Correcting TLS Estimation for Shading by Other Trees Using a Horvitz-Thompson-like Estimator

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1. Introduction

In circular plot sampling, a sample plot is defined by the plot location, and trees within a given distance (called plot radius) from that point constitute a sample. However, not all trees may be visible to the center point of the plot because they are hidden by the other tree stems or other obstacles (such as rocks) that may be present on the sample plot. In traditional field inventories, this is not a problem because the field crew can temporarily move from the plot center to see all trees. However, that is not the case if a terrestrial laser scanner is used for data collection using single scan from the plot center. For example, Seidel and Ammer (2014) reported that approximately 2.5-7.5% of the plot area may be not sampled due to this shadowing effect. Therefore, there is a need for methods to adjust the estimators of populations totals from TLS sampling for this non-detection.

We are not the first authors to tackle this problem. Lovell et al. (2011) outlined a method based on a gap probability in a Poisson forest. Duncanson et al (2014) and Astrup et al (2014) have proposed methods based on classical distance sampling. Seidel and Ammer (2014) determined a correction factor based on the shadowed area. Olofsson and Olsson (2018) proposed an estimator that is based on using the area visible to the scanner as a sampling window. Their method was further extended by Kuronen et al (2019) to allow different correction factors for different detection conditions for the observed trees. That is, the estimator can take into account how big proportion of a tree stem should be visible to make the tree observable to the laser scanner. In the method of Kuronen et al. (2019), the plot edge is partially at the applied maximum radius of the plot or at edges of the observed tree stems. Therefore, the estimator is biased because the realized tree locations determine the plot size, and there are lot of trees that are located on the plot border, in similar ways as in the point-to-object sampling (see e.g. Ducey 2018).

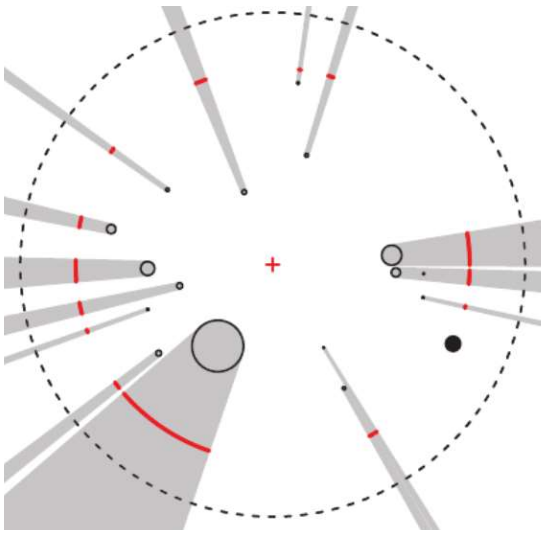

Figure 1. Illustration of the proposed estimation approach when the condition for detectability is visibility of the center point of the tree to the scanner for tree number 17 on a plot delineated by the dashed line (Kansanen et al 2020).

Published in: Markus Hollaus, Norbert Pfeifer (Eds.): Proceedings of the SilviLaser Conference 2021, Vienna, Austria, 28–30 September 2021.
Technische Universität Wien, 2021. DOI: 10.34726/wim.1861
This paper was peer-reviewed. DOI of this paper: 10.34726/wim.1914

In this paper, we discuss a new estimator (Kansanen et al 2020) that is based on the ordering of the trees according to their distance from the plot center. The estimator is unbiased under the assumption of complete spatial randomness (CSR) of tree locations in the hidden part of the plot. The estimation is based on CSR, but it is conditioned on the observed tree locations. In practice, it means that the model assumptions affect the estimation only in the hidden parts of the sample plot. An estimator for the variance of the estimator is also presented and used for constructing 95% confidence intervals for estimated stand density.

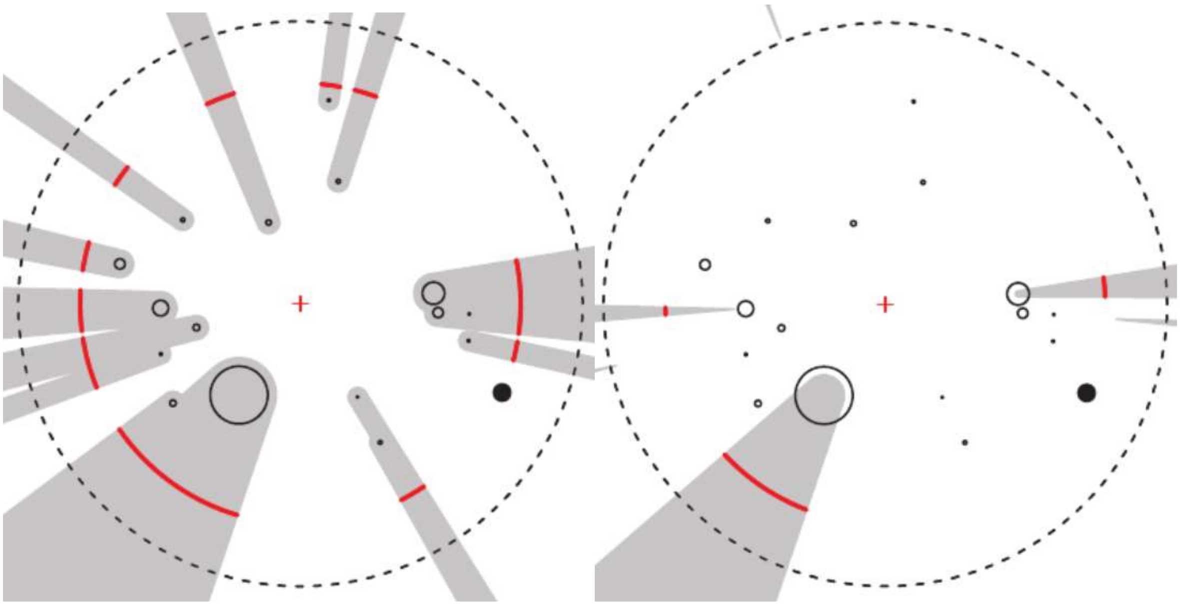

Figure 2. Illustration of the proposed estimation approach when the condition for detectability is full visibility (left) and visibility of any part of the tree the tree (right) to the scanner for tree number 17 on a plot delineated by the dashed line (Kansanen et al 2020).

2. Data and methods

Consider trees observed by a TLS device on a fixed plot and order them according to their distance from the plot center. We refer closer trees here as "earlier" in such an ordered sequence. The first tree of the sequence is observed for sure, because there are no trees behind which to hide. Let us then consider the second tree, and condition on its distance r_2 from the plot center. Assuming that a tree remains unobserved if its center point is hidden behind the earlier trees, the second tree would have been unobserved if it were located on such part of the perimeter of a r_2-radius disc that is hidden behind the earlier trees. This provides an estimated detection probability for the tree as a ratio of the visible part and the total perimeter length of the r_2-radius circle centered at the origin. In the same way, we can compute the detection probabilities for the other trees as well. For example, the red line in Figure 1 illustrates those sections of perimeter of a r_{17}-radius circle where the 17[th] tree of a would be hidden. In Figure 1, a tree is assumed to be detectable when the center point of the stem is visible to the scanner (detection condition "center"). Figure 2 illustrates the two other detection conditions, called "any" and "full".

After the detection probabilities have been estimated, tree characteristics can then be estimated using a Horvitz-Thompson-like estimator

$$\hat{T} = \sum \frac{t_i}{\hat{\pi}_i}$$

where $\hat{T}$ is the estimator of the population total T, t_i is the total of observed tree i, and $\hat{\pi}_i$ is the detection probability of tree i. The estimator is called Horvitz-Thompson-like estimator because the detectability is an estimate of the inclusion probability of sampling unit i, not a known true inclusion probability. When stand density (trees per plot) is estimated, t_i=1 for all trees i. Therefore, the estimator essentially includes for each observed tree a number $n_i = \frac{1}{\hat{\pi}_i} > 1$, which gives the estimated number of trees similar to the observed tree i. The later the tree is in the ordered sequence, the larger is n_i. An R-implementation of the estimator is available in function HTest_cps of R-package lmfor (Mehtätalo 2019).

The proposed estimator is evaluated using simulated forests where the spatial pattern varies from strong regularity to strong clustering. In addition, a data set of 111 square 30 by 30 meter mapped forest plots from Eastern Finland are used to evaluate the estimator, by simulating circular, 10-meter radius TLS plots on them. The spatial pattern of tree locations on these plots is slightly regular.

3. Results and discussion

We show that the estimator is unbiased if the tree locations follow the assumption of complete spatial randomness and present an estimator for its variance. The performance of the estimator is illustrated in plots of simulated forests of different spatial patterns as well as on real mapped forests. The empirical results showed better or similar performance than the estimator of Kuronen et al (2019) and Olofsson and Olsson (2019). In the field plots, the relative RMSE of our estimator on 10-meter plots was 4.6, 6.2 and 8% for the number of stems under the "any", "center" and "full" detection conditions, respectively, and the mean errors were 0.4, 2.1 and 4.1%. The constructed confidence intervals under the nominal 95% level of confidence covered the true number of trees in 96.5-97.5% of the cases, which indicates that the variance estimator is slightly biased but the bias happens to a safe, conservative direction under regular pattern of tree locations. Under simulated plots with complete spatial randomness, the observed coverage probabilities were very close to the nominal ones.

We also discuss, from a statistical point of view, the question of using single scans from multiple plots or multiple scans from a smaller number of plots in practical inventories. Application of similar ideas in individual tree detection based on aerial inventories are also discussed.

Acknowledgements

The work has been funded by Academy of Finland (grant 310073).

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