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ARTICLE

Comparing the stock-change and gain–loss approaches for estimating forest carbon emissions for the aboveground biomass pool

Ronald E. McRoberts, Erik Næsset, and Terje Gobakken

Abstract: Two approaches to greenhouse gas (GHG) inventories are common, namely the stock-change approach and the gain–loss approach. With the stock-change approach, mean annual emissions are estimated as the ratio of the difference in stock estimates at two points in time and the number of intervening years. The stock-change approach is fairly easy to implement for countries with well-established forest sampling programs. However, countries without established forest sampling programs more commonly use the gain–loss approach. With this approach, emissions are estimated as the product of the areas of classes of land use change, characterized as activity data, and the responses of carbon stocks for those classes, characterized as emission factors. Regardless of the approach, the Intergovernmental Panel on Climate Change (IPCC) good practice guidelines specify that GHG inventories produce neither over- nor under-estimates and reduce uncertainties to the degree possible. For a study area in southeastern Norway, the objectives of the study were to compare the stock-change and gain–loss approaches with respect to estimates of carbon emissions for the aboveground biomass pool and to illustrate statistically rigorous methods for complying with the two IPCC good practice guidelines for both approaches. The primary conclusions were that the two approaches produced comparable estimates of mean annual emissions, but that the stock-change approach produced considerably smaller estimates of uncertainty.

Key words: statistical estimators, remote sensing, uncertainty.

Résumé : Deux méthodes d'inventaire des gaz à effet de serre (GES) sont couramment utilisées : la méthode de différence des stocks et la méthode gains-pertes. Dans le cas de la méthode de différence des stocks, les émissions annuelles moyennes sont estimées par le rapport entre la différence des estimations des stocks à deux moments et le nombre le nombre d'années écoulées entre les deux. Cette méthode est relativement facile à implanter dans les pays où des programmes d'inventaire forestier sont bien établis. Cependant, les pays où ce n'est pas le cas utilisent généralement la méthode gains-pertes. Avec cette méthode, les émissions sont estimées par le produit de la variation dans la superficie des classes d'utilisation des terres, caractérisées comme données d'activités, et de la réaction des stocks de carbone correspondant à ces classes, caractérisée comme facteur d'émission. Peu importe l'approche, le guide des bonnes pratiques du Groupe d'experts intergouvernemental sur l'évolution du climat (GIEC) précise que l'inventaire des GES ne devrait ni surestimer, ni sous-estimer tout en cherchant à réduire dans la mesure du possible les incertitudes. À partir d'une zone d'étude située dans le sud de la Norvège, cette étude avait pour but de comparer les méthodes de différence des stocks et de gains-pertes en ce qui concerne les estimations des émissions de carbone pour le réservoir de biomasse aérienne et de présenter des méthodes statistiquement rigoureuses pour respecter les directives du guide des bonnes pratiques du GIEC pour les deux méthodes. Les principales conclusions sont que les deux méthodes produisent des estimations comparables des émissions annuelles moyennes mais que l'incertitude estimée par la méthode de différence des stocks est considérablement plus faible. [Traduit par la Rédaction]

Mots-clés : estimateurs statistiques, télédétection, incertitude.

1. Introduction

Greenhouse gas (GHG) inventories focus on carbon accounting and assess the scale of carbon emissions for multiple land uses including the Agriculture, Forestry, and Other Land Use sector (Intergovernmental Panel on Climate Change (IPCC) 2006, Volume 4). Two primary approaches to GHG inventories are common, the stock-change approach and the gain–loss approach (IPCC 2006, Volume 4, Chapter 2, p. 2.10; GFOI 2016, p. 22). With the stock-change approach (equivalently stock-difference approach), mean annual carbon emissions for land subject to human activities such as deforestation and forest degradation are estimated as the ratio of the difference in carbon stock estimates at two points in time and the number of intervening years (IPCC 2006, Volume 4, Chapter 4, Section 4.2.1.1; GFOI 2016, Chapter 3). For countries with established forest sampling programs such as national forest inventories (NFIs), the stock-change approach is fairly easy to implement. However, for countries without established NFIs, particularly countries with remote and inaccessible forests, the gain–loss approach may be the only alternative. With the gain–loss approach, emissions are defined as the net balance of additions to and removals from a carbon pool and are estimated as the product of the areas of "human activity causing emissions and removals", characterized as activity data, and the responses of carbon stocks for those activities, characterized as emission fac-

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tors (IPCC 2006, Volume 1, Chapter 1, Section 1.2; GFOI 2016, pp. xvii, 22).

The IPCC characterizes GHG methods with respect to three tiers or levels of detail (GFOI 2016, p. 19). Tier 1 is the default method and permits use of global emission factors, thus making it applicable for any country. Tier 2 is based on the same conceptual structure as Tier 1 but with the expectation that national level data such as emission factors are be used. Tier 3 methods typically entail more complex models and finer resolution land use and land-use change estimates. Both the stock-change and gain–loss methods can be implemented at Tier 2 and Tier 3 levels, but only the gain–loss method is used at the Tier 1 level because of the more extensive data requirements associated with the stock-change method (IPCC 2003, p. 3.25). Within tiers, the IPCC further documents Approaches 1, 2, and 3 for estimating activity data, all involving land use class areas (GFOI 2016, p. 19). Approach 1 uses land use class areas such as would be reported by an NFI but without regard to the specific locations of individual segments of those land use classes; Approach 2 differentiates among land use change classes but like Approach 1 does not identify the specific locations of individual segments of the classes; and Approach 3 tracks individual land parcels over time.

Regardless of whether Approach 1, 2, or 3 is used and whether the stock-change or gain–loss method is used, the IPCC specifies two good practice guidelines for GHG inventories: (*i*) "neither over- nor underestimates so far as can be judged", and (*ii*) "uncertainties are reduced as far as practicable" (IPCC 2006, Volume 1, Chapter 1, Section 1.2; GFOI 2016, p. 15). From a statistical perspective, satisfaction of these criteria requires use of unbiased estimators and, at minimum, rigorous estimation of uncertainty. In particular, there can be little assurance that uncertainties are reduced until they are first rigorously estimated (Gregoire et al. 2016).

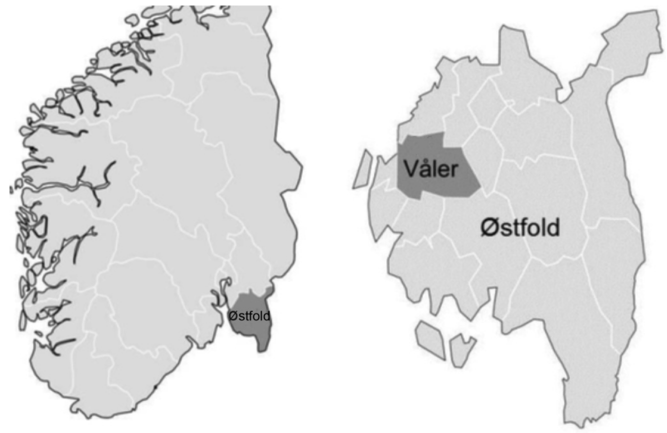
Although the conceptual and technical aspects of the stock-change and gain–loss methods are documented and compared in multiple publications (IPCC 2006; GFOI 2016), few if any rigorous comparisons of estimates obtained using the two approaches have been reported. Magnussen et al. (2014) used Monte Carlo methods to estimate uncertainties associated with the two approaches using German NFI data and concluded that uncertainty in stock-change estimates is dominated by sampling variability, whereas uncertainty in gain–loss estimates is dominated by model prediction uncertainty. However, due to lack of complete information, no direct comparisons of estimates obtained with the two methods were reported. Röhling et al. (2016) described differences between the stock-change and gain–loss approaches, concurred with Magnussen et al. (2014) regarding the most important sources of uncertainty for the two approaches, and also used German NFI data to assess changes in gain–loss emission factors within and between periodic inventory dates. Again, however, no comparisons of estimates for the two approaches were reported. Thus, a statistically rigorous comparison of the stock-change and gain–loss approaches with respect to the accuracy and precision of emission estimates is warranted.

The objectives of the study were two-fold: (*i*) to compare variations of the stock-change approach and the gain–loss approach for carbon change estimation for the aboveground biomass pool, and (*ii*) to illustrate statistically rigorous methods for complying with the two good practice criteria for both approaches. The focus of the current study is primarily Tier 2 and Approach 3 within that tier. Although the analyses focused exclusively on the aboveground biomass pool, the analyses would be similar, regardless of the pools assessed.

2. Data

The 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. Lands with forest and non-forest use were delineated during the course of an operational field inventory. A quasi-systematic sample of 86 circular, 200 m² forest inventory plots was selected from the 522.7 ha of land with forest use. Individual tree, aboveground, living biomass was predicted for both 1999 and 2010 using allometric models based on field observations of species and measurements of diameter at breast height (1.3 m) and height (Marklund 1988). Uncertainty in the allometric model predictions was considered negligible relative to sampling variability for this study (McRoberts et al. 2016*a*). Plot-level, aboveground, living tree biomass was predicted as the sum of individual tree biomass predictions, scaled to a per unit area basis, multiplied by a biomass-to-carbon conversion factor of 0.5, and denoted C (Mg·ha⁻¹). Plot-level change in C was calculated and denoted $\Delta C = C_{2010} - C_{1999}$. For this study, the term "emissions" refers to the net result of C additions to and removals from the aboveground, live tree biomass pool. Losses of forest C in the form of aboveground living tree biomass are indicated by negative values of ΔC or, equivalently, negative emissions, whereas gains in forest C in the same form are indicated by positive values of ΔC or, equivalently, positive emissions.

Fig. 1. Study area in Våler Municipality in southeastern Norway.



Wall-to-wall airborne laser scanning (ALS) data were acquired for the study area in 1999 and 2010. Pulse densities were approximately 1.2 pulses·m² in 1999 and 7.3 pulses·m² in 2010. For each year, distributions of first echo heights were constructed for the 200 m² plots and 200 m² square cells that tessellated the study area and served as population units. A threshold of 1.3 m above the ground surface was used to remove the effects of echoes from ground vegetation not included in tree-level biomass. For each plot and cell, heights corresponding to the 10th, 20th, …, 100th percentiles of the distributions of echo heights 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 and Næsset 2008). Differences between the 2010 and 1999 values of the 20 ALS metrics were used as predictor variables for constructing ΔC models.

3. Methods

3.1. Overview

All analyses were based on three underlying assumptions: (*i*) a finite population consisting of N = 26 135 units in the form of the square, 200 m² cells; (*ii*) a quasi-systematic probability sample consisting of n = 86 observations of ΔC for the 200 m^2 plots; and (*iii*) availability of auxiliary data in the form of the ALS metrics for all plots and population units. For this study, finite population correction factors were ignored because of the small sampling intensity of 0.0033. Both the stock-change and gain–loss approaches were used to estimate mean annual carbon emissions for the aboveground biomass pool. Both approaches used an activity class map constructed using plot-level activity class observations, ALS metrics, and multinomial logistic regression (Section 3.2).

3.1.1. Stock-change approach

With the stock-change approach, three statistical estimators were used with plot-level ΔC observations to estimate mean carbon emissions per unit area. First, the simple expansion estimators (Royall and Herson 1973) were used with only the plot-level ΔC observations (Section 3.3.1). Second, as a means of increasing precision, post-stratified estimators were used with the plot-level ΔC observations and a stratification based on the activity class map (Section 3.3.2). Third, based on accumulating evidence that the model-assisted, generalized regression estimators increase precision even more than the post-stratified estimators (McRoberts et al. 2013), the regression estimators were used with the plot-level ΔC observations and predictions from a linear model of the relationship between ΔC and the ALS metrics. For all three estimators, mean annual emissions were estimated by multiplying the mean per unit area estimates by A_{total} = 522.7 ha and dividing by Δt = 11 years.

3.1.2. Gain–loss approach

With the gain–loss approach, mean emissions per unit area were estimated as the sum over activity classes of the products of activity class area proportion estimates and activity class emission factors per unit area. Mean annual emissions were estimated by multiplying the mean per unit area estimates by A_{total} = 522.7 ha and dividing by Δt = 11 years. Activity class area proportions were estimated using post-stratified estimators with plot-level activity class observations and a stratification based on the activity class map (Section 3.4.1). Emission factors per unit area for activity classes were estimated using simple expansion estimators with the plot-level ΔC and activity class observations (Section 3.4.2).

3.2. Activity class map

The activity class map depicted three forest activities: deforestation, forest degradation, and undisturbed forest. Of these classes, the former two are included under the UNFCCC REDD (Reducing Emissions from Deforestation and Forest Degradation program) (UNFCCC 2011; GFOI 2016, p. ix). Technical definitions of deforestation and forest degradation vary considerably, both by country and by application. For example, deforestation is often defined in terms of a permanent land use conversion, whereas for the illustrative purposes of this study, it is defined simply in terms of loss of biomass without regard to permanence. For this study, 200 m^2 areas of land with loss of C ($\Delta C < 0$) greater in absolute value than $0.95{\cdot}C_{1999}$ were considered deforested, and 200 m^2 areas of land with loss of C ($\Delta C < 0$) but no more in absolute value than $0.95{\cdot}C_{1999}$ were considered degraded. These definitions are acknowledged to be arbitrary but were deemed sufficient for illustrative purposes for this study. Based on these two definitions, the three activity classes were indexed by c and defined as follows:

$$\text{Activity} = \begin{cases} \text{deforested } (c = 1) & \Delta C < 0, |\Delta C| > 0.95 \cdot C_{1999} \\ \text{degraded } (c = 2) & \Delta C < 0, |\Delta C| \le 0.95 \cdot C_{1999} \\ \text{undisturbed } (c = 3) & \text{all other lands} \end{cases} \tag{1}$$

An activity class map was constructed using the plot-level activity class observations based on the class definitions from eq. 1, the ALS metrics, and a multinomial logistic regression model (Seber 1984; McRoberts 2009, 2011). With multinomial logistic regression, one response variable class is arbitrarily designated the Mth class. The probability that the ith population unit belongs to the mth class with $m < M$ is predicted as

$$\hat{q}_{mi} = \left[1 + \exp\left(\sum_{j=1}^{J} \hat{\beta}_{mj} x_{mi}\right)\right]^{-1} \tag{2a}$$

where m indexes the classes, j indexes predictor variables, and the $\hat{\beta}$s are parameter estimates. The probability that the ith population unit belongs to the Mth class is predicted as

$$\hat{q}_{Mi} = \left[1 + \exp\left(\sum_{m=1}^{M-1}\sum_{j=1}^{J} \hat{\beta}_{mj} x_{mi}\right)\right]^{-1} \tag{2b}$$

All parameters of the multinomial logistic regression model can be estimated simultaneously using a variety of software packages such as SAS with the CATMOD procedure or R with the VGAM library.

3.3. Stock-change analyses

3.3.1. Simple expansion estimators

With equal probability sampling designs, the simplest approach to inference is to use the familiar simple expansion (EXP) estimators (Royall and Herson 1973) for means and their variances

$$\overline{\Delta C}^{\text{per ha}}_{\text{EXP}} = \frac{1}{n}\sum_{i=1}^{n} \Delta C_i \tag{3a}$$

and

$$\widehat{\text{Var}}\left(\overline{\Delta C}^{\text{per ha}}_{\text{EXP}}\right) = \frac{1}{n(n-1)}\sum_{i=1}^{n}\left(\Delta C_i - \overline{\Delta C}^{\text{per ha}}_{\text{EXP}}\right)^2 \tag{3b}$$

where i indexes the n sample units, and ΔC_i is the C change observation for the ith plot. The primary advantages of the EXP estimators are that they are intuitive, simple, and unbiased when used with a simple random sampling design; the disadvantage is that variances are frequently large, particularly for small sample sizes and (or) populations with large variability among population unit observations.

3.3.2. Post-stratified estimators

Post-stratified (PStr) estimators were also used to estimate mean carbon emissions per unit area. The response variable was plot-level ΔC, plots were assigned to the activity class-based strata that included their centers, and stratum weights were map activity class area proportions. For each stratum, h,

$$\overline{\Delta C}_h = \frac{1}{n_h}\sum_{i=1}^{n_h} \Delta C_{hi} \tag{4a}$$

and

$$\hat{\sigma}_h^2 = \frac{1}{n_h - 1}\sum_{i=1}^{n_h}\left(\Delta C_{hi} - \overline{\Delta C}_h\right)^2 \tag{4b}$$

are estimators of the within-stratum mean and variance, where i indexes plots within strata, and n_h is the within-stratum sample size. For the three activity-based strata used for this study, the PStr estimator of mean carbon change per unit area is

$$(4c)\qquad \overline{\Delta C}^{\text{per ha}}_{\text{PStr}} = \sum_{h=1}^{3} w_h \overline{\Delta C}_h$$

with variance estimator

$$(4d)\qquad \widehat{\text{Var}}\left(\overline{\Delta C}^{\text{per ha}}_{\text{PStr}}\right) = \sum_{h=1}^{3}\left[w_h\frac{\hat{\sigma}^2_h}{n} + (1 - w_h)\frac{\hat{\sigma}^2_h}{n^2}\right]$$

where w_h is the stratum weight for the hth stratum and n is the total sample size (Cochran 1977, p. 135). Of importance, classification errors in the activity class map used as the source of stratification data do not induce bias into the estimators of eqs. 4*c* and 4*d*, although they generally decrease the precision of the estimators.

3.3.3. Model-assisted estimators

Model-assisted estimators rely on models of relationships between response variables and auxiliary data to reduce variances. However, because the validity of an inference is still based on probability samples, the estimator is characterized as design-based. For this study, a linear model of the relationship between ΔC and the ALS metrics was formulated as

$$(5)\qquad \Delta C_i = \beta_0 + \beta_1 x_{1i} + \cdots + \beta_p x_{pi} + \varepsilon_i$$

where i indexes plots, x denotes an ALS metric, the β are parameters to be estimated, and ε_i is a residual term. A forward selection procedure was used to select ALS metrics for inclusion into the model.

A synthetic (Syn) estimator of the mean carbon change per unit area is

$$(6a)\qquad \overline{\Delta C}_{\text{Syn}} = \frac{1}{N}\sum_{i=1}^{N}\widehat{\Delta C_i}$$

where N is the population size and $\widehat{\Delta C_i}$ is the model prediction for the ith population unit. However, systematic model lack of fit induces bias into this estimator (Lohr 1999) and would result in failure to comply with the first IPCC good practice guideline. For equal probability samples, an estimator of the bias is

$$(6b)\qquad \widehat{\text{Bias}}(\overline{\Delta C}_{\text{Syn}}) = \sum_{i=1}^{n}\hat{\varepsilon}_i$$

where n is the sample size and $\hat{\varepsilon}_i = \Delta\hat{C}_i - \Delta C_i$. The model-assisted generalized regression (GREG) estimator of mean carbon change per unit area is formulated as the difference between the synthetic estimator and its bias estimator

$$(6c)\qquad \overline{\Delta C}^{\text{per ha}}_{\text{GREG}} = \frac{1}{N}\sum_{i=1}^{N}\widehat{\Delta C_i} - \frac{1}{n}\sum_{i=1}^{n}\hat{\varepsilon}_i$$

with variance estimator

$$(6d)\qquad \widehat{\text{Var}}\left(\overline{\Delta C}^{\text{per ha}}_{\text{GREG}}\right) = \frac{1}{n(n-p)}\sum_{i=1}^{n}(\hat{\varepsilon}_i - \bar{\hat{\varepsilon}})^2$$

where p is the number of parameters in eq. 5 and $\bar{\hat{\varepsilon}} = \frac{1}{n}\sum_{i=1}^{n}\hat{\varepsilon}_i$ (Särndal et al. 1992; Särndal 2011).

3.3.4. Mean annual emissions

For all three stock-change estimators, mean annual stock-change emissions were estimated as

$$(7a)\qquad \overline{\Delta C}^{\text{mn an}} = \frac{1}{\Delta t}A_{\text{total}}\overline{\Delta C}^{\text{per ha}}$$

with standard error

$$(7b)\qquad \text{SE}(\overline{\Delta C}^{\text{mn an}}) = \frac{1}{\Delta t}A_{\text{total}}\sqrt{\widehat{\text{Var}}(\overline{\Delta C}^{\text{per ha}})}$$

3.4. Gain–loss analyses

3.4.1. Activity class area proportions

Areas for the deforested, degraded, and undisturbed activity classes can be estimated as the sum of the areas of all map units assigned to each of the three classes. However, classification errors induce bias into this pixel-counting estimator and would result in failure to comply with the first IPCC good practice guideline. An unbiased approach to estimating activity area proportions uses stratified or post-stratified estimation for which the map activity classes serve as strata and the map class area proportion estimates serve as stratum weights. For both stratified and post-stratified analyses, the strata are indexed by h and the reference activity classes based on the field observations are indexed by c. Each plot is cross-referenced with respect to map and reference classes, h and c. For activity reference class c, the estimator of the within-stratum class area proportion is

$$(8a)\qquad \hat{p}_{hc} = \frac{n_{hc}}{n_{h\cdot}}$$

where n_{hc} is the number of plots assigned simultaneously to stratum h and reference activity class c, and the total number of plots assigned to stratum h, regardless of reference activity class. The corresponding within-stratum variance estimator is

$$(8b)\qquad \hat{\sigma}^2_{hc} = \hat{p}_{hc}(1 - \hat{p}_{hc})$$

The unbiased PStr estimator of the area proportion for activity class c is

$$(8c)\qquad \hat{p}_c = \sum_{h=1}^{3} w_h \hat{p}_{hc}$$

where w_h is the stratum weight. The corresponding PStr variance estimator is

$$(8d)\qquad \widehat{\text{Var}}(\hat{p}_c) = \sum_{h=1}^{3}\left[w_h\frac{\hat{\sigma}^2_{hc}}{n} + (1 - w_h)\frac{\hat{\sigma}^2_{hc}}{n^2}\right]$$

where n is the total sample size (Cochran 1977, p. 135) and $\text{SE}(\hat{p}_c) = \sqrt{\widehat{\text{Var}}(\hat{p}_c)}$.

This approach is similar to the approach reported in GFOI (2016, Chapter 5), except that the PStr variance estimator of eq. 8*d* for use with simple random sampling differs slightly from the GFOI stratified variance estimator for use with stratified random sampling.

3.4.2. *Emission factors*

The EXP estimators were used to estimate emission factors for each activity class c as

$$\widehat{\mathrm{EF}}_c = \frac{1}{n_c}\sum_{i=1}^{n_c}\Delta C_{ci} \tag{9a}$$

with

$$\widehat{\mathrm{Var}}(\widehat{\mathrm{EF}}_c) = \frac{1}{n_c(n_c-1)}\sum_{i=1}^{n_c}(\Delta C_{ci} - \widehat{\mathrm{EF}}_c)^2 \tag{9b}$$

and $\mathrm{SE}(\widehat{\mathrm{EF}}_c) = \sqrt{\widehat{\mathrm{Var}}(\widehat{\mathrm{EF}}_c)}$, where ΔC_{ci} is the carbon change observation for the ith plot assigned to activity class c based on ground observations and n_c is the number of plots assigned to activity class c. Of importance, the emission factor estimates are based on plots assigned to activity classes based on the ground observations, not the activity class map. If the activity class map were used, map classification errors would induce bias into the estimators via assignment of some plots to incorrect classes, and the resulting estimates would not comply with the first IPCC good practice guideline.

3.4.3. *Mean annual emissions*

Mean emissions per unit area were estimated as the sum over activities of the products of estimates of activity class area proportions and estimates of corresponding activity class emission factors

$$\overline{\Delta C}^{\text{per ha}} = \sum_{c=1}^{3}\hat{p}_c\widehat{\mathrm{EF}}_c \tag{10a}$$

where c denotes activities, $\hat{p}_c$ is the estimate of the area proportion for activity class c from Section 3.3.3, and $\widehat{\mathrm{EF}}_c$ is the estimate of the emission factor for the same activity class from Section 3.3.4 (IPCC 2006, Volume 1, Chapter 1, Section 1.2; GFOI 2016, pp. xvii, 22). An estimator of the variance of $\overline{\Delta C}^{\text{per ha}}$ was formulated using a first-order Taylor series as

$$\widehat{\mathrm{Var}}(\overline{\Delta C}^{\text{per ha}}) = \sum_{c=1}^{3}\Big[\hat{p}_c^2\,\widehat{\mathrm{Var}}(\widehat{\mathrm{EF}}_c) + 2\hat{p}_c\widehat{\mathrm{EF}}_c\,\widehat{\mathrm{Cov}}(\hat{p}_c, \widehat{\mathrm{EF}}_c) + \widehat{\mathrm{EF}}_c^2\,\widehat{\mathrm{Var}}(\hat{p}_c)\Big] \tag{10b}$$

(Appendix A). If activity areas and emission factors are estimated independently, then $\mathrm{Cov}(\hat{p}_c, \widehat{\mathrm{EF}}_c) = 0$ may be assumed. For this study, the same data were used to estimate activity areas and emission factors so that $\mathrm{Cov}(\hat{p}_c, \widehat{\mathrm{EF}}_c) = 0$ cannot be assumed. However, to better mimic many actual analyses, for this study, variance estimates were calculated assuming $\widehat{\mathrm{Cov}}(\hat{p}_c, \widehat{\mathrm{EF}}_c) = 0$ but with the result that $\widehat{\mathrm{Var}}(\overline{\Delta C}^{\text{per ha}})$ is a lower bound for the variance. The gain–loss estimate of mean annual emissions is

$$\overline{\Delta C}^{\text{mn an}}_{\text{gain-loss}} = \frac{1}{\Delta t}A_{\text{total}}\overline{\Delta C}^{\text{per ha}} \tag{11a}$$

with standard error

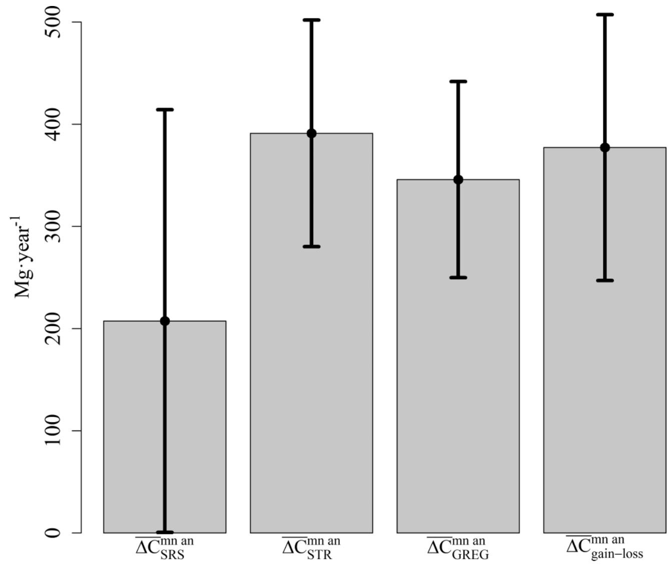
$$\mathrm{SE}\left(\overline{\Delta C}^{\text{mn an}}_{\text{gain-loss}}\right) = \frac{1}{\Delta t}A_{\text{total}}\sqrt{\widehat{\mathrm{Var}}(\overline{\Delta C}^{\text{per ha}})} \tag{11b}$$

4. Results and discussion

4.1. Stock-change analyses

The EXP, PStr, and GREG estimators were all used to estimate mean annual C emissions for the aboveground biomass pool:

Fig. 2. Estimates with standard error bars.



$\overline{\Delta C}^{\text{mn an}}_{\text{EXP}} = 207.31$ Mg·year^{-1}, with SE $(\overline{\Delta C}^{\text{mn an}}_{\text{EXP}}) = 206.91$ Mg·year^{-1}
$\overline{\Delta C}^{\text{mn an}}_{\text{PStr}} = 391.04$ Mg·year^{-1}, with SE $(\overline{\Delta C}^{\text{mn an}}_{\text{PStr}}) = 110.90$ Mg·year^{-1}
$\overline{\Delta C}^{\text{mn an}}_{\text{GREG}} = 345.75$ Mg·year^{-1}, with SE $(\overline{\Delta C}^{\text{mn an}}_{\text{GREG}}) = 95.93$ Mg·year^{-1}

See Fig. 2 for a visual comparison of the three estimators. The much smaller EXP estimate can be attributed to the difference between the 0.162 proportion of plots in the deforested activity class (Table 1) and the 0.076 proportion of the study area in the same class (Table 2). Although the difference of 0.086 is relatively small, the deforested activity class had the greatest estimated carbon change per unit area. Thus, even the small difference in proportions had a substantial influence on estimates of mean annual emissions. This phenomenon can likely be at least partially attributed to the small sample size for the deforested activity class.

Estimates obtained using the PStr and GREG stock change estimators were similar, deviating by approximately 45 Mg·year^{-1}, which was less than half of either of the corresponding standard errors. The PStr and GREG standard errors were on the order of 50% of the EXP standard error, demonstrating the utility of the ALS data for accomplishing the second IPCC guideline of reducing uncertainties. For the GREG estimators, the 40th height percentile and the 10th density percentile were selected as predictor variables and produced $R^2 = 0.78$ (Fig. 3). The GREG bias estimate was less than 0.01 Mg·ha^{-1}, which confirms the quality of fit of the model to the data.

4.2. Gain–loss analyses

4.2.1. *Activity class map*

A two-way contingency table analysis of the multinomial logistic regression model predictions showed that all classes were well-predicted, although the degraded class was somewhat confused with both other classes (Table 1; Fig. 4). Accuracies were relatively large given the small sample sizes, although the large overall accuracy is strongly influenced by the large sample size and large accuracy for the undisturbed class.

4.2.2. *Gain–loss estimates*

The area proportion estimates obtained using the PStr estimators of eqs. 8*c* and 8*d* were of the same order of magnitude as the map class proportions. However, confusion for the degraded class caused the greatest proportional difference and the greatest standard error among classes, both in absolute terms and relative to the proportion estimates (Table 2). Confusion for the degraded

Table 1. Activity class confusion matrix.

	Reference class				
	Deforested	Degraded	Unchanged	Count	User's accuracy
Map class					
Deforested	8	1	0	9	0.89
Degraded	3	6	0	9	0.67
Unchanged	0	1	67	68	0.99
Count	11	8	67	86	
Producer's accuracy	0.73	0.75	1.00		OA = 0.94

class and the consequent smaller classification accuracies and larger standard errors should be expected when the classes are distinguished using an arbitrary threshold for a continuous criterion such as carbon change. Across all activity classes

$$\overline{\Delta C}^{\text{mn an}}_{\text{gain}-\text{loss}} = 377.12\ \text{Mg·year}^{-1}, \text{ with } \mathrm{SE}(\overline{\Delta C}^{\text{mn an}}_{\text{gain}-\text{loss}}) = 130.08\ \text{Mg·year}^{-1}$$

The relationships among emission factor estimates were as expected with the undisturbed class experiencing a net C gain and the degraded and deforested classes experiencing net C losses with greater loss for the deforested class than for the degraded class (Table 2). The standard error for the degraded class estimate was greater than for the other two class estimates, both in absolute terms and relative to estimated means.

For the deforested and undisturbed classes, ratios of standard errors to estimates were greater for the emission factor estimates than for the area proportion estimates, suggesting that uncertainty in emission factor estimates contributes more to uncertainty in mean annual emissions estimates than does uncertainty in the activity class area estimates. This result was confirmed by brief additional analyses that showed that increases in within-stratum standard errors for activity area estimates by factors of 0.05 increased standard errors of mean annual emissions estimates by factors of approximately 0.015, whereas comparable increases in within-stratum standard errors of emission factors increased standard errors of mean annual emissions by factors of approximately 0.035.

4.3. Stock-change versus gain–loss estimates.

The PStr and GREG stock change estimates of mean annual emissions were similar to the gain–loss estimate with a small range among the three of less than 50 Mg·year^{-1}, which is only approximately half of the smallest of the three standard errors (Fig. 2). Although estimates of mean annual emissions were similar, the PStr and GREG stock change standard errors were 85% and 75% smaller, respectively, than the gain–loss standard error. As noted in Section 3.3.5, gain–loss standard errors for this study are lower bounds, so that these percentages may be even smaller. The most important findings were that the EXP estimator produced an unreliable estimate of mean annual emissions; the PStr, GREG, and gain–loss estimators produced similar estimates of mean annual emissions; and the PStr and GREG standard errors were smaller than the gain–loss standard error.

4.4. Additional considerations

The primary focus of the study was the relative effects of differences in estimates and standard errors among the estimators used for the stock-change and gain–loss approaches. With these estimators, the only source of uncertainty considered was sampling variability. An additional source that has been receiving increased attention, but was considered negligible for this study, is the uncertainty in allometric model predictions (e.g., Breidenbach et al. 2014; McRoberts et al. 2015, 2016*a*; Magnussen and Negrete 2015; Temesgen et al. 2015; Wayson et al. 2015; Weiskittel et al. 2015; McRoberts and Westfall 2016). Although results vary for individual studies and generalizations should be made with caution, McRoberts et al. (2016*a*) reported that relative to the effects of sampling variability, the combined effects of uncertainty in allometric model predictions, tree diameter and height measurements, wood densities, and biomass to carbon conversion factors on large area standard errors were negligible with the possible exception of cases for which the effects of sampling variability were reduced via the use of remotely sensed auxiliary data. Thus, although standard errors reported for this study may be slightly underestimated, the relative comparisons among approaches and methods should not be affected.

Although the methodological results of the study are well-supported, caution should be exercised in generalizing the results. First, only the aboveground biomass pool was considered; inclusion of emissions from other pools would alter estimates. Second, different definitions of forest cover, deforestation and forest degradation may be considered. For example, deforestation is often regarded as a permanent change in land use, whereas permanence may or may not be the case for this study area. Third, the results depend considerably on sample sizes, most of which were small for this study. For example, the within-stratum sample sizes for two activities were less than 10, whereas if interpretations of aerial photography rather than ground observations were used as reference data, these sample sizes and the resulting precision could be considerably greater (Pengra et al. 2015; Stehman et al. 2007; Olofsson et al. 2013; McRoberts et al. 2018). Fourth, stock-change and emission factor estimates for this study were based on field crew observations for a relatively small study area with similar management practices and generally uniform topographical, climatic, and growth conditions. Standard errors for estimates for larger, less homogeneous areas with more species are likely to be greater. Because the latter factor affects both stock-change and gain–loss estimates of mean annual emissions, predicting the relative consequences would be difficult. Fifth, sample sizes for the stock-change and gain–loss estimators were equal for this study as a means of facilitating comparisons; such may not generally be the case.

Sixth, use of the ALS auxiliary data likely contributed to greater precision than may be realized with other sources of auxiliary data such as coarser resolution spectral data. Standard errors for the PStr and GREG stock-change estimators, which used the ALS auxiliary data, were approximately 50% less than the standard error for the EXP estimators, which did not use the auxiliary data. For the gain–loss approach, the ALS auxiliary data produced a quite accurate activity class map, which, in turn, contributed to greater precision for the both stock-change and activity class proportion stratified estimators than may be possible using maps based on other sources of auxiliary data. For example, the 30 m × 30 m, Landsat-based, Global Forest Change (GFC) dataset is often used as a source of forest/non-forest and forest/non-forest change information (McRoberts et al. 2015, 2018; Næsset et al. 2016; Sannier et al. 2016). Although extremely useful where other such information is not available, the GFC percent tree canopy cover predictions must be converted to forest/non-forest, a procedure that introduces additional uncertainty. Further, the threshold for this conversion varies considerably by region: for a study area in Gabon, Sannier et al. (2016, section 3.1) selected a threshold of 70%; for a study area in Tanzania, Næsset et al. (2016, table 5) selected a threshold of 40%; for a study area in Santa Catarina, Brazil, McRoberts et al. (2016*b*, table 2) selected a threshold of 95%; and for a study area in Minnesota, USA, McRoberts et al. (2018) selected a threshold of 52%.

5. Conclusions

The primary objectives of the study were methodological: to compare the stock-change and gain–loss approaches for carbon change estimation with respect to emissions estimates for the

Table 2. Gain–loss estimates.

Activity class (c)	Map class proportions	Area proportion $\hat{p}_c$	$SE(\hat{p}_c)$	Emission factor $\widehat{EF}_c$ ($Mg \cdot ha^{-1}$)	$SE(\widehat{EF}_c)$ ($Mg \cdot ha^{-1}$)	Mean annual emissions* $\widehat{AC}_c^{mn\ an}$ ($Mg \cdot year^{-1}$)	$SE(\widehat{AC}_c^{mn\ an})$ ($Mg \cdot year^{-1}$)
Deforested	0.076	0.098	0.016	–67.997	8.507	–315.549	65.570
Degraded	0.090	0.081	0.020	–45.573	9.522	–174.440	57.050
Unchanged	0.834	0.822	0.012	22.205	2.457	867.106	96.786
Total	1.000	1.000	—	—	—	377.117	130.083

*$\widehat{\Delta C}_c^{mn\ an} = A_{total}\hat{p}_c\widehat{EF}_c/\Delta t$ with A_{total} = 522.7 ha and Δt = 11 years.

Fig. 3. Observed versus predicted carbon change with 1:1 line.

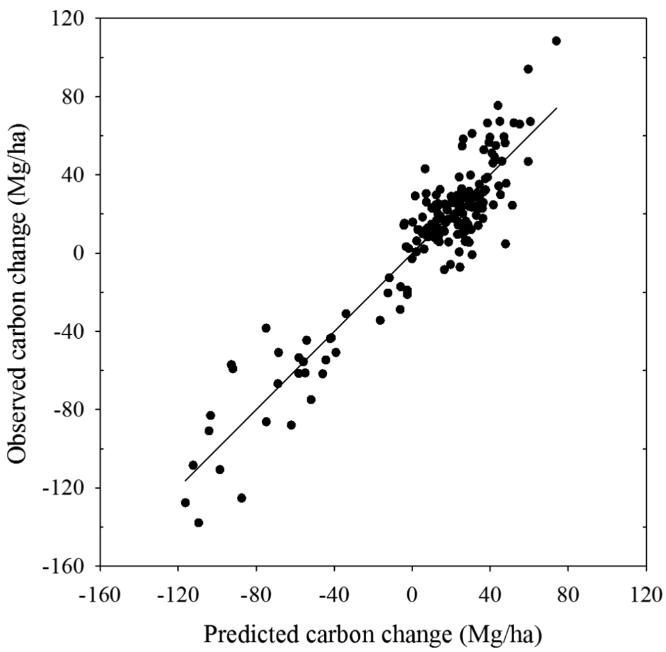
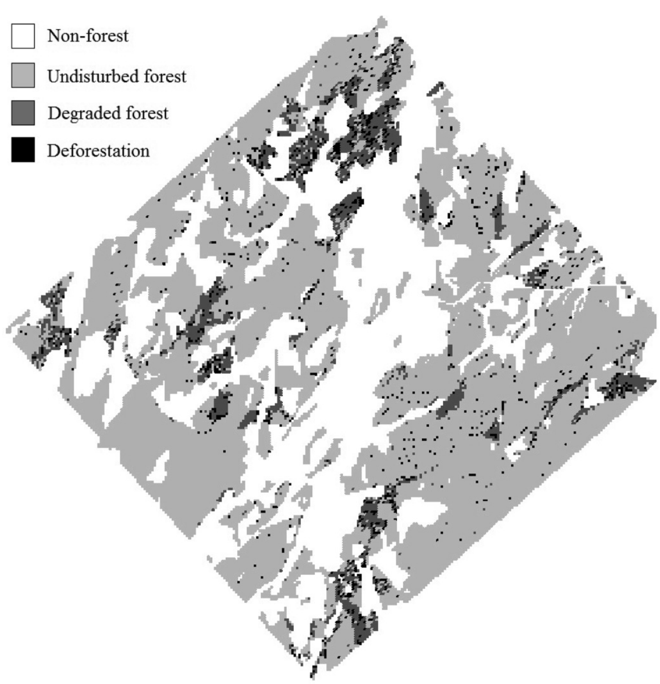


Fig. 4. Activity class map.



aboveground biomass pool and to illustrate statistically rigorous methods for complying with the IPCC good practice guidelines for both approaches. Four methodological conclusions were drawn from the study. First, use of unbiased estimators of means, rigorous estimators of variances, and reduction of variances via use of the post-stratified and model-assisted estimators complies with the IPCC good practice guidelines. Second, all except the simple expansion estimators produced similar estimates of mean annual emissions with all within a range of less than half the smallest standard error. Third, the post-stratified and generalized regression stock-change estimators were more precise than the gain–loss estimator. Fourth, for the gain–loss approach, uncertainty in estimates of emission factors had a greater impact on the uncertainty of mean annual emissions than did uncertainty in estimates of the activity class areas.

In addition, although the objectives were primarily methodological, all estimates of mean annual emissions were positive, meaning that between 1999 and 2010, the study area sequestered more carbon in the aboveground biomass pool than it emitted.

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Appendix A

A product, P = AB, may be approximated using a first-order Taylor series expansion as

$$AB \approx \hat{A}\hat{B} + \frac{\partial P}{\partial A}(A - \hat{A}) + \frac{\partial P}{\partial B}(B - \hat{B})$$

where $\hat{A}$ and $\hat{B}$ are estimates of A and B, respectively. Subtracting $\hat{A}\hat{B}$ from both sides and noting that $\frac{\partial P}{\partial A} = B$ and $\frac{\partial P}{\partial B} = A$, yields

$$(AB - \hat{A}\hat{B}) \approx B(A - \hat{A}) + A(B - \hat{B})$$

Squaring and taking expectations, $E(.)$, of both sides yields

$$\begin{aligned}\mathrm{Var}(\hat{A}\hat{B}) &= E(AB - \hat{A}\hat{B})^2 \\ &\approx B^2E(A - \hat{A})^2 + 2ABE[(A - \hat{A})(B - \hat{B})] + A^2E(B - \hat{B})^2 \\ &= B^2\mathrm{Var}(\hat{A}) + 2AB\mathrm{Cov}(\hat{A}, \hat{B}) + A^2\mathrm{Var}(\hat{B})\end{aligned}$$

Substituting $\hat{A}$ for A and $\hat{B}$ for B yields

$$\widehat{\mathrm{Var}}(\hat{A}\hat{B}) = \hat{B}^2\widehat{\mathrm{Var}}(\hat{A}) + 2\hat{A}\hat{B}\widehat{\mathrm{Cov}}(\hat{A}, \hat{B}) + \hat{A}^2\widehat{\mathrm{Var}}(\hat{B})$$