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3D modelling of individual trees using a handheld camera: Accuracy of height, diameter and volume estimates

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ABSTRACT

Accurate tree measurement is necessary for applications such as resource appraisal, and biophysical and ecological modelling. This research tests the potential to use a low-cost hand-held camera alongside structure-from-motion with multi-view stereo-photogrammetry (SfM-MVS) to accurately measure trees. SfM-MVS is a computer vision technique, in which the geographic coordinates of objects are calculated from a series of photographs, resulting in a 3D point cloud model. This research tested the ability of SfM-MVS to reconstruct spatially accurate 3D models from which 2D (height, crown spread, crown depth, stem diameter) and 3D (volume) tree metrics could be estimated. Thirty small, potted trees were photographed and measured with traditional dendrometry to evaluate SfM-MVS derived tree size estimates. Tree volume was obtained via the water displacement approach xylometry. SfM-MVS estimates of 2D tree metrics had errors (RMSE – root mean squared error) as low as 3.74% ($RMSE_{tree\ height}$ = 3.74%, $RMSE_{crown\ depth}$ = 11.93%, $RMSE_{crown\ spread}$ = 14.76%, $RMSE_{DBH}$ = 9.6%). SfM-MVS estimates of 3D tree metrics were better for the main stem than for the slender branches ($RMSE_{Stem}$ = 12.33%, $RMSE_{Branches}$ = 47.53%, $RMSE_{Total\ Volume}$ = 18.53%). Apart from height and crown depth, all modelled variables had negative bias, suggesting that SfM-MVS tends to underestimate the size of trees. The results show that SfM-MVS is capable of producing estimates of 2D and 3D metrics with accuracy comparable to that of laser scanning (i.e. LiDAR). Factors like the position of the tree relative to its surroundings, the background scene and the ambient lighting, appear to affect model success. SfM-MVS provides a low-cost alternative to remote sensing technologies currently used such as terrestrial laser scanning and, as no specialised equipment is required, it is able to be used by people with little expertise or training. Future research is required for exploring the suitability of SfM-MVS for specific applications requiring accurate dendrometry.

1. Introduction

The ability to obtain accurate tree metrics is important for a variety of applications within the fields of commercial forestry (Henning and Radtke, 2006), urban forestry (Tanhuanpää et al., 2014), ecology (Dandois and Ellis, 2010) and horticulture (Rosell et al., 2009). Dendrometry, the measure of tree structure and dimension, is fundamental for resource appraisal (e.g. wood volume, biomass and tree growth) and analysing forest structure (Næsset, 2002), particularly for commercial forest management. Biophysical and ecological information to be derived from tree metrics include carbon stocks (Houghton, 2005), biofuel potential (Dassot et al., 2011), habitat size and quality (Moskal and Zheng, 2011), storm water attenuation (Xiao and McPherson, 2011) and contribution to reduction of urban air pollution (Nowak et al., 2013). Traditional field methods of dendrometry are prone to error, so they do not always adequately measure tree size and architecture (Bragg, 2008; Kitahara et al., 2010). As a consequence, error is inherently introduced into commercial, biophysical and ecological characteristics which rely on accurate mensuration.

Structure-from-motion with multi-view stereo-photogrammetry (SfM-MVS) is a relatively new photogrammetric approach allowing automated reconstruction of 3D models using sets of overlapping 2D digital images (James and Robson, 2012). Like LiDAR, SfM-MVS produces spatially accurate point clouds (Dandois and Ellis, 2013; Fritz et al., 2013; Liang et al., 2014a; Morgenroth and Gomez, 2014), and thus has the potential to provide accurate estimations of tree size and architecture.

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The method is relatively unused in the fields of geoscience and natural resources (Westoby et al., 2012), but it has been the focus of an increasing number of studies in recent years. Few studies have examined the suitability of SfM-MVS for tree mensuration and those that have mainly focused on linear metrics. In their proof of concept, Morgenroth and Gomez (2014) measured linear metrics (DBH, height, crown spread) of three trees using SfM-MVS. Likewise, Liang et al. (2014a) focused on linear metrics (DBH) and location of the tree stems within a small plot. Fritz et al. (2013) measured tree stem radius using aerial SfM-MVS above an oak-dominated forest. None of these three studies attempted to obtain any volumetric information. To the best of our knowledge the only SfM-MVS studies with a volumetric element indirectly estimate volume from a canopy height model (CHM). These studies acquired stereo-photographs from an aerial platform and do not directly estimate volume, rather they indirectly derive volume from tree heights estimated from the CHM (Bohlin et al., 2012; Dandois and Ellis, 2013; Järnstedt et al., 2012).

Here we test the ability of SfM-MVS to reconstruct spatially accurate 3D models of individual trees from which volume and linear tree metrics can be estimated. The volume estimates made by SfM-MVS were validated using destructive sampling in conjunction with xylometric (water displacement) methods (Özçelik et al., 2008) in a laboratory setting and all linear estimates were validated with ground truth data.

2. Methods

2.1. Image acquisition for structure from motion multi-view stereo-photogrammetry

We photographed and measured 30 trees at Christchurch City Council's nursery in Christchurch, New Zealand (43°28′04″S, 172°35′17″E). The trees were individually planted in 25 L or 50 L plastic pots and included 12 large-leaved linden (*Tilia platyphyllos*), 10 field maple (*Acer campestre*), five walnut (*Juglans regia*) and three red maple (*Acer rubrum*).

Photography began in late autumn (May, 2014), by which time the trees had lost all their leaves, and continued through to midwinter (July, 2014). Images of each tree were captured with an un-calibrated, hand-held, commercially available digital SLR camera (Nikon D5000, lens: AF-S NIKKOR 35 mm) from photopoints at regular intervals along concentric circular paths around the perimeter of each tree. Photos were taken in such a way to obtain a minimum of 50% overlap between any sequential pair; this was achieved by moving only one or two steps (0.5–1 m) sideways between each photopoint in the inner circle and five steps (5 m) between each photopoint in the outer circle, resulting in 70–90 photos for each circular path. Depending on the size of each tree, either two or three circular paths were completed, resulting in 150–180 photos per tree. No distance was prescribed from which to take photos from; the inner circle photos were taken from a distance where the whole tree could fit within the camera frame and be captured in one photo (usually 4–5 m away). Outer circle photos were taken from distance where the tree took up about half of the image frame. The shape of each circle was approximate rather than exact (Fig. 1).

2.2. 3D model reconstruction with structure-from-motion and multi-view stereo-photogrammetry

Once photos were acquired, we used PhotoScan Professional software (Agisoft LLC, St. Petersburg, Russia) to produce a 3D model of each tree using the SfM-MVS methodology. The stages of model development can be seen in Fig. 2 and are described hereafter. Default point cloud optimisation settings were used in the workflow (i.e. camera = 10 pixels; marker accuracy = 0.001 m; marker placement = 0.1 pixels; alignment accuracy = 'high'; pair pre-selection = 'generic'). There are three main stages for model reconstruction in PhotoScan. The first stage is to upload images and align them to produce a sparse point cloud model. In PhotoScan, point markers and masking may be used to help alignment if it will not work automatically, but these techniques were not necessary for our data. The second stage is to generate a dense point cloud model, which typically contains three to four times as many points as the sparse point cloud (James and Robson, 2012). The third stage involves generation of a solid 3D mesh surface, which is draped on the structure of the dense points. This step improves the visual quality of the 3D model and is required if volume of the model is to be calculated. For a more comprehensive description of the SfM-MVS method, refer to Miller (2015).

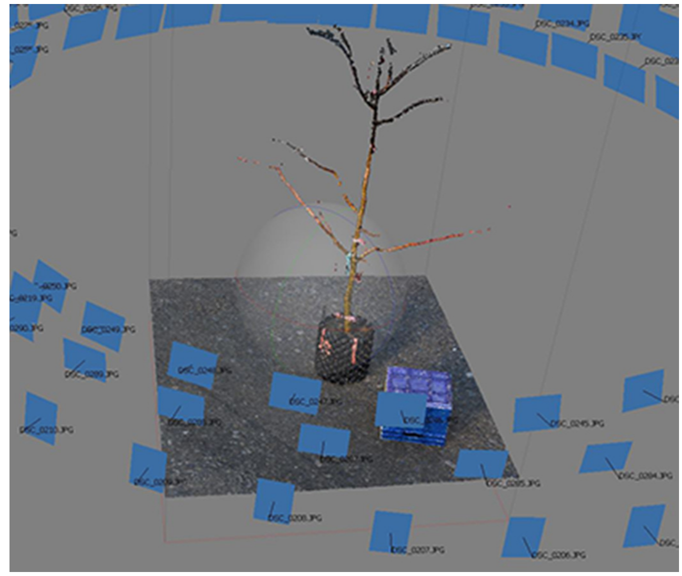

Fig. 1. The blue squares indicate the estimated locations from which each of the photos was taken. (For interpretation of the references to color in this legend, the reader is referred to the web version of the article.)

Models in PhotoScan do not have any spatial scale or geographic position. These had to be assigned manually through calibration with an object of known size in each model. A cube-shaped plastic box (35.5 cm × 32 cm × 29 cm) was positioned on the ground next to each tree as it was being photographed. This box, also modelled in the 3D point cloud, allowed easy application of an arbitrary co-ordinate system and spatial scale to the model such that measurements could be made. Calibration objects would normally have regular shape to allow a high degree of accuracy in their measurement. Because we used an irregularly shaped plastic box for this research, we may have introduced a small degree of error into the 3D tree model.

2.3. Measurements in PhotoScan

Linear measurements were made on the 3D model to estimate tree height, stem diameter (at multiple points), crown diameter, and crown depth. To ensure that linear measurements estimated from the model corresponded to the exact same linear distances measured in the field (methods described below), red tape was attached to the tree to mark the measurement points. The red tape was applied prior to photographing and so was visible in the 3D point clouds. Within the PhotoScan Pro software, point markers were placed on the model where the red tape was visible; the distance between point markers was measured to estimate the

Fig. 2. The four stages of model generation: (top left) the original photo; (top right) the sparse point cloud model following SfM photo alignment; (bottom left) the dense point cloud following MVS; (bottom right) mesh model. Each point in the model represents a pixel in the original photo. Dense cloud models contain several million points.

linear tree metrics. For stem diameter measurements, two perpendicular transects were measured through the stem and average of the two recorded. This technique was repeated at all regularly spaced (50 cm) stem diameter measurement points for each tree (5–6 points depending on the height of the tree). Crown spread was estimated in two ways, true crown spread (TCS) and visible crown spread (VCS). TCS was estimated using the red tape, which represented the true extremities of the selected branches. VCS was necessary because sometimes the entire length of the selected branches leading to the red tape were not modelled. This was due to an insufficient number of points in the dense point cloud, which was a consequence of branch slenderness.

The volume of each nursery tree model was estimated in PhotoScan Pro by first generating a 'watertight' polygonal 'mesh' surface, which was based on the dense cloud points. Interpolation was disabled for this step. In parts of the tree where the stem or branches were only partly captured in the dense cloud model, the subsequent mesh generation created planes of mesh across the points, rather than an enclosed cylindrical shape, leaving many holes and gaps. These gaps and holes were closed with the 'close holes' tool in PhotoScan to produce a 'watertight' model. From this watertight model, total volume was estimated. Each tree was also subdivided into 'main stem' and 'remaining branches' and the volume for each was estimated separately. Volume was recorded to 0.001 L (1 ml) resolution.

2.4. Ground truth validation of SfM-MVS models

Traditional dendrometry techniques were used to validate estimates of linear and volumetric tree metrics derived from SfM-MVS models. Tree height was measured by laying each tree on its side and measuring from the base of the trunk to highest point of the main stem with a flexible measuring tape. Crown diameter was measured by averaging two perpendicular transects through the

Table 1
A comparison of measured and modelled values for 2D and 3D tree metrics. Mean values with their corresponding standard errors in parentheses are presented with the root mean squared error (RMSE) and bias of the modelled values.

Metric	$\text{Mean}_{\text{measured}}$	$\text{Mean}_{\text{modelled}}$	RMSE (%)	Bias (%)
Height	296.82 (13.11)	301.97 (13.61)	3.74	1.74
Crown depth (cm)	230.77 (10.43)	233.3 (11.13)	11.93	1.10
True crown spread (cm)	112.75 (5.71)	108.65 (6.08)	14.76	−3.47
Visible crown spread (cm)	112.75 (5.71)	103.77 (6.01)	21.06	−9.51
DBH (mm)	21.98 (1.3)	20.99 (1.38)	9.60	−4.52
Combined stem diameters (mm)	17.96 (0.91)	18.06 (0.88)	11.93	−0.88
Stem volume (cm^3)	1408.63 (135.53)	1293.18 (138.44)	12.33	−8.20
Branch volume (cm^3)	410.67 (53.08)	272.08 (41.52)	47.53	−33.75
Total volume (cm^3)	1819.47 (179.03)	1552.68 (171.7)	18.53	−14.66

crown. Crown depth was measured as the linear distance between the base of the first major branch and the highest points on the main stem. Stem diameter was measured with Vernier callipers at several points along the main stem. Starting from the highest point of the main stem, diameter was measured at 50 cm intervals down to the base, resulting in 5–6 measurement points depending on the height of the tree. At each of these points diameter was measured. These were labelled 'Stem-Diameter' 1–6, with Stem Diameter 1 being the highest point on the main stem. In addition to these, diameter at breast height (DBH-standard New Zealand measurement of diameter at 1.4 m above ground) was measured. For all stem diameter measurements, two perpendicular measurements were made and the average between the two recorded. All linear measurements were rounded to 0.5 mm accuracy.

The volumes of the nursery trees were determined with xylometry (water displacement), the most accurate method of volume measurement (Özçelik et al., 2008). The trees were chopped into smaller sections (10–20 cm) with secateurs to ensure that no biomass was lost, as would occur if a saw had been used. The resulting tree sections were secured in bundles with plastic cable ties. The main stem and remaining branches of each tree were bundled and measured separately. A 20 L plastic tub was filled with water and placed on a scale that provided accuracy to 0.01 g. Each bundle was immersed in the tub and held just below the water surface with metal rods, and the increase in weight recorded. Prior to measurement, bundles were submerged in water for 48 h to minimise absorption of water during measurement. The tare weight was reset to zero between each measurement to account for water lost through removing the bundle. The volume of the cable ties and immersed sections of the metal rods were also accounted for. A wooden block of known volume was measured to calibrate the method.

2.5. Statistical analysis

All data was analysed in R statistical package, v. 3.1.2 (R Core Team, 2014). As in Kankare et al. (2013), the accuracy of estimated tree metrics were evaluated using root mean square error (RMSE) and bias. As defined in Eqs. (1) and (2);

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

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

where n is the number of estimates, y_i is the value estimated by SfM-MVS and $\hat{y}_i$ is the ground truth value.

A linear regression analysis was also conducted between the measured values and model-estimated values to obtain R^2 values for each of the tree metrics. This was to provide additional statistics to align and allow a more direct comparison with previous literature.

3. Results

3.1. Height and crown metrics

Point cloud densities were sufficient to enable the heights and crown depths of all 30 trees to be estimated. The mean, standard error, RMSE and bias for the ground truth and SfM-MVS-estimated data are presented in Table 1. Height was estimated with an RMSE of 11.11 cm (3.74%) and a bias of 5.15 cm 1.74%). The positive bias shows that SfM-MVS had a tendency to slightly overestimate tree heights. The linear regression results indicate that SfM-MVS estimated tree height accurately, with a strong linear relationship present between the measured and estimated height values that approaches unity ($R^2 = 0.982$, Fig. 3). Crown depth was estimated with a high level of accuracy, with RMSE of 27.53 cm (11.93%) and bias of 2.54 cm 1.1%). Regression analysis of crown depth estimates show they were correlated strongly with measured values ($R^2 = 0.975$, Fig. 3).

Point cloud densities were sufficiently high to enable visible crown spread (VCS) measurements at 54 of 60 model measurement locations and true crown spread (TCS) measurements at 56 of 60 model measurement locations. Sparseness or complete absence of points prevented measurements being made at the remainder of measurement locations. VCS was estimated with RMSE 23.75 cm (21.06%) and bias of −10.72 cm (−9.51%). TCS was estimated with an RMSE of 16.64 cm (14.76%) and bias of −3.91 cm (−3.47%). Both VCS and TCS had negative bias, indicating that SfM-MVS had a tendency to underestimate them. TCS and VCS were both correlated with ground truth values, with respective R^2 values of 0.872 and 0.777 (Fig. 4).

3.2. Stem diameter metrics

The trees were reconstructed well enough for stem diameter estimates to be made at 166 of the 169 model measurement locations and 30 of 30 DBH measurements. The mean for the true stem diameters and the SfM-MVS modelled width were 17.96 and 18.06 mm respectively. The combined stem diameters were estimated with RMSE of 2.14 mm (11.93%) and bias of −0.16 mm (−0.88%). They correlated strongly with ground truth values (adjusted $R^2 = 0.968$, Fig. 5). The bias indicates stem diameters were slightly underestimated by SfM-MVS. DBH was estimated to similar accuracy, with RMSE of 2.11 mm (9.6%) and bias of −0.99 mm (−4.52%). The negative bias shows that SfM-MVS had a slight tendency to underestimate DBH. SfM-MVS estimates of DBH correlated strongly with ground truth values (adjusted $R^2 = 0.935$, Fig. 5).

3.3. Volume

Volume estimates were able to be made for all 30 tree models. The volume of the main stem of each tree was estimated

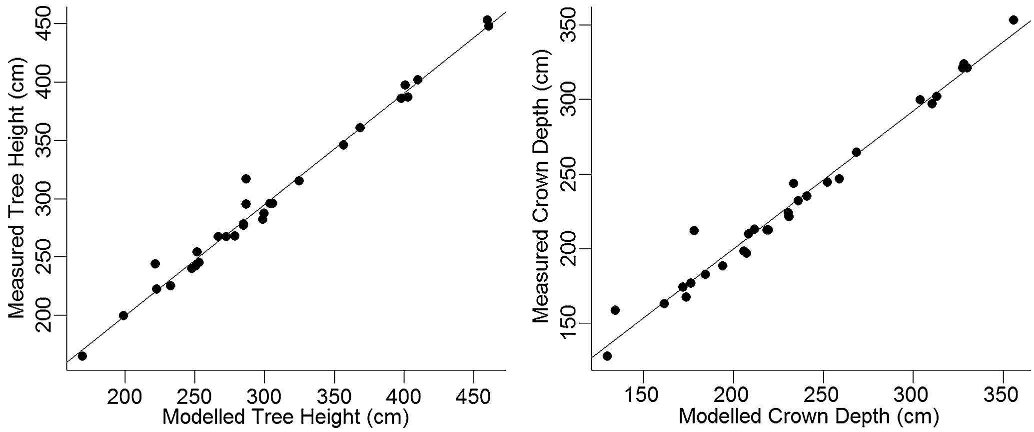

Fig. 3. Regression analysis of SfM-MVS estimates of height (left, adjusted $R^2 = 0.982$) and crown depth (right, adjusted $R^2 = 0.975$) against ground truth values.

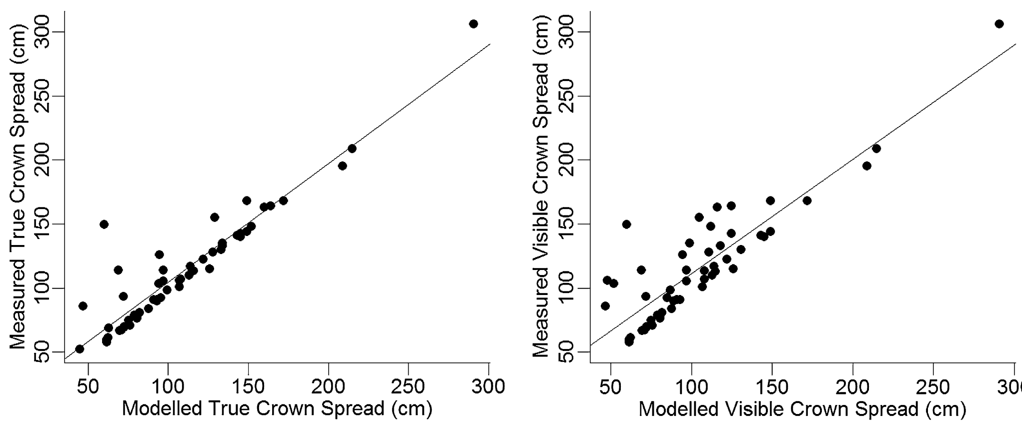

Fig. 4. Regression analysis of SfM-MVS estimates of true crown spread (left, adjusted $R^2 = 0.872$) and visible crown spread (right, adjusted $R^2 = 0.777$) against ground truth values.

far more accurately than the remaining branch volumes; main stem volume was estimated with an RMSE of 173.72 cm^3 (12.33%) and bias of −115.45 cm^3 (−8.2%). The ground truth stem volume values correlated strongly with the SfM-MVS estimated values (adjusted $R^2 = 0.968$, Fig. 6) Remaining branch volume estimation had an RMSE of 195.17 cm^3 (47.53%) and bias of −138.59 cm^3 (−33.75%). The linear relationship for the remaining branches was not so strong (adjusted $R^2 = 0.761$, Fig. 6) The strong bias present, particularly for the 'remaining branches' shows a tendency for SfM-MVS to underestimate volume. Total volume (sum of main stem and remaining branches) was estimated with an RMSE of 337.08 cm^3 (18.53%) and bias of −266.8 cm^3 (−14.66%). The main stem accounted for 78% of the total tree volumes on average, which reduced the influence remaining branch volume estimation had on total volume. Estimated values for total volume correlated strongly with true values (adjusted $R^2 = 0.951$, Fig. 6).

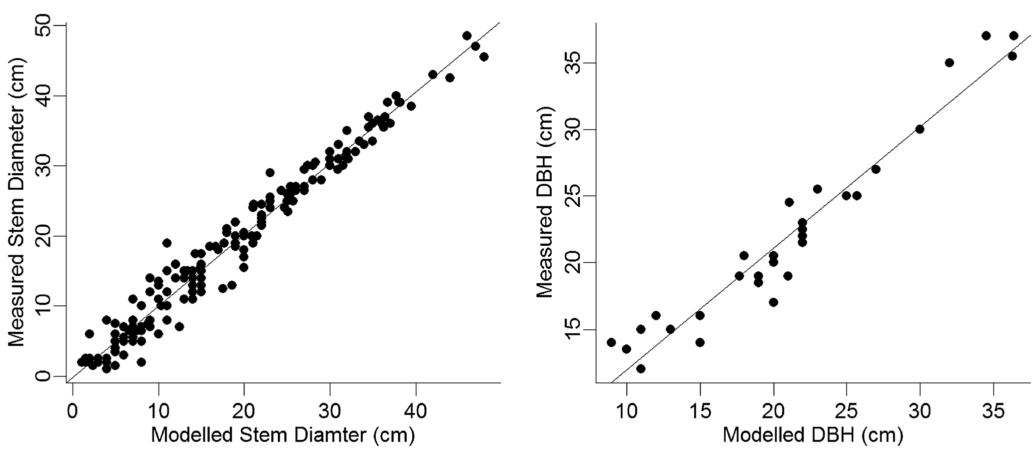

Fig. 5. Regression analysis of SfM-MVS estimates of DBH (right, adjusted $R^2 = 0.935$) and combined stem diameters (left, adjusted $R^2 = 0.968$) against ground truth values.

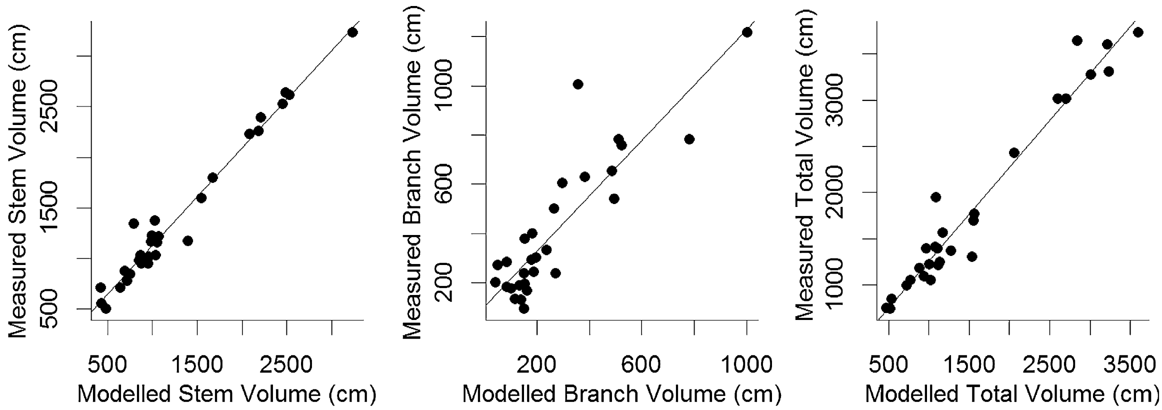

Fig. 6. Regression analysis of SfM-MVS estimates of stem volume (left, adjusted R^2 = 0.968), remaining branch volume (centre, adjusted R^2 = 0.761) and total volume (right, adjusted R^2 = 0.951) against ground truth values.

4. Discussion

4.1. SfM-MVS linear estimation

The results show that high accuracy was achieved in estimation of linear metrics. The most accurate of these was tree height (RMSE 3.74% and bias 1.74%) which correlated well with ground truth data, with adjusted R^2 value of 0.982. In the only other ground-based SfM-MVS study to date that estimates tree height, Morgenroth and Gomez (2014) reported an error of 2.6% for their three study trees, two landscape trees and one potted tree. To critically assess our results, it is necessary to expand beyond the limited SfM-MVS literature and explore the accuracy of another remote sensing technology, namely terrestrial laser scanning (TLS). TLS offers perhaps the most relevant method for comparison as it is commonly used to generate 3D models of trees and sets the benchmark for accuracy.

Retrieval of tree heights using TLS has been relatively successful, with many studies producing accuracies within 10% of true height, though very few have produced as little error as the RMSE 3.74% in this study. Hopkinson et al. (2004) underestimated the heights of mature, plantation-grown red pine and sugar maple in a mixed deciduous forest by roughly 7% which was due to occlusion of the top of trees. Likewise, Maas et al. (2008) underestimated the heights of mature mixed and coniferous forest plots dominated by spruce trees by 0.64 m. Eitel et al. (2013) reported an RMSE of <1 cm for TLS height estimates of five small (<1 m) harvested saplings in a lab setting, while Kankare et al. (2013) reported an RMSE of 8% for estimating the heights of mature, forest-grown Scots pine and Norway spruce.

True crown spread (TCS) was estimated with RMSE 14.76%, while VCS was estimated with RMSE 21.06%. For comparison, Fernández-Sarría et al. (2013) reported a mean TLS crown spread estimate of 8.33 m compared with the ground truth mean of 7.91 m (RMSE 5%) for thirty *Platanus hispanica* street trees. Moorthy et al. (2011) also reported strong correlations between TLS crown spread estimates and ground truth data with R^2 values of 0.97 and 0.96 for 24 orchard-grown olive trees (*Olea europaea* L.).

DBH was estimated with RMSE of 2.11 mm (9.6%). The model estimates correlated strongly with measured values with an adjusted R^2 value of 0.935. The combined stem diameters were slightly less accurate than DBH, with an RMSE of 2.14 mm (11.93%). These results are comparable with other research using SfM-MVS as well as other forms of remote sensing. Using terrestrial SfM-MVS Morgenroth and Gomez (2014) reported an error of 3.7% for estimation of stem diameters. Also using terrestrial SfM-MVS, Liang et al. (2014a) achieved DBH accuracy of RMSE 6.6–12.1% for Scots pine (*Pinus sylvestris* L.) and birch (*Betula* sp. L.) trees in a mixed forest. Using an unmanned aerial vehicle (UAV) flying 55 m above ground level, Fritz et al. (2013) used SfM-MVS to estimate the stem radius of oak (*Quercus robur*), hornbeam (*Carpinus betulus*), and maple (*Acer pseudoplatanus*) trees, achieving a Pearson's correlation coefficient, r = 0.696.

Using terrestrial laser scanning Hopkinson et al. (2004) and Henning and Radtke (2006) both reported DBH estimates within 10 mm of the true value. Both studies were conducted in pine (*Pinus* sp.) plantations while Hopkinson et al. also included data from a mixed deciduous forest. Eitel et al. (2013) bettered this by achieving an R^2 value of 0.99 and RMSE of 22 mm for ten mature Ponderosa Pine (*Pinus ponderosa*) and Douglas-fir (*Pseudotsuga menziesii*) in a coniferous forest. Both Kankare et al. (2013) and Olofsson et al. (2014) reported a DBH accuracy of RMSE 7.1% for Scots pine trees in mixed boreal forests, though error in estimation of deciduous trees (including outliers) was far greater at 75 mm (34.1%). Liang et al. (2014b) reported DBH estimation of forest-grown Scots pines with RMSE of 8 mm (4.2%).

4.2. SfM-MVS volume estimation

The results show that SfM-MVS was able to produce models with reasonable spatial accuracy, from which volumetric estimates could be derived. Each volume metric was underestimated. Total volume was estimated moderately well (RMSE of 18.53%, bias of −14.66% and an adjusted R^2 of 0.951). The young trees displayed apical dominance and held the majority of their mass in their stems (78% on average). This meant overall accuracy of each tree volume was largely determined by the accuracy of the stem volume and the remaining branches did not have a large influence on total volume. This is supported by the fact that stem volume was estimated accurately (RMSE 12.33% and bias −8.2%) while estimation of the volume of remaining branches was highly inaccurate with a large amount of error present and a strong tendency for underestimation (RMSE 47.53% and bias −33.75%).

With so little existing research on utilising SfM-MVS for tree mensuration it is difficult to directly compare our results with those found in other studies. Therefore, we describe how SfM-MVS performs in relation to terrestrial laser scanning. Numerous studies have used TLS to estimate volume and biomass, though few of these have utilised destructive sampling to validate TLS output as we have.

Hopkinson et al. (2004) analysed the volumes of mature, plantation-grown red pine and sugar maple in a mixed deciduous forest with TLS. RMSE of 7% was reported in both total tree and merchantable stem volume estimation. Dassot et al. (2012) managed to estimate stem volume of 42 forest-grown trees (differing species and size classes) to within 10% RMSE and evaluated the output with destructive sampling. Like this study, the accuracy of remaining branch volume was low, with almost half the trees being estimated between ±10 and 30% of the manual volume estimation. Kankare et al. (2013) used TLS and destructive sampling to estimate the stem volume and total volume of individual Scots pine and Norway spruce in a boreal forest. Stem volume was estimated with RMSE 15.3% (bias 0.7%) while total tree volume was estimate with RMSE 16.7% (bias −2.7%). Kankare et al. (2013) also reported poor estimation of the biomass of the remaining living and dead branches, with the respective RMSEs for living and dead branches being 23.4% and 31.1%. Liang et al. (2014b) used destructive sampling to measure the stem curve and volume of forest-grown pine and spruce trees. TLS was able to achieve some of the most accurate TLS results so far, with an RMSE of 9.5% and bias of −5.9%.

These results show that SfM-MVS performs well relative to TLS. The RMSE of 12.33% achieved for stem volume using SfM-MVS is slightly less accurate than what was achieved in most other studies using TLS. The findings of previous studies for volume estimation are relatively consistent with the results in this study and show similarities with a tendency for overall underestimation and poor accuracy in estimation of remaining branch volume.

4.3. Determinants of model success

The results of this study have shown that SfM-MVS can be used to estimate stem volume, height and DBH to a level of accuracy that is comparable to other remote sensing methods currently used. However, poor results for visible crown spread and remaining branch volume highlight that reconstruction of some parts of the tree (slender branches and stems) was not very successful, and that precautions will need to be taken in the method to ensure that images acquired are suitable for facilitating adequate model reconstruction. Image resolution and shadowing of the tree surface can lead to poor model reconstruction, as can insufficient overlap between successive images, though in this study overlap was more than sufficient. Below we briefly discuss the effects of these determinants, but a more comprehensive explanation can be found in Miller (2015).

4.4. Image resolution and keypoint recognition

Poor point cloud reconstruction of slender branches is caused by insufficient pixels in the imagery available to provide recognisable keypoints. This may be caused by poor camera resolution or by the images being captured too far away from the tree.

The error in visible crown spread and remaining branch volume was caused by the inability of SfM-MVS to reconstruct the entire length of the branches that were selected for crown spread measurement (Fig. 7) These branches were very slender at their extremities (<5 mm), and often the last 20–30 cm were not reconstructed at all in the model. Kankare et al. (2013) and Morgenroth and Gomez (2014) also encountered difficulty when measuring the slender upper stem and branch diameters of their study tree models, while Liang et al. (2014a) reported a negative correlation between the quality of the point cloud model and distance from which the imagery was acquired. Poor point cloud representation of slender branches resulted in a failure to produce a mesh model with a fully enclosed surface. This is problematic for volume estimation as it results in reduced model volume output.

The stem, on the other hand, provided the thickest part of the tree and therefore offered the most surface area and therefore pixels (keypoints) of any part of the tree to be captured in the imagery. This meant it was reconstructed well, which is highlighted by the results of the five *Juglans regia* trees, which on their own were found to have an RMSE of 5% for stem volume (compared with the overall RMSE of 12.3%) and also had the five largest DBH values (mean 26 mm compared with the overall mean of 19 mm).

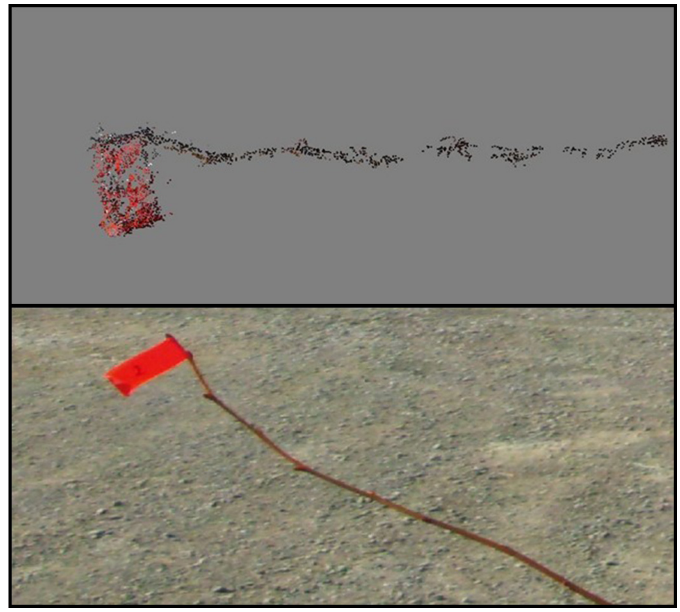

Fig. 7. The tops of the stems and the slender branches of some of the nursery trees were represented by only a thin scattering of points.

As image overlap was sufficient, improved reconstruction of slender branches would require images to be captured from very close range or with a very-high resolution camera in order for these branches to be represented with a greater number of pixels. James and Robson (2012) describe the ratio between estimate accuracy and distance from of the photopoint from the target object as ∼1:1000, which means where 1 mm precision is sought, the images should be captured from photopoints 1 m away. Future work using this technique should consider this ratio, especially if high quality reconstruction of slender branches is sought.

4.5. Weather and ambient lighting

Diffuse lighting is best in order to reduce shadows and also prevent highly contrasted and over-exposed images from direct sunlight. Photographs should be captured at an appropriate time of day (such as noon with the high-sun) and over a period no longer than 30 min, as the sun's azimuth as well as surface albedo will change enough to affect the model quality (Bemis et al., 2014; Gienko and Terry, 2014). Photography around reflective surfaces should also be avoided (Bemis et al., 2014). These have the effect of removing the ability to examine surface shape or texture, meaning recognition of keypoints is not possible and the shadowed side of the model is prevented from developing properly, in both the dense point cloud and mesh models (Fig. 8). Photography should not be undertaken in windy conditions if it can be avoided as the wind will cause too much movement in leaves and small branches.

4.6. Point cloud attributes in PhotoScan

Perhaps what is fundamental to the easy visualisation of the tree and its components in PhotoScan is that point cloud models are coloured (they include spectral data), making it simpler to extract information than in laser scanning (Bemis et al., 2014). The coloured point cloud simplified placement of point markers for linear measurements, and made it easy to determine which points represented the tree and which points were irrelevant noise that needed to be removed. Though laser scanning derived point

Fig. 8. Bright sunlight caused half of some models to be in shadow, reducing the surface detail (left). This is reflected in the subsequent mesh generation (right), where the same stem fails to be enclosed in a complete cylinder.

clouds do not include spectral data, they can be fused with aerial photographs or satellite imagery to assign each point one or more spectral values (Xu et al., 2015).

The red tape used to mark measurement locations proved to be an invaluable tool for making measurements in PhotoScan. The red tape was easy to identify in the point cloud, given that the absence of red colour on the tree and in the background meant that any red in the point cloud could only be from the tape. Without the tape it would have been very difficult to ascertain whether the terminus of a branch in the model was truly the end, or whether SfM-MVS had failed to reconstruct the remainder of the branch. The usefulness of the tape is particularly evident when measuring the crown spread, as showcased by the difference in error between true crown spread (RMSE 14.76%) and visible crown spread (RMSE 21.06%).

The small size of our study trees (mean height: 296.82 m; mean DBH: 21.98 mm) must be considered when comparing our results to other research and the applicability of SfM-MVS to mature trees. Virtually all other aforementioned research focuses on mature trees (usually >10 m in height with DBH >20 cm). Using mature trees was impractical and would have prevented moving trees around the study site (to ensure minimal occlusion by other objects) and the destructive sampling necessary to obtain accurate volume measurements.

5. Conclusion

This research has shown that SfM-MVS is capable of reconstructing 3D point cloud models with high spatial accuracy. Accurate estimates of linear (2D) and volumetric (3D) metrics were able to be obtained. Height, DBH, and tree volume estimates generally as accurate as the estimates produced by terrestrial laser scanning. Stem volume was estimated more accurately than branch volume. Crown spread could be estimated with relatively good accuracy, though the greatest challenge faced is reconstruction of slender stems and branches. These results give rise to the possibility of using SfM-MVS for urban forest inventory, though this would depend on the viability of estimating geographic coordinates for each mapped tree. The small, potted trees we used in this study provided a scenario where experimental settings could be optimised to support better model generation, i.e. the ability to relocate the trees meant occlusion was not an issue and the potential for background noise could be reduced. These conditions are not reflective of real field settings where conditions cannot be modified. Moreover because we tested only small trees, we cannot be certain that the method can be used with the same success for large trees. These limitations represent opportunities for further research.

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