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The uncertainty in conifer plantation growth prediction from multi-temporal lidar datasets

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Abstract

An evaluation of the use of airborne lidar for multi-temporal forest height growth assessment in a temperate mature red pine (*Pinus resinosa* Ait.) plantation over a five-year period is presented. The objective was to evaluate the level of uncertainty in lidar-based growth estimates through time so that the optimal repeat interval necessary for statistically meaningful growth measurements could be evaluated. Four airborne lidar datasets displaying similar survey configuration parameters were collected between 2000 and 2005. Coincident with the 2002 and 2005 acquisitions, field mensuration for 126 trees within 19 plots was carried out. Field measurements of stem height were compared to both coincident plot-level laser pulse return (LPR) height percentile metrics and stand level raster canopy height models (CHM).

The average plot-level field heights were found to be 23.8 m (standard deviation (σ) = 0.4 m) for 2002 and 25.0 m (σ = 0.6 m) for 2005, with an approximate annual growth rate of 0.4 m/yr (σ = 0.5 m). The standard deviation uncertainty for field height growth estimates over the three year period was 41% at the plot-level (n = 19) and 92% at the individual tree level (n = 126). Of the lidar height percentile metrics tested, the 90th (L90), 95th (L95) and maximum (Lmax) LPR distribution heights demonstrated the highest overall correlations with field-measured tree height. While all lidar-based methods, including raster CHM comparison, tended to underestimate the field estimate of growth, Lmax provided the most robust overall direct estimate (0.32 m/yr, σ = 0.37 m). A single factor analysis of variance demonstrated that there was no statistically significant difference between all plot-level field and Lmax mean growth rate estimates (P = 0.38) and, further, that there was no difference in Lmax growth rate estimates across the examined time intervals (P = 0.59). A power function relationship between time interval and the standard deviation of error in growth estimate demonstrated that over a one-year period, the growth uncertainty was in the range of 0.3 m (~100% of total growth) reducing to less than 0.1 m (~6% of total growth) after 5 years. Assuming a 10% uncertainty is acceptable for operational or research-based conifer plantation growth estimates, this can be achieved at a three-year time interval.

Keywords: Lidar; Laser scanning; Red pine; Canopy height; Tree growth; Uncertainty; Plantation

1. Introduction

Airborne lidar (light detection and ranging) data are commonly used to create high-resolution digital elevation models (DEMs) of the ground or digital surface models (DSMs) of vegetation canopy and urban surfaces. Small-footprint discrete-return (SFD) systems are increasingly being adopted in the survey and mapping industry, as the data acquired are analogous to traditional ground survey point data. While data volumes can be high, the resultant point data architecture can be handled in many computed aided design (CAD), geographical information systems (GIS) and image analysis software packages. Current technology can collect multiple laser pulse returns at pulse repetition frequencies (PRF) exceeding 160,000 pulses per second, and can cover a ground swath greater than 3000 m depending on flying altitude and scan angle. The resultant laser pulse return (LPR) data can be dense (up to and exceeding 10 LPRs per m^2) and positional accuracy is typically at the decimetre to metre level (Fowler, 2001). For a more detailed introduction to lidar technology see Baltsavias (1999) and Wehr and Lohr (1999).

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Many studies have investigated the use of lidar for tree height measurement and found good relationships to field measures with r^2 values typically ranging from 0.85 to 0.95 (Maclean & Krabill, 1986; Magnussen & Boudewyn, 1998; Means et al., 2000; Næsset, 1997; Næsset, 2002; Næsset & Økland, 2002; Popescu et al., 2002; Ritchie, 1995; Witte et al., 2001). For example, Næsset (1997) reported that for conifer stands in Norway, sampled grid-based maximum LPR heights (Lmax) above the ground level tended to correlate well with Lorey's mean tree height ($r^2=0.91$) despite a range of observed bias from −0.4 m to 1.9 m. Magnussen and Boudewyn (1998) expanded upon this work by finding that a canopy LPR quantile-based approach applied to conifer plots in western Canada could predict canopy height to within 6% of field measurements. Many lidar canopy height estimation studies illustrate a tendency to underestimate height (Lim et al., 2003a,b), and this is typically attributed to: (i) laser pulse penetration into foliage (Gaveau & Hill, 2003; Hopkinson, 2007; Hopkinson et al., 2005); (ii) insufficient representation of canopy apices due to low sample point density (St-Onge et al., 2000) or (iii) ground height overestimation due to minimal pulse penetration through dense vegetation (e.g. Hopkinson et al., 2004a,b; Reutebuch et al., 2003; Weltz et al., 1994).

A large number of studies have demonstrated high correlations between certain LPR metrics such as Lmax, and 90th (L90) or 95th (L95) percentile LPR distribution height within the canopy. LPR frequency distributions through the canopy, however, can be influenced by: vegetation structural characteristics such as foliage density (e.g. Magnussen & Boudewyn, 1998); and lidar data acquisition factors such as pulse repetition (Chasmer et al., 2006a), footprint size and energy (Hopkinson, 2006), flying altitude (Goodwin et al., 2006; Hopkinson, in press; Næsset, 2004), and scan angle (Holmgren et al., 2003). The simplest and most robust approach yet adopted to infer canopy height is to isolate the localised maximum LPR elevation and subtract the associated ground elevation (e.g. Næsset, 1997). This approach is often implicitly adopted during the rasterisation of lidar data to create DSMs for grid based canopy height models (CHMs) (e.g. Hopkinson et al., 2005). Canopy height estimates based on upper LPR frequency distribution approaches are simple and robust but pulse spacing and the shape of tree crown apices can influence the probability of the LPR distribution detecting the highest foliage elements within a sample area (Magnussen & Boudewyn, 1998).

With the decimetre level mapping capability of airborne lidar, it follows that the technology can be used for accurate detection of changes in landscape features at a high resolution. This has been demonstrated in several studies. For example seasonal and annual variations in coastal morphology following storm-related erosion events have been observed by comparing lidar DEMs through time (e.g. White & Wang, 2003; Woolard & Colby, 2002). Snowpack depth distribution (Hopkinson et al., 2004b), glacier melt rates and volumes (Hopkinson & Demuth, 2006), and urban building development processes (Vosselman et al., 2004) have all been mapped using lidar DEM inter-comparison processes.

Despite a wealth of literature demonstrating that lidar can be used both for forest mensuration and as an effective means of change detection at the decimetre to metre level, few studies have investigated and quantified the suitability of SFD lidar data for forest growth assessment from multiple datasets collected over a number of years. Yu et al. (2004) provided an assessment of Norway spruce (*Picea abies* (L.) Karst.) and Scots pine (*Pinus sylvestris* L.) canopy growth within a Boreal forest site from two lidar acquisitions 21 months apart. Growth was estimated by observing differences in raster canopy height models (CHMs) for individually segmented tree crowns that could be identified in both datasets. It was found that after adjusting DEM heights to account for observed canopy height underestimations, plot-level growth could be estimated at a precision level of 10 to 15 cm. In a study by St-Onge and Vepakomma (2004) conducted over a five-year period it was shown that changes in forest height and gap fraction estimated from two SFD lidar datasets were generally consistent with expected growth patterns. However, the results were not compared directly to field validation data and the wide variation in survey configuration between the two acquisitions led to some uncertainty in the estimates of dynamic canopy conditions being assessed (St-Onge & Vepakomma, 2004). Næsset and Gobakken (2005) assessed changes in LPR metrics over a two-year time period in mature and immature conifer plots. It was found that while LPR data were able to predict growth at a statistically significant level, the accuracy of the predictions was weak. In most cases the predictions were slightly biased and the precision was low over a two year time period (Næsset & Gobakken, 2005). Finally, Yu et al. (2006) compared two lidar datasets collected 5 years apart to assess the ability to measure growth at the individual tree level. They compared L85, L90 and L95 and the best correspondence with field data achieved an r^2 of 0.68 and an RMSE of 43 cm. From these five lidar forest growth studies, it is clear that growth is detectable over time periods ranging from two to five years but the time interval necessary for an accurate and statistically significant estimation of growth rate is unclear.

This study evaluates the application of lidar for plot-level mean tree height growth assessment within a red pine (*Pinus resinosa* Ait.) conifer plantation over a five-year period using multiple lidar datasets. The specific questions addressed are:

1. Is it possible to accurately estimate conifer plantation rates of height growth from changes in plot-level lidar-derived canopy heights observed over annual and inter-annual time periods?
2. Of the quantile and raster CHM height assessment methods typically employed to assess canopy height, which is most appropriate for growth monitoring?
3. Are lidar estimated rates of growth consistent through time?
4. How does the statistical uncertainty in growth rate prediction vary with increasing time interval between repeat acquisitions?
5. What is the minimum repeat acquisition time interval necessary for an accurate and statistically significant estimate of height growth for the red pine plantation studied?

Any lidar-based investigation of canopy height change through time to quantify forest growth rate is expected to be

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complicated by variations in spatio-temporal canopy structure and phenology, and data collection parameters. To minimize the influence of these effects, this study focused on a homogeneous conifer plantation and employed lidar datasets with similar acquisition settings and point densities.

2. Study area

The study was conducted in the southern Great Lakes (SGL) ecozone, on the edge of the Oak Ridges Moraine at the Vivian Forest research site within the York Regional Forest, 50 km north of Toronto, Canada (Fig. 1). This area was chosen for long-term study in the year 2000 for two reasons: 1) The regional forest resource inventory (FRI) data for the area were updated in 1999 and made available to the authors; and 2) The Vivian Forest is adjacent to the airborne laser terrain mapper (ALTM) (Optech Inc., Toronto, Ontario, Canada) calibration site used by the manufacturer. Consequently, acquiring lidar datasets over the study area could be achieved with relative ease during optimal conditions. In addition, the field site has been the focus of other lidar forest related studies (e.g. Chasmer et al., 2006a,b; Hopkinson et al., 2004a,b) and a wealth of field data have been collected to supplement existing knowledge and datasets.

From Fig. 1, it is clear that there are many small forest compartments of heterogeneous species composition. The particular forest stand chosen for investigation was a 60-year-old red pine (*P. resinosa* Ait.) plantation rated with a site index of 75 (Chris Gynan, Silv-Econ Ltd. Newmarket, personal communication), which, based on growth and yield table predictions, indicates that the growth rate should approximate 0.34 m/yr (Huebschmann & Martin, 1996). The stand possessed relatively uniform stem spacing, tree height and crown depth with no understory. No silvicultural treatments were applied to the stand during the five year study period.

3. Methods

3.1. Field data collection

Field mensuration data collection took place during mid- to late July 2002 and again in mid-November 2005. During the 2002 field campaign, 180 trees within a 60 × 60 m area were tagged with a unique ID, and ground level stem locations were accurately surveyed to the dm level using a POS LS (Applanix, Toronto, Ontario) backpack-mounted inertial survey system (see Hopkinson et al., 2004b). During both field campaigns, tree heights were manually measured using a Vertex sonic clinometer (Haglof, Madison, Missouri) with an estimated measurement error of approximately 0.5 m in the pine stand. During the second field acquisition, nineteen 11 × 11 m subplots within the extent of the previous campaign were sampled. The plots were uniformly spaced and the locations are illustrated in Fig. 1. In total, there were 126 geolocated trees that were common to both field campaigns, with a minimum of four trees in a single plot, a mean number of seven trees per plot, a maximum of 11, and a standard deviation of two.

3.2. Airborne lidar data collection

Several airborne lidar datasets were collected by Optech Incorporated (Toronto, Ontario) during routine Airborne Laser

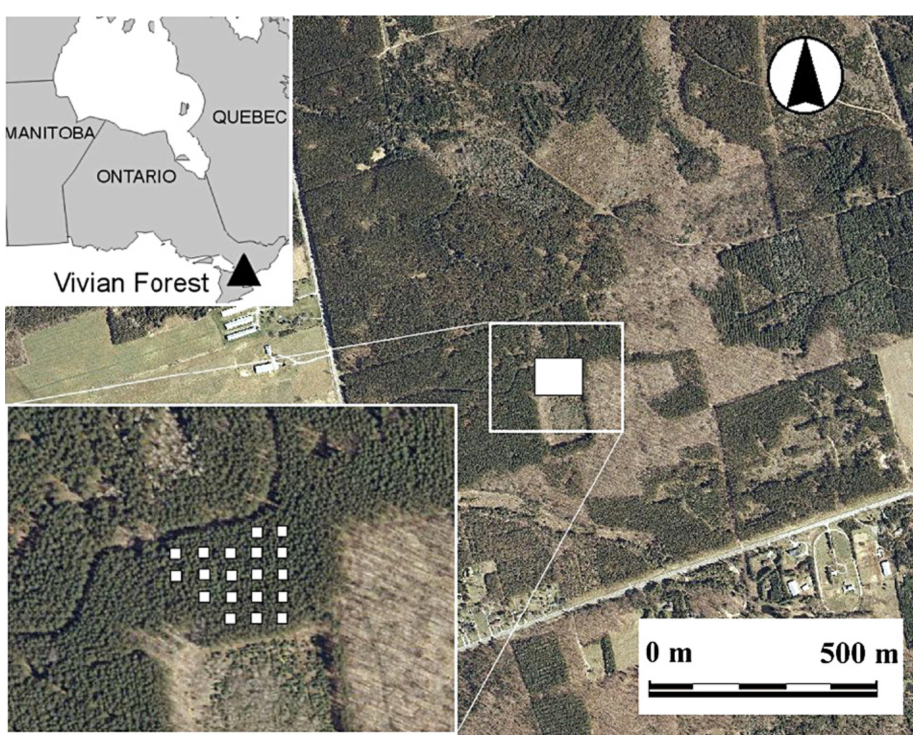

Fig. 1. The Vivian Forest study area in Ontario, Canada showing conifer plot locations (inset). Aerial photograph acquired in 1999.

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Terrain Mapper (ALTM) calibration flights adjacent to the Vivian Forest research site within the 2000 to 2005 time period (Table 1). Of the lidar datasets collected, there was significant variation in acquisition settings and seasonal survey timing. Part of this is due to the rapid evolution of the technology over the five year period, and part is due to the differing objectives associated with individual data collections. Based on the knowledge that the interaction of laser pulses with forest canopy surfaces is influenced by sensor settings (Chasmer et al., 2006a,b) and survey configuration (Hopkinson, 2007) it was assumed that the ability to detect small changes in canopy conditions from one lidar acquisition to the next would improve if sensor and flight settings were kept reasonably constant.

Additionally, the seasonal timing of data acquisition was critical, as stem growth is an intermittent rather than a continual process during the growing season (Kozlowski & Ward, 1961). Differences in climate, soils, and topography influence the periodicity of height growth (Cook, 1941). For red pine (*P. resinosa* Ait.), based on data latitudinally similar to the study area, shoot elongation occurs from early May to mid-late July with peak growth in late June (Kramer, 1943; Lotan & Zahner, 1963). Therefore, in order to control the experimental assessment of growth, it was necessary to omit any acquisitions that displayed outlying survey configurations or that were collected during the period of rapid growth early in the spring and summer.

There were four surveys demonstrating comparable sensor and survey configuration with acquisition dates after the peak growth periods and so these were chosen for temporal comparison (Table 1). All four datasets display similar point spacing; all scanner fields of view were between 24 and 36° (i.e. half angles from 12 to 18°); all laser pulse power ratings were between 11 and 16 W m^{-2}; all survey altitudes were between 800 m and 1000 m above ground level; and all flight lines had a 50% swath overlap (i.e. every area of ground was sampled two times). While a 50% overlap might be considered high in some circumstances it is becoming more common place to acquire data in this fashion over forested environments due to the asymmetry in ground and canopy level data collected at varying scan angles (e.g. Holmgren et al., 2003). All lidar surveys were registered to the same GPS base station located at the airport that the survey aircraft operated out of, 17 km south of the survey area. The field and airborne data collections in July 2002 were less than a week apart, while those in late 2005 were less than a month apart; in both cases, it was assumed the time between field and airborne acquisitions are sufficiently close to be considered coincident.

3.3. Lidar data processing

All lidar sensor data (GPS trajectory, attitude, range, scan angle) were integrated within the REALM software environment (Optech, Ontario, Canada) to generate WGS84 datum UTM projection co-ordinate points for every first, last and only LPR collected over the study area (intermediate returns collected using more modern ALTM sensors were ignored to ensure comparability). To correct for slight GPS trajectory or other system related bias, point elevations were compared over highway surfaces less than 500 m west and south of the study area (see Fig. 1). If necessary, a small (dm level at most) block adjustment of the raw LPR elevations was performed to ensure all four datasets were vertically co-registered to the first data collection in September 2000. Block adjustment of lidar data is a necessary task to ensure data accuracy and consistency and was carried out here in the *Terrascan* software environment (Terrasolid, Finland). It is a simple and commonplace procedure in the processing of any lidar dataset but is especially important for change detection applications so that the propagation of any small but systematic bias into the assessment of change is avoided (e.g. Hopkinson & Demuth, 2006).

Following vertical co-registration of all datasets over control surfaces, all LPR data were classified into ground and non-ground using a proprietary filtering technique based on an algorithm described by Axelsson (1999) within *Terrascan*. The ground returns from all acquisitions were combined, filtered again to provide an average but dense point cloud surface, and then interpolated to a 1 m raster DEM of the ground beneath the vegetation canopy using an inverse distance weighted algorithm (Lloyd & Atkinson, 2002). The non-ground lidar elevation data for each of the four acquisitions were then converted to heights above ground surface by subtracting from all first, last and only LPRs the corresponding elevation of the ground DEM. Some interpolation error is expected in lidar DEMs but this is expected to be at the centimetre to decimetre level (e.g. Hodgson & Bresnahan, 2004; Hopkinson et al., 2005; Töyrä et al., 2003) and of negligible influence to the overall LPR height distribution.

3.4. Quantile-based growth assessment

The topographically adjusted LPR canopy height data for each of the 19 plots were masked and extracted for each of the four dates of acquisition. All LPR heights within 2 m of the ground surface were removed from the point cloud so that the canopy LPR height distributions would not be influenced by

Table 1
Lidar sensor and survey configurations for acquisitions over the Vivian Forest from 2000 to 2005

Date	Lidar survey configuration							
	ALTM sensor model	Pulse power (W)	PRF (kHz)	Sensor altitude (m a.g.l.)	Scan rate (Hz)	Scan angle (°)	Emitted point spacing (m)	Returned point density (m^{-2})
9/09/2000	1225	15.9	25	800	30	±12	0.9	2.5
29/07/2002	2050	11.2	50	850	44	±15	0.8	3.6
16/11/2004	3100	13	50	1000	33	±18	0.9	2.8
13/12/2005	3100	13	50	1000	33	±18	0.9	3.2

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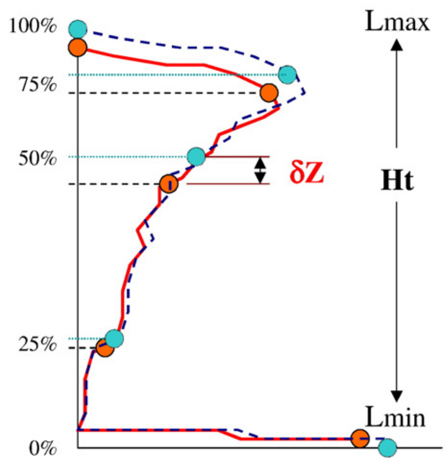

Fig. 2. Hypothetical example of vertical canopy laser pulse return frequency distribution comparison illustrating growth. Red profile illustrates the minimum, maximum and inter-quartile heights for a base line lidar data collection, while the blue profile illustrates the same height distribution statistics for a subsequent acquisition after a period of canopy height growth.

variable rates of LPR penetration to ground level. From these above ground plot-level LPR point clouds, 76 independent frequency distributions were generated and percentile height metrics extracted. Based on observations in the literature that upper percentile heights typically correlate with plot-level tree height (e.g. Magnussen & Boudewyn, 1998; Næsset, 1997), all the major upper height percentiles from the median to the max were extracted and correlated to field height values; i.e. median (L50), upper quartile (L75), 90th percentile height (L90), 95th percentile height (L95) and maximum LPR height (Lmax). Pearson's rank correlations between plot-level field-measured mean tree height and all LPR percentile heights were performed both for July 2002 and November/December 2005.

Based on the outcome of the correlation analysis, LPR percentile heights were compared through time to quantify differences in the LPR distribution height that might be associated with tree growth. Fig. 2 provides an illustration of the process of comparing LPR percentile heights for two distributions from the same plot collected at two different times. If the distribution is sensitive to changes in canopy height due to growth, then this should result in an upward shift in the percentile heights through time. In the analysis presented here, changes in LPR percentile height were compared with the changes in field-measured heights at the plot-level. The ability to estimate growth rate from LPR percentile heights was evaluated in two ways: i) by performing a *t*-test to assess whether or not there was a statistically significant difference between the lidar and field growth rates; and ii) by assessing the similarity in lidar growth rate across all combinations of time periods between the four acquisition dates. Assuming a relatively constant growth rate from year-to-year, the lidar-derived growth rate should demonstrate minimal variability. This was assessed by: a) calculating the lidar growth rate for all plots for each time period; b) performing *t*-tests to compare LPR plot-level heights between each consecutive acquisition to discern whether or not the observed growth was statistically significant; c) comparing average growth rates in a single factor Analysis of Variance (ANOVA) to test for statistical differences amongst all time periods.

3.5. Raster growth assessment

A further evaluation of lidar growth was performed by quantifying the level of surface height change between consecutive raster CHMs. A digital surface model (DSM) of the 60 × 60 m area bounding the study plots was rasterized from the previously classified non-ground LPR point clouds for each date. To mitigate against downwards interpolation bias in the DSM, the lidar data were filtered so that only the highest points within each 1 × 1 m window were used for rasterisation. As with the ground DEM, an inverse distance weighted rasterisation procedure was adopted. A 1 m raster CHM was then created by subtracting the DEM from the DSM. From the field data, it was known that each plot contained an average of seven trees. By dividing this number into the size of each plot (121 m^2), it was estimated that on average each 16 m^2 area would contain one tree crown. Therefore, a box filter was applied to the raster CHM to extract the highest CHM value within each 4 m × 4 m window. This method provided 225 estimates of canopy height for each dataset or 225 estimates of growth between datasets.

4. Results and discussion

4.1. Lidar tree height estimation

The average plot-level field height from 126 trees within 19 plots was found to be 23.8 m (standard deviation (σ) = 0.4 m) for 2002 and 25.0 m (σ = 0.6 m) for 2005, which produced an estimated annual growth rate of 0.4 m/yr (σ = 0.5 m). This was slightly higher than the published site index 75 growth rate of 0.34 m/yr derived from growth and yield tables for this type of conifer plantation (Huebschmann & Martin, 1996), but was within the bounds of error. If minimum and maximum growth rates are recalculated based on a standard deviation of error either way in the plot height estimates for each date, the maximum range in possible growth rates becomes 0.1 m/yr to 0.7 m/yr. The

Table 2
Pearson rank correlation coefficients between plot-level LPR distribution percentile heights and mean tree height (*P*-values in brackets.)

Year	L50	L75	L90	L95	Lmax	*N*
2002	0.07 (0.78)	0.18 (0.47)	0.36 (0.13)	0.37 (0.12)	0.30 (0.21)	19
2005	0.47 (0.04)	0.60 (<0.01)	0.63 (<0.01)	0.59 (<0.01)	0.56 (0.01)	19
Combined years	0.60 (<0.01)	0.73 (<0.01)	0.80 (<0.01)	0.79 (<0.01)	0.79 (<0.01)	38

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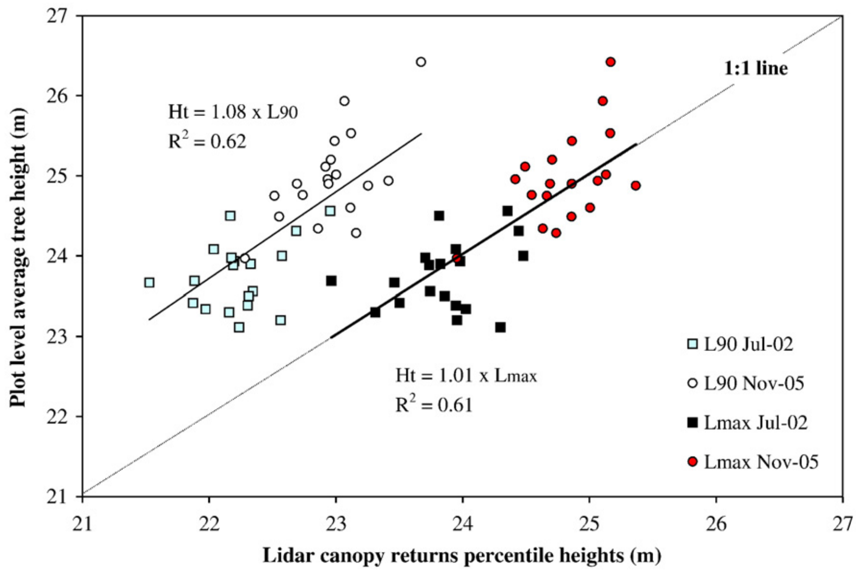

Fig. 3. Plot-level average field-measured tree heights over L90 and Lmax percentile heights for all 19 plots in July 2002 and November 2005. Results for L95 have not been presented here because they plot almost exactly between L90 and Lmax.

standard deviation uncertainty for field height growth estimates over the three year period was 1.1 m (92% of the mean growth) for individual tree measurements (n=126) and 0.5 m (41% of mean growth) at the plot-level (n=19).

From the 76 extracted plots, the average number of LPR points recorded per plot was 534 with a minimum of 294 and a maximum of 667. Of the LPR percentiles tested, L90, L95 and Lmax demonstrated the highest correlations with field-measured tree height (Table 2). Correlations were low in individual years due to the small range in observed plantation canopy heights. The correlation increases, however, when data from both years were combined due to the increase in canopy height range over the three-year period. For individual years, L90 and L95 displayed a stronger correlation than Lmax, and this was

Table 3
Estimated field and Lmax heights and growth associated with each data collection

Plot #	Plot-level field heights (m)		Growth (m)	Plot-level Lmax heights (m)				Lmax change (m)		
	Jul-02	Nov-05	2002–05	Sep-00	Jul-02	Nov-04	Dec-05	2000–02	2002–04	2004–05
1	24.3	25.5	1.2	23.05	24.44	24.87	25.17	1.39	0.42	0.30
2	23.7	24.0	0.3	22.51	23.46	23.87	23.96	0.95	0.41	0.09
3	24.6	26.4	1.9	23.42	24.36	24.97	25.17	0.93	0.61	0.20
4	23.4	24.8	1.3	22.74	23.50	24.37	24.67	0.76	0.87	0.30
5	24.1	25.4	1.4	23.79	23.95	24.31	24.86	0.16	0.36	0.55
6	23.1	25.0	1.9	22.90	24.30	24.66	25.13	1.40	0.37	0.47
7	23.3	24.9	1.6	23.50	24.03	24.04	24.86	0.53	0.01	0.82
8	24.5	24.8	0.3	22.77	23.82	23.73	24.55	1.04	−0.09	0.82
9	23.7	24.5	0.8	21.94	22.96	24.41	24.86	1.02	1.44	0.45
10	23.9	25.9	2.0	23.29	23.98	24.86	25.11	0.69	0.88	0.25
11	23.6	24.3	0.8	23.30	23.74	24.90	24.63	0.44	1.15	−0.26
12	23.9	25.2	1.3	23.53	23.74	24.41	24.71	0.21	0.67	0.30
13	23.9	25.1	1.2	23.15	23.82	24.43	24.49	0.68	0.61	0.06
14	23.5	24.3	0.8	23.25	23.86	24.46	24.74	0.61	0.60	0.28
15	24.0	25.0	1.0	22.93	23.71	24.30	24.42	0.77	0.60	0.11
16	23.2	24.9	1.7	23.22	23.96	24.46	25.07	0.73	0.50	0.61
17	23.3	24.9	1.6	22.88	23.31	24.05	24.69	0.43	0.74	0.64
18	23.4	24.6	1.2	23.41	23.95	24.85	25.01	0.54	0.90	0.16
19	24.0	24.9	0.9	23.39	24.48	24.28	25.37	1.09	−0.20	1.09
Min	23.8	25.0	0.3	21.94	22.96	23.73	23.96	0.16	−0.20	−0.26
Max	24.6	26.4	2.0	23.79	24.48	24.97	25.37	1.40	1.44	1.09
Average	22.5	23.7	1.2	23.10	23.86	24.43	24.81	0.76	0.57	0.38
Annual average			0.4					0.38	0.29	0.38
SD	0.4	0.6	0.5	0.43	0.39	0.36	0.33	0.35	0.40	0.32
T-test *P* value			<0.01					<0.01	<0.01	<0.01

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likely due to these percentile heights being a function of the entire plot-level LPR distribution, whereas Lmax was derived from the height of a single point. When the sample was doubled in the combined dataset, however, the distribution range was increased and the difference in correlation coefficients reduced significantly, suggesting that all three LPR metrics are equally good indicators of plot-level height. When plotting L90 and Lmax against field heights it was apparent that Lmax displayed an almost 1:1 relationship (Fig. 3) and thus despite a slightly lower correlation, was probably a better all round indicator of plot height through time.

4.2. Lidar tree growth estimation

While there was a near 1:1 relationship observed between Lmax and average field-measured tree height (Fig. 3), the changes in plot-level Lmax heights, on average, were smaller than observed in the field. A frequency distribution of field and Lmax heights illustrates the average change in plot-level Lmax height of +0.95 m was slightly below the +1.2 m observed in the field (Table 3 and Fig. 4). The root mean square error (RMSE) between field and Lmax height difference was 0.58 m, or approximately half of the difference observed over the three year time period. Examining the frequency histogram of plot-level field and Lmax growth (Fig. 4) it was evident that growth estimates based on field data were widely distributed, demonstrating a mode that was higher than the mean, while the Lmax distribution was more tightly clustered. The frequency histogram for individual tree growth (Fig. 4, inset) appeared more normally distributed, but the plot-level data may have been influenced by the number of trees within the plots sampled (ranging from 4 to 11). Increasing the size of the plots to include more trees in each, may improve the correspondence between plot-level Lmax and field estimates of growth, since the LPR distribution was possibly influenced by tree crowns that were not fully within the plots. Nonetheless, a single factor ANOVA test demonstrated that there was no statistically significant difference between all plot-level field and Lmax mean growth rate estimates ($P = 0.38$).

Lmax height estimates were less variable than field estimates. Field plot height standard deviations were 0.4 m and 0.6 m for 2002 and 2005, respectively, while Lmax plot height standard deviations ranged from 0.32 m to 0.43 m. This is likely influenced by the reduced measurement precision of the manual field method (dm) compared to the lidar method (cm) but also could be because Lmax is less sensitive to plot-level tree height variability. For example, Lmax will be influenced by individual tall canopy elements (Næsset, 1997) and, unlike manual methods, will not accurately record the level of within plot canopy heterogeneity. Further, the systematic penetration of laser pulses into canopy before being returned (Gaveau & Hill, 2003; Hopkinson, 2007) and the low probability of capturing all canopy apices (St-Onge et al., 2000) could act to reduce lidar canopy surface height variability.

4.3. Temporal growth sensitivity

The lidar-derived growth observations for the three time periods from 2000 to 2002, 2002 to 2004 and 2004 to 2005 were each statistically significant at the 99% confidence level (Table 3). Further, the rates of lidar estimated growth were close to (but slightly less than) the observed field growth estimate for the 2002 to 2005 period. Visual inspection of the change in LPR distribution percentile heights over time illustrated in Fig. 5, and the average Lmax growth rates reported in Table 3, indicate that the changes in lidar derived growth estimates were relatively consistent through time. Although all LPR percentile heights plotted close to the five-year growth trend-line (Fig. 5), all percentile heights illustrated a slight upwards deviation in 2002 (increased growth) and a downwards deviation in 2004 (decreased growth). These slight deviations away from the long-term trend correspond to a reduced Lmax growth rate of 0.29 m/yr estimated

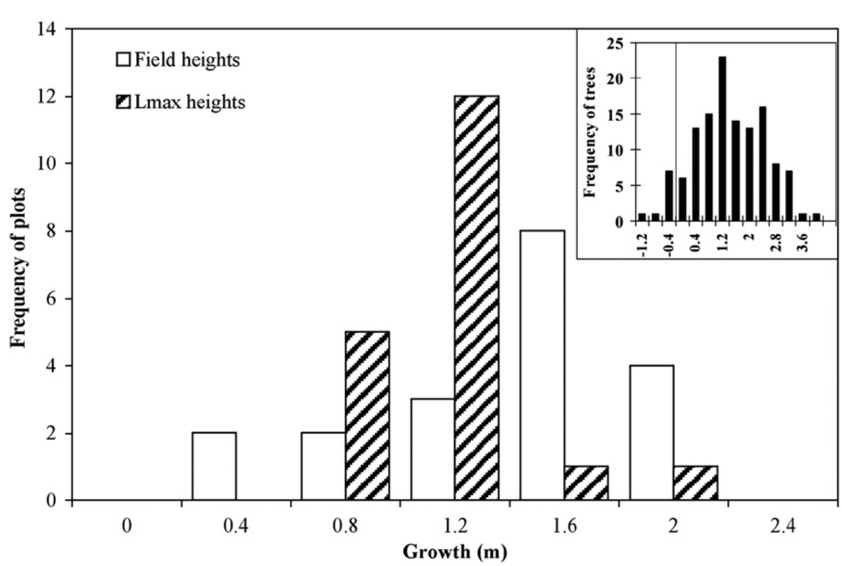

Fig. 4. Plot-level height growth histogram from field validation data and Lmax predicted growth between 2002 and 2005. Individual tree growth observations from field validation data inset.

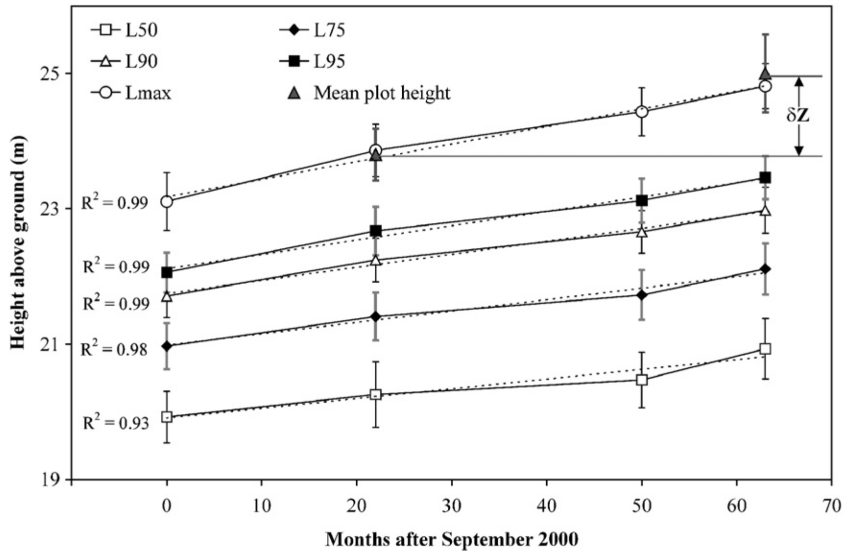

Fig. 5. Average plot-level heights for L50 to Lmax through time illustrating the long-term growth vector (dashed line). Field-measured plot heights are also illustrated for comparison and the observed growth is illustrated by δZ. Error bars represent the plot-level standard deviation. R^2 values demonstrate the closeness of fit between LPR percentile heights for each data collection relative to the long-term growth trend.

for the 2002 to 2004 time period compared to the 0.38 m/yr observed for the previous and following time periods (Table 3). However, the general similarity and lack of statistical difference in Lmax growth rates bodes well for the potential resilience of lidar-based growth rate estimation for conifer plantation canopies.

Based on a single factor ANOVA test, the average Lmax growth rates across six time periods ranging from 1 to 5 years demonstrated no statistical difference ($P = 0.59$). However, as the amount of growth increased through time so the variability in growth estimate reduced (Fig. 6). A power function relationship between time interval and the standard deviation in growth estimate was established. This relationship suggests that over a one-year period, the uncertainty is in the range of 0.3 m (~100% of observed growth) but this reduces to less than 0.1 m (~6% of observed growth) after 5 years. This illustrates how allowing longer time intervals for growth estimation leads to increasingly precise results. Operationally, repeat plot-level field measurements of forest canopy height are typically made at 5 to 20 year intervals (e.g. Vivian, 1999). The results presented here illustrate that lidar can potentially provide accurate conifer plantation growth results at shorter time intervals.

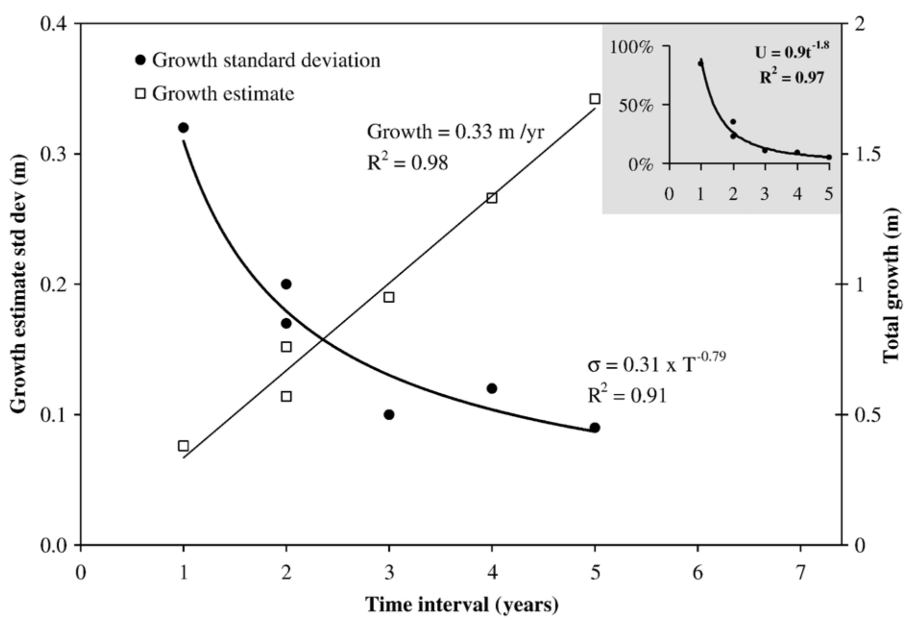

Fig. 6. Lmax predicted growth (right axis) and the associated error (standard deviation) (left axis) plotted over time interval for the six possible combinations of growth periods from the four data acquisitions. Inset: Growth prediction uncertainty (U) is the ratio of Lmax growth error to the total observed growth for a given time interval in years.

From the uncertainty prediction curve illustrated in the inset of Fig. 6, it is apparent that if a 10% level of uncertainty were acceptable for forest management purposes, then this could be achieved with a three-year repeat time interval. After three years, Lmax growth uncertainty continues to decrease (i.e. accuracy and precision both increase) but at an ever diminishing rate. This suggests that if high temporal resolution data are deemed desirable (e.g. disease monitoring, phenological or climate change research, treatment monitoring, growth/yield table evaluation) then the enhanced accuracy provided by increasing the repeat time interval beyond three years might be of minimal value. For comparison, the plot-level estimate of growth from the field height measurements, also collected over a three-year period, recorded an uncertainty of 42%; i.e. for the same time interval, the field estimate of growth is four times less precise than the lidar estimate. Therefore, to achieve a 10% uncertainty in growth estimate, much longer time intervals would be necessary using the field clinometer measurement techniques adopted in this study.

4.4. Raster CHM growth assessment

The visualisation of the 60 × 60 m raster CHM for each lidar acquisition in Fig. 7 provides a visual record of canopy height change through time. Only canopy surface heights above 22 m are illustrated to emphasise the changes at the upper height ranges. The height increases associated with individual tree crowns and clusters of tree crowns are clearly evident. Even within this homogeneous conifer plantation, the CHMs illustrate considerable spatial and vertical variation in canopy surface morphology. Unlike a previous lidar study investigating tree growth change from raster CHMs (Yu et al., 2004), no attempt was made to segment individual trees or their associated tree growth. This was because a preliminary visual inspection of the canopy surface models illustrated significant lateral movements of up to several grid nodes for individual tree crowns from one acquisition to the next (possibly due to wind or phototrophic growth conditions), making accurate registration challenging and restricted to dominant tree crowns. While this observation could be the subject of another study, the raster-based assessment of height and growth presented here was restricted to a comparison of the mean maximum heights extracted from the 4 × 4 m box filter (Fig. 8).

The filtered CHM height estimates significantly under-predicted field heights by approximately 1 m ($P < 0.01$) and this observation is consistent with those of Yu et al. (2004). This is likely due, in part, to penetration of laser pulses into foliage before being returned (Gaveau & Hill, 2003), the reduced

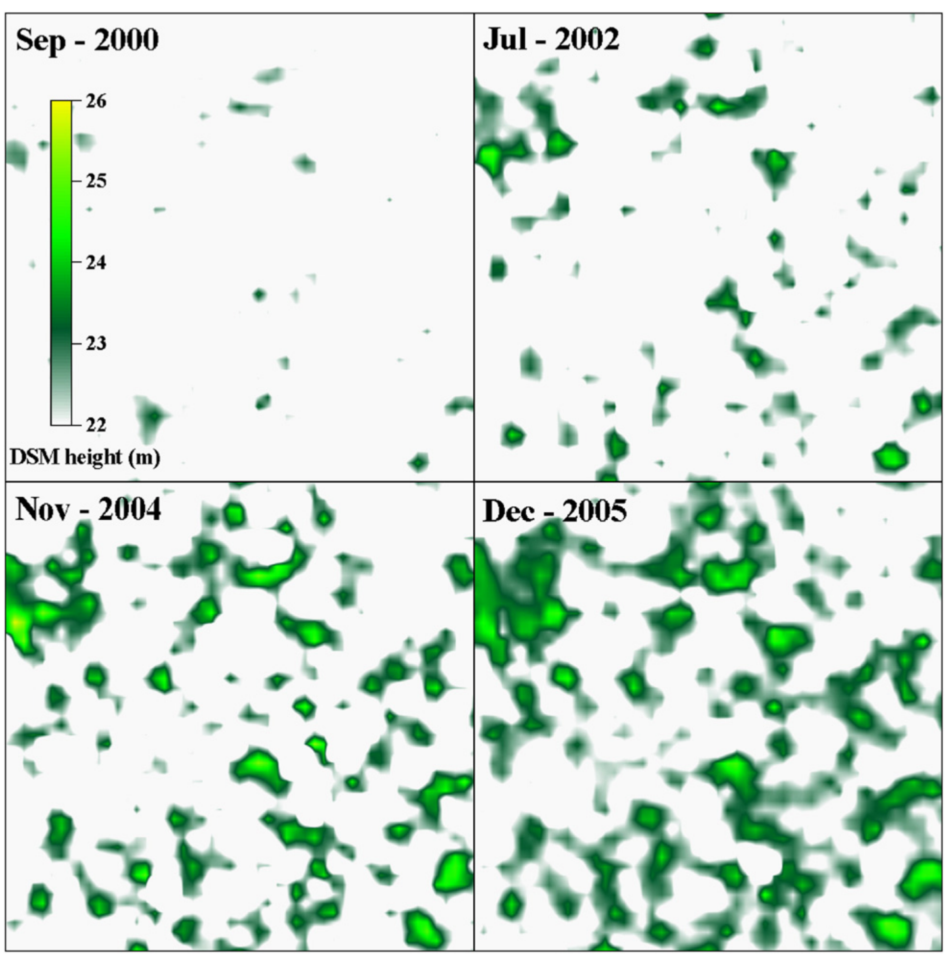

Fig. 7. Raster canopy height models for 2000, 2002, 2004 and 2005 to illustrate changes in height associated with the upper conifer tree crown surfaces within the area surrounding the field plots.

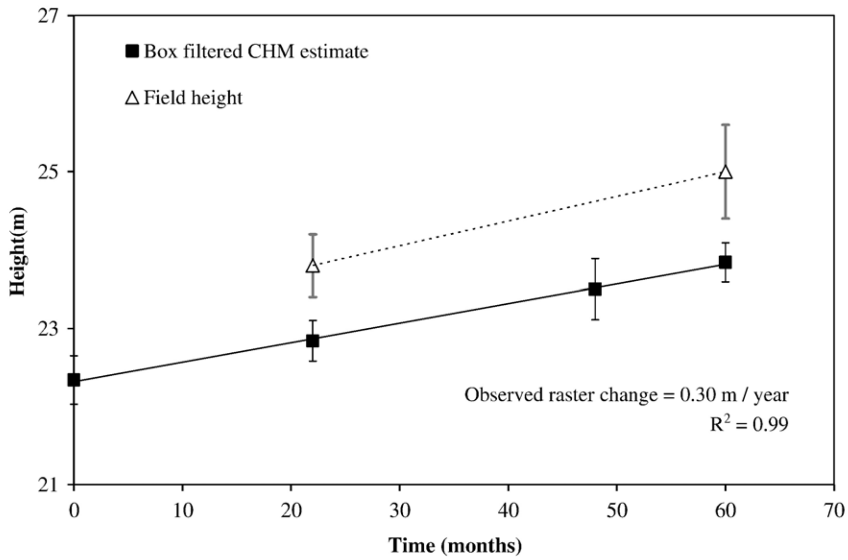

Fig. 8. Plot-level field-measured and box-filtered raster lidar DSM height change through time. Trend lines illustrate the mean growth vector, while error bars signify a standard deviation of error.

probability of capturing all canopy apices (St-Onge et al., 2000), and to the moderating influence of the IDW interpolation algorithm when averaging heights around individual grid nodes. As with LPR height estimates, the CHM rate of growth was also low (0.3 m/yr) compared to field data (0.4 m/yr), but the difference was not significant ($P > 0.1$). Following correction of the CHM by applying a calibration scale-factor based on the difference between field and CHM heights, the CHM height and growth rate approached those observed in the field. However, LPR percentile height approaches such as Lmax appear to provide a better first estimate of actual plot-level height without the need for calibration and, further, do not incur the horizontal data smoothing influences associated with interpolation.

4.5. Inter-annual growth variability

Although the CHM comparisons were insufficiently sensitive to detect inter-annual variation in growth rate, the slight Lmax height and growth deviations observed in Figs. 5, 6 and 9, warrant further investigation, as it may be instructional to postulate possible mechanisms for such a change in growth rate. The primary possibilities to consider must be those associated with analytical error. In this study such errors could result from: i) differences in the lidar survey configuration leading to systematic differences in canopy surface representation and height estimation (e.g. Chasmer et al., 2006b; Hopkinson, 2007); or ii) in the assumption that each lidar acquisition captured the canopy

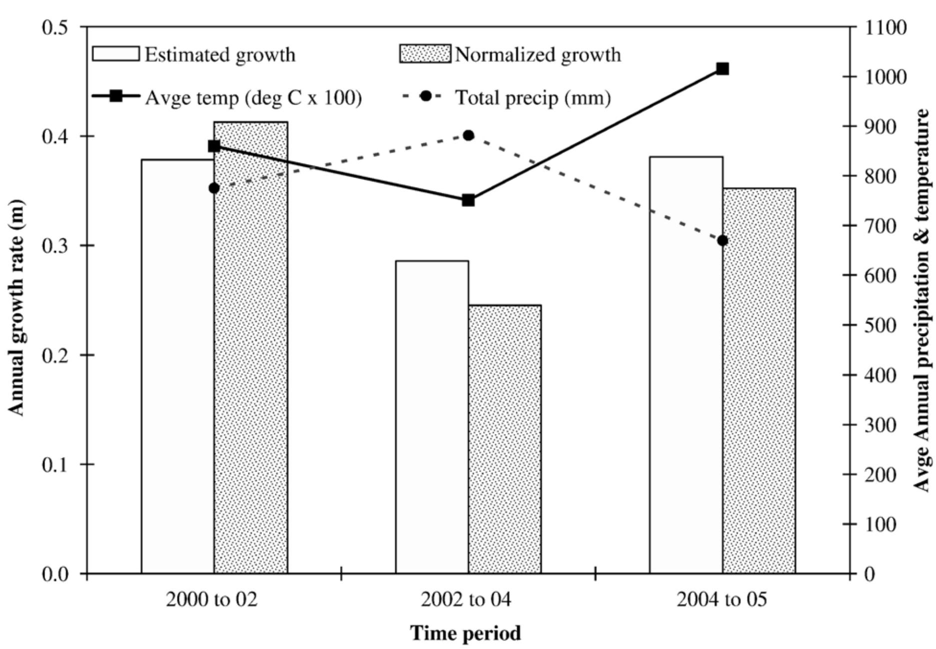

Fig. 9. Inter-annual variation in climatic conditions and Lmax estimated growth rate. Normalized growth is calculated based on assuming an unrealistic constant rate of change in tree height between lidar acquisitions.

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conditions sufficiently late in the growing season to be representative of the year.

Of the four datasets, the only one that displays both a growth rate deviation and an outlying data acquisition configuration is that of 2002. The main difference for the 2002 acquisition compared to the others is that it had the highest sample point density with the lowest peak pulse power (Table 1), while recording an elevated rate of growth relative to the long-term trend. Based on the work of Hopkinson (2007), large reductions in pulse power can lead to a slight reduction in tree height estimation due to increased pulse penetration into foliage, while increased sample point density leads to a slight increase in tree height estimation. Further, Chasmer et al. (2006a,b) studied multiple lidar datasets collected over the same study site and found that increasing the pulse repetition frequency (and therefore decreasing pulse power) also led to a slight upshift in the LPR percentile height distribution. However, while systematic differences in LPR height to field height relationships between datasets cannot be discounted, they are not believed to be completely responsible for the growth rate deviations observed here. This is due to the limited range of variability in the survey configurations (Table 1) relative to the wide range that is permitted. For example, survey altitudes can range from <100 m to >3000 m above ground, peak pulse power can range from <5 W to >30 W, scan angles typically vary from 0° (profile) to >30°, and point density can vary from <0.1 point/m^2 to >10 points/m^2.

With regard to survey timing, all acquisitions were performed after the peak growth period but there was significant variation in the actual time of year, from the end of July to mid-December. If the acquisitions are not fully representative of tree height at the end of the growing season, then some normalization can be applied based on the number of months between each acquisition. However, by applying such an adjustment to the data, as illustrated in Fig. 9, seasonal phenology is effectively ignored, and in any case it is found that this only acts to increase the variability and therefore is an unsatisfactory explanation for the observed growth variability.

If data acquisition configuration and timing are not likely to introduce all of the systematic growth rate deviations observed, then it is possible that some of the change in Lmax estimated growth rate is a function of actual growing conditions over the site during the period investigated. The site was not fertilised during the study, which suggests soil and nutrient conditions were likely similar throughout the years of observation from 2000 to 2005. After nutrient loading, the next most logical influences to pine tree growth rate are likely to be changes in climatic conditions related to moisture availability and temperature (e.g. Gholz, 1982; Vose et al., 1994). In Fig. 9, average annual temperature and average total annual precipitation values for the nearby town of Richmond Hill (<10 km away) have been plotted (data provided by the Metrological Service of Canada). Although there are only three values for each of the variables compared, it is evident that growth, precipitation and temperature each display large variations from one time interval to the next. While it is outside the scope of this paper to study the processes controlling growth rate, it is possible that the variations in climatic conditions at the site are responsible for the differences in growth rate observed. This suggests that with sufficient operational control and a long enough time interval, temporal airborne lidar data could be a viable tool to assess the influence of silvicultural treatments and land management practices to plantation productivity.

5. Conclusions

For red pine conifer plantations possessing growth patterns similar to those in southern Ontario, Canada it can be concluded that airborne lidar methods are sensitive enough to detect growth at an annual time step. For both LPR and raster methods, the lidar-based estimate of growth (>0.3 m/yr) was close to published growth/yield table expectations but slightly below that observed in the field (~0.4 m/yr). The differences were within the bounds of measurement error and were not statistically significant. Moreover, the estimates of growth were relatively consistent from one time interval to the next, indicating a level of robustness to the method. While there was no statistically significant difference in growth rate across time periods, there were subtle variations that could have been related to local climatic influences.

The results of this analysis have implications both for operational practices and the potential development of research to assess long-term phenology. While it has been shown that growth can be detected with confidence at an annual time interval for a southern Ontario red pine plantation, the level of standard deviation uncertainty is approximately 100%. Operationally, this would be unacceptable. However, both the absolute and relative magnitudes of plot-level uncertainty decrease in a power–function relationship with the annual time increment, such that after three years the level of uncertainty in the lidar growth estimate rapidly drops to an operationally acceptable level of approximately 10%; with additional time providing minimal increases in accuracy. This is shorter than a typical five-year time interval of field-based repeat height assessment for similar conifer plantations.

From a research perspective, it is apparent that we can use lidar-based methods to study both high-resolution spatial and temporal processes at the canopy and stand level. Multiple lidar acquisitions over periods of years provide insight into the canopy structural development at the individual crown level, which could enhance our understanding of tree-level competition and local resource (light, water, nutrient) uptake processes. At the stand level, multi-temporal lidar datasets can be used to provide further insight into growth responses to climatic forcings, silvicultural treatments and land management practices.

An important limitation of the analysis presented, is that it was conducted over a homogeneous conifer plantation precisely for the reason that this is the type of environment for which lidar would be expected to be most sensitive to uniform changes in canopy height. Natural forests or managed regeneration stands do not possess the same levels of species and age homogeneity, and uniform stem spacing as conifer plantations. Consequently, the growth signal within and between plots taken from more natural forest environments are expected to be more difficult to isolate. More research is needed, therefore, to quantify the appropriate

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time intervals between repeat lidar acquisitions that are necessary to achieve required levels of prediction certainty in such environments. Further, the analysis presented utilised comparable lidar datasets and operationally, this can be difficult to achieve. Consequently, work is needed to better understand sensor and survey configuration influences to lidar data properties, and to develop lidar data normalisation routines to facilitate the comparison of non-comparable datasets.

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