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Inter-comparison of remote sensing platforms for height estimation of mango and avocado tree crowns

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ABSTRACT

To support the adoption of precision agricultural practices in horticultural tree crops, prior research has investigated the relationship between crop vigour (height, canopy density, health) as measured by remote sensing technologies, to fruit quality, yield and pruning requirements. However, few studies have compared the accuracy of different remote sensing technologies for the estimation of tree height. In this study, we evaluated the accuracy, flexibility, aerial coverage and limitations of five techniques to measure the height of two types of horticultural tree crops, mango and avocado trees. Canopy height estimates from Terrestrial Laser Scanning (TLS) were used as a reference dataset against height estimates from Airborne Laser Scanning (ALS) data, WorldView-3 (WV-3) stereo imagery, Unmanned Aerial Vehicle (UAV) based RGB and multi-spectral imagery, and field measurements. Overall, imagery obtained from the UAV platform were found to provide tree height measurement comparable to that from the TLS (R^2 = 0.89, RMSE = 0.19 m and rRMSE = 5.37 % for mango trees; R^2 = 0.81, RMSE = 0.42 m and rRMSE = 4.75 % for avocado trees), although coverage area is limited to 1–10 km^2 due to battery life and line-of-sight flight regulations. The ALS data also achieved reasonable accuracy for both mango and avocado trees (R^2 = 0.67, RMSE = 0.24 m and rRMSE = 7.39 % for mango trees; R^2 = 0.63, RMSE = 0.43 m and rRMSE = 5.04 % for avocado trees), providing both optimal point density and flight altitude, and therefore offers an effective platform for large areas (10 km^2–100 km^2). However, cost and availability of ALS data is a consideration. WV-3 stereo imagery produced the lowest accuracies for both tree crops (R^2 = 0.50, RMSE = 0.84 m and rRMSE = 32.64 % for mango trees; R^2 = 0.45, RMSE = 0.74 m and rRMSE = 8.51 % for avocado trees) when compared to other remote sensing platforms, but may still present a viable option due to cost and commercial availability when large area coverage is required. This research provides industries and growers with valuable information on how to select the most appropriate approach and the optimal parameters for each remote sensing platform to assess canopy height for mango and avocado trees.

1. Introduction

Research on horticultural tree crops and precision agriculture is underpinned by remote sensing technologies (Rosell and Sanz, 2012; Robson et al., 2016). Datasets from different remote sensing platforms such as satellites, aircraft and Unmanned Aerial Vehicles (UAVs) have been applied in horticultural areas to measure and map important biophysical and functional parameters (Tu et al., 2019a; Sola-Guirado et al., 2017; Sarron et al., 2018; Machovina et al., 2016; Rahman et al., 2018; Salgadoe et al., 2018; Robson et al., 2017; Salgadoe et al., 2019; Anderson et al., 2018). Canopy height is one of the most critical geometrical parameters of horticultural tree crops (Rosell and Sanz, 2012), as it can affect optimal light interception, yield, health, fruit quality and harvest cost for mango and avocado trees (Hadari, 2004; Davenport, 2006; Platt, 1976; Thorp and Stowell, 2001; Yeshitela et al., 2005). Mango and avocado trees follow a predictable growth pattern throughout the year. Vegetative growth, flowering and fruit development are three crucial major growth cycle events for both tree crops (Meurant and Kernot, 1999; Vock et al., 2001). Annual pruning has become a common practice in Australia for mango, avocado and other

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horticultural tree crops. As a guideline for avocado growers in Australia, it is suggested that tree height must be no higher than 80 % of the row width to ensure optimal light penetration for avocado trees (Menzel and Le Lagadec, 2014). Most commercial mango orchards in Australia are pruned to a height of 3.5 m–4.5 m and it is recommended that the tree height is kept below 50 % of the row width to allow sufficient light penetration and air circulation (Davenport, 2006; Meurant and Kernot, 1999). Tree pruning is an expensive practice, which can account for 20–30 % of the annual cultivation cost (Farinelli, 2011). Canopy height is also a key parameter for sprayer calibration, as it can be used at least annually to achieve appropriate spray volume and adequate coverage (i.e. cover the full height without wasting spray above the tree) (Newett et al., 2001; Furness et al., 1998). Previous research has assessed the relationship between forest tree height and a number of beneficial attributes, including the evaluation of different remote sensing platforms to obtain this measure (Rosca et al., 2018; Wang et al., 2019; Yu et al., 2015). However, to our knowledge, there is no research or guide on how to select a suitable remote sensing platform for height estimates of horticultural tree crops. Therefore, this study fills an essential knowledge gap by providing information on the accuracy, cost, spatial coverage and flexibility of capture with which tree height and be derived from different remote sensing platforms and sensors. This information may be used as a guide for industries and growers for selecting the most appropriate remote sensing dataset and associated acquisition parameters to assess canopy heights of mango and avocado trees.

Laser scanning (LS) is used extensively for forest resource studies, both in research and at operational levels (Wang et al., 2019; White et al., 2016). Due to the high accuracy and relatively large area coverage of airborne laser scanning (ALS), it is becoming a standard of tree height measurements at plot and stand levels (White et al., 2016). However, the accuracy of ALS-based tree height measurements is often influenced by the quality of digital terrain models (DTMs), sensor type, flight and sensor configuration, and the local environment (Leckie et al., 2003). ALS data may underestimate tree height if no laser pulses are returned from the apex of tree crowns, which could occur due to relatively low point density and other related specifications such as laser footprint size, pulse repetition rate, altitude and intensity of the return (Wang et al., 2019; Goodwin et al., 2006). On the other hand, Terrestrial Laser Scanning (TLS) data provide very high point densities, but it can lead to underestimation of tree heights due to possible occlusions in the upper canopy (Krooks et al., 2014). Wilkes et al. (2017) reported that canopy density and height can affect the scanning range of a terrestrial laser scanner. Krooks et al. (2014) Wang et al. (2019) demonstrated that TLS data tend to underestimate canopy height for trees taller than 15 m when compared with ALS data and field measurements. However, ALS, TLS and field measurements show a high consistency for measuring tree height of less than 10 m regardless of the complexity of stands (Wang et al., 2019). Nowadays, LS data are commonly used for forest canopy height estimation (Wang et al., 2019; Hadaś and Estornell, 2016), similar evaluation and adoption is seen for horticultural tree crops (Estornell et al., 2014). Some research on mapping the canopy height of olive trees using ALS data (Estornell et al., 2014; Miranda-Fuentes et al., 2015) has shown that ALS can produce highly accurate canopy height results when compared to field measured tree height (R^2 = 0.67 and RMSE = 0.19 m) (Estornell et al., 2014).

Although ALS data are considered to be most accurate and robust for canopy height mapping, stereo imagery from satellite platforms can potentially provide plant canopy height information over large areas at a lower cost and at a high temporal resolution (Wang et al., 2019; Yu et al., 2015; Persson and Perko, 2016). By capturing overlapping images from different positions, digital photogrammetry can transform two-dimensional (2D) images into three-dimensional (3D) data to provide digital surface models (DSMs) and canopy height models (CHMs) (Yu et al., 2015). Previous studies indicated that high spatial resolution stereo imagery acquired from the WorldView-2 (WV-2), Cartosat-1 and IKONOS sensors are capable of mapping vegetation canopy height if high quality DTMs are available, in order to normalize photogrammetric measurements and calculate the difference between surface and ground elevation (Persson and Perko, 2016; Neigh et al., 2014; Straub et al., 2013). A thorough review of current literature failed to identify any publications demonstrating the use of satellite stereo imagery for mapping canopy height of horticultural tree crops. Persson and Perko (2016) demonstrated that plot level (457 plots with 10 m radius) hemi-boreal and boreal canopy height measurements from WV-2 stereo imagery with a relative RMSE of 6 %–10 %, had a higher accuracy than traditional field inventory methods, although a general underestimation of tree height was observed. Yu et al. (2015) showed that plot level (32 m × 32 m and 16 m × 16 m) mean CHMs generated from WV-2 imagery was only slightly worse (RMSE = 1.12 m vs RMSE = 1.40 m) than those produced from ALS data, when compared with field measurements using an electronic hypsometer within a boreal forest zone in Finland.

UAVs have recently become popular for mapping canopy height of forests and orchards (Tu et al., 2019a; Mohan et al., 2017). As UAV imagery is generally collected with high forward overlap and sidelap, it is possible to generate high accuracy 3D photogrammetric point clouds using Structure from Motion (SfM) and Multi-View Stereo (MVS) techniques (Kuželka and Surový, 2018). Studies have indicated that UAV imagery can provide accuracies comparable with LS systems in both horticultural and forest applications (Zarco-Tejada et al., 2014; Thiel and Schmullius, 2017). Although UAV imagery can produce CHMs with high flexibility in spatial and temporal resolutions and at high accuracy and low cost, they only cover a limited area (typically < 1 km^2) (Johansen et al., 2018). Mlambo et al. (2017) found a strong correlation (R^2 = 0.75) between CHMs generated from UAV (DJI Phantom 2) data and ALS data for trees with a sparse canopy structure which are located around an agricultural area. UAV-based measurements have become a competitor to ALS data for tree height measurements and have the potential to replace the traditional ground-based tree height measurements for forest monitoring (Mlambo et al. (2017); Krause et al., 2019). However, UAV imagery tended to underestimate the canopy height when compared to the canopy height estimates from field measurements (Krause et al., 2019; Panagiotidis et al., 2017). For instance, Krause et al. (2019) demonstrated that a CHM of Scots Pine derived from UAV based SfM has a similar accuracy to field measured tree height with a tendency of underestimation when compared with destructive methods. In addition, very high precision (RMSE = 0.138 m) was achieved when they compared the canopy height estimations derived from two independent UAV missions. Lee and Ehsani 2009) demonstrated that mobile LiDAR system (LMS200 laser scanner mounted on a test vehicle) can produce a highly accurate (mean relative error = −0.37 %) CHM for citrus trees when compared against manual field measurements. Li et al. (2019) compared the CHM accuracy between a commercial UAV LiDAR system (including a Hexa-rotor UAV with a Riegl VUX-1 laser scanner) and a low cost UAV LiDAR system (including a DJI M600Pro UAV with a Velodyne Puck VLP-16). Although the lower cost Velodyne LiDAR-derived CHM achieved comparable accuracies (R^2 = 0.998, RMSE = 0.323 m) to the Riegl VUX-1 system, the lower point density of the Velodyne scanner limited its ability to estimate low and complex trees.

Our study inter-compared the accuracies of different remote sensing platforms and sensors with TLS data for calculating individual tree crown height of mango and avocado tree crops. These platforms and sensors included ALS, WorldView-3 (WV-3) satellite and RGB and multi-spectral UAV data, as well as field-based measurements (with a laser rangefinder and measuring staff). We then compared and evaluated the accuracy, cost, spatial coverage and flexibility (potential repetitiveness in data acquisitions) of the derived canopy height as well as the different accuracies between mango and avocado trees. Results from this study provide guidance on which technology may be suitable

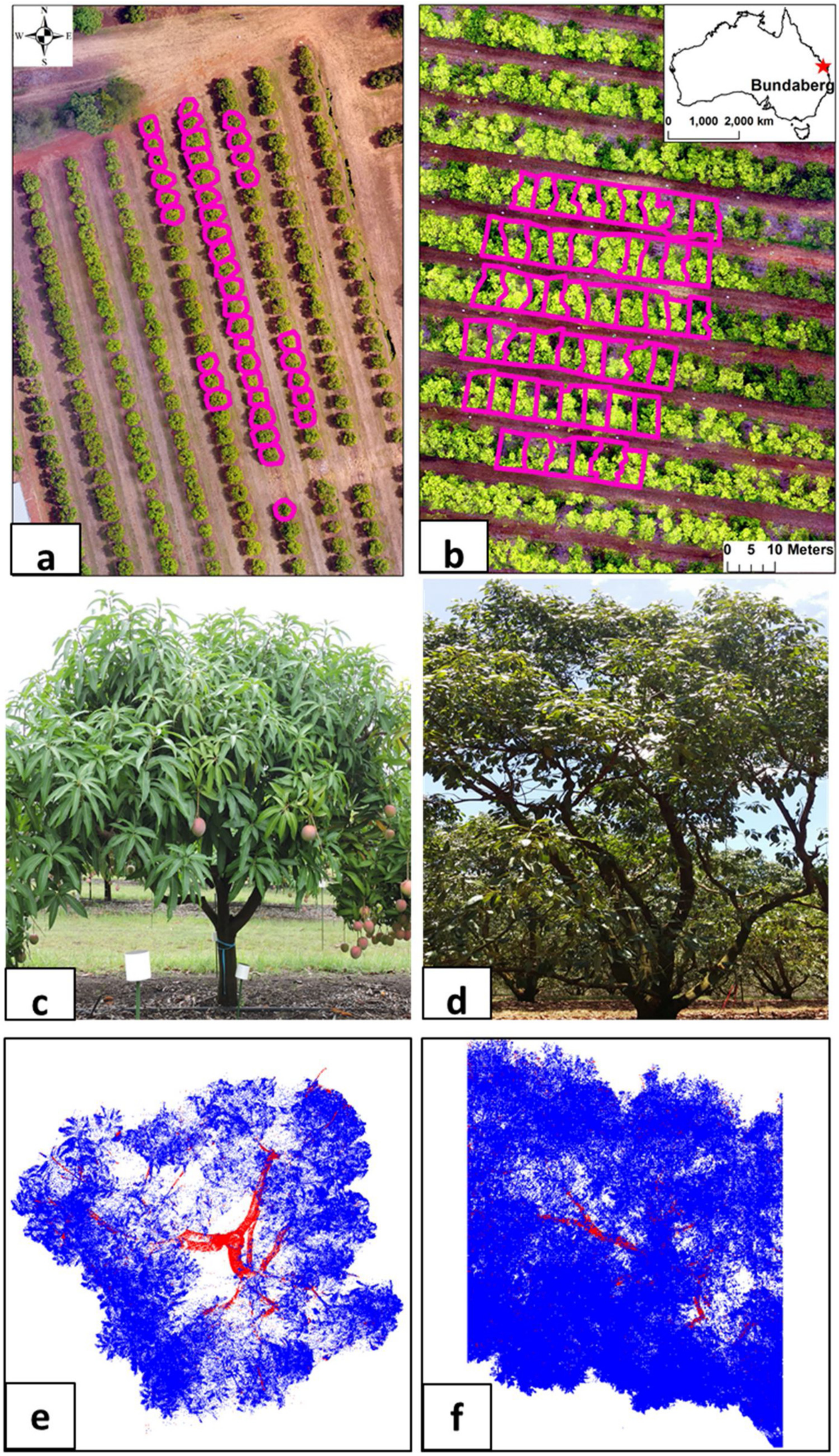

Fig. 1. (a) UAV image of a mango and (b) avocado orchard and tree crown delineation (pink outlines) of those tree crops covered by both terrestrial laser scanning data and UAV imagery of the Bundaberg growing region (insert- red star); field photos of (c) a mango tree and (d) an avocado tree within the imaged locations; and the classified terrestrial laser scanning point cloud (blue points: leaves, red points: trunk and branches) observed from a bird's-eye view of (e) a mango and (f) an avocado tree. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

for future industry adoption.

2. Methods

2.1. Study area

For this study, mango (*Mangifera indica*) cv. Calypso and avocado (*Persea americana*) cv. Hass trees were selected for height assessment from two commercial orchards near the township of Bundaberg, South East Queensland, Australia (Fig. 1). For mango production, Queensland and the Northern Territory account for about 95 % of Australia's total mango crop (Australian Mangoes, 2014). Along with the Burdekin and Mareeba regions, Bundaberg is one of the three main mango producing regions in Queensland (Queensland Government, 2020), and also one of the three major avocado production regions in Australia (Horticulture Innovation Australia, 2020; Avocados Australia, 2020). The Bundaberg region has a subtropical climate, with a mean annual rainfall of 1021.8 mm (1942–2019) (Bureau of Meteorology, 2016), and eight hours of average annual daily sunshine (Bureau of Meteorology, 2020).

2.2. Datasets and estimation of tree height

2.2.1. Datasets

To calculate and compare the canopy height of mango and avocado trees, we collected TLS data using the RIEGL VZ-400 TLS system, ALS data from the RIEGL LMS-Q 1560 ALS system, WV-3 stereo satellite imagery, UAV-based Parrot Sequoia multi-spectral and Phantom-4 Red-Green-Blue (RGB) imagery, as well as field derived maximum canopy height measurements using a laser rangefinder for avocado trees and a measuring staff for mango trees. Data were collected within four periods spanning from April 2016 to September 2017 (Table 1). Within each of the four data collection periods, datasets were collected within a month. All datasets were geometrically referenced, and tree crowns were manually delineated in ArcMap 10.6 (Esri, Redlands, United States) based on visual interpretation and fieldwork knowledge of canopy shape and spacing. The maximum height or height at the 99th percentile of each delineated tree crown was then calculated using the "Zonal Statistics as Table" tool in ArcMap 10.6 from each dataset for comparison. We used height at the 99th percentile for the TLS and ALS datasets to exclude outliers caused by noise in the datasets, which in some cases produced point clouds with unrealistic tree heights (e.g. a laser return from a bird or a bee). A detailed flowchart of the individual data processing steps for measuring tree crown height of individual trees is presented in Fig. 2.

2.2.2. Terrestrial laser scanning data collection and processing

The RIEGL VZ-400 TLS system was mounted on a tripod at the height of approximately 1.5 m above ground level. The RIEGL VZ-400 scanner records up to four returns per emitted pulse.The scan resolution of the TLS data is 0.06°. Through inclination sensors and an internal compass, the RIEGL VZ-400 also collects pitch, roll and yaw information. The information on the applied TLS settings is provided in Table 2. To minimize occlusion issues of the TLS data, 8–10 scan locations were used from the avocado orchard while eight scan locations were selected for the mango orchard in each of the four campaigns. A vertical scan was conducted at each location for the mango trees, while a vertical and 90 degrees tilt scan were collected at each scan location for avocado trees to ensure that the entire tree was scanned. Multiple cylindrical reflectors were set up around scan locations to ensure each two locations included at least the same four reflectors. This allowed data from different scan locations to be co-registered based on the same reflectors and then combined to achieve the maximum coverage of trees. To register the TLS data to real world coordinates for comparison, firstly a reference TLS scan collected from August 2016 was registered to ALS data using the RiSCAN PRO (RIEGL, Horn, Austria) coarse registration tool, then, the multi Station Adjustment tool in RiSCAN PRO was applied to improve registration. The reflector targets measured in TLS scans from each separate position were then used to register other scan positions. All other TLS scans collected from other dates were registered to the data collected in August 2016 using the coarse registration tool and multi Station Adjustment tool in RiSCAN PRO. Tree height at the 99th percentile within each defined pixel was derived to create a single CHM using lascanopy in LAStools (rapidlasso GmbH, Gilching, Germany) for each orchard and each sampling event. Finally, the maximum height within each delineated tree crown was calculated for accuracy analysis.

2.2.3. Airborne laser scanning data capture and processing

The ALS data were provided by AAM Australia using an airborne small-footprint RIEGL LMS-Q 1560 laser scanner. The average flying height was 600 m above ground level with a 1064 nm wavelength, a pulse repetition of 400 kHz, at an off-nadir angle of up to 30 degrees, a

Table 1
Overview of collected data types used for assessing and comparing height measurements of avocado and mango tree crops at four different campaigns, i.e. April/May 2016, July/Aug2017, February 2017 and September 2017. The number of trees used for comparison between the different data collection methods for each of the campaigns is specified.

Image Datasets	Tree Crop Type	April/May 2016	July/Aug 2016	Feb 2017	Sep 2017
Terrestrial Laser Scanning	Avocado	7 May 52 trees	15 August 74 trees	5 February 60 trees*	
	Mango	3, 4 May 77 trees	15 August 79 trees	3 February 39 trees	7 September 39 trees
Airborne Laser Scanning	Avocado		31 July 74 trees		
	Mango		31 July 79 trees		
WorldView-3 Stereo imagery	Avocado	7 April 52 trees			
	Mango	7 April 77 trees			
UAV based multi-spectral imagery	Avocado			2 February 60 trees	
UAV based RGB imagery	Mango			3 February 39 trees	
Laser rangefinder measurements	Avocado			2 February 20 trees	
Measuring staff measurements	Mango				21 September 39 trees

* 20 trees used to do the inter-comparison with field measurements.

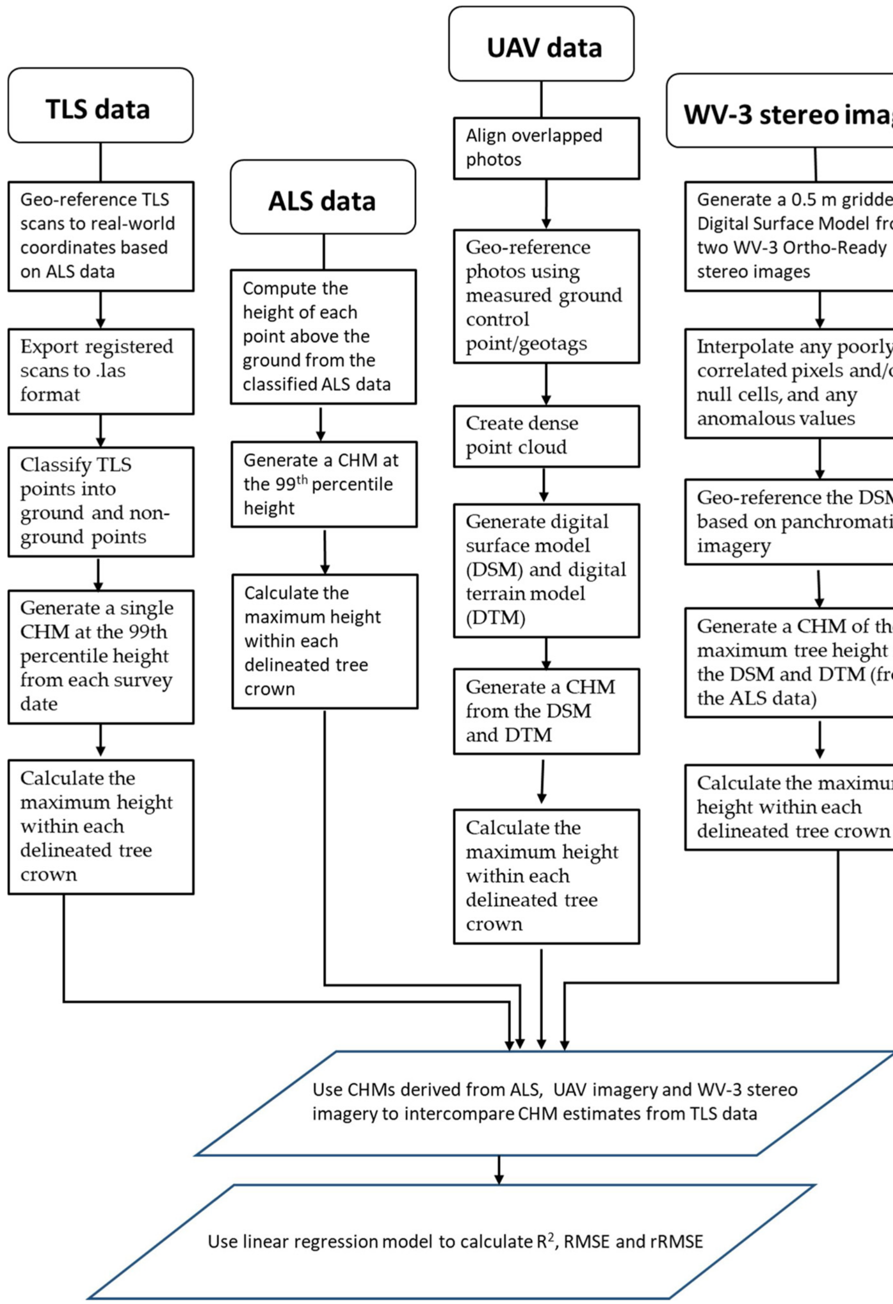

Fig. 2. Flowchart of evaluating the accuracies of canopy height estimates from Ground Laser Scanning (TLS) data, Airborne Laser Scanning (ALS) data, Unmanned Aerial Vehicle (UAV) imagery and WorldView-3 (WV-3) stereo imagery.

Table 2
RIEGL VZ-400 scanner settings for data acquisitions at each of the four campaigns.

Beam divergence	0.35 mrad (i.e. at the range of 50 m the beam footprint size = 0.0175 m)
Pulse repetition rate	300 kHz
Minimum range	1.5 m
Maximum range	160 m (at 20 % target reflectance) 350 m (at 90 % target reflectance)
Azimuth range	0
Zenith range	30- 130°
Recorded data	Full waveform & up to four returns per emitted pulse

beam divergence of 0.5 mrad and a scan overlap of 25 %. The average emitted pulse density was 10.32 pulses/m^2 and the full point density was calculated at 13.63 points/m^2 with a maximum of seven returns. The reported vertical and horizontal accuracies were 0.03 m and 0.02 m, respectively, based on 120 ground control points. ALS data in. las format were classified into ground, vegetation and unclassified by the data provider. Tree height at the 99th percentile within each defined pixel was derived to create a single CHM using lascanopy in LAStools (rapidlasso GmbH, Gilching, Germany) for each orchard. The maximum height of each tree crown was used for the accuracy analysis.

2.2.4. WorldView-3 stereo image capture and processing

WV-3 is a commercial satellite owned and operated by DigitalGlobe (Westminster, Colorado, United States). A WV-3 Ortho-Ready Standard Level 2A panchromatic stereo image pair was captured on 07 April

Table 3
Acquisition parameters of the WorldView-3 image pair.

	Acquisition Date	Overlap	In-track view angle (°)	Cross-track view angle (°)	Off-nadir view angle (°)	Azimuth angle of the satellite (°)
WorldView-3 imagery 1	07 April, 2016	100 %	−13.3	−5.8	14.5	353.3
WorldView-3 imagery 2	07 April, 2016	100 %	14.6	−4.1	15.0	211.6

2016. The two images had 100 % overlap over the study area and were collected on the same satellite orbit and with different look angles (Table 3). SOCET GXP® (Arlington, Virginia, United States) was used in the stereo matching, and the Next Generation Automatic Terrain Extraction (NGATE) algorithm in SOCET GXP was used to generate a DSM. Poorly correlated pixels and null cells were interpolated, and the DSM was georeferenced using WV-3 panchromatic imagery that was collected on the same date and covered the same area. An accurate DTM was available from the ALS data collected on 31 July 2016, and was used in combination with the WV-3 derived DSM to create a CHM for deriving the maximum height of each tree crown.

2.2.5. UAV data collection and processing

The multi-spectral UAV imagery was collected with a Parrot Sequoia® multi-spectral camera (Parrot Drone SAS, Paris, France) mounted on a 3DR Solo (3D Robotics, Berkeley, USA) quadcopter under clear sky conditions. The Parrot Sequoia sensor consists of four bands located in the green, red, red edge and NIR part of the spectrum (Table 4). Agisoft MetaShape Pro (previously called Agisoft PhotoScan Pro, Agisoft LLC, St. Petersburg, Russia) was used to process the multi-spectral UAV imagery. A limit of 40,000 key points and 10,000 tie points was set for photo alignment. Ten AeroPoints® (54 cm × 54 cm × 3.5 cm in size) were evenly deployed within the study area. The coordinates of each AeroPoint were recorded for five hours and post-processed using the Propeller® network based on the nearest base station, which is located in Bundaberg about 26 km from the fieldwork site. The ground control points (GCP) derived from the AeroPoint centres were then used for the geometric correction. The root-mean-square error (RMSE) of the GCPs was 0.07 m and the overall projection error was 0.6 pixel. To ensure most points were included, a mild noise filter was applied to densify the point cloud. The densified point cloud was used to identify ground points and generate a digital surface model (DSM) and a digital terrain model (DTM). Three critical parameters were used to classify the ground points – max angle, max distance and cell size. A maximum angle of 15 degrees was used as the study site has a nearly flat terrain and a maximum distance of 28 cm was used to separate points from the terrain model. Cell size indicates the largest feature in the study area, which was set to 10 m to correspond to the maximum avocado canopy diameter in the study area. Finally, a CHM was generated by subtracting the DTM from the DSM and the maximum CHM value within each canopy was used for the accuracy analysis.

Phantom 4 RGB UAV imagery was collected on 3 February 2017 (Table 5). Pix4Dmapper (Pix4D S.A., Lausanne, Switzerland) was used to process the RGB UAV imagery for photo alignment. The mean projection error was 0.2 pixel. The point cloud was densified before classification. Ground points were classified in Pix4Dmapper using a machine learning algorithm. The Delaunay triangulation algorithm was used to generate a DSM, and a DTM was created by the interpolation of classified ground points only. Next, we subtracted the DTM from the DSM to produce a CHM. The 3D point cloud was automatically geo-referenced through geotags embedded in the photos, but to improve the horizontal geo-referencing accuracy, the CHM was then georeferenced based on the CHM from the TLS data. Finally, a maximum CHM value for each tree crown was calculated for comparison with the canopy height estimates from the TLS data.

Table 4
Parrot Sequoia multi-spectral UAV imagery acquisition parameters.

Image bands and band width	Green (550 nm, 40 nm bandwidth), red (660 nm, 40 nm bandwidth), red edge (735 nm, 10 nm bandwidth), and NIR (790 nm, 40 nm bandwidth)
Flight pattern	Along tree rows
Flying height	75 m above ground level
Photo overlap	80 % sidelap, 92 % forward overlap
Time and date	2:11–2:25 pm, 2 February 2017
Flight speed	5 m/s
Solar elevation angle	60°
Pixel size	0.14 m

Table 5
RGB UAV image acquisition parameters.

Imagery bands	Blue, green and red band
Flight pattern	Along tree row
Flying height	50 m above ground level
Photo overlap	80 % sidelap, 85 % forward overlap
Time and date	8:48-8:51 am, 3 February 2017
Flight Speed	5 m/s
Solar elevation angle	44°
Pixel size	0.10 m

2.2.6. Field canopy height measurements

A measuring staff was used to measure the height of the individual mango trees. This method was feasible due to the limited height (2 − 4 m) of the assessed mango trees, the sufficient spacing between trees and the ease of visually identifying the highest point of each tree crown. The use of a measuring staff was not possible for the avocado trees because of their height (7 − 10 m) and their complex canopy structure, which made it difficult to identify the tallest point of the individual tree crowns. While the use of a laser rangefinder was found more suitable for the avocado trees, especially when used from a distance > 15 m, in many cases it was not possible to achieve this distance because of the close proximity of trees and lack of spacing between rows, which caused other trees to visually obstruct parts of the tree crowns. While special care was taken, potential errors in the angular measurements between the trunk base and the tree apex may have caused over- or underestimation of avocado tree height. As the base of the trunk of the avocado trees was often offset in relation to the tallest part of the tree, we aimed at obtaining the angular measurements from a direction where the vertical distance to the trunk base and the tree apex was the same.

2.2.7. Inter-comparison of canopy height estimates

The measured height comparisons were conducted in data set pairs. TLS data were collected at each of the four campaigns. Therefore, canopy height estimates derived from the ALS data, WV-3 stereo imagery, Phantom-4 RGB imagery, Parrot Sequoia multi-spectral imagery and field measurements could consistently be compared with canopy height estimates from TLS data, separately. Although, TLS data tend to underestimate tall trees (e.g. > 15 m (Wang et al., 2019)), in an orchard environment where all the sampled trees are shorter (Figs. 3 and 4) and sufficiently spaced, TLS data were considered most appropriate for an inter-comparison of canopy height measured from different remote sensing platforms and sensors. The position of the TLS scans was registered to the ALS data using the coarse registration tool and multi Station Adjustment tool in RiSCAN PRO as outlined in Section 2.2.2.

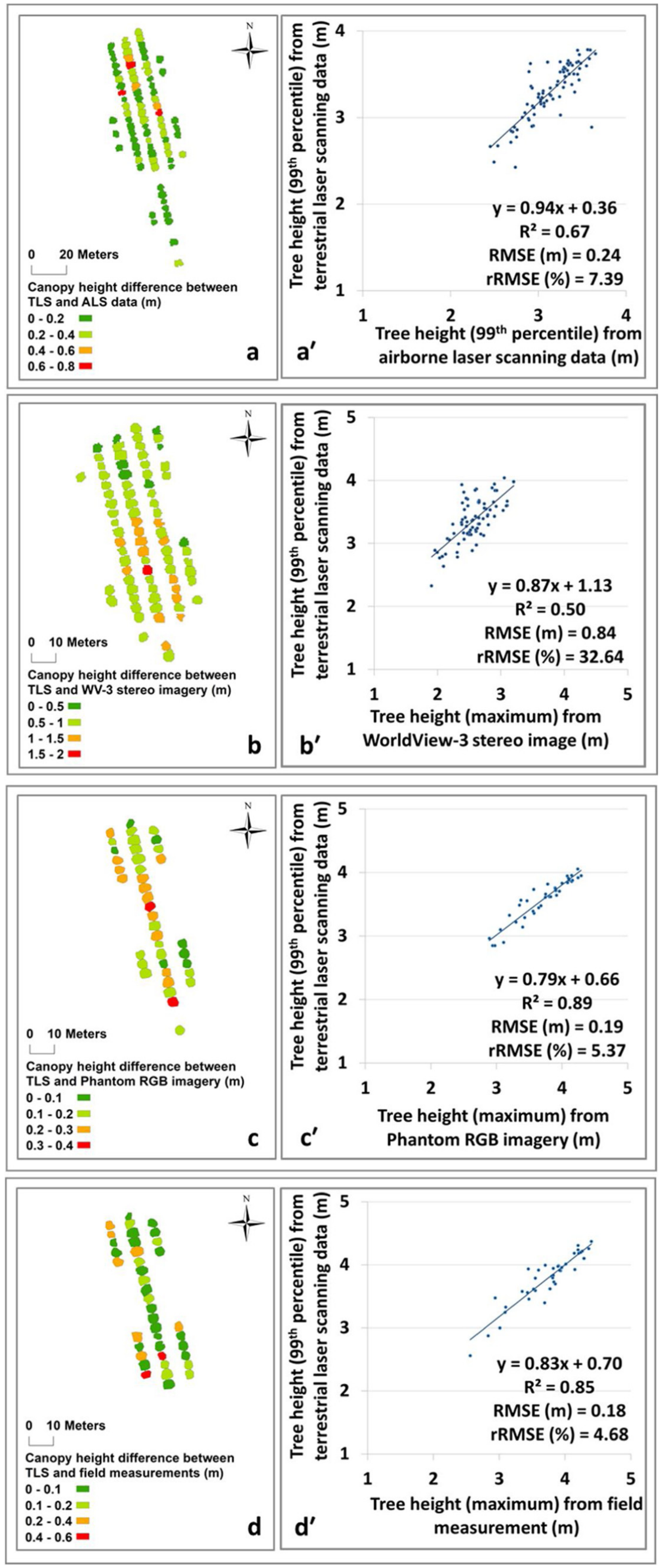

Fig. 3. Canopy height difference and linear regressions of canopy heights for mango trees between two different datasets, i.e., TLS data collected on 15 August 2016 vs. ALS data collected on 31 July 2016 (a, a′), TLS data collected on 3 and 4 May 2016 vs. WorldView-3 stereo imagery collected on 7 April 2016 (b, b′), TLS data collected on 3 February 2017 vs. Phantom 4 imagery collected on 3 February 2017 (c, c′), and TLS data collected on 7 September 2017 vs. field measurements using a measuring staff collected on 21 September 2017 (d, d′).

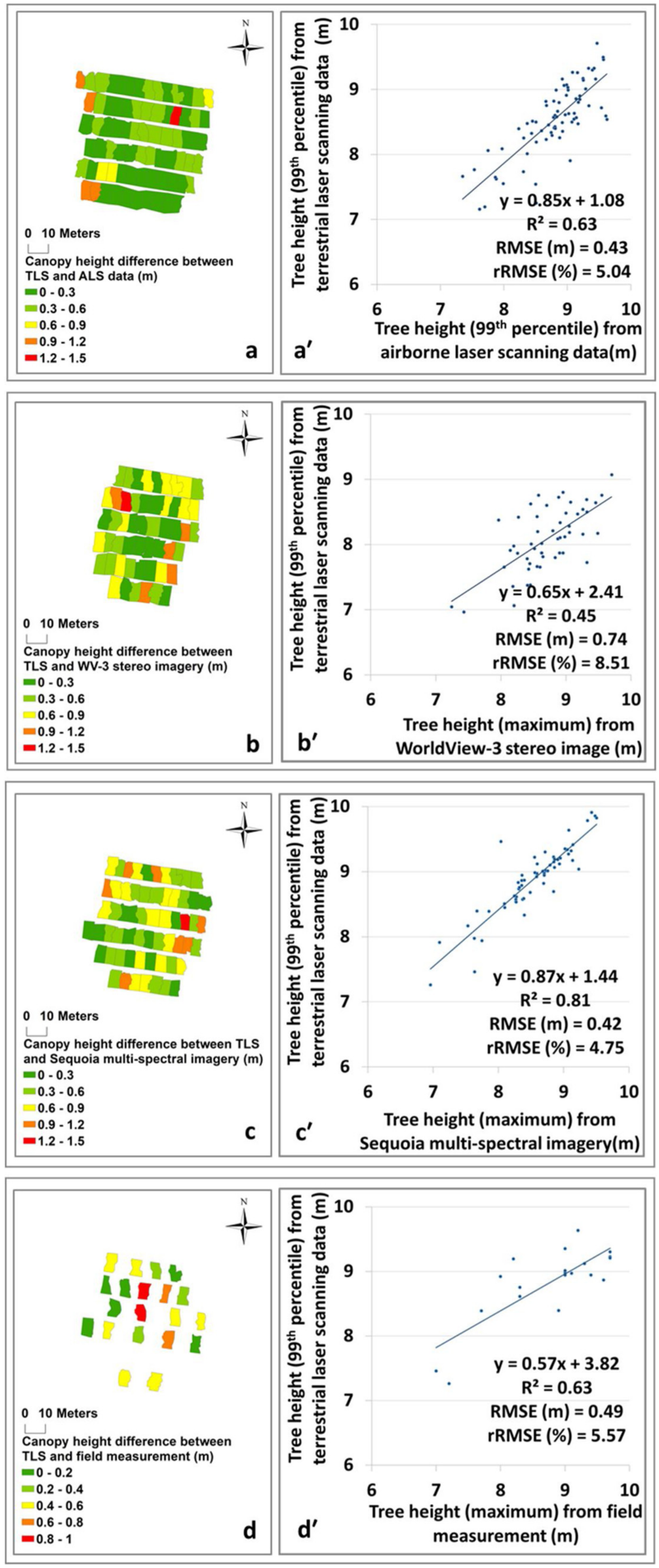

Fig. 4. Canopy height difference and linear regressions of canopy height for avocado trees between two paired datasets, i.e., TLS data collected on 15 August 2016 vs. ALS data collected on 31 July 2016 (a, a′), TLS data collected on 7 May 2016 vs. WorldView-3 stereo imagery collected on 7 April 2016 (b, b′), TLS data collected on 5 February 2017 vs. UAV multispectral imagery collected on 2 February 2017 (c, c′), and TLS data collected on 5 February 2017 vs. field (laser rangefinder) measurements collected on 5 February 2017 (d, d′).

CHMs from WV-3 stereo imagery, Phantom-4 RGB imagery, and Parrot Sequoia multi-spectral imagery were also georeferenced to the ALS CHM. To examine the magnitude of the canopy height difference, maximum, minimum and average height, deviations were calculated between each evaluated dataset and the TLS data. Also, the coefficient of determination (R^2) using linear regression between the maximum tree crown heights derived from the TLS data and all the other datasets were calculated. RMSE and relative RMSE (rRMSE) were used for error estimations (Persson and Perko, 2016; Hyndman and Koehler, 2006). To include the maximum number of trees for each analysis, the sample size was different for each paired dataset. rRMSE is independent of sample size, and therefore, it is suitable for assessing model performance in this study. Model accuracy was considered excellent if $rRMSE < 10\ \%$, good if $10\ \% < rRMSE < 20\ \%$, fair if $20\ \% < rRMSE < 30\ \%$ and poor if $rRMSE > 30\ \%$ (Despotovic et al., 2016).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (\widehat{X_i} - X_i)^2}{n}} \tag{1}$$

$$rRMSE = \frac{RMSE}{\overline{X}} \tag{2}$$

where n is the number of sampled tree crowns, $\widehat{X}$ is the CHM value from the assessed datasets (i.e. ALS, WV-3 stereo imagery, UAV RGB and multi-spectral imagery, and field measurements) and X_i is the CHM value derived from the TLS data. $\overline{X}$ represents the mean sampled CHM value from the TLS data.

3. Results

3.1. Canopy height estimates for mango trees

Using the 99th percentile for crown height estimates from TLS data as a reference, Fig. 3 shows the accuracy of canopy height derived from ALS data, WV-3 stereo imagery, UAV RGB imagery, and field measurements using a measuring staff. All linear models were significant ($p < 0.001$). The crown height estimates produced from the Phantom RGB imagery had the highest accuracy ($R^2 = 0.89$, rRMSE = 5.37 %) when assessed against the TLS based tree heights, closely followed by field measurements ($R^2 = 0.85$, rRMSE = 4.68 %) and then ALS data ($R^2 = 0.67$, rRMSE = 7.39 %). The height estimates derived from the WV-3 stereo imagery produced the lowest accuracy ($R^2 = 0.50$, rRMSE = 32.64 %) (Fig. 3a′,b′,c′,d′).

In most cases (72 out of 81 trees), crown height estimates were underestimated by ALS data. This underestimation can be the effect of many factors, such as point density, the laser footprint size, flight altitude, pulse repetition rate, intensity of the returns and the quality of the DTM (Wang et al., 2019; Yu et al., 2012; Maltamo et al., 2004). Low point density and a large footprint size can cause underestimation of tree heights due to the possibility of missing the maximum height of the canopy (Roussel et al., 2017).

The canopy height estimates were consistently underestimated by the WV-3 stereo imagery in relation to the TLS data (77 out of 77 trees). Forest canopy height estimation from WV stereo imagery has been reported to achieve high accuracy (adjusted $R^2 > 0.81$, rRMSE < 10 %) (Persson and Perko, 2016), but in our case the stereo imagery only achieved an $R^2 = 0.50$ and an rRMSE = 32.64 % for mango trees. The underestimation of canopy height achieved in the orchard environment may have been attributed to the small tree crown size (average crown diameter = 2.7 m), the pruned and hence sparse canopy centre of individual tree crowns (Fig. 1 (e)).

The height estimates derived from the RGB UAV imagery were slightly overestimated in relation to the TLS derived measurements (average absolute height deviation = 0.18 m) in 37 out of 39 cases. According to the data processing report from Pix4Dmapper, the RMSE of the vertical geolocation accuracy was 0.62 m, which might have contributed to the height overestimation. Underestimation of canopy height can also be caused by coarse spatial resolution relative to tree canopy size, inaccuracies of 3D reconstruction, insufficient forward overlap and sidelap, and overestimation of the DTM elevation when used to produce the CHM together with the DSM (Tu et al., 2019a; Swinfield et al., 2019; Tu et al., 2019b). Underestimations were also detected on canopy height estimates from UAV data for avocado, lychee and olive trees (Tu et al., 2019a; Johansen et al., 2018; Díaz-Varela et al., 2015). Flying heights and the accuracy of 3D construction on branches may influence the accuracy of canopy height estimation of horticultural tree crops (Tu et al., 2019a; Johansen et al., 2018).

There was no clear bias of mango canopy height from the field measurements using the measuring staff. Twenty-three out of 39 trees were underestimated in relation to the TLS derived height measurements. The average absolute height deviation from TLS data was only 0.12 m, making it a reliable although time-consuming means for tree crown height estimation of short (< 5 m) trees. Wang et al. (2019) indicated that the increasing complexity of forest stand and tree height increases the uncertainty and underestimation of field canopy height measurements. Easy field access (row distance = 9 m) and low tree height (< 5 m) contributed in this case to the high accuracy of the field derived canopy height measurements of the mango trees.

3.2. Canopy height estimates for avocado trees

Fig. 4 illustrates the accuracy of canopy height estimates, assessed against TLS measurements, of individual avocado trees from ALS data, WV-3 stereo imagery, UAV multi-spectral imagery and field measurements using a laser rangefinder. All linear regression models were significant ($p < 0.001$). The derived tree height estimates from UAV multi-spectral imagery had the highest accuracy ($R^2 = 0.81$, rRMSE = 4.75 %), followed by ALS data ($R^2 = 0.63$, rRMSE = 5.04 %) and field measurements ($R^2 = 0.63$, rRMSE = 5.57 %) The WV-3 stereo imagery had the lowest accuracy ($R^2 = 0.45$, rRMSE = 8.51 %) (Fig. 4a′,b′,c′,d′).

The CHM for most of the avocado trees (60 out of 74 trees) was overestimated by the ALS data in relation to the TLS data. ALS data were collected at a time when avocado trees were due for annual pruning. Most of the avocado trees in this study were between 7 − 10 m tall with dense and multi-layered canopy structure. Dense and structurally complex canopy can reduce ground point returns for DTM interpolation (Chasmer et al., 2006). The low ground point density has contributed to a less accurate DTM which contributed errors in the canopy height estimation (Leitold et al., 2015; Clark et al., 2004).

Canopy height estimates of avocado trees were mostly underestimated when using the WV-3 stereo imagery (48 out of 52 trees). The complex and somewhat open canopy structure of the mature avocado trees, and the relatively coarse spatial resolution (0.50 m) of the WV-3 stereo imagery attributed to the height underestimation. The WV-3 stereo image derived DSM pixel values represented an average height of the different canopy layers, branches and the ground. Hence, an open canopy structure is likely to cause an underestimation of tree height.

Underestimation of canopy height also occurred when using the UAV based multi-spectral imagery (56 out of 60 trees), which was consistent with other canopy height estimation studies using UAV imagery (Tu et al., 2019a; Johansen et al., 2018; Díaz-Varela et al., 2015). With a flying height of 75 m, the viewing angle of trees is not as extreme as for lower flight altitudes. Increasing the flying altitude has been attributed to the underestimation of CHMs in other UAV based studies of horticultural tree crops (Johansen et al., 2018). Although we used mild filtering in the processing of the dense point cloud to retain as much detail of each tree crown as possible for the 3D reconstruction, studies have shown that the adaptive threshold algorithms can produce similar results with a shorter data processing time (Salamí et al., 2019).

Similar to the mango trees, there was no clear trend of

Table 6
Comparison of accuracy assessments between mango and avocado canopy height estimation from ALS data, WorldView-3 stereo imagery, UAV imagery (Phantom 4 imagery for mango trees and Parrot Sequoia multi-spectral imagery for avocado trees) and field measurements assessed against TLS derived canopy height.

	RMSE (m)	rRMSE (%)	R^2	Mean absolute height deviation (m)	Over- or underestimation
ALS (mango)	0.24	7.39	0.67	0.20	underestimation
ALS (avocado)	0.43	5.04	0.63	0.33	overestimation
WorldView-3 stereo imagery (mango)	0.84	32.64	0.50	0.84	underestimation
WorldView-3 stereo imagery (avocado)	0.74	8.51	0.45	0.49	underestimation
Phantom 4 imagery (mango)	0.19	5.37	0.89	0.18	overestimation
Sequoia multispectral imagery (avocado)	0.42	4.75	0.81	0.37	underestimation
Field measurement (mango)	0.18	4.68	0.85	0.12	N/A
Field measurement (avocado)	0.49	5.57	0.63	0.41	N/A

underestimation or overestimation of canopy height from the field based laser rangefinder measurements in this study, as 50 % of the tree height measurements were over- and underestimated in relation to the TLS data. While special care was taken to identify the tree apex when undertaking the laser rangefinder measurements, it was often difficult to determine if the vertical distance to the trunk base and the tree apex was the same. Hence, the triangulation measurements might have been inaccurate in some cases, causing over- or underestimation of tree crown height in relation to the TLS measurements.

3.3. Comparison of canopy height estimation accuracy between mango and avocado trees

With the exception of the WV-3 stereo imagery, all the other data types produced higher measurement accuracies of height for the mango trees compared to the avocado trees (Table 6). However, it is worth noting that while the RMSE was higher for the avocado trees for the ALS, UAV and field datasets, the percentage height over- and/or underestimation was similar for the mango and avocado trees.

The ALS data produced rRMSE and R^2 values that were very similar for both the mango and avocado trees. However, the RMSE was almost twice as high for the avocado trees (0.43 m) than the mango trees (0.24). It is also interesting to note that when compared to TLS canopy height estimates, most (72 out of 81 trees) mango trees were underestimated, while the majority (60 out of 74 trees) of avocado trees was overestimated by the ALS data. ALS data generate lower point densities than TLS data, and because of the somewhat open and complex canopy structure of the avocado trees, the footprint of each ALS returns may not represent the tallest parts of the canopy or the intensity of the returned pulses, representing the tallest parts of the trees, may not fall above the threshold required for registration. Hence, it was surprising to observe an overestimation of avocado tree crown height. It is likely that the DTM might have been affected by the limited number of ground returns due to the avocado tree structure and limited spacing between hedgerows. The mean ground point density for the mango orchard was 5.39 points/m^2 while it was only 3.59 points/m^2 for the avocado orchard. Also, the hedgerow structure might have caused neighbouring trees to overlap with the delineated avocado trees and hence caused some trees' height to be overestimated. One last explanation of the observed ALS overestimation of avocado tree height could be the inability of the TLS to measure the upper avocado tree crowns due to occlusion caused by the canopy height and the limited spacing between hedgerows, especially for trees located further away from the scan locations. Other studies have reported occlusion issues of tall and dense trees causing canopy height underestimation using TLS data (Wang et al., 2019).

The low spatial resolution (0.5 m pixels) of the DSM generated from the WV-3 stereo imagery in relation to the small canopy size of mango trees was attributed to the lower accuracy of the canopy height estimates compared to those for the avocado trees. If assessed in relation to height, the percentage underestimation of avocado trees (rRMSE = 8.51 %) was much lower than that for the mango trees (rRMSE = 32.64 %). This indicates that WV-3 stereo imagery may be better suited for height estimation of tree crops above 10 m, where the relative height error is minimized. Large trees, representing more pixels, with a dense and flat canopy might produce even better results than those recorded for the avocado trees.

Using the UAV imagery for tree height measurements produced the highest accuracy for both mango and avocado trees. The UAV-based SfM used to derive tree height produced a higher accuracy for mango trees than that for avocado trees. The relatively high spatial resolution of the Phantom 4 RGB imagery (0.10 m) for mango trees and the Parrot Sequoia multi-spectral imagery (0.14 m) for the avocado trees allowed a dense point cloud, and hence a DSM to be generated using SfM and MVS for both tree crop types. Spacing between tree rows allowed identification of ground points so that a DTM could be derived for the generation of a CHM. While the multi-spectral UAV imagery, including the red edge and NIR bands, in theory should be better suited for identification of tree crowns than RGB imagery, the somewhat open and complex canopy structure of the avocado trees compared with the denser and more compact crown structure of the mango trees is likely to have produced higher height accuracies for the mango trees than for the avocado trees.

Field derived height measurements of the mango trees (R^2 = 0.85, RMSE = 0.18 m and rRMSE = 4.68 %) achieved higher accuracy than that for the avocado trees (R^2 = 0.63, RMSE = 0.49 m and rRMSE = 5.57 %). These differences can be directly related to the denser and shorter mango trees in relation to the structurally more complex and higher avocado trees. While one person was holding the measuring staff next to the mango trees, it was relatively easy for an observer to identify the tree apex and related height on the measuring staff, whereas this approach was not feasible for the taller avocado trees.

4. Discussion

All the datasets used for measuring tree height in this study exhibited advantages and disadvantages in terms of the data coverage, flexibility of acquisition, and accuracy levels. The fact that the TLS data (RIEGL VZ-400) had the highest spatial resolution TLS and were collected for all four campaigns made it the most appropriate reference data set for canopy height inter-comparison between the other remote sensing platforms and sensors. However, the spatial coverage of the TLS data is limited to a small number of nearby trees due to occlusion issues, scanning range limits and intensive time and labour requirements. Due to occlusion issues, it is generally not possible to "see" behind trees. Reflectors need to be set up at every plot to enable geo-referencing of multiple TLS scans, which can be time-consuming Wilkes et al. (2017); Wu et al. (2018). On the other hand, TLS data provide a very dense and accurate point cloud for detailed 3D tree structure assessment (Wu et al., 2018; Newnham et al., 2012).

Currently, UAVs can only collect imagery for smaller areas (0.01–10 km^2), depending on flying height, speed and type of platform (multi-rotor or fixed-wing) due to limited battery life (and hence flying time) and government based drone flight restrictions. Both the Phantom 4 and 3DR Solo mounted with the Parrot Sequoia multispectral camera can only fly for about 15 – 25 min, whereas a fixed-wing UAV may fly for up to 90 min (senseFly, 2020). Although a fixed-wing UAV such as the eBee X platform can cover up to 5 km^2 at around 120 m flying height within 90 min (senseFly, 2020) the line-of-sight regulation (regulation implemented in many countries, e.g. the US (Federal Aviation Administration, 2020), UK (de Miguel Molina, 2018) and Australia (Australian Goverment Civil Aviation Safety Authority, 2020)) and optimal UAV flight variables (e.g. overlap, flying height and solar angle elevation requirements) still reduce the coverage of UAV imagery to smaller areas (< 10 km^2). Orchard size varies a lot, but most of the avocado and mango orchards are smaller than 0.5 km^2. Therefore, UAVs are suitable for canopy height mapping at the orchard level. The SfM derived high point cloud density and the flexibility of use make UAV imagery highly suitable for canopy height estimates at the orchard level at a very high temporal and spatial resolution.

With an average revisit time of 4.5 days (at 20° off-nadir or less) (Satellite Imaging Corporation, 2020), WV-3 stereo imagery can cover a large area (25–10,000 s km^2). However, in this study, due to the coarser spatial resolution (0.5 m pixels) in relation to the small canopy size of horticultural tree crops and the row-based orchard environment, WV-3 stereo imagery did not produce satisfactory height estimates of mango trees and had lower canopy height estimates for avocado trees compared to those derived from the other remote sensing datasets. However, the percentage underestimation of tree height was reduced for taller avocado trees and with the use of a calibration factor to account for the underestimation, the WV-3 stereo imagery may be suitable for large area measurements of tree height for tall horticultural tree crops. It is suggested that a higher spatial resolution is required for this application, compared to a forest environment because of the single-standing trees. Persson and Perko (2016) concluded that spatial resolution is a vital factor to accurately estimate canopy height using stereo imagery and canopy height of sparse forests tends to be underestimated. Lagomasino et al. (2015) assessed a forested area in southern Mozambique and also found that stereo imagery is better suited for estimating canopy height of taller trees. Laser pulses from small-footprint airborne LiDAR sensors can penetrate through the canopy to the ground (Clark et al., 2004). Laser returns classified as ground points from ALS data can be used to produce a Triangulated Irregular Network (TIN), which can be rasterised to derive a DTM (Montealegre et al., 2015). ALS data have become a common technology to derive a DTM over large areas with high precision, and it is also regarded as the only tool to produce a high quality DTM under dense canopies (Clark et al., 2004; Montealegre et al., 2015). A WV-3 stereo image derived DTM can be created using a filtering approach by removing non-ground areas from the DSM and then using interpolation methods to fill the holes (Perko et al., 2015). In a dense orchard environment (e.g. avocado orchards), ALS data tend to achieve higher DTM accuracy than stereo imagery WV-3 stereo imagery if the ground is obstructed by the canopy. The DTM from WV-3 imagery can still be used to calculate canopy height if the orchard floor is flat. However, for orchards on sloping land, a highly accurate and high spatial resolution DTM from ALS data can improve canopy height estimations from WV-3 imagery.

Traditional field measurements can achieve an accuracy that is comparable to LS and photogrammetric canopy height measurements (Wang et al., 2019; Krause et al., 2019). Wang et al. (2019) suggested that appropriately trained people can provide canopy height measurements at higher precision. Therefore, effective field canopy height measurements by experienced people at the orchard level is an option for growers too, but might be affected by the lack of hedgerow spacing, especially for tall and dense trees for which the tree apex may be difficult to identify due to visual obstruction from neighbouring trees. Field measurement instruments such as laser rangefinders require restricted observation positions, the angular measurements need to be obtained from a direction where the vertical distance to the trunk base and the tree apex was the same. Wang et al. (2019) reported that the occlusion by neighbouring trees and hilly terrains introduce errors to field canopy height measurements.

Although orchard size varies considerably, the majority of the avocado and mango orchards within the Bundaberg region are smaller than 0.5 km^2. Some commercial growers own multiple orchards, including Simpson Farms in Bundaberg, which covers 7.7 km^2 of avocado orchards and 0.8 km^2 of mango orchards (Simpson Farms, 2020). Developed countries like the US and Australia tend to have larger orchard sizes than developing countries. Some exceptions, however, include avocado orchards in Florida, where most of the orchards cover less than 0.06 km^2 (Evans and Lozano, 2014). The majority of mango production occurs in developing countries (e.g. India, Thailand, Mexico, Indonesia), where orchard sizes vary. For example, the average mango orchard size per household in Thailand is about 0.04 km^2 (Phavaphutanon, 2015). Large-scale macadamia farms are found in China and South Africa, whereas Kenya has approximately 200,000 small farms (Australian Macadamia Society, 2020; Gitonga et al., 2009). Therefore, traditional field based canopy height measuring methods are still suitable for growers with orchards covering smaller areas (< 0.5 km^2). Although canopy height measurements for horticultural tree crops are desired on an annual basis to guide pruning and sprayer calibration, it is not a routine practice in Australia for growers to measure tree height. As such there is no industry standard for required mapping accuracies. Field canopy height measurements in this study provided high accuracy for both mango (R^2 = 0.85 and RMSE = 0.18 m) and avocado trees (R^2 = 0.63 and RMSE = 0.49 m). For industries or growers to adopt a new technology to measure canopy height, it should be at a similar or higher level of accuracy compared to the conventional field measurements collected by experienced people. Based on our results, both UAV imagery and ALS data can produce comparable or higher accuracy compared to field measurements (Figs. 3 and 4). Field-based methods are either inaccurate, inconsistent or are not suited for measuring other canopy structural parameters such as canopy cover at the orchard level (Miranda-Fuentes et al., 2015; Jiménez-Brenes et al., 2017). The remote sensing data sets (TLS, ALS, UAV, WV-3) tested in this research all have the capability to be used for other canopy structural measurements such as canopy cover, which can provide additional information on irrigation, fertilisation and suitable pruning techniques (Johansen et al., 2018; Lordan et al., 2015). Hence, future work should focus on integrating height measurements and other canopy structural parameters (e.g. canopy cover) for more informed and improved pruning and sprayer calibration approaches. Relating these structural measurements as well as various pruning and sprayer calibration approaches to yield and fruit quality should also be a focus of future work.

This study showed that UAVs offer an alternative to traditional field based tree height measurement methods and are capable of providing measurements of similar levels of accuracy. While the collection of UAV imagery is more costly for small areas than field based measurements, UAV based measurements can be extended to larger areas. The UAV data collection process will generally be faster than that for field based measurements for larger areas, but subsequent image processing and height derivation methods for individual tree crowns add additional time and costs to the process. However, a UAV image dataset allows further information suitable for horticultural management practices to be extracted coincidently (e.g. tree condition (Tu et al., 2019a), biophysical parameters such as canopy extent (Johansen et al., 2018), plant projective cover (Tu et al., 2019a; Johansen et al., 2018), information suitable for pruning practices (Johansen et al., 2018; Jiménez-Brenes et al., 2017), and irrigation information if thermal sensors are used concurrently (Espinoza et al., 2017)), which is useful input for precision agriculture of individual tree crops. Also, UAV image based datasets can be collected frequently and enable retrospective studies to be undertaken. Finally, the processing workflow of UAV image data has the potential to be automated and hence substantially reduce costs and ensure consistency related to information extraction

(Lisein et al., 2013). Based on an experiment with avocado trees, Tu et al. (2019b) concluded that optimal tree height estimates can be obtained if flying along the hedgerow, with a small pitch angle, at high solar elevation, with 75 % image sidelap and high forward overlap (> 80 %). However, further studies need to be conducted based on other sensors and UAV platforms as well as different types of tree crops.

Extraction of individual tree crowns allows crop condition to be monitored at the individual tree level (Jiménez-Brenes et al., 2017). High spatial resolution UAV and satellite imagery has been investigated for automatic tree crown delineation of horticultural tree crops (Tu et al., 2019a; Johansen et al., 2018; Mu et al., 2018; Johansen et al., 2019). Previous research has concluded that the overlapping tree crowns within continuous hedgerows of horticultural trees prevent automatic extraction of individual tree crowns even from very high spatial resolution imagery. For example, Tu et al. (2019a) found that avocado tree crowns cannot be automatically extracted from multi-spectral UAV images with 14 cm pixels and Johansen et al. (2019) (in review) concluded that 30 cm WV-3 pan-sharpened imagery was not capable of automatically delineating individual macadamia tree crowns. Both avocado and mango trees were manually delineated in this study. While developing an automated tree crown delineation approach for horticultural tree crowns was not the focus of this research, automatic tree crown delineation of mango trees might be possible due to their spacing. Hence, it is recommended for future work to focus on assessing the mapping accuracies of mango tree crown delineation approaches.

While 3D information obtained from UAV-based SfM can produce highly accurate canopy height estimates, traditional satellite stereo imagery are generally restricted to two sensor viewing angles at a set spatial resolution. In this study, the WV-3 stereo imagery produced the lowest accuracy of height measurements for both mango and avocado trees (Figs. 3 and 4). The relatively high cost (~US $70/km^2) and coarser spatial resolution of WV-3 stereo imagery compared to UAV imagery make this type of dataset less suitable for estimating canopy height at the orchard level. WV-3 imagery is available to users after about a week of acquisition (including the quality assurance time from the imagery provider). It is suggested that a higher spatial resolution can create more accurate canopy height estimates (Straub et al., 2013; Zarco-Tejada et al., 2014; Johansen et al., 2018). WV-3 stereo imagery achieved a much higher accuracy for forest canopy height estimates (adjusted $R^2 > 0.81$, rRMSE < 10 %) (Persson and Perko, 2016) than for the mango ($R^2 = 0.50$, rRMSE = 32.64 %) and avocado trees ($R^2 = 0.45$, rRMSE = 8.51 %) assessed in this study. It is likely that WV-3 stereo imagery may be better suited for a continuous forest cover than horticultural tree crops grown separately or in hedgerows. Due to the phenological cycle and canopy management requirement (e.g. pruning and hedging) for horticultural tree crops, timing is crucial for measuring canopy height. While the WV-3 sensor has a high temporal repeat cycle, cloud cover may still impact the collection of suitable data at crucial times.

As opposed to satellite stereo imagery, the collection of ALS data is generally not affected by clouds, which facilitate data collection at crucial times coincidently with important phenological events. Estimates of canopy height derived from ALS data in this study proved accurate regardless of the height of trees, crown shape, and species (Wang et al., 2019). However, depending on point density and footprint size in relation to tree structures, ALS data may underestimate tree height. To accurately identify the highest point of a tree crown, a footprint of a laser beam will need to hit the exact location of the tree apex, but at the same time the return from the part of the tree crown representing the apex will need to be strong enough to be registered (Goodwin et al., 2006; Gaveau and Hill, 2003). Hence, it is important to carefully consider the flight acquisition parameters of ALS data to ensure that the acquired data are fit for purpose. By testing different flight altitudes (400 m, 800 m and 1500 m), Yu et al. (2012) concluded that the increase in flight altitude increases the level of underestimation of canopy height. Although there was no significant statistical difference in height estimated collected at 400 m and 800 m, a significantly higher canopy height underestimation was at 1500 m. Yu et al. (2012) and Persson et al. (2020) found that the laser footprint size was not a key factor in estimating canopy height of forest. They also found that the pulse density to be a critical factor that affects canopy height estimation Yu et al. (2012); Persson et al. (2020). Although this may vary between tree species,Roussel et al. (2017) reported that to achieve an accuracy with a mean bias of less than 10 cm, approximately 10 pulses/m^2 are required. There is no study on optimal ALS data acquisition parameters for different horticultural tree crops. However, ALS data acquisition parameters for this study were based on these suggested parameters in forestry areas (e.g. the average flight altitude = 600 m and the average pulse density = 10.32 pulses/m^2). (Table 6). Based on our results, the selected ALS acquisition specification were suitable although future studies may benefit from an increased pulse density with smaller footprints for better identification of the tree apex of structurally complex crowns.

TLS data are the most accurate and precise dataset of those tested for measuring canopy height as long as the TLS can be set up with at a distance providing a view of the canopy and its apex. The distance requirements to cover the upper canopy depends on the scanner's zenith view angle and tree height. A high precision TLS (i.e. RIEGL VZ-400) costs about US $105,000, while some low cost TLS instruments are also available on the market (Kelbe et al., 2015). While TLS is a reliable measuring approach of canopy height for horticultural tree crops, it is mainly suited for small areas, for research purposes and for collection of highly accurate data for validation of other tree height measurement approaches. Traditional field measurements conducted by appropriately trained people can provide cost-effective canopy height measurements at high accuracy for small areas (< 1 km^2). UAV imagery can provide tree crown measurements with high accuracy for larger areas than both TLS and field data and at a much lower cost than TLS data (Table 7). However, for areas > 10 km^2, UAV imagery becomes less feasible due to the time required for data collection and associated issues with varying solar elevation and azimuth angles, the size of the datasets and the subsequent data processing. For areas > 10 km^2, ALS data become a better option than UAV data. High point density ALS data (> 10 points/m^2) provide accurate horticultural canopy height estimates over larger area (10 – 1000s km^2) (Table 7). However, further research is required to determine the suitable point density, footprint size, flying altitude, and pulse repetition rate in relation to different horticultural tree crops. Based on this and other studies (e.g. (Yu et al., 2012)), a flight altitude is between 400 m – 800 m and a point density higher than 10 points/m^2 are required. However, due to the high cost (US $500-1000/km^2) (Table 7), ALS data are not suitable for canopy height measurements at the orchard level for individual growers. For very large area mapping (> 10,000 km^2), stereo-capable satellites with a spatial resolution similar to WV-3 become the best possible solution, although only suitable with moderate accuracy for larger horticultural tree crops with a crown diameter > 4 m and a tree height > 5 m. Data fusion may be an option for large area horticultural trees growth monitoring in the future. For example, canopy height estimates from WV stereo imagery may be calibrated based on the ALS data to use WV-3 stereo imagery as the primary source for monitoring tree growth over large areas. However, it will be important to identify scenarios when WV-3 stereo image may or may not be suited, which would require ALS data for calibration for the area being monitored. While these recommendations are based on the findings of this study, further research is required to determine the suitability and accuracy of image datasets used for other horticultural tree crops with different canopy size, canopy shape, structure and planting density.

5. Conclusions

Canopy height and density measures are critical parameters to

Table 7
Comparison of cost and accuracy between TLS, ALS, WV-3 imagery, UAV imagery and field measurements. In this case, flexibility is defined as the potential repetitiveness in data acquisitions. The vertical accuracy of TLS data was from the specification of the RIEGL VZ-400. The vertical accuracy of other datasets are the RMSE (m) and the rRMSE (%) assessed against the 99th percentile of the TLS derived canopy height.

	Accuracy	Coverage	Flexibility	Cost
TLS (i.e. RIEGL VZ-400)	0.005 m (range accuracy)	< 0.1 km^2	High flexibility but time consuming	~US $105,000+ labour costs for deployment (some lower cost TLS instruments are available, but this study only used the RIEGL VZ-400 as an example)
ALS	RMSE = 0.24 m & rRMSE (%) = 7.39 (mango trees) RMSE = 0.43 m & rRMSE (%) = 5.04 (avocado trees)	10 – 1000s km^2	Low	US $500-1000/$km^2$ (The costs will vary depending on the size of the study area, location, and terrain)
WV-3 stereo imagery	RMSE = 0.84 m & rRMSE (%) = 32.64 (mango trees) RMSE = 0.74 m & rRMSE (%) = 8.51 (avocado trees)	25 – 10,000 s km^2	Medium	~US $70/$km^2$
UAV imagery	RMSE = 0.19 m & rRMSE (%) = 5.37 (mango trees) RMSE = 0.42 m & rRMSE (%) = 4.75 (avocado trees)	0.01 – 10 km^2	Very high	Upfront cost for a DJI Phantom 4 and batteries of ~US $2000 ~US $3870 with upfront cost for a 3DR Solo + a Parrot Sequoia camera + labour costs for deployment and subsequent image processing
Field measurements	RMSE = 0.18 m & rRMSE (%) = 4.68 (mango trees) RMSE = 0.49 m & rRMSE (%) = 5.57 (avocado trees)	< 1 km^2	Very high	~US $20/hour

measure for mango and avocado trees, as they affect optimal light interception, yield, fruit quality, harvest cost and pruning practices. This study used canopy height estimates from TLS data as a reference to evaluate the accuracy, cost, spatial coverage and flexibility of capture of other remote sensing platforms and sensors, including ALS data, UAV based RGB and multi-spectral imagery, and WV-3 satellite stereo imagery as well as traditional field measurements. It was found that UAV imagery provided the highest accuracies and level of flexibility for measurements of tree height and that it is suitable for collecting tree height information from approximately $1-10$ km^2. Below 1 km^2, field based measurements may be more appropriate, while for areas larger than 10 km^2, ALS data become most cost-effective. WV-3 stereo imagery was found not suitable for small tree crops (< 5 m) such as the mango trees assessed in this study, while moderate accuracies could be achieved for larger and taller tree crops such as mature avocado trees. This information may help industries and growers select the most appropriate approach, remote sensing dataset and associated acquisition parameters to assess canopy height for mango and avocado trees.

There are many other horticultural tree crops for which the measurements of individual tree crown height are equally important, e.g. macadamia, citrus, apple and olive trees. All of these tree species have different structural and spectral characteristics, which may affect measurements of tree height. Hence, further experiments are needed to test the accuracy of measuring tree height based on canopy structure variations (e.g. size, shape, and density), differences in leaf colour, and different planting densities. With a large array of available UAV-based RGB and multi-spectral sensors, there is also future scope for assessing which characteristics of different sensors are most influential on tree height measurements. Although we only used two UAV sensors in our experiment, our findings related to UAV-based imagery should be applicable to other 2D imaging sensors, as the 3D reconstruction technique to produce DSMs is the same. While optimal UAV-based flight planning parameters for mapping avocado tree height have already been identified in another study, future work may provide different results for other tree crops. With clear guidelines for when to use different datasets in relation to the accuracy, cost, spatial coverage and flexibility of data collection, remote sensing approaches such as those applied in this study have the potential to better inform management practices and assess their implications at the individual tree level to increase productivity and yield quality. Such guidelines may ensure that growers are able to meet the requirements of an increasingly competitive market and regionally and globally contribute to optimized growing practices required to feed a growing population.

Author contribution

D.W., K.J., S.P., and A.R. jointly conceived and designed this study; D.W. lead the field data collection with the contribution of K.J., S.P., A.R. and Y.T.; D.W. processed and analysed the data with the contribution of K.J. and Y.T., and led the writing of the paper with all authors making contributions.

Declaration of Competing Interest

The authors declare no conflict of interest.

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