Correcting the nondetection bias of angle count sampling

Tim Ritter[1,✉], Arne Nothdurft[2] & Joachim Saborowski[1,3]

[1] University of Göttingen - Dept. Ecoinformatics, Biometrics and Forest Growth
[2] Forest Research Institute Baden-Württemberg - Dept. of Biometrics and Informatics
[3] University of Göttingen - Dept. Ecosystem Modelling

✉ Büsgenweg 4 ; 37077 Göttingen ; tritter@gwdg.de

Applied Statistics in Ecological and Environmental Sciences
November 7-9, 2012 - Freiburg i.Br.

Two well established sampling techniques

Angle count sampling (ACS) [Bitterlich, 1952, 1984]

- ACS estimates basal are density, i.e. the basal area of trees per area unit of a forest.
- ACS assumes total visibility of objects, overlooking objects leads to a nondetection bias.
- This bias comes occurs especially when sampling rare objects (often of high ecological value, e.g. admixed tree species or dead wood).

Point Transect Sampling (PTS) [Buckland et al, 1993]

- PTS estimates abundance (object density) of all kind of biological populations, mainly vertebrates.
- PTS focuses on the number of objects but not their size (e.g. basal area).
- The central idea of PTS is to count objects and to model the detection probability.

Tim Ritter
tritter@gwdg.de

Combining ACS and PTS

Basic idea

- Estimating the basal area density with ACS
- Modeling the detection probability of objects with PTS
- Correcting the nondetection bias of ACS, using the detection probability obtained by PTS

Anticipated Result

- (Approx.) unbiased estimators of the basal area density

Tim Ritter
tritter@gwdg.de

Angle count sampling (ACS)

Sampling procedure

At each sample plot in an arbitrary forest, each tree is targeted with the relascope.
A tree is counted if its diameter in 1.3 m height (DBH) appears to be wider then the marks of the relascope.

Bitterlich Relascope (1955)

"Bitterlich" - Android App by Janek Kaas: https://play.google.com/store/apps/details?id=ee.deskis.adnroid.relascope

Angle count sampling (ACS)

Tim Ritter
tritter@gwdg.de

Estimator [Bitterlich, 1984]

The relascope has an opening angle α, which determines the basal area factor k and the radius R of the marginal inclusion circle for a tree with DBH d.

$$k = \sin^2\left(\frac{\alpha}{2}\right) = \frac{d^2}{4R^2} \tag{1}$$

The basal area density is estimated as:

$$\hat{\hat{G}} = k \cdot z \tag{2}$$

Point transect sampling (PTS)

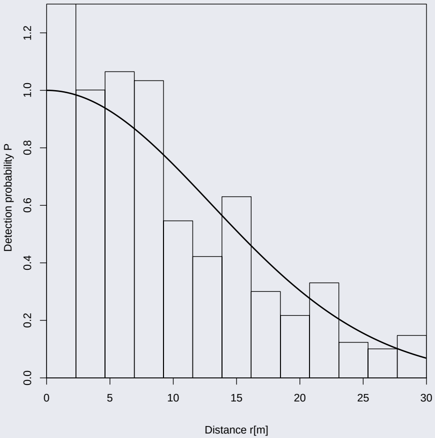
Sampling procedure

At each sample point in an arbitrary forest, the distances r_j to any tree j sighted from that point is measured (e.g. by laser rangefinder) and recorded.

Laser rangefinder

Point transect sampling (PTS)

Detection function



$$\hat{P}_a = \frac{2}{\omega^2} \int_0^{\omega} r\hat{g}(r)dr \quad (3)$$

Estimated half-normal detection function $\hat{g}(r)$ and histogram of detection distances.
The histogram is normalized by the methods shown in Buckland et al [2001, pp. 147-150].

Point transect sampling (PTS)

Tim Ritter
tritter@gwdg.de

Density estimator

The density estimator according to Buckland et al [2001] is

$$\hat{D} = \frac{m}{\pi\omega^2 \hat{P}_a} = m \cdot \left(2\pi \cdot \int_0^{\omega} r\hat{g}(r)\, dr\right)^{-1} \tag{4}$$

BcACS1

Heuristic

Expand each tree count by the tree's **individual** inverse estimated detection probability to correct for the negative bias introduced by overlooking trees.

Additional sampling effort

The distance r_j from the plot center to each sighted tree, which is supposed to be counted by ACS, has to be measured.

Estimator

$$\hat{\hat{G}}_{BcACS1} = k \cdot \sum_{j=1}^{z_i} \frac{1}{\hat{g}(r_j)} \tag{5}$$

Tim Ritter
tritter@gwdg.de

BcACS2

Heuristic

Expand each tree count by the inverse estimated **mean** detection probability of all trees which have the same DBH d_j (and therefore also the same marginal inclusion circle) and are supposed to be counted at any sample point.

Additional sampling effort

The diameter of each counted tree has to be measured. This is e.g. done in the repeated German national forest inventories to estimate volume increment [Polley, 2005]. Measuring all distances r_j is **not** necessary, as long as enough measurements are taken to estimate $g(r)$.

BcACS2

Tim Ritter
tritter@gwdg.de

Mean detection probability of trees from within their marginal inclusion circle

The radius of the marginal inclusion circle is $R_j = d_j/(2\sqrt{k})$. The probability to detect a tree with DBH d_j from a random point within its marginal inclusion circle can be estimated by

$$\hat{P}_{a_j} = \frac{2}{R_j^2} \int_0^{R_j} r g(r) dr \tag{6}$$

Estimator

$$\hat{\hat{G}}_{BcACS2} = k \cdot \sum_{j=1}^{z} \frac{1}{\hat{P}_{a_j}} = \sum_{j=1}^{z} \frac{d_j^2}{4R_j^2 \hat{P}_{a_j}} \tag{7}$$

Tim Ritter
tritter@gwdg.de

Inclusion probabilities

Horvitz-Thompson estimator

The Horvitz-Thompson estimator of the total of Y over N trees, is given by

$$\hat{Y}(x) = \sum_{j=1}^{z} \frac{Y_j}{\pi_j} \quad \text{with} \quad \pi_j = \frac{\pi R_j^2}{A^*} \tag{8}$$

A^*: Area of the forest to be inventoried extended by the peripheral zone [Mandallaz, 2008, Gregoire and Valentine, 2008]
$R_j = d_j/(2\sqrt{k})$

Inclusion probabilities

Corrected Horvitz-Thompson estimator

As trees may be overlooked, the inclusion probability π_j must be corrected:

$$\begin{aligned} \pi_j^+ &= P\left(\{x \in K_j\} \cap \{\text{j is detected}\}\right) \\ &= P\left(x \in K_j\right) P\left(\text{j is detected} \mid x \in K_j\right) = \pi_j P_{a_j} \end{aligned} \tag{9}$$

This leads to the unbiased estimator

$$\hat{Y}(x) = \frac{1}{A^*} \sum_{j=1}^{z} \frac{Y_j}{\pi_j^+} = k \sum_{j=1}^{z} \frac{Y_j}{(\pi/4) d_j^2 P_{a_j}} \tag{10}$$

of the Y total per area unit.

Application to basal area density estimates

BcACS2

If the response variable Y is the basal area density $\bar{G}$, the corrected Horvitz-Thompson estimator can be simplified to

$$\hat{\hat{G}}(x) = k \sum_{j=1}^{z} \frac{1}{P_{a_j}} \tag{11}$$

Replacing P_{a_j} by $\hat{P}_{a_j}$ leads to the approx. unbiased estimator $\hat{\hat{G}}_{BcACS2}$

Tim Ritter
tritter@gwdg.de

Application to the new estimators

BcACS1

Under the assumption of CSR,
and if $x \in K_j$ for a tree with DBH d_j, it holds

$$E\left(g(r_j)|d_j\right) = \frac{1}{\pi R_j^2} \int_0^{R_j} g(r) 2\pi r \; dr = P_{a_j} \qquad (12)$$

Thus, $\hat{\hat{G}}_{BcACS1}$ can also approx. correct for the nondetection bias in ACS.

Tim Ritter
tritter@gwdg.de

Materials and methods

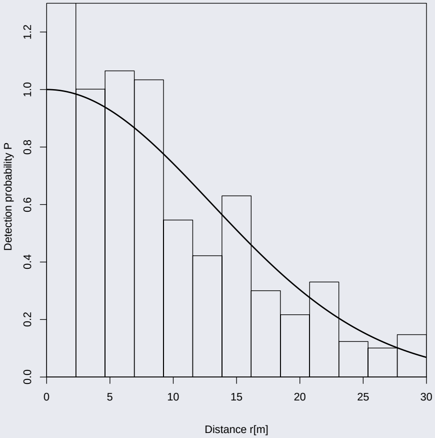
Dataset

- Standing dead wood (SDW) with a DBH ≥ 7 cm
- 235 plots in the forest district Reinhausen
- Sampling techniques:
  - PTS
  - ACS
  - Fixed area sampling (FAS) on circular sample plots with 13 m radius

Additionally, the DBH of every sighted piece of SDW was obtained by cross calipering.

Results

Object density



Estimated half-normal detection function $\hat{g}(r)$ and histogram of detection distances. The histogram is normalized by the methods shown in Buckland et al [2001, pp. 147-150].

$$\hat{D} = 18.63 \text{ ha}^{-1}$$
$$\widehat{\text{SE}}(\hat{D}) = 2.08 \text{ ha}^{-1}$$

Tim Ritter
tritter@gwdg.de

Results

Estimation of basal area density

Estimator	k	$\hat{\hat{G}}$	$\widehat{SE}(\hat{\hat{G}})$
ACS	1	0.421	0.059
BcACS1	1	0.609	0.095
BcACS2	1	0.686	0.107
FAS	-	0.654	0.117

Comparison of estimated basal area of standing dead wood per area unit ($\hat{\hat{G}}$)[m^2 ha^{-1}] for the different sampling methods and corresponding $\widehat{\text{SE}}$s [m^2 ha^{-1}]

Discussion

Tim Ritter
tritter@gwdg.de

Dataset

Extreme case:

- Dense understorey
- Stumps ($h \geq 1.3$ m) can easily be overlooked

Results

- Steep detection function
- True value is unknown, therefore we cannot asses bias
- Nevertheless, there are strong hints, that ACS is severely biased in this case study

Tim Ritter
tritter@gwdg.de

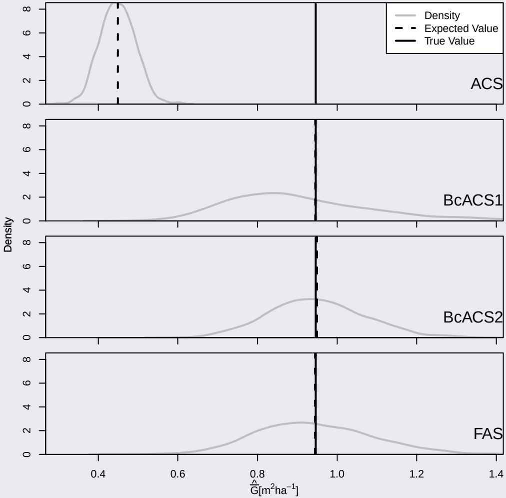
Materials and methods

Dataset

- Two simulated point patterns
  - Complete spatial randomness (Poisson process)
  - Clustered population (log-Gaussian Cox process), derived from the Hainich dataset
- Marks derived from the Hainich dataset (two parametric Weibull distribution)
- Detection function from case study A
- 999 simulation runs with 225 sample points on
  - randomized positions
  - a systematic sampling grid with random starting point

Results

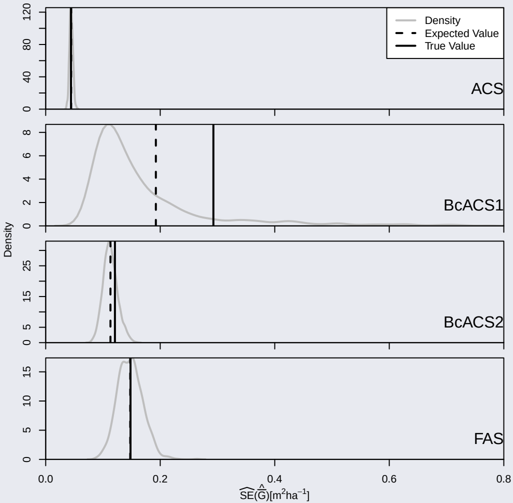
Point estimates



Point estimators (CSR and simple random sampling), $k = 1$ for all ACS estimators. Gaussian kernel density estimation of the pdf of $\hat{G}$.

Results

SE estimates



SE estimates (CSR and simple random sampling), $k = 1$ for all ACS estimators. Gaussian kernel density estimation of the pdf of $\widehat{SE}(\hat{\hat{G}})$.

Discussion

Point estimates

- BcACS1 depends on the assumption of CSR, however it turned out to be robust against violations of this assumption in our case study.
- The SE of BcACS2 is smaller than that of BcACS1, which was expected because $g(r)$ is only an estimate for the correct bias correction by P_{a_j}.

SE estimates

- Analytic SE estimation for BcACS1 is biased.
- Jackknife or Bootstrap estimators may be an alternative.

Conclusions

- ACS is severely biased
- BcACS1 and BcACS2
  - produced approx. unbiased point estimates.
  - proved to be practicable during the field work
- For a given number of sample plots, the smallest RMSE can be achieved with BcACS2.
- Sampling effort for BcACS2 is higher than for BcACS1, unless diameters are measured for other reasons anyway.
  - In this case, BcACS2 should be preferred to BcACS1.
  - Otherwise, time studies are needed to evaluate if the smaller RMSE and better SE estimation of BcACS2 compensate for the extra sampling effort.

Acknowledgements

- We gratefully acknowledge the support of the German Research Foundation (DFG) under grant number SA 415/4-1.
- We thank Jürgen Bauhus (University of Freiburg) and Christian Wirth (University of Leipzig) for providing the Hainich data set.
- We thank Otto Beck, Harald Höhne and Henning Freiesleben (Lower Saxony State Forest District Reinhausen) for their hospitality and cooperation and for the opportunity to work on "their" sites.
- We thank André Hardtke, Garlef Kalberlah, Birte Krause and Phillip Schlotzhauer for their assistance during the fieldwork.

Thank you for your attention!

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