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Automated Volumetric Measurements of Truckloads through Multi-View Photogrammetry and 3D Reconstruction Software

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Abstract

Since wood represents an important proportion of the delivered cost, it is important to embrace and implement correct measurement procedures and technologies that provide better wood volume estimates of logs on trucks. Poor measurements not only impact the revenue obtained by haulage contractors and forest companies but also might affect their contractual business relationship. Although laser scanning has become a mature and more affordable technology in the forestry domain, it remains expensive to adopt and implement in real-life operating conditions. In this study, multi-view Structure from Motion (SfM) photogrammetry and commercial 3D image processing software were tested as an innovative and alternative method for automated volumetric measurement of truckloads. The images were collected with a small UAV, which was flown around logging trucks transporting Eucalyptus nitens pulplogs. Photogrammetric commercial software was used to process the images and generate 3D models of each truckload. The levels of accuracy obtained with multi-view SfM photogrammetry and 3D reconstruction obtained in this study were comparable to those reported in previous studies with laser scanning systems for truckloads with similar logs and species. The deviations between the actual and predicted solid volume of logs on trucks ranged between –3.2% and 3.5%, with an average deviation of –0.05%. In absolute terms, the average deviation was only 0.5 m^3 or 1.7%. Although several aspects must be addressed for the operational implementation of SfM photogrammetry, the results of this study demonstrate the great potential for this method to be used as a cost-effective tool to aid in the determination of the solid volume of logs on trucks.

Keywords: volumetric measurements, truckloads, multi-view photogrammetry, structure from motion, 3D reconstruction, Eucalyptus nitens, Australia

1. Introduction

Worldwide, pulpwood is usually measured by its weight, green or dry. One of the drawbacks of this method is the inherent variation in the moisture content of wood and chips, and the time and cost involved for its determination in an operational context. On the other hand, measuring volume manually (with wood sticks, tapes, etc.) results in time-consuming, inconsistent and inaccurate volumetric measurements (Knyas and Maksinov 2014). Given that wood represents on average about 1/3 of the delivered cost, it is key to adopt correct measurement procedures and technologies that provide better wood volume estimates (Nylinder et al. 2008). Poor measurements will not only impact the revenue obtained by haulage contractors and forest companies but also might affect their contractual business relationship.

The advantages of solid volume as a unit of measuring and payment for wood and chips have recently been recognised by an increasing number of forest companies worldwide, many of which have commenced to embrace commercial mechanisms and implement rate systems based on volumetric measurements (Nylinder et al. 2008). At least three technologies (laser scanning, stereoscopic cameras, and photogrammetry and 3D reconstruction) have evolved and improved substantially over the last decade (Harvin and Lucieer 2012), providing quicker and more accurate measurements of standing trees, logs and woodchips (Murphy et al. 2010, Skarlatos and Kiparissi 2012). All of them generate a cloud of points that can be captured and manipulated by algorithms and visual computing libraries and implemented in pieces of software developed for specific operational uses. The implementation of these technologies in real life operations requires that commercial mechanisms are adopted and implemented. This must also take into consideration the legal and commercial terms associated with implementing new measurement systems for payment on a volume basis, as well as the capital and running costs of the technology to be implemented (Schmithüsen et al. 2014).

Laser technology and the algorithms developed for volumetric calculations provide quick and more accurate measurements of standing trees, logs and woodchips (Gutzeit et al. 2011), as well as for volumetric measurements of wood truckloads while the vehicle positions itself on the weight scale (Nylinder et al. 2008). Laser scanning systems for volumetric measurements of wood truckloads are based on laser technology combined with dedicated processing software that creates 3D model images of trucks to accurately estimate the volume of the material loaded in a truck or trailer bin.

On its initial development (release), laser technology has surpassed traditional close-range photogrammetry, because of its accuracy and automation level (Skarlatos and Kiparissi 2012). However, laser technologies, in general, are more expensive to install and maintain than photogrammetric and stereoscopic technologies. Furthermore, laser scanning for wood truckloads can be limited outside factory facilities (Galsgaard et al. 2015). Modern image-based techniques have also become more popular over recent years, proving to be cost-effective, convenient and practical alternative to laser scanning.

Photogrammetry techniques and 3D modelling software have evolved to a point where now open-source and commercial software solutions can be used by non-vision experts. Multi-view 3D reconstruction is a technology that uses complex algorithms from computer vision to create 3D models of a given target scene from overlapping 2D images obtained from a digital camera (Favalli et al. 2012). It is based on a photogrammetric technique called Structure from Motion (SfM), which improves the quality of 3D data derived from overlapping imagery by incorporating advancements in soft-copy triangulation and image-based terrain extraction algorithms (Westoby et al. 2012). Furthermore, SfM can accurately reconstruct scene geometry using high-resolution overlapping imagery obtained with single lens reflex (SLR) cameras and consumer point-and-shoot cameras, rather than relying on stereoscopic cameras, thus enhancing the accessibility and accuracy of 3D photogrammetric modelling for an array of uses.

The fundamental advantage of SfM is that the geometry of the photographed scene, camera positions, and orientation are evaluated without the need for a priori specification of targets with known 3D positions (Snavely et al. 2008). Rather, SfM photogrammetry determines these parameters simultaneously with a highly redundant and iterative bundle adjustment procedure, which is based on a dataset of invariant features extracted from multiple overlapping images (Westoby et al. 2012). These features are tracked from image to image, enabling initial estimates of camera position and object coordinates, which are then refined iteratively using non-linear least squares minimisation (Fonstad et al. 2013).

This process produces a point cloud of identifiable features present in the input photographs. Once georeferenced, this point cloud can be used to generate an array of digital elevation metrics to quantify 3D characteristics. Automating the process from identification of control points to the 3D reconstruction of scene geometry makes SfM substantially more practical and cost-effective than traditional photogrammetric methodologies. Multiple studies have validated the accuracy of SfM techniques for high-resolution 3D topographic reconstruction and analysis (Micheletti et al. 2015), and in some cases found SfM to be highly comparable to substantially more expensive LIDAR techniques (Hartley and Zisserman 2003). It is an inexpensive, effective, flexible, and user-friendly photogrammetric technique for obtaining high-resolution datasets of complex topographies at different scales.

In the forestry sector, SfM and remote sensing have been mainly employed to complement existing ground-based techniques, providing spatially representative characteristics of investigated forest stands in a more efficient manner (White et al. 2016). Data captured over varying spatial, spectral, and temporal scales has been shown to contain information, which can be used to measure and monitor various aspects of a complex forest structure (Zellweger et al. 2013). Advances in the acquisition of this information have led to high spatial resolution three-dimensional (3D) remote sensing becoming an important tool in forest modelling over time (St-Onge et al. 2013). One reason for the forest community's interest in photogrammetry is the cost, with SfM methods estimated to be one-third to one-half the cost of laser scanning technology (White et al. 2016).

The recent development of small-size unmanned aerial vehicles (mini UAVs of less than 5 kg) represents a low-cost remote sensing alternative to airborne and satellite platforms. When equipped with sensors, small UAVs can produce cost-effective data at local scales (e.g., for areas the size of traditional forest plots up to areas of several km^2), with an unrivalled combination of spatial and temporal resolution (Wallace et al. 2016). Equipping UAVs with sensors capable of detecting 3D structure has led to the systems being increasingly used to provide an understanding of the structure and variability of forests (Tang and Shao 2015). Lisein et al. (2013) presented the potential of combining UAV with photogrammetric workflows for collecting multi-temporal data for canopy height modelling.

In the literature, there are very few studies using digital imagery to assist in the calculation of volume of logs on trucks, (Sosa et al. 2015), and on piles (Kruglov and Chiryshev 2017). However, to our best knowledge, nothing has been published on the use of multi-view photogrammetry and 3D reconstruction for the volumetric measurements of log truckloads, and this study is a first attempt to determine the levels of accuracy obtained with this technology as well as its potential to be implemented in operating conditions. Thus, this study aimed to assess the combination of multi-view SfM photogrammetry and commercial 3D image processing software as a more affordable alternative to laser scanning systems for automated volumetric measurements of log truckloads. Specific objectives included: 1. Developing a regression model to predict the solid volume of pulplogs on trucks with low-cost SfM photogrammetry, and 2. Calculating the deviations between the actual and predicted solid volume.

2. Material and methods

2.1 Trial site and data collection with UAV

Data from 10 semitrailer truckloads delivering debarked shinning gum (*Eucalyptus nitens* (H. Deane & Maiden)) logs to the Surrey Hills chip mill, Tasmania, Australia were collected with an Unmanned Aerial Vehicle (UAV) between 18th July and 20th July 2016. The UAV was a Phantom 4 drone developed by the company DJI™. The Phantom 4 is a 1.38 kg drone, with a maximum speed of 20 m/s and a maximum flight time of 28 minutes. It comes with a GPS/GLONASS system that allows geotagging of the pictures that are taken during the flight. The specifications of the built-in camera are shown in Table 1.

Table 1 Technical specifications of the camera mounted on the Phantom 4

Specification	Value
Camera model	FC330
Effective pixels	12.4 M
Sensor	1/1.3" (6.17 x 4.55 mm) CMOS
Resolution	4000x3000
Focal length	3.61 mm
Pixel size	1.56 x 1.56
Video recording modes	FHD: 1920×1080 24 / 25 / 30 / 48 / 50 / 60 / 120p HD: 1280×720 24 / 25 / 30 / 48 / 50 / 60p
Format photos	JPEG, DNG (raw)
Format videos	MP4, MOV

Flights were planned using the DJI Go 4™ app installed on an iPad Air 2™. Among others, this app allows to auto take-off and land the drone with just a swipe of the finger on the mobile device, track the drone's position on a map, and using this map set a new home point and even activate return to home, making flying easy and simple. The app also includes intelligent flight modes such as »Course Lock«, »Home Lock«, »Follow Me«, »Waypoints«, and »Point of Interest«.

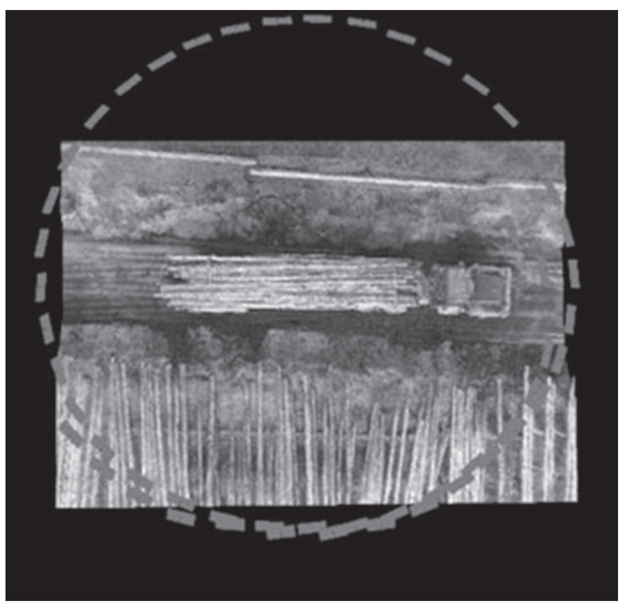

Fig. 1 Camera locations above logging trucks during data capture with UAV

Flights around logging trucks were performed at a height that ranged between 12.4 and 18.6 metres. For this purpose, a »Point of Interest« intelligent flight mode was selected, where each truckload was set as the point of interest, and the UAV continuously circled around it while photos were recorded every 3 seconds. This allowed forward and side overlaps of about 80% between consecutive images (Fig. 1).

2.2 Processing images of each truckload with 3D reconstruction software

Between 30 and 66 photos (average = 48 photos) were collected from the ten truckloads. Processing of the images collected with the drone was performed with the software AgiSoft PhotoScan™ version 1.3.2. PhotoScan is an advanced image-based 3D modelling solution for creating professional quality 3D content from still images. Based on the latest multi-view 3D reconstruction technology, it operates on arbitrary images and is efficient in both controlled and uncontrolled conditions. The photos can be taken from any position, provided that an object to be reconstructed is visible on at least two photos. Both image alignment and 3D model reconstruction are fully automated. It supports the following input formats: JPEG, TIFF, PNG, BMP, JPEG Multi-Picture Format (MPO), and the following output formats: Wavefront OBJ, 3DS Max, PLY, VRML, COLLADA, Universal 3D, PDF (Agisoft 2018a).

The technology behind the software allows for very fast processing. Processing times were within 30 min with a computer with a 6th Generation Intel Core i7 Processor, with four CPU cores, 32 GB of RAM, and a graphics card of 2 GB, providing highly accurate results (up to 3 cm for aerial, and up to 1 mm for close-range photography) (Agisoft 2018a). The package has a linear project-based workflow (Fig. 2) that is intuitive and can be easily mastered even by a non-specialist, while professional photogrammetrists have complete control over the results accuracy, with a detailed report being generated at the end of processing (more details about the linear workflow in Agisoft (2018b)). Photorealistic, highly detailed 3D models, classified dense point clouds, fine resolution Digital Elevation Models (DEMs) generated with the software can be used in wide range of applications, from visual effects industry to engineering projects. Also, high accuracy of polygonal models and digital surface models reconstructed with the software guarantees precise area and volume measurements. This feature made it possible to use this technology and software for volumetric measurements of truckloads.

After the photos were loaded and aligned in PhotoScan, the software found the camera position and orientation for each photo, identifying and matching features in a set of images using an algorithm based on the scale invariant feature transform (SIFT) object recognition system (Lowe 2004). Also, bundle adjustment algorithms implemented in the software estimated the 3D geometry of the truckloads, as well as the internal and external camera orientation parameters, producing a sparse, unscaled 3D point cloud in arbitrary units. The density of this point cloud for the ten truckloads ranged between 24 128 and 35 596 points.

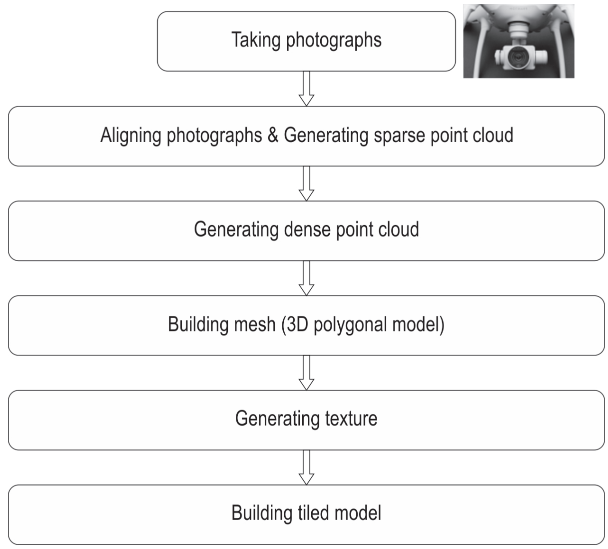

Fig. 2 Agisoft PhotoScan's project workflow for image processing and 3D reconstruction

After alignment and optimisation, the dense multi-view 3D reconstruction algorithm was executed by implementing a multi-view stereo (MVS) image matching algorithm. PhotoScan tends to produce extra dense point clouds, which are of almost the same density, if not denser, as LIDAR point clouds. Thus, point cloud densities ranged between 607 000 and 1 374 000 points for the ten truckloads.

In a next step, a mesh (3D model) was created from the dense point cloud. The use of a high-quality dense cloud as a source data resulted in longer processing times. The number of faces and vertices in the 3D models ranged between 180 000 and 274 400, and between 90 500 and 138 000, respectively. Subsequently, pixel data from the photographs were used to generate a 3D model texture, and a high-resolution tiled model was generated for each truckload.

2.3 Estimating solid volume from gross volume

After the tiled model (3D textured) was generated, it was imported in the software Autodesk Remake™

Table 2 Summary of the flight performed around the 10 logging trucks

	Truckload									
	1	2	3	4	5	6	7	8	9	10
# Aligned images	37	37	36	51	66	46	54	55	64	30
Flying altitude, m	18.6	13.2	14.8	17.3	14.1	12.4	12.8	15.0	15.2	16.4
Ground resolution, mm/pix	6.2	4.5	5.4	5.6	5.4	4.6	4.9	5.3	5.2	5.5
Coverage area, m^2	40.9	54.6	30.1	29.1	28.8	31.0	36.8	31.6	29.2	65.9

and extruded to facilitate the calculation of gross volume (solid volume of logs including air spaces) by a dedicated algorithm included in the tool. The mesh report provides information about the number faces and vertices, as well as area and volume of the 3D model.

In addition to the gross volume calculated from SfM photogrammetry and 3D reconstruction, each truckload was physically measured on the ground for actual solid wood volume. For that purpose, 1605 fully debarked logs were measured for mid-diameter and total length. Mid-diameter was measured to the nearest millimetre with a calliper, whereas the length of each log was measured to the nearest 0.1 m with a tape. Both mid-diameter and length data were recorded with a Windows tablet for further processing. The solid volume of the logs was calculated using Huber's equation, which uses mid-diameter and length as inputs. Huber's volume equation is as follows (Eq. 1):

$$Sv = \frac{1}{1000\,000} \times \pi \times \frac{Dm^2}{4} \times L \qquad (1)$$

Where:

Sv solid volume, m^3

Dm mid-diameter, mm

L log length, m.

To predict the solid volume of each truckload, a linear regression model between the explanatory variable »Gross volume« (from photographs and 3D reconstruction) and the response variable »Solid volume« (from measurement on the ground) was developed. The linear regression model had the following form (Eq. 2):

$$\text{Solid volume } [m^3] = a + b \times \text{Gross volume } [m^3] \qquad (2)$$

Predicted solid volume of each truckload was then compared to their actual solid volume, and both absolute and percentage deviations were calculated to determine the accuracy of the predictions.

3. Results

3.1 Summary of flights around logging trucks and processing of images

Table 2 shows a summary of the flights performed around the 10 logging trucks, including aligned images, flying altitude, ground resolution and coverage area. The ground resolution was high given the short distance between the camera allocation and the trucks. It was evident that the ground resolution increased at lower flight altitudes. For example, at a flight altitude of 12.4 m (Truckload #6), the ground resolution was 4.6 mm/pix, while at a flight altitude of 18.6 m (Truckload #1), the ground resolution was 6.2 mm/pix.

Fig. 3 shows an image of the sparse point cloud generated with PhotoScan. On average, around 29 000 points were generated from the photos of each truckload. Matching time ranged between 1.6 and 10.1 minutes (average = 4.5 minutes), while alignment time ranged between 0.16 and 0.5 minutes (average = 0.2 minutes).

Fig. 4 shows an image of the dense cloud (whole truck) generated with Agisoft PhotoScan. On average, around 1 019 000 points were generated for each truckload. Processing times were much longer than in the case of the sparse point cloud. Depth maps

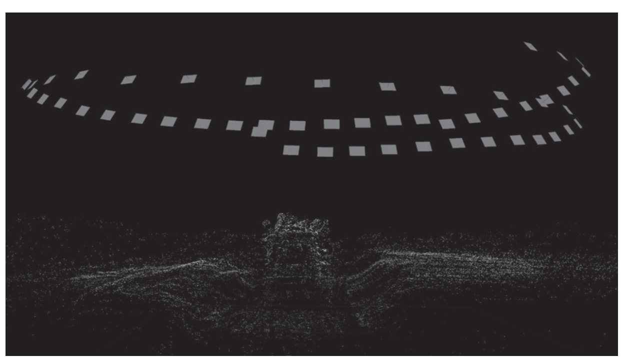

Fig. 3 Sparse point cloud generated with Agisoft PhotoScan

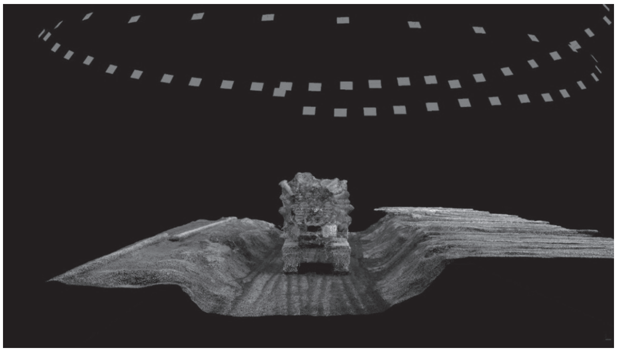

Fig. 4 Dense point cloud generated with Agisoft PhotoScan

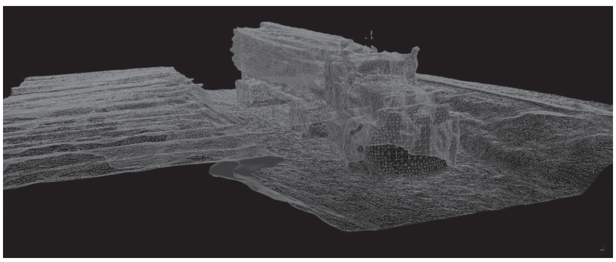

Fig. 5 3D model (mesh) generated with Agisoft PhotoScan

generation time ranged between 4.0 and 34.8 minutes (average = 18.7 minutes), while dense cloud generation time ranged between 0.8 and 6.5 minutes (average = 3.2 minutes).

An image of the 3D model (mesh for a whole truck) is shown in Fig. 5. On average, around 214 000 faces and 107 660 vertices were generated for each truckload. In this case, processing time ranged between 0.5 and 1.2 minutes (average = 0.9 minutes).

Finally, Fig. 6 shows the tiled model (size = 256 pixels) generated from the dense cloud with PhotoScan. Processing time ranged between 1.4 and 2.5 minutes (average = 2.1 minutes).

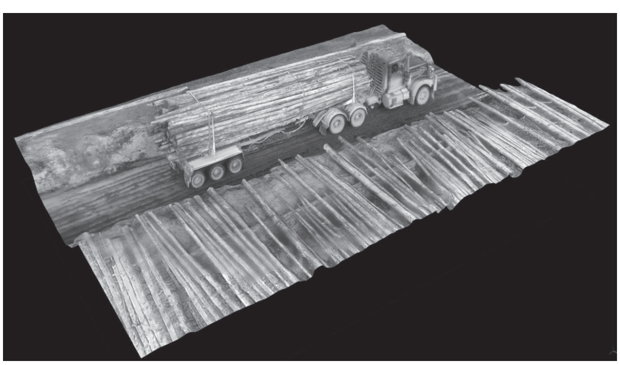

Fig. 6 Tile model generated with Agisoft PhotoScan

3.2 Processing time for 3D reconstruction of truckloads

Total processing time (including processing to generate the tiled model) ranged between 10.1 and 52.2 minutes (average = 30.9 minutes). The variation in total time is explained by the number of images to generate the 3D model as well as the average flight altitude when capturing the photographs. Processing time increases as more images are used to generate the models and when these photographs are captured at a lower altitude. The regression model is as follows (Eq. 3):

$$\text{Processing time [min]} = 36{,}9 + (1.01 * \#\text{Images}) - (3.6 * \text{Altitude [m]}),\ \text{Adj. } r^2 = 0.86 \quad (3)$$

The standard error of the estimate was 6.391, while the *p*-values for the intercept and coefficients associated with explanatory variables #Images, and Altitude

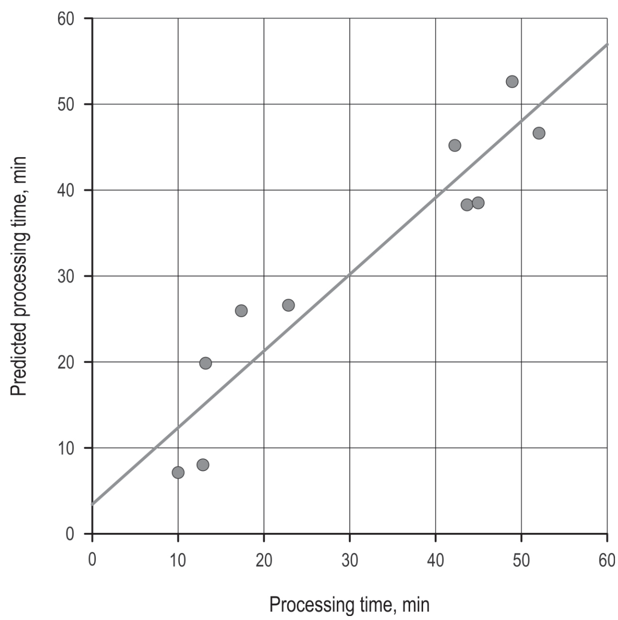

Fig. 7 Regression model between actual and predicted processing time

were 0.012, <0.001, and 0.014, respectively. A regression model between actual and predictive processing time is shown in Fig. 7.

3.3 Summary statistics of truckloads

Table 3 presents a summary of the statistics of the logs being transported by the ten trucks included in the study (1605 logs). These include the mid-diameter measured in the centre of the logs, the total length, and the solid volume calculated with the Huber equation.

Table 3 Summary of statistics for the long logs measured in the study

	Mid-diameter, mm	Log length, m	Solid volume, m^3
Min.	80.0	2.0	0.01
Max.	361.0	13.3	1.11
Mean	163.1	9.6	0.23
Median	158.0	10.9	0.19
Std. dev.	47.2	2.4	0.16

Table 4 shows summary statistics for Gross Vehicle Mass (GVM), tare, net payload, solid volume, gross volume calculated from 3D models, and solid-to-gross ratio by truck.

There was a big difference in GVM (8.8 tonnes) and net payload (7.5 tonnes) between the lightest and the heaviest trucks, although their difference in tare was only 3.1 tonnes. The inclusion of these two trucks did not affect the average GVM, tare, and net payload, which were around 45.8, 15.8, and 30.0 tonnes, respectively, for the ten trucks included in the study.

Regarding solid volume, there was a difference of 5.4 m^3 between the lightest and the heaviest truck. The average solid volume was 28.5 m^3 for the ten trucks, which was lower than the 30.2 m^3 calculated in a previous study from 54 truckloads (Acuna and Herd 2016). This difference is explained in part by the date of each trial (end of summer in the previous trial and mid-winter in the case of the present study), as well as the volume equation used (Smalian in the previous trial and Huber in the case of the present study). Also, there was a high correlation between net payload and solid volume (Pearson coefficient of correlation = 0.87). This high correlation can be explained in part by the fact that all the loads were moved from the forest to the chip mill immediately after harvesting, consisting of logs with similar moisture content and basic density.

Regarding gross volume, the gap between the lightest and the heaviest truck was 6.7 tonnes, which was bigger than the gap in solid volume, and with greater variation among the trucks. The average gross volume was 44.8 m^3 for the ten trucks, which was lower than the 47.9 m^3 calculated in a previous study from 54 truckloads (Acuna and Herd 2016). This difference is explained in part by the method being used to determine the gross volume (pictures taken from both sides of the trucks in the previous trial and multi-view photogrammetry and 3D reconstruction in the present study). The average solid-to-gross ratio in the present study for ten trucks (0.64) was very close to the one calculated in the previous trial for 54 trucks (0.63). The difference between the maximum and minimum values (0.05) and the standard variation (0.02) was smaller in the present study than in the previous one.

Table 4 Summary statistics for the 10 truckloads included in the study

Truck	GVM, tonnes	Tare, tonnes	Net payload, tonnes	Solid volume, m^3	Gross volume, m^3	Solid-to-Gross volume ratio
1	45.90	14.95	30.95	29.04	43.73	0.66
2	45.55	15.35	30.20	28.52	45.92	0.62
3	50.35	16.10	34.25	31.64	47.56	0.67
4	41.55	14.75	26.80	26.20	40.85	0.64
5	46.00	15.65	30.35	29.09	45.40	0.64
6	46.00	15.70	30.30	29.13	45.15	0.65
7	45.35	14.95	30.40	28.86	45.97	0.63
8	46.10	15.15	30.95	28.73	45.95	0.63
9	46.50	17.85	28.60	27.15	43.13	0.63
10	45.35	15.50	29.85	28.80	44.83	0.64
Min.	41.55	14.75	26.80	26.20	40.85	0.62
Max.	50.35	17.85	34.25	31.64	47.56	0.67
Average	45.88	15.78	30.09	28.54	44.85	0.64
Std. dev.	2.00	1.05	1.87	1.46	1.87	0.02

Table 5 Summary of gross and solid volume, and errors by truck

	Truck									
	1	2	3	4	5	6	7	8	9	10
Gross volume*, m^3	43.7	45.9	47.6	40.8	45.4	45.1	46.0	45.9	43.1	44.8
Actual solid volume, m^3	29.0	28.5	31.6	26.2	29.1	29.1	28.9	28.7	27.2	28.8
Predicted solid volume, m^3	28.0	29.4	30.5	26.1	29.1	28.9	29.4	29.4	27.6	28.7
Deviation, m^3	1.05	–0.90	1.15	0.10	0.01	0.22	–0.58	–0.71	–0.44	0.09
Deviation, %	3.45	–3.16	3.48	0.38	0.00	0.69	–1.73	–2.44	–1.47	0.35

* Calculated with photogrammetry and 3D reconstruction

3.4 Estimating solid volume from gross volume

A good prediction of solid volume from gross volume was achieved with a regression model that combined the data of the ten truckloads (Fig. 8). The regression equation obtained was as follows (Eq. 4):

$$\text{Solid volume [m}^3\text{]} = -0.617 + (0.654 * \text{Gross volume [m}^3\text{]}),\ \text{Adj. } r^2 = 0.76 \quad (4)$$

The standard error of the estimate was 0.737, while the p-values for the intercept and coefficient associated with explanatory variable Gross Volume were 0.009, <0.001, respectively.

A significant dependence relation was observed between the solid and gross volume, even though the model was only developed from 10 truckloads. This is also supported by the results presented in Table 5, which shows a summary by truck of the gross and solid volume, predicted solid volume with the above regression model, and the errors (deviations) between the actual and the predicted solid volume. Positive deviations mean that the actual solid volume was bigger than the predicted solid volume (the model underestimates solid volume), while negative deviations mean that the actual solid volume was smaller than the predicted solid volume (the model overestimates solid volume). As shown in Table 6, the deviation for the 10 trucks ranged between –0.9 and 1.2 m^3, with an average value of 0.5 m^3. However, the absolute deviation only ranged between 0.0 and 1.2 m^3, with the same average value of 0.5 m^3. These values represent a maximum absolute deviation of 3.5%, with an average value of only 1.7% for the 10 trucks.

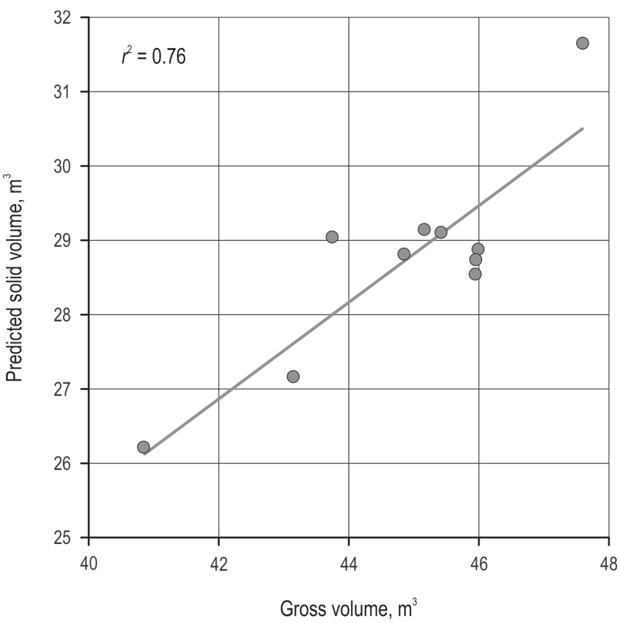

Fig. 8 Regression model between gross and predicted solid volume of logs on trucks

4. Discussion

The main objective of this study was to assess the combination of multi-view photogrammetry and

Table 6 Summary of gross and solid volume, and errors for the 10 trucks in the study

	Min.	Max.	Average	Std. dev.
Gross volume*, m^3	40.8	47.6	44.8	1.9
Actual solid volume, m^3	26.2	31.6	28.7	1.4
Predicted solid volume, m^3	26.1	30.5	28.7	1.2
Deviation, m^3	–0.9	1.2	0.5	0.4
Absolute deviation, m^3	0.0	1.2	0.5	0.4
Absolute deviation, %	0.0	3.5	1.7	1.4

* Calculated with photogrammetry and 3D reconstruction

commercial 3D image processing software as a more affordable alternative to laser scanning systems for automated volumetric measurements of log truckloads. Specific objectives included developing a regression model to predict the solid volume of pulplogs on trucks with low-cost SfM photogrammetry and determining the errors of those predictions.

A UAV was the choice for the collection of the images during the study because of their ease of use and affordability. Data capture with UAVs is limited by weather conditions such as rain, snow, high winds, dust, and low light conditions, which can have a negative impact on the quality of the images collected. Thus, if a photogrammetric is to be implemented operationally, it is recommended that it is based on photo-measuring stations, for example with several cameras mounted on masts that allow capturing images of the trucks from different angles through a more controlled and protected photo capture system.

The levels of accuracy obtained with SfM photogrammetry and 3D reconstruction in this study were quite similar to the ones reported in previous studies with laser scanning systems for truckloads with pulplogs of similar species. For example, in the study conducted by Nylinder et al. (2008), deviations between gross volume measured manually and estimated with laser scanning systems ranged between –4.5% and 1.7% for *Eucalyptus globulus* pulplogs. In our study, the deviations between actual and predicted solid volume of logs on trucks ranged between –3.2% and 3.5%, with an average deviation of –0.05%. In absolute terms, the average deviation was only 0.5 m^3 or 1.7%. These results confirm the great potential for multi-view SfM photogrammetric and 3D reconstruction methods to be used as a cost-effective tool to aid in the determination of the solid volume of logs on trucks.

Commercial software and algorithms to process the photographs and generate the 3D profiles are progressing quite rapidly, and the approach has demonstrated to be as accurate as the one based on laser scanning systems, but a more affordable option (Koci et al. 2017). In this study, a relatively high coefficient of determination (r^2=0.76) was obtained between the response variable (solid volume) and the explanatory variable (gross volume). Despite the high r^2 value of the regression model, the greater variability of solid volume could be explained if additional explanatory variables were added to the regression model. One of these variables could be the solid volume of the logs situated in the periphery of the load, which might be reconstructed in 3D during the scanning process. This has already been done by some commercial laser scanning units such as the Logmeter (WoodTech 2018), which captures cross-sectional point cloud data during the scanning of truckloads and fits circles in each cross section to allows the 3D reconstruction of the logs in the periphery of the load. A similar approach could be used and implemented with the SfM photogrammetric approach used in this study, but this will require developing efficient algorithms to edit, process, and manipulate the point cloud data generated from the photos captured with a UAV or fixed cameras.

A major advantage of SfM is the relatively low cost of the instruments to collect and process photogrammetric data. In our study, we utilised a lightweight UAV equipped with a 12.4 MP camera, whose total weight did not exceed 2 kg and whose cost was ~ $AUD 2500 including all the accessories. In addition, the cost of one Agisoft™ Academic licence was about US$ 700. The SfM instrument costs are much lower than LiDAR (laser) systems; while LiDAR systems are becoming smaller and more compact, they are still orders of magnitude more expensive than small-scale UAVs with a digital camera (Mlambo et al. 2017). The low SfM survey instrument costs mean they can be purchased outright and deployed rapidly. In Australia, lightweight drones (<2 kg) can be used without a remote pilot license (CASA 2018), representing a very affordable option to collect photogrammetric data as compared to another sensor technology. In our study, data collection with the UAV took approximately 2.4 minutes per flight using Phantom 4's »Point of Interest« intelligent flight mode, with an average of 48 photos collected per flight (range between 30 and 66 images).

Related to the above, one of the biggest limitations of photogrammetry and 3D reconstruction is their application in operating conditions due to the processing times involved to generate a 3D model of the truckloads. The high number and resolution of images captured during SfM surveys demand substantial computing resources for data storage, processing and analysis. In our study, processing time up to completion of the 3D models averaged 30.0 minutes on a computer with a 6th Generation Intel Core i7 Processor, with four CPU cores, 32 GB of RAM, and a graphics card of 2 GB. Such computational demands may limit the scale and uses at which SfM is currently applied, in particular to users of the technology who do not have access to high-performance computers. However, rapid advances in computing capability, for example through improvements to Graphics Processing Units and the implementation of parallel computing, are revolutionising SfM workflows (Koci et al. 2017). In our study, as expected, the number of images to be processed was a statistically significant variable to explain processing time (at a rate of about 1 minute of extra processing time per image). However, no correlation was observed between the number of images used for the 3D reconstruction and the deviations between actual and predicted solid volume. For example, for one of the truckloads, processing of 30 images took only 13.0 minutes with a deviation of 0.09 m^3 between actual and predicted solid volume, whereas, for another truckload, processing of 64 images took 52.2 minutes with a deviation of –0.44 m^3 between actual and predicted solid volume. Due to these results, future tests will focus on determining the minimum number of images that are required to be captured without compromising the accuracy of the volumetric predictions of logs on trucks. It is expected that a reduction in the time required for capturing the images with the UAV, as well as in the processing time due to an improvement of SfM algorithms and better computing capabilities, will lead to the commercial implementation of these methods for the automated volumetric measurements of truckloads.

5. Conclusions

Structure from Motion with Multi-View Stereo photogrammetry (SfM) is being increasingly utilised by forestry practitioners as a cost-effective method of rapidly acquiring high resolution topographic and forest resource data across a range of scales and landscapes but has not been tested to determine the solid volume of logs on trucks accurately. Implementing innovative technology and correct measurement procedures of truckloads will impact the contractual business relationships between haulage contractors and forest companies positively, and will enable the correct implementation of commercial payment mechanisms along the supply chain based on volumetric measurements of truckloads.

Although laser scanning has become a mature and more affordable technology in the forestry domain, it remains expensive to adopt and implement in real-life operating conditions. The main goal of this study was to test multi-view structure from motion (SfM) photogrammetry and commercial 3D image processing software as an innovative and alternative method for automated volumetric measurement of truckloads. The levels of accuracy obtained with multi-view SfM photogrammetry and 3D reconstruction obtained in this study were comparable to those reported in previous studies with laser scanning systems for truckloads with similar logs and species. The deviations between actual and predicted solid volume of logs on trucks ranged between –3.2% and 3.5%, with an average deviation –0.05%. In absolute terms, the average deviation was only 0.5 m^3 or 1.7%.

Although several aspects must be addressed for the operational implementation of SfM photogrammetry, including further testing and refinement of different methodological approaches to improve model accuracy and reduce processing times, the results of this study demonstrate the great potential of this method to be used as a cost-effective tool to aid in the determination of the solid volume of logs on trucks.

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