

Article

Synthesizing Local Capacities, Multi-Source Remote Sensing and Meta-Learning to Optimize Forest Carbon Assessment in Data-Poor Regions

Kamaldeen Mohammed ^{1,*} , Daniel Kpienbaareh ², Jinfei Wang ¹ , David Goldblum ³ , Isaac Luginaah ¹ , Esther Lupafya ⁴ and Laifolo Dakishoni ⁴

¹ Department of Geography and Environment, Western University, 1151 Richmond Street, London, ON N6A 3K7, Canada

² Department of Geography, Geology and the Environment, Illinois State University, Normal, IL 61790-400, USA

³ Department of Geography and Tourism, Brock University, 1812 Sir Isaac Brock Way, St. Catharines, ON L2S 3A1, Canada

⁴ Soils, Food and Healthy Communities (SFHC), Ekwendeni P.O. Box 36, Malawi

* Correspondence: kmoham27@uwo.ca

Abstract: As the climate emergency escalates, the role of forests in carbon sequestration is paramount. This paper proposes a framework that integrates local capacities, multi-source remote sensing data, and meta-learning to enhance forest carbon assessment methodologies in data-scarce regions. By integrating multi-source optical and radar remote sensing data alongside community forest inventories, we applied a meta-modelling approach using stacked generalization ensemble to estimate forest above-ground carbon (AGC). We also conducted a Kruskal–Wallis test to determine significant differences in AGC among different tree species. The Kruskal–Wallis test ($p = 1.37 \times 10^{-13}$) and Dunn post-hoc analysis revealed significant differences in carbon stock potential among tree species, with *Azelia quanzensis* ($\bar{x} = 12$ kg/ha, P-holm-adj. = 0.05) and the locally known species *M'buta* ($\bar{x} = 6$ kg/ha, P-holm-adj. = 5.45×10^{-9}) exhibiting a significantly higher median AGC. Our results further showed that combining optical and radar remote sensing data substantially improved prediction accuracy compared to single-source remote sensing data. To improve forest carbon assessment, we employed stacked generalization, combining multiple machine learning algorithms to leverage their complementary strengths and address individual limitations. This ensemble approach yielded more robust estimates than conventional methods. Notably, a stacking ensemble of support vector machines and random forest achieved the highest accuracy ($R^2 = 0.84$, RMSE = 1.36), followed by an ensemble of all base learners ($R^2 = 0.83$, RMSE = 1.39). Additionally, our results demonstrate that factors such as the diversity of base learners and the sensitivity of meta-learners to optimization can influence stacking performance.

Keywords: forest; above-ground carbon; participatory GIS; remote sensing; stacking



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1. Introduction

As the adverse impacts of the climate crisis become more imminent, there are increasing global efforts to mitigate climate change threats through carbon abatement and sequestration. One of the key approaches to carbon sequestration is through natural carbon sinks such as forest ecosystems [1–3]. Forest ecosystems are the largest terrestrial carbon

sinks and account for 62–78% of all terrestrial carbon sinks [4,5]. Forests in tropical regions are projected to sequester between 0.5 and 3.6 GtCO₂ year^{−1} by 2050 [2]. Improved estimation of forest carbon sinks is needed to evaluate forests' carbon sequestration potential, especially at macro and micro scales in the Global South. Improved sequestration is particularly relevant for the United Nations Framework Convention on Climate Change (UNFCCC) emission reduction initiatives such as Reducing Emissions from Deforestation and Forest Degradation (REDD+) and other sustainable forest conservation and management incentives. Quantifying forest carbon stocks in Sub-Saharan Africa (SSA) remains a challenge due to the limited capacity for forest inventories, the lack of relevant data, and appropriate carbon assessment techniques.

The most accurate method of estimating forest above-ground carbon (AGC) is destructive sampling, which is labour-intensive and impractical for the large-scale estimation of forest carbon pools [6]. While ground-based forest inventory approaches for estimating AGC through allometric equations are relatively accurate at micro scales, they are expensive and time-consuming to implement at macro scales. Nevertheless, advancement in photogrammetry technology such as Light Detection and Ranging (LIDAR) allows the measurement of tree dimensions to develop allometric equations or estimate forest ecosystem above-ground biomass and carbon stocks [7–9]. However, LIDAR technology is also expensive and has limited coverage in rural communities in SSA, where carbon storage estimation for indigenous trees is nascent, and the resources and expertise to implement forest carbon monitoring are lacking.

Forest inventory has historically been the purview of foresters due to prejudice on the quality and credibility of community-generated forest data [10,11]. However, recent studies have successfully engaged rural communities to collect quality and credible environmental data [11–14] that complement data collected with other methods to provide accurate and crucial data about local forest ecosystems. These community-based approaches to generating forest data mark a paradigm shift in research focusing on strengthening and empowering local communities in environmental monitoring and management. Strengthening local capacities can enable local communities to conduct forest inventories to generate relevant data for assessing forest carbon stocks.

Although field-based forest inventories remains essential for forest carbon stock estimation, remote sensing technologies are increasingly utilized to extend forest carbon monitoring to landscape scales. Radar and optical remote sensing, for instance, have proved to be useful in estimating the above-ground biomass (AGB) and AGC of tropical forests [15–17]. The use of remote sensing presents opportunities to reduce the labour requirements and costs associated with field-based methods and increase the spatial coverage over macro landscapes [18,19]. However, there are challenges associated with using remote sensing data for forest carbon assessment in SSA, including image quality issues due to environmental factors such as cloud covers [20] and sensor errors [21]. Nevertheless, integrating remote sensing and machine learning methods has become popular in estimating forest AGB and AGC stocks. These methods include random forest, support vector, gradient boosting, and neural networks [22–25]. We hypothesize that complementing the spatial coverage of remote sensing data and meta-learning analysis with locally generated forest field data would significantly improve forest carbon prediction accuracy.

Thus, we propose using meta-learning that integrates participatory forest inventory data with multi-source remote sensing to optimize the estimation of forest AGC. Specific research questions are: (i) Can participatory forest inventories provide forest data to support forest carbon stock assessment in local communities? (ii) Can optical and radar remote sensing data complement local inventory data to enhance AGC estimation? (iii) How do

machine learning and meta-learning models that utilize remote sensing and local inventory data perform in predicting forest AGC?

2. Materials and Methods

2.1. Study Area

The study area (Figure 1) is the Mzimba District in northern Malawi, which is considered one of the country's most vulnerable regions to the adverse effects of climate change [26]. Malawi is located between latitudes 9° and 17° south of the equator and is characterized by features such as Lake Malawi and the Great Rift Valley. The Mzimba district covers an approximate land area of 10,400 km² and a population of 940,184 [27]. The climate of Mzimba is mainly sub-tropical, with average monthly maximum temperatures between 27 °C and 33 °C and annual rainfall varying between 600 mm in the rift valley floor and about 1600 mm in the mountainous areas [28]. Mzimba is part of the Miombo woodlands biome, which is characterized by subtropical savanna and shrubland [29].

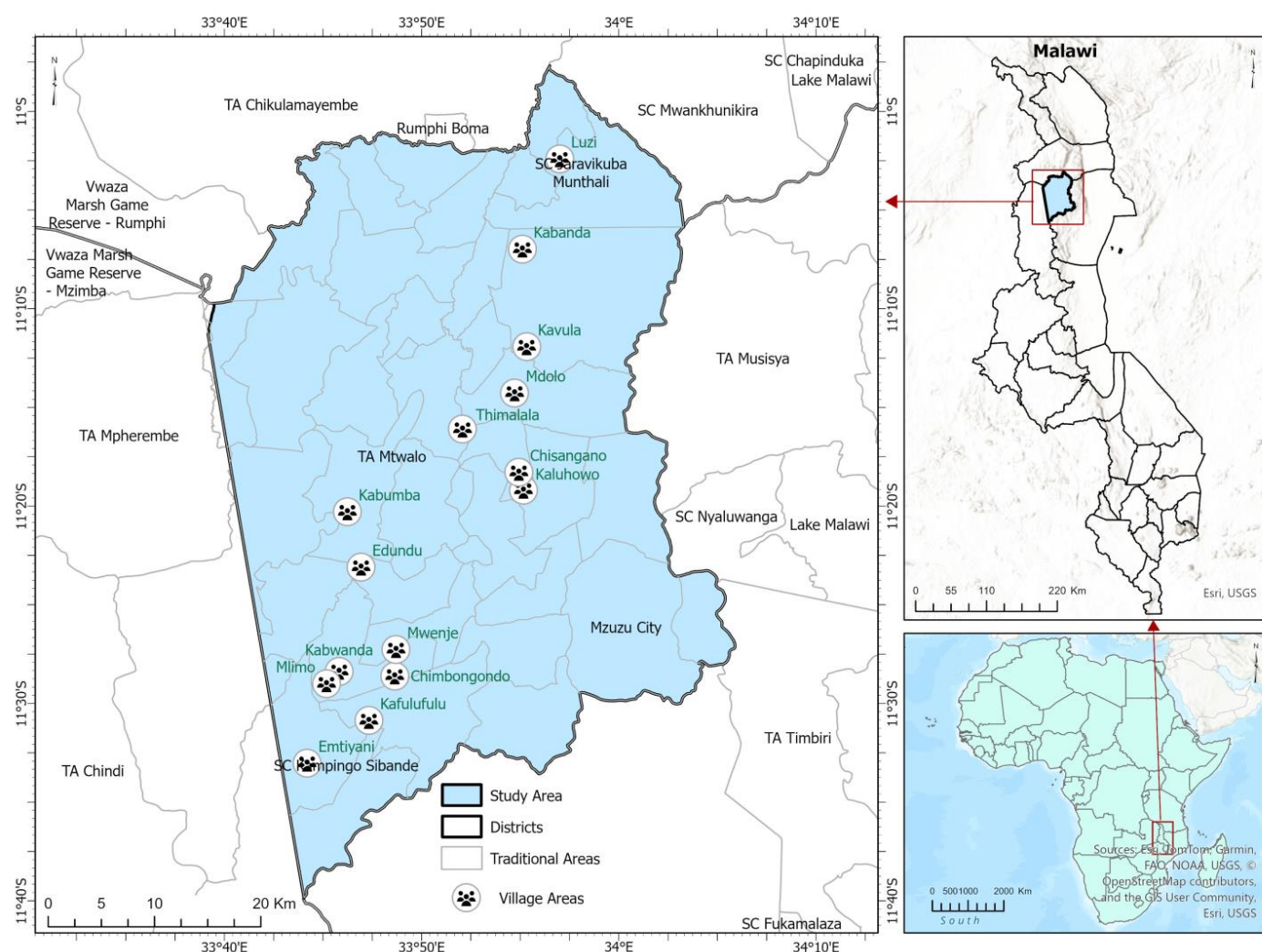


Figure 1. Map of study area: northern Mzimba. Note: Map lines of northern Mzimba delineate study area boundaries and do not necessarily depict accepted national boundaries.

The Miombo woodlands are a vital ecological zone characterized by a unique combination of vegetation and climatic conditions [30]. The Miombo woodlands are part of the broader woody savanna vegetation that span more than 2.7 million km² in southern and central Africa [31]. The woodland is deciduous and sheds leaves during the dry season. The

Miombo is also characterized by an open canopy, allowing sunlight to penetrate through to support an understory of grasses and shrubs. The Miombo woodlands in Malawi have been heavily altered through deforestation [29]. In Mzimba and Malawi, the major causes of forest loss include human settlement expansion, agricultural land expansion, wildfires, timber extraction, and charcoal production [13]. The main threat is anthropogenic deforestation. Malawi has an estimated 3,237,000 ha of forest cover, which represents about 34% of Malawi's total land area [32]. Between 2001 and 2023, Mzimba experienced a reduction of 34.6 thousand hectares in tree cover, representing a 24% decline since 2000. This loss corresponds to an estimated 14.6 Mt of CO₂ emissions [33]. It is with this context that we estimate forest AGC in Mzimba, Malawi.

2.2. Study Design

Participatory Forest Inventory

We used a participatory forest inventory involving local farmers, academics, and a local NGO. We leveraged local knowledge and stakeholder engagement for a forest carbon density assessment—measuring the amount of carbon stored per unit area within a forest ecosystem. By engaging local communities, the study leveraged indigenous expertise and observations to complement traditional inventory methods, improving data quality and fostering local stewardship and ownership of community resources such as forests. A total of ten community members were selected and trained to collect tree-level data (e.g., measuring height, diameter, shrub samples, and species diversity) from 15 communities (village areas). We used traditional forest inventory data collection methods and spatial mapping. Integrating local knowledge systems with geospatial tools to represent the spatial knowledge of community members is also known as Participatory GIS (PGIS) [34]. Integrating community participation in forest inventory and carbon assessment can enhance the prospects for building local skills and capacities for self-sufficiency in environmental assessments in rural communities in the Global South [14].

Before the field forest inventory, we designed a training program to build the capacity of selected community members to collect the forest field data. The training module is centred on forest plot establishment and assessment, GPS systems, tree measurements (height and diameter), and recording (Figure 2). A multistage sampling approach was employed in this study. First, we selected 15 village areas in Mzimba based on a belt transect. We created a belt transect to cover the middle section of the study area along the longest boundary (Figure 2). We selected communities (village areas) along the transect in partnership with the local non-profit organization. Our local partner recommended about 20 eligible communities based on their knowledge and experience of the local landscape. Key considerations included the accessibility and safety of the landscape and communities as well as spatial coverage of the transect. A total of 15 communities were selected for the participatory inventory. The data collection was from May to August, 2023. Ethical approval was granted by Western University Research Ethics Board.

2.3. Data Collection and Processing

2.3.1. Plot Demarcation and Assessment

An adaptive sampling approach was employed to select forest plots in the communities ($n = 15$). Adaptive sampling allows for the collection of forest inventory data while adjusting the sampling strategy based on the information gathered during the inventory process [35]. Adaptive sampling is noted to optimize resources and minimize the mean error of forest biomass estimates [35–37]. The size and spacing of forest inventory plots ($n = 66$) were based on community members' visual assessments of forest characteristics such as forest size, tree sparseness, and the presence of farms and other human footprints.

We used circular plots (Figure 3) with a radius of 20 m for sparse forests, 10 m for dense forests and an initial plot interval of 40 m, which was adjusted based on specific forest and landscape characteristics (e.g., participants visual assessment of forest size, tree sparseness). During the plot measurement, the participants also discussed each plot's forest ownership, the management practices, and the level of forest plot degradation based on visual inspection (e.g., felled trees, extensive grazing, dried/dead branches and leaves) and local knowledge/practices. Also, participants reported the major soil types using a simplified ribbon test—by rubbing soil between fingers to assess the texture (gritty = sand, sticky = clay, and a mixture of smooth with gritty and sticky = loam) [38].



Figure 2. Images from participatory GIS and forest inventory training in Mzimba, Malawi. Source: By authors.

2.3.2. Tree Measurements

The participants inventoried each plot by measuring the diameter at breast height (DBH), approximately 1.37 m above the ground, using a DBH tape measure, as required in standard forestry practices [39]. Tree height was measured using a True Pulse 360 laser range finder. Participants identified tree species in their local languages, which were translated into their respective scientific names. Community members also used a Garmin GPS receiver to record the center coordinate of each plot. After each plot measurement, a random sample of trees was remeasured by a different participant to assess the accuracy of height, location, and DBH data.

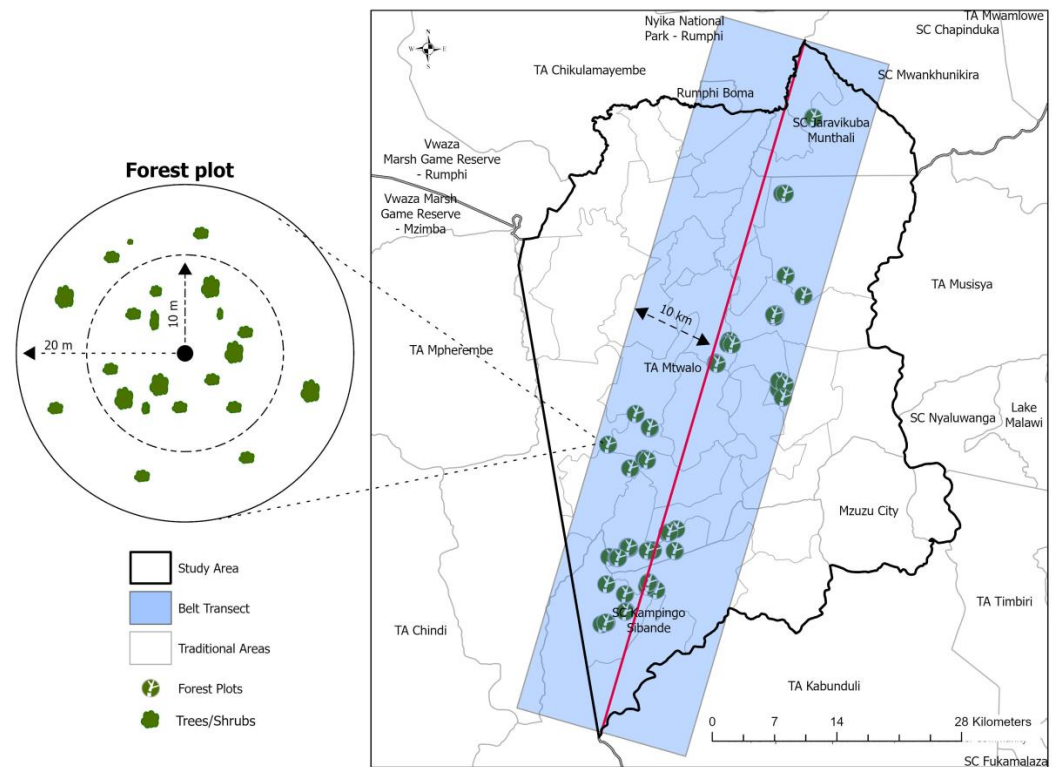


Figure 3. Illustration of the implementation of forest plots sampling in the study communities. The red line indicates the centre of the belt transect.

2.4. Analysis

2.4.1. Ecological Indices

We computed forest ecological indices such as the wood density, tree density, and Shannon index. The wood density was derived from the BIOMASS package in R using the ‘getWoodDensity’ function. This package retrieves the wood density of trees given the species, genus, family, and geographical region. The tree density was computed as the number of trees per hectare. The Shannon index is widely used in ecology to measure species diversity, accounting for species richness, evenness, and abundance. The Shannon index (H') is mathematically expressed in (Equation (1))

$$H' = - \sum_{i=1}^S p_i \times \ln(p_i) \quad (1)$$

where S = the total number of species, p_i = proportion of the tree species (i) relative to the total, and $\ln$ is the natural logarithm [40].

2.4.2. Forest Above Ground Biomass Using Allometric Equations

We reviewed the literature on allometric equations suitable for estimating mixed species forest AGB in Mzimba. A total of nine allometric equations were identified, three specifically from Malawi [41–43], four from neighbouring countries within the Miombo woodland [44–47], and two global allometric equations [48,49] (Table 1). Since there is no observed AGB data, we used bootstrapping to create multiple resampled datasets from the original data, and we then estimated the variability (e.g., bias, Std error) of the estimates by comparing the results across the multiple resampled datasets. After computing AGB, AGC was calculated by multiplying AGB by the carbon content conversion factor of 0.50 [50–52].

Also, the Kruskal Wallis test with Holm–Bonferroni adjustment and the Dunn test was used to test differences in tree species median AGC.

Table 1. Allometric equations for estimating forests AGB in Malawi.

Reference	Allometric Equation	Geography
[49]	$0.0673 \times (wd \times h \times dbh^2)^{0.976}$	Global
[48]	$0.1359 \times dbh^{2.32}$	Global
[47]	$0.1027 \times dbh^{2.4798}$	Tanzania
[44]	$0.0446 \times dbh^{2.765}$	Zambia
[45]	$0.0905 \times dbh^{2.4718}$	Kenya
[42]	$0.1428 \times dbh^{2.271}$	Malawi
[41]	$0.103685 \times dbh^{1.921719} \times h^{0.844561}$	Malawi
[46]	$0.6 \times dbh^{2.012} \times h^{0.71}$	Tanzania
[43]	$0.0637 \times dbh^{2.4788}$	Malawi

h = height, dbh = diameter at breast height, wd = wood density.

2.4.3. Optical and Radar Remote Sensing

We acquired publicly available satellite images from the European Space Agency’s Sentinel-1 and 2 program (Table 2). Sentinel-1 radar imagery has a sun-synchronous orbit with a revisit of 6 days, and it operates at an altitude of nearly 690 km. Sentinel-1 is equipped with the C-band Synthetic Aperture Radar (SAR), making it reliable for capturing vegetation characteristics because of the high cloud penetration. The pre-processing of the Sentinel-1 images included subsetting using the study area boundary and orbital correction to improve the geolocation of the satellite. Next, radiometric correction was performed to convert the digital numbers to backscatter values. We also applied speckle filtering (i.e., Lee) to reduce speckle noise. Terrain correction (i.e., the Range–Doppler method) was used to correct radiometric distortions because the study areas have an uneven topography. Geometric correction was performed, and the data was converted from backscatter values to decibels. We computed texture features (i.e., Gray-Level Co-Occurrence Matrix [GLCM]), backscatter coefficients, and principal component analysis to be used as predictors of the forests’ AGB (Table 2).

Table 2. Remote sensing data sources and characteristics.

Data Sources	Acquisition Data	Processing Level	Spectral Bands/Polarization	Spatial Resolution	Sensors
Sentinel-1	26 May 2023	Level 1 SLC	C-band, VV and HH polarizations	Interferometric Wide Swath (IW) 5 by 20 m	Aperture Radar (SAR)
Sentinel-2	25 May 2023	Level 2A	13 multispectral bands, 2.5% cloud cover	10 m (B2, B3, B4 and B8); 20 m (B5, B6, B7, B8a, B11 and B12); 60 m (B1, B9 and B10)	Synthetic Opto-electronic multispectral sensor

The availability of open-source multispectral satellite imagery such as Sentinel-2 has increased satellite remote sensing applications in environmental change analysis, including the estimation of forest AGB and AGC [15,53,54]. Sentinel-2 comprises two satellites, Sentinel-2A (launched in 2015) and Sentinel-2B (launched in 2017). Both constellations are equipped with 13-band multispectral sensors and together have a revisit cycle of 5 days. We used Sentinel-2A to compute indices including vegetation, texture features, biophysical, and principal component analysis. These indices are widely used as predictors of forest characteristics including forest biomass and carbon [25,55,56]. A total of 70 variables were generated from the Sentinel-1 and 2 images (Table 3).

Table 3. Description of indices from Sentinel-1 and 2 used as predictors of AGC.

Data	Measure	Indices	Description
Sentinel 2	Vegetation Indices	ARVI	Atmospherically Resistant Vegetation Index $\frac{NIR - 2 \times Red + Blue}{NIR + 2 \times Red + Blue}$
		DVI	Difference Vegetation Index $\frac{NIR}{Red}$
		GEMI	Global Environmental Monitoring Index $\eta(1 - 0.25 \times \eta) - \frac{Red - 0.125}{1 - red}, \text{ where } \eta = \frac{2 \times (NIR^2 - Red^2) + 1.5 \times Red}{NIR + Red + 0.5}$
		GNDVI	Green Normalized Difference Vegetation Index $\frac{NIR - Green}{NIR + Green}$
		IPVI	Infrared Percentage Vegetation Index $\frac{NIR}{NIR + Red}$
		MCARI	Modified Chlorophyll Absorption in Reflectance Index $(RedEdge - Red) - 0.2 \times (RedEdge - Green) \times \frac{RedEdge}{Red}$
		IRECI	Inverted Red Edge Chlorophyll Index $\frac{NIR - RedEdge}{RedEdge / Red}$
		MTCI	MERIS Terrestrial Chlorophyll Index $\frac{NIR - RedEdge}{RedEdge - Red}$
		MSAVI	Modified Soil-Adjusted Vegetation Index $\frac{2 \times NIR + 1 - \sqrt{(2 \times NIR + 1)^2 - 8 \times (NIR - Red)}}{2}$
		MSAVI2	Second Modified Soil-Adjusted Vegetation Index $\frac{1}{2} \left(\frac{2 \times NIR + 1 - \sqrt{(2 \times NIR + 1)^2 - 8 \times (NIR - Red)}}{2} \right)$
		NDI45	Normalized Difference Index 45 $\frac{NIR - RedEdge}{NIR + RedEdge}$
		NDVI	Normalized Difference Vegetation Index $\frac{NIR - Red}{NIR + Red}$
		PSSRA	Pigment Specific Simple Ratio $\frac{NIR}{Red}$
		S2REP	Sentinel-2 Red Edge Position $705 + 35 \times \frac{RedEdge - Red}{NIR - Red}$
		SAVI	Soil-Adjusted Vegetation Index $\frac{NIR - Red}{NIR + Red + L} \times (1 \times L)$
		TNDVI	Transformed NDVI $\frac{\sqrt{NIR} - \sqrt{Red}}{\sqrt{NIR} + \sqrt{Red}}$
		TSAVI	Transformed Soil-Adjusted Vegetation Index $a \frac{NIR - a \times Red - b}{Red + a \times NIR - a \times b + X \times (1 + a^2)}$ Where <i>a</i> and <i>b</i> are slope and intercept of soil line, and <i>X</i> is a scaling factor
		WDVI	Weighted Difference Vegetation Index $NIR - a \times Red, \text{ where } a \text{ is the slope of the soil line}$
		EVI	Enhanced Vegetation Index $G \times \frac{NIR - Red}{NIR + C1 \times Red - C2 \times Blue + L},$ where <i>G</i> , <i>C1</i> , <i>C2</i> , and <i>L</i> are coefficients
	Texture	GLCM of 5 × 5 window size	Gray Level Co-occurrence Matrix Mean, Contrast, Dissimilarity, Energy, Entropy, Correlation, Variance, Homogeneity, Angular Second Moment (ASM)
	Biophysical	PCA	Principal component analysis
		FAPAR	Fraction of Absorbed Photosynthetically Active Radiation
		FCOVER	Fraction of vegetation cover
		LAI	Leaf Area Index
		Lai Cab	Chlorophyll content in the leaf
		Lai CWC	Canopy Water Content

Table 3. Cont.

Data	Measure	Indices	Description
Sentinel-1	Texture	GLCM of 5×5 window size (VV, VH)	Gray Level Co-occurrence Matrix Mean, Contrast, Dissimilarity, Energy, Entropy, Correlation, Variance, Homogeneity, Angular Second Moment (ASM)
		Backscatter (Decibels [dB])	VH dB (vertical transmit and horizontal receive), VV dB (vertical transmit and vertical receive)
		PCA	Principal component analysis

2.4.4. Base Machine Learners

The association between remote sensing data and forest AGC is complex and requires experimentation to understand the suitability and strengths of various machine learning methods in predicting forest AGB. Thus, we compared the suitability of four machine learners, including Multiple Linear Regression (MLR), Random Forest (RF), Support Vector Machines (SVM) and Gradient Boosting (GB) in predicting forest AGB. We implemented appropriate hyperparameter tuning for each machine learning method using grid search. K-fold cross-validation was used to minimize overfitting and to provide more accurate model performance. Details of the techniques used in this paper are shown in the methodological framework (Figure 4).

Multiple Linear Regression (MLR)

MLR is a parametric regression technique that uses multiple predictor variables (e.g., the remote sensing variables) to estimate an outcome variable (e.g., forest AGC). MLR explains the direction and magnitude of the linear relationship between the predictor variables and the outcome. We used MLR to generate a linear function that models the relationship between remote sensing-derived parameters and forest AGC. MLR is simple and easy to interpret; however, it is insufficient for modelling non-linear relationships.

Random Forest (RF)

We used RF to model the non-linear association between the remote sensing predictors and AGC. Random forest is a non-parametric approach using ensemble learning and a decision tree framework for classification and regression [57,58]. Ensemble learning uses multiple models trained over a given set of data and averages the results of each model (i.e., a decision tree) to generate the most accurate and robust prediction [57]. Breiman explained RF as “a combination of tree predictors such that each tree depends on the values of a random vector sampled independently and with the same distribution for all trees in the forest” [57]. Random forest is based on a combination of multiple decision trees, with each decision tree voting for the assignment of the most common input class [16,59]. The majority vote among the trees informs the class prediction outcome. As a result, greater classifier stability is achieved, and the generalization error converges as the number of trees increases, avoiding data overfitting. RF exponentially increases computational intensity with increased calibration of data and covariates and is also highly sensitive to the predictions of the input data quality [57].

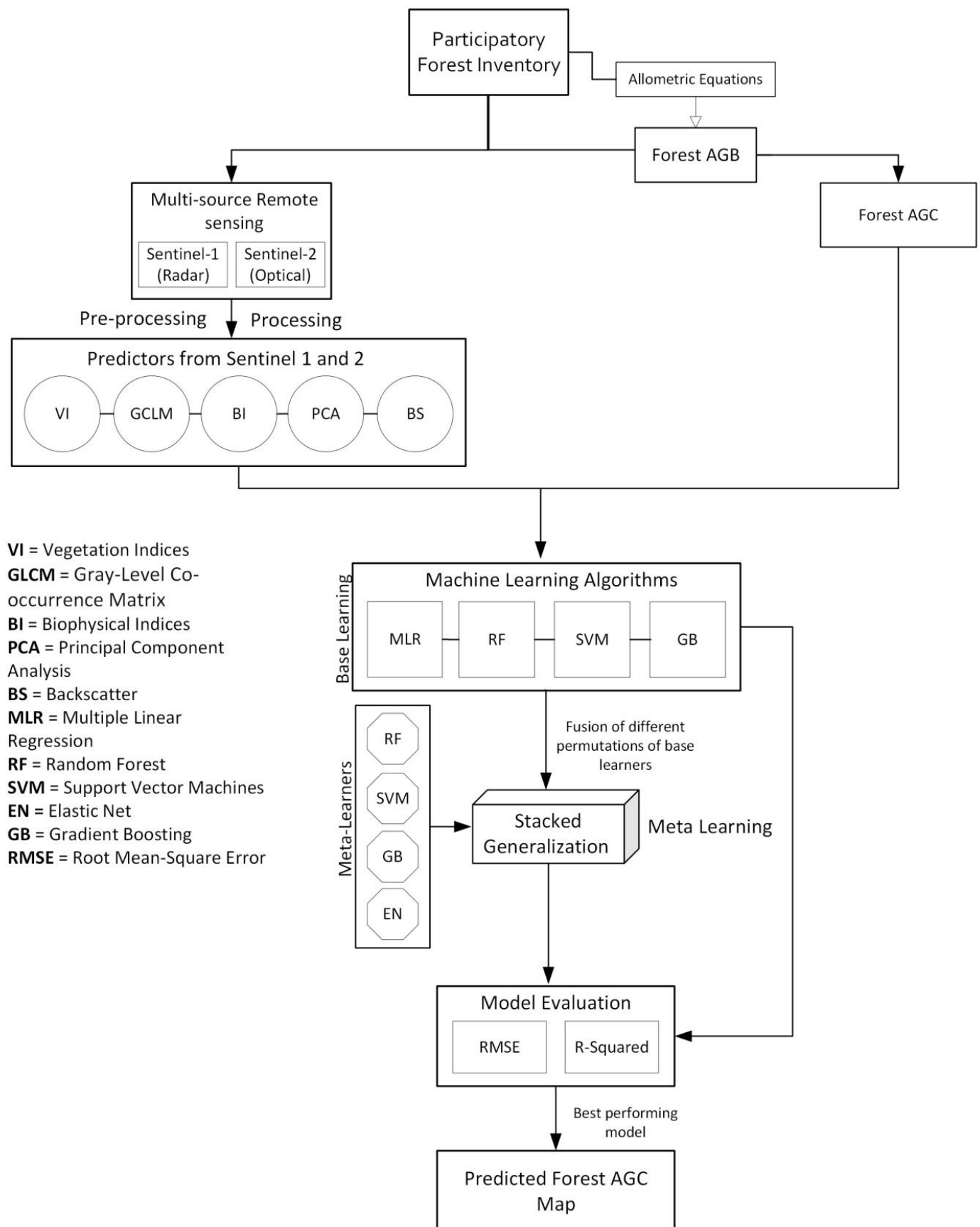


Figure 4. Methodological framework for estimating forest AGC using participatory forest inventory, multi-source remote sensing, and meta-modelling.

Support Vector Machine (SVM)

SVM uses a linear hyperplane that optimally separates two classes by projecting the input data into a higher Hilbert space [60,61]. Applying SVM learning in regression involves introducing an ϵ -insensitive loss function, known as the ϵ -tube, which redevelops the optimization problem to find the function with a maximum deviation ϵ from a specific target value that best approximates the continuous-valued function [62]. The SVM regression formulates convex optimizations by identifying the maximum margin separating the hyperplane [63]. SVM offers advantages over other algorithms. It reduces the upper bound of generalization error by increasing the distance of the hyperplanes separating the two classes. This process ensures a low generalization error. SVM also uses a function known as the kernel trick to explore data in two-dimensional space. Thus, SVM's performance can depend on selecting an appropriate kernel function, including sigmoid, polynomial, radial basis, and linear kernels [64]. SVM has some limitations that are worth noting—they may not be suitable for large datasets and do not perform effectively with very noisy data as target classes may overlap [64].

Gradient Boosting (GB)

Gradient boosting machines have shown considerable accuracy and efficiency in various applications of environmental monitoring [58,65,66]. GB is a learning method that combines a set of weak learners to produce a more robust and accurate model [65]. Weak learners are models that perform marginally better than random guessing. By sequentially training these weak learners, boosting creates a robust predictive model that is more accurate and efficient. GB is usually used with decision trees of a fixed size as weak learners. GB decision trees are primarily considered one of the best off-the-shelf machine learning algorithms [65]. GB often begins with a simple decision tree model to make predictions on the training data, and the errors are calculated. Subsequent models are then trained to predict the residuals, thus correcting existing errors in the initial simplistic models. GB also provides many options for tuning hyperparameters and loss functions, making it more flexible and accurate [58].

2.4.5. Meta-Learning Using Stacked Generalization Ensemble

We used a stacked generalization ensemble to combine multiple base learners to produce a meta-learning model. Stacking was first proposed by [67] as a method for reducing the generalization error rate of one or more machine learning models. Stacking can be viewed as a form of meta-learning because it uses a “meta-learner” that learns how to combine the predictions of multiple base models [68,69]. Rather than training directly on the raw input data, the meta-learner is trained on the outputs of base models, effectively learning from models instead of solely learning from data. However, meta-learning in the broader sense refers to methods that help models learn new tasks quickly [70]. Stacking focuses on combining heterogeneous machine learning prediction algorithms into a single meta-predictive model [71]. Unlike other forms of ensemble methods (e.g., bagging, boosting) that generate predictions and classifiers using the same learning model, stacking is based on generating predictions from different algorithms [72]. Since each learning algorithm employs distinct methods to represent knowledge and incorporates varying learning biases, it explores the hypothesis space from unique perspectives, thus combining predictions from all models are expected to produce more accurate predictions than individual models [72,73]. For example, while the predictions of a traditional RF model and other ensemble models focus on model consensus through either majority voting or averaging, stacking can assign varying weights to models that disagree within the ensemble based on their performance [67,73].

In this paper, we used stacking by training multiple base models (level 0 models) fed into the meta-models (known as level 1 models) to generate predictions (Figure 4). Here, MLR, RF, SVM, and GB were the base models. We selected these base learners because they offer diverse methodological approaches, thereby creating a more robust ensemble. For instance, random forests use a bagging ensemble of decision trees to make predictions while gradient boosting iteratively (i.e., uses a boosting ensemble) refines a series of trees to correct previous errors. However, support vector machines identify the optimal hyperplane in high-dimensional spaces, and linear regression models linear relationships. Therefore, diverse base learning models in stacking capture different aspects of the data, reducing the likelihood of correlated errors and improving the model performance [67]. By integrating algorithms with varying complexities and learning mechanisms, we aimed to create a balanced and robust prediction. A total of nine different combinations of the base learning regression models were combined using stacked generalization to assess the performance of the various permutations of base learners using indices from Sentinel-1 and 2. We also explored different regression methods as meta-learners, including RF, SVM, GB, and Elastic Net (EN). EN is a regularized regression that combines Lasso and Ridge regression to minimize overfitting [74]. In principle, base learners can have several layers before the meta-learner. Also, level 0 and level 1 models can belong to any known class of machine learning algorithms [75].

2.4.6. Evaluation of Base and Meta Models

We used the R^2 (Equation (1)), and Root Mean Square Error (RMSE) as the key metrics for model evaluation and comparison to understand the difference in the performance of the base and meta-models. A higher R^2 and a lower RMSE indicate better model accuracy. The R^2 metric quantifies the proportion of variance in the dependent variable explained by the predictor variable(s) in the regression model. The RMSE (Equation (2)) measures the average differences between observed and predicted values. The R^2 (Equation (2)) and RMSE (Equation (3)) are mathematically expressed as follows:

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2} \quad (2)$$

where y_i represents the observed value (i.e., observed AGC), $\hat{y}_i$ denotes the estimated value of forest AGC, and $\bar{y}$ refers to the mean of the observed forest AGC.

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (\hat{y}_i - y_i)^2}{N}} \quad (3)$$

In Equation (2) 'N' represents the number of samples, $\hat{y}_i$ is the estimated value of forest AGC for the sample point 'i', and y_i is the observed value of forest AGC for the sample point 'i'.

3. Results

3.1. Participatory Forest Inventory: Ecological Insights and Management Practices

The forest inventory results conducted by local communities provided valuable ecological insights of forest characteristics and management practices (Table 4). Community members reported that most forest plots (76%) are natural, while nearly 24% are planted forests (Table 4). The communities also surveyed forest management practices (Table 4).

Table 4. Forest inventory plot characteristics.

Practice/Management	Frequency (%) (N = 66)
Forest type	
Natural	50 (75.8%)
Planted	16 (24.2%)
Forest ownership	
Community	27 (40.9%)
Private	39 (59.1%)
Protected status	
Not Protected	11 (16.7%)
Protected	55 (83.3%)
Weeding	
No	59 (89.4%)
Yes	7 (10.6%)
Pruning	
No	57 (86.4%)
Yes	9 (13.6%)
Firebreaks	
No	9 (13.6%)
Yes	57 (86.4%)
Thinning	
No	49 (74.2%)
Yes	17 (25.8%)
Grazing	
Alot of grazing	2 (3.0%)
Little grazing	30 (45.5%)
No grazing	34 (51.5%)
Fuelwood	
Major	3 (4.5%)
Minimal	37 (56.1%)
No	26 (39.4%)
Agriculture	
No	48 (72.7%)
Yes	18 (27.3%)
Forest damage	
Few	41 (62.1%)
Major	4 (6.1%)
No	21 (31.8%)
Number of morphospecies	
<5	8 (12.1%)
5–10	25 (37.9%)
10–15	19 (28.8%)
>15	14 (21.2%)
Soil texture	
Clay	11 (16.7%)
Loam	9 (13.6%)
Sand	46 (69.7%)

3.1.1. Tree Species, Diameter, and Height

Tree heights, DBH, and species types varied among the 1864 trees inventoried (Figure 5). *Julbernadia globiflora*, known locally as ‘Kamphoni’ was the most abundant species in northern Mzimba, constituting 32% of the inventoried tree species. Other important species included *Combretum molle* (6.2%), *Azelia quanzensis* (6%), *Diplorhynchus condylocarpon* (5.3%), *Lanea discolor* (2.8%), *Cussonia laciniata* (2.4%), *M’buta** (2.3), and *Dalbergia nitidula* (2%).

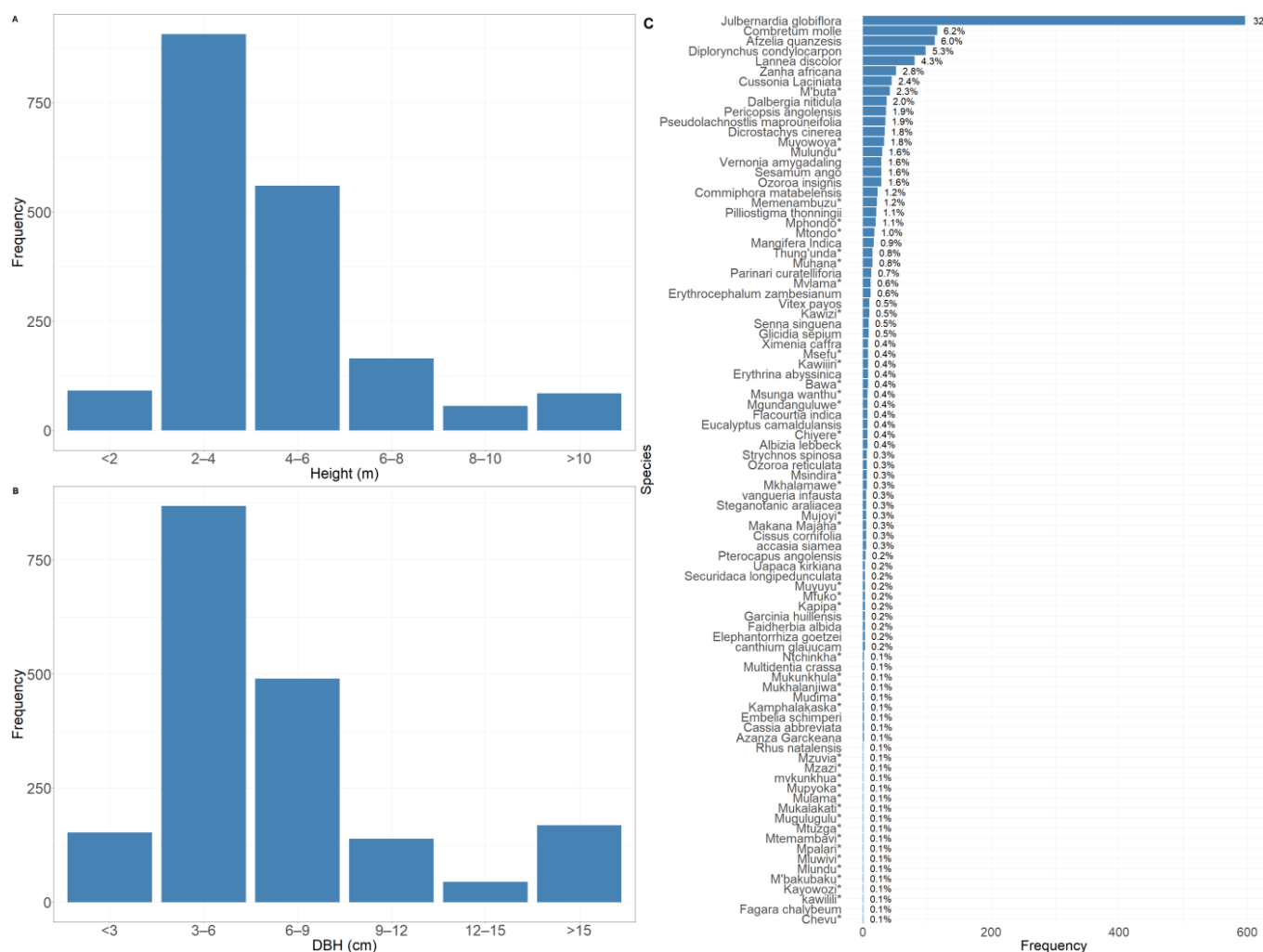


Figure 5. Distribution of the frequency of tree height (A), DBH (B), and species type (C). * Species are labelled in the local name.

The mean DBH across the 15 village areas ranges from 5.00 cm in *Chisangano* to 14.8 cm in *Mdolo*, with considerable standard deviations, indicating a high variability in tree sizes within and across village areas (Table 5). Village areas such as *Kabanda* and *Kabumba* have relatively higher mean DBHs (10.4 cm and 10.6 cm, respectively). The mean tree height varies from 3.17 m in *Kafulufulu* to 7.20 m in *Mdolo*. Village areas with higher mean tree heights included *Mdolo* and *Kabumba* (6.46 m).

3.1.2. Forest Stand Density and Species Diversity

Basal area, a measure of the cross-sectional area of trees per hectare, ranged from 1.60 m²/ha in *Kaluhowo* to 20.16 m²/ha in *Mdolo* (Table 5). High basal areas in villages such as *Mdolo* and *Kabumba* (9.76 m²/ha) reflect areas with larger or more densely packed trees, which is critical for carbon sequestration assessments and forest management practices. Wood density, an indicator of wood quality and biomass, shows relatively less variation, with mean values ranging from 0.60 g/cm³ in *Kabumba* to 0.81 g/cm³ in *Kaluhowo* (Table 5). Wood density variability is essential for understanding the mechanical properties of the wood and its potential uses. Tree density, measured in trees per hectare, varied across the villages, with the highest density observed in *Thimalala*, which had 328 trees/ha, while *Kaluhowo* had the lowest at 119 trees/ha (Table 5).

Table 5. Forest inventory and tree measurement across village areas.

Village Area	Plot	Area	Trees	DBH (cm)	Height (m)	Species Richness	Basal Area	Wood Density	Tree Density	Shannon Index
	No.	ha	No.	Mean (sd)	Mean (sd)	No.	m ² ha ^{−1}	g/cm ³	Stems/ha	
Chimbongondo	6	0.754	198	5.50 (4.27)	3.68 (1.51)	33	4.01	0.70 (0.09)	263	2.34
Chisangano	3	0.377	83	5.00 (4.92)	3.46 (1.70)	17	3.37	0.72 (0.07)	220	1.46
Edundu	5	0.628	114	5.44 (3.88)	3.45 (1.83)	31	2.55	0.64 (0.15)	181	2.70
Emtiyani	6	0.754	151	6.04 (9.72)	3.77 (1.44)	38	8.20	0.73 (0.08)	200	2.52
Kabanda	3	0.377	46	10.4 (9.15)	5.79 (2.07)	14	7.24	0.69 (0.11)	122	1.75
Kabumba	2	0.251	54	10.6 (5.69)	6.46 (5.51)	18	9.76	0.60 (0.15)	215	1.97
Kabwanda	3	0.377	117	5.66 (1.85)	3.88 (1.28)	25	3.45	0.73 (0.10)	310	2.10
Kafulufulu	6	0.754	197	5.03 (4.39)	3.17 (1.20)	37	3.65	0.75 (0.10)	261	2.56
Kaluhowo	2	0.251	30	6.09 (2.37)	4.82 (1.97)	14	1.60	0.81 (0.08)	119	2.12
Kavula	3	0.377	123	7.72 (5.61)	5.77 (1.54)	19	9.31	0.72 (0.10)	326	1.67
Luzi	4	0.503	122	8.14 (2.55)	4.57 (1.39)	15	5.53	0.73 (0.08)	243	1.20
Mdolo	6	0.754	125	14.8 (13.0)	7.20 (7.23)	29	20.16	0.76 (0.08)	166	1.92
Mlimo	7	0.880	169	10.6 (7.48)	5.48 (3.17)	32	10.09	0.67 (0.13)	192	2.15
Mwenje	5	0.628	129	6.48 (2.45)	4.97 (1.33)	31	3.11	0.72 (0.10)	205	2.34
Thimalala	5	0.628	206	7.83 (7.26)	5.02 (3.89)	34	11.70	0.80 (0.09)	328	2.48
Total	66	8.293	1864			94				

Species richness showed substantial differences across the villages (Table 5). *Emtiyani* has the highest number of total species (38), while *Luzi* has the lowest (15). The Shannon biodiversity index ranges from 1.20 in *Luzi* to 2.70 in *Edundu*, indicating varying levels of species diversity across the villages. Higher Shannon index values in villages like *Edundu* (2.70) and *Kafulufulu* (2.56) suggest more diverse trees in the forest ecosystems.

3.2. Evaluation of Allometric Equations for Estimating Forest AGB

We evaluated the selected allometric equations using bootstrapping to determine the most suitable allometric equation for predicting the AGB in Mzimba (Table 6). The proposed allometric equation by [42] had the lowest error, bias, and Akaike Information Criteria (AIC). Thus, it was selected as the most suitable allometric equation to estimate the forest AGB in the study context.

Table 6. Evaluation of mixed species allometric equations for estimating forest AGC using bootstrapping.

Allometric Equation	AGB ($\bar{x}$)	Std Error	Bias	CI (95%)		AIC
[49]	40.84	4.35	0.05	32.66	49.86	24,745.57
[48]	38.54	3.71	0.14	31.67	46.27	24,180.21
[47]	48.80	5.37	0.05	39.09	59.91	25,551.57
[44]	55.55	7.62	0.20	41.86	72.10	26,802.37
[45]	41.99	4.43	0.15	33.84	50.71	24,958.97
[42]	34.51	3.20	0.01	28.64	41.16	23,628.54
[41]	58.20	5.70	0.11	47.66	69.70	25,756.50
[46]	326.3	31.45	1.31	266.49	390.32	32,160.07
[43]	30.17	3.36	0.03	23.99	37.12	23,756.75

$\bar{x}$ = mean, CI = confidence interval, AIC = Akaike information criteria.

3.3. Forest Species and Carbon Stocks

Azelia quanzensis recorded the highest mean (55 kg/ha) and median (12 kg/ha) AGC. Next was the locally known *M'buta* with a mean and median AGC of 34 k/g and 6 k/g, respectively, (Figure 6). *Dalbergia nitidula* recorded the lowest mean and median AGC.

We used the Kruskal–Wallis non-parametric test to assess the significant differences in medians among the top 10 abundant tree species (Figure 7). The Kruskal–Wallis test indicates that at least one species' median AGC is significantly ($p = 1.37 \times 10^{-13}$) different from other species. To further understand the group differences, we performed the Dunn post-hoc analysis, indicating the groups of tree species with significantly different medians (Figure 7). For example, *Azelia quanzensis* (P-holm-adj. = 0.05) had a significantly higher median than *Combretum molle*, *Dalbergia nitidula*, *Julbernagia globiflora*, and *Lannea discolor*.

(Figure 7). *M'buta* (P -holm-adj. = 5.45×10^{-9}) also had a significantly higher median than all these species (Figure 7).

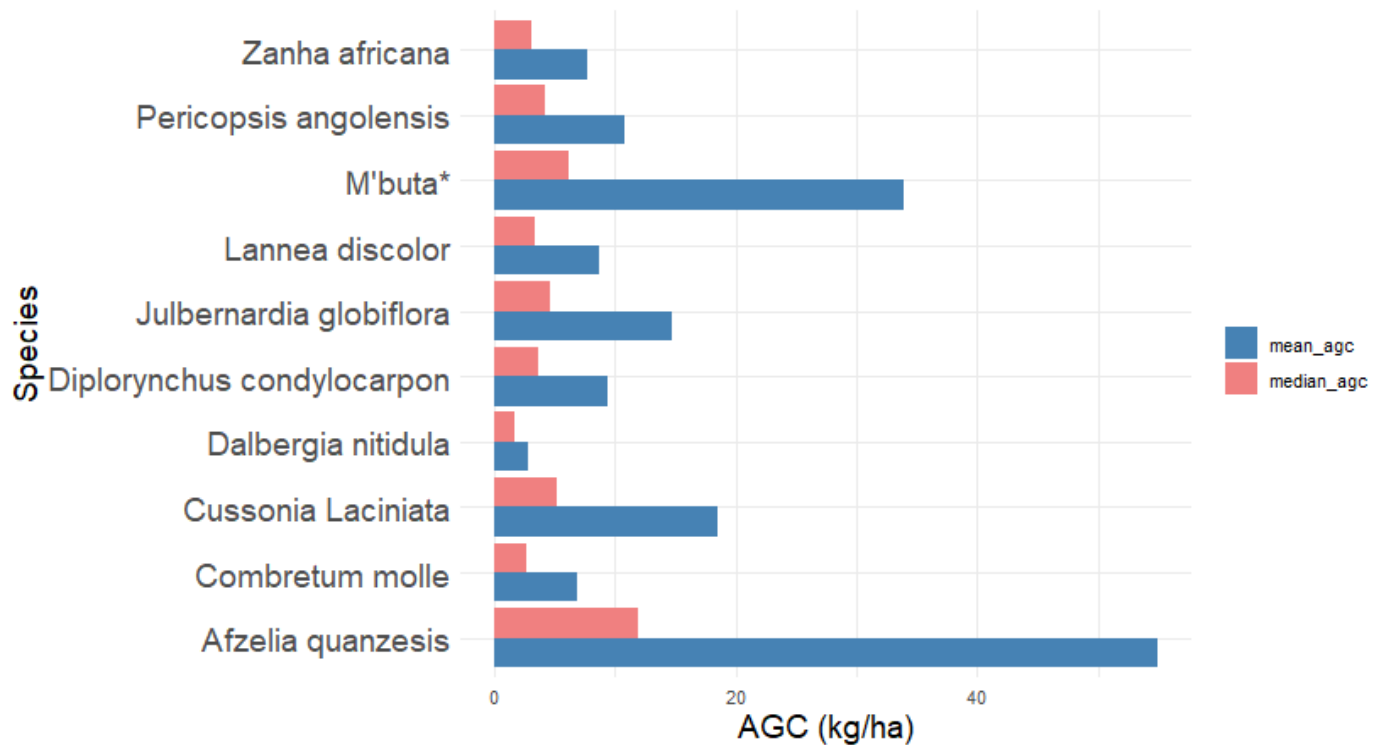


Figure 6. Mean and median AGC of the top 10 abundant species in forest inventory. * Species are labelled in the local name.

3.4. AGC Prediction Using Multi-Source Remote Sensing and Machine Learning

The Pearson correlation (Figure 8) shows the 34 predictor variables from the Sentinel-1 and Sentinel-2 imagery that were significantly and highly correlated with the AGC. At the minimum, only indices with a correlation coefficient (r) of 0.2 with $p < 0.05$ were considered. At the same time, the covariates exhibited multicollinearity, as most of them were strongly correlated with other variables. Including highly correlated variables in a regression may produce large errors due to information redundancy [17,76]. To avoid information redundancy among predictors, variables that were highly correlated within the same indices/measures were eliminated, and the predictors with the highest Pearson correlation coefficient were retained. For instance, though MCARI, NDVI, and NDI45 were all strongly correlated with forest AGC, they also exhibited multicollinearity. Since they were within the same predictor group (i.e., vegetation indices from Sentinel-2), only MCARI was retained since it had the highest correlation ($r = 0.70$, $p < 0.001$) with the forest AGC. A total of eight variables were selected for predicting the forest AGC (Table 7).

Table 7. Selected predictors of forest AGC based on Pearson product-moment correlation coefficients.

Imagery Type	Indices/Measure	Predictor	R (p -Value)
Sentinel-1	Backscatter	VH db	0.25 *
	GLCM Texture	VH Contrast	0.25 *
Sentinel-2	Vegetation Indices	Mcari	0.70 ***
		s2rep	−0.39 **
	Biophysical	Lai CWC	0.42 ***
		Fcover	0.46 ***
	GLCM Texture	B12 GLCM Mean B4 Contrast	−0.33 ** 0.45 ***

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

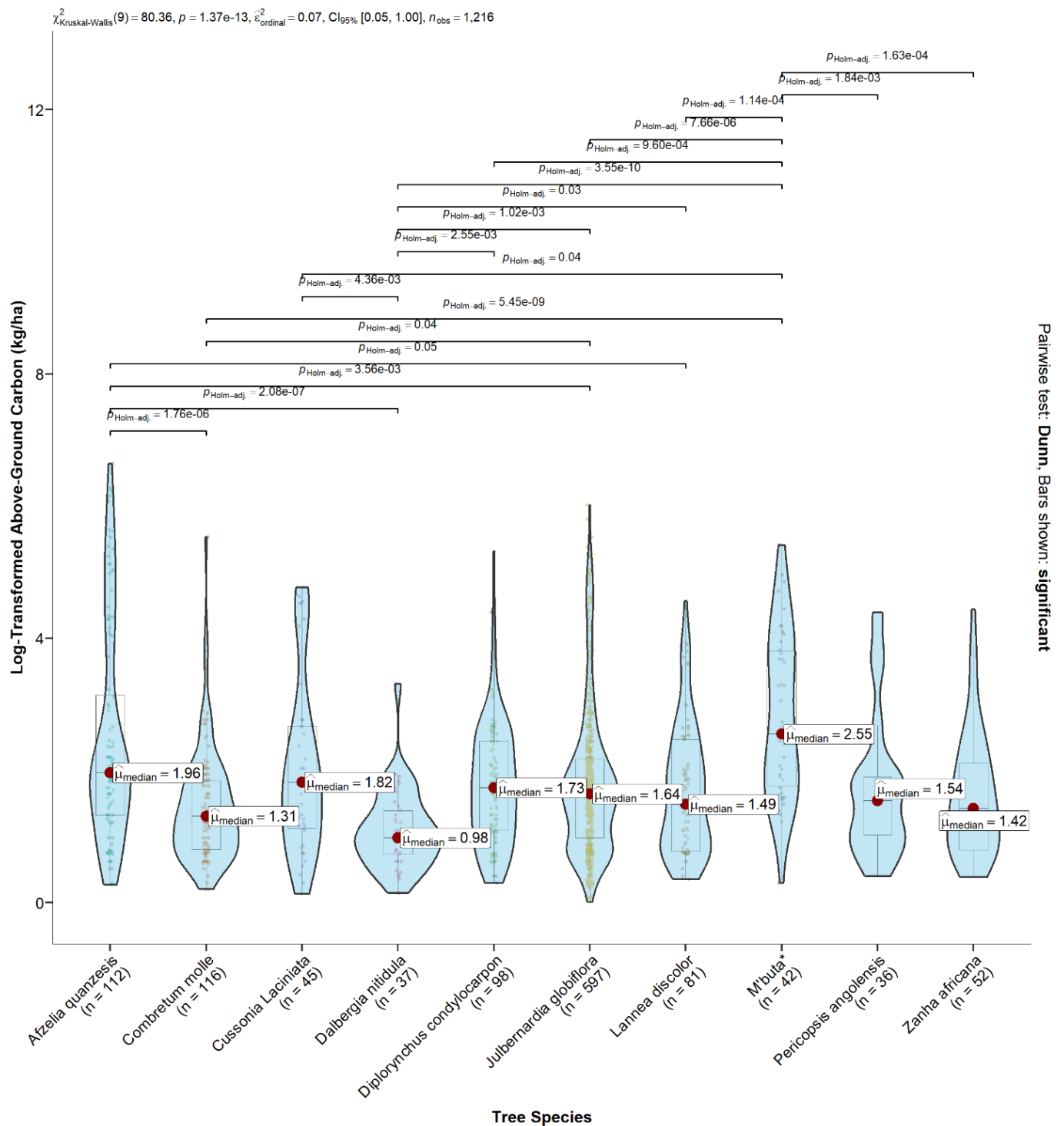


Figure 7. Kruskal–Wallis pairwise test of median tree species with Holm–Bonferroni adjustment for multiple group comparison and the Dunn pairwise post-hoc test for group differences.

Based on the eight predictor variables selected from the correlation matrix, four regression models were used to explore the relationship between these predictors and the AGC. The scatter diagram (Figure 7) shows the performance of the different machine learning models using data from only from Sentinel-1 (Figure 9A), Sentinel-2 (Figure 9B), and both (Figure 9C). The performance of the machine learning regression models was assessed using the R^2 and RMSE. The RF model consistently had better prediction accuracy than all other models using the single and combined datasets. Overall, using the RF and predictors from both Sentinel-1 and 2 showed the highest prediction accuracy ($R^2 = 81$,

RMSE = 1.81). Also, indices from optical remote sensing, such as vegetation and biophysical indices, generally performed better in predicting the AGC than using indices from radar remote sensing.

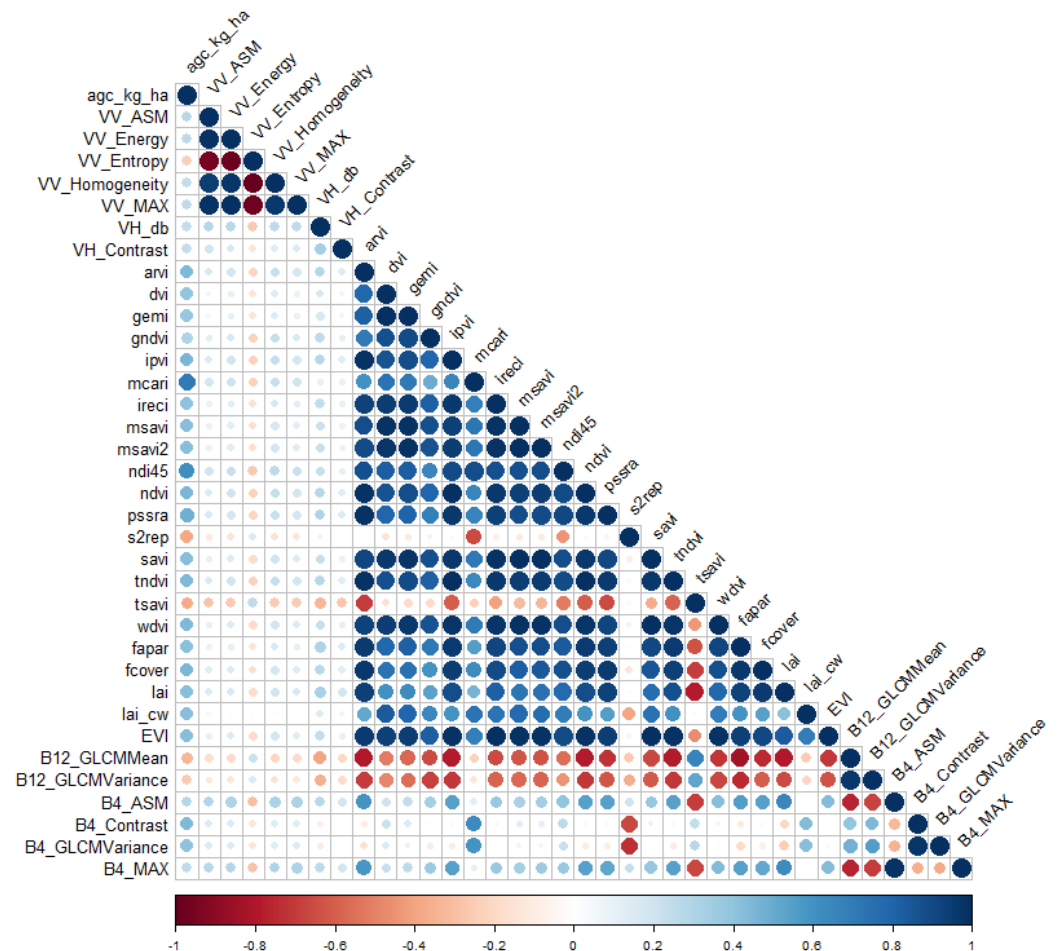


Figure 8. Pearson correlation matrix of predictor variables and forest AGC.

RF is noted to be less sensitive to outliers and noise. The RF model is also less likely to overfit data comparatively. The GB model performed better than SVM and MLR. GB also provides better prediction accuracy because it sequentially builds multiple models, each correcting the errors from previous iterations. The use of regularizations (e.g., shrinkage, interaction depth, and bag fraction) and cross-validation also minimize the likelihood of overfitting in GB. Except for using only Sentinel-1, all non-parametric methods (i.e., RF, SVM, and GB) performed better than the parametric regression model (i.e., MLR). This indicates that the association between remote sensing imagery indices and the AGC is multifaceted and non-linear, explaining why the non-parametric regression methods performed better than the parametric MLR.

3.5. Forest AGC Prediction Stacked Generalization

The prediction accuracy of meta-models varied by the combination of base learners and the type of meta-regressor used (Figure 10). Using EN as a meta-learner produced one of the most optimal model performance (Figure 8). When using EN as a meta-learner, a combination of RF and SVM produced the highest accuracy ($R^2 = 84$, RMSE = 1.36). A combination of all the base learners (i.e., MLR, RF, SVM and GB) and MLR and RF had the next-best prediction performance with an R^2 and RMSE of 0.83 and 1.39, respectively. Others included MLR, RF, and SVM ($R^2 = 82$, RMSE = 1.43) and RF, SVM, and GB ($R^2 = 81$,

RMSE = 1.48). The use of RF and SVM as meta-models also produced optimal model performance. However, using GB as a meta-learner did not improve prediction accuracy.

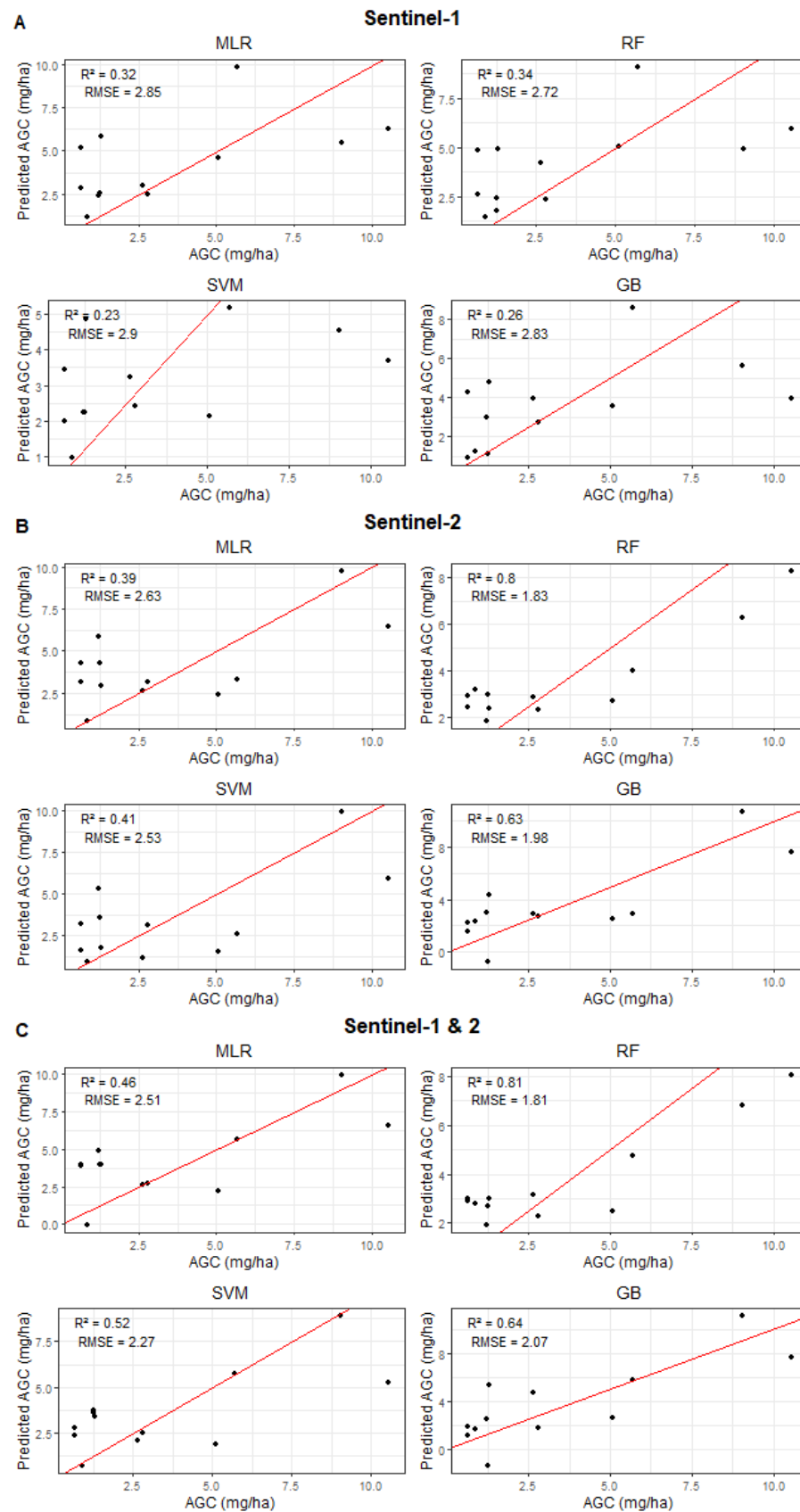


Figure 9. Scatter plots comparing the performance of machine learning regression models in predicting AGC using data Sentinel-1 data (A), Sentinel-2 (B), and both (C).

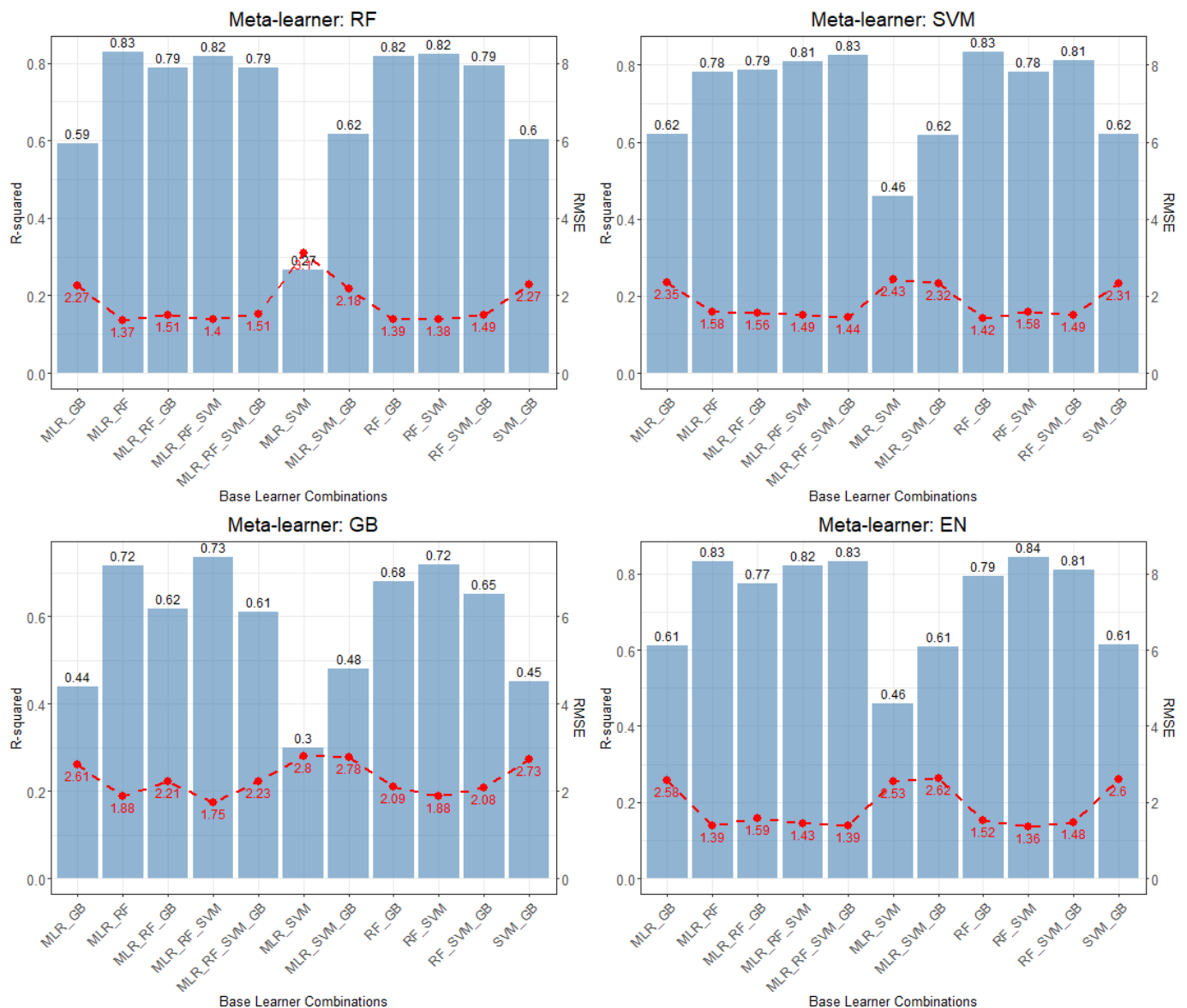


Figure 10. Evaluation of the stack generalization ensemble prediction using data from Sentinel-1 and 2 and learning from four base learners. The red line indicates the RMSE, and the bars represents R^2 .

3.6. Spatial Distribution of Forest AGC

The spatial distribution of predicted AGC is shown over the entire study area using the meta-model with the best prediction accuracy (using EN to combine RF and SVM) (Figure 11). The AGC density ranges between 0.8 Mg/ha and 20 Mg/ha. The highest AGC density is along the northeast to southeast, including parts of the Kaning'inga Forest Reserve in the southeast of the Mzimba district. Generally, the area shows a comparatively low carbon pool, which may reinforce the role of deforestation and forest depletion in hindering terrestrial AGC sinks in Mzimba Malawi.

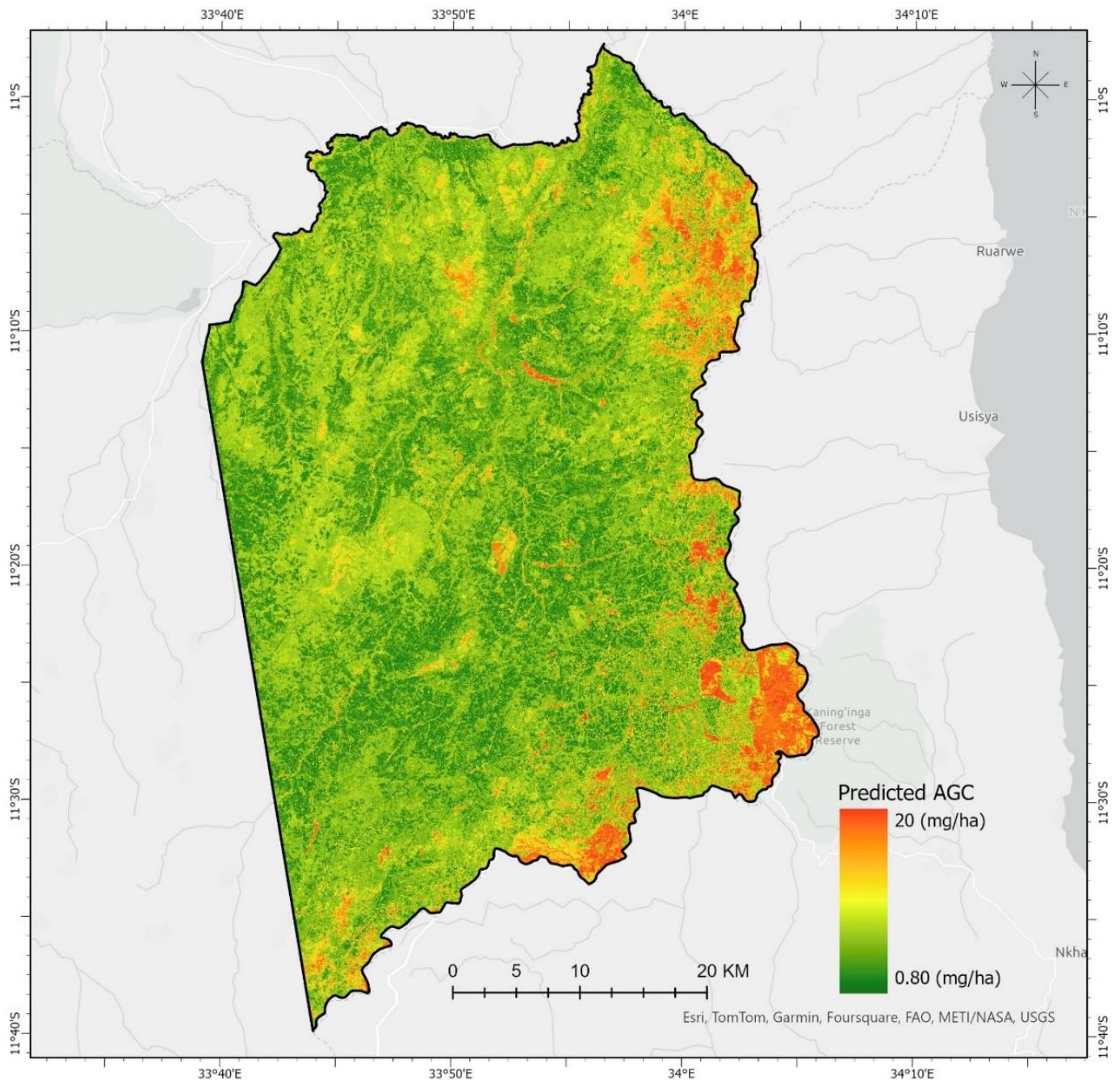


Figure 11. AGC prediction map using stacking (RF and SVM) and Sentinel-1 and 2.

4. Discussion

The role of forest ecosystems in carbon sequestration makes it crucial to improve the efficiency and effectiveness of the methods for assessing forest carbon sinks, especially in data-poor regions such as SSA. While the use of remote sensing and machine learning has become popular in estimating AGC [15,17,24], forest inventory data remain relevant for training machine learning models, validating and improving the accuracy of forest carbon predictions. In this paper, we contend that leveraging local capacities through a participatory forest inventory, optical and radar remote sensing, and meta-learning can improve the accuracy of forest carbon assessment in the Miombo woodlands of Malawi.

4.1. Participatory Inventories and Local Knowledge in Assessing Tree Species' Carbon Stocks

Findings from the participatory forest inventory provide valuable ecological insights and characteristics of forests in the Miombo Woodlands of Malawi, including species abundance, richness, and potential for carbon sequestration. Local communities are more familiar with and have an in-depth understanding and indigenous knowledge of local landscapes, including forest and tree species [77]. Therefore, strengthening the capacities of local communities through participatory methods can integrate indigenous forest knowledge systems with technical expertise for an in-depth ecological understanding of local landscapes. The forest inventory results showed significant differences in the carbon stock potential of the most abundant tree species in Mzimba. For example, the typical AGC of tree species such as *Azelia quanzensis* (locally known as *Mpapa*) and the local species *M'buta* was significantly higher than most other species, indicating that these species may be more suitable for carbon sequestration. Factors such as stand density, species richness, soil characteristics, and forest management can affect the AGC of tree species. *Azelia quanzensis* belongs to the sub-family *Fabaceae Caesalpinioideae*, and is characterized by many branches, dense wood, high durability and resistant to pests and as such are more suitable as carbon sinks in the Miombo woodlands than other species [78]. The policy implication is that conservation and restoration efforts in the Miombo woodlands of Africa should target tree species with higher AGC stock potential such as *Azelia quanzensis* and *M'buta* to enhance carbon sequestration for climate change mitigation. As demonstrated by our study, a participatory approach to inventorying forests would enhance the researchers' ability to identify diverse tree species that can sequester more carbon.

4.2. Integrating Optical and Radar Remote Sensing for Improved Forest AGC Prediction

The remote sensing indices that were relevant for predicting AGC included vegetation indices (e.g., *Mcari*, *s2rep*), biophysical indices (*Lai* and *Fcover*), texture (contrast and mean), and radar backscatter (*VH*). Generally, indices computed from optical remote sensing were more useful in predicting the AGC than radar remote sensing, which is consistent with findings from [17,56]. Optical remote sensing, such as Sentinel-2, has multiple spectral bands, which are sensitive to different forest and tree characteristics such as canopy structure, leaf area, and chlorophyll content. These biophysical properties are directly related to forest AGB and are more likely to be correlated with AGC and relevant for predictions. Moreso, while the radar signal of Sentinel-1 easily penetrates cloud, the C-band of Sentinel-1 has limited forest canopy penetration due to saturation [79]. Thus, radar signals might not vary significantly with varying forest AGB and AGC. The results showed that combining Sentinel-1 and 2 considerably improved forest AGC prediction, corroborating other studies' findings [80,81] that show that radar and optical remote sensing provide complementary capabilities for mapping forest characteristics such as the AGB and AGC. Since optical and radar sensors capture different characteristics of landscapes such as forests, integrating detailed spectral information from optical remote sensing and structural information from radar can significantly increase the accuracy of forest carbon assessment in rural tropical SSA. Methodologically, this finding contributes to growing research that focuses on integrating the diverse properties of different satellite images to improve environmental monitoring and decision-making.

4.3. Advancing Forest AGC Prediction Through Stacking: Examining Learner Diversity and Model Sensitivity

Among the conventional machine learning methods, random forest had the best prediction performance, which corroborates with studies that indicate that RF is a suitable modelling approach for estimating forest AGB and AGC [56,82]. However, stacked gener-

alization enhanced the prediction accuracy and consistency of forest above-ground carbon (AGC), outperforming all conventional single-machine learning models. Our finding corroborates other studies showing that aggregating the strengths of multiple learning models using stacked generalization can increase overall model performance [73,83,84]. Different machine learning methods capture unique features and patterns in the relationship between remote sensing predictors and forest AGC. By leveraging the strengths of diverse machine learning models while minimizing individual model limitations, stacking ensemble reduces the risks of overfitting, bias, and variance, resulting in more robust predictions of forest AGC. Also, we found that the permutation of base learners used in stacking influenced model optimization. For example, meta-models that included RF outperformed all other meta-models that excluded RF, which is consistent with findings from [85] that the diversity of ensemble models and individual model prediction capabilities influences the performance of base learner permutations in stacking learning. Meta-learning approaches such as stacked generalization ensembles decrease structural fluxes in individual base-learners to improve prediction accuracy [6]. Importantly, our findings further indicated that forest AGC prediction using stacked generalization is sensitive to the type of meta-learning regression used.

While EN, RF, and SVM generally produced optimal performance and increased prediction accuracy, using GB as a meta-learner did not provide optimal accuracy compared to some single-conventional machine learning models such as RF. The underperformance of GB can be attributed to several factors. One plausible explanation for Gradient Boosting's underperformance lies in its high sensitivity to hyperparameter tuning and sample size [86,87]. Since hyperparameter optimization was implemented for only base models, GB may have either overfitted or underfitted when used as a meta-learner without hyperparameter tuning. Also, boosting algorithms such as GB may perform poorly with small samples. Since, boosting depends on iterative error correction, the optimal number of boosting iterations is difficult to ascertain when there are few data points [87]. Consequently, the model may terminate too early and underfit or continue too long and overfit. Therefore, the underperformance of GB may be attributed to the small sample size of the study and the lack of tuning in the meta-learners.

While our findings provide an efficient method for optimizing forest carbon assessments, the limited sampled forest plots and remote sensing data sources (i.e., lidar and hyperspectral optical data) hindered more robust experimentations using deep learning approaches for base and meta-modelling. Therefore, future studies should broaden the scope of remote sensing data sources to include lidar and higher spatial and spectral resolution optical images. Also, larger forest plot samples (by including more community members in inventories) and appropriate deep learning methods such as convolutional neural networks (CNN) and artificial neural networks (ANN) may produce more robust predictions.

5. Conclusions

In this paper, we propose an integrated approach for improving the efficiency and accuracy of forest carbon assessments that involves leveraging local capacities in forest inventory data collection, multi-source remote sensing (optical and radar), and meta-modelling techniques. The study underscores the value of integrating optical and radar data, highlighting how distinct spectral and structural information complement each other. Additionally, participatory inventories showcase how integrating local knowledge systems can guide ecologically and culturally relevant research interventions in forest assessment. From a policy perspective, identifying tree species with a higher carbon sequestration potential, such as *Afzelia quanzensis* and *M'buta*, can inform targeted conservation strategies and reforestation programs. By focusing on these native species that hold substantial

carbon stocks, policymakers can bolster climate change mitigation efforts while preserving biodiversity. Also, participatory methods can foster stronger community engagement and ownership in sustainable forest management practices. Involving local stakeholders ensures that management strategies reflect local realities and indigenous knowledge. Such an approach can improve policy compliance, optimize resource allocation, and sustain conservation efforts in SSA.

Moreover, this paper underscores the value of integrating optical and radar data for forest assessment. We show that distinct spectral and structural information from multi-source remote sensing complement each other. The study further illustrates that stacking can improve predictive accuracy for forest above-ground carbon (AGC) and provides insight into how diverse machine learning models can complement one another. Stacked generalization harnesses the advantages of diverse and multiple machine learning methods. Stacking identifies and corrects the biases of individual learners to improve prediction accuracy and makes better generalizations to unseen data. Also, the study reinforces the critical role of meta-learner optimization, as variations in both meta-model architecture and hyperparameter configurations can substantially influence predictive outcomes. By balancing base-learner heterogeneity and meta-learner sensitivity, stacked generalization provides optimal methodological framework in environmental modeling, offering more nuanced and robust estimates of forest carbon stocks.

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References

1. Anyona, S.; Rop, B. Mitigating Against Conflicts in the Kenyan Mining Cycle: Identification of Gaps in the Participation and Recourse for Rights Holders (Civil Society & Community). *E3S Web Conf.* **2017**, *15*, 02005.
2. Fawzy, S.; Osman, A.I.; Doran, J.; Rooney, D.W. Strategies for Mitigation of Climate Change: A Review. *Environ. Chem. Lett.* **2020**, *18*, 2069–2094. [[CrossRef](#)]
3. Kauppi, P.E.; Stål, G.; Arnesson-Ceder, L.; Hallberg Sramek, I.; Hoen, H.F.; Svensson, A.; Wernick, I.K.; Högberg, P.; Lundmark, T.; Nordin, A. Managing Existing Forests Can Mitigate Climate Change. *For. Ecol. Manag.* **2022**, *513*, 120186. [[CrossRef](#)]
4. Hagedorn, F.; Landolt, W.; Tarjan, D.; Egli, P.; Bucher, J.B. Elevated CO₂ Influences Nutrient Availability in Young Beech-Spruce Communities on Two Soil Types. *Oecologia* **2002**, *132*, 109–117. [[CrossRef](#)] [[PubMed](#)]
5. Keenan, T.F.; Williams, C.A. The Terrestrial Carbon Sink. *Annu. Rev. Environ. Resour.* **2018**, *43*, 219–243. [[CrossRef](#)]
6. Tang, K.; Zhao, X.; Xu, Z.; Sun, H. A Stacking Ensemble Model for Predicting Soil Organic Carbon Content Based on Visible and Near-Infrared Spectroscopy. *Infrared Phys. Technol.* **2024**, *140*, 105404. [[CrossRef](#)]
7. Alonzo, M.; Bookhagen, B.; Roberts, D.A. Urban Tree Species Mapping Using Hyperspectral and Lidar Data Fusion. *Remote Sens. Environ.* **2014**, *148*, 70–83. [[CrossRef](#)]

8. Cao, L.; Coops, N.C.; Sun, Y.; Ruan, H.; Wang, G.; Dai, J.; She, G. Estimating Canopy Structure and Biomass in Bamboo Forests Using Airborne LiDAR Data. *ISPRS J. Photogramm. Remote Sens.* **2019**, *148*, 114–129. [CrossRef]
9. Patenaude, G.; Hill, R.A.; Milne, R.; Gaveau, D.L.A.; Briggs, B.B.J.; Dawson, T.P. Quantifying Forest above Ground Carbon Content Using LiDAR Remote Sensing. *Remote Sens. Environ.* **2004**, *93*, 368–380. [CrossRef]
10. Danielsen, F.; Jensen, P.M.; Burgess, N.D.; Altamirano, R.; Alviola, P.A.; Andrianandrasana, H.; Brashares, J.S.; Burton, A.C.; Coronado, I.; Corpuz, N.; et al. A Multicountry Assessment of Tropical Resource Monitoring by Local Communities. *BioScience* **2014**, *64*, 236–251. [CrossRef]
11. Mateo-Vega, J.; Potvin, C.; Monteza, J.; Bacorizo, J.; Barrigón, J.; Barrigón, R.; López, N.; Omi, L.; Opu, M.; Serrano, J.; et al. Full and Effective Participation of Indigenous Peoples in Forest Monitoring for Reducing Emissions from Deforestation and Forest Degradation (REDD+): Trial in Panama's Darién. *Ecosphere* **2017**, *8*, e01635. [CrossRef]
12. de Vos, A.; Preiser, R.; Masterson, V.A. Participatory Data Collection. In *The Routledge Handbook of Research Methods for Social-ecological Systems*; Routledge: London, UK, 2021; p. 119.
13. Kpienbaareh, D.; Mohammed, K.; Luginaah, I.; Wang, J.; Bezner Kerr, R.; Lupafya, E.; Dakishoni, L. Local Actors, Farmer Decisions and Landscape Crop Diversity in Smallholder Farming Systems: A Systems Perspective. *Agric. Ecosyst. Environ.* **2024**, *374*, 109138. [CrossRef]
14. Mukama, K.; Mustalahti, I.; Zahabu, E. Participatory Forest Carbon Assessment and REDD+: Learning from Tanzania. *Int. J. For. Res.* **2012**, *2012*, 126454. [CrossRef]
15. Dos Reis, A.A.; Werner, J.P.S.; Silva, B.C.; Figueiredo, G.K.D.A.; Antunes, J.F.G.; Esquerdo, J.C.D.M.; Coutinho, A.C.; Lamparelli, R.A.C.; Rocha, J.V.; Magalhães, P.S.G. Monitoring Pasture Aboveground Biomass and Canopy Height in an Integrated Crop–Livestock System Using Textural Information from PlanetScope Imagery. *Remote Sens.* **2020**, *12*, 2534. [CrossRef]
16. Mohajane, M.; Costache, R.; Karimi, F.; Bao Pham, Q.; Essahlaoui, A.; Nguyen, H.; Laneve, G.; Oudija, F. Application of Remote Sensing and Machine Learning Algorithms for Forest Fire Mapping in a Mediterranean Area. *Ecol. Indic.* **2021**, *129*, 107869. [CrossRef]
17. Zhang, F.; Tian, X.; Zhang, H.; Jiang, M. Estimation of Aboveground Carbon Density of Forests Using Deep Learning and Multisource Remote Sensing. *Remote Sens.* **2022**, *14*, 3022. [CrossRef]
18. Anees, S.A.; Mehmood, K.; Khan, W.R.; Sajjad, M.; Alahmadi, T.A.; Alharbi, S.A.; Luo, M. Integration of Machine Learning and Remote Sensing for above Ground Biomass Estimation through Landsat-9 and Field Data in Temperate Forests of the Himalayan Region. *Ecol. Inform.* **2024**, *82*, 102732. [CrossRef]
19. Aziz, G.; Minallah, N.; Saeed, A.; Frnda, J.; Khan, W. Remote Sensing Based Forest Cover Classification Using Machine Learning. *Sci. Rep.* **2024**, *14*, 69. [CrossRef]
20. Haque, M.A.; Reza, M.N.; Ali, M.; Karim, M.R.; Ahmed, S.; Lee, K.-D.; Khang, Y.H.; Chung, S.-O. Effects of Environmental Conditions on Vegetation Indices from Multispectral Images: A Review. *Korean J. Remote Sens.* **2024**, *40*, 319–341. [CrossRef]
21. Tian, L.; Wu, X.; Tao, Y.; Li, M.; Qian, C.; Liao, L.; Fu, W. Review of Remote Sensing-Based Methods for Forest Aboveground Biomass Estimation: Progress, Challenges, and Prospects. *Forests* **2023**, *14*, 1086. [CrossRef]
22. Ali, N.; Khati, U. Forest Aboveground Biomass and Forest Height Estimation Over a Sub-Tropical Forest Using Machine Learning Algorithm and Synthetic Aperture Radar Data. *J. Indian Soc. Remote Sens.* **2024**, *52*, 771–786. [CrossRef]
23. El Masri, B.; Xiao, J. Comparison of Global Aboveground Biomass Estimates From Satellite Observations and Dynamic Global Vegetation Models. *J. Geophys. Res. Biogeosci.* **2025**, *130*, e2024JG008305. [CrossRef]
24. Le, A. Estimating Tropical Forest Above-Ground Biomass at the Local Scale Using Multi-Source Space-Borne Remote Sensing Data. PhD Thesis, UNSW Sydney, Sydney, NSW, Australia, 2023.
25. Rana, P.; Popescu, S.; Tolvanen, A.; Gautam, B.; Srinivasan, S.; Tokola, T. Estimation of Tropical Forest Aboveground Biomass in Nepal Using Multiple Remotely Sensed Data and Deep Learning. *Int. J. Remote Sens.* **2023**, *44*, 5147–5171. [CrossRef]
26. Government of Malawi. *The Malawi Growth and Development Strategy (MGDS) III: Building a Productive, Competitive and Resilient Nation*; Government of Malawi: Lilongwe, Malawi, 2017.
27. Malawi Statistical Office. *Main Report*; Malawi Statistical Office: Zomba, Malawi, 2018; Volume 8.
28. World Bank. *Climate Change Knowledge Portal: Malawi*; World Bank: Washington, DC, USA, 2020.
29. Kuyah, S.; Sileshi, G.W.; Njoloma, J.; Mng'omba, S.; Neufeldt, H. Estimating Aboveground Tree Biomass in Three Different Miombo Woodlands and Associated Land Use Systems in Malawi. *Biomass Bioenergy* **2014**, *66*, 214–222. [CrossRef]
30. Gondwe, M.F.K.; Geldenhuys, C.J.; Chirwa, P.W.C.; Assédé, E.S.P.; Syampungani, S.; Cho, M.A. Tree Species Composition and Diversity in Miombo Woodlands between Co-Managed and Government-Managed Regimes, Malawi. *Afr. J. Ecol.* **2021**, *59*, 225–240. [CrossRef]
31. Mwase, W.F.; Bjørnstad, Å.; Bokosi, J.M.; Kwapata, M.B.; Stedje, B. The Role of Land Tenure in Conservation of Tree and Shrub Species Diversity in Miombo Woodlands of Southern Malawi. *New For.* **2007**, *33*, 297–307. [CrossRef]
32. FAO. *The State of Food and Agriculture 2015 (SOFA): Social Protection and Agriculture: Breaking the Cycle of Rural Poverty*; FAO: Rome, Italy, 2015.
33. Global Forest Watch Mzimba, Malawi Deforestation Rates & Statistics | GFW. Available online: <https://www.globalforestwatch.org/dashboards/country/MWI/17/> (accessed on 31 October 2022).

34. Pascual, C.; Mauro, F.; Hernando, A.; Martín-Fernández, S. Inventory Techniques in Participatory Forest Management. In *Quantitative Techniques in Participatory Forest Management*; CRC Press: Boca Raton, FL, USA, 2013; ISBN 978-0-429-08886-5.
35. Yang, H.; Magnussen, S.; Fehrmann, L.; Mundhenk, P.; Klein, C. Two Neighborhood-Free Plot Designs for Adaptive Sampling of Forests. *Environ. Ecol. Stat.* **2016**, *23*, 279–299. [\[CrossRef\]](#)
36. Marchant, B.P.; Lark, R.M. Adaptive Sampling and Reconnaissance Surveys for Geostatistical Mapping of the Soil. *Eur. J. Soil Sci.* **2006**, *57*, 831–845. [\[CrossRef\]](#)
37. Rousselle, F.; Knaus, C.; Zwicker, M. Adaptive Sampling and Reconstruction Using Greedy Error Minimization. *ACM Trans. Graph.* **2011**, *30*, 1–12. [\[CrossRef\]](#)
38. Thien, S.J. A Flow Diagram for Teaching Texture-by-Feel Analysis. *J. Agron. Educ.* **1979**, *8*, 54–55. [\[CrossRef\]](#)
39. Brokaw, N.; Thompson, J. The h for Dbh. *For. Ecol. Manag.* **2000**, *129*, 89–91. [\[CrossRef\]](#)
40. Shannon, C.E. A Mathematical Theory of Communication. *Bell Syst. Tech. J.* **1948**, *27*, 379–423. [\[CrossRef\]](#)
41. Kachamba, D.J.; Eid, T.; Gobakken, T. Above- and Belowground Biomass Models for Trees in the Miombo Woodlands of Malawi. *Forests* **2016**, *7*, 38. [\[CrossRef\]](#)
42. Kuyah, S.; Sileshi, G.W.; Rosenstock, T.S. Allometric Models Based on Bayesian Frameworks Give Better Estimates of Aboveground Biomass in the Miombo Woodlands. *Forests* **2016**, *7*, 13. [\[CrossRef\]](#)
43. Malakini, M.; Makungwa, S.; Mwase, W.; Maganga, A.M. Allometric Models for Estimating Above- and below- Ground Tree Carbon for Community Managed Miombo Woodlands: A Case of Miyobe Village Forest Area in Northern Malawi. *Trees For. People* **2020**, *2*, 100024. [\[CrossRef\]](#)
44. Chidumayo, E.N. Forest Degradation and Recovery in a Miombo Woodland Landscape in Zambia: 22 Years of Observations on Permanent Sample Plots. *For. Ecol. Manag.* **2013**, *291*, 154–161. [\[CrossRef\]](#)
45. Kuyah, S.; Dietz, J.; Muthuri, C.; Jamnadass, R.; Mwangi, P.; Coe, R.; Neufeldt, H. Allometric Equations for Estimating Biomass in Agricultural Landscapes: I. Aboveground Biomass. *Agric. Ecosyst. Environ.* **2012**, *158*, 216–224. [\[CrossRef\]](#)
46. Malimbwi, R.E.; Solberg, B.; Luoga, E. Estimation of Biomass and Volume in Miombo Woodland at Kitulungalo Forest Reserve, Tanzania. *J. Trop. For. Sci.* **1994**, *7*, 230–242.
47. Mugasha, W.A.; Eid, T.; Bollandsås, O.M.; Malimbwi, R.E.; Chamshama, S.A.O.; Zahabu, E.; Katani, J.Z. Allometric Models for Prediction of Above- and Belowground Biomass of Trees in the Miombo Woodlands of Tanzania. *For. Ecol. Manag.* **2013**, *310*, 87–101. [\[CrossRef\]](#)
48. Brown, S. *Estimating Biomass and Biomass Change of Tropical Forests: A Primer*; FAO: Rome, Italy, 1997; Volume 134.
49. Chave, J.; Réjou-Méchain, M.; Búrquez, A.; Chidumayo, E.; Colgan, M.S.; Delitti, W.B.C.; Duque, A.; Eid, T.; Fearnside, P.M.; Goodman, R.C.; et al. Improved Allometric Models to Estimate the Aboveground Biomass of Tropical Trees. *Glob. Change Biol.* **2014**, *20*, 3177–3190. [\[CrossRef\]](#)
50. Ma, S.; He, F.; Tian, D.; Zou, D.; Yan, Z.; Yang, Y.; Zhou, T.; Huang, K.; Shen, H.; Fang, J. Variations and Determinants of Carbon Content in Plants: A Global Synthesis. *Biogeosciences* **2018**, *15*, 693–702. [\[CrossRef\]](#)
51. Martin, A.R.; Thomas, S.C. A Reassessment of Carbon Content in Tropical Trees. *PLoS ONE* **2011**, *6*, e23533. [\[CrossRef\]](#) [\[PubMed\]](#)
52. Weggler, K.; Dobbertin, M.; Jüngling, E.; Kaufmann, E.; Thürieg, E. Dead Wood Volume to Dead Wood Carbon: The Issue of Conversion Factors. *Eur. J. For. Res.* **2012**, *131*, 1423–1438. [\[CrossRef\]](#)
53. Venkatappa, M.; Sasaki, N.; Anantsuksomsri, S.; Smith, B. Applications of the Google Earth Engine and Phenology-Based Threshold Classification Method for Mapping Forest Cover and Carbon Stock Changes in Siem Reap Province, Cambodia. *Remote Sens.* **2020**, *12*, 3110. [\[CrossRef\]](#)
54. Vicharnakorn, P.; Shrestha, R.P.; Nagai, M.; Salam, A.P.; Kiratiprayoon, S. Carbon Stock Assessment Using Remote Sensing and Forest Inventory Data in Savannakhet, Lao PDR. *Remote Sens.* **2014**, *6*, 5452–5479. [\[CrossRef\]](#)
55. Walde, A.U.; Trier, Ø.D.; Salberg, A.-B. Forest Mapping and Monitoring in Africa Using Sentinel-2 Data and Deep Learning. *Int. J. Appl. Earth Obs. Geoinf.* **2022**, *111*, 102840. [\[CrossRef\]](#)
56. Wang, C.; Zhang, W.; Ji, Y.; Marino, A.; Li, C.; Wang, L.; Zhao, H.; Wang, M. Estimation of Aboveground Biomass for Different Forest Types Using Data from Sentinel-1, Sentinel-2, ALOS PALSAR-2, and GEDI. *Forests* **2024**, *15*, 215. [\[CrossRef\]](#)
57. Breiman, L. Random Forests. *Mach. Learn.* **2001**, *45*, 5–32. [\[CrossRef\]](#)
58. Cai, J.; Xu, K.; Zhu, Y.; Hu, F.; Li, L. Prediction and Analysis of Net Ecosystem Carbon Exchange Based on Gradient Boosting Regression and Random Forest. *Appl. Energy* **2020**, *262*, 114566. [\[CrossRef\]](#)
59. Jensen, J.R. *Introductory Digital Image Processing: A Remote Sensing Perspective*, 4th ed.; Pearson series in geographic information science; Pearson Education Inc.: Glenview, IL, USA, 2016; ISBN 978-0-13-405816-0.
60. Awad, M.; Khanna, R. Support Vector Regression. In *Efficient Learning Machines: Theories, Concepts, and Applications for Engineers and System Designers*; Awad, M., Khanna, R., Eds.; Apress: Berkeley, CA, USA, 2015; pp. 67–80, ISBN 978-1-4302-5990-9.
61. Sheykhmousa, M.; Mahdianpari, M.; Ghanbari, H.; Mohammadimanesh, F.; Ghamisi, P.; Homayouni, S. Support Vector Machine Versus Random Forest for Remote Sensing Image Classification: A Meta-Analysis and Systematic Review. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2020**, *13*, 6308–6325. [\[CrossRef\]](#)

62. Lipkowitz, K.B.; Cundari, T.R.; Boyd, D.B. *Reviews in Computational Chemistry, Volume 23*; John Wiley & Sons: Hoboken, NJ, USA, 2007; ISBN 978-0-470-11643-2.
63. Vapnik, V. *The Nature of Statistical Learning Theory*; Springer Science & Business Media: Berlin/Heidelberg, Germany, 1999; ISBN 978-0-387-98780-4.
64. Cortes, C.; Vapnik, V. Support-Vector Networks. *Mach. Learn.* **1995**, *20*, 273–297. [\[CrossRef\]](#)
65. Biau, G.; Cadre, B.; Rouvière, L. Accelerated Gradient Boosting. *Mach. Learn.* **2019**, *108*, 971–992. [\[CrossRef\]](#)
66. Natekin, A.; Knoll, A. Gradient Boosting Machines, a Tutorial. *Front. Neurobot.* **2013**, *7*. [\[CrossRef\]](#) [\[PubMed\]](#)
67. Wolpert, D.H. Stacked Generalization. *Neural Netw.* **1992**, *5*, 241–259. [\[CrossRef\]](#)
68. Dey, R.; Mathur, R. Ensemble Learning Method Using Stacking with Base Learner, A Comparison. In Proceedings of the International Conference on Data Analytics and Insights, ICDAI 2023, Kolkata, India, 11–13 May 2023; Chaki, N., Roy, N.D., Debnath, P., Saeed, K., Eds.; Springer Nature: Singapore, 2023; pp. 159–169.
69. Mishra, D.; Naik, B.; Dash, P.B.; Nayak, J. SEM: Stacking Ensemble Meta-Learning for IOT Security Framework. *Arab. J. Sci. Eng.* **2021**, *46*, 3531–3548. [\[CrossRef\]](#)
70. Kuang, H.; Deng, K.; Wang, Q.; Ye, W.; Qu, H.; Li, J. Deep Meta-Learning Approach for Regional Parking Occupancy Prediction Considering Heterogeneous and Real-Time Information. *Adv. Eng. Inform.* **2025**, *64*, 102969. [\[CrossRef\]](#)
71. Naimi, A.I.; Balzer, L.B. Stacked Generalization: An Introduction to Super Learning. *Eur. J. Epidemiol.* **2018**, *33*, 459–464. [\[CrossRef\]](#)
72. Sesmero, M.P.; Ledezma, A.I.; Sanchis, A. Generating Ensembles of Heterogeneous Classifiers Using Stacked Generalization. *WIREs Data Min. Knowl. Discov.* **2015**, *5*, 21–34. [\[CrossRef\]](#)
73. Healey, S.P.; Cohen, W.B.; Yang, Z.; Kenneth Brewer, C.; Brooks, E.B.; Gorelick, N.; Hernandez, A.J.; Huang, C.; Joseph Hughes, M.; Kennedy, R.E.; et al. Mapping Forest Change Using Stacked Generalization: An Ensemble Approach. *Remote Sens. Environ.* **2018**, *204*, 717–728. [\[CrossRef\]](#)
74. Altelbany, S. Evaluation of Ridge, Elastic Net and Lasso Regression Methods in Precedence of Multicollinearity Problem: A Simulation Study. *J. Appl. Econ. Bus. Stud.* **2021**, *5*, 131–142. [\[CrossRef\]](#)
75. Bakurov, I.; Castelli, M.; Gau, O.; Fontanella, F.; Vanneschi, L. Genetic Programming for Stacked Generalization. *Swarm Evol. Comput.* **2021**, *65*, 100913. [\[CrossRef\]](#)
76. Sarker, L.R.; Nichol, J.E. Improved Forest Biomass Estimates Using ALOS AVNIR-2 Texture Indices. *Remote Sens. Environ.* **2011**, *115*, 968–977. [\[CrossRef\]](#)
77. Sufo Kankeu, R.; Tsayem Demaze, M.; Sonwa, D.J. Using Local Capacity To Assess Carbon Stocks In Two Community Forest In South-East Cameroon. *J. Sustain. For.* **2020**, *39*, 92–111. [\[CrossRef\]](#)
78. Baul, T.K.; Chakraborty, A.; Nandi, R.; Mohiuddin, M.; Kilpeläinen, A.; Sultana, T. Effects of Tree Species Diversity and Stand Structure on Carbon Stocks of Homestead Forests in Maheshkhali Island, Southern Bangladesh. *Carbon Balance Manag.* **2021**, *16*, 11. [\[CrossRef\]](#)
79. Huang, X.; Ziniti, B.; Torbick, N.; Ducey, M.J. Assessment of Forest above Ground Biomass Estimation Using Multi-Temporal C-Band Sentinel-1 and Polarimetric L-Band PALSAR-2 Data. *Remote Sens.* **2018**, *10*, 1424. [\[CrossRef\]](#)
80. Fernandez-Ordóñez, Y.; Soria-Ruiz, J.; Leblon, B.; Fernandez-Ordóñez, Y.; Soria-Ruiz, J.; Leblon, B. Forest Inventory Using Optical and Radar Remote Sensing. In *Advances in Geoscience and Remote Sensing*; IntechOpen: London, UK, 2009; ISBN 978-953-307-005-6.
81. Sinha, S.; Mohan, S.; Das, A.K.; Sharma, L.K.; Jeganathan, C.; Santra, A.; Santra Mitra, S.; Nathawat, M.S. Multi-Sensor Approach Integrating Optical and Multi-Frequency Synthetic Aperture Radar for Carbon Stock Estimation over a Tropical Deciduous Forest in India. *Carbon Manag.* **2020**, *11*, 39–55. [\[CrossRef\]](#)
82. Gao, Y.; Lu, D.; Li, G.; Wang, G.; Chen, Q.; Liu, L.; Li, D. Comparative Analysis of Modeling Algorithms for Forest Aboveground Biomass Estimation in a Subtropical Region. *Remote Sens.* **2018**, *10*, 627. [\[CrossRef\]](#)
83. Sharma, S.R.; Singh, B.; Kaur, M. A Novel Approach of Ensemble Methods Using the Stacked Generalization for High-Dimensional Datasets. *IETE J. Res.* **2023**, *69*, 6802–6817. [\[CrossRef\]](#)
84. Yuan, Z.; Meng, L.; Gu, X.; Bai, Y.; Cui, H.; Jiang, C. Prediction of NOx Emissions for Coal-Fired Power Plants with Stacked-Generalization Ensemble Method. *Fuel* **2021**, *289*, 119748. [\[CrossRef\]](#)
85. Shi, J.; Li, C.; Yan, X. Artificial Intelligence for Load Forecasting: A Stacking Learning Approach Based on Ensemble Diversity Regularization. *Energy* **2023**, *262*, 125295. [\[CrossRef\]](#)
86. Bentéjac, C.; Csörgő, A.; Martínez-Muñoz, G. A Comparative Analysis of Gradient Boosting Algorithms. *Artif. Intell. Rev.* **2021**, *54*, 1937–1967. [\[CrossRef\]](#)
87. Blagus, R.; Lusa, L. Gradient Boosting for High-Dimensional Prediction of Rare Events. *Comput. Stat. Data Anal.* **2017**, *113*, 19–37. [\[CrossRef\]](#)

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