GLOBAL ABOVEGROUND BIOMASS DENSITY ESTIMATION FROM SENTINEL-2 IMAGERY

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ABSTRACT

The assessment of above ground biomass density (ABGD) is essential for understanding the global carbon cycle and its impact on environmental dynamics. Despite advances in remote sensing technologies, the accurate estimation of biomass at fine spatial resolutions still presents challenges due to data gaps. Here, we propose a deep learning approach using Convolutional Neural Networks (CNNs) for global AGBD estimation at a 10-meter ground sampling distance. This approach is informed by near-real-time Sentinel-2 multispectral imagery and sparse GEDI LiDAR data. Our method, which adapts a CNN architecture initially created for canopy height mapping, is systematically assessed through various experiments considering geolocation, topographical, and climate data inputs. The best performing model achieves a mean absolute error of 35.9 Mg/ha, a root mean square error of 81.1 Mg/ha and a mean absolute percentage error of 79.6, showcasing competitive performance across continents against a global test set of over 300,000 samples. Notably, the inclusion of elevation information and geo-coordinates considerably improves AGBD predictions compared to the base model. The proposed method operates effectively without the need for extensive ground survey data, offering the potential for frequent updates to biomass density maps thanks to the revisit capability of the Sentinel-2 satellites.

1 INTRODUCTION

Forest biomass plays a crucial role in sustainable forest management, recognized by the United Nations as a vital component in the global carbon cycle Zhang et al. (2019). Accounting for over 30% of the terrestrial carbon pool, aboveground biomass (”biomass”) is shaped by various environmental factors, and is associated with land cover conversion and greenhouse gas emissions Herold et al. (2019). Biomass serves as the foundation for essential natural resources such as food, water, energy, and wood, and contributes to hazard mitigation and the development of sustainable conservation strategies for climate and biodiversity targets Mo et al. (2023). In recent years, satellite remote sensing has emerged as a cost-effective and efficient method for large-scale environmental monitoring, providing valuable insights into land cover dynamics Food & of the United Nations (2020). Multiple studies have demonstrated the general feasibility of inferring biomass using multispectral data, although with notable instances of underestimation and overestimation at very high or very low biomass levels Gasparri et al. (2010), Li et al. (2020). While the launch of the GEDI LiDAR sensor represents a significant advancement in biomass measurement capabilities Duncanson et al. (2022), achieving continuous and seamless measurements remains challenging due to significant spatial and temporal gaps. Building upon existing research (e.g. Shendryk (2022), Schwartz et al. (2023), Lang et al. (2023)), this study aims to leverage Convolutional Neural Networks to estimate global biomass distribution using near-real-time multispectral Sentinel-2 imagery and sparse GEDI Level 4 AGBD data. Specifically, we evaluate an architecture proposed by Lang et al. (2023) for canopy height mapping, adapting it for above ground biomass estimation.

Dataset	Description	Resolution
GEDI L4 AGBD	LiDAR-based Biomass Density	25m footprints
Sentinel-2	Multispectral Imagery	10m
ESA WorldCover	Land Cover Classification	10m
WTE	Ecosystem Distribution	250m
CopDEM	Digital Elevation Model	30m

Table 1: Summary of datasets used in this study. GEDI L4A coverage is constrained to ± 51.6 degrees latitude, all other datasets have global coverage.

Dataset Characteristics	Training and Validation Set	Test Set
Number of Samples	2,110,311	332,544
Temporal Coverage	2019-2020	2021
Location (Coverage)	$\pm 51.6\,\mathrm{deg}$ latitude (GEDI coverage)	

Table 2: Quantitative description of the dataset specifications used for this study.

2 DATASETS

We curated a comprehensive dataset comprised of over 2 million samples, integrating multispectral Sentinel-2 Level-2A imagery ESA (2021) using 11 bands (namely B02, B03, B04, B05, B06, B07, B08, B8a, B09, B11, B12) and GEDI L4A-derived AGBD labels Dubayah et al. (2022). In different experiments, we combined the multispectral data with elevation data from ESA CopDEM ESA (2019), land cover information from ESA WorldCover Zanaga et al. (2022) and USGS World Terrestrial Ecosystems (WTE) data Sayre et al. (2020) to train several CNN models with the proposed architecture. The spatial resolution of the data was set at 10 x10 m. Data were split allocating 80% for training and 20% for validation purposes, with an additional independent test set comprising over 300,000 samples. Please see Figure 4 for an example of a training data sample. Figure 5 illustrates the spatial distribution of ecosystems across training samples, covering a broad variety of ecosystems. Pre-prossessing procedures were conducted on individual datasets to compose a single HDF5 file containing all data samples. After spatio-temporal matching of Sentinel-2 L2A and GEDI L4 data, a strict quality check was performed on the GEDI, CopDEM, and Sentinel-2 data to ensure that only high-quality, cloud-free observations with a terrain slope below 15 degrees were used for analysis Shendryk (2022). The coordinate information was incorporated as the sine and cosine of the geo-coordinates. Table 1 presents a summarized description of each dataset, along with its characteristic specifications.

3 METHODOLOGY

A CNN architecture featuring residual blocks and depth-wise separable convolutions was used to capture diverse spatial information from multiple data sources. An end-to-end deep learning pipeline was established, encompassing data preprocessing, model training, and validation processes as illustrated in Figure 1. The base CNN architecture is built based on ResNet (Residual Network), a deep neural network which utilizes residual blocks, each containing several convolutional layers, batch normalization layers, and activation functions, to pass data inputs He et al. (2016). This architecture was originally designed to process data derived from Sentinel-2 level 2A bands to predict canopy height (Lang et al., 2023). It comprises distinct components, including an entry block and 8 identical separable convolution blocks. The original model's architecture was modified by incorporating skip connections, which enable the bypassing of certain blocks and their subsequent merging with the output activation map. The neural network is trained with a batch size of 32 and weight decay of 0.001, using the Adam optimizer. Several training strategies are evaluated, including the use of geolocation information, vegetation indices, land cover information, climate data, and Monte Carlo dropout.

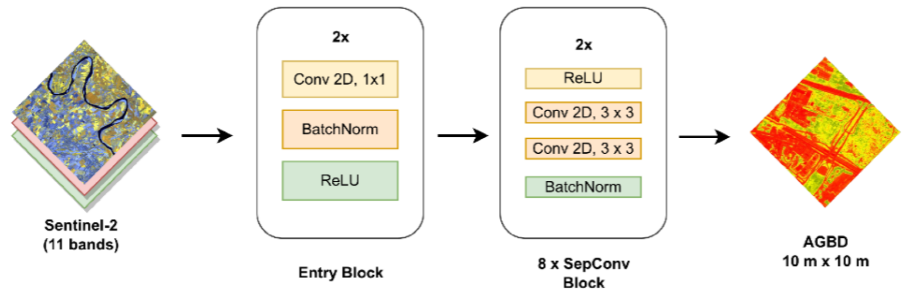

Figure 1: Methodology overview for the base model

Bin [start, end]	0, 50	50, 100	100, 150	150, 200	200, 250	250, 300
Number of Samples	207038	57944	27606	17276	10126	5342

Table 3: Number of test samples per bin in Figure 3

3.1 Evaluation Metrics

The Mean Absolute Error (MAE) is the predominant metric we use to assess our model's accuracy in estimating Aboveground Biomass Density (AGBD), reported in megagrams per hectare (Mg/ha). The MAE captures the average difference between predicted values and ground truth, providing a direct measure of prediction precision.
Root Mean Square Error (RMSE) can give a more comprehensive evaluation of model accuracy. This is because RMSE, unlike MAE, amplifies and severely penalizes larger prediction errors. Therefore, it's particularly useful for datasets with extreme values or outliers. Using both metrics thus offers a more robust assessment of our model's performance in predicting Aboveground Biomass Density (AGBD).
Mean Absolute Percentage Error (MAPE) measures the average magnitude of errors in predictions, expressed as a percentage of the actual values, providing an intuitive understanding of the model performance across various data points.

4 Results and Discussion

The results of the study indicate that CNNs exhibit a robust potential for estimating the global aboveground biomass density (AGBD) using a combination of Sentinel-2 data and auxiliary data as input. Table 4 presents a quantitative summary of the model evaluation metrics. The baseline model, which relied solely on Sentinel-2 multispectral bands, marked the starting benchmark with an average RMSE of 82.4 Mg/ha, an MAE of 37.7 Mg/ha and a MAPE of 86.6 % across the entire test dataset. Notable enhancements in model performance were observed upon integrating ancillary information such as elevation and geographical coordinates, resulting in an RMSE of 81.1 Mg/ha, a MAE of 35.9 Mg/ha and a MAPE of 79.6 % as illustrated in table 4. The introduction of additional datasets such as ESA WorldCover and World Terrestrial Ecosystems had mixed effects on the model performance. The used land cover information is dated back to 2021. This could potentially skew the results by unintentionally overfitting to outdated land cover information. While certain additional input features resulted in improvements over the baseline, particularly over higher AGBD targets, others negatively affected the model performance. Interestingly, the model using land cover information as additional input feature achieves the lowest MAPE for very low AGBD values. As all models show the highest absolute relative errors for low AGBD values, which are often related to arid regions, providing information about the land cover seems to reduce the tendency of the model to overestimate AGBD in these conditions. The CNN model, despite performing well under a broad spectrum of forest types and climates, confirmed the persistent challenge in estimating very low and very high AGBD values, particularly within dense tropical and sub-tropical forests—a limitation predominantly associated with the saturation of spectral signals in optical remote sensing (see Figure 2). The achieved results are well aligned with Shendryk (2022), who reported an RMSE of 59 to 86 Mg/ha for Australia and the continental Unites States using a LightGBM algorithm in combination with Sentinel-2 data and land cover information.

Exp	Model Inputs	RMSE [Mg/ha]	MAE [Mg/ha]	MAPE [%]
1	Sentinel-2 only	82.4	37.7	86.6
2	Sentinel-2, DEM, geo-coordinates	**81.1**	**35.9**	79.6
3	Sentinel-2, ESA WorldCover	82.7	36.1	**71.5**
4	Sentinel-2, WTE	83.2	37.95	87.4
5	Sentinel-2, Vegetation Indices	83.59	37.05	83.7
6	Sentinel-2, Monte Carlo Dropout	83.6	37.1	76.2

Table 4: Quantitative evaluation of CNN models for global above ground biomass density estimation.

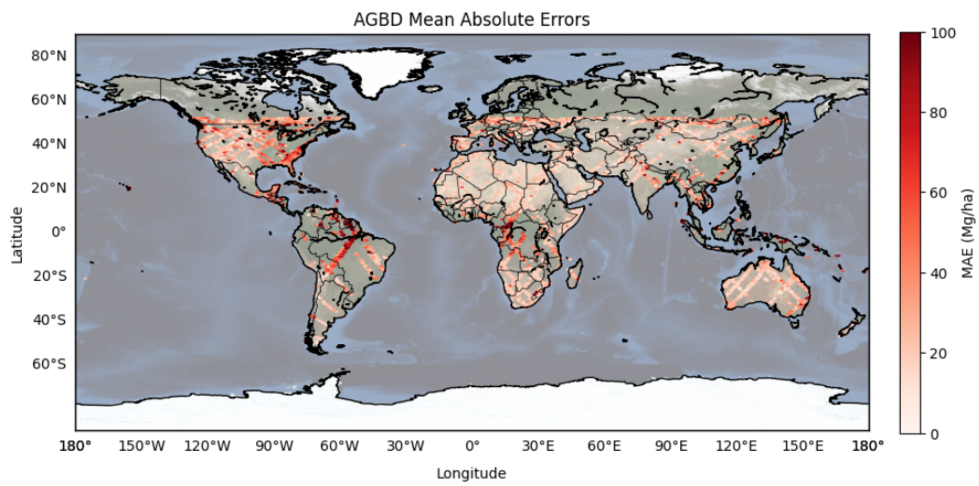

Figure 2: Global distribution of MAE in AGBD prediction using the model from experiment 2

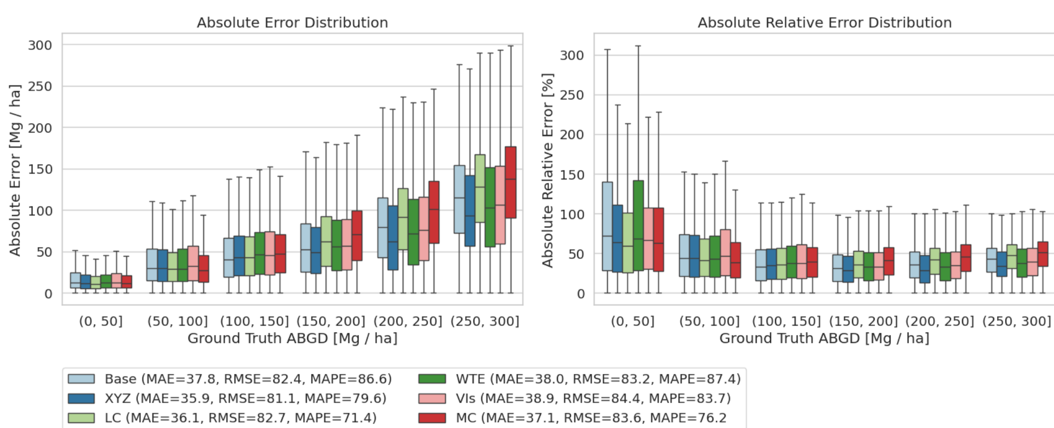

Figure 3: Binned absolute and relative error of AGBD predictions from each experiment. All models utilize Sentinel-2 bands. Base denotes Sentinel-2 only, XYZ denotes geolocations + DEM, LC denotes ESA WorldCover, VIs denotes NDVI (Normalized difference vegetation index), NDWI (Normalized Difference Water Index) and LAI (Leaf Area Index), MC denotes Monte Carlo Dropout. The number of samples in each bin is shown in table 3

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5 Summary and Outlook

The proposed method showcases the feasibility of estimating aboveground biomass density globally at a 10-meter resolution and provides an efficient alternative to the collection of on-site survey data. The global CNN regression model, utilizing Sentinel-2 multispectral bands, elevation, and geo-coordinates, demonstrates acceptable performance that is in line with results reported by studies focusing on specific regions (e.g. Shendryk (2022)). This facilitates frequent updates in biomass mapping using Sentinel-2 imagery, enabling the tracking of natural and human-induced changes such as land use conversion and forest fires. A limitation of the current methodology is its tendency to underestimate very high AGBD, particularly in very tall and dense forests common in tropical and subtropical climates, as well as very low AGBD, as often seen in arid and mountainous regions. To enhance generalization, local calibration and spatial aggregation can be employed to better align the model with local features. Another strategy involves using CNN model ensembles, at the expense of increased computational costs, to mitigate model bias, quantify model uncertainty and improve overall performance. Future work is warranted to refine the CNN architecture, balance the training dataset, and explore methodologies like sensor data fusion, spatial aggregation, and multi-temporal analysis to counteract these pitfalls and enhance model reliability.

The outcome of this study provides a basis for various downstream applications. In forest management, this data-driven approach allows for sustainable harvesting directives and assessing the impacts of disturbances such as wildfires. For climate change policy and research, these accurate measures of ABGD enable precise computation of carbon emissions and stocks, representing significant metrics in global efforts to curb climate change and meeting biodiversity goals.

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A APPENDIX

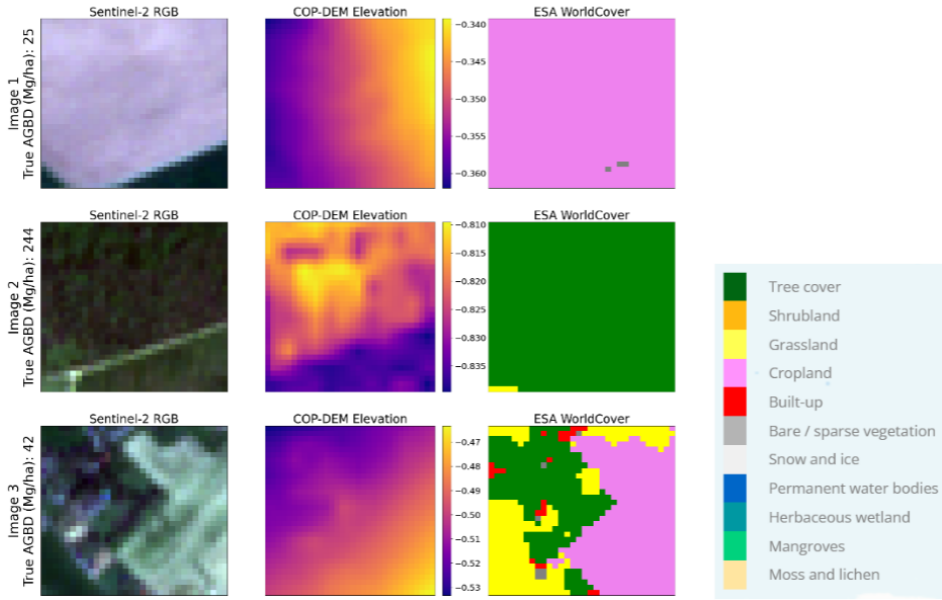

Figure 4: Example of training images (32 x 32 pixels) (left: Sentinel-2 true colour composite; middle: normalized elevation in meters from COP-DEM; right: ESA WorldCover land cover class)

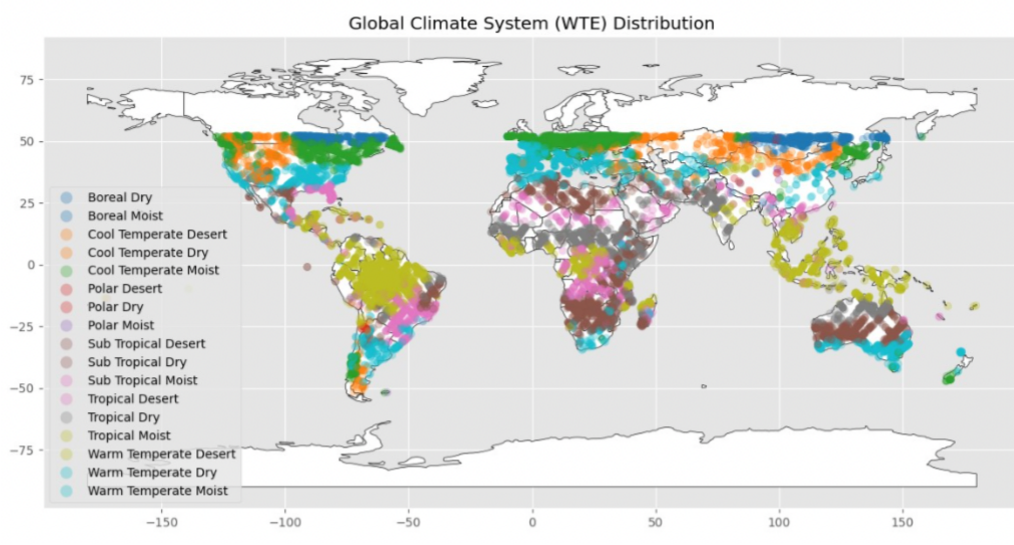

Figure 5: Spatial distribution of ecosystems over training samples