Remotely Sensed Crown Structure as an Indicator of Wood Quality

A comparison of metrics from Aerial and Terrestrial Laser Scanning

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Abstract

Aerial LiDAR offers a fast and efficient means to estimate wood quantity, but there has been little work to date on wood quality. In this study we investigate the hypothesis that remotely sensed crown structure from Aerial Laser Scanning (ALS) can be used as an indicator of log quality at an individual tree level.

A New Zealand Pinus radiata forest was flown with aerial LiDAR at 8 pts per m$^2$. Five trees from within the forest were scanned with a terrestrial laser scanner (TLS) to determine external signs of log quality. These measurements were diameter at breast height (DBH), volume, taper, sweep, lean, circularity and average internode distance. In this study we develop a series of metrics from ALS point clouds for each tree to describe the crown structure, which are then correlated against the TLS data. To derive these metrics, novel algorithms were developed for TLS data which extend the level of detail previously obtainable. These algorithms are also detailed in this paper.

As only five trees were studied, the results are proof-of-concept more than outright proofs. The purpose of this paper is to document techniques which will be employed in the future over a much greater sample, proving the preliminary findings presented here. In this small sample we found that crown area from ALS had a moderately strong correlation with DBH and sweep. Crown density from ALS was also moderately correlated to average internode distance. The correlations show that there is at least a moderate connection between crown structure and log properties, and that at higher LiDAR pulse densities and a larger sample size we can expect to describe this connection with greater certainty.

In further studies we also hope to correlate ALS and TLS metrics with internal wood properties, as found from destructive sampling.

Keywords

Aerial LiDAR, Terrestrial LiDAR, ALS, TLS, crown shape, stem shape, wood properties

1. Introduction

There have been numerous studies to quantify the biomass content of forests (Lefsky et al., 2005; Stephens, 2010). For commercial forest managers it is important to know not just the quantity but also the quality of wood. This is the research question that we address here.

1.1 Wood Quality

Wood quality is the basis on which the value and use of timber is decided, and has been quantified – rigorously or not – for centuries. For an excellent overview of wood quality and its applicability to be remotely sensed the reader is directed to van Leeuwen et al., 2011. In this study we use the term log quality to mean externally detected wood quality indicators on single trees.

Indicators of log quality from Terrestrial Laser Scanning (TLS) and field measurements were compared for with crown metrics from Aerial Laser Scanning (ALS) for five Pinus radiata trees
from a commercial plantation in New Zealand. Log quality indicators derived in high detail from field measurement and TLS are extremely time-consuming and costly. The hypothesis tested here is that the canopy structure is related to log quality, and so ALS can offer surrogate indicators across a much larger scale and at a greatly reduced cost per tree.

1.2 LiDAR

Light Detection and Ranging – or LiDAR – has been used in forestry since the early 80s for providing 3D point cloud information on forests (Nelson et al., 1984). Lim et al., (2003) gives a thorough description of the technology, whilst Adams et al., (2011) details the applications for New Zealand commercial forestry. Within commercial forestry LiDAR is predominantly operated from two platforms – aerial and terrestrial. For an explanation of ALS and TLS systems the reader is directed to Lim et al., (2003).

2. Method

2.1 Study site and data collection

Five mature 30 year old trees in Kaingaroa forest, New Zealand were selected as representative in-stand trees. The area was flown with ALS at 8pts per m² in August 2006 by New Zealand Aerial Mapping with an Optech ALTM 3100 EA. The trees were selected to be in a flight line overlap where they would receive double the point density. They were subsequently scanned with TLS in December 2010 with a RIEGL PTM98 Laser Profile Measuring System supplied by Aerial Surveys, set with a horizontal and vertical scan step of 0.036°. Each tree was scanned twice from opposite sides, and three artificial markers were used for scan alignment. After scanning, the trees were measured for diameter at breast height (DBH), felled and the branch locations noted.

2.2 Metric extraction

Table 1 gives a brief summary of the TLS and ALS metrics are given below, followed by an in-depth description.

<table>
<thead>
<tr>
<th>TLS</th>
<th>ALS</th>
</tr>
</thead>
<tbody>
<tr>
<td>DBH</td>
<td>Diameter at breast height. The mean diameter 1.4m above the ground</td>
</tr>
<tr>
<td>Stem volume</td>
<td>The total stem volume from 0.4m above the ground to 25m</td>
</tr>
<tr>
<td>Form value</td>
<td>A value indicating taper, see equation 5</td>
</tr>
<tr>
<td>Sweep</td>
<td>The maximum deviation of the centreline in any 5m section between 0.4 and 20m up the stem</td>
</tr>
<tr>
<td>Lean</td>
<td>The elevation angle between the stem centre points at 0.4m and 20m, and a horizontal plane</td>
</tr>
<tr>
<td>Stem circularity</td>
<td>The average circularity (see equation 3) of the stem between 0.4 and 6m</td>
</tr>
<tr>
<td>Median internode distance</td>
<td>The median vertical distance between detected branch nodes in the bottom 25m of the tree</td>
</tr>
<tr>
<td>Crown area</td>
<td>The projected area of the crown viewed from directly above</td>
</tr>
<tr>
<td>Crown volume</td>
<td>The net volume of the crown, fitted by convex hull</td>
</tr>
<tr>
<td>Crown circularity</td>
<td>The average circularity (see equation 3) of the crown as viewed from above</td>
</tr>
<tr>
<td>Crown density</td>
<td>The number of LiDAR canopy returns divided by the crown volume</td>
</tr>
<tr>
<td>Net bending moment</td>
<td>The net bending moment on the stem base if every LiDAR return had unit mass</td>
</tr>
<tr>
<td>Net water transport distance</td>
<td>The total travel distance required to supply all detected foliage elements with water from the stem base</td>
</tr>
</tbody>
</table>
2.3 TLS data

Initially the two TLS scans for each tree are centred on the mean position of the artificial markers (which were placed around the tree), and clipped to remove points belonging to other trees. The centre points \( (P_1, P_2) \) of the artificial markers are found in both scans and the least-squares solution to

\[
RP_1 + T = P_2
\]  

(1)

is obtained, where \( R \) is the rotation matrix and \( T \) is the translation vector. This is solved using Horn’s quaternion-based method without scaling in Matlab (MathWorks, 2000). In some instances a fourth datum was used – normally a distinctive branch fork high in the tree visible in both scans – to improve the fit in 3D. Once the scans are aligned they are merged. Figure 1 shows a merged point cloud with the two scans in different colours.

2.4 Fitting a geometric model to the stem

The model starts with 0.1m vertical slices of the point cloud, for which the centre is found by a least squares circle fit as in Bienert et al., (2007). If the tree is approximately centred at \((a,b)\) with radius \(r\), we look to minimise the error term \(\varepsilon\) in

\[
(x - a)^2 + (y - b)^2 - r^2 = \varepsilon
\]  

(2)

Where \(x\) and \(y\) are the coordinates of each return. This minimisation is performed in Matlab using the \texttt{fminsearch} function, which is an unconstrained nonlinear optimisation algorithm based on the Nelder-Mead simplex method (Lagarias et al., 1999). The crucial difference here is that we are only looking for an approximate centre, not the diameter of the circle as in Bienert.

This approach is widely used and accepted, but can be thrown off by buttressing, or material close to the stem such as branches or dead needles. To minimise this effect points are removed that are at a distance of \(1.25 \times\) the previous radius but this is still not perfect, particularly when there is a lot of dead foliage. Figure 2 shows examples of this.

![Figure 1 – Aligned point cloud from two scans](image)
In this study we are looking for log quality information, so it is crucial to describe the stem as accurately as possible. To get around the circle-fitting limitations, we describe the stem cross section as a circular harmonic. In polar coordinates $(\rho, \theta)$ with the origin on our approximate centre $(a, b)$, we remove any points more than 0.05m away from our circular fit. The remaining points are then binned according to $\theta$ into 100 equally spaced bins from $-\pi$ to $\pi$ radians. To eliminate the effects of branches and litter, the smallest value of $\rho$ is taken for each bin. The remaining values for $\rho(\theta)$ can be approximated by a Fourier series, and by restricting the number of terms we can eliminate the higher frequency components to produce a smooth curve. Five terms were sufficient to allow for most features. This process is shown in figure 3 for the 4m height section shown in figure 2a. The stem sections shown in figure 2 are shown again in figure 4 with the improved fit (black line), which will be referred to as the harmonic fit. In addition the mean of the harmonic fit gives a slightly improved centre estimate, shown by the blue diamond in figure 4.
The stem tends to become obscured behind branches and other trees higher up. If the algorithm fails to find a good circular fit the vertical window is increased by a further 0.1m. This increase will continue until either a good fit is reached, or the algorithm fails on a 1m section in which case it gives up and moves further up the tree. The failed section can be interpolated later, although in general the data becomes sparse 20-25m up the tree. We have not analysed any of the data above 25m as it is too unreliable. Fortunately wood from the top of the tree is seldom used as timber due to its young age and narrow diameter. Figure 5 shows the series of stem shapes stacked to produce a meshed model of the stem viewed from the side and above.

2.5 Describing the stem

From the above analysis, it is easy to extract a centre point \((x,y,z)\) for each slice, a circumference \(d\), and a mean radius \(r\).

We can also define stem circularity as \(S\) where

\[
S = \frac{1}{4\pi} \frac{d^2}{A}
\]  

(3)

Where \(d\) is the circumference, and \(A\) is the area. Note that \(S\) is a unitless variable, independent of size. For a circle \(S=1\), and will increase as the ratio of circumference to area increases.

In order to remove noise in \(r\), the equivalent of a moving average filter is run across the series. Instead of taking the average value for the window, the 20th percentile was taken, as the values...
have a much greater tendency to over-estimate than underestimate. After this filter a 6\textsuperscript{th}-order polynomial is fitted to the calculated metrics $x, y, r$ and $S$ as in Bienert \textit{et al.}, (2007). Figure 6 shows the curve fitting for these metrics.

We now define single values to describe our tree – DBH, volume, form value, sweep, lean and circularity. DBH is defined as twice the mean radius at 1.4m. Volume is the sum of the volumes of each 0.1m slice assuming a circular cross section of radius $r_{\text{mean}}$, given in equation 4.

$$V = \sum (0.1\pi r^2)$$

Form factor $f$ represents taper, and is essentially the ratio of space filled by the stem vs. the available space if it had no taper. We consider the usable stem from 0.4m to 25m. Schardt \textit{et al.}, (2002) gives the following equation for $f$.

$$f = \frac{4V}{\pi dh^2}$$

Sweep is initially defined at every point on the stem between 2.5m and 17.5m based on a 5m sliding window. Within each window position, two points at the top and bottom $X_1$ and $X_2$ define the average lean. The sweep for that window is then defined as the maximum deviation of any other centre point from that line. To calculate this we use the distance from a point to a line in 3D as given in Anton (2010).

$$d = \frac{|(X_0-X_1)\times(X_0-X_2)|}{|X_1-X_2|}$$

The maximum of these values is retained and used to quantify the sweep in the tree.

The angle between the stem at 0.4m and 20m was used to define lean. Circularity is defined as the average circularity of the bottom 6 metres of the stem (before it is affected by branching).

2.6 Finding branch nodes

Internode distance is also an important metric of log quality. In \textit{Pinus radiata} branches tend to occur in nodes, and the distance between these nodes is crucial for log grading.
Once we have mapped the stem we can orientate each horizontal slice on the centre line, effectively straightening the tree. After removing points on the stem, the remainder are due to branches and leaf litter (which accumulate on the stem near branch clusters). To find branch clusters we adapt the theory behind a Hough transform – which looks for straight lines in space. We know that all branches must radiate from the stem, and that they should occur in an angle greater than 0° and less than 90° from horizontal.

Figure 7 - Diagram of conical search for branches. Note returns from the stem would normally be removed prior to analysis

Figure 8 - Plot of $n(h, \phi)$, showing local maxima relating to branch clusters
So we construct a conical search around our stem, counting all points in the TLS point cloud that fall within a cone of width $w$ and angle $\phi$ from a horizontal plane at height $h$ (see figure 7). We sweep this cone through $\phi$ from 15° to 80°, and move $h$ up the tree in 0.05m increments. In the end we have a value $n(h,\phi)$ for every combination of $h$ and $\phi$. Local maxima in $n(h,\phi)$ are likely locations of branch clusters, defined in terms of the height at which they intercept the stem and their average angle $\phi$. A plot of $n(h,\phi)$ is shown in figure 8. Note that maxima in $h$ are much more apparent than in $\phi$. This is because the branches in a cluster can have a range of $\phi$, but all have a similar $h$.

If we define $N(h)$ as the sum of $n(h,\phi)$ across all $\phi$ we get the plot shown in figure 9, shown alongside the centred point cloud for comparison. Locations with a high $N(h)$ are more likely to contain a branch cluster than locations with low $N(h)$. A simple first-derivative peak detection algorithm has been used to identify the peaks in $N(h)$, which can then be compared with the known branch locations (measured in the field) as shown in figure 10. In figure 10a the measured branches (shown in blue) are scaled in length and width by the average branch diameter. In figure 10b the detected branches (shown in red) are shown scaled in width and length by $N(h)$.

In figure 10 it is apparent that the automatic detection does a good job of detecting the large branches that are lower in the tree. The algorithm is less dependable with higher and smaller branches. In this study we are interested in a single value to describe the general internode distance, so we take the median of the spacing between the detected clusters. In comparison, if we perform this median spacing approach on the real data (between all branches >40mm in diameter) we get a comparable set of values, as shown in figure 11. This value is not meant to explicitly represent the exact internode distance – which varies up the tree and is largely dependent on what constitutes a branch – but is a comparable value that gives a general impression of log quality in terms of branch cluster spacing.
Figure 10 – a) Branches measured in the field and b) detected branches.

Figure 11 – Comparison of median internode distance for five trees as measured on the tree and automatically detected in the TLS point cloud.
2.7 Individual branch searching

To extend this work, it would be possible to retain $\theta$ as an independent variable, and count the number of points $n(h, \varphi, \theta)$. Local maxima in $n(h, \varphi, \theta)$ in 3D space would relate to individual branches. Individual branches could be identified, and potentially branch diameters determined. Figure 12 shows an example of this algorithm in operation. However, $\theta$ was not collected in the field for the branches on our study trees, so there was no way of verifying our findings. In addition, ALS will never pick up individual branches (except special cases in which the tree overhangs a road or compartment edge), so individual branch metrics were not used in this study. However, individual branch detection remains an interesting problem for future work.

Figure 12 - Example of individual branch detection algorithm. Red lines show detected branches, blue dots show the point cloud. As there was no field data to verify the results this algorithm was not used to generate the final set of TLS metrics.

2.8 ALS data

For comparison with our TLS log quality metrics we derive a similar set from ALS to describe the structure of the crown.

2.9 Segmenting crowns from ALS data

Before the crowns could be analysed, they had to be segmented from the full set of ALS data. GPS points were taken with a Trimble ProXRT on each stump after felling to minimise the effect of canopy on GPS accuracy. All coordinates were differentially corrected and reported to be of sub-metre accuracy. Automatic segmentation is never perfect, so in this study an automatic segmentation was manually improved to give the best point clouds possible.

2.10 Crown area, volume, circularity and density

Once the crowns have been segmented a polygon was fitted to the 2D projection of the crown (figure 13a) and a convex hull to the canopy (figure 13b). To determine the 2D crown area, the centre point is set as the origin (defined as the mean of returns from the bottom $\frac{2}{3}$ of the tree), and the points converted to polar form. All points are then binned according to $\theta$, and the maximum value of $\rho$ is taken for each bin. Bins with no points are not included as vertices. Connecting these points results in our polygon which can be used to find the crown area $A$. Also the circumference $d$ can be obtained and the circularity found as per equation 3.
\[ S = \frac{1}{4\pi} d^2 \]  

(3)

The volume of the crown \( V \) is defined as the volume of a convex hull containing all crown returns. Convex hulls were created in Matlab using the `convhull` function, which is based on the Qhull algorithm in Barber et al., (1996). Once \( V \) has been calculated the crown density is calculated as \( \frac{N_{\text{crown}}}{V} \), where \( N_{\text{crown}} \) is the number of LiDAR returns in the crown.

![Figure 13 – a) Aerial view of crown with circumference defined (black line) and b) canopy with convex hull overlaid](image)

2.11 Net bending moment

For this metric, we assume that every above-ground return relates to foliage or branch matter that is connected to the stem. This assumption is heavily dependent on good segmentation. If the assumption is true, then the mass (whatever it is) must exert a net bending moment on the stem. For example, if during the life of a tree its neighbour died opening up a canopy gap next to the tree, the tree is likely to grow towards the gap, perhaps straightening up again if the gap became filled. This would lead to the canopy being heavily weighted on one side of the stem, and would lead to compression wood on the side towards the gap. If we assume the net moment \( M \) is

\[ M = |\sum r_i \times F_i| \]  

(7)

where \( r_i \) is the distance from the LiDAR return \( i \) to the point at which the stem joins the ground. \( F_i \) is the force exerted by the mass at that point. Obviously we don’t know the mass of the reflecting foliage – if it was foliage – but is a reasonable assumption to suggest that the foliage mass doesn’t vary significantly across the regions in which it is detected. As we are only looking for relative measures, we can assign unit mass to each LiDAR point making
\[ F_i = m_i g \approx \begin{bmatrix} 0 \\ 0 \\ 10 \end{bmatrix} \] (8)

Where \( g \) is the acceleration due to gravity. A larger assumption is to assume that the foliage detected is representative of all of the foliage on the tree. Many authors (Chasmer et al., 2006; Hilker et al., 2010) have noted that ALS tends to bias the upper canopy. We can justify this assumption by noting that under closed canopy conditions the lower canopy is hemmed-in, and any asymmetry is much more likely to become apparent in the upper canopy. In order to determine \( r_i \), the distance from each LiDAR return to the base of the stem - we must also make an assumption as to where this base actually is. As the path of the laser is always close to the zenith, the stems are generally obscured by the foliage and returns from the stem are rare and unreliable. So we make the assumption that the lower canopy is likely to be centred on the stem whilst the upper canopy is freer to deviate. Thus we determine our approximate stem-base location as the average of the returns from the lowest \( \frac{2}{3} \) of the point cloud. This allows us to find \( r_i \), and hence \( M \).

2.12 Net water transport distance

If each LiDAR return in the canopy represents foliage, then there must be sufficient stem and branch infrastructure to supply it with water for photosynthesis to occur. The work of Pont (2003) shows that the stem diameter at any point can be related to distance above it that water must be transported to the foliage. Again, we do not know the exact path that the branches (and hence water) take, so we have to approximate a path that goes vertically from the stem base to the height of the return, and then radially outwards from there. If each return \( i \) is defined in cylindrical coordinates as \((r, \theta, z)\), then \( W \), the net water transport distance is

\[ W = \sum \eta_i + z_i \] (9)

3. Results

Results for the five trees are given in table 2. Table 3 shows a correlation coefficient matrix (\( R \)) between the TLS metrics and the ALS metrics.

<table>
<thead>
<tr>
<th>Method</th>
<th>Metric</th>
<th>Tree 1</th>
<th>Tree 2</th>
<th>Tree 3</th>
<th>Tree 4</th>
<th>Tree 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>TLS</td>
<td>DBH</td>
<td>0.472</td>
<td>0.485</td>
<td>0.516</td>
<td>0.399</td>
<td>0.474</td>
</tr>
<tr>
<td></td>
<td>Volume</td>
<td>2.12</td>
<td>2.80</td>
<td>2.57</td>
<td>1.44</td>
<td>1.80</td>
</tr>
<tr>
<td></td>
<td>Form value</td>
<td>0.492</td>
<td>0.617</td>
<td>0.498</td>
<td>0.468</td>
<td>0.414</td>
</tr>
<tr>
<td></td>
<td>Sweep (m)</td>
<td>0.020</td>
<td>0.057</td>
<td>0.054</td>
<td>0.034</td>
<td>0.038</td>
</tr>
<tr>
<td></td>
<td>Lean (°)</td>
<td>3.23</td>
<td>1.70</td>
<td>2.59</td>
<td>4.41</td>
<td>3.20</td>
</tr>
<tr>
<td></td>
<td>Stem circularity</td>
<td>1.0081</td>
<td>1.0086</td>
<td>1.0148</td>
<td>1.0123</td>
<td>1.0048</td>
</tr>
<tr>
<td></td>
<td>Median internode distance (m)</td>
<td>1.11</td>
<td>1.46</td>
<td>1.38</td>
<td>1.46</td>
<td>0.96</td>
</tr>
<tr>
<td>ALS</td>
<td>Crown area (m²)</td>
<td>25.9</td>
<td>34.1</td>
<td>49.4</td>
<td>27.7</td>
<td>41.9</td>
</tr>
<tr>
<td></td>
<td>Crown volume (m³)</td>
<td>568</td>
<td>891</td>
<td>1117</td>
<td>720</td>
<td>1191</td>
</tr>
<tr>
<td></td>
<td>Crown circularity</td>
<td>3.41</td>
<td>3.12</td>
<td>1.58</td>
<td>2.03</td>
<td>2.69</td>
</tr>
<tr>
<td></td>
<td>Crown density (returns m⁻³)</td>
<td>0.304</td>
<td>0.448</td>
<td>0.538</td>
<td>0.556</td>
<td>0.427</td>
</tr>
<tr>
<td></td>
<td>Net bending moment (Nm)</td>
<td>2390</td>
<td>786</td>
<td>3610</td>
<td>1780</td>
<td>820</td>
</tr>
<tr>
<td></td>
<td>Net water-transport distance</td>
<td>5220</td>
<td>10700</td>
<td>17800</td>
<td>11400</td>
<td>13500</td>
</tr>
</tbody>
</table>
4. Discussion

The purpose of this study is to investigate whether crown structure has any relationship to log quality, and if the structure can be quantified by aerial remote sensing. Although our small sample size of five trees is not sufficient for conclusive proof, it can suggest indicative TLS log quality metrics that can be approximated with ALS canopy metrics. DBH correlates moderately well with crown area ($R^2 = 0.48$). This is not surprising, and is similar to the work of Popescu et al. (2003b). Crown volume also correlates well with crown area (not shown), with an $R^2$ of 0.84, although the DBH responds only weakly to crown area with an $R^2$ of 0.26.

It is surprising that stem volume does not correlate particularly well with crown volume ($R^2 = 0.04$), in contrast with Chen et al., (2007) who obtained an $R^2$ of 0.78 with a similar linear relationship. Values for individual crown volume and area are extremely dependant on the segmentation, and it is likely this may have caused some errors. The fact that crown area was better than crown volume suggests that insufficient returns were obtained from the canopy base to reliably estimate the volume. In addition the good results from Chen et al. are based on summing individual crowns together to obtain a net volume for a stand. This technique is used as it makes up for poor segmentation, as omissions and commissions generally cancel out. It is very unlikely they would have got such a good result for individual trees. If timber volume is the principle aim, then empirical functions such as Stephens (2010) to determine volume over an area give better results than single trees analyses (Scharadt et al., 2002).

Form factor does not show any promising correlations, perhaps due to its lack of variation across the five trees. Stem circularity also is very similar across our sample (the variation from maximum to minimum was only 2.5%). As a result, whilst this does show good correlations with net bending moment and crown density, it is unlikely that these models would hold on larger numbers of trees and samples with values for circularity ranging beyond those measured here.

Sweep exhibits moderate positive correlations with crown area, volume and density. This would imply that trees with more foliage are more prone to sweep. This agrees with the findings of Suarez et al. (2010) who found that stem straightness was inversely proportional to stand spacing. It is well known that canopy size and volume are proportional to stand spacing.

Lean did not correlate well with any ALS metrics, perhaps again because there was not a significant degree of variation within our sample. The median internode distance shows a moderate positive correlation with crown density, implying that as crowns become denser the branches become bigger and more spread out. This is feasible, as fewer larger branches would be likely to yield a greater number of LiDAR returns than many small branches due to the blind spot in discrete aerial LiDAR (see Reitberger et al., 2008)).
Canopy metrics such as area, volume and density give better correlations than net bending moment and net water transport distance. This is probably due to the fact that the latter two metrics are extremely dependant on the supposed stem location – which simply cannot be inferred accurately from aerial LiDAR. The lack of correlation of lean with any metrics confirm that the canopy does not necessarily track symmetrically with stem, and thus our assumption of the stem base being the mean value of the returns from the bottom $\frac{2}{3}$ of the point cloud is likely to be false.

We have only been able to assess five trees. With a greater number of trees, and larger range in metric values, we may have been able to detect more correlations and achieve more meaningful correlations on those that we did pick up. Of the correlations we were able to detect, surrogate variables can be derived from ALS for DBH, sweep and internode distance. However the correlations were only moderate. There are two potential reasons for this:

- Crown structure is only moderately correlated to log quality
- ALS at 8pts per m$^2$ had insufficient resolution to determine canopy structure accurately enough

It is the author’s opinion that the reality is a combination of the two, and more heavily weighted on the latter. By showing even moderate correlations between crown structure and log quality we know that canopy does - to some extent – indicate log quality. As remote sensing technology improves and becomes more affordable (higher point densities, greater resolution, improved canopy penetration etc.) it is extremely likely that these correlations will improve. Theoretically these correlations would asymptote to a value which expresses the ‘complete knowledge’ connection between crown structure and log quality, without any reduction due to remote sensing inaccuracies. The values shown in this study are more a statement about the ability of ALS (and subsequent algorithms) to describe crowns, than the actual correlation between crown structure and log quality. As technology improves we can get closer and closer to this theoretical ‘complete knowledge’ value, but we have shown that even with modest technology we can gain moderate inferences of practical use and value.

A subsequent part of this investigation will be to investigate links between ALS crown shape, TLS stem shape and internal wood properties.

5. Conclusion

Five mature *Pinus radiata* trees in Kaingaroa forest, New Zealand were flown with Aerial LiDAR (ALS) at 8pts per m$^2$ and scanned with terrestrial LiDAR (TLS). Novel algorithms were developed for the TLS data to extract log quality metrics for the trees. These were tree diameter at breast height (DBH), volume, taper, sweep, lean, stem circularity and internode distance.

The five study trees were manually segmented from the aerial LiDAR point cloud. Metrics were derived for each individual tree to describe the crown area, volume, density, circularity, net bending moment and water-transport distance.

Despite the small sample size, a promising relationship was found between ALS-derived crown area with DBH, and stem sweep. Crown density also showed potential as an indicator for internode distance. Net bending moment and net water transport distance did not show good correlations, most likely due to our inability to pinpoint the stem base in aerial LiDAR.

It is thought that the correlation between crown structure and log quality is greater than these results suggest, and the moderate strength correlations are due to poor resolution in the ALS. Higher point densities and technological improvements should increase the strength of these correlations.
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