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Evaluation of sampling strategies to estimate crown biomass

Krishna P Poudel[1], Hailemariam Temesgen[1*] and Andrew N Gray[2]

Abstract

Background: Depending on tree and site characteristics crown biomass accounts for a significant portion of the total aboveground biomass in the tree. Crown biomass estimation is useful for different purposes including evaluating the economic feasibility of crown utilization for energy production or forest products, fuel load assessments and fire management strategies, and wildfire modeling. However, crown biomass is difficult to predict because of the variability within and among species and sites. Thus the allometric equations used for predicting crown biomass should be based on data collected with precise and unbiased sampling strategies. In this study, we evaluate the performance different sampling strategies to estimate crown biomass and to evaluate the effect of sample size in estimating crown biomass.

Methods: Using data collected from 20 destructively sampled trees, we evaluated 11 different sampling strategies using six evaluation statistics: bias, relative bias, root mean square error (RMSE), relative RMSE, amount of biomass sampled, and relative biomass sampled. We also evaluated the performance of the selected sampling strategies when different numbers of branches (3, 6, 9, and 12) are selected from each tree. Tree specific log linear model with branch diameter and branch length as covariates was used to obtain individual branch biomass.

Results: Compared to all other methods stratified sampling with probability proportional to size estimation technique produced better results when three or six branches per tree were sampled. However, the systematic sampling with ratio estimation technique was the best when at least nine branches per tree were sampled. Under the stratified sampling strategy, selecting unequal number of branches per stratum produced approximately similar results to simple random sampling, but it further decreased RMSE when information on branch diameter is used in the design and estimation phases.

Conclusions: Use of auxiliary information in design or estimation phase reduces the RMSE produced by a sampling strategy. However, this is attained by having to sample larger amount of biomass. Based on our finding we would recommend sampling nine branches per tree to be reasonably efficient and limit the amount of fieldwork.

Keywords: Aboveground biomass; Crown; Sampling strategies; Pacific Northwest

* Correspondence: Hailemariam.Temesgen@oregonstate.edu
[1]Department of Forest Engineering, Resources, and Management, College of Forestry, Oregon State University, 280 Peavy Hall, Corvallis, OR 97331, USA
Full list of author information is available at the end of the article

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Background

The global issue of climate change and an increasing interest in the reduction of fossil fuel carbon dioxide emissions by using forest biomass for energy production has increased the importance of forest biomass quantification in recent years. Different national and international reports have presented the amount of carbon sequestered by forest ecosystems. For example, the Intergovernmental Panel on Climate Change reports that forests contain about 80% of aboveground and 40% of belowground carbon stock (IPCC 2007). Additionally, it is reported that the amount of carbon stored in dry wood is approximately 50% by weight (Brown 1986; Paladinic et al. 2009; Sedjo and Sohngen 2012).

Biomass, in general, includes both above and below ground living and dead mass of trees, shrubs, vines, and roots. However, most of the researches on biomass estimation have focused on aboveground biomass because of the difficulty in collecting belowground data (Lu 2006). The amount of biomass in a forest is influenced by various site factors such as stand density and site productivity; soil characteristics such as texture and moisture content; and tree characteristics such as species and age. On the other hand, distribution of crown biomass affects the carbon cycle, soil nutrient allocation, fuel accumulation, and wildlife habitat environments in terrestrial ecosystems and it governs the potential of carbon emission due to deforestation (Lu 2005). The major components of aboveground tree biomass are merchantable stem biomass (bole including bark and wood), stump biomass, foliage biomass, and branches/top biomass (Zhou and Hemstrom 2009).

The common biomass estimation approach selects some trees, which are representative of the populations of interest, for destructive sampling and weighs their components. Regression models are then fit to relate some easily measurable attributes, such as diameter at breast height and total tree height, with tree (or component) biomass. The amount of biomass distributed in different components is dependent on species and their geographic location (Pooreter et al. 2012), management practices (Tumwebaze et al. 2013) and tree size and stand density (Jenkins et al. 2003). Ritchie et al. (2013) found that for the given DBH and crown ratio, thinned stands had more foliage biomass but slightly less branch biomass than unthinned stands. Similarly, the contribution of component biomass to the total aboveground biomass varies by tree size (de-Miguel et al. 2014b). Henry et al. (2011) found differences in biomass due to floristic composition, tree species and growth strategies for the tree species within a given climatic zone. Thus, the component biomass estimations, for example branch or crown biomass, bole biomass, and bark biomass, are important to account for the variability within the tree.

The common understanding among researchers and practitioners is that an accurate carbon stock estimate requires improved and consistent methods for tree and component biomass estimation (Hansen 2002; Zhou and Hemstrom 2009).

Crown biomass is the oven dry weight of the entire crown, including the leading shoot above the last-formed whorl, excluding the main bole (Hepp and Brister 1982). The components of crown biomass are wood, bark, and foliage weights. Crown biomass accounts for a significant portion of total tree biomass but the amount and its distribution vary by tree and site characteristics. Using the data from two Alaskan *Picea mariana* ecosystems, Barney et al. (1978) reported that foliage comprised 17% to 37% of the total tree mass for the lowland stands and 17% to 50% of the total tree mass in the upland stands. Total bole mass ranged from 11% to 58% in lowland stands and 21% to 61% in the upland stands. In a study to determine the patterns of biomass allocation in dominant and suppressed loblolly pine (*Pinus taeda*), Naidu et al. (1998) found that the dominant trees allocated 24.5% of biomass to the crown (13.2% in branch and 11.3% in needle) and the suppressed trees allocated 12.3% (6.7% in branch and 5.6% in needle). Kuyaha et al. (2013) found that crown biomass formed up to 26% (22% in branch and 4% in needle) of aboveground biomass in farmed eucalyptus species. In assessing the importance of crown dimensions to improve tropical tree biomass estimate, Goodman et al. (2013) found the trees in their study to have nearly half of the total aboveground tree biomass in branches (44% ± 2%).

Estimates of crown biomass for each stand condition is necessary to understand nutrient depletion and for evaluating the economic feasibility of crown utilization for energy production or forest products (Hepp and Brister 1982). Furthermore, estimates of crown biomass aid in fuel load assessments and fire management strategies (He et al. 2013) because it is one of the important input variables in most wildfire models (Saatchi et al. 2007). Much of the focus in estimating crown biomass has been in the form of regression models and in the selection of predictor variables rather than in the methods of sample selection. In addition, comparisons of sampling strategies have been carried out mainly for foliar biomass sampling rather than the total crown (branch wood, bark, and foliage) biomass. Thus, the evaluation of different sampling designs and sample size in estimating crown biomass is an important aspect of aboveground biomass estimation.

Common sampling strategies used in aboveground biomass estimation include simple random sampling, systematic sampling, stratified random sampling, and randomized branch sampling. The suitability of a technique

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is determined by the availability of funds, required accuracy, structure and composition of vegetation, and desired specificity of estimation (Catchpole and Wheeler 1992). Additionally, the amount of time a particular technique takes to implement in the field is also important. The simple random sampling is generally used as the basis to evaluate the performance of other sampling designs (e.g. Snowdon 1986; Temesgen 2003).

Gregoire et al. (1995) have proposed a number of sampling procedures (randomized branch sampling, importance sampling, control-variate sampling, two-stage and three-stage sampling) that can be used to estimate foliage and other characteristics of individual trees. The randomized branch sampling (RBS) was originally introduced by Jessen (1955) to determine the fruit count on orchard trees. Valentine and Hilton (1977) used this method to obtain estimates of leaf counts, foliar area, and foliar mass of mature *Quercus* species. Good et al. (2001) have employed RBS with importance sampling for estimating tree component biomass. Since the sample is accumulated sequentially along the path, RBS does not require locating and counting the total number of branches beforehand. However, Chiric et al. (2014) posed some doubts on the effectiveness of RBS in sampling big trees or trees with irregular forms. According to Valentine and Hilton (1977), the accuracy of RBS is largely dependent on the probability assignment and the time required to take RBS samples depends on the size of the trees and experience of those taking the samples.

Swank and Schreuder (1974) compared stratified two-phase sampling, two-phase sampling with a regression estimator, and two-phase sampling with a ratio-of-means estimator. They found the stratified two-phase sampling as the most precise and appropriate method for estimating surface area and biomass for a young eastern white pine forest. Temesgen (2003) found that stratified random sampling produced the lowest mean squared error value in comparing five sampling designs to quantify tree leaf area. Stratification in branch biomass sampling can be done in many different ways. Snowdon (1986) showed improved accuracy of estimates by stratification based on crown position compared to those obtained by simple random sampling, especially at low sampling intensities. Their findings suggest that stratification by whorl was slightly but not significantly inferior to stratification based on crown position or branch diameter. Another approach used in selecting branches for estimating crown biomass is to divide the bole into sections and pile up the branches from each section into different size classes and randomly select a number of branches proportional to the total number of branches in each size class (e.g. Harrison et al. 2009, Devine et al. 2013). In an evaluation of ten different sampling strategies, Temesgen et al. (2011) found that systematic sampling

with ratio estimation as the most efficient estimate of individual tree foliage biomass. de-Miguel et al. (2014a) developed generalized, calibratable, mixed-effects meta-models for large-scale biomass prediction. One of their objectives was to investigate and demonstrate how the biomass prediction differed when calibration trees were selected using different sampling strategies. They found that a stratified sampling was better compared to the simple random sampling. Thus there is no strong rationale to support one method as being superior to another.

Crown biomass is difficult to predict because of the variability within and among species and various sites. A good allometric equation for predicting aboveground biomass should be based on data collected with an appropriate (precise and unbiased) sampling method. In this context, the objective of this study was to evaluate different sampling strategies to estimate crown biomass. We also evaluated how the performance of different methods was affected when different number of branches (3, 6, 9, and 12) per tree was sampled in estimating crown biomass.

Methods
Study area
This study was conducted in the McDonald-Dunn Forest, an approximately 4,550 ha property, managed by the Oregon State University in the western of the edge of the Willamette Valley in Oregon and on the eastern foothills of the Coast Range (123°15' W, 44°35' N, 120 m elevation). The forest consists predominantly of the Douglas-fir (*Pseudotsuga menziesii* (Mirbel) Franco) and a small Grand fir (*Abies grandis* (Dougl. ex D. Don) Lindl.) and has a wide range of overstory age-class distribution with majority of the stands less than 80 years old and some stands that are 80 to 120 years old. The forest receives approximately 110 cm of annual rainfall and average annual temperature ranges from 6°C to 17°C.

Data
Twenty sample trees (11 Douglas-fir and 9 Grand fir) were subjectively selected from stands of different ages for destructive sampling avoiding the trees with obvious defects and trees close to stand edges. The field work was carried out between the first week of July and third week of September 2012. Trees that were forked below breast height and with damaged tops were not included in sampling. Tree level attributes including total height, height to the base of first live branch, crown width, and main stem diameter at 0.15, 0.76, 1.37, and 2.40 m above ground, and every 1.22 m afterwards were recorded. The branches were divided into four diameter classes (1.3 cm class = 0–2.5 cm, 3.8 cm class = 2.6–5.1 cm, 6.4 cm class = 5.2–7.6 cm, 8.9 cm class = 7.7–10.2 cm). For all first order branches, height to- and diameter- at branch base were measured.

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For the first and every third branch, when proceeding from the base, in each diameter class, length and weight of both live and dead branches were recorded. From those selected branches, four branches per diameter class were weighed with and without foliage. The needles were removed in the field to obtain the green weight of foliage and branch wood with bark. Two of these four branches were taken to the lab, keeping branch and foliage in separate paper bags, for drying. The branches were chipped in to small pieces to expedite the drying process and placed in a kiln for drying at 105°C. The oven dry weight was recorded by tracking the weight lost by each sample until no further weight was lost. Table 1 presents the tree and branch level summary of the felled-tree data used in this study.

Individual branch biomass

Kershaw and Maguire (1995) developed a tree specific log linear model (Equation 1) using branch diameter (BD) and depth into the crown (DINC: the distance from tip to the base of the branch) as covariates to estimate branch foliage biomass. Temesgen et al. (2011) successfully used this model in comparing sampling strategies for tree foliage biomass estimation.

$$\ln\left(y_{ij}\right) = \beta_{0i} + \beta_{1i}\ln\left(BD_{ij}\right) + \beta_{2i}\ln\left(DINC_{ij}\right) + \varepsilon_{ij} \qquad (1)$$

This model was modified by replacing DINC with branch length (Equation 2). The modified model provided the best fit (Adj-R^2 = 0.93), therefore was used to predict individual branch biomass within each tree.

$$\ln\left(y_{ij}\right) = \beta_{0i} + \beta_{1i}\ln\left(BD_{ij}\right) + \beta_{2i}\ln\left(BL_{ij}\right) + \varepsilon_{ij} \qquad (2)$$

where y_{ij}, BD_{ij} and BL_{ij} are oven dry weight (kg) of branch (wood, bark, and foliage combined), branch diameter (cm), and branch length (m) of the jth branch on i^{th} tree respectively; β_{ij} 's are regression parameters to be estimated; $\ln(\cdot)$ is the natural logarithm; and ε_{ij} 's are the random error. The full model included other variables such as height to the base of the branch, crown width and crown length, but were dropped because they were not statistically significant (p-value > 0.05). Lengths for the $2/3^{rd}$ branches (not measured in the field) were obtained by fitting the following log linear model (Adj-R^2 = 0.74):

$$\ln\left(BL_{ij}\right) = \beta_{0i} + \beta_{1i}\ln\left(BD_{ij}\right) + \beta_{2i}\ln\left(RBD_{ij}\right) + \varepsilon_{ij} \qquad (3)$$

where BD_{ij}, BL_{ij} and ε_{ij} are same as defined in Equation 2 and RBD_{ij} is the relative branch depth (relative position of the subject branch from the crown base) of jth branch in i^{th} tree and is computed as follows (Ishii and Wilson 2001):

$$RBD = \frac{\text{total tree height–height to the base of subject branch}}{\text{total tree height–height to the base of lowest live branch}}$$

The RBD is 1.0 for the first live branch. The logarithmic regressions are reported to result in a negative bias when data are back transformed to arithmetic scale. The commonly used remedy to this is to multiply the back transformed results by a correction factor $\left[exp\left(\frac{MSE}{2}\right)\right]$, where MSE is the mean squared error obtained by the

Table 1 Summary of felled-tree and branch-level attributes used in this study

Variable	n	Mean	SD	Minimum	Maximum
Tree data					
DBH (cm)		62.8	27.0	23.9	114.0
Height (m)		34.6	10.3	18.3	46.5
Crown base height (m)		10.2	6.3	0.8	23.7
Crown length (m)		24.4	6.2	12.2	34.4
Crown width (m)		8.6	2.4	5.2	13.4
Branch data					
Diameter (cm)	3464	3.7	2.1	0.8	10.4
Length (m)	1178	2.8	1.6	0.1	10.2
Total green weight (kg)	1102	4.14	5.61	0.05	46.99
Green weight of branch wood (kg)	326	3.98	5.61	0.05	38.01
Green foliage weight (kg)	264	1.80	1.84	0.05	9.71
Total dry weight (kg)	128	3.44	4.08	0.12	18.40
Dry weight of branch wood (kg)	128	2.68	3.49	0.07	15.37
Dry foliage weight (kg)	128	0.76	0.79	0.04	4.58

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least-squares regression. However, there are conflicting remarks about the correction factor itself. For example Beauchamp and Olson (1973) and Flewelling and Pienaar (1981) suggested that this correction factor was still biased because the sample variance is consistent but it is biased for finite sample sizes. We did not use the correction factor in our study. The trend in the relationship between crown biomass and branch diameter and length was similar but the variability in biomass increased with increasing branch length (Figure 1). All statistical procedures were performed using statistical software R (R Core Team 2014).
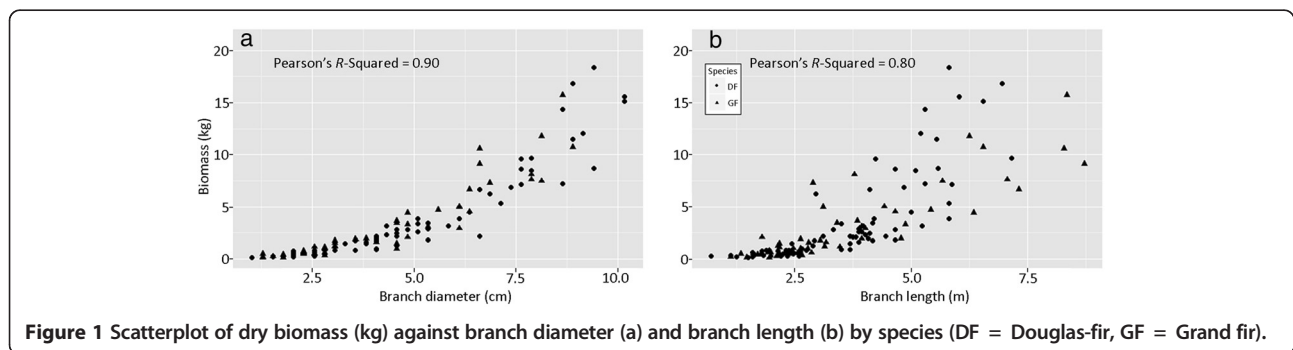
Methods for crown biomass sampling

We evaluated 11 sampling methods to select branches for estimating crown biomass. The 11 sampling strategies belonged to three main categories: simple random sampling, systematic sampling, and stratified sampling. Methods 1 and 2 are based on simple random sampling (SRS) strategy. In each of these methods, each branch was chosen randomly such that each individual branch has equal probability of selection at any stage of selection. The difference in these methods is in the estimation of total tree biomass: method 1 uses SRS estimator while method 2 (SRS-RAT) uses the ratio estimator with squared branch diameter as auxiliary information. Method 1 is also the basis for comparing the performance of other methods.

Method 3, probability proportional to size (PPS), uses branch size as auxiliary information in sample selection. Total crown biomass in this method was calculated using Horvitz-Thompson estimator (Horvitz and Thompson 1952). Methods 4 (SYS) and 5 (SYS-RAT) are systematic sampling with similar design phase but different estimation phase. Method 4 uses the SRS estimator while method 5 uses the ratio estimator. The fractional interval systematic sample selection procedure was used in the systematic selection of the branches because it ensures the equal probability of selection for all the branches (Temesgen et al. 2011). The interval was determined based on the total number of branches in each tree. In fractional interval systematic sample

selection, first a random starting point between 1 and total number of branches was randomly chosen, the interval then is added obtaining exactly n (sample size) branches. Then the numbers are divided by the sample size and rounded to the nearest whole number to get the selected samples.

Methods 6–11 belonged to different stratified sampling strategies. The stratified sampling method divides the population into subpopulations of size n_h, where n_h is the number of elements in stratum h. The total crown length was divided into three sections having equal number of branches as three strata. In methods 6 (STR) and 7 (STR-RAT), $n/3$ branches were randomly selected with equal probability, where n is the sample size. Again, the difference between these two methods lies in the estimation of total crown biomass. STR method uses the SRS estimation technique while STR-RAT method uses the ratio estimation technique to obtain the total crown biomass. Method 8 (STR-PPS), stratified sampling with PPS, selected branches in each stratum with probability proportional to the square of branch diameter. Total crown biomass in this method was obtained by summing the stratum total crown biomass calculated using Horvitz-Thompson unequal probability estimator (Horvitz and Thompson 1952).

Methods 9–11 (stratified, unequal) are based on the idea that the distribution of crown biomass in different strata depends on the relative position of the branches in the tree. Ishii and McDowell (2001) found that mean branch volume increased from upper- to lower-crown. For a given density, biomass (oven dry weight) is the function of volume. Therefore, the stratified sampling method was modified to incorporate the variability of biomass distribution within a tree. Trees were first divided into three sections having equal number of branches. Then, 4, 3, and 2 branches from the lower, middle, and upper section of the trees were selected respectively. This corresponds that the number of branches selected in each section is proportional to the observed biomass in that section of the tree. Because stratification based on crown length resulted in the biased estimation of crown biomass, the balanced stratification method was applied. The total number of

Figure 1 Scatterplot of dry biomass (kg) against branch diameter (a) and branch length (b) by species (DF = Douglas-fir, GF = Grand fir).

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Table 2 Summary of methods used for crown biomass estimation in this study

Methods	Equations for total crown biomass	Selection probability	Inclusion probability
Simple random sampling			
SRS	$\hat{\tau}_i = NB_i\left(\frac{1}{n}\sum_{j=1}^{n} y_{ij}\right)$	$\left(\frac{1}{NB_i}\right)^n$	$\frac{n}{NB_i}$
SRS-RAT	$\hat{\tau}_i = \frac{\sum_{j=1}^{n} y_{ij}}{\sum_{j=1}^{n} BD_{ij}^2}\sum_{j=1}^{NB_i} BD_{ij}^2$	$\left(\frac{1}{NB_i}\right)^n$	$\frac{n}{NB_i}$
PPS	$\hat{\tau}_i = \sum_{j\in S}\frac{y_{ij}}{\pi_{ij}^{PPS}}$	$\pi_{ij} = \frac{BD_{ij}^2}{\sum_{j=1}^{NB} BD_{ij}^2}$	$\pi_{ij}^{PPS} = 1-\left(1-\pi_{ij}\right)^n$
Systematic sampling			
SYS	$\hat{\tau}_i = NB_i\left(\frac{1}{n}\sum_{j=1}^{n} y_{ij}\right)$	$\frac{n}{NB_i}$	$\frac{n}{NB_i}$
SYS-RAT	$\hat{\tau}_i = \frac{\sum_{j=1}^{n} y_{ij}}{\sum_{j=1}^{n} BD_{ij}^2}\sum_{j=1}^{NB_i} BD_{ij}^2$	$\frac{n}{NB_i}$	$\frac{n}{NB_i}$
Stratified sampling			
STR	$\hat{\tau}_i = \sum_{h=1}^{H}\sum_{j=1}^{n_h}\frac{N_{ih}}{n_h} y_{ijh}$	$\frac{BD_{ij}^2}{\sum_{j=1}^{NB} BD_{ij}^2}$	$\frac{n_h}{N_{ih}}$
STR-RAT	$\hat{\tau}_i = \frac{\sum_{h=1}^{H}\sum_{j=1}^{n_h}\frac{N_{ih}}{n_h}y_{ijh}}{\sum_{h=1}^{H}\sum_{j=1}^{n_h}\frac{N_{ih}}{n_h}BD_{ijh}^2}$	$\frac{BD_{ij}^2}{\sum_{j=1}^{NB} BD_{ij}^2}$	$\frac{n_h}{N_{ih}}$
STR-PPS	$\hat{\tau}_{i(STR-PPS)} = \sum_{h=1}^{H}\sum_{j\in S_h}\frac{y_{ijh}}{\pi_{ijh}^{(STR-PPS)}}$	$\frac{BD_{ijh}^2}{\sum_{j=1}^{NB_{ih}} BD_{ijh}^2}$	$\pi_{ij}^{STR-PPS} = 1-\left(1-\pi_{ij}\right)^n$

Notation: $\hat{\tau}_i$ is the estimated total crown biomass for i^{th} tree; y_{ij} is the oven dry weight of jth branch on i^{th} tree; NB_i is the number of branches on i^{th} tree; n is number of branches sampled; N_{ih} is the number of branches in h^{th} stratum on i^{th} tree; and n_h is the number of branches sampled in h^{th} stratum.

branches selected in each tree (nine) was determined based on the amount of biomass sampled. Total crown biomass in each stratum was computed using the SRS estimation technique in method 9 (Un-STR), PPS in method 10 (Un-PPS), and ratio estimation in method 11 (Un-STRRAT). Total crown biomass in each tree was computed by summing the crown biomass in each stratum. The unequal branch selection strategy was also evaluated using similar evaluation statistics used for the other eight methods.

Performances of first eight methods were evaluated by selecting four different sample sizes (3, 6, 9, and 12) in each tree. These sample sizes were chosen for the ease of distributing samples into three different strata in stratified sampling with equal number of branches per stratum. Methods 9–11 were based on selecting nine branches in each tree. Table 2 summarizes the inclusion probability, selection probability, and the estimator of the total crown biomass in each of the sampling strategies evaluated in this study.

Evaluation of sampling strategies

We evaluated the performance of 11 sampling strategies to estimate crown biomass using the following six statistics estimated from 5,000 iterations. These measures were successfully used to evaluate the performance of sampling strategies to estimate foliage biomass in Temesgen et al. (2011).

Table 3 Average bias (kg) produced by different sampling methods and sample sizes based on 5,000 simulations

Sample size	Sampling strategies							
	SRS	SRS-RAT	PPS	SYS	SYS-RAT	STR	STR-RAT	STR-PPS
3	0.237	−4.091	−0.158	0.433	−9.320	−0.659	−3.554	−0.104
6	0.215	−1.711	0.010	0.139	−1.922	0.399	−1.387	−0.101
9	−0.081	−0.937	−0.068	0.133	0.166	0.191	−0.857	−0.094
12	−0.030	−0.894	0.158	0.043	−0.078	−0.242	−0.776	−0.073

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Table 4 Relative bias (percent) produced by different sampling methods and sample sizes based on 5,000 simulations

Sample size	Sampling strategies							
	SRS	SRS-RAT	PPS	SYS	SYS-RAT	STR	STR-RAT	STR-PPS
3	0.101	−2.437	−0.169	0.107	−6.086	−0.321	−2.107	−0.034
6	−0.001	−1.115	0.024	0.061	−1.061	0.197	−0.900	−0.012
9	0.063	−0.600	−0.027	0.038	0.033	0.148	−0.543	−0.069
12	−0.011	−0.523	0.100	0.037	0.032	−0.035	−0.439	−0.040

1. **Bias:** For each tree the bias (kg) was calculated as the mean difference between observed and predicted total crown biomass for that tree as follows:

$$B_i = \frac{1}{5000}\sum_{s=1}^{5000}(\tau_{is} - \hat{\tau}_{is})$$

where τ_{is} and $\hat{\tau}_{is}$ are the observed and predicted total crown biomasses for i^{th} tree in s^{th} iteration, respectively.

2. **Relative bias:** Relative bias percentage is the ratio of bias to the total observed crown biomass for that tree and computed as follows:

$$RB_i = \frac{1}{5000}\sum_{s=1}^{5000}\frac{(\tau_{is} - \hat{\tau}_{is})}{\tau_{is}}$$

where all the variables are same as defined previously.

3. **Root mean square error (RMSE):**

$$RMSE_i = \sqrt{\frac{1}{5000}\sum_{s=1}^{5000}(\tau_{is} - \hat{\tau}_{is})^2}$$

4. **Relative RMSE:**

$$R{-}RMSE_i = \sqrt{\frac{1}{5000}\sum_{s=1}^{5000}\left(\frac{\tau_{is} - \hat{\tau}_{is}}{\tau_{is}}\right)^2}$$

5. **Biomass sampled (BS):** Amount of cost for crown biomass estimation is directly proportional to the amount of crown biomass sampled. Therefore the amount of crown biomass sampled was also used as a criterion for the evaluation of sampling strategies. The amount of crown biomass sampled (sampling intensity) is calculated as follows:

$$BS_i = \frac{1}{5000}\sum_{s=1}^{5000}\sum_{j\in S} y_{ijs}$$

y_{ijs} is the observed total crown biomasses for i^{th} tree, j^{th} sample branch in s^{th} iteration.

6. **Relative biomass sampled (RBS%)** indicates the proportion of crown biomass sampled with respect to the total crown biomass measured and is calculated as follows:

$$RBS_{ij} = \frac{1}{5000}\sum_{s=1}^{5000}\sum_{j\in S}\frac{y_{ijs}}{\tau_{ijs}}$$

Results and discussions

Except for the ratio estimators, the estimators of population totals were unbiased, with biases close to zero for all sample sizes (Tables 3 and 4). The squared bias for these methods ranged from zero to 0.435 kg. Ratio estimators resulted in greater bias than the other methods. The absolute bias of the ratio estimators decreased with increasing sample size as expected.

As expected, the RMSE (and relative RMSE) decreased with increasing sample size (Tables 5 and 6) for all sampling strategies. Based on the RMSE values obtained from 5,000 simulations, the stratified sampling with PPS estimation was the superior method compared to

Table 5 Average RMSE produced by different sampling methods and sample sizes based on 5,000 simulations

Sample size	Sampling strategies							
	SRS	SRS-RAT	PPS	SYS	SYS-RAT	STR	STR-RAT	STR-PPS
3	88.57	42.56	38.04	113.17	48.54	85.05	42.08	34.95
6	60.49	30.01	29.23	57.94	29.98	58.54	29.56	27.99
9	48.60	23.92	25.19	37.88	22.12	46.48	23.55	24.46
12	40.77	20.18	22.78	30.77	17.91	38.89	19.75	22.33

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Table 6 Relative RMSE percent produced by different sampling methods and sample sizes based on 5,000 simulations

Sample size	Sampling strategies							
	SRS	SRS-RAT	PPS	SYS	SYS-RAT	STR	STR-RAT	STR-PPS
3	55.70	25.72	23.46	72.02	28.80	53.41	25.61	21.57
6	38.07	17.93	18.23	35.23	17.53	36.63	17.78	17.59
9	30.38	14.19	15.83	23.58	13.29	29.03	14.07	15.55
12	25.42	11.92	14.40	18.37	11.11	24.27	11.76	14.22

all other methods when sample size is 3 or 6 branches per tree. However, while using PPS, stratification of the crown into sections did not reduce the RMSE and relative RMSE significantly. On the other hand, when at least nine branches per tree were sampled, the SYS-RAT was the best and the SRS-RAT was the second best method. Number of branches required to achieve desired precision is another important aspect of estimating crown biomass. On average, the RMSE decreased by 34.3% when the sample size increased from three branches per tree to six branches per tree. The RMSE further decreased by 22.1% and 15.4% when the sample size increased from 6 to 9 and 9 to 12 respectively.

The amount of biomass sampled determines the cost that would be incurred in estimating crown biomass. Biomass sampled and relative biomass sampled in different sampling strategies are presented in Tables 7 and 8. The Strategy-Cost-Accuracy graph (Figure 2) shows the efficiency trade-off across the strategies compared in the study. The SRS and SYS methods resulted in the lowest amount of biomass sampled. On average, the amount of biomass sampled using the PPS method was 1.6, 1.5, 1.4, and 1.4 times higher than the amount of biomass sampled in stratified random sampling when 3, 6, 9, and 12 branches per tree were selected respectively.

On average, selecting 12 instead of 9 branches per tree increased the amount of biomass sampled by 29.2%. Therefore, nine branches in each tree were selected in evaluating the performance of unequal stratified sampling strategy. Results from unequal branch selection are presented in Table 9. This strategy reduced the relative RMSE by 0.6%, 4.5% and 3.5% compared to selecting 9 branches using stratified random sampling, stratified sampling with ratio estimation, and stratified sampling with PPS respectively. This reduction in relative RMSE

is obtained by sampling just a little more amount of biomass (1.03 times on average).

Use of allometric equations is inevitable in above-ground biomass estimation because weighing the trees and their components for direct biomass determination is destructive and prohibitively expensive. Choice of biomass sampling strategy determines the quality of data available for fitting such equations. Use of auxiliary information in design and/or estimation phase (ratio estimation and PPS) produced better results in terms of RMSE compared to the methods that do not make use of such information in this study. Previous researches (e.g. Temesgen et al. 2011) have also shown the benefits from using auxiliary information in the design and/or estimation concerning tree biomass.

The model used in estimating branch biomass which is later used as a dependent variable in the test population, was a logarithmic model (Equation 2). There is an inherent negative bias in this method because the dependent variable is transformed prior to estimation (Snowdon 1991). The ratio estimation strategies, SRS-RAT, SYS-RAT, and STR-RAT in this study, were negatively biased. However, in terms of RMSE, these strategies were clearly superior methods compared to the SRS approach. As noted in Temesgen et al. (2011), however, the efficiency of sampling strategies with ratio estimation may be affected by the amount of work and difficulty in implementing these techniques in the field.

The amount of biomass sampled determines the cost that would be incurred in estimating crown biomass. Choice of a sampling strategy determines the amount of biomass and relative biomass sampled. This ultimately determines the amount of time and cost required for a biomass estimation project. The SRS and SYS methods resulted in the lowest amount of biomass sampled. Our
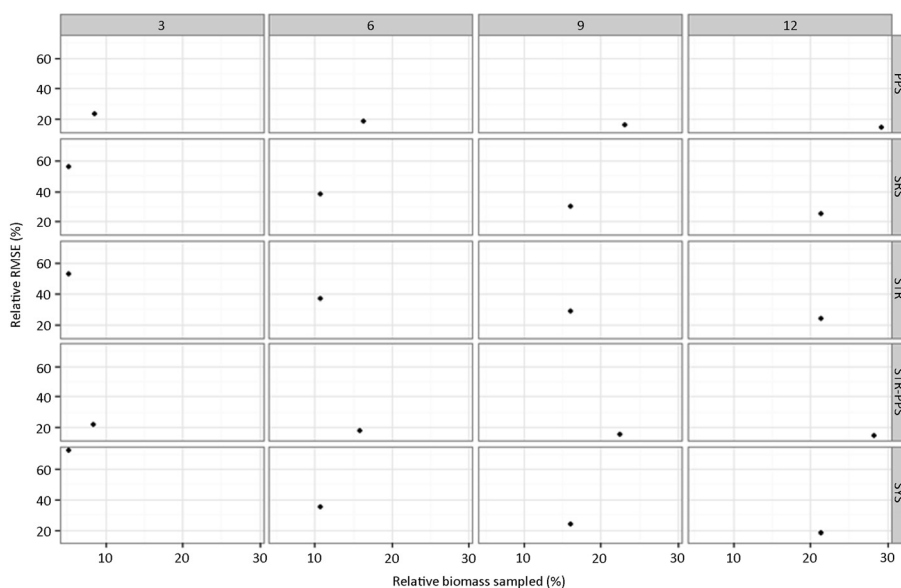
Table 7 Amount of biomass sampled (kg) by different sampling strategies and sample sizes

Sample size	Sampling strategies				
	SRS	PPS	SYS	STR	STR-PPS
3	7.74	12.58	7.73	7.68	12.40
6	15.49	23.79	15.46	15.50	23.29
9	23.17	33.77	23.18	23.19	33.05
12	30.91	42.83	30.92	30.86	41.79

Table 8 Relative amount of biomass sampled (%) by different sampling strategies and sample sizes

Sample size	Sampling strategies				
	SRS	PPS	SYS	STR	STR-PPS
3	5.36	8.67	5.35	5.33	8.45
6	10.71	16.37	10.71	10.72	15.87
9	16.08	23.16	16.06	16.07	22.45
12	21.42	29.27	21.43	21.40	28.33

Figure 2 Relative RMSE (%) produced Vs. relative biomass sampled (percent of total crown mass) in different sampling strategies and sample sizes.

results in terms of RMSE values reported and the amount of biomass sampled by each strategy are consistent with the findings of Temesgen et al. (2011) in estimating foliar biomass of Douglas-fir (*Pseudotsuga menziesii* var. *menziesii*) and ponderosa pine (*Pinus ponderosa*).

Conclusions

Crown biomass estimation is a complex process that requires intensive manual field work involving destructive sampling. The amount of fieldwork required and the accuracy of biomass estimation is dependent on the sampling strategy used. Furthermore, the accuracy of the estimation can be improved by adopting appropriate techniques in both the design and estimation phases, beginning with the selection of sample plots and sample trees through model development. In this study, we evaluated 11 different sampling strategies that belonged to three main categories: simple random sampling, systematic sampling and stratified sampling. The SRS, PPS, and ratio estimation techniques were used to obtain the total crown biomass in each tree.

Based on the RMSE values obtained from 5,000 simulations, the stratified sampling with PPS estimation produced better results as compared to all other methods when 3 or 6 branches per tree were sampled. However,

the SYS-RAT was the best and the SRS-RAT was the second best method when at least nine branches per tree were sampled. It should also be noted that the lower RMSE values in the PPS estimation techniques are obtained with an increased amount of biomass sampled in each tree. On the other hand, if the auxiliary information on branch size is not used, the systematic sampling provided better results than the SRS or STR method when at least 6 branches per trees were selected. Thus the selection of a specific sampling strategy is dependent on the availability of the time and cost for the given biomass sampling project. Based on our finding we would recommend sampling 9 branches per tree to obtain reasonable efficiency and amount of work involved in the field.

The logic for selecting unequal numbers of branches per stratum within a tree is justified by the fact that the biomass distribution within a tree is not uniform. Selecting equal branches per stratum produced approximately similar results to unequal sampling when the SRS estimation technique was used. However, making use of auxiliary information on branch size in the design and estimation phases further decreased the relative RMSE. Once again, the decreased RMSE by use of auxiliary information is attained by having to sample slightly higher

Table 9 Evaluation statistics produced when selecting 4, 3, and 2 branches from lower, middle, and upper stratum

Method	Bias	Relative bias	RMSE	Relative RMSE	Biomass sampled	Relative biomass sampled
Un-STR	0.100	0.061	46.16	28.87	24.25	16.87
Un-STRRAT	−0.731	−0.491	22.58	13.44		
Un-PPS	0.140	0.063	23.67	15.00	33.85	23.04

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amount of biomass. Findings of this study should prove beneficial for the stakeholders working in the field of aboveground biomass and carbon estimation. Additional work using the data from different species and location should be done to further validate the findings in this study.

Author details
[1]Department of Forest Engineering, Resources, and Management, College of Forestry, Oregon State University, 280 Peavy Hall, Corvallis, OR 97331, USA. [2]USDA Forest Service, PNW Research Station, 3200 SW Jefferson Way, Corvallis, OR 97331, USA.

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