Introduction to Remote Sensing

Image classification: Classification principles

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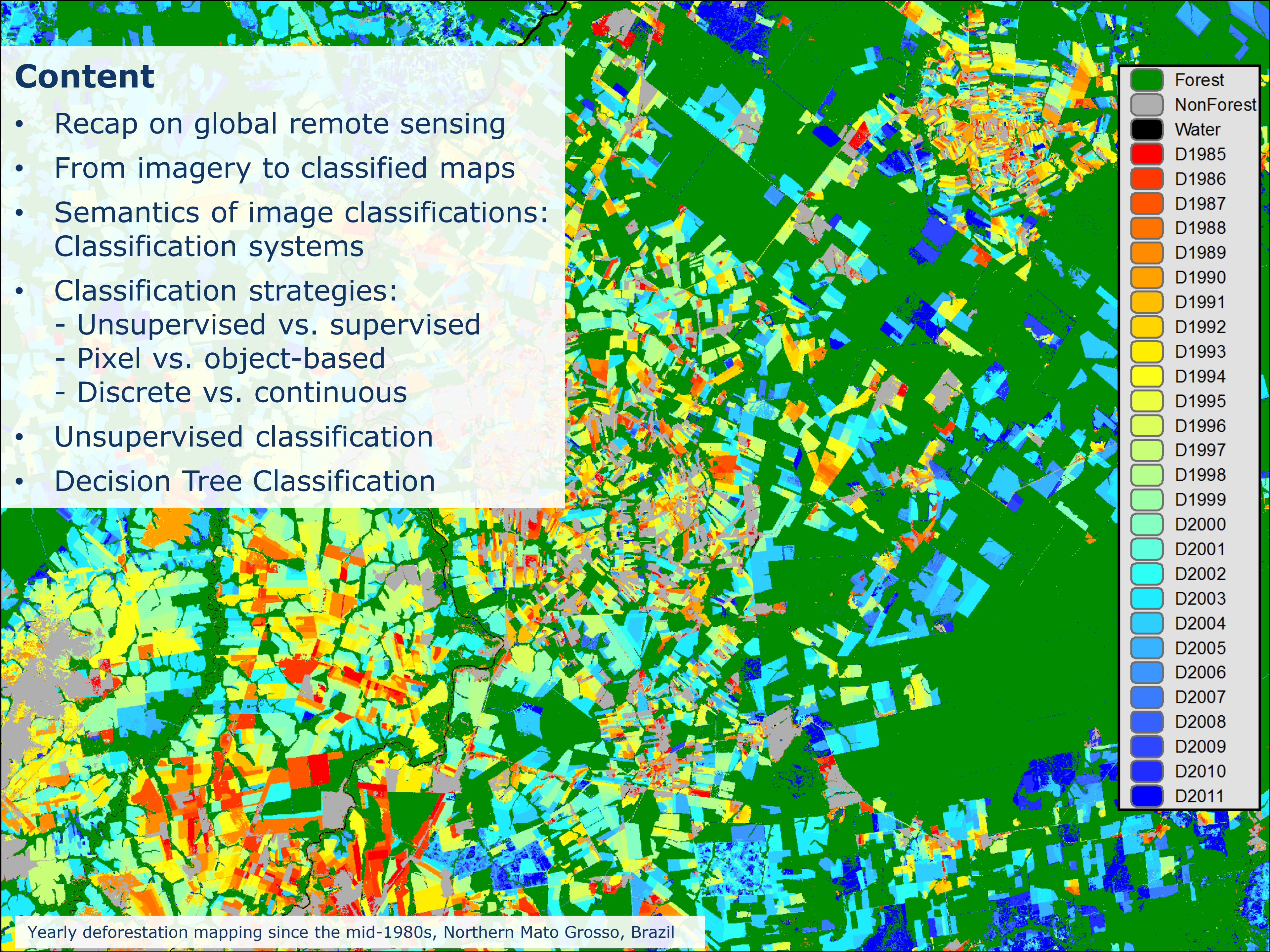
RUD 16, 2‘226

Content

- Recap on global remote sensing
- From imagery to classified maps
- Semantics of image classifications: Classification systems
- Classification strategies:
  - Unsupervised vs. supervised
  - Pixel vs. object-based
  - Discrete vs. continuous
- Unsupervised classification
- Decision Tree Classification



Yearly deforestation mapping since the mid-1980s, Northern Mato Grosso, Brazil

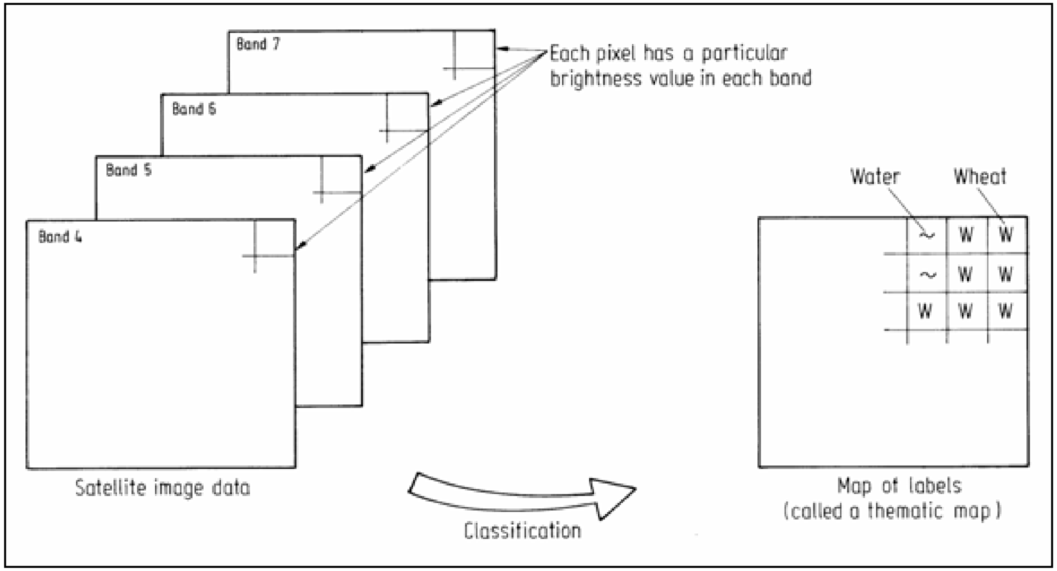
Recapitulation of last week`s topics

(1) Read
Estel, S., Kuemmerle, T., Alcántara, C., Levers, C., Prishchepov, A., & Hostert, P. (2015). Mapping farmland abandonment and recultivation across Europe using MODIS NDVI time series. *Remote Sensing of Environment, 163, 312-325*

(2) Pose questions

Why classifying imagery into maps?

- Converting spectral information into classes is on the one hand an information loss: we compress continuous radiances or reflectances in a few classes
- On the other hand, it's information extraction: we group "meaningless" spectra into geographically meaningful classes



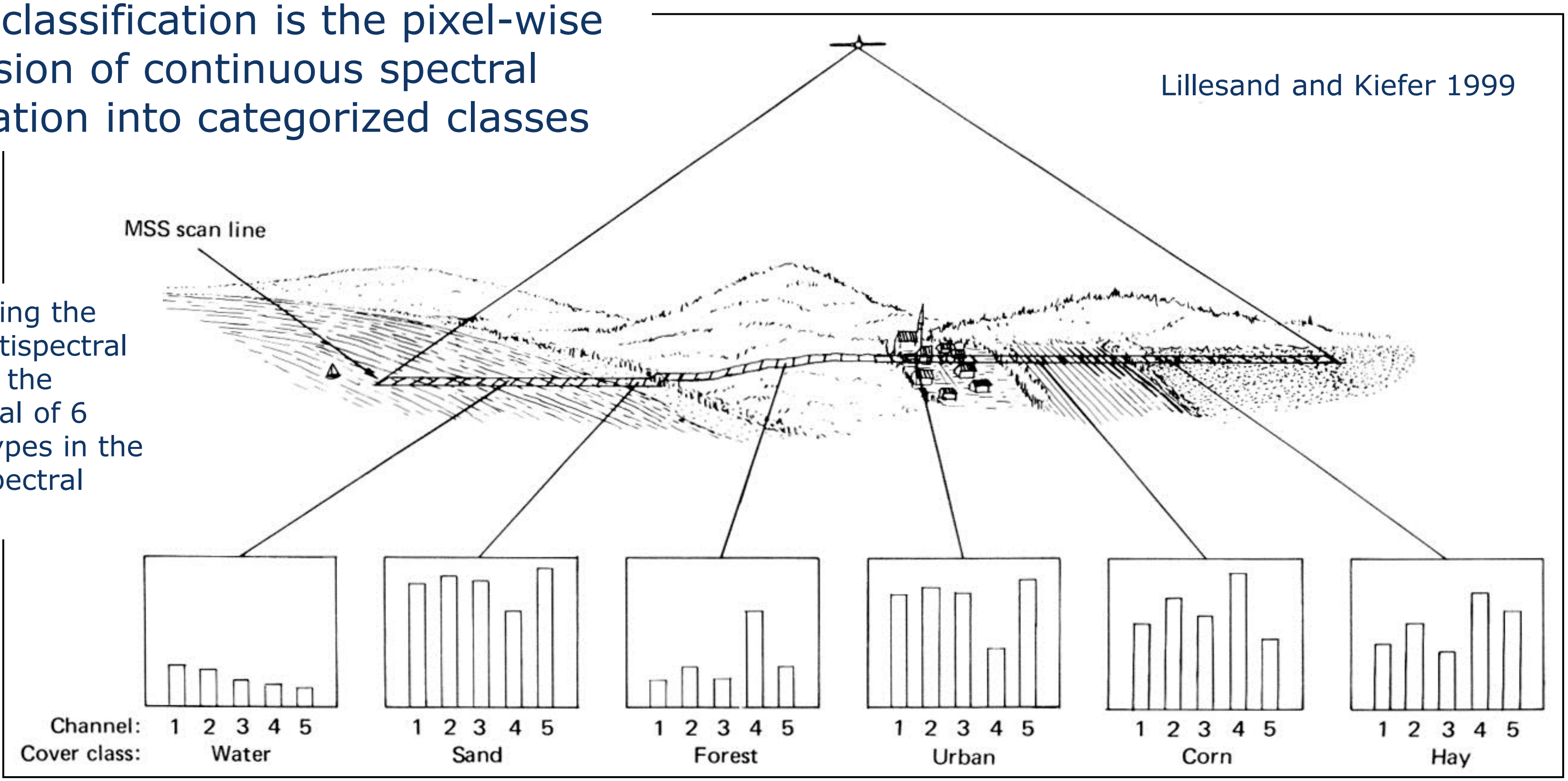
Scheme of classifying a 4-band information for each pixel of an image into a map

(Richards & Jia 1999)

- bottomline: the classes of an image classification are always chosen depending on the research question to be answered

From imagery to classified maps

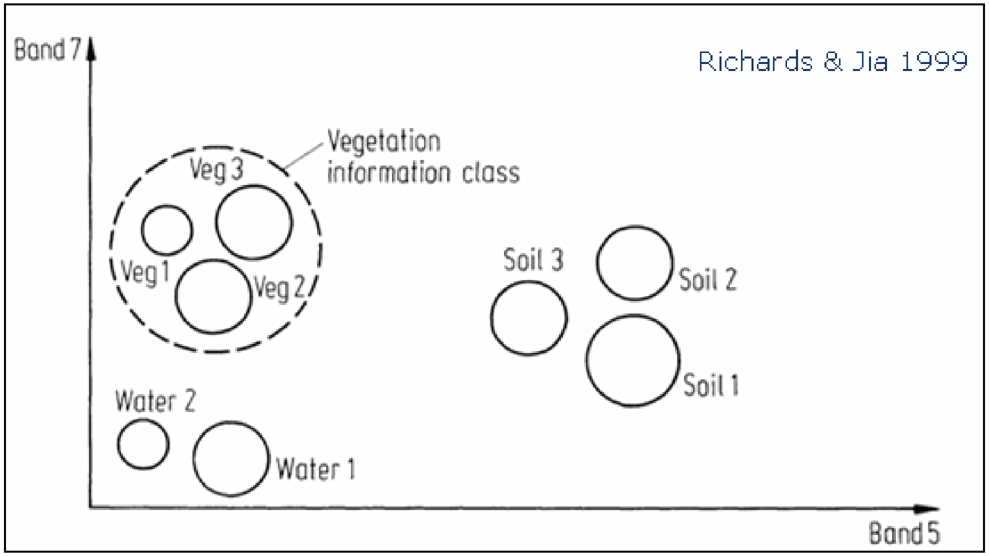
- The basis for any kind of map from remote sensing data is the spectral information content of satellite or airborne imagery
- In multi- or hyperspectral data, this means continuous, spectral information in different wavelengths, i.e. spectral bands
- Image classification is the pixel-wise conversion of continuous spectral information into categorized classes



Sketch showing the Airborne Multispectral Scanner and the spectral signal of 6 land cover types in the sensor's 5 spectral bands

From imagery to classified maps

- Pixels with similar spectral patterns are likely to belong to the same thematic class



The spectral characteristics of 3 different vegetation types, 3 different soils and 2 water types shown in 2 spectral bands

(Richards & Jia 1999)

- however: similar land covers / land uses might have very different spectral expressions
- Or even more problematic: different LCs/LUs might have very similar spectral characteristics
- The latter cannot be solved from remote sensing data alone or at least need specific RS-based inputs (e.g. time series to differentiate via different phenologies)

From imagery to classified maps

Spectral Class	Identity of Spectral Class	Corresponding Desired Information Category
Possible Outcome 1		
1	Water	Water
2	Coniferous trees	Coniferous trees
3	Deciduous trees	Deciduous trees
4	Brushland	Brushland
Possible Outcome 2		
1	Turbid water	Water
2	Clear water	
3	Sunlit conifers	Coniferous trees
4	Shaded hillside conifers	
5	Upland deciduous	Deciduous trees
6	Lowland deciduous	
7	Brushland	Brushland
Possible Outcome 3		
1	Turbid water	Water
2	Clear water	
3	Coniferous trees	Coniferous trees
4	Mixed coniferous/deciduous	
5	Deciduous trees	Deciduous trees
6	Deciduous/brushland	Brushland

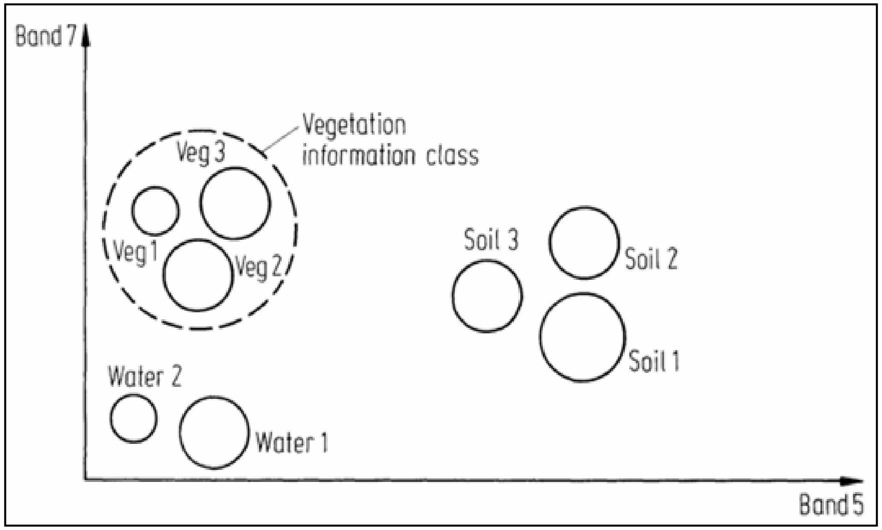
Lillesand & Kiefer 1999

Land use, land cover, spectral classes

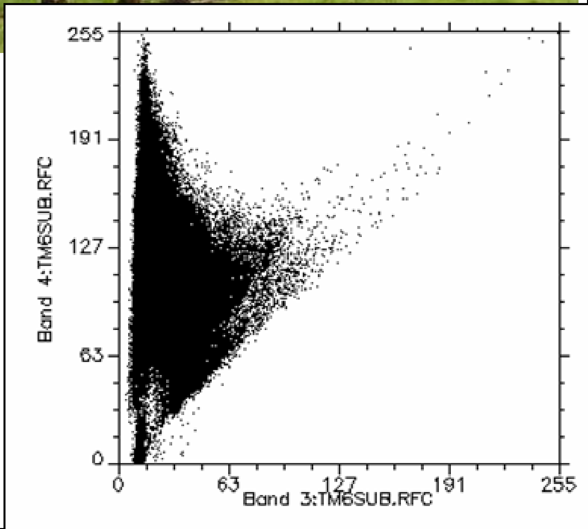
- Remote sensing imagery directly relates to land cover, i.e. the physical material at the surface of the Earth
- We are often rather interested in land use than land cover, though
- Further complicated, as different thematic classes (LU or LC) are often composed by several spectral classes

Probably similar land covers from the satellite view, but different land uses

Darstellung einer reellen Datenverteilung im Merkmalsraum (rot – nIR)

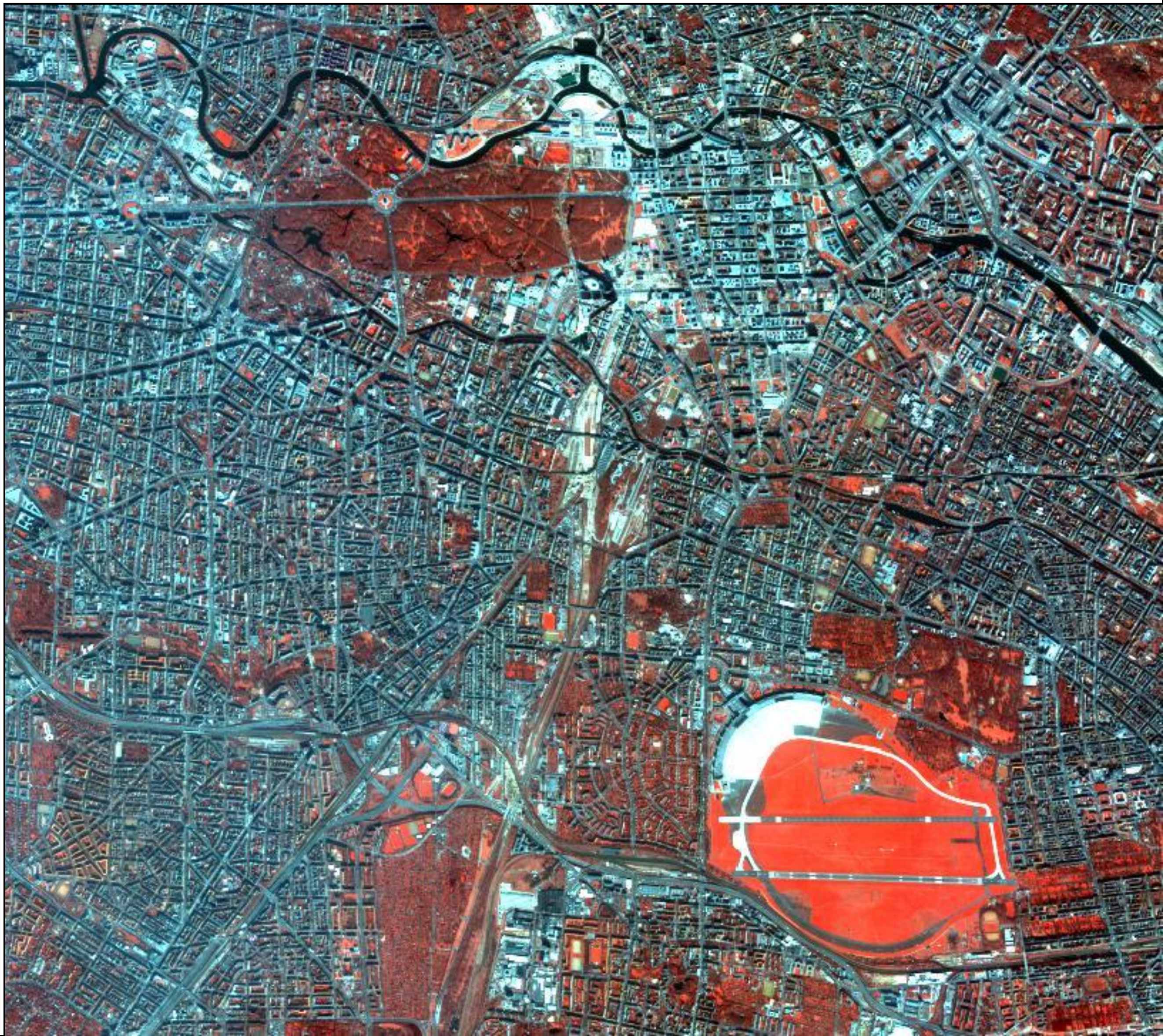


Idealized spectral class properties in spectral feature space (left, Richards and Jia 1999) vs. real-world distribution of spectral values (right, from Berlin Landsat data)



LULC classes vs. spectral classes - brainstorming

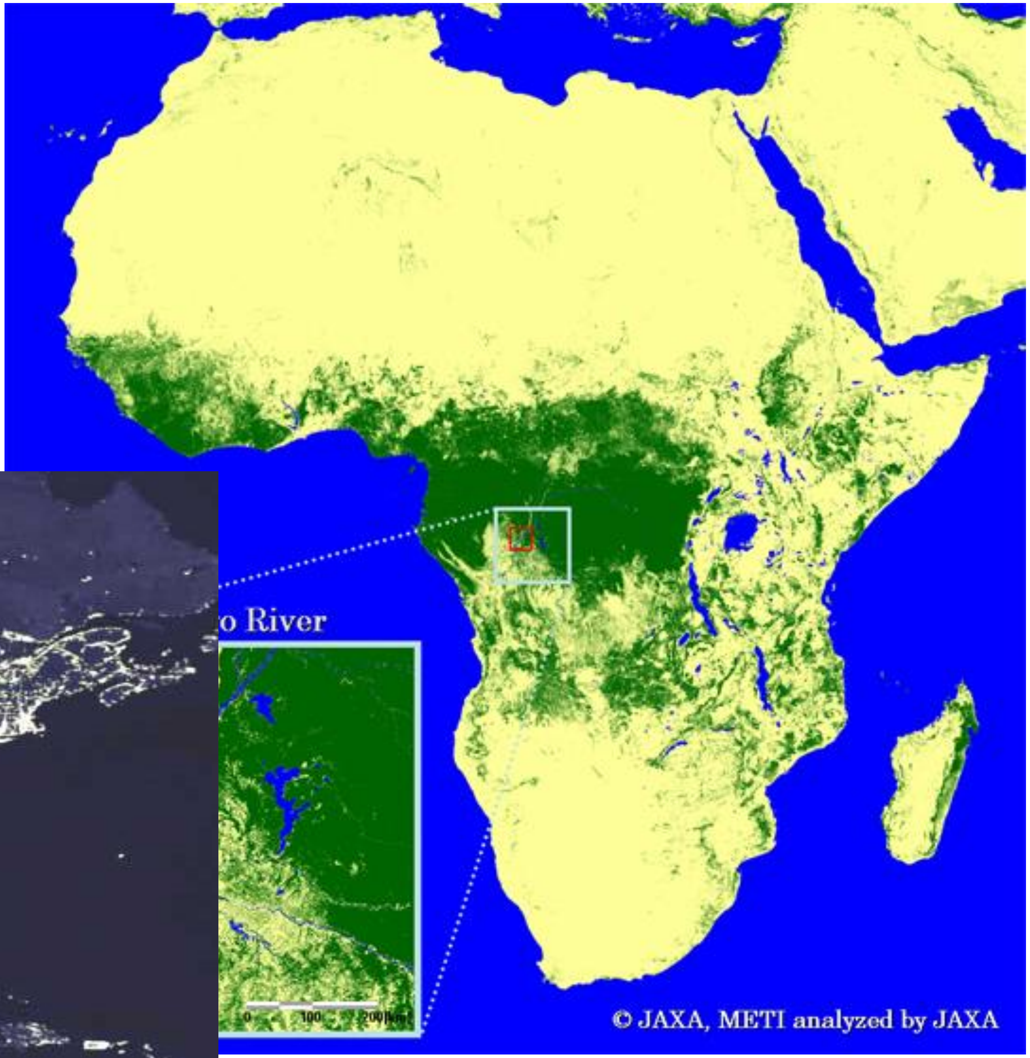
- Quickbird false color (for QB spectral bands see last lecture)
- 2.8 m spatial resolution
- RGB: NIR-red-green
- Which land covers can you identify?
- Which land uses?
- How many homogeneous spectral classes will we need to adequately describe urban (i.e. sealed) surfaces?
- Discuss!



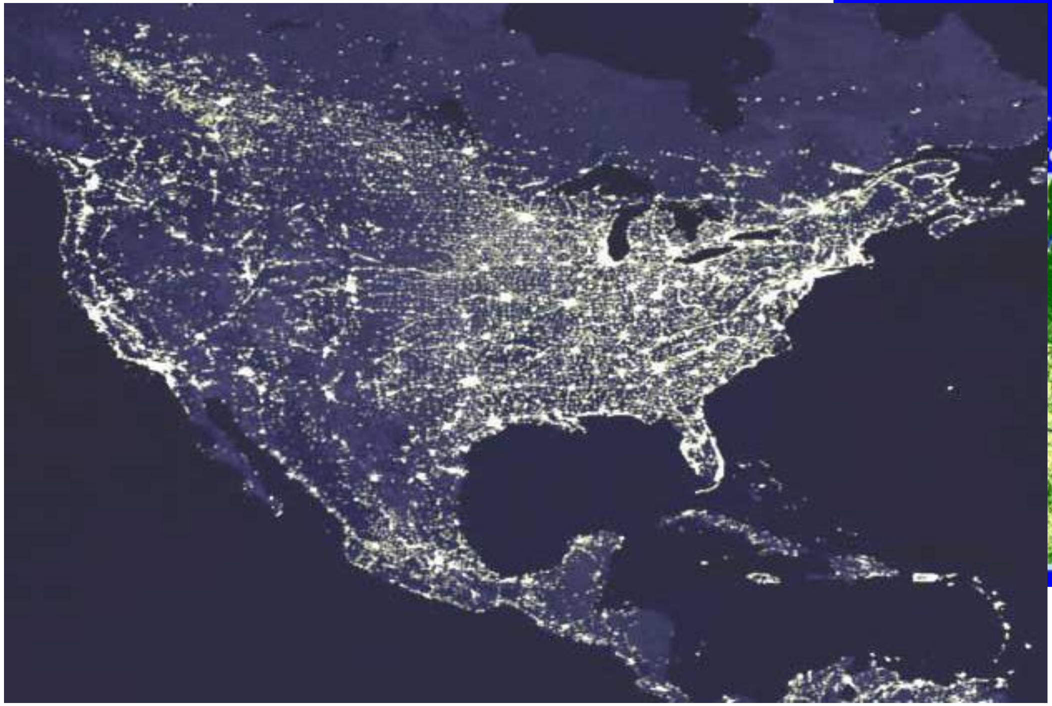
Classification systems

Binary classification

- Binary classifications are the simplest:
  - forest / non-forest
  - urban / non-urban
  - flooded / non-flooded areas



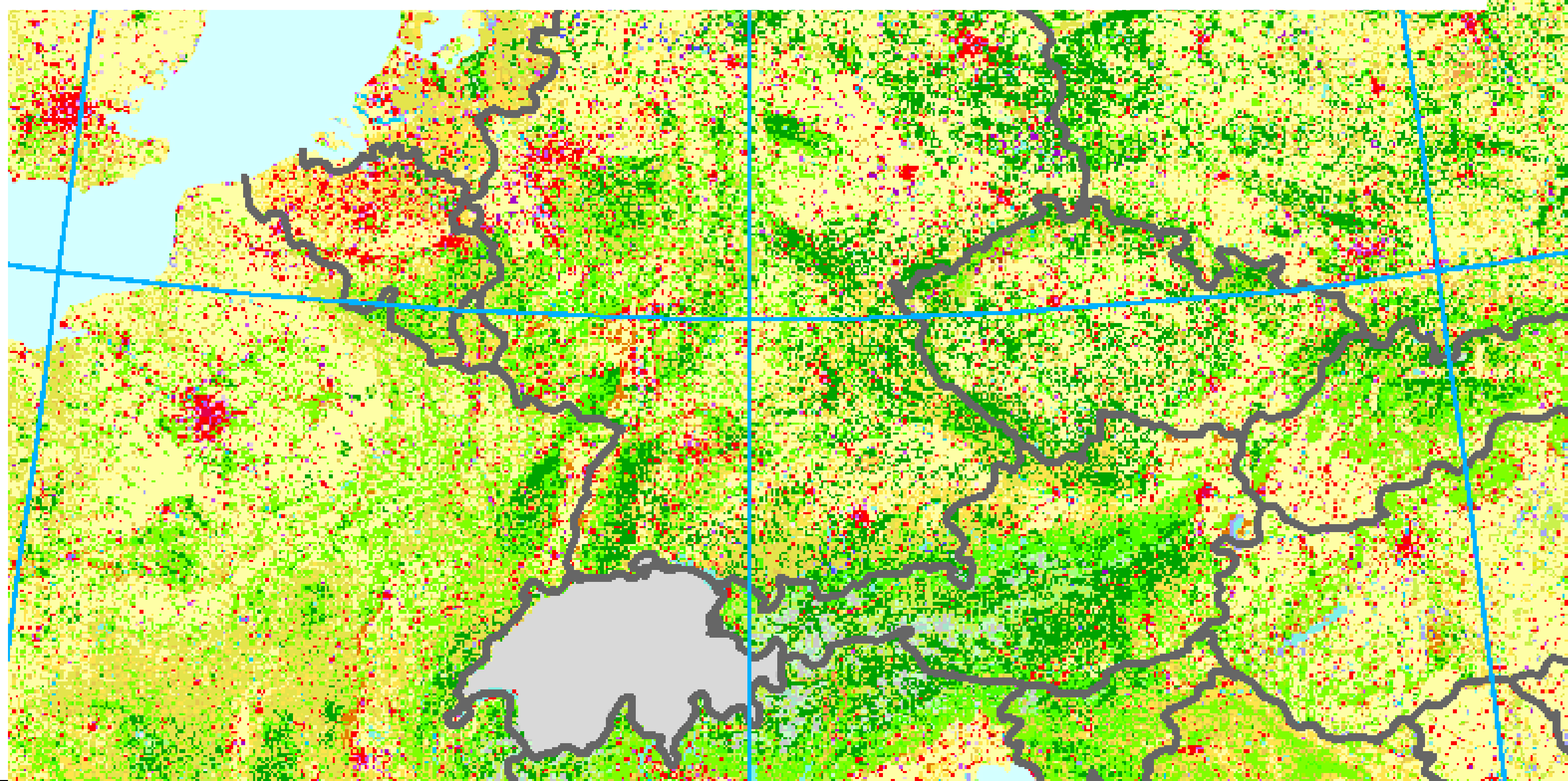
http://www.jaxa.jp/press/2010/10/20101021_daichi_e.html



http://www.nasa.gov/vision/earth/lookingatearth/NIGHTLIGHTS.html

Generic classification schemes

- Many land cover / land use classifications follow a broad, generic approach
- Such classifications often serve multiple purposes
- Important for Europe: Coordinated Information on the European Environment (CORINE) Land Cover Classification
- 1990, 2000, 2006 and 2012



CORINE land cover classes

ARTIFICIAL SURFACES

URBAN FABRIC
- 111 Continuous urban fabric
- 112 Discontinuous urban fabric

INDUSTRIAL, COMMERCIAL AND TRANSPORT UNITS
- 121 Industrial, commercial and public units
- 122 Road and rail networks and associated land
- 123 Port areas
- 124 Airport

MINES, DUMPS AND CONSTRUCTION SITES
- 131 Mineral extraction sites
- 132 Dump sites
- 133 Construction sites

ARTIFICIAL NON-AGRICULTURAL VEGETATED AREAS
- 141 Green urban areas
- 142 Sport and leisure facilities

AGRICULTURAL AREAS

ARABLE LAND
- 211 Non-irrigated arable land

PERMANENT CROPS
- 221 Vineyards
- 222 Fruit trees and berries plantations

PASTURES
- 231 Pastures

HETEROGENEOUS AGRICULTURAL AREAS
- 242 Complex cultivation patterns
- 243 Land principally occupied by agriculture, with significant areas of natural vegetation

FOREST AND SEMINATURAL AREA

FORESTS
- 311 Broad-leaved forest
- 312 Coniferous forest
- 313 Mixed forest

SCRUBS AND/OR HERBACEOUS VEGETATION
- 321 Natural grassland
- 322 Moors and heathland
- 324 Transitional woodland-scrub

OPEN SPACES WITH LITTLE OR NO VEGETATION
- 331 Beaches, dunes, sand
- 332 Bare rock
- 333 Sparsely vegetated areas
- 334 Burnt areas
- 335 Glaciers and perpetual snow

WETLANDS

INLAND WETLANDS
- 411 Inland marshes
- 412 Peat bogs

COASTAL WETLANDS
- 421 Salt marshes
- 423 Intertidal flats

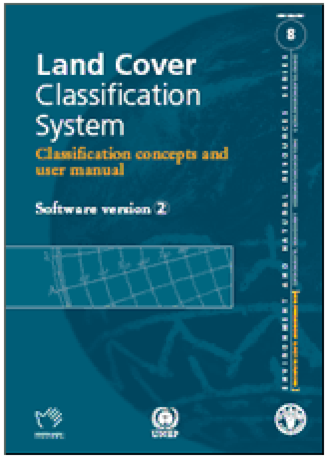
WATER BODIES

INLAND WATERS
- 511 Water courses
- 512 Water bodies

MARINE WATERS
- 521 Coastal lagoons
- 522 Estuaries
- 523 Sea and ocean

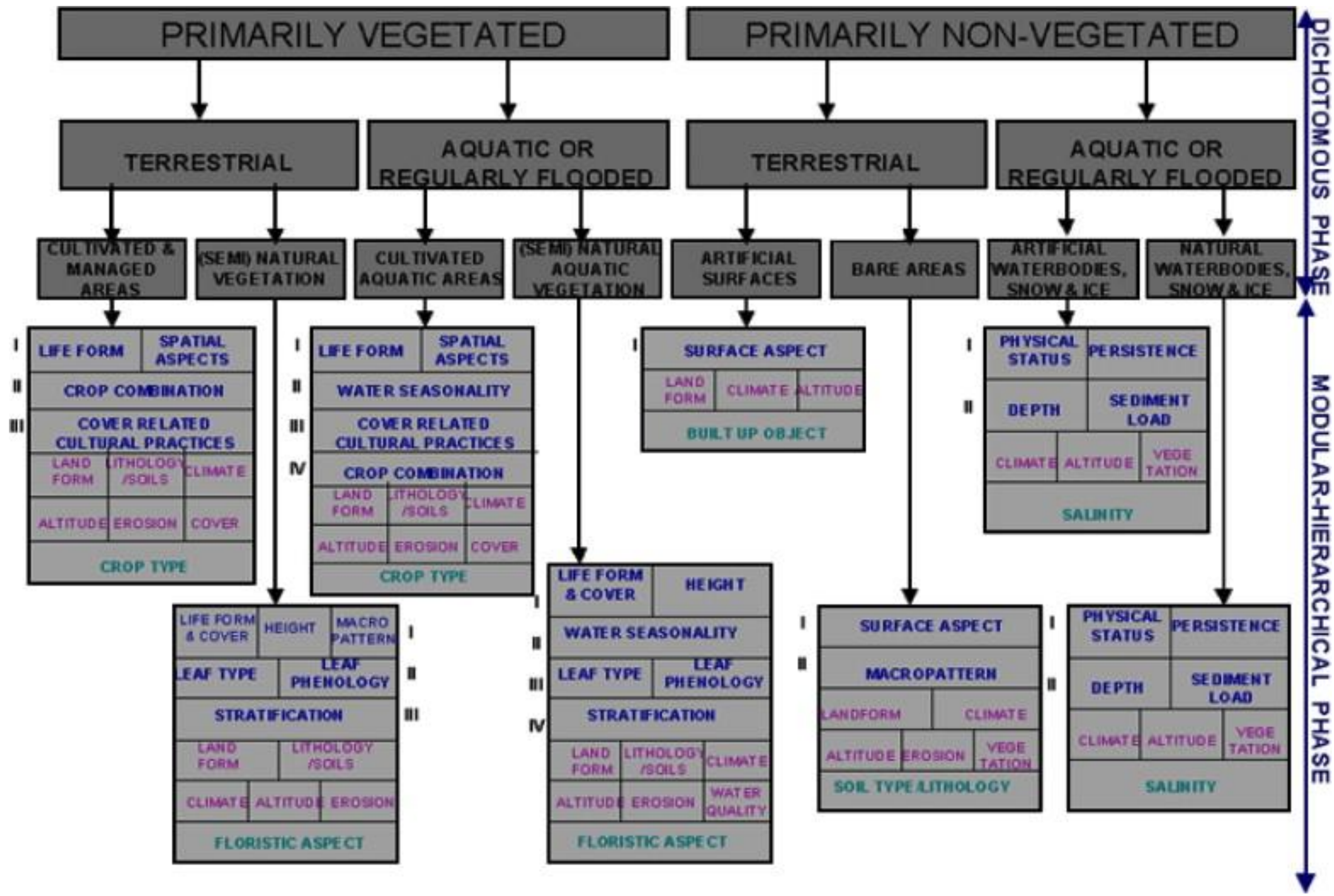
Hierarchical classification schemes

- Classification systems usually come with some trade-offs, such as
  - serves a specific scale, i.e. might be to coarse or to detailed for others
  - is often not comparable between different sites or regions
  - might be good for mapping, but not for monitoring (next week's lecture)
  - often mixes land cover and land use
- The Food and Agricultural Organization therefore developed the generic "Land Cover Classification System" (LCCS)



- LCCS is supposed to serve as a reference system, being:
  - comprehensive, scientifically sound and practically oriented
  - meets the needs of a variety of users
  - facilitates comparisons between classes derived from different classifications
  - flexible and to be used at different scales and at different levels able to describe the complete range of land cover features (e.g., forest and cultivated areas as well as ice and bare land, etc.)
  - clear and systematic class descriptions (based on diagnostic criteria independent of e.g. climate, floristic composition or altitude)

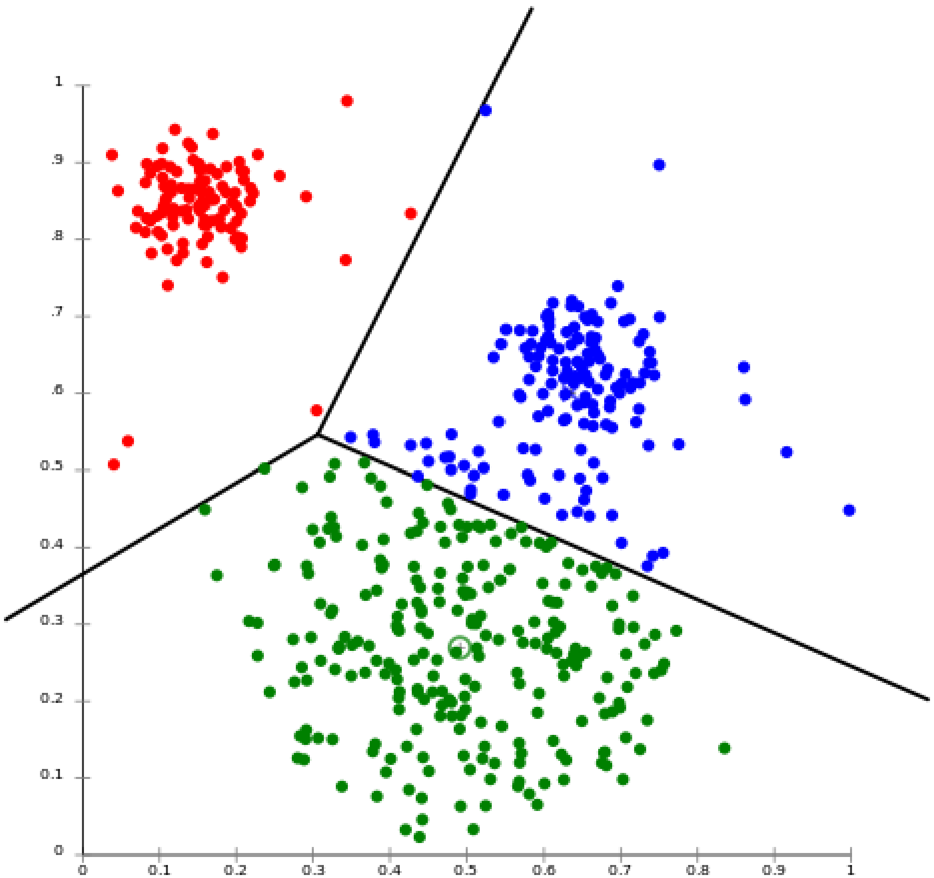
Hierarchical classification schemes: FAO LCCS



Classification strategies

"Classic" division: unsupervised and supervised classification

- LCLU classification strategies vary widely, mainly depending on the complexity of the problem to be solved (i.e. number and separability of classes)
- Personal skills and available time, funds and software resources (and skills) also play a vital role
- The broadest categories are "supervised vs. unsupervised" classifiers
- Unsupervised classifiers basically cluster multivariate data (i.e. millions or billions of multispectral pixels) into classes



Example of data clustered into 3 classes
http://en.wikipedia.org/wiki/Data_clustering

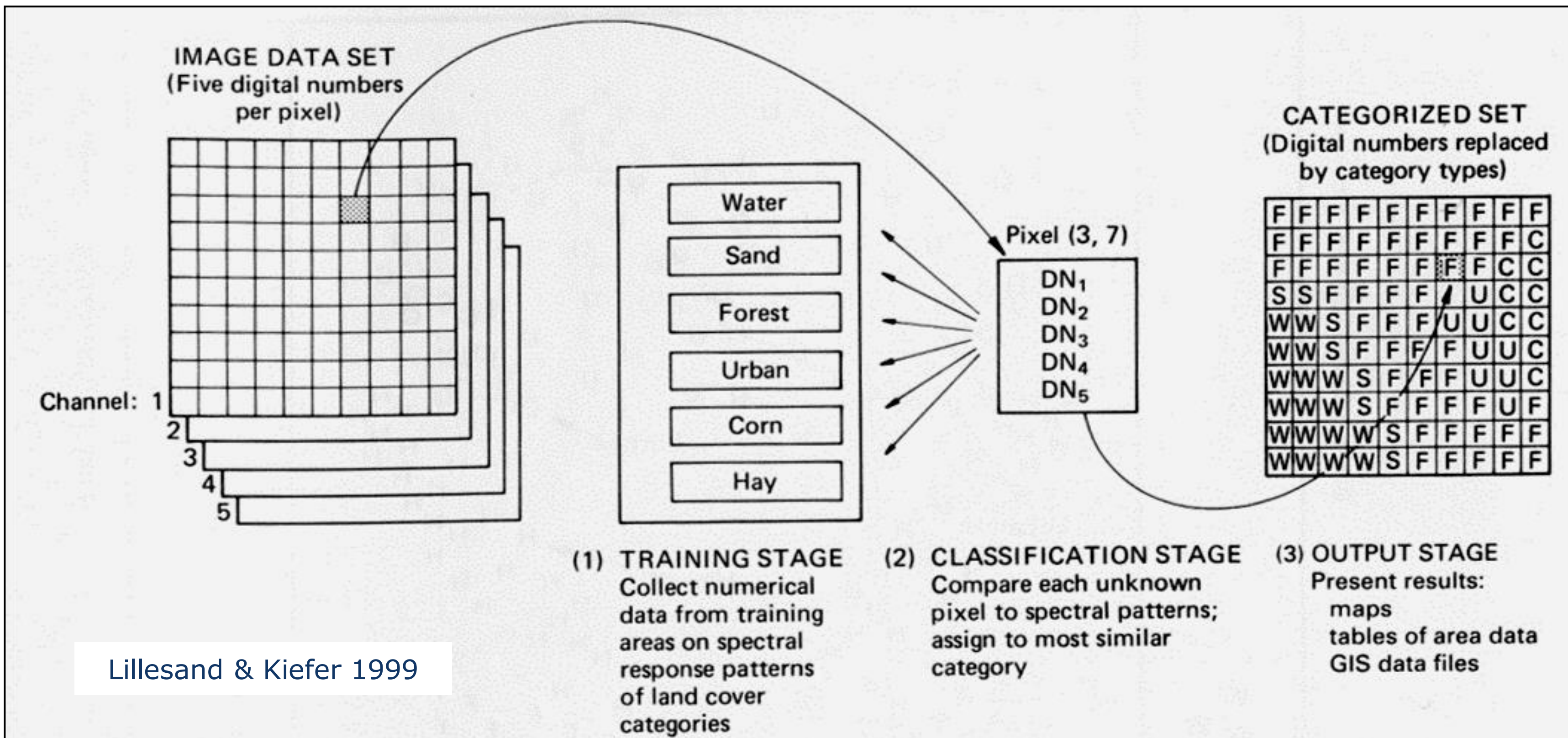
Unsupervised classification

- We use unsupervised classification e.g. to get an initial idea about different LCLU classes for a region that we don't know well
- If we need quick results, unsupervised classifiers can be a good choice ("click the button")
- Unsupervised classifiers purely rely on image statistics for clustering
- Unsupervised classifiers work well in "simple" areas (few classes, good separability): "find the oasis in the desert" will work pretty good …
- … and usually fail in providing accurate results otherwise!

http://ga.water.usgs.gov/edu/gallery/freshwater-nile.html

Supervised classification

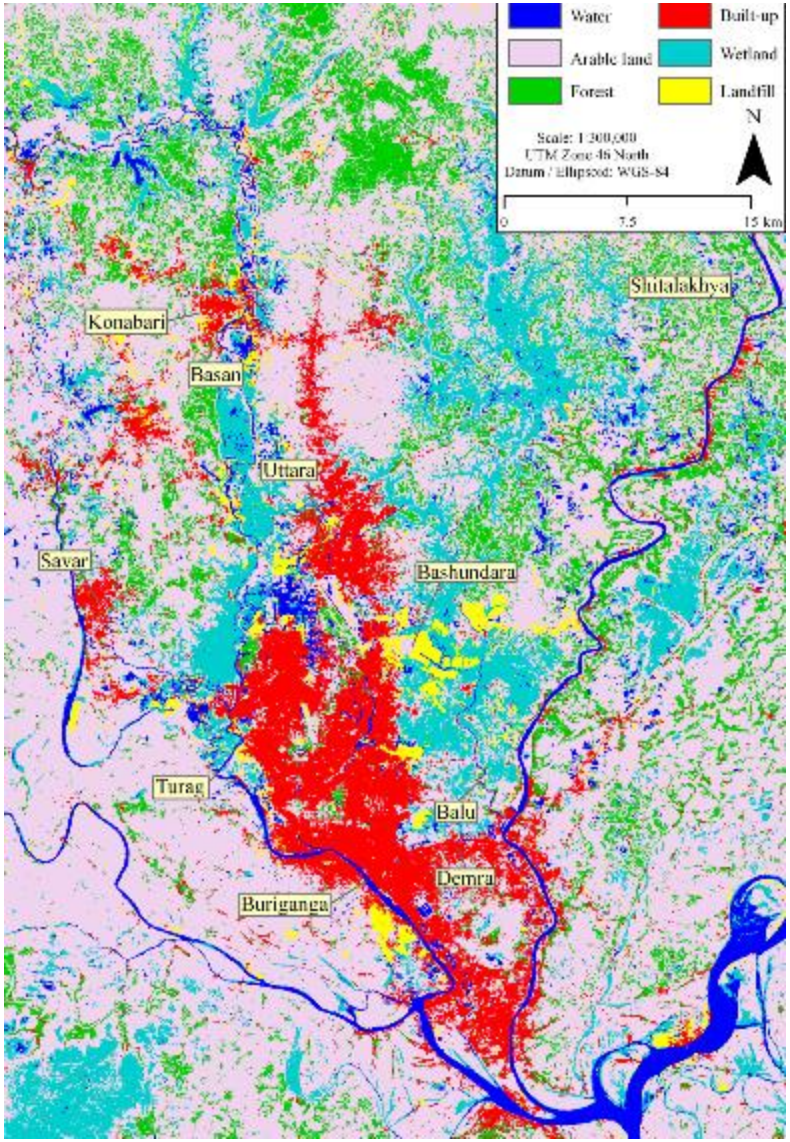
- In supervised classification, you guide the image processing software to decide how to classify spectral features into classes
- you first extract values from the image that represent classes of interest
- the classifier compares these *training signatures* with every image pixel and assigns the pixel to the best-fitting class



Lillesand & Kiefer 1999

Discrete vs. continuous classifications

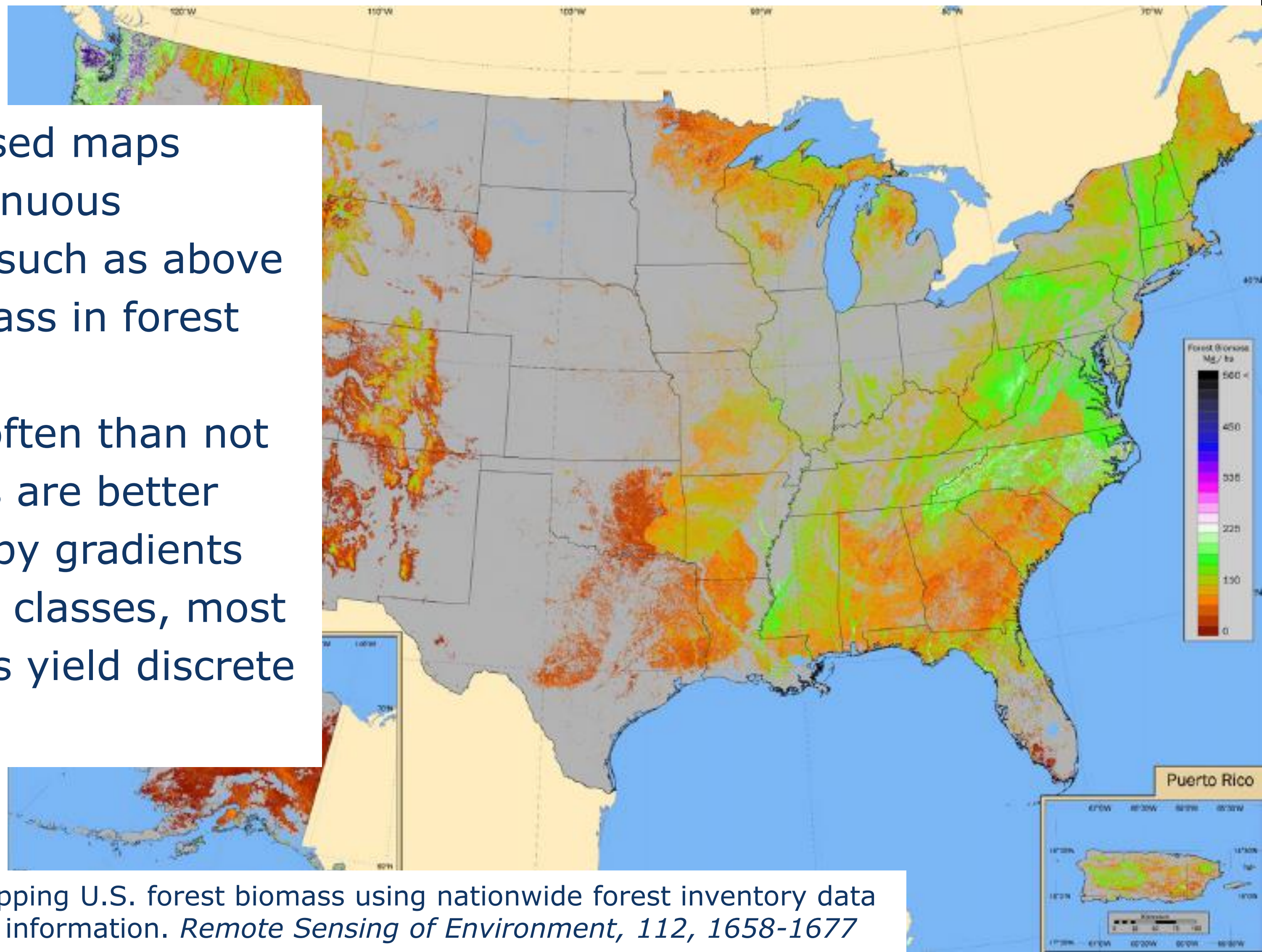
- The most common map type from remote sensing data is a land cover / land use (LCLU) classification
- Most RS-based maps present discrete classes



Griffiths, P., Hostert, P., Gruebner, O., & van der Linden, S. (2010). Mapping megacity growth with multi-sensor data. *Remote Sensing of Environment, 114, 426-439*

Discrete vs. continuous classifications

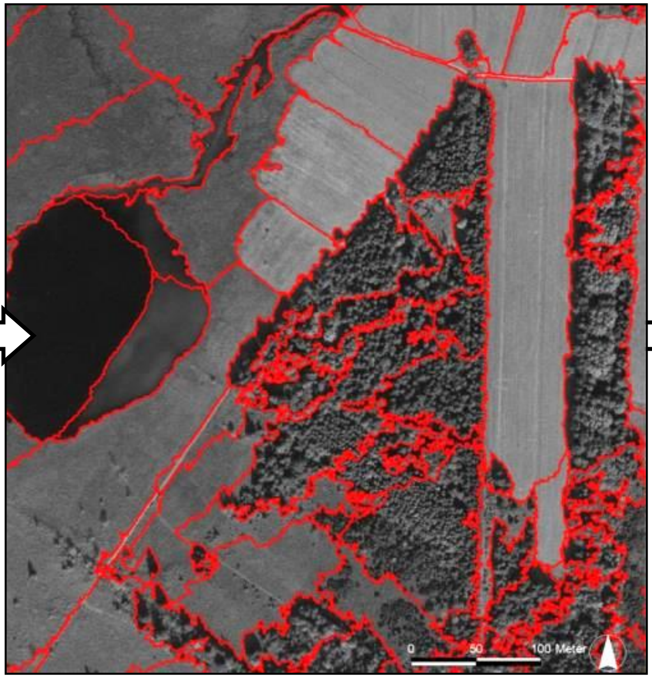
- Some RS-based maps present continuous information, such as above ground biomass in forest vegetation
- While more often than not land surfaces are better represented by gradients than discrete classes, most classifications yield discrete classes



Blackard et al. 2008. Mapping U.S. forest biomass using nationwide forest inventory data and moderate resolution information. *Remote Sensing of Environment, 112, 1658-1677*

Object-based vs. pixel-based classification

- Object-based classifiers are often used for classifying very high resolution data (e.g. airborne data, IKONOS, QuickBird, WorldView, Rapid Eye, SPOT)
- Often implemented for complex LULC classifications (e.g. urban classifications) or for mapping landscape features with distinct textures or forms (e.g. street network mapping, tree counting)



ID	Meandiff.t	Shapeindex	Prozentual
3	29,61	1,12	0,00
6	14,46	2,37	59,48
11	12,31	1,54	70,13
22	8,19	1,13	100,00
32	-14,62	1,20	9,52
35	9,37	1,46	65,22
36	-19,63	1,44	14,81
42	10,30	1,61	89,47
59	11,92	1,59	100,00
73	13,95	1,90	48,00
79	27,98	1,70	14,29
85	12,12	1,51	67,86
137	18,88	1,06	50,00
149	8,41	1,33	100,00
181	9,83	1,24	62,50
198	11,43	1,58	90,00

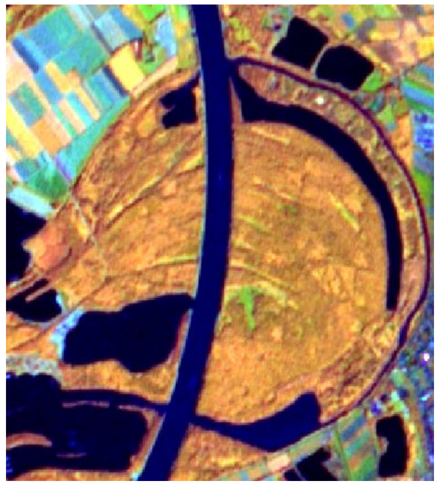
IKONOS 08/2001

Segments

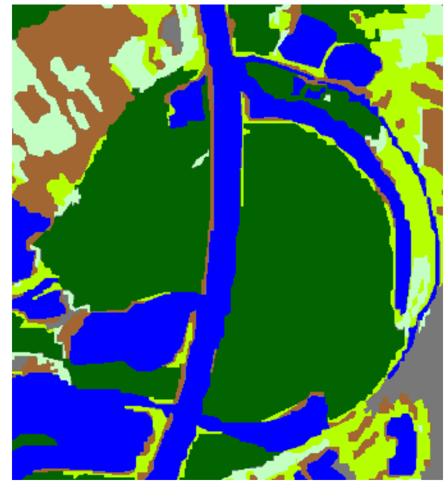
Mott, C., 2003:
Objektorientierte Klassifikationsstrategien zur Erfassung der Landnutzung aus hochauflösenden Fernerkundungsdaten

Object-based vs. pixel-based classification

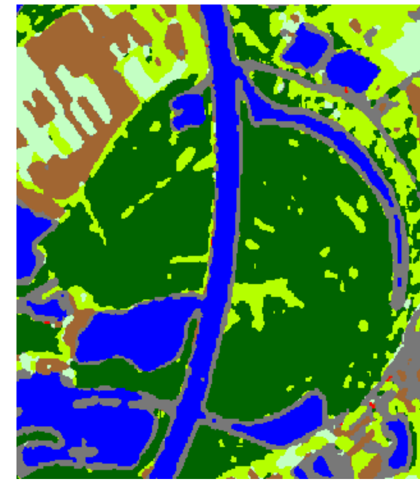
- Object-based maps appear more similar to conventional maps and show no salt-and-pepper effect, while pixel-based maps prevail more detail



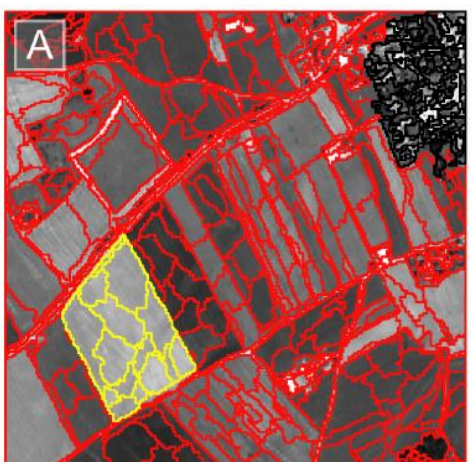
False color image

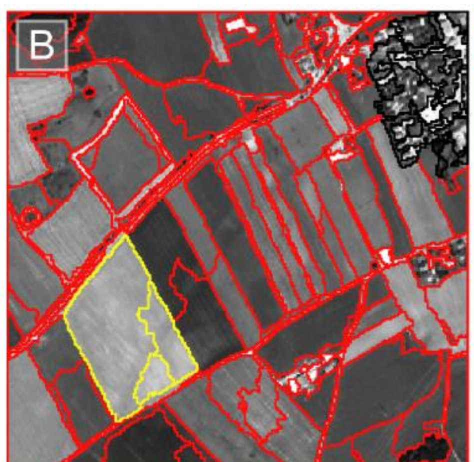


object–based result



pixel-based result





- “Scale” and object-based features are used to derive appropriate homo-geneity levels

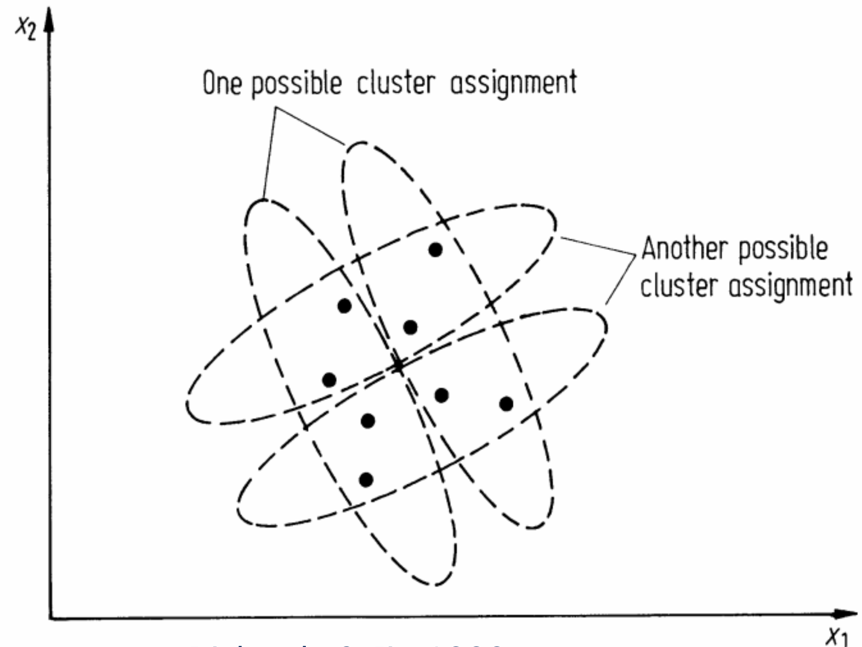
Mott, C., 2003: Objekt-orientierte Klassifikations-strategien zur Erfassung der Landnutzung aus hoch auflö-senden Fernerkundungsdaten

Example:
Unsupervised image classification

Unsupervised classification: Clustering

- Unsupervised classification usually puts each pixel into its respective class based on so called „clustering approaches", i.e. solely based on statistical measures in spectral feature space that define the most coherent „spectral clumps"

- Numerous clustering algorithms exist:
  - Single Pass Algorithm
  - Agglomerative Hierarchical
  - Iterative Optimization (also referred to as „Migrating Means", „K-Means" or „Isodata")



Richards & Jia 1999

- In any case, a distance measure is used as a criterium to assign pixels to clusters

Unsupervised classification: Distance measures

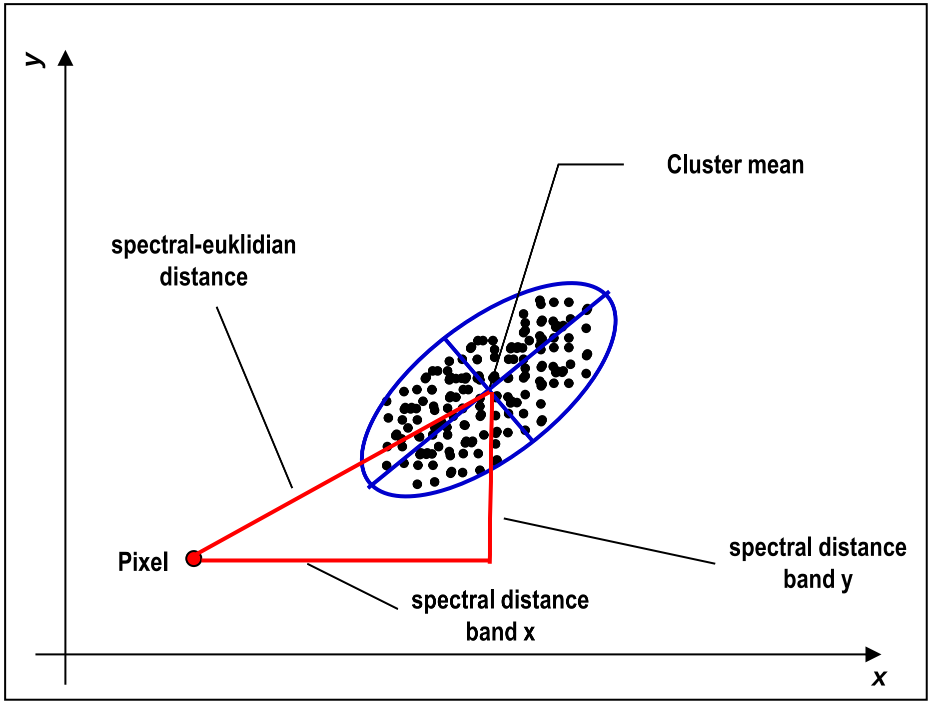
- a distance measure quantifies spectral similarity to allow pixel-wise cluster assignment

- Spectral distance is usually measured relative to a (to be defined) cluster center

- a common distance measure is the so-called „spectral-euklidian distance“:

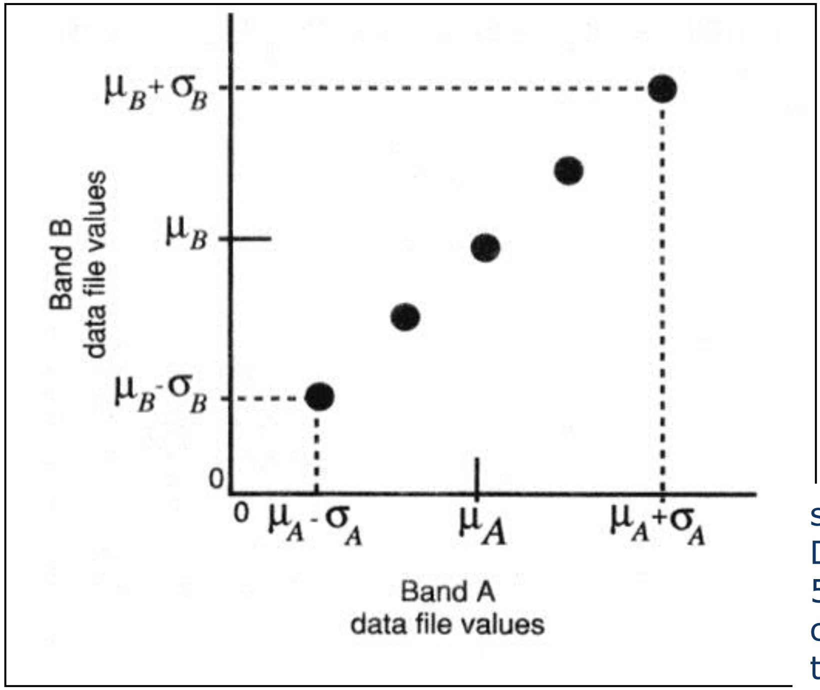
$$d_{p,c} = \sqrt{\sum_{i=1}^{n} \left(x_{p,i} - y_{c,i}\right)^2}$$

n: no of spectral bands



Iterative Optimization

- iterative clustering optimizes the pixel assignment to clusters in repeated cycles, until a termination criterium is fulfilled
- In the most simple case, the user only determines the number of classes to be created and the termination criterium



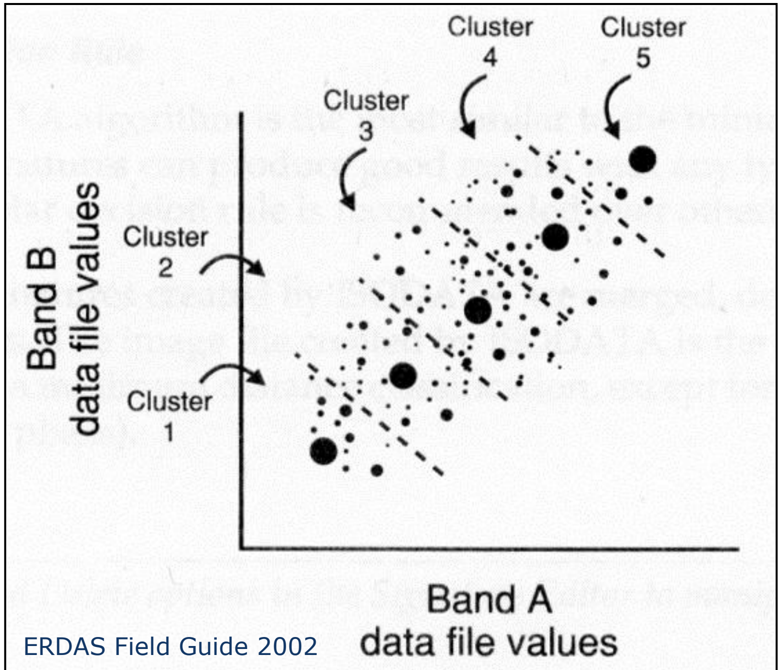
ERDAS Field Guide 2002

symmetric Distribution of 5 initial classes around the respective spectral band mean values

- 1st step: defining cluster number and initializing the respective means
- Initialization may be random, but it is useful to cover the spectral feature space in an optimized way

Iterative Optimization

- After initialization, pixels are assigned to the next cluster centre (spectral-euklidian distance to cluster mean)

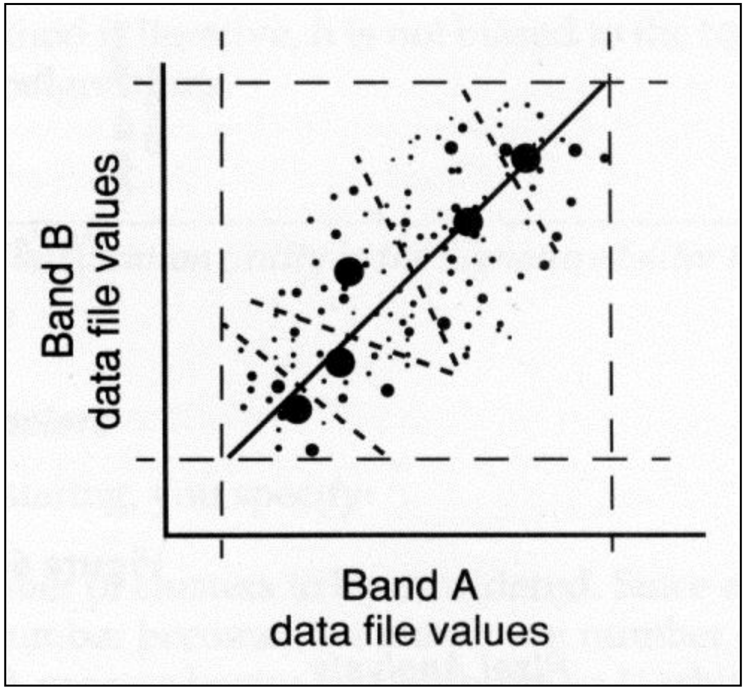


ERDAS Field Guide 2002

- the spectral feature space is obviously inadequately divided after this first iteration
- The spectral-euklidian distance of cluster means to individual pixels is not optimized yet, i.e. relatively high
- In other words: cluster means don‘t represent the pixel‘s class assignments well

Iterative Optimization

- Cluster centres are accordingly shifted to represent the mean of each class' pixel distribution



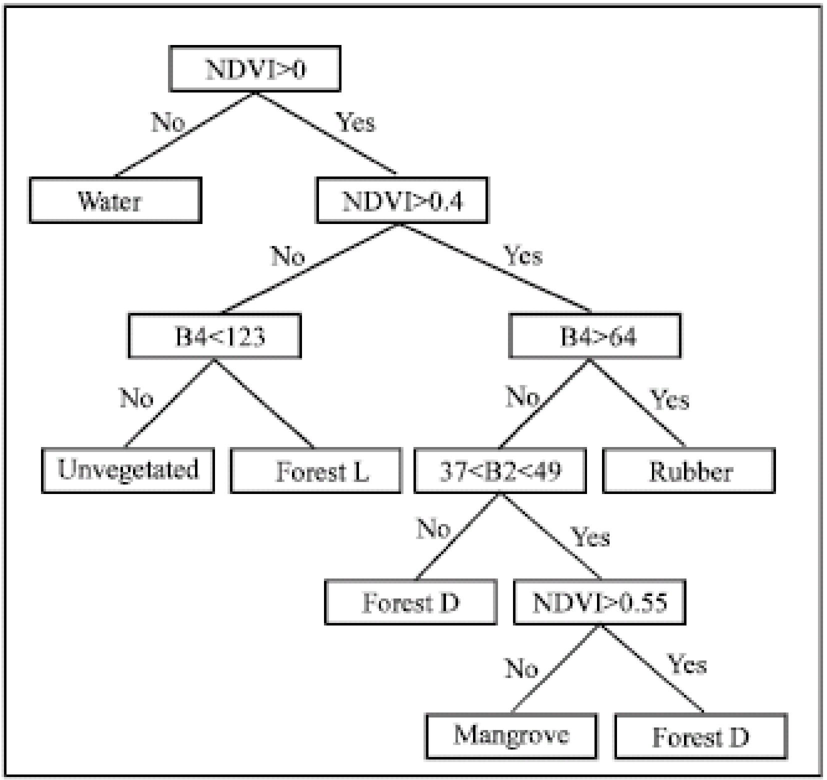
ERDAS Field Guide 2002

- This leads to new class boundaries, i.e. pixels are shifted to neighboring classes
- Then we start over again – shifting cluster centres to their new mean value, shifting class borders, shifting pixels between classes…
- A termination criterium stops this iterative process
- Termination criteria may be a specified maximum number of allowed iterations or a maximum number of pixels that may be shifted between classes after an iteration

Example:
Decision Tree Classifier

Decision Tree Classifier

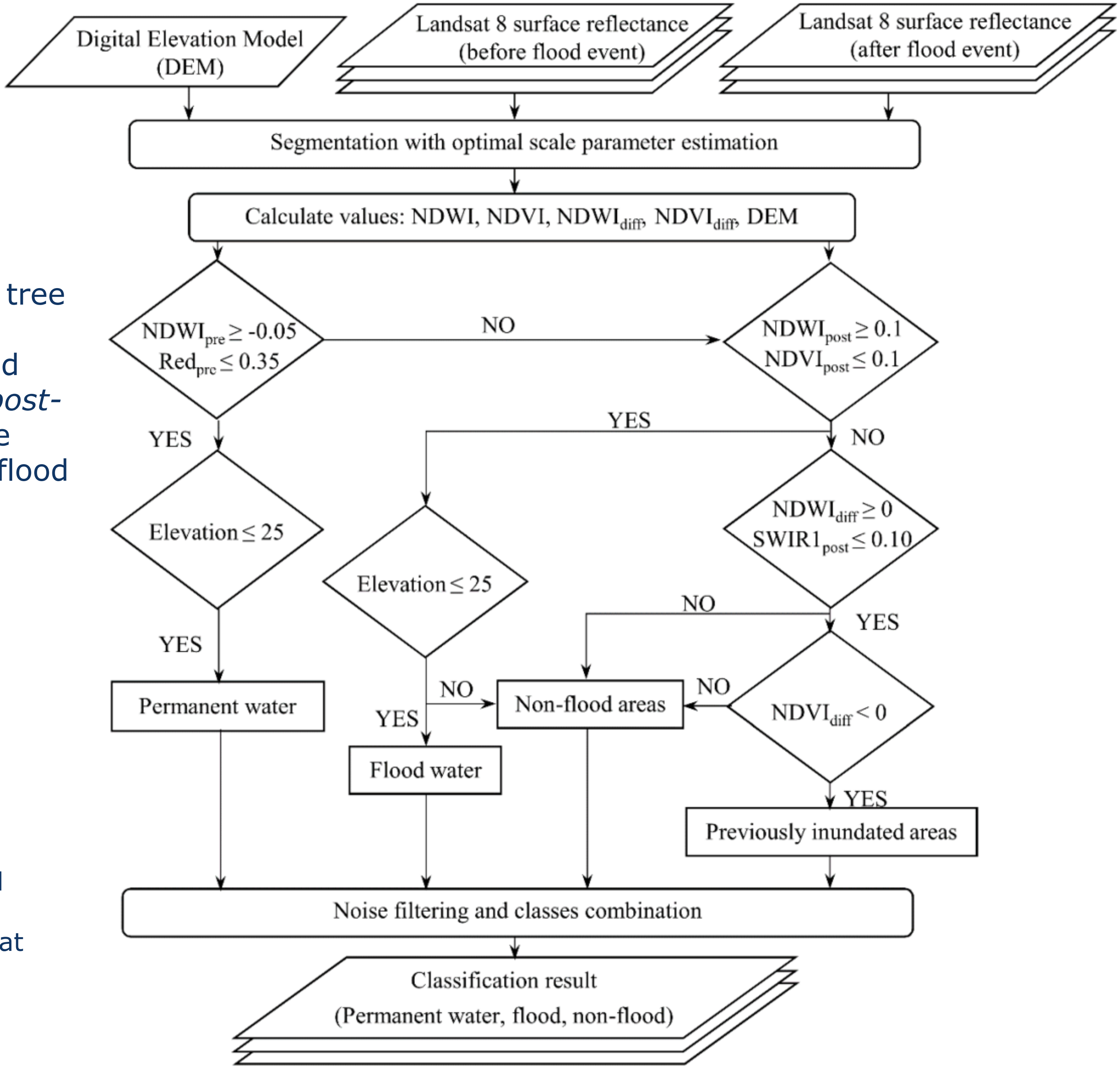
- Decision tree (DT) classifiers perform multistage classifications by using a series of binary decisions to assign pixels to classes
- In its simplest form, a decision tree is generated interactively
- Decision rules are generated by using expert knowledge that define rules for meaningful class splits
- DTs are intuitive and allow relatively easy image classification
- They reach their limits with more complex classification problems or high-dimensional feature spaces



Shafri, H., & Ramle, F. (2009). A Comparison of Support Vector Machine and Decision Tree Classifications Using Satellite Data of Langkawi Island. *Information Technology Journal, 8, 64-70*

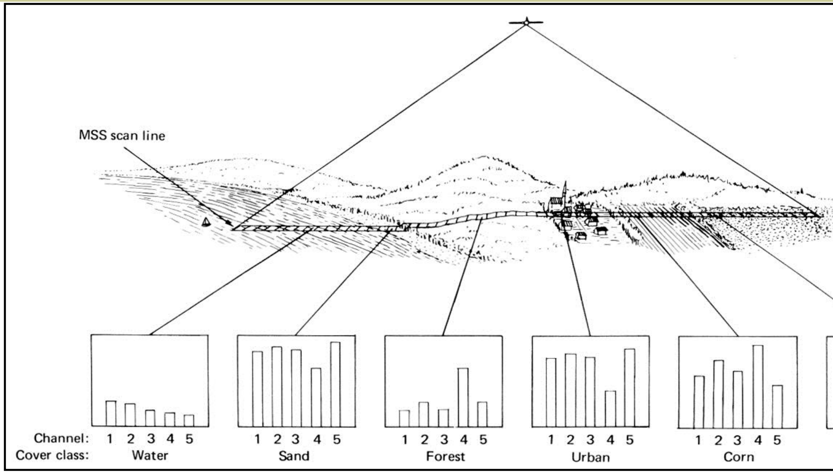
Example DT

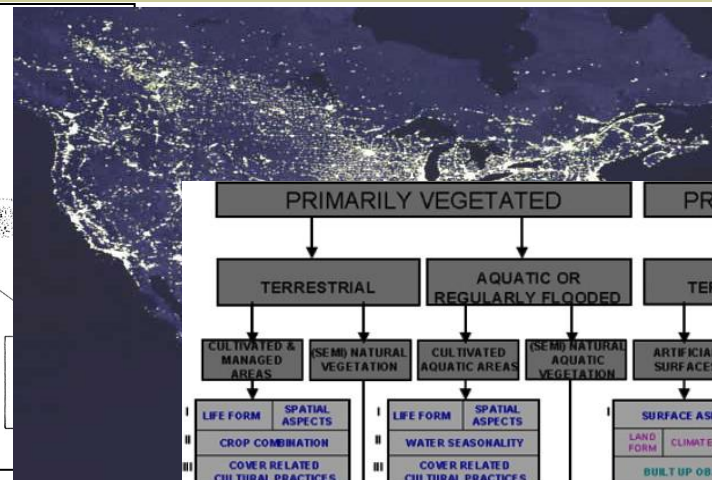
Flow chart of a decision tree for flood monitoring. Subscripts *pre*, *post*, and *diff* indicate *pre-flood*, *post-flood*, and the difference between pre- and post-flood stages, respectively

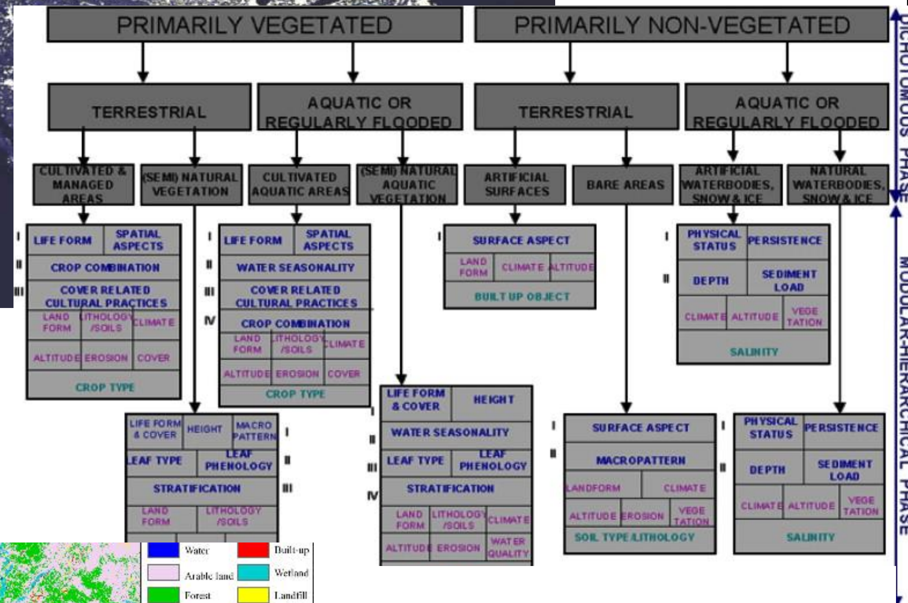


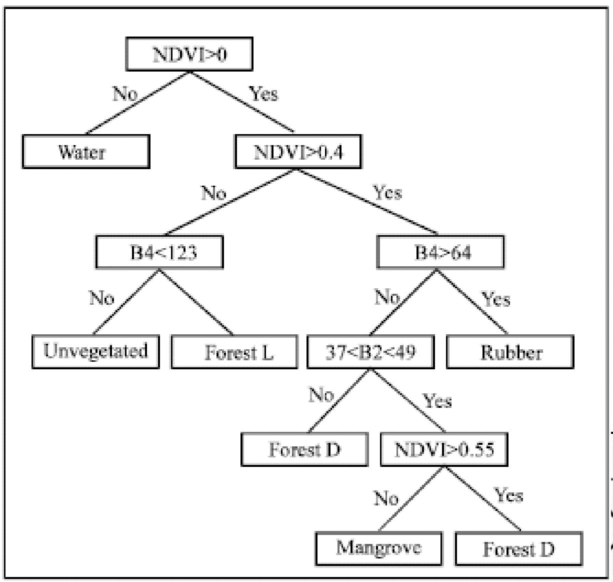
Dao, P.D., & Liou, Y.-A. (2015). Object-Based Flood Mapping and Affected Rice Field Estimation with Landsat 8 OLI and MODIS Data. *Remote Sensing, 7, 5077-5097*

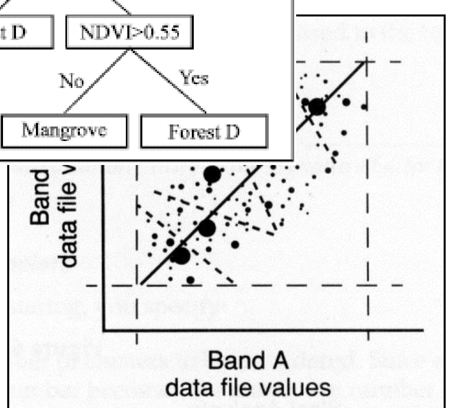
Summary

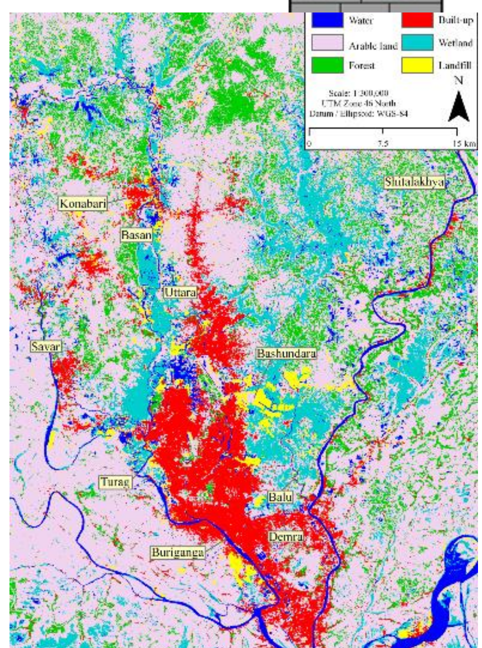

MSS scan line
Channel: 1 2 3 4 5
Cover class:
Water
Sand
Forest
Urban
Corn

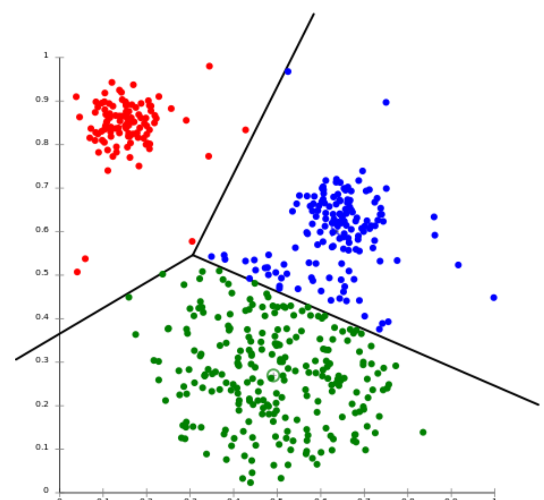



PRIMARILY VEGETATED
PRIMARILY NON-VEGETATED
TERRESTRIAL
AQUATIC OR REGULARLY FLOODED
CULTIVATED & MANAGED AREAS
(SEMI) NATURAL VEGETATION
CULTIVATED AQUATIC AREAS
(SEMI) NATURAL AQUATIC VEGETATION
ARTIFICIAL SURFACES
BARE AREAS
ARTIFICIAL WATERBODIES, SNOW & ICE
NATURAL WATERBODIES, SNOW & ICE
LIFE FORM
SPATIAL ASPECTS
CROP COMBINATION
COVER RELATED CULTURAL PRACTICES
WATER SEASONALITY
SURFACE ASPECT
BUILT UP OBJECT
PHYSICAL STATUS
PERSISTENCE
DEPTH
SEDIMENT LOAD
SALINITY
CROP TYPE
HEIGHT
LEAF TYPE
LEAF PHENOLOGY
STRATIFICATION
MACROPATTERN
SOIL TYPE LITHOLOGY
DICHOTOMOUS PHASE
MODULAR-HIERARCHICAL PHASE


NDVI>0
No
Yes
Water
NDVI>0.4
B4<123
B4>64
Unvegetated
Forest L
37<B2<49
Rubber
Forest D
NDVI>0.55
Mangrove
Forest D


Band B data file values
Band A data file values


Water
Built-up
Arable land
Wetland
Forest
Landfill
N
Konabari
Basan
Uttara
Savar
Bashundara
Turag
Balu
Demra
Buriganga
Shitalakhya



Recapitulation for next session

(1) Read
Horning, N. (2004). Land cover classification methods. (available on Moodle)

(2) Pose questions!

(3) Why is a decision tree a good entry point for understanding image classification?

Outlook

Next week we will focus on:

Supervised classification and training automated classifiers

Thanks for your attention!