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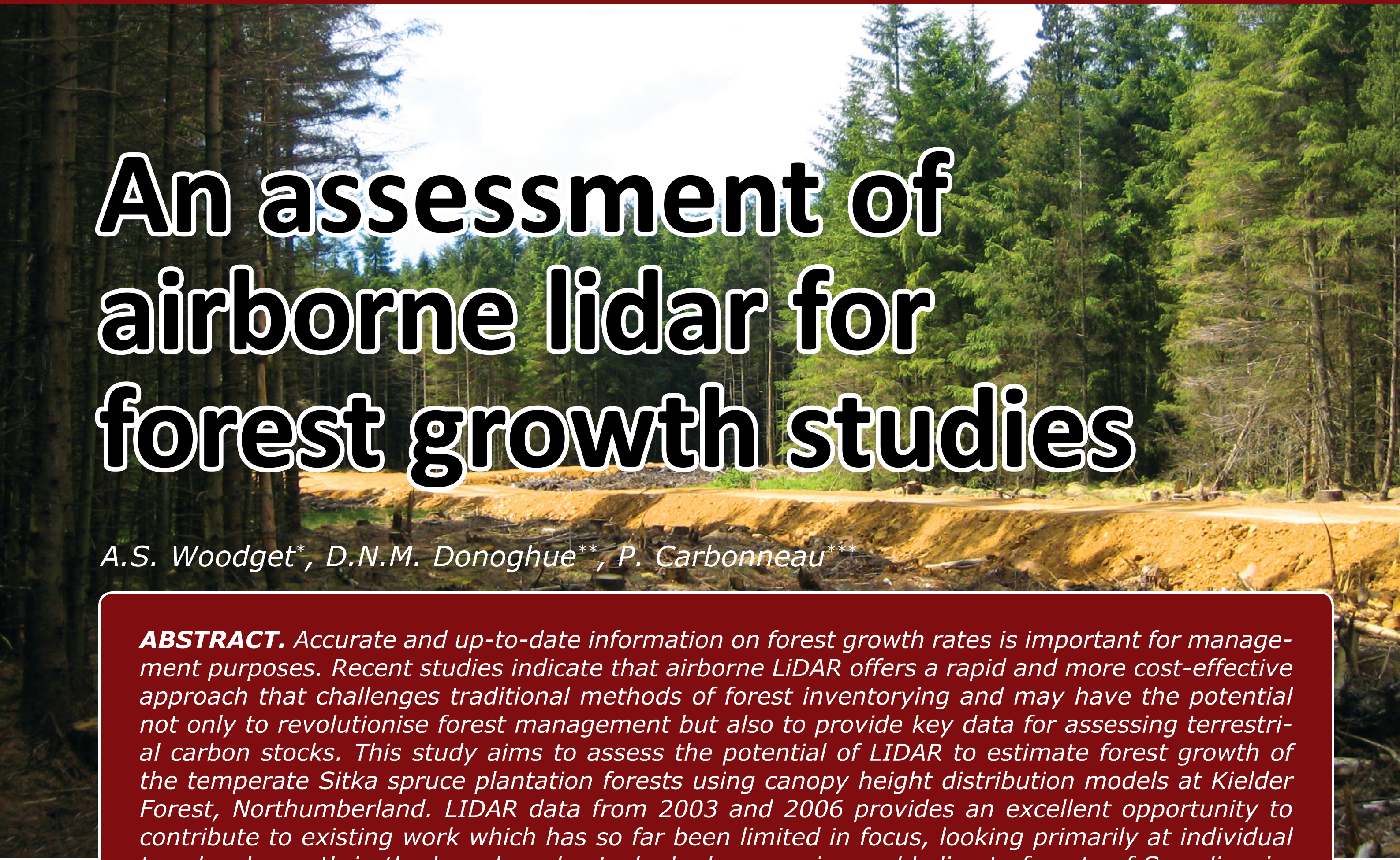

An assessment of airborne lidar for forest growth studies

A.S. Woodget[*], D.N.M. Donoghue[**], P. Carbonneau[***]

ABSTRACT. *Accurate and up-to-date information on forest growth rates is important for management purposes. Recent studies indicate that airborne LiDAR offers a rapid and more cost-effective approach that challenges traditional methods of forest inventorying and may have the potential not only to revolutionise forest management but also to provide key data for assessing terrestrial carbon stocks. This study aims to assess the potential of LIDAR to estimate forest growth of the temperate Sitka spruce plantation forests using canopy height distribution models at Kielder Forest, Northumberland. LIDAR data from 2003 and 2006 provides an excellent opportunity to contribute to existing work which has so far been limited in focus, looking primarily at individual tree level growth in the less densely stocked, slow-growing, cold climate forests of Scandinavia. LIDAR point cloud data from the first and last pulse returns are filtered and classified. Ground returns are used to create digital elevation models (DEM), and first returns used to create digital canopy height models (DCHM). Processed LIDAR data from both years are compared to estimate forest growth. In continuation, LIDAR plot height and growth values are extracted. The results are compared with plot level ground-based data. Height correlations are strong and positive. Growth is detected at all plot locations but correlations with ground-based data are weak and mostly negative. Potential explanations for the lack of correlation are presented and discussed. Further study is necessary to quantify and eliminate systematic and random error within both the LiDAR and ground-based data before LIDAR may be used routinely for forest management purposes.*

KEYWORDS: *LiDAR, Forestry, Growth, Kielder.*

CLASSIFICATION *(COBISS)**: 1.04***

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1. Introduction

There is a need for accurate and up-to-date information on tree growth rates for forest management purposes. Traditionally such data have been collected in the field or from remote sensing using aerial photography. Recent studies however, indicate that LIDAR may offer a quicker and more cost-effective method of data collection with the potential not only to revolutionise forest management but also to provide important data concerning forest carbon stocks.

Much of the research into the use of LIDAR for forest applications has assessed variables such as tree height, volume and biomass. Such studies have found high levels of correlation between LiDAR derived variables and the equivalent measures obtained from ground-based measurements (Nelson *et al*, 1988; Nilsson, 1996; Næsset and Bjerknes, 2001; Næsset and Økland, 2002; Donoghue and Watt, 2006). However, few studies have attempted to quantify forest growth using LiDAR and the work of Yu *et al*, 2004, 2006 suggests this is a complicated task with the potential for large errors. The results of Yu *et al*, 2004 object-orientated approach indicated that errors of growth estimation were larger than the estimated growth itself. Follow up work in 2006 produced growth values of a more acceptable accuracy, with correlations between LiDAR and ground-based growth measures as strong as 0.68 (Yu *et al*, 2006). The work of Næsset and Gobakken, 2005 took a different approach, attempting to quantify growth at a coarser spatial scale. However, comparison with field data

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suggested LiDAR growth predictions had low levels of accuracy and precision.

Multi-temporal LiDAR data acquired over Kielder Forest (Northumberland, England) provides an excellent opportunity to further these existing growth studies which have so far been limited in focus, looking primarily at the less densely stocked, slow growing, cold climate forests of Scandinavia. This study uses data from 2003 and 2006 to assess the potential of airborne LiDAR for estimating the growth of Sitka spruce (*Picea sitchensis*) plantation forestry using canopy height distribution models. LiDAR derived growth metrics are compared with ground-based measurements and potential sources of errors are considered.

2. Material and Methods

2.1 Study Site

The 6km^2 study area lies within Kielder Forest, a plantation forest located in the county of Northumberland in Northern England (Figure 2-1). It is owned and managed by the UK Forestry Commission and Sitka spruce is the primary commercial crop.

2.2 LIDAR Data

Two airborne laser scanning surveys were acquired over the study site in March 2003 and May 2006. The 2003 data was collected using an Optech ALTM 2033 laser scanner by the Environment Agency on behalf of the Forestry Commission. In 2006, an Optech ALTM 3033 instrument was flown by the National Environmental Research Council's Airborne Research and Survey Facility (NERC ARSF) onboard their Dornier 228-101 aircraft. These are both small footprint, discrete return systems which recorded first and last pulses and intensity.

Table 2-1. Ground Classification Parameters

Ground Classification Parameter	Setting
Maximum Building Size	100m
Terrain Angle	88°
Iteration Angle	8°
Iteration Distance	0.5m

2.3 LIDAR Processing

The following processing chain was performed on both the 2003 and 2006 LiDAR datasets. Initially, point clouds were filtered for erroneous returns using the TerraScan software (TerraSolid). Last returns were then classified as ground using the embedded TIN (Triangulated Irregular Network) densification algorithm developed by Axelsson 2000. The specific ground classification parameters used are shown in Table 2-1. This TIN was then used to create the digital elevation model (DEM). First returns which fell between 2m and 45m were then classed as canopy. Those hits falling below 2m were excluded to eliminate the effects of small shrubs and other low lying material. The upper limit of 45m was set using *a priori* information concerning maximum tree heights reached within this geographical area. Canopy hits were adjusted to the DEM to give them a height above the ground and were then interpolated to create a canopy height model.

Following this, those points classified as ground and canopy were exported to the statistical software package STATA for extraction of mean heights (Donoghue *et al*, 2007). This program was used to grid the data into 5m by 5m pixels and to calculate mean height for each of these cells. This data was next imported in ArcGIS and processed into raster format to produce height maps.

The use of any multi-temporal data requires special considering in terms of accurate positioning. The Kielder 2006 LiDAR dataset was found to be offset by roughly 5m in a northerly direction from the 2003 dataset. This was determined by highlighting clearly identifiable features in both raster images and measuring the shift in their location. Given the simple linear nature of this offset, the process of correction was fairly straightforward, although the reason for this shift is unclear.

Difference imaging was next performed, by subtracting the 2006 mean height maps from the 2003 mean height maps to produce growth maps of the study area. Finally, GIS data was overlain on the maps, and LiDAR height and growth data extracted from the location of each plot.

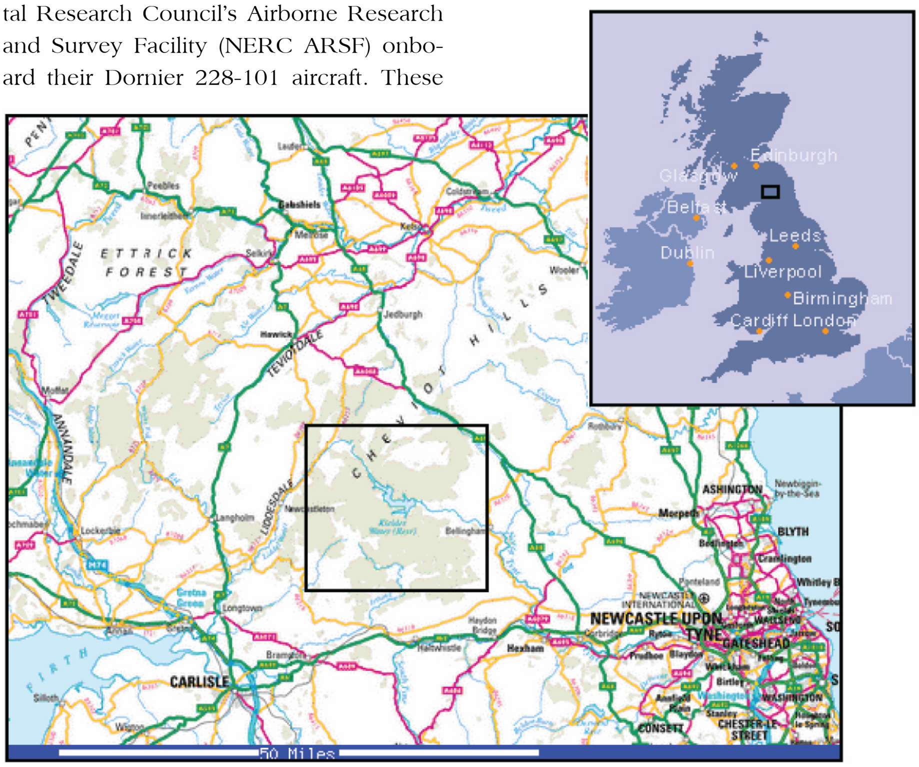

Figure 2-1. Location map for Kielder Forest (URL-1)

2.4 Ground-Based Measurements

Ground-based data were collected by the Forestry Commission in 2003 and each tree marked for future identification. A field team from Durham University collected the ground-based data from the same plots in 2006. Both datasets were collected following standard the UK forest inventorying practices. A total of 22 plots of various ages were surveyed for growth in tree height and diameter over the 3 year period. The majority of plots were circular and 0.02ha in size, however a small number were square and 0.01ha in size. Plots were navigated to using a handheld GPS and plot centre and tree locations recorded using a Leica series 300 differential GPS. Tree height was measured using a Vertex III hypsometer for all those trees taller than 1.37m and a tape measure for those smaller than 1.37m. Diameter at breast height (dbh) was measured using a diameter tape. Tree status (e.g. double leader, dead etc) and species type were also noted, however only a handful of trees throughout the entire study area were not Sitka spruce. Figure 2-2 shows the plot

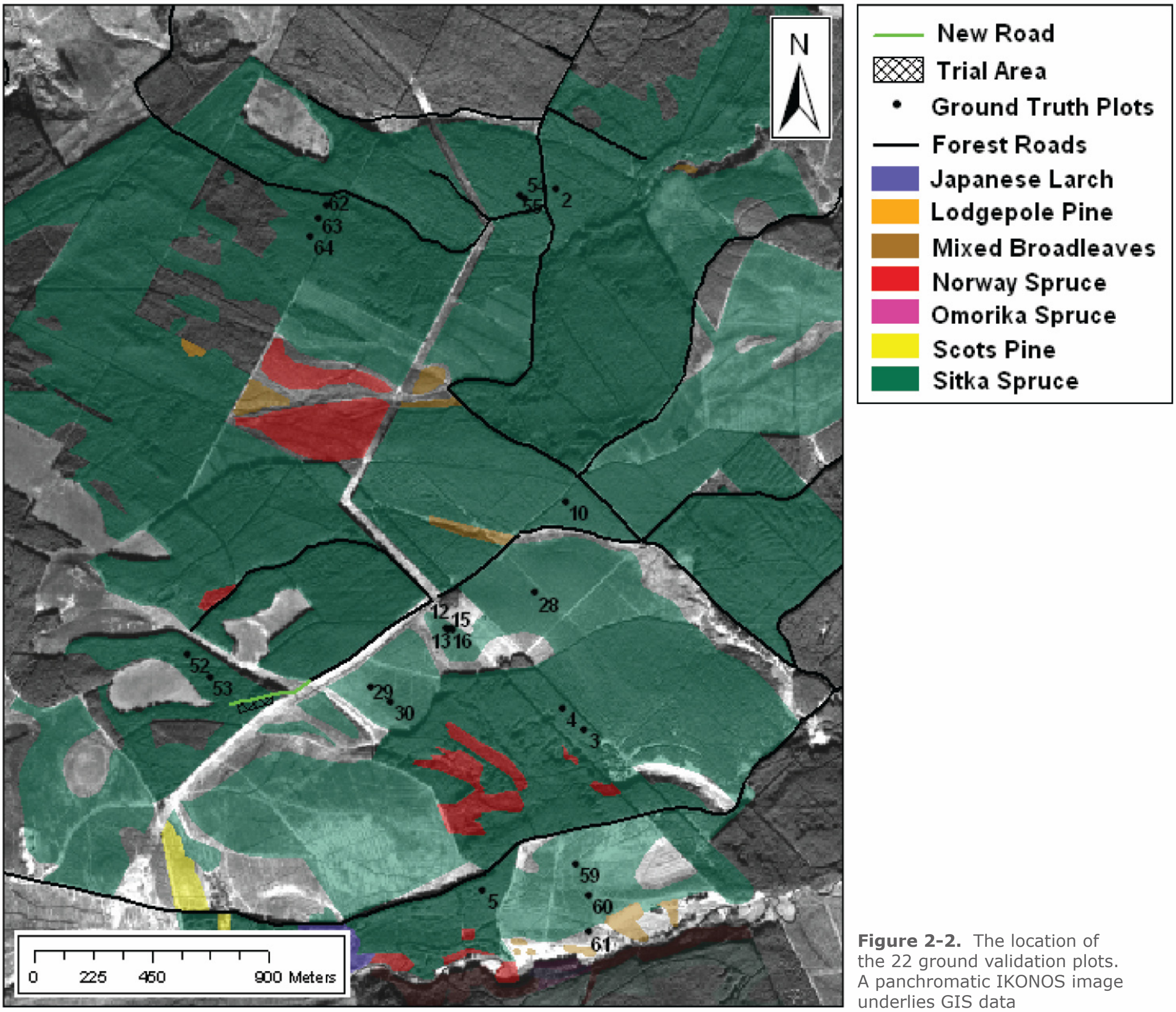

Figure 2-2. The location of the 22 ground validation plots. A panchromatic IKONOS image underlies GIS data

locations displayed in the GIS.

Average ground-based plot heights were calculated as Lorey's Mean Height (LMH). This averages tree height per plot using basal area as a weighting function as shown in Equation 1, where g is basal area and h is tree height. This was then compared with the average LiDAR mean height and growth values at each plot location. These LiDAR averages took the unweighted mean of all pixels falling within the plot area, regardless of whether this was the entire pixel or otherwise.

$$h_L = \sum_i \frac{g_i h_i}{\sum_i g_i}$$

Equation 1. Lorey's Mean Height

3. Results

3.1 Growth Estimates

Figure 3-1 is a LiDAR growth map for the 6km² Kielder study area, created by difference imaging of the mean height maps for the two years. The darkest areas of this map represent negative height change, ranging through to the lightest areas of positive change. The white blocks represent areas of no data where problems of dense canopy prevented an accurate estimation of the DEM and thus also the CHM.

Areas of clear-fell can clearly be seen as the darkest areas in Figure 3-1, as can other small dark regions which have been subject to windblow. Large areas of open ground can be identified in the mid-grey and canopy stands in the lighter grey. Some variation in colour, indicating variation in the amount of growth, can also be observed within the stand areas.

A more quantitative representation of plot level growth as detected by the LiDAR is shown in Figure 3-2. Unweighted mean LiDAR growth plotted against planting year shows that growth has been detected at the locations of all plots and that an age-related trend can be observed. Young plots exhibit the least amount of growth, and middle-aged plots the most. This matches the expected pattern of growth for this species, as defined by the UK Forestry Commission's empirically derived growth estimates for Sitka spruce (Edwards and Christie, 1981). Thus at this point it might be concluded that the multi-temporal LiDAR data has successfully detected forest growth. However, it is necessary to assess the accuracy and precision of the LiDAR growth estimates by comparing them with the results from the ground-based measurements.

3.2 Validation using Ground-Based Data

3.2.1 Height Correlations

Plot level LiDAR-derived mean height and ground-based height data from each single year were regressed first to check if results mirrored those described elsewhere in the literature. The regression between LMH and unweighted LiDAR height for 2003 gave a correlation coefficient of 0.94. The equivalent regression for 2006 data gave a correlation coefficient of 0.97. Both values indicate a strong positive association between ground-based and LiDAR average plot heights. However, it

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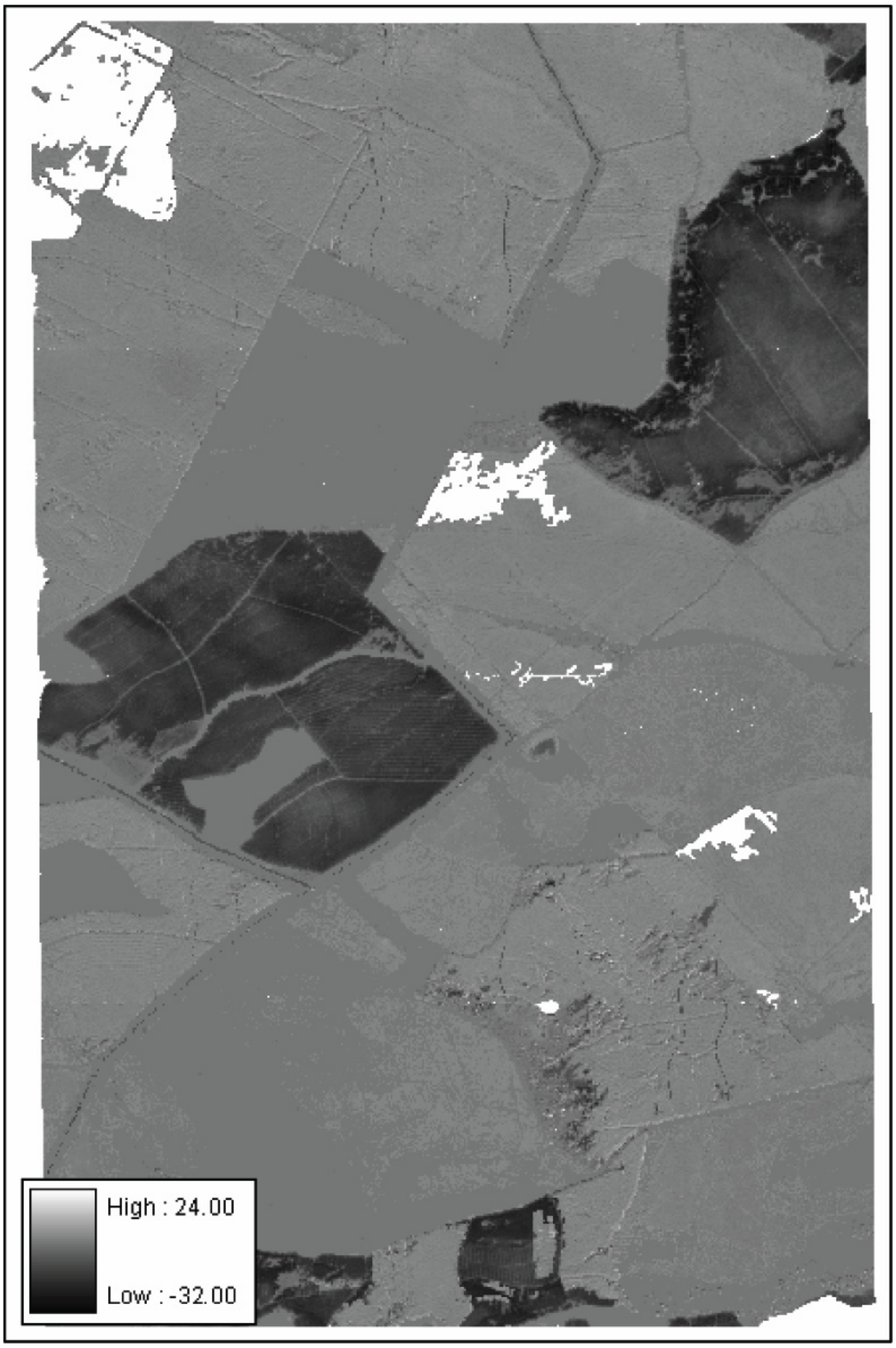

Figure 3-1. LiDAR Growth Map

is also necessary to explore the accuracy and precision of the LiDAR height estimates. For the 2003 data, the mean difference between LiDAR and ground-based heights was -1.53m and for the equivalent 2006 data it was -1.63m. This indicates that the LiDAR is underestimating the ground-based height measurements. Furthermore the standard deviations were calculated at 2.17m for the 2003 and 1.25m for the 2006 datasets, indicating much variation within the data. Thus, despite high levels of correlation, measures of accuracy and precision are not especially strong.

3.2.2 Growth Correlations

The correlation coefficient for the regression performed between LMH growth and unweighted LiDAR mean growth is negative and not as strong as those recorded for height (R^2 = -0.30). This indicates a lack of association between LiDAR and ground-based measurements of tree growth. This is somewhat surprising given that the LiDAR detected growth at all plot locations (Figure 3-2) and given the strong correlations with height measures for individual surveys. The mean difference (or bias) between the LiDAR and ground-based growth values is low at -0.06m. This indicates a slight under-prediction of ground-based growth values by the LiDAR. However, measurement precision of growth is poor with a standard deviation of 2.69m.

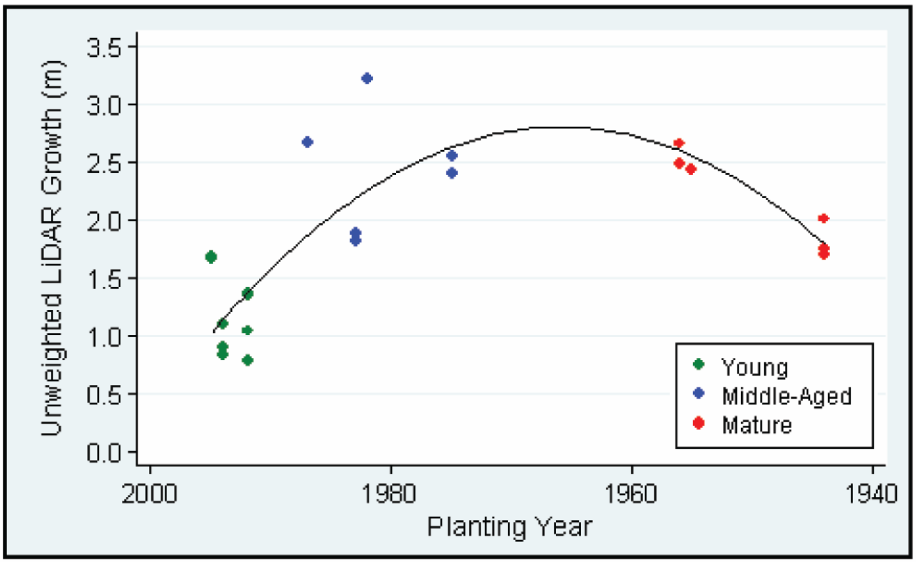

Figure 3-2. Plot level LiDAR growth plotted against planting year. Young plots: planted after 1990. Middle-aged plots: planted between 1970 and 1990. Mature plots: planted before 1970

4. Discussion

Strong and positive relationships exist between LiDAR and ground-based height values for both years. This is encouraging and reflects the findings of many other studies (Nilsson, 1996; Næsset, 2002; Næsset, and Bjerknes, 2001; Næsset and Økland, 2002; Popescu *et al*, 2002). However, despite these strong correlations, levels of variation within the data were high and mean difference values showed the LiDAR to be underestimating the heights predicted by ground-based measurements. LiDAR height underestimation is well documented in studies such as this and is widely accepted to be due to laser pulses over-sampling the shoulders of dominant trees rather than their peaks (Aldred and Bonner, 1985; Nelson, 1988; Nilsson, 1996; Næsset, 1997; Næsset, 2002; Popescu, *et al*, 2002; Yu *et al*, 2004).

The growth correlation was weak and negative. This seems strange given such strong height correlations and might suggest that multi-temporal LiDAR surveys are

Table 4-1. Technical specifications of the LiDAR systems

Sensor	Optech ALTM 2033	Optech ALTM 3033
Date of Survey	26.03.03	05.05.06
Scan Angle	10°	16.5°
Pulse Density	2/m^2	4/m^2
Flying Altitude	950m	1750m

unable to accurately estimate forest growth. However it is first necessary to explore the potential reasons for this lack of association between the LiDAR and ground-based growth estimates.

Firstly, in order to fairly assess forest growth it is imperative that datasets are directly comparable. In this study, comparability may have been compromised by three key factors; positioning error, set up of the LiDAR systems and scale. Furthermore, error within the ground-based data may also be responsible for the poor growth correlation observed here.

4.1 Positioning Error

It is clear from the offset between the LiDAR datasets that some kind of positioning error was introduced to one or both of the datasets. Fortunately this offset was easily corrected in this study due to its systematic nature. Positioning errors may result from one or more of the following:

• Errors in the recorded GPS- this usually results from poor geometric precision or a long operational baseline. These were checked for the 2003 and 2006 LiDAR datasets and both were found to fall within the limits of acceptable results thereby suggesting this is not the cause of the offset.

• Errors introduced in the post-processing routine. The details of the routines used were not available and thus this remains somewhat of a black box issue.

• Errors in the DEMs and CHMs. All generated surfaces are likely to contain some error as they are a smoothed representation of the true surface. The challenge is to keep the error (or misrepresentation) to a minimum. Much research is currently being channelled into developing superior DEM generation algorithms for this purpose, particularly in steep and heavily wooded terrain (Hyyppä *et al*, 2005; Hollaus *et al*, 2006; Zaksek and Pfeifer 2006; Kobler *et al*, 2007). It is possible that specifically tailored DEM and CHM generation routines would improve the quality of the results presented here. However, in this study exactly the same DEM routines were used for both datasets. As a result they should be directly comparable and thus DEM error is not sufficient to explain strong height correlations simultaneous with poor growth correlations.

4.2 System Set Up

Another potential source of error is the set up of the LiDAR systems. As detailed in Table 1, the specifications of the two individual LiDAR systems used within this study were quite different from each other. The differences in 3 key areas may have compromised the comparability and thus the quality of the growth estimates here;

• Scan Angle: Many studies have found errors associated with both DEM generation and canopy height estimation to increase with increasing scan angle (Nilsson, 1996; Ahokas *et al*, 2003; Holmgren *et al*, 2003; Lovell *et al*, 2005; Goodwin *et al*, 2006; Friess, 2007 pers. comm.). It is anticipated that this results from a lower intensity of reflectance at greater scan angles, as dictated by Lambert's Cosine Law. The 2003 data used within this study was collected with a scan angle of 10o, and the 2006 with a scan angle of 16.5°. The fact that the scan angles are different between the datasets means that different amounts of error will have been introduced into each dataset. Whilst this does not seem to have adversely affected the regressions between ground-based and LiDAR derived heights, it may have made the 2003 and 2006 datasets less comparable thereby affecting the growth correlation.

• Flying Altitude: A number of studies have found that greater platform altitudes seem to incur lower density returns (Goodwin *et al*, 2006; Takahashi *et al*, 2007). It is thought that the larger distance between sensor and target causes a reduction in the intensity of the return pulse in accordance with Newton's Inverse Distance Law. If this intensity falls below a certain threshold, the pulse becomes indistinguishable from random noise and therefore is not recorded. This is much more likely to happen at greater flying altitudes. Furthermore, recent work by Takahashi *et al*, 2007 demonstrates that an increase in both systematic and random errors of mean tree height estimates is observed with increasing altitude. As a consequence, they recommend a flying height of less than 1000m for tree height studies. In light of this research, it seems possible that the 2006 LiDAR survey flying height of 1750m is incurring a greater amount of random error into the DEM and tree height estimates than the 2003 survey, which was flown at 950m, thereby making the datasets less comparable. This is certainly an area which deserves further study.

• Pulse Density: Further to differences in flying altitude, there was also a difference in pulse density between the 2003 (2 hits per m^2) and 2006 (4 hits per m^2) datasets. It might be expected that the higher resolution 2006 data would produce better quality height estimates, and this is possible given the stronger correlation co-efficient for 2006. However, further study is necessary before this can be concluded with any certainty. Again though, this difference in pulse density introduces further incomparability between the datasets.

4.3 Ground-Based Measurement Error

It is possible that the explanation for the poor growth correlation lies somewhere other than in the LiDAR data or system set up. To date little attention has been paid to the accuracy and precision of the instruments and equipment used to collect the forest ground-based data to which the LiDAR data is usually compared (often called 'ground truth' data). The Vertex hypsometer, Suunto clinometer and height poles have been used extensively for measuring tree heights, yet an exhaustive assessment and comparison of these techniques remains long overdue. Some initial work by the author indicates that the random error associated with Vertex measures of tree height may be problematic for growth studies over short timescales. However, it seems that further study aimed at researching the variation of random error with tree height is necessary before any firm conclusions may be made.

4.4 Scale

A number of studies have found that the scale at which height and growth is studied using LIDAR has significant implications for the accuracy, precision and reliability of the results (Woodcock and Strahler 1987; Naesset, 2002; Gobakken and Naesset, 2004). Næsset, 2002 recommends the use of coarser spatial resolutions for tree height studies. His reasoning lies in the fact that smaller sample plots experience greater levels of inherent variation of canopy height measures. Therefore, the 'averaging-out' effect of larger plots reduces standard deviations of mean plot values, thereby increasing the precision of height and growth estimates.

Furthermore, if growth were studied

over a longer temporal scale the amount of growth might exceed the errors associated with growth estimation, thereby allowing it to be successfully and more accurately detected by the LiDAR. Future growth studies would benefit enormously from further investigation into the quantitative effects of different spatial and temporal resolutions. However, it is important to keep in mind that there is a balance to be struck between resolution modification and cost.

5. Conclusion

Results showed the multi-temporal LiDAR surveys to be capable of detecting growth over a variety of Sitka spruce plantation plots over a three year period. As found by many other studies, the single year LiDAR plot level height estimates were strongly correlated with ground-based height data for both 2003 and 2006. However, despite growth being detected by the LiDAR, no correlation was observed between LiDAR estimates and ground-based measurements. Reasons for this lack of correlation probably lie in the lack of comparability between the 2003 and 2006 LiDAR datasets. This may have been precipitated by an error in the positioning of one or both of the LiDAR datasets or may result from the differences in system set up. Further to this, issues of ground-based measurement error and spatial and temporal scale may be responsible. This certainly is an area for future study. However, if such issues can be successfully resolved then it is likely that multi-temporal LiDAR studies will be able to offer a great deal to the forest management community; by providing a rapid, cost-effective, non-invasive, repeatable technique for forest monitoring and timber production forecasting. LiDAR surveys of this nature may also provide key data concerning forest carbon stocks and therefore may have a part to play in the current global climate change debates. Thus, it is important that studies such as this are continued and improved in the future.

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