10TH ADVANCED TRAINING COURSE ON LAND REMOTE SENSING

Forest cover monitoring and change detection with optical and radar remote sensing

Prof. Dr. Christiane Schmullius, Dept. for Earth Observation, University Jena, Germany

Jena – City of Light: the heritage of Zeiss, Schott and Abbe

Acknowledgement

Friedrich-Schiller University Jena

Department for Earth Observation

SAREDU remote sensing education initiative

eo college

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robert.eckardt@uni-jena.de
nesrin.salepci@uni-jena.de
carsten.pathe@uni-jena.de & Education Team

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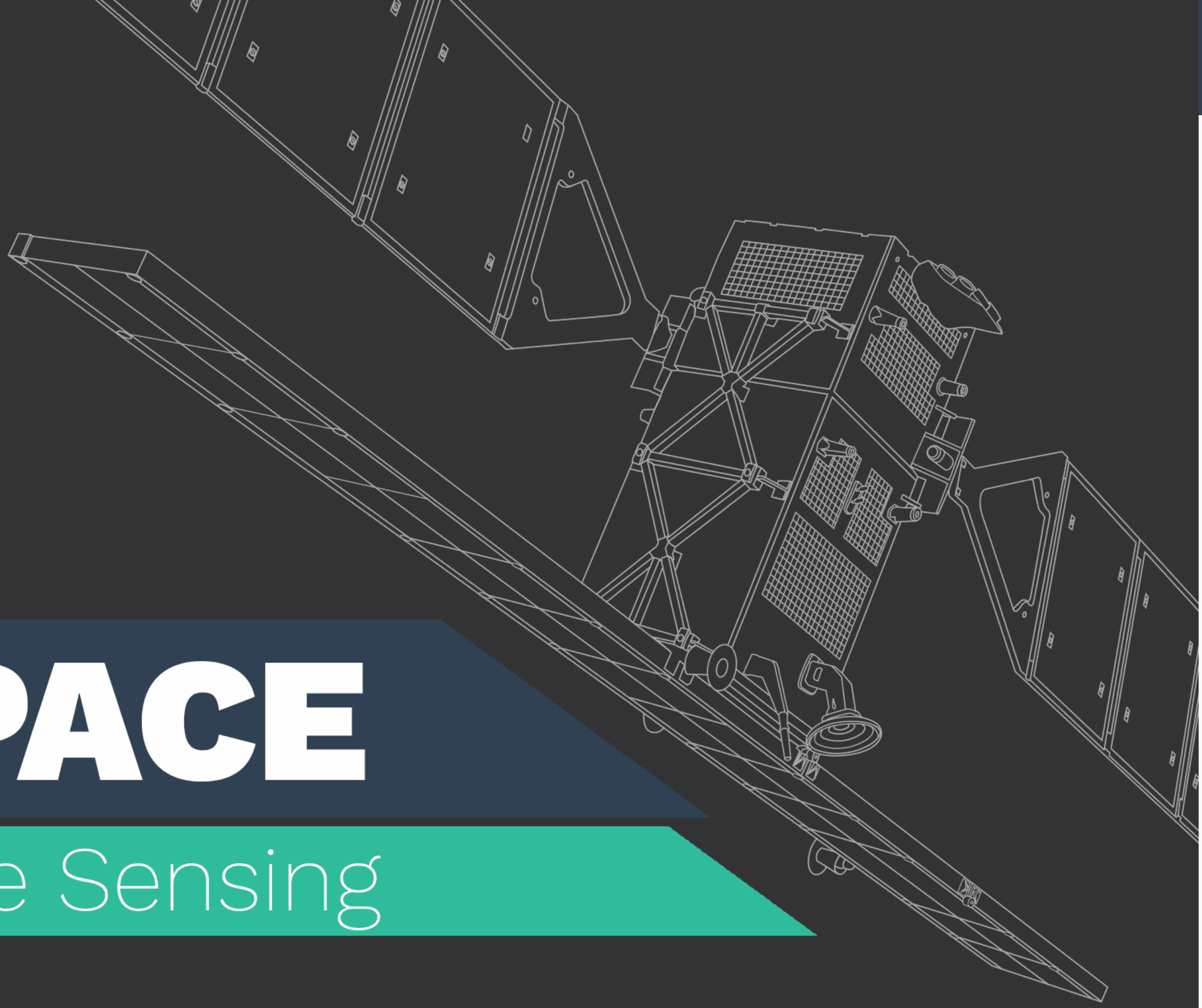
ECHOES IN SPACE

Introduction to Radar Remote Sensing



FREE OF CHARGE

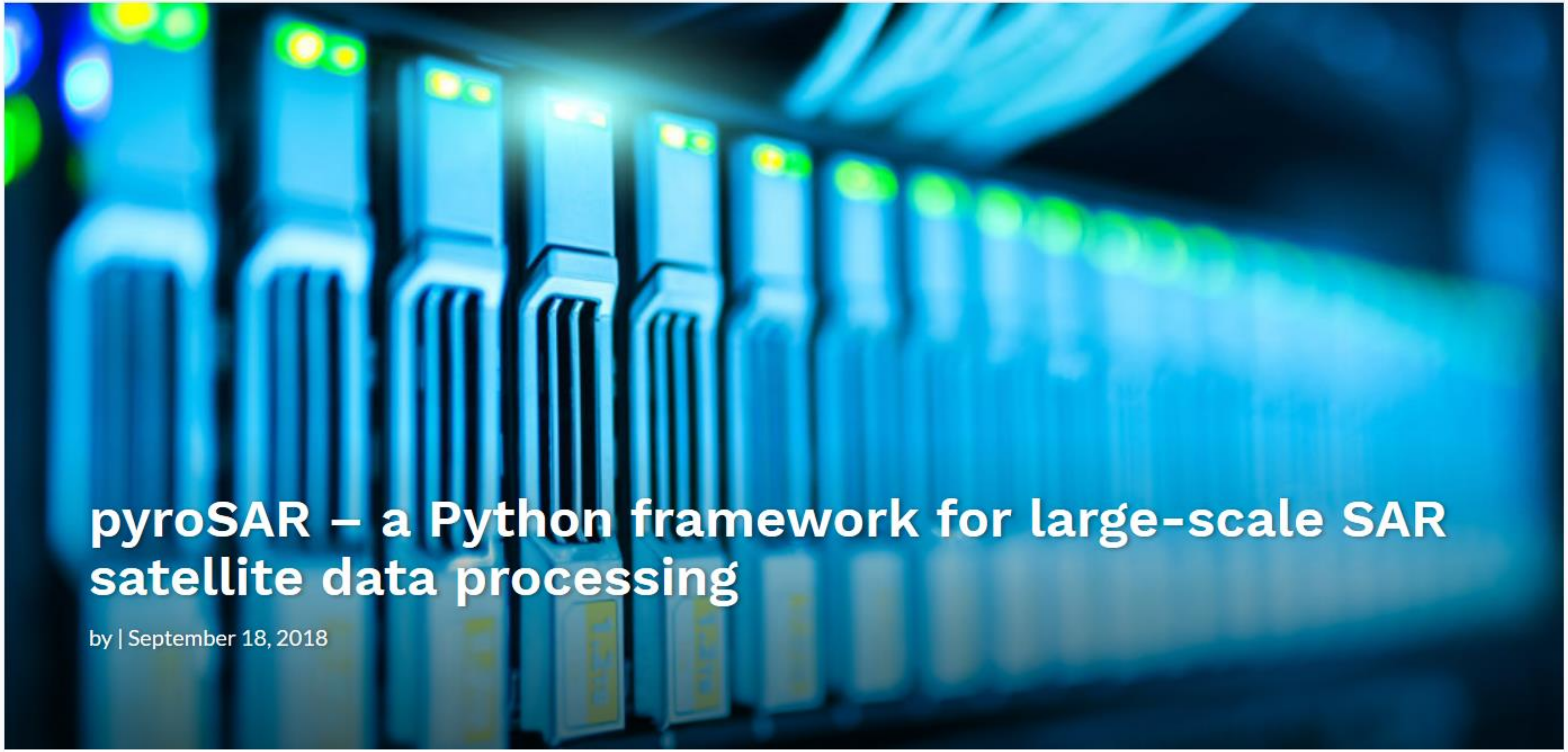
OPEN TO ANYBODY

SELF-PACED LEARNING

START: 09-OCT-2017

5 LESSONS

CERTIFICATE FOR COMPLETION



pyroSAR – a Python framework for large-scale SAR satellite data processing

by | September 18, 2018

John

EO College Educational Resources

BASICS		MATHE-MATICS	DATA PROCESSING	SAR IMAGING		
METHODS	IMAGE PROCESSING	INSAR	POLSAR	PASSIVE MICROWAVE	RADAR-GRAMMETRY	TOMOGRAPHY
APPLICATIONS	ANTHROPO-SPHERE	BIOSPHERE	CRYOSPHERE	HYDRO-SPHERE	LITHO-SPHERE	OCEANO-GRAPHY

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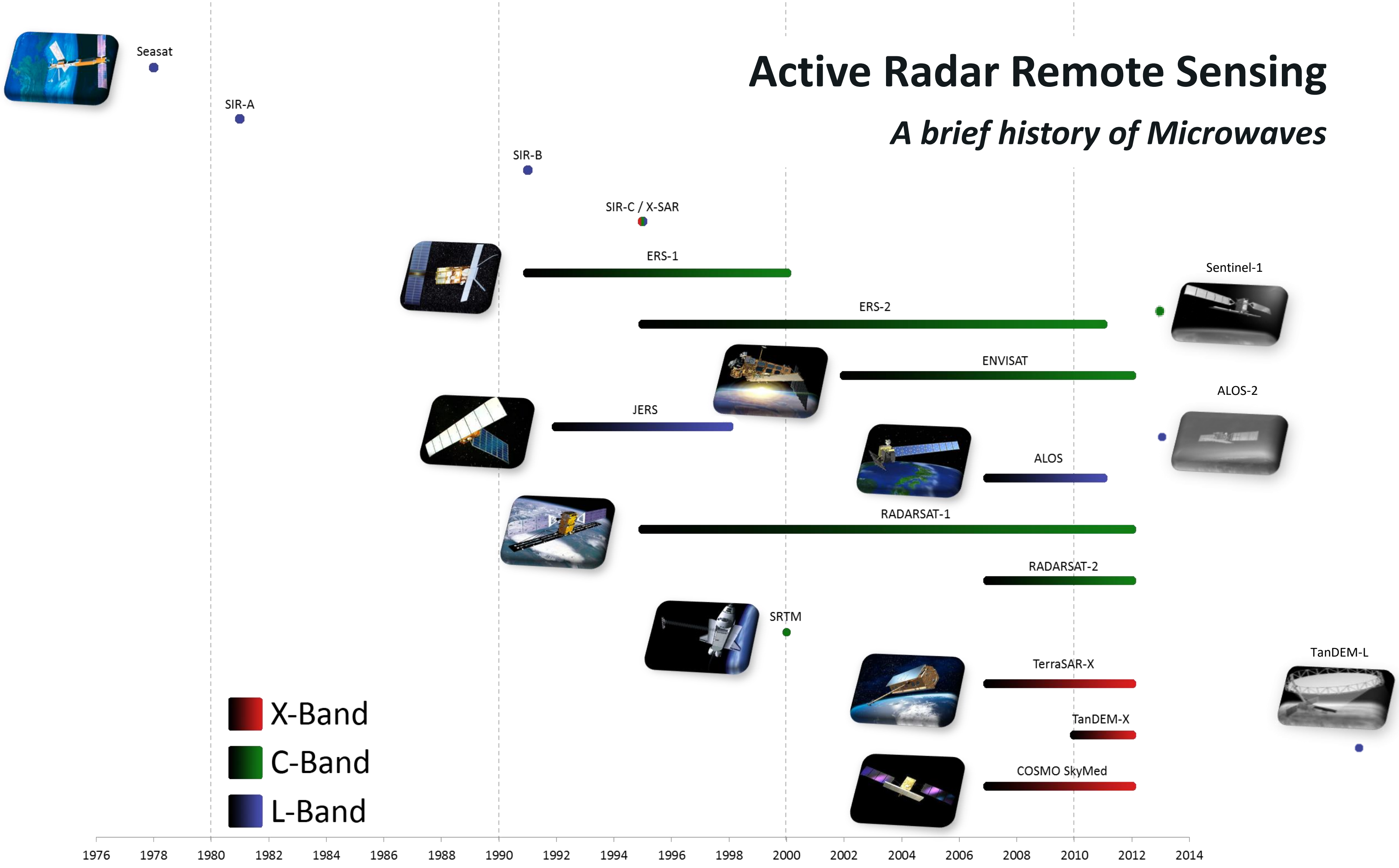
Educational Objectives of this Lecture

- To understand the fundamental differences of optical and radar data
- To understand advantages of SAR techniques
- To understand the limitations of SAR data
- To learn how SAR data can be used for biomass estimation
- To be able to investigate optimal sensor and acquisition parameters for forest cover monitoring
- To learn about change detection techniques
- Introduction to Accuracy Assessment

Active Radar Remote Sensing

A brief history of Microwaves



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What is forest structure? What is biomass?

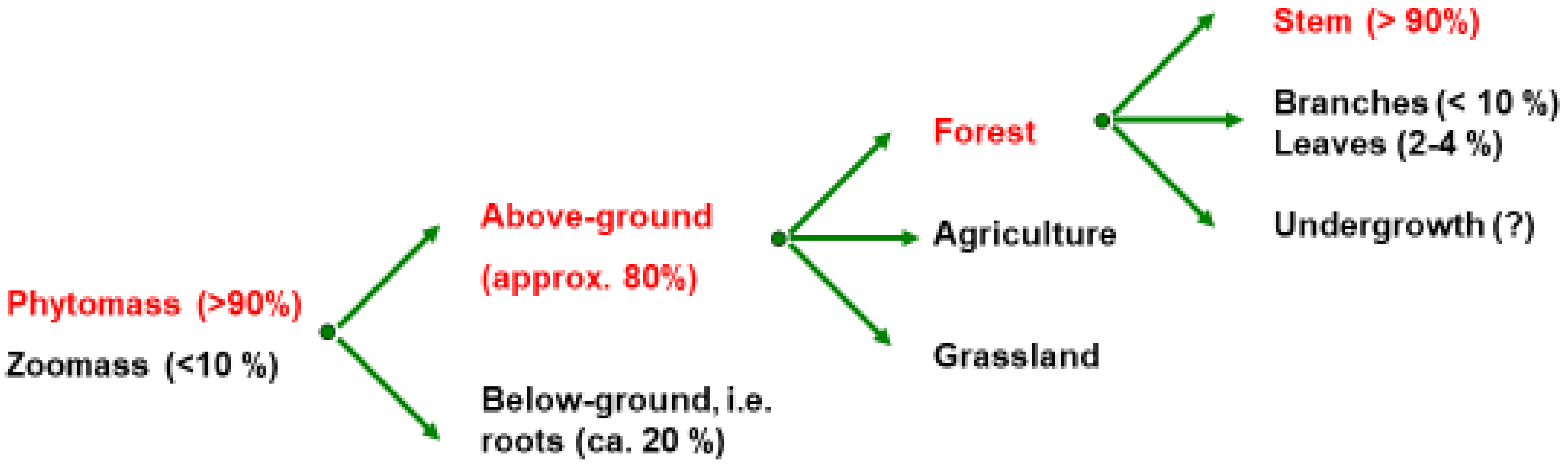


Fig.: Global Biomass (after METTE et al., 2002).

Here we will mainly address living terrestrial above-ground vegetation biomass, in particular woody biomass.

Fundamental differences of optical and radar data - 1

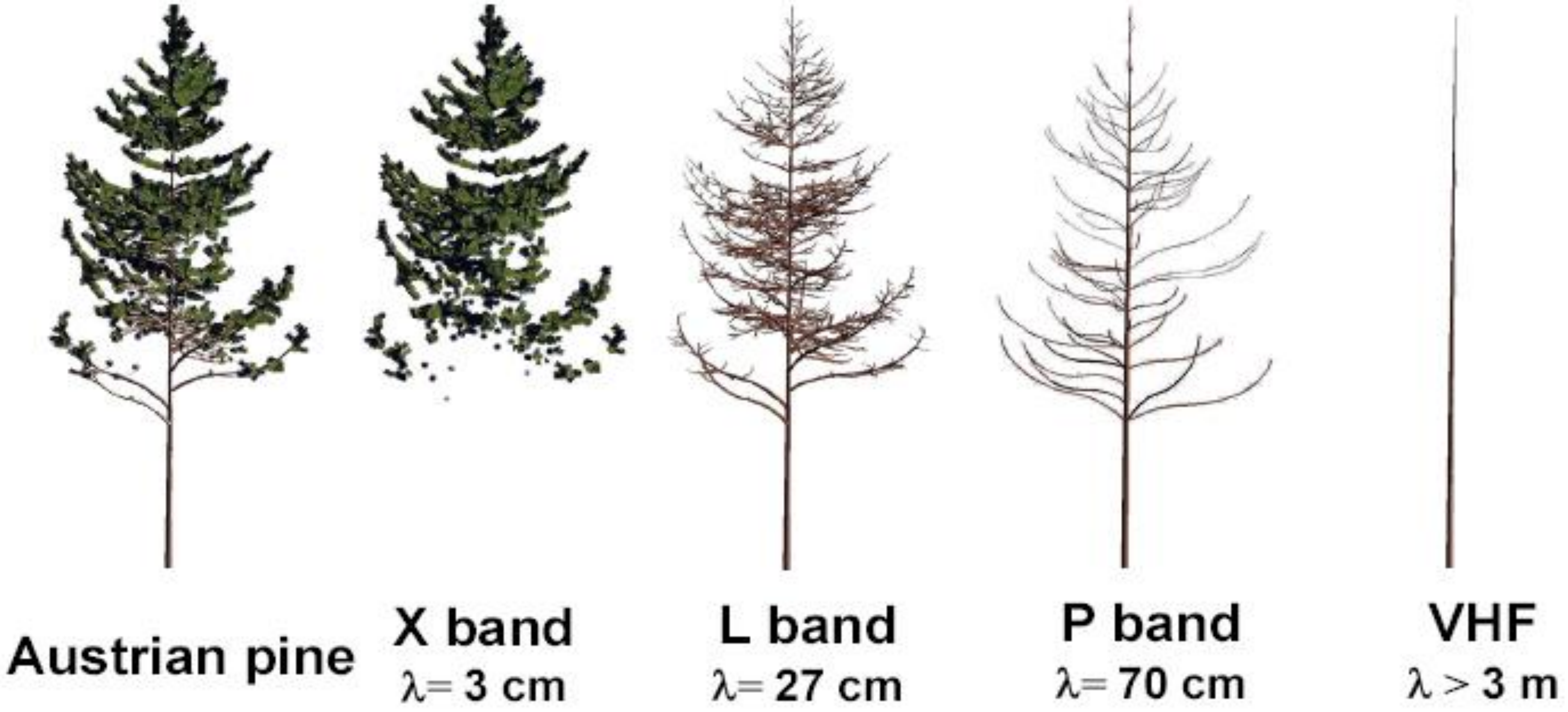
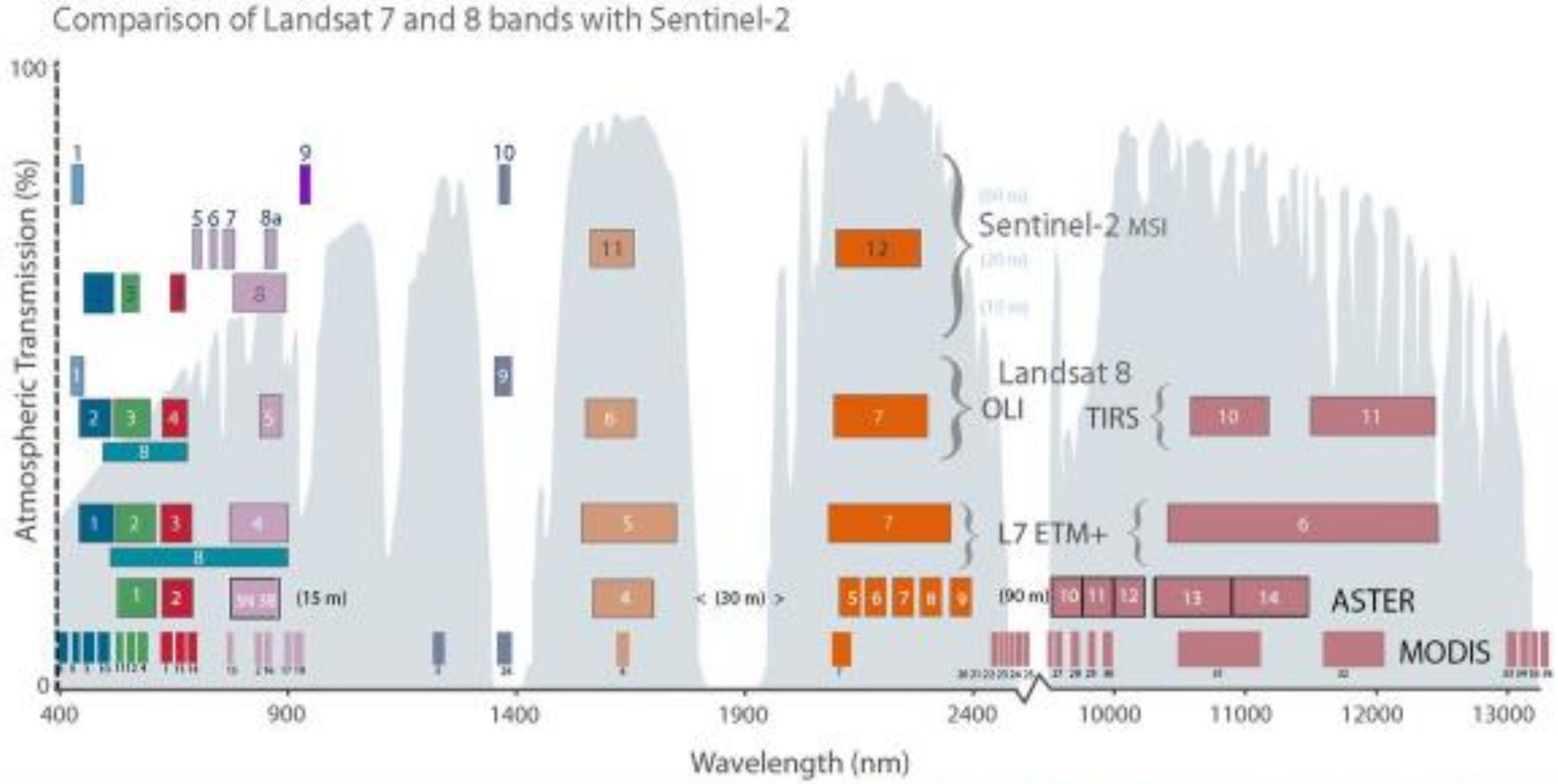


Fig. and Tab.: Main scatterers at different frequencies (Image credentials: THUY LE TOAN, Tab from LE TOAN ET AL., 2001).

Fundamental differences of optical and radar data - 2



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Quelle: https://gis.stackexchange.com/questions/276871/convertion-of-spectral-indices-formulas-from-landsat-to-sentinel
https://i.stack.imgur.com/F695R.jpg [Zugriff 28. Juni 2021]

10 / 15

Spectral signatures from bark beetle infested spruce

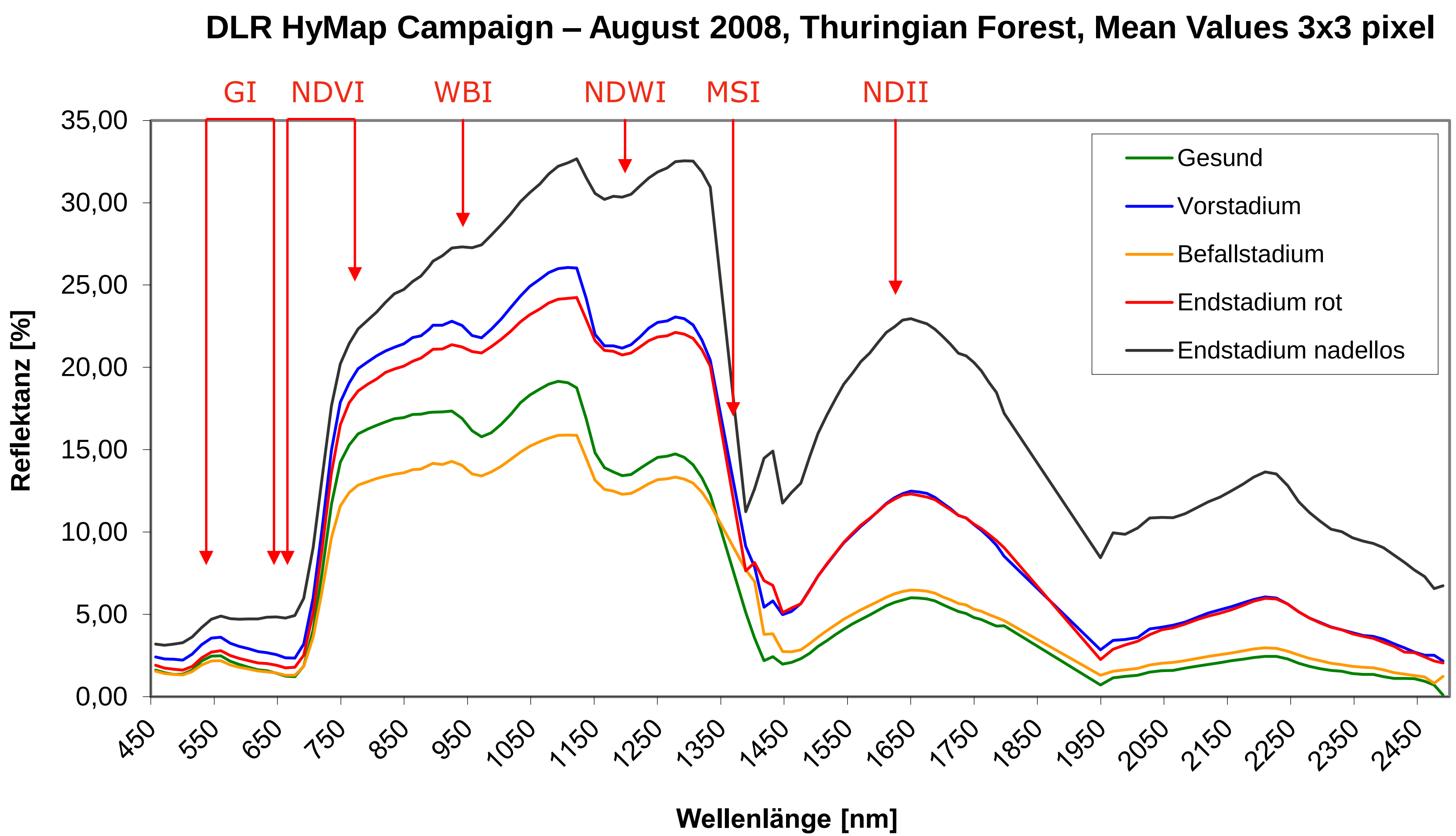
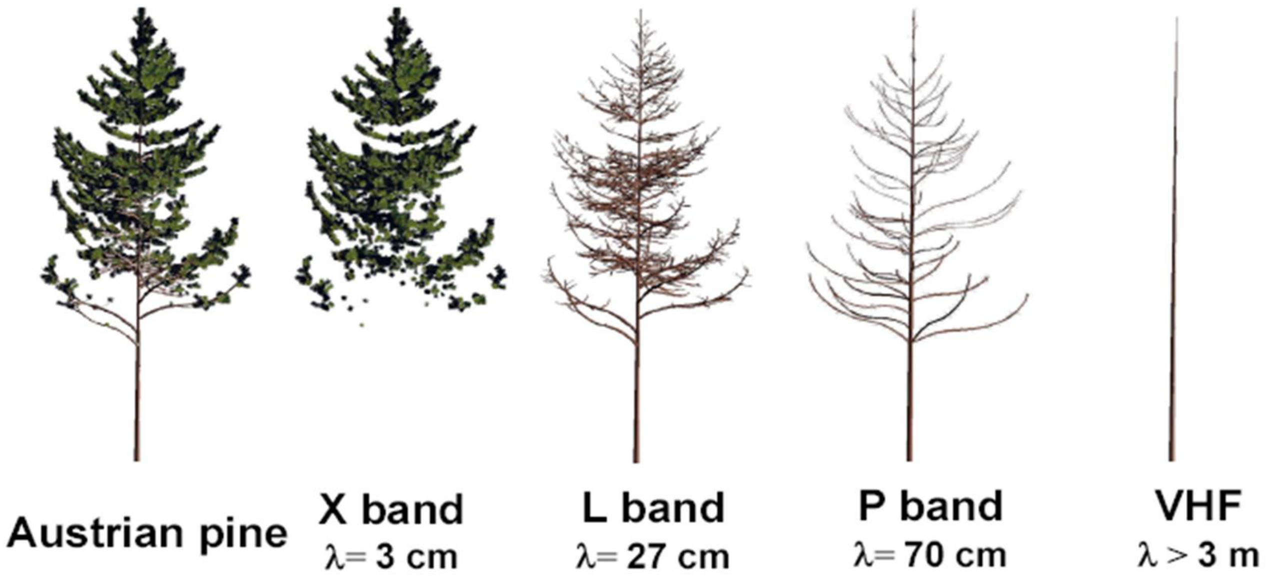


Abb.: Abgeleitete Spektren für die 5 Befallskategorien für 3x3 Pixel. [Courtesy: C. Schmullius, Univ. Jena, unpublished]

Fundamental differences of optical and radar data



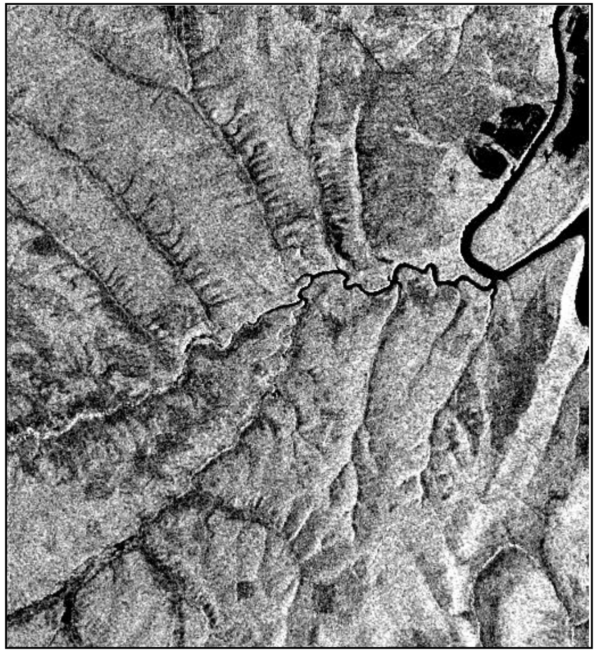
Frequency band	X	C	L	P	VHF
Main scatterers	Leaves, Twigs	Leaves Small branches	Branches	Branches & Trunk	Trunk

Fig. and Tab.: Main scatterers at different frequencies (Image credentials: THUY LE TOAN, Tab from LE TOAN ET AL., 2001).

The main scatterers in a canopy are those elements having the dimension of the order of the wavelength used.

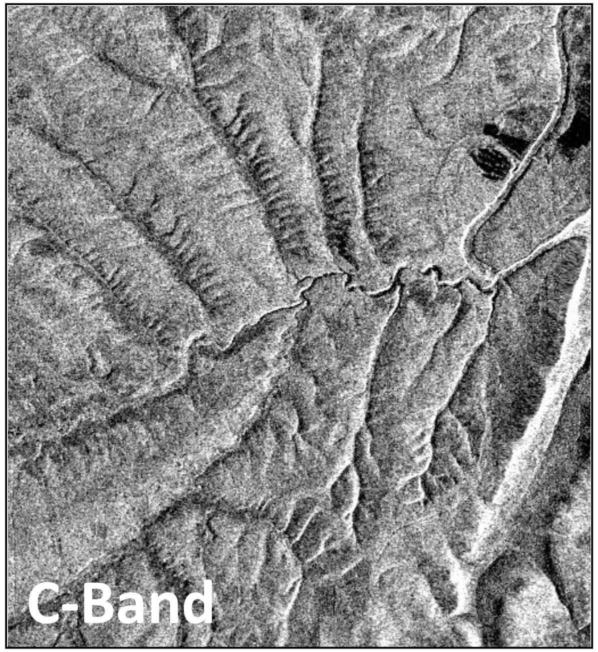
Different wavelengths for forest cover mapping in Siberia

- *Small dynamic range*
- *Variable response to water*
- *Variable response to open areas*
- *Can be used as indicator of environmental effects effecting the coherence*



- *Medium dynamic range*
- *Stable response to water*
- *Possible to identify agricultural fields*
- *Higher frame to frame variations*

Different wavelengths for forest cover mapping in Siberia



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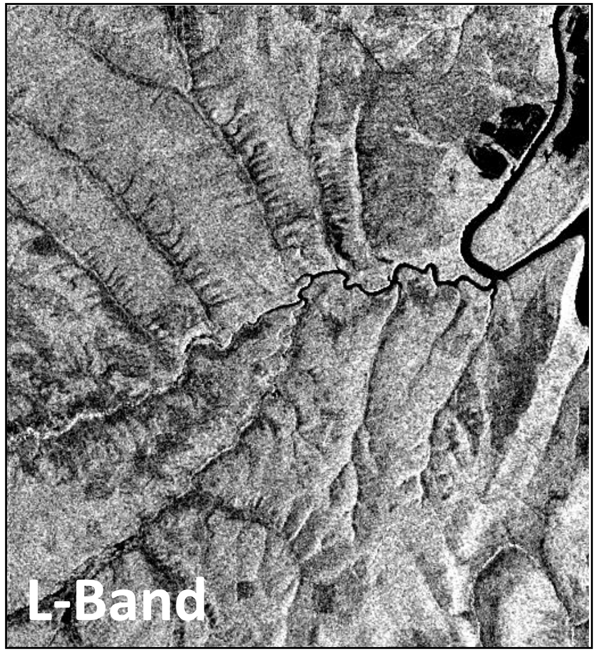
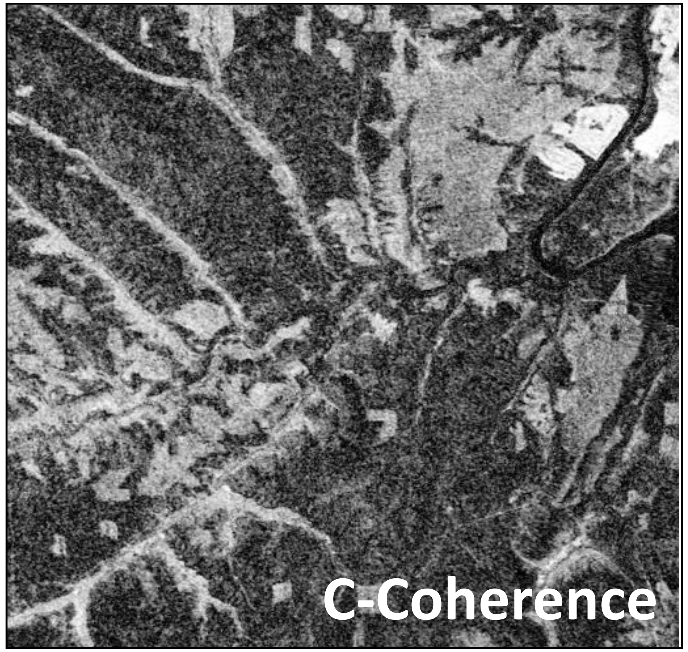


- *Medium dynamic range*
- *Stable response to water*
- *Possible to identify agricultural fields*
- *Higher frame to frame variations*



- *Higher contrast between forest/non forest*
- *Higher sensitivity to forest volume*
- *Confusion between water and dense forest*
- *Frame to frame variations*

Courtesy: SIBERIA Project, Univ. Jena

Different wavelengths for forest cover mapping in tropics

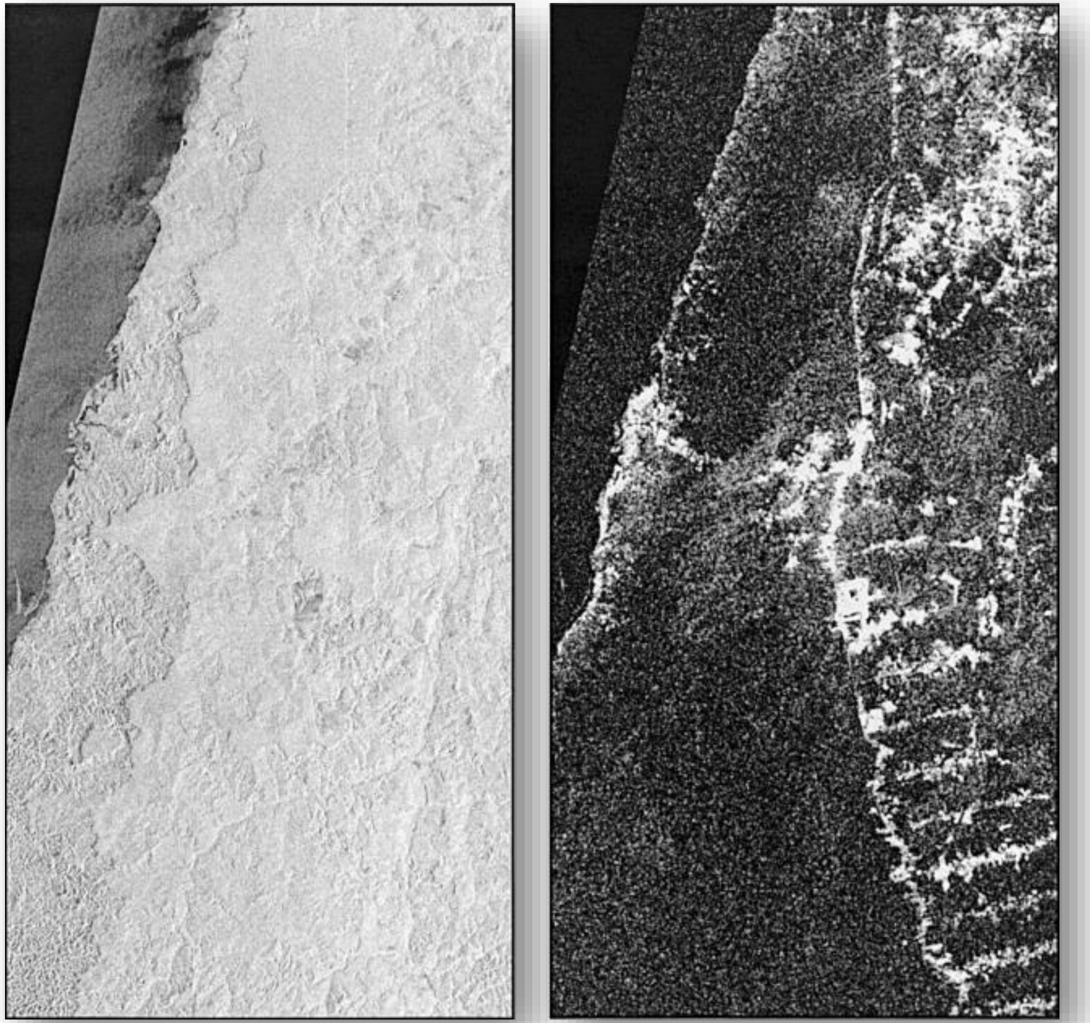


Fig.: ERS-Tandem intensity image and 1-day repeat-pass phase coherence image (size 50 km by 100 km) (LUCKMAN et al., 2000).

Different wavelengths for forest cover mapping in tropics

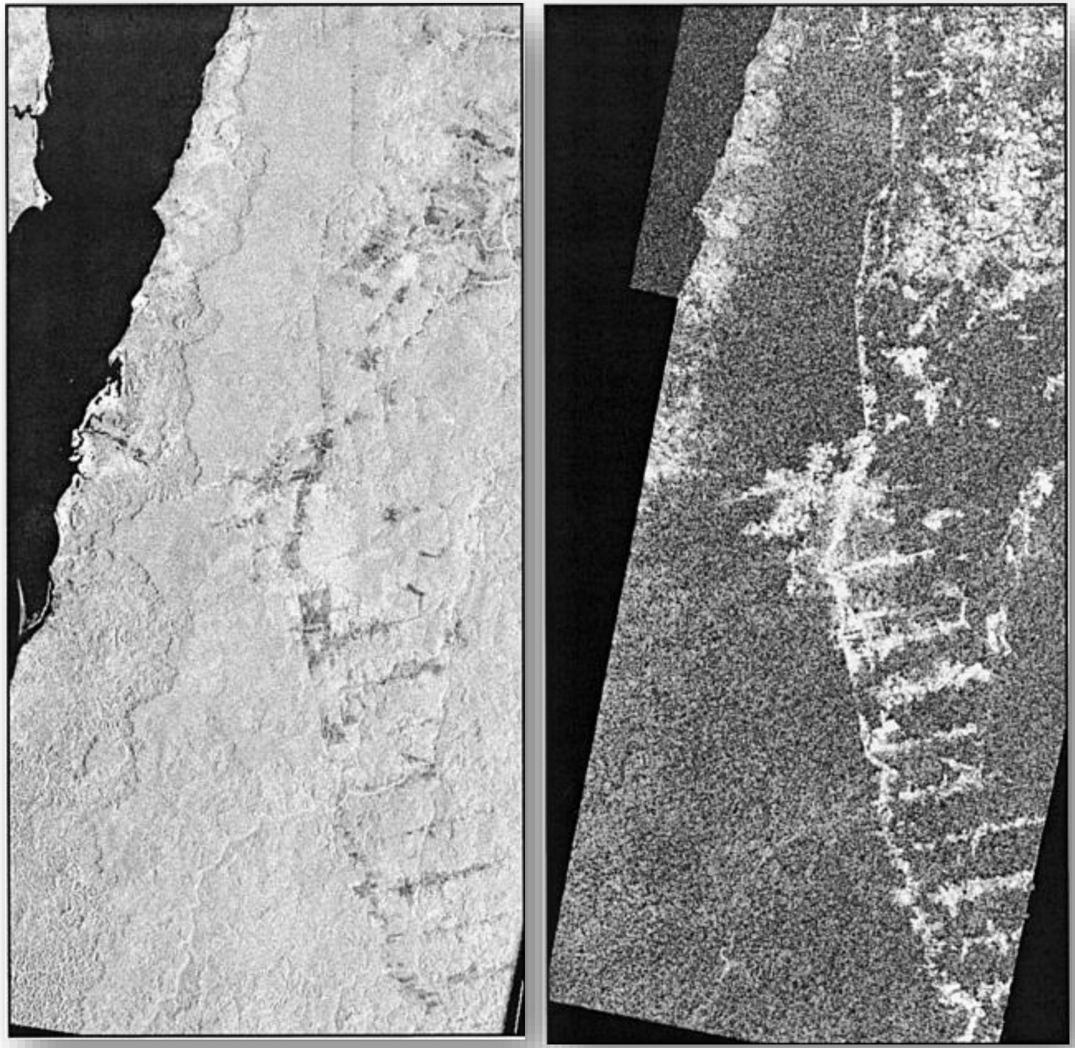


Fig.: JERS intensity image and 44-day repeat-pass phase coherence image (size 50 km by 100 km) (LUCKMAN et al., 2000).

Different wavelengths for forest cover mapping in tropics

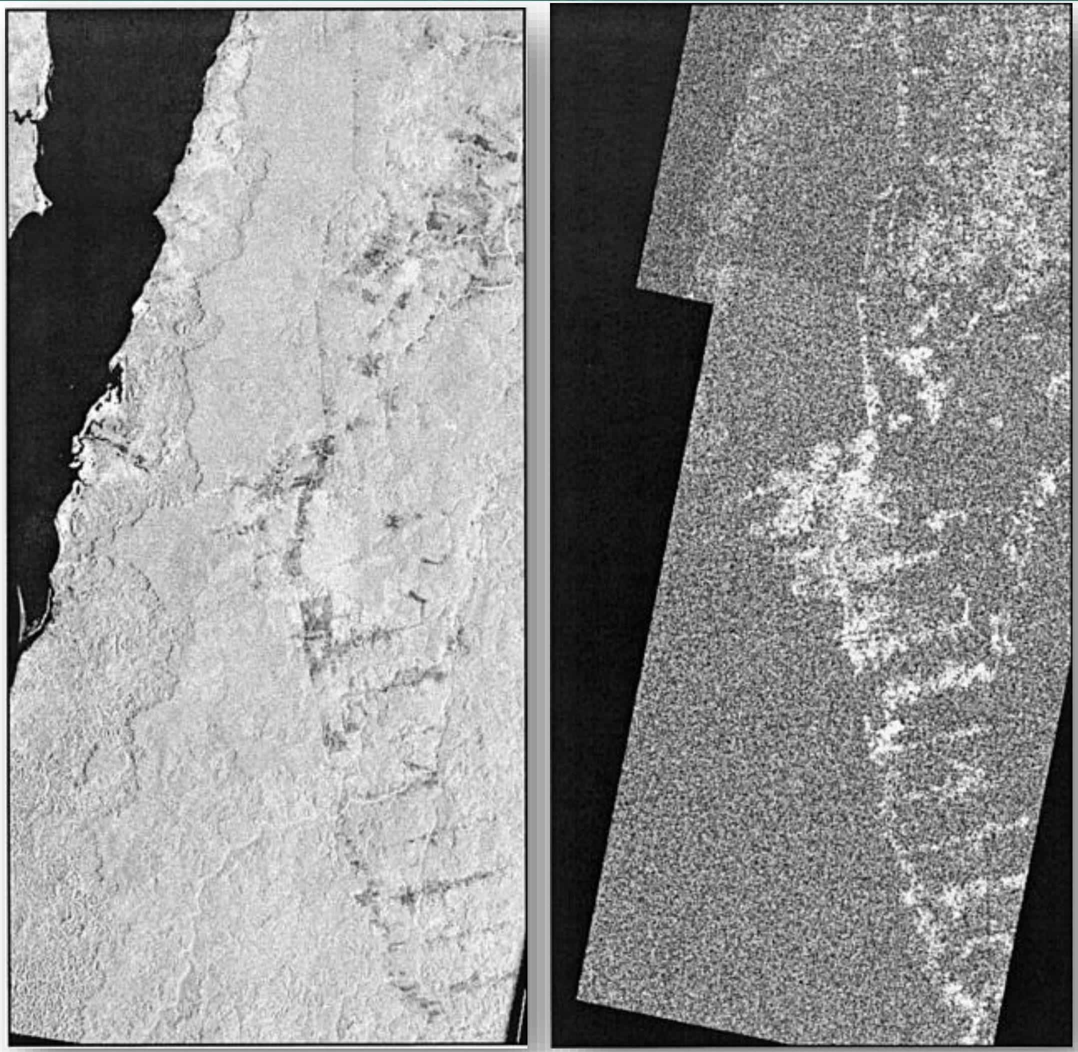


Fig.: JERS intensity image and 132-day repeat-pass phase coherence image (size 50 km by 100 km) (LUCKMAN et al., 2000).

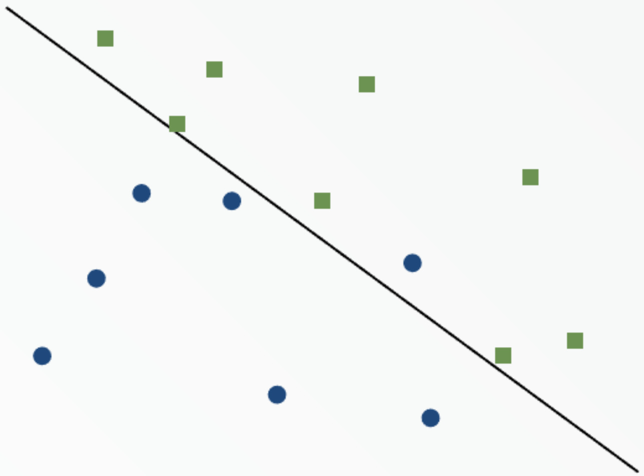
EXCERPT FROM:

HYPER EDU

Buddenbaum et al. 2020

Tree Species Classification

- Mapping tree species is one of the most common tasks in forest remote sensing.
- Since all green vegetation has similar spectra, tree species and/or age class classification is challenging
- Often additional information is used: time series, structural information from secondary data sources such as Lidar or Radar, or texture information (Buddenbaum et al. 2005, Sommer et al. 2015).
- Multi-temporal data is essential for differentiating between tree species. However, owing to frequent cloud cover in many regions of the world, it is an important challenge to collect observations from the required phenological stages (Stoffels et al. 2015).

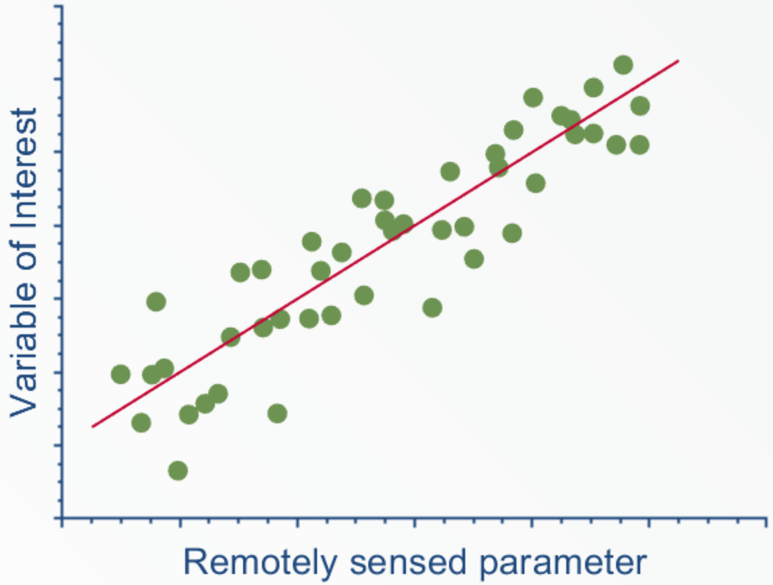


Two classes, not perfectly separated by a straight line

Buddenbaum et al. 2020

05 Regression: Mapping continuous forest traits

- While classification assigns each pixel to a category, regression methods flag each pixel with a value on a continuous scale.
- Most common approaches are (Verrelst et al., 2015, 2019):
  - Parametric regression (e.g. using a spectral index or PLSR),
  - Non-parametric regression (e.g. machine learning)
  - Physically-based model inversion (e.g. using InFoRM to derive chlorophyll contents)
  - Hybrid regression methods (e.g. using a reflectance model to train a parametric regression)



Further Reading

(1) Hill et al. 2019, https://doi.org/10.1007/s10712-019-09514-2

(2) Malenovský et al. 2019, https://doi.org/10.1007/s10712-019-09534-y

(3) Verrelst et al. 2019, https://doi.org/10.1007/s10712-018-9478-y

(4) Spruyt 2014, https://www.visiondummy.com/2014/04/curse-dimensionality-affect-classification/

(5) Asner et al. 2017, https://doi.org/10.1126/science.aaj1987

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H. Buddenbaum, J. Hill (2020). **Imaging Spectroscopy of Forest Ecosystems**, HYPERedu, EnMAP education initiative, August 2020, Trier University.

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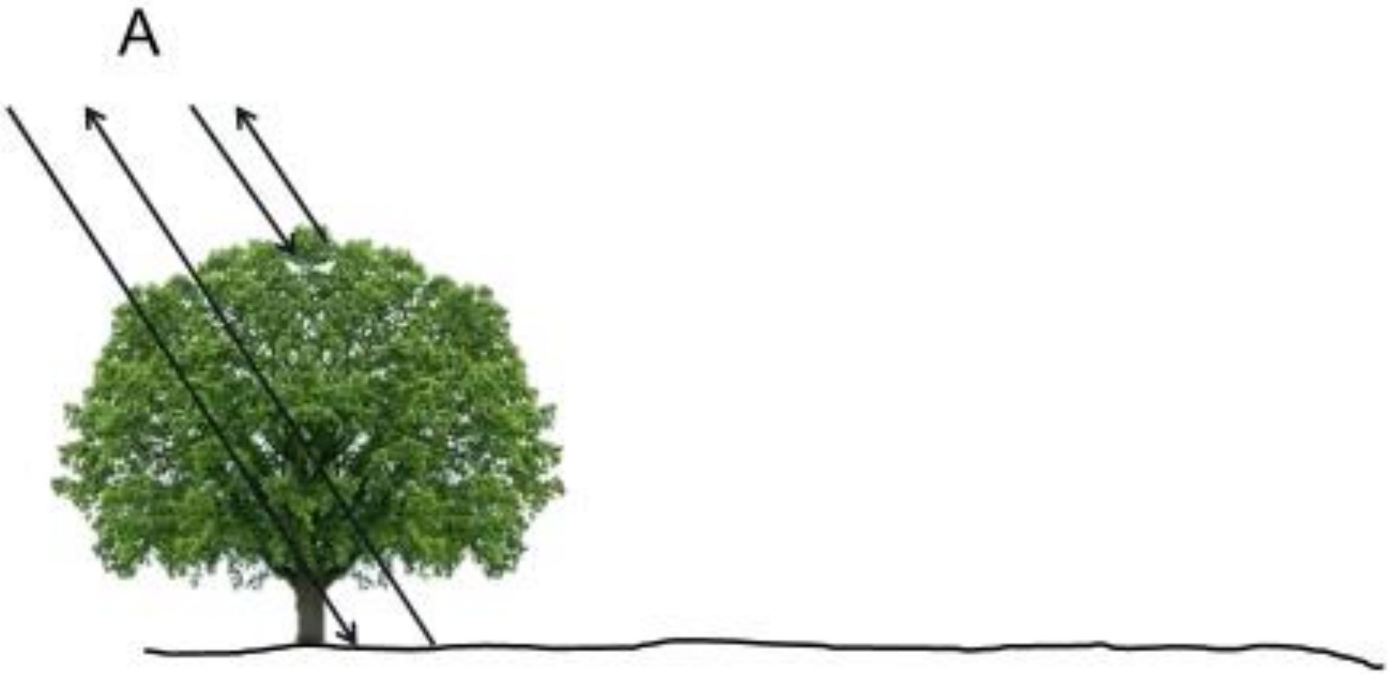
Supported by:

Federal Ministry for Economic Affairs and Energy

on the basis of a decision by the German Bundestag

Back to Backscatter Mechanisms - Specular



A - When a wave reflects off only one target and returns to the instrument this is known as direct scattering (or "single bounce"). This occurs when the wave hits a target that is at an orientation such that the wave is returned directly to the radar.

Fig.: Global Biomass (after METTE et al., 2002).

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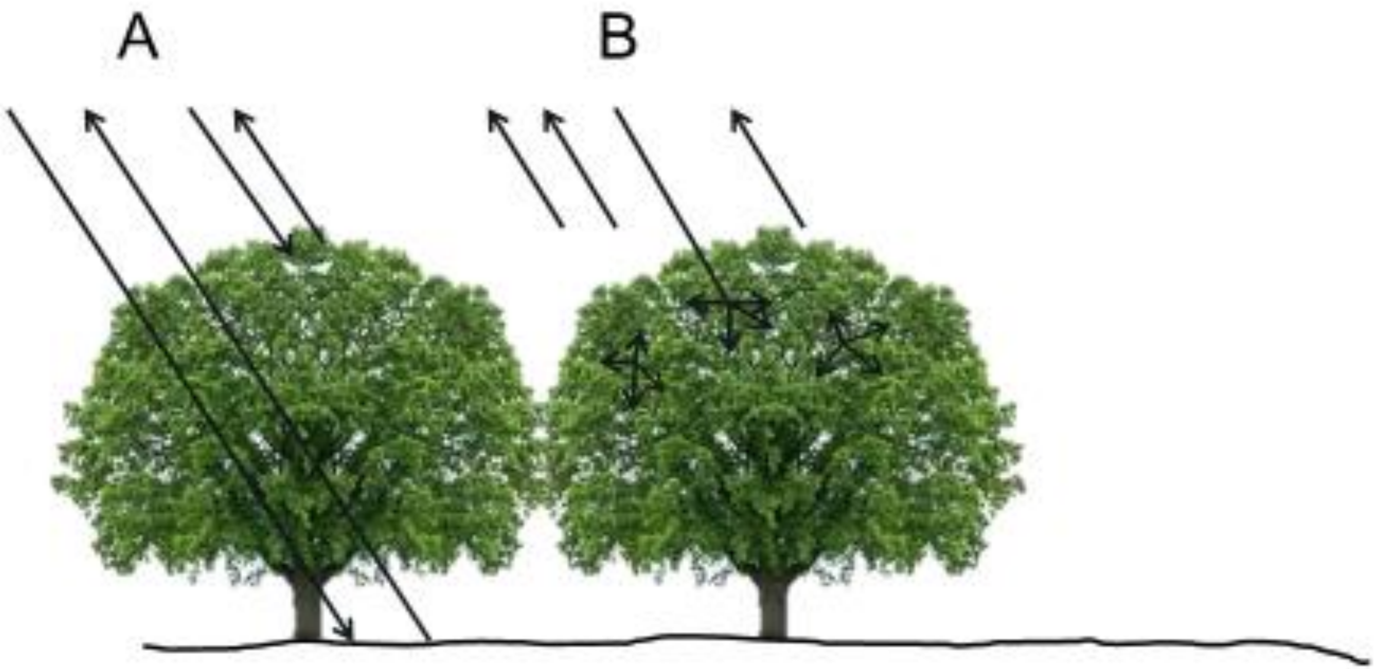
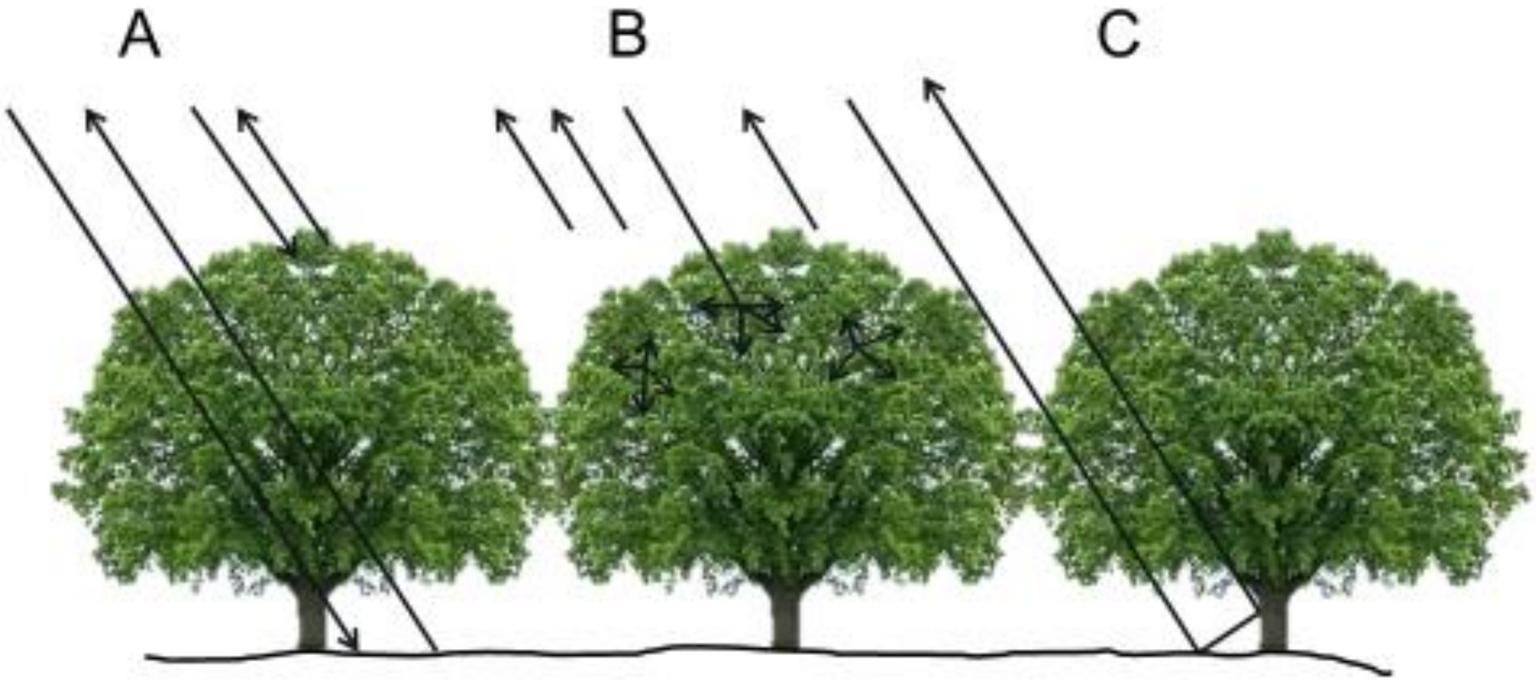
Backscatter mechanism - Volumetric



B - Cases of more than two bounces are known as multiple scattering and occur frequently in environments such as dense forest canopies between trunks, branches, and twigs.

Fig.: Global Biomass (after METTE et al., 2002).

Backscatter mechanism – Double Bounce



C - If the wave reflects off two surfaces before returning to the instrument, such as often arises in urban areas between ground and wall, or in forests between ground and tree trunks or between trunks and twigs, this is termed "double bounce".

Fig.: Global Biomass (after METTE et al., 2002).

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Radar Retrieval Methods (biomass case)

AGB

Backscatter

Relating the backscatter values to field biomass measurements using regression analysis

InSAR

Examining the coherence of two SAR images collected from similar viewing positions with a short time-lag

regression

Conversion from forest parameter

e.g. forest height estimates from single frequency polarimetric-interferometric SAR data

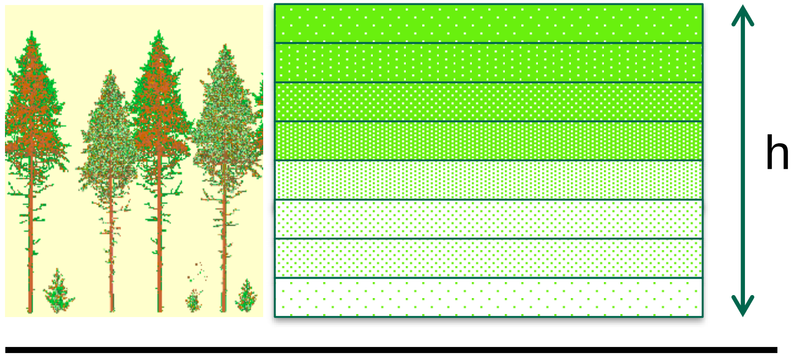
Conversion through allometric height-biomass relations

indirectly

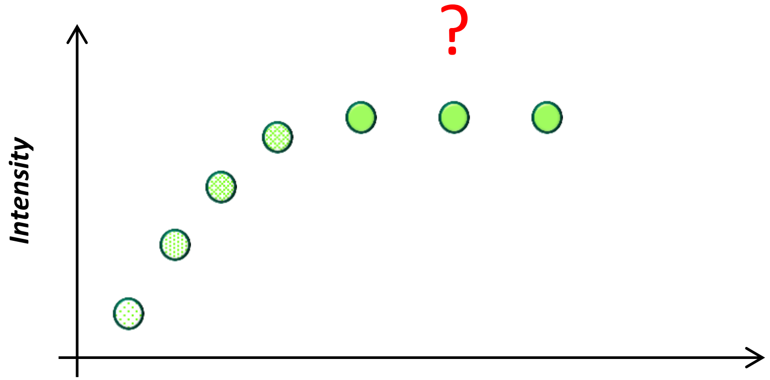
[after GHASEMI, 2011]

The Water Cloud Model

A patch of vegetation



The Ground



Amount of "stuff" (ABG)

FIG.: WOODHOUSE

For applications it can be written in terms of growing stock volume

$$\sigma^o_{for} = \sigma^o_{veg}\left(1 - e^{-\beta V}\right) + \sigma^o_{gr} e^{-\beta V}$$

Unknown

σ_{gr}	ground backscatter
σ_{veg}	canopy backscatter
β	forest transmissivity coefficient

[after WOODHOUSE; THIEL, 2012]

The Saturation Problem

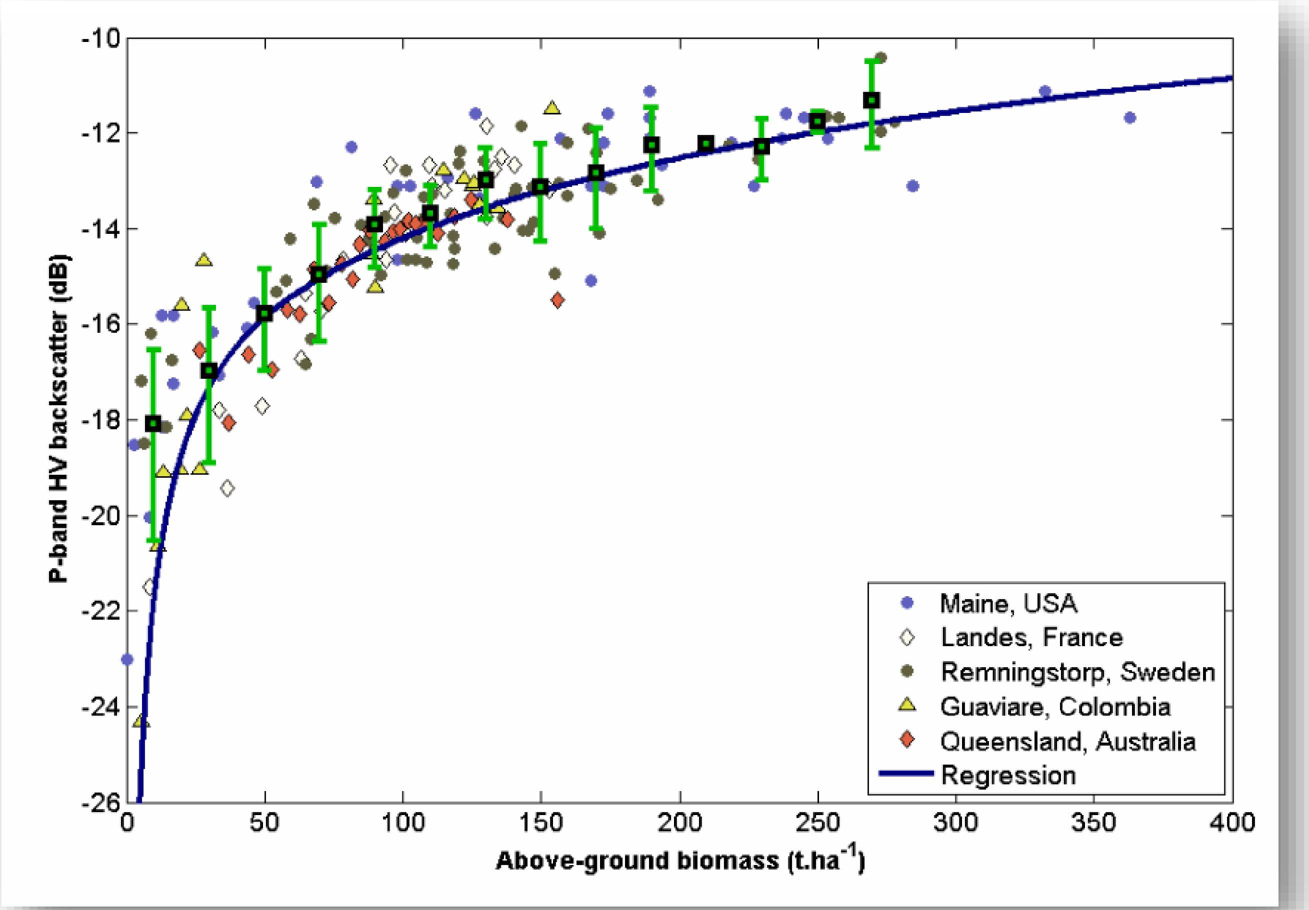
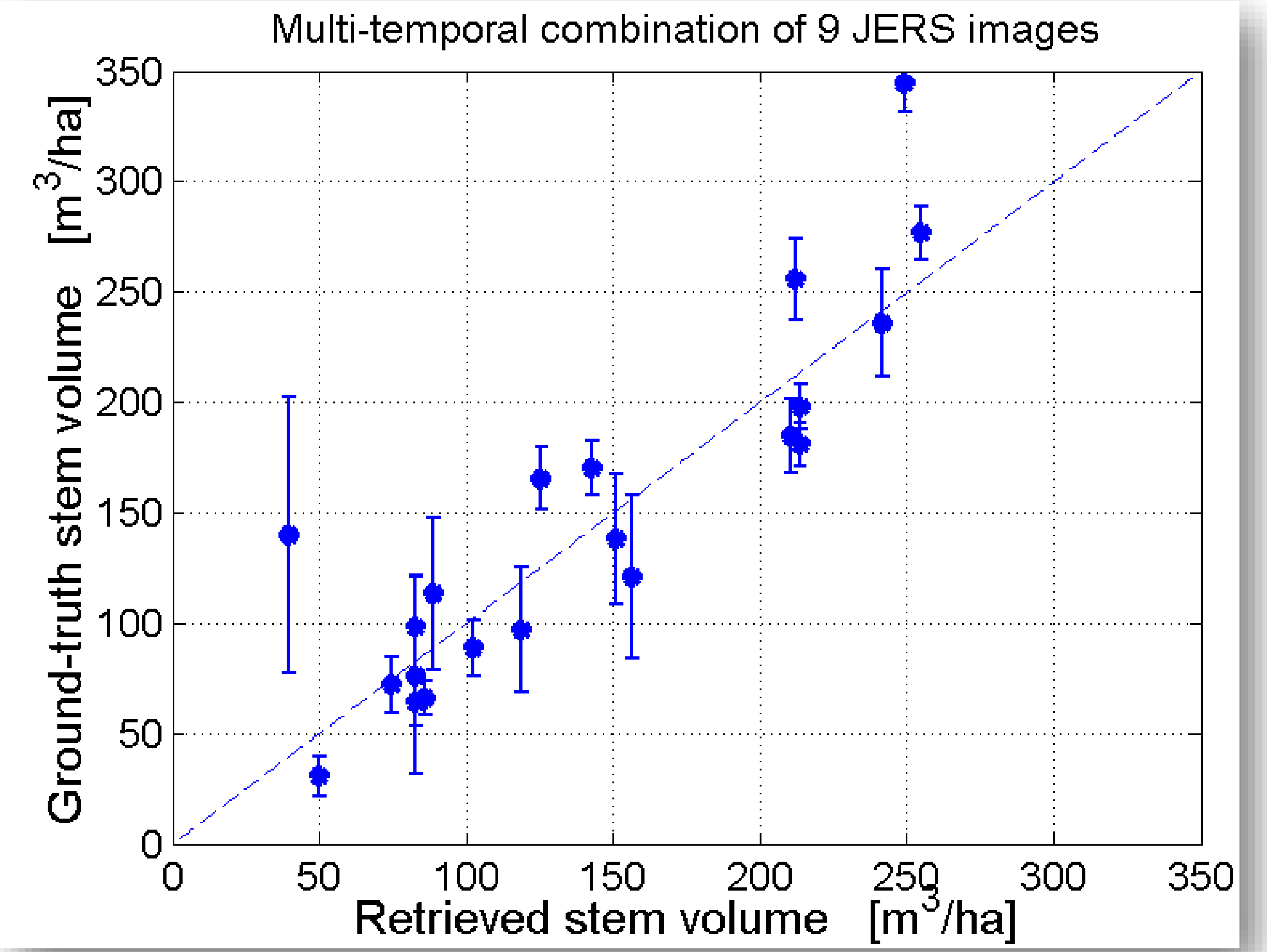


Fig.: Regression analysis of radar backscatter with forest AGB. P-band HV backscattering coefficient plotted against AGB from experiments conducted at five different forests. The green points with error bars represent the mean value and standard deviation of all points falling within a biomass bin of +/- 10 tons/ha. The line is a regression curve applied to the full dataset. The corresponding RMSE in biomass is 51.6 tons/ha and the coefficient of determination r^2 = 0.67 (Credis: LE TOAN, in ESA, 2008).

Strength of multi-temporal data - Backscatter



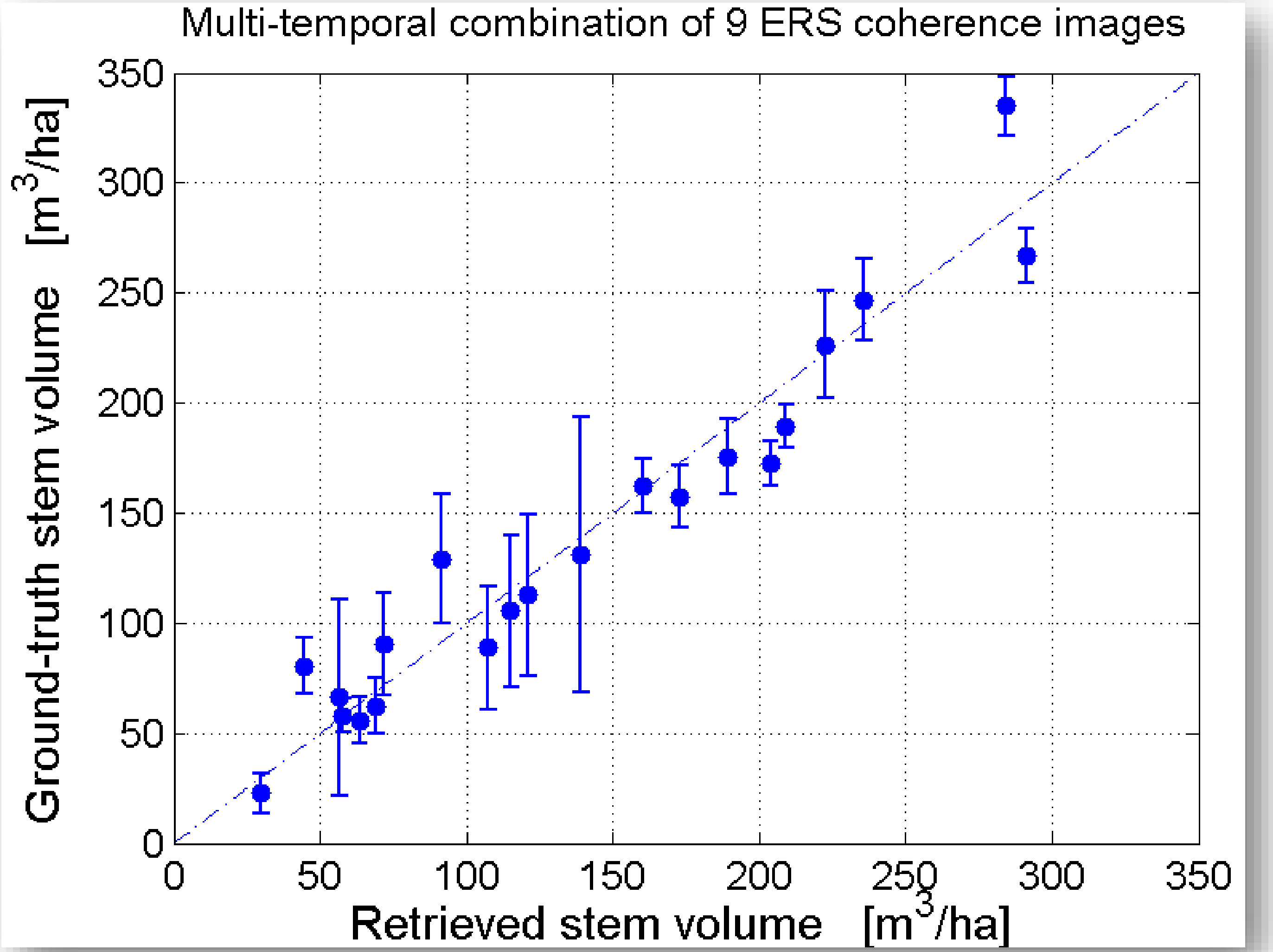
<u>JERS Backscatter</u>

RMSE: 33 m³/ha

Relative RMSE: 22 %

Fig.: Multitemporal data (Santoro et al., 2006).

Strength of multi-temporal data - Coherence



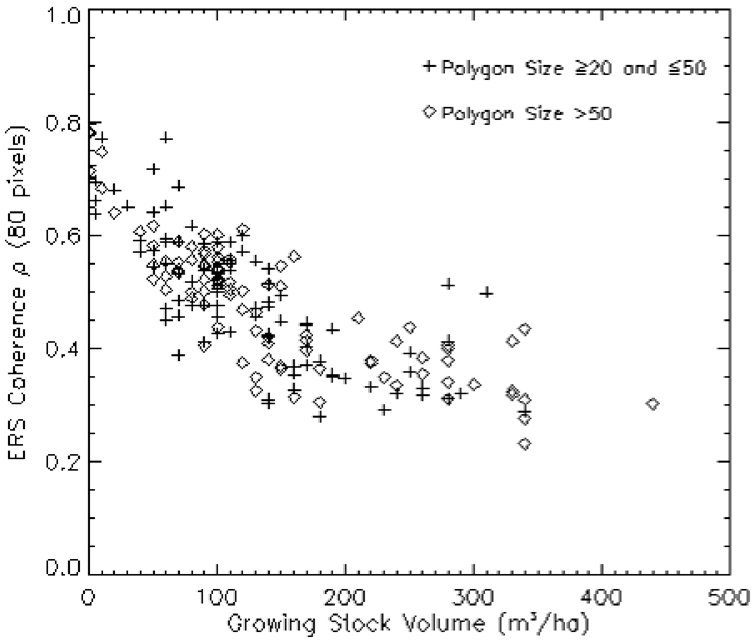
ERS Tandem Coherence

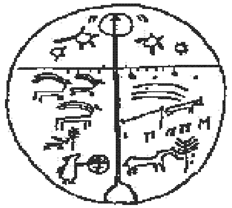
RMSE: 10 m^3/ha

Relative RMSE: 7 %

Fig.: Multitemporal data (Santoro et al., 2002).

Wall-to-wall forest cover mapping – the SIBERIA project





Model definition for coherence

$$\gamma(v) = \gamma_\infty + (\gamma_0 - \gamma_\infty) \cdot e^{-\frac{v}{V_\gamma}}$$

$$\gamma_\infty \approx \gamma_{75}$$

$$\gamma_0 = a_\gamma + b_\gamma \cdot \gamma_{75}$$

$$\gamma(v) = \gamma_{75} + \left(a_\gamma + (b_\gamma - 1)\gamma_{75}\right) \cdot e^{-\frac{v}{V_\gamma}}$$

$$\gamma(v) = \gamma_{75} + \left(0.330 + 0.581 \cdot \gamma_{75}\right) \cdot e^{-\frac{v}{122.1}}$$

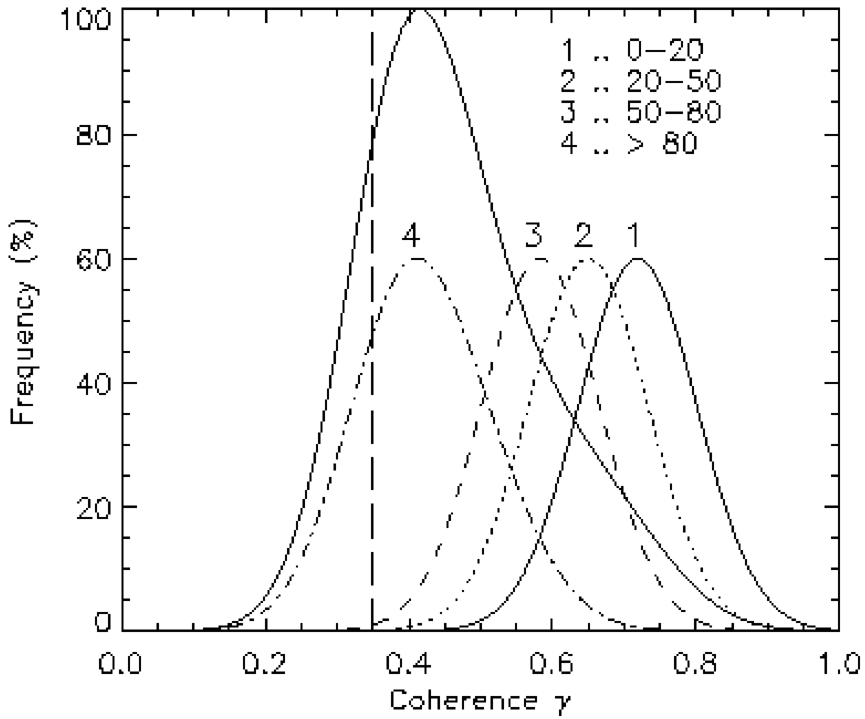
v = growing stock volume

γ_0 = coherence at *v* = 0 m^3/ha (non-forest)

γ_∞ = coherence for asymptotic values of *v* (corresponding to dense forest)

γ_{75} = value where the coherence distribution reach 75% of the maximum value (Fig.)

V_γ = characteristic *v* value where the exponential function has decreased by e^{-1}



Wagner et al., 2003

In the year 2000: SIBERIA Project

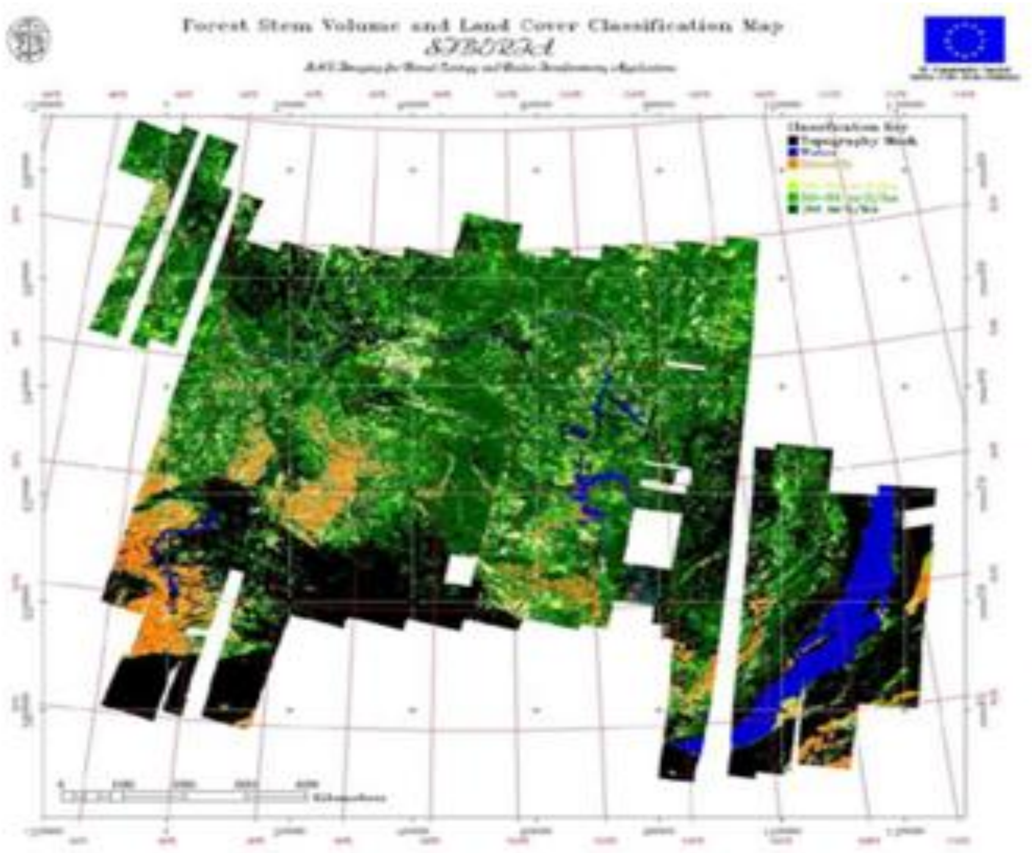
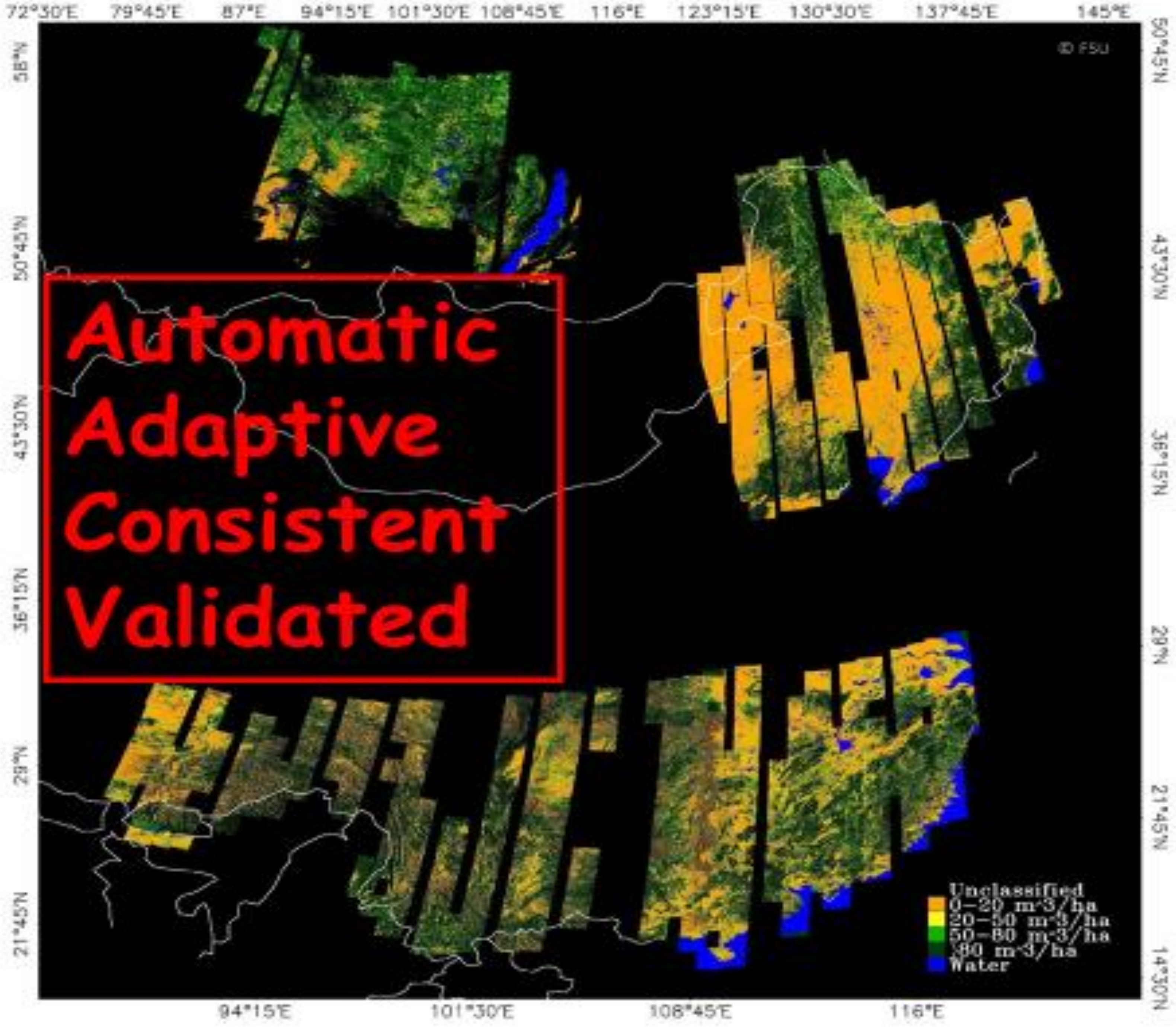


Fig.: Final forest biomass map – Siberia project (© SIBERIA Project 1999, 2000)

- Nothing as yet global and accessible as Above Ground Biomass
- Regional – SIBERIA (1 Mio. km² at 50 m, 1998) based on SAR interferometry

THE EUROPEAN SPACE AGENCY

DRAGON project



Courtesy ESA DRAGON Project (O. Cartus, M. Santoro)

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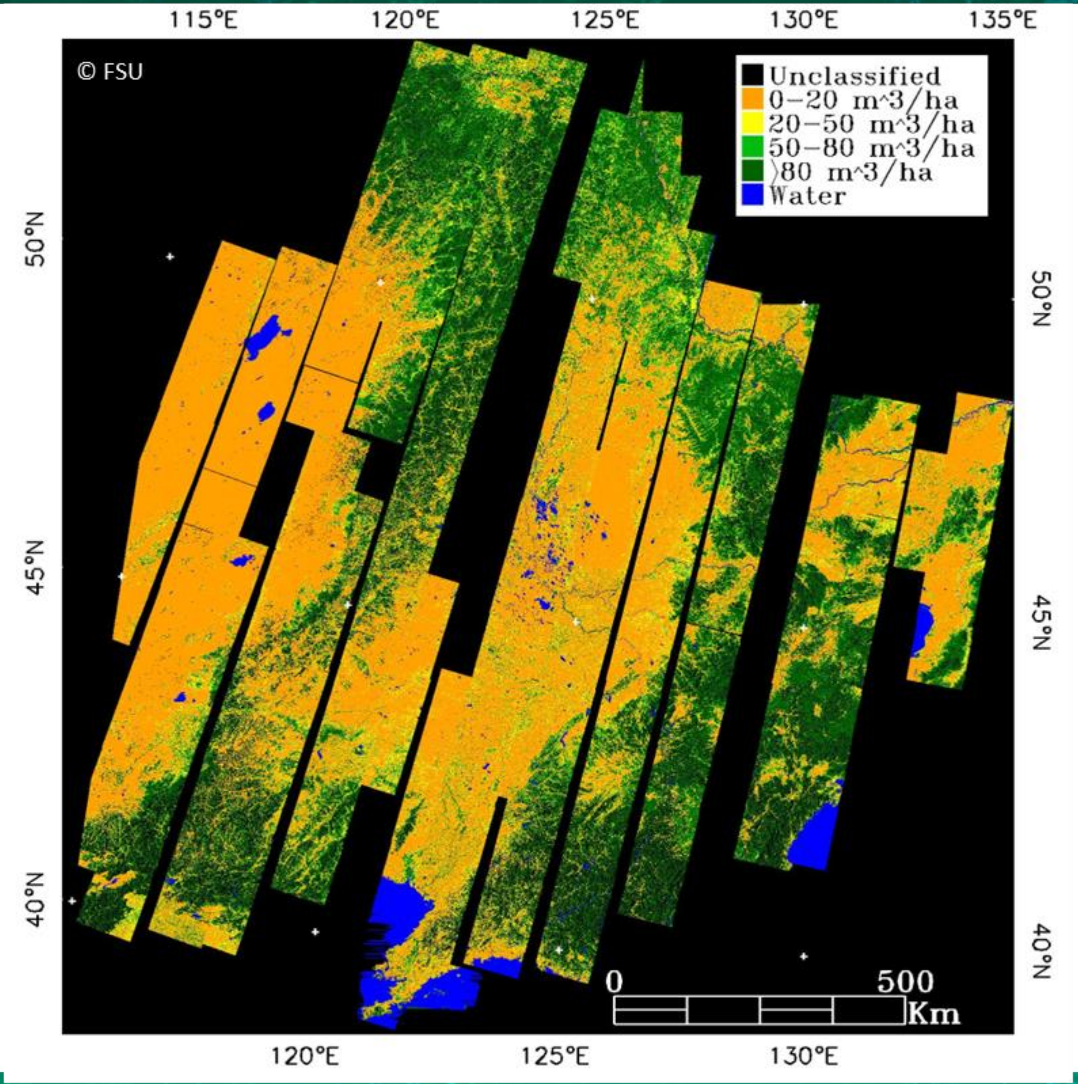
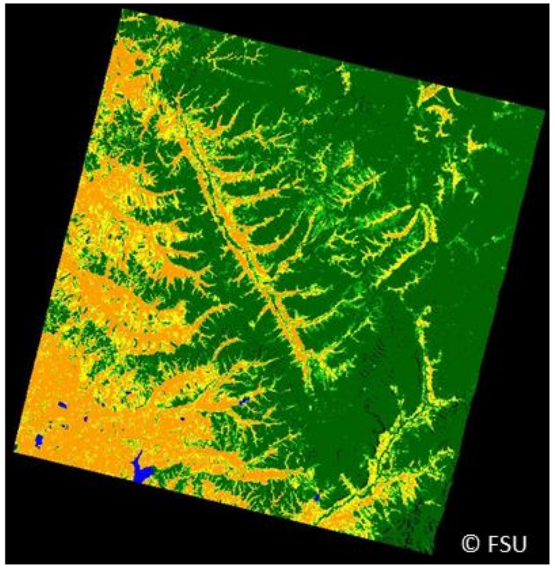
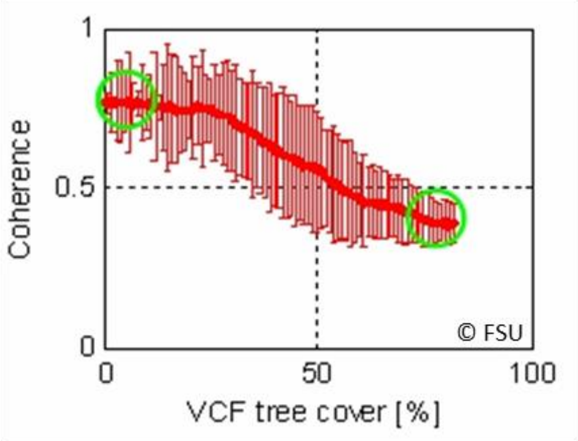
Radar model training with optical product VCF







Courtesy ESA DRAGON Project (O. Cartus, M. Santoro)

DRAGON-2 Change Product

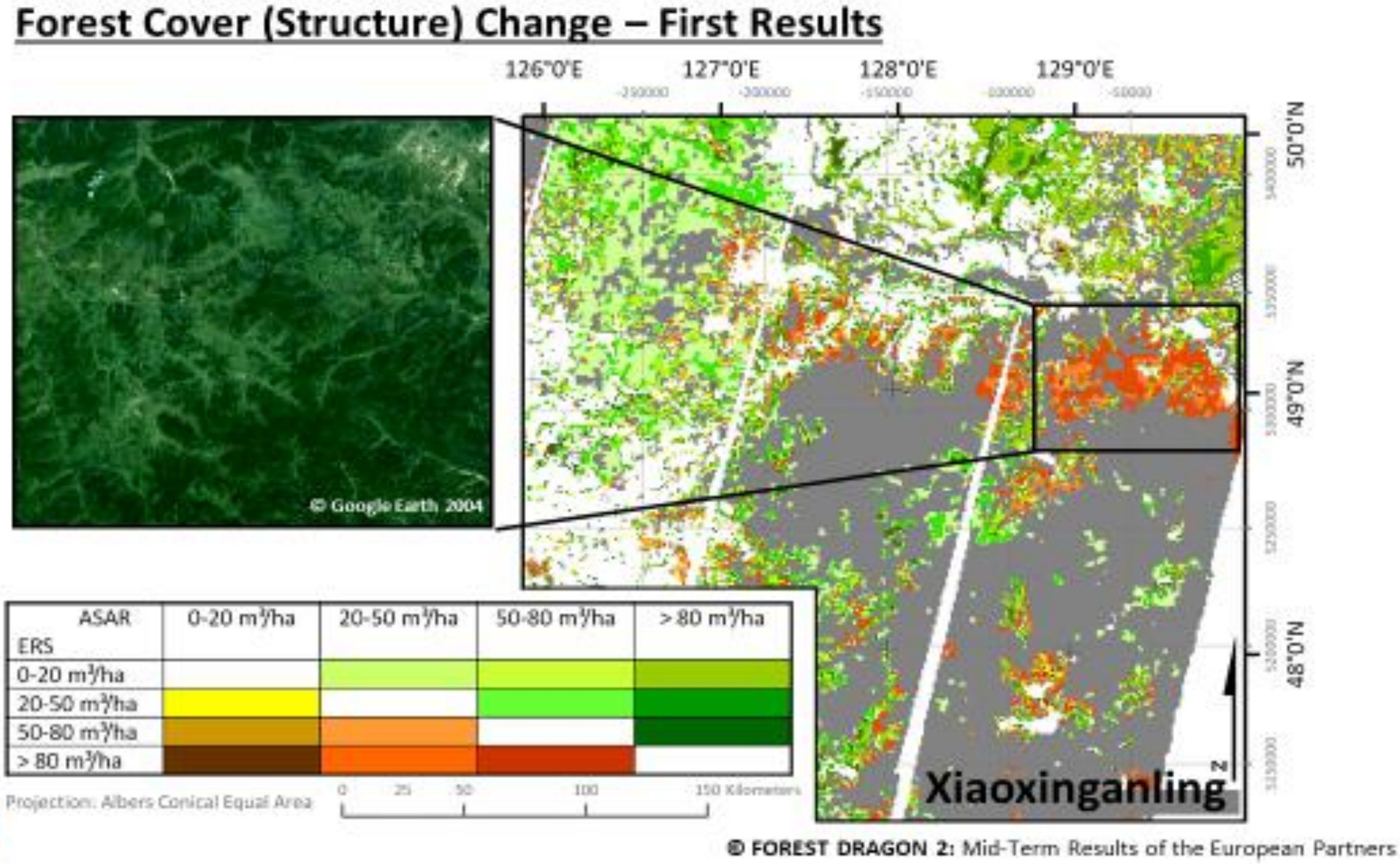


Image Classification - 1

Classification:

- Systematic arrangement [of data] in groups or categories according to established criteria (https://www.merriam-webster.com/dictionary/classification)
- Method for attaching labels to pixels according to their spectral character (Richards & Jia 2006)
- Automatic categorization of all image pixels into land cover classes (Lillesand & Kiefer 2000)

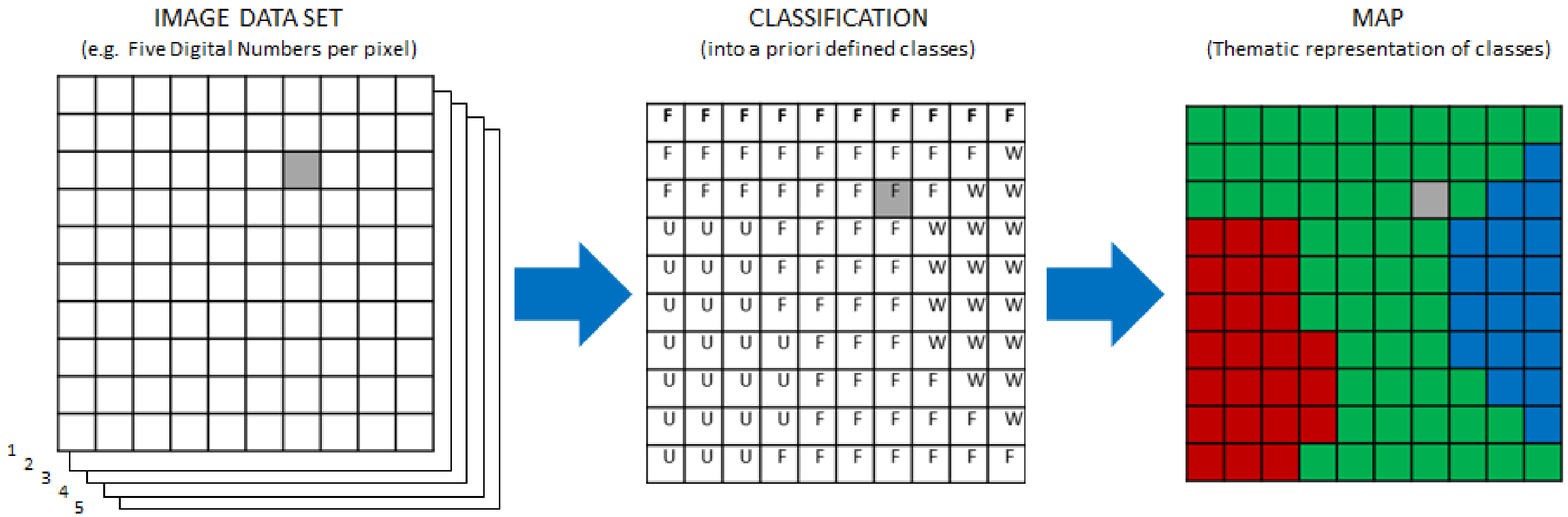
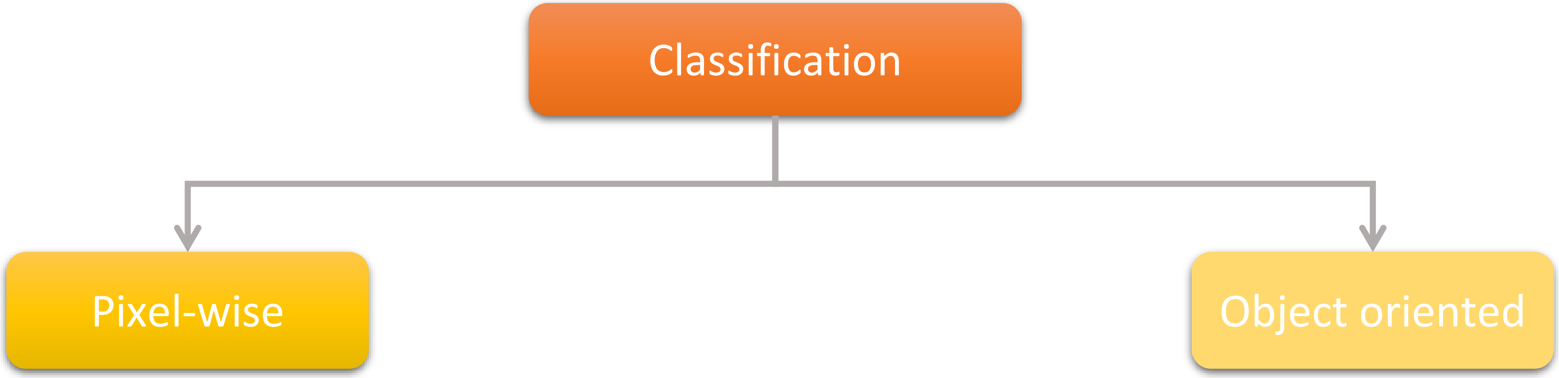


Image classification
(Source: after Lillesand & Kiefer 2000)

Image Classification - 2

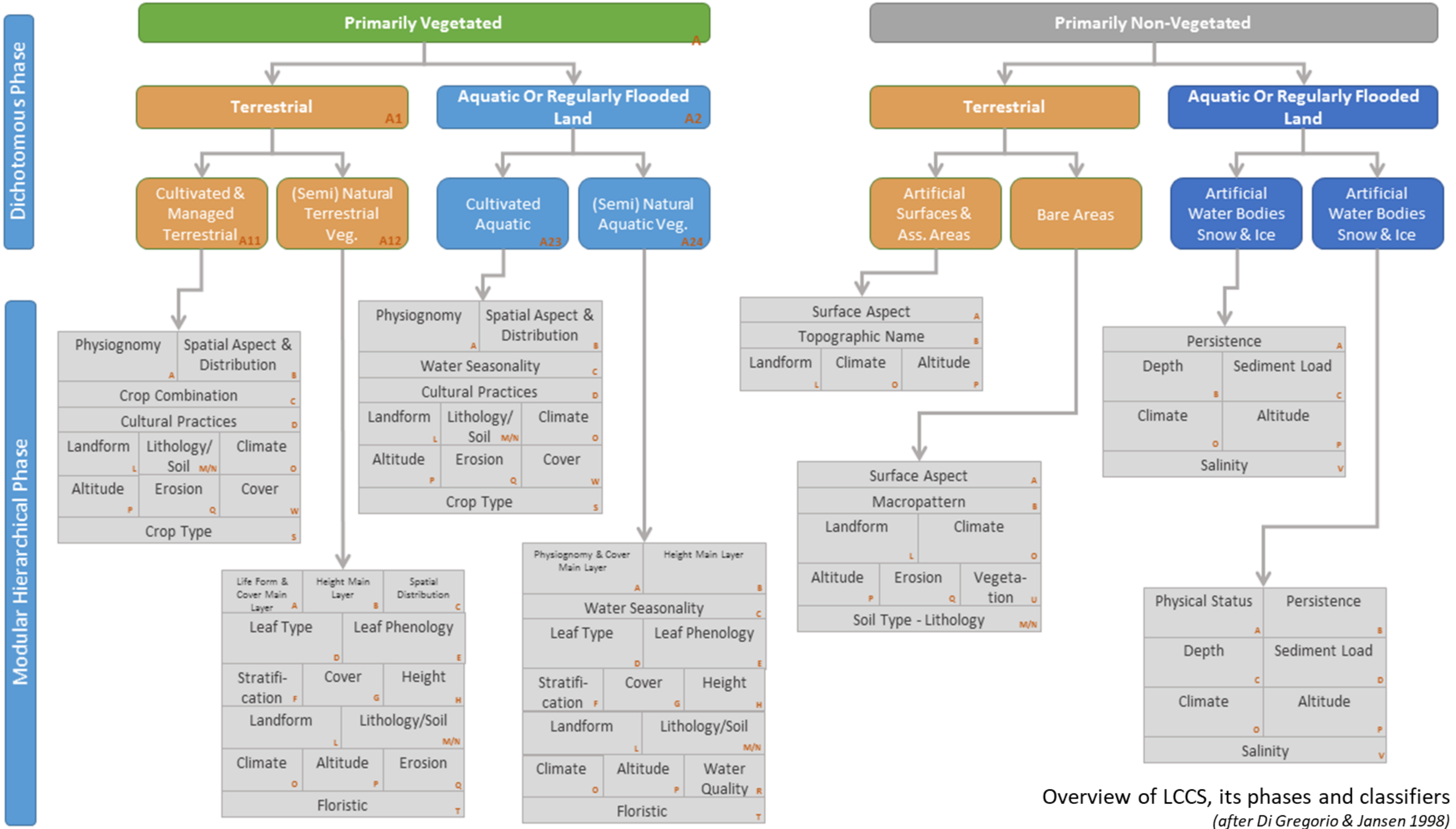
- Further differentiation of classification concepts:



- **Pixel:**
  - Picture element, smallest geometrical unit of image data set
  - Point information on spectral characteristics, e.g. radar backscatter

- **Object:**
  - Derived from group of pixels with common characteristics and relations
  - Represents a geographical entity
  - Created by segmentation
  - Uses spectral statistics, shape, size, texture, context

Image Classification - 3



Overview of LCCS, its phases and classifiers

(after Di Gregorio & Jansen 1998)

Land Cover Classification Accuracy Assessment

Accuracy Assessment

A classification is not complete until its accuracy is assessed.
(Lillesand & Kiefer, 2000)

Accuracy Assessment

- Every classification contains errors
- None of the classification method is perfect
- Possible error sources:
  - Geometric errors in input data
  - In case of optical data, un-complete atmospheric correction
  - Clusters incorrectly labeled after unsupervised classification
  - Training sites incorrectly labeled before supervised classification
  - Un-distinguishable classes

Accuracy Assessment

- According to Merriam-Webster English Dictionary, accuracy means:
  - freedom from mistake or error
  - conformity to truth
- Accuracy is determined empirically by selecting a sample of pixels from classified map and checking them against classes determined from reference data (Richards & Jia 2006)
- Reference data
  - Also called “ground truth”
  - Are a sample of the physical reality
  - Retrieved during field visits, from topographic maps, biotope mappings, orthophotos, etc.
  - Can be collected using different sampling schemes

Accuracy Assessment – Number of Samples

- How many samples do need at least?

$$N = \frac{Z^2 pq}{E^2}$$

Z = 2 (2 σ [standard deviations] covering 95.4% of the image)

p = expected percent accuracy

$q = 100 - p$

E = allowable error

Example:

$$N = \frac{2^2 (85 \cdot 15)}{5^2}$$

$$N = 204$$

If an accuracy of 85% at an error of 5% is exepected, then 204 samples should be taken

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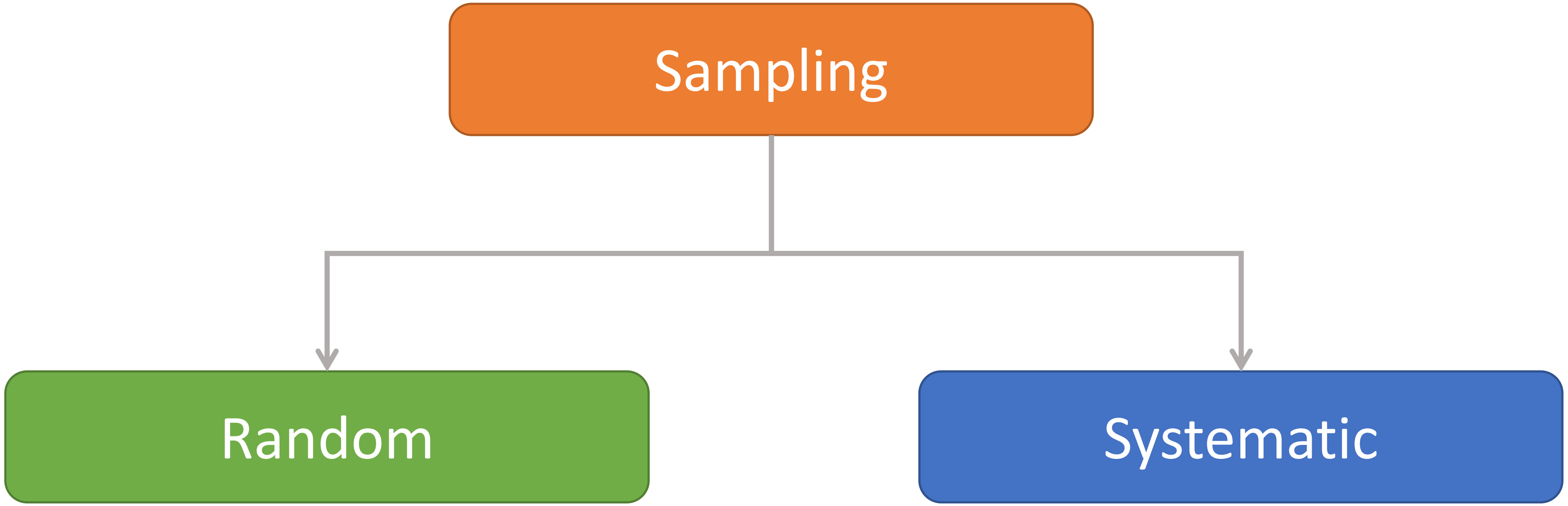
Accuracy Assessment – Sampling Schemes

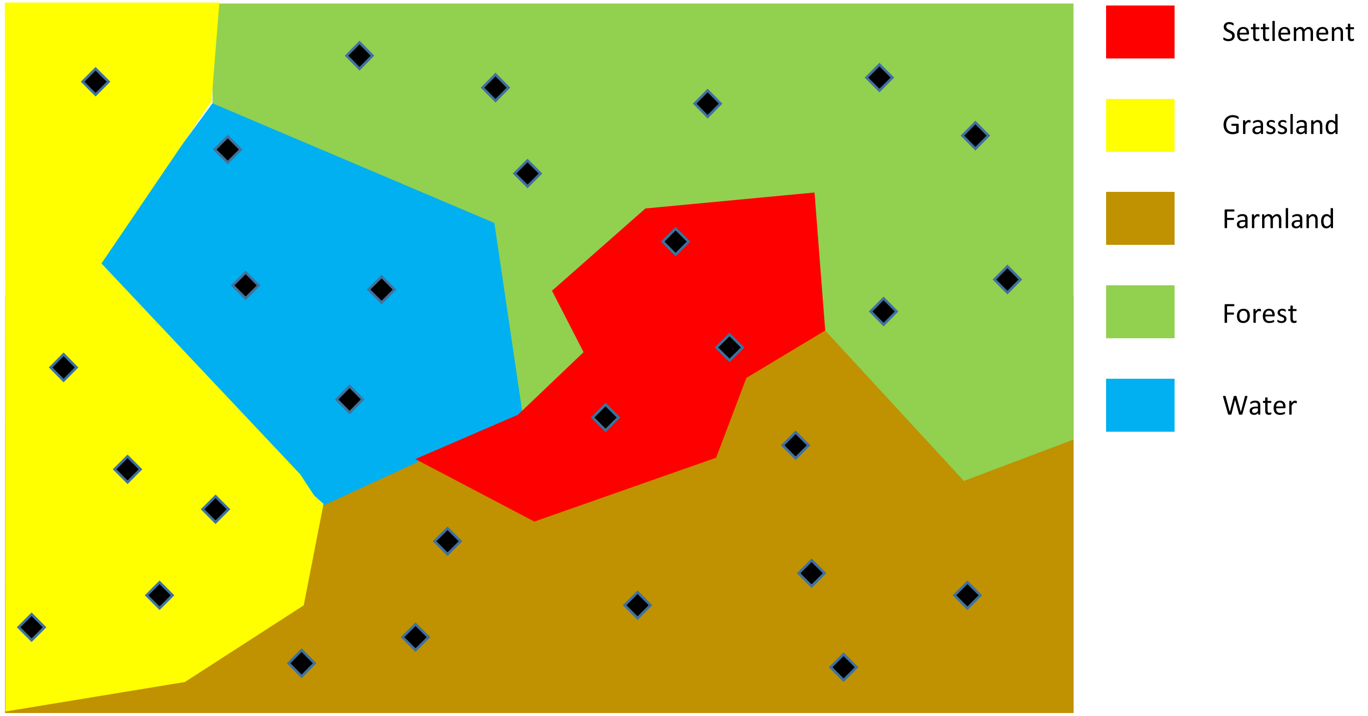
- How should the samples be distributed over the study area?
- For this different sampling schemes are available:
  - Simple random sampling
  - Stratified random sampling
  - Systematic sampling
  - Systematic non-aligned sampling
  - One- or two-stage cluster sampling

Accuracy Assessment – Sampling Schemes



Accuracy Assessment – Sampling Schemes

- Simple random sampling
  - samples taken at random locations
  - each sample unit has equal chance of being selected
  - method my underestimate small but important areas; very small areas may be missed completely



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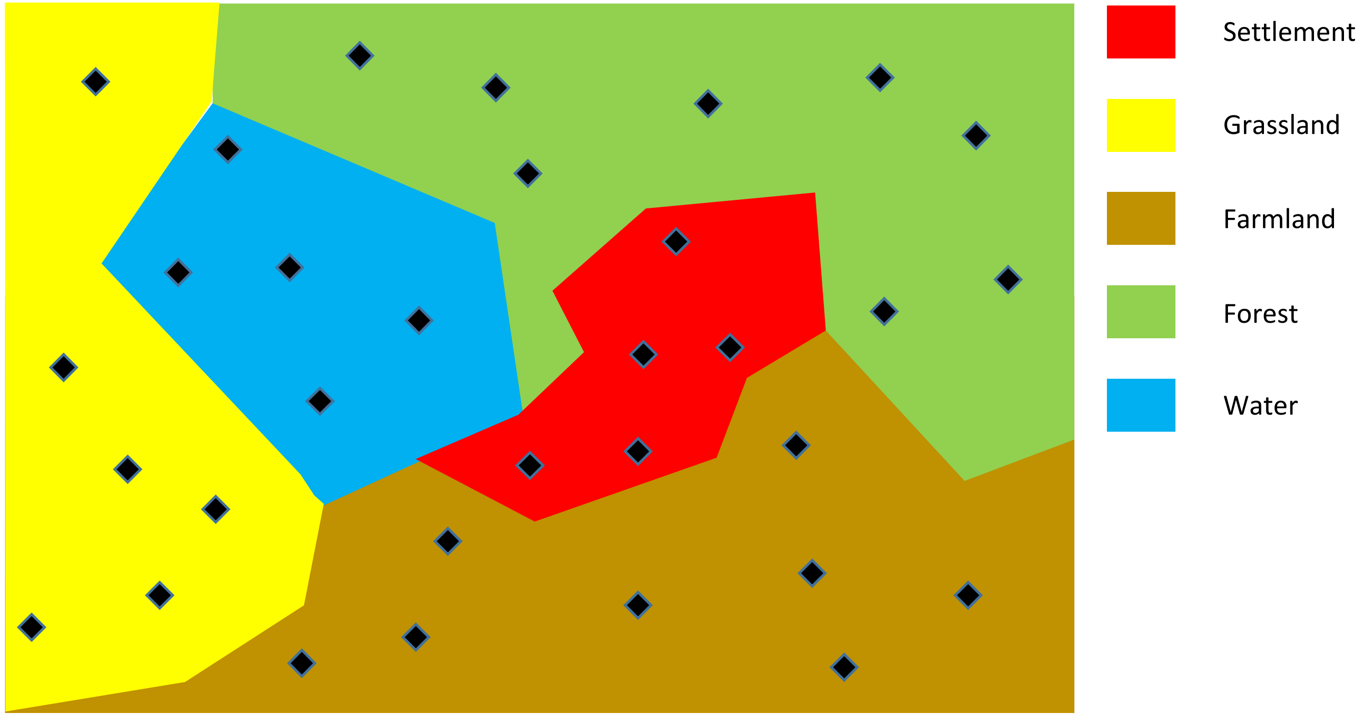
Accuracy Assessment – Sampling Schemes

- Stratified random sampling
  - requires some prior knowledge about study area to divide area into strata
  - Minimum number of samples taken for each strata
  - Samples within strata randomly distributed



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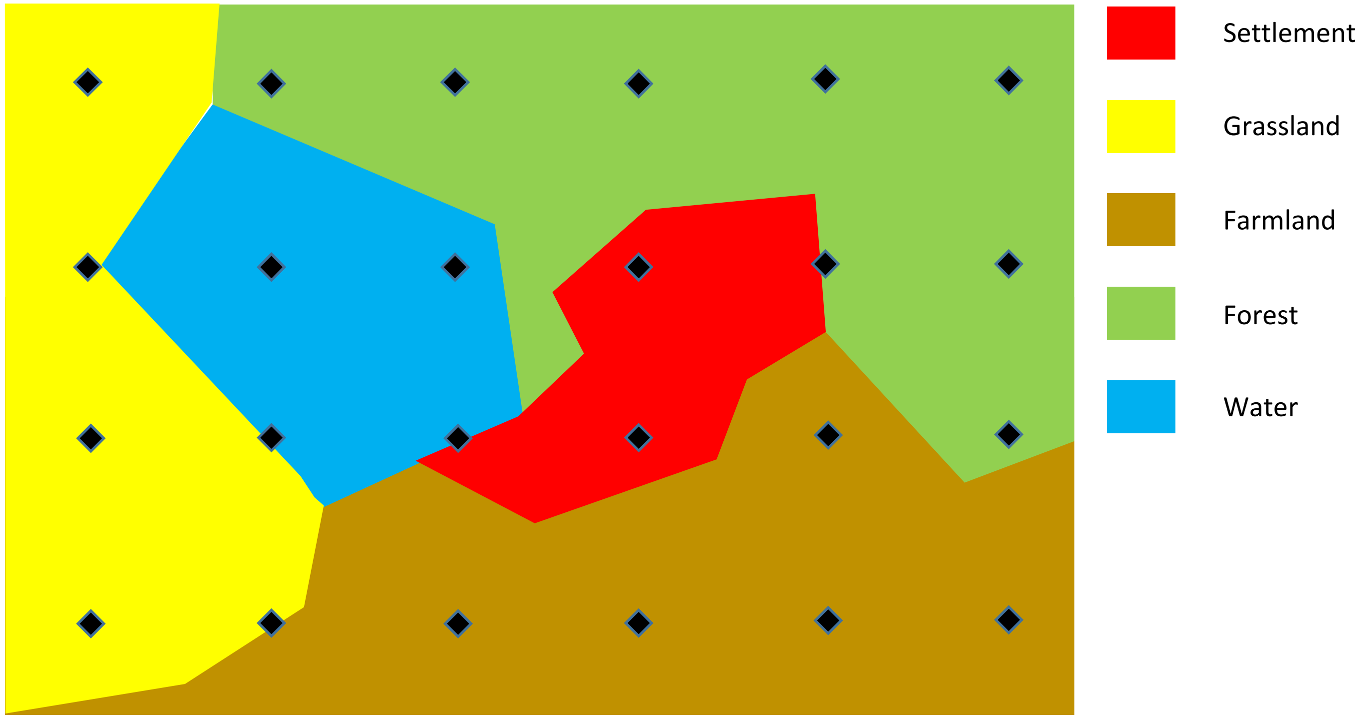
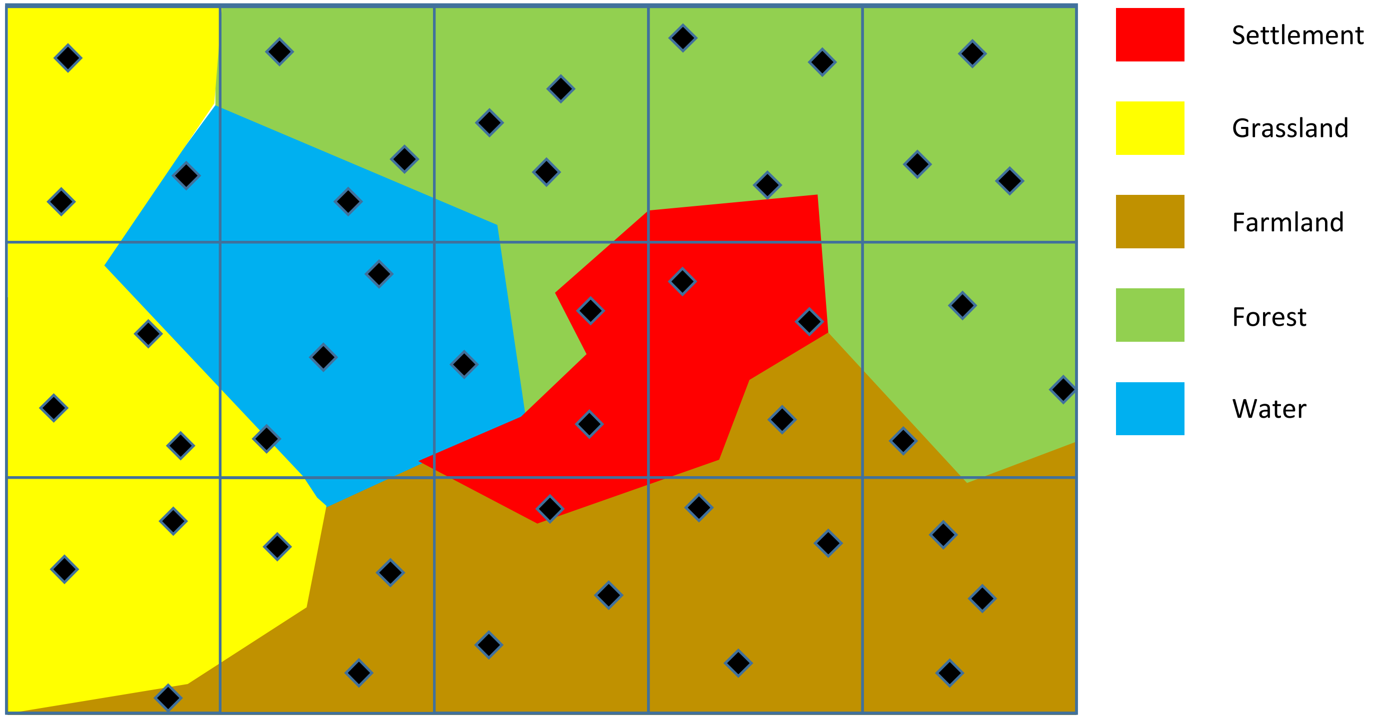
Accuracy Assessment – Sampling Schemes

- Systematic sampling
  - samples placed at equally spaced positions
  - major advantage is ease of sampling uniformly over study area



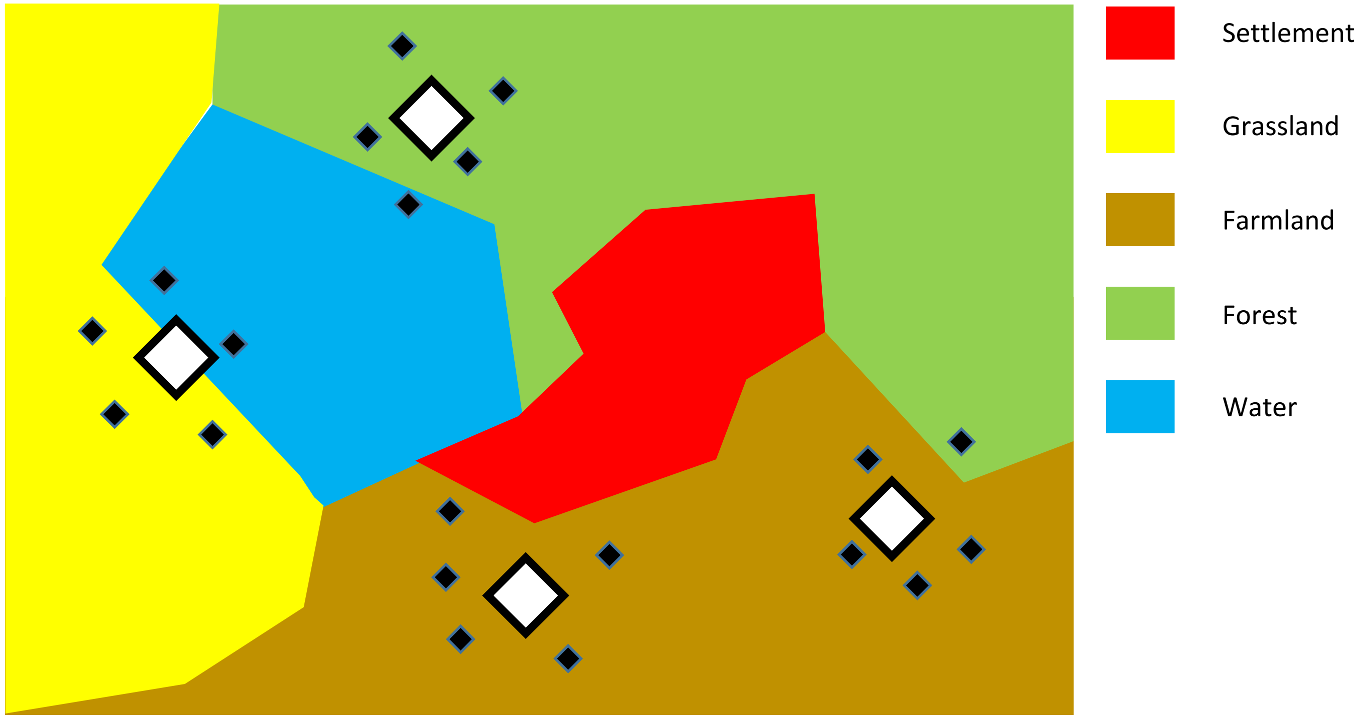
Accuracy Assessment – Sampling Schemes

- Systematic non-aligned sampling
  - combines randomness and stratification
  - grid used to guarantee even distribution of random samples



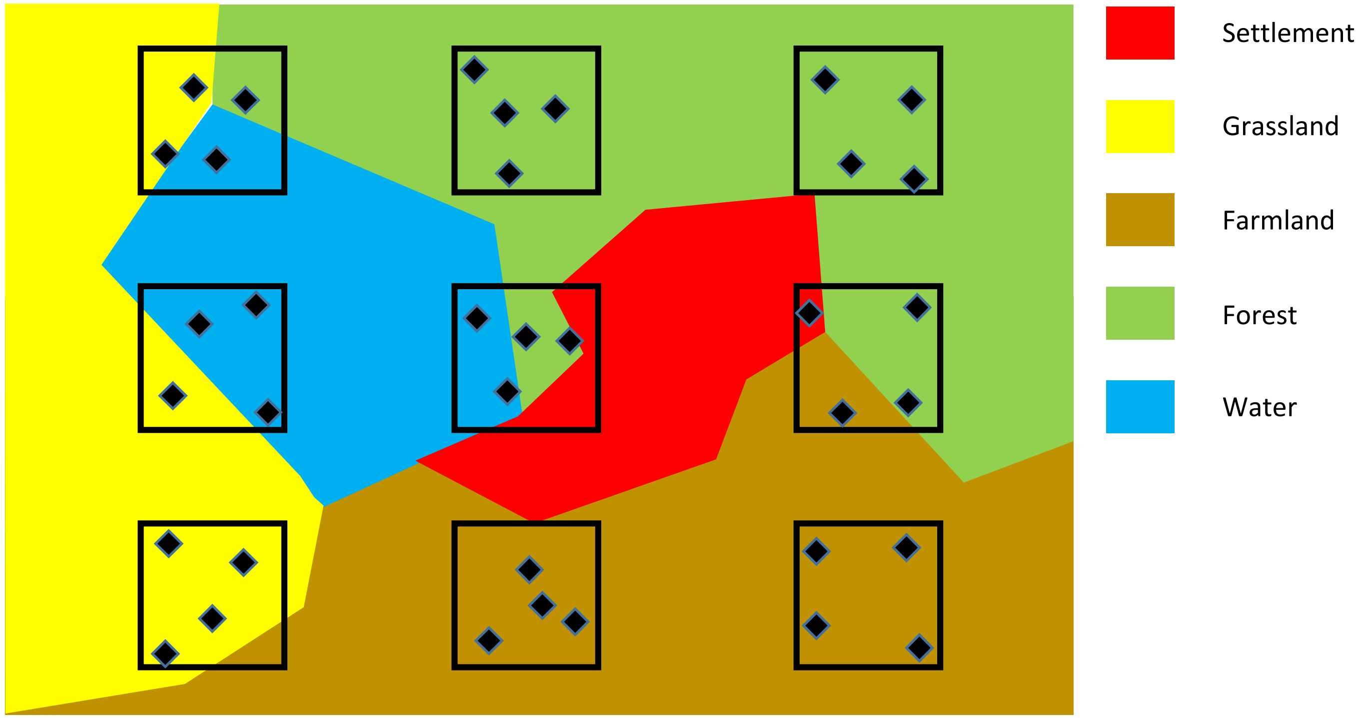
Accuracy Assessment – Sampling Schemes

- One-stage cluster sampling
  - centroids are distributed randomly and serve as base for nearby samples
  - these samples may be taken randomly or systematically



Accuracy Assessment – Sampling Schemes

- Two-stage cluster sampling
  - In this Example
    - First stage: Clusters are selected by systematic protocol
    - Second stage: Samples are randomly selected
  - First-stage clusters may also be distributed using random scheme
  - Second-stage samples may also be taken using a systematic scheme



Accuracy Assessment – Accuracy of ground truth

- Term truth may be misleading
- Accuracy of ground truth rarely known but is usually assumed to be correct
- But:
  - Ground truth is almost never completely correct due to:
    - Differences between the time the imagery (input data for classification) was acquired and the time ground truth data were collected
    - Inconsistencies in assigning classes to ground truth
    - Other factors based on human judgment.

(Carlotto 2009)

- If ground truth is assumed to be correct but is not, classification errors are blamed on the algorithm or the data, wrongly lowering the classification accuracy (Congalton 1991).

Accuracy Assessment – Error Matrix

- Error matrix is a way for representing accuracy assessment

		Reference Data					
		Settlement	Grassland	Farmland	Forest	Water	**Row total**
Classification Data	Settlement	480	20	0	0	0	500
	Grassland	5	320	25	0	0	350
	Farmland	10	30	780	20	0	840
	Forest	0	0	10	550	0	560
	Water	0	0	0	0	120	120
	Column total	495	370	815	570	120	2370

Producer's Accuracy

Settlement	480/495	96,97%
Grassland	320/370	86,49%
Farmland	780/815	95,71%
Forest	550/570	96,49%
Water	120/120	100,00%

User's Accuracy

Settlemen	480/500	96,00%
Grassland	320/350	91,43%
Farmland	780/840	92,86%
Forest	550/560	98,21%
Water	120/120	100,00%

Overall Accuracy = (480+320+780+550+120)/2370 = 94,94%

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Accuracy Assessment – Error Matrix

Correct according to reference data

Classification Data		Reference Data					
		Settlement	Grassland	Farmland	Forest	Water	**Row total**
	Settlement	480	20	0	0	0	500
	Grassland	5	320	25	0	0	350
	Farmland	10	30	780	20	0	840
	Forest	0	0	10	550	0	560
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	Column total	495	370	815	570	120	2370

Producer's Accuracy			**User's Accuracy**		
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Grassland	320/370	86,49%	Grassland	320/350	91,43%
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Forest	550/570	96,49%	Forest	550/560	98,21%
Water	120/120	100,00%	Water	120/120	100,00%

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Accuracy Assessment – Error Matrix

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Off-diagonals – misclassified according to reference data

Off-diagonals – misclassified according to reference data

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Water	120/120	100,00%

Overall Accuracy = (480+320+780+550+120)/2370 = 94,94%

Accuracy Assessment – Overall Accuracy

Overall accuracy = sum of the diagonals divided by the grand total (expressed as a percent)

		Reference Data					
		Settlement	Grassland	Farmland	Forest	Water	**Row total**
Classification Data	Settlement	480	20	0	0	0	500
	Grassland	5	320	25	0	0	350
	Farmland	10	30	780	20	0	840
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Overall Accuracy = (480+320+780+550+120)/2370 = 94,94%

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Accuracy Assessment – Individual Class Accuracy

Individual Class Accuracy is given by the diagonal value divided by the row **or** column total (expressed as a percent).

Example for class Farmland:
(780/840) * 100 = 93.71%
or
(780/815) *100 = 92.86%

		Reference Data					
		Settlement	Grassland	Farmland	Forest	Water	**Row total**
Classification Data	Settlement	480	20	0	0	0	500
	Grassland	5	320	25	0	0	350
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Accuracy Assessment – Individual Class Accuracy

Individual Class Accuracy is given by the diagonal value divided by the row **or** column total (expressed as a percent)

Example for class Farmland:
780/840 = 93%
or
780/815 = 96%

Why are there two values for describing the individual class accuracy for the class „Farmland“?

Because there are two types of errors!

Accuracy Assessment – Error Types

- Errors of omission
  - sites that were not included and are now falsely part of other classes
- Example for class "Farmland":
  - 10 pixels from class "Settlement", 30 pixels from class "Grassland", and 20 pixels from class "Forest" have been falsely classified, which actually should belong to class "Farmland"

		Reference Data					
		Settlement	Grassland	Farmland	Forest	Water	**Row total**
Classification Data	Settlement	480	20	0	0	0	500
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Overall Accuracy = (480+320+780+550+120)/2370 = 94,94%

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Accuracy Assessment – Error Types

- Errors of commission
  - Sites that are included in a class but are part of other classes
- Example for class “Farmland”:
  - Class “Farmland” contains 25 pixels belonging to class “Grassland” and 10 pixels belonging to class “Forest”

		Reference Data					
		Settlement	Grassland	Farmland	Forest	Water	**Row total**
Classification Data	Settlement	480	20	0	0	0	500
	Grassland	5	320	25	0	0	350
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Accuracy Assessment – Error Types

- Errors of commission and omission linked with two specific accuracy measures
- Producer’s Accuracy
  - Describes how often are real features on the ground are correctly shown on the classified map
  - Is the probability that a certain land cover of an area on the ground is classified as such.
- User’s Accuracy
  - Describes how often the class on the map will actually be present on the ground
  - This is referred to as reliability.

Accuracy Assessment – Error Types

- Producer's Accuracy for a class is calculated from the diagonal value divided by the column total.
- Example for class "Farmland": (780/815) * 100 = 95.71%

		Reference Data					
		Settlement	Grassland	Farmland	Forest	Water	**Row total**
Classification Data	Settlement	480	20	0	0	0	500
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Overall Accuracy = (480+320+780+550+120)/2370 = 94,94%

Accuracy Assessment – Error Types

- Users's Accuracy for a class is calculated from diagonal value divided by the row total.
- Example for class "Farmland": (780/840) * 100 = 92.86%

		Reference Data					
		Settlement	Grassland	Farmland	Forest	Water	**Row total**
Classification Data	Settlement	480	20	0	0	0	500
	Grassland	5	320	25	0	0	350
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Overall Accuracy = (480+320+780+550+120)/2370 = 94,94%

Accuracy Assessment – "*KHAT*"

- Theoretically also a totally random assignment of pixels to classes will result in a certain percentage of correct values in an error matrix. Such a classification may lead to a relatively good classification result
- Therefore the $\hat{k}$ *("KHAT")* can be used as measure of the difference between observed agreement between the reference data and the classification result and the chance agreement between the reference data and the classification result.

$$\hat{k} = \frac{observed\ accuracy\ - chance\ agreement}{1\ - chance\ agreement}$$

☞

Accuracy Assessment – Kappa Coefficient

$$\hat{k} = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}(x_{i+} \cdot x_{+i})}{N^2 - \sum_{i=1}^{r}(x_{i+} \cdot x_{+i})}$$

r = number of rows in the error matrix
x_{ii} = number of observations in row i and column i (on major diagonal)
x_{i+} = total of observations in row i
x_{+i} = total od observations on column i
N = total number of observations included in matrix

- KHAT may range between *0* for a totally random distribution (complete disagreement) and *1* for an exact agreement between the reference data and the classification result; these ideal cases are not observed in reality
- *KHAT* includes all elements of the error matrix (also errors of omission and commission)

Lillesand & Kiefer 2000

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Accuracy Assessment – Kappa Coefficient

$$\sum_{i=1}^{r} x_{ii} = 480+320+780+550+120 = 2250$$

$$\sum_{i=1}^{r} (x_{i+} \cdot x_{+i}) = (495*500) + (370*350) + (815*840) + (570*560) + (120*120) = 1,395,200$$

$$\hat{k} = \frac{(2370*2250) - 1,395,200}{2370^2 - 1,395,200}$$

$$= 0.9326$$

		Reference Data					
		Settlement	Grassland	Farmland	Forest	Water	**Row total**
Classification Data	Settlement	480	20	0	0	0	500
	Grassland	5	320	25	0	0	350
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	Forest	0	0	10	550	0	560
	Water	0	0	0	0	120	120
	Column total	495	370	815	570	120	2370

Accuracy Assessment – Further reading

- Lillesand, T. M., Kiefer, R. W., Chipman, J. W. (2000): Remote Sensing and Image Interpretation. *John Willey & Sons, New York, pp. 568-575*
- Congalton, R. G., Green, K. (2002): Assessing the Accuracy of Remotely Sensed Data: Principles and Practices. *CRC Press*
- Stehman, S. V. (2009). Sampling designs for accuracy assessment of land cover. *International Journal of Remote Sensing*, 30(20), *pp. 5243-5272.*

- *NOTE – not specifically adressed:*
  - *Accuracy assessment of change*
  - *Bias and uncertainty of field measurements*

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Change Detection

Introduction to Principles and Methods

Types of changes

- **short term change**

  (synoptic weather events)

- **cyclic change**

  (seasonal phenology)

- **directional change**

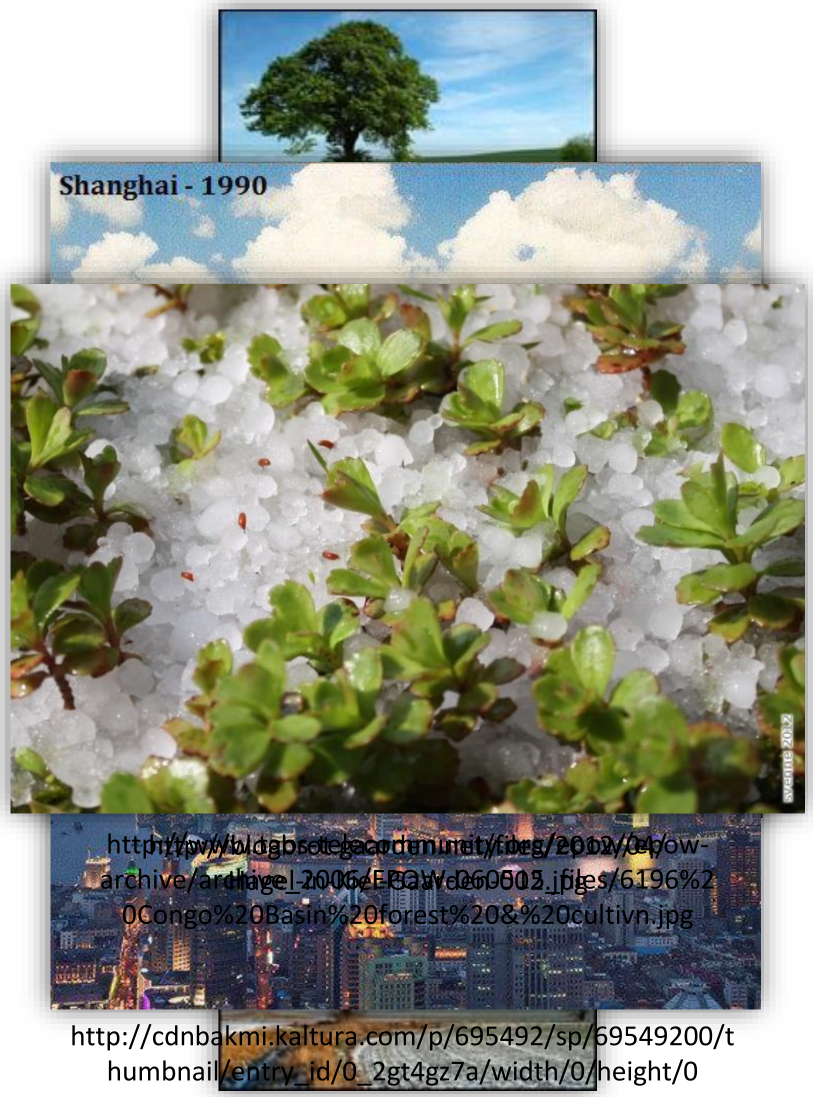
  (urban development)

- **multidirectional change**

  (deforestation & regeneration)

- **event change**

  (catastrophic fires)



http://...2012/04/snow- archive/...files/6196%2 0Congo%20Basin%20forest%20&%20cultivn.jpg

http://cdnbakmi.kaltura.com/p/695492/sp/69549200/t humbnail/entry_id/0_2gt4gz7a/width/0/height/0

http://www.bohrturm.at/templates/ images/top/jahreszeiten.jpg

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Unwanted Change

...and ways to work around it

- Phenological changes
  - ➔ Anniversary date aquisitions
- Sun angle effects
  - ➔ Radiometric Calibration
  - ➔ Similar incidence angles
  - ➔ Similar time of day
- Atmospheric effects
  - ➔ Radiometric Calibration
- Geometric
  - ➔ Coregistration

images/top/jahreszeiten.jpg

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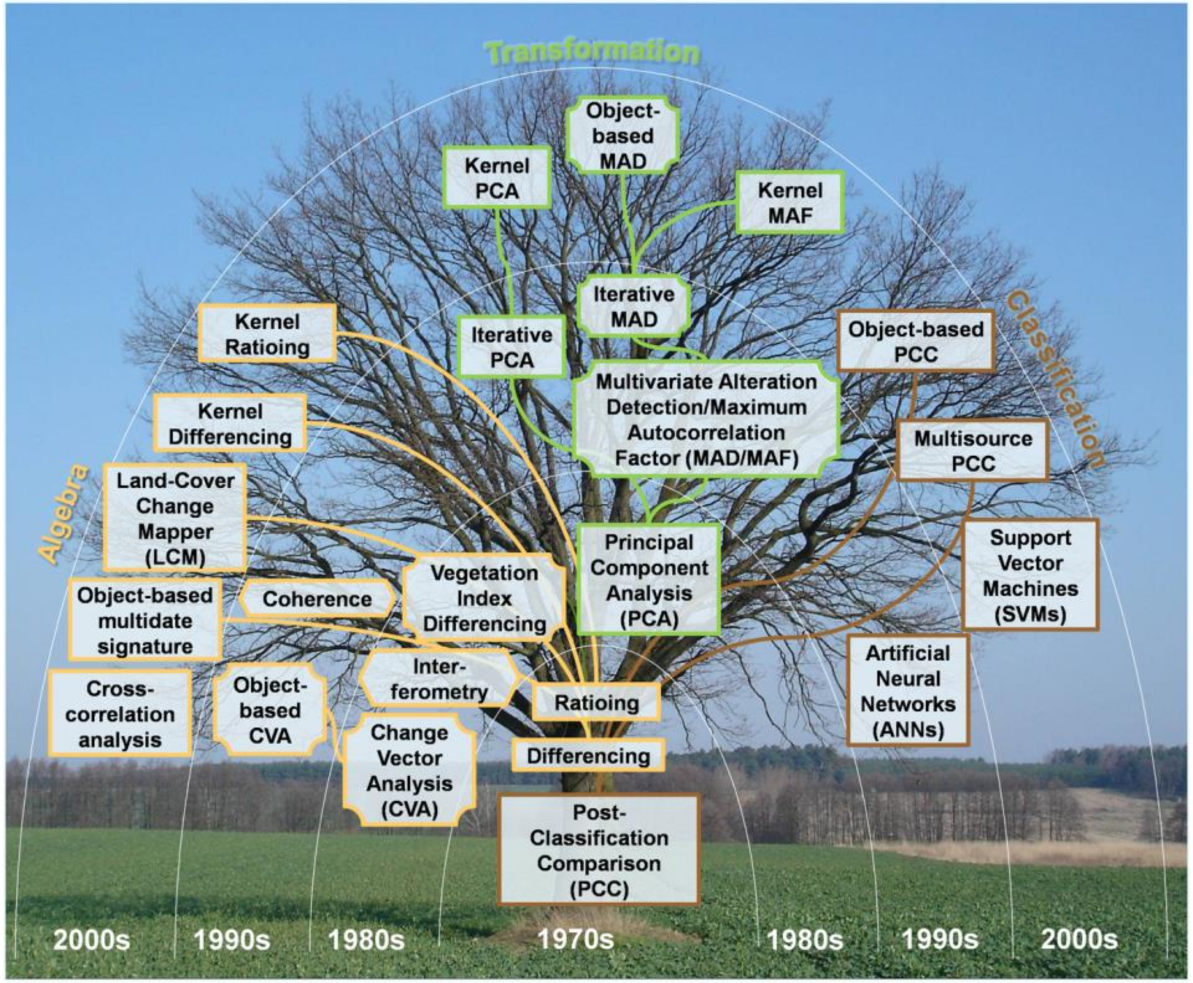
Change detection techniques

- Overview



- Algorithm for SAR data
- Algorithm for optical data
- Algorithm for both, optical and SAR data

THONFELD, HECHELTJEN, BRAUN & MENZ (2010)

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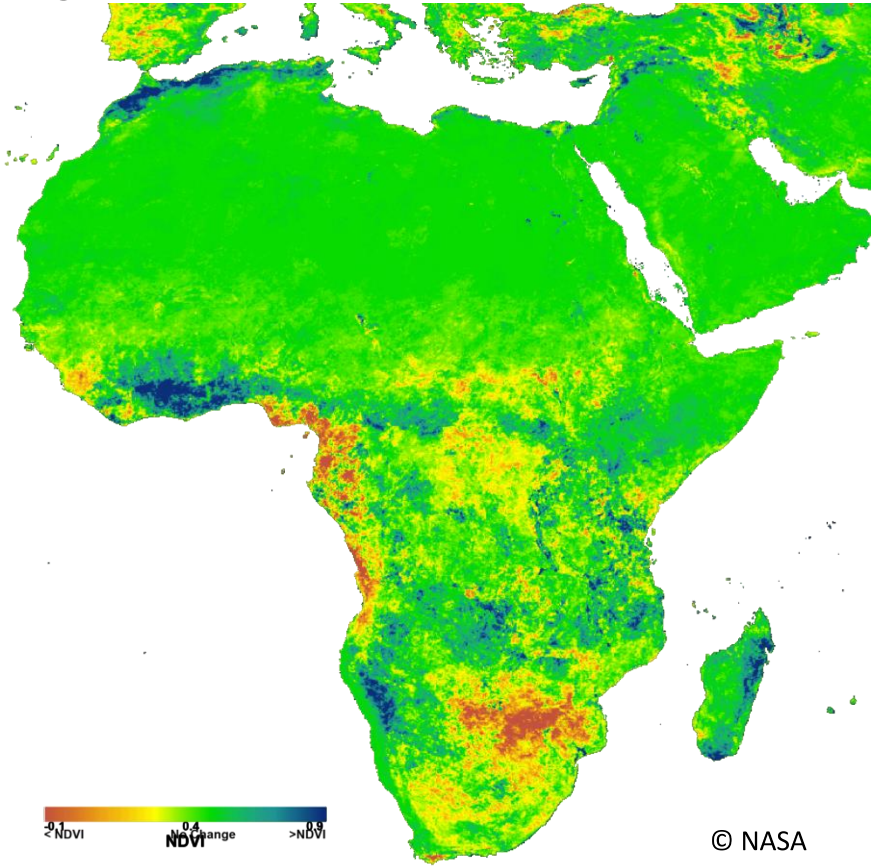
Image Differencing

- Simple Processing
- Robust
- Continous Change Values

- Requires atmospheric calibration
- Difference is absloute
  - → same value may have different meanings



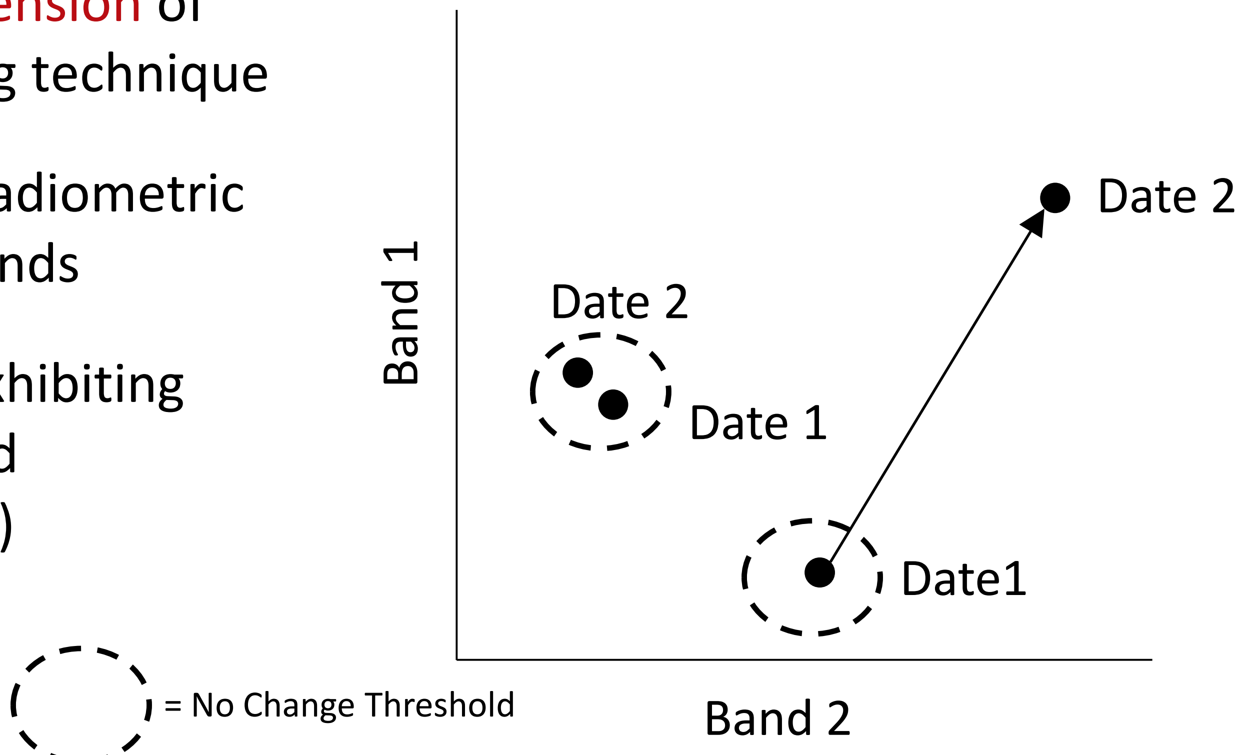
NDVI March 2000
NDVI March 2012
Difference Image

Change Vector Analysis

+
- Capability to analyse change concurrently in all data layers

−
- Requires accurate rad. Calibration
- Requires exact threshold definition

- Multidimensional extension of the image differencing technique
- Difference between radiometric values for multiple bands
- Change differences exhibiting vectors (direction) and magnitudes (intensity)

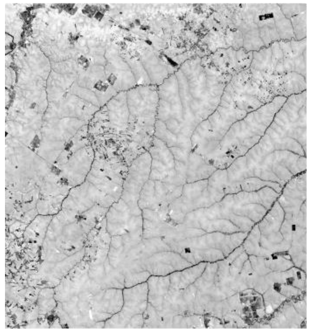


Ratios

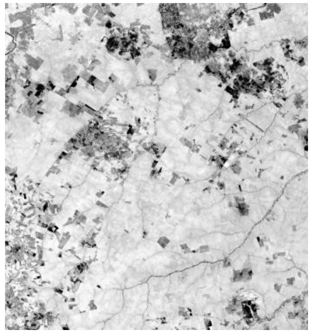
- Simple Processing
- Robust
- Continous Change Values

- Requires atmospheric calibration
- Same magnitude of change causes different ratios
  → (50/100 = 0.5; 100/50 = 2.0)

TM Band 4 1986 / TM Band 4 - 1999 © USGS
Landsat TM5 1986 – Band 4 © USGS
Landsat TM5 1999 – Band 4 © USGS



1986



1999

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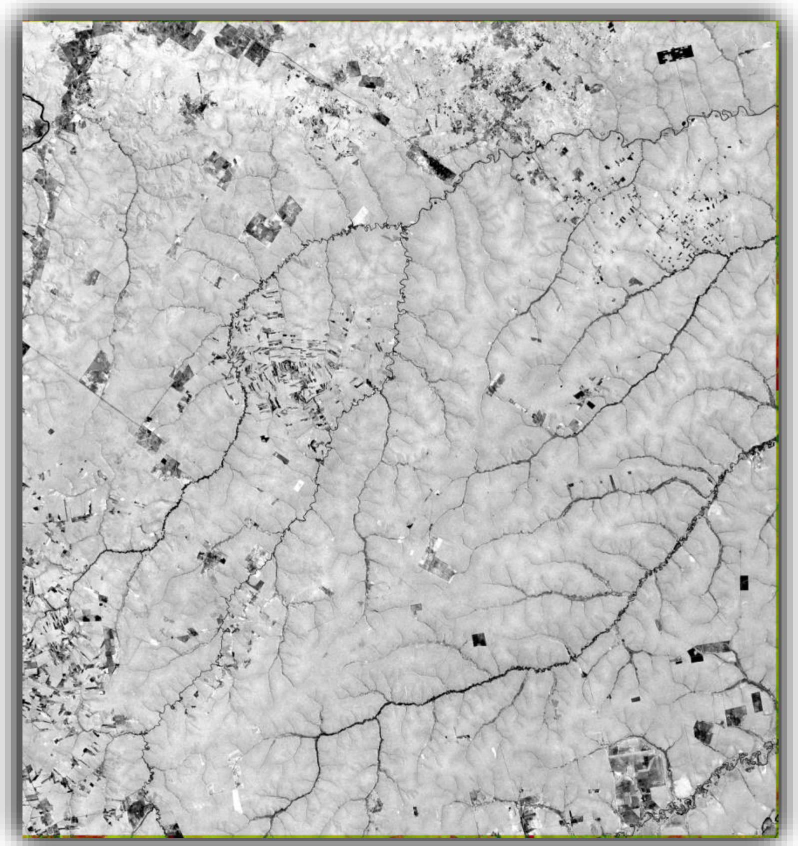
Image Composites

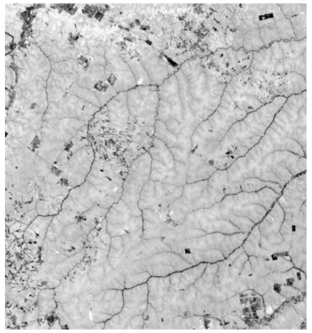
- Simple Processing

- Requires prior knowledege of the test area
- Complex classification scheme (due to two input dates)

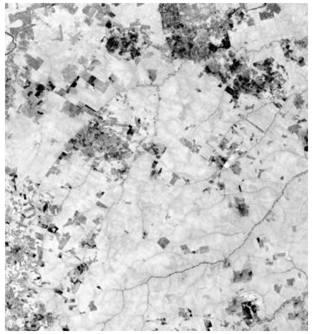


Landsat TM5 1985 – Band 4 ©USGS

Landsat TM5 1986 1999 – Band 4 Ratio 1986/1999 ©USGS



1986



1999

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Image Transformations

- Usually very good results
- Allows designation of occurring change type

- Methodological more complex

Principa

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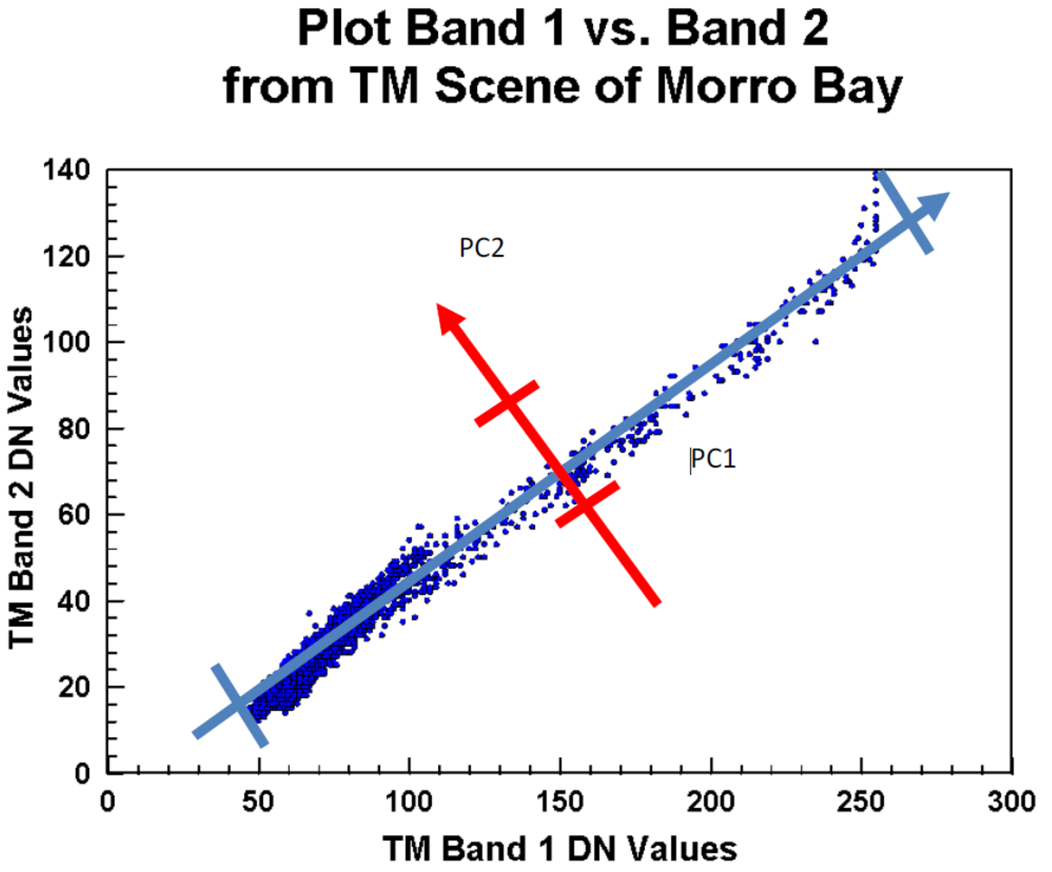

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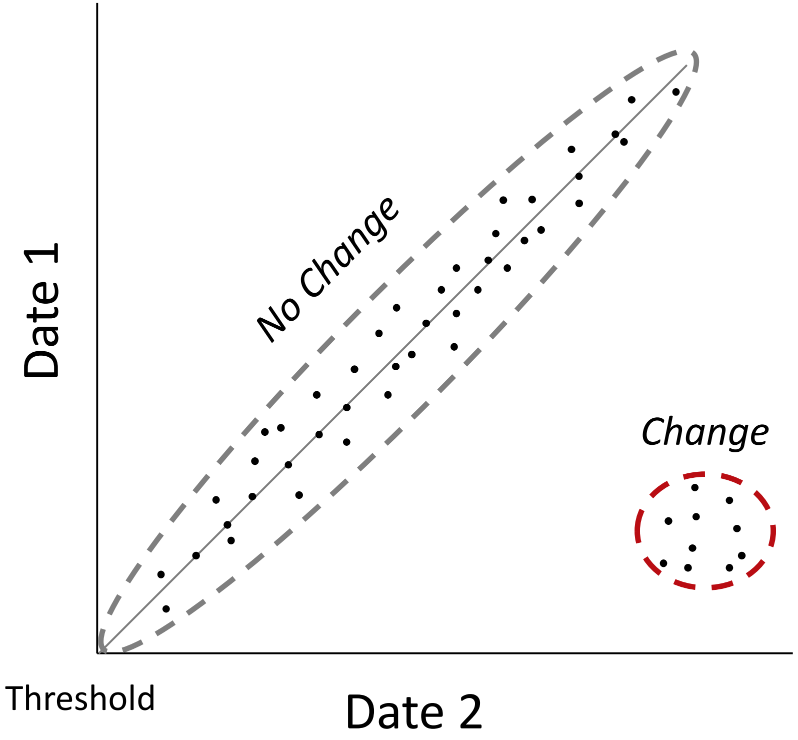
Image Regressions

+ • Based on statistical values

− • Accurate threshold definition necessary

- Mathematical model
- Describes the fit between two multi-date images
- Assumptions: Spectral properties have not changed for most pixels
  ➔ outliers = change



= No Change Threshold

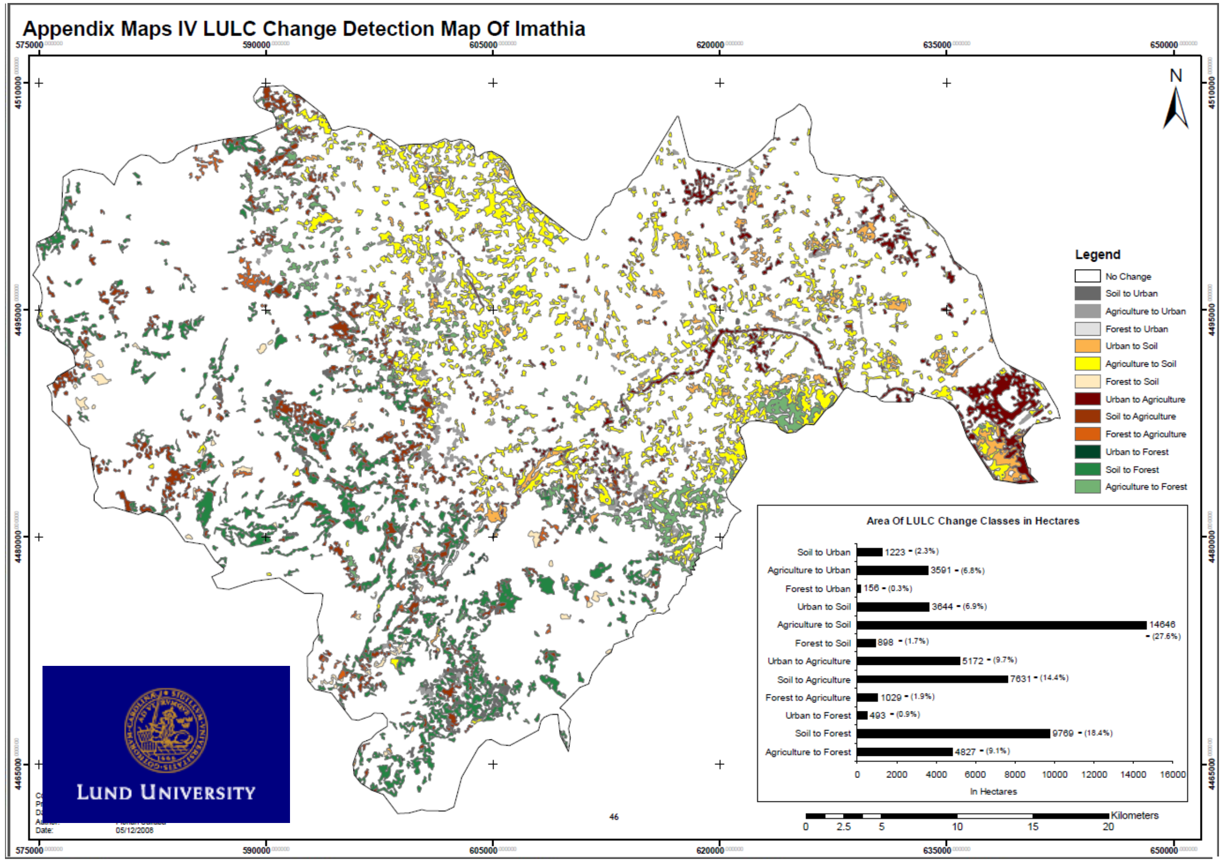
Post Classification

➕
- Less prone to radiometrical differencess

➖
- Strong dependence on the classification accurracy
  → error propagation

Example:
LULC change in northern Greece

Sallaba (2009)

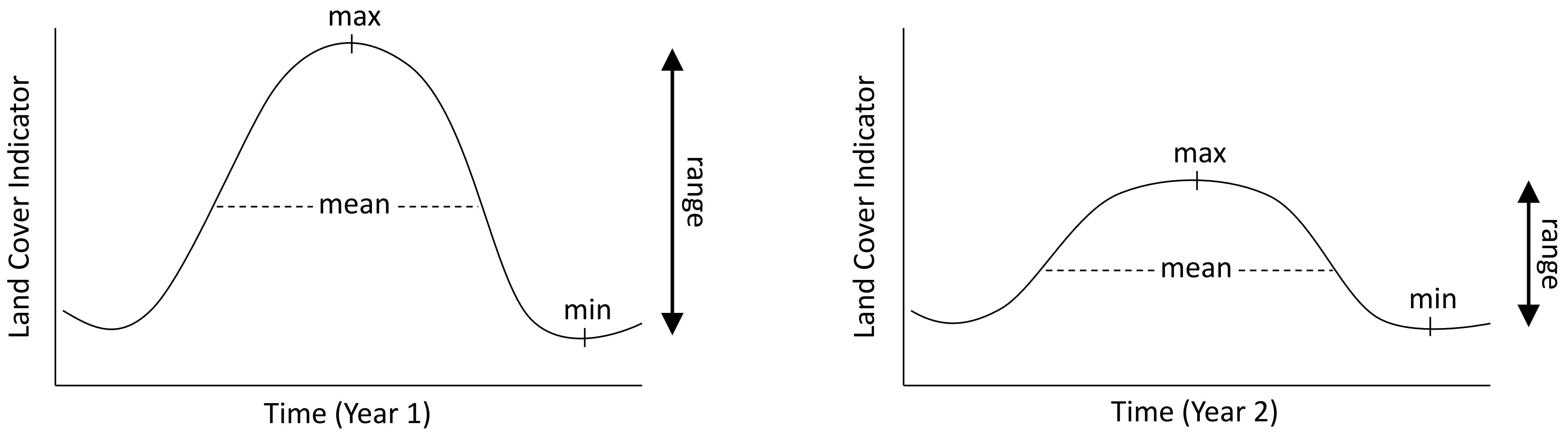


Temporal trajectory analysis

- Exact characterization of phenologocal modifications

- High data demand

Example: Temporal NDVI profile



Redrawn from Borak et al. (2000)

Temporal metrics:

- Annual Maximum
- Annual Minimum
- Annual Range
- Annual Mean
- Temporal Vector

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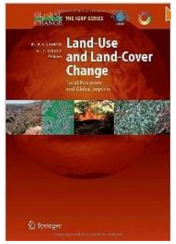

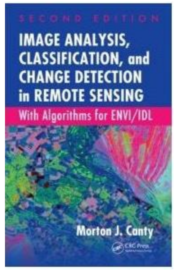

Further Reading

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Summary - SAR techniques for forest monitoring

- **Backscatter analysis** (wavelength, polarisation, incidence angle, number of images)
- **Interferometry: coherence analysis** (wavelength, polarisation, incidence angle, temporal and spatial baseline, number of images, acquisition conditions)
- **Interferometry: phase analysis** (wavelength, incidence angle, high coherence required, acquisition conditions)
- **Polarimetry** (wavelength, incidence angle, number of images)
- **Polarimetric interferometry** (wavelength, polarisation, incidence angle, temporal and spatial baseline)
- **SAR (polarimetric) tomography** (wavelength, polarisation, incidence angle, spatial baseline, high coherence required, number of images)

Advantages of SAR data vs. Optical and In-situ

- Higher spatial coverage
- Higher temporal resolution (repeat cycle e.g. 11 days)

⇒ Remotely sensed data therefore can be used to fill spatial, attributional, and temporal gaps in forest inventory data

- Contactless

⇒ Detection of unknown regions

- Retrospective analysis
  (archived SAR data since 1991 (but not globally))
- Microwaves enable a weather- and illumination-independent imaging process

FAO, 2009, Balzter, 2001

Disadvantages of SAR data vs. Optical and In-situ

- Backscatter saturation, especially in mature forests with complex stand structure
- In rugged or mountainous regions, topography affects backscatter and influences relationships between radar data and e.g. Above-ground Biomass → topographic correction is necessary

Thank you for your attention and greetings from

the Jena Earth Observation team (during its yearly winter retreat)

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