National Centre for Earth Observation
NATURAL ENVIRONMENT RESEARCH COUNCIL

UNIVERSITY OF LEICESTER

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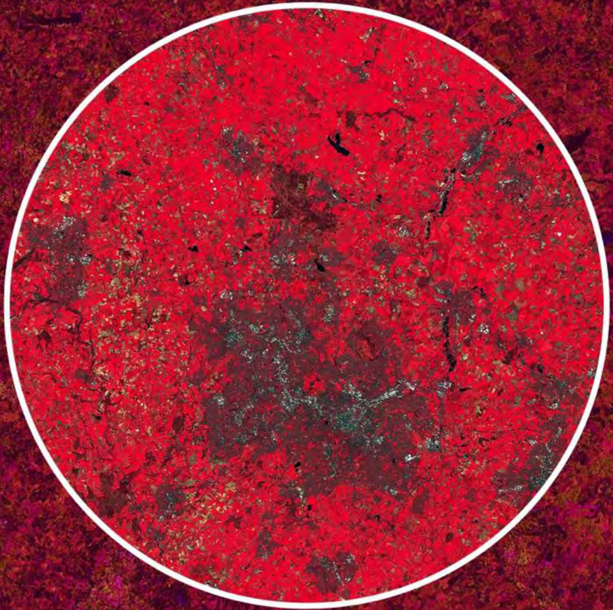
→ 8th ADVANCED TRAINING COURSE ON LAND REMOTE SENSING

10–14 September 2018
University of Leicester | United Kingdom



Land cover land use theory

Mário Caetano, DGT and NOVA IMS

10/09/2018

In Land Cover Land Use studies, mot of the times, we are interested on Land Cover and Land Use characterization through time

Land Cover and Land Use (LCLU)

Land Cover and Land Use Change Detection (LCLUC)

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There is a general tendency for evolving from LCLU mapping into LCLU monitoring, in order to somehow guarantee temporal consistency among LCLU maps for different moments in time. (Fry et al., 2011).

Furthermore LCLU monitoring is a more inclusive term since it also includes LCLUC. This is true because most studies on LCLU monitoring also includes the identification and characterisation of changes.

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Summary

1 Setting the scene

2 The need for LCLU monitoring data

LCLU: a cross-cutting environmental variable

LCLU monitoring and environmental legislation

Relation between two European initiatives (Copernicus and INSPIRE) and LCLU monitoring

Hard and soft LCLU maps

The Land Cover Classification System

3 From data to information: some important advances in LCLU monitoring

Two different approaches for LCLU monitoring

Spectral and class change detection

Image classification for LCLU mapping

4 LCLU monitoring operational programs

At country level (NLCD from USA)

At European level (Land monitoring service within Copernicus)

At Global level (GLOBCOVER)

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Land cover *versus* Land use

Land cover (LC) - Physical and biological cover of the earth's surface including artificial surfaces, agricultural areas, forests, (semi-)natural areas, wetlands, water bodies.

Land use (LU) - Territory characterised according to its current and future planned functional dimension or socio–economic purpose (e.g. residential, industrial, commercial, agricultural, forestry, recreational).

Functional definition of LU
description of land in terms of its socio-economic purpose (e.g. agricultural, residential, forestry)

→ LU can be inferred from LC

Sequential definition of LU
description of land based on series of operations on land, carried out by humans, with the intention to obtain products and/or benefits through using land resources.

→ LU cannot be inferred from LC. Other information sources are needed.

Source: INSPIRE Directive

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The need for LCLU monitoring data

Hydrology

Biogeochemical cycles

Biodiversity

Climate change

Ecology

LCLU
The most important environmental variable

Natural disasters

Soil erosion

Epidemiology

Sustainability

Land management

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The need for LCLU monitoring data

LCLU data

Landscape characterisation (composition, condition and dynamics)

Input for environmental models

As surrogate/proxies for other variables

- Atmospheric emissions in air quality models
- Potential for food production in models of food security
- Fuel availability in models of wildfire risk
- Ground permeability in flood risk models

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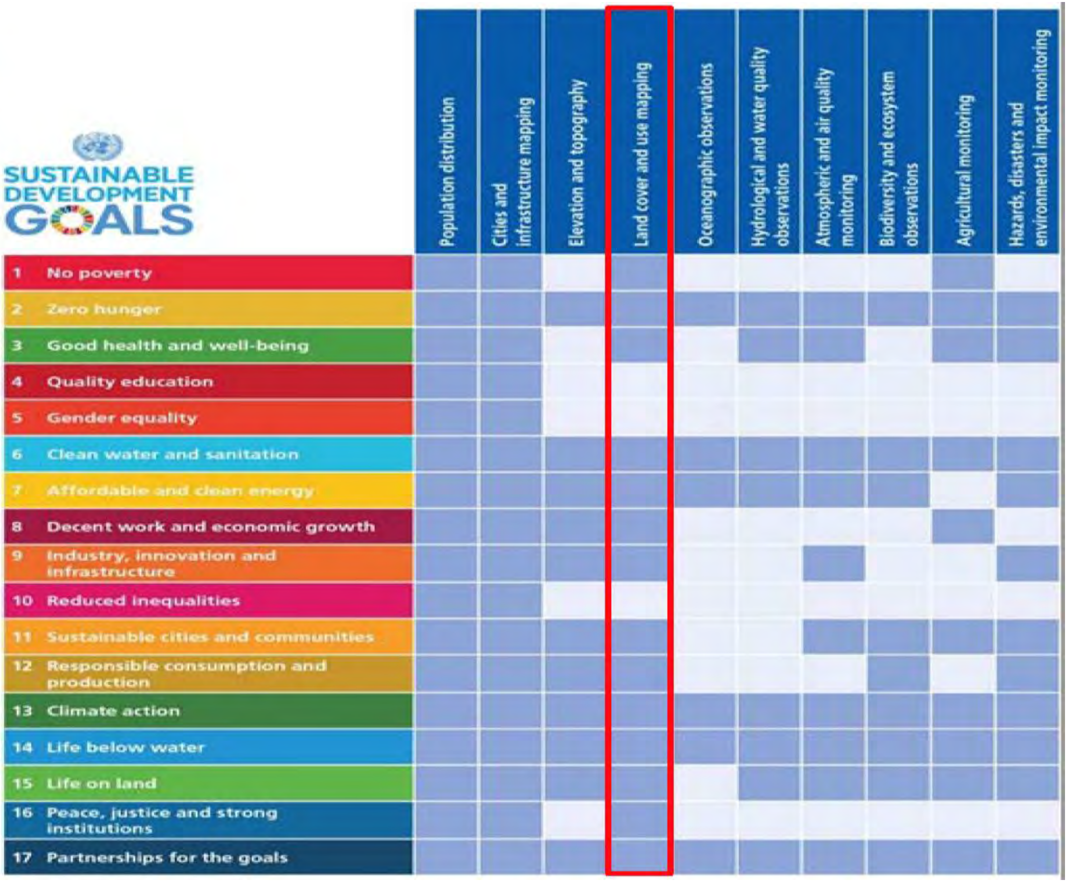
GEO GROUP ON EARTH OBSERVATIONS

EO4SDGs

1) Support the Indicators

2) Advance the Targets



Source: Ryan (2017)

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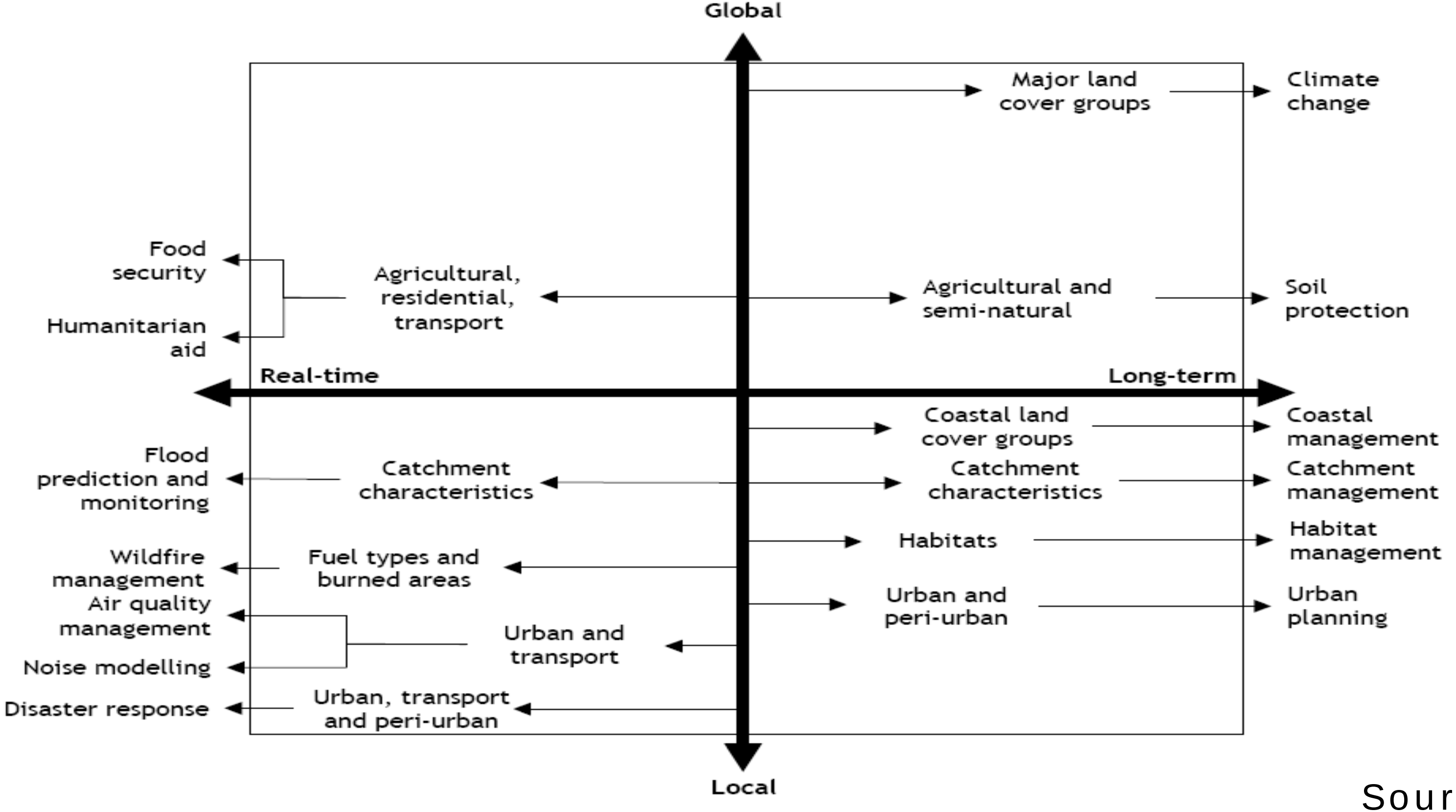
The diversity of needs for LCLU monitoring data



Source: EC (2004)

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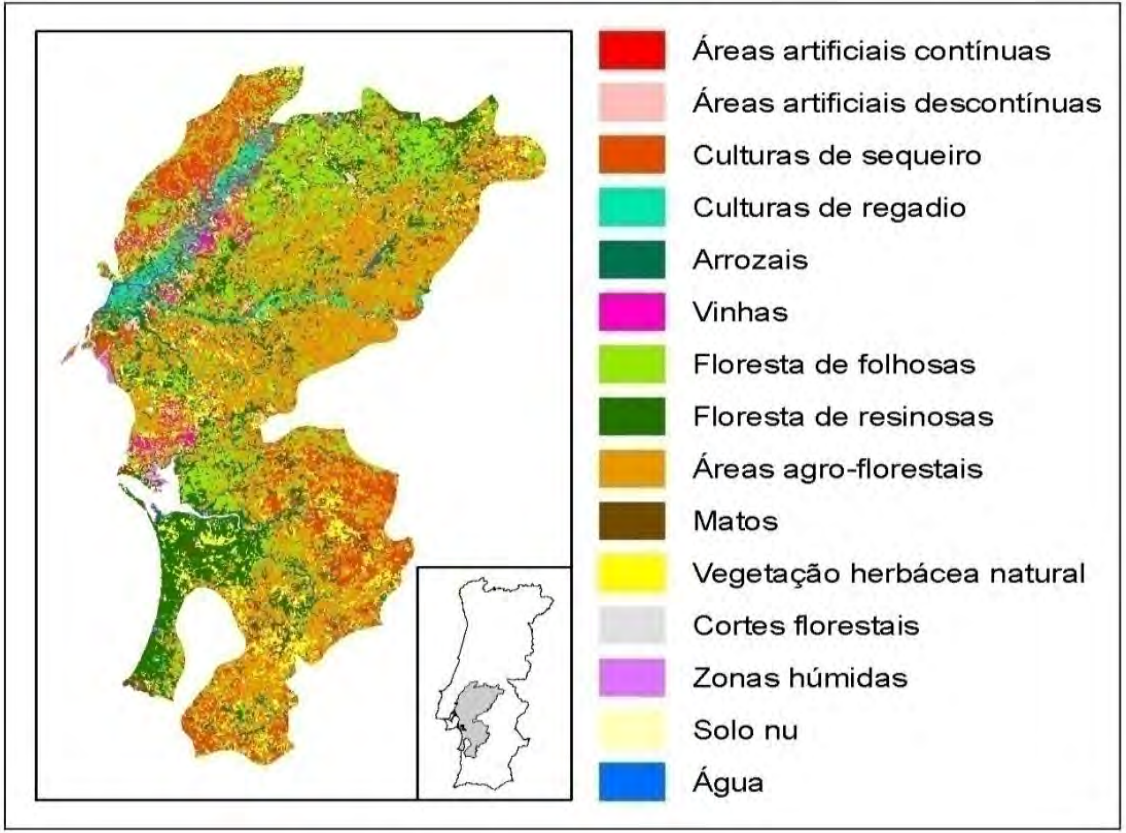

The traditional LCLU map

Spatial representation of a small number of classes that are mutually exclusive

Source: Boyd and Foody (2011)

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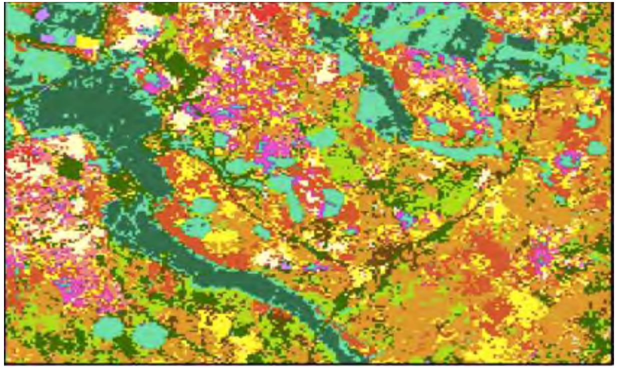
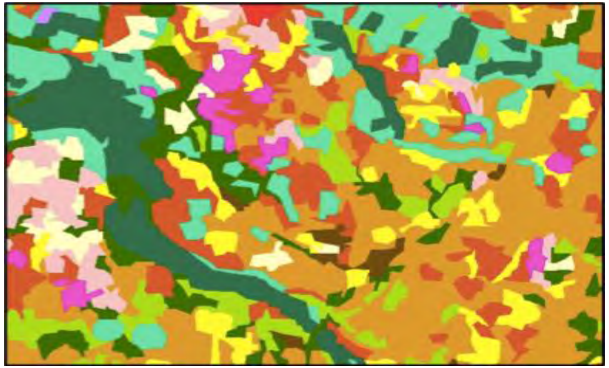
The traditional LCLU map





Data model	raster	vector
Minimum Mapping Unit	pixel	polygon

In each spatial unit (i.e. pixel, vector) there is one, and only one, class from a nomenclature that has a small number of classes.

Traditional LCLU maps in operational LCLU monitoring

National Land Cover Database

1992

2001, 2006, 2011

CORINE Land Cover EEA

1990

2000, 2006, 2012

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Traditional land cover map

In each spatial unit (i.e. pixel, vector) there is one, and only one, class from a nomenclature with a small number of classes.

But....

The real world is not hard but a continuum i.e. there are no crisp spatial borders between classes (Rocchini, D., e C. Ricotta, 2007)

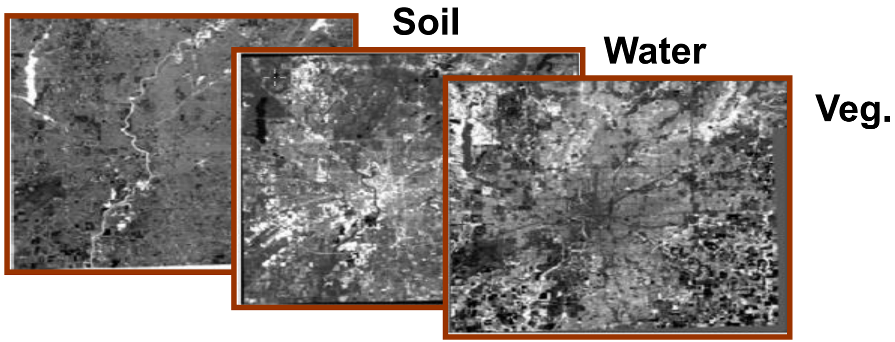
Each pixel can have more than one class

Mixed pixel

Gradient maps

Continuum maps

Fraction maps



Representation of the abundance of a small number of classes (that usually represent land cover elements)

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National Land Cover Database

1992 2001, 2006, 2011

Pixel - 30 m

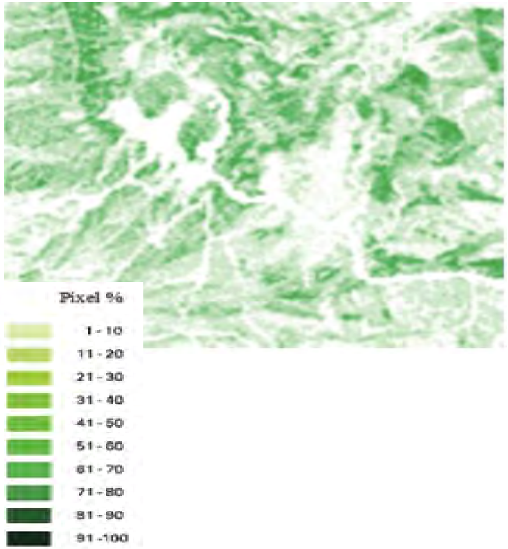
CORINE Land Cover EEA

1990 2000, 2006, 2012, 2015

Pixel - 20 m

% urban imperviousness

% tree canopy



% imperviousness
2006, 2009, 2012, 2015

2012
% imperviousness
% forest
% grassland
% water
% wetland

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1972

A Land Use and Land Cover Classification System for Use with Remote Sensor Data

By JAMES R. ANDERSON, ERNEST E. HARDY, JOHN T. ROACH, and RICHARD E. WITMER

GEOLOGICAL SURVEY PROFESSIONAL PAPER 964

A revision of the land use classification system as presented in U.S. Geological Survey Circular 671

Anderson et al. (1976)

1985

CORINE land cover

EUROPE ENVIRONMENT

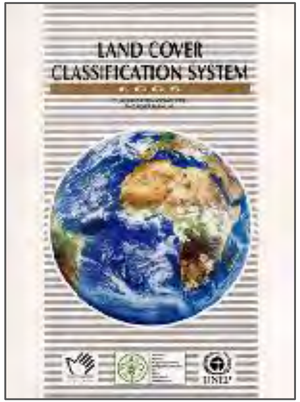
JOINT FUTURE

OR THE QUALITY OF LIFE

EEA

Bossard et al. (2000)

2000



Land Cover Classification System (LCCS) is an universal system

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LCCS – Land Cover Classification System

LCCS - instead of using pre-defined classes, it uses universally valid pre-defined set of independent diagnostic attributes, or classifiers.

Any land cover class, regardless of its type and geographic location, can be identified by a pre-defined set of classifiers.

LCCS is:

- Independent of map scale;
- Independent of data source and data collection methodology;
- Independent of geographic location;
- Independent of application.

Source: Di Gregorio (2005)

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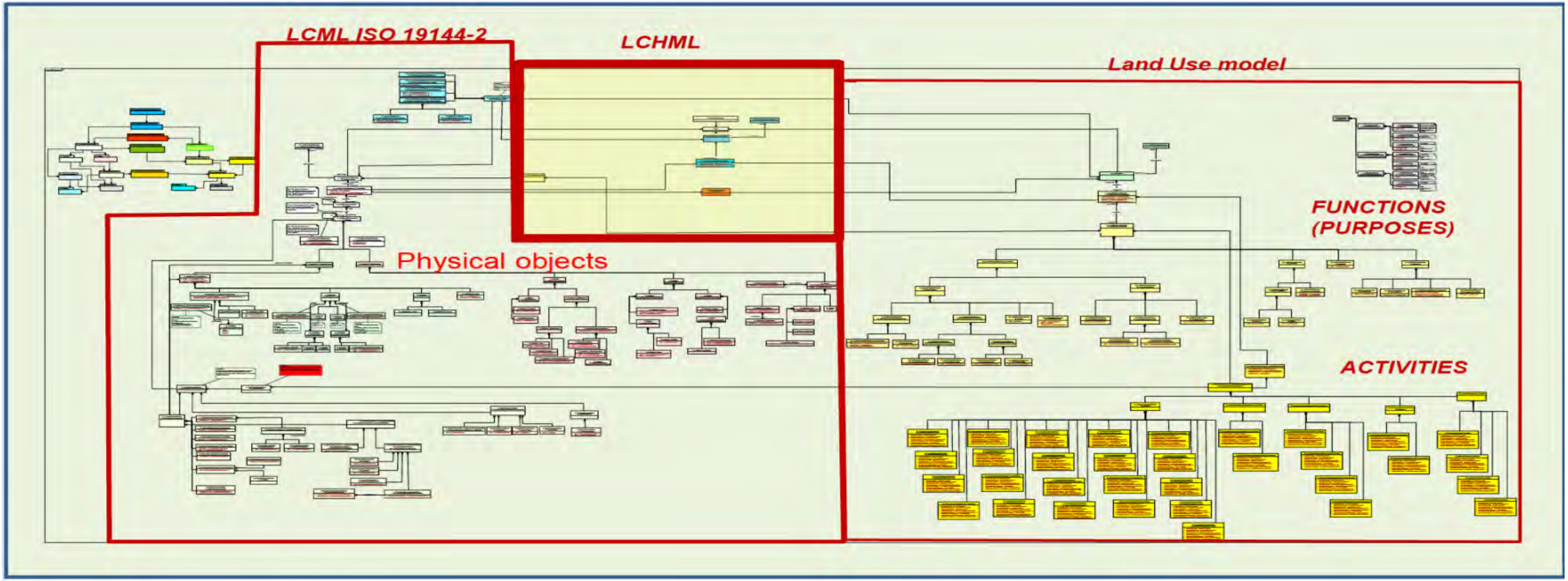
FAO presented the LCHML – Land Characterisation Meta Language



Source: Di Gregorio (2017)

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EAGLE model – from classification to characterisation

EAGLE objective

To elaborate a future-oriented conceptual solution that would support of a European information capacity for land monitoring built on existing or future national data sources.

Information on landscape described with three separate blocks:

I.) LAND COVER Components – LCC
Abiotic (Artificial + Natural), Vegetation, Water Surfaces

II.) LAND USE Attributes – LUA
Agriculture, Forestry, Mining, Residential, Transportation etc.

III.) CHARACTERISTICS – CH
spatial pattern, bio-physical parameters, cultivation measures, land management practices, status/condition etc.

https://land.copernicus.eu/eagle

Source: Smith et al. (2017)

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LCLU monitoring

It is related to characterisation over time and the moments in time usually refer to different years.

Most important LCLU monitoring programs also include the mapping of LCLU changes through the years, i.e. change identification and characterisation. This means that those programs include not only LCLU but also LCLUCC mapping.

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LCLU monitoring

Change detection techniques can also be applied to images for the same year but from different seasons. In this case one is not doing LULCC mapping but capturing different conditions of the same LCLU classes instead (i.e. forest fires, phenology of agriculture crops).

One should differentiate:

- changes within classes - modification
- changes between classes - conversion (Giri, 2012).

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LCLU monitoring

There are two types of land cover monitoring:

- LCLU maps for different years are independently produced (e.g. GLOBCOVER)
- LCLU maps are produced in a temporarily consistent manner (e.g. CORINE LC and current NLCD)

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LCLU monitoring by independent LCLU map production

LCLU maps for different years are produced through the independent application of image classification techniques to the images of the different years.

Change detection and/or characterisation (i.e. LCLUC) is done through post-classification map comparison.

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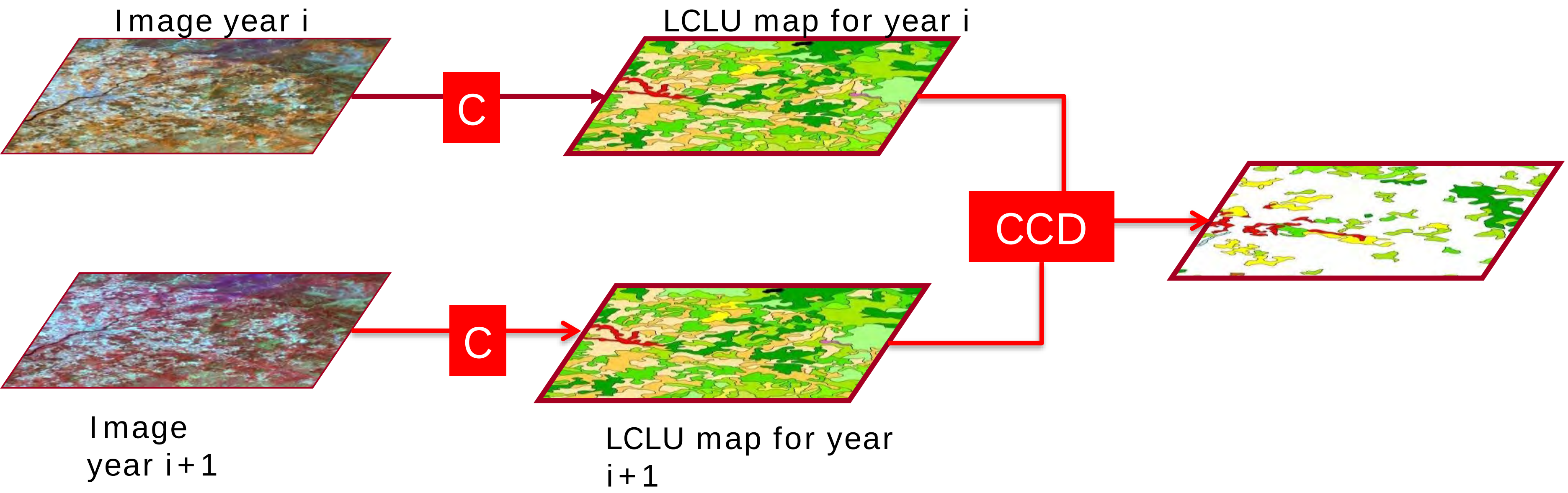
LCLU monitoring by independent LCLU map production



LCLUC most likely does not indicate real changes but instable classifications instead

C Image classification

CCD Class Change Detection

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LCLU monitoring by a temporally consistent manner

A first LCLU is produced for a given year.

The production of a LCLU map for a following year is produced based on spectral change detection techniques followed by image classification

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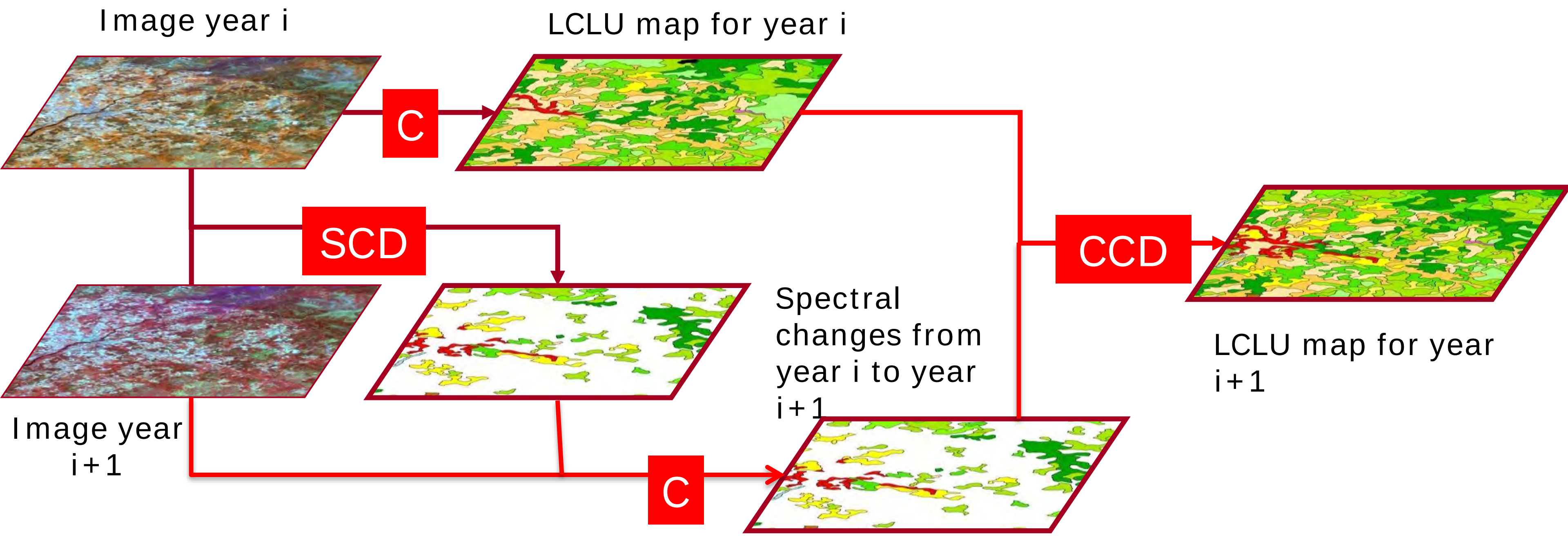
LCLU monitoring by a temporally consistent manner



SCD Spectral Change Detection
C Image classification
CCD Class Change Detection

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Change detection

Spectral change detection

Change detection techniques are applied to identify changes on the spectral characteristics of the spatial units (e.g. pixels). It also includes techniques that take into account the spatial arrangement of the pixels (i.e. contextual information)

Class change detection

Change detection consists on a post-classification comparison (i.e. GIS overlay)

This is a very simple way to approach change detection. There are other approaches much more comprehensive.

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Although a large number of change detection applications have been implemented and different change detection techniques have been tested, the question of which method is best suited for a specific study area remains unanswered. No single method is suitable for all cases. The method selected depends on an analyst's knowledge of the change detection methods and skills in handling remote sensing data, the image data used, and characteristics of the study areas. Lu et al. (2011)

Examples of simple methods for spectral change detection

Change vector analysis

Principal Component Analysis

Image differencing (bands, NDVI)

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NDVI image differencing

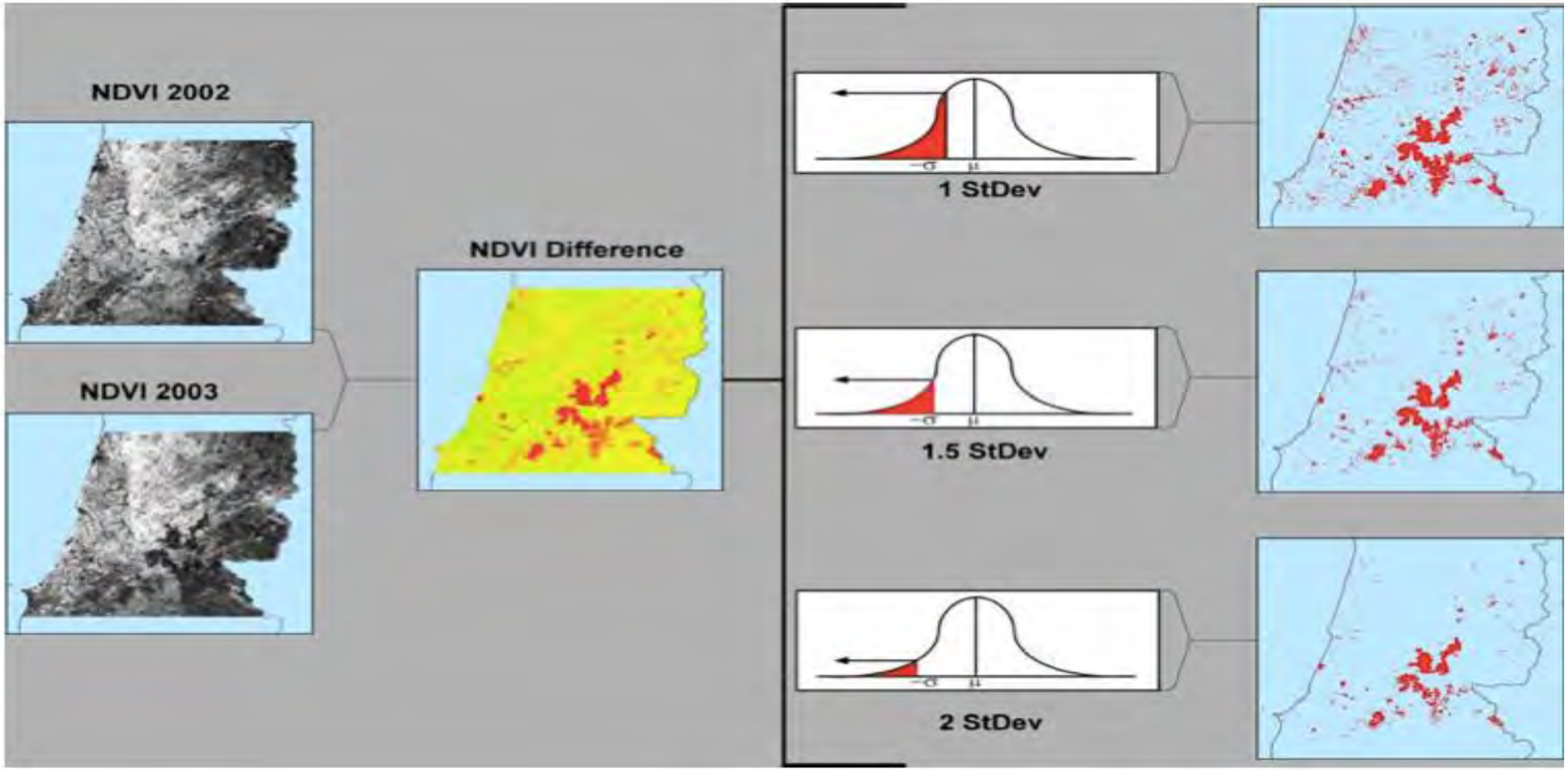

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Image classification for LCLU mapping

1 An integrated approach for LCLU mapping

2 Most common problems in image classification and how to solve them

e.g. mixed pixel problem, lack of normality of the training data, Hughes phenomenon

3 Most important advances in satellite image classification

e.g. from pixel to object, from hard to soft classifiers, from parametric to non-parametric classifiers

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The traditional approach for LCLU mapping

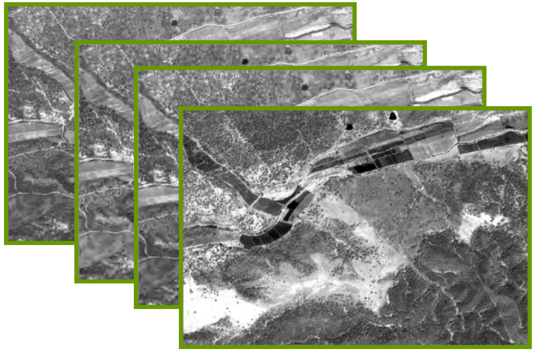
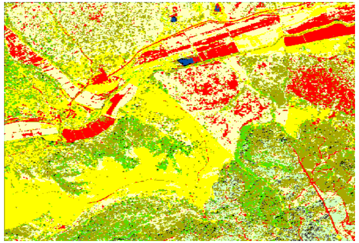


Image classification
at pixel level



Map of categorical classes

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For many years the research emphasis has been on the classification step itself.

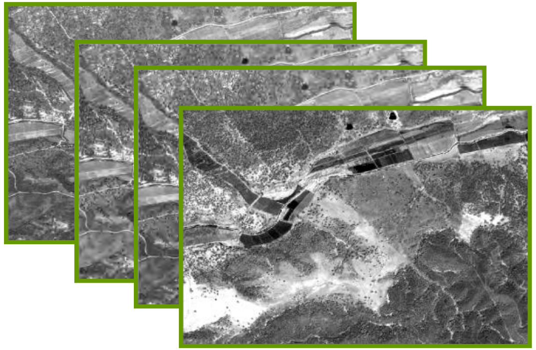
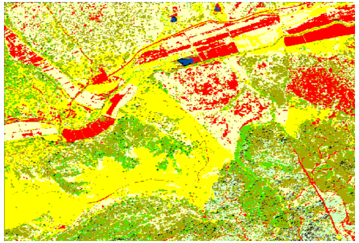


Image classification at pixel level



Map of categorical classes

Does it satisfy the user needs?

Recent research

New classification algorithms

A new spatial unit of analysis

Spatial analysis for map generalisation

Redefine the approach for thematic information extraction

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Recent advances in satellite image classification

1. Development of **components of the classification algorithm**, including training, learning and approaches to class separation

   e.g. artificial neural networks, decision trees, random forests

2. Development of **new systems-level approaches** that augment the underlying classifier algorithms

   e.g. fuzzy or similar approaches that soften the results of a hard classifier, multiclassifier systems that integrate the outputs of several classification algorithms

3. Exploitation of **multiple** types of data or ancillary information (numerical and categorical) in the classification process

   e.g. use of structural or spatial context information from the imagery, use of multitemporal data, use of multisource data, use of ancillary geographical knowledge in the overall classification system

Source: Foody et al. (2009) and Wilkinson (2005)

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Thematic information extraction from satellite images

1. Definition of the mapping approach *
2. Geographical stratification
3. Image segmentation
4. Feature identification and selection *
5. Classification *
6. Ancillary data integration
7. Post-classification processing
8. Accuracy assessment *

* mandatory

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1 Definition of the mapping approach *

2 Geographical stratification

3 Image segmentation

4 Feature identification and selection *

5 Classification *

6 Ancillary data integration

7 Post-classification processing

8 Accuracy assessment *

* mandatory

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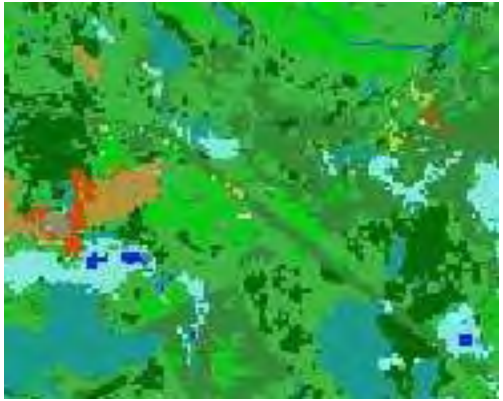
1. Definition of the mapping approach

The mapping approach has to take into account, e.g.

Characteristics of the satellite data to be used	→	Definition of the spatial unit of analysis
Technical specifications of the final map (e.g. MMU)	→	Definition of the spatial unit of analysis
Characteristics of the geographical area to be mapped	→	Decision on stratifying the study area
Availability of ancillary data	→	Decision on the use of ancillary data

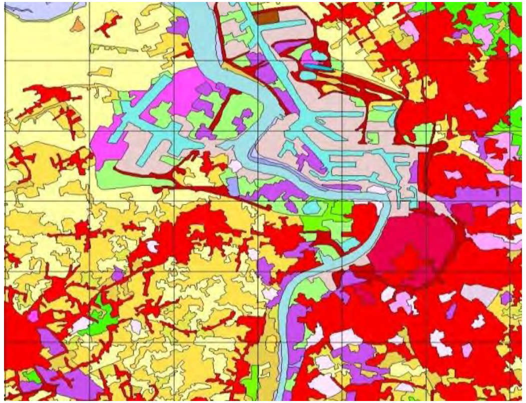
MMU = Minimum Mapping Unit

1. Definition of the mapping approach



Minimum Mapping Unit (MMU)

The MMU is the smallest area that is represented in a map



In raster maps the MMU usually is the pixel

- e.g. in the NLCD 2001 (USA) the MMU is 30x30 m pixel

In vector maps the MMU is the smallest object/polygon that is represented in the map

- e.g. in the CORINE Land Cover (CLC) maps (from EEA) the MMU is 25 ha

NLCD = National Land Cover Database

EEA – European Environment Agency

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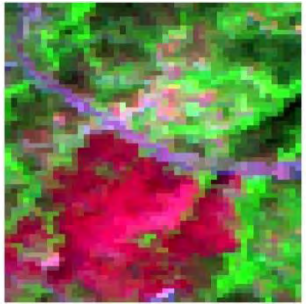
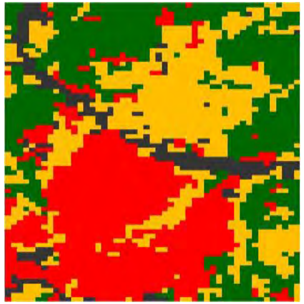
1. Definition of the mapping approach

Spatial unit of analysis This is the unit to which the classification algorithms will be applied

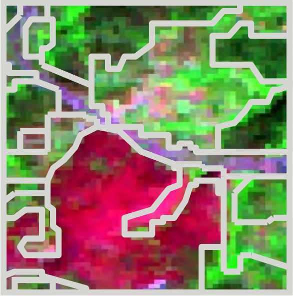
Image pixel





Per pixel or sub-pixel classification

Object



Object oriented image classification

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1. Definition of the mapping approach

The selection of the **spatial unit of analysis** depends on:

Spatial resolution of the satellite image

Type of thematic information we want to extract, e.g. land cover, land use

Format of the map we want to produce, i.e. vector or raster

Minimum Mapping Unit of the final map

Post-processing tasks that we are planning to apply

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1. Definition of the mapping approach

The steps required to information extraction depend on the defined mapping approach:

Map format = raster

MMU = pixel size of input satellite data

Feature selection > Image classification > accuracy assessment

MMU > pixel size of input satellite data

Feature selection > Image classification > post-processing > accuracy assessment

upscaling

Map format = vector

Spatial unit of analysis = image pixel

Feature selection > Image classification > post-processing > accuracy assessment

Generalisation + Raster to vector conversion

Spatial unit of analysis = object

Image segmentation > Feature selection > Image classification > post-processing > accuracy assessment

Generate the objects

Generalisation

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Thematic information extraction from satellite images

1 Definition of the mapping approach *

2 Geographical stratification

3 Image segmentation

4 Feature identification and selection *

5 Classification *

6 Ancillary data integration

7 Post-classification processing

8 Accuracy assessment *

* mandatory

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2. Geographical stratification

Geographical stratification – the study area is divided into smaller areas (strata) so that each strata can be processed independently.

Five general concepts are useful in geographical stratification:

- economics of size,
- type of physiography,
- potential land cover distribution,
- potential spectral uniformity,
- edge-matching issues.

Data that can be used for geographical stratification

Slope

Aspect

Elevation

Existent land cover/use maps

Climate data

Vegetation maps

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2. Geographical stratification

Geographical stratification used on the production of the US National Land Cover Database (NLCD) - 2001

Input data

- 83 Level III ecoregions developed by Omernik
- NLCD 1992
- AVHRR normalized greenness maps

AVHRR - Advanced Very High Resolution Radiometer

Source: Homer et al. (2004)

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* mandatory

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3. Image segmentation

This step is only required if the spatial unit of analysis is the **object**.
Segmentation is the division of an image into spatially continuous, disjoint and homogeneous regions, i.e. the objects.

Segmentation of an image into a given number of regions is a problem with a large number of possible solutions.

There are no “right” or “wrong” solutions to the delineation of landscape objects but instead **“meaningful” and “useful” heuristic approximations** of partitions of space.

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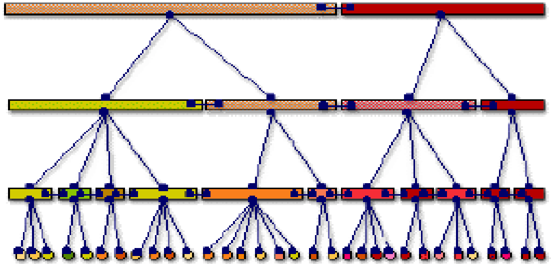
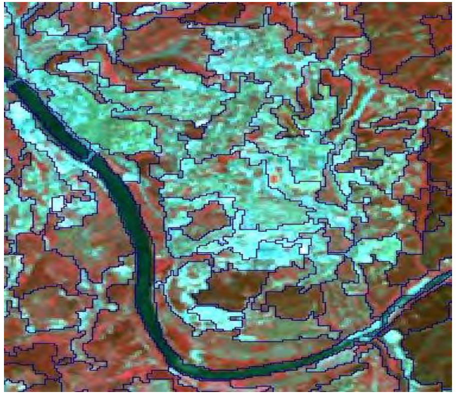
3. Image segmentation

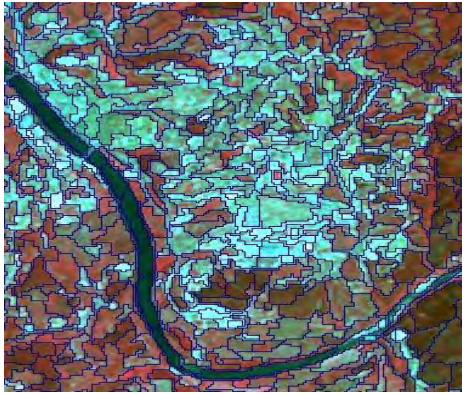
A type of segmentation that is very common is the **multi-resolution segmentation**, because of its ability to deal with the range of scales within a single image.



Super-objects

Sub-objects





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4. Feature identification and selection

What type of features can we use for information extraction?

Should we, for some reason, manipulate the feature space?

How can we select the best features for class discrimination?

Manipulation and selection of features are used to **reduce the number of features without sacrifying accuracy**

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4. Feature identification and selection

Spectral measurements — *1st order measurements*

From a single date (Unitemporal approach)

From multiple dates (Multi-temporal approach

Secondary measurements derived from the image — *2nd order measurements*

Measurements of the spatial unit being classified

Measurements related to the neighbourhood

- Quantification of the spatial variability within the neighbourhood
- Texture
- Spatial features
- Semantic relationships of a spatial unit with its neighbours

Ancillary information

This term is generally used for non-spectral geographical information

Data from images with different characteristics can also be considered as ancillary information. The approaches used for multisensor data may fall within data fusion.

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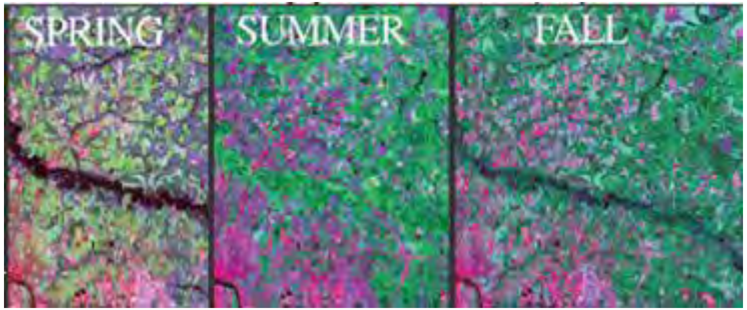
4. Feature identification and selection

1st order measurements

Unitemporal approach

Multi-temporal approach



The production of the US National Land Cover Database (NLCD) – 2001 is based on a multi-temporal approach

It helps to discriminate classes with different phenology

Irrigated and rain fed agriculture

Permanent and deciduous forests

Source: Homer et al. (2004)

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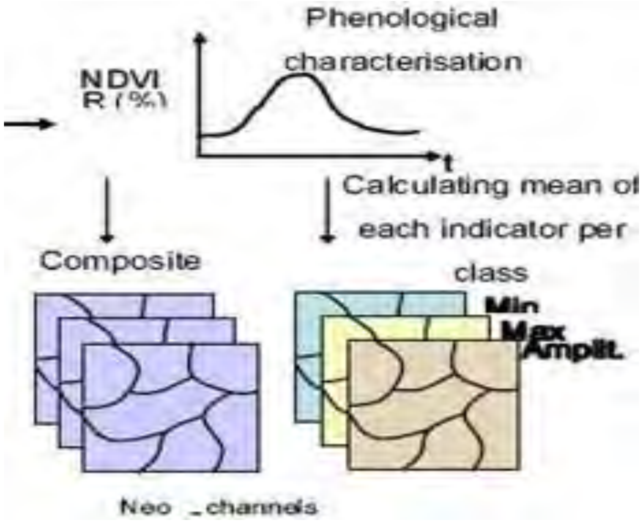
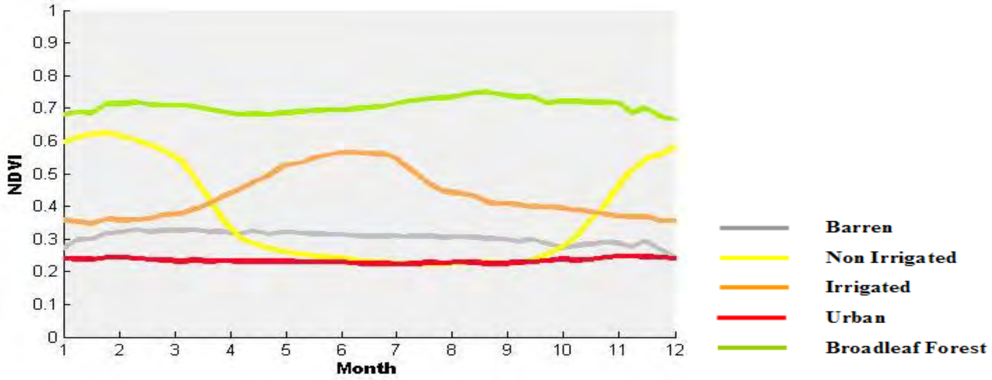
4. Feature identification and selection

2nd order measurements

Measurements of the spatial unit being classified



In the GLOBCOVER project (ESA) a set of new-channels based on the annual NDVI profile are derived.



Source: Defourny et al. (2005)

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4. Feature identification and selection

2nd order measurements

Measurements related to the neighbourhood (contextual information)

Most mapping approaches operate at a **pixel level**, ignoring its context

Contextual information and semantic relationships with neighbours is always used by photo-interpreters in **visual analysis**.

Several attempts have been carried out to take into automatic classification the contextual information.

- Texture
- First order statistics in the spatial domain
  (e.g. mean, variance, standard deviation, entropy)
- Second order statistics in the spatial domain
  (e.g. homogeneity, dissimilarity, entropy, angular second moment, contrast, correlation)
- Geostatistics
  (e.g., variogram, correlogram, covariance function)
- Fractals

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4. Feature identification and selection

…some considerations on object oriented image classification

In **object oriented image classification** one can use features that are very similar to the ones used on visual image interpretation

Shape and size of the objects

Spectral homogeneity within objects

Semantic relationships of a spatial unit with its neighbours

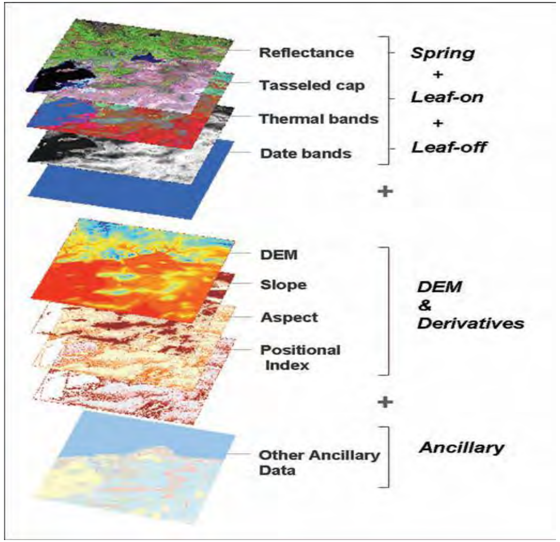
Before object oriented image classification there was the **per-field classification**. In this approach the objects are not extracted from the satellite image through segmentation but instead from an existent geographical data base with landscape units, i.e. fields.

4. Feature identification and selection

Ancillary information

continuous — e.g. elevation, slope, aspect

categorical — e.g. soil type, existent land cover maps



US National Land Cover Database 2001

Source: Homer et al. (2007)

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Thematic information extraction from satellite images

1 Definition of the mapping approach *

2 Geographical stratification

3 Image segmentation

4 Feature identification and selection *

5 Classification *

6 Ancillary data integration

7 Post-classification processing

8 Accuracy assessment *

* mandatory

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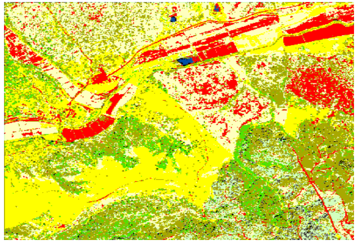
5. Classification

Image spatial space

Allocation of a class to each spatial unit of analysis (SUA)



Map of categorical classes

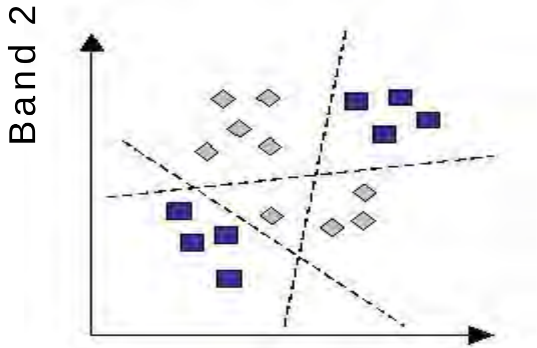


Image feature space

Each SUA is represented by a vector, consisting of a set of measurements (e.g. reflectance)

Definition of decision boundaries to separate classes

Definition of the decision rule, i.e. the algorithm that defines the position of a SUA with respect to the decision boundaries and that allocates a specific label to that SUA

The word classifier is widely used as a synonym of the term decision rule

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5. Classification

- satellite image classification

- natural language processing
- syntactic pattern recognition
- search engines
- medical diagnosis
- bioinformatics
- cheminformatics
- stock market analysis
- classifying DNA sequences
- speech recognition,
- handwriting recognition
- object recognition in computer vision
- game playing
- robot locomotion

Artificial intelligence

Computer sciences

Pattern recognition

Data mining

Statistics

Machine learning

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5. Classification

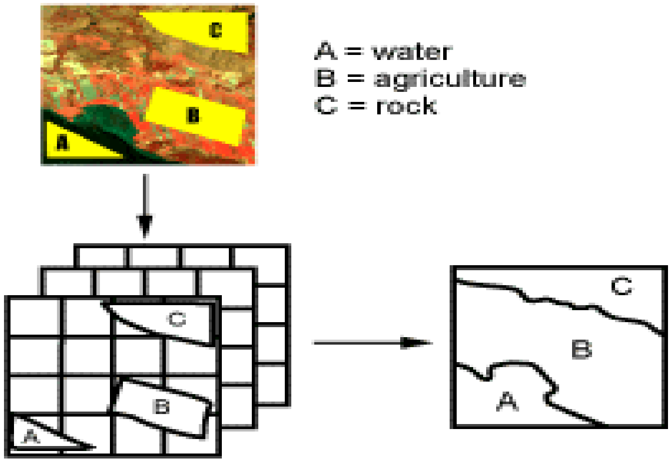
Different possibilities to categorise classifiers

- **Type of learning**
  - supervised
  - unsupervised
- **Assumptions on data distribution**
  - Parametric
  - Non-parametric
- **Number of outputs for each spatial unit**
  - Hard (crisp)
  - Soft (fuzzy)

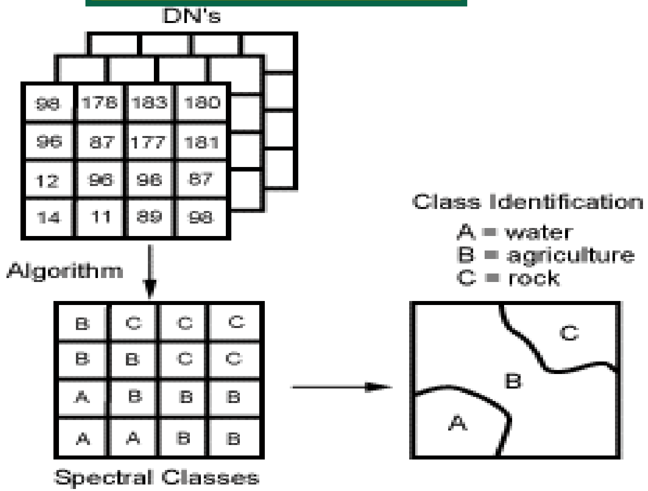
5. Classification

Type of learning

Supervised classification



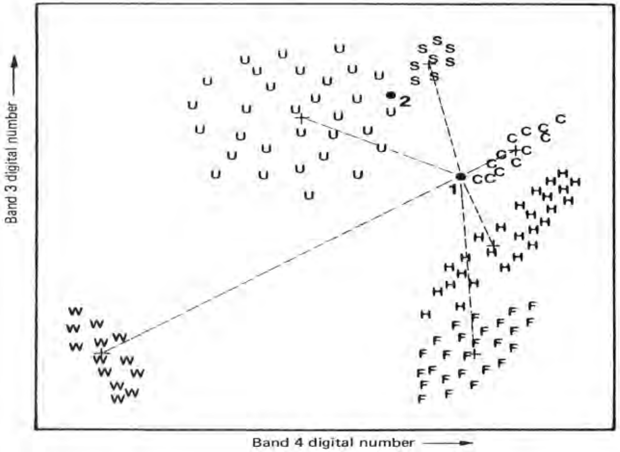
Unsupervised classification



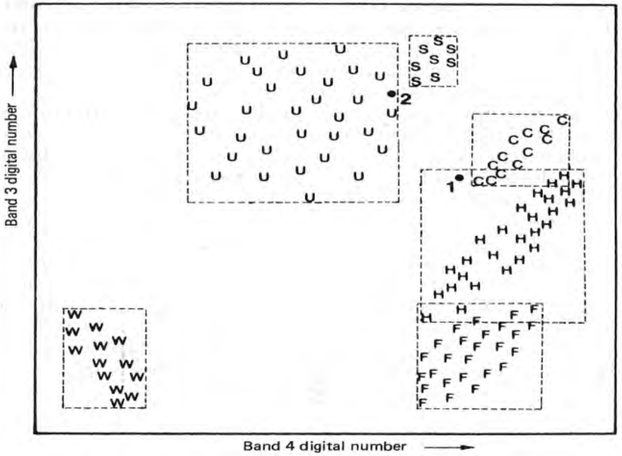
Source: CCRS

5. Classification

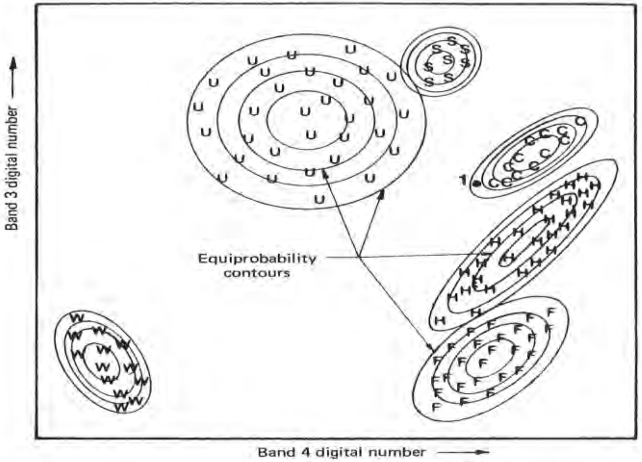
Classic supervised classifiers



Minimum distance



Parallelepiped



Maximum likelihood

Source: Jensen (1996)

5. Classification

Most important advanced supervised classifiers

- Maximum likelihood
- Nearest neighbour
- Artificial neural networks
- Decision trees
- Support vector machines
- Spectral Mixture Analysis

Source: Jensen et al. (2009), Lu and Weng (2007), Wilkinson (2005)

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5. Classification

Some considerations on the training stage…

- The **training phase is decisive** on the final results of image classification. In fact, in thise phase we collect the data that will be used to train the algorithm.
- The usual **restrictions on sampling** (cost, availability of data and accessibility) may lead to an **inadequate sampling**.
- In case of **parametric** classifiers the **number of sample observations** affect strongly the estimates of the **statistical parameters**.
- As the dimensionality of the data increases for a fixed sample size so the precision of the statistical parameters become lower (i.e., **Hughes phenomenon**).
- It is common that even **mixed pixels dominate the image**, only **pure pixels** are selected for training. However, this may lead to unsatisfactory classification accuracy.

5. Classification

Assumptions on data distribution

Parametric classifiers

e.g., maximum likelihood classifier

Non-parametric classifiers

e.g., decision trees, artificial neural networks, support vector machines, nearest neighbour

- Traditionally most classifiers have been grounded to a significant degree in **statistical decision theory**.
- These classifiers rely on **assumptions of data distribution**.
- The **performance** of a parametric classifier depends largely on how well the data match the pre-defined models and on the accuracy of the estimation of the model parameters.
- They suffer from the **Hughes phenomenon** (i.e. curse of dimensionality), and consequently it might be difficult to have a significant number of training pixels.
- They are not adequate to integrate **ancillary data** (due to difficulties on classifying data at different measurement scales and units).

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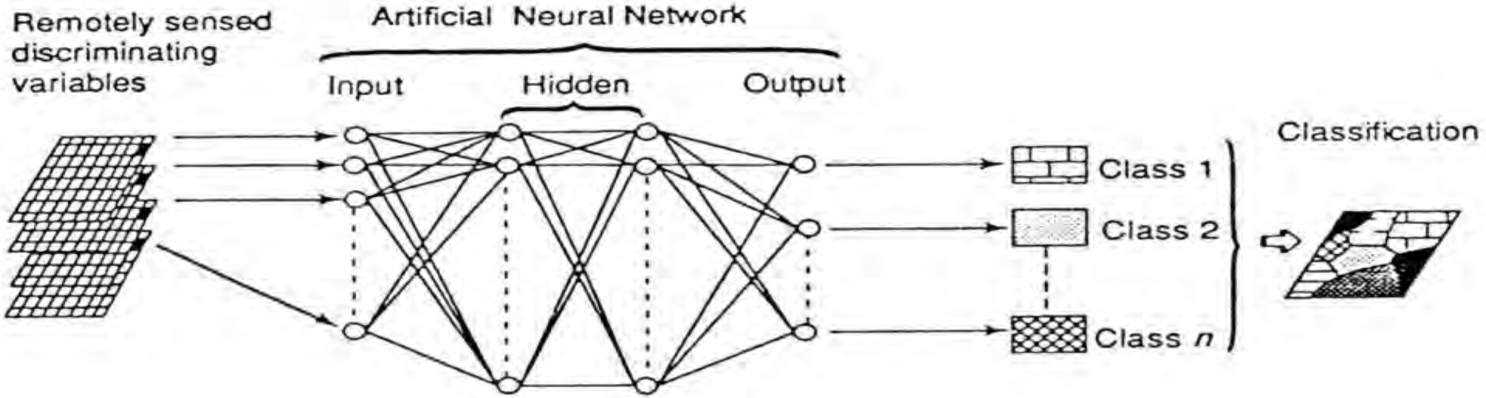
5. Classification

Non-parametric classifiers Artificial Neural Networks

An ANN is a form of artificial intelligence that imitates some functions of the human brain.

An ANN consists of a series of layers, each containing a set of processing units (i.e. neurones)



All neurones on a given layers are linked by weighted connections to all neurones on the previous and subsequent layers.

During the training phase, the ANN learns about the regularities present in the training data, and based on these regularities, constructs rules that can be extended to the unknown data

Source: Foody (1999)

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5. Classification

Non-parametric classifiers Artificial Neural Networks

Type of learning

ANN → Supervised | Unsupervised

Number of output labels

ANN → Hard | Soft

Most common types of ANN

- Multi-layer perceptron with back-propagation
- Self-organised feature map (SOM)
- Hopfield networks
- ART (Adaptive Ressonance Theory) Systems

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5. Classification

Non-parametric classifiers Artificial Neural Networks

Advantages of ANN

- It is a **non-parametric classifier**, i.e. it does not require any assumption about the statistical distribution of the data.
- **High computation rate**, achieved by their massive parallelism, resulting from a dense arrangement of interconnections (weights) and simple processors (neurones), which permits real-time processing of very large datasets.

Disadvantages of ANN

- ANN are **semantically poor**. It is difficult to gain any understanding about how the result was achieved.
- The **training** of an ANN can be computationally demanding and slow.
- ANN are perceived to be **difficult to apply successfully**. It is difficult to select the type of network architecture, the initial values of parameters (e.g., learning rate, the number of iterations, initial weights)

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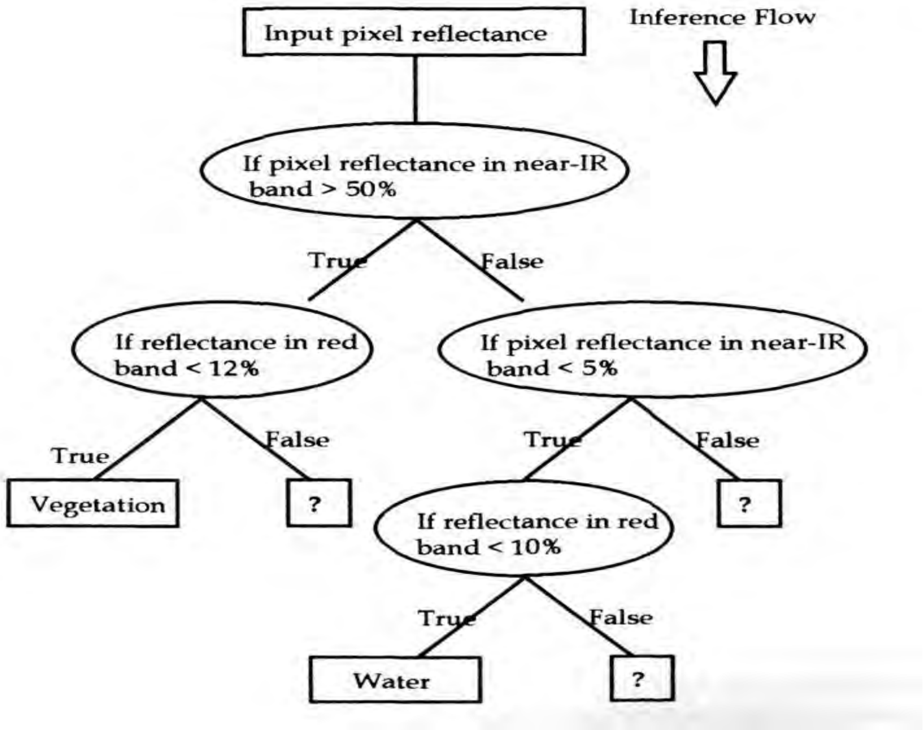
5. Classification

Non-parametric classifiers Decision Trees



DT are knowledge based (i.e. a method of pattern recognition that simulates the brains inference mechanism).

DT are hierarchical rule based approaches.

DT predict class membership by recursively partitioning a dataset into homogeneous subsets.

Different variables and splits are then used to split the subsets into further subsets.

There are hard and soft (fuzzy) DT.

Source: Tso and Mather (2001)

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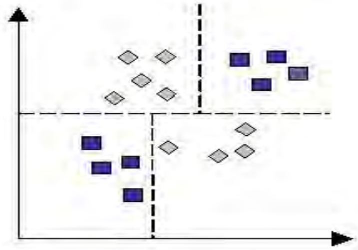
5. Classification

Non-parametric classifiers   Decision Trees

Advantages of DT

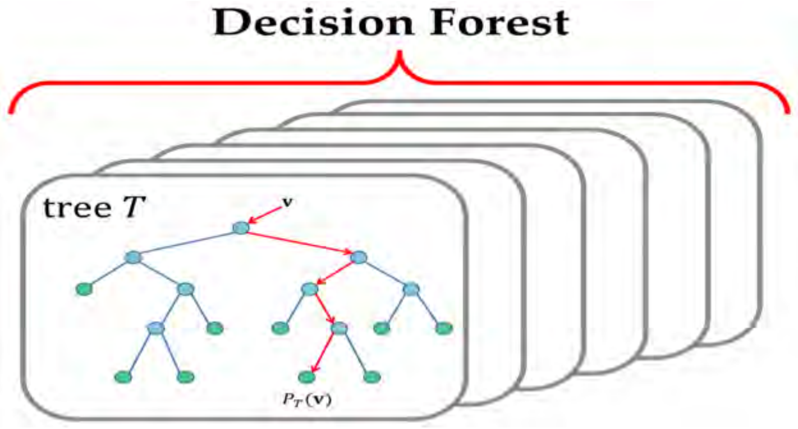
- Ability to handle **non-parametric** training data, i.e. DT are not based on any assumption on training data distribution.
- DT can reveal **nonlinear and hierarchical** relationships between input variables and use these to predict class membership.
- DT yields a set of rules which are **easy to interpret** and suitable for deriving a physical understanding of the classification process.
- DT, unlike ANN, **do not need an extensive** design and training.
- Good **computational efficiency**.



Disadvantages of DT

- The use of hyperplane **decision boundaries parallel to the feature** axes may restrict their use in which classes are clearly distinguishable.

Non-parametric classifiers — Random forest



https://dimensionless.in/introduction-to-random-forest/

Random forest is a collection of multiple decision trees (typically hundreds).

Random forest is an ensemble learning method, which is used for classification and regression problems

The output of a random forest is commonly the class that is:
- **the mode of the classes (classification)**

or
- **mean prediction (regression) of the individual trees.**

5. Classification

Non-parametric classifiers — Random Forest

Advantages of RF

- Inherit the advantages of decision trees
- Enables bagging (bootstrap aggregation), which is a technique for reducing the variance of an estimated prediction
- Calculates variable Importance
- Less prone to overfitting than decision trees

Disadvantages of RF

- The bias of a random forest is the same as the bias of any of the individual sampled trees.

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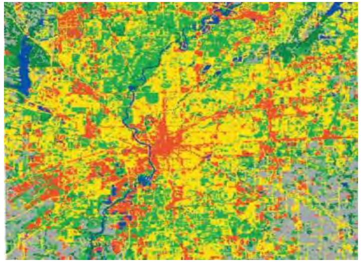
5. Classification

Hard (crisp) classification

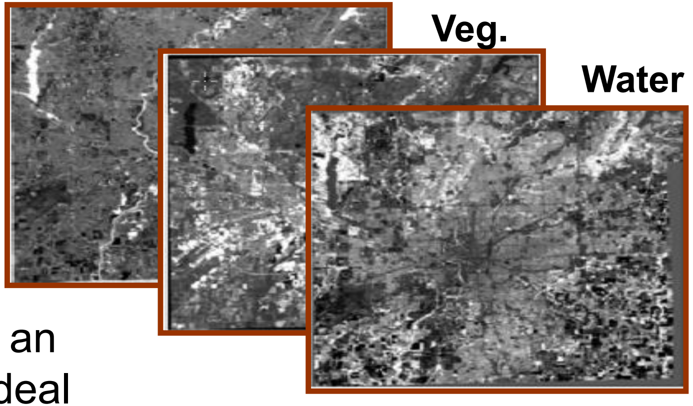
Number of outputs for each spatial unit

Soft (fuzzy) classification

each pixel is forced or constrained to show membership to a single class.



each pixel may display multiple and partial class membership.



Soft classification has been proposed in the literature as an alternative to hard classification because of its ability to deal with **mixed pixels**.

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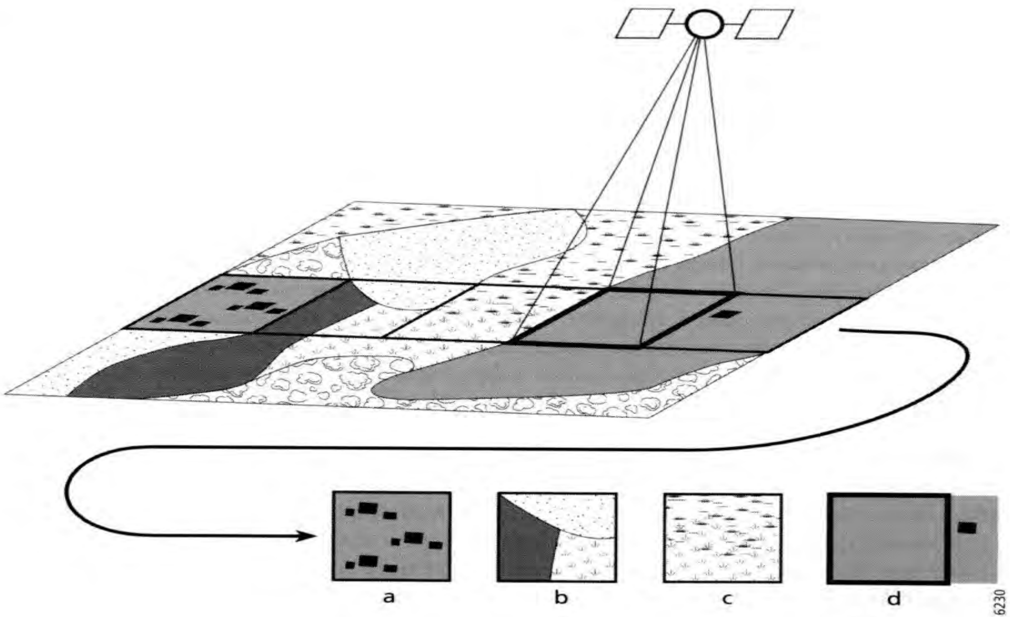
5. Classification



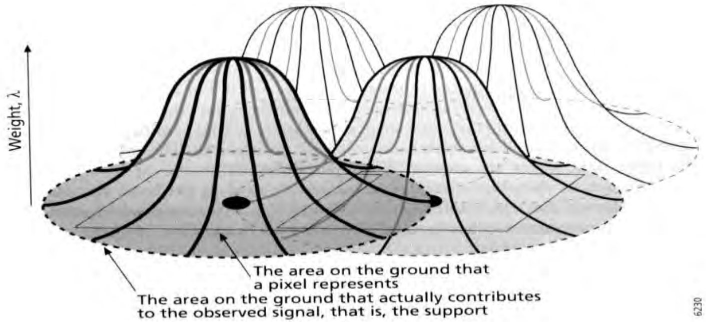
The mixed pixel problem

A – presence of small, sub-pixel targets

B – presence of boundaries of discrete land cover classes

C – gradual transition between land cover classes (continuum)

D – contribution of areas outside the area represented by a pixel



Source: Foody (2004)

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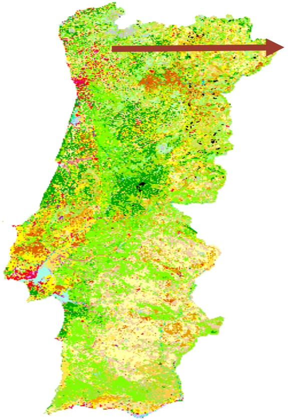
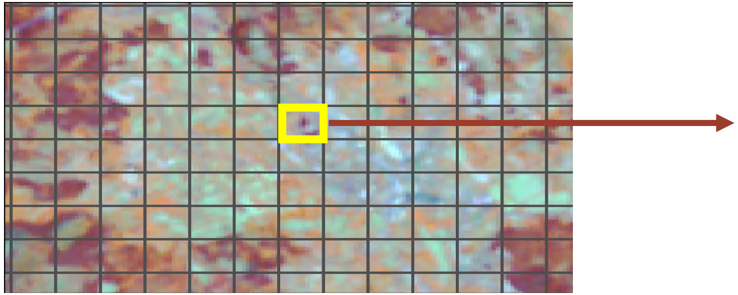
5. Classification

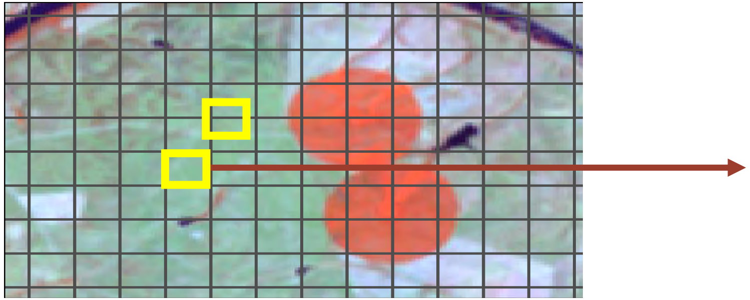
The number of mixed pixels in an image varies mainly with:

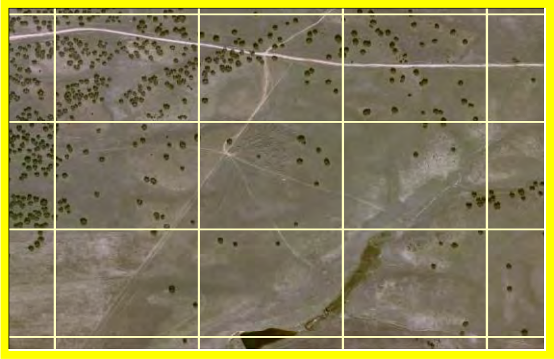
- Landscape fragmentation
- Sensor's spatial resolution

The mixed pixel problem









MERIS FR pixels

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5. Classification

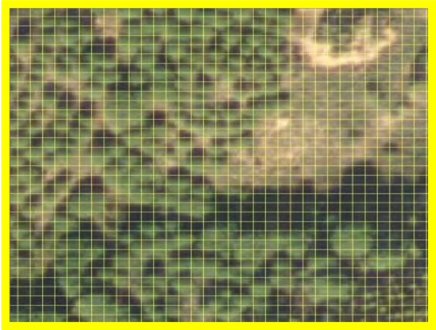
The mixed pixel problem

The problem of mixed pixels exist in coarse and fine resolution images:

In course resolution images the mixed pixels are mainly due to co-existence in the same pixel of different classes.

MERIS FR

In fine resolution images the mixed pixels are mainly due to co-existence in the same pixel of different components (e.g., houses, trees).



IKONOS

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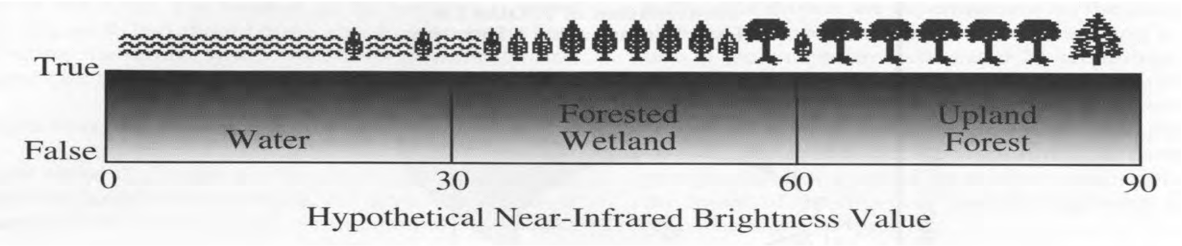
5. Classification

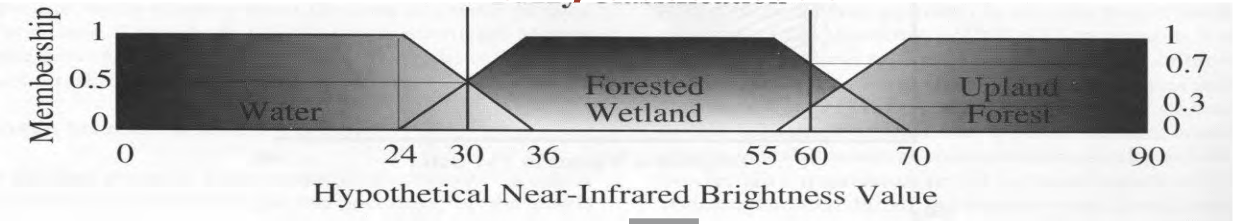
Hard classification



Decision rules

0 – 30 -> Water
30 - 60 -> Forest wetland
60 - 90 -> Upland forest

Fuzzy classification



Decision rules are defined as membership functions for each class.
Membership functions allocates to each pixel a real value between 0 and 1, i.e. membership grade.

But, wow can we represent the sub-pixel information?

Source: Jensen (1996)

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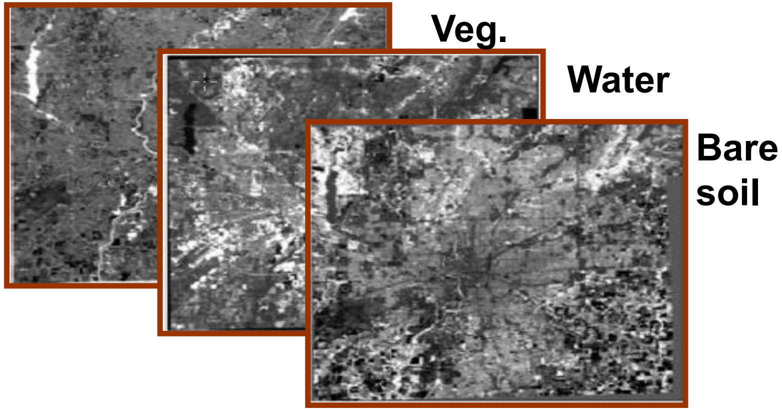
5. Classification

How can we represent the sub-pixel information?

Sub-pixel scale information is typically represented in the output of a soft classification by the **strength of membership a pixel displays to each class.**

It is used to reflect the relative proportion of the classes in the area represented by the pixel



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5. Classification

How can we represent the sub-pixel information?

Map with primary and secondary classes

Entropy image

The pixel value translates a degree of mixing (entropy is minimised when the pixel is associated with a single class and maximised when membership is partitioned evenly between all of the defined classes).

Hill' s diversity numbers image

The pixel values provides information on the number of classes, the number of abundant classes and the number of very abundant classes.

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Soft classifiers

Most common soft classifiers

- Maximum likelihood classification
- Fuzzy c-means
- Possibilistic c-means
- Fuzzy rule based classifications
- Artificial neural networks

Approaches based on fuzzy set theory

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Soft classifiers *Some considerations on uncertainty*

Maximum likelihood classifier (MLC)

- MLC is one of the **most widely** used hard classifier.
- In a standard MLC each pixel is allocated to the class with which it has the **highest posterior probability of class membership**.
- MLC has been adapted for the derivation of **sub-pixel information**.
- This is possible because a **by-product** of a conventional MLC are the **posterior probabilities** of each class for each pixel.
- The posterior probability of each class provides is a relative measure of **class membership**, and can therefore be used as an **indicator of sub-pixel proportions**.
- Some authors use the term **Fuzzy MLC**, to discriminate it from the (hard) MLC.

Conceptually, there is not a direct link between the proportional coverage of a class and its posterior probability. In fact, posterior probabilities are an indicator of the uncertainty in making a particular class allocation. However many authors have find that in practice useful sub-pixel information can be derived from this approach.

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5. Classification

Soft classifiers
The continuum of classification fuzziness

In the literature the term fuzzy classification has been used for cases where fuzziness is only applied to the allocation stage – which does not seem to be completely correct.

If we apply the concept of fuzziness to all stages of image classification we can create a continuum of fuzziness, i.e. a range of classification approaches of variable fuzziness.

Completely-crisp classification	Classification stages	**Fully-fuzzy classification**
Dominant class	Training	Individual class proportions
Pixel is allocated to a single class	Allocation	Membership grade to all classes
Dominant class	Testing	Individual class proportions

Source: Foody (2004)

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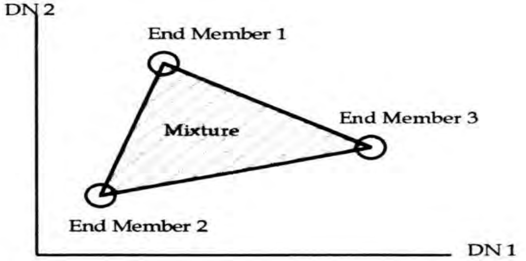
Spectral unmixing

Spectral unmixing = spectral mixture modelling = spectral mixture analysis

Spectral unmixing is an alternative to soft classification for sub-pixel analysis.

Spectral unmixing is based on the assumption that spectral signature of satellite images results essentially from a mixture of a small number of pure components (endmembers) with characteristic spectra.

If so, it is then possible to use a limited number of components so that mixtures of these component spectra adequately simulate the actual observations.



Source: Tso and Mather (2000)

Linear mixture models are the most common models used in satellite image analysis

$$DN_c = \sum_1^N F_n DN_{n_1 c} + E_c$$

DN*c* –image radiance for band c
N – is the number of endmembers
F_n – is the relative fraction of endmember *n*
DNn.c – is the endmember *n* inner radiance
Ec –residual fitting error

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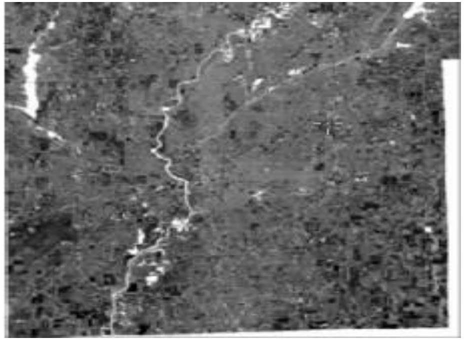
5. Classification

Spectral unmixing — A case study: urban mapping

Lu and Weng (2004) used Spectral Mixture Analysis for mapping the Urban Landscape in Indianapolis with Landsat ETM+ Imagery.

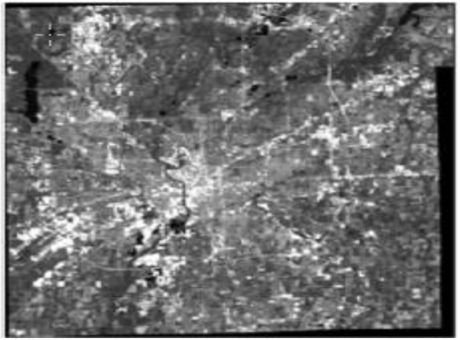
SMA was used to derive fraction images to three endmembers: shade, green vegetation, and soil or impervious surface

Output of spectral unmixing



Shade fraction

Vegetation fraction



Soil or impervious surface fraction

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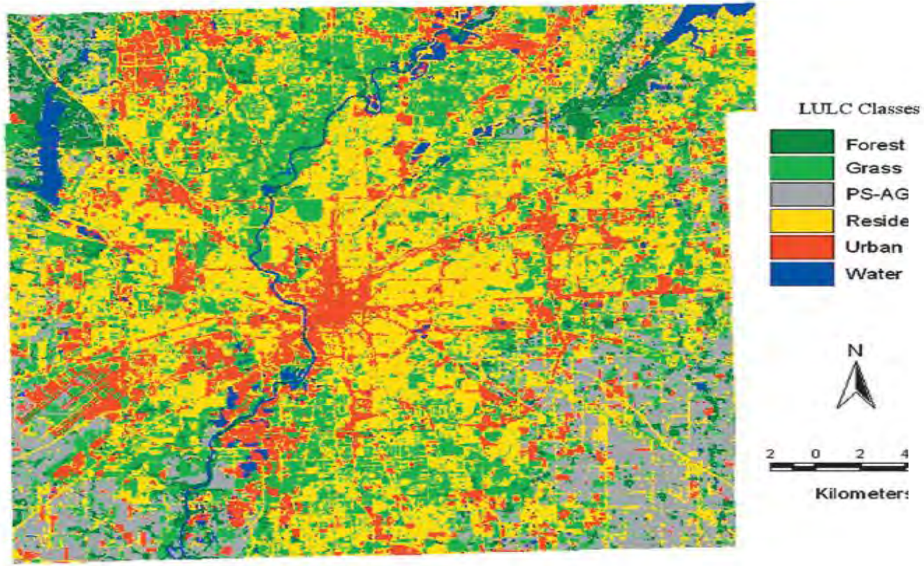
5. Classification

Spectral unmixing

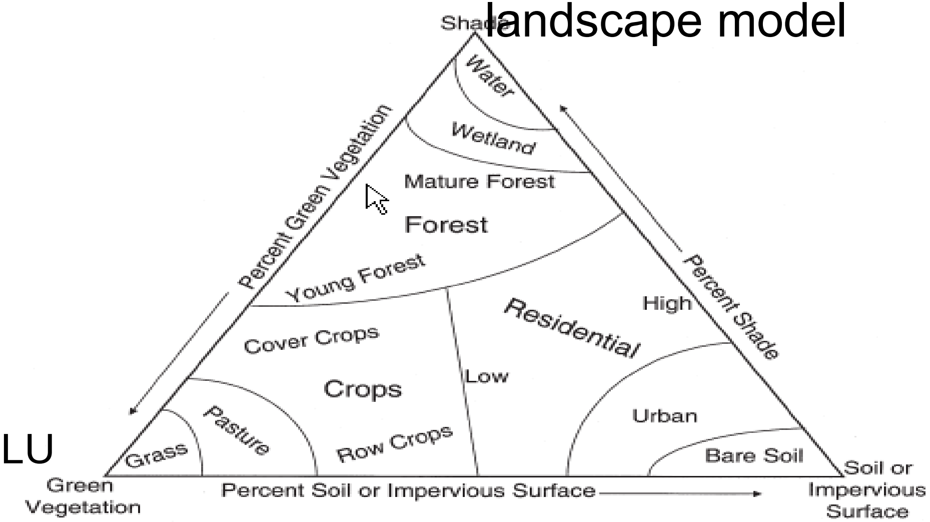


The fraction images were used to classify LCLU classes based on a hybrid procedure that combined maximum-likelihood and decision-tree algorithms.

A case study: urban mapping

Pasture and Agricultural lands

Lu-Weng urban landscape model



Source: Lu and Weng (2004)

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5. Classification

Sub-pixel classification Super-resolution mapping

Although classification at sub-pixel level is informative and meaningful it fails to account for the spatial distribution of **class** proportions within the pixel.

Super-resolution mapping (or sub-pixel mapping) is a step forward.

Super-resolution mapping considers the spatial distribution within and between pixels in order to produce maps at sub-pixel scale.

Several approaches of super-resolution mapping have been developed:

- Hopfield neural networks
- Pixel-swapping solution (based on geostatistics)
- Linear optimization
- Markov random fields

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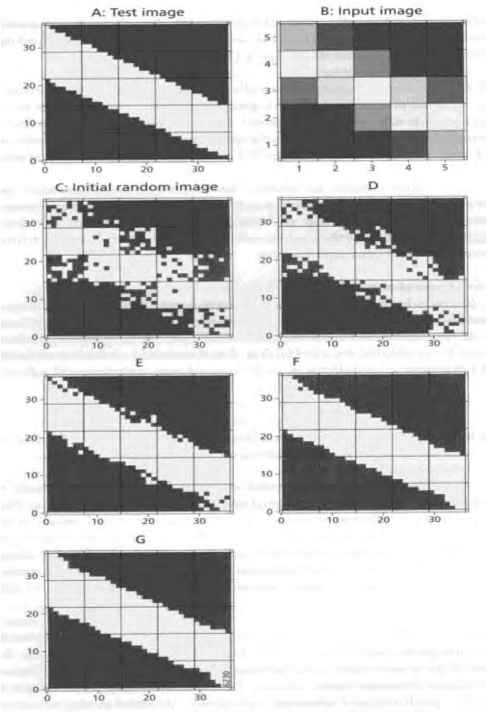
5. Classification

Sub-pixel classification Super-resolution mapping

Pixel-swapping solution – this technique allows sub-pixel classes to be swapped within the same pixel only.

Swaps are made between the most and least attractive locations if they result in **an increase in spatial correlation** between sub-pixels.



Source: Atikson (2004)

Multiple classifiers approach

Rationale

- Different classifiers originate different classes for the same spatial unit
- There are several studies on the comparison of different classifiers
- There is not a single classifier that performs best for all classes. In fact it appears that many of the methods are complementary
- Combination of decision rules can bring advantages over the single use of a classifier

*In the multiple classifiers approach the classifiers should be independent. To be independent the classifiers must use **an independent feature set** or be trained on **separate sets of training** data.*

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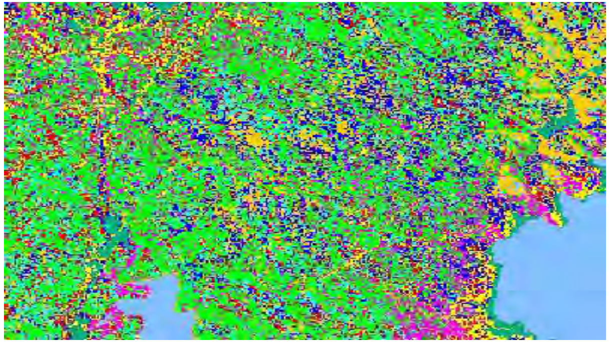
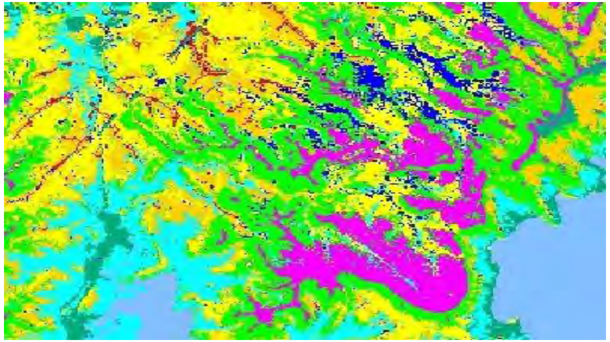
5. Classification

Multiple classifiers approach

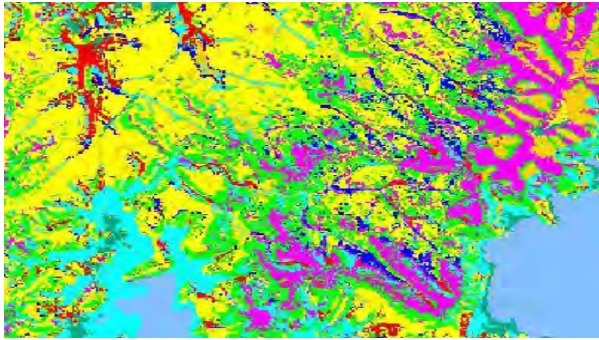
How different the results from different classifiers can be?



Maximum likelihood



Artificial Neural Networks



Decision tree

Source: Gahegan and West (1998)

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5. Classification

Multiple classifiers approach

Methods for combining classifiers

Voting rules

The label outputs from different classifiers are collected and the majority label is selected (i.e. **majority vote rule**). There are some variants, such as the comparative majority voting (it requires that the majority label should exceed the 2nd more voted by a specific number).

Bayesian formalism

It is used with multiple classifiers that output a probability. The probabilities for a spatial unit for each class resulting from different classifiers are accumulated and the final label is the one that has the greatest **accumulated probability**.

Evidential reasoning

It associates a **degree of belief** with each source of information, and a formal system of rules is used in order to manipulate the belief function.

Multiple neural networks

It consists on the use of a neural network to produce a single class to each spatial unit, **fed with the outputs** from different classifiers.

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Thematic information extraction from satellite images

1 Definition of the mapping approach *
2 Geographical stratification
3 Image segmentation
4 Feature identification and selection *
5 Classification *
6 Ancillary data integration
7 Post-classification processing
8 Accuracy assessment *

* mandatory

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6. Ancillary data integration

Ancillary data can be integrated after image classification in order to improve the results.

Post-classification sorting - application of very specific rules to classification results and to geographical ancillary data (e.g., elevation, slope, aspect)

There are several strategies based on expert systems, rule based systems and knowledge base systems

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1 Definition of the mapping approach *

2 Geographical stratification

3 Image segmentation

4 Feature identification and selection *

5 Classification *

6 Ancillary data integration

7 Post-classification processing

8 Accuracy assessment *

* mandatory

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7. Post-classification processing

Post processing is required in two cases

The Minimum Mapping Unit of the very final map is larger than the spatial unit used in the classification

Map generalisation

Upscaling

The final map has a vector format and the Spatial Unit of Analysis was the pixel

Raster to vector conversion

7. Post-classification processing

The steps required to information extraction depend on the defined mapping approach:

Map format = raster

MMU = pixel size of input satellite data

Feature selection > Image classification > accuracy assessment

MMU > pixel size of input satellite data

Feature selection > Image classification > post-processing > accuracy assessment

upscaling

Map format = vector

Spatial unit of analysis = image pixel

Feature selection > Image classification > post-processing > accuracy assessment

Generalisation + Raster to vector conversion

Spatial unit of analysis = object

Image segmentation > Feature selection > Image classification > post-processing > accuracy assessment

Generate the objects

Generalisation

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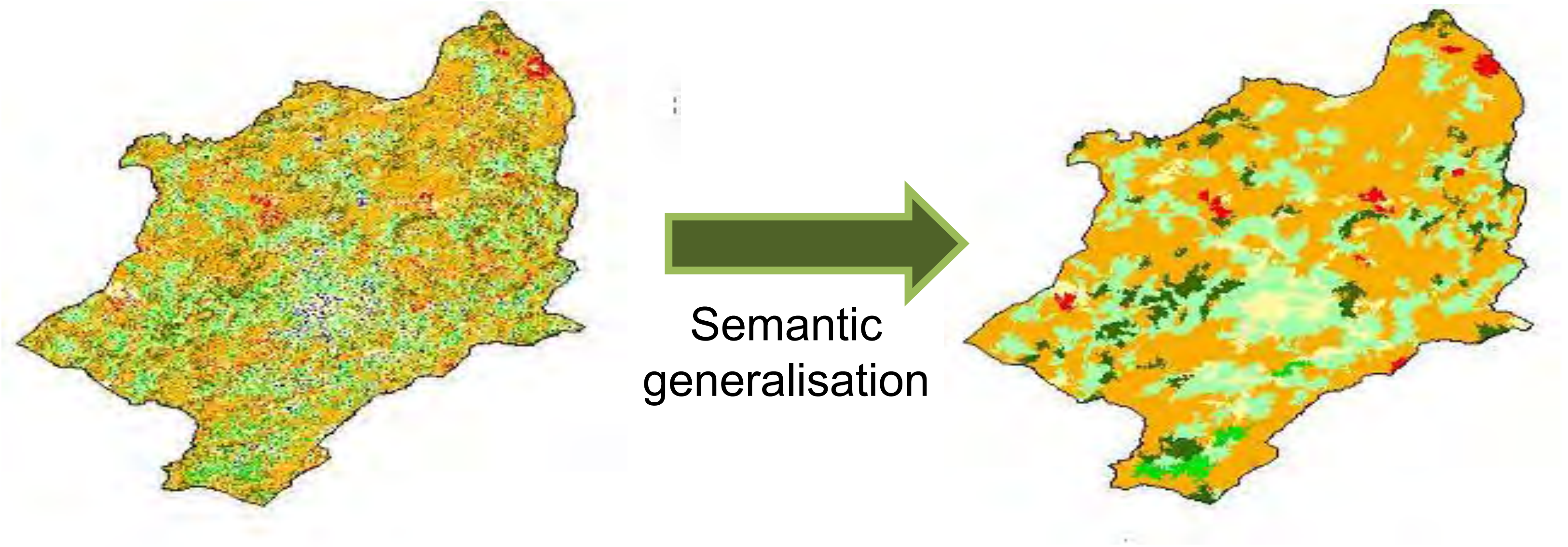
7. Post-classification processing

Semantic generalisation



MMU = 1 pixel (30mx30m)

MMU = 5 ha

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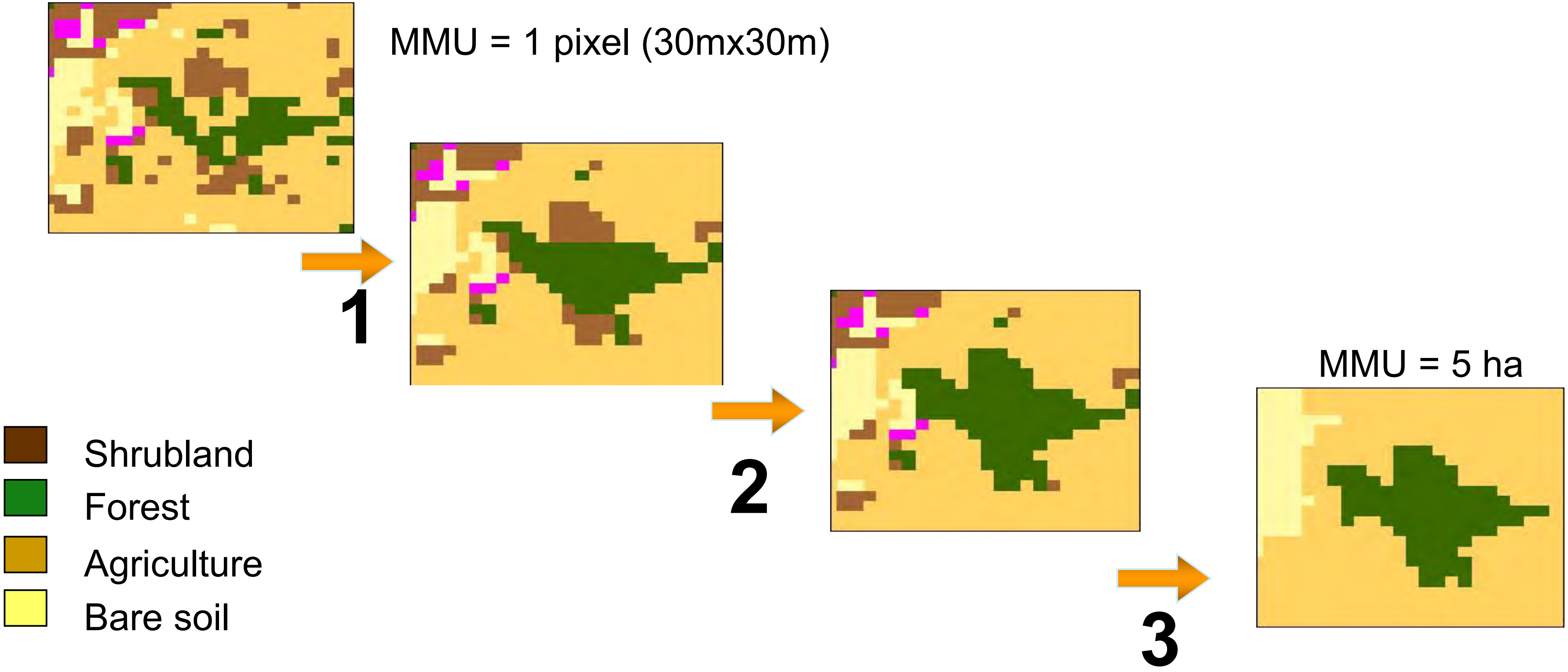
7. Post-classification processing

Semantic generalisation



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Thematic information extraction from satellite images

1 Definition of the mapping approach *
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8 Accuracy assessment *

* mandatory

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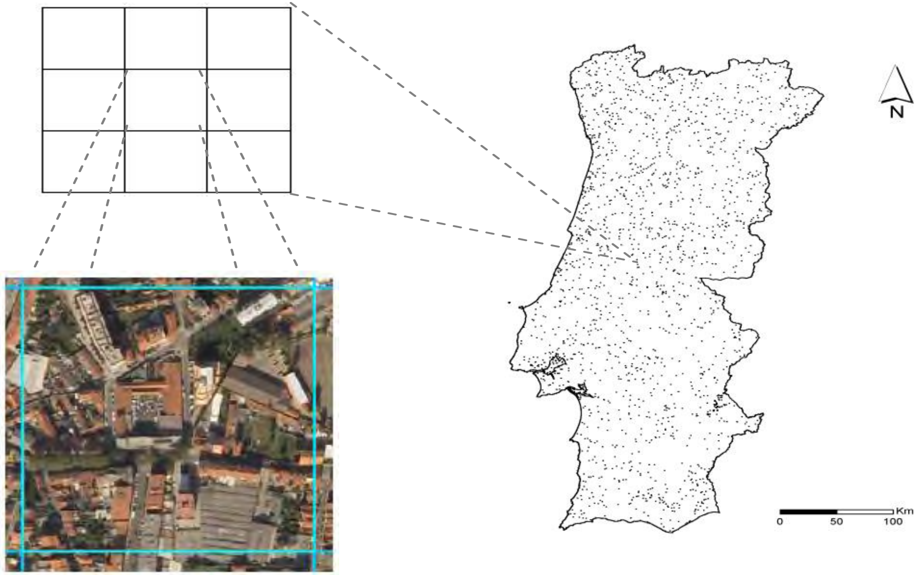
8. Accuracy assessment

Accuracy assessment allows users to evaluate the utility of a thematic map for their intended applications.

The most widely used method for accuracy assessment may be derived from a **confusion or error matrix**.

The confusion matrix is a simple cross-tabulation of the mapped class label against the observed in the ground or reference data for a **sample set**.



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8. Accuracy assessment

Main steps

1 Selection of the reference sample

sampling units

sampling design

Probability sampling is necessary if one wants to extend the results obtained on the samples to the whole map.

Probability sampling requires that all inclusion probabilities be greater than zero, e.g. one cannot exclude from sampling inaccessible areas or landscape unit borders.

2 Response design

The definition of the response design depends on the process for assessing agreement (e.g., primary, fuzzy or quantitative).

3 Analysis and estimation

One has to take into account the known areas (marginal distributions) of each map category to derive unbiased estimations of the proportion of correctly mapped individuals.

Source: Stehman (1999), Stehman and Foody (2009)

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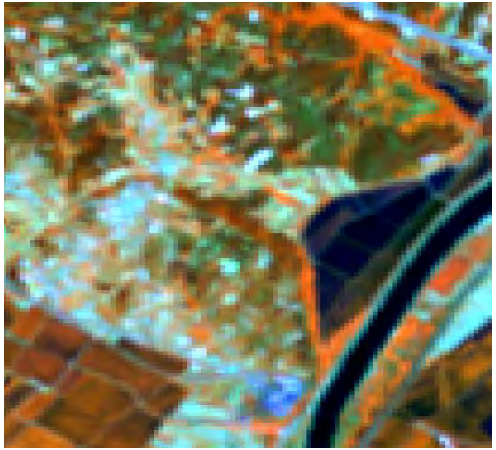
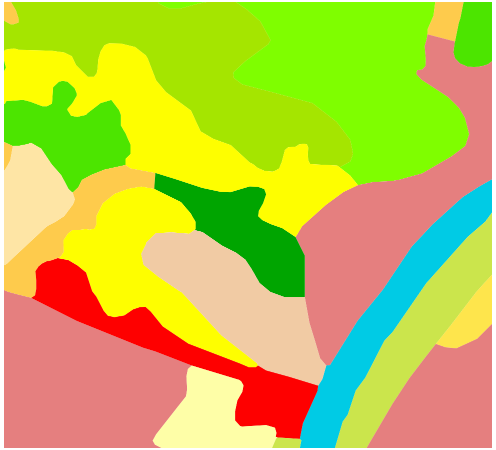
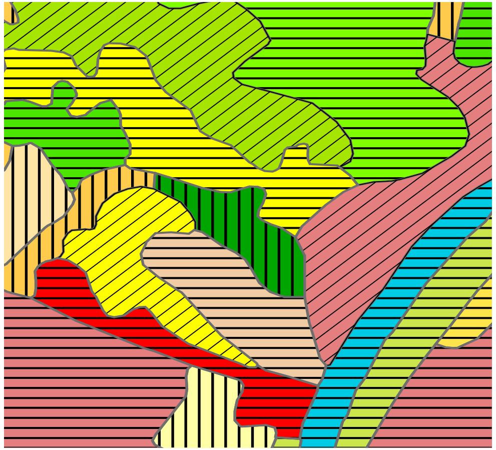
8. Accuracy assessment





Overall accuracy: **86%**



Small uncertainty

Moderate uncertainty

Large uncertertainty

But, where is the error?

Uncertainty mapping

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Summary

1 Setting the scene

2 The need for LCLU monitoring data

- LCLU: a cross-cutting environmental variable
- LCLU monitoring and environmental legislation
- Relation between two European initiatives (Copernicus and INSPIRE) and LCLU monitoring
- Hard and soft LCLU maps
- The Land Cover Classification System

3 From data to information: some important advances in LCLU monitoring

- Two different approaches for LCLU monitoring
- Spectral and class change detection
- Image classification for LCLU mapping

4 LCLU monitoring operational programs

- At country level (NLCD from USA)
- At European level (Land monitoring service within Copernicus)
- At Global level (GLOBCOVER)

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US National Land Cover Database (NLCD)

MCRL has been the umbrella for many US programs, which require landcover data for addressing their agency needs, namely the 2 National Land Cover Databases:

NLCD 1992 A single product: a land cover map Vogelmann et al. (2001)

NLCD 2001 Multiple products: land cover map, land cover change 1992-2001 (retrofit), percent tree canopy and percent urban imperviousness.
Homer et al. (2004, 2007)

NLCD 2006 Multiple products: land cover map, land cover change 2001-06, and percent developed imperviousness Fry et al. (2011)

NLCD 2011 Multiple products: similar to 2006 but with more change products and Homer et al. (2015)

NLCD 2016 In construction Smith (2017)

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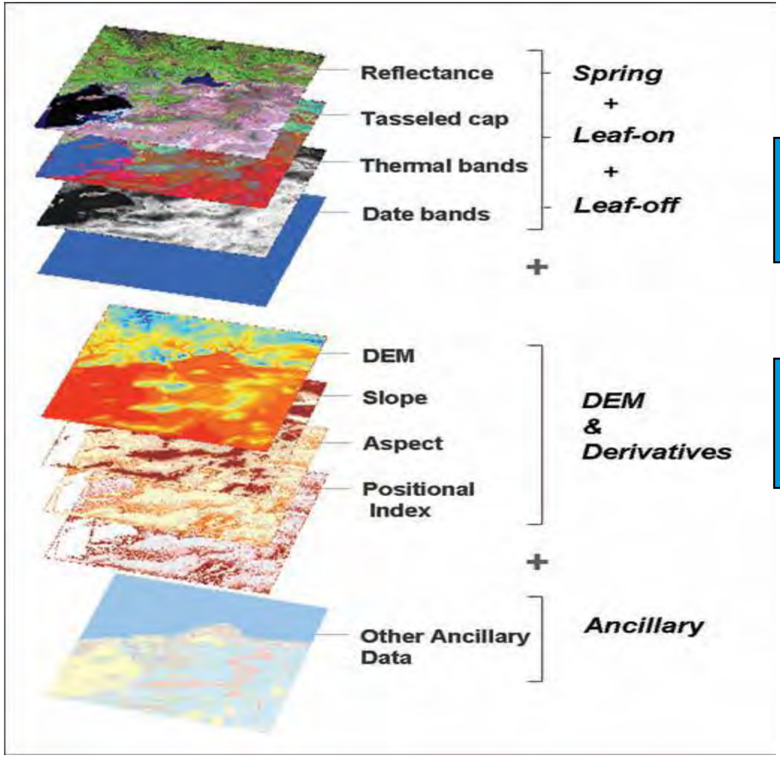
US National Land Cover Database (NLCD) - 2001



Mapping Zone Input Layers

Decision Tree (See5) → Land cover map

Regression Tree (See5) → Percent tree canopy

Percent urban imperviousness

Source: Homer et al. (2007)

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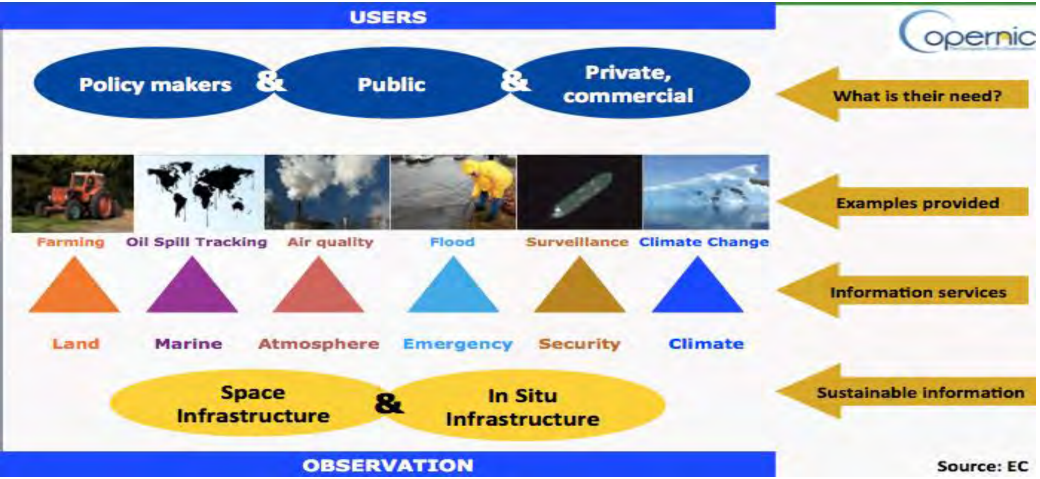

Copernicus
The European Earth Observation Programme

6
services

Land Monitoring Service

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Copernicus Land Monitoring Service – 3 components

Global

Bio-geophysical variables

Information on:
Vegetation (e.g. LAI, NDVI)
Energy (e.g., Land Surface Temperature)
Water (e.g. Lake Water Quality)
Cryosphere (e.g. Snow cover extent)

Pan-European

CORINE Land Cover

Five High Resolution Layers

Soil sealing
Forest
Grassland
Wetland
Water

Local

Urban Atlas

Riparian areas

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Copernicus Land Monitoring Service – 3 components and in sit data

This service is more than LCLU or LCLUC. It also includes variables related to vegetation status and water cycle (i.e. biophysical variables).

http://land.copernicus.eu

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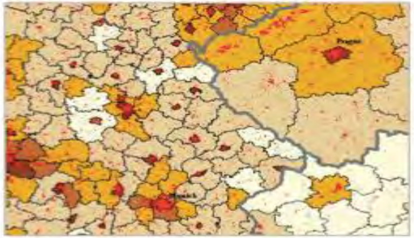
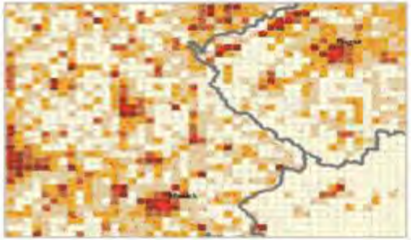
From lump statistics on administrative units



to geospatial explicit information (grid-based indicators)



Source: Georgi and Hauffmann (2012)

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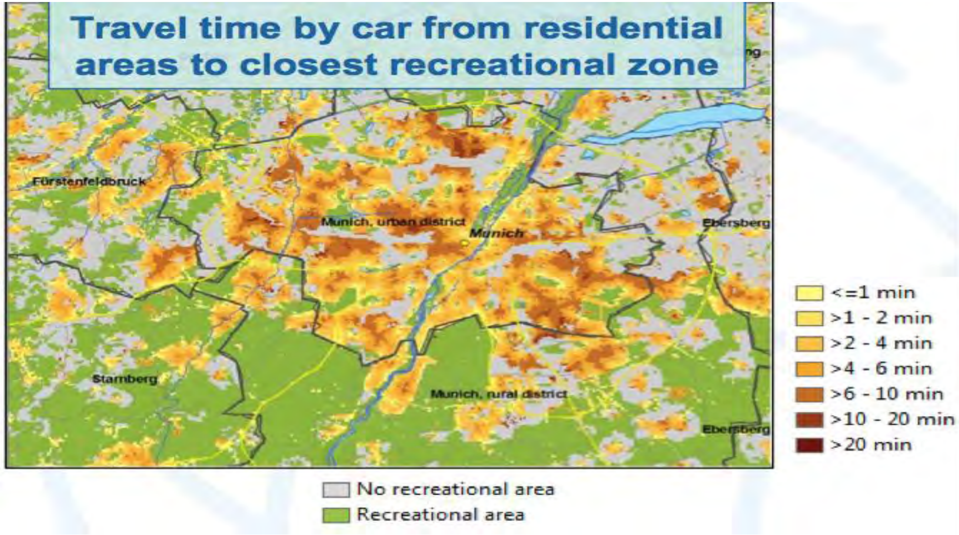

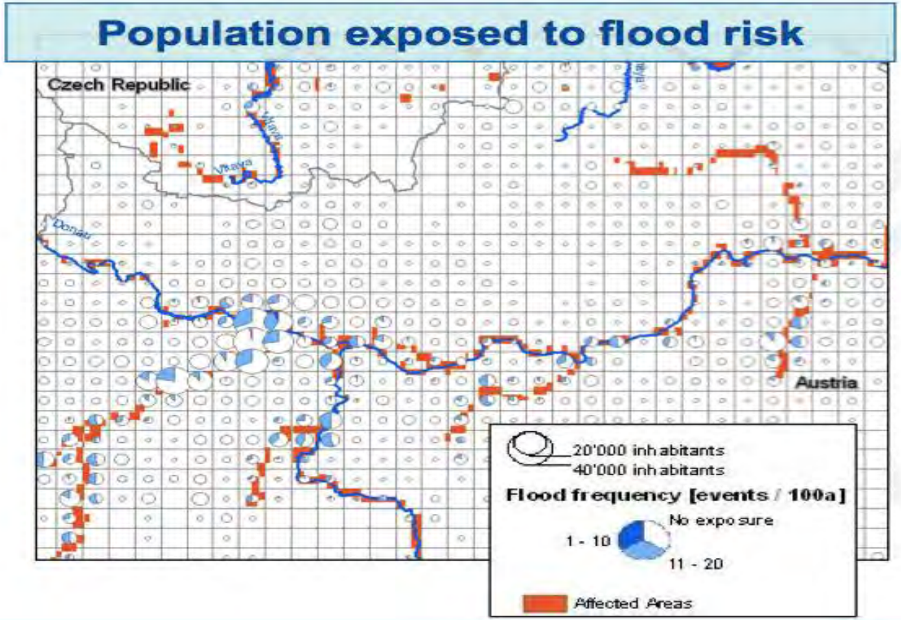

Source: Georgi and Hauffmann (2012)

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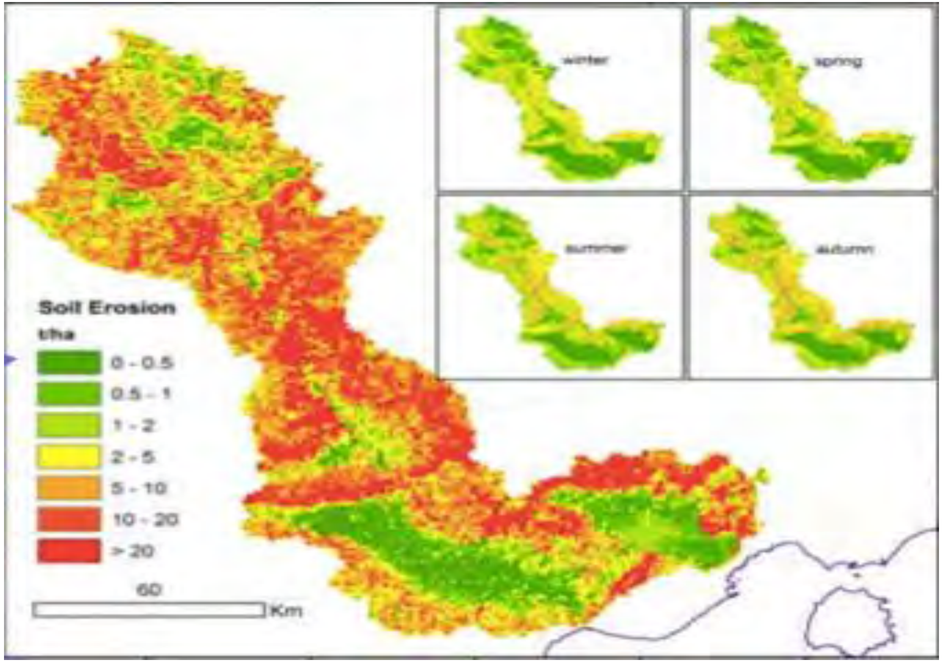

Soil sealing HR layer

Soil erosion map

http://eusoils.jrc.ec.europa.eu/projects/Geoland2/data.html

Source: Jochum and Lacaze (2012)

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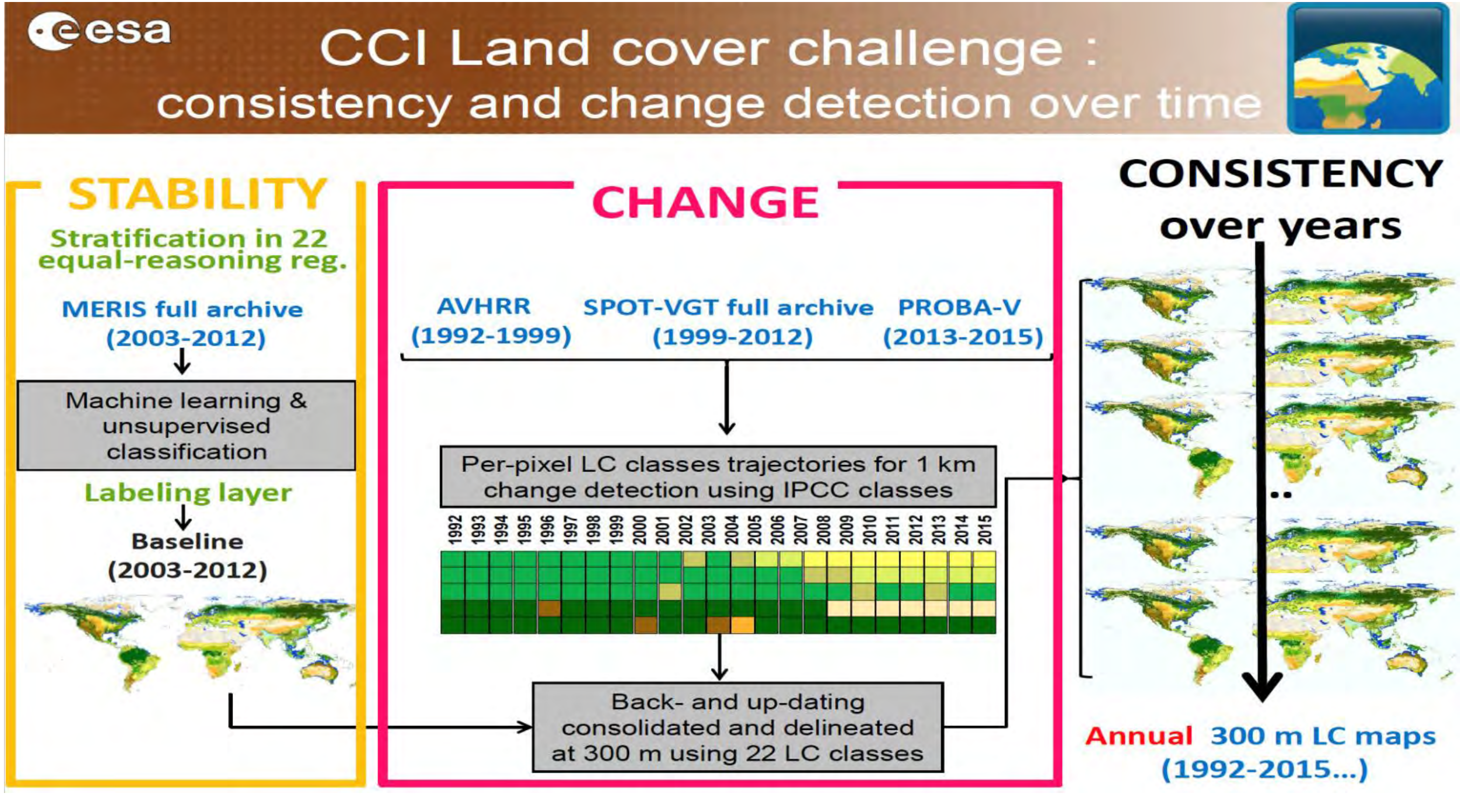

Source: Defourny et al. (2017)

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Growing availability of different types of images (the era of the multi-)

Specific missions

L2andL3 products

Free access data policy

New paradigma in Earth observation

New methodologies

New products

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