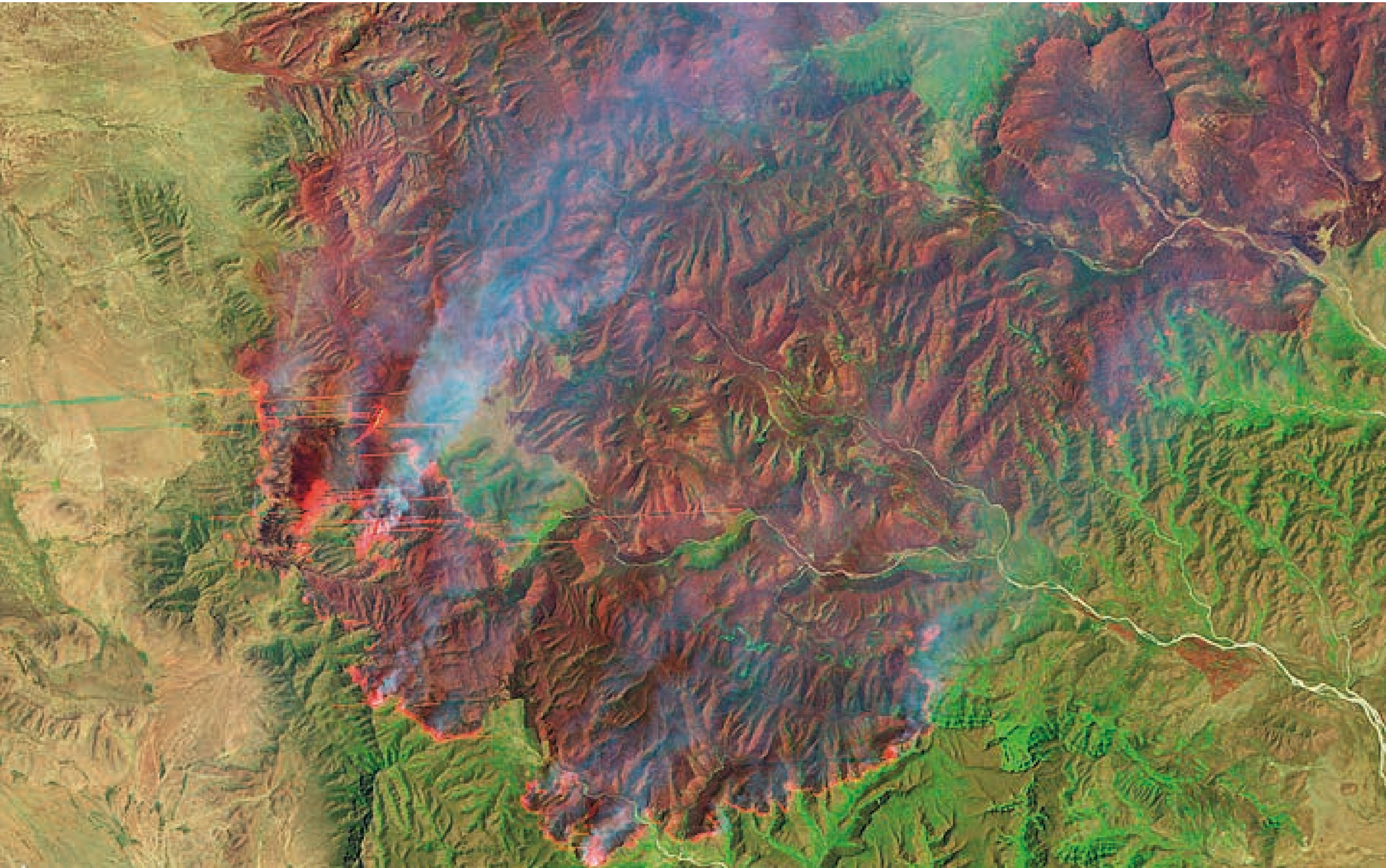
Grundlagen Fernerkundung - 12

Image classification

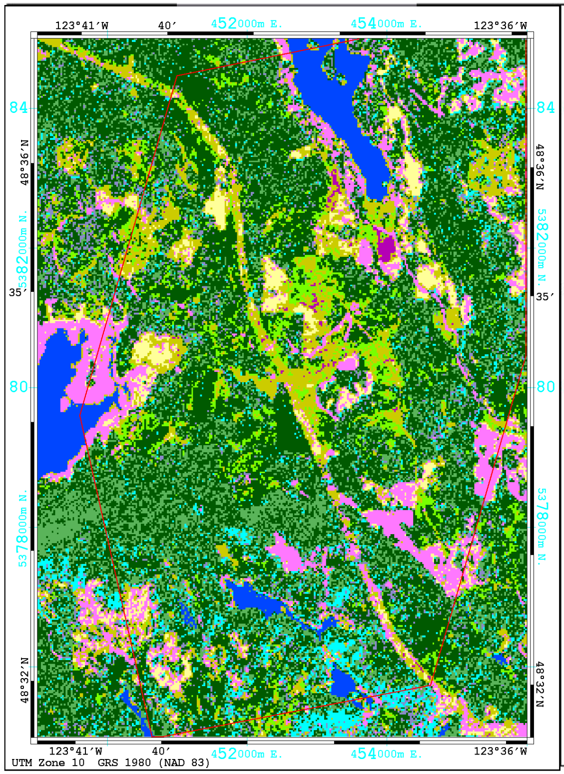
GEO123.1, FS2015

Michael Schaepman, Rogier de Jong, Reik Leiterer



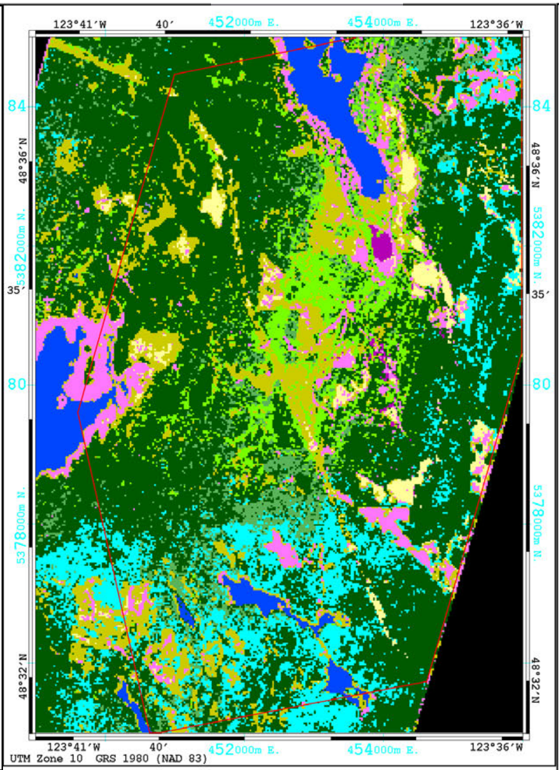
Landcover Classification Improvement

75.0%



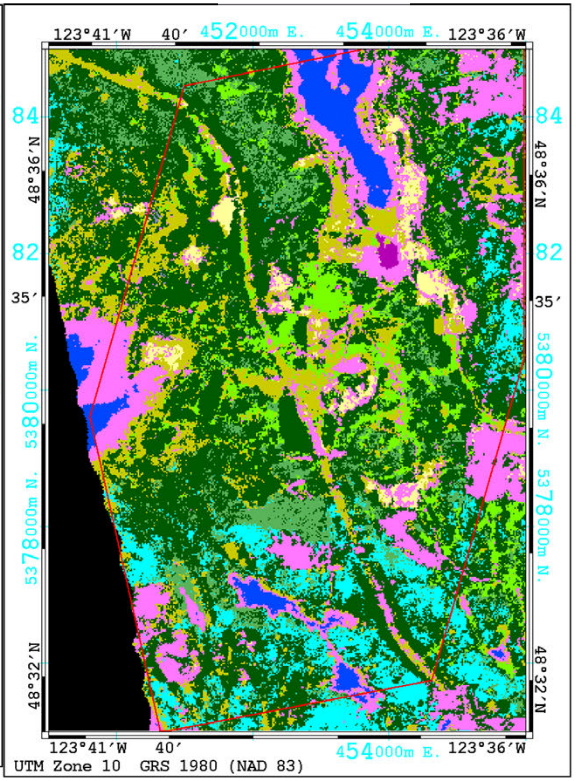
Landsat-7 ETM+ Classification
September 10, 2001

90.0%



Hyperion Classification
September 10, 2001

92.1%



AVIRIS MNF Classification
August 10, 2001

🟪 Exposed land
🟦 Water body
🟨 Shrub, low
🟪 Herb graminoids
🟨 Swamp area
🟩 Red alder, dominant
🟩 Hemlock, dominant
🟦 Lodgepole pine dominant
🟪 Western redcedar
🟩 Douglas-fir, dominant
⬛ Unclassified

Today's topics & learning goals

Feature space

- How are land cover classes separated from each other?

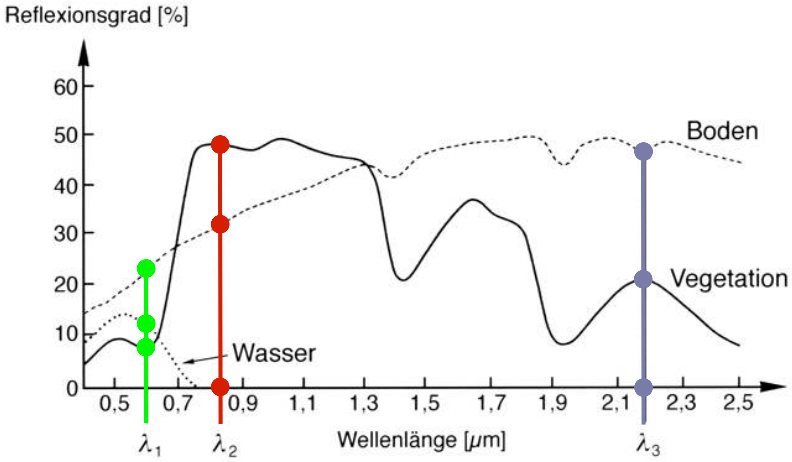
Classification algorithms

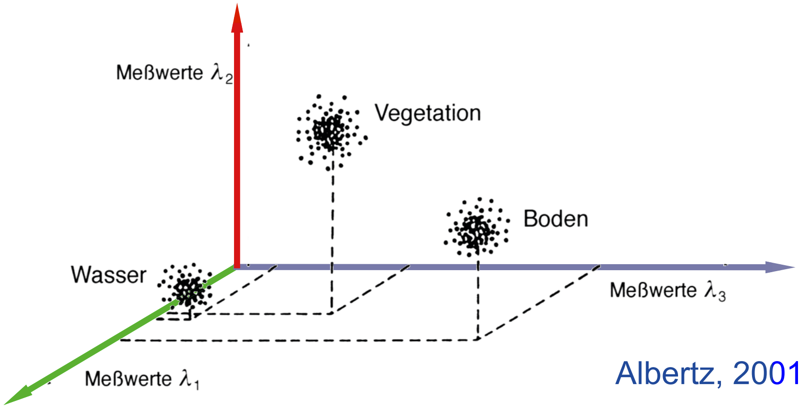
- Which algorithms exist and how do they differ?

Accuracy measures

- How valid is a classification result?

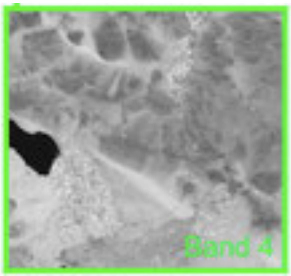
Feature Space (Eigenschaftsraum / Merkmalsraum)

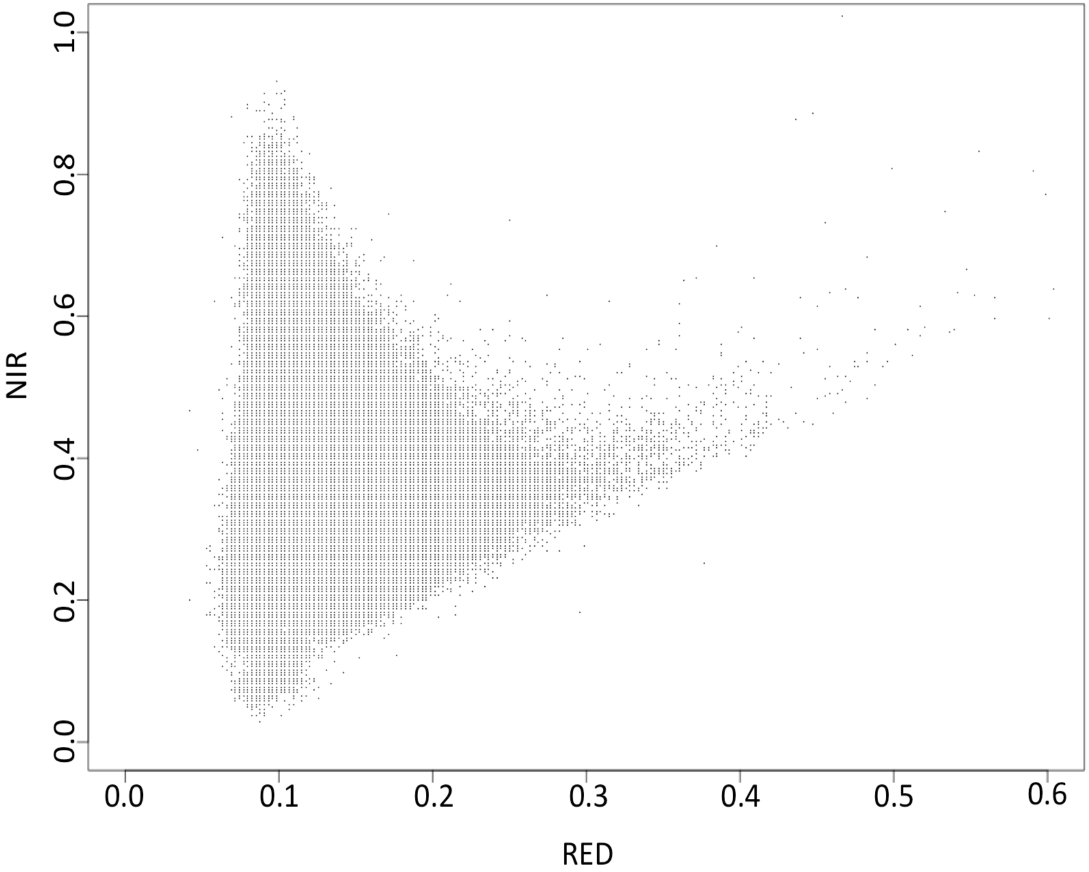


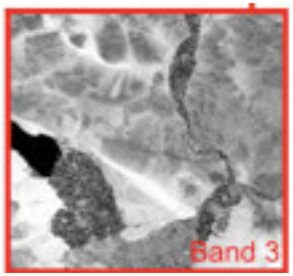


Albertz, 2001

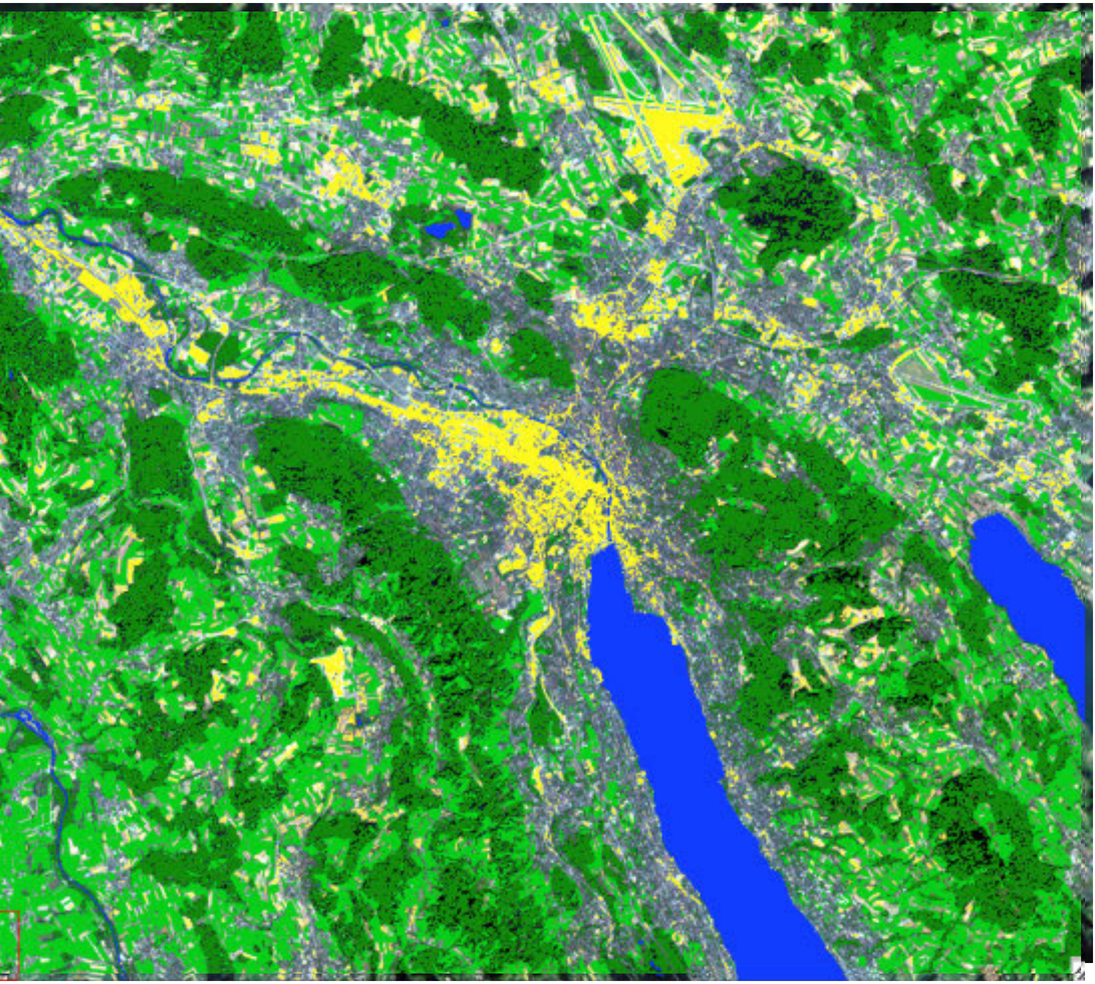
Feature space: NIR vs RED

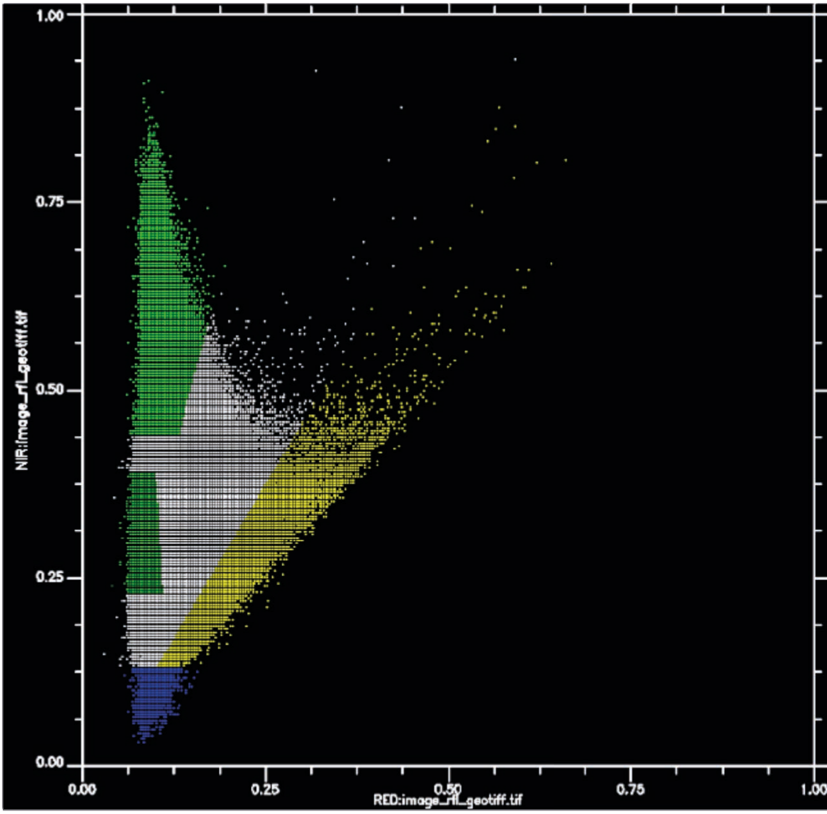






Feature space: NIR vs RED



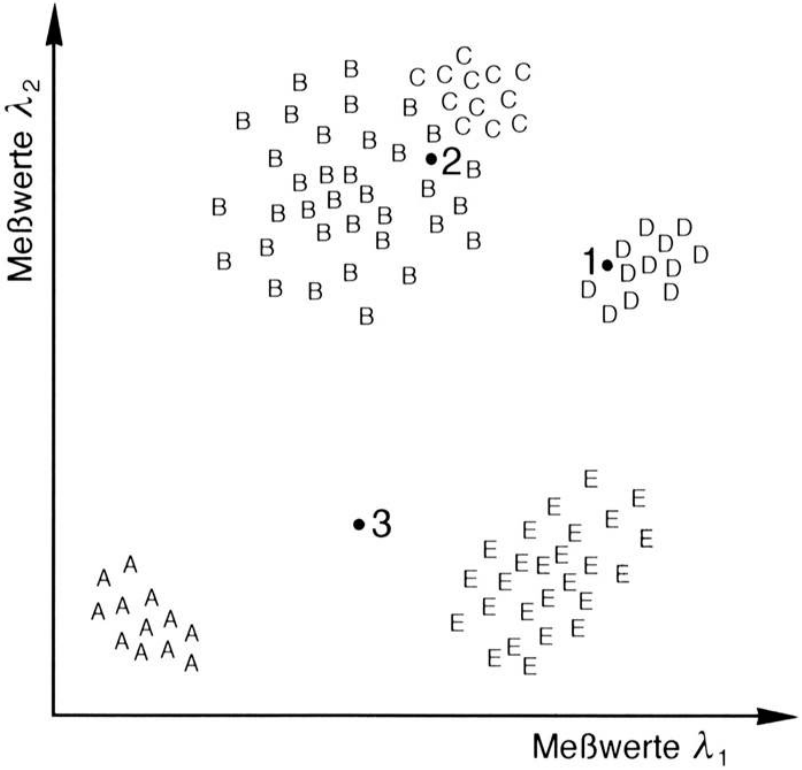


Statistical description of “spectral clusters”

- Histogram / distribution curve
- Min, Mean, Max values
- Standard deviations

Spectral clustering using the feature space

- Ground features are defined based on their spectral response
- Points 1-3 are unknown features that need to be assigned to A-E

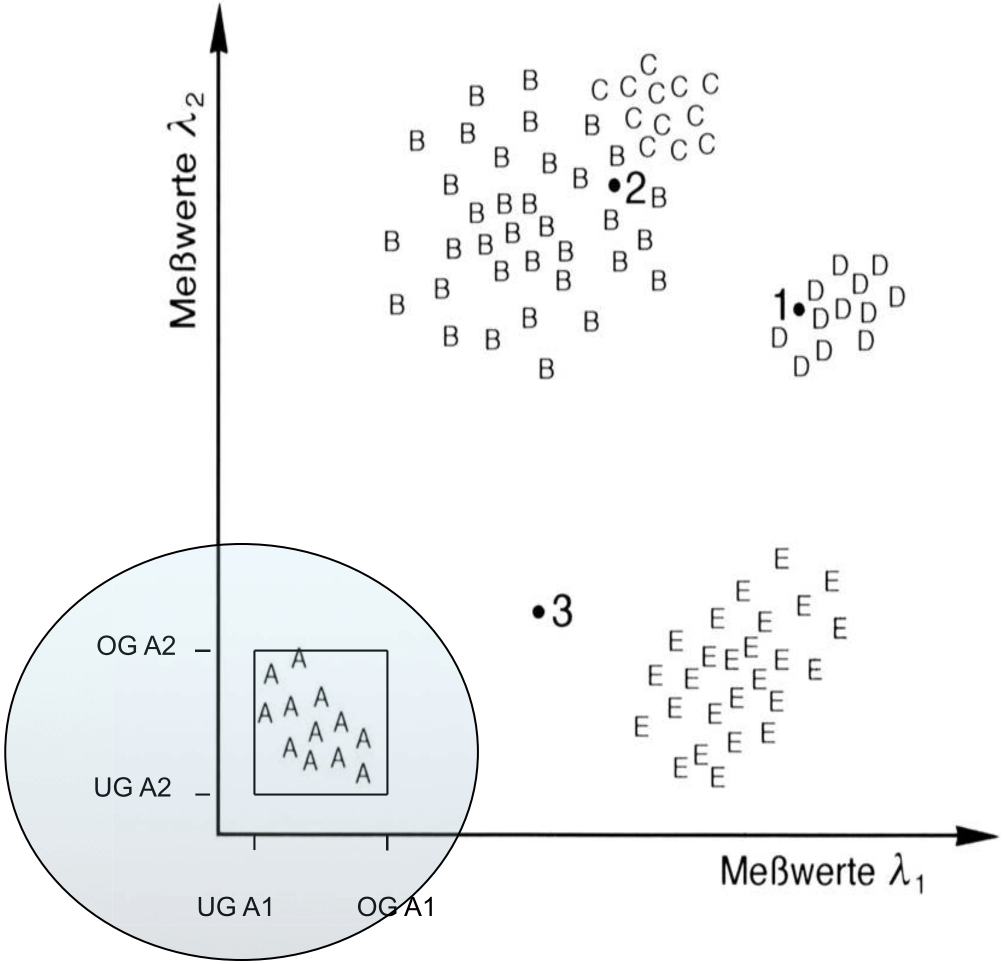


λ = wavelength
Messwerte = reflectance

Method 1: Parallelepiped classification

OG = Obergrenze (upper limit)

UG = Untergrenze (lower limit)



Method 1: Parallelepiped classification

OG = Obergrenze (upper limit)

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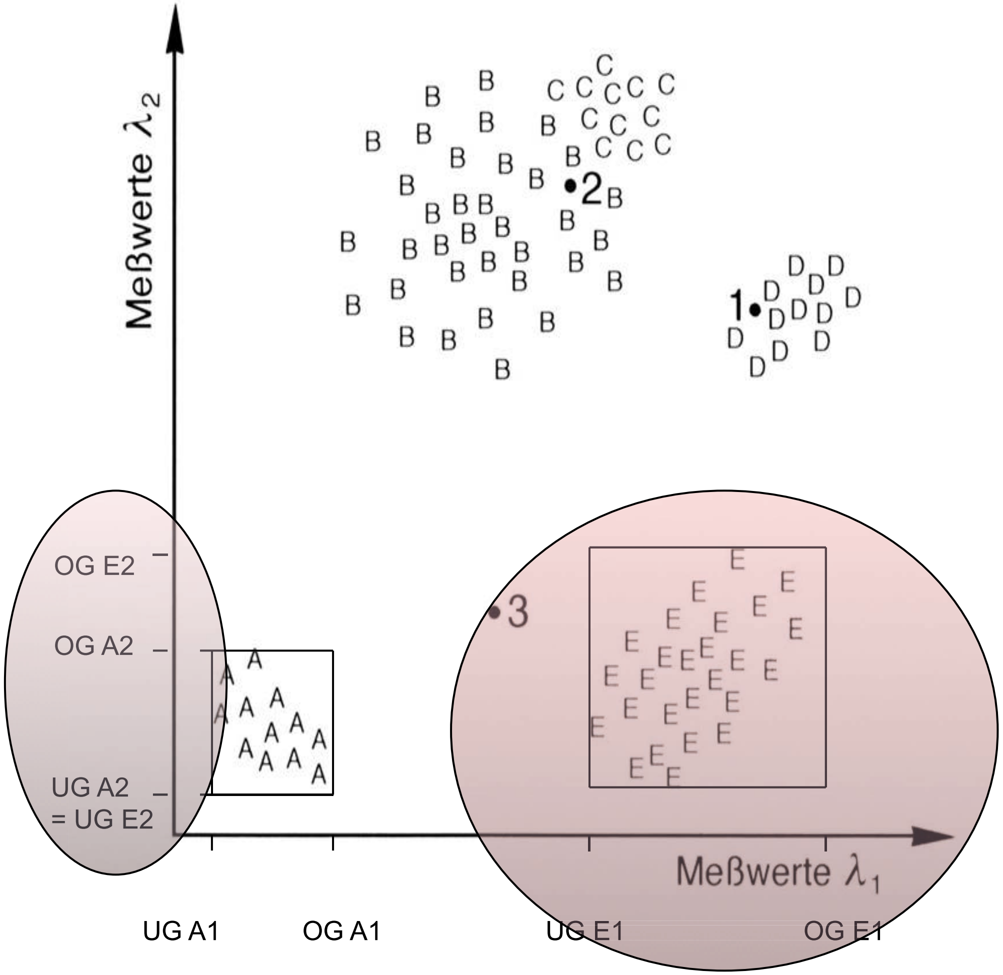
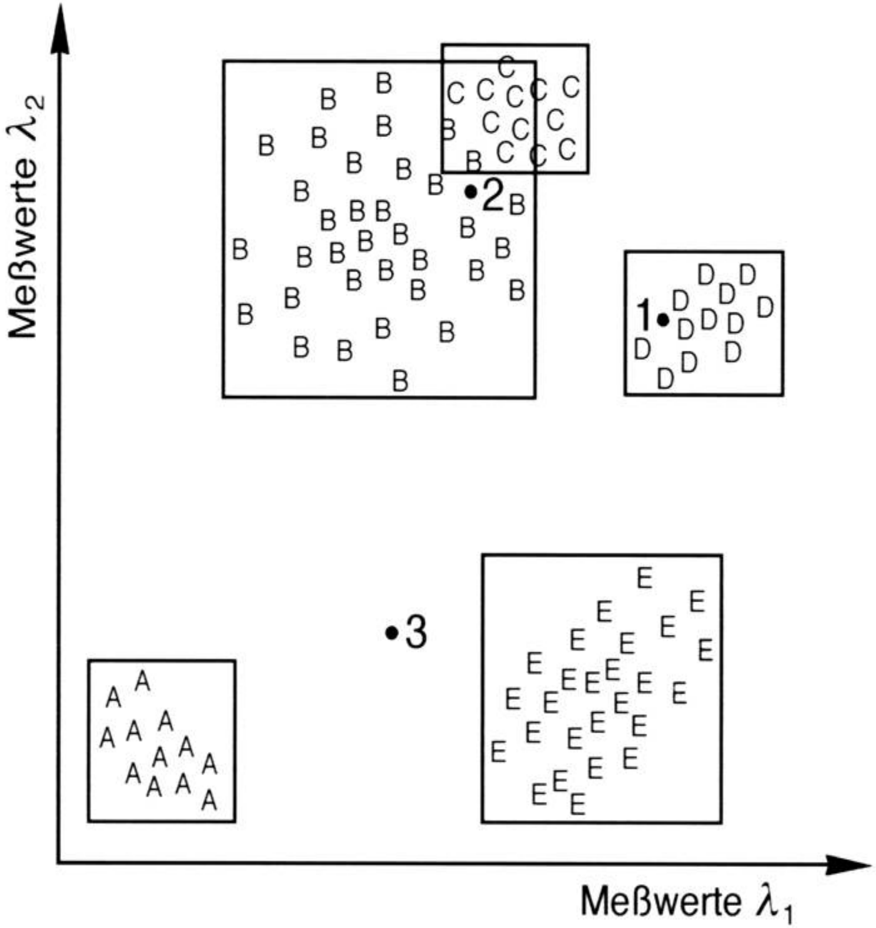


Method 1: Parallelepiped classification

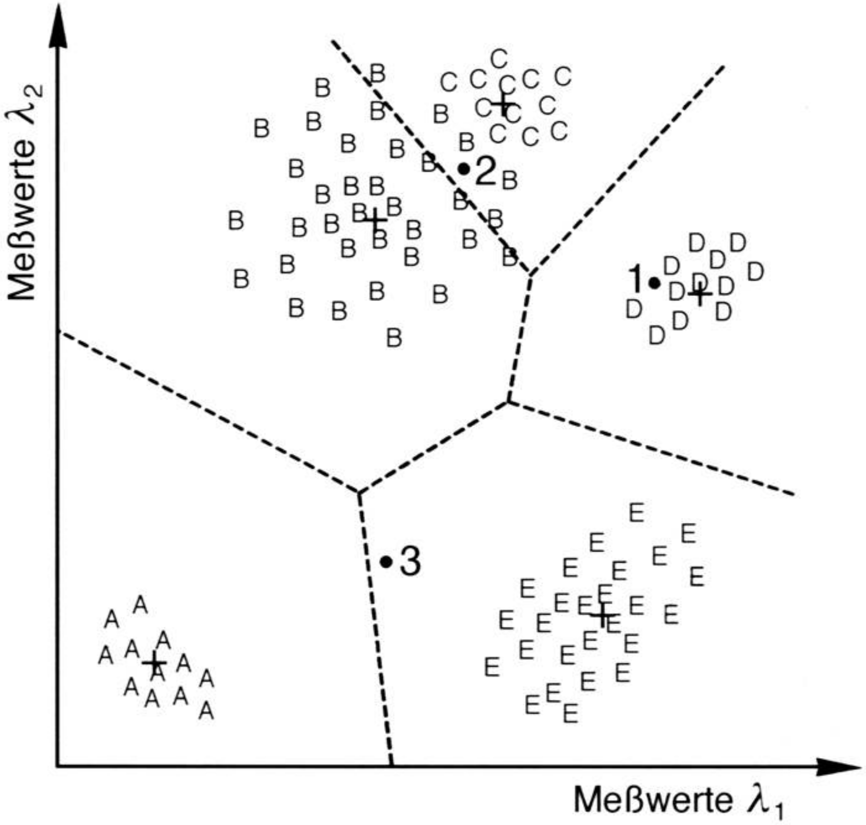


- Features B and C cannot be distinguished. You'll need to try other spectral channels for this purpose.
- Point 2 is therefore the most uncertain but with only this information classified as B

Method 2: Minimum-distance classification

- Criterium: smallest Euclidean distance to the mean value of the class (+)

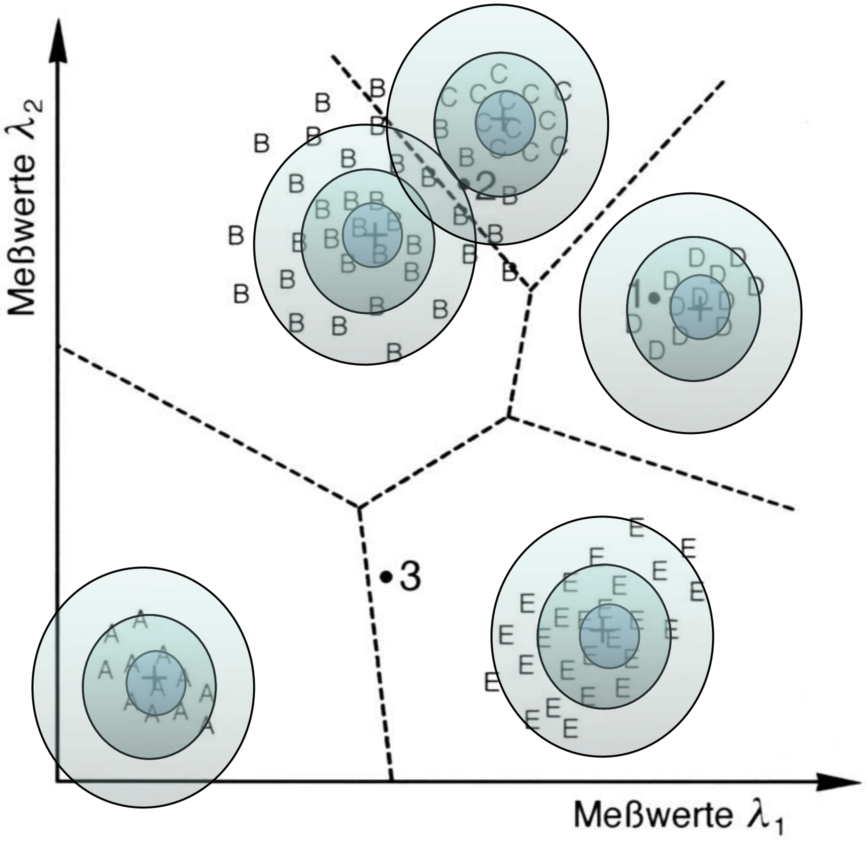
- Boundaries are perpendiculars (“Mittelsenkrechte”)



λ = wavelength
Messwerte = reflectance

Method 2: Minimum-distance classification

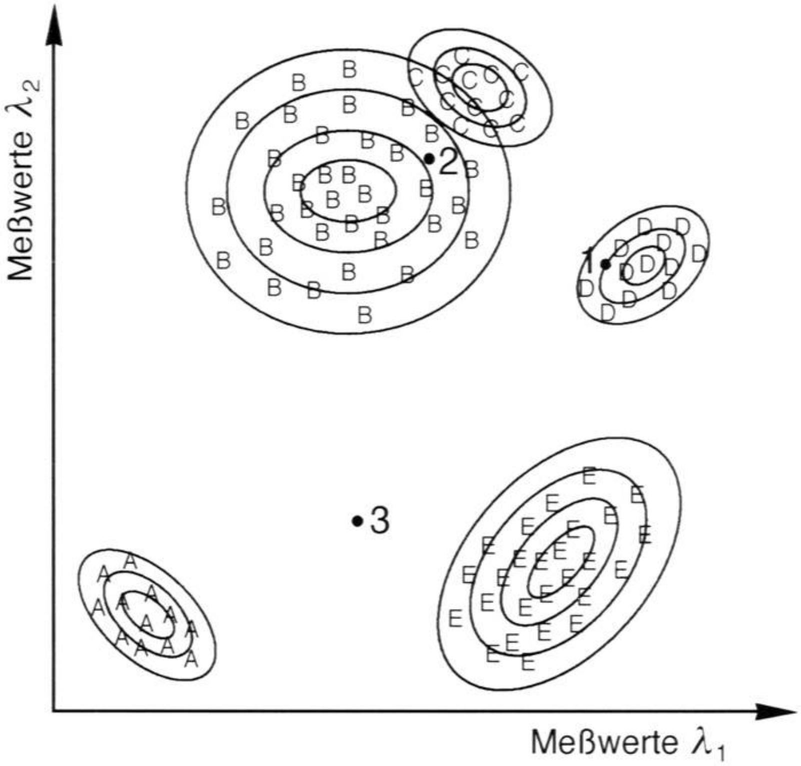
- Without a “max-distance threshold”, point 3 changed from unclassified to E
- Point 2 has changed from B to C
- Less overlap between class B and C but more misclassifications of Bs as Cs?



Method 3: Maximum-likelihood classification

- Criterium: maximum likelihood (“Mutmasslichkeit”) according to a probability-density function (“Wahrscheinlichkeits-dichte-Funktion”)

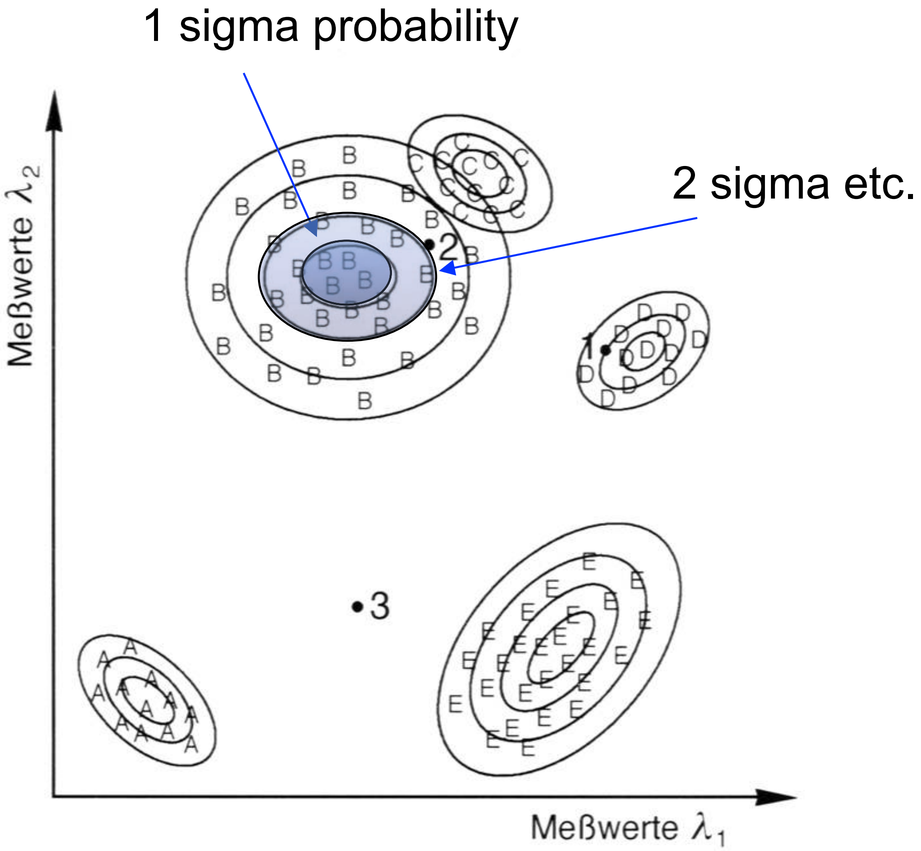
- Boundaries: number of standard deviations (sigma)



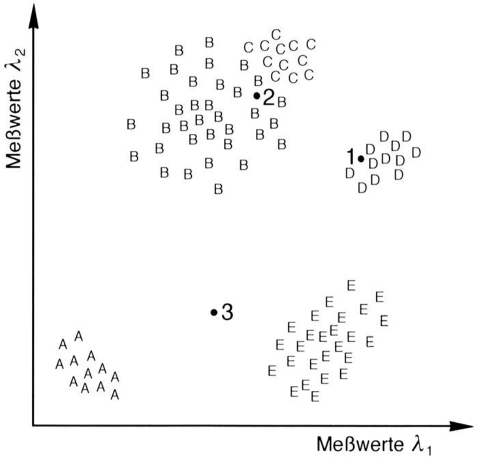
Method 3: Maximum-likelihood classification

- Point 3: more than x sigma distance and thus unclassified

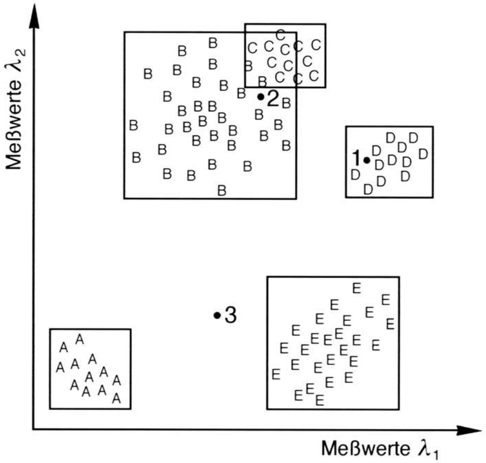
- Point 2: class B with 2 sigma distance



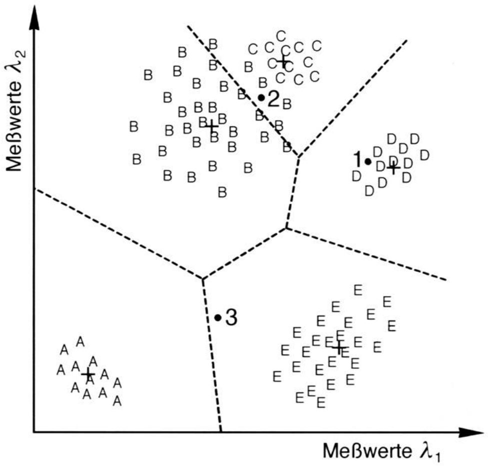
Common classification algorithms: overview



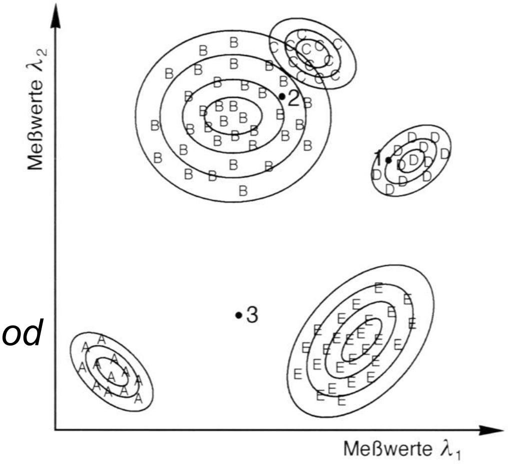
Parallelepiped



Minimum Distanz



Maximum Likelihood



User supervision ("Überwachung")

Unsupervised classification

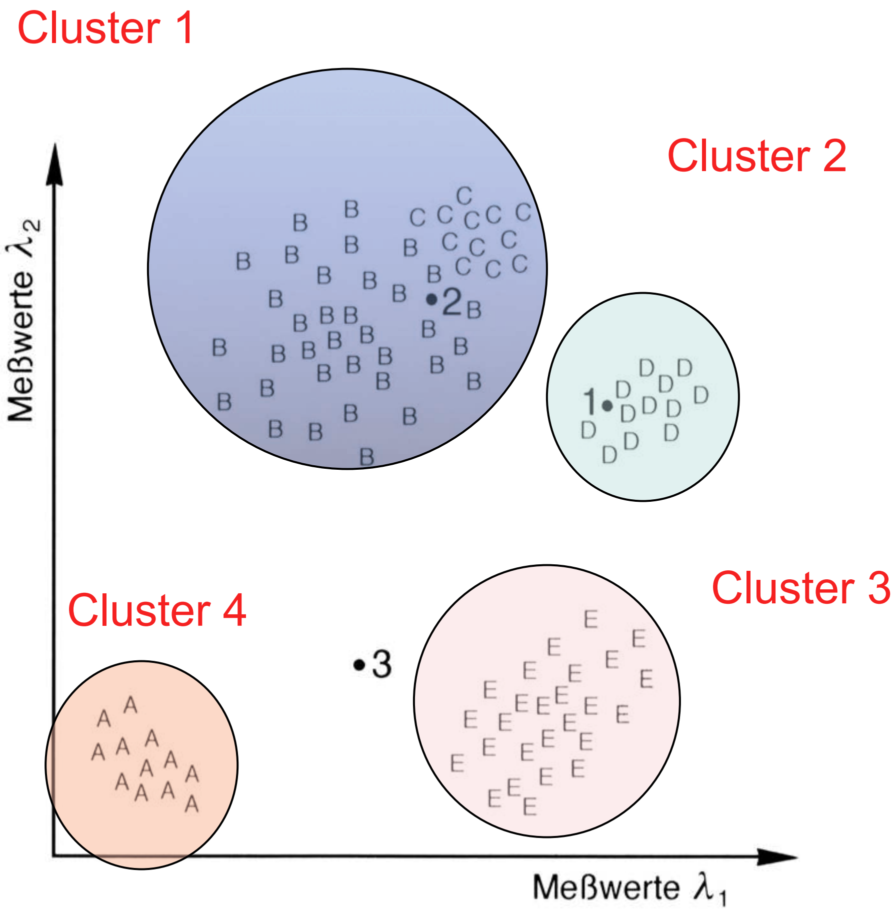
- The user does not provide information with respect to the classes
- Classes are defined based on statistical properties
- Given the same dataset and same method, each user obtains the identical result

Supervised classification

- The user defines training classes to which unclassified pixels are being compared
- The result depends on the definition of the training classes and is therefore likely to change between users

Method 4: Unsupervised clustering

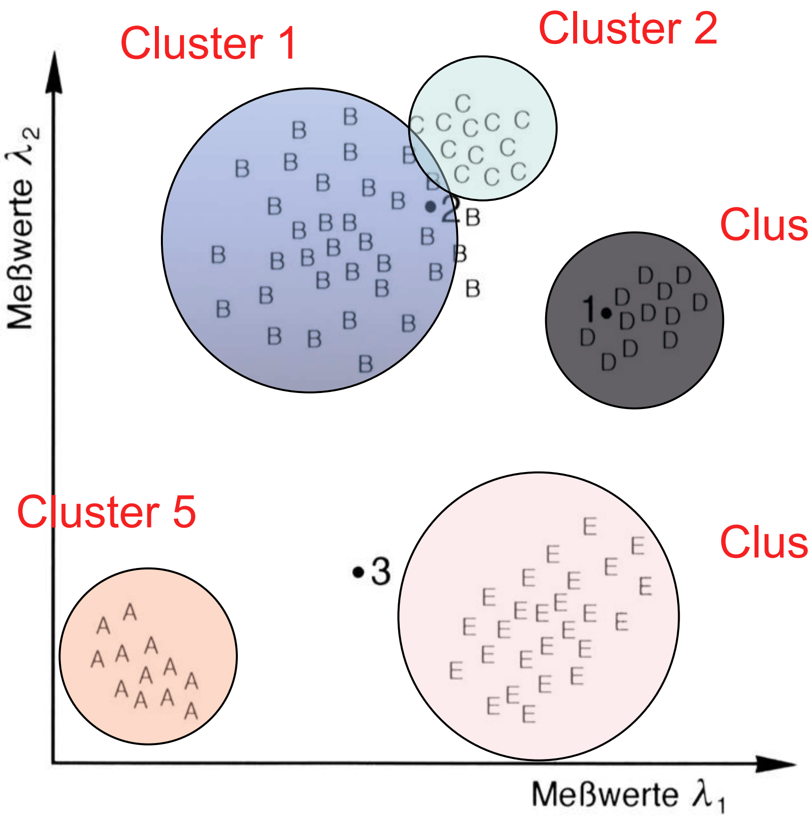
- Option 1:
  no a-priori information at all, (number of) clusters are estimated from statistics



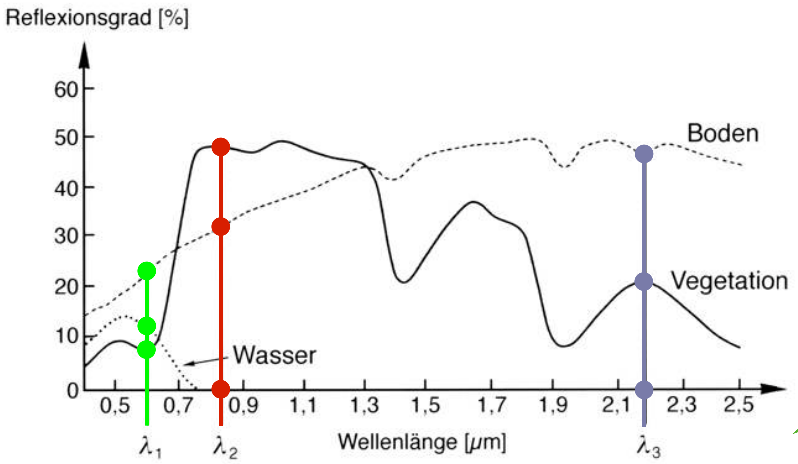
Method 4: Unsupervised clustering

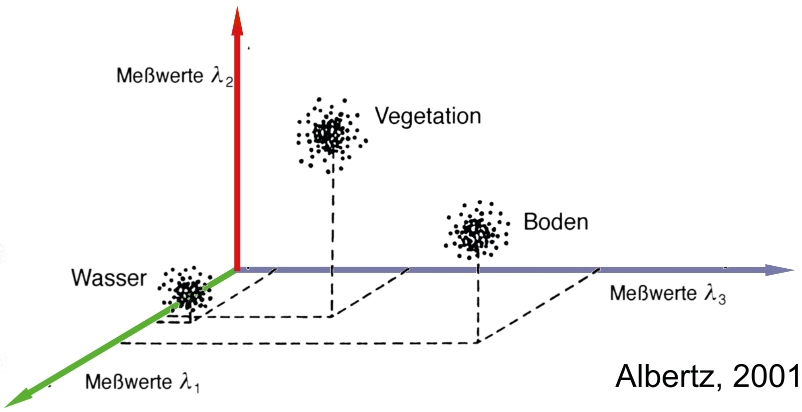
- Option 2:
  the user defines (only) the number of classes, i.e. 5

- After classification (option 1 or 2), clusters may be assigned to features of interest based on user knowledge



Classification methods





Albertz, 2001

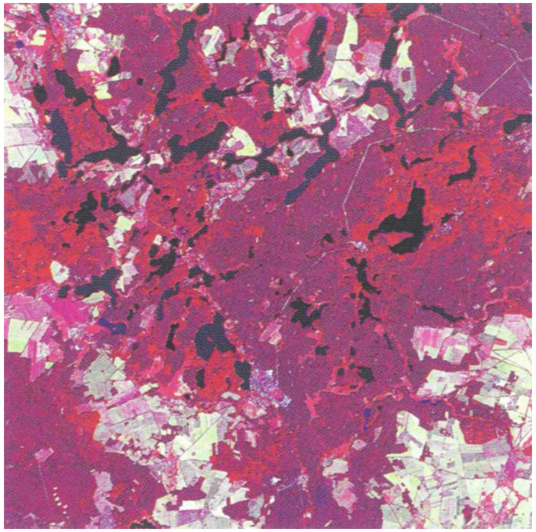
Unsupervised classification

Clustering, (Segmentation)
. . .

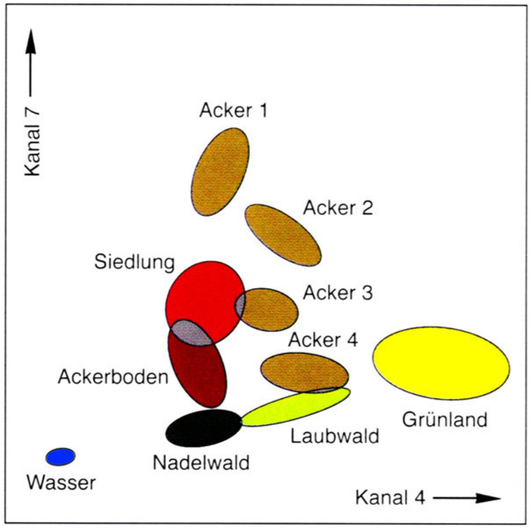
Supervised classification

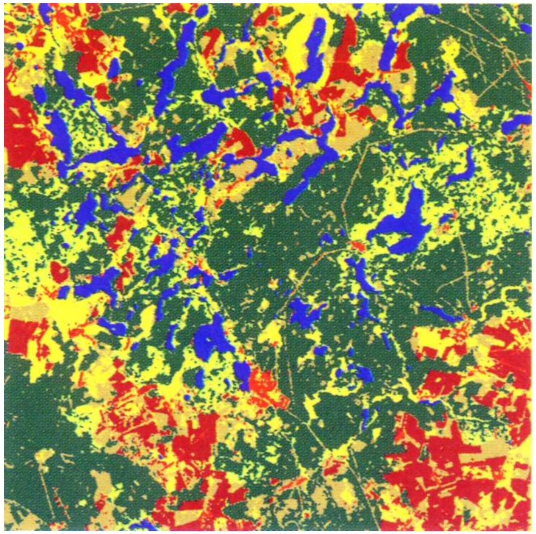
Parallelepiped, Minimum distance,
Maximum likelihood
. . .

How accurate is your classification?



Landsat *Thematic Mapper*, K 2,4,7



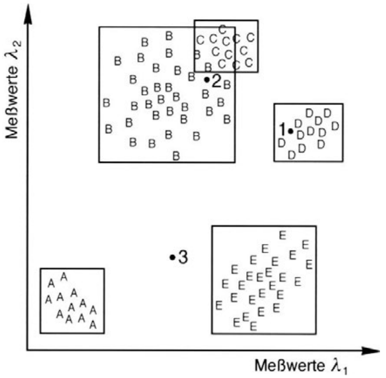


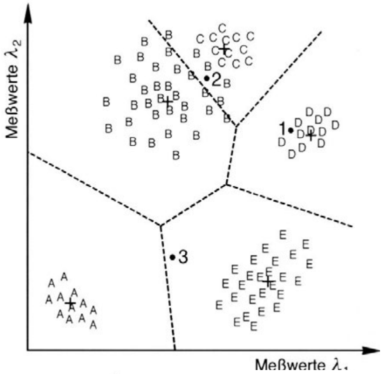
- Looks good!
- Seems plausible!

- Is that enough though?

A classification is not complete until it has been assessed.

(R.G. CONGALTON 1991:35)


Meßwerte λ2
Meßwerte λ1
1
2
3
A
B
C
D
E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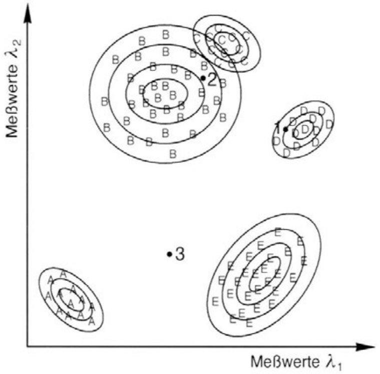
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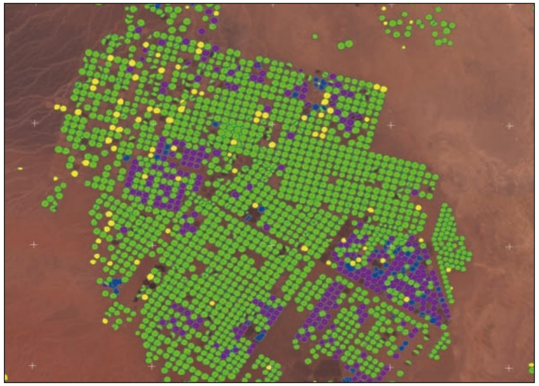
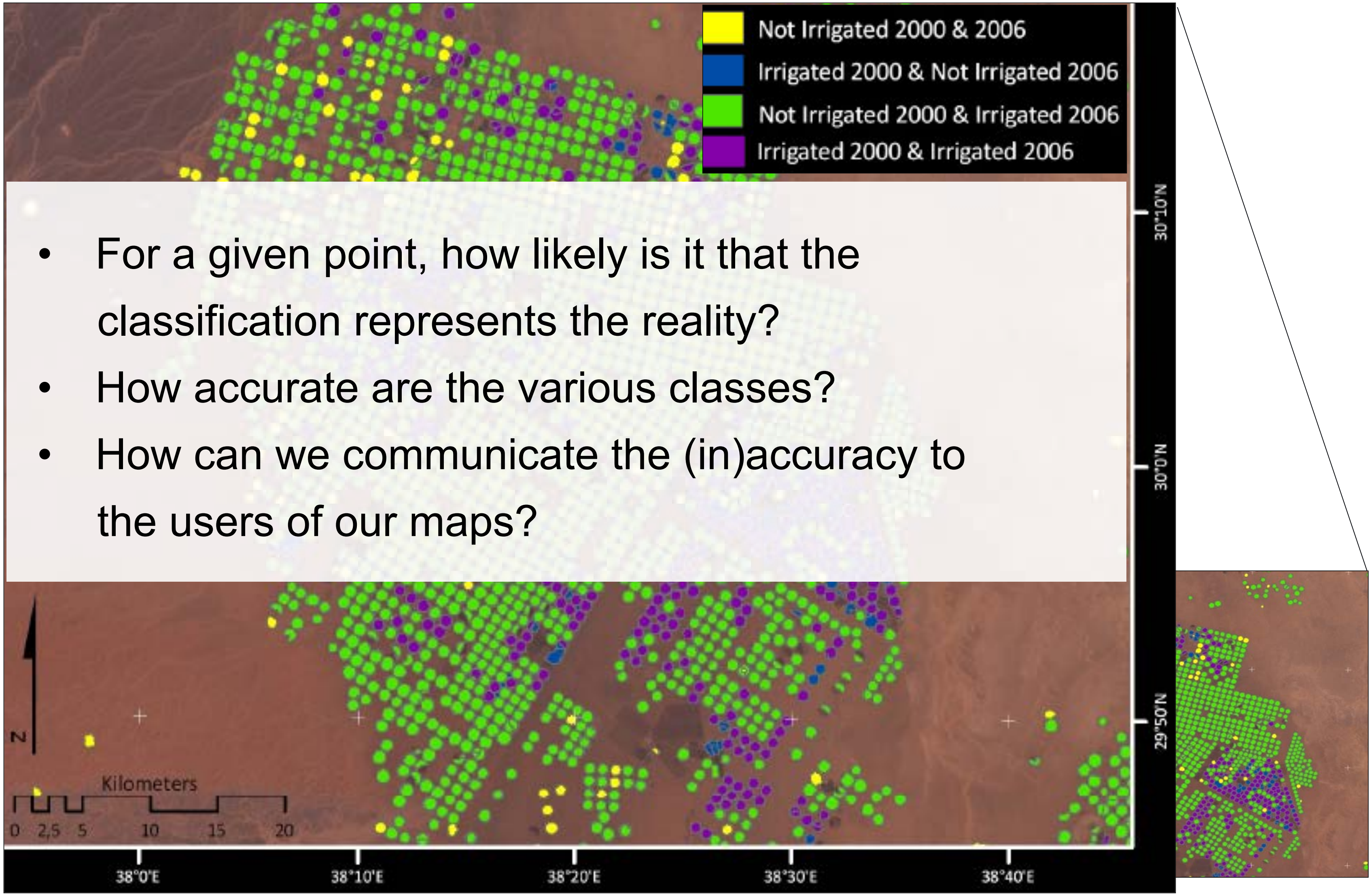




- For a given point, how likely is it that the classification represents the reality?
- How accurate are the various classes?
- How can we communicate the (in)accuracy to the users of our maps?

Options for accurcay assessment

Vergleich mit Bild (visuell) -> sehr unzuverlässig, **nicht-quantitativ**

Vergleich mit Karte (visuell) -> unzuverlässig, **nicht-quantitativ**

Vergleich mit *ground truth* (visuell) -> bedingt abschätzbar, **nicht-quantitativ**

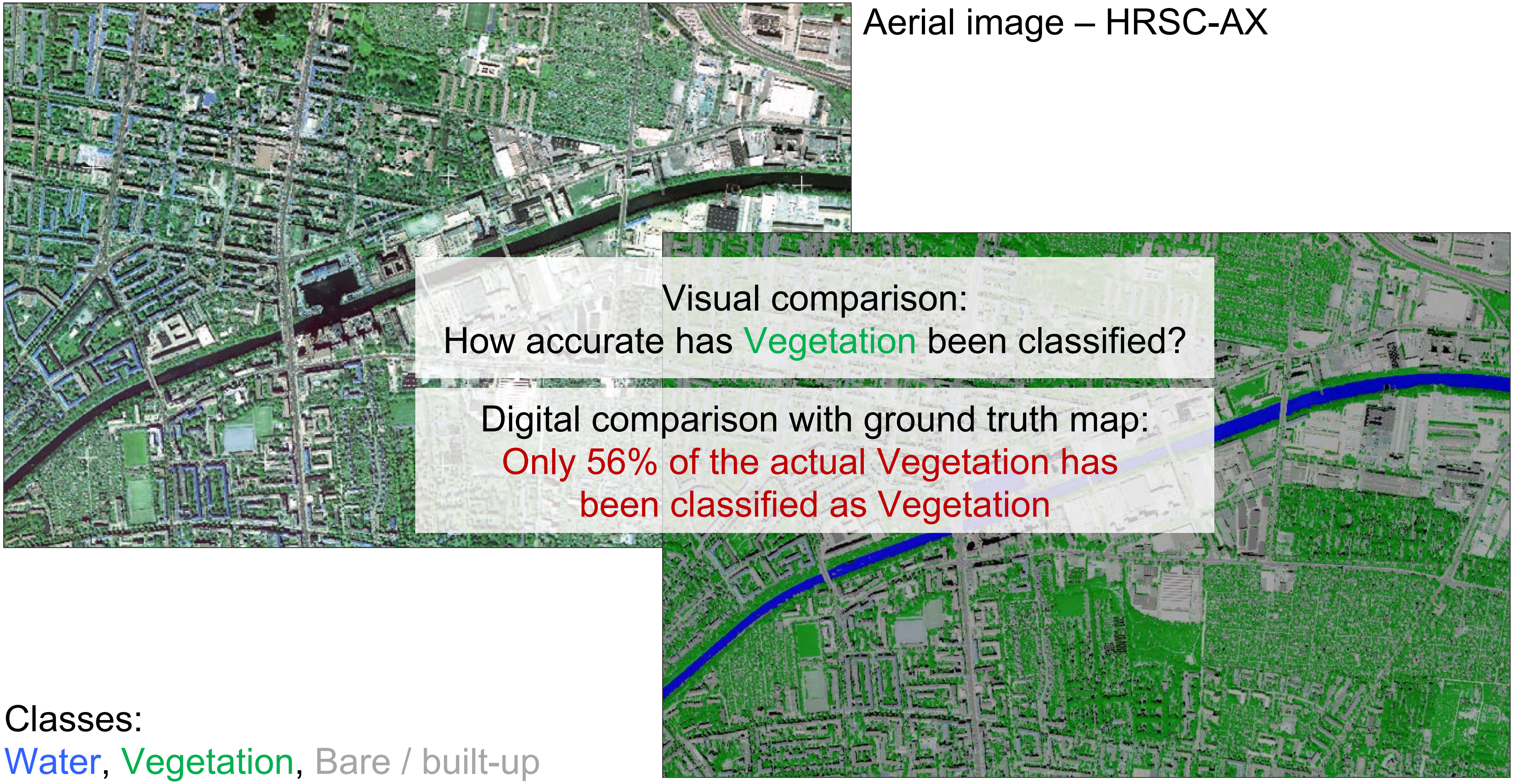
Vergleich mit *ground truth* (digital) -> zuverlässig, häufig angewendet, **quantitativ**

Unabhängige Verwendung von *ground truth* für Training des Klassifikators und Validierung (digital) -> zuverlässig, häufig angewendet, **quantitativ**

Vergleich mit unabhängiger/ statistisch basierter Referenz (digital) -> „*best practice*“, sehr zuverlässig, **quantitativ**

Accuracy assessment

Aerial image – HRSC-AX



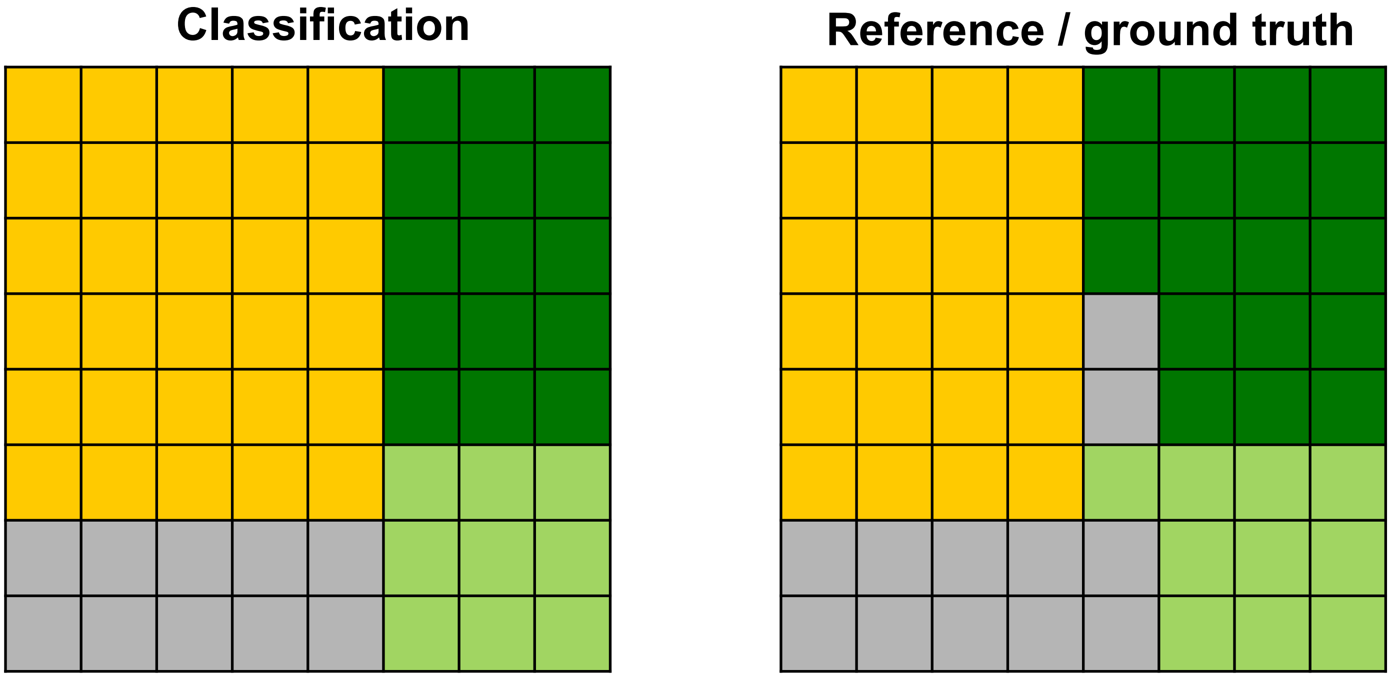
Visual comparison:
How accurate has Vegetation been classified?

Digital comparison with ground truth map:
Only 56% of the actual Vegetation has been classified as Vegetation

Classes:
Water, Vegetation, Bare / built-up

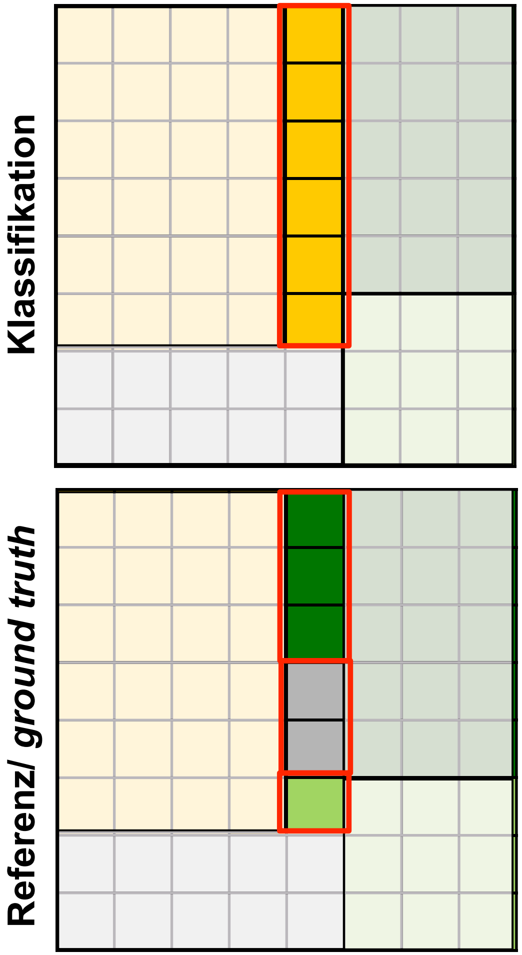
Error matrix („Fehlermatrix“)

(synonym: confusion matrix, matching matrix, contingency table)



🟩 Forest
🟨 Arable
🟩 Other vegetation
⬜ Bare / built-up

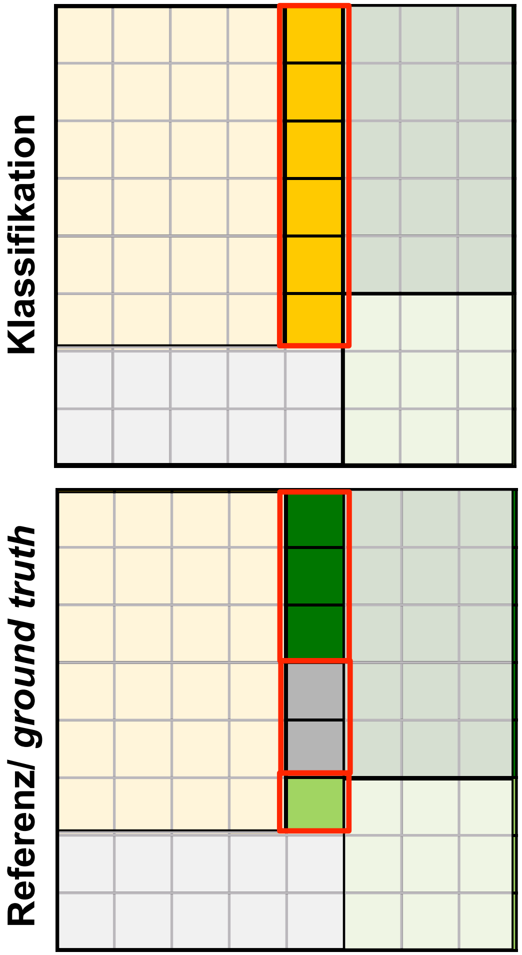
Error matrix



		Referenz/ *ground truth*				
		A	**B**	**C**	**D**	**Σ**
Klassifikation	**A**	15	0	0	0	15
	B	0	9	0	0	
	C	3	1	24	2	
	D	0	0	0	10	
	Σ	18				

🟩 Forest
🟨 Arable
🟩 Other vegetation
⬜ Bare / built-up

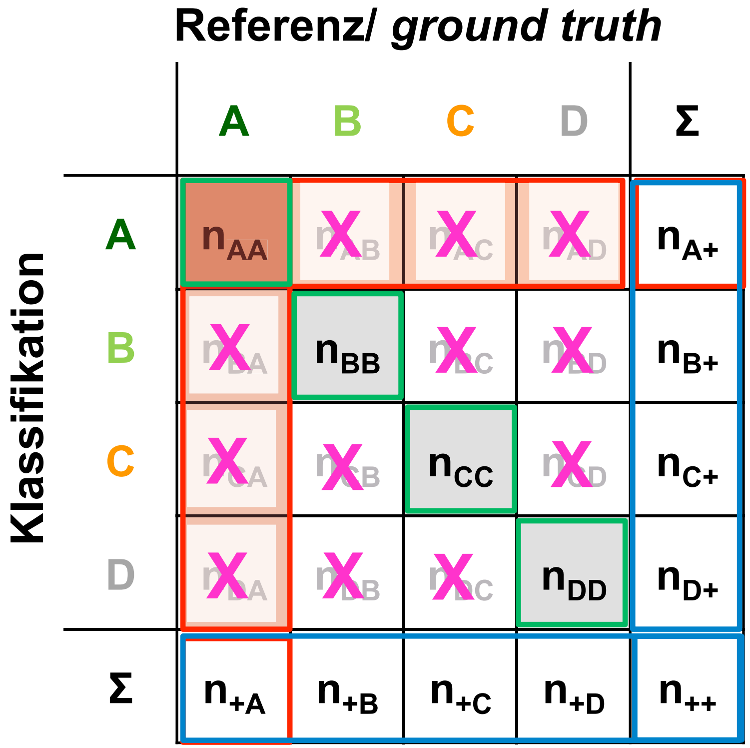
Error matrix



		Referenz/ *ground truth*				
		A	B	C	D	Σ
Klassifikation	A	15	0	0	0	15
	B	0	9	0	0	9
	C	3	1	24	2	30
	D	0	0	0	10	10
	Σ	18	10	24	12	64

🟩 Forest
🟨 Arable
🟩 Other vegetation
⬜ Bare / built-up

Error matrix



Referenz/ *ground truth*

Klassifikation

	A	B	C	D	Σ
A	n_{AA}	X ~~n_{AB}~~	X ~~n_{AC}~~	X ~~n_{AD}~~	n_{A+}
B	X ~~n_{BA}~~	n_{BB}	X ~~n_{BC}~~	X ~~n_{BD}~~	n_{B+}
C	X ~~n_{CA}~~	X ~~n_{CB}~~	n_{CC}	X ~~n_{CD}~~	n_{C+}
D	X ~~n_{DA}~~	X ~~n_{DB}~~	X ~~n_{DC}~~	n_{DD}	n_{D+}
Σ	n_{+A}	n_{+B}	n_{+C}	n_{+D}	n_{++}

N_{A+} Number of pixels *classified* as A

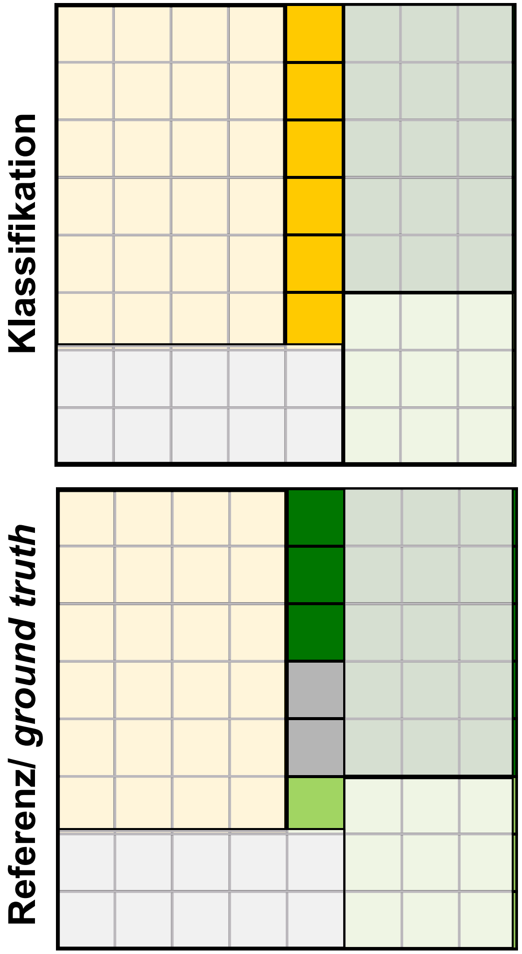
N_{+A} Number of pixels found to be A in *reference*

Correctly classified
(classification == reference)

Incorrectly classified
(classification ≠ reference)

Grand total (total pixel count)

Error matrix



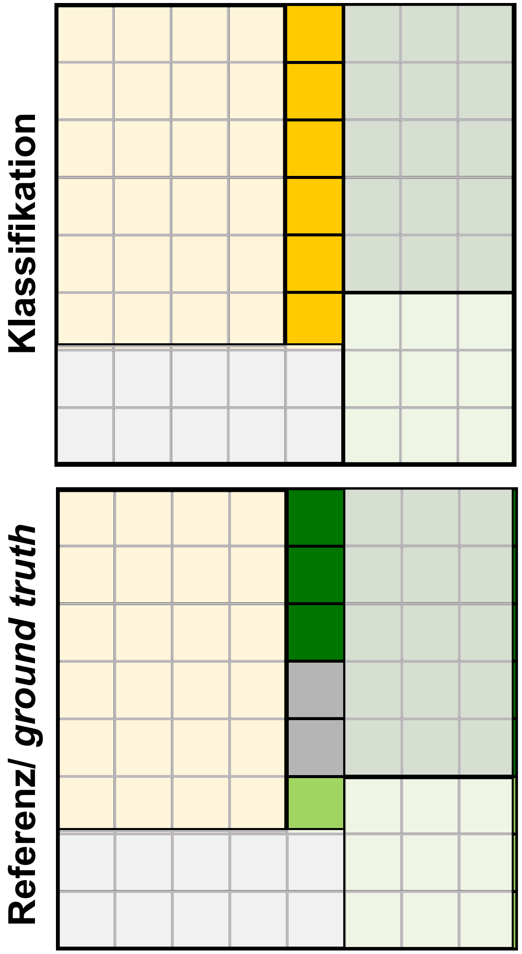
		Referenz/ *ground truth*				
		A	**B**	**C**	**D**	**Σ**
Klassifikation	**A**	**15**	**0**	**0**	**0**	**15**
	B	**0**	**9**	**0**	**0**	**9**
	C	**3**	**1**	**24**	**2**	**30**
	D	**0**	**0**	**0**	**10**	**10**
	Σ	**18**	**10**	**24**	**12**	**64**

Correctly classified
classification == reference

Incorrectly classified
classification ≠ reference

🟩 Forest
🟨 Arable
🟩 Other vegetation
▨ Bare / built-up

Type 1 (commission) and type 2 (omission) error



		Referenz/ *ground truth*				
		A	B	C	D	Σ
Klassifikation	A	15	0	0	0	15
	B	0	9	0	0	9
	C	3	1	24	2	30
	D	0	0	0	10	10
	Σ	18	10	24	12	64

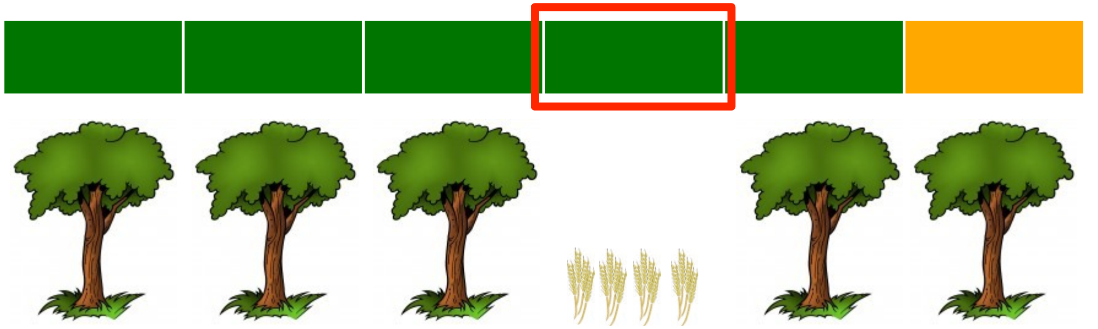
Incorrectly classified
classification ≠ reference

- Type 1:
  Commission Error
  Pixels were included in the class, although they should not have been

- Type 2:
  Omission Error
  Pixels were not included in the class, although they should have been

Type 1 (commission) and type 2 (omission) error

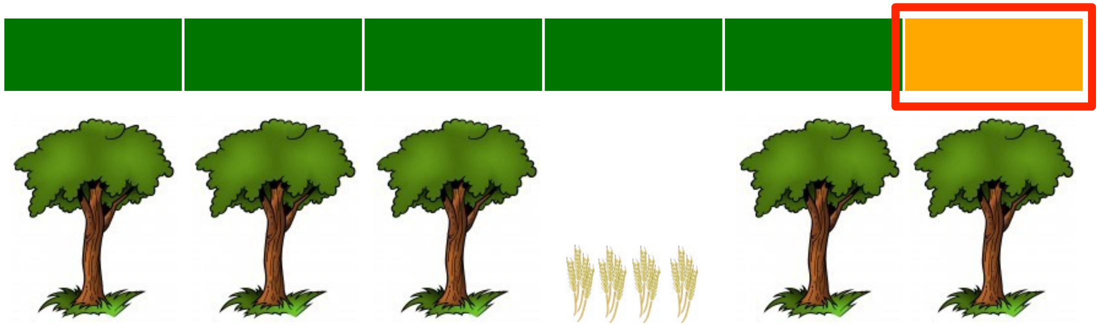
Type 1 (commission error) – example for class **Forest**



Klassifikation

Referenz/ *ground truth*

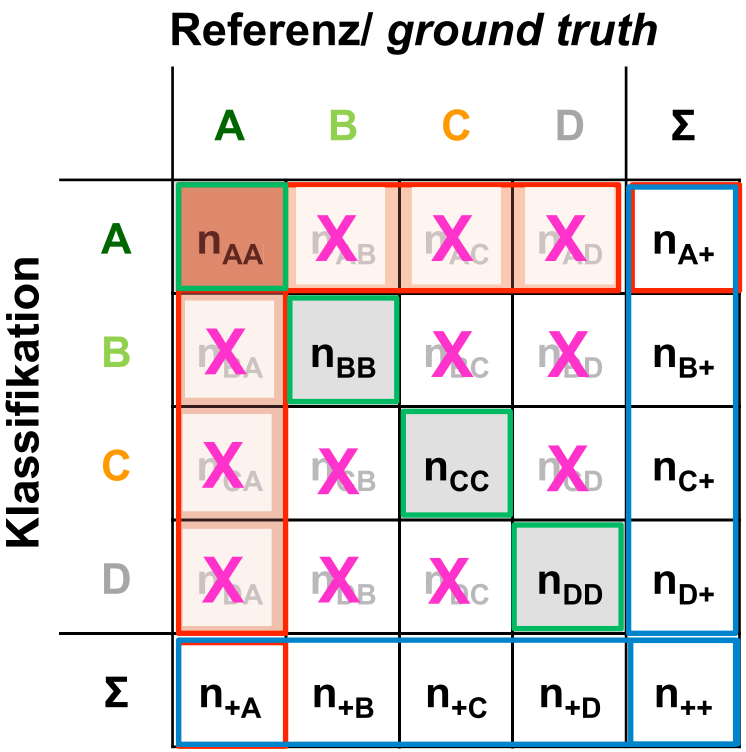
Type 2 (ommission error) – example for class **Forest**



Klassifikation

Referenz/ *ground truth*

Accuracy metrics (or: error metrics)



Referenz/ *ground truth*

Klassifikation

	A	B	C	D	Σ
A	n_{AA}	$\xcancel{n_{AB}}$	$\xcancel{n_{AC}}$	$\xcancel{n_{AD}}$	n_{A+}
B	$\xcancel{n_{BA}}$	n_{BB}	$\xcancel{n_{BC}}$	$\xcancel{n_{BD}}$	n_{B+}
C	$\xcancel{n_{CA}}$	$\xcancel{n_{CB}}$	n_{CC}	$\xcancel{n_{CD}}$	n_{C+}
D	$\xcancel{n_{DA}}$	$\xcancel{n_{DB}}$	$\xcancel{n_{DC}}$	n_{DD}	n_{D+}
Σ	n_{+A}	n_{+B}	n_{+C}	n_{+D}	n_{++}

N_{A+} Number of pixels *classified* as A

N_{+A} Number of pixels found to be A in *reference*

Correctly classified (classification == reference)

Incorrectly classified (classification ≠ reference)

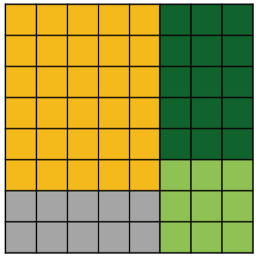
Grand total (total pixel count)

Accuracy **metrics**: measures for classification accuracy based on the error **matrix**

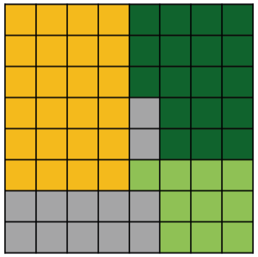
Accuracy metrics

English	*Deutsch*
Overall Accuracy	**Gesamtgenauigkeit**
Producer Accuracy	**Produzenten-Genauigkeit**
User Accuracy	**Nutzer-Genauigkeit**
Average Accuracy	durchschnittliche Genauigkeit
Mean Accuracy	mittlere Genauigkeit
Kappa Coefficient	Kappa Koeffizient

Overall/ Total Accuracy (OA)



Klassifikation



Referenz

Klassifikation	Referenz/ *ground truth*				
	A	**B**	**C**	**D**	**Σ**
A	**15**	**0**	**0**	**0**	**15**
B	**0**	**9**	**0**	**0**	**9**
C	**3**	**1**	**24**	**2**	**30**
D	**0**	**0**	**0**	**10**	**10**
Σ	**18**	**10**	**24**	**12**	**64**

$$\text{Overall Accuracy} = \frac{\text{Count of correctly classified pixels}}{\text{Grand total (total pixel count)}} = \frac{58}{64} = 0.90625$$

(~90.6%)

Genauigkeitsmasse – Overall/ Total Accuracy (OA)

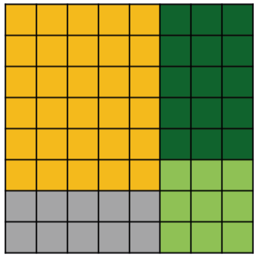
Die **Overall Accuracy** ist ein einfaches Genauigkeitsmass,
aber **wenig aussagekräftig**!

Fehler 1. Art (Commission) und **Fehler 2. Art** (Omission)
werden **nicht berücksichtigt**!

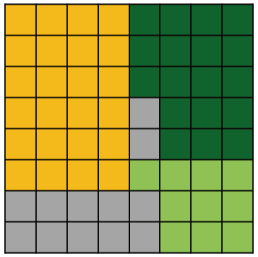
$$\text{Overall Accuracy} = \frac{\text{die Summe der richtig klassifizierten Pixel}}{\text{Gesamtanzahl aller Pixel/ Grundgesamtheit}} = \frac{58}{64} = 0.90625$$

(~90.6%)

Producer‘s Accuracy (PA)



Klassifikation



Referenz

		Referenz/ *ground truth*				
		A	**B**	**C**	**D**	**Σ**
Klassifikation	**A**	**15**	**0**	**0**	**0**	**15**
	B	**0**	**9**	**0**	**0**	**9**
	C	**3**	**1**	**24**	**2**	**30**
	D	**0**	**0**	**0**	**10**	**10**
	Σ	**18**	**10**	**24**	**12**	**64**
	PA	83.33	90	100	83.33	

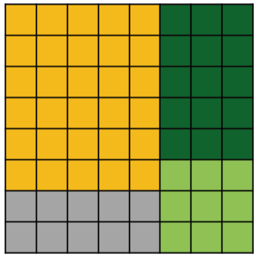
The **producer** needs to know how well her/his classification (e.g. for **class A**) matches with the reference

== Omission Error
How many pixels should have been in the class but were not

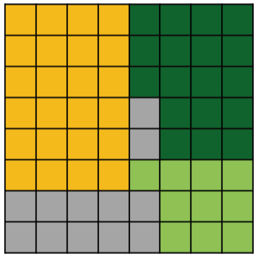
$$\text{Producer‘s Accuracy} = \frac{\text{count of correctly classified pixels in class}}{\text{count of pixels in same reference class}} = \frac{15}{18} = 0.8333$$

(~83.3%)

User‘s Accuracy (UA)



Klassifikation



Referenz

		Referenz/ *ground truth*					
		A	**B**	**C**	**D**	**Σ**	UA
Klassifikation	**A**	**15**	**0**	**0**	**0**	**15**	100
	B	**0**	**9**	**0**	**0**	**9**	100
	C	**3**	**1**	**24**	**2**	**30**	80
	D	**0**	**0**	**0**	**10**	**10**	100
	Σ	**18**	**10**	**24**	**12**	**64**	

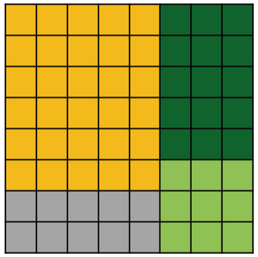
The **user** needs to know how well a class (e.g. **A**) matches with the reality

== Commission Error
How many pixels are in the class but should not have been

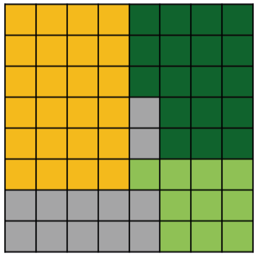
$$\text{User‘s Accuracy} = \frac{\text{count of correctly classified pixels in class}}{\text{count of all pixels in that class}} = \frac{15}{15} = 1$$

(100%)

Accuracy metrics – OA, PA, UA



Klassifikation



Referenz

	Referenz/ *ground truth*					
Klassifikation	**A**	**B**	**C**	**D**	**Σ**	**UA [%]**
A	15	0	0	0	15	100
B	0	9	0	0	9	100
C	3	1	24	2	30	80
D	0	0	0	10	10	100
Σ	18	10	24	12	64	
PA [%]	83.33	90	100	83.33		

OA [%] 90.63

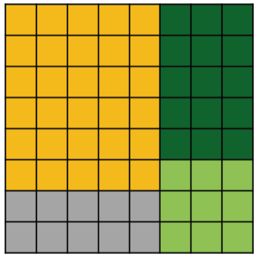
If I classified a pixel as forest (A), there is in 100% of the cases indeed forest at that location

I have captured 100% of the existing arable land (C) with my classification

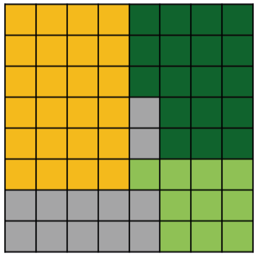
But: 20% of the classified arable land (C) pixels has another land cover in reality

But: 16.67% of the existing forest (A) was not captured

Accuracy metrics – OA, PA, UA



Klassifikation



Referenz

		Referenz/ *ground truth*					
		A	B	C	D	Σ	UA [%]
Klassifikation	A	15	0	0	0	15	100
	B	0	9	0	0	9	100
	C	3	1	24	2	30	80
	D	0	0	0	10	10	100
	Σ	18	10	24	12	64	
PA [%]		83.3	90	100	83.3		

OA [%] 90.63

90.63% of all classified pixels matches with the reference / reality

Hands-on!

A	A	A	B	B
A	A	A	B	B
A	A	A	B	B
B	B	B	B	B

Klassifikation

A	A	A	A	B
A	A	A	B	B
A	A	A	B	B
B	B	B	B	B

Referenz/ *ground truth*

		Referenz			
		A	B	Σ	UA [%]
Klassifikation	A				
	B				
	Σ			20	
PA [%]					
OA [%]					

Hands-on!

A	A	A	B	B
A	A	A	B	B
A	A	A	B	B
B	B	B	B	B

Klassifikation

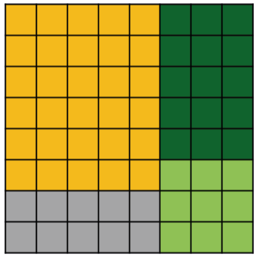
A	A	A	A	B
A	A	A	B	B
A	A	A	B	B
B	B	B	B	B

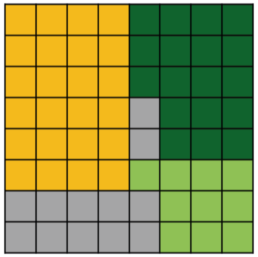
Referenz/ *ground truth*

		Referenz			
		A	B	Σ	UA [%]
Klassifikation	A	9	0	9	100
	B	1	10	11	90.9
	Σ	10	10	20	
PA [%]		90	100		

OA [%] 95.00

Mean UA (or: average accuracy)


Klassifikation


Referenz

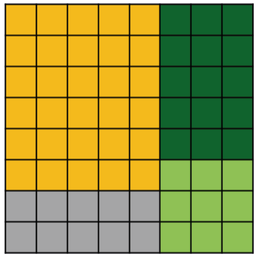
		Referenz/ *ground truth*					
		A	**B**	**C**	**D**	**Σ**	**UA [%]**
Klassifikation	**A**	15	0	0	0	15	100
	B	0	9	0	0	9	100
	C	3	1	24	2	30	80
	D	0	0	0	10	10	100
	Σ	18	10	24	12	64	
	PA [%]	83.33	90	100	83.33		

Overall Accuracy
90.63 %

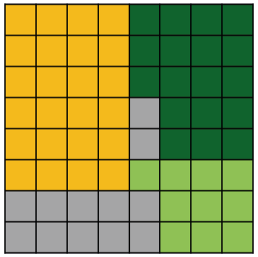
Mean UA
95.00 %

$$\text{Average Accuracy} = \frac{\text{sum of all user accuracies}}{\text{number of classes}} = \frac{380\%}{4} = 95\%$$

Mean classification accuracy



Klassifikation



Referenz

		Referenz/ *ground truth*					
		A	B	C	D	Σ	UA [%]
Klassifikation	A	15	0	0	0	15	100
	B	0	9	0	0	9	100
	C	3	1	24	2	30	80
	D	0	0	0	10	10	100
	Σ	18	10	24	12	64	
	PA [%]	83.33	90	100	83.33		

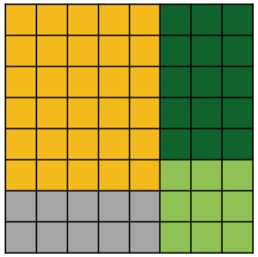
Overall Accuracy
90.63 %

Mean UA
95.00 %

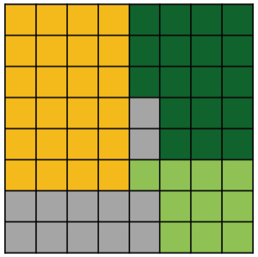
Mean Accuracy
92.82 %

$$\text{Mean Accuracy} = \frac{\text{Overall Accuracy + Mean UA}}{2} = \frac{185.63}{2} = 92.82\%$$

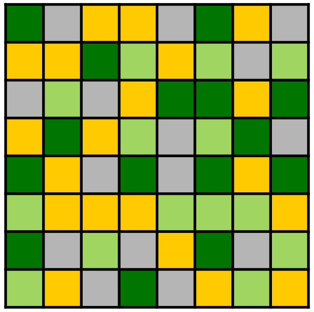
Genauigkeitsmasse – Kappa Coefficient/ KHAT statistic



Klassifikation



Referenz



Zufalls-Klassifikation

Referenz/ *ground truth*

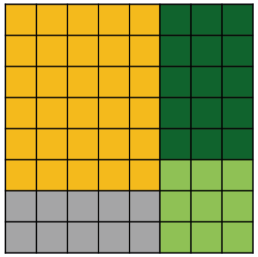
Klassifikation	A	B	C	D	Σ
A	**15**	**0**	**0**	**0**	**15**
B	**0**	**9**	**0**	**0**	**9**
C	**3**	**1**	**24**	**2**	**30**
D	**0**	**0**	**0**	**10**	**10**
Σ	**18**	**10**	**24**	**12**	**64**

Unterschied der Übereinstimmung zwischen **Klassifikation –> Referenz** und **Zufallsklassifikation –> Referenz**.

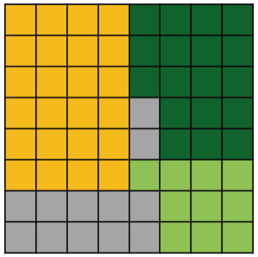
Zu welchem Anteil sind die „korrekt“ klassifizierten Pixel **zufällig** richtig?

Um welchen Prozentsatz ist meine Klassifikation **besser im Vergleich zu einer rein zufälligen Klassifikation**?

Genauigkeitsmasse – Kappa Coefficient



Klassifikation

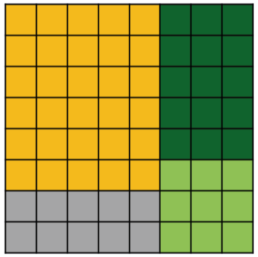


Referenz

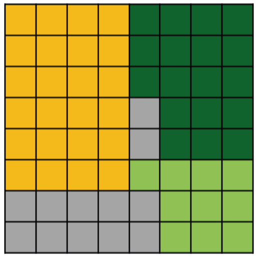
		Referenz/ *ground truth*				
		A	**B**	**C**	**D**	**Σ**
Klassifikation	**A**	15	0	0	0	15
	B	0	9	0	0	9
	C	3	1	24	2	30
	D	0	0	0	10	10
	Σ	18	10	24	12	64

$$\text{Kappa Coefficient } (\hat{k}) = \frac{\text{Overall Accuracy} - \text{Zufallsübereinstimmung}}{1 - \text{Zufallsübereinstimmung}}$$

Genauigkeitsmasse – Kappa Coefficient



Klassifikation



Referenz

Klassifikation \ Referenz/ *ground truth*	A	B	C	D	Σ
A	**15**	0	0	0	15
B	0	**9**	0	0	9
C	3	1	**24**	2	30
D	0	0	0	**10**	10
Σ	18	10	24	12	**64**

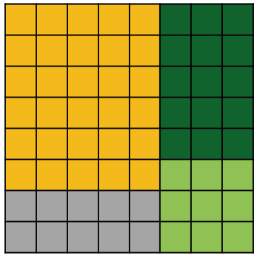
Summe der richtig klassifizierten Pixel = 15+9+24+10 = 58

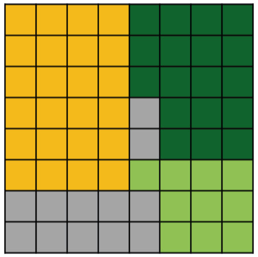
Grund-gesamtheit = 64

Overall Accuracy = 0.90625

$$\text{Kappa Coefficient} = \frac{\text{Overall Accuracy} - \text{Zufallsübereinstimmung}}{1 - \text{Zufallsübereinstimmung}}$$

Genauigkeitsmasse – Kappa Coefficient


Klassifikation


Referenz

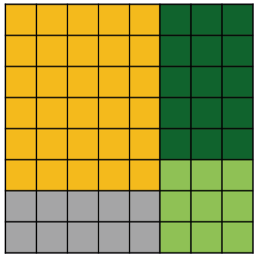
		Referenz/ *ground truth*				
		A	**B**	**C**	**D**	**Σ**
Klassifikation	**A**	**15**	**0**	**0**	**0**	**15**
	B	**0**	**9**	**0**	**0**	**9**
	C	**3**	**1**	**24**	**2**	**30**
	D	**0**	**0**	**0**	**10**	**10**
	Σ	**18**	**10**	**24**	**12**	**64**

Overall Accuracy = 0.90625

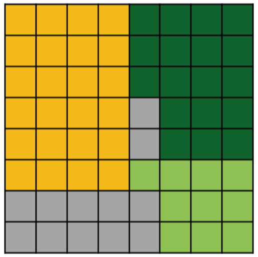
$$\text{Zufalls\"ubereinstimmung} = \frac{\text{Summe der Produkte der Zeilen- und Spaltensummen}}{\text{Grundgesamtheit}^2}$$

$$\text{Kappa Coefficient} = \frac{0.90625 - \text{Zufalls\"ubereinstimmung}}{1 - \text{Zufalls\"ubereinstimmung}}$$

Genauigkeitsmasse – Kappa Coefficient



Klassifikation



Referenz

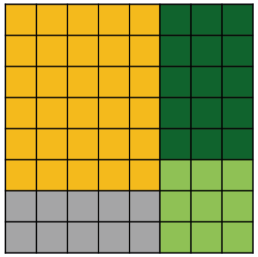
		Referenz/ *ground truth*				
		A	**B**	**C**	**D**	**Σ**
Klassifikation	**A**	15	0	0	0	15
	B	0	9	0	0	9
	C	3	1	24	2	30
	D	0	0	0	10	10
	Σ	18	10	24	12	64

$$\text{Overall Accuracy} = 0.90625$$

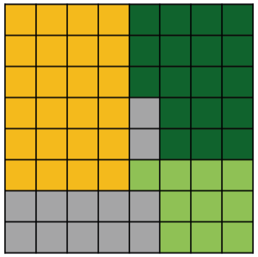
$$\text{Zufallsübereinstimmung} = \frac{\text{Summe der Produkte der Zeilen- und Spaltensummen}}{\text{Grundgesamtheit}^2}$$

$$\text{Kappa Coefficient} = \frac{0.90625 - \text{Zufallsübereinstimmung}}{1 - \text{Zufallsübereinstimmung}}$$

Genauigkeitsmasse – Kappa Coefficient



Klassifikation



Referenz

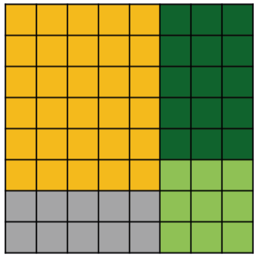
Klassifikation	Referenz/ *ground truth*				
	A	**B**	**C**	**D**	**Σ**
A	15	0	0	0	15
B	0	9	0	0	9
C	3	1	24	2	30
D	0	0	0	10	10
Σ	18	10	24	12	64

Overall Accuracy = 0.90625

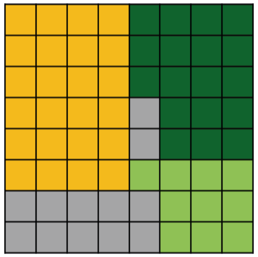
$$\text{Zufallsübereinstimmung} = \frac{\textbf{Summe der Produkte der Zeilen- und Spaltensummen}}{4096}$$

$$\text{Kappa Coefficient} = \frac{0.90625 \quad - \quad \text{Zufallsübereinstimmung}}{1 \quad - \quad \text{Zufallsübereinstimmung}}$$

Genauigkeitsmasse – Kappa Coefficient



Klassifikation



Referenz

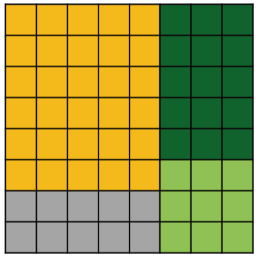
		Referenz/ *ground truth*				
		A	**B**	**C**	**D**	**Σ**
Klassifikation	**A**	15	0	0	0	15
	B	0	9	0	0	9
	C	3	1	24	2	30
	D	0	0	0	10	10
	Σ	18	10	24	12	64

Overall Accuracy = 0.90625

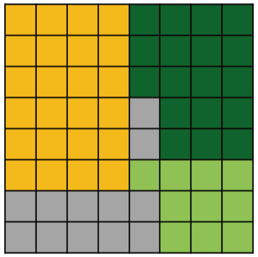
$$\text{Zufallsübereinstimmung} = \frac{(15\text{x}18)+(9\text{x}10)+(30\text{x}24)+(10\text{x}12)}{4096}$$

$$\text{Kappa Coefficient} = \frac{0.90625 - \text{Zufallsübereinstimmung}}{1 - \text{Zufallsübereinstimmung}}$$

Genauigkeitsmasse – Kappa Coefficient



Klassifikation



Referenz

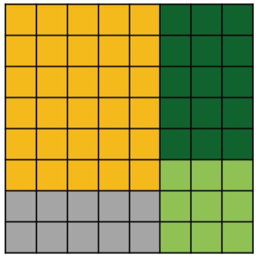
		Referenz/ *ground truth*				
		A	**B**	**C**	**D**	**Σ**
Klassifikation	**A**	15	0	0	0	15
	B	0	9	0	0	9
	C	3	1	24	2	30
	D	0	0	0	10	10
	Σ	18	10	24	12	64

Overall Accuracy = 0.90625

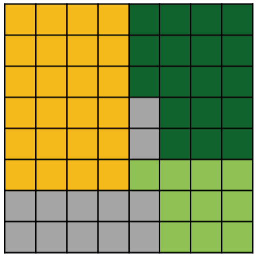
$$\text{Zufalls-übereinstimmung} = \frac{1200}{4096} = 0.2929$$

$$\text{Kappa Coefficient} = \frac{0.90625 - \text{Zufallsübereinstimmung}}{1 - \text{Zufallsübereinstimmung}}$$

Genauigkeitsmasse – Kappa Coefficient



Klassifikation



Referenz

		Referenz/ *ground truth*				
		A	**B**	**C**	**D**	**Σ**
Klassifikation	**A**	**15**	**0**	**0**	**0**	**15**
	B	**0**	**9**	**0**	**0**	**9**
	C	**3**	**1**	**24**	**2**	**30**
	D	**0**	**0**	**0**	**10**	**10**
	Σ	**18**	**10**	**24**	**12**	**64**

Overall Accuracy = 0.90625

Zufalls-übereinstimmung = 0.2929

$$\text{Kappa Coefficient} = \frac{0.90625 - 0.2929}{1 - 0.2929} = \mathbf{0.8674}$$

Kann interpretiert werden als:
Meine Klassifikation ist 86.74% besser im Vergleich zu einer rein zufälligen Klassifikation!

Genauigkeitsmasse – Kappa Coefficient

- vielfältig interpretierbar -> es existieren verschiedene Richtwerte für die Beurteilung des Koeffizienten

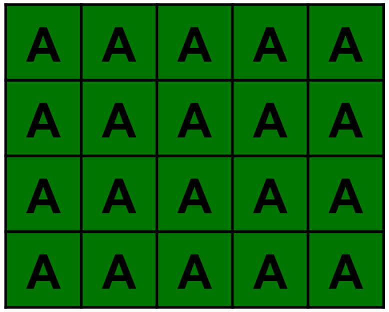
Kappa - Coefficient	***Level of Agreement to Reference***
0.00	poor / -
0.00 – 0.20	slight / schwach
0.21 – 0.40	fair / leicht
0.41 – 0.60	moderate / mittelmäßig
0.61 – 0.80	substantial / gut
0.81 – 1.00	almost perfect / sehr gut

(Grouven et al. 2007:66)

- keine allgemeingültigen Aussagen möglich!

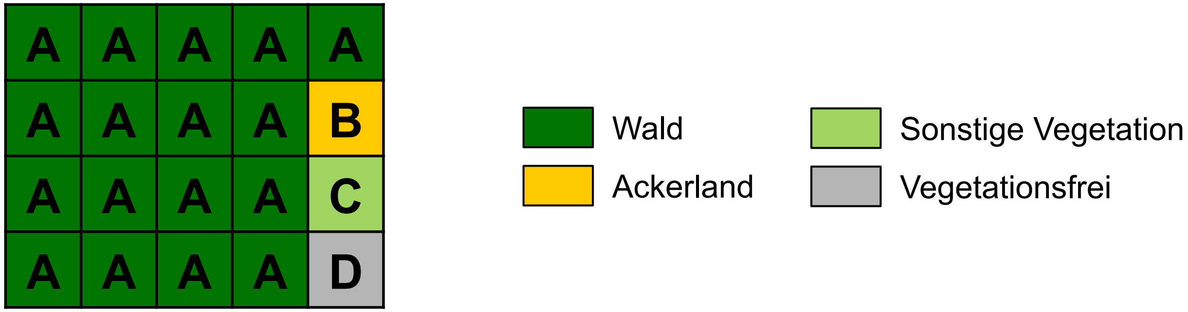
Genauigkeitsmasse – Kappa Coefficient

- keine allgemeingültigen Aussagen möglich!



A	A	A	A	A
A	A	A	A	A
A	A	A	A	A
A	A	A	A	A

Klassifikation



A	A	A	A	A
A	A	A	A	B
A	A	A	A	C
A	A	A	A	D

🟩 Wald
🟨 Ackerland
🟩 Sonstige Vegetation
⬜ Vegetationsfrei

Referenz/ *ground truth*

Kappa Coefficient = 0

OA = 85%

Kappa - Coefficient	*Level of Agreement to Reference*
0.00	poor / -
0.00 – 0.20	slight / schwach
0.21 – 0.40	fair / leicht
0.41 – 0.60	moderate / mittelmäßig
0.61 – 0.80	substantial / gut
0.81 – 1.00	almost perfect / sehr gut

Accuracy assessment – summary

Referenz

Klassifikation

	A	**B**	**C**	**D**	**Σ**
A	n_{AA}	n_{AB}	n_{AC}	n_{AD}	n_{A+}
B	n_{BA}	n_{BB}	n_{BC}	n_{BD}	n_{B+}
C	n_{CA}	n_{CB}	n_{CC}	n_{CD}	n_{C+}
D	n_{DA}	n_{DB}	n_{DC}	n_{DD}	n_{D+}
Σ	N_{+A}	N_{+B}	N_{+C}	N_{+D}	n

$$\textit{Overall Accuracy} = \frac{\sum_{i=1}^{q} n_{ii}}{n}$$

$$PA = \frac{n_{ii}}{n_{+i}} \qquad UA = \frac{n_{ii}}{n_{i+}}$$

$$\textit{Mean UA Accuracy} = \frac{\sum_{i=1}^{q} UA}{n}$$

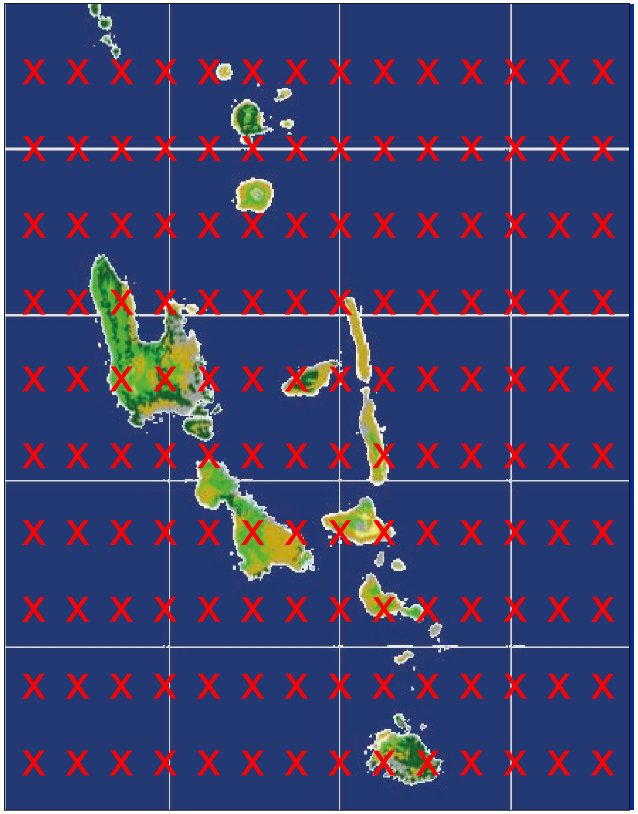
$$\textit{Mean Accuracy} = \frac{OA + \textit{Mean UA Accuracy}}{2}$$

q = *Anzahl an Klassen*
n = *Grundgesamtheit*

n_{ii} = *Anzahl übereinstimmender Pixel*
n_{i+} = *Summe der Zeilenwerte*
n_{+i} = *Summe der Spaltenwerte*

Accuracy metrics – applying them correctly

Accuracy metrics depend on the sampling scheme of the reference



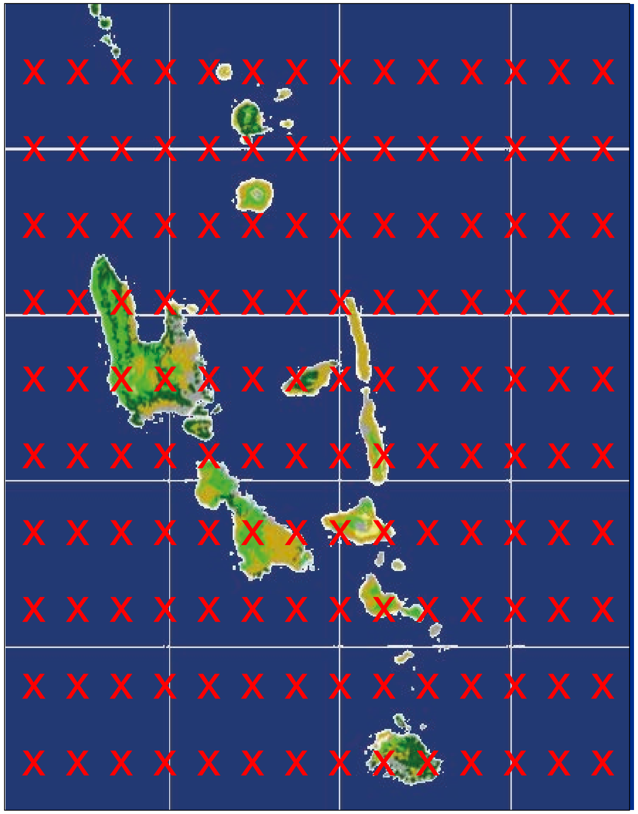
OA = 95.6%

🟩 Forest (≥20%)
🟨 Forest (< 20%)
🟩 Grassland
🟦 Water

		Referenz/ *ground truth*				
		A	**B**	**C**	**D**	**Σ**
Klassifikation	**A**	2	1	0	0	3
	B	2	3	1	0	6
	C	0	2	5	0	7
	D	0	0	0	124	124
	Σ	4	6	6	124	140

Accuracy metrics – applying them correctly

Accuracy information depend on the choice of metric



OA = 95.6%

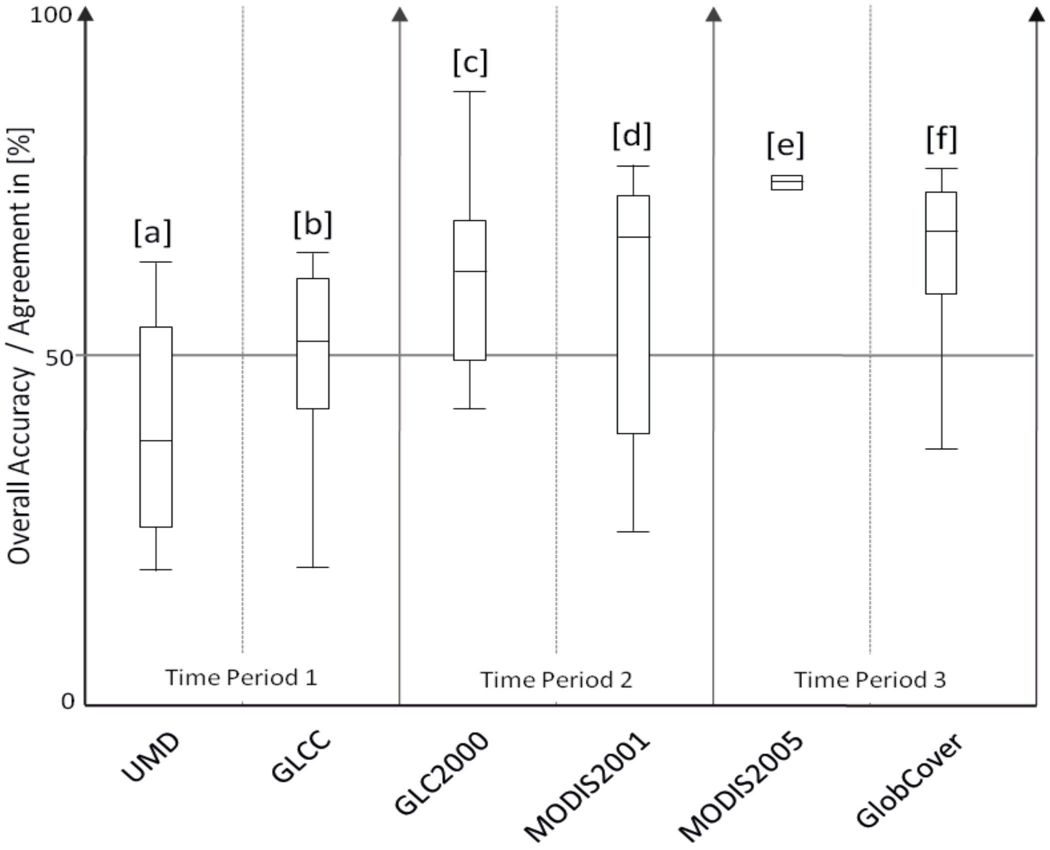
Mean user accuracy = 72.0%

Mean classification accuracy = 83.9%

	PA	UA
🟩 Forest (≥20%)	0.5	0.7
🟨 Forest (< 20%)	0.5	0.5
🟩 Grassland	0.8	0.7
🟦 Water	1.0	1.0

Accuracy metrics – applying them correctly

Accuracy information depend on the interpretation of the metric



Accuracy – Take-Home Messages

- "A classification is not complete until it has been assessed."
- You need multiple accuracy metrics to get a good representation of the actual accuracy; a single metric may lead to an incorrect assessment
- The reference dataset must be representative for the classification
- Be critical when you communicate your classification to your users

Requirements regarding the previous *two lectures (on “Image analysis” and “Image classification”)*

Image analysis

- Understand the concepts of (visualizing) spectral bands
- Understand simple band operations and what they can be used for
- Know various change-detection techniques (concepts, no tech. details)
- Be able to describe and recognize low-pass and high-pass filters

Classification

- Know different (types of) algorithms (characteristics, pros and cons), be able to describe them and to conceptually apply them
- Be able to describe and apply the various accuracy metrics

Thank you for your attention!