High-throughput plant height measurement for the field peanuts from low-cost UAV photogrammetry

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Abstract

Plant height is, as a crucial indicator, capable of reflecting the health status and growth vigor at various growth stages. It provides essential information for increasing crop yield, optimizing cultivation strategies, and improving varieties. Traditional plant height measurements using tapes or rods are labour-intensive, time-consuming, subject to human errors, and inadequate for large-scale observations. In recent years, unmanned aerial vehicles (UAVs) equipped with RGB cameras have demonstrated significant advantages in terms of efficiency and cost-effectiveness, enabling detailed 3D reconstruction of complex farmland environments through photogrammetry techniques. Therefore, we develop a high-throughput plant height measurement approach for the field peanuts from low-cost UAV photogrammetry. First, a UAV platform equipped with RGB camera is used to collect high-resolution imagery, covering the entire peanut growth stages. Following this, the aerial images are processed and precisely aligned with positional and orientation system (POS) data, subsequently generating Digital Surface Models (DSMs). Among these DSMs, the one representing the bare soil period was considered as the Digital Elevation Model (DEM). Afterwards, each plot is clipped based on its minimum bounding rectangles, creating Canopy Height Models (CHMs) by subtracting the DEM from the corresponding DSMs. Finally, Peanut plant heights are estimated via histogram distribution analysis of CHMs and validated with manually measured heights in Wangbian Community, Ningyang County, Tai'an City, Shandong Province. Experimental results indicate excellent effectiveness and reliability, achieving coefficients of determination (R^2) of 0.9424 and RMSE of 2.26 cm. These observations demonstrate UAV photogrammetry's practical potential for large-scale crop phenotyping applications.

1. Introduction

Peanuts are an important economic and oilseed crop, holding a significant role in global agriculture and the food industry (Yang et al., 2021). Plant height is, as a crucial indicator, capable of reflecting the health status and growth vigor at various growth stages. It provides essential information for increasing crop yield, optimizing cultivation strategies, and improving varieties (Zang et al., 2023). Additionally, plant height can be used to optimize agricultural management and cultivation techniques, such as appropriate planting density, fertilization, and irrigation strategies, thereby improving crop yield and quality. Moreover, changes in plant height can serve as indicators to study the effects of environmental stresses (such as drought, salinity, and low temperatures) on plants, aiding in the development of corresponding countermeasures. Therefore, accurate measurement and analysis of plant height are of great importance for advancing agricultural scientific research and practice.

Traditional plant height measurements using tapes or rods are labour-intensive, time-consuming, subject to human errors, and inadequate for large-scale observations. With the development of sensors and automatic control technology, unmanned aerial vehicles (UAVs) equipped with various devices have shown superior characteristics such as high efficiency, low cost, and flexible operation, making them more suitable for complex farmland environments. To date, accurate and rapid vegetation height monitoring based on UAV remote sensing has been gained increasing interests. Some studies explored UAV platforms equipped with various sensors such as LiDAR (Luo et al., 2021), ultrasonic (ten Harkel et al., 2019) and RGB cameras, etc. (Lu et al., 2021), which are widely used in plant height measurement of crops such as maize (Niu et al., 2024), wheat (Hassan et al., 2019) and rice (Lin et al., 2023). Yuan et al. (2018) successfully estimated wheat height using a UAV equipped with ultrasonic sensor, with Root Mean Square Error (RMSE) and correlation of 0.05m and 0.97, respectively. However, the ultrasonic divergence angle is relatively wide, which would lead to the decrease in the measurement accuracy. The high-frequency pulses of the LiDAR can penetrate the vegetation canopy to reach the ground, obtaining not only detailed information about the vertical canopy structure but also the terrain information below the canopy. It provides a reliable solution for three-dimensional (3D) reconstruction of crop canopy structure. However, the relatively high cost of LiDAR sensors has restricted its expansion from a scientific research method to agricultural production applications.

With the development of photogrammetry and computer vision technology, lots of scholars have focused on using high-resolution RGB cameras based on UAV platforms to obtain multi-temporal images of field crops. On this basis, a high-precision 3D point cloud model of crop canopy is reconstructed from a set of overlapping images using the Structure-From-Motion (SfM) technique (Yang et al., 2024). Previous studies have confirmed the feasibility of using the reconstructed 3D point cloud model to estimate the height of various crops, which is of great significance for accurately studying the structure of crop canopies (Xie et al., 2021). For instance, Fujiwara et al. (2022) used UAV images to estimate the maize height through the SfM algorithm, with the coefficient of determination (R^2) and the mean absolute error (MAE) of 0.803 and 0.039m, respectively. Zhou et al. (2023) also studied the height estimation of winter wheat by reconstructing three-dimensional point cloud models, with R^2 of 0.90 and 0.78 for winter wheat and sorghum, respectively.

Therefore, we develop a high-throughput plant height measurement approach for the field peanuts from low-cost UAV photogrammetry. In our approach, we conduct the SfM algorithm on the high-resolution aerial images to generate 3D point clouds of field peanuts at different growth stages. In order to eliminate the impact of topographic relief on plant height measurement, we

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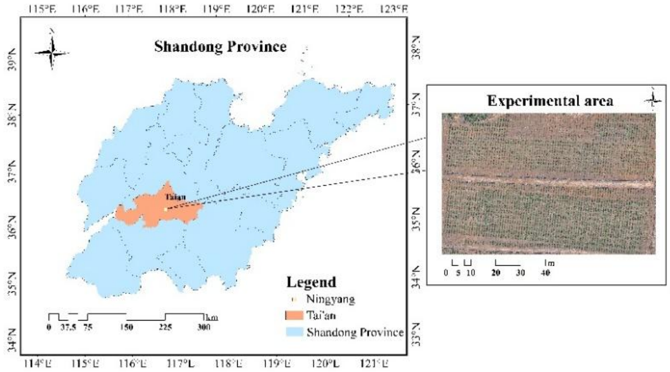


Figure 1. Location and distribution of the study area.

normalized the DEM and DSM to obtain a canopy height model (CHM). Finally, the histogram analysis of the CHM was used to calculate the peanut height of different varieties at different times, providing a practical method for rapid, efficient, and non-destructive peanut plant height estimation.

2. Materials and Methods

2.1 Study Area and Data Sets

2.1.1 Description of the Study Area: The study area is located at Wangbian Community, Ningyang City, Shandong Province, China (latitude: 35°45′40.9″N, longitude: 116°49′12.5″E, altitude: 70-200 meters). It is a semi-humid temperate climate with four distinct seasons and simultaneous rain and heat. The average annual temperature is 15.1°C, the average annual precipitation is 901.4 mm, the annual sunshine hours are 2759.1 hours, and the frost period is 199 days. Figure 1 shows location and distribution of the study area. This study area is divided into a total of eighty columns from south to north, each of which was composed of ten plots. In order to find out high-efficiency peanut varieties for nitrogen, and to compare the characteristics of high-nitrogen and low-nitrogen peanut plant height estimation, we planted high-nitrogen and low-nitrogen experimental regions. Therefore, 1596 plots were planted on 28 May 2024, where 798 varieties of peanuts were sown within high-nitrogen and low-nitrogen experimental regions, respectively.

2.1.2 UAV Image Collection: The experiment used the DJI M350RTK UAV and the DJI Zenmuse P1 equipped with a full-frame camera. Flying height is 12 metres, and the heading and sidetrack overlap rates are shown in Figure 2, with 80% heading overlap and 70% sidetrack overlap. The main parameters of the DJI MATRICE 350 RTK are shown in Table 1. The DJI Zenmuse P1 is equipped with a 45-megapixel full-frame sensor, combined with TimeSync 2.0 microsecond-level time synchronization technology and a new generation of real-time pose compensation technology to achieve centimetre-level precise data collection and a wide range of controllable rotation. It can capture high-resolution images of field peanuts. The specific parameters of the acquisition system parameter settings and camera information are shown in Table 2. The UAV images were collected between 10:00 a.m. and 14:00 p.m. on a clear day with no wind and no clouds. The take-off position, flight route and flight altitude were kept consistent for each operation.

2.1.3 Field data acquisition: To validate the reliability of the estimated peanut plant heights from high-resolution UAV imagery, manual measurements were carried out as ground truth. At each DAS stage, plant height was manually measured for each plot. To minimize discrepancies arising from peanut lodging over time, manual measurements were conducted within three hours of the corresponding UAV image acquisition. During measurements, two researchers collaborated: one researcher measured the peanut plant height using a measuring tape, while the other recorded the data. To minimize observational errors, researchers maintained a horizontal line of sight level with the measuring tape, thus avoiding inaccuracies caused by upward or downward viewing angles. Each plot was measured three times, and the average of these measurements was calculated to represent the actual peanut plant height.

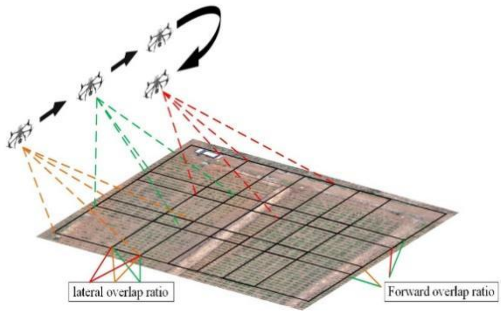


Figure 2. Overlap ratio of the heading and lateral direction of the UAV.

Parameter	Parameter Value
Maximum take-off weight	9.2KG
Maximum flight time	55Min
Maximum flight altitude	7000m
RTK position accuracy	1 cm +1 ppm (horizontal) 1.5 cm +1 ppm (vertical)
Maximum rotational angular velocity	Pitch axis: 300°/sec Heading axis: 100°/sec
Maximum Pitch Angle	30°
Maximum horizontal flight speed	23m/s

Table 1. Parameters of DJI M350RTK

Parameter	Parameter Value
Mass (with paddles and batteries)	800g
Planar Accuracy	3cm
Elevation accuracy	5cm
Pixel size	4.4 μm
Vector overlap rate	80%
Side overlap ratio	70%
Effective pixel	45 million
Controlled rotation range	Pitch: -130° to +40° Traverse roll: -55° to +55° Pan: ±320°

Table 2. Parameters of DJI Zenmuse P1

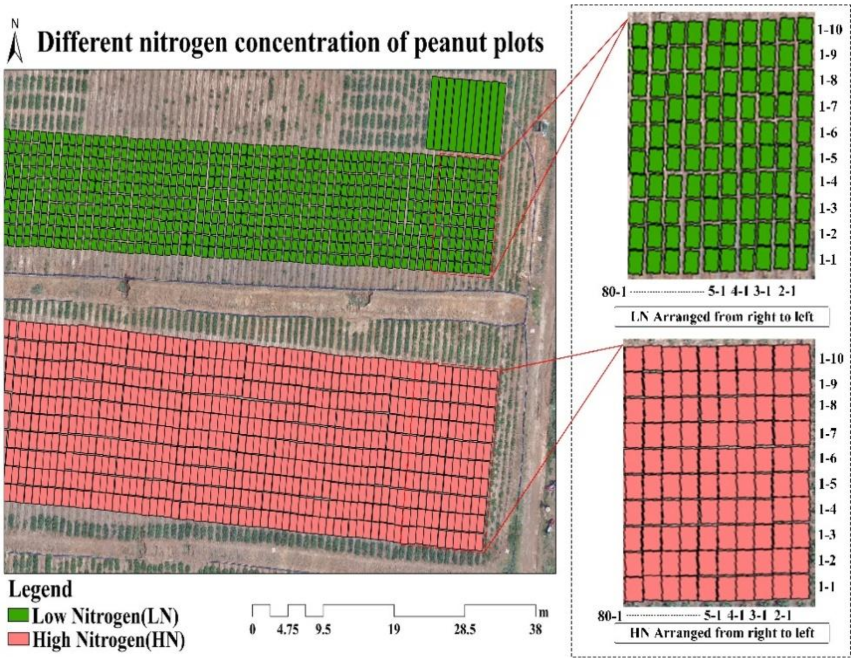


Figure 3. Spatial distribution of peanut plots.

2.2 UAV Data Splicing Alignment and Cropping

After the UAV images are collected, these aerial images are aligned using the POS with the DJI Terra 3.7.0 software and stitched to generate the DOM and DSM. The coordinate system is the UTM49N belt, and the reference frame is WGS84. Since calculating the height of a plant requires a common reference surface, a high-precision DEM is usually used. In our implementation, the DSM corresponding to the bare soil period is considered as the DEM. Then, the ENVI 5.3.1 software is used to crop the smallest bounding rectangle of each plot for subsequent peanut plant height calculation. The DOM acquired on 36 DAS was selected for offering the location information of each plot because almost the peanuts was in the flowering and needling stage. The peanut plots were growing more vigorously, and they did not merge then, making it easy to observe the location of different peanut plots and facilitate the drawing of rectangular-shaped peanut plots. The corresponding plot shapes were drawn for the peanut plots in the HN and LN regions. Here, the rectangular shapes drawn for the HN region are consistent, and the rectangular shapes drawn for the LN region are consistent. To exclude edge regions that contain points from neighboring plots and plot gaps, the split plots are noted to correspond strictly to the peanut locations, and the corresponding names are labeled for the peanut rectangle plots at different locations. Its peanut shape plot nomenclature and the plot division are shown in Figure 3.

2.3 Data Normalization and Plant Height Calculation

In this section, the DSM and DEM obtained by the UAV were normalized to obtain the CHM, as shown in Figure (4). Specifically, as shown in Equation (1), the DSM was subtracted pixel by pixel from DEM to obtain a normalized CHM. In order to further remove noisy points and abnormally low points, a height threshold of 0.005 m was set, and only valid vegetation points above the pre-defined threshold were retained. Finally, the normalized CHM from multiple UAV flight missions were saved. The obtained CHM reflect the actual height of vegetation points and eliminate the influence of terrain undulation, providing basic data support for subsequent vegetation growth analysis and research on dynamic changes over time.

$$H_i = DSM_i - DEM(i = 1,2,3 \cdots) \quad (1)$$

where i denotes the identification number of different peanut’s plots.

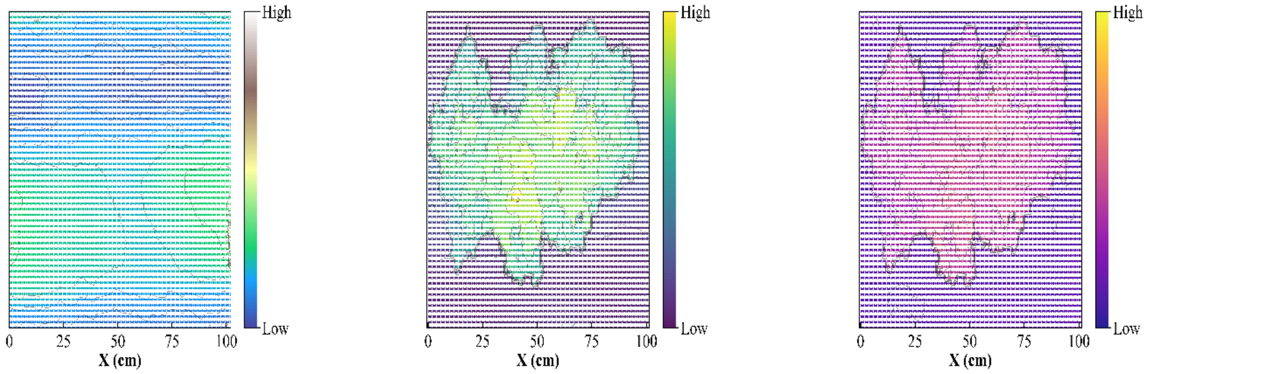
In order to obtain the height distribution characteristics of peanuts at different growth period, height statistics and visualization were performed on the CHM. For each plot, we calculate the height histogram distribution by height statistics and locate the percentile (95th percentile) of the height histogram. The representative peanut plant height of each plot was calculated and recorded using the 0th percentile (ground height) and 95th percentile (upper limit of the main plant height) of the height histogram distribution. This value is used as the representative plant canopy height, which effectively reduces the interference of extreme outliers on the plant height statistics. In addition, a histogram of the canopy height histogram distribution of each plot is generated, and a vertical line is drawn in the graph to mark the position of the extracted 95% representative plant canopy height. The above calculation results are systematically recorded and saved for further analysis of the dynamic changes in peanut plant canopy height at different growth stages.

2.4 Evaluation Metrics for Plant Measurement

To evaluate the reliability of the estimated plant height, we calculated the R^2 and RMSE. First, we used the least squares linear regression fitting method to analyze the relationship between the estimated and the measured value. To evaluate the goodness of fit of the model, we calculate the R^2, which is defined as follows:

$$R^2 = 1 - \frac{SS_{residual}}{SS_{total}} \quad (2)$$

where $SS_{total} = \sum(y_i - \bar{y})^2$ is the sum of the squares of deviation, y_i is the measured value, $\bar{y}$ is the average of all the measured values. $SS_{residual} = \sum(y_i - \hat{y}_i)^2$ is the sum of the squares of the residuals, which indicates the error between the



(a) DEM (b) DSM (c) CHM

Figure 4. Visualization of DEM, DSM, and CHM. The different positions are rendered using different colors according to the size of pixel values.

estimated value $\hat{y}_i$ and measured value y_i. The value of R^2 ranges from 0 to 1, where a value closer to 1 indicates a better fit and a stronger correlation between the predicted and actual values. The value of R^2 ranges from 0 to 1, where a value closer to 1 indicates a better fit and a stronger correlation between the estimated and actual values.

In addition, we calculated the RMSE to reflect the average deviation between the estimated value and the measured value, which is defined as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum(y_i - \hat{y}_i)^2} \tag{3}$$

where n is the number of samples, y_i is the measured value, $\hat{y}_i$ is the estimated value, and its unit is consistent with the measured value (cm). The smaller the RMSE, the smaller the estimation error of the model and the higher the accuracy.

3. Results and Analysis

3.1 Comparisons of Plant Heights at Different Growth Periods

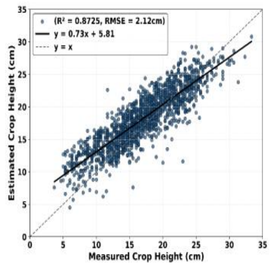
The least squares linear regression was used to analyze the estimated and measured peanut plant heights, as shown in Figure 5 and Table 3. The R^2 of the estimated plant height on 36 DAS was the lowest at 0.8725, and the RMSE was 2.12cm. On 43 DAS, the R^2 slightly raised to 0.9258, and the RMSE dropped to1.65cm. On 48 DAS, the R^2 reached a maximum of 0.9892, and the RMSE also went up to 2.52cm. Although the RMSE showed a slight increase, the coefficient of determination (R^2) is improved, indicating that the model captured more of the overall variance in the data. Since R^2 reflects the model's explanatory power and its ability to represent data trends, it was used as the primary criterion for model evaluation and selection in this study.

When we linearly fit the estimated plant height to the measured values for the entire period, the R^2 reached to 0.9424, and the RMSE reached to 2.26cm. From 36 DAS to 48 DAS, it is now in the peanut flowering and needle stage. In this process, the peanut grows luxuriantly, the leaf area grows rapidly, and the layered growth structure also has a significant impact on the measurement of the peanut plant height. However, the estimated effect exhibited less fluctuation over time, with the R^2 value ranging from 0.9 to 0.95. This effectively mitigated the issue of inaccurate plant height estimation caused by the complex and dense structure of the peanut canopy.

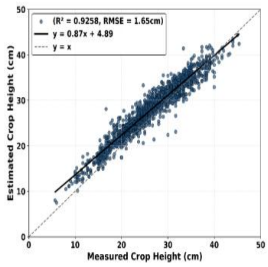
3.2 Comparison of Plant Height in HN and LN Regions

An analysis of plant height information from different regions during the same growth period is shown in Figure 6 and Table 4. On 36 DAS, the linear fitting of plant height in the HN region had an R^2 of 0.7748 and an RMSE of 1.77 cm, compared to an R^2 of 0.9327 and an RMSE of 1.97 cm in the LN region. By 43 DAS, the estimation performance had improved, with the R^2 for the HN region increasing to 0.9013 and the RMSE stabilizing at 1.86 cm. In the same period, the R^2 for the LN region was higher than that for the HN region at 0.9124, and the RMSE had declined to 1.18 cm. Finally, on 48 DAS, the R^2 values for both the HN and LN regions increased to 0.9755 and 0.9930, respectively. The RMSE for the HN region was 2.57 cm, while the RMSE for the LN region was lower at 2.33 cm.

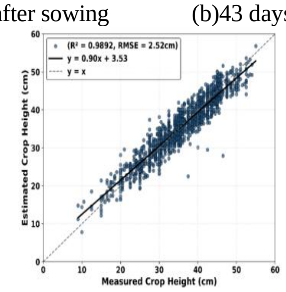
According to the above analysis, the R^2 value increased with DAS in both the HN and LN regions, which aligns with the previously



(a)36 days after sowing



(b)43 days after sowing



(c)48 days after sowing

Figure 5. Relationship between estimated and measured plant height at different ADS.

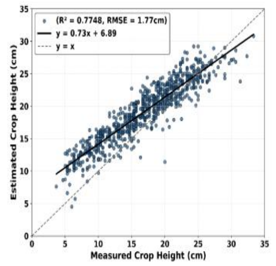
DAS	R^2	RMSE
36	0.8725	2.12
43	0.9258	1.65
48	0.9892	2.52
All periods	0.9424	2.26

Table 3. R^2 and RMSE between estimated and measured plant height at different ADS

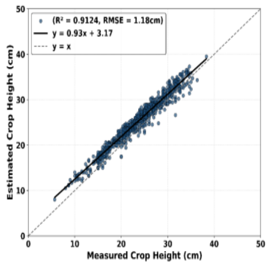
described research content. Additionally, it is evident that the estimation of plant height in the LN region is more accurate than in the HN region. This is because, in the LN region, during the flowering and pegging stages, the synthesis of proteins, nucleic acids, and chlorophyll is hindered. As a result, peanut plants are shorter, have fewer branches, and exhibit slower growth. Consequently, unlike the HN region, which has a denser and more complex canopy structure, the LN region's less dense growth allows for more accurate plant height estimations.

4. Summary and Outlook

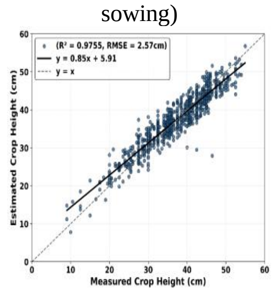
In precision agriculture, plant height is a crucial parameter that reflects the growth status of crops. Accurate measurement of crop plant height is of significant importance in the process of agricultural modernization. In this research, DEM and DSM were used to normalize the data and eliminate the effects of topographic relief. The height trends of peanut plants were analyzed based on CHM data from different growth periods.



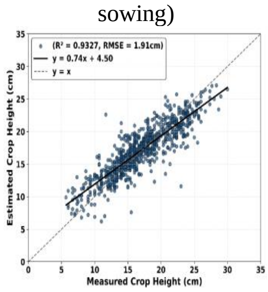
(a) HN region (36 days after sowing)



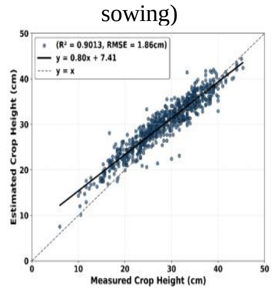
(b) HN region (43 days after sowing)



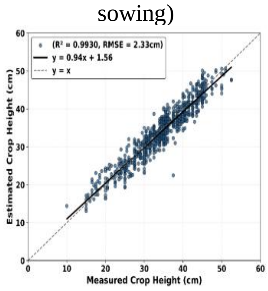
(c) HN region (48 days after sowing)



(d) LN region (36 days after sowing)



(e) LN region (43 days after sowing)



(f) LN region (48 days after sowing)

Figure 6. Relationship between estimated and measured plant height at different ADS and regions.

Region	DAS	R^2	RMSE
High Nitrogen	36	0.7748	1.77
	43	0.9013	1.86
	48	0.9755	2.57
Low Nitrogen	36	0.9327	1.97
	43	0.9124	1.18
	48	0.9930	2.33

Table 4. R^2 and RMSE between estimated and measured plant height at different ADS and regions

Additionally, the accuracy of peanut plant height estimation using UAVs was verified with measured plant height data. The results indicated that CHM can effectively acquire peanut plant height estimations. The R^2 between the estimated and measured values at different growth stages remained high, up to 0.9892, with an RMSE as low as 1.65 cm.

Further analysis showed that the overall effect of plant height estimation in the LN area was better than in the HN area. This improvement is attributed to the slower growth and simpler canopy structure of peanuts in a low nitrogen environment. The peanut plant height estimation method based on high-resolution UAV measurements can achieve fast, non-destructive, and highly accurate plant height measurements, providing substantial technical support for crop growth monitoring and precision agriculture.

Finally, during the experiment, some differences were noted between the remote sensing height measurement method and the traditional agronomic height measurement method. It is necessary to integrate the characteristics of peanut plant structures and address specific scientific issues to optimize the crop plant height extraction method. This optimization will better meet the needs of both scientific research and practical applications. In addition, taking into account environmental factors that affect image quality—such as variable lighting, wind, and ground surface interference—can further improve the robustness and generalizability of the method, thereby enhancing its applicability in broader crop phenotyping applications.

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References

Fujiwara, R., Kikawada, T., Sato, H. & Akiyama, Y. J. F. i. P. S. 2022. Comparison of remote sensing methods for plant heights in agricultural fields using unmanned aerial vehicle-based structure from motion. 13, 886804.

Hassan, M. A., Yang, M., Fu, L., Rasheed, A., Zheng, B., Xia, X., Xiao, Y. & He, Z. J. P. M. 2019. Accuracy assessment of plant height using an unmanned aerial vehicle for quantitative genomic analysis in bread wheat. 15, 1-12.

Lin, Y., He, J., Liu, G., Mou, B., Wang, B., Fu, R. J. P. E. & Sensing, R. 2023. UAS-based multi-temporal rice plant height change prediction. 89, 301-310.

Lu, W., Okayama, T. & Komatsuzaki, M. J. R. S. 2021. Rice height monitoring between different estimation models using UAV photogrammetry and multispectral technology. 14, 78.

Luo, S., Liu, W., Zhang, Y., Wang, C., Xi, X., Nie, S., Ma, D., Lin, Y., Zhou, G. J. C. & Agriculture, E. i. 2021. Maize and soybean heights estimation from unmanned aerial vehicle (UAV) LiDAR data. 182, 106005.

Niu, Y., Han, W., Zhang, H., Zhang, L. & Chen, H. J. B. E. 2024. Estimating maize plant height using a crop surface model constructed from UAV RGB images. 241, 56-67.

Ten Harkel, J., Bartholomeus, H. & Kooistra, L. J. R. S. 2019. Biomass and crop height estimation of different crops using UAV-based LiDAR. 12**,** 17.

Xie, T., Li, J., Yang, C., Jiang, Z., Chen, Y., Guo, L., Zhang, J. J. C. & Agriculture, E. i. 2021. Crop height estimation based on UAV images: Methods, errors, and strategies. 185**,** 106155.

Yang, B., Dong, Z., Liang, F. & Mi, X. 2024. *Ubiquitous Point Cloud: Theory, Model, and Applications*, CRC Press.

Yang, S., Zhang, J., Geng, Y., Tang, Z., Wang, J., Guo, F., Meng, J., Wang, Q., Wan, S. & Li, X. J. P. 2021. Transcriptome analysis reveals the mechanism of improving erect-plant-type peanut yield by single-seeding precision sowing. 9**,** e10616.

Yuan, W., Li, J., Bhatta, M., Shi, Y., Baenziger, P. S. & Ge, Y. J. S. 2018. Wheat height estimation using LiDAR in comparison to ultrasonic sensor and UAS. 18**,** 3731.

Zang, X., Liu, J., Zhao, J., Liu, J., Ren, J., Li, L., Li, X. & Yang, D. J. J. o. P. P. 2023. Uncovering mechanisms governing stem growth in peanut (Arachis hypogaea L.) with varying plant heights through integrated transcriptome and metabolomics analyses. 287**,** 154052.

Zhou, X., Xing, M., He, B., Wang, J., Song, Y., Shang, J., Liao, C., Xu, M. & Ni, X. J. D. 2023. A ground point fitting method for winter wheat height estimation using UAV-based SfM point cloud data. 7**,** 406.