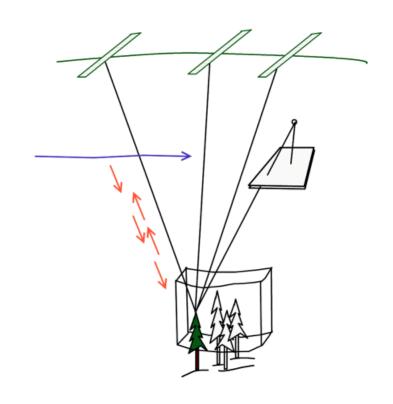
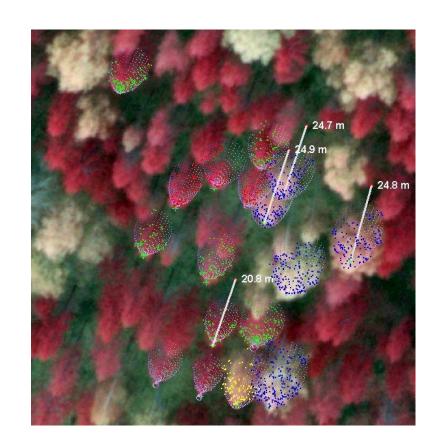
Using discrete-return small-footprint LiDAR for tree species recognition

Ilkka Korpela

Dept. For. Res. Management, Helsinki Faculty of Forest Sciences, Joensuu

ILKKA.KORPELA@HELSINKI.FI ILKKA.KORPELA@HUT.FI





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Objectives

Introduction to LiDAR signal

Experiment in Hyytiälä – with results

Objectives

Airborne laser scanning (ALS, LiDAR) is an effective, newish tool for assessing "environmental geometry" **in 3D**

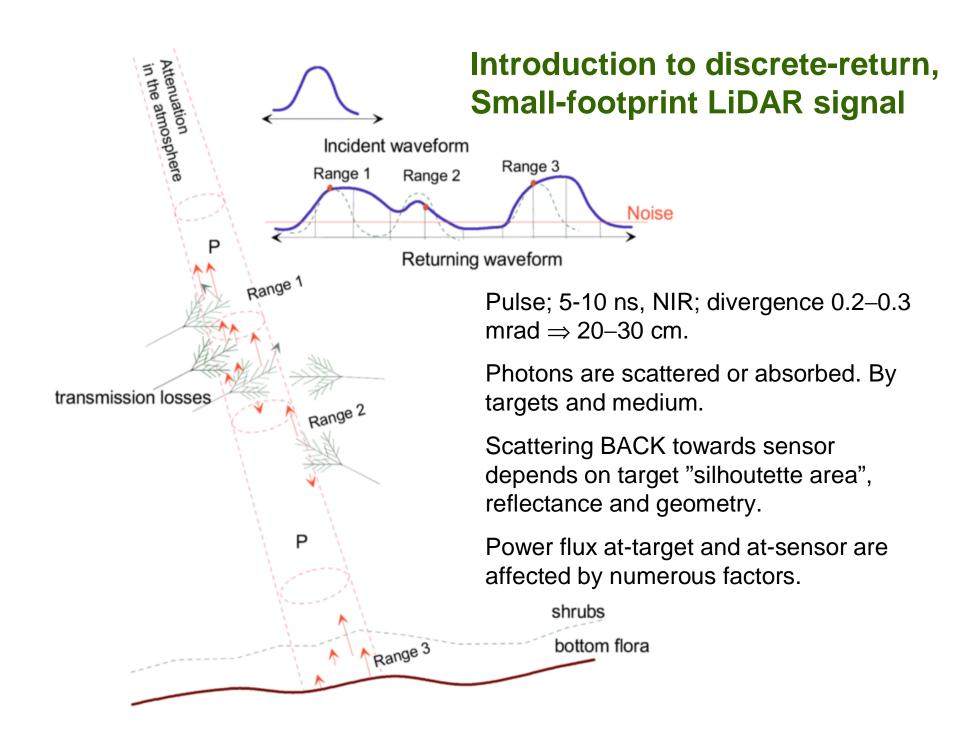
Terrain profile
Canopy modeling, gaps
Canopy vertical density + allometry ⇒ Tree Biomass

<u>Tree Biomass</u> needed on per species basis; consider e.g. management, wood procurement, stratification issues

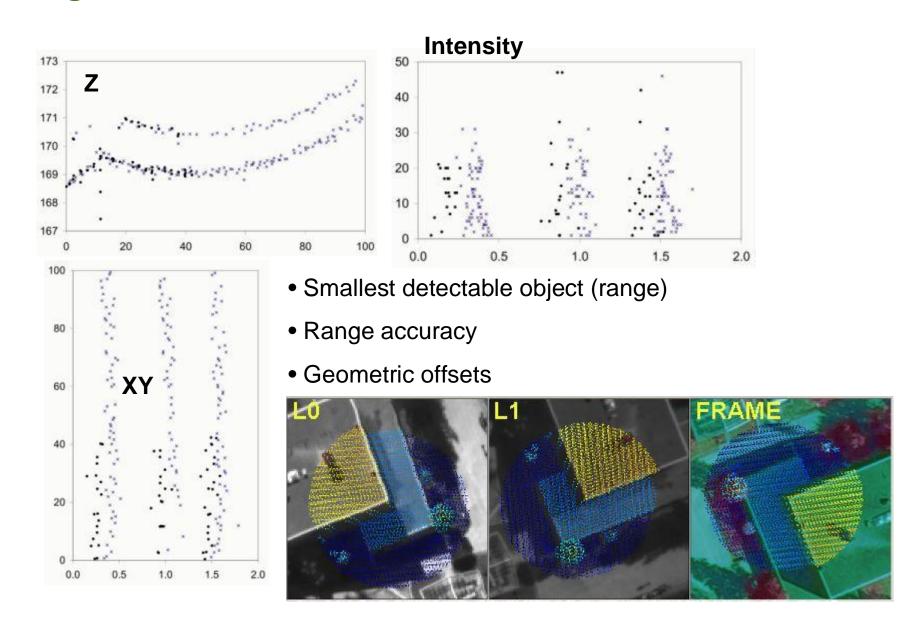
Allometric reasoning works better with the correct species information, LAI-estimation alike.

Objectives - specific

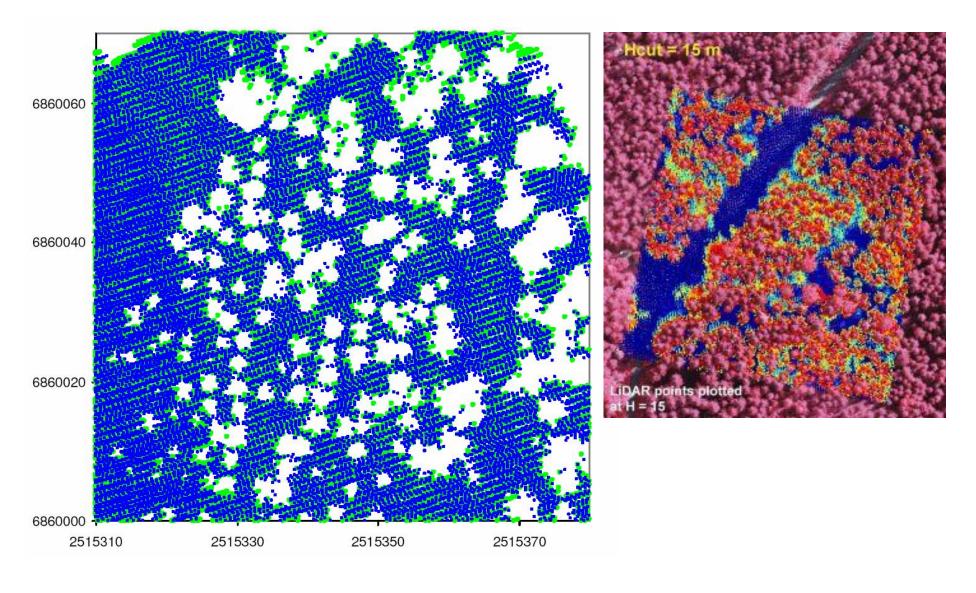
- What are the meaningful LiDAR features for tree species recognition?
- Are these <u>invariant to</u> other properties in trees / <u>affected by</u> for example site type / stand age which are known to exercise and effect on crown structure, and geometric-optical properties of leaves, needles and other scatterers?
- What is the accuracy achievable using LiDAR data?



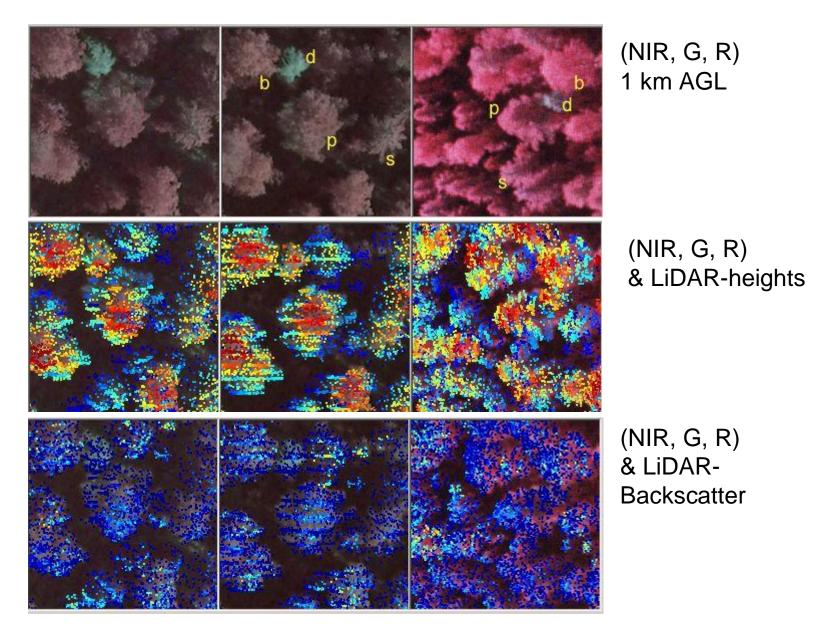
Introduction to discrete-return, Small-footprint LiDAR signal – GEOMETRY AND RADIOMETRY



Introduction to discrete-return, Small-footprint LiDAR signal – GEOMETRY – pulses or points?



Is LiDAR all about geometry?



LiDAR in SP-recognition

Flying heights of 100–750 m, footprint of 10–20 cm.

Holmgren and Persson (2004) in Sweden, 95% pine and spruce. N = 562

Brandtberg (2007) in WVA. 64% three broadleaved sp.

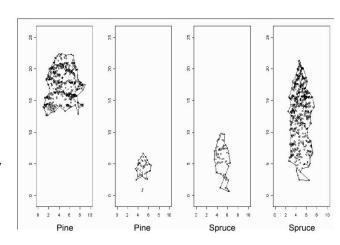
Orka et al. (2007) in Norway, 74% spruce, birch, aspen. N = 224

Vauhkonen (2008).

Reitberger et al. in Bavaria. Höfle et al. & Wagner et al. Austria. FW-data.

Korpela et al. (2008) Saplings & other flora. 1 km data, with images.

- Geometric features
 each point has height, distance from crown.
 Crown shape, vertical (foliage) point distribution.
- **Intensity metrics** Characteristics of the intensity values of the LiDAR point reflecting from the tree.
- Waveform metrics

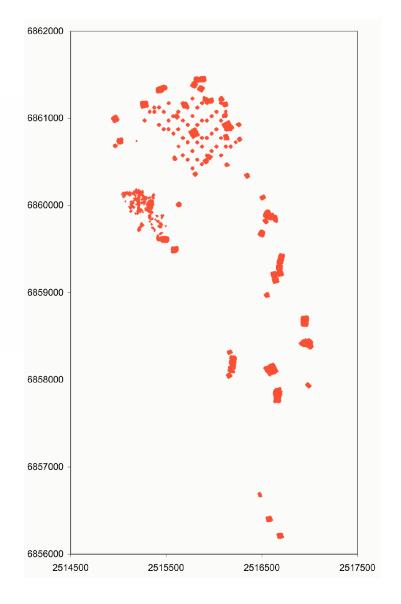


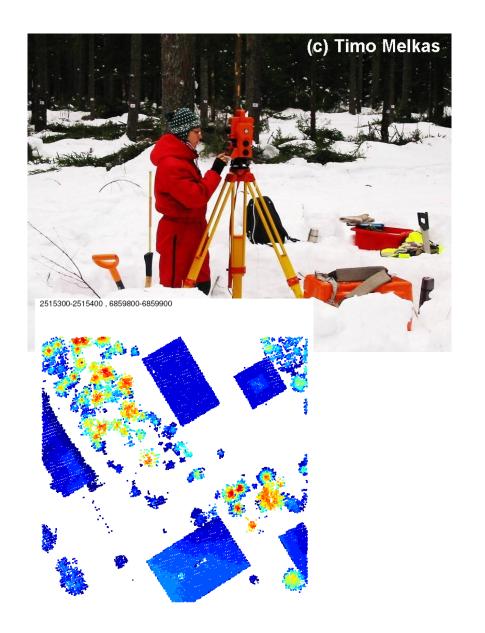
Instrument	ALTM3100	ALS50-II
Date	July 25, 2006	July 4, 2007
Pulse frequency	100 kHz	115.8 kHz
Scan frequency	70 Hz	52 Hz
Footprint	25-28 cm	17-18 cm
Range	840-950 m	770-820 m
Scan angle	± 14°	± 15°
Air humidity, 2 m	48-52%	60-75%
AGC	-	8 bits

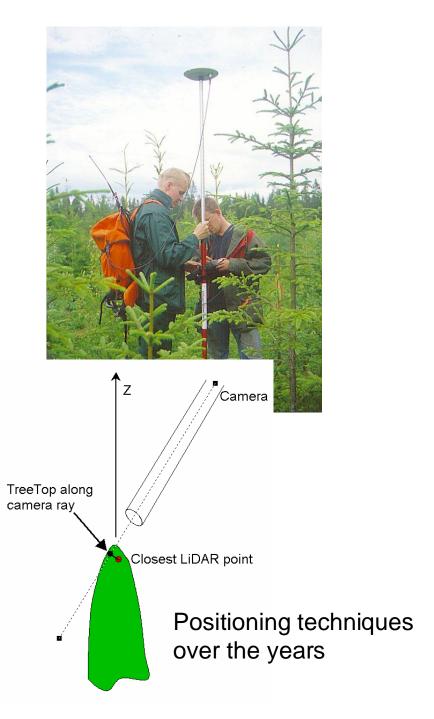
Table 1. Characteristics of the LiDAR datasets.

LiDAR in 2004, **2006**, **2007**, 2008 Trees > 2002; over **17000 positioned trees** (d > 25 – 60 mm); **118 "plots"**.

"Establishment" by author in 1994; combination of research projects, student exercises etc.









Researcher A maps all trees; B measures vars X1..Xn, making it possibly to C to study problem Y by adding measurements of Xn+1...Xm.

Metsähallitus: providing funding and reasonable management of forests.

Hyytiälä: Labour & equipment,

SMEAR!

<u>Funding:</u> 1997-2009 over

180,000 € invested in RS and

field data.





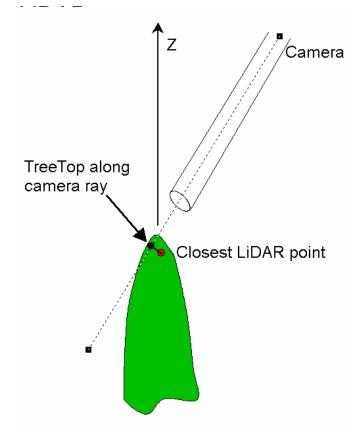






- 1) Extract LiDAR points that have echoed from tree j, j=1...17000
- 2) Compute statistical features using the h and intensity values
- 3) Analyze the features for their potential in SP-recognition

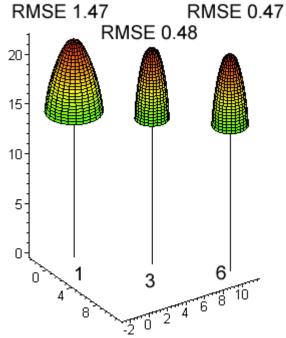
- 1) POINT EXTRACTION FOR TREES
- a) Update (X,Y,Z)top to 2006-2007 using aerial images and



- \Rightarrow of the 17000+ trees with h > 5 m, 13890 trees were visible in the images and LiDAR. h_{rel was} mostly > 0.5 i.e. the remaining trees were dominant or intermediate.
- b) "Automatic crown modeling" using WLS of 40% deep crown models, non-linear, with 3 parameters. Initial approximation of max crown width was derived from sp, d13 and height, using local regression models.

- 1) POINT EXTRACTION FOR TREES
- b) Simplified 40% long crowns, accept LiDAR points inside the envelope and max one SD (RMSE) away from the surface.





2) Compute statistical features using the h and intensity values

Feature	Description
im, isd	Mean and SD of intensity
imsurf, isdsurf	As above, but < 0.3 m from the envelope
id1-id10	Deciles of the intensity distribution
hdl-hdl0	Deciles of the relative height distribution
iMin	Minimum intensity $(id10 = IMax)$
iq l=iq4	Mean intensity 0-10%, 10-20%, 20-30%,
	30-40% down the top
iq12, iq13, iq14	Transformations iq l/iq2, iq l/iq3, iq l/iq4

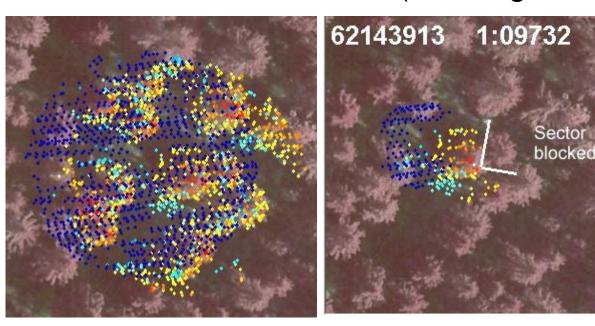
Table 2. Features derived from the LiDAR data assigned to a tree. Intensity features were computed using first-return data only. hd features make use of all points.

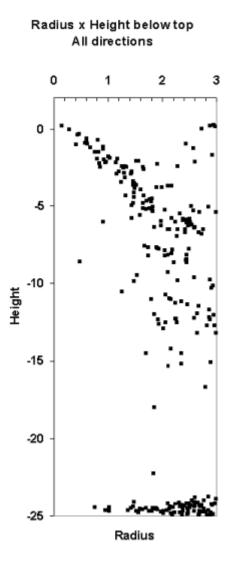
Points of two sensors fused; ALTM3100 (2006) and ALS50 (2007) by normalization of intensity data.

First-return points used for intensity metrics of 1-4 possible.

Additional features / explanatory variables

- Crown overlap percentage (by neighbors)
- h-relative
- Site Index (Site type, local H100-value)
- Age of stand / tree
- Standard stand variables (stocking related)





3) Analyze the features for their potential in SP-recognition

There were differences in the mean intensity of first-return points in 20–135-yr-old pine, birch and birch trees (Table 3).

+	→						
		Pine,		Spruce,		Birch,	
		n=5007		n=6120		n=1979	
	im	37.3	5.1	45.5	5.9	52.6	10.1
	isd	16.0	2.2	19.1	2.2	20.2	3.6

Table 3. Mean and SD of features im and isd. Living pine, spruce and birch trees.

3) Analyze the features for their potential in SP-recognition

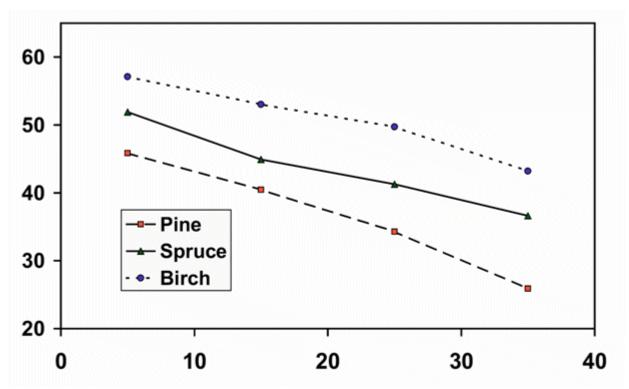


Figure 3. Mean intensity values at relative heights of 0-10%, 10-20%, 20-30% and 30-40% down from the top for 20-135-yr-old pine, spruce and birch trees.

Distribution of relative height values (deciles) separates spruce from pine & birch (crown shape)

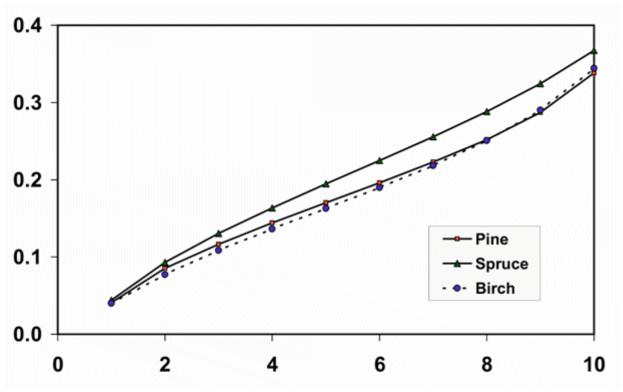


Figure 4. Height deciles, *hd1-hd10* for living pine, spruce and birch trees.

Age / Size affects mean intensity – Betula spp.

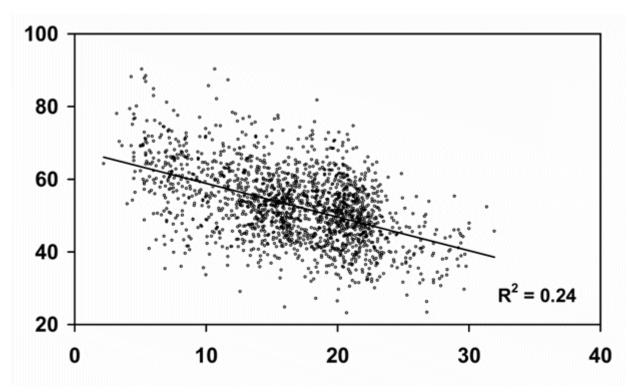


Figure 5. im × tree height in 20-135-yr-old birches (n=1979).

Age / Size AND mean intensity – P. abies

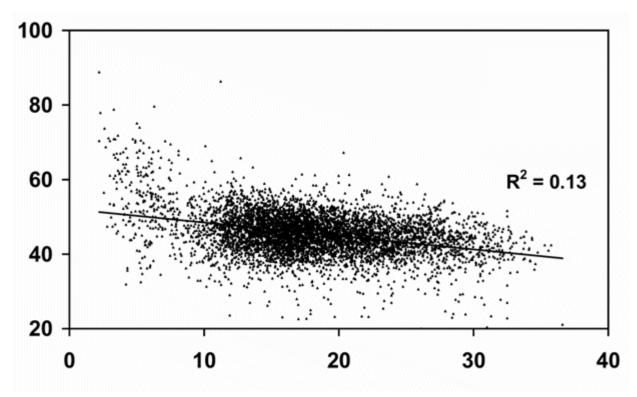


Figure 6. im × tree height in 20-135-yr-old spruces (n=6120).

Age / Size AND mean intensity – P. sylvestris

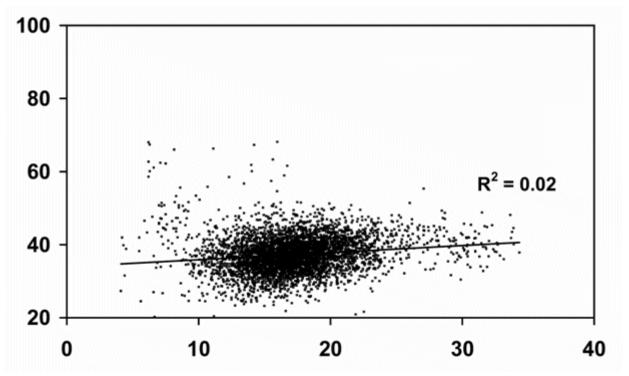


Figure 7. im × tree height in 20-135-yr-old pines (n=5007).

3.2 Classification of pine, spruce and birch

Using a set of 12933, 20-135-yr-old trees from diverse site conditions, and ten explanatory variables {*im, isd, iq1, iq12, iq2 iq13, iq3, iq4, hd2/hd8, hd5*} with leave-one-out cross-validation in k-NN, an overall classification accuracy of 81% was achieved (Table 4) for pine (89%), spruce (78%) and birch (720/)

 \oplus (72%).

+		Pine	Spruce	Birch	All
	Pine	4429	403	165	4997
	Spruce	349	4671	1003	6023
	Birch	100	434	1379	1913
	All	4878	5508	2547	12933

Table 4. Confusion matrix of k-NN classification. Kappa=0.69.

If birch was excluded, the accuracy was 92% (κ =0.84) for pine and spruce. In young trees, height of below 18 m (n=7307), the accuracy improved to 82% and 93% (κ =0.86) for the 3-class and binary cases, respectively. In the old trees, the accuracies were 85% and 91%. Birch and spruce were confused in 20–25% of the cases. Separation of was more reliable in the older stands. The discrimination of pine and spruce was very reliable, with accuracies above 90%.

Exotic spp.

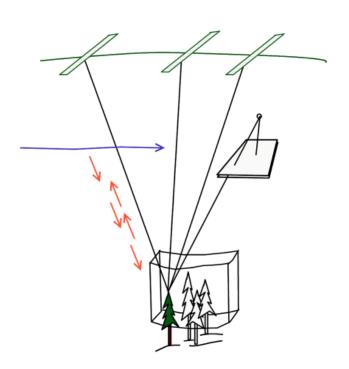
	• •					
#						
	Species	n	Mean	SD		
	Norway Maple	30	72.1	11.0		
	Goat willow	66	66.5	11.2		
	Rowan	32	66.0	13.8		
	Siberian fir	45	64.5	9.2		
	Small-leaved lime	9	59.5	8.1		
	Alder	89	57.2	11.1		
	Siberian larch	17	56.9	9.6		
	Grey alder	16	53.9	11.0		
	Douglas fir	2	53.4	3.3		
	Wych elm	7	52.3	7.3		
	Cembra pine	9	51.4	5.1		
	Aspen	64	49.9	11.3		
	Birch	100	45.3	10.9		
	Spruce	32	44.3	5.8		
	Pine	38	43.9	6.3		
	Contorta pine	2	37.9	4.9		

Table 5. Mean intensity (im) in trees in the vicinity of the Hyytiälä forest station. 50% of birch and all maple samples represent open-grown trees.

Conclusions and Outlook

- 1) High-density LiDAR offers potential (91-93%) for the separation of P.sylvestris and P. abies. Betula spp. confuse with P. abies. ⇒ In images they differ in NIR-reflectance ⇒ COMBINE!
- 2) The foliage density/crown structure, vigour, foliage reflectance, inter alia, might be affected by Age, Site conditions and ??

Important factors in the modeling and model imputation steps.



3) Populus tremula can be very difficult to seprate from spruce. Salix caprea and Alnus spp. differ from the economic quadruplet.

OUTLOOK

- 4) We will analyze the effect of site type and age more carefully. Maybe also some silvicultural treatments (post-establishment of test sites proven difficult). New data in site type gradients.
- 5) FW-data could offer better separation (echo width in addition to echo amplitude = intensity).
- 6) We will combine LiDAR features with ADS40, DMC and UCD imagery to test the gain of having both and the differences between cameras.

THANK YOU!

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