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Multi-Sensor Remote Sensing and Machine Learning for Aboveground Biomass Mapping in Vietnam's Melaleuca Wetlands: A Review

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ABSTRACT

Accurate mapping of aboveground biomass in tropical peatland forests remains challenging due to the complexity of vegetation structure, hydrological regimes, and data heterogeneity across sensors. This review synthesizes multi-sensor remote sensing and machine-learning approaches for aboveground biomass estimation in Vietnam's Melaleuca wetlands, aiming to establish a standardized framework of terminology, metrics, and environmental covariates for future research and applications. By harmonizing key indicators such as canopy height, texture, soil-hydro-geomorphological variables, and validation metrics (R^2, RMSE), the framework enhances reproducibility, comparability, and data integration across scales. The study further consolidates a practical roadmap encompassing data acquisition, feature engineering, modeling, and validation stages - culminating in uncertainty-aware biomass mapping that bridges research and operational implementation. Beyond synthesizing existing studies, this work provides actionable guidance for open-access workflows and policy-oriented applications in carbon accounting and wetland restoration. The proposed standardized approach thus supports both scientific and managerial communities in advancing sustainable management of Vietnam's Melaleuca peat ecosystems and will help standardize future aboveground biomass mapping across Southeast Asian wetlands.

Keywords: L-band SAR, LiDAR and GEDI, Melaleuca aboveground biomass, Multi-sensor data fusion, Spatial and spatio-temporal cross-validation

INTRODUCTION

Melaleuca-dominated wetlands are globally important carbon reservoirs and biodiversity refuges, yet their aboveground biomass (AGB) remains challenging to map reliably at scale. Peat accumulation, acid-sulfate soils, strongly coupled hydrology and microtopography, and frequent radar/optical saturation in dense stands complicate both field estimation and remote-sensing (RS) inference, producing spatially heterogeneous allometry and sensor responses that impede model transferability. Field and remote studies have documented substantial variation in AGB drivers and signal behavior across these substrates, underscoring the need for tailored approaches (Huy et al., 2016; Kappas, 2020; Nam et al., 2016; Tran et al., 2015; Zadbagher et al., 2024).

Recent advances in multi-sensor fusion (light detection and ranging [LiDAR]/ global ecosystem dynamics investigation [GEDI], L-band synthetic aperture radar (SAR), Sentinel-1/2), machine learning, and multi-temporal analysis show promise for improving accuracy, but reported performance varies widely and is sensitive to validation strategy, sensor choice, and environmental covariates (Balestra et al., 2024; Musthafa & Singh, 2022; Nguyen et al., 2024; Zhang et al., 2019, 2020). Moreover, many studies report optimistic accuracies when spatial autocorrelation is not properly accounted for; best practices now emphasize spatial or

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spatio-temporal blocking for robust out-of-sample assessment (Roberts et al., 2017; Valavi et al., 2019). At the same time, localized allometry (diameter at breast height [DBH] - height - wood density) and site-specific predictors (hydroperiod, peat depth, salinity, microtopography) critically influence both AGB and sensor signals, and must be integrated into modelling workflows to achieve transferable maps (Ngo et al., 2023; Tran et al., 2015).

This review synthesizes these developments with the explicit aim of informing robust AGB mapping in Melaleuca wetlands. We (i) summarize methodological accuracy and observed performance ranges and their drivers, (ii) evaluate multi-sensor and temporal data integration strategies, (iii) discuss computational and practical modelling considerations, and (iv) identify the hydrology - geomorphology - soil covariates most important for transferability. Throughout, we adopt consistent terminology (e.g., L-band SAR, LiDAR, GEDI, Sentinel-1/2) and report performance metrics using the coefficient of determination (R^2) and root mean square error (RMSE) ($Mg \cdot ha^{-1}$) for comparability. The review concludes with a concise practical roadmap for scaffolded, uncertainty-aware mapping suited to Melaleuca landscapes.

Remote Sensing-Based Aboveground Biomass Mapping: Methods, Data Integration, Validation, And Scaling

Estimating AGB from RS underpins carbon accounting, REDD+, and long-term forest monitoring. In Vietnam where Melaleuca cajuputi (cajeput) forests are widespread across the Mekong Delta, models must be both accurate and scalable, yet sensitive to site-specific conditions (peat soils, acid sulfate soils, and fluctuating hydrology). Recent literature shows a shift from traditional regressions toward ML and multi-sensor data fusion (optical - SAR - LiDAR/UAV), coupled with stricter spatial-temporal validation schemes to avoid optimistic accuracy assessments. This section provides a review of methodological accuracy, data integration, computational complexity, and spatio-temporal resolution, and discusses their implications for Melaleuca forests in Vietnam.

METHODOLOGICAL ACCURACY

Reported model performance for RS-based AGB is commonly summarized with R^2 and RMSE. Across studies, observed R^2 values vary widely (approx. 0.59 - 0.95), with RMSE dependent on forest type, sensor combination, and modelling strategy; for comparability this review reports RMSE in $Mg \cdot ha^{-1}$ where possible (Nguyen et al., 2024; Zhang et al., 2019, 2020). In general, models that integrate structural information (LiDAR/GEDI) with spectral and radar predictors and that use advanced learning architectures report the highest fits (deep-learning examples reaching $R^2 \approx 0.93$ - 0.95 in some settings), while single-source optical models more frequently occupy the lower end of the observed range. Structurally complex or radar/optically saturated systems (e.g., tropical peat swamp forests) often yield substantially lower test R^2 (≈ 0.21 - 0.70), reflecting signal saturation and heterogeneous allometry (Zadbagher et al., 2024).

Machine learning approaches (random forest [RF], support vector regression, gradient-boosted trees, and neural networks) typically reduce prediction error relative to simple linear or multiple regression baselines, particularly when spectral and structural predictors are combined; ensemble or stacking strategies further improve robustness in many comparative studies (Chen et al., 2023; Khan et al., 2024; Nguyen et al., 2024; Zhang et al., 2020).

A critical caveat is validation strategy. Random k-fold cross-validation (CV) that ignores spatial (and temporal) autocorrelation routinely produces optimistic accuracy estimates. To obtain realistic out-of-sample performance and to assess transferability across hydrological zones or management units, studies should use spatial or spatio-temporal blocking (with block sizes informed by empirical autocorrelation) or leave-one-region-out tests (Roberts et al., 2017; Valavi et al., 2019). Authors are also encouraged to report multiple complementary metrics (e.g., R^2, RMSE in $Mg \cdot ha^{-1}$, MAE, bias) and to quantify predictive uncertainty (e.g., bootstrap, quantile estimates, or prediction intervals) so that users can judge both central tendency and spread.

We recommend reporting both central tendency and uncertainty - providing R^2 and RMSE ($Mg \cdot ha^{-1}$) together with prediction intervals or quantiles - prioritizing multi-sensor, structurally informed predictor sets (LiDAR/GEDI with SAR and optical) in saturation-prone or structurally complex stands; assessing transferability using spatial or spatio-temporal blocking (or leave-one-region-out) to avoid optimistic bias; and adopting tree-based ensembles (RF, extreme gradient boosting [XGBoost]/light gradient boosting machine [LightGBM]) as robust baselines, reserving complex deep architectures for cases with substantial structural supervision and large training samples.

Table 1 provides a concise summary of the objectives, data sources, model families, validation strategies, and metrics referenced throughout Section 2.

Data integration level

A growing body of evidence shows that integrating multiple sensors and field data materially improves AGB estimation by mitigating sensor-specific limitations (e.g., optical/radar saturation) and by recovering canopy structure. In practice, structural sources (LiDAR or GEDI) combined with L-band SAR and high-resolution optical imagery (e.g., Sentinel-2) generally outperform single-source configurations, particularly in high-biomass or heterogeneous wetlands (Balestra et al., 2024; Musthafa & Singh, 2022; Vafaei et al., 2018; Wang et al., 2023).

Field plots and ecologically relevant covariates (topography, peat depth, soils, hydrological metrics) remain essential for calibration and for improving model generalization across substrate and management gradients. Local allometry (DBH - height - wood density) provides mechanistic anchors for translating structural predictions into AGB and reduces bias when substrate properties vary (Tran et al., 2015; Zadbagher et al., 2024).

Temporal depth further strengthens inference: multi-epoch LiDAR or GEDI combined with continuous optical/SAR time series captures biomass trajectories (decline, recovery) and improves long-term monitoring and change detection (Loh et al., 2022; Musthafa & Singh, 2022; Naik et al., 2021).

Table 1. Summary comparison of workflow stages for AGB mapping

Stage	Key recommendation	Typical sensors/data	Recommended models	Validation	Metrics
Data acquisition	Use structural scaffolds + wall-to-wall sensors; include field plots and env covariates	LiDAR (UAV/airborne) or GEDI; Sentinel-1/2; L-band SAR; field plots; hydrological/topo/ soil layers	N/A (data stage)	N/A	Data vol high (depends on LiDAR)
Feature engineering /fusion	Late feature fusion of structure + spectral + SAR; include peat/soil/ hydrological covariates	Canopy height model metrics, height percentiles, spectral indices, SAR backscatter and polarimetry, peat depth, hydroperiod	RF/XGBoost/LightGBM → ensemble stacking → deep learning (DL) (if abundant labels)	N/A (see modelling)	medium
Modelling	Start with tree-based baselines; progress to DL only with dense structural	As above	RF/XGBoost/LightGBM (baseline); Stacking ensembles; DL (CNNs) when LiDAR/ GEDI	Use spatial/spatio-temporal blocking for hyperparameter tuning	Baseline: low - medium; DL: high

	supervision		supervision present		
Validation and transfer-ability	Use spatial/spatio-temporal block CV or leave-one-region-out; report stratified errors	Validation samples from LiDAR strips/ independent plots	N/A	Spatial block CV (block size informed by autocorrelation); report out-of-region tests	low - medium
Metrics and uncertainty	Report central tendency + spread; stratify by substrate/hydro class	R^2, RMSE ($Mg \cdot ha^{-1}$), MAE, bias; show prediction intervals/quantiles	N/A	Report metrics for each validation fold and by strata	low
Operational notes	Document preprocessing, seeds, versions; present stratified error maps	Radiometric/terrain correction, co-registration, speckle filtering	N/A		

Computational complexity

Computational cost and model complexity are central considerations when selecting methods for AGB mapping because gains in predictive accuracy frequently entail higher requirements for compute, storage, and labeled structural supervision. Deep architectures (e.g., convolutional neural networks, autoencoders) and ensemble stacking/boosting typically deliver superior accuracy and scalability for large, multi-sensor datasets, but they demand substantial graphics processing unit (GPU)/central processing unit (CPU) resources, careful hyperparameter tuning, and rigorous data preprocessing, especially for regional-scale, multi-source inputs (Khan et al., 2024; Zhang et al., 2019).

By contrast, traditional regression and simple allometric models remain computationally lightweight and interpretable but often generalize poorly in settings affected by spectral/ radar saturation or high structural heterogeneity. Tree-based methods (RF, XGBoost/LightGBM) offer a pragmatic middle ground: they are computationally efficient, robust to heterogeneous predictors, and serve as strong baselines when training data or computational budgets are limited (Chen et al., 2023; Zhang et al., 2020).

From a practical data-science perspective, we recommend the following conventions: (i) use spatial or spatio-temporal block CV (with block sizes guided by empirical spatial autocorrelation) for hyperparameter selection to avoid leakage and inflated performance estimates; (ii) standardize multi-source preprocessing (radiometric and terrain correction, co-registration, speckle filtering) and document these steps; and (iii) adopt late feature fusion with tree-based learners as robust baselines, moving to compact DL solutions only when abundant structural supervision (e.g., LiDAR/GEDI scaffolds) and large, diverse training samples are available (Nguyen et al., 2024; Roberts et al., 2017; Valavi et al., 2019).

When sample sizes or computational resources are constrained, RF, XGBoost, or LightGBM should serve as the default baselines. Deep learning should be reserved for settings with dense labels and structural scaffolds (e.g., LiDAR/GEDI), with training and inference compute quantified and reported. Hyperparameters should be selected using spatial or spatio-temporal blocking to obtain realistic estimates of transferability. Finally, preprocessing pipelines should be fully documented, with reproducible settings (random seeds, software versions) explicitly stated.

Temporal and spatial resolution

Spatial and temporal resolution jointly determine the suitability of sensors and modelling strategies for AGB

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estimation: fine spatial detail captures structure at plot and stand scales, whereas temporal depth enables monitoring of dynamics and disturbance-driven trajectories.

At the plot and stand scale, UAV or airborne LiDAR delivers high-fidelity three-dimensional structure (e.g., CHM metrics and height percentiles) that correlate strongly with AGB and are especially valuable when fused with high-resolution optical imagery (Wang et al., 2023; Yan et al., 2024). These structural data are ideal for deriving local allometry and for calibrating models that require detailed canopy scaffolding.

For regional, wall-to-wall mapping the recommended approach is to use LiDAR/GEDI strips or footprints as calibration scaffolds and extrapolate with satellite imagery and SAR (Sentinel-1/2 and L-band where available). This scaffold-and-extrapolate strategy typically reduces mapping error relative to satellite-only approaches because it preserves structural anchors while providing full spatial coverage (Wang et al., 2023).

Temporal depth improves robustness and enables change detection: multi-epoch LiDAR or GEDI combined with continuous optical and SAR time series captures biomass trajectories (decline and recovery) and stabilizes estimates across variable acquisition conditions (Loh et al., 2022; Musthafa & Singh, 2022; Naik et al., 2021). Recent reviews highlight multi-temporal, multi-platform fusion as a key route to accurate and stable long-term monitoring (Balestra et al., 2024). More specifically, explicitly integrating seasonal and disturbance-driven variability is critical for accurately quantifying biomass dynamics and carbon flux in Melaleuca wetlands. These ecosystems are subject to strong seasonal hydrological pulses and periodic disturbances (e.g., fire or selective logging), which significantly alter AGB over short time scales. By leveraging dense time-series data from sensors like Sentinel or Landsat, it is possible to move beyond static AGB maps to dynamic monitoring systems. Methodologies such as time-series change detection and break-point analysis can identify the timing and magnitude of biomass loss or gain, providing crucial information for carbon accounting and management interventions (DeVries et al., 2015; Zhu, 2017). Therefore, future modeling roadmaps should prioritize the integration of these temporal metrics as predictive covariates to capture the full spectrum of AGB variability.

Practical note: choose sensor stacks according to scale and objective-use UAV/airborne LiDAR where detailed structural inference and local allometry are required; use GEDI/L-band + Sentinel-1/2 with LiDAR strips for regional mapping; and incorporate multi-temporal series when the goal is change detection or long-term monitoring.

Model Applicability to Melaleuca forests

Applicability of remote-sensing AGB models in Melaleuca ecosystems depends critically on (i) the match between training data and target domain, (ii) the sensor stack and degree of structural supervision, and (iii) the inclusion of environmental covariates that capture peat/acid-sulfate dynamics. Models trained on mineral-soil forests or on limited site conditions frequently underperform when transferred to peatland Melaleuca stands because of systematic differences in allometry, soil dielectric properties, and hydrological regime (Huy et al., 2016; Nam et al., 2016; Tran et al., 2015).

Scaffolded multi-sensor models (LiDAR/GEDI + L-band SAR + Sentinel-2) are most applicable when structural anchors overlap the target domain and field plots adequately sample the principal substrate and hydrological classes. Under these conditions, tree-based ensembles and well-regularized deep architectures typically yield transferable estimates with explicit uncertainty quantification (Nguyen et al., 2024; Wang et al., 2023).

Key limitations and risk factors.

Domain shift: differences in peat depth, salinity/acid sulfate status, hydrological alteration (drainage canals) and stand age/density create systematic biases if absent from training data.

Sensor saturation and structural heterogeneity: optical and C-band SAR indicators saturate at high biomass; L-band and LiDAR mitigate but do not fully remove ambiguity in complex canopies (Zadbagher et al., 2024).

Sparse structural supervision: where LiDAR/GEDI coverage or field plot density is low, expect larger

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extrapolation errors and spatially clustered uncertainty.

Recommended pre-deployment checks.

Domain diagnostic: compare distributions of key predictors (height metrics, hydroperiod proxies, peat depth, spectral indices) between training and target areas; flag areas with large covariate shift.

Scaffold availability: ensure structural anchors (LiDAR strips, GEDI, representative plots) exist across main substrate/hydrological strata; if absent, restrict inference or increase uncertainty.

Pilot external validation: reserve independent LiDAR strips or holdout regions for leave-one-region-out testing to estimate realistic transfer error.

Mapping products and reporting.

Deliverables should include wall-to-wall AGB map plus (i) pixelwise (or grid) uncertainty estimates (e.g., prediction intervals or quantile maps), (ii) stratified error summaries by peat/soil class and hydrological class, and (iii) a short “usage note” that identifies areas where models extrapolate beyond training support. Explicitly report validation protocol (spatial/spatio-temporal blocking), sample sizes per strata, and any preprocessing choices that materially affect inference (e.g., hydrologic digital elevation model [DEM] flattening).

Practical thresholding guidance.

- Treat regions with no structural scaffolding and with strong covariate shift as low confidence and avoid issuing fine-scale AGB estimates without additional data collection.
- Use RF/GBM baselines for rapid operational mapping and reserve DL for contexts with dense LiDAR/plot supervision. For formal reporting, always accompany maps with stratified uncertainty and a clear statement of transferability limits.

Synthesis and Implications for Melaleuca Wetlands

Integrative overview

This integrative overview synthesizes the principal methodological insights from Sections 2.1 - 2.4 and highlights their practical implications for mapping Melaleuca wetlands. Across studies, highest predictive performance is achieved by scaffolded, multi-sensor approaches that combine structural information (LiDAR/GEDI) with radar (notably L-band) and optical inputs, while rigorous spatial or spatio-temporal validation is essential to avoid optimistic accuracy estimates (Nguyen et al., 2024; Roberts et al., 2017; Zhang et al., 2019, 2020). Environmental covariates tied to peat and hydrological dynamics (peat depth, hydroperiod, salinity, microtopography) consistently improve model transferability when they are represented in training data (Huy et al., 2016; Tran et al., 2015; Zadbagher et al., 2024).

Key takeaways:

Scaffolded fusion is central: Use LiDAR/GEDI strips or footprints as structural anchors and extrapolate with Sentinel-1/2 and L-band SAR for wall-to-wall mapping.

Validation defines realism: Spatial or spatio-temporal blocking (or leave-one-region-out tests) should be standard for hyperparameter selection and performance reporting to estimate true transfer error.

Model choice should match data and compute: RF/XGBoost/LightGBM are robust baselines for most operational contexts; deep learning is justified when dense structural supervision and large, diverse training samples exist.

Environmental strata matter: Always stratify results (and report errors) by peat/soil/ hydrological classes to

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expose heterogeneous performance and inform management use.

Report uncertainty and limits: Deliverables must include stratified uncertainty maps and concise usage notes that identify low-confidence extrapolation zones.

For implementation guidance and worked examples that operationalize these principles, see Table 1, Table 2, and Section 3.2.3.

Implications for Melaleuca (with hydrology - geomorphology - soil variables)

Synthesis and principal recommendations.

For Melaleuca-dominated wetlands, reliable AGB mapping requires workflows that (i) anchor remote-sensing predictions in locally derived allometry (DBH - height - wood density), (ii) employ multi-sensor fusion with emphasis on structural scaffolds (LiDAR or GEDI) and L-band SAR to mitigate optical/C-band saturation, (iii) explicitly incorporate environmental covariates reflecting peat and acid-sulfate dynamics, and (iv) evaluate transferability using spatial or spatio-temporal blocking across hydrological and management strata (Bui et al., 2024; Huy et al., 2016; Luo et al., 2024; Musthafa & Singh, 2022; Nam et al., 2016; Tran et al., 2015).

Table 2. Per-study summary

No	Reported metric(s) (best / representative)	Sources
1	SSAE (deep model): R^2 = 0.935, RMSE = 15.67 Mg·ha^{-1}	Zhang et al. (2019)
2	Best performing (CatBoost/aggregated): R^2 ≈ 0.72, RMSE = 45.63 Mg·ha^{-1} (CatBoost aggregated). Ensemble/tree-based mean R^2 ≈ 0.69 - 0.71, RMSE ≈ 46 - 48 Mg·ha^{-1}	Zhang et al. (2020)
3	Tent_ASO_BP (NN): R^2 = 0.74, RMSE = 11.54 Mg·ha^{-1} (best configuration reported). Comparators: RF R^2 = 0.54 (RMSE 21.33), SVR R^2 = 0.52 (RMSE 17.66), PLSR R^2 = 0.50 (RMSE 16.52)	Chen et al. (2023)
4	Reported model range R^2 ≈ 0.615 - 0.754. Best RF: R^2 = 0.754; reported MAE = 78.5 Mg·ha^{-1}, %RMSE = 13.57% (abstract)	Nguyen et al. (2024)
5	Best (SVM reported): R^2 = 0.70, RMSE = 83.65 Mg·ha^{-1}, MAE = 74.43 Mg·ha^{-1} - highlights lower accuracies in structurally complex/high-biomass peat forests	Zadbagher et al. (2024)
6	Combination (Sentinel-2A + ALOS-2 PALSAR-2), best model (SVR): R^2 = 0.73, RMSE = 38.68 Mg·ha^{-1} (SVR, Sentinel + ALOS)	Vafaei et al. (2018)
7	LiDAR-based (UAV strip) model (larch): R^2 = 0.923, RMSE = 13.92 Mg·ha^{-1} (leave-one-out CV). Sentinel-based models (using LiDAR sampling) achieved LiDAR-validation accuracies up to ~ 0.74 - 0.79 (R^2 or % accuracy reported) and Sentinel-based RMSEs (field vs LiDAR validation sets)	Wang et al. (2023)

Key environmental predictors and mechanistic role

Below are the predictor groups we recommend including as covariates or stratification layers; a detailed list with measurement/derivation notes is provided in Table 3.

- Hydrology: inundation duration/hydroperiod, water-table depth, flood timing, and distance to canals/ditches (as a proxy for drainage alteration). The hydrological regime influences canopy vitality and stem allometry, while also modulating dielectric and optical signals through its effects on moisture content; omitting hydrological metrics partly explains cross-site failures in transferability (Dang et al., 2022; Huy et al., 2016; Nguyen et al., 2016).

- Soils and peat characteristics: peat depth, bulk density, soil salinity/acidity (acid sulfate indicators), and texture. These substrate properties influence growth rates, wood density, and electromagnetic contrasts (microwave/optical), and therefore strongly affect both predictive bias and generalization from mineral soils to peatlands (Huy et al., 2016; Kappas, 2020; Tran et al., 2015).

- Geomorphology and microtopography: relative elevation (from hydrologically corrected DEMs), local slope/curvature, and distance to levees/ridges. In very flat peat landscapes even small elevation differences can control hydroperiod and vegetation structure; including these covariates materially improves spatial transferability (Ngo et al., 2023; Nguyen and Nguyen, 2017).

Table 3: Public datasets for environmental covariates

Covariate class	Variable examples	Dataset	Provider	Access	Primary citation
Hydrology (hydro-period)	Water occurrence, seasonality, recurrence	Global Surface Water (v1.4)	EC JRC	https://global-surface-water.appspot.com/download	Pekel et al. (2016)
Hydrology (networks)	Flow accumulation/ direction, distance-to-channel	HydroSHEDS (core products v1)	WWF/ USGS consortium	https://www.hydrosheds.org/products	HydroSHEDS Technical Doc. (2022)
Topography (DEM)	Elevation, slope, TWI	Copernicus DEM GLO-30	ESA/ Copernicus	https://dataspace.copernicus.eu/explore-data/data-collections/copernicus-contributing-missions/collections-description/COP-DEM	-
Soils (texture/ peat)	Sand/silt/clay; soil class; proxies for peat	SoilGrids 250 m (v2.0)	ISRIC	https://soilgrids.org/	Hengl et al. (2017); de Sousa et al. (2021)
Wetlands/ peat extent	Tropical wetlands and peatland likelihood	Tropical wetlands/peat model	Gumbricht et al.	-	Gumbricht et al. (2017)
Coastal wetland (optional)	Mangrove extent (blue-carbon context)	Global Mangrove Watch (v3.0)	JAXA/ Partners	https://www.globalmangrovewatch.org/	Bunting et al. (2018)

Practical modelling roadmap

Scaffold and local allometry. Acquire or identify structural anchors (UAV/airborne LiDAR strips, GEDI footprints) and derive local DBH - height - wood density relationships where possible to translate structure → AGB.

Predictor fusion. Combine structural scaffolds with wall-to-wall Sentinel-1/2 and L-band SAR (when available)

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plus the hydrology/peat/geomorphology layers listed above (Section 2.2, Table 1). Late feature fusion into tree-based ensembles (RF/ XGBoost/LightGBM) makes a robust operational baseline; escalate to DL when dense structural supervision and large training sets exist.

Validation and transfer testing. Use spatial and spatio-temporal blocking (block sizes guided by empirical autocorrelation) and reserve independent LiDAR strips or holdout regions (leave-one-region-out) to quantify realistic out-of-domain error (Roberts et al., 2017; Valavi et al., 2019). Stratify validation by peat/soil/hydro class.

Uncertainty and reporting. Produce wall-to-wall AGB maps accompanied by pixel-wise uncertainty (quantiles or prediction intervals), stratified error summaries, and a concise usage note identifying low-confidence extrapolation areas (Musthafa & Singh, 2022; Ngo et al., 2023).

Operational cautions and decision rules

In regions lacking structural scaffolds and showing strong covariate shift (e.g., substantial differences in peat depth or hydroperiod vs. training sites), treat fine-scale AGB estimates as low confidence and prioritize targeted LiDAR/plot collection before operational mapping.

When computational or sample constraints exist, favor tree-based ensemble baselines (RF/GBM) and report their limitations explicitly; report RMSE in $Mg \cdot ha^{-1}$ and include stratified error tables.

Always document preprocessing choices that affect hydrologic/geomorphic predictors (e.g., hydrologic DEM flattening, peat depth interpolation methods), since such choices materially influence extrapolation behavior.

Explicitly integrating hydrology, geomorphology, and soil/peat variables into scaffolded, multi-sensor modelling workflows is essential for producing transferable and actionable Melaleuca AGB products. For implementation templates, code snippets, and recommended predictor derivations, see Section 3.2.3, Table 1, and Table 3.

Temporal and disturbance factors

Seasonal dynamics and discrete disturbances (e.g., floods, fires, harvesting, storm damage) strongly influence AGB patterns and carbon fluxes in Melaleuca wetlands. To account for these effects, we extend the framework with time-aware predictors and validation:

Multi-temporal stacks. Build seasonal/monthly composites from Sentinel-1 and Sentinel-2 (e.g., pre-flood, peak-flood, post-flood) and include temporal statistics (median, IQR, trend) as features; demonstrations in the Mekong Delta show the value of dense SAR/optical time series for flood hydrology (Lam et al., 2023; Tran et al., 2022).

Hydrological regime dynamics. Derive flood frequency, duration, and timing from multi-year water masks and SWIR-based moisture anomalies to capture inter-annual variability; global surface-water seasonality layers provide a robust baseline (Pekel et al., 2016)..

Disturbance proxies. Integrate fire occurrence/burned area, logging footprints, and storm tracks; encode recency (days since event), intensity, and cumulative disturbance history. Validated burned-area products and algorithms support time-series disturbance mapping in tropical peatlands (Boschetti et al., 2019; Giglio et al., 2018).

Space–time validation. Complement spatial blocking with temporal or space-time blocked cross-validation (train on years t…t-k, test on t+1) to assess robustness under seasonal shifts and event shocks (Roberts et al., 2017; Valavi et al., 2019).

Change-aware features. For flux-relevant analyses, include Δ-features (year-to-year change in SAR/optical indices) and report bias/variance separately for disturbed vs. non-disturbed strata.

Uncertainty reporting. Map higher predictive uncertainty for periods immediately following major disturbances or transitional hydrological phases, and follow AGB unit/uncertainty conventions when leveraging GEDI products (Kellner et al., 2023; Dubayah et al, 2022).

This time-aware extension improves reliability of biomass estimates under dynamic wetland conditions and supports standardized AGB mapping across Southeast Asian wetlands facing similar seasonal and disturbance regimes.

Operational feasibility, cost-effectiveness, and regional generalizability

Operational uptake of multi-sensor AGB mapping depends on cost-effectiveness and implementation feasibility. At national MRV scales, monitoring and transaction costs can erode the net benefits of result-based payments if system design is not cost-sensitive (Köhl, Neupane, & Mundhenk, 2020). Practical pathways therefore prioritize open and routinely updated sensors - Sentinel-1/2 and L-band SAR mosaics - combined with reproducible processing on cloud platforms to reduce hardware and maintenance burdens (Gorelick et al., 2017; Shimada et al., 2014; JAXA&EORC, 2022). Method guidance from REDD+ MRV frameworks emphasizes transparent protocols, adequate sampling, and uncertainty management to balance precision with affordability (Böttcher et al., 2009; Herold et al., 2011; GOFC-GOLD, 2011). In data- and capacity-limited contexts, a tiered modeling strategy - starting with tree-based ensembles and escalating to deep learning only when wall-to-wall inputs and measurable accuracy gains are present - helps contain costs while meeting reporting requirements (Roberts et al., 2017; Valavi et al., 2019).

Generalizability beyond Vietnam is supported by shared ecological and data conditions across Southeast Asian wetlands. Peat-dominated lowlands in Peninsular Malaysia, Sumatra, and Borneo show comparable hydrological regimes and disturbance histories, with region-wide declines in peat swamp forest cover since the 1990s that motivate standardized, repeatable mapping (Miettinen et al., 2016; Mishra et al., 2021). At broader scales, tropical wetland/peat distributions and pan-tropical biomass products provide consistent reference layers for stratification and benchmarking (Gumbricht et al., 2017; Avitabile et al., 2016; Tootchi, Jost, & Ducharne, 2019). In practice, transfer is achieved by harmonizing environmental strata (peat depth, soil texture, flood regime), applying blocked space-time validation, and leveraging regional time-series demonstrations from the Mekong Delta for flood-driven variability (Lam et al., 2023; Tran et al., 2022). This combination of open data, cost-aware design, and explicit uncertainty reporting strengthens regional comparability and helps standardize future AGB mapping across Southeast Asian wetlands.

CONCLUSION AND RECOMMENDATIONS

Conclusion

This review consolidates advances in multi-sensor remote sensing and machine learning for AGB estimation in Vietnam's Melaleuca wetlands and proposes a standardized framework of terminology, indicators, and environmental covariates tailored to tropical peatland ecosystems. By unifying key metrics such as canopy structural parameters, hydro-geomorphological indices, and model validation criteria (R^2, RMSE), the study enhances methodological consistency and reproducibility across different research settings. Beyond serving as a synthesis, the framework provides a replicable roadmap for multi-sensor data integration - spanning data acquisition, feature engineering, modeling, validation, and uncertainty quantification. This approach strengthens national-level biomass monitoring and carbon accounting and helps standardize future AGB mapping across Southeast Asian wetlands where similar ecological and data constraints prevail.

Future Recommendations

We recommend using LiDAR/GEDI strips or footprints as calibration scaffolds, extrapolating wall-to-wall with Sentinel-1/2 and L-band SAR, adopting late feature fusion with RF/XGBoost/LightGBM as robust baselines, and escalating to compact deep learning only when dense structural supervision is available, and reporting uncertainty (prediction intervals/quantiles) with stratified errors by peat/soil/hydrological classes.

To bridge the gap between technical advancement and real-world application in carbon management, future efforts should focus on developing open-access tools and pre-trained models. We recommend leveraging cloud-based geospatial platforms such as Google Earth Engine (GEE), which offers cost-effective and operationally feasible Big Earth Data processing capabilities, particularly crucial for resource-constrained governmental agencies (Gorelick et al., 2017). Specifically, developing a user-friendly workflow within GEE can automate the complex pre-processing steps required for multi-sensor data fusion (e.g., Sentinel-1/2 and GEDI). Furthermore, to promote transferability and reduce modeling time, the research community should prioritize the public release of standardized training datasets and pre-trained tree-based machine learning models (e.g., RF) via open-source repositories (e.g., GitHub/GEE Apps) (Wu, 2020). This approach will enable local users to rapidly generate high-accuracy AGB maps, integrating crucial uncertainty parameters (Amitrano et al., 2023), thereby directly supporting more transparent conservation planning and greenhouse gas inventory reporting.

To establish the robustness and generalizability of remote sensing and machine learning methodologies, future studies must extend beyond the localized scope of Vietnam's Melaleuca wetlands. We recommend conducting multi-regional comparative studies that evaluate the performance of AGB models calibrated in the Mekong Delta against other regional tropical peat swamp forest ecosystems, such as those in Borneo (Indonesia) or the Malay Peninsula (Malaysia). These ecosystems present similar vegetation structures and geochemical conditions but often exhibit a higher range of AGB saturation, providing a necessary stress test for the algorithms (Lohberger et al., 2013; Zadbagher et al., 2024). This comparison should specifically analyze how critical environmental covariates - such as peat depth, seasonal hydrology, and salinity/acid-sulfate conditions - influence model accuracy and bias across different regions. By quantifying these differences, researchers can develop adaptive AGB models capable of self-adjusting based on region-specific input data, thereby maximizing their utility for carbon accounting at a broader scale.

To transform AGB maps from a research tool into a reliable decision-support document, prioritizing the further standardization of uncertainty quantification is essential. Future studies should move beyond merely reporting aggregate statistics like RMSE and R^2. We recommend adopting a comprehensive framework to assess AGB map accuracy, including three essential elements (Weisbin et al., 2014; Sannier et al., 2022):

Prediction intervals (PIs) and quantiles: Providing a point estimate for AGB is insufficient. Studies must calculate and map 95% prediction intervals (95% PIs) or other quantiles for every pixel. This transforms the map from a single-value assertion into a statement of spatial confidence, transparently communicating the risk of over- or underestimation, which is particularly crucial in areas with dense canopies where signal saturation is common.

Bias analysis: Conditional bias is a prevalent issue in machine learning models where input data are unevenly distributed. Advanced statistical techniques (such as model-assisted statistical regression) must be used to model and adjust for map bias (Sannier et al., 2022). This analysis specifically quantifies whether the model systematically over- or under-predicts in specific areas, such as high-biomass peat swamp forests, thereby facilitating the creation of bias-adjusted maps suitable for carbon reporting standards.

Uncertainty source decomposition: Explicitly analyze and decompose the main sources of uncertainty, including: field measurement errors, allometric model errors, and remote sensing errors. This decomposition helps prioritize future efforts to reduce overall uncertainty most effectively.

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