

Using multilevel remote sensing and ground data to estimate forest biomass resources in remote regions: a case study in the boreal forests of interior Alaska

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Abstract. The emergence of a new generation of remote sensing and geopositioning technologies, as well as increased capabilities in image processing, computing, and inferential techniques, have enabled the development and implementation of increasingly efficient and cost-effective multilevel sampling designs for forest inventory. In this paper, we (i) describe the conceptual basis of multilevel sampling, (ii) provide a detailed review of several previously implemented multilevel inventory designs, (iii) describe several important technical considerations that can influence the efficiency of a multilevel sampling design, and (iv) demonstrate the application of a modern multilevel sampling approach for estimating the forest biomass resources in a remote area of interior Alaska. This approach utilized a combination of ground plots, lidar strip sampling, satellite imagery (multispectral and radar), and classified land cover information. The variability in the total biomass estimate was assessed using a bootstrapping approach. The results indicated only marginal improvement in the precision of the total biomass estimate when the lidar sample was post-stratified using the classified land cover layer (reduction in relative standard error from 7.3% to 7.0%), whereas there was a substantial improvement in the precision when the estimate was based on the biomass map derived via nearest-neighbor imputation (reduction in relative standard error from 7.3% to 5.1%).

Résumé. L'émergence d'une nouvelle génération de technologies de télédétection et de géo-positionnement de même que les progrès réalisés dans les domaines du traitement d'images, de l'informatique et des techniques inférentielles ont permis le développement et l'implantation de plans d'échantillonnage multiniveaux de plus en plus efficaces et économiques pour les inventaires forestiers. Dans cet article, (i) on décrit la base conceptuelle de l'échantillonnage multiniveaux, (ii) on présente une revue détaillée de plusieurs plans d'inventaire multiniveaux déjà développés, (iii) on décrit plusieurs aspects techniques importants qui peuvent influencer l'efficacité d'un plan d'échantillonnage multiniveaux et (iv) on démontre l'application d'une approche contemporaine d'échantillonnage multiniveaux pour l'estimation des ressources en biomasse forestière dans une région isolée de l'intérieur de l'Alaska. L'approche est basée sur l'utilisation d'une combinaison de parcelles au sol, d'échantillons de bandes lidar, d'images satellite (multispectrales et radar) et de l'information classifiée sur le couvert. La variabilité des estimations de biomasse totale a été évaluée à l'aide d'une approche d'amorçage «bootstrapping». Les résultats montrent seulement une amélioration marginale de la précision de l'estimation de la biomasse totale lorsque l'échantillon lidar était post-stratifié à l'aide de la couche de couvert classifié (réduction de l'erreur type relative de 7,3 % à 7,0 %), tandis qu'on observait une amélioration substantielle de la précision lorsque l'estimation était basée sur la carte de la biomasse dérivée de l'imputation par le plus proche voisin (réduction de l'erreur type relative de 7,3 % à 5,1 %).

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Introduction

Monitoring of the boreal forests is critical to understanding the global carbon cycle and quantifying the possible effects of climate change on rates of carbon loss and storage (Le Quere et al., 2009). The ecological impacts of climate change are expected to be particularly acute in the boreal forest biome, which is expected to experience the greatest rates of temperature increase over the next century, possibly leading to significant changes to ecosystem processes including thawing permafrost, increasingly severe and extensive fires, decreased tree productivity due to drought stress, and large-scale shifts in vegetation composition and structure (Christensen, 2007; Barrett and Gray, 2010; Beck et al., 2011). At the same time, there is increasing demand for more accurate and extensive information on the availability of forest biomass resources to support bioenergy production in rural communities of interior Alaska that are disproportionately impacted by the rising costs of fossil fuels (Crimp, 2007). The development of an innovative forest monitoring design for interior Alaska, making extensive use of remote sensing data collected at a variety of resolutions and scales to offset the reduction in the number of highly expensive ground plots, has been identified as a strategic priority of the Forest Inventory and Analysis (FIA) program which is the national forest inventory (NFI) program of the United States (USDA Forest Service, 2007).

The primary objectives of this paper are as follows: (i) describe the conceptual basis of multilevel inventory systems in statistical sampling terms; (ii) provide a detailed review of several previously implemented multilevel forest inventory systems, with particular emphasis on two inventory designs used in interior Alaska in the 1950s and 1980s and the Canadian NFI program; (iii) describe several important considerations (ground plot design, ground data collection protocols, and types of remote sensing data collected at various levels) that can significantly affect the efficiency of multilevel inventory programs; and (iv) present a specific example of a novel, multilevel forest inventory system designed to provide precise estimates of aboveground biomass resources over a relatively large and remote area within the boreal forests of interior Alaska.

This design used a combination of ground plot data and multiple sources of remote sensing data, collected at different scales and resolutions (airborne lidar, multispectral satellite imagery, and satellite dual-polarization synthetic aperture radar). In addition, we describe an approach to estimate the uncertainty of the total biomass estimate obtained from this design using a bootstrapping technique.

Background

Statistical sampling considerations in multilevel forest inventories

Sampling at several different levels, where the sampling intensities, size of the sampling units, as well as the level of detail or cost-per-unit vary at each level is a well-known approach to increase the precision of a forest inventory for a given cost. According to Schreuder (2004), “multilevel sampling” is defined as “a sampling design where more than one phase or stage of sampling is used. The first levels are used to collect information on covariates useful for more efficient estimation of the ultimate parameters of interest for which information is usually collected at the last stage or phase.” As indicated in the above statement, multilevel sampling usually takes one of three forms, (i) “multiphase sampling”, (ii) “multistage sampling”, or (iii) a combination of these two approaches. In multiphase sampling for ratio or regression estimation, information is collected on a relatively large number of sampling units in the earlier phases (at a relatively low cost per unit) and then the parameter of interest is measured on a subsample of these units in the final phase (Schreuder et al., 1993). Alternatively, the data collected in earlier phases can be used to stratify the data from the final phase to increase precision of overall estimates. The design used in the USDA Forest Service FIA program is a good example of “two-phase sampling for stratification”, where a large number of photo plots (or increasingly, satellite-image plots) are used to determine the proportion of forested plots in the population, and these forested plots are then sampled on the ground (Reams et al., 2005).

The gain in precision from using a multiphase sampling design for regression estimation (over a single level design) is directly related to the strength of the correlation between (low-cost) information collected at early stages and the parameter of interest. In multistage sampling, the population is divided into groups of population elements (clusters) which are then subsampled. The gain in precision from using multistage sampling is directly related to the variability within the clusters compared with the overall variability within the population; if within-cluster variability is high and between-cluster variability is relatively low, then there can be substantial advantages to multistage sampling over single-level sampling. In some cases, a multilevel approach can incorporate elements of both multistage and multiphase sampling (Särndal et al., 1992).

Multilevel sampling can also utilize either “model-based” or “model-assisted” designs. In model-based designs, all inferences are conditional on the assumption that the model is correct, while model-assisted designs depend upon probability sampling at each level to ensure that resulting estimators are design unbiased. This is usually a desirable, or even necessary, property in national forest inventory programs, which are often used to establish baseline and trend

data to support national and even international resource policy (e.g., carbon accounting, etc.).

"Spatially balanced" sampling, where sampled points are more or less evenly distributed over the spatial extent of the population of interest, is often another desirable property of multilevel designs for resource inventories. For example, very large disturbance patterns, such as fires in interior Alaska, can lead to a high degree of correlation between sampled units that are relatively close to each other, and it is therefore desirable to ensure some minimum spacing between units to increase the efficiency of the inventory (Stevens and Olsen, 2004; Barrett and Gray, 2011). Another potential advantage to multilevel designs is that auxiliary mapped information can be collected over the entire spatial extent of a cluster, in which case the mapped clusters themselves can be used to measure spatial (e.g., ecological) patterns that occur over a much different spatial scale than can be measured on a much smaller population unit (e.g., ground plot) (Hunsaker et al., 1994).

Multilevel sampling designs are particularly well suited for inventories of large, remote regions of the world, where logistical difficulties and high costs typically limit the number of ground plots that can be established, and this limited ground sample must be supplemented with remote sensing information to attain the level of precision required for the inventory. For these reasons, there is a long history of utilizing multilevel sampling designs to support forest inventory in the boreal forests of Alaska, a vast sparsely populated region with very little transportation infrastructure. In the following sections, we provide a review of several previous multilevel forest inventory programs, with particular emphasis on two historical forest inventories in interior Alaska and the current NFI program in Canada.

Examples of multilevel sampling approaches in previous forest inventories of interior Alaska

The 1950s Alaska Forest Survey

In the late 1950s and early 1960s, the Alaska Forest Survey carried out a highly ambitious plan to inventory the forest resources of the entire state (Hutchison, 1968). As Geier (1998) stated, this inventory was designed to minimize the labor requirements, maximize speed, and maximize the usefulness of the data for managers interested in commercial forest development.

The interior Alaska component of this inventory design consisted of three levels of sampling, and incorporated elements of both multistage and multiphase design. The first phase consisted of large scale (1:5000) aerial photography collected along strips flown at 48 km intervals, where the strips were collected in 10 major river basins and oriented perpendicular to the dominant drainage systems. The aerial photo strip sampling resulted in 17 700 km of flight lines and 31 000 photographs. The first level of sampling involved interpretation of a half-acre area near the center of the each aerial photo, where forest classes and volume estimates were interpreted for

each plot. A second level of sampling consisted of an air check of approximately 10% of the aerial photo plots. The air check was a intermediate phase that involved flying an aircraft at a very low flying height (300 m above ground level) above the selected photo plot and checking the photo-interpreted information on the plot from the air (Geier, 1998). The third level of the sample consisted of a very limited subsample of the air-checked plots that were visited and measured on the ground. For the interior Alaska inventory, the total number of photo plots was 37 177, the total number of air-checked plots was 3774, and the total number of ground plots was 355. The air checks were used to develop correction factors that were applied to the photo-interpreted forest classes and areas, while ground plots were used to correct photo-interpreted volume estimates. In this sense this inventory used elements of both multiphase (i.e., strip and (or) cluster sampling) and multiphase designs (ground plots used to correct remote sensing estimates). This inventory allowed for estimation and reporting for a wide variety of forest characteristics across the entire region of interior Alaska, including forest area, size class, species composition, and volume, and although the sampling errors associated with these estimates for interior Alaska were not reported, they were likely quite large, given the relatively small number of plots measured at each level.

The Alaska Integrated Resource Inventory System

A four-phase, multilevel inventory design (the Alaska Integrated Resource Inventory System (AIRIS)) was implemented in another inventory of the Tanana valley of interior Alaska in the 1980s. The different levels of this inventory consisted of a 5 km × 5 km regular grid of thirty-six 50 m × 50 m pixels (approx. 8 ha) extracted from multispectral Landsat MSS imagery, a 10 km × 10 km grid of photo plots using high-altitude (1:60 000) color infrared (CIR) aerial photography, a 20 km × 20 km regular grid of photo plots using low altitude (1:3000) CIR stereo aerial photography, and a 40 km × 40 km regular grid of ground plots (Li et al., 1984; Winterberger, 1984; LaBau and Winterberger, 1989; Schreuder et al., 1995). Vegetation class was interpreted at all remote sensing levels, and a larger set of variables including volume, stand size class, foliar cover by vegetation class, understory component, tree crown diameters, tree and (or) shrub heights, and land use were estimated only in the low altitude photographs. Low-altitude photos were located using LONG RANGE Navigation (LORAN) and OMEGA radio-based geolocation systems (AIRIS was implemented before the advent of the satellite-based GPS program). The standard suite of inventory variables (tree species, diameter, height, understory vegetation, damage, etc.) was then collected at the ground plots. Due to a variety of factors, including shifting inventory objectives (i.e., multiresource to timber), inability to accurately register remote sensing data to ground plots, and very small sample sizes for some important forest types, the results obtained from this sampling design were largely

disappointing (Schreuder et al., 1993). One important conclusion from Schreuder et al. (1993) was that the sampling strategy was probably too ambitious given the technology available at the time; the design may be much more cost-effective today, given the dramatic improvements in remote sensing, geopositioning, image processing, and computing that have taken place over the last 20–25 years (Schreuder et al., 1995).

Examples of multilevel forest inventory designs outside of Alaska

There are numerous other examples of multilevel sampling designs for forest inventory elsewhere in the United States and in other countries. The Canadian NFI system is one of the more noteworthy examples of a modern large-scale, multilevel forest resource monitoring program designed to “assess and monitor the extent, state, and sustainable development of Canada’s forests in a timely and accurate manner” (Gillis et al., 2005). The basic design of the Canadian NFI system has the following components: (i) a systematic grid of photo plots (each 2 km × 2 km in size) across Canada to ensure comprehensive coverage, with a preferred spacing of 20 km × 20 km; (ii) a stratification of the entire country into terrestrial ecozones where the sampling intensity of plots varies by strata to meet standards for statistical reliability; and (iii) a subsample of photo plots visited on the ground to measure attributes unattainable from remotely sensed data, where the ratio of ground to photo plots is 1:10 and the minimum number of ground plots per ecozone is 50. Satellite imagery is used as a surrogate for aerial photos to reduce the costs of plot acquisition in the very remote northern regions of Canada (Falkowski et al., 2009).

Schreuder and Czaplewski (1993) proposed a complex multilevel design for a forest health monitoring system in the state of Minnesota that utilized satellite imagery (e.g., 15 000 km²), strip samples of aerial videography (e.g., 0.5 km × 500 km), aerial photo plots (e.g., 4–40 km²), and ground cluster plots (e.g. 10 m² × 100 m² plots). This design was intended to address three objectives, including (i) generation of descriptive statistics, (ii) detection of changes in these statistics, and (iii) possible identification of cause–effect relationships.

Lee et al. (2002) described a multilevel sampling design to monitor forest condition in heterogeneous woodlands of Australia, which consisted of (i) wall-to-wall mapping with Landsat Thematic Mapper (TM) imagery and other regional-scale vegetation classifications, (ii) systematic (4 km × 4 km) grid sample of airborne lidar sampling units (e.g., 500 m × 150 m), with large-scale stereo photography (1:4000) centered on each lidar sampling unit, and (iii) stratified random sampling of fixed-area ground plots (33.25 ha) collected within a subset of lidar plots.

Asner et al. (2011) used multiple levels of remotely sensed data, including airborne lidar and a Landsat TM-based

vegetation classification layer, in combination with ground plot data to map forest carbon over the island of Hawaii.

Important technical and procedural considerations when implementing multilevel forest inventory systems

Accurate spatial registration of ground plots

One of the more important considerations in the implementation of a modern multilevel inventory system is ensuring the accurate registration of the plot data to remote sensing data. In the four-phase AIRIS sampling design implemented in Alaska in the 1980s, there was considerable difficulty in accurately registering the ground plots to other levels of information, which contributed to disappointing results of the program (Schreuder et al., 1995). With the advent of the global positioning system (GPS) in the 1990s, this goal has become much more achievable.

However, the use of GPS in forestry applications has always been negatively impacted by the interaction (attenuation and multipathing) between the satellite radio signals and the woody components of the forest canopy. Recent studies have indicated that much of the error due to forest canopy can be reduced through the use of dual-frequency survey-grade GPS receivers that incorporate sophisticated filtering algorithms to reduce multipathing and also have the capability to observe signals from the Russian (GLONASS) and eventually, European (GALILEO) satellite geopositioning systems (Næsset, 1999; Næsset et al., 2000; Andersen et al., 2009b). The use of additional satellite constellations increases the number and the geometric configuration of available satellites observed through canopy gaps, and therefore increases the accuracy of the positions obtained under canopy. These studies have shown that, in general, it is possible to consistently obtain positions with sub-metre error under forest canopy using survey-grade GPS receivers. It should be noted that the use of survey-grade GPS requires the availability of nearby base station data that are used to differentially correct the roving receiver data (i.e., remove errors due to atmospheric delay and clock errors); however, a recent study in a remote area of interior Alaska showed that sub-metre geopositioning errors in various forest canopy conditions can still be obtained even with baselines up to 100 km (Andersen et al., 2009b). Although the relative importance of accurate plot locations is a function of the spatial variability of the forest, accurate plot locations are generally much more important in heterogeneous canopies, where even a few metres of error can lead to dramatic decorrelation between field and remote sensing based measurements, recent studies confirmed that error in plot location can have deleterious effects on the statistical precision of inventory estimates in a multilevel inventory design (McRoberts, 2010; Andersen et al., 2011).

Ground plot size and measurement protocol

There are other characteristics of the ground sampling design and protocol that can influence the efficiency or the relationship between the sample size and the precision of the estimate of multilevel inventory, including the size of the ground plot and the type of tree measurements collected on the plot. The influence of plot size on the efficiency of multilevel sampling designs has been documented in previous studies (e.g., Gobakken and Næsset, 2008). Plot size affects the efficiency of multilevel designs in several ways. First, larger plots are less susceptible to influence of edge effects, which can lead to discrepancies between the measurement of tree crowns (in remote sensing data) to tree stems (measured in the field); therefore, the use of large, single fixed-area plots will typically strengthen the correlations between various phases of a multilevel design, leading to a higher overall statistical precision for inventory estimates. On the other hand, the use of large plot clusters (possibly involving many relatively small subplots distributed over a large area) can be a very efficient design in a multistage design but can be susceptible to the same edge effect problems mentioned previously when used in a multiphase design. For example, in the AIRIS design the ground plots consisted of a cluster of 19 subplots spaced 75 m apart and distributed over 8 ha, while the current FIA cluster plot consists of four 1/60 ha subplots spaced approximately 36 m apart (Bechtold and Scott, 2005). Research in interior Alaska indicated that use of a smaller (1/60 ha) plot will contribute to lower precision for inventory estimates than larger plots (1/30 ha) in a multilevel sampling design, most likely due to edge effects (Andersen et al., 2011). Other elements of the plot protocol can also contribute to the overall efficiency of a multilevel sampling design, such as the diameter thresholds for tree measurements. In some cases, the choice of diameter threshold, to reduce the number of small trees measured on the main inventory plot, can lead to a significant loss of spatially explicit forest structure information over the extent of the field plot. For example, in the standardized ground sampling protocol for the FIA program, only trees larger than 12.5 cm (5 inches) are measured on the 1/60 hectare subplots (trees less than 12.5 cm are measured on a much smaller 1/742 ha microplot). In the context of a multiphase inventory design, the diameter threshold for trees measured over the larger plot area (versus a much smaller microplot area), introduces another source of sampling error in the estimation of plot-level forest structure. This can further contribute to discrepancies (or lack of correlation) between measurements obtained from high-resolution remote sensing and those obtained in the field. This effect is obviously most pronounced in forests where the mean stem diameter for the forest is relatively close to, or less than, the diameter threshold (in many black spruce stands in interior Alaska, the mean stand diameter is well under 12.5 cm). In such cases, the use of a modified plot protocol with a lower

diameter threshold will likely improve correlations with remotely sensed data (Andersen et al., 2011).

Sources of remote sensing data for multilevel inventory systems

Airborne lidar sampling

Airborne lidar has emerged as the preeminent remote sensing tool for forest measurement in recent years (Lefsky et al., 2002). Structural metrics derived from the three-dimensional lidar point cloud have been shown to be highly correlated with various forest inventory parameters (volume, biomass, basal area, etc.), across a wide variety of forest biomes and conditions. Furthermore, because lidar is delivered as a directly georeferenced and digital product, it lends itself to automated (i.e., batch) processing, even over very large areas (i.e., millions of hectares). Although lidar is still largely unable to provide detailed information on species, progress has been made in this area in recent years (Kim et al., 2009; Ørka et al., 2009).

Lidar data is still relatively expensive to collect wall-to-wall over a large area (at a cost of approximately US\$2–3 per hectare); however, there has been increasing interest in the use of airborne laser scanning (lidar) as a sampling tool and a component of a multilevel inventory design (Andersen et al., 2009a; Andersen et al., 2011; Gregoire et al., 2011; Ståhl et al., 2011). As lidar is a scanning system typically mounted on a fixed-wing aircraft platform, it is highly efficient to collect lidar over continuous linear swaths. When lidar is collected in single swaths spaced several kilometres apart covering the entire area of interest, this sample can be considered a systematic probability sample. Ground plots can then be established within the lidar coverage, which are then used to develop models for predicting forest inventory variables over the entire extent of the lidar coverage. From a statistical standpoint, the multilevel data collected in this manner has been treated as a model-based sampling design (Andersen et al., 2011; Ståhl et al., 2011) and a model-assisted sampling design (Andersen et al., 2009a; Gregoire et al., 2011). Model-based approaches do not require a probability (i.e., random) sample of ground data which can reduce costs in remote and inaccessible areas, but will not provide design-unbiased estimators. In contrast, model-assisted designs require a probability sample (where each population element within the lidar coverage has a known, nonzero, probability of being sampled in the field), and will provide (approximately) design-unbiased estimators, albeit with higher variances (Särndal et al., 1992).

Multispectral satellite imagery

Wall-to-wall satellite imagery provides spatially comprehensive information across the entire area of interest and therefore represents an important component of a multilevel

inventory design. Several types of satellite imaging systems are typically used for land cover classification. Multispectral satellite imaging systems, such as NASA's Landsat TM and the SPOT (System Pour l'Observation de la Terre), can provide relatively low-resolution, two-dimensional information on species class, forest condition, and canopy cover over very large areas (Cohen et al., 2001). In fact, the LAND-FIRE program uses a combination of LANDSAT and auxiliary mapped information to develop several layers (existing vegetation class, canopy cover, canopy height) that are currently used for forest fire risk assessment throughout the United States (Rollins et al., 2006). FIA is making increasing use of LANDSAT TM-based forest cover classifications for determining forest versus nonforest, a critical component of the post-stratification component that is used to improve the precision of inventory estimates (Reams et al., 2005). Recent work indicated that spectral trajectories developed from a time series of Landsat TM imagery can be used to accurately predict various inventory parameters, including biomass (Powell et al., 2010). Satellite imagery has been used along with other spatial layers to map several forest inventory variables over the landscape using various nearest-neighbor (NN) methods, including gradient NN (Ohmann and Gregory, 2002) and k -NN (Franco-Lopez et al., 2001; Katila and Tomppo, 2002; McRoberts et al., 2006). Hudak et al. (2008) evaluated several different NN methods in the forest inventory context using structural metrics derived from airborne lidar. The statistical properties of inventory estimates obtained from NN techniques are continuing to be developed (McRoberts et al., 2007; Magnussen et al., 2009). However, to our knowledge the use of NN methods within a multilevel inventory sample design (i.e., with intermediate layer(s) of sampled remote sensing information) has yet to be explored.

Dual-polarization synthetic aperture radar

Synthetic aperture radar (SAR) operates in the microwave portion of the electromagnetic spectrum and can provide two-dimensional information on biomass over a large area. Microwave energy transmitted from the satellite interacts with the canopy and ground, with some of the energy reflected (backscattered) back to the satellite receiver. The magnitude of the radar backscatter will depend upon the electromagnetic interaction between the microwaves and the features in the scene. With a wavelength of approximately 23 cm, L-band radar is especially sensitive to features in the canopy at the scale of large branches and tree stems (Waring et al., 1995). Therefore, analyzing the correlation between backscatter strength and the number of branches and stems allows for estimation of tree biomass within the imaged area.

One significant disadvantage of SAR is that the relationship between biomass and radar backscatter saturates at biomass levels that depend on wavelength. Previous studies have indicated that the biomass saturation levels are 100 Mg/ha for P-band (0.44 GHz), 40 Mg/ha for L-band

(1.25 GHz), and 20 Mg/ha for C-band (5.3 GHz), although more recent studies have shown that dual-polarization L-band SAR saturates at biomass levels of approximately 150 Mg/ha in boreal forests of Alaska (Suzuki et al., 2007; Atwood and Andersen, 2010).

Fusion of multiple data sources

There have been relatively few previous studies that have utilized multiple sources of remotely sensed data in an imputation context. Poso et al. (1999) used a combination of aerial photography, satellite imagery, and historical stand information to estimate stem volumes in Finland. Holmström and Fransson (2003) utilized a combination of SPOT multispectral satellite imagery and airborne CARABAS-II VHF SAR to estimate forest variables in Sweden via a k -NN imputation procedure, demonstrating the potential for employing multiple sources of remotely sensed data, including both passive optical and active microwave systems, within the statistical estimation framework of NN imputation.

In the next sections, we present a case study that demonstrates the application of a multilevel inventory system, employing both regression and NN imputation techniques, that was designed to provide precise estimates of above-ground biomass resources over a relatively large and remote region of interior Alaska.

Project description and data sources

Tok study area

The study area was a 201 226 ha area (of which 163 913 ha are forested) in the upper Tanana valley of interior Alaska, surrounding the communities of Tok and Tanacross (**Figure 1**). The forests in this area are characteristic of the boreal forests of interior Alaska, with lowland forests primarily composed of white spruce (*Picea glauca*) in well-drained areas and black spruce (*Picea mariana*) in poorly drained areas. Upland forests are predominantly composed of paper birch (*Betula papyrifera*) and quaking aspen (*Populus tremuloides*). Recently burned areas are composed of remnant spruce snags, and in some cases a blanket of regenerating young aspen. Balsam poplar (*Populus balsamifera*) is common along rivers.

Multilevel sampled data

Three levels of data were collected for this study, including ground plots, airborne lidar strip samples, and wall-to-wall Landsat TM multispectral imagery and ALOS PALSAR dual-polarization synthetic aperture radar (PolSAR) satellite imagery (**Figure 1**).

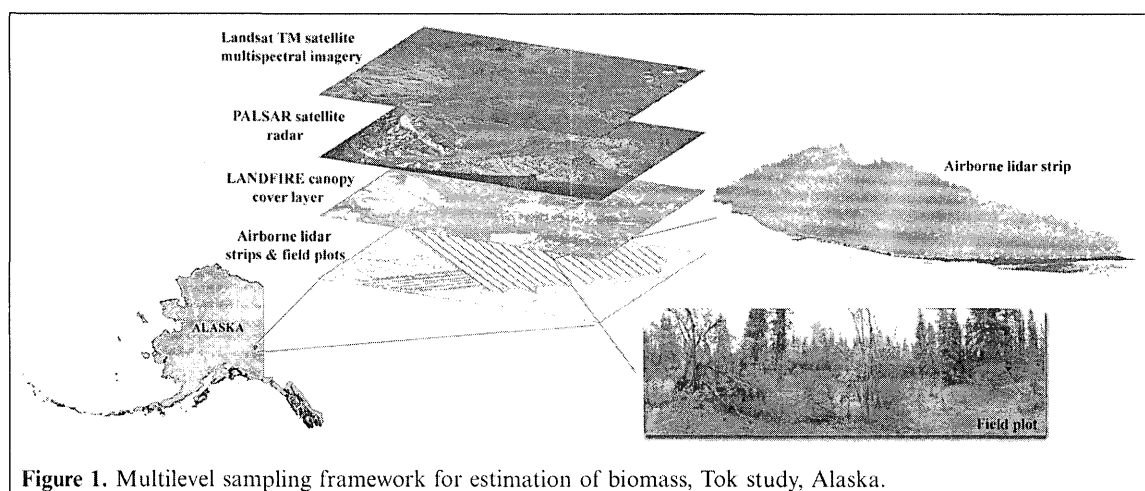


Figure 1. Multilevel sampling framework for estimation of biomass, Tok study, Alaska.

Ground plot data

In August and September 2009, 79 ground plots were established within the coverage of the lidar strips (Figure 1). At each plot, each tree with diameter at breast height (dbh) greater than 7.62 cm (3 inches) was measured within a circular 1/30 ha (1/12 acre) plot with a fixed radius of 10.36 m (34 ft). Trees with dbh between 2.5 cm and 7.62 cm (1 inch and 3 inches) were measured within a smaller 1/422 ha (1/171 acre) circular plot with a fixed radius of 2.74 m (9 ft). To maximize the efficiency of the ground data collection, plots were collected in pairs spaced approximately 600 m apart. Details related to the ground data collection are provided in Andersen et al. (2011). A summary of the ground plot data is shown in Table 1.

The locations of the plot centers were measured with sub-meter error using a survey-grade GPS + GLONASS receiver (Javad Maxor GGD), and data were post-processed using a dedicated local base station (Andersen et al., 2009b). Because most of the area is inaccessible without a helicopter, all ground plots were located within reasonable hiking distance (1 km) of a road, trail, or river. Within these accessible areas that overlapped the coverage of the lidar strips, the location of plots were randomly located across different forest stand types (based on a polygon geographic information system layer provided by the Alaska Department of Natural Resources) and historical forest fire perimeter data. Using individual tree-level data collected

for all common species by researchers at the University of Alaska-Fairbanks (Yarie et al., 2007), we developed allometric equations to estimate total aboveground biomass for each tree species based on measurements of dbh, squared dbh, and height, using a stepwise regression model development procedure in the *R* statistical software environment (<http://www.r-project.org/>). These equations were applied to the trees measured on each plot to obtain a plot-level estimate of aboveground tree biomass.

Airborne lidar

High-density airborne lidar data were collected along 27 single swaths spaced approximately 2.5 km apart (Figure 1). The sampling intensity for the lidar flight acquisition was based on the available funding; however, it was felt that this spacing would provide adequate coverage to characterize the range of variability present across the study area. Because of flight safety considerations, the strips in the northern part of the study area were oriented in a northwest–southeast direction, whereas strips in the southern part of the area were oriented in the southwest–northeast direction (so as to avoid flying perpendicular to steep mountainous slopes). Specifications for the lidar acquisition are shown in Table 2. The total cost of the lidar acquisition was approximately US\$61 000. Previous experience has shown that approximately 10% of this total is

Table 1. Summary of ground plot data on forested plots (78 ground plots*) established in the study area, located in the upper Tanana valley of interior Alaska, USA.

Plot variable	Minimum	Maximum	Mean	Standard deviation
Biomass (Mg/ha)	1.1	253.5	78.1	65.9
Mean dbh (cm)	3.3	26.8	9.1	4.4
Mean tree height (m)	2.9	17.2	7.8	3.1
Trees per ha	59	18078	3233	3302

* One ground plot was nonforested and was excluded from this summary table, as all values were zero. However, this nonforested plot was included in the analysis, as it was a valid observation.

Table 2. Specifications for lidar strip sampling flights over the study area, located in the upper Tanana valley of interior Alaska, USA.

Lidar system	Optech Gemini
Flying height	750 m
Pulse repetition frequency	125 kHz
Scan angle	± 9 degrees
Scan rate	103 Hz
Speed	160 knots
Swath width	240 m
Point spacing	≤ 0.4 m cross track and down track
Beam divergence	0.3 mRad

fixed costs (mobilization, etc.) and the remainder is linearly related to flight time.

Multispectral satellite imagery

A Landsat TM scene (path 65, row 16, acquired 3 August 2002) covering the study area was geometrically and radiometrically calibrated in the ENVI software environment (Chavez, 1989; ITT, 2009). We used six Landsat TM bands in our analysis, including bands 1–3 (visible), band 4 (near infrared), and bands 5 and 7 (middle infrared).

Dual-polarization satellite SAR data

The Alaska Satellite Facility at the University of Alaska-Fairbanks provided dual-polarization L-band PALSAR satellite radar images covering the study area, consisting of HH and HV polarizations. A multitemporal data stacking technique was used to reduce the noise in the radar backscatter for both HH and HV images (Atwood and Andersen, 2010). Previous analysis showed that both HH and HV polarimetric radar backscatter (σ_0) were correlated with aboveground tree biomass for biomass levels below 150 Mg/ha. (Figure 2).

Canopy cover classification map

Often there are existing vegetation classifications that can be used to support a multilevel inventory effort. For example, the LANDFIRE project in the United States, a joint program supported by both the US Forest Service and US Department of Interior, generates digital maps of current vegetation composition and structure (height, cover) over the entire United States at a 30 m resolution (Rollins et al., 2006). In this project, the LANDFIRE canopy cover layer was used to stratify the landscape into four different forest canopy cover classes: 0–10% (nonforested), 10–25%, 25–60%, and 60–100%. The forest–nonforest stratification was used to define the sampling frame for all estimates, and the more detailed classification was used for post-stratified estimates.

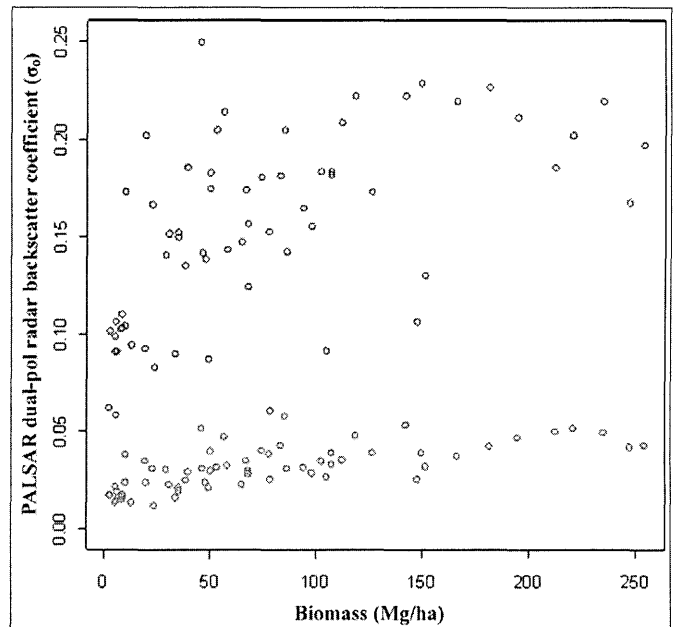


Figure 2. Relationship between field-based biomass and PALSAR L-band radar backscatter coefficient (σ_0) for HH and HV polarizations, Tok study area, Alaska. Blue points represent HH polarization, and red points represent HV polarization (from Atwood and Andersen, 2010).

Project methodology

Prediction of biomass within lidar strip samples

Lidar-derived structural metrics, which collectively provide a detailed quantitative summary of the 3-D distribution of all canopy components, are generally highly correlated to aboveground biomass (Means et al., 2000; Andersen et al., 2006). In this study, we generated lidar structural metrics from the lidar point cloud extracted from the 1/30 ha ground plot areas. In addition, the area covered by the lidar strips was divided into grid cells of equal area (18 m $\times$ 18 m) and the same set of lidar structural metrics were extracted from each grid cell. These structural metrics included maximum height, mean height, coefficient of variation of height, 10th percentile height, 25th percentile height, 50th percentile (or median) height, 75th percentile height, 90th percentile height, canopy cover above 2 m, and canopy cover above 5 m. Canopy cover values were calculated as the percentage of first returns above a given threshold height (i.e., 2 or 5 m in this case, where these thresholds correspond to overstory and understory canopy layers as defined in the FIA Phase 2 vegetation profile protocol (Schulz et al., 2009)). We applied a square-root transform to the dependent variable (aboveground biomass) to linearize the relationship with the lidar structural metrics (the functional form of the allometric relationship between tree height and biomass is curvilinear) and to homogenize the error variance. Because the ground plots were not a true probability sample over the entire extent of the lidar strips, the estimate of biomass within the

lidar strips is a model-based estimate (Schreuder et al., 1993). In the model-based sampling framework, the so-called superpopulation of biomass values at each lidar grid cell i is therefore distributed according to the regression model

$$Y_i = (\alpha + \beta_1 X_1 + \dots + \beta_p X_p + e_i)^2$$

where $\text{Variance}_m(e_i) = \sigma^2$, the subscript m indicates conditioning on the underlying superpopulation model, Y_i denotes the total aboveground tree biomass for a given grid cell area, the subscript p indicates the number of predictor variables in the model, X indicates the various lidar structural parameters that are correlated with biomass, and α , β indicate the coefficients of this superpopulation model. The coefficients of this model were determined using a stepwise automated variable selection procedure in the R statistical package (R Development Core Team, 2008). As we were interested in predicting biomass in the original units (Mg/ha), we back-transformed the predicted “sqrt” (biomass) values and then applied a correction factor to remove the bias that is introduced in the backtransformation (Miller, 1984). **Figure 3** shows the relationship between lidar-predicted biomass and the field-based values at the plot level ($R^2 = 0.74$). This regression model was then used to predict biomass at each 18 m $\times$ 18 m (1/30 ha) grid cell over all forested areas covered by the lidar strip samples (where forest area was defined by the LANDFIRE canopy cover classification). However, it should be noted that the lidar strips themselves are a probability (systematic) sample over the entire extent of the study area, and can be viewed as a single-stage cluster sampling design, with model-based biomass estimation within each cluster

(Andersen et al., 2011; Ståhl et al., 2011). The total biomass for all forested area within the study area, $\hat{Y}_{\text{total}}$, can be estimated by applying the ratio-to-size estimator as described by Cochran (1977)

$$\hat{Y}_{\text{total}} = M_0 \left(\sum^n \hat{Y}_k / \sum^n M_k \right)$$

where n is the number of lidar strips, $\hat{Y}_k$ is the estimated total biomass for the k th lidar strip, M_k is the total number of elements in the k th lidar strip and M_0 is the total number of elements in the population (total number of forested grid cells within the study area), and lidar strips are randomly distributed and selected with equal probabilities. In this study, the total size of the study area was 201 227 ha (**Figure 1**), and the total forested area was estimated to be 163 913 ha. Andersen et al. (2011) provided details on a resampling-based variance estimator for this lidar-based estimate of total biomass. In Andersen’s study, the estimate of total biomass within the study area was reported to be 8 138 278 Mg. The estimated precision of this estimate (standard deviation) in the single-stage cluster sampling framework, obtained via resampling (bootstrapping) inference, was reported to be 377 626 Mg (4.6%), and when the modeling error was incorporated into the estimate of variability, the standard deviation of the bootstrap distribution increased to 691 825 (8%).

Post-stratification with the LANDFIRE canopy cover layer

Because the lidar strip samples only cover a limited portion of the entire study area, the precision of the lidar-based estimate of total biomass could potentially be improved by incorporating the estimates of the total proportion of area in various canopy cover classes provided by the LANDFIRE classification. If the canopy cover classification explains a significant amount of the total variability in lidar-derived biomass, then the post-stratification can increase the precision of the total biomass estimate considerably. The ratio-to-size estimator (described above) can be modified to provide a post-stratified estimate of total biomass

$$\hat{Y}_{\text{total}_{ps}} = \sum^h M_h \frac{\sum^{n_h} \hat{Y}_k}{\sum^{n_h} M_k}$$

where h denotes the various canopy cover strata (10%–25%, etc.).

Nearest-neighbor imputation of biomass using satellite imagery

The concept of post-stratification described previously can be extended to incorporate the use of wall-to-wall coverage provided by satellite-based image data (Landsat TM and PALSAR polarimetric SAR) in the context of a multilevel inventory system. The use of satellite imagery,

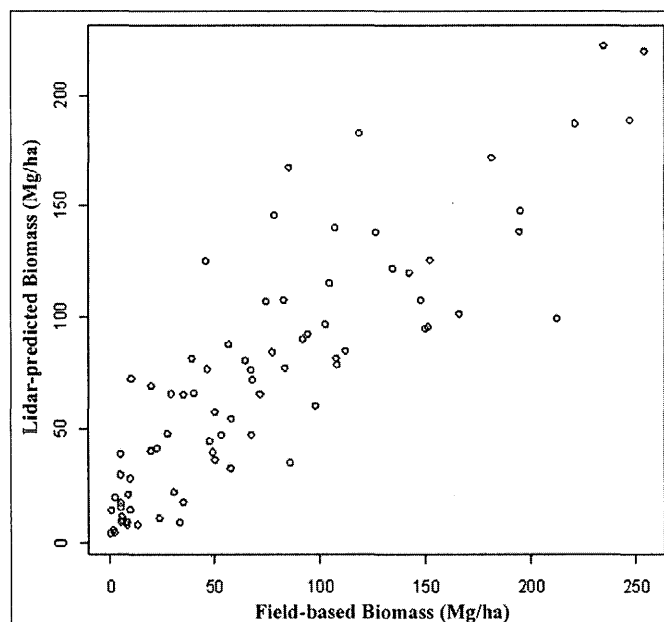


Figure 3. Relationship between lidar-based biomass predictions and field-based values, Tok study area, Alaska.

where forest structure is measured indirectly at the scale of an individual pixel either through the multispectral signature or the magnitude of the radar backscatter, provides the capability to estimate (i.e., map) biomass in a spatially explicit manner across the entire landscape. In a multilevel sampling context, this provides an opportunity to potentially increase the precision of parameter estimates by extending the post-stratified model-based sampling framework to incorporate this mapped information. Although either parametric (e.g., regression) or nonparametric approaches could be used in this case to predict a univariate response variable (biomass), we chose to employ a nonparametric NN approach to develop a mapped estimate of the biomass distribution over the entire landscape. This approach, implemented through the *yaimpute* package in *R*, provides a straightforward means to develop a map and allowed us to clearly demonstrate the extension of our model-based estimation to multiple levels of remotely sensed data (Crookston and Finley, 2008). In addition, the use of a nonparametric approach allows for relatively easy extension to the multivariate context in future studies.

Following McRoberts (2007), in NN imputation we had a dataset Y of response variables (e.g., biomass values) with sample size n drawn from a population of size N . For each element Y_i , we had an associated set of ancillary variables X , and the geometric space defined by this vector is termed the “feature” space. This dataset, composed of elements with values for both response variable Y and

ancillary variables X , is considered to be the “reference” dataset. Often the reference dataset consists only of plot data, but in our case the reference data were the entire set of grid cells within the lidar strip samples. At each of these grid cells, we have a lidar-predicted biomass value (Y_{is}) and a vector of ancillary variables (X_{is}) obtained from the Landsat TM multispectral image and the polarimetric SAR image. In this case, the X_{is} included the spectral reflectance value from Landsat TM bands 1–5 and band 7 (i.e., thermal band 6 excluded), and PALSAR HH and HV backscatter values. In NN parlance, the set of units at which predictions are desired, and for which only ancillary variables X are available, is termed the “target” dataset. The NN prediction for the i th element in the target set is the Y value associated with the “nearest” element in the reference dataset, where “nearest” is defined as having the smallest value of a distance metric d between the respective X vectors in feature space, or: $d_{ij} = (X_i - X_j)'M(X_i - X_j)$, where M is a square matrix. There are several choices for the matrix M , including the identity matrix, where d becomes the squared Euclidian distance, or the Mahalanobis distance, where M is the inverse of the covariance matrix of the X values in feature space. In our case, the Mahalanobis distance was used because it is scale-invariant and takes into account the covariance structure of the X ancillary variables. The result of the NN imputation in our case was a continuous map of biomass over the entire study area (**Figure 4**), which could then be used to develop an estimate of total biomass.

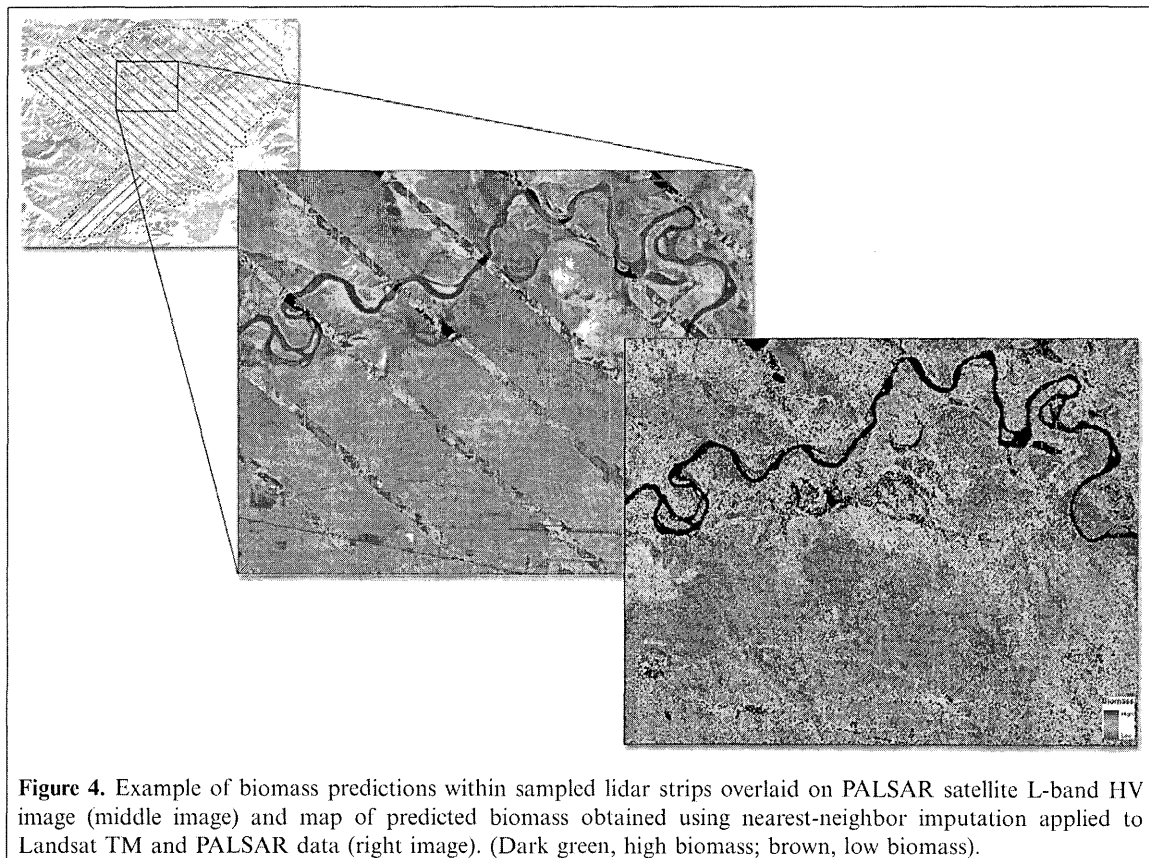


Figure 4. Example of biomass predictions within sampled lidar strips overlaid on PALSAR satellite L-band HV image (middle image) and map of predicted biomass obtained using nearest-neighbor imputation applied to Landsat TM and PALSAR data (right image). (Dark green, high biomass; brown, low biomass).

Estimating the precision of total biomass estimates

The resampling approach described in Andersen et al. (2011) can be extended to estimate the variability associated with both the post-stratified estimator using LANDFIRE canopy cover and the estimate obtained from the NN imputation approach using Landsat TM and PALSAR. In a sense, it is a resampling-based analogue to the analytical formulation of the variance estimator for model-based lidar sampling provided by Ståhl et al. (2011). In the case of post-stratification via LANDFIRE canopy cover layer, the resampling occurs at the level of the plot data (with replacement) and the lidar strip samples (without replacement from a pseudo-population according to Andersen et al. (2011) to account for finite population of strips), while the strata totals are considered to be fixed constants (i.e., there is no sampling or modeling error associated with the canopy cover classification). Although in reality there is certainly error associated with the LANDFIRE canopy cover classification, for purposes of clarity this component of the error was ignored in our study.

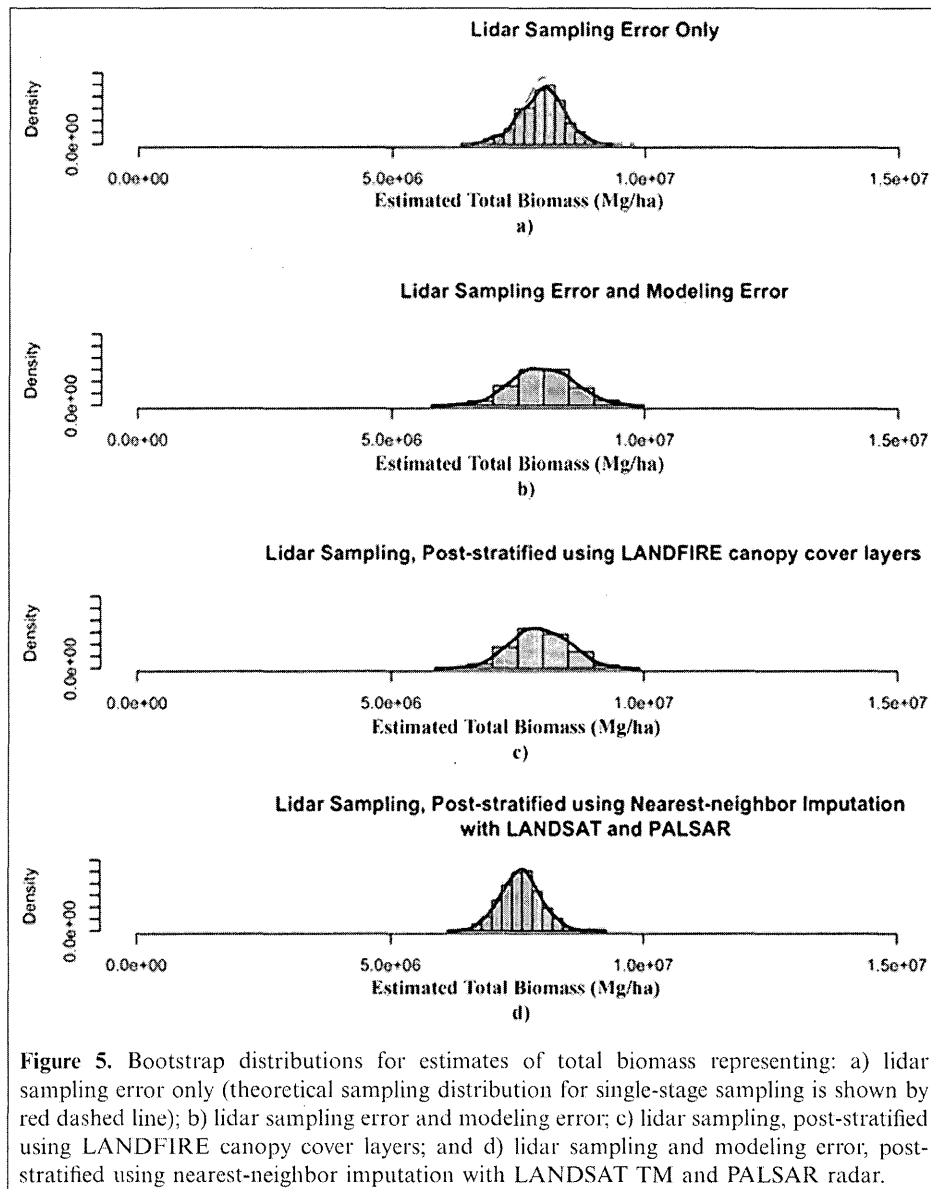
Several techniques for estimating the variability of estimates derived via NN imputation in a forest inventory context have emerged recently (McRoberts et al., 2007; McRoberts, 2009; Magnussen et al., 2009). While most of these techniques for variance estimation have been developed analytically, several resampling-based approaches have also been proposed that rely on either bootstrapping or jack-knifing. Franco-Lopez et al. (2001) developed a bootstrapping approach to estimate the precision of estimates of forest stand density and volume using k -NN. McRoberts (2007) developed the statistical basis for resampling-based variance estimators in the context of NN imputation. These approaches were not directly applicable to the multilevel inventory framework used in our study. In this sense, we attempted, for each draw of the bootstrap sample, to simulate the variability that would be introduced, or potentially reduced, by each component of the multilevel inventory design. Specifically, two sources of random variability were introduced in the resampling procedure: variability in choice of model form and coefficients of the lidar biomass model, and sampling error in the systematic lidar strip sample. In addition, another level of information, either a mapped biomass layer obtained via NN imputation or a classified LANDFIRE canopy cover layer, was also incorporated into the bootstrapping procedure to assess its potential utility in decreasing the variability of the total biomass estimate. In all cases, the number of bootstrap replications was 500 (according to Efron and Tibshirani (1994), it is rare that more than 200 bootstrap replications are necessary for estimating a standard error). The following steps of the bootstrap procedure were used in this analysis:

1. Draw a sample (with replacement) from a ground plot sample.
2. Use this sample to develop a regression model via stepwise regression.
3. Draw a sample of lidar strips (without replacement) from a "pseudopopulation" of lidar strips (replicate each lidar strip N/n times, where n is the number of sampled strips and N is the population of strips). This "without replacement (WOR) bootstrapping" helps account for sampling from a finite population (which is usually not assumed in traditional "with replacement (WR) bootstrapping").
4. Use the regression model obtained in Step 2 to predict biomass at each grid cell within the lidar strips selected in Step 3.
5. (Use this step only for NN approach.) Use k -NN nearest-neighbor imputation ($k = 1$; Mahalanobis distance metric) to predict biomass within each (forested) grid cell over the entire study area, using lidar grid cells as the reference data and the satellite/PolSAR data as the target data (Figure 4).
6. For the NN approach, sum the biomass predictions over all grid cells to obtain an estimate of total biomass; or for the LANDFIRE post-stratification approach, use the stratum areas obtained from the LANDFIRE canopy cover layer to generate a weighted estimate of total biomass (Cochran, 1977).
7. Repeat steps one to six 500 times to obtain a bootstrap distribution.

Results

The bootstrap distributions corresponding to the various sampling frameworks are shown in Figure 5, and the summary statistics for these distributions are shown in Table 3. As discussed in Andersen et al. (2011), Figure 5a and the first two rows of Table 3 indicate that the bootstrap distribution incorporating lidar sampling error only corresponds very closely to the theoretical sampling distribution for the estimate of the population total using a single-stage cluster sampling design (Cochran, 1977). Incorporating the error associated with modeling error into the bootstrap variance estimate increases the variability of the bootstrap distribution significantly (relative standard error increases from 5.3% to 7.3%). It should be noted that variability due to both sampling error and modeling is incorporated into all subsequent bootstrapping results (i.e., post-stratified using LANDFIRE and NN imputation). Using the LANDFIRE canopy layers to post-stratify the estimate obtained from the lidar strip sample (Figure 5c, fourth row in Table 3) results in a marginal decrease in variability (relative standard error decreases from 7.3% to 7.0%).

The result of the NN imputation is a continuous map of biomass over the entire study area (Figure 4). The results indicate that using the Landsat TM and PALSAR dual-polarization radar backscatter images to post-stratify the lidar strip sample (Figure 5d, last row in Table 3) results in a significant decrease in the variability of the total biomass estimate (from 7.3% to 5.1%). It should also be noted that the



mean of the bootstrap distribution was fairly similar for the estimate using lidar strips only and that obtained using lidar strips post-stratified by the LANDFIRE canopy cover layer (7 941 351 Mg vs. 7 940 091 Mg), while the mean obtained from NN imputation using Landsat TM and PALSAR satellite radar was substantially lower (7 568 641 Mg). However, Efron and Tibshirani (1994) caution that estimates of bias obtained from bootstrapping are usually less reliable than estimates of standard errors.

Discussion

The results indicated that the precision of total biomass estimates in remote regions, such as interior Alaska, can be significantly improved through the combined use of remotely sensed and ground data, where remote sensing is acquired in a multilevel framework (i.e., at several different

resolutions and sampling intensities). In contrast, and somewhat surprisingly, using the LANDFIRE canopy cover layer did not result in a substantial improvement in the precision of the total biomass estimate, even though canopy cover is generally correlated with biomass. This was likely due to classification error in the LANDFIRE canopy cover layer, although this result certainly warrants further investigation. Given the very strong relationship between height and biomass for most boreal tree species, it is possible that including the LANDFIRE height layer could improve the result, although it should be noted that that this layer is inferred height, not a direct measurement of canopy height, so it is unlikely to result in substantial improvements.

In contrast, the use of NN imputation applied to lidar biomass estimates acquired along strip samples and a combination of Landsat TM and PALSAR satellite radar led to substantial improvements in precision of total biomass

Table 3. Summary statistics for theoretical sampling distribution and bootstrap distributions of total biomass.

	Mean	Standard deviation	Relative standard error
Theoretical single-stage cluster sampling	7 978 372	355 199	4.5%
Bootstrap distribution, lidar sampling error only	7 941 351	423 132	5.3%
Bootstrap distribution, lidar sampling error and modeling error	7 980 615	585 669	7.3%
Bootstrap distribution, lidar sampling, post-stratified with LANDFIRE canopy cover layer	7 940 091	555 577	7.0%
Bootstrap distribution, post-stratified using nearest-neighbor imputation with LANDSAT and PALSAR	7 568 641	388 114	5.1%

estimates. In a sense, a map derived from NN imputation can be thought of as an optimal post-stratification, as the imputation procedure simply estimates the proportion of the overall landscape that is associated with each lidar grid cell. Therefore, in effect, each lidar grid cell is its own stratum and the within-stratum variance is likely very low due to the large number of lidar grid cells that are well-distributed across the full range of forest conditions within the study area.

In addition, the inclusion of both spectral (Landsat TM) and L-band SAR backscatter information provided a highly complementary set of ancillary data that contained information on three-dimensional forest structure (L-band) and species composition (Landsat TM), probably the two most important attributes in quantifying aboveground forest biomass. It should also be noted that the L-band SAR data used in this study was a multitemporal stack of PALSAR scenes from snow-free months (Atwood and Andersen, 2010). Using a multitemporal data stack likely reduced the speckle noise component inherent to SAR imagery, in essence increasing the signal-to-noise ratio and improved our ability to detect more subtle differences in target dielectric properties, such as volume scattering associated with dense branches and stems (Santoro et al., 2011). The use of dual-polarization SAR also likely improved the ability to measure more subtle variation in biomass levels. Although the overall range of variability of the cross-polarized HV backscatter was considerably lower than for the HH SAR image, the relationship to biomass linearly increased up to levels of 200 Mg/ha (**Figure 2**), indicating that the use of multitemporal data stacks of dual-polarization L-band SAR may be able to surmount the saturation problem that has limited the utility of single-polarization L-band radar in previous biomass and aboveground carbon assessments. However, it should be noted that, in general, there will be much lower sensitivity even in the dual-polarization L-band SAR signal to variability in biomass levels above 200 Mg/ha, and this may reduce the accuracy of the mapped biomass estimates within forest areas with higher biomass levels. At the same time, the biomass levels observed in the plot data indicated that a relatively small proportion of the total study area contains forests with biomass levels exceeding 200 Mg/ha, so it was unlikely that radar saturation issues had a significant effect on the statistical results reported in this study.

Given that the allometric relationships between tree dimensions and biomass can differ significantly between boreal species (Yarie et al., 2007), the inclusion of Landsat TM multispectral information likely enabled us to capture complex interactions between dual-polarization L-band SAR backscattering characteristics and species composition that would have been difficult to model using a parametric approach.

It should be noted that the ground data collected in this study can be considered a representative sample, but cannot be considered a true probability sample, as inaccessible areas were excluded from the ground sampling frame. Therefore, the design used in this study must be considered model-based, not model-assisted, and the resulting estimators were not design-unbiased. Although the quality of design-unbiasedness is certainly desirable in an operational inventory context, these advantages might be offset by the lower cost of an inventory design such as that described in this paper, which combined a representative (but not probability) ground sample with a design-based (probability) sample of high resolution data and wall-to-wall coverage with satellite imagery.

It should also be noted that the systematic sample of high-resolution airborne remote sensing data (lidar strip samples in this case) provided spatial balance, a highly desirable feature of a large-area inventory design (Stevens and Olsen, 2004). As is the case with many inventory programs using a systematic sample (e.g., the FIA program in the United States), our assumption that the lidar strips are a simple random sample from the finite population, instead of a systematic design, in the variance estimation procedure will lead to an overestimation of the variability of the total biomass estimate. Although outside the scope of the current study, explicitly accounting for the systematic sampling design in the bootstrapping algorithm would be an interesting topic for future work.

Conclusions

The combined use of (i) characteristic, and accurately georeferenced, ground data covering the full range of variability within a study area, (ii) sampled high-resolution airborne lidar, and (iii) wall-to-wall satellite multispectral and dual-polarized L-band SAR imagery provided a powerful set

of data within the framework of a multilevel biomass inventory. Given the extremely high cost of establishing ground plots in remote areas of the world (e.g., approximately US\$8000 per plot in areas of interior Alaska (R. Koleser, Team Leader, Alaska FIA Data Collection, personal communication, 2007)) and the increasing demand for accurate carbon and biomass stock assessment and monitoring in these remote regions, the inventory solution will require the innovative use of combined sources of remotely sensed data. In addition, modified ground protocols, such as the use of more accurate geopositioning equipment, that facilitate direct comparison to remotely sensed information and enable model calibration and validation, will help to make precise biomass assessments more cost-effective in remote regions.

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