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Indirect and direct estimation of forest biomass change using forest inventory and airborne laser scanning data

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A B S T R A C T

Remote sensing-based change estimation typically takes two forms. Indirect estimation entails constructing models of the relationship between the response variable of interest and remotely sensed auxiliary variables at two times and then estimating change as the differences in the model predictions for the two times. Direct estimation entails constructing models of change directly using observations of change in the response and the remotely sensed auxiliary variables for two dates. The direct method is generally preferred, although few statistically rigorous comparisons have been reported. This study focused on statistically rigorous, indirect and direct estimation of biomass change using forest inventory and airborne laser scanning (ALS) data for a Norwegian study area. Three sets of statistical estimators were used: simple random sampling estimators, indirect model-assisted regression estimators, and direct model-assisted regression estimators. In addition, three modeling approaches were used to support the direct model-assisted estimators. The study produced four relevant findings. First, use of the ALS auxiliary information greatly increased the precision of change estimates, regardless of whether indirect or direct methods were used. Second, contrary to previously reported results, the indirect method produced greater precision for the study area mean than the traditional direct method. Third, the direct method that used models whose predictor variables were selected in pairs but with separate coefficient estimates and models whose predictor variables were selected without regard to pairing produced the greatest precision. Finally, greater emphasis should be placed on the effects of model extrapolations for values of independent variables in the population that are beyond the range of the variables in the sample.

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1. Introduction

1.1. Motivation

Estimates of forest aboveground biomass (AGB) and AGB change are crucial for national strategic planning and satisfying Kyoto Protocol reporting requirements. National forest inventories (NFI) are the primary source of AGB data. However, one effect of the large sampling variability characteristic of many forests is that plot-based estimates of parameters related to inventory variables such as AGB and AGB change are often imprecise. Airborne laser scanning (ALS) data have been shown to be a source of auxiliary information that can substantially increase the precision of AGB change estimates (Andersen, Reutebuch, McGaughey, d'Oliveira, & Keller, 2014; Næsset et al., 2013; Skowronski, Clark, Gallagher, Birdsey, & Hom, 2014).

1.2. Direct and indirect methods

Remote sensing-based change estimation typically relies on one of two methods. The indirect method entails constructing a model of the relationship between observations of the response variable of interest and the auxiliary variables for each of two dates. Mean change per unit area is estimated as the mean over population units of the differences in the two model predictions, possibly adjusted to compensate for model prediction errors. The direct method entails constructing a model of the relationship between observations of change in the response variable of interest and observations of auxiliary remotely sensed variables for the same two dates. The model is then used to predict change for each population unit, and mean change per unit area is estimated as the mean over population units of model predictions, again possibly adjusted to compensate for model prediction error. The direct method is often considered preferable because only a single set of prediction errors must be accommodated (e.g., Bollandsås, Gregoire, Næsset, & Øyen, 2013; Fuller, Smith, & Devereux, 2003; GFOI, 2013, Section 3.6; Skowronski et al., 2014). However, because change data used for constructing models are calculated as differences in two values, each of which is subject to observation, measurement, and intermediate

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model prediction error, change in a response variable may be more difficult to predict precisely than the response variable itself. The result is that change prediction errors may be larger than response variable prediction errors. Thus, a question of interest is whether conditions exist for which the two sets of possibly smaller errors associated with the indirect method produce greater precision than the single set of possibly larger errors associated with the direct method.

Few statistically rigorous approaches to inference for AGB change have been reported. Næsset et al. (2013) demonstrated that AGB change could be estimated using observations for a sample of field plots and wall-to-wall ALS data. Deforested, thinned and degraded, and unchanged forest areas were distinguished, and AGB change for those areas was precisely estimated using ALS metrics. The study was the first to use the statistically rigorous model-assisted regression estimators to adjust for estimated bias and to estimate precision. Skowronski et al. (2014) used plot-based estimates of forest AGB and repeated ALS data with a model-assisted estimator to estimate mean AGB change per unit area. Estimates obtained using a direct, model-assisted estimator were more precise than estimates obtained using an indirect, model-assisted estimator. Andersen et al. (2014) estimated AGB change resulting from low-impact selective logging in Brazil. A model of the relationship between AGB and ALS metrics was constructed for 2010 and then applied to ALS data for both 2010 and 2011. To accommodate this unique data situation, an indirect, model-based approach to inference was used. AGB change was estimated for the entire study area and for sub-areas that were and were not subject to logging. Although few in number, these three studies convincingly document the utility of ALS metrics for estimating AGB change and statistically rigorous approaches to inference.

Models of change constructed for the direct method typically use differences over time in the observations of the response variable of interest as the dependent variable and differences over time in the observations of the auxiliary, remotely sensed, independent variables. An assumption underlying this approach is that the contributions of the two observations of any particular auxiliary variable are equally important as predictors of change with the result that a single parameter is estimated for the difference rather than a separate parameter for each observation of the variable used to calculate the difference. However, no evaluations of this assumption are known to have been reported.

1.3. Objectives

The objectives of the study were twofold. First, estimates of mean AGB change per unit area and corresponding standard errors (SEs) were compared for simple random sampling estimators that used no auxiliary information, and both indirect and direct model-assisted estimators that used ALS data as auxiliary information. Second, for the direct, model-assisted estimators, estimates and their precision were compared for three approaches to constructing models of the relationship between AGB change and the ALS metrics.

2. Data

The 853-ha study area was located in a boreal forest region in Våler Municipality in southeastern Norway (Fig. 1). Norway spruce (*Picea abies* (L.) Karst.) and Scots pine (*Pinus sylvestris* L.) are the dominant species, with younger stands having large proportions of deciduous species. Forests in the study area are actively managed with clear-cutting and commercial thinning on productive sites and selective logging on poor sites. Regeneration is often by planting following clear-cutting and natural regeneration following selective logging. The study area was delineated into four classes related to stand age and species dominance: (1) recently regenerated forest, (2) young forest, (3) mature, spruce dominated forest, and (4) mature, pine dominated forest. Sampling intensities were approximately equal for the first three strata, but for the fourth stratum the intensity was only approximately one-third of that for the other three strata (Næsset et al., 2013). The four classes were used as strata for stratified estimation (Section 3.1).

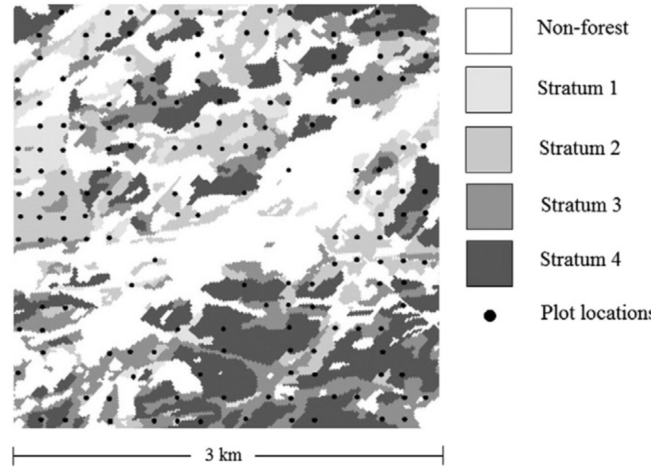

Fig. 1. Study area with stratification and plot locations.

Measurements were obtained for 176 systematically-distributed, circular, 200-m^2 forest inventory plots. Tree-level AGB was estimated for both 1999 and 2010 using statistical models based on field observations of species and measurements of diameter at-breast-height (1.3 m) and height (Marklund, 1988). For both years, plot-level AGBs were then estimated as the sums of individual tree AGB predictions, scaled to Mg/ha, and considered to be observations without error (McRoberts & Westfall, 2014).

Wall-to-wall ALS data were acquired for the study area in 1999 and 2010. Pulse densities were approximately 1.2 pulses per m^2 in 1999 and 7.3 pulses per m^2 in 2010. Holmgren (2004), Maltamo, Eerikainen, Packalén, and Hyyppä (2006), and Gobakken and Næsset (2008) all demonstrated that pulse densities of 0.1 pulse per m^2 and greater are adequate for estimating forest attributes such as basal area and growing stock volume, both of which are closely related to AGB. For each year, distributions of first echo heights were constructed for the 200-m^2 plots and 200-m^2 square cells that tessellated the study area. A threshold of 1.3 m above the ground surface was used to remove the effects of echoes from ground vegetation whose biomass is not included in tree-level AGB. For each plot and cell, heights corresponding to the 10th, 20th, …, 100th percentiles of the distributions were calculated as were canopy densities calculated as the proportions of echoes with heights greater than 0%, 10%, …, 90% of the range between 1.3 m above ground and the 95th height percentile (Gobakken & Næsset, 2008). Thus, 20 ALS metrics were available for inclusion as independent variables for the AGB models, and 40 ALS metrics were available for the AGB change models. Næsset et al. (2013) provide more details for the study area and the dataset.

3. Methods

3.1. Stratified estimation

Stratified estimation of the population mean was necessary to accommodate the different sampling intensities. One approach was to aggregate the three strata with the approximately same sampling intensities into a single stratum, thereby forming two strata for estimation purposes. However, because estimates and variances were expected to differ substantially for the four strata, they were also maintained separately as a means of increasing the precision of estimates, thereby forming four strata for estimation purposes. The stratified estimators are,

$$\hat{\Delta\mu}_{STR} = \sum_{h=1}^{H} w_h \cdot \hat{\Delta\mu}_h, \tag{1a}$$

and

$$\hat{Var}\left(\hat{\Delta\mu}_{Str}\right) = \sum_{h=1}^{H} w_h^2 \cdot \hat{Var}\left(\hat{\Delta\mu}_h\right), \tag{1b}$$

where $h = 1, 2, \ldots, H$ indexes strata, w_h is the stratum weight calculated as the proportion of the study area in the hth stratum, and $\hat{\Delta\mu}_h$ and $\hat{Var}\left(\hat{\Delta\mu}_h\right)$ denote estimates of the mean AGB change and its variance, respectively, for the hth stratum (Cochran, 1977).

Three approaches were used to estimate the stratum means and variances: (i) simple random sampling using only the plot data, (ii) model-assisted regression estimation using the indirect method, and (iii) model-assisted regression estimation using the direct method. For all three approaches, variances may be overestimated as the result of using systematic rather than simple random sampling (Särndal et al., 1992, p. 83).

3.2. Simple random sampling estimators within strata

The simple random sampling estimators use only the plot data and are the simplest and most familiar method for estimating the within-stratum parameters:

$$\hat{\Delta\mu}_h = \frac{1}{n_h} \sum_{i \in S_h} \Delta y_i \tag{2a}$$

and

$$\hat{Var}\left(\hat{\Delta\mu}_h\right) = \frac{1}{n_h \cdot (n_h - 1)} \sum_{i \in S_h} \left(\Delta y_i - \overline{\Delta y}\right)^2, \tag{2b}$$

where S_h is the sample for the hth stratum and n_h is the corresponding sample size, y_i^{1999} and y_i^{2010} are 1999 and 2010 plot-level AGB for the ith plot, $\Delta y_i = y_i^{2010} - y_i^{1999}$, and $\overline{\Delta y} = \frac{1}{n_h} \sum_{i \in S_h} \Delta y_i$.

3.3. Indirect, model-assisted regression estimators within strata

The indirect model-assisted regression method requires construction of models of the relationship between AGB and the ALS metrics. For each year, a linear regression model was formulated as,

$$y_i = \beta_0 + \beta_1 \cdot x_{1i} + \cdots \beta_p \cdot x_{pi} + \varepsilon_i, \tag{3}$$

where i indexes plots, y_i is the plot-level AGB, x_{ji} is the jth ALS metric, p is the number of metrics selected, ε_i is a random residual with mean zero, and the βs are the parameters to be estimated. ALS metrics serving as independent variables in Eq. (3) were selected using a basic stepwise selection technique based on the F-test with entry and removal levels of significance of $\alpha = 0.05$ (Efroymson, 1960).

Linear models of the form of Eq. (3) are familiar and are easily constructed. However, linear models have the potential to produce negative and excessively large positive predictions, particularly when the model is extrapolated to values of independent variables in the population that are beyond the ranges of those variables in the sample. To circumvent this potential difficulty, a nonlinear asymptotic logistic model was formulated as,

$$y_i = \frac{\alpha}{1 + \exp\left(\beta_0 + \beta_1 \cdot x_{1i} + \cdots + \beta_p \cdot x_{pi}\right)} + \varepsilon_i \tag{4}$$

where α and the βs are the parameters to be estimated and the independent variables were those selected for the corresponding linear model. With this model all predictions are non-negative, and they cannot exceed the upper asymptote, α, which is estimated from the sample data when fitting the model.

For both 1999 and 2010, linear and asymptotic logistic models were constructed separately for each stratum. In addition, common, pan-stratum linear and asymptotic logistic models were constructed for the entire study area.

The within-stratum mean and variance of the mean were estimated using the model-assisted, generalized regression estimators (Särndal, 1984, 2011; Särndal et al., 1992, Section 6.5),

$$\hat{\Delta\hat{\mu}}_h = \frac{1}{N_h} \sum_{i \in U_h} \hat{\Delta y}_i - \frac{1}{n_h} \sum_{i \in S_h} \varepsilon_i \tag{5a}$$

and

$$\hat{Var}\left(\hat{\Delta\hat{\mu}}_h\right) = \frac{1}{n_h \cdot (n_h - 1)} \sum_{i \in S_h} \left(\varepsilon_i - \overline{\varepsilon}\right)^2, \tag{5b}$$

where U_h is the portion of the population in the hth stratum, N_h is the number of population units in U_h, $\hat{y}_i^{1999}$ and $\hat{y}_i^{2010}$ are model predictions, $\hat{\Delta y}_i = \hat{y}_i^{2010} - \hat{y}_i^{1999}$, $\varepsilon_i = \hat{\Delta y}_i - \Delta y_i$, and $\overline{\varepsilon} = \frac{1}{n_h} \sum_{i \in S_h} \varepsilon_i$. The first term on the right-hand side of Eq. (5a) is simply the mean of model predictions over all population units in the stratum, and the second term adjusts for estimated bias resulting from systematic model prediction error.

3.4. Direct, model-assisted regression estimators within strata

Three forms of linear models were used to represent the relationship between AGB change and the ALS metrics. The most common approach is to use differences in the ALS metrics as the independent variables. With this approach, the model is formulated as,

$$\Delta y_i = \beta_0 + \beta_1 \cdot \left(x_{1i}^{2010} - x_{1i}^{1999}\right) + \cdots + \beta_p \cdot \left(x_{pi}^{2010} - x_{pi}^{1999}\right) + \varepsilon_i, \tag{6}$$

where p is the number of pairs of metrics included in the model. This model is designated as Model 1 and assumes that both ALS metrics in each pair have the same coefficient, albeit with different signs. Relaxation of this assumption so that each metric in each pair may have different coefficient estimates produces a model of the form,

$$\begin{aligned} \Delta y_i = \beta_0 &+ \left(\beta_{11} \cdot x_{1i}^{2010} - \beta_{12} \cdot x_{1i}^{1999}\right) + \cdots \\ &+ \left(\beta_{p1} \cdot x_{pi}^{2010} - \beta_{p2} \cdot x_{pi}^{1999}\right) + \varepsilon_i \end{aligned} \tag{7}$$

which is designated as Model 2. Models 1 and 2 both assume that the ALS metrics appear in the models in pairs. Relaxation of this assumption leads to Model 3,

$$\begin{aligned} \Delta y_i = \beta_0 &+ \left(\beta_{11} \cdot x_{1i}^{2010} + \cdots + \beta_{p1} \cdot x_{pi}^{2010}\right) \\ &+ \left(\beta_{12} \cdot x_{1i}^{1999} + \cdots + \beta_{q2} \cdot x_{qi}^{1999}\right) + \varepsilon_i, \end{aligned} \tag{8}$$

where p and q denote the number of metrics for 2010 and 1999, respectively. With Model 3, metrics selected for 1999 are not necessarily selected for 2010 and vice versa. As for the indirect method, stepwise selection was used to select the particular metrics that served as independent variables for Models 1, 2, and 3.

Similar to linear AGB models, linear AGB change models may produce excessively negative and positive predictions, particularly for extrapolations. Asymptotic models similar to those used for AGB models were considered, but the sample data did not include sufficient indicators of asymptotes to facilitate fitting such models. The approach that was used to circumvent extrapolation problems included two steps. First, for each stratum, the maximum AGB loss was limited to the largest plot AGB observation for the stratum in 1999. The rationale is that the maximum AGB removal cannot exceed the maximum that was initially present. Second, for each stratum, the maximum increase in AGB was limited to the largest observed or predicted increase in AGB for the stratum.

Regardless of the approach and model used for the direct method, the within-stratum population mean and its variance were estimated using Eqs. (5a) and (5b). The only difference in the within-strata estimators used for the indirect and direct methods was that with the indirect method $\hat{\Delta y}_i$ was calculated as the difference in biomass predictions calculated for individual years using Eq. (4), whereas with the direct method $\hat{\Delta y}_i$ was calculated directly using one of Eqs. (6), (7), or (8).

3.5. Analyses

The proportion of variance in the sample data explained by each model was calculated as,

$$R^2 = \frac{\sum_{i \in S} (z_i - \bar{z})^2 - \sum_{i \in S} (z_i - \hat{z}_i)^2}{\sum_{i \in S} (z_i - \bar{z})^2}, \quad (9)$$

where S denotes a stratum-level subsample, i indexes sample units, z_i denotes an observation of either AGB (y_i) or AGB change (Δy_i), $\bar{z}$ denotes the sample mean, and $\hat{z}_i$ denotes a model prediction. For the nonlinear asymptotic logistic model, Eq. (9) is a pseudo-R^2 and is denoted R^{2*}, because the formal definition of R^2 requires linear models with intercepts (Anderson-Sprecher, 1994).

The analyses consisted of estimation and comparisons of stratified means and SEs using both two and four strata; using the four stratum-level models and the common models; and using the SRS estimators, the indirect model-assisted regression estimators, and the direct model-assisted regression estimators with each of Models 1, 2, and 3 within strata.

4. Results and discussion

4.1. Models

The stratum-level, asymptotic logistic models of the relationship between AGB and the ALS metrics exhibited slightly greater quality of fit than the corresponding linear models with R^{2*} values ranging from 0.688 to 0.910 (Table 1, Fig. 2). For the stratum-level linear models of relationships between AGB change and the ALS metrics, R^2 ranged from 0.324 to 0.877 for Model 1; from 0.557 to 0.929 for Model 2; and from 0.625 to 0.904 for Model 3 (Table 1, Fig. 3). The slightly smaller R^2 values for Model 3 compared to Model 2 are attributed to the manner in which the stepwise selection technique selected ALS metrics to serve as independent variables. The bias adjustment estimates for the model-assisted estimator of Eq. (5a) also reflect the quality of fit of the models to the sample data. For the AGB models for the indirect approach, stratum-level bias estimates for AGB change estimates were less than 0.67 for all except one stratum. For the AGB change models for the direct approach, bias estimates were less than 0.02 for all combinations of models and strata. For the common, pan-stratum models, deviations between plot observations and model predictions were larger and produced both greater bias estimates and greater SEs.

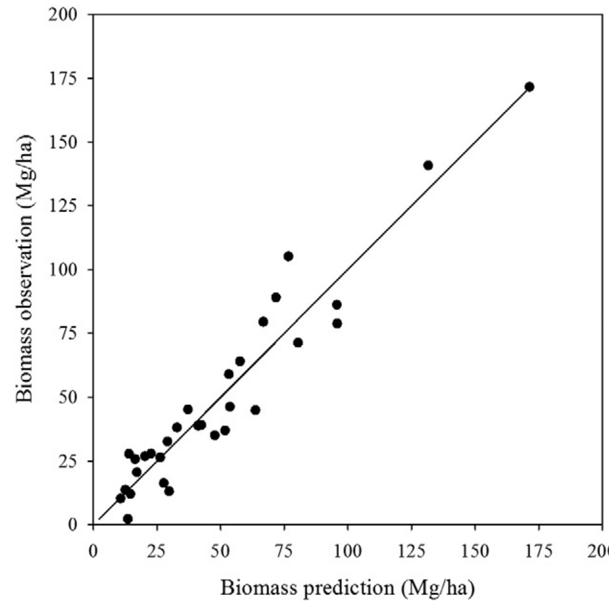

Fig. 2. Biomass observations versus predictions for 1999, Stratum 1.

4.2. Comparisons

Over all combinations of number of strata, estimators, and models, the estimates of mean AGB change per unit area for the entire study

Table 1
Modeling results.

Stratum	Year	Response variable							
		Biomass		Biomass change					
		No. of variables	Pseudo-R^{2a}	Model 1[b]		Model 2[c]		Model 3[d]	
				No. of variable pairs	R^2	No. of variable pairs	R^2	No. of variables	R^2
1	1999	2	0.881	1	0.403	2	0.557	4	0.648
	2010	3	0.910						
2	1999	2	0.906	1	0.324	4	0.666	4	0.625
	2010	2	0.867						
3	1999	2	0.716	4	0.877	7	0.929	4	0.890
	2010	2	0.867						
4	1999	2	0.688	1	0.877	1	0.904	2	0.904
	2010	2	0.889						
1–4	1999	2	0.822	2	0.780	4	0.835	6	0.832
	2010	3	0.820						

[a] Pseudo-R^2 because the model is nonlinear.
[b] Model 1: Independent variables selected in pairs; pair variables have common coefficient but of different sign.
[c] Model 2: Independent variables selected in pairs; pair variables have separate coefficients.
[d] Model 3: Independent variables selected without regard to pairing.

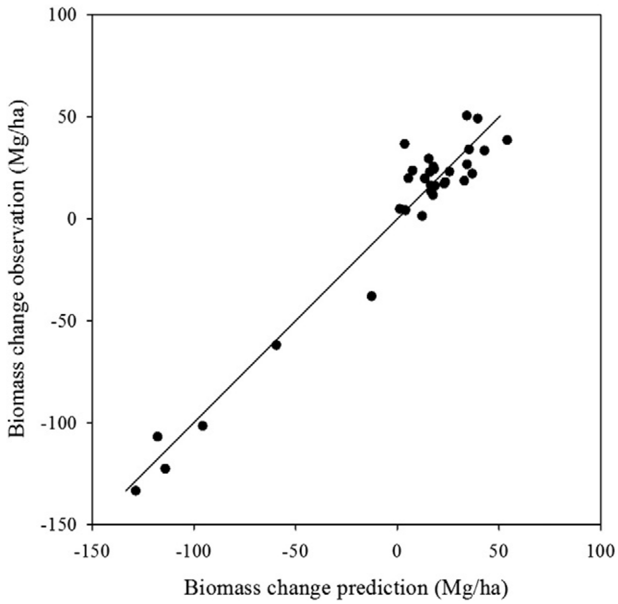

Fig. 3. Biomass change observations versus change predictions for Stratum 4.

area ranged from 11.04 to 14.01 Mg/ha when model predictions were not constrained and from 12.09 to 14.01 Mg/ha when predictions were constrained (Table 2). Differences in the estimates are attributed to random variation, because all the estimators are either unbiased or nearly unbiased (Särndal, 1984). The stratum-level models always produced smaller SEs than the common models, suggesting that relationships between AGB change and ALS metrics differ by strata. Therefore, results for the common models are not discussed further.

Næsset et al. (2013) analyzed the same data as used for this study, but in addition to the same four pre-sampling strata also used three post-strata related to degree of disturbance. Models similar to Model 1 for this study were used, but were fit separately for the deforestation and degradation post-strata, and for each of the four pre-sampling strata within the undisturbed post-stratum. For a similar indirect model-assisted regression estimator, the estimate of mean AGB change for the entire study area was 13.7 Mg/ha with SE of 2.1 Mg/ha, and for a direct model-assisted estimator using a model similar to Model 1, the estimate was 11.9 Mg/ha with SE of 1.6 Mg/ha. These estimates of the means were of the same order of magnitude as estimates obtained for the current study.

When using the stratum-level models, the 2-strata approach produced slightly smaller SEs than the 4-strata approach, except for the SRS estimators (Table 2). SEs for the 4-strata SRS estimates were smaller than for the 2-strata SRS estimates because the SEs are based on deviations between plot observations and their strata means. As expected, the variability of the plot observations for the combination of strata 1–3 around their combined mean was greater than their variability around their individual stratum-level means. The greater sample size for the combination of strata 1–3 did not compensate for this greater variability. For the model-assisted approaches, the SEs were based on deviations between plot observations and model predictions. Because the four stratum-level models were used, even when estimation was for only two strata, the deviations were the same for both the 2- and 4-strata approaches. Thus, the same deviations but with larger within-stratum sample sizes for the 2-strata approach produced comparable or slightly smaller SEs.

Smaller SEs were obtained for both the indirect and direct model-assisted estimators than for the SRS estimators. This result is as expected because of the strong relationships between both AGB and AGB change and the ALS metrics. The indirect, model-assisted estimators produced smaller SEs for the overall mean than the traditional approach reported in the literature based on the direct, model-assisted estimators using Model 1. This result held regardless of whether two or four strata were used and whether strata-level or common models were used. The result is contrary to recommendations in the literature (Fuller et al., 2003; GFOI, 2013, Section 3.6) and previously results reported in the literature. For example, for a mountainous region in southeastern Norway, Bollandsås et al. (2013) found that predictions from models

Table 2
Estimates of mean biomass change per unit area (Mg/ha).

Stratum	Weight	Sample size	Within-stratum estimator									
			Simple random sampling		Model-assisted							
					Indirect		Direct					
							Model 1[a]		Model 2[a]		Model 3[a]	
			Mean	SE	Mean	SE	Mean	SE	Mean	SE	Mean	SE
Four stratum-level models, 4-strata estimation												
1	0.126	31	66.86	5.94	71.03	3.68	64.95	4.59	69.61	3.95	69.69	3.52
2	0.231	55	56.34	6.66	45.72	3.81	44.55	5.47	40.64	3.85	42.12	4.07
3	0.269	58	−35.32	13.38	−42.47	4.53	−30.37	4.70	−37.24	3.56	−32.35	4.44
4	0.374	32	1.17	8.84	11.50	3.20	8.79	3.11	10.48	2.74	10.48	2.74
All	1.000	176	12.40	5.17	12.42	1.97	13.62	2.21	12.09	1.73	13.75	1.89
Four stratum-level models, 2-strata estimation												
1–3	0.626	144	21.68	7.22	13.05	2.45	16.50	2.97	13.04	2.21	15.70	2.47
4	0.374	32	1.17	8.84	11.50	3.20	8.62	3.11	10.48	2.74	10.48	2.74
All	1.000	176	14.01	5.60	12.47	1.95	13.55	2.19	12.09	1.72	13.75	1.86
Common model, 4-strata estimation												
1	0.126	31	66.86	5.94	59.64	7.01	62.61	5.66	61.29	5.42	61.00	5.29
2	0.231	55	56.34	6.66	46.89	5.28	51.14	5.75	45.27	5.20	44.92	5.14
3	0.269	58	−35.32	13.38	−34.43	5.39	−31.90	5.36	−30.81	4.47	−29.80	4.57
4	0.374	32	1.17	8.84	8.44	4.83	6.51	5.16	9.06	4.14	9.25	4.49
All	1.000	176	12.40	5.17	12.27	2.76	13.58	2.84	13.30	2.40	13.53	2.49
Common model, 2-strata estimation												
1–3	0.626	144	21.68	7.22	15.22	3.47	17.89	3.30	15.84	2.91	16.12	2.91
4	0.374	32	1.17	8.84	8.44	4.83	6.51	5.16	9.06	4.14	9.25	4.49
All	1.000	176	14.01	5.60	12.68	2.82	13.63	2.83	13.30	2.39	13.55	2.48

[a] See footnotes for Table 1 for model descriptions.

of AGB change versus ALS metrics produced smaller RMSEs for sample data than did differences in predictions from models of AGB versus ALS metrics. For the same data used for this study, Næsset et al. (2013) obtained smaller SEs for mean AGB change using the direct model-assisted method than for the indirect model-assisted method. For a study area in New Jersey in the USA, Skowronski et al. (2014) found that precision for the indirect model-assisted method was no greater than when the ALS data were not used as auxiliary information. However, SEs for the direct, model-assisted regression estimators when using Models 2 and 3 were smaller than SEs for the indirect, model-assisted estimators.

For the direct model-assisted regression estimators, Model 2 produced slightly smaller SEs than Model 3 which, in turn, produced considerably smaller SEs than Model 1. Models 1 and 2 both used pairs of ALS metrics as independent variables; the difference was that Model 1 used the same coefficient apart from sign for each metric in a pair, whereas Model 2 permitted different coefficients for each metric in a pair. Model 1 is the least flexible and as expected produced smaller R^2 values and larger SEs than Models 2 and 3. However, although Model 3 is more flexible than Model 2, R^2 values were larger and SEs were smaller for Model 2 than for Model 3. This seemingly unexpected result is attributed to the particular ALS metrics selected as independent variables by the stepwise selection technique. Although Model 2 produced greater precision, it has the disadvantage that specialized software is required for implementation of the stepwise technique. The reason is that pairs of variables, rather than single variables, must be selected for each iteration of the stepwise procedure for Model 2. Statistical software packages that implement stepwise procedures do so for single independent variables, but not multiple variables.

4.3. Extrapolations

4.3.1. Indirect, model-assisted regression estimators

Extrapolations were defined as model predictions for population units for which the value of at least one independent variable was beyond the range of that variable in the sample. Total extrapolations for the linear AGB models were 14.2% for 1999 and 9.5% for 2010. In the population, 6.1% of model predictions were negative in 1999 and 7.6% were negative in 2010. The percentages of excessively large model predictions, defined as predictions greater than the largest value in the sample, were less than 0.5% for both years. These negative and excessively large predictions are not necessarily a result of extrapolations but could also result from particular values of independent variables that were still within the ranges of the variables in the sample. The nonlinear asymptotic logistic model resolved these adverse effects. Of necessity, on the basis of the model form, there were no negative model predictions. In addition, the percentages of model predictions exceeding the largest AGB observation in the sample were less than 0.5% for both years.

The overall effects on estimates of using the nonlinear models rather than the linear models were meaningful. For the linear models, the estimate of mean AGB change was 14.45 Mg/ha with SE of 2.24 Mg/ha, whereas the estimate for the nonlinear models was 12.42 Mg/ha with SE of 1.97 Mg/ha. Thus, the beneficial effects of the nonlinear models over the linear models were fourfold: (i) circumventing extrapolation problems, (ii) eliminating negative predictions, (iii) moving the estimate of the mean closer to the SRS estimate, and (iv) increasing precision.

4.3.2. Direct, model-assisted regression estimators

The percentage of model predictions characterized as extrapolations for the AGB change models were 11.3% for Model 1, 14.8% for Model 2, and 13.0% for Model 3. In the population, the percentages of AGB change predictions that were less than the smallest observation ranged from 2 to 3.5%, depending on the model, while the percentages of predictions that were greater than the largest observation were less than 0.7% for all three models. For all three models, the minimum within-strata population AGB change predictions were considerably less than the minimum within-strata sample observations (Table 3). These deviations were substantially reduced using the approach for dealing with extrapolations described in Section 3.4, but they were still large. However, the small proportions of population units for which model predictions were so limited reduced the effects of the deviations. The overall effects of limiting model AGB change predictions were minimal for Model 1, increasing the mean AGB change estimate from 13.45 Mg/ha to only 13.62 Mg/ha. However, for Model 2 the mean AGB change estimate increased from 11.04 Mg/ha to 12.09 Mg/ha, and for Model 3 the increase was from 12.81 Mg/ha to 13.75 Mg/ha.

Table 3
Minimum within-strata sample observations and population predictions.

Stratum	Sample observation	Population			
		Predictions		Proportions	
		Unlimited	Limited	Extrapolations	Limited predictions
Model 1					
1	21.30	−154.01	−154.01	0.006	0.001
2	−40.76	−461.45	−272.42	0.026	0.002
3	−275.83	−438.35	−349.12	0.038	0.001
4	−133.45	−175.40	−175.40	0.041	0.001
Model 2					
1	21.30	−203.01	−171.58	0.007	<0.001
2	−40.76	−796.16	−272.42	0.064	0.005
3	−275.83	−459.07	−349.12	0.043	0.001
4	−133.45	−147.28	−147.28	0.032	0.000
Model 3					
1	21.30	−220.17	−171.58	0.019	<0.001
2	−40.76	−724.51	−272.42	0.039	0.004
3	−275.83	−300.81	−300.81	0.040	0.000
4	−133.45	−147.28	−147.28	0.032	0.000

4.4. Issues for further investigation

Direct methods are subject to the constraint that observations of the same ground locations must be acquired at both times. Thus, direct methods are not always applicable, such as when historical data are used to assess bias and precision at the earlier time or when NFI temporary plot data are used. This study showed that contrary to recommendations, indirect methods may produce greater precision than traditional direct methods based on models of the form of Model 1. Of interest, the indirect methods produced greater precision when using the nonlinear logistic model, but not when using linear models. Thus, indirect methods based on nonlinear models should receive greater consideration.

A relevant question pertains to the relationship between the separate coefficient estimates for the two metrics in each pair for Model 2. Of the 17 pairs of ALS metrics selected for Model 2, four pairs had coefficient estimates with the same sign, while 13 pairs had coefficient estimates with different signs. For the 13 pairs with different signs, the coefficient estimate was larger for the 1999 metric for four pairs, whereas the coefficient was larger for the 2010 metric for 10 pairs. This imbalance could be attributed to greater importance for 2010 metrics, perhaps for biological reasons or perhaps because the 2010 LiDAR metrics were based on considerably greater pulse densities. Metrics selected were approximately equally distributed between height and density metrics with mid-level metrics selected most frequently.

The study highlighted issues related to applying a model constructed using sample data to an entire population. The assumption underlying this technique is that the distributions of observations for both the response and auxiliary variables for the sample are similar to the corresponding distributions for the population. Further, a model that characterizes the relationship between the response and auxiliary variables for the sample data is assumed to also characterize the relationship in the population from which the sample was taken. When ranges for predictor variables in the population are greater than corresponding ranges in the sample, this assumption may be challenged. Depending on the model, the resulting extrapolations may be biologically unreasonable such as negative or excessively large biomass predictions. Large and randomized samples contribute to minimizing, but not necessarily eliminating, these adverse effects of extrapolations. However, even a small number of extrapolations may induce bias into the large area estimation procedure when there are no constraints on model predictions, such as is the case with linear models. Further, this bias cannot be readily detected in advance from the sample data. Models with asymptotes that are estimated from the sample data limit model predictions and thereby contribute to minimizing the adverse effects of extrapolations. In other cases, arbitrary constraints on model predictions may be necessary, although they should have as much scientific basis as possible. These findings suggest that models that adequately represent the relationship between response and independent variables for the sample data should nevertheless be evaluated for the reasonableness of their predictions in the population from which the sample was taken.

5. Conclusions

Three primary conclusions may be drawn from the study. First, both the indirect and direct model-assisted estimators that used the ALS auxiliary information produced substantially greater precision for estimates of mean AGB change per unit area than did the SRS estimators that did not use the ALS auxiliary information. This conclusion has been reported previously. Second, the indirect model-assisted regression estimators produced greater precision than the direct model-assisted estimators using the traditional modeling approach whereby coefficients for pairs of predictor variables have the same absolute value but with different sign. Third, for the direct method, estimation of separate coefficients for individual ALS metrics in each pair produced greater precision than the traditional approach that uses the same coefficient estimates for both metrics in the same pair. The direct method that selects independent variables without regard to pairing also produced greater precision than the traditional approach. Although the former approach produced slightly greater precision than the latter approach, the latter approach is considerably easier to implement if independent variables are selected using stepwise techniques. The latter two conclusions are not known to have been reported previously.

Two secondary findings merit comment. First, caution must be exercised when a model is extrapolated to calculate predictions for population units whose values of predictor variables extend beyond the ranges of those variables in the sample. For these extrapolations, the model predictions may be biologically unreasonable, particularly when the predictions are not limited. For this study, two approaches were used to minimize such adverse effects. The stratum-level, nonlinear asymptotic models of AGB versus ALS metrics described by Eq. (4) were effective for this purpose, although the estimate of the upper asymptote must be assessed as biologically reasonable. For the AGB change models, predicted loss of AGB between 1999 and 2010 within strata was limited to the greatest predicted AGB for 1999 within the same strata.

The second issue for future investigation pertains to conditions under which indirect estimators produce more precise AGB change estimates than direct methods. For this study, the indirect method produced substantially greater precision than the traditional direct method. Additional investigations should be conducted to determine conditions under which these results can be generalized.

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