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Technical Note

An assessment of UAV laser scanning and photogrammetric point clouds for the measurement of young forestry trials.

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Summary: With the advent of Unmanned Aerial Vehicles (UAVs) for data capture in forestry, it is becoming increasingly practical and cost-effective to collect aerial data. In addition, the ability to collect wall-to-wall data of an entire stand, is extremely useful. Due to limitations in size, flight time, and legislative barriers to larger area capture, we investigated a particular use case that maximises the ability of UAVs to cover a small area in great detail: the measurement of forestry trials. We focused on sites with younger trees as this provides an excellent use-case for foresters and there appears to be a gap in the literature on this topic at the time of writing.

In this study, two commercially available UAV-based data sources, UAV-borne lidar (ULS) and structure from motion photogrammetry (SfM), were analysed to see how effectively tree heights can be measured remotely.
ULS offers a fast and reliable way to detect and measure the heights of individual young trees, while UAV SfM is a more cost-effective alternative for tree detection.

ULS point clouds and SfM point clouds were produced, from which canopy height models could be generated and then a local maxima algorithm applied to detect individual trees. The peaks were then delineated into individual trees so that tree-level metrics for height could be calculated and compared with field measurement data to evaluate the precision of each point cloud source.

We found that ULS had the greater level of precision, with a very good agreement of R^2 = 0.96 and RMSE 4.6%, with SfM also returning a very good level of agreement (R^2 = 0.84 and RMSE 15.2%). Both technologies had a bias towards the under-estimation of tree heights (MBE = -0.11 m and - 0.50 m for ULS and SfM respectively).
This technical note has shown that both technologies have the potential to be viable options for carrying out forest trial measurements.

Figure 1. Scion genetics trial April 2019 UAV image mosaic at 1:125 scale.

1. Introduction

Remotely sensed data are widely used in the forestry sector and have largely been sourced from satellite or airborne sensors. Recently, UAVs have emerged as a new platform for acquiring remotely sensed data. In contrast to satellites and aircraft, UAVs are relatively inexpensive and can be rapidly deployed to collect data with greater frequency. UAVs allow for quicker data capture, potentially collecting data across a whole stand, as opposed to the sampling methods that are common with traditional inventory, and can help to alleviate issues created by skills shortages and hazardous environments by having fewer staff collect more data, automating various aspects of the analysis processes, and allowing forestry data to be collected by staff not trained in forestry disciplines, such as mensuration.

Many of the commercially available craft on the market have restricted flight times and payload capacity, limiting the potential range of applications and the type of sensors that can be carried. These attributes are likely to see UAVs fill a niche for the collection of remotely sensed data to serve a variety of novel applications. One such application is to regularly carry out comprehensive measurement of forestry trials. Although UAVS do fill such a niche that could be explored further it is worth noting that UAVs become cost-prohibitive over larger areas, in their current form, owing to the increased setup and flying times.

To increase yields, plantation forestry uses a variety of methods to improve the genetic stock of the trees planted. Forest genetic trials are established to evaluate the performance of provenances, families and individuals (Costa e Silva, et al., 2001). Similarly, silvicultural and treatment trials are established to determine the optimal growing conditions for the crop. Compared to their agricultural counterparts, forestry trials can suffer from higher inter-plot variability due to their larger size, lower topographic uniformity and competition from neighbouring trees (Costa e Silva, et al., 2001). Additionally, measurement of forestry trials can be time-consuming and difficult, as trials are often planted on hilly terrain or hard to access areas. With current skills shortages in the sector, trials often remain unmeasured or a high turnover of staff can result in sub-standard, inaccurate measurements from inadequately trained staff.

With the miniaturisation of airborne laser scanners (ALS) to be flown from UAVs (UAV laser scanning/ULS), it is now feasible to carry out ULS surveys for fast and reliable detection and measurement of individual young trees. Although prices have fallen, ULS sensors remain relatively expensive. In comparison, methods based on structure from motion photogrammetry (SfM) require only densely overlapping imagery from consumer-grade cameras to generate a 3D point cloud - potentially enabling similar assessment from a more cost-effective solution.

UAVs provide a means of capturing higher resolution aerial imagery (1-30cm resolution) than manned aircraft (typically 0.5-1m, but down to ~3cm, subject to minimum economical areas) or satellites (2-30m). The recent miniaturisation of UAV sensors allows the capture of three dimensional (3D) point clouds using either Lidar (Jaakkola, et al., 2010; Wallace, et al., 2012) or through the use of imagery captured from digital still cameras (Dandois, et al., 2013; Lisein, et al., 2013; Shin, et al., 2018), with data from this latter source processed using techniques such as Structure from Motion, SfM (Lowe, 2004).

A key limitation of SfM photogrammetry is that, due to the passive nature of the sensor, very little of the light from beneath the forest canopy reaches the camera. Within a mature canopy, these models are not truly three dimensional as they characterise the surface of the canopy well but provide little information around the ground surface. However, within younger trials, where the canopy has not yet reached closure, the ground may be better characterised. Little research has tested whether this is the case in real-world trials and how the use of SfM impacts the overall precision of the canopy height model (CHM), which is derived as the difference between the digital surface model (DSM) and digital terrain model (DTM).

ALS or ULS, otherwise known as a light detection and ranging (lidar) scanners, on the other hand, are active sensors, and as such generate their own light signal, which can then penetrate through gaps in the canopy to detect spatial information on the ground beneath the canopy.

Although the acquisition of point cloud data across an entire trial may provide a more cost-effective and precise method for collecting difficult-to-measure stand attributes, such as tree height, the authors are aware of only limited research that has investigated this possibility, particularly for small trees, which are representative of many trials.

This technote presents results from a comparison of ULS, SfM and traditional field measurement methods, with the latter considered to be the benchmark for measurement of young trials. We then discuss the utility of these approaches as practical tools for large forestry trials.

2. Materials

2.1 Study Area

The study was carried out using the Scion genetics trial, located in the nursery at Scion in Rotorua (Figure 2).

The highly regular planting within the genetics trial site, in the Scion nursery, offered a valuable

Figure 2. Map of the study site, the area of interest (blue box) and the layout of GCPs across the site, along with an example of a typical GCP marker, as deployed in this trial (inlaid top left).

opportunity to robustly test the tree height measurements. In this trial, each tree is classified as its own plot and regular measurements are made at a tree level basis. The genetics trial in question was made up of 610 live *Pinus radiata* D. Don trees and hence contained 610 plots. The trial has trees growing in atypical forestry conditions, planted in exact rows, with short-cropped grass and a bounding fence, allowing for easy access by trained technicians who meticulously measure every tree at three-month intervals. The focus of this trial was to define the absolute accuracy of alternative point cloud sources. This required idealised conditions to minimise other error sources. The UAV data contained remarkably little ground clutter due to the absence of weeds and logging debris found at commercial forestry sites. Compared to an average commercial forestry site, the genetics trial also contains a good range of young tree heights, approximately 1-6 m tall (Table 1) at the time of measurement (March 2019).

Table 1. Summary Statistics for the Scion genetics trial

Height (m)	Mean	Range	SD
Actual	4.25	1.6 – 6.1	0.81
ULS	4.14	1.5 – 6.0	0.86
SfM	3.74	1.0 – 6.1	0.98

2.2 UAV Methodology

The Initial stage of the capture involved planning the operations. On top of the standard pre-operational activities, such as booking in flights, risk assessments and managing logistics, this involved accessing a site map and establishment records to ascertain the best places to set up ground control. Once the initial planning was completed, flight plans were created for the site, that described appropriate flight parameters, including overlap, ground sample distance (GSD), altitude, flight line spacing, speed, orientation, overflight, and siting of take-off location. This process generally takes between four to eight hours to complete for a site.

During the day of the capture, ground control was first established. According to best practice for a small site[1], a minimum of five GCPs were established on the site to achieve even coverage across the area of interest (AOI) (Figure 2). Ground control points were surveyed in using a Trimble Geo7X handheld GPS unit (Trimble Inc., Sunnyvale, CA, USA).

Flight operations were carried out using a combination of UAVs to capture the SfM photogrammetry and ULS data. The photogrammetry was captured by a DJI Phantom 4 Pro (DJI Ltd., Shenzen, China), with its integrated 1-inch 20MP RGB camera. The ULS was captured by a combination of a LidarUSA Snoopy V-series system (Fagerman Technologies, INC., Somerville, AL, USA), comprising a Riegl MiniVUX-1 UAV scanner (RIEGL, Horn, Austria). This was mounted on a DJI Matrice 600 Pro hexacopter (DJI Ltd., Shenzen, China). Details of the craft and flight parameters are described in Table 2.

Table 2: Table of UAV Flight Parameters

Data	Craft	Sensor	Software	Altitude (m AGL)	Overlap / line spacing	Point Density (Pt/m²)	Speed (m/s)	GSD (cm/pxl)
RGB	DJI Phantom 4 Pro	DJI P4p 20MP	Map Pilot	60m	85%:80%	938.92	3 m/s	1.57
Lidar	DJI Matrice 600 Pro	LidarUSA Snoopy V-Series	UgCS	45m	21m	375.62	5 m/s	n/a

Flight planning was carried out using Map Pilot (Drones Made Easy, San Diego, CA, USA) for the photogrammetry, and UgCS (SPH Engineering, Rīga, Latvia) software for the Matrice 600 Pro, to capture the ULS data.

The field measurements were taken by Scion technicians between March 17th and March 29th, as part of routine trial measurements. Heights were measured using a Vertex hypsometer (Haglöf, Langsele, Sweden).

3. Methodology

There are three main steps in the processing pipeline for UAV point cloud data. Firstly, processing the raw data involved taking the raw data from the UAV-mounted sensor into a geo-referenced point cloud. Secondly, the point cloud data must be quality checked to remove noise, classify the ground, height-normalise the data, and then create a DTM and DSM. Finally, the processed point cloud data needs to be analysed with a series of algorithms and statistical techniques to generate a CHM, detect peaks, delineate individual trees, and finally calculate individual tree metrics from the point cloud.
It should also be mentioned that, due to logistics, the field measurements were not carried out by the same team who captured the UAV data. Consequently, some of the UAV data was captured later than the field data, or vice versa and so to ensure that the field measurements and UAV data were still comparable, a height correction was added to the field data to account for any potential growth that could have taken place during the gap. This was done in accordance with growth rates calculated by Watt, et al. (2003).

3.1 Processing Raw Data

ULS
All ULS data were processed from the manufacturer's native data format into the more universal LAS format. For this research, a LidarUSA Snoopy V-Series was used, which uses two software packages to process the raw data: Inertial Explorer (NovAtel Inc., Calgary, AB, Canada), and ScanLook PC (Fagerman Technologies, Inc., Somerville, AL, USA).
The PPK (post-processed kinematic) process involves two stages. The first stage involves post-processing the trajectory data from the GNSS rover on the scanner with the base station GNSS log data using Inertial Explorer to increase the accuracy of the GNSS data. The second stage involves inserting the post-processed trajectory data, along with the raw sensor data, into ScanLook PC, and processing the two together into a point cloud (LAS or LAZ format). This stage also allows for some initial quality control and basic filtering to be applied to the data to remove anomalous data such as points from above a certain angle (i.e. above the scanner), or within a certain distance from the scanner (for example if the craft was flying at least 20m above the target then any points falling within 20m of the scanner can be filtered out).

Importantly, the ScanLook PC software also applies two crucial factors to the data: boresight calibration angles and lever arm offsets. The boresight angles are the X, Y and Z offsets between the laser scanner and the IMU (inertial measurement unit) of the ULS (Gonçalves, et al., 2011), and the lever arm offset is

[1] Best practices as described on Pix4D support website: https://support.pix4d.com/hc/en-us/articles/202557489-Step-1-Before-Starting-a-Project-4-Getting-GCPs-on-the-field-or-through-other-sources-optional-but-recommended#label1

the X, Y, and Z offset between the IMU and the GNSS antenna. When these corrections are applied to the data it removes any inherent error within the data, which can manifest as mismatching point data from opposing flight lines (often referred to as ghosting), or errors in the orientation of points in a single flight line.

SfM

There is a range of software packages available for SfM photogrammetry such as Pix4D Mapper (Pix4D), PhotoScan (AgiSoft LLC), and ReCap (Autodesk Inc) that can be applied to imagery from the majority of modern, UAV-mountable digital cameras. Other platforms include cloud-based processing software suites, such as DroneDeploy (DroneDeploy) or freeware such as OpenDroneMap (WebODM) and Meshroom (Alice Vision). The SfM process involves feeding the raw data (overlapping aerial images) into software, which then uses complex algorithms to carry out a range of feature recognition and matching steps, adding geolocation, and then producing the desired 2D and 3D outputs.

For this research, Pix4D Mapper was used to generate the SfM outputs. The workflow for Pix4D involves 3 basic phases: 1) initial processing, 2) point cloud and mesh generation, and 3) DSM production, orthomosaicing and indexing.

In the initial processing stage, algorithms go through the raw data and identify characteristic points in the imagery that can be found across multiple images in the dataset, also called key points. Next, the key points are matched, finding which images hold common features. The data is then optimised for the camera model, assessing the internal (focal length, image width and length, lens model etc), and external parameters (orientation, angle, direction etc) of the camera. The final stage of the phase is to locate the model, using the geolocational information, written into the metadata from the crafts GNSS.

In the next stage, the point cloud (and 3D textured mesh, if desired), is created through a process of point densification, in which the overlapping nature of the dataset is exploited to create additional tie points that are used to build and populate a 3D model.
The final stage of this process is to create other derived products, such as a DSM, orthomosaic or reflectance maps. Several studies have compared software suites for generating photogrammetric point clouds, with Pix4D and PhotoScan often quoted as the best for these tasks (Jensen, et al., 2016; Mohan, et al., 2017; Morgenroth, et al., 2014; Panagiotidis, et al., 2017; Wallace, et al., 2016). Niederheiser, et al. (2016) found that PhotoScan can produce denser and more complete point clouds, however, Gross, et al. (2016) found that PhotoScan produced significantly more artefacts during image stitching than Pix4D across a range of vegetation types. Noting that Pix4D and PhotoScan can produce comparable results (Niederheiser, et al., 2016), it was decided that Pix4D would be used due to a greater familiarity with the software and a simplified workflow.

3.2 Point Cloud Processing and Analysis

The initial point cloud was de-noised and ground classified using tools from the LAStools suite, such as *lasnoise* and *lasground*.

A plot Shapefile was created and georeferenced to the documented trial layout. The processed 3D point cloud was then clipped to the extent of the trial area to compute a CHM, as shown in Figure 3. The CHM is then fed into a peak detection algorithm inspired by Popescu, et al. (2004) that detects local maxima using a moving window with a diameter of 2m. The result of the treetop detection algorithm is then fed into the tree segmentation algorithm (Silva et al., 2016) available within the *lidR* software library, which combines the treetop locations and the CHM to segment individual trees within the point cloud (Figure 3). In this study, the number of trees and their positions were already known so that the algorithm could be fine-tuned until the outputs matched the expected values in terms of spatial location and count. This was done by inspecting omissions and commissions in the data and referencing ground measurements in order to get the optimum result, matching the peaks with the trees from the trial, so that precise comparisons could be made between trees.

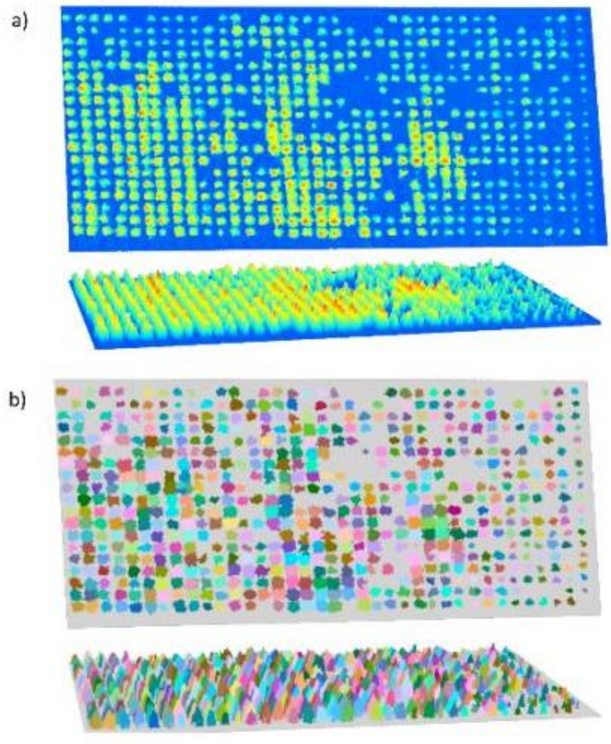

Figure 3. a) Canopy height model (CHM) created from the ULS data covering the southern section of the site.

b) An example of peak detection and tree delineation using the selected algorithm.

4. Results

Once the peaks had been detected, the heights of the predicted treetops were compared with the field measurements. The results are summarised in Table 3.

Table 3. Error statistics

Statistics – Height vs LiDAR predicted				Statistics – Height vs RGB predicted			
RMSE (m)	RMSE (%)	R^2	MBE (m)	RMSE (m)	RMSE (%)	R^2	MBE (m)
0.20	4.60	0.96	-0.11	0.65	15.2	0.84	-0.50

4.1 Prediction of measurements

The results for UAV lidar (ULS) showed a very strong relationship between predicted measurements and field measurements (Figure 4). The R^2 value of 0.96 showed a very high level of agreement and the bias was also very low with a mean bias error (MBE) of -0.11 m, and RMSE% of 4.6%, showing a slight underestimation of tree height.

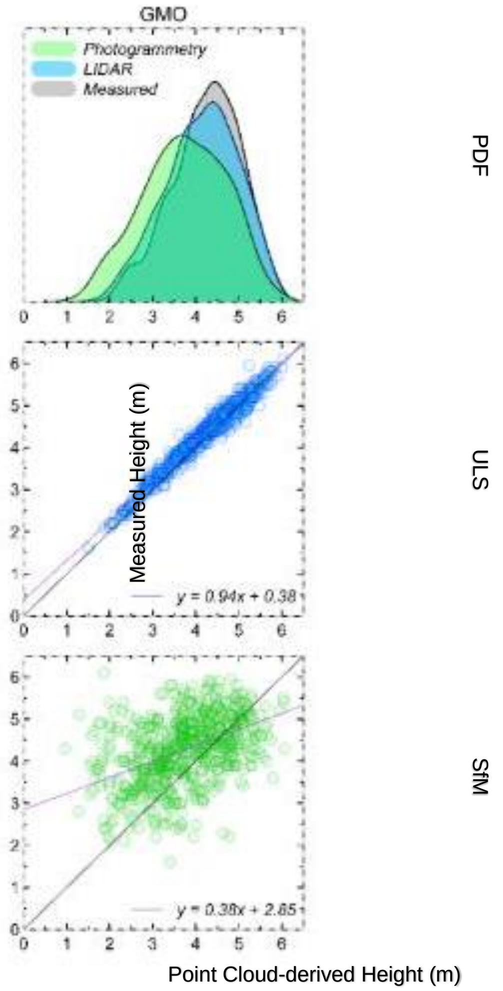

Figure 4. Distribution and fit of sensor data versus measured data. Top row: Probability distribution functions graphs for the study site.

The predictions of tree height from SfM photogrammetry were markedly less precise than the ULS predictions but still showed a strong correlation. The R^2 value for the trial was 0.84 still shows a strong correlation, however, there is a marked increase in bias, with an RMSE% of 15.4% and an MBE of -0.50 m.

5. Discussion

The results of our research indicate that both technologies are showing promise as tools for measuring forestry trials.

Figure 5 shows typical cross-sections of the ULS and SfM point clouds and the location of these transects on the trial map.

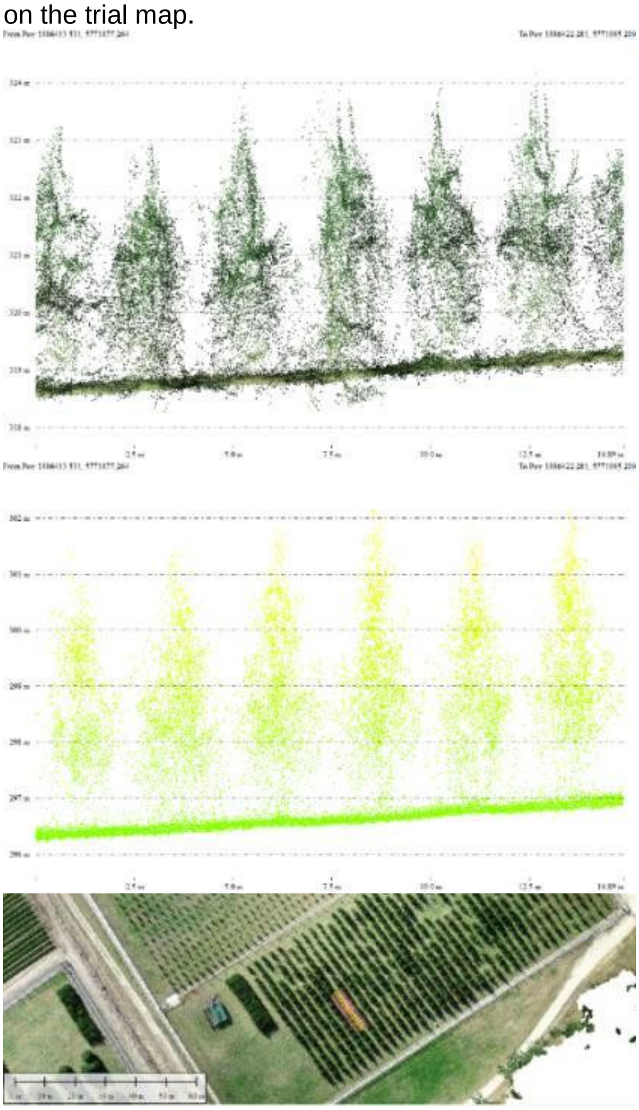

Figure 5. Cross-sections of ULS and SfM (top and middle respectively) point clouds from the genetics trial, and location of the transect (bottom).

5.1 ULS vs field measured heights

The results from this study showed a very strong correlation between field measurements and predicted heights from the ULS. The regular layout of the genetics trial at Scion provided an excellent baseline on which to test the efficacy of these new technologies. The ULS model showed an R^2 value of 0.96, showing that this technology, under ideal conditions, produces accurate height estimates with low bias (MBE= -0.11 m).

Our results align well with the literature. Wallace, et al. (2014) achieved a mean RMSE of 0.52m comparing ULS to hypsometer measured heights in *Eucalyptus globulus* plantations that contained trees with heights of between ~4-11m. The RMSE for ULS measurements in our study was 0.20m, which is an improvement on this. However, the trees in Wallace et al.'s (2016) study were larger and may not have had the same apical dominance of *P. radiata*. Wallace, et al. (2016) found ALS data from a manned aircraft provided an RMSE of 0.92m, a bias of 0.34m and an R^2 of 0.84 – results showing a strong correlation, but not to the same extent as those found in our study. Sankey, et al. (2017) achieved an R^2 of 0.90 between field-measured tree heights and ULS captured with their Velodyne HDL32-E laser scanner (Velodyne Acoustics, Inc., Morgan Hill, CA), again similar to the results in this study.

The majority of the literature has focused on using lidar for measuring larger trees (Birdal, et al., 2017; Ota, et al., 2017; Sankey, et al., 2017; Ullah, et al., 2017; Wallace, et al., 2016; Wallace, et al., 2014), and as far as we are aware, few studies have focused on ULS or ALS to predict tree heights in smaller trees. Our study has proved that it is possible to predict the height of trees as low as 1m tall with a high level of precision. We have also shown that precision does not deteriorate down to a height of 1 m (Figure 4).

There was a noticeable trend in the data for under-predicting tree heights. This underprediction has been identified in previous studies (Andersen, et al., 2006; Roussel, et al., 2017). Roussel, et al. (2017) have identified that ALS data is prone to a bias in the metrics of maximum height and mean height of the canopy and that this can be attributed to various combinations of the pulse density, scan pattern, and beam footprint; which they noted as being especially true of coniferous trees where the apex presents a very small target for the laser to intercept. These concepts are discussed further in Appendix A.

5.2 SfM vs Measured Heights

The SfM data from our site showed a strong correlation with the field measured data (R^2 = 0.84), although our results were not as strong as between the ULS predicted heights and the field measurement. When we compare this to the rest of the literature we can see that this is consistent with previous literature such as Shin, et al. (2018), who used SfM point clouds to model canopy fuel loads in *Pinus ponderosa* forests (R^2 = 0.71) Wallace, et al. (2016) (R^2 = 0.68) and Ota, et al. (2017) (R^2 = 0.91).

Like the ULS data, the SfM data also generally tended towards underestimating tree heights (Table 3), although there was a much lower correlation between the SfM data and the field measured data, with an RMSE of 0.65 m and an MBE of -0.50 m. This is displayed well in the probability distribution function graph (PDF) in Figure 4, where the distribution of the heights is clearly lower than the ULS or field measured heights. This aligns well with the literature, as other studies have found tree height to be less strongly related to SfM than lidar predictions (Lisein, et al., 2013; Wallace, et al., 2016).

One reason for this systematic underestimation could be due to the small size of the treetops. The apex of young coniferous trees is always going to pose a challenge to the SfM algorithms because of its slender geometry and small size. The topmost point of young *P. radiata* presents a target of no more than two to four pixels width in this imagery.

As well as the actual size and geometry of the apex, the background of the imagery could also influence the effectiveness of the SfM algorithms in detecting the tree tips. It could be understandable that trying to identify the tree tip, which may only be a single line of pixels wide in the imagery, against a very noisy background, could cause difficulties in detection. Even trying to pick out a green tree tip against a background of other trees within the imagery could be difficult (see Figure 6). Further studies could look at ways of making the tree tip stand out more clearly, which could include assessing the effect of different background textures or colours (i.e. what is on the ground surrounding the trees), or exploring capture using different spectral bands to assess the effect this would have on the algorithms' ability to detect the tree tips against a noisy background.

Figure 6. ~1.5cm GSD imagery from the GMO trial showing the oblique angle of tree tips against a complexed background of shadow, other trees or grass.

5.4 SfM Data Quality

Through our research, we have been actively testing this equipment out at other forestry sites and have found that image quality has a large part to play in the precision of the measurements.

When carrying out a thorough QC on SfM and ULS point clouds collected at one of the of GCFF (Growing Confidence in Forestry's Future) accelerator trial sites located in Rangipo, North Island, NZ, we can start to see some errors in the SfM point cloud, which would have a significant impact on the precision of the measurements. Figure 7 shows an example of a cross-section of the Rangipo ULS and SfM point clouds, demonstrating a clear error in the SfM.

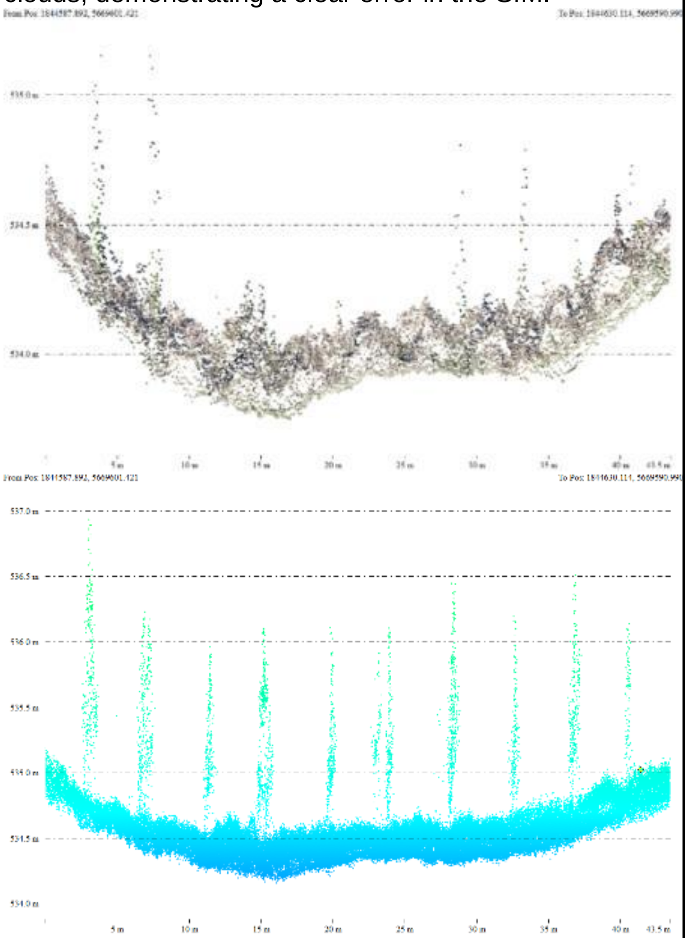

Figure 7 - Graphs plotting a 45m long cross section of the Rangipo point clouds in SfM (top) and ULS (bottom) datasets.

Dandois, et al. (2015) found that there were errors introduced into the absolute position of point clouds created from imagery on cloudy days as compared to clear days. They linked this to a reduction in contrast in the camera settings to account for lower light levels. They also observed some indication that imagery captured at lower sun angles produced a poorer quality point cloud. They hypothesised that shadows, caused by low sun angles, could have some effect by obscuring parts of the canopy Dandois, et al. (2015). The sun angle is obvious in both the Kaingaroa 861 and Rangipo sites, and so this could be a good explanation for why we are seeing such a dramatic reduction in the model's precision if parts of the tree canopies are not being recreated in the point cloud.

We recommend future studies into the effect of introduced noise (shadow, background objects, colour) on the ability to delineate and model narrow tree tips using SfM algorithms, and stricter parameters for weather and environmental conditions when capturing SfM data.

5.5 Further Work

This study focused on comparing two methods for measuring tree heights in a trial site with highly geometric planting, flat ground, and minimal background noise (other tall objects). This was a good way to benchmark and assess the potential of this technology; however, the reality of most commercial forestry sites is quite different.

The next stage is to test this equipment in more complex environments, with different terrain, different establishment patterns, and background noise, such as logging debris, weed growth or regeneration from previous rotations. Scion has been busy applying these methods to the series of accelerator trials that have been established across New Zealand as part of the GCFF project and will be looking to publish on this soon so that we can see how this technology performs on commercial sites.

From initial trials on these sites, we are seeing a significant increase in omissions and commissions on sites with logging debris and so our team is fine-tuning the algorithms to reduce these errors, as demonstrated in Figure 8 below:

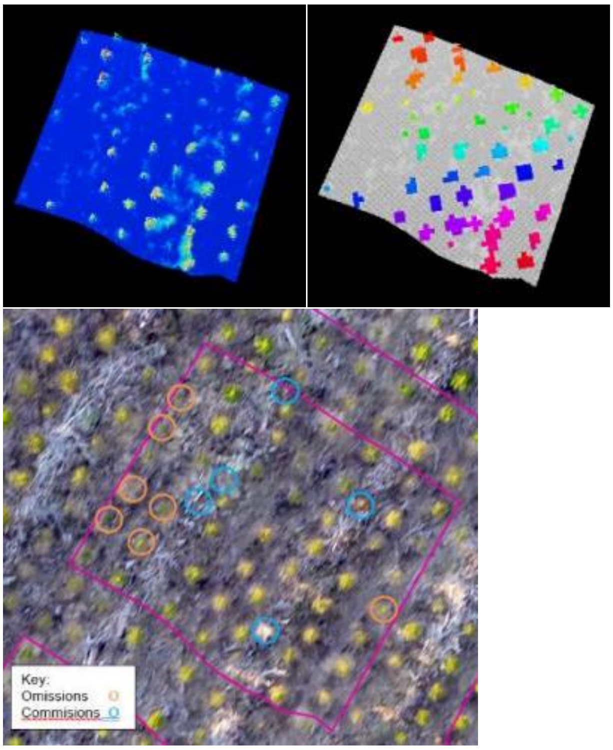

Figure 8. CHM, tree delineation and errors of omission and commission from Kaingaroa compartment 861 Accelerator trial site, indicating the difficulties faced when computing individual tree metrics.

The results of this study have also led us to question whether other SfM processing software, such as Agisoft Photoscan, may be able to reconstruct more of the tree peak in the point cloud. Within the various SfM software, the user can change the parameters for point cloud generation, which may be able to produce better reconstructions of individual trees. This project was processed on the default settings for Pix4D (Image Scale ½ (Half image size, Default); Point Density: Optimal; Minimum Number of Matches: 3), however, further research is being carried out to assess the effect of fine-tuning these settings, and comparing these outputs, to comparable outputs from PhotoScan.

Conclusion

Our research has shown that both techniques show promise for measuring forestry trials and that ULS is showed greater precision. There are very strong correlations between ULS and SfM-based methods for measuring tree heights in point clouds with field measurements. ULS and SfM both consistently underestimate the height of the trees measured and with ULS, there could be some scope for developing a metric to account for this underestimation. With the SfM measurements, there are still unknown factors driving the lower correlations and greater underestimation of heights seen with SfM measurements as compared to ULS.

More work needs to be done in understanding the factors impacting the SfM point cloud generation and how this can be affected by the data capture (lighting and shadow, surrounding environment, altitude, GSD, overlap, point density) and the SfM process itself (point density, fine-tuning of the algorithm to suit the task, which software works best for detection of tree tips). Once these avenues have been explored, and the correlation has been fine-tuned to the extent that it becomes more consistent, then it might be possible to develop some metrics to account for the underestimation of tree heights in SfM too. Despite the decreasing cost of ULS, a consumer grade UAV, such as that used in this study, can be purchased for a fraction of the price of the Riegl scanner used in this study, and even the less expensive ULS sensors would need to be reduced in price ten-fold before they could compete with the cost of these consumer grade UAVs. SfM provides a cheaper tool for foresters, and more research in this space will help to unlock the full potential of this method.

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Appendix A.

On the effect of canopy shape and footprint location on true peak detection

Achieving sub-decimetre accuracy on lidar-based height measurements of young trees is understandably challenging from a geometric point of view. In fact, from all the uses of lidar height ranging, e.g. urban environments, land surface, and even broad-leaved trees, it would be harder to imagine a more challenging geometric object that is harder to measure accurately than a coniferous tree. The highest point of a pine tree is, generally, a single thin structure pointing skywards. The probability of multiple laser beams striking this small surface area and enough being returned to register a pulse is very low. For near nadir beams it is far more likely that the lower top crown stems that have a larger horizontal component to their orientation will be hit. For off-nadir beams, the probability of hitting the apex increases, although again the top of this stem is likely to be missed. In their paper on removing bias from lidar-based estimated of canopy height, Roussel, et al. (2017) explored this concept looking at the difference between true maximum height and observed maximum height. They found that due to the larger trees having a wider, flatter apex the laser has a higher chance of hitting part of the canopy that is closer to the true maximum height than on narrower canopies (see Figure 9). Although in their example they compare the difference between large canopy trees and smaller-crowned coniferous trees in a plot-based height sampling method, the principles of their findings are relevant to our study.

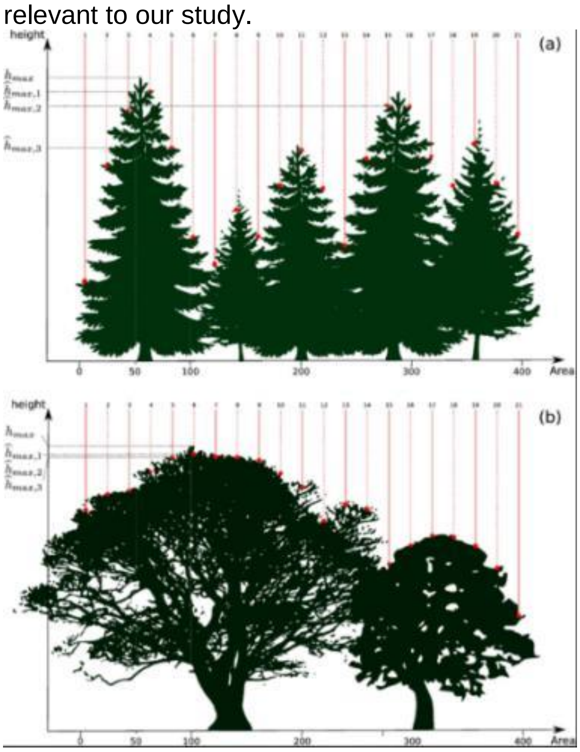

Figure 9 - the effect of canopy shape on the likelihood of the true maximum tree height being captured by a lidar scan. Adapted from Roussel, Caspersen et al (2017)

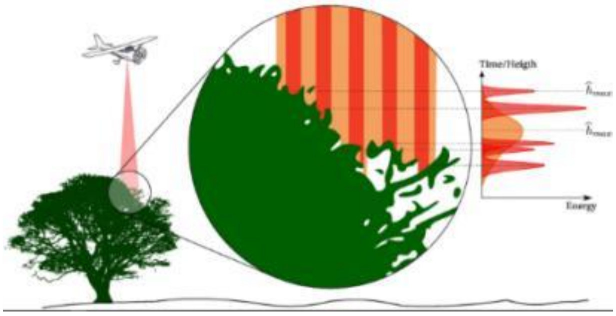

Figure 10 - effect of footprint size on the observed maximum height. The red lines represent smaller footprint beams averaging a smaller range of heights, and the orange representing a single, wider footprint beam. Adapted from Roussel, Caspersen et al (2017)

Beam divergence and beam footprint size are other possible explanations for the underestimation of tree heights by the lidar (Disney, et al., 2010; Hancock, et al., 2015; Hirata, 2004). Roussel, et al. (2017), explain that this is due to the effect of the standard deviation of the heights that the footprint senses when coming into contact with the canopy. As the size of the footprint increases, so too does the potential variance in the heights of the surface increase, and when expressed as a Gaussian curve, the local maximum return from each is averaged out over a potentially wider range (See figure 10).

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