ALS-based tree trunk detection and its potentials

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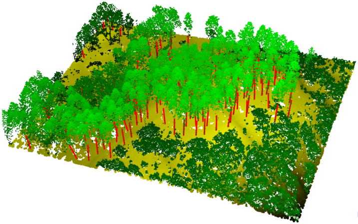
Trier University,
Remote Sensing & Geoinformatics Department



Relevance

- sustainable forest management
  - key parameters: stem number, tree species, timber stock, LAI, ...
  - ALS for a characterisation on the level of single trees
- crown delineation
  - raster- vs. point-based
  - make use of crown shape, point distribution etc.
  - disadvantage: crown shape often ambiguous
- tree trunk/stem detection
  - "distinctive" linear geometry
  - specific attributes (angle of inclination, position, ...)

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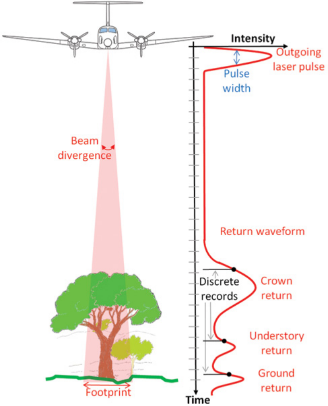

ALS ≙ **A**irborne **L**aser **S**canning; Figure: Diaz 2011

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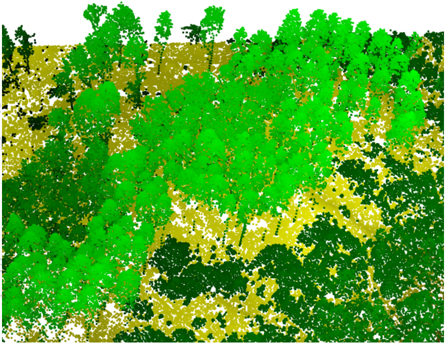

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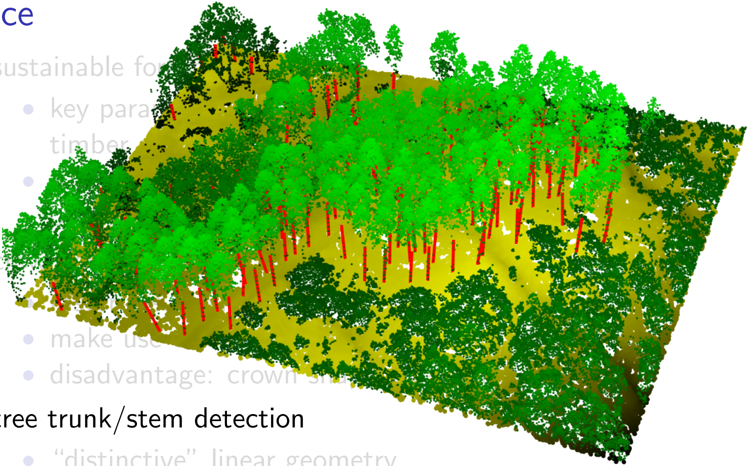

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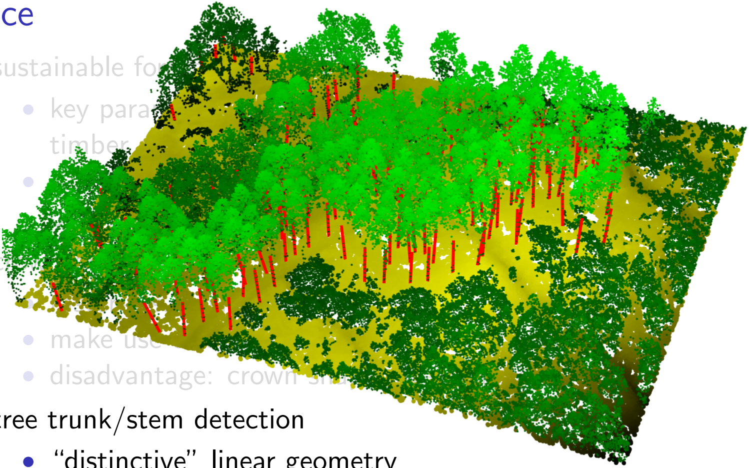

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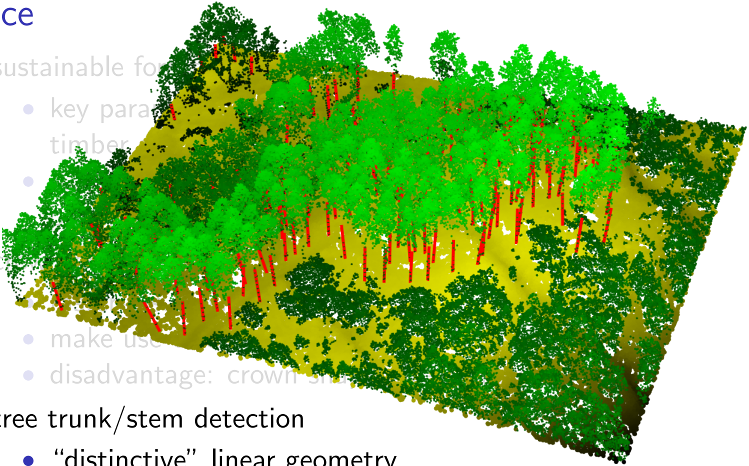

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Methods for Trunk Detection

	Rahman et al. 2009	Reitberger et al. 2007, 2009	Lu et al. 2014
Data	70 $\frac{\text{Points}}{\text{m}^2}$, leaf-off	10-25 $\frac{\text{Points}}{\text{m}^2}$	10 $\frac{\text{Points}}{\text{m}^2}$, leaf-off
Primary aim	single tree extraction	derivation of stem positions	extraction of tree stems and crown segmentation
Limits	– estimation of trunk diameter necessary – high point densities needed	– crown base height inaccurate for dominated trees – omissions at segment borders	– intensity threshold has to be estimated – not all trunk points can be extracted

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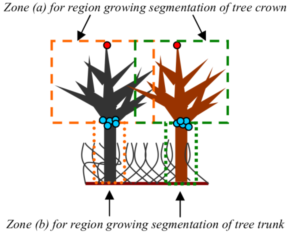
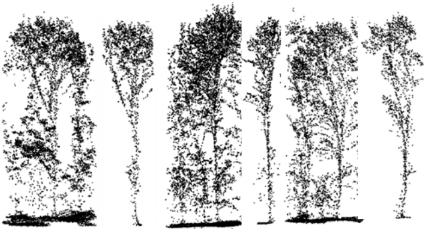


region growing segmentation



extracted trees

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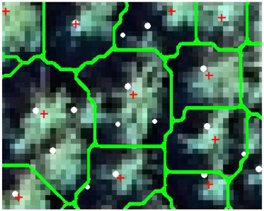
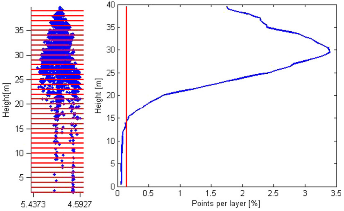
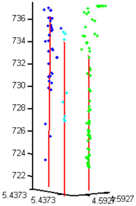


watershed-based crown segmentation



crown base height estimation



stem detection

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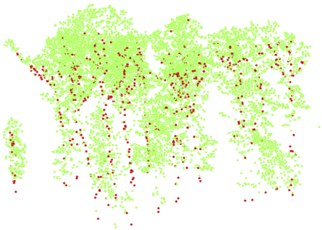
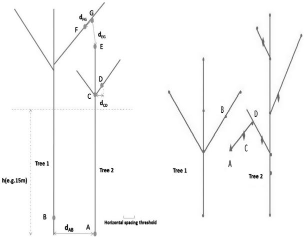


extraction of trunk points



trunk growing

Objective

- method development
  - requirements: independent, robust, fast
- evaluation of the results
  - detection rate
  - positioning accuracy
  - angle of inclination (azimuth, zenith)

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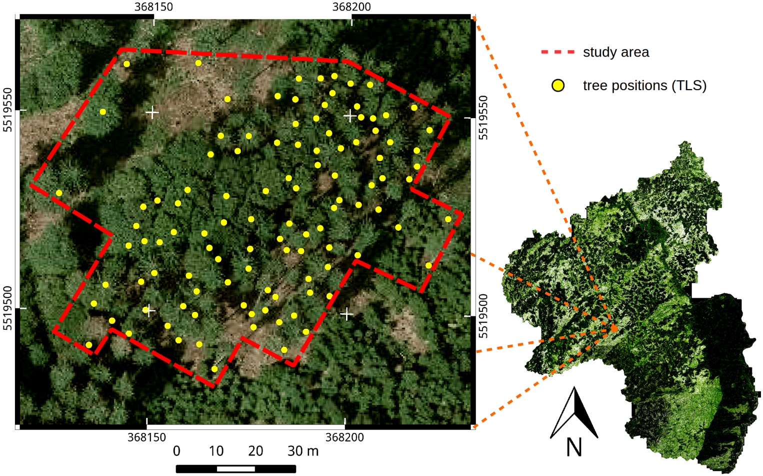
Study Area

- 59 manually recorded trees
- 2/3 Norway Spruce, 1/3 European Beech
- reference positions
  - 8 terrestrial LiDAR scans
  - slicing-approach ⇒ stem centre points & trunk position
- further measurements
  - diameter at breast height
  - differential GPS

Study Area



TLS ≙ **T**errestrial **L**aser **S**canning

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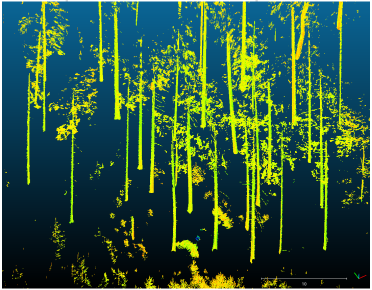

LiDAR ≙ **Li**ght **D**etection **A**nd **R**anging

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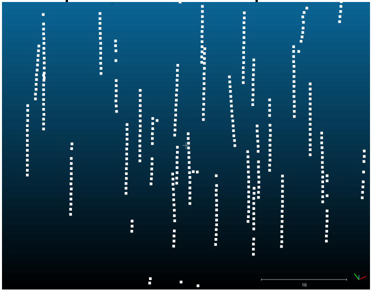

slicing approach: cf. Bienert et al. 2006

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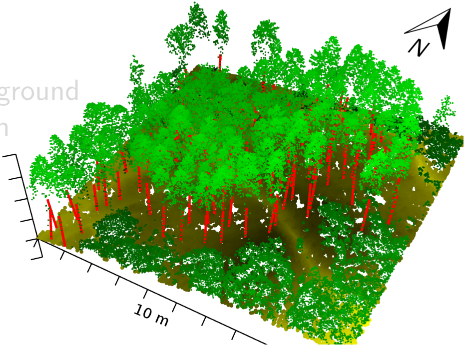
GPS ≙ **G**lobal **P**ositioning **S**ystem

ALS Data

- absolute horizontal accuracy: 0,30 m
- vertical accuracy: 0,15 m (open terrain)
- average point density: 7,7 $\frac{\text{Points}}{\text{m}^2}$
- preprocessing
  - point classification
    $\Rightarrow$ ground vs. non ground
  - height normalisation



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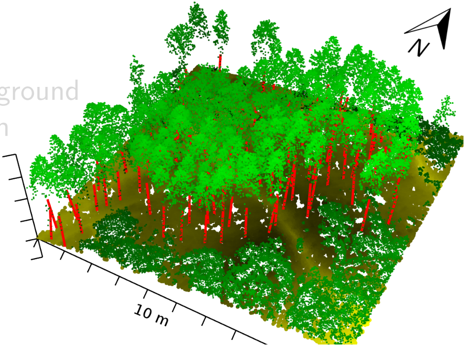

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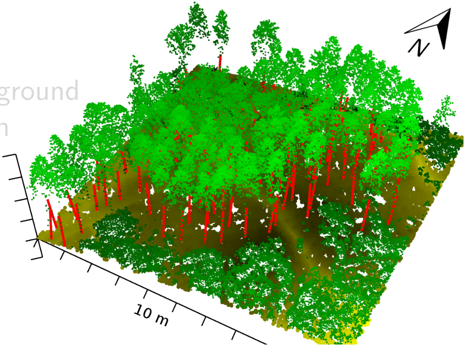

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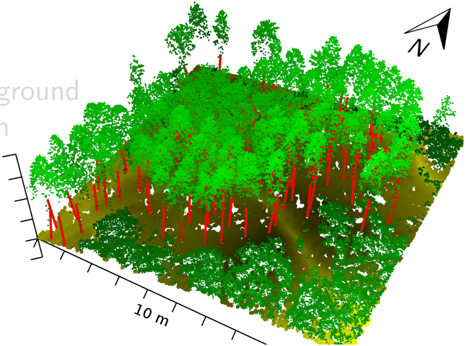

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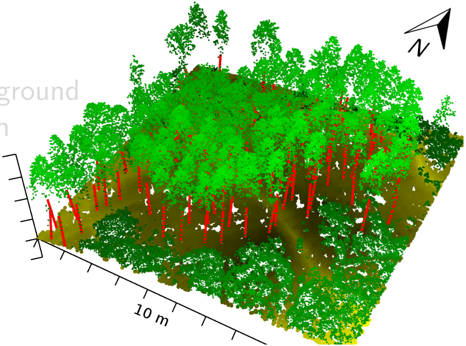

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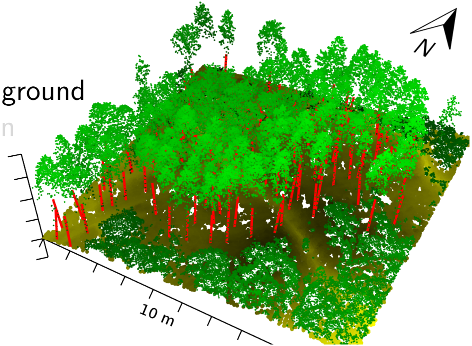

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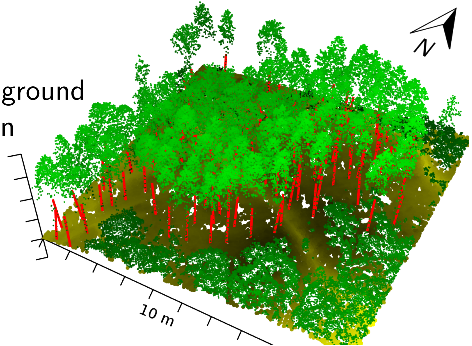
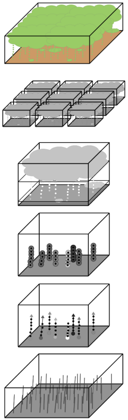


Partitioning of the Point Cloud

- input data
  - height-normalised point cloud
  - non ground points only
- splitting into rectangular subsets
  - overlap area ⇒ reduces omissions
  - allows local crown base height adaptation
  - *Divide & Conquer* implementation

⇒ parameters
  - maximum size of a sample
  - overlap width



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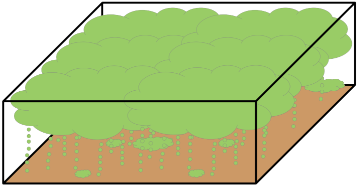

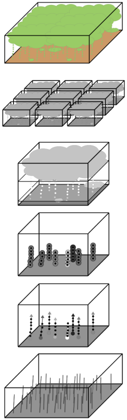

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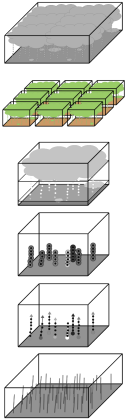

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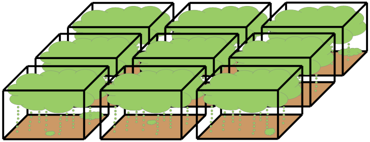

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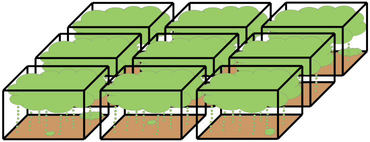
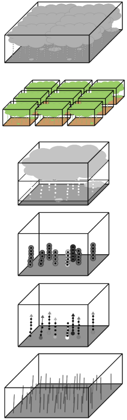
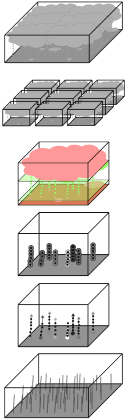




Identification of Potential Trunk Points



⇒ parameters

- ground threshold
- density threshold

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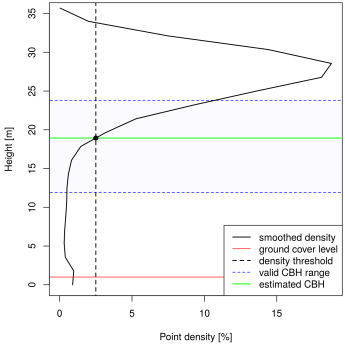
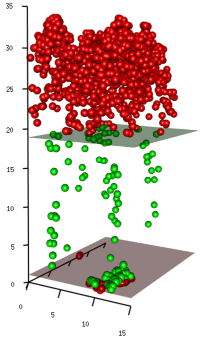


analysis of the vertical histogram



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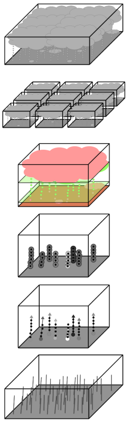

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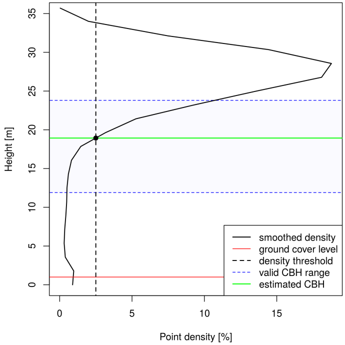

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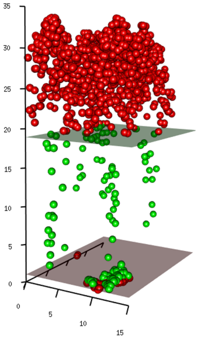

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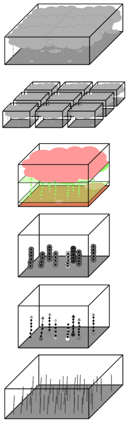

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Trunk Identification

- 3D Clustering
- variant of the DBSCAN
- optional scaling of the z-axis

⇒ parameters

- radius
- minimum number of neighbours
- minimum number of points
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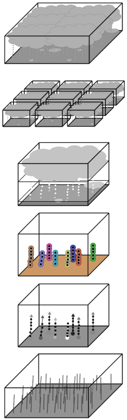

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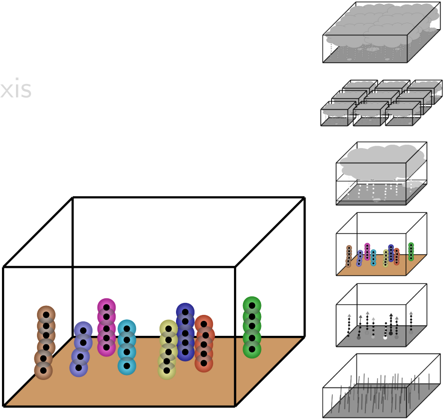

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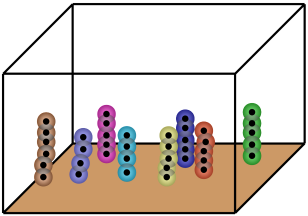

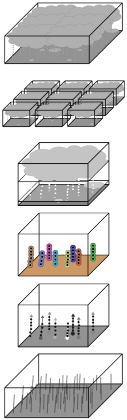

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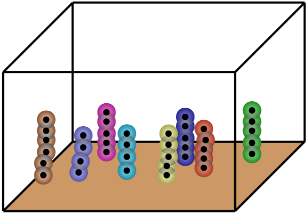

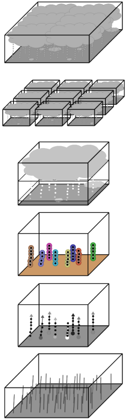

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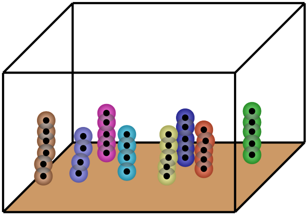

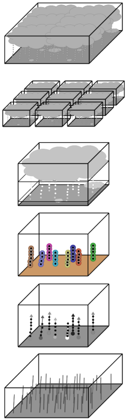

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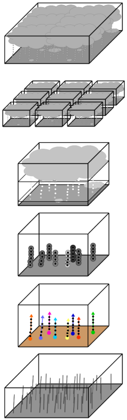

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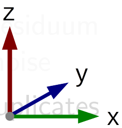

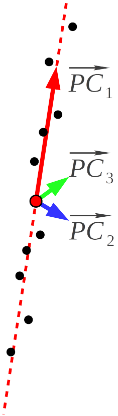

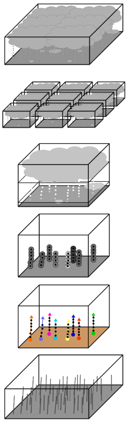

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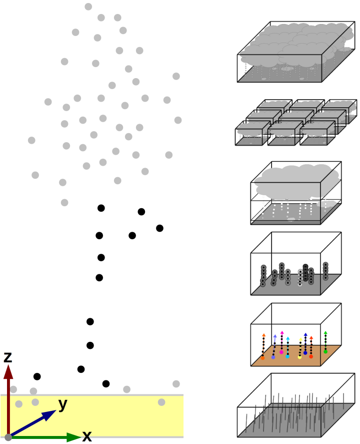

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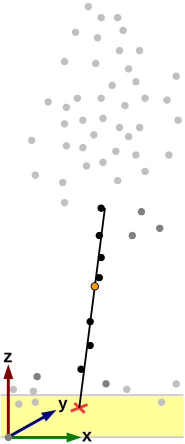

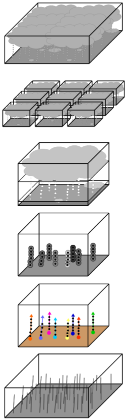

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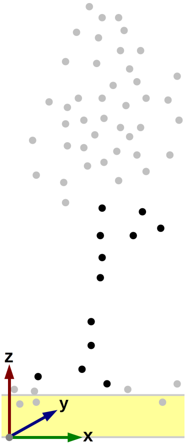

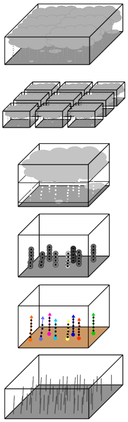

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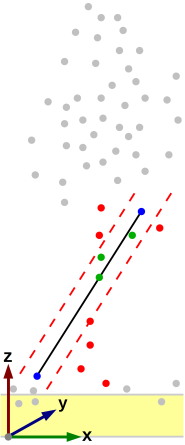

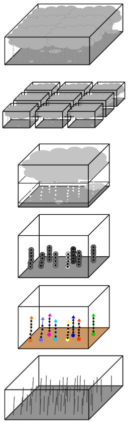

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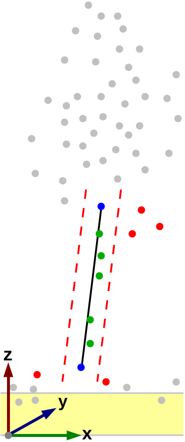

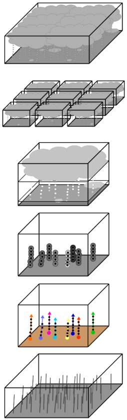

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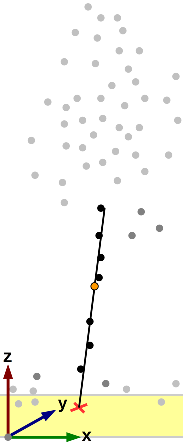

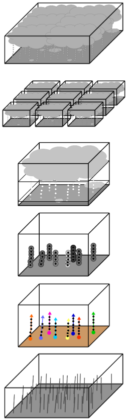

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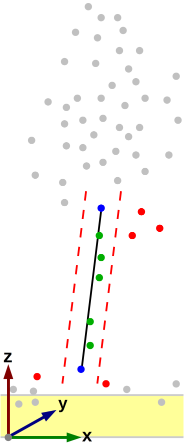

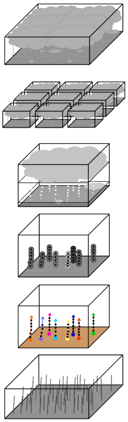

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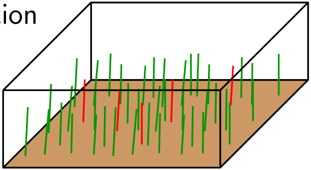

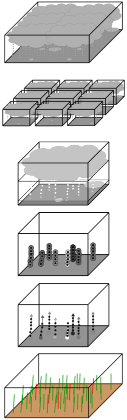

Assignment of Reference Positions

- reference: TLS-positions (slicing-approach)
- automatic assignment of positions
  - translation and rotation of the reference positions (2D)
  - assignment to the closest reference position
  - maximum distance: 4 m
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watershed segmentation: cf. Chen et al. 2006, Koch et al. 2006, Hyyppä et al. 2012

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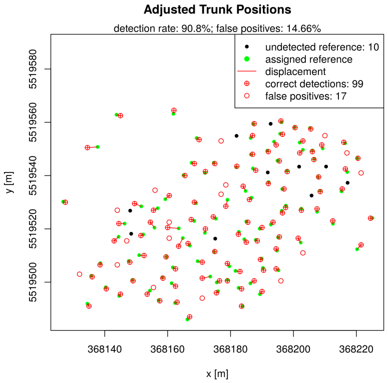

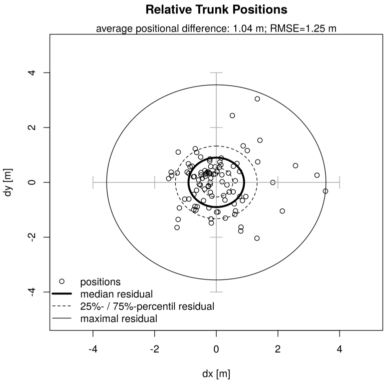

Watershed vs. TLS

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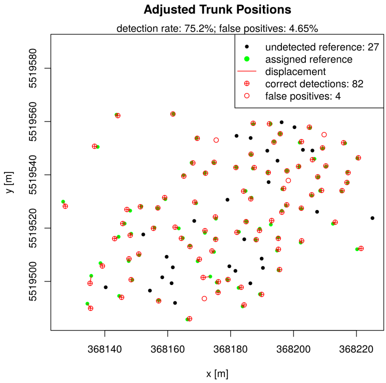

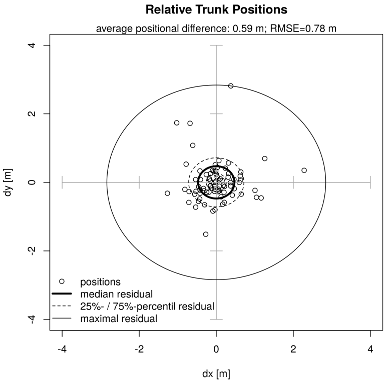

aTrunk vs. TLS

Accuracy Assessment

Approach	Detection Rate	Precision	Overall Accuracy	Position Error Average	Position Error RMSE
watershed	91%	85%	88%	1.04 m	1.25 m
aTrunk	75%	95%	84%	0.59 m	0.78 m
matching	69%	96%	80%	0.64 m	0.82 m
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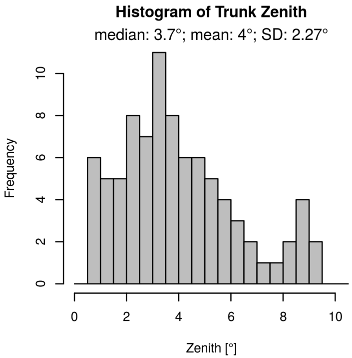
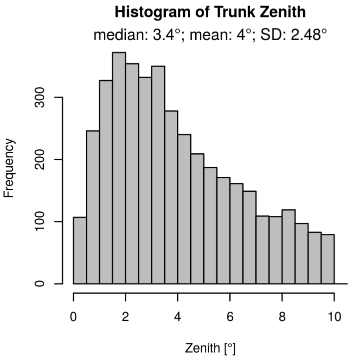
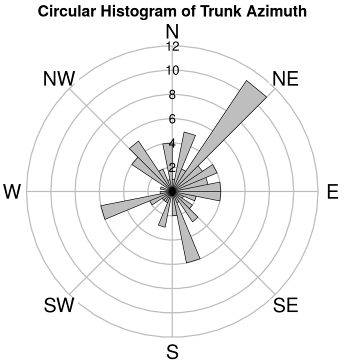


study area ($N = 83$)



1 km^2-dataset ($N = 4604$)

Results: Azimuth Angle



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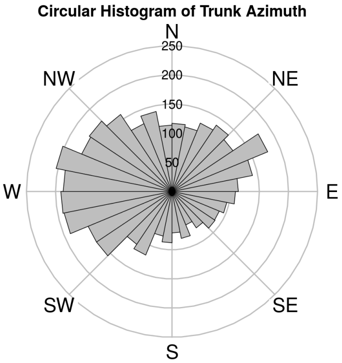

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- combination of complementary detection approaches (crown segmentation & trunk detection)
  - improved detection rate
  - higher precision
  - higher positioning accuracy
    - simplified validation
    - simplified combination of ALS and TLS
- further studies (angle of inclination)
  - stand characteristics (wind throw risk, soil, ...)
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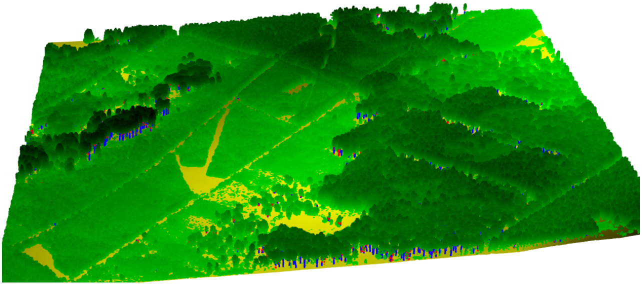


Bienert, A.; Maas, H.-G.; Scheller, S. In *Workshop on 3D Remote Sensing in Forestry*, Viena, 2006, pp 1–6.

Chen, Q.; Baldocchi, D.; Gong, P.; Kelly, M. *Photogrammetric Engineering and Remote Sensing* **2006**, *72*, 923–932.

Chum, O.; Matas, J.; Kittler, J. en In *Pattern Recognition*, Michaelis, B., Krell, G., Eds.; Lecture Notes in Computer Science 2781; Springer Berlin Heidelberg: Jan. 2003, pp 236–243.

Diaz, J. *Imaging Notes* **2011**, *26*, 31.

Ester, M.; Kriegel, H.-P.; Sander, J.; Xu, X. In *Kdd*, 1996; Vol. 96, pp 226–231.

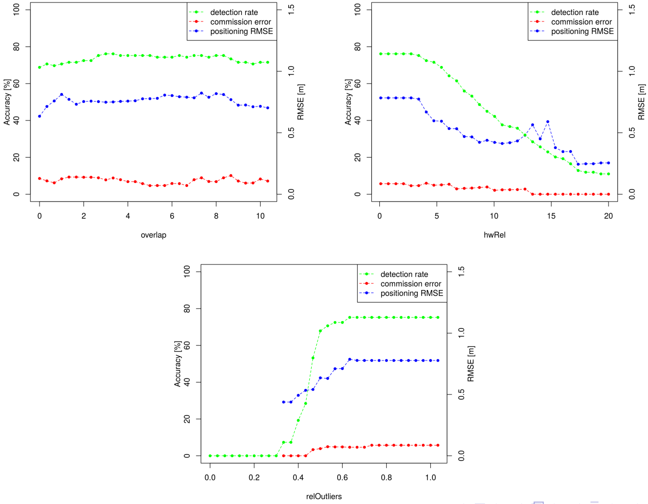
- Hyyppä, J.; Yu, X.; Hyyppä, H.; Vastaranta, M.; Holopainen, M.; Kukko, A.; Kaartinen, H.; Jaakkola, A.; Vaaja, M.; Koskinen, J.; Alho, P. en *Remote Sensing* **May 2012**, *4*, 1190–1207.
- Koch, B.; Heyder, U.; Weinacker, H. *Photogrammetric Engineering & Remote Sensing* **2006**, *72*, 357–363.
- Lamprecht, S.; Stoffels, J.; Dotzler, S.; Haß, E.; Udelhoven, T. *Remote Sensing* **2015**, *7*, 9975.
- Lu, X.; Guo, Q.; Li, W.; Flanagan, J. *ISPRS Journal of Photogrammetry and Remote Sensing* **2014**, *94*, 1–12.
- Rahman, M.; Gorte, B.; Bucksch, A. In *Proceedings ISPRS Workshop Laserscanning 2009, September 1-2, France, IAPRS, XXXVIII (3/W8), 2009*, 2009.

Reitberger, J.; Schnörr, C.; Krzystek, P.; Stilla, U. *ISPRS Journal of Photogrammetry and Remote Sensing* **Nov. 2009**, *64*, 561–574.

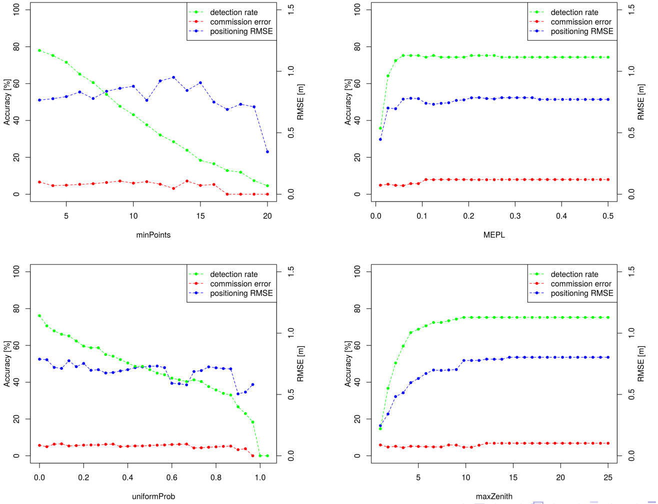
Reitberger, J; Heurich, M; Krzystek, P; Stilla, U *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences* **2007**, *36*, 139–144.

Wold, S.; Esbensen, K.; Geladi, P. *Chemometrics and Intelligent Laboratory Systems* **Aug. 1987**, *2*, 37–52.

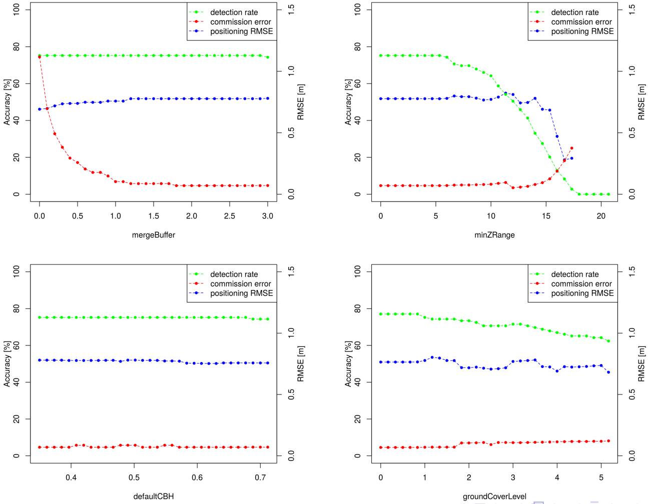
Analysis Effort



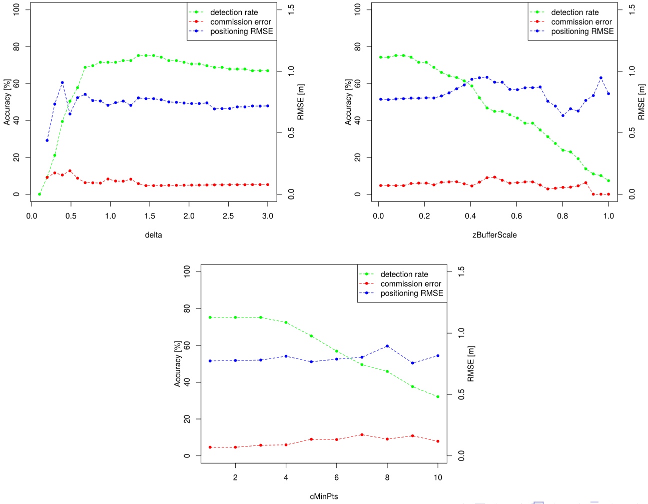
Model Characteristics



Stand Structure



Clustering


detection rate
commission error
positioning RMSE
Accuracy [%]
RMSE [m]
delta
zBufferScale
cMinPts

Crown Base Height