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Unmanned aerial vehicle based tree canopy characteristics measurement for precision spray applications

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ABSTRACT

The critical components for applying the correct amount of agrochemicals are fruit tree characteristics such as canopy height, canopy volume, and canopy coverage. An unmanned aerial vehicle (UAV)-based tree canopy characteristics measurement system was developed using image processing approaches. The UAV captured images using a high-resolution red-green-blue (RGB) camera. A digital surface model (DSM) and a digital terrain model (DTM) were generated from the captured images. A tree canopy height map was generated from the subtraction of DSM and DTM. A total of 24 apple trees were randomly targeted to measure the canopy characteristics. Region of interest (ROI) was generated across the boundary of each targeted tree. The height of all pixels within each ROI was computed separately. The pixel with maximum height was considered as the height of the respective tree. For computing canopy volume, the sum of all pixel heights from individual ROI was multiplied by the square of ground sample distance (GSD) of 5.69 mm·pixel^{-1}. A segmentation method was employed to calculate the canopy coverage of the individual trees. The segmented canopy pixel area was divided by the total pixel area within the ROI. The results showed an average relative error of 0.2 m(6.64%) while comparing automatically measured tree height with ground measurements. For tree canopy volume, a mean absolute error of 0.25 m^3 and a root mean square error of 0.33 m^3 were achieved. The study estimated the possible agrochemical requirement for spraying the fruit trees, ranging from 0.1 to 0.32 l based on tree canopy volumes. The overall investigations suggest that the UAV-based tree canopy characteristics measurements could be a potential tool to calculate the pesticide requirement for precision spraying applications in tree fruit orchards.

1. Introduction

Accurate and precise agrochemical application based on tree canopy characteristics is important for sustainability as it can assist in reducing excessive chemical usage, especially for tree fruit crop production [1]. Tree canopy characteristics include height, canopy volume, and canopy coverage. Canopy height is recognized as an acceptable representation of biomass [2,3]. Canopy volume is an important attribute that measures the three-dimensional structure of trees. Canopy coverage approximates variations of tree canopies in the orchard blocks. Measurement of these characteristics appears thus a highly appealing endeavor to apply the correct amount of agrochemicals and reduce spray drift.

Technologies have been developed to measure these characteristics using different ground-based sensing systems, such as mobile platforms and tractors with either camera sensor [4,5], ultrasonic sensors also called sonar [6,7] or with light detection and range (LiDAR) sensors often called laser sensors [8,9]. However, ground-based sensing systems have limitations in uneven and hilly terrains and may not be effective for canopy characteristics measurements in undrivable orchard conditions or remote regions. Travel speed is considered as another limitation, and the ground-based system may not be efficient when driving through large-scale orchards with variable slopes. In recent years, unmanned aerial vehicles (UAVs) equipped with sensors have been used for various agricultural crop phenotyping applications due to their flexibility in acquiring ultra-high spatial and temporal resolution data at any time under suitable conditions [10] and ability to quickly cover large areas

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[11]. Sensors, such as cameras (visible, multispectral, and hyperspectral) and LiDAR can be attached to the UAV to measure canopy characteristics including plant height [12]. However, canopy volume and canopy coverage measurements require accurate visualization details of every feature of tree canopies from real orchards. LiDAR gives only the point clouds of canopies which cannot produce accurate details of features. Conversely, high-resolution RGB camera attached with a UAV captures images that can be stitched together to create an orchard model which provides visual details of all features of tree canopies. Another advantage of using RGB sensors over LiDAR is they are low in cost and high in versatility [13]. Recent successes of RGB sensors on UAV systems for crop phenotyping in field conditions [14,15] show promise for canopy characteristics measurements.

Advances in image processing algorithms have contributed to the evolution of UAV technologies by estimating 3D-structure of crops from 2D-image sequences. The Structure-from-motion (SfM) technique [16] has been used to retrieve 3D crop information, which does not need any prior calibration because intrinsic camera parameters are automatically estimated during the processing [15]. The SfM algorithm generates a 3D digital surface model (DSM), which includes the height of the objects, such as crops. Holman et al. [17] used SfM to measure crop height of wheat and achieved a Root Mean Squared Error (RMSE) of 0.03 m compared with manual measurement. Han et al. [18] estimated sorghum plant height using SfM and obtained a correction (R^2) of >0.80 while comparing ground truth. Many efforts have been reported in height measurement for field crops using SfM, but little has been done in tree fruits that need to be investigated.

The SfM algorithm provides a good description of a DSM but generation of a digital terrain model (DTM) is needed to calculate the tree canopy height and volume which is dependent on clear visibility of the ground [19]. Fruit trees grow in a row with a certain tree-to-tree and row-to-row distance, which makes the ground easily visible in DSM and is therefore suitable for DTM generation. Retrieving canopy volume from DSM and DTM models requires height estimation of all individual tree pixels. Estimation of total tree pixel heights requires searching pixels within a specific cluster. The K-means clustering algorithm can be applied to group pixels or points of individual trees [20]. This can be a useful approach to finding pixels in a cluster but it may lead to inaccurate results due to tree canopies touching adjacent trees. Generation of a region of interest (ROI) for each tree can be an effective solution before conducting search operations for individual tree canopy volume measurement.

Estimating tree canopy coverage often necessitates segmenting trees from the ground. Usual segmentation methods are color based and involve thresholding a green canopy index map computed from RGB bands. One of the potential approaches to segment green canopies is the Canopeo algorithm introduced by Patrignani et al. [21]. Ashapure et al. [22] used this algorithm to extract green canopies of cotton to develop a yield prediction model and achieved an R^2 of $\sim$0.9 while comparing predicted and observed yields. Wang et al. [23] applied the Canopeo algorithm to segment and estimate green turfgrass canopy coverage. Although this algorithm has been utilized for other crops, little or no application has been reported for fruit trees, especially for apple trees; thus, it may be a potential method for tree canopy coverage measurement.

There have been a few attempts to measure tree canopy characteristics using UAV systems. Sinha et al. [24] estimated apple tree canopy parameters including tree-row-volume, leaf-wall-area, and canopy volume. They used the "zonal statistics" plugin from QGIS for the estimation where the canopy volume was calculated as a cuboid by multiplying maximum canopy height, ROI width and length. However, an apple tree has a pyramidal shape where canopies vary with sections across the height. Kothawade et al. [25] estimated apple tree canopy volume in a v-trellis architecture and achieved inferior results compared with manual measurements. Moreover, none of previous studies estimated the possible spray volume required for apple trees. The spray volume estimation is important for fruit growers to budget the agrochemical expenses. The spray volume has a direct relationship with tree canopy characteristics. Trees with less canopy will require less spray volume. Conversely, trees with high canopy volume will require high spray volume. Tree canopy characteristics will help control the sprayer's nozzles to reduce excessive chemical applications.

The main goal of this study was to measure height, canopy volume, and canopy coverage of apple trees and estimate the possible agrochemical or spray volume requirement of individual trees using a UAV-based system. The specific objectives were to 1) apply imaging algorithm with SfM for apple tree canopy height measurement, 2) examine image processing with k-means clustering approach for canopy volume measurement and approximate the spray volume requirement of trees, 3) implement Canopeo based segmentation algorithm for canopy coverage measurement.

2. Materials and methods

2.1. Study site and referencing

Field experiments were conducted in a GoldRush apple cultivar orchard block at the Penn State Fruit Research and Extension Center (PENN-FREC) (39°56′15.5″N 77°15′22.1″W) in Biglerville, PA, USA (Fig. 1). Total area of the experimental field was approximately 0.9 acres, consisting of six rows with 36 trees in each row. The trees were planted in 2009 and trained in a tall spindle architecture with a tree-to-tree spacing of 1.2 m and a row-to-row spacing of 6.1 m. The block was not completely flat and had an elevation difference of approximately 0.3 m from upper eastern part to lower western part. The block was mowed using a reel mower on as-need basis before experiments to lower the height of grasses in the orchard. The trees received adequate irrigation through the season to promote growth and to prevent stress.

A total of 12 white paper boards were placed on reference trees. The board dimension was 0.51 m $\times$ 0.76 m(width $\times$ height). Trees at the left and right rows from the board were considered as references for canopy characteristics measurements. A total of 24 trees were randomly chosen for the manual and UAV-based tree height and canopy volume measurements. The canopy coverage was measured for all trees in the site to generate the canopy coverage map. A total of 12 ground control points (GCPs) were marked based on 12 board locations. An Inertial Navigation System-Global Navigation Satellite System (INS-GNSS) (INS-D, Inertial Labs, Paeonian Springs, VA, USA) with 1 cm position accuracy was used to collect the geographical location of the GCPs.

2.2. Ground measurements of tree canopy characteristics

Ground measurements of tree canopy characteristics were performed before the aerial image data collection. Apple tree heights were manually measured for 24 selected trees using a measuring tape (Lufkin 25′, Cooper Hand Tools, Apex, NC, USA) by climbing to the top of the tree with a steel ladder.

A 3D light detection and ranging (LiDAR)-guided canopy sensing system developed by Mahmud et al. [9] was used to measure the ground-based apple tree canopy volume. The LiDAR first scanned the trees and then stored the scanned data in a 64-bit Dell 3541 laptop computer (Dell, Round Rock, TX, USA). The travel speed of the system was approximately 4.5 km·h^{-1} ($\pm$0.5) during scans. The LiDAR to tree distance was 3.05 m and the system was driven at the center of the row. The open-source VeloView software (Velodyne LiDAR, San Jose, CA, USA) was used to record the scanning data. The scan data were preprocessed to remove unwanted point clouds (points from ground, non-targeted trees, and other objects sited in the orchard). Only the point clouds from targeted tree canopies were segmented by setting an ROI. The ROI of -1.0 to 1.0 min the x-axis, 2 to 4 m (for left side tree) or -4 to -2 m (for right-side tree) in the y-axis, and -1.8 to 1.8 min the z-axis were selected. The preprocessed points were used to reconstruct

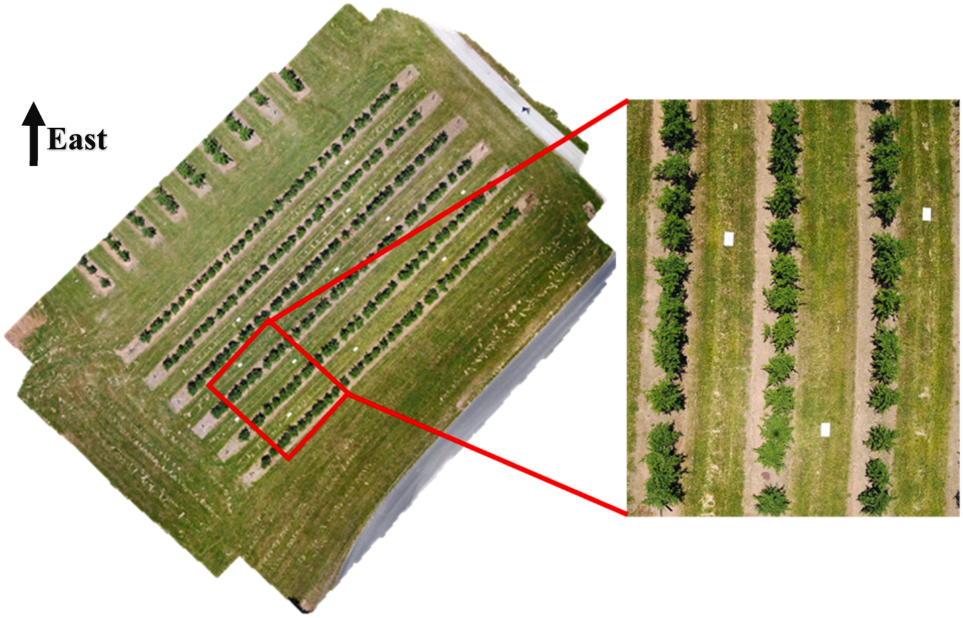

Fig. 1. Experimental site with white paper boards that marked the reference tree positions.

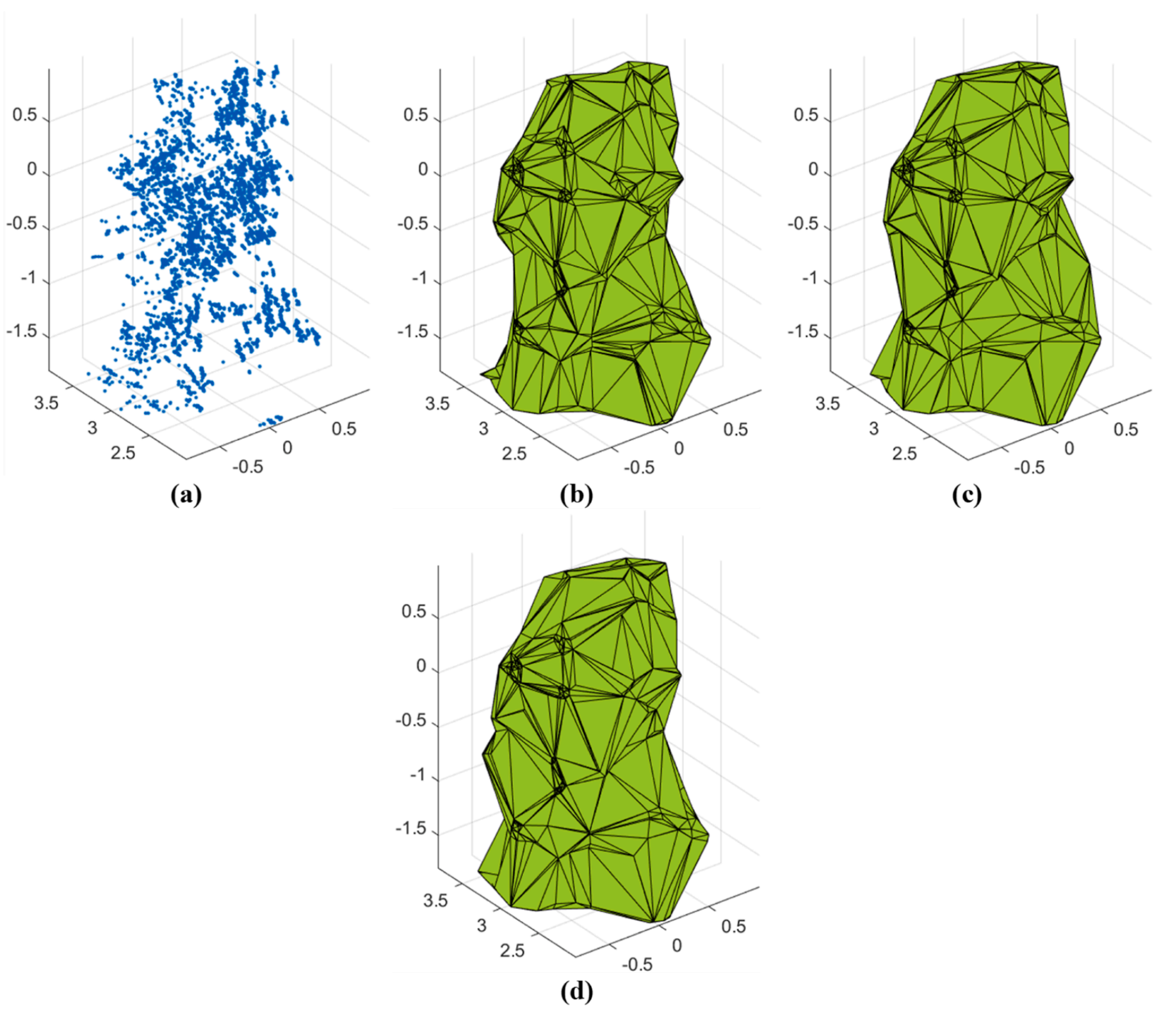

Fig. 2. LiDAR-guided tree canopy volume measurements using an alpha shape algorithm (a) segmented individual tree point clouds (b) a 3D reconstructed canopy volume with alpha value of 0.35 (c) a 3D reconstructed canopy volume with alpha value of 0.40 (d) a 3D reconstructed canopy volume with alpha value of 0.45.

the tree shape to calculate canopy volume. An alpha shape algorithm (Dylan [26]) was used with three alpha values (0.35, 0.40, and 0.45) to calculate individual tree volume (Fig. 2). The canopy point clouds preprocessing and processing steps were described in detail by Mahmud et al. [9], while it did not measure any ground-based canopy coverage due to the complexity and impracticality compared to aerial measurement.

2.3. Aerial image data collection

Images were acquired using a rotary-wing unmanned aerial vehicle (UAV) DJI Matrice 200 (DJI Technology Inc., Shenzhen, China) with a high-resolution RGB Zenmuse X5S camera (DJI Technology Inc., Shenzhen, China) on June 21, 2021 (Fig. 3). The flight control Pix4D-capture software (Pix4D Inc., Lausanne, Switzerland) was used to generate the flight path (setting waypoints), set flight speed and altitude, and capture images. Images were captured from a constant flying altitude of 30 m above ground level (AGL) from the take-off location. The flight path and speed (5.76 km·h^{-1}) were planned according to 30 mAGL. A 75% forward and sideward overlap was used between subsequent images for the UAV image data collection. The flight was operated at noon eastern daylight time (EDT) during apple tree's petal fall growth stage by a licensed unmanned aerial system (UAS) remote pilot with a visual observer. Each captured image resolution was 5280 × 3956 pixels (width × height), resulting in a GSD or spatial resolution of 5.69 mm. pixel^{-1}. A total of 59 images were captured over the orchard. The captured images were stored on a secure digital (SD) card for further processing. All of the captured images included geographical coordinates from the onboard UAV geographical positioning system (GPS). Weather conditions on the image collection day were recorded from a local weather station at PENN FREC, Biglerville, PA. Weather conditions included a relative humidity of 53%, a low wind speed condition with a wind direction of 234°, an air temperature of 89.2°F, and full sun.

2.4. Image analysis for tree canopy characteristics

Fig. 4 illustrates the procedure for preprocessing and processing steps of UAV-captured images.

2.4.1. Pre-processing

The preprocessing steps included alignment of individual acquired images, geometric correction, dense point cloud generation, classification of ground and tree points, mesh and texture generation, orthomosaic map, DSM (digital surface model), and DTM (digital terrain model) generation. The UAV captured images were uploaded and the recorded

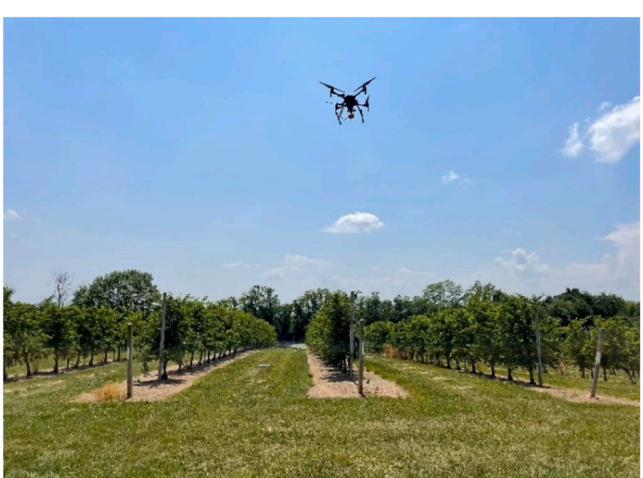

Fig. 3. UAV in flight at the experimental apple orchard.

GCPs were imported from the computer. The images were then aligned using Agisoft Metashape Pro software (Agisoft LLC, St. Petersburg, Russia). The WGS 84 zone (EPSG: 4326) was chosen as the output coordinate system. The aligned images contained location bias due to geographical coordinates collected from the low accuracy onboard UAV GPS. Geometric correction was performed using the 12 ground collected GCPs to bind the true location so that the stitched image could reduce the location bias value. Dense point clouds were generated from the geographically corrected images based on SfM algorithm [16] using Agisoft Metashape Pro software. The dense point clouds are a group of elevation points in thousands or millions of point resulting from the UAV image photogrammetry process. Dense point clouds from the ground, trees, and other objects were classified using a built-in "multi-class classification" function in Agisoft Metashape Pro software (Agisoft, LLC. St. Petersburg, Russia). The mesh and texture were generated to produce maps. An orthographic high-resolution image or map of the entire experimental orchard was obtained by stitching the corrected images. The DSM and DTM (with geometric classification function "Classify Ground Points") were then generated with the software by considering classified dense point clouds after correcting the location bias (Fig. 5a & Fig. 5b). For the DSM, all dense point clouds including ground, trees, and other objects were used. However, only the ground point clouds were used for DTM generation. The accuracy of georeferencing was about 0.03 m(3 cm) in DSM and DTM generation. An orchard orthomosaic image or map was also generated with the corrected location. All the maps were geo-referenced.

A subtraction between DSM and DTM generated a height map of apple trees (Fig. 5c). The DSM of the orchard included elevation information for the apple trees and ground relative to the mean sea level. The DTM included elevation information for only ground relative to the mean sea level. Therefore, the subtraction of these two models provided only heights for the apple trees. The raster calculator from the open-source Quantum GIS (or QGIS) software [27] was used to perform the subtraction of geo-reference images.

2.4.2. Image processing for tree height and canopy volume measurements

An image processing algorithm was developed for individual tree height measurement using the resulting subtracted image. The algorithm was developed in MATLAB®. The algorithm began by reading the image, then generating a pixel intensity histogram to find the lowest and highest intensity values. The image was then adjusted based on setting the ground intensity level as the lower limit and highest intensity value as the upper limit. There were no objects other than trees in the image, hence the highest intensity value must be recorded from one of the trees in the orchard. This step was important to avoid calculating tree height from lower than ground level. The Speeded-Up Robust Features (SURF) algorithm [28] was used to perform the 3D reconstruction of the resulting map from the DSM and DTM substruction, and then a built-in plotting tool was used to visualize the image pixel intensity in 3D space showing all tree heights (Fig. 6). The adjusted image was displayed in a jet colormap to generate the color height map of trees. The height map was cropped and rotated. The algorithm capable of rotating based on given rotational degree. The next step was to separate individual tree pixel intensity to extract height. The ROI was generated by manually inserting the required number and size of the ROI into the algorithm and placed over the targeted trees that were used for manual tree height measurements. A total of 24 ROIs were generated to extract and measure the height of 24 targeted trees (Fig. 7). The non-zero intensity pixel within the ROIs were identified. The non-zero intensity pixels were tree canopy pixels where zero intensity pixels were ground pixels. The K-means clustering algorithm [29] was used to extract the non-zero intensity pixels by assigning an index value of 2 (one for non-zero intensity pixels and another from zero intensity pixels). The maximum intensity value within the extracted non-zero intensities of pixels of an ROI was considered as height of the particular tree. The mean intensity value within the ROI was also calculated, but it was not suitable to

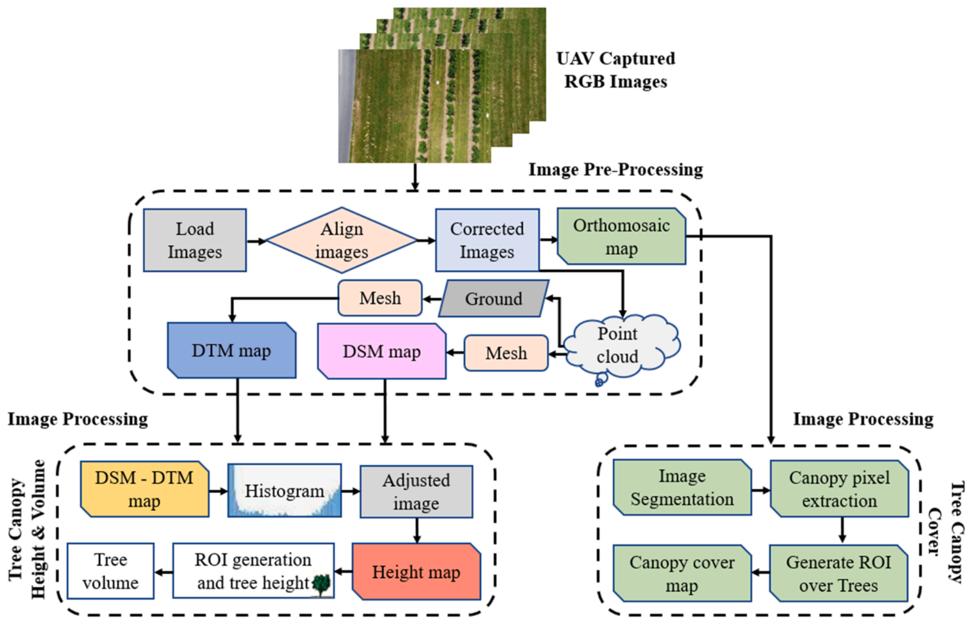

Fig. 4. Steps for tree canopy characteristics measurements through image analysis.

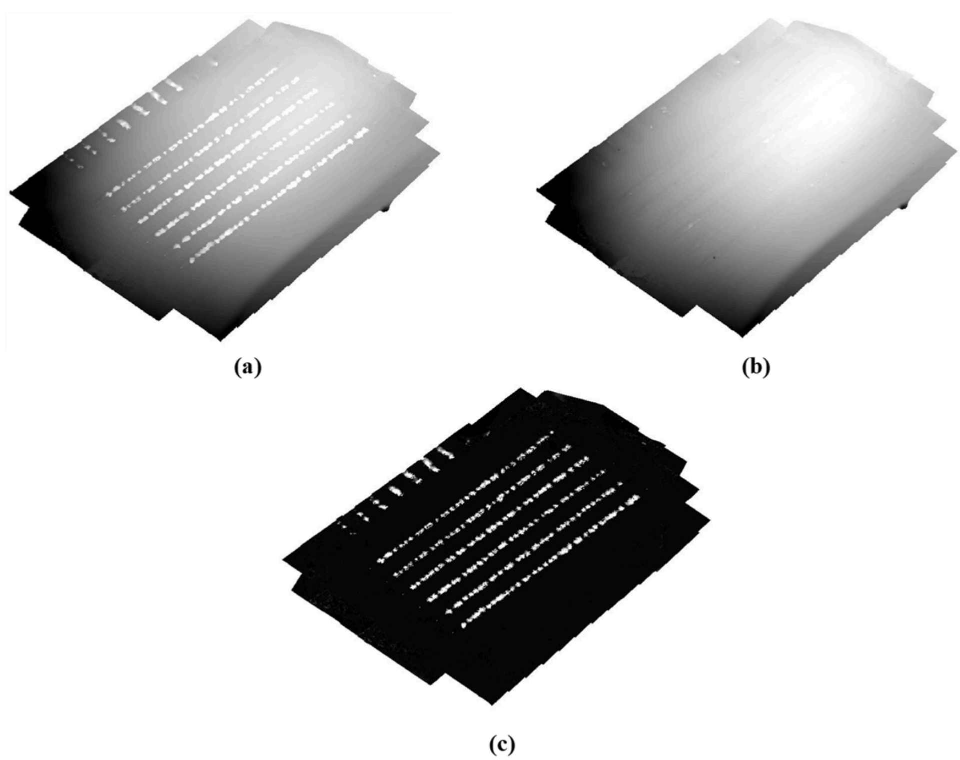

Fig. 5. Preprocessing step of UAV captured images (a) generated DSM (b) generated DTM (c) a resulting apple tree height map from DSM and DTM subtraction.

consider as tree height. The apple trees were in a pyramidal shape hence some of intensity values from side canopies were low and the calculated mean was lower than the actual tree height.

The total intensity height from all pixels within the ROI was calculated to measure the individual tree canopy volume. The canopy volume of the targeted trees (Eq. 1) was computed by multiplying total height of the intensity of all pixels with the area of GSD. A graphical illustration of the tree canopy volume procedure is presented in Fig. 8.

$$\text{Tree Canopy volume } (m^3) = \sum_{i=1}^{n} \text{Height of the pixel}_i \times GSD^2 \quad (1)$$

where Height of the pixel$_i$ is the height of the ith pixel and n is the total number of pixels for a tree.

2.4.3. Approximation of agrochemical requirement

The possible chemical requirement for spraying each experimental tree was estimated to provide the growers with an understanding of their

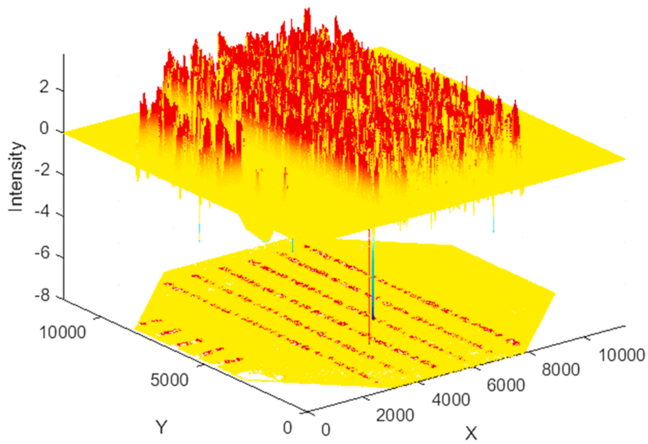

Fig. 6. Visualizing pixel intensities from all trees in 3D space.

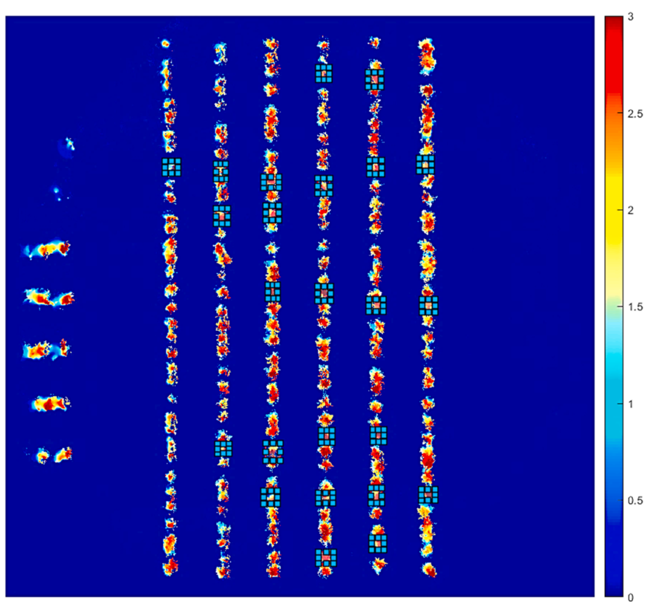

Fig. 7. Apple tree color height map with 24 generated ROIs over 24 targeted trees. The color bar at the right shows the tree height in meter. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

agrochemical expense in tree fruit orchards. The chemical requirement was computed based on the maximum spray liquid retention capability of the fruit trees. At this spray volume, all canopy foliage surfaces are supposed to be wetted to the point of the first run-off. According to Furness et al. [30], the usage of 80 l of spray volume is standard for 1000 m^3 of tree canopy volume, considering the maximum canopy retention volume. Therefore, this study employed the chemical use of 0.08 l per m^3 of tree canopy volume while calculating the spray volume for the selected 24 experimental trees.

2.4.4. *Image processing for canopy coverage measurement*

The canopy coverage percentage was computed by a Canopeo segmentation algorithm [21] using Eqs. (2) and (3). The RGB orthomosaic was converted into a binary map based on Eq. (2) where white pixels represent tree canopies, and black pixels represent non-canopy. The white pixels between apple tree rows represented grass. The ground area under each tree area did not include any grass; therefore, calculating white pixels from that area only represented tree canopies. ROIs were generated over the apple tree rows. The canopy pixels and the total number of pixels within each ROI were computed. The ratio of canopy pixels and total pixels within each ROI was calculated using Eq. (3) to compute the percentage canopy coverage of the experimental orchard.

$$\text{Tree Canopy} = \left(\frac{B}{G} < 0.95\right) \text{ AND } \left(\frac{R}{G} < 0.95\right) \text{ AND } ((2G - B - R) > 20) \tag{2}$$

where B is the blue color channel, G is the green color channel, and R is the red color channel.

$$\text{Canopy Coverage} = \left(\frac{\left(\sum (GSD^2)\text{if canopy}\right)}{\sum (GSD^2)} \times 100\right) \tag{3}$$

where GSD is the distance between two consecutive pixel centers measured on the orchard ground.

2.5. *Statistical analysis*

Results of the UAV-based tree height and canopy volume measurements using RGB sensors were compared with manual tree height and LiDAR canopy volume measurements by calculating MAE and RMSE. A paired t-test was also performed. The canopy volume measurement measured with difference alpha-values were compared with the UAV-based measurement. The data were plotted in the box to observe the variation using two methods. The canopy coverage percentage was computed to observe the difference of canopies within the experimental orchard.

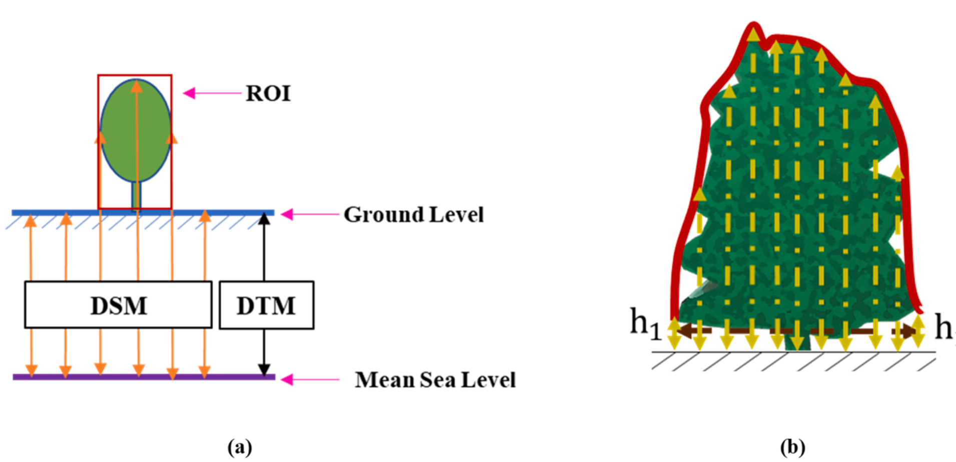

Fig. 8. Schematics of (a) tree height measurements (b) a graphical illustration of all pixels height measurement (h_1 *to* h_i: pixel height of 1^{st} to i^{th} pixel).

3. Results and discussion

3.1. Tree canopy height measurement

The results of manual and UAV-based measurements for 24 apple tree canopy heights are shown in Table 1. Variation of tree canopy heights using the two methods is presented in Fig. 9. A paired t-test between the two measurement methods indicated that there was no significant difference in tree canopy height. The average tree canopy height was 3.07 min manual measurement, where the average height was 3.05 min UAV-based measurement. The measurement errors ranged from 0 to 0.73 m with an average of 0.20 m, equivalent to a 6.64% error relative to the manual measurement. These results indicated the potential of UAV-based apple tree canopy height measurement to quantify individual tree height with less than 10% error. The MAE and RMSE were 0.21 m and 0.28 m, respectively. Previous studies also reported similar results for tree height measurement. Krause et al. [31] measured forest tree height (i.e., Scots Pine) using a UAV-based photogrammetric approach and achieved an RMSE of ~0.30 m when compared to manual method. Bridal et al. [32] reported an RMSE of 0.28 m for UAV-based forest tree height measurement.

Overestimation and underestimation were reported through the UAV-based measurement compared to manual measurement. For instance, trees no. 2, 3, 13, 14, and 19 were overestimated, and 5, 6, 8, 10, and 24 were underestimated. These might be explained by two main reasons: spatial resolution of UAV imagery and elevation variation in the experimental orchard. The overestimation was also observed in other studies while using SfM for plant height measurement or estimation [33, 34], which agreed with the results of this study. The previous studies observed that the SfM lacked the ability to reconstruct accurately the top of the plant canopy. This might be due to the coarse spatial resolution of the RGB camera as compared to the size of the branches or canopies at the top of the apple tree. High spatial resolution could improve the results, but it might lead to a noisier dense cloud with more gaps over vegetated or canopy areas [35]. Use of appropriate camera focal length is important, which may help the SfM algorithm to obtain more accurate estimates of the plant height in the dense cloud through the increase of disparity in the view configurations [36]. Conversely, the underestimation might be due to variation in elevation between the eastern part and western part of the orchard. The generated DSM, DTM, and canopy height map considered the orchard as a flat surface from the UAV take-off point without any elevation difference. However, the experimental orchard had a maximum elevation difference of 0.3 m. Therefore, the trees located at a lower elevation than the take-off point were partially underestimated. Orchard slope variation and elevation difference information could be included in the DSM and DTM generation to avoid this underestimation problem. Even though the manual measurement of tree heights was taken carefully, there is a likelihood that some of tall tree heights were not measured accurately due to the limitation of the experimenter reaching the top of the trees. This might also cause the error of measurement for some of the tree canopy heights.

Table 1
Results of manual and UAV-based apple tree canopy height measurements.

Tree no.	Manual measurement (m)	UAV-based measurement (m)	Absolute error (m)	(%)
1	2.69	2.93	0.24	8.92
2	2.90	3.45	0.55	18.97
3	2.87	3.32	0.45	15.68
4	3.12	3.09	0.03	0.96
5	3.20	2.96	0.24	7.50
6	3.30	2.97	0.33	10.00
7	3.40	3.36	0.04	1.18
8	3.63	2.90	0.73	20.11
9	2.97	3.02	0.05	1.68
10	2.95	2.88	0.07	2.37
11	2.97	2.69	0.28	9.43
12	2.78	2.78	0.00	0.00
13	2.79	3.02	0.23	8.24
14	3.10	3.20	0.10	3.23
15	3.33	3.04	0.29	8.71
16	3.18	3.15	0.03	0.94
17	3.09	2.85	0.24	7.77
18	3.25	3.33	0.08	2.46
19	2.92	3.41	0.49	16.78
20	3.40	3.39	0.01	0.29
21	2.84	2.89	0.05	1.76
22	2.82	2.72	0.10	3.55
23	2.92	2.84	0.08	2.74
24	3.25	3.05	0.20	6.15
Average	**3.07**	**3.05**	**0.20**	**6.64**

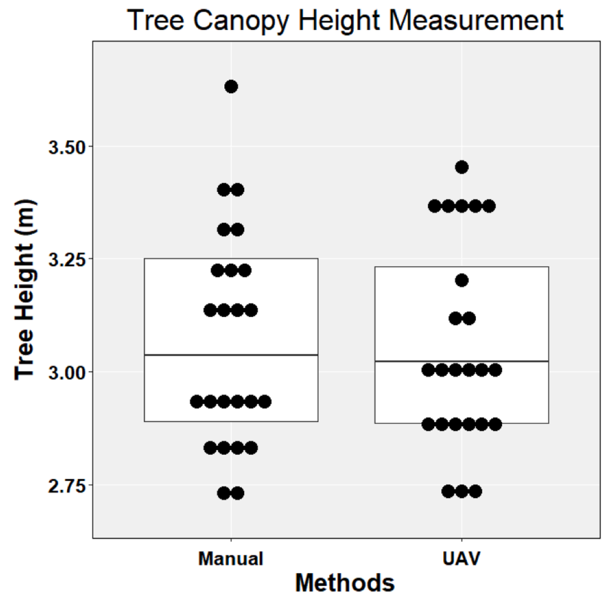

Fig. 9. Tree canopy height measurements using two methods: manual and UAV-based imaging. The white boxes represent 25th to 75th percentile range.

3.2. Tree canopy volume measurement and possible agrochemical requirement

The UAV-based tree canopy volumes were compared with the ground-based LiDAR measurement of 24 targeted trees. The ground-based canopy volumes varied with different α values using the alpha shape algorithm due to approximating the size of each scanned point cloud differently. The tree canopy volumes from LiDAR (using different α values) and UAV measurements were plotted side-by-side to observe their variations (Fig. 10). The α value of 0.35 achieved the highest coefficient of determination ($R^2 = 80.14\%$) with UAV measurement than α value of 0.4 ($R^2 = 79.51\%$) and 0.45 ($R^2 = 77.25\%$) (Figs. 11, 12 & 13). However, the calculated MSE and RMSE errors with the α value of 0.35 and 0.45 were higher than those with the α value of 0.4 (Fig. 14). The results showed certain errors in the UAV-based measurement when compared with the LiDAR measurements. Similar to tree height measurements, a portion of these errors might be caused by coarser spatial resolution and elevation difference of the orchard. However, the major reason could be explained by the reliability of the ground truth measurements. Although the LiDAR measurement was considered as ground truth, it might be possible that the alpha shape algorithm underestimated or overestimated the individual tree canopy volume. This is because the ground truths used for comparison were approximated tree canopy volumes. So far, there are no methods available to measure or estimate tree canopy volume fully and accurately because of the irregularity of the tree shape. Compared to the traditional methods, LiDAR-derived methods can measure tree characteristics accurately [37] and

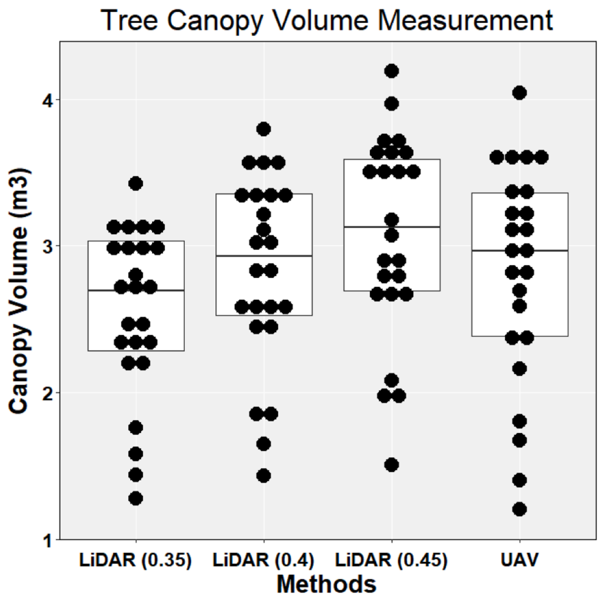

Fig. 10. Tree canopy volume measurements using ground-based alpha shape algorithm with three different α values (0.35, 0.4, 0.45) and UAV-based imaging. The white boxes represent 25th to 75th percentile range.

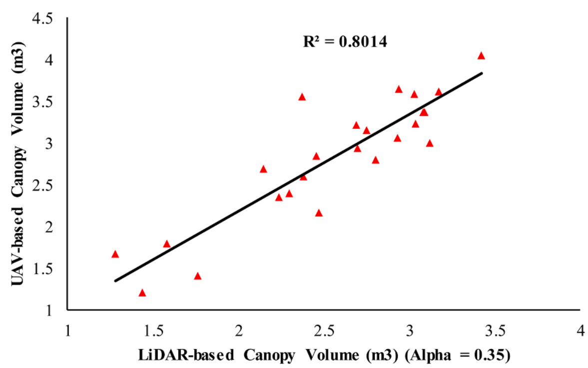

Fig. 11. Correlation between LiDAR measured tree canopy volume with α value of 0.35 and UAV-based measurement.

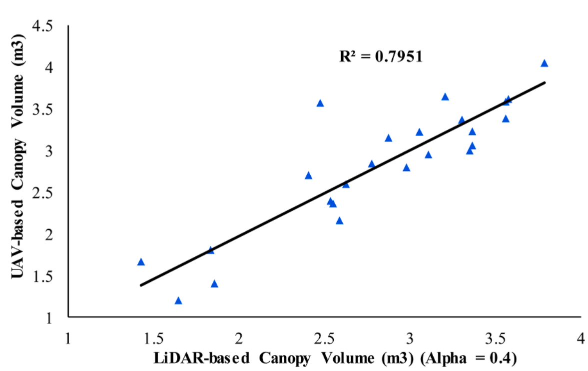

Fig. 12. Correlation between LiDAR measured tree canopy volume with α value of 0.4 and UAV-based measurement.

were therefore used for ground truth measurements. The LiDAR has broad applications in tree canopy characteristics due to its accurate measurement capability reported in previous studies [38,39,9]. On the other hand, the use of different α values helped to identify a better correspondence with UAV-based measurements. Another reason for

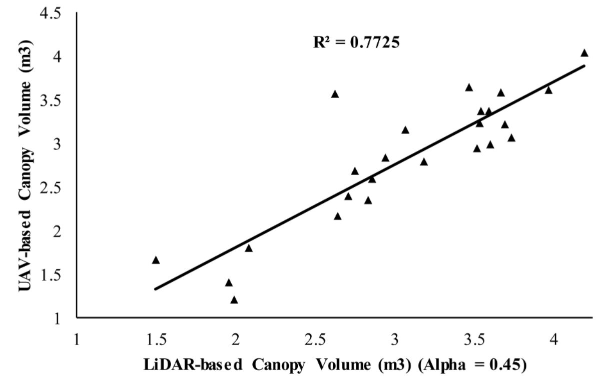

Fig. 13. Correlation between LiDAR measured tree canopy volume with α value of 0.45 and UAV-based measurement.

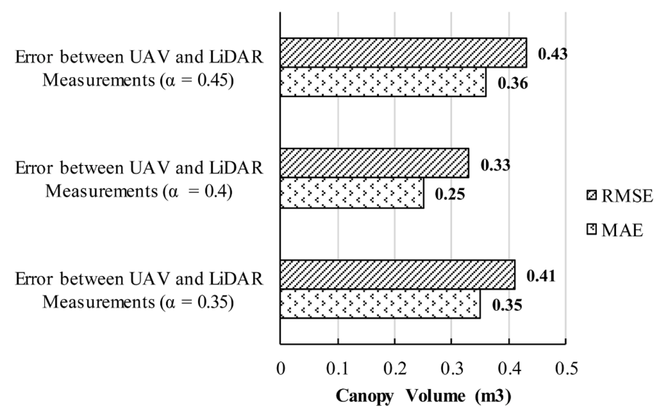

Fig. 14. Calculated MAE and RMSE between LiDAR and UAV-based tree canopy volume measurements.

these errors could be the overestimated UAV-based tree canopy volumes. The image processing algorithm used for tree canopy volume considered the height of all pixels at the top layer of the tree. There was a possibility that some of the tree shapes were narrower at the bottom portion, which could cause the overestimation. Despite the errors reported in the measurements, which were not high, a strong correlation of these two methods indicated that the UAV-based canopy volume measurement could be effective considering the shorter measurement time and efficacy.

The possible agrochemical requirement of the 24 experimental trees was estimated (Fig. 15). The tree canopy volumes measured with the α value of 0.4 were used. The estimation ranged from 0.1 to 0.32 l. The

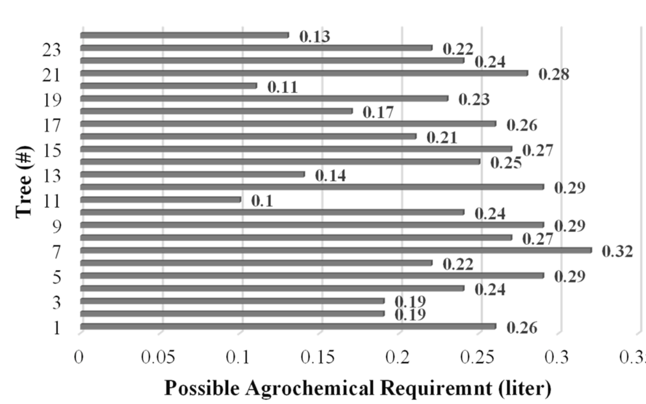

Fig. 15. Estimation of agrochemical amounts required for the experimental trees.

variation between the agrochemical requirements was due to the difference in tree canopy volumes. Although the possible agrochemical requirement was determined for 24 trees, the method can be used for all trees to approximate the agrochemical expense of an orchard site. This study did not compare the actual agrochemical usages with estimated agrochemical requirements, which would be evaluated in future studies.

3.3. Tree canopy coverage measurement

The percentage of canopy coverage for all trees located in the experimental orchard was calculated (Fig. 16), which ranged from 0 to 100% (Fig. 16c). The highest percentage indicates the ROI included more canopies, whereas the lowest percentage indicates the ROI contained less or no canopies.

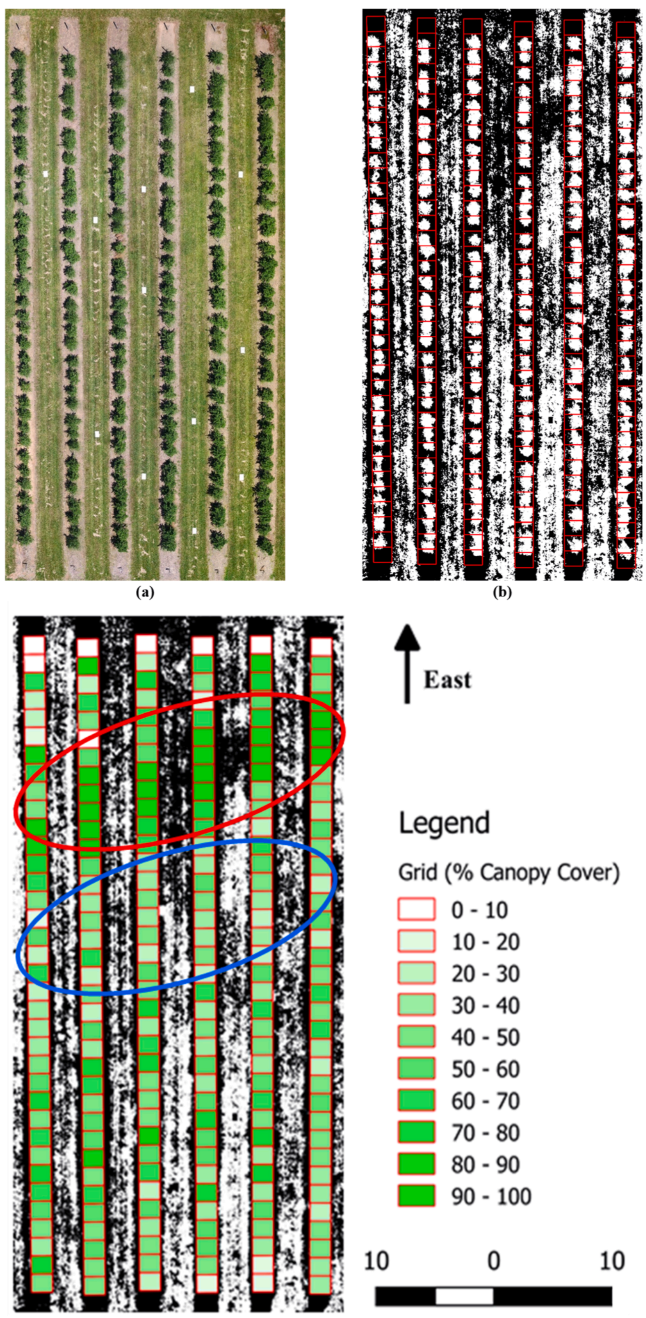

Fig. 16. Results of UAV-based tree canopy coverage measurement (a) orthomosaic map (b) segmented image of the orchard (c) tree canopy coverage map. The red circle represents high canopy density area and the blue circle represents comparatively low canopy density area. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Currently, there are no approaches to measure ground truth accurately for tree canopy coverage; therefore, the UAV-based tree canopy measurement results were not directly comparable. However, evaluation could be made based on visual assessments of orthomosaic, segmented, and canopy coverage maps (Fig. 16). For example, the ROIs of the six rows at the eastern part included no canopies, and thus they show white color. The high canopy density area marked with a red circle in Fig. 16c can be compared with the orthomosic map. This area had trees with high density or more canopies. Similarly, the marked blue area in Fig. 16c showed comparatively fewer canopies. Trees in this area are comparatively narrower, and there were certain gaps between trees. Despite there being a slight shadow presented on the left side of each tree (when facing the orthomosaic map), the Canopeo algorithm was able to measure tree canopy coverage accurately. The shadow appeared as black color where the Canopeo algorithm segmented the green pixels and avoided the influence of shadow.

3.4. Discussion and recommendations for future study

This study investigated the feasibility of a UAV-based imaging approach to measure the apple tree canopy characteristics (i.e., canopy height, volume, and cover). The results demonstrated that the UAV-based system could be used as high precision, time-efficient, and cost-effective approach to measure tree canopy characteristics to calculate appropriate pesticide requirements during spraying. Acquiring high-resolution images is crucial for accurately measuring canopy characteristics which can be greatly affected by factors including camera sensor, flying altitude, forward and side overlap, spatial resolution, and weather conditions [40,41,42]. These factors should be considered carefully since they affect the quality of images and, therefore orthomosaics, DSM, and DTM, which in turn affect the accuracy of tree canopy characteristics. The timing of image data collection plays a significant role in the accuracy of measurements. The images were captured when the sun was at its zenith to avoid the shading effect; however, differences in image capture time may have influenced the overall quality of data which needs to be considered in future studies. Additionally, flying altitude also determines the quality of the image data. Lower flying altitude provides finer spatial resolution, and conversely, higher altitude gives a coarser spatial resolution. The flying altitude used in this study has been widely applied for different UAV-based research, but the elevation difference increased the altitude from the ground in the western part of the orchard, which decreased the accuracies of the measured tree canopy characteristics.

The results of tree canopy characteristics measurement were comparable to that of other studies using UAV-based methods. Kothawade et al. [25] obtained a correlation of 0.62 and Sinha et al. [24] achieved an R^2 of 64% for apple tree canopy volume measurement when comparing UAV-based tree canopy volume with manual measurement. Sun et al. [43] calculated the maximum average relative error was 3.42% for apple tree height measurement while flying at different altitudes. With a relative error of ~6% and R^2 of ~0.80, the developed UAV-based approach could provide accurate information for numerous crop management practices.

This study illustrated limitations while measuring the canopy characteristics. The blockage of the lower canopies due to obstruction by higher branches was considered one of the limitations, which might have led to the overestimation of the tree canopy volume. These effects might not influence the tree canopy height because it was calculated from the height of the maximum canopy pixel. Influence of these effects depended on the density of the canopies: high-density trees (trees with more canopies) might have more effect than low density trees. Modern tree fruit orchards are planted with 2-dimensional walls that might be less affected by this problem. Another limitation was the overlapping between some of the neighboring trees, which could lead to the underestimation of the canopy volume and canopy coverage. Overlapping-removal approaches could be applied according to the different tree canopy densities. Elevation difference in the orchard was considered as a major problem, leading to ambiguity in the tree canopy height, volume, and cover measurements. The DTM is generated as a flat surface in this experiment using Agisoft Metashape Pro software by interpolation. This software did not consider any elevation difference in the ground surface, which caused inaccurate estimation if any elevation difference was presented. The elevation difference within the orchard must be considered while generating orthomosaics, DSM and DTM to compensate for this problem, which will be studied in the future. It will be helpful to make this system applicable to any orchard terrain conditions.

The UAV-based tree canopy characteristics measurement approach presented could be beneficial to growers and the scientific community on various management practices, including precision spray applications. The growth of the canopy volume and canopy coverage should be an important factor to determine the amount of spray required during the season. The developed methodology could be used to accurately measure tree canopy height, volume, and cover and their respective maps. These maps could be used to develop prescription agrochemical application maps. Information on the prescription maps could be used to control the precision sprayer nozzles and has the potential to reduce off-target wastage and ensure adequate spray deposition. These maps might help growers in canopy vigor management (pruning and thinning) alongside the spraying task. Although the study focused only on apple tree canopy characteristics measurements, it is not limited to this specific crop. The developed methodology could be transferred to other tree crops, such as peaches, pears, and citrus. Thus, the UAV-based tree canopy characteristics measurement technology would have great potential to help agricultural research economically and also towards sustainable crop management, especially when the farm contains many hectares of orchards.

4. Conclusions

Appropriate agrochemical application is a major challenge in tree fruits such as apple. UAV-based imaging methods were established in this study to measure apple tree canopy characteristics by analyzing high resolution aerial RGB imagery. This UAV-based method provided a relatively fast approach to calculate major tree characteristics in order to estimate spray requirement. Results showed that the study successfully measured tree canopy characteristics such as canopy height, canopy volume, and canopy coverage and were subsequently validated with ground measurements.

The image processing methods used yielded a low average relative error for tree height measurement and a strong correlation between UAV-based and ground-based tree canopy volume measurements. The study experienced overestimation and underestimation problems with canopy coverage measurements due to aspects including coarse spatial resolution, elevation difference, blockage of the lower canopy and overlapping trees. Future studies are necessary to compute tree canopy characteristics with approaches that consider those aspects, especially elevation difference and spatial resolution. Studies are also recommended to evaluate the robustness of the proposed imaging methods in quantifying tree canopy characteristics variation at different growth stages in an entire growing season. Integration of these approaches with the spraying unit is also necessary to evaluate their potential for crop management.

Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

Data will be made available on request.

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