



Assessment of sugarcane carbon sequestration using UAV-based data

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Abstract

Sugarcane is a major economic crop in Thailand and has a high potential for carbon sequestration through biomass accumulation, which can contribute to the reduction of greenhouse gas emissions from the agricultural sector. However, the assessment of carbon stock in sugarcane at the field scale remains challenging due to the reliance on field-based measurements that require considerable time, labor, and resources. These limitations restrict large-scale spatial assessment and long-term monitoring. Although standard equations for estimating carbon stock from sugarcane biomass are available, their application in combination with spatial data is still limited and lacks flexibility for practical use. This study aimed to develop a Machine Learning model for estimating carbon sequestration in sugarcane using data obtained from varietal test plots, with the Khon Kaen 3 cultivar selected as a case study. Unmanned aerial vehicle (UAV) imagery was integrated with empirical equations established by the Department of Agriculture, which were used as a reference for carbon calculation. UAV data were processed to generate Digital Surface Models (DSM) and Digital Terrain Models (DTM), from which the Canopy Height Model (CHM) was derived. Structural variables of sugarcane at the clump level were extracted from the CHM and used as input variables for Machine Learning model development. The results indicated that the maximum canopy height showed a strong positive relationship with sugarcane carbon stock. The Artificial Neural Network model provided the best performance, with a coefficient of determination (R^2) of approximately 0.84 and a root mean square error (RMSE) of about 1.6 tons of carbon per rai. These findings demonstrate that the proposed approach effectively links UAV-derived structural information with carbon stock estimation and extends the applicability of standard carbon calculation equations to spatial-scale assessments. The approach can support carbon management and promote sustainable agricultural development in the future.

Keywords: Sugarcane, Carbon sequestration, Unmanned aerial vehicle (UAV), Canopy height model, Machine learning, Allometric equation

1. Introduction

Sugarcane is a major economic crop in Thailand, serving as a primary raw material for the sugar and bioenergy industries, and providing a significant source of income for many farmers nationwide. In the 2024/2025 production year, Thailand cultivated over 11.1 million rai of sugarcane, processing a total of 92.04 million tons, reflecting sugarcane's crucial role in the country's economic and agricultural sectors [1]. Beyond its economic importance, sugarcane possesses significant potential for carbon sequestration in the form of biomass due to its high photosynthetic rate and rapid biomass accumulation. This makes sugarcane a vital resource for reducing agricultural greenhouse gas emissions and supporting carbon management and sustainable development goals.

However, assessing sugarcane carbon at the field level faces limitations due to reliance on traditional field data collection methods that rely on cutting and weighing biomass. While these methods provide accurate results, they are labor-intensive, time-consuming, and costly [2]. Such conventional approaches are often based on destructive sampling, which limits their applicability for repeated measurements and large-scale monitoring [3]. This limits spatial assessment at the large-scale field level and long-term monitoring. Failure to develop effective assessment methods will result in insufficient data for agricultural carbon management, greenhouse gas reduction potential assessment, and environmental policy formulation. Conversely, developing appropriate assessment methods will enhance opportunities for effective carbon management. And create added value for the sugarcane production sector in the long term.

In recent years, empirical and allometric equations have been developed for calculating sugarcane biomass and carbon content from field data, which have been widely accepted and used [2]. Previous studies have also demonstrated that structural variables such as plant height and stem characteristics are strongly related to sugarcane biomass and carbon content [4-5]. However, at the same time, a number of research studies have applied satellite data in conjunction with machine learning models to estimate sugarcane biomass and

yield at a wide area level, relying on spectral and time-based data [6]. Nevertheless, this approach has limitations in terms of spatial resolution and lacks the use of plant structure data, which is directly related to biomass and carbon accumulation at the field level. UAV-based studies have further shown that the CHM can effectively represent crop structural characteristics for biomass estimation [7]. In addition, integrating structural and spectral data has been reported to improve prediction accuracy [8].

Currently, UAV technology is receiving widespread attention for surveying and monitoring plant growth because it can provide high-resolution spatial data and is flexible in data collection. Research in Thailand has shown that using UAVs in conjunction with allometric equations can estimate sugarcane yield. This can be done accurately, yielding an R^2 value higher than 0.9 when compared to field data [9]. However, previous research has focused only on yield assessment, while the use of UAVs to directly assess sugarcane carbon sequestration, especially in the context of sugarcane variety testing plots in Thailand, has been studied in a limited scope.

Therefore, this research aims to develop a method for assessing sugarcane carbon sequestration at the field level by applying structured data obtained from UAVs in conjunction with standard carbon calculation equations. This data will then be used to develop a Machine Learning model to increase the accuracy and flexibility of carbon estimation. The study was conducted in Khon Kaen 3 sugarcane variety testing plots aged 6, 9, and 12 months, focusing on assessing above-ground carbon at the clump level. The expected results will improve the spatial assessment of sugarcane carbon, support agricultural carbon management, promote sustainable agriculture development, and contribute to policy and future planning.

2. Materials and methods

This study designed a systematic workflow to assess sugarcane carbon sequestration by linking structural data from UAVs (HG Robotic, Thailand) with biomass calculations and machine learning model development. The entire workflow can be summarized in a workflow diagram as shown in Figure 1.

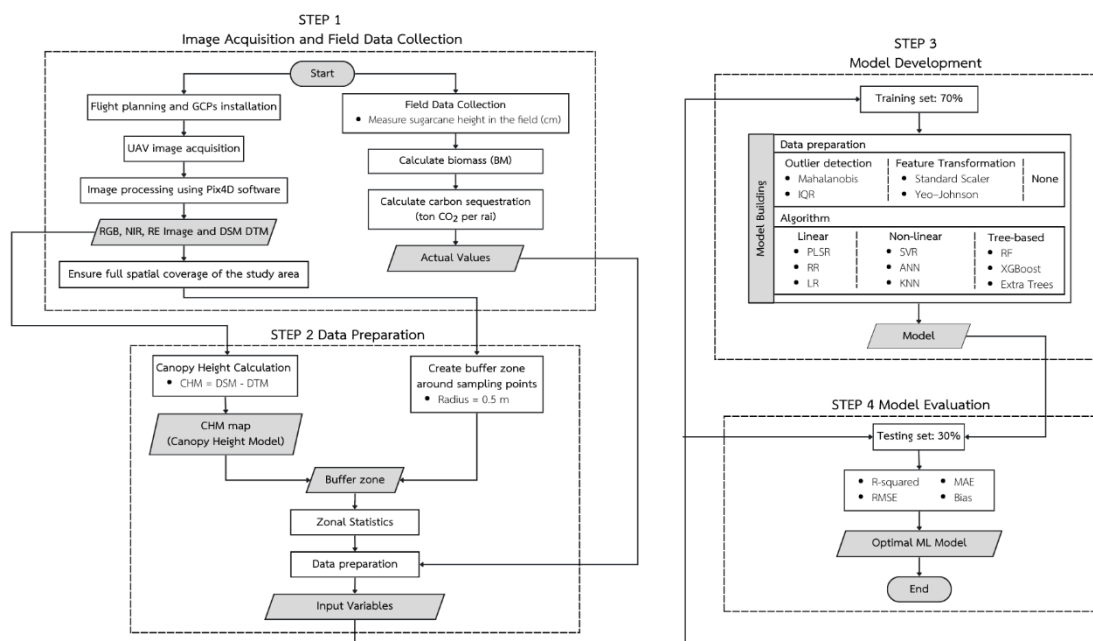


Figure 1 Workflow diagram for sugarcane carbon sequestration assessment

2.1 Study area and field data collection

This study was conducted in the Khon Kaen 3 sugarcane variety experimental plot at the breeding plot in Phu Khiao District, Chaiyaphum Province, Thailand, a major sugarcane growing area in the Northeast region. Field data was collected from February to April 2023, covering sugarcane aged 6, 9 and 12 months to reflect changes in plant structure at each growth stage. Sugarcane at these selected growth stages (6, 9, and 12 months) represents key developmental phases, including early growth, intermediate growth, and maturity, which are associated with significant differences in canopy structure and biomass accumulation.

Sampling points were determined using systematic sampling along the planting rows, totaling 110 points: 48 points for 6-month-old sugarcane, 31 points for 9-month-old sugarcane, and 29 points for 12-month-old sugarcane. At each sampling point, the height of the sugarcane stalk from the base to the tip was measured, and the diameter of the sugarcane stalk at a height of 1 m from the ground was measured. Field data collection: Spatial coordinates were recorded using an RTK GPS receiver. (HG Broccoli BROCC-RTK). This field data was used as a ground truth for verifying and developing models from the UAV data in the next step.

2.2 Data collection with UAVs

Spatial data collection was performed using a VESPA HEX650 multirotor UAV (HG Robotic, Thailand) equipped with a multispectral camera (MicaSense Inc., Seattle, WA, USA) capable of recording data in the Blue, Green, Red, Red Edge, and Near Infrared (NIR) wavelengths. Prior to flight, at least 5 Ground Control Points (GCPs) were installed around each experimental plot, and their coordinates were verified using an RTK GPS receiver to increase the positional accuracy of the imagery.

The aerial survey was conducted under stable conditions, with a flight altitude of approximately 44 m above the ground, a ground sampling distance (GSD) of approximately 3 cm/pixel, a flight speed of 5–7 m/s, and a front and side image overlap rate of

approximately 75–80%. Flights were conducted between 10:00 AM and 3:00 PM under clear and even weather conditions. To ensure consistency of photographic data throughout the study:

2.3 Image processing and vegetation height modeling

Aerial photographs were processed using photogrammetry techniques in Pix4Dmapper software (Pix4D SA, Lausanne, Switzerland) to generate orthomosaic photogrammetry maps, Digital Surface Models (DSMs), and Digital Terrain Models (DTMs). A canopy height model (CHM) was then calculated to separate vegetation height from ground level using Equation 1.

$$\text{CHM} = \text{DSM} - \text{DTM} \quad (1)$$

The CHM represents vegetation height above ground level and is widely used for assessing crop structural characteristics and biomass estimation [7].

To extract structural information at the sugarcane clump level, a buffer zone was created around each sample point with a radius of 0.5 m. The Zonal Statistics function in QGIS (QGIS Development Team, Switzerland) was then used to calculate statistical values from CHM and DSM within this buffer zone. These values include the mean, median, minimum, maximum, standard deviation, variance, and various spatial distribution indicators. The maximum canopy height (CHM_max) was used to represent the sugarcane clump height for further analysis.

2.4 Biomass and carbon calculation

The carbon content of sugarcane in this research began with the calculation of above-ground biomass (BM) using the empirical equation specific to the Khon Kaen 3 sugarcane variety, developed by the Department of Agriculture [2], which shows the relationship between biomass and sugarcane plant height. The equation used is shown in Equation 2.

$$\text{BM} = 0.028\text{H} \quad (2)$$

where

BM = Above-ground biomass of sugarcane (t/rai)

H = Height of sugarcane plant (cm)

In this work, the value is replaced with CHM_max obtained from the unmanned aerial vehicle data. Then, the amount of carbon stored in sugarcane biomass is calculated using the carbon-to-biomass ratio according to the IPCC [10] guidelines, which defines the carbon ratio as 47% of the dry biomass, as shown in Equation 3.

$$\text{C} = \text{BM} \times 0.47 \quad (3)$$

where

C = Amount of carbon stored in sugarcane biomass (tons of carbon per rai)

To assess the greenhouse gas absorption potential, carbon quantities were converted to carbon dioxide equivalent (CO₂ eq) using the molecular weight ratio of carbon dioxide to carbon, as shown in Equation 4. The calculated biomass, carbon, and CO₂ equivalent values were used as reference standards for further model development.

$$\text{CO}_2 \text{ eq} = \text{C} \times 44 / 12 \quad (4)$$

2.5 Machine Learning model development and evaluation

The model development and evaluation were carried out in a step-by-step process as shown in the workflow diagram (Figure 1). The focus was on ensuring that the model training and evaluation reflected its ability to predict sugarcane carbon sequestration from data that had not previously appeared in the learning process. The entire process was designed to allow for systematic comparison of model performance under identical conditions.

2.5.1 Data splitting

All data was divided into a training set and a test set using a stratified split method based on sugarcane age groups. This ensured an appropriate distribution of sugarcane of each age group in both data sets. The training set comprised 70% of the total data, totaling 77 samples: 36 samples of 6-month-old sugarcane, 20 samples of 9-month-old sugarcane, and 19 samples of 12-month-old sugarcane. The test set comprised 30% of the total data.

2.5.2 Data preparation

The model was developed using a sample of 33 points, divided into 12 points for 6-month-old sugarcane, 11 points for 9-month-old sugarcane, and 10 points for 12-month-old sugarcane. This data division reduces model bias toward any particular age group and increases the reliability of the performance evaluation.

2.5.3 Feature selection

Before model development, outlier detection was performed using Mahalanobis distance and Interquartile Range (IQR) to assess the multiple data fit. Then, feature transformation approaches were tested to compare their impact on model performance. Three

approaches were considered: scaling with StandardScaler, transforming with Yeo–Johnson transformation, and no transformation (baseline/none).

2.5.4 Feature selection

The relationship between the sugarcane structural variables from AUD data and the outcome variables was evaluated using Spearman correlation, which is suitable for potentially nonlinear data. Next, the top 10 most correlated variables (Top 10 best-features) were selected to be used as the main set of variables for training and comparing the models.

2.5.5 Modeling

Regression models covering different learning concepts were tested to compare their ability to explain the relationship between the structural variables of sugarcane from unmanned aerial vehicle data and carbon sequestration. The models were grouped into three main categories: linear models, including Partial Least Squares Regression (PLSR), Ridge regression, and Linear regression; non-linear models, including Support Vector Regression (SVR), Artificial Neural Network (ANN), and K-Nearest Neighbors (KNN); and tree-based models, including Random Forest, Extreme Gradient Boosting (XGBoost), and Extra Trees. All models were developed using the selected input variables within the same dataset. To ensure fair comparison of the performance of different model types:

2.5.6 Calibration and evaluation

A 5-fold cross-validation method was used on a training set to select the best-performing models. Hyperparameter tuning was then performed within the cross-validation framework. The top 5 best-performing models were then selected for final evaluation on a test rig. The evaluation indicators used included the coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), and bias. Results were reported for both the training performance and the test performance to determine the most suitable model for evaluating sugarcane carbon absorption at the field level.

3. Results and discussion

3.1 Relationship between structural variables from UAVs and carbon content

Analysis of the relationship between structural variables extracted from the Canopy Height Model (CHM) and sugarcane carbon content using Spearman correlation coefficients, as shown in Table 1, revealed that variables related to sugarcane canopy height have a high positive correlation with carbon content. CHM_max showed the highest correlation coefficient ($r = 0.8023$), followed by CHM_mean and CHM_median, which had similar r values (greater than 0.79).

In contrast, variables reflecting height variability, such as CHM_CV and some canopy density variables, showed negative correlations or lower correlation coefficients. This indicates that sugarcane carbon content is more directly related to the structural size and height of the canopy than to the canopy irregularity within the clump.

These findings are consistent with previous UAV-based studies. Bendig et al. [7] reported that canopy height derived from UAV imagery is strongly correlated with crop biomass. Similarly, Zhu et al. [8] showed that structural variables obtained from UAV data, particularly canopy height, play an important role in biomass estimation.

In addition, satellite-based approaches combined with machine learning have also shown strong potential for biomass and carbon estimation. For example, Suwanlee et al. [6] demonstrated that sugarcane biomass and carbon stock can be effectively estimated using Sentinel-based data together with machine learning algorithms.

Furthermore, structural variables derived from remote sensing data have been identified as key predictors of carbon stock. Liu et al. [11] reported that height-related variables are among the most important predictors, as they effectively represent vegetation structure.

Table 1 Relationship between structural variables from UAVs and carbon content using the Spearman method

No.	Feature	Spearman
1	CHM_max	0.8023
2	CHM_mean	0.7997
3	CHM_median	0.7974
4	CHM_majority	0.7515
5	CHM_minority	0.7265
6	CHM_min	0.7265
7	CHM_CV	-0.5742
8	dsm_CanopyDensity	-0.5164
9	CHM_CanopyDensity	0.5124
10	dsm_CV	0.5124

3.2 Model performance after scaling and calibration

The results of testing the Machine Learning models after data preparation and scaling are shown in Table 2. It was found that models in the Artificial Neural Network (ANN) and Support Vector Regression (SVR) groups performed better than other model types, especially when using CHM_max and CHM_median as input variables.

Considering the results of calibration using the 5-fold cross-validation method, the ANN model using StandardScaler and Yeo–Johnson transformation achieved a maximum R^2 value of approximately 0.84 and an RMSE in the range of approximately 1.6–1.7 tons of carbon per rai. This reflects the model's ability to explain data variance well and its error range is acceptable for spatial estimation.

Similar findings have been reported in previous studies. Cheng et al. [12] showed that machine learning models can effectively estimate carbon stock using remote sensing data. Nguyen [13] also reported strong performance of non-linear algorithms in carbon estimation, while Ilarionova et al. [14] highlighted the effectiveness of advanced models in improving prediction accuracy.

Conversely, some models that used overly strict outlier management methods or did not scale the data showed reduced performance, highlighting the importance of data preparation steps to model performance. In addition, previous studies have emphasized the importance of data preprocessing in improving model performance. For example, Liu et al. [11] reported that appropriate preprocessing techniques significantly enhance prediction accuracy when using remote sensing data.

Table 2 Model performance after scaling and calibration

Feature	Preparation	Algorithm	Train set				Calibration (cross validation 5-fold)			
			R ²	RMSE	MAE	Bias	R ²	RMSE	MAE	Bias
CHM_max	standard	ANN	0.8564	1.5749	1.1788	0.0007	0.8438	1.6429	1.2125	-0.0142
CHM_max	yeojohnson	ANN	0.8567	1.5733	1.1726	0.0005	0.8425	1.6494	1.2438	-0.0081
CHM_median	yeojohnson	ANN	0.8562	1.5761	1.2064	-0.0033	0.8411	1.6565	1.3027	0.0113
CHM_max	standard	SVR	0.8459	1.6317	1.1401	-0.0176	0.8398	1.6634	1.1876	-0.0424
CHM_max	none	SVR	0.8459	1.6317	1.1401	-0.0176	0.8398	1.6634	1.1876	-0.0424
CHM_max	iqr	SVR	0.8459	1.6317	1.1401	-0.0176	0.8398	1.6634	1.1876	-0.0424
CHM_max	yeojohnson	SVR	0.8452	1.6353	1.1439	-0.0357	0.8395	1.6651	1.1919	-0.0140
CHM_max	mahalanobis	SVR	0.8448	1.6422	1.1530	-0.0162	0.8383	1.6764	1.2141	-0.0371
CHM_median	standard	ANN	0.8543	1.5865	1.2452	0.0030	0.8370	1.6780	1.3309	0.0161
CHM_median	mahalanobis	SVR	0.8319	1.6897	1.2466	-0.0444	0.8220	1.7388	1.3204	-0.0510

*standard1 = StandardScaler

3.3 Evaluation of the best model and comparison of predictions

The results of the selection of the best-performing model and the final evaluation are shown in Table 3. It was found that the ANN model using the CHM_median and CHM_max variables yielded the most stable predictions, with R² values in the test set ranging from 0.79–0.81, although slightly lower than in the calibration stage. This is normal behavior for the model when tested with previously unseen data.

Table 3 Performance of the best model after parameter adjustment

Feature	Preparation	Algorithm	Best parameter	Calibration (cross validation 5-fold)				Validation (cross validation 5-fold)			
				R ²	RMSE	MAE	Bias	R ²	RMSE	MAE	Bias
CHM_median	YeoJohns on	ANN	- hidden_layer_sizes: (50, 50) - alpha: 0.0001	0.8411	1.6565	1.3027	0.0113	0.8110	1.7100	1.3223	0.1954
CHM_median	standard	ANN	- hidden_layer_sizes: (50, 50) - alpha: np.float64 (0.046415888336127774)	0.8391	1.6672	1.3160	0.0105	0.8016	1.7523	1.3676	0.2391
CHM_max	standard	ANN	- hidden_layer_sizes: (50, 50) - alpha: np.float64 (0.00046415888336127773)	0.8443	1.6400	1.2394	-0.0177	0.7996	1.7610	1.4093	0.2832
CHM_median	mahalanobis	SVR	- kernel: rbf - gamma: scale - C: np.float64 (61.584821106602604)	0.8282	1.7081	1.3464	-0.0427	0.7940	1.7853	1.3100	0.1292
CHM_max	YeoJohns on	ANN	- hidden_layer_sizes: (50, 50) - alpha: np.float64 (0.00021544346900318845)	0.8427	1.3487	1.2464	-0.0071	0.7917	1.7955	1.3961	0.3052

Considering the relationship between actual and model-predicted values in the form of a scatter plot (Figures 2–4), it was found that most data points are distributed near the 1:1 line in the training, calibration, and test sets. This indicates that the model can adequately capture the trend of changes in carbon content. However, in the high carbon content range, the model tends to predict values that are closer to each other, which may reflect the limitations of the sample size in that range.

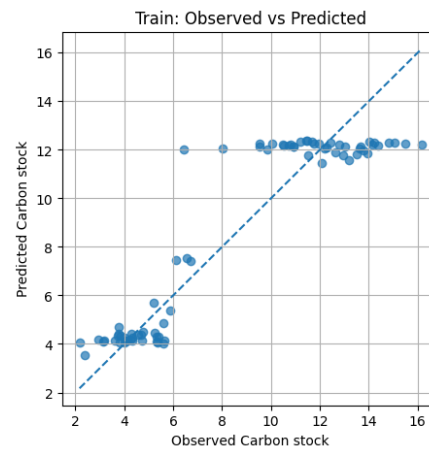


Figure 2 Relationship between actual and predicted values in the training set

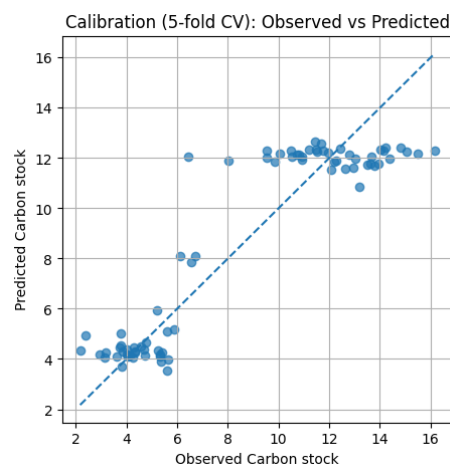


Figure 3 Relationship between actual and predicted values in the Calibration phase (5-fold CV)

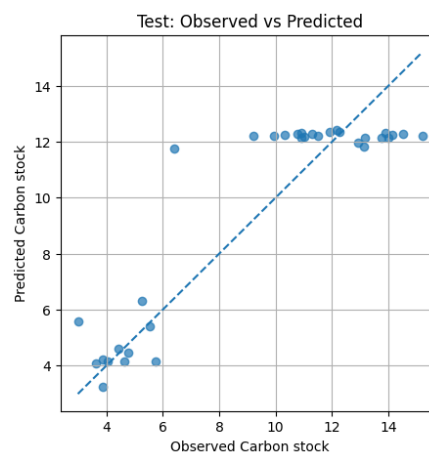


Figure 4 Relationship between actual and predicted values in the test set

4. Conclusions

This study demonstrates that sugarcane structural data obtained from UAVs can be effectively used to assess carbon sequestration at the plot level. Spearman correlation analysis revealed that variables from the CHM, particularly CHM_max and CHM_median, showed a high positive correlation with carbon content, with correlation coefficients of 0.8023 and 0.7974, respectively.

Machine learning model development showed that the Artificial Neural Network model using CHM_median combined with Yeo-Johnson transformation performed best, achieving a R^2 of 0.8411 during calibration and maintaining good predictive capability on the test rig with an R^2 of 0.8110. The RMSE was 1.7100 tonnes of carbon per rai and the MAE was 1.3223 tonnes of carbon per rai.

Although the model had a bias of 0.1954, reflecting a slight overestimation tendency in some data points. Overall, the results demonstrate that the developed approach can systematically link structured data from UAVs to assess sugarcane carbon sequestration and has the potential for appropriate application in field-level carbon assessment and carbon management in the agricultural sector.

5. Limitations

Although the proposed approach demonstrated strong performance in estimating sugarcane carbon sequestration, several limitations should be considered. The dataset used in this study was relatively limited, particularly in the higher carbon content range, which may affect the model's ability to fully capture variability under high biomass conditions. In addition, the study was conducted in a specific experimental plot using a single sugarcane variety (Khon Kaen 3), which may limit the generalizability of the model to other varieties, environmental conditions, or management practices.

Furthermore, the model relied primarily on structural variables derived from UAV data, particularly canopy height. While these variables showed strong predictive power, integrating additional data sources such as spectral indices or environmental variables may further enhance model performance. These limitations may influence the application of the model in carbon credit mechanisms and agricultural carbon management, especially when applied to larger or more diverse production systems. In particular, reliable estimation of carbon stock is essential for carbon credit schemes, where model uncertainty may affect the accuracy of carbon accounting and decision-making processes.

Future research should focus on expanding the dataset, incorporating multi-source data, and validating the approach across different regions to improve model robustness and applicability. Despite these limitations, the proposed method provides a practical and scalable approach for estimating sugarcane carbon sequestration at the field level, with strong potential for supporting carbon management and sustainable agricultural development.

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