Absent or overlooked? Approaches to overcome the problem of non-detection in forest inventories

Ausente ou negligenciado? Procedimentos para superar a não detecção nos inventários florestais

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Non-detection

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- However, with increasing interest, society looks the forests as future carbon sinks, potential biomass energy resources, wildlife habitat, water resources, and for other ecosystem services, so that the demand for assessing these aspects has increased (Ducey, 2014; Kenning et al., 2005)
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    - in highly structured forests
    - with limited sighting conditions

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Distance sampling – an alternative method to overcome the problem of non-detection

- Widely used for estimating the abundance of all kinds of biological populations, especially birds and mammals Thomas et al. (2012)
- Based on the work of Anderson & Pospahala (1970); further developed over the years; standard text books by Buckland et al. (2001, 2004)
- Two main methods
  - Line transect sampling (LTS)
  - Point transect sampling (PTS)
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Distance sampling applications in forestry...

...are –still– quite rare:

Point transect sampling (PTS)

- **Deadwood volume and carbon storage** (Ritter & Saborowski, 2010, 2012, 2014)
- **Bias correction of angle count sampling** (Ritter et al., 2013)
- **Bias correction of terrestrial laser scanning** (Ducey & Astrup, 2013; Astrup et al., 2014)

Line transect sampling (LTS)

- **Habitat trees** (Bäuerle et al., 2009; Didas, 2009; Bäuerle & Nothdurft, 2011)
- **Low abundance tropical tree species** (Kissa & Sheil, 2012)
- **Logging damage** Siebert & Ritter (in preparation)

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Originally published as:

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RITTER, T.; SABOROWSKI, J. (2014): *Efficient integration of a deadwood inventory into an existing forest inventory carried out as 2-phase sampling for stratification.* In: **Forestry 87**(4): 571-581, doi: 10.1093/forestry/cpu016

Lower Saxony state forest district inventory (BI)

Two-phase sampling for stratification (2-SS) in a cycle of 10 years (Böckmann et al., 1998).

Phase I:

- Systematic sampling grid (100 m × 100 m)
- Interpretation of CIR arial images
- Allocation to one of eight strata:

Dominating species group	Age class			
	0-40	>40-80	>80-120	>120
Decidous	dec1	dec2	dec3	dec4
Coniferous	con1	con2	con3	con4

Phase II:

- Random selection of sample points within each stratum
- Two concentric circular sample plots (6 m and 13 m radius)

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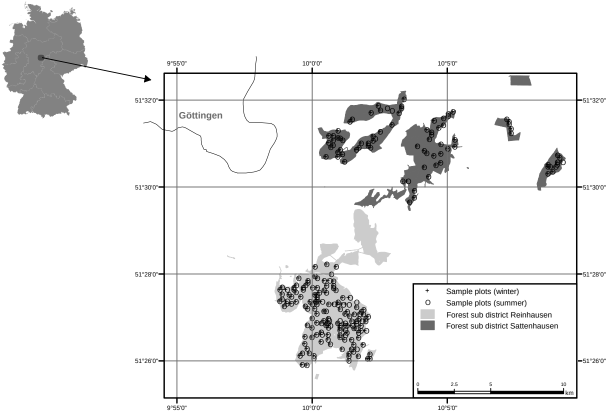
Area under investigation

2416 ha, located in the heart of Germany:



State forest district Reinhausen

- Sub district Reinhausen
- Sub district Sattenhausen

Subsample of the BI

- First inventory in summer (235 plots)
- Repeated inventory in winter (228 plots)

Pilot study

Sampling techniques

Downed coarse woody debris ($d_{max} \geq 7$ cm)

- Fixed area sampling (FAS) on 13 m radius plots
- Line Intersect Sampling (LIS)
- Point Transect Sampling (PTS)

Standing deadwood (DBH ≥ 7 cm)

- Fixed area sampling (FAS) on 13 m radius plots
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Measurements

- Tree species (if possible)
- Decay class (using the key of Müller-Using & Bartsch, 2009)
- DBH
- Height

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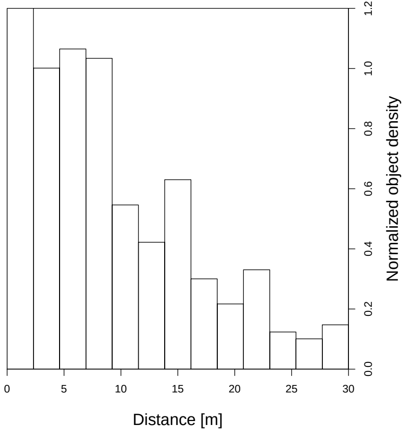
Point Transect Sampling

Detection function



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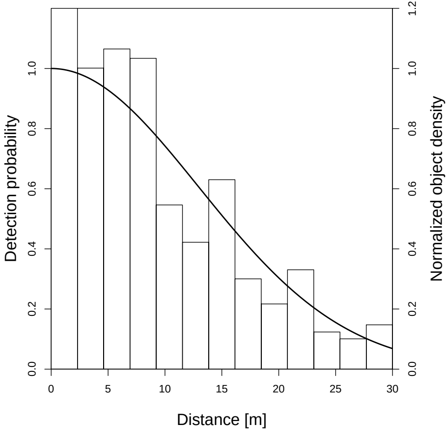

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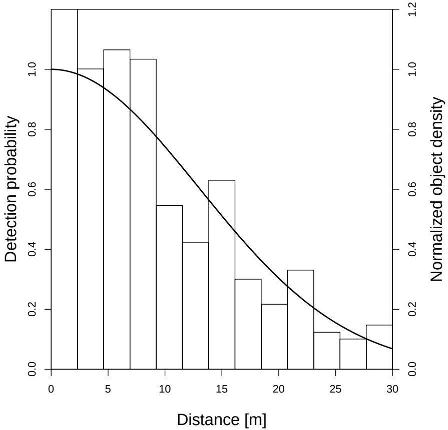

Detection probability

$$\hat{P}_{a_h} = \frac{\int_0^{\omega} g(r) 2\pi r \, dr}{\pi \omega^2} = \frac{2}{\omega^2} \int_0^{\omega} r \cdot \hat{g}(r) dr \quad (1)$$

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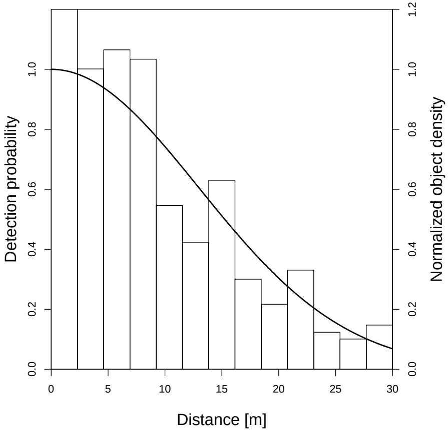

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Object density

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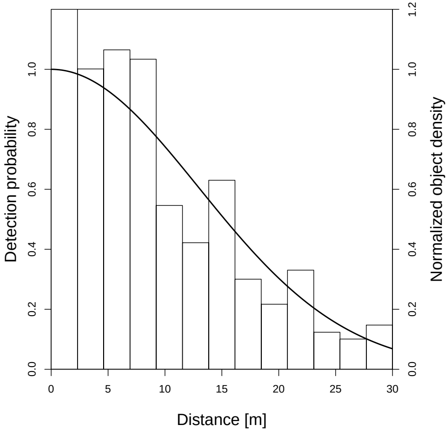

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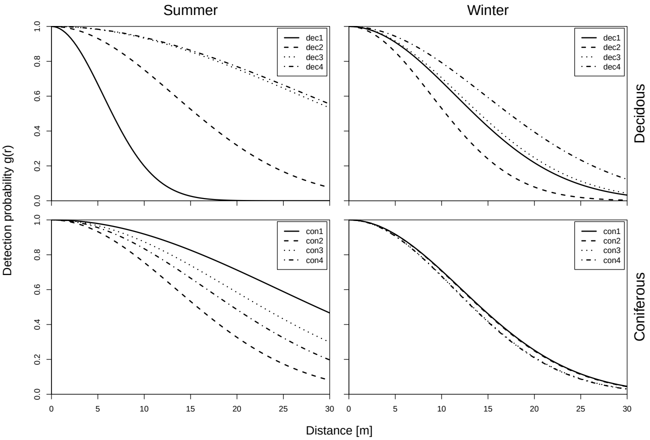
Volume

$$\hat{\hat{Y}}_h = \hat{D}_h \cdot \hat{E}(s) \quad (3)$$

Detection probability within the different strata



AIC based model selection:

$$\hat{g}(r) = e^{-0{,}5r^2/\hat{\sigma}_h^2}$$

with

$$\hat{\sigma}_h = \hat{\alpha}_0 \; e^{\hat{\alpha} h} \qquad (4)$$

Volume estimation

Sampling campaign	Sampling technique	$\hat{\hat{Y}}$ [m^{3}ha^{-1}]	SE($\hat{\hat{Y}}$) [m^{3}ha^{-1}]	$\hat{T}$ [min]
Summer (n=235)	FAS	2.54	0.56	421
	PTS	3.04	0.39	831
Winter (n=228)	FAS	3.86	1.15	413
	PTS	3.05	0.42	923

Optimization

Sampling campaign	Sampling technique	n	$\text{SE}(\hat{\hat{Y}})$ [m^3ha^{-1}]	$\hat{T}$ [min]
Summer	**FAS** (All ph-2 plots)	600	**0.366**	**1062**
	PTS (All ph-2 plots)	600	0.175	2148
	PTS (Optimal allocation)	79	0.365	301
Winter	**FAS** (All Ph-2 plots)	600	**0.599**	**1085**
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Approach 1

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

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

Approach 2

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 K_j) and are supposed to be counted at any sample point.

Additional sampling effort

- The diameter of each counted tree has to be measured.
- Measuring all distances r_j is *not* necessary, as long as enough measurements are taken to estimate $g(r)$.

Mean detection probability within the 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 K_j can be estimated by $\hat{P}_{a_j} = \frac{2}{R_j^2} \int_0^{R_j} r g(r) dr$

Estimator

$$\hat{\hat{G}}_{BcACS2} = k \cdot \sum_{j=1}^{z} \frac{1}{\hat{P}_{a_j}} = \sum_{j=1}^{z} \frac{d_j^2}{4R_j^2 \hat{P}_{a_j}} \qquad (6)$$

Theoretical justification

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

$$\hat{Y}(x) = \sum_{j=1}^{z} \frac{Y_j}{\boldsymbol{\pi}_j} \quad \text{with} \quad \boldsymbol{\pi}_j = \frac{\pi R_j^2}{A^*} \tag{7}$$

$A^* =$ Inventory area extended by the peripheral zone (Mandallaz, 2008)

$R_j = d_j/(2\sqrt{k})$

As trees may be overlooked, the inclusion probability $\boldsymbol{\pi}_j$ must be corrected:

$$\begin{aligned} \boldsymbol{\pi}_j^+ &= P\left(\{x \in K_j\} \cap \{\text{j is detected}\}\right) \\ &= P\left(x \in K_j\right) P\left(\text{j is detected} \mid x \in K_j\right) = \boldsymbol{\pi}_j P_{a_j} \end{aligned} \tag{8}$$

This leads to the unbiased estimator

$$\hat{Y}(x) = \frac{1}{A^*} \sum_{j=1}^{z} \frac{Y_j}{\boldsymbol{\pi}_j^+} = k \sum_{j=1}^{z} \frac{Y_j}{(\pi/4) d_j^2 P_{a_j}} \tag{9}$$

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

$$\hat{\hat{G}}(x) = k \sum_{j=1}^{z} \frac{1}{P_{a_j}} \tag{10}$$

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

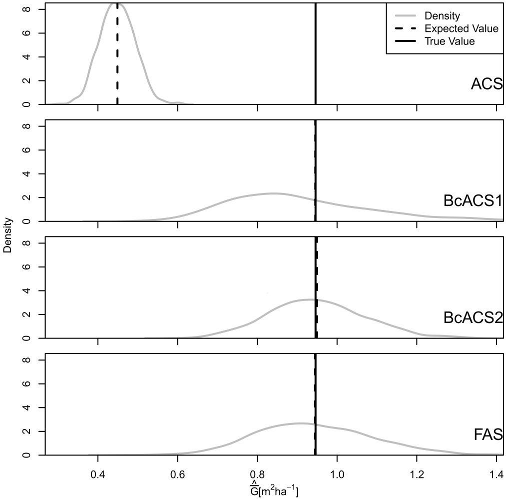
BcACS1

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

$$E\left(g(r_j)|d_j\right) = \frac{1}{\pi R_j^2} \int_0^{R_j} g(r) 2\pi r \, dr = P_{a_j} \tag{11}$$

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

Performance of the estimators



Simulation study

- Poisson distributed trees
- Simple random sampling
- $k = 1$ for all ACS-estimators
- "Density" represents the Gaussian kernel density estimation of the probability distribution function of $\hat{\hat{G}}$.

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Sample sites & data acquisition

Sample sites

- 12 mature forest stands in southern Norway
- dominated by Norway spruce (*Picea abies* L.) and Scots pine (*Pinus sylvestris* L.)
- varying mixtures of broadleaved species (mainly birch (*Betula pubescens* Ehrh. and *Betula pendula* Roth.))

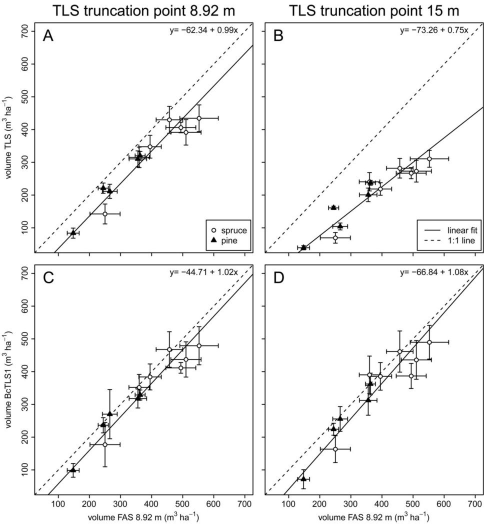
Data acquisition

- 20 m × 20 m inventory grid
- FAS on 250 m^2 sample plots
- FARO LS 880
    - Tripod-mounted
    - Full horizontal scan (360° horizontal and 320° vertical fields of view)
    - Resolution of 0.009° (vertical) and 0.00076° (horizontal).
    - Truncation points at 8.92 m and 15 m

Data analysis

- Stem extraction was done by a commercial TLS operator (Treemetrics Ltd.) using their proprietary software Autostem Forest
- A list of all detected trees, including their position and the diameter of the stem estimated for each 10 cm section was provided for all plots
- This data set can be treated as a FAS sample (uncorrected TLS)
- As the scanner-tree distances of all detected trees are known, the dataset can also be treated as a PTS sample (bias corrected TLS)

Comparison of stand-level volume estimates



Comparison of the FAS reference values with:

- Uncorrected TLS data (A & B)
- Bias corrected TLS data (C & D)

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Conclusions

- PTS (and distance sampling in general) is quit new to forestry, but is well established in other fields
- PTS is a very efficient and cost-saving sampling technique for rare objects
- PTS can easily be integrated into existing forest inventories
- PTS-theory can be applied to existing inventory techniques (ACS & TLS) to correct for non-detection

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Obrigado pela sua atenção!

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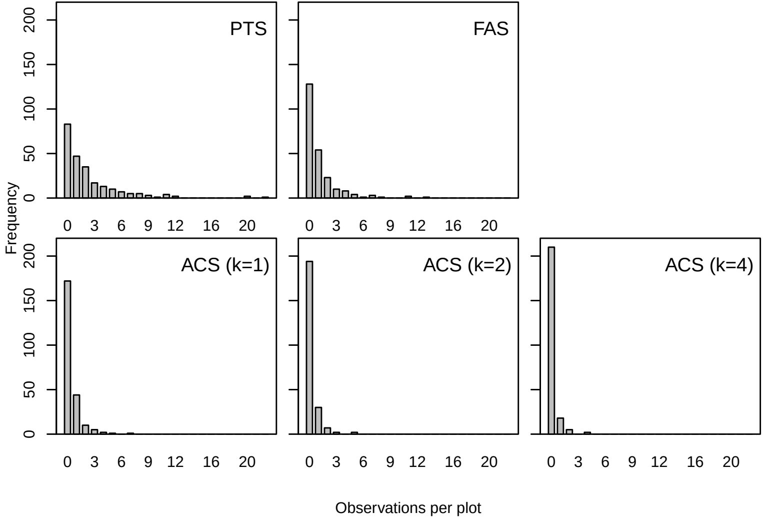
Liegendes Totholz - Vorrat

Type of DW	Sampling campaign	Sampling technique	$\hat{\hat{Y}}$ [m^{3}ha^{-1}]	SE($\hat{\hat{Y}}$) [m^{3}ha^{-1}]
CWD ($d \geq$ 15cm)	Summer	FAS	8.54	0.95
		LIS	7.73	1.18
	Winter	FAS	7.97	0.99
		LIS	7.96	1.18
CWD ($d \geq$ 7cm)	Summer	FAS	13.10	1.10
		LIS	13.90	1.37

Liegendes Totholz - Effizienzvergleich

Type of DW	Sampling campaign	Sampling technique	N	$\hat{T}$ [min]	SE($\hat{\hat{Y}}$) [m^{3}ha^{-1}]	CV($\hat{\hat{Y}}$) [%]
CWD ($d \geq 15$cm)	Summer	LIS (all ph-2 points)	600	3626	0.682	8.8
		FAS (all ph-2 points)	600	8471	0.535	6.3
		FAS (optimal allocation)	285	4086	0.682	8.0
		FAS (allocation prop. to ph-1)	311	4398	0.682	8.0
		FAS (allocation prop. to ph-2)	367	5176	0.682	8.0
	Winter	LIS (all ph-2 points)	600	3053	0.681	8.6
		FAS (all ph-2 points)	600	5866	0.549	6.9
		FAS (optimal allocation)	323	3176	0.681	8.6
		FAS (allocation prop. to ph-1)	356	3420	0.681	8.6
		FAS (allocation prop. to ph-2)	387	3788	0.681	8.6
CWD ($d \geq 7$cm)	Summer	LIS (all ph-2 points)	600	3918	0.793	5.7
		FAS (all ph-2 points)	600	15747	0.622	4.8
		FAS (optimal allocation)	277	7566	0.793	6.1
		FAS (allocation prop. to ph-1)	302	8213	0.793	6.1
		FAS (allocation prop. to ph-2)	368	9656	0.793	6.1

"'Zero-Inflation"'



Auswahl der Entdeckungsfunktion

AIC basierte Modellauswahl

- $\hat{g}(r) \propto \text{key}(r)[\text{series}(r)]$
- Straten als Kovariate
- Alle möglichen Kombinationen von Schlüsselfunktion (key) und seriellem Anpassungsterm max. 5 Grades (series)

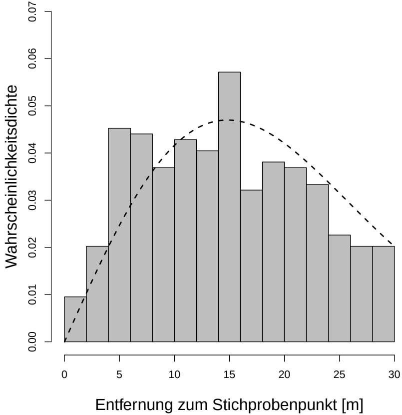
Schlüsselfunktionen

- Uniform: $\hat{g}(r) = 1/\omega$
- Halb-Normal: $\hat{g}(r) = e^{-0{,}5r^2/\sigma^2}$
- Hazard-Rate: $\hat{g}(r) = 1 - e^{-(r/\sigma)^{-b}}$

Serielle Anpassungsterme

- Cosin: $\sum_{k=2}^{q} a_k \cos\left(\frac{k\pi r}{\omega}\right)$
- Polynominal: $\sum_{k=2}^{q} a_k \left(\frac{r}{\omega}\right)^{2k}$
- Kein Anpassungsterm

Wahrscheinlichkeitsdichte



Anpassung von $\hat{f}(r)$ an die empirischen Daten,

$g(r)$ ergibt sich dann aus

$$g(r) = \frac{r \cdot f'(0)}{f(r)}$$

Die Objektdichte kann direkt aus der pdf geschätzt werden:

$$\hat{D} = \frac{m \cdot \hat{f}'(0)}{2\pi n}$$

da

$$P_a = \frac{2}{\omega^2 f'(0)}$$

Schätzung des mittleres Objektvolumen

Log-Transformation:

$$z_i = log_e(s_i)$$

Mittleres (transformiertes) Volumen der entdeckten Objekte:

$$\hat{E}_d(z|r) = a + b \cdot \hat{g}(r)$$

Mittleres Objektvolumen:

$$\hat{E}(z) = \hat{E}_d(z|r = 0) = a + b$$

$$\hat{E}(s) = e^{a+b+\widehat{\mathrm{var}}(\hat{z})/2}$$

Analytische Varianzschätzung beim PTS

Die Varianzschätzung beim PTS erfolgt nach der Delta-Methode (Seber, 1982; zitiert nach Buckland et al., 2001):

$$\widehat{\text{var}}\left(\hat{\hat{Y}}_h\right) = \hat{\hat{Y}}_h^2 \cdot \left(\frac{\widehat{\text{var}}\left(m_h\right)}{m_h^2} + \frac{\widehat{\text{var}}\left(a \cdot \hat{P}_{a_h}\right)}{\left(a \cdot \hat{P}_{a_h}\right)^2} + \frac{\widehat{\text{var}}\left(\hat{E}_h(s)\right)}{\left(\hat{E}_h(s)\right)^2} \right)$$

mit

$$\begin{aligned}
\widehat{\text{var}}(m_h) &= \frac{1}{n_h(n_h-1)} \sum_{i=1}^{n_h} (m_{hi} - \bar{m}_h)^2 \\
\widehat{\text{var}}\left(a \cdot \hat{P}_{a_h}\right) &= \frac{1}{m_h \hat{\sigma}_h^4} \\
\widehat{\text{var}}(\hat{E}_h(s)) &= e^{2(a+b)+\widehat{\text{var}}(\hat{z})} \cdot \left(1 + \frac{\widehat{\text{var}}(\hat{z})}{2}\right) \cdot \frac{\widehat{\text{var}}(\hat{z})}{m_h}
\end{aligned}$$

Bootstrap Varianzschätzung beim PTS

Die Bootstrapvarianz (Davison et al., 1986) kann analytisch aus den Bootstrapvarianzen der einzelnen Komponenten zusammengesetzt werden:

$$\widehat{\text{var}}_{B1}\left(\hat{\hat{Y}}_{hB}\right) = \hat{\hat{Y}}_{hB}^{2} \cdot \left(\frac{\widehat{\text{var}}_{hB}\left(m_{hB}\right)}{m_{hB}^{2}} + \frac{\widehat{\text{var}}_{B}\left(a \cdot \hat{P}_{a_h B}\right)}{\left(a \cdot \hat{P}_{a_h B}\right)^{2}} + \frac{\widehat{\text{var}}_{B}\left(\hat{E}(s)_B\right)}{\left(\hat{E}(s)_B\right)^{2}} \right)$$

Alternativ kann sie direkt geschätzt werden (Buckland et al., 2001):

$$\widehat{\text{var}}_{B2}\left(\hat{\hat{Y}}_{hB}\right) = \frac{\sum_{i=1}^{B}\left(\hat{\hat{Y}}_{h(i)} - \hat{\hat{Y}}_{hB}\right)^{2}}{B-1}$$

Konfidenzintervalle

Analytisches Konfidenzintervall für $\bar{Y}_h$:

$$CI_{A(\bar{Y})} = \left[\frac{\hat{\bar{Y}}_h}{e^{z_\alpha \cdot \sqrt{\widehat{\text{var}}\left(log_e \hat{\bar{Y}}_h\right)}}} \;\; ; \;\; \hat{\bar{Y}}_h \cdot e^{z_\alpha \cdot \sqrt{\widehat{\text{var}}\left(log_e \hat{\bar{Y}}_h\right)}} \right]$$

unter der Voraussetzung $m_i \overset{i.i.d.}{\sim} \text{LN}(\mu, \sigma^2)$ (Burnham et al., 1987).

Bootstrap-Konfidenzintervall für $\bar{Y}_h$:

$$CI_{B(\bar{Y})} = \left[\hat{\bar{Y}}_{h\ (B+1)\alpha} \;\; ; \;\; \hat{\bar{Y}}_{h\ (B+1)(1-\alpha)} \right]$$

unter der Voraussetzung $m_i \overset{i.i.d.}{\sim}$ D

Softwarebug bei der Schätzung von var(m)

Designbasierter Varianzschätzer $P2$ (Fewster et al., 2009):

$$\widehat{\text{var}}_{P2}\left(\frac{1}{n}\sum_{r=1}^{n}\frac{m_r}{t_r}\right) = \frac{1}{n(n-1)}\sum_{i=1}^{n}\left(\frac{m_i}{t_i} - \frac{1}{n}\sum_{r=1}^{n}\frac{m_r}{t_r}\right)^2$$

$P2$ gewichtet Stichprobenpunkte unabhängig von ihrem t_i gleich.
Modellbasierter Varianzschätzer $P3$ (Fewster et al., 2009):

$$\widehat{\text{var}}_{P3}\left(\frac{m}{T}\right) = \frac{1}{T(m-1)}\sum_{i=1}^{m} t_i\left(\frac{m_i}{t_i} - \frac{m}{T}\right)^2$$

$P3$ gewichtet Stichprobenpunkte mit hohem t_i stärker als solche mit niedrigem t_i.

Softwarebug bei der Schätzung von var(m)

Gleichheit der Schätzer Wenn $t_i = t$ (für alle i) gilt (Fewster et al., 2009):

$$\widehat{\text{var}}_{P1}\left(\frac{m}{nt}\right) = \widehat{\text{var}}_{P2}\left(\frac{1}{n}\sum_{r=1}^{n}\frac{m_r}{t_r}\right) = \widehat{\text{var}}_{P3}\left(\frac{m}{T}\right) = \widehat{\text{var}}\left(\frac{\bar{m}}{t}\right) = \frac{1}{t^2k(k-1)}\sum_{i=1}^{k}(n_i-\bar{n})^2$$

Wenn $t_i = 1$ (für alle i) gilt, ist $T = n$ und somit eine weitere Vereinfachung möglich:

$$\widehat{\text{var}}_{P1}\left(\frac{m}{nt}\right) = \widehat{\text{var}}\left(\frac{m}{n}\right) = \frac{1}{n\,(n-1)}\sum_{i=1}^{n}(m_i-\bar{m})^2$$

Im Falle der von uns durchgeführten Totholzinventur ist (innerhalb einer Aufnahmekampagne) $t_i = 1$ (für alle i) und somit

$$\widehat{\text{var}}_{P1}\left(\frac{m}{nt}\right) = \widehat{\text{var}}_{P2}\left(\frac{1}{n}\sum_{r=1}^{n}\frac{m_r}{t_r}\right) = \widehat{\text{var}}_{P3}\left(\frac{m}{T}\right) = \widehat{\text{var}}\left(\frac{m}{n}\right) = \frac{1}{n^2}\widehat{\text{var}}\,(m)$$

Arbeitszeiten

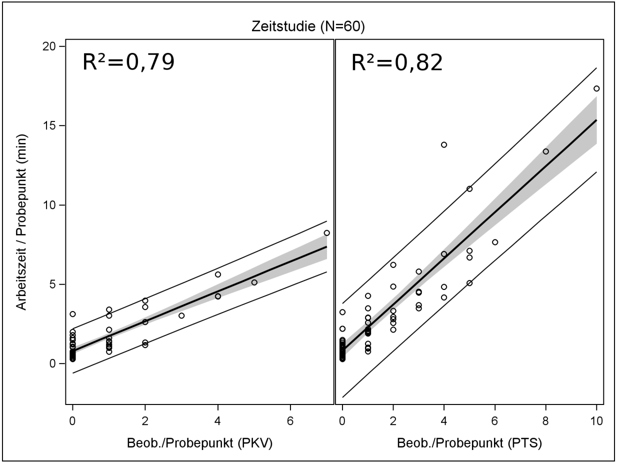
Grundidee:
Einteilung in

- Entscheidungsrelevante Arbeitszeit (Suchen und Vermessen der Totholzobjekte am Stichprobenpunkt)
- Entscheidungs**ir**relevante Arbeitszeit (Fahrtzeiten, Aufsuchen und Einmessen der Stichprobenpunkte)

Zeitstudie:
Mit *eingespielten* Aufnahmeteams wurde die entscheidungsrelevante Arbeitszeit an einigen Stichprobenpunkten t_i ermittelt
Schätzung der fehlenden Daten mittels linearer Regression:

$$\hat{t}_i = \beta_0 + \beta_1 \cdot m_i$$

Arbeitszeiten 2



Die niedersächsische Betriebsinventur

Mittleres Volumen über alle Straten (Cochran, 1977):

$$\hat{\hat{Y}} = \sum_{h=1}^{L} \frac{n'_h}{n'} \hat{\hat{Y}}_h = \sum_{h=1}^{L} \left(\frac{n'_h}{n'} \frac{1}{n_h} \sum_{i=1}^{n_h} Y_{hi} \right) \tag{12}$$

Varianz (Saborowski et al., 2010):

$$\widehat{\text{var}}\left(\hat{\hat{Y}}\right) = \frac{1}{n'-1} \left(\sum_{h=1}^{L} \frac{n'_h - 1}{n'} \, n'_h \widehat{\text{var}}\left(\hat{\hat{Y}}_h\right) + \sum_{h=1}^{L} \frac{n'_h}{n'} \left(\hat{\hat{Y}}_h - \hat{\hat{Y}}\right)^2 \right) \tag{13}$$

Optimierung von Stichprobenumfang und Allokation

Notwendiger Stichprobenumfang, um eine geforderte Genauigkeit zu erreichen (Cochran, 1977)

- Fixe Arbeitszeit T

$$n = \left(T \sum_{h=1}^{L} n'_h S_h / \sqrt{\bar{t}_h} \right) \left(\sum_{h=1}^{L} n'_h S_h \sqrt{\bar{t}_h} \right)^{-1}$$

- Fixer SE

$$n = \left(\sum_{h=1}^{L} \frac{n'_h}{n'} S_h \sqrt{\bar{t}_h} \right) \left(\sum_{h=1}^{L} \frac{n'_h}{n'} S_h / \sqrt{\bar{t}_h} \right) \left(\mathrm{var}(\hat{\hat{Y}}) + \frac{1}{n'} \sum_{h=1}^{L} \frac{n'_h}{n'} S_h^2 \right)^{-1}$$

Optimale Allokation der Stichprobenpunkte (Cochran, 1977)

$$n_h = n \ \left(n'_h \ S_h / \sqrt{\bar{t}_h} \right) \left(\sum_{h=1}^{L} n'_h \ S_h / \sqrt{\bar{t}_h} \right)^{-1}$$

Zusammenhang von Stichprobenumfang und Schätzgenauigkeit

Innerhalb eines Stratums gilt:

$$n_{\text{notwendig}} = \frac{\text{SE}^2_{\text{Pilotinventur}} \cdot n_{\text{Pilotinventur}}}{\text{SE}^2_{\text{gefordert}}}$$

bzw.

$$\text{SE}^2_{\text{resultierend}} = \frac{\text{SE}^2_{\text{Pilotinventur}} \cdot n_{\text{Pilotinventur}}}{n_{\text{bezahlbar}}}$$

Überblick

Datensatz

- Zwei simulierte Punktmuster
  - Vollständig zufällige räumliche Verteilung (Poisson-Prozess)
  - Geklumpte Population (Log-Gauss-Cox-Prozess), angepasst an den "'Hainich Datensatz"' (Bauhus & Wirth, unveröffentlicht)
- Durchmesserverteilung aus dem Hainich Datensatz abgeleitet (2-parametrige Weibull-Verteilung)
- Entdeckungsfunktion aus den Feldaufnahmen
- 999 Simulationsläufe mit 225 Stichprobenpunkten
  - zufällig verteilt
  - systematisches Stichprobengitter mit zufälligem Startpunkt

Punktprozesse

Poisson-Prozess N:

N zeichnet sich durch zwei Eigenschaften aus (Illian et al., 2008):

- Die Anzahl der Punkte von N in allen finiten Teilmengen B folgt einer Poisson-Verteilung mit Mittelwert $\lambda\nu(B)$.
- Die Anzahl der Punkte von N in k disjunkten Teilmengen bildet k stochastisch unabhängige Zufallsvariablen

Log-Gauss-Cox-Process (LGCP):

Ein LGCP ist ein inhomogener Poisson-Prozess mit zufälligem Intensitäts-Prozess

$$\Lambda(x) = \exp\left(Z(x)\right)$$

wobei $Z(x)$ ein stationäres und isotropes Gauss-Zufallsfeld ist (Illian et al., 2008). Die Intensität des LGCP ist (Møller & Waagepetersen, 2003)

$$\lambda = E\Lambda(x) = \exp\left(\mu + \frac{\theta^2}{2}\right)$$

Realisation der Punktprozesse