Finding hidden trees in remote sensing of forests by using stochastic geometry, sequential spatial point processes and the HT-like estimator

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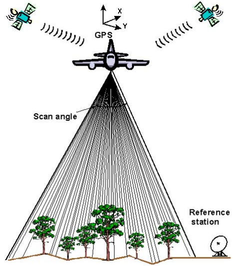
Outline

Laser scanning in forest inventories



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

tlskuva.png

Airborne laser scanning

- 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, which allow detection of individual tree crowns.

Terrestrial laser scanning

- A laser scanner, installed on a tripod, rotates 360^0 and measures the distances to the closest obstacles with a very high pulse density.
- Individual tree stems can be detected from the point cloud.

In both cases

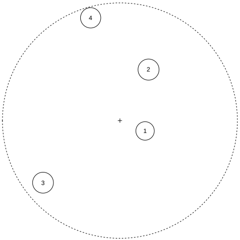
- The detected trees can be ordered according to their shortest distance to the censor
- Trees can be hidden if they are located behind "earlier" trees.

The method

Assume that TLS is used to detect the stem discs at the height of 1.3 meters above the ground. The n observed trees out of the all N trees within a circular sample plot are ordered according to the distance r_i to the plot center, which is for convenience at the origin. Consider the total of variable m, $\tau = \sum_{i=1}^{N} m_i$. The Horvitz-Thompson like estimator is

$$\widehat{\tau}_m = \sum_{i=1}^{n} \frac{m_i}{p_i},,$$

where the inclusion probability p_i is called detectability.



- For tree 1, $p_1 = 1$.
- Assuming that a tree is detected if the center point is visible to the scanner and CSR of tree locations, the detectabilities for the latter trees are computed using

$$p_i = 1 - \frac{\left|\left(\bigcup_{j=1}^{i-1} A_j\right) \cap S(r_i)\right|}{|S(r_i)|},$$

where A_j is the gray shaded area behind tree j and $S(r_j)$ is a origin-centered circle of radius r_j. [a]

[a]Kansanen et al 2020

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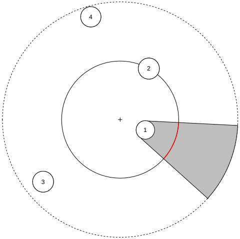

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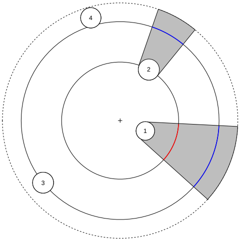

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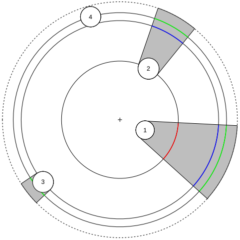

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Expected value of the estimator under CSR

Denote by S_j that part of the r_j-radius circle that is hidden behind earlier trees, by S_j^c the part that is not hidden, and their relative lengths by $|S_j|$ and $|S_j^c|$ so that $|S_j|+|S_j^c|=1$.
Write the HT-like estimator as

$$\widehat{\tau}_m = \sum_{i=1}^{N} \frac{m_i I_i}{p_i},$$

where I_i ia an indicator that specifies whether tree i was detected. Now

$$\mathrm{E}(\widehat{\tau}_m) = \sum_{i=1}^{N} \frac{m_i \mathrm{E}(I_i)}{p_i}.$$

If tree locations are generated by the homogeneous Poisson process, then $\mathrm{E}(I_i) = 1 \times |S_i^c| + 0 \times |S_i| = p_i$ and

$$\mathrm{E}(\widehat{\tau}_m) = \sum_{i=1}^{N} m_i = \tau_m$$

Variance under CSR

An unbiased estimator of the classical Horvitz-Thompson estimator is

$$\widehat{\mathrm{var}}(\widehat{\tau}_m) = \sum_{i=1}^{n} \left(\frac{1}{p_i^2} + \frac{1}{p_i} \right) m_i^2 + 2 \sum_{i=1}^{n} \sum_{j>i} \left(\frac{1}{p_i p_j} - \frac{1}{p_{ij}} \right) m_i m_j \,,$$

where p_{ij} is the joint inclusion probability of trees i and j.
In our sequential construction

$$p_{ij} = p_{j|i} p_i = p_i p_j$$

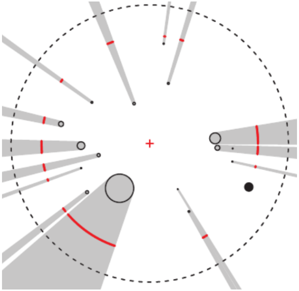
and therefore the variance can be estimated by

$$\widehat{\mathrm{var}}(\widehat{\tau}_m) = \sum_{i=1}^{n} \left(\frac{1}{p_i^2} + \frac{1}{p_i} \right) m_i^2 \,.$$

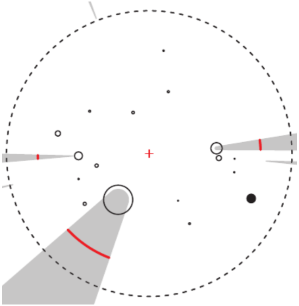
Generalizations to other detection conditions

The previous formulation assumed that the center point is visible to the scanner. Extensions are based on applying a erosion/dilation using a buffer of width $|\alpha|r_i$ to the shadowed area before intersecting with the r_j-radius circle:

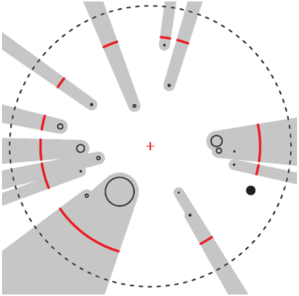
Visibility condition 'Center' ($\alpha = 0$)



Visibility condition 'Any' ($\alpha = 1$)

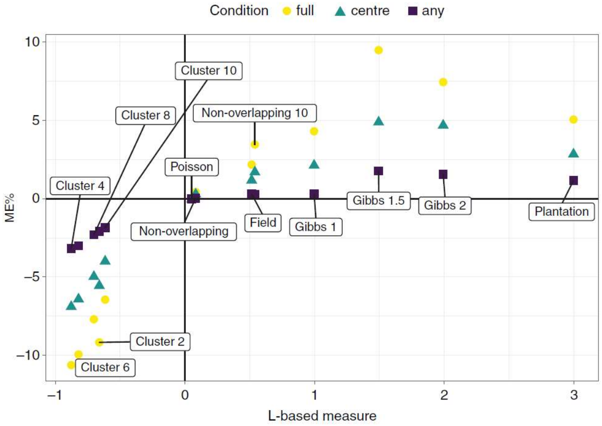


Visibility condition 'Full' ($\alpha = -1$)



Bias vs spatial pattern

Evaluation was based on process-simulated plots and mapped large sample plots.



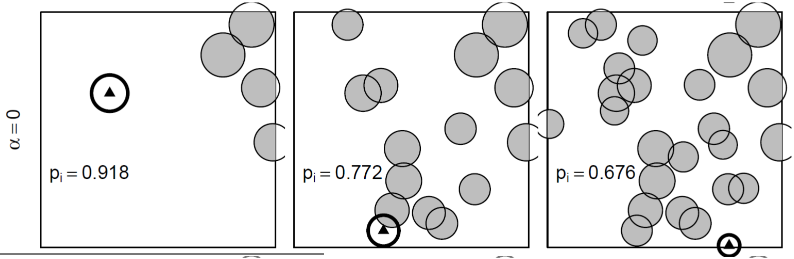
Coverage of approximate confidence intervals

		Interval		
Data	**Condition**	**90%**	**95%**	**99%**
Field	Full	94.0	97.5	99.5
	Center	94.1	97.4	99.3
	Any	93.4	96.5	98.8
Poisson	Full	90.0	94.9	98.7
	Center	89.9	94.5	98.7
	Any	90.5	94.9	98.4

Application to the aerial case

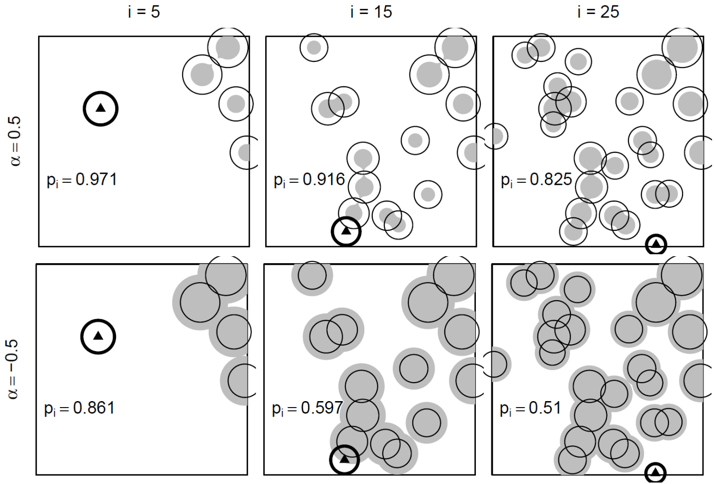
- ALS is used to detect the tree crowns (= their projections to the ground C_i).
- The n observed trees within a sample plot window W are ordered according to the distance to the censor (= height from largest to smallest).
- We use the Horvitz-Thompson like estimator $\widehat{\tau_m} = \sum_{i=1}^{n} \frac{m_i}{p_i}$ to estimate $\tau = \sum_{i=1}^{N} m_i$.
- Assuming that a tree is detected if the center point is visible to the scanner and tree locations follow CSR, the detectability for tree i is [1]

$$p_i = 1 - \frac{\left| W \cap \bigcup_{j=1}^{i-1} C_j \right|}{|W|}$$



[1] Kansanen et al 2015, Kansanen et al 2019

Extension to other detection conditions



Dilate ($\alpha < 0$) or erode ($\alpha > 0$) using $|\alpha| r_i$ wide buffer, where $0 \leq |\alpha| \leq 1$.

The effect of spatial pattern of tree locations

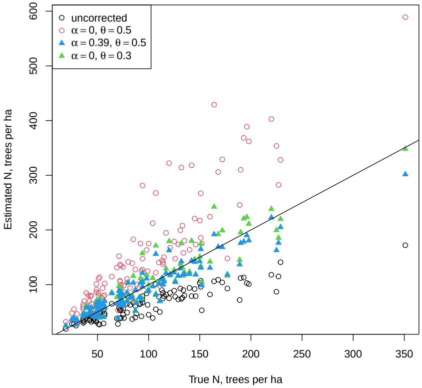
- The parameter α could be derived based on the applied tree detection algorithm.
- It can also be estimated empirically e.g. by matching a field-measured number of trees on the HT-like estimate in a training data set, and using the resulting estimate as a fixed known parameter thereafter. In that case, α simultaneously models the departure from CSR and detection condition.
- A sequential spatial point process (SSPP) model could be used to model the spatial pattern explicitly [2]. The model will be presented later today by Adil Yazigi.
- The SSPP model is used to predict the density in the hidden parts relative to that in the visible part as $\frac{\theta}{1-\theta}$. The value $\theta = 0.5$ corresponds to CSR.
- Thereafter the population total can be estimated using

$$\hat{\tau}_m = \sum_{i=1}^{n} m_i + \frac{\theta}{1-\theta} \sum_{i=1}^{n} \left[\left(\frac{1}{p_i} - 1 \right) m_i \right] .$$

- In our empirical training data,
  - the mean of estimated α when $\theta = 0.5$ was $\widehat{\alpha} = 0.39$
  - the mean of estimated θ when $\alpha = 0$ was $\widehat{\theta} = 0.30$

[2] Yazigi et al. Revised MS

Tentative results with empirical data



Method	bias, %	RMSE, %
uncorrected	-35	48.8
$\alpha = 0, \quad \theta = 0.5$	57	80.9
$\alpha = 0.39, \quad \theta = 0.5$	-3.5	20.0
$\alpha = 0, \quad \theta = 0.30$	3.5	22.5

- 111 square 30 by 30 meter plots from Eastern Finland
- Field-measured tree locations, diameters and heights were available
- ALS data were used to detect individual trees using an ITD algorithm [a]

[a] Lähivaara et al 2014

Conclusions

1. A sequential construction of trees is highly useful in ALS inventories, where trees hide behind each others.
2. Methods are connected with distance sampling. Difference to classical HT-estimator arises from the model-based estimation of the inclusion probability (detectability).
3. In ALS, the order is based on tree size, whereas in TLS the distance and size are unrelated (but small trees still may hide more easily than the large trees if $\alpha \neq 0$).
4. In the ALS-application, a regression approach where the parameters α and/or θ are predicted using ALS point cloud features [3] might result in further improvements of the method.
5. In the TLS application, improvements might be obtained by estimating the point process based on the observed trees and conditioning estimation on it.
6. Implemetations of the proposed algorithms are available in R-package `lmfor`.

[3] Häbel et al 2021

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