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Unmanned aerial vehicle – derived carbon stock estimation in cocoa agroforestry: Integrating red, green, blue imagery and modified allometric models for climate mitigation in smallholder landscapes of Indonesia

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ABSTRACT

This study addresses methodological and contextual gaps in carbon stock estimation by developing a UAV-based model tailored for cocoa agroforestry systems in tropical smallholder landscapes. As nature-based solutions gain traction in climate change mitigation, reliable monitoring of agroforestry systems, marked by spatial heterogeneity and farmer-managed canopies, becomes increasingly vital. The research aims to develop a biomass estimation model based on RGB sensor-derived UAV imagery and a modified allometric equation. A total of 35 cocoa agroforestry plots were selected in Luwu Timur, South Sulawesi, based on strict biophysical and accessibility criteria. RGB imagery collected via DJI Phantom 4 UAVs was used to generate Canopy Height Models (CHMs), which were validated against field measurements of tree height and diameter. A modified allometric equation incorporating both variables were used to estimate above-ground biomass (AGB), which was subsequently converted into carbon stock values. The UAV-estimated tree heights demonstrated strong correlation with field observations (R^2 = 0.7344), confirming model reliability. This technique has proven capable of substituting for tree height estimation using LiDAR, which requires more advanced and costly equipment. Estimated carbon stocks ranged from 18.41 to 134.49 tCO_2e/ha, highlighting the variability across agroforestry systems shaped by diverse management practices. This study presents a replicable and scalable framework for integrating UAV-based methods into carbon finance schemes.

Keywords: Unmanned aerial vehicle, multispectral, plantation, cocoa, carbon

INTRODUCTION

Biomass assessment is a crucial component of forest productivity research, playing a vital role in understanding nutrient cycles and energy flows within ecosystems. Forests are among the most significant ecosystems on Earth, providing critical services that sustain biodiversity and regulate the global climate. As the largest carbon reservoirs on land, forests play a crucial role in the global carbon cycle by absorbing and storing atmospheric CO_2. This carbon sequestration helps mitigate the impacts of climate change, a key driver of which is the imbalance in the carbon budget (Li et al., 2020; Nandy et al., 2021). Given their pivotal function in regulating atmospheric CO_2, forests are central to climate change mitigation strategies. However, deforestation and forest degradation, especially in tropical regions, have resulted in substantial carbon emissions, posing a challenge to global climate targets. In Indonesia, the forestry sector accounted for 48% of total greenhouse gas (GHG) emissions in 2009, primarily due to deforestation, land degradation, and frequent forest fires (KLH, 2009). Addressing these challenges requires comprehensive approaches that emphasize reducing emissions, conserving existing carbon stocks, and enhancing carbon sequestration through both reforestation and agroforestry initiatives (Kemenhut, 2011).

Indonesia's forests cover approximately 120 million hectares, representing around 64% of the country's total land area. This vast expanse includes 68.8 million hectares of production forests, 22.1 million hectares of conservation forests, and 29.6 million hectares of protected forests (KLHK, 2020). Within the production forest category, plantation forests occupy 4.3 million hectares (KLHK, 2020). These plantation forests are crucial not only for boosting the economic value of forested areas but also for their significant role in carbon sequestration. Plantation forests help capture CO_2 both in biomass and soil, thereby contributing to Indonesia's efforts in mitigating climate change (Pan et al., 2025).

However, the conversion of natural forests to agricultural land has led to a significant loss of carbon stocks. For example, transforming natural forests into multistrata coffee plantations reduces carbon stocks from 262 to 82 tons per hectare, while monoculture systems result in even greater reductions, with carbon stocks dropping to 52 tons per hectare (Van Noordwijk et al., 2002). One promising alternative is the cultivation of cocoa (*Theobroma cacao* L.), a tropical crop known for its potential to sequester significant amounts of carbon (Hartemink, 2005). As of 2016, Indonesia had 1.65 million hectares of cocoa plantations, with Sulawesi Island alone accounting for 58% of the total area (965,000 hectares) (Kementerian Perkebunan, 2017).

Cocoa, as a widely cultivated plantation crop in Indonesia, holds a strategic position in enhancing carbon sequestration and contributing to the mitigation of global warming (Asrul, 2013). However, cocoa production in Indonesia has faced several challenges, including aging trees, pest infestations, soil degradation, and the shifting focus of farmers toward more lucrative crops like oil palm and maize (Baja et al., 2021; Dröge, Bemelmans, et al., 2025; Mithöfer et al., 2017; Nasution et al., 2019; Wartenberg et al., 2018).

As a woody plant, cocoa absorbs CO_2 from the air and stores it as carbon (C) in its biomass. This CO_2 absorption process also influences the rate of photosynthesis, as CO_2 is a key component in carbon fixation within plants, particularly cocoa. Therefore, measuring the amount of carbon stored in the biomass of living plants in a field can indicate the amount of atmospheric CO_2 absorbed by the plants. The greater the biomass of cocoa plants, the higher the amount of CO_2 absorbed, leading to a reduction in atmospheric CO_2 levels (Mustari et al., 2020). Under optimal conditions, the photosynthesis rate of cocoa reaches 7.5 mg of CO_2 per dm^2 of leaf area (Wessel, 1985), or equivalent to 60 mg per dm^2 per day, assuming photosynthesis occurs from 8:00 AM to 4:00 PM (Abdoellah, 2008). Cocoa plants can absorb 80,000 kg of CO_2 per hectare per year while releasing 63,000 kg of CO_2 per hectare per year, resulting in a net CO_2 sequestration of 17,000 kg per hectare per year (Abdoellah, 2008).

Agroforestry systems, particularly those involving cocoa cultivation, have gained attention for their potential role in enhancing carbon sequestration while maintaining agricultural productivity in tropical landscapes. However, the accurate quantification of carbon stocks within such complex and heterogeneous systems remains a significant challenge, especially in smallholder-dominated regions like Luwu Timur, South Sulawesi, where traditional field-based measurements are time-consuming, labor-intensive, and spatially constrained. Recent advancements in remote sensing, particularly the deployment of unmanned aerial vehicles (UAVs) equipped with multispectral and LiDAR sensors, offer promising solutions for biomass and carbon estimation at fine spatial resolutions (Wallace et al., 2012; Iizuka et al., 2018; Corte et al., 2020). However, the high cost of LiDAR sensors has led researchers to explore alternative approaches, such as the structure from motion (SfM) technique (Ullman and Brenner, 1979). SfM reconstructs three-dimensional models from two-dimensional images, generating point clouds that closely resemble those produced by LiDAR systems. Originally developed for cultural heritage mapping (Elkhrachy, 2022), SfM has more recently been applied to biomass estimation (Estornell et al., 2024)

This study aims to fill a critical knowledge gap by developing an accurate method for estimating above-ground carbon stocks in cocoa-based agroforestry systems using UAV-derived RGB imagery in Luwu Timur, South Sulawesi. The central hypothesis is that UAV-based remote sensing utilizing RGB sensors can offer a reliable and scalable approach for carbon stock quantification in smallholder agroforestry landscapes – an area that remains underexplored in the Indonesian context.

MATERIAL AND METHODS

Collection of data

Study area

For this study, we selected five villages across Luwu Timur, South Sulawesi: Lauwo, Lambarese, Lumbewe, Balai Kembang, and Sumber Alam. The research focused on lowland areas (below 100 m a.s.l.) with gentle slopes (under 20 °) to ensure the feasibility of UAV surveys. Characterized by cocoa-based agroforestry systems interwoven with shade trees, this region was selected to evaluate its carbon sequestration potential using UAV remote sensing technology. Research data collection activities were carried out in July and October 2023. The research location map is presented in (Figure 1).

Plot selection

The selection of survey plots was based on a voluntary sustainability standards (VSS) socioeconomic survey conducted by Bemelmans (2024) in Luwu Timur, Luwu Utara, and Luwu in 2022. This survey covered ten villages per district, including both certified and non-certified farmers. From this dataset, five villages were selected based on land slope, elevation, and plot characteristics to ensure accessibility and suitability for research..

The selection of cocoa plantations was based on specific criteria to ensure consistency and relevance. The cocoa trees had to be at least three years old and actively producing fruit. Additionally, each plantation needed a minimum area of 0.2 hectares to accommodate a 20 × 20-meter research plot (Figure 2) and a terrain slope of no more than 20° to ensure optimal conditions for drone-based mapping. The study identified 35 eligible cocoa plantations, Despite the smaller sample size, the selected plantations ensured a representative dataset for analyzing cocoa farming sustainability.

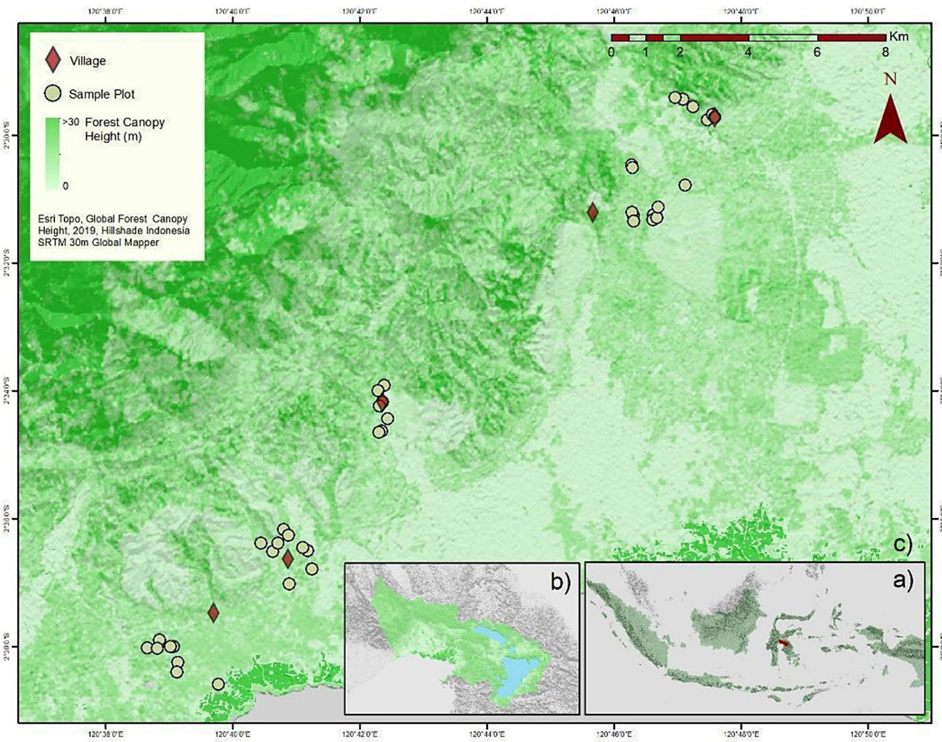

Figure 1. Location of the island Sulawesi (a) and district Luwu Timur (b) in Indonesia (a), and map of the sample plots in Luwu Timur (c). We revisited the villages included in a socioeconomic survey on cocoa certification conducted in Luwu Timur in 2022 (Bemelmans, 2024) and selected 35 cocoa plantations located in five villages (5 to 7 plantations per village) for our environmental assessment. Basemap showing ESRI Topo, the GLAD Global Forest Canopy Height 2019 (Potapov et al., 2021), and Hillshade Indonesia SRTM 30 m Global Mapper

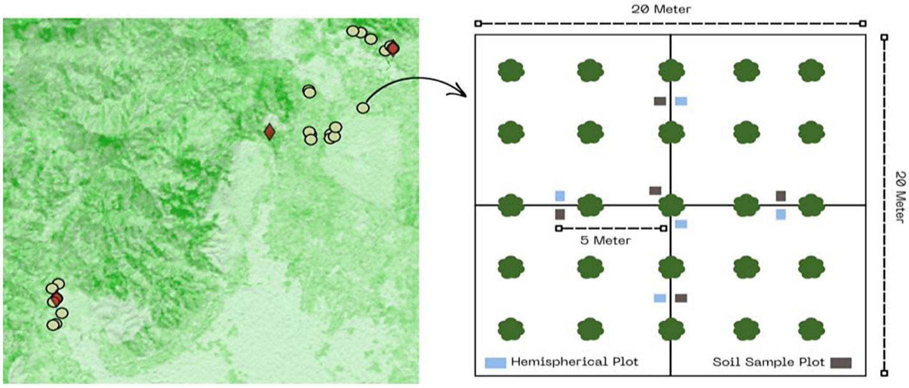

Figure 2. Research plot

Research flow

Image acquisition of the plots was conducted using a DJI Phantom 4 quadcopter equipped with an RGB sensor. Flights were carried out in the morning at an altitude of 60 meters with a nadir orientation and 85.75% sidelap and frontlap to ensure optimal image overlap. Flight planning was performed using GS Pro software. Simultaneously, field measurements were taken, including tree height and trunk circumference (measured at 30 cm above the ground) using a phi band, as well as GPS coordinates recorded with a Garmin GPSMAP 64s device (Dröge et al., 2025). The UAV imagery data were subsequently processed to generate orthomosaic images of each plot, which were then converted into 3D models using Pix4D Mapper. From these models, a DSM, a DTM, and a CHM were derived (Figure 3).

Data analysis

UAV Data Processing

Data processing in this study utilized PIX4DMapper software, which employs the structure from motion (SfM) algorithm (Fraser and Congalton, 2018). This algorithm can automatically generate three-dimensional (3D) data from two-dimensional (2D) images, offering a cost-effective solution that requires minimal expert supervision compared to conventional aerial photography (Micheletti et al., 2019). Moreover, the algorithm effectively extracts terrain geometry, point clouds, and image positions, providing alternative attributes for Earth surface modeling, including digital terrain model (DTM) and digital surface model (DSM) data. These datasets are further processed to derive canopy height model (CHM) (Figure 4).

Canopy height model

CHM represents the extraction of maximum tree height from individual trees, serving as a key parameter for estimating tree height. In contrast, field observations of individual trees were conducted using high-accuracy measurement tools, particularly for tree height assessment (Begashaw, 2018).

$$CHM = DSM - DTM \tag{1}$$

where: *CHM* is canopy height model, *DSM* is digital surface model, and *DTM* is digital terrain model.

The next stage, after obtaining the CHM data, is to estimate tree data by extracting sample values based on tree coordinates. A statistical test is then conducted in the form of a classical assumption test to ensure that the data meets the requirements for linear regression analysis, ensuring that the regression results are valid and unbiased. Some of the tests performed include the Kolmogorov-Smirnov normality test (2) and the heteroscedasticity test (3):

$$D = sup\ x\ \mid Fn(x) - F(x) \mid \tag{2}$$

where: D is K-S test statistic, $Fn(x)$ is Empirical distribution function (EDF) of the sample, $F(x)$ is Cumulative distribution function (CDF) of the expected distribution (for normality), and $sup\ x$ is The supremum (maximum difference) over all values of x.

$$|ei| = A + B\,Xi + vi \tag{3}$$

where: $|ei|$ is the absolute value of the residual (dependent variable), A is intercept (the absolute value of the residual when $X = 0$), B is slope (the average change in $|ei|$ for every one unit change in X), and Xi is independent variable, and vi = The error component for the i-th observation

Next, simple linear regression was used to assess and establish a predictive relationship between the observed tree height (H.Obs) and the estimated tree height (H.Est), as well as between the observed tree diameter (D.Obs) and estimated tree height. The choice for linear regression was based on the expectation of a first-order relationship between observed and measured variables. Linear models are widely used in forest remote sensing studies due to their transparency and low risk of overfitting, especially when sample sizes are moderate, and the predictor variable (tree

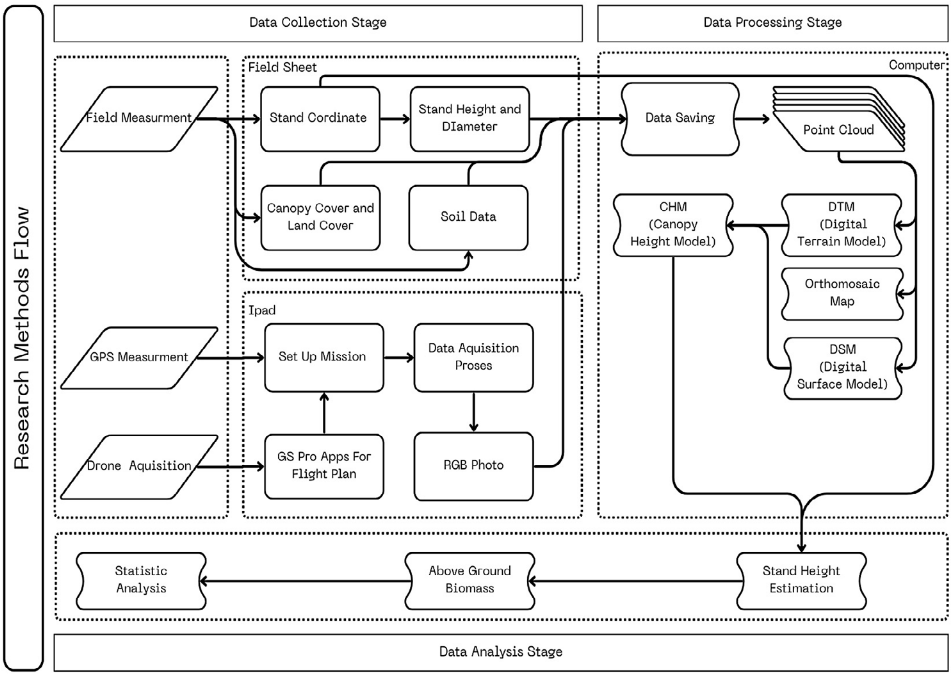

Figure 3. Research flow method

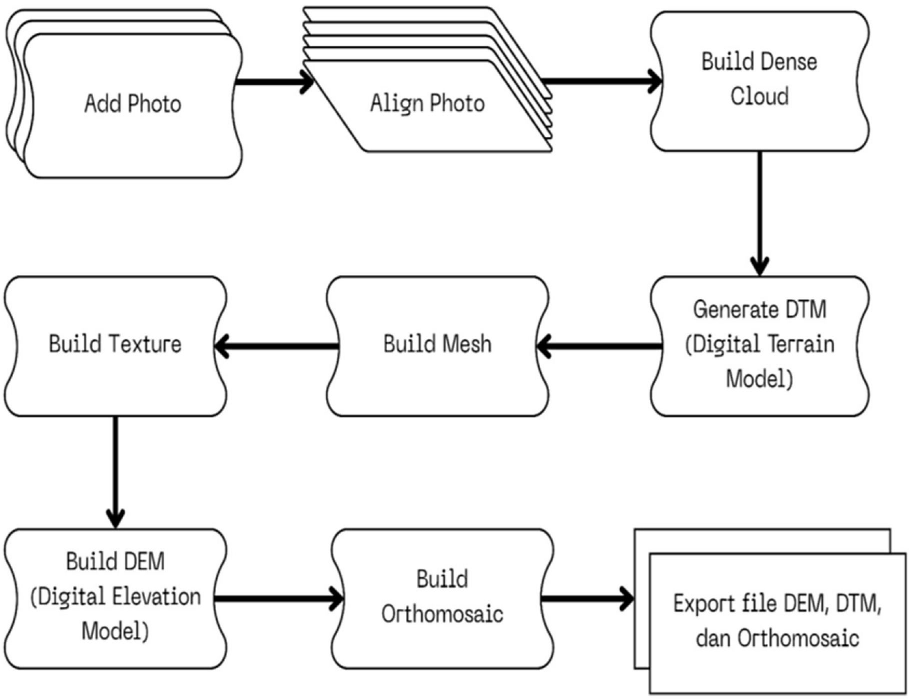

Figure 4. Data processing for acquired UAV data

height from UAV) is derived from geometrically structured data such as CHM. The classical assumption tests conducted (normality and homoscedasticity) confirmed that the linear model was statistically valid for the observed data. R-squared (R^2) (Equation 3) (Walpole, 1995) were used to assess the ability of the independent variable to predict the dependent variable. It ranges from 0 to 1, with values closer to 1 indicating a better model, as the dependent variable can be more accurately explained by the independent variable, with the following formula:

$$R^2 = \left[\left(n(\Sigma xy) - (\Sigma x)(\Sigma y)\right)^2\right] / \quad / \left[(n(\Sigma x^2) - (\Sigma x)^2)(n(\Sigma y^2) - (\Sigma y)^2)\right] \tag{4}$$

where: R^2 is coefficient of determination, Σx is total number of observations for variable X, Σy is total number of observations for variable Y, Σxy is total sum of the product of variables X and Y, Σx^2 is total sum of squares of observations for variable X, Σy^2 is Total sum of squares of observations for variable Y, and n is number of pairs of observations of X and Y.

Root mean square error (RMSE) is based on the total square of the deviation between the model results and the observations, with the formula:

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y} - y)^2}{n}} \tag{5}$$

where: $RMSE$ is root mean squared error, n is the total number of data points. y^ is predicted values (or the estimated values), and y is actual observed values.

Biomass and carbon storage

In this study, the allometric equation proposed by Yuliasmara et al. (2009) was used to estimate above-ground biomass (AGB). The original equation:

$$AGBest = 0.01208 \times D\text{^}1.98 \tag{6}$$

was modified by incorporating tree height (H) into the calculation to improve accuracy, This modification for the vertical growth component enhances the precision of biomass estimation in cocoa plantations, resulting in the following adapted formula::

$$AGBest = 0.01208 \times D1.98 \times H \tag{7}$$

where: AGB is above ground biomass, D is tree diameter at breast height, and H is tree height (m).

After calculating the above-ground biomass for each tree, the total biomass per hectare (BHA) was estimated using the standardized method from SNI (BSN, 2011):

$$BHA = \sum \frac{Bx}{1000} \times \frac{10000}{Lp} \tag{8}$$

where: BHA is biomass content per hectare for each tree in each plot (tons/ha), Bx is biomass content of each tree in each plot (kg), Lp is area of measuring plot (m^2)

Carbon storage (C) was then derived following the SNI standard formula:

$$C = B \times 0.5 \tag{9}$$

where: C is carbon savings (tons/ha), B is biomass (tons/ha), 0.5 is carbon content.

RESULT AND DISCUSSION

Accuracy of drone imagery

Data were collected using an aerial platform flying at an altitude of 60 meters, which allowed a balance between coverage area and image resolution. The 90-degree camera angle (nadir position) was pointed directly downward, which is ideal for creating accurate orthophotos and spatial data. The overlap and side overlap values were set at 85% and 75%, respectively. These high image overlap values ensure that every point on the ground is captured in multiple images, which improves the accuracy and quality of 3D reconstruction and tree point identification. The ground sampling distance (GSD) was 4.12 cm, indicating that each pixel in the captured image represents 4.12 centimeters on the ground, a resolution that supports detailed analysis. Data acquisition took place between 08:30 and 11:30 AM, a time window chosen to minimize shadows and ensure optimal lighting conditions. Overall, these parameters reflect a methodical approach aimed at achieving high-accuracy tree point data through aerial surveys.

Canopy height model

The image illustrates the creation of a CHM by subtracting the DTM from the DSM. DSM represents surface elevations, including vegetation and buildings, while DTM represents bare ground elevation. The resulting CHM highlights the height of vegetation for the next step of analysis (Figure 5).

These results are in line with previous studies stating that CHM data obtained from UAVs can be used effectively to estimate tree height with a high level of accuracy (Haridiansyah et al., 2020; Aryanti et al., 2021; Sasongko and Widiartono, 2024). However, several factors such as uneven distribution of point clouds at the treetops and variations in crown structure can cause deviations between the estimated height and the observed height of the tree. Therefore, additional validation using field measurement methods is still needed to improve the accuracy of the estimate.

Data processing in this study utilized PIX-4DMapper software, which employs the SfM algorithm (Fraser and Congalton, 2018). This algorithm can automatically generate three-dimensional (3D) data from two-dimensional (2D) images, offering a cost-effective solution that requires minimal expert supervision compared to conventional aerial photography (Micheletti et al., 2019). Moreover, the algorithm effectively extracts terrain geometry, point clouds, and image positions, providing alternative attributes for Earth surface modeling, including DTM and DSM data. These datasets are further processed to derive CHM data (Equation 1).

CHM represents the extraction of maximum tree height from individual trees, serving as a key parameter for estimating tree height. In contrast, field observations of individual trees were conducted using high-accuracy measurement tools, particularly for tree height assessment.

The field data collection process was carefully designed to ensure accessibility to the target trees, making them easily detectable through remote sensing methods, such as drone-based aerial imagery used in this study. Subsequently, a predictive relationship was established between H.Obs and H.Est as well as D.obs and H.Est. The results of this analysis are presented in (Figure 6) and (Table 1), based on a simple linear regression model.

The linear regression analysis between H.Obs and H.Est, based on UAV data processing results, indicates a strong relationship. The linear regression equation obtained is H.Est _H.Obs = 0.7846x + 0.4924, with a coefficient of determination (R^2) of 0.7344 or 73.44% (Table 1). This value suggests that the estimated tree height variable explains 73.44% of the variability in observed tree height, while the remaining 26.56% is influenced

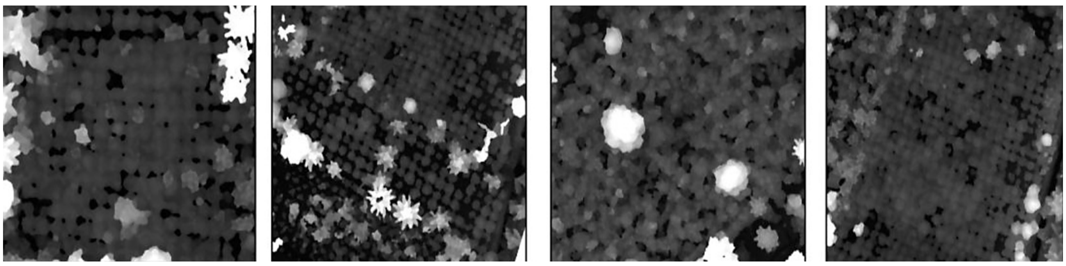

Figure 5. Canopy height model visualization examples from several agroforestry cacao plots

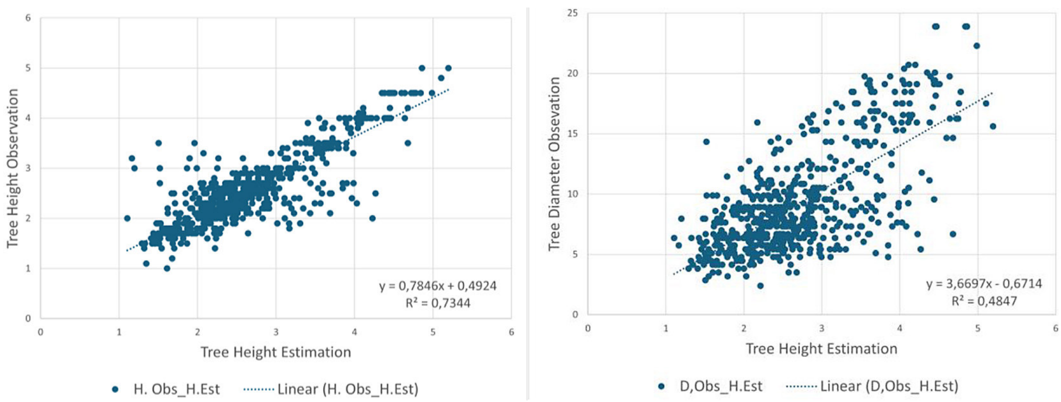

Figure 6. (a) The linear regression model between H.Obs and H.Est (b). the linear regression model between D.obs and H.Est

Table 1. Linear regression model between D.Obs_H.Obs and D.Obs_H.Est

Correlation	Linear regression equation	R^2	RMSE (%)	F.test
H.Obs_H.Est	y = 0.7846x + 0.4924	0.7344	1.35	6029,686
D.Obs_H.Est	y = 3.6697x – 0.6714	0.4847	36.18	414,470

Note: **significant ($p < 0.0$ 1).

by other factors not included in the model. The RMSE value of 1.35% indicates that the model's prediction error is relatively low. Additionally, the F-statistic value of 6029,686 with a significance level of $p < 0.01$ confirms that the regression model is significant and can be used for tree height estimation based on UAV data.

In addition to the relationship between H.Obs and H.Est, a linear regression analysis was also conducted to examine the relationship between D.Obs and H.Est. The obtained regression equation is D.Obs_ H.Est = 3.6697x – 0.6714, with a coefficient of determination (R^2) of 0.4847 or 48.47% (Table 1). This value suggests that tree diameter has a weaker influence on estimated tree height compared to observed tree height. The RMSE value of 36.18% indicates a higher prediction error than the relationship between H.Obs and H.Est. However, with an F-statistic value of 414,470 and a significance level of $p < 0.01$, this relationship remains statistically significant.

The results of this linear regression analysis are also presented in graphical form (Figure 6) to visualize the data distribution points in this test. The results of the linear regression test (Figure 7a) show that the data points scattered around the regression line indicate a strong relationship between the observed tree height and the estimated tree height variables. Meanwhile, the results of the linear regression test (Figure 6b) show that the data points are more widely dispersed, indicating a moderate correlation between tree diameter and estimated tree height. These findings suggest that observed tree height is a stronger predictor variable than tree diameter in estimating tree height.

Before performing these analyses, a classical assumption test was conducted to ensure the validity of the regression model. The results of this test are presented in (Table 2).

The normality test using the Kolmogorov-Smirnov method indicates that all variables have significance values above 0.05, specifically 0.200* for the H.Obs-H.Est relationship and 0.200* for the D.Obs-H.Est relationship (Table 2). These significance values indicate that the data for both variables follow a normal distribution, making them suitable for regression analysis. This finding aligns with the study by Koirala et al. (2017), which stated that tree diameter growth and tree height are correlated. Similarly, the relationship between observed tree height and estimated tree height also shows a correlation (Birdal et al., 2017; Lizuka et al., 2018).

Based on the results of the heteroscedasticity test using the scatterplot graph (Figure 7a and 7b), the points are randomly distributed and spread both above and below zero on the dependent axis. This indicates the absence of heteroscedasticity, meaning that the residual variance is homogeneous within the regression model used. Additionally, the Glejser test was conducted by regressing the absolute residual values against the independent variables (Glejser, 1969).

The results of the heteroscedasticity test show no presence of heteroscedasticity in the model, with significance values of 0.200** for the H.Obs_H.Est relationship and 0.275** for the D.Obs_H.Est relationship (Table 2). All independent variables have significance values greater than 0.05, indicating that none of the independent variables statistically significantly influence the dependent variable (Abs.residual). Therefore, the regression model used in this study can be considered valid and meets the classical assumptions of linear regression.

Table 2. The results of the Kolmogorov-Smirnov normality test and the heteroscedasticity test

Variable		Kolmogorov-Smirnov test	Heteroscedasticity test
X	Y	Sig.	Sig.
H.Obs	H.Est	0.200*	0.200**
D.Obs	H.Est	0.200*	0.275**

Note: *The residuals follow a normal distribution ($p > 0.05$), ** The residual variance is homogeneous ($p > 0.05$)/ indicating no heteroscedasticity.

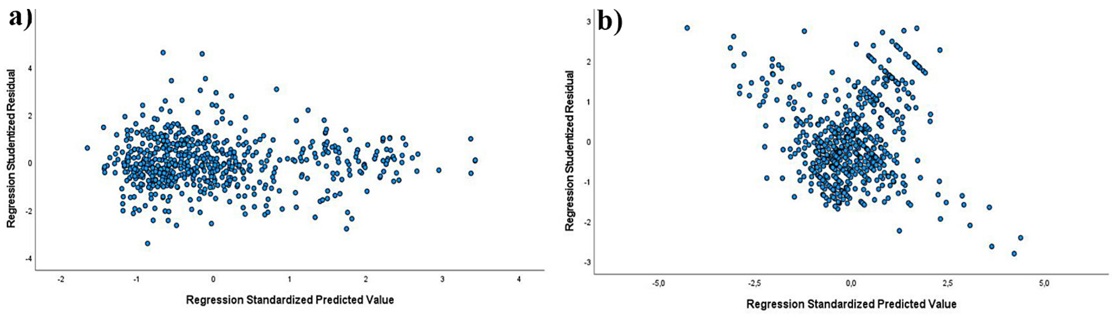

Figure 7. (a). Residual scatter plot graph between D.Obs and H.Est (b). Scatter plot graph of residuals between H.Obs and H.Est

Carbon stock estimation

The analysis results from the (Table 3) above indicate that the estimation of carbon stock based on estimated tree height (H_Est) and observed tree diameter (D_Obs) does not produce a significant difference. This can be seen from the relatively similar biomass and carbon stock values across the observed plots. The similarity in these values suggests that the estimation approach using H_Est is fairly reliable in representing actual field conditions.

Furthermore, the comparison between H_Est and H_Obs shows that the estimated tree height values closely align with direct field measurements. This finding is reinforced by the results of linear regression analysis, which indicate a strong relationship between the two variables. These results suggest that measurement methods based on unmanned aerial vehicle (UAV) technology can provide reasonably accurate estimates of tree characteristics, making them a viable alternative for biomass and carbon stock calculations across various ecosystem types. Previous studies have shown similar results, indicating that UAVs can effectively estimate tree height and diameter with high accuracy and strong correlation (Aryanti, 2021; Islami, 2021).

Therefore, the use of UAV-based methods in this study presents an efficient and effective solution for carbon stock estimation, particularly on a large scale. UAV technology can deliver results that closely match the accuracy of direct field measurements, making it a reliable tool for carbon monitoring. These findings open opportunities for further research to optimize this technique in different environmental conditions and vegetation types.

Additionally, carbon estimation in cocoa plantations demonstrates that the carbon generated by cocoa plantations plays a crucial role in climate change mitigation efforts. Research conducted by Supriadi (2014) emphasizes that cocoa management can enhance carbon stock and reduce greenhouse gas emissions, thus contributing to climate change mitigation. Moreover, other studies have found that agroforestry systems based on cocoa cultivation can increase tree biomass and carbon reserves compared to monoculture systems, further supporting climate change mitigation efforts (Saleh, 2022).

DISCUSSION

UAV as a tool for agroforestry carbon assessment

This study demonstrates a robust correlation between UAV-derived H.Est and H.Obs within cocoa agroforestry systems, with a coefficient of determination (R^2) of 0.7344. This value reflects strong predictive power consistent with ecological research standards. Comparable findings were reported by Wang and Glenn (2008), who validated the efficacy of linear regression models in accurately estimating tree canopy height using airborne remote sensing data. It validates UAVs as a scalable tool for carbon stock quantification. The unexplained 26.56% variability is not merely a statistical artifact; it reflects the ecological and methodological complexities inherent to tropical agroforestry. Unlike monocultures, where homogeneous canopies simplify remote sensing (Alonzo et al., 2018), cocoa systems are dynamic mosaics: shade trees obscure cocoa crowns, farmer pruning alters growth patterns, and microtopography distorts spectral signals. These challenges mirror findings in mixed-species forests, where UAV accuracy declines with canopy heterogeneity (Haridiansyah et al., 2020).

Table 3. Carbon stock estimation

Plot	H.Est_D.Obs				H.Obs_D.Obs			
	Biomass		Carbon stock		Biomass		Carbon stock	
	(kg)	(ton/ha)	(ton/ha)	(ton CO_2e)	(kg)	(ton/ha)	(ton/ha)	(ton CO_2e)
1	295.05	7.38	3.69	13.54	284.35	7.11	3.55	13.04
2	309.63	7.74	3.87	14.20	310.32	7.76	3.88	14.24
3	193.64	4.84	2.42	8.88	182.57	4.56	2.28	8.38
4	157.32	3.93	1.97	7.22	161.15	4.03	2.01	7.39
5	229.44	5.74	2.87	10.53	247.81	6.20	3.10	11.37
6	1518.70	37.97	18.98	69.67	1472.65	36.82	18.41	67.56
7	1777.25	44.43	22.22	81.53	1676.46	41.91	20.96	76.91
8	209.86	5.25	2.62	9.63	227.97	5.70	2.85	10.46
9	627.76	15.69	7.85	28.80	623.19	15.58	7.79	28.59
10	218.61	5.47	2.73	10.03	200.95	5.02	2.51	9.22
11	798.44	19.96	9.98	36.63	820.10	20.50	10.25	37.62
12	1266.35	31.66	15.83	58.09	1254.84	31.37	15.69	57.57
13	705.35	17.63	8.82	32.36	708.35	17.71	8.85	32.50
14	917.35	22.93	11.47	42.08	910.85	22.77	11.39	41.79
15	302.67	7.57	3.78	13.89	256.68	6.42	3.21	11.77
16	455.81	11.40	5.70	20.91	454.47	11.36	5.68	20.85
17	1012.82	25.32	12.66	46.46	903.41	22.59	11.29	41.44
18	1874.96	46.87	23.44	86.01	1826.37	45.66	22.83	83.78
19	2931.72	73.29	36.65	134.49	2819.86	70.50	35.25	129.36
20	442.55	11.06	5.53	20.30	426.48	10.66	5.33	19.56
21	394.64	9.87	4.93	18.10	376.18	9.40	4.70	17.26
22	2347.89	58.70	29.35	107.71	2309.54	57.74	28.87	105.95
23	1251.38	31.28	15.64	57.41	1202.76	30.07	15.03	55.18
24	733.63	18.34	9.17	33.66	600.43	15.01	7.51	27.54
25	329.73	8.24	4.12	15.13	306.07	7.65	3.83	14.04
26	345.26	8.63	4.32	15.84	346.17	8.65	4.33	15.88
27	281.27	7.03	3.52	12.90	382.25	9.56	4.78	17.54
28	133.70	3.34	1.67	6.13	121.80	3.04	1.52	5.59
29	391.52	9.79	4.89	17.96	431.82	10.80	5.40	19.81
30	581.86	14.55	7.27	26.69	556.90	13.92	6.96	25.55
31	167.43	4.19	2.09	7.68	140.49	3.51	1.76	6.44
32	305.09	7.63	3.81	14.00	329.44	8.24	4.12	15.11
33	176.90	4.42	2.21	8.12	176.05	4.40	2.20	8.08
34	489.55	12.24	6.12	22.46	492.70	12.32	6.16	22.60
34	407.86	10.20	5.10	18.71	408.05	10.20	5.10	18.72

Notably, while the cacao cultivation system is labeled as agroforestry, in Luwu Timur, shade trees are predominantly used as plot boundaries rather than forming a vertically layered canopy typical of ecological agroforestry systems. This structural deviation influences UAV imagery accuracy, as the vertical profile captured by UAVs does not fully represent the layered dynamics found in previous studies (Haridiansyah et al., 2020). The enthusiasm surrounding UAVs may overshadow their limitations. Although the technology democratizes data collection, the use of nadir-view cameras (90° angle) fails to capture sub-canopy complexity especially in systems where shade trees serve more of a socio-spatial function than ecological contribution to carbon. To overcome this, future approaches should integrate oblique imaging or LiDAR technology, which can better penetrate multi-layered canopies (Corte et al., 2020). UAVs alone are blunt instruments; their potential lies in hybrid methodologies.

The assoication between observed diameter and estimated height was moderate ($R^2 = 0.4847$). It underscores the inherent variability in stem diameter that cannot be fully captured through height-based remote sensing proxies. This is expected in agroforestry systems, where pruning, shade competition, and farmer management decouple the height–diameter relationship common in monoculture forests and exposes critical limitations in applying traditional forestry-based allometric models to cacao plantations. Rather than being a methodological weakness, this outcome highlights the ecological complexity of cocoa agroforestry and supports the argument that remote sensing must be interpreted within the socio-ecological context of the land-use system. In future work, machine learning models may be tested to further improve prediction accuracy, though with caution to avoid loss of ecological interpretability.

In cocoa agroforestry systems, the relationship between tree height and diameter is not straightforward. Traditional allometric models often assume that tree height increases proportionally with diameter, a relationship observed in monoculture forests. However, in agroforestry systems like cocoa, where trees are shaded and pruned, this assumption does not hold. The stunted vertical growth of cocoa trees under shade competition, coupled with farmer-mediated pruning, disrupts the typical linearity between diameter and height (Koirala et al., 2017). This flaw in applying timber-centric allometric models to cocoa agroforestry systems further complicates accurate carbon stock estimates.

Agroforestry as climate mitigation

The carbon stock estimates in cocoa agroforestry systems (ranging from 18.41 to 134.49 tCO_2e/ha) underscore their potential contribution to climate change mitigation. However, reducing agroforestry to mere carbon metrics risks perpetuating ecological reductionism. In Luwu Timur, for instance, cocoa plots serve not only as carbon sinks but also as crucial habitats for endemic species such as the Sulawesi dwarf kingfisher (*Ceyx fallax*), whose survival hinges on landscape connectivity provided by agroforestry mosaics. Yet, such biodiversity co-benefits remain largely absent from Indonesia's climate policy framework, including its Nationally Determined Contributions (NDCs), echoing a global trend in which carbon accounting overshadows conservation.

UAVs, paradoxically, offer a means to transcend this carbon-centric paradigm. High-resolution imagery from UAVs can be harnessed to identify biodiversity-rich plots those with high shade tree diversity or ecological integrity which could qualify for carbon credits. This approach presents an innovative pathway to integrate carbon finance with conservation outcomes. Without such integrative models, agroforestry risks devolving into a "carbon monoculture," where the rich ecological functions of these systems are flattened into spreadsheet metrics.

Study limitations and temporal constraints in UAV measurements

Although methodologically robust, this study's focus on 35 cocoa plots in Luwu Timur introduces inherent limitations in terms of generalizability. Agroforestry systems in Sulawesi may differ significantly from those in other cocoa-growing regions such as Sumatra or Papua, where variations in land tenure, cultural practices, and biodiversity compositions create distinct ecological and socio-political contexts. Therefore, caution must be exercised when extrapolating these findings across Indonesia's diverse agro-ecological landscapes.

Furthermore, UAV data collection was limited to a narrow temporal window (08:30–11:30 AM) to minimize shadow interference. While this approach improves image clarity, it potentially excludes critical diurnal spectral variations that influence biomass estimation. Sun angle, often regarded as technical "noise" can, in fact, carry ecological "signal," offering valuable insights into phenological states and vertical canopy dynamics.

To overcome these limitations, future research should incorporate light detection and ranging (LiDAR) and high-precision GNSS-GPS systems. LiDAR enables high-resolution, three-dimensional mapping that can penetrate complex canopy structures, thereby improving the detection of sub-canopy vegetation and biomass. Meanwhile, advanced GNSS-GPS tools, such as real-time kinematic (RTK) or post-processed kinematic (PPK) systems, provide centimeter-level spatial accuracy, enhancing the alignment between UAV imagery and ground reference data especially in topographically varied terrain.

By integrating these technologies, UAV-based monitoring can evolve beyond a tool for carbon quantification to a holistic instrument for assessing agroecological health capturing indicators such as shade tree diversity, pollinator presence, and soil organic matter content. Ultimately, bridging precision technology with ecological complexity and local knowledge will be essential in advancing agroforestry as a model for both climate resilience and social equity.

CONCLUSIONS

This study delivers a scientifically validated carbon estimation framework tailored to cocoa agroforestry systems—a land use type often overlooked in high-resolution biomass studies due to its structural complexity and heterogeneous social context. The UAV-derived canopy height model, which achieved a coefficient of determination (R^2) of 0.7344 when compared to field-measured tree heights, demonstrates a reliable remote sensing approach for carbon quantification in dynamic smallholder-dominated landscapes. This technique has proven capable of substituting for tree height estimation using LiDAR, which requires more advanced and costly equipment.

The key scientific contribution lies in demonstrating that traditional forest-based allometric models, when modified to integrate UAV-estimated tree height, can be adapted to heterogeneous agroforestry mosaics. This adaptation not only improves accuracy but also enhances the feasibility of landscape-level carbon monitoring across vast and fragmented agricultural zones. Furthermore, the study challenges the prevailing assumption that agroforestry can be treated as structurally equivalent to forest systems, by empirically revealing the spectral and morphological inconsistencies that arise from farmer management practices such as pruning, selective shading, and boundary planting.

Ultimately, this work contributes both a methodological advancement and a conceptual clarification: precision ecological monitoring in agroforestry systems requires tools and models that are as diverse and adaptable as the systems themselves.

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