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Review

# Lidar sampling for large-area forest characterization: A review

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ABSTRACT

The ability to use digital remotely sensed data for forest inventory is often limited by the nature of the measures, which, with the exception of multi-angular or stereo observations, are largely insensitive to vertically distributed attributes. As a result, empirical estimates are typically made to characterize attributes such as height, volume, or biomass, with known asymptotic relationships as signal saturation occurs. Lidar (light detection and ranging) has emerged as a robust means to collect and subsequently characterize vertically distributed attributes. Lidar has been established as an appropriate data source for forest inventory purposes; however, large area monitoring and mapping activities with lidar remain challenging due to the logistics, costs, and data volumes involved.
The use of lidar as a sampling tool for large-area estimation may mitigate some or all of these problems. A number of factors drive, and are common to, the use of airborne profiling, airborne scanning, and spaceborne lidar systems as sampling tools for measuring and monitoring forest resources across areas that range in size from tens of thousands to millions of square kilometers. In this communication, we present the case for lidar sampling as a means to enable timely and robust large-area characterizations. We briefly outline the nature of different lidar systems and data, followed by the theoretical and statistical underpinnings for lidar sampling. Current applications are presented and the future potential of using lidar in an integrated sampling framework for large area ecosystem characterization and monitoring is presented. We also include recommendations regarding statistics, lidar sampling schemes, applications (including data integration and stratification), and subsequent information generation.


**Contents**



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## 1. Introduction

Timely and accurate measurements of vegetation structure are increasingly needed across large areas to support a wide range of activities related to sustainable forest management and carbon accounting (Rosenqvist et al., 2003). Remote sensing has provided a means to measure vegetation structure across large areas (Kerr & Ostrovsky, 2003); however, because the spatial extent and spatial resolution of a given sensor are inversely related (Franklin et al., 2002), large area characterizations of vegetation structure based upon remotely sensed data often have sub-optimal precision for many applications (Xie et al., 2008). Integrating information from sensors that acquire data with different levels of detail in a multi-phase sampling framework can provide a means to obtain large-area estimates of forest structure with a level of precision sufficient for many applications. Airborne or space lidars can be incorporated in such frameworks to supply height measurements (e.g., Goetz et al., 2010; Hyde et al., 2006; Ni-Meister et al., 2010; Popescu et al., 2004). The use of lidar for large-area monitoring and characterization will enable additional capture of vertical structural conditions.

To accommodate the needs of industrial forestry and in an effort to better understand how lidar can be used to produce relevant management and reporting information, much research has emphasized the importance of wall-to-wall characterizations of forests. Building upon an increased understanding of lidar measures and on-going needs for the characterization of large areas as well as to control data acquisition costs, opportunities for the development of sampling frameworks that integrate lidar measures following statistically supported monitoring practices show increasing potential, particularly for those applications that do not require spatially explicit wall-to-wall information. Under the latter scenario, a series of lidar transects would be acquired over an area of interest, and established procedures from sample-based forest inventories could be adapted and applied to these lidar samples. As an example, lidar samples may be used in a manner similar to field plots, wherein the information generated is used in combination with other spatial data (such as classified optical satellite data) in order to facilitate stratification, thereby enabling the extension of attributes (e.g., height) across large areas. Alternatively, with forethought and careful planning, lidar data can be employed in a sampling design to infer or estimate characteristics of interest (e.g., volume, biomass, carbon) across a larger area or population. The presence of strata within a given population enables the representation of conditions over smaller sub-areas and provides spatial context to aid in model development. The former case, attributing strata, is more flexible to the actual layout of lidar samples than when statistical inference is planned (as in the latter case).

The overall goal of this communication is to present the case for lidar sampling as a means to enable timely and robust large-area characterizations of vertically distributed forest attributes (e.g., height, volume, biomass, etcetera). In support of this goal, we review the potential of airborne profiling, scanning (discrete and waveform recording) lidars, and spaceborne lidar, for large-area sampling of forest conditions. Based upon data availability and application examples, we then principally focus on airborne profiling and scanning systems as sampling tools. With these data sources in mind, we address sample design options, including theoretical and statistical considerations such as model-based versus design-based approaches, and issues associated with estimation. We also consider data integration, which enables biophysical estimates from the lidar to be extended over larger areas, as well as the opportunities afforded by repeated acquisitions of lidar over the same area. Finally, we discuss implementation opportunities and considerations, and make recommendations, based on our own collective experience, for lidar sampling surveys.

## 2. Lidar fundamentals

Lidar systems are based on laser ranging, which measures the distance between a sensor and target based on half the elapsed time between the emission of a pulse and the detection of a reflected return (Baltsavias, 1999). Critical to the adoption of lidar as a survey tool, however, is the capacity to simultaneously measure both vertical and horizontal vegetation structure and terrain morphology in detail and with high accuracy.

Lidar systems are classified as either *discrete return* or *full waveform recording*, and may be further divided into profiling (recording only along a narrow line directly below the sensor) or scanning systems (recording across a wide swath on either side of the sensor) (Dubayah & Drake, 2000; Lefsky et al., 2002; Lim et al., 2003). Full waveform recording lidar systems digitize the entire reflected energy from a return, resulting in complete sub-meter vertical vegetation profiles. In contrast, discrete return systems record single or multiple returns from a given laser pulse. As the laser signal is reflected back to the sensor, large peaks, (i.e., bright returns), are interpreted to represent discrete objects in the path of the beam and are recorded as discrete points. Thus, within a forest environment, full waveform systems record the entire waveform for analysis, while discrete return systems record clouds of points representing intercepted features.

Waveform recording instruments have been considered as large-footprint profilers, with a circle of illumination on the ground that is typically 10 m in diameter or greater; however, recent advances have seen full waveform instruments with increasingly smaller footprint sizes (Wagner et al., 2006, 2008). Examples include SLICER (Scanning Lidar Imager of Canopies by Echo Recovery), and early acquisitions by the airborne Laser Vegetation Imaging Sensor (LVIS) (Blair et al., 1999), and the spaceborne Geosciences Laser Altimeter System (GLAS) (Schutz et al., 2005). The three above-mentioned systems, the first and last of which no longer collect data, are research tools.

Currently, the majority of operational system providers offer an optional waveform digitizing capability for their small footprint lidars sensors. However, small footprint discrete return sensors are used for virtually all operational applications (Lim et al., 2003; Næsset, 2004a; Wulder et al., 2008a) although full waveform small footprint systems are becoming more available. At typical operating altitudes, these discrete return systems generally have footprints of up to several decimeters in diameter. Examples of commonly used sensors include those developed by Optech[1], TopoSys[2], Leica[3], and Riegl[4]. Depending on the desired footprint size and density of returns, a variety of platform- and sensor-dependent parameters must be considered when planning a survey, including flying height and speed, mirror scan frequency, pulse repetition frequency, maximum scan angle,

[1] Optech Inc. http://www.optech.ca.
[2] TopoSys GmbH. http://www.toposys.com.
[3] Leica Geosystems: http://www.leica-geosystems.us.
[4] Riegl Laser Measurement Systems: http://www.riegl.com.

**Table 1**
Typical parameterization of a lidar survey for forest applications.

| Platform | Fixed wing aircraft | Fixed wing aircraft | Helicopter |
|---|---|---|---|
| Sensor | Optech ALTM 3100C | Leica ALS50-II | Riegl LMS-Q140i-60 |
| Sensor model year | 2004 | 2004 | Not reported |
| Maximum number of returns per emitted pulse | 4 | 4 | Not reported |
| Wavelength (nm) | 1064 | 1064 | 900 |
| Flying height (m) | 700 | 930 | 150 |
| Footprint diameter (m) | 0.18 | 0.16–0.18 | 0.45 |
| Maximum scan angle (°) | 14 | 15 | 30 |
| Swath width (m) | 350[a] | 500[a] | 173 |
| Pulse return frequency (kHz) | 100 | 115.8 | 30 |
| Scan frequency (Hz) | 70 | 52 | Not reported |
| Resulting laser pulse density ($m^{-2}$) | 7.7 | 6–8 | Up to 4 |
| Information gathered from | Næsset (2009b) | Korpela et al. (2010) | Barbier et al. (2011) |
| Application, information need | Detect small trees in the alpine tree line and estimate their heights | Vegetation classification | Characterizing the structure of tropical forests |

[a] Not reported by the authors, calculated using the swath width equation found in Baltsavias (1999, p. 204): $SW = 2h \tan(\theta/2)$, where SW is swath width, $h$ is flying height, and $\theta$ the scan angle.

and in the case of wall-to-wall coverage, the desired amount of overlap between swaths (Reutebuch & McGaughey, 2008). Table 1 provides an example of a typical lidar survey configuration. The basic relationships between these parameters are described in Baltsavias (1999), while the implications of varying flight and survey configurations on vegetation metrics and biophysical estimates have also been previously examined (Gobakken & Næsset, 2008; Goodwin et al., 2006; Hopkinson, 2007; Magnusson et al., 2007; Næsset, 2004b, 2005, 2009a; Ørka et al., 2010a), including the capture of small trees (Næsset, 2009b). The examples presented in Table 1 show the various trade-offs made when configuring an instrument for a given survey. From a sampling and transect collection perspective, Table 1 also shows the in-built limitation in swath width as a function of scan angle. The instruments presented in Table 1, while commonly used, have been superseded by newer instruments and models (Table 2). In Table 2 instruments from different companies representing the model years 2010/11 show the impact of increased scan angles. For instance, for the Optech and Leica instruments presented, the increase in scan angles with the newer generation instruments has effectively doubled the swath width possible from a similar flying height. Generally, forest applications necessitate scan angles that are less than 15° (Reutebuch & McGaughey, 2008). It is also worth noting that the swath width values presented are calculated based on flying height and scan angle only, considerations of pulse rates and desired posting for instance, also need to be considered prior to the operational realization of these actual swath widths. Furthermore, each of these systems is commercially available and based upon proprietary technology.

Regardless of type, an airborne lidar system consists of three complementary technologies: a laser to measure distance to target; an inertial navigation system (INS), also referred to as an inertial measurement unit (IMU), to record the pitch, roll and yaw of the platform; and a kinematic global satellite positioning system (e.g., the U.S. GPS — Global Positioning System, the Russian GLONASS — Global Navigation Satellite System) to record position. By combining information from each of these technologies using accurate time referencing, the absolute position of a reflecting surface can be solved (Lefsky et al., 2002). Indeed, it is the parallel advances of these technologies that have provided the impetus for the increasing number of applications for lidar technology (Lim et al., 2003).

**Table 2**
Examples of state-of-the-art lidar survey systems.

| Sensor | Optech ALTM Orion (M/C 200)[a] | Optech ALTM Gemini[b] | RIEGL LMS-Q680i[c] | Leica ALS70 (HA/HP/CM)[d] |
|---|---|---|---|---|
| Sensor model year | 2011 | 2011 | 2010 | 2011 |
| Maximum number of returns per emitted pulse | 4 | 4 | Unlimited (full waveform) | Unlimited (full waveform) |
| Maximum flying height (m) | 2500 (M), 1000 (C) | 4000 | 5500 | 5000 (HA), 3500 (HP), 1600 (CM) |
| Laser beam divergence (mrad) | 0.25 | 0.25 and 0.8 | ≤0.5 | ~0.15 |
| Footprint size (m) | 0.25 increase per 1000 m distance and 0.25 mrad | 0.25 increase per 1000 m distance and 0.25 mrad; 0.8 increase per 1000 m distance and 0.8 mrad | 0.5 increase per 1000 m distance and 0.5 mrad | 0.15 increase per 1000 m distance and 0.15 mrad |
| Maximum scan angle (°) | 25 | 50 | 30 | 37.5 |
| Maximum swath width (m)[e] | 2332 (M), 933 (C) | 1068 | 6350 | 7673 (HA), 5371 (HP), 2455 (CM) |
| Wavelength (nm) | 1064 (M), 1541 (C) | 1064 | 1550 | 1064 |
| Intensity | 12-bit | 12-bit | 16-bit | 16-bit |
| Pulse return frequency (kHz) | 50–200, 100–200 (based on model) | 33–167 | Up to 400 | Up to 250, 500 (based on model) |
| Scan frequency (Hz) | 0 to 70 | 0 to 70 | 10–200 | 60–200 (based on scan pattern and model) |

[a] http://www.optech.ca/pdf/ALTM_Orion_SpecSheet_110708web.pdf.
[b] http://www.optech.ca/pdf/ALTM_Gemini_SpecSheet_110309_Web.pdf.
[c] http://www.riegl.com/uploads/tx_pxpriegldownloads/10_DataSheet_LMS-Q680i_20-09-2010.pdf.
[d] http://www.leica-geosystems.com/downloads123/zz/airborne/ALS70/brochures/Leica_ALS70_6P_BRO_en.pdf.
[e] Not reported, calculated using the equations found in Baltsavias (1999, p. 204): $SW = 2h \tan(\theta/2)$, where SW is swath width, $h$ is flying height, and $\theta$ the scan angle.

## 3. Overview of lidar for large-area sampling of forest characteristics by sensor type

Given the complexity of sampling theory, it may be helpful to the reader to briefly clarify some key concepts that emerge in the following sections. First is the distinction between multi-phase and multi-stage sampling. In a multi-phase sampling design, information is acquired from some or all sample units in the first phase, and then in the second (and subsequent) phase(s) more detailed information is acquired from a sub-set of sample units. Information from the first phase may be used to stratify the population, or serve as supplementary information at the second phase. For example, a two phase design might be employed in a situation where two variables are related (e.g., tree height and biomass) and the first, variable 1, is easy to measure and the second, variable 2, more difficult or expensive to measure. A model relating the two is employed (e.g. a ratio estimator or a predictive equation); a large first-phase sample or census of variable 1 is acquired, and a smaller sample of variable 2 is acquired on a subset of the 1st phase measurements. If only a portion of the entire population of interest is sampled at the first phase, the two-phase sample design is often referred to as a double sample. In a multi-stage sampling design, the sample units at each stage are sub-sampled from the sample units selected at the previous stage (Dodge, 2006). First-stage units are commonly referred to as primary sample units, second-stage units as secondary sample units, and so on. With a multistage sample, no model or quantitative relationship is required to develop regional estimates. Rather, the information of interest is collected on observations selected in the secondary sample units in a two-stage design or in the tertiary sample units of a three-stage design. These measurements are then "blown-up" or expanded to the region of interest based on the probability of inclusion of a given observation in the sample.

Second is the distinction between two approaches to statistical inference: design-based and model-based approaches. Statistical inference involves generalizing sample information to characterize a larger unknown population and determining the level of uncertainty associated with that characterization. Design-based inference is commonly associated with traditional sampling theory (Cochran, 1977) and assumes that a population is finite and fixed in time, while model-based inference assumes that a population is infinite and fixed in time. In design-based inference, the sample is considered just one realization of a random process, i.e., the sample selected is just one of many possible samples that could have been selected. Conversely, in model-based inference, the population (not the sample) is considered just one realization of a random process, i.e., the population being measured is just one realization drawn from an infinite number of populations called a superpopulation. In design-based inference, the reference distribution is established by the sample design, and the variability of this reference distribution is described by the variance or standard error of the estimator, thus the estimator must match the sampling design in order to be unbiased. In a model-based approach, the sample design plays a minimal role in inference—the sample itself is assumed to be a true representation of the population, and the reference distribution is defined by the limitless realizations of the population (Gregoire, 1998). In short, design-based inference is conditioned on the sample, while model-based inference is conditioned on the population. One simple way to tell the two approaches apart is to look for inclusion probabilities in the statistical formulations. These inclusion probabilities, often denoted by the symbol, pi, or their reciprocals, sometimes called expansion factors or blow-up factors, are fundamental to a design-based approach. Inclusion probabilities play no essential role in model-based approaches.

In each of the following sub-sections, we highlight the application of four different groups of lidar instruments for large-area sampling and characterization of forests: airborne profiling lidar, airborne scanning lidar, airborne full waveform recording lidar, and lastly, spaceborne lidar. The goal is to demonstrate how these different lidar instruments may be used as sampling tools in a forestry context.

### 3.1. Airborne profiling lidar

Profiling lidar instruments are well suited to applications that seek to characterize forest attributes over large areas by means of sampling (Boudreau et al., 2008; Nelson et al., 2003a, 2004), or that seek to characterize changes in these attributes over time (Wulder et al., 2007). One of the main advantages of lidar (either profiling or scanning) is a significant reduction in fieldwork, since ground data is only required to calibrate models—at least when following a model-based approach; once the models are established, additional field data are then not necessary to support subsequent, similar lidar acquisitions for the same site, providing a similar sensor and survey configuration are used (Nelson et al., 2003a). In some cases however, the acquisition of additional field samples coincident with the lidar coverage may be preferable in subsequent years. Such ground measures can be used to capture growth and revise models, or increase the representativeness of the sample. Fig. 1 illustrates the linkage between the sensor and the data collection mode, and the nature of the information captured.

The Portable Airborne Laser System (PALS, Nelson et al., 2003b) is a profiling lidar system, built from off-the-shelf components, which have been deployed in research studies over a wide range of forest types and in a number of large area sampling applications. Other profiling lidar systems have been used in a forestry context (e.g., Sweda, 1998); however, commercial systems are primarily designed for terrain mapping applications. For example, Nelson et al. (2003a, 2004) used transects of profiling lidar to estimate forest merchantable volume, biomass, and above-ground carbon for the state of Delaware (5205 $km^2$). Profiling lidar transects covering a total of 1300 km were spaced 4 km apart, resulting in a sampling intensity of 0.15 km per $km^2$. Estimates of merchantable volume and above-ground dry biomass for the state were within 15 and 16% respectively of USDA Forest Service estimates. In a similar study, Nelson et al. (2005) used 2539 km of PALS data to estimate the areal extent of various canopy height and crown closure classes in Delaware and then used these outputs to predict for suitable Delmarva fox squirrel (*Sciurus niger cinereus*) habitat.

Profiling lidar systems have afforded the exploration of many research questions that impact the use of lidar as a sampling tool for large-area forest characterization. For example, Nelson et al. (1988) examined the repeatability of near-coincident laser flight line height measurements and modeled volume and biomass estimates. They found that comparable flight-line height, biomass, and volume means varied 3–6% and documented the fact that laser heights tend to underestimate field-measured heights by ~28%. As part of the same study, the authors examined the spatial autocorrelation of laser pulses along a transect and determined that the adjacency bias inherent in laser pulses (and in the resulting estimates of biomass and volume) could be removed by using semivariograms to account for the average size of trees or stands (and thereby reducing the number of pulses used in estimation). Information such as this can be useful for determining the lidar instrument parameters required by a particular application and for establishing a suitable sampling strategy.

Nelson et al. (2003a) posited that an appropriate sampling intensity (measured in kilometers of flight line) to use with a profiling lidar instrument will be a function of the prevalence of the forest type on the landscape, the spatial distribution of the forest (random versus clustered), and the intrinsic variability of the forests (homogenous versus mixed stands). Nelson et al. (2003a, 2008) provide a number of sampling intensity guidelines in this paper, accounting for the information need (e.g., biomass estimates for all cover types or only one cover type) and the characteristics of the area being surveyed.

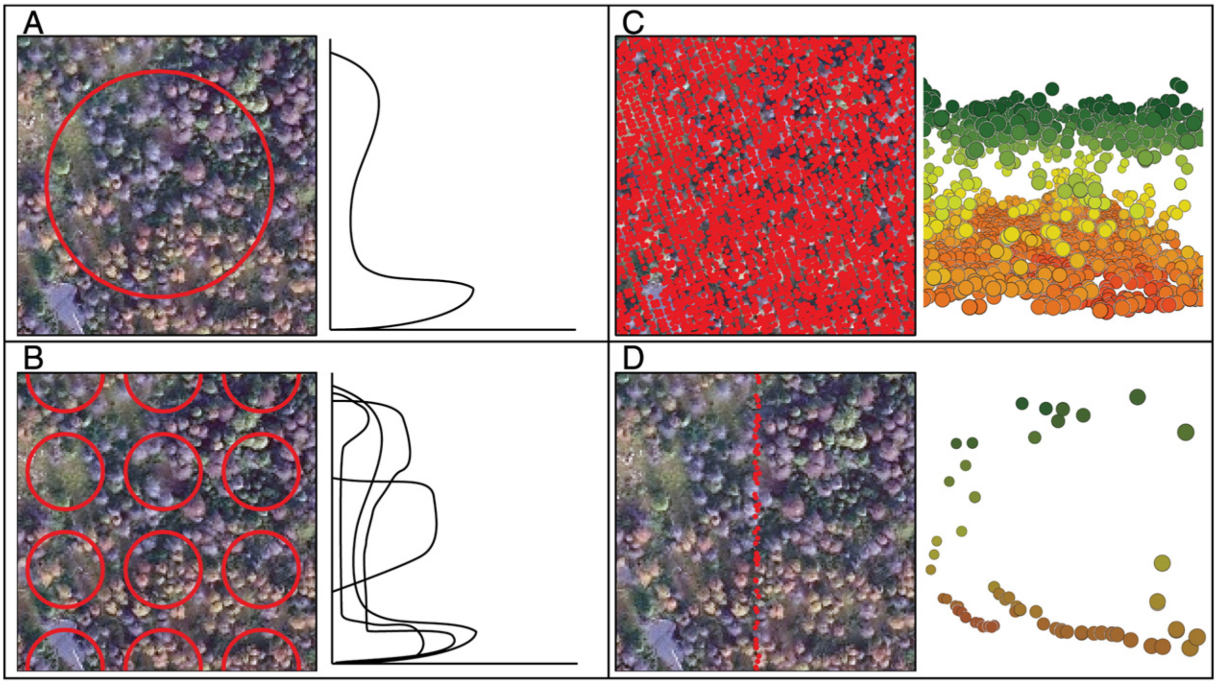


**Fig. 1.** Illustration of differing lidar sensors, presenting the relationship between footprint size and general recording mode (e.g., waveform or describe return). A) spaceborne lidar footprint (e.g., GLAS, ~60 m in diameter) and waveform; (B) airborne large-footprint waveform-recording lidar footprints (e.g., LVIS, ~20 m in diameter) and multiple waveforms; (C) small footprint, discrete-return scanning lidar returns and point cloud; and (D) small footprint, discrete-return profiling lidar returns and data. The base image is a 0.50 m true color digital aerial image of a forest stand taken in central British Columbia, Canada.

Nelson et al. (1988) also assessed the precision of lidar-derived estimates of mean canopy height, volume, and biomass by collecting profiling data for two overpasses of three different flight lines. Estimates of mean canopy height, volume, and biomass for all three attributes were found to vary by 3–6% between different overpasses of the same flight line and by less than 1.5% when data from flight lines of individual overpasses were grouped to provide overall estimates. Similarly, Nelson et al. (2003a) found that statewide estimates of aboveground biomass could be repeatedly estimated to within 7 metric tons of biomass per hectare. Finally, Nelson et al. (2008) investigated the use of different variance estimators to mitigate inflationary tendencies associated with the treatment of a systematic sample as a random sample.

Profiling lidar has demonstrated utility for enabling a sample-based approach to monitoring forest structure, volume, biomass, carbon stocks, and habitat over large areas. These data are cost effective (Petrie & Toth, 2009), and may be particularly useful in areas where there is little or no pre-existing inventory data, in areas that are inaccessible or difficult to survey by other methods, or in areas that experience rapid changes in forest cover (Nelson et al., 2003b). In such cases, the acquisition of conventional ground data may be precluded by logistics or costs. Estimates generated from profiling lidar may be provided for large areas, either through the integration of the lidar with other data sources as in Boudreau et al. (2008) and Wulder et al. (2007, 2009), or through the use of line intercept sampling techniques (Nelson et al., 2005).

Nelson et al. (in press) used a profiling lidar to sample a 27,390 km$^2$ area in southeastern Norway, Hedmark County. They acquired 105 parallel flight lines spaced 3 km apart, a total of 8309 linear km, and used these first/last returns to estimate forest aboveground dry biomass for the entire County. A map of Hedmark was produced using Landsat ETM+ and DTM data, dividing the County into four forest and four non-forest cover types. The profiling data were used to attribute these eight strata. Using a model-based approach, the laser-based estimate ($38.9 \pm 1.1$ Mg ha$^{-1}$, 1 SE (standard error)) was within 3.3% of the ground-based estimate ($37.6 \pm 0.9$ Mg ha$^{-1}$) across all cover types, and within 8.2%, on average, at the stratum level. The Hedmark profiling study was conducted jointly with a companion airborne laser scanning sampling study in Hedmark reported by Gobakken et al. (in press) and discussed in the following section. The sampling capabilities of profiling versus ALS systems may be made by directly comparing the results reported in these two studies.

mprovements in technology have resulted in more powerful lasers that increase the potential utility of these instruments, allowing airborne platforms to collect lidar data from higher altitudes, increasing the likelihood of lidar penetration of dense canopies, and improving positional accuracy. Notwithstanding the demonstrated usefulness of profiling lidar, their use in forestry applications continues to be overshadowed by the proliferation of scanning lidar instruments and applications.

### 3.2. Airborne scanning lidar

Airborne laser scanning (ALS) systems are the most common type of lidar sensors, with a number of system developers and an increasing pool of commercial vendors supporting acquisition and analysis. While profiling systems essentially collect a swath with a width equal to the diameter at target of a single lidar pulse, airborne scanning systems distribute these pulses across a width (determined by factors such as desired pulse density, scan angle, and flying height). A swath width of 500 to 1000 m is common for typical applications in forestry. As such, a single transect of scanning lidar data will yield vertical structural information across a specified swath width, with stand-level characterizations possible, and an increased attribute suite compared to profiling lidar systems. Lidar applications in forestry typically summarize data using a rasterized grid with cells sized to enable the vertical structure of a number of trees to be captured. Thus, each cell within the grid is populated with a range of metrics (such as mean height, height percentiles, height coefficient of variation, and so on), enabling model development (with field plots encompassed) and later extension using other spatial data layers or statistical models. Further, each cell on the grid can be considered as a lidar plot, conferring unique, locally detailed information. Lidar-plots can be used to support large-area mapping and monitoring activities as well as providing detailed information on forest structure over remote areas in a systematic fashion to support research activities.

Næsset et al. (2004a) summarized a number of different research trials in which ALS had been used to inventory forests over large areas, particularly if the forest was dominated by coniferous species. In these studies, wall-to-wall lidar coverage was acquired and a two-step process was followed: first, a sample of field plots was used to develop empirical relationships between the lidar data and biophysical variables measured in the field; second, the developed relationships were used to predict stand-level attributes for all forest stands in the area of interest. When estimating stand-level attributes, the studies cited by Næsset et al. (2004) indicate that variability in topographic and laser sampling density has limited impact on variable estimation results, and that the lidar data produced estimates with an acceptable level of bias, and with a level of precision that was higher for most of the stand-level attributes than those obtained by traditional inventory methods.

Recently, the use of scanning lidars as sampling tools has drawn the attention of researchers. Asner et al. (2010) describe a procedure wherein they develop regressions to predict biomass and carbon by overflying recently measured ground plots on a 43,000 $km^2$ area in Peru. The authors then spatially extend those ground observations by acquiring a sample of linear flight transects across their area of interest (AOI), developing a wall-to-wall map of the area using ancillary optical data, and then attributing the land cover types identified with the optical data with biomass estimates wherever their lidar transects intersect land cover polygons.

Andersen et al. (2009) used a design-based approach and sampled the western Kenai Peninsula south of Anchorage, Alaska, incorporating both lidar and all Forest Inventory and Analysis (FIA) plots in the area. They found that the variance of the estimate of biomass for the Kenai obtained using the lidar and the design-based approach was larger than the variance of the estimate based on the entire sample grid of FIA ground plots alone. The somewhat higher estimated error for the two-stage design may be due to the fact that the sample was assumed to be random while it truly was a systematic sample in both stages (ground plots and ALS strips).

Gobakken et al. (in press) systematically collected 53 parallel ALS flight lines 6 km apart to inventory Hedmark County, Norway. They overflew national forest inventory ground plots systematically spaced along these flight lines, developed biomass models, and used these models to estimate biomass on eight land cover strata mapped using optical and DTM data. They employed both a design-based and a model-based approach. Employing a model-based approach, their estimates of aboveground dry biomass ($40.8 \pm 1.2$ Mg $ha^{-1}$, 1 SE) were within 8.5% of the ground-based national forest inventory ($37.6 \pm 0.9$ Mg $ha^{-1}$). Estimates of biomass based on the design-based approach ($36.7 \pm 1.2$ Mg $ha^{-1}$) were within 2.4% of the county-wide ground estimates. Research towards the use of lidar as both a stand-alone sampling tool (e.g., Næsset et al., 2009), and as a source of calibration/validation data to augment mapping initiatives that use other remotely sensed data (e.g., radar; Solberg et al., 2010), is currently underway in many countries. The incorporation of these data into new or existing monitoring programs promises to improve our capacity to generate information on a variety of biophysical variables in a manner that is not only economically viable, but also accurate and spatially explicit.

Parker and Evans (2007) present an interesting alternative to all of the research reported above by utilizing only that ALS data immediately adjacent to existing ground plots. They compared the precision of a lidar and ground double-sample inventory to a strictly ground-based inventory of 23 age classes of southern pine in Louisiana. They allocated nine airborne lidar plots to each ground plot, with one of the nine coincident with the ground plot to facilitate development of regressions to predict basal area and volume and to serve as a correction term in the calculation of the mean per-hectare estimates. They concluded that, although the inclusion of the ALS plots reduced overall sampling error from 2.7% to 2.2%, "…there was not much statistical gain for the additional expense of the lidar data." However, significant statistical gains were noted when smaller numbers of ground plots per stratum were considered both in ground-only and ground-lidar surveys. This research suggests that lidar acquisitions specifically targeted at existing ground plots, as opposed to approaches which handle long, continuous flight lines, may result in variance reductions while also reducing data acquisition and data post-processing costs. For instance, could the precision and accuracy of USFS-FIA county-level estimates be greatly improved by acquiring ALS observations on and around the FIA plots? More work is needed to answer this type of question.

New Zealand is one of the first jurisdictions to use lidar sampling in an operational context, having developed a plot-based forest carbon inventory system that relies on the use of ALS. By means of circular plots that are 0.06 ha in size located on a systematic 4 km grid, lidar measures are used to estimate carbon stock exchange for the first commitment period of the Kyoto Protocol (Beets et al., 2010; Stephens et al., 2012). Hilker et al. (2008) demonstrated the feasibility of employing lidar transects and high spatial resolution optical data to update a forest inventory. At a 400 ha study site on Vancouver Island, British Columbia, Canada, Hilker et al. (2008) demonstrated the feasibility of employing lidar transects and high spatial resolution optical data to update a forest inventory. No significant difference ($r = 0.89$, $p < 0.001$) was found between lidar-derived stand heights obtained from a complete lidar coverage and stand heights obtained from a single 400 m wide transect of lidar. The authors conclude that further investigation in different stand conditions with different forest types is required in order to validate these results.

Moffiet et al. (2010) and Armston et al. (2009) describe the use of ALS data in a sample-based approach to validating Landsat-based vegetation indices using sampled field plots and lidar transects in Queensland, Australia. ALS data were collected along 19 transects where each transect was between 10 and 20 km long and approximately 300 m wide. Limited by vehicle access to field sites, the transects were not randomly established; the acquisitions were, however, stratified to capture the range of dominant structural formations and vegetation communities found in the state (Armston et al., 2009). For example, using field measured stand basal area as calibration data, the authors developed a variety of state-wide, Landsat-derived models based on parametric and machine learning algorithms to predict overstorey foliage projective cover (FPC). Independent FPC estimates were then derived using field and lidar data to compare the accuracy and precision of the various models. Armston et al. (2009) highlighted the fact that employing lidar as a large area sampling tool was not only cost-effective strategy, but also avoided the need to rely solely on field-based allometric estimates of FPC.

Andersen et al. (2011) used a model-based approach and a combination of 27 systematic lidar transects spaced 2.5 km apart and 79 co-located ground plots to estimate total aboveground tree biomass over a 201,226 ha area in the Tanana Valley, Alaska. Biomass was estimated with a relative standard error of 8%, with 4.6% of this error attributed to the sample design (i.e., transects of lidar versus wall-to-wall coverage), and the remaining 3.4% of error attributed to model selection.

### *3.3. Airborne full waveform recording lidar*

Large area forest characterization is limited by the availability of large-footprint waveform instruments, as currently only LVIS is operational, and as an experimental system developed and operated by NASA, LVIS has limited availability to the scientific community at large. As a result, literature describing applications of waveform lidar for large area sampling and monitoring is limited. Studies are generally conducted on a small number of plots in relatively small study areas; however, some attempts have been made to determine the portability of biophysical parameters and metrics derived from large-footprint waveform lidar over different ecological regions or biomes. Lefsky et al. (2002) established a model from SLICER measurements that explained 84% of the variance in above-ground biomass in three different biomes, specifically: boreal coniferous, temperate coniferous, and temperate deciduous forest. These results indicate that a single equation can describe the relationship between biomass and lidar measurements in distinctly different forest communities. Anderson et al. (2006) tested the model developed by Lefsky et al. (2002) with SLICER measurements from a northern temperate mixed forest, finding that only 55% of the variance in above-ground biomass was explained (RMSE = 28.0%). However, the results obtained with the model developed by Lefsky et al. (2002) were only slightly weaker than those obtained with the most accurate single-term model (Anderson et al., 2006). Drake et al. (2003) conducted similar research with LVIS in tropical wet ($R^2 = 0.89$ and RMSE = 22.54 Mg/ha) and tropical moist forest ($R^2 = 0.82$ and RMSE = 39.10) sites in Costa Rica and Panama.

Only a few studies have used waveform lidar for forest characterization (e.g., Höfle et al., 2008; Reitberger et al., 2008). The waveform signal in small footprint lidar is typically decomposed into discrete x, y, and z points. These points are used in a similar manner as discrete return small-footprint data. The main advantages of waveform decomposition over the use of discrete return data are the increase in the number of echoes for each pulse (Persson et al., 2005; Reitberger et al., 2008) and knowledge of the algorithms used to extract the echoes (recall that commercial discrete return systems use proprietary echo trigger mechanisms that are not known to the scientific community). Wagner et al. (2004) tested different standard detection methods likely being used in the currently available lidar discrete-return sensors and found that different detection algorithms would provide different point clouds, with range values varying by ~0.4 m for a 1 m footprint. Therefore, decomposing the waveform data may allow for some control over the trigger mechanism "error" that is inherent in discrete return data, which may be particularly relevant for large area monitoring applications, where multiple (different) sensors may be necessary to complete a survey in a timely manner.

### 3.4. Spaceborne lidar

The Geoscience Laser Altimeter System (GLAS) was a large-footprint spaceborne full waveform profiling lidar carried on the Ice, Cloud, and land Elevation Satellite (ICESat). GLAS was the first spaceborne lidar and the global measurement of canopy height was one of the science objectives of the ICESat mission (Zwally et al., 2002). The size and shape of the GLAS footprints vary from 50 to 65 m in diameter and from elliptical to circular, depending on the date of the acquisition (Abshire et al., 2005). The pulses are spaced approximately 172 m apart (Schutz et al., 2005).

Forest canopy metrics can be generated from the GLAS waveforms (Duncanson et al., 2010; Lefsky, 2010; Lefsky et al., 2007; Rosette et al., 2008; Xing et al., 2010) and these metrics can, in turn, be used to generate estimates of aboveground biomass (Baccini et al., 2008; Boudreau et al., 2008; Helmer et al., 2009; Lefsky et al., 2005) and carbon (Nelson, 2010). Several recent studies have used GLAS data in a sample-based approach to generate large-area estimates of biomass (Boudreau et al., 2008; Nelson et al., 2009a) and volume (Nelson et al., 2009b).

Slopes are known to broaden the waveform response of large footprint sensors (Nelson, 2010) and convolve the forest-canopy structure with the underlying topography, thereby reducing the accuracy of forest height estimates (Lefsky et al., 2005, 2007; Nelson et al., 2009b; Rosette et al., 2008). To mitigate this problem, researchers have limited their analyses to areas with <10° slope (Nelson, 2010) or have used Shuttle Radar Topography Mission (SRTM) data to correct for the broadening effect (Lefsky et al., 2007). In October 2008, the final laser on ICESat-I failed, limiting the utility of GLAS data for vegetation assessment to those data acquired between 2003 and 2008 (Lee et al., 2011; Nelson, 2010).

Boudreau et al. (2008) and Nelson et al. (2009a) report on a design-based, two-phase approach to estimate forest volume, biomass, and carbon in Quebec, Canada, an area of 1.27 million km$^2$, using GLAS waveforms, an airborne profiling lidar, and ground plots measured by the Ministry of Natural Resources, Quebec. Regression equations were developed to estimate ground-measured biomass as a function of airborne profiling metrics. The profiler was then flown along GLAS orbital transects and used to estimate biomass on individual GLAS pulses. A second model was then formulated that predicted biomass as a function of GLAS measurements. Thus, GLAS becomes the regional/sub-continental sampling tool used to estimate forest biomass on land cover strata that tessellate the province of Quebec. Results indicated that GLAS estimates of volume and biomass were within 10% of ground-based estimates when compared in the southern half of the province.

Nelson et al. (2009b) employed a two-phase sampling design in Siberia where 51 GLAS shots were sampled on the ground to accumulate the ground-satellite observations needed to develop a GLAS-based equation to predict timber volume. Though the ground sample was extremely sparse, regional volume estimates on the 811,400 km$^2$ area were within 1.1% of an independent, ground-based study. All three studies discussed in this paragraph included covariance terms in the error estimators to account for the fact that samples in adjacent and near-adjacent cover types acquired along linear transects (orbits) were not independently selected. But as Nelson et al. (2009a) suggests, this may not be an optimal solution. The authors infrequently encountered situations where a negative covariance term overwhelmed the between-orbit variance component, driving the overall variance term negative. These findings pointed to a need for the development of new variance estimators and/or new airborne lidar sampling procedures that pay more strict attention to assumptions underlying the acquisition of the ground and airborne lidar data sets.

Full waveform instruments such as GLAS (and LVIS and SLICER) must use high pulse energies in order to penetrate dense canopy and detect the ground surface. As a result of the high pulse energies, the pulse rate must be low, which limits the spatial sampling and resolution of these instruments. Furthermore, the width of the pulse "acts as a low pass filter, thereby smoothing the waveform and limiting the vertical resolution of the canopy features. This also broadens the return from the ground, and reduces its amplitude thus making its detection more difficult" (Harding et al., 2011). Slope Imaging Multi-polarization Photon-counting Lidar (SIMPL) is a high repetition rate, low pulse energy, single photon laser ranging instrument, designed as a test instrument to inform future spaceborne laser altimeters. Through combining high vertical and spatial resolution, it is believed that photon-counting systems can overcome the limitations of full waveform low detector sensitivity and restricted vertical and spatial resolution. However, initial investigations using photon counting lidars with two different wavelengths and two different polarization rates to measure canopy structure have found no significant differences in height distributions arising from these different parameters (Harding et al., 2011).

In terms of future spaceborne lidar missions, ICESat-II, a follow on to ICESat-I that will have a 10 kHz, 532 nm micropulse photon counting laser altimeter, is scheduled to launch in 2016–2018 (Nelson, 2010). Another system that was under development – Deformation, Ecosystem Structure, and Dynamics of Ice (DESDynI) – was postponed indefinitely in February 2011, much to the disappointment of the scientific community (Goetz, 2011).

## 4. Sample design

Selection of an appropriate sample design will depend on the information needs of a particular application, available resources, statistical considerations, and the type of lidar data to be collected. Due to the myriad of sample design options available, the desired level of precision, and the specific circumstances of any given application and/or study area, the input of a statistician to aid in the determination of sample design, sample size,, and statistical power is recommended (Curran-Everett & Benos, 2004; Hudak et al., 2002).

In the context of lidar, sample design is somewhat limited by the nature of the platform on which the instrument is mounted (i.e., aircraft or satellite) and as a result, is always linear. While orbits of spacecraft are somewhat fixed, lidar transects acquired from aircraft may be collected as simple random, systematic, stratified, or clustered samples. In Fig. 2, we present a selection of common transect-based survey options. In a multi-stage design, the flight line is often used as the primary sampling unit, while some sub-unit of the flight line, either defined by a regularized grid for scanner data (Næsset et al., 2009), by equal-length units for profiling, or by some other means, is used as the secondary sampling unit (Gregoire et al., 2011).

Nelson et al. (2003a), describing the use of profiling lidar as a sampling tool for regional forest inventory, include a discussion on sampling intensity that is equally relevant to ALS surveys. For a given forest type, an optimal sampling intensity will be a function of that forest type's spatial extent, spatial distribution, and within-type variability. First, the more ubiquitous the forest type is within an area of interest, the more likely transects are to intercept it. Second, the more randomly arranged the forest type is, the more likely it is to be intercepted by systematic transects. Finally, the smaller the variability of biophysical variables of interest (e.g., height, biomass) the fewer the number of times a forest type must be intercepted to be adequately characterized.

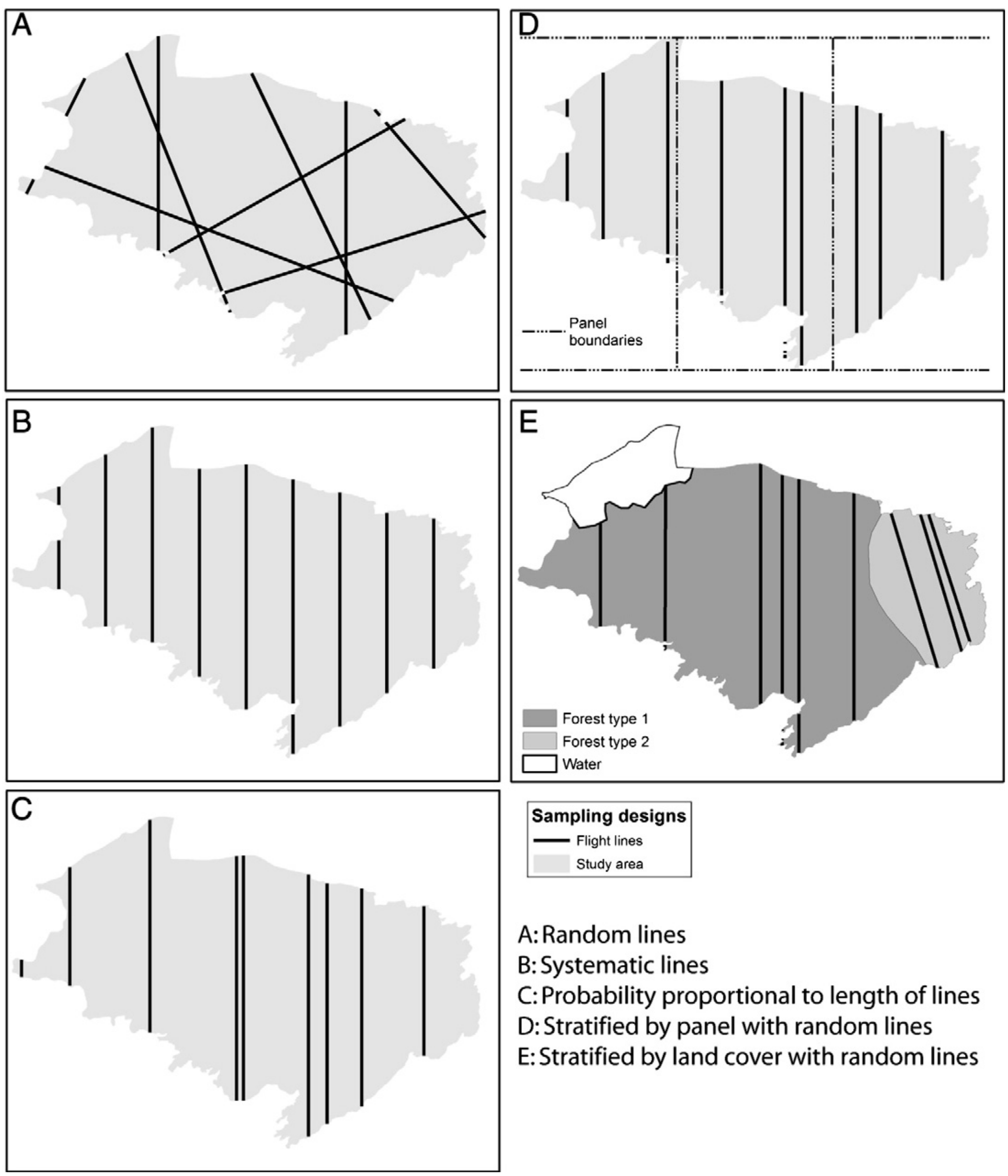


**Fig. 2.** Lidar sample survey design and implementation considerations. For a given population (gray), transects may be selected: A) randomly, B) systematically, C) with probability proportional to size or length (e.g., where the study area is irregular in shape, the probability of selecting a line is proportional to its length); Stratification strategies may also be based upon D) panels, whereby transects are spatially constrained and randomized by panel, or E) using land cover to guide the transect layout to maximize capture of the attribute (e.g., forest) of interest. Combinations of the above scenarios are also possible. Further, the yield of data along the transects may also be modulated, as the spatial autocorrelation of measures precludes the need for the use of all measures.

Næsset et al. (2009) reports on the motivation behind the Hedmark County, Norway study (previously discussed in Sections 3.1 and 3.2), an investigation which ultimately resulted in the development of two laser-based sampling designs described by Gregoire et al. (2011) and Ståhl et al. (2011). The two approaches are similar in that they both incorporate ground plot data and airborne profiling or ALS transect samples, but they differ markedly with respect to requirements placed on the attributes of the ground data set and how these ground data are used in conjunction with the airborne lidar data for inference. As mentioned previously, both ALS and profiling data were acquired for this project to augment a systematic sample of National Forest Inventory (NFI) ground plots. Parallel flight lines were flown along the grid of systematically distributed NFI field plots. The area was stratified into eight cover classes and independent regression models were developed to predict above-ground dry biomass (Gobakken et al., in press; Gregoire et al., 2011; Nelson et al., in press; Ståhl et al., 2011).

Ståhl et al. (2011) take a model-based approach, which has an underlying assumption that the model(s) developed to predict biomass as a function of lidar data are correct, that is, the model(s) does not deviate from the true but unknown model(s) for the AOI. An assumption is made that the ground plots overflown by the airborne lidar that are used to train the predictive models represent the full range of conditions expected on the AOI. These ground plots can be selected in any manner deemed appropriate (including purposeful selection) as long as the resultant models are believed to be close to the true models for the study area. In the same study area, Gregoire et al. (2011) reports on a design-based approach, which requires that the ground plots be allocated across the landscape as a probability sample (e.g., a county, state, provincial, or national forest inventory). In this approach, the models used to predict biomass are not assumed to be identical to the true models, rather the ground plot estimates are used to correct coincident lidar predictions in order to adjust stratum-level estimates. In fact, any model can be used — it need not even be developed within the AOI, but the magnitude of the error will depend on the deviation between biomass predicted for the plots with the applied model and the ground-based biomass estimate.

In the Hedmark ALS work reported by Gobakken et al. (in press) and the Hedmark profiling work reported by Nelson et al. (in press), the model-based design provided more statistically robust estimates of land cover means and variances. The estimates based on the design-based approach were more unstable, a characteristic that was exacerbated as the AOI decreased in areal extent. The instability of the design-based approach manifests itself in the form of occasionally negative cover class variances and, rarely, negative mean estimates of biomass. The negative estimates arise because the design-based approach requires ground plot sample sizes large enough to calculate realistic correction terms to adjust laser estimates to ground. When sample sizes, within a flight line for a given stratum, fall below a certain threshold, the correction term can fluctuate markedly. The size of that threshold varies, with Thompson (2002, pg. 159) suggesting that stratum/flight line sample sizes should be $\geq 5$ and Särndal et al. (1992, pg. 407) suggesting that they should be $\geq 10$. These fluctuations greatly increase within-flight line variances and can overwhelm the mean estimates of biomass, resulting in the negative estimates noted above.

Research conducted by Ene et al. (under revision) with a Hedmark County Monte Carlo simulator has shown that Gregoire et al. (2011), Gobakken et al. (in press), and Ståhl et al. (2011) for this particular study area may have reported biomass standard errors $>4$ times larger than what would have been the case had flight lines been randomly instead of systematically allocated. We hypothesize that, given a systematic lidar acquisition, one way to mitigate this inflationary effect is to actually treat a systematic sample as a true systematic sample instead of assuming a random allocation. For this purpose Nelson et al. (2008) proposed using the so-called Newton's Method estimator (NM) and a Successive Differences estimator (SD). Simulation studies with these estimators suggest that for Hedmark County the mentioned estimators may produce standard error estimates quite close to the true errors (Ene et al., under revision).

## 5. Theoretical and statistical considerations and recommendations

Sampling theory and practical experience suggest that a number of factors should be considered when selecting an appropriate sampling design and variance estimator for an airborne- or space-based lidar survey. Based on the collective experience of the authors, the following considerations and recommendations are made. They are not intended to be prescriptive, as circumstances (i.e., information needs of a particular application, available resources, statistical considerations, and the type of lidar data to be collected) will vary.

(1) Individual flight lines or, in the case of satellite lidar acquisitions, orbital transects, should be considered as a basic sampling construct or unit of observation. This approach overcomes two significant problems: (a) it obviates the need to consider and account for within-flight-line spatial autocorrelation among adjacent and nearby lidar pulse returns (Nelson et al., 2009a, 2009b); (b) it recognizes the fact that a flight line or orbital transect is a cluster sample, that is, an observation with an inclusion probability assigned to the flight line (Ståhl et al., 2011).

(2) If the study area is stratified, then the sampling unit becomes a stratum within the flight line. If a flight line does not intercept a given stratum, then the lidar-based estimate of, for instance, biomass for that stratum in that flight line, is zero. In other words, for a given flight line, a non-intercepted stratum should be treated as an estimate of zero biomass; it should not be treated as "no information", nor should the flight line be dropped from consideration with respect to the calculation of stratum estimates of means, totals, or variance (Gregoire et al., 2011).

(3) Flight lines may be spatially autocorrelated, especially in situations where ecotones are sampled and the flight lines run perpendicular to the regional gradient. With respect to spaceborne lidars, e.g., ICESat/GLAS and the upcoming ICESat-II launch, adjacent and near-adjacent orbital tracks may be spatially autocorrelated. Given the near-polar orbits of the ICESat platforms, the likelihood of autocorrelated orbital observations will increase as latitude increases and as the distance between orbits decreases as a function of the cosine of the latitude (Nelson et al., 2009b).

(4) Systematic flight lines are, in general, logistically easier to plan and cheaper to fly, so some consideration must be given to limitations imposed by acquisition of systematic samples. It is a common practice to treat a systematic sample as a random sample, however, in some situations, this practice can result in inflated variance estimates relative to the variance that would have been calculated had the sample been acquired randomly (Gregoire et al., 2011). If a regional gradient exists and if it is desirable to collect systematic flight lines and process these data assuming that they were randomly sampled, then flight lines should be run across the gradient. For instance, if you have a marked biomass gradient south to north, where forests are large in the south and small/nonexistent in the north, run the lines north–south. The aim should be to capture as much biomass variation as possible within a given flight line so as to decrease between-flight line variability.

(5) The potential for variance inflation associated with the treatment of a systematic sample as random (see (4) directly above) can be mitigated by considering alternative variance estimators. Work by Nelson et al. (2008) (profiling lidar in Delaware, USA) and Ene et al. (under revision) (scanning lidar in Hedmark County,

Norway) suggested that the NM and SD estimators, which accumulate squared differences between adjacent flight lines rather than between individual flight lines and the mean, tend to mitigate the inflationary characteristics of the variance estimator employed for simple random sampling (Ståhl et al., 2011).

(6) Given the current uncertainty associated with the location of profiling lidar flight lines, ALS swaths, and satellite orbits, most laser sample data should be treated as a post-stratified sample. The uncertainty considered here does not have to do with pointing knowledge. The locations of ALS pulses, for instance, are typically known to within decimeters of the location actually illuminated by a given pulse. The uncertainty associated with airborne acquisitions therefore stems from the lack of prior knowledge of exactly where the aircraft will fly and where the profiling line or ALS scan will track as the aircraft attitude and altitude above terrain changes. As an example, the uncertainty associated with a satellite acquisition has to do with the lack of prior knowledge of exactly where a particular GLAS orbit will track on the Earth's surface. Sequential orbits can wander up to a kilometer off the nominal orbital track (Nelson et al., 2009b). Stratum identifiers, then, must be assigned to lidar observations after the acquisition and after the actual positions of the flight lines (or orbits) are known (Ståhl et al., 2011).

(7) An appreciable amount of work has been done exercising design-based approaches, and the trends so far indicate that this type of approach (Section 7.1) must be employed in a ground-data rich environment and (Section 7.2) should be used only in situations where adequate sample sizes within stratum within flight line can be maintained. The ground plots must be distributed across the landscape as a probability sample where an inclusion probability can be assigned to each ground plot intercepted by the lidar (Gregoire et al., 2011; Ståhl et al., 2011).

Over the past decade, notable progress has been made with respect to developing sampling designs and variance estimators that more truly represent the actual error associated with a lidar sample; however, other error sources exist that have not been characterized and incorporated into variance estimators. Nelson et al. (2004, pg 508) list these error sources, one of which, ground-laser regression error, has already been addressed implicitly in the design-based, two-phase approaches taken by Parker and Evans (2004), Andersen et al. (2009), and Gregoire et al. (2011) and explicitly in the model-based approach taken by Ståhl et al. (2011).

The impact of system characteristics on sampling and estimation is difficult to quantify, particularly because some of the characteristics, such as platform altitude, lidar point spacing, and footprint size, are interdependent (Disney et al., 2010; Næsset, 2009a). Furthermore, many of these characteristics are also influenced by canopy structure (Hopkinson, 2007). There is some uncertainty associated with the impact of footprint size on height estimation. While some studies have reported an increase in height with increasing footprint size (Goodwin et al., 2006; Hyyppä et al., 2009), other studies have reported a decrease in height with increasing footprint size (e.g., Hopkinson, 2007).

Assessing the validity of inference is not straightforward when complex designs are involved. A possible approach would be using a sampling simulator where an artificial population represents the 'ground truth' and the properties of the estimators are investigated using simulated sampling. As mentioned previously, Ene et al. (under revision) created an artificial population based on a large multivariate dataset containing field observations and ALS metrics taken from Hedmark County, Norway. The aim was to create an artificial population that at least mimicked the main geographical trends of Hedmark County, which was the target area in the studies by Gobakken et al. (in press), Gregoire et al. (2011), Nelson et al. (in press), and Ståhl et al. (2011). A copula function was fitted to the empirical observations, and then it was generalized over the study area using satellite imagery and nearest-neighbor imputations. The properties of several design-based and model-based variance estimators—among them are those derived by Gregoire et al. (2011) and Ståhl et al. (2011), were investigated using simulated sampling and the accuracy of ALS-based and ground-based estimates was compared. The main results indicated that the ALS-based survey produced valid inference under both the design-based and model-based frameworks. The variance estimators performed well under simple random sampling without replacement, but they overestimated true standard errors by a factor of 4 under systematic sampling. Of note, the true precision of ALS estimation was approximately 2.4 times better in terms of standard error compared to that of the field survey.

The most obvious error source not yet considered or incorporated into the variance estimators deals with ground allometry. In order to estimate aboveground biomass and carbon, laser metrics must be tied, via parametric or nonparametric methods, to these ground measurements of interest. Short of destructive sampling, these ground measurements are themselves estimates derived from ground-measurements of tree diameter at breast height (dbh) and perhaps, tree height. There are, then, errors associated with the use of these ground models that should be incorporated into the final estimate of the error of a lidar-based sample mean or total. This allometric error can be appreciable, especially in situations (such as in large-area implementations) where national-level equations are used to derive the ground measurements used in a regional, national, or (sub-) continental survey (Van Breugel et al., 2011). The magnitude of this error is illustrated for the USA in Figs. 2 and 3 of Jenkins et al. (2003) and for Canada in Lambert et al. (2005), Figs. 4 and 5.

Finally, additional work is needed to incorporate model error associated with three-stage or three-phase lidar sampling, analogous to the design-based, two-stage work of Gregoire et al. (2011) and model-based two-phase work reported by Ståhl et al. (2011). The challenge here is to include error due to the use of two regression models in those situations where ground measurements are related to airborne lidar observations and then airborne estimates of, for instance, biomass, are subsequently modeled as a function of satellite observations. Attempts have been made to deduce such a variance estimator from first principles, but the problem may well be intractable. One alternative may be to use bootstrapping techniques to develop empirical estimates of means and/or totals to determine how they vary with repeated sampling.

## 6. Estimation

Thompson (2002) suggests that design-based inference is advantageous for obtaining unbiased estimators that are acceptable to a wide-range of users and for avoiding bias in sample selection. Model-based inference, on the other hand, is useful for assessing the efficiency of both sampling designs and estimators under different assumptions concerning the population, deriving estimators that make the most efficient use of sample and auxiliary data, and managing sample data collected in the absence of a proper sampling design.

Nelson et al. (2009a) use a sampling framework that combines certain aspects of design-based and model-based inference, but suggest that a purely model-based framework that uses mixed models with random effects to account for interactions between pulses (GLAS), segments (airborne profiling lidar) or plots (airborne scanning lidar), and fixed effects to account for differences in cover-type, would be preferable for regional, lidar-based inventories. As per Nelson et al. (2008), the authors compared three variance estimators (simple random sample, successive differences, and Newton's method) to test for stability of estimates in the absence of truth.

Næsset (2002) applied a double sampling approach with a leave-one-out cross validation procedure to assess the predictive value of developed models. Estimated attributes included mean tree height, dominant height, mean diameter, stem number, basal area, and timber volume. The majority of stand-level predictions were unbiased ($p > 0.05$). Parker and Evans (2004) make the case for a double-sample design using ALS and traditional ground sampling methods, indicating that the strength of lidar lies in the precision with which lidar can produce reliable estimates of stem density and tree height. By using ground samples in a double-sampling approach, biases in lidar heights (and subsequently biases in volume or basal area) are adjusted by the regression estimator in a double-sample model, negating the need to define the nature or direction of the bias.

The implications of ground plot size in a double-sampling context have also been investigated (see Frazer et al., 2011; Gobakken & Næsset, 2008). In general, smaller plots are impacted more by geolocation error and edge-effects. A small plot moved slightly, based upon differing position information, will relate with a unique set of lidar returns. Small plots also have more opportunity for a greater proportion of trees (relative to larger plots) to be only partially within the plot. Partial crowns incorporated in the lidar that are not measured on the ground will also impact regression model development. Using a simulated lidar data set, Frazer et al. (2011) demonstrate the impacts of geolocation and plot size upon equation development, with biomass as the example attribute of interest. Key findings indicated that larger plots (25 m versus 10 m) provided improved biomass prediction accuracy, and that larger plots were found to maintain a higher degree of spatial overlap over a range of GPS error simulations.

## 7. Implementation: considerations and recommendations

### 7.1. Ground data for calibration

One of the challenges for large-area forest characterization with lidar is the need for the simultaneous acquisition of a large number of ground sample plots that can be used for model development; however, accessibility and cost often preclude the collection of extensive ground samples, particularly for large areas. Junttila et al. (2010) present an approach whereby ground plots collected in association with previous lidar surveys in different, but similar forests, may be used in the development of Bayesian models. The approach presented by Junttila et al. (2010) addresses two problems: how to reconcile differences between diverse lidar instruments that have acquired data under varying conditions, and how to avoid bias in the estimation of forest stand parameters. Although the approach presented by Junttila et al. (2010) is promising, it perpetuates reliance on the availability of ground data for model calibration and validation. In some remote and inaccessible forest areas, the collection of ground data is not possible, and even in managed forest areas, the acquisition of ground data may be precluded by time or cost constraints.

Additionally, the capacity of an aircraft pilot to remain on a pre-specified flight line can be difficult for long transects as well, with fatigue and atmospheric conditions (especially wind and avoidance of smoke) chief among the considerations. Newer generation lidar instruments offer the potential to acquire wider swaths while maintaining scan angles suitable for forest applications (±15°). Wider swaths offer a greater opportunity to intersect with ground plots and to concurrently enable larger plots (as recommended by Gobakken and Næsset, 2008 and Frazer et al., 2011) or cluster plot configurations (that are often collected in support of National Forest Inventories). The ability to fly a single transect once to intersect with a given ground plot configuration will mitigate costs, as an instrument with a narrow swath may require two overpasses to capture, or ensure capture, of ground plots. Not only are flying costs mitigated by the single overpass enabling plot intersection, but data processing is also reduced, with no need to incorporate points from multiple flight lines.

Another related issue has to do with the use of allometric equations (developed from ground measures) for predicting certain attributes such as volume and biomass. The lidar are used to predict heights, which are then input to allometric equations to predict volume and biomass. Not only will the lidar predicted heights have an error associated with them, but also the allometric equations will have an associated error as well. Van Breugel et al. (2011) considered the impact of uncertainties associated with allometric biomass equations, concluding that "local models may provide more accurate AGB estimates than foreign models, but because carbon stocks are highly variable across rural landscapes, developing local models is only justified when landscape [ground] sampling is sufficiently intensive." Hence, large-area studies may be forced to use generic or national allometric equations, which may have greater uncertainty associated with them. Further research is required to determine the impact of large-area implementations of these allometric equations.

### 7.2. Data integration

It is important to acknowledge that not all applications involving large areas can be satisfied with a sample-based statistical characterization of forest vertical structure. For example, certain applications, such as carbon flux modeling, require spatially explicit wall-to-wall mapping of vertical structure at a spatial resolution of less than one hectare (Hurtt et al., 2010). However, given the current costs associated with lidar acquisition and processing, it is unlikely (at least in the short-term), or atypical, that lidar data would be used to provide such a wall-to-wall product. Rather, an optical remotely sensed data source with an appropriate spatial resolution, such as Landsat, or some other modeling approach, could be used to model forest vertical structure, with samples of lidar providing critical calibration and validation data for the model (Gonzalez et al., 2010; Helmer et al., 2010; Hudak et al., 2002).

Previous studies have demonstrated that sample-based scanning lidar data may be used to extend estimates of biophysical variables to larger areas using synoptic optical imagery or radar. Furthermore, the incorporation of additional data sources, such as optical remotely sensed data, may improve the accuracy and reduce the bias of lidar-based estimates. For example, Ørka et al. (2010b) demonstrate how the inclusion of ancillary data can improve the robustness of lidar-based estimates and enable large-area coverage. Using a combination of a sample of ALS transects, which covered approximately 8% of the study area, as well as Landsat (NDVI and tasseled cap transformation (TCT) brightness and wetness), and DEM (elevation and slope) data, both of which covered the entire study area, the area of the boreal-alpine transition zone was delineated. Lidar plots were generated from the ALS transects, with the same size as the Landsat image pixel, spaced every 3 km along the transect. The canopy cover proportion was computed from the ALS data and was input, along with the Landsat and DEM derivatives, into a random forest, non-parametric classifier (Breiman, 2001). The lidar plots were assigned to one of three classes: boreal, alpine, or transition zone; the wall-to-wall coverage of the Landsat and DEM allowed the classification to be extended across the study area as a whole. The lidar classification was validated with ground data; however, no ground data were used for calibration or in the development of the model. Such an approach is particularly necessary in those remote forest areas that are not included in the national forest inventory or in any other national monitoring systems (Næsset et al., 2009).

Goetz et al. (2010) used GLAS data, combined with MODIS and Landsat data, to assess post-fire disturbance and recovery in Alaska. In their study, MODIS reflectance data was used to generate strata of different vegetation cover types and densities, while burn severity maps, generated from Landsat data, were used to further stratify the lidar measures. Dolan et al. (2009) used GLAS data, combined with Landsat-based disturbance history maps to assess forest regeneration rates in three regions of the eastern United States, concluding that spaceborne large footprint lidar data can be used to measure vertical growth rates when averaged spatially. Lefsky (2010) used MODIS and GLAS data to generate a map of global forest canopy height. The MODIS data were used to generate forest patches and the 90th percentile patch height was calculated directly from the GLAS data when the GLAS transect intersected a patch. For those forest patches without any corresponding GLAS observations, regression analysis was used. The 90th percentile patch height was estimated with a mean $R^2$ of 0.67 and a mean RMSE of 5.9 m. Baccini et al. (2008) generated above-ground biomass estimates of tropical Africa from MODIS data using GLAS height metrics (average height and height of median energy or HOME metrics). They note that "… there are currently limited high quality field biomass estimates available at sufficient spatial extent to develop and independently validate maps of AGB across tropical regions …" and that alternate data sources, such as lidar, may be required to enable the extension of estimates across larger areas. Helmer et al. (2009) estimated a landscape-level rate of aboveground woody biomass accumulation in secondary humid lowland tropical forests in Amazonia by combining a dense time series of Landsat imagery to estimate forest age combined with biomass estimates generated from GLAS.

Simard et al. (2006) employed C-band data collected by the Shuttle Radar Topography Mission (SRTM) to map tree height and biomass in the Everglades National Park (ENP), located in Florida, USA. The SRTM data were calibrated using a high resolution DEM developed by the United States Geological Survey (USGS), sampled lidar data, and field data. A 30 by 30 m mean filter was applied to the lidar data, which consisted of four 360 m-wide transects, to conform to the spatial resolution of the SRTM data. First, the SRTM ground elevation estimates were leveled using the USGS DEM. The raw SRTM vegetation height estimates, which correspond to the interferometric phase center located within the canopy, were then calibrated to top of canopy estimates using the lidar data and a quadratic regression model. The result was a 30 m spatial resolution map of mean tree height with an RMSE of 2.0 m. Finally, field data were used to derive a relationship between mean height and biomass. Simard et al. (2006) then applied this equation directly to the SRTM/lidar-derived mean tree height estimates to map the spatial distribution of mangrove biomass across the ENP. Through provision of large-area image coverage of forest structural information SAR and InSAR data are a natural match for integration with lidar data. Radar data will typically provide a more generalized, mid-canopy response, with lidar offering a complementary data source to calibrate and refine the SAR or InSAR measures. Additional data integration examples for lidar and SAR can be found in Solberg et al. (2010), Breidenbach et al. (2008), and Hyde et al. (2006). It is through the integration of optical and samples of lidar data, based upon the above findings, that measures in support of REDD+ programs may be generated.

### 7.3. Repeat pass

To determine the capacity of lidar in a monitoring capacity, Bater et al. (2011) evaluated data flown over the same forest stands four times during the same day. A transect was provided to a commercial data provider with the goal of flying the same line, allowing for invariant stand conditions to be captured enabling an exploration of resultant lidar data and derived metrics. Chief amongst the findings was the capacity to capture the same vertical structural characteristics with differing scan angles and hit densities. Flying the exact same transect proved difficult, as expected. The ability to take advantage of the overlap possible through the use of a scanning lidar system indicates a scientific and operational data collection and monitoring opportunity. Further, these results support those found using a large footprint waveform system by Wulder et al. (2008b).

## 8. Conclusions

The use of lidar instruments has become an operational data collection option for detailed forest characterizations. Various types of lidar systems have demonstrated a capacity to capture an increasingly broad range of vegetation characteristics in a consistent and transparent manner. While additional research can provide improvements, best practices are currently well communicated, enabling the application of lidar to address a range of operational and research information needs. Sample-based approaches are well established for large-area (including national) inventories utilizing ground plot data. The primary motivation for using lidar sampling is to emulate ground plots, acknowledging that some ground data is needed to calibrate the lidar measures. Regional and national monitoring programs can be informed using sample based applications of lidar in a statistically robust and reliable manner. Further, lidar measures can be combined with wall-to-wall image data source to capture change and enable the use of lidar as an integral component of a monitoring system. As demonstrated in this communication, transect-based applications of lidar can be used to represent in a timely and increasingly cost effective manner the forest conditions present over large regions. Alternately, lidar data can be treated as independent measures to generate estimates of forest attributes or to provide independent structural measures in scientific studies.

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