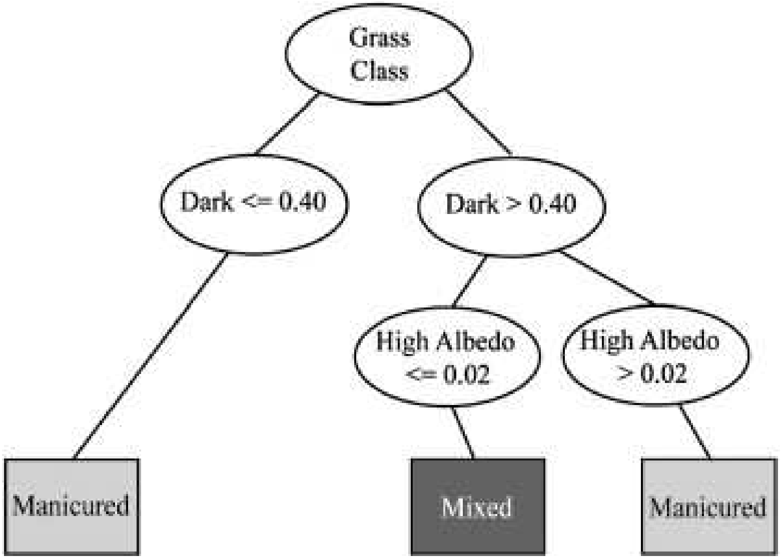
White dots are sites of stream sediments that were analyzed for trace elements and gold concentration. This data will be used for locating target sites for detailed remote sensing and geochemical studies in an attempt to identify potential source rocks. http://www.uh.edu/ sdkhan/projects/gold.php

Training Sites example



Source http://www.sciencedirect.com/science/article/pii/S003442571000091X

Decision Tree



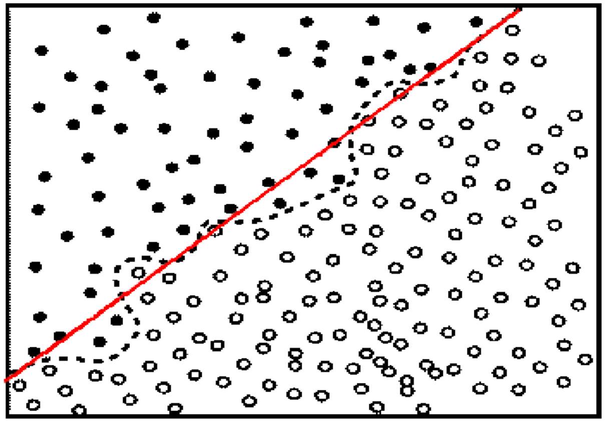
Advantages:

- Conceptually easy
- Mostly clear interpretation of decisions
- Gives reasonably good results is many cases

Disadvantages

- Per simple decision only 1 feature dimension is considered
- Too simplistic

Linear separation



The decision boundary between two classes in feature space is (part of) a (hyper)plane

Hyperplane in $\mathbb{R}^n$ is given by an equation of the form

$$g(\mathbf{x}) \; = \; w_1x_1 + w_2x_2 + \ldots w_nx_n \; + w_0 \; = \; \mathbf{w}^T \cdot \mathbf{x} + w_0 \; = \; 0$$

with $\mathbf{w}$ the weight vector and w_0 the offset.

Question. What are the hyperplanes in $\mathbb{R}^2$? What in $\mathbb{R}^3$?

Question. What is the dimension of the hyperplane for classifying Landsat 7 data?

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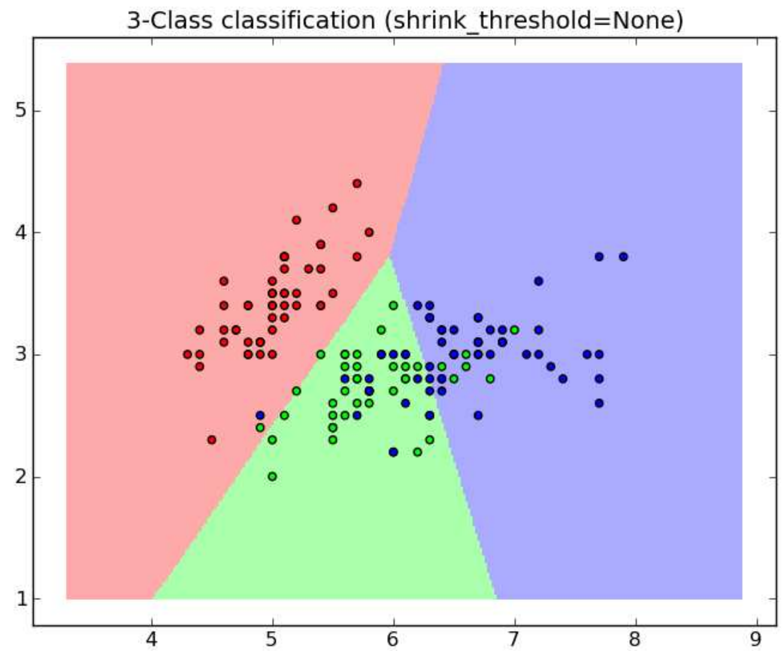
Nearest centroid classification



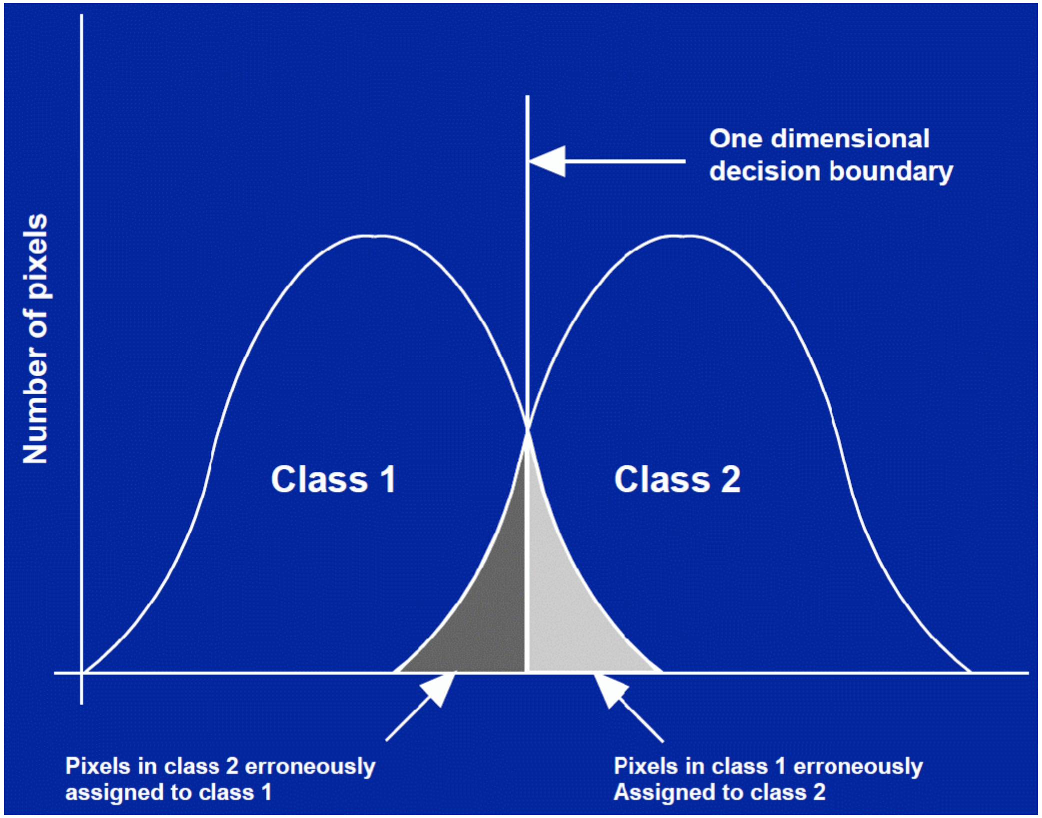
In k-D feature space:

1. Determine the centroid (mean) of the training pixels of each class
2. Get the Voronoi diagram of the centroids in k-D.

Remark: also called Minimum Distance Classification

Image source: http://scikit-learn.org/dev/auto_examples/neighbors/plot_nearest_centroid.html Also has Python implementations

Problem with linear separation



Source: (Jensen, 1996)

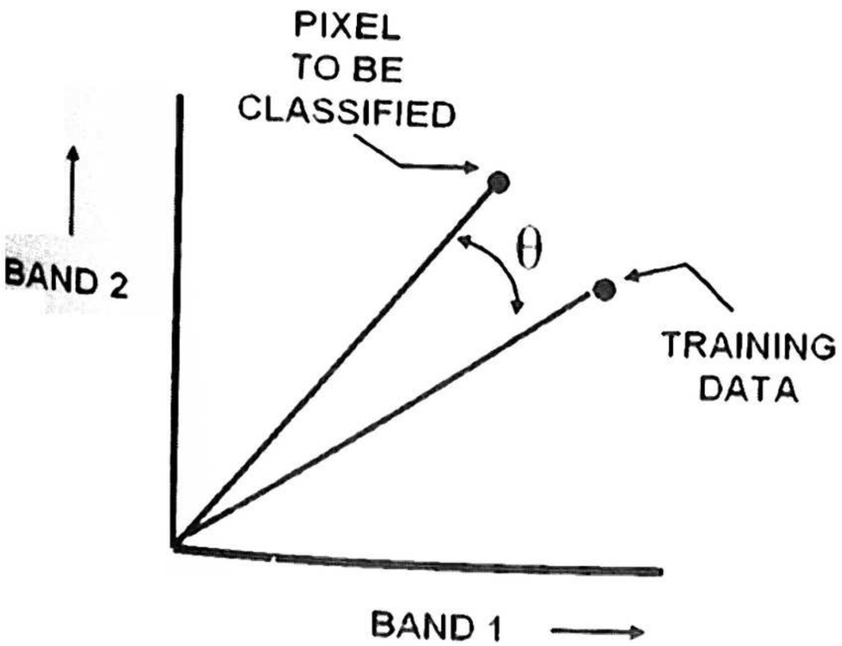
Spectral Angle Mapping

Idea: use "polar coordinates"

Determine the angle between

- a pixel to be classified, and each,
- class centroid

Assign pixel to class with the most similar k dimensional angle



Advantage

- Less sensitive to brightness variations

Question:
What could cause brightness variations?

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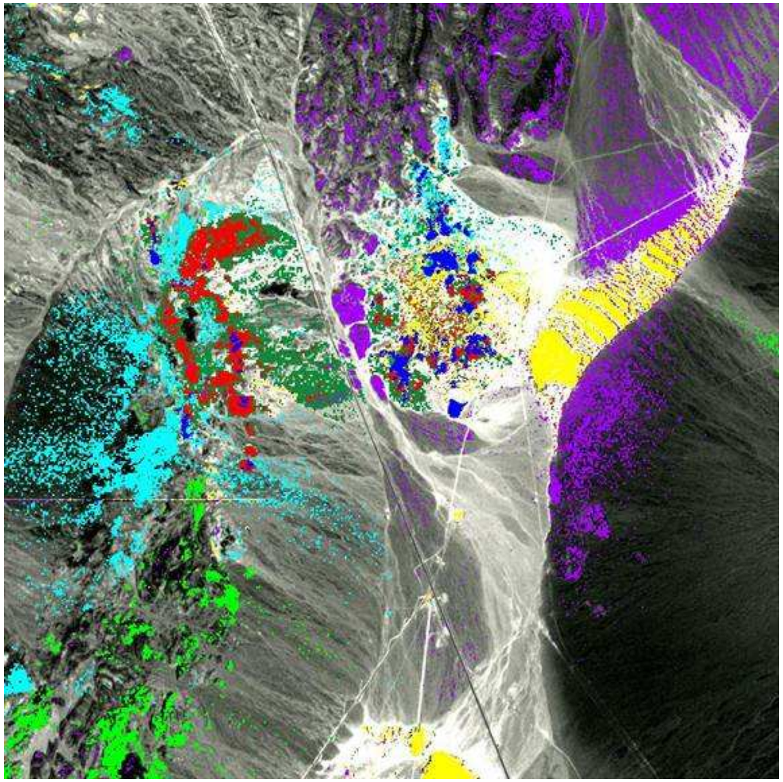
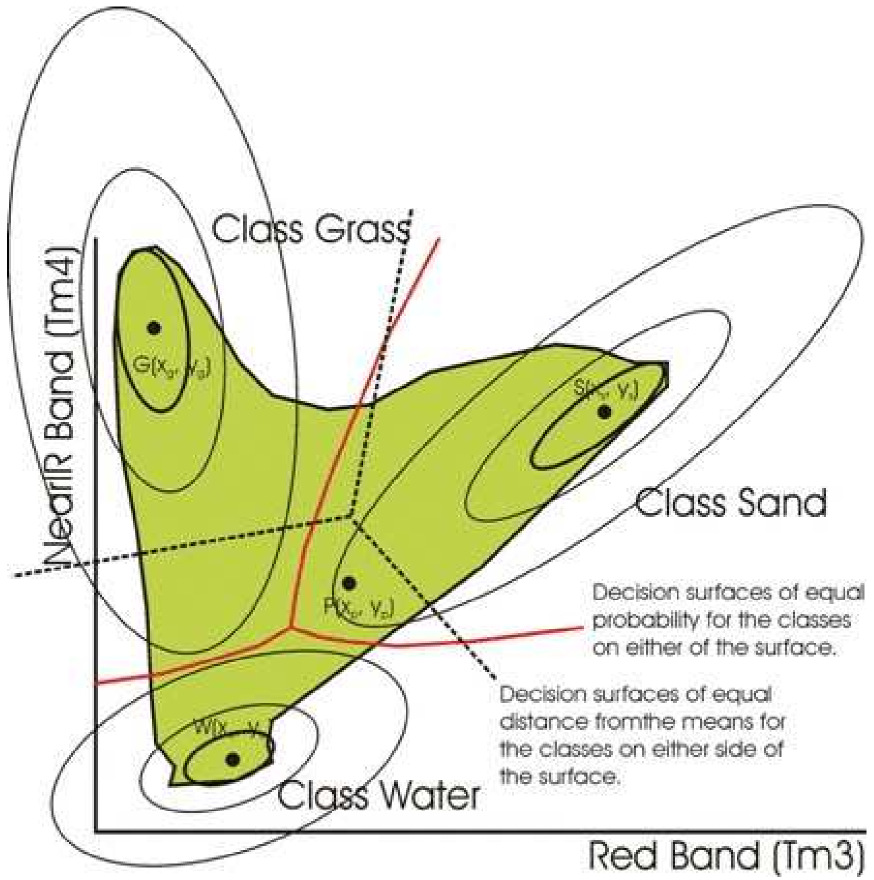
SAM mineral classification



Left. ASTER SWIR bands 4-6-8 as a RGB composite. Right. Spectral Angle Mapper classification results. blue=kaolinite; red=alunite; light green=calcite; dark green=alunite+kaolinite; cyan=montmorillonite; purple=unaltered; yellow=silica or dickite

Source https://asterweb.jpl.nasa.gov/content/03_data/05_Application_Examples/geology/default.HTM

Maximum Likelihood



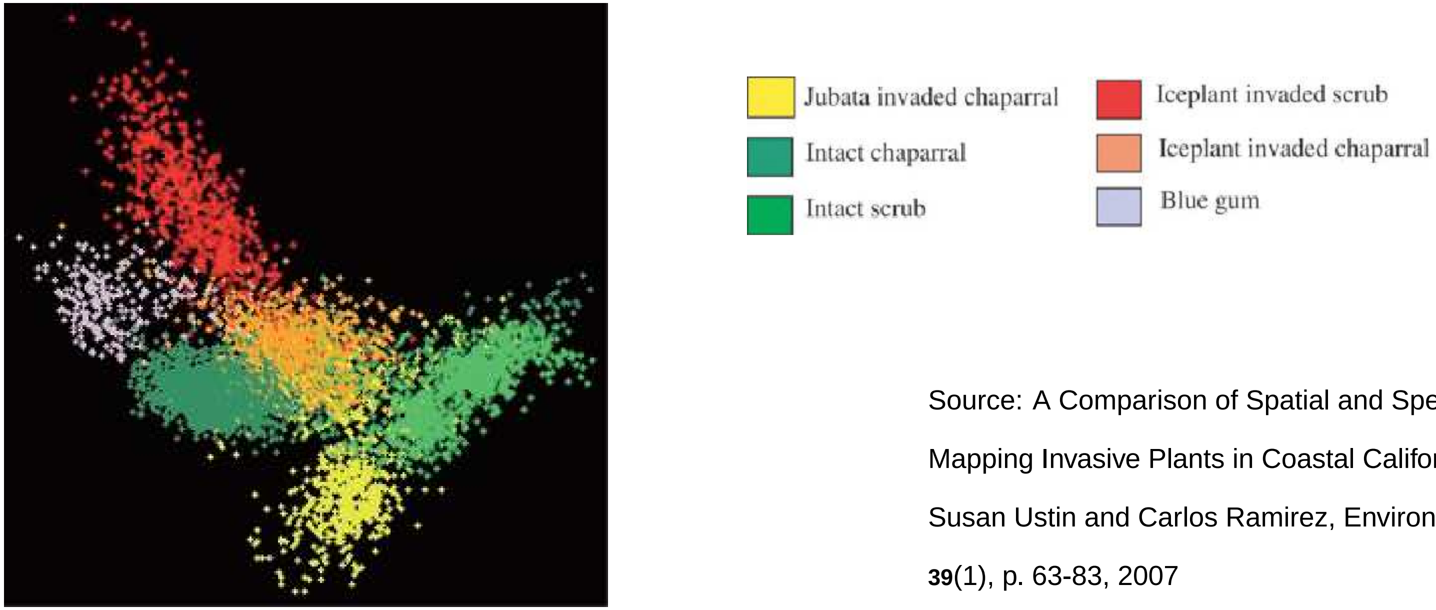
Choose the class that maximizes the probability of a correct classification, given the information in the training data.

Source http://www.seos-project.eu/modules/classification/classification-c05-p01.html

Maximum Likelihood Algorithm

Given: training data

1. Model the probability distribution of each class using the training data.
2. Estimate the likelihood that a given pixel belongs to (each) class.
3. Pick the most likely class.



Source: A Comparison of Spatial and Spectral Image Resolution for Mapping Invasive Plants in Coastal California, Emma Underwood, Susan Ustin and Carlos Ramirez, Environmental Management, **39**(1), p. 63-83, 2007

Principle MLE

Required Information MLE:
Probability Density Function.

Remark.
Best classifier
The error of misclassification is guaranteed to be minimal if $p(\mathbf{x}|B_i)$ is normally distributed.

Here $p(\mathbf{x}|B_i)$ denotes the probabilit density function of class B_i.

Assumption
Each probability density function is normal (and notably has one peak)

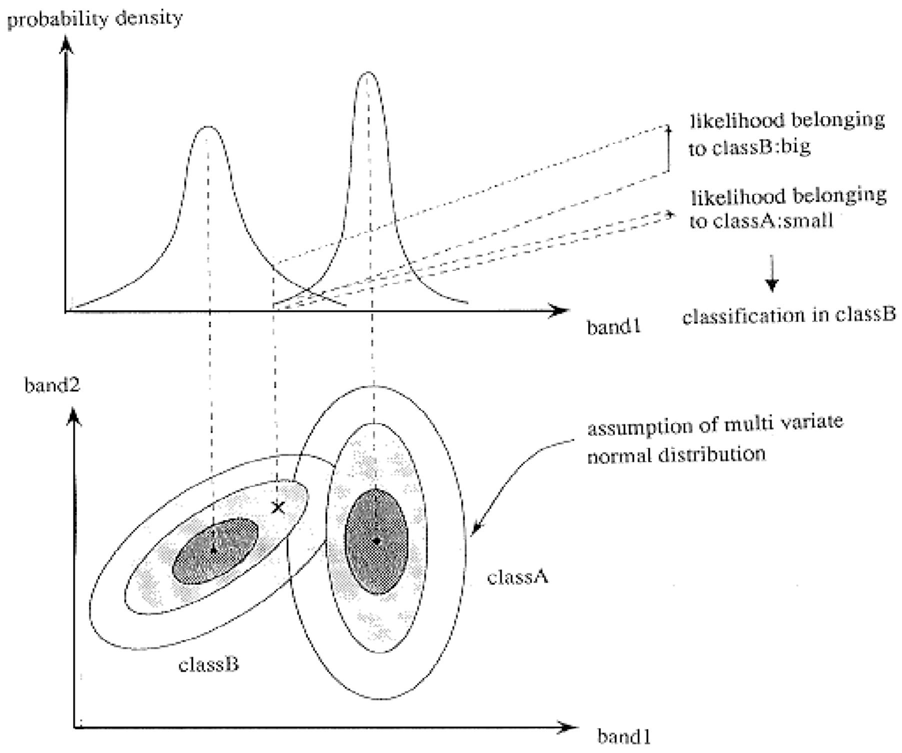


Figure 11.7.1 Concept of Maximum Likelihood Method

Source:

http://stlab.iis.u-tokyo.ac.jp/ wataru/lecture/rsgis/rsnote/contents.htm

Landsat classification results

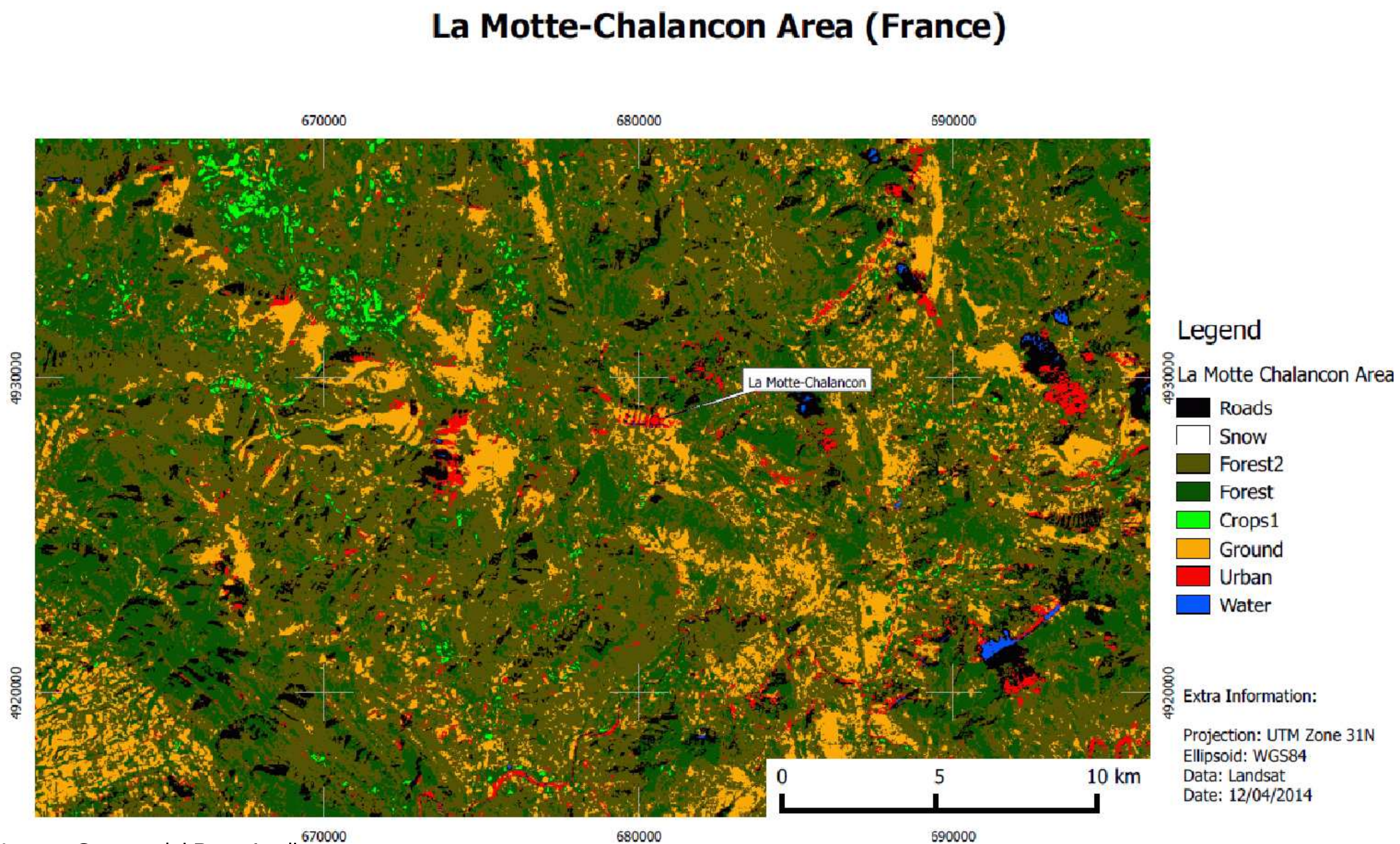
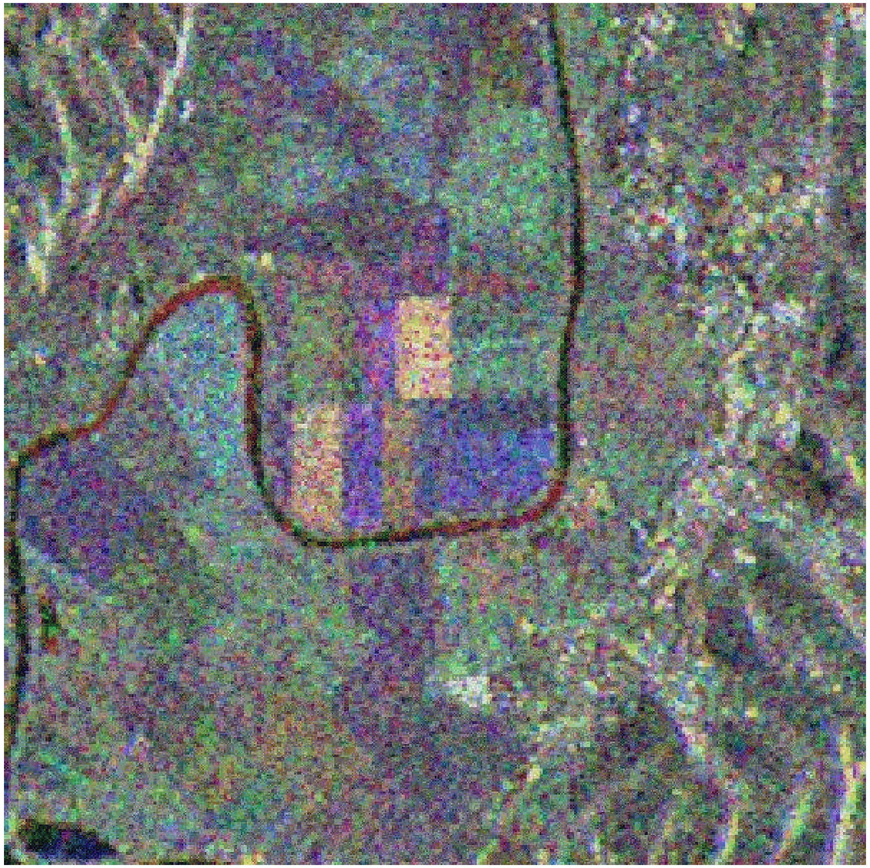
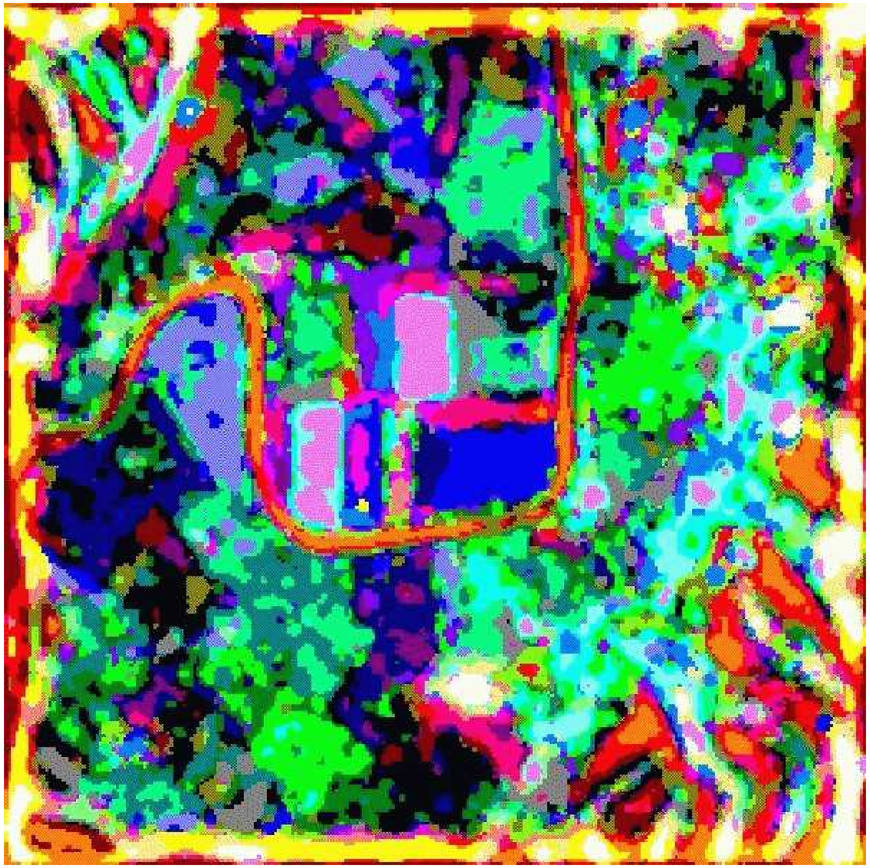


Image: Susana del Pozo Aguilera

C. Unsupervised classification

Unsupervised methods

Left: Multi-temporal ERS-1 SAR scene, Tiber Valley north of Rome

Right: Unsupervised classification obtained by a Neural Network

(Source: http://earth.esa.int/applications/data_util/SARDOCS/spaceborne/Radar_Courses/Radar_Course_III/classification_ERS.htm)

Unsupervised I: Clustering

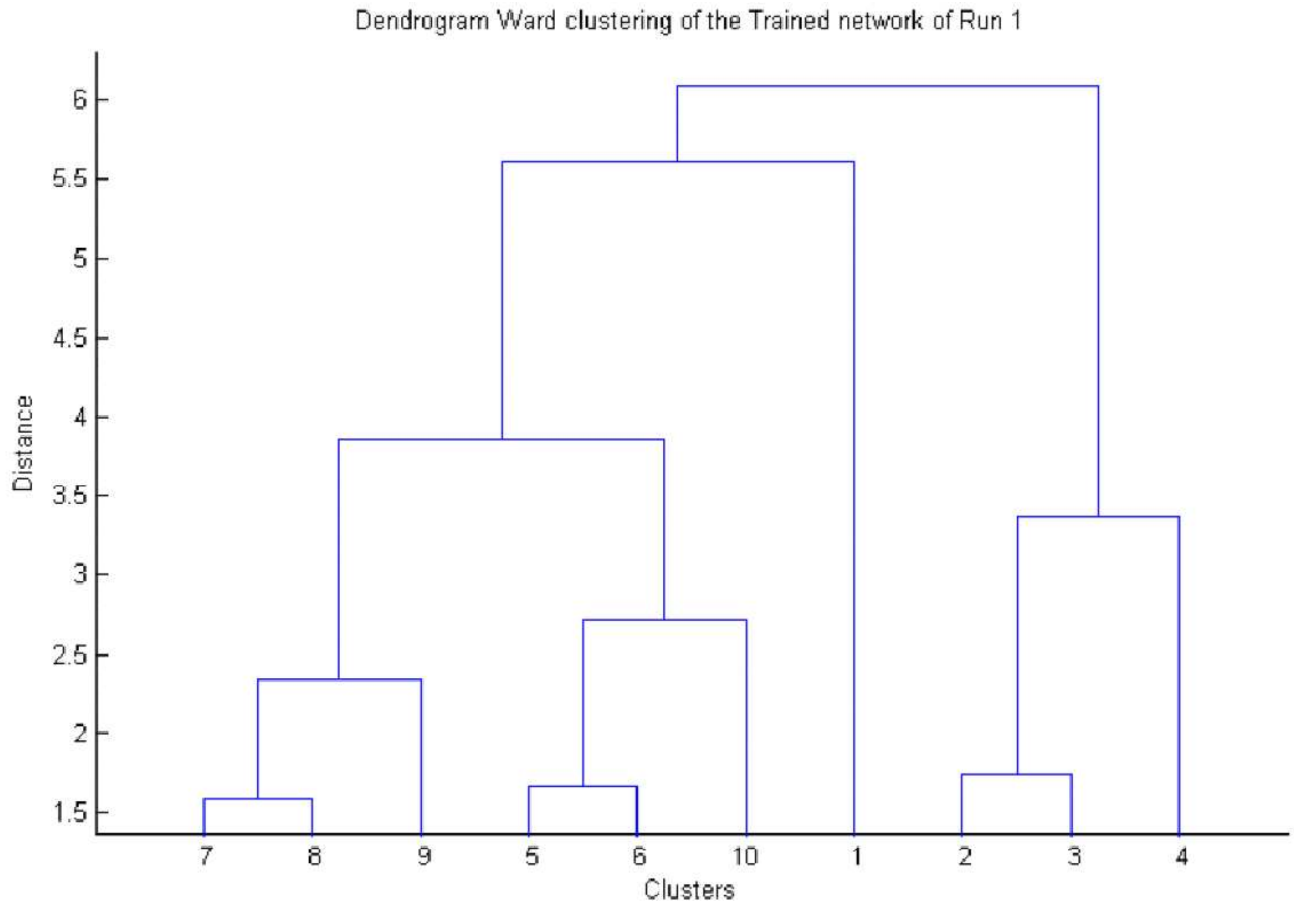
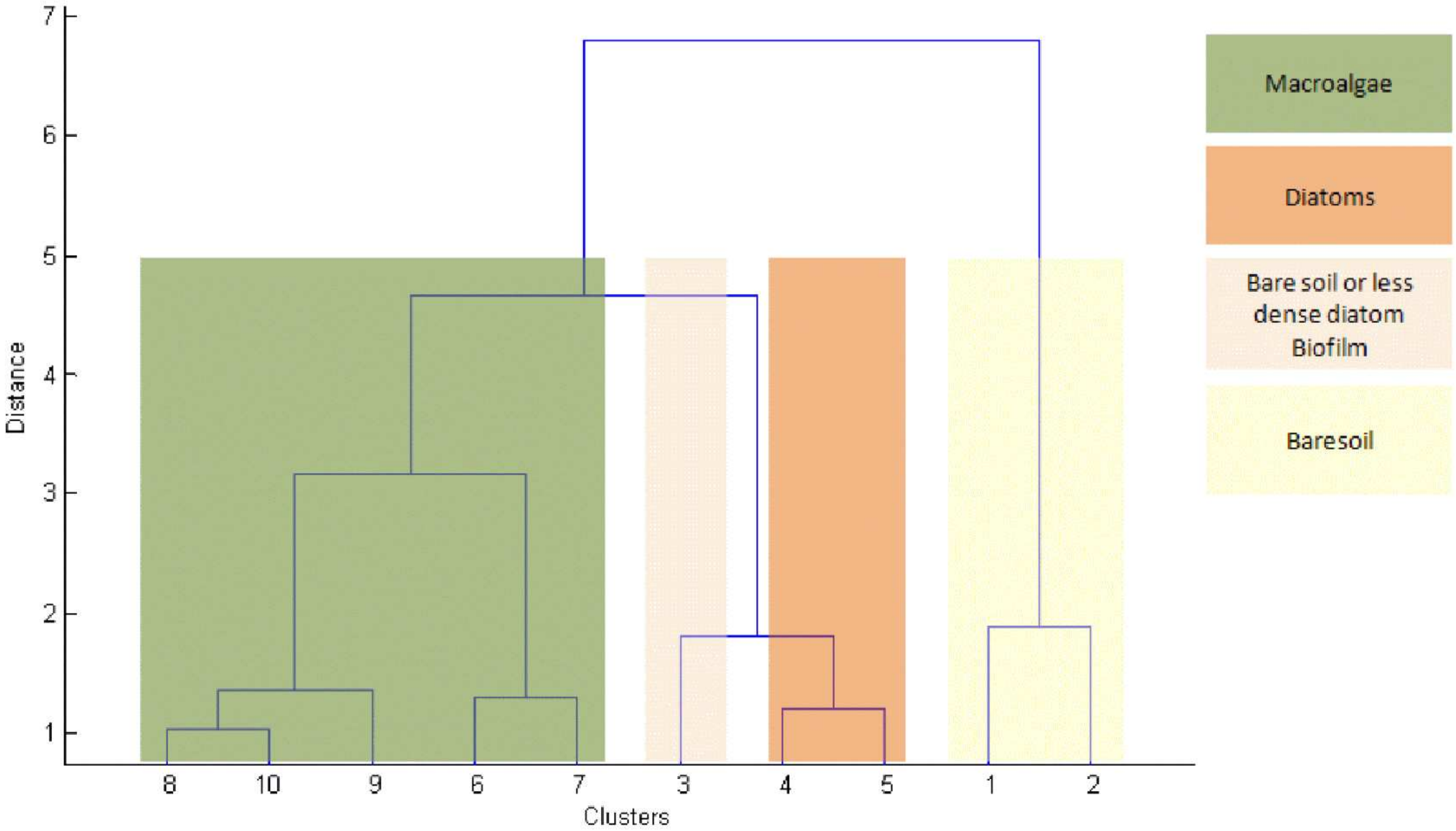


Figure 5-17: Dendrogram of Trained network

Unsupervised 2: Assigning classes



Source: Automatic detection of benthos & birds on the Galgeplaat mudflat using terrestrial imagery, (2012), P. Rammos, MSc thesis Geomatics, Delft University of Technology

Unsupervised Classification

Make link to physical classes after clustering the data.

Popular clustering techniques:

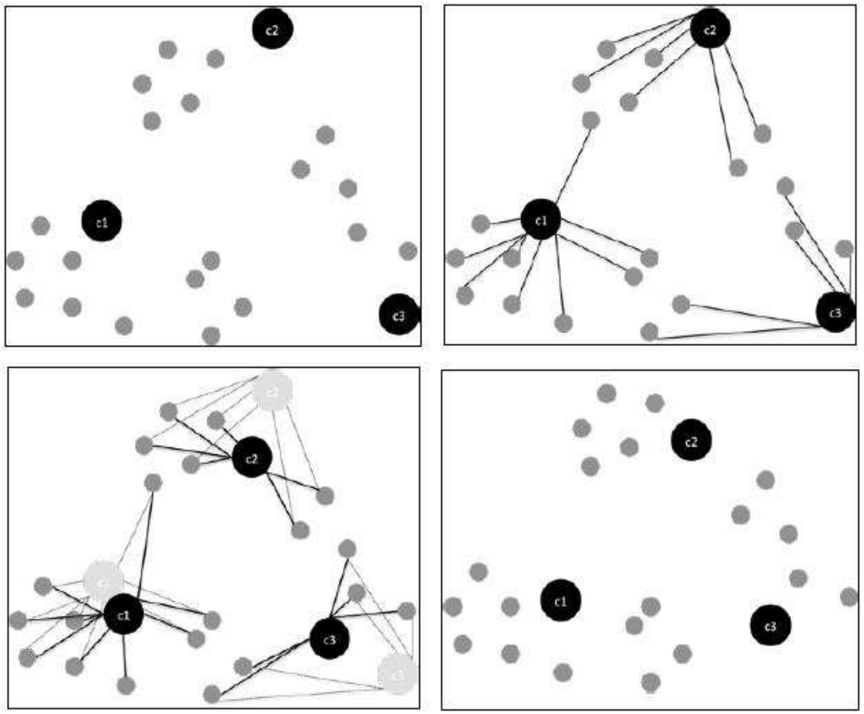
- Principal Component Analysis
- K-means
- Isodata
- . . .

Question (Dis)advantages Unsupervised?

- ...
- ...
- ...
- ...
- ...

K-means clustering

1. Specify the number of clusters
2. Assign centre coordinates to each cluster
3. Use a rule to assign each pixel to one cluster
4. Recalculate the centre coordinates of each cluster, based on its pixel members
5. Repeat Steps 3-4 until, say, no more then 1 % of the pixels is changing cluster.



K-means rule

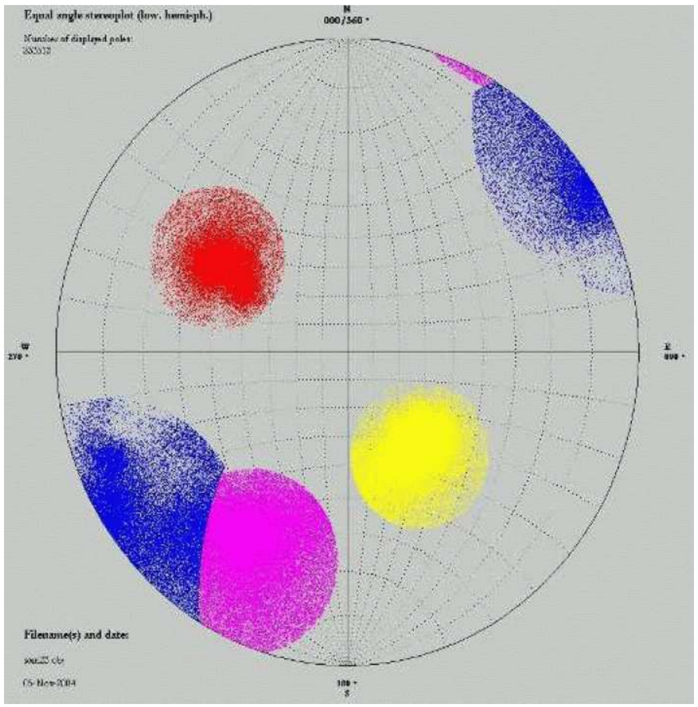
Use Euclidean distance to assign pixels to cluster centers.

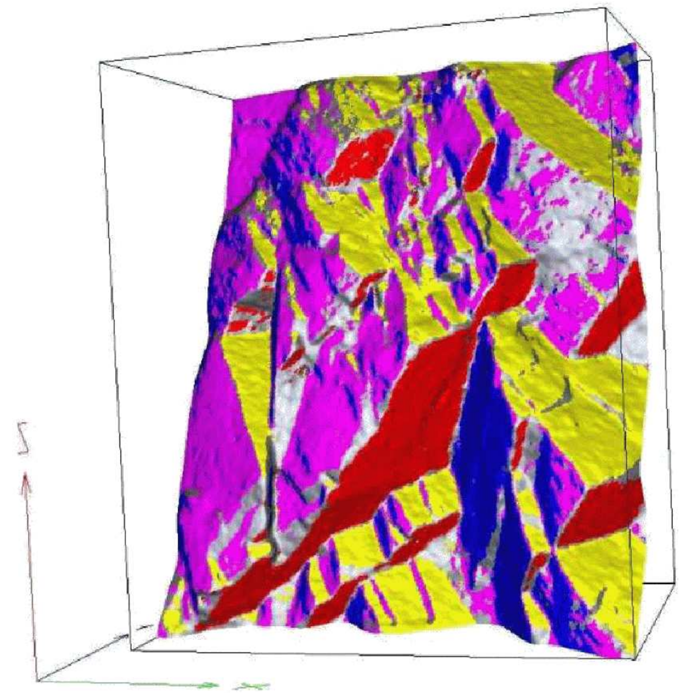
Question. How to assign centre coordinates to each cluster?

Parameters of the method:

1. Nr. of clusters
2. Nr. of iterations / Termination condition

Rock orientations





Polar plot of orientations of rock facets derived by fuzzy k-means clustering followed by a testing procedure.

3D surface model of a rock face, colored by orientation.

Source: Slob et al., (2005), A method for automated discontinuity analysis of rock slopes with three-dimensional laser scanning, *Transportation Research Record, 1913, pp. 187 -194*

K-means properties

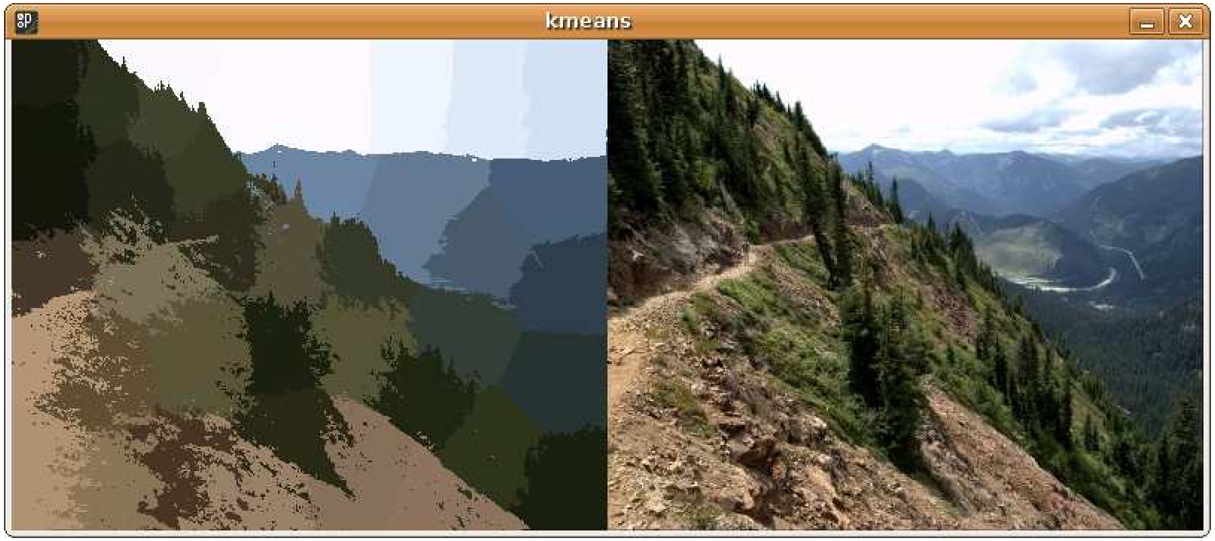
Remark.
The resulting clusters do not necessarily have a clear physical meaning.

Question Can the algorithm get stuck, swapping between two solutions? Is it always guaranteed to converge to a unique solution?

Question.
How to a priori relate the clustering to training data?
(Make it supervised).

Question. Possible extensions?

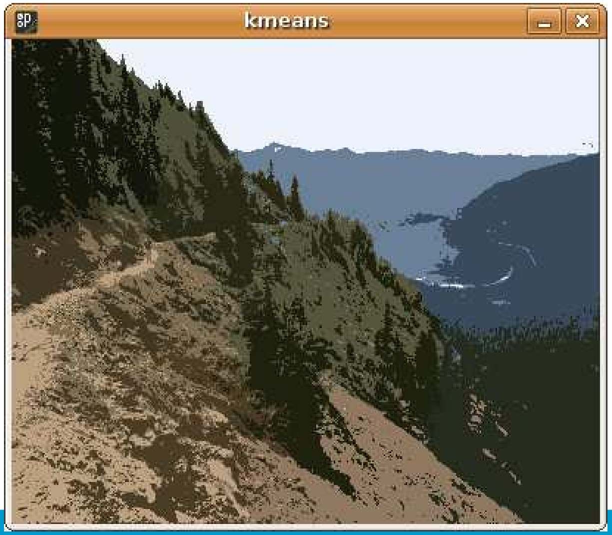
K-means: location or color values?



⇐ Input photo

⇑ Clustering result obtained by taking both pixel location and pixel RGB values into account

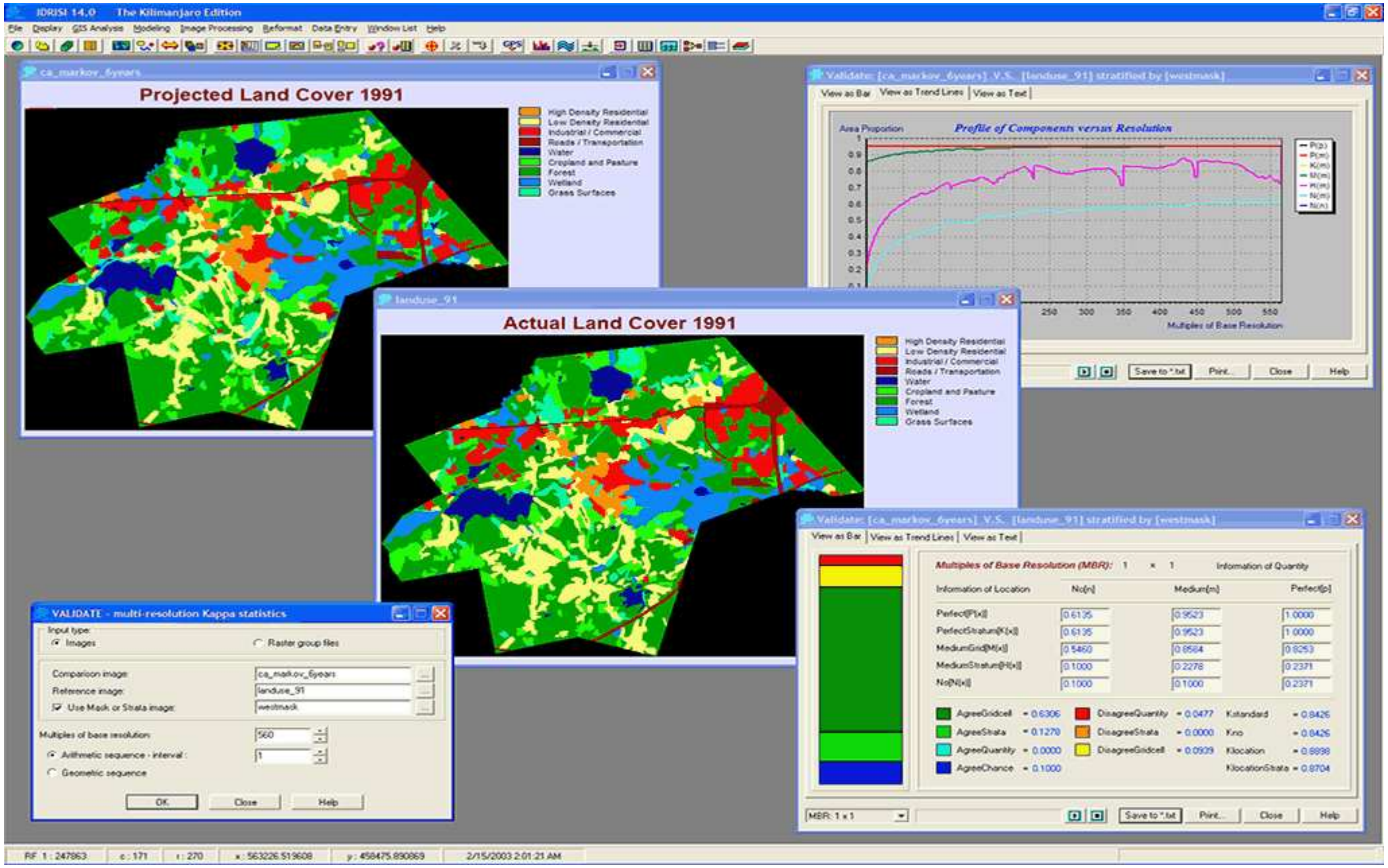
Clustering result obtained by taking only RGB values into account ⇒



Source: http://code.google.com/p/binarymillenium/wiki/KMeansCluster

D. Validation classification results

Classification Validation



Source: http://geoiconica.com

Validating classification results

Compare to ground truth data.

Commission error: a pixel falsely attributed to a class
Omission error: a pixel falsely omitted from a class

Commission example: a pixel is classified as water allthough it actually represents a forest

Omission example: A pixel that should have been classified as water was classified as forest.

Confusion Matrix

	Reference Data				
Classification Data	W	B	HV	U	Total
W	2573	398	185	6	3162
B	644	1175	457	21	2297
HV	706	1873	7410	216	10205
U	44	81	507	4438	5070
Total	3967	3527	8559	4681	15596

Table 1. Confusion matrix

Class	Prod. Acc. (%)	User Acc. (%)	Prod. Acc. (pixels)	User Acc. (pixels)
W	81.37	64.86	2573/3162	2573/3967
B	51.15	33.31	1175/2297	1175/3527
HV	72.61	86.58	7410/10205	7410/8559
U	87.53	94.81	4438/5070	4438/4681

Table 2. Classification results

Entries, confusion matrix

$n \times n$ matrix $\mathcal{E}$, with n the number of classes.

e_{ij}	-	Number of pixels from class i classified as class j
e_{ii}	-	Correctly classified pixels
e_{ij}, $i \neq j$	-	Wrongly classified pixels.

Question. Where are the omission and commission errors in the confusion matrix?

Ref: e.g. Introduction to Remote Sensing, 5th ed., Campbell and Wynne, Guilford Press, 2011.

Confusion matrix

Compare, class by class, the relationship between reference data (ground truth) and the corresponding results to be validated

1. Producer's accuracy: probability that a reference pixel has the same class as the corresponding classified pixel.
2. User accuracy: probability that a classified pixel has the same class as the corresponding pixel in the reference data
3. Overall accuracy: probability that a pixel randomly taken from the classified data has the same class as the corresponding pixel in the reference data and vice versa.

Question.

1. How to compute the Producer's accuracy?
2. And how to determine the User's accuracy?
3. And the Overall accuracy?

Kappa

$$\kappa = \frac{\text{observed} - \text{expected}}{1 - \text{expected}}$$

Observed accuracy: Proportion of correctly classified pixels
Expected agreement: Proportion of pixels that could be expected to be classified correctly by chance.

$$\hat{\kappa} = \frac{n\sum_{i=1}^{r} e_{ii} - \sum_{i=1}^{r}(e_{i+} \cdot e_{+i})}{n^2 - \sum_{i=1}^{r}(e_{i+} \cdot e_{+i})},$$

r	-	Nr. of rows in the confusion matrix;
e_{ii}	-	observation in row and column i;
e_{i+}	-	the total number of observations in row i
e_{+i}	-	total number of observations in column i
n	-	Nr. of matrix entries.

Question. What is κ for our example?

Conclusions

Classification (also called Machine Learning) is a huge topic. We only considered a few of the most popular methods.

Classification can be used as a black box: just validate the outcomes and check if you are satisfied.

Validation is reasonably straightforward given good ground truth data.

Knowledge of classification methods may help dealing with issues like

- Computational feasibility
- Robustness
- Improving quality of results
- Implementational issues
- Understanding and tuning of parameters

Exercises

Feature space dimension

Exercise 8.1

What is the dimension of the feature space in the following classification problems?

a). Clustering of regions in a BW photograph according to gray level

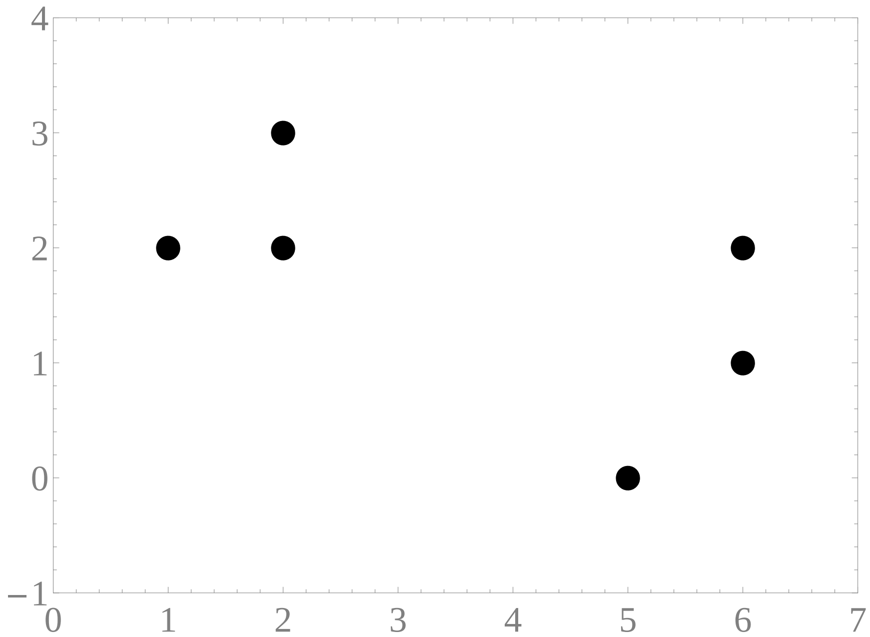
b). Clustering of regions in a color photograph according to RGB values

c). Classification of a Landsat 7 scene according to spectral band values

d). Classification of a Landsat 7 scene according to spectral band values and elevation as obtained from superimposed ASTER GDEM data

e). Classification of a Landsat 7 scene according to spectral band values, elevation and location.

Clustering



Exercise 8.2 In the figure the points $p_1 = (1, 2)$, $p_2 = (2, 3)$, $p_3 = (2, 2)$, $p_4 = (5, 0)$, $p_5 = (6, 1)$ and $p_6 = (6, 2)$ are shown.

a). Run 2-means clustering on the points. Start once with a point from each of the two obvious clusters, and once with two points outside these clusters. What is the difference between the cluster centers after three iterations?

Suppose points p_1, p_2 and p_3 belong to class C_1 and the other three points to class C_2.

b). What is the division of the plane in two classes according to nearest centroid classification?

c). Sketch the (contour) lines of the probably density function of classes C_1 and C_2. Indicate, based on your sketch, which part of the rectangle would belong to classes C_1 and C_2 according to maximimum likelihood classification.

d). What is the angular difference between a pixel at location $(2, 0)$ and the centers of the classess C_1 and C_2? To what class does location $(2, 0)$ belong according to SAM?

Exercise, Confusion Matrix

Matrix A

Actual land use	Interpreted land use: Urban	Agriculture	Range	Forest	Water	Total
Urban	510	110	85	23	10	738
Agriculture	54	1,155	235	253	35	1,732
Range	15	217	930	173	8	1,343
Forest	37	173	238	864	27	1,339
Water	5	17	23	11	265	321
Total	621	1,672	1,511	1,324	345	5,473

Exercise 8.3

Refer to Matrix A. Results of a spectral classification (interpretation) of land use are compared to actual land use.

a). Which class shows the highest error of commission?

b). What class was most often confused with agricultural land?

c). Which class was most accurately classified? Which class has the lowest accuracy?

d). Which class shows the highest number of omission errors?

Answers, Exercise 8.1

1. BW photo, 1 band, only gray level, so dimension feature space is 1.
2. Color photo, 3 bands, R, G and B, so dimension feature space is 3.
3. According to website, `http://landsat.usgs.gov/band_designations_landsat_satellites.php`, Landsat 7 has eight bands, so dimension feature space is 8.
4. In this case there is an extra elevation band (from ASTER GDEM), so dimension feature space is 9.
5. To fix a location on Earth we need two parameters (e.g. latitude and longitude, so 2 more bands, dimension becomes 11.

Answers, Exercise 8.2

1. First run, choose e.g. $p_L := p_1$ and $p_R := p_6$ as cluster centres. Determine the distances from all 6 points to p_1 and p_6:

$$\text{To } p_L : (0., 1.41, 1., 4.47, 5.10, 5)$$

$$\text{To } p_R : (5., 4.12, 4., 2.24, 1., 0.)$$

Indeed, p_1, p_2 and p_3 are more close to p_L, the other three points are more close to p_R. Now determine the new cluster centres: $p_L = (p_1 + p_2 + p_3)/3)$ and $p_R = (p_4 + p_5 + p_6)/3)$ and after that, the updated distances:

$$\text{To } p_L : (0.75, 0.75, 0.47, 4.07, 4.53, 4.35)$$

$$\text{To } p_R : (5., 4.12, 4., 2.24, 1., 0.)$$

Of course p_1, p_2 and p_3 are still most close to p_1, the others most close to p_6. Nothing changes, so we are done
Second try. Start with $p_L = (0, 0)$ and $p_R = (4, 4)$. The locations are clearly outside the clusters:

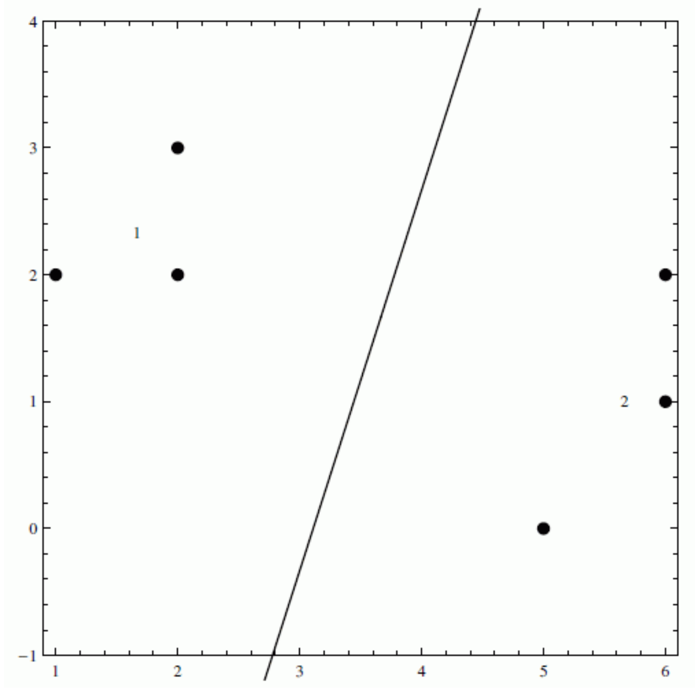
$$\text{To } p_L : (2.24, 3.6, 2.83, 5., 6.08, 6.32)$$

$$\text{To } p_R : (3.6, 2.24, 2.83, 4.12, 3.61, 2.83)$$

Points p_1 and p_3 are closer to p_L, the other points are closer to p_R. So new cluster centres: $p_L = (p_1 + p_3)/2)$ and $p_R = (p_2 + p_4 + p_5 + p_6)/4)$. Determine new distances, and you'll see that allready points p_1, p_2 and p_3 are closer to p_L and the other three closer to p_R, so we are done again (compare 1st case)

Answers, Exercise 8.2 (coninued)

3. In the figure, Voronoi diagram of the centroid of the two clusters (indicated with ‘1‘ and ‘2‘)
4. No answer yet
5. No answer yet



Answers, Exercise 8.3

1. ommission error: pixels assigned to the wrong class
   Assigned to urban: 621; Wrongly assigned: 621-510 = 111; Percentage: 18%
   Assigned to agriculture 1672; Wrongly assigned: 1672-1155=517; Percentage: 31%
   Assigned to range:1511; Wrongly assigned to range: 1511-930=581: Percentage: 38%
   Assigned to forest:1324; Wrongly assigned to forest: 1324-864=460: Percentage: 35%
   Assigned to water:345; Wrongly assigned to water: 345-265=90: Percentage: 26%
   So largest commission error for the range class
2. Confusions with agriculture:
   From urban: 54 + 110 = 164 confusions;
   From range: 217 + 235 = 452 confusions;
   From forest: 253 + 173 =426 confusions;
   From water: 35 + 17 = 52 confusions;
   So, most confusions with range.
3. User accuracies: percentage of pixels correctly assigned to a class
   Urban: 510/621 =82%
   Agriculture:1155/1672=69%
   Range: 930/1511=62%
   Forest: 864/1324=65%
   Water: 265/345=77%
   Producer accuracies: percentage of class pixels classified as that class
   Urban: 510/738=69%
   Agriculture:1155/1732=67%
   Range: 930/1343=69%
   Forest: 864/1339=65%
   Water: 265/321=83%
4. Number of ommission errors per class:
   Urban: reference pixels: 738 - correct: 510 = 228;
   Agriculture: 1732 - 1155 =577
   Range: 1343 - 930 = 413
   Forest: 1339 - 864 =475
   Water: 321 - 265 = 56
   So highest nr. of ommissions for agricultue