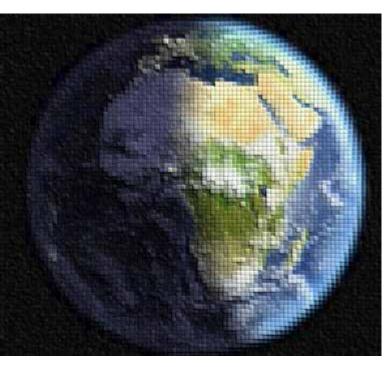# Physical Principles and Methods of Remote Sensing

Methods of Image Classification

Dr. Claudia Künzer

German Remote Sensing Data Center, DFD
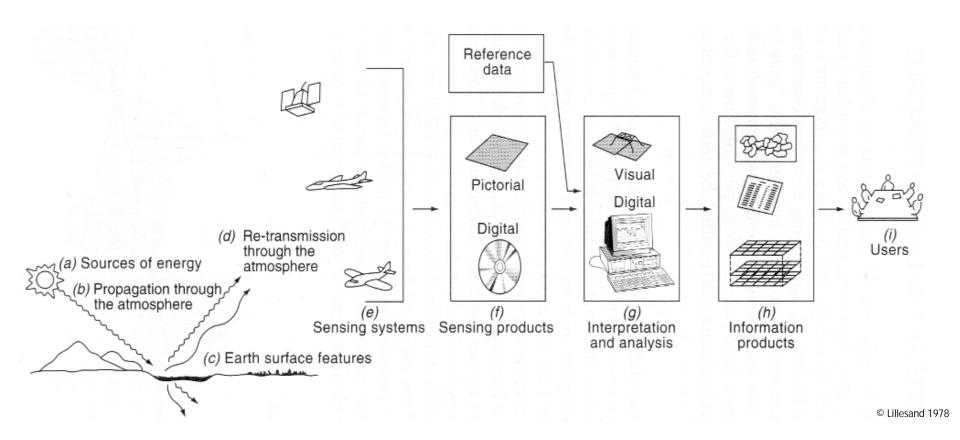German Aerospace Center, DLR
email: claudia.kuenzer@dlr.de
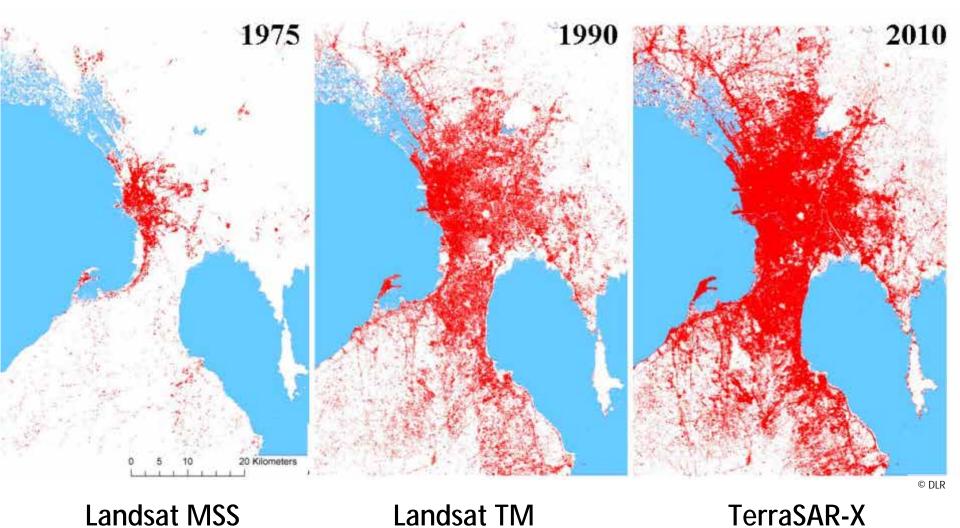fon: +49 – 8153 – 28-3280

§ **Classification**: grouping of elements according to common properties

© Lillesand 1978

Landsat MSS   Landsat TM   TerraSAR-X

© WWF, Uryu et a. 2007

Legend (1982 map):
- Forest on peatland remaining
- Forest on non peatland remaining
- Waste land
- Other land covers

Legend (2007 map):
- Acacia plantation
- Oil palm plantation
- Small holder oil palm plantation
- Cleared
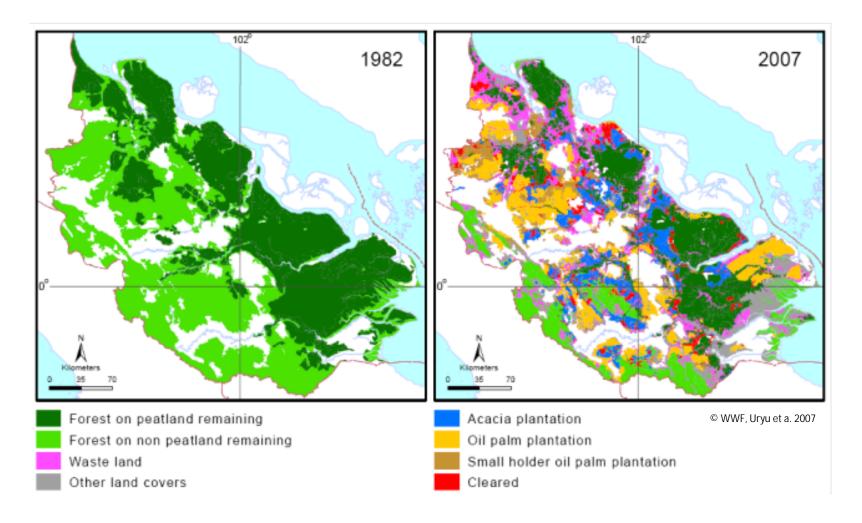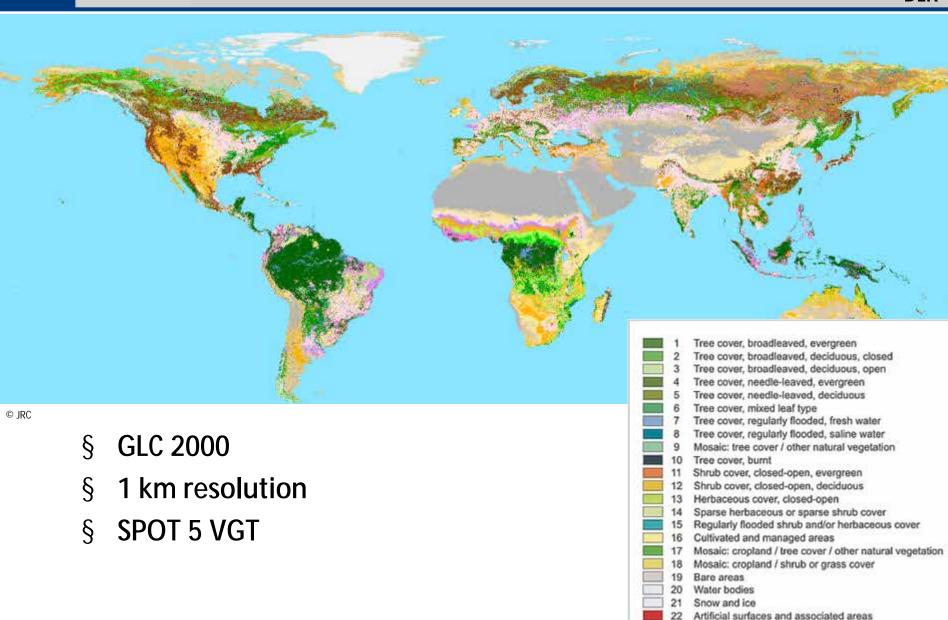
§   Land use change from 1982 until 2005 in Sumatra, Indonesia

© JRC

§ GLC 2000

§ 1 km resolution

§ SPOT 5 VGT

	1	Tree cover, broadleaved, evergreen
	2	Tree cover, broadleaved, deciduous, closed
	3	Tree cover, broadleaved, deciduous, open
	4	Tree cover, needle-leaved, evergreen
	5	Tree cover, needle-leaved, deciduous
	6	Tree cover, mixed leaf type
	7	Tree cover, regularly flooded, fresh water
	8	Tree cover, regularly flooded, saline water
	9	Mosaic: tree cover / other natural vegetation
	10	Tree cover, burnt
	11	Shrub cover, closed-open, evergreen
	12	Shrub cover, closed-open, deciduous
	13	Herbaceous cover, closed-open
	14	Sparse herbaceous or sparse shrub cover
	15	Regularly flooded shrub and/or herbaceous cover
	16	Cultivated and managed areas
	17	Mosaic: cropland / tree cover / other natural vegetation
	18	Mosaic: cropland / shrub or grass cover
	19	Bare areas
	20	Water bodies
	21	Snow and ice
	22	Artificial surfaces and associated areas
	23	No data

Post classification change detection on the basis of MOD12Q1 land cover product
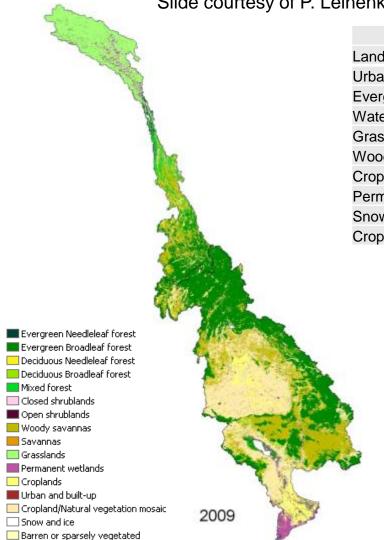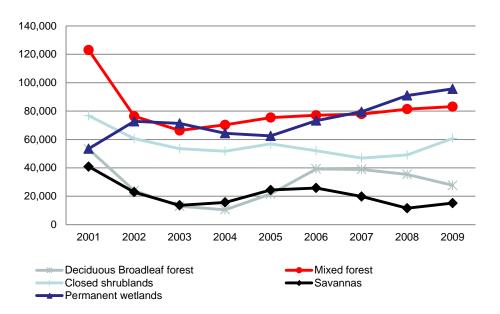
Slide courtesy of P. Leinenkugel

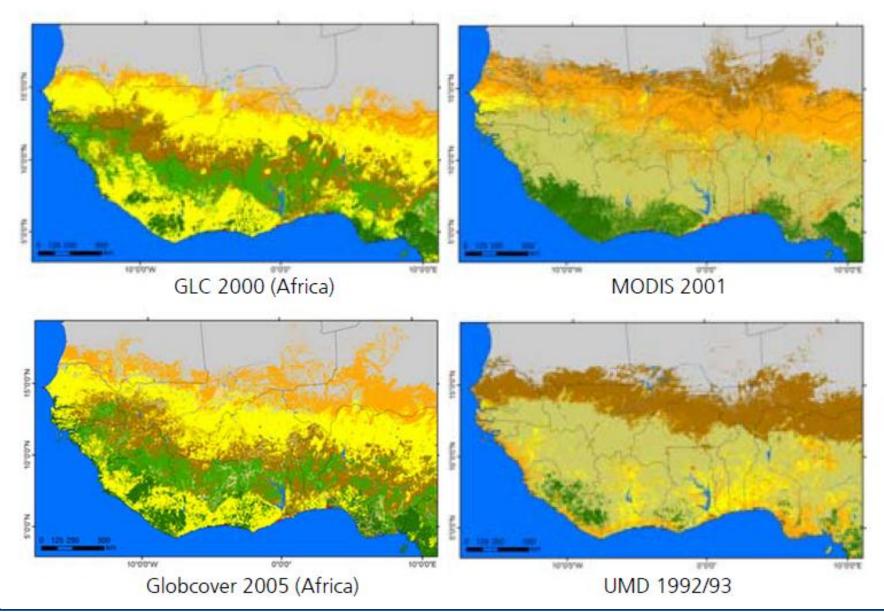Slide courtesy of P. Leinenkugel

Stable Pixels 2001-2009			
Land Cover Type	Per Cent	Land Cover Type	Per Cent
Urban and built-up	98%	Evergreen Needleleaf forest	22%
Evergreen Broadleaf forest	80%	Mixed forest	17%
Water	64%	Closed shrublands	12%
Grasslands	63%	Barren or sparsely vegetated	2%
Woody savannas	38%	Open shrublands	1%
Cropland/Natural vegetation mosaic	34%	Deciduous Needleleaf forest	0%
Permanent wetlands	33%	Deciduous Broadleaf forest	0%
Snow and ice	24%	Savannas	0%
Croplands	23%		

Evergreen Needleleaf forest
Evergreen Broadleaf forest
Deciduous Needleleaf forest
Deciduous Broadleaf forest
Mixed forest
Closed shrublands
Open shrublands
Woody savannas
Savannas
Grasslands
Permanent wetlands
Croplands
Urban and built-up
Cropland/Natural vegetation mosaic
Snow and ice
Barren or sparsely vegetated

2009

GLC 2000 (Africa)

MODIS 2001

Globcover 2005 (Africa)

UMD 1992/93

8
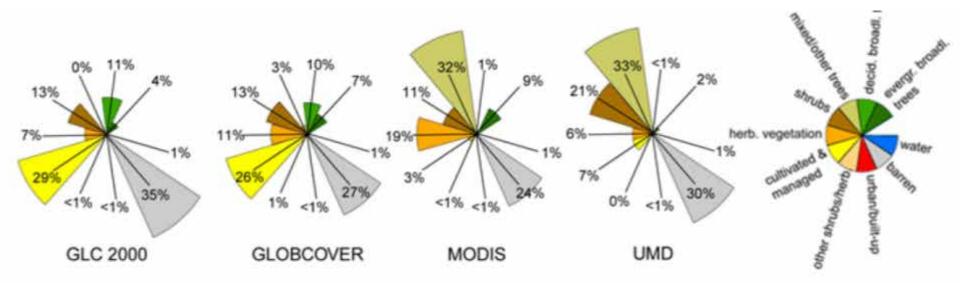
Table 1. Generalized land cover legend for map comparison in West Africa including labels of the Land Cover Classification System (LCCS).
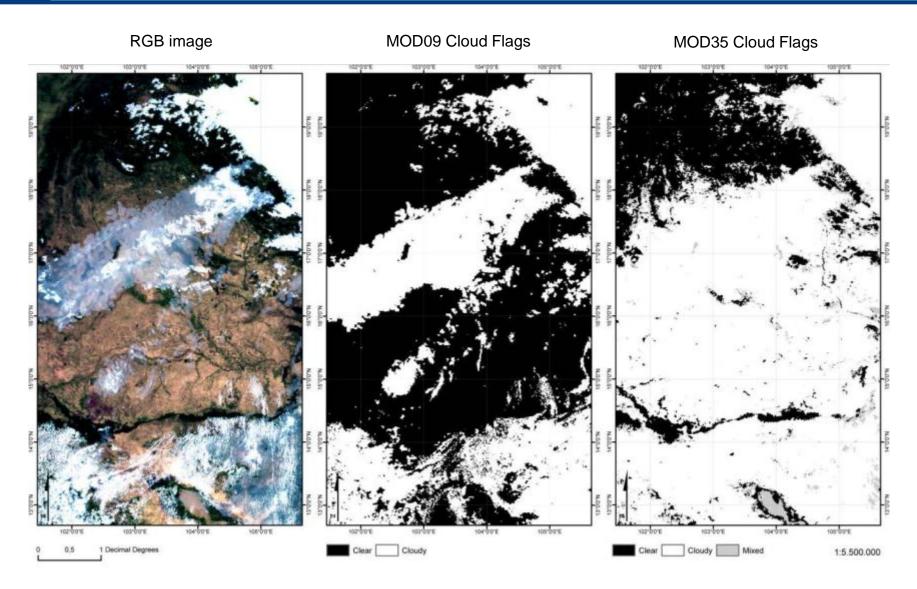
Generalized class		LCCS Label
evergreen broadleaf trees		A12-A3.A20.B2.XX.D1.E1 and A12-A3.A10.B2.XX.D1.E1 and A24-A3.A20.B2.XX.D1.E1
decidous broadleaf trees		A12-A3.A20.B2.XX.D1.E2 and A12-A3.A10.B2.XX.D1.E2
mixed/other trees		A12-A3.A20.B2 and A24-A3.A20.B2
shrubs		A12-A4.A20.B3
herbaceous vegetation		A12-A2.A20.B4
cultivated and managed vegetation/ agriculture (incl. mixtures)		A11 and A23
other shrub/herbaceous vegetation		A24-A2 and A24-A4
urban/built up		B15
barren		B16 and A12-A1.A14 and A12-A2.A14
water		B27-A1 and B28-A1

RGB image   MOD09 Cloud Flags   MOD35 Cloud Flags

Slide courtesy of P. Leinenkugel

Land Cover, GLC_____

Precipitation ECMWF (0.25°)

Wind Speed, ECMWF (_____

Temperature, ECMW_____

PAR, ECMWF (0.25_____

LAI, SPOT (1 km)

Photosynthetic Reactions

CO_2

H_2O & O_2

Input Data

University of California Museum of Paleontology's Understanding Evolution

Chart:
- GPP for period 2002/2003 [tC/km²]
- NPP for period 2002/2003 [tC/km²]
- LAI for trees [m²/m²]

Y-axis left: NPP [tC/km²]
Y-axis right: LAI [m²/m²]
X-axis: Julian Day [d]
182 212 242 272 302 332 362 27 57 87 117 147 177

Model Output:
- Gross- and Net- Primary-Productivity
  Maintainance Respiration
  à NPP = GPP - MR

Landsat-7 ETM+ Satellite Map of Parts of Xinjiang Uigur Autonomous Region, China

Histogram of the data set
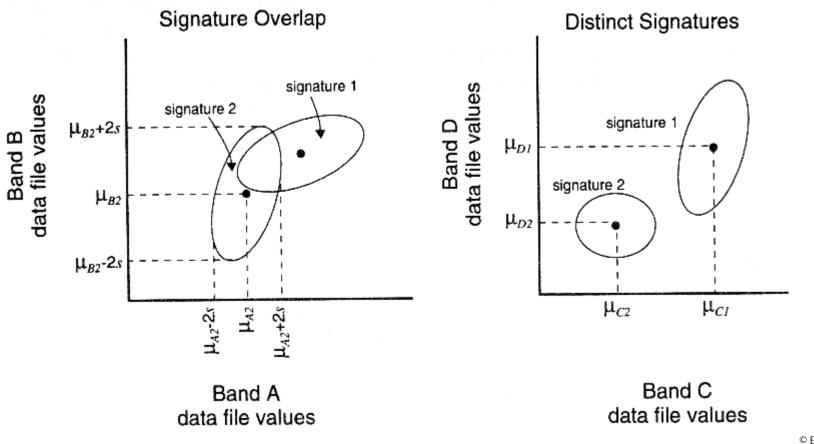
Grey value transfer function

(Class code)

© ERDAS 1997
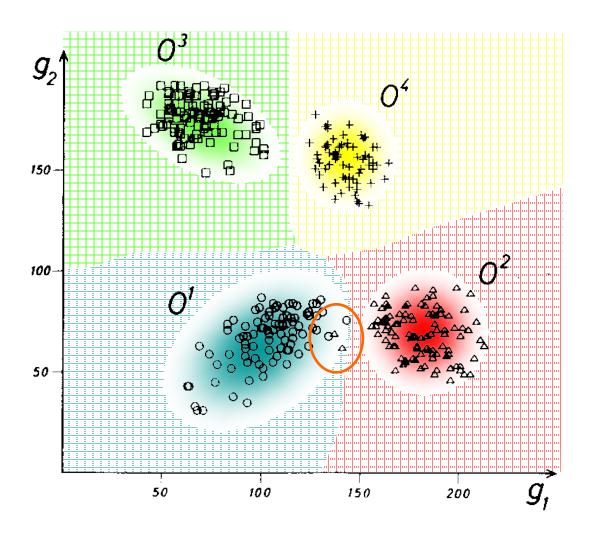
§ position of two pixel clouds in a two dimensional feature space
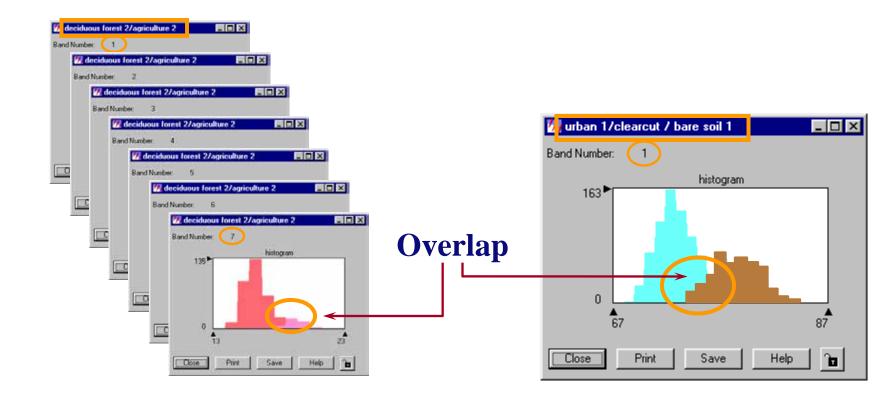
§ **Illustrates the distribution of signatures**

§ **Shows possible confusion in signatures**

Overlap

DLR

§ **Supervised: interactive**

§ The supervised classification is based on utilising known **training areas** for classification

§ The user **defines training areas** for each class in the **satellite image** and the classification algorithm searches for further pixels with similar properties (statistical analysis of the entire scene)

§ The spectral properties of each class are derived from the regional **mean values** of the training areas and the respective **covariance**

§ **Result: homogeneous classes with explicit labels**

§ E.g. *box -, parallelepiped -, minimum distance -, spectral angle mapper -, maximum likelihood - classification*

§ **Characteristic properties of the class Oi are**

- Mean value

$$\overline{g}_k^i = \frac{1}{N} \sum_{l=1}^{N} g_{k,l}^i \qquad\qquad k = 1, K$$
$$i = 1, I$$

k   ...   Band index

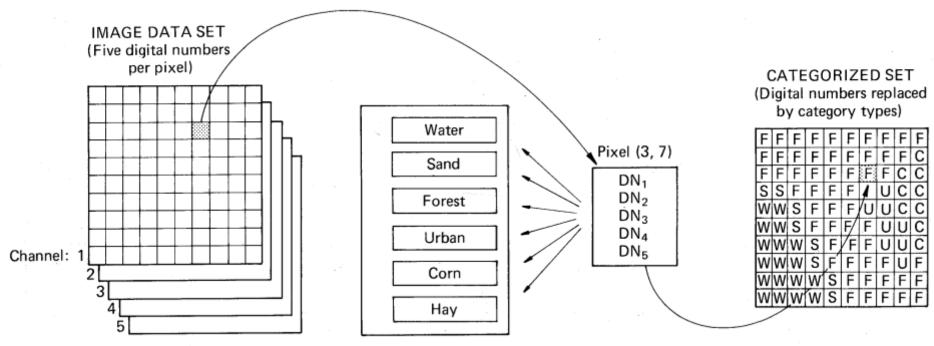N   ...   Number of pixel in the training area

i   ...   Class index

- Standard deviation (for individual bands) or variance-covariance function

$$s_k^i = \sqrt{\frac{\sum_{l=1}^{N} \left(g_{k,l}^i - \overline{g}_k^i\right)^2}{N - 1}} \qquad\qquad k = 1, K$$
$$i = 1, I$$

IMAGE DATA SET
(Five digital numbers per pixel)

Channel: 1 2 3 4 5

Water
Sand
Forest
Urban
Corn
Hay

Pixel (3, 7)
DN_1
DN_2
DN_3
DN_4
DN_5

CATEGORIZED SET
(Digital numbers replaced by category types)

(1) TRAINING STAGE
Collect numerical data from training areas on spectral response patterns of land cover categories

(2) CLASSIFICATION STAGE
Compare each unknown pixel to spectral patterns; assign to most similar category

(3) OUTPUT STAGE
Present results:
maps
tables of area data
digital data files

© Lillesand 1978

§ **Unsupervised: without user interaction**

§ Purely mathematical, statistical analysis of spectral bands

§ Cluster analysis for the determination of discriminable classes in a defined **n-dimensional feature space (**n = number of bands)

§ Purely mathematical approach; no semantics, meaning of the features has no relevance

§ Algorithm groups image pixels into clusters **(grouping is based on statistical properties)**

§ Result: homogenous classes without any thematic connotation

§ The thematic meaning of each cluster has to be assigned by the user in a further step (**class assignment**)

§ e.g. *isodata* algorithm, *k-means* algorithm

Unsupervised classification	Supervised classification
Computational intensive, adequate for quick 'snapshot': which classes are spectrally well discriminable?	Computational less intensive
Previous knowledge not required (but desirable!)	Knowledge on study area should exist (ground truth, GPS)
Definition of number of classes is critical: If to high – classes not discriminable, if to low – unnecessary merging of classes	Selection of training areas critical: risk of being not representative, not enough, extreme overlap of classes in the feature space
Results are objective (class assignment subjective!)	Results depend on selected training areas selected by the user
Applicable to arbitrary data sets; however, class assignment individually for each data set!	For each new EO-data: possibly new training sites necessary (illumination- and atmospheric conditions, land cover dynamics…)
‚New', unknown classes in the study area can be identified	Only already defined classes (based on training sites) can be identified
Accuracy often insufficient	Approved method
Both approaches can be performed with prevalent remote sensing software packages	

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Supervised/ unsupervised classification

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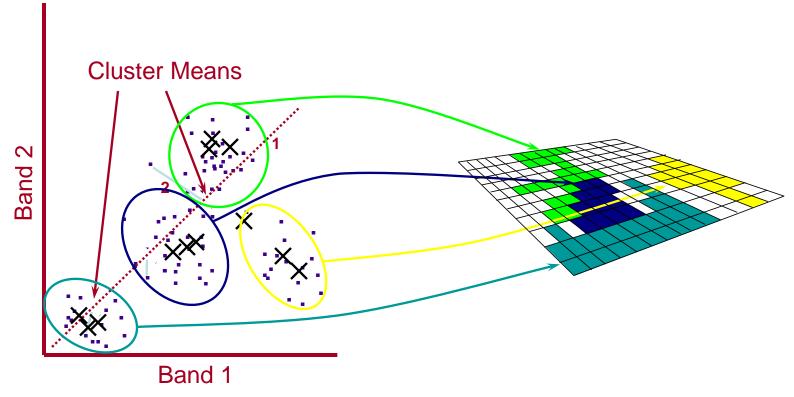| Unsupervised classification	Supervised classification
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- § **Iterative algorithm**
- § Divides pixels successively into **subpopulations (clusters)**
- § **Iterative grouping into clusters is determined according to spectral distance to the clusters' mean value**
- § Each pixel is iteratively assigned to the class with the shortest spectral distance to the class centre point
- § Input parameters by the user: **number of clusters, number of iterations, termination condition**

The ISODATA algorithm uses the minimum spectral distance formula to form clusters. After the initial clusters are formed the process repeats itself, locating new means. These new means are then used in the next iteration, and the next until either the maximum number of iterations has been performed OR the maximum percentage of unchanged pixel assignments has been reached.

Disadvantage

§ **Computational intensive**

§ Accuracy often **insufficient**

Advantage
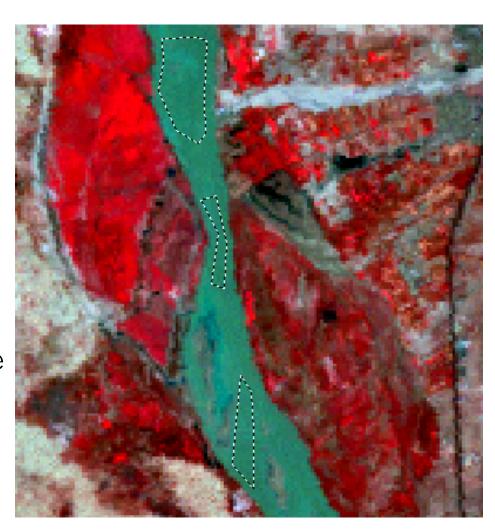
§ adequate for quick '**snapshot**': which classes are spectrally well discriminable?

§ 'New', **unknown classes** in the study area can be identified

§ **Previous knowledge** not required

§ Results objective, only **spectral properties** are assessed

§ **Standard method**, implemented in all remote sensing software packages

- § User defines several training sites (TS) for each class

- § The more heterogeneous the class, the more TS required

- § TS should be as homogenous as possible

- § Selection of TS should be evenly distributed over the entire image

- § TS also usable as cluster centres

- § Numerous 'supervised ' classification algorithms e.g. MinDist, MaxLikeli,...

§ **Determination of multidimensional 'boxes' around the class centre points (in consideration of the standard deviation)**

§ **Uses Euclidian distance**

§ **Considers statistics** (calculation of standard deviation for each band)

© Lillesand 1978

§ **Distinctive feature:**

- Box surrounding mean value with extent of h-fold standard deviation

§ Consideration of variance

§ May generate overlapping classes in the feature space
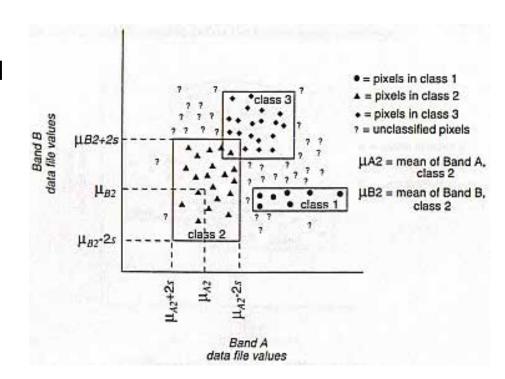
§ Class membership of each pixel is assessed
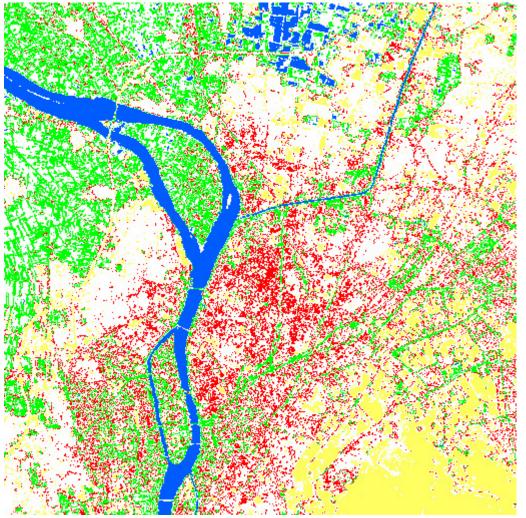
§ ‚Parallel piped' classification of Cairo based on Landsat TM

§ Pseudo colour TM 7, 5, 2 und 4, 2, 1

© ESA
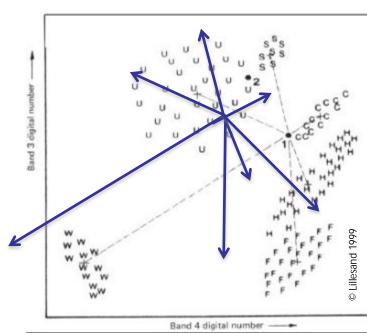
§ *Minimum distance to mean values*

§ Class representation:

- Mean -Vector:

$$\overline{\mathbf{g}}^{\mathbf{i}} = \left(\overline{g}_1^{\,i} \;\; ... \;\; \overline{g}_k^{\,i} \;\; ... \;\; \overline{g}_K^{\,i} \right)^{T}$$

§ Class assignment

- Each pixel is assigned to the class with the minimum distance to the class' mean value in the feature space

§ Discriminator

- in 2D-space: perpendicular bisector

- in nD-space: Hyper-plane

© Lillesand 1999

Band 3 digital number

Band 4 digital number

§ **Calculation of Euclidian distance between pixel U and centre points O^i:**

$$d = \sqrt{(\mathbf{g} - \overline{\mathbf{g}}^i)^T (\mathbf{g} - \overline{\mathbf{g}}^i)}$$

$$d^2 = (\mathbf{g} - \overline{\mathbf{g}}^i)^T (\mathbf{g} - \overline{\mathbf{g}}^i)$$
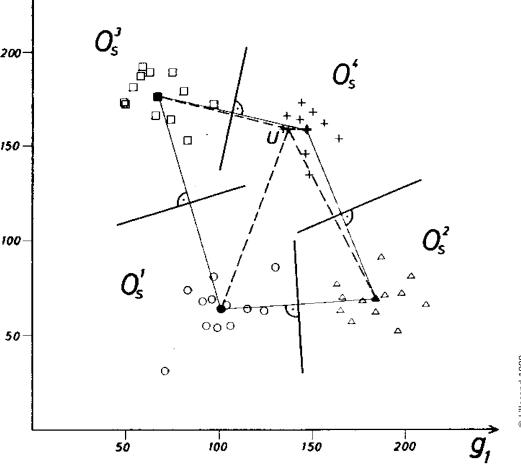
§ **Advantage**
- Easy calculation
- In order to avoid misinterpretations: small assignment radii

§ **Disadvantage**
- Inadequate statistical rationale
- Does not account for range of dispersion
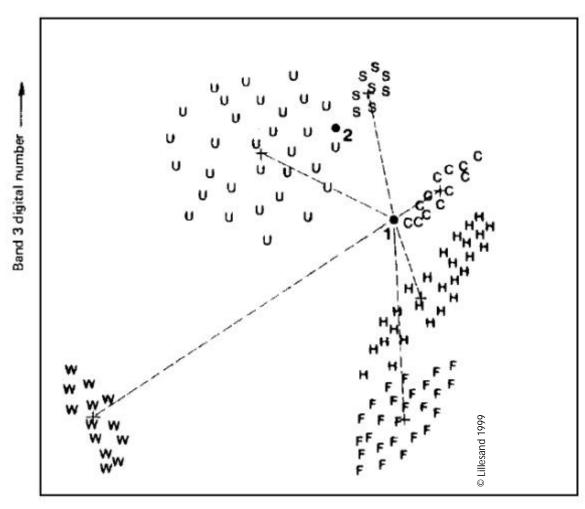
© Lillesand 1999

© Lillesand 1999
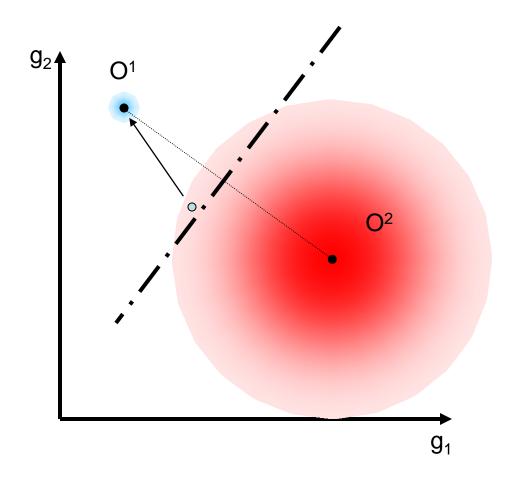
§ Example for „unjustified" assignment

- Class 1: homogeneous (e.g. water surface)

- Class 2: heterogeneous class (e.g. settlement)

- Pixel close to the perpendicular bisector may be assigned to the homogenous class, although membership to the inhomogeneous class is more probable
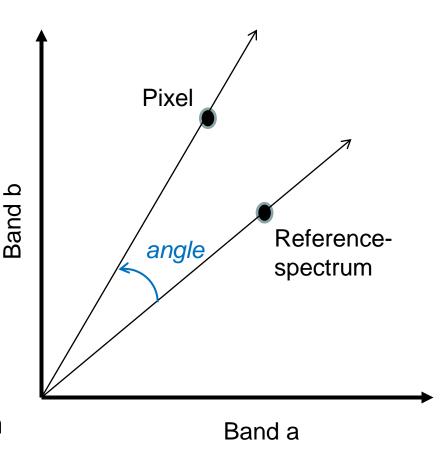
- § The **SAM-Method** is based on the estimation of the spectral similarity in the (n-dimensional) feature space
- § Signature is described by a vector, starting at the coordinate system's origin
- § Length of the vector resembles reflection intensity
- § Difference between spectra is described by the angle
- § By **assessing the angle difference** between pixel and reference spectrum an image can be divided in any number of classes

Band b

Pixel

angle

Reference-spectrum

Band a

§ Calculation of angle α is based on trigonometric function of the arc cosine, for which for all bands *nb*, all angles between the sum of all target pixels *t,* and all reference pixels *r* is calculated

$$\alpha = \cos^{-1}\left(\frac{\sum\limits_{i=1}^{nb} t_i r_i}{\left(\sum\limits_{i=1}^{nb} t_i^2\right)^{1/2}\left(\sum\limits_{i=1}^{nb} r_i^2\right)^{1/2}} \right)$$

α = spectral angle between vectors
nb = number of spectral bands
t = target pixel
r = reference pixel

§ **A pixel is assigned to the class whose spectrum has the smallest angle with the respective pixel**

§ Size of the angle in radiant

§ Angle is assessed, not the length of the vector!
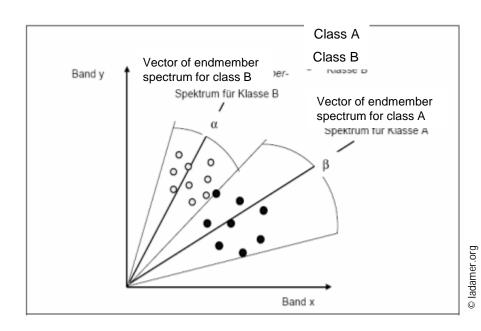
§ **Advantage**

- Fast and easy approach

- Comprehensible for the user

- Relative robust against Illumination differences (topography, light source, sensor, etc.)

- Comparability of image spectra with lab spectra

Class A
Class B

Vector of endmember spectrum for class B

Vector of endmember spectrum for class A

Band y

Spektrum für Klasse B

α

β

Spektrum für Klasse A

Band x

© ladamer.org

§ **Disadvantage**

- Illumination tolerance is accompanied by insensitivity for detecting certain physiologic changes

- Similar spectra, which only significantly differ in their albedo (e.g. needle leaf and broad leaf forests), are wrongly classified

Mean value:

$$\overline{g}_k = \frac{1}{N} \mathring{\sum}_{l=1}^{N} g_{k,l} \qquad k = 1, K$$

$$\overline{\mathbf{g}} = \begin{pmatrix} \overline{g}_1 & \dots & \overline{g}_k & \dots & \overline{g}_K \end{pmatrix}^T$$

Variance-Covariance-Matrix:

$$\mathbf{C} = \begin{pmatrix} s_1^2 & \llcorner & s_{1K} \\ \mathbb{M} & & \mathbb{M} \\ s_{K1} & \llcorner & s_K^2 \end{pmatrix} \qquad s_{ij} = s_{ji}$$

© Simpsons

Matrix diagonal: variances of the single variables

Other fields: co-variances between the image bands

Variance = square of standard deviation:

$$s_k^2 = \frac{1}{N-1} \mathring{\sum}_{l=1}^{N} \left(g_{k,l} - \overline{g}_k \right)^2 \qquad k = 1, K$$

Covariance (for multiple variables):

Measure for correlation between two or more variables

$$s_{ij}^2 = \frac{1}{N-1} \mathring{\sum}_{l=1}^{N} \left(g_{i,l} - \overline{g}_i \right)\left(g_{j,l} - \overline{g}_j \right) \qquad i, j = 1, K$$

variable 1   variable 2

$$f\begin{pmatrix} g_1 \\ g_2 \end{pmatrix} = \frac{1}{2p\sqrt{s_1^2 s_2^2 - s_{12}^2}} \exp\left(-\frac{s_1^2 s_2^2}{2(s_1^2 s_2^2 - s_{12}^2)}\left(\frac{(g_1 - \overline{g}_1)^2}{s_1^2} - 2s_{12}\frac{(g_1 - \overline{g}_1)(g_2 - \overline{g}_2)}{s_1^2 s_2^2} + \frac{(g_2 - \overline{g}_2)^2}{s_2^2}\right)\right)$$

$$\frac{s_1^2 s_2^2}{(s_1^2 s_2^2 - s_{12}^2)}\left(\frac{(g_1 - \overline{g}_1)^2}{s_1^2} - 2s_{12}\frac{(g_1 - \overline{g}_1)(g_2 - \overline{g}_2)}{s_1^2 s_2^2} + \frac{(g_2 - \overline{g}_2)^2}{s_2^2}\right) \pounds h^2$$

Lines of similar probability densities in **2D-case ellipse**

© Albertz 1991
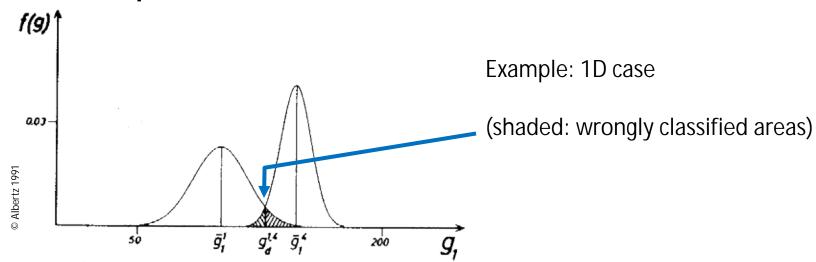
Porbability density function 3D case
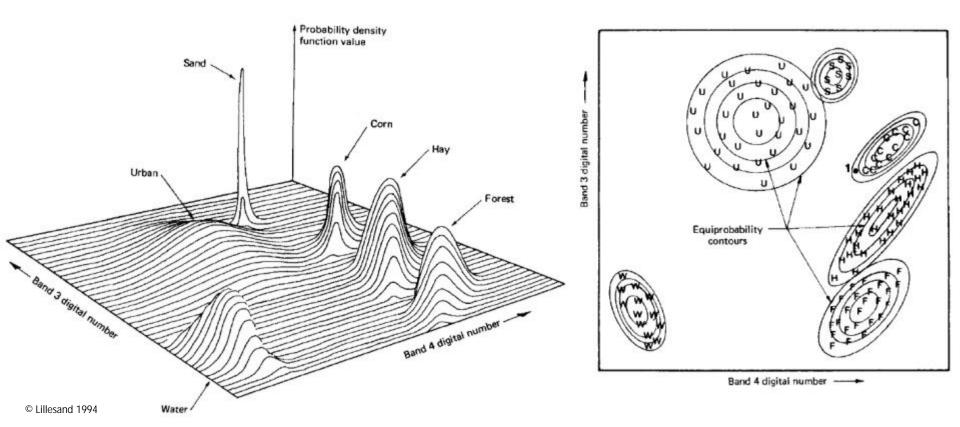
§ **Is based on k-dimensional normal distribution**

§ **Class membership is based on highest probability density**

§ **Discriminator:**

- **Isolines with equal probability density between the respective classes**

Example: 1D case

(shaded: wrongly classified areas)

© Albertz 1991

47

© Lillesand 1994

- § Probability density function calculated on the basis of mean vector and covariance matrix
- § Vertical axis: probability of class membership
- § Each spectral class has a probability density function (bell shaped) of class membership
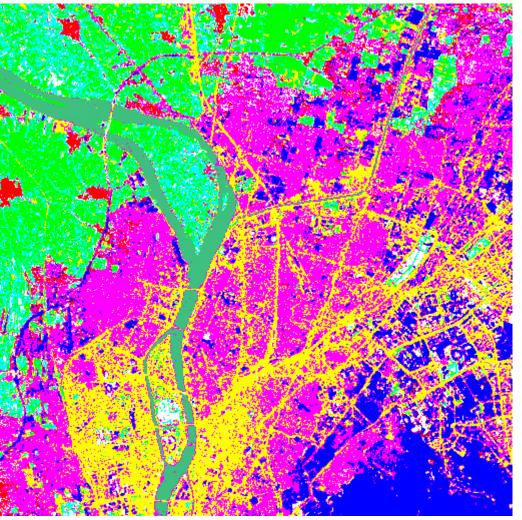
§ **Maximum Likelihood Classification of Cairo City based on Landsat TM**

§ **Pseudo colour TM 7, 5, 2 und 4, 2, 1**

© ESA

§ **Support Vector Machines (SVM)**

§ **Large margin classifier**

§ **Groups a population within an d-dimensional feature space in classes so that the margin between the classes is maximised**

§ **Starting position**
- **n training data** $(x_1\ y_1)$, $(x_2\ y_2)$, ..., $(x_n\ y_n)$
- with $x_i \epsilon R_g$
- and $y_i \epsilon \{-1, +1\}$ (i=1,2,...N)

§ **Geometrical approach**
- Group samples in the feature space into two classes using a hyperplane
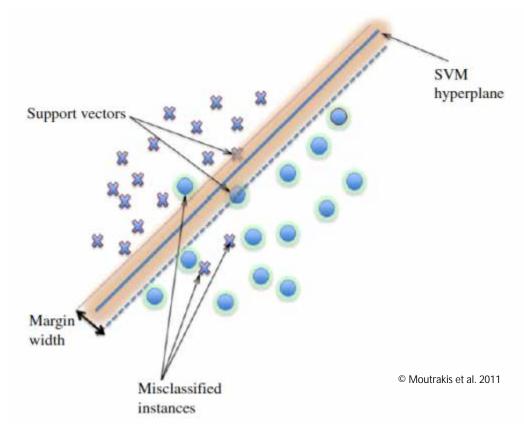
© ESA

§ Optimisation problem: Maximising distance between classes and hyper plane

© Moutrakis et al. 2011
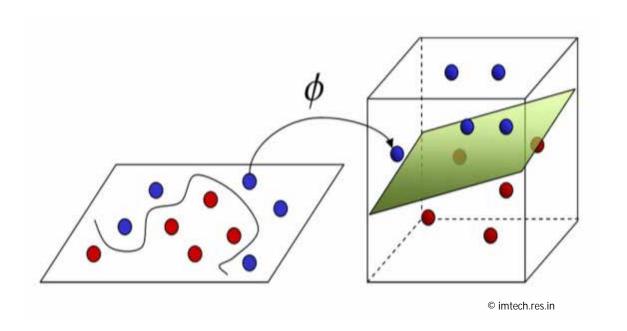
- § Also in n-dimensional feature space applicable
- § Also for non-linear discriminable classes applicable

© imtech.res.in
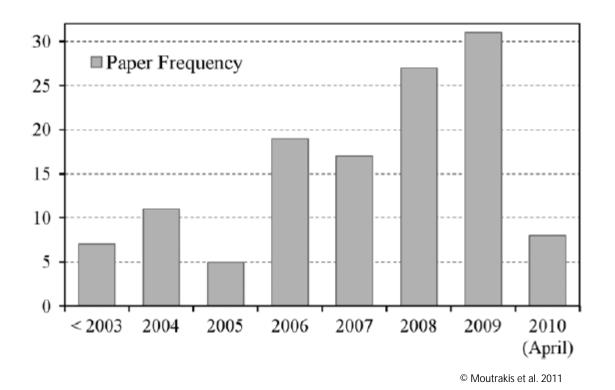
§ **Popularity of SVMs in remote sensing analyses within the last decade**

© Moutrakis et al. 2011

⊖ Disadvantage

§ New training data required for each input data set (even after e.g. atmospheric correction differences in class variance

§ Non-linear discriminable data require additional computing time
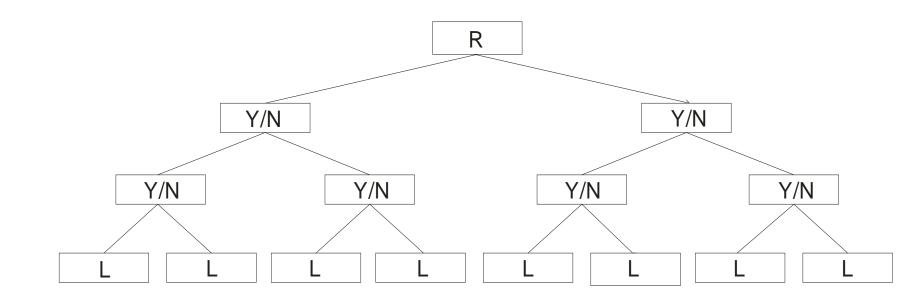
⊕ Advantage

§ Little computational costs (based only on a few support vectors)

§ Good generalisation (performs well for heterogonous classes)

§ Good results with only a small number of training data

§ works well also with high number of dimensions (multi/hyperspectral)

- § Many global land cover classifications
- § Friedl & Brodley, Hansen et al., Cihlar et al., Wen & Tateishi, …
- § Well suited for differentiation of vegetation types
- § Often used for local surface extraction (cloud, snow, ice …)
- § Terms: Root, Branches, Nodes, Leaf

Disadvantage

§ A-priori knowledge required

§ Construction of tree is labour- and time-intensive

§ Decision rules are only transferable with limitations (variation in time and space)

Advantage

§ Quite flexible and versatile applicable

§ Standardised and comparable results

§ Only little additional efforts once the decision tree is constructed

§ very focused with respect to band and feature selection

§ decisions are based on physical properties

§ extendable and transferable (with certain efforts for adaptation)

§ Only little previous knowledge required to apply existing tree

§ reasonable for large areas

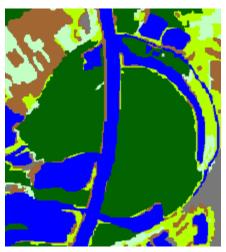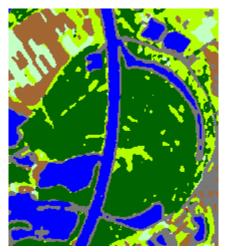§ Implemented in all commercial remote sensing software packages

Fields of application

§ High resolution data (Airborne, IKONOS, QuickBird, ETM+, ASTER)

§ Complex land use classes (Urban areas, commercial areas, road networks,...especially images with 'structures')

§ Detailed land use and vegetation classification

§ Software: eCognition (Definiens Developer)

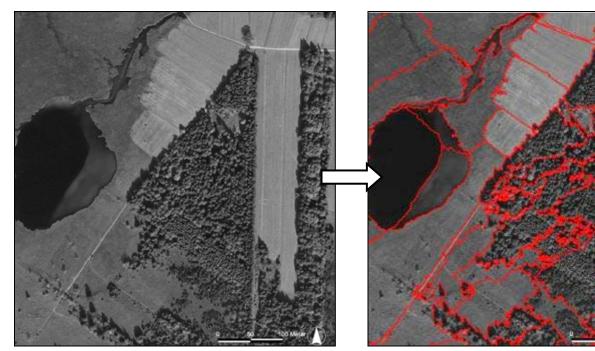Satellite Image   object–oriented result   pixel based result

Supervised: Object-oriented classification (II)

Data

Segmentation

Object DB

IKONOS 08/2001

Segments

© Mott, TU München 2003

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

§ Segmentation: the scale-parameter

"scale" parameter increases: generalisation increases

"scale" parameter decreases: level of detail increases

© Mott, 2005

Object

Grey level

Form

Texture

Context

Object

Grey level

Form

Texture

Context

Additional Information

Object

Grey level

Form

Texture

Context

Additional Information

...

IKONOS 08/2001

© Mott, TU München 2003

§ **Construction of a semantic network**

§ **Objects of various scale levels are interconnected**
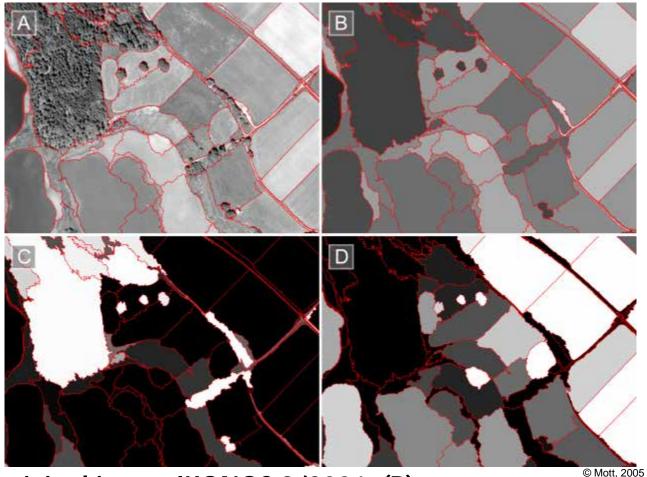
Level 2

Level 1

© Mott, 2005

"Bottom up region merging technique" starts on the 1-pixel-object level. The objects that are created on different scales are connected by a hierarchical network.

§ **Object features**

© Mott, 2005

§ (A)original image IKONOS 8/2001, (B) mean,
(C) standard deviation, (D) ,compactness'

§ **Construction of class descriptions via fuzzy-membership curves for significant object features**

Y = Degree of fuzzy-membership

X = object value

"crisp"   "fuzzy"   "crisp"   "fuzzy" "crisp"

© Mott, 2005

UNIVERSITÄT WÜRZBURG
Julius-Maximilians-

DLR

Area wide classification

- ■ wetland
- ■ LW - meadow
- ■ LW - maize
- ■ LW – grass land typ 1
- ■ LW – grass land typ 2
- ■ Needle-leaved forest
- ■ Broad-leaved forest
- ■ Settlement/ impervious surface
- ■ Water surface

„ **Distinctive land cover classes in ArcView-Shape format**
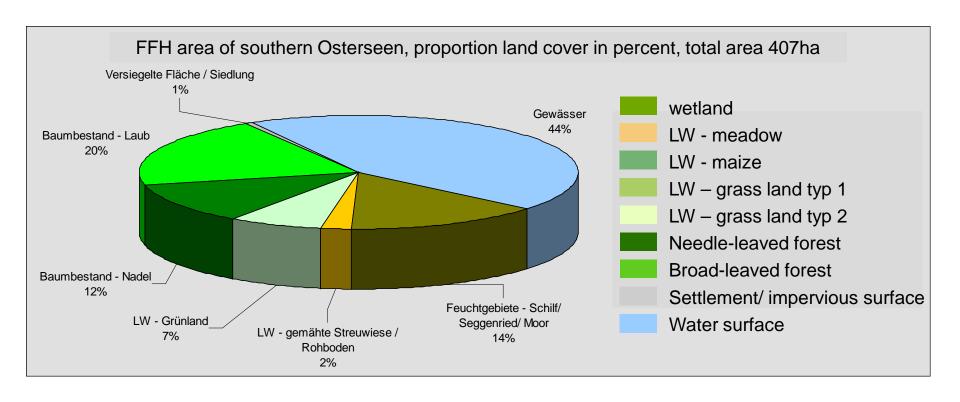
„ **Classification by NSG/FFH**

IKONOS 08/2001

0   250   500   1.000 Meters

N

© Mott, TU München 2004

§   Quantitative statements possible

FFH area of southern Osterseen, proportion land cover in percent, total area 407ha

- wetland
- LW - meadow
- LW - maize
- LW – grass land typ 1
- LW – grass land typ 2
- Needle-leaved forest
- Broad-leaved forest
- Settlement/ impervious surface
- Water surface

Versiegelte Fläche / Siedlung
1%

Gewässer
44%

Baumbestand - Laub
20%

Baumbestand - Nadel
12%

LW - Grünland
7%

LW - gemähte Streuwiese /
Rohboden
2%

Feuchtgebiete - Schilf/
Seggenried/ Moor
14%

IKONOS 08/2001

© Mott, TU München 2004

	wetland
	LW - meadow
	LW - maize
	LW – grass land typ 1
	LW – grass land typ 2
	Needle-leaved forest
	Broad-leaved forest
	Settlement/ impervious surface
	Water surface
	Single trees

0   125   250   500   Meter

N

„ Landscape elements can be detected automatically

„ Relationships between adjacent objects!

SPOT5 satellite image

(24.03.2010)

N

0   3.75   7.5   15 km

pixels: 10m resolution
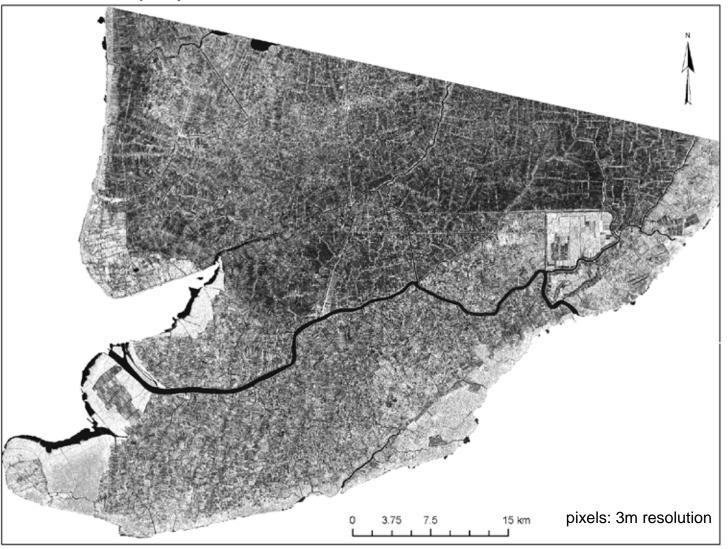
TerraSAR-X Stripmap HH mosaic

(31.12.2009; 13.02.2010; 24.02.2010)
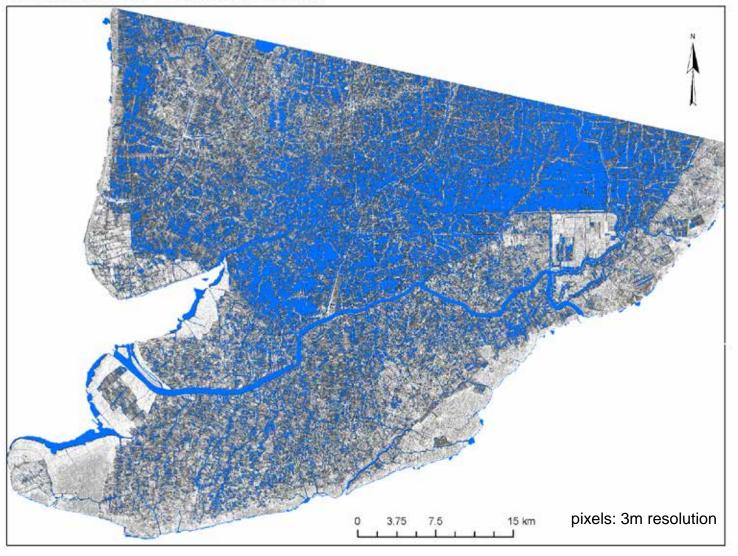
0   3.75   7.5   15 km

pixels: 3m resolution

Watermask from TerraSAR-X mosaic
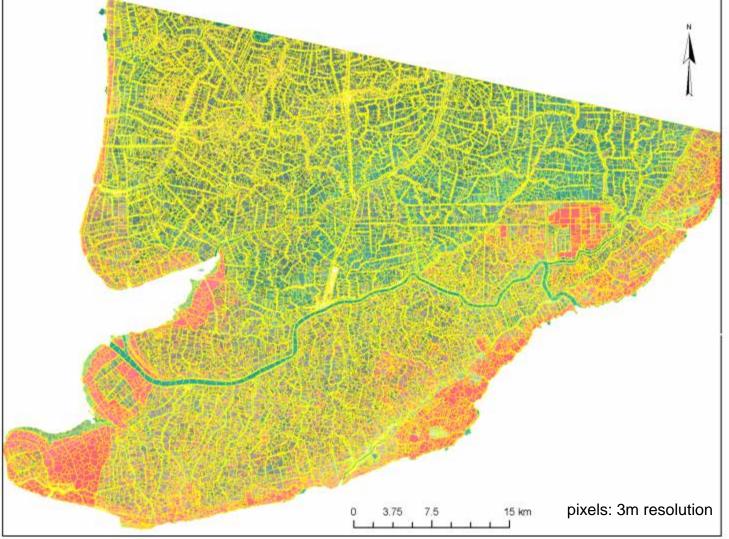
pixels: 3m resolution

SPOT5 Image segmentation

(24.03.2010)

pixels: 3m resolution
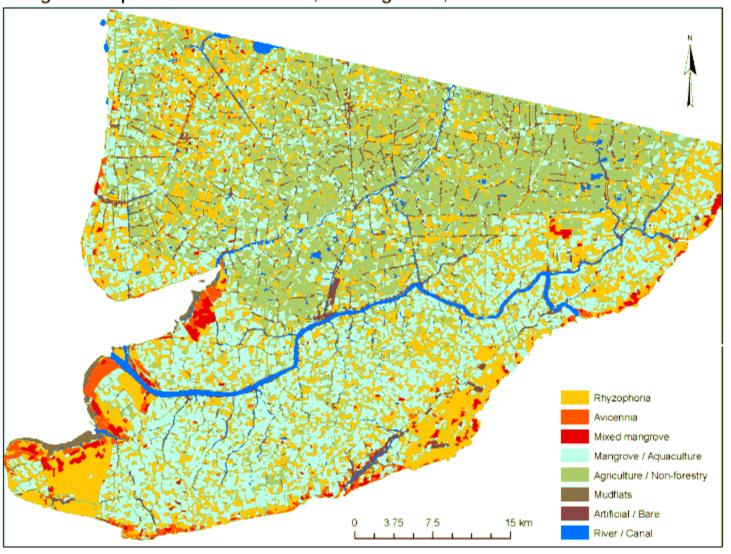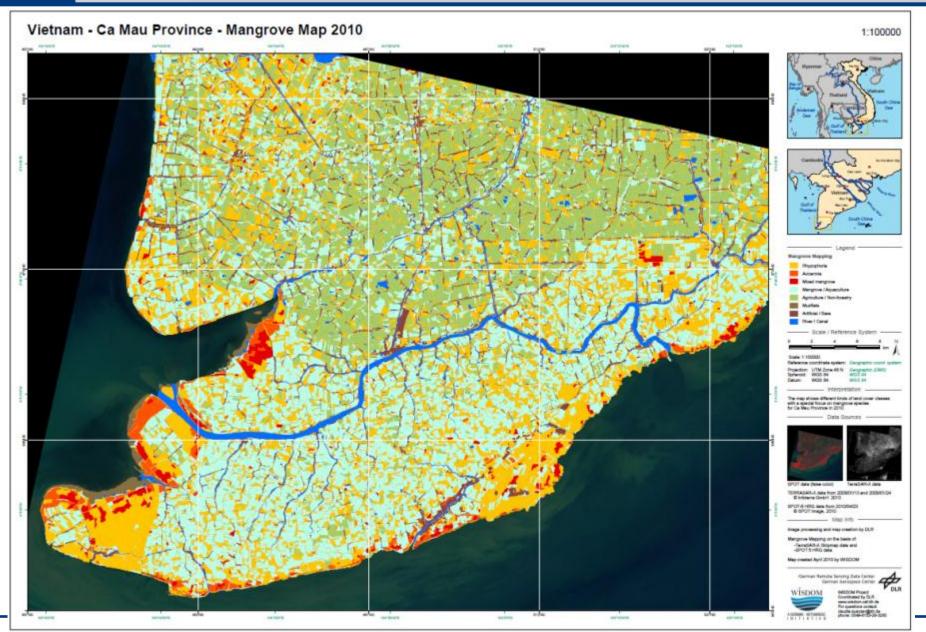
Mangrove Map for Ca Mau Province, Mekong Delta, Vietnam. 2010.

Legend:
- Rhyzophoria
- Avicennia
- Mixed mangrove
- Mangrove / Aquaculture
- Agriculture / Non-forestry
- Mudflats
- Artificial / Bare
- River / Canal

0   3.75   7.5   15 km

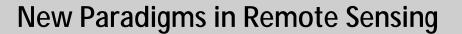Vietnam - Ca Mau Province - Mangrove Map 2010

⊖ Disadvantages

- Only few, relatively expensive(!) software solutions (dongle)
- Iterative, very(!) time consuming process
- Quality highly dependent on competence of user
- Rule set often only partly transferable
- Ok for smaller areas, but not so much for mass data throughput

⊕ Advantages

- Very high accuracies can be obtained
- Direct post-processing in GIS
- Fuzzy logic rationale applicable
- Additional object features (beside spectral information) can be used for classification
- Very useful if spectral variance within a class is higher then spectral variance between classes (e.g. urban)

How much is too much???

Do you really want to see every single car?

Too much information also creates confusion.

300 channels are usually not more useful than 150. The same might apply for spatial resolution: at one point its all too much.

There are 2 essential questions you need to ask for each classification:

1. How accurate is the classification?

2. How was the accuracy recorded?

If these questions are not answered adequately, then there is reasonable doubt ...

- § **Different users have different demands for accuracy assessment**
- § **Proper registration of the data**
- § **Errors in the basis for comparison are propagated**
- § **Reference maps**
  - Often not up to date
  - Accuracy unknown
  - Different classification scheme
- § **Field campaign**
  - Time of recording?
  - Expensive
  - Field data is also a type of classification
- § **Data with higher resolution**
  - Time of recording ?
  - Are the classes clearly detectable?
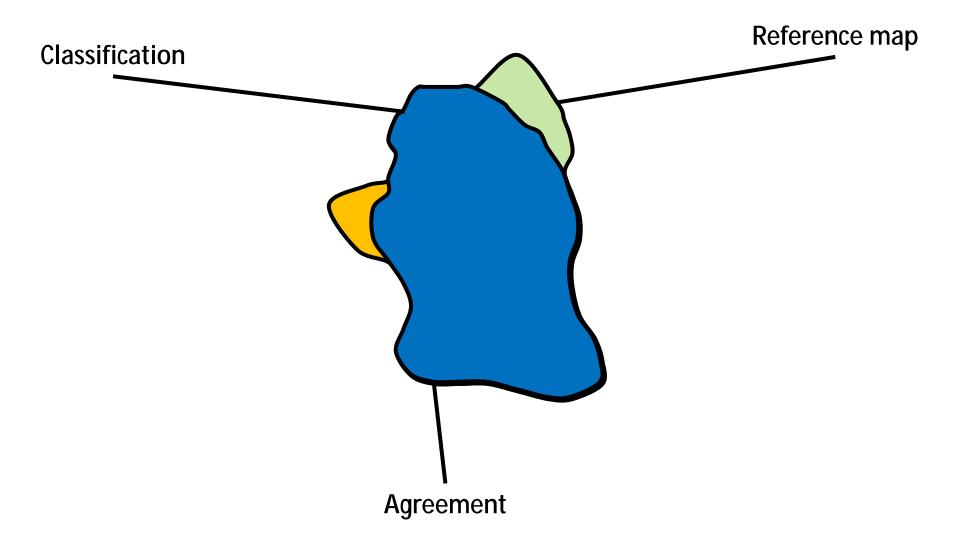 - Spectral resolution (Landsat 7 bands – IKONOS 4 bands)

§ GCPs are **control points** or sample points

- GPS points, which classes were collected in a field survey

- Sample points, which are chosen on the record of this data set or another data set (larger scale: aerial photography, high resolution data)

- Selection of sample points in the image and subsequent field survey (if possible) = **ground truthing**

§ For each control point the „true" class is determined

§ **Accuracy assessment** means:
Comparison of the classification with the assigned „true" class

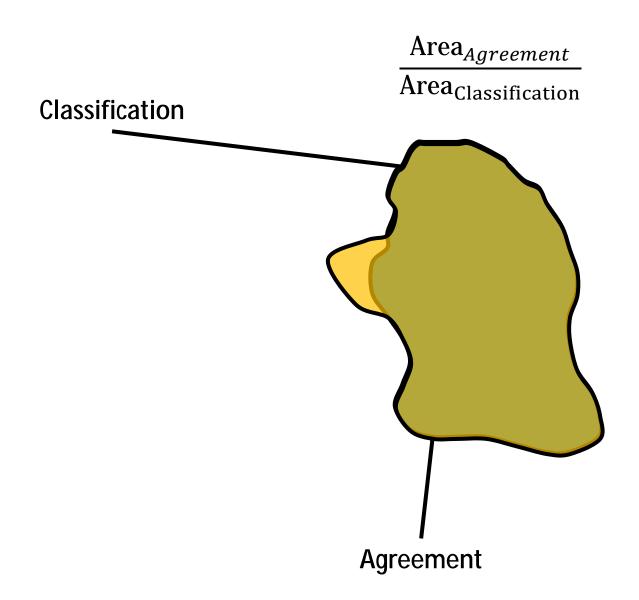§ Results will be shown and analysed in a confusion matrix

Classification

Reference map

Agreement

$$\frac{\text{Area}_{Agreement}}{\text{Area}_{\text{Classification}}}$$

Classification

Agreement

$$\frac{\text{Area}_{\text{Agreement}}}{\text{Area}_{\text{Reference map}}}$$

Reference map

Agreement

E.g.: Class „Forest"

Producer Accuracy: 91 %

User Accuracy: 84 %

Mapped „Forest"

Classification „Forest"

Mapped „Forest"

Mapped „Pasture"

Classification „Forest"

Mapped „Water"

How many % of the training area were correctly classified

Probability, that a pixel, assigned to this class, really belongs to that class

Comparison of the target classes to the actual classes
The reference pixel in the matrix

Referenzkl.	Klassifizierungergebnis				
	Klasse 1	Klasse 2	...	Klasse k	TOTAL
Klasse 1					
Klasse 2					
...					
Klasse k					
TOTAL					

Beispiel:

Referenzkl.	Klassifizierungergebnis				
	Wald	Stadt	Wiese	Industrie	TOTAL
Wald	179	5	10	3	209
Stadt	9	203	57	12	281
Wiese	13	25	176	2	216
Industrie	0	0	0	28	28
TOTAL	201	233	243	45	722

Ground truth polygon that have been mapped during a field campaign

Overall Classification Accuracy : 89.41%

class	Producer Accuracy (%)	User Accuracy (%)
agrar sparse	52.94	93.26
agrar medium	91.08	84.05
agrar dense	96.26	93.26
calcite	76.14	100.00
coal pure	97.56	98.30
coal related	95.70	31.45
desert vegetation sparse	95.45	90.57
desert vegetation medium	81.79	83.75
desert vegetation dense	80.10	70.83
lake deep	87.20	86.51
lake shallow	81.60	100.00
limestone dark	98.61	97.82
limestone light	88.72	61.35
metamorph dark	74.81	94.84
metamorph light	68.97	100.00
mountain vegetation sparse	78.27	88.73
mountain vegetation dense	88.64	52.00
river deep	97.65	82.82
river shallow	80.81	96.85
sand crusted	92.45	24.50
sand dune	86.81	98.14
sand pure	98.65	95.38
sandstone	71.61	100.00
settlement	88.27	100.00
weathered coarse	95.09	85.05
weathered medium	100.00	56.04
shadow	91.92	88.55

- § Aerial photographs or higher-resolution data are considered as a good basis for comparison (Congalton, 1991)

- § Assumption: Interpretation of the higher-resolution data is 100% correct (applies not always)

- § There are also existing land use maps for reference.
  Note: These maps are often not up to date and their accuracy is not well known

§ In order to prevent the „**distortion**" **of the quality measure** certain homogeneous or **uninteresting classes** are usually **excluded** from the validation

§ Depending on the problem, e.g.

- Large bodies of water
- Clouds and cloud shadows
- Snow

Class definition

§ Reference data should be collected under the same assumptions and in the **same class scheme (same classes and decision criteria**), as the classification to be tested

Adequate spatial resolution –

§ **Reference data should be collected in the same scale level** (same MMU). The sample unit (e.g. pixels, pixel clusters, polygons) specifies the level of detail.

Sample number

§ At least ~ **50 Sample per class** it should be. When dealing with a very large study area (> 400,000 ha) or many classes (> 12) the sample number should be increased. (e.g. 75 – 100 per class). The sample number is to be adjusted, dependent on the importance of the class und the class-specific variability in the feature space.

Sampling plan

§ A stratified, randomly distributed sampling plan for each class is to be made. This ensures that all classes are examined.

§ The organization of a field campaign is to be conducted according to the classification.

§ When ground truth data are collected at the beginning of a project it is recommended to distribute the samples randomly. Important is the logical distinction between training and reference areas.

Summarized from **Congalton and Green 1999**

§ **Also known as**
- Spectral Mixture Analysis
- Sub Pixel Classification
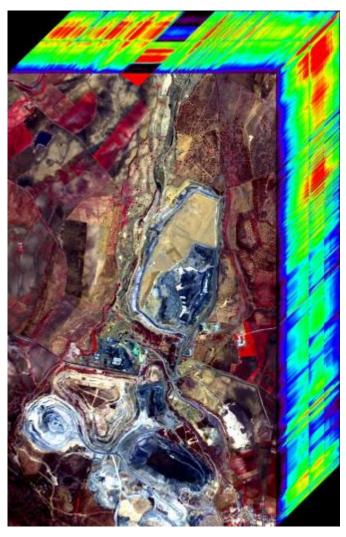
§ **Idea:**
- The majority of the pixels measure the reflectance of more than one „pure" object class („mixed pixels")
- Multispectral data of one pixel include – depending on the area fraction – a weighted average of the reflectance's of the participating object classes
- The task of the „unmixing" is to determine the area fraction of each pixel
- The sub-pixel classification does not determine the sub-pixel location of the classes, but only the portion
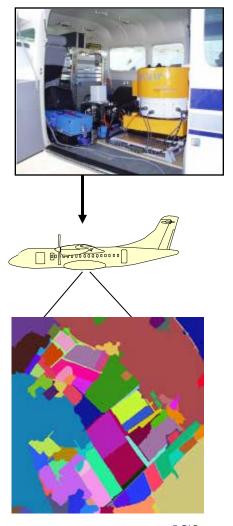
© DLR

© DLR
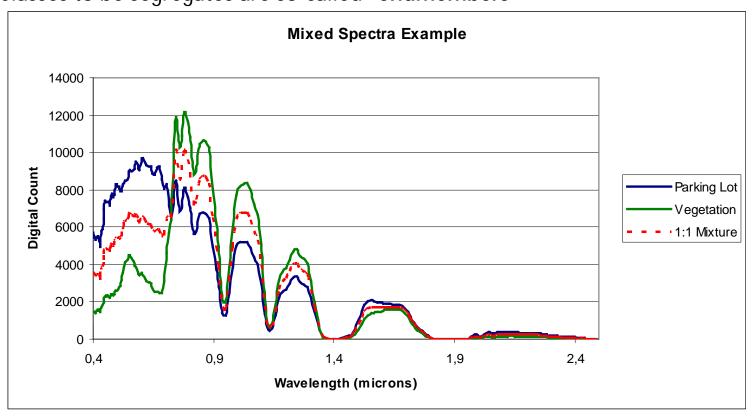
§ Pixel spectrum is **rarely 'pure'**

§ E. g. mixed pixels from two or more object classes (50:50 mixture of „parking" and „vegetation" - edge pixels of a parking lot)

§ Classes to be segregates are so-called **"endmembers"**

Mixed Spectra Example

© DLR

§ Example

PUR	**PUR**
PUR	**MIX**

UNMIXING →

UNMIXING ↘

1.0	**0.0**
1.0	**0.5**

Red Fraction Image

0.0	**1.0**
0.0	**0.5**
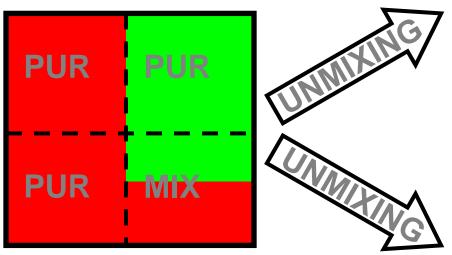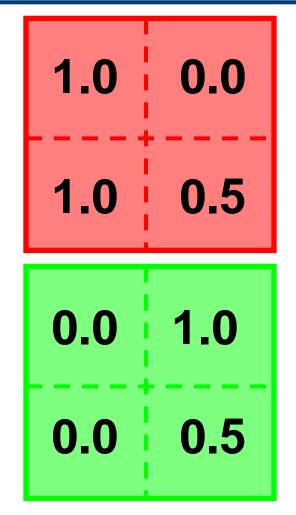
Green Fraction Image

As a result of the **unmixing process** of the multispectral input image a so-called **fraction-(endmember)-image** is produced. The number of spectral bands of the new image are corresponding to a maximum of those of the original.
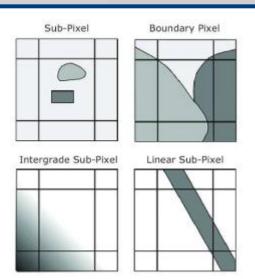
© Künzer 2005

© Fisher 1997

$$A \cdot X = R \quad and \quad X = A^{-1} \cdot R$$

where,
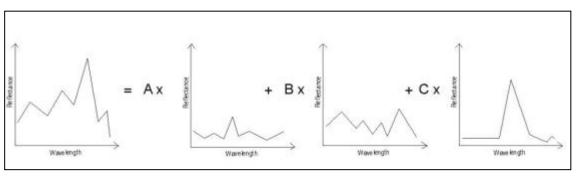
A = m × n-matrix of spectral endmembers (spectral library) in n spectral bands

X: vector of unknown abundances of the endmembers

R: measured reflection of the image pixel

$$R_i = \sum_{j=1}^{n} f_j \times RE_{ij} + e_i \quad and \quad \sum_{j=1}^{n} f_j = 1$$

where,

R_i: spectral reflectance of a mixed spectrum in image band i

f: fraction of each endmember j calculated band by band

RE_{ij}: reflectance of the endmember spectrum j in band i

i: band number
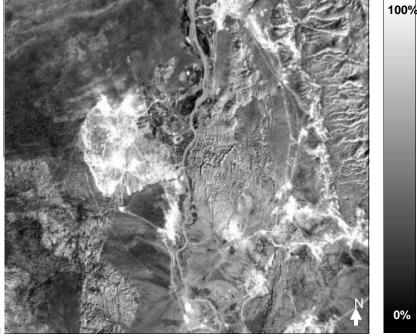
j: each of the n image endmembers

e_i: residual error or the difference between the measured and the modeled DN in band i

e_i: modeling error in band i

n: number of endmembers

© Künzer 2005

Result of *unmixing* of Landsat TM in area of Wudan, China. Brightness: 'coal'-share

§   **Theory of linear unmixing:**

$$g'_i = \sum_{e=1}^{N} g_{i,e} f_e + e_i \qquad i = 1, k$$

k=number of bands

- $g_{i,e}$ known grey values of the e-th endmember in the i-th band
- g'_i Grey value of a pixel in the i-th band
- f_e *Fraction* components (=unknown), noise!
- E_i Error term (=improvement in the sense of adjustment)

☞ It can not be determined more fraction components than error equations can be set up, i.e. not more than bands than are available in the original image.

§ **First step:**

- Search for „pure" endmembers in the original image (i.e. spectrally distinct classes that do not consist of mixed pixels)
- Extracting the spectral features of these endmembers
- **P**ixel **P**urity **I**ndex Calculations (**PPI**)

§ **Second step:**

- Setting up a system of equations
- Solved by the method of least squares

§ **Third step:**

- The found endmember components are sequentially multiplied by all pixels
- Result: **fraction images** in relation to the selected endmembers
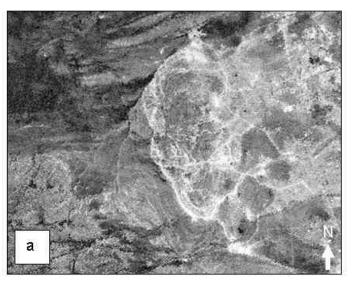
4 *Endmember*
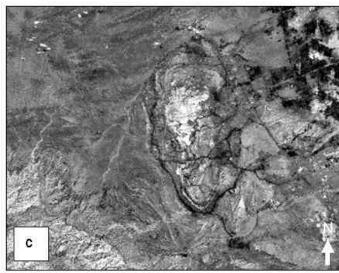
A: Coal
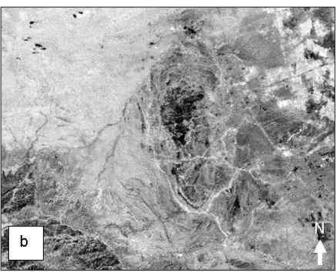
B: Desert sand
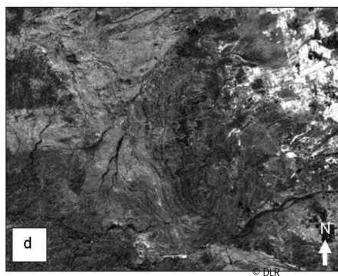
C: Arkose Sandstone

D: Vegetation

© Künzer

© DLR

Laboratory spectra
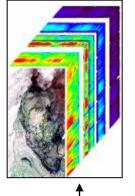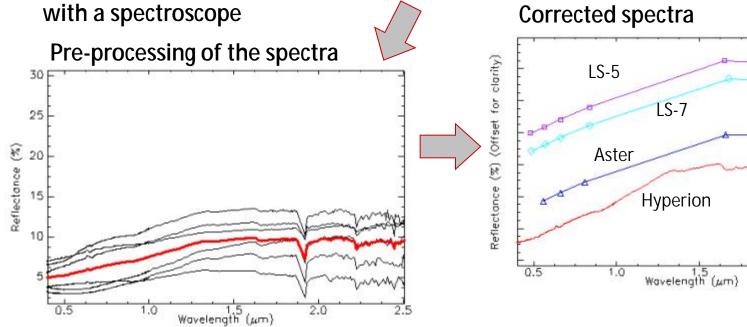
Field measurements
with a spectroscope

Pre-processing of the spectra

Corrected spectra

© DLR

Advantages:
- Physical method of this method
- Objective method without subjective influence of the producer
- Quantitative results on sub-pixel basis
- Also detected objects that are not perceived visually
- Especially suitable for chemical, geological and mineralogical investigations
- Not only for hyper spectral data

Disadvantages:
- Pre-processing of the images and spectra is very complex
- Can be performed only by experts
- Difficult in topographically heterogeneous areas (DTM Quality!)
- Minimum number of recording channels is required!
- Software packages with programming interface are needed (e.g. ENVI(IDL, C))

§ **Aim**

- Comparison of the pixel spectrum with a reference spectrum
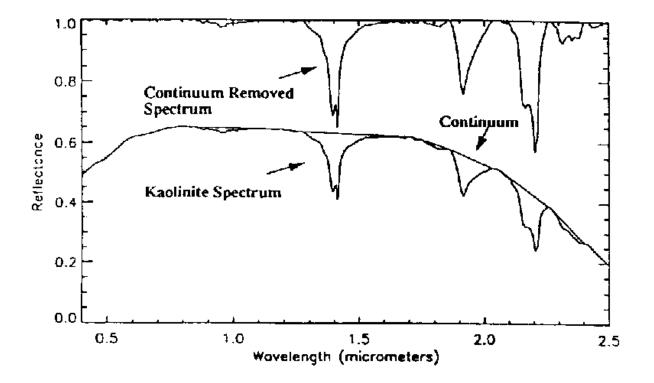
§ **Method**

- Based on ‚least squares – best-fit' approach:
  ‚The better the fit, the smaller the sum of the squared distances between the two spectra compared'

  - The measure for this is the *Root Mean Square Error* (RMS)

  - It will be generated a corresponding RMS-image

  - The RMS-image shows which are **similar** to the **selected endmember spectrum**

  - Or comparison of the input data set with the complete spectra database O

  - The comparison of the spectra is only useful if the "Continuum" has been removed.

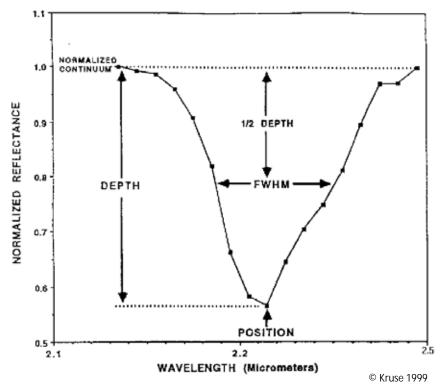§ A "continuum" for each input spectrum is defined (local maxima are determined and connected linearly)

© Kruse 1999

§ Minima of the corrected spectrum are determined

© Kruse 1999

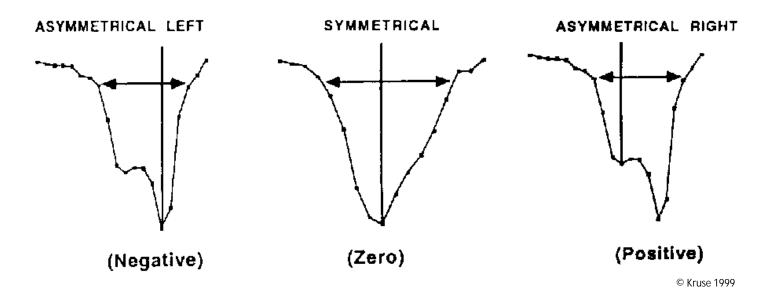**The 10 strongest absorption regions per spectrum are determined**

§ **Wavelength, position, depth, width at half maximum depth** (full width at half the maximum depth (FWHM)) and **asymmetry** for all **10 distinct absorption regions** are determined and listed in a table

§ **Comparison with reference spectrum**

ASYMMETRICAL LEFT   SYMMETRICAL   ASYMMETRICAL RIGHT

(Negative)   (Zero)   (Positive)

© Kruse 1999

Advantages:

- Has proven particularly useful in geology
- Effective in the search of "known" objects/materials
- Useful method for the incorporation of the spectral databases and spectrometer measurements in the study
- Physical background of the method
- Objective method without subjective influence of the producer
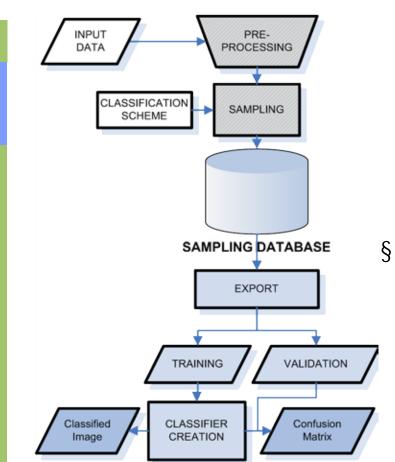- Not only for hyper spectral data

Disadvantages:

- Very laborious and time consuming (PhD thesis?)
- Pre-processing of the images and spectra is very complex
- Can be performed only by experts
- Difficult in topographically heterogeneous areas (DTM Quality!)
- Minimum number of recording channels is required!
- Software packages with programming interface are needed (e.g. ENVI(IDL, C))

TWOPAC – Twinned o**bject and** p**ixel-based** a**utomated** c**lassification chain**

§ **Standardized interface for process control
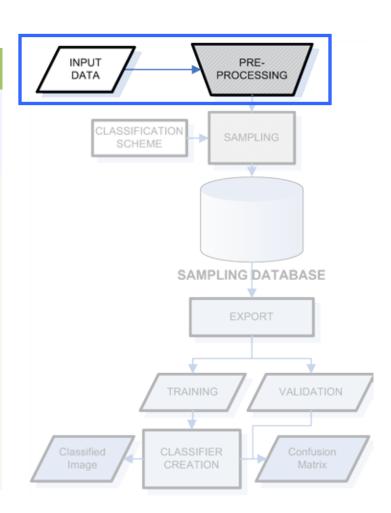– OGC Web Processing Services (WPS) –**

§ **MODIS (NIR, RED, NDVI, 250m)**
Annual time series, calculation of mean, standard deviation, maximum, minimum, amplitude
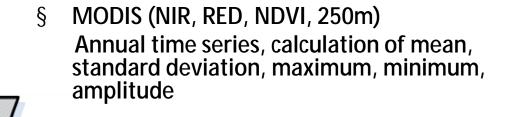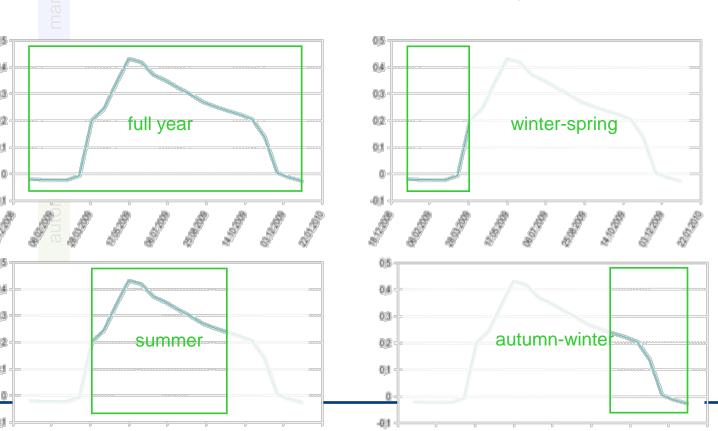
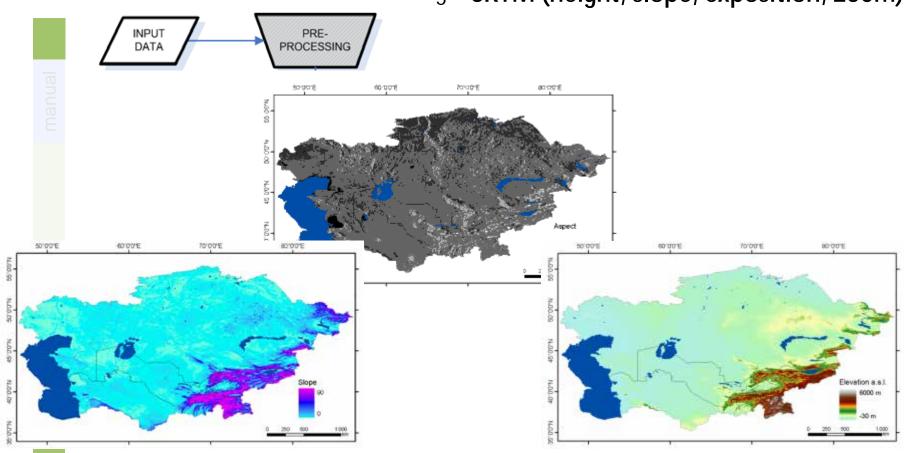§ **Rather mean values with guaranteed stability than single values (transfer and comparability)**

Correlation matrix between variables, layer with too high correlation indices to be eliminated (e.g. NDVI full year max. and NDVI summer max.)
Layer Stack: > 50

§ **MODIS (NIR, RED, NDVI, 250m)**

§ **SRTM (height, slope, exposition, 250m)**
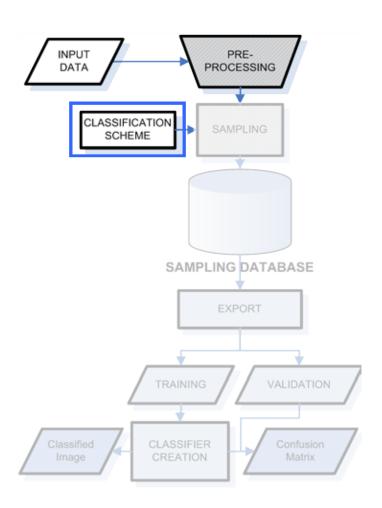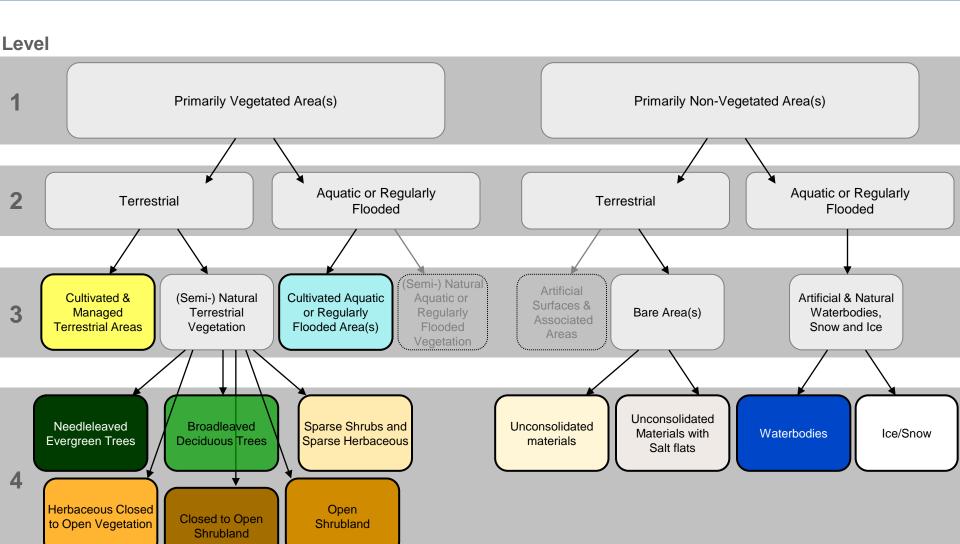
§ **Based on the standards of the Land Cover Classification System (LCCS)**

Level

1

| Primarily Vegetated Area(s) | Primarily Non-Vegetated Area(s) |

2

Terrestrial | Aquatic or Regularly Flooded | Terrestrial | Aquatic or Regularly Flooded

3

Cultivated & Managed Terrestrial Areas | (Semi-) Natural Terrestrial Vegetation | Cultivated Aquatic or Regularly Flooded Area(s) | (Semi-) Natural Aquatic or Regularly Flooded Vegetation | Artificial Surfaces & Associated Areas | Bare Area(s) | Artificial & Natural Waterbodies, Snow and Ice

4

Needleleaved Evergreen Trees | Broadleaved Deciduous Trees | Sparse Shrubs and Sparse Herbaceous | Unconsolidated materials | Unconsolidated Materials with Salt flats | Waterbodies | Ice/Snow

Herbaceous Closed to Open Vegetation | Closed to Open Shrubland | Open Shrubland
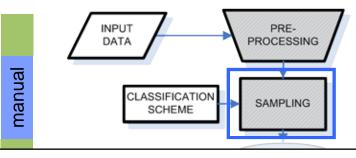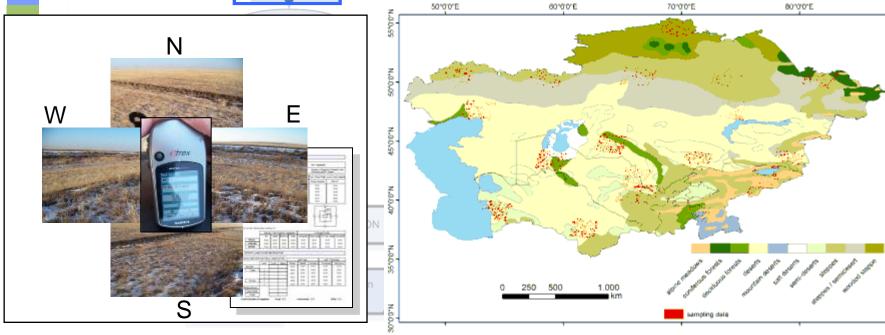
manual

INPUT DATA → PRE-PROCESSING

CLASSIFICATION SCHEME → SAMPLING

Landsat scenes: evenly distributed, segmented, trained; Same year as MODIS (spring and fall to collect phenological differences)

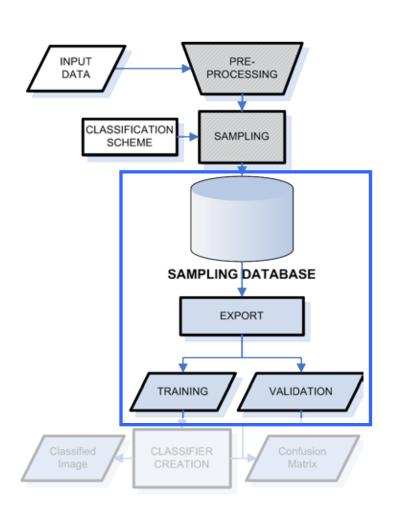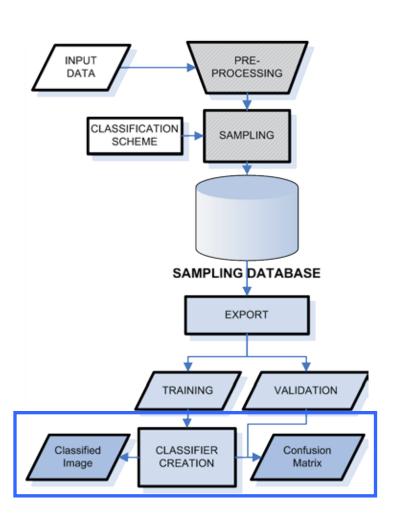§ sample Database
(PostgreSQL with PostGIS)

manual

automated

§ Classification methods:
- Support Vector Machine
- Maximum Likelihood
- **C5.0 Rulesets (Decision Tree)**

```
Rules:

Rule 1: (1067/1, lift 6.4)
    ndvi_mi_su > 635
    ndvi_r_su <= 626
    ndvi_m_ws <= 817
    red_m_aw > 1239
    nir_m_su <= 2624
    nir_ma_ws > 2183
    nir_m_ws <= 4342
    ->  class 17  [0.998]

Rule 2: (501, lift 6.4)
    ndvi_ma_su <= 1608
    red_r_aw > 4280
    nir_ma_su > 1728
    nir_r_su > -25575
    nir_m_ws <= 2550
    ->  class 17  [0.998]

Rule 3: (404, lift 6.4)
    ndvi_mi_yr > -871
    ndvi_m_yr > 1822
    ndvi_r_yr > 3951
    ndvi_ma_aw <= 2306
    ndvi_m_ws <= -217
    red_mi_aw <= 841
    nir_ma_aw > 5298
    ->  class 17  [0.998]
```
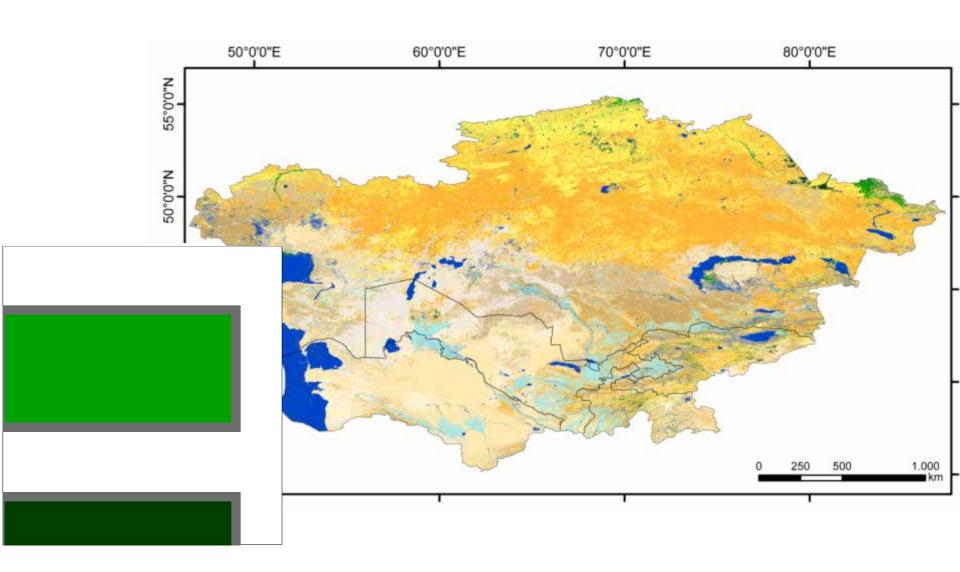
§ C5: freely available software that performs a discriminant analysis to separate the variables

§ Originally not created for image processing, but you can use it for that

§ Output for the separability of the classes (derived from the training data) is an ASCII text file

§ Python script transfers the ASCII file automatically into an applicable decision tree

(MCD12Q1, Land Cover Type1 IGBP)

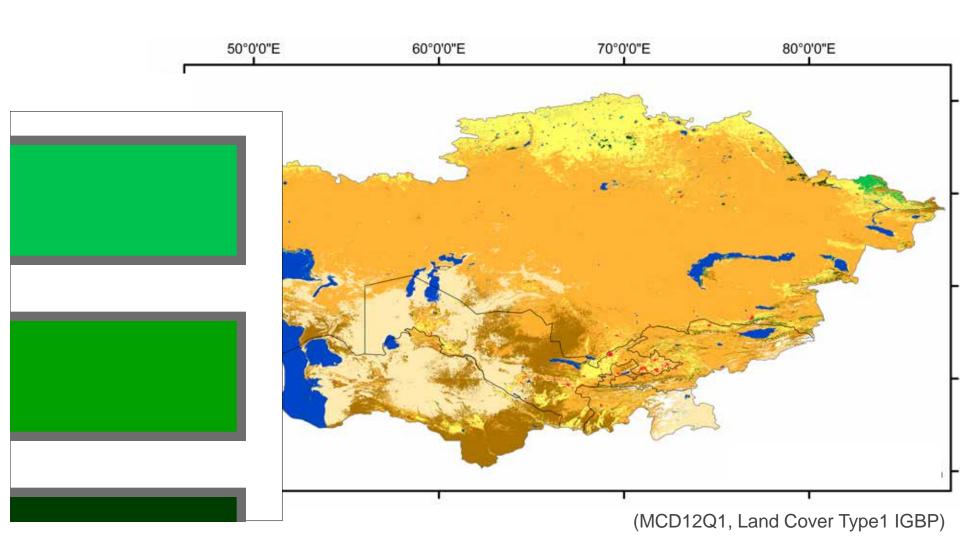Irrigated agriculture (Landsat)
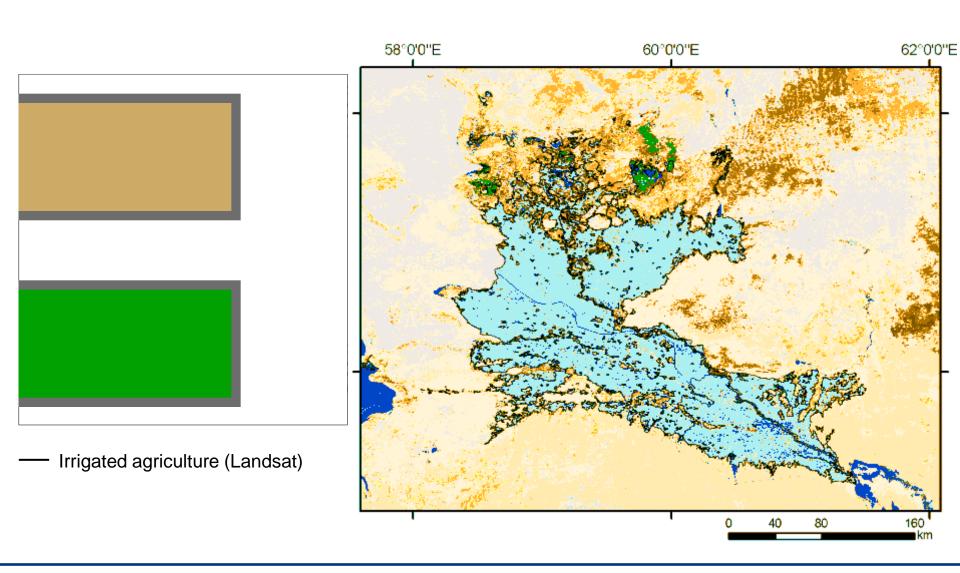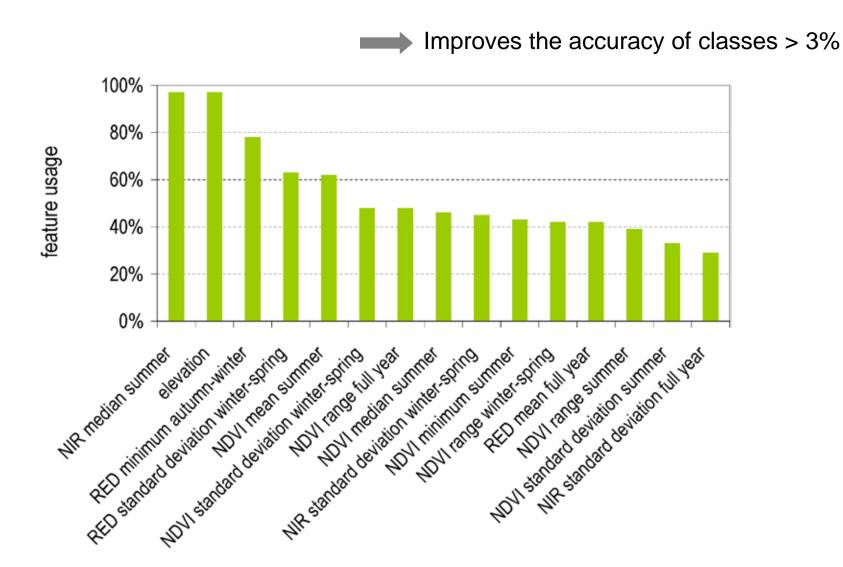
class	C5 user's accuracy	C5 producer's accuracy
cultivated and managed terrestrial area	92.8	94.1
cultivated aquatic or regularly flooded area	93.6	90.7
needleleaved evergreen trees	80.8	80.8
broadleaved deciduous trees	92.7	93.1
sparse shrubs and sparse herbaceous	96.3	96.6
herbaceous closed to open vegetation	91.0	91.3
closed to open shrubland	94.5	94.0
open shrubland	94.1	94.3
bare area, unconsolidated materials	96.5	96.2
bare area, unconsolidated materials with salt flats	95.8	95.8
ice	75.1	77.4
waterbodies	98.3	98.6

Improves the accuracy of classes > 3%