ESTIMATION OF ABOVEGROUND CARBON STOCK OF BANANA (*Musa* spp.) PLANTATIONS IN THE COLOMBIAN CARIBBEAN

Luis Miguel Torres Ustate, Martha Ligia Castellanos Martínez and Jairo Rene Escobar Villanueva

SUMMARY

Banana is the most important agricultural product in northern Colombia. It is cultivated using intensive monoculture systems with a significant volume of standing biomass, which contributes to carbon capture. This study aimed to (1) compare field-observed height data with Unmanned Aerial Vehicle (UAV)-estimated height data for estimating Aboveground Biomass (AGB), and (2) quantify the carbon stock in standing banana biomass. The study was conducted on a banana farm in Colombia. Height measurements from the field and UAV estimates were obtained for 54 banana plants in two different Areas: Area 1, which covers 0.5ha (dense), and Area 2, which covers 1.5 hectares (dispersed). Pseudostem samples were collected from 18 banana plants to determine moisture and carbon content in the laboratory. The results showed determination coefficients (R^2) of 0.76 for Area 1 and 0.61 for Area 2 when comparing field heights with those estimated from the Canopy Height Model (CHM). Additionally, the results revealed average carbon reserve values in Area 1, derived from field data (1.27kg/plant and 1.01 Mg/ha) and CHM data (1.27kg/plant and 1.02Mg/ha). In Area 2, the average values were 1.34kg/plant and 3.22 Mg/ha in the field, and 1.09kg/plant and 2.62Mg/ha in CHM. Validation indicates high precision in carbon reserve estimates for Area 1, while precision is lower for Area 2.

Introduction

Estimating carbon stock in crops is crucial for understanding their role in mitigating climate change (Jhariya *et al*., 2021). While climate change threatens agriculture, it also contributes to phenomena such as the temperature increase described by global warming. Greenhouse gas emissions from agriculture are estimated to range between five and seven $GtCO_2$/year (Reppin *et al*., 2020), equivalent to 14% of total anthropogenic emissions (Pachauri *et al*., 2014). However, agriculture can help mitigate climate change. Agricultural mitigation can be achieved through a various practices that enhance carbon sequestration in biomass by creating and improving carbon sinks through capturing carbon from the atmosphere via photosynthesis and storing carbon in the soil through the decomposition of dry biomass residues (Reppin *et al*., 2020). In particular, banana crops (*Musa* spp.) are significant carbon reservoirs in many tropical regions due to carbon fixation through photosynthesis and the storage of residues generated by pruning and natural decomposition of their parts (pseudostem, rachis, leaves and flower) (Aeberli *et al*., 2021, 2023; Calou *et al*., 2020; Danarto & Hapsari, 2015; Ganeshamurthy, 2023; Kamusingize *et al*., 2018; Ortiz-Ulloa *et al*., 2021; Schneidewind *et al*., 2019; Stevens *et al*., 2020). Accurately estimating carbon stock in these agricultural systems is essential for assessing their contribution to climate change mitigation and for designing strategies that maximize carbon capture.

Remote sensing technologies, especially the use of Unmanned Aerial Vehicles (UAV), have emerged as powerful tools for monitoring and managing agricultural crops (Alabi *et al*., 2022; Gomez Selvaraj *et al*., 2020; Kestur *et al*., 2018; Ye *et al*., 2020; S. Zhang *et al*., 2022). UAV offer an efficient and precise solution for capturing spatial and spectral data, allowing detailed assessment of aerial biomass (Estornell *et al*., 2024; Fujimoto *et al*., 2019; J. Lin *et al*., 2022). These technologies provide informed data for

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ESTIMACIÓN DE RESERVAS DE CARBONO SOBRE EL SUELO DE PLANTACIONES DE BANANO (*Musa* spp.) EN EL CARIBE COLOMBIANO

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RESUMEN

El banano es el producto agrícola más importantes al norte de Colombia. Se basa en sistemas intensivos de monocultivo con un gran volumen de biomasa en pie que contribuye a la captura carbono. Este estudio se realizó con el objetivo de (1) comparar los datos de altura observadas en campo y las estimadas a partir de un Vehículo Aéreo no Tripulado (UAV) para la estimación de Biomasa Aérea (AGB), y (2) cuantificar las reservas de carbono de la biomasa en pie de banano. El estudio se llevó a cabo en una finca bananera de Colombia. Se determinaron medidas de altura observadas y estimadas a partir de 54 plantas en dos áreas diferentes: área 1 de 0,5ha (densa) y el área 2 de 1,5ha (dispersa). Se tomaron muestras pseudotallo de 18 plantas de banano para determinar humedad y contenido de carbono en laboratorio. Los resultados mostraron coeficientes de determinación (R^2) de 0,76 para el Área 1 y 0,61 para el Área 2, al comparar las alturas obtenidas en campo con las estimadas a partir de Modelo de Altura del Dosel (CHM). Además, mostraron valores promedio de reservas de carbono en el Área 1, obtenidos de datos en campo (1,27kg/planta y 1,01Mg/ha) y de datos CHM (1,27 kg/planta y 1,02 Mg/ha), mientras que en el Área 2 los valores promedio fueron de 1,34kg/planta y 3,22Mg/ha en campo y 1.09 kg/planta y 2,62Mg/ha en CHM. La validación indica una alta precisión en las estimaciones de reservas de carbono en el Área 1, mientras que en el Área 2 la precisión es menor.

ESTIMATIVA DO ESTOQUE DE CARBONO ACIMA DO SOLO EM PLANTIOS DE BANANA (*Musa* spp.) NA REGIÃO CARIBENHA DA COLÔMBIA

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RESUMO

A banana é o produto agrícola mais importante no norte da Colômbia. Ela é baseada em sistemas de monocultura intensiva com um grande volume de biomassa em pé que contribui para a captura de carbono. Este estudo foi realizado com os objetivos de (1) comparar os dados de altura observados em campo com os dados de altura estimados por Veículo Aéreo Não Tripulado (VANT) para a estimativa da Biomassa Acima do Solo (BAS) e (2) quantificar o estoque de carbono na biomassa de banana em pé. O estudo foi conduzido em uma plantação de banana na Colômbia. Medidas de altura observadas em campo e estimadas por VANT foram obtidas para 54 plantas de banana em duas áreas diferentes: Área 1, que cobre 0,5ha (densa), e Área 2, que cobre 1,5 ha (dispersa). Amostras de pseudocaule foram coletadas de 18 plantas de banana para determinar o teor de umidade e o conteúdo de carbono no laboratório. Os resultados mostraram coeficientes de determinação (R^2) de 0,76 para a Área 1 e 0,61 para a Área 2 ao comparar as alturas obtidas em campo com as estimadas pelo Modelo de Altura de Dossel (CHM). Além disso, os resultados revelaram valores médios de reserva de carbono na Área 1, derivados dos dados de campo (1,27kg/planta e 1,01Mg/ha) e dos dados do CHM (1,27kg/planta e 1,02Mg/ha), enquanto na Área 2 os valores médios foram 1,34 kg/planta e 3,22Mg/ha no campo e 1,09kg/planta e 2,62Mg/ha no CHM. A validação indica alta precisão nas estimativas de reserva de carbono na Área 1, enquanto a precisão é menor na Área 2.

decision-making in agricultural management and the implementation of practices that promote sustainability and climate resilience. A scenario analysis that considers climate change is essential for agricultural management to support climate change mitigation and adaptation.

The widespread availability of remote sensing technology in recent decades and the continuous advances in sensors, as well as the various spectral, spatial, and temporal resolutions of the data, have allowed agricultural managers and researchers to use these data in combination with field data as a complementary information sources to obtain spatially explicit information about agricultural resources (Ali Hussin, 2022; Fadil *et al*., 2024; Jhariya *et al*., 2021). The estimation of above-ground carbon in banana crops can be carried out using the Canopy Height Model (CHM), which represents the canopy height of vegetation from images captured by UAV. The is generated by subtracting the Digital Terrain Model (DTM) from the Digital Surface Model (DSM) or Digital Elevation Model (DEM), thus providing an approximate representation of vegetation height. This technique is particularly useful for biomass and carbon estimation, as canopy height is closely related to the amount of biomass a plant can support (Bazzo *et al*., 2023; Ferreira *et al*., 2024; Liu, Feng, *et al*., 2023; Shu *et al*., 2023).

This study investigates the estimation of above-ground carbon stock in banana plantations in the Colombian Caribbean using UAV imagery. The results include the selection of the study Area, the planning and execution of flights, image processing and analysis, and the estimation of carbon stock at both the plant and Area levels, with corresponding validation. To date, few studies have estimated above-ground carbon stock in banana plantations using UAV data, primarily in Australia and Costa Rica (Aeberli *et al*., 2021, 2023; Machovina *et al*., 2016). These studies explored UAV point clouds to detect individual plants and calculate the CHM. Following a similar methodology, this study represents the first attempt in the literature to estimate banana plant biomass using UAV-CHM data for the Colombian

Caribbean. Additionally, for the first time, two study Areas are compared, enabled by the distribution of the cultivar, allowing for an assessment of the efficiency of UAV systems in estimating carbon stock.

Materials and Methods

Study location

Object-based image analysis was employed to delineate the potential banana planting Area on a 13ha commercial farm located in Zona Bananera, Magdalena, Colombia (10°48'57.3"N, 74°09'58.5"W). UAV data were collected in two Areas of the crop: Area 1, 0.5ha, characterized by a high density of plants, and Area 2, 1.5ha, with a moderately dispersed density. Six and twelve sampling points were established, respectively, and three measurements were taken per point. The sample selection was justified using previous studies that determined the number of plants needed to obtain representative results when comparing UAV and field data is 15 plants per 0. ha (Aeberli *et al*., 2023) and 12 plants at harvest stage to determine carbon content (Ortiz-Ulloa *et al*., 2021), which were randomly selected at each location. These Areas were selected because they contained standing plants, whereas the remaining Area had been cleared as part of the crop transition (Figure 1).

The study Area has a tropical savanna climate with moderately warm dry months (December to March) and rainy seasons (April to November). Available local climatic data from the meteorological stations: Carmen El [code: 29060140], Padelma [code: 29065020], Proyectos Los [code: 29060250], Prado Sevilla [code: 29065030], and Media Luna - Aut [code: 29065000] from IDEAM-Instituto de Hidrología, Meteorología y Estudios Ambientales (https://dhime.ideam.gov.co/), show that temperatures during the dry season have an average maximum of 30.6°C and average minimums in the rainy season of 25.6°C. Precipitation occurs mainly in the summer, with a maximum monthly average in the rainy season of 635.8mm and a minimum of 0.0mm in the dry months. The surrounding region hosts land uses for forests, agriculture (mainly banana), and residential Areas. This irrigated site cultivates approximately 700 banana plants of different varieties, with the Musa AAA Cavendish variety predominating, which affects the height and aerial biomass content of the plants. They are spaced at 2.5m apart, with planting patterns in “row” and “triangle”, a general age of the plants of over five years (since June 2018), and new plantations established as needed. Each banana plant produces fruit only once during its life. However, new stems are continuously produced from each plant. The fruit is harvested around nine months after planting; then, new stems produce fruit every three to four months.

Estimation of carbon stock

The carbon stocks at the plant level were estimated from the height measured in the field and the height estimated using the UAV. The procedure consisted of four main steps: (i) UAV flight and CHM generation; (ii) collection of allometric data; (iii) estimation of Aboveground Biomass (AGB) and determination of plant carbon content; and (iv) estimation of standing banana crop carbon stocks (Figure 2).

UAV flight and CHM generation

The flight design for collecting the images was carried out by Area (two flights) on November 9, 2023. In both cases, the design was identical, using a Phantom 4 Multirotor Drone equipped with a 12Mpx camera and a mechanical shutter. The flights followed a grid pattern at an altitude of 47 meters, with 80% overlap (72% lateral) and a 70° camera angle, ensuring consistent planning to obtain high-quality 3D models and orthomosaics. After collecting the images, the first step in the post-processing of UAV aerial images in photogrammetric mapping was to align the overlapping image pairs using Pix4Dmapper software. This software is capable of adjusting geometric and radiometric effects, extracting pixels in images that share a common view to produce 3D point clouds, which can be used to create a texture model and finally project them onto an orthomosaic (Neupane *et al*., 2019). The characteristics of the flight data and photogrammetric processing are shown in Table I.

The images were first radiometrically corrected using reference data. Then, geometric corrections were made based on a UAV-derived DTM and ground GPS data. Finally, atmospheric corrections were applied using QGIS, high-density point clouds were generated from the captured images, which were used to create high-resolution orthomosaics and produce a DSM and DTM based on ground points. Subsequently, a Canopy Height Model (CHM) was calculated (Equation 1), which represents the height of the plants above the ground surface by subtracting DTM values from DSM values (Qin *et al*., 2021). The image processing was performed on a computer with the following specifications: 32GB of RAM, an Intel Core i7-6700HQ CPU @ 2.60GHz, an Intel HD Graphics 530GPU, and a solid-state drive (SSD) for fast data access and processing, running on Windows 10 Enterprise, 64-bit.

$$\mathrm{CHM} = \mathrm{DSM} - \mathrm{DTM} \qquad \text{(Eq.1)}$$

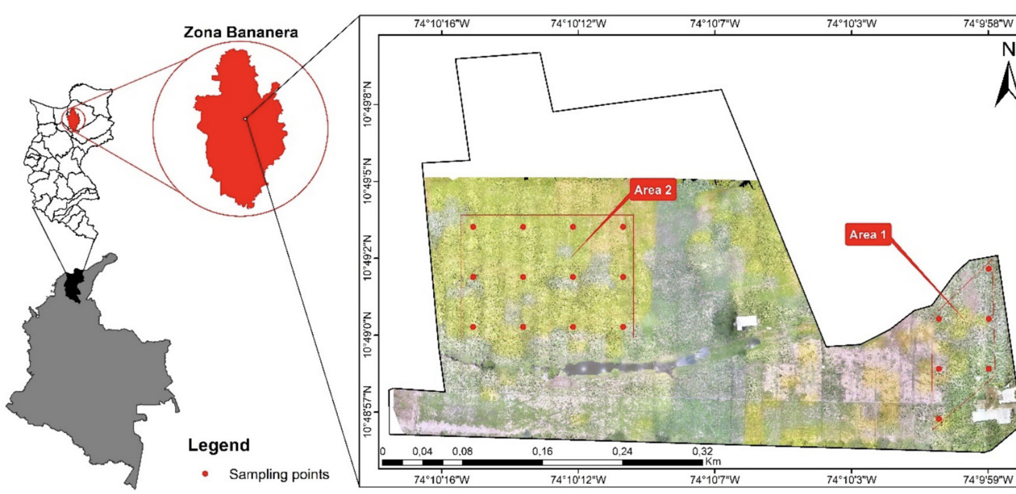

Figure 1: Study Area location.

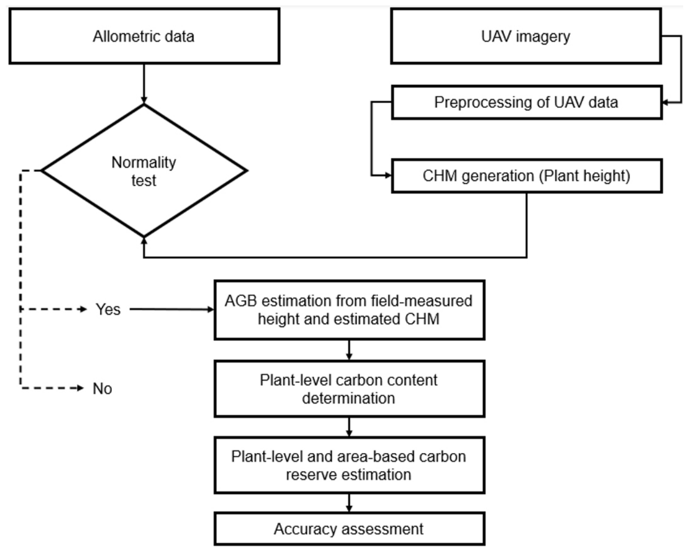

Figure 2: Flowchart of the estimation of carbon stocks at the banana plant level.

To determine the differences between the CHM and the field data, three height measurements per sampling point were taken in each Area, within a range of two to five meters in diameter considering the GPS error in the field. This resulted in a total of 54 estimated measurements (18 points in Area 1 and 36 in Area 2). To determine if the UAV data can provide a solid representation of the plants, the heights taken in the CHM were compared with field measurements. The coefficient of determination (R^2) and the Root Mean Square Error (RMSE) were calculated to assess the relationship between field-derived measurements and UAV-derived measurements for the entire dataset.

Allometric data and carbon stock estimation

Field measurements and UAV flights were carried out simultaneously. On November 9, 2023, a fieldwork campaign was conducted where the height of a total of 54 banana plants was measured at 18 sampling points (3 plants per sampling point). The height was measured from the ground to the apex of the canopy using a measuring tape. Navigation to each sampling point was done using a GPS *eTrex* 10. Carbon Stock (CS) was calculated in Mg/ha (Equation 2) using the Planted Area (PA), Carbon Content (CC), and AGB on a Dry Basis (DB) (Qin *et al*., 2021).

In this study, AGB is reported in kg/plant based on its Height (H), because height is the dominant factor in estimating carbon stock when a non-destructive estimation of crops is desired, which is consistent with previous studies (Latifi *et al*., 2011, 2012; Qin *et al*., 2017, 2021). For the non-destructive estimation of AGB in banana crops at the harvest stage, Equation 3 was used (Ortiz-Ulloa *et al*., 2021). This equation was chosen due to its ability to directly correlate plant height with aerial biomass, providing an accurate estimate without damaging the crops. Two AGBs are estimated: the first replacing the height of the banana plants measured in the field (observed values) and the second using height values estimated from the CHM (estimated values). AGB in standing position was considered only as the pseudostem biomass, since the bunch and flowers are cut, and the roots are left in the soil to support the new plant. The PA was calculated in plants/ha, using Equation 4, where the number 10000 is used to convert m2 to ha, Sep is the average separation of the selected plants with their neighboring plants in meters, and A is the Area in ha (Ortiz-Ulloa *et al*., 2021).

$$\mathrm{RC} = \frac{\mathrm{PA} \cdot \mathrm{AGB} \cdot \mathrm{DB} \cdot \mathrm{CC}}{1000} \qquad \text{(Eq.2)}$$

$$\mathrm{AGB} = 5.743 \times 10^{-5} \cdot \mathrm{H}^{9.68} + 86.43 \qquad \text{(Eq.3)}$$

$$\mathrm{PA} = \frac{10000}{\mathrm{Sep}^2} \cdot \mathrm{A} \qquad \text{(Eq.4)}$$

To determine the CC and Moisture Content (MC), pseudostem samples of approximately 300g were collected to obtain a representative quantification of their moisture and carbon content. In total, 36 samples from 18 plants corresponding to the 18 sampling points were collected. The analysis was carried out in the Environmental Sciences laboratory at the Universidad de La Guajira. In the laboratory, the samples were handled following the methodology used by (Ortiz-Ulloa *et al*., 2021); they were dried in an oven at 105°C for 24 hours to determine the MC and dry weight (kg/plant). The dried samples were ground using a blade grinder and sieved using a 60-mesh sieve (i.e., particles with apparent dimensions <0.25mm). The carbon content (CC) analysis was conducted using dry matter samples of one to three mg, which were placed in ceramic crucibles and burned at 975°C in a CHNS/O analyzer (PerkinElmer Series II CHNS/O 2400). This equipment offers high precision (≤0.002) and accuracy (≤0.003) in carbon measurement and was calibrated to ensure reliable results, ensuring that variations in moisture content did not affect the carbon estimates (PerkinElmer, 2011). The CC is expressed as a percentage of carbon in the sample.

Evaluation of accuracy

To assess the accuracy in estimating carbon stock in banana plants between the two Areas (Area 1 and Area 2), five measures of accuracy were employed, after applying a normality test to determine if the data comes from a normal distribution. The R^2 (Equation (5)), RMSE (Equation (6)), and Mean Absolute Error (MAE) (Equation (7)) have been widely used to assess prediction (Qin *et al*., 2017, 2021). The Percentage Root Mean Square Error (PRMSE) is expressed as a percentage of the mean value (Equation (8)), while the Root Mean Square Percentage Error (RMSPE) represents the average deviation of an observed value (Equation (9)) (Table II). Both metrics (PRMSE and RMSPE) are scale-independent and help assess predictive performance. In Equations 5 – 9, n represents the number of samples, and y_i y $\hat{y}_i$ are the observed and predicted values, respectively, for the i-th sample, and $\bar{y}$ is the average observed value of all samples. Additionally, the Overall Prediction Performance (OPP) (Equation (10)) and the model Uncertainty (U_C) (Equation (11)) were calculated. Lower values of uncertainty increase the reliability of the predictions. All these metrics, as well as the graphical outputs, were computed using programming in R software. Table II shows the indicators used to evaluate the accuracy in the estimation of carbon stock in banana plants.

$$R^2 = \frac{\sum_{i=1}^{n}(x_i - \bar{x})^2 (y_i - \bar{y})^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2} \qquad \text{(Eq. 5)}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \qquad \text{(Eq. 6)}$$

$$MAE = \frac{1}{n}\left[\sum_{i=1}^{n} abs(\hat{y}_i - y_i)\right] \qquad \text{(Eq. 7)}$$

$$PRMSE = \left(\frac{RMSE}{\bar{y}}\right) \times 100 \qquad \text{(Eq. 8)}$$

$$RMSPE = \left(\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{\hat{y}_i - y_i}{y_i}\right)^2}\right) \times 100 \qquad \text{(Eq. 9)}$$

$$OPP = 100 - \frac{PRMSE + RMSPE}{2} \qquad \text{(Eq. 10)}$$

$$U_C = R^2 - OPP \qquad \text{(Eq. 11)}$$

Results and Discussion

Comparison of heights: Field data vs. CHM estimates

The results of the Shapiro-Wilk normality test indicate that the plant height data

TABLE I
UAV FLIGHT AND PHOTOGRAMMETRIC PROCESSING DATA IN BANANA CROPS

Category	Characteristic	Dense Crop (Area 1)	Dispersed Crop (Area 2)
p	Multicopter Drone	Phantom 4	Phantom 4
	Date	November 9, 2023	November 9, 2023
	Location	Area 1 (Figure 1)	Area 2 (Figure 1)
Flight Design	Type of flight	Grid (point of interest)	Grid (point of interest)
	Flight zone dimensions	308m x 284m	308m x 284m
	Flight height	47m	47m
	Overlap	80% (72% lateral)	80% (72% lateral)
	Camera angle	70°	70°
	Number of images taken	336	334
	Total flight path length	4428m	4310m
	Flight duration	14 min 38s	14 min 21s
Processing Results	GSD (cm/pixel)	2.33	2.38
	Covered Area (ha)	9.45	9.51
	Calibrated images (%)	98% (331/336)	99% (333/334)
	Key points per image (median)	65,875	58,223
	Matches per image (median)	4433.55	7412.35
	Mean reprojection error (pixels)	0.206	0.207
Orientation Accuracy	Absolute camera position uncertainty (m)	X: 0.261, Y: 0.261, Z: 0.632	X: 0.242, Y: 0.242, Z: 0.586
	Absolute camera orientation uncertainty (degrees)	Omega: 0.247, Phi: 0.239, Kappa: 0.125	Omega: 0.230, Phi: 0.223, Kappa: 0.115
	Relative camera position uncertainty (m)	X: 0.011, Y: 0.011, Z: 0.014	X: 0.009, Y: 0.010, Z: 0.014
	Relative camera orientation uncertainty (degrees)	Omega: 0.017, Phi: 0.017, Kappa: 0.009	Omega: 0.017, Phi: 0.018, Kappa: 0.008
Geolocation Accuracy	Absolute geolocation error (m)	Mean: -0.014911, Sigma: 0.605784, RMS: 0.605968	Mean: -0.027345, Sigma: 0.546391, RMS: 0.547075
	Relative geolocation error (%)	X: 0%, Y: 0%, Z: 0%	X: 0%, Y: 0%, Z: 0%
	Geolocation orientation uncertainty (degrees)	Omega: 1.498, Phi: 1.231, Kappa: 3.552	Omega: 1.332, Phi: 1.127, Kappa: 3.461
Point Cloud Density	Densified 3D points	65,045,250	72,718,983
	Average point cloud density (per m³)	629.99	1082.6
Processing Time	Initial processing time (without report) (h:m:s)	0:34:40	2:31:05
	Point cloud densification time (h:m:s)	2:42:14	3:40:39
	DSM generation time (h:m:s)	1:43:55	0:20:30
	Orthomosaic generation time (h:m:s)	0:38:16	1:12:04
Resolution of Product	DSM resolution (cm/pixel)	2.33	2.38
	DTM resolution (cm/pixel)	11.65	11.90

measured in the field and from CHM for both Areas follow a normal distribution (p-value > 0.05), with a p-value of 0.83 for Area 1 and 0.61 for Area 2. For each sample Area, a comparison of CHM heights (Figure 3) with field height measurements was performed. The heights obtained in Area 1 by the UAV positively correlated with field measurements, yielding an R^2 value of 0.76, an RMSE of 0.18m, and an average underestimation of plant heights from the CHM, with an average from the UAV of 2.52m and a field average of 2.58m based on 18 observations (Figure 4a). The heights obtained in Area 2 by the UAV positively correlated with field measurements, yielding an R^2 value of 0.61 and an RMSE of 0.78m. Plant height based on CHM data was underestimated, with an average from the UAV of 1.43m and a field average of 2.29m based on 36 observations (Figure 4b). When comparing the regression results (R^2 =0.61 in Area 2) with other studies conducted on banana crops, the R^2 values is lower than those reported by (Aeberli *et al.*, 2021) (R^2 =0.84) and (Aeberli *et al.*, 2023) (R^2 =0.77) with a similar flight height (50m). In the dense Area (R^2 =0.76), the R^2 value is lower than those reported by (Aeberli *et al.*, 2021) but similar to those of (Aeberli *et al.*, 2023). It is considered that the density of plantations can influence image capture and the accuracy of orthomosaic reconstruction. Flight planning options, such as flight altitude, speed, flight pattern, and shutter speed, as well as

TABLE II
INDICATORS OF GOODNESS OF FIT

Name	Symbol	Description	Unit	Range	Direction	References
Coefficient of Determination	R²	Proportion of variability explained by the measurements	ad	[0, 1]	The closer to 1, the better	(Fadil *et al*., 2024; Liu *et al*., 2023; X. Zhang, 2019)
Mean Absolute Error	MAE	Average of the errors between observed and predicted values	kg/plant	[0, ∞)	The closer to 0, the better	(Fadil *et al*., 2024; Li *et al*., 2019; Qin *et al*., 2021)
Root Mean Square Error	RMSE	Square root of the average of the squared errors between observed and predicted values	kg/plant	[0, ∞)	The closer to 0, the better	(Li *et al*., 2019; Liu, Lei, *et al*., 2023; Qin *et al*., 2017)
Percent Root Mean Square Error	PRMSE	Percentage error of the root mean square error relative to the mean of the observed values	%	[0, ∞)	The closer to 0, the better	(Li *et al*., 2019; Liu, Lei, *et al*., 2023; Qin *et al*., 2021)
Relative Root Mean Square Percentage Error	RMSPE	Percentage error of the relative root mean square error relative to the observed values	%	[0, ∞)	The closer to 0, the better	(Gülci *et al*., 2021; Li *et al*., 2019; C. Lin *et al*., 2016)
Overall prediction performance	OPP	Overall prediction performance, representing overall accuracy in estimation	%	[−∞, 100]	The closer to 100, the better	(Lin *et al*., 2016; Qin *et al*., 2021)
Uncertainty	U_C	Measure of the lack of precision in predictions	ad	(−∞, ∞)	The closer to 0, the better	(Lin *et al*., 2016; Qin *et al*., 2021)

R^2: coefficient of determination. MAE: Mean Absolute Error. RMSE: Root Mean Square Error. PRMSE: Percent Root Mean Square Error. RMSPE: Relative Root Mean Square Percentage Error. OPP: Overall Prediction Performance. U_c: Uncertainty.

processing workflows, can improve results (Tu *et al*., 2019). However, this remains a topic that requires further research to determine the optimal flight conditions for ensure the best results.

Figure 3 illustrates that the dispersed crop (Area 2) provides a better reconstruction of the banana canopy due to the higher point cloud density and the greater number of correspondences per image. The current flight design, with 80% overlap and a 70° camera angle, is suitable for the 3D reconstruction of the banana plant canopy, but variability in processing quality suggests that factors such as lighting, vegetation type, and other uncontrolled conditions may influence results. Processing results show that the dispersed crop has more correspondences per image (7412.35 *vs*. 4433.55) and a higher point cloud density (1082.6 *vs*. 629.99). This difference translates into a better 3D reconstruction of the banana plant canopy, especially in dense areas, where the greater number of tie points allows for more accurate capture of canopy structure. Although differences in camera calibration (0.67% *vs*. 3.94%) and mean reprojection error are minimal, the higher point cloud density in the dispersed crop suggests a better representation of the banana plant canopies.

Although aerial images are a good indicator for estimating plant height, six outliers were identified in Area 2 (Figure 4b) that could be associated with plant dispersion in the crop, low image resolution, inaccurate 3D reconstruction of smaller plants, or the scarcity of leaves on plants cut due to damage caused by black sigatoka. Previous studies have demonstrated that UAV-based remote sensing is capable of producing orthomosaics and height data. However, challenges in height accuracy persist. Gaden (2020) indicates that some limitations are related to the exclusion of small trees, which can underestimate AGB, image calibration issues due to differences in flight parameters, the need for high image overlap, and variability in the allometric equations used. Hashem (2019) notes limitations including GPS inaccuracy in locating trees and plot centers, difficulties in measuring the height of tall trees due to dense vegetation, and the inability to select large plots

Figure 3: CHM derived from photogrammetric processing of RGB images.

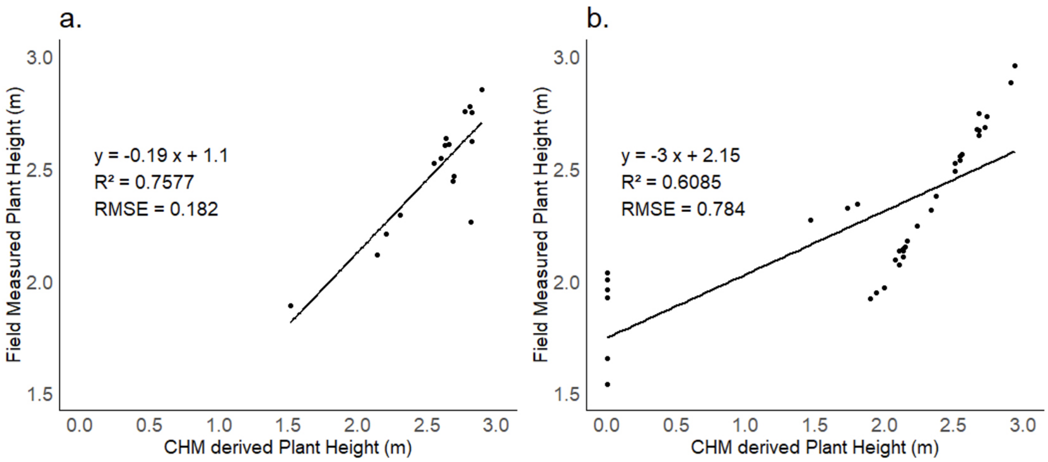

Figure 4: Scatter plot and linear regression of banana plant height derived from CHM compared to field-measured height in (a) Area 1 and (b) Area 2.

due to inaccessibility and rugged terrain. Jayathunga *et al.* (2018) report errors related to the limited ability of UAV images to penetrate the canopy layer, often leading to an overestimation of lower height percentiles and canopy density values. In banana crops, Aeberli *et al.* (2021, 2023) found that errors in height measurement from CHM were associated with outliers due to inaccurate 3D reconstruction of small plants and leaves emerging vertically from the center of the canopy and then spreading horizontally, which can alter plant height.

Other studies conducted on banana crops using UAV image analysis indicate that errors increase and are related to the azimuth of the sun, the angle of light reflectance, and the UAV camera height (Neupane *et al.*, 2019). Additionally, Gomez Selvaraj *et al.* (2020) indicate that using low (10m to 60m), medium (0.3m to 3m), and high (0.03m) spatial resolution images to classify banana plants is a major challenge. Low-resolution pixels, combined with sparse banana plantations, would provide only a spectral signature of different classes, resulting in similar vegetation index (VI) responses and incorrect classification models. Kestur *et al.* (2018) demonstrate that other errors affecting data accuracy include the presence of noisy pixels due to low spectral variability between classes, leading to incorrect classification of banana plants, and the irregular shape of banana plant canopies causing the addition of 'false positive' pixels.

Carbon stock estimation

In Table III and Figure 5, descriptive statistics of observed and estimated data related to AGB, CC, and CS in kilograms per plant and tons per hectare for each area are shown. The mean carbon content in the pseudostem is 35% (dry weight basis) and the moisture content is 96%, results that are consistent with Ortiz-Ulloa *et al.* (2021). However, other studies indicate similar moisture content ranging from 92% to 97% (Jayaprabha *et al.*, 2011; Shivashankar *et al.*, 2006), but the carbon content differs. Ganeshamurthy (2023) and Basak *et al.* (2016) have found average carbon percentages in the pseudostem of 0.465% and 38%, respectively. These authors conducted elemental analyses on different types of bananas, suggesting that the carbon content may depend on factors such as banana variety or growing conditions.

For Area 1, average values from field data show CS of 1.27kg/plant and 1.01Mg/ha, and average values from CHM show CS of 1.27kg/plant and 1.02Mg/ha. In contrast, for Area 2, average values from field data show CS of 1.34kg/plant and 3.22Mg/ha, and average values from CHM show CS of 1.09kg/plant and 2.62Mg/ha. These values are related to those reported by Armecin and Gabon (2008), for another family of Musaceae (*Musa textilis* Nee), who report that aerial biomass could vary from 1 to 1.5kg/plant at harvest, with nearly two-thirds corresponding to pseudostem biomass. This suggests that, in a one-hectare plot, the aerial biomass varies from 2.5 to 3.75Mg/ha (with planting at 2m × 2m distance between plants), which can be equated to 1.5–2.5Mg/ha of pseudostem biomass. However, other authors have reported that these values may vary for other banana species with values between 0.91 and 9.7kg/plant (Danarto and Hapsari, 2015) . According to the authors, these values depend on the circumference at the base and at breast height of the pseudostem and not just the plant height, which presents a challenge in estimating CS with UAV.

The differences between Areas 1 and 2 in the estimated data are due to the CHM height, which may be affected by the ortho-mosaic reconstruction in Area 2 at the plant level. The observed differences in CS between Areas 1 and 2 could be comparable to the observations of Hashem (2019), who noted that the accuracy in biomass estimation in plantations with different densities may vary due to the quality of ortho-mosaic reconstruction. This inaccuracy presents a challenge in estimating CS on the ground in banana crops using UAV images, as it affects the accuracy of calculating planting density and leads to either underestimation or overestimation of CS.

Figure 5 shows significant differences in carbon stocks between the two areas. Area 1 exhibits higher accuracy in estimates, while Area 2 shows greater variability and lower precision, which poses a challenge in estimating carbon stocks using UAV data in banana crops. These differences may be attributed to difficulties in accurately detecting and counting banana plants with the UAV, which could be related to planting density, flight conditions, or orthomosaic reconstruction. Neupane *et al.* (2019) have noted that factors such as image resolution, lateral and frontal overlap during flight planning, calibrations and stitching during orthomosaic generation, wind during flight, plant shadows, and sun azimuth can cause the same plant to become distorted or blurred, thereby affecting the accuracy of estimates.

In detail, at the Area level (Figure 5a), Area 1 shows less variability in the data, while Area 2 exhibits significantly greater variability due to crop dispersion (areas without planted plants).This variability is attributable to agricultural management and specific diseases affecting banana crops (Gomez Selvaraj *et al.*, 2020). When comparing carbon stocks at the plant level (Figure 5b), Area 1 still presents more accurate carbon estimates. However, the differences between Area 1 and Area 2 are not as pronounced, with results showing more similarity and less divergence. This pattern

TABLE III
DESCRIPTIVE STATISTICS OF CARBON RESERVES AT PLANT LEVEL AND BY AREA FOR OBSERVATIONS AND ESTIMATES

Area	MC (%)	CC (%)	Field Data AGB (kg/plant)	Field Data CS (kg/plant)	Field Data CS (Mg/ha)	Estimated Data AGB (kg/plant)	Estimated Data CS (kg/plant)	Estimated Data CS (Mg/ha)
Area 1								
Min	94.79	30.59	86.67	0.94	0.75	86.91	0.94	0.75
Max	97.02	42.32	87.54	1.67	1.34	87.71	1.67	1.34
Range	2.23	11.73	0.88	0.73	0.59	0.80	0.73	0.59
SD	0.82	4.53	0.32	0.29	0.24	0.35	0.29	0.23
Average	95.94	35.91	87.08	1.27	1.01	87.28	1.27	1.02
Area 2								
Min	94.74	28.11	86.45	0.97	2.33	86.43	0.00	0.00
Max	96.88	48.13	87.29	1.96	4.72	87.35	1.96	4.72
Range	2.14	20.03	0.84	0.99	2.38	0.92	1.96	4.72
SD	0.60	6.64	0.28	0.29	0.69	0.31	0.58	1.40
Average	95.60	35.21	86.80	1.34	3.22	86.78	1.09	2.62

MC: Moisture Content. CC: Carbon Content. AGB: Aboveground Biomass CS: Carbon Stock. SD: Standard Deviation.

suggests that individual plant-level estimates tend to be more consistent than estimates between areas. This may be due to greater homogeneity in plant canopy cover in Area 1, where canopies overlap, in contrast to Area 2, which features gaps between plants (Aeberli *et al*., 2021). Canopy overlap facilitates the identification of canopy height patterns, while in Area 2, patterns are less discernible due to less defined canopies and the presence of empty spaces that hinder plant detection (Piermattei *et al*., 2018). Therefore, accuracy in detecting individual trees directly influences point cloud data at the Area level (Miraki *et al*., 2021).

Carbon stocks in banana crops have been previously determined, considering different cultivars. The average observed and estimated values per hectare in this study is 2.11 and 1.84Mg/ha, respectively. Previous studies have estimated carbon stocks of bananas from 3.65 to 5.21Mg/ha in Ecuador (Ortiz-Ulloa *et al*., 2021), 0.98Mg/ha in Indonesia (Danarto and Hapsari, 2015), 4.33Mg/ha in India (Ganeshamurthy, 2023), 1.45 to 4.1Mg/ha in Bolivia (Schneidewind *et al*., 2019), and 0.37 to 1.64Mg/ha in Uganda (Kamusingize *et al*., 2018). The variation in these numbers indicates that each location should conduct specific studies to determine the corresponding carbon stock. The size and weight depend on factors such as variety, phenological stage, and agricultural practice related to the number of leaves per plant (~10 leaves) (Churchill, 2011; Ortiz-Ulloa *et al*., 2021), which could explain the differences in average AGB values across plantation.

The average AGB content of the pseudostem in this study is 0.04kg/kg on a dry weight basis, which is comparable to the 0.40kg/kg value reported by Ortiz-Ulloa *et al*. (2021) for Musa AAA Cavendish. In contrast, Nyombi *et al*. (2009) found AGB values ranging from 0.25 to 2.57kg/kg on a dry weight basis for different varieties and ages. (Ganeshamurthy (2023) also demonstrated that AGB values vary by variety and region. These differences highlight the need for specific studies on AGB in local contexts to obtain more accurate carbon estimates. For example, the ABB has been found to captures more carbon per plant, followed by the AAB group, with the AAA group capturing the least (Nyombi *et al*., 2009; Ortiz-Ulloa *et al*., 2021). In this regard, the banana cultivation area in northern Colombia suggests a significant carbon reserve that needs to be quantified. Developing models for AGB estimation using various physical parameters of banana plants, such as height, circumference at breast height, circumference at the base, number of leaves, and average plant spacing in different cultivation areas and plant ages is necessary (Nyombi *et al*., 2009; Ortiz-Ulloa *et al*., 2021).

Validation test between carbon stocks at the plant level

The R^2 for these models estimating carbon stocks at the plant level ranged from 0.99 in Area 1 to 0.96 in Area 2, respectively. Area 2 exhibited the lowest R^2 value of the two areas for tree-level carbon stocks. Besides the coefficient of determination, four statistical accuracy indices - MAE, RMSE, PRMSE, and RMSPE- were used to assess model bias in estimating tree-level carbon stocks. As shown in Table IV, was 0.003kg for Area 1 and 0.497kg for Area 2. RMSE values were 0.004 kg for Area 1

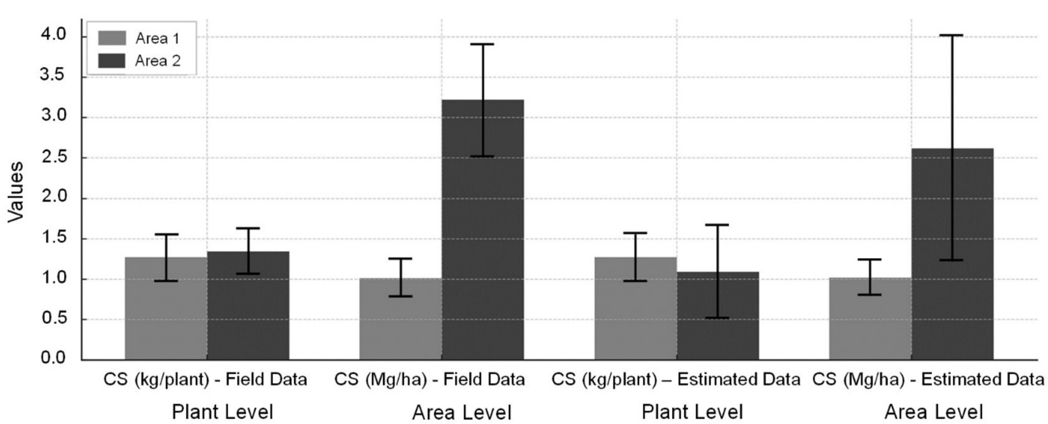

Figure 5. Carbon stocks at the plant level and by area from observations and estimates.

and 0.608kg for Area 2. PRMSE was 0.30% for Area 1 and 55.6% for Area 2, while RMSPE was 0.35% for Area 1 and 40.8% for Area 2. Area 1 demonstrates super predictive capability and lower error in the estimates compared to Area 2.

The OPP and uncertainty values were 99.7 and 51.8 for Areas 1 and 2 respectively. The considerable variation in uncertainties for all models ranged from −0.7 to −44.2. The considerable variation in OPP and uncertainty between the two areas indicates that estimates in Area 1 are more accurate and reliable for accounting for variations in carbon stocks at the plant level compared to Area 2.

The differences in results between Areas 1 and 2 suggest that the precision of carbon stock estimates at the plant level may be influenced by the accuracy of the Global Navigation Satellite System (GNSS) receiver and the quality of geospatial data (Zhang and Zhu, 2023). Statistical indices such as MAE, RMSE, PRMSE, and RMSPE show greater error in Area 2, which could be attributed to issues in correcting and generating the orthomosaic, DSM, and DTM (Aeberli *et al*., 2021, 2023). Additionally, flight altitude and sensor size play a significant roles; larger sensor can anhance image quality and reduce errors (Aasen *et al*., 2018). Improved results can be achieved by using high-precision equipment and rigorous techniques to enhance reliability in carbon stock quantification using UAV in banana plantations.

TABLE IV
PREDICTION ERROR AND PERCENTAGE ERROR IN CARBON STOCK ESTIMATES AT THE PLANT LEVEL

Area	R^2	RMSE	MAE	PRMSE	RMSPE	OPP	U_C
Area 1	0.990	0.004	0.003	0.299	0.352	99.674	− 0.665
Area 2	0.959	0.608	0.497	55.636	40.825	51.769	− 44.175

R^2: coefficient of determination. RMSE: Root Mean Square Error. MAE: Mean Absolute Error. PRMSE: Percent Root Mean Square Error. RMSPE: Relative Root Mean Square Percentage Error. OPP: Overall Prediction Performance. U_c: Uncertainty.

Conclusions

This study estimates carbon stocks using field-measured heights and estimates derived from the CHM. Results underscore the utility of CHM as an effective tool for estimating banana plant heights while highlighting the need to address potential variations related to 3D reconstruction improvements before generating orthomosaics and achieving higher image resolution in banana crops with dispersed planting densities. Measuring AGB from height data is straightforward and non-destructive, but specific allometric equation models must be developed for banana crops in Colombia for accurate AGB estimation. This study revealed a significant difference in total carbon stocks between dense (Area 1) and sparse (Area 2) crops using UAV data. Notably, there was a 19% discrepancy between observed and estimated values in the sparse crop's carbon stock estimation capability, despite a better 3D reconstruction of the banana plant canopy. Goodness-of-fit indicators reveal that estimates in Area 1 are more accurate and reliable in capturing variations in plant-level carbon stocks compared to Area 2. This study can serve as a valuable resource for researchers and banana farms by providing more accurate estimates of plant-level and area-based carbon stocks and offering rapid assessments of carbon reserves in banana production systems.

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