

Mapping tree species from combined hyperspectral and LiDAR data - thoughts on **spectral resolution** and **scale**

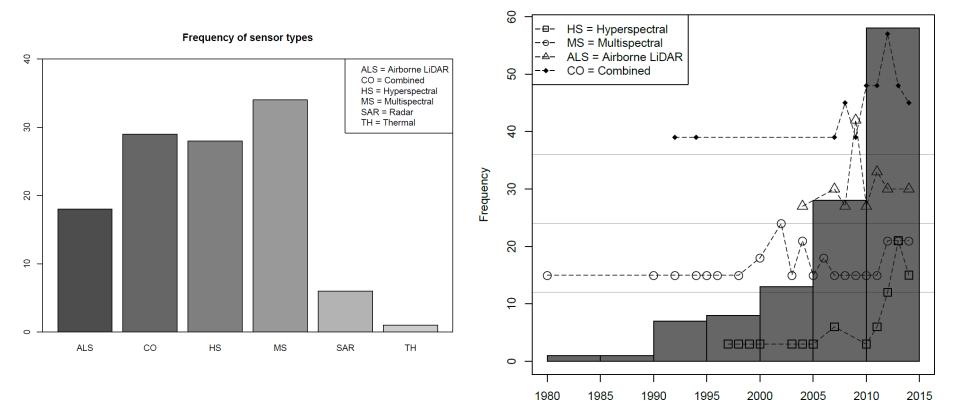


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Overview





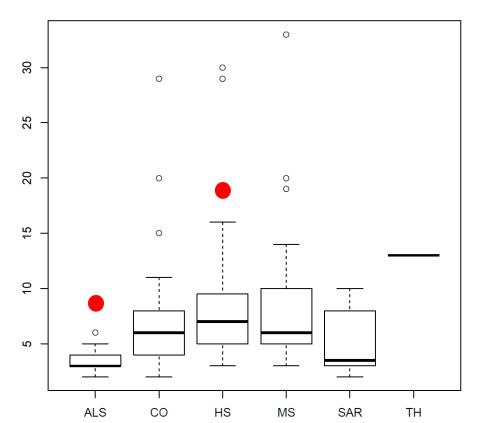
Frequency of studies over time

Descriptive statistics compiled from 116 selected studies focusing on tree species mapping









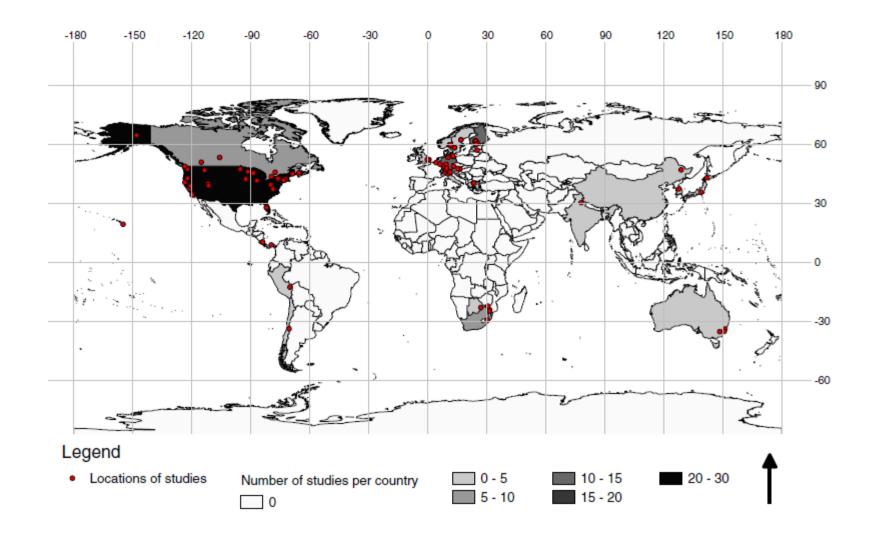
Number of species per sensor

Descriptive statistics compiled from 116 selected **studies focusing on tree species mapping**











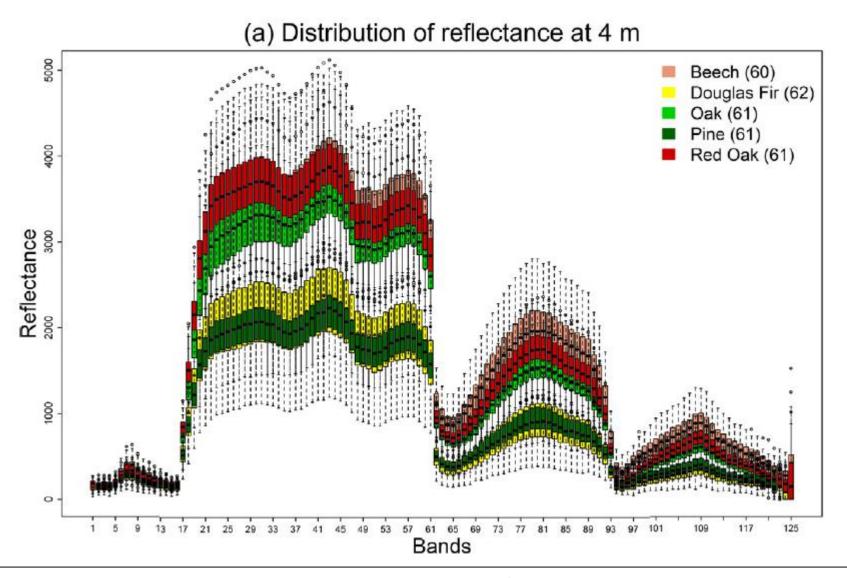


Hyperspectral data



Hyperspectral data





ForBioSensing-Workshop, BIAŁOWIEŻA, 1st of Dec. 2016





Spectral resolution and range



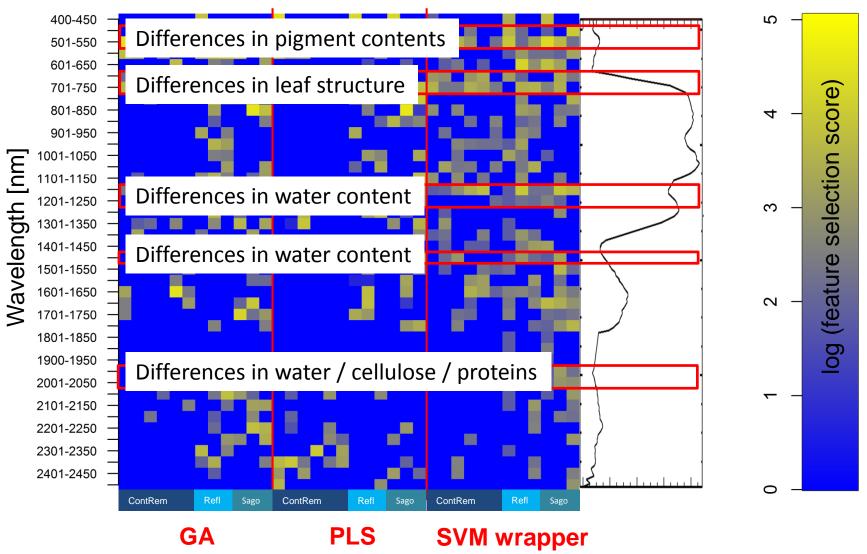


Do we need to cover the full VIS-SWIR region?

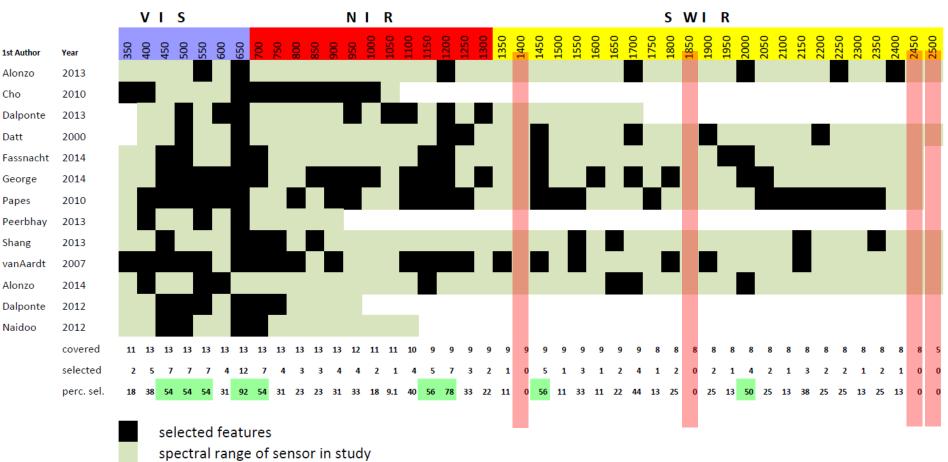
How narrow should the bands be?

How to deal with spectral resolution in an operational approach?

Importance of spectral regions



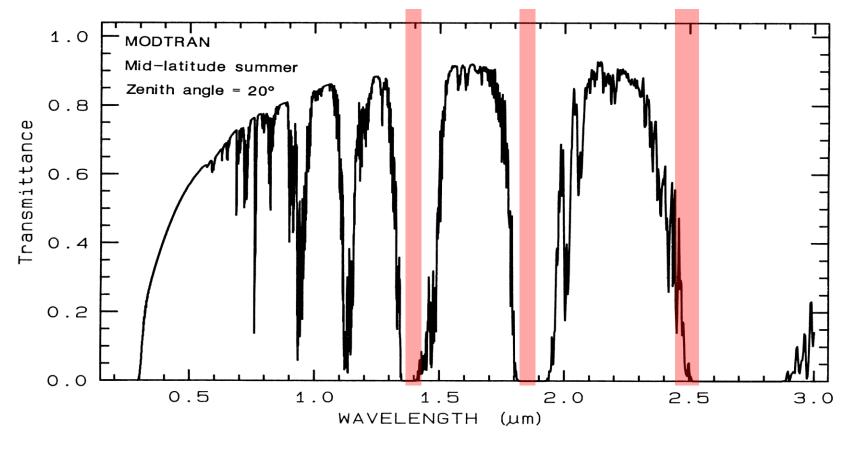
Fassnacht, F. E. et al. (2014): Comparison of Feature Reduction Algorithms for Classifying Tree Species With Hyperspectral Data on Three Central European Test Sites. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing (J-STARS) 7(6), pp. 2547–2561.



selected in more than 50% of the considered studies

Summary of important wavelength regions as identified by 13 studies making use of hyperspectral data and feature selection approaches. Covered = number of studies that covered the wavelength region; selected = number of studies that selected the wavelength region as being relevant for tree species discrimination.

10



http://speclab.cr.usgs.gov/PAPERS.refl-mrs/giff/300dpi/fig3a3.gif





Do we need to cover the full VIS-SWIR region?

Based on the studies so far: Yes!

But: some regions are more important than others

➔ optimize processing speed?



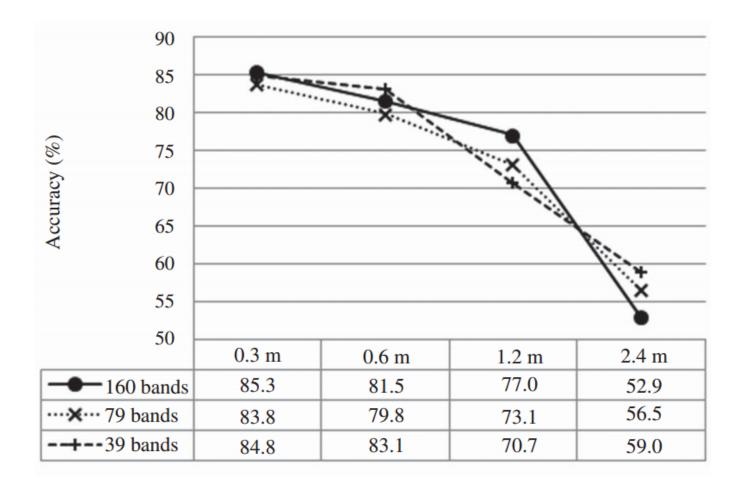


How narrow should the bands be?

Question is connected to processing speed (number of predictors)

Radiometric noise vs. ability to capture subtle absorption features

Hardly any systematic investigation available so far



Results for SAM classifier applied to noise-reduced image (MNF)

Pena, M.A., Cruz, P. & Roig, M. (2014). The effect of spectral and spatial degradation of hyperspectral imagery for the Sclerophyll tree species classification. Int. J. of Rem. Sens., 34(20), 7113-7130.





How narrow should the bands be?

"Gut feeling / hypothesis":

A sensor with 100-150 narrow bands (VIS-SWIR) should do the job

Having very narrow 400 bands won't add a lot of useful information in a classification problem (co-linearity)

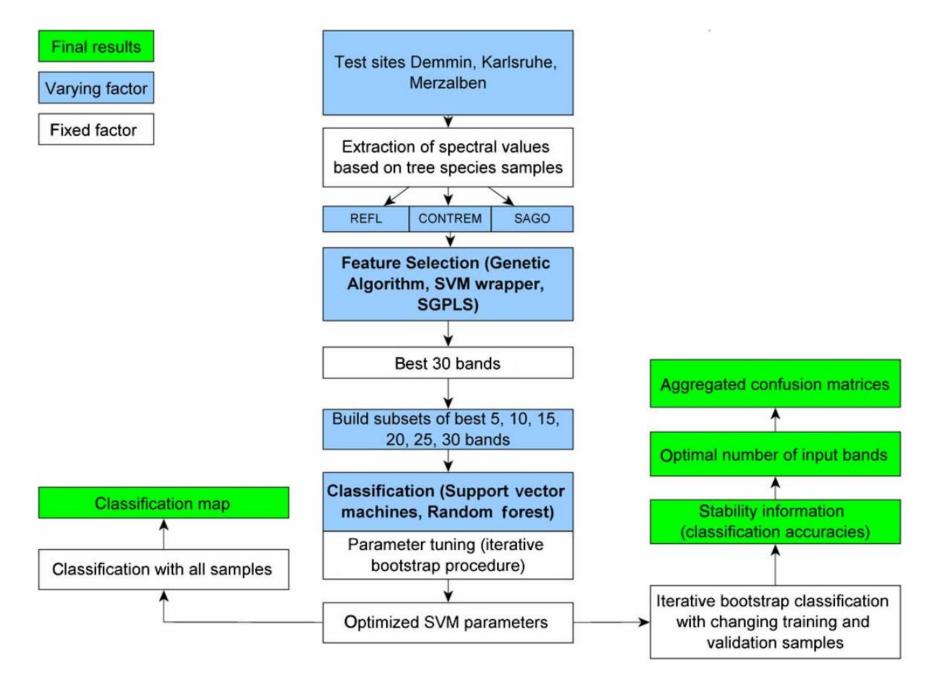




How to deal with spectral resolution in an operational approach?

Experiences from a case study conducted over three test sites in Germany

Characteristics		Site 1 (Demmin)	Site 2 (Karlsruhe)	Site 3 (Merzalben)
Bio- geograph ical	General	North of Germany, shows properties of a riparian forest; flat terrain	Relatively warm climate due to the influence of the Upper-Rhine; more continental than typical German conditions; flat terrain	Typical low mountain range; relative humid and cool climate; mountainous terrain
	Dominant tree species	Black Alder (Alnus, glutinosa); Willow, (Salix caprea), Birch, (Betula pendula), Ash (Fraxinus excelsior), European Beech (Fagus, sylvatica), Norway Spruce (Picea Abies (L.) Karst)	Scots Pine (<i>Pinus sylvestris</i>), European Beech Sessile Oak (<i>Quercus petreae</i>), Pedunculate Oak (<i>Quercus robur</i>), Douglas Fir (<i>Pseudo-tsuga menziesii</i>), Norway, Spruce, Larch (<i>Larix sp.</i>)	European Beech, Sessile Oak, Pedunculate Oak, Scots Pine Norway Spruce, Douglas Fir, Larch (small occurrences)
Hyper- spectral dataset	Sensor; (spectral range); date Pixel size	AISA Eagle & Hawk; (400–2450 nm); 29/06/2011 3 m	HyMap; (450–2480 nm); 20/08/2010 (Cocks et al. (43)) 4 m	HyMap; (450–2480 nm); 05/08/2009 5 m
	Processing level	Destriped and atmospherically and geographically corrected by the GFZ using ATCOR4 software	Atmospherically and topographically corrected by DLR using ATCOR4 and ORTHO software	Atmospherically and topographically corrected by DLR using ATCOR 4 and ORTHO software



	PLS feature	SVM wrapper	Genetic Algorithm	Reference	Reference
	selection			all bands	MNF
Demmin					
Input dataset	REFL	CONTREM	CONTREM		MNF
Classifier	SVM	SVM	SVM	SVM	SVM
Nr. of bands	20	15	20	125	20
Min.	0.650	0.750	0.723	0.729	0.848
Median	0.729	0.816	0.802	0.798	0.910
Max.	0.807	0.891	0.875	0.862	0.923
Karlsruhe					
Input dataset	SAGO	CONTREM	SAGO		MNF
Classifier	SVM	SVM	SVM	SVM	SVM
Nr. of bands	20	20	20	125	10
Min.	0.710	0.725	0.726	0.680	0.924
Median	0.806	0.817	0.826	0.783	0.960
Max.	0.889	0.886	0.916	0.875	1.0
Merzalben					
Input dataset	CONTREM	SAGO	SAGO		MNF
Classifier	RF	SVM	SVM	SVM	\mathbf{RF}
Nr. of bands	25	15	15	125	10
Min.	0.365	0.441	0.396	0.375	0.507
Median	0.513	0.559	0.528	0.510	0.629
Max.	0.629	0.675	0.678	0.623	0.724





How to deal with spectral resolution in an operational approach?

All bands → MNF (feature extraction) → Classification

By far best approach on all three test sites

Reduced set of predictors but almost all information is preserved



Spectral Resolution



Scale





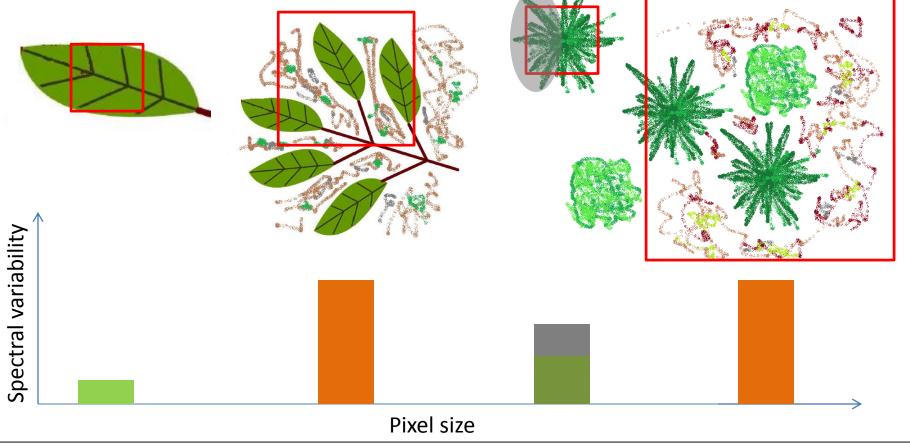
Was is the optimal spatial unit to obtain species information?



Spectral Resolution



What is the optimal pixel size for classifying tree species?







Experiences from case studies (I)

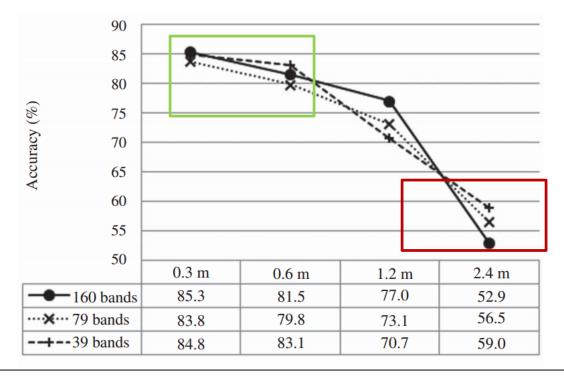
Sensor	Classifier	Num. of Features	OA (%)	Κ		OA (%)	K	
	SVM	160 52	92.6 92.8	0.869 0.873		78.0 77.3	0.604 0.590	
Hyspex VNIR 1600	RF	160 52	89.7 90.1	0.816		75.7 73.6	0.564 0.523	
	GML	160 52	- 87.0	- 0.777	0.4 m	-	-	1.5 m
Hyspex SWIR 320i	SVM	130 42	81.7 8 0.9	0.680 0.665	Pixel	63.3 65.4	0.341 0.377	Pixel
	RF	130 42	75.9 77.0	0.571 0.590	Size	65.0 65.4	0.378	Size
	GML	130 42	- 67.3	- 9. 398	<-	- 56.4	0.223	<-
Hyspex VNIR 1600 + Hyspex SWIR 320i	SVM	290 64	92.4 91.8	0.867 0.855		77.0 75.5	0.589 0.560	
	RF	290 64	87.9 82.5	0.785 0.687		74.8 71.5	0.555 0.497	Dalpo Classif
	GML	290 64	- 83.5	- 0.703		-	-	Hyper And R

Dalponte et al. (2013). Tree Species Classification in Boreal Forests With Hyperspectral Data. IEEE Trans. On GeoSc. And Rem. Sens., 51(5), 2632-2645.





Experiences from case studies (II)



Pena, M.A., Cruz, P. & Roig, M. (2014). The effect of spectral and spatial degradation of hyperspectral imagery for the Sclerophyll tree species classification. Int. J. of Rem. Sens., 34(20), 7113-7130.





Experiences from case studies (III)

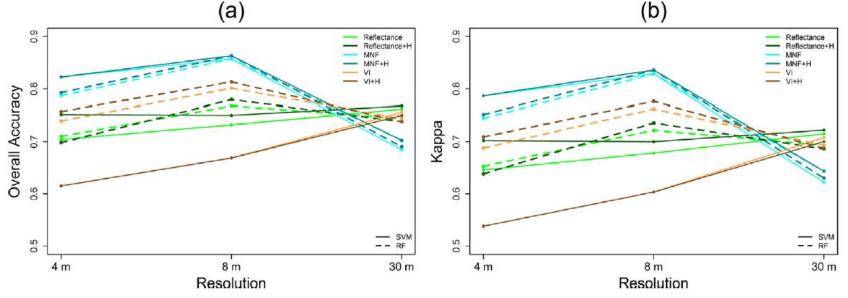


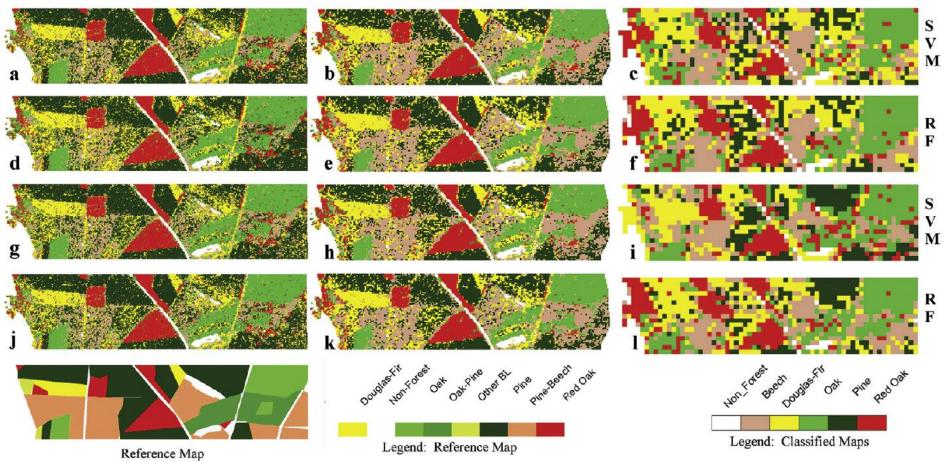
Fig. 6. Behavior of (a) OA and (b) kappa against the spatial resolution for all predictor layers and classifiers.

Ghosh, A., Fassnacht, F. E. et al. (2014). A framework for mapping tree species combining hyperspectral and LiDAR data: Role of selected classifiers and sensor across three spatial scales. *Int. J. of Appl. Earth Obs. and Geoinf.*, *26*, 49–63.



8 m

30 m



Tree species maps obtained with MNF (and MNF+H) as predictor layer.

Ghosh, A., Fassnacht, F. E. et al. (2014). A framework for mapping tree species combining hyperspectral and LiDAR data: Role of selected classifiers and sensor across three spatial scales. *Int. J. of Appl. Earth Obs. and Geoinf.*, *26*, 49–63.





Case studies suggest:

Either possibly small pixels (< 0.5 m) Or: pixels close to the size of an individual crown

BUT: So far the spatial unit was a pixel!





Three obvious approaches:

(I) Pixel(II) Single-tree objects(III) Stands or other operational unit





Results from the literature are mixed:

Ørka et al. 2013: Single-tree approach better than area-based approach (combined hyperspectral / ALS datasets).

Clark et al. 2005: Leaf Scale is better than crown level, crown level is better than pixellevel (hyperspectral data – crown level = averaging all pixels of a crown).

Clark et al. 2012: Pixel spectra are better than crown-mean spectra, pixel-majority voting is better than pixel spectra (hyperspectral data).

Hans Ole Ørka, Michele Dalponte, Terje Gobakken, Erik Næsset & Liviu Theodor Ene (2013) Characterizing forest species composition using multiple remote sensing data sources and inventory approaches, Scandinavian Journal of Forest Research, 2013, 28:7, 677-688.

Clark, M.L.; Roberts, D.A.; Clark, D.B. Hyperspectral discrimination of tropical rainforest tree species at leaf to crown scales. *Remote Sens. Environ.* 2005, 96, 375–398.

Clark, M.L., Roberts, D.A. Species-Level Differences in Hyperspectral Metrics among Tropical Rainforest Trees as Determined by a Tree-Based Classifier, *Remote Sensing*, **2012**, 4, 1820-1855





Advantages of object-based approaches (single tree and standlevel) in case accurate objects can be obtained:

- Meaningful units (practitioners work with it)
- Combination of LiDAR and Hyperspectral becomes more powerful:
 - normalization of spectra (sunlit parts of the crowns)
 - Majority voting approaches
 - single-tree based geometric information (crown-base height, canopy transects, crown volume, ...)
 - Density information from LiDAR + spectral information from satellites





Challenges of object-based approaches (single tree and standlevel):

- The quality of the results largely depends on the delineation success
- Classifications on stand-level-objects have to consider that differing forest densities may lead to very distinct reflectance signals for the identical species composition





Some other points...





Do we need more definitions?

Tree species classification/discrimination (HAS to be on single-tree level?)

Tree species mapping (Quite a notable number of paper didn't present maps!)

Forest composition classification (HAS to be object-based? What do we actually need? Mixture information? Dominant species?)

Forest composition mapping (What to put in the map?)

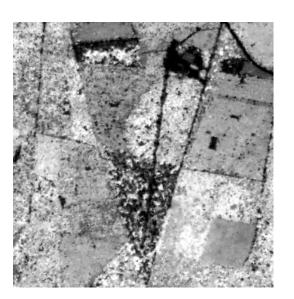




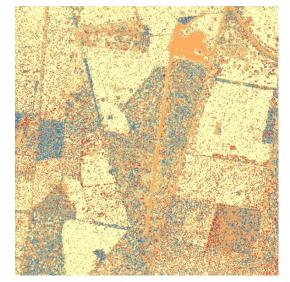
One LiDAR flight is enough...

Do we need regular LiDAR/ Hyperspectral flights? New options with VHR satellite data

Height (photogrammetry) => Proxy for DBH



 $\frac{\text{Tree species}}{\Rightarrow \text{Species specific}}$ Biomass allometry



<u>Forest density</u> => Proxy for number of stems / single tree delin.

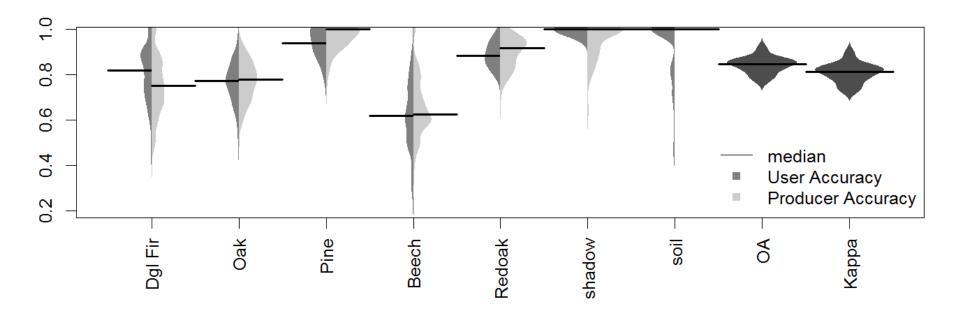


Some other points...



One LiDAR flight is enough...

Do we need LiDAR/ Hyperspectral flights?



Tree Species classification results with WV-2 data (SVM)



Conclusions



Fassnacht, F. E., Latifi, H., Sterenczak, K., Modzelewska, A., Lefsky, M., Waser, L. T., Straub, C., Ghosh, A. (2016): Reviewof studies on tree species classification from remotely sensed data. Remote Sensing of Environment 186, pp. 64–87.



Conclusions



Conclusions

Complete coverage of the VIS-SWIR region is desirable

Operational perspective: Processing speed could be optimized by reducing the number of bands (still not fully clear how).

Questions related to scale have rarely been adressed

Optimal scale still unclear; single-tree-level seems promising, BUT: delineation quality, processing speed, ...







References (first three graphs)

Fassnacht, F. E., Latifi, H., Sterenczak, K., Modzelewska, A., Lefsky, M., Waser, L. T., Straub, C., Ghosh, A. (2016): Reviewof studies on tree species classification from remotely sensed data. Remote Sensing of Environment 186, pp. 64–87.