The potential of Sentinel-2 data to classify tree species

Wessel, M., Brandmeier, M., Tiede, D. September 2017





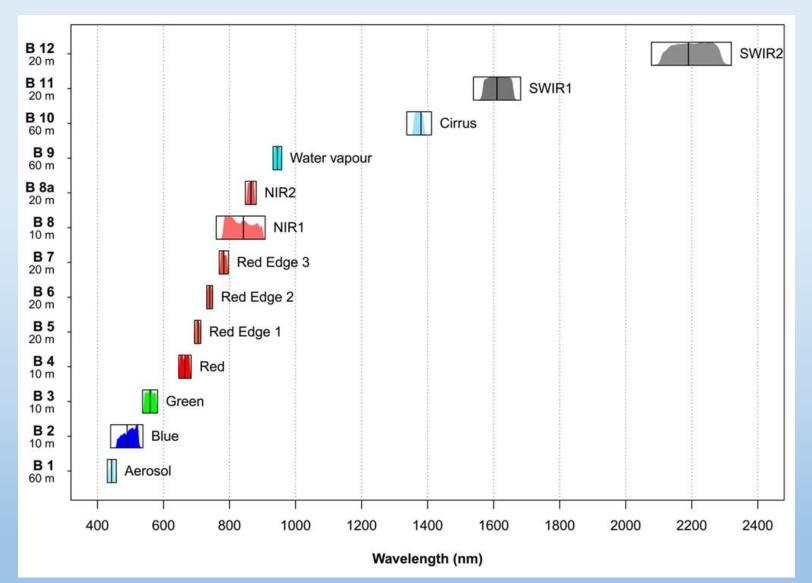


Outline of Presentation

- 1. Introduction
- 2. Classification and Machine Learning Approaches
- 3. Accuracy Assessment and Transferability
- 4. Conclusions



http://blog.astronomieschule.de/2015/06/23/sentinel-2a-erfolgreich-gestartet/



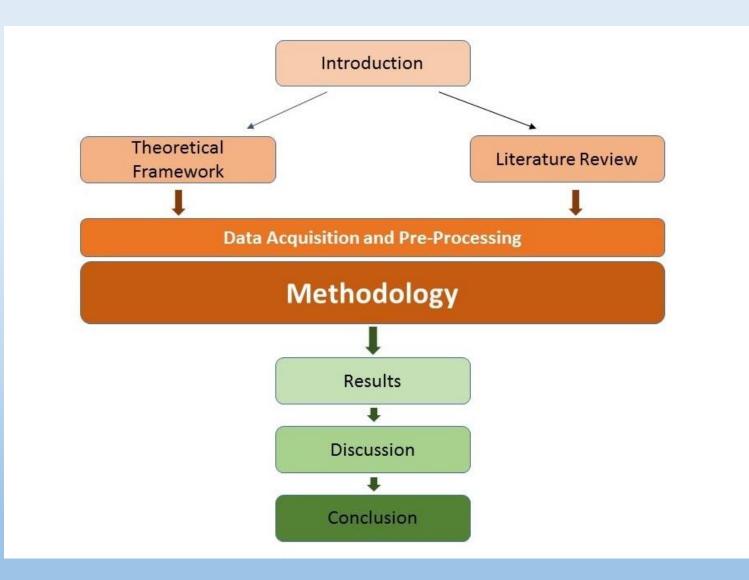
http://www.mdpi.com/remotesensing/remotesensing-08-00166/article_deploy/html/images/remotesensing-08-00166-g002-1024.png

"How valuable is the **potential** of **Sentinel-2 data** to **classify tree species** using **GIS software**?"

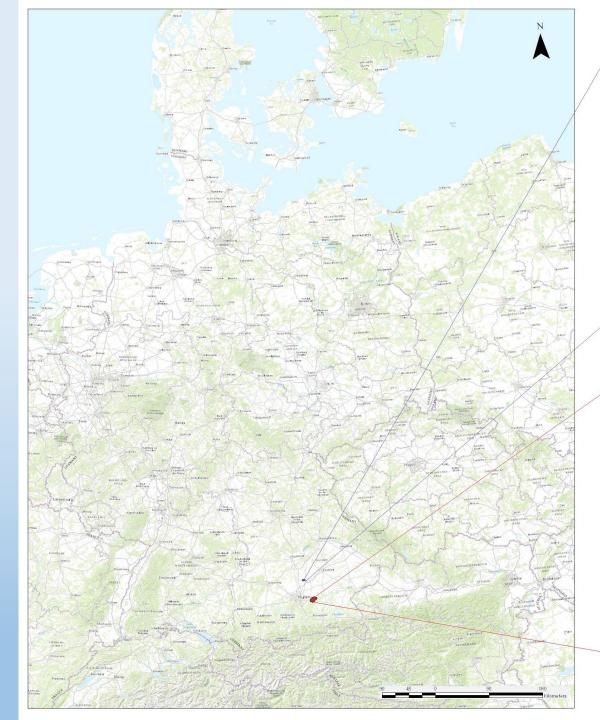
Which role does the red edge part play?

Can S-2 compete with high resolution, cost-intense hyperspectral earth monitoring satellite data?

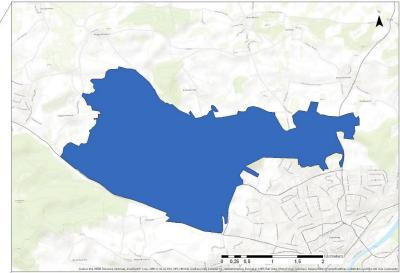
Is the resolution sufficient enough for detailed forest / tree species classifications?



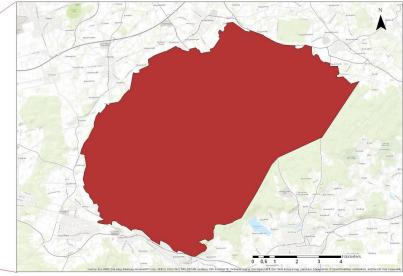
- Primarily use of statistical machine learning classifiers (SVM and RF)
- Use of ArcGIS Pro
- Focus on scientific relevance (arrangements and discussions with the LWF "Landesanstalt für Wald und Forstwirtschaft Bayern")
- Importance of Validation Procedure



Freisinger Forest



Ebersberger Forest



Data Aquisition

a) Sentinel-2 data

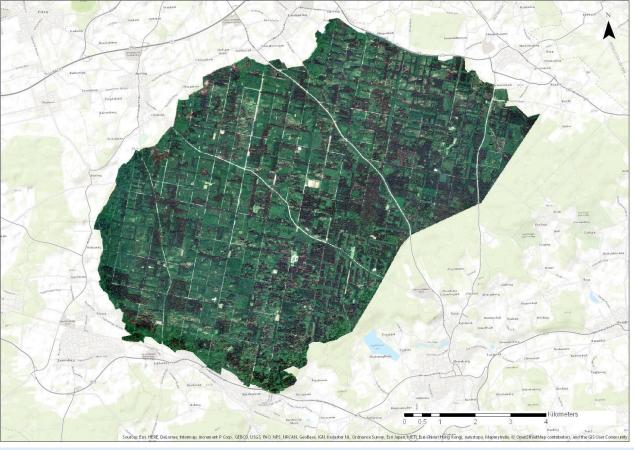
 Freely available in the "Copernicus Open Access Hub" (non-atmosphere corrected level 1C data)

https://scihub.copernicus.eu/dhus/#/home

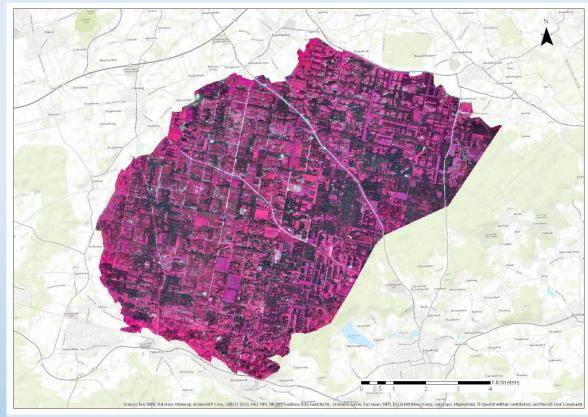
- 0% cloud coverage as important factor
- 3 different dates for multitemporal analysis (May, August, September)

Sentinel-2 data:

Date	Product Name	Cloud Coverage%	Product Level	
22 May 2016	S2A_OPER_PRD_MSIL1C_PDMC_2016052 2T182438_R065_V20160522T102029_201 60522T102029.SAFE	28.7	1C	
09 August 2016	S2A_OPER_PRD_MSIL1C_PDMC_2016080 9T050727_R022_V20150704T101337_201 50704T101337.SAFE	4.5	1C	
29 September 2016 EF*	S2A_OPER_PRD_MSIL1C_PDMC_2016092 9T185141_R065_V20160929T102022_201 60929T102344.SAFE	0.0	1C	
29 September 2016 FF*	S2A_OPER_PRD_MSIL1C_PDMC_2016092 9T181908_R065_V20160929T102022_201 60929T102344.SAFE	0.0	1C	
EF = Ebersberger Forest FF = Freisinger Forest				



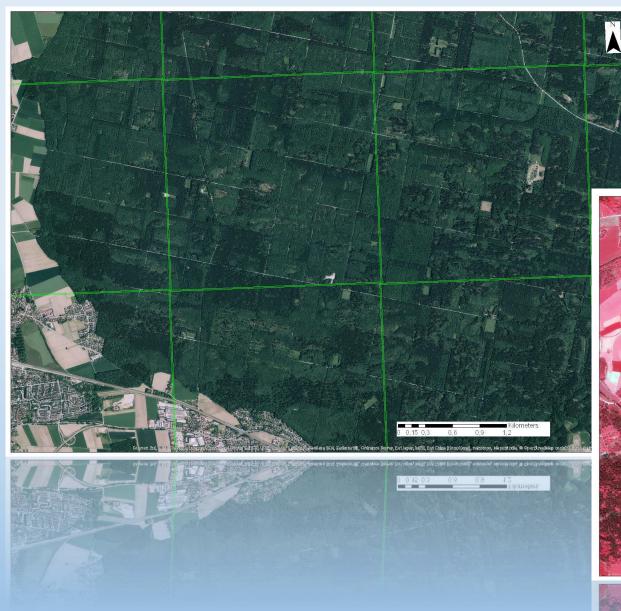






b) Aerial Images

- RGB and CIR with a 20cm resolution
- Useful for validation analysis and classification steps
- Sensed in January 2016 and May 2015

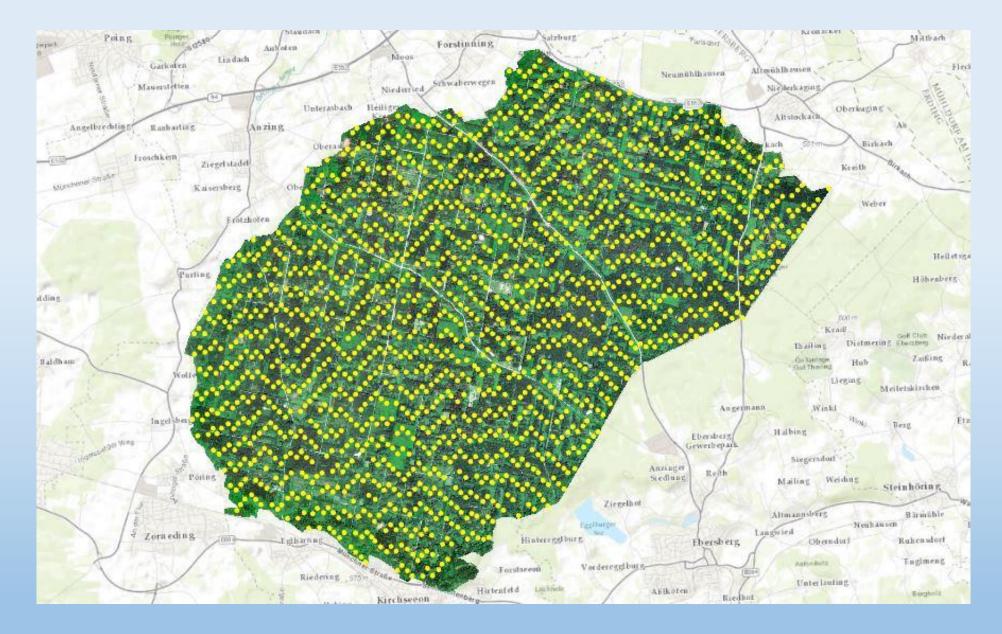




(Geobasisdaten © Bayerische Vermessungsverwaltung)

c) Inventory Data

- Inventory data consists of circles with a procentual distribution of different tree species (11-12m circle radius)
- Only usage of circles which contain a 100% dominance of a single tree type
- Actual data from January/November 2016



(Inventory Data@Bayerische Staatsforsten)

Challenge: No linear distribution of tree species!

Tree Type	Ebersberger Forest	Freisinger Forest
Spruce	777	70
Pine	2	1
Larch	6	2
Fir	1	2
Other Coniferous	8	2
Beech	75	4
Oak	21	2
Other Deciduous	63	11

Atmosphere Correction:

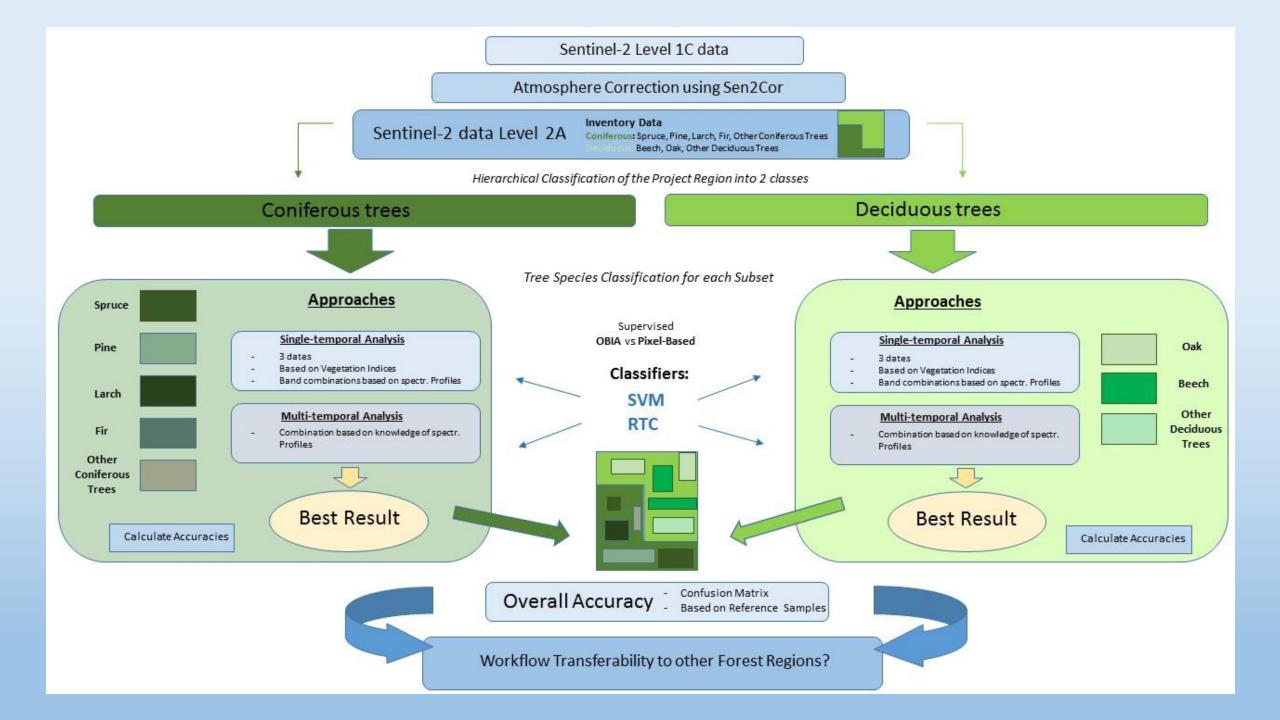
Tool: Sen2Cor (not undisputed by researchers) Alternate tools: ATCOR

Sen2Cor can be used within SNAP or with Python Anaconda

Main aim:

Top of Atmosphere (TOA) Reflectance \rightarrow Bottom of Atmosphere (BOA) Reflectance

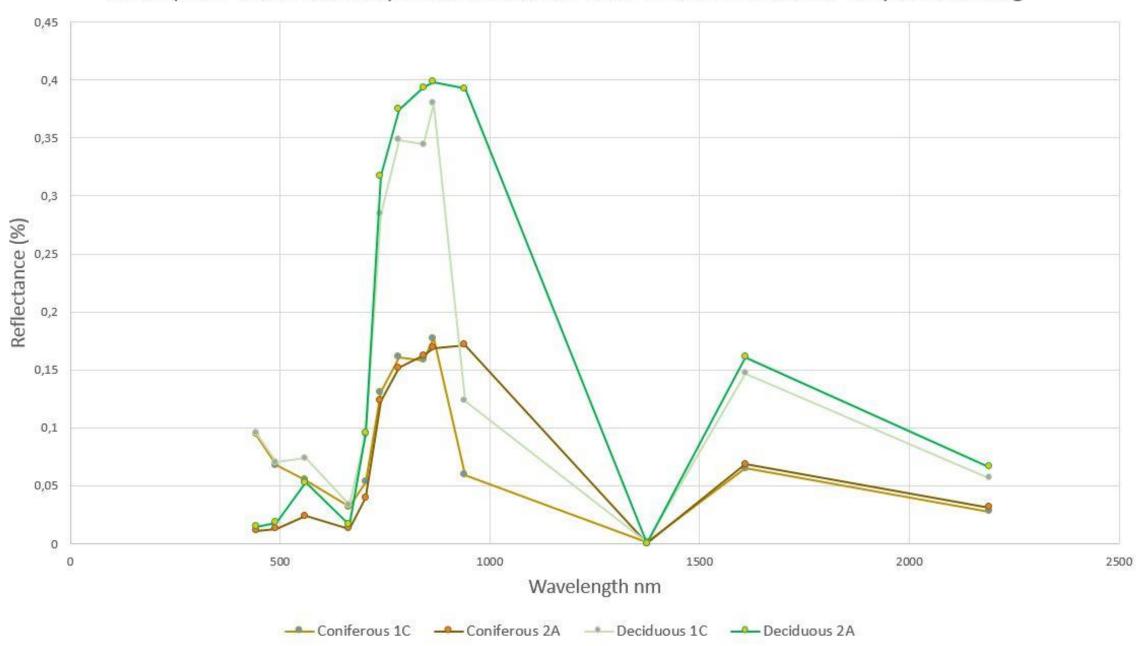
Level 1C \rightarrow Level 2A



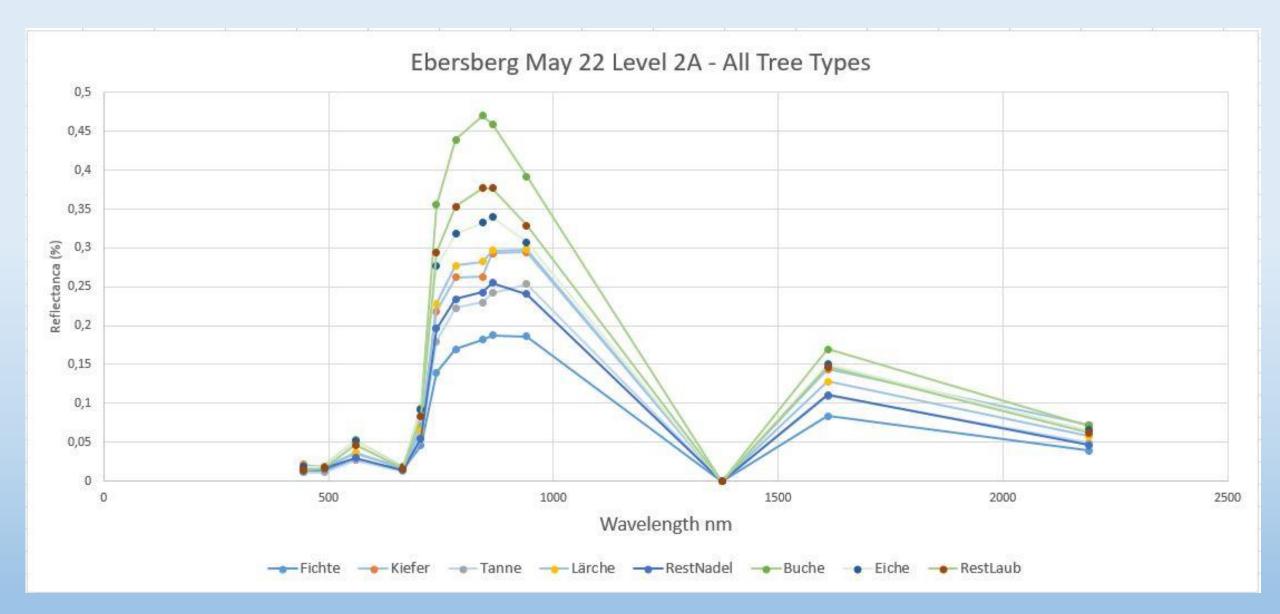
Spectral Profiles:

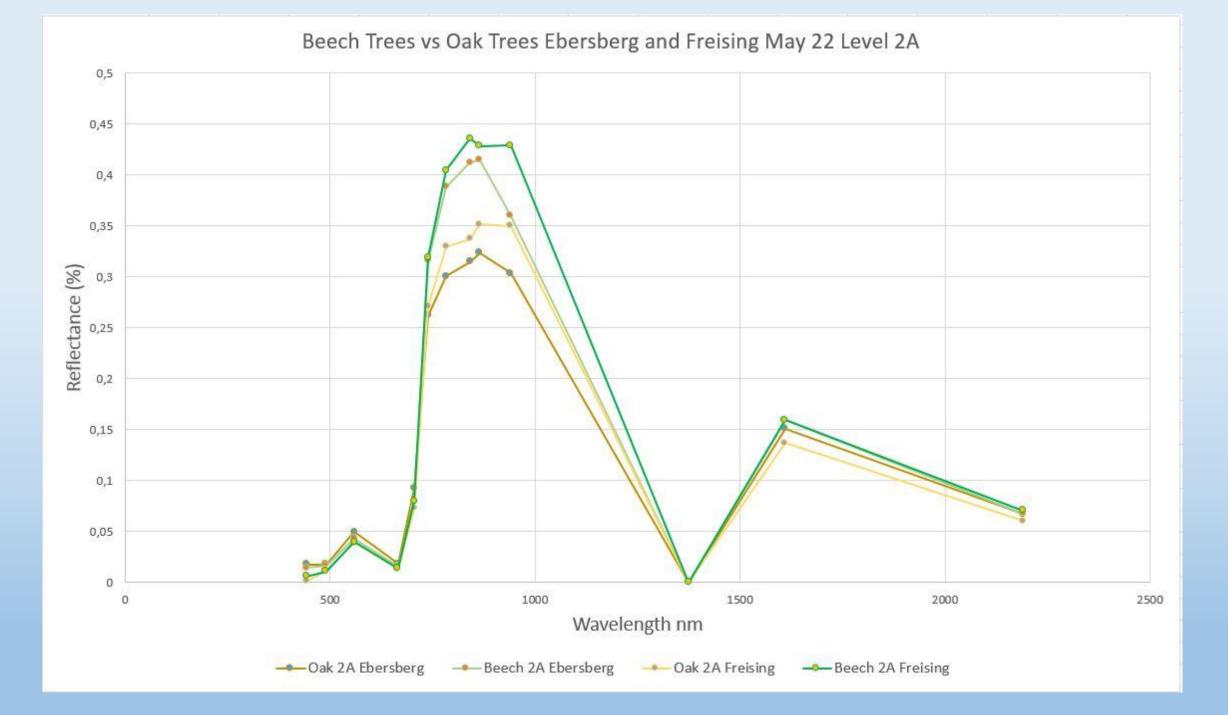
Why is it useful to use spectral profiles?

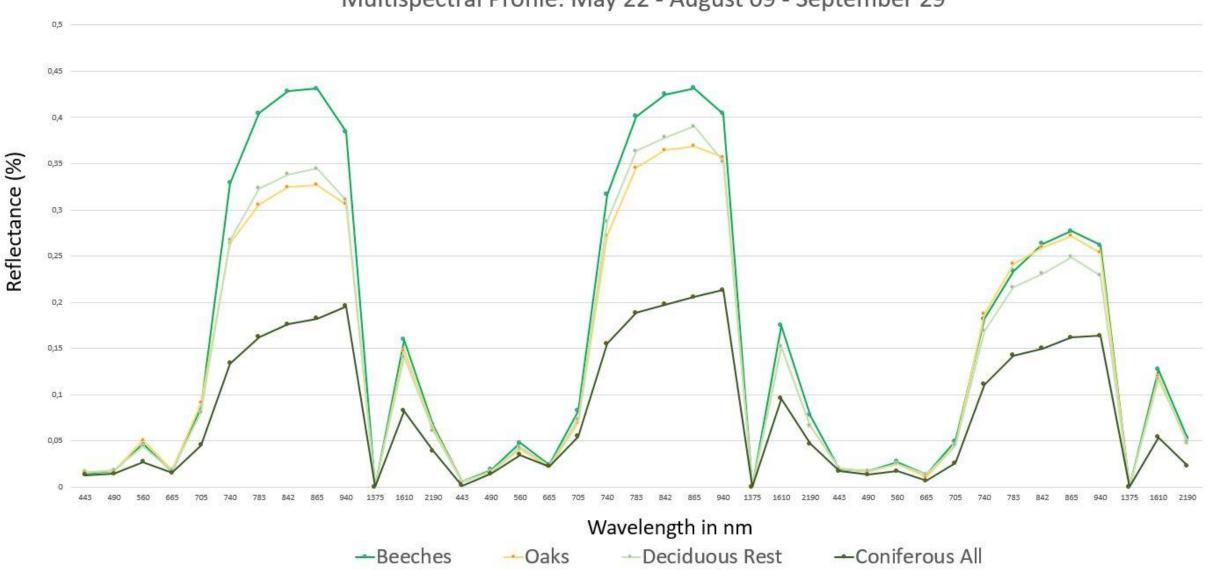
- →Important wavelength regions (bands) can be estimated by displaying reflectance values
- Based on training samples (based on inventory data)
- Can be easily exported and displayed within e.g. Word
- Multitemporal profiles can be created



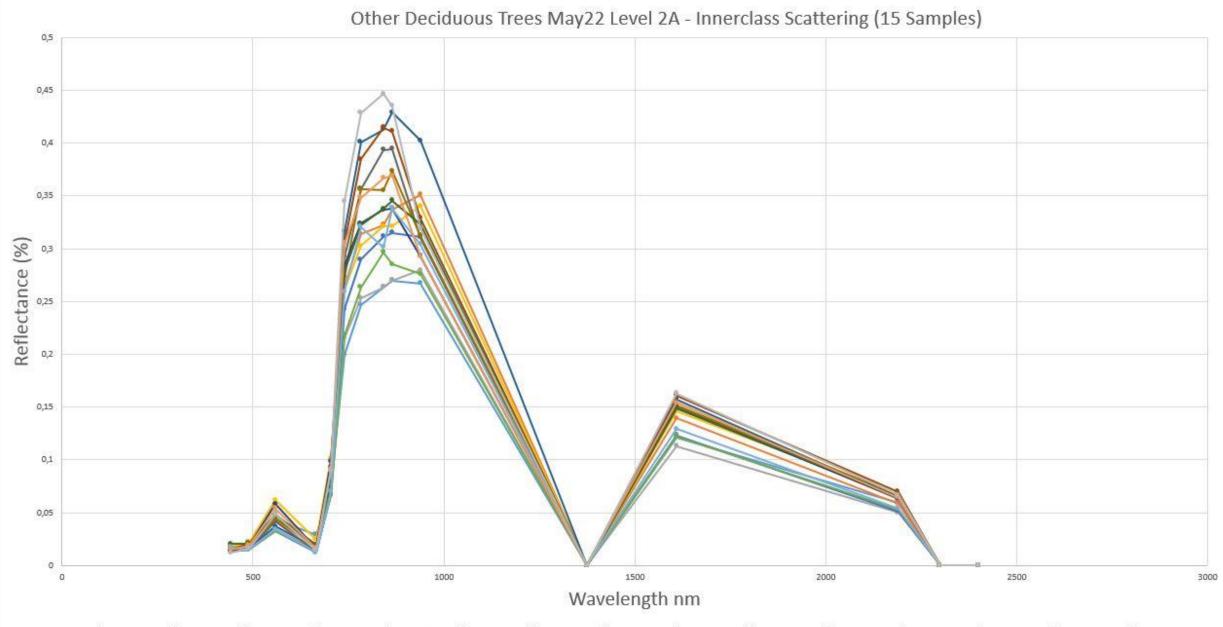
Atmosphere Correction Comparison Coniferous Forest vs Deciduous Forest - May 22 Ebersberg







Multispectral Profile: May 22 - August 09 - September 29



Coniferous- and **Deciduous** Forest Classification

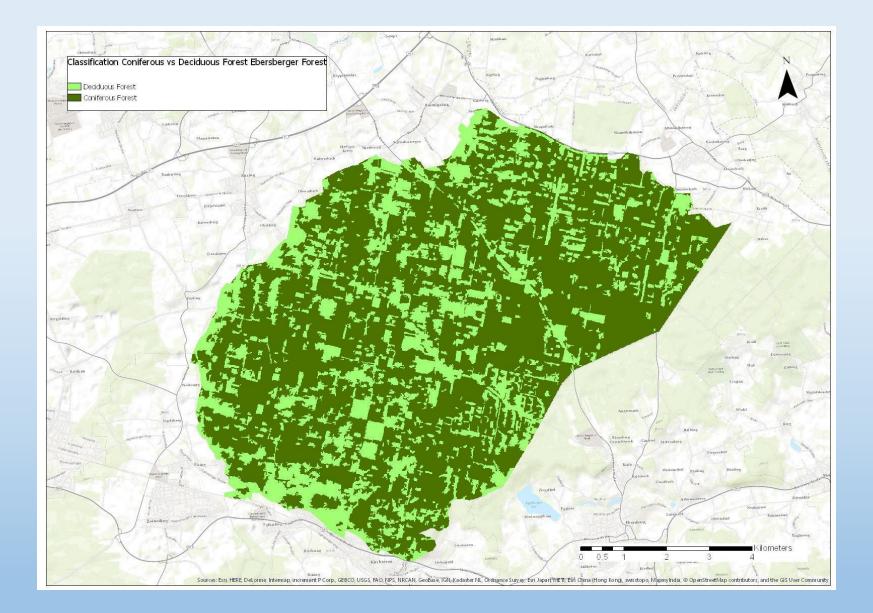
<u>Method:</u> supervised classification, pixel-based and object-based

Classifier: SVM, RT

Segmentation knowledge based on spectral profiles information

Coniferous- and Deciduous Forest Classification

	Workfl	ow Clas	sification Con	ferous Forest	vs. Deciduous Forest	c				
Accuracy	Method	Classifier	Segmented Image			Segmentation Settings				
95,2	OBIA	SVM	May22 / bands 8 7 6				DS			
86,8	OBIA	RTC	May22 / bands 8 7 6	/22 / bands 8 7 6			DS			
92,3	PB	SVM	May22 / bands 8 7 6	y22 / bands 8 7 6			DS			
90,2	OBIA	SVM	May 22 / bands 8 4	ay 22 / bands 8 4 3			DS			
74	OBIA	RTC	May 22 / bands 8 4	y 22 / bands 8 4 3			DS			
97	PB	SVM	May 22 / bands 8 4	ay 22 / bands 8 4 3			DS			
87	OBIA	SVM	May 22 / bands 8 4	1ay 22 / bands 8 4 3			SegSize 5			
85	OBIA	SVM	Multitemporal / M	/ultitemporal / May 3, Aug 8, Sept 7			DS			
86,6	OBIA	RTC	Multitemporal / M	/ultitemporal / May 3, Aug 8, Sept 7			DS			
83	PB	SVM	Multitemporal / M	Iultitemporal / May 3, Aug 8, Sept 7			DS			
97,2	OBIA	SVM	Multitemporal / M	Iultitemporal / May 8, Aug 8, Sept 8			DS			
92,4	OBIA	SVM	Multitemporal / M	ultitemporal / May 8, Aug 8, Sept 8			SegSize 5			
81,6	OBIA	RTC	Multitemporal / M	/ultitemporal / May 8, Aug 8, Sept 8			DS			
89,8 PB	РВ	SVM	Multitemporal / M	ay 8, Aug 8, Sept 8			DS			
	Method	Classifier	Input Image	Segmented addit	tional Image		Segmentation Settings			
92,6	OBIA	SVM	August - all bands	Multitemporal / M	ay 8, Aug 8, Sept 8		DS			
97,2	OBIA	SVM	August PCA 1 to 4	Multitemporal / M	ay 8, Aug 8, Sept 8		DS			



97.2% accuracy

Best results with: OBIA SVM Multitemporal approach (IR bands)

Deciduous Tree Species Classification: Beech, Oak, Other Broadleaf Trees

- Hierarchical analysis of coniferous and deciduous tree types
- Based on polygon masks
- "Segment Mean Shift" algorithm for a first segmentation (30 in total)
- Best "SMS" results is used as "additional input image" in a further segmentation step (all bands of the input image are accounted)
- 3 Broadleaf species: Beech, oak and other deciduous tree types
- 15 training samples are set for each type

	Workflow Classification Deciduous Trees Segment Mean Shift			Class	ificatio	n Classify Tool with additional N	lean Shift Segmented Input Raster	
Wor				Accuracy Method Classifier Input Image			Segmented additional Image	Segmentation Settin
VVOI	KIIOW CI	assilication Decladous frees segment mean shirt		54,3 OBIA	SVM	S_23456789_PCA1_2	May 22 / bands 8 3 2, segSize 5	SegSize 5
ccuracy Meth	od Classifi	er Segmented Image	Segmentation Settings	49,4 OBIA 71,7 OBIA	SVM SVM	S_23456789_PCA1_2 S 23456789 PCA1-4	May 22 / bands 8 3 2, segSize 5 May 22 / bands 8 3 2, segSize 5	SegSize5 + SA 1-6 SegSize 5
63 OBIA	SVM	Multitemporal / May 8, Aug 8, Sept 8	DS	67,3 OBIA	SVM	S 23456789 PCA1-5	May 22 / bands 8 3 2, segsize 5 May 22 / bands 8 3 2, segSize 5	SegSize5 + SA 1-6
50 OBIA	RTC	Multitemporal / May 8, Aug 8, Sept 8	DS	59 OBIA	SVM	S_23456789_PCA1-6	May 22 / bands 8 3 2, segSize 5	SegSize5 + SA 1-2-5
				61,6 OBIA	RTC	S_23456789_PCA1-7	May 22 / bands 8 3 2, segSize 5	SegSize 5
62 PB	SVM	Multitemporal / May 8, Aug 8, Sept 8	DS	63,3 PB	SVM RTC	S_23456789_PCA1-8 S 23456789 PCA1-9		
86,8 OBIA	SVM	May 22 - all bands	SegSize 5	76,2 PB 80,7 OBIA	SVM	May S 832 PCA1-9	May 22 / bands 8 3 2, segSize 5	SegSize 5
64 OBIA	SVM	May22 / bands 8 7 6	DS	76 OBIA	SVM	May_NDVI&PCA1-4	May 22 / bands 8 3 2, segSize 5	SegSize 5
61 OBIA	SVM	May 22 / bands 8 4 3	DS	65 OBIA	SVM	May 832+ NDVI	May 22 / bands 8 3 2, segSize 5	SegSize 5
50 OBIA	SVM	May 22 / band 4 3 2	DS	75,7 OBIA 74,3 OBIA	SVM SVM	May_Sentinel 98732 May_98732_PCA_1-4_NDVI_May	May 22 / bands 8 3 2, segSize 5 May 22 / bands 8 3 2, segSize 5	SegSize 5 SegSize 5
				55 PB	SVM	May 98732 PCA 1-4 NDVI May	Way 227 Danus 6 5 2, Segsize 5	3683176 2
50 PB	SVM	May 22 / band 4 3 2	DS	75,1 PB	RTC	May_98732_PCA_1-4_NDVI_May		
81 OBIA	SVM	May 22 / bands 8 3 2	DS	87,2 OBIA	SVM	May 765	May 22 / bands 8 3 2, segSize 5	SegSize 5
87,4 OBIA	SVM	May 22 / bands 8 3 2	SegSize 5	59,9 OBIA 78,8 OBIA	SVM SVM	May 765 & PCA 1_4 May 765	May 22 / bands 8 3 2, segSize 5 May 22 / bands 8 3 2, segSize 5	SegSize 5 SegSize5 + SA 1-2-3-4
74 OBIA	SVM	May 22 / bands 8 3 2	SegSize 2	53,7 PB	SVM	May 765	Way 227 Dalius o 5 2, segsize 5	36821562 ± 2M 1-5-2-4
46 OBIA	SVM	May 22 / bands 8 3 2	SegSize 10	67,1 OBIA	RTC	May 765	May 22 / bands 8 3 2, segSize 5	SegSize 5
78 OBIA				87,2 OBIA	SVM	May 765 & NDVI	May 22 / bands 8 3 2, segSize 5	SegSize 5
	SVM	May 22 / bands 8 3 2	SegSize 5/spa/spec 18/18	87,2 OBIA 62,5 OBIA	SVM RTC	May 7654 May 7654	May 22 / bands 8 3 2, segSize 5 May 22 / bands 8 3 2, segSize 5	SegSize 5 SegSize 5
83,3 OBIA	SVM	May 22 / bands 8 3 2	SegSize 5/spa/spec 10/10	80,3 OBIA	SVM	May 7, Aug 6, May5	May 22 / bands 8 3 2, segsize 5	SegSize 5
58 OBIA	RTC	May 22 / bands 8 3 2	DS	61,8 OBIA	SVM	May - all bands	May 22 / bands 8 3 2, segSize 5	SegSize 5
66 PB	SVM	May 22 / bands 8 3 2	DS	89,1 OBIA	SVM	August - all bands	May 22 / bands 8 3 2, segSize 5	SegSize 5
				63,1 OBIA 46 PB	RTC SVM	August - all bands August - all bands	May 22 / bands 8 3 2, segSize 5	SegSize 5
72 OBIA	SVM	May 22 / bands 7 6 5 (Red Edge)	DS	65,2 OBIA	SVM	August - all bands & PCA May 1-4	May 22 / bands 8 3 2, segSize 5	SegSize 5
75 OBIA	RTC	May 22 / bands 7 6 5 (Red Edge)	DS	80,5 OBIA	SVM	Aug 765	May 22 / bands 8 3 2, segSize 5	SegSize 5
71 OBIA	SVM	May 22 / bands 7 6 5 (Red Edge)	SegSize 5	80,7 OBIA	SVM	Aug 832	May 22 / bands 8 3 2, segSize 5	SegSize 5
58 OBIA	RTC	May 22 / bands 7 6 5 (Red Edge)	SegSize 5	60,9 OBIA 63,3 OBIA	SVM SVM	Sept - all bands May PCA 1-12	May 22 / bands 8 3 2, segSize 5 May 22 / bands 8 3 2, segSize 5	SegSize 5 SegSize 5
35 OBIA	SVM	May 22 / bands 8 4 2	DS	60 OBIA	SVM	May all bands & May PCA 1-4	May 22 / bands 8 3 2, segsize 5	SegSize 5
				90,9 OBIA	SVM	August PCA 1-12	May 22 / bands 8 3 2, segSize 5	SegSize 5
57 OBIA	RTC	May 22 / bands 8 4 2	DS	78,3 OBIA	SVM	August - PCA1	May 22 / bands 8 3 2, segSize 5	SegSize 5
66 PB	SVM	May 22 / bands 8 4 2	DS	86,3 OBIA 53,3 OBIA	SVM RTC	August PCA 1-4 August PCA 1-4	May 22 / bands 8 3 2, segSize 5 May 22 / bands 8 3 2, segSize 5	SegSize 5 SegSize 5
70 OBIA	RTC	May 22 / bands 8 4 2	SegSize 5	51 PB	SVM	August PCA 1-4	May 227 bands 0 52, segure 5	0680126.0
69 OBIA	SVM	Aug 09 / bands 8 3 2	DS	90,5 OBIA	SVM	August PCA 1-5	May 22 / bands 8 3 2, segSize 5	SegSize 5
60 OBIA	SVM	Aug 09 / bands 8 3 2	SegSize 5	84,5 OBIA	SVM	August PCA 1-6	May 22 / bands 8 3 2, segSize 5	SegSize 5
				85,2 OBIA 80,8 OBIA	SVM SVM	August PCA 1-7 august pca 1-10	May 22 / bands 8 3 2, segSize 5 May 22 / bands 8 3 2, segSize 5	SegSize 5 SegSize 5
37 OBIA	SVM	Sept 29 / bands 8 3 2	DS	81,9 OBIA	SVM	august pca 1-11	May 22 / bands 8 3 2, segSize 5	SegSize 5
66 OBIA	SVM	Multitemporal / Sept 2, Aug 3, May 8	DS	90,9 OBIA	SVM	august pca 1-12	May 22 / bands 8 3 2, segSize 5	SegSize 5
62 OBIA	RTC	Multitemporal / Sept 2, Aug 3, May 8	DS	72,3 OBIA	SVM	August PCA 1 & 4	May 22 / bands 8 3 2, segSize 5	SegSize 5
38 OBIA	SVM	Multitemporal / Sept 8, Aug 3, May 2	DS	74,8 OBIA 78,3 OBIA	SVM SVM	August PCA 2-3-4 August PCA 1 only	May 22 / bands 8 3 2, segSize 5 May 22 / bands 8 3 2, segSize 5	SegSize 5 SegSize 5
				82,3 OBIA	SVM	PCA May all - PCA Aug all	May 22 / bands 8 3 2, segsize 5 May 22 / bands 8 3 2, segSize 5	SegSize 5
_				77,2 OBIA	SVM	PCA all Aug - PCA allSep	May 22 / bands 8 3 2, segSize 5	SegSize 5

Best SMS result:

May 22 Bands 8, 3, 2 OBIA SVM P3.5 OBIASYMAugust PCA 1:12 & NOVIMay 22 / bands 83 2, segSize 5Best final accuracy:
S-2 scene for August
PCA 1-12
Segmentation min size: 5px

May 22 / bands 8 3 2, segSize 5

May 22 / bands 8 3 2, segSize 5

SegSize 5

SegSize 5

SegSize 5

SegSize 5

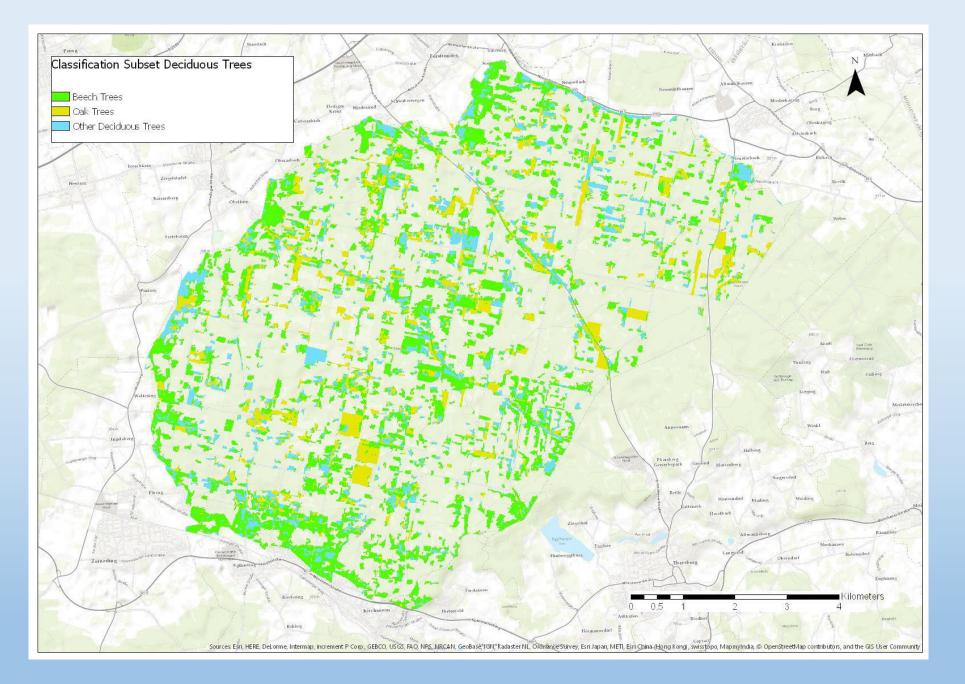
66 OBIA SVM PCA all May - PCA 1-12 Aug - PCA 1-12 Sep May 22 / bands 8 3 2, segSize 5

67.7 OBIA SVM

80,8 OBIA SVM

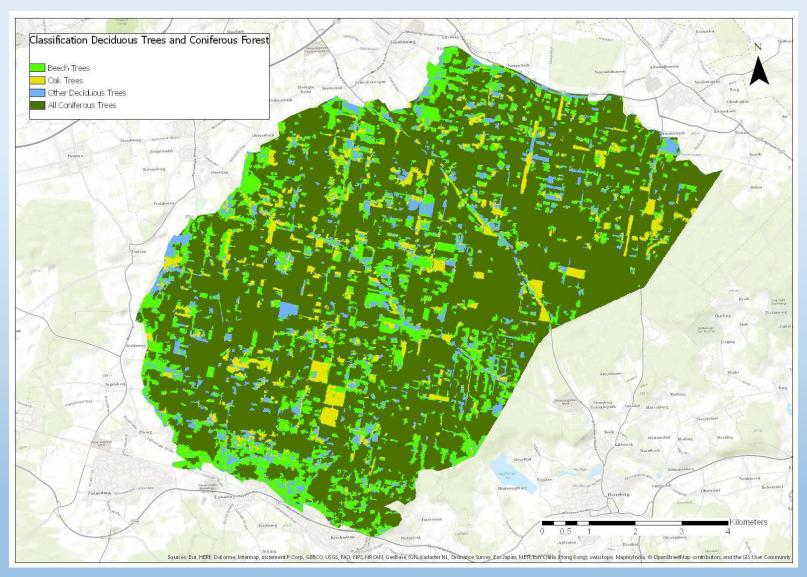
PCA 1-12 Sept

NDVI August



Accuracy of 90.9%

Final Classification



87% accuracy

4 classes:

- Beech
- Oak
- Other deciduous trees
- Coniferous trees

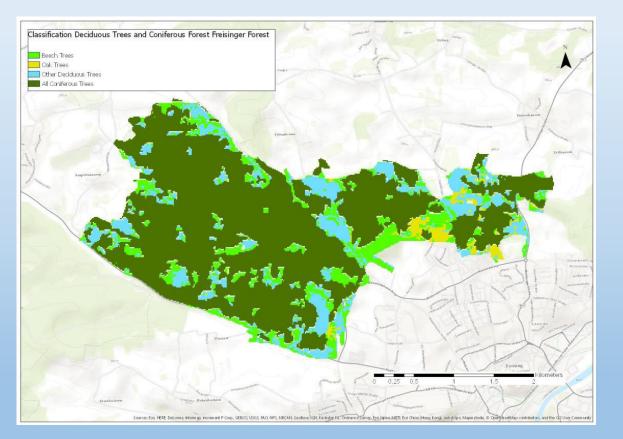
- Validation based on training samples with unused inventory circles
- Accuracy Assessment: confusion matrix

→ Calculation of Users's (UA), Producer's (PA) and Overall Accuracy (OA)

• Cohens Kappa is not highlighted due to ist controversial character (Death to Kappa)

Transferability:

To test, if conditions in one region are transferable to similar other regions (based on new invenory samples and new input data)



Freisinger Forest:

Seperation of Coniferous/Deciduous Forests: 91.2% (cf. 97.2%)

Broadleaf Tree Species: 79.4% (cf. 90.9%)

Overall Accuracy: 85% (cf. 87%)

Validation with tools (Collector for ArcGIS)

Visual in-field validation to control input data:



- Inventory data can be inaccurate!

4. Conclusions

- Results are strongly dependent of the quality (and also quantity) of input data
- Usage of visual and infrared 10m bands was most efficient for the analysis
- Red Edge region showed great potential but the resolution is to low for single tree types classification issues
- Results are only marginal worse compared to expensive commercial high resoltuion data

Thank you for listening! 😳

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