

Article

UAV-SfM Photogrammetry for Canopy Characterization Toward Unmanned Aerial Spraying Systems Precision Pesticide Application in an Orchard

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Abstract: The development of unmanned aerial spraying systems (UASSs) has significantly transformed pest and disease control methods of crop plants. Precisely adjusting pesticide application rates based on the target conditions is an effective method to improve pesticide use efficiency. In orchard spraying, the structural characteristics of the canopy are crucial for guiding the pesticide application system to adjust spraying parameters. This study selected mango trees as the research sample and evaluated the differences between UAV aerial photography with a Structure from Motion (SfM) algorithm and airborne LiDAR in the results of extracting canopy parameters. The maximum canopy height, canopy projection area, and canopy volume parameters were extracted from the canopy height model of SfM (CHM_{SfM}) and the canopy height model of LiDAR (CHM_{LiDAR}) by grids with the same width as the planting rows (5.0 m) and 14 different heights (0.2 m, 0.3 m, 0.4 m, 0.5 m, 0.6 m, 0.8 m, 1.0 m, 2.0 m, 3.0 m, 4.0 m, 5.0 m, 6.0 m, 8.0 m, and 10.0 m), respectively. Linear regression equations were used to fit the canopy parameters obtained from different sensors. The correlation was evaluated using R^2 and $rRMSE$, and a t -test ($\alpha = 0.05$) was employed to assess the significance of the differences. The results show that as the grid height increases, the R^2 values for the maximum canopy height, projection area, and canopy volume extracted from CHM_{SfM} and CHM_{LiDAR} increase, while the $rRMSE$ values decrease. When the grid height is 10.0 m, the R^2 for the maximum canopy height extracted from the two models is 92.85%, with an $rRMSE$ of 0.0563. For the canopy projection area, the R^2 is 97.83%, with an $rRMSE$ of 0.01, and for the canopy volume, the R^2 is 98.35%, with an $rRMSE$ of 0.0337. When the grid height exceeds 1.0 m, the t -test results for the three parameters are all greater than 0.05, accepting the hypothesis that there is no significant difference in the canopy parameters obtained by the two sensors. Additionally, using the coordinates x_0 of the intersection of the linear regression equation and $y = x$ as a reference, CHM_{SfM} tends to overestimate lower canopy maximum height and projection area, and underestimate higher canopy maximum height and projection area compared to CHM_{LiDAR} . This to some extent reflects that the surface of CHM_{SfM} is smoother. This study demonstrates the effectiveness of extracting canopy parameters to guide UASS systems for variable-rate spraying based on UAV oblique photography combined with the SfM algorithm.

Keywords: UAV-SfM; canopy characteristic; precision pesticide application; UASS; orchard



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1. Introduction

With the widespread adoption of plant protection drones for pesticide application, their operational effectiveness in controlling crop pests and diseases and regulating pesticide use has become increasingly significant, drawing more attention to related research. Adjusting spraying parameters (e.g., pesticide amount, droplet size, droplet velocity) based on the actual canopy conditions during application can help improve the quality of pesticide application [1,2]. The canopy of fruit trees is characterized by unevenness and discontinuity. The density of fruit tree leaves changes with the seasons, and parameters such as canopy height, volume, and projected area also change as the trees grow. In the same orchard, the canopy conditions of fruit trees vary by location. The actual pesticide requirements of fruit tree canopies in specific locations are related to various characteristic parameters of the canopies, which have been studied and analyzed in previous research [3]. Simultaneously, droplets with identical parameters such as size, velocity, and surface tension exhibit different deposition effects (e.g., uniformity, penetration, and droplet deposition density) in canopies under different conditions. The complex structure of fruit tree canopies can also affect droplet deposition by influencing the airflow carrying the droplets [4–7]. This implies that fruit trees have uneven and discontinuous characteristics, making effective application challenging.

The premise for variable-rate spraying based on fruit tree canopy characteristics is that the spraying system can obtain the relevant canopy parameters at the corresponding locations. An important method for achieving this is by constructing three-dimensional remote sensing models of fruit trees using remote sensing data to extract canopy characteristics. Common three-dimensional remote sensing data sensors include airborne LiDAR, satellite remote sensing data, multispectral cameras, and visible light cameras [8]. Structure from Motion (SfM), based on computer vision, can compute 3D information from overlapping images without the need for prior knowledge of camera position and orientation, allowing for the use of cost-effective imaging platforms, both for aerial and terrestrial application [9]. The application of a Structure from Motion (SfM) algorithm based on drone aerial images has been widely studied in the fields of agriculture and forestry [10,11]. Relevant studies have also investigated the optimal parameter settings for establishing canopy height models using the SfM algorithm, including camera tilt angle, flight height, and overlap rate, and have evaluated the impact of different parameter settings on the accuracy of canopy modeling [12–17]. Over the past 20 years, airborne LiDAR has been widely used in the field of forestry management and is often considered a standard data source for forestry management [9,12,15,17–19]. Fruit tree canopy height models (CHMs) established through the SfM algorithm can be used to guide research related to variable-rate pesticide application [20]. Cai [21] divided the canopy point cloud scanned by the laser scanner into different grids to guide variable-rate spraying. However, airborne LiDAR also presents challenges in terms of high economic costs and large data processing requirements. Since both the SfM algorithm combined with aerial imagery and airborne LiDAR can be used to obtain canopy characteristics for guiding variable-rate spraying, what are the differences between the two methods?

Researchers have evaluated the differences in canopy characteristics obtained using the two methods. Liu's research [22] indicates that compared to CHMs constructed with LiDAR, CHM models generated through photogrammetric methods tend to overestimate canopy heights of trees below 3 m and underestimate canopy heights of trees above 3 m. Ziliani compared the canopy heights extracted using the SfM algorithm with those extracted using LiDAR point clouds, and the results showed a strong correlation between the two ($R^2 = 0.77\text{--}0.99$, $rRMSE = 0.44\%\text{--}0.85\%$) [23]. Giannetti conducted ground measurements using airborne laser scanning (ALS) and evaluated the correlation between the

UAV-SfM model and the ALS model using RMSE and NSE [24]. Cao acquired LiDAR and digital aerial photogrammetry (DAP) data of a forest at a same time by UAV and compared their accuracy [25]. The results showed that the UAV-DAP data are useful and comparable to LiDAR for forest inventory and sustainable forest management in planted forests, by providing accurate estimations of forest structural attributes. De Lima assessed the effects of flying altitude and lateral and longitudinal overlaps on digital aerial photogrammetry (DAP) processing and the ability of its products to provide point clouds for forestry inventory [14]. They used a nationwide airborne laser scanning (ALS) dataset as reference data. They also provided insights into the effects of flight settings on DAP outputs for future applications in similar forest stands, emphasizing the benefits of overlaps for comprehensive scene reconstruction and altitude for canopy surface detection. Aguilar employed very accurate Terrestrial Laser Scanning (TLS)-derived ground points as ground reference to estimate the UAV-SfM DTM vertical error in each reference plot [26]. They accomplished the workflow consisting of SfM absolute image alignment based on field-surveyed ground control points, very dense point cloud generation, ground points filtering and outlier removal, and DTM interpolation from labeled ground points that provide valuable insights and references for related research processes. A four-way ANOVA was applied to investigate the variability and relationship of some plot-level features on DTM accuracy. Lamping [17] evaluated the capabilities of low-cost off-the-shelf Unmanned Aerial Systems (UASs) with Digital Aerial Photogrammetry (DAP) and High-Precision Global Positioning System (HPGPS) under various forest conditions, comparing them with LiDAR and field observations, to create accurate 3D data and predict key forest attributes. The study also explored whether oblique imagery provides more accurate 3D data and forest attribute predictions. The results indicated that the DAP model combined with high-precision positioning systems could accurately predict key forest attributes under various forest types, canopy densities, and structural conditions. Escolà extracted a set of geometric parameters (canopy height, projected area, and volume) of a vineyard, an intensive peach orchard, and an intensive pear orchard by UAV-DAP and MTLs-LiDAR and performed a comparison between both kinds of measurements, accounting for the length of the sections in which the crop hedgerows were divided to extract the geometric parameter [27].

Variable-rate prescription mapping technology is often used to guide drones in variable-rate spraying, dividing the CHM into several grids and calculating the corresponding spray amount based on the canopy characteristics within each grid. This study follows the grid-based approach of variable-rate prescription mapping to investigate the potential differences in canopy parameters extracted from the two canopy height models. Fourteen grid heights, each 4.8 m wide to match the planting rows, were used to extract canopy parameters from both the CHM_{SfM} and CHM_{LiDAR} , focusing on the maximum canopy height, canopy projection area, and canopy volume within the grids, and evaluated the effects of modeling methods on grid-based canopy parameters. This study further evaluates the differences in canopy parameters extracted using various grid sizes from the CHM_{SfM} and CHM_{LiDAR} models, providing insights into the feasibility of generating variable-rate prescription maps from low-cost drone aerial imagery and SfM modeling for guiding variable-rate spraying.

2. Materials and Method

2.1. Study Area

The mango plot (Figure 1) (108°17'14" E, 22°51'6" N) is located in Nanning City, Guangxi Zhuang Autonomous Region, China, and covers an area of 1800 m² area. The region has a tropical monsoon climate with a mean annual precipitation of 1248 mm and

a mean annual temperature of 21.6 °C. The terrain of the study area is generally flat, but there is a sudden 2 m drop on its southeastern side, adjacent to a lake. The average spacing between the center lines of parallel planting rows is 4.8 m, and the distance between mango trees in the same planting row is 3.5 m.

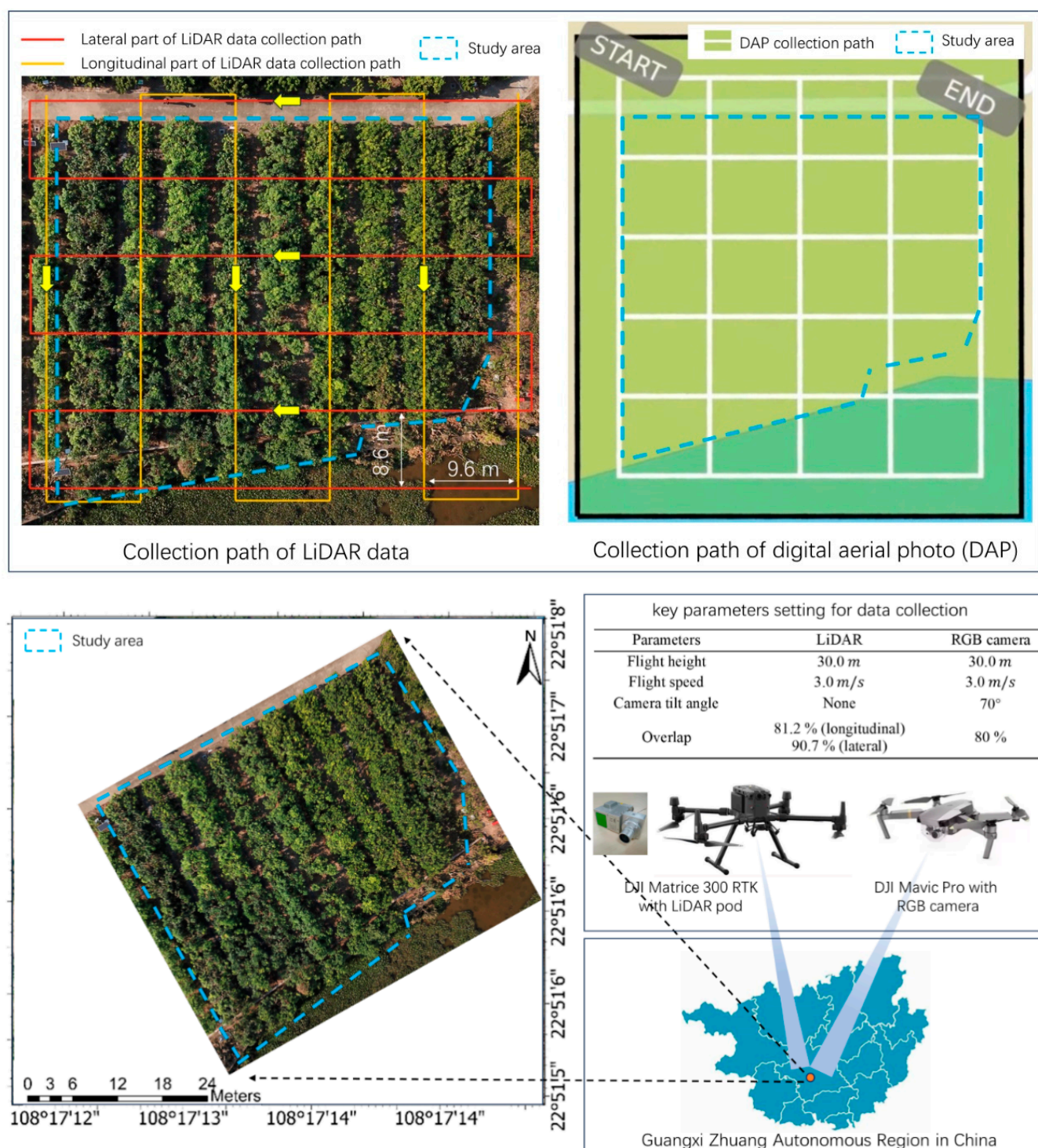


Figure 1. In the 1800 m² study area, the mango trees are in rows 4.8 m apart and the distance between mango trees in the same planting row is 3.5 m. We utilized an airborne LiDAR and an aerial drone with an RGB camera to collect point cloud data and aerial imagery from the study area.

2.2. UAV Data Collection and Processing

2.2.1. UAV Images and LiDAR Point Cloud Collection

Aerial images of the mango tree canopy were acquired using a drone equipped with an RGB camera (DJI Technology Co., Ltd., Shenzhen, China, Figure 1). The parameters of the Mavic Pro (DJI Technology Co., Ltd., Shenzhen, China) and RGB camera are given in Table 1. The SfM algorithm was then used to reconstruct the canopy model and generate a 3D point cloud of the mango trees.

Table 1. Parameters of Mavic Pro and its RGB camera.

Units	Parameters	Values
Mavic Pro	Weight	734 g
	Maximum horizontal flight speed	65 km·h ^{−1}
	Vertical positioning accuracy	10 cm
	Horizontal positioning accuracy	30 cm
Digital camera (RGB)	Effective pixels	1235 × 10 ⁴
	FOV	78.8°
	Aperture	f/2.2

As a low-cost photogrammetric method, the ‘Structure from Motion’ algorithm could reconstruct the three-dimensional structure of the modeled object from a series of images with different, but overlapping, positions. When capturing images, the camera’s position and posture parameters are recorded simultaneously. The algorithm recognizes and matches the same feature recorded by different images and then calculates the spatial coordinates of the modeling object based on the camera’s position and altitude parameters that reconstruct the 3-D model of the target object [28].

The digital aerial photos (DAPs) of the mango tree canopy were captured by a DJI Mavic Pro UAV equipped with an FC220 RGB camera (4000 × 3000 pixels). Flight routes for collecting RGB images were planned using Pix4D Capture (version 4.11.0, PIX4D).

There are five parameters that need to be taken into consideration when designing the flight route: flight speed, flight height, camera angle, overlap, and exposure value (EV), which may influence the accuracy in CHM construction processes mainly. To ensure the quality of imaging and modeling, the UAV’s flight altitude was set as low as possible, and the flight speed was kept as slow as possible when capturing aerial images of the mango tree canopy. Overlap rate refers to the proportion of the field of view overlapping between UAV images (Figure 2). Considering that the oblique view could result in a more accurate three-dimensional reconstruction, the angle between the lens’s central axis and the horizontal plane was set to 70 degrees. To balance modeling quality and data acquisition efficiency, the overlap rate was set to 80%. The double-grid flight route is generated by Pix4D Capture automatically after the four parameters are entered and the research area is selected.

During the tree-image collection stage, LiDAR point cloud data were also collected using the LiAir VH Pro (GreenValley International Inc. (GVI), Berkeley, CA, USA) carried by a DJI M300 RTK (DJI Technology Co., Ltd., Shenzhen, China). The parameters of the LiDAR are shown as Table 2.

While collecting the LiDAR point cloud, the LiDAR point density was set to 1897 points/m². The echo mode of LiDAR was set to single echo because point cloud data occupy a large storage space. Original LiDAR point cloud datasets were processed using Ligeoreference (1.3.3) software. Then, the processed datasets were input into LiDAR360 (5.4.3.0) to resample, filter noise, and generate DTM and DSM, which were saved in TIFF

format. While generating DTM, its resolution was set at 0.06 m. CHM from LiDAR point cloud was also produced by subtracting DTM from DSM by ArcGIS Pro (3.4.0).

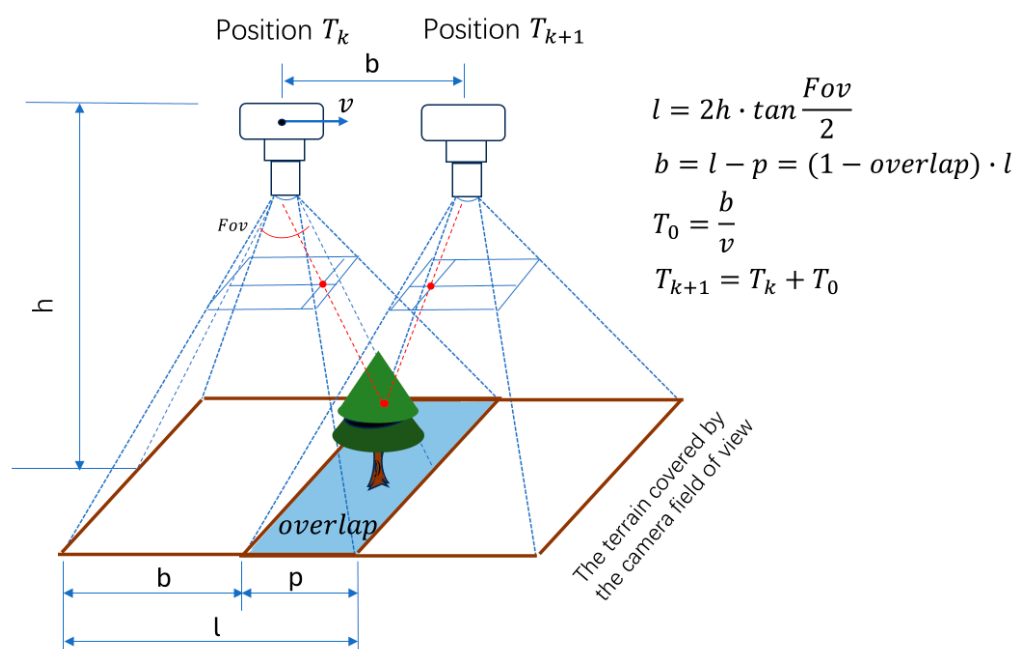


Figure 2. Diagram about Structure from Motion (SfM) algorithm data acquisition. Obtaining images of the object overlapping each other and recording the camera's positional parameters to reconstruct a three-dimensional model of the object. The diagram illustrates spatial position coordinates of matching points based on UAV multi-view images.

Table 2. Parameters of LiDAR.

Name	Parameters	Values
LiAir VH Pro	Scan Range(@100 klx)	320 m @ 80% reflectivity
	System Accuracy	± 5 cm @ 70 m
	Field of view	70.4° (horizontal) $\times$ 4.5° (vertical)
	Scan Rate	240,000 points/s (single return wave)
	Wavelength	905 nm
	Angle Accuracy	$< 0.1^\circ$

2.2.2. Canopy Height Model Generation

RGB images were imported into Pix4D Mapper and processed to generate corresponding 3D models, data surface model (DSM), and data terrain model (DTM) by the Structure from Motion algorithm. Noise was filtered simultaneously. The dataset with a camera angle set at 70° had the average ground sampling distance (GSD) at 1.10 cm/pixel. The DSM image was exported from the same point cloud model at the same GSD. Next, we used ArcGIS Pro version 2.8.0 to process DSM and DTM in TIFF format, subtracting the DTM from DSM to generate CHM in TIFF format (Figure 3). Additionally, in this study, the Georeferencing tool in ArcGIS Pro (3.4.0) software was used to correct the geographical coordinates of the model.

A canopy surface model constructed from UAV RGB images was used to estimate mango tree canopy height Figure 4. The CHM in TIFF model (Figure 5) contains longitude, latitude, and elevation information for each pixel. This spatial positional information for the mango tree canopies forms the basis for calculating their canopy surface area.

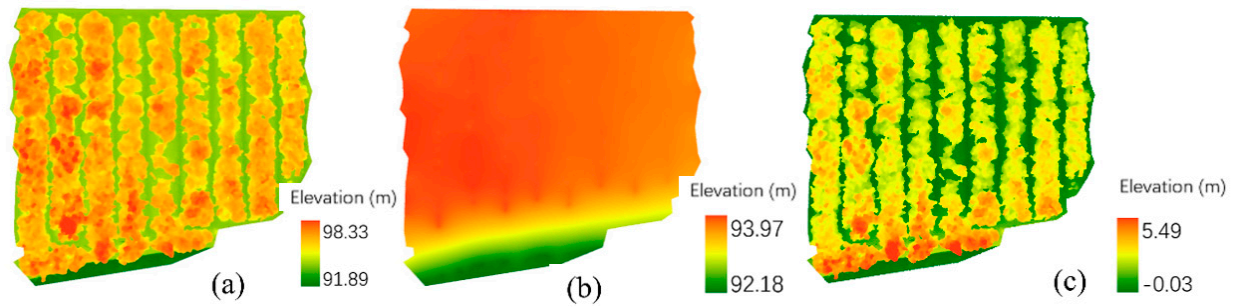


Figure 3. The process of CHM generation: (a) digital surface model (DSM); (b) digital terrain model (DTM); (c) canopy height model (CHM) of the mango trees in the orchard. The transition of the color of the pixel from green to yellow to red represents an increase in the elevation of that point on the model.



Figure 4. One of the mango trees in the orchard: (a) flat view image; (b) top view image; (c) top view of its 3D model generated by the SfM algorithm.

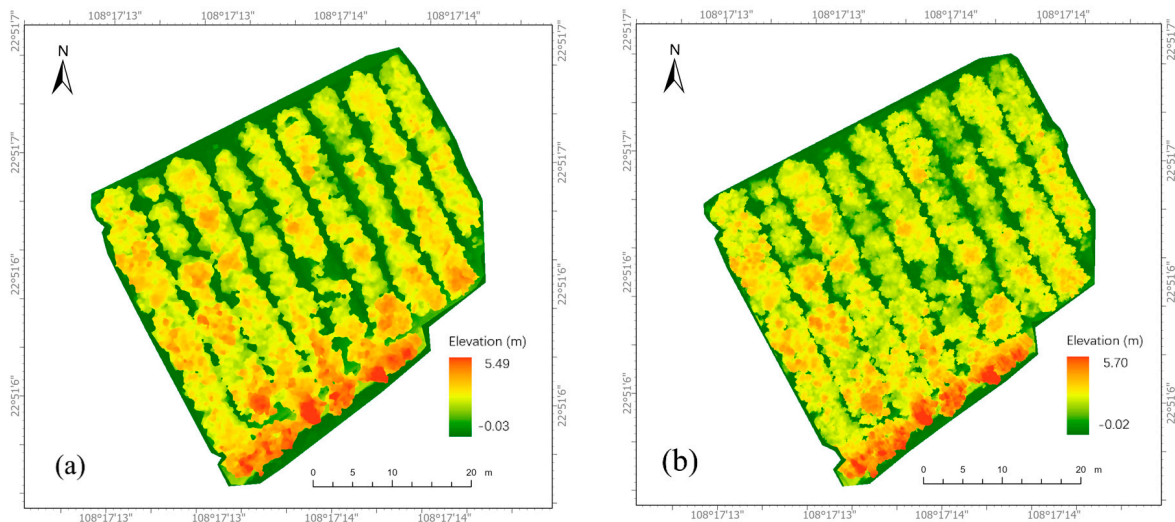


Figure 5. Canopy height model in raster format: (a) canopy height model generated from the SfM algorithm; (b) canopy height model generated from the LiDAR point cloud. The height of the points on the model is represented by the color. From green to yellow to red, the height of the canopy increases in turn. Pixels of ground were not separated from the canopy height model. A lower generated DSM or a higher generated DTM could both result in a normalized CHM model with lower elevations or negative ground point elevation values.

2.2.3. Extraction and Analysis of Canopy Character with Grid in Different Size of Grid

To provide a reference for variable-rate pesticide application in orchards based on canopy characters, this article analyzed three related parameters extracted from CHM_{SfM} and CHM_{LiDAR} . Commonly used canopy characteristic parameters related to ground variable-rate pesticide application include canopy height, leaf wall area (LWA), tree row volume (TRV), leaf area density (LAD), tree canopy density (TCD), and leaf area index (LAI) [3]. Due to the different perspectives while spraying, for agricultural drones, the parameters of canopy TWA used to guide ground equipment in variable-rate pesticide application should be replaced with the vertical projection area of the canopy. Cameras are often used to obtain data for evaluating crop diseases, pests, weeds, and nutritional status. The SfM algorithm constructs a point cloud and three-dimensional model based on two-dimensional images, making it possible to extract a tridimensional figure from images. It is precise to extract canopy dimensional parameters from the LiDAR point cloud. To some extent, the density of the point cloud can reflect the density of the canopy. Previous studies have shown that there is a strong correlation between some canopy characteristic parameters [29]; so in this article, canopy local maximum height, canopy projection area, and canopy volume of canopy characters were selected to be extracted from CHM_{LiDAR} and CHM_{SfM} then compared.

Variablerate application prescription map technology guides equipment to adjust application parameters based on the actual conditions of the canopy to optimize application effectiveness. The variablerate application prescription map, which is based on the characteristics of the canopy, requires calculating the application amount within each grid based on the canopy conditions within the grid. Sultan [3] divided the canopy into different sections to extract canopy characteristics. Referencing this approach, to compare the differences between CHM_{LiDAR} and CHM_{SfM} at different scales, this paper divides the pixels of the canopy height model in TIFF format into grids and extracts the maximum canopy height, canopy projection area, and canopy volume within each grid. The tree row width of the research mango orchard is 5 m so that the width of the grids were set to 5 m, also. The heights of the grid represent the length of the grid along the row direction of the orchard. The grid heights for extracting canopy features include 14 different dimensions: 0.2 m, 0.3 m, 0.4 m, 0.5 m, 0.6 m, 0.8 m, 1.0 m, 2.0 m, 3.0 m, 4.0 m, 5.0 m, 6.0 m, 8.0 m, and 10.0 m. A Cartesian coordinate system (Figure 6) orthogonal to the planting rows in the orchard was established to divide the grids. Taking the southeast corner of the study area (108.287105° E, 22.8515641° N) as the origin O, the coordinate axes were set orthogonal to the crop-planting rows to form a two-dimensional Cartesian coordinate system. Each pixel was assigned to a grid based on its projected distance on the coordinate axes. As an example, Figure 7 shows the partitioning effect of the canopy height model while the grid height and width were set to 5 m.

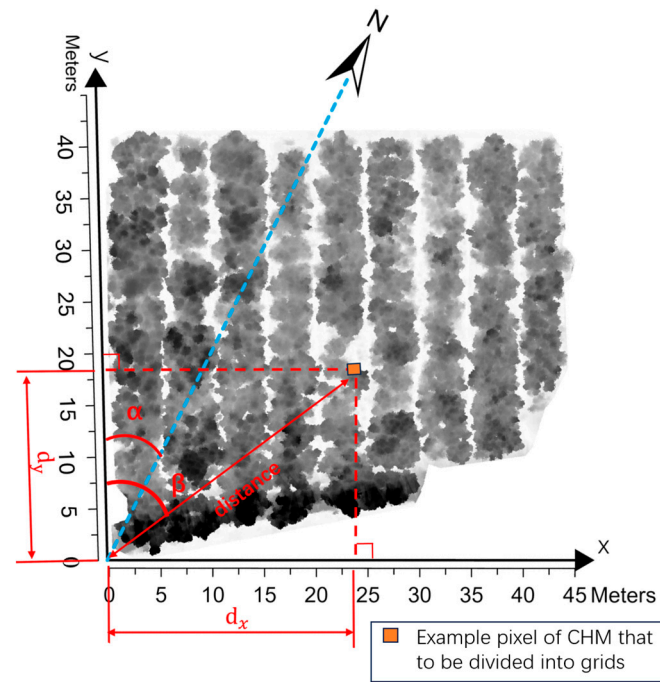


Figure 6. Diagram of pixel division into a grid. distance: distance between origin of the coordinate and the pixel; α : angle between north direction and the positive direction of the y axis; β : angle between the connecting line from and the positive direction of the y axis; origin point toward pixels and the positive direction of the y axis; $d_x = \sin \beta \times \text{distance}$; $d_y = \cos \beta \times \text{distance}$; the x-coordinate of the pixel's corresponding grid: $\text{grid}_x = \left\lfloor \frac{d_x}{\text{grid}_{\text{width}}} \right\rfloor$; the y-coordinate of the pixel's corresponding grid: $\text{grid}_y = \left\lfloor \frac{d_y}{\text{grid}_{\text{height}}} \right\rfloor$.

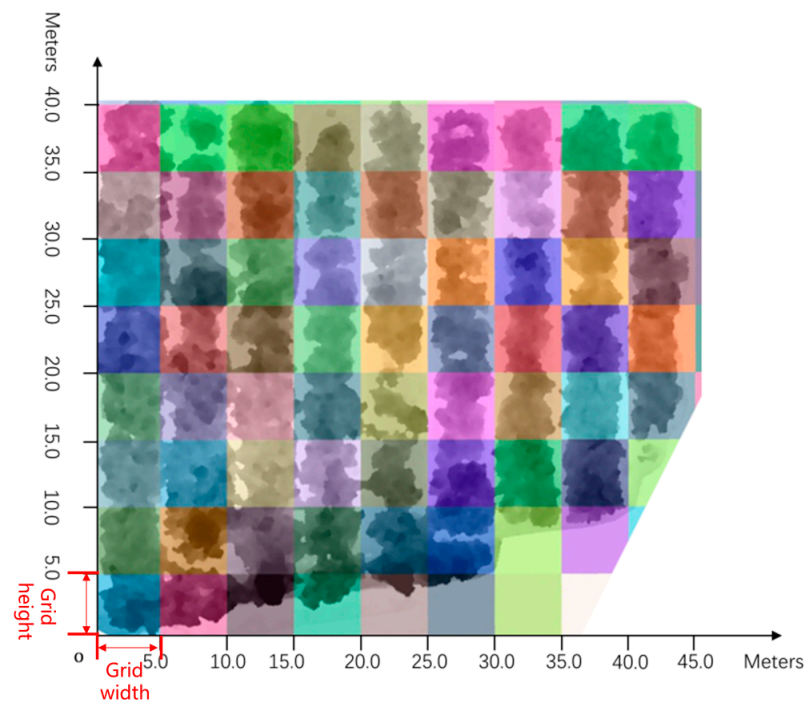


Figure 7. Grid division schematic diagram (using a 5 m $\times$ 5 m grid as an example).

The formula for calculating the canopy projection area in the grid with coordinates (x,y) is as follows:

$$CPA_{(x,y)} = \sum_{i=1}^{m_{(x,y)}} h \cdot w = m_{(x,y)} \cdot h \cdot w \quad (1)$$

$CPA_{(x,y)}$: The canopy projection area in the grid with coordinates (x,y) .

i : The serial number of a pixel in the grid with coordinates (x,y) .

$m_{(x,y)}$: The number of pixels with elevation > 0.5 m in the grid with coordinates (x, y) .

h : The actual length represented by the height of a single pixel.

w : The actual length represented by the width of a single pixel.

e_i : The elevation of the i th pixel in the grid with coordinates (x, y) .

The formula for calculating the canopy volume in the grid with coordinates (x, y) is as follows:

$$V_{(x,y)} = \sum_{i=1}^{n_{(x,y)}} h \cdot w \cdot e_i \quad (2)$$

$V_{(x,y)}$: the canopy volume in the grid with coordinates (x,y) ; i : the index of a pixel in the grid with coordinates (x, y) ; n : numbers of pixels whose elevation is higher than 5 m in grid (x, y) ; h : the length represented by the height of a single pixel in real-world space; w : the length represented by the width of a single pixel in real-world space; e_i : the elevation (>0.5 m) of the pixel whose index is i in the grid (x, y) . Parameters h and w are constant so that the actual volume represented by a single pixel in the real space is proportional to the canopy height within the pixel. Given that h and w are constant values, the canopy volume represented by a single pixel is therefore proportional to the canopy height within that pixel.

2.3. Mathematical Methods for Evaluating the Canopy Parameter Differences Between CHM_{SfM} and CHM_{LiDAR}

We calculated the determination coefficient (R^2), root mean square error ($RMSE$), and relative $RMSE$ ($rRMSE$) to illustrate the relationship between the parameters extracted by grids from CHM_{SfM} and CHM_{LiDAR} [30].

The correlation coefficient expresses the nature of the relationship between variables, whether it is positive or negative. The square of the correlation coefficient is the determination coefficient; it expresses the degree to which the relationship between the variables is close.

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - x_i)^2}{\sum_{i=1}^n (y_i - \bar{y}_n)^2} \quad (3)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - x_i)^2} \quad (4)$$

$$rRMSE = \frac{RMSE}{\bar{x}_n} \quad (5)$$

n represents the number of sample points taken from the CHM.

Linear regression Equation (6) was used in this study to fit the relationship between variables for the scatter plot drawn in this study. It can be inferred from Equation (7) that when x equals $\bar{x}$, $\hat{y}$ must equal $\bar{y}$.

$$\hat{y} = a + bx \quad (6)$$

$$a = \bar{y} - b\bar{x} \quad (7)$$

$$b = \frac{\sum (x - \bar{x})(y - \bar{y})}{\sum (x - \bar{x})^2} \quad (8)$$

The t -test is used to determine whether there is a significant difference between the means of two populations to which the samples belong. In this study, the maximum canopy height, canopy projection area, and canopy volume parameters were extracted from the CHM_{SfM} and CHM_{LiDAR} using grids, resulting in paired data where the difference factor is the type of sensor. Since the data describe the same study area, the analysis only requires testing the hypothesis that the means of the canopy parameters extracted by grid from CHM_{SfM} and CHM_{LiDAR} are consistent, to assess whether the differences between them are significant.

From CHM_{SfM} and CHM_{LiDAR} , the canopy parameters extracted based on the grid are denoted as y_1 and y_2 , respectively. A total n pairs of canopy parameters are obtained, and the difference for each pair is defined as $d = y_1 - y_2$ and their mean value is $\bar{d} = \bar{y}_1 - \bar{y}_2$.

The standard error of the mean difference: $s_{\bar{d}} = \sqrt{\frac{\sum(d - \bar{d})^2}{n(n-1)}}$. The t -value is equal to $\frac{\bar{d} - \mu_d}{s_{\bar{d}}}$ with degrees of freedom $\nu = n - 1$. While μ_d is equal to zero, the t -value is equal to $\frac{\bar{d}}{s_{\bar{d}}}$. Based on the calculated t -value and degrees of freedom, the corresponding p value is determined to assess whether to reject the null hypothesis.

The specific workflow of this article is shown in Figure 8.

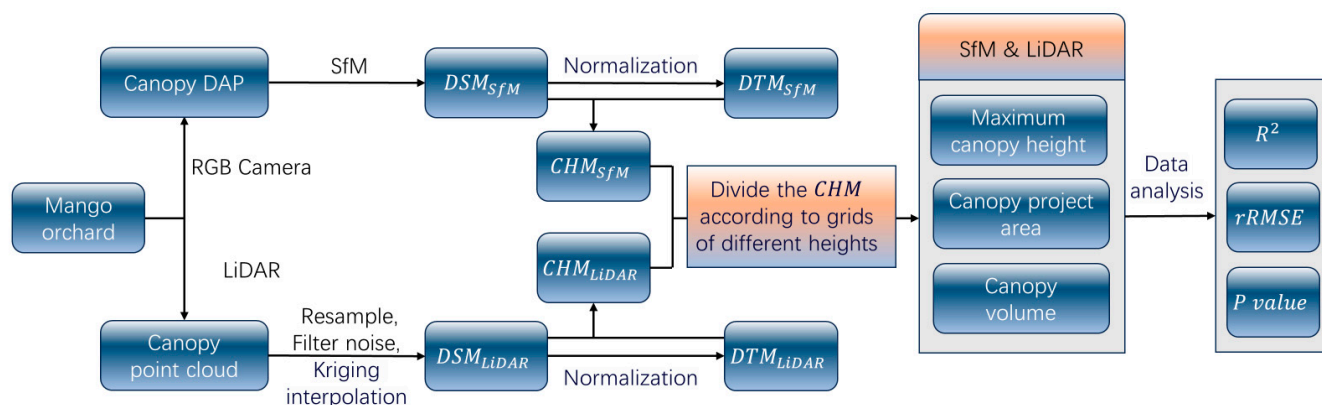


Figure 8. Data processing flow of this study.

3. Discussion

3.1. Comparison of Canopy Characters Extracted from CHM

3.1.1. Analysis of Canopy Maximum Height Extracted by Different Sizes of Grids

In this study, the differences in canopy volume extracted from SfM data and LiDAR data using grids of various sizes are evaluated. Considering the width of the planting rows, the grid width for extracting canopy height parameters is set to 5.0 m, with lengths set to 5.0 m, with 14 lengths set at between 0.2 m and 10.0 m (Figure 9). Table 3 shows the original situation of the canopy height extracted from different heights of the grid. For the canopy heights extracted from two data sources using grids of the same size, the correlation between the two is evaluated using a t -test ($\alpha = 0.05$). The linear regression equation is used to fit the extracted heights from CHM_{LiDAR} and CHM_{SfM} , obtaining the R^2 , $rRMSE$, regression equation $y = a + bx$, and the intersection coordinates x_0 of the regression equation with the line $y = x$ (Table 4).

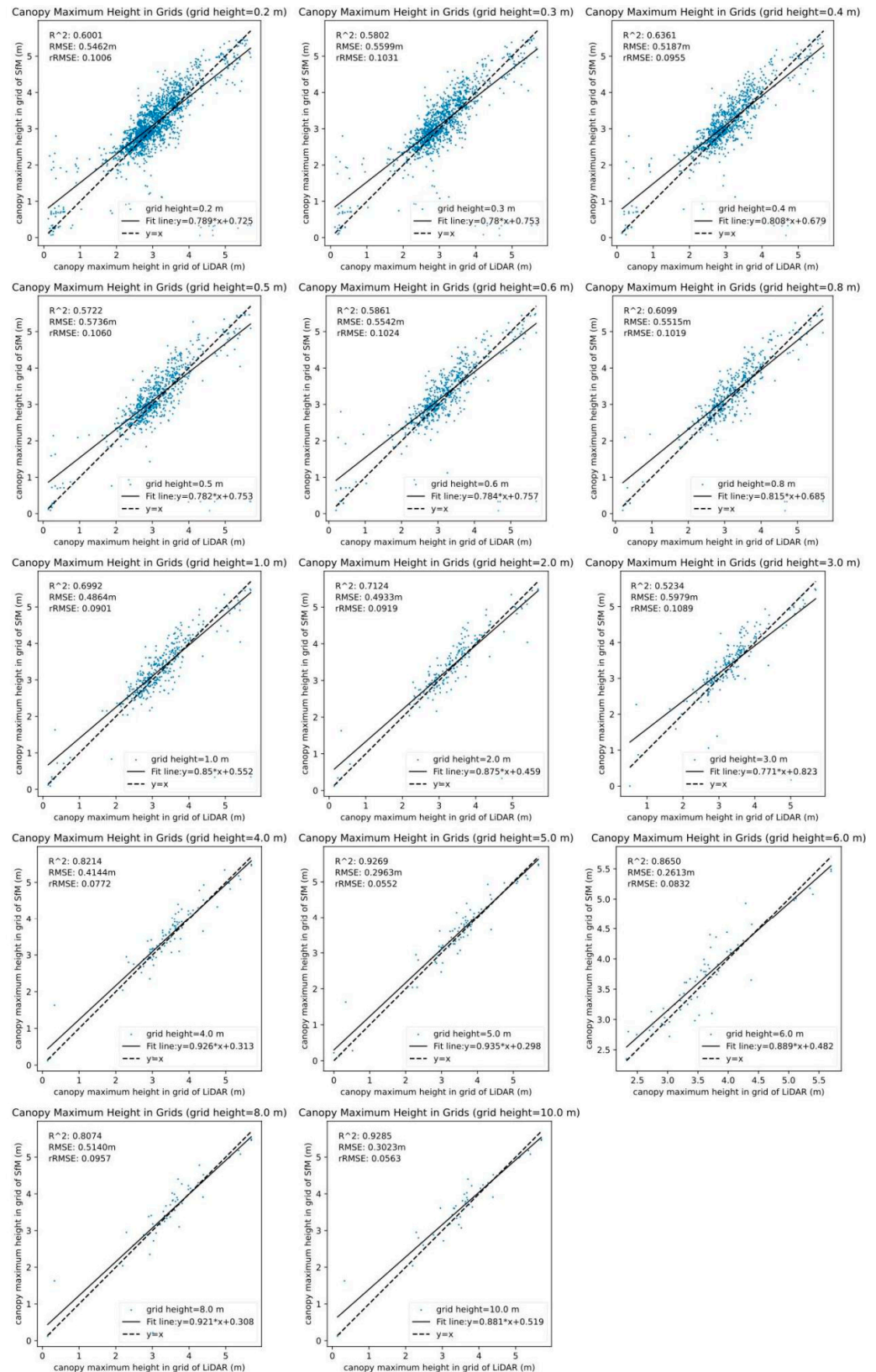


Figure 9. Scatter plots of the maximum canopy height extracted from the two canopy height models using grids of different sizes. From the scatter plot, it is evident that as the grid height increases, the number of scatter points obtained from the study area gradually decreases. Slopes of fitting lines $y = a + bx$ are always less than 1. To the left of the intersection with the line $y = x$, the canopy height obtained through SfM modeling is greater than that obtained through LiDAR modeling.

Table 3. Extraction of the maximum canopy height data within grid cells of varying sizes. As the grid height gradually increases, the mean value of the maximum height extracted from CHM_{LiDAR} and CHM_{SfM} also gradually increases. This is because smaller grid heights increase the number of samples taken from lower canopy heights.

Data Source	Grid Width (m)	Grid Height (m)	N	Minimum (m)	Maximum (m)	Mean Value (m)	Standard Deviation (m)
LiDAR	5.0	0.2	1669	0.12	5.70	3.03	0.85
SfM	5.0	0.2	1669	0.06	5.49	3.12	0.86
LiDAR	5.0	0.3	1116	0.12	5.70	3.06	0.84
SfM	5.0	0.3	1116	0.06	5.49	3.14	0.86
LiDAR	5.0	0.4	838	0.14	5.70	3.09	0.85
SfM	5.0	0.4	838	0.06	5.49	3.18	0.86
LiDAR	5.0	0.5	674	0.14	5.70	3.11	0.85
SfM	5.0	0.5	674	0.08	5.49	3.19	0.88
LiDAR	5.0	0.6	559	0.20	5.70	3.14	0.84
SfM	5.0	0.6	559	0.08	5.49	3.22	0.86
LiDAR	5.0	0.8	423	0.20	5.70	3.27	0.85
SfM	5.0	0.8	423	0.08	5.49	3.35	0.88
LiDAR	5.0	1.0	342	0.14	5.70	3.21	0.87
SfM	5.0	1.0	342	0.09	5.49	3.28	0.89
LiDAR	5.0	2.0	176	0.14	5.70	3.34	0.89
SfM	5.0	2.0	176	0.12	5.49	3.38	0.92
LiDAR	5.0	3.0	120	0.20	5.70	3.41	0.85
SfM	5.0	3.0	120	0.09	5.49	3.47	0.87
LiDAR	5.0	4.0	92	0.14	5.70	3.47	0.97
SfM	5.0	4.0	92	0.12	5.49	3.52	0.99
LiDAR	5.0	5.0	78	0.00	5.70	3.41	1.14
SfM	5.0	5.0	78	0.12	5.49	3.49	1.10
LiDAR	5.0	6.0	61	2.32	5.70	3.65	0.75
SfM	5.0	6.0	61	2.35	5.49	3.73	0.72
LiDAR	5.0	8.0	50	0.14	5.70	3.48	1.15
SfM	5.0	8.0	50	0.12	5.49	3.52	1.18
LiDAR	5.0	10.0	42	0.14	5.70	3.50	1.25
SfM	5.0	10.0	42	0.12	5.49	3.60	1.14

Table 4. Fitting parameter of the maximum canopy height extracted from CHM_{LiDAR} and CHM_{SfM} . When the grid height is greater than 4.0 m, the R^2 for the fitting of the maximum canopy height extracted from the two datasets is greater than 0.8, indicating a good correlation between them. All of the fitted line slopes, b value, are smaller than 1.0. Meanwhile, all the intersections between the fitted lines and the line $y = x$ have horizontal coordinates x_0 ranging from 3.4 to 4.5. That indicates that, taking x_0 as reference, compared to LiDAR, the SfM algorithm tends to overestimate the heights of lower canopies and underestimate the heights of higher canopies.

Grid Height (m)	R^2 (%)	$rRMSE$	b	a	x_0	p Value of t -test ($\alpha = 0.05$)
0.2	60.01	0.1006	0.789	0.725	3.436	0.004
0.3	58.02	0.1031	0.780	0.753	3.423	0.029
0.4	63.61	0.0955	0.808	0.679	3.536	0.038
0.5	57.22	0.1060	0.782	0.753	3.454	0.110
0.6	58.61	0.1024	0.784	0.757	3.505	0.124
0.8	72.16	0.0835	0.861	0.535	3.849	0.185
1.0	69.92	0.0901	0.850	0.552	3.680	0.285
2.0	71.24	0.0919	0.875	0.459	3.672	0.669
3.0	60.84	0.1003	0.799	0.747	3.716	0.587
4.0	82.14	0.0772	0.926	0.313	4.230	0.701
5.0	92.69	0.0552	0.935	0.298	4.585	0.667
6.0	86.50	0.0832	0.889	0.482	4.342	0.558
8.0	80.74	0.0957	0.921	0.308	3.899	0.890
10.0	92.85	0.0563	0.881	0.519	4.361	0.697

We analyze the significance of the difference between the two through a t -test. The hypotheses are as follows:

H0: *There is no significant difference in the maximum canopy height within the same grid size extracted from the two data sources.*

H1: *There is a significant difference in the maximum canopy height within the same grid size extracted from the two data sources.*

The p value of the t -test for CHM_{LiDAR} vs. CHM_{SfM} is significant ($p < 0.05$) only at grid heights of 0.4 m or less (Table 4), demonstrating that the two methods provide significantly different maximum canopy heights, rejecting H_0 . As grid height increases beyond 0.4 m, the t -test values obtained from CHM_{LiDAR} and CHM_{SfM} gradually increase, making the differences increasingly distant from significance. The overall result is that when the grid height is >0.5 m, there is no significant difference in the maximum canopy heights within grids extracted from the two data sources, accepting H_0 .

The reason may be that as the grid height decreases, the number of grids increases, resulting in a larger sample size for the same study area. When the grid size is larger, although there may be horizontal errors in the modeling, most of the points in the canopy height model reconstructed by the two methods can find their corresponding points within the grid. However, when the grid size is smaller than the horizontal error of the modeling, corresponding points on CHM_{LiDAR} and CHM_{SfM} are divided into different grids, and the horizontal position error between the two models amplifies the difference in canopy heights. This hypothesis can be tested further by manually adjusting the modeling error of CHM_{SfM} or by reducing the horizontal error during the SfM algorithm modeling process by adding ground control points.

Based on the mean values in Table 4, it can be seen that the average canopy height within the grids obtained from the two sensors increases as the grid height increases. This may be due to the fact that, when the grid height is smaller, the proportion of grids with lower maximum canopy heights increases. The data distribution was analyzed using box plots. The box plots indicate that, as the grid height increases, the median and quartiles also increase, suggesting a lower proportion of sampling points with lower heights. However, because the total number of samples for large grids is smaller and the total number of samples for small grids is greater, the mean maximum canopy height obtained with smaller grid sizes may be closer to the actual canopy height.

From the scatter plot, it can be observed that when the grid size is set to less than 1 m, the number of points deviating from the line $y = x$ increases (highlighted by red circles in Figure 10). These points represent large differences in the maximum canopy heights within the same coordinates' application grids between the LiDAR and SfM data. The SfM algorithm tends to produce a smoothing effect when fitting the surface of objects (Figure 11) leading to the possible loss of branches and leaves at the canopy edges during the SfM modeling process, while the LiDAR point cloud data retain these details. Consequently, there are fewer significantly deviating points in red rectangle B compared to red rectangle A in Figure 10. To verify this, the maximum canopy height points were visualized.

Given that the airborne LiDAR used in this study employs centimeter-level RTK positioning, its accuracy is deemed higher than the sub-meter GPS positioning of the Mavic Pro UAV. Taking the LiDAR point cloud data as the ground truth, significant differences between the two data sources indicate that the parameters extracted from the CHM constructed using the SfM algorithm differ considerably from the true values. In such cases, the CHM based on the SfM algorithm is not suitable for high-precision crop phenotyping research.

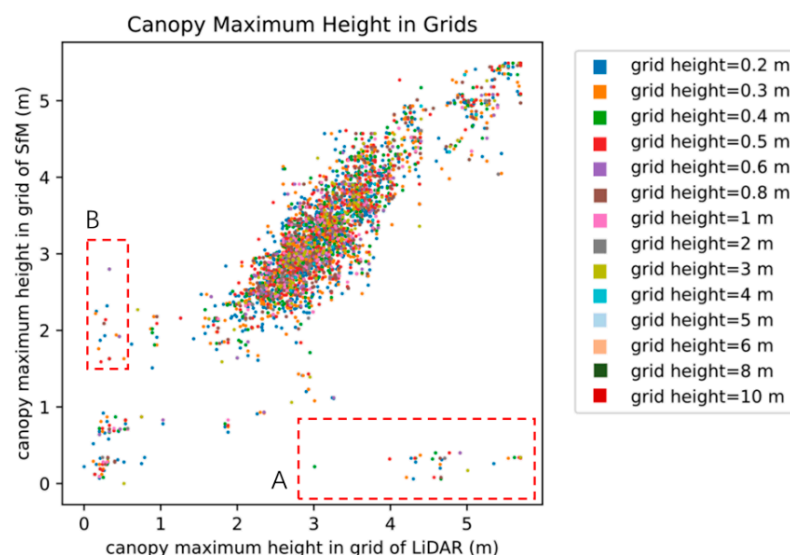


Figure 10. A scatter plot of the maximum canopy height extracted from the two canopy height models using grids of different sizes. The distribution of canopy maximum height fitting points extracted from grids of different sizes from the two models shows no clear separation and appears to be concentrated in the same areas. The points located on the far right or top side represent the canopy maximum height points obtained by LiDAR or SfM algorithms across the entire study area. The points marked within the red rectangle represent a difference of more than 1 m in canopy height values extracted from the two models. This may indicate that the grid's pixels in one model are primarily ground points or lower canopy, while the grid with the same coordinates in the other model includes a higher canopy. Such a situation can be caused by horizontal modeling errors. There are fewer significantly deviating points in red rectangle B compared to red rectangle A in Figure 10.

For the study area, when the application grid width is 5 m and the height is greater than 0.5 m, there is no significant difference ($\alpha = 0.05$) in the prescription values generated based on canopy height using either the SfM algorithm or LiDAR point cloud data. Therefore, in such scenarios, aerial imagery obtained from a UAV, which is lower in cost and data volume, can be used to generate variable-rate application maps.

The maximum canopy heights extracted from different-sized application grids are displayed on a single scatter plot, showing no significant demarcation between data from different parameter settings. The bar chart below demonstrates that, regardless of the application grid size, the mean maximum canopy height within the grid obtained using the SfM algorithm is consistently higher. The reason for this is that the SfM algorithm tends to overestimate lower canopies and underestimate higher canopies. The distinction between high and low is determined by the intersection of the corresponding fitting line with $y = x$. Additionally, as the grid size increases, the mean maximum canopy height within all grids of the canopy height model also increases.

The box plot (Figure 11) demonstrates that, regardless of the grid height used to extract the maximum canopy height, the median (Q2) and upper quartile (Q3) of the maximum canopy heights extracted from CHM_{SfM} are consistently higher than those extracted from CHM_{LiDAR} . This indicates that for the mango tree in the study area, the maximum canopy heights derived from the CHM_{SfM} are generally higher. As the grid height increases, the lower quartile (Q1), median (Q2), and upper quartile (Q3) all increase, and the number of outliers gradually decreases.

For the maximum canopy heights within grids extracted using different sizes of application grids, the slopes value b of the fitted curves are all less than 1 and intercept the y axis at values greater than 0. This indicates that for canopy heights in the range $(0, x_0)$, the heights reconstructed using the SfM method are greater than those modeled using

LiDAR. Conversely, for canopy heights greater than the intersection coordinate, the heights reconstructed using the SfM method are less than those modeled using LiDAR. Although the intersection coordinates may vary, this trend consistently holds true throughout this study. A similar conclusion was drawn in the research by Liu et al. [24]. They found that stratified mean difference in canopy heights increased gradually from negative to positive when the canopy heights were greater than 3 m, which means that photogrammetry tends to overestimate low canopy heights and underestimate high canopy heights. This explains why the surface of the canopy height model generated using the SfM algorithm is smoother (Figure 12). The coordinates of the demarcation point may be influenced by factors such as light intensity, tree variety, and canopy density. In this study, the overall canopy height of mango trees in the study area is lower than the height of the demarcation point, resulting in CHM_{SfM} being higher than CHM_{LiDAR} overall.

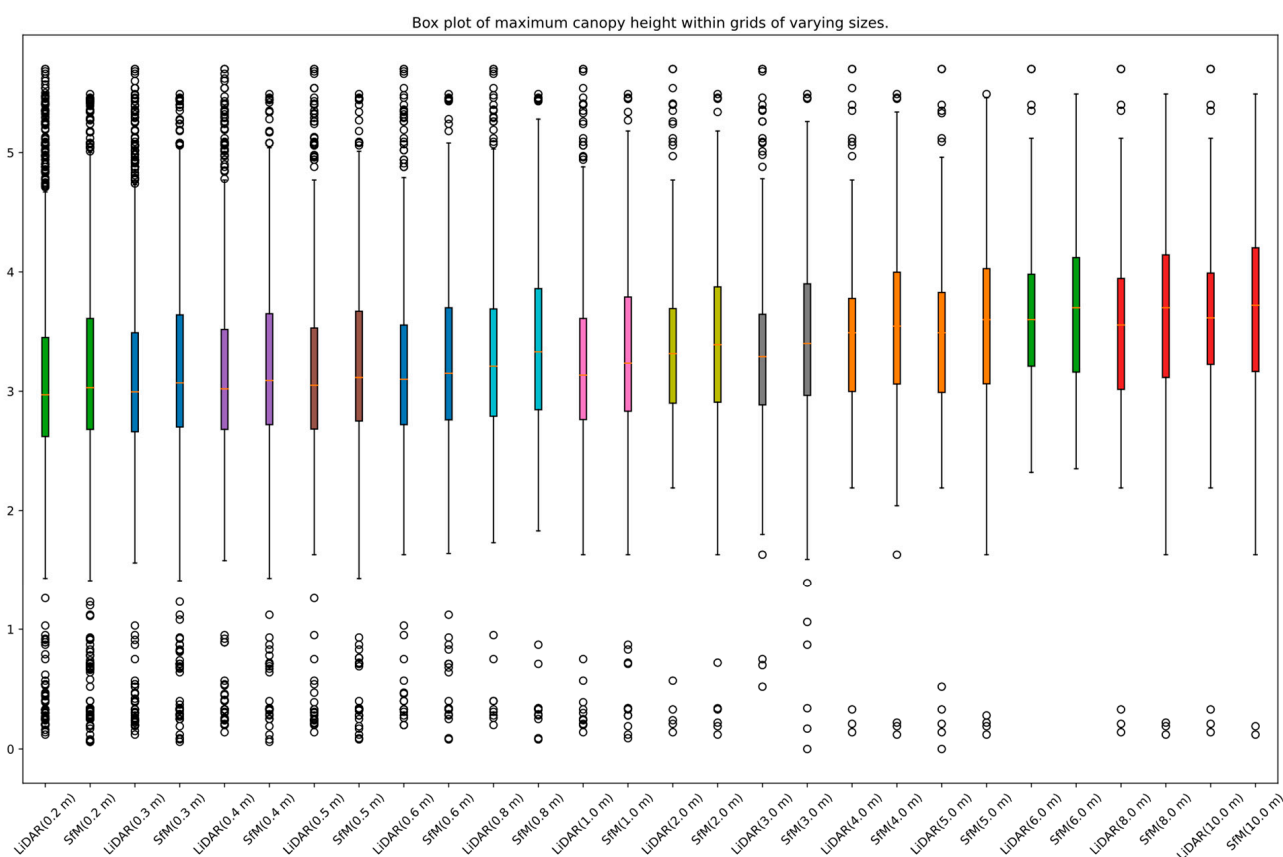


Figure 11. Box plot of maximum canopy height within grids of varying sizes. In the figure, the box plots with the same color represent the maximum canopy height within grids of the same height extracted from the two canopy height models. Regardless of the grid height used to extract the maximum canopy height, the median (Q2) and upper quartile (Q3) of the maximum canopy heights extracted from CHM_{SfM} are consistently higher than those extracted from CHM_{LiDAR} .

To evaluate the height accuracy of CHM_{SfM} , this study selected 14 points within the research area to measure the canopy height of mango trees and compared these measurements with the canopy heights at corresponding locations in the CHM_{SfM} . The selected points included both the edge and center parts of the mango tree canopies (Figure 13). The data analysis results indicate that the coefficient of determination (R^2) between the CHM height and the field-measured canopy height is 0.9466, with an RMSE of 0.084 m, which is superior to the comparison results between CHM_{SfM} and CHM_{LiDAR} (Figure 14). This suggests that, in the absence of ground control points, the primary source of error between CHM_{SfM} and CHM_{LiDAR} may be positioning errors rather than canopy height errors.

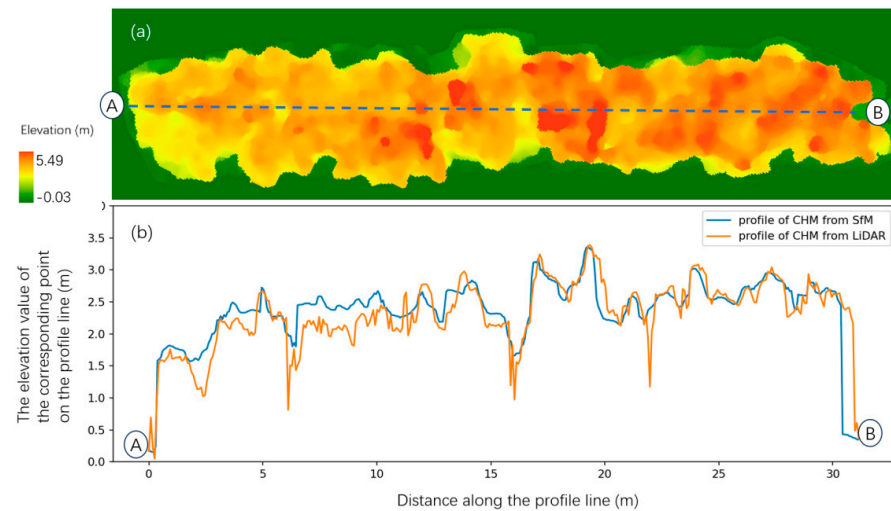


Figure 12. A selected profile line (a) was used to create profile diagrams (b) for the two canopy height models. A and B represent the starting and ending positions of the profile line. The results indicate that, compared to the CHM_{LiDAR} , the surface of CHM_{SfM} is smoother. Additionally, CHM_{SfM} tends to overestimate lower canopies.



Figure 13. The schematic diagram shows the positions of the field-measured height points within the orchard. The sampling points include those at the edges of the canopy as well as those at the center of the canopy.

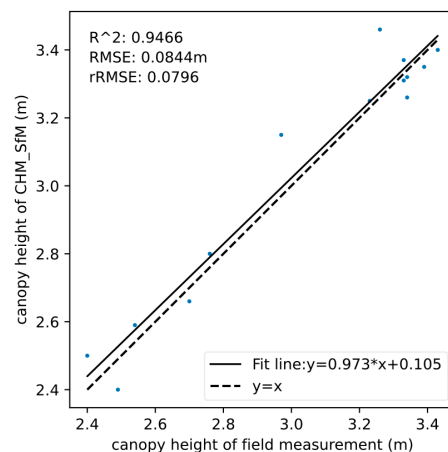


Figure 14. The field-measured canopy heights are compared with those obtained from the canopy height model, and an analysis is conducted.

3.1.2. Analysis of Canopy Project Area Extracted by Different Sizes of Canopy Grids

By adjusting the grid height, canopy projection areas within grids were extracted in 14 different sizes of grids. Table 5 illustrates the minimum, maximum, mean, and standard deviation of canopy projection areas extracted using grids of 14 different heights. The scatter plot below illustrates the data distribution as outlined in Figures 15 and 16. The maximum canopy projection area within the grid does not exceed the grid area, resulting in a clear boundary line in the scatter plot. Points near the boundary line represent the canopy projection areas extracted from the height models established by both sensors for grids of the same size, with at least one area close to filling the entire grid.

Table 5. Extraction of canopy projection area within grid cells of varying sizes. This table illustrates the minimum, maximum, mean, and standard deviation of canopy projection areas extracted using grids of 14 different heights.

Data Source	Grid Width (m)	Grid Height (m)	N	Minimum (m ²)	Maximum (m ²)	Mean Value (m ²)	Standard Deviation (m ²)
LiDAR	5.0	0.2	1625	0.0000	1.0172	0.8090	0.1906
SfM	5.0	0.2	1625	0.0110	1.0158	0.7694	0.2003
LiDAR	5.0	0.3	1080	0.0035	1.5241	1.2171	0.2766
SfM	5.0	0.3	1080	0.0055	1.5100	1.1567	0.2960
LiDAR	5.0	0.4	814	0.0070	2.0169	1.6168	0.3769
SfM	5.0	0.4	814	0.0110	2.0041	1.5363	0.4010
LiDAR	5.0	0.5	658	0.0000	2.5132	1.9998	0.5092
SfM	5.0	0.5	658	0.0138	2.5203	1.9041	0.5199
LiDAR	5.0	0.6	544	0.0176	3.0165	2.4157	0.5751
SfM	5.0	0.6	544	0.0414	3.0144	2.2977	0.6068
LiDAR	5.0	0.8	413	0.0070	4.0197	3.1894	0.8111
SfM	5.0	0.8	413	0.0607	4.0082	3.0328	0.8393
LiDAR	5.0	1.0	336	0.0035	5.0158	3.9215	1.1123
SfM	5.0	1.0	336	0.0028	5.0157	3.7333	1.1119
LiDAR	5.0	2.0	171	0.0070	9.9964	7.7025	2.2984
SfM	5.0	2.0	171	0.0193	10.0177	7.3343	2.3035
LiDAR	5.0	3.0	118	0.0704	14.6989	11.1609	3.8768
SfM	5.0	3.0	118	0.3202	15.0086	10.6305	3.6965
LiDAR	5.0	4.0	89	0.0070	19.6056	14.8049	5.0083
SfM	5.0	4.0	89	0.0193	20.0133	14.0918	5.0151
LiDAR	5.0	5.0	73	0.0035	24.2870	18.0498	6.3805
SfM	5.0	5.0	73	0.0138	24.9324	17.1801	6.2735
LiDAR	5.0	6.0	61	0.2006	29.0705	21.6006	6.7235
SfM	5.0	6.0	61	0.3202	29.2221	20.5639	6.5188
LiDAR	5.0	8.0	47	0.0070	39.0001	28.0348	10.9639
SfM	5.0	8.0	47	0.0193	37.6194	26.6845	10.4545
LiDAR	5.0	10.0	39	0.0070	47.6941	33.7855	14.1969
SfM	5.0	10.0	39	0.3616	46.7041	32.1577	13.4583

Using linear regression equations to fit the canopy projection area parameters extracted from the same-sized grids from two data sources, we obtained R^2 , $rRMSE$, the regression equation $y = a + bx$, and the coordinates of the intersection of the regression equation with the line $y = x$ Table 6. A t -test was used to assess the significance of the differences in canopy projection area extracted from the same-sized grids from the two data sources, with $\alpha = 0.05$. The hypotheses were:

H0: No significant difference in canopy projection area extracted from the same-sized grids from the two data sources.

H1: Significant difference in canopy projection area extracted from the same-sized grids from the two data sources.

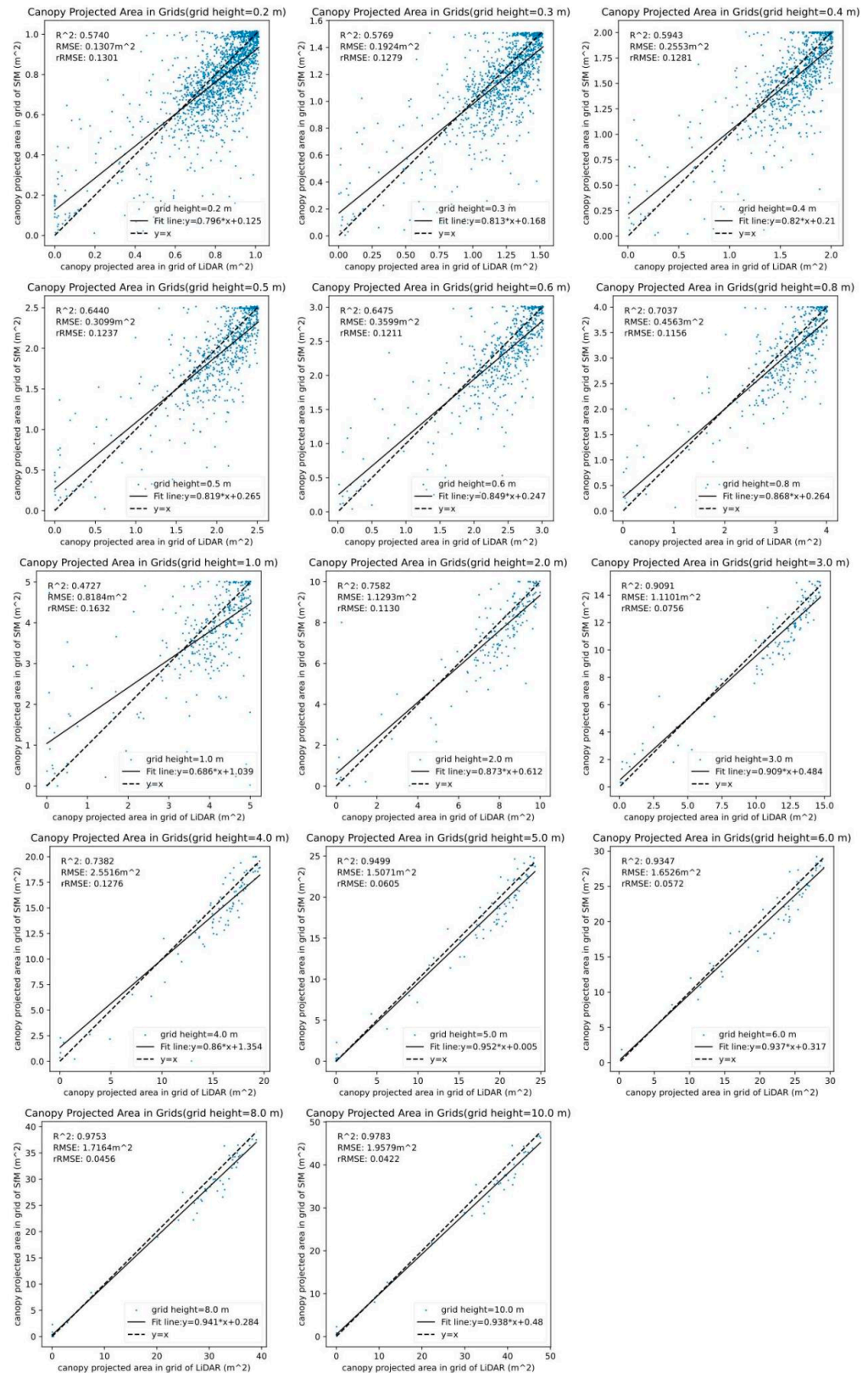


Figure 15. Extract the canopy projection area from the two canopy height models using grids of different heights, and create scatter plots for grids at the same coordinates. The canopy projection area within a grid cannot exceed the grid area, so the scatter plot forms a clear boundary line near the grid area. The intersection of the fitted line with $y = x$ indicates that, compared to CHM_{LiDAR} , CHM_{SfM} tends to overestimate smaller canopy projection areas and underestimate larger canopy projection areas, using the intersection point x_0 as the boundary.

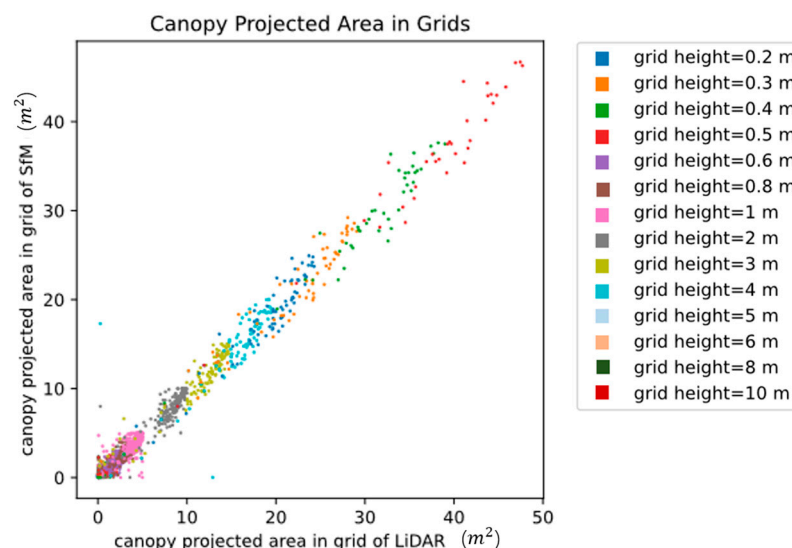


Figure 16. Figure that integrated scatter plots of canopy projection areas extracted from grids of all sizes in this study.

Table 6. Fitting parameter of canopy projection area extracted by same size of grid cells from SfM and LiDAR. Based on R^2 and $rRMSE$, it can be observed that as the grid height increases, the correlation of the canopy projection area extracted from both models increases, and the relative error gradually decreases.

Grid Height (m)	R^2 (%)	$rRMSE$	b	a	x_0	p Value of t -Test ($\alpha = 0.05$)
0.2	57.40	0.1301	0.796	0.125	0.613	<0.001
0.3	57.69	0.1279	0.813	0.168	0.898	<0.001
0.4	59.43	0.1281	0.820	0.210	1.167	<0.001
0.5	64.40	0.1237	0.819	0.265	1.464	<0.001
0.6	64.75	0.1211	0.849	0.247	1.636	0.001
0.8	70.37	0.1156	0.868	0.264	2.000	0.007
1.0	44.00	0.1657	0.663	1.133	3.362	0.029
2.0	75.82	0.1130	0.873	0.612	4.819	0.140
3.0	90.91	0.0756	0.909	0.484	5.319	0.283
4.0	73.82	0.1276	0.860	1.354	9.671	0.344
5.0	94.99	0.0605	0.952	0.005	0.104	0.453
6.0	93.47	0.0572	0.937	0.317	5.032	0.389
8.0	61.58	0.1705	0.748	5.707	22.647	0.543
10.0	97.83	0.0422	0.938	0.480	7.742	0.605

From the p value of the t -test in Table 6, it is evident that the significance of differences in canopy projection area extracted from the same-sized grids from the two data sources varies with grid height between 1.0 m and 2.0 m: as grid height increases, the confidence in differences in canopy projection area extracted from the same-sized grids from the two data sources decreases. When the grid height is less than or equal to 1.0 m, there is a significant difference in canopy projection area extracted from the two data sources, rejecting the null hypothesis H_0 . When the grid height is greater than or equal to 2.0 m, there is no significant difference in canopy projection area extracted from the two data sources, accepting the null hypothesis H_0 .

The differences in maximum canopy height within different data grids occurred within the [0.4 m, 0.5 m] grid height range, while differences in projection area occurred within the [1.0 m, 2.0 m] grid height range. Specifically, within the [0.5 m, 1.0 m] interval, although there is no significant difference in maximum canopy height within the grid, there is a significant difference in canopy projection area within the grid.

The differences in maximum canopy height within different data grids occurred within the [0.4 m, 0.5 m] grid height range, while differences in projection area occurred within the [1 m, 2 m] grid height range. Specifically, within the [0.5 m, 1.0 m] interval, although there is no significant difference in maximum canopy height within the grid, there is a significant difference in canopy projection area within the grid.

In this experiment, the range of slopes b of the fitted lines under grid settings is [0.663, 0.952], all less than 1, and a is greater than 0 for all cases. The coordinates of the intersection points of the fitted lines with the line $y = x$ are all greater than 0. Points above and below the line $y = x$ represent canopy projection areas extracted from CHM_{SfM} that are greater or smaller than those extracted from CHM_{LiDAR} under a certain grid height setting.

Considering the linear regression equations fitted with scatter data, at the intersection point x_0 of the regression equation and $y = x$, when x is less than x_0 , canopy projection areas extracted from CHM_{SfM} tend to be larger than those extracted from CHM_{LiDAR} .

Formula (8) shows that the canopy projection area within a grid is related to the spatial resolution of the canopy height model and the number of pixels representing the canopy. Given that the spatial resolution of pixels is a constant value, the analysis of the projection areas from both models can be used to evaluate the number of pixels representing the canopy in each model. The spatial resolution of CHM_{SfM} is 0.0525 m, which is smaller than the spatial resolution of CHM_{LiDAR} at 0.0593 m. In the interval $[0, x_0]$, where CHM_{SfM} represents a smaller actual spatial area per pixel, the canopy projection area extracted from CHM_{SfM} still tends to be larger than that from CHM_{LiDAR} . This indicates that CHM_{SfM} represents a greater number of pixels representing the canopy in this interval.

$$\frac{h_{SfM} \cdot w_{SfM}}{h_{LiDAR} \cdot w_{LiDAR}} = 0.7838$$

$$CPA_{SfM(x,y)} = m \cdot h \cdot w$$

$$b = \frac{\widehat{CPA}_{SfM(x,y)}}{\widehat{CPA}_{LiDAR(x,y)}} = \frac{m_{SfM(x,y)} \cdot h_{SfM} \cdot w_{SfM}}{m_{LiDAR(x,y)} \cdot h_{LiDAR} \cdot w_{LiDAR}}$$

3.1.3. Analysis of Canopy Volume Extracted by Different Sizes of Canopy Grids

Figures 17 and 18 illustrate the extraction of the projected canopy area within grids at different heights. A t -test was conducted on the canopy volume parameters extracted from two data sources at different grid heights, with $\alpha = 0.05$. H_0 : There is no significant difference in canopy volume extracted from CHM_{SfM} and CHM_{LiDAR} models at a certain grid size $\Leftrightarrow H_1$: There is a significant difference in canopy volume extracted from CHM_{SfM} and CHM_{LiDAR} models at a certain grid size. Table 7 illustrates the minimum, maximum, and mean of canopy projection areas extracted using grids of 14 different heights.

The p value of the t -test of canopy volume determined by CHM_{SfM} vs. CHM_{LiDAR} is significant ($p < 0.05$) only at grid heights of 0.3 m or less (Table 8). Compared to the maximum canopy height and canopy projection area within the grid, the differences in canopy volume parameters between the two data sources can be reduced to the set significance level at smaller grid heights. This indicates that among the three parameters, the difference in canopy volume obtained from CHM_{SfM} and CHM_{LiDAR} is the smallest.

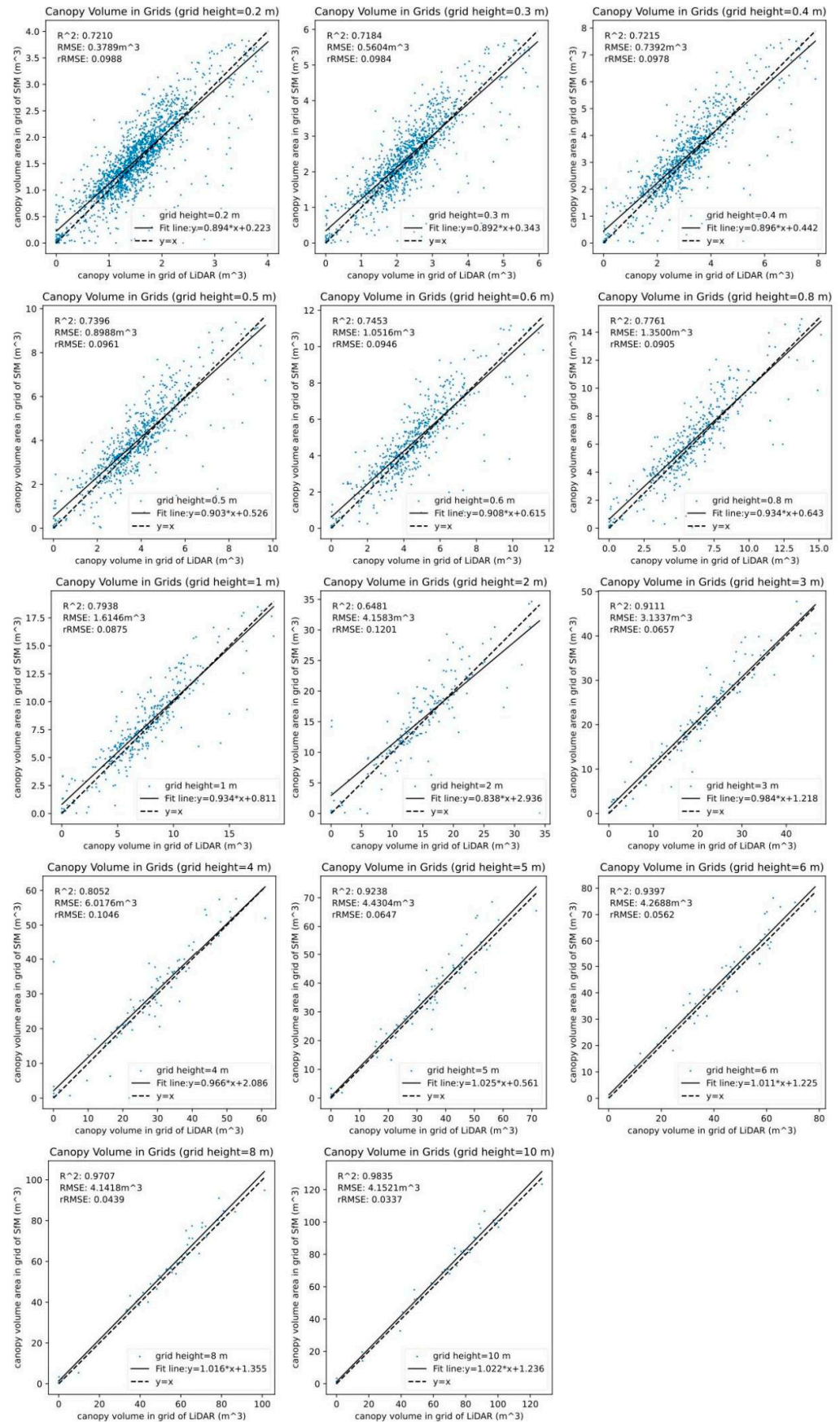


Figure 17. Scatter plot of canopy volume extracted within grids of varying heights. As the grid height increases, the number of grids decreases, the correlation coefficient between scatter points gradually increases, and the $rRMSE$ gradually decreases.

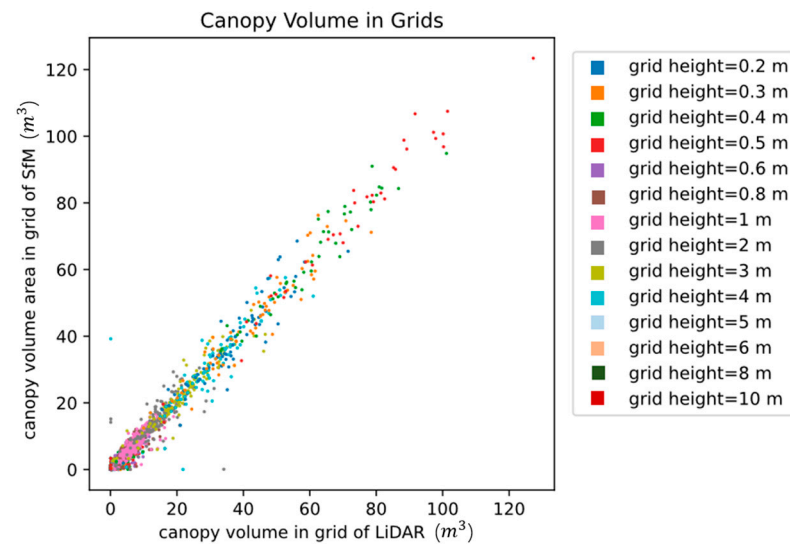


Figure 18. Scatter plots of canopy data extracted using grids of different sizes. With the increase in grid height, the scatter points show a good linear trend.

Table 7. Distribution of canopy volume within grid cells of varying sizes. This table illustrates the minimum, maximum, and mean of canopy projection areas extracted using grids of 14 different heights.

Data Source	Grid Width (m)	Grid Height (m)	N	Minimum (m ³)	Maximum (m ³)	Mean Value (m ³)
LiDAR	5.0	0.2	1669	0.00	4.01	1.51
SfM	5.0	0.2	1669	0.00	3.83	1.57
LiDAR	5.0	0.3	1116	0.00	5.96	2.28
SfM	5.0	0.3	1116	0.00	5.70	2.38
LiDAR	5.0	0.4	838	0.00	7.89	3.05
SfM	5.0	0.4	838	0.01	7.57	3.18
LiDAR	5.0	0.5	674	0.00	9.66	3.79
SfM	5.0	0.5	674	0.02	9.37	3.95
LiDAR	5.0	0.6	559	0.00	11.68	4.57
SfM	5.0	0.6	559	0.03	11.15	4.76
LiDAR	5.0	0.8	423	0.00	15.14	5.98
SfM	5.0	0.8	423	0.03	14.95	6.23
LiDAR	5.0	1.0	342	0.01	18.97	7.43
SfM	5.0	1.0	342	0.02	18.47	7.74
LiDAR	5.0	2.0	176	0.01	34.12	14.44
SfM	5.0	2.0	176	0.03	34.66	15.04
LiDAR	5.0	3.0	120	0.01	46.60	21.03
SfM	5.0	3.0	120	0.08	47.77	21.92
LiDAR	5.0	4.0	92	0.01	61.04	27.91
SfM	5.0	4.0	92	0.03	57.57	29.06
LiDAR	5.0	5.0	78	0.01	71.53	34.03
SfM	5.0	5.0	78	0.02	68.54	35.43
LiDAR	5.0	6.0	61	0.09	78.48	40.72
SfM	5.0	6.0	61	0.30	76.29	42.40
LiDAR	5.0	8.0	50	0.01	101.14	54.00
SfM	5.0	8.0	50	0.44	94.85	56.22
LiDAR	5.0	10.0	42	0.01	127.27	63.69
SfM	5.0	10.0	42	0.16	123.39	66.31

Table 8. Fitting parameter of canopy volume extracted by the same size of grid cells from SfM and LiDAR. Compared to the canopy height and canopy projection area parameters, the slope of the scatter plot fitting for canopy volume parameters exceeds 1 after the grid height exceeds 5.0 m. However, the trend of increasing p -values in the t -test with increasing grid height still persists.

Grid Height (m)	$R^2(\%)$	$rRMSE$	b	a	x_0	p Value of t -Test ($\alpha = 0.05$)
0.2	72.10	0.0988	0.894	0.223	2.104	0.001
0.3	71.84	0.0984	0.892	0.343	3.176	0.030
0.4	72.15	0.0978	0.896	0.442	4.250	0.063
0.5	73.96	0.0961	0.903	0.526	5.423	0.092
0.6	74.53	0.0946	0.908	0.615	6.685	0.113
0.8	77.61	0.0905	0.934	0.643	9.742	0.201
1.0	79.38	0.0875	0.934	0.811	12.288	0.238
2.0	64.81	0.1201	0.838	2.936	18.123	0.424
3.0	91.11	0.0657	0.984	1.218	76.125	0.514
4.0	80.52	0.1046	0.966	2.086	61.353	0.563
5.0	92.38	0.0647	1.025	0.561	−22.440	0.591
6.0	93.97	0.0562	1.011	1.225	−111.364	0.591
8.0	97.07	0.0439	1.016	1.355	−84.687	0.660
10.0	98.35	0.0337	1.022	1.236	−56.182	0.721

3.1.4. The Canopy Upper Surface Area Difference Between CHM_{SfM} and CHM_{LiDAR}

To compare the differences in calculating canopy surface area from different datasets, the canopy surface area was calculated on a per-crop row basis. There were nine planting rows in the mango orchard. The coefficient of determination (R^2) of two canopy coverage datasets was 94.6%. Their MAE was 114.5868 m^2 , $RMSE$ was 115.8603 m^2 , and $rRMSE$ was 3.06%. The data analysis indicated that when using the same method to calculate canopy coverage, there are discrepancies between the canopy coverage calculated by SfM and the canopy coverage calculated by LiDAR. CHMs were generated by subtracting DTM from DSM. However, different algorithms and parameter settings may fit the ground surface into different DTMs. Factors such as leaf litter covering the ground in the orchard and abrupt changes and undulations in the orchard terrain ultimately impact the calculation of canopy point heights. Meanwhile, whether CHM_{LiDAR} or CHM_{SfM} , the models express the structure of mango tree canopies in a certain manner, but they all have a degree of distortion. In this study, the canopy upper coverage defined to conduct the variable spraying research is an abstract plane that does not actually exist in physical space, so it is difficult to obtain a certain canopy coverage value.

A Gaussian filter was applied to the CHM_{LiDAR} to filter out small surface details. Subsequently, the calculated canopy surface area on CHM_{SfM} accounted for 81.19% of the surface area on CHM_{LiDAR} , demonstrating that LiDAR's characterization of canopy details during modeling indeed led to differences in calculated area to some extent (Figure 19).

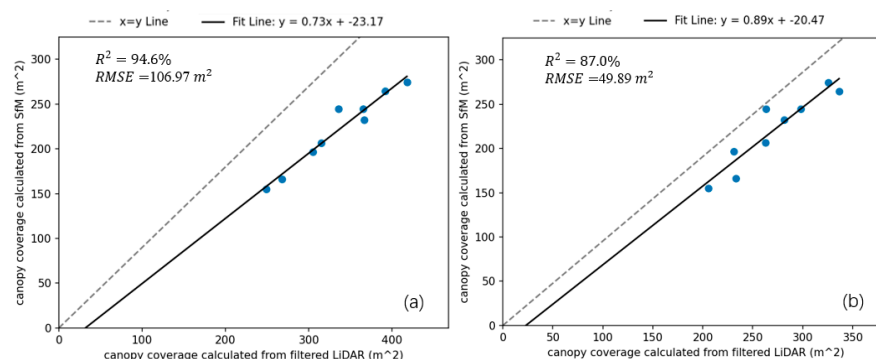


Figure 19. Comparison of surface area on the canopy calculated based on CHM_{LiDAR} and CHM_{SfM} . (a) The relationship between $CUA_{LiDAR-filtered}$ and CUA_{SfM} , $R^2 = 87.0\%$. (b) The relationship between CUA_{LiDAR} and CUA_{SfM} , $R^2 = 94.6\%$.

3.1.5. The Differences Between the Two Canopy Height Models

To analyze potential differences in extracting tree canopy-related parameters and generating application prescription maps based on CHM_{SfM} and CHM_{LiDAR} , this study extracted and compared three parameters (maximum canopy height, canopy projection area, and canopy volume) from the two canopy height models using grids of fourteen different heights.

In this study, canopy features were extracted using grids of different heights. To achieve grid-based extraction of canopy parameters, it is necessary to assign the canopy height model pixels in TIFF format into grids. This study's implementation method is as follows: a corner of the study area is selected as the coordinate origin, and a coordinate system orthogonal to the crop walking direction is established. Projection distances of the pixels on the coordinate axes are then rounded down to obtain the horizontal and vertical coordinates of the grid. In addition to being applied to pixel division, this method can also be used in UAV variable-rate spraying operations to read the grid corresponding to the current position. During UAV spraying, the CHM pixel's latitude and longitude coordinates are replaced with the UAV's current positioning latitude and longitude, thus determining the spraying grid corresponding to the UAV's current location. This study successfully extracted canopy parameters related to variable-rate spraying from canopy height models based on grids. These parameters can be further processed into application parameters such as pipe flow rate, providing a reference for guiding UAVs in variable-rate spraying according to prescription maps. In future work, this method can be applied to UAV variable-rate spraying controllers. Through field experiments, the controller's response speed in reading the prescription value of the current position and adjusting the spraying parameters can be tested.

Different grid sizes were used to extract canopy features, showing that as grid height increased, the R^2 of the maximum canopy height, canopy projection area, and canopy volume extracted from two models generally increased, while $rRMSE$ generally decreased, and the p value of the t -test increased. This result indicates that as grid height increases, the differences in the maximum canopy height, canopy projection area, and canopy volume extracted from the two models decrease. This is likely due to positional errors in the two modeling methods. In this study, ground control points (GCPs) were not used when constructing the CHM_{SfM} , focusing on the differences in canopy parameters between CHM_{SfM} without GCPs and CHM_{LiDAR} . In future work, GCPs can be added during the construction of CHM_{SfM} , and orthogonal experiments can be conducted to determine the influence of modeling methods and GCPs on modeling accuracy through F-tests. Additionally, even without GCPs, when the grid height is above 1.0 m, there is no significant difference in the canopy parameters extracted from CHM_{SfM} and CHM_{LiDAR} . This suggests that when the grid height is above 1.0 m, the CHM_{SfM} can guide variable-rate spraying prescription maps to a degree comparable to CHM_{LiDAR} .

This study primarily focuses on the mango tree canopy in the study area. The selected study area has a single tree species, a small sample size, and flat terrain. In future studies, the number of tree species and sample sizes can be increased, or the influence of terrain factors on canopy height model parameters can be discussed [31]. Meanwhile, the study compares results based on a regular grid structure. However, it would be valuable to discuss whether using irregularly distributed locations might yield different insights. In future research work, it can be considered to extract the canopy features by using irregularly shaped grids based on the actual canopy conditions, so as to better reflect the canopy situation.

The effectiveness of variable spraying prescription maps generated based on canopy characteristics involves issues of timeliness. After obtaining the data of the fruit tree canopy,

the trees continue to grow, and the canopy structure may change with the seasons. If there is a long interval between obtaining the original data for the prescription map and the spraying operation, the prescription map may no longer reflect the current actual situation of the canopy. Therefore, it is necessary to collect temporal characteristic data of the fruit trees. For different fruit tree species, the timeliness of variable spraying prescription maps based on canopy parameters should be analyzed in combination with the growth and changes in the fruit tree canopy.

This study can provide a reference for the feasibility of generating variable spraying prescription maps based on fruit tree canopy characteristics using aerial drone data with sub-meter GPS positioning accuracy.

In future studies, it also could be attempted to select samples with more independent canopy structures or calculate the upper surface area of mango tree canopies after performing single tree segmentation, although it is reasonable to base the variable-rate pesticide spraying application on tree rows. This approach would help to increase the sample size and facilitate the analysis of the reasons for the differences in calculated mango tree upper surface area based on different datasets. In this study, resolutions of CHM_{SfM} and CHM_{LiDAR} are 5.2 cm/pixel and 6.0 cm/pixel. This resolution level is higher than what is required for UAV variable spraying prescription maps in orchards. If UAV variable spraying for fruit trees in orchards is to be guided, it may be necessary to adjust the resolution based on the achievable resolution of UAV variable spraying technology. Meanwhile, the process of extracting canopy feature parameters based on raw data from UAV oblique photography, as discussed in this study, is relatively complex. In practical applications, these data processing workflows should be integrated and simplified to enhance efficiency.

3.1.6. Spatial Distribution Analysis of Canopy Point Clouds Generated by Two Methods

In addition to the canopy height model, the raw data of the two sensors were also processed to generate point cloud data for the study area. Pix4D Mapper was used to process the images to generate 3D models and format point cloud files. Ligeoreferance was used to solve the original point clouds collected by LiDAR and trajectory adjust the point clouds combined with the flight path files recorded by the RTK system. After point cloud cutting, resampling, denoising and normalizing, canopy height models in a point cloud format were obtained (Figure 20). The point cloud data at this stage still includes ground point clouds such as soil, weeds, and fallen leaves. The sample data used for model training should only include the point clouds of the target mango tree canopy to reduce data redundancy and interference on the point cloud recognition results. The Cloth Simulation Filter (CSF) can be used to separate irrelevant ground points from mango tree points [32,33]. The point cloud of the separated mango tree overlapped heavily, making it difficult to manually segment the edges of individual trees through visual inspection.

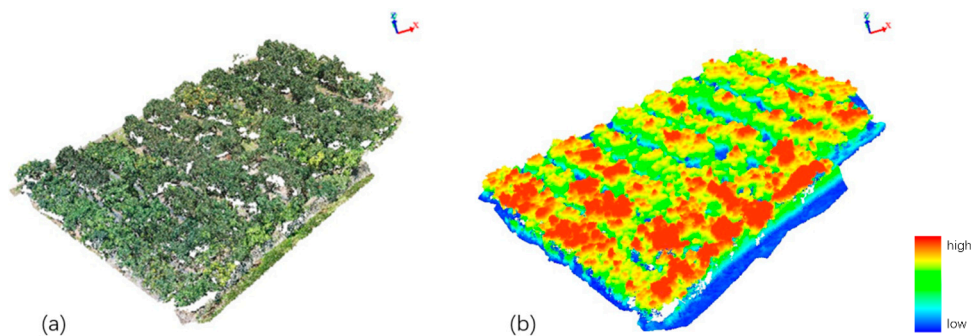


Figure 20. Diagram of CHM in point cloud format constructed from (a) SfM and (b) LiDAR point cloud.

After separating ground points using the CSF algorithm (Figure 21), the mango tree canopy point cloud file generated by LiDAR contains 5,344,603 points, while the mango tree canopy point cloud file generated by SfM contains 931,845 points. The mango tree canopy point cloud acquired by LiDAR is far denser than the point cloud generated by the SfM algorithm (Figures 22–24).



Figure 21. Wipe off point cloud of ground by CSF algorithm.

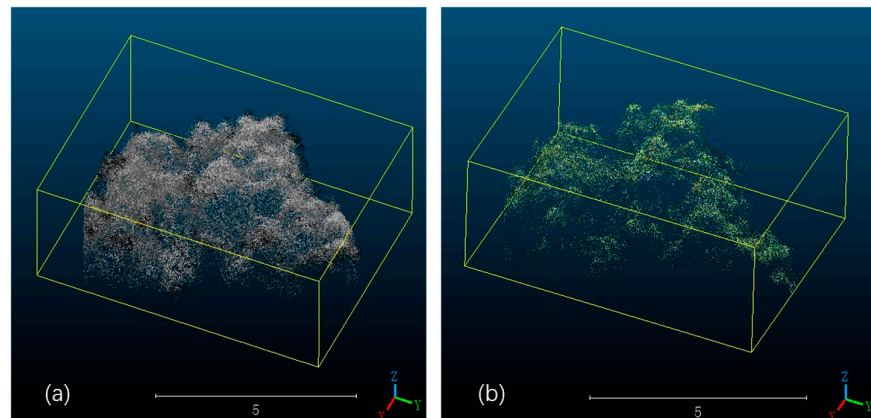


Figure 22. Comparison of the point clouds of the same mango tree generated by the SfM algorithm and LiDAR. (a) The point cloud of the mango tree collected by LiDAR. (b) The point cloud of the mango tree generated by the SfM algorithm. Obviously, for the same tree, the LiDAR point cloud is denser compared to the SfM point cloud.

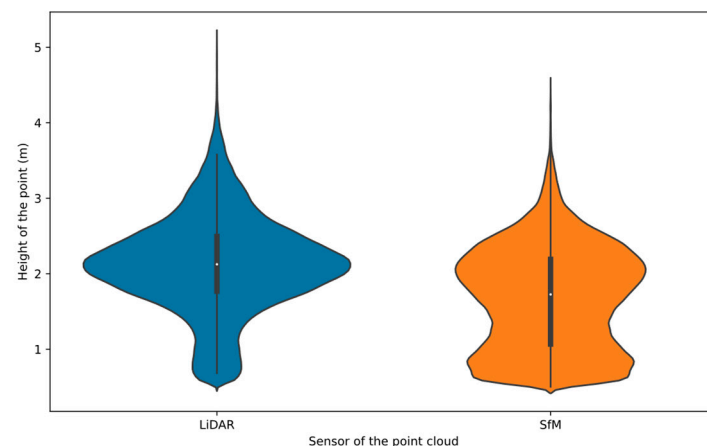


Figure 23. Violin plot of the elevation of the study area point cloud generated by LiDAR sensors and the SfM algorithm. A violin plot can display the shape of the data distribution, the degree of data concentration, and the presence of outliers. The violin plot shows that the canopy point cloud generated by LiDAR is mainly concentrated around a height of 2.1 m, while the canopy point cloud generated by SfM displays two peaks, with distributions at heights of 2.0 m and 0.7 m.

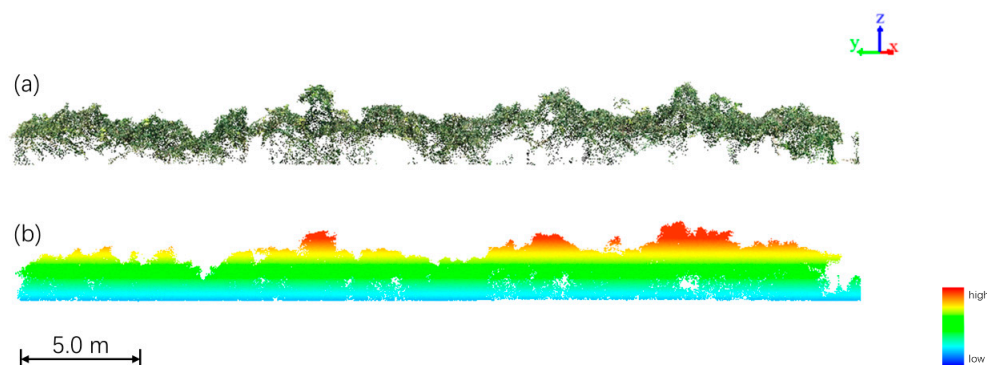


Figure 24. Cross-sectional view of two kinds of point cloud at the same location in the orchard: (a) Cross-sectional view of the point cloud generated by the SfM algorithm. (b) Cross-sectional view of the point cloud obtained by LiDAR.

There has been a lot of research of tree species classification based on airborne LiDAR data [34]. Compared to image data, point cloud data is unordered, making it impossible to directly use image-based neural network models to extract 3D features from point clouds. In 2017, Charles et al. proposed PointNet, a neural network model that utilizes a multi-layer perceptron (MLP) to directly extract effective features from point clouds [35]. The maximum value of a certain feature in a point cloud is not affected by the order in which the features are arranged. PointNet addresses the challenge of extracting features from unordered point clouds by using a higher-dimensional representation to extract feature maxima. To address the model's insufficient ability to recognize local features in point clouds, subsequent research introduced PointNet++, which enhanced the network's capability to recognize local features in point clouds [36]. Numerous crop phenotyping studies have employed these two models for point cloud recognition and segmentation. Sun [37] used the PointNet++ network to assess branch length in point clouds of apple trees during the leaf fall period. Fan [38] demonstrated the feasibility of using the PointNet++ network for tree species classification with airborne LiDAR point clouds and explored the optimal settings for training parameters.

The deep learning-based algorithms for tree species point cloud classification and segmentation provide new methods for orchard variable-rate pesticide application systems. The canopy parameters that can be extracted from orchard point cloud data include canopy height, canopy projection area, canopy volume, and LAI, all of which can guide variable-rate pesticide application. In this study, the point clouds generated by SfM and LiDAR for the same mango tree canopy area show differences in point cloud density and spatial distribution. Will these differences affect the performance of deep learning-based point cloud classification? Can the point cloud recognition neural network trained on SfM-generated point clouds still effectively identify LiDAR-generated tree canopy point clouds? Future research could evaluate the generalizability of point cloud classification models trained on both sources of data.

4. Conclusions

Unmanned aerial spraying systems have the ability to adjust pesticide application rates based on target conditions, allowing for reduced application rates in many situations. The structural characteristics of orchard canopies are crucial for guiding the pesticide application system, and this study used data from drone aerial images and airborne LiDAR point clouds to establish an effective model for estimating variations in the canopy of mango orchards. From this canopy height model, three fruit tree canopy parameters (canopy height, canopy projection area, and canopy volume) were extracted using grids of the same width and various heights from low to high.

The study found that for the three canopy parameters involved, the correlation between the three parameters extracted from the two canopy height models increases as the grid height increases. When the grid height is greater than 1.0 m, there are no significant differences in the three parameters of canopy height, canopy projection area, and canopy volume extracted from CHM_{LiDAR} and CHM_{SfM} , indicating that the variable-rate pesticide application maps generated based on the canopy data obtained from drone aerial images and the ones generated from airborne LiDAR point clouds have similar accuracy. Additionally, using the coordinates x_0 of the intersection of the linear regression equation and $y = x$ as a reference, CHM_{SfM} tends to overestimate lower canopy maximum height and projection area, and underestimate higher canopy maximum height and projection area compared to CHM_{LiDAR} . This to some extent reflects that the surface of CHM_{SfM} is smoother. This study demonstrates the effectiveness of extracting canopy parameters to guide UASS systems for variable-rate spraying based on UAV oblique photography combined with the SfM algorithm.

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Abbreviations

The following abbreviations are used in this manuscript:

CHM	canopy height model
CHM_{SfM}	canopy height model constructed from Structure from Motion dataset
CHM_{LiDAR}	canopy height model constructed from LiDAR point cloud dataset
CUA_{LiDAR}	canopy upper surface area calculated based on LiDAR point cloud dataset
CUA_{SfM}	canopy upper surface area calculated based on images

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