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# Post-stratified estimation of forest area and growing stock volume using lidar-based stratifications

Ronald E. McRoberts a,\*, Terje Gobakken b, Erik Næsset b

- <sup>a</sup> Northern Research Station, U.S. Forest Service, 1992 Folwell Avenue, Saint Paul, Minnesota, USA
- <sup>b</sup> Department of Ecology and Natural Resource Management, Norwegian University of Life Sciences, Ås, Norway

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#### ABSTRACT

National forest inventories report estimates of parameters related to forest area and growing stock volume for geographic areas ranging in size from municipalities to entire countries. Landsat imagery has been shown to be a source of auxiliary information that can be used with stratified estimation to increase the precision of estimates, although the increase is greater for estimates of forest area than for estimates of growing stock volume. The objective of the study was to assess the utility of lidar-based stratifications for increasing the precision of mean proportion forest area and mean growing stock volume per unit area. Stratifications based on nonlinear logistic regression model predictions of volume obtained from lidar data reduced variances of mean growing stock volume estimates by factors as great as 3.2 and variances of mean proportion forest area estimates by factors as great as 1.5.

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#### 1. Introduction

National forest inventories (NFI) report estimates of parameters related to forest area and growing stock volume for geographic areas such as counties, states, and provinces based on data collected from arrays of field plots. Because of budgetary constraints and natural variability among plots, sufficient numbers of plots frequently cannot be measured to satisfy precision guidelines for the estimates of some parameters unless the estimation process is enhanced using auxiliary information. Remotely sensed data has been shown to be a source of auxiliary information that can be used with stratified estimation to increase the precision of estimates.

#### 1.1. Stratified estimation

Stratified estimation is a statistical technique that can be used to increase the precision of estimates without increasing sample sizes. The essence of stratified estimation is to aggregate observations of the response variable into groups or strata that are more homogeneous than the population as a whole. The population mean and its variance are estimated as weighted means of within-strata means and variances where the weights are based on strata sizes.

If the stratification is accomplished prior to sampling and the within-stratum variances are known or can be easily estimated, then greater precision may be achieved by selecting within-strata sampling intensities to be proportional to within-strata variances (Cochran, 1977). However, NFIs often use permanent plots whose locations are

based on systematic grids or tessellations and use sampling intensities that are constant over large geographic areas, if not the entire population. In such cases, even though stratified sampling is not possible, considerable increase in precision may still be achieved simply by using post-sampling stratification, also characterized as post-stratification.

#### 1.2. Applications

Aerial photography served as the earliest source of remotely sensed information for constructing stratifications. With this approach, characterized as double sampling for stratification, an extensive sample of photo plots on aerial photographs is interpreted, photo plots are assigned to strata using ocular methods, and strata weights are estimated as proportions of photo plots assigned to strata. Field crews then visit a subset of the photo plots and observe and measure plot attributes. Plots are assigned to the strata of their corresponding photo plots. Estimates based on these data are then calculated using stratified estimation techniques (Cochran, 1977). Examples of double sampling for stratification using aerial photography are provided by Bickford (1953, 1960), Lawrence and Walker (1954), Kendall and Sayn-Wittgenstein (1961), Macpherson (1962), and Poso (1972), and the topic is addressed in textbooks such as Loetsch and Haller (1964) and Gregoire and Valentine (2008).

More recently, satellite imagery has served as a source of information for constructing stratifications. With this approach, image pixels with centers in the population are classified with respect to land cover attributes, and the classes or aggregations of the classes are then used as strata. Strata weights are calculated as the proportions of pixels in strata, and plots are assigned to strata on the basis of the strata assignments of the pixels containing the plot centers. In Finland, Poso et al. (1984,

<sup>\*</sup> Corresponding author. Tel.: +1 651 649 5174; fax: +1 651 649 5285. E-mail address: rmcroberts@fs.fed.us (R.E. McRoberts).

1987), Poso et al. (1987) derived stratifications from unsupervised classifications of satellite imagery. In the United States of America (USA), Hansen and Wendt (2000) constructed strata by collapsing the classes of the Gap Analysis Program (GAP) classification (Scott et al., 1993) into forest and non-forest strata and then constructing forest edge and non-forest edge strata along forest/non-forest boundaries. Two sets of stratified estimates of forest area and growing stock volume for the states of Illinois and Indiana, USA, were compared: 1986 estimates obtained using a double sampling for stratification approach based on first-phase interpretation of aerial photographs and 1998 estimates using the GAP classification as basis for stratification. Although variances of estimates for the image-based stratification were slightly larger than for the photo-based stratification, the image-based stratification was much more consistent and much less costly to construct.

Also in the USA, McRoberts et al. (2002a) used the 1992 National Land Cover Dataset (NLCD) (Vogelmann et al., 2001) to construct strata similar to those used by Hansen and Wendt (2000). Variances of estimates of mean proportion forest area for the American states of Indiana, Iowa, Minnesota, and Missouri were reduced by factors ranging from 1.72 to 3.22. For two study areas in Minnesota, McRoberts et al. (2002b) used a nearest neighbors approach to predict proportion forest from Landsat imagery with 30-m x 30-m resolution and NFI plot observations of forest/non-forest. Classes of proportion forest predictions were then aggregated into four strata for use in a post-stratification approach. For estimating mean proportion forest area, variances were reduced by factors in the range 4.3-5.6. For study areas in the American states of Minnesota and Wisconsin, McRoberts et al. (2006) used a logistic regression model to predict the probability of forest for Landsat pixels. Classes of the probability of forest were then aggregated into strata for a similar approach to post-stratification. Reductions in variances of estimated mean proportion forest were in the range 3.6-5.9 and reductions for growing stock volume were in the range 1.3-2.5.

Liknes et al. (2004) and Holden et al. (2005) investigated the effectiveness of 250-m x 250-m resolution MODIS-based maps as bases for stratifications. Liknes et al. (2004) focused on stratified estimation of mean proportion forest area and found that although the MODISbased stratified estimates were more precise than the simple random sampling estimates, they were less precise than Landsat-based stratified estimates. The latter result was attributed to the finer spatial resolution of the Landsat imagery. Holden et al. (2005) used a MODIS-based biomass map as the basis for stratified estimation of biomass for 11 states in the north central region of the USA. The map was only marginally effective at increasing the precision of biomass estimates. This result can be attributed to a weak relationship between plot-level biomass and corresponding MODIS-based predictions. The weakness of the relationship can, in turn, be attributed to the difficulty of predicting below-canopy attributes such as biomass from spectral data that responds primarily to canopy-level attributes. In addition, the spatial size difference between the 62,500-m<sup>2</sup> MODIS pixels and the approximately 672-m<sup>2</sup> plots was likely also a contributing factor.

The important lessons from the Liknes et al. (2004), Holden et al. (2005), and the McRoberts et al. (2002a,b, 2006) studies are that the effectiveness of stratifications based on spectral information from satellite imagery is much greater for canopy-level attributes such as mean proportion forest area than for below-canopy attributes such as mean biomass per unit area and when using imagery whose resolution is closer to the plot size.

Recent reports of strong relationships between below-canopy forest attributes such as growing stock volume and lidar metrics suggest that lidar-based stratifications may be effective for increasing the precision of estimates of parameters related to growing stock volume, biomass, and carbon. For example, Næsset (2002) reported that 80–93% of the variability in field measured volume could be explained by models that use lidar metrics, and Næsset and Gobakken (2008)

reported that 88% of the variability in above-ground biomass could be explained with models using lidar metrics. Similar results have also been reported for multiple other studies including Frazer et al. (2011), Li et al. (2008), and Zhao et al. (2009).

#### 1.3. Objectives

The objective of the study was to assess the utility of lidar data as the basis for post-stratifications for increasing the precision of estimates of mean proportion forest area (FOR) and mean growing stock volume  $(m^3/ha)$  (VOL).

#### 2. Data

The study area is in Hedmark County, Norway, mostly in Åmot and Stor-Elvdal municipalities (Fig. 1). The study area consists of 2385 km<sup>2</sup> and features altitudinal variations ranging from 204 to 1134 m above sea level (asl) with a mean of 570 m asl. The dominant tree species are Norway spruce (*Picea abies* (L.) Karst.) and Scots pine (*Pinus sylvestris* L.). For the period 1961–1990, mean January and July temperatures were  $-11^{\circ}$  and  $13^{\circ}$  Celsius, respectively (Norwegian Meteorological Institute, 2012).

#### 2.1. Lidar data

A PA31 Piper Navajo aircraft carried the Optech ALTM 3100 laser scanning system. The laser scanner data were acquired between 15 July 2006 and 12 September 2006 from a height of approximately 1700 m with average speed of 75 ms $^{-1}$ . The pulse repetition frequency was 50 kHz, and the scan frequency was 31 Hz. The maximum scan angle was 16°, which corresponded to an average swath width of approximately 975 m. Pulses transmitted at scan angles that exceeded 14° were excluded from the final dataset. The mean footprint diameter was approximately 50 cm, and the average point density was 0.7 m $^{-2}$ .

The initial processing of the data was accomplished by the contractor (Blom Geomatics, Norway). Planimetric coordinates and ellipsoidal height values were computed for all echoes. Ground echoes were found and classified using the progressive Triangular Irregular Network (TIN) densification algorithm (Axelsson, 2000) of the TerraScan software (Anonymous, 2005). A TIN was created from the planimetric coordinates and corresponding heights of the laser echoes classified as ground points. The ellipsoidal height accuracy of the TIN model was expected to be around 20-30 cm (Kraus & Pfeifer, 1998; Reutebuch et al., 2003). The heights above the ground surface were calculated for all echoes by subtracting the respective TIN heights from the height values of all echoes recorded. The ALTM 3100 sensor is capable of recording up to four echoes per pulse. Data for only single echoes or the first of multiple echoes were used. For each plot and population unit, height distributions were estimated for heights greater than 2 m. Echoes with heights less than 2 m were considered to have been reflected from non-tree objects such as shrubs, grass, or the ground.

The study area was tessellated into population units consisting of square grid cells with the same  $250\text{-m}^2$  area as the field plots (Section 2.2). For each plot and population unit, heights corresponding to the 10th, 20th, ..., 100th percentiles of the distributions were denoted  $h_1, h_2, \ldots, h_{10}$ , respectively. In addition, mean heights and coefficients of variation for the canopy height distributions were calculated. Canopy densities were also calculated as the proportions of echoes with heights greater than 0%, 10%, ..., 90% of the 95th height percentile and denoted  $d_0, d_1, \ldots, d_9$ , respectively (Gobakken & Næsset, 2008).

#### 2.2. Field data

The field measurements were obtained from Norwegian NFI field plots. The Norwegian NFI is a continuous forest inventory system with

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