A comparison of photogrammetric software for deriving structure-from-motion 3D point clouds and estimating tree heights

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Abstract

The use of structure-from-motion (SfM) photogrammetry from unmanned aerial vehicles (UAVs) is becoming an increasingly popular means of characterising key forestry biophysical variables such as tree height. Despite the wide array of software that is available to process 3D point clouds from SfM, little research has investigated how the precision of predictions vary between software. This study compared the accuracy of tree height estimates for a young *Pinus radiata* trial (height range 1.4 – 6.1 m) obtained from 10 different software packages, which were used to derive canopy height models (CHMs) from UAV-acquired SfM point clouds. To ensure a fair comparison, the default parameters for each software were used without any data tuning.

Predictions of tree height ranged widely in terms of both precision (R^2 range: 0.61 – 0.86) and bias (mean bias error (MBE) range: 0.28 – 3.37 m). Height predictions with the highest precision and lowest bias were made using 3DF Zephyr (R^2 = 0.86; MBE = 0.58 m), Pix4DMapper (R^2 = 0.78; MBE = 0.28 m) and Maps Made Easy (R^2 = 0.85; MBE = 0.85 m). The availability of numerous software options provides choice to the user and this study helps to identify the best software for estimating tree heights from SfM-derived point clouds.

Introduction

Accurate forest inventory is critical for monitoring crop health and damage, optimisation of silvicultural operations and the prediction of forest volume and value. Traditionally, such information has been acquired through labour-intensive and time-consuming field inventory practices that measure or estimate key biophysical variables such as height, diameter, volume and density at various spatial scales. The use of remotely sensed forest data captured over different spatial and temporal scales has revolutionised inventory practices and has been used to supplement and sometimes replace traditional field inventory (Dash et al., 2015).

Light detection and ranging (LiDAR), a laser-based ranging system that measures the return time taken by a pulse of laser energy to travel between a sensor and target (Dubayah & Drake, 2000), has been widely used in forestry (De Gouw et al., 2020). LiDAR can be used to scan environments through either airborne (ALS) or terrestrial laser scanning (TLS) platforms. In forestry, the capability of LiDAR to penetrate the forest canopy has provided 3D data for the extraction of the most common biophysical variables at both the tree level and on an area basis. However, ALS is costly, and TLS is labour-intensive and time-demanding (Brede et al., 2017).

In recent years, airborne laser scanners have been miniaturised and can now be deployed from unmanned aerial vehicles (UAVs). UAVs have increased in popularity as an alternative to airborne and satellite platforms for collecting forestry data at local scales as they are inexpensive and easy to operate over relatively small areas (Mendes et al., 2015). For example, in New Zealand 83% of forestry companies have used UAVs to collect aerial imagery of their forests, while 17% have used UAVs to collect LiDAR data for their forests (De Gouw et al., 2020). There is a growing body of research into UAV laser scanning (ULS) for forestry applications, and this method often provides highly accurate estimates of many key forestry metrics (Hartley et al., 2020). ULS sensors are, however, still relatively expensive and therefore alternative methods for creating 3D models of forests have been developed and applied, including most notably structure-from-motion (SfM) photogrammetry (Wallace et al., 2016; Puliti et al., 2020).

Depending on the level of detail during image capture, 3D point clouds can be derived from UAV imagery using techniques that combine computer vision and photogrammetry, commonly referred to as SfM (Wallace et al., 2016). SfM photogrammetry is a method whereby multiple images are acquired from various camera viewpoints and then combined to form 3D models (Mathews & Jensen, 2013). SfM makes use of algorithms, such as scale invariant feature transform (SIFT) (Lowe, 1999), to find multiple key points in images, match images and create tie points (Mendes et al., 2015). The other key processes in the SfM reconstruction workflow include bundle adjustment that leads to sparse point clouds, which is then followed by dense image matching to create dense point clouds using algorithms such as multi-view stereo (MVS) (Iglhaut et al., 2019).

A number of software packages have been developed to produce dense 3D point clouds from UAV imagery using SfM algorithms. These include cloud-based software packages, in which images are uploaded to servers, processed and downloaded as point clouds thereafter (e.g. Maps Made Easy and DroneDeploy). Desktop-based tools such as Agisoft Metashape (previously known as Agisoft Photoscan and hereafter referred to as Agisoft), Pix4Dmapper and PhotoModeler are alternatives to the cloud-based software tools. There are also a number of free and open source SfM software such as COLMAP. Among commercial packages, the most widely used software within forestry research are Agisoft and Pix4D (Lipwoni, 2020).

SfM photogrammetry acquired from UAVs is increasingly being utilised for forestry applications. SfM software packages have been used to process UAV data across a range of forest types (Lipwoni, 2020), including plantation forests (Wallace et al., 2016). Topographic models, including digital surface models (DSMs), digital terrain models (DTMs), normalised digital surface models (nDSMs) and canopy height models (CHMs), can be interpolated from SfM generated point clouds. These are subsequently used to estimate a range of biophysical variables, including tree heights (Mlambo et al., 2017), volume and biomass (Iglhaut et al., 2019), tree counts, and crown cover area (Gülci, 2019) and tree structure (Morgenroth & Gómez, 2014; Miller et al., 2015), as well as being used for individual tree delineation (Maturbongs et al., 2019).

Previous research has shown that the image acquisition process is an important factor for producing high-quality 3D point clouds from photogrammetric data (Dandois et al., 2015; Frey et al., 2018). However, once acquired, images can be processed by numerous SfM software packages and the selection of the most appropriate tool has become an important issue for most projects (Turner et al., 2013). Different factors (such as ease of use, accuracy, processing time, precision and cost) are likely to influence software choice.

Despite the clear need to understand how software choice impacts results (Forsmoo et al., 2019), few studies have compared the performance of different software packages for assessing forest biophysical variables. Using UAV imagery from a Douglas-fir plantation, recent research examined the effects of tree segmentation and algorithms that generate point clouds on tree

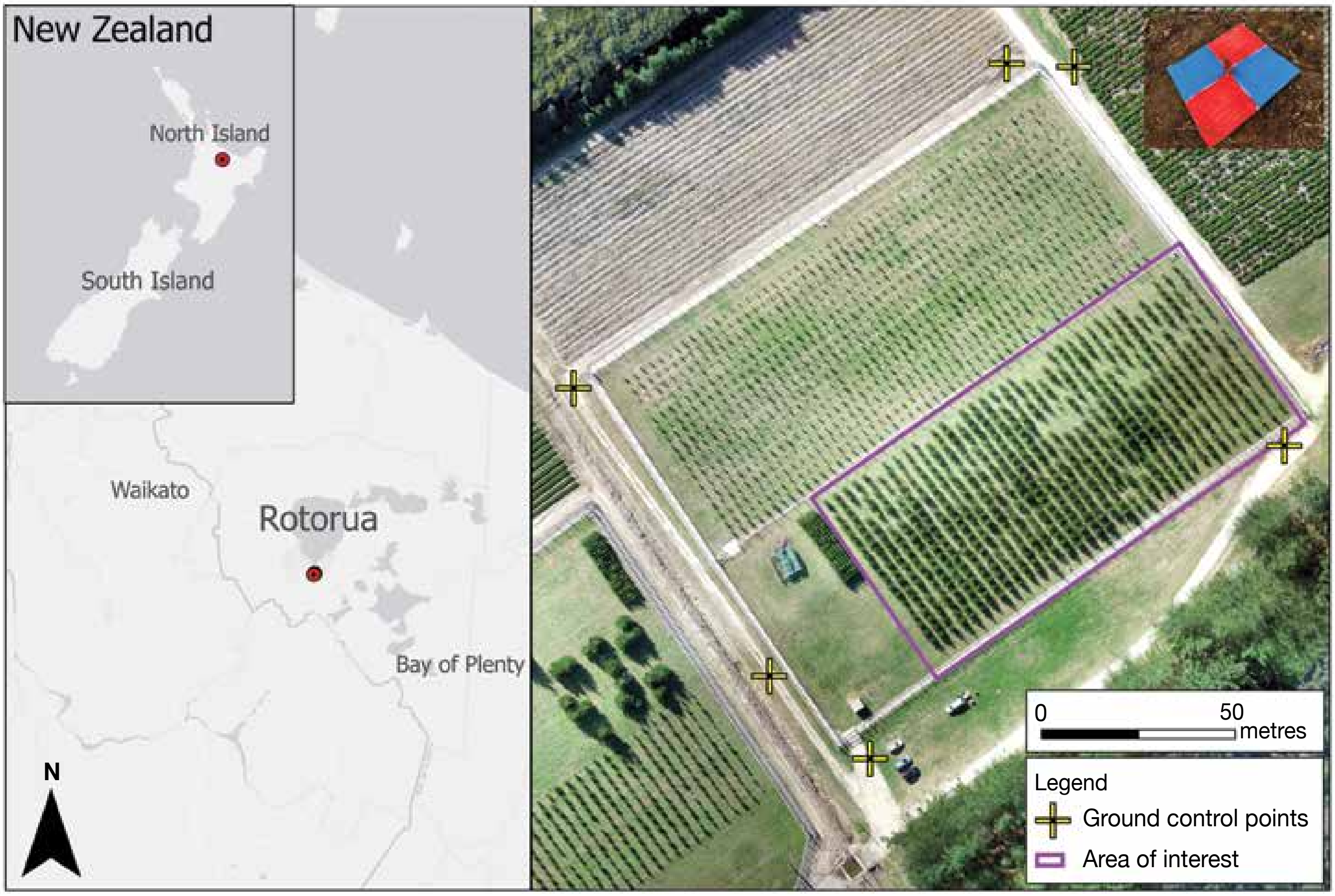

Figure 1: Location of trial plot at Scion in Rotorua. The area of interest is bounded on the map in purple and the layout of ground control points (GCPs) is marked with yellow crosses. The upper right inset shows a GCP

identification and the precision of height predictions (Maturbongs et al., 2019). This study found significant differences in estimates of tree height between images processed using Agisoft and Pix4Dmapper.

In this study, we expand the scope of these comparisons beyond the two most widely used SfM software for predictions of tree height. Height measurements and SfM models from a UAV were obtained from a trial of the widely grown plantation species *Pinus radiata* D. Don (radiata pine) that covered a height range of 1.4 – 6.1 m. Using these data our objective was to compare the precision and bias of predictions of tree height made using 10 SfM software.

Materials and methods

Study site

The study area was located at the New Zealand Forest Research Institute Limited (Scion) tree nursery in Rotorua, New Zealand (Figure 1). The flat site measured 55 m x 110 m and was planted with *P. radiata* in rows with a spacing of 2.5 m x 3 m. The grass at this site was regularly mowed. Following a recommendation from a previous study (Hartley et al., 2020) this site was selected as acquisition conditions were optimal. Through eliminating variation attributable to terrain and understory development this study was able to examine the influence of different SfM software on predictions of tree height.

Feature annotations of the 610 individual trees inside the area of interest were created manually using ArcGIS Pro version 2.5.1 (ESRI Inc., 2019). The RGB orthomosaic (Figure 1) and field data were used as the reference for locating and labelling the individual trees. These feature annotations were exported as shapefiles and used as input in the tree height extraction.

Field data collection

Field measurement of tree heights was undertaken between 17 and 29 March 2019. Heights of individual trees that were ≤ 5 m were measured and recorded using a survey-grade height pole with a resolution of 1 cm. A Vertex IV hypsometer (Haglöf Sweden AB, Långsele, Sweden) with a resolution of 10 cm was used for measuring trees over 5 m. The Vertex IV has been found to have a relative error of between –0.19% and –1.23% for tree heights in coniferous species (Stereńczak et al., 2019). The measured tree heights ranged from 1.4 – 6.1 m with a mean of 4.24 m (Figure 2).

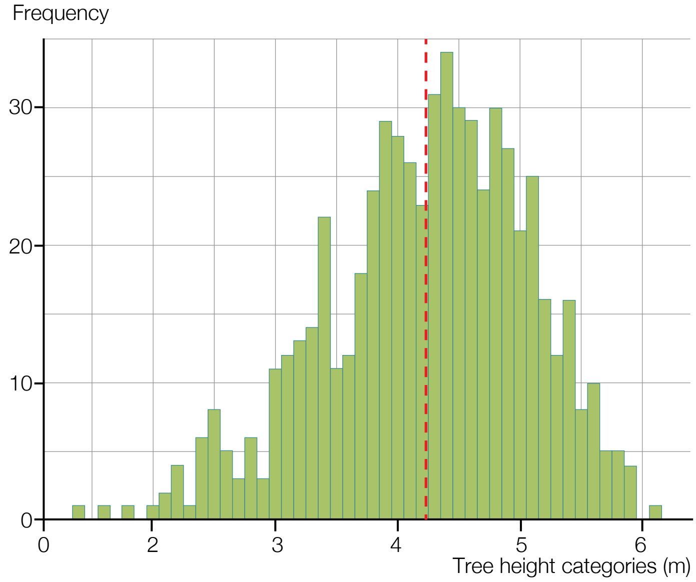

Figure 2: Distribution of field measured heights

UAV data acquisition

Data was captured by a DJI Phantom 4 Pro (DJI Ltd, Shenzen, China) using the integrated DJI RGB camera with a 1” CMOS 20-megapixel sensor. The camera creates an image of 5472 x 3648 pixels and has a field of view of 84 degrees. A flight plan was created considering key flight parameters, including image overlap, ground sample distance (GSD), altitude, flight line spacing, orientation, overflight and the location of the take-off and landing. The flight was undertaken on 4 April 2019 at 3pm using the Map Pilot flight control app (Drones Made Easy, San Diego, CA, USA). The flight was carried out at an altitude of 60 m above ground level, providing an average GSD of 1.6 cm. The image overlap was set at 85% forward and 80% side overlap. A total of 422 RGB images were captured in JPEG format.

Table 1: SfM software selected for the study

Software	Version	Platform	Availability
Pix4Dmapper	4.6.3	Desktop-based	Commercial
Agisoft	1.5.2	Desktop-based	Commercial
COLMAP	3.5	Desktop-based	Free and open source
RealityCapture	1.0.3 10393RC	Desktop-based	Commercial
UASMaster	9.0	Desktop-based	Commercial
3DF Zephyr	4.519	Desktop-based	Commercial
Maps Made Easy	N/A	Web-based	Commercial
DroneDeploy	N/A	Web-based	Commercial
ContextCapture	10.17.0.39	Desktop-based	Commercial
PhotoModeler	Premium 2019.1.2	Desktop-based	Commercial

Table 2: Variation between software in the number of points, point density and point spacing (software are sorted in descending order regarding above ground point density)

	Total number of points (x 10^3)		Point density (pts m^{-2})		Avg point spacing (m)
	Ground	Above ground	Ground	Above ground	Ground
ContextCapture	65,653	37,144	3,402	2,042	0.02
Pix4Dmapper	4,447	5,754	239	300	0.06
3DF Zephyr	557	5,436	29.5	283	0.18
PhotoModeler	273	4,167	14.6	216	0.26
Agisoft	3,785	2,826	199	179	0.07
RealityCapture	5,224	2,461	271	150	0.06
Maps Made Easy	3,991	2,321	218	122	0.07
COLMAP	2,917	1,655	152	94.7	0.08
UASMaster	3,764	358	195	26.6	0.12
DroneDeploy	608	185	32.4	9.79	0.18

The imagery was georeferenced using eight GCPs that were distributed across the study site, with the majority concentrated around the trial plot and a few close to the permanent structures within the nursery (Figure 1). These points were surveyed on the day of the flight using a Trimble Geo7X handheld GPS unit (Trimble Inc, Sunnyvale, CA, USA) with a Trimble Zephyr Model 2 external aerial. GPS fixes were captured over each ground target by averaging a minimum of 180 point fixes captured over a time period of approximately three minutes. The resulting root mean square error (RMSE) of the collected points was 0.03 m.

SfM software

Ten SfM software were used to generate point clouds from the UAV images. Among these, nine were commercial and one was free and open source software (Table 1). DroneDeploy and Maps Made Easy are web-based, while the remainder were desktop-based software. All desktop software were installed on a 64-bit Windows 10 enterprise desktop computer with an Intel(R) Xeon (R) CPU E5-1650v3 @ 3.50GHz, 128 GB RAM and an NVIDIA QuadroM4000 73,638MB graphics card.

For each of the software assessed, the processing of the point clouds generally followed four key steps: loading of the images, feature extraction, feature matching and point cloud reconstruction. GCPs were added to each model in line with the specified procedure for the respective software. The resultant point clouds were exported in LAS format. The default settings for all parameters were adopted within each software during data processing. While the workflows across the software were comparable, there were some differences. The specifics of these differences are not included here, but are described in Lipwoni (2020).

Web-based software

Maps Made Easy is a pay-as-you-go service that provides systematic instructions on its webpage requiring little customisation of processing parameters. Once a user account was created, images were uploaded and export parameters were selected. Maps Made Easy did not have provision for loading GCPs, and an image location verification procedure using a 'Georeferencing tab' was undertaken instead.

DroneDeploy cloud processing can be carried out using two possible modes: Terrain and Structure. The former, which was chosen for this study, is best suited for areas with small differences in elevation and the latter for areas with large differences in elevation. After uploading images and GCPs, images were reviewed with the aim of excluding blurry or over-exposed photos. The automatic GCP detection procedure enabled accurate location of individual GCPs. Image processing commenced once final upload was confirmed.

Desktop-based software

One challenge of comparing desktop-based software was that each had different parameter settings and processes. The optimisation of parameter settings was beyond the scope of this study, but has previously been studied (Maturbongs et al., 2019; Hartley et al., 2020). Instead, we chose to run the software with default processing parameter values.

Workflows for the desk-based commercial software consisted of between three and four main processes as detailed in user manuals (e.g. Agisoft, 2019). The initial processing step produced sparse point clouds without spatial reference. Thereafter, GCPs were used to optimise image alignment and orientation of the sparse point clouds. Each of the eight GCPs were located and manually marked in at least five images. An iterative process of aligning images was adopted for best results.

After optimisation and further alignment, the final process was dense point cloud reconstruction for each software package.

Point cloud description

The point cloud creation process resulted in point clouds with varying densities (Table 2) that were determined using the 'lasinfo' function in LASTools (Isenburg, 2019). Ground point density averaged 475 pts m^{-2}, while the average above ground point density was 342 pts m^{-2}. ContextCapture produced point clouds with a markedly higher density than that of any of the other nine software (Table 2), with ground point densities of 3,402 pts m^{-2} and above ground point densities of 2,042 pts m^{-2}.

Extracting tree heights

The dense point clouds were processed using LAStools version 190404 (Isenburg, 2019). LAStools was initially designed for LiDAR point cloud processing, but has increasingly been used to process UAV-derived point clouds (e.g. Mlambo et al., 2017). Each point cloud was tiled at 100 m resolution with 10 m buffers, except for the ContextCapture dataset. As the file size from ContextCapture was very large the point cloud was tiled at 10 m with 2 m buffers. All the datasets were then denoised using 'lasnoise' twice – with the first step parameters of 0.25 m for XY, 0.5 m for Z and 32 minimum isolated points, while the second step parameters used were 0.25 m for XY and Z and eight minimum isolated points.

The 'lasground_new' function was used to classify ground points with a step size of 10 m. Once ground classified, the 'lasheight' function was implemented to derive the normalised heights for each point. Lastly, the tile buffers were removed using 'lastile' then 'las2las' was used to merge the tiles into one normalised height LAS file. This normalised point cloud was then input into R, in which the shapefile of individual tree crowns was used to segment the point cloud into areas representing the individual trees. Tree heights were then derived by iterating through each individual tree segment and creating a CHM using the 'grid_canopy' function from the LidR library (Roussel et al., 2018) The highest point inside each individual tree segment was extracted as the tree height. The R software version 3.6.0 was used in these analyses (R Core Team, 2020).

Statistical analysis

The accuracy of SfM-derived tree heights was evaluated by comparing them to field measured heights. Statistical analysis was carried out using standard descriptors commonly used for similar methods in other studies (e.g. Torresan et al., 2018), and included the coefficient of determination (R^2), root mean square error (RMSE) and mean bias error (MBE). These metrics were calculated using the following equations:

$$R^2 = \frac{\sum_i (\hat{y}_i - \bar{y})^2}{\sum_i (y_i - \bar{y})^2} \tag{1}$$

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

$$MBE = \frac{1}{n} \sum_{i=1}^{n} y_i - \hat{y}_i \tag{3}$$

where y_i represents field measured heights, $\hat{y}_i$ represents predicted heights from UAV point clouds, $\bar{y}$ is the average of the observed values and n represents the sample size. The percentage RMSE (RMSE%) was also determined through expressing RMSE as a percentage of $\bar{y}$ as RMSE% = 100 (RMSE/$\bar{y}$).

Analyses were undertaken using R to determine if the software precision was significantly related to the point metrics described in Table 2. Using a linear model, we fitted correlations between the software precision (as described by R^2) and the measures of point density. The correlation coefficient and significance were extracted from these five correlations.

Results

Overview

Plots of measured height against predictions from all 10 software packages are shown in Figure 3. All software generally under-predicted tree height across the range, but the extent of this bias varied widely.

The software could be categorised into three general groupings (Figure 4) based on precision (R^2) and bias (MBE). Tree height predictions with high precision and moderate bias were made by Pix4DMapper, 3DF Zephyr, Maps Made Easy, Agisoft and to a lesser extent ContextCapture (Figure 4). Software which predicted height with moderate precision and moderate bias included RealityCapture, COLMAP and PhotoModeler. DroneDeploy and UAS Master predicted height with high precision but high bias (Figure 4).

Software prediction precision, bias and accuracy

There were moderate-to-strong linear correlations (R^2 = 0.61 – 0.86) between predicted and measured tree height for all software (Figure 4). The software with the highest correlation was 3DF Zephyr (R^2 = 0.86), followed by Maps Made Easy and ContextCapture (R^2 = 0.84 – 0.85). COLMAP, the only free software, yielded predictive precision of R^2 = 0.69. Maps Made Easy was the most precise web-based application (Figure 4). In terms of accuracy, as measured by RMSE, values ranged from 0.57 m – 3.43 m (RMSE% = 13.5% – 80.9%), with Pix4D having the best accuracy, followed by 3DF Zephyr and Maps Made Easy. Height predictions from DroneDeploy and UASMaster had the poorest accuracy.

All software under-predicted height for the entire height range, with the exception of Pix4D in which predictions for very tall trees were over-predicted (Figure 3). Tree height prediction bias ranged between MBE = 0.28 m – 3.37 m. The least biased predictions were made by Pix4D (0.28 m) and 3DF Zephyr (0.58 m) (Figure 4).

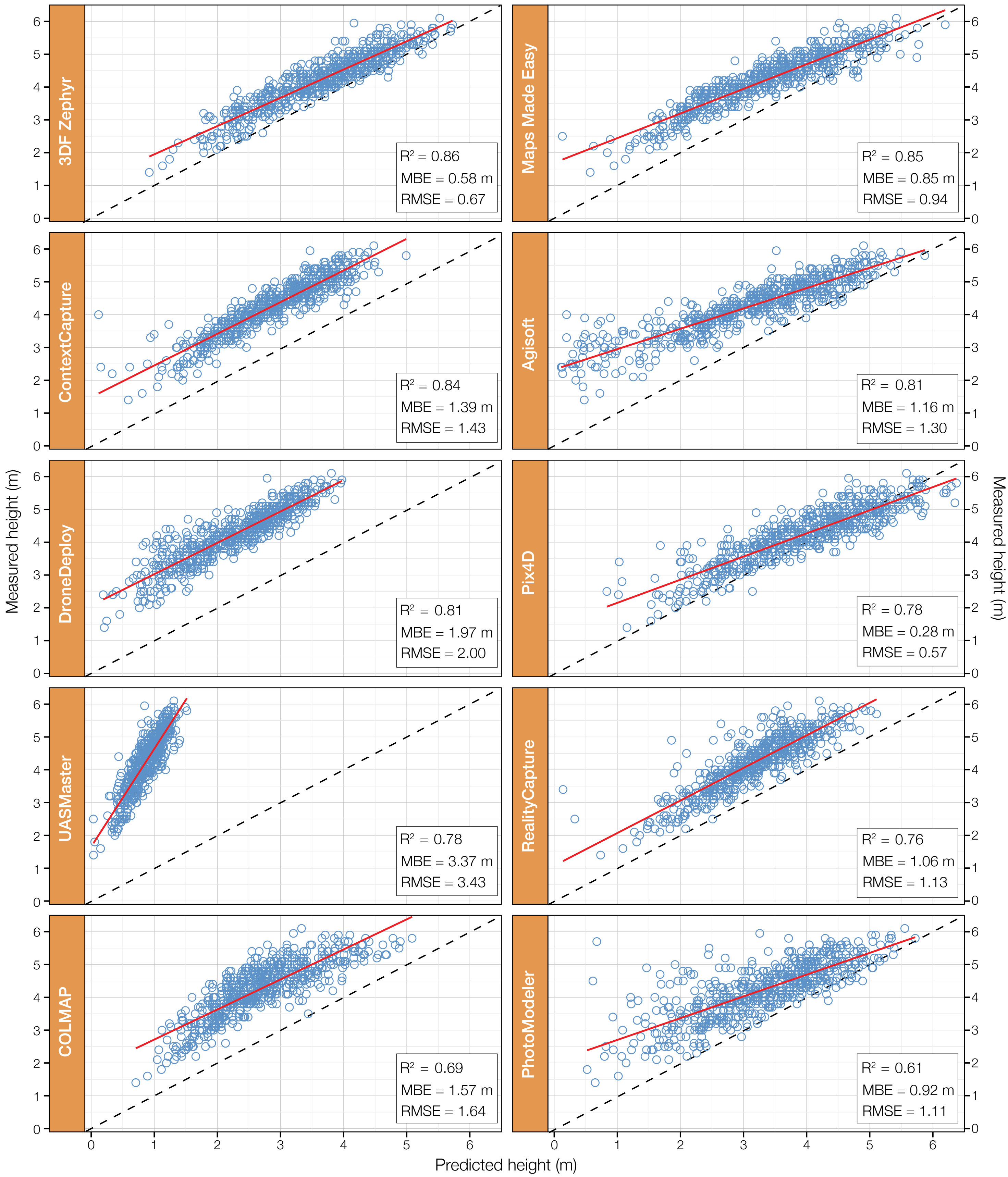

Figure 3: Linear regression of field-measured heights against predicted heights from the 10 software. The solid red line shows a linear regression fitted to the data and the dashed line represents the 1:1 relationship. The panels are sorted from panel (a) – (j) in order of descending values for the coefficient of determination (R^2) between predicted and measured height (shown bottom right). Also shown bottom right is the mean bias error (MBE) and root mean square error (RMSE)

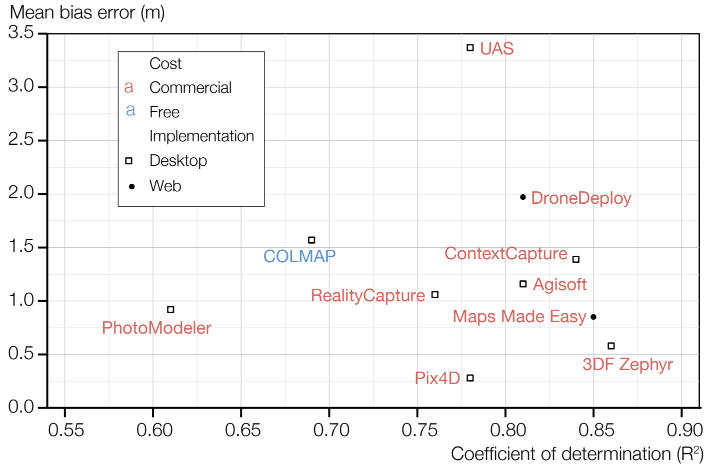

Figure 4: Variation in mean bias error and the coefficient of determination for predictions of height made by the 10 software

In contrast, height predictions from DroneDeploy (MBE = 1.97 m) and UASMaster (MBE = 3.37 m) were the most biased.

Relationships between model precision and point density

Regressions were constructed between model precision, as described by the R^2, and the five metrics describing the number of points and point density (see Table 2), to determine if model precision was significantly affected by point density. These five relationships were weak and insignificant, with P values ranging from 0.18 – 0.45 (data not shown).

Discussion

Results from this study clearly show the quality of tree height predictions using SfM is dependent on the software used to process the point clouds. In terms of precision, accuracy and bias, Pix4DMapper, 3DF Zephyr and Maps Made Easy out-performed all other tested software using default values. Predictive precision from the 10 software ranged from moderate-to-high and although all software underestimated tree height the extent of this bias ranged widely. This variation shows that software choice represents a considerable source of error in predictions of tree height using SfM.

Predictions from the most accurate software (Pix4D Mapper and 3DF Zephyr) were broadly comparable to previous studies that have used SfM to predict tree height. Previous research demonstrates a wide range in accuracy and precision between studies, with the RMSE% ranging from 1.89% to 19.4% and the coefficient of determination, R^2, ranging from 0.21 to 0.99 (Lipwoni, 2020). Our predictions were at the more precise end of the coefficient of determination range (R^2 = 0.86), but the less accurate end of the RMSE% range (13.46%).

The percentage RMSE was comparatively inaccurate as predictions were made for smaller trees than those typically studied, which has been shown to inflate RMSE% values (Hartley et al., 2020). This occurs as an equivalent RMSE will be a greater percentage of the mean for a smaller than a taller tree and our results generally show high RMSE for the smaller trees in the study. For example, there was convergence between the fitted prediction line and the 1:1 line with increasing tree height for the three most precise and accurate software (Pix4DMapper, 3DF Zephyr and Maps Made Easy, Figure 3), indicating that RMSE was on average higher for smaller trees. When height error was expressed in absolute terms, our predictions (RMSE = 0.57) were somewhat less accurate than other studies that have found estimates from SfM to be within 0.5 m of field-measured heights (Lipwoni, 2020).

Default parameter settings were used to allow software to be fairly compared and to realistically assess the quality of predictions that will be available to most users who do not typically tune software. However, it is worth noting that less biased predictions may be obtained when software settings are optimised. Previous research has found that by fine-tuning the 'dense point quality' and 'image alignment' parameters, the percentage of tree heights accurately measured could be improved by 13% (Maturbongs et al., 2019). The same study found that Pix4D could also be optimised through manipulation of the point density and image scale parameters, with an increase of 10% in the percentage of tree heights accurately measured.

In practice, high values of MBE are unlikely to be as concerning as a low coefficient of determination because high MBE can be corrected using a calibration dataset that includes tree measurements. Predictions can be adjusted to correct for the bias, either within the processing software or through use of a linear regression to re-scale predictions before large-scale height prediction is undertaken. However, ideally predictions should have both low bias and high precision to avoid these tuning operations which are time-consuming for users of the software.

Previous research has shown that SfM point clouds cannot describe the underlying terrain as accurately as laser scanning, particularly when captures are made over undulating terrain and/or in dense forests with undergrowth (Wallace et al., 2016). However, as the studied site was very flat with no understory, previous research has found the integration of a DTM derived from a high-density UAV LiDAR capture (SfM-UTM) did not improve height predictions (Hartley et al., 2020). Previously documented height predictions for this dataset made by Pix4D using both SfM and SfM-UTM (Hartley et al., 2020) show little variation in precision (R^2 = 0.80 vs 0.81) and a slight deterioration in bias using the SfM-UTM (MBE = 0.4 vs 0.45 m).

Further research should compare the performance of SfM software at predicting tree dimensions in stands with more developed and diverse understory weed species that encompass a greater range in terrain. Ideally, this research across more challenging and realistic environments should identify the conditions under which it is most efficient to combine a LiDAR DTM with the SfM point cloud.

While this study focused on the quality of height predictions, there are a number of other criteria against which SfM software can be compared. Previous research has compared more qualitative aspects of SfM software, including the financial cost, computational cost, ease of use, the range of data products available, the degree to which software can be customised, and the benefits and drawbacks of cloud versus desktop applications (Brach et al., 2019; Forsmoo et al., 2019).

In this study commercial desktop-based software were generally found to have a faster processing time than freely available software. Data was processed in less than three hours using Agisoft and RealityCapture and less than four hours using Pix4D, UASMaster and 3DF Zephyr. COLMAP took almost 21 hours to complete processing, possibly because the processing algorithms cannot be parallelised (Turner et al., 2013). Out of the four processing steps (see SfM software section in *Materials and methods*), point cloud reconstruction accounted for 48% to 92% of the total processing time for all desktop-based software.

The web-based software Maps Made Easy and DroneDeploy completed point cloud processing after approximately six hours. Although the process was longer overall for the two web-based applications, less than 15 minutes was required to load the images and set up the project, with the remainder of the time used for cloud-based processing. The benefits of these two web-based solutions include moving the computational load of the process to the cloud, reducing the load on the user's own machine and allowing for multiple projects to be processed simultaneously (Brach et al., 2019).

The price of the SfM software varied greatly. The clear advantage of the open source software packages, such as COLMAP, are that they are available at no cost to the user. Monthly costs of the commercial software ranged from free for small projects (Maps Made Easy, 3DF Zephyr), to between USD302 and USD910 for RealityCapture, depending on the licence level purchased. Point cloud processing is only available as a pay-as-you-go option with Maps Made Easy. This is a points-based system, with points calculated on the density of the resulting output in gigapixels. Projects are free for models of up to 250 points or points can be purchased in bulk as a form of credit at a cost ranging from USD7.99 for 300 points up to USD669 for 50,000 points. As an indicator of cost, a model of the 55 m x 110 m trial area described in this study would cost around 360 points in Maps Made Easy.

Conclusions

This study compared the performance of 10 SfM software for tree height prediction from 3D point clouds. Using default settings, predictions from Pix4D, 3DF Zephyr and Maps Made Easy were the most accurate and precise. Software choice had a clear impact on the quality of tree height estimates and consequently represented a major source of potential error in predictions of tree height. The wide variation in point density and the number of points between the 10 different SfM point clouds was not significantly related to the precision of predictions. Although this study clearly shows the utility of SfM for predicting tree height, practitioners and researchers should be judicious in their choices when selecting software for this purpose.

Acknowledgements

This research was funded by Scion's Strategic Science Investment Funding (SSIF) provided by the Ministry of Business Innovation and Employment (MBIE). Additional co-funding was provided by the Forest Growers Levy Trust. The authors would also like to acknowledge Peter Massam for assisting with the UAV data capture, Honey Jane Estarija for assistance with the site map and the Scion Plant Biotech field team for diligently measuring the field trials on a regular basis. The authors declare that they have no conflict of interest.

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