

OBIA – Tutorial

Introduction to Object-based Image Analysis

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Disclaimer

This tutorial was built upon teaching material for courses on advanced remote sensing, delivered by Dr. S. Lang and Prof. T. Blaschke between 2002 and 2006. Explanations are partly quotes from literature.

Its purpose is to give an introduction to the emerging field of object-based image analysis and to provide a comprehensive overview of methods involved and the respective background.

The tutorial is available as 'slide set only' or 'slide set with additional text notes'. Both are provided in PDF (Acrobat® Reader® required for display).

Dissemination of this **Version 1.0** of the OBIA Tutorial is free. Please obey 'fair-use' conditions as being commonly understood.

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OBIA – Tutorial

Introduction to object-based image analysis

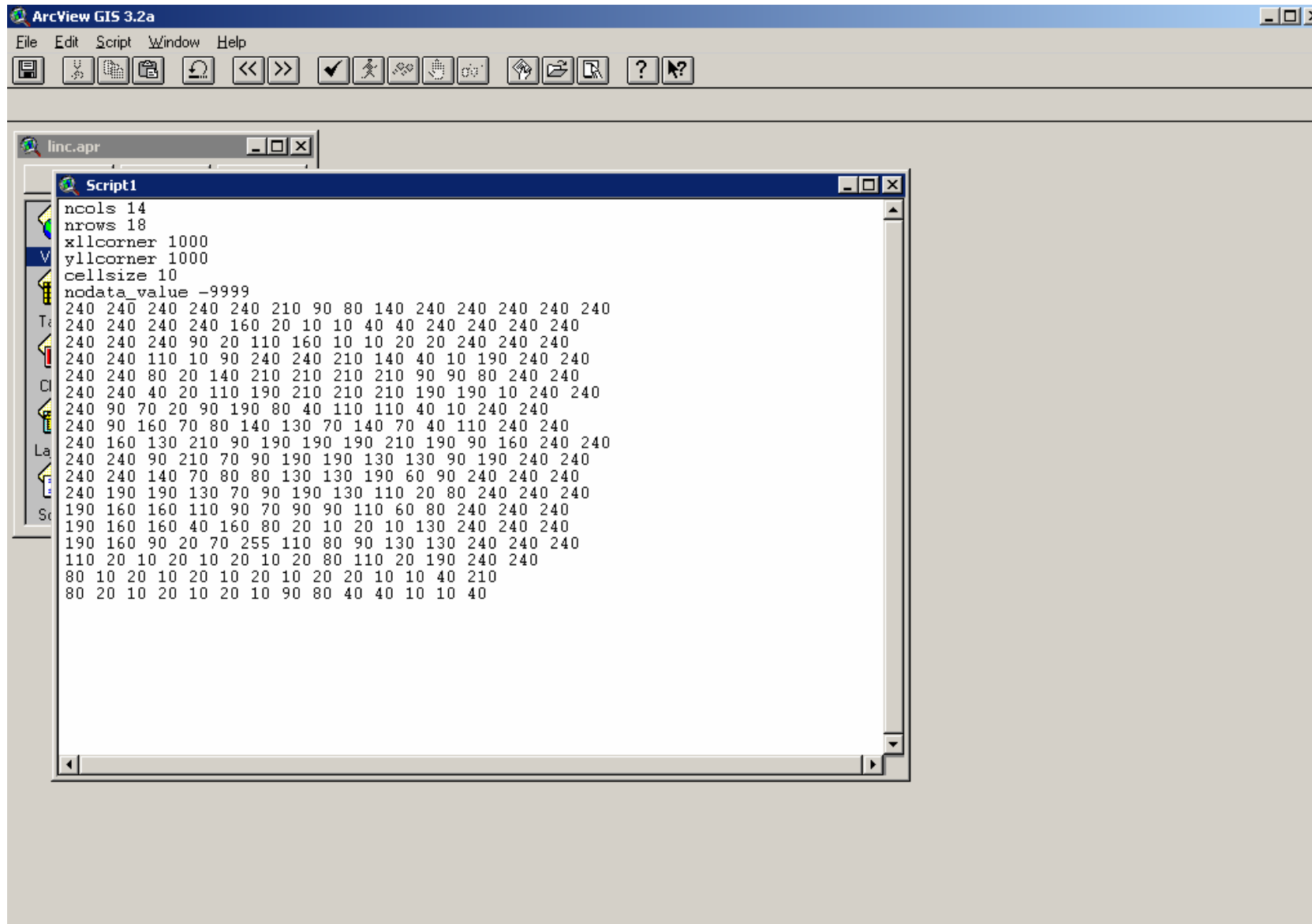
Chapter 1

Image interpretation and perception

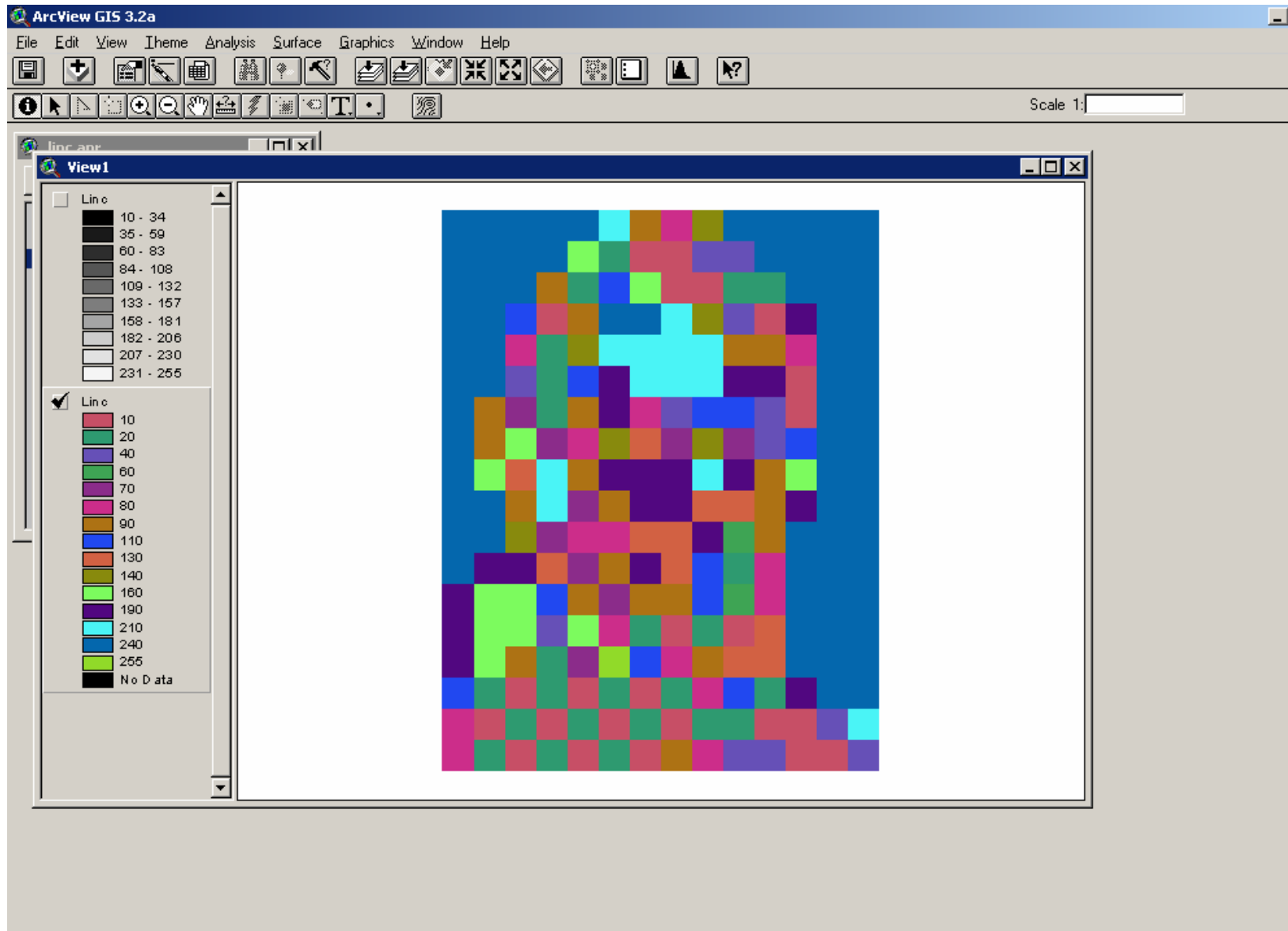
Outline

- **Visual perception**
- **Image context**
- **Role of experience**
- **Pixel- vs. object-scope**
- **Using objects**
- **Visual delineation vs. machine-based segmentation**

Visual perception



Visual perception (2)



Visual perception (3)

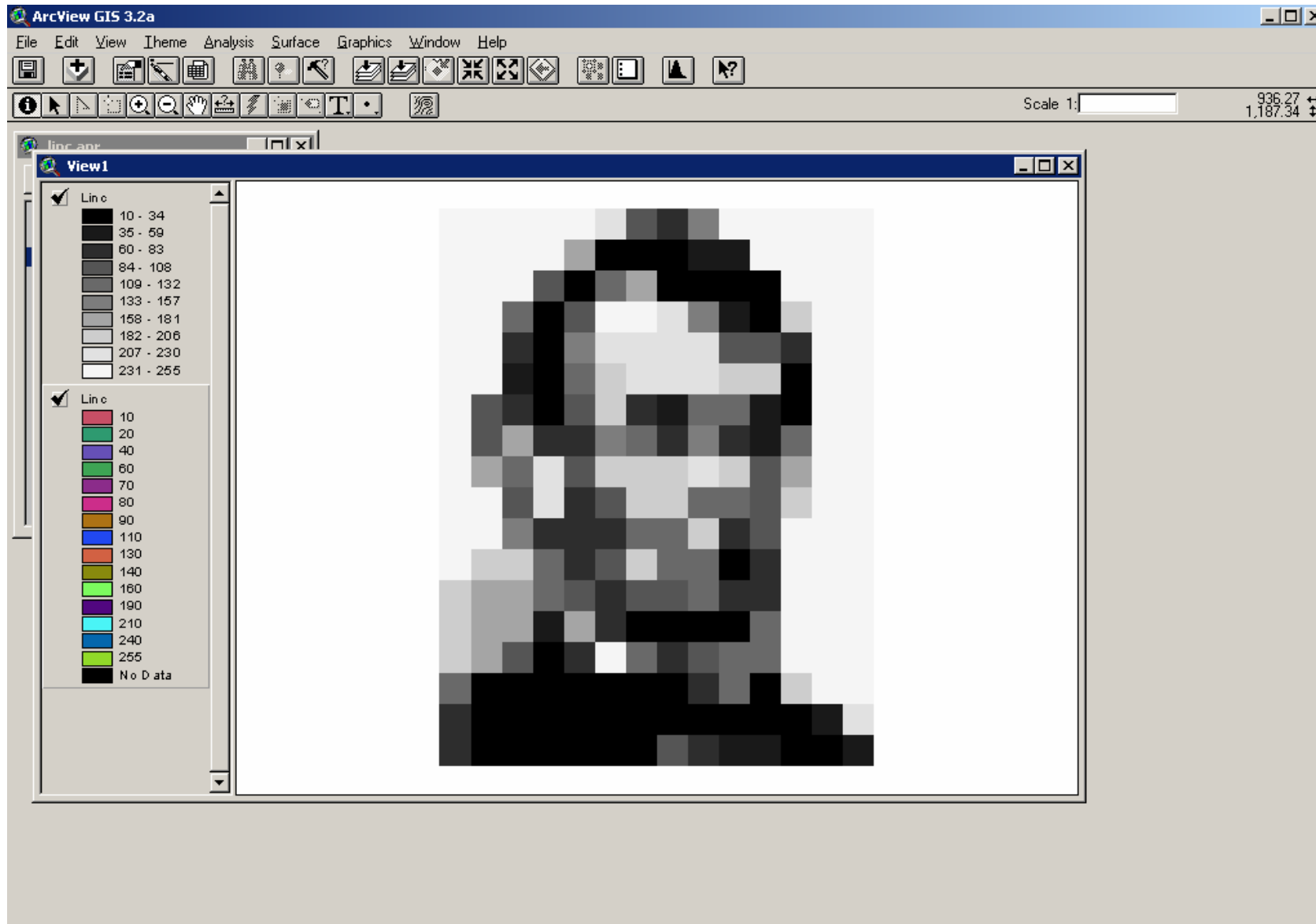
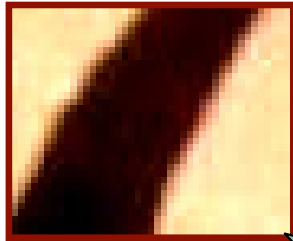
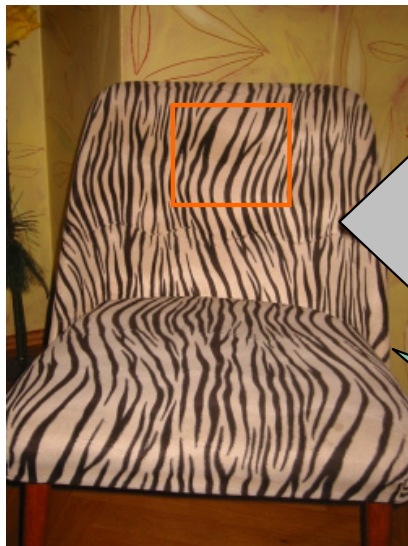
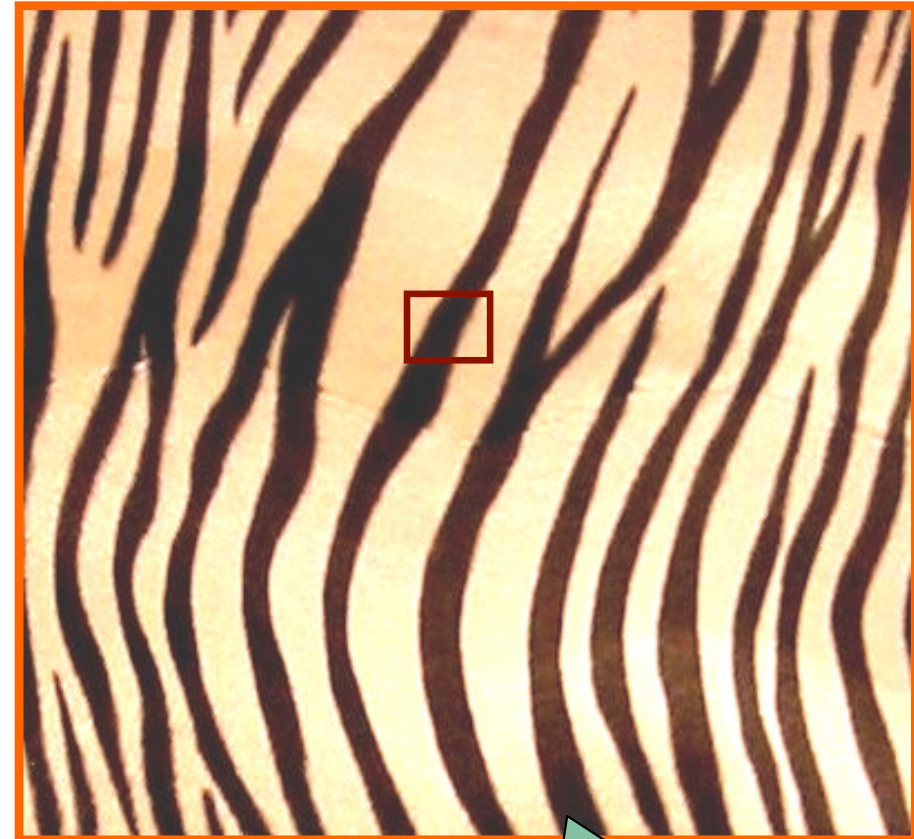


Image context



contrast b/w and shape:
“black line in white area”



mainly shape (pattern
suppressed): **“chair with
zebra pattern”**

contrast b/w and shape
(elongated but acute):
**“certain stripes pattern
→ zebra”**

Role of Experience

- **Human vision is well adapted for complex image interpretation tasks**
 - **Experience built up since early childhood**
 - **But human vision is challenged when dealing with remote sensing imagery:**
 - Applying an overhead view
 - Dealing with spectral characteristics beyond the visual spectrum
 - Working with unfamiliar scales and resolutions
- > Experience is an important prerequisite for skillful and successful interpretation**

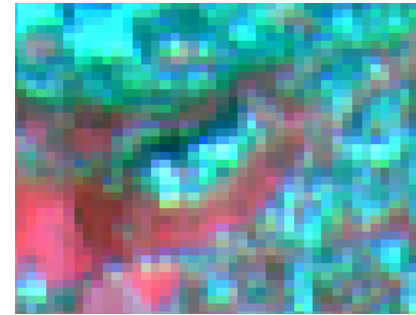
Images of the Fortress in Salzburg, Austria



Quickbird; bands 3,2,1



Quickbird; bands 4,3,2

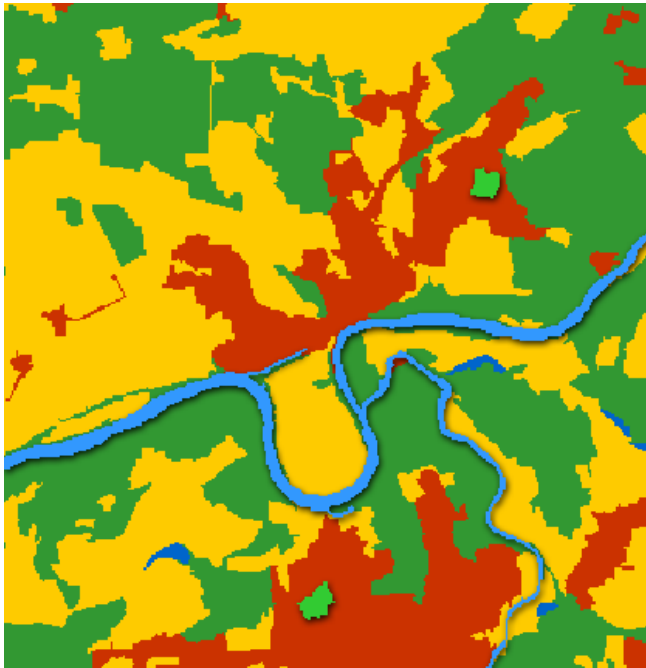


Aster; green, red, infrared



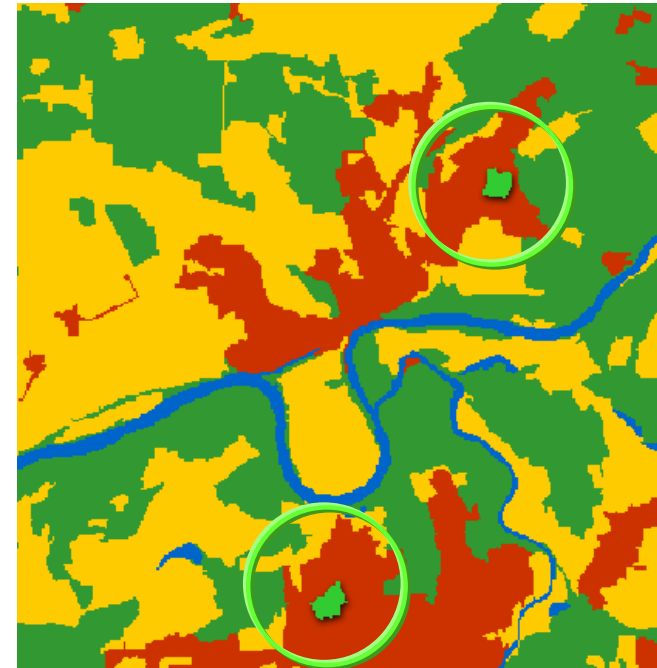
Color Photo

Pixel- vs. object-scape



river

- spectral properties
- specific form/shape



municipal park

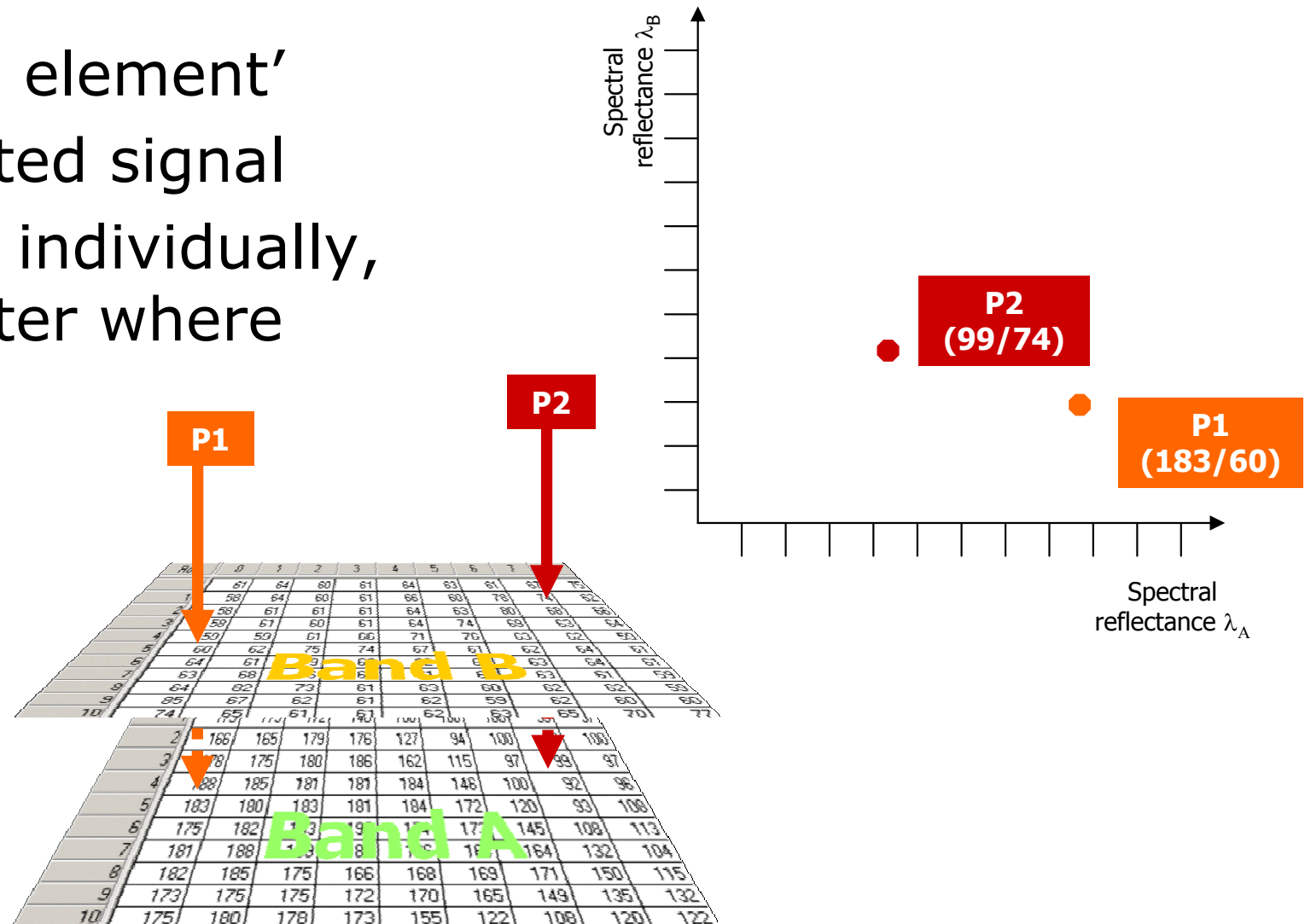
- spectral properties
- specific spatial context

From Definiens, 2004

Pixel- vs. object-scape (2)

■ **Pixel**

- 'picture element'
- integrated signal
- treated individually, no matter where located



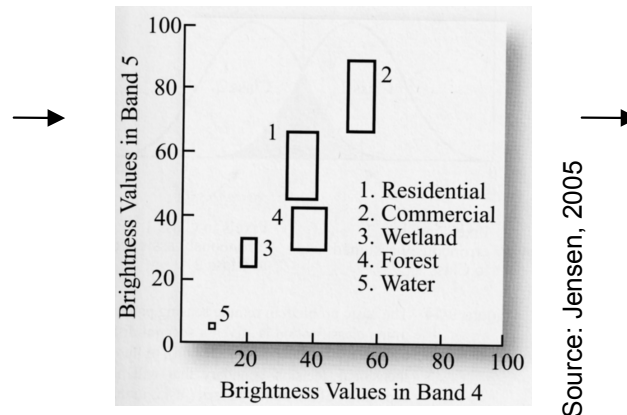
Pixel- vs. object-scape (3)

■ Pixel-based classification process

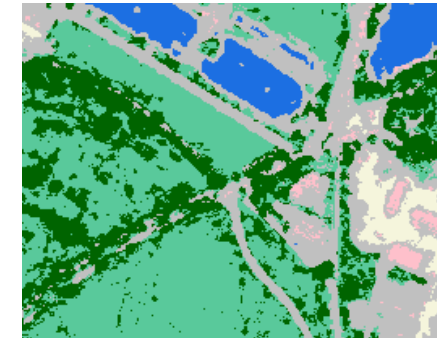
Raw image



Feature space



Classified image



■ Problems

- Spectral values belong to more than one information class
- No spatial relationships used in classification
- Pixel artificial spatial unit
- 'Artifacts' (salt-and-pepper effect)



Pixel- vs. object-scape (4)

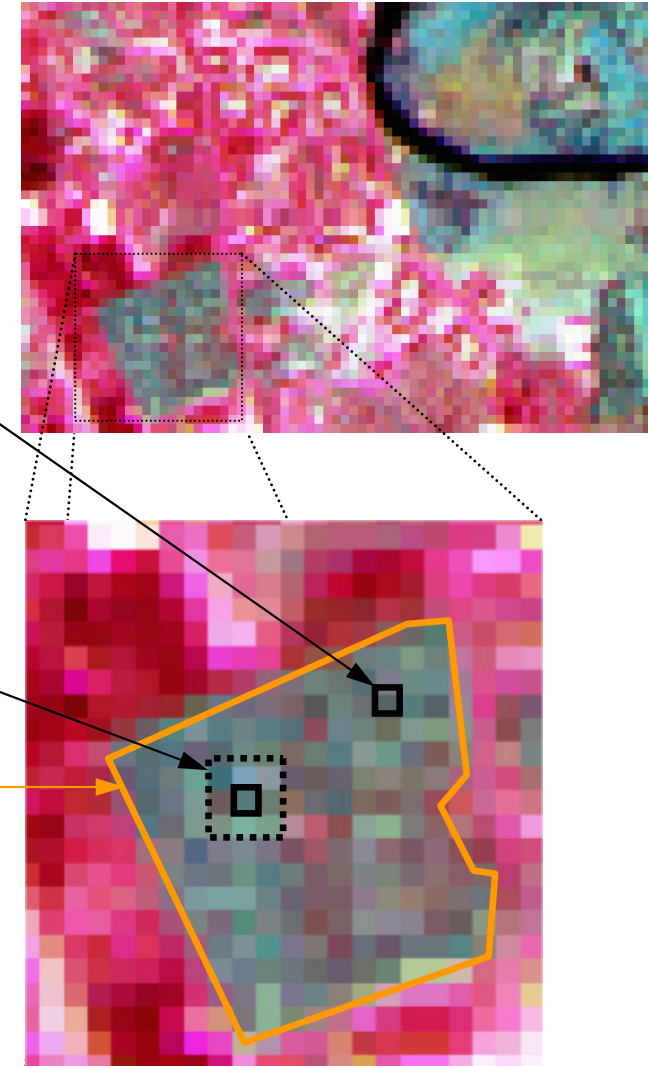
Limitations of **pixel-based analysis**

considering

- **Colour** (spectral reflectance in n Bands)
- **Texture** (certain environment, e.g. 3*3 pixels)

but not

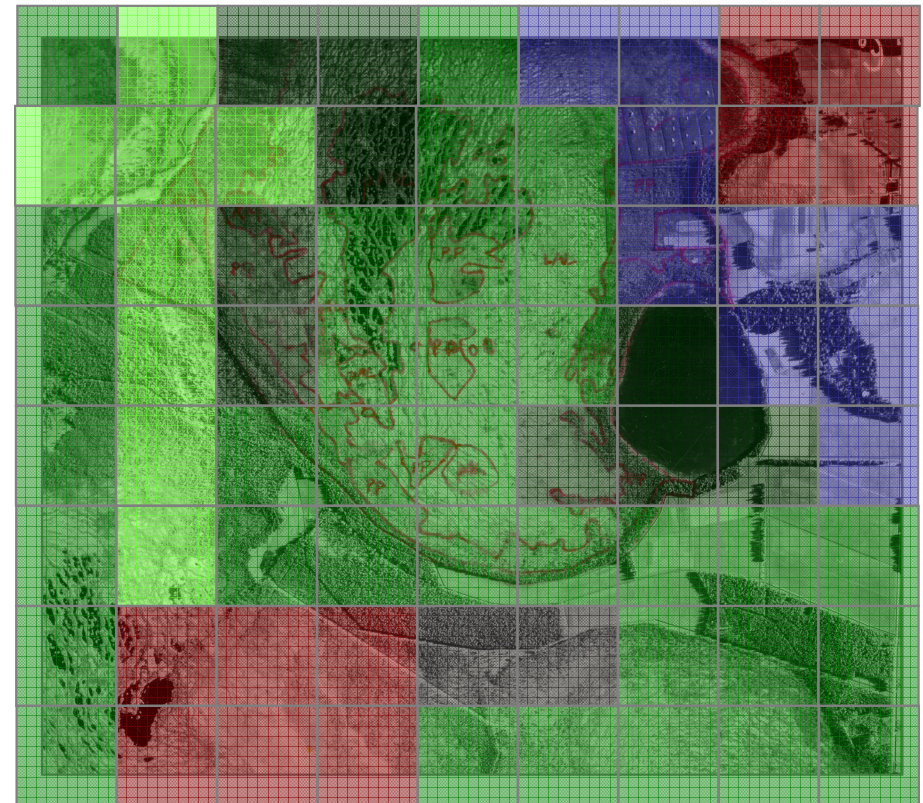
- **Form & shape**
- **Neighbourhood**
- **Context**
- **Levels**



Using objects

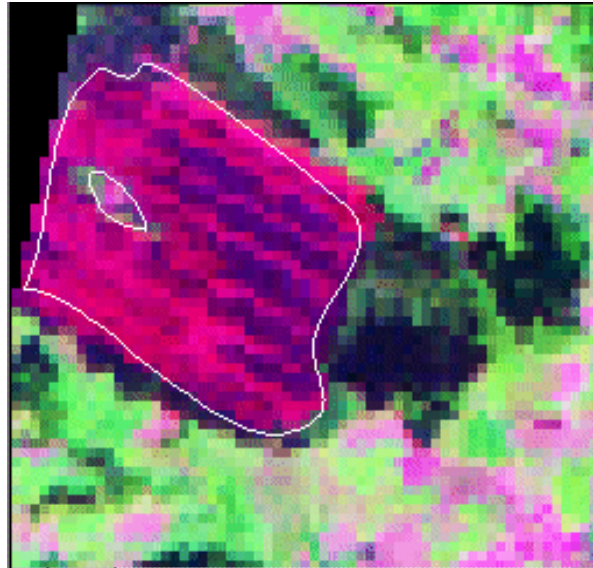
- **Relation between target objects and spatial resolution**

- Increasing importance of VHR EO data
- High level of detail provides extended set of target classes
- Addressing these target classes in a Landsat-imagery would fail

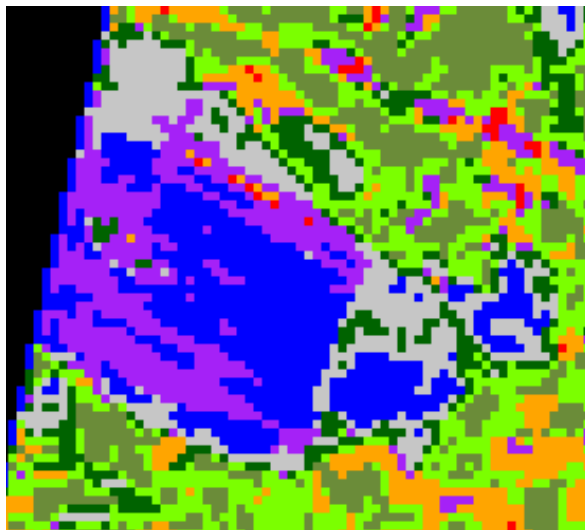


Using objects (2)

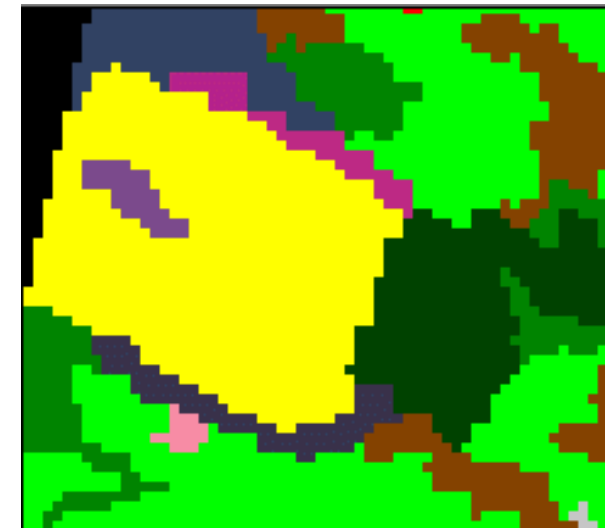
**Manual
delineation
(„Bog“)**



**Pixel-based
classification**

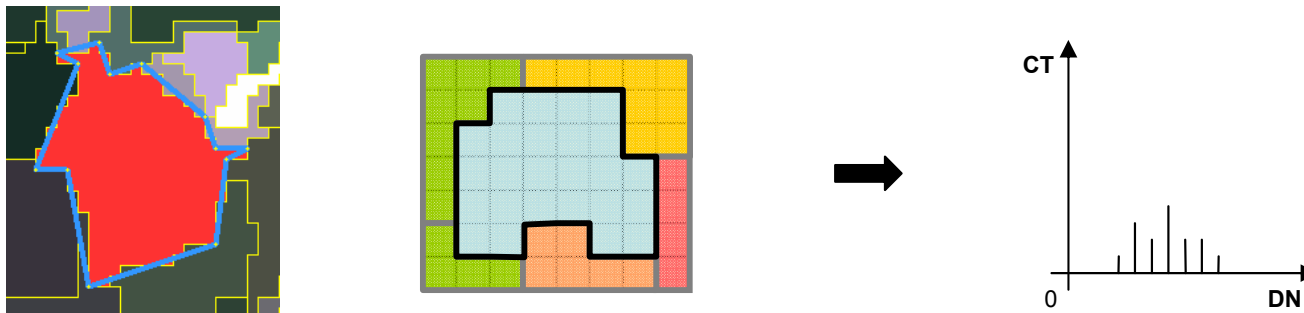


**Object-based
classification**



Using objects (3)

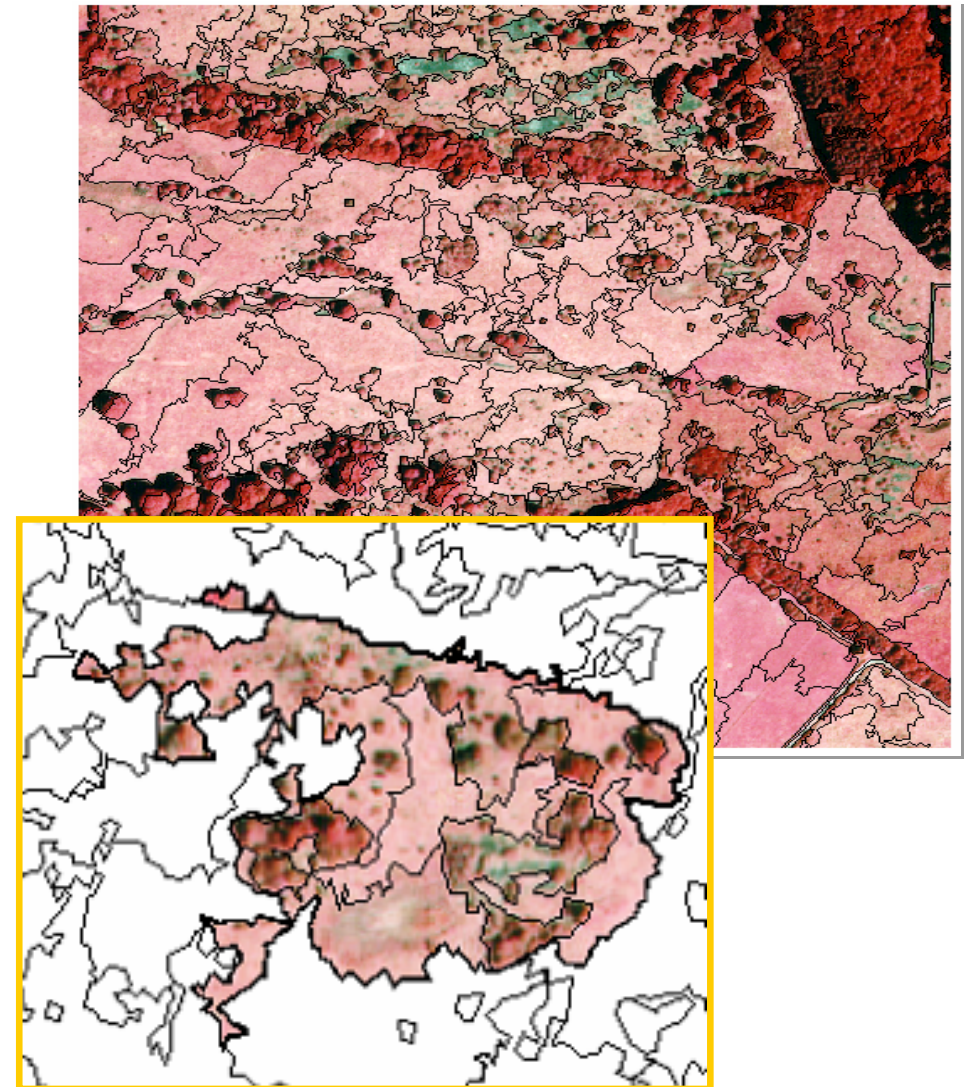
- **Meaningful objects**
- **Improved reliability of statistics**
 - Several measurements (pixels) per object
 - Clear boundaries



- **Augmented, uncorrelated feature space**
 - Texture within objects, shape, neighbours, hierarchy

Using objects (4)

- → **Integration** of **Remote Sensing** and **GIS**
- GIS users are 'used to' **polygon** environment
- **Aggregation** of information (highly textured images like VHR data or radar)
- Modelling of scale-specific ecological processes through **multi-scale representation**



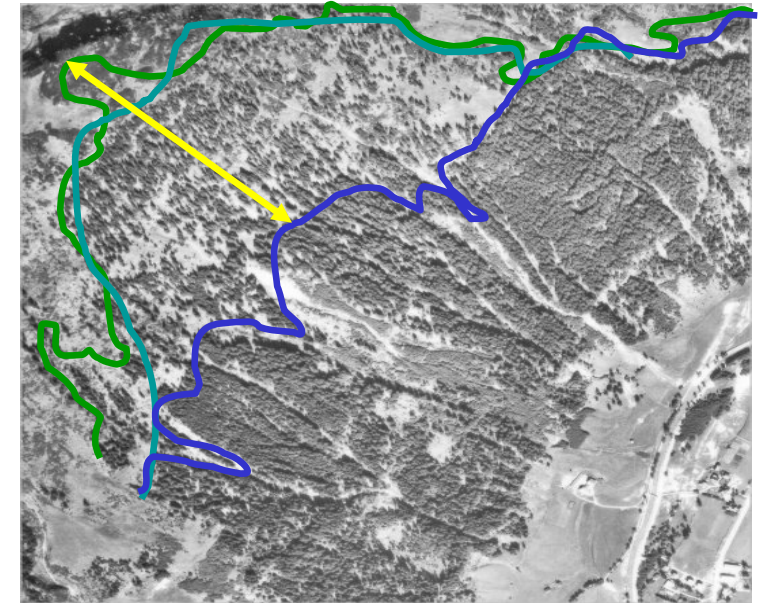
Visual delineation vs. machine-based segmentation

- **Problems occurring with visual delineation visually (may be solved via segmentation):**

- selection of appropriate levels of generalization
- Individual delineations
- placement of boundaries when there is a graded transition

- **Problems that challenge machine-based segmentation:**

- Delineating conceptual boundaries (e.g. the 'outline' of an orchard, see below)



Several possibilities for the delineation of 'Forest'

Visual delineation vs. machine-based segmentation (2)

- **Image Objects = Landscape Units?**
 - Usually landscape analysis or -planning is based on landscape units
→ manual interpretation
 - **Leads** image segmentation to **similar results?**
- **Image objects not *per se* ,real world objects'**
 - not **object recognition**
 - Any raster layer can be used for segmentation (e.g. DEM)
- **object merge can improve appropriateness of objects**

CIR
interpretation

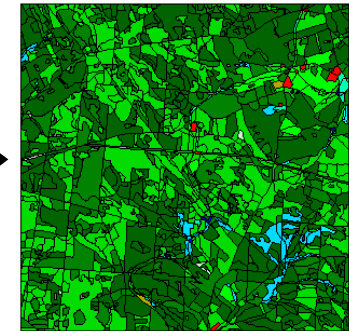
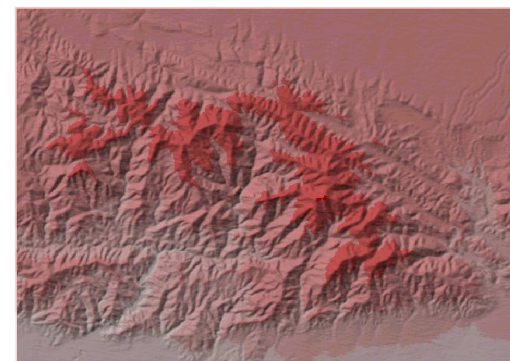
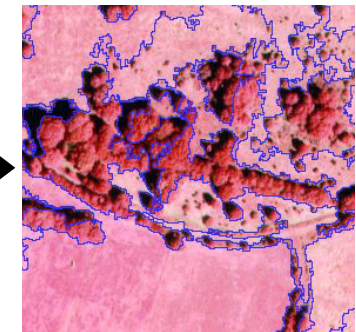


Image
segmentation



Visual delineation vs. machine-based segmentation (3)

- **Some more aspects**
 - Results not necessarily more correct, but more intuitive, more convincing, more practical
 - object generation suitable for textured or low-contrast image data
 - VHR-satellite imagery
 - Airborne optical scanner data
 - Airborne laser scanning (ALS) data
 - Synthetic aperture radar (SAR) data
 - Semi-automated image interpretation
 - Supports image understanding by solving complex semantic problems
 - Monitoring of known structures
 - e.g. existing land use classification can be used as pre-defined boundaries for segmentation

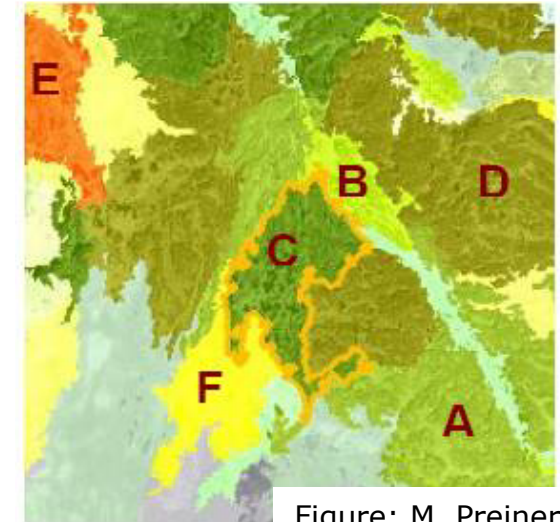


Figure: M. Preiner

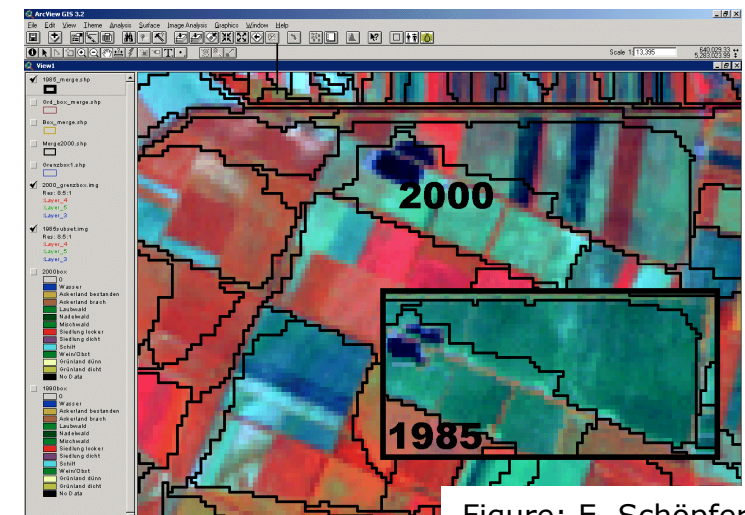


Figure: E. Schöpfer

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Introduction to object-based image analysis

Chapter 2

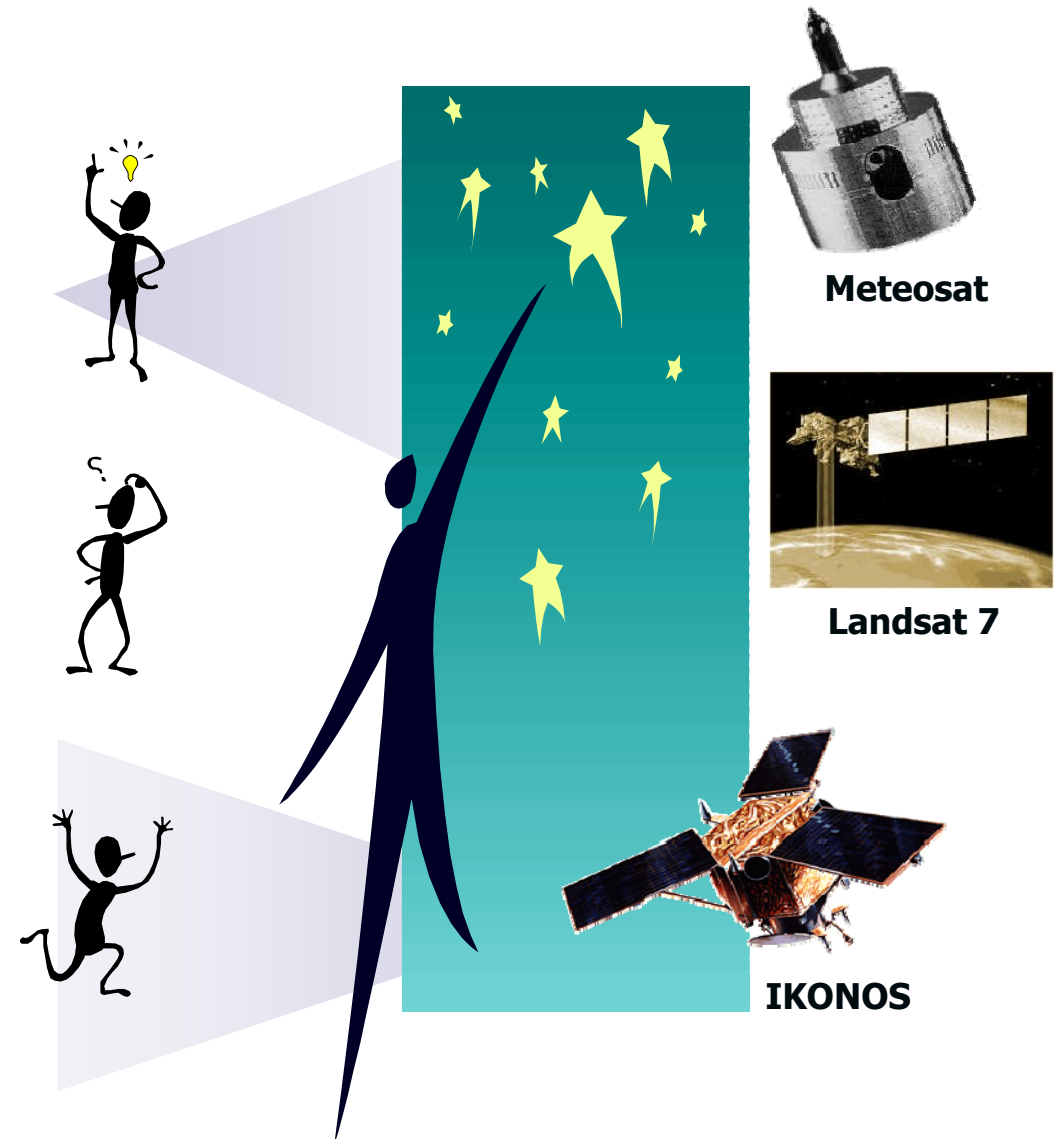
Some basic concepts of hierarchy theory

Outline

- **Relevance of multi-scale representation**
- **Scales and scaled representation**
- **Decomposition and holarchy**
- **Multi-scale approach with remote sensing**
- **Hierarchical patch dynamics paradigm**

Relevance of multi-scale representation

- **General remarks**
 - **Sensor resolution nowadays enters the scale of human activity**
 - **Field of potential applications is increasing**
 - **More and more detailed object levels can be represented**
 - **Complexity of analysis tasks increases as well**



Scales and scaled representation

- **Scale**

Refers to the size of objects that appear in the landscape or in a representation of it (e.g. a map or a satellite image)

- **Different objects have different scales**

Every object has its inherent scale

It only appears in a certain range of scale

- **Depending on the elevation of our viewpoint we see certain objects**

Different Views – Different Scales – Different Objects?

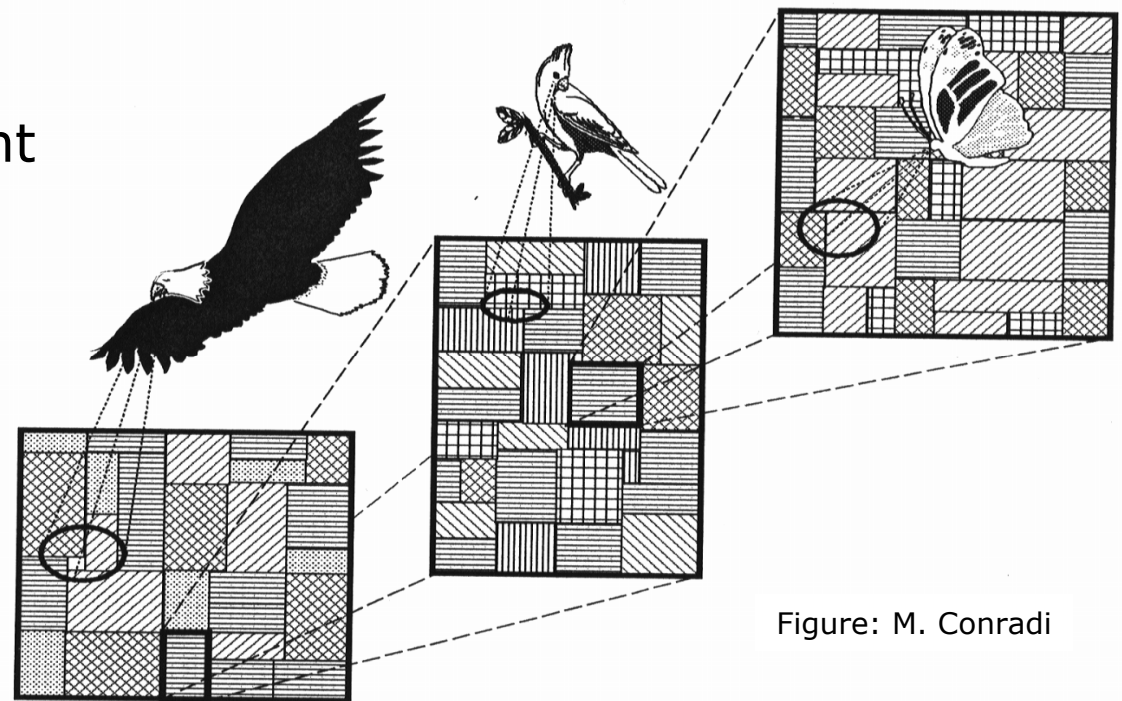


Figure: M. Conradi

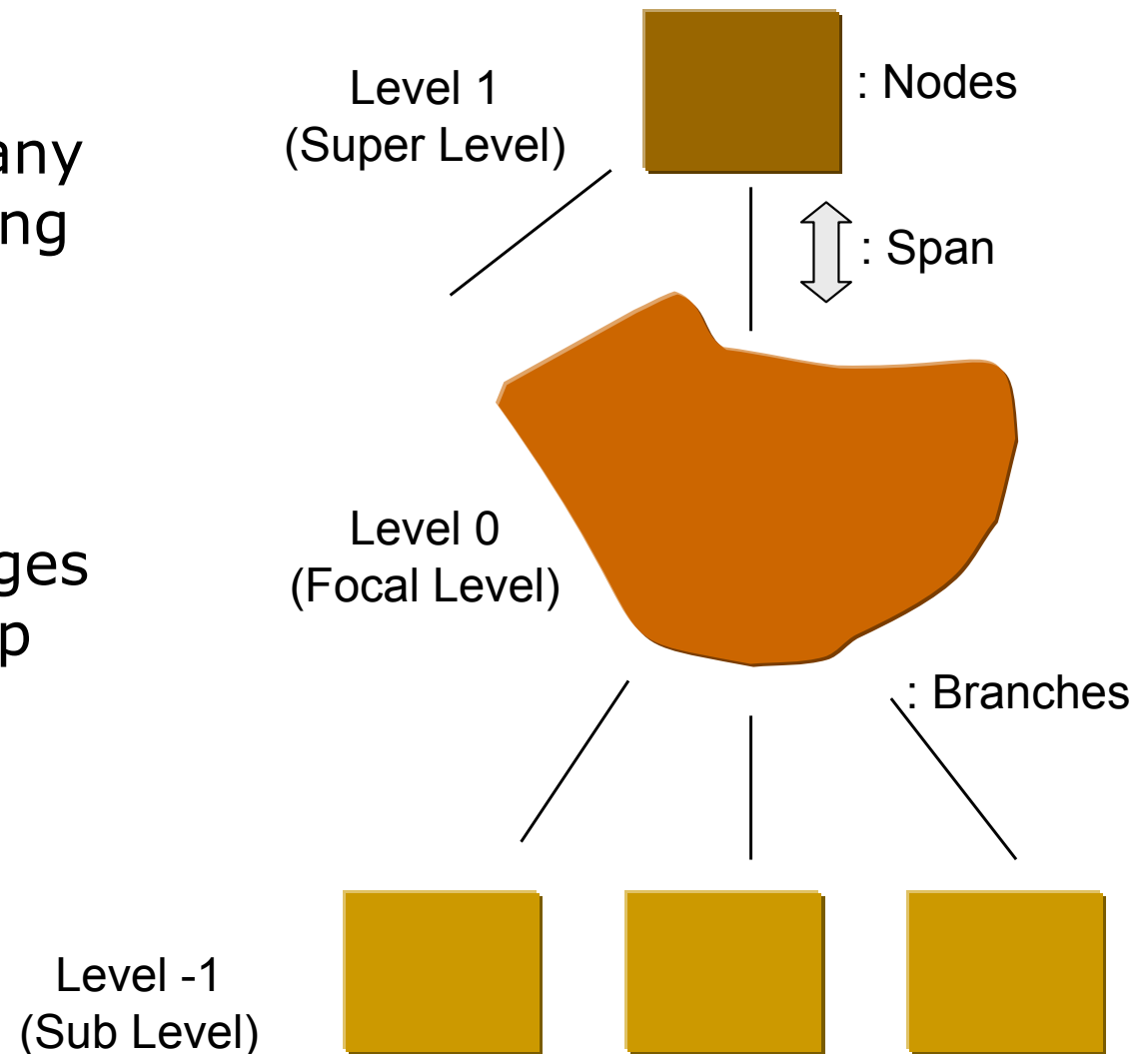
Scales and scaled representation (2)

■ **Scaling Ladder**

Every portion of land contains objects of many different scales resulting in a series of scales

■ **Boundaries within the scale spectrum**

Thresholds between ranges of scale are never crisp



Hierarchical patch dynamics paradigm

- **HPDP – combining hierarchy theory and patch dynamics**

A hierarchical scaling strategy dealing with spatial heterogeneity

- **Holon = patch = ecological unit at a particular scale**

- **Interaction of components**

Loose vertical and horizontal coupling in structure and function

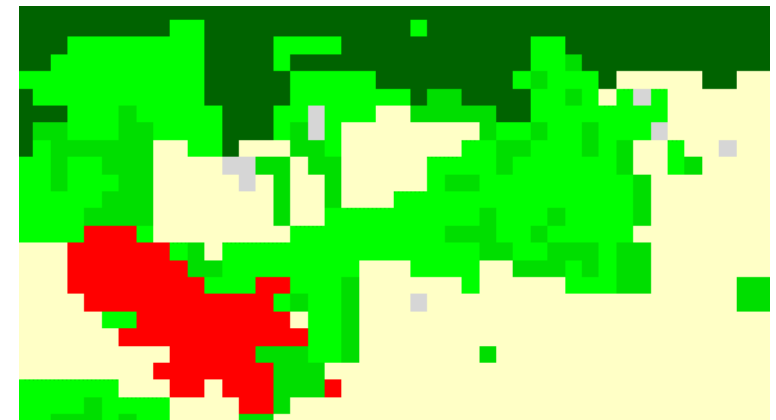
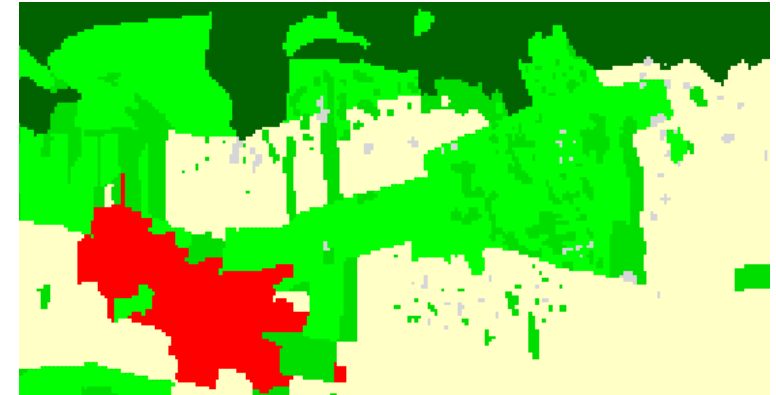
Hierarchical patch dynamics paradigm (2)

- **Wu (1999)**

- Ecological systems as spatially nested patch hierarchies
- Dynamics of an ecological system derived from the dynamics of interacting patches
- Pattern and process are related and change with scale
- Non-equilibrium and stochastic processes do not necessarily work against stability

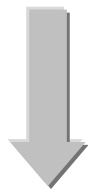
Scales and scaled representation (3)

- Relevant range of the scale spectrum for landscape analysis
 - Grain
minimum area at which an organism responds
comparable to resolution (spatial, spectral, temporal) in an image
 - Extent
coarsest scale of spatial heterogeneity
extent of the whole scene (total area, bandwidths, covered temporal duration)

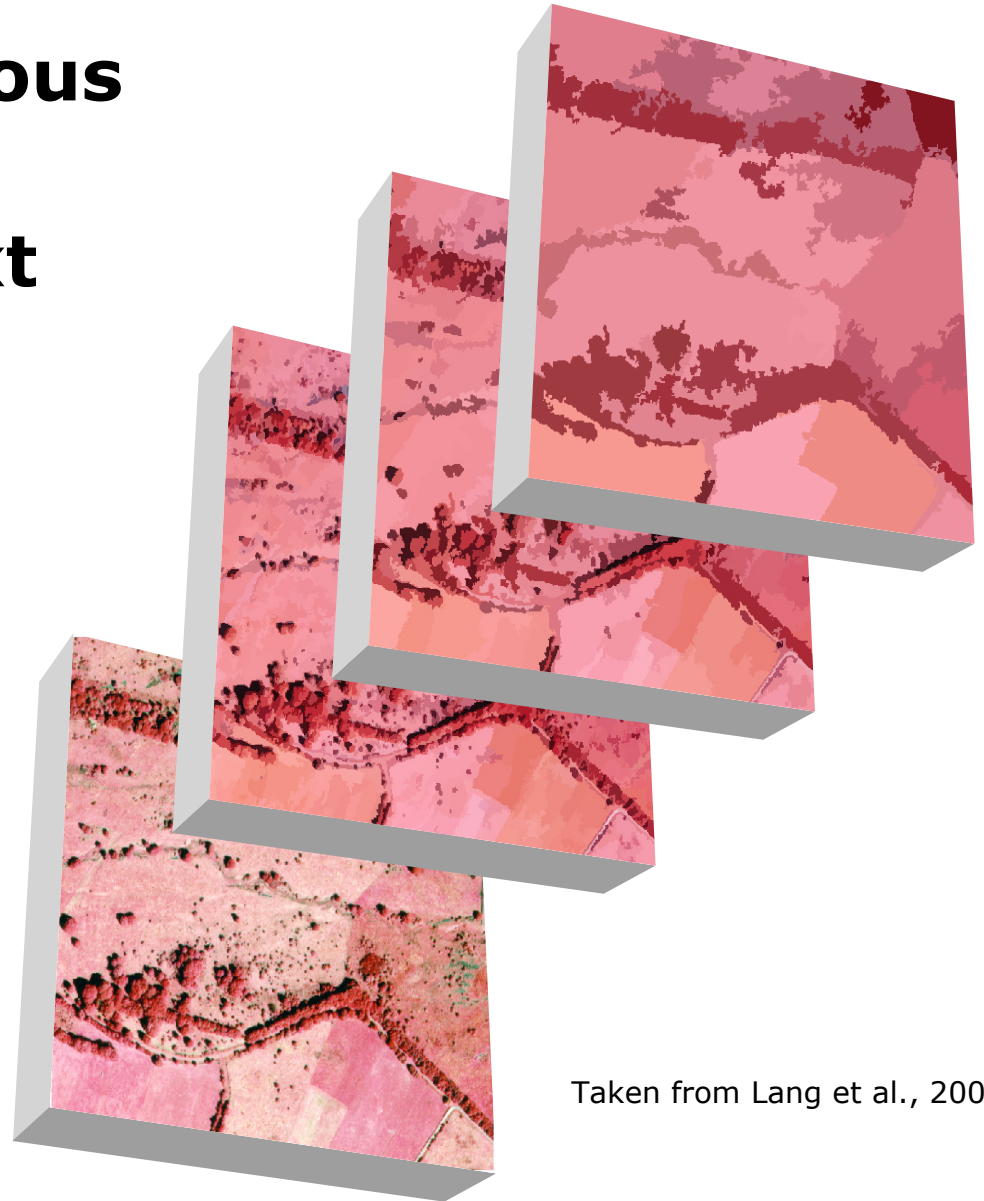


Scales and scaled representation (4)

- **Representation in various levels simultaneously**
- **Each knows it's context and hierarchical neighbourhood**



Object hierarchy



Taken from Lang et al., 2004

Decomposability and Holarchy

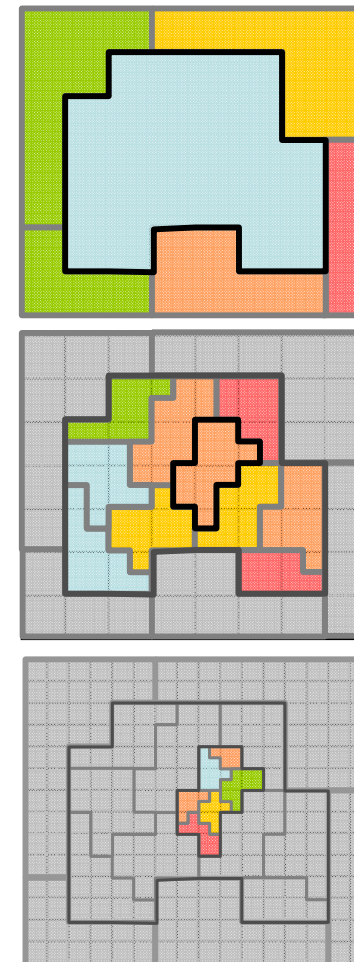
- **Landscape as a system**

Consisting of interacting subsystems

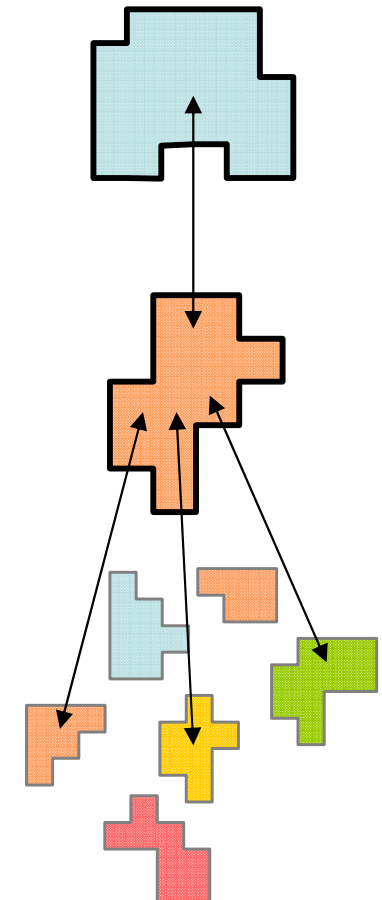
- **Decomposition**

Separating a system into its components according to their scale and ordering them hierarchically

Separation



Hierarchical organization



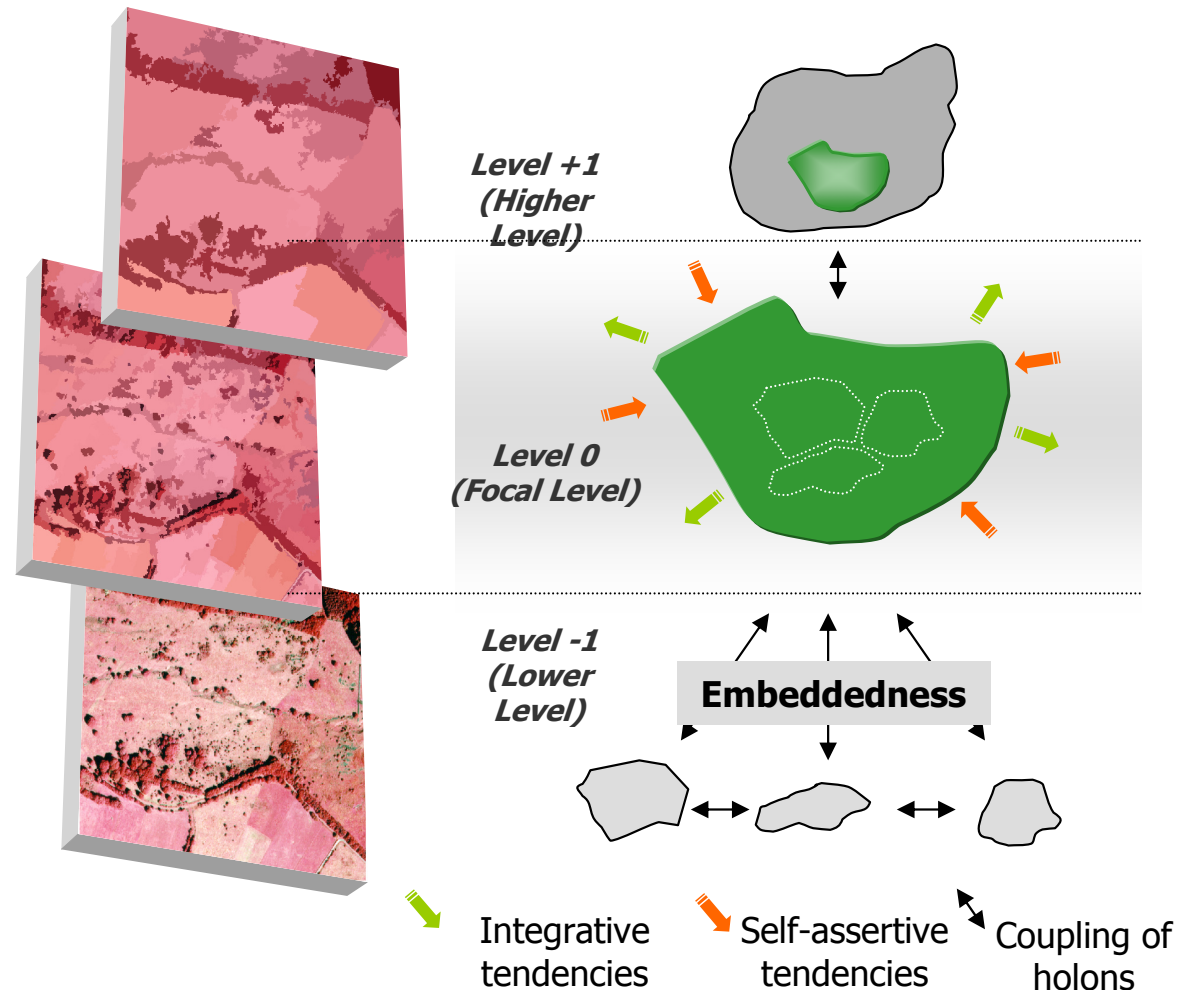
Decomposition and Holarchy (2)

- Subsystems are rather independent from each other

Horizontal and vertical coupling

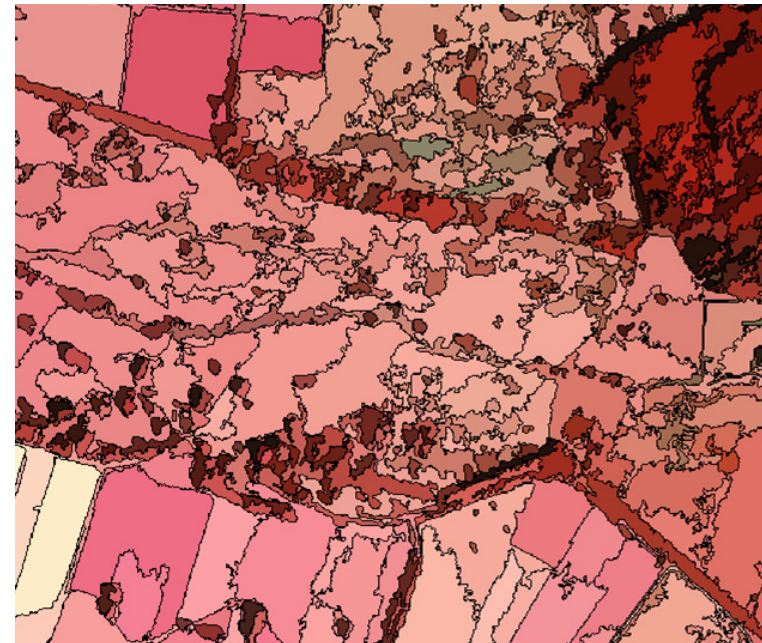
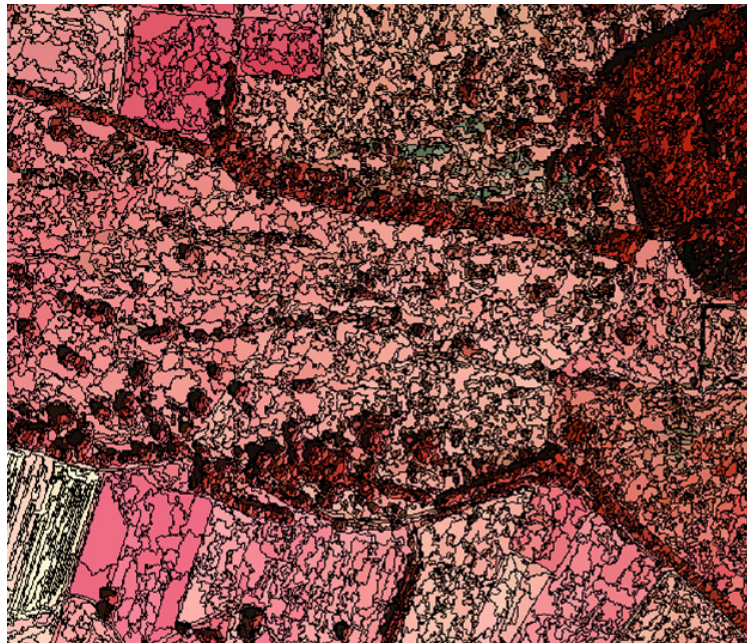
- But still have integrative tendencies

Part-being of constituting elements



Multi-scale approach with remote sensing

- **Definition of fundamental objects in remote sensing images**
Integrated objects vs. aggregate objects
- **Interaction of objects within and across scale domains**
 - What scales should be chosen for the different objects?
 - At what scale should hierarchies be established?



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Chapter 3 Knowledge representation

Outline

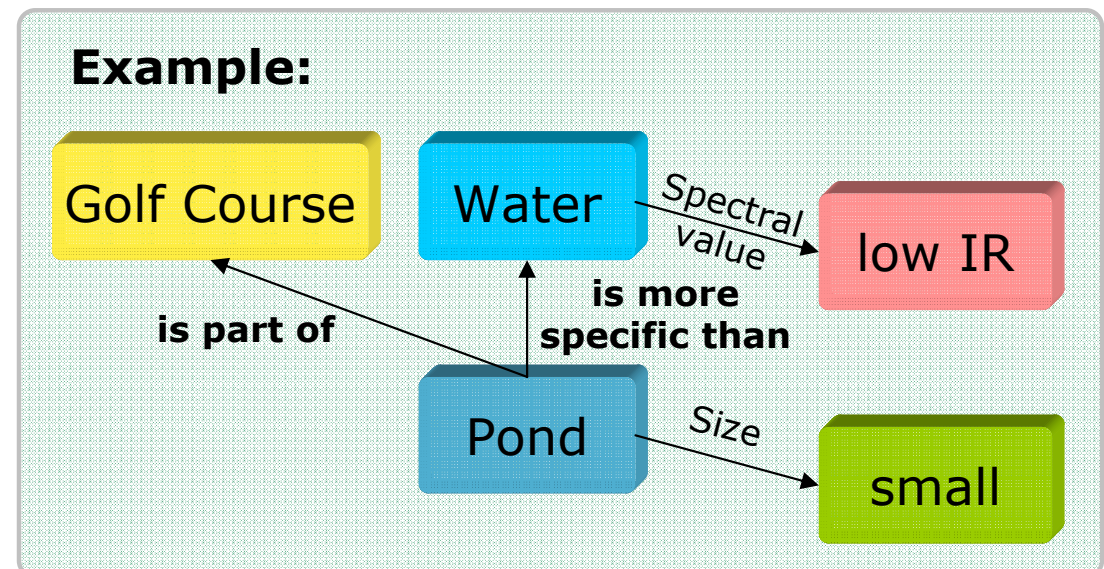
- **What is knowledge?**
- **Cognition networks**
- **Image understanding**
- **Production systems vs. adaptive learning**

What is knowledge?

- **Knowledge plays key role in image interpretation part of remote sensing**
 - Implicit human knowledge is supplemented with explicit knowledge by training
- **Artificial intelligence distinguishes knowledge into:**
 - Procedural knowledge (specific computational functions)
 - Represented by a set of rules
 - Structural knowledge (how concepts of a domain are interrelated)
 - For image understanding in remote sensing: Are there links established between image objects and 'real world' geographical features?
 - Rich semantic content
 - Represented by a semantic network

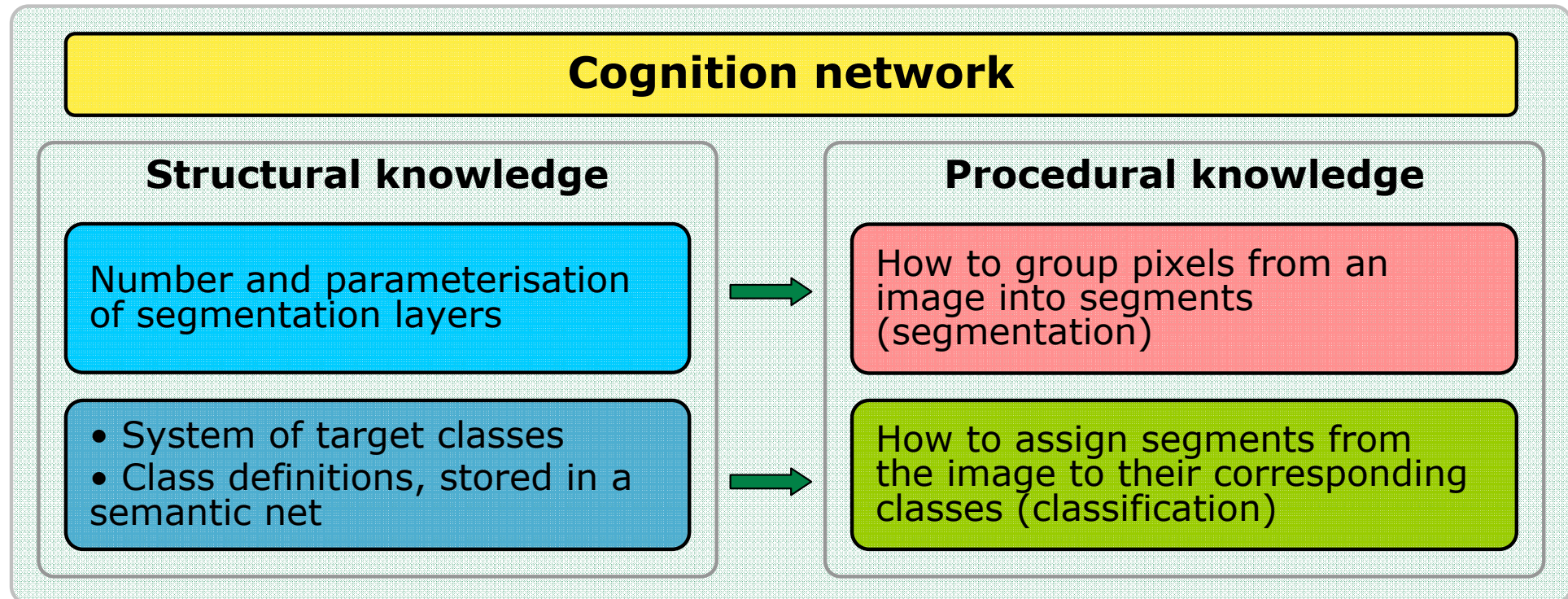
What is knowledge? (2)

- **Structural knowledge can be organized in knowledge organizing systems**
 - Realised as graphic notations such as semantic nets or frames
 - Semantic knowledge representation (using inheritance concept, e.g. 'is part of', 'is more specific than', 'is an instance of') as formal framework for image analysis
- **Semantic net**
 - To be created
 - Control over existing connections, once established
 - Transparency and operability



compare to Pinz, 1994; p. 94

Cognition network



- **Purpose of the cognition network**
 - Documentation of every step and setting in the process of image understanding
- **Usefulness of the approach**
 - Transparent, a suitable means for communication
 - Reproducible
 - To a high degree comprehensible
 - Technically transferable to other scenes

Image understanding

1. Definition

Image understanding (IU) is a process leading to the description of the image content
(= reconstruction of an imaged scene)

2. Extent of IU

Reaching from signals (image data) to a Symbolic representation of the scene content

6. Involved disciplines

- Image processing
- Pattern recognition
- Artificial Intelligence

Image understanding

4. Output description

- Description of real-world objects and their relationships in the specific scene
- Resulting in thoroughly described features (not mere listing and labelling of features)

5. Knowledge input

- Process is driven by
- utilisation of procedural knowledge
 - transformation of structural knowledge

3. Conditions for IU

- Outcome depends on the domain of interest of the interpreter, defined by:
- Underlying research question
 - Specific field of application
 - Pre-existing knowledge and experience of the interpreter

Image understanding (2)

**Utilization and transformation
of knowledge**

**Scene description
as conceptual reality**

**Modelling (categorizing
the image objects)**

**Planning of the image
description outcome and segmentation**

- which target objects, scales and classes
(dependent on the domain of interest)
- multi-scale segmentation

Image understanding (3)

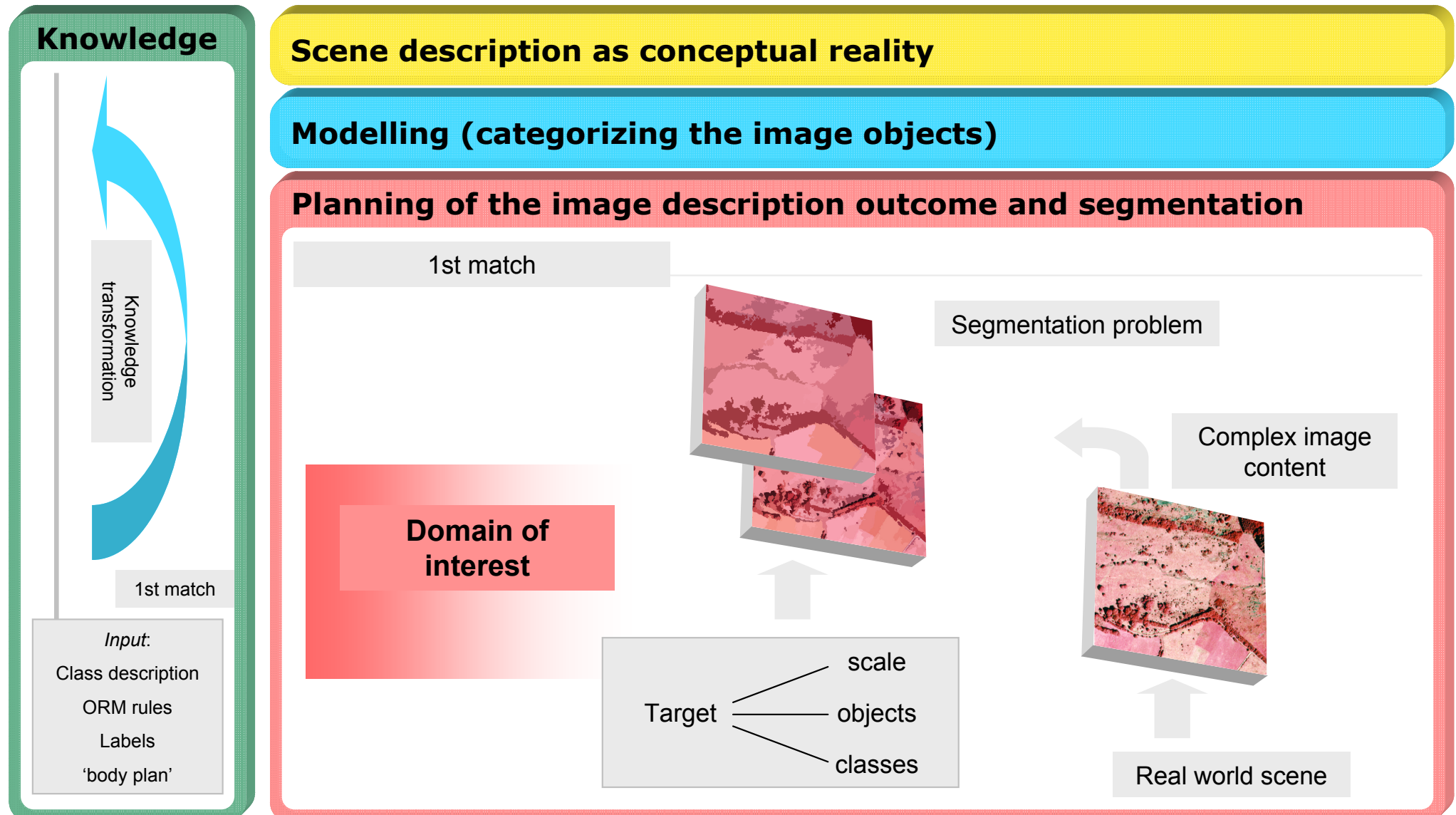


Image understanding (4)

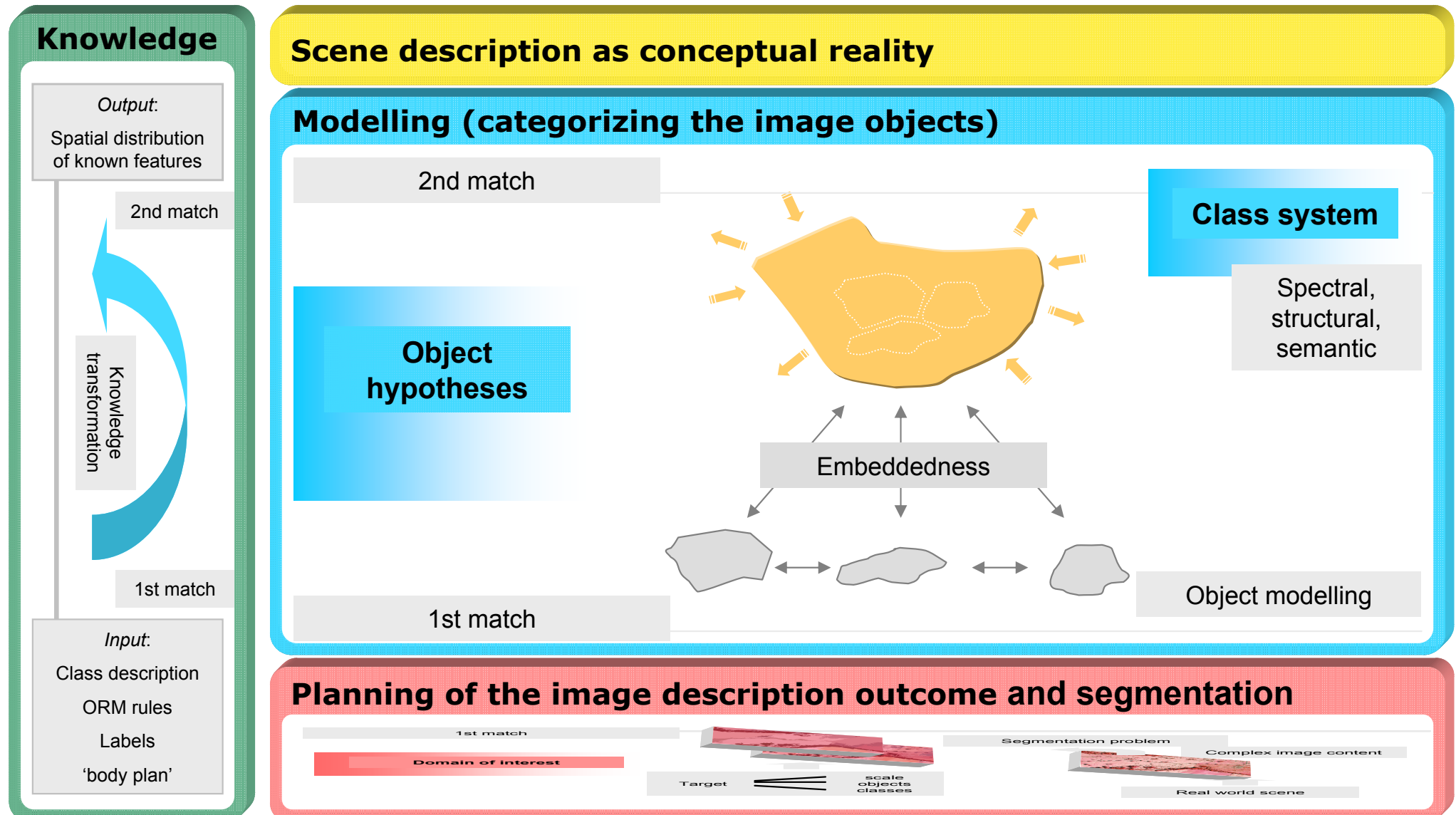


Image understanding (5)

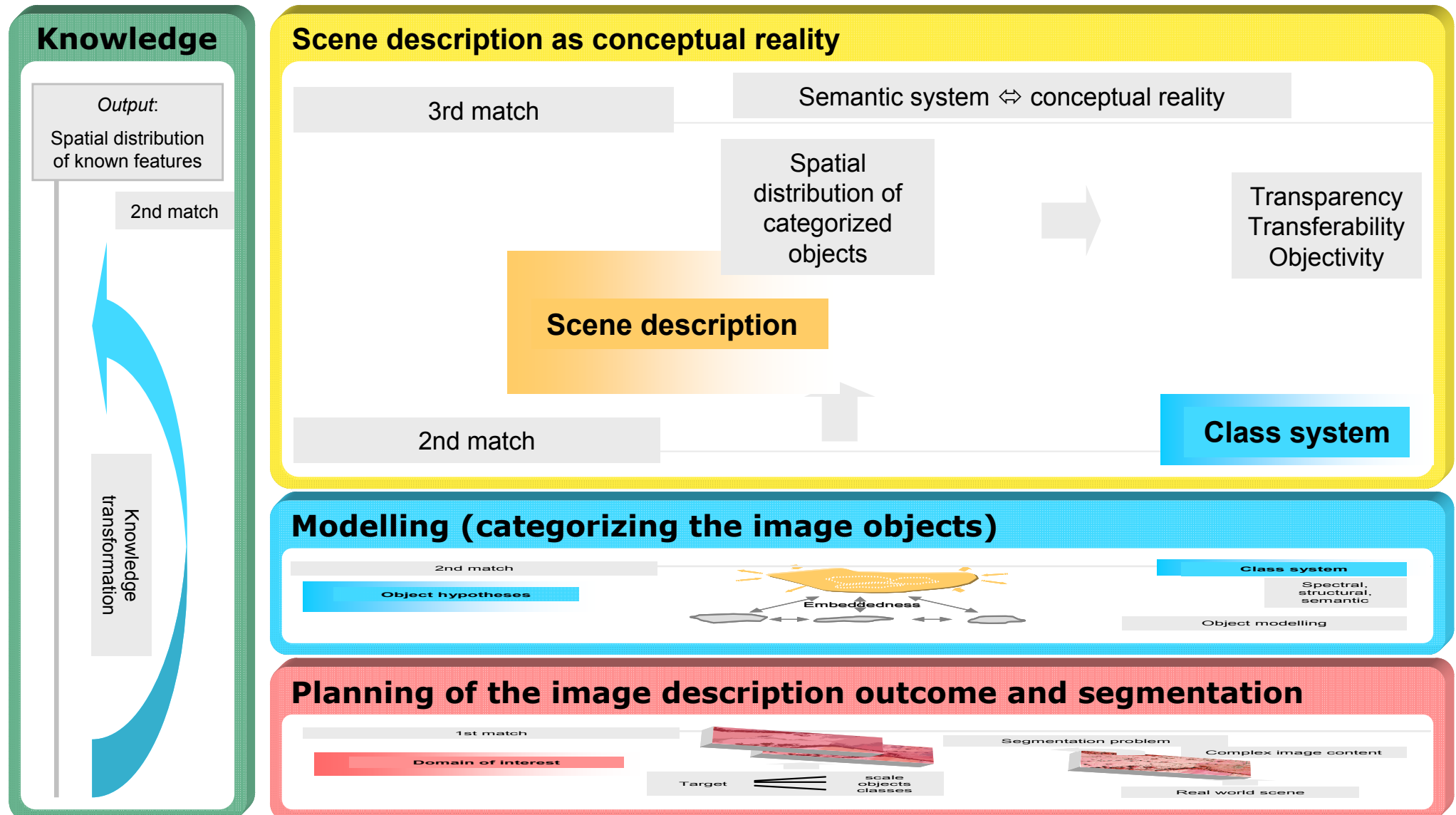
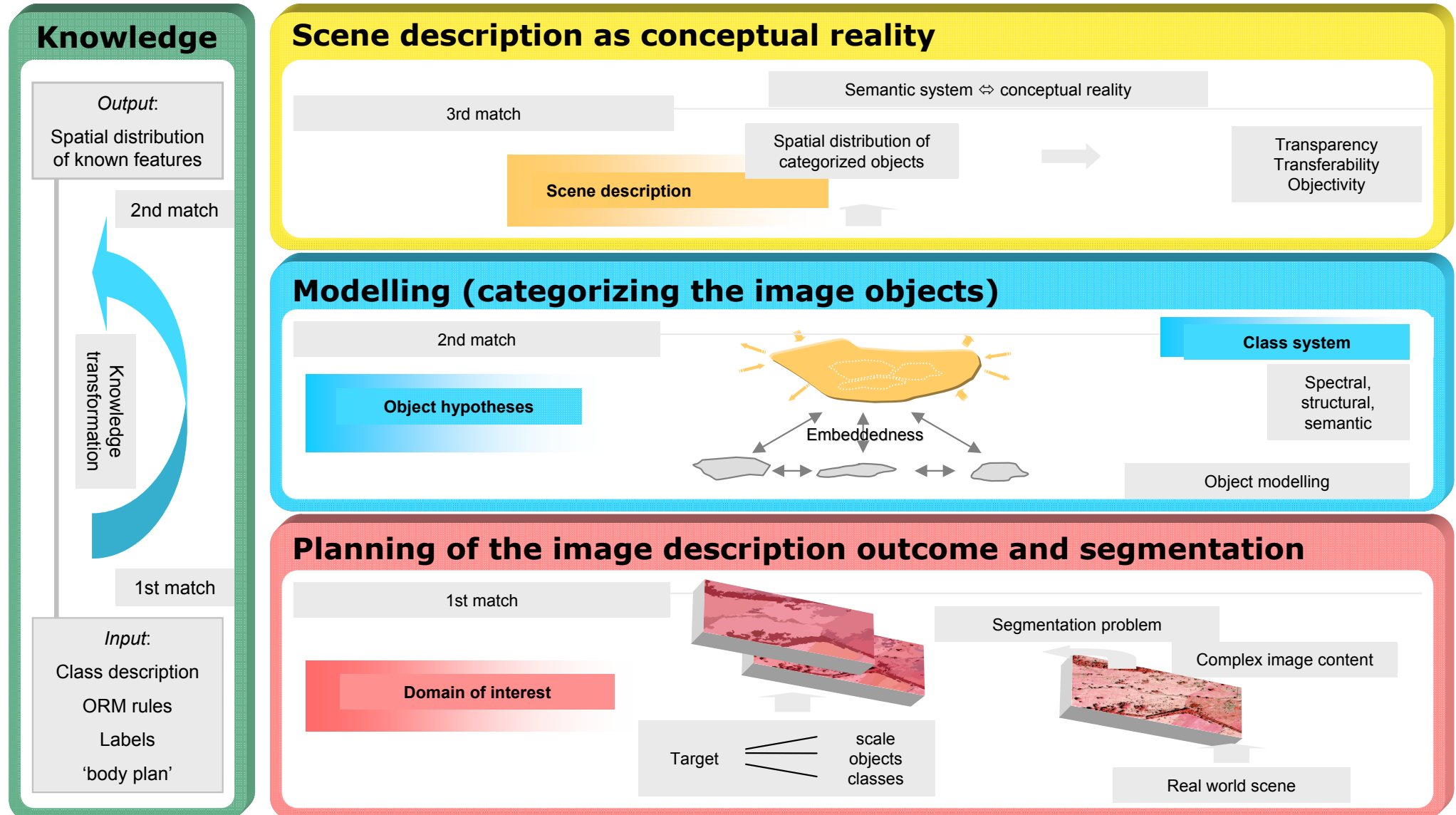


Image understanding (6)



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Chapter 4 Image segmentation

Outline

- **Short history**
- **Image segmentation in remote sensing**
- **Categories of segmentation algorithms**
 - Histogram-based/pixel-based segmentation
 - Region-based segmentation
 - Edge-based segmentation
- **Scale space analysis - Image Objects and Blobs**
- **Multiresolution Segmentation algorithm**
 - Region merging and scale
 - Local mutual best fitting approach
 - Colour and shape homogeneity

Short history

- **1980ies: first developments of image segmentation**

Major driver: industrial vision

- **Rarely made use of in remote sensing until the late 1990ies**

Reason: little progress in segmentation of multi-band images, algorithms not made for EO data

- **Since then a high number of segmentation algorithms has been developed**

- Availability in commercial products made use of segmentation of EO data more common

Image segmentation in remote sensing

- **Division of an image into regions so that**
 - the **whole scene is covered** by regions (spatially continuous, exhaustive segmentation)
 - the **regions do not overlap**
 - the **regions are homogeneous** within themselves
 - the homogeneity criteria of **neighbouring regions differ**
- **Region (token):**
 - aggregate of pixels grouped together (*directly or indirectly*)
- **Homogeneity as overarching principle**
 - 'relatively' homogeneous regions reflect better the 'Near-decomposability' of natural systems
 - High heterogeneity creates boundary to neighbouring patches, low remaining heterogeneity within patches
 - Homogeneity criterion: grey value, colour, texture, form, altitude, etc.

Categories of segmentation algorithms

- **Pixel-based or histogram-based**

Thresholding techniques

Segmentation in the feature space

- **Region-based**

Region growing, merging and splitting

- **Edge-based**

Laplace filter, Sobel-operator, representativeness, ...

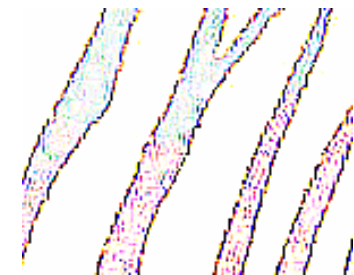
- **Non-image-related/
non content expecting**

Tiling image with a honeycomb or chessboard structure

Finding homogenous objects



Detecting edges between objects [and background (matrix)]

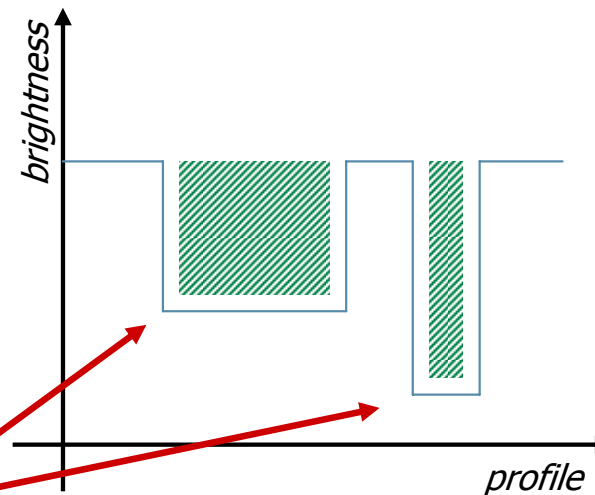
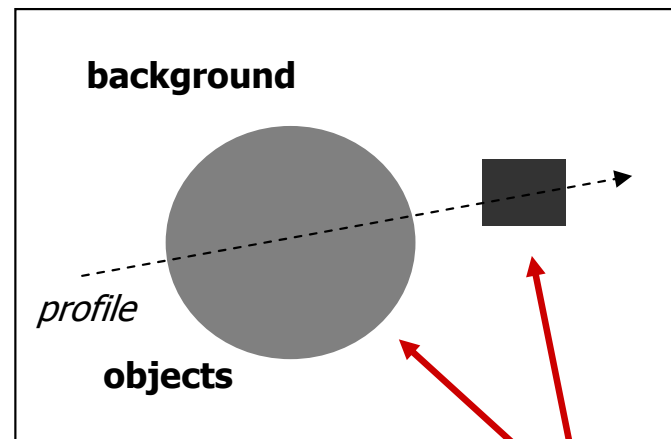


Regions defined without information from the image

Objects as Tokens

- **Objects** vs. background (**matrix**) in a grey value image
- → **tokens** (token set)

Region (token): aggregate of pixel grouped according to homogeneity criterion (*directly or indirectly*)



Constellation token

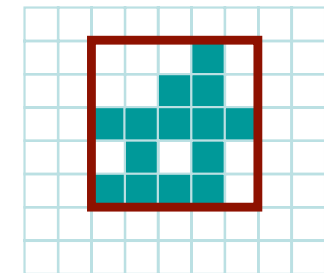
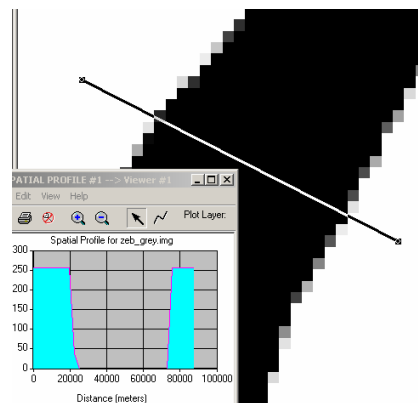
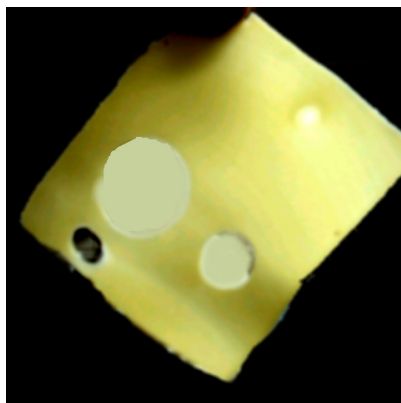


Image events (**tokens**)

Histogram-based

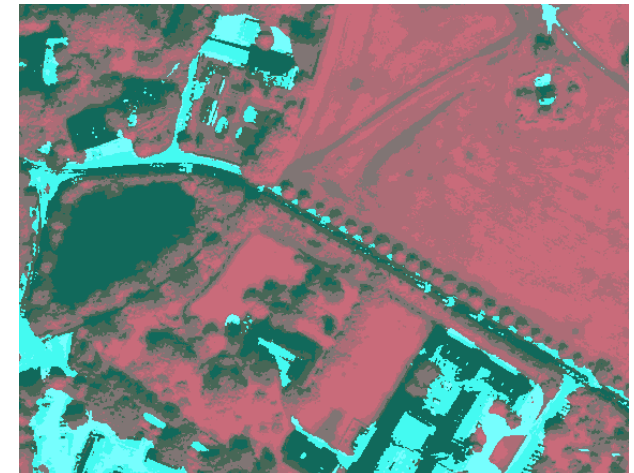
- **Histogram Thresholding:**
simplest way to accomplish
exhaustive regional segmentation
- → '*Swiss cheese*' segmentation
for punched parts
- One- or bimodal distribution of
grey values, threshold has to be
determined



Quickbird: band 1, thresholded



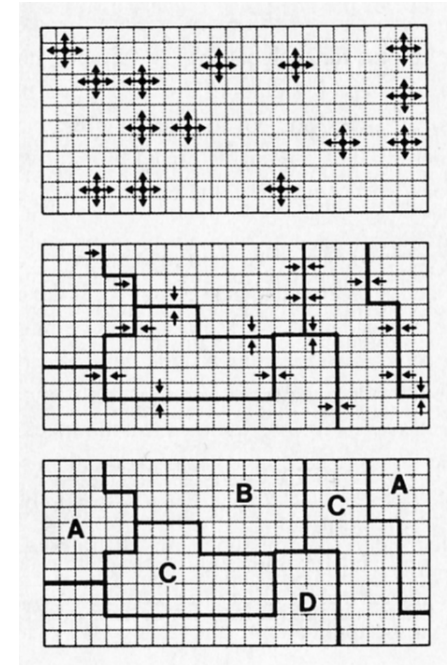
Quickbird: 6 classes Isodata
classification



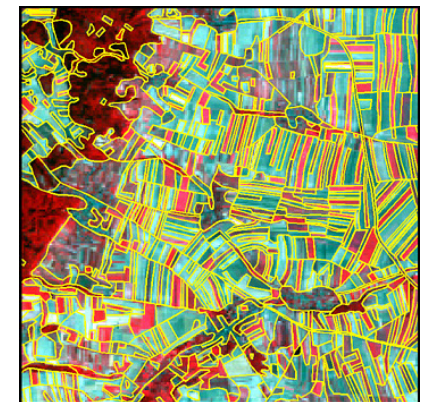
Region-based segmentation

■ **Region growing**

- Seed cells are distributed over image
 - Bottom up (randomly)
 - Top-down (content expected)
- Neighbours (4- or 8-neighbourhood) are included into region, if
 - they do not belong to another region yet
 - the homogeneity criterion H applies
- Two neighbouring regions are unified, if H applies

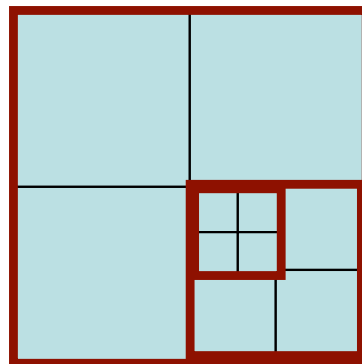


Campbell, p. 346



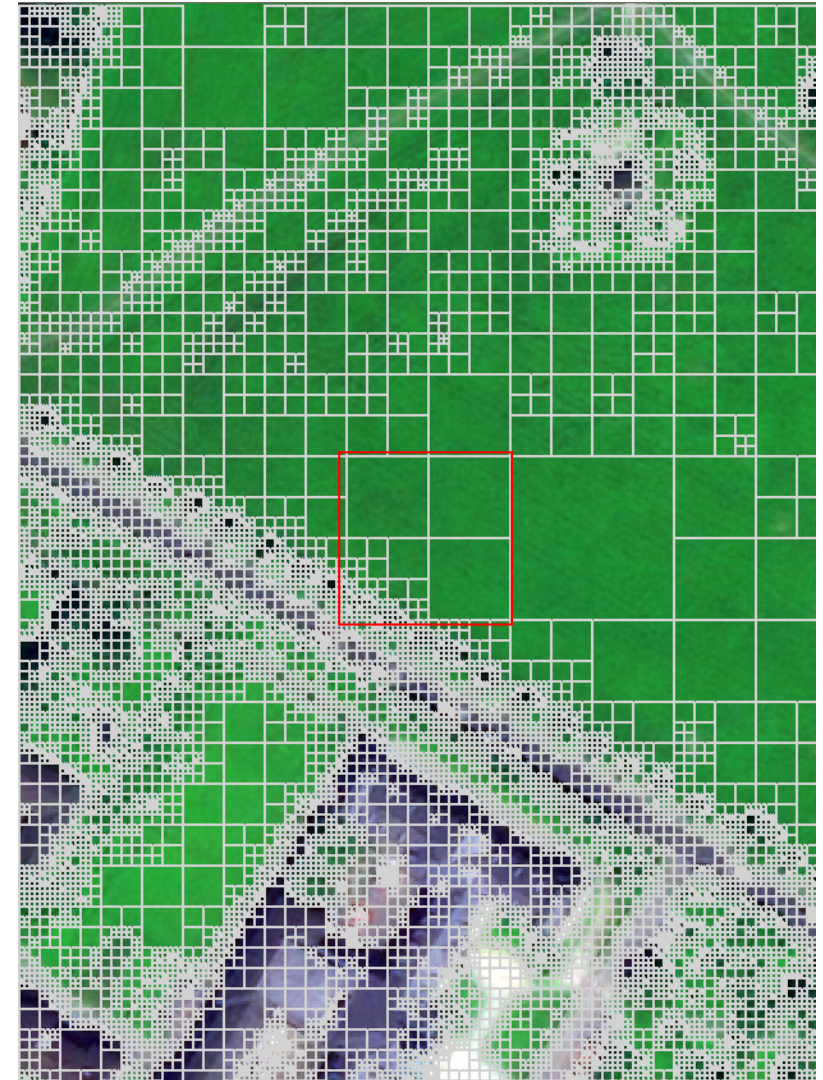
Region-based segmentation (2)

- **'Split and Merge'**
 - Combination **of coarse segmentation and merge**
 - Example: Quadtree
 - **Initially:** image as one object → division into 4 parts, if **H** does not apply
 - Resulting **quadtree** structure
 - Merge of homogenous quadtree areas



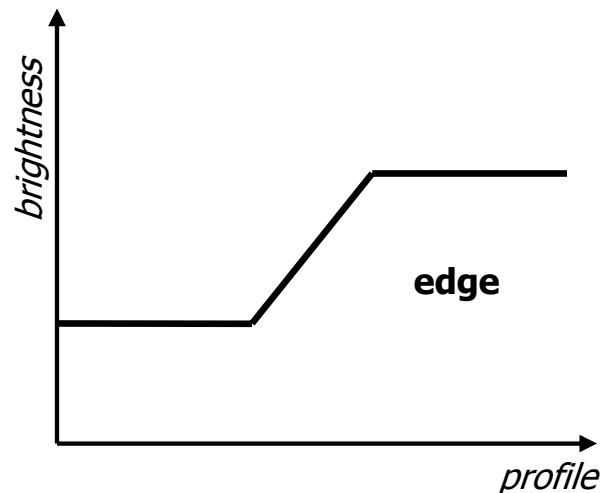
Region-based segmentation (3)

Quadtree structure in a Quickbird Image of Salzburg, generated with eCognition

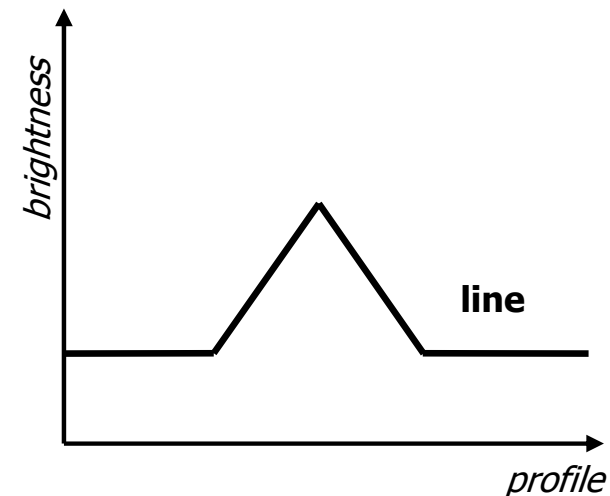


Edge-based segmentation

- Region-based segmentation makes sense when **large, compact** and **coherent** objects occur ('blobs')
- → edge-based segmentation for **elongated structures**
- **Edge**: boundary between homogenous areas



Build the
derivative



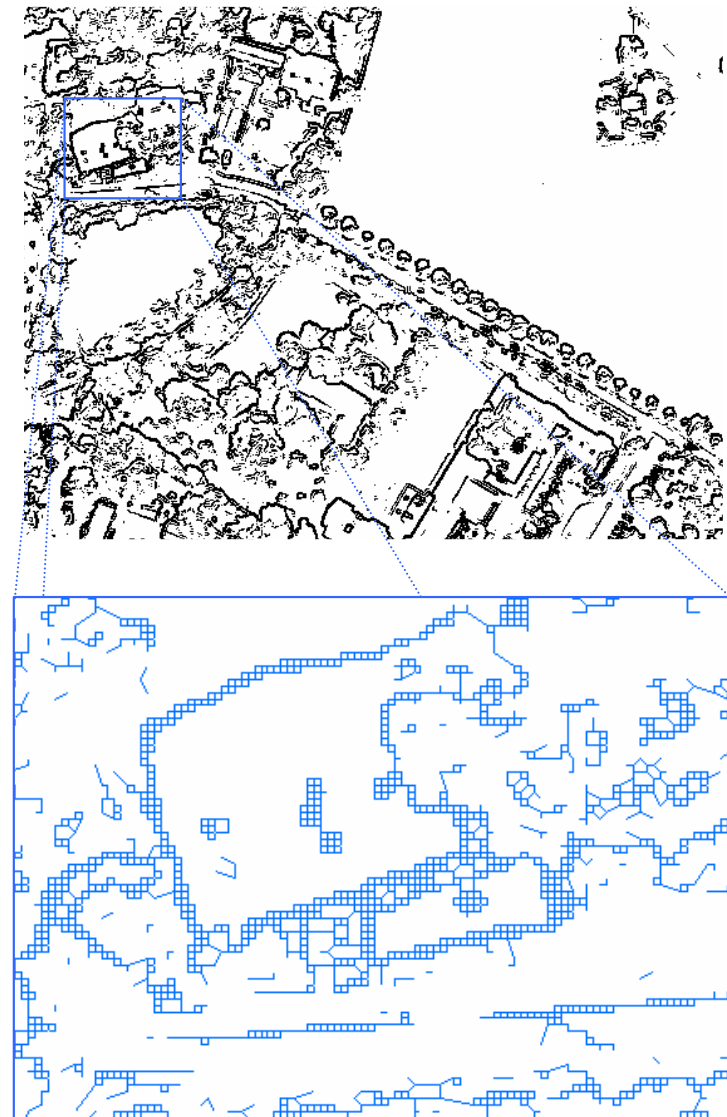
Edge-based segmentation (2)

■ Workflow

1. Edge detection

- Filtering – smoothing to decrease noise in the image
- Enhancement – revealing local changes in intensities
- Detection – select edge pixels, e.g. by thresholding
 - Closing of gaps / deleting artefacts
 - Combining, extending of lines

2. Linking the edge pixels to form the region boundaries



Edge-based segmentation (3)

■ **Enhancement filters (examples)**

- Sobel operator
- Laplace filter
- Compass edge
- ...

1	2	1
0	0	0
-1	-2	-1

horizontal

-1	0	1
-2	0	2
-1	0	1

vertical

0	1	0
1	-4	1
0	1	0

1	4	1
4	-20	4
1	4	1

-1	-2	-1
0	0	0
1	2	1

0°

-2	-1	0
-1	0	1
0	1	2

45°

-1	0	1
-2	0	2
-1	0	1

90°

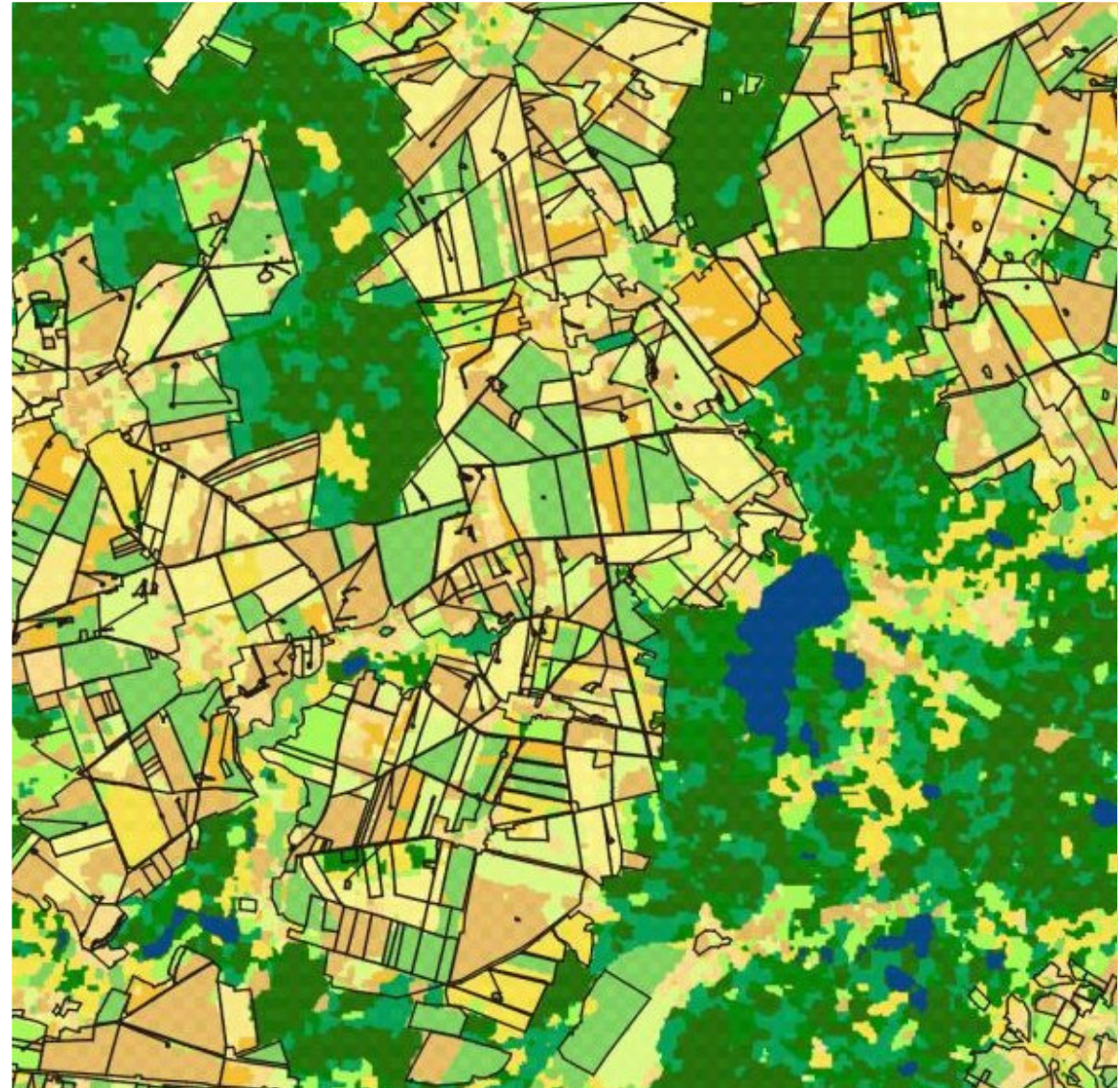
0	1	2
-1	0	1
-2	-1	0

135°

The resulting filter
is the combination
of all eight directions.

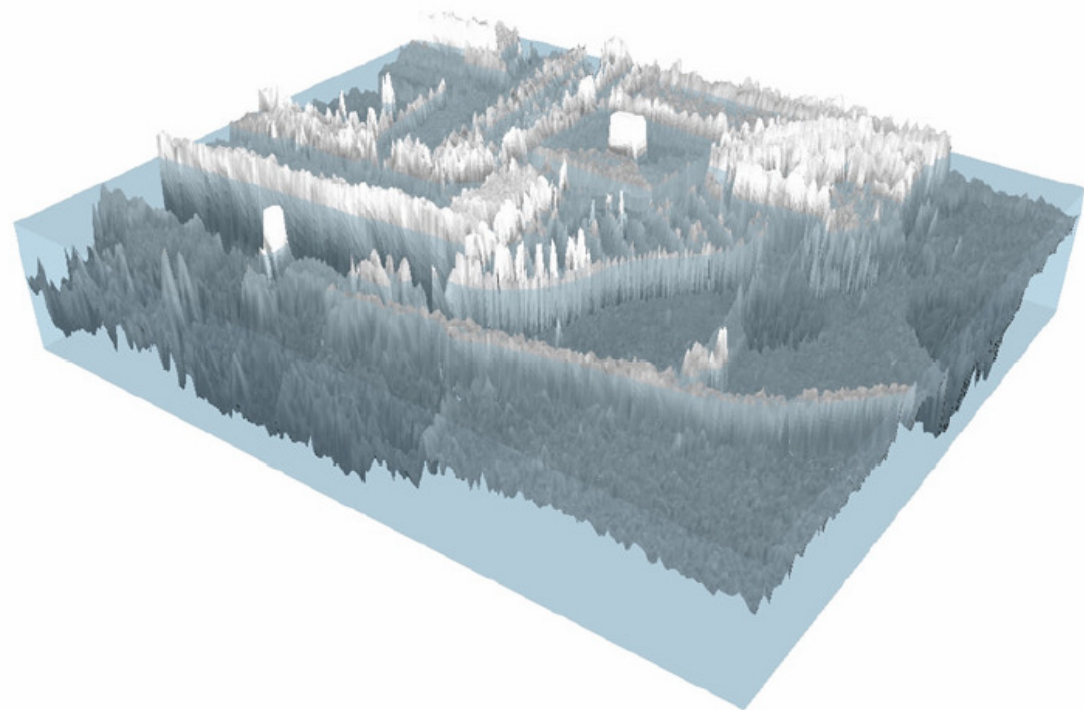
Edge-based segmentation (4)

- **Segmentation by representativeness measures**
- Calculate a representativeness of each pixel for its neighbours
- The minima represent unsteadiness and indicate edges
- Vectorised minima delimit areas with similar spectral properties



Watershed segmentation

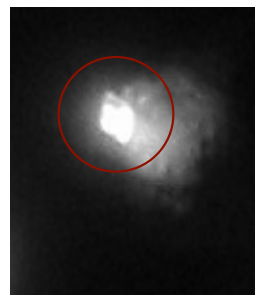
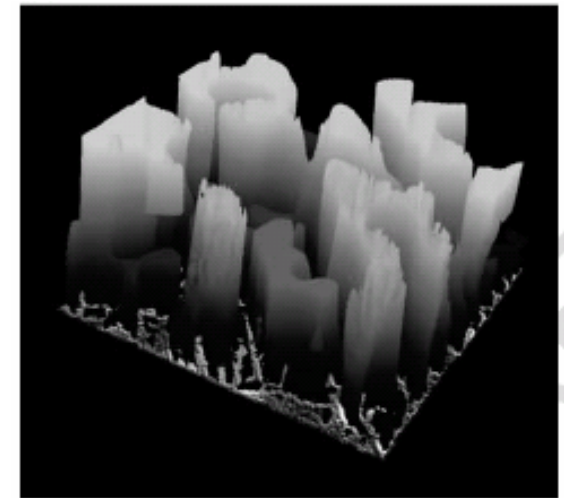
- **Watershed segmentation**



© by SLang 2005

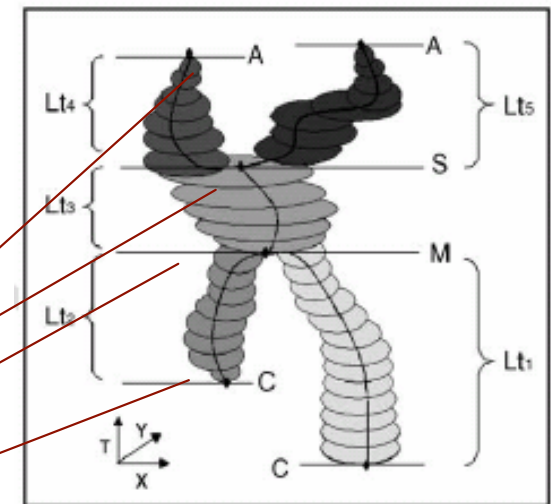
Scale space analysis - Image Objects and Blobs

- Blobs
 - Compact image object
 - usually with a clear centroid
 - Temporal aspect → image events
- Scale space blobs
 - Significant within scale domains → defined by spatial extension, brightness, scale (4D)
- Detection
 - Repetitive Gaussian filtering
 - Local maxima are determined
 - Shapes are drawn around centroids (circle, polygon)



**Hyper blob with
image events**

- Annihilation
- Split
- Merge
- Creation



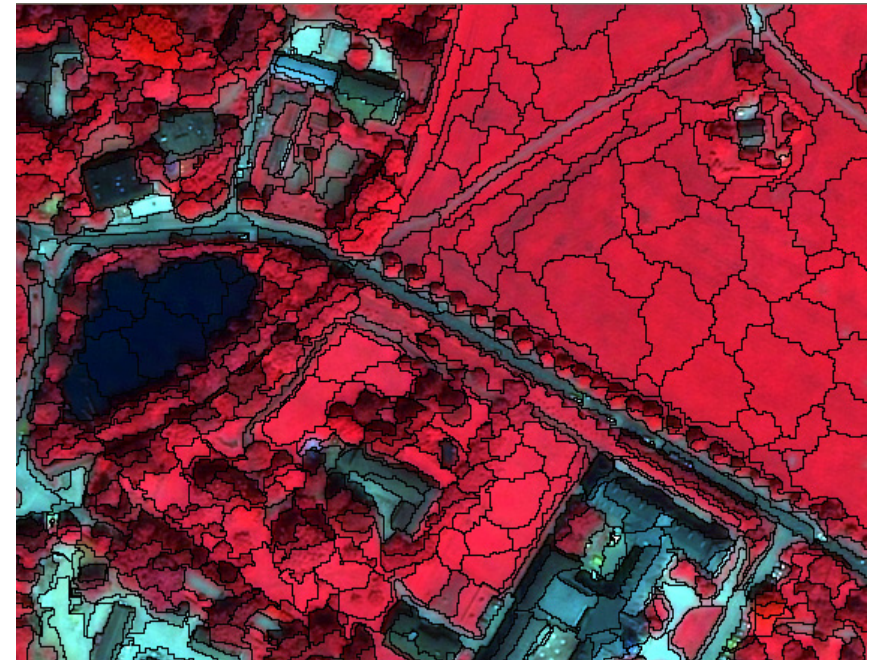
Multiresolution Segmentation algorithm

■ **Design goals**

- „Convince the human eye“
- Multi-resolution (strictly hierarchic)
- **Similar resolution**
- Reproducibility
- **Universality**
- Performance (i.e. speed 😊)

■ **Overview**

- Region merging technique
- Decision heuristics
- Homogeneity criterion
 - Colour homogeneity
 - Shape homogeneity
compactness and smoothness



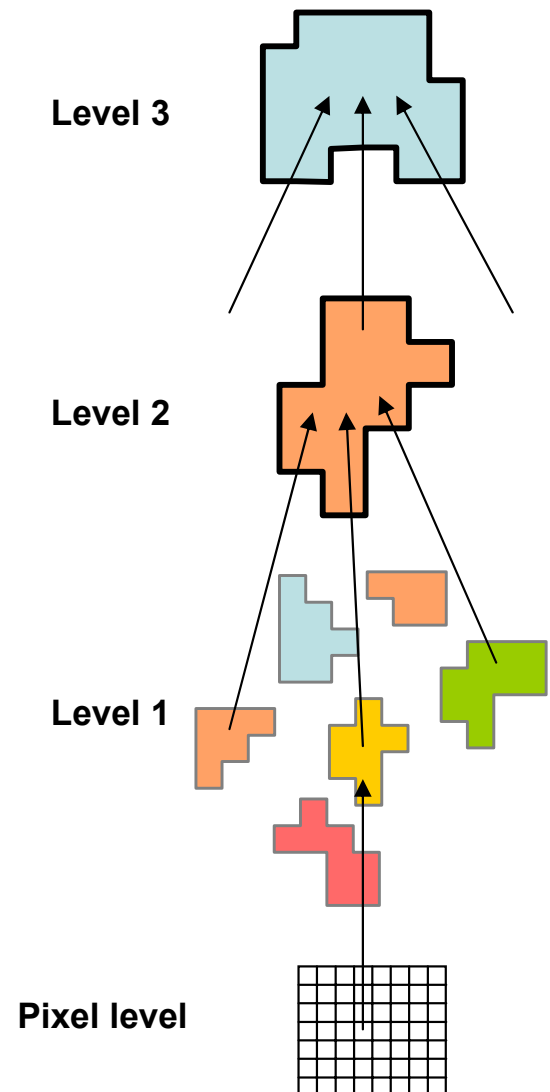
Region merging and scale

- **Bottom up region merging technique**

- Starting with each pixel being a region
- A pair of regions is merged into one region, each merge having a merging cost (degree of fitting)
- Objects are merged into bigger objects as long as the cost is below a 'least degree of fitting' (scale parameter)
= the merge fulfils the homogeneity criterion
- Starting points for merging distributed with maximum distance
- Pair wise clustering process considering smallest growth of heterogeneity

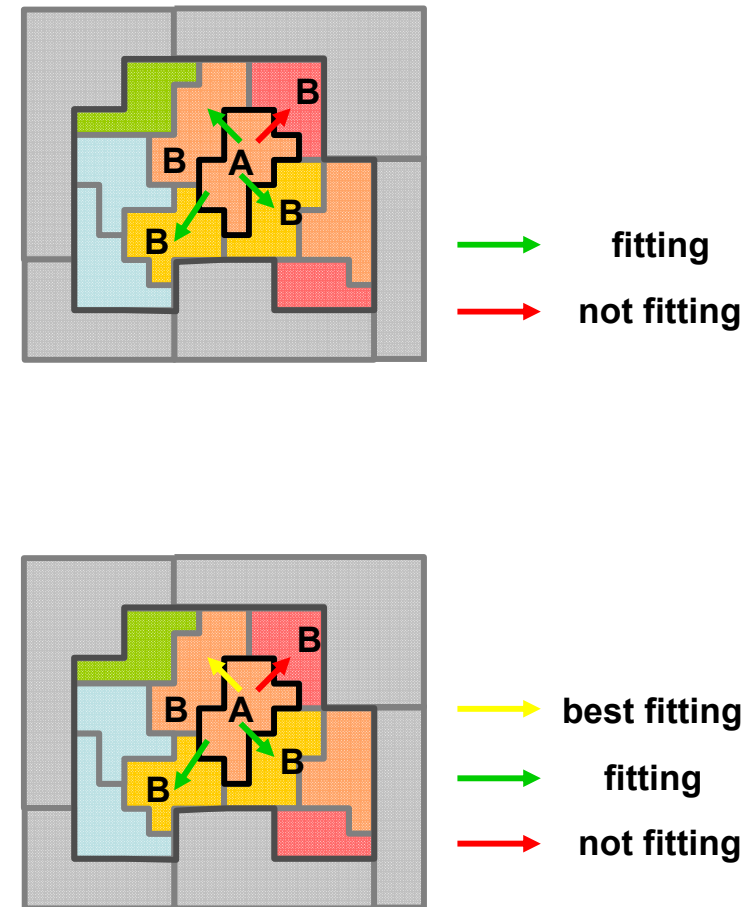
- **Establishing segmentation levels on several scales using different scale parameters**

(e.g. 2nd level based on 1st level: larger scale parameter results in larger objects consisting of the objects of the 1st level)



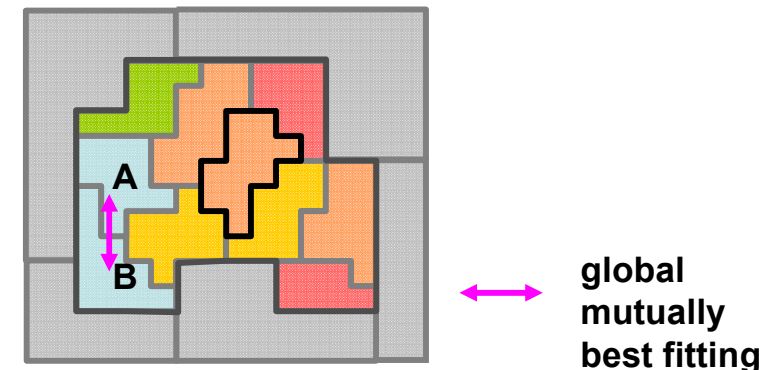
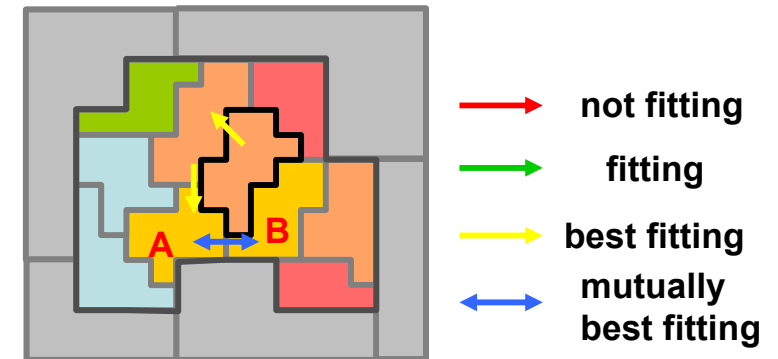
Decision heuristics

- Finding an adjacent object B for an arbitrary object A for merging them
1. Fitting: when the homogeneity criterion is fulfilled
 2. Best fitting: when the homogeneity criterion is fulfilled, and the merge between B and A produces the best degree of fitting compared to the merge between A and any other adjacent object of A



Decision heuristics (2)

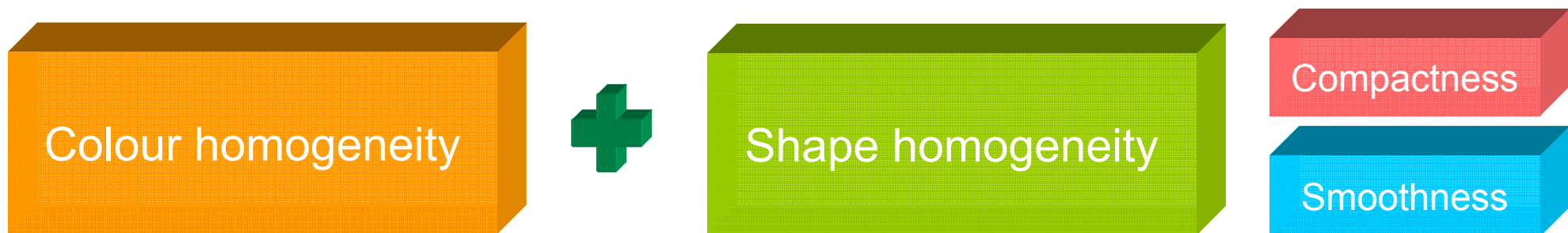
1. Fitting
 2. Best fitting
 3. **Local mutually best fitting:**
find the best fitting object B for the object A, then find the best fitting object C for the object B. Confirm that object C is the object A, otherwise take B for A and C for B and repeat the procedure.
=> find best fitting pair of objects in the local vicinity of A following the gradient of homogeneity
 4. **Global mutually best fitting:**
merge the pair of objects for which the homogeneity criterion is fulfilled best in the whole image
- **Distributed treatment order**
Use starting points with maximum distance to all other points treated before (treatment order defined over pixels or segments)



Homogeneity criterion

Definition of the degree of fitting

- Colour and shape homogeneity are weighted against each other
- Compactness and smoothness make up the shape homogeneity and are weighted against each other



Two objects are similar which are near to each other in a certain feature space

Compactness: ideal compact form of objects (objects don't become lengthy)
Smoothness: boundaries of the edges don't become fringed

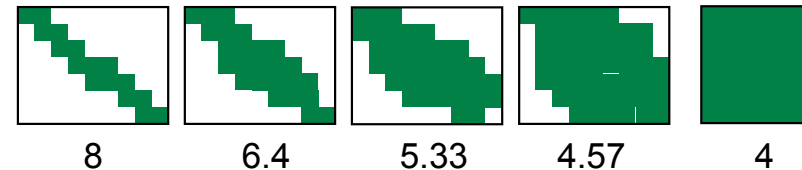
Homogeneity criterion (2)

Compactness

$$h_{\text{compact}} = \frac{l}{\sqrt{n}}$$

Relation between boundary length l of the object and the square root of the number n of the pixels of the object (square root of n equals the side of a square with n pixels)

$h_{\text{compact}} =$



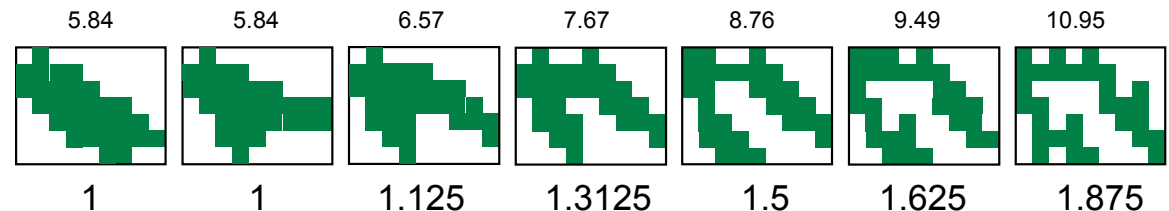
Smoothness

$$h_{\text{smooth}} = \frac{l}{b}$$

Relation between boundary length l of the object and the perimeter of the bounding box of the object (bounding box: shortest possible boundary length)

$h_{\text{compact}} =$

$h_{\text{smooth}} =$



OBIA – Tutorial

Introduction to object-based image analysis

Chapter 5 Object-based classification

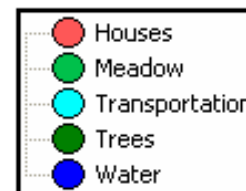
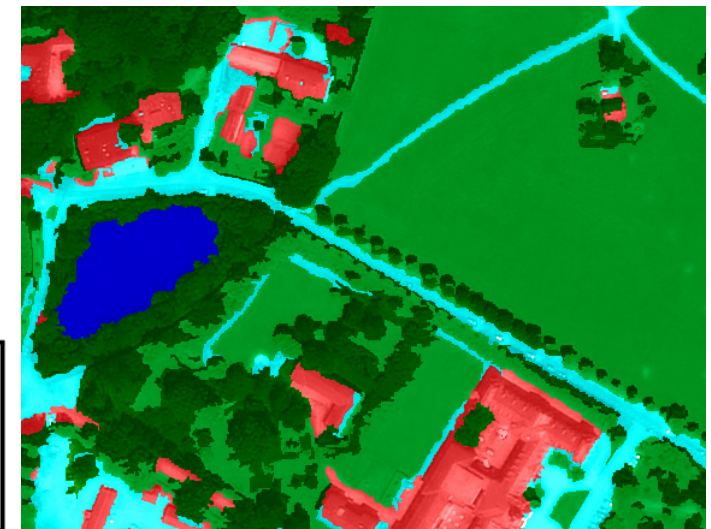
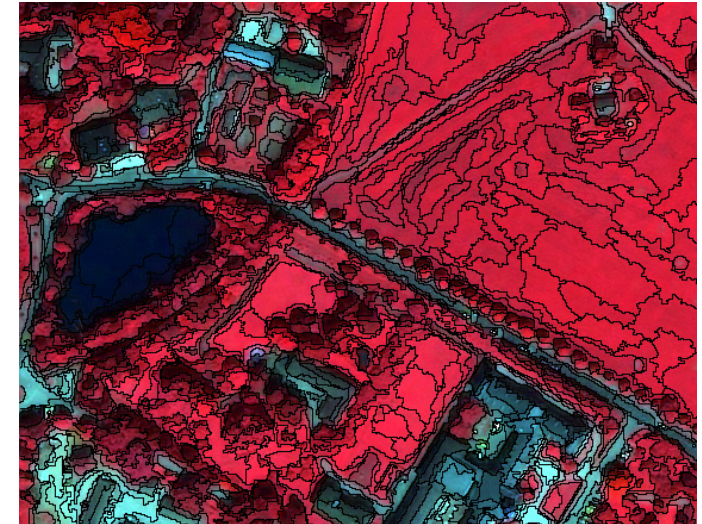
Outline

- **Introduction**
- **Available features for classification**
- **Sample- vs. rule-based classification**
- **Fuzzy classification**
- **Class hierarchy**
- **Class-related features**
- **Strengths of object-based classification**

Introduction

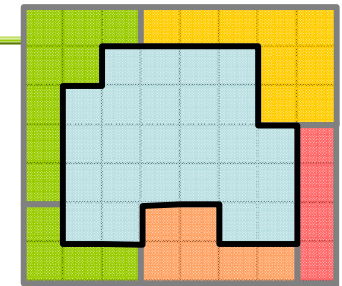
■ Classifying

- Assigning objects to a certain class according to the class's description
- Feature space segmented into distinct regions which leads to a many-to-one relationship between the objects and the classes
- Definition of the class descriptions
 - Available object features
 - Sample-based or rule-based classification strategy

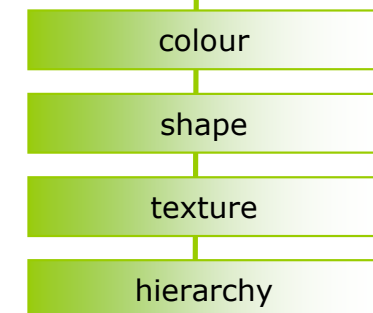


Available features for classification

- **layer values**
 - mean
 - std-dev
- **geometrical properties**
 - size, shape, ...
- **textural properties**
 - layer value texture (e.g. mean of sub objects: std-dev)
 - shape texture (e.g. directions of sub objects)
- **hierarchical properties**
 - number of higher levels
 - number of super or sub objects

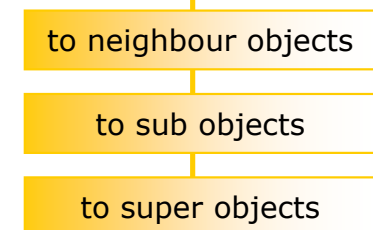


object features



- **relations to classes of ...**
 - neighbour objects
 - sub objects (relative area of ...)
 - super objects
- **membership to ...**

class related features



Sample- vs. rule-based classification

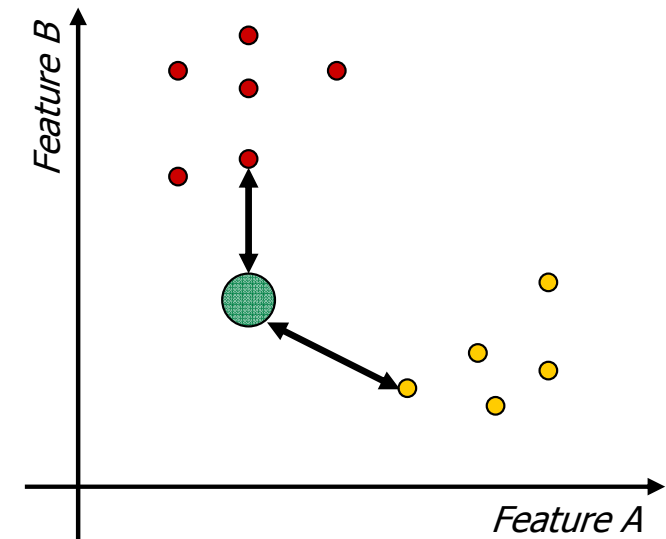
- **Sample-based classification**

- Define class membership by similarity to selected samples
 - Sample has to be representative for its class
 - Use features clearly distinguishing the sampled class from other classes

- Nearest neighbour classifier

- Object will be assigned to the class whose samples are closest to it in the feature space

Useful approach, if knowledge about the scene's content is limited



Sample- vs. rule-based classification (2)

- **Rule-based classification**

- Define a class by a rule on one feature or by rules on several features
- Fuzzy or crisp rule definition
- Hierarchical relations of classes
- Rules can address different kinds of features
 - Object features
 - Class-related features

- **Advantages compared to sample-based classification**

- Incorporation of expert knowledge in the classification
- Formulation of complex class descriptions
- Transparency (especially compared to neural networks)
- Transferability

Fuzzy classification

■ **Fuzzy vs. crisp classification**

- Uncertainties about class descriptions
 - Approximate real-world knowledge in its complexity
 - Uncertain human knowledge about the world, imprecise human thinking
 - Vague (linguistic) class descriptions
 - Other:
 - Uncertainty in sensor measurements
 - Class mixtures due to limited (spatial and spectral) resolution
 - Possibilities of fuzzy classification
 - Express each object's membership to more than one class
 - Probability of an object to belong to other classes
- ⇒ No sharply defined boundaries between classes as in crisp classification

Fuzzy classification (2)

■ **Transition from a crisp to a fuzzy system**

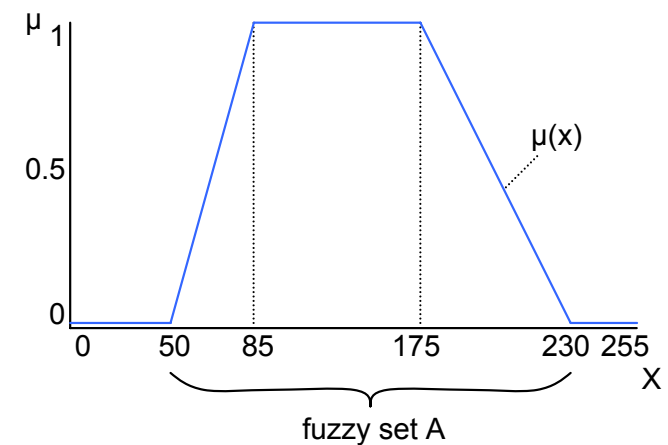
(To decide if a feature value belongs to a fuzzy set)

- The fuzzy set (A):
 - Is a certain subset of values of the whole range of an object feature X (e.g. NIR-band)
 - represents an object feature class (e.g. forest) within one object feature
- Replace boolean logic ("false" and "true") of the membership value μ by a continuous range of $[0, \dots, 1]$
- Define membership function $\mu(x)$
 - Assigning to every object feature value x a membership value μ
 - If $\mu > 0$, then x belongs to the fuzzy set A
 - Relation between object feature and classification

⇒ Choice and parameterisation of the membership function influence the quality of the classification

⇒ Introducing expert knowledge

Example:



X = feature range μ = membership value
x = feature value $\mu(x)$ = membership function
A(X) = fuzzy set

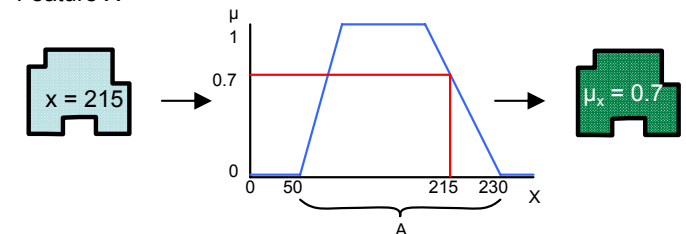
Fuzzy classification (3)

Fuzzy rule-base

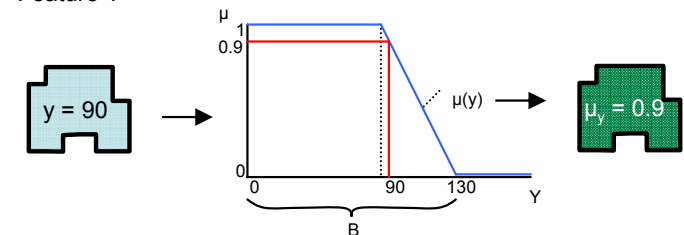
- Fuzzy rule “if – then” for assigning an object to a class
 - If feature value x (of the object) is member of the fuzzy set (e.g. associated with the class forest), the image object is a member of the land-cover forest
- Combination of fuzzy sets to create advanced fuzzy rules
 - Operator “AND” – Minimum operation
 - Operator “OR” – Maximum operation
 - Operator “NOT” – inversion of a fuzzy value: returns 1 – fuzzy value
- Fuzzy rule-base (combination of the fuzzy rules of all classes) delivers a fuzzy classification
 - Every object has a tuple of return values assigned to it with the degrees of membership to each class/degrees of class assignment
 - Since these values are possibilities to belong to a class, they don't have to add up to 1 (unlike probabilities)

Class “forest” defined by
Feature X AND Feature Y

Feature X



Feature Y



$$\begin{aligned}\mu_{\text{forest}} &= \mu_x \text{ AND } \mu_y = \text{Min}(\mu_x, \mu_y) \\ &= \text{Min}(0.7, 0.9) = 0.7\end{aligned}$$

μ_{forest}	= 0.7
μ_{pasture}	= 0.4
μ_{water}	= 0.05
...	

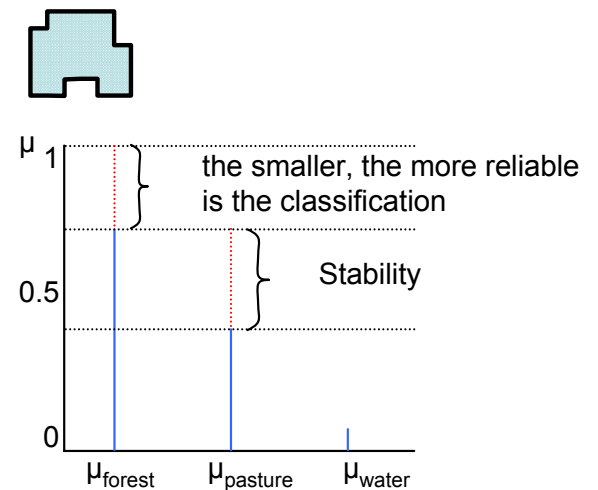
Fuzzy classification (4)

- **Comparison of membership degrees**

- Reliability of class assignment
The higher the degree of the most possible class, the more reliable is the assignment
- Stability of classification
Stable classification for differences between highest membership value and other values
- Equal membership degrees
 - high values – reliability for both classes: classes cannot be distinguished with the provided classification
 - Low values – unreliable classification (use threshold of a least required membership degree to ensure quality of classification)

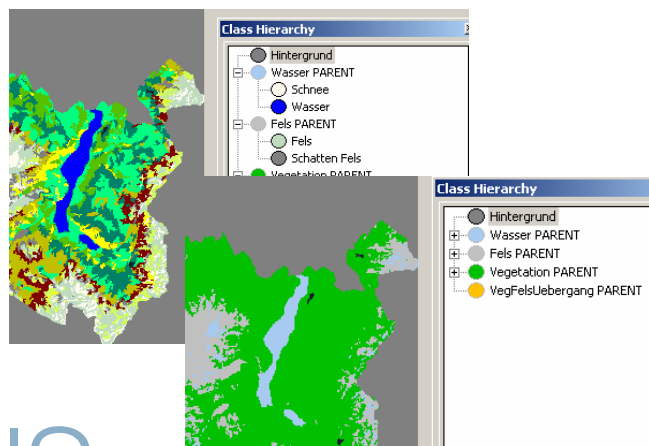
- **Defuzzification**

- Maximum membership degree of fuzzy classification used as crisp classification



Class hierarchy

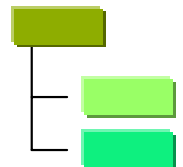
- Classes are embedded in a **heritage system** → i.e. child classes inherit all spectral props from their parents
- Classes can be grouped **semantically**
- Classification can be shown on different **semantic levels**



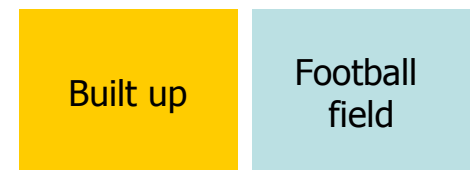
Bright vegetation



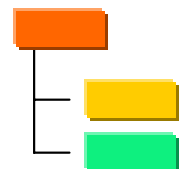
Feature-based
inheritance



Urban area

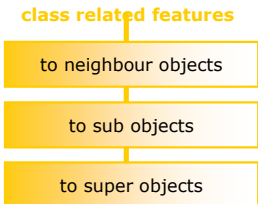


Semantic
inheritance



Class-related features

- **Classifying an object based on the classification of other objects**
 - Class of other objects works as a context feature
 - E.g. a *green* area (class contains parks, meadows,...) is classified as *urban park* because it is embedded in *urban* area
 - Newly classified object may be a context feature itself for other objects
- **Iterative Process**
 - Possibly indeterministic or even unstable
 - Mutual and circular dependencies (should be avoided if possible)



Strengths of object-based classification

- **Additional information** can be utilized (**shape, texture, relationship to neighbours**)
- 'Overcoming' texture through **segmentation**
 - Especially useful with VHSR-data and radar data
- **Objects**: increased signal/noise ratio
- Decreased number of units to be classified
- Adaptable **image resolution**
- 'Click and classify' – since based on objects
- Classification: **data base query**

OBIA – Tutorial

Introduction to object-based image analysis

Chapter 6

Accuracy assessment

Outline

- **Definitions**
- **Non-site specific accuracy assessment**
- **Site-specific accuracy assessment**
- **Error matrix**
- **Limitations of the error matrix**
- **Specifics of object-based accuracy assessment**

Definitions

- **Accuracy**

- Degree of correctness of a map or classification (degree to which the derived image classification agrees with reality or conforms to the 'truth') (Foody, 2002)

- **Error**

- Discrepancy between the situation depicted on the thematic map and reality (Foody, 2002)

- **Significance of accuracy for**

- Usefulness of thematic maps for land management
- The validity of maps for scientific investigations

Definitions (2)

■ **Accuracy assessment**

- Meaningfully quantify the accuracy of digital land cover classifications; “A classification is not complete until its accuracy is assessed” (Lillesand, Kiefer; 2000)
- Comparison of
 1. Pixels or polygons in a remote sensing-derived classification (**the map to be evaluated**)
 2. Ground reference test information (**reference map**) (Jensen, 2005)

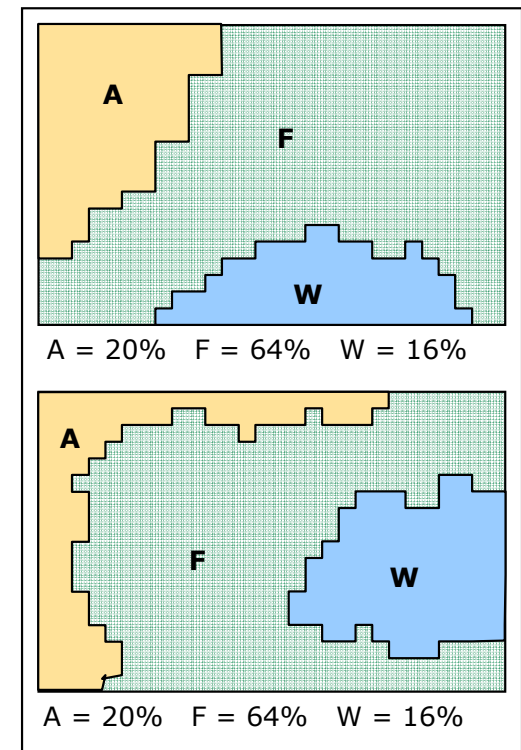
Non-site-specific assessment

- Comparing area percentages of categories in classified and reference map (inventory error can be assessed)
- Disadvantage:
 - Inaccurate method (e.g. classes have similar proportions but may appear in different locations of the mapped area)

Example of non-site-specific accuracy assessment

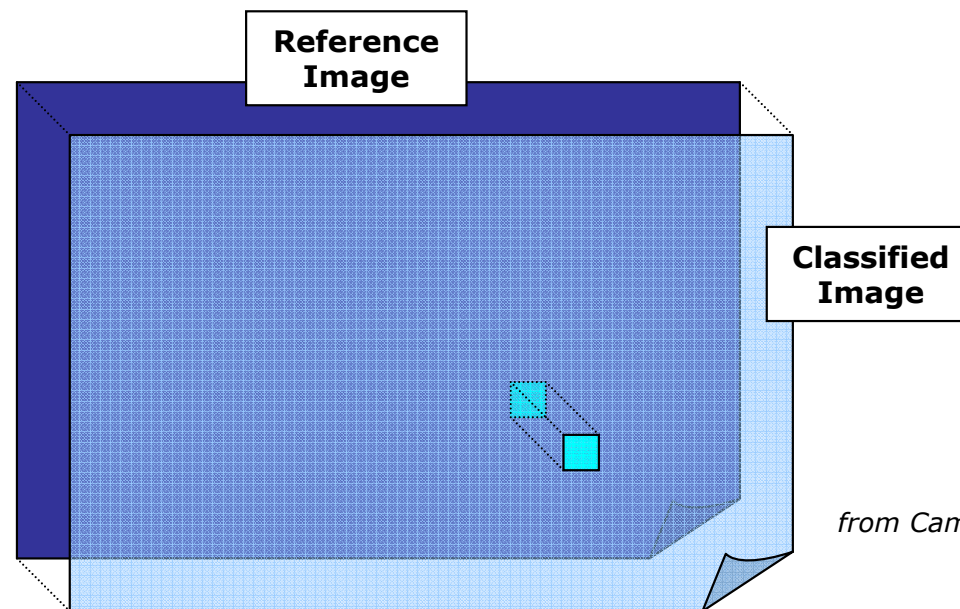
	Classified Image	Reference Map	<i>Difference</i>
Forest	42,00%	40,00%	2,00%
Meadow	13,00%	17,00%	-4,00%
Sealed	25,00%	22,00%	3,00%
Water	18,00%	19,00%	-1,00%
Bare Rock	2,00%	2,00%	0,00%
	100,00%	100,00%	

Two maps that are similar according to non-site-specific accuracy assessment



Site-specific accuracy assessment

- Agreement between categories in classified and reference map **at specific locations**
 - Based on site-by-site comparison (using pixels, clusters of pixels or polygons)
 - Every site can only be occupied by one class (for a clear statement of “error” or “correctly classified”)
- Calculation of error matrices



from Campbell, 2002

Error Matrix

- **Identification of overall errors and misclassifications (by category)**
- **$n \times n$ array; where n is the number of categories**
- **Every cell summarizes the number of sample units assigned to a particular category in the classification relative to the actual category**
 - Diagonal cells (upper left to lower right): correctly classified units
 - Off-diagonal cells: error in the remote sensing classification relative to the ground reference information

Error matrix (schematic representation)

		IMAGE TO BE EVALUATED							
		URBAN	CROP	RANGE	WATER	FOREST	BARREN	TOTAL	ROW MARGINALS
REFERENCE IMAGE	URBAN								
	CROP								
	RANGE								
	WATER								
	FOREST								
	BARREN								
TOTAL									COLUMN MARGINALS

■ DIAGONAL ENTRIES GIVE CORRECTLY CLASSIFIED PIXELS ("RANGE CLASSIFIED AS RANGE")
 ■ SUM OF DIAGONAL ENTRIES GIVE TOTAL NUMBER OF CORRECTLY CLASSIFIED PIXELS

from Campbell, 2002

Error Matrix (2)

- Percentage correct (overall accuracy)

- Sum of diagonal entries divided by total observations

- Errors of omission

- ⇔ Errors of commission

- Regarding an error from two different viewpoints
- Error of omission:** correct class hasn't been recognised by the classification process (exclusion from category)
- Error of commission:** by mistake the unit has been assigned to the wrong class (error of inclusion)

- Producer's accuracy

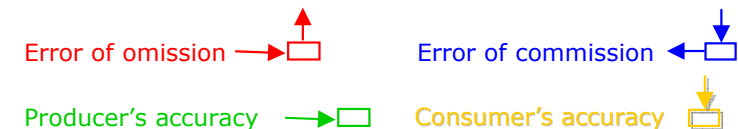
- ⇔ Consumer's accuracy

- Accuracies of individual categories
- Producer's accuracy** (a measure of omission error): indicates probability of a reference unit being correctly classified
- Consumer's accuracy** (user's accuracy, a measure of commission error): probability of a classified unit on the map actually representing that category on the ground

Example of an error matrix

		IMAGE TO BE EVALUATED						TOTAL	PA%
		URBAN	CROP	RANGE	WATER	FOREST	BARREN		
REFERENCE IMAGE	URBAN	150	21	0	7	17	30	225	66.7
	CROP	0	730	93	14	115	21	973	75.0
	RANGE	33	121	320	23	54	43	594	53.9
	WATER	3	18	11	83	8	3	126	65.9
	FOREST	23	81	12	4	350	13	483	72.5
	BARREN	39	8	15	3	11	115	191	60.2
TOTAL		248	979	451	134	555	225	1748	
CA%		60.5	74.6	71.0	61.9	63.1	51.1		

Note: Percentage correct = sum of diagonal entries/total observations = 1748/2592 = 67.4%; CA, consumer's accuracy; PA, producer's accuracy



from Campbell, 2002; modified

Error Matrix (3)

- **Kappa coefficient (\hat{k})**

- Need for a more objective accuracy assessment
- Compensation of the effect of chance agreement
- Example:
 - **Random assignment** of pixels into 3 classes
 - ➔ Results in 33% correctly classified pixels (= overall accuracy)
 - 4 classes ➔ 25% correct
 - 5 classes ➔ 20% correct

⇒ **Kappa coefficient**

Measure of difference between **observed agreement** (between a classification and reference information) and **agreement by chance**

Error Matrix (4)

■ **Kappa coefficient ($K_{\hat{}}$)**

$$\hat{K} = \frac{\text{Observed agreement} - \text{expected agreement}}{1 - \text{expected agreement}}$$

■ **If:** Observed agreement $\uparrow 1$
Expected agreement $\downarrow 0$ } \Rightarrow **Then:** $\hat{K} \uparrow 1$

$\kappa = 1 \Rightarrow$ perfect agreement between classification and reference data

$\hat{K} = 0 \Rightarrow$ agreement is not better than a random classification

^

■ Explanation of the formula:

- Observed agreement = overall accuracy
- Expected agreement = sum of the products of the consumer's accuracy (CA) and the producer's accuracy (PA) of each class

$$\text{Kappa coefficient} = \frac{n \sum_{k=1}^q n_{kk} - \sum_{k=1}^q n_{k+} n_{+k}}{n^2 - \sum_{k=1}^q n_{k+} n_{+k}}$$

Quelle: Foody, 2002; S. 188

Limitations of the error matrix

- **Error matrix not a standardized measure**
Many different indices, none of them ideal for every single problem
- **Used samples**
Sampling design (stratified, random...) and sample size can be limiting factors
- **Type of error**
thematic error vs. error of location
- **Accuracy of the reference data accuracy**
 - Ground "truth" data is a classification itself and may contain error
 - Often remotely sensed data is used as a surrogate for ground data
- **No assessment of the spatial distribution of error**
- **Severity of an error is equalized**
 - Minor errors between relatively similar classes vs. major errors between very different classes
 - Attempts to represent continua by a set of discrete classes
- **Problem with mixed pixels containing more than one class**
Classes are not mutually exclusive within this pixel (which is a problem for site-specific accuracy assessment)

Specifics of object-based accuracy assessment

Need for a different handling of object-based accuracy assessment

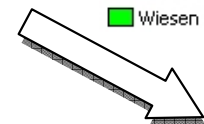
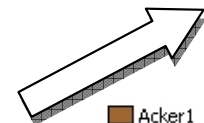
- **Thematic assessment of object-based classification**
 - Site-specific approach (making use of **random points** within objects)
 - Selecting **objects** prior to training process to be used as reference information
 - Selecting **small test areas** where every single object is assessed in terms of its label
 - **Geometry assessment of image objects**
 - Visually checking classified images against manual delineation
 - Quantitative assessment with GIS overlay techniques
 - **Difficulties in object-based accuracy assessment**
 - No 100% geometrical fit between reference objects and objects to be evaluated (due to different ways of segmentation and delineation)
 - When using a fuzzified rule base thematic classes are not mutually exclusive
- ⇒ Accuracy is a matter of geometrical and semantic agreement

Specifics of object-based accuracy assessment (2)

Visually checking classified images against manual delineation

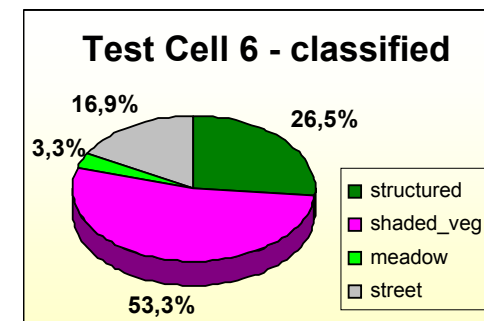


Subset of areal
photo with a
randomly selected
15x15m cell

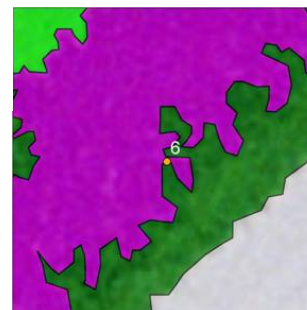


Acker1
 Acker2
 Gewässer
 Haus
 Schatten_NonVeg
 Schatten_Veg
 Strasse
 Strukturiert
 Wiesen

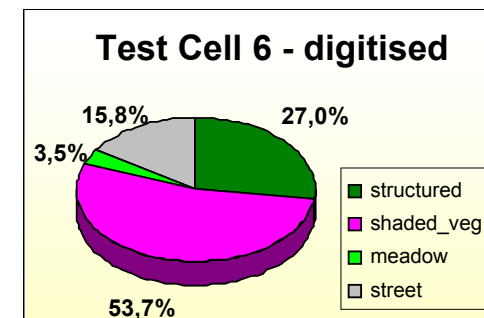
Classification result of Test Cell #6



Resulting thematic content



Visual delineation result of Test Cell #6



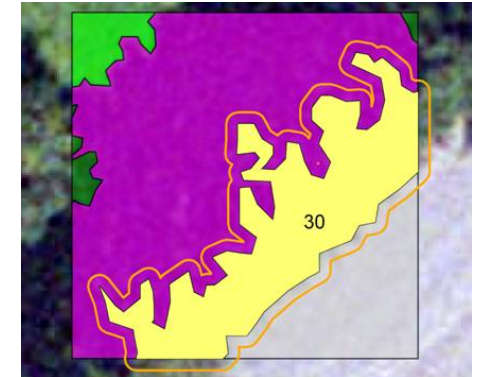
Design: D. Hölbling

Specifics of object-based accuracy assessment (3)

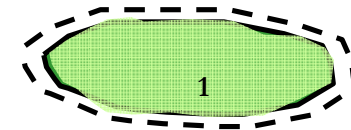
- **Quantitative assessment of object geometry accuracy**
 - Defining a tolerance (spatial overlay strictness) to allow minor differences in the object outlines
 - Testing of objects
 - Classification object has the same extent as the reference polygon ("stable object")
 - Reference object doesn't match and is split into several objects of the classification
 - Complex geometry with objects not having the same boundaries
 - Characterisation of object relationship ("object fate", similar to object-based change analysis)
 - Good objects
 - Expanding objects
 - Invading objects

⇒ Approach needs further development

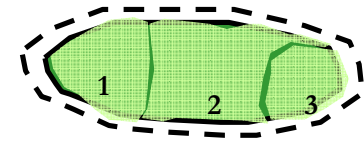
Tolerance buffer:
Selected digitised polygon with 0.5m buffer



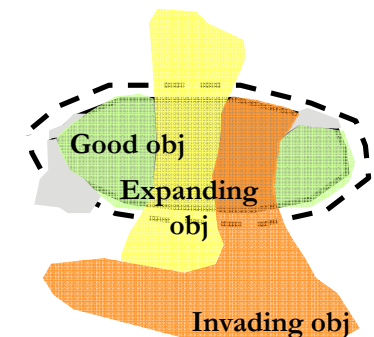
Case 1:
Object stays the same



Case 2:
Object splits into n sub-objects



Case 3:
Complex geometry with expanding and intruding objects



Outlook

- A next version of this tutorial is under preparation. We will include the following topics:
 - **Scale-specific** vs. **scale-adaptive** segmentation
 - **Class modelling** ⇒ segmentation and classification as a cyclic process
 - Basics of **CNL** (cognition network language)
 - More on **object fate** ⇒ object-based change detection and object-based accuracy assessment
 - Application **showcase** (forestry, urban studies, habitats and wetlands, etc.)

References

- **A – J**
 - Note that – with a few exceptions – only literature is listed from which text was taken
 - Figures in brackets ([]) indicate the respective chapters

References

- **L – Z**
 - Note that – with a few exceptions – only literature is listed from which text was taken
 - Figures in brackets ([]) indicate the respective chapters