



Modeling and Mapping Aboveground Biomass Using Landsat 8 and ALOS-2 PALSAR-2 Data in Cocoa Plantations, Ghana

Emmanuel Donkor^{1*}, Samuel Ato Andam-Akorful², Edward Matthew Osei Jnr², Addo Koranteng³, Stephen Adu-Bredu⁴

¹Resource Management Support Centre, Forestry Commission, Kumasi, Ghana

²Department of Geomatic Engineering, Kwame Nkrumah University of Science and Technology, Kumasi, Ghana

³Institute of Research, Innovation and Development, Kumasi Technical University, Kumasi, Ghana

⁴Forestry Research Institute of Ghana, Council for Scientific and Industrial Research, Kumasi, Ghana

Email: *dadad105@yahoo.com

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Abstract

Mapping of cocoa aboveground biomass (AGB) is essential, as it provides estimates of the total AGB locked up in cocoa plantations in the form of carbon. If this carbon is released into the atmosphere, it will increase the concentration of greenhouse gases, which will contribute to climate change. Remote sensing data has become an important tool for assessing forest and tree plantation biomass. This paper aims to map the spatial distribution of AGB of cocoa plantations in Juaboso and Bia West districts of Ghana by developing a regression model using Landsat 8 and ALOS-2 PALSAR-2 data and measured cocoa AGB. Multi Linear Regression (MLR) model was developed using forty (40) field-measured AGB at the plot level as the dependent variable and the Difference Vegetation Index (DVI) of Landsat 8 and HV backscatter coefficient of ALOS-2 PALSAR-2 images as independent variables. The model was validated using Coefficient of Determination (R^2) and Root Mean Squared Error (RMSE) as the metrics for evaluating its accuracy. This model was used for the prediction of cocoa AGB. Geostatistical interpolation techniques using universal kriging, ordinary kriging, inverse distance weighting and radial basis function were tested, and the best method was used to develop AGB map of cocoa plantations in the study area. The best interpolation method was selected using R^2 , Index of Agreement (I_A), P-values, RMSE, and Mean Absolute Error (MAE) metrics. The MLR used for the prediction of cocoa AGB is $AGB (Mg/ha) = 6.97 * 10^{-4}DVI + 3.56HV + 74.88$. The best interpolation method is universal kriging, which was used to develop the AGB map of the cocoa plantations in the study area. The total AGB estimated for the cocoa plantations in the study area is in

the range of (4973833.80 - 5240128.92) Mg. The model developed can be used to quantify AGB and subsequently CO₂ equivalent, which are very important under the REDD + project for estimating emission levels in the cocoa plantations in the cocoa landscape. The results of this study have shown that the cocoa plantations have a substantial amount of AGB, which sequesters more carbon dioxide from the atmosphere and deposits it in their sinks as carbon; therefore, cocoa plantations provide a lot of climate change mitigation.

Subject Areas

Environmental Sciences

Keywords

Aboveground Biomass, Cocoa Landscape, HV Backscatter Coefficient, Difference Vegetation Index (DVI), Multi Linear Regression, Universal Kriging

1. Introduction

Climate change has been recognized as the foremost environmental problem, which has a significant impact on both human activity and natural ecosystems and has attracted considerable interest from the international community [1] [2]. Effects of climate change include higher temperatures, increases in precipitation patterns, rising sea levels, weather-related natural disasters, increased drought, declining biodiversity, severe wildfires and decreased food security [3]. In order to develop national and international plans to reduce atmospheric carbon dioxide concentration and to combat global climate change, correct assessment and mapping of forest and tree plantation biomass are essential [4]. Natural forests accumulate a large quantity of carbon [5]; therefore, most of the carbon estimation research works in Ghana are carried out in natural forests. Tree crops can be possible way for combating climate change mitigation by sequestering carbon dioxide from the atmosphere [6]. Information on carbon sequestration in forest plantations and natural forests is widely available, on the contrarily information on tree crop plantations carbon is insufficient [7]. In Ghana, large tracts of land are under tree crop cultivation, such as cocoa, rubber, oil palm, citrus, mango and cashew plantations, which sequester substantial amount of carbon with inadequate carbon stock data [8]. Among these tree crops, cocoa cultivation is the largest, with an estimated area of 1.6 million hectares [9].

The function of cocoa systems for climate change mitigation and adaptation has increased substantially because of their capability to sequester carbon dioxide from the atmosphere and deposit it in the cocoa trees as carbon [10]. In Indonesia, carbon stock analysis for cocoa plantations has reported carbon sequestration levels ranging from 25.52 Mg/ha to 33.19 Mg/ha [11], whilst in Central America, levels were estimated at around 49 Mg/ha [12]. [7] estimated cocoa carbon stock

at the Agricultural Research Centre at Kade in Eastern Region of Ghana to be 65 MgC/ha.

In Ghana, cocoa is cultivated in nine out of the sixteen regions, which cover a large area. However, only a handful of studies have been conducted for cocoa AGB estimation at the plot level [13]. Biomass estimation for tropical forests and other woody vegetation has received much consideration in recent years because the change in biomass is deemed an important component of climate change [14]. Mapping carbon stocks in forests and other woody vegetation gives estimate of the total carbon locked up in the vegetation. This carbon has considerable value to the world; if it is released into the atmosphere, it will increase greenhouse gas concentration [15].

Remote sensing data has become an important tool for assessing forest and tree plantation biomass. Biomass estimation using remotely sensed data is an evolving innovation and is increasingly used to inventory forest and plantation biomass [14]. Remote sensing data can efficiently provide a synoptic view over large areas and greatly increase the efficiency and usefulness of conventional ground-based methods [16]. Satellite data from optical, radar, and lidar sensors have been used to map aboveground biomass [17] [18]. However, due to the optical sensors' saturation at a low level of spectral bands, using optical data to determine woody biomass is difficult [19]. Also, optical data are usually contaminated by frequent cloud cover present in the tropics [20]. On the other hand, active remote sensing such as radar can penetrate through clouds and provide data day and night [21]; therefore, radar has appeared as a potential tool for measuring AGB with great accuracy in the tropics [22]. Synthetic aperture radar (SAR) data, such as ALOS PALSAR data, have been used in numerous research works to estimate biomass [23], other research works have discovered positive outcomes when SAR and optical data are combined [17] [24]. Satellite images in combination with field inventory data have been used to assess AGB [25].

Regression-based models are the most common biomass estimation method when using remote sensing data [26] [27]. Regression models can be linear, such as simple linear regression, multiple linear regression or nonlinear, such as exponential, power, logarithmic, quadratic, or polynomial functions. The important thing is to find appropriate remote sensing variables that correlate well with biomass [26].

Some studies have been conducted using modeling and spatial technology to map AGB in forest ecosystems and tree plantations [20] [28]. [29], used spectral indices of Landsat 8 with field-measured data to develop and compare AGB models in Omo Biosphere Reserve, Nigeria. The model with Enhanced Vegetation Index (EVI) as the explanatory variable was chosen as the best spectral model with Omo Biosphere Reserve having a mean AGB of 162.40 Mg/ha. [30] used ALOS PALSAR 50 m mosaic data to estimate AGB in Cambodia. The AGB was estimated using field-measured biomass and backscattering properties of PALSAR data. The relationship between the PALSAR backscatter coefficients HV and HH/HV with

field measured biomass was strong with $R^2 = 0.67$ and 0.56 , respectively. [31] conducted research in Yok Don National Park in the Central Highlands of Vietnam with the objective of improving the biomass estimates by a combination of ALOS-2 SAR, Landsat 8 and field plots data. The best combination parameters which consist of maximum NDVI from optical data, backscatter from forest objects and texture from ALOS-2 SAR were used to produce the aboveground biomass map in Yok Don National Park with $RMSE\% = 21.70\%$. [32], carried out research in Afram Headwaters forest reserve, Ghana, using optical and radar images to model and estimate the AGB of the reserve. Two radar images namely ALOS PALSAR and ENVISAT and ASTER were used in this research. The research showed that strong correlation was identified between L band HV cross polarization and AGB of natural forest. Very weak correlation was found in agroforestry and plantation forest.

The use of various geostatistics interpolation techniques for mapping the spatial distribution of diverse environmental elements has significantly increased in recent years [33]. Geostatistics is a subdiscipline of spatial statistics; it is a class of statistical techniques for forecasting the value of a continuous spatial process at unobserved places using values from known locations [34] [35]. There are two main groupings of interpolation methods: deterministic and geostatistical (also known as stochastic). Deterministic approaches generate surfaces based on the degree of homogeneity or resemblance of the studied points and examples include inverse distance weighting (IDW), radial basis function (RBF), local polynomial and global polynomial [36]. Geostatistical approaches consider the geographical arrangement of the sample points near the forecast location and measure the spatial autocorrelation among measured points [37]. Kriging is mostly employed in geostatistical interpolation and some examples include Ordinary Kriging, Simple Kriging, Universal Kriging, Indicator Kriging and Probability Kriging [38].

This paper aims to map the spatial distribution of AGB of cocoa plantations in the Juaboso and Bia West districts of Ghana by developing a regression model using Landsat 8 and ALOS-2 PALSAR-2 images and measured cocoa AGB.

2. Study Area and Dataset

2.1. Study Area

The study was conducted in the Juaboso and Bia West districts of the Western North region in Ghana's cocoa landscape. Juaboso and Bia West districts are among the highest cocoa - producing districts in Ghana. The study area is situated between latitude $6^{\circ}13'N$ and $6^{\circ}50'N$ and longitude $2^{\circ}40'W$ and $3^{\circ}16'W$, covering an area of 2571.26 square kilometres (**Figure 1**). Cocoa farming is the major land-use system, which occupies a greater percentage of the land in the area. Apart from cocoa farms, other land use/cover which include food crop farms, fallow lands, patches of grassland and also communities in relatively low-lying areas. Within the study area are Krokosua Hills forest reserve, a portion of Bia Tributaries North forest reserve, and Bia National Park [39].

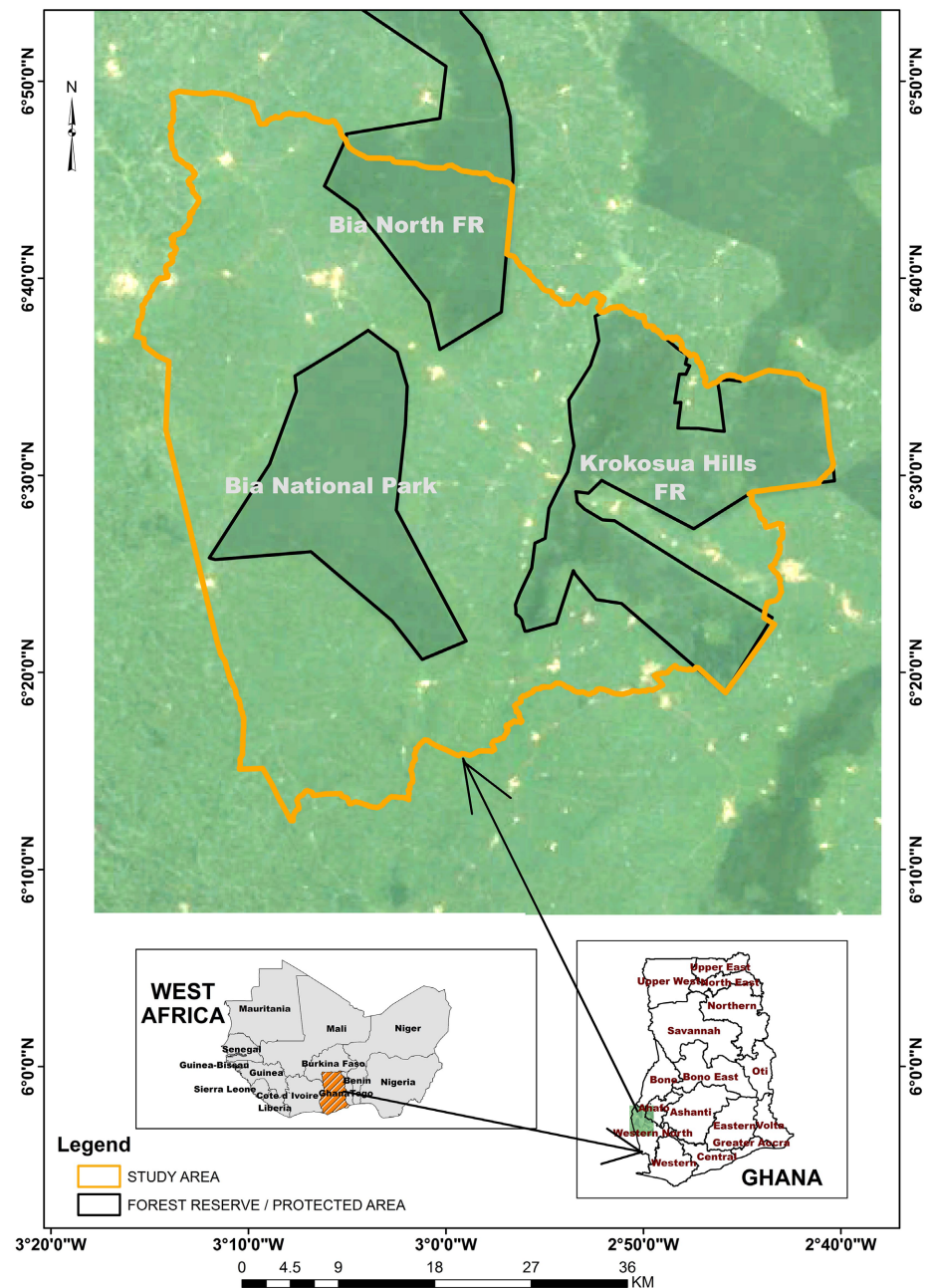


Figure 1. Map of the study area showing the cocoa mosaic landscape of Juaboso and Bia West districts of Ghana (Image source: Landsat and Copernicus from Google Earth Engine).

With a mean annual temperature between 25.5°C and 26.5°C, the area has a tropical climate marked by warm temperatures. The annual rainfall levels are between the ranges of 1250 - 2000 mm, with June and October as its peak months. The area is very undulating, with the elevation of the terrain ranging between 137 and 594 m above mean sea level. The study area falls within Moist Evergreen, Moist Semideciduous Northwest and Moist Semideciduous Southeast subtypes of ecological zones [40]. The soils are mainly Oxisols and Ochrosols [41] with underlying Birimian and Hornblende parent rocks.

2.2. Sample Plots for Data Collection

Field data were collected from 40 square plots, each of dimensions 30 m × 30 m, with an area of 900 m², from 5th to 19th January 2022. Enumeration was carried out for only live cocoa trees with a diameter at breast height (DBH) ≥ 5 cm. For each cocoa tree, DBH was measured and recorded (Appendix 1).

2.3. Acquisition of Satellite Dataset

Two Landsat 8 level-2 product 2022 scenes were downloaded; details of the Landsat 8 data used in this study are shown in **Table 1**.

Table 1. Landsat 8 data used in this study.

NO	TILE ID	Observation Date	Path/Row
1	LCO8L2SP195055_20220121_02_T1.tar.gz	21st January 2022	195/055
2	LCO8L2SP195056_20220121_02_T1.tar.gz	21st January 2022	195/056

Two ALOS-2 PALSAR-2 level 2.1 scenes from 2022 were downloaded with a resolution of 25 m, and details are shown in **Table 2**.

Table 2. ALOS-2 PALSAR-2 mosaic data used in this study.

NO	TILE ID	Observation Date	Polarization
1	N07W003-22-MOS-F02DAR.Zip	24th January 2022	HH + HV (Dual-Pol data)
2	N07W004-22-MOS-F02DAR.Zip	24th January 2022	HH + HV (Dual-Pol data)

3. Methods

3.1. Processing of Satellite Data

For Landsat 8, image processing entails pre-processing and post-processing. For the pre-processing, the original unscaled digital numbers (DNs) were converted to scaled surface reflectance values using Equation (1)

$$\rho = (\text{DN} \times 0.0000275) - 0.2 \quad (1)$$

where,

ρ is scaled surface reflectance, DN is pixel value in the Landsat band, 0.0000275 is reflectance scale factor and -0.2 is reflectance additive offset.

Cloud, cloud-shadow and other low-quality pixels were identified and removed using the QA_PIXEL quality-assurance band. The post-processing activities performed include deriving the various Vegetation Indices (VIs) from the scaled surface reflectance values and retrieving VIs values using the sample plot points. In this study, five (5) VIs were computed. Details of the VIs are summarized in **Table 3**.

These VIs were selected for this study because they reveal both the abundance of green vegetation cover and biomass [47]. The shapefiles of the sample plot points were imported into the VIs to extract their values.

Table 3. Vegetation indices and equations used.

Indices	Equation	Reference
1) Normalized Difference Vegetation Index (NDVI)	$NDVI = \frac{NIR - Red}{NIR + Red}$	[42]
2) Ratio Vegetation Index (RVI)	$RVI = \frac{Red}{NIR}$	[43]
3) Transformed Vegetation Index (TVI)	$TVI = \sqrt{NDVI} + 0.5$	[44]
4) Difference Vegetation Index (DVI)	$DVI = NIR - Red$	[45]
5) Enhanced Vegetation Index (EVI)	$EVI = \frac{2.5 * (NIR - Red)}{1 + NIR + 6 * Red - 7.5 * Blue}$	[46]

For ALOS-2 PALSAR-2, the sample plot points shapefiles were imported on both the HH and HV polarized images to extract their digital values. The digital values extracted do not represent the radar backscatter coefficient (γ°); therefore, they were converted to the radar backscatter coefficient in decibel units using Equation (2).

$$\gamma^\circ (\text{dB}) = 10\log_{10}(\text{DN}^2) - 83.0 \quad (2)$$

where,

γ° (dB) is the radar backscatter coefficient in decibels, DN is the digital number, and -83 is the calibration factor for ALOS-2 PALSAR-2.

3.2. Sample Plots Distribution and AGB Calculation

Supervised image classification was performed with Sentinel-2 imagery to derive Land Use Land Cover (LULC) classes of the study area. The classification resulted in five (5) LULC classes of: closed forest, open forest, cocoa, other vegetation and settlement/bare surface. The study area was divided into grids of 5 km by 5 km after an exploratory analysis of the entire study area and the grids that were on the cocoa LULC class were selected. The cocoa LULC class was found to occupy a total area of 135329.87 ha (52.63%) of the study area. Using a sample intensity of 0.003%, 40 sample plots were generated, and they were uniformly distributed over the cocoa farms.

The number of cocoa trees enumerated in the 40 sample plots totaled 4367 trees. The parameter measured in the field for the cocoa trees was Diameter at Breast Height (DBH); thus, diameter measured at 1.3 cm from the ground. **Table 4** displays the descriptive statistics of the cocoa trees across all sample plots.

Table 4. Descriptive statistics of the sample plots' cocoa trees.

	Min	Max	Sum	Mean	Std Error	Std Dev
Stem Per Plot	51	200	4367	109.0	5.52	34.92
Mean DBH (cm)	10.05	19.36	524.89	13.12	0.34	2.17

Allometric equation developed by [48] (Equation (3)) was used to calculate the AGB of cocoa trees in the sample plots

$$AGB = 0.7217\rho(D^2)^{0.921} \quad (3)$$

where,

AGB is aboveground biomass for cocoa tree (kg), D is the measured cocoa tree diameter at breast height (cm), and ρ is cocoa wood density, which is 0.4 g/cm^3 . This model was most appropriate, as it was developed to estimate AGB for cocoa plantations in Ghana. Biomass estimates from local site-specific equations are considered accurate in forestry and plantation applications [49].

The descriptive statistics of the AGB (Mg/ha) for all the sample plots are shown in Table 5.

Table 5. Descriptive statistics of the AGB (Mg/ha) for the sample plots.

Min	Max	Sum	Mean	Std Error	Std Dev
34.62	44.73	1632.5	40.81	0.36	2.31

3.3. Model Development and Validation

Different models were developed, namely: simple linear model (Equation (4)), power model (Equation (5)), and exponential model (Equation (6)). The predictive performance of each model was evaluated based on its coefficient of determination (R^2) (Equation (7)) and root mean squared error (RMSE) (Equation (8)). The chosen model for AGB estimation was the model with the highest R^2 and the lowest RMSE.

Multi-linear regression (MLR) (Equation (9)) was performed using the parameters of the best model for both Landsat 8 and ALOS-2 PALSAR-2 as the independent variables and their corresponding measured AGB as the dependent variable. Validation of the MLR model was carried out by assessing the coefficient of determination (R^2) and the root mean squared error (RMSE). To obtain a more reliable and robust estimate of model predictive performance, a repeated 10-fold cross-validation procedure was performed over five independent repetitions. The mean R^2 and mean RMSE and their associated uncertainties were calculated to test whether the model transfer across the study area. Regression diagnostics were also conducted to assess whether the assumptions underlying the multiple linear regression model were reasonably satisfied. Regression diagnostics performed include: residual behaviour, influential observations and correlation between the satellite parameters. Residual behaviour was evaluated using residual-versus-fitted plots and normal Q-Q plots. The Shapiro-Wilk test was used to assess the distribution of residuals. Influential observations were evaluated to identify data points that have unusually large effect on the fitted multiple-linear-regression model using Cook's distance and leverage test. The Pearson correlation (r) was used to evaluate the association between the two satellite parameters, while the variance inflation factor (VIF) was calculated to quantify the extent of multicollinearity.

linearity among the predictors prior to fitting the multiple-linear-regression model.

$$\text{Simple Linear Model: } \text{AGB} = \beta_1 X + \beta_0 \quad (4)$$

where,

AGB is aboveground biomass (dependent variable), X is the independent variable, β_1 is the model coefficient for X , and β_0 is the intercept.

$$\text{Power Model: } \text{AGB} = aX^b \quad (5)$$

where a is a non-zero coefficient, $a \neq 0$, and b is a real number.

$$\text{Exponential Model: } \text{AGB} = ae^{bx} \quad (6)$$

where a is a non-zero coefficient, $a \neq 0$, and b is a real number.

e = exponential constant = 2.7182818

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (7)$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^N (y_i - \hat{y}_i)^2} \quad (8)$$

where y_i , $\hat{y}_i$ represent the measured and predicted values, respectively, and N is the sample size.

$$\text{Multi-Linear Regression: } \text{AGB} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 \quad (9)$$

where,

AGB is aboveground biomass, X_1 is vegetation index, X_2 is backscatter coefficient, β_0 is the intercept, β_1 is the model coefficient for X_1 and β_2 is the model coefficient for X_2 .

3.4. AGB Mapping

The study area was divided into grids with each grid cell of dimension $2 \text{ km} \times 1 \text{ km}$ after exploratory analysis, which yielded 1273 grids and the grids centre coordinates were extracted. The difference vegetation index (DVI) model of Landsat 8 and the HV model of ALOS-2 PALSAR-2 were the best models using R^2 and RMSE as validation metrics. The extracted plot points shapefiles were imported onto the DVI raster file to extract their DVI values as well as those of HV of ALOS-2 PALSAR-2 to extract their DN values. The DN values were converted to radar backscatter coefficients in decibels. A multilinear regression model (Equation (10)) was used to calculate the predicted AGB for all 1273 grids.

$$\text{AGB (Mg/ha)} = 6.97 * 10^{-4} \text{DVI} + 3.56 \text{HV} + 74.88 \quad (10)$$

Geostatistics interpolation techniques using universal kriging (UK), ordinary kriging (OK), inverse distance weighting (IDW), and radial basis function (RBF) were tested, and the best method was used to develop AGB map of cocoa plantations in the study area. Forty (40) observations were used to validate UK, OK, IDW, and RBF interpolation methods. Efficiency-based and error-based metrics were used to assess the performance of the interpolation methods. The efficiency-

based metrics used in this research include the R^2 (Equation (7)), the Index of Agreement (I_A) (Equation (11)), and P-values.

$$I_A = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (|\hat{y}_i - \bar{y}_i| + |y_i - \bar{y}_i|)^2} \quad (11)$$

where y_i , $\hat{y}_i$ and $\bar{y}_i$ represent the measured, predicted, and mean AGB, respectively, whereas n is the sample size.

Error-based metrics considered include RMSE (Equation (8)) and Mean Absolute Error (MAE) (Equation (12)).

$$MAE = \frac{1}{n} \sum |\hat{y}_i - y_i| \quad (12)$$

where y_i , $\hat{y}_i$ represent the measured and predicted AGB, respectively, whereas n is the sample size.

4. Results and Discussion

4.1. Model Development and Validation Using Landsat 8 Data

Fifteen (15) models were developed: simple linear regression, power, and exponential models with their R^2 and RMSE (Mg/ha) as the evaluation metrics. The output models with their R^2 and RMSE (Mg/ha) are shown in **Table 6**.

Table 6. Models of AGB and VIs of Landsat 8.

MODEL	NDVI	RVI	TVI	DVI	EVI
Linear	AGB = 37.35NDVI + 24.07 (0.72, 1.12 Mg/ha)	AGB = -38.80RVI + 54.89 (0.71, 1.13 Mg/ha)	AGB = 17.10TVI + 21.21 (0.55, 1.40 Mg/ha)	AGB = 0.00115DVI + 27.6 (0.79, 0.97 Mg/ha)	AGB = -0.47EVI + 37.34 (0.44, 1.56 Mg/ha)
Power	AGB = 55.66NDVI ^{0.385} (0.71, 1.33 Mg/ha)	AGB = 27.80RVI ^{-0.395} (0.72, 1.38 Mg/ha)	AGB = 38.38TVI ^{0.457} (0.54, 1.42 Mg/ha)	AGB = 2.36DVI ^{0.304} (0.70, 1.14 Mg/ha)	AGB = 34.57EVI ^{0.087} (0.54, 1.42 Mg/ha)
Exponential	AGB = 26.57e ^{0.955NDVI} (0.65, 1.39 Mg/ha)	AGB = 58.51e ^{-0.945RVI} (0.64, 1.41 Mg/ha)	AGB = 24.57e ^{0.442TVI} (0.47, 1.71 Mg/ha)	AGB = 29.31e ^{0.0000278DVI} (0.68, 1.31 Mg/ha)	AGB = 37.56e ^{-0.011119EVI} (0.41, 1.80 Mg/ha)

From **Table 6**, difference vegetation index (DVI) using a linear model (Equation (13)) gives the highest predictive accuracy with R^2 (0.79) and RMSE (0.97 Mg/ha), and EVI gives the lowest accuracy performance with R^2 (0.43) and RMSE (1.57 Mg/ha) using an exponential model. From the best model, 79% of the estimated AGB was explained by the observed AGB.

$$AGB = 0.00115DVI + 27.6 \quad (13)$$

4.2. Model Development and Validation Using ALOS-2 PALSAR-2 Data

Six (6) models were developed: simple linear regression, power, and exponential models using measured AGB with HV and HH backscatter coefficients. The R^2 and RMSE (Mg/ha) were used as performance metrics, and the output models are presented in **Table 7**.

Table 7. Models of AGB with backscatter coefficients of HV and HH.

MODEL	HV	HH
Linear	AGB = 6.17HV + 114.28 (0.63, 1.29 Mg/ha)	AGB = -1.87HH + 28.01 (0.04, 1.84 Mg/ha)
Power	AGB = 3442.91HV ^{-1.79} (0.61, 1.33 Mg/ha)	AGB = 23.12HH ^{0.30} (0.04, 1.84 Mg/ha)
Exponential	AGB = 244.84e ^{0.15HV} (0.62, 1.34 Mg/ha)	AGB = 29.30e ^{-0.05HH} (0.04, 1.85 Mg/ha)

From **Table 7**, HV using linear model (Equation (14)) gives the highest accuracy of R^2 (0.63) and RMSE (1.29 Mg/ha) and HH gives the least accuracy with R^2 (0.04) and RMSE (1.85 Mg/ha) using the exponential model. From the best model, about 63% of the estimated AGB was explained by the observed AGB.

$$\text{AGB} = 6.17\text{HV} + 114.28 \quad (14)$$

4.3. Model Development and Validation Using DVI and HV Parameters

The Multi Linear Regression (MLR) model using DVI and HV is shown in Equation (15).

$$\text{AGB (Mg/ha)} = 6.97 * 10^{-4}\text{DVI} + 3.56\text{HV} + 74.88 \quad (15)$$

where,

AGB = predicted aboveground biomass, DVI = difference vegetation index of Landsat 8, and HV = HV backscatter coefficient of ALOS-2 PALSAR-2.

The model produced: $R^2 = 0.83$, RMSE = 0.96 Mg/ha. Thus, 83.0% of the variation in measured AGB was explained jointly by DVI and HV in the fitted model.

The repeated 10-fold cross-validation process with five repetitions showed that the AGB model had very good and consistent predictions in validation. The mean validation R^2 was 0.81 ± 0.006 , showing that 81% of the variation in the observed AGB was explained by the model in validation, and the corresponding mean validation RMSE was 0.99 ± 0.015 Mg/ha. This RMSE indicates low prediction error in AGB. The little variation in R^2 and RMSE for the repeated cross-validation also shows consistent model performance. The above-mentioned results show that the model had good predictive accuracy and robust validation performance for estimating AGB.

4.4. Multilinear Model Regression Diagnostics

The regression diagnostics results demonstrated strong relationships between measured AGB and both remotely sensed parameters. The DVI exhibited a strong positive relationship with AGB ($r = 0.83$); this indicates that plots with greater DVI values generally had greater measured biomass. The HV showed an even stronger relationship with AGB, but the relationship was negative ($r = -0.90$); thus, increasing HV values were associated with decreasing AGB. The two predic-

tors were also strongly negatively correlated ($r = -0.82$); the negative correlation means that higher DVI values tend to occur with lower HV values. The variance inflation factor (VIF) for both DVI and HV was approximately 3.07. Although DVI and HV were strongly correlated ($r = -0.82$), the VIF values were below commonly used thresholds of 5 to 10. Therefore, the model did not exhibit severe multicollinearity according to the VIF criterion.

Residual-versus-fitted plot (**Figure 2**) was examined to assess linearity and homoscedasticity, while Q-Q plot (**Figure 3**) was used to assess the approximate normality of residuals. Shapiro-Wilk test gave result of $W = 0.986$, which indicates that there is insufficient evidence to reject normality of the residuals.

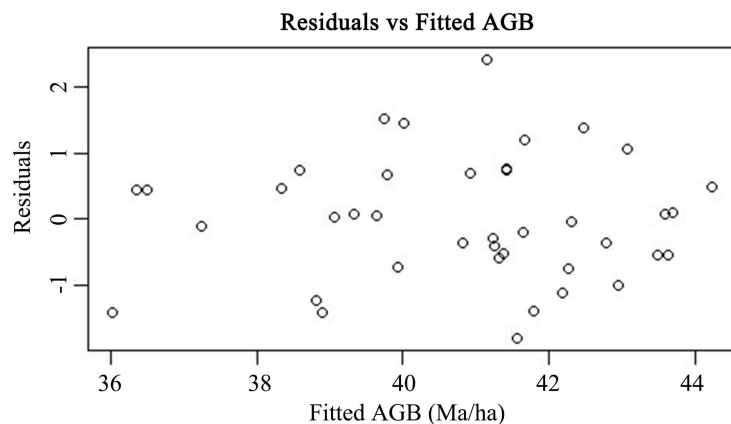


Figure 2. Residuals vrs fitted plot.

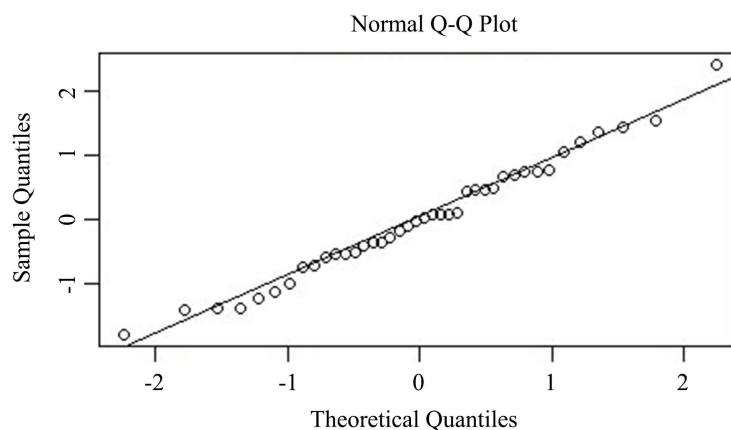


Figure 3. Normal Quantile-Quantile(Q-Q) plot.

From **Figure 2**, the residuals are evenly spread around zero with no systematic curvature or changes in distribution across fitted AGB values, suggesting that the linear model seems to be appropriate for the relationship between the satellite data-derived predictors and the AGB.

From **Figure 3**, the normal Q-Q plot indicated that the model residuals were approximately normally distributed, as most observations closely followed the theoretical normal distribution line, with only minor deviations at the tails.

The influence diagnostics (**Figure 4** and **Figure 5**) indicated that the most extreme observations were observation 3 and observation 14. Observation 14 had a Cook's distance of 0.154 and a leverage of 0.063, while observation 3 had the largest value of Cook's distance (0.164) and the largest value of leverage (0.161). The maximum Cook's distance of 0.164 was well below the conventional threshold of 1.0, indicating that no individual observation exerted extreme influence on the fitted multiple-linear-regression model. Although observations 3 and 14 were flagged for diagnostic screening based on commonly used influence and leverage criteria, they were not excluded because influence does not necessarily indicate error measurements. The observations were therefore retained because they may represent genuine field measurements in aboveground biomass and/or the associated satellite-derived DVI and HV measurements.

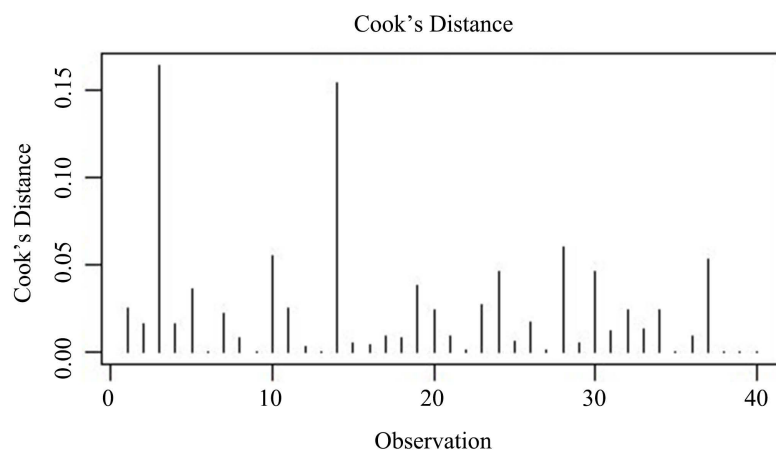


Figure 4. Cook's distance observation influence.

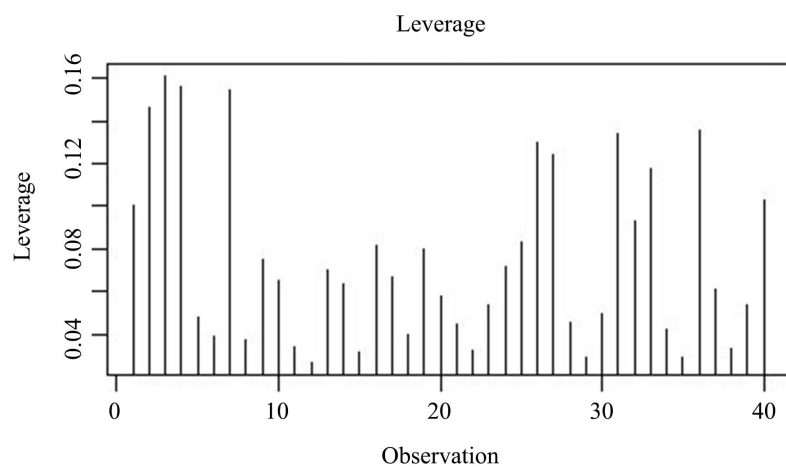


Figure 5. Leverage observation influence.

4.5. Comparing Models

Table 8 presents the best model of Landsat 8 and ALOS-2 PALSAR-2 as well as the MLR model with their R^2 and RMSE.

Table 8. Results of the best models of Landsat 8, ALOS-2 PALSAR-2 and MLR model.

Image	Model	R^2	RMSE
Landsat 8	$AGB = 0.00115DVI + 27.6$	0.79	0.97 Mg/ha
PALSAR -2	$AGB = 6.17HV + 114.28$	0.63	1.29 Mg/ha
Combined Landsat 8 and PALAR-2	$AGB = 6.97 * 10^{-4}DVI + 3.56HV + 74.88$	0.83	0.96 Mg/ha

Results from **Table 8** showed that the MLR model, $AGB = 6.97 * 10^{-4}DVI + 3.56HV + 74.88$, produced the highest performance ($R^2 = 0.83$, $RMSE = 0.96$ Mg/ha); hence, this model was used to predict AGB of cocoa plantations for the study area.

Combining DVI and HV using multi linear regression produced R^2 of 0.83 and RMSE of 0.96 Mg/ha as presented in **Table 8**. This shows that combining Landsat 8 and ALOS-2 PALSAR-2 parameters improved AGB estimates. This result is in line with the findings of research conducted by [17], where they pointed out that combining Landsat and SAR images can increase the accuracy of estimating AGB. In this study, Landsat 8 data could only be used to estimate cocoa AGB with moderate accuracy, whereas ALOS-2 PALSAR-2 data alone would produce poor AGB estimates for cocoa AGB. Integration of Landsat 8 data and ALOS-2 PALSAR-2 produced the highest AGB estimation; this shows that combining images from different sensors improves AGB estimation.

4.6. AGB Mapping

Table 9 displays the performances of the UK, OK, IDW, and RBF interpolation methods.

Table 9. Performances of the interpolation methods.

Interpolation Method	Efficiency			Error	
	R^2	I_A	P-value	RMSE	MAE
UK	0.86	0.89	2.20×10^{-16}	0.71	0.59
OK	0.85	0.88	9.09×10^{-15}	0.73	0.61
IDW	0.71	0.81	1.21×10^{-11}	0.95	0.77
RBF	0.67	0.79	1.18×10^{-10}	1.05	0.82

Quantitative comparisons of these four interpolation methods, UK, OK, IDW, and RBF, are based on their efficiencies (R^2 , I_A , P-value) and their errors (RMSE and MAE) associated with their predictions. Selection of the best interpolation method is based on the highest R^2 , the highest I_A , the lowest P-value, and the smallest error values. The R^2 ranged from 0.67 to 0.86, with the UK having the highest value of 0.86 and the lowest, 0.67, obtained by RBF. The R^2 performance of OK is 0.85, which is very close to the UK. The I_A has a minimum value of 0.79 for RBF and a maximum of 0.89 for UK. The lowest P-value of 2.20×10^{-16} is for the UK

and the highest value of 1.18×10^{-10} is for RBF.

The RMSE ranged from 0.71 to 1.05 and MAE from 0.59 to 0.82, with UK and RBF obtaining the lowest and highest errors, respectively. In all aspects of the comparison, the performance of OK is close to UK (**Table 9**). The best interpolation method based on R^2 , I_A , P-value, RMSE, and MAE is UK, followed by OK, IDW and the least is RBF. The UK interpolation method was used to produce the final AGB map with total AGB in the range (4973833.80 - 5240128.92) Mg for cocoa plantations in the study area.

4.7. Universal Kriging Trend Model, Variogram Selection and Cross Validation

Universal kriging was used to model the AGB with satellite-derived predictors and the residual spatial component. The trend component was specified as a multiple linear regression of AGB on DVI and HV, expressed as $AGB(s) = \beta_0 + \beta_1 DVI(s) + \beta_2 HV(s) + \varepsilon(s)$, where $\varepsilon(s)$ represents spatial residual component. Data set of 40 observations was used in fitting the trend component; the fitted trend equation was $AGB = 74.88 + 6.97 \times 10^{-4} DVI + 3.56 HV$, with R^2 of 0.83. The residual semi variogram estimated from pairwise distances between observations and fitted using spherical, exponential and Gaussian models. The models were assessed using the residual sum of squared (RSS) differences and the model with the least RSS was selected. Model comparison based on the RSS differences identified the Gaussian model as the best-fitting candidate, although its advantage over the spherical model was small (**Table 10**). The fitted variogram indicated a relatively large nugget term and weak partial sill, suggesting limited residual spatial dependence within the sampled area. Leave-one-out cross validation was used to evaluate the predictive performance of the model, whereby each observation was withheld sequentially and predicted from the remaining observations. The resulting cross-validated RMSE was 0.98 Mg/ha, MAE was 0.79 Mg/ha, and cross-validated R^2 was 0.81. These results indicate good predictive performance, while the weak residual spatial structure suggests that most of the predictive information was provided by the DVI and HV trend component.

Table 10. Model statistics.

Model	Nugget	Partial sill	RSS
Spherical	0.8678	0.0001	0.134071
Exponential	0.8678	0.0000	0.134071
Gaussian	0.8662	0.0735	0.134054

4.8. Estimates of AGB

Equation (15), $AGB = 6.97 \times 10^{-4} DVI + 3.56 HV + 74.88$, was used to predict AGB for 1273 plots and to develop a map of AGB for cocoa plantations in the study area (**Figure 6**). The AGB estimates ranged between 30.4 and 42.2 Mg/ha; the estimated AGB range is a little lower than the field AGB (**Table 5**).

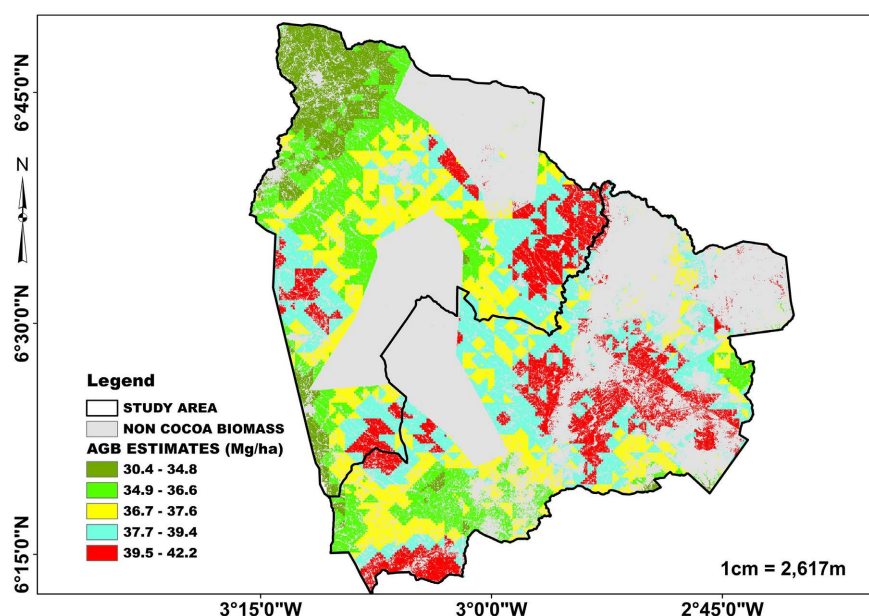


Figure 6. AGB distribution map of cocoa plantations in Juaboso and Bia West Districts, Ghana.

5. Conclusion

The study developed regression models between AGB and satellite parameters of Landsat 8 vegetation indices and backscatter coefficients of ALOS-2 PALSAR-2 data to predict AGB of cocoa plantations, which was used to produce an AGB map of cocoa plantations in the Juaboso and Bia West districts of Ghana. This map provides information on the spatial distribution of AGB of cocoa plantations in the study area, which is critical for national greenhouse gas inventories. The models developed in this study can quantify AGB and subsequently CO₂ emissions, which are crucial for estimating emission levels in cocoa plantations as part of the REDD + project within the cocoa landscape. Integration of Landsat 8 data and the ALOS-2 PALSAR-2 produced the highest AGB estimation; therefore, this study has confirmed that combining images from different sensors improves AGB estimation. The results of this study have shown that the cocoa plantations have a substantial amount of AGB, which sequesters more carbon dioxide from the atmosphere and deposits it in their sinks as carbon; therefore, cocoa plantations provide a lot of climate change mitigation.

Author Contributions

Emmanuel Donkor (ED): Conceptualization, investigation, data collection, formal analysis, writing—original draft, writing—review and editing, visualization. Samuel Ato Andam-Akorful (SAAA): Formal analysis, writing—original draft, writing—review and editing, supervision. Edward Matthew Osei Jnr (EMO): Writing—original draft, writing—review and editing, supervision. Addo Koranteg (AK): Formal analysis, writing—original draft, writing—review and editing. Stephen Adu-Bredu (SAB): Formal analysis, writing—original draft, writing—review and

editing, supervision. Finances are borne by the authors. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

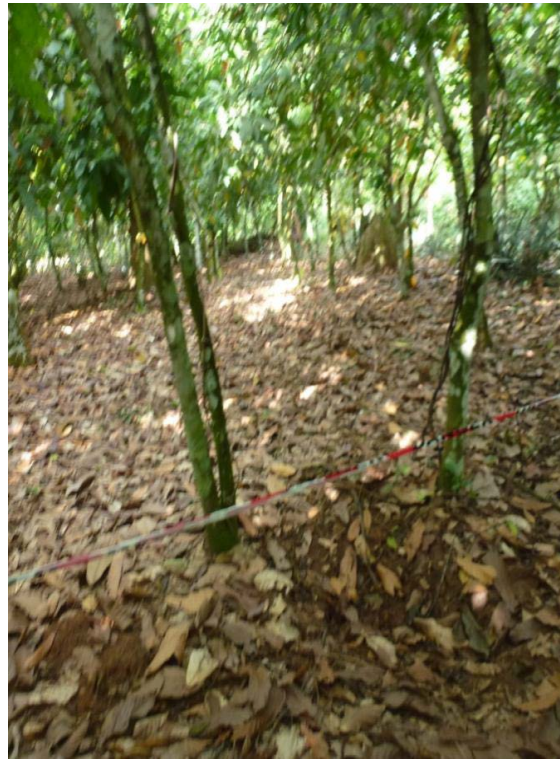
- [1] Watson, R.T., Gitay, H., Suarez, A. and Dokken, D.J. (2002) Climate Change and Biodiversity. Intergovernmental Panel on Climate Change.
- [2] Chen, Q. (2015) Modeling Aboveground Tree Woody Biomass Using National-Scale Allometric Methods and Airborne Lidar. *ISPRS Journal of Photogrammetry and Remote Sensing*, **106**, 95-106. <https://doi.org/10.1016/j.isprsjprs.2015.05.007>
- [3] Mojid, M.A. (2020) Climate Change-Induced Challenges to Sustainable Development in Bangladesh. *IOP Conference Series: Earth and Environmental Science*, **423**, Article ID: 012001. <https://doi.org/10.1088/1755-1315/423/1/012001>
- [4] Chen, W., Chen, J., Liu, J. and Cihlar, J. (2000) Approaches for Reducing Uncertainties in Regional Forest Carbon Balance. *Global Biogeochemical Cycles*, **14**, 827-838. <https://doi.org/10.1029/1999gb001206>
- [5] Chave, J., Olivier, J., Bongers, F., Châtelet, P., Forget, P., van der Meer, P., *et al.* (2008) Above-Ground Biomass and Productivity in a Rain Forest of Eastern South America. *Journal of Tropical Ecology*, **24**, 355-366. <https://doi.org/10.1017/s0266467408005075>
- [6] Albrecht, A. and Kandji, S.T. (2003) Carbon Sequestration in Tropical Agroforestry Systems. *Agriculture, Ecosystems & Environment*, **99**, 15-27. [https://doi.org/10.1016/s0167-8809\(03\)00138-5](https://doi.org/10.1016/s0167-8809(03)00138-5)
- [7] Kongsager, R., Napier, J. and Mertz, O. (2013) The Carbon Sequestration Potential of Tree Crop Plantations. *Mitigation and Adaptation Strategies for Global Change*, **18**, 1197-1213. <https://doi.org/10.1007/s11027-012-9417-z>
- [8] Mohammed, A.M., Robinson, J.S., Midmore, D. and Verhoef, A. (2016) Carbon Storage in Ghanaian Cocoa Ecosystems. *Carbon Balance and Management*, **11**, Article No. 6. <https://doi.org/10.1186/s13021-016-0045-x>
- [9] Ministry of Food and Agriculture (MoFA) (2015) Agriculture in Ghana: Facts and Figures 2015. Statistics, Research and Information Directorate (SRID), Ministry of Food and Agriculture.
- [10] Acheampong, E., Dawoe, E., Bosu, P. and Asante, W. (2014) Moving Forward with REDD + in Ghana: Shade Systems, Crown Cover, Carbon Stocks and Socio-Economic Dynamics of Smallholder Cocoa Agroforestry Systems. REDD + Energy and Agriculture Programme.
- [11] Mustari, K., Asrul, L., Kaimuddin, and Faradilla, L. (2020) Carbon Stock Analysis of Some Cocoa Planting Systems in South Sulawesi. *IOP Conference Series: Earth and Environmental Science*, **486**, Article ID: 012085. <https://doi.org/10.1088/1755-1315/486/1/012085>
- [12] Asrul, L. (2013) Cocoa Agribusiness. Nation Media Publisher.
- [13] Afele, J.T., Dawoe, E., Abunyewa, A.A., Afari-Sefa, V. and Asare, R. (2021) Carbon Storage in Cocoa Growing Systems across Different Agroecological Zones in Ghana. *Pelita Perkebunan (a Coffee and Cocoa Research Journal)*, **37**, 32-49. <https://doi.org/10.22302/iccricri.jur.pelitaperkebunan.v37i1.395>

- [14] Galidaki, G., Zianis, D., Gitas, I., Radoglou, K., Karathanassi, V., Tsakiri-Strati, M., *et al.* (2017) Vegetation Biomass Estimation with Remote Sensing: Focus on Forest and Other Wooded Land over the Mediterranean Ecosystem. *International Journal of Remote Sensing*, **38**, 1940-1966. <https://doi.org/10.1080/01431161.2016.1266113>
- [15] Mitchard, E.T., Saatchi, S.S., Baccini, A., Asner, G.P., Goetz, S.J., Harris, N.L., *et al.* (2013) Uncertainty in the Spatial Distribution of Tropical Forest Biomass: A Comparison of Pan-Tropical Maps. *Carbon Balance and Management*, **8**, Article No. 10. <https://doi.org/10.1186/1750-0680-8-10>
- [16] Avtar, R., Komolafe, A.A., Kouser, A., Singh, D., Yunus, A.P., Dou, J., *et al.* (2020) Assessing Sustainable Development Prospects through Remote Sensing: A Review. *Remote Sensing Applications: Society and Environment*, **20**, Article ID: 100402. <https://doi.org/10.1016/j.rsase.2020.100402>
- [17] Cutler, M.E.J., Boyd, D.S., Foody, G.M. and Vetrivel, A. (2012) Estimating Tropical Forest Biomass with a Combination of SAR Image Texture and Landsat TM Data: An Assessment of Predictions between Regions. *ISPRS Journal of Photogrammetry and Remote Sensing*, **70**, 66-77. <https://doi.org/10.1016/j.isprsjprs.2012.03.011>
- [18] Kelsey, K. and Neff, J. (2014) Estimates of Aboveground Biomass from Texture Analysis of Landsat Imagery. *Remote Sensing*, **6**, 6407-6422. <https://doi.org/10.3390/rs6076407>
- [19] Lucas, R.M., Mitchell, A.L. and Armston, J. (2015) Measurement of Forest Above-Ground Biomass Using Active and Passive Remote Sensing at Large (Subnational to Global) Scales. *Current Forestry Reports*, **1**, 162-177. <https://doi.org/10.1007/s40725-015-0021-9>
- [20] Lu, D. (2006) The Potential and Challenge of Remote Sensing-Based Biomass Estimation. *International Journal of Remote Sensing*, **27**, 1297-1328. <https://doi.org/10.1080/01431160500486732>
- [21] Asner, G.P. (2001) Cloud Cover in Landsat Observations of the Brazilian Amazon. *International Journal of Remote Sensing*, **22**, 3855-3862. <https://doi.org/10.1080/01431160010006926>
- [22] Joshi, N., Mitchard, E., Schumacher, J., Johannsen, V., Saatchi, S. and Fensholt, R. (2015) L-Band SAR Backscatter Related to Forest Cover, Height and Aboveground Biomass at Multiple Spatial Scales across Denmark. *Remote Sensing*, **7**, 4442-4472. <https://doi.org/10.3390/rs70404442>
- [23] Mermoz, S., Réjou-Méchain, M., Villard, L., Le Toan, T., Rossi, V. and Gourlet-Fleury, S. (2015) Decrease of L-Band SAR Backscatter with Biomass of Dense Forests. *Remote Sensing of Environment*, **159**, 307-317. <https://doi.org/10.1016/j.rse.2014.12.019>
- [24] Goh, J., Miettinen, J., Chia, A.S., Chew, P.T. and Liew, S. (2014) Biomass Estimation in Humid Tropical Forest Using a Combination of ALOS PALSAR and SPOT 5 Satellite Imagery. *Asian Journal of Geoinformatics*, **13**, 59-72.
- [25] Guo, Y., Zhu, M., Wu, Y., Ni, J., Liu, L. and Xu, Y. (2023) Estimating Forest Above-ground Biomass Combining Pléiades Satellite Imagery and Field Inventory Data in the Peak-Cluster Karst Region of Southwestern China. *Forests*, **14**, Article 1760. <https://doi.org/10.3390/f14091760>
- [26] Lu, D., Chen, Q., Wang, G., Moran, E., Batistella, M., Zhang, M., *et al.* (2012) Above-ground Forest Biomass Estimation with Landsat and Lidar Data and Uncertainty Analysis of the Estimates. *International Journal of Forestry Research*, **2012**, Article ID: 436537. <https://doi.org/10.1155/2012/436537>
- [27] Kumar, P., Sharma, L.K., Pandey, P.C., Sinha, S. and Nathawat, M.S. (2013) Geospa-

- tial Strategy for Tropical Forest-Wildlife Reserve Biomass Estimation. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, **6**, 917-923. <https://doi.org/10.1109/jstars.2012.2221123>
- [28] Vaglio Laurin, G., Puletti, N., Chen, Q., Corona, P., Papale, D. and Valentini, R. (2016) Above Ground Biomass and Tree Species Richness Estimation with Airborne Lidar in Tropical Ghana Forests. *International Journal of Applied Earth Observation and Geoinformation*, **52**, 371-379. <https://doi.org/10.1016/j.jag.2016.07.008>
- [29] Adeniyi, P. and Ezekiel, A. (2017) Modelling and Comparison of Above-Ground Tree Biomass of Omo Biosphere Reserve Using Field and Landsat 8 Data. *British Journal of Applied Science & Technology*, **19**, 1-10. <https://doi.org/10.9734/bjast/2017/32166>
- [30] Avtar, R., Suzuki, R., Takeuchi, W. and Sawada, H. (2013) PALSAR 50 m Mosaic Data Based National Level Biomass Estimation in Cambodia for Implementation of REDD+ Mechanism. *PLOS ONE*, **8**, e74807. <https://doi.org/10.1371/journal.pone.0074807>
- [31] Viet Nguyen, L., Tateishi, R., Kondoh, A., Sharma, R., Thanh Nguyen, H., Trong To, T., et al. (2016) Mapping Tropical Forest Biomass by Combining ALOS-2, Landsat 8, and Field Plots Data. *Land*, **5**, Article 31. <https://doi.org/10.3390/land5040031>
- [32] Nga, T.N. (2010) Estimation and Mapping of above Ground Biomass for the Assessment and Mapping of Carbon Stocks in Tropical Forest Using SAR Data: A Case Study in Afram Headwaters Forest, Ghana. Master's Thesis, International Institute for Geo-Information Science and Earth Observation.
- [33] Karami, O., Fallah, A., Shataee, S.H. and Latifi, H. (2018) Assessment of Geostatistical and Interpolation Methods for Mapping Forest Dieback Intensity in Zagros Forests. *Caspian Journal of Environmental Sciences*, **16**, 71-84.
- [34] Corzo, G. and Varouchakis, E. (2018) Spatiotemporal Analysis of Extreme Hydrological Events. Elsevier.
- [35] Calder, C.A. and Cressie, N. (2009) Kriging and Variogram Models. In: Kitchoin, R. and Thrift, N., Eds., *International Encyclopedia of Human Geography*, Elsevier, 49-55. <https://doi.org/10.1016/b978-008044910-4.00461-2>
- [36] Al-Mamoori, S.K., Al-Maliki, L.A., Al-Sulttani, A.H., El-Tawil, K. and Al-Ansari, N. (2021) Statistical Analysis of the Best GIS Interpolation Method for Bearing Capacity Estimation in An-Najaf City, Iraq. *Environmental Earth Sciences*, **80**, Article No. 683. <https://doi.org/10.1007/s12665-021-09971-2>
- [37] Isaaks, E.H. and Srivastava, R.M. (1989) An Introduction to Applied Geostatistics. Oxford University Press.
- [38] Goovaerts, P. (1997) Geostatistics for Natural Resources Evaluation. Oxford University Press.
- [39] Ghana Statistical Service (2014) District Analytical Report: Juaboso and Bia West Districts.
- [40] Hall, J.B. and Swaine, M.D. (1981) Distribution and Ecology of Vascular Plants in a Tropical Rain Forest: Forest Vegetation in Ghana. Springer.
- [41] Anim-Kwapong, G.J. and Frimpong, E.B. (2004) Vulnerability and Adaptation Assessment under the Netherlands Climate Change Studies Assistance Programme Phase 2 (NCCSAP2). Cocoa Research Institute of Ghana.
- [42] Rouse, J.W., Haas, R.H., Schell, J.A. and Deering, D.W. (1974) Monitoring Vegetation Systems in the Great Plains with ERTS. *NASA Special Publication*, **35**, 309.
- [43] Richardson, A.J. and Weigand, C. (1977) Distinguishing Vegetation from Soil Background Information. *Photogrammetric Engineering and Remote Sensing*, **43**, 183-191.

- [44] Deering, D.W., Rouse, J.W., Haas, R.H. and Schell, J.A. (1975) Measuring “Forage Production” of Grazing Units from Landsat MSS Data. *Proceedings of the 10th International Symposium on Remote Sensing of Environment*, **II**, 1169-1178.
- [45] Jordan, C.F. (1969) Derivation of Leaf-Area Index from Quality of Light on the Forest Floor. *Ecology*, **50**, 663-666. <https://doi.org/10.2307/1936256>
- [46] Liu, H.Q. and Huete, A. (1995) A Feedback Based Modification of the NDVI to Minimize Canopy Background and Atmospheric Noise. *IEEE Transactions on Geoscience and Remote Sensing*, **33**, 457-465. <https://doi.org/10.1109/tgrs.1995.8746027>
- [47] Silleos, N.G., Alexandridis, T.K., Gitas, I.Z. and Perakis, K. (2006) Vegetation Indices: Advances Made in Biomass Estimation and Vegetation Monitoring in the Last 30 Years. *Geocarto International*, **21**, 21-28. <https://doi.org/10.1080/10106040608542399>
- [48] Donkor, E., Adu-Bredu, S., Jnr, E.M.O., Andam-Akorful, S.A. and Mohammed, Y. (2023) Biomass Estimation Models for Cocoa (*Theobroma cacao*) Plantations in Ghana, West Africa. *Open Journal of Applied Sciences*, **13**, 1588-1618. <https://doi.org/10.4236/ojapps.2023.139126>
- [49] Intergovernmental Panel on Climate Change (IPCC) (2006) 2006 IPCC Guidelines for National Greenhouse Gas Inventories: Volume 4—Agriculture, Forestry and Other Land Use, Chapter 4—Forest Land. Institute for Global Environmental Strategies (IGES).

Appendix



Cocoa plantation with sample plot delineated with caution tape



DBH measurement of cocoa tree