



AI-powered multisensor fusion for forest biomass mapping: photogrammetric canopy profiles improve estimates in Southeastern North Carolina

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Received: 12 November 2025 / Accepted: 1 May 2026 / Published online: 30 May 2026
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Abstract

Context Spatially accurate estimates of forest above-ground biomass (AGB) are indispensable for carbon-stock accounting and sustainable silviculture. Existing mapping approaches face challenges in densely vegetated Coastal Plain forests because of seasonal optical variability, radar–optical saturation, and limited wall-to-wall structural information.

Objectives We aimed to (i) develop and evaluate a multisensor, AI-enabled fusion framework for landscape-scale AGB mapping, (ii) quantify the added value of seasonal optical data and photogrammetric canopy-height profiles, and (iii) interpret model drivers using explainable artificial intelligence (AI) to relate predictors to forest structure and composition.

Supplementary Information The online version contains supplementary material available at <https://doi.org/10.1007/s10980-026-02377-0>.

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Methods We mapped AGB across ~10,500 km² in southeastern North Carolina using wall-to-wall predictors from optical, radar, and photogrammetric sources. Forest Inventory and Analysis plot data (n=305) were used to train and evaluate an ensemble of gradient-boosted tree models (CatBoost, LightGBM, XGBoost) and a neural network (RealMLP) via cross-validation. Model behavior was interpreted using feature importance and partial dependence analysis.

Results Expanding Sentinel-2 temporal coverage from summer-only to four-season composites improved normalized RMSE by 8.7%. Incorporating canopy-height profiles from NAIP produced the largest accuracy gain, lowering nRMSE by 15.9–18.0% relative to the multisensor baseline, which underscores the critical value of structural information for AGB prediction. Three key predictors illustrated complementary ecological dimensions: the 10th

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percentile canopy height captured canopy openness, L-band polarimetric alpha indicated volume-scattering regime, and spring red-edge reflectance captured vegetation biochemistry. These findings show that fusing structure, polarimetry, and spectral phenology yields robust AGB maps and improves generalizability across heterogeneous landscapes.

Conclusions This transferable, broadly accessible framework integrating structural, polarimetric, and spectral phenology data enables landscape-scale AGB monitoring and supports targeted conservation planning, restoration tracking, and adaptive management for carbon sequestration. The incorporation of high-resolution wall-to-wall structural data is particularly valuable for improving the accuracy and usability of forest AGB maps, thereby informing more responsive decision-making.

Keywords Aboveground biomass · Multisensor remote sensing · Photogrammetric canopy-height profiles · NAIP imagery · L-band SAR · Coastal plain forests

Introduction

Forest ecosystems are fundamental to global ecological balance, providing essential habitats for a wide range of species and influencing local temperature and moisture conditions through processes such as evaporative cooling and carbon sequestration (Hua et al. 2022; Flores et al. 2024). Beyond their ecological functions, forests are cornerstones of the global carbon cycle, acting as significant carbon sinks that absorb and store atmospheric carbon dioxide. For example, they store roughly 80% of all terrestrial above-ground carbon and currently offset nearly one-quarter of global CO₂ released to the atmosphere annually (Pan et al. 2011, 2013, 2024; Mo et al. 2023; Walker et al. 2022; Xu et al. 2021).

The accurate estimation of above-ground biomass (AGB), including both high statistical accuracy and sufficient spatial detail, is therefore pivotal for quantifying national forest carbon stocks, informing forest management and carbon-accounting needs (Mohd Zaki and Abd Latif 2017; Moomaw et al. 2019; Goetz et al. 2015). Within this broader context, the southeastern United States contains extensive pine plantations, bottomland hardwoods, and mixed

pine–hardwood forest stands that collectively store some of the nation’s largest carbon stocks, undergo rapid structural change, and support emerging carbon-offset programs (Aguilar et al. 2022; Streeter et al. 2023).

Traditionally, forest plot-level inventories provide the most accurate AGB estimates but are costly, labor-intensive, and impractical for continuous coverage over large areas (Chave et al. 2014; Lu et al. 2016). The emergence of remote sensing technologies has revolutionized AGB mapping by enabling frequent, spatially extensive and continuous observations at lower cost (Narine et al. 2020; Tamiminia et al. 2024).

Among these, optical sensors (e.g., Landsat and Sentinel-2) offer broad spatial coverage and multi-spectral information sensitive to vegetation properties and phenological changes. However, optical signals tend to saturate in high-biomass forest stands, where increases in leaf area and sub-canopy structure are weakly expressed at the top of the canopy (Puliti et al. 2021; Ehlers et al. 2022). Additionally, they are constrained by clouds, illumination, and atmospheric conditions. Beyond data acquisition challenges, optical sensors also struggle with phenological variability in deciduous forests and cannot penetrate complex vertical canopy structure in mixed-species stands. Conversely, multi-seasonal optical composites that capture both leaf-on and leaf-off conditions have shown promise for improving species discrimination and biomass prediction in mixed forests (Ehlers et al. 2022), yet the incremental value of full four-season Sentinel-2 coverage remains largely unquantified, particularly in Coastal Plain forests where deciduous and evergreen species exhibit distinct seasonal signatures (Tamiminia et al. 2024; Chrysafis et al. 2019).

Synthetic Aperture Radar (SAR, e.g., Sentinel-1 and ALOS PALSAR-2), in contrast, is an active microwave system that can penetrate clouds and provide information related to canopy structure (Fatoyinbo et al. 2021), making it particularly valuable in regions with persistent cloud cover. Nevertheless, backscatter signals saturate in dense forests, with sensitivity strongly dependent on wavelength (e.g., C, L, and P bands) (Yu and Saatchi 2016; Silva et al. 2021). Additionally, radar signals are affected by multiple confounding factors including ecosystem type, soil moisture, sensor characteristics (e.g., polarization and incidence angle), topography, and methodological

choices (Fassnacht et al. 2014; Lu et al. 2016; Sa et al. 2024). As a result, regional AGB estimates in dense forests based on SAR data can exhibit relative errors frequently exceeding 20%, especially in high-biomass ecosystems where saturation in optical and radar systems further complicates the interpretation of vegetation structure and biomass (Saatchi et al. 2011).

Different from optical and SAR sensors, Light Detection and Ranging (LiDAR) is considered the reference standard for mapping forest structure (Hyde et al. 2007; Næsset et al. 2011; Dubayah et al. 2022). Airborne LiDAR systems, such as those deployed through the USGS 3D Elevation Program (3DEP), provide high-resolution, wall-to-wall coverage across much of the conterminous U.S. (Sugarbaker et al. 2014). These systems deliver accurate three-dimensional measurements of canopy height, vertical structure, and volume without saturation issues in high-biomass forests. Complementing these airborne systems, spaceborne LiDAR missions, including NASA's GEDI (launched 2018) and ICESat-2 (launched 2018), have enabled global-scale forest structure measurements through billions of footprint samples of canopy height and vertical profiles (Neuenschwander and Pitts 2019; Dubayah et al. 2020; Dubayah et al. 2022). GEDI data have proven valuable for regional and continental canopy structure and AGB mapping (Duncanson et al. 2022; Wang et al. 2025), demonstrating strong correlations between canopy structure metrics and field-measured biomass across diverse forest types.

However, both airborne and spaceborne LiDAR face practical limitations for operational forest monitoring. Airborne LiDAR surveys are expensive and typically limited in spatial extent and temporal frequency, with acquisitions often restricted to leaf-off conditions that may not capture the full structural complexity critical for biomass estimation in hardwood-dominated forests (Sugarbaker et al. 2014). Furthermore, existing airborne datasets are spatiotemporally heterogeneous due to disparate acquisition dates, inconsistencies in quality levels (e.g., Quality Level 1 vs. 2), and the lack of systematic cross-calibration (Ribas-Costa et al. 2024). Spaceborne alternatives such as GEDI and ICESat-2 missions, while providing global coverage, are sampling systems that deliver discrete footprints (~25 m diameter for GEDI, laser transects for ICESat-2) rather than wall-to-wall coverage (Dubayah et al. 2020). Generating

continuous forest structure maps from these data requires interpolation or modeling approaches that introduce additional uncertainty. These practical constraints include high cost, limited temporal coverage, spatial discontinuity, and data heterogeneity. Such limitations motivate the evaluation of alternative data sources for wall-to-wall 3D forest canopy structure mapping.

An emerging cost-effective alternative to LiDAR is Digital Aerial Photogrammetry (DAP) from high-resolution imagery, which reconstructs 3D point clouds that resolve the top of dense forest canopies (Puliti et al. 2020; Ritz et al. 2022). The National Agriculture Imagery Program (NAIP) administered by the U.S. Department of Agriculture provides sub-meter aerial imagery across the United States, enabling wall-to-wall canopy height model (CHM) derivation through Structure-from-Motion techniques (Schroeder et al. 2022; Liu et al. 2024). Recent studies have demonstrated the potential of NAIP DAP for achieving high accuracy on forest height estimations, with $R^2 \approx 0.93$ in conifer stands (Ritz et al. 2022). Performance in structurally complex hardwood forests has shown more variability (Schroeder et al. 2022), suggesting performance may benefit from integration with multi-source remote sensed data.

However, most large-area DAP studies summarized canopy structure using a single statistic, typically 95th-percentile height at 10–30 m resolution, because point density is often insufficient and the point clouds rarely sample below the upper canopy (Schroeder et al. 2022; Ritz et al. 2022). Because photogrammetry primarily reconstructs the canopy surface, DAP-derived percentiles summarize horizontal variation in canopy surface heights rather than LiDAR-derived within-canopy vertical structure. Consequently, reducing DAP to a single height statistic can discard potentially informative structural signals. LiDAR studies show that richer sets of vertical profile metrics capture successional stage and foliage distribution more effectively than single top-of-canopy height, extend the dynamic range for biomass prediction without saturation, and reduce residual bias in multi-layered stands (Meyer et al. 2018; Puliti et al. 2020). Although DAP cannot provide the same within-canopy information as LiDAR, canopy-surface profile features may still add predictive value beyond a single height layer by characterizing heterogeneity in upper-canopy structure. However, it remains

unclear whether replacing a single 95th-percentile height metric with a richer set of canopy-surface profile features meaningfully improves AGB prediction, particularly in hardwood-dominated landscapes where canopy heterogeneity is greatest.

These single-sensor limitations motivate fusion approaches: optical data saturate at high biomass and are affected by clouds and phenology; radar penetrates clouds but also saturates in dense canopies; and 3D structural data provide critical vertical information but remain spatially and temporally heterogeneous. Multisensor fusion mitigates these complementary weaknesses by integrating foliage, moisture, and structural signals, and consistently outperforms single-source approaches in AGB mapping (Zolkos et al. 2013; Avitabile et al. 2016; Bouvet et al. 2018; Duncanson et al. 2022; Ehlers et al. 2022; Guerra-Hernández et al. 2022; Zhang et al. 2023; Tamiminia et al. 2024). For instance, including height information extends the dynamic range of biomass sensitivity and helps mitigate saturation in dense forests, while longer-wavelength radar and leaf-off optical scenes further improve separability, especially in mixed hardwood-softwood canopies. Studies that add explicit structural features, such as top-canopy-height layers, often report the largest gains and better transferability across stand age and disturbance regimes (Meyer et al. 2018; Ehlers et al. 2022; Tamiminia et al. 2024). However, the spatial distribution of these gains, which forest types, biomass ranges, or management contexts benefit most from additional inputs, is rarely mapped explicitly, limiting the ability to identify where prediction uncertainty remains high and where additional data collection would be most impactful.

Given the heterogeneity and nonlinearity of fused remotely sensed predictors, artificial intelligence (AI) and machine learning methods have become the standard approach for AGB estimation (Ehlers et al. 2022; Duncanson et al. 2022; Yan et al. 2023; Zhang et al. 2023; Li et al. 2024). These methods offer flexible modeling of complex, non-linear interactions among optical, radar, terrain, and structural variables. In practice, fusion can be implemented at three levels: (i) feature-level (early) fusion by stacking predictors from each sensor; (ii) model-level (late) ensembling of sensor-specific models; and (iii) representation-level (mid) fusion by learning joint feature embeddings before prediction (Wang et al. 2024; Hanan

et al. 2025). In forestry applications, early fusion paired with non-linear learners (e.g., tree ensembles, gradient boosting, residual multilayer perceptrons) is most common due to simplicity and strong performance (Yan et al. 2023; Li et al. 2024). While algorithm choice can matter, no single learner dominates in all settings, and performance depends on predictors, landscape context, and evaluation design (Wang et al. 2015, 2025). Accordingly, comparative evaluation and ablation tests that isolate seasonal and structural contributions are recommended to reveal ecological drivers as well as predictive gains. This study contributes to the growing integration of AI with landscape ecology by demonstrating how interpretable multisensor fusion can reveal the ecological drivers of landscape-scale biomass variation while maintaining transparency in AI-driven ecological modeling (Kirti et al. 2025; Eigenbrod et al. 2026).

Despite this progress, three specific gaps persist in the context of dense, heterogeneous Coastal Plain forests. First, the marginal value of multi-season Sentinel-2 compositing over a standard single-summer acquisition has not been rigorously isolated in high-biomass southeastern forests where deciduous and evergreen species exhibit distinct seasonal signatures. Second, the predictive value of DAP-derived canopy-surface profile features relative to a single height layer remains undemonstrated in hardwood-dominated landscapes where structural complexity is greatest. Third, the spatial distribution of prediction uncertainty across management gradients and biomass ranges, information critical for prioritizing future field inventory and remote sensing acquisition efforts, is rarely characterized explicitly in fusion-based AGB studies.

Motivated by these complementary limitations and opportunities, we develop an early-fusion framework for AGB mapping in the Coastal Plain of southeastern North Carolina (~10,500 km²), a high-biomass, actively managed landscape with strong structural heterogeneity that intensifies common remote-sensing challenges such as signal saturation and canopy complexity, making it an ideal setting for evaluating multisensor fusion approaches. The framework fuses multi-temporal Sentinel-2 composites, Sentinel-1 C-band backscatter and interferometric coherence, UAVSAR L-band polarimetric metrics, LiDAR-derived terrain attributes, and NAIP DAP-derived features. Our mapping target is a landscape-scale

AGB surface representative of circa 2018–2019 conditions at 25 m resolution, aligned with the primary remote-sensing acquisition window. In addition to addressing methodological challenges, the scale of our analysis also provides an opportunity to explore ecological and management patterns of forest biomass distribution. Guided by a three-stage experimental design, we address the following research questions. First, how much does expanding Sentinel-2 coverage from a single summer composite to full four-season composites reduce AGB prediction error? Second, relative to a multisource spectral-radar-terrain baseline, how much additional accuracy is gained by adding canopy structure, and how do single-layer height metrics compare with percentile-based NAIP-DAP canopy surface profiles? Third, where across the landscape do additional remote-sensing inputs most reduce prediction uncertainty or alter inferred AGB estimation patterns? Finally, what landscape-scale spatial patterns of AGB emerge across the southeastern North Carolina Coastal Plain?

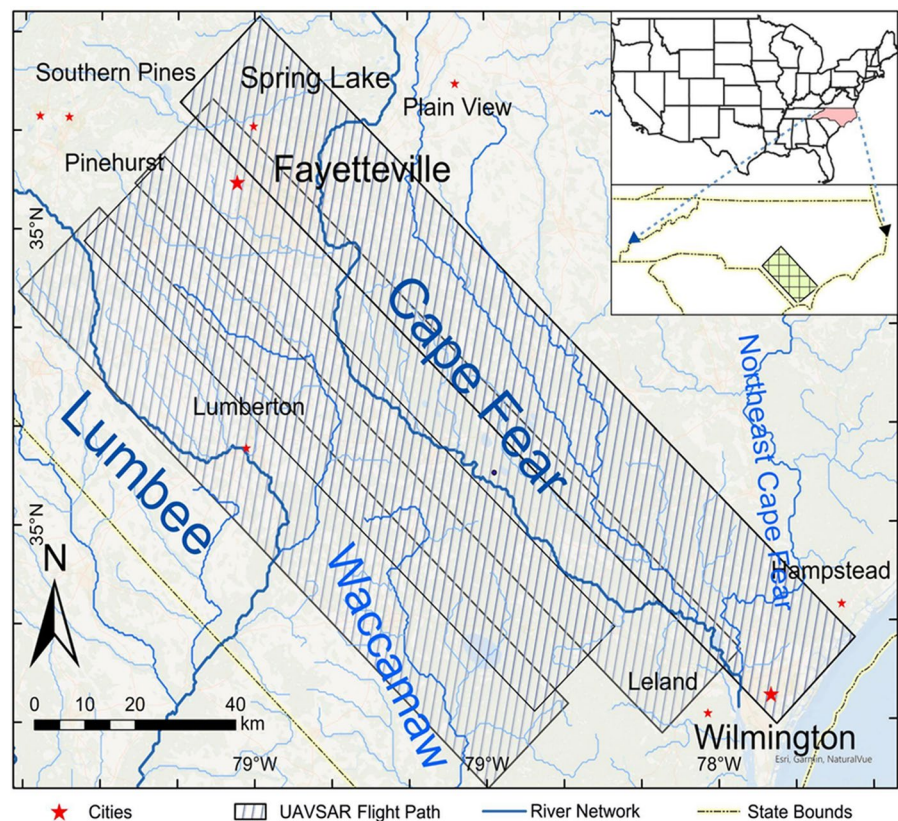
Methodology

This study aims to develop and evaluate biomass prediction models by leveraging various remote sensing features and techniques. The methodology is structured into several key components: data collection, data preprocessing, data splitting, model development, model training and hyperparameter tuning, model evaluation, impact analysis, software and tools, and reproducibility.

Study area

Our study site is located in southeastern North Carolina (NC), USA, covering an area of about 10,500 km² (Fig. 1). Situated within the Southern Coastal Plain, the region has a humid subtropical climate and supports a diverse range of forested ecosystems, including coastal plain forests, bottomland hardwood forests, and pine-dominated forest stands, with Loblolly pine (*Pinus taeda*) being the most prevalent species (Brown and Lambert 2024). These

Fig. 1 Study Area in southeastern North Carolina (Four UAVSAR scenes (i.e., gray slash polygons) collected on 18 September 2018.)



forests provide critical wildlife habitat and sustain the region's ecological and economic vitality, with timberland comprising over 70% of land area in several counties. The area has also been subject to frequent extreme weather events, most notably Hurricane Florence in 2018, which caused widespread flooding and economic damage (Wang et al. 2022).

The combination of ecological diversity and disturbance history makes southeastern NC an ideal setting for investigating spatial patterns of forest biomass across varying stand compositions and disturbance regimes. Our research specifically focuses on leveraging machine learning algorithms and multi-source remote sensing data to improve AGB estimation across the region.

Datasets

We used multiple datasets (Table S1) to support AGB modeling, including multisource optical and SAR imagery from airborne and spaceborne platforms, together with U.S. Forest Service Forest Inventory and Analysis (FIA) plot data.

Optical dataset from NAIP and Sentinel 2

NAIP 4-band visible–infrared aerial imagery (Fall 2018, ~0.6 m resolution) was used in this study. To balance spectral information retention and computational efficiency, NAIP imagery was processed using Principal Component Analysis (PCA) to leverage spectral information from all four bands, with the first component used for texture feature extraction (Table S2). PCA decorrelates the highly collinear NAIP bands, ensuring texture metrics capture genuine spatial variability in canopy structure rather than redundant spectral covariance. Following Ehlers et al. (2022), texture features related to crown diameter were derived as the ratio of variances at 2 m and 3 m spatial resolutions within 25 m grids.

Sentinel-2 Level-2A imagery (2018–2019) was generated into seasonal composites for spring (Mar–May), summer (Jun–Aug), fall (Sep–Nov), and winter (Dec–Feb) using median per-band values to minimize atmospheric noise and sensor artifacts (Wang et al. 2025). Spectral bands and vegetation indices (Table S3) were derived to capture canopy and seasonal variation. Multi-season Sentinel-2 composites capture intra-annual phenological variation

in canopy reflectance, which aids discrimination among forest types with differing structure and biomass. PCA was not applied to these features because preliminary experiments showed no improvement in cross-validated performance (Fig. S2). Additionally, PCA-transformed components obscure the direct link between individual variables and their biophysical properties, making it difficult to attribute features to specific ecological mechanisms through SHAP analysis.

SAR dataset from Sentinel-1, PALSAR-2 and UAVSAR

Three SAR configurations were included to provide complementary sensitivity across the canopy vertical profile: C-band backscatter is primarily sensitive to surface and upper-canopy scattering; C-band coherence reflects temporal stability of canopy scattering; and L-band polarimetry penetrates deeper into the canopy, encoding volume scattering and double-bounce contributions from larger woody structure.

We used Sentinel-1 C-band SAR data (Table S4), including normalized global backscatter (VV and VH polarizations at 38° incidence angle; 2016–2017), which was processed by Bauer-Marschallinger et al. (2019). We also used seasonal InSAR coherence (VV polarization; 6–48 day intervals, Table S3), which was preprocessed by Kelldorfer et al. (2022).

ALOS-2/PALSAR-2 L-band SAR data (Table S4) from the 2019 Global Yearly Mosaic (v2) provided gamma-naught backscatter in HH and HV polarizations at 25 m resolution, offering superior canopy penetration for vegetation structure characterization (Shimada et al. 2014).

UAVSAR polarimetric L-band data (Table S4) were acquired by NASA's Gulfstream-III aircraft on September 18, 2018. The acquisition covered southeastern North Carolina across four flight lines (13,510, 13,511, 31,509, and 31,510) at approximately 5 m spatial resolution. Following radiometric normalization (Wang et al. 2025), we extracted polarimetric decomposition features including Pauli (3 features), Freeman-Durden (3 features), and Cloude-Pottier (4 features) decompositions (Cloude & Pottier, 1997; Freeman & Durden, 1998; Xie et al. 2018).

Sentinel-1 and PALSAR-2 data were obtained as terrain-corrected products with DEM-based radiometric normalization applied by the data providers (Bauer-Marschallinger et al., 2019; Shimada et al.

2014). UAVSAR data were radiometrically terrain-corrected in this study using a 3DEP-derived DEM to account for local incidence angle effects (Wang et al., 2022).

Terrain elevation data

We acquired 1-m Digital Elevation Models (DEM, Table S5) from the USGS 3DEP which provided bare-earth terrain references. From the DEM data, we derived supplementary topographic variables including slope, aspect, and hillshade as predictor variables for AGB modeling.

NAIP-DAP point cloud dataset

In 2018, the USDA National Resource Conservation Service (NRCS) acquired NAIP imagery (40 cm ground sample distance, 30% side lap) for North Carolina using Leica ADS-100 SH100 push-broom sensors. The sensor captured imagery at three look angles: forward (25.6°), nadir, and backward (19.4°). NAIP-DAP point clouds were produced by the data provider using the Leica XPro's Semi-Global Matching module and delivered in LAZ

1.4 format with embedded RGB and color-infrared values. The nominal point spacing was set to twice the native image resolution, resulting in an average point density of approximately 1 point per square meter. We rasterized a 1-m digital surface model from the NAIP-DAP point clouds, and subtracting the 3DEP DEM produced a 1-m canopy height model (CHM_1m).

Canopy height profile derivation

We generated canopy height profiles for each 25×25 m grid cell (hereafter "stand") by computing percentile statistics (10th, 25th, 50th, 75th, 98th) from all 625 CHM_1m pixels within each stand (Fig. 2, Table S5). These percentiles characterize the horizontal structural variation of canopy heights within each forest stand, ranging from lower canopy surfaces (10th percentile) to near-maximum heights (98th percentile). This approach provides a standardized representation of within-stand canopy structure. The 10th percentile represents the lowest visible canopy-surface heights within a stand, reflecting canopy gaps and short-stature zones rather than understory height as captured by LiDAR.

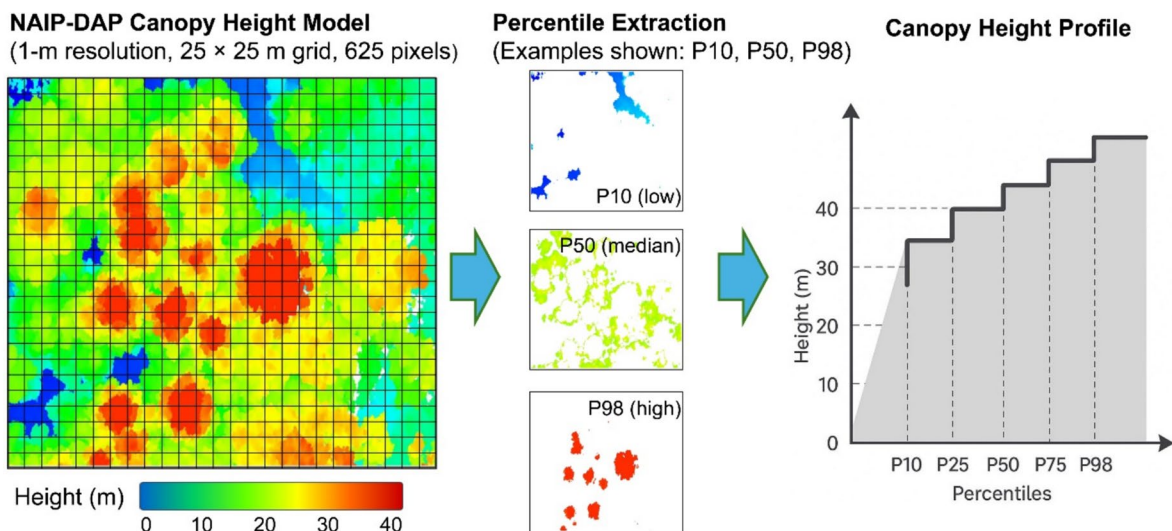


Fig. 2 Derivation of NAIP-DAP canopy height profiles for each 25×25 m stand. Left: High-resolution canopy height model (CHM_1m, background imagery adapted from Yu et al. 2024) with representative 25×25 m grid cell outlined. Center: Example pixels corresponding to different height percentiles

within the selected cell (P10=lowest canopy, P50=median, P98=near-maximum). Right: The resulting canopy height profile summarizes within-stand height distribution using five percentiles (10th, 25th, 50th, 75th, 98th)

GEDI-derived canopy height at 25 m

We incorporated a wall-to-wall 25-m canopy height product derived from GEDI footprints modeled with multisource predictors, hereafter referred to as "GEDI-derived CHM25" (Wang et al. 2025). This product represents top-of-canopy height and was used as (i) a single-layer structural predictor and (ii) a substitute for NAIP-DAP profiles in ablation experiments to evaluate the contribution of high-resolution canopy structure.

Compilation of the AGB training dataset

We used several tree variables from the U.S. Forest Service's FIA database to derive the biomass reference data. Specifically, we combined DRYBIO_AG (oven-dry above ground biomass of wood and bark in pounds), SPCD (species code), and STATUSCD (indicating live, dead and removed trees) to get biomass for each live softwood and hardwood tree, then we multiplied tree-level biomass by TPA_UNADJ (trees per acre) to get biomass per-acre. Tree-level biomass estimates were summed to produce total live aboveground biomass (in Mg/ha) for each FIA plot, calculated separately for live hardwood and softwood components. Following Ehlers et al. (2022), FIA plot

locations were spatially aligned with multisource remote-sensing features, and paired with plot-level AGB data filtered within the 2015–2022 window. Records with missing features were removed, yielding a final tabular dataset of 305 plots. Given the limited sample size, we partitioned the data into training (80%, 244 plots) and test (20%, 61 plots) sets using stratified sampling on total AGB to preserve the biomass distribution. Model performance was evaluated on the held-out test set. Due to the confidentiality requirements established by the FIA program, the spatial coordinates of FIA plots cannot be shared and therefore are not included in figures. Instead, a county-level map is provided, showing the number of FIA plots used in this study per county (Fig. S4).

Feature-group design and experiment framework

We organized raw features from Sentinel-2, NAIP, SAR, NAIP-DAP canopy height profiles, and terrain layers (Table S6) into 20 feature families, combined into feature group configurations for experimental comparison (Table 1). These groups were selected based on established physical relationships with forest AGB, as described in Sects. "Optical Dataset from NAIP and Sentinel 2"-["Canopy Height Profile Derivation"](#). To preserve interpretability, we retained

Table 1 Remote-sensing feature groups for biomass modelling across three experimental stages: (A) Sentinel-2 seasonality evaluation, (B) height metric incremental value, and (C) spatial uncertainty ablation analysis

Stage	ID	Feature stack (key layers)	Primary purpose/question addressed
A 1	G-Sum	S2_SUM	Leaf-on optical baseline (summer composite) / Q1
A 2	G-SumWin	S2_SUM + S2_WIN	Peak-greenness + leaf-off "structural" contrast / Q1
A 3	G-4Seas	S2_ALL (four seasons)	Full seasonal Sentinel-2 stack / Q1
B 1	G-CHM25	GEDI-derived CHM25	Height-only increment / Q2
B 2	G-Profile	NAIP-DAP	CHM_Metrics-only increment / Q2
B 3	G-Base + CHM	BASE_RS + CHM	Add height to multisource RS / Q2
B 4	G-Base + Profile	BASE_RS + NAIP_CHM_Metrics	Add CHM_Metrics to multisource RS / Q2
C 1	G-Base	BASE_RS (S2_ALL + S1_BS + PALSAR2_BS + TERRAIN)	"Multisource RS" baseline (satellite optical & C- and L-bands SAR imagery & topo, no height layers; can be applied to large area) / Q3
C 2	G-Base + NAIP	BASE_RS + NAIP_OPT	Baseline + airborne optical & texture / Q3
C 3	G-Base + UAVSAR	BASE_RS + UAVSAR_POL	Baseline + airborne SAR polarimetry / Q3
C 4	G-Full	ALL (BASE_RS + NAIP_OPT + UAVSAR_POL + CHM + NAIP_CHM_Metrics)	Upper-bound multisensor fusion model / Q3

*BASE_RS = multisource baseline including four-season Sentinel-2, Sentinel-1 C-band backscatter, PALSAR-2 L-band backscatter, and terrain attributes. Feature group naming: G- indicates seasonal composition (Sum, SumWin, 4Seas), individual sensors (CHM, Profile, NAIP, UAVSAR), combinations (Base + CHM), or complete fusion (Full)

physically meaningful predictors rather than applying dimensionality reduction, relying instead on the models' built-in ability to handle correlated inputs (Holzmüller et al. 2024). This design also enabled interpretation through SHAP analysis and feature-group ablation (Sect. "Explainable AI reveals structural drivers of AGB variation"). Evaluation proceeded in three main sequential stages (A–C), each addressing a specific research question (Q1–Q3) defined in the Introduction section.

Stage A (Q1): Sentinel-2 seasonality

To isolate the phenological contribution of multispectral optical data, we trained three models on Sentinel-2 composites with increasing seasonal coverage: 1) summer only (ID G-Sum, $S2_SUM$); 2) summer + winter (ID G-SumWin, $S2_SUM + S2_WIN$) and 3) four seasons (ID G-4Seas, $S2_ALL$). The configuration with the lowest cross-validated nRMSE became the reference optical stack for all subsequent stages. In addition, to assess whether redundant predictors influenced Stage A results, we repeated the seasonality comparison under three feature-set treatments: FULL (all predictors), TOPk feature selection (Holzmüller et al. 2024), and PCA. Results (Fig. S2) were consistent across treatments, indicating that predictor redundancy did not alter the seasonal ranking or accuracy estimates.

Stage B (Q2): Structural-height contribution

To evaluate the added value of canopy structure beyond spectral and backscatter information, we trained five models using the best tuned learner for each algorithm (Fig. S1). The reference model used the multisource feature stack (BASE_RS; ID G-Base), which included optical, radar, and terrain variables (Table 1). We then tested two configurations that used canopy structure alone: (i) GEDI-derived CHM25 as a single top of canopy height layer (ID G-CHM25) and (ii) NAIP-DAP canopy height profiles expressed as multi-percentile metrics (ID G-Profile). We further integrated canopy height information into the multisource stack: ID G-Base + CHM25 augmented BASE_RS with GEDI-derived CHM25, whereas ID G-Base + Profile augmented BASE_RS with NAIP-DAP canopy height profiles. Comparisons among these

configurations quantify how different representations of three-dimensional structure reduce nRMSE relative to BASE_RS.

Stage C (Q3): Spatial uncertainty ablation analysis

To understand where additional remote sensing inputs provide the greatest uncertainty reduction for AGB estimation spatially, we examined the spatial distribution of prediction differences from feature-group ablation experiments (detailed methodology in Sect. "Feature-group ablation analysis"). This analysis identifies which landscape types or ecological conditions benefit most from specific sensor capabilities.

Machine learning algorithms

Machine learning models depend on hyperparameters that influence training and performance (Wu et al. 2019; Liyew et al. 2025). Practitioners often choose between weak library defaults and expensive hyperparameter optimization (HPO). Defaults can limit model potential, while heavy HPO can be too costly in time and compute (Grinsztajn et al. 2022). Tuned-default (TD) learning offers a practical alternative by using prior benchmark knowledge to supply stronger pre-tuned configurations.

In this study, we adopted tabular regressors from the PyTabKit benchmark: CatBoost, LightGBM, XGBoost, and RealMLP (a residual multilayer perceptron) (Holzmüller et al. 2024). Each was run with TD configurations (Table S7). Because exhaustive HPO across all composite and feature-stack variants was computationally prohibitive, we performed a targeted HPO sensitivity analysis on a representative configuration (the four-season Sentinel-2 stack, $S2_ALL$). Within the training partition, every model was evaluated using fivefold cross-validation, yielding $5 \times 4 = 20$ fitted estimators (one per fold and algorithm). Early stopping (patience = 50) was applied for both gradient boosting libraries to reduce overfitting. The TD vs HPO comparison and its compute trade-offs are reported in the Supplement (Fig. S1 and Fig. S2; details in Supplementary Methods and Supplementary Results), and the main experiments use TD unless HPO improved performance beyond cross-validation uncertainty.

Model evaluation

We evaluated model performance using normalized Root Mean Square Error (nRMSE) and the Coefficient of Determination (R^2), which together capture relative error and explained variance. The nRMSE was defined as $RMSE/\sigma_y$, where σ_y is the standard deviation of target AGB in the corresponding evaluation set. We applied five-fold cross-validation within the training set for model selection and reserved the independent test set to provide an unbiased estimate on unseen data. We reported mean nRMSE ± 1 standard deviation across folds to account for the small sample size. Statistical significance was assessed using paired t-tests on fold-wise nRMSE values.

Model interpretability and analysis

SHAP-based individual feature importance

To interpret feature contributions, we employed SHAP (SHapley Additive exPlanations), which assigns importance value to individual features based on cooperative game theory (Lundberg and Lee 2017). For the best-performing model configuration (feature group G-Full with XGBoost-TD), we used TreeSHAP to compute exact Shapley values for tree-based models (Lundberg et al. 2018). TreeSHAP provides both local explanations (feature contributions for individual predictions) and enables aggregation for global model understanding.

We calculated the mean absolute SHAP values across all predictors in the dataset to rank global feature importance, reporting the top-20 most influential predictors. Mean absolute values capture the average magnitude of each feature's contribution regardless of direction, providing an unbiased importance ranking that facilitates direct comparison across disparate predictor types, such as spectral indices, backscatter coefficients, and canopy-height percentiles. Additionally, we also examined SHAP value distributions to distinguish features with uniform versus contextually variable contributions (Lundberg et al. 2020).

Individual feature behavior analysis

We analyzed SHAP partial dependence plots (Lundberg et al. 2020) to reveal nonlinear relationships between features and their contributions to AGB

estimation. Six representative features spanning canopy height percentiles, spectral indices, and radar backscatter were selected to illustrate behavior across sensor types. We included confidence intervals derived from locally weighted regression smoothing and marginal density distributions to indicate data support and reliability of the estimated relationships (Lundberg et al. 2020).

Feature-group ablation analysis

We quantified the contribution of each feature group with leave-one-out ablations starting from the full model. For each group, we removed it, retrained with the same cross-validation setup, and compared performance to the full model. The groups were: “3D Structure” (i.e., NAIP-DAP canopy height profiles and GEDI-derived CHM25), “Airborne Data” (UAVSAR polarimetry, NAIP Optical, NAIP-DAP), “UAVSAR Polarimetry” (L-band polarimetric decomposition), “SAR Coherence” (Sentinel-1 InSAR coherence), and “NAIP Optical” (NAIP RGBN reflectance). We measured the drop in R^2 and the percent increase in RMSE. To study spatial effects, we produced wall-to-wall predictions for each ablated model and mapped pixel-wise absolute differences from the full model.

Results

Influence of temporally aggregated Sentinel-2 metrics on AGB prediction

Using XGBoost-TD with library defaults, the summer composite (G-Sum: S2_SUM) set our optical-only baseline with an independent-test nRMSE of 0.599 ± 0.10 (Fig. 3). Incorporating winter data to capture leaf-off structure (G-SumWin: SUM + WIN) significantly lowered nRMSE to 0.562 ± 0.10 (***, $p < 0.001$ compared with G-Sum, Fig. 3). The full four-season stack (G-4Seas: S2_ALL) further reduced nRMSE to 0.547 ± 0.10 , remaining highly significant relative to G-Sum (***, $p < 0.001$, Fig. 3) and G-SumWin (**, $p < 0.05$, Fig. 3). Overall, expanding from summer-only to four seasons improved accuracy by 8.7%, with significant incremental gains from adding winter (6.2%) and from adding spring and autumn (2.8%).

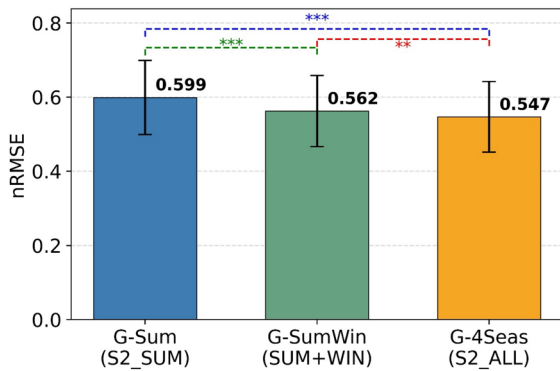


Fig. 3 Seasonality effect on AGB prediction (Stage A). Bars show fivefold CV mean nRMSE $\pm$ 1 s.d. for XGBoost-TD using (i) G-Sum (summer Sentinel-2 composite), (ii) G-SumWin (summer + winter composites), and (iii) G-4Seas (four seasonal composites). Lower nRMSE indicates higher accuracy. Brackets indicate paired t-tests on fold-wise nRMSE (*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$)

NAIP-DAP and GEDI-derived canopy height metrics to AGB prediction

Stage B of the study evaluated the contribution of GEDI-derived CHM25 and NAIP-DAP canopy height profiles to AGB prediction beyond the spectral baseline (BASE_RS, mean nRMSE = 0.54 to 0.57, Table S8). Replacing spectral bands with the GEDI-derived CHM25 layer alone (feature group G-CHM25) produced non-significant changes for all tree-based models except RealMLP (Fig. 4, Table S8). Specifically, tree-based models showed slight nRMSE increases of 0.7 to 2.5% (i.e., 0.56 ± 0.07 for XGBoost, 0.55 ± 0.07 for CatBoost, 0.55 ± 0.06 for LightGBM; all $p > 0.1$, Fig. 4), while RealMLP recorded a significant 6.1% reduction (0.53 ± 0.07 , $p < 0.01$). In contrast, configurations using NAIP-DAP canopy height profiles demonstrated substantial improvements. NAIP-DAP canopy height profiles alone (G-Profile, Fig. 4, Table S8) achieved significant error reductions of 7.4–18.8% compared to baseline, with nRMSE values ranging from 0.46 ± 0.08 (RealMLP, $p < 0.001$) to 0.50 ± 0.07 (XGBoost, $p < 0.01$). All models showed statistically significant improvements ($p < 0.01$, Table S8).

The greatest performance gains occurred when combining NAIP-DAP canopy height profiles with multisensor baseline (G-Base + Profile), reducing nRMSE by 15.5–18.7% across all models: XGBoost

(0.45 ± 0.07), CatBoost (0.46 ± 0.07), LightGBM (0.45 ± 0.06), and RealMLP (0.46 ± 0.08). All improvements were highly significant ($p < 0.001$, Table S8). This performance exceeded both GEDI-derived CHM25 (G-CHM25) and NAIP-DAP profiles alone (G-Profile; Fig. 4).

Assessment of multisensor feature contributions

SHAP analysis of the fused XGBoost model (Fig. 5) shows a strong dominance of canopy-height percentile metrics derived from the 1 m NAIP-DAP canopy-height model within each 25×25 m grid cell. Among these, the 10th-percentile height alone accounts for a mean absolute SHAP value of 19.18. Together with the 98, 75, 50 and 25th percentiles, these metrics explain roughly 41% of the total explanatory power. In a secondary importance tier, the GEDI-derived CHM25 (mean|SHAP| = 2.82) and UAVSAR polarimetric entropy (1.66) highlight the complementary value of detailed structural and polarimetric volume scattering. A third-tier groups optical and C-band SAR variables related to canopy water status and temporal stability (Fig. 5, e.g. spring red-edge B4, winter NDMI, 12-day Sentinel-1 coherence), each contributing between 1.2 and 1.4. Although the remaining 97 predictors together supply a sizeable cumulative |SHAP| of 52.6, their individual influence averages less than 0.6, indicating a long-tailed distribution in which a few predictors dominate model performance while many others contribute small but collectively meaningful effects (Fig. 5a). Overall, the SHAP ranking confirms a strong synergy between height structure variability and spectral–microwave information in explaining stand-scale AGB variation.

Partial-dependence diagnostics of the selected six features (Fig. 6, see Methods section for selection criteria) reveal the specific functional relationships that underline these global importance scores from Fig. 5, illustrating how the model combines heterogeneous sensor signals. The 10th-percentile canopy height follows a sigmoidal response (Fig. 6a): its SHAP contribution rises from roughly -20 t ha^{-1} at bare-ground levels to about $+40 \text{ t ha}^{-1}$ once the value exceeds 20 m. This inflection defines a practical biomass threshold: when the shortest 10% of trees in a 25×25 m grid reach ~ 15 m, the stand has essentially attained mature-forest stature, prompting the model to classify it as high biomass. The α -angle derived

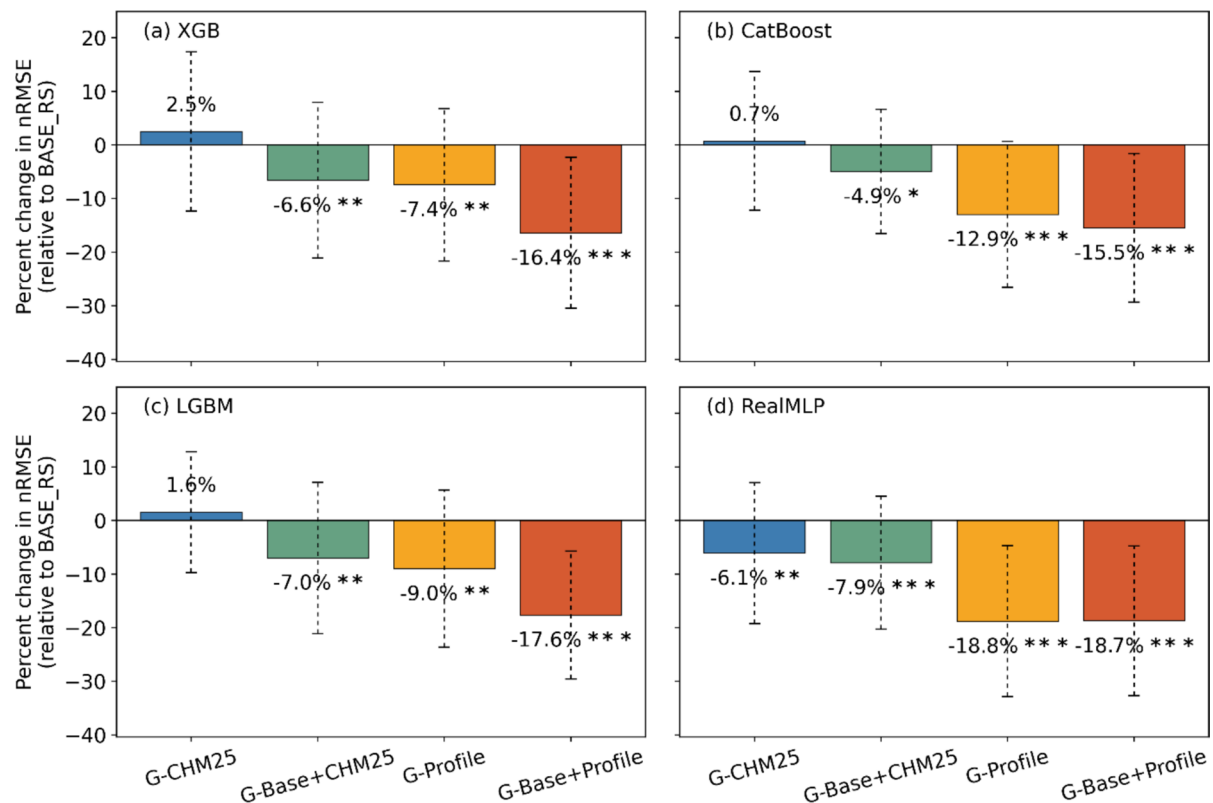


Fig. 4 Percentage change in cross-validated nRMSE relative to the multisource spectral baseline (BASE_RS, four-season Sentinel-2 plus Sentinel-1, PALSAR-2, and terrain) after adding canopy-structure information. Panels show **a** XGBoost, **b** CatBoost, **c** LightGBM, and **d** RealMLP. Each panel compares four configurations from Stages B: G-CHM25 (GEDI-derived

CHM25 only), G-Base+CHM25 (BASE_RS+GEDI-derived CHM25), G-Profile (NAIP-DAP canopy height profiles only), and G-Base+Profile (BASE_RS+NAIP-DAP profiles). Negative values indicate error reductions with asterisks indicating statistical significance relative to BASE_RS (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$)

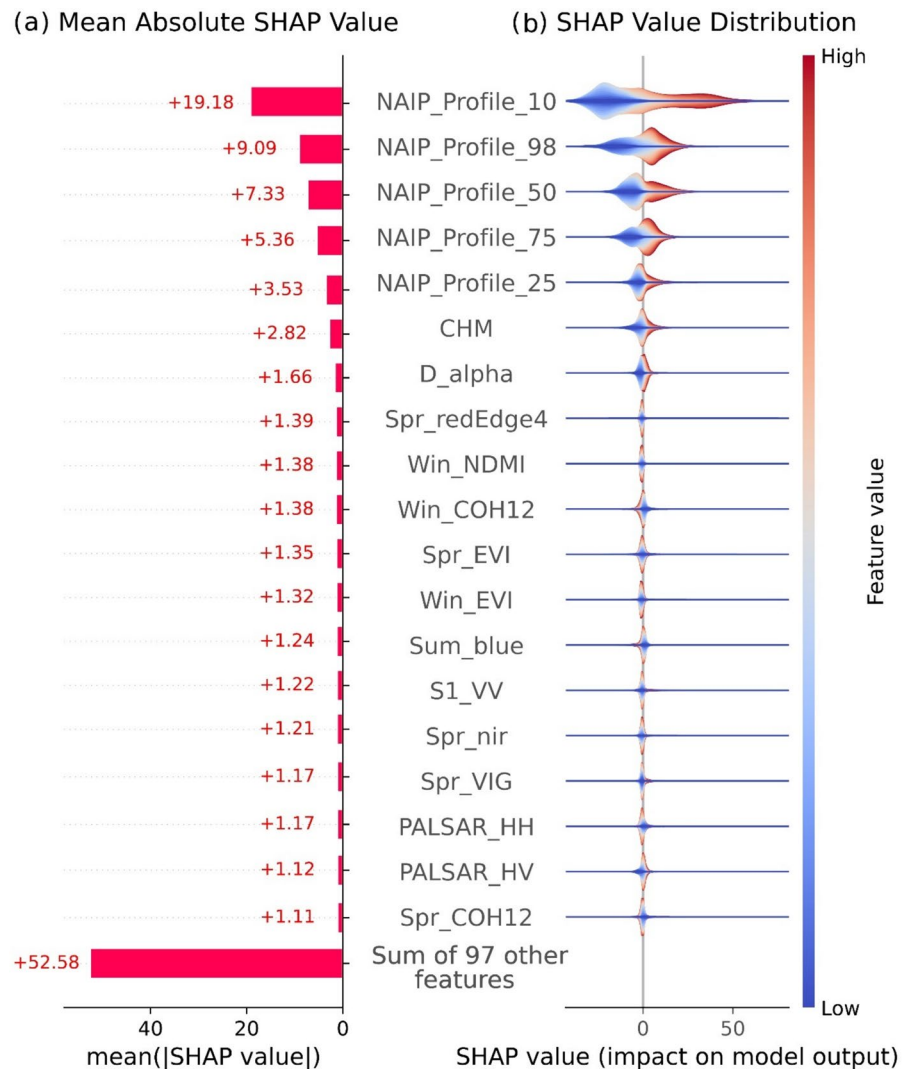
from polarimetric decomposition exhibits a similar threshold-like behavior (Fig. 6b). SHAP values change sign near $47\text{--}48^\circ$, marking the transition from mixed surface/volume scattering toward fully developed volume scattering, as expected for dense canopy crowns. In contrast, 12-day winter coherence declines almost linearly across its range and shows a negative relationship with SHAP values (Fig. 6d). Specifically, low coherence from C-band InSAR indicates rapid temporal decorrelation within structurally complex canopies, thereby increasing the predicted AGB, whereas high coherence depresses it. PALSAR-2 HH backscatter follows a U-shaped curve (Fig. 6f), with negative contributions near -6 dB and positive tails at both low and high backscatter, reflecting the combined influence of soil moisture, double-bounce

artefacts and L-band saturation in extremely dense stands.

Spatial patterns of predicted forest AGB

Using the optimized multisensor model, we produced a seamless wall-to-wall AGB map for the study area (Fig. 7). Predicted values ranged from < 20 Mg ha^{-1} in recently clear-cut areas and urban zones to > 250 Mg ha^{-1} in riparian corridors and mature forest stands. High-biomass forests (> 200 Mg ha^{-1}) formed elongated corridors that traced the dendritic pattern of major river systems, including the Cape Fear River, Northeast Cape Fear River, and Lumbee River. The highest AGB concentrations (> 250 Mg ha^{-1}) occurred in two

Fig. 5 SHAP analysis of XGBoost AGB model showing importance and directional influence of the 20 most influential predictors. **a** Global feature importance, expressed as mean absolute SHAP values (bars), quantifies each predictor's average contribution to model predictions; larger bars indicate greater influence on AGB estimates. **b** Local feature effects, shown as violin plots, summarize the distributions of SHAP values across all predictions. Plot width indicates the frequency of SHAP magnitudes, and color (red = high feature value, blue = low feature value) shows the direction of influence. Positive SHAP values increase predicted AGB, while negative values decrease it. For example, high values of NAIP-DAP 10th percentile canopy height produce positive SHAP values (increasing predicted AGB), whereas low values are associated with negative SHAP values



distinct regions: the Waccamaw River corridor in the southeastern portion of the study area and the Cape Fear River floodplain extending northeast from Wilmington. These riparian zones formed a continuous network of high-biomass forest across the landscape. In contrast, upland forests displayed moderate AGB values (100–150 Mg ha⁻¹), creating a relatively uniform matrix across the central basin. The Lumberton urban area appeared as a prominent low-biomass zone (<50 Mg ha⁻¹) in the central-western portion of the study area. Numerous circular to elliptic patches with very low AGB (<30 Mg ha⁻¹) were distributed away from the main

river channels, corresponding spatially to recent forest harvest units, small lakes, and wetland complexes. Linear low-biomass features associated with roads and infrastructure fragmented the otherwise continuous forest cover.

Feature-group contributions to AGB prediction

Feature-group ablation quantified the relative contribution of each data source to AGB prediction (Fig. 8). Removing 3D structure produced the largest degradation ($\Delta R^2=0.603$, 96.5% RMSE increase), indicating that canopy height information was the most influential predictor set. Removing all airborne

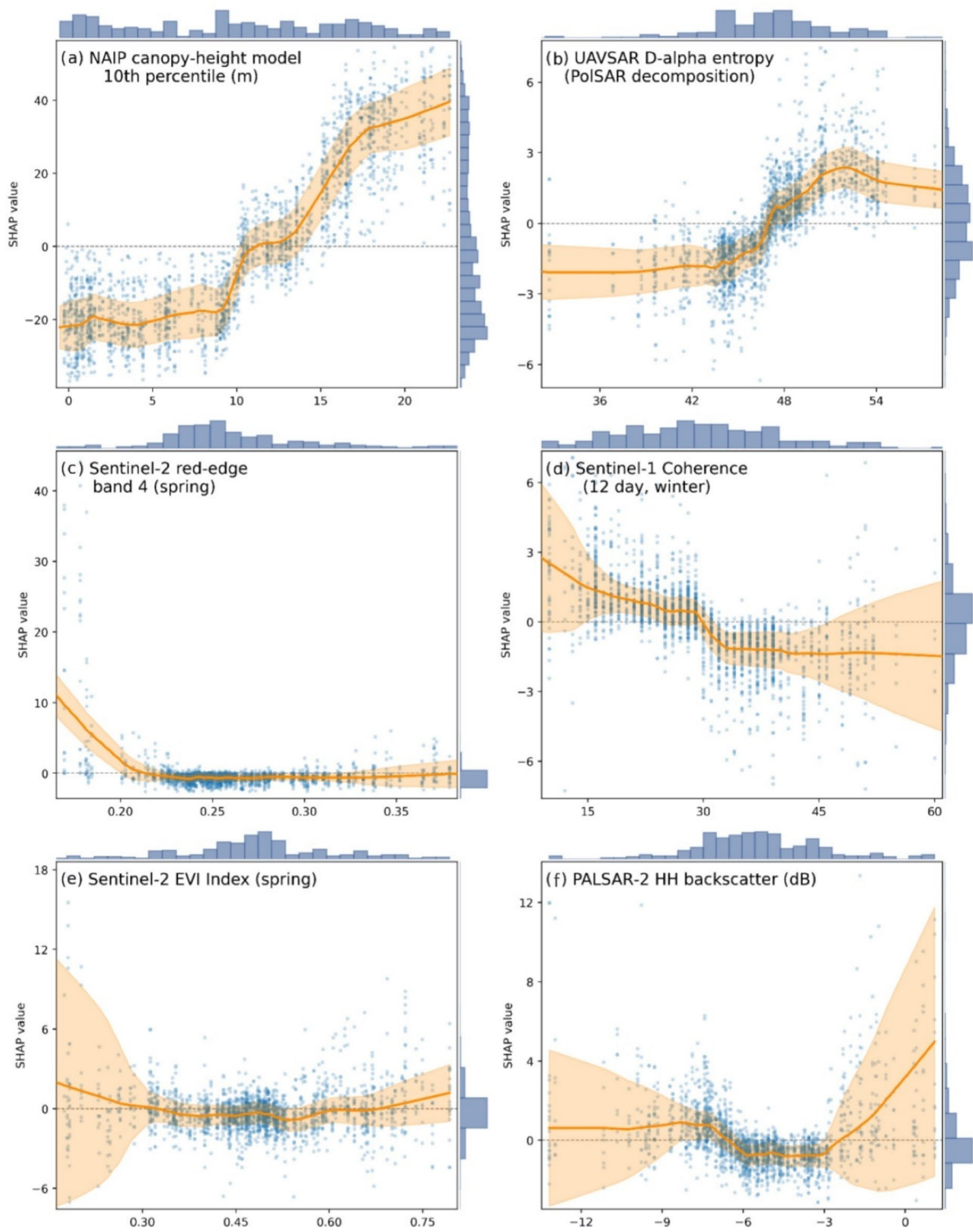


Fig. 6 SHAP-based partial dependence plot of the six representative features from the top 10 importance features. Values are plotted with a scatter plot and a regression line represented with the orange line of mean and shade of SD. On the SHAP axis, SHAP=0 indicates no change in the model prediction relative to the baseline, positive values increase and negative values decrease the prediction. Histograms on the right and top of each plot are distributions of the SHAP and values of variables

data caused the next largest drop in performance ($\Delta R^2=0.461$, 79.4% RMSE increase). Removing UAVSAR polarimetry also reduced model accuracy, but to a smaller extent ($\Delta R^2=0.056$; 10.7% RMSE increase). In contrast, removing Sentinel 1 coherence ($\Delta R^2=0.016$; 3.2% RMSE increase) or NAIP optical inputs ($\Delta R^2=0.001$; -0.2% RMSE change) resulted in only minor effects.

Spatial ablation maps (Fig. 9) showed where these losses were concentrated. The model without 3D structure produced the most extensive and intense differences from the full model (mean difference 22.6 Mg ha⁻¹; Fig. 9a and Fig. 7), especially along narrow, dendritic corridors that follow the drainage network, such as upstream reaches of the Lumbee River and the Waccamaw River. The model without airborne data showed a very similar spatial pattern, although with slightly lower magnitude (mean 18.7 Mg ha⁻¹; Fig. 9b). When UAVSAR polarimetry is removed, the differences are mostly low but still visible in the central to eastern part of the study area, with clearer patches along the Waccamaw River (mean 7.3 Mg ha⁻¹; Fig. 9c and Fig. 7). Removing Sentinel 1 coherence produces only very small differences that are scattered and do not follow a strong ecological pattern (mean 5.8 Mg ha⁻¹; Fig. 9d), which supports the quantitative result that coherence was the least critical of the tested groups (Fig. 8).

Discussion

Interpretable multisensor fusion for landscape-scale AGB estimation

Integrating phenological information through seasonal compositing

In the southeastern North Carolina Coastal Plain, seasonal compositing enhanced our model

performance by adding phenological contrast that single-date imagery cannot capture. Moving from summer-only (G-Sum) to winter–summer stacks (G-SumWin) and then to four-season stacks (G-4Seas) systematically reduced nRMSE, with the all-season approach performing best (Fig. 3). These gains were robust to dimensionality reduction, indicating that the additional information stems from phenology rather than from increases in raw feature count alone. Feature rankings help explain the mechanism. The spring composite of red-edge-4 (~865 nm) consistently outranked other reflectance predictors, consistent with the heightened early-season sensitivity of the NIR shoulder and reduced pigment confounding at that wavelength. Because red-edge-4 lies closer to the NIR plateau, it is more responsive to leaf and small-branch density and less perturbed by pigment-driven variation or moderate spring atmospheric variability. By contrast, red-edge-2 exhibits greater pigment sensitivity and spectral redundancy with visible–NIR bands, which likely reduces its unique contribution to biomass estimation in our setting. To our knowledge, no previous study has systematically evaluated the incremental value of full four-season Sentinel-2 compositing for AGB estimation in the southeastern North Carolina Coastal Plain. The closest comparable work, Ehlers et al. (2022), used a two-season (summer + winter) Landsat composite in the same region. Our results (Fig. 3) show that autumn and spring composites capture phenological transitions that provide additional structural and biochemical information beyond what a two-season stack offers in this landscape.

We employed seasonal compositing rather than explicit phenological metric extraction for methodological reasons. While curve-derived metrics such as start-of-season timing, end-of-season timing, and curvature parameters can provide valuable insights, they require model and parameter selections that are challenging to validate at large scales. Our findings demonstrate that dense time-series data summarized using non-parametric statistics, specifically seasonal medians, effectively capture key seasonal vegetation states while maintaining lower analytical complexity. This approach aligns with recent evidence indicating that layer-wise summaries of optical time series effectively support ecosystem-scale monitoring of vegetation productivity and biomass (Kooistra et al.

Fig. 7 Spatial distribution of predicted AGB across the study area, derived from the final multisensor model. Warmer colors indicate higher AGB values, while cooler colors represent lower biomass estimates. Major rivers and administrative boundaries are overlaid for reference

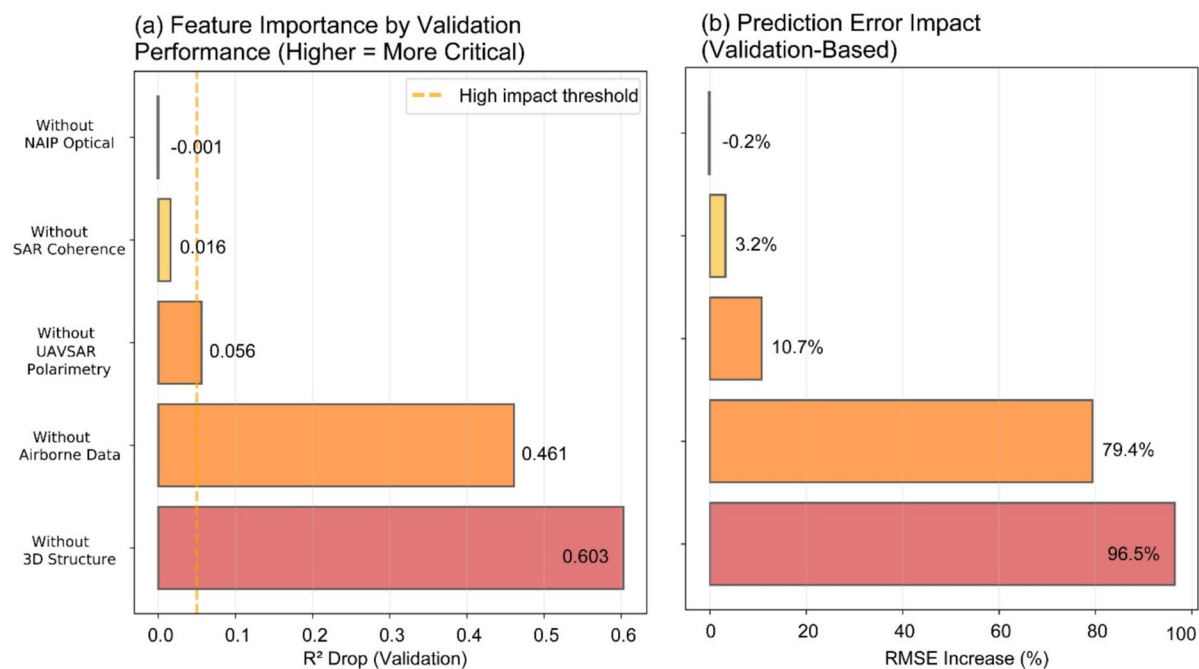
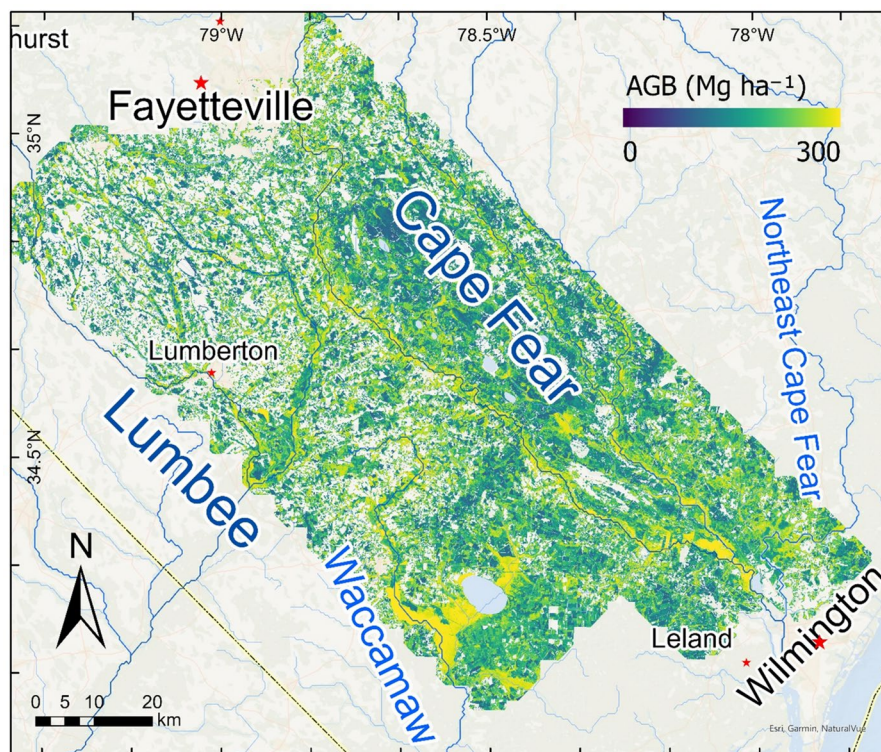


Fig. 8 Ablation analysis illustrating the contribution of major predictor sets to AGB modeling performance, **A** Change in validation performance expressed as the drop in R^2 ; the dashed line marks a high-impact threshold. **B** Corresponding increase in RMSE (%)

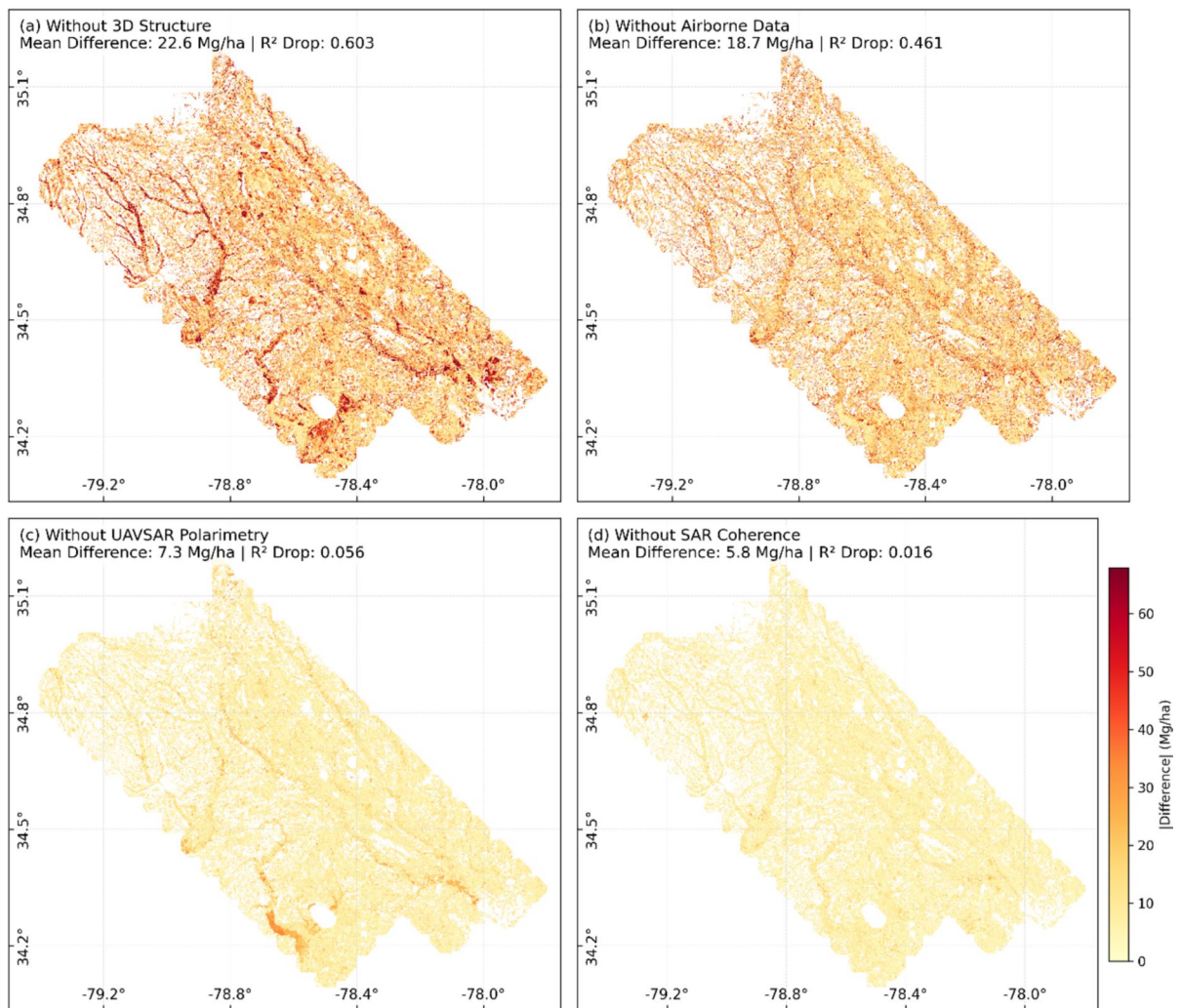


Fig. 9 Spatial effect of feature-group ablations on AGB mapping for the North Carolina Coastal Plain. Panels (a–d) show absolute difference maps relative to the full model after remov-

ing 3D structures, all airborne data, UAVSAR polarimetry, and Sentinel 1 coherence, respectively. Warmer colors indicate larger deviations (Mg ha^{-1})

2024). Furthermore, these results are consistent with our previous applications of vegetation seasonality indices for land cover classification, where simplified phenology-aware summaries enhanced classification accuracy over large areas (Wang et al. 2016).

The benefits we observe align with prior reports that multi-season optical data improve vegetation species-diversity mapping (Chrysafis et al. 2020; Cai et al. 2024). They also agree with studies showing that multi-temporal Sentinel-2 optical imagery, when combined with airborne LiDAR data, can further boost tree-species classification and structural predictions by leveraging seasonal variations (Jiang et al.

2025). Together, these converging lines of evidence suggest that phenology-aware compositing is a practical, scalable route to inject biologically meaningful variation into biomass models without incurring the overhead of full curve fitting.

NAIP-DAP for canopy structure characterization

Our results demonstrate that high-resolution canopy height metrics derived from NAIP-DAP serve as an effective structural data source for AGB estimation in Coastal Plain forests. NAIP-DAP offers several operational advantages over LiDAR: publicly available

wall-to-wall coverage, low marginal cost, and regular repeat acquisition on a ~2–3 year cycle across the conterminous United States.

Incorporating NAIP-DAP canopy height profiles into our multisensor baseline yielded the largest accuracy gain (15.9–18.0% reduction in nRMSE, Fig. 4), with the 10th percentile emerging as the most important feature across all model architectures. Notably, this finding complements our previous LiDAR-based study in the same region (Ehlers et al. 2022), indicating that the relative importance of lower canopy metrics differs in this Coastal Plain landscape depending on sensor physics. NAIP-DAP captures the upper canopy surface as viewed from above, whereas LiDAR actively penetrates the canopy to measure vertical structure throughout the profile. Consequently, the 10th percentile from NAIP-DAP characterizes the lowest visible canopy surface at high spatial resolution, which is sensitive to canopy gaps, recent disturbances, and short-stature stands rather than understory height as captured by LiDAR. In heterogeneous or mixed stands, it provides a lower-bound constraint on the visible canopy surface and can reduce overestimation when coarser pixels mix low-stature vegetation with adjacent taller canopy, consistent with the threshold response indicated by the SHAP analysis (Fig. 6a). The NAIP imagery used here was acquired between October and November 2018, when many hardwoods in southeastern North Carolina still retained foliage (Fig. S6). Under these largely leaf-on conditions, phenology-related differences in point cloud density between hardwood and pine stands were likely limited. Thus, the elevated errors in hardwood-dominated areas are more plausibly attributable to greater canopy structural complexity and higher within-class AGB variability; resolving these mechanisms would require multi-date DAP across contrasting phenological stages.

The percentile-based metrics (i.e., 10th, 25th, 50th, 75th, 95th) derived from NAIP-DAP point clouds effectively characterize the horizontal canopy structure within forest stands in an ecologically meaningful way. Unlike LiDAR's vertical profile, which captures the vertical stratification of the canopy layering from the ground to canopy top, NAIP-DAP profiles describe the spatial heterogeneity of the upper canopy surface. Collectively, these statistical metrics form a reproducible structural 'fingerprint' across a landscape. They capture stand-level patterns

by integrating information on tree-size distributions, canopy gaps, and spatial heterogeneity, all of which are critical for accurate AGB prediction. It is worth noting that the distinction between LiDAR's vertical penetration and photogrammetry's horizontal surface characterization has important implications for model interpretation. Consequently, identical percentiles (e.g., 10th) capture fundamentally different structural information depending on the sensor technology used. While percentile-based photogrammetric canopy metrics from very high-resolution satellite imagery (e.g., Pléiades) have demonstrated usefulness in structurally simple plantation forests (Pearse et al. 2018), their relative importance in hardwood-dominated Coastal Plain landscapes had not been evaluated prior to this study.

Looking forward, the regular repeat acquisition of NAIP imagery creates opportunities beyond static biomass mapping. Many states (e.g., Tennessee and Virginia) now have multiple temporal acquisitions spanning decades, enabling forest change detection and growth estimation that could complement traditional field inventory cycles (Schroeder et al. 2022). Additionally, photogrammetric canopy height models derived from commercial high-resolution satellite imagery (including WorldView-3, Pléiades, and Planet SkySat) offer potential to extend coverage and increase revisit frequency beyond NAIP's 2–3 year cycle (Pearse et al. 2018; Bhushan et al. 2021; Liu et al. 2021; Zubkov et al. 2023; Pourrahmati et al. 2024). At finer spatial scales, uncrewed aerial system (UAS) photogrammetry provides flexible, on-demand acquisition at centimeter-level resolution, making it well suited for site-level monitoring, calibration, and validation of wall-to-wall estimates (Jayathunga et al. 2019). Such platforms could extend coverage to regions outside the U.S. or provide more frequent updates. However, using commercial data incurs acquisition costs, whereas NAIP imagery is freely available with systematic coverage across the conterminous U.S.

Explainable AI reveals structural drivers of AGB variation

Model interpretability analyses via SHAP (Fig. 5 and Fig. 6) revealed why canopy structural metrics, particularly NAIP-DAP canopy height profiles, emerge as the dominant predictors of AGB in the southeastern

North Carolina Coastal Plain, refining prior multisensor findings for this region (Ehlers et al. 2022). It is evident that, among canopy height metrics, lower-canopy statistics, especially the 10th percentile, exert a disproportionate influence on model predictions (Fig. 5). This pattern underscores the ecological significance of lower-canopy metrics: the 10th percentile captures canopy gaps and low-stature vegetation zones while simultaneously reflecting the minimum height threshold of closed-canopy forest (Fig. 2). It thus provides a sensitive indicator of within-stand structural heterogeneity that integrates information about both forest development stage and spatial complexity, extending beyond simple top-of-canopy or mean height measurements. As discussed above, this metric represents the lowest visible canopy surface in photogrammetric data rather than true understory height as captured by LiDAR. Consequently, it is particularly responsive to canopy openness, spatial heterogeneity in tree heights, and recent disturbance history, all of which influence biomass accumulation patterns. Future work could explore additional structural metrics, such as the standard deviation of height within each stand, to directly quantify vertical heterogeneity and assess whether explicit variability measures further enhance predictive performance.

Partial dependence patterns for the 10th percentile (Fig. 6a) showed a sigmoidal response with a threshold near 15 m, after which biomass estimates stabilize with strongly positive correlation. This pattern indicated that taller 10th percentile values (> 15 m) signal higher overall stand biomass, reflecting dense canopy cover with minimal openness. The threshold behavior reinforces a fundamental distinction between photogrammetry and LiDAR: unlike LiDAR, which penetrates canopy gaps to measure understory structure, NAIP-DAP captures only the visible upper canopy surface. Consequently, low 10th percentile values (< 15 m) may be indicative of either truly short-stature stands or taller forests with substantial canopy openness, both of which correspond to lower biomass. This finding is consistent with LiDAR-based evidence that structural complexity, not just maximum height, drives biomass variation (Rodda et al. 2024).

Radar and optical features complement this structural backbone without redundancy. L-band HV backscatter from PALSAR increases with biomass, reflecting volume scattering in dense canopies, whereas HH

exhibits a U-shaped relation (Fig. 6f) consistent with shifts among surface, volume, and double-bounce scattering under wet or flooded conditions. These patterns correspond with structural inferences reported for PALSAR and UAVSAR data in forested landscapes (Bouvet et al. 2018; Marks et al. 2014). The winter Sentinel-1 coherence (12-day) showed a negative relationship with AGB (Fig. 6d). Low coherence values, which indicate temporal decorrelation, are associated with high biomass due to canopy movement of tall trees, while high coherence corresponds to stable, low-biomass surfaces with minimal vegetation or simple structure. Consequently, coherence provides a complementary, time-sensitive proxy for temporal canopy stability and moisture dynamics that are not captured by static canopy height measurements. A similar saturation tendency is expected in high-biomass Coastal Plain forests, particularly in riparian corridors where AGB may exceed 250 Mg ha^{-1} . In such stands, optical reflectance indices approach asymptotic behavior and C-band backscatter becomes less sensitive to additional biomass increments (Puliti et al. 2021; Yu and Saatchi 2016; Saatchi et al. 2011). Consistent with these saturation effects, the spatial ablation analysis (Fig. 9, Sect. "Feature-group contributions to AGB prediction") shows that NAIP-DAP structural inputs and L-band polarimetry contributed the largest accuracy gains precisely in riparian corridors where AGB is highest. Thus, multisensor fusion partially mitigates but does not fully eliminate the known saturation effects in dense forest conditions.

These interpretations are consistent with multisource benchmarks across various ecosystems globally (Li et al. 2024; Avitabile et al. 2016; Bouvet et al. 2018). For instance, in Japanese forests, fusing Sentinel-2, ALOS PALSAR-2, and airborne LiDAR underscored radar's structural role, consistent with our high importance for L-band HV (Li et al. 2024). In tropical systems, optical-SAR combinations have been shown to reduce biomass estimation error, but performance often saturates at high biomass levels (Avitabile et al. 2016; Bouvet et al. 2018).

Our ablation analysis (Fig. 8) showed that removing UAVSAR polarimetry degraded performance ($\Delta R^2 = 0.056$, 10.7% RMSE increase), confirming that L-band polarimetric information captures scattering mechanisms distinct from C-band backscatter alone. This finding aligns with Zhang et al. (2017), who demonstrated that biomass estimation using

UAVSAR L-band polarimetric data achieved R^2 of 0.59–0.77 with radar alone, but improved substantially ($R^2=0.76$ –0.86, RMSE reduction of 20–28%) when incorporating top-of-canopy height from PRISM stereo imagery. Zhang et al. (2017) further showed that modeling forest types separately (deciduous, evergreen, mixed) reduced errors, though improvements were modest. We address this limitation more effectively by incorporating seasonal Sentinel-2 indices in our fusion. The available evidence indicates that multisensor fusion does not merely accumulate redundant information; rather, it integrates distinct ecological gradients, such as stand stature, scattering complexity, foliage chemistry and temporal stability. This interpretability-focused approach extends recent work in this Landscape Ecology special collection on AI and landscape ecology. For instance, Kirti et al. (2025) used explainable ML for spatial biophysical estimation and Eigenbrod et al. (2026) advocated for transparent modeling frameworks. Our study demonstrates the efficacy of SHAP-based attribution and feature-group ablation in identifying the ecological mechanisms driving landscape-scale AGB spatial variation across heterogeneous forests.

Spatial patterns of predicted AGB reveal landscape ecological drivers

The landscape-scale AGB map reveals distinct spatial patterns across the North Carolina Coastal Plain (Fig. 7). High-biomass forests form dendritic networks along riparian corridors rather than following simple coastal-inland gradients, interspersed with a fragmented upland matrix shaped by harvest history and urban development.

Hydrological control emerges as the dominant natural driver. Elongated high-biomass zones trace the major river networks, reflecting enhanced productivity of alluvial floodplains where moisture availability and nutrient-rich soils promote forest growth (Naiman and Décamps 1997; McClain et al. 2003; Sutfin et al. 2016; Clifton et al. 2024). The Waccamaw River swamps and lower Cape Fear floodplain exhibit particularly high AGB concentrations ($>200 \text{ Mg ha}^{-1}$). These areas potentially represent resilient carbon stocks (Dybala et al. 2019). This spatial signature confirms that our multisensor approach

successfully captures first-order biophysical gradients governing forest productivity.

Anthropogenic modifications create sharp discontinuities in the natural landscape, from areas next to rivers to higher land. Recent timber harvests appear as squared clearings with AGB values of less than 50 Mg ha^{-1} , while urban expansion, notably in the Lumberton area, shows similar low-biomass signatures (Fig. 7). The model's sensitivity to these disturbances validates its usefulness for operational forest monitoring and change detection (Zhao et al. 2022; Carter et al. 2024). High-resolution NAIP-DAP structural metrics and multi-temporal optical composites enabled this detection capability.

The spatial coherence of predicted AGB with known ecological gradients provides evidence for model reliability beyond point-level accuracy metrics (Ploton et al. 2020). High predictions cluster in environmentally favorable locations (e.g., bottomland hardwoods and intact swamps), while low predictions align with known disturbances and young stands. This spatially explicit characterization demonstrates how multisensor fusion translates into ecological understanding at a landscape level. It also provides actionable information for landscape-scale carbon management, identifying priority conservation targets and potential restoration areas (Matzek et al. 2020; Udawatta et al. 2023).

Spatial heterogeneity of feature-group contributions

The spatial heterogeneity in ablation impacts (Fig. 9) reveals important insights about where different data sources provide unique value. High-biomass riparian corridors and structurally complex stands in the southeastern North Carolina Coastal Plain showed substantially larger prediction errors when airborne data or 3D structure were removed (Fig. 8a, b), while many upland areas maintained similar accuracy across models (Fig. 9a, b). This indicates that NAIP-DAP canopy height profiles and other airborne layers contribute most strongly in bottomland hardwood and riparian systems characterized by complex canopy structure. In contrast, managed upland pine plantations with simpler architecture can be adequately captured by coarser spaceborne data (Fig. 9b). These results suggest that optimal data collection strategies in this Coastal Plain landscape should prioritize high-resolution structural acquisitions in riparian and

structurally complex areas, while accepting coarser resolution in simplified plantation landscapes where marginal accuracy gains do not justify additional costs. To our knowledge, no prior study has explicitly characterized the spatial distribution of multisensor fusion gains across management gradients in the southeastern North Carolina Coastal Plain, where high-biomass riparian corridors and structurally complex bottomland hardwood systems present the greatest challenge for optical and C-band SAR-based estimation.

The modest contribution of C-band coherence (3.2% RMSE increase upon removal, Fig. 8b) is consistent with this spatial pattern. In humid subtropical climates, C-band coherence degrades rapidly due to temporal decorrelation driven by dynamic canopy structure and frequent precipitation (Zebker and Villasenor 1992; El Idrissi Essebtey et al. 2019), with decorrelation magnitude increasing with canopy height (Simard et al. 2012). As a result, its structural signal is largely subsumed by the stronger NAIP-DAP height profiles and L-band polarimetry already present in the model. Coherence thus contributes complementary canopy moisture and stability information rather than independent biomass signal.

Limitations and sources of uncertainty

Several constraints should be acknowledged when interpreting model behavior and generalization potential. First, the limited sample size of FIA plots ($n=305$) provides a justification for the use of fold-based inference with t -intervals and a held-out test set. In addition, FIA plot measurement dates span multiple years, leading to a subset of plots temporally offset from the 2018–2019 imagery window. Domain-wide disturbance analysis using Global Forest Watch (Hansen et al. 2013) and LandTrendr (Kennedy et al. 2010) (Fig. S5) indicates that cumulative forest disturbance remained below 12% of the modeled area during this period, suggesting that temporal mismatches are unlikely to dominate model error at the landscape scale. However, residual mismatches at the plot level, attributable to uncaptured growth or harvest events, are still anticipated and may contribute to residual error. Because this study compares relative predictor contributions across model configurations, such noise is expected to inflate variance similarly across all configurations without systematically

favoring any particular predictor type. Although our model demonstrated stable bias across hardwood fractions, increased uncertainty was observed at high hardwood fractions (Fig. S3).

Second, multisource sensor integration introduces limitations related to the acquisition timing and processing. For instance, the 2018–2019 window omits subsequent disturbances, potentially increasing residuals in areas affected by post-2019 harvests or storms. Coverage and acquisition timing varied across input sensors: UAVSAR L-band offered partial, flight-line coverage shortly after Hurricane Florence; NAIP imagery was collected on staggered dates (October 21–November 21, 2018). In addition, Sentinel-1 backscatter/coherence and PALSAR-2 mosaics did not consistently align with Sentinel-2 optical seasons, which may dampen radar–optical synergies. While a four-season configuration demonstrated the greatest efficacy in this study, the optimal temporal granularity likely depends on the biome, canopy type, and sensor characteristics. NAIP-DAP quality can be compromised in dense, leaf-off hardwoods, and mismatches in spatial resolution among inputs (sub-meter to ~5 m sources aggregated to 25 m grids) can smooth sub-stand heterogeneity (Schroeder et al. 2022). Consequently, periodic re-evaluation will be necessary as acquisition protocols and atmospheric correction pipelines evolve, particularly for large-scale applications.

Because FIA plot coordinates are confidential and were not available for spatial partitioning, the stratified random splits used in this study may yield optimistic performance estimates in spatially autocorrelated landscapes. Spatially explicit prediction error maps could not be produced for the same reason; instead, spatial ablation analyses were used to examine where model predictions are most sensitive to different data sources. Additionally, plot density varies across counties (Fig. S4), which may introduce geographic bias in model training and should be considered when interpreting spatial patterns of AGB estimates. Future analyses conducted within secure FIA environments should incorporate spatial block cross-validation and spatially explicit validation to provide more conservative assessments of generalization.

Finally, the interpretation of attribution in high-dimensional, correlated predictor sets should be approached with caution. Despite the benefits of feature selection and seasonal compositing in reducing

redundancy, the presence of correlated predictors can complicate the separation of effects (Wang et al. 2025). SHAP magnitudes for related bands and indices reflect partially shared contributions, and collinearity has the potential to yield imprecise attributions or even sign reversals under off-manifold combinations (Li et al. 2024). In this study, we evaluated both individual predictor contributions and aggregated feature-group importance through ablation analysis. While individual rankings may shift among correlated variables, the dominance of canopy structural predictors at the feature-group level remained consistent. To address the concern of potential high-dimensionality effects, we used cross-validated hyperparameter tuning, evaluated all models on an independent held-out test set, and confirmed through dimensionality reduction experiments (FULL vs. TOPk vs. PCA, Fig. S2) that removing low-importance predictors produced negligible changes in test-set performance.

Future directions: from methods to ecological understanding

Emerging sensors and methods for landscape-scale AGB monitoring

The recent launches of new spaceborne radar systems are expected to significantly enhance multisensor AGB monitoring capabilities. For instance, the NASA-ISRO NISAR satellite, launched in 2025, will provide open-access, frequent-revisit global L-band backscatter and InSAR coherence data for all-weather forest structure monitoring. In addition, ESA's BIOMASS mission, also launched in 2025, will offer P-band radar with increased sensitivity to large woody-components (e.g., tree trunks and branches). It will potentially improve AGB estimation in tall, high-AGB stands and riparian corridors, where optical and C/L-band products tend to saturate (Avitabile et al. 2016).

From an AI perspective, interpretable machine learning has received increasing attention in AGB estimation. Systematic cross-model interpretability studies could clarify when structural detail, spectral diversity, or radar sensitivity matters most for predictive accuracy. A promising avenue for future work is systematic analysis of feature interactions across model architectures, which can reveal how ecological drivers are captured differently by various learners.

Limited research has systematically evaluated the relative contributions of different feature groups across machine learning algorithms or examined the underlying mechanisms driving model-specific performance with particular input types. Comparative analysis across model architectures would guide feature engineering and model selection for operational applications.

Toward dynamic carbon monitoring

From an operational perspective, extension to multi-year time series can transform static AGB snapshots into trajectories of carbon flux, enabling monitoring of growth and disturbance impacts. The incorporation of disturbance layers (e.g., hurricanes, harvests) and pixel-level uncertainty estimates can serve to align products with established Tier-2/3 carbon accounting frameworks and enable more transparent decision-making (Tang et al. 2020). The framework's reliance on open data streams (e.g., Sentinel-1/2, NAIP, PALSAR-2) facilitates routine monitoring updates for resource-limited agencies. Spatial scaling beyond the Coastal Plain to test transferability across ecoregions and integration with emerging sub-meter global canopy-height datasets (Tolan et al. 2024) represent priority next steps. The recent release of embeddings from Google's Geospatial Foundation Model, AlphaEarth (Brown et al. 2025), can be leveraged to effectively support annual global AGB estimation.

Conclusion

We developed and evaluated an AI-driven multisensor fusion framework to map forest AGB across the southeastern U.S. Coastal Plain by integrating NAIP-DAP canopy height profiles with multi-season optical, radar, and terrain predictors. The approach demonstrated that adding wall-to-wall photogrammetric canopy structure, increasingly available through routine UAS and aerial survey campaigns, can substantially improve AGB estimation accuracy relative to satellite-only baselines using broadly accessible data and open-source methods. Integrating structural information with seasonally informed optical and radar predictors enables scalable, high-accuracy AGB mapping across structurally heterogeneous Coastal Plain forests.

The resulting maps support landscape-scale prioritization of carbon sequestration, contribute to carbon inventory efforts, and inform conservation planning and adaptive forest management. By emphasizing transferability and cost efficiency, the framework lowers barriers to routine AGB assessment and monitoring over large areas.

Future work should extend the framework to multi-year time-series for tracking AGB change. The incorporation of observations from emerging open-access L-band and P-band radar missions (e.g., NISAR and ESA Biomass mission) is expected to further improve sensitivity to forest structure and moisture conditions, and evaluate performance across additional forest types and disturbance regimes. Broader validation with independent plots, spatially explicit validation designs, and targeted uncertainty assessment in high-biomass stands will further strengthen regional forest carbon monitoring applications.

Acknowledgements This research was partially supported by a USDA Forest Service Forest Inventory and Analysis program under Collaborative Research agreement (22-CR-11330145-046) and partially supported by a USDA Natural Resources Conservation Service Collaborative Research agreement (NR243A750023C007) with the University of North Carolina at Chapel Hill. Portions of this manuscript were prepared by U.S. government employees as part of their official duties and are therefore in the public domain and not subject to copyright.

Author Contribution Conceptualization, C.W., C.S., and T.A.S.; methodology, C.W., C.S., T.A.S., T.M.P.; software, C.W., C.S. and Y.F.; validation, C.W., C.S., Y.F. and F.Y.; formal analysis, C.W., C.S., T.A.S. F.Y., and F.Y.; investigation, C.W., C.S., T.M.P., Z.Y., Y.F. and F.Y.; resources, C.W., C.S. T.A.S.; data curation, C.W. T.A.S. and C.S.; writing original draft, C.W.; review and editing, C.W., C.S., T.A.S., T.M.P., Z.Y., F.Y. and Y.F.; visualization, C.W., C.S., T.A.S., T.M.P., F.Y. and Y.F.; supervision, C.S.; project administration, C.S. and T.A.S.; funding acquisition, C.S. and T.A.S. All authors have read and agreed to submit the manuscript.

Funding Funding for this research was provided by the United States Department of Agriculture.

Data availability Most remote sensing datasets, including NAIP 4-band aerial imagery (2018), Sentinel-2 Level-2A surface reflectance imagery (2018 to 2019), and Sentinel-1 C-band SAR data, were accessed through Google Earth Engine. ALOS-2/PALSAR-2 L-band SAR Global Yearly Mosaic (v2, 2019), provided by the Japan Aerospace Exploration Agency, was also accessed via Google Earth Engine. UAVSAR polarimetric L-band data (2018) were obtained from the NASA Jet Propulsion Laboratory UAVSAR data portal (<https://uavsar.jpl.nasa.gov/>). One-meter Digital Elevation Models from the United States Geological Survey 3D Elevation Program, were

accessed through Google Earth Engine. The GEDI-derived 25 m canopy height product used from Wang et al. (2025) is publicly available via Zenodo (<https://doi.org/10.5281/zenodo.11176727>, accessed on 18 February 2026), while the original GEDI data products are distributed by NASA's Land Processes Distributed Active Archive Center and are accessible through Google Earth Engine. The code used to reproduce all figures and analyses has been archived in a GitHub repository (https://github.com/ChaoEcohydroRS/NC_SoutheastBiomass) and permanently preserved via Zenodo (<https://doi.org/10.5281/zenodo.18688899>, submitted on 20 February 2026).

Declarations

Conflict of interest The authors declare no competing interests.

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