Canadian Journal of Forest Research
Revue canadienne de recherche forestière

Post-stratified change estimation for large-area forest biomass using repeated ALS strip sampling

Journal:	<i>Canadian Journal of Forest Research</i>
Manuscript ID	cjfr-2017-0031.R2
Manuscript Type:	Article
Date Submitted by the Author:	08-Mar-2017
Complete List of Authors:	Strimbu, Victor; Norwegian University of Life Sciences, Department of Ecology and Natural Resource Management Ene, Liviu; Norwegian University of Life Sciences, Department of Ecology and Natural Resource Management Gobakken, Terje; Norwegian University of Life Sciences, Department of Ecology and Natural Resource Management Gregoire, Timothy; Yale University Astrup, Rasmus; Norwegian Institute of Bioeconomy Research Næsset, Erik; Norwegian University of Life Sciences, Department of Ecology and Natural Resource Management
Keyword:	airborne laser scanning, above ground biomass, change estimation, stratified estimation, parametric bootstrapping

SCHOLARONE™
Manuscripts

Post-stratified change estimation for large-area forest biomass using repeated ALS strip sampling

Victor Felix Strîmbu (corresponding)

Department of Ecology and Natural Resource Management, Norwegian University of Life Sciences, P.O. Box 5003, NO-1432 Ås, Norway

victor.strimbu@nmbu.no

Tel. +4797044678

Liviu Theodor Ene

Department of Ecology and Natural Resource Management, Norwegian University of Life Sciences, P.O. Box 5003, NO-1432 Ås, Norway

liviu.ene@nmbu.no

Terje Gobakken

Department of Ecology and Natural Resource Management, Norwegian University of Life Sciences, P.O. Box 5003, NO-1432 Ås, Norway

terje.gobakken@nmbu.no

Timothy G. Gregoire

School of Forestry and Environmental Studies, Yale University, New Haven, CT 06511-2104, USA

timothy.gregoire@yale.edu

Rasmus Astrup

Norwegian Institute of Bioeconomy Research, P.O. Box 115, NO-1431 Ås, Norway

rasmus.astrup@nibio.no

Erik Næsset

Department of Ecology and Natural Resource Management, Norwegian University of Life Sciences, P.O. Box 5003, NO-1432 Ås, Norway

erik.naesset@nmbu.no

Abstract

Post-stratified model-assisted (MA) and hybrid (HY) estimators are used with repeated airborne laser scanning (ALS) strip sampling and national forest inventory field data for stratum-wise and overall estimation of above ground biomass (AGB) stock and change. The study area covered the southern portion of the Hedmark County in Norway. Both MA and HY estimation substantially reduced the uncertainty in AGB change when compared to estimation using the field survey only. Relative efficiencies (relative variance) of 4.15 (MA) and 3.36 (HY) for overall estimates were found. The results suggest the MA estimator for single-time estimation and the HY as more appropriate for change estimation by cover class. With the HY estimator, a nested post-stratification scheme is demonstrated, combining cover classes with change classes, which enables detailed reporting for change according to cause within each cover class, and has the potential to improve the estimation precision. Finally, parametric bootstrapping is demonstrated as an empirical alternative to estimate the model-error component in the HY estimator. The model-error estimated with parametric bootstrapping converged to the analytically determined value of the HY estimator within 1000 bootstrap samples.

Key words: airborne laser scanning, above ground biomass, change estimation, stratified estimation, parametric bootstrapping

1 INTRODUCTION

The international community, through various organizations, frameworks and formal resolutions (e.g. Intergovernmental Panel on Climate Change (IPCC), United Nations Programme on Reducing Emissions from Deforestation and Forest Degradation (UN-REDD and REDD+), Paris Agreement), becomes increasingly coherent and articulated when expressing the need to quantify and monitor the forest carbon stocks and carbon stock change. As the world’s forests have been identified as a major carbon sink (Pan et al. 2011), the scientific community feels mandated to investigate and propose methods to estimate large-scale forest biomass and biomass change, and do so efficiently, mindful of both cost and uncertainty (IPCC 2006).

This sets us in the domain of large-area forest survey (i.e., regional or national scale), where the role of remotely sensed data is resolute. Airborne laser scanning (ALS) has been an excellent source of auxiliary data in forest surveys, with great predictive power for forest attributes such as above ground biomass (AGB) or wood volume. As the acquisition cost for such data remains relatively high, ALS sampling has been proposed as a feasible alternative for large-area AGB estimation (Andersen et al. 2011; Gobakken et al. 2012; Gregoire et al. 2011; Næsset 2005; Næsset et al. 2013b; Saarela et al. 2015; Ståhl et al. 2011). Typically, the ALS survey follows a strip sampling design, which together with field plot data are used to estimate AGB. A certain amount of experience has been gained in estimating forest parameters using ALS strip sampling, and while there have been several studies that use repeated wall-to-wall ALS surveys to estimate the change in these parameters (Bollandsås et al. 2013; Magnussen et al. 2015; McRoberts et al. 2015; Næsset et al. 2013a; Skowronski et al. 2014), large-area change estimation via ALS strip sampling is of more recent opportunity. In fact, change estimation following repeated ALS strip survey has only been tackled in Ene et al. (2017) where change in AGB was estimated in miombo woodlands in a district in Tanzania. With respect to estimation following ALS strip sampling, two distinct

approaches have been proposed: two-stage model-assisted (MA) (Gregoire et al. 2011) and two-phase hybrid (HY) (Ståhl et al. 2011). While the MA estimation relies exclusively on design-based inference, the HY estimation, a notion introduced by Corona et al. (2014), combines design-based inference with model-based inference. For a discussion on the difference between design-based and model-based inferences, see Gregoire (1998). Ståhl et al. (2016) gives an overview on how design-based and model-based inferences can be used separately or combined in large-area forest surveys.

The main objective of the present study was to estimate forest biomass and biomass change over a period of five years in a large area spanning the southern portion of Hedmark County, Norway. With respect to this objective, it counterparts Ene et al. (2017), using a sample of ALS and NFI plots to estimate change, this time in a boreal forest. Here, more specific objectives were: (i) to introduce post-stratified MA and HY change estimation, (ii) test a nested stratification scheme, by cover class and change class, and (iii) to demonstrate parametric bootstrapping as an empirical alternative to estimate the model-error component. Demonstrated on HY estimation, the nested stratification scheme aimed to increase the estimation precision as well as to enable and demonstrate detailed reporting of forest biomass change according to cause of change, in each cover class. Parametric bootstrapping entails sampling from the multivariate distribution of the model parameters. The role of this exercise was twofold. First, it serves as mutual validation with the analytically determined model-error component, as both methods are yet to be established in the literature (i.e., at least for two-phase post-stratified change estimation). In addition, parametric bootstrapping could be the feasible alternative in situations where the model-error component becomes too complex for analytical determination, due to either design complexity (i.e., multistage, stratification) or error propagation from multiple modeling steps.

2 MATERIALS AND METHODS

2.1 MATERIALS

The study area is the southern portion of Hedmark County in Norway (Fig.1), covering approximately one third of the region (9758 km² out of 27390 km²). Restricting the study to a fraction of the region was constrained by the extent of the repeated ALS acquisition campaign. The area is considered to have some of the most productive forests in Norway, with dominant tree species typical to the boreal forests of the Nordic region: Norway spruce (*Picea abies* (L.) Karst.), Scots pine (*Pinus sylvestris* L.) as well as a minor proportion of white birch (*Betula pubescens* Ehrh.)

The Norwegian National Forest Inventory (NFI) provided the field data. The NFI survey (Tomppo et al. 2010) consists in 250 m² circular plots distributed systematically on a 3x3 km grid, with 20% revisited every year according to a Latin square design with blocks of 45x45 km. The AGB for individual trees was predicted with allometric models (Marklund 1988), aggregated at the plot level, and scaled to per-hectare values.

The years of reference for this study are 2006 and 2011. Field plots measured under the ninth inventory cycle of the NFI in 2005, 2006, and 2007 constitute the observations for the first point in time (2006), and the same plots revisited five years later under the tenth inventory cycle in 2010, 2011, and 2012 are ascribed to the second point in time (2011). For the entire area, 322 plots were overlapped by the ALS strip survey, six of which were discarded on grounds of inconsistency between ALS data and field measurements. These inconsistencies were, in some cases, caused by forest that suffered changes between the field survey and ALS acquisition in either 2006 or 2011. The mean AGB of the remaining 316 plots was 60.8 Mg/ha (2006) and 67.1 Mg/ha (2011). For modeling, only observations with nonzero AGB on both 2006 and 2011 were used (234 plots). This filtering was necessary as the models were

fitted on log transformed variables, and with a pair-wise correlation structure (i.e. compound symmetry) that requires observations from both times (2006 and 2011).

The ALS survey consists in two sets of 24 E-W flight lines spaced 6 km apart and with a swath width of approximately 500 m (Fig. 1). The survey was conducted in three acquisition campaigns (see Table 1), with the same flight lines being overflown a second time. The ALS data were tessellated with a grid cell size of 15.81 m, matching the area of an NFI plot, and portions of the strips that did not spatially overlap for the 2006 and 2011 acquisitions were discarded, assuring a one-to-one correspondence between 2006 and 2011 at the grid cell level.

Two different types of stratification were used: by cover class and change class. Cover class stratification was done for the entire area, based on land use maps and satellite imagery as described in (Gobakken et al. 2012). Here we use five cover classes (proportion in parenthesis): nonproductive/non-forest (24%), young forest (31%), low productive forest (13%), medium productive forest (21%), and high productive forest (12%). The nonproductive/non-forest cover class aggregates the following categories: nonproductive forest, mountain forest (>850 m altitude), developed areas, and open water.

Stratification by change class was done at the level of the ALS strip sample following a rule-based classification. Four change classes were defined as follows (proportion in parentheses, followed by the rule):

- unchanged forest (84.5%), laser echoes above 1.3 m on both occasions (2006 and 2011)
- clear-felled forest (1.6%), laser echoes above 1.3 m only on the first occasion (2006)
- regenerated forest (1.8%), laser echoes above 1.3 m only on the second occasion (2011)
- unchanged non-forest (12.1%), no laser echoes above 1.3 m on either occasion (2006 or 2011).

2.2 MODELS

The relation between ALS data and field estimated AGB was modeled via height and density metrics (Gobakken et al. 2012). The height metrics include 10 height percentiles ($h_{00}, h_{10}, h_{20}, \dots, h_{90}$), maximum height (h_{max}), and the coefficient of variation (h_{cv}). Density metrics ($d_0, d_1, \dots, d_9$) for 10 equal height levels between 1.3 m and the 95th height percentile, were calculated as the proportion of laser echoes above the respective height to the total number of echoes (including those below 1.3 m). The ALS sensors can record many echoes per pulse. In the current study, we used the three echo categories classified as single, first of many, and last of many. The single and first of many echoes were pooled into one dataset denoted as first echoes, and correspondingly, the single and last of many echoes were pooled into a dataset denoted as last echoes. All ALS metrics were calculated separately for first and last return laser echoes, resulting in a total of 44 variables. Response and predictor variables were log transformed to ameliorate their nonlinear relationship. The models were selected and fit independently for each cover class using generalized least squares (GLS) (Table 2). The correlation structure was specified by compound symmetry, pairing the observations from the two times on the same field plot. The variable selection process was semi-automated. Initially, 20 variable combinations were selected using best subset method with Bayesian information criterion (BIC) and restricting the maximum number of variables to five. In the next step, the models with variance inflation factor (VIF) greater than five were filtered out and the best of the remaining models was selected for further inspection. To allow likelihood tests in the automated selection phase, parameter fitting was done using maximum likelihood (ML), and the selected model was subsequently refitted using restricted maximum likelihood (REML) (Pinheiro et al. 2013; Zuur et al. 2009).

2.3 STATISTICAL METHODS

2.3.1 Estimators

MA and HY estimators are used to estimate mean AGB (Mg/ha) values for each time as well as the change in AGB over the five year period. In the MA estimation, the ALS and the field surveys are used in a two-stage sampling design, a method initially proposed by Gregoire et al. (2011) and further developed by Ringvall et al. (2016) to address the dependencies between stratum-wise estimates, a consequence that follow when ALS strips intersect several strata . The hybrid estimator combines design-based and model-based inferences to estimate uncertainty by considering the sampling error of the ALS survey as well as the model error (Ståhl et al. 2011).

A feature shared by both estimators is the predictive model linking the remotely sensed data to the variable of interest. Let us generically define this relation as $\hat{y} = f(\hat{\beta}, x)$, where $\hat{\beta}$ is a vector of model parameter estimates and x a vector of predictor variables considered error-free. Furthermore, let S1 denote the ALS strip sampling survey, and S2 the field plot survey. In the context of MA estimation, the meaning of these are: S1 – first stage sample (m ALS strips), S2 – second stage sample (n field plots).

The parameter of interest in this study is mean AGB. The overall mean across all strata is estimated as:

$$(1) \quad \hat{\mu}_* = \sum_{h=1}^H W_h \hat{\mu}_{*,h}$$

where H is the number of strata, W_h is the area proportion of stratum h , and $\hat{\mu}_{*,h}$ is the estimated mean in stratum h . Here $*$ stands for either MA or HY, indicating the framework. The stratum-wise mean is

$$(2) \quad \hat{\mu}_{*,h} = \frac{\sum_{i=1}^m \hat{t}_{*,ih}}{\sum_{i=1}^m A_{ih}}$$

173 where $\hat{t}_{*,ih}$ and A_{ih} are the total predicted AGB and the area of stratum h in ALS strip i . These totals are
 174 estimated differently in MA and HY frameworks:

$$175 \quad (3) \quad \hat{t}_{MA,ih} = \sum_{k=1}^{N_{ih}} \hat{y}_{kh} + \frac{N_{ih}}{n_{ih}} \sum_{k=1}^{n_{ih}} (y_{kh} - \hat{y}_{kh})$$

$$176 \quad (4) \quad \hat{t}_{HY,ih} = \sum_{k=1}^{N_{ih}} \hat{y}_{kh}$$

177 where n_{ih} is the number of field plots in strip i , stratum h , N_{ih} the total number of cells in strip i ,
 178 stratum h , $\hat{y}_{kh}$ are synthetic predictions of AGB via a stratum specific model $f_h(\hat{\beta}_h, \mathbf{x})$, and y_{kh} are the
 179 values from the field survey (k indexes cells), considered error-free. The second term in the MA
 180 estimator (Eq. 3) is a bias correction based on the second stage sample.

181 The variance estimators of these estimators are:

$$182 \quad (5) \quad \widehat{Var}(\hat{\mu}_{MA}) = \mathbf{W}^T \widehat{Cov}_{S1(MA)} \mathbf{W} + \mathbf{W}^T \widehat{Cov}_{S2} \mathbf{W}$$

$$183 \quad (6) \quad \widehat{Var}(\hat{\mu}_{HY}) = \mathbf{W}^T \widehat{Cov}_{S1(HY)} \mathbf{W} + \mathbf{W}^T \widehat{Cov}_M \mathbf{W}$$

$$184 \quad (7) \quad \widehat{Var}(\hat{\mu}_{MA,h}) = \widehat{Cov}_{S1(MA)}[h, h] + \widehat{Cov}_{S2}[h, h] = \widehat{Var}_{S1(MA)}(\hat{\mu}_{MA,h}) + \widehat{Var}_{S2}(\hat{\mu}_{MA,h})$$

$$185 \quad (8) \quad \widehat{Var}(\hat{\mu}_{HY,h}) = \widehat{Cov}_{S1(HY)}[h, h] + \widehat{Cov}_M[h, h] = \widehat{Var}_{S1(HY)}(\hat{\mu}_{HY,h}) + \widehat{Var}_M(\hat{\mu}_{HY,h})$$

186 where $\mathbf{W}$ is the stratum proportion vector of length H , and $\widehat{Cov}_{S1(*)}$, $\widehat{Cov}_{S2}$, $\widehat{Cov}_M$ are $H \times H$
 187 covariance matrices:

$$188 \quad (9) \quad \widehat{Cov}_{S1(*)}[h, h'] = \frac{1}{A_h A_{h'}} \left(\frac{1}{m} - \frac{1}{M} \right) \frac{\sum_{i=1}^m ((\hat{t}_{*,ih} - \hat{\mu}_{*,h} A_{ih})(\hat{t}_{*,ih'} - \hat{\mu}_{*,h'} A_{ih'}))}{m-1}$$

$$189 \quad (10) \quad \widehat{Cov}_{S2}[h, h'] = \begin{cases} 0, h \neq h' \\ \frac{1}{m M A_h^2} \sum_{i=1}^m \widehat{Var}(\hat{t}_{MA,ih}), h = h' \end{cases}$$

$$190 \quad (11) \quad \widehat{Cov}_M[h, h'] = \frac{1}{A_h A_{h'}} \hat{\mathbf{t}}_h^T \widehat{Cov}_{\beta, h, h'} \hat{\mathbf{t}}_{h'}$$

where h and h' index two strata, $\bar{A}_h$ is the mean area of stratum h across the m ALS strips crossing the stratum, and $\widehat{Var}(\hat{t}_{MA,ih})$ is the within-strip variance of total AGB in stratum h (Ringvall et al. 2016, eq. 16). In Eq. 11, $\hat{\mathbf{t}}'_h = \frac{1}{m} \sum_{i=1}^m \hat{\mathbf{t}}'_h$ and $\hat{\mathbf{t}}'_h = \sum_{k=1}^{N_{ih}} \nabla f_h(\hat{\boldsymbol{\beta}}_h, \mathbf{x}_{hk})$. Since ∇f_h is the gradient of f_h with respect to $\hat{\boldsymbol{\beta}}_h$ parameters, $\hat{\mathbf{t}}'_h$ is a vector of the same dimension as $\hat{\boldsymbol{\beta}}_h$ (i.e., equal to the number of parameters in the model for stratum h). If $\hat{\boldsymbol{\beta}}_h$ and $\hat{\boldsymbol{\beta}}_{h'}$ have dimensions P_h and $P_{h'}$, then $\widehat{Cov}_{\boldsymbol{\beta}_h, \boldsymbol{\beta}_{h'}}$ is a $P_h \times P_{h'}$ covariance matrix estimating the uncertainty in model parameters $\hat{\boldsymbol{\beta}}_h$ and $\hat{\boldsymbol{\beta}}_{h'}$.

First, note that these variances (Eq. 5-8) add two components that correspond to independent sources of uncertainty. The first component in both MA and HY frameworks is the sampling variance of the strip sampling survey ($S1$), caused by variation between estimated strip means ($\widehat{Cov}_{S1(*)}$). The second variance component has different interpretations for MA and HY frameworks. In the case of MA, the second component cumulates the variances of estimated means within each strip. These variances are estimated via the residuals calculated for plots that belong to particular strip and stratum. As $S2$ is assumed to be independently conducted in each stratum, $\widehat{Cov}_{S2}$ is a diagonal matrix. In the HY framework, the second component ($\widehat{Cov}_M$) is the variance attributed to uncertainty in the model parameters. The $\widehat{Cov}_M$ matrix depends on the correspondence between prediction models and the strata (see section 2.3.2)

In this study, we adopted the indirect change estimation, a method that estimates change by taking the difference between single-time biomass estimates: $\hat{\mu}_{(\Delta)} = \hat{\mu}_{(2006)} - \hat{\mu}_{(2011)}$. The other alternative is to estimate change directly via a “change model” (see McRoberts et al. (2015) for a comparison of the two methods). Opting for the former method was on the one hand constrained by the few plots available in some strata, resulting in poor change models, and on the other hand motivated by the advantage of being able to report single-time AGB values, as well as change that is consistent with them (i.e., with direct change estimation, $\hat{\mu}_{(\Delta)} \neq \hat{\mu}_{(2006)} - \hat{\mu}_{(2011)}$).

214 Indirect estimates of change for the i -th ALS strip is

$$215 \quad (12) \quad \hat{t}_{(\Delta),ih} = \hat{t}_{(2006),ih} - \hat{t}_{(2011),ih}$$

216 and at the stratum level

$$217 \quad (13) \quad \hat{\mathbf{t}}'_{(\Delta)h} = \hat{\mathbf{t}}'_{(2006)h} - \hat{\mathbf{t}}'_{(2011)h}.$$

218 These relations (Eq. 12, 13) hold only when these totals are calculated on perfectly overlapped ALS strip
219 samples, which is the case in this study.

220 To assess the advantage of using the ALS sample to support the field survey, the precisions of MA and
221 HY estimators are compared to that obtained by direct estimation using only the field sample. Here we
222 use the Horvitz-Thompson (HT) estimator following stratified random sampling (Särndal et al. 1992). Let
223 $\hat{\mu}_{HT}$ denote the estimated mean AGB and $\widehat{Var}(\hat{\mu}_{HT})$ the estimated variance. The relative efficiency of
224 MA and HY estimators with respect to the HT estimator is calculated as the ratio of variances: $\frac{\widehat{Var}(\hat{\mu}_{HT})}{\widehat{Var}(\hat{\mu}_{MA})}$,
225 and $\frac{\widehat{Var}(\hat{\mu}_{HT})}{\widehat{Var}(\hat{\mu}_{HY})}$.

226 2.3.2 Post-stratification

227 In this study, two different stratification schemes were tried: by cover class only, and by cover class and
228 change class. The first scheme is a simple one and has been used before. With stratification by cover
229 class, there is a one to one correspondence between the five strata and the models that predict AGB
230 values in these strata (see Table 2). In this case, the matrix $\widehat{Cov}_{\beta,h,h'} = \mathbf{0}$ when $h \neq h'$ due to the use of
231 independent models in each stratum, and $\widehat{Cov}_M$ is a 5x5 diagonal matrix. The stratification by cover
232 class and change class is a nested stratification, in the sense that each area unit (or grid cell) belongs to a
233 cover class as well as a change class. It is a nested stratification, as the change class may break down
234 each cover class, and conversely, each change class can be further divided into cover classes. This means

that the effective number of strata is expanded to 20 (five cover classes x four change classes). With this stratification scheme, $\widehat{Cov}_M$ is a 20x20 matrix with a block diagonal structure (4x4 blocks). Here, $\widehat{Cov}_{\beta,h,h'} = \mathbf{0}$ whenever h and h' come from different cover classes. For reporting purposes, following estimation, the nested strata may be collapsed by either cover class or change class. In this study, we use this stratification scheme only with the HY estimation. Having many strata relative to the size of the S_2 sample has a detrimental effect on estimating $\widehat{Cov}_{S_2}$ as a large of number of ALS strip-strata combinations would not overlap any field plots. With the nested stratification scheme, there are 480 (24x20) strip-strata combinations and only 316 field plots. Both cover classes and change classes are assumed to be known without error.

2.3.3 Parametric bootstrapping

An alternative method to estimate $\widehat{Cov}_M$ is via parametric bootstrapping, by sampling from the multivariate distribution of the estimated model coefficients. With post-stratification by cover class we generated $B = 1000$ bootstrap samples corresponding to the same number of sets of model coefficients ($\hat{\beta}_h$) in each stratum. For each set of model coefficients, new AGB predictions are calculated along the ALS strips, and $\hat{\mu}_{HY,h}$ is re-estimated. $\widehat{Cov}_{M(boot)}$ is then calculated as the variance-covariance matrix of the resulting $H \times B$ mean AGB estimates ($\hat{\mu}_{HY,h}$). The rationale here is that since the model coefficients are the only values being changed in the bootstrap sample, $\widehat{Cov}_{M(boot)}$ will isolate the model error component of the HY estimator and may be compared to analytically derived $\widehat{Cov}_M$. It is expected that $\widehat{Cov}_{M(boot)}$ matrix will converge to $\widehat{Cov}_M$ as the bootstrap sample size increases. As a measure of convergence, we use the mean absolute difference (MAD) between corresponding elements of $\widehat{Cov}_{M(boot)}$ and $\widehat{Cov}_M$ matrices.

3 RESULTS AND DISCUSSION

3.1 STRATIFICATION BY COVER TYPE

The results of MA estimation are presented in Table 4, HY estimation in Table 5, and direct estimation using field measurements only in Table 6. The precision of the estimates is reported in terms of standard error (SE) (i.e. square root of the estimated variance). In general, the results indicate an increase in mean AGB over the 5-year period. Among the cover classes, the young forest stratum seemed to have the largest net gain in biomass, a result indicated by all three estimation methods and explained by the otherwise expected high growth rate in a young forest.

For single-time estimates, MA was in general more precise than HY (Table 3). One observation concerning MA estimation is that the within strip variance of mean AGB, which reflects the $\widehat{Cov}_{S2}$ matrix, had a minor contribution to the overall variance: 2.5% for across strata estimates in both 2006 and 2011, and between 0.4% and 9.5% for individual strata (Table 4). We identified several potential factors that are expected to affect $\widehat{Cov}_{S2}$ estimation. First, the lack of field plots in each ALS strip and stratum underestimates the second stage variance. This happens because $\widehat{Cov}_{S2}$ cumulates the estimated within strip variances $\widehat{Var}(\hat{t}_{MA,ih})$ (Eq. 10), which in the absence of field plots cannot be estimated, and are instead assigned a value of 0. In our case, there were 120 ALS strip-stratum combinations (i.e., 24 ALS strips x 5 strata), 17 of which had either none or only one field plot. By contrast, ignoring an expected negative covariance between strata in $\widehat{Cov}_{S2}$ results in overestimation (Gregoire et al. 2016). Ringvall et al. (2016) used simulations to evaluate this overestimation at around 6% of the standard error. Finally, ignoring the systematic sampling design is expected to inflate the apparent variance of the estimators. This concerns both the first stage ($\widehat{Cov}_{S1(*)}$) and the second stage sampling ($\widehat{Cov}_{S2}$), so that the MA estimator will likely be more affected than the HY estimator. In the HY

estimation, the model error $\widehat{cov}_M$ had a substantial contribution to the total variance (Table 5). It accounted for 31.5% (2006) and 40.8% (2011) of the variance for overall across strata estimates, and ranged between 20.1% and 77.3% for individual strata (both times).

Even though the estimated precision of the single-time ALS-aided estimates did not always exceed that of direct estimates, for change estimation both MA and HY estimators outperformed the direct estimation (Table 3). While the MA estimator seems more precise than HY in estimating overall across strata change (Table 3, last row, last column block), the stratum-wise change is substantially more precisely estimated by the HY estimator. The latter observation regarding stratum-wise estimates is in accord with Ene et al. (2017) who tested similar MA and HY estimators without stratification. There are several factors that concur to this result. First, in HY estimation, the strip post-stratum AGB values are synthetic, unadjusted by the field sample, and consistently predicted by the same model on both times. The synthetic predictions at the strip level are highly correlated between 2006 and 2011, in contrast to the bias correction terms, which are less well correlated. For instance, the Pearson correlation coefficient between $\hat{t}_{(2006)HY,ih}$ and $\hat{t}_{(2011)HY,ih}$ ranged from 0.972 to 0.997 for the five cover classes, while for the corresponding bias correction terms (i.e., second term in Eq. 3) the correlation coefficients were between 0.574 and 0.848. This has an asymmetric effect in the sampling error ($S1$) of MA and HY change estimators, since the bias correction term introduces more variation in the difference between single-time estimates at the strip level. Another aspect is that, compared to single-time estimation, when estimating change, the model error contributed less to the total variance (Table 5). The only instance with an increase in model error contribution for change is the low productive forest stratum. Here the inversed tendency owes to an unusually high sampling variance ($S1$) for the single-time estimates, a component that cancelled out for change, allowing a larger proportion for the model error component.

3.2 NESTED POST-STRATIFICATION BY COVER CLASS AND CHANGE CLASS

Figure 2 illustrates the cover classes, change classes, and AGB change along a strip segment. In general, in terms of precision, the HY estimation with nested post-stratification, was slightly less precise compared to HY estimation with post-stratification by cover class only. When collapsing the nested post-stratified estimates by cover class, a slight increase in precision or similar precision was noticed for the single-time estimates by cover class (Table 3). This is due to a reduction of sampling error because of each cover class being further broken down by change classes. The effect, however, is small as the change class has greatly unbalanced proportions, unchanged forest being dominant in most cover classes (see “stratum size” column in Table 7). A notable exception is the non-productive/non-forest cover class, where the unchanged forest and unchanged non-forest change classes have relatively balanced proportions. Here indeed, the improvement is visible with estimated standard error decreasing from around 2.24 Mg/ha (2006) and 2.26 Mg/ha (2011) (Table 5) to 1.76 Mg/ha (2006) and 1.74 Mg/ha (2011) (Table 7, 5th row block), paralleled by an increase in model error contribution from 58.8% (2006 and 2011) (Table 5) to 86.5% (2006) and 90.2% (2011) (Table 7, 5th row block). Low productive forest also had a noteworthy unchanged non forest proportion (8.2%) with some impact on single-time HY estimation precision: SE decreased from 7.51 Mg/ha (2006) and 7.57 Mg/ha (2011) (Table 5) to 6.69 Mg/ha (2006) and 6.72 Mg/ha (2011) (Table 7, 5th row block) whereas the model error contribution increased from 20.1% (2006) and 23.2% (2011) (Table 5) to 25% (2006) and 29.5% (2011) (Table 7, 5th row block). As earlier asserted, the increase in model error contribution did not coincide with an increase in model error, which remained largely constant, but rather a decrease in sampling error (*S1*). While the nested post-stratification did not help to increase the estimation precision for overall single-time or change estimates, this approach retains its merits with respect to detailed reporting for change. Collapsing the post-strata by change class (Table 7, last row block), gives an insight on the contribution of different change classes on the overall change balance. Clear felling affected around 1.6% of the study

area where an average of 87.3 Mg/ha (SE = 4.53 Mg/ha) was lost. This means that for the entire study area clear felling contributed a negative balance of 1.34 Mg/ha (SE = 0.069 Mg/ha). Regeneration, that covered 1.8% of the study area, had a net contribution of 0.17 Mg/ha (SE = 0.03 Mg/ha). Finally, the net forest growth in the unchanged forest post-stratum, covered 84.5% of the study area, and contributed an estimated positive balance of 4.35 Mg/ha (SE = 0.91 Mg/ha). Nested post-stratification revealed where a certain change class occurred preponderantly. For instance, total biomass lost to clear felling in each cover class might be of interest. To this end, the mean AGB values in the second row block in Table 7 can be transformed to totals: 146324 Mg (SE = 30835 Mg) in non-productive/non forest, 284548 Mg (SE = 36238 Mg) in young forest, 38192 Mg (SE = 11842 Mg) in low productive forest, 257316 Mg (SE = 14005 Mg) in medium productive forest, and 582282 Mg (SE = 28877 Mg) in high productive forest.

3.3 PARAMETRIC BOOTSTRAP SIMULATION

After 1000 bootstrap samples, the $\widehat{Cov}_{M(boot)}$ converged to the analytically derived $\widehat{Cov}_M$ (Fig. 3, left column). Accordingly, the SE of the mean AGB (2006, 2011, and change), that was calculated based on $\widehat{Cov}_{M(boot)}$, converged to its analytical counterpart (i.e., those in Table 6, calculated with $\widehat{Cov}_M$) (Fig. 3, right column).

The role of demonstrating this alternative estimation method was twofold. First, it is a way to validate the theoretical HY estimators. In fact, we can see it as mutual validation especially in post-stratified two-stage change estimation, which is not yet established in literature. Second, parametric bootstrapping is a viable alternative to isolate the model error effect when the analytical estimation becomes too complex (i.e., due to sampling design; multistage, post-stratification, etc.). One instance where this alternative simulative approach may attain its full potential is in situations that involve several modeling steps where error propagation must be accounted for. In fact, even in this study we assumed that the AGB in the NFI plots is known without error, whereas it was predicted using allometric models. Similarly, we

assumed the post-strata to be determined without error, whereas they are typically predicted using logistic models (e.g., Næsset et al. 2013a) or other classification methods that are not exempt from errors. Given that the error structures of all models involved are properly estimated, parametric bootstrapping has the potential to integrate their effect and provide a reliable estimate of the overall variance due to the errors in all modeling steps. Investigating this would be an interesting direction for further research. It may worth mentioning that, when large scale wall-to-wall mapping and estimation of change is of interest, the estimation methods described in this study are still applicable as the first stage (MA) / phase (HY) variance ($\widehat{Cov}_{S1}$) vanishes. Besides, it is also possible to combine the non-exhaustive ALS sample with inexpensive wall-to-wall auxiliaries. Here most opportunities lie within the model based inference framework, as it enables for errors to be estimated at the pixel level. For instance, a hierarchical, model based estimation approach using three sources of data and two modeling steps proposed by Saarela et al. (2016) can be also applied for change estimation. Here, parametric bootstrapping would be an excellent approach to error estimation, as it can ease the error propagation, given the multiple modeling steps.

4 CONCLUSIONS

Model-assisted and hybrid estimators were demonstrated and compared in a large area survey with the objective to estimate the change in above ground biomass over a 5-year period. Several conclusions can be drawn from this study:

1. The potential to increase the precision of forest parameter estimation for single-time estimates using MA and HY estimators with ALS strip sampling has been demonstrated before (Ene et al. 2013; Gregoire et al. 2011; Ståhl et al. 2011). Here we found that for change estimation the increase in precision was even more pronounced.

2. The efficiency of MA and HY estimators varies with the type of parameter estimated (i.e., single-time versus change or stratum-wise versus overall across-strata), thus comparing their performance in absolute terms is inconclusive, and may depend on the study area as well. Here, MA seems to be more precise in overall across-strata single-time and change estimation as well as stratum-wise single-time estimation, and HY is more precise in estimating stratum-wise change.

3. Parametric bootstrapping is a reliable alternative to analytical estimation of the model-error component.

4. A nested stratification scheme, by cover class and change class, enables detailed change reporting, and facilitates decision making. In addition, it has the potential to increase the estimation precision given a balanced presence of more change classes within a cover class.

REFERENCES

-
- Andersen, H.-E., Strunk, J., and Temesgen, H. 2011. Using Airborne Light Detection and Ranging as a Sampling Tool for Estimating Forest Biomass Resources in the Upper Tanana Valley of Interior Alaska. *Western Journal of Applied Forestry* **26**(4): 157-164.
- Bollandsås, O.M., Gregoire, T.G., Næsset, E., and Øyen, B.-h. 2013. Detection of biomass change in a Norwegian mountain forest area using small footprint airborne laser scanner data. *Statistical Methods & Applications* **22**(1): 113-129. doi: 10.3097/LO.200701.
- Corona, P., Fattorini, L., Franceschi, S., Scrinzi, G., and Torresan, C. 2014. Estimation of standing wood volume in forest compartments by exploiting airborne laser scanning information: model-based, design-based, and hybrid perspectives. *Canadian Journal of Forest Research* **44**(11): 1303-1311. doi: 10.1139/cjfr-2014-0203.

- 391 Ene, L.T., Næsset, E., Gobakken, T., Bollandsås, O.M., Mauya, E.W., and Zahabu, E. 2017. Large-scale
392 estimation of change in aboveground biomass in miombo woodlands using airborne laser scanning
393 and national forest inventory data. *Remote Sensing of Environment* **188**: 106-117.
- 394 Ene, L.T., Næsset, E., Gobakken, T., Gregoire, T.G., Ståhl, G., and Holm, S. 2013. A simulation approach
395 for accuracy assessment of two-phase post-stratified estimation in large-area LiDAR biomass surveys.
396 *Remote Sensing of Environment* **133**(0): 210-224.
- 397 Gobakken, T., Næsset, E., Nelson, R., Bollandsas, O.M., Gregoire, T.G., Stahl, G., Holm, S., Orka, H.O., and
398 Astrup, R. 2012. Estimating biomass in Hedmark County, Norway using national forest inventory field
399 plots and airborne laser scanning. *Remote Sensing of Environment* **123**: 443-456. doi:
400 10.1016/j.rse.2012.01.025.
- 401 Gregoire, T.G. 1998. Design-based and model-based inference in survey sampling: appreciating the
402 difference. *Canadian Journal of Forest Research* **28**(10): 1429-1447. doi: 10.1139/x98-166.
- 403 Gregoire, T.G., Ringvall, A.H., Ståhl, G., and Næsset, E. 2016. Conditioning post-stratified inference
404 following two-stage, equal-probability sampling. *Environmental and Ecological Statistics* **23**(1): 141-
405 154. doi: 10.1007/s10651-015-0332-9.
- 406 Gregoire, T.G., Ståhl, G., Næsset, E., Gobakken, T., Nelson, R., and Holm, S. 2011. Model-assisted
407 estimation of biomass in a LiDAR sample survey in Hedmark County, Norway. *Canadian Journal of*
408 *Forest Research* **41**(1): 83-95. doi: 10.1139/X10-195.
- 409 IPCC. 2006. Guidelines for National Greenhouse Gas Inventories. Institute for Global Environmental
410 Strategies, Japan.
- 411 Magnussen, S., Næsset, E., and Gobakken, T. 2015. LiDAR-supported estimation of change in forest
412 biomass with time-invariant regression models. *Canadian Journal of Forest Research* **45**(11): 1514-
413 1523. doi: 10.1139/cjfr-2015-0084.

- 414 Marklund, L.G. 1988. Biomass functions for pine, spruce and birch in Sweden. Swedish University of
415 Agricultural Sciences, Department of Forest Survey, Umeå.
- 416 McRoberts, R.E., Næsset, E., Gobakken, T., and Bollandsås, O.M. 2015. Indirect and direct estimation of
417 forest biomass change using forest inventory and airborne laser scanning data. *Remote Sensing of*
418 *Environment* **164**: 36-42.
- 419 Næsset, E. 2005. Towards a laser-scanner based biomass monitoring system. *In* SNS Meeting, Forest
420 Inventory and Planning in Nordic Countries, Sjusjøen, Norway. pp. 117-119.
- 421 Næsset, E., Bollandsås, O.M., Gobakken, T., Gregoire, T.G., and Ståhl, G. 2013a. Model-assisted
422 estimation of change in forest biomass over an 11 year period in a sample survey supported by
423 airborne LiDAR: A case study with post-stratification to provide "activity data". *Remote Sensing of*
424 *Environment* **128**: 299-314. doi: 10.1016/j.rse.2012.10.008.
- 425 Næsset, E., Gobakken, T., Bollandsås, O.M., Gregoire, T.G., Nelson, R., and Ståhl, G. 2013b. Comparison
426 of precision of biomass estimates in regional field sample surveys and airborne LiDAR-assisted
427 surveys in Hedmark County, Norway. *Remote Sensing of Environment* **130**(0): 108 - 120.
- 428 Pan, Y., Birdsey, R.A., Fang, J., Houghton, R., Kauppi, P.E., Kurz, W.A., Phillips, O.L., Shvidenko, A., Lewis,
429 S.L., Canadell, J.G., Ciais, P., Jackson, R.B., Pacala, S.W., McGuire, A.D., Piao, S., Rautiainen, A., Sitch,
430 S., and Hayes, D. 2011. A Large and Persistent Carbon Sink in the World's Forests. *Science* **333**(6045):
431 988-993. doi: 10.1126/science.1201609.
- 432 Pinheiro, J., Bates, D., DebRoy, S., Sarkar, D., and Team, R.C. 2013. nlme: Linear and Nonlinear Mixed
433 Effects Models.
- 434 Ringvall, A.H., Ståhl, G., Ene, L.T., Næsset, E., Gobakken, T., and Gregoire, T.G. 2016. A poststratified
435 ratio estimator for model-assisted biomass estimation in sample-based airborne laser scanning
436 surveys. *Canadian Journal of Forest Research* **46**(11): 1386-1395. doi: 10.1139/cjfr-2016-0158.

- 437 Saarela, S., Grafström, A., Ståhl, G., Kangas, A., Holopainen, M., Tuominen, S., Nordkvist, K., and Hyypä,
 438 J. 2015. Model-assisted estimation of growing stock volume using different combinations of LiDAR
 439 and Landsat data as auxiliary information. *Remote Sensing of Environment* **158**: 431-440.
- 440 Saarela, S., Holm, S., Grafström, A., Schnell, S., Næsset, E., Gregoire, T.G., Nelson, R.F., and Ståhl, G.
 441 2016. Hierarchical model-based inference for forest inventory utilizing three sources of information.
 442 *Annals of Forest Science* **73**(4): 895-910. doi: 10.1007/s13595-016-0590-1.
- 443 Skowronski, N.S., Clark, K.L., Gallagher, M., Birdsey, R.A., and Hom, J.L. 2014. Airborne laser scanner-
 444 assisted estimation of aboveground biomass change in a temperate oak–pine forest. *Remote Sensing*
 445 *of Environment* **151**: 166-174. doi: 10.1016/j.rse.2013.12.015.
- 446 Ståhl, G., Holm, S., Gregoire, T.G., Gobakken, T., Næsset, E., and Nelson, R. 2011. Model-based inference
 447 for biomass estimation in a LiDAR sample survey in Hedmark County, Norway. *Canadian Journal of*
 448 *Forest Research* **41**(1): 96-107. doi: 10.1139/X10-161.
- 449 Ståhl, G., Saarela, S., Schnell, S., Holm, S., Breidenbach, J., Healey, S.P., Patterson, P.L., Magnussen, S.,
 450 Næsset, E., McRoberts, R.E., and Gregoire, T.G. 2016. Use of models in large-area forest surveys:
 451 comparing model-assisted, model-based and hybrid estimation. *Forest Ecosystems* **3**(1): 5. doi:
 452 10.1186/s40663-016-0064-9.
- 453 Särndal, C.-E., Swensson, B., and Wretman, J.H.k. 1992. *Model Assisted Survey Sampling*. Springer-
 454 Verlag, New York.
- 455 Tomppo, E., Gschwantner, T., Lawrence, M., and McRoberts, R.E. 2010. *National Forest Inventories*.
 456 Springer Netherlands.
- 457 Zuur, A.F., Ieno, E.N., Walker, N.J., Saveliev, A.A., and Smith, G.M. 2009. *Mixed Effects Models and*
 458 *Extensions in Ecology with R*. Springer.
- 459

Table 1. ALS survey summary

Time	Date	ALS strips	Data vendor	Laser scanner	Pulse density (m ⁻²)
2006	22 July 2006 – 16 Sept. 2006	24*	Blom Geomatics, Norway	Optech ALTM 3100	2.8
2011	04 Aug. 2011 – 24 Sept. 2011	15	Terratec, Norway	Leica ALS70	~5
	29 Aug. 2012 – 30 Sept. 2012	9			

Note: * in 2006 a total of 53 ALS strips were scanned covering the entire Hedmark County. Since the 2011-2012 acquisitions covered 24 strips, we were constrained to use only the 24 overlapping strips from 2006, as well as to limit the study area accordingly.

Table 2. Models summary

Cover class	Model mean function	RSE (Mg/ha)	n
Nonproductive/non-forest	$\ln(AGB) = \ln(h_{80(l)}) + \ln(d_{5(f)})$	56	16x2
Young forest	$\ln(AGB) = \ln(d_{3(f)}) + \ln(h_{\max(l)})$	69	73x2
Low productive forest	$\ln(AGB) = \ln(h_{40(l)}) + \ln(h_{90(l)}) + \ln(d_{0(f)})$	53	38x2
Medium productive forest	$\ln(AGB) = \ln(h_{50(l)}) + \ln(d_{5(f)}) + \ln(d_{0(l)})$	51	62x2
High productive forest	$\ln(AGB) = \ln(h_{40(f)}) + \ln(d_{4(l)}) + \ln(h_{\max(f)})$	50	45x2

Note: h : height percentile, d : density, (f) : first echo, (l) : last echo. Residual standard error (RSE) is transformed back to linear scale and scaled up to per-hectare values.

Table 3. Relative efficiencies of the estimators supported by the ALS survey with respect to the direct estimator

Cover class	2006			2011			Change		
	MA	HY	HY*	MA	HY	HY*	MA	HY	HY*
Nonproductive/Non-forest	2.82	3.74	6.05	5.65	4.38	7.39	1.70	41.66	13.96
Young forest	3.84	0.71	0.74	2.93	0.73	0.74	1.03	2.63	1.97
Low productive forest	0.89	0.68	0.86	1.12	0.79	1.00	1.49	4.38	4.38
Medium productive forest	4.91	1.86	1.88	4.97	2.78	2.75	6.16	7.18	7.25
High productive forest	4.48	4.14	4.46	3.09	4.73	4.73	2.04	11.62	12.70
All cover classes	1.92	0.81	0.70	2.51	1.05	0.88	4.15	3.36	3.22

Note: Bolded values (>1) indicate estimated variance greater than that of the direct estimator. HY* is the hybrid estimator with stratification by both cover class and change class (collapsed by cover class).

Table 4. Model-assisted estimation results

Cover class	2006			2011			Change		
	Mean (Mg/ha)	SE (Mg/ha)	%	Mean (Mg/ha)	SE (Mg/ha)	%	Mean (Mg/ha)	SE (Mg/ha)	%
Nonproductive/Non-forest	18.1	2.58	4.2	17.1	1.99	6.7	-1.00	1.09	10.5
Young forest	54.7	2.22	4.8	61.1	2.87	4.0	6.36	1.44	7.4
Low productive forest	61.6	6.56	0.4	62.6	6.35	0.6	0.94	1.85	3.4
Medium productive forest	113.4	3.48	9.5	110.2	3.69	4.8	-3.16	2.16	12.4
High productive forest	139.2	5.41	2.5	140.8	7.04	2.1	1.59	6.07	1.3
All cover classes	69.1	2.03	2.5	70.4	1.93	2.5	1.36	0.81	8.5

Note: % denotes the percentage of variance due to the second stage sampling ($\widehat{Cov}_{S2}$)

Table 5. Hybrid estimation results

Cover class	2006			2011			Change		
	Mean (Mg/ha)	SE (Mg/ha)	%	Mean (Mg/ha)	SE (Mg/ha)	%	Mean (Mg/ha)	SE (Mg/ha)	%
Nonproductive/Non-forest	18.9	2.24	58.8	19.6	2.26	58.8	0.77	0.22	56.1
Young forest	53.4	5.16	72.8	60.3	5.73	77.3	6.83	0.90	49.5
Low productive forest	59.6	7.51	20.1	65.3	7.57	23.2	5.63	1.08	73.3
Medium productive forest	110.2	5.65	43.8	109.4	4.94	53.5	-0.83	2.00	9.4
High productive forest	135.8	5.63	64.2	137.8	5.69	67.6	1.95	2.54	21.6
All cover classes	67.6	3.12	31.5	70.6	2.99	40.8	3.05	0.90	11.0

Note: % denotes the percentage of variance due to the model error ($\widehat{Cov}_M$)

Table 6. Direct estimation using field data only

Cover class	2006		2011		Change	
	Mean (Mg/ha)	SE (Mg/ha)	Mean (Mg/ha)	SE (Mg/ha)	Mean (Mg/ha)	SE (Mg/ha)
Nonproductive/Non-forest	16.4	4.33	17.9	4.73	1.52	1.42
Young forest	31.3	4.35	41.9	4.91	10.62	1.46
Low productive forest	48.6	6.20	51.4	6.71	2.76	2.26
Medium productive forest	111.8	7.71	119.9	8.23	8.14	5.36
High productive forest	129.6	11.45	135.6	12.37	6.02	8.66
All cover classes	58.4	2.81	64.8	3.06	6.38	1.65

Table 7. Hybrid estimation results with nested stratification by cover class and change class.

Change class	Cover class	Estimated stratum size (km ²)	2006			2011			Change		
			Mean (Mg/ha)	SE (Mg/ha)	%	Mean (Mg/ha)	SE (Mg/ha)	%	Mean (Mg/ha)	SE (Mg/ha)	%
Unchanged forest	Non-forest	878.6	41.9	3.89	92.5	43.7	3.94	92.9	1.83	0.44	69.3
	Young	3017.9	55.5	5.31	73.9	63.7	6.03	78.0	8.12	1.02	56.1
	Low	1125.7	66.3	7.45	25.2	72.9	7.49	29.6	6.61	1.19	76.5
	Medium	2050.4	110.1	5.63	43.9	110.5	5.01	53.1	0.40	1.98	9.9
	High	1176.7	134.4	5.52	64.5	141.3	5.84	67.5	6.92	2.46	27.9
Clear felled	Non-forest	62.8	23.3	4.91	99.1				-23.28	4.91	99.1
	Young	31.9	89.2	11.36	58.5				-89.22	11.36	58.5
	Low	12.4	30.8	9.55	4.7				-30.75	9.55	4.7
	Medium	16.4	156.9	8.54	56.5				-156.88	8.54	56.5
	High	26.3	221.4	10.98	75.9				-221.36	10.98	75.9
Regeneration	Non-forest	63.1				22.4	4.67	99.4	22.45	4.67	99.4
	Young	92.4				1.5	0.15	80.6	1.49	0.15	80.6
	Low	16.3				1.7	0.23	94.6	1.70	0.23	94.6
	Medium	2.1				11.5	1.95	26.8	11.55	1.95	26.8
	High	2.6				7.1	1.15	27.1	7.14	1.15	27.1
Unchanged non-forest	Non-forest	1026.4									
	Young	48.9									
	Low	103.6									
	Medium	1.9									
	High	1.6									
All change classes	Non-forest	2030.9	18.9	1.76	86.5	19.6	1.74	90.2	0.77	0.38	54.4
	Young	3191.1	53.4	5.07	72.8	60.3	5.71	77.8	6.83	1.04	55.6
	Low	1258.1	59.6	6.69	25.0	65.3	6.72	29.5	5.63	1.08	75.5
	Medium	2070.8	110.2	5.62	43.2	109.4	4.96	53.1	-0.83	1.99	9.5
	High	1207.3	135.8	5.42	63.6	137.8	5.69	67.5	1.95	2.43	27.4
Unchanged forest		8249.4	80.4	3.90	29.4	85.5	3.86	37.3	5.15	1.08	13.6
Clear felled	All cover classes	149.7	87.3	4.53	53.4				-87.30	4.53	53.4
Regeneration		176.6				9.2	1.67	99.2	9.21	1.67	99.2
Unchanged non-forest		1182.5									
All	All	9758.1	69.3	3.35	29.7	72.5	3.27	37.3	3.18	0.92	11.5

Note: First four row blocks (separated by dashed lines) show estimates of the 20 expanded strata (four change classes x five cover classes). The 5th and 6th row blocks (separated by solid lines) are estimates collapsed by cover class and change class respectively. % denotes the percentage of variance due to the model error ($\widehat{Cov}_M$). For cover classes, a short notation is used.

Fig. 1. Study area: southern portion of Hedmark County, Norway. The black dots are the locations of the NFI plots, and the white stripes are ALS flight lines.

Fig. 2. Cover classes, change classes, and AGB change predictions along an ALS strip segment.

Fig. 3. Convergence plots for the parametric bootstrap simulation. Plots on the left show the mean absolute difference (MAD) between the $H \times H$ elements of $\widehat{Cov}_{M(boot)}$ and $\widehat{Cov}_M$ matrices. Plots on the right show the SE calculated with $\widehat{Cov}_{M(boot)}$, and the gray line is the SE calculated with $\widehat{Cov}_M$

Draft

(A) Cover class

(B) Change class

(C) AGB change (Mg/ha)