

Article

Low-Cost and Rapid Construction of 3D Point Clouds for Field-Grown Cotton and Evaluation of Canopy-Level Traits

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Abstract

Canopy 3D architecture is a critical determinant of light interception, photosynthetic efficiency, and final yield in cotton, yet its rapid and accurate characterisation remains challenging in field conditions. To achieve efficient, non-destructive, and quantitative monitoring of the canopy structure of field-grown cotton, this study proposes a 3D structure-based technology stack for high-efficiency, low-cost, and high-precision phenotyping extraction. This stack directly addresses the technical bottlenecks of traditional 3D data acquisition, namely high cost, long processing time, and low operational efficiency, which have hindered large-scale application. We developed a pipeline that integrates a fast reconstruction algorithm with a scale-recovery mechanism using ground control points (GCPs), enabling the generation of true-scale 3D point clouds from UAV aerial images in a cost- and time-effective manner. Using only 141 UAV images and with a reconstruction time of approximately 20 min, we efficiently reconstructed high-quality, scale-accurate point clouds of two 5.5 m × 5.5 m cotton plots, significantly outperforming SfM-MVS and Instant-NGP in terms of both reconstruction efficiency and point cloud completeness. This method, whose current validation is confined to a single season, one growth stage, and two experimental plots, not only achieves a breakthrough by using fewer input images with high efficiency, but also ensures point cloud accuracy and completeness, showing strong potential for rapid field monitoring and real-time management. Based on the high-quality reconstructed point clouds, we further quantitatively evaluated canopy characteristics at harvest, analyzing the coefficient of variation of canopy height, porosity distribution, and canopy volume fraction. The core shortcomings and optimization strategies for the existing canopy structure were identified, providing scientific data support and practical technical references for precision cultivation management and mechanization-compatible planting in cotton.

Keywords: field-grown cotton; UAV aerial images; ground control points; 3D point cloud; canopy structure



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1. Introduction

Cotton, as one of the most economically important crops worldwide [1], not only provides the core natural fiber raw material for the textile industry, but also serves as a significant oilseed and cash crop. Its industrial chain plays an irreplaceable supporting role in global rural employment and economic stability [2–4]. Xinjiang, as the major cotton-producing region in China, holds a strategically irreplaceable role in ensuring the

supply security of the national cotton industry [5]. With the rapid advancement of agricultural mechanization and smart farming technologies, Xinjiang cotton has achieved a high degree of mechanization in key production processes such as sowing and harvesting, greatly improving production management efficiency and reducing labor dependence. However, the current analysis of canopy characteristics for field-grown cotton still relies primarily on traditional manual field survey methods, which suffer from high labor intensity, strong subjective bias in observation, limited sampling coverage, and insufficient spatial representativeness [6,7], making it difficult to achieve large-scale, refined, and time-series dynamic monitoring and quantitative evaluation of canopy characteristics at the field scale [8,9]. Therefore, it is necessary to develop efficient and scalable technical approaches for quantitative analysis and comprehensive evaluation of canopy structure and growth status in field-grown cotton populations, thereby providing scientific data support and technical foundations for growth diagnosis, cultivation regulation, and population optimization [10,11].

To overcome the limitations of the aforementioned manual surveys, the rapid development of UAV remote sensing technology and three-dimensional (3D) reconstruction methods in recent years has brought new technical opportunities for crop canopy analysis. By equipping UAVs with RGB cameras, multispectral sensors, or even LiDAR, researchers can acquire both two-dimensional spectral information and three-dimensional spatial structural information of the canopy, and subsequently estimate key phenotypic parameters such as plant height, leaf area index, biomass, and canopy porosity [12–15]. Among these, 3D point cloud data, owing to their ability to faithfully reconstruct the stereoscopic spatial configuration of the canopy, exhibit unique advantages in canopy vertical stratification analysis, light radiation interception assessment, population ventilation and light transmission diagnosis, and planting density optimisation [16]. In recent years, deep learning-based 3D reconstruction methods have made significant progress, among which Neural Radiance Fields (NeRF) and 3D Gaussian Splatting (3DGS) have become research hotspots in this field [17,18]. NeRF can generate high-quality, photorealistic 3D reconstructions from sparse-view 2D images, demonstrating unique advantages in fine-scale plant structure modelling. 3DGS, on the other hand, explicitly represents scene geometry via Gaussian primitives, showing remarkable potential in reconstruction efficiency and scalability. These two types of methods have been applied in phenotypic studies of various crops, including wheat [19] and pepper [20], and have demonstrated promising application prospects in tasks such as plant organ segmentation, yield-related trait prediction, and large-scale field reconstruction [21]. However, current mainstream methods for field 3D data acquisition still face significant technical bottlenecks and engineering obstacles. On one hand, although LiDAR systems based on ground or UAV platforms can directly acquire high-precision 3D point clouds, they suffer from high equipment costs, large data volumes, and complex pre-processing workflows [22–24]. Moreover, under field conditions, the multiple-return signals of LiDAR are susceptible to canopy occlusion and wind-induced disturbances, leading to data redundancy and local information loss [25]. On the other hand, traditional point cloud generation methods based on Structure from Motion (SfM) require a large number of UAV aerial images and high overlap rates—typically hundreds or even thousands of images per experimental plot—resulting in lengthy reconstruction times and heavy computational resource consumption. Furthermore, under complex field illumination, mutual plant occlusion, and repetitive leaf texture conditions, these methods are prone to point cloud voids, excessive noise, and reduced geometric accuracy. These technical bottlenecks make it difficult for existing 3D canopy monitoring methods to achieve a balance among cost, efficiency, and accuracy, and thus they cannot truly meet the practical demands of rapid field monitoring, real-time diagnosis, and large-scale application [20,26,27].

To address the above issues, this study aims to explore a low-cost, high-efficiency, and few-image-input method for constructing 3D point clouds of field-grown cotton, and to carry out quantitative evaluation of canopy characteristics and population structure diagnosis based on high-quality point clouds. Using UAV aerial images as the sole data source, this study innovatively integrates the Splatfacto [28,29] reconstruction algorithm with the 3DGS-to-PC combined point cloud generation technique [30–32], while introducing ground control points (GCPs) placed in the field as geometric scale references. This effectively corrects scale drift during reconstruction, restores the generated cotton canopy point clouds to true physical dimensions, and ensures the accuracy and comparability of subsequent phenotypic parameter calculations. Based on this technical pathway, we systematically conduct research on the low-cost and rapid construction of 3D point clouds for field-grown cotton [33]. Compared with traditional methods, this technical pathway significantly reduces the reliance on the number of images and computational resources, achieving a technical breakthrough in reconstructing with fewer input images and high efficiency while ensuring point cloud reconstruction accuracy and completeness, greatly improving the acquisition efficiency and engineering practicality of 3D data for field cotton. On the basis of obtaining high-fidelity, true-scale 3D point clouds, we further carry out systematic quantitative evaluation of the canopy characteristics of cotton populations at the harvest stage. By extracting key canopy phenotypic indicators from point cloud data and performing quantitative calculations and comparative analyses, we systematically reveal the current structural characteristics, spatial heterogeneity patterns, and weak links of the field population canopy structure [34], and identify the core shortcomings and optimisation directions of the population structure. This provides scientific and reliable data support for precision cultivation management, canopy structure optimisation, and mechanisation-adapted planting in cotton [35]. Ultimately, the findings of this study will contribute to the sustainable development of the cotton industry towards high quality, large scale, and intelligence, providing a novel, scalable, and readily deployable technical paradigm for field crop phenotyping and population optimisation in the era of smart agriculture. Nonetheless, the present validation has been carried out only in a single season, one growth stage, and two experimental plots, and further validation involving multiple seasons and varieties is already underway to strengthen the applicability of these results.

2. Materials and Methods

2.1. 3D Reconstruction Workflow for Field-Grown Cotton

2.1.1. Data Acquisition

The data acquisition area was located at Huaxing Farm, Changji City, Changji Hui Autonomous Prefecture, Xinjiang Uygur Autonomous Region, with geographic coordinates of 44°02' N, 87°30' E, as shown in Figure 1. The acquisition area is located in a large-scale commercial field planting zone for industrial crops. The cotton variety used in this study was Zhongmian 113GK (National Certified Cotton Variety 20253014), bred by the Institute of Cotton Research, Chinese Academy of Agricultural Sciences. This variety is a conventional cultivar of upland cotton (*Gossypium hirsutum* L.) with a well-defined genetic background and stable transgenic insect-resistant traits. It exhibits a relatively open plant architecture, with clear spatial distribution patterns of branching configuration and leaf area. These genotype-determined morphological characteristics directly shape the canopy spatial structure and height uniformity, providing a validation scenario with a clear biological benchmark for 3D reconstruction algorithms. Irrigation, fertilisation, and other field management practices were implemented uniformly in accordance with local standardised large-scale production protocols to ensure the reproducibility of data acquisition conditions. In this study, two plots with dimensions of 5.5 m × 5.5 m each

were established, and each plot contained six standardized cotton rows with a row spacing of 0.6 m and a plant spacing of 0.1 m. The data acquisition campaign was conducted on 25 October 2025, during the cotton harvest period under clear skies, no precipitation, and stable illumination conditions, effectively ruling out the interference of meteorological variability on data quality. The average wind speed from ground level to take-off altitude was approximately 1 m/s (corresponding to Beaufort Force 1), falling within the calm to light air range. Despite the low wind speed, the cotton canopy leaves and bolls exhibited continuous slight oscillation, and since the 3D Gaussian Splatting (3DGS) reconstruction algorithm strictly relies on the static scene assumption, wind-induced deformation constituted a potential factor affecting reconstruction accuracy. The current algorithm does not explicitly model wind-induced deformation; instead, the acquisition strategy relied on two mitigation measures. First, the extremely short single exposure time (1/2000 s) ensured that leaf displacement within this integration period was far smaller than the ground sampling distance, rendering motion blur within individual frames negligible. Second, the high overlap rate and short shooting intervals resulted in a baseline distance of approximately 0.5 m between adjacent along-track images, with each spatial point being covered by multiple overlapping views. The shooting interval between adjacent images was 1 s. If leaf positions exhibited observable changes due to wind during this interval, the 60% overlap rate ensured that every spatial point was recorded from a large number of views at different instants. The random positional deviations among views caused by wind were effectively averaged out through multi-constraint joint adjustment during the estimation of 3D Gaussian parameters, thereby mitigating their systematic impact on canopy structure reconstruction. A total of 141 RGB images were acquired in this campaign, all collected within a single day, ensuring the timeliness and spatial consistency of the dataset.

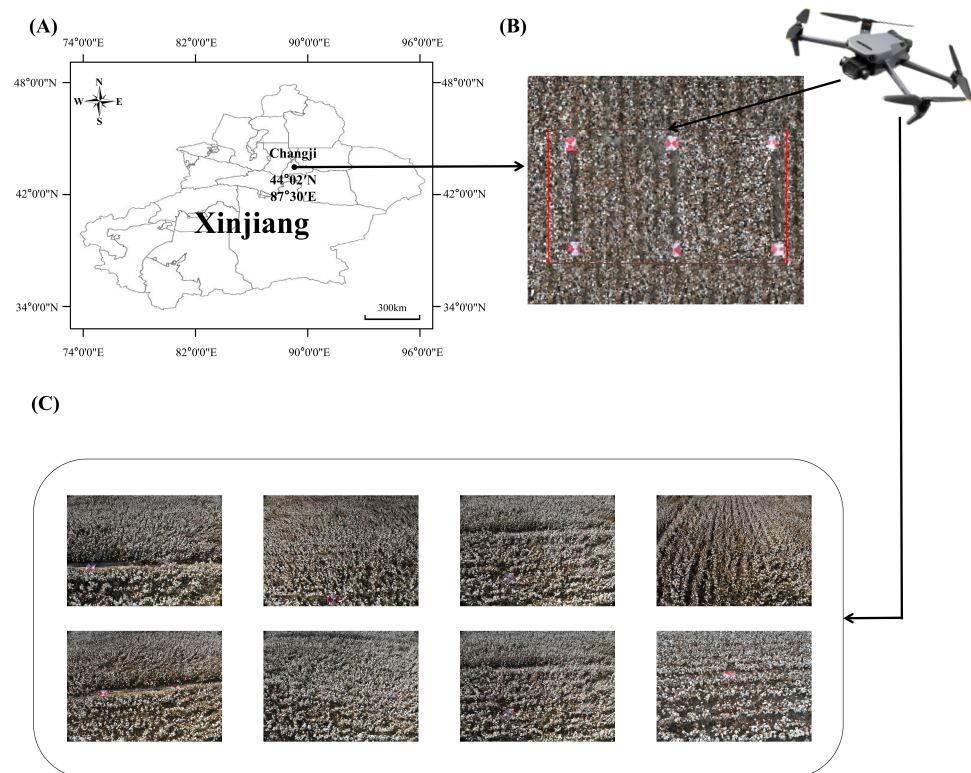


Figure 1. Overview of image data acquisition for field-grown cotton. (A) Location map of the sampling site. (B) Photograph of the field experimental acquisition area. (C) Multi-view images of field-grown cotton acquired by the UAV.

2.1.2. UAV Flight Route Planning and Design

In this study, a DJI Mavic 3M UAV (DJI, Shenzhen, China) was employed for field image acquisition of field-grown cotton. The flight height was set to 5 m above ground level, and the flight speed was set to 0.5 m/s, which served as the core operational parameters for flight route planning. All acquired images were saved in JPG format, with a minimum resolution of 5280×3956 pixels per image. Each image was accompanied by GPS positioning, flight attitude, camera parameters, and absolute flight altitude information, providing comprehensive data support for high-precision 3D reconstruction of cotton from multiple viewpoints. A grid-based flight route was specifically designed for data acquisition in this study, and the route layout is illustrated in Figure 2. Although this grid route does not possess the capability of the CCO (crop canopy-oriented) route to penetrate the occlusion of upper canopy leaves and fully capture the detailed images of middle and lower plant organs [36,37], our study aimed to construct point clouds of field-grown cotton rapidly and efficiently. Therefore, the grid route allowed for the rapid acquisition of images from four viewing angles with substantially higher collection efficiency. The camera inclination angle was set to 45° , with both heading and side overlap ratios set to 60%, and the shooting interval was 1 s, thereby enabling automatic temporal continuity and precise spatial alignment.

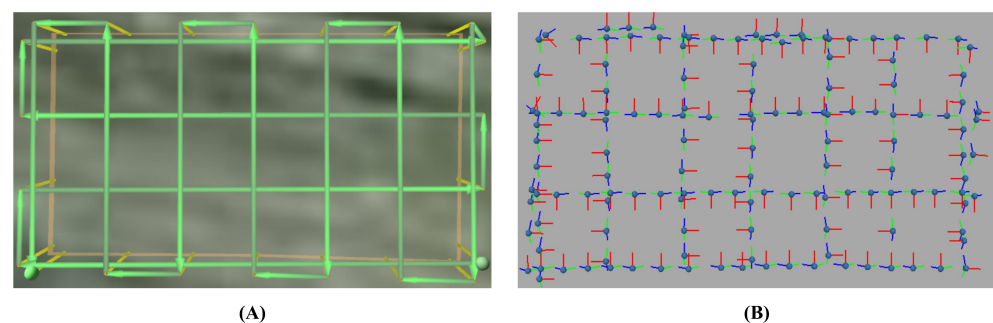


Figure 2. Design of the UAV-based flight route for data acquisition. (A) Flight trajectory of the grid route. (B) Distribution of image capture points along the grid route.

2.1.3. GCP-Based Georeferencing and Scale Calibration for 3D Canopy Reconstruction

The acquired aerial images were imported into Agisoft Metashape Professional Software (Version 2.2.2) [38] to complete the full photogrammetric processing workflow. This software, based on the Structure from Motion (SfM) algorithm, performs image stitching and registration to construct a sparse 3D point cloud model of field-grown cotton. In this study, ground control points (GCPs) were placed at the four corners of the acquisition area as georeferencing references for photogrammetric processing. The GCPs provide absolute control for the UAV images, effectively correcting geometric distortions caused by flight attitude variations, camera lens distortion, and GPS positioning errors, eliminating cumulative drift errors generated during the aerial triangulation process of 3D reconstruction, and significantly improving the absolute positioning accuracy of the model in both planar and elevational directions. More critically, the GCPs also serve a core function in establishing the true physical dimensions for the reconstructed model. During the SfM processing stage, the GCPs deployed in this study have already enabled georeferencing and absolute scale calibration of the imagery. Through bundle adjustment optimisation, a sparse point cloud model with true physical dimensions and precise camera pose information was obtained. However, the subsequent Splatfacto reconstruction model, whose input consists of normalised camera poses and image features, outputs the scene's 3D structure in a normalised representation, the reconstructed result is constrained within a normalised coordinate space, where geometric parameters including distances and vol-

umes are expressed in relative proportions, inherently lacking a scale correspondence to the real physical world. Consequently, although the dense point cloud produced by Splatfacto reconstruction exhibits superior local geometric details and completeness compared to the SfM sparse point cloud, its spatial scale has deviated from true physical dimensions. To address this scale loss problem, this study leverages the precisely measured GCP coordinates obtained during the SfM stage to establish a correspondence between the GCPs in the normalised point cloud space and their true physical dimensions. Specifically, based on the known physical size of the GCP markers (80 cm × 80 cm) and the distances between their corresponding corner points in the Splatfacto-reconstructed point cloud, a global scale factor between the normalised space and the real physical space is calculated. This scale factor is then applied to the entire point cloud, transforming it from normalised coordinates to true physical coordinates, thereby restoring the geometric metrics such as distances, areas, and volumes to their actual field values. Through this GCP-based post-calibration strategy, the final cotton canopy 3D point clouds not only preserve the high-precision geometric details offered by Splatfacto, but also possess a dimensionally consistent basis that matches the actual field scale, providing a reliable scale reference for subsequent accurate quantitative analyses of phenotypic parameters such as canopy height, volume fraction, and porosity [39–41]. Moreover, the large 80 cm × 80 cm size significantly enhances the detectability of GCPs in UAV aerial imagery, ensuring stable and repeatable corner detection even under challenging conditions such as high flight altitudes, varying illumination, or partial canopy occlusion. This effectively reduces uncertainties in scale recovery and georeferencing, further improving the robustness and engineering practicality of the overall technical workflow. The GCP coordinates were collected using a Qianxun SR3 Pro RTK receiver (Qianxun Spatial Intelligence Inc., Shanghai, China), and the layout of the control points is shown in Figure 3. For the image subsets corresponding to each plot, only a small number of GCPs were manually annotated, while the remaining control points were automatically matched and annotated by the software and associated with the imported measured coordinate data. This approach ensures the accuracy and reliability of the 3D modelling and spatial registration workflow. Finally, camera pose information was exported to provide foundational pre-data for the subsequent Splatfacto-based dense point cloud reconstruction.

2.1.4. Point Cloud Reconstruction of Field-Grown Cotton

The point cloud reconstruction of field-grown cotton in this study began by importing the original acquired images into Agisoft to perform image alignment, obtaining the estimated camera poses for each image within the data acquisition area. This information served as a critical initial condition for the subsequent 3D reconstruction model training, significantly improving the model convergence speed and reconstruction accuracy. Subsequently, the original images and their corresponding camera pose data were converted into a standard data format compatible with the Splatfacto model, thereby constructing a standardized training dataset. Given that the core objective of this study was the low-cost and rapid construction of 3D point clouds for field-grown cotton plants, the Splatfacto reconstruction method was selected (see the official documentation at <https://docs.nerf.studio/nerfology/methods/splat.html> (accessed on 18 August 2026)). This method offers distinct advantages over approaches such as SfM-MVS and Instant-NGP, including faster training speed, higher rendering efficiency, and lower requirements for the number of input images. However, it should be noted that the output of the Splatfacto model is not a direct 3D point cloud, but rather a Gaussian splatting representation consisting of a large number of 3D Gaussian ellipsoids, each characterizing the local color, opacity, and geometric distribution information of the scene. Meanwhile,

the point cloud generated during model training resides in a normalized coordinate system, lacking real-world spatial scale information, and thus cannot be directly used for quantitative analysis at actual field dimensions. To enable the reconstruction results to serve subsequent canopy structure analysis and phenotypic parameter extraction, it was necessary to convert them into dense 3D point clouds suitable for geometric measurement and spatial analysis, and to restore them to real-world scale. To this end, the 3DGS-to-PC conversion tool was further introduced in this study to efficiently transform the Gaussian representation into high-density, high-precision dense 3D point clouds of cotton. This tool parsed the spatial positions, scales, and color information of each Gaussian ellipsoid, and employed spatial sampling and density-weighted strategies to generate point cloud data with explicit geometric coordinates, effectively preserving the canopy contours, leaf layers, and fine structures of middle and lower plant organs of the cotton plants. On this basis, we applied the GCP-based post-calibration strategy described above to transform the normalised point cloud obtained from Splatfacto reconstruction into the real physical coordinate space via the global scale factor, ultimately yielding true-scale 3D point clouds of field-grown cotton that fully meet the requirements for fine-scale 3D reconstruction in complex cotton field scenarios (visualisation of the reconstructed point clouds is shown in Figure 4). The overall workflow is summarised in Figure 5.

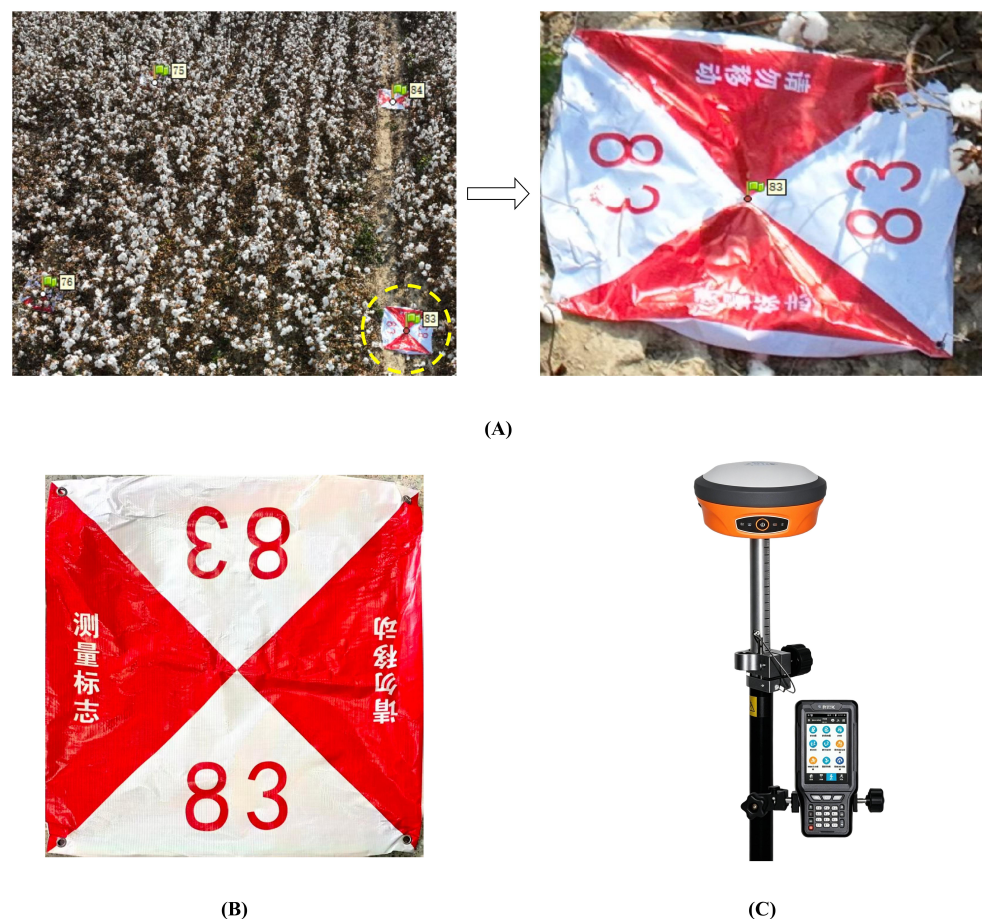


Figure 3. Layout of ground control points and RTK measurement calibration for field-grown cotton. (A) GCP layout and calibration matching scene in the field. (B) Pattern of the GCP marker. (C) RTK measurement device.



Figure 4. True-scale 3D point clouds of field-grown cotton. (A) Plot No. 1. (B) Plot No. 2.

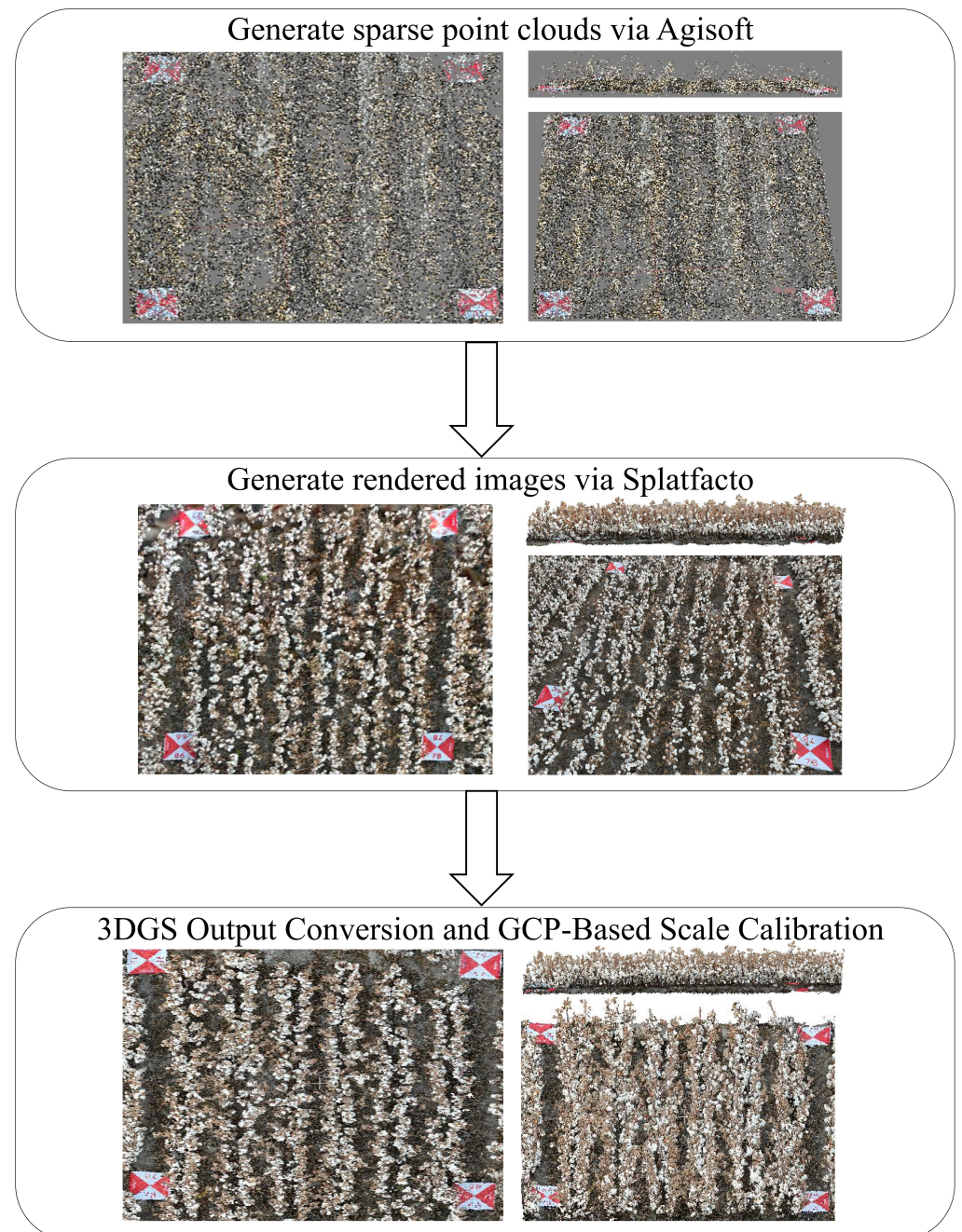


Figure 5. Overall workflow of point cloud reconstruction for field-grown cotton.

2.2. Canopy Evaluation of Field-Grown Cotton Based on 3D Point Clouds

At the cotton harvest stage, most leaves had already senesced and fallen, making traditional spectral-based vegetation indices ineffective for reflecting population structure information. In contrast, 3D point clouds can directly characterize the spatial geometric features of the canopy and precisely quantify the distribution patterns of stems, branches, and bolls. To this end, based on the high-density point clouds reconstructed through the above steps, a canopy height model (CHM) was constructed after ground filtering and height normalization, from which a total of 13 parameters across four categories were extracted. (1) Population coverage and biomass: canopy coverage, mean canopy height, maximum canopy height, and canopy volume. (2) Height distribution characteristics: 50th percentile height, 90th percentile height, and coefficient of variation of canopy height. (3) Vertical structure and surface morphology: vertical distribution uniformity, canopy porosity, canopy surface roughness, and volume fraction above the median height. (4) Spatial pattern: global spatial autocorrelation index (Moran's I). These parameters quantitatively describe, from different dimensions, the spatial occupancy capacity, vertical biomass allocation, surface undulation patterns, and spatial aggregation characteristics along the planting rows of the cotton canopy at the harvest stage, thereby providing clear and quantifiable decision-making bases for the optimization of subsequent cultivation management practices. Brief definitions and units for each parameter are listed in Table 1.

Table 1. Canopy structure parameters of field-grown cotton at the harvest stage.

Parameter	Description	Unit
CC	Proportion of the plot area occupied by vertical canopy projection	—
MCH	Mean value of all canopy pixel heights	m
MaxCH	Maximum value of canopy height	m
CV	Cumulative sum of canopy pixel height multiplied by pixel area	m ³
H50	Height below which 50% of canopy pixels are located	m
H90	Height below which 90% of canopy pixels are located	m
PA	Effective area of the plot covered by the point cloud	m ²
CVH	Ratio of the standard deviation to the mean of canopy height	—
CP	Proportion of pixels with height below 0.1 m	—
VDU	Variance of point cloud proportions across height layers	—
CSR	Mean value of local height standard deviation (3 × 3 window)	m
VF_MH	Ratio of volume above the median height to total canopy volume	—
Moran's I	Moran's I quantifying canopy height spatial aggregation	—

Based on the 13 canopy structure parameters extracted above, the mathematical definitions and calculation formulas for each parameter are provided accordingly. The CHM pixel resolution is $\Delta x = \Delta y = 0.05$ m, and the specific formulas are as follows.

CC: the proportion of pixels with height greater than 0.2 m in the CHM to the total number of pixels.

$$\text{Cover} = \frac{N_{\text{canopy}}}{N_{\text{total}}} \quad (1)$$

where N_{canopy} is the number of pixels with height greater than 0.2 m in the CHM, and N_{total} is the total number of pixels.

MCH: the arithmetic mean of the heights of all canopy pixels with height greater than 0.2 m.

$$\bar{h} = \frac{1}{N_{\text{canopy}}} \sum_{i=1}^{N_{\text{canopy}}} h_i \quad (2)$$

MaxCH: the maximum height value in the CHM.

$$h_{\text{max}} = \max(h_i) \quad (3)$$

CV: the cumulative sum of each canopy pixel height multiplied by the pixel area.

$$V = \Delta x \Delta y \sum_{i=1}^{N_{\text{canopy}}} h_i \quad (4)$$

H50: the 50th percentile of canopy pixel heights.

$$h_{50} = \text{median}(h_i) \quad (5)$$

H90: the 90th percentile of canopy pixel heights.

$$h_{90} = \text{percentile}(h_i, 90) \quad (6)$$

PA: the rectangular area enclosed by the X and Y coordinate ranges of the point cloud.

$$A = (x_{\text{max}} - x_{\text{min}}) \times (y_{\text{max}} - y_{\text{min}}) \quad (7)$$

CVH: the ratio of the standard deviation to the mean of canopy pixel heights.

$$CV_h = \frac{\sigma_h}{\bar{h}} \quad (8)$$

where σ_h is the standard deviation of canopy pixel heights.

CP: the proportion of pixels with height below 0.1 m in the CHM to the total number of pixels.

$$\text{Gap} = \frac{N_{\text{gap}}}{N_{\text{total}}} \quad (9)$$

where N_{gap} is the number of pixels with height less than 0.1 m in the CHM.

VDU: the point cloud is divided equally into 5 layers in the vertical direction, and the variance of the point proportion of each layer is calculated.

$$U = \frac{1}{5} \sum_{j=1}^5 \left(p_j - \frac{1}{5} \right)^2 \quad (10)$$

where the point cloud is divided equally into 5 layers in the vertical direction, and p_j is the point proportion of the j layer.

CSR: a 3×3 window is slid over the CHM, the standard deviation of heights within each window is calculated, and then the mean of the standard deviation values corresponding to all canopy pixels is taken.

$$R = \frac{1}{N_{\text{canopy}}} \sum_{i \in \text{canopy}} \sigma_{\text{local}}(i) \quad (11)$$

where $\sigma_{\text{local}}(i)$ is the standard deviation of heights within the 3×3 window centered at pixel i .

VF_MH: the ratio of the canopy volume above the median height to the total canopy volume.

$$\rho = \frac{\sum_{h_i > h_{50}} h_i}{\sum_{i=1}^{N_{\text{canopy}}} h_i} \quad (12)$$

Moran's I: a measure of the spatial aggregation degree of canopy height.

$$I = \frac{n \sum_{i=1}^n \sum_{j=1}^n w_{ij} (h_i - \bar{h})(h_j - \bar{h})}{\sum_{i=1}^n \sum_{j=1}^n w_{ij} \sum_{i=1}^n (h_i - \bar{h})^2} \quad (13)$$

where n is the total number of CHM pixels, h_i is the pixel height, $\bar{h}$ is the mean height, and w_{ij} is the element of the rook contiguity weight matrix.

2.3. Experimental Setup

To ensure the fairness of comparative experiments, the reliability of the results, and the reproducibility of the study, none of the comparative models used for field-grown cotton reconstruction were initialised with pre-trained weights. Instead, all models were trained from scratch and employed identical training configurations. Image data preprocessing uniformly utilised the sparse reconstruction results generated by Agisoft Metashape to produce standardised neural datasets. Specifically, Agisoft Metashape was employed for feature extraction and sparse reconstruction of the acquired aerial images, with the key-point limit set to 400,000 and the reconstruction accuracy set to “High”, ensuring that the sparse point clouds possessed sufficient geometric feature density and registration quality to provide standardised input data for the subsequent training of neural rendering models. During the model training stage, the number of training iterations was uniformly fixed at 30,000 steps for all comparative models, with camera optimisation disabled, original image resolution preserved (no downsampling), and scale regularisation enabled. For the Splatfacto model, the number of exported dense point clouds after training was set to 15 million points, ensuring that the point cloud density sufficiently characterises the fine geometric details of the cotton canopy while maintaining computational efficiency for subsequent processing. All model training and evaluation were conducted under identical software and hardware environments, with the model structure being the only variable. The experimental hardware platform was a server equipped with an NVIDIA GeForce RTX 4090 GPU (Santa Clara, CA, USA), and all models were implemented using the PyTorch v2.2.2 deep learning framework. Through the standardised data processing workflow, uniform training configurations, and clearly defined point cloud export parameters described above, this study ensured the fairness and reproducibility of the comparative results among different models, providing a reliable data foundation for the subsequent quantitative evaluation of canopy structure parameters.

3. Results

3.1. Comparison of Reconstruction Performance

The high-density, high-precision dense point clouds of field-grown cotton ultimately generated in this study overcame the bottlenecks of sparse point clouds and missing details inherent in the SfM-MVS method, while effectively addressing key issues such as the slow training speed and high memory consumption of existing NeRF-based models, as well as the difficulty of native 3D Gaussian splatting in directly outputting point clouds and adapting to large-scale cotton fields. These point clouds accurately reconstruct the three-dimensional structures of fine-grained cotton organs, including bolls and stems, providing a high-quality data source for subsequent evaluation of canopy characteristics.

To visually verify the advantages of the Splatfacto model in cotton field scene reconstruction, multiple comparative experiments were conducted and visualization results were generated. As shown in Figure 6, which presents the overall reconstruction performance of different methods in cotton field scenes, the point clouds generated by our method exhibited higher completeness and lower noise levels compared with SfM-MVS [42], Instant-NGP [43], NeRFacto, and NeRFacto-huge [44] models. The cotton plants could be clearly distinguished from the background, and the overall structural continuity of the plants was excellent. As shown in Figure 7, which presents the local detail comparison of different methods in cotton field scenes, a local region along the same plant row was selected for magnified analysis. To ensure fair comparison, the point cloud sizes of

all compared groups were controlled at approximately 2.2 million points. The experimental results demonstrate that our method exhibited significant advantages in geometric detail restoration, boundary sharpness, and anisotropic structural representation, with more uniform distribution and higher density of local point clouds, effectively preserving the fine geometric features of cotton organs and providing reliable support for applications such as phenotypic parameter extraction in cotton fields. Finally, to more intuitively demonstrate the effectiveness of the reconstruction method, point clouds of individual cotton plants were extracted, with the specific results shown in Figure 8.

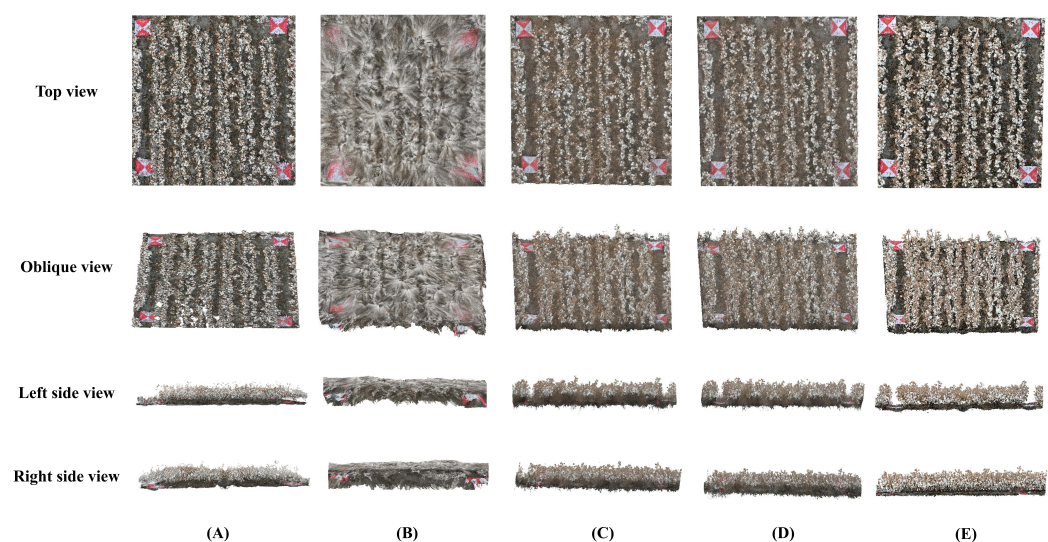


Figure 6. Comparison of overall reconstruction performance of different methods in cotton field scenes. (A) SfM-MVS. (B) Instant-NGP. (C) NeRFacto. (D) NeRFacto-huge. (E) Splatfacto.

In addition to the visual comparison, to comprehensively evaluate the practicality of each model, Table 2 presents the training time comparison of Splatfacto with SfM-MVS, Instant-NGP, NeRFacto, and NeRFacto-huge models under identical experimental conditions and the same dataset size, further validating the efficiency of the Splatfacto model in cotton field scene applications.

Table 2. Comparison of training efficiency of different reconstruction methods in cotton field scenes.

Method	Training Time (min)	Export Time (min)	Total Time (min)	GPU Memory (GB)
SfM-MVS	286	5	291	3
Instant-NGP	34	47	81	44
NeRFacto	33	31	64	12
NeRFacto-huge	204	48	252	24
Splatfacto	12	0.5	12.5	1.3

3.2. Evaluation of Canopy Characteristics

Based on the field-grown cotton point clouds synthesized above, this study extracted 13 parameters across four categories to quantitatively evaluate the structural characteristics and spatial distribution patterns of the population canopy. Canopy coverage directly reflects the spatial occupancy efficiency of the population on the ground. Mean height, maximum height, and percentile heights jointly reveal the dominant layers and extreme heights of vertical plant growth. Canopy volume comprehensively reflects the expansion capacity of plants in both horizontal and vertical directions. The coefficient of variation of canopy height characterizes the dispersion degree of height distribution, with larger values indicating greater heterogeneity of canopy surface undulation. Canopy porosity directly

quantifies the light-transmitting gaps within the canopy and affects the light environment of the lower canopy layers. Vertical distribution uniformity measures the balance of biomass allocation across different height layers. Canopy surface roughness characterizes the micro-topographic undulation features of the upper canopy. The volume fraction above median height reflects the contribution proportion of the upper canopy to the overall structure. The global spatial autocorrelation index discriminates the spatial aggregation or dispersion trends of canopy height from a spatial statistical perspective. To systematically verify the effectiveness and reproducibility of the canopy characterization method for cotton populations, two adjacent sampling plots were selected, and the evaluation scope was appropriately expanded to ensure the completeness of canopy structure characterization. Meanwhile, to further validate the accuracy of data analysis, a manual five-point sampling method was employed for field validation. Five sampling points were uniformly arranged within each of the two plots, and at each sampling point, 10 normal cotton plants with plant heights exceeding 0.2 m were randomly selected for canopy height measurement, avoiding interference from short, weak, and dwarf plants as well as surface weeds. This is consistent with the screening criterion of setting a 0.2 m canopy height threshold in the point cloud analysis to exclude bare soil and low-vegetation interference. The field-measured canopy heights were generally consistent with the model-derived evaluation results, effectively validating the reliability of the parameter extraction method. The statistical results of all canopy structure parameters are presented in Table 3.

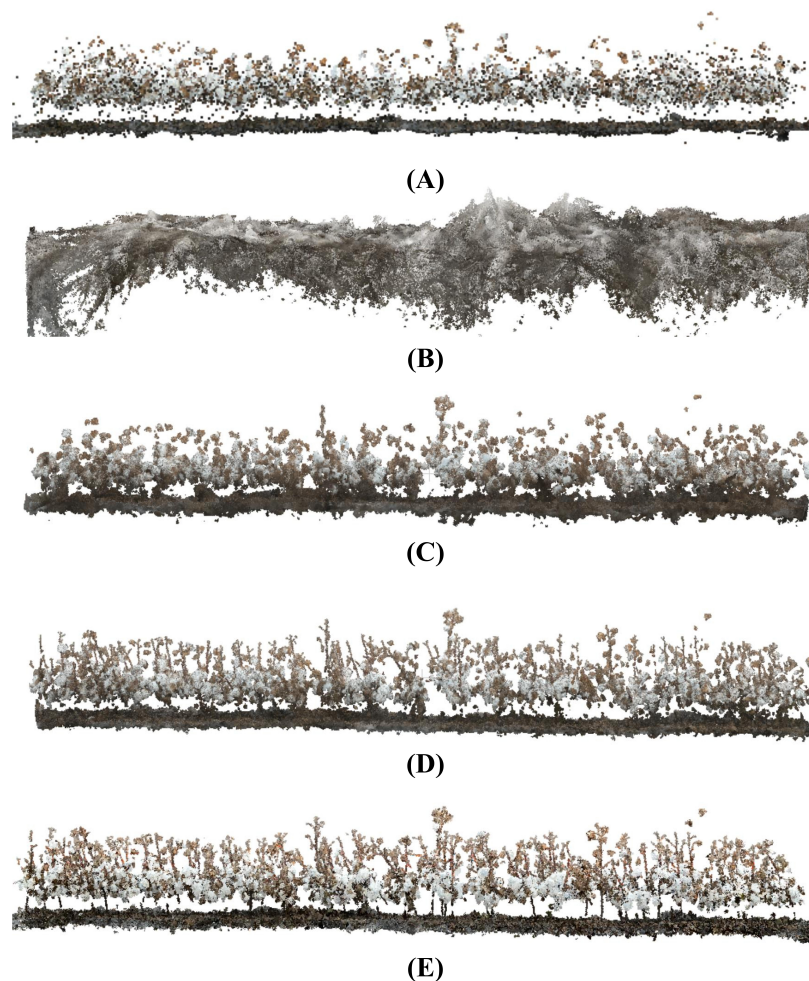


Figure 7. Comparison of local details of different methods in cotton field scenes. (A) SfM-MVS. (B) Instant-NGP. (C) NeRFacto. (D) NeRFacto-huge. (E) Splatfacto.



Figure 8. Visualization of point clouds of individual cotton plants.

To intuitively characterize the canopy structure features of the cotton population, a visual analysis of canopy characteristics was conducted in this study. Based on the field cotton point cloud data reconstructed by the UAV, a canopy height model (CHM) was constructed through ground elevation correction and grid interpolation, as shown in Figure 9. This model clearly presents the spatial undulation patterns and height variation rules of the field cotton canopy in a two-dimensional grid format, effectively distinguishing the canopy coverage areas from the bare soil gaps in the field. From the statistical results of the two experimental plots, parameters such as canopy coverage, mean height, and maximum height exhibited good consistency, while the coefficient of variation of canopy height and surface roughness also remained at comparable levels. This indicates that the canopy reconstruction method based on UAV point clouds can stably extract population structure features with satisfactory reproducibility. The quantitative retrieval of the above parameters all relied on the raster data foundation provided by the CHM.

The vertical point cloud distribution histogram is shown in Figure 10, which presents the quantitative distribution characteristics of effective canopy point clouds along the vertical height gradient, intuitively reflecting the vertical growth stratification characteristics and the concentrated distribution interval of plant height for cotton plants. From the statistical results of the two experimental plots, indicators such as percentile heights and the volume fraction above median height exhibited relatively high consistency, with the upper canopy volume fraction maintaining approximately 60% in both plots, indicating that the upper canopy contributed dominantly to the overall structure. The extremely low values of vertical distribution uniformity suggested that biomass was not evenly distributed across different height layers, but rather exhibited pronounced aggregation characteristics. Canopy porosity also remained at similar levels between the two plots. The above analytical results exhibited a certain degree of consistency between adjacent sampling plots, preliminarily suggesting that the proposed method may have application potential for point cloud reconstruction and canopy phenotypic parameter extraction in field-grown cotton. However, since the current conclusions are based on only two sets

of observational data, further validation with more sampling points is required, and the relevant stability and reliability remain to be examined.

Table 3. Statistical results of canopy structure parameters for different plots.

Parameter	Plot No. 1	Plot No. 2
CC	0.650159	0.653577
MCH (m)	0.505977	0.475288
MaxCH (m)	0.999493	0.866403
CV (m ³)	12.638042	10.085611
H50 (m)	0.490962	0.460812
H90 (m)	0.678097	0.645609
PA (m ²)	38.417500	32.467500
CVH	0.251489	0.247311
CP	0.099694	0.129899
VDU	0.016899	0.018305
CSR (m)	0.100926	0.090743
VF_MH	0.600433	0.598703
Moran's I	0.804040	0.834066

Note: All parameters were calculated based on height relative to the ground level. The CHM resolution is 0.05 m, and the canopy threshold was set to 0.2 m.

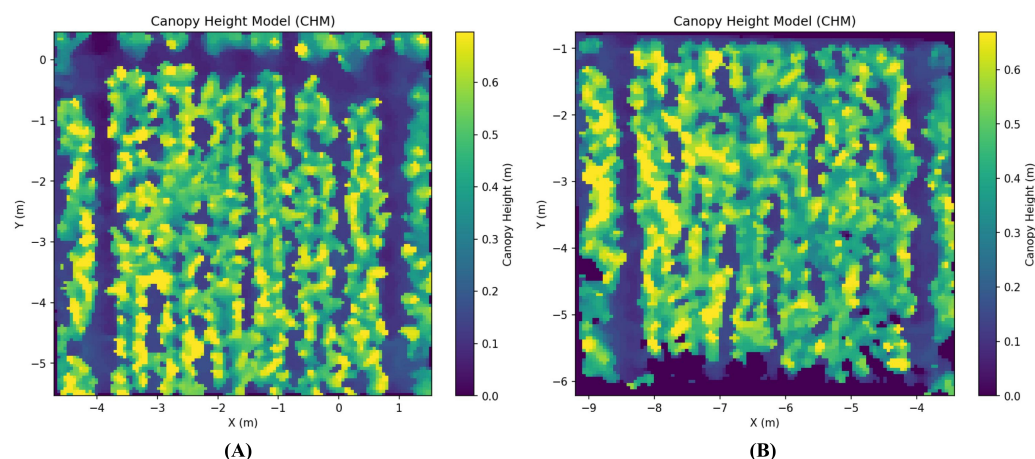


Figure 9. Canopy height model of the cotton population. This model presents the spatial undulation patterns of the cotton canopy in a two-dimensional raster grid format, where the blue-to-yellow color gradient represents the continuous variation of canopy height from low to high, with blue areas corresponding to lower canopies or bare soil gaps, and yellow areas corresponding to higher canopies. (A) Plot No. 1. (B) Plot No. 2.

Finally, to further verify the application feasibility of the proposed 3D reconstruction method in cotton phenotyping research, the five-point sampling method was adopted in this study, and individual cotton plants covering different plant types and growth gradients were selected as typical samples. Considering existing research findings and the practical requirements of population phenotyping evaluation, this experiment focused on the core parameters that accurately characterize plant morphological structure, and ultimately determined eight quantitative indicators, including plant height, crown width in the X/Y directions, projected area, canopy volume, vegetation coverage, plant type compactness, and canopy gap fraction.

As shown in the combined heatmap of Figure 11, Figure 11A clearly presents the heterogeneity of phenotypic traits among different plant samples through data standardization. The correlation matrix in Figure 11B further reveals the highly complex associations and collinearity characteristics among the structural parameters. In terms of growth potential, crown width in the X-direction showed a strong positive correlation with projected

area, and plant height exhibited a strong positive correlation with canopy volume, indicating that the expansion of two-dimensional horizontal projected biomass was primarily driven by lateral growth, while three-dimensional spatial biomass was highly dependent on vertical elongation. Notably, the heatmap accurately captured the trade-off effects among architectural parameters, specifically that plant type compactness was significantly negatively correlated with both crown width in the Y-direction and projected area. This quantitative result confirmed, from a spatial geometry perspective, that the widening of lateral crown width leads to increased plant looseness, providing an intuitive quantitative basis for the introduction and breeding of the “ideal plant type” in cotton. Furthermore, the absolute negative correlation between vegetation coverage and canopy gap fraction was fully consistent with physical optical mechanisms, corroborating the robustness of the phenotyping extraction algorithm.

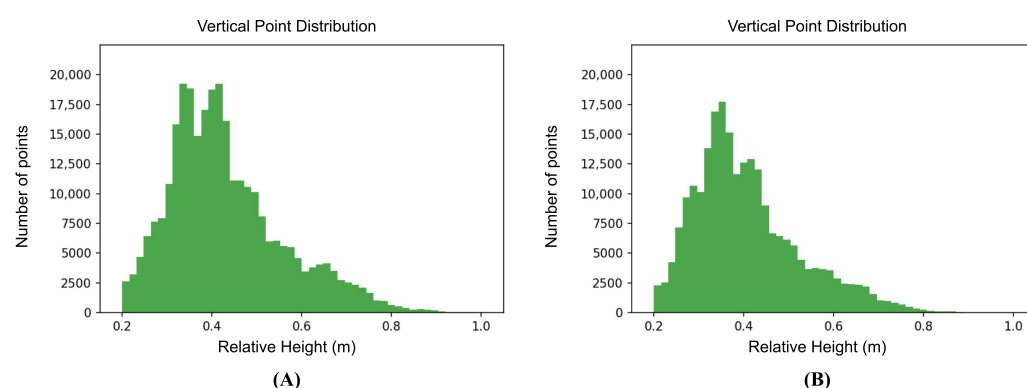


Figure 10. Vertical point cloud distribution histograms of the two experimental plots. The histograms present the quantitative distribution of effective canopy point clouds along the vertical height gradient, reflecting the vertical growth stratification characteristics and the concentrated distribution interval of plant height for cotton plants. (A) Plot No. 1. (B) Plot No. 2.

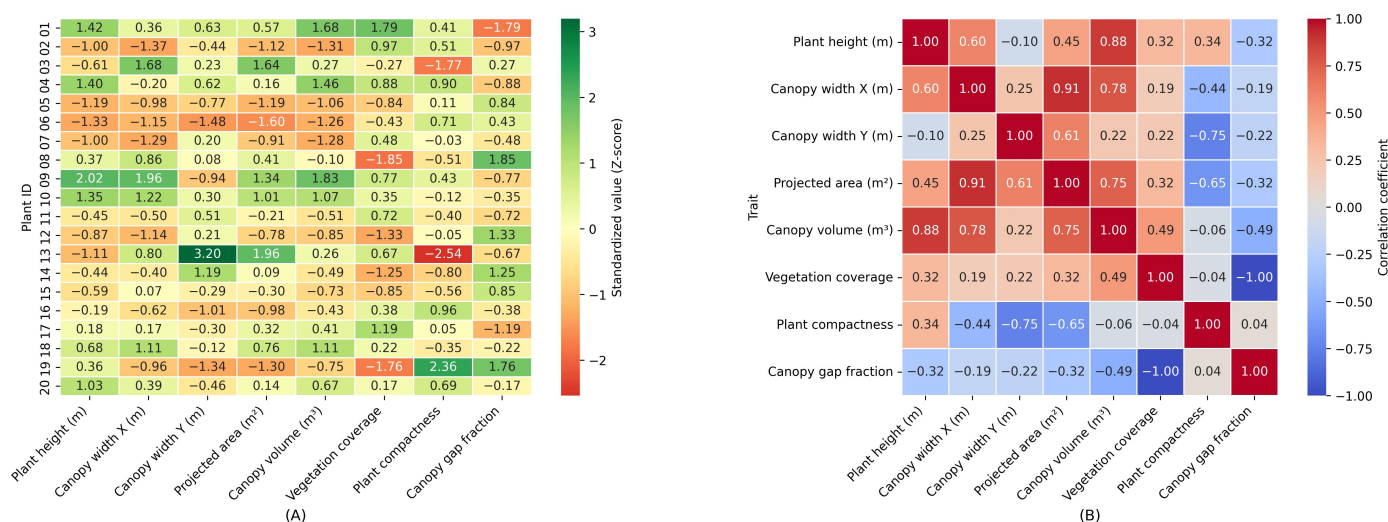


Figure 11. Combined heatmap of phenotypic parameters of individual cotton plants. (A) Normalized heatmap (Z-score) of each plant indicator, with colors ranging from green to red representing the relative levels of indicator values (red: higher, green: lower), used for comparing phenotypic differences among different plants. (B) Pearson correlation heatmap among indicators, with the values in the colored blocks representing correlation coefficients (red: positive correlation, blue: negative correlation), where color intensity reflects the strength of correlation, used to reveal synergistic or constraining relationships among traits.

Further comparison between the phenotyping values derived from 3D reconstruction and the field manual measurements showed extremely high consistency, fully validating the accuracy and practicality of this method in cotton phenotyping analysis. On this basis, a canopy height model (CHM) was constructed through ground elevation correction and grid interpolation, as shown in Figure 12, achieving high-spatial-resolution visualization of the canopy structure of individual cotton plants.

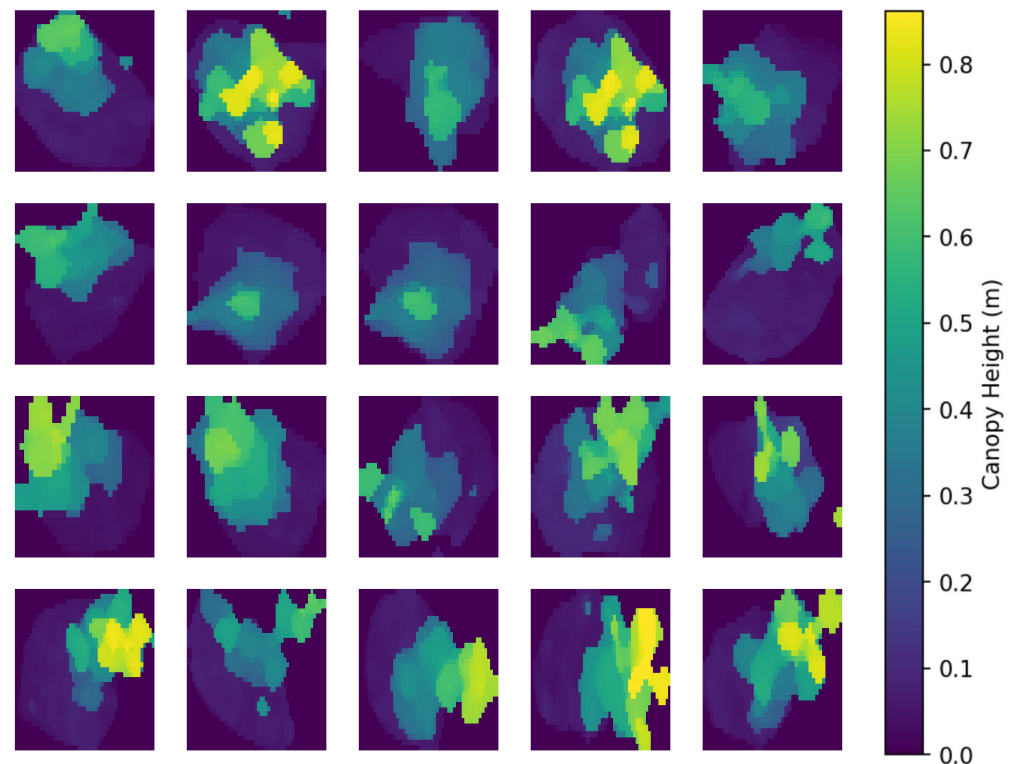


Figure 12. Canopy height model of individual cotton plants.

Through ground elevation correction and raster interpolation, a canopy height model (CHM) was constructed, as shown in Figure 12, enabling high-spatial-resolution visualization of the canopy structure of individual cotton plants. Furthermore, the phenotypic estimates derived from the 3D reconstruction were compared with field manual measurements, and the results showed high consistency between the two, validating the accuracy and practicality of this method for cotton phenotyping. Figure 13 presents the coefficients of determination (R^2), root mean square errors (RMSE), and relative root mean square errors (rRMSE) for three indicators—Height, Crown width X, and Crown width Y—between the manual measurements and the point cloud CHM-derived values. The R^2 values for all three indicators exceeded 0.77, indicating that the point cloud-based canopy height model exhibits good reliability and consistency in characterising the spatial structure of the cotton canopy.

3.3. Analysis of Canopy Structure Issues and Optimization Directions

Based on the above evaluation of population canopy characteristics, we found that three phenotypic parameters—coefficient of variation of canopy height, canopy porosity, and volume fraction above median height—exhibited certain anomalies, necessitating a systematic analysis of the issues and corresponding improvement strategies.

First, the coefficients of variation of canopy height for the two plots were both close to 0.25. For cotton at the harvest stage, this value is at a moderately high level, indicat-

ing prominent spatial heterogeneity of population plant height, insufficient field growth uniformity, and marked differentiation in growth vigor among individual plants. This characteristic reduces the efficiency of light interception and utilization by the population, exacerbating the growth disadvantages of weaker plants. Meanwhile, it is detrimental to the smooth progression of mechanized harvesting operations, leading to reduced picker efficiency and increased field boll shedding losses, thereby constraining the large-scale and standardized production efficiency of cotton. Therefore, population uniformity is one of the core traits that need to be prioritized for optimization in subsequent cultivation management.

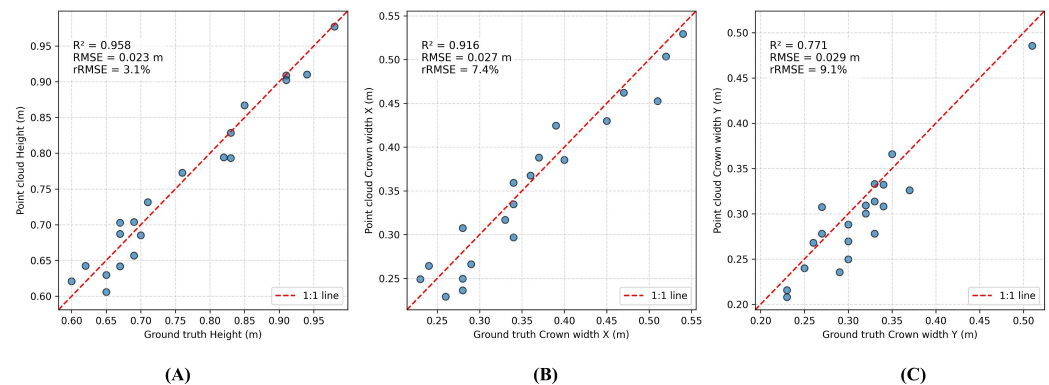


Figure 13. Correlation analysis between manual measurements and point cloud CHM-derived values. (A) Height. (B) Crown width X. (C) Crown width Y.

Second, the canopy porosity values of the two plots were 0.10 (approximately 10%) and 0.13 (approximately 13%), respectively, which are notably low, reflecting excessive canopy closure and poor internal ventilation and light penetration conditions. Excessive canopy closure at the harvest stage tends to increase the humidity of the field microclimate, elevating the occurrence probability of boll rot and leaf diseases. It also results in insufficient light availability in the middle and lower canopy layers, inducing premature senescence of fruit branches and boll abscission in these layers, thus limiting the full release of yield potential. Furthermore, a closed canopy increases the operational resistance of harvesting equipment, further aggravating harvest losses, indicating a significant gap from the ideal canopy structure requirements for cotton at the harvest stage.

Finally, the volume fractions above median height for the two plots were both close to 0.6 (approximately 60%), which is relatively high, indicating an imbalanced vertical spatial allocation of the canopy, with the dominant canopy excessively concentrated in the upper-middle layers and an insufficient spatial proportion in the middle-lower canopy. This characteristic reflects excessively strong apical dominance of the plants, with overgrowth of upper branches and leaves encroaching upon the light and nutrient supply for the middle and lower fruit branches, resulting in retarded development of middle-lower fruit branches and low boll setting rates, and thus the boll-setting potential of the middle-lower layers was not fully exploited. Meanwhile, excessive growth of the upper canopy further aggravates canopy closure, forming a superimposed effect of structural deficiencies that affects population photosynthetic efficiency and yield formation.

In response to the above issues, we further conducted manual field investigations to verify the existence of the related anomalies. Based on the analysis, the primary cause lies in the planting process. To avoid poor seedling emergence and growth inhibition in individual planting holes, the practice of sowing two seeds per hole was adopted, ultimately leading to excessive planting density in the field, which triggered a series of canopy structure deficiencies. To address these issues, subsequent cultivation management will be optimized

from the following aspects. First, planting density and row-spacing configuration should be scientifically regulated to avoid excessive population crowding, thereby improving canopy ventilation and light penetration conditions from the source and establishing a suitable population environment for cotton growth. Second, chemical regulation measures should be implemented in a timely manner during the critical growth stages of cotton to effectively inhibit apical dominance, control the overgrowth of upper branches and leaves, promote robust development of middle-lower fruit branches, and optimize the vertical spatial allocation of the canopy.

4. Discussion

4.1. Comparative Analysis of the Proposed Method and Traditional SfM-MVS

The Splatfacto-based reconstruction method proposed in this study, with only 141 input images—significantly fewer than the hundreds to thousands typically required by traditional SfM-MVS—still produces 3D point clouds with good completeness, low background noise, and clear cotton plant contours. The reconstruction time is approximately 20 min, representing an order-of-magnitude improvement over the processing time of several hours for SfM-MVS. This efficiency gain is attributed to the explicit point cloud initialisation and the tile-based parallel differentiable renderer used in Splatfacto, which greatly reduces the need for dense sampling computations along each ray, thereby achieving faster convergence while maintaining reconstruction accuracy.

However, the performance boundaries of the two methods differ considerably, and their applicable scenarios are complementary:

(1) Image input requirements and robustness: SfM-MVS imposes stringent requirements on the number and overlap rate of input images, and is prone to point cloud voids and reduced geometric accuracy under complex field illumination, repetitive leaf textures, and mutual plant occlusion. The proposed method greatly reduces the dependence on image quantity, but at the cost that its reconstruction quality heavily relies on the quality of the Agisoft sparse point cloud initialisation. If feature extraction fails or generates excessive outliers in the initial stage, the subsequent Gaussian splatting optimisation may converge to a local optimum, resulting in floating artefacts or structural fractures.

(2) Reconstruction accuracy and detail preservation: Under conditions with sufficient image numbers and ideal illumination, SfM-MVS-reconstructed point clouds exhibit better global consistency and absolute scale fidelity (via GCP calibration). The proposed method has advantages in recovering local geometric details, but its scale fidelity must be guaranteed through the GCP-based post-calibration strategy.

(3) Computational efficiency and scalability: The reconstruction time of SfM-MVS grows approximately linearly with the number of images, leading to huge computational resource consumption in large-scale scenarios. The training time of the proposed method is less affected by the number of images, making it more suitable for high-throughput, rapid-response monitoring in large fields.

In summary, SfM-MVS is more appropriate for fine modelling with small extents and high accuracy requirements, whereas the proposed method is better suited for large-scale, rapid, survey-style phenotyping acquisition in field conditions.

4.2. Canopy Structure Anomaly Diagnosis and Cultivation Optimisation Directions

Based on the 13 canopy structure parameters extracted from high-quality point clouds, this study identified three key indicators that deviate from the ideal ranges, suggesting systemic issues in the current field population structure (detailed in Section 3.3). Specifically, the elevated coefficient of variation of canopy height (CVH) reflects insufficient population uniformity, which is unfavourable for mechanical harvesting efficiency. The low

canopy porosity (CP) indicates excessive canopy closure and deteriorated internal ventilation and light transmission. The high volume fraction above median height (VF_MH) reveals an over-concentration of canopy biomass in the upper-middle layers, indicating an imbalance in vertical spatial allocation. These three indicators are not independent: a high VF_MH directly exacerbates light deficiency in the middle and lower layers, thereby reducing the effective photosynthetic area of lower leaves; a low CP further worsens the micro-environmental conditions inside the canopy. Together with the high CVH, they constitute a chain effect of “structural crowding–light environment deterioration–growth differentiation intensification”.

Preliminary field investigations verified the existence of these anomalies, and the underlying cause can be traced back to planting density settings. To avoid poor seedling emergence per hole, a seeding practice of two seeds per hole was adopted, which ultimately led to excessive population density and triggered the series of canopy structure shortcomings mentioned above. Based on this, subsequent cultivation management should be promoted from the following two aspects. First, scientifically regulate planting density and row-spacing configuration to improve canopy ventilation and light transmission from the source. Second, implement chemical regulation at critical growth stages to suppress apical dominance, control excessive upper-branch growth, and promote the development of middle and lower fruiting branches, thereby optimising the vertical spatial allocation of the canopy.

4.3. Method Limitations

Although the proposed method demonstrates significant advantages in reconstruction efficiency and adaptability to complex cotton field scenarios, several limitations remain. First, the method's performance is sensitive to the quality of the preliminary SfM sparse reconstruction. The Splatfacto model uses the SfM-output sparse point cloud as the initialisation input for 3D Gaussian splatting. If this initial point cloud suffers from insufficient feature extraction, numerous outliers, or geometric distortions, the subsequent Gaussian splatting optimisation may converge to a local optimum, resulting in floating artefacts, canopy structural fractures, or local geometric deformations. This implies that the method cannot completely eliminate its reliance on traditional photogrammetric preprocessing tools in practical applications. Second, the normalised point cloud produced during the Splatfacto reconstruction stage must be restored to true physical scale through the GCP-based post-calibration strategy, which introduces additional manual steps (GCP placement and corner matching) and reduces the full automation of the technical workflow. For historical image data lacking GCPs or for scenarios where control points cannot be deployed, the scale recovery mechanism of the proposed method would be ineffective. Furthermore, the experimental scenarios in this study only covered two cotton fields, with data collection concentrated at a single growth stage (harvest period), thus covering a limited range of cotton varieties and growth phases. Canopy structures vary considerably among different varieties, growth stages, and planting densities, and the reconstruction stability and parameter extraction accuracy of the proposed method under diverse conditions have yet to be systematically validated.

5. Conclusions

In this study, to address the challenges of sparse point clouds, missing geometric details, and low efficiency of existing methods for 3D reconstruction of field-grown cotton, we proposed a low-cost and rapid 3D point cloud construction approach based on the Splatfacto model, and conducted a systematic evaluation of population canopy characteristics using the high-quality point clouds generated. The main contributions of this

study are threefold. First, at the methodological level, we innovatively integrated the Splatfacto reconstruction algorithm with a GCP-based post-calibration strategy, enabling the rapid generation of high-fidelity cotton canopy point clouds with true physical scale under few-image input conditions, thereby effectively overcoming the technical bottleneck between cost and efficiency inherent in traditional methods. Second, at the experimental validation level, through systematic comparisons with mainstream methods including SfM-MVS, Instant-NGP, NeRFacto, and NeRFacto-huge, we demonstrated the comprehensive advantages of our method in terms of reconstruction completeness, background noise suppression, geometric detail preservation, and training speed. The reconstruction time was approximately 20 min, representing an order-of-magnitude improvement over conventional approaches. Third, at the application level, we extracted 13 canopy structure parameters across four categories from the reconstructed point clouds, verified their accuracy through manual measurements, and identified the core shortcomings of the current population structure through anomaly diagnosis—namely, elevated coefficient of variation of canopy height, low canopy porosity, and high volume fraction above median height. Based on these findings, we proposed a cultivation optimisation strategy combining density regulation and chemical control, demonstrating the complete application chain of our method from data acquisition to production decision-making.

Despite the significant advantages of our method in reconstruction efficiency and adaptability to complex cotton field scenarios, several limitations remain. The method's performance is sensitive to the quality of the SfM sparse point cloud initialisation, and its reliance on the GCP-based post-calibration strategy for scale recovery reduces the degree of full automation to some extent. In addition, the current experimental scenarios cover only two cotton fields at the harvest stage, and the generalisability of the method requires further validation.

Based on the above limitations and the current state of research, future work will be pursued in the following four directions. First, we will explore end-to-end Gaussian splatting initialisation strategies to reduce reliance on conventional SfM preprocessing tools. Second, we will integrate multimodal remote sensing data, including multispectral and thermal infrared imagery, to establish a multi-dimensional phenotyping evaluation system that links canopy structure, physiological status, and yield potential. Third, we will substantially expand the data collection scope to cover cotton samples of different varieties, planting densities, growth stages, and ecological conditions across the major cotton-producing regions of Xinjiang, and establish standardised reconstruction and phenotyping workflows to comprehensively improve the method's generalisability. Fourth, we will fuse structural parameters with spectral indicators to develop a robust and transferable yield estimation model, thereby providing technical support for precision management and sustainable development of the cotton industry in Xinjiang.

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Abbreviations

The following abbreviations are used in this manuscript:

GCPs	Ground Control Points
CC	Canopy coverage
MCH	Mean canopy height
MaxCH	Maximum canopy height
CV	Canopy volume
H50	50th percentile canopy height
H90	90th percentile canopy height
PA	Plot area
CVH	Coefficient of variation of canopy height
CP	Canopy porosity
VDU	Vertical distribution uniformity
CSR	Canopy surface roughness
VF_MH	Volume fraction above median height
Moran's I	Global spatial autocorrelation index

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