Estimation of forest characteristics using airborne laser scanning: could stochastic geometry help?

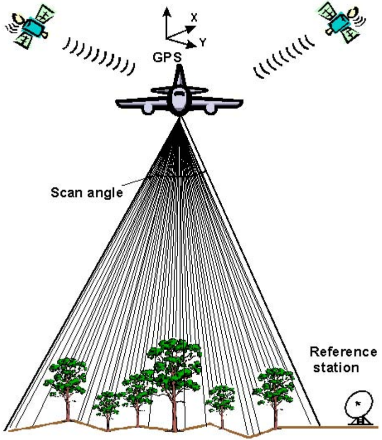
Lauri Mehtätalo and Kasper Kansanen

School of Computing
University of Eastern Finland, Joensuu campus

12th French-Danish Workshop on Spatial Statistics and Image Analysis in Biology / 23-25.5.2018 / Aalborg

Outline

Airborne laser scanning of forests (ALS)



from Hyyppä J, Laserkeilaimen käyttö puustotunnusten mittaamisessa.
http://www.fgi.fi/osastot/projektisivut/kk_www_portaali/rswww/lasercase1.html

The principle

- A laser scanner measures the distance from an aircraft to forest canopy
- Some pulses return from canopies, others from forest floor
- Produces point-wise measurements of canopy height

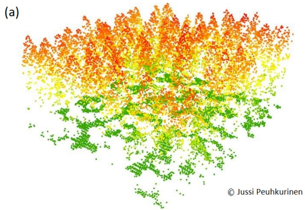
Commonly used devices have

- Scan angle 0-20 degrees.
- Laser footprint diameter $\approx$0.5 meters
- Pulse density $\approx$0.5-5 pulses per m^2.

Use of ALS in forest inventories

Forest inventories are used to assess the forest resources over the area of interest. The main characteristics are the amount, size, and species of trees.
ALS can be used in inventories in two ways

- Find individual tree canopies from a high-density point cloud
  → *Individual tree detection (ITD)*.
  + field data not needed
  - extra trees and hidden trees,
  - estimation of stem diameter and volume
- Estimate relation of ALS data and field measurements at locations of field sample plots and generalize it to the unsampled locations
  → *Area-Based Approach (ABA)*.
  + works with low point density,
  + relates ALS directly to variables of interest
  - field data needed,
  - tree species identification

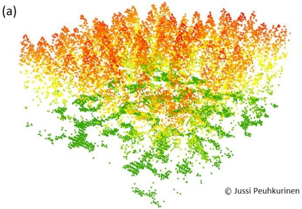


ALS data over a forest area.

Use of ALS in forest inventories

Forest inventories are used to assess the forest resources over the area of interest. The main characteristics are the amount, size, and species of trees.
ALS can be used in inventories in two ways

- Find individual tree canopies from a high-density point cloud
  → *Individual tree detection (ITD)*.
  + field data not needed
  - extra trees and hidden trees,
  - estimation of stem diameter and volume
- Estimate relation of ALS data and field measurements at locations of field sample plots and generalize it to the unsampled locations
  → *Area-Based Approach (ABA)*.
  + works with low point density,
  + relates ALS directly to variables of interest
  - field data needed,
  - tree species identification

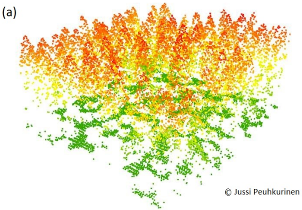


ALS data over a forest area.

Use of ALS in forest inventories

Forest inventories are used to assess the forest resources over the area of interest. The main characteristics are the amount, size, and species of trees.
ALS can be used in inventories in two ways

- Find individual tree canopies from a high-density point cloud
  $\rightarrow$ *Individual tree detection (ITD)*.
  \+ field data not needed
  \- extra trees and hidden trees,
  \- estimation of stem diameter and volume
- Estimate relation of ALS data and field measurements at locations of field sample plots and generalize it to the unsampled locations
  $\rightarrow$ *Area-Based Approach (ABA)*.
  \+ works with low point density,
  \+ relates ALS directly to variables of interest
  \- field data needed,
  \- tree species identification



ALS data over a forest area.

Possible solutions based on stochastic geometry (ITD)

- Simplify tree crowns to discs that are projected to the ground. [1]
- Assume that a tree is visible if the center is not within a larger tree. A tree is detected iff it is visible.
- The crown radius is distributed according to a parametric pdf/pmf with unknown parameters.
- Assume the Boolean model for crown discs. The proportion of canopy hits (cc) provides a measurement of area fraction. Equating it to the area fraction of the Boolean model $p = 1 - e^{-\lambda \mathrm{E}(Z)}$ and solving for λ yields an area fraction -based estimator of intensity

$$\hat{\lambda}_{AF} = -\frac{\ln(1 - cc)}{\mathrm{E}(Z)} \quad (1)$$

where $\mathrm{E}(Z)$ is the mean crown area over **all** trees.
- The Horvitz-Thompson estimator is

$$\hat{\lambda}_{HT} = \sum_{i=1}^{n} \frac{1}{\pi(z_i)} . \quad (2)$$

- Both estimators need a formula for detectability $\pi(z_i)$ ($\widehat{\lambda}_{AF}$ needs it for $\mathrm{E}(Z)$).

[1] Mehtätalo 2006, Can J. For. Res.

Possible solutions based on stochastic geometry (ITD)

- Simplify tree crowns to discs that are projected to the ground. [1]
- Assume that a tree is visible if the center is not within a larger tree. A tree is detected iff it is visible.
- The crown radius is distributed according to a parametric pdf/pmf with unknown parameters.
- Assume the Boolean model for crown discs. The proportion of canopy hits (*cc*) provides a measurement of area fraction. Equating it to the area fraction of the Boolean model $p = 1 - e^{-\lambda \mathrm{E}(Z)}$ and solving for λ yields an area fraction -based estimator of intensity

$$\hat{\lambda}_{AF} = -\frac{\ln(1 - cc)}{\mathrm{E}(Z)} \quad (1)$$

  where $\mathrm{E}(Z)$ is the mean crown area over **all** trees.
- The Horvitz-Thompson estimator is

$$\hat{\lambda}_{HT} = \sum_{i=1}^{n} \frac{1}{\pi(z_i)} . \quad (2)$$

- Both estimators need a formula for detectability $\pi(z_i)$ ($\widehat{\lambda}_{AF}$ needs it for $\mathrm{E}(Z)$).

[1] Mehtätalo 2006, Can J. For. Res.

Detectability $\pi(z)$ under the Boolean model

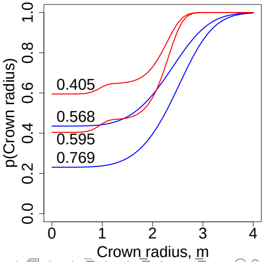
- Consider trees with crown area above a fixed z. The trees with $Z > z$ form also a Boolean model, with area fraction

$$p_{Z>z} = 1 - e^{-\lambda_{Z>z}\mathrm{E}_{Z>z}(Z)}$$

where the exponent is $-\lambda \int_z^\infty tf(t)\mathrm{d}t$ (or a corresponding sum if crown area Z is thought as discrete.
- The detectability is directly

$$\pi(z;\lambda) = 1 - p_{Z>z} = e^{-\lambda_{Z>z}\mathrm{E}_{Z>z}(Z)}.$$

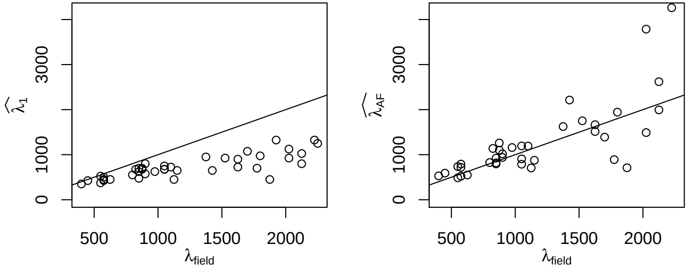
Detectability in hypothetical stands with unimodal (blue) and bimodal (red) size distribution of trees and two stand densities. The values show the canopy closure.



Empirical evaluation

- 40 square 400 m^2 Pine-dominated sample plots in North Carelia, Finland.
- The algorithm of Pitkänen (2004) [2] was used to detect tree crowns from ALS data.
- Weibull distribution was used for crown radius. ($\widehat{\lambda}_{HT}$ was not implemented.) [3]

Estimator	RMSE	bias
$\lambda_1 = \frac{N_{detected}}{\|W\|}$	629	-500
$\lambda_{AF} = -\frac{ln(1-cc)}{E(Z)}$	568	-31



[2] Pitkänen, Maltamo, Hyyppä and Yu, 2004. Proceedings of ISPRS working group VIII/2

[3] Vauhkonen and Mehtätalo 2015, Can. J. For. Res.

Adding empirical detectability and erosion

- Mehtätalo 2006 and Vauhkonen and Mehtätalo 2015 unnecessarily assumed the Boolean model in estimation of the detectability and λ. However, one can directly use the observed union of crown discs with $Z > z$ to compute the empirical detectability [a]

$$\pi_E(z) = 1 - \widehat{p}_{Z>z}$$

  where $\widehat{p}_{Z>z}$ is the empirical area fraction for crowns larger than z.

- The detectability rule can further be relaxed: a target tree with crown area z remains undetected if the center point lies within an erosion set of the union of crown discs with $Z > z$. The erosion buffer width is αr (here $z = \pi r^2$), where α is a erosion buffer size to be estimated.

[a] Kansanen, Vauhkonen, Lähivaara and Mehtätalo, 2016, Can. J. For. Res.

Adding empirical detectability and erosion

- Mehtätalo 2006 and Vauhkonen and Mehtätalo 2015 unnecessarily assumed the Boolean model in estimation of the detectability and λ. However, one can directly use the observed union of crown discs with $Z > z$ to compute the empirical detectability [a]

$$\pi_E(z) = 1 - \widehat{p}_{Z>z}$$

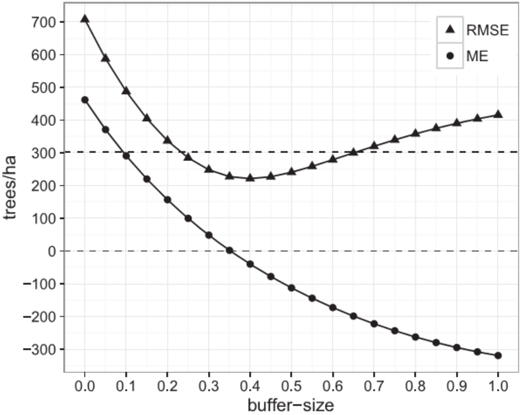
  where $\widehat{p}_{Z>z}$ is the empirical area fraction for crowns larger than z.

- The detectability rule can further be relaxed: a target tree with crown area z remains undetected if the center point lies within an erosion set of the union of crown discs with $Z > z$. The erosion buffer width is αr (here $z = \pi r^2$), where α is a erosion buffer size to be estimated.

[a] Kansanen, Vauhkonen, Lähivaara and Mehtätalo, 2016, Can. J. For. Res.

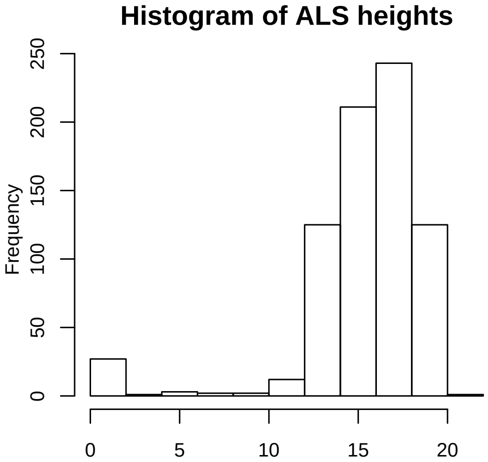
Results for estimation of λ

Fig. 3. The RMSE and ME of Horvitz–Thompson estimators with the empirical detectability as a function of the buffer size. A line marking the RMSE of AF–BMB, 303.1 trees·ha^{-1}, has been added to give a comparison point to the other presented methods.



Marginal distribution of canopy height in 3D- data

- In the previous approach, we started from the projections of detected crowns (ITD)
- In the ABA approach, one wants to estimate forest characteristics using the marginal distribution of canopy heights over a sample plot.



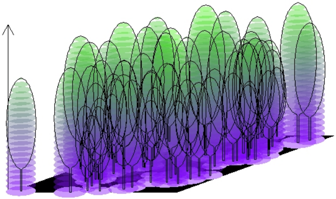
Marginal distribution of canopy height in 3D- data, cont.

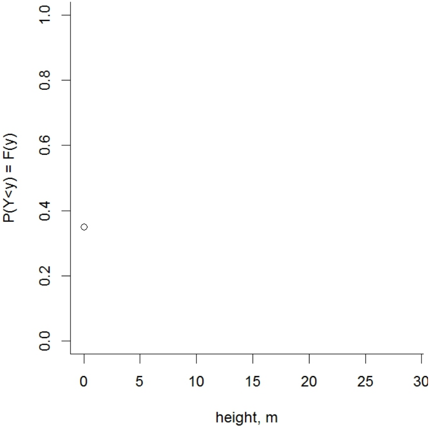
- Consider a 2-dimensional germ-grain model of crown intersections at height y above the ground. Let $Y(u)$ be the height of forest canopy at fixed point u within the sample plot. Now

$$F(y) = P(Y \leq y) = 1 - P\left(u \in \bigcup_{i=1}^{\infty} \mathbb{Z}_i(y)\right) = 1 - p(y),$$

where $\mathbb{Z}_i(y)$ is th cross-section of tree crown i at height y above the ground and $p(y)$ is the area fraction of the crown intersections at height y.

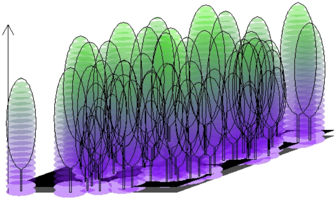
Illustration, Boolean model case

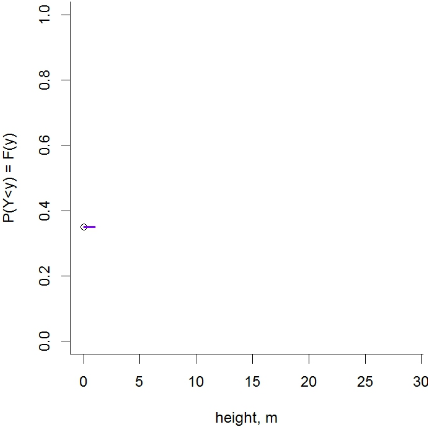




$$F(y) = P(Y \leq y) = 1 - P\left(u \in \bigcup_{i=1}^{\infty} \mathcal{Z}_i(y)\right) = 1 - p(y)$$

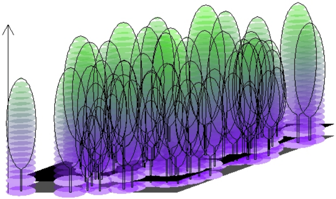
Illustration, Boolean model case

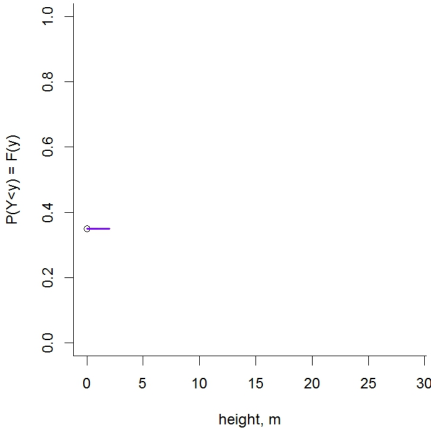




$$F(y) = P(Y \leq y) = 1 - P\left(u \in \bigcup_{i=1}^{\infty} \mathcal{Z}_i(y)\right) = 1 - p(y)$$

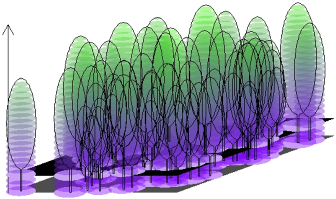
Illustration, Boolean model case

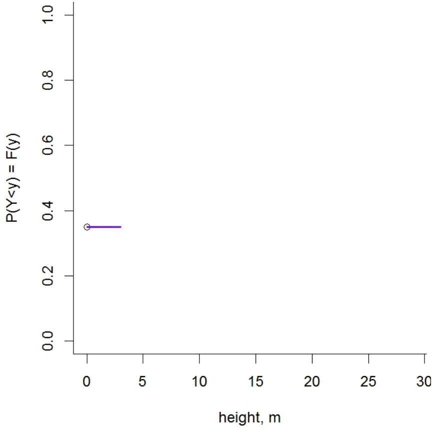




$$F(y) = P(Y \leq y) = 1 - P(u \in \bigcup_{i=1}^{\infty} \mathcal{Z}_i(y)) = 1 - p(y)$$

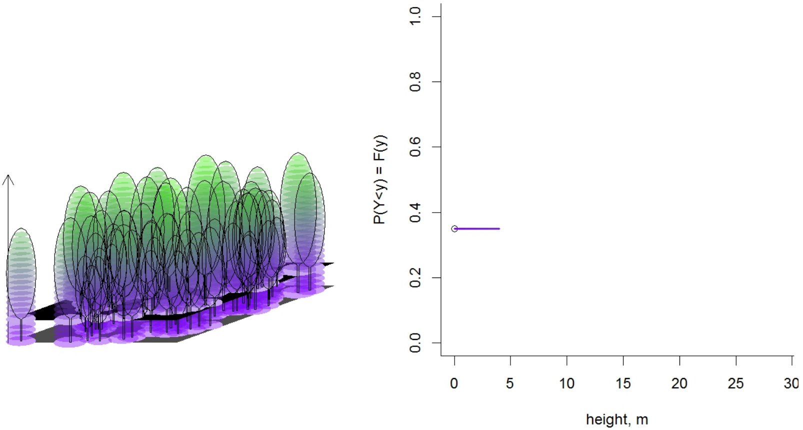
Illustration, Boolean model case





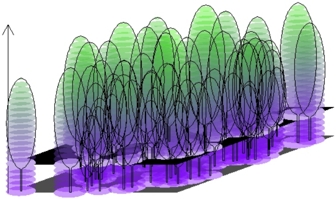
$$F(y) = P(Y \leq y) = 1 - P\left(u \in \bigcup_{i=1}^{\infty} \mathcal{Z}_i(y)\right) = 1 - p(y)$$

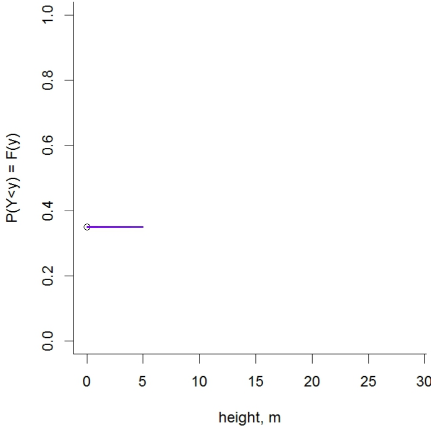
Illustration, Boolean model case



$$F(y) = P(Y \leq y) = 1 - P\left(u \in \bigcup_{i=1}^{\infty} \mathcal{Z}_i(y)\right) = 1 - p(y)$$

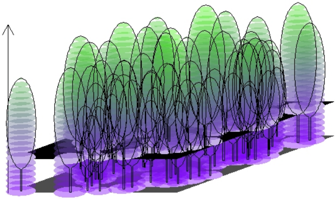
Illustration, Boolean model case

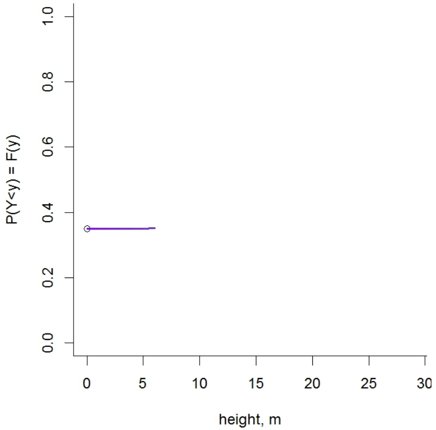




$$F(y) = P(Y \leq y) = 1 - P\left(u \in \bigcup_{i=1}^{\infty} \mathcal{Z}_i(y)\right) = 1 - p(y)$$

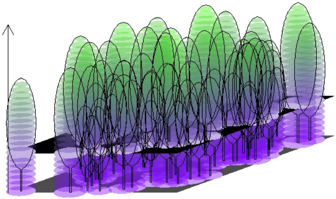
Illustration, Boolean model case

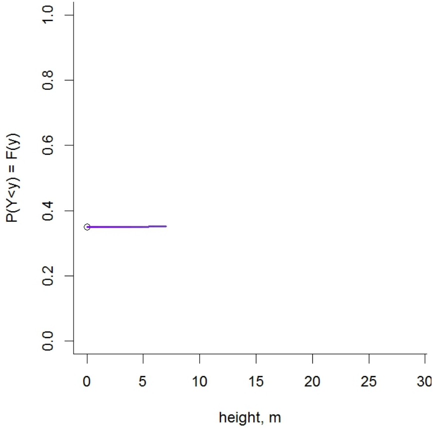




$$F(y) = P(Y \leq y) = 1 - P(u \in \bigcup_{i=1}^{\infty} \mathcal{Z}_i(y)) = 1 - p(y)$$

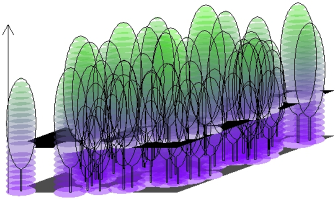
Illustration, Boolean model case

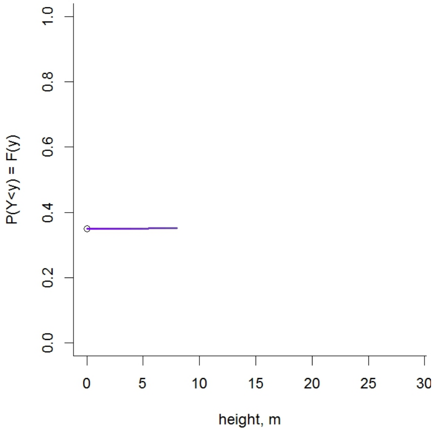




$$F(y) = P(Y \leq y) = 1 - P(u \in \bigcup_{i=1}^{\infty} \mathcal{Z}_i(y)) = 1 - p(y)$$

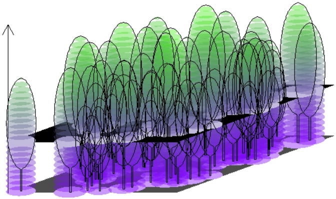
Illustration, Boolean model case

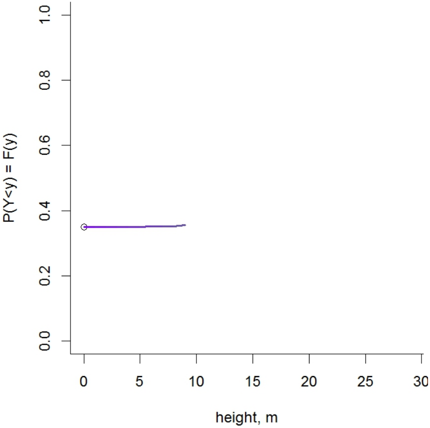




$$F(y) = P(Y \leq y) = 1 - P\left(u \in \bigcup_{i=1}^{\infty} \mathcal{Z}_i(y)\right) = 1 - p(y)$$

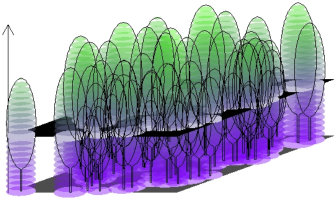
Illustration, Boolean model case

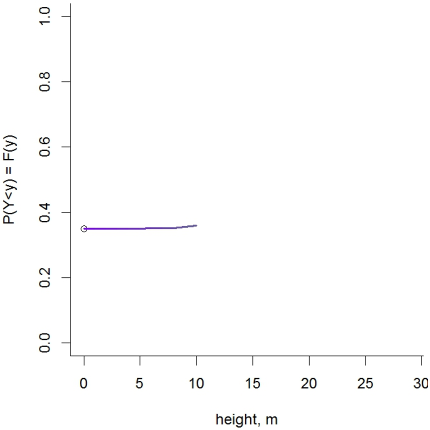




$$F(y) = P(Y \leq y) = 1 - P\left(u \in \bigcup_{i=1}^{\infty} \mathcal{Z}_i(y)\right) = 1 - p(y)$$

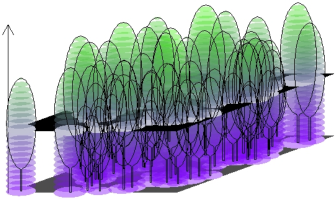
Illustration, Boolean model case

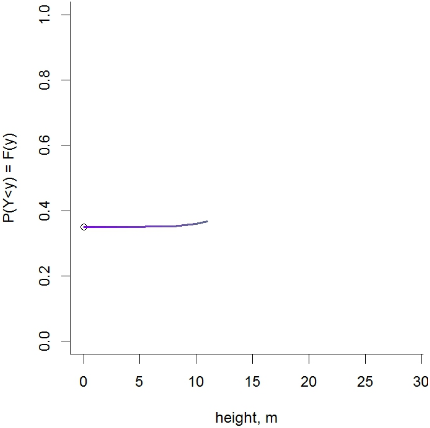




$$F(y) = P(Y \leq y) = 1 - P(u \in \bigcup_{i=1}^{\infty} \mathcal{Z}_i(y)) = 1 - p(y)$$

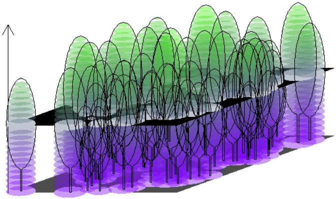
Illustration, Boolean model case

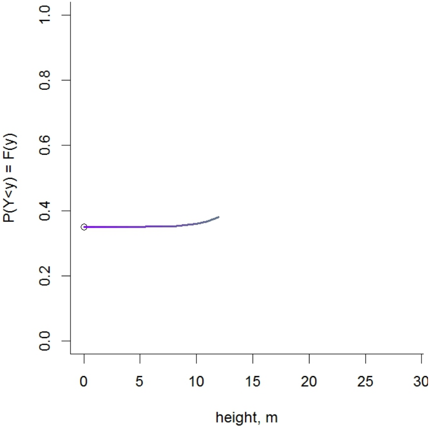




$$F(y) = P(Y \leq y) = 1 - P\left(u \in \bigcup_{i=1}^{\infty} \mathcal{Z}_i(y)\right) = 1 - p(y)$$

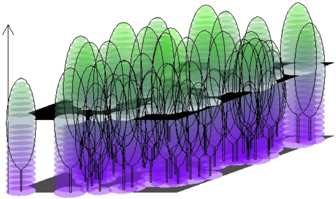
Illustration, Boolean model case

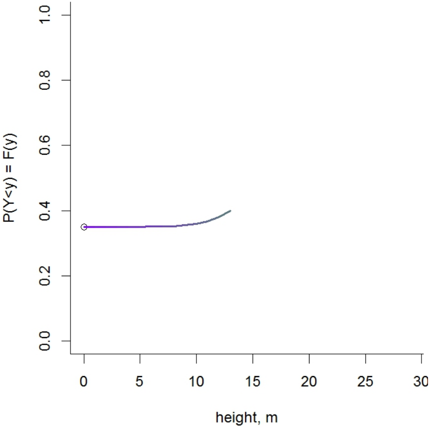




$$F(y) = P(Y \leq y) = 1 - P\left(u \in \bigcup_{i=1}^{\infty} \mathcal{Z}_i(y)\right) = 1 - p(y)$$

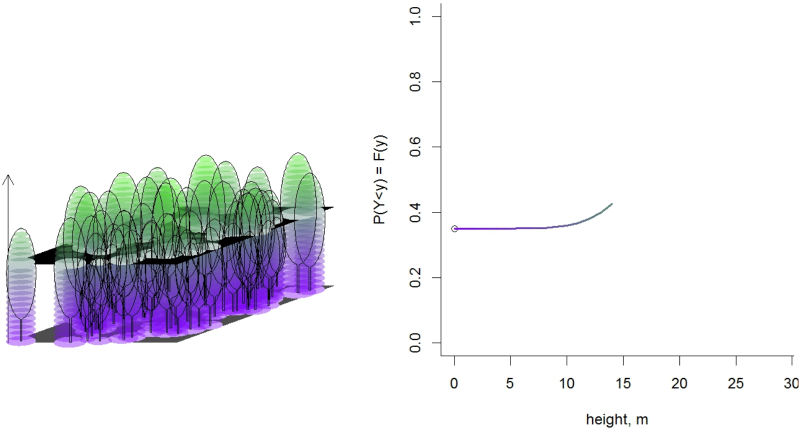
Illustration, Boolean model case





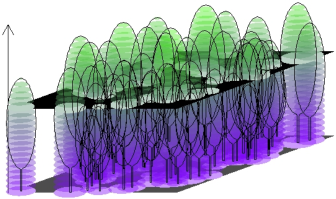
$$F(y) = P(Y \leq y) = 1 - P\left(u \in \bigcup_{i=1}^{\infty} \mathcal{Z}_i(y)\right) = 1 - p(y)$$

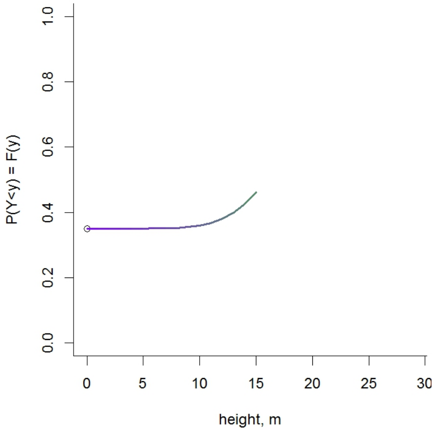
Illustration, Boolean model case



$$F(y) = P(Y \leq y) = 1 - P\left(u \in \bigcup_{i=1}^{\infty} \mathcal{Z}_i(y)\right) = 1 - p(y)$$

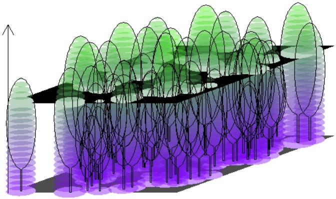
Illustration, Boolean model case

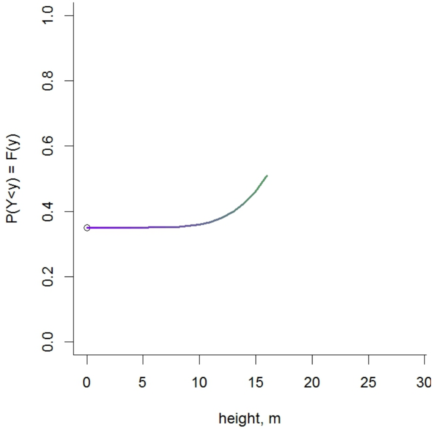




$$F(y) = P(Y \leq y) = 1 - P\left(u \in \bigcup_{i=1}^{\infty} \mathcal{Z}_i(y)\right) = 1 - p(y)$$

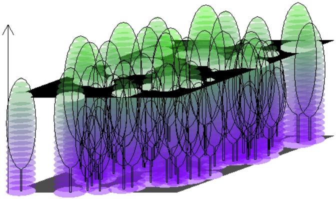
Illustration, Boolean model case

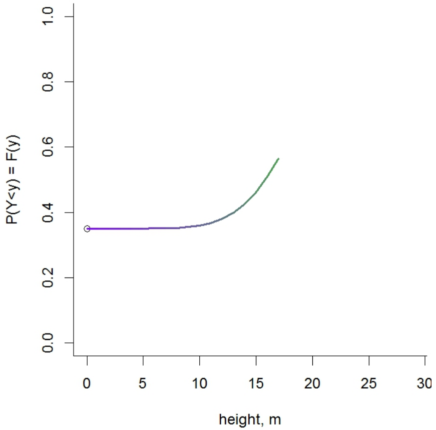




$$F(y) = P(Y \leq y) = 1 - P\left(u \in \bigcup_{i=1}^{\infty} \mathcal{Z}_i(y)\right) = 1 - p(y)$$

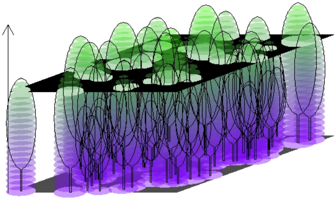
Illustration, Boolean model case

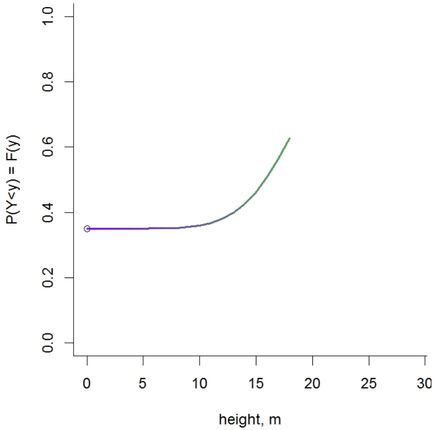




$$F(y) = P(Y \leq y) = 1 - P\left(u \in \bigcup_{i=1}^{\infty} \mathcal{Z}_i(y)\right) = 1 - p(y)$$

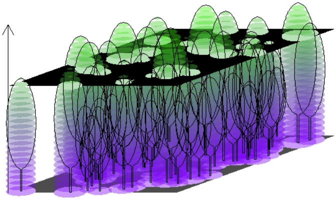
Illustration, Boolean model case

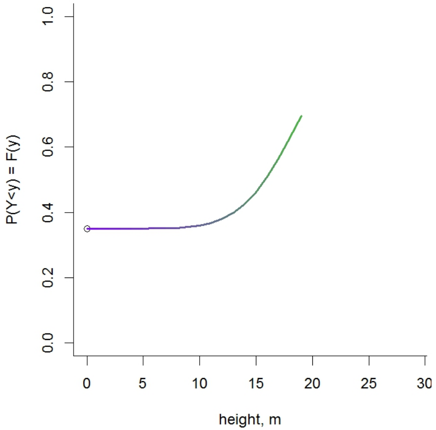




$$F(y) = P(Y \leq y) = 1 - P\left(u \in \bigcup_{i=1}^{\infty} \mathcal{Z}_i(y)\right) = 1 - p(y)$$

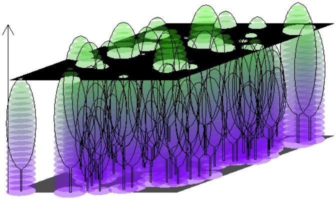
Illustration, Boolean model case

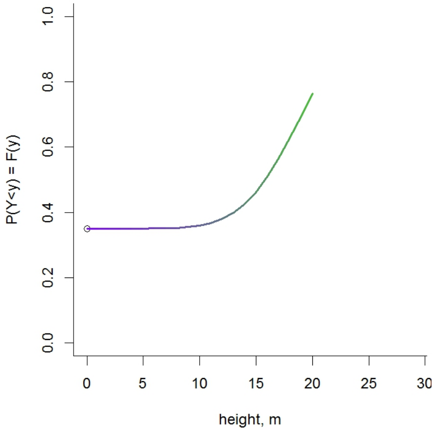




$$F(y) = P(Y \leq y) = 1 - P\left(u \in \bigcup_{i=1}^{\infty} \mathcal{Z}_i(y)\right) = 1 - p(y)$$

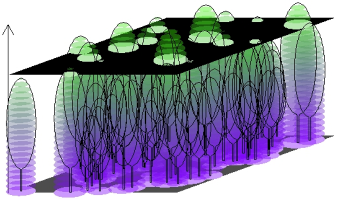
Illustration, Boolean model case

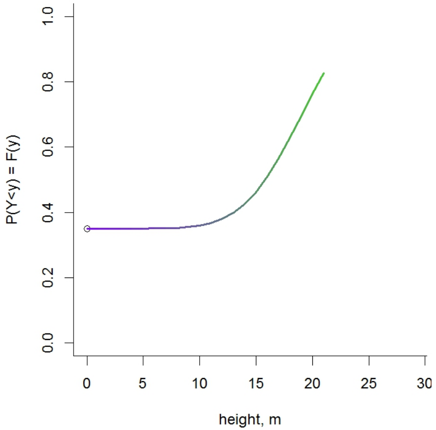




$$F(y) = P(Y \leq y) = 1 - P\left(u \in \bigcup_{i=1}^{\infty} \mathcal{Z}_i(y)\right) = 1 - p(y)$$

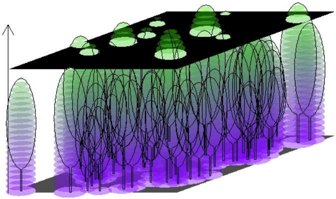
Illustration, Boolean model case

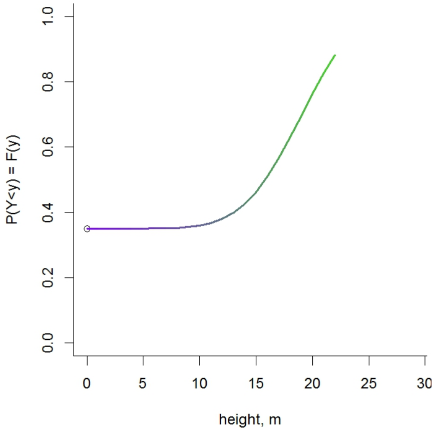




$$F(y) = P(Y \leq y) = 1 - P\left(u \in \bigcup_{i=1}^{\infty} \mathcal{Z}_i(y)\right) = 1 - p(y)$$

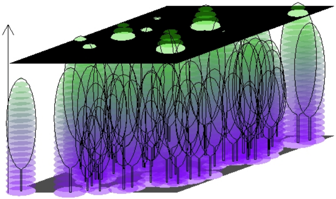
Illustration, Boolean model case

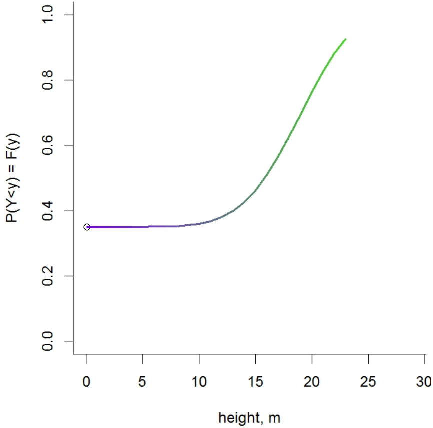




$$F(y) = P(Y \leq y) = 1 - P\left(u \in \bigcup_{i=1}^{\infty} \mathcal{Z}_i(y)\right) = 1 - p(y)$$

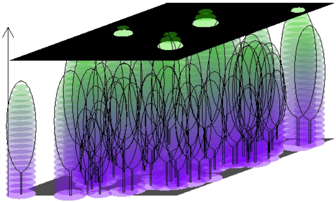
Illustration, Boolean model case

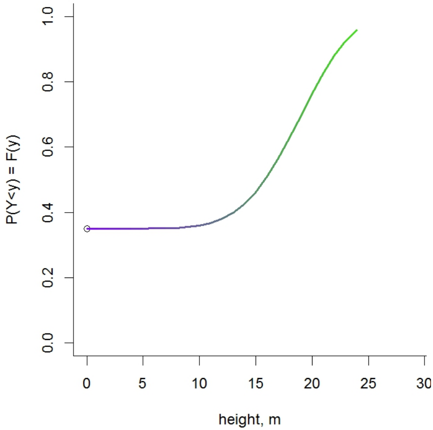




$$F(y) = P(Y \leq y) = 1 - P\left(u \in \bigcup_{i=1}^{\infty} \mathcal{Z}_i(y)\right) = 1 - p(y)$$

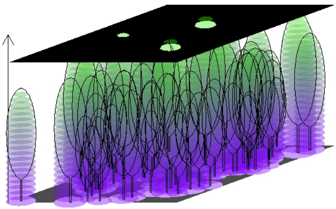
Illustration, Boolean model case

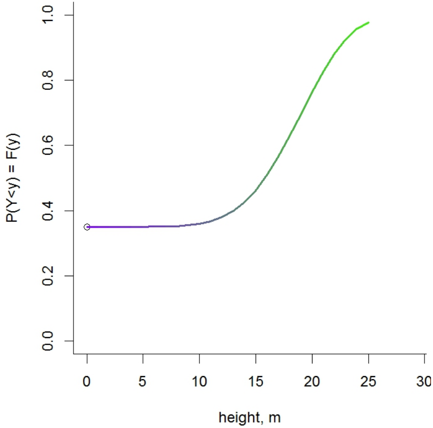




$$F(y) = P(Y \le y) = 1 - P\left(u \in \bigcup_{i=1}^{\infty} \mathcal{Z}_i(y)\right) = 1 - p(y)$$

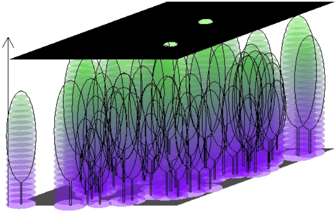
Illustration, Boolean model case

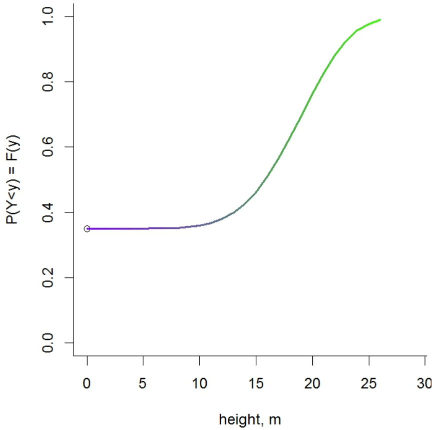




$$F(y) = P(Y \leq y) = 1 - P\left(u \in \bigcup_{i=1}^{\infty} \mathcal{Z}_i(y)\right) = 1 - p(y)$$

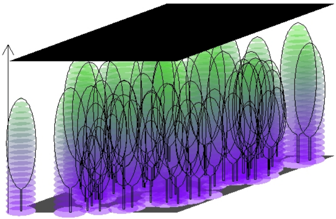
Illustration, Boolean model case

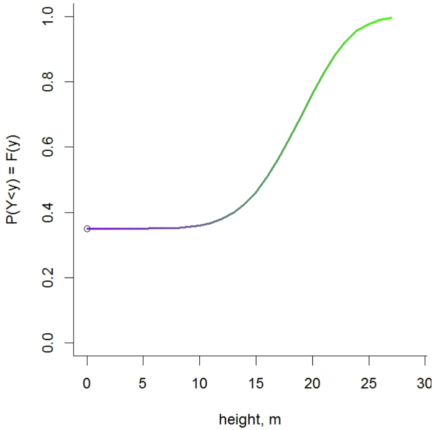




$$F(y) = P(Y \leq y) = 1 - P(u \in \bigcup_{i=1}^{\infty} \mathcal{Z}_i(y)) = 1 - p(y)$$

Illustration, Boolean model case





$$F(y) = P(Y \leq y) = 1 - P\left(u \in \bigcup_{i=1}^{\infty} \mathcal{Z}_i(y)\right) = 1 - p(y)$$

The model formulation

1. We started by parameterizing $F(y)$ using stand density λ, parameters of tree height distribution (Weibull, two parameters) and two parameters for tree crown shape (ellipsoidial shape, two parameters) under the Poisson process for tree locations y [4] and square grid pattern of tree locations. [5]
2. Estimation is based on Maximum Likelihood.
3. In practice, the model could be used as a two-step approach:[6]
    1. Given the field-measured stand density and height distribution, estimate canopy shape parameters for the sample plots and
    2. Given the estimates from step 1, estimate the stand density and height distribution for unsampled locations.

   It is also possible to estimate all parameters in a single step. [7]
4. The model is, however too simple for practical use. It seems we need to include
    - randomness in tree crown shape
    - penetration of laser pulses
    - a more general point pattern model

   These extensions lead to computational challenges. [8]

[4] Mehtätalo and Nyblom 2009, For. Sci

[5] Mehtätalo and Nyblom 2012, For. Sci.

[6] Mehtätalo, Virolainen, Tuomela, Nyblom, 2010. Proceedings of SilviLaser 2010

[7] Mehtätalo, Virolainen, Tuomela and Packalen 2015. IEEE JSTARS.

[8] Mehtätalo, Nyblom and Virolainen 2014. In: Springer, Managing Forest Ecosystems 27, pp 193-211.

Conclusions

1. Forest canopy is a union of tree canopies, therefore aerial forest inventories are an interesting application of stochastic geometry.
2. Individual tree detection combined with estimation of hidden trees using stochastic geometry is potentially useful application. We are currently doing spatio-temporal modelling of measured point patterns to include a model for interaction between trees.
3. Estimation of tree height distribution and stand density using marginal distribution of canopy heights is another interesting application, but the current model was too simple for practical use.
4. We have not yet been able to beat the empirical ABA methods in estimation using either of the approaches (except for stand density)

Bibliography

- Kansanen, K., Vauhkonen, J., Lähivaara, T., Mehtätalo, L. 2016. Stand density estimators based on individual tree detection and stochastic geometry. Canadian Journal of Forest Research 46(11): 1359-1366. 10.1139/cjfr-2016-0181. IF: 1.657, JUFO: 3.
- Lähivaara, T., Seppänen, A., Kaipio, J.P., Vauhkonen, J., Korhonen, L., Tokola, T., and Maltamo, M. 2014. Bayesian approach to tree detection based on airborne laser scanning data. IEEE T. Geosci. Remote 52(5): 2690-2699. doi:10.1109/ TGRS.2013.2264548
- Mehtätalo, L. (2006). Eliminating the effect of overlapping crows from aerial inventory estimates *Can. J. For. Res. 36*, 1649–1660.
- Mehtätalo, L. and Nyblom, J 2009. Estimating forest attributes using observations of canopy height: a model-based approach. For. Sci. 55(5): 411-422
- Mehtätalo, L. and Nyblom, J. 2012. A model-based approach for ALS inventory: application for square grid spatial pattern. Forest Science 58(2): 106-118.
- Mehtätalo, L. Virolainen. A, Tuomela, J. and Nyblom, J. 2010. A model-based approach for estimating the height distribution of eucalyptus plantations using low-density ALS data. Proceedings of SilviLaser 2010, The 10th annual conference on lidar applications for assessing forest ecosystems. Freiburg, Germany.
- Mehtätalo, L., Nyblom, J., and Virolainen, A. 2014. A model-based approach for the recovery of forest attributes using ALS data. Book chapter in Maltamo, M., Næsset, E. and Vauhkonen, J. (editors). Forestry applications of airborne laser scanning- Concepts and Case Studies. Springer, Managing Forest Ecosystems 27, pp 193-211
- Mehtätalo, L., Virolainen, A., Tuomela, J. and Packalen, P. 2015. Estimating tree height distribution using low-density ALS data with and without training data. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 8(4): 1432-1441. DOI: 10.1109/JSTARS.2015.2418675.
- Pitkänen, J., Maltamo, M., Hyyppä, J., and Yu, X. 2004. Adaptive methods for individual tree detection on airborne laser based canopy height model. In Proceedings of ISPRS working group VIII/2: Laser-Scanners for Forest and Landscape Assessment. Edited by M. Theis, B. Koch, H. Spiecker, and H. Weinacker. University of Freiburg, Freiburg, Germany. pp. 187-191.
- Vauhkonen, J. and Mehtätalo, L. 2015. Matching remotely sensed and field measured tree size distributions. Canadian Journal of Forest Research 45(3): 353-363

Thank You!