Alternative subsampling designs derived from aerial and terrestrial remote sensing technology

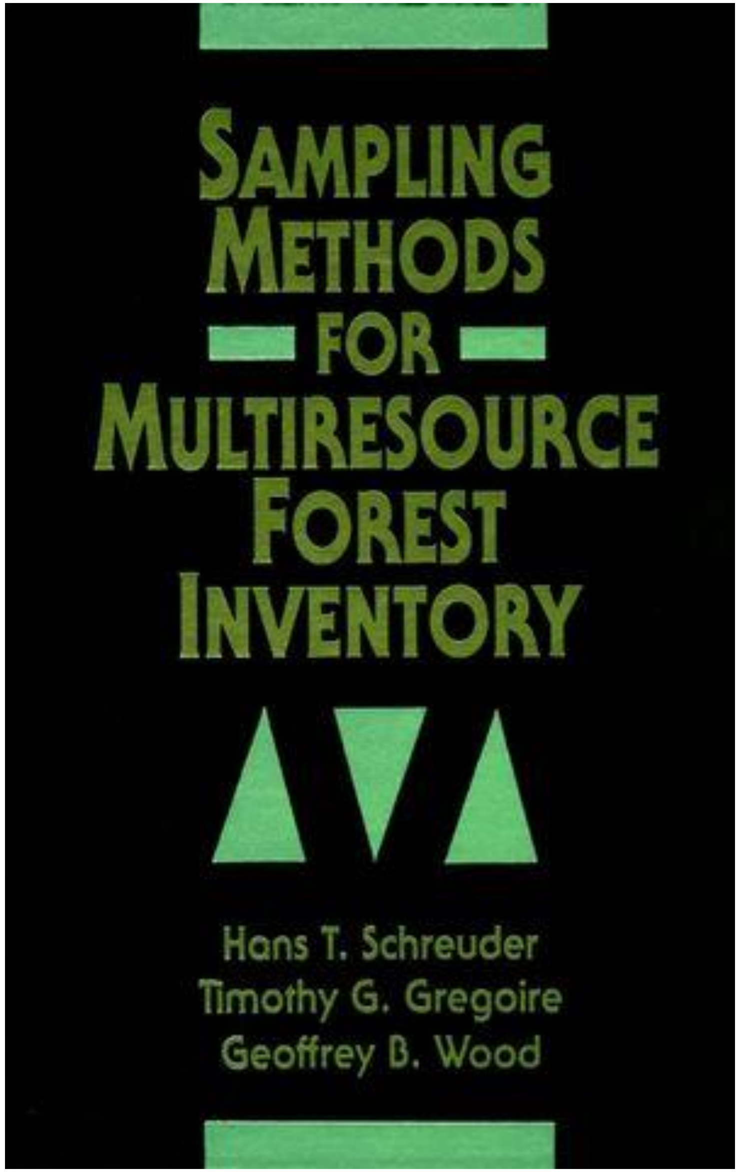
Dr. John Kershaw

Faculty of Forestry and Environmental Management

University of New Brunswick

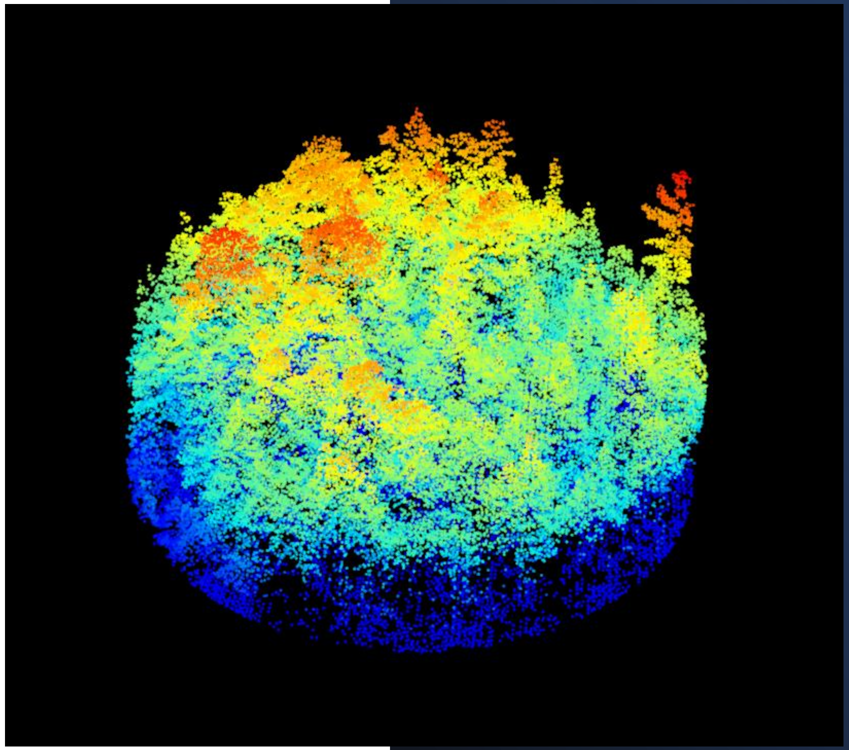
The curmudgeons in the balcony

In the beginning….



Then came remote sensing to the garden…

…and we forget Forests are biological systems not point clouds



(so called) Enhanced forest inventory

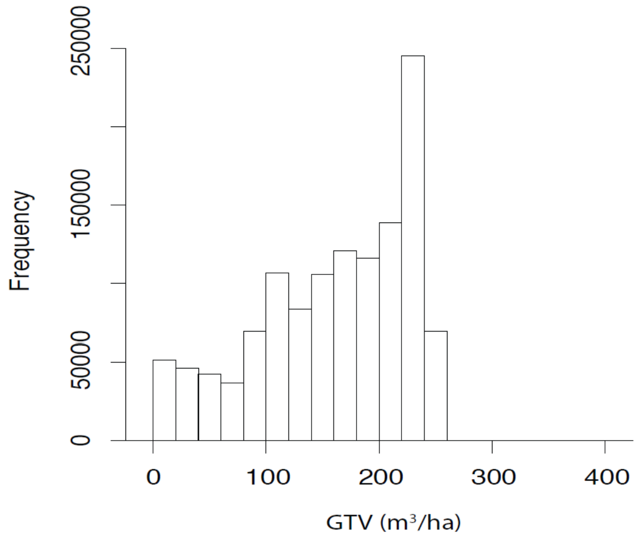


Figure 3.5 Histogram of enhance forest inventory gross total volume (GTV) distribution across study area (by 20m EFI cells).

From: Chen 2019, Hierarchical Variable Probability Sampling For Carbon Estimation. MSc Thesis, UNB

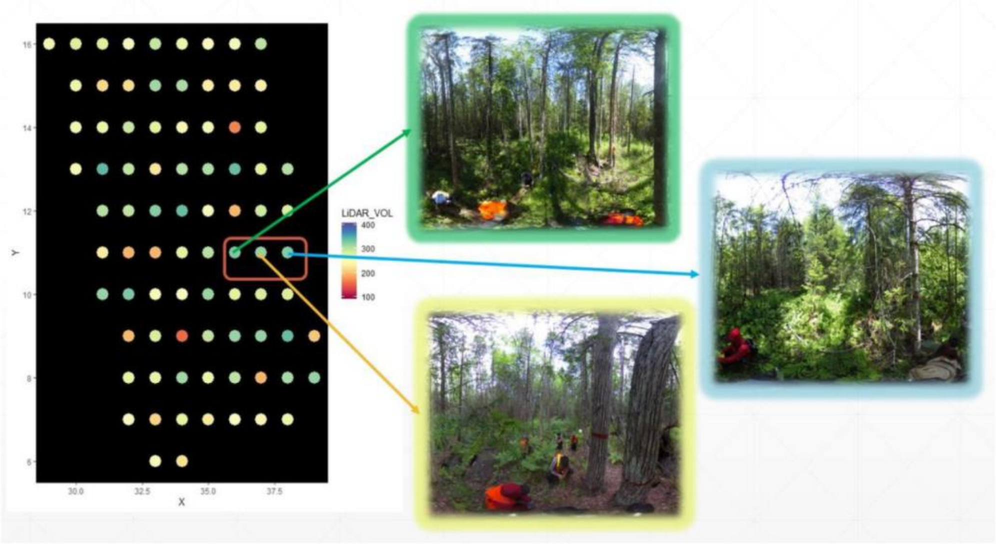


Figure 1.1. Three ground plot photos corresponding to the same LiDAR-derived estimate of volume per hectare

From: Yang 2021 A Systems Approach for Estimating Forest Attributes from LiDAR. PhD Dissertation, UNB

(so called) Enhanced forest inventory

(so called) Enhanced forest inventory

From: Yang 2021 A Systems Approach for Estimating Forest Attributes from LiDAR. PhD Dissertation, UNB

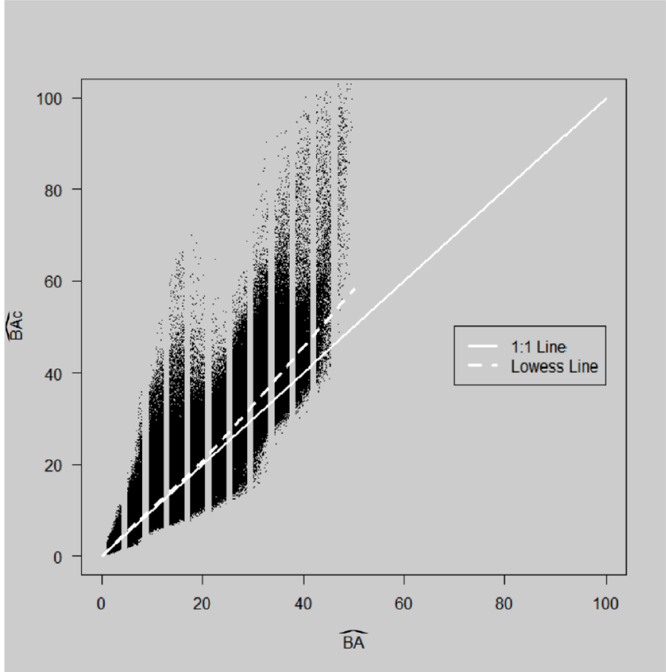


Figure 4.2. Comparisons between LiDAR EFI BA prediction ($\widehat{BA}$) and BA calculation ($\widehat{BA}_C$) substituted by LiDAR EFI QMD and N (Eq. 4-3).

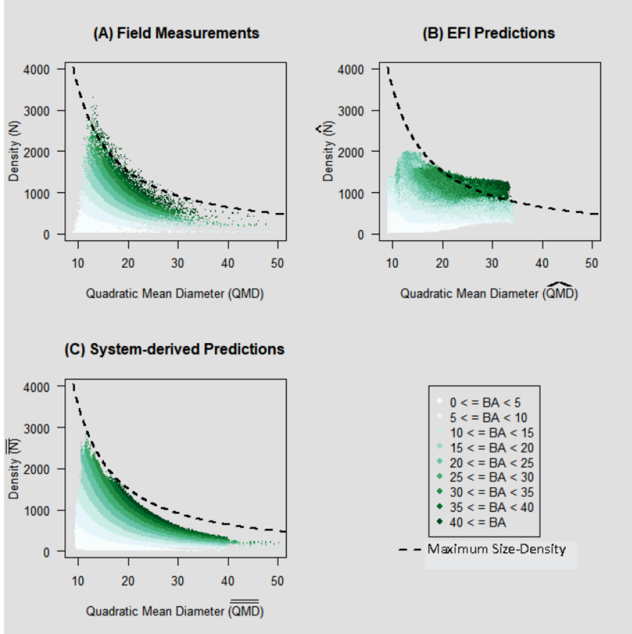


Figure 4.4. Comparisons of Reineke Stand Density Index Space made by three data sources: (A) Field measurements (QMD, N, BA); (B) EFI predictions ($\widehat{QMD}, \hat{N}, \widehat{BA}$); and (C) system-derived estimates ($\overline{\overline{QMD}}, \overline{\overline{N}}, \overline{\overline{BA}}$). The maximum stand density is made by quantile regression with tau=0.99.

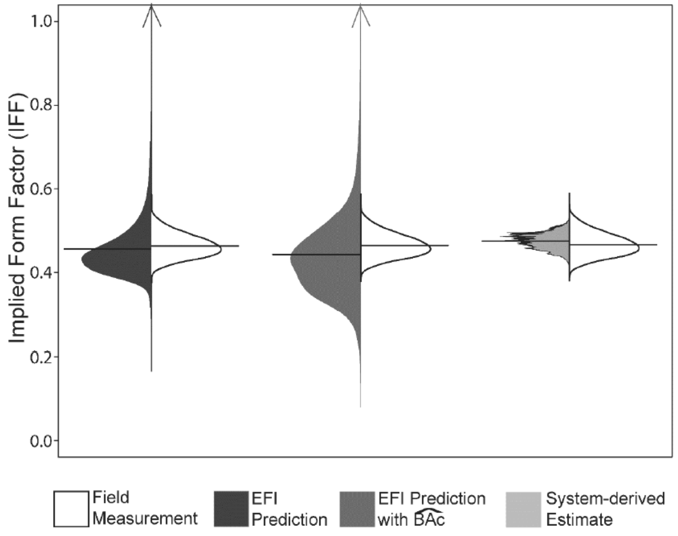


Figure 4.5. The distribution and average of implied form factor (IFF, eq. 4-4; unitless) calculated from field measurements, EFI predictions ($\widehat{VOL}, \widehat{HT}_L, \widehat{BA}$), EFI calculations, $\widehat{BA}_C$ ($\widehat{VOL}, \widehat{HT}_L, \widehat{QMD}, \hat{N}$), and system-derived estimates ($\overline{\overline{VOL}}, \overline{\overline{HT}}_L, \overline{\overline{BA}}$).

Highlight some recent work from my lab

- Sampling to correct LiDAR EFI
- Sampling with covariates derived from remote sensing
- Sector subsampling using a spherical camera

Some energetic and creative collaborators

Sampling to correct

- LiDAR-derived EFI and other mapped forest attribute estimates are becoming readily available
- Those estimates have errors and biases, especially when applied at smaller spatial scales
- Can we use those estimates as covariates to design efficient sampling to correct procedures?

Sampling to correct

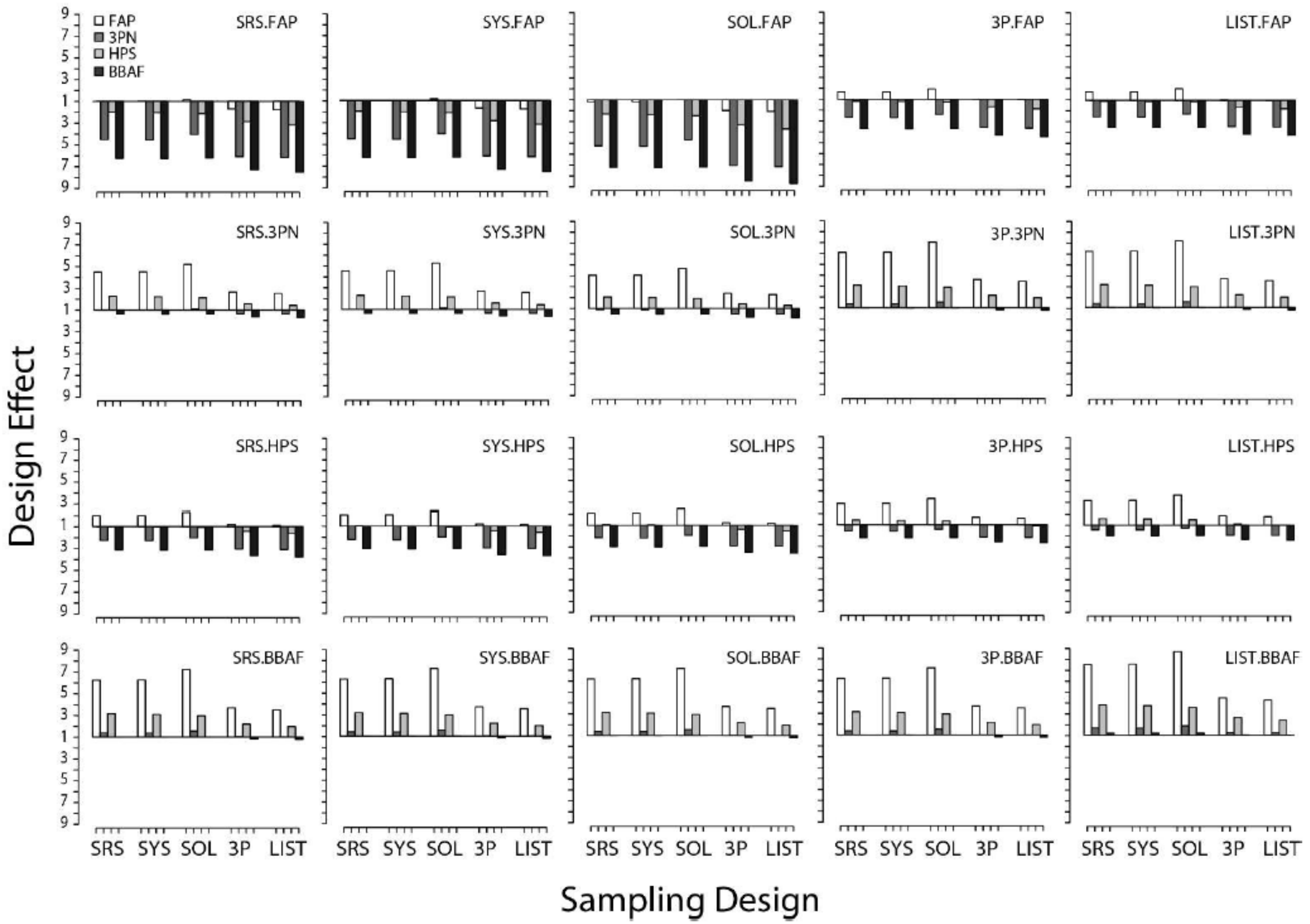


Figure 2.4 Cost-based design effect comparisons by five sample selection methods and four plot types. Sample size calculations were based on a desired standard error of 5%. Upward pointing

From: Hsu 2019 Applications Of Variable Probability Sampling Using Remotely Sensed Covariates, UNB

Sampling with covariates derived from remote sensing

- Rather than using LiDAR EFI predictions, can we use LiDAR attributes directly to develop efficient sample designs?
- Do we need LiDAR to do this? Can we use cheaper, more accessible technology?

Sampling with covariates derived from remote sensing

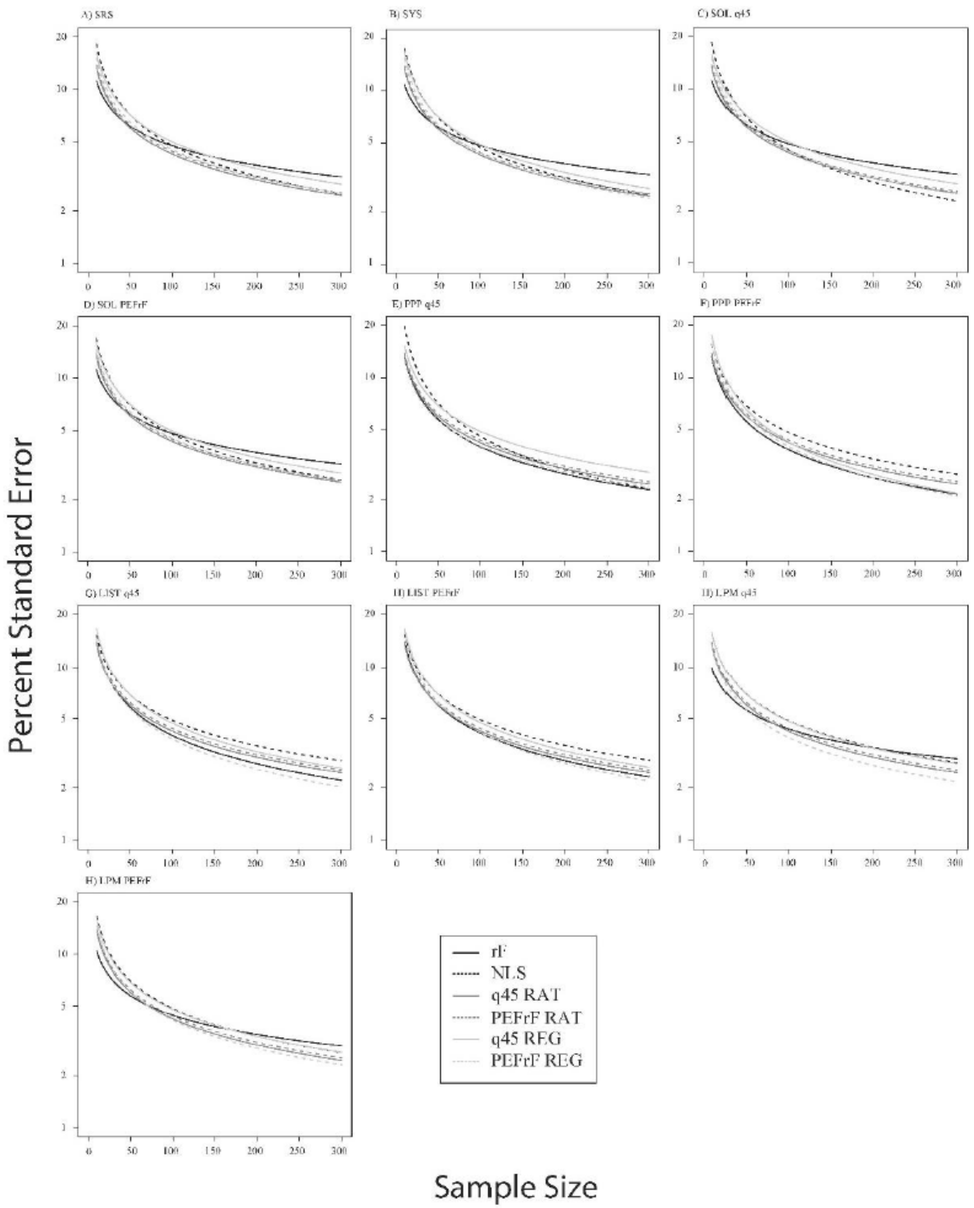


Figure 2.4. Percent standard error (%SE) by selection method, sample size, and estimation method: A) simple random sampling, SRS; B) spatial systematic sampling, SYS; C) systematic sampling from an ordered list built by q45, SOL(q45); D) systematic

From: Yang 2021 A Systems Approach for Estimating Forest Attributes from LiDAR. PhD Dissertation, UNB

Sampling with covariates derived from remote sensing

From: Hsu 2019 Applications Of Variable Probability Sampling Using Remotely Sensed Covariates, UNB

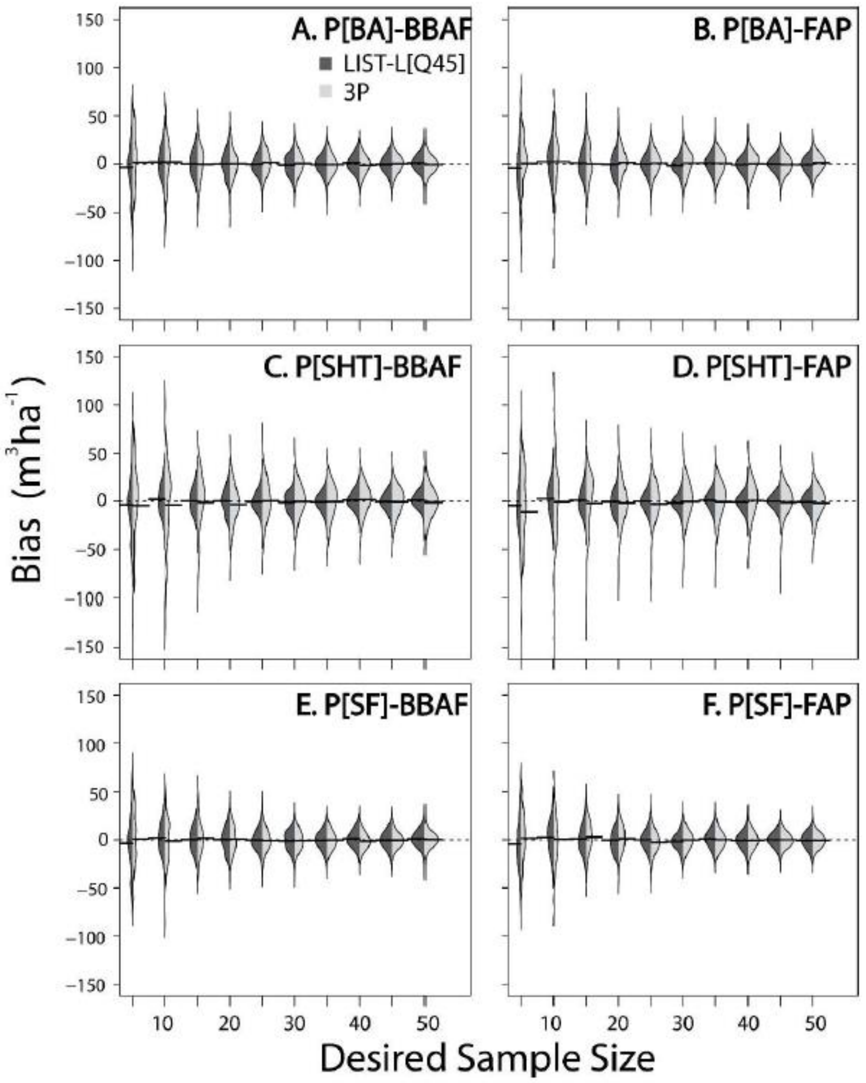


Figure 3.2 The mean and distribution of bias of $\overline{VOL}_{jk}$ by sampling covariate, plot type, and sample size. (FAP = fixed area plot, BBAF = big BAF sample plot, L[Q45] = height

Sector subsampling using a spherical camera

- What more can we derive from these spherical images?
- How can we best utilize measurements directly from the spherical images?

Sector subsampling using a spherical camera

Big BAF sampling

Chen et al. (2019) showed that big BAF sampling was an efficient sampling method for estimating biomass

- A subsampling variant of HPS
  - A small angle gauge is used to project a horizontal angle
    - Identify count trees

PBA=# of in trees x BAF

  - A larger BAF angle gauge is used to select measure trees to measure attributes
  - Biomass to basal area ratio (BBAR)

However, big BAF sampling requires trees to be closer to the plot center

Close “In” trees (Big BAF)

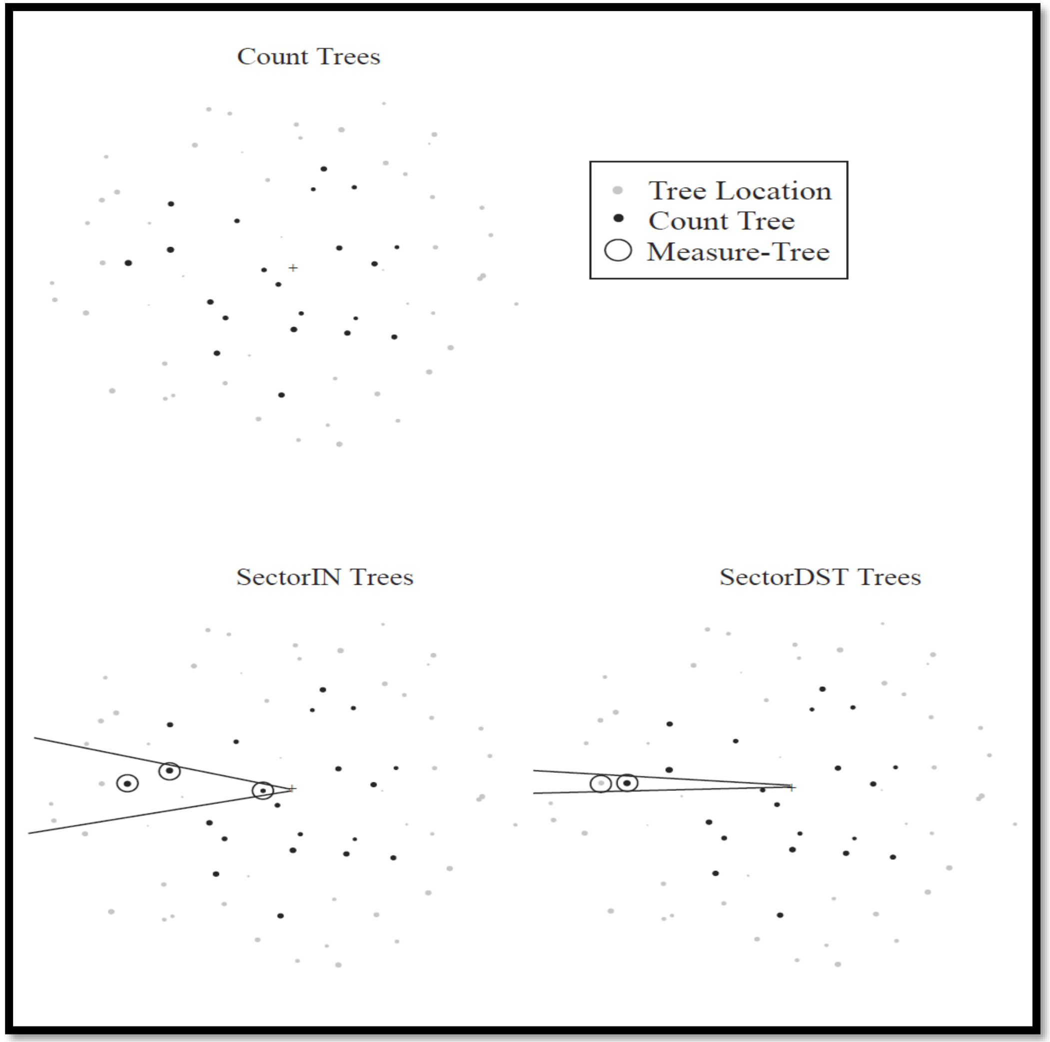
Are there alternative subsample selection methods?

Count tree selection and sector subsample selection methods

Sector subsampling

S e c t o r

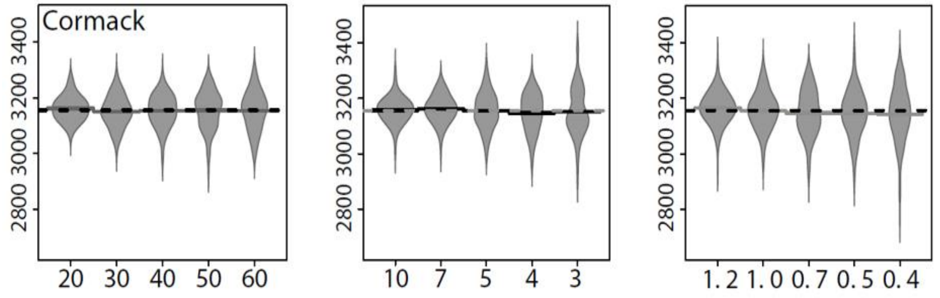
A given percent of a circle



Simulated Sector Sample Results

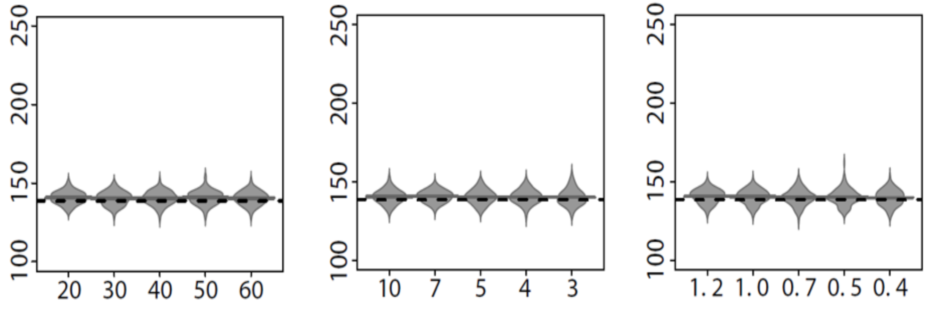
Simulated BBAR (tonnes/m^2)

bigBAF SectorIN SectorDST

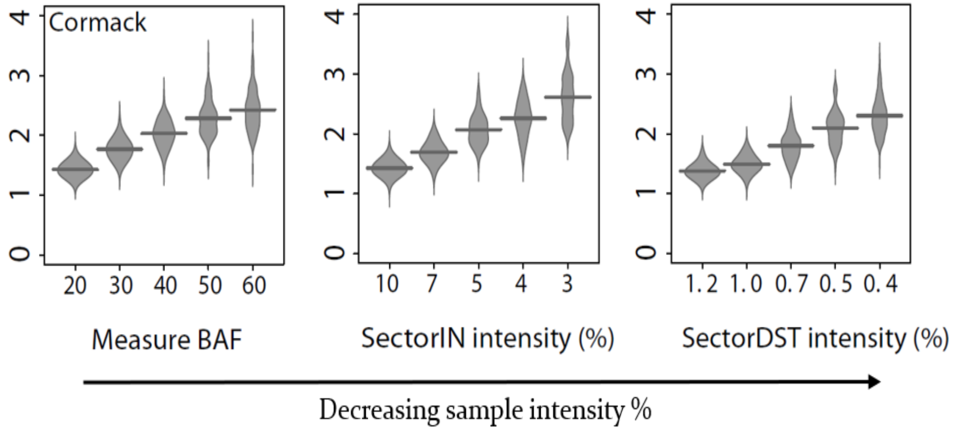


Simulated Biomass(tonnes/ha)

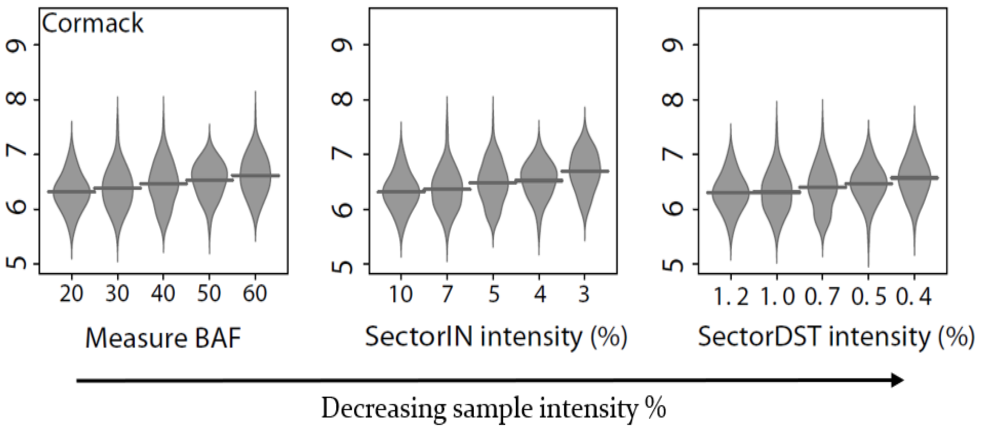
bigBAF SectorIN SectorDST



Errors of BBAR



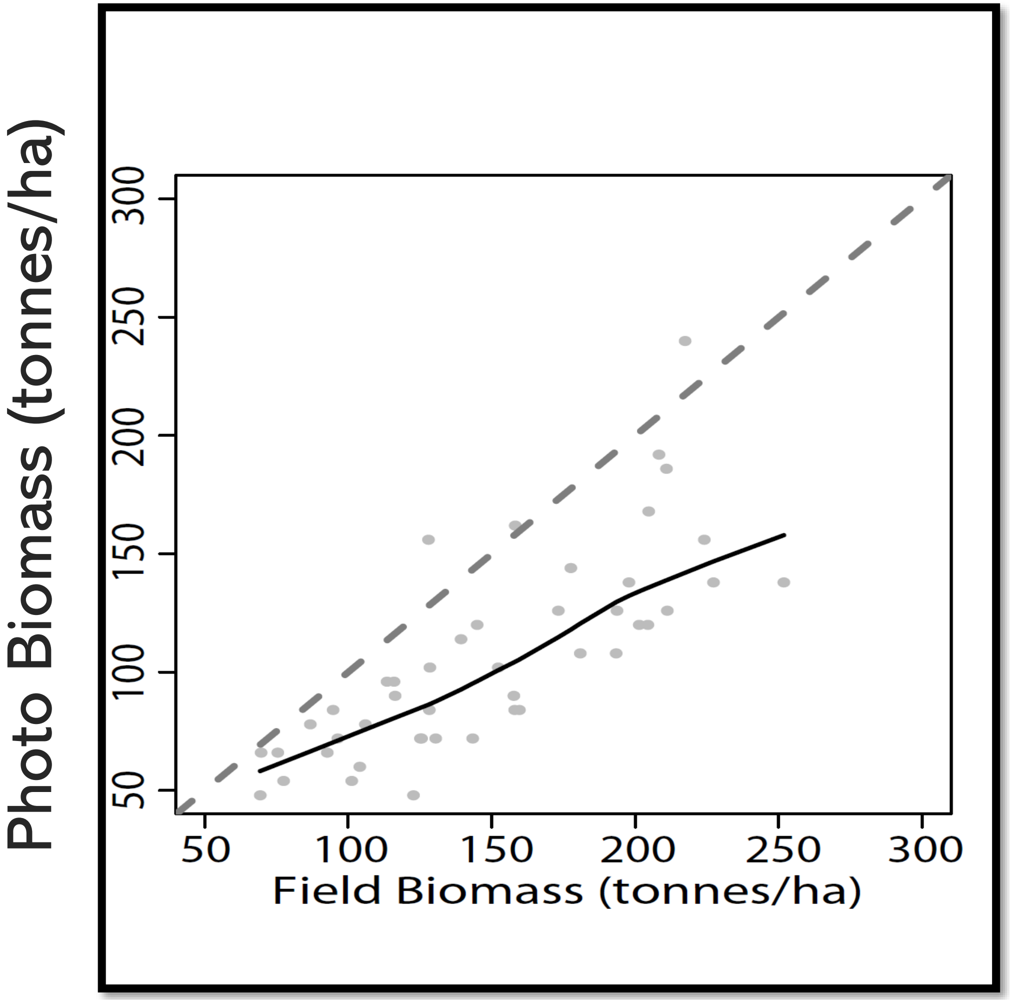
Errors of Simulated Biomass



Close “In” trees (Big BAF)

A random sector is extracted from each photo (A sector will be converted to 2 vertical lines)

Bias Due to Occluded Trees



- The occluded trees can never be avoided, there is always a big under-estimation.
- Selection of measure-trees did not produce biases
- The underestimation of basal area from the spherical images (PBA) resulted in serious underestimation of biomass

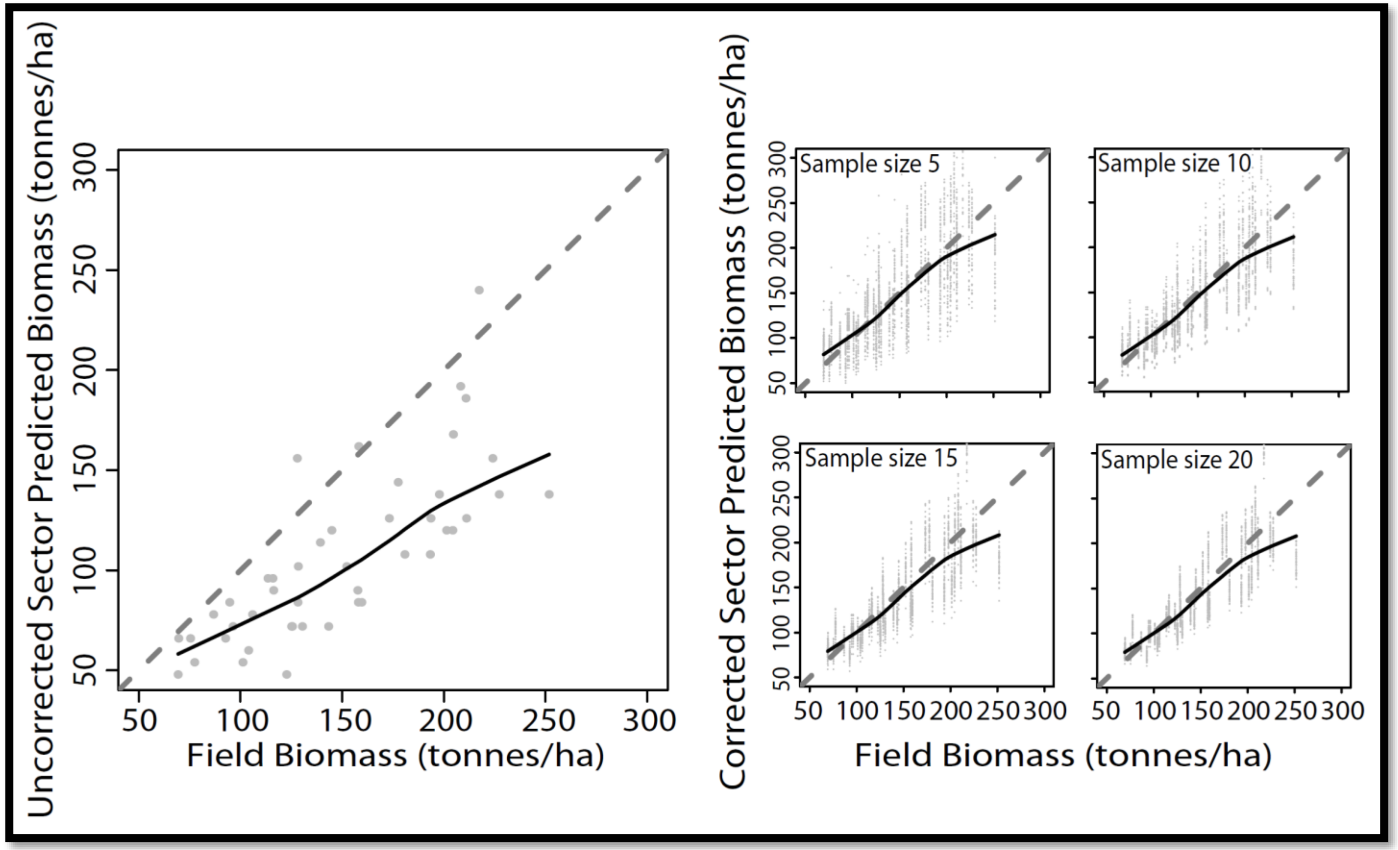
Occluded Tree Correction

- Field BA: photo BA correction (field to photo basal area ratio, FPBAR)
  - $\overline{\mathrm{FPBAR}} = \frac{\sum_{i=1}^{j} \mathrm{FBA_i}}{\sum_{i=1}^{j} \mathrm{PBA_i}}$
- Corrected biomass estimate ($\overline{\mathrm{CBM}}$) became:
  - $\overline{\mathrm{CBM}} = \overline{\mathrm{FPBAR}} \cdot \overline{\mathrm{PBA}} \cdot \overline{\mathrm{BBAR}}$
- Corrected se%:

$$\%\mathrm{se}(\overline{\mathrm{CBM}}) = \sqrt{\%\mathrm{se}(\overline{\mathrm{FPBAR}})^2 + \%\mathrm{se}(\overline{\mathrm{BBAR}})^2 + \%\mathrm{se}(\overline{\mathrm{PBA}})^2}$$

Results

Comparison between corrected/uncorrected sector prediction with field measured biomass under 4 different sample sizes 5, 10, 15, 20



- The predicted biomass were corrected efficiently
- 5 samples was sufficient to correct
- As the number of field counts increased, the variability decreased; but the mean trends are not different

- Trivial Masters research or something important here?

Source	Biomass Estimate				
Sample Size	Mean	Standard Error	# trees measured (field)	# trees measured (Photo)	Cost
Field Measured	148.9	7.3	4000	0	Around $10, 000 ($2.46 per tree, 4,100+ trees)
TLS Prediction	148.8	17.2	4000	0	$11,855 + field$
PBA Prediction	149.3	19.9	4000	0	$1,700 + field$
Sector Subsampling					
Uncorrected	102.9	5.4	0	53	$800
5	148.5	30.1	0	53	$855
	{95.5, 241.7}				
10	146.4	19.7	0	53	$911
	{105.8, 191.4}				
15	144	13.2	0	53	$966
	{108.8, 171.2}				
20	143.9	10.3	0	53	$1018
	{121.9, 163.5}				

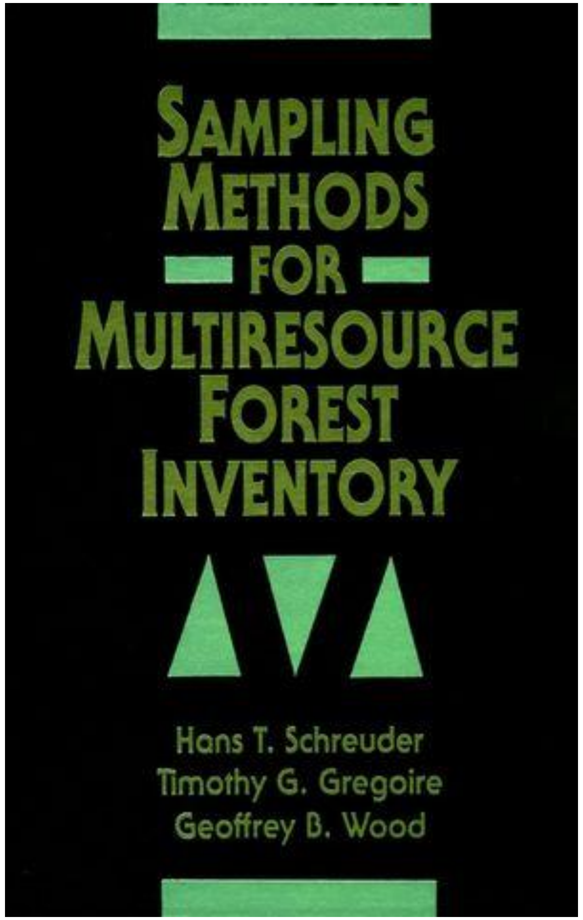
Hierarchical variable probability sampling

Integrate information across various spatial scales and sources into an efficient sampling design to produce compatible biological estimates

…returning to some first principles

- Forests have biological and mathematical interrelationships
  - Sample and model estimates need to reflect that
- Our sample gives us the total (Kim Iles)
  - LiDAR and other remote sensing tools just help us spread that total across the landscape
- The most efficient sample is the one that selects proportional to the parameter of interest (Basu/”Beer’s Law”)

In the beginning….



Then came remote sensing.

Some energetic and creative collaborators