High Resolution 3D Crop Analysis and Decision Support using UAV LiDAR Technology

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Abstract.

Accurate monitoring of coffee plantations is essential for precision agriculture applications, yet conventional field measurements are labor-intensive and difficult to scale. This study presents an Unmanned Aerial Vehicle (UAV) equipped with a Light Detection and Ranging (LiDAR) sensor for the characterization of coffee crops, enabling the estimation of plant height, biomass, carbon stock, and carbon dioxide equivalent (CO_2e) at the individual plant level. The proposed system combines an Ouster OS1 LiDAR sensor mounted on a UAV platform with an onboard acquisition unit for synchronized storage of LiDAR and inertial data. The collected point clouds were processed using a MATLAB-based workflow comprising trajectory correction through Simultaneous Localization and Mapping (SLAM), ground classification, terrain normalization, canopy height model (CHM) generation, and marker-controlled watershed segmentation for individual plant delineation. The methodology was evaluated in a coffee plantation located in Santa Rita do Sapucaí, Minas Gerais, Brazil. The segmentation process successfully identified all 41 coffee plants contained within the selected crop row, matching the field observations. Height validation against ground-truth measurements resulted in a coefficient of determination (R^2) of 0.74, a root mean square error (RMSE) of 9.36 cm, and a mean absolute error (MAE) of 7 cm, demonstrating good agreement between the estimated and measured values. Furthermore, the extracted canopy metrics enabled the estimation of above-ground biomass, carbon stock, and CO_2 sequestration indicators. The results demonstrate the potential of UAV-LiDAR systems for reliable plant-level characterization of coffee plantations while reducing the effort associated with conventional field surveys. In addition, this work discusses challenges related to large-scale LiDAR data processing and outlines future opportunities involving embedded computing and wireless communication technologies for scalable agricultural monitoring systems.

Keywords.

LiDAR, precision agriculture, remote sensing, UAV, Watershed segmentation.

Introduction

Agriculture is one of the most significant economic activities in Brazil, with coffee cultivation playing a particularly prominent role in the state of Minas Gerais, which leads national production (USDA FAS 2025). During the early stages of the coffee crop development, systematic monitoring practices are essential to evaluate the spatial uniformity of plant growth and overall crop establishment, as they are highly sensitive to pest incidence, climatic variability, and soil heterogeneity (Naik et al. 2021; Pham et al. 2019; Santinato et al. 2021). Such observations support management decisions by enabling the identification of areas requiring specific interventions, including the localized application of pesticides and essential nutrients for plant metabolism, such as nitrogen, potassium, and magnesium (Ali et al. 2024). Nevertheless, current monitoring practices are still largely based on manual and time-consuming procedures, often relying on broad large-scale assessments that provide limited support for site-specific management decisions. As a result, insufficient or inaccurate monitoring can lead to improper pesticide application rates and inefficient nutrient management, potentially causing environmental contamination of crops, soil, and water resources, while also posing risks to human health and surrounding ecosystems (Hunt et al. 2020).

Precision agriculture has emerged as an important approach for improving crop management through the integration of advanced sensing, communication, and data analysis technologies, enabling automated and data-driven decision-making processes (Soussi et al. 2024). These technologies support site-specific management strategies, promoting more efficient use of agricultural inputs while reducing operational costs and environmental impacts. Among the technologies employed in precision agriculture, remote sensing has become a fundamental tool for large-scale crop monitoring and agricultural mapping (Hunt et al. 2020). Remote sensing platforms, particularly those based on Unmanned Aerial Vehicles (UAVs), allow the acquisition of high-resolution spatial and temporal data, supporting the assessment of plant health, canopy development, biomass distribution, and stress conditions (Tsouros et al. 2019; Khanal et al. 2020).

Conventional imaging approaches based on RGB (red, green, and blue) and multispectral sensors have demonstrated significant potential for agricultural applications; however, these techniques are often limited by illumination variability, canopy occlusion, and reduced capability to accurately characterize the three-dimensional structure of vegetation (Abreu et al. 2022; Barbosa et al. 2021). In this context, Light Detection and Ranging (LiDAR) sensor technology has emerged as a promising alternative due to its ability to acquire high-resolution three-dimensional information, enabling more accurate environmental characterization and crop monitoring (Farhan et al. 2024). LiDAR is an active remote sensing technology that uses laser pulses to measure distances, enabling the direct acquisition of highly accurate three-dimensional structural information. Its operating principle is based on measuring the time-of-flight between the emission and reception of laser pulses, allowing data collection independently of ambient illumination conditions. The acquired data are represented as georeferenced three-dimensional point clouds, in which each point contains spatial coordinates, intensity values, and additional attributes (Rivera et al. 2023, Yuan et al. 2022). This spatial representation supports the estimation of key crop structural parameters, such as plant height, canopy geometry, and vegetation volume, which are fundamental for deriving productivity-related indicators, including biomass and crop vigor (Karim et al. 2024).

Recent advances in UAV-based LiDAR sensing have demonstrated significant potential for agricultural monitoring, particularly for estimating crop height and characterizing canopy structure. Dhami et al. (2020) demonstrated the feasibility of estimating crop height from UAV-based 3D LiDAR point clouds for high-throughput phenotyping applications. Similarly, the use of UAV-based LiDAR was investigated for estimating crop height and biomass in potato, sugar beet, and winter wheat fields, demonstrating the capability of airborne laser scanning to retrieve structural crop parameters with high accuracy (Ten Harkel et al. 2019). The estimation of maize and soybean heights using UAV-LiDAR point clouds has also indicated that canopy height models derived from airborne laser scanning can effectively represent structural variations between crops with distinct canopy geometries (Luo et al. 2021). Beyond crop height estimation, Hütt et al. (2023) employed UAV-LiDAR metrics to monitor biomass, and nitrogen uptake in winter wheat fields, demonstrating strong correlations between LiDAR-derived structural descriptors and agronomic parameters. Debnath et al. (2023) highlighted the capability of LiDAR systems for retrieving canopy volume, leaf area distribution, and vegetation structural traits in agricultural environments. Jin et al. (2021) reviewed aerial and ground-based phenotyping platforms for crop trait estimation and discussed the relevance of LiDAR sensing for extracting structural vegetation parameters with high spatial accuracy. Furthermore, the application of LiDAR sensors in agriculture was investigated by Karim et al. (2024), emphasizing their ability to characterize crop structure and working environments under complex vegetation conditions. These studies reinforce the advantages of LiDAR compared to conventional RGB and multispectral approaches, particularly in scenarios involving dense vegetation and irregular canopy architectures.

Although UAV-LiDAR applications have advanced considerably for several agricultural crops, studies specifically focused on coffee plantations remain relatively limited. Most existing works involving coffee monitoring still rely primarily on RGB or multispectral imagery obtained from UAV platforms (dos Santos et al. 2020a; dos Santos 2020b). Among the few studies employing UAV-LiDAR systems for coffee crops, Bento et al. (2025) investigated the use of airborne LiDAR for mapping coffee plant height and soil compaction variability across plantations. However, the estimation of additional structural parameters, such as vegetation volume and biomass, remains still scarcely explored for coffee crops using UAV-LiDAR data. Furthermore, limited attention has been given to the processing and communication challenges associated with the large volume of data generated by LiDAR sensors, particularly considering future large-scale and near-real-time precision agriculture applications.

This study proposes a precision agriculture framework for coffee crop monitoring using a UAV-based LiDAR system combined with structural parameter estimation in the MATLAB environment. The proposed approach enables the estimation of plant height, vegetation volume, and biomass from LiDAR point clouds, supporting the identification of regions requiring localized agricultural interventions and more efficient crop management practices. In addition to the agronomic analysis, this work also discusses the challenges associated with handling large LiDAR datasets in agricultural environments and presents a preliminary perspective on the use of embedded processing platforms and wireless communication technologies to support future scalable and near-real-time monitoring architectures for precision coffee agriculture.

Materials and Methods

Study Area

The study area, illustrated in Fig. 1, consists of a coffee plantation (Coffea arabica L.) located in Santa Rita do Sapucaí, Minas Gerais, Brazil (22°21’11.1” S, 45°68’07.1” W). The region lies at an altitude within the range of 820-830 m and has a subtropical highland climate, with average annual temperatures of approximately 21 °C and typical monthly variations from 11 °C to 27 °C. Annual precipitation averages roughly 1,416 mm, concentrated primarily in the October–March rainy season. In the experimental area, the coffee plants are arranged in straight rows on flat terrain. LiDAR data were acquired on February 27th, 2026, and ground-truth coffee plant heights were measured on the same day using a measuring tape, with 41 samples collected in the second row of the plantation.

UAV-LiDAR Configuration

Fig. 2 illustrates the full system configuration, including the UAV platform, LiDAR sensor, interface box, onboard computer, and batteries. The UAV platform used in this study was a DJI

Fig. 1 Location of the study area in Santa Rita do Sapucaí, Minas Gerais, Brazil. Satellite image source: Google Earth.

Agras MG-1P multirotor, which supports a maximum takeoff weight of 24.8 kg and operates at speeds of up to 12–15 m/s, with typical hovering times ranging from 9 to 20 minutes. The LiDAR sensor (OS1, Ouster) offers full 360° horizontal coverage and up to 45° of vertical field of view (FOV). It produces high-resolution point clouds (32/64/128 channels) at rates reaching 2.6 million points/s, providing a measurement range of 120 m with an accuracy of approximately ±3 cm. The sensor employs an eye-safe 865 nm Class 1 laser, operates at rotation rates of 10 or 20 Hz, and integrates a three-axis inertial measurement unit (IMU) that streams synchronized accelerometer and gyroscope data at high frequency. The built-in IMU is primarily used to timestamp and stabilize the LiDAR packets, providing orientation cues that enhance the temporal alignment of scans. An interface box supplied regulated power to the sensor and supported high-throughput data transmission via Gigabit Ethernet.

The onboard computer was implemented using an NVIDIA Jetson Orin NX platform with 128 GB of storage, running a Linux-based operating system for real-time data handling and system control. A customized acquisition service was developed to manage the entire LiDAR data pipeline. After a 60-second startup delay, the service automatically initializes and begins streaming LiDAR and IMU packets directly from the sensor via Gigabit Ethernet. The system records a configurable capture window, set to 5 minutes in this study, saving all incoming packets sequentially into a time stamped .pcap file. The corresponding sensor metadata and acquisition parameters are automatically stored in separate .json files. To support autonomous operation, the LiDAR sensor and the onboard computer were powered by two dedicated 12 V lithium-ion batteries integrated into the drone platform, ensuring stable and reliable power delivery to all units.

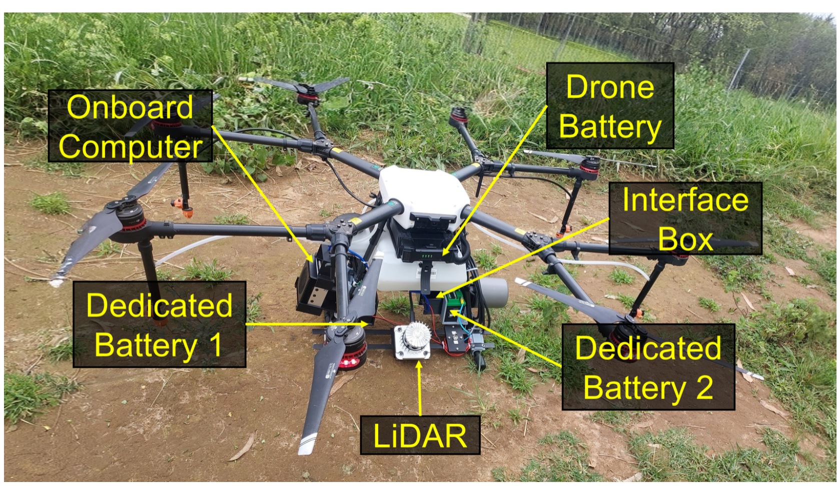

Fig. 2 UAV–LiDAR system configuration employed for data acquisition and storage.

Data Processing

The complete workflow adopted in this study is presented in Figure 3 and comprises a sequence of processing stages, including point cloud generation, trajectory correction, ground classification, terrain normalization, individual plant delineation, and the estimation of biomass, carbon stock, and carbon dioxide equivalent (CO_2e). By progressively transforming raw spatial measurements into quantitative plant-level descriptors, this workflow enables a comprehensive assessment of crop structure and environmental indicators.

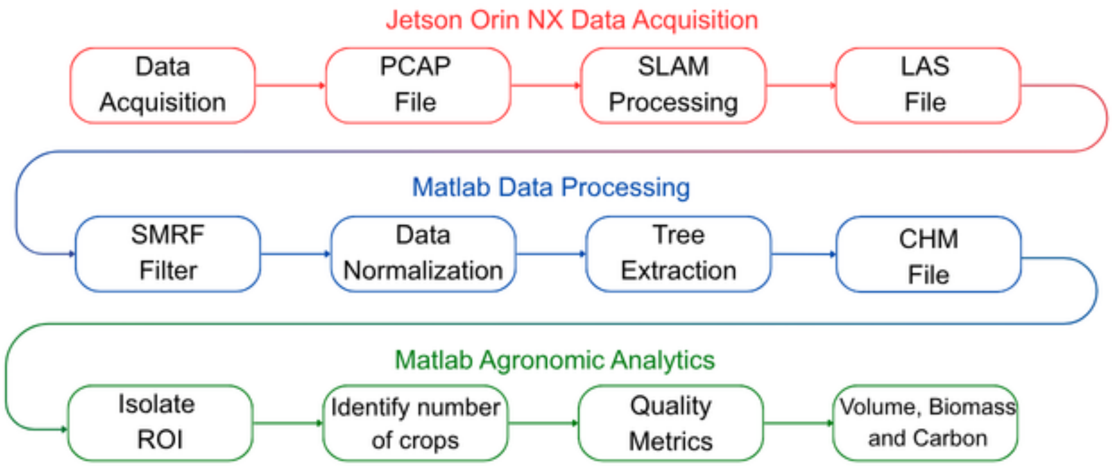

Fig. 3. Flowchart of the system, since data processing to agronomic analytics.

The initial phase of data processing involves acquiring raw data packets from the UAV-mounted LiDAR sensor via the onboard Jetson computer and storing them in PCAP format. To support spatial analysis, these packets are converted into LAS format, which stores individual LiDAR channel information for each point in the cloud. Due to inherent UAV flight dynamics, such as high-frequency vibrations, position correction is mandatory. This is achieved using Simultaneous Localization and Mapping (SLAM), a robust technique for correcting drift errors and predicting the true trajectory, thereby preserving the spatial integrity of the point cloud and accurately reconstructing the real environment. Specifically, this study employs the Keep It Small and Simple Iterative Closest Point (KISS-ICP) algorithm, a modern and computationally lightweight LiDAR odometry pipeline (Vizzo et al. 2023). The KISS-ICP methodology requires precise tuning of spatial parameters, including the minimum and maximum point ranges and the voxel map resolution. These parameters were set to 1.5 meters, 150 meters, and 0.75 meters, respectively.

After generating the LAS file, the data is transferred from the onboard system to a high-performance workstation with hardware configuration containing a 12th Gen Intel Core i7-12700G processor and running Ubuntu 24.04.4 LTS. The code for processing all data was generated in MATLAB [version 2025b]. The MATLAB 'LiDAR Viewer' application is used to empirically determine the optimal parameters for the Simple Morphological Filter (SMRF). The SMRF algorithm effectively segregates ground (terrain) points from non-ground (surface) points. The selected parameters for this study were: a grid resolution of 1, a maximum window radius of 18, a slope threshold of 0.15, an elevation threshold of 0.5, and an elevation scaling factor of 1.

Once the ground points are classified, terrain normalization is conducted to prevent natural topographic slopes from distorting agronomic measurements. This process involves generating a Digital Terrain Model (DTM) from the SMRF-filtered ground points and subtracting it from the raw point cloud. This normalization establishes a flat baseline, ensuring that the Z-axis exclusively represents the absolute above-ground height of the vegetation. Since the primary objective is to analyze specific coffee crops, a maximum height filter is applied to exclude non-target vegetation, such as trees. The Canopy Height Model (CHM) is then produced by subtracting the DTM from the Digital Surface Model (DSM).

To optimize computational efficiency and restrict analysis to the Region of Interest (ROI), a polygonal boundary is manually defined over the specific target row, corresponding to the second line of the plantation. This approach isolates the target coffee crop and enables direct comparison with ground-truth field measurements. The next step involves individual crop delineation to quantify the number and height of each coffee plant. This process initiates by identifying topological markers within the CHM, which correspond to the biological local maxima, or the highest central peak, of each plant. After locating these peaks, the CHM is mathematically inverted, and a marker-controlled watershed algorithm is applied. The selection of this algorithm is supported by recent literature (Liu et al. 2024b; Wang et al. 2025), which demonstrates that combining topological markers with watershed segmentation significantly mitigates the under-segmentation of overlapping canopies. This classical image segmentation technique simulates flooding in the valleys of the inverted surface until the simulated water levels converge. The intersection lines of these water levels delineate the physical boundaries of each plant, effectively separating coffee branches into discrete, quantifiable entities.

The maximum heights extracted from these delineated peaks are then statistically validated against real field measurements to establish the reliability of the model, using the Coefficient of Determination (R^2), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). The formulas are expressed as follows in Equations 1, 2 and 3 (Zhou et al. 2020; Liu et al. 2024a):

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \overline{y_i})^2} \quad (1)$$

$$RMSE = \sqrt{\sum_{i=1}^{N}\frac{(y_i - \hat{y}_i)^2}{N}} \quad (2)$$

$$MAE = \frac{\sum_{i=1}^{N}|y_i - \hat{y}_i|}{N} \quad (3)$$

where N is the number of samples, y_i and $\hat{y}_i$ are the measured and estimated height, respectively, and $\overline{y}_i$ is the average measured height. The R^2 metric assesses how well the estimated values align with the actual field measurements, whereas RMSE and MAE provide measures of the prediction errors, with RMSE penalizing large errors through outliers and MAE reflecting the overall scale of errors. Additionally, residual errors were analyzed on a plant-by-plant basis to identify potential systematic biases and estimate dispersion.

Following the geometric delineation and height validation, individual plant volumes and biomass are estimated to create a comprehensive agronomic profile. First, the total volume for each plant is calculated by multiplying the base area of a single pixel by its elevation value CHM and then adding up these discrete micro-volumes of all pixels contained within the contoured boundaries of that plant. Furthermore, these derived volumetric metrics are multiplied by an empirically established crop calibration constant to estimate the total above-ground dry biomass (AGB) in kilograms, as shown in Equation 4.

$$AGB = V_{plant} \cdot 2.85 \quad (4)$$

One key outcome from biomass analysis is the mass of carbon retained, denoted as C, which signifies the pure carbon component in the plant. This computation employs a universally recognized conversion factor (0.47), established by the Intergovernmental Panel on Climate Change (IPCC 2006). Its formula can be expressed as follows in Equation 5.

$$C = AGB \cdot 0.47 \quad (5)$$

Finally, the quantified carbon stock values were converted into equivalent retained carbon dioxideCO_{2e}, enabling the translation of structural point cloud data into an environmental metric, as shown in Equation 6.

$$CO_{2e} = C \cdot 3.667 \quad (6)$$

The conversion factor of 3.667 reflects the stoichiometric molecular mass ratio between carbon dioxide (44 g/mol) and elemental carbon (12 g/mol). Thus, for every 1 kg of carbon stored in plant biomass, approximately 3.667 kg of CO_2 are removed from and retained out of the atmosphere (IPCC 2006).

Experimental Results and Discussions

Height Estimation and Validation

The first stage of the analysis involved generating the CHM, which serves as the basis for extracting plant-level structural parameters. The resulting canopy height distribution is illustrated in Figure 4 as a heatmap representation of the surveyed area. The red color represents the solid ground baseline, while the yellow and green tones demonstrate the varying height levels of surface objects and vegetation, up to the established maximum height of 1.6 meters. The white areas primarily indicate the masking of higher structures that fall outside the established limits of interest. The CHM effectively differentiated the topographical baseline from the vegetative surface, thereby establishing a coherent geometric foundation for visualization and interpretation.

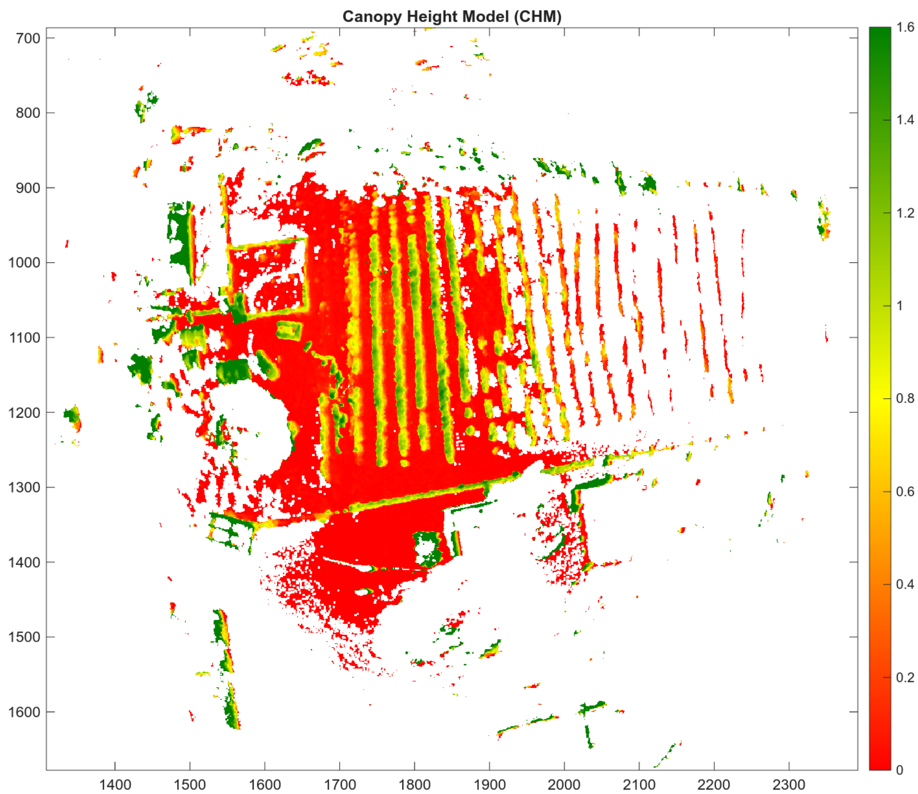

Fig. 4. Canopy Height Model (CHM) of the coffee plantation represented as a heatmap.

Following the generation of the canopy height heatmap, the Region of Interest (ROI) corresponding to the second row of the plantation was isolated for detailed analysis, as shown in Figure 5. This area was selected because it contains the coffee plants for which ground-truth height measurements were collected during the field campaign. Subsequently, the marker-controlled watershed algorithm was applied to the normalized CHM to perform individual coffee plant segmentation. The procedure began with the identification of local maxima within the canopy surface, corresponding to the highest points of each plant. These topological markers were then used to guide the watershed segmentation process, enabling the automatic delineation of individual canopies and the separation of adjacent plants, even in regions with high canopy proximity. Figure 5 shows the isolated ROI boundaries alongside the segmented coffee plant peaks. Each black triangle represents a topological peak associated with an identified segment. A total of 41 individual coffee plants were detected within the ROI, corresponding exactly to the

41 plants expected in the selected crop row and measured during the field survey. The enlarged view on the right side of the figure further illustrates the effectiveness of the segmentation process, highlighting the successful separation of neighboring plants and the consistency of the identified boundaries.

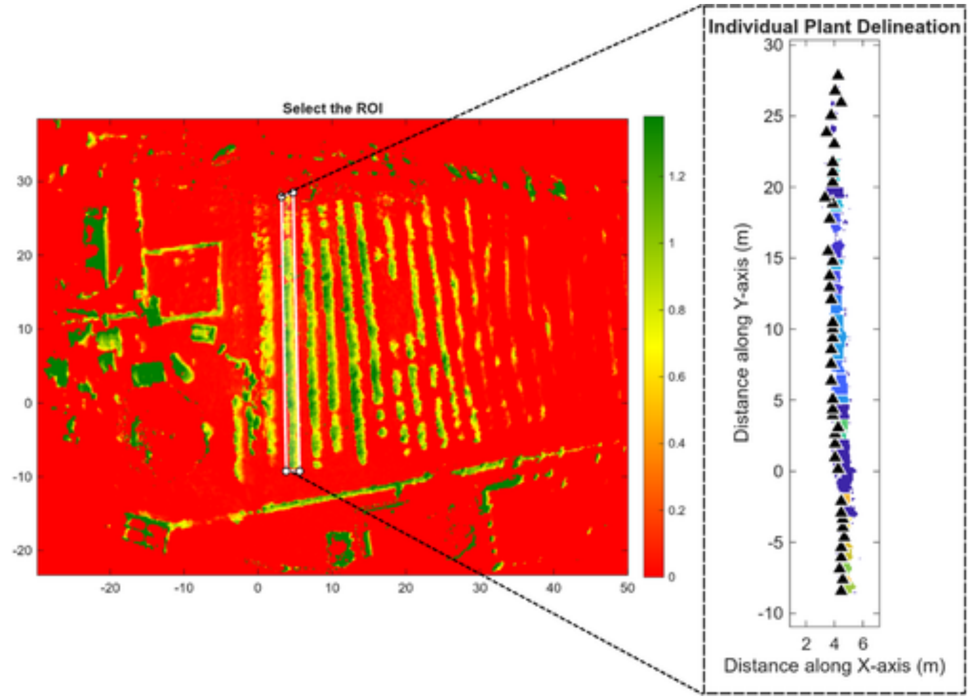

Fig. 5. Selection of the ROI and subsequent individual plant delineation using marker-controlled watershed segmentation.

To quantify system accuracy, the extracted canopy heights were statistically validated against the field measurements collected during the survey campaign. A total of 41 segmented plants were evaluated, enabling a direct comparison between the UAV-LiDAR estimates and the corresponding ground-truth measurements. Figure 6 compares the height profile obtained from the UAV-LiDAR system with the field measurements for each individual plant. The estimated heights closely follow the variations observed along the crop row, demonstrating the capability of the proposed methodology to capture the structural variability of the plantation. The resulting RMSE was 9.36 cm, indicating a good agreement between the LiDAR-derived estimates and the reference measurements.

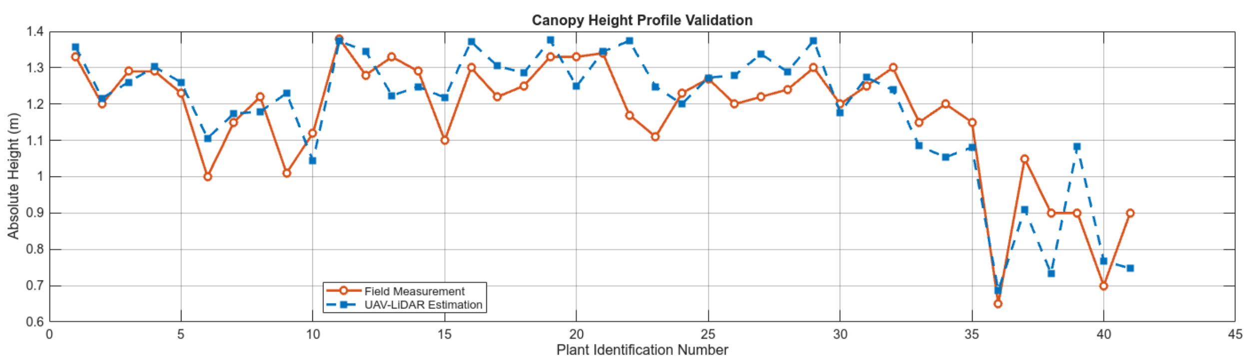

Fig. 6. Comparison between ground-truth field measurements (orange) and UAV-LiDAR estimated heights (blue).

The correlation analysis shown in Figure 7 further confirms the reliability of the proposed approach displaying both linear fits alongside all 41 points mapped on a 2D plane comparing field-measured versus LiDAR-estimated heights. The linear regression yielded a coefficient of determination (R^2 = 0.744) showing a modest improvement over similar methodologies reported by Bento et al. (2025). Additionally, both the RMSE (0.0936 m) and MAE (0.0750 m) remained below the 10 cm threshold, which is considered highly acceptable given the irregular and dense structure of coffee canopies. Furthermore, the linear regression analysis produced a fit equation of, $y = 0.9497x + 0.0753$ which closely approximates the ideal $y = x$ baseline that represents a perfect 1:1 correspondence between estimated and actual measurements.

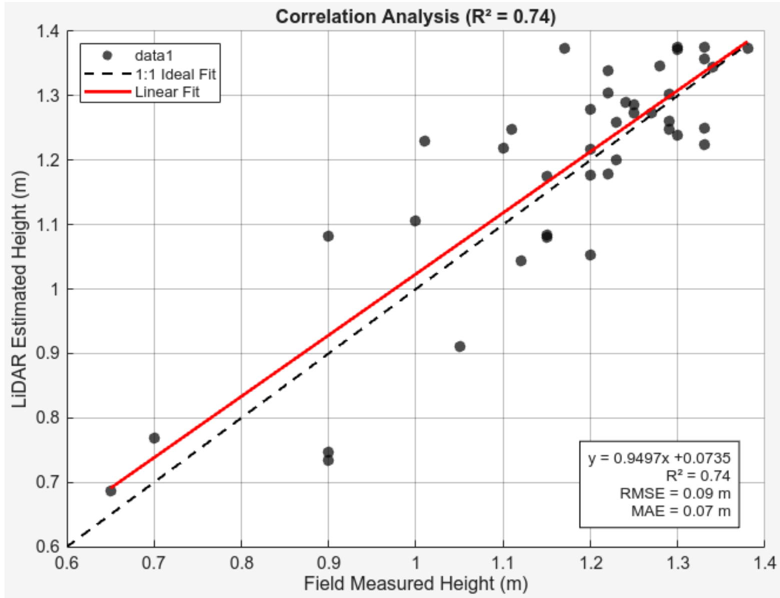

Fig. 7. Statistical validation of the LiDAR-estimated height metrics, linear regression analyzes, and quality metrics.

To further assess the estimation performance, Figure 8 presents the residual error distribution for all segmented plants. This graph illustrates the deviation of the LiDAR-derived height estimates from the corresponding field measurements, providing additional insight into the accuracy and consistency of the proposed methodology.

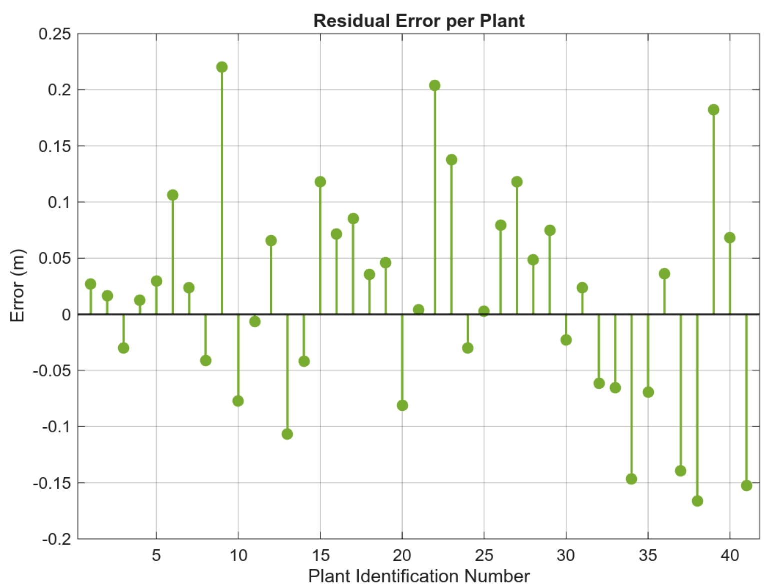

Fig. 8. Residual errors distribution across the individual segmented coffee crop.

The residual analysis revealed an average error of 0.0146 m, indicating a slight overall tendency toward overestimation. The maximum positive deviation was 0.22 m, while the maximum negative deviation reached −0.1663 m, corresponding to the largest overestimation and underestimation errors observed, respectively. Despite these isolated deviations, most residuals remained concentrated near zero, with no evident systematic trend along the analyzed crop row. These results demonstrate that the proposed UAV-LiDAR workflow provides consistent height estimates across different plants and is suitable for plant-level structural characterization in coffee plantations.

Agronomic Analytics

In addition to geometric validation, the conversion of spatial data into AGB and analysis of retained carbon dioxide generates critical sustainability metrics for contemporary agriculture. The LiDAR-derived biomass parameters were calibrated using the allometric models for *Coffea arabica* developed by Segura et al. (2006). Applying these field-validated models to the specific plant heights measured in this study yielded a theoretical dry biomass of approximately 2.65 kg per plant. Because the LiDAR pipeline determined an average individual crown volume of 0.9303 m^3, a volumetric crop calibration constant of 2.85 kg/m^3 was applied to perfectly align the 3D remote sensing volume with this established biological metric.

Furthermore, applying Equations (4), (5), and (6), the total estimated above-ground dry biomass for the defined ROI was 108.70 kg, yielding an average of 2.65 kg per plant. The total retained carbon across the 41 segmented coffee plants was quantified at 51.09 kg, which translates to a total equivalent retained carbon dioxide of 187.35 kg. The comprehensive agronomic profile for each individual plant, detailing cup volume, biomass, and maximum LiDAR-derived height, is illustrated in Figure 9.

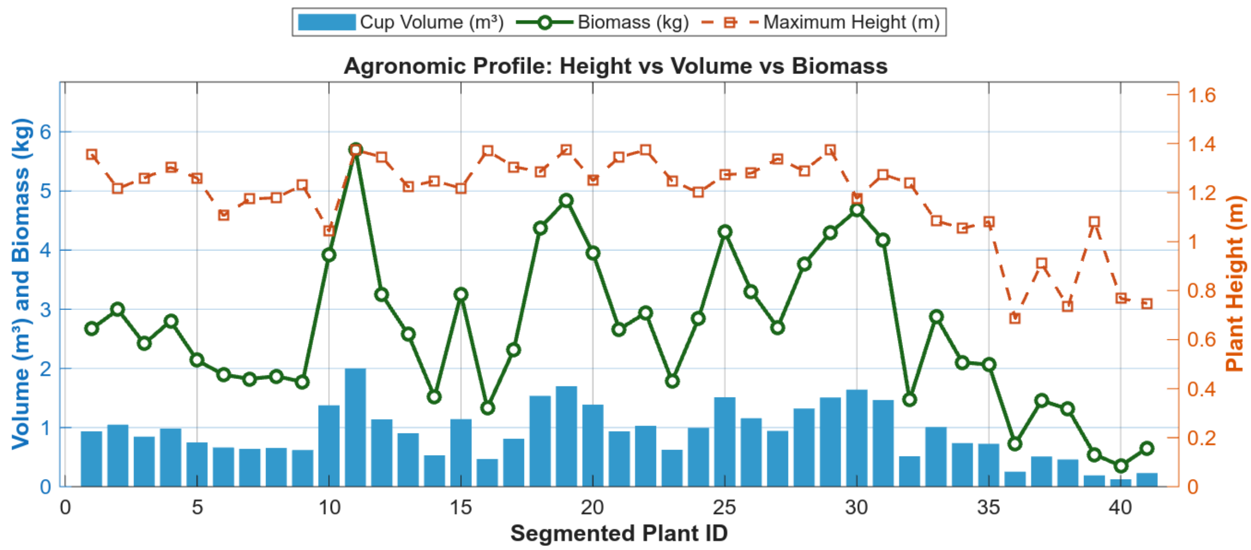

Fig. 9. Agronomic profile of the studied ROI, illustrating individual plant variations in estimated height, cup volume, and above-ground biomass.

One may notice that plants of similar heights may have different volumes, indicating that height alone is insufficient to fully capture the vegetative development of coffee trees. Overall, the ability to accurately calculate this equivalent retained carbon dioxide retention demonstrates the system capability to rapidly quantify vegetative carbon stocks, providing a highly scalable, non-destructive auditing framework for precision agriculture and modern carbon credit markets. It is important to highlight that ground-truth measurements acquired in dense agricultural environments are inherently subject to manual uncertainties, which may introduce discrepancies during the validation process. Furthermore, the biomass estimates presented in this study were derived from theoretical allometric relationships rather than direct destructive sampling, which may affect the absolute accuracy of the biomass and carbon assessments.

Key Challenges and Future Research Directions

Although the results demonstrate the effectiveness of UAV-LiDAR systems for plant-level characterization of coffee plantations, several challenges remain before such solutions can be deployed on a large operational scale. One of the primary limitations is the substantial volume of data generated during LiDAR surveys. High-resolution sensors operating at millions of points per second produce large point cloud datasets that require significant storage capacity, computational resources, and processing time. In the proposed workflow, data acquisition, trajectory correction, point cloud generation, segmentation, and agronomic analysis were performed offline, requiring the transfer of data from the onboard platform to a dedicated workstation. While suitable for research applications, this approach may become impractical for frequent monitoring campaigns covering extensive agricultural areas.

Another challenge is the computational complexity associated with point cloud processing algorithms. Tasks such as SLAM-based trajectory correction, ground classification, canopy segmentation, and biomass estimation demand considerable processing resources, particularly when high spatial resolutions are required. Reducing the latency between data acquisition and agronomic decision-making therefore remains an important research objective for precision agriculture systems. Recent advances in embedded computing platforms provide a promising pathway toward addressing these limitations. The integration of edge computing techniques may enable partial or complete execution of processing pipelines during flight, reducing the need for post-processing and allowing the generation of actionable agronomic information immediately after data acquisition.

In parallel, the evolution of wireless communication technologies opens new opportunities for scalable agricultural monitoring architectures. High-capacity wireless links based on the fifth generation (5G) and future sixth generation (6G) networks may support the transmission of processed features, compressed point clouds, or selected regions of interest from UAVs to edge servers or cloud platforms in near real time. In rural environments, alternative communication technologies such as TV White Space (TVWS) networks also represent a promising solution due to their long transmission range and favorable propagation characteristics over large agricultural areas (Islam et al. 2021). Such architectures could enable continuous monitoring of extensive coffee plantations while distributing computational workloads between onboard processors, edge infrastructure, and centralized cloud resources.

Future research should therefore focus on the development of integrated sensing, computing, and communication frameworks capable of supporting near-real-time agricultural analytics. Particular attention should be given to onboard artificial intelligence algorithms for plant detection and health assessment, adaptive point cloud compression techniques, energy-efficient embedded processing, and the integration of UAV-LiDAR systems with next-generation wireless networks. These advances have the potential to transform UAV-based LiDAR monitoring from an offline mapping tool into a scalable digital agriculture platform capable of supporting continuous crop management and environmental monitoring.

Conclusion

This work presented a UAV-LiDAR-based methodology for the characterization of coffee plantations, integrating spatial data acquisition, point cloud processing, plant segmentation, and agronomic parameter extraction into a unified workflow. The findings indicate that a UAV-mounted LiDAR system offers high reliability for advanced agronomic analyses. The combination of an onboard acquisition platform for spatial data capture and alignment with a MATLAB-based processing pipeline enabled the conversion of raw point clouds into actionable cultivation metrics.

The generated canopy height model and marker-controlled watershed segmentation enabled the accurate delineation of individual coffee plants within the selected crop row, correctly identifying all 41 plants evaluated during the field campaign. The subsequent height validation demonstrated good agreement between the UAV-LiDAR estimates and the reference measurements, yielding an R^2 of 0.74 and an RMSE of 9.36 cm. These results confirm the capability of the proposed methodology to accurately characterize the structural variability of coffee plantations at the individual plant level. Beyond height estimation, the extracted structural parameters enabled the quantification of canopy volume, above-ground biomass, carbon stock, and CO_2 equivalent, highlighting the potential of UAV-LiDAR systems to support both agronomic management and environmental assessment.

Finally, this study discussed the challenges associated with the storage, transmission, and processing of large LiDAR datasets in agricultural environments. Future research should focus on reducing the latency between data acquisition and agronomic analysis through the integration of embedded computing platforms, artificial intelligence techniques, and advanced wireless communication technologies, enabling scalable and near-real-time monitoring architectures for precision coffee agriculture.

Acknowledgments

This work was partially supported by the Brasil 6G project (01245.020548/2021-07, funded by RNP/MCTI); the xGMobile Project code XGM-AFCCT-2024-2-15-1, through the EMBRAPII/MCTI (Grant 052/2023 PPI IoT/Manufacturing 4.0); by FAPEMIG (PPE-00124-23, Ciência para Elas project grant APQ-04523-23, Programa de Apoio a Instalações Multiusuários grant APQ-01558-24, Fomento à Internacionalização das ICTMGs grant APQ-05305-23, and Redes Estruturantes, de Pesquisa Científica ou de Desenvolvimento Tecnológico grant RED-00194-23); by FAPESP (SEMEAR project grant 22/09319-9 and SAMURAI Project grant 20/05127-2); and CNPq (grant 303282/2021-5).

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