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EarthArXiv Team
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Dear Team,

We wish to submit as a non-peer-reviewed preprint entitled **"Spectral indices outperform AlphaEarth foundation embeddings for aboveground biomass estimation in tropical Andean Forests"** for consideration for publication in EarthArXiv

This paper addresses the critical question of whether general purpose Earth observation foundation models can surpass domain-specific, interpretable spectral methods in complex ecological modeling. While foundation models like Google's AlphaEarth have been presented as "all-in-one" solutions to overcome data scarcity and environmental heterogeneity, there is a lack of empirical evidence regarding their performance in high-biomass, topographically complex regions.

Using a comparative framework across the tropical Andean Forests, we show that traditional spectral indices still significantly outperform AlphaEarth embeddings in predicting aboveground biomass (AGB). Our findings are significant because they challenge the prevailing "more parameters are better" narrative, highlighting that foundation models may not yet fully capture the fine-scale ecological nuances required for accurate forest carbon monitoring in heterogeneous landscapes.

We believe these findings will be highly relevant to your audience from ecologists to machine learning practitioners as they provide a necessary "reality check" and a roadmap for the more effective integration of foundation models in operational carbon accounting.

Thank you for your valuable time and consideration.

Sincerely,
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Spectral indices outperform AlphaEarth foundation embeddings for aboveground biomass estimation in tropical Andean Forests

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Abstract

Rising greenhouse gas emissions, particularly carbon dioxide (CO_2), are accelerating climate change. Forests are an important carbon store, but measuring how much carbon is stored in large tracts of diverse forests is challenging. Satellite imagery provides consistent measures of forests across space and time, which is an opportunity for accurate estimation of forest aboveground biomass (AGB), which is a foundational measure of carbon dynamics and ecosystem health. Recent advances in neural networks have shown strong potential for capturing complex spectral–spatial relationships, yet deep learning approaches remain difficult to implement for many practitioners due to data, computational, and technical barriers. Emerging alternatives, including foundation-model embeddings and relatively simple artificial neural networks, offer potentially accessible pathways to leverage neural representations without fully custom deep learning pipelines. In this study, we evaluate two such pathways: (1) Artificial Neural Networks (ANN) as a comparatively straightforward neural modeling approach, and (2) AlphaEarth foundation-model embeddings, which distill deep learning representations into plug-and-play features that can be integrated into conventional machine-learning workflows. We conduct our study in Cauca, Colombia, a region with diverse forest types and steep environmental gradients that provide a strong test of model generalization across ecological conditions. Persistent cloud cover and limited field data also make it an ideal setting to evaluate satellite-based biomass estimation where traditional approaches often fall short. We compare the performance of AlphaEarth embeddings with traditional feature-engineered predictors derived from Sentinel-2A spectral indices (e.g., NDVI, EVI, SAVI) using both Random Forest (RF) and ANN models. Results show that ANN consistently outperformed RF, achieving the highest accuracy (79.0%). However, incorporating AlphaEarth embeddings did not improve performance relative to traditional spectral indices across either modeling approach. These findings suggest that while accessible neural approaches such as ANN can enhance biomass prediction, foundation-model embeddings do not yet provide added value over spectral indices for AGB estimation in complex forest ecosystems. Spectral indices therefore remain robust, interpretable predictors, even as neural methods continue to gain prominence in Earth observation.

Keywords: Forest aboveground biomass, Machine Learning, Sentinel 2A, embeddings, Alpha Earth Foundations.

1. Introduction

Tropical forests play a central role in the global carbon cycle: they store large amounts of above-ground biomass (AGB) and act as critical carbon sinks that help mitigate climate change (Matiza et al. 2023). Despite decades of research and repeated warnings from the Intergovernmental Panel on Climate Change (IPCC), large uncertainties persist about the contribution of tropical-forest biomass to the global carbon budget (Bloom et al. 2016). Although the IPCC recognizes these forests as among the Earth's most important carbon reservoirs, reliably quantifying their ABG at scale remains a major scientific challenge (Csillik et al. 2019).Field measurements are expensive, time-consuming, and limited to accessible areas (Marvin et al. 2014). Furthermore, field plots often represent small, localized samples that fail to capture the structural and ecological diversity of tropical forests (Graves et al. 2018). These constraints hinder large-scale monitoring and make it difficult to evaluate the effects of deforestation, degradation, and recovery on global and regional carbon budgets.

Remote sensing has become a cornerstone for estimating above-ground biomass (AGB) across ecosystems because it offers time-efficient and cost-effective coverage that field inventories alone cannot provide (Belloli et al. 2022; Cunliffe et al. 2022; Dong et al. 2020; Eliyajrj et al. 2021). Both active sensors (e.g., LiDAR, SAR) and passive optical sensors have been extensively applied to biomass mapping, often in complementary ways: LiDAR and SAR provide structural information about canopy height and vertical complexity, while optical imagery delivers high-spectral information linked to vegetation condition and cover (He et al. 2013). Long-running missions such as the Landsat series (TM, ETM+, OLI) have supported rich temporal analyses of biomass dynamics across diverse landscapes (Zhu et al. 2024). The Sentinel-2 constellation adds important advantages for biomass estimation through its combination of high spatial resolution, frequent revisit, and red-edge bands that are sensitive to vegetation properties. These characteristics make Sentinel-2 particularly well suited for fine-scale studies in environmental and ecological applications (Li et al. 2021). When field inventory data are integrated with spectrally derived predictors from passive sensors, researchers have shown that robust biomass models can be derived from reflectance-based indices and summary metrics (Li et al. 2021; Fan et al. 2022; Jiang et al. 2022; Muhe and Argaw 2022).

Pairing satellite imagery with predictive models enables scaling plot-level measurements to landscape and national maps (Tian et al. 2023). However, traditional approaches rely on manual feature engineering, such as spectral indices or vegetation metrics, which is labor-intensive, depends on expert knowledge, and may overlook subtle spatial and temporal patterns important for AGB estimation (Sarith Divakar et al. 2022).

AlphaEarth geospatial embeddings offer a promising alternative to handcrafted predictors by automatically summarizing multi-source Earth observation data into compact, informative representations that can capture complex forest structure and seasonal dynamics. By distilling the representational power of deep neural networks into lightweight feature vectors, these embeddings enable users to leverage state-of-the-art deep learning without running computationally intensive pipelines (Doda et al. 2024), allowing seamless integration into familiar workflows such as Random Forests, regression, or spatial models (Bommasani et al. 2022). This has the potential to democratize access to high-performance geospatial prediction. However, despite their promise, AlphaEarth embeddings remain largely untested in applied ecological settings, and their practical strengths, limitations, and added value relative to traditional predictors are still poorly understood (Brown et al. 2025).

Deep learning has shown strong potential for modeling complex, nonlinear relationships between aboveground biomass (AGB) and remotely sensed data, but its practical application remains challenging due to high computational demands, large data requirements, and specialized expertise. In ecologically diverse and structurally complex tropical forests, where biomass reflectance relationships are rarely linear (Caughlin et al. 2021). Traditional parametric models, such as linear regression, often fail to capture these nonlinear dynamics (Matiza et al. 2023). To address these limitations, machine learning algorithms developed within the broader field of artificial intelligence have emerged as powerful non-parametric alternatives for mapping AGB (Xu et al. 2025). These approaches can automatically model intricate interactions between predictors, enabling improved generalization across heterogeneous landscapes. However, choosing an appropriate machine-learning algorithm is crucial for accurately estimating AGB in natural forests (Su et al. 2020; Safari et al. 2017). In practice, researchers must balance predictive accuracy, robustness to limited training samples, interpretability, and computational cost. Random Forests (RFs) have become a default choice in many remote-sensing biomass studies because they are robust to noisy and heterogeneous predictors, require relatively little tuning, and provide useful measures of variable importance (Lu et al. 2016). Alternatively, Artificial Neural Networks (ANNs) represent a more robust class of empirical modeling techniques that can better predict, analyze, and classify complex datasets, offering more flexibility than conventional regression and machine learning approaches like RF (Faria et al. 2024). The Back Propagation ANN has been extensively used for estimating forest biomass (Wang & Guan, 2007; Liu et al., 2008a; Wang & Xing, 2008; Wang et al., 2017) and agricultural yields, including crops like corn and rice (Panda et al., 2010).

The tropical forests of Cauca, Colombia, offer an ideal setting for developing advanced biomass estimation approaches due to their exceptional ecological diversity, steep elevation gradients, and heterogeneous vegetation structure. These complex conditions challenge conventional remote sensing methods, making the integration of multi-source information through AlphaEarth embeddings particularly valuable. This study systematically compares aboveground biomass (AGB) estimates in the Las Piedras River sub-basin (Cauca, Colombia) using different combinations of input data and modeling approaches. We evaluate Sentinel-2 imagery with engineered spectral and vegetation index features alongside AlphaEarth embeddings, representing one of the first applications of these embeddings for biomass estimation in tropical montane forests. For the AlphaEarth analysis, we use the 64 bands provided by the dataset that are stored in Google Earth Engine which capture spectral, spatial, and temporal context. For our modeling comparison, we apply Random Forest and Artificial Neural Network models across the two types of inputs: (i) traditional feature-engineered predictors derived from S2, and (ii) AlphaEarth embeddings. We also conducted a visual comparison of the resulting biomass maps to highlight spatial differences in model performance. This systematic approach allows us to evaluate the added value of AlphaEarth representations over handcrafted features to improve AGB estimation. The overarching goal is to identify the most effective workflow for spatially explicit AGB mapping across a heterogeneous montane landscape, which will improve regional AGB stock assessments and inform conservation and climate mitigation strategies.

2. Material and methods

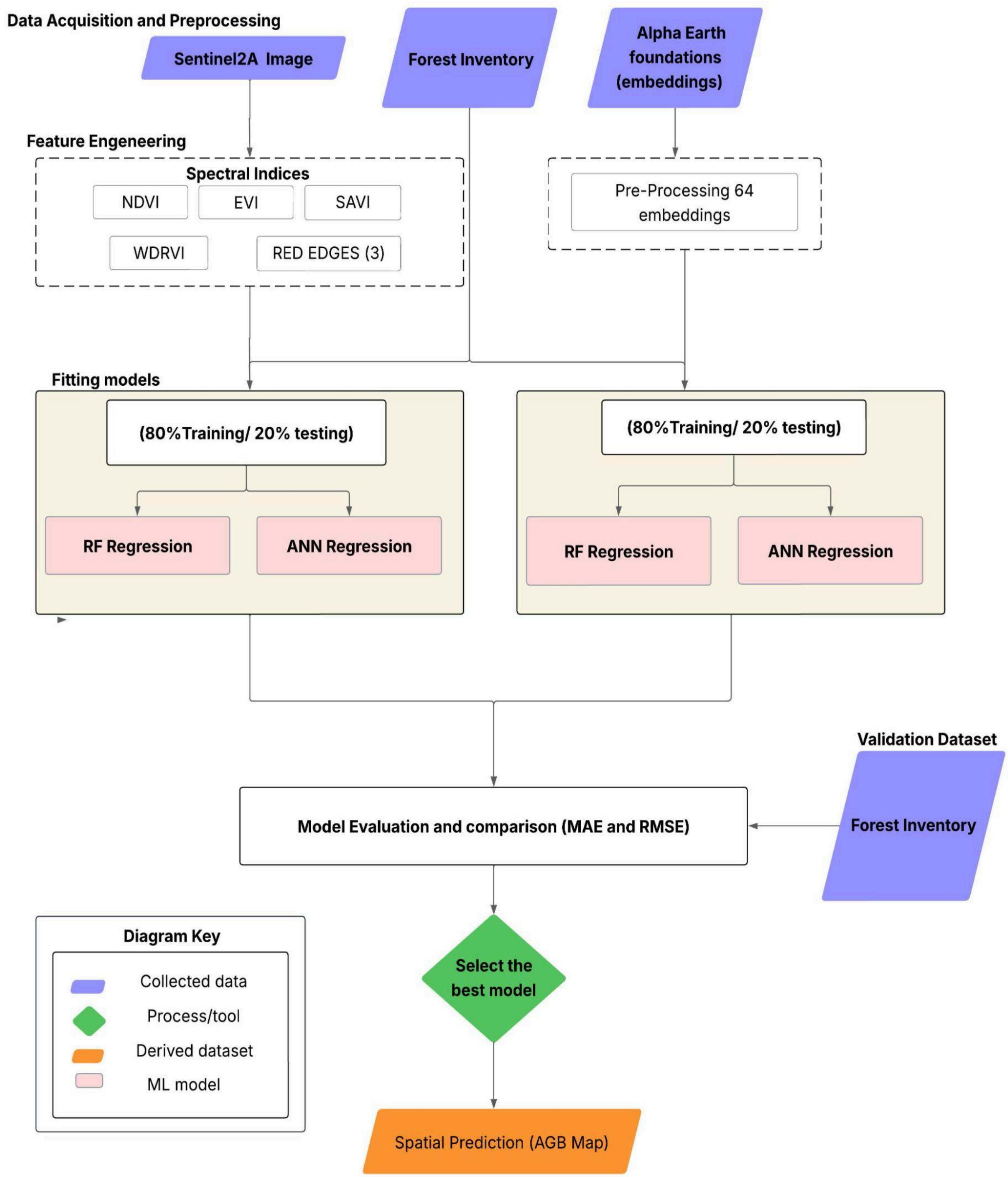


Figure 1. Methodology to estimate spatial distribution of AGB.

2.1 *Study Area*

We conducted this study in the Las Piedras River sub-basin (Fig. 2), located in the northeastern part of the municipality of Popayán, between latitudes 2°26'57.658" N and 2°25'28.161" N, longitudes 76°31'13.995" W and 76°23'8.273" W. This area is roughly 1.300 hectares with elevation ranging from 1,980 to 3,820 meters above sea level. The administrative districts of Quintana and Las Piedras have jurisdiction over this area and it is characterized by the presence of moorland, sub-moorland, high-Andean, Andean, and sub-Andean forests. Additionally, the sub-basin serves as the primary water source for the municipality of Popayán.

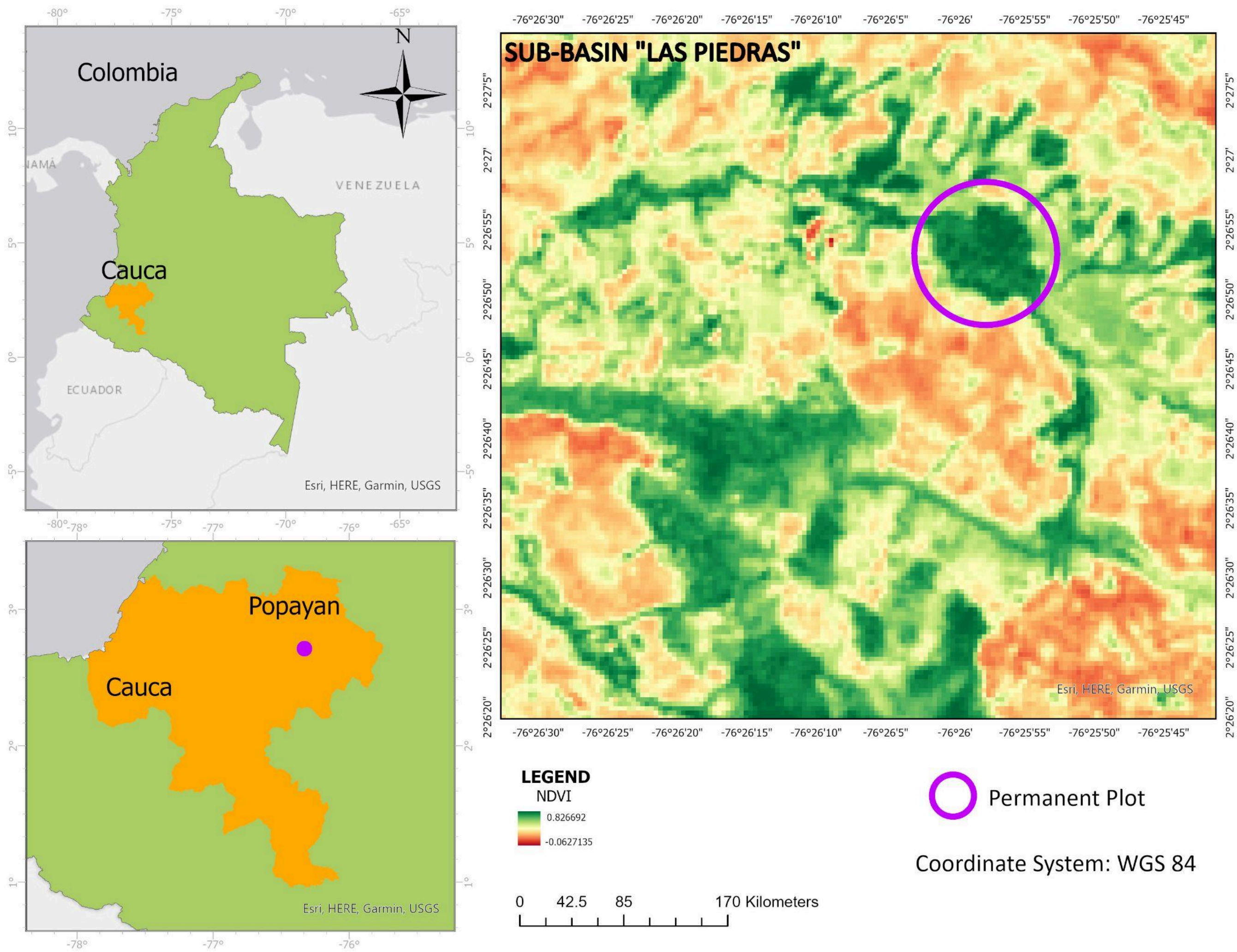


Figure 2. The study area. The study area is located in the department of Cauca, southwestern Colombia.

2.2 Data

2.2.1 Field Measurements

Field data for aboveground biomass were collected from a permanent 100 × 100 m forest plot maintained by the Environmental Studies Research Group (GEA) at the University of Cauca (Valencia 2015). To ensure systematic and spatially representative sampling, the plot was subdivided into 25 × 25 m sub-quadrants, capturing fine-scale spatial variability. Within this framework, a total of 1,055 individual trees and shrubs across multiple species were inventoried following the Andean Forest classification system (Cortes et al., 2020), which considers local environmental conditions and the altitudinal gradients characteristic of these ecosystems (Kattán, 2003).

To estimate aboveground biomass (AGB), we applied an allometric model developed by (Alvarez et al. 2012), which is widely used for Andean forests and integrates DBH, height, and wood-specific characteristics. This model allowed us to convert the collected dasometric data into AGB estimates suitable for subsequent modeling and remote sensing analysis.

2.2.2 Sentinel-2A Data Spectral Information

We extracted the satellite data used in this research from the Sentinel-2A multispectral sensor (Phiri et al. 2020). These images were selected for their spatial and temporal resolution, as well as their potential to assess biophysical parameters such as leaf area index, themes related to terrestrial carbon, forest monitoring, and vegetation (Tovar Blanco et al. 2020). The image selection process was based on the date of the forest inventory, which dates back to the year 2015. We identified and selected an image collected on 16 September 2016 that had minimal cloud cover to reduce the effects of cloud contamination.

Considering that the satellite images are orthorectified and have radiance levels above the atmosphere, the freely available SNAP (Sentinel Application Platform) software and the Sen2Cor tool were employed (Louis et al. 2019). These tools allowed for the correction of radiometric and geometric distortions in the images, resulting in a Level-2A processing level. This correction process transformed the reflectance data to the Bottom of Atmosphere level generating more accurate data by eliminating atmospheric contamination (Mendoza 2018).

Following this process, and given that the Sentinel-2 bands have different spatial resolutions, a bilinear interpolation was carried out to standardize the spatial resolution (Gascon et al. 2017). The purpose of this step was to enable operations between bands for the computation of variables, in this case, vegetation indices for the study. The resampling was performed at a spatial resolution of 10 meters.

We subsequently partitioned the dataset into a training set (80%) and a validation set (20%).

2.2.3. Calculating vegetation indices from spectral bands.

The selection of vegetation indices involved identifying, based on previous studies, their ability to estimate above-ground biomass in dense vegetation. The chosen spectral indices are presented in Table 1.

Table 1. Spectral indices used as input features.

Spectral Index	Equation	Reference
Normalized Difference Vegetation Index (NDVI)	$NDVI = \frac{NIR-RED}{NIR+RED}$	(Pettorelli et al. 2005)
Normalized Difference Green Vegetation Index (NDVIG)	$GNDVI = \frac{NIR-GREEN}{NIR+GREEN}$	(Moges et al. 2005)
Enhanced Vegetation Index	$EVI = 2.5\frac{NIR-RED}{NIR+6RED-7.5BLUE+1}$	(Setiawan et al. 2014)
Adjusted Ground Vegetation Index	$SAVI = 1 + L\frac{NIR-RED}{NIR+RED+L}$	(Prabhakara et al. 2015)
Wide Dynamic Range Vegetation Index	$WDRVI = \frac{0.1*NIR-RED}{0.1*NIR+RED}$	(Gitelson 2004)
Normalized Difference Green-Red Edge 1 Vegetation Index	$GNDVIre1n = \frac{REDedge1-GREEN}{REDedge1+GREEN}$	(Tovar Blanco et al. 2020)
Normalized Difference Green-Red Edge 2 Vegetation Index	$GNDVIre2n = \frac{REDedge2-GREEN}{REDedge2+GREEN}$	
Normalized Difference Green-Red Edge 3 Vegetation Index	$GNDVIre3n = \frac{REDedge3-GREEN}{REDedge3+GREEN}$	

Rededge1: Red-Edge Band (1), Rededge2: Red-Edge Band 2 (2); Rededge3: Red-Edge Band 3 (3).

2.2.4 AlphaEarth Foundations

In addition to traditional spectral indices, we leveraged the Google Satellite Embedding dataset produced by AlphaEarth Foundations. These embeddings are 64-dimensional vectors generated by integrating multisource Earth Observation data, including multispectral optical imagery, radar backscatter, LiDAR-derived elevation, and climate layers, into compact pixel-level representations (Brown et al. 2025). Each embedding corresponds to a $10 \times 10\,\text{m}$ pixel, matching the spatial resolution of Sentinel-2A high-resolution bands, and provides complete coverage of the study area. The embeddings are generated using a deep neural network trained on sequences of satellite observations, treating them like “videos” over time. Before training, raw inputs are normalized, and acquisition dates are encoded to help the model understand temporal patterns. The model summarizes information over specific time periods for each data source, ensuring that temporal trends are captured. By capturing both spectral and spatial patterns, the embeddings offer a rich and consistent summary of land surface characteristics, which can improve the predictive modeling of aboveground biomass (Brown et al. 2025).

2.3 Machine Learning Modeling for Estimation of AGB

2.3.1 *AGB Estimation in Forest Aerial Biomass Using Allometric Models*

The quantification of AGB was conducted based on dendrometry data provided by the Environmental Studies Group (GEA), implementing the allometric model proposed by Alvares et al. 2012. This model enables the calculation of individual tree aerial biomass using variables such as Diameter at Breast Height (DBH) and wood density (Bordoloi et al. 2022).

The model designed by Alvarez et al. (2012) is fitted to the specific dynamics of natural forests in the country and is also specific to the life zones identified and described within the study as humid forests according to Holdridge et al. (1971). This model takes into account the altitudinal range and evapotranspiration potential.

$$\ln(AGB) = a + b1 \ln(D) + b2 (\ln(D))^{2} + b3 (\ln(D))^{3} + d \ln(\rho) \qquad \text{Eq (1)}$$

Where: $\boldsymbol{AGB}$ (Kg) = Above-Ground Biomass. $\boldsymbol{a}$ = 1.836, $\boldsymbol{b1}$ = -1.255, $\boldsymbol{b2}$ = 1.169, $\boldsymbol{b3}$ = -0.122, $\boldsymbol{d}$ = -0.222, $\boldsymbol{D}$ = Diameter at Breast Height (expressed in cm), ρ = Wood Density (expressed in g cm^{-3}).

2.3.2 Random Forest

Machine learning techniques have become widely used in remote sensing for the estimation of biophysical parameters, such as aboveground biomass, due to their ability to capture complex, nonlinear relationships between spectral data and field measurements (Su et al. 2020; Sivakumar et al. 2024). Among ML algorithms, Random Forest (RF) is particularly suitable for remote sensing applications because it is robust to noisy data (Wang et al. 2016a), can handle high-dimensional inputs, and provides measures of variable importance (Tariq et al. 2023), which are valuable for feature selection and model interpretation (AhmedK et al. 2013; Arfa-Fathollahkhani and Minaei 2024; Boston et al. 2022).

In this study, the RF model was implemented using Google Earth Engine (GEE), which offers several advantages for large-scale geospatial analyses. GEE simplifies data access and preprocessing, provides high-performance cloud computing, and integrates seamlessly with multi-temporal and multi-sensor satellite datasets (Wu et al. 2024; Gorelick et al. 2017; Kolarik et al. 2024). Using GEE, RF was applied to analyze the relationships between Sentinel-2A spectral bands, derived vegetation indices, and field-measured biomass. A sensitivity analysis determined that 50 trees were sufficient to achieve stable model performance while maintaining computational efficiency.

2.3.3 Artificial Neural Network Generation

Among various ML algorithms, Artificial Neural Networks (ANNs) are one of the most widely used approaches for modeling nonlinear relationships (Haykin 1994). Developing an ANN requires careful selection of network structure including the number of hidden layers and neurons, weight initialization, learning rate, and the training algorithm (Wang et al. 2016b).

The configuration of the ANN was carried out in MATLAB following a structured, two-stage identification process, using a prior division of field data into training and validation sets. During this process, the network design and structure including the number of hidden layers and neurons were systematically evaluated to identify the optimal configuration for accurate predictions.

Influential spectral indices were incorporated into the network by testing various combinations of vegetation indices, guided by the errors internally generated by the ANN and its performance when validated against field measurements. The network structure was iteratively refined based on key performance metrics, including Mean Absolute Error (MAE), to select the architecture that minimized prediction error and maximized generalization. This approach ensured the identification of the most suitable spectral combination and network configuration for modeling forest attributes.

After identifying the most suitable spectral combination, the Adam (Adaptive Moment Estimation) algorithm was employed as the optimizer due to its robustness and efficiency in modeling nonlinear relationships common in remote sensing data (Bera and Shrivastava 2020). For the activation functions, Rectified Linear Units (ReLU) were implemented following Agarap, (2018), given their effectiveness in overcoming vanishing gradient issues and accelerating convergence. The ReLU function introduces nonlinearity while maintaining computational efficiency by activating neurons only when the input is positive. Subsequently, the number of hidden layers and neurons was systematically adjusted, and the Mean Absolute Error (MAE) for each configuration was evaluated to determine the optimal network architecture that achieved the best balance between model complexity and predictive accuracy.

2.4 Assessment and metrics

Model performance was evaluated using the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE). R^2 quantifies the proportion of variance in observed biomass explained by the model:

$$R^2 = 1 - \frac{\Sigma(y_1 - \widehat{y_1})^2}{\Sigma(y_1 - \widehat{y_1})^2} \qquad \text{Eq (2)}$$

Prediction errors were measured using:

$$RMSE = \sqrt{\frac{1}{n}\Sigma(y_1 - \widehat{y_1})^2} \qquad \text{Eq (3)}$$

$$MAE = \frac{1}{n}\Sigma\left|y_1 - \widehat{y}_1\right| \qquad \text{Eq (4)}$$

The dataset was randomly split into training (80%) and testing (20%) subsets, and metrics were computed on the testing data to assess the accuracy of the Random Forest model combining Sentinel-2A bands, vegetation indices, and AlphaEarth embeddings.

2.5 Experimental setup

To extend the biomass assessment through remote sensing, the predictive performance of two RF models was evaluated for estimating AGB using GEE. The first model used AEF embeddings, incorporating 64 pre-trained spectral bands to capture complex ecological and spectral patterns. The second model relied on traditional feature engineering, using manually derived spectral indices (Table 1). Both models were trained and validated on the same dataset, and their performance was assessed using Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) for the training and validation stages (Table 2).

3. Results

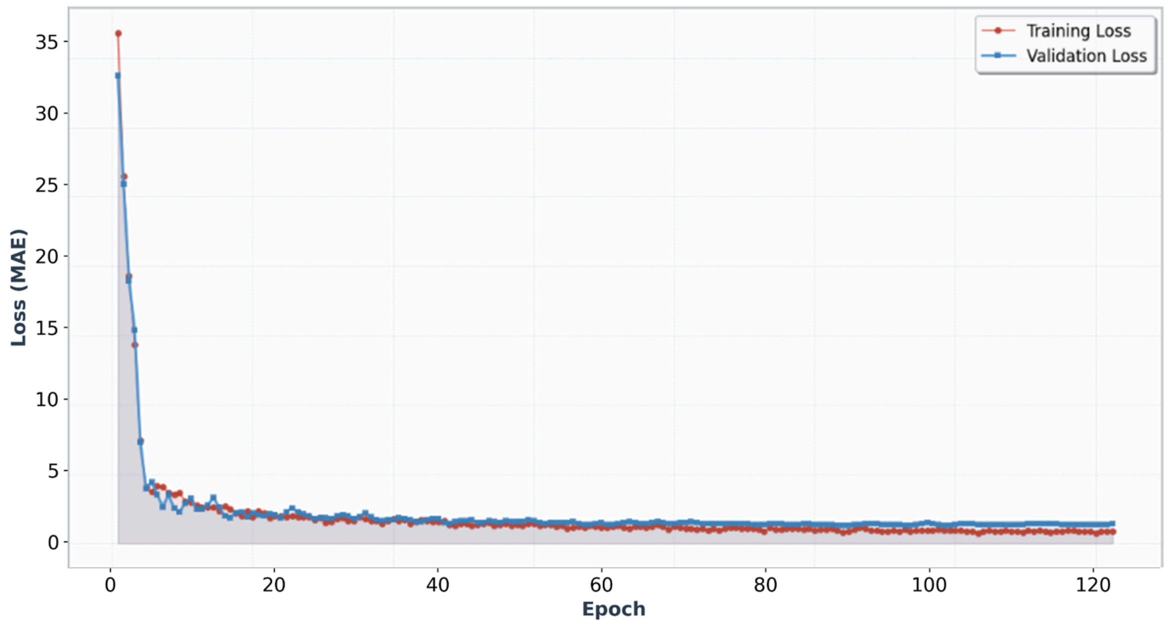
Once we applied the allometric model, the total above-ground biomass (AGB) of the forest was estimated at 364.6 t/ha, corresponding for 656 individuals with DBH > 10 cm, representing 62.2% of the inventoried population. Both DBH and AGB exhibited positive skewness, with lower values occurring more frequently, characteristic of a young, regenerating forest (Bokkestijn, 2017; Cortés et al., 2020). Standard deviation increased with DBH range and decreased with the number of individuals, from the lowest SD in the 10–20 cm class (336 individuals) to the highest in the 80–100 cm class (SD = 0.97; Table 2). *Quercus humboldtii* contributed the largest share of biomass (22.5%), followed by *Myrcianthes* sp. O. Berg (10.6%) and *Nectandra reticulata* Mez (10%).

Two ML models, Random Forest (RF) and Artificial Neural Network (ANN), were developed to estimate aboveground biomass (AGB) using (i) traditional spectral indices and (ii) AlphaEarth Foundation embeddings derived from satellite imagery. The performance metrics of both models are summarized in Table 2.

Table 2. The performance metrics of the two models.

Models	**Training Stage**		**Validation Stage**		**R^2**
	RMSE	MAE	RMSE	MAE	
Model 1 RF + Embeddings	0.927	0.689	0.923	0.690	0.510
Model 2 RF+ Feature Engineering	0.550	0.330	0.627	0.426	0.703
Model 3 ANN + Embeddings	0.609	0.457	0.713	0.599	0.672
Model 4 ANN + Feature Engineering	**0.660**	**0.420**	**0.70**	**0.580**	**0.79**

The best performance for the ANN using spectral indices was achieved with a hidden layer configuration of two hidden layers with 85 and 45 neurons, while the ANN with embeddings performed optimally using two hidden layers with 10 and 40 neurons. Figure 3 presents the loss curves for both models, comparing spectral indices (top panel) and embeddings (bottom panel) as input features. In both cases, the loss decreased sharply during the first 10 epochs, reflecting rapid initial learning. After this initial drop, both models quickly stabilized. The ANN trained on spectral indices reached a stable loss around Epoch 25, whereas the model using embeddings exhibited a slightly smoother convergence and attained a marginally lower final validation loss over the 175 epochs. Importantly, the training and validation loss curves remain closely aligned in both scenarios, indicating strong generalization and suggesting that neither input feature set led to substantial overfitting.



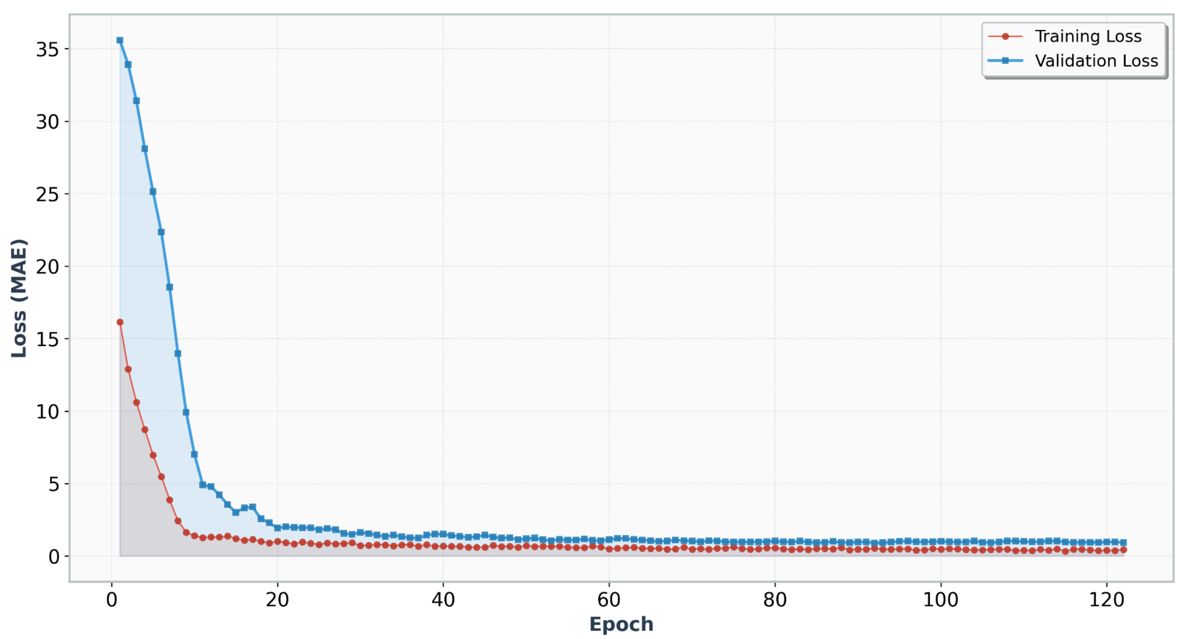


Figure 3. Training and validation loss (MAE) versus epoch for the ANN model,The upper one shows ANN + spectral indices, and the lower one shows ANN + AlphaEarth embeddings. Both show a rapid decrease in error during the first epochs followed by

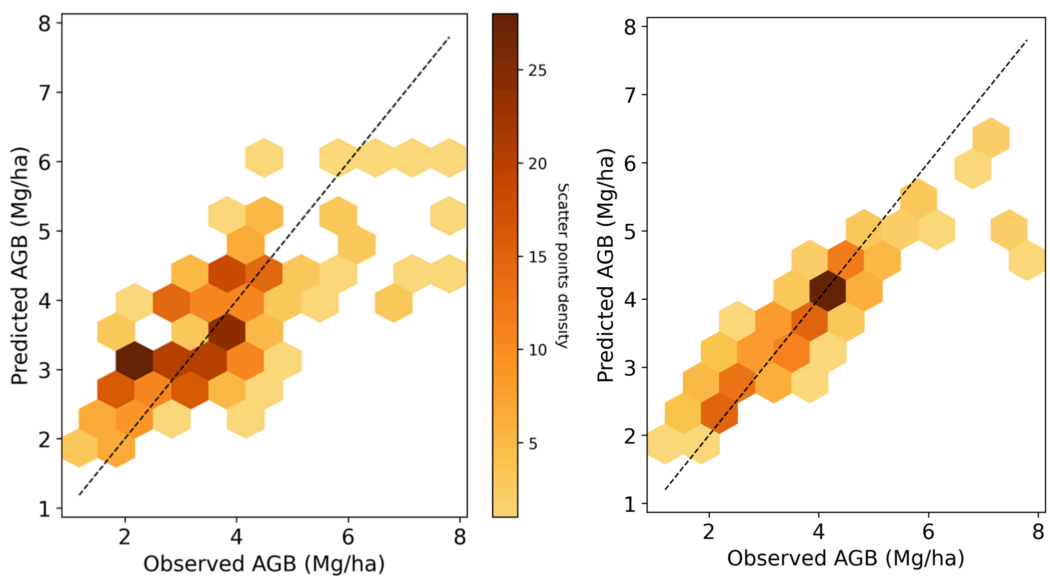
stable convergence, with closely aligned training and validation curves indicating good generalization and minimal overfitting.

The incorporation of AlphaEarth embeddings did not improve model performance. As summarized in Table 2, ANN models trained with embeddings showed loss curves similar to those using only spectral indices, indicating that the embeddings neither accelerated convergence nor reduced validation loss (Figure 3). In contrast, traditional feature engineering consistently outperformed the embeddings, and for the Random Forest models, the improvement was substantial. These results suggest that, in this study, the embeddings did not provide additional predictive value over carefully engineered features.

The model's predictive performance for AGB is presented in the Density Plot (Figure 4), which compares Predicted AGB against Observed AGB (in Mg/ha).

a) RF + *AphaEarth* Embeddings

b) RF + Spectral Indices



c) ANN + *AphaEarth* Embeddings

d) ANN + Spectral indices

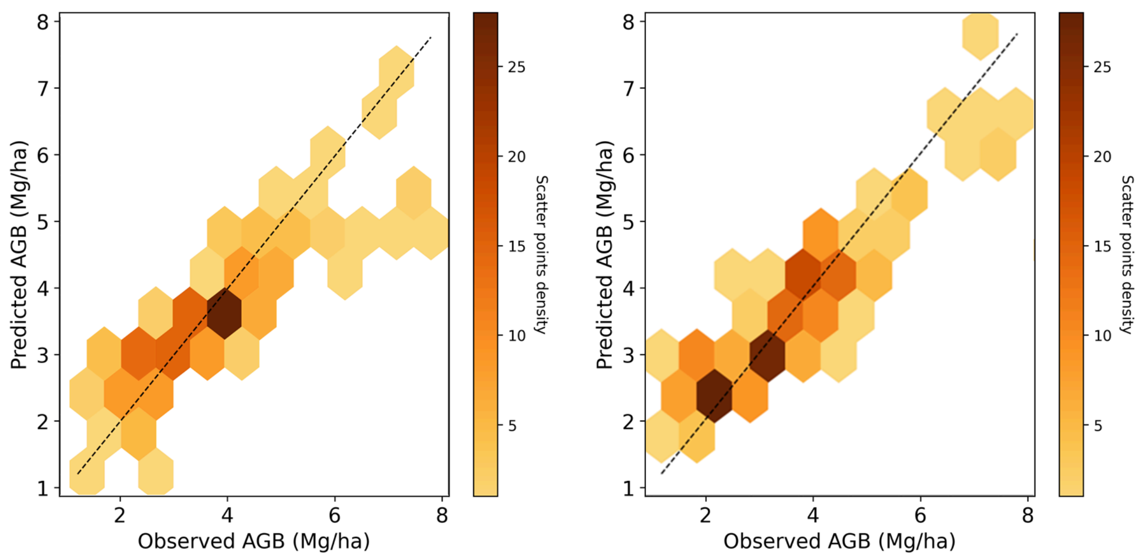
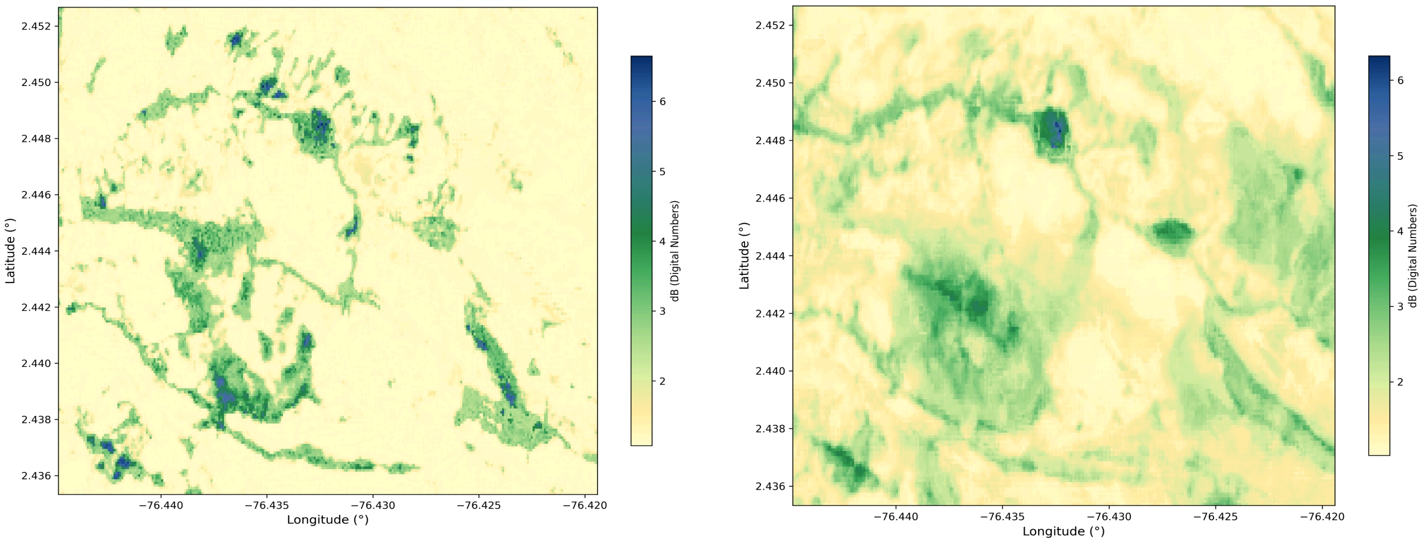


Figure 4. Comparison between predicted and observed aboveground biomass (AGB) for models using spectral indices and AlphaEarth embeddings: (a) Random Forest (RF) with embeddings, (b) RF with spectral indices, (c) Artificial Neural Network (ANN) with embeddings, and (d) ANN with spectral indices. Overall, models based on spectral indices outperform those relying on AlphaEarth embeddings, with the ANN combined with spectral indices achieving the highest predictive performance.

Differences in spatial predictions across methods

The comparison of predicted and observed aboveground biomass (AGB) across the four models indicates that both Random Forest (RF) and Artificial Neural Network (ANN) approaches can effectively capture AGB patterns, though their performance varies with the type of input data. Subsequently, the spatial distribution of AGB is shown in figure 5.

(a) RF + Spectral Indices **(b) RF + AlphaEarth Embeddings**



(c) ANN + Spectral Indices **(d) ANN + AlphaEarth Embeddings**

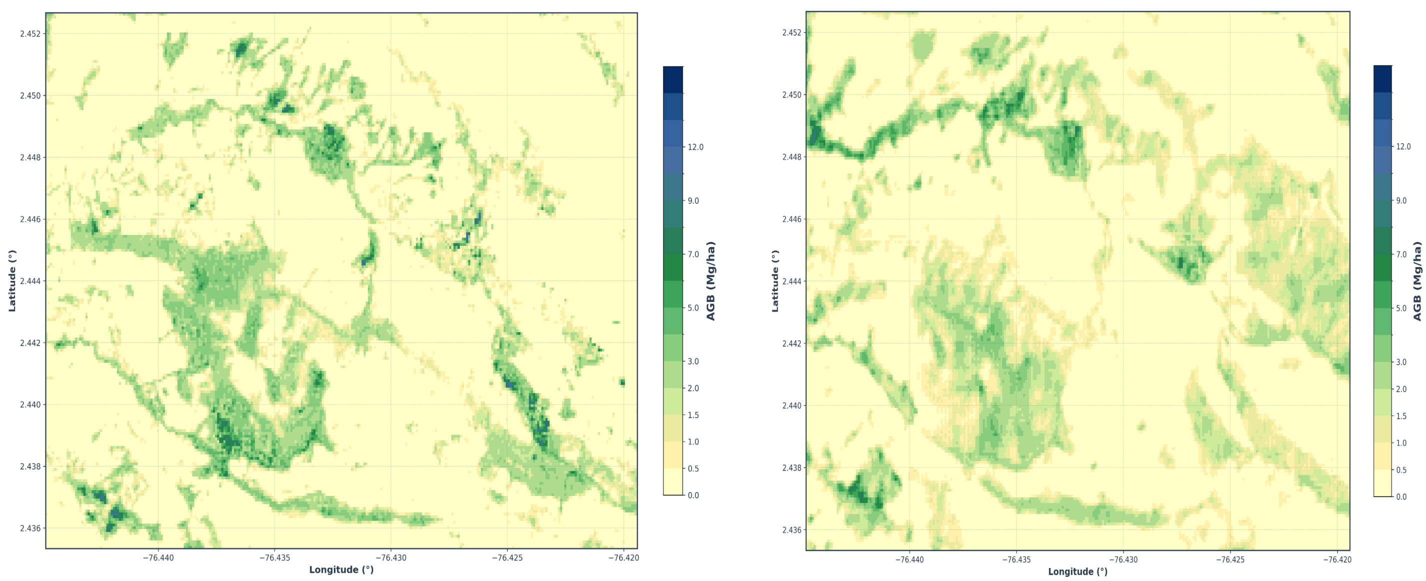


Figure 5. The aboveground biomass (AGB) maps produced by the four modeling approaches: (a) RF + spectral indices, (b) RF + AlphaEarth embeddings, (c) ANN + spectral indices, (d) ANN + AlphaEarth embeddings. The models using spectral indices (a–c) show clearer spatial patterns and more realistic biomass gradients, reflecting their superior predictive performance compared to the embedding-based models (b–d).

Dense forests on the surrounding slopes appear as darker green regions and correspond closely to the high-AGB zones. Similarly, the broad central valley characterized by pastures and agricultural fields matches the low-AGB regions.

In contrast, the ANN + Spectral Indices model (Figure 5c) and the RF + Spectral Indices model (Figure 5a) generate the most spatially detailed and ecologically realistic biomass predictions among all approaches. Both models accurately delineate pasturelands with consistently low AGB, capture narrow riparian corridors, and identify dense forest stands with sharply defined high-biomass clusters. These models maintain fine-scale spatial variability, reveal subtle ecological gradients across slopes and valleys, and preserve the fragmented structure characteristic of Andean landscapes. This approach evidences the ability to reflect true vegetation patterns and local heterogeneity, demonstrating that direct canopy reflectance information remains essential for capturing biomass dynamics at high spatial resolution.

In contrast, models using alphaEarth embeddings showed lower predictive performance across both algorithms, with the RF + alphaEarth embeddings model yielding the lowest performance overall. This is likely because the embeddings compress complex spectral and textural information into a lower-dimensional representation optimized for general scene understanding rather than biomass-specific biophysical signals. Consequently, fine-scale variability is smoothed out, small forest patches and riparian corridors are often overlooked, and subtle differences in vegetation structure are not captured. These limitations reduce the ability of embedding based models to identify detailed ecological features, leading to a loss of local heterogeneity and underrepresentation of fragmented landscapes.

Likewise, The ANN + AlphaEarth embeddings model (Figure 5d) improves upon the RF + embeddings approach by capturing more spatial variability and better aligning high AGB values with forested areas. This improvement is partly because ANN is more robust than RF at identifying complex, nonlinear relationships in the data, allowing it to better leverage the embedding features. However, the model still falls short of describing the full spatial dynamics of the landscape because embeddings compress complex spectral–textural information into lower-dimensional representations, which smooth out fine-scale variability. As a result, small forest patches, ecotones, and subtle biomass gradients remain underrepresented. While ANN + alphaEarth embeddings provide smoother and more spatially structured predictions than RF + alphaEarth embeddings, it cannot match the fine-scale ecological realism achieved by models using spectral indices, which directly leverage canopy reflectance features sensitive to local vegetation structure.

4. DISCUSSION

4.1 Model Performance and Feature Engineering Superiority

Feature-engineered models consistently outperformed embedding-based models in predicting aboveground biomass (AGB). The ANN model using traditional vegetation indices achieved lower prediction error (MAE = 0.580) than the model built with AlphaEarth embeddings. This result suggests that domain-driven features, in this case spectral indices derived from S2, remain highly effective for AGB estimation in complex Andean forest ecosystems.

The relatively poorer performance of the embedding-based approach likely stems from several factors. First, AlphaEarth embeddings are generic global representations, trained to summarize multi-sensor Earth observation data rather than to optimize for biomass-specific biophysical parameters (Brown et al., 2025). Their dimensions make it difficult to isolate the spectral, structural, and environmental signals directly related to forest biomass. Finally, tropical montane ecosystems exhibit fine-scale spectral heterogeneity driven by canopy layering, topography, and mixed-species stands, which may not be fully captured by the embeddings' spatially smoothed features. In contrast, vegetation indices retain explicit relationships with canopy greenness, chlorophyll concentration, and vegetation density factors that directly influence biomass accumulation (Cunliffe et al., 2020; Coltri et al., 2013; Cao et al., 2020).

4.2 The strength of Artificial Neural Networks (ANNs) over Random Forests (RF)

The ANN outperformed the RF model (R^2 = 0.79 vs. 0.70), highlighting its ability to capture nonlinear and hierarchical relationships among spectral indices. The multilayer structure of the ANN allows neurons to learn increasingly complex transformations of the input reflectance features, enabling the model to represent subtle spectral gradients particularly in red-edge and NIR wavelengths that are associated with canopy density and biomass accumulation. Because the ANN is trained through gradient-based optimization, it adapts the contribution of each spectral variable continuously, which improves generalization across heterogeneous ecological conditions. In contrast, the RF relies on axis-aligned splits that can miss smooth, multidimensional relationships common in vegetation reflectance data, leading to mild underfitting in this context.

This architectural limitation of RF also explains why its performance benefited from spectral indices but declined when using embeddings. Spectral indices are low-dimensional, physically interpretable, and directly linked to vegetation properties, making them well-suited for RF's threshold-based decision rules. Embeddings, however, are high-dimensional and encode abstract contextual information that is optimized for deep learning models rather than tree-based algorithms. Because RF cannot disentangle the complex interactions embedded in these dense feature vectors, the model extracted less meaningful structure and showed reduced predictive accuracy. Together, these results emphasize that while RF performs reliably with carefully engineered spectral features, ANN architectures are better equipped to leverage both spectral complexity and latent feature representations for biomass prediction.

4.3 Toward Next-Generation AGB Monitoring

Although feature engineering proved more effective in this study, embedding-based approaches still hold potential for large-scale applications. With improved training strategies such as biome-specific fine-tuning or temporal disaggregation, AlphaEarth embeddings could capture sub-annual canopy dynamics and structural diversity more accurately. Future work should focus on combining interpretable spectral indices with learned features through hybrid modeling frameworks, where embeddings provide contextual information (e.g., terrain, climate, canopy height) and spectral indices retain direct biophysical meaning. Such integration could bridge the gap between data-driven AI models and process-based ecological understanding, enabling robust and scalable AGB monitoring in tropical mountain systems.

From a methodological perspective, this work provides an operational framework for AGB mapping in data-scarce mountainous environments, integrating field measurements with freely available remote sensing and machine learning tools. The findings suggest that ANN-based models trained with Sentinel-2 vegetation indices provide a powerful approach for regional AGB accounting, ecosystem monitoring, and REDD+ reporting, as they capture fine-scale spatial variability with high ecological fidelity. However, ANNs also present practical limitations: they require more extensive hyperparameter tuning, computational resources, and technical expertise, and currently cannot be deployed natively within platforms like Google Earth Engine. RF models, while slightly less detailed in their spatial predictions, remain highly attractive for operational use due to their stability, ease of implementation, and availability in widely used remote sensing frameworks. Future research should therefore explore hybrid strategies that combine the interpretability and accessibility of spectral-indices-based RF models with the representational power of ANN architectures or fine-tuned embeddings, aiming to improve transferability across ecosystems while retaining both accuracy and practical applicability.

5. Conclusion

This study demonstrated the potential of combining field-based allometric models, Sentinel-2A spectral indices, and machine learning techniques to accurately estimate aboveground biomass (AGB) in Andean montane forests. Through systematic model comparison, the results showed that feature-engineered models grounded in interpretable vegetation indices outperformed embedding-based approaches, confirming that explicit biophysical predictors remain more effective than abstract geospatial embeddings for biomass estimation at local scales. While AlphaEarth embeddings encode rich multisource information, their annual temporal granularity and lack of biophysical interpretability limited their capacity to capture the fine-scale spectral and structural variability characteristic of heterogeneous mountain ecosystems.

These findings highlight a broader lesson: deep learning and neural network architectures provide powerful tools for AGB estimation, but their practical utility depends on careful integration with biophysically meaningful predictors. By combining satellite imagery with advanced modeling approaches, we move closer to high-resolution, data-driven AGB monitoring in tropical forests offering actionable insights for land management, climate mitigation, and sustainable development planning.

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