ABSTRACT

Variable probability selection methods are regarded as the most efficient sampling design because sample selection is based on parameters of interest. However, a lack of prior knowledge of covariates for study areas restrict the application in practice. This thesis explored the use of covariates derived from airborne light detection and ranging (LiDAR) scanning (ALS) and a consumer-based spherical camera in selecting sample locations with variable probability. Results show that list sampling with big BAF sample plots is a highly efficient and cost-effective sampling strategy for effectively calibrating ALS-derived estimates to local conditions. For the spherical photography study, ratio estimation also showed the capability to calibrate imprecise covariate estimates; however, sampling efficiency under variable probability selection was not improved relative to simple random sampling. The low correlation between the photo-derived covariate and parameter of interest most likely impacted these results. Optimal covariates need further exploration to improve sampling efficiency.
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Chapter 1: General Introduction
1.1 Introduction

Forest inventory is the first step in development of any forest management strategy, because any decision making is based on the information about condition of resources (Clutter et al. 1983; Bettinger et al. 2017). Ideally, a census can provide complete knowledge of forest conditions, but it is too expensive and time-consuming in practice, and any measurement errors result in biases (Freese 1962; Cochran 1977; Iles 2003; Kershaw et al. 2016). Thus, sampling to estimate forest attributes is necessary. In statistical theory, a random selection mechanism is required to obtain an unbiased estimate (Cochran 1977; Shiryayev 1984). A precise estimate of a population parameter requires large sample sizes to produce low sampling errors, especially for highly variable populations. However, sample size is usually restricted in practice by the budget of time and cost (Smith 1938; Freese 1962; Lynch 2017). Appropriate sample selection methods play a crucial role in forest inventory design.

In addition to sample selection methods, forest inventory design needs to consider how trees will be selected for measurement (i.e., type of sampling unit – fixed area plot, horizontal point sample, or some other selection mechanism) and ultimately depends on the estimation methods. Commonly, the individual tree selection mechanism is either a fixed area plot or a horizontal point sample (Kershaw et al. 2016). Like the sampling unit selection process, in statistical terms, these are really either equal probability or variable probability sample selection schemes.

Finally, the estimation approach can greatly influence the precision of inventory results and the inferences that can be drawn from them. Design-based estimates have broader
inference space, but model-based estimates are widely used in forest inventory (Schreuder et al. 1993; Gregoire 1998; Gregoire and Valentine 2008). Ratio estimation with some form of double sampling can be a very effective design-based approach for forest inventory.

1.2 Sample Design

1.2.1 Estimation method

Mean and standard deviation are two basic and common statistical parameters used to describe populations. Sample means ($\bar{x}$) and standard deviations ($s$) are estimators for population means and standard deviations. Based on a fully randomized selection mechanism, both the sample mean and standard deviation can be estimated unbiasedly:

$$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n}$$  \hspace{1cm} (1)

and

$$s = \sqrt{\frac{\sum_{i=1}^{n} (x_i - \bar{x})^2}{n - 1}}$$  \hspace{1cm} (2)

To assess sampling error ($E$), the standard deviation of sample means (i.e., standard error; $se$), is an important measurement. Sampling error is calculated using the formula (Iles 2003):

$$E = t \cdot se = t \cdot \frac{s}{\sqrt{n}}$$  \hspace{1cm} (3)
where \( t = t\)-value associated the required confidence and degrees of freedom (\( n-1 \)) and \( n \) = sample size. Since \( s \) is an estimate of population variability, standard error is influenced by both the inherent population variance and the sample size obtained. To estimate the required sample size given a specified sampling error and confidence eq. 3 is solved for:

\[
n = \left( \frac{t \cdot s}{E} \right)^2
\]

(4)

Though the population variance cannot be controlled, appropriate sample selection methods may be able to reduce the resulting standard errors and minimum required sample sizes.

The relationship between two or more forest attributes is also of interest in forest inventory, because some forest attributes are difficult or expensive to measure (e.g., tree height). If a difficult-to-measure attribute can be estimated from an easy-to-measure covariate, measurement efforts can be reduced. Regression estimation and ratio estimation are two common estimation methods. These estimation methods can also be applied in the sampling process when there is a larger sample of covariates \( (X_i) \), and smaller sample of the measured parameter of interest \( (Y_i) \).

In regression estimation, \( Y \) is estimated using regression coefficients. A simple linear regression is of the form:

\[
\hat{Y}_i = b_0 + b_1 \cdot X_i + e_i
\]

(5)

where \( \hat{Y} \) = the estimate from regression, \( b_0 = \) the y-intercept required to have the regression line pass through the point \( \{ \bar{X}, \bar{Y} \} \), and \( b_1 = \) the slope estimated as the ratio of the covariance of \( X \) and \( Y \) to the variance of \( X \), and \( e = \) is the residual error \( (Y_i - \hat{Y})^2 \).
The purpose of regression is to minimize the residual error, and the root mean square error (rMSE) is a measurement the goodness of regression fit. In a sampling context, the rMSE becomes a part of the sampling error.

In ratio estimation, the $\overline{Y}$ is estimated or adjusted using a simple ratio of $Y$ to $X$ (ratio estimation assumes the y-intercept is 0). There are two ways of calculating the mean ratio. The “ratio of means”:

$$\overline{R} = \frac{Y}{X} = \frac{\sum_{i=1}^{n} Y_i}{\sum_{i=1}^{n} X_i} = \frac{\sum_{i=1}^{n} Y_i}{\sum_{i=1}^{n} X_i}$$

(6)

is used in the equal probability sampling processes, while the “mean of ratios”

$$\overline{R} = \left(\frac{1}{n}\right) \sum_{i=1}^{n} \left(\frac{Y_i}{X_i}\right)$$

(7)

is applied in variable probability sampling (Iles 2003). The mean of $Y$ is estimated by multiplying the mean of $X$ by the ratio or by using the regression estimate from eq. 5.

The standard error of the estimated $\overline{Y}$ can be calculated using Bruce’s formula (Goodman 1960):

$$se(Y) = \sqrt{se(R)^2 + se(X)^2}$$

(8)

where $se(R) =$ standard error of the mean ratio and $se(X) =$ the standard error of mean covariate. The advantage of ratio or regression estimation is that they reduce the variability of sample estimates and improve sampling efficiency.
1.2.2 Sampling unit type

While individual trees are the units we actually measure, foresters rarely select individuals, but rather select groups of individuals at a location in the forest commonly referred to as a sample point, sample location, or sample plot. A fixed area plot (FAP) is one of the more basic sampling units used in forest inventory. A predefined area is determined and located centered on the sample point, and all trees included in the predefined area are selected for measurement. The plot shape can be circular, square, rectangular or triangular, but circular plots are commonly used because plot boundaries are easy to establish in the field. FAP selects trees with equal probability. Each selected tree represents a constant number of trees per ha which is inversely related to plot area. Horizontal point sampling (HPS), which was first introduced by Bitterlich (1947), uses a projected angle to determine the selected trees. Trees as large or larger than the projected angle are selected for measurement. HPS is a form of variable probability sampling, and can be considered an efficient tree sampling scheme for size-based attributes, such as volume or biomass, because the selection probability is proportional to tree size (basal area). The selection angle selects trees such that each tallied tree represents a constant basal area per unit area. This can provide a quick estimate of stand basal area without any direct tree measurements. Therefore, HPS is widely used in forest inventory.

To further reduce the cost and effort of tree measurement, subsampling processes in FAP or HPS are frequently used. While many commonly used subsampling techniques are ad hoc or non-probabilistic (e.g., measuring the tallest tree, the biggest diameter tree, every ith tree, or haphazardly selecting trees to measure), probabilistic schemes are easy to implement in the field and ratio or regression estimation can be applied to obtain efficient
estimates of the parameter of interest. The common (non-probabilistic) methods may not improve the sampling precision (Marshall et al. 2004). On the other hand, a variable probability sampling scheme can be used as a subsampling process and significantly improve sample efficiency. For example, sampling with probability proportional to prediction (3P sampling) can be applied with FAP or HPS (commonly called point 3P sampling). Trees with higher predictions have higher probabilities of selection. For HPS, since larger BAFs (i.e., larger projected angles) have fewer tallied trees, a large BAF can be used to subsample measured trees. This method, called big BAF sampling, was introduced by Bell et al. (1983), discussed by Iles (2003), and further examined by Marshall (2004) and Yang et al. (2017).

1.2.3 Sampling unit selection method

Simple random sampling (SRS) is a standard sampling scheme in which every sampling unit is independently selected with equal probability (Freese 1962). However, although SRS can provide an unbiased estimate of both the population mean and variance, it is not the most efficient selection method in practice (Kershaw et al. 2016). For example, travel costs would usually increase because plots are not distributed regularly and a mapping process is usually required before the sampling process (Kershaw et al. 2016). In addition, with small samples, typical of those used in forest inventory, it is hard to ensure spatial coverage and representativeness. Systematic sampling (SYS), another example of equal probability selection, is widely applied in the field, because samples are easily distributed over the entire spatial extent. The regular pattern makes travel between sampling units easier. However, while systematic samples yield an unbiased estimate of
the mean, the standard error of the mean is not unbiased (Cochran 1977; Iles 2003; Kershaw et al. 2016). Because of the regularity in systematic sampling, sampling units are not selected independent of one another. Once the first plot is selected, all other plots are predetermined based on the pattern of spatial spread. Applying the formula for simple random sampling to estimate the standard error generally results in overestimating standard error (Cochran 1977; Iles 2003; Kershaw et al. 2016).

When sampling heterogeneous populations, stratified sampling may be more efficient than SRS or SYS. Stratified sampling involves dividing the population into several strata, and subsampling within strata. Stratified sampling can result in more precise estimations for population parameters with a smaller sample size, if strata are designed properly. The goal of stratification is to minimize variance within strata and maximize variance between strata. If strata are more homogeneous, fewer samples are required to achieve desired error levels and the forest-level error is the pooled (average) error across all strata:

\[
se = \sqrt{\sum_{i=1}^{M} P_i^2 \frac{s_i^2}{n_i}}
\]

where \(M\) = the number of strata, \(P_i\) = proportion of the \(i\)th stratum in population, \(s_i\) = sample standard deviation of \(i\)th stratum, and \(n_i\) = the sample size of \(i\)th stratum.

Double sampling, or two-phase sampling, can further reduce sampling effort using a subsampling process with ratio or regression estimation. In double sampling, there are two phases: the first phase for a larger sample with an easily-measured covariate of the parameter of interest, and the second phase is a smaller subsample with detailed measurement of the parameter of interest (Cochran 1977; Iles 2003; Kershaw et al. 2016).
Then, regression or ratio estimation can be used to adjust or calibrate the covariate to estimate the population mean or total of the parameter of interest. This sampling scheme can improve sampling efficiency, especially for estimating forest attributes that are difficult or expensive to measure.

While equal probability selection methods (e.g., SRS and SYS) are widely used in forest inventory designs; variable probability selection methods are considered more efficient because the selection probability is based on the parameters of interest (Basu 1969). The typical variable section methods in forest inventory are sampling with probability proportional to size (i.e., list sampling) suggested by Hansen and Hurwitz (1943) and sampling with probability proportional to prediction (i.e., 3P sampling) introduced by Grosenbaugh (1964, 1965). To determine the selection probability for each sample unit, the two variable probability sampling schemes require information about the population (the population list), which can be regarded as the larger sample in double sampling. In 3P sampling, the population list is generated as a set of predictions as the sample proceeds through the population. With list sampling, the population list needs to be known a priori. Because of the requirement of a population list, variable probability selection methods are relatively difficult to apply in the field, and have not been widely used in forest inventories. However, if an appropriate list of covariates could be available or easily generated in the field, variable probability selection could greatly improve sample efficiency in forest inventories.
1.2.4 Variable probability selection methods using remotely sensed covariates

As an alternative to field-based covariates for variable probability selection, remote sensing techniques may be a logical, efficient, and cost-savings choice (Yang et al. In Press). Remote sensing techniques have a long history in forest inventory. In the 1920s, aerial photography was first used in forest and stand type classification (Robbins 1929). With the development of stereo-photography techniques, quantitative measurements were extracted from aerial photographs (Spurr 1952). Since the 1980s, airborne light detection and ranging (LiDAR) and scanning (ALS) have been used to estimate forest attributes (Aldred and Bonner 1985; Næsset 2002; Lim et al. 2003; Wulder et al. 2008; Gregoire et al. 2011). Compared to photo interpretation, ALS strengthens the capability to capture both horizontal and vertical information (Lim et al. 2003).

Photography and LiDAR techniques can also be applied on the ground. Although they cannot give the landscape-level forest estimates that aerial remote sensing provides, they may be able to improve the efficiency in plot-level parameter estimation. Panorama or spherical photographs can record the horizontal and vertical information which can then be used in estimating various forest attributes (Fastie 2010; Dick 2012; Perng et al. 2018). Hemispherical photos are usually used in leaf area index and gap fraction estimation (Chen et al. 1991; Demarez et al. 2008). Ground-based/terrestrial LiDAR can record the three-dimensional forest conditions at a very high resolution (100s of points per m\(^2\) compared to 10s of points per m\(^2\) for ALS). Compared to ALS, ground-based LiDAR can provide more detailed information for understory conditions which has potential for species identification, canopy parameter assessment, and estimating stem diameter and volume (Dassot et al. 2011).
As with all inventory procedures, time and costs are major considerations or limitations to sample design. For digital technology to be widely adapted, it must prove more efficient than traditional ground-based measures. LiDAR, with its high spatial resolution, has been a seductive technology that has managed to avoid this cost and efficiency barrier, despite limited understanding of how these high-resolution predictions should be used in forest management decision making or how accurate and efficient they really are. Like other remote sensing technologies before LiDAR, it is viewed as the magic solution to avoiding field work. However, LiDAR predictions are derived from field estimates and the quality of those estimates are only going to be as good as the field data used in their derivation (Yang et al. In Press). Sampling design becomes even more important when high resolution forest inventory estimates are produced. Understanding the limits of these estimates within the underlying sampling framework of the field data has not been explored in great detail.

1.3 Objectives

Although there are various remote sensing techniques that can provide covariates for variable probability selection methods, ALS and spherical photograph estimates may be more suitable to apply in practice. In many region, ALS-derived forest estimations are becoming readily and freely available to the public. For areas without ALS data coverage, a consumer-based 360° spherical camera may provide a rapid, permanent record and enable estimation at a reduced cost. The potential to extract covariates that could be used in the prediction process in 3P sampling has not been fully explored.
The main objective of this thesis is to explore the use of two remote sensing techniques for the design of small scale (stand- or block-level) inventories. The study is divided into two chapter-papers. The first, “Sampling to correct LiDAR-assisted forest inventory for small woodlots” examines procedures to enable operational foresters or small woodlot owners to calibrate landscape-level forest inventory estimates to local conditions. The second chapter explores how imprecision in covariates with 3P selection impacts sample results. This is a preliminary assessment of the use of a 360° spherical camera in a 3P sampling scheme.

1.4 References


Freese F (1962) Elementary forest sampling. US Department of Agriculture


Grosenbaugh LR (1965) THREE-PEE SAMPLING THEORY and program “THRP” for computer generation of selection criteria. USDA Forest Service, Pacific Southwest Forest Experiment Station


Lynch TB (2017) Optimal plot size or point sample factor for a fixed total cost using the Fairfield Smith relation of plot size to variance. Forestry 90:211–218


Robbins CR (1929) Air survey and forestry. Emp For J 8:205–228


Chapter 2 Sampling to Correct LiDAR-Assisted Forest Inventory Estimates for Small Woodlots

Chapter was submitted to Forest Science as:


Forest Science
2.1 Introduction

Airborne Light Detection and Ranging (LiDAR) scanning (ALS) is a remote sensing technique that can provide three-dimensional spatial information about forest canopies and the underlying topographies. Based on this information, different forest attributes, such as tree height, diameter, crown width and volume, can be estimated (Næsset 2002; Wulder et al. 2008).

In Canada, and elsewhere in the world, ALS has been used to produce high-resolution (20 m pixel or smaller) spatial estimates of forest inventory attributes (e.g. Corona and Fattorini 2008; Asner et al. 2011; Hayashi et al. 2015). Inventories which incorporate such estimates are commonly referred to as Enhanced Forest Inventories (EFI) in eastern Canada. In New Brunswick, the provincial government is in the process of producing a freely available EFI for the entire province. The advantage of EFI is that it provides high-resolution forest inventory estimates across the landscape-level (Andersen et al. 2011). However, these estimates are derived from relative sparse ground data sets; as a result, these estimates are really a strategic-level inventory in which local errors average out over extensive areas. There is no evidence that these estimates are accurate for smaller forest areas. So, while landscape-level estimates may be unbiased, local estimates could be significantly biased (Hayashi et al. 2015).

Localized bias can arise due to many factors. Differences in past management treatments, microsites and disturbance regimes can all produce substantial differences in stand structure and area-based forest attributes (Clutter et al. 1983; Oliver and Larson 1996). The high spatial resolution provided by EFI may connote an accuracy that is not realized on the ground. Evaluation and, if necessary, calibration of these estimates is required to
ensure appropriate forest management decisions are made on a local basis. One solution to this problem is to locally calibrate EFI estimates using double sampling selection and ratio or regression estimation (Iles 2003).

A ground-based “sampling to correct” approach can be separated into two components. The first component is the sample selection method. In practice, systematic sampling is the most common way, since sample points can easily cover the target area (Freese 1962; Zenger 1964; Payandeh and Ek 1971; Iles 2003); however, applying variable probability selection methods, where selection probabilities are dependent on parameters of interest (EFI volume or biomass estimates), has the potential for being the most efficient sampling strategy (Basu 1969). The second component is the sampling unit (plot type). Fixed area plots and horizontal point sampling are commonly used in North America (Kershaw et al. 2016). Controlling the number of trees per sample unit results in trade-offs between increasing variability between sample units (i.e., increasing required sample sizes) and decreasing time spent on each sampling unit (Freese 1961; Gambill et al. 1985; Lynch 2017). Probabilistic subsampling for detailed tree measurements can improve sample efficiencies in many situations (Grosenbaugh 1979; Bell et al. 1983; Iles 2003; Marshall et al. 2004; Kershaw et al. 2016)

This paper explores the efficiency of different sample selection methods and different sampling unit types (plot types), including subsampling within plots, on developing cost-effective and locally-calibrated LiDAR-assisted inventories for small woodlots. The specific objectives include: 1) assessment of different sample selection methods; 2) assessment of different plot types and subsampling designs within plots; and 3)
assessment of required sample sizes and associated inventory costs of different sample selection method × plot type combinations.

2.2 Sampling to Correct

The “sampling to correct” approach is basically a form of double sampling (Iles 2003, p. 443). In double sampling, a large sample of an easily measured covariate is obtained along with a small subsample of the variable of interest which is often difficult or expensive to measure (Freese 1962; Iles 2003; Dahl et al. 2008; Kershaw et al. 2016). Since the measured variables in the two-phase sample are dependent or correlated, the covariate can be “corrected” to estimate the variable of interest using ratio estimation or regression estimation (Freese 1962; Dahl et al. 2008; Kershaw et al. 2016). When the large sample is a census of the population of interest and true mean of the covariate is known, it is referred to as regression sampling (Cochran 1977; Kershaw et al. 2016).

2.2.1 Field Sample Point Selection

Simple random sampling (SRS) and systematic sampling (SYS) are two equal probability selection methods that are frequently used to select both the large and/or small samples in double sampling. SYS is typically applied spatially, but also can be applied with ordered lists of factors of interest (Iles 2003). In systematic ordered-list sampling (SOL), the sampling units available for selection are sorted from smallest to largest by some factors of interest (usually the easily measured covariate), and a random starting point is selected. Then, sample units are selected at a regular interval across the range of the covariate. While SYS ensures the equal distribution of sample plots over the area of interest, SOL ensures the equal distribution over the range of the covariate. SRS and SYS
are frequently used because they are familiar sample selection methods and they do not require prior information about the covariate before deciding the small samples (Freese 1962; Parker and Evans 2004). SOL requires the complete enumeration of the covariate which has limited its application in forest inventories in the past. However, because EFI provides such an enumeration, sampling across the range of EFI by SOL may provide a more efficient double sampling scheme than either SRS or SYS.

As pointed out above, the most efficient sample selection method should select sample units based on the proportion of their contribution to the population total (Yang et al. In Press; Grosenbaugh 1967; Basu 1969). Horizontal point sampling is an example of a variable probability selection method common in forest inventory (Bitterlich 1984; Kershaw et al. 2016) applied at the sample unit level. Two variable probability selection methods used in forest inventory are sampling with probability proportional to prediction (3P) and list sampling (LIST) (Freese 1962; Grosenbaugh 1967; Iles 2003; Kershaw et al. 2016; Lam et al. 2018).

3P is a sampling to correct approach based on predictions (Iles 2003), and was introduced by Grosenbaugh (1964, 1965). 3P selects samples based on a prediction and uses ratios to convert predictions to field measures (Mesavage 1965; Grosenbaugh 1979; Kershaw et al. 2016). Following Iles’ (2003) procedure, the cruiser predicts (or estimates) the attribute related to the variable of interest for each individual in the population (tree, plot, ALS cell, etc.), and compares this prediction to a uniform random number drawn from the expected range of predictions. If the prediction is equal to or greater than the random number, then the individual would be measured. The ratio of measurement to prediction for each individual is calculated, and an average of all the individual ratios is used to
correct or adjust the mean or total predicted attribute of interest in the end. 3P is a form of regression sampling where the entire enumeration of the covariate is obtained via predictions and the small samples are obtained using a variable probability selection based on the prediction of the individual. The sample size in 3P is uncertain because it cannot be precisely controlled. In its original derivation, rejection symbols were incorporated into the selection criteria to control the sample size (Mesavage 1965). A similar approach that has the same effect as rejection symbols is to control the range of the random numbers for obtaining the desired sample size (Iles 2003). The maximum random number, KZ, is a function of the expected value of the predictions (K) and the proportion of rejections (Z) required to control the number of individuals selected (Iles 2003). KZ can be calculated using:

\[
KZ = \frac{K}{p} = K \cdot \left(\frac{N}{n}\right)
\]

where KZ = the maximum value of the random numbers generated; K = the expected value (mean) of the predictions; p = proportion of population to be sampled; N = population size; and n = desired sample size. 3P was widely applied in the southeastern United States in the 1960s and 1970s (Steber and Space 1972; Grosenbaugh 1979), but has seen limited application in recent years because of the requirement to completely enumerate the population at the prediction phase (West 2015).

LIST is based on the probability proportional to contribution to the population total. The selection probability depends on previous listed quantities associated with the population (Grosenbaugh 1967; Kershaw et al. 2016). In the procedure, as illustrated by Kershaw et al. (2016), the list can be any quantity of compartments (or stands), and the quantity is
first cumulated across the whole population. After the random number between 0 and the total accumulation is drawn, a compartment is selected if a random number lies within the range of the cumulated sums. Thus, a compartment that has a larger quantity will have higher probability of being selected and measured in detail. In addition, LIST is conducted with replacement so that a listed compartment may be selected more than once from the population of interest. However, LIST requires the listing factor to be completely known in advance of sample selection. As a result, LIST is not often easily applied in practice (Furnival et al. 1987).

For SOL and the two variable probability selection methods, EFI provides a readily available listed covariate (or prediction) for the entire population. Combining the available listing factor from EFI and variable probability selection methods may provide an extremely efficient sampling to correct and locally calibrate EFI values derived from ALS for small woodlots.

2.2.2 Field Plot Type

Sample plots are commonly used to select individual trees for measurements. Two major approaches used in forest inventory are fixed area plots (FAP) and horizontal point sampling (HPS). FAP is the dominant tree selection method used in most LiDAR-assisted forest inventories (e.g., Corona and Fattorini 2008; Clementel et al. 2012; Melville et al. 2015), due to the perceived relationship between a space on the ground and an associated ALS point cloud. In the case of circular FAPs, the inclusion zones are all circles of equal size. On the other hand, HPS selects trees using imaginary inclusion zones of varying size proportional to tree cross-sectional area (Kershaw et al. 2016). The difference between the two methods is typically the number of trees measured at a given sample point. FAPs
generally lead to more measured trees per sample point so that FAPs are generally more expensive than HPS on a sample point basis. At the same time, HPS also incurs more inventory costs to achieve the same level of sampling error as FAPs because more sample points are required. The trade-off between costs of measuring more trees versus costs of establishing more sample points becomes an important consideration in making decisions between FAP and HPS.

The cost of tree measurements can be controlled by plot size, angle gauge size, or developing a subsampling scheme within sample points. Two probabilistic schemes are big BAF sampling (BBAF) and point-3P sampling (3PN). BBAF sampling using two angle gauges is an extension of HPS (Iles 2003; Marshall et al. 2004; Yang et al. 2017). A smaller angle gauge is used to count trees and estimate basal area per unit area, and a larger one selects trees for doing detailed measurements. The volume to basal area ratio (VBAR) is calculated from the measured trees for estimating plot and stand volumes.

3PN sampling is similar to the 3P selection described above. The desired tree attributes from measured trees are first predicted, and then the prediction is compared to a random number drawn from an appropriate range. Those trees whose predictions are greater than the random number will be measured in detail. As a result, the predicted attribute can be determined precisely, and the ratio between the measured and predicted values can be used to correct all of the predictions for a given point. Such subsampling schemes can be used to reduce field sample effort and associated field costs (Grosenbaugh 1967; Stamatellos 1995; Kershaw et al. 2016; Yang et al. 2017).
2.3 Methods

2.3.1 Study Area

The study area was the 80-ha Femelschlag Research Site on the Noonan Research Forest (NRF; N 45°59′12″, W 66°25′15″), managed by the University of New Brunswick’s Faculty of Forestry and Environmental Management in New Brunswick, Canada. The NRF has a permanent grid of big BAF (BBAF) inventory plots located on a North-South/East-West grid at 100 m spacing. The forest inventory is conducted every 10 years, with the inventory used in this study collected in 2012. The count BAF was 2M (i.e., each tallied tree represented 2 m$^2$ha$^{-1}$) and the measure BAF was 27M. For each count tree, diameter at breast height (DBH, nearest 0.1 cm), status (live/dead), and species were measured and recorded. On the measured trees, total height (TOTHT, nearest 0.1 m) was measured in addition to DBH. There were 1735 count trees and 100 measured trees recorded on the 83 sample points contained within the Femelschlag Research Site. The Femelschlag Research Site was established in 2014 with 83 fixed area sample plots (FAP) established on the same 100m by 100m forest inventory grid using the same plot centers as the BBAF. The fixed area plots had a radius of 11.28m (0.04 ha). The tree species, status, DBH and TOTHT were recorded for 6252 sample trees. Table 2.1 summarizes the plots and tree measurements for both the BBAF and FAP data.

The EFI estimates were provided by the Department of Energy and Resource Development, New Brunswick. The EFI estimates were derived from ALS collected in 2015. The cell resolution was 20 m by 20 m, and a total of 2181 cells covered the Femelschlag Research Site. While the EFI provides estimates of several forest attributes for each EFI cell, only gross total volume (GTV, m$^3$ha$^{-1}$) was used in this study.
Because our sampling grid and sample points were established prior to, and independent of, the LiDAR-assisted EFI, we did not have perfect spatial alignment with the EFI cells. Nor did we have wall-to-wall coverage in our field data. We are assuming that our grid is a representative sample of the area around the sample locations, and our goal is to use the EFI as a covariate and the field plots as the small sample for correction. Thus, in the simulation, each EFI cell was assigned to one of the 83 sample points based on nearest neighbor distances calculated from the cell center to the sample point. This will add variability to our results, but will demonstrate the power of the sampling to correct approach. As Iles (2003) pointed out, the covariates do not have to be correct, only consistent. Operationally, aligning field samples with EFI cells will produce more accurate results; however, we demonstrate that existing data can be effectively used in a sampling to correct approach.

2.3.2 Plot Compilation

For each of the 83 sample points, FAP and BBAF data were available. Four sample tree selection systems (plot types) were considered in this study: (1) fixed area plots with all trees measured (FAP); (2) fixed area plots with 3P subsampling of measured trees (3PN); (3) horizontal point sampling with all trees measured (HPS); and (4) big BAF sampling (BBAF).

Plot types (1) and (2) utilize the FAP data collected at each sample point. Plot type (1) is the full FAP data including all DBH and TOTHT measurements. The 3PN was simulated using height predictions based on a height-diameter model (MacPhee et al. 2018). As with 3P, predicted heights were compared to uniform random numbers between 0 and KZ (eq. 1, where K is the expected value of TOTHT, N is the total number of plot trees, and
n is the desired number of measure trees). If the predicted height ≥ the random number, the measured tree height would be used. The desired tree sample size (n) was set at the same level of effort as observed in the big BAF samples (n = 100 trees across the 83 field plots). KZ (the maximum random number) was calculated using average predicted height (K = 11.51 m), and N = 6252 sample trees. Volume per hectare (m³ha⁻¹) for full FAP plot was calculated by estimating total volume for each tree using the measured DBHs, TOTHTs and Honer et al.’s (1983) metric volume equations, and then summing over all trees on the plot and multiplying by the FAP expansion factor (25 for 11.28 m radius FAPs). For the 3PN plots, the ratio of measured TOTHT to predicted TOTHT (R_{TOTHT}) was calculated for each selected “measure” tree and averaged across all measure trees in the sample (\bar{R}_{TOTHT}). The mean ratio was then multiplied by each predicted TOTHT, and the adjusted TOTHTs and measured DBHs were used to estimate volume using the same process used on the full FAP.

To expand the BBAF data to mimic HPS data (Plot type 3), the NRF height-diameter model (MacPhee et al. 2018) was used to predict TOTHT on all count trees. Volume was then estimated using Honer et al.’s (1983) metric volume equations and multiplied by each tree’s associated expansion factor (varies with tree DBH) and summed to obtain volume per hectare (m³ha⁻¹) for each sample point. For the BBAF (Plot type 4), volume and VBAR were calculated for each measured tree across all samples, and the mean VBAR was then multiplied by each plot’s basal area per hectare (m²ha⁻¹) to estimate volume per hectare (m³ ha⁻¹) for each sample point (Iles 2003; Marshall et al. 2004).
2.3.3 Sample Simulation

As described above, the EFI cells formulate our large sample of covariates and we will select a smaller subsample of these cells to obtain field measurements. Five sample selection methods were simulated: (1) simple random sampling (SRS); (2) spatial systematic sampling (SYS); (3) systematic ordered-list sampling (SOL); (4) 3P sampling (3P); and (5) list sampling (LIST). At each selected EFI cell, four plot types (i.e., ground plots) were assigned to the selected cell: (1) full FAP; (2) 3PN; (3) full HPS; and (4) BBAF. Thus, there were 20 different sample designs explored (5 sample selection methods × 4 plot types).

As mentioned above, the grid point (field sample point) nearest the center of the EFI cell was assigned to each selected EFI cell. Sample sizes between 10 and 50, in steps of 5, were simulated for each of the five sample selection methods and each plot type was used at each selected cell. Each sample selection method × sample size was simulated 100 times. Sampling was conducted without replacement except for LIST which was conducted with replacement. Preliminary analyses showed that the EFI cells for Femelschlag Research Site did not have appreciable bias (approximately 2% - 9%, depending on plot type) relative to the field plots (bias was calculated as cell GTV – Field Volume, based on the nearest EFI cells). To test our hypothesis that the sampling to correct approach can be used to correct bias in EFI cells and provide meaningful comparisons between the different sample design combinations, we added multiplicative biases into each EFI cell by generating random numbers between 1.05 and 1.15 for 10% bias and 1.15 and 1.25 for 20% bias. All sample simulations were carried out in the R statistical program (R Development Core Team 2016).
2.3.4 Sample Compilation

Ratio estimation (Kershaw et al. 2016) was used to correct the EFI estimates with the small sample field volume estimates. For ith selected EFI cell in jth replicate sample in the kth sample design combinations (sample selection method × plot type × sample size), the ratio between EFI volume (GTV) and field volume (VOL) was calculated using:

\[ R_{ijk} = \frac{\text{VOL}_{ijk}}{\text{GTV}_{ijk}} \]  

(2)

where \( R_{ijk} \) = the ratio between EFI volume and field volume; \( \text{VOL}_{ijk} \) = field estimated volume per ha using one of the 4 plot types; and \( \text{GTV}_{ijk} \) = the EFI estimated volume per ha for the ith 20 m by 20 m cell in the jth replicate sample. The mean ratio was then calculated for jth replicate sample in the kth sample design combinations:

\[ \bar{R}_{jk} = \frac{\sum_{i=1}^{m} R_{ijk}}{m_{jk}} \]  

(3)

where \( \bar{R}_{jk} \) = the mean ratio of jth replicate sample within kth sample design combination; and \( m_{jk} \) = the number of samples. Adjusted EFI volume is then obtained using:

\[ \hat{\text{VOL}}_{ijk} = \bar{R}_{jk} \cdot \text{GTV}_{i} \]  

(4)

The mean adjusted volume was then calculated as:

\[ \frac{\sum_{i=1}^{N} \hat{\text{VOL}}_{ijk}}{N} \],

(5)

and sample error was calculated using Bruce’s (Goodman 1960) formula:
\[
se\% (\text{VOL}_{jk}) = \sqrt{se\% (\text{R}_{jk})^2 + se\% (\text{GTV})^2}
\]  

where \(se\% (\text{VOL}_{jk})\) = the percent standard error of the mean adjusted volume;

\(se\% (\text{R}_{jk})\) = the percent standard error of the mean ratio; and \(se\% (\text{GTV})\) = the percent standard error of the EFI estimated volume. The percent standard error was calculated using:

\[
se\% (X) = 100 \times \left( \frac{s(X) / \sqrt{m}}{X} \right) = \left( \frac{CV(X)}{\sqrt{m}} \right);
\]

where \(X = R\) or \(GTV\); \(\bar{X} = \bar{R}\) or \(\bar{GTV}\) (averages); \(s(X)\) = standard deviation of \(X\), \(m\) = sample size; and \(CV(X)\) = coefficient of variation of \(X\).

### 2.3.5 Data Analyses

#### 2.3.5.1 Sample Design Effects

The effects of the different sample design combinations on the distributions of \(\text{VOL}_{jk}\) and \(se\% (\text{VOL}_{jk})\) are examined using horizontal error bar plots and bean plots (Kampstra 2008), respectively. To assess overall sampling efficiency and determine the variance contributions of selection methods and plot types, a nonlinear mixed effects model was fitted:

\[
se\% (\text{VOL}_k) = \frac{b_0}{m^{b_1}}
\]
where $m = \text{sample size}$; and $b_i = \text{regression coefficients}$. Random effects were fitted using sample selection method and plot type nested within sample selection method to both coefficients. With the use of equation 8, minimum sample size requirements were determined for the 5% error level, and the design effect (Särndal et al. 1992) was calculated using:

$$DE_{rs} = \frac{m_{5\%}, r}{m_{5\%}, s}$$

where $DE_{rs} = \text{the design effect between sample design } r \text{ and } s$; $m_{5\%}, r = \text{the sample size requirement to achieve 5\% error from sample design } r$; and $m_{5\%}, s = \text{the sample size requirement to achieve 5\% error from sample design } s$. For display purposes, we show $DE_{rs}$ in the positive (up) direction when design $s$ is more efficient than design $r$, and we show the inverse of $DE_{rs}$ (i.e., $DE_{sr}$) when design $r$ is more efficient than design $s$ (this scales the two ratios to the same level and facilitates display and comprehension of design effects).

### 2.3.5.2 Influence of Cost Constraints on Optimal Sample Design

A field survey design usually needs to consider not only statistical efficiency, but also time and cost (Smith 1938). Both Lynch (2017) and Yang et al. (2017) showed that optimal sample design varies in relationship to cost constraints. Yang et al. (2017) showed that, when inventory resources were limited, sampling design became more critical to optimizing resource allocation than when inventory resources were more abundant. Building upon the work of Lynch (2017), Yang et al. (2017) expressed total inventory cost as:

$$C_{\text{Tot}} = C_{\text{Overhead}} + C_{\text{Mans}} + C_{\text{Travel}}$$

(10)
where \( C_{\text{Tot}} \) = total inventory cost; \( C_{\text{Overhead}} \) = the fixed overhead cost (e.g. the planning, preparation and compilation), \( C_{\text{Meas}} \) = the total sample point measurement cost; and \( C_{\text{Travel}} \) = the plot-to-plot travel cost. Because \( C_{\text{Overhead}} \) is a fixed cost, only \( C_{\text{Meas}} \) and \( C_{\text{Travel}} \) depend on sample size. \( C_{\text{Meas}} \) is composed of plot establishment costs, plot tree identification costs, and tree measurement costs:

\[
C_{\text{Meas}} = C_p + k \cdot E[c] \cdot m + r \cdot M
\]  

(11)

where \( C_p \) = the sample point establishment cost; \( k \) = the per tree cost to determine an “in” tree, identify species, and measure DBH; \( E[c] \) = the expected number of trees per sample point; \( m \) = the required sample size; \( r \) = the cost of measurement of other tree attributes (TOTHT, in this study); and \( M \) is the total number of measure trees \( (M = m \cdot \text{number of measure trees per plot}) \). Zeide (1980) estimated the travel distance between two sampling points using a square grid: \( d = \sqrt{A/m} \) \( (A \) is total area of forest in square of units of distance). The equation for \( C_{\text{Travel}} \) can then be expressed as:

\[
C_{\text{Travel}} = C_d \cdot m \cdot \sqrt{A/m} = C_d \cdot \sqrt{A \cdot m}
\]  

(12)

where \( C_d \) = the travel cost per meter.

Given equations 10, 11, and 12, costs for a given sample size and sample design were estimated. Finally, the design effect was expressed as the ratio of costs:

\[
DE_{rs} = \frac{C_{5\%,r}}{C_{5\%,s}}
\]  

(13)

The inventory costs used in this study were based on ancillary data collected on the NRF (Yang et al. 2017): \( C_0 = 1300, C_p = 2.70, k = 0.675, r = 4.41, \) and \( C_d = 0.0945 \) (Canadian dollars). Crew size was assumed constant (2 people) for all designs.
2.4 Results

The differences in mean adjusted volumes $\overline{VOL}_{jk}$ and their standard errors across the three bias levels (no bias, 10%, and 20% bias added) were negligible, except for SRS; therefore, we only present results based on 10% bias to illustrate the ability of the “sampling to correct” approach.

2.4.1 Sample Design Effects

Figure 2.1 shows the mean and range of estimated $\overline{VOL}_{jk}$ by different sample designs with the level of 10% added bias. Field measured volume varied with plot types (Figure 2.1): fixed area plots with full measurement (FAP) averaged $272.8$ m$^3$ha$^{-1}$; fixed area plots with 3P subsampling (3PN) averaged $270.5$ m$^3$ha$^{-1}$; horizontal point sampling (HPS) averaged $247.0$ m$^3$ha$^{-1}$; and big BAF sampling (BBAF) averaged $256.2$ m$^3$ha$^{-1}$.

Although the range of $\overline{VOL}_{jk}$ for equal probability selections were greater than the 95% confidence interval (CI) of 83 field plot measured volumes and variable probability selection, average $\overline{VOL}_{jk}$ for every combination was close to the mean field measured volume (Figure 2.1), except for systematic ordered-list sampling (SOL). As sample size increased from 10 (Figure 2.1A) to 40 (Figure 2.1D), the range of $\overline{VOL}_{jk}$ for 3P and LIST generally produced narrower ranges in estimated $\overline{VOL}_{jk}$ than equal probability selection methods. SOL consistently had the most extreme $\overline{VOL}_{jk}$ when sample size equaled to 10 (Figure 2.1A); however, this difference was minimal as sample size increased. 3P generally had the smallest range of estimated $\overline{VOL}_{jk}$ for most plot types.
and sample sizes, except LIST had smaller ranges than 3P for HPS and BBAF plots for sample sizes 20 (Figures 2.1B). Minimal differences were observed for the largest sample size (Figure 2.1D).

The $\text{se}(\overline{\text{VOL}}_{jk})$ decreased with increasing sample size for all sample design combinations (Figure 2.2). While all selection methods produced many sample instances with low $\text{se}(\overline{\text{VOL}}_{jk})$, the equal probability methods often produce extreme values which increased their mean $\text{se}(\overline{\text{VOL}}_{jk})$. 3P and LIST had lower mean $\text{se}(\overline{\text{VOL}}_{jk})$ than all the equal probability selection methods. Plots using subsampling methods (3PN and BBAF) had smaller mean $\text{se}(\overline{\text{VOL}}_{jk})$ than the plots where all trees were measured (FAP and HPS; Figure 2.2).

The fixed effects component of q. 8 only explained 13% of the variation in $\text{se}(\overline{\text{VOL}}_{jk})$ and the full model including the random effects explained 19% with an overall root mean square error of 3.5%. The fixed parameter estimates were: $b_0 = 25.0915 (1.98981)$ and $b_1 = 0.4223 (0.02181)$. The standard errors for the random effects associated with sample selection method were: $s(b_0) = 4.2605$ and $s(b_1) = 0.0431$; and those associated with plot type nested within sample selection method were: $s(b_0) = 3.0578 \times 10^{-8}$ and $s(b_1) = 3.1263 \times 10^{-2}$. While the model accounts for a small percentage of the variation due to high variability in some sample designs (especially in SOL), the results are still informative and useful for sample design comparisons.

Table 2.2 shows the combined fixed + random effects coefficient estimates by sample selection methods and plot types. The $b_0$ is the theoretical maximum standard error, and the $b_1$ represents the rate of standard error reduction with increasing sample size.
Theoretically, \( b_1 \) should equal 0.5. The \( b_0 \) of SRS and SYS were similar; SOL had the largest \( b_0 \) estimate, and 3P had the lowest estimate. The \( b_0 \) estimate of LIST was higher than SRS and SYS. The \( b_1 \) coefficients for SRS and SYS were usually lower than the ones obtained for variable probability selection methods. The \( b_1 \) estimates were slightly lower than 0.5 in general, except for LIST with the two fixed area plot types (FAP and 3PN). Based on the same sample selection method, the use of subsampling within plots (3PN and BBAF) also had higher \( b_1 \) coefficients than all trees measured within plots (FAP and HPS). Larger \( b_1 \) coefficients represent more efficient designs while larger \( b_0 \) coefficients represent more variable designs.

Table 2.3 shows the required sample sizes for 5% standard error derived from eq. 8. The required sample sizes did not increase substantially across the different bias levels, except for SRS. For SRS, the required sample sizes increased proportionally to the bias level increment (Table 2.3). LIST required the lowest sample sizes for all plot types and bias levels. Figure 2.3 shows the design effect based on minimum required sample sizes. FAP under SRS and SYS were more efficient than HPS and BBAF, except when these plot types were selected using 3P or LIST. 3P and LIST for all plot types were generally more efficient than other selection methods, especially for the two fixed area plot types (FAP and 3PN). LIST with 3PN was more efficient than all other sample selection method × plot type combinations.

### 2.4.2 Costs

Unlike the higher design effects (i.e., more sample efficiency) derived from sample sizes associated with FAP (Figure 2.3), when costs were considered, FAP no longer had any positive design effects except when used with variable probability selection methods.
(Figure 2.4). As with sample size (Figure 2.3), variable probability selection was more efficient than equal probability designs (Figure 2.4). Subsampling plot types had larger cost-based design effects than the plot types with full tree measures (Figure 2.4). As a result, the total costs associated with 3PN and BBAF were much less than the plot types without subsampling (Figure 2.5). Because fixed area plots had more expected “in” trees per plot than HPS (Table 2.3), even though 3PN had lower required sample sizes than BBAF (Table 2.3 & Figure 2.3), the costs for 3PN were still higher than BBAF (Figures 2.4 & 2.5).

2.5 Discussion

Under the “sampling to correct” approach, auxiliary variables which support a sampling process should not be a source of bias (Iles 2003) as long as the primary variable (small sample) is unbiased. As a result, bias can be corrected using ratio estimation without substantially increasing sampling effort. Our results support this opinion, except for SRS (Table 2.3). Because SRS does not consider any information about the population and the added bias increased population variance, SRS required more samples as bias increased (Table 2.3). SYS and SOL, which also are equal probability selection procedures, ensure spatial or distributional coverage across the population range, and, as a result, the added bias did not have a substantial impact on sample sizes (Table 2.3).

In theory, SOL should be more efficient than SRS and SYS because SOL samples across the range of the population (Iles 2003). However, in our case, SOL produced the most extreme volume estimates (Figure 2.1) and required more samples to achieve a given standard error (Table 2.3 & Figure 2.2). This results from our calculation of the ratios of field volume to EFI volume using the nearest field plot to the selected EFI cell, rather
than a field plot measured at the same position. Given the 100 m spacing of field plots, EFI cells could be as much as 71 m away from the field plot. While our study area was relatively uniform, local variation can be large. A large-valued field plot, coupled with an EFI cell centered on a small gap or at edge, can result in a very large ratio, which could bias the overall average ratio and subsequent corrected volume estimate. Given that SOL ensures sampling across the range of EFI values, these extreme estimates were more likely given our data limitations, especially at the lowest sample sizes (Figure 2.1A). At the larger sample sizes (Figures 2.1C & 2.1D), SOL was on par with SYS and slightly better than SRS.

While most ALS inventory studies align field plots and ALS cells (White et al. 2013), this was not done here because the pre-existing field plot data sets that were established prior to and independent of the EFI cells developed by the province of NB. We further added to variability by using all EFI cells and matching closest field plots. This was purposely done to increase the population size (large sample) and variability for our sample simulations. Despite this, the sampling to correct approach was still robust, producing unbiased estimates with relatively small, cost-effective sample sizes. This study demonstrates that it is possible to use existing ground data that does not exactly align directly with EFI cells for the purpose of locally calibrating LiDAR-assisted predictions. In practice, only the EFI cell that contained the field plot center would be used for developing correction ratios. The fundamental outcome of this study is the requirement for an underlying, probabilistic sample at the second stage (Iles 2003). The small sample enables us to estimate a total, the large sample enables us to spread that total over the area of interest (Freese 1962; Iles 2003).
Variable probability selection, which allows sampling with probability proportional to the variable of interest (Basu 1969; Iles 2003; Kershaw et al. 2016), minimized extreme value estimates (Figure 2.1), reduced overall sample size requirements (Table 2.3, Figures 2.2 & 2.3), and reduced inventory costs (Figures 2.4 & 2.5). Both 3P and LIST were superior to any of the equal probability selection methods for all criteria evaluated in the study. In traditional forest inventory, these methods were not widely implemented because of the census demands (either a priori for LIST or concurrent for 3P). ALS can provide suitable lists of covariates for LIST and 3P. Besides the EFI-estimated volume that was used in this study, covariates extracted directly from ALS point cloud data also can be used (Yang et al. In Press). Similar to Yang et al.’s (In Press) work, Parker and Evans (2004, 2009) applied double sampling with LiDAR to estimate forest and individual tree attributes; their results showed that double sampling could be an effective approach to LiDAR enhanced inventory estimation, but only used systematic plot selection methods. Other authors have explored additional sample selection criteria, such as space filling designs (Junttila et al. 2013) and local pivotal methods (Grafström et al. 2012; Grafström and Ringvall 2013). These designs are similar to SOL in that they attempt to balance sample allocation across multiple spatial and statistical dimensions. Yang et al.’s (In Press) results found that the local pivotal method performed as well as 3P and LIST when developing forest-level LiDAR-assisted inventories. We did not consider these designs in this study.

Inventory costs are often viewed as a constraint (Husch 1980) rather than a design factor (Lynch 2017; Yang et al. 2017). The cost of a sample procedure is influenced by two factors: (1) required sample size, which is mainly influenced by sample selection
methods (Table 2.3, Figures 2.2 & 2.3); and (2) the number of “in” trees (E[c]) and measured trees (M) which are dependent on plot type and size. Because the spatial extent in this study was only 83 ha, which can be considered a stand-level or small woodlot inventory, the cost for tree measurement is much higher than for traveling between plots (Yang et al. 2017). Thus, plot type was the major factor impacting total costs rather than selection methods. Sample size generally is the main factor considered in sample design and assessment of sample efficiency; however, our study shows the importance of considering plot type and numbers of individual trees measured per plot (Figures 2.4 & 2.5). HPS, as a variable probability selection method, has lower numbers of “in” trees than FAP (Table 2.3) and is easy to apply in field. Although in our study area, HPS and BBAF required larger sample sizes than FAP and 3PN, they still had lower costs. Plot types with subsampling saved much more effort in measuring trees than on plot types where all measurements are made (Table 2.3). 3PN and BBAF use ratios between the estimates and subsampled measurements. Ratios are an effective approach for reducing variation between individual measurements (Iles 2003; Marshall et al. 2004). Larger landscape or forest level inventory efforts will result in different unit costs, especially in the travel between plots. Effective sampling designs would need to take these costs into consideration. Stratified sampling or cluster sampling may be more effective as spatial scale increases (Schreuder et al. 1993; Gregoire and Valentine 2008). However, even with these designs, the principles of variable probability sampling can be applied to individual sampling unit selection and should be considered. Our study shows how LiDAR-assisted forest inventory estimates can be corrected for localized conditions, and the potential for sampling to correct as an approach for local
calibration. Sampling to correct can be applied to not only LiDAR-assisted estimates but other remote sensing techniques, such as satellite data and even ground-based optical sensors (Hsu In Prep.). As ALS data become more readily available (efforts in Atlantic Canada are underway to make ALS point cloud data and EFI estimates publicly available), the applications presented in this study become feasible for both large industrial forest landholders as well as smaller private woodlot owners, giving them high-resolution forest information that is locally calibrated to support management decisions. This approach can be used to estimate any parameter of interest, including biomass or carbon content (Chen et al. In Prep.); providing a flexible and general approach to working with high resolution ALS enhanced forest inventory estimates.

2.6 References


Bell JF, Iles K, Marshall D (1983) Balancing the ratio of tree count-only sample points and VBAR measurements in variable plot sampling. In: Bell J.F. and Atterbury,


Chen Y, Kershaw JA Jr, Lavigne MB, et al (In Prep.) Carbon estimation using sampling to correct LiDAR-assisted forest inventory


Freese F (1962) Elementary forest sampling. US Department of Agriculture


Gambill CW, Wiant HV, Yandle (1985) Optimum plot size and BAF. For 31:587–594


Grosenbaugh LR (1979) 3P sampling theory, examples, and rationale. US Department of Interior, Bureau of Land Management


Grosenbaugh LR (1965) THREE-PEE SAMPLING THEORY and program “THRIP” for computer generation of selection criteria. USDA Forest Service, Pacific Southwest Forest Experiment Station


Honer TG, Ker MF, Alemdag IS (1983) Metric timber tables for the commercial tree species of central and eastern Canada. Canadian Forestry Service, Maritimes Forest Research Centre

Hsu Y-H (In Prep.) Applications of variable probability sampling using remotely sensed covariates. University of New Brunswick


Lynch TB (2017) Optimal plot size or point sample factor for a fixed total cost using the Fairfield Smith relation of plot size to variance. Forestry 90:211–218


Steber GD, Space JC (1972) New inventory system sweeping the south. J For 70:76–79
West PW (2015) Tree and forest measurement, 3rd edn. Springer International Publishing


Table 2.1 Minimum, average, and maximum of total number of trees per plot, total number of species per plot, total number of trees per hectare, basal area (m²/ha), diameter at breast height (DBH, cm) total height (TOTHT, m) for fixed area plots and big BAF points.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Fixed Area Plots</th>
<th>Big BAF Points¹</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Min.</td>
<td>Mean</td>
</tr>
<tr>
<td>Number of Trees (stems/plot)</td>
<td>23</td>
<td>75</td>
</tr>
<tr>
<td>Number of Species (per plot)</td>
<td>2</td>
<td>5.4</td>
</tr>
<tr>
<td>Density (stems/ha)</td>
<td>575</td>
<td>1883</td>
</tr>
<tr>
<td>Basal Area (m²/ha)</td>
<td>20.86</td>
<td>40.18</td>
</tr>
<tr>
<td>DBH (cm)</td>
<td>6.0</td>
<td>14.5</td>
</tr>
<tr>
<td>TOTHT (m)</td>
<td>3.1</td>
<td>12.0</td>
</tr>
<tr>
<td>Measure Trees (stems/plot)</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>Number of Measure Species (per plot)</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>Measure DBH (cm)</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>Measure TOTHT (m)</td>
<td>---</td>
<td>---</td>
</tr>
</tbody>
</table>

¹ On big BAF points, only DBH was measured on the count tree
Table 2.2 Coefficient estimates (fixed + random effects) of the nonlinear mixed effect model (Eq. 8) for estimating minimum sample size requirements for the scenario with 10% added bias by selection method and plot type. (Five sample selection methods: SRS = simple random sampling, SYS = systematic sampling, SOL = systematic ordered-list sampling, 3P = sampling with probability proportional to prediction, LIST = list sampling. Four plot types: FAP = fixed area plot, 3PN = fixed area plots with 3P subsampling of measured trees, HPS = horizontal point sampling, BBAF = big BAF sampling.)

<table>
<thead>
<tr>
<th>Plot Type</th>
<th>SRS</th>
<th>SYS</th>
<th>SOL</th>
<th>3P</th>
<th>LIST</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$b_0$</td>
<td>$b_1$</td>
<td>$b_0$</td>
<td>$b_1$</td>
<td>$b_0$</td>
</tr>
<tr>
<td>FAP</td>
<td>22.4523</td>
<td>0.3867</td>
<td>22.5925</td>
<td>0.3879</td>
<td>32.8344</td>
</tr>
<tr>
<td>3PN</td>
<td>22.4523</td>
<td>0.3976</td>
<td>22.5925</td>
<td>0.4011</td>
<td>32.8344</td>
</tr>
<tr>
<td>HPS</td>
<td>22.4523</td>
<td>0.3445</td>
<td>22.5925</td>
<td>0.3480</td>
<td>32.8344</td>
</tr>
<tr>
<td>BBAF</td>
<td>22.4523</td>
<td>0.3629</td>
<td>22.5925</td>
<td>0.3654</td>
<td>32.8344</td>
</tr>
</tbody>
</table>
Table 2.3 The required sample sizes under 5% sampling error for each combination of sample selection methods and plot types by three bias levels (No bias; 10% bias, and 20% bias). (Five sample selection method: SRS = simple random sampling, SYS = systematic sampling, SOL = systematic ordered-list sampling, 3P = sampling with probability proportional to prediction, LIST = list sampling. Four plot types: FAP = fixed area plot, 3PN = fixed area plots with 3P subsampling of measured trees, HPS = horizontal point sampling, BBAF = big BAF sampling. \(E[c]\) = the expected number of trees per sample point, Meas = the expected number of tree measurements per sample point.)

<table>
<thead>
<tr>
<th>Plot Type</th>
<th># trees/plot ((E[c]/) Meas)</th>
<th>Selection Method</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SRS</td>
<td>SYS</td>
</tr>
<tr>
<td></td>
<td>No bias</td>
<td>10%</td>
</tr>
<tr>
<td>FAP</td>
<td>75.3/ 75.3</td>
<td>43</td>
</tr>
<tr>
<td>3PN</td>
<td>75.3/ 1.3</td>
<td>39</td>
</tr>
<tr>
<td>HPS</td>
<td>20.9/ 20.9</td>
<td>61</td>
</tr>
<tr>
<td>BBAF</td>
<td>20.9/ 1.2</td>
<td>52</td>
</tr>
</tbody>
</table>
Figure 2.1 Comparison of field measured volumes with 95% confidence intervals based on the full 83 samples and the mean and range of \overline{\text{VOL}} (with 10% bias added) for the 100 replicates by five sample selection methods and four plot types. (Five sample selection methods: SRS = simple random sampling, SYS = systematic sampling, SOL = systematic ordered-list sampling, 3P = sampling with probability proportional to prediction, LIST = list sampling. Four plot types: FAP = fixed area plot, 3PN = fixed area plot with 3P subsampling of measured trees, HPS = horizontal point sampling, BBAF = big BAF sampling. ave. \overline{\text{VOL}} = average of the 100 \overline{\text{VOLs}}, \overline{\text{GTV}} = uncorrected EFI volume with 10% bias, \overline{\text{Field.VOL}} = mean of field measured volume. For FAP and 3PN, the field volume is based on the fixed area plot measures; and for HPS and BBAF, it is based on the big BAF points with predicted heights)
Figure 2.2 The averages and distributions of $\text{se} \% \left( \overline{\text{VOL}} \right)$ with 10% bias by five sample selection methods and four plot types across the range of sample sizes (10 to 50). (Five sample selection method: SRS = simple random sampling, SYS = systematic sampling, SOL = systematic ordered-list sampling, 3P = sampling with probability proportional to prediction, LIST = list sampling. Four plot types: FAP = fixed area plot, 3PN = fixed area plot with 3P subsampling of measured trees, HPS = horizontal point sampling, BBAF = big BAF sampling.)
Figure 2.3 Sample size-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 (positive) bars indicate that the sampling design in the panel name is more effective than the sample design on the x-axis (DE was calculated as x-axis sample size/panel sample size). Downward pointing (negative) bars indicate the x-axis design is more efficient than the named panel design (DE was calculated as panel design sample size /x-axis sample size). (Five sample selection method: SRS = simple random sampling, SYS = systematic sampling, SOL = systematic ordered-list sampling, 3P = sampling with probability proportional to prediction, LIST = list sampling. Four plot types: FAP = fixed area plot, 3PN = fixed area plot with 3P subsampling of measured trees, HPS = horizontal point sampling, BBAF = big BAF sampling.)
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 (positive) bars indicate that the sampling design in the panel name is more cost-effective than the sample design on the x-axis (DE was calculated as x-axis cost/panel cost). Downward pointing (negative) bars indicate the x-axis design is more cost-efficient than the named panel design (DE was calculated as panel design cost/x-axis cost). Five sample selection method: SRS = simple random sampling, SYS = systematic sampling, SOL = systematic ordered-list sampling, 3P = sampling with probability proportional to prediction, LIST = list sampling. Four plot types: FAP = fixed area plot, 3PN = fixed area plot with 3P subsampling of measured trees, HPS = horizontal point sampling, BBAF = big BAF sampling.)
Figure 2.5 Total costs by five sample selection methods and four plot types across three bias levels (No bias; 10% bias, and 20% bias). (Five sample selection method: SRS = simple random sampling, SYS = systematic sampling, SOL = systematic ordered-list sampling, 3P = sampling with probability proportional to prediction, LIST = list sampling. Four plot types: FAP = fixed area plot, 3PN = fixed area plot with 3P subsampling of measured trees, HPS = horizontal point sampling, BBAF = big BAF sampling.)
Chapter 3 3P sampling using a 360 spherical camera
3.1 Introduction

In practice, forest inventory is designed to obtain estimates of forest conditions under time and cost constraints. Enhancing sampling efficiency is an important consideration in sampling design (Freese 1962; Husch 1971; Grosenbaugh 1979; Bitterlich 1984; Iles 2003; Lynch 2017; Yang et al. 2017). Following the sampling principle claimed by Basu (1969), the most efficient sampling design is the one in which the selection probability is proportional to the parameters of interest, suggesting that variable probability selection methods should be considered. Variable probability sampling, which is regarded as a variant of double sampling, can be divided into two components: (1) selection criteria and (2) estimation method. For the selection criterion, the original idea was sampling with probability proportional to size (i.e., list sampling). List sampling selects proportional to the sampling unit’s contribution to the population (Freese 1962; Cochran 1977; Kershaw et al. 2016); however, it requires a prior census of the entire covariate population. Suitable listed covariates in advance of an inventory are usually hard to obtain, so that the application of list sampling is restricted in practice (Furnival et al. 1987). To address this issue, sampling with probability proportional to prediction (3P sampling) was introduced by Grosenbaugh (1965).

The idea of 3P sampling is to establish a selection probability based on a prediction of sampling units. Following the procedure from Iles (2003), the parameter of interest or a variable closely related to the parameter of interest for each sampling unit is predicted and compared with a uniform random number drawn from a predetermined range. If the prediction is greater than or equal to the random number, then the sampling unit is selected for detailed measurement. Since the prediction can be made in the field, there is
no need for the census prior to selection process. In fact, the census is developed during the sampling process. At the second step of the sampling process, ratio estimation methods are applied to convert (or calibrate) the prediction to the parameter of interest (Freese 1962; Grosenbaugh 1965; Iles 2003; Kershaw et al. 2016). The mean ratio between the subsample of measurements and predictions is calculated and used to adjust all predictions. The advantage is that any bias in the prediction can be corrected when the covariate measurements are unbiased, and the precision of estimate can be improved using the ratio estimate (Grosenbaugh 1965; Iles 2003; Hsu et al. In Review).

Since all sampling units need to be visited and predicted in the 3P sampling process, obtaining reliable and repeatable predictions rapidly in field can make the process more efficient. Traditionally, visual estimates were made; however, a potential method could be to generate predictions using a 360° spherical camera. Photographic techniques have been used in forest inventory for decades (MacLeod 1919; Andrews 1936; Husch 1947). DeCourt (1956) proposed the use of angle count sampling with terrestrial photographs. Grosenbaugh (1963) developed a detailed treatise on optical dendrometer theory including applications to photographs. Stewart (2004) applied DeCourt’s (1956) ideas to digital photographs and developed distortion corrections for individual photos. Ducey and Kershaw (2011) developed methods for using digital cameras to assist in vertical point sampling. Fastie (2010) and Dick (2012) independently developed methods to estimate stand basal area from 360° horizontal panoramas.

The methods proposed by Fastie (2010) and Dick (2012) required multiple photos acquired in the field and significant post-processing of the photos in the office to stitch and extract basal area estimates. The post-processing time may be greater than the time
required to obtain the measurements in the field, and the estimates are most likely negatively biased due to occluded (hidden) trees. The recently available consumer-grade 360° spherical cameras offer an alternative digital source that can rapidly record a full view of forest conditions, including the vertical forest structure, in a single image. Rather than extracting complicated tree and stand measurements, such as those obtained by Perng et al. (2018), we propose the use of spherical images to obtain an easy covariate to be used in a 3P sampling scheme.

The purpose of this study was to evaluate the sampling efficiency of 3P sampling with different photo-derived covariates. List sampling using attributes derived from aerial light detection and ranging scanning (ALS) is used as the benchmark comparison in this study, because it was found to be the most efficient sampling process in two recent studies (Hsu et al. In Review; Yang et al. In press). In addition, the effect of plot type (fixed area plot versus big BAF sample plot) is also explored. Therefore, the main objectives are (1) to assess and compare sampling efficiency of 3P sampling using covariates derived from spherical photograph versus list sampling via ALS attributes; and (2) to explore the effect of plot type on sampling efficiency.

3.2 Methods

3.2.1 Study Site and Field Data

The study area is the 80 ha Femelschlag Research Site located in the Noonan Research Forest (NRF), managed by the University of New Brunswick, Canada. Operationally, the NRF is inventoried using big BAF sample plots on a 100m × 100m sample grid across the entire forest, and 83 of these sample points are located within the Femelschlag
Research Site. These points are re-measured every 10 years, with the last measurement in summer 2012. The big BAF sampling process employed on the NRF used a 2M BAF angle gauge (i.e., each count tree represents $2 \text{ m}^2 \text{ha}^{-1}$ basal area) for selecting count trees. Species, diameter at breast height (DBH, nearest 0.1 cm, breast height = 1.3 m) and status (live/dead) were measured and recorded for all count trees. A 27M BAF angle gauge was used to select measure trees. Total height (HT, nearest 0.1 m) was measured on these trees, and individual tree volume was estimated using Honer et al. (1983) volume equations. The volume to basal area ratio (VBAR) for each measure tree was calculated. Mean VBAR ($\overline{\text{VBAR}}$) was estimated from the individual ratios and was multiplied by the basal area per hectare ($\text{m}^2 \text{ha}^{-1}$) of each sample point to estimate volume ($\text{m}^3 \text{ha}^{-1}$).

Within the Femelschlag Research Site, $1/25^{\text{th}}$ ha fixed area plots (11.28m radius circular plots) were established on the same 83 sample points as the big BAF operational inventory in 2014. For each tree $\geq 6.0 \text{ cm at DBH}$, species, status (live/dead), DBH, and HT were measured and recorded. As with the big BAF plots, Honer et al. (1983) volume equations were used to estimate individual tree volume and volume per ha ($\text{m}^3 \text{ha}^{-1}$) obtained by summing individual tree volume and multiplying by the plot expansion factor (25 in this study).

The ALS data for the NRF were obtained in October 2011 under leaf-off conditions. The height of the 45th quantile of point cloud (L[Q45]) in 20 m by 20 m cells centered on the 100 m grid was used as the listing attribute in this study based on previous results on the NRF (Yang et al. In press; Hayashi et al. 2015).

In summer 2018, spherical photos of the 83 Femelschlag Research Site sample points were obtained using a Ricoh Theta 360° spherical camera (https://theta360.com/en/).
spherical camera was set at 1.6 m above ground at each sample point. Two sample points were disturbed by harvesting activities associated with the Femelschlag study in 2016. This makes the field measurements irreconcilable with the photo estimates; thus these two sample points were excluded from this study, leaving 81 sample points for the sampling simulations described below.

3.2.2 Spherical camera attributes

In this study, three covariates were derived from the spherical photographs and used as predictors in the 3P sampling process. Ranked (highest to lowest) by the amount of time required to process estimates in field, the three photo-derived covariates were: (1) stand basal area \( P[BA] \); (2) sum of square heights per hectare \( P[SHT] \); and (3) stem fraction \( P[SF] \).

\( P[BA] \) was estimated from the spherical photographs using a modified horizontal point sampling (HPS) process derived from the processes described by DeCourt (1956), Stewart et al. (2004), and Dick (2012). A custom processing program, developed by Wang (In Prep.), was used to obtain tree counts. The spherical photographs were transformed into cylindrical projections (panoramas), and the trees counted using a 2M BAF target along the vertical center of the panorama photos (1.6 m in this case). The number of count trees in each photo was multiplied by the BAF to obtain an estimate of \( P[BA] \) \( \text{m}^2\text{ha}^{-1} \) for each plot. For a complete description of the processing program and workflows see Wang et al. (In Prep).

Ducey and Kershaw (2011) showed that vertical point sampling (VPS) could be an effective covariate in a double sampling framework using vertical digital photographs.
VPS is a variant of HPS introduced by Hirata (1955). In VPS, the radius of the inclusion zone is proportional to tree height, rather than proportion to tree diameter. As a result of the selection geometry, the square of tree height factor (SHF) is the constant factor in VPS and is calculated using:

$$\text{SHF} = \frac{10000 \cdot \tan \phi}{\pi}$$  \hspace{1cm} (1)

where $\phi = \text{the vertical angle (90 - zenith angle)}$. The SHF used in this study was 4520.9 m$^2$ha$^{-1}$ associated with a 50° vertical angle (40° zenith angle). To apply VPS using a spherical photograph, a line drawn at the 50° parallel (40° zenith angle) on the cylindrical projection (panorama view) is used to count trees. Trees taller than the line are counted on each photograph. The number of count trees was then multiplied by the SHF to yield an estimate of the sum of square height (P[SHT]) for each plot.

Stem fraction (P[SF]), defined as the proportion of the photograph occupied by stem wood, was computed as the stem coverage weighted in different zenith angle using a hemispherical projection of the spherical photograph (Wang In Prep.). The algorithms for hemispherical image transformation and image pixel classification (stem, foliage and sky) were developed by Wang (In Prep.). The Beer-Lambert law, a theoretical calculation of light transmission through suspended particles (Lambert 1760; Beer 1852), is frequently used to extract canopy structure attributes from hemispherical photos (Fournier et al. 2017). Light transmission through the canopy is assumed to be equivalent to light penetrating a medium with randomly distributed particles, and the proportion of light passing is reduced as distance passed through the medium increases (in this case as
zenith angle increases). In this study, the pixel weight (wt) for different zenith angles (\( \theta \)) was calculated using a formula adapted from the Beer-Lambert law:

\[
wt = 1 - e^{\left(1 - \frac{\pi}{2\theta}\right)}
\]  

(2)

The function gives the highest weight to the pixel at \( \theta = 0 \), and decreases as \( \theta \) increases. If the pixel is classified as stem wood, then the weight (wt) for that zenith angle is assigned to that pixel, otherwise 0 is assigned to that pixel. P[SF] is obtained by summing the pixel weights and dividing by the total number of pixels.

### 3.2.3 Sample Simulation

To test the use of the covariates derived from the spherical photo as 3P predictors for volume, sample simulation was used. Two key issues were addressed in this paper: (1) the efficiency and accuracy of using the three covariates for volume estimation; and (2) the effect of using different plot types. To assess the performance of the covariates derived from spherical camera with 3P sampling, list sampling using L[Q45] from ALS as the listing factor was used as a comparison control. Because ALS attributes are available before field inventory processes, it is more appropriate to use list sampling rather than 3P. However, since list sampling is theoretically more efficient than 3P sampling, to explore the potential effect of different selection methods, the results of both list and 3P sampling with L[Q45] are presented. Finally, to explore effects of plot type, sample efficiency based on ratios derived from volume estimates using detailed measurements on fixed area plots (FAP) were compared to those obtained using big BAF sample points (BBAF).
3.2.3.1 3P Sample Selection

Sample selection in 3P sampling is determined by comparison of predictions to uniform random numbers. As a result, sample size is difficult to regulate precisely and differences in sample sizes will occur. By controlling the range of random numbers, sample size can be regulated (Grosenbaugh 1965, 1979; Mesavage 1965; Iles 2003). In the original formulation of 3P, the random numbers ranged from 0 to the expected maximum prediction (Grosenbaugh 1965). This approach results in oversampling and random rejection symbols were introduced to control sample size (Mesavage 1965). Iles (2003) proposed adjusting the maximum random number (KZ) by the inverse of the sampling fraction:

\[
KZ = \frac{K}{P} = K \cdot \left( \frac{N}{n} \right)
\]

where \(K = \) expected value (mean) of the prediction, \(P = \) the proportion of population to be selected, \(N = \) the population size, and \(n = \) the desired sample size. A larger KZ is equivalent to a larger rejection region, which leads to a smaller sample size.

For each sample size and photo covariate, KZ was determined and the spherical photo covariates were used as the prediction in the 3P sampling process. Each of the 81 plots were “visited”, a prediction based on one of the three photo covariates was obtained, and a random uniform number between 0 and KZ generated. If the photo covariate was greater than the random number, then the plot was selected for detailed sampling. The detailed sample estimate was the volume estimate based on either the fixed area plot (FAP) or big BAF sample plot (BBAF). The desired sample sizes ranged from 5 to 50, in steps of 5. Thus, there were 10 desired sample sizes \( \times \) 3 photo covariates combinations.
Each combination was repeated 100 times and each set was “corrected” using field measurements based on FAP and BBAF estimates.

### 3.2.3.1 Ratio estimation in 3P and List Sampling

Data from each plot (i) from each replicate (j) for each simulation scenario (k) were used to estimate the mean ratio and associated sampling errors. In ratio estimation, there are two main approaches for calculating mean ratio: “ratio of means” approach and “mean ratio” approach. For SRS or other equal probability sampling, the “ratio of means” is used while for variable probability approaches. The mean ratio is typically used:

\[
\bar{R}_{jk} = \frac{\sum_{i=1}^{m} \frac{\text{VOL}_{Sijk}}{C_{Sijk}}}{m} = \frac{\sum_{i=1}^{m} R_{ijk}}{m} 
\]

(4)

where \(\bar{R}\) = the mean ratio of plot volume to prediction, \(\text{VOL}_{Sijk}\) = the volume of selected plots (m\(^3\)ha\(^{-1}\)), \(C_{Sijk}\) = the covariate (prediction) of selected plots (e.g., L[Q45], P[BA], P[SHT] and P[SF]), \(R_{ijk}\) = the ratio of volume to prediction for selected plots, and \(m\) = the number of selected plots. The mean ratio of each replicate (j) for each simulation scenario (k) was then multiplied by the plot covariate to convert \(C\) to plot volume:

\[
\text{\widehat{VOL}}_{ijk} = C_{ijk} \cdot \bar{R}_{jk} 
\]

(5)

where the \(\text{\widehat{VOL}}_{ijk}\) = the adjusted volume estimate for the ith sample point, \(C_{ijk}\) = the covariate for the ith sample point, and \(\bar{R}_{jk}\) = the mean ratio. The mean volume estimate for each replicate was then calculated using:
\[
\text{VOL}_{jk} = \frac{\sum_{i=1}^{N} \text{VOL}_{ijk}}{N}
\]  

(6)

where \(\text{VOL}_{jk}\) = the mean estimated volume for the jth replicate under the kth simulation scenario, and \(N\) = the population size (81 in this study).

### 3.2.4 Data Compilation and Analysis

To assess the efficiency and accuracy of using the three spherical-photo-derived variables as predictors in 3P sampling, comparisons against results obtained using the ALS attribute L[Q45] with list sampling were made. Bias (Observed – Predicted) and standard error were the criteria used for comparison across the different sample sizes. The bias of mean estimated volume (\(\text{VOL}_{jk}\)) is calculating assuming the mean volume of 81 field plots is the true value (note there are two truths: FAP and BBAF):

\[
\text{bias} = \overline{\text{VOL}}_f - \overline{\text{VOL}}_{jk}
\]  

(7)

where \(\overline{\text{VOL}}_f\) = the mean volume of 81 field plots (from FAP or BBAF).

The sampling error for the estimated volume is a function of the variance of the ratio and the variance of the covariate (prediction). Using Bruce’s formula (Goodman 1960) percent standard error is:

\[
\text{se\%}(\overline{\text{VOL}}_{jk}) = \sqrt{\text{se\%}(\overline{R}_{jk})^2 + \text{se\%}(\overline{C}_k)^2}
\]  

(8)

where \(\text{se\%}(\overline{\text{VOL}}_{jk})\) = the percent standard error of mean estimated volume, \(\text{se\%}(\overline{R}_{jk})\) = the percent standard error of the mean ratio, and \(\text{se\%}(\overline{C}_k)\) = the standard error of the
mean prediction across the population of interest. Percent standard error of \( \overline{R}_{jk} \) and \( \overline{C}_k \) is generally calculated using:

\[
\text{se}\% (\overline{X}) = 100 \cdot \left( \frac{s(X)}{\overline{X}} \right) = \left( \frac{\text{CV}(X)}{\sqrt{n}} \right)
\]

(9)

where \( X = R_{ijk} \) or \( C_{ijk} \); \( \overline{X} \) = average of \( R \) or \( C \); \( s(X) \) = standard deviation of \( X \), \( n \) = sample size; and \( \text{CV}(X) \) = coefficient of variation of \( X \). To further explore the sampling efficiency under different covariates and plot types, a nonlinear mixed effect model for \( \text{se}\% (\overline{VOL}_{jk}) \) and sample size was fitted:

\[
\text{se}\% (\overline{VOL}_{jk}) = \frac{b_0}{m^{b_1}}
\]

(10)

where \( m \) = the number of selected plots (sample size); and \( b_1 \) = regression coefficients. Random effects were fitted using covariate and plot type nested within covariate to both coefficients. And the minimum sample size requirement for 5% standard error was calculated from the resulting models.

3.3 Results

3.3.1 Plot and Covariate Summaries

Table 3.1 shows the field plot summary for the 81 big BAF sample plots (BBAF) and fixed area plots (FAP). The mean and coefficient of variation (CV) of field measured volume were 256.8 \( \text{m}^3\text{ha}^{-1} \) (25.83%) for BBAF and 271.8 \( \text{m}^3\text{ha}^{-1} \) (22.39%) for FAP. Density estimates were 1887 and 1883 stems per ha for BBAF and FAP, respectively. Basal area per ha estimates were 42.0 \( \text{m}^2\text{ha}^{-1} \) and 40.0 \( \text{m}^2\text{ha}^{-1} \), respectively.
Table 3.2 summarizes the four covariates used in this study. SF had the overall lowest se%, while SHT had the highest. Overall, variation within the covariates was relatively low. L[Q45] had the highest correlation with estimated volume for both plot types, while SF had the lowest (Table 3.2). Correlation was similar between plot types but was consistently higher for FAP than BBAF except for the BA covariate.

3.3.2 3P versus List Selection using LiDAR Attribute

The differences between LIST and 3P sampling using L[Q45] as the covariate were minimal (Figure 3.1). Overall, mean biases were approximately 0 for all sample sizes for LIST and 3P sampling and for both plot types (FAP versus BBAF). Similarly, comparing standard errors of \( \overline{\text{VOL}_{jk}} \) for LIST versus 3P sampling were essentially identical (Figure 3.1). The biggest differences occurred between plot types. Since BBAF plots are inherently more variable than FAP plots, standard errors and the ranges of observed biases were slightly larger for BBAF than for FAP. However, the differences overall are small, and, in terms of sample size requirements, it requires approximately 20 – 25 BBAF plots to consistently reach a sampling error of 5% and about 15 – 20 FAPs.

In practice, list sampling is the more appropriate selection method when the covariate information is available prior to sampling. Given the results presented in this section using the covariate L[Q45], we will use LIST sampling with L[Q45] as the benchmark to compare with the results obtained using photo-derived covariates with 3P selection.
3.3.3. 3P Selection Using Spherical Photo-Derived Covariates

Although the correlations with field measured volume varied among the three spherical photo covariates (Table 2), there were no discernible biases in the resulting volume estimates (Figure 3.2). As expected, using list sampling with L[Q45] as the covariate resulted in the narrowest ranges of bias across all sample sizes (Figure 3.2); however, differences between LIST sampling using L[Q45] and 3P sampling using the photo-derived covariates were minimal except P[SHT] or at the lowest sample sizes (Figure 3.2). Identical to the results for correlation (Table 3.2), P[SF] typically had narrower ranges of bias followed by P[BA] and then P[SHT]. In terms of bias, no differences between plot types were observed (Figure 3.2).

While plot type did not influence bias, it did impact $\text{se}\% \left( \frac{VOL_{jk}}{ \bar{V} } \right)$ (Figure 3.3). With the exception of P[BA], the means of $\text{se}\% \left( \frac{VOL_{jk}}{ \bar{V} } \right)$ for FAP were generally smaller than those for BBAF across all sample sizes (Figure 3.3), though the differences decreased as sample size increased (Figure 3.3). For P[BA], $\text{se}\% \left( \frac{VOL_{jk}}{ \bar{V} } \right)$ was smaller for BBAF than for FAP. This makes sense because volume estimates using BBAF were also based on HPS process: in BBAF, $\text{VOL} = \text{VBAR} \cdot \text{BA}$; given that P[BA] also is an estimate of BA, the $\text{se}\% \left( \frac{VOL_{jk}}{ \bar{V} } \right)$ is really a function of $\text{VBAR}$.

The main differences in $\text{se}\% \left( \frac{VOL_{jk}}{ \bar{V} } \right)$ were in comparison to LIST with L[Q45] (Figure 3.3). Although the $\text{se}\% \left( \frac{VOL_{jk}}{ \bar{V} } \right)$ decreased with increasing sample size for all covariates, the mean and range of $\text{se}\% \left( \frac{VOL_{jk}}{ \bar{V} } \right)$ for photo-derived variables were all higher than
those for L[Q45] (Figure 3.3). Although P[SF] had the lowest correlation with stand volume (Table 3.2), the \( \text{se}\% \left( \overline{\text{VOL}_{jk}} \right) \) was the lowest of the three photo-derived covariates because of the low \( \text{se}\% \left( \overline{C} \right) \) (Figure 3.3 & Table 3.2). While BA had the highest correlation with field measured volume, it also had relatively high \( \text{se}\% \left( \overline{C} \right) \) (Table 3.2) and, thus, increased \( \text{se}\% \left( \overline{\text{VOL}_{jk}} \right) \). P[SHT], which had low correlation and high \( \text{se}\% \left( \overline{C} \right) \) (Table 3.2), had the greatest mean and range of \( \text{se}\% \left( \overline{\text{VOL}_{jk}} \right) \), making it the least efficient sampling covariate (Figure 3.3C & 3.3D).

3.3.4 Sample Size Estimation

The fixed effect parameter estimates and their associated standard errors for eq. 10 were: \( b_0 = 22.8595 \pm 2.8019 \) and \( b_1 = 0.3924 \pm 0.0105 \). The standard deviations for the random effects associated with covariate were: \( s(b_0) = 5.3921 \) and \( s(b_1) = 0.0148 \), and for plot type nested within covariate were: \( s(b_0) = 2.0011 \) and \( s(b_1) = 0.0164 \). Table 3.3 shows the coefficient estimates (fixed + random effect) for eq. 10 by sampling covariate and plot type. Values for \( b_1 \) were around 0.4 for all combinations (Table 3.3). Theoretically, these values should be 0.5 based on the standard error calculation under simple random sampling. For all sampling covariates, the \( b_0 \) coefficients were larger for BBAF than for FAP, indicating the higher variability in BBAF than FAP (Figures 3.2 & 3.3); however, the values for the \( b_1 \) coefficient were also consistently higher (Table 3.3). Higher \( b_1 \) coefficients indicate larger reductions in \( \text{se}\% \) with increasing sample size. This result is again consistent with what was observed in Figures 3.2 and 3.3, where BBAF results

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were more variable than FAP results at smaller sample sizes, but the differences become minimal as sample size increased.

In terms of sample size requirements, BBAF generally required more samples than did FAP, except for P[BA] (Table 3.3). List sampling with L[Q45] had the lowest minimum sample size requirements (Table 3.3). P[SF] was the most efficient covariate with 3P sampling (Table 3.3).

### 3.4 Discussion

Theoretically, list sampling is expected to be more efficient than 3P sampling, because selection probabilities are based on the exact proportion contributed to population rather than a prediction (Freese 1962; Cochran 1977). In this study 3P sampling using the same covariate performed as well as list sampling (Figure 3.1). This is in contrast to results recently reported by Yang et al. (In press) for the entire Noonan Research Forest. In their study, list sampling using L[Q45] outperformed all other selection methods and covariates. The Femelschlag Research Site is characterized by relatively uniform stand structure that the coefficient of variations of the volume and DBH are relatively small in this area (Table 3.1). Differences that do exist are primarily in species composition, not stem size distribution. The narrow range of variability in this area (Table 3.1) coupled with low correlation between volume and the covariate (Table 3.2) probably contributed to this result. The results for 3P sampling with the photo-derived covariates (Figures 3.2 & 3.3) support this claim as well. The resulting \( \text{se}\% \left( \overline{\text{VOL}} \right) \) was largely a function of covariate variation rather than correlation with volume. P[SF] had the lowest correlation with volume and the lowest variability. The low variability in P[SF] resulted in ratios
with lower variability. Because $\text{se}\% \left( \text{VOL} \right)$ is a function of both $\text{se}\% \left( R \right)$ and $\text{se}\% \left( C \right)$ (eq. 8, Goodman 1960), the majority contribution to error, in this situation, is $\text{se}\% \left( C \right)$, which is fixed and independent of the subsampling procedure (Freese 1962; Iles 2003; Kershaw et al. 2016). While we refer to our procedures as 3P sampling, it is really point 3P sampling (Schreuder et al. 1993). As Schreuder et al. (1993) pointed out, the exact variances for point 3P sampling are not known. The population size in this case is also relatively small which could be regarded as a finite population. Thus, in this case, the use of the Goodman (1960) formula may be an oversimplification since it ignores the effect of finite population. More exact formulations provided by Freese (1962) or Kershaw et al. (2016) might be more appropriate in this situation.

Despite the lack of overall improved sampling efficiency, the power of ratio estimation for bias correction is demonstrated in these results. Ratio estimation can be an effective sampling approach to correct for potential biases and reduce sampling costs (Hsu et al. In Review; Freese 1962; Iles 2003; Kershaw et al. 2016; Lam et al. 2018). As shown in Figure 3.2, the corrected mean $\text{VOL}$ had no biases across both the four covariates and the two plot types, except at some of the lower sample sizes. Only sample precision was affected by the quality of covariates. L[Q45] and P[BA], which had higher correlations with field measured volume (Table 3.2), had a narrower range of biases (Figure 3.2). That lower $\text{se}\% \left( \text{VOL} \right)$ resulting from list sampling with L[Q45] was the lowest is in agreement with the results reported by Yang et al. (In press) and Hsu et al.’s (In Review) studies. In Yang et al.’s (In press) study, both selection method and estimation technique
were compared using LiDAR derived covariates. Sampling error was primarily impacted by estimation technique, with ratio estimation outperforming model-derived estimates using both random Forest imputation (Breiman 2001) and nonlinear least squares. In Hsu et al.’s (In Review) study, only selection method and plot type were examined, with selection method being the most important factor driving sampling efficiency. In this study, covariate variation is the driving factor. The uniformity of the study area and the relatively small number of field plots limits the inferences that can be drawn from this study.

As expected, the baseline sample using list sampling with L[Q45] as the covariate was the optimal sampling design; however, this sampling design requires readily available ALS data. In regions without readily available ALS data, this study shows the potential to apply 3P sampling using covariates derived from a consumer-grade spherical camera. Based on our sampling efficiency results, P[SF] was the most efficient covariate; however, this might not be the case in situations with greater variability than what was encountered in this study. In this study, se% (VOL) was impacted more by se% (C) than by se% (R), thus favoring P[SF] over the other photo-derived variables. In conditions with more variability in volume, it is expected that P[BA] or P[SHT] might be more highly correlated with volume than P[SF]. In these situations it is expected that se% (R) may play a larger role in determining se% (VOL), in which case more highly correlated covariates would perform better.
Despite these uncertainties, the use of ratio estimation was very effective and reduced require sample sizes with all covariates other than P[SHT]. Yang et al. (In press) demonstrated that estimation technique was more important than selection method, and showed that ratio estimation performed better than regression estimation and model-derived estimates using random Forest imputation and nonlinear least squares. The spherical photo covariates used here could be used with any selection method in a double sampling or regression sampling framework and produce efficient estimates. While variable probability sampling is theoretically more efficient (Basu 1969), the low correlation observed among the photo-derived covariates may not have produced selection probabilities proportional to volume, further contributing to the reduced efficiency. To further improve the correlation, the accuracy of pixel classification can be enhanced, or a different weighting function can be tested.

P[SF] was not only more efficient, but also the most automatic photo-derived covariate. Both P[BA] and P[SHT] require user interaction to obtain the predictions. P[SF], however, is more subject to photo quality than the other two measures (Appendix A). Sun flecks and shade flecks can impact P[SF]. Simulation results of the impact of fleck intensity on sampling efficiency (Appendix A) showed that flecks had very little impact. Again, these results have to be considered within the context of this study and the low variability and low correlations. In situations with higher variability and higher correlations, flecks may play a greater role. Thus, a study with a broader range of conditions is required to better understand the results obtained here.

Plot type had very little impact on the results in this study. This is similar to the results Hsu et al. (In Review) found for sampling to correct LiDAR enhanced forest inventories.
The biggest differences among plot types are the number of trees counted and measured. Subsampling techniques with ratio estimation have consistently been shown to be more efficient in a number of sampling situations (Hsu et al. In Review; Bell et al. 1983; Corrin 1998; Desmarais 2002; Marshall et al. 2004; Yang et al. 2017; Chen et al. 2019). Unless there are other inventory considerations, BBAF is recommended to be used as a sampling method to reduce inventory costs (Yang et al. 2017; Chen et al. 2019), especially for small woodlots (Hsu et al. In Review).

Forest inventory has historically been a field to rapidly adopt new technology (Schreuder et al. 1993). This trend continues today, as demonstrated by the wide-scale adoption of LiDAR in forest inventory applications (Næsset 2002; Corona and Fattorini 2008; Wulder et al. 2008; Asner et al. 2011; Hayashi et al. 2015). However, new technology does not obviate sound statistical sampling designs to produce unbiased estimates of totals (Yang et al. In press). New technology can also be prohibitively expensive, especially for small woodlot owners. The techniques developed here can be an efficient and cost-effective alternative to LiDAR applications.

3.5 References

Andrews GS (1936) Tree-heights from air photographs by simple parallax measurements. For Chron 12:152–197

Sankhyä: The Indian Journal of Statistics 31:441–454

Beer A (1852) Bestimmung der Absorption des rothen Lichts in farbigen Flüssigkeiten  
[Determination of the absorption of red light in colored liquids]. Annalen der  
Physik und Chemie 86:78–88

Bell JF, Iles K, Marshall D (1983) Balancing the ratio of tree count-only sample points  
and VBAR measurements in variable plot sampling. In: Bell J.F. and Atterbury,  
T. (eds.). Proceedings: Renewable Resource Inventories for Monitoring Changes  
and Trends. College of Forestry, Oregon State University, Corvallis, OR, pp 699–  
702

International, Slough, England


estimating carbon on small woodlots. Forest Ecosystems 6:. doi: 10.1186/s40663-  
019-0172-4


Corona P, Fattorini L (2008) Area-based lidar-assisted estimation of forest standing  

DeCourt N (1956) Utilisation de la photographie pour mesurer les surfaces terrières (The use of photography for measuring basal area). Rev For Fran 8:505–507


Freese F (1962) Elementary forest sampling. US Department of Agriculture


Grosenbaugh LR (1979) 3P sampling theory, examples, and rationale. US Department of Interior, Bureau of Land Management

Grosenbaugh LR (1965) THREE-PEE SAMPLING THEORY and program “THRP” for computer generation of selection criteria. USDA Forest Service, Pacific Southwest Forest Experiment Station


Honer TG, Ker MF, Alemdag IS (1983) Metric timber tables for the commercial tree species of central and eastern Canada. Canadian Forestry Service, Maritimes Forest Research Centre
Hsu Y-H, Chen Y, Yang T-R, Kershaw JA Jr (In Review) Sampling to correct LiDAR-assisted forest inventory estimates for small woodlots. Forest Science

Husch B (1971) Planning a forest inventory. FAO, Rome, Italy


Lambert JH (1760) Photometria sive de mensura et gradibus luminis, colorum et umbrae [Determination of the absorption of red light in colored liquids]. Klett, Augsburg, German

Lynch TB (2017) Optimal plot size or point sample factor for a fixed total cost using the Fairfield Smith relation of plot size to variance. Forestry 90:211–218

MacLeod MN (1919) Mapping from air photographs. Geogr J 53:382–396


BAF under cost constraints. Forestry 90:649–660. doi:
https://doi.org/10.1093/forestry/cpx020

Table 3.1 Plot-level per ha averages for the 81 sample points by plot type. (FAP = fixed area plot, BBAF = big BAF sample plot, QMD = quadratic mean diameter, Range = (min, max), CV = coefficient of variation)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>BBAF</th>
<th></th>
<th></th>
<th>FAP</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Range</td>
<td>Mean</td>
<td>CV</td>
<td>Range</td>
<td>Mean</td>
<td>CV</td>
</tr>
<tr>
<td>Volume (m³ha⁻¹)</td>
<td>(124.0, 413.5)</td>
<td>256.8</td>
<td>25.83%</td>
<td>(112.1, 432.0)</td>
<td>271.8</td>
<td>22.39%</td>
</tr>
<tr>
<td>Density (stem ha⁻¹)</td>
<td>(457, 4233)</td>
<td>1887</td>
<td>41.68%</td>
<td>(575, 4375)</td>
<td>1883</td>
<td>43.38%</td>
</tr>
<tr>
<td>BA (m²ha⁻¹)</td>
<td>(24.0, 62.0)</td>
<td>42.0</td>
<td>22.90%</td>
<td>(20.9, 53.8)</td>
<td>40.0</td>
<td>16.39%</td>
</tr>
<tr>
<td>QMD (cm)</td>
<td>(11.0, 27.0)</td>
<td>17.6</td>
<td>19.38%</td>
<td>(10.5, 26.8)</td>
<td>17.3</td>
<td>19.96%</td>
</tr>
</tbody>
</table>
Table 3.2 The range, mean and $se\%\left(\overline{C}\right)$ by Sampling Covariate and their associated correlation with the field measured volume by plot type. (FAP = fixed area plot, BBAF = big BAF sample plot, Range = (min, max), $L[Q45] = \text{height of the 45th quantile of LiDAR point cloud}$, $P[BA] = \text{photo-derived basal area}$, $P[SHT] = \text{photo-derived sum of squared heights}$, and $P[SF] = \text{photo-derived stem fraction}$)

<table>
<thead>
<tr>
<th>Sampling Covariate</th>
<th>Range</th>
<th>Mean</th>
<th>SE%</th>
<th>Correlation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>BBAF</td>
</tr>
<tr>
<td>$L[Q45]$ (m)</td>
<td>(6.0, 13.4)</td>
<td>9.6</td>
<td>2.11%</td>
<td>0.559</td>
</tr>
<tr>
<td>$P[BA]$ (m$^2$ha$^{-1}$)</td>
<td>(14.0, 56.0)</td>
<td>33.4</td>
<td>3.01%</td>
<td>0.478</td>
</tr>
<tr>
<td>$P[SHT]$ (m$^2$ha$^{-1}$)</td>
<td>(3793.5, 64489.0)</td>
<td>34094.4</td>
<td>4.23%</td>
<td>0.324</td>
</tr>
<tr>
<td>$P[SF]$</td>
<td>(0.231, 0.587)</td>
<td>0.448</td>
<td>1.83%</td>
<td>0.310</td>
</tr>
</tbody>
</table>
Table 3.3 Coefficient estimates (fixed + random effects) for the nonlinear mixed effect model (eq. 8) and the estimated minimum sample size requirements by plot type and sampling covariate. (FAP = fixed area plot, BBAF = big BAF sample plot, L[Q45] = height of the 45th quantile of LiDAR point cloud, P[BA] = photo-derived basal area, P[SHT] = photo-derived sum of squared heights, P[SF] = photo-derived stem fraction)

<table>
<thead>
<tr>
<th>Sampling Covariate</th>
<th>BBAF</th>
<th>FAP</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>b0</td>
<td>b1</td>
</tr>
<tr>
<td></td>
<td>Sample size</td>
<td>Sample size</td>
</tr>
<tr>
<td>L[Q45]</td>
<td>19.1345 0.4203</td>
<td>25</td>
</tr>
<tr>
<td>P[BA]</td>
<td>22.3212 0.3825</td>
<td>50</td>
</tr>
<tr>
<td>P[SHT]</td>
<td>32.7542 0.3782</td>
<td>144</td>
</tr>
<tr>
<td>P[SF]</td>
<td>21.8611 0.4236</td>
<td>33</td>
</tr>
</tbody>
</table>
Figure 3.1 The mean and distribution of bias of $\overline{\text{VOL}}_{jk}$ and $\text{se}\%\left(\overline{\text{VOL}}_{jk}\right)$ for list and 3P sampling using L[Q45] as the covariate for big BAF sample plots (BBAF) and fixed area plots (FAP) by sample size. (L[Q45] = height of the 45th quantile of LiDAR point cloud)
Figure 3.2 The mean and distribution of bias of $\overline{\text{VOL}}_{jk}$ by sampling covariate, plot type, and sample size. (FAP = fixed area plot, BBAF = big BAF sample plot, L[Q45] = height of the 45th quantile of LiDAR point cloud, P[BA] = photo-derived basal area, P[SHT] = photo-derived sum of squared heights, and P[SF] = photo-derived stem fraction)
Figure 3.3 The mean and distribution of $\text{se}\% \left( \frac{\text{VOL}_{jk}}{\mu} \right)$ by sampling covariate, plot type, and sample size. (FAP = fixed area plot, BBAF = big BAF sample plot, L[Q45] = height of the 45th quantile of LiDAR point cloud, P[BA] = photo-derived basal area, P[SHT] = photo-derived sum of squared heights, and P[SF] = photo-derived stem fraction)
Chapter 4 Conclusions
Variable probability selection methods are regarded as highly efficient sampling schemes and ratio estimation has the added benefit of improving sample precision (Iles 2003). However, their application has been restricted by a lack of suitable covariates (prior information) for many study areas. This thesis explored the potential of using airborne light detection and ranging (LiDAR) scanning (ALS) and a consumer-grade spherical camera to assist with variable probability selection methods, and to assess the capability of ratio estimation for addressing biased or imprecise covariates.

ALS has great potential to enhance forest inventories by generating high-resolution forest estimates at the landscape level. However, since ALS estimates are derived from ground-based field inventories, which often are spatially sparse, bias may occur in local areas which can impact decision-making in forest management strategies. These impacts can be especially important for small, private woodlot owners. A “sampling to correct” approach, using double sampling with ratio estimation to calibrate bias (Iles 2003), was an easy-to-apply approach used in this thesis (Chapter 2). Although simple random or systematic selection methods usually could be applied in double sampling, ALS-derived estimates provide a ready source of completely enumerated covariates. Variable probability selection methods were found to improve sampling efficiency over other selections methods. In our first study, our results show that list sampling with big BAF sample plots was a highly efficient and cost-effective sampling strategy. In addition, ratio estimation effectively calibrated for bias and produced accurate estimates of total volume. Although the sampling strategy was developed for small woodlots to correct estimates of volume, there is potential to apply this approach in larger forest areas with complete ALS coverage. Because the Femelschlag Research Site was fairly homogeneous in terms of
volume distribution, stratification was not considered in this thesis. For larger forest areas, stratified or two-stage list sampling could be used. For example, Chen (In Prep.) applied list sampling to estimate carbon using gross total volume from a LiDAR-derived enhanced forest inventory as the listing factor for the 44,000 ha forest management zone on the 5th Division Canadian Forces Base Gagetown. Although Chen (In Prep.) used previously interpreted aerial photography as the basis for her stratification, stratification could also be obtained directly from LiDAR on the basis of canopy heights, canopy surface roughness, or other LiDAR-derived attributes. The local pivotal method (Yang et al. In Press; Grafström and Ringvall 2013), another form of variable probability sampling that attempts to achieve spatial balance, could be used instead of stratification; however, Yang et al. (In Press) did not find that the local pivotal method performed any better than unconstrained list sampling at the scale of 1,500 ha. Given the inability to apply LiDAR-derived models from one area to another area of similar composition, Hayashi et al. (2015) suggests that stratification may be an important, but poorly understood, component within LiDAR-derived forest inventories.

While LiDAR-derived forest inventory estimates provide a ready source of covariates for variable probability sampling, and are rapidly becoming freely available in many jurisdictions, they are not universally available. For areas without ALS coverage, efficient acquisition of covariates is a barrier to applying variable probability methods operationally. The second part of this thesis explored the potential to apply 3P sampling using covariates derived from a spherical camera. A consumer-grade spherical camera is relatively inexpensive (around CAD$ 400 in 2019), and can provide a quick record of the full 360° view of forest conditions for estimating various forest attributes (Chen et al.
1991; Macfarlane et al. 2007; Dick 2012; Perng et al. 2018). In this study, we focused on comparing the sampling efficiency and accuracy of 3P sampling using three covariates derived from spherical photos. Although the correlation between the three photo-derived covariates and volume was low in this study, there were generally no biases in volume estimates across all covariates via ratio estimation. However, higher correlations between covariates and volumes would have resulted in more accurate estimates.

Unlike the results obtained in Chapter 2 where the effects on sampling efficiency were driven more by different sampling selection methods, in Chapter 3, sampling efficiency was more a function of the variation within covariates. The correlation between covariates and parameters of interest can impact sampling efficiency, but it was minimal in this study because of the low number of the field plots (81). As expected, list sampling using a covariate derived directly from ALS (45th quantile of the point cloud height distribution) was more efficient than any of the photo-derived covariates under 3P sampling; this was the result of a combination of list sampling being theoretically more efficient than 3P sampling, but also because ALS-derived covariates have low variation and higher correlation with volume. Stem fraction was the optimal photo-derived covariate of the three used. It also was the most automatic covariate to estimate in the field using the spherical photos and a simple smartphone app without any human interaction (Wang In Prep.). This shows the potential to use a spherical camera to assist in 3P sampling. However, since the study area was in a relatively uniform stand structure, and the number of field sample points was limited, the inference of this study was restricted. It requires more exploration and testing in different stand conditions and larger study areas.
Since stem fraction was derived from the hemispherical projections of the spherical photos, sun and shade flecks could impact the quality of photographs and result in under- or over-estimation of stem fraction. In Appendix A, we focused on exploring the effects of different levels of sun and shade effect probabilities on the 3P sampling process. Our results show that imprecise covariates can provide precise estimates using ratio calibration if sample sizes are sufficient. We found that sample intensities of 35% - 50% were required, but that sun and shade flecks did not impact sample intensity.

Stem fraction did show some potential to assist as the prediction in 3P sampling, and the power of ratio estimation was demonstrated in this thesis. However, as measured in this thesis, stem fraction was still a poorly correlated covariate with volume and had a relatively narrow range across our study area. In addition, the relatively uniform stand structures within the study area restrict the inferences of our results. To improve the application of 3P sampling with a spherical camera and make it more effective and more feasible in practice, the precision of covariates and the correlation between covariates and the parameters of interest need to be improved. In addition, the process should be tested on larger and more variable forest areas.

4.1 Future work

In this study, we demonstrated potential applications of using two remotely sensed estimates as covariates in the sampling process. Very few studies examine the effects of different covariates derived from different remote sensing techniques. For example, rather than using ALS-derived inventory estimates, the raw LiDAR metrics (i.e., the information directly extracted from LiDAR point clouds) could also be considered as
potential covariates (Yang et al. In Press). Methods for meaningfully stratifying LiDAR are also lacking and needs further refinement. Development of a more systems-based approach using biologically meaningful LiDAR attributes, rather than the common machine learning approaches currently applied in most LiDAR-derived forest inventories, would greatly advance our understanding of the relationship between forest structure and LiDAR point cloud distributions.

The sampling efficiency of variable probability selection methods relies on the correlation between covariates and the parameters of interest, but there are very few studies that explore the effects of correlation in this context. In Chapter 3, the effects of correlation between volume and the different covariates was masked by the effects of the variability within covariates. The limited sampling space used in this study limits the inferences of this study and our ability to differentiate the roles of variability within covariates and correlation between target variables (volume, in this case) and the covariates. To further explore the effect of correlation on sampling efficiency, the sampling process needs to be tested with more sample units which may reduce the influence of standard errors of covariates on overall sampling efficiency. Also, since the 3P sampling process used in Chapter 3 was actually point-3P sampling because the large sample did not cover the whole population (Illes 2003), the exact standard error of prediction was unknown (Schreuder et al. 1993). The small population size should be regarded as a finite population. Using Bruce’s formula (Goodman 1960) in calculating overall standard error may be too simplified in this situation due to the lack of consideration of a finite population, thus a more exact formulation may be required (Schreuder et al. 1993). Additional simulation studies examining the impacts of
variability within covariates and the correlation between covariates and target variables are required to fully understand the impacts these factors have on overall sampling efficiency.

There are several potential ways to improve the correlation between stem fraction and volume. Since the relationship between stem fraction and volume may not be a simple linear relationship and may be impacted by other forest attributes (e.g., density), a more complex relationship may be required for use in volume estimation, rather than using a simple ratio estimate. The quality of the covariate also could be enhanced. For example, the accuracy of stem classification in photos could be improved. Other weighting formulas could be considered, and stem fractions from different zenith angles could be tested. The use of spherical photo-derived covariates to assist 3P sampling is still in the preliminary stage. This thesis has demonstrated the potential of this application, and there are many potential ways to further explore and develop sound sampling procedures from this new technology.

4.2 References


Chen Y, Kershaw JA Jr, Lavigne MB, et al (In Prep.) Carbon estimation using sampling to correct LiDAR-assisted forest inventory


Appendix A. The effect of sun and shade flecks in spherical photographs on 3P sampling results

A.1 Introduction

In Chapter 3, stem fraction (SF) was suggested as the most efficient and automatic photo-derived covariate to serve as the prediction in 3P sampling. However, the quality of estimates derived from a hemispherical view can be influenced by different sky conditions or exposures. Uniform sky conditions are required for optimal use of hemispherical photographs for gap fraction analyses (Fournier et al. 2017). Sun flecks on sunny days or shade flecks on partly cloudy days can result in significant errors in stem fraction estimates (Hall et al. 2017). Theoretically, these errors should not impact the estimates adjusted by ratio estimation in 3P sampling process (Iles 2003), but this should be assessed. The main purpose of this section is to explore the effects of varying sky conditions on the sampling efficiency for 3P sampling selection method, and the accuracy of volume estimates via ratio estimation process. A simulation study of the effects of increasing variability in sun/shade flecks on sample estimates and sample size requirements is conducted. Sampling error and bias of ratio estimates are assessed to evaluate the capability of ratio estimation for addressing imprecision in covariates.

A.2 Method

A.2.1 Study Material

Because this is an extension section of Chapter 3, the same study area is used (the 80 ha Femelschlag Research Site). The 81 sample points in the study area were distributed on
the 100 m × 100 m sample grid. The field measured volume (m³ha⁻¹) was estimated using a big BAF sample plot for each sample point. The stem fraction (SF) was estimated from the hemispherical view of spherical photo taken at each sample point. The detailed information about field measurement and SF estimation process is found in Sections 3.2.1 and 3.2.2.

### A.2.2 Simulation of Sun and Shade Flecks

To explore the effect of sun and shade flecks, we added random noise to the SF values by simulating a distribution of sun and shade flecks using a beta distribution. We assumed that sun flecks could reduce SF by 0% to 25% and that shade flecks could increase SF by 0% to 15%. The fleck effect was sampled from a four-parameter Beta distribution (Bury 1975). For the sun flecks, the two shape parameters were set to \( \lambda_1 = 5 \) and \( \lambda_2 = 5 \), while they were set to \( \lambda_1 = 2 \) and \( \lambda_2 = 4 \) for shade flecks. The total fleck probability was varied between 0% - 70% divided between sun and shade in steps of 10%. For example, if total fleck probability = 20% the possible combinations were sun = 20%, shade=0% (SU20SH00), sun = 10%, shade = 10% (SU10SH10) and sun = 0%, shade= 20% (SU00SH20). This resulted in a total of 36 combinations of fleck altered SFs. The 3P sample selection procedure was the same as Section 3.2.3.1, and the desired sample size for each scenario was from 5 to 50, in steps of 5. As described in Chapter 3, 100 iterations of each combination and sample size were simulated.

### A.2.3 Data analysis

The ratio estimation process is given in Section 3.2.3. The mean ratio of each replicate (j) for each simulation scenario (k) was calculated using:
\[
\bar{R}_{jk} = \frac{\sum_{i=1}^{m} \frac{\text{VOL}_{Sijk}}{\text{SF}_{Sijk}}}{m} = \frac{\sum_{i=1}^{m} \text{R}_{ijk}}{m}
\]  

(1)

where \( \bar{R}_{jk} \) = the ratio of plot volume to stem fraction, \( \text{VOL}_{Sijk} \) = the volume of selected plots (m\(^3\)ha\(^{-1}\)), \( \text{SF}_{Sijk} \) = the stem fraction of selected plots, \( m \) = the number of selected plots, and \( \text{R}_{ijk} \) = the ratio of stem fraction to volume for selected plots. Then \( \bar{R}_{jk} \) is multiplied to SF of all sample points to convert SF to volume, and the mean volume estimate for each replicate was calculated using:

\[
\overline{\text{VOL}}_{jk} = \frac{\sum_{i=1}^{N} \text{VOL}_{ijk}}{N} = \frac{\sum_{i=1}^{N} \text{SF}_{ijk} \cdot \bar{R}_{jk}}{N}
\]  

(2)

where \( \overline{\text{VOL}}_{jk} \) = the mean estimated volume for jth replicate under kth simulation scenario, \( \overline{\text{VOL}}_{ijk} \) = the adjusted volume estimate for the ith sample point, \( \text{SF}_{Sijk} \) = the stem fraction of selected plots, and \( N \) = the population size (81 in this case).

The sampling error for the estimated volume is a function of the variance of the ratio and the variance of the prediction. Using Bruce’s formula (Goodman 1960) percent standard error was:

\[
\text{se} \% (\overline{\text{VOL}}_{jk}) = \sqrt{\text{se} \% (\bar{R}_{jk})^2 + \text{se} \% (\text{SF}_k)^2}
\]  

(3)

where \( \text{se} \% (\overline{\text{VOL}}_{jk}) \) = the percent standard error of mean estimated volume, \( \text{se} \% (\bar{R}_{jk}) \) = the percent standard error of the mean ratio, and \( \text{se} \% (\text{SF}_k) \) = the standard error of the
mean stem fraction across the population of interest. Percent standard error of $\bar{R}$ and $\bar{SF}_k$ was generally calculated using:

$$\text{se}\% (\bar{X}) = 100 \left( \frac{s(X)/\sqrt{n}}{\bar{X}} \right) = \left( \frac{CV(X)}{n} \right)$$

(4)

where $X = R$ or $SF$; $\bar{X}$ = average of $R$ or $SF$; $s(X)$ = standard deviation of $X$, $n$ = sample size; and $CV(X)$ = coefficient of variation of $X$.

A.3. Results

Figure A.1 shows the means and ranges of $\bar{VOL}_{jk}$ across different simulation scenarios and sample sizes. The overall mean of field measured volume was $256.2 \text{ m}^3\text{ha}^{-1}$. As expected, the range of $\bar{VOL}_{jk}$ decreases as sample size increases from 10 to 40 for almost all fleck scenarios. There was no consistent pattern to the fluctuations in the ranges of $\bar{VOL}_{jk}$ as fleck probability increased. Ranges in $\bar{VOL}_{jk}$ are generally larger than the 95% confidence interval for the full 81 field plots, except at larger sample sizes (Figure A.1).

At sample size $= 40$, the range of $\bar{VOL}_{jk}$s were nearly equal to (or even slightly smaller than) the 95% confidence interval for the full 81 field plots (Figure A.1D). Increasing sun fleck probability had a greater impact than increasing shade fleck probability (Figure A.2). This is most likely due to the increasing variability in SF associated with increasing sun fleck probability (Figure A.2).

The $\text{se}\% (\bar{SF}_k)$ nearly doubled from 1.79% to 2.13% as the sun fleck probability increased (Figure A.2B). However, the fleck probability only influenced $\text{se}\% (\bar{VOL}_{jk})$ at
the smallest sample sizes (Figure A.3). At sample size = 10, \( \text{se}\% \left( \text{VOL}_{jk} \right) \) varied between 8.0% and 9.2%, while at the larger samples sizes the variation was much lower with most \( \text{se}\% \left( \text{VOL}_{jk} \right) \) nearly equal to the value obtained without flecks. Because \( \text{se}\% \left( \text{VOL}_{jk} \right) \) is a combination of \( \text{se}\% \left( \text{SF}_k \right) \) and \( \text{se}\% \left( \overline{R}_{jk} \right) \) (eq. 3), we know that \( \text{se}\% \left( \text{VOL}_{jk} \right) \) is more influenced by \( \text{se}\% \left( \overline{R}_{jk} \right) \) than \( \text{se}\% \left( \text{SF}_k \right) \), especially at lower sample sizes. As the sample size increased, \( \text{se}\% \left( \overline{R}_{jk} \right) \) decreased from 8.16% at sample size = 10 to 4.08% at sample size = 40. While this decrease will increase the effect of \( \text{se}\% \left( \text{SF}_k \right) \) on \( \text{se}\% \left( \text{VOL}_{jk} \right) \), the effect is not very noticeable because \( \text{se}\% \left( \text{SF}_k \right) \) is still relatively low compared to \( \text{se}\% \left( \overline{R}_{jk} \right) \).

### A.4 Discussion

In gap fraction analyses and estimation of plant structural components such as leaf area and its distribution, the effect of sun or shade flecks is one of the major issues influencing the use of hemispherical photographs (Fournier et al. 2017). However, if SF is used as an auxiliary variable, as in this study, the errors in SF estimation caused by sun or shade flecks are less important (Figures A.1 – A.3). In a sampling to correct framework, the accuracy of the covariate does not bias the corrected estimate (Hsu et al. In Review; Iles 2003), but may impact sample efficiency and required sample sizes. In our results, increasing fleck probability did not influence the estimates of mean volume (Figure A.3). In terms of sampling error (eq. 3), even though \( \text{se}\% \left( \overline{SF} \right) \) almost doubles as sun fleck
probability increased from 0% to 50% (Figure A.3), it resulted in very little impact on
\( \text{se} \left( \frac{\text{VOL}}{\sqrt{N}} \right) \). The main factor influencing \( \text{se} \left( \frac{\text{VOL}}{\sqrt{N}} \right) \) was \( \text{se} \left( \overline{R} \right) \). The ratio is
influenced by both the variability in volume and the variability in SF. As variation in SF
increases, this will impact \( \text{se} \left( \overline{R} \right) \); however, as shown in Figure A.3, this impact can be
minimized by controlling sample size. In this case, when the sample size was up to 30 –
40, which was approximate 35% – 50% of the amount of sample units (81), the effect of
sun and shade flecks was minimal.

In this section, the power of ratio estimation at error adjusted is proved, since there were
no biases in volume estimations across all combinations of sun and shade probability.
This is expected because the prediction in 3P sampling does not need to be correct, it just
needs to be consistent (Hsu et al. In Review; Iles 2003). The result of this section
eliminates the doubt in the impact of sun and shade fleck, so that the feasibility and
practicality of using photo-derived covariates as the prediction in 3P sampling are
increased.

A.5 References


Photographs in Forest Environments: From Planning to Archiving Photographs.
In: Fournier RA, Hall RJ (eds) Hemispherical Photography in Forest Science:
Theory, Methods, Applications. Springer Netherlands, Dordrecht, pp 85–114


Hsu Y-H, Chen Y, Yang T-R, Kershaw JA Jr (In Review) Sampling to correct LiDAR-assisted forest inventory estimates for small woodlots. Forest Science

Figure A.1. Comparison of field measured volumes with 95% confidence intervals based on the full 83 samples and the mean and range of $\overline{\text{VOL}}$, across the different fleck simulation scenarios across sample sizes. (SUXX = XX% of sun effect probability; and SHXX = XX% of shade effect probability).
Figure A.2. The $\overline{SF_k}$ and the $\text{se}\%\left(\overline{SF_k}\right)$ across the simulation scenarios of different sun and shade effect probability. (Dashed line = $\overline{SF}$ or $\text{se}\%\left(\overline{SF}\right)$ of the original PF; SUXX = XX% of sun effect probability, and SHXX = XX% of shade effect probability).
Figure A.3. The averaged of $\text{se} \left( \overline{\text{VOL}} \right)_{jk}$ across the simulation scenarios of different sun and shade effect probability. (Dashed line = $\text{se} \left( \overline{\text{VOL}} \right)$ of the original PF (SU00.SH00); SUXX = XX% of sun effect probability, and SHXX = XX% of shade effect probability).
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Sampling to correct LiDAR-assisted forest inventory estimates for small
woodlots. Forest Science

Yingbing Chen, Ting-Ru Yang, Yung-Han Hsu, John A. Kershaw, Jr., and Dale
Prest. (2019) Application of big BAF sampling for estimating carbon on small
woodlots. Forest Ecosystems.

TzengYih Lam, Yung-Han Hsu, Ting-Ru Yang, John A. Kershaw, Jr., Sheng-Hsin Su. (2018) Sampling with probability proportional to prediction: rethinking
rapid plant diversity assessment. Forestry 91:17-26

Ting-Ru Yang, Yung-Han Hsu, John A. Kershaw, Jr., Elizabeth McGarrigle, Dan
Kilham. (2017) Big BAF sampling in mixed species forest structures of
northeastern North America: Influence of count and measure BAF under cost
Conference Presentations:

(2018) Sampling to correct LiDAR assisted forest inventory. 2018 Western Mensurationists Annual Meeting, Flagstaff, AZ, United States

(2018) 3P sampling using a Ricoh 360 camera. 2018 Joint Southern Mensurationists and Northeastern Mensurationists Meeting, Blacksburg, VA, United States