Growing confidence in forestry's future Research Programme

SCION FORESTS ▪ PRODUCTS ▪ INNOVATION

Date: June 2019
Reference: GCFF TN023

Technical Note

Testing UAV-borne Riegl Mini VUX-1 scanner for phenotyping a mature genetics trial

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Summary: We collected an ultra-high density UAV laser scanning dataset using a Riegl miniVUX-1 UAV scanner embedded within a LidarUSA system over a mature genetics trial. This was supplemented by an extensive field dataset that was used to validate the utility of the resultant UAV point cloud for measuring phenotypic traits in forest trees. We examined the dataset and found good laser penetration to the lower parts of the tree, the understorey and the terrain. We quantified the vertical accuracy of the UAV dataset using a set of independent ground control points and found it to have high accuracy (RMSE = 0.26 m). We developed methods to adapt a tree identification and delineation algorithm to the UAV data and extracted individual tree point clouds from which we could extract tree position and height. We compared the height of trees extracted from the UAV dataset at both the plot and tree-level and found that the plot level comparison was very similar (RMSE = 1.57 m) but was less accurate at the tree-level although considerable errors associated with trees with broken tops which were not well identified using the tree-identification approach trialled. Once these were removed the tree-level height comparison revealed improved accuracy (RMSE = 2.9 m). We discussed the sources of error in the collected dataset and suggested directions for further research in this area.

Introduction

Detailed measurement of tree phenotypic traits can support tree breeding programmes when linked to information on the genetic worth of individuals within experimental trials. Traditional methods for measuring tree phenotypic traits have relied on manual field measurements. These methods are limited due to the amount of measurements that can be accurately captured by a field team within budgetary and resource constraints. For larger trees, the accuracy of many measurements is also lower because many traits of interest, including tree height and assessments of features in the upper stem, are very difficult to collect in larger trees. Therefore, new methods that can provide accurate, cost-effective measurements over larger areas are required. Within the Growing Confidence in Forestry's Future (GCFF) programme significant developments have been made towards tree-level phenotyping of forest trees and these have been successfully linked to data on the genetic composition of trees to improve the deployment of tree breeding research (Pont, 2016; Pont et al., 2015). This research has primarily focussed on the use of data from conventional manned aerial platforms and offers encouraging results. The acquisition cost of these data can be prohibitively high for frequent measurement of trials or measurement of smaller areas. Unmanned aerial vehicles (UAV) potentially provide an alternative data collection platform as, once equipped with appropriate sensors, they can provide flexible and highly detailed data collection on tree phenotype over moderately sized areas. Furthermore, in recent years there have been substantial developments in UAV technology and in the development of the associated miniaturised sensors required. One such development has been the emergence of light weight laser scanning systems (Dandois and Ellis, 2013; Dash et al., 2019; Wallace et al., 2012) that can be mounted on a UAV and can provide potentially provide detailed data on the canopy structure of forest trees.

supported by forestgrowers commodity levy

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This programme is also funded by Scion and the Ministry of Business, Innovation and Employment, New Zealand.

Significant efforts have been made towards developing data collection procedures (Puliti et al., 2019) and methods for extracting useful metrics from this emerging data source. However, much research effort has been focussed on smaller trees because of the limited power and accuracy of the earlier UAV mounted laser scanners. For fast growing species such as *Pinus radiata* higher powered sensors are required that can accurately resolve both the treetops and the local ground surface so that tree heights and other canopy features of interest can be extracted. This was not feasible using earlier iterations of commercially available UAV-borne laser scanners due to range limitations and significant errors and noise in the resultant datasets. Subsequent systems often built around more modern scanners such as the Riegl miniVUX-1 UAV (RIEGL, Horn, Austria) offer greater range and higher accuracy thanks to the increased sophistication of the various system components and the scanner itself.

In late 2018 Scion acquired a new miniaturised laser scanning system that can be mounted on a UAV and can potentially provide accurate information on tree and forest dimensions. Early trials with this scanner indicate that it has sufficient power to provide detailed depiction of trees and to penetrate through to the tree stem, lower branches, and the terrain below the forest canopy. To understand the performance of this new device we designed a trial where we collected an extensive experimental dataset to develop data collection procedures and to test whether we can extract useful information on tree and forest dimensions.

In this study we installed a case study in a mature genetics trial to develop and test initial methods for extracting key phenotypic traits from UAV laser scanning (UAV-LS) data and to validate the accuracy of these measurements against an extensive conventional field survey.

Method

Study site

This study was located in Tarawera Forest in the Bay of Plenty district close to Pukemaire Road. The study site encompasses a 3.6 ha clonal genetics trial (FR203/3) that was planted with advanced generation breeding population *Pinus radiata* in 1993 and aged 26 years old at the time of measurement. The trial is in stand TAWE/5/5/4A and is managed by Hancock Forest Management. The site is 200 m, currently has a stand density of ~304 sph, and is pruned to 5.5 – 6 m. Site preparation included a pre-plant herbicide spray, line-raking, ripping, and mounding. Tarawera forest is known for moderate fertility, a relatively fine branching habit, and freedom from excessive weeds.

Experimental Design

The original study trial design was a single-tree-plot trial with replication. The trial has three sets, with 30 families per set including controls. All sites have 25 replications and control seedlots were used in each set. Readers are advised to refer to (Stovold, 1993) for further information on the trial design including extensive detail on the genetic composition. Within the trial plots are demarcated with numbered treated stakes in each corner (Figure 1). These pegs were located and reinstated where required during a field visit prior to study commencement. The original plot boundaries were used to provide a field dataset for this study. The trial consists of 75 rectangular plots with a size of 24 x 20m (0.048 ha) and the trial spacing is 4 x 4 m. Each plot originally contained 30 trees although several trees per plot have been removed due to thinning or mortality.

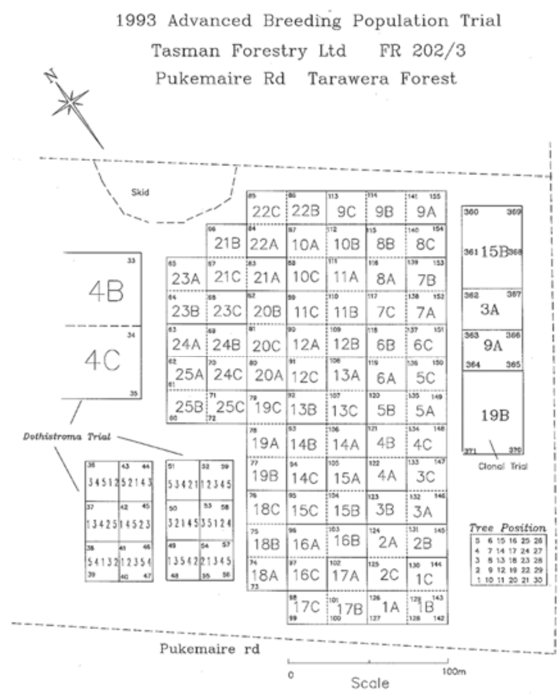

Figure 1. Map of the original trial layout for the FR203/3 genetics trial showing the plot boundaries and tree locations used in this study

Datasets

The following datasets were collected to meet the study objectives.

Field Data

Detailed ground verification data is vital to develop and validate the UAV based measurement methods that were the focus of this experiment. The highest standards of care were employed during data collection to improve the accuracy of the field dataset. This ensured that it will provide a valuable data source for this study and subsequent analysis. Diligent auditing and data assurance were used to improve data quality. All study trees were measured to enable a full genetic analysis of the trial to be completed by other research groups at Scion.

Accurately locating the trial and the trees within it was extremely important. The accuracy of Global Navigation Satellite System (GNSS) data collected below the forest canopy remains a major problem regardless of equipment used. A significant effort was exerted to accurately fix the trial location through collection of a set of differentially corrected GNSS (dGNSS) points over the trial pegs along the northern edge of the trial. In this area the adjacent trees had been removed as part of road line harvesting of the stand and so we could be more confident of collecting data with high positional accuracy. Other trial pegs within the stand were also fixed using a dGNSS but exhibited substantial variation and so the pegs at the northern edge were used to locate the trial. As the trial was planted on a strict grid with a 4 x 4 m spacing this was sufficient to locate the trial and to approximate the position of the study trees. The tree locations and numbering scheme of the original genetics trial was used for the study dataset and trees were re-numbered by the field team. Unfortunately, the matching of mature trees in both field and UAV datasets remains a difficult task and is likely to introduce substantial errors.

Within each plot numerous external phenotypic traits were measured on each tree. The traits of interest included:

- Tree height collected to decimetre precision;
- Diameter at breast height (DBH at 1.4 m) using a dbh tape;
- Stem straightness;
- Branching pattern;
- Stem malformation;
- Stem dominance status

Tree height was measured on all trees using an ultrasonic vertex. Heights were measured from two different angles to reduce the probability of erroneous measurement caused by occlusion or the identification of false treetops. Field crews noted many instances where tree heights would have been incorrect based on the initial measurement and finding an additional angle for measurement improved tree height accuracy. Where tree lean was observed, the initial height measurement was taken at a 90° angle from the direction of maximum lean. Tree height measurements were audited on a randomly selected sample of 60 study trees by an expert auditor to improve the dataset and to quantify expected error levels within the field data.

Diameter at breast height (DBH) was measured on all plot trees at 1.4 m above the true ground surface on the uphill side of the stem. Measurements were taken to the nearest mm using a DBH tape avoiding parts of the stem affected by branch whorls or other forms of nodal swelling.

Stem straightness, branching patterns, and malformations were assessed using the overlapping feature cruise methodology commonly collected within the Plotsafe software (Silmetra Ltd., Tokoroa, NZ). Stem straightness was assessed visually as the deviation of stem form from a straight line assessed over appropriate saw log assessment lengths. Branching regions are classified according to the maximum branch size and the height of changes in branch characteristics are recorded for each stem. The start and end heights of all other features that lead to a value downgrade in log-product output (e.g. nodal swelling, damage, rot) are also recorded. The Plotsafe user guide provides a detailed description of these methods. In addition to the normally collected data the dominance status of the stem should be recorded as either dominant, co-dominant, or suppressed.

UAV Data

UAV data was collected across the entire study area (wall to wall) on 17th April 2019. Prior to data collection ground control points (GCPs) were established to allow accurate co-registration of all data sources and to provide a means of quantifying the vertical positional accuracy of the UAV-LS data. The GCPs were located on roads or open cutover surrounding the trial and were visible in all UAV datasets.

All data collection was carried out using a DJI Matrice 600 Pro piloted hexacopter platform (DJI Ltd., Shenzen, China). UAV Airborne laser scanning (UAV-LS) data were collected from the UAV platform using Scion's Riegl VUX-1 sensor embedded within a LidarUSA system (Fagerman Technologies, INC., Somerville, AL, USA). All flight manoeuvres including turning and altitude adjustments should be completed outside of the area of interest to reduce the possibility of flight artefacts in the trial dataset. Data collection was completed in fine and still weather conditions

Point cloud analysis

Point cloud analysis was completed on this dataset to meet the requirements of the GCFF milestone. The focus of this analysis was on quantifying the properties of the mini VUX-1 point cloud and assessing its utility for detailed measurement of the trees in the genetics trial in both a quantitative and qualitative manner. The number of ground returns, proportion of stem hits, and capacity to detect large branching and significant stem deformations were of interest.

Data were extracted from the native Riegl format using Scanlook software v1.0.190 (Fagerman Technologies, Inc., Somerville, AL, USA), and processed with trajectory data that was post-processed using the Inertial Explorer software package (NovAtel Inc., Calgary, AB, Canada). Subsequent processing was completed using the LAStools software (RapidLasso, Gilchin, Germany). This processing included ground classification, noise removal, and interpolation of a digital terrain model (DTM). The DTM was used both to normalise the point cloud to the local terrain so that tree and canopy could be extracted and to quantify the vertical accuracy of the point cloud through a comparison with the GCPs. A canopy height model (CHM) was calculated from the ALS point cloud to provide an input into tree detection and delineation. The properties of the point cloud were summarised to provide insight into the canopy penetration and accuracy levels. The proportion of ground returns and the density of returns at different points of the canopy were extracted and plotted. The amount of stem hits and the capacity of the point cloud to resolve branching and other stem deformations was made qualitatively through visual examination of the point cloud.

Tree identification and delineation was carried out using a range of algorithms available through the LidR v2.0.2 (Roussel and Auty, 2019) R library. The library offers a complete solution specifically designed for the identification and delineation of forest trees and other forms of analysis of ALS data. A number of delineation algorithms are available within the library and the algorithms “silva2016” (Silva et al., 2016) and “dalponte2016” (Dalponte and Coomes, 2016) were trialled in this analysis. Both algorithms require a set of local maxima extracted from a CHM raster to serve as surrogate treetops and provide a seeding point for segmentation. These approaches work well in many conifer species that maintain strong apical dominance, self-prune, and have narrow crowns. Unfortunately, mature *Pinus radiata* does not have these properties as the high crown plasticity means that in many cases branches can become emergent from the canopy and appear as false treetops. The lidR package provides a function to find local maxima in a smoothed CHM using a moving window size specified by the user. The moving window size has a major influence on the number of maxima identified. Following initial investigations, we found that a moving kernel size of 3 m provided a closer approximation of the actual tree numbers in the trial than the other settings trialled. Using this approach, a representation of the trees in the trial was extracted from the UAV-LS point cloud (Fig. 2).

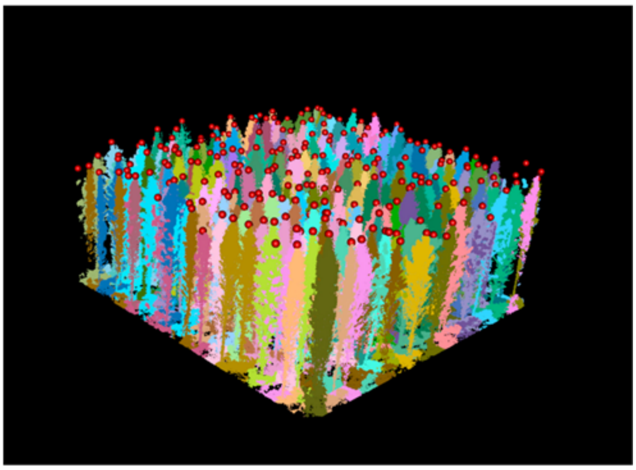

Figure 2. The delineated UAV-LS point cloud. Each colour represents a different tree identified in the point cloud. The red spheres show the locations of local maxima used to seed the delineation algorithm.

There were two outputs from the tree identification and delineation process. The first was a shapefile containing the local maxima identified from the CHM that is assumed to represent the top of each study tree. These data are used to estimate the tree location in the shapefile and also to provide a start point for the tree delineation algorithm. The second output was the delineated point cloud containing all points that were assigned as belonging to a specific tree by the tree delineation algorithm. This output can then be used to calculate any desired metrics from the point cloud associated with each tree and also to estimate the canopy size and shape by fitting a two-dimensional Voroni polygon to the individual tree point cloud. In this manner estimates of tree height and canopy width and volume were extracted. All spatial analysis was undertaken using the simple features (sf) package (Pebesma, 2018) in the R programming language.

Tree matching

Matching the trees identified in the UAV point cloud with the field measured trees is a significant challenge. In this analysis we attempted to use the regular planting pattern of the trial trees to match the two datasets. A shapefile representing the locations of the study trees was produced assuming a regular planted spacing of 4 X 4 m. The grid was orientated and located using the plot boundaries provided by the northern boundary of the trial fixed with the highest GNSS accuracy in the field. The grid was manually adjusted in a GIS until it closely matched the observed tree positions in both the UAV imagery and the CHM produced from the UAV-ALS point cloud. The field measurements were then merged with this shapefile and stored as a simple features dataframe that included all tree measurements and an estimated location for each tree in the field dataset. Rotten and thinned trees were removed from the dataset and then a spatial match was used to link the field trees to the local maxima file identified from the CHM as part of the tree identification process. The accuracy of tree matching was assessed by comparing plot level tree counts in the UAV and field datasets and through comparing the accuracy of the tree height

Accuracy statistics

To assess the equivalence of the field and UAV derived height estimates the root mean square error (RMSE), and mean bias (MBE) were calculated. The accuracy statistics were calculated using the following equations:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{n}}$$

$$MBE = \frac{1}{n}\sum_{i=1}^{n} y_i - \hat{y}_i$$

where y_i is the observed value, $\hat{y}$ is the predicted value in plot i, $\bar{y}$ is the average of the observed values, and n is the number of plots. The RMSE was also expressed as a proportion of the field measured dataset ($RMSE_{\%}$) to provide an easily interpretable measure of accuracy.

Results

The results obtained from the trial are summarised in the following sections.

Field data

In total 2,250 trees were assessed by the field crews including trees that had been thinned or were absent for other reasons. All the originally planted trees were accounted for in the field dataset. There were 30 trees assessed in each of the 75 plots measured. Of the total trees assessed 1,113 trees were recorded as having been thinned leaving a total of 1,137 standing trees in the trial. A further 14 of these trees were dead standing, recorded as being rotten, and not measured for this trial. Broken tops were observed in 66 trees (5.9%) distributed throughout the study area. The relationship between Height and DBH and the distributions of tree heights and DBH are shown in Fig. 3.

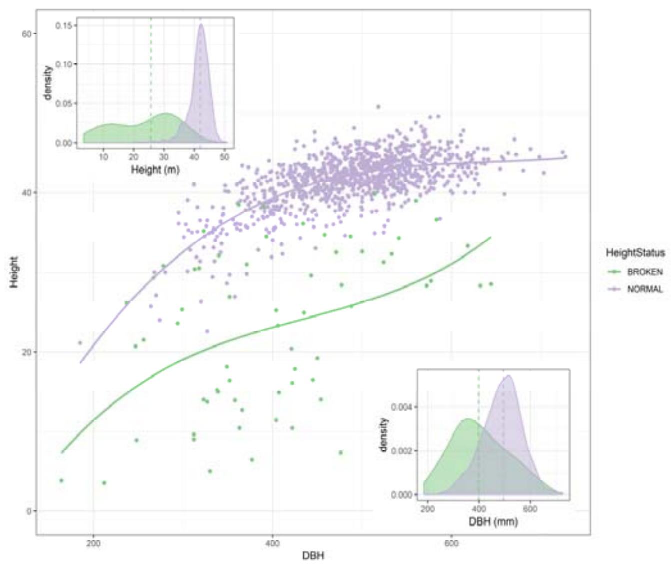

Figure 3. The relationship between Height and DBH in the study trees

Sixty of the 1,123 live standing trees (5%) were audited by an expert assessor as the measurement error identified in tree height was of particular interest. Assuming the field measured height to be y_i and the audit height to be $\hat{y}$, in the equation above, the RMSE on height measurement was 1.28 m ($RMSE_{\%}$ = 3%). This level of field height accuracy is greater than anticipated for trees greater that are 40 m tall. The mean bias error (MBE) of the height prediction was 0.29 m and the observed height error ranged from -3.2 m to 3.3 m (Fig. 4)

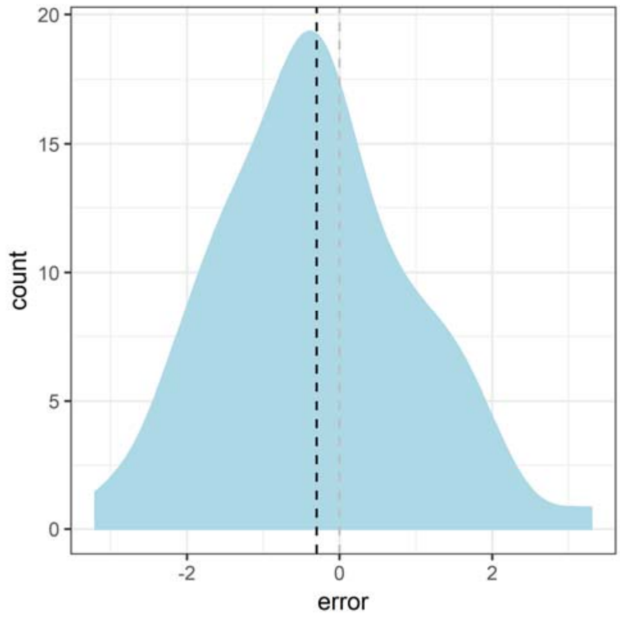

Figure 4. Density plot of the height errors observed in the field dataset based on the audit results. The grey dashed line shown is at zero and the black dashed line shows the mean bias error.

UAV point cloud description

Following processing to remove duplicates, clipping of the point cloud to the study area and classification of the ground returns, the properties of the UAV-LS point cloud were summarised (Table 1). This showed that the Riegl MiniVUX-1 UAV scanner produced a rich and extremely detailed point cloud. Unlike previous less sophisticated scanners trialled by Scion the Riegl miniVUX-1 UAV captured multiple returns and recorded up to 6 returns per pulse emitted. The study area included 97,238,107 points at a density of 1,589 pts/m^2 which is at the higher end reported in published UAV-LS studies (Puliti et al., 2015). Only 2,284,43 (0.2%) were classified as reaching the forest floor (Table 1). Clearly, most returns originated in the forest canopy, this result is unsurprising due to the closed canopy and the high canopy biomass of mature *Pinus radiata* stands. The point spacing for both the “all points” and “last only” points was approximately equivalent to the footprint size of the scanner (~0.1 m).

Table 1. The properties of the study UAV point cloud.

Variable	Value
Total # of points	97,238,107
Max. returns per pulse	6
Total # of ground returns	228,443
Point density (pts/m^2)	1,589
Point spacing (m)	0.03
Point spacing (last only)	0.05

Studying the heights of the return profile of the point cloud provides more useful information on the point cloud properties (Fig. 5) The majority of points in the point cloud were first returns originating in the green crown of the canopies of the trial trees between approximately 23 m and 45 m with a mode at 37 m. The maxima of this distribution is analogous with the tree heights of the dominant trees in the trial and the minima probably approximates the height of the base of the green crown. A substantial number of second returns originated in the same part of the canopy with a mode of approximately 31 m. This result shows the impressive capability of the scanner to resolve backscattering from targets within close proximity (~6 m) to each other and promises a significant level of detail from the upper and mid canopy. This is a feature of the Riegl scanners that is not available from other units. Below 23 m there were substantially fewer returns but these returns originate in the branches and stems of the study trees. There is another peak in return count at around 6 m, probably associated with larger understory vegetation (trees, shrubs, ferns), and finally a large number of returns associated with the ground and near ground objects and vegetation. Most of the higher number returns (3,4,5,6) originate below ~5m.

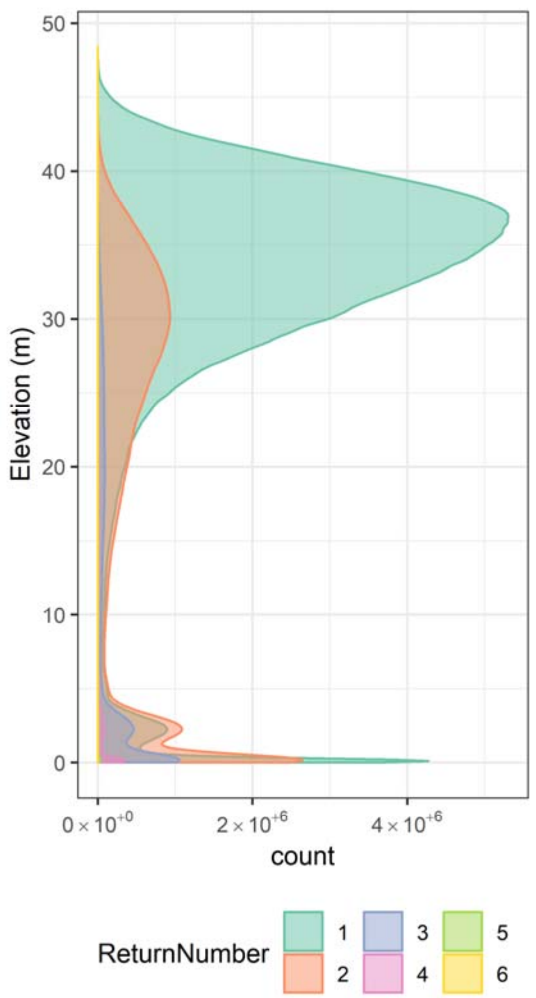

Figure 5. The return profile of returns within the point cloud covering the trial.

Clearly the point cloud contains significant detail on the forest canopy. This was supported through a visual examination of the point cloud. Clipping areas of the point cloud from the centre of the trial (e.g. Fig. 6) reveals significant canopy penetration even in areas with dense foliage and total canopy closure. Numerous features of the tree architecture are apparent including branches and returns originating on the tree stem all the way down to ground level.

From initial examination of the point cloud in the interior of the stand it is apparent that objects within the lower canopy and the tree stem are represented in the point cloud. This raises the question of whether techniques designed to process terrestrial laser scanning can be applied to this data type. We examined sections of the point cloud at various heights for several heights and concluded that it is unclear whether sufficient returns occur around the stem to be able to fit cylinders and circles to the point cloud based on the current UAV data collection procedures.

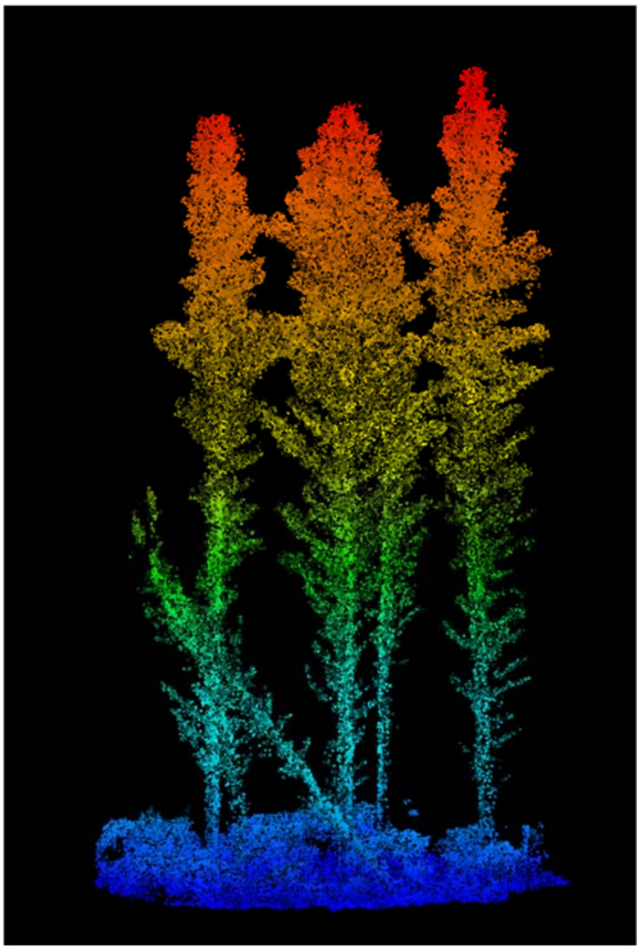

Figure 6. An example screenshot from point cloud in the trial interior.

Point cloud accuracy

We compared the point cloud accuracy by comparing a set of dGNSS points collected in open areas with the DTM extracted from the UAV-LS point cloud. This analysis revealed a RMSE of 0.26 m. This is indicative of best quantitative estimate of the total vertical positional error in the point cloud in open areas and on a reasonably hard surface. We would expect the positional error for returns originating in the vegetation to be larger due to the porosity of the vegetation surface and vegetation movement caused by airflow near the canopy.

Tree identification and delineation

Plot level results

To provide an estimate of the accuracy of the tree counts and heights extracted from the UAV-LS point cloud at the plot level the delineated point cloud was intersected with a shapefile containing the plot boundaries. The plot level comparison showed that the UAV-LS height estimates were consistent with the plot level heights measured in the field (Fig. 7). The plot level height RMSE was 1.57 m ($RMSE_{\%}$ = 3.84%). There was some evidence of bias with the UAV-LS extracted heights being slightly higher than the field measures. This RMSE value is not substantially greater than the measurement error we would expect on tree height based on the results of the field audit.

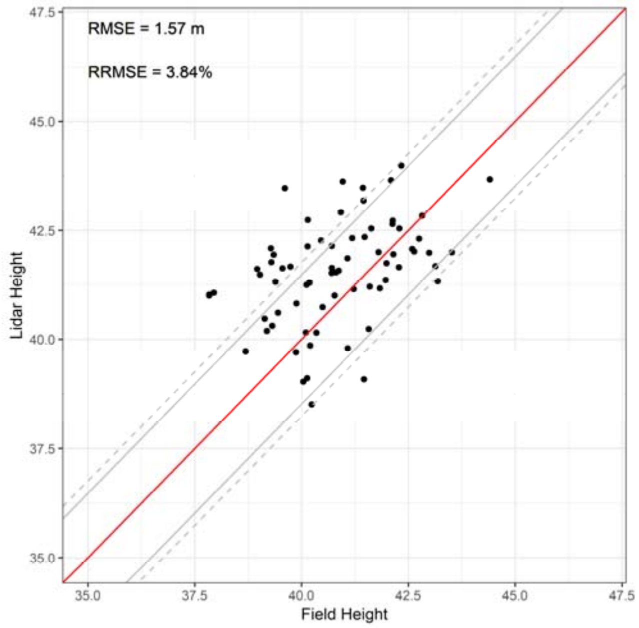

Figure 7. The plot-level relationship between UAV-LS (Lidar Height) and field measured heights. The red line shows a perfect 1:1 correspondence, the grey solid line shows the RMSE from the field audit, and the grey dashed line shows the additional error that estimated from the accuracy of the point cloud based on the dGNSS data.

Tree level results

Following matching of the trees identified in the UAV-LS point cloud with the field data we compared both datasets to investigate the accuracy of tree-level prediction. Tree matching remains a difficult process in mature *Pinus radiata* stands and we sought to make the process as automated and reproducible as possible. To that end, no manual positional adjustments to the idealised tree planting locations were made. We then used a nearest neighbour spatial intersection (k=1, maximum search distance = 4m) to link trees in the field dataset with those identified in the UAV-LS point cloud. The resulting tree-level comparison revealed that there was a poor correspondence between UAV-LS derived and field derived tree heights when all trees were considered (RMSE = 6.3 m, $RMSE_{\%}$ = 15%). However, this result was heavily influenced by the presence of trees with broken tops in the trial dataset. Unbroken trees showed significantly better correspondence with field measurement (RMSE = 2.9 m, $RMSE_{\%}$ = 6.8%) than trees with broken tops (RMSE = 16.2 m, $RMSE_{\%}$ = 56%). The relationship between field and UAV-LS tree heights confirms that for trees with broken tops the relationship is very poor whilst for unbroken trees the relationship is stronger (Fig. 8).

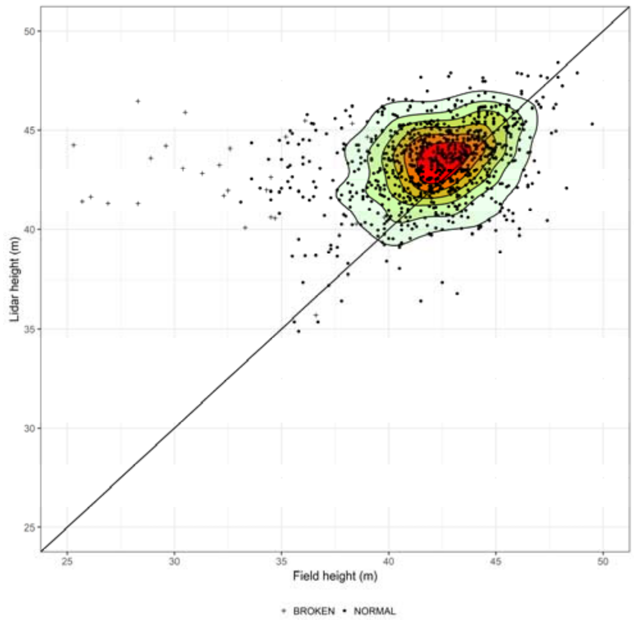

Figure 8. The relationship between UAV-LS and field measured tree heights for the trial. Colours relate to the density of points (green = low, red = high)

Discussion

In this study we successfully collected a UAV-LS dataset using a Riegl miniVUX-1 UAV laser scanning system over a mature *Pinus radiata* genetics trial. In addition, we collected an extensive field dataset that was used to validate the UAV based estimates of tree height and will be used in subsequent research. We employed methods for tree identification and delineation from the ultra-high resolution (1,589 pts/m^2) point cloud using methods available in an open-source library in the R programming language. The results of the validation of tree heights showed promise and were accurate at the plot level. At the tree-level the results were less accurate and the height of trees within broken tops could not be accurately estimated using the methods used.

A detailed and high-quality field dataset was collected as part of this study. Phenotypic traits were recorded on all trees within the trial and used to test the capacity of the UAV-LS data to identify and delineate trees and to estimate tree heights. This field dataset will also provide significant additional value as an input into tree-breeding research and for future analysis of the UAV-LS data. For mature trees the field measurement of tree height is both expensive and known to be inaccurate. This means that it is regularly not measured in genetics trials and is a good candidate for replacement by UAV-LS. To characterise and reduce the variance in the field dataset in this study we carried out a detailed audit of field heights. This revealed that the height measurements were unbiassed (MBE = 0.23 m) and the error was only moderate on average (RMSE = 1.28 m, $RMSE_{\%}$ = 3%) but that the errors in tree height ranged from -3.2 – 3.3 m. These results help to interpret the accuracy of the UAV-LS derived and improved the quality of the field dataset by replacing field measurements that were found to be in error. Measurement of error is frequently ignored in forest measurement research and this dataset should provide a useful perspective for ongoing research.

Using the UAV data collection procedures developed a coherent and useful point cloud was collected over the trees in the study trial. Analysis of the point cloud showed that there was good laser penetration that characterised the entirety of the tree stems, the understorey vegetation, and the terrain below the forest canopy. This is an encouraging result as earlier lower-powered scanners struggled to provide adequate penetration to the ground below mature stands. Using this dataset, a high-quality DTM was produced and used to normalise the point cloud so that local tree heights could be extracted. A thorough inspection of sections of the point cloud for several trees throughout the stand revealed that although major features upon the tree were resolved there was not a good representation of points around the stem. Methods developed for extracting tree dimensions from TLS rely on fitting circles or cylinders to the points originating on the stems. Our examination suggested that in this dataset there was not good representation of all sides of the stem. Further research is required to investigate whether this level of detail is adequate to extract measurements using a TLS type analysis approach. An alternative approach to estimation of phenotypic traits such as DBH from ALS data have been successfully developed through extracting tree heights and crown width from the point cloud and using these to predict DBH (Aubry-Kientz et al., 2019). This might provide a good template for further research using this dataset and should be explored further.

The vertical accuracy of the UAV-LS point cloud was assessed by using a series of dGNSS points collected in clear areas near the trial. A comparison of the elevations extracted from the UAV-LS DTM and the dGNSS points revealed that the point cloud had good accuracy (RMSE = 0.26 m). This level of accuracy is comparable with commercial ALS data and is significantly higher than the accuracy experienced from earlier UAV-LS datasets.

Initial methods were developed for tree identification and delineation. These methods could likely be improved through further exploration of the effect of different parameters such as CHM smoothing, window size when identifying local maxima, and algorithm hyperparameters. Nevertheless, a realistic tree identification and delineation was achieved from the point cloud. The field dataset was used to assess the accuracy of tree heights and tree counts at the plot level and to compare UAV-LS and field tree heights. At the plot-level there was good consistency between the heights extracted from the UAV-LS and the field dataset. In fact, once the variance associated with field height measurement error and the vertical positional error in the UAV-LS data are considered the difference between both data sources is minimal at the plot level. This suggests that the UAV-LS point cloud is capable of very accurately measuring tree heights and this is consistent with previous research (Puliti et al., 2019; Wallace et al., 2012). The tree-level findings were considerably less accurate. This was in part due to the failure of the method used to extract meaningful heights for trees with broken tops. This result is not surprising as tree identification methods based on identification of the local maxima in the CHM will be challenged by broken trees. Alternative methods have been proposed to identify broken trees within other forest types based on the intensity values of ALS data (Wing et al., 2015). A similar approach may be effective in *Pinus radiata* plantations and future research should investigate this as the intensity values from the Riegl scanner appear to contain meaningful data. In addition to the broken tops there are several other sources of error that contribute to the significant variation between tree-level UAV-LS and field tree heights. These included positional errors in the dGNSS data used to locate the trial, tree matching errors resulting from forked or leaning trees, and a failure in the tree identification and delineation procedures.

Conclusion

This study has shown that Scion's recently acquired Riegl miniVUX-1 UAV1 has the capacity to provide an accurate representation of the canopy structure in large and mature *Pinus radiata* trees. We found good laser penetration even to the tree stems, understory, and ground and characterised the vertical accuracy of the dataset to be similar to ALS from commercial providers. We compared the tree level height measurements at both a plot and tree level. This showed that although the results were accurate at the plot level significant discrepancies remain at the tree-level. This was primarily the result of a failure in the tree matching process rather than any issues with the UAV-LS dataset.

Acknowledgements

Funding for this research came from the “Growing Confidence in Forestry’s Future” research programme (C04X1306), which is jointly funded by the Ministry of Business Information and Employment (MBIE) and the Forest Growers Levy Trust, with the support of the NZ Forest Owners Association (FOA) and the NZ Farm Forestry Association (FFA). Field data and auditing was carried out by Interpine. Peter Massam and Liam Wright of Scion assisted with collection of UAV and dGNSS data.

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