The role of LiDAR in sustainable forest management

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ABSTRACT

Forest characterization with light detection and ranging (LiDAR) data has recently garnered much scientific and operational attention. The number of forest inventory attributes that may be directly measured with LiDAR is limited; however, when considered within the context of all the measured and derived attributes required to complete a forest inventory, LiDAR can be a valuable tool in the inventory process. In this paper, we present the status of LiDAR remote sensing of forests, including issues related to instrumentation, data collection, data processing, costs, and attribute estimation. The information needs of sustainable forest management provide the context within which we consider future opportunities for LiDAR and automated data processing.

Key words: LiDAR, airborne laser altimetry, forest inventory, height, volume, biomass, update, remote sensing

RÉSUMÉ

La représentation des forêts à partir de données LiDAR (détection de la lumière et calcul de la distance) a attiré dernièrement beaucoup d'attention tant scientifique qu'opérationnelle. Le nombre de variables d'inventaire forestier qui peuvent être mesurées directement par LiDAR est limité, mais lorsqu'on considère le contexte de toutes les variables mesurées et dérivées requises pour compléter un inventaire forestier, le LiDAR peut constituer un outil précieux du processus d'inventaire. Nous présentons dans cet article un portrait de la télédétection des forêts par LiDAR, ainsi que les questions portant sur l'appareillage, la collecte des données, les coûts et l'estimation des variables. Les besoins d'information en matière d'aménagement forestier durable constituent le contexte que nous retenons pour les possibilités d'application future du LiDAR et du traitement automatisé des données.

Mots clés : LiDAR, altimétrie par laser aéroporté, inventaire forestier, hauteur, volume, biomasse, mise à jour, télédétection

Introduction

Forest inventories are designed to measure the extent, quantity, composition, and condition of forest resources (Kangas *et al.* 2006). In support of sustainable forest management, up-to-date forest inventories are required to assess the composition, structure, and distribution of forest vegetation that, in turn, can be used as base information for management decisions that span across a range of spatial and temporal scales. At the operational level, forest inventories are used for harvest planning, road layout, assessment of growing stock, and planning of silvicultural activities. At the strategic level, forest inventories provide data for long-term forest management plans and, in concert, support a multitude of decisions relevant to forest protection and wildlife management. In Canada, the production of a forest inventory follows a series of stages, culminating in the development of a digital spatial database that is stored, maintained, and manipulated in a Geographic Information System (GIS) (Leckie and Gillis 1995, Gillis 2001).

Extensive sustainable forest management practices prevail in Canada where there are over 400 million ha of forest and other wood land that are largely publicly owned and managed for multiple purposes (Siry *et al.* 2005, Wulder *et al.* 2007a). As a result, low-cost monitoring approaches are typically followed, such as those based upon air photo acquisition and interpretation, and augmented with a sparse network of field plot measurements (Gillis *et al.* 2005). In contrast, intensive forest management practices are more common in nations with a small landbase and less forest land, and where forests are primarily privately owned and managed for wood fibre production (Löfman and Kouki 2003, Mielikäinen and Hynynen 2003). As a consequence, while we examine light detection and ranging (LiDAR) applications from around the globe in this paper, our objective is to focus upon the implications of these applications in the extensive sustainable forest management context prevailing in Canada.

Air photo interpretation for forest inventory involves delineating the forest landbase into relatively homogenous units based on characteristics such as species, composition, age, disturbance, and stand structure (Leckie and Gillis 1995). These homogenous units are typically referred to as forest inventory polygons or forest stands. Stand height and crown closure are common descriptors of forest stands from which a number of other important forest attributes can be derived such as site index and stand volume. Forest inventories typically report a representative estimate of height for an entire forest stand that is often defined as the average height of dominant and co-dominant trees (Gillis and Leckie 1993).

To date, research and development activities have focused upon using LiDAR as a tool for characterizing vertical forest structure—primarily the estimation of tree and stand heights, with volume and biomass also of interest (Lim *et al.* 2003). With increasing availability of LiDAR data, forest managers

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have seen opportunities for using LiDAR to meet a wider range of forest inventory information needs (Nelson *et al.* 2003). For instance, height estimates generated from airborne remotely sensed LiDAR data were found to be of similar, or better accuracy than corresponding field-based estimates (Næsset and Økland 2002) and studies have demonstrated that the LiDAR measurement error for individual tree height (of a given species) is less than 1.0 m (Persson *et al.* 2002) and less than 0.5 m for plot-based estimates of maximum and mean canopy height with full canopy closure (Næsset 1997, Magnussen and Boudewyn 1998, Magnussen *et al.* 1999, Næsset 2002, Næsset and Økland 2002). Additional attributes, such as volume (Nilsson 1996), biomass (Popescu *et al.* 2003, 2004; Hyde *et al.* 2007), and crown closure (Holmgren *et al.* 2003), are also well characterized with LiDAR data (Means *et al.* 2000, Lim *et al.* 2003, Thomas *et al.* 2006). This paper presents a brief background into LiDAR data acquisition followed by the application of LiDAR for estimation of forest attributes. This application focus will be placed within the context of information needs to support sustainable forest management and the considerations necessary for operational use of LiDAR technologies in forestry.

LiDAR background

Table 1 provides a glossary of commonly used LiDAR terms that may be unfamiliar to some readers. LiDAR sensors directly measure the 3-dimensional distribution of vegetation canopy components as well as sub-canopy topography, resulting in an accurate estimate of both vegetation height and ground elevation. As illustrated in Fig. 1, LiDAR systems can be classified into either discrete return or full waveform sampling systems, and may be further characterized by whether they are profiling systems (i.e., recording only along a narrow transect), or scanning systems (i.e., recording across a wider swath) (Lefsky *et al.* 2002). Full waveform sampling LiDAR systems generally have a more coarse spatial resolution (i.e., a large footprint: 10 m to 100 m) combined with a fine and fully digitized vertical spatial resolution, resulting in full sub-meter vertical profiles. Full waveform LiDAR are generally profiling systems and are most commonly used for research purposes (for background see Lefsky *et al.* (2001) and Harding *et al.* (2001). Although there are currently no systems that provide large-footprint full waveform LiDAR data commercially, the Geoscience Laser Altimeter System (GLAS) onboard the Ice, Cloud and land Elevation Satellite (ICESat) is a large-footprint full waveform LiDAR system that may be used for forest characterization (Zwally *et al.* 2002) and for the development of generalized products for modeling. For example, Lefsky *et al.* (2005) used data from GLAS to derive forest canopy height and aboveground biomass. More recently, Sun *et al.* (2008) evaluated GLAS data for determining forest vertical structure. Small-footprint full waveform systems are just becoming commercially available; however, given the limited use of full waveform LiDAR systems in an operational forestry context at present, the remainder of this paper will focus solely on small-footprint discrete return LiDAR systems for forest attribute estimation.

Discrete return LiDAR systems (with a small footprint size of 0.1 m to 2 m) typically record only 1 to 5 returns per laser footprint (Lim *et al.* 2003) and are optimized for the derivation of sub-meter accuracy terrain surface heights (Blair *et al.* 1999, Schenk *et al.* 2001). These systems are used commercially for a wide range of applications including topographic mapping, power line right-of-way surveys, engineering, and natural resource characterization (Lefsky *et al.* 2002).

Discrete return scanning LiDAR yields a cloud of points, with the lower points representing the ground and the upper points representing the canopy. One of the first steps undertaken when processing LiDAR data involves the separation of ground versus non-ground (i.e., canopy) hits—a function that is often undertaken by LiDAR data providers using software such as TerraScan, LP360, or the data provider's own proprietary software. Typically, this processing employs iterative algorithms that combine filtering and thresholding methods (Kraus and Pfeifer 1998, Axelsson 1999). Analysis can commence once all LiDAR points have been classified into ground or non-ground returns. Ground hits are typically gridded to produce a bare-earth Digital Elevation Model (DEM) using standard software approaches such as triangulated irregular networks, nearest neighbour interpolation, or spline methods. As the point spacing of the LiDAR observations is significantly finer than the spatial detail typically observable on aerial photography, the DEMs generated from LiDAR often contain significantly more horizontal and vertical resolution than elevation models generated from moderate-scale aerial photography (Anderson *et al.* 2006).

Fig. 2 shows an example of a DEM derived from 1:25 000 aerial photographs (as part of the provincial Terrain Resource Inventory Mapping (TRIM) program in British Columbia) and a DEM of the same area generated from LiDAR ground return data gridded to 1-m spatial resolution. Clear differences are evident in the enhanced capacity of the LiDAR to detect fine-scale topographic variations, especially small drainage links and riparian features, as well as topographic features associated with abrupt changes in relief. Once the DEM is created, estimates of vegetation height are derived by subtracting non-ground hits from the terrain surface represented by the DEM to generate a canopy height model (CHM) (Lim *et al.* 2003, Leckie *et al.* 2003).

Airborne LiDAR surveys using discrete return LiDAR systems are often designed to have a dense and evenly distributed point spacing. However, in canopies with a greater amount of leaf area, the gap fraction (i.e., the fraction of open sky not obstructed by canopy elements [Jonckheere *et al.* 2005]) is reduced, resulting in datasets containing a large number of vegetation returns and a relative paucity of terrain information. This lack of ground returns has implications for the quality of derived DEMs and subsequent representation of terrain morphology, as well as for the accurate estimation of canopy height and other vegetation metrics. Previous research has shown that the accuracy of a DEM varies with changes in terrain and land cover type (e.g., Hodgson and Bresnahan 2004, Su and Bork 2006). The selection of an appropriate algorithm for DEM interpolation can be an important decision, especially in uneven terrain or over differing stand densities. Limitations to the development of an accurate and consistent DEM directly affect the LiDAR-based attribute estimates (Leckie *et al.* 2003). Liu (2008) provides a comprehensive review of the considerations associated with the use of LiDAR data for DEM generation.

LiDAR technical characteristics

In contrast to passive sensors that measure the sun's reflected energy (i.e., Landsat, QuickBird), LiDAR are active sensors that emit near-infrared energy at high pulse frequencies.

Table 1. Glossary of terms common to LiDAR acquisition, processing, and applications. Definitions are based largely on information found in Baltsavias (1999), Maune (2001), Lefsky *et al.* (2002) and Lim *et al.* (2003).

Term	Definition
apparent foliage profile (AFP)	The vertical foliage profile obtained from an active airborne sensor. May be biased towards the upper canopy as the sensor is looking from the top down.
beam divergence (beamwidth)	A measure of how quickly a laser beam expands along its path. Expressed in milliradians (mrad).
canopy height model (CHM)	A continuous digital dataset representing vegetation heights.
differentially corrected global positioning system (dGPS)	A GPS system employing one or more reference receivers which collect data as a LiDAR survey is flown. Observations collected by the reference receivers are then used to correct the observations made by the LiDAR's GPS onboard the aircraft.
digital elevation model (DEM)	A continuous digital dataset representing terrain heights. Created by applying an interpolation routine to ground returns. Also commonly referred to as a digital terrain model (DTM).
discrete return	A LiDAR system that records reflected pulses as discrete points in 3-dimensional space. State-of-the-art sensors may record multiple returns for each emitted pulse.
filtering	Classification of LiDAR returns with reference to the surfaces from which they were reflected, such as ground, non-ground, vegetation, building, and so on. Though automated to some degree, a significant amount of operator intervention is often required.
footprint	The diameter of a laser pulse's circle of illumination on the ground. LiDAR sensors may be small footprint (typically 0.1-2 m) or large footprint (typically 10-100 m).
ground returns	Laser pulse returns that have been classified as having been reflected by the ground.
inertial navigation system (INS)	A component of a LiDAR system that records the pitch, roll and yaw of the aircraft to correct the orientation of the sensor at the time of pulse emission.
intensity	The ratio of received to transmitted energy for a laser pulse return.
interpolation	The estimation of values at unsampled locations within the range of a set of measured points. Natural neighbour, splining, and kriging are commonly used algorithms employed to generate continuous digital elevation and canopy height models from LiDAR returns.
light detection and ranging (LiDAR)	An active remote sensing system employing a laser to measure distance to a target. Currently, the majority employed operationally are airborne, discrete return, small footprint systems. Also referred to as laser altimetry.
non-ground returns	Laser pulse returns that have been classified as having intercepted surfaces above the ground, such as vegetation or buildings.
point cloud	Raw LiDAR returns projected using a three dimensional coordinate system. When viewed with visualization software, the returns, particularly in vegetated areas, resemble a cloud.
posting distance	The average horizontal distance between LiDAR returns.
pulse	A laser pulse generated and emitted from the LiDAR sensor.
pulse duration or width	Duration of a laser pulse, usually defined as the time elapsed between the 50% power peaks on the leading and trailing edges of a pulse. Expressed in nanoseconds (ns).
pulse energy	Energy output per laser pulse. Expressed in microjoules (μJ).
pulse repetition rate	The rate at which a sensor emits individual laser pulses each second. Expressed in kilohertz (kHz).
return	A pulse that is reflected off a target and returned to a detector on the LiDAR sensor and recorded.
scan angle or field of view (FOV)	The angular breadth of a scan line, determined by a sensor's scanning mechanism. Expressed in degrees (deg).
scan rate	The rate at which laser pulses are directed across the flight line each second. Typically expressed in hertz (Hz).
swath width	The strip of terrain below a sensor which is sampled by a scan line. Expressed in metres.
triangulated irregular network (TIN)	A vector-based representation of a continuous surface such as terrain. Typically based on Delaunay triangulation, which joins points with x, y and z coordinates using non-overlapping triangles.
waveform recording	A LiDAR system with the capacity to continuously measure reflected radiation through a vertical profile. May be referred to as "full waveform data."
wavelength	The distance between successive peaks of an electromagnetic wave. Near-infrared lasers are typically employed for terrestrial mapping applications. Expressed in micrometres or nanometres (μm).

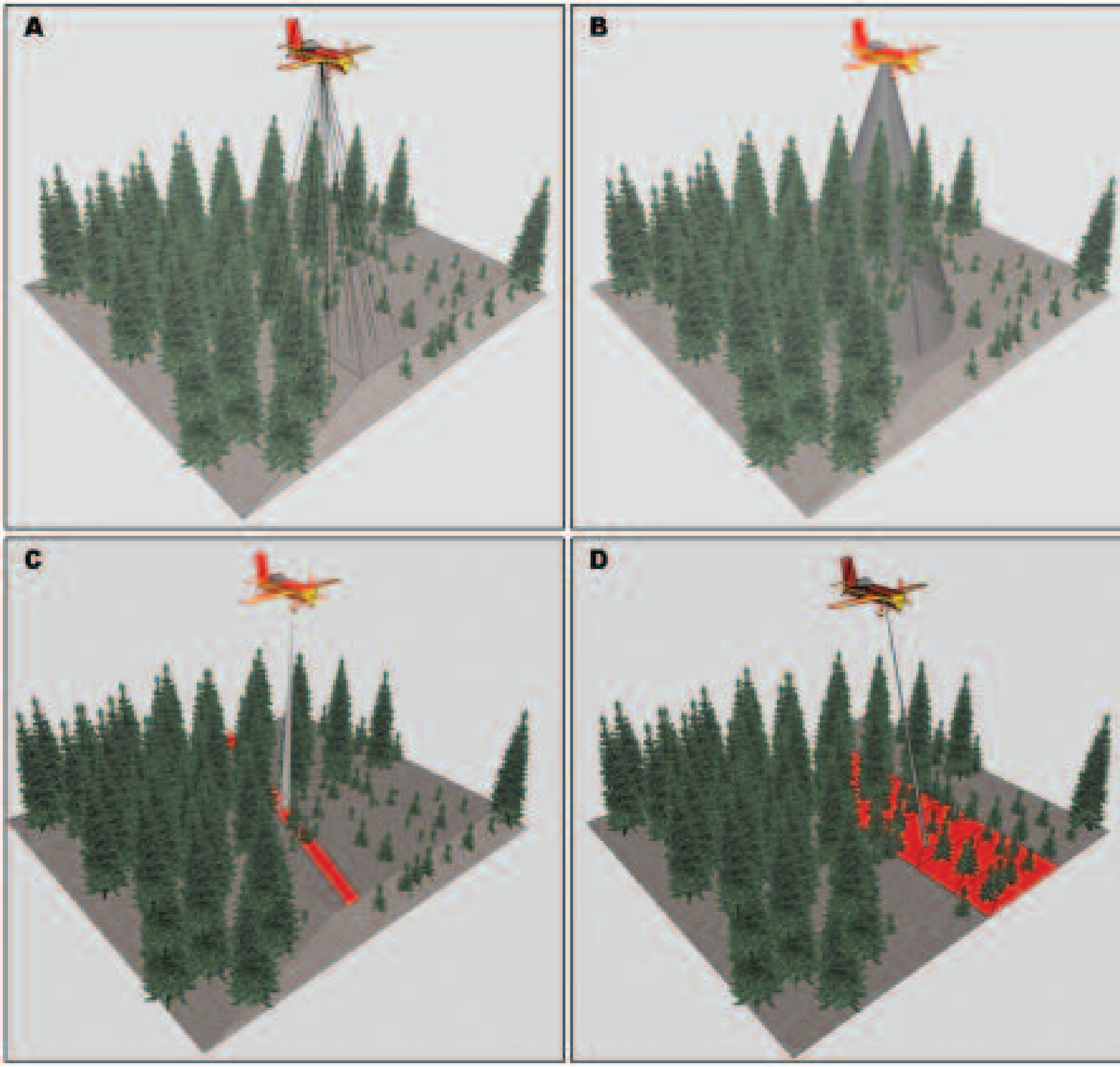

Fig. 1. LiDAR systems can be classified as either (A) discrete return or (B) full waveform sampling systems. Furthermore, some LiDAR systems are profiling systems (C), meaning they collect data along a narrow swath, or are scanning systems (D), meaning the laser moves from side to side as the platform (e.g., airplane) moves forward, and records across a wider swath.

Depending on the nature of the surface, a portion of the reflected pulse may be returned to the instrument where, if the pulse's magnitude exceeds a predefined threshold, the time elapsed between emittance and reflectance is recorded (Goodwin *et al.* 2006). Based on our knowledge of the speed at which light travels, the time required for the emitted pulse to return to the sensor is converted to a distance. Although each pulse is emitted from the sensor as a single unit, it may return to the sensor in multiple parts, known as returns. Discrete return LiDAR systems have the capacity to receive and record different numbers of returns, while full waveform systems have the capacity to receive and record all returns. For example, imagine that a discrete return LiDAR sensor emits a laser pulse over a forested area. The first surface the pulse intercepts is the forest canopy and a portion of the pulse's energy is reflected back to the sensor. The remaining pulse continues to travel through the canopy (depending on canopy structure and the strength of the pulse) and may eventually intercept the ground. As the pulse intercepts these other surfaces, a portion of the pulse's energy is returned to the sensor. The time it takes for each of these returns to travel back to the sensor is recorded and converted to a distance. Then another pulse is emitted and the process of measuring the returns is repeated. In its simplest form, LiDAR data processing will often involve identifying the first return as vegetation canopy, and the last return as bare ground.

Airborne LiDAR systems will include an onboard differentially corrected Global Positioning System (*d*GPS) that

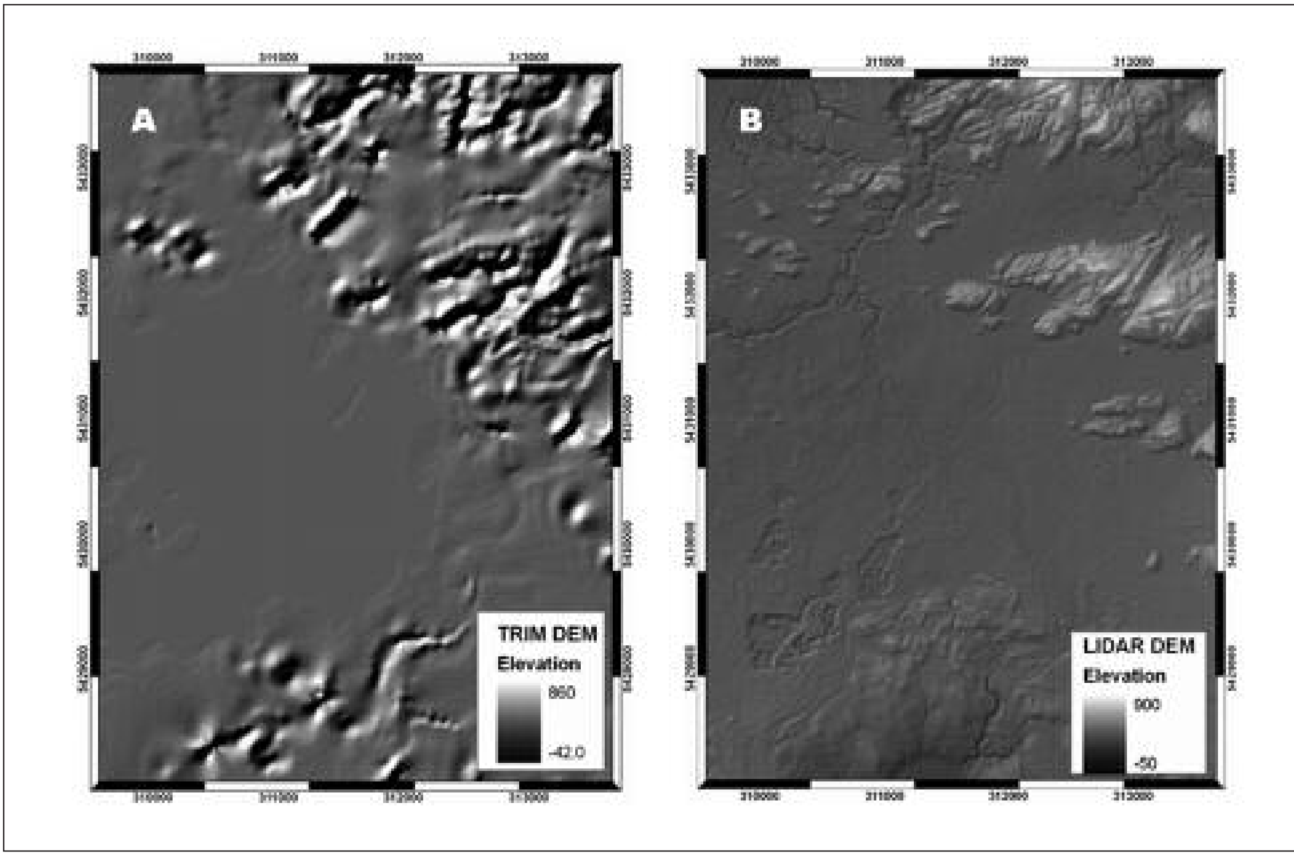

Fig. 2. Digital elevation models (DEMs) derived from 1:25 000 aerial photography (A) and LiDAR data (B). The DEMs have a spatial resolution of 20 m (A) and 1 m (B), respectively.

records the aircraft's location. The aircraft's orientation is obtained from an Inertial Navigation Systems (INS) (Wehr and Lohr 1999). This information allows for the precise computation of height and location of the surface from which a pulse is reflected (Gaveau and Hill 2003) with accuracies of approximately 15 and 40 cm, respectively (Davenport *et al.* 2004). Early LiDAR systems typically recorded only a single pulse returning from the ground or vegetative surface, requiring multiple overpasses to capture both bare ground and canopy conditions. More recently, systems have been developed that record first and last returns of a single pulse, with current state-of-the-art systems able to record greater than 5 returns per pulse. While beyond the scope of this paper, small-footprint, full waveform systems have also been developed in the past 2 years, offering even finer-scale vertical discrimination (Wagner *et al.* 2006).

Forest Attribute Estimation and Approaches

The estimation of vertical forest structure such as canopy height from LiDAR data is arguably of greatest interest to foresters (Lim *et al.* 2003). From this information, other biophysical parameters (e.g., volume, above-ground biomass) are derived that describe the function and productivity of forest ecosystems (Dubayah and Drake 2000). The approaches for extracting forest attributes from small-footprint discrete return LiDAR data can generally be separated into individual tree-based and plot-based assessment (Reutebuch *et al.* 2005).

Individual tree-based assessment

When small-footprint LiDAR data are acquired at very high densities, approaching (4 to 5 returns per m^2) individual tree crowns can readily be observed in the point clouds, often with the apex and boundary of the crown discernable by visually examining the data (Andersen *et al.* 2006). Computer-based algorithms have therefore successfully been applied to automatically identify tree crown structures and extract individual tree attributes, including total height, crown height, and crown diameter (Ziegler *et al.* 2000; Persson *et al.* 2002; Schardt *et al.* 2002; Næsset *et al.* 2004, 2005; Popescu and Wynne 2004; Bortolot and Wynne 2005; Falkowski *et al.* 2006; Næsset and Nelson 2007). Fig. 3 shows data obtained from a LiDAR survey collected at 1-m spacing. Fig. 3(A) shows the entire area and Fig. 3(B) highlights a small subset of the area, illustrating that even at 1-m posting, large tree crowns are easily discernable from other non-ground returns (e.g., returns with height >1 m). At spacings of 20 cm to 30 cm, more individual tree detail will be apparent (Popescu 2007, Popescu and Zhao 2008).

The extraction of individual tree dimensions from LiDAR observations collected with lower postings raises a number of issues that need to be considered. Popescu *et al.* (2003) showed that although individual tree heights can be estimated using lower-density LiDAR data (i.e., >1 point per m) it is difficult to accurately measure other crown attributes, such as crown width, especially in mixed deciduous forest types

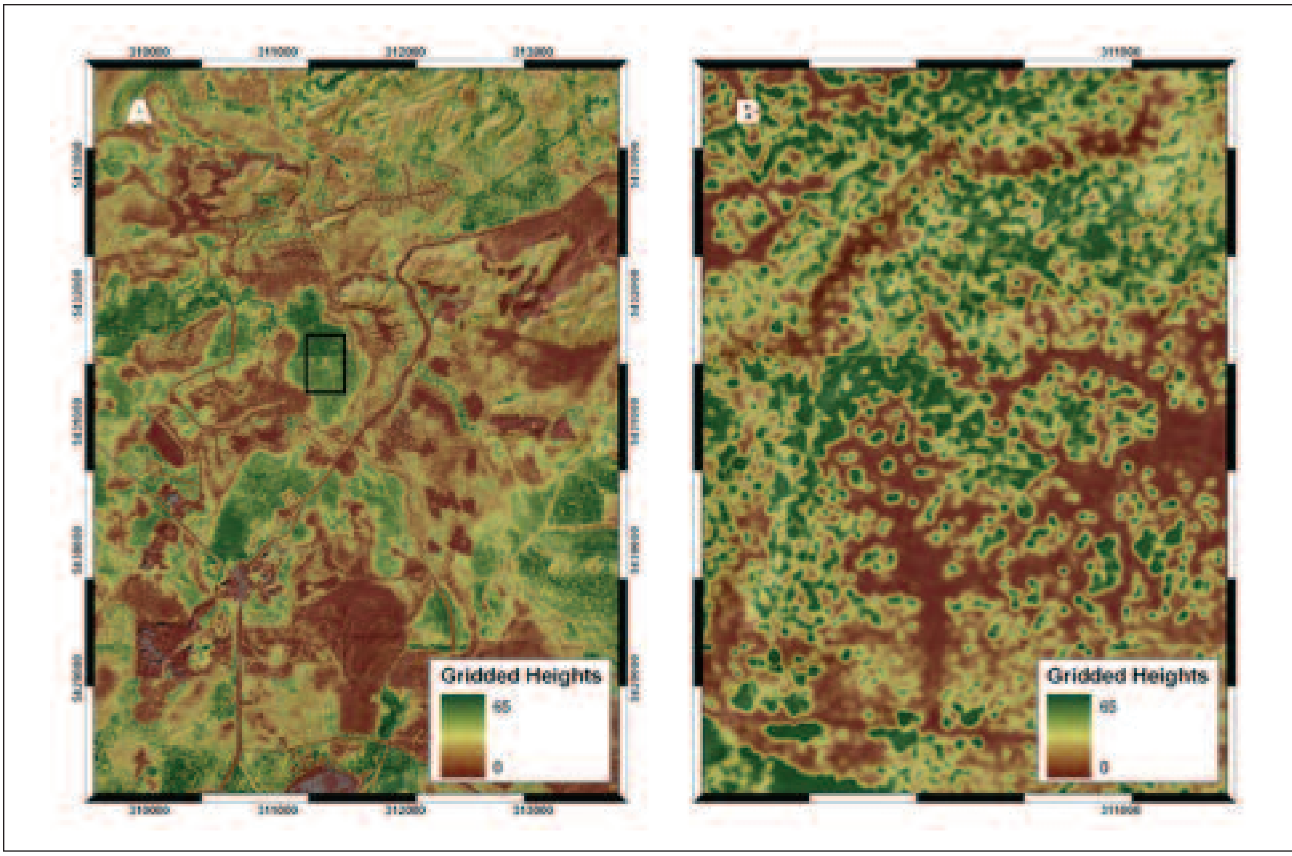

Fig. 3. Data obtained from a LiDAR survey collected at 1-m spacing. Maximum vegetation heights are shown across the entire study area (A), while in (B) a small subset of the study area is shown and illustrates that even at 1-m spacing, large tree crowns are easily discernable from non-ground returns (>1 m in height).

(Reutebuch *et al.*, 2005). Similarly Næsset and Økland (2002) found an average point spacing of 1 m was insufficient to accurately estimate individual crown attributes (height to green canopy and crown length) in a Norway spruce (*Picea abies* (L.) Karst.) and Scots pine (*Pinus sylvestris* L.) forest, whilst Takahashi *et al.* (2005) required data as dense as 8.8 LiDAR returns per m^2 to successfully estimate tree heights to within 1 m of field estimates in sugi (*Cryptomeria japonica* D. Don) plantation forests.

Plot-based assessment

A second common approach to extracting forestry attributes from small-footprint LiDAR data involves accumulating all LiDAR hits within a given area and then through empirical (i.e., statistical) relations, comparing the statistical properties of these grouped LiDAR pulses to a range of plot-level forestry attributes such as height, basal area, stem volume, above-ground biomass, and stem density (McCombs *et al.* 2003, Popescu *et al.* 2004, Reutebuch *et al.* 2005, van Aardt *et al.* 2006, Coops *et al.* 2007). The reason these relationships have proven to be so stable across so many forest types and structures is because these grouped LiDAR responses essentially represent a detailed measurement of all surfaces within a canopy volume (foliage, branches, and stems). So even when LiDAR data are collected at a lower hit density (i.e., 1-m to 2-m spacing between LiDAR hits), or when the vertical structure of the forest is complex (i.e., composed of multiple canopy strata, with a significant understorey component) meaningful relationships to plot-level forest attributes may still be generated. It must be noted that similar to empirical relationships developed from remotely sensed optical data, the relationships generated from LiDAR data will often be specific to the project area and the data collection parameters used. For instance, data thinning to reduce perceived redundancies or to facilitate the development of an elevation layer would alter the vertical point density and possibly impact empirical relationships with forest attributes. As a result, empirical relationships will need to be generated for each project independently. A number of approaches have been developed relating metrics based on LiDAR hits with plot-level forest inventory data including maximum, mean, or Lorey's mean height (defined as product of tree height and its basal area), cover estimates, height percentiles, curve fitting, canopy volume and variance measures and some of these are addressed in the following sections (Hall *et al.* 2005).

Mean, maximum, and Lorey's height

Research has shown that stand heights in moderate to dense canopy forests are commonly underestimated with LiDAR data as the probability of a laser pulse intercepting the apex of a tree crown is relatively small (Nilsson 1996, Næsset 1997). As a result, canopy heights are often biased toward lower values (Popescu *et al.* 2002). A number of approaches have been developed to reduce this bias, including: selecting a base height threshold under which all points are removed (such as 5 m) and then computing the average of the remaining points using the maximum, rather than the mean, LiDAR height within a stand; or stratifying the plot into a number of smaller grid cells, and then extracting the heights within each grid cell (e.g., Næsset 1997, Hilker *et al.* 2008). These heights from the grid cells are then averaged to obtain a stratified dominant height estimate. Næsset (1997) and Lovell *et al.* (2003) both applied this method by dividing the LiDAR plots into 4 sub-plots, with the highest return in each sub-plot averaged to obtain a dominant height estimate for the plot. The expected difference between mean tree height and the laser-based mean canopy height is discussed in detail in Magnussen and Boudewyn (1998). In their work, geometrical probabilities were used to estimate the average vertical positions of laser hits given an average crown size. This position was then compared to the actual tree height for stands in the study area and a mean tree height was computed by adding the calculated difference to the laser estimated tree height. Adding the estimated difference to the laser-based height improved the correlation between field and laser estimates from 0.61 to 0.83.

Height percentiles

Rather than simply utilizing the maximum or mean height estimates, an alternative method of estimating stand height involves characterizing the distribution of all hits within a pre-defined window of LiDAR data and calculating key metrics along the cumulative distribution. These height estimates, called height percentiles, are most often calculated at 5% or 10% intervals, with other forestry attributes then correlated to one or more of these percentiles. Næsset *et al.* (2004) developed a suite of equations relating a number of plot-level forest inventory attributes such as mean height, dominant height, mean diameter, stem number, basal area, and volume, to LiDAR-derived percentiles and found statistically significant relationships with most variables. For example, stand volume and LiDAR-derived height percentiles had an r^2 between 0.76 and 0.94, depending on the forest type. Height percentiles can also be derived by subdividing a target area into a grid with fixed cell areas and then selecting a maximum canopy height from each cell (Aldred and Bonnor 1985, Ritchie 1995, Nilsson 1996, Næsset 1997), which in essence also selects a quantile of available laser canopy heights (Magnussen and Boudewyn 1998). Magnussen and Boudewyn (1998) showed that these canopy height percentiles can be used to estimate canopy leaf area if the quantile of laser heights is matched in probability to the fraction of leaf area above a desired height.

Attribute estimation through curve fitting

Rather than extracting height percentiles from the distribution of LiDAR hits, a number of researchers have developed methods to estimate the projected vertical foliage density profile. Owing to the inability of the vertical view to resolve foliage angle distribution, clumping and non-foliage elements (Chen and Leblanc 1997), the profiles derived are not the same as the true foliage density profiles, hence the derived profiles are referred to here as apparent foliage profiles. The difference between the true and apparent profiles depends on the canopy structure and type as discussed by Ni-Meister *et al.* (2001). Derivation of the apparent foliage profile from LiDAR observations has been well described (Lovell *et al.* 2003, Riano *et al.* 2003), and once derived, several different distributions can be fitted to the foliage density profile in order to stabilize the distribution and to provide a convenient summary of the vertical form. The most commonly applied distribution is a Weibull function, due to its flexibility in characterizing foliage distributions of various species (Vose 1988, Kershaw and Maguire 1995, Xu and Harrington 1998, Lovell *et al.* 2003). As discussed by Bailey and Dell (1973) and Xu and Harrington (1998), the α parameter provides a vertical scaling and positioning factor for movement of the distribution and the ß provides the capacity to increase or decrease the breadth of the distribution (Coops *et al.* 2007). This distribution, as defined by the Weibull function parameters α and ß, has also been used (Magnussen *et al.*1999) to examine the distribution of canopy heights from airborne LiDAR systems by comparing the probability of LiDAR height quantiles above a desired height with the distribution of leaf area. The height parameter may either be fitted or set to the height of the highest return.

Canopy volume

An alternative method to model canopy structure using LiDAR data is the examination of filled and open volumes within a forest canopy. Lefsky *et al.* (1999a) developed a technique to examine and model 3-dimensional canopy structure (canopy volume profiles). The method superimposed a 3-dimensional matrix over the forest canopy composed of 10-m by 10-m wide and 1-m tall cells (referred to as voxels), which are then classified as either "filled" or "empty" depending on whether a LiDAR return originated from that space in the canopy. Filled cells are labelled either "euphotic" zone, if the cell is located within the uppermost 65% of all filled volumes, or "oligophotic" zone if it is located below this location in the vertical profile. This approach effectively provides a broad classification of the canopy into active and less active photosynthetic zones. Although the method of Lefsky *et al.* (1999a) was developed with full waveform LiDAR, Coops *et al.* (2007) demonstrated that similar canopy volume information can be derived from discrete return small-footprint LiDAR (Fig. 4). By binning multiple data points into fixed cell areas (e.g., 20 m by 20 m), Coops *et al.* (2007) found that the estimated canopy volumes were related to changes in Douglas-fir (*Pseudotsuga menziesii* (Mirb.) Franco var. *menziesii*) stand structure—with significant correlations to one or more stand attributes including crown volume, stem density, and basal area.

Cover estimates

The amount of vegetation cover may be estimated by comparing the total number of incoming laser pulses to those that pass unimpeded through any given vertical layer of the canopy (Fig. 5C-5E). As a result, LiDAR data has the capacity to predict vegetated cover for any given layer of the forest canopy, including overstorey, midstorey, understorey, and in some cases, ground cover. For example, Riano *et al.* (2004) utilized LiDAR data to produce accurate and spatially explicit estimates of a number of forest cover estimates for forest fire fuel estimation such as information on canopy cover, and canopy base height. Morsdorf *et al.* (2006) used small-footprint discrete return LiDAR to estimate Leaf Area Index (LAI) and fractional cover (fraction of ground covered by vegetation over uncovered ground), with the latter computed as the fraction of laser vegetation returns over the total num-

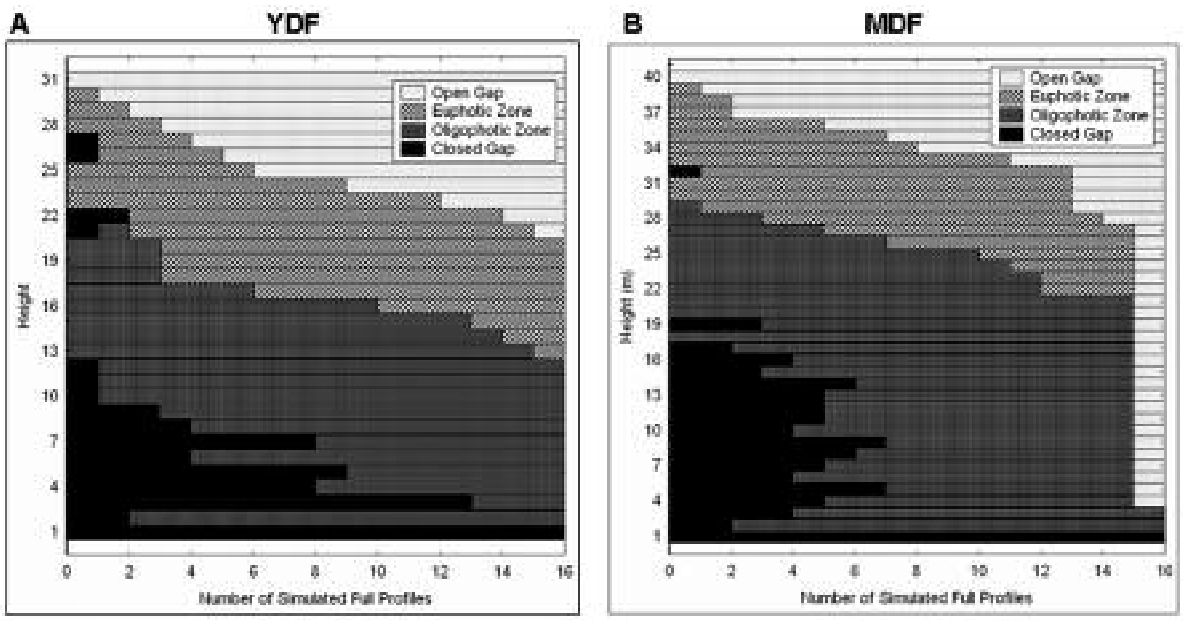

Fig. 4. Canopy volume profile estimates for a (A) young and (B) mature Douglas-fir stand.

ber of laser returns per unit area, and a proxy for LAI was likewise generated as the fraction of first and last return types in the canopy. Similarly, Solberg *et al*. (2006) estimated gap fraction as the ratio of the total number of returns to the total number of below-canopy returns (with canopy returns being those returns above 1 m). It must be noted that estimation of gap fraction, fractional cover, and LAI will vary with sensor parameters (e.g., sampling density), and data processing (e.g., data thinning). Furthermore, in order to get consistent estimates of canopy cover certain assumptions are made: an appropriate height threshold is selected to identify canopy hits (e.g., returns >1 m), and that every laser pulse produces a return. Lee and Lucas (2007) used a small-footprint discrete return LiDAR system with a 1-m data posting to develop the Height-Scaled Crown Openness Index (HSCOI). This index quantitatively measures the relative penetration of LiDAR pulses into the canopy, thereby allowing stems to be located regardless of the stems' position in the forest vertical profile. The HSCOI in intended to be complementary to a CHM, and expands the information available from discrete return systems (in the sub-canopy).

Variance-based approaches

In Fig. 5F, the coefficient of variation (CV) of height is mapped, relating the variation in height values found within a 5-m by 5-m moving window. The CV is used to depict attribute variability visually, as well as to provide a model input indicative of local heterogeneity (Drake *et al.* 2002, Næsset and Økland 2002, Frazer *et al.* 2005). Donoghue *et al.* (2007) used CV of LiDAR height to discriminate between different species groups.

Information Needs for Sustainable Forest Management

The past decade has seen an increased focus on sustainable forest management, defined as implementing practices that maintain and enhance the long-term health of forest ecosystems for the benefit of all living things while providing environmental, economic, social and cultural opportunities for present and future generations (Natural Resources Canada 2007). Sustainable forest management has become a global phenomenon (Siry *et al.* 2005) characterized by a growing emphasis on balancing multiple objectives for forest resources. This has resulted in an increased need for spatially explicit, accurate, and cost-effective forest information. For instance, the British Columbia Forest and Range Practices Act (FRPA), identifies 11 different forest resource values including timber, biodiversity, recreation, water, forage, fish, riparian, and visual quality. Each of these resource values is assessed and monitored using a suite of criteria and indicators, which may be intensive or extensive, and which are typically collected using a combination of field-based surveys and air photo interpretation.

LiDAR remote sensing offers the ability to accurately assess many of these indicators at the landscape level. Table 2 provides examples of FRPA resource values and a selection of indicators used for monitoring. Based on our understanding of the literature, the technology, and of the information needs associated with these indicators, we have provided a subjective rating indicating the capacity of LiDAR for estimating each of these indicators. For example, natural hazards are one of the indicators associated with recreation resources. Most natural hazards are linked to terrain morphology and LiDAR data may be used to generate an accurate, high spatial resolu-

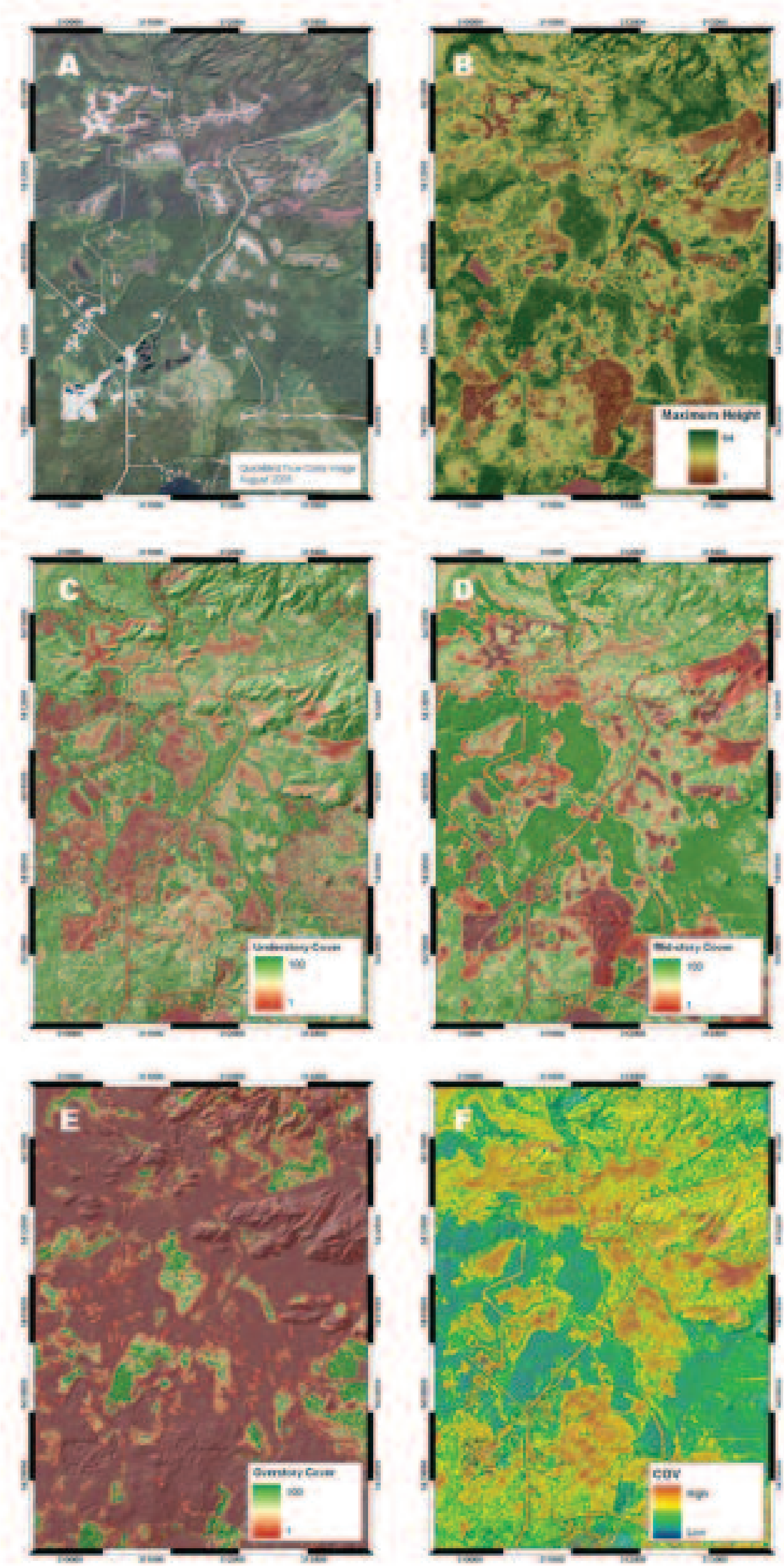

Fig. 5. A QuickBird image displaying a portion of Vancouver Island, British Columbia, Canada (A), and corresponding LiDAR-derived maximum height (B), understorey (C), midstorey (D), and overstorey (E) cover, and height coefficient of variation (F).

Table 2. British Columbia Forest and Range Practices Act resource values, selected indicators, and how LiDAR data may be used to estimate them. Note that several of the resource values are currently under development by the provincial government.

FRPA Resource Values	Indicators	Capacity of LiDAR to estimate indicator	Notes
Timber		See Table 3.	
Stand-level biodiversity		See Tables 3 and 4.	
Forage and associated plant communities	Plant community descriptions (e.g., vegetation species, browsing intensity)	Limited	Limited ability to estimate vegetation species and browsing intensity.
	Stream riparian functions	Moderate	DEM evaluation provides information on channel morphology at the reach scale. Use standard LiDAR vegetation metrics to monitor vegetation structure. Limited ability to estimate flow regimes, biotic communities, and water quality.
	Erosion/deposition	Moderate	DEM evaluation, but scale of enquiry limited by vegetation cover and survey parameterization. Rills and gullies will not be detected.
Visual quality	Visual quality objective	High	Determine tree heights; may be useful for estimating volume removed. When combined with optical data, DSM may provide height information for 3D visualizations.
Recreation resources	Forest health, invasive plants	Moderate	Identify changes in canopy structure (e.g. defoliation) using vegetation returns. Not useful for invasive plant identification.
	Natural hazards	High	DEM evaluation for landslide chutes, slope mapping, tsunami hazard zones, and so on.
Resource features	Size of retention areas surrounding karst resources	High	Map size and height using vegetation returns. Possible to estimate amounts of windthrow and harvesting within retention areas.
	Soil disturbances, amounts of logging slash	None	
Water	Condition of plant community	Moderate	Use standard LiDAR vegetation metrics to monitor riparian vegetation structure.
	Livestock management practices	None	
Cultural heritage	Monitoring culturally sensitive natural resources, resource gathering areas	Moderate	Use standard LiDAR vegetation metrics to monitor forest structure.
	Identify culturally modified trees	None	
Fish/riparian	Point indicators (e.g. % moss, # of insect types)	None	
	Channel morphology	Moderate	DEM evaluation, map platform and cross-sectional morphology. Not useful for analysing sediments, bank characteristics and so on.

Table 3. Examples of timber inventory and stand-level biodiversity indicators from the British Columbia Forest and Range Practices Act (FRPA). Relevant references from the literature are provided. Note that the FRPA timber resource value was in development at the time of this writing; the indicators listed below are typical variables measured in the field.

Indicator	Sampling density (pulses/m^2)	Individual tree, plot- or polygon-based	Species	Reference
Diameter	1.2	Plot	Norway spruce, Scots pine	Næsset 2002
	0.2	Plot	Douglas-fir	Magnussen and Boudewyn 1998, Magnussen *et al.* 1999
Height	0.6–2.3	Individual tree, plot	Norway spruce, Scots pine	Næsset and Økland 2002
	6	Individual tree	Douglas-fir, ponderosa pine	Andersen *et al.* 2006
Volume	4-5	Individual tree	Norway spruce, Scots pine, silver birch, downy birch	Maltamo *et al.* 2004
Pathological indicators (e.g. scars, broken tops)	Not recommended using LiDAR			
Growth	10	Individual tree	Scots pine	Yu *et al.* 2006
Species	4.7	Individual tree	Norway spruce, Scots pine	Holmgren and Persson 2004
Height to base of crown	0.6–2.3	Individual tree, plot	Norway spruce, Scots pine	Næsset and Økland 2002
Crown diameter	1.4	Individual tree	White oak, chestnut oak, northern red oak, southern red oak, yellow poplar, red maple, Virginia pine, loblolly pine, shortleaf pine, pignut hickory, scarlet oak, black oak, blackgum, American beech	Popescu *et al.* 2003
Number of trees per hectare	1.2 4–5	Plot Individual tree	Norway spruce, Scots pine Norway spruce, Scots Pine, silver birch	Næsset 2002 Maltamo *et al.* 2004

tion DEM, which can then subsequently be used to locate and characterize these natural hazards. For other indicators such as the identification of vegetation species, LiDAR can only provide limited information—particularly when considered in an operational context or in contrast to lower-cost aerial photography.

As expected, many key indicators of forest sustainability listed in Table 2 concern timber attributes, such as diameter, height, and volume (Table 3). Traditionally, these types of inventory attributes are collected as part of field-based inventories; however, many studies have demonstrated approaches for accurate determination using LiDAR remote sensing technology. As discussed previously, analyses may be based on individual trees or plots, depending on the hit density of the LiDAR survey. At a very dense point spacing, studies have demonstrated that different tree architectures facilitate species recognition for individual trees (Holmgren and Persson 2004, Brandtberg 2007), as well as delineation of crown boundaries (Popescu *et al.* 2003, Lee and Lucas, 2007). At the plot-level, mean stand height and maximum height are accurately estimated (Næsset and Økland 2002), while other attributes such as diameter, volume, and stocking are estimated using allometric relationships based on height (e.g., Næsset 2002).

The assessment of forest stand indicators of biodiversity includes the examination of many of the same variables obtained from forest inventories; however, the data is often augmented by additional information on species and structure (Tables 3 and 4). The horizontal and vertical organization of forest canopies can provide managers with information relating to the development of plant communities, canopy function, and habitat conditions for wildlife (Lefsky *et al.* 2002, Nelson *et al.* 2005). Information on the vertical and horizontal arrangement of elements within the forest canopy is readily obtainable from LiDAR data and, as indicated in Tables 3 and 4, studies have shown LiDAR data can provide information pertaining to crown closure (Popescu *et al.* 2003), canopy volume (Lefsky *et al.* 1999a), estimation of windthrow (Reutebuch *et al.* 2005), coarse woody debris (Lefsky *et al.* 1999b), tree life stage (Bater *et al.* 2007), and diameter distribution (Suárez *et al.* 2005). As LiDAR responds to structural rather than functional elements in the canopy, it is not possible to discern some attributes from LiDAR data directly; examples include attributes related to plant function, ecophys-

Table 4. Additional indicators of stand-level forest biodiversity from the British Columbia Forest and Range Practices Act, with references to previous studies using LiDAR technology.

Indicator	Sampling density (pulses/m^2)	Individual tree, plot- or polygon-based	Species	Reference
Species		See Table 3		
Diameter		See Table 3		
Height		See Table 3		
Crown closure, canopy volume	0.7	Plot	Douglas-fir, western hemlock, western red cedar, red alder	Coops *et al.* 2007
Ecological anchors (e.g., bear den, cavity nest, wildlife trails)		Not recommended using LiDAR remote sensing		
Invasive plants		Not recommended using LiDAR remote sensing		
Coarse woody debris	1.4	Plot	Lodgepole pine, unspecified spruce/fir	Seielstad and Queen 2003

iology, and/or invasive species identification. The acquisition of these attributes will continue to require field-based surveys, or some other remotely sensed data source. Furthermore, as the uses of information on stand indicators of biodiversity are highly varied, so too are the methods used and the attributes extracted from LiDAR data. As a result, there remains little convergence on standard metrics of stand structural diversity—either measured in the field or extracted from LiDAR data (Frazer *et al.* 2005).

LiDAR has the potential to provide additional data to water quality and riparian management activities due to its capacity to provide fine-scale information on surface features under the forest canopy, such as gullies and channel morphology, as well as information on canopy height and vegetation cover density (Table 2). However, LiDAR data provide limited utility for assessing indicators such as soil compaction or the impacts of livestock grazing. Management of forest visual quality has emerged as an important issue with the increased recreational use of forests as well as increased public expectations surrounding forest practices and conservation (British Columbia Ministry of Forests and Range 2006). Visual quality objectives are management criteria reflecting both the physical characteristics and a supposition of the public's desired level of visual quality for a landscape. LiDAR is an important data source for realistic visual simulations and the visual impact assessment process (Sheppard 2004, Fujisaki 2005, Evans *et al.* 2006).

Operational Considerations

When planning a LiDAR-based survey, parameters may be optimized for forest management information needs. The quality of the LiDAR data product depends on the properties of the LiDAR hardware and the parameters chosen for the survey. In addition, the costs of data acquisition often prohibit spatially exhaustive measurements, especially over large areas, thereby requiring trade-offs to be made between the area covered by the survey and total survey cost. The physical properties of LiDAR sensors vary with the type of application a particular instrument was developed for and can generally be characterized by a number of attributes, including the laser wavelength (μm), pulse duration (ns), pulse energy (μJ), pulse repetition rate (kHz), beamwidth (mrad), scan angle (deg), scan rate (Hz), flying height (m), and size (m) of laser footprint on ground (Table 1) (Baltsavias 1999). Laser wavelength, pulse duration, and pulse energy have implications for the sensor's ability to capture the vertical canopy structure (vertical resolution), as low levels of emitted pulse energy may result in insufficient (i.e., non-detectable) rates of return energy, especially when being reflected from surfaces with low reflectivity. The increased capacity of a sensor to distinguish between different levels of returned intensity when using high energy levels can potentially be used to identify structural and compositional features of the forest canopy (Donoghue *et al.* 2007). Pulse duration and pulse energy are typically in the range of 5 ns to 10 ns and up to 20 μJ, respectively (Utkin *et al.* 2003), with the most LiDAR instruments operating in the near infrared part of the electromagnetic spectrum to optimize for reflectance of vegetation elements and for eye safety considerations.

Laser footprint size and pulse frequency will determine the horizontal and vertical resolution that is observable from LiDAR. For instance, a larger footprint may enhance the probability of obtaining multiple returns from different height levels within the canopy, thus enhancing the vertical resolution; however, the energy received from a returning pulse will decrease with an increasing footprint size, as the energy will be distributed over a larger area. Likewise, higher pulse rates can increase the point density and therefore ground coverage, while the level of energy available per emitted laser pulse decreases (Chasmer *et al.* 2006, Wagner *et al.* 2006). Laser pulses emitted from small-footprint LiDAR instruments typically span a diameter of up to a few meters, with the pulse rate ranging between 20 kHz and 167 kHz (e.g., Optech Gemini).

Scan angle and flying height of the instrument need to be selected with regard to both data acquisition costs and the measurement detail desired. While greater flight altitudes promise more ground coverage per overpass due to an increased potential swath-width, the level of detail observable by the instrument will decrease, as flying height influences point spacing, footprint size, and pulse energy (Goodwin *et al.* 2006, Hopkinson 2007). Likewise, an increase in scan-angle can widen the swath observed per overpass; however, the quality of data decreases the further a measurement is taken off-nadir, which also decreases the rate at which laser pulses are directed across the flight line (scan rate). Typical flying heights are generally up to 500 m for fixed-wing aircraft. Airborne LiDAR systems typically feature moderate levels of pulse energy at high sampling rates, whereas higher-altitude instruments require higher energy levels, which often results in reduced point densities (Wagner *et al.* 2006). Table 5 provides a typical LiDAR system configuration required to obtain approximately 0.5 to 0.8 LiDAR hits per m^2, while Table 6 provides a listing of system parameters for 3 common discrete return small-footprint LiDAR systems. When considering the systems listed in Table 6, it may be useful to recall that when variables such as flying height and speed are held constant, sensors with a higher pulse rate will generally result in a higher posting (more returns per m^2).

Considerable and recent progress has been demonstrated in the development of LiDAR instrumentation owing to technical improvements in optical systems and precise real-time positioning using dGPS/INS. Current developments include the enhancement of pulse rate and number of LiDAR returns observable per pulse. Modern systems allow sampling frequencies of up to 167 kHz (e.g., ALTM 3100 EA, Optech Kiln, MS, USA), which corresponds to >20 LiDAR returns per m^2 observed, depending on speed and altitude of the sampling aircraft. However, despite the increase in pulse rate, trade-offs will still need to be made between pulse rate and flying height, as the speed of light limits the rate at which the LiDAR pulse can return to the sensor. At a higher flying altitude, laser pulses will take longer to return to the sensor, and emitted pulses may start to overlap with returning pulses. Small-footprint full waveform systems, such as the recently developed LMS-Q560 (Riegl Laser Measurement Systems GmbH, Horn, Austria), are able to record all returning echoes from an emitted small-footprint pulse. The latter hold promise for facilitating highly detailed measurements of canopy structure in both the overstorey and understorey.

Table 5. Typical LiDAR system parameters and flight specifications

Parameter	Example parameters required to obtain 0.5 to 0.8 hits per m^2
Sensor	Mark II[a]
Laser scan frequency	25000 Hz
Laser impulse frequency	40000 Hz
Laser power	<4 Watt
Maximum scan angle	<20°
Type of scanning mirror	Oscillating
Laser beam divergence	<0.5 milliradians
Measurement density	0.5 to 0.8 hits per sq meter
Datum	NAD83
Projection	UTM Zone 10
Platform	Bell 206 Jet Ranger helicopter
Flight altitude above ground	900 m
Flight speed	25–30ms^{-1}

[a]LiDAR system developed and operated by Terra Remote Sensing, Sidney, BC, Canada.

While difficult to generalize, LiDAR data cost approximately $5.00 CDN per hectare[4] for a configuration resulting in approximately 1 hit per metre (including costs for both data acquisition and basic processing). Costs therefore may present a key obstacle in using LiDAR as tool for large-area forest inventories (Wulder and Seemann 2003). LiDAR acquisition costs are comparable to those of airborne remote sensing applications and include costs for instrument purchase and maintenance, aircraft ferry time to the study site, acquisition time, and other variable costs determined by the specified survey parameters. Table 7 provides a summary of data acquisition considerations and the associated implications for survey costs. Table 8 lists expected costs for data postings of 30, 90, and 150 cm. Per-hectare costs will decrease as the spatial extent of the study area increases. However, the acquisition of full wall-to-wall LiDAR data coverage over large areas is rare (Nelson *et al.* 2003, 2005; Næsset *et al.* 2004). Possible ways increase the cost-effectiveness of LiDAR acquisition include cost-sharing consortia with multiple stakeholders (Reutebuch *et al.* 2005), and strategic combinations of LiDAR samples (e.g., transects) with wall-to-wall image coverage, such as using aerial photography or moderate to high spatial resolution satellite imagery (e.g., Landsat or QuickBird) (Hudak *et al.* 2002, Wulder and Seemann 2003, Nelson *et al.* 2003, Wulder *et al.* 2007b), and thereby extrapolating structural information across the larger area based on empirical relationships between the spectral properties of the canopy and the LiDAR data.

In some respects, operational adoption of LiDAR technology is constrained by the inventory methods that are mandated by provincial government agencies through policy agreements (Lim *et al.* 2003). As a result, the use of any new techniques must be carefully scrutinized by governing agencies to ensure results produced are compliant within the policies established under tenure arrangements granted to the forest industry. Cost-sharing data acquisition and joint industry–government trials may enhance operational adoption of LiDAR for forest inventory.

Discussion and Future Prospects

Over the past decade, LiDAR has emerged as a data source for meeting forest measurement needs. The ability to make direct measurements of vertical attributes, rather than relying on empirical relationships, has been welcomed. The nature of LiDAR data, as opposed to typical remotely sensed image data sources, has resulted in some confusion about the information that can be extracted from LiDAR data. An end user's understanding of optical remotely sensed data may be applied

[4]http://www.csc.noaa.gov/crs/rs_apps/sensors/LiDAR.htm; with equivalent cost of approx $6.00 / ha reported for flight, LiDAR collection, post-processing, and delivery

Table 6. Comparative listing of system parameters for 3 small-footprint discrete return LiDAR systems

Parameter	Sensor ALTM 3100EA (Optech)	Falcon III (TopoSys)	ALS50-II (Leica Geosystems)
Type	Discrete return (waveform recording optional)	Discrete return (waveform recording optional)	Discrete return (waveform recording optional)
Maximum pulse repetition rate (kHz)	100	125	150
Laser wavelength (μm)	1.064	1.560	1.064
Beam divergence (mrad)	0.3 or 0.8	0.7	0.22
Intensity capture (bits)	12	12	8
Number of samples per emitted pulse	4	9	4
Minimum separation between returns (m)	2.0	2.0	2.8
Scan rate (Hz)	70	165 to 415	90
Scan angle (°)	± 25	28° fixed	± 37.5
Flying height (m)	80 to 3500	30 to 2500	200 to 6000
Scanning mechanism	Oscillating mirror (sawtooth)	Fibre scanner	Oscillating mirror (sinusoid)

Table 7. LiDAR acquisition operational considerations and cost implications

Data acquisition considerations	Fixed and variable elements
Sensor availability	• Geographic location • Time of year • Scheduling (length of advance notice to data provider) • Scheduling flexibility may allow for negotiation of a lower price • Survey size (length of time sensor required)
Fixed costs for data provider	• Capital equipment (depreciation) • Survey costs (≈10 to 20% of costs) • Aircraft • Aircraft ferry time to acquisition area included • Fuel • Field crew • Overhead (*i.e.*, insurance, warranty on sensor, profit)
Cost control for client	• Optimize use of capital asset (partners, purchase in volume) • Match data requirements to data specifications (do not purchase unnecessarily high postings) • Provide own ground support • Do own data processing
Product definition	• What is required, posting, survey area, data characteristics, ancillary data (intensity, GPS observable), required vertical and horizontal accuracies
Price model	• Typically based upon a fixed base price, ferry time to site, acquisition time, and variable costs based upon requested survey parameters.

Table 8. Expected costs for LiDAR data for a range of postings from 30 to 150 centimetres. The posting is the interval of the spacing of LiDAR hits that is expected for a particular configuration of aircraft location and sensor specification.

Posting (cm)	Price / ha (CDN$)	Price / km^2 (CDN$)
150	3	300
90	5	500
30	10	1000

to the understanding of LiDAR data and products. For instance, in forestry, the linkage between spatial resolution (pixel size) and the concomitant objects that can be characterized (trees, stands) is well understood, with high spatial resolution data enabling single tree identification and analyses, and lower spatial resolution data sources enabling coarser stand-level (or broader) analyses (Wulder *et al.* 2004). The point or hit density (posting) of a given LiDAR survey can be considered analogous to the spatial resolution/information content of optical remotely sensed data. At very high postings, characterizations of individual tree morphology may be made.

As postings decrease, individual trees may be identified; however, lower postings result in an inability to characterize individual trees and result in stand-level evaluations (Leckie *et al.* 2003, St-Onge *et al.* 2003).

The number of forest inventory attributes that may be directly measured with LiDAR is limited. However, when considered within the context of all the measured and derived attributes required to complete a forest inventory, the information on height and structure provided by LiDAR can be a valuable tool in the inventory process. Combining LiDAR data with remotely sensed optical data (e.g., aerial photography or high spatial resolution remotely sensed imagery) broadens the range of forest attributes that may be characterized and ideally aerial photography should always be co-collected with LiDAR data.

Capturing elevation data for road-building and harvest block layout may be of greater interest for operational forestry than developing refined forest inventory attributes to meet long-term information needs. The costs and sophisticated, often custom, processing needs associated with LiDAR data are key limitations that need to be addressed in order to enable further adoption of LiDAR into operational forest management and monitoring programs. Rather than supplanting existing approaches, LiDAR data can be integrated into current forest inventory processes. For example, LiDAR data can provide samples of height data to calibrate existing ocular or modeled height estimates, and LiDAR data can be used to support forest inventory update activities, riparian management, and site quality assessment.

Using appropriately designed surveys, repeated LiDAR observations enable measurement of tree height growth over time (Yu *et al.* 2006, 2008; Næsset and Nelson 2007). A marked change in tree height, however, can only be measured if the height increase is greater than any biases in the LiDAR measurement. LiDAR measurements may be biased as a result of several factors, including instrument specifications, flying height, species architecture, and the measurement method used. These sources of bias manifest as measurement errors (reported accuracy) that can range from a few centimetres up to a few meters (e.g., Aldred and Bonnor 1985, Chen and Ni 1993, Ritchie 1995, Latypov 2002). The objectives of a survey must again be considered when communicating accuracy. The accommodations that may be required to undertake an operational larger area survey will typically result in lower accuracies in tree, or canopy, height estimation than focused plot-based studies.

To aid in consideration of the implications of LiDAR attribute estimation error when monitoring growth with an operationally focused survey (at approximately a 1 m posting), we present Fig. 6 as an example of bias in LiDAR measurement against expected increase in height for a range of site index classes found within a 2-km by 2-km study area dominated by Douglas-fir near Campbell River, Vancouver Island, British Columbia, Canada. Expected annual growth increment (in metres), by age (Fig. 6(A)) and estimated height by age (Fig. 6(B)) are used to model expected annual growth increment by age and site index (Fig. 6(C)). Fig. 6(C) illustrates the operational constraints to using LiDAR to detect changes in stand heights over time in the context of an inventory update. Fig. 6(C) assumes a LiDAR measurement bias of 1 m; the horizontal axis shows the site index and the vertical axis shows the stand age in 5-year intervals. The values within Fig. 6(C) represent the expected growth increments within the 5-year period for the different site index values. The different shading symbolizes the time period after which new LiDAR-based measures for inventory update can reasonably be made (i.e., when growth increment exceeds assumed measurement bias). The time for the height growth to exceed the bias of the LiDAR system is site-, species-, and age-dependent and can vary from 2 years to a few decades. As height growth is greatest for young trees under good environmental conditions, the most appropriate use for LiDAR-based inventory updates may be found within young forests with a high site index. For such stands, new measurements can be made almost every 2nd year. Older stands with a lower site index will take considerably more time for their height increment to exceed the bias of the LiDAR system. While the appropriateness of 1 m as an expectation of measurement error may be debated, users should consider that there is likely to be some error and that this error should be contrasted with expected growth if LiDAR is to be used for monitoring growth or as an inventory update data source. Further, from an operational monitoring perspective, it may be preferable to model growth (with established growth and yield relationships) from an initial LiDAR survey, followed by the subsequent use of optical imagery to monitor for change, rather than specifying multiple LiDAR surveys. The combination of optical imagery (for depletions) and modeling (for growth) provides a cost-effective option with fewer data acquisition and processing requirements than a repeat LiDAR survey.

LiDAR-based forest attributes, in particular height related parameters, have been shown to be more precise and cost-effective than field measured data (Wulder and Seemann 2003, Lefsky *et al.* 2005, Nelson *et al.* 2003, Weller *et al.* 2003), with errors related to tree height of less than 1 m (Næsset *et al.* 2005). In addition, a large number of studies have demonstrated that there is good agreement between field-measured canopy attributes, such as crown dimensions (Lovell *et al.* 2003, Coops *et al.* 2007), canopy volume (Lefsky *et al.* 2005, Coops *et al.* 2007), diameter at breast height (DBH), basal area (Lefsky *et al.* 1999a, Chen *et al.* 2007) and growth rates (Yu *et al.* 2008) making LiDAR useful for the assessment of forest inventory, forest sustainability and ecosystem quality (Lefsky *et al.* 2002, Bater *et al.* 2007).

Future efforts by the LiDAR instrument research and development community may include the design of smaller, more user-friendly instruments and, although difficult, another useful design goal would be reduced power consumption. Also helpful would be the development of software tools that allow the user to design surveys and configure the LiDAR instrument to satisfy specific information requirements. Development of laser instruments that have the power and frequency to fly at higher altitudes within the constraints discussed earlier, while still collecting data with high ground hit density (posting), are desired for forest attribute characterization. An increase in instrument power may be enhanced with concurrent improvements to detectors, while an increase in acquisition altitude may allow for the matching of the LiDAR swath with a camera's or multispectral sensor's field-of-view. In addition, increased acquisition altitudes will require research to better characterize and understand off-nadir LiDAR hits. The opportunity to generate waveform-like data from discrete return instruments would also be welcomed by the forestry community. The small-footprint

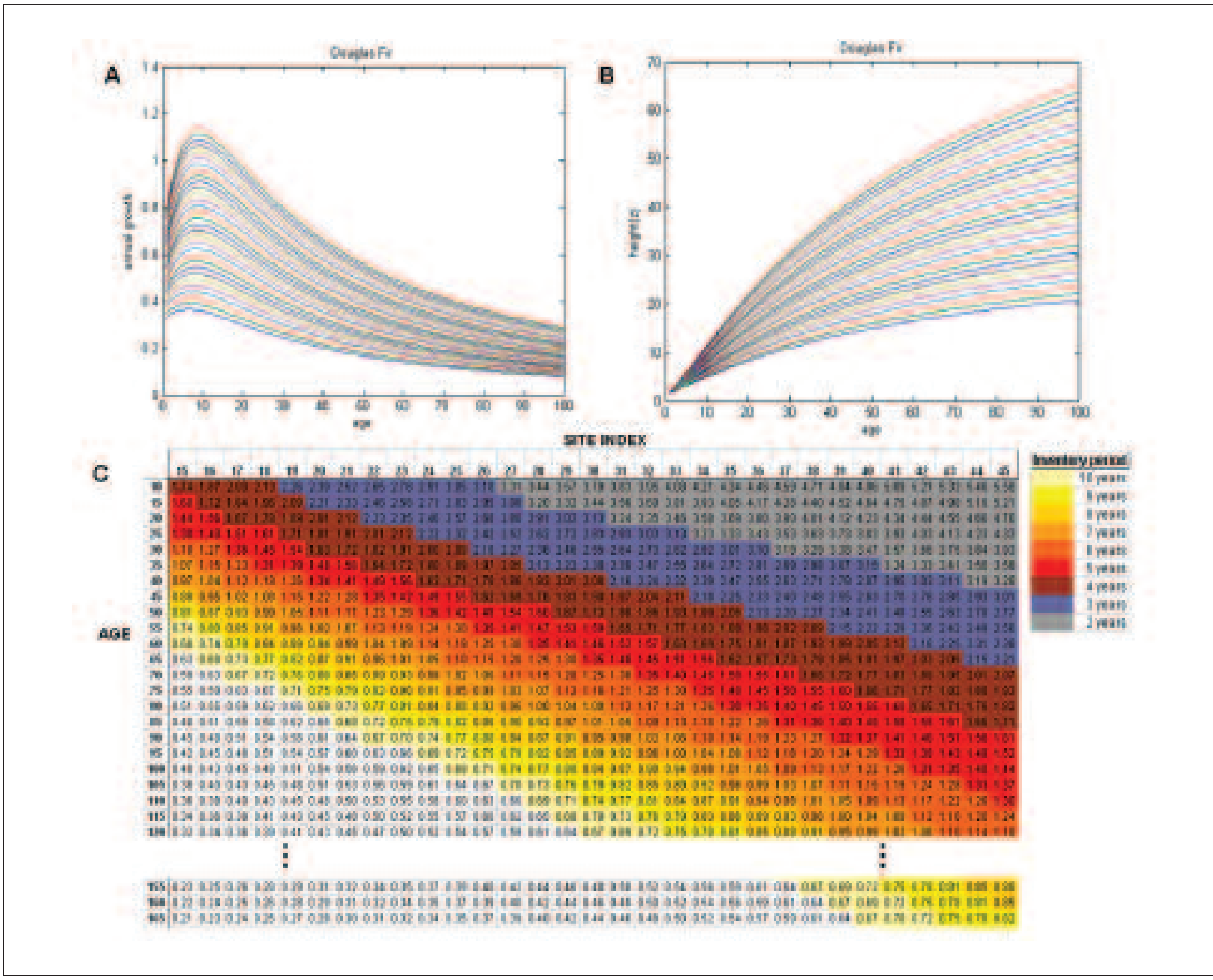

Fig. 6. Expected annual growth increment (m) (A) and estimated height (m) (B) for a given age of Douglas-fir, and the expected annual growth increment for a given age (in 5-year increments) and site index (C). Assuming a bias in height measurement using LiDAR of 1 m, the recommended remeasurement period is shaded accordingly. For example, a 30-year-old Douglas-fir with a site index of 41 has an expected annual growth increment of approximately 3.57 m. With an assumed LiDAR bias of 1 m, it is expected that changes in height could be accurately captured every 2 years.

discrete return systems listed in Table 6 have the capacity to collect data in full waveform mode.

The collection of full digital data sets, including LiDAR and image data, would allow for estimation of forest attributes at a scale useful for management purposes. Forest attributes, such as height, are currently well characterized utilizing LiDAR data. Any sensor or software developments that result in decreased costs for LiDAR data acquisition and processing will aid in the integration of LiDAR into forest management and monitoring. One impediment to the integration of LiDAR into operational forest management is the lack of qualified personnel. The collection and processing of LiDAR data is not a skill that is currently widely taught in Canadian universities. The value-added geomatics community has the capacity to collect and process LiDAR data and several companies in Canada provide this service. The actual estimation of forest attributes continues to have a strong research component, whereby the needs of the data user and elements particular to the data collected and the forest and terrain present, require custom applications. The development of turn-key applications for LiDAR data is aided by current research efforts in data processing, multi-source data integration, and attribute estimation over a range of forest and terrain configurations.

Summary

Forest managers, especially those with provincial stewardship mandates, should examine current sustainable forest management information needs to identify shortcomings in existing data acquisition protocols. These shortcomings can in turn serve as a guide for identifying possible opportunities for the use of LiDAR data. Again, the differences in information needs between strategic large-area surveys and operational surveys must be noted. The information required for stand-level strategic planning and decision-making is more generalized relative to the capacity of LiDAR surveys to generate detailed tree-level characterizations. Canada has large forest areas under extensive forest management practices. In this context, the use of LiDAR as a primary data source is precluded by cost and logistical issues. Furthermore, the estimation of required attributes is not sufficiently refined to provide forest managers with a clear business case for supplanting current strategic forest inventory practices at this time. In an operational context, users must make the distinction between measurement accuracies achieved and reported through controlled research experiments and realistic measurement accuracies that may be expected when methods are applied over large (and highly variable) forest environments. In addition, data users should be mindful of the relationships between hit densities (postings) and the attributes that can be conferred.

The greatest opportunities for LiDAR at the present time appear to be for engineering purposes. LiDAR elevation data is accurate and processing algorithms are increasingly robust and standardized. Elevation data can provide forest managers with immediate cost savings for activities such as road-building and harvest planning. For less topographically variable areas of Canada, lower postings (e.g., 1 return every 5 m) can still produce an elevation model useful for addressing a range of information needs. At a strategic level, LiDAR data, especially with high postings, may not provide the same value, and users may find they are paying for more information than is required. Efforts should focus on supplementing current data acquisition approaches with LiDAR information. The incremental integration of LiDAR-generated attributes into existing forest inventory data will, over the short term, promote the increased use of LiDAR for a range of forest applications, ultimately enabling time and cost savings for future implementations. The costs associated with LiDAR data will likely continue to be relatively high when compared to other data sources, as instrument costs need to be amortized, and regular survey costs, such as fuel, mobilization and aircraft ferrying charges, need to be borne. The judicious and appropriate use of LiDAR data can enhance sustainable forest management practices by building upon existing knowledge and expertise in the forest management community.

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