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Estimating biomass in Hedmark County, Norway using national forest inventory field plots and airborne laser scanning

Terje Gobakken [a,*], Erik Næsset [a], Ross Nelson [b], Ole Martin Bollandsås [a], Timothy G. Gregoire [c], Göran Ståhl [d], Sören Holm [d], Hans Ole Ørka [a], Rasmus Astrup [e]

[a] Dept. of Ecology and Natural Resource Management, Norwegian University of Life Sciences, PO Box 5003, NO-1432, Ås Norway
[b] 614.4/Biospheric Science Branch, NASA-Goddard Space Flight Center, Greenbelt, MD 20771, USA
[c] School of Forestry and Environmental Studies, 360 Prospect St., Yale University, New Haven, CT 06511–2189, USA
[d] Dept. of Forest Resource Management, Swedish University of Agricultural Sciences, SE-90183 Umeå, Sweden
[e] Norwegian Forest and Landscape Institute, PO Box 115, NO-1431, Ås Norway

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ABSTRACT

In this paper two sampling and estimation strategies for regional forest inventory were investigated in detail and results were presented for various geographical scales. Airborne laser scanner (ALS) data were acquired to augment data from a systematic sample of National Forest Inventory (NFI) ground plots in Hedmark County, Norway (27,390 km^2). Approximately 50% of the NFI field plots were covered by the systematic ALS sample of 53 parallel flight lines spaced 6 km apart. The area was stratified into eight cover classes and independent log-transformed regression models were developed for each class to predict total above-ground dry biomass (AGB). The two laser-ground estimation strategies tested were a model-dependent (MD), two-phase approach that rests on the assumption that the predictive models are correctly specified, and a model-assisted (MA) approach with a two-stage probability sampling design which utilizes design-unbiased estimators. ALS AGB estimates were reported by land cover class and compared to the NFI ground estimates. The ALS-based MA and MD mean estimates differed from the NFI AGB estimates by about 2% and 8%, respectively, for the entire County. At the county level the smallest estimated standard error (SE) for the estimates was obtained using the field data alone. However, the SEs calculated from field and ALS data were based on unequal numbers of ground plots. When considering only the NFI plots in the ALS strips, the smallest SEs were obtained using the MD framework. However, we also illustrated the sensitivity of the estimates of applying different plausible models. All the applied estimators assumed simple random sampling while the selection of flight lines as well as ground plots followed a systematic design. Thus, the estimates of SE were most likely conservative. Simulated sampling undertaken in a parallel research effort suggests that the over-estimation of the SEs was probably much larger for the ALS-based estimates compared to the NFI estimates. ALS-based estimates were also derived for sub-county political units and thereby demonstrated how limited sample sizes affect the standard error of the biomass estimates.

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1. Introduction

The world's forests sequester and conserve more carbon than all other terrestrial ecosystems and account for 90% of the annual carbon flux between the atmosphere and the Earth's land surface (Winjum et al., 1993). The importance of forest as a carbon sink has been realized and countries ratifying the Kyoto Protocol to the United Nations Framework Convention on Climate Change are committed to report their direct human induced emissions and removals of carbon dioxide in the commitment period 2008–2012 (UNFCCC, 2008). However, monitoring carbon in forests with high spatial variation of tree density poses a major challenge (Fahey et al., 2010). Field-based forest inventory programs, such as the Forest Inventory and Analysis program of the United States Department of Agriculture Forest Service or National Forest Inventory programs in Europe, use large administrative areas as units of analysis (Rypdal et al., 2005; Woodbury et al., 2007), but are not designed to provide more local estimates. In addition, the financial cost of field-based forest inventory can render it

* Corresponding author. Tel.: +47 64965755; fax: +47 64968890.
E-mail addresses: Terje.Gobakken@umb.no (T. Gobakken), Erik.Naesset@umb.no (E. Næsset), Ross.F.Nelson@nasa.gov (R. Nelson), Ole.Martin.Bollandsas@umb.no (O.M. Bollandsås), Timothy.Gregoire@yale.edu (T.G. Gregoire), Goran.Stahl@slu.se (G. Ståhl), Soren.Holm@slu.se (S. Holm), Hans-Ole.Orka@umb.no (H.O. Ørka), Rasmus.Astrup@skogoglandskap.no (R. Astrup).

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infeasible as the sole method for estimating the forest carbon of extensive areas (Andersen, 2011; Gonzalez et al., 2010).

Remote sensing, calibrated by field measurements, addresses these challenges (Gonzalez et al., 2010). Light Detection And Ranging (LiDAR) is one of the most promising remote sensing technologies for estimation of various biophysical properties of forests (e.g. Holmgren et al., 2003; Næsset, 2002; Nilsson, 1996; Ritchie et al., 1993) and for characterization of forest canopy elements in three dimensions (e.g. Harding et al., 2001; Lovell et al., 2003) while accurately mapping the terrain below forest canopies (Hodgson & Bresnahan, 2004; Kraus & Pfeifer, 1998; Reutebuch et al., 2003). In comparative studies LiDAR has produced more accurate estimates of forest biomass than optical satellite sensors (Gonzalez et al., 2010; Lefsky et al., 2001), airborne multi- and hyperspectral sensors (Lefsky et al., 2001), and airborne synthetic aperture radar sensors (Hyde et al., 2006; Nelson et al., 2007; Sexton et al., 2009). In addition, biomass values above 1300 Mg ha^{-1} have been estimated without revealing saturation problems (Lefsky et al., 2002), while other remote sensing techniques tend to display asymptotic tendencies at biomass values above, say, 200 Mg ha^{-1} (e.g. Cohen & Spies, 1992; Imhoff, 1995; Santos et al., 2003). Thus, airborne LiDAR holds potential for a valuable data source for estimation of tree biomass components that complies with requirements of the international conventions that relate to carbon stored in trees.

Since 1995, extensive research efforts have been carried out in Scandinavia to develop airborne LiDAR as an operational tool for "wall-to-wall" mapping of forest stands for planning purposes (Næsset, 1997). LiDAR is now used operationally in commercial, stand-based forest management inventories (McRoberts et al., 2010b; Næsset, 2004a; Næsset et al., 2004). However, the small-footprint, discrete-return airborne laser scanner (ALS) data sets used to estimate forest biomass and carbon are relatively expensive (Gonzalez et al., 2010), and these costs constrain their use in wall-to-wall mapping of larger regions such as counties, states, or nations.

Two different approaches using LiDAR have been developed and demonstrated in operational projects. These are (1) the use of an airborne profiling laser designed for sampling-based inventories (Nelson et al., 2003b), and (2) the use of an airborne laser scanner (ALS) for wall-to-wall mapping of forest stands for practical forest planning (Næsset, 2002; Næsset & Bjerknes, 2001). The profiling system developed at the National Aeronautics and Space Administration (NASA) (Nelson et al., 2003a), labeled "Portable Airborne Laser System" (PALS), is a simple device with low developmental- and operational costs. It is designed for large-area sampling-based applications, and its potential has been demonstrated in several projects (e.g. Boudreau et al., 2008; Nelson et al., 2004). A profiling system only collects a narrow line of data on the ground, and does not provide data for wall-to-wall mapping. In contrast, each flight-line of a scanning system typically has a swath width of up to several hundred meters. Scanning systems thereby can provide data for a continuous area. This suggests its application as a tool to collect data at the stand level.

Airborne profiling lasers can provide reliable estimates of forest volume and biomass (e.g. Nelson et al., 2008). Profiling sampling designs typically comprise a number of flight lines flown as parallel strips that are separated by a certain distance. Even though data acquisition costs are larger, ALS systems can be used to collect strip samples. The increased amount of data per km of flight is considered to be an advantage of ALS which makes it a useful tool also for regional monitoring purposes. ALS has been applied on the western lowlands of the Kenai Peninsula of Alaska (Andersen et al., 2009). In addition, Parker and Evans (2004) and Beets et al. (2010) used scanning lasers in double-sampling applications to assess volume and biomass. In these studies only the laser data that coincided with predefined plots were utilized to estimate biomass. The concept of the current study has previously been presented by Næsset (2005), Næsset et al. (2009), and McRoberts et al. (2010a). Gregoire et al. (2011) and Ståhl et al. (2011) provided empirical examples based on the same dataset as used in the current study.

When using LiDAR in sampling surveys, standard sampling estimators of mean or total and corresponding variance estimators cannot be applied due to the complex structure of the surveys, where scanning swaths may extend over several cover classes (e.g. Nelson et al., 2008). Furthermore, many different sources of errors are involved. Model-dependent (MD) approach to estimation and inference, sometimes called model-based approach (Ståhl et al., 2011), is so named because it depends heavily on the properties of the model or models used. However, we would like to emphasize that the MD approach dealt with by Ståhl et al. (2011) and in the current study deviate from model-based approach as it is usually perceived by accounting for sampling variability in a conventional design-based way (see further details below). The MD approach has mainly been applied in sampling surveys, however, previous studies (e.g. Nelson et al., 2008) have not accounted for model-related errors in the uncertainty assessment. Model-assisted (MA) approaches (Särndal et al., 1992) might also be an alternative. The latter approach requires a probability sample, with measured target variables from the sample units in the area of interest. Recently, Ståhl et al. (2011) developed a general framework for MD inference and error assessment, accounting for both sampling and model errors, in cases where regression models are applied to predict the target variables. In addition, Gregoire et al. (2011) developed estimators as well as estimators of their variance in a MA framework. For an appreciation of the distinctions between inference based on the sampling design versus model-based inference, see Gregoire (1998).

Recently, the MA and MD approaches were also assessed in a simulated sampling effort undertaken by Ene et al. (2012). The study by Ene (2012) evaluated the validity of the estimators developed by Ståhl et al. (2011) and Gregoire et al. (2011) under random sampling and concluded that the estimators behaved as expected, i.e., that the MA estimators were unbiased and that the empirical variances derived through repeated simulations for both approaches were nearly identical to the analytical variances. However, using a systematic design the ALS-based analytical estimators overestimated the empirical (real) variances. Ene et al. (2012) worked with a synthetic population of Hedmark County (HC). Although their population differed from the true but unknown population of HC, which is the target of the current study, Ene et al. (2012) claimed their population to resemble some of the major trends in the true population (e.g. decreasing biomass with increasing latitude and altitude). Two of the major objectives of Ene's (2012) study were to assess the performance of variance estimators for ALS-aided inventories, and to assess the relative gain in accuracy obtained using auxiliary ALS data. Thus, we believe Ene's results may shed some light on the current work.

The MD estimator developed by Ståhl et al. (2011) is rather simple to apply even if it is rather computationally intensive like other model-based approaches (cf. McRoberts, 2010). MD and other model-based estimates often have low variance but the estimator can also be seriously biased, especially for smaller areas when the applied model does not fit local conditions (Särndal et al., 1992). The estimator does not provide any means for controlling potential bias and it depends entirely on correctly specified models. Therefore, Särndal (1978, p. 35) has recommended that a "representative" sample, rather than one of extreme values, used for model development to reduce the risk of bias (Särndal, 1978), although the main objective of the data collection under a MD strategy is model development and not validity of the estimation.

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