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Review Article

Three Decades of Forest Biomass Estimation in Southeast Asia: A Systematic Review of Field, Remote Sensing, and Machine Learning Approaches (1995–2025)

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ABSTRACT

Aboveground biomass plays a pivotal role in estimating tropical forest carbon stocks, particularly in Southeast Asia, a region rich in biodiversity but threatened by deforestation and land-use change. This systematic review analyzes 71 peer-reviewed studies published between 1995 and 2025, selected from an initial pool of 8,509 articles. The review aims to evaluate methodological developments and performance across three major approaches: field-based and allometric models, remote sensing including Unmanned Aerial Vehicle (UAV) platforms, and Machine Learning (ML) with data fusion, within key tropical forest countries: Indonesia, Malaysia, and Vietnam. These countries were selected due to their high forest cover, rapid land-use change, and central roles in the implementation of Reducing Emissions from Deforestation and Forest Degradation ($REDD^+$). Field-based models, particularly those calibrated locally, consistently produced high accuracy, with R^2 values generally ranging from 0.80 to 0.96. Remote sensing techniques, particularly the integration of airborne LiDAR and optical–SAR, demonstrated strong predictive performance ($R^2 > 0.85$) and relatively low Root Mean Square Error (RMSE), typically below 30 Mg/ha. ML approaches such as Random Forest, Support Vector Machines, and LightGBM also achieved competitive results, with R^2 typically between 0.75 and 0.85 and RMSE below 40 Mg/ha when trained on high-quality input data. Mangrove and dipterocarp forests emerged as the most frequently studied ecosystems. While methodological innovations are evident, notable gaps remain in model harmonization and representation of ecosystem diversity. The review recommends integrating species-specific allometric models with remote sensing and machine learning pipelines, supported by open-access datasets, to enhance national forest monitoring systems and $REDD^+$ readiness across Southeast Asia.

1. Introduction

Aboveground biomass (AGB) plays a critical role in global carbon accounting and climate change mitigation strategies, particularly in the context of forest-based carbon sinks. Forest ecosystems in Southeast Asia are among the most carbon-rich and biodiverse terrestrial systems on Earth, making substantial contributions to global ecosystem functioning and reducing greenhouse gas concentrations through carbon sequestration (Sulabha et al. 2025; Tian et al. 2023). Tropical forests in this region can store up to 250–500 Mg/ha of AGB, depending on forest type and condition, with corresponding carbon stocks ranging between 115–230 Mg.C/ha (Basuki et al. 2009; Maulana et al. 2016). For example, intact lowland dipterocarp forests in Indonesia were found to have an average AGB of 361 Mg/ha and carbon stocks of 180 Mg.C/ha (Jachowski et al. 2013; Laumonier et al. 2010). However, these carbon reservoirs are increasingly threatened by deforestation, land-use change, and forest degradation. The region accounted for a significant share of global forest loss, with Indonesia and Malaysia alone contributing over 1.2 million ha of forest loss in 2022 (Global Forest Watch 2024). Such disturbances contribute to substantial uncertainty in biomass and carbon stock estimations, which is further compounded by variations in forest structure, measurement techniques, and model generalization (Nguyen et al. 2019; Yuen et al. 2016; Zaki et al. 2016a).

To address these challenges, various AGB estimation methods have been developed and applied globally (Tian et al. 2023), including in Southeast Asia (Yuen et al. 2016). These methods range from traditional field-based allometric approaches to more advanced remote sensing (RS) techniques and machine learning algorithms. In particular, high-resolution optical satellite imagery (e.g., QuickBird, WorldView-2, IKONOS) has demonstrated effectiveness for small-scale biomass estimation in heterogeneous tropical landscapes; however, issues such as spectral saturation and cloud cover limit its applicability in dense forest conditions (Ahmad et al. 2021; Borsah et al. 2023).

Synthetic Aperture Radar (SAR), particularly L-band sensors like ALOS PALSAR, offers a viable alternative due to its ability to penetrate the vegetation canopy and operate under all-weather conditions. SAR backscatter coefficients and polarimetric decomposition metrics have been widely used for AGB modeling in tropical forests, although variability in biomass density and sensor configurations often results in methodological inconsistencies (Sulabha et al. 2025). Likewise, LiDAR technology, both airborne (ALS) and terrestrial (TLS), has emerged as the most accurate remote sensing approach for estimating AGB by capturing three-dimensional structural parameters of forest canopies and individual trees (Borsah et al. 2023; Xu et al. 2021).

More recently, Unmanned Aerial Vehicle (UAV) equipped with RGB or multispectral sensors have gained traction for fine-scale AGB estimation due to their high spatial resolution, cost-effectiveness, and flexibility in data acquisition (Poley and McDermid 2020). While UAV-based methods show great promise, challenges remain in standardizing data processing workflows and in their limited scalability for national or regional monitoring programs. Machine learning (ML) has significantly enhanced the capacity of RS-based biomass estimation, especially when integrated with multi-sensor data fusion approaches. Algorithms such as Random Forest (RF), Support Vector Machines (SVM), and Gradient Boosting (GB) have been successfully implemented in several Southeast Asian contexts, often outperforming traditional regression models in terms of accuracy and generalizability (Matiza et al. 2023; Saim and Aly 2025). The combination of ML with fused datasets (e.g., SAR-optical, LiDAR-optical) further improves AGB predictions by leveraging complementary information from various sensors.

Despite these advancements, Southeast Asia faces several region-specific challenges. A major limitation is the scarcity of locally calibrated allometric equations for many land cover types, species, and ecological zones. Existing biomass models are often derived from a limited number of destructive sampling studies, most of which are concentrated in specific regions such as Sumatra, Kalimantan, and Java, while vast areas in Brunei, Laos, Papua New Guinea, and Timor-Leste remain underrepresented (Anitha et al. 2015; Yuen et al. 2016). This geographic imbalance contributes to uncertainties in national greenhouse gas inventories and hampers the implementation of Reducing Emissions from Deforestation and Forest Degradation ($REDD^+$) mechanisms (Komiyama et al. 2008).

Given these gaps, there is a pressing need for a systematic and critical review of AGB estimation methodologies applied specifically within Southeast Asia. Such a review should assess the evolution of technologies and modelling approaches, evaluate their strengths and limitations across various forest types, and identify methodological and geographical gaps that must be addressed in future research. This is especially important because Southeast Asia comprises a highly diverse set of ecosystems, ranging from peatlands and mangroves to lowland dipterocarp and montane forests, each with unique structural and compositional attributes that affect biomass estimation (Murdiyarso et al. 2015). Despite the increasing availability of tools such as LiDAR, SAR, and optical remote sensing, their applicability and accuracy across these forest types remain uneven and often untested at scale (Avitabile et al. 2016). Moreover, many countries in the region are still developing their national forest monitoring systems under $REDD^+$ frameworks, making it crucial to identify the methodologies that are most suitable given the region's specific biophysical and socio-political contexts (Herold and Skutsch 2011). A region-specific synthesis will provide valuable guidance for researchers, forest managers, and policy-makers striving to enhance the accuracy, consistency, and scalability of biomass estimation in support of sustainable forest management and climate policy.

2. Materials and Methods

This study employs a systematic literature review to examine the evolution of AGB and carbon stock estimation methodologies in Southeast Asia over thirty years, from 1995 to 2025. Reviews in biomass studies have proven effective for mapping methodological advancements and identifying key knowledge gaps across remote sensing, modeling, and field-based approaches (Saim and Aly 2025; Tian et al. 2023).

Relevant literature was retrieved from three major academic databases: Google Scholar, Scopus, and Web of Science (WoS). The search was conducted using combinations of keywords such as "aboveground biomass" and "carbon stock estimation", in conjunction with country-specific identifiers for Southeast Asia. This keyword formulation aligns with previous systematic reviews that emphasize the growing integration of remote sensing technologies and data fusion approaches in AGB estimation (Matiza et al. 2023; Sulabha et al. 2025).

To ensure regional relevance, only studies explicitly conducted in or referring to Southeast Asian countries were considered. These countries include Indonesia, Malaysia, Thailand, Vietnam, the Philippines, Myanmar, Cambodia, Laos, Brunei Darussalam, Singapore, and East Timor (also known as Timor-Leste). This geographic filter is crucial, as numerous reviews have demonstrated that AGB models developed in other tropical regions (e.g., the Amazon or Central Africa) often lack transferability due to ecological, climatic, and species-specific differences (Anitha et al. 2015; Yuen et al. 2016). The inclusion criteria focused on peer-reviewed articles and reviews published in English between 1995 and 2025 that examined the estimation of aboveground biomass (AGB) or carbon stock in Southeast Asia. Eligible studies employed approaches such as field measurements, allometric models, remote sensing, or machine learning. Publications were selected based on their methodological relevance and regional focus. At the same time, non-peer-reviewed and non-English sources were excluded to maintain academic rigor, in line with established review practices (Borsah et al. 2023).

A structured screening process was applied in three stages. First, all search results were filtered by title and abstract to eliminate irrelevant studies. Second, full-text articles were reviewed against the inclusion criteria. Third, the reference lists of selected papers were manually reviewed to identify any additional studies not captured during the database search. During the final selection phase, each paper was coded based on key attributes including country, sensor type, data resolution, forest type, modelling technique, and validation methods.

Data extraction focused on categorizing the methodological approaches into key thematic areas, including field-based and allometric models, remote sensing and UAV approaches, as well as machine learning and data fusion. Particular attention was given to studies that integrated multi-source data or advanced statistical models, which are increasingly considered best practices in biomass estimation (Poley and McDermid 2020; Saim and Aly 2025; Xu et al. 2021). In general, AGB estimation methods in Southeast Asia can be grouped into three main categories: (i) destructive and semi-destructive field-based measurements, which are highly accurate but limited in spatial scale; (ii) allometric models, often based on diameter at breast height (DBH), height, and wood density, which allow for non-destructive estimation at plot and landscape levels; and (iii) remote sensing-based methods such as LiDAR, SAR, and multispectral imagery, which enable large-scale biomass mapping. These remote sensing approaches are often calibrated using field data and supported by statistical or machine learning algorithms, such as random forest, SVM, or deep learning networks, to enhance prediction accuracy (Avitabile et al. 2016). This categorization facilitates a clearer understanding of methodological trends and the evolution of AGB estimation techniques across the region.

By systematically mapping these studies, the review aims to identify regional patterns in method adoption, technological progression, and current research gaps. This will support future efforts to enhance the precision, scalability, and regional calibration of AGB and carbon stock estimation in Southeast Asia's diverse forested landscapes.

3. Results and Discussion

3.1. Overview of Selected Studies

This review was conducted through a rigorous multi-stage screening process to ensure relevance and quality. Initially, a total of 8,509 articles were identified through various academic databases and sources using predefined keywords related to AGB and carbon stock estimation. Following an initial title screening, this number was reduced to 457 articles. Further abstract screening narrowed the list to 120 articles. After a thorough full-text evaluation focusing on methodological rigor, geographical relevance, and clarity of biomass estimation metrics, 71 peer-reviewed studies were finally selected for detailed analysis (**Table 1**). Across Southeast Asia, the most commonly applied approach for estimating AGB is the field-based allometric method, which forms the empirical backbone for many subsequent remote sensing and modeling efforts. Approximately 40% of the 71 studies reviewed employed allometric equations derived from plot measurements to estimate AGB, either as standalone methods or for calibration and validation of remote sensing models. Indonesia and Malaysia lead in the application of these equations, which are often customized for species-rich dipterocarp and mangrove forests. Meanwhile, the adoption of remote sensing technologies, particularly optical imagery (e.g., Landsat, WorldView-2) and radar systems (e.g., ALOS-PALSAR, Sentinel-1), has grown significantly, accounting for nearly 35% of studies. Machine learning (ML) and data fusion approaches—such as Random Forest, Support Vector Machine, and LightGBM—represent a smaller but rapidly expanding share (~25%), especially in Vietnam, Thailand, and the Philippines.

Table 1. Summary of reviewed studies categorized by method

Method category	Country	Method	Ecosystem	Author
Field-Based and Allometric Models	Indonesia	Allometric (Systematic Review)	Tropical Mixed Forest	(Anitha et al. 2015)
	Indonesia	WorldView-2 + Allometric	Mangrove	
	Indonesia	Allometric	Abandoned Land	(Kamal et al. 2022)
	Malaysia	Allometric	Mangrove	
	Cambodia	Forest Measurement	Seasonal Forest	(Karyati et al. 2019)
	Vietnam	SUR Allometric	Dipterocarp and Evergreen	
	Indonesia	Field Inventory	Hill Dipterocarp	(Khan et al. 2025)
	Indonesia	Allometric	Mangrove (*Rhizophora* spp.)	
	Indonesia	Allometric	Agroforestry (Nutmeg)	(Kiyono et al. 2017)
	Indonesia	Allometric	Papua Forest	
	Vietnam	Allometric	Evergreen	(Kralicek et al. 2017)
	Indonesia	Allometric + Field Inventory	Peat Urban Green Space	
	Malaysia	Allometric	Mangrove	(Laumonier et al. 2010)
	Laos	Landsat + Inventory	Mixed Deciduous	
	Indonesia	Allometric + Economic Valuation	Special Purpose Forest (KHDTK)	(Ledheng et al. 2022)
	Malaysia	Allometric	Secondary Forest	
	Indonesia	Transect + Allometric	Mangrove	(Mardiatmoko et al. 2019)
	Malaysia	Quadratic Allometric	Dipterocarp	
	Indonesia	Allometric	Pine-Mahogany Mix	(Maulana et al. 2016)
	Indonesia	Allometric	Sengon Plantation	
	SE Asia	Review of Allometric	Major Land Covers (Forest, Agroforest, Plantation)	(Nam et al. 2016)
	Indonesia	Optical RS + Allometric	Mangrove	
	Philippines	Field Inventory + Allometric	Ultramafic Forest	(Ng et al. 2021a)
	Vietnam	Field Inventory	Natural Forest	
	Indonesia	NDVI + Allometric	Agroforestry	(Ong et al. 2004)
	Indonesia	WorldView-2 + Allometric	Mangrove	
	Indonesia	Allometric (Species-based)	Secondary Tropical Forest	(Vicharnakorn et al. 2014)
	Indonesia	Allometric + Inventory	Montane Forest	
	Indonesia	UAV + Allometric	Mangrove	(Rahmadwiati et al. 2022)
	Indonesia	Allometric	Lowland Dipterocarp	
Machine Learning and Data Fusion	Cambodia	Carbon Stock Modeling	Dry Forest	(Kenzo et al. 2009)
	Vietnam	Machine Learning (RF)	National Park	
	Malaysia	Non-linear Regression	Dipterocarp	(Windarni et al. 2018)
	Thailand	ML (SVM) + RS	Mangrove	
	Vietnam	LightGBM + TDO (Metaheuristic ML)	Upland Forest	(Zaki et al. 2016a)

Method category	Country	Method	Ecosystem	Author
Remote Sensing and UAV Approaches	Malaysia	Fourier Texture + Optical	Mixed Tropical Forest	
	Indonesia	UAV Photogrammetry	Mangrove + Converted Land	(Ikhsan et al. 2021a)
	Indonesia	Texture SAR	Tropical Forest	
	Vietnam	Sentinel-2 NDVI	Coastal Mangrove	(Hossain et al. 2023)
	Indonesia	SAR (PiSAR-L2)	Tropical Forest	
	Malaysia	High-res Optical (IKONOS)	Montane Rainforest	(Yuen et al. 2016)
	Malaysia	Discrete LiDAR	Dipterocarp	
	Indonesia	PolSAR (RadarSAT-2)	Peatland	(Hastuti et al. 2018)
	Cambodia	SAR (PALSAR)	National Forest	
	Malaysia	Airborne LiDAR	Mangrove	(Coracero and Malabrigo 2020)
	Malaysia	Double Sampling + LiDAR	Tropical Forest	
	Indonesia	SAR + Texture	Natural Forest	(Dong et al. 2020)
	Vietnam	Sentinel-1A SAR + GIS	Tropical Evergreen Forest	
	Indonesia	WorldView-2 + GEOBIA	Mangrove	(Hartoyo et al. 2025)
	Cambodia	Airborne LiDAR	Seasonal Forest	
	Indonesia	LiDAR	Lowland Forest	(Candra et al. 2016)
	Malaysia	LiDAR	Dipterocarp Complex	
	Cambodia	GEOBIA + LiDAR	Mixed Tropical Forest	(Hashimoto et al. 2004)
	Indonesia	Time-series SAR (PALSAR-2)	Tropical Forest	
	Indonesia	Spaceborne LiDAR (GLAS)	Tropical Forest	(Culmsee et al. 2010)
	Vietnam	MLP Neural Network + SAR	Mangrove	
	Malaysia	LiDAR + WorldView-3	Dipterocarp Forest	(Basyuni et al. 2025)
	Philippines	KNN + Landsat	Pine Forest	
	Indonesia	SAR (ALOS-2)	Restored Mangrove	(Basuki et al. 2009)
	Malaysia	SAR	Tropical Forest	
	Malaysia	SAR (PALSAR)	Tropical Forest	(Kiyono et al. 2010)
	Malaysia	SAR (PALSAR)	Mangrove	
	Philippines	Airborne LiDAR	Old-growth Mangrove	(Dang et al. 2019a)
	Thailand	RS + Field	Dipterocarp	
	Thailand	TLS + Indices	Dry Evergreen	(Zaki et al. 2016a)
	Malaysia	ALS + TLS	Tropical Forest	
	Malaysia	TLS (Terrestrial Laser)	Rainforest	(Jachowski et al. 2013)
	Philippines	Field + GIS	Muyong Forest	
	Thailand	QuickBird + Individual Crown	Mangrove	(Bui et al. 2024)
	Indonesia	Hybrid RS + Soil	Mangrove	

The selected literature predominantly covers empirical and modelling-based studies of AGB across tropical regions of Southeast Asia, particularly in countries such as Indonesia, Malaysia, Vietnam, Thailand, Cambodia, and the Philippines. AGB refers to the total biomass of living vegetation above the soil, including stems, branches, bark, and leaves, and is a crucial parameter in estimating forest carbon stocks and understanding forest structure, productivity, and climate mitigation potential (Avtar et al. 2020). The studies reviewed employed various AGB estimation methods, ranging from direct field-based measurements using allometric equations to advanced remote sensing and machine learning approaches.

Field-based allometric studies, such as those by Basuki et al. (2009), Komiyama (2000), Komiyama et al. (2008), and Maulana et al. (2016), remain foundational due to their high precision and suitability for species-specific or local-scale estimations. These methods often involve destructive sampling or the application of regionally calibrated allometric models that use variables such as DBH, tree height, and wood density. However, given the logistical and ecological limitations of field measurements over large areas, remote sensing has emerged as a dominant method in recent years. Techniques such as SAR, LiDAR, and high-resolution optical imagery are widely adopted due to their ability to provide large-scale, repeatable, and cost-effective assessments of biomass. SAR-based methods (e.g., using ALOS-PALSAR and Sentinel-1) have demonstrated good correlations with field AGB estimates in mangrove and evergreen forests, despite some limitations related to signal saturation in dense canopies (Hamdan et al. 2014; Waqar et al. 2020). Similarly, airborne and terrestrial LiDAR systems offer high structural sensitivity, making them ideal for mapping AGB in heterogeneous forest landscapes (Ota et al. 2015; Rahman et al. 2017; Wong et al. 2024). In addition, a subset of studies employed machine learning algorithms such as random forest, support vector machines, and LightGBM, often in combination with remote sensing data, to model complex relationships between forest structure and AGB more effectively (Bui et al. 2024; Kabinesh et al. 2025; Pham et al. 2017). These models have demonstrated promising results in improving the prediction accuracy of biomass, particularly in areas with limited ground truth data or high spatial variability.

The ecosystem classification (**Fig. 1**) of the reviewed studies reveals a strong focus on mangrove (18 studies), dipterocarp (14 studies), and tropical mixed forests (12 studies), highlighting the ecological and carbon significance of these biomes in the region. Less frequently studied ecosystems include agroforestry systems, peatlands, and montane rainforests, which nonetheless exhibit considerable carbon sequestration (Brown et al. 2018; Hartoyo et al. 2025b; Ng et al. 2021). Spatially, Indonesia contributed the most studies (39), followed by Malaysia (15), Vietnam (10), the Philippines (5), and other Southeast Asian countries, underscoring the regional prioritization in carbon accounting research.

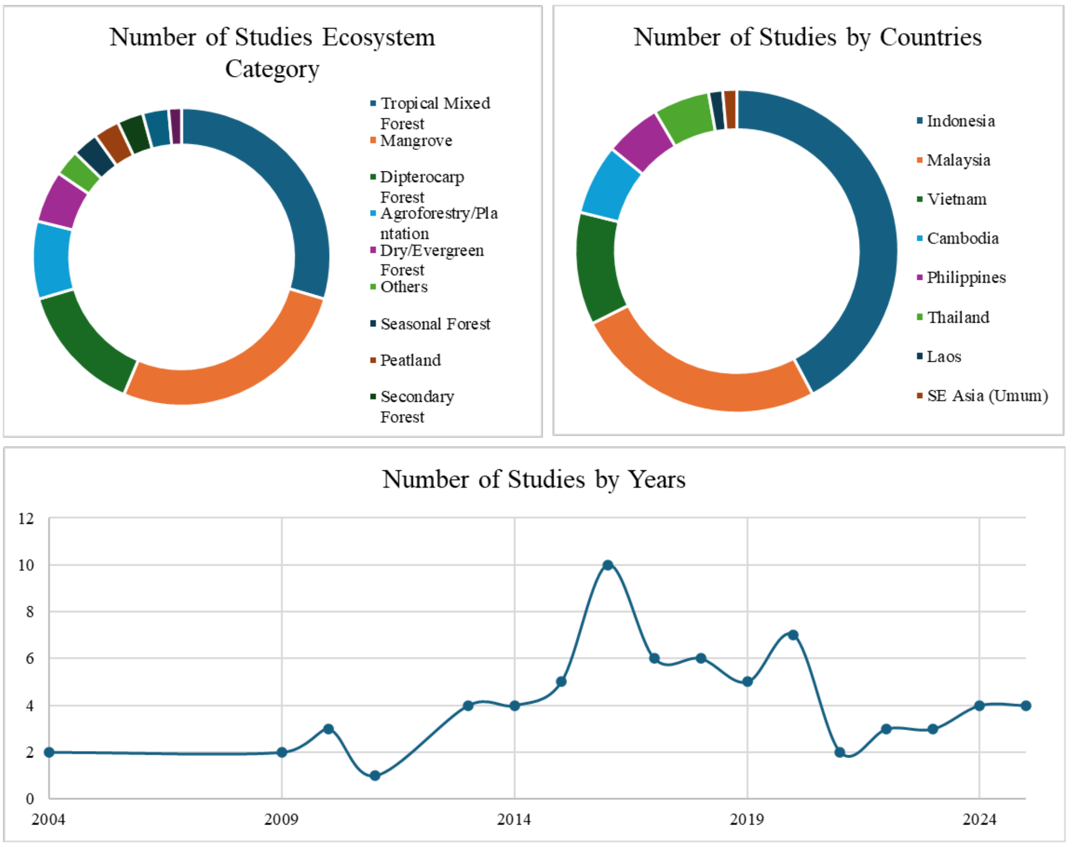

Fig. 1. Distribution of the selected studies in terms of (top left) ecosystem categories, (top right) country of research, and (bottom) publication year.

This illustrates the distribution of AGB studies in Southeast Asia across ecosystem types, countries, and publication years (**Fig. 1**). The dominance of mangrove, dipterocarp, and tropical mixed forests highlights the ecological importance of these biomes in regional biomass assessments. Indonesia, Malaysia, and Vietnam are the most represented countries, reflecting their active engagement in carbon stock research. The temporal trend shows a marked increase in publications post-2010, peaking around 2016, indicating growing academic and policy interest in forest biomass estimation across the region.

3.2. Field-Based and Allometric Models

The field-based and allometric models reviewed in this study reveal a consistent emphasis on developing accurate, site-specific, and species-specific equations to estimate AGB and carbon stock across various forest ecosystems in Southeast Asia (**Table 2**). These models, rooted in destructive or non-destructive field measurements, predominantly use parameters such as DBH, tree height, and wood density to predict biomass. Many studies, particularly those conducted in Indonesia and Malaysia, have developed local equations that significantly outperform generic or pan-tropical models in terms of accuracy and precision.

Table 2. Summary of allometric equations

Country	Forest Type	Allometric Equation	R^2 / RMSE	Author
Indonesia	Agroforestry (Nutmeg)	$Y = 134.353 \times DBH^{2.424}$	R^2 (adj) = 0.977	(Mardiatmoko et al. 2019)
Indonesia	Papua Forest	$Y = 0.115 \times DBH^{2.19} \times H^{0.88}$; $Log(TAGB) = -0.267 + 2.23\ Log(DBH) + 0.649\ Log(WD)$	R^2 = 0.95; RMSE = 0.149	(Maulana et al. 2016)
Malaysia	Mangrove	$\log AGB = 2.420 \log GBH - 1.832$	–	(Ong et al. 2004)
Laos	Mixed Deciduous	$AGB = -27.91 + 1.59 \times NDVI$	R^2 = 0.74	(Vicharnakorn et al. 2014)
Indonesia	Mangrove	$AGB = 0.1848 \times DBH^{2.3624}$	–	(Windarni et al. 2018)
Malaysia	Dipterocarp	$Y = a + b \times DBH + c \times DBH^2$	R^2 = 0.88	(Zaki et al. 2016b)
Indonesia	Sengon Plantation	$AGB = 0.0806 \times DBH^{2.368}$	–	(Hossain et al. 2023)
Indonesia	Lowland Dipterocarp	$\ln(TAGB) = -1.201 + 2.196 \times \ln(DBH)$	R^2 = 0.96	(Basuki et al., 2009)
Cambodia	Seasonal Forest	AGB gain = 0.0165 × Initial AGB + 2.20	R^2 = 0.4531	(Kiyono et al. 2017)
Malaysia	Mangrove	AGB = f(D^2H parameter)	R^2 = 0.63–0.96; RMSE = 19.4 Mg/ha	(Khan et al. 2025)
Vietnam	Dipterocarp and Evergreen	AGB = f($D^2 \times H \times WD$); BGB = f($D^2 \times H$ or D)	R^2 = 0.85	(Kralicek et al. 2017)
Indonesia	Mangrove	Species-specific vs Generic AGB (Simple Ratio VI)	R^2 = 0.2175 (generic), 0.1801 (species-specific)	(Kamal et al. 2022)
Indonesia	Abandoned Land	$H = 0.4642 \times DBH + 3.2344$	R^2 = 0.3339	(Karyati et al. 2019)

For instance, Imam et al. (2016) formulated a model for the Papua forest using a power function of DBH and height, achieving a high coefficient of determination ($R^2 = 0.95$) and low RMSE (0.149), demonstrating the advantage of incorporating multiple biometric parameters. Similarly, Mardiatmoko et al. (2019) proposed a locally calibrated allometric equation for nutmeg agroforestry systems in Maluku, using only DBH as a predictor, which achieved $R^2 = 0.977$, reinforcing the reliability of DBH-based models when supported by species specificity. Windarni et al. (2018) also reported a successful mangrove biomass estimation model based on DBH with the form $AGB = 0.1848 \times DBH^{2.3624}$, which was useful for quantifying carbon in coastal zones.

Several studies highlighted the limitations of applying generalized, pan-tropical allometric models across Southeast Asia. Nam et al. (2016), for instance, demonstrated that in Vietnamese evergreen forests, such models overestimated AGB by up to 27% and belowground biomass (BGB) by as much as 150% when compared to locally calibrated equations. This means that the pan-tropical models produced AGB estimates that were nearly one-third higher and BGB estimates that were more than double the actual values measured using local parameters. These discrepancies stem from the inability of generalized models to capture site-specific variations in species composition, forest structure, and edaphic conditions typical of Southeast Asian ecosystems. Similarly, Yuen et al. (2016) reported up to 60% variability in AGB estimates across REDD$^+$ projects in the region due to inconsistent equation use, underscoring the need for harmonization and localization in biomass modeling to ensure accuracy and comparability in carbon accounting.

In mangrove ecosystems, Kamal et al. (2022) and Ong et al. (2004) compared generic and species-specific models, concluding that species-specific equations, although complex, provided superior estimation accuracy. Kamal et al. (2022) observed R^2 values of 0.2175 and 0.1801 for their generic and species-specific models, respectively, suggesting the need for further model refinement. Conversely, Hossain et al. (2023) and Ikhsan et al. (2021) developed effective models for plantation species (sengon and pine-mahogany mix), supporting their utility in community forestry and carbon credit schemes.

A few studies incorporated advanced regression techniques such as quadratic and log-linear transformations. For instance, Zaki et al. (2016a) proposed a quadratic model for Dipterocarp forests, yielding R^2 of 0.88, while Basuki et al. (2009) utilized a log-linear model, $\ln(TAGB) = -1.201 + 2.196 \times \ln(DBH)$, achieving a high R^2 of 0.96. These transformations helped to linearize relationships and reduce heteroscedasticity in biomass prediction.

The reviewed studies consistently affirm that field-based and allometric models remain vital for biomass estimation due to their interpretability, cost-effectiveness, and alignment with traditional forest inventory practices. However, their limitations, particularly in scaling up across heterogeneous landscapes, suggest that integration with remote sensing and machine learning approaches, as recommended by Yuen et al. (2016) and Anitha et al. (2015), could enhance accuracy and spatial coverage. For instance, in Indonesia, several studies, including those by Basuki et al. (2009), Maulana et al. (2016), and Mardiatmoko et al. (2019), have developed robust site-specific equations well-suited to local forest conditions, such as lowland dipterocarps and agroforestry systems. In Malaysia, allometric models have been refined for mangroves and dipterocarp forests, as seen in studies by Zaki et al. (2016a) and Ong et al. (2004), which highlight both aboveground partitioning and regression-based estimations. Meanwhile, Vietnam demonstrates the advantages of integrating ecological parameters (DBH, H, WD) and stratified models for evergreen and dipterocarp forests (Kralicek et al. 2017; Nam et al. 2016), with evidence suggesting that generalized pan-tropical models may significantly overestimate local biomass stocks. These national contexts collectively underscore the importance of context-specific modeling, while also pointing to the need for regional harmonization in allometric practices. Field-based and Allometric Models have historically served as the backbone of biomass estimation. The reviewed studies demonstrate that locally developed, species-specific allometric equations consistently outperform pan-tropical models in terms of accuracy.

3.3. Remote Sensing and UAV

Model accuracy, as shown in **Fig. 2**, is evaluated using the coefficient of determination (R^2) and Root Mean Square Error (RMSE) across studies that employ remote sensing and UAV-based approaches, revealing significant spatial and methodological variability in performance. Studies conducted in Malaysia have consistently demonstrated the highest R^2 values, frequently exceeding 0.90, as seen in Rahman et al. (2017), who achieved an R^2 of 0.973 using terrestrial laser scanning (TLS), and Wong et al. (2024), who reported an R^2 of 0.92 using airborne LiDAR in mangrove ecosystems. These results indicate the precision of LiDAR-based approaches for estimating individual tree and stand-level AGB, especially in structurally complex tropical forests. Similarly, Indonesia yielded robust model performances, with R^2 values ranging from 0.80 to 0.95. For instance, Basyuni et al. (2023) applied UAV-derived canopy metrics and obtained R^2 values between 0.85 and 0.97, while Hayashi et al. (2015) achieved $R^2 = 0.883$ using GLAS spaceborne LiDAR. In contrast, models in Vietnam, although still useful, tended to report slightly lower R^2 values, ranging between 0.63 and 0.81, as observed in studies by Thuy et al. (2020) and Dang et al. (2019), which employed Sentinel-2 NDVI and machine learning regression, respectively. Nonetheless, exceptional results were noted in select Vietnamese studies using advanced integration, such as Pham et al. (2017), who obtained high model accuracy (RMSE = 21.4 Mg/ha) using a multilayer perceptron neural network and SAR data.

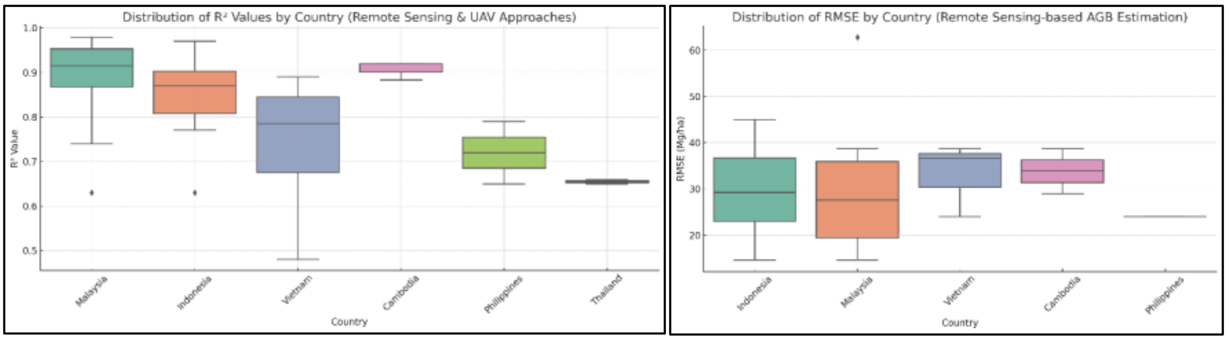

Fig. 2. Statistical distribution of AGB estimation accuracy by country using remote sensing and UAV approaches: (a) Coefficient of determination (R^2); (b) Root mean square error (RMSE).

In terms of RMSE, which reflects the average deviation between estimated and actual biomass values, Malaysia consistently demonstrated low errors, typically ranging from 14 to 30 Mg/ha. For example, Wan-Mohd-Jaafar et al. (2017) reported an RMSE of 14.8% using discrete LiDAR data for dipterocarp forests, and Jucker et al. (2018) achieved an RMSE of 19 Mg C/ha with minimal bias (0.6%) in Bornean forests. Indonesia exhibited a wide range of RMSE values, from as low as 14.6 Mg/ha (Wong et al. 2024) to as high as 62.8 Mg/ha in SAR time-series models (Hayashi et al. 2019), highlighting the variation that depends on sensor type and forest conditions. Vietnam and Cambodia showed RMSEs typically in the range of 28–42 Mg/ha, with Ota et al. (2015) reporting RMSE of 29 Mg/ha in seasonal forests using airborne LiDAR, and Hirata et al. (2018) reporting RMSE of 38.7 Mg/ha using LiDAR–QuickBird fusion.

Airborne LiDAR consistently yields superior performance compared to optical and SAR-based methods, corroborating findings from prior reviews (Borsah et al. 2023; Matiza et al. 2023). Furthermore, texture-based enhancements and vegetation indices (e.g., NDVI, VH, HV textures) have been shown to improve SAR performance (Nesha et al. 2020; Thapa et al. 2015), although

SAR remains susceptible to signal saturation above 150–200 Mg/ha in dense canopies (Hamdan et al. 2014). Overall, the integration of field inventory data, species-specific allometric models, and multi-source remote sensing, particularly LiDAR and UAV-derived models, emerged as the most reliable approaches for accurate AGB estimation across diverse tropical ecosystems in Southeast Asia.

These findings collectively underscore that AGB estimations in Southeast Asia, particularly in Malaysia, Indonesia, and Vietnam, are highly influenced by methodological choices, forest types, and data resolution. Malaysia's extensive use of LiDAR over structured forest types has yielded consistently low RMSE and high R^2 values. In contrast, Indonesia's diverse forest conditions necessitate more adaptive models that combine UAV and SAR. In Vietnam, despite slightly lower statistical accuracies, advanced integration of machine learning with radar data demonstrates strong potential. This regional comparison highlights the importance of tailoring AGB estimation techniques to ecological and technological contexts, ensuring both accuracy and operational feasibility in forest carbon monitoring. Remote Sensing and UAV Approaches have significantly advanced the scalability of biomass assessments, offering spatially explicit data over large and inaccessible regions. Optical satellite imagery (e.g., WorldView-2, QuickBird, Sentinel-2) and radar systems (e.g., ALOS PALSAR, RadarSAT-2) have enabled the development of regression models based on spectral indices and textural metrics.

3.4. Machine Learning and Data Fusion

Machine learning and data fusion techniques have increasingly been utilized to enhance the accuracy and efficiency of AGB estimation across Southeast Asia, particularly in forest ecosystems with structural complexity. Among the reviewed studies, performance in terms of predictive strength (R^2) and estimation error (RMSE) demonstrated promising results. For instance, Basuki et al. (2009) achieved a very high R^2 of 0.96 using a mixed-species allometric model based on logarithmic transformation, highlighting the robustness of integrating DBH with site-specific parameters in lowland dipterocarp forests of Indonesia. Similarly, in Vietnam, Dang et al. (2019) reported an R^2 of 0.81 and RMSE of 36.67 Mg/ha by applying Random Forest regression using Sentinel-2 bands, particularly the SWIR and red-edge as input features, which were shown to be highly responsive to vegetation structure.

Other machine learning approaches also yielded favourable accuracy. Bui et al. (2024) utilized LightGBM in combination with a metaheuristic TDO algorithm, resulting in an R^2 of 0.797 and the lowest RMSE among the group (13.88 Mg/ha), underscoring the potential of hybrid optimization techniques in estimating upland forest biomass. Jachowski et al. (2013) applied a Support Vector Machine (SVM) approach using GeoEye-1 imagery for mangrove forests in Thailand, achieving R^2 of 0.76, with AGB estimated at 250 Mg/ha and associated carbon stock of 155 Mg C/ha (± 32.6). Although the RMSE was not explicitly provided, the study noted considerable variation in total biomass estimates (± 72.5 Mg/ha), reflecting high natural heterogeneity in mangrove ecosystems.

For instance, Kiyono et al. (2010) did not directly report R^2 or RMSE, but presented carbon stock estimates with an uncertainty range of ± 12% in Cambodian dry forests. This range is consistent with $REDD^+$ Tier 2 requirements for national forest monitoring systems, indicating its potential applicability for policy implementation. These findings collectively suggest that machine learning and data fusion models can offer accuracy levels comparable to traditional methods, while also allowing for scalable, cost-effective, and reproducible AGB estimation. The effectiveness of these approaches largely hinges on the quality of input variables, such as canopy height, texture metrics, or spectral indices, and the representativeness of the field data used for training and validation. This supports prior syntheses, which emphasize that hybrid and ensemble methods, especially those integrating remote sensing and environmental covariates, tend to outperform simpler linear models in heterogeneous tropical landscapes (Borsah et al. 2023; Matiza et al. 2023).

Estimating AGB accurately is pivotal for carbon stock assessment and climate mitigation strategies such as REDD$^+$. Over the last two decades, various methodological paradigms have emerged, ranging from field-based allometric models to remote sensing, UAV-based approaches, and, more recently, machine learning and data fusion techniques. The diversity of methods reflects not only technological advancements but also varying ecological contexts and policy demands across Southeast Asia's tropical forest ecosystems. Despite methodological advancements, challenges persist in standardizing protocols across studies, particularly in biomass validation, reporting accuracy metrics (RMSE, R^2), and aligning outputs with policy frameworks such as IPCC tiers and REDD$^+$ MRV guidelines. These frameworks, especially the IPCC's Tier 2 and Tier 3 approaches, require country-specific data and higher-resolution estimates to improve national greenhouse gas inventories. Similarly, REDD$^+$ implementation requires consistent, transparent, and verifiable monitoring systems, which underscores the role of NFMS in institutionalizing biomass monitoring at the national level. This review emphasizes the importance of hybrid approaches that combine the mechanistic accuracy of field-based models with the scalability of remote sensing and the predictive capabilities of AI/ML algorithms (Borsah et al. 2023; Thapa et al., 2023). Collaborative efforts to build regional AGB model repositories and open-access training datasets would greatly accelerate progress in this field and strengthen the technical foundation for meeting international climate commitments.

4. Conclusions

Field-based and allometric methods remain the cornerstone of carbon stock assessments, particularly in Southeast Asian countries such as Indonesia, Malaysia, and Vietnam. In Indonesia, locally derived allometric equations have shown high accuracy in estimating AGB across diverse ecosystems such as lowland dipterocarp forests, mangroves, and agroforestry systems. However, challenges persist due to species heterogeneity and the difficulty of scaling these models over vast and inaccessible terrains. Malaysia has made significant progress in deploying airborne LiDAR and Terrestrial Laser Scanning (TLS), achieving high estimation precision ($R^2 > 0.90$), particularly in dipterocarp and mangrove forests, thanks to better technological access and institutional capacity. In Vietnam, while remote sensing and machine learning applications are growing, variability in AGB estimates remains higher due to terrain complexity and the limited availability of calibration data. Remote sensing and UAV technologies have proven vital in bridging gaps between site-level data and large-scale biomass assessments. These technologies, when combined with ground-based observations, provide scalable, efficient, and repeatable approaches for biomass estimation. Despite their promise, limitations such as cost, data availability, and sensor-specific issues (e.g., SAR signal saturation in dense forests) must be addressed. Machine learning and data fusion techniques, particularly in Vietnam and Malaysia, show promise in modeling AGB across complex landscapes. However, they require consistent, high-quality ground data for training and validation. This emphasizes the need for strong National Forest Monitoring Systems (NFMS) aligned with IPCC Tier 2/3 guidelines and REDD+ MRV protocols to ensure transparency and reliability in biomass reporting. Integrating allometric models, remote sensing tools, and AI-driven approaches offers a path toward robust, policy-relevant AGB estimation. Future research should invest in regional model harmonization, open-access data infrastructures, and policy alignment to enhance AGB monitoring and support climate mitigation strategies across Southeast Asia.

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Author Contributions

S.L.: Conceptualization, Methodology, Software, Validation; A.R.P.: Formal Analysis, Investigation, Resources, Data Curation, Writing – Original Draft Preparation; S.G.: Writing – Review and Editing, Visualization, Supervision, Project Administration, Funding Acquisition; M.A.: Writing – Review and Editing, Visualization, Supervision, Project Administration, Funding Acquisition; M.I.P.: Formal Analysis, Investigation, Resources, Data Curation; L.R.A.K.: Formal Analysis, Investigation, Resources; R.P.P.: Formal Analysis, Investigation, Resources.

Conflict of Interest

The authors declare no conflict of interest.

Declaration of Generative AI and AI-Assisted Technologies in the Manuscript Preparation

During the preparation of this work, the authors utilized ChatGPT (OpenAI), Rayyan AI, and Publish or Perish (PoP) to assist with language refinement, systematic review article screening, literature search management, and organization of scientific writing. After using these tools, the authors carefully reviewed, validated, and edited all generated outputs as needed, and take full responsibility for the content and integrity of the final publication.

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