ESTIMATION OF GROWTH RATES AT KIELDER FOREST USING AIRBORNE LASER SCANNING

A.S. Woodget*, D.M.N. Donoghue and P.E. Carbonneau.

Department of Geography, University of Durham, Science Laboratories, South Road, Durham. DH1 3LE UK
*Corresponding Author- a.s.woodget@durham.ac.uk

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ABSTRACT:

A growing need exists for the collection of accurate and up-to-date information on forest growth rates for management purposes. Recent studies indicate that airborne laser scanning (ALS) offers a quicker and more cost-effective approach than the traditional methods of forest inventorying. Indeed, individual tree growth studies by the likes of Yu *et al.,* (2004, 2006) suggest that ALS has the potential to revolutionise forest management and also provide data concerning carbon stocks thereby playing a part in the current global climate change debates. High quality ALS data from 2003 and 2006 from Kielder Forest provides an excellent, unique opportunity to contribute to existing work which has so far been limited in focus, looking primarily at individual tree growth in the less densely stocked, slow-growing, cold climate forests of Scandinavia. This study aims to assess the potential of ALS to estimate forest growth rates of the temperate Sitka spruce plantation forests using canopy height distribution models at Kielder Forest, Northumberland. ALS point cloud data from first and last pulse returns are filtered and classified. Ground returns are used to create a digital elevation model (DEM), which first returns are then adjusted to, resulting in the formation of a digital canopy height model (DCHM). The processed ALS data from both years is then compared to estimate forest growth. The results are validated against ground truth data. Height correlations are strong (R2= 0.98) yet growth correlations are very poor (R2= 0.12). Suggestions for improving such correlations in the future are presented and discussed.

1. INTRODUCTION

There is an increasing need for the collection of accurate and up-to-date information for commercial forest management purposes on a continuous timescale. Remotely sensed data, such as aerial photography, has long been used in the UK to help quantify the 1.4 million hectares of forest resources (Forestry Commission, 2004). Additionally, recent studies suggest that airborne laser scanning (ALS) now offers a faster and furthermore, a cost-effective means of forest inventorying. It offers significant advantages in terms of multi-temporal surveying and data acquisition in otherwise difficult to access areas. Also, it has been suggested that LiDAR remote sensing has the potential to provide data concerning carbon stocks locked up within forestry and thus play a part in the current global climate change debates (Drake *et al*. 2002; Gobakken and Naesset 2004; Watt 2005; Henning and Radtke 2006; Yu *et al.* 2006).

Within the last decade or so, a number of studies have indicated that ALS can be used to accurately predict forest variables such as mean height, basal area, volume and biomass (Naesset 2002; Naesset and Bjerknes 2001; Naesset and Okland 2002; Nelson et al., 1988; Nilsson 1996; Popescu et al., 2002; Watt 2005; Yu et al., 2004; Yu et al., 2006). Such studies have found high levels of correlation between LiDAR- and ground truth-derived forest metrics. It is often noted that LiDAR height estimates are of equal if not better accuracy than ground truth data or that obtained by other remote sensing techniques. However, it has also often been reported that ALS systems consistently underestimate the 'true' height of the trees.

Yu et al., (2004) first studied the use of small footprint LiDAR systems for change detection within the cold climate, slow growing Scandinavian forests to estimate growth at the individual tree level. Like others before them, they noted that individual tree heights were underestimated. In this case, the underestimation caused the errors of growth estimation to be larger than the estimated growth itself. Further studies in 2005 and 2006 built on this work to improve correlations between ground measured and LiDAR derived growth from 0.2 to 0.6.

Few studies have so far assessed LiDAR for estimating growth at plot or stand level however. Furthermore, most research has focussed on the slow growing, cold climate forests of Scandinavia. Thus, the data collected over Kielder Forest provides a unique opportunity to assess the use of airborne laser scanning for quantifying plot and stand level growth rates of a fast-growing, temperate conifer forest in Northern England.

2. STUDY AREA AND DATASETS

2.1 Study Area

The test site for this research is Kielder Forest in Northumberland, England (Figure 1). The forest is owned and managed by the Forestry Commission and is the largest in the UK covering approximately 62,000 hectares. Kielder is a commercial plantation forest, comprised mainly of *Picea sitchensis* (Sitka spruce), established in 1926 by the Commission principally for timber production. Today the forest continues to produce up to 1300 tonnes of timber daily (www.kielder.org) and given the anticipated rise in annual British timber production in coming years (Watt 2005), efficient management of this forest is paramount. This is especially true when considering the short forest rotations and fast growth rates of trees at Kielder. The plantation forest lies at a mean altitude of 270m and has a mean slope angle of 6°. Thinning is very rarely carried out which allows canopy closure within roughly 20 years of planting.

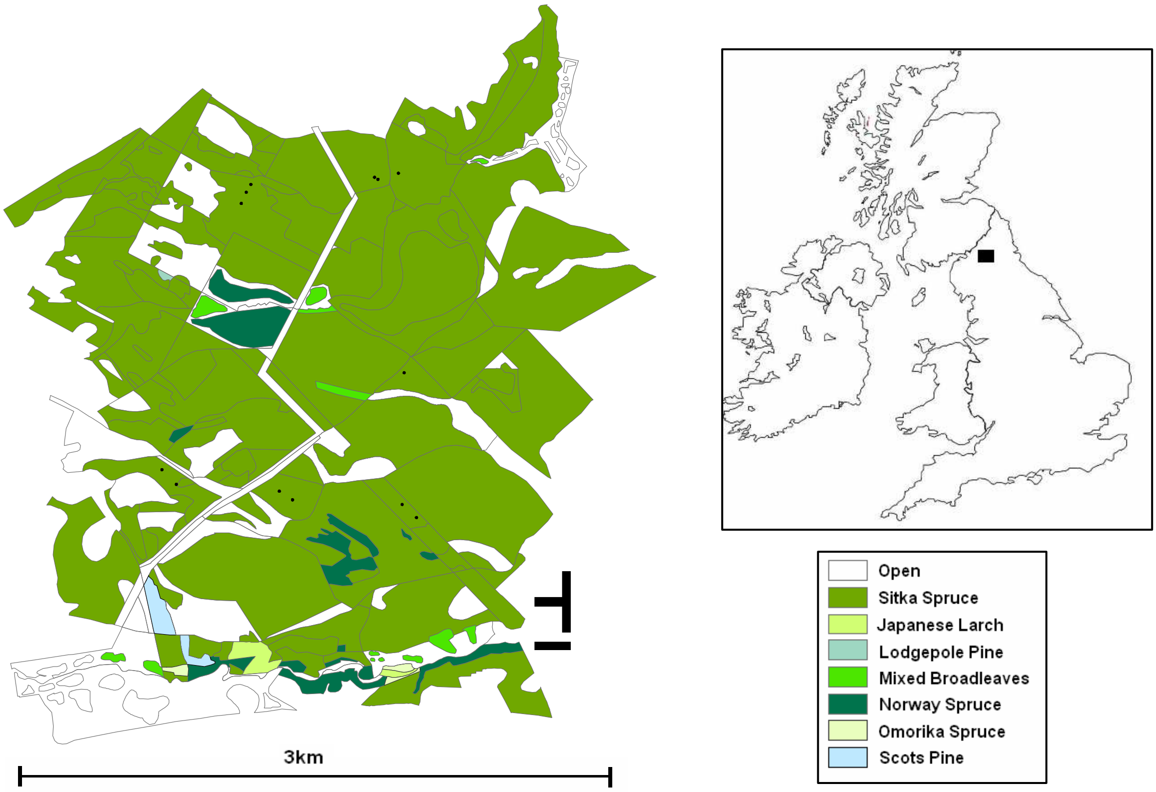

Figure 1. Kielder Forest, UK. Field plots are marked by black dots.

2.2 Sensors and Datasets

The multi-temporal laser data was collected during the summers of 2003 and 2006 using the Optech 2033 (Environment Agency) and 3033 (NERC-ULM) scanners respectively (Table 1). These are small footprint, discrete return systems which recorded first and last pulses and intensity.

2.3 Reference Data

Ground truth data was collected by the Forestry Commission in summer 2003 and by a field team from Durham University in summer 2006 following standard UK forest inventorying practices.

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

Table 1. Technical Specifications.

A total of thirteen 0.02ha circular plots of various ages were assessed for growth in tree height and diameter over the three year period. Plots were navigated to using a handheld GPS and plot centre and tree locations recorded using a Leica series 300 differential GPS. A Vertex hypsometer was used to measure all trees >1.37m tall and a tape measure to those <1.37m. Diameter at breast height (dbh) was measured using a diameter tape. Tree status (e.g. double leader, dead etc) and species were also noted, although only a handful of trees throughout the entire study area were not Sitka spruce. Figure 1 displays the plot locations and an overview of descriptive statistics for these sixteen plots is shown in Table 2.

	Mean	**St. Dev**	**Min**	**Max**
Age (years)	35.31	19.33	11.00	62.00
Density (Trees/m²)	0.24	0.07	0.15	0.36
Height (m)	11.0	4.33	4.00	16.60
Diameter (cm)	14.45	5.45	5.90	22.70

Table 2. Summary of statistics for 16 field plots (taken from 2006 data).

3. METHODOLOGY

3.1 Filtering and Classification

Last return laser points were loaded into the TerraScan software and classified as ‘ground’ and ‘non-ground’ using the embedded TIN densification algorithm developed by Axelsson (2000). The specific ground classification parameters chosen were based on work by Watt (2005) and are shown in Table 3.

Ground Classification Parameter	**Setting**
Max. Building Size	100m
Terrain Angle	88^o
Iteration Angle	8^o
Iteration Distance	0.5m

Table 3. Ground Classification Parameters

3.2 DTMs and DCHMs

A Digital Terrain Model (DTM) for each year was then created by generating a Triangulated Irregular Network (TIN) of those points classified as ground. Next, first returns were added to any remaining last returns in TerraScan that had not been included in the DTM. All these points were assumed to represent tree canopy hits and therefore were adjusted to the DTM to give them a height above ground level, rather than just an elevation value. In an attempt to remove the effects of low lying vegetation, all first returns that fell within 2m of the last returns were excluded. This practise is well documented and also helps reduce data file sizes in order to improve processing speeds (Naesset 1997; Naesset and Bjerknes 2001; Naesset and Økland 2002).

Following this, points were exported into the statistical software package STATA for extraction of key variables. This program gridded the data into 5m pixels and calculated key variables within each of these cells. Such variables included mean, maximum and minimum height, standard deviation and a number of height percentiles. Variable data was then exported as an ASCII file for display in other packages, such as ArcMap.

Given that the LiDAR surveys were conducted using different instruments and at different times it is necessary to ensure that they are registered correctly before growth may be estimated. It was found that the 2006 dataset was offset by as much as 7m in x and y from the 2003 dataset. This was corrected by georeferencing using easily identifiable features in both datasets.

3.3 Growth Estimation

Growth between 2003 and 2006 was then calculated (for the whole study area) as the difference between extracted variables. Reference data from the thirteen ground truth plots were regressed against laser derived values for these same plots as a means of validation.

4. RESULTS

4.1 Growth Estimates

Figure 2 shows the LiDAR derived growth for the study area, calculated from mean heights. Areas of clear fell can be clearly seen in dark blue, as can other smaller regions which have been affected by wind blow. Areas where no change has occurred are observed in lime green and represent open ground. Growth of stands is seen in light green through to orange and allows a range of growth to be seen.

For each of the reference plots height and growth metrics were calculated (Table 4). Lorey's Mean Height (Equation 1) averages tree height per plot using basal area as a weighting function. Unweighted mean height takes an average of all trees within the plot.

$$h_L = \sum_i \frac{g_i h_i}{\sum_i g_i} \qquad (1)$$

where g = basal area
h = tree height

In terms of extracting height and growth estimates from the 5m pixel LiDAR growth map, two plot averaging methods were used. The first of these weighted all pixel values within each plot by the number of trees falling within that pixel (Equation 2). The second took the unweighted mean of all pixels falling within the plot area, regardless if this was the entire pixel or otherwise. This unweighted mean growth is the same as that displayed in Figure 2.

$$h_W = \sum_i \frac{t_i \; p_i}{\sum_i t_i} \qquad (2)$$

where t = number of trees within plot
p = pixel value

4.2 Validation using Ground Truth Data

4.2.1 Height Correlations

Height metrics from reference data were regressed against those from the LiDAR surveys (Table 5). High levels of correlation were found between all mean values, both weighted and unweighted. For the 2003 data, the best correlation was between Lorey's Mean Height (LMH) and Weighted LiDAR Mean Height. For 2006, the best correlation was between Lorey's Mean Height and Unweighted LiDAR Mean Height. The mean difference between LMH and Unweighted LiDAR Mean Height for 2006 is -1.79. That is, the LiDAR underestimates the ground truth height by an average of 1.79m. The standard deviation of this difference is 0.97m. Therefore, although the correlation is positive and strong, there is still much variation within the data.

4.2.2 Growth Correlations

Regressions calculated between ground truth and LiDAR growth metrics are shown in Table 6. The correlation co-efficients are all low, showing no clear relationship between ground truth and LiDAR growth estimates. For the most positive correlation (UMH and Weighted Mean LiDAR Height- Figure 3), the mean difference between ground truth and LiDAR values is 0.89m. The standard deviation of this difference is 1.09m. When negative data was removed from this regression, the correlation co-efficient was improved slightly to 0.1998.

	Reference Data						LiDAR Data					
	Lorey's Mean Height (m)			Unweighted Mean Height (m)			Weighted Mean Height (m)			Unweighted Mean Height (m)		
Plot ID	2003	2006	Growth	2003	2006	Growth	2003	2006	Growth	2003	2006	Growth
2	14.03	13.77	*-0.26*	13.10	12.80	*-0.30*	9.58	12.41	*2.83*	9.55	12.19	*2.64*
3	16.43	17.92	*1.49*	15.40	16.60	*1.20*	13.59	15.85	*2.26*	13.08	15.94	*2.86*
4	16.17	17.33	*1.16*	14.70	15.60	*0.90*	13.15	15.10	*1.95*	12.87	15.05	*2.18*
10	9.41	11.08	*1.68*	7.70	9.52	*1.82*	5.54	7.78	*2.24*	5.62	7.96	*2.34*
29	0.00	4.58	*4.58*	2.80	4.00	*1.20*	1.05	1.56	*0.51*	1.06	1.46	*0.40*
30	0.00	4.81	*4.81*	2.70	4.30	*1.60*	1.13	1.91	*0.78*	1.08	1.87	*0.79*
52	18.66	18.35	*-0.31*	14.88	14.53	*-0.35*	14.77	16.82	*2.05*	14.34	17.18	*2.84*
53	15.64	15.89	*0.25*	13.07	13.21	*0.14*	14.07	14.33	*0.26*	14.50	14.65	*0.15*
54	7.60	7.98	*0.38*	5.40	5.80	*0.40*	4.76	5.66	*0.90*	4.80	5.95	*1.15*
61	8.03	8.31	*0.28*	7.10	7.30	*0.20*	4.83	6.10	*1.27*	4.67	6.08	*1.41*
62	15.23	15.11	*-0.12*	12.20	12.10	*-0.10*	12.83	14.25	*1.42*	12.87	14.31	*1.44*
63	16.41	16.29	*-0.12*	13.30	13.00	*-0.30*	15.58	16.08	*0.50*	15.29	16.30	*1.01*
64	16.01	15.73	*-0.27*	14.50	14.20	*-0.30*	14.39	15.05	*0.66*	14.29	14.94	*0.65*

Table 4. Ground Truth and LiDAR Data by Plot

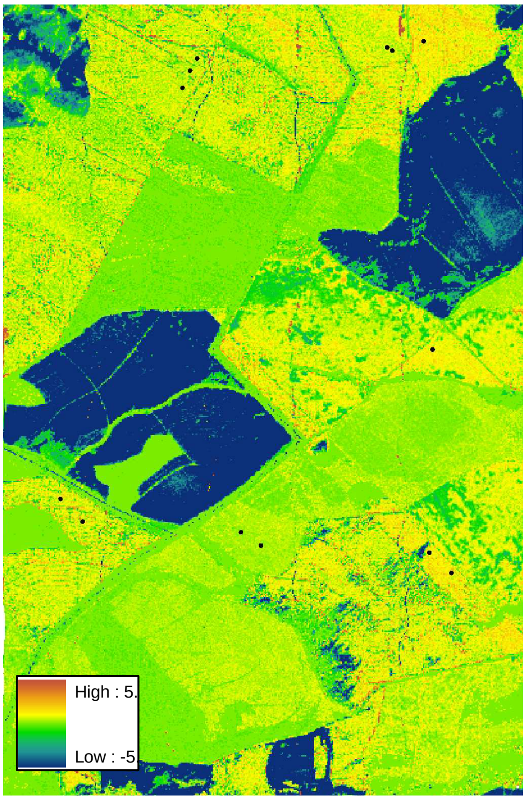

Figure 2. Growth Map. Plots shown by black dots.

	LiDAR Derived Metrics		
Ground Truth Derived Metrics	**2003**	**UMH**	**WMH**
	LMH	0.9277	0.9317
	UMH	0.9130	0.9225
	2006	**UMH**	**WMH**
	LMH	0.9841	0.9837
	UMH	0.9254	0.9338

Table 5. Co-efficients of Determination for Height Correlations

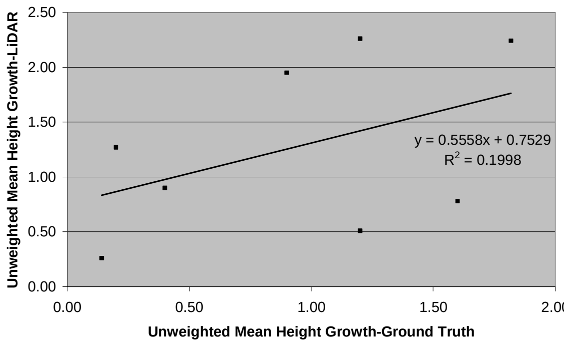

Figure 3. Scatter graph and regression line between field measured and LiDAR derived Unweighted Mean Height Growth.

	LiDAR Derived Metrics		
Ground Truth Metrics	**Growth**	UMH	WMH
	LMH	-0.0763	-0.0498
	UMH	0.0019	0.0082

Table 6. Co-efficients of Determination for Growth Correlations

5. DISCUSSION

5.1 Relationship between LiDAR and Ground Truth Metrics

5.1.1 Ground Truth Metrics

For height regression it is evident that Lorey's Mean Height provides stronger correlations between ground truth and LiDAR height values than unweighted mean height. Given that LMH is weighted by basal area, this average gives more weight to trees with a larger diameter. Such trees are also likely to be the tallest and most dominant within the plot. Consequently they are also most likely to be detected by the ALS system rather than those lying beneath the height of the main canopy. Thus the strength of the correlation is improved. However, in terms of growth estimations, LMH causes problems in very young stands. In plots where the majority of trees were smaller than 1.37m in 2003, dbh and therefore basal area is recorded as 0. Of course this does not represent the true average plot height in 2003 and therefore skews growth estimations, making them seem larger than they really are. In comparison, unweighted mean plot height for ground truth data takes no account of basal area and is therefore less well correlated with the LiDAR derived height metrics. However, it is not distorted by plots of smaller trees and consequently performs better for growth regressions.

5.1.2 LiDAR Metrics

Weighted Mean LiDAR Height, which takes into account the number of trees falling within each plot pixel, does not perform significantly differently from Unweighted Mean LiDAR Height with respect to height or growth correlations. When correlated with Unweighted Mean Ground Truth Height it produces the most significant growth co-efficient of determination. However the relationship is very weak.

5.1.3 Height and Growth Correlations

Very strong, positive relationships exist between all ground truth and LiDAR derived height metrics. This reflects the findings of other height studies and is encouraging (Naesset 2002; Naesset and Bjerknes 2001; Naesset and Okland 2002; Nilsson 1996; Popescu et al., 2002). It should be noted however that despite these strong correlations, levels of variation within the data are high. For example, the mean difference between LMH and Unweighted LiDAR Mean Height for 2006 is -1.79m. The standard deviation of this difference is 0.97m. This shows that the LiDAR is underestimating the ground truth tree heights by an average of 1.79m plus or minus 0.97m. 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; Naesset 1997; Naesset 2002; Popescu et al., 2002; Yu et al., 2004). However, such variation means that errors of height estimation by the LiDAR may be as large as 2.76m. When growth over the 3 year period rarely rises above 2m, it becomes indistinguishable from height error. In other words, the errors of growth estimation are larger than the estimated growth itself and thus no correlation is observed.

5.2 Possible Error Sources and Improvements

It becomes evident then that the errors of tree height estimation need to be reduced if growth at plot level is to be accurately predicted using ALS. This might be accomplished in a number of ways.

- Assessing growth over a longer timescale. This may allow the amount of growth to be greater than the height error, meaning it can then be observed. Other studies have found this to improve the strength of LiDAR and ground truth correlations (Yu et al., 2005).
- Removal of all negative growth values within the ground truth data. These result partially from recording errors yet largely from dead trees where the top of the tree is breaking off. Such trees mostly lie beneath the main canopy and therefore are not observed by the LiDAR. Consequently the ground truth data becomes skewed, reducing the strength of the correlation with the LiDAR data.
- Use of LiDAR systems with the same technical specifications. Despite Goodwin et al.,'s findings that platform altitude has a negligible effect on canopy height estimation (Goodwin et al., 2006), it is likely that some errors result from the use of different ALS systems under different survey conditions (Table 1).
- Assessment of the error associated with the collection of ground truth data. It is taken for granted that the reference data collected in the field represents the 'true' height of the trees. Instrument accuracy and the effects of user variability have largely been ignored in the literature to date. Consequently, it seems that if any conclusions concerning the 'accuracy' of LiDAR growth estimates are to be relied upon, it is first necessary to obtain an idea of the accuracy of the reference data.

Furthermore, it is important to recognise that a number of assumptions are made during processing of the LiDAR data. Such assumptions are necessary for the efficient running of the processing sequence, and it is likely that they to do not adversely affect the process for the majority of the time. However, it remains important to be aware of such assumptions.

The first is that the lowest returns are presumed to represent the ground surface. Filtering of obviously erroneous points goes most of the way to removing this problem, yet some errors may remain due to recording inaccuracies in the Time Measurement Unit (TMU) or multi-pathing of the return pulse (Hurn 1993; Watt 2005).

Secondly, during creation of the TIN it is assumed that there is at least one laser return per window. However, given the window size of 100m x 100m used in this particular study, it is highly unlikely that this would cause any problems here.

6. CONCLUSION

In conclusion then, this paper has shown how multi-temporal LiDAR surveys can be used to confidently predict tree heights at the plot level in a temperate, coniferous forest in Northern England. Therefore, it can be confirmed that ALS has a great deal to offer to the forest management community in terms of tree height estimation.

However, it has also been found that tree growth at plot level cannot be predicted using ALS. Despite strong positive correlations between height metrics, the errors of height estimation are larger than any estimated growth over the three year period. This essentially causes the growth to be 'lost' and therefore no correlation between ground truth and LiDAR growth metrics is observed.

It is anticipated that regression relationships may be improved in a number of ways, these include; increasing the timescale over which growth is analysed; ignoring all negative ground truth growth values; using multi-temporal LiDAR surveys taken by the same system under the same conditions; and by investigating ground truth instrument error and variation introduced by different users. Indeed, if any conclusions concerning the accuracy of LiDAR growth estimates are to be relied upon, then issues like those listed must first be addressed. Such research is of benefit to researchers and non-academics, foresters and climatologists alike and therefore should not only continue but be enhanced in the future.

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