Biomass Distribution Mapping of Boreal Forests using GEDI, Sentinel-2, and SRTM Data

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Keywords: Biomass, Parametric modelling, Random forest, Acadia forest, Taiga forest, GEDI.

Abstract

Estimating carbon stock is important for understanding ecosystem dynamics and mitigating climate change. However, biomass mapping in boreal forests faces challenges due to harsh conditions and limited ground truth data for large scale studies. This study presents a parametric model for accurate biomass estimation in the Acadia and Taiga Forest using GEDI Level 4A, Sentinel-2, and SRTM DEM data. We integrated these datasets, and developed the parametric model consisting of spectral bands, vegetation indices, and topographic information with regression techniques, Random Forest and K-nearest neighbour. Results showcase performance of the parametric model with relative weights of variables for accurate Aboveground Biomass Density (AGBD) predictions for the two forest sites. With an average RMSE ranging between 9 Mg/ha to 31 Mg/ha and R^2 values of 0.54 to 0.60, the study reveals the importance of variables like slope, aspect and specific vegetation indices along with raw bands of Sentinel-2 data. Results also demonstrate potential and accuracy limitations of the proposed model with for biomass estimation with high resolution open-source satellite data without ground control. Further research include assessing the model robustness across diverse ecosystems and geographical settings, contributing to sustainable resource management practices.

1. Introduction

Understanding the carbon cycle and quantifying carbon stocks and fluxes for boreal forests located in high latitudes and altitudes are crucial for assessing carbon sequestration potential and mitigating climate change (Musthafa and Singh, 2022; Ni et al., 2021a; Utla et al., 2025a; Wang et al., 2024). Boreal forests play a significant role in global carbon cycling, acting as substantial carbon sinks. Monitoring boreal forests is challenging due to dynamic natural disturbances, human activities like logging and mining, and climate change impacts (Niemela et al., 1999; Thiffault et al., 2019). Additionally, biomass mapping aids in assessing ecosystem health by detecting disturbances like deforestation and guides conservation efforts (Mohite et al., 2024). Furthermore, it supports biodiversity conservation and informs land management decisions for sustainable development while minimizing environmental degradation (Francini et al., 2022; Li et al., 2021). However, boreal forest ecosystems are highly complex, which are characterized by harsh climatic conditions, including long, cold winters and short, mild summers, which impact vegetation growth patterns and accessibility for fieldwork. Additionally, the vast spatial expanse and rugged terrain of these forests make comprehensive ground truth data collection challenging.

For boreal forests, located in tactically challenged terrain, satellite remote sensing has emerged as a highly efficient and cost-effective tool for global modelling and monitoring ecosystems. Multispectral optical data from the Sentinel-2 mission, elevation data from Shuttle Radar Topographic Mission (SRTM), and canopy and biomass data from Global Ecosystem Dynamics Investigation (GEDI) Level 4A (L4A) are image data sources, which are derived from both active and passive sensors. While Sentinal-2 provides surface reflectance in multiple bands and allows calculations of various vegetation indices, GEDI provides estimates of aboveground biomass density (AGBD), and vegetation structure and forest cover (canopy height, canopy structure, vegetation cover) within geo-located laser footprints observed by the International Space Station (Bruening et al., 2023; Dubayah et al., 2020). On the other hand, SRTM DEM data provides highly accurate elevation models of the earth surface offering a resolution of 1 arc-second (30 meters). Various studies integrated these satellite data in parametric models involving spectral data, vegetation indices, terrain information (e.g. aspect, slope) and linked with GEDI Level 2A (L2A) waveform metrics to exploit high resolution, open-source images for biomass mapping for large forests. In addition, researchers prefer to use commercial satellite products as well as ground truth data of biomass to improvise accuracy. The integration of ground truth data helped achieving higher accuracy due to reduced variation within the datasets, validating the models more effectively (Amuyou et al., 2022; Chen et al., 2023; Francini et al., Morin et al., 2022; Musthafa and Singh, 2022; Mohite et al., 2024; Ni et al., 2021b; Silleos et al., 2006; Sothe et al., 2022).

Despite its significance, biomass mapping of boreal forests using satellite images faces significant challenges as harsh climatic conditions, difficult terrain, limited accessibility, larger spatial expanse, and remote locations of the forests restrict comprehensive and precise ground truth data collection for traditional biomass measurement methods (Bruening et al., 2023). Moreover, integrating multiple attributes of these datasets in computationally efficient manner for biomass estimation of boreal forests also poses additional challenges. Firstly, the integration of two data sets, such as GEDI and Sentinel-2 is inherently complex due to different spatial resolutions, temporal frequencies, and data formats. In addition, these datasets require pre-processing steps to ensure compatibility and consistency. The process is further complicated when incorporating topographic data, necessitating additional adjustments to account for terrain effects on biomass distribution. Secondly, while indices from Sentinel-2 are valuable for capturing vegetation characteristics, combining them with GEDI’s vertical structure metrics and DEM-derived slope and aspect information involves careful consideration (Nguyen and Kappas, 2020). Therefore,

https://doi.org/10.5194/isprs-annals-XI-3-2026-829-2026

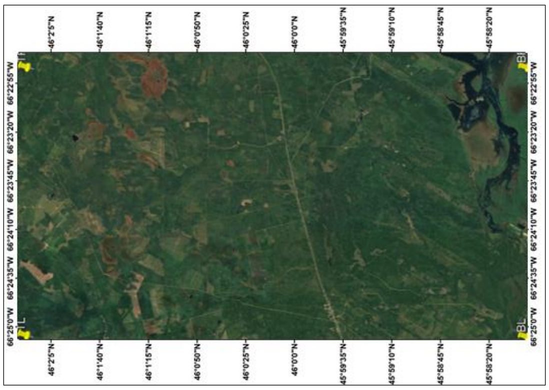
which combinations of variables provide the most reliable AGBD without introducing redundant or noisy data is also difficult for harsh climate boreal forests, where obtaining ground truth is difficult. In the view of above, this paper proposes to examine potential of parametric models derived from Sentinal-2, GEDI Level 4(A), and SRTM DEM for large boreal forests sites without ground truth data. The objective of the paper is to develop a generic biomass model leveraging advantages of high resolutions spectral bands and vegetation indices derived from Sentinal-2, topographic data (slope and aspect) from SRTM 30m DEM, and GEDI Level 4A data providing biomass estimates at 25m resolution for Acadia Forest of Canada and Taiga Forest of Russia . The study also examines performance of two algorithms, namely, Random Forest (RF) and k-nearest neighbour (KNN) algorithms for regression modelling between Sentinel-2 imagery along with SRTM 30-m DEM as independent variables and GEDI Level 4A data as the training target (dependent variable) for AGBD estimation of for years 2021-2022.

2. Materials and Methods

2.1 Study Area

The Acadian Forest in Canada and the Taiga Forest in Russia are shown in Figure 1. The Acadian Forest, spanning approximately 17,000 km², lies between latitudes 47°15'25" N to 46°10'19" N and longitudes 68°26'2" W to 66°48'29" W, covering New Brunswick and Maine. It features a temperate climate with four distinct seasons, characterized by humid summers and cold, snowy winters. Average temperatures are around -8.2°C in January and 17.5°C in July, with precipitation annualy 1275 mm, of which 20% is snowfall. The region's biodiversity includes around 32 tree species, such as maple, oak, and spruce, creating unique habitats for wildlife (Albert et al., 2023; Natural , 2022; Taylor et al., 2017).

The Taiga Forest is located on Sakhalin Island, Russia, covering approximately 7,280 km² between latitudes 49°45'46" N and 50°56'9" N and longitudes 142°49'51" E to 143°36'46" E. This ecoregion features mixed larch forests at lower elevations and shrubby areas at higher altitudes. The subarctic climate has mild summers and cold, snowy winters, with average annual temperatures around 1.21ºC and annual precipitation between 600 to 1,200 mm southeast area experiencing over 100 rainstorms per year (Syrjänen et al., 1993). The forest transitions from light taiga in north to dark taiga in south, presenting a dense canopy and complex structure.



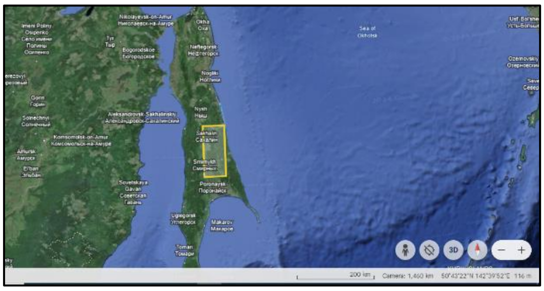


Figure 1. Google Earth image of Acadia Forest (Canada) and Taiga Forest (Russia) study

2.2 Dataset

2.2.1 Sentinel-2

For estimating biomass of the large forest area, we used Sentinel-2 Level 2A (L2A) data. Sentinel-2 offers high-resolution multi-spectral imagery with 13 spectral bands, covering visible to shortwave infrared wavelengths (Mohite et al., 2024). The L1C data were processed to L2A using the ATCOR algorithm through the Sen2Cor plugin, correcting for atmospheric effects (Askar et al., 2018). We selected specific bands and variables from the Sentinel-2 data including vegetation indices to serve as input features for biomass estimation. Table 1 shows the selected variables, band information, and significance of band for biomass estimation.

Categories	Variable/ Feature	Significance	Reference
Raw spectral features	Coastal aerosol (60m)	Atmospheric correction, especially for aerosol detection and water vapour correction	(Nuthammachot et al., 2020)
	Blue (10m)	Crucial for assessing vegetation health, density, and biomass	(Nguyen and Kappas, 2020)
	Green (10m)	Sensitive to vegetation greenness	(Nguyen and Kappas, 2020)
	Red (10m)	Sensitive to changes in chlorophyll content and leaf structure and capture subtle variations in vegetation density and structure	(Nguyen and Kappas, 2020)
	Vegetation red edge (Band 5-20m)	Indicate the amount and health of vegetation	(Nuthammachot et al., 2020)
	Vegetation red edge (Band 6-20m)	Can penetrate through the canopy to some extent, providing	(Nuthammachot et al., 2020)

		information about the vegetation structure beneath the canopy	
	Vegetation red edge (Band 7-20m)	Sensitive to vegetation characteristics such as leaf structure and water content	(Nuthammachot et al., 2022)
	NIR (10m)	Sensitive to the structural properties of vegetation, such as leaf area and canopy structure	(Nguyen and Kappas, 2022)
	Vegetation red edge (Band 8A-20m)	Sensitive to changes in vegetation health, biomass, and structure	(Nuthammachot et al., 2022)
	Water vapour (60m)	Sensitive to vegetation water content	(Nuthammachot et al., 2022)
	SWIR (20m)	Sensitive to vegetation properties such as water content and biomass density	(Nuthammachot et al., 2022)
	SWIR (20m)	Sensitive to vegetation water content and canopy structure	(Nuthammachot et al., 2022)
	TCI (10m)	Determine stress on vegetation by temperatures and excessive wetness	(Nuthammachot et al., 2022)
Vegetation indices	VARI (10m)	Reduces the influence of soil background and non-photosynthetic vegetation.	(Croci et al., 2022)
	EVI (10m)	Sensitive to vegetation health and density and more responsive to variations in canopy structure.	(Croci et al., 2022; Nguyen and Kappas, 2020)
	MTVI2 (10m)	Capturing information about chlorophyll content, canopy structure and leaf area	(Croci et al., 2022)
	NDVI (10m)	provides a measure of the health and density of vegetation	(Croci et al., 2022)
	SAVI (10m)	Reduction of Soil Influence and Improved Vegetation Estimation	(Croci et al., 2022; Nguyen and Kappas, 2020)
	MSAVI (10m)	minimize the influence of soil brightness	(Croci et al., 2022)
	DVI (10m)	used to assess vegetation health, vigor, and biomass density	(Croci et al., 2022)

Table 1**.** Raw bands and vegetation indices used in the study

2.2.2 Digital Elevation Model

SRTM datasets are DEM products prepared by collaborative efforts involving National Aeronautics and Space Administration, National Geospatial-Intelligence Agency, and contributions from the German and Italian space agencies (Nguyen and Kappas, 2020). These products have a spatial resolution of 1 arc-second (30 meters) at the equator. The DEM attributes (elevation, slope, and aspect each at 30m cell size), which characterize terrain and environmental conditions, are selected as topographical features for the biomass model for the two study sites. These attributes directly influence light and water availability, soil condition, and other factors essential for biomass estimation studies. Consequently, DEM data enhances the accuracy and reliability of AGBD estimation models.

2.2.3 Global Ecosystem dynamics Investigation (GEDI)

The study used monthly GEDI Level 4A (L4A) (version 2) predictions of AGBD as target or dependent variables. GEDI, equipped with full-waveform Lidar at 1064nm, illuminates Earth's surface with footprints of approximately 25 meters and collects detailed three-dimensional data about Earth's forests and topography. Specifically, GEDI gathers canopy height, canopy structure, biomass estimates, ground elevation, and vegetation cover data from the International Space Station, providing insights into carbon stocks in forests (Mohite et al., 2024). The L4A product, derived through parametric linear models, correlates GEDI L2A waveform metrics with AGBD, encompassing broad forest vegetation coverage (Morin et al., 2022).

3. Methodology

In this study, as mentioned in section 1, we integrated GEDI Level 4A product, Sentinel-2 multi-spectral images, and SRTM DEM data for the months from May to September for the year 2021-2022 due to visible vegetation and no snow cover. Spectral indices were computed from pre-processed Sentinel-2 data to capture essential vegetation characteristics. Subsequently, GEDI data points served as the target variable, while Sentinel-2 bands and spectral vegetation indices, along with DEM derived slope and aspect were used as feature variables. Noise removal techniques were applied to eliminate sensor-specific artefacts, followed by atmospheric correction. Cloud masking was then implemented to exclude cloud-covered pixels, preventing bias in vegetation indices and biomass estimation. After correction and masking, various vegetation indices were computed for their correlation with biomass, offering insights into vegetation health. For GEDI data, specific pre-processing steps were taken to integrate and align it with the study. Individual trajectory files were merged for a comprehensive dataset covering the Acadia Forest in Canada and the Taiga Forest in Russia, ensuring continuous biomass measurements. Slope and aspect information from DEM data was also derived and integrated, as these terrain characteristics affect biomass distribution. Following the pre-processing steps, a Random Forest model was used to train and test the datasets for predicting AGBD. It was rigorously trained using an 80:20 training-testing split, demonstrating high accuracy and efficiency in handling complex interactions between variables.

3.1 Implementation

The methodology is implemented systematically in a series of steps. Before deriving various variables from the data sets, pre-processing steps were undertaken for Sentinel-2 and GEDI data to ensure data quality and compatibility. Initially, Sentinel-2 images were compiled to create a comprehensive image composite covering the study area, with a cloud cover threshold of less than 1% to minimize atmospheric interference. Processing Sentinel-2 Level 1-C to Level-2A using the ATCOR algorithm followed by mosaicking images. Subsequently, raw bands, vegetation indices (VIs), and textures as input variables are derived. Seven VIs were chosen based on comparative analysis and relevant studies for biomass estimation (Askar et al., 2018; Amuyou et al., 2022; Croci et al., 2022; Li et al., 2021; Nguyen and Kappas, 2020; Potapov et al., 2021; Sothe et al., 2022; Tamga et al., 2023; Wang et al., 2024; Zhang et al., 2024).

GEDI data points were consolidated into a cohesive dataset, while DEM data from SRTM were processed to derive slope and aspect information. Employing a RF regression algorithm and KNN algorithm, we developed two biomass estimation models for each of the two sites. The datasets of each site were split into 80% and 20% ratios for training and testing sets to train and evaluate the model performance, respectively. This methodology was assessed by calculating $RMSE$ and R^2 values.

In addition to developing the biomass estimation model, we calculated the variable importance as weights using the RF algorithm to determine the contribution of each feature to the model accuracy. Variable importance scores were computed for all input variables, spectral bands, vegetation indices, and terrain variables (slope and aspect). Importance of each variable was assessed based on the decrease in the model accuracy when that variable was removed, providing insights into which features driving AGBD distribution and informed the selection of the most relevant predictors for the parametric model highlighting the critical environmental and spectral characteristics that contribute to biomass.

4. Results and Discussion

The proposed parametric model is implemented for the two study sites. For the Acadia Forest site, $RMSE$ of 9.29 $\mathrm{Mg/ha}$ and R^2 of 0.94 for the training set, and $RMSE$ of 23.52 $\mathrm{Mg/ha}$ and R^2 of 0.60 for the test set were obtained. Whereas, for the Taiga Forest (second site) $RMSE$ of 14.20 $\mathrm{Mg/ha}$ and R^2 of 0.89 for the training set, and $RMSE$ of 27.35 $\mathrm{Mg/ha}$ and R^2 of 0.54 for the test set were obtained by the Random Forest algorithm. Figure 2 shows the biomass modelling by input and output variables with 80:20 percentage ratios.

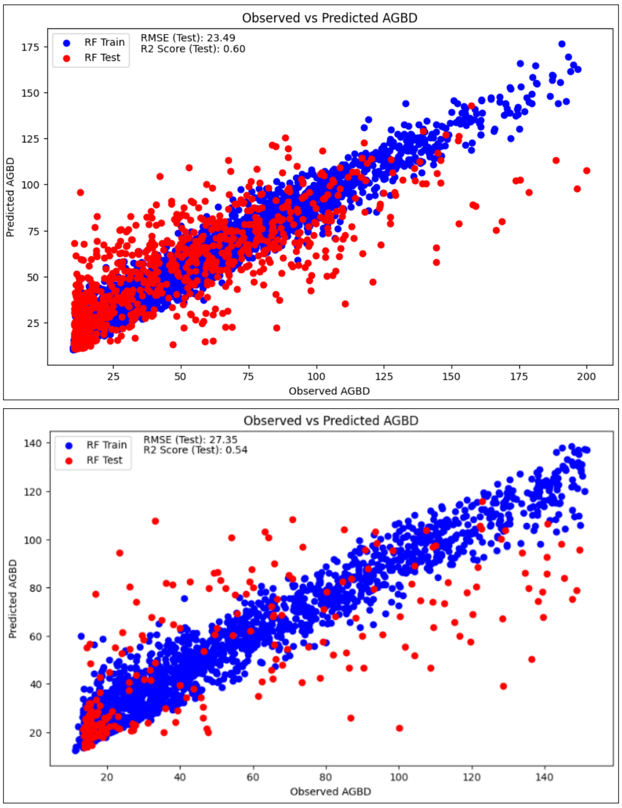


Figure 2. Observed and predicted values of AGBD for Acadia forest (top) & Taiga Forest (down).

RF algorithm calculates variable importance (Figure 5 below) of features for biomass model. From figure 3 below, Band-4 and Band-12, EVI and MTVI2, SLOPE are found to be high importance features for both Acadia and Taiga forest as these provide insights about vegetation health, growth affecting their storage (biomass distribution) (Amuyou et al., 2022; Croci et al., 2022; Nguyen and Kappas, 2020). Band-1, Band-2, Band-5, Band-8, Band-9, Band-11, VARI, ASPECT are observed to be moderate importance variables for both study cases. It is because, these features reduces atmospheric inference, and known for detection of forest cover, vegetation health, biomass and stress (Nuthammachot et al., 2022).

Band-3 (green), Band-6, Band-7, and Band-8A (all in the red-edge spectrum), are variables of low importance for estimating AGBD using RF algorithm for both Acadia and Taiga Forest. The developed AGBD model for Acadia forest for year 2021 is validated with Utla et al. (2025b) method, which uses demographic models and airborne LiDAR data for biomass estimation and obtained a correlation coefficient of 0.9046. Figure 4 below shows the validation of the biomass values generated by the parametric model developed against Utla et al. (2025b).

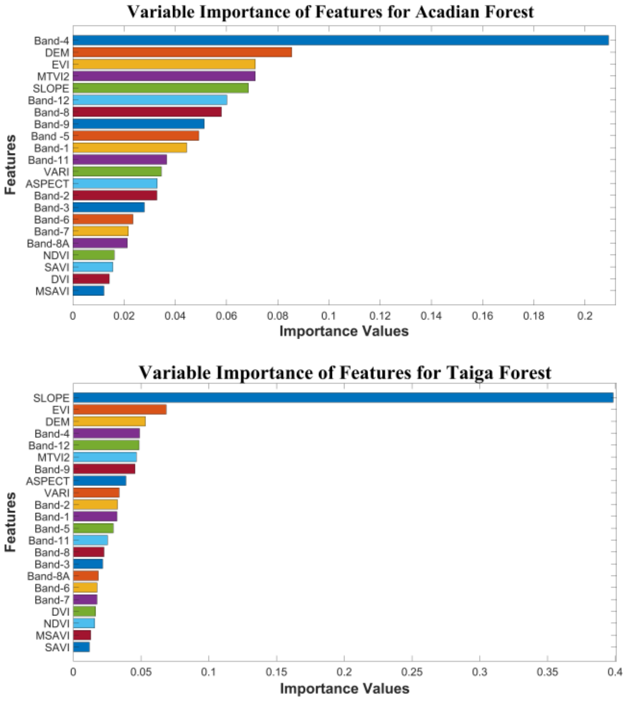


Figure 3. Variable importance (weights) values of AGBD for Acadia Forest (top) & Taiga Forest (down) from RF.

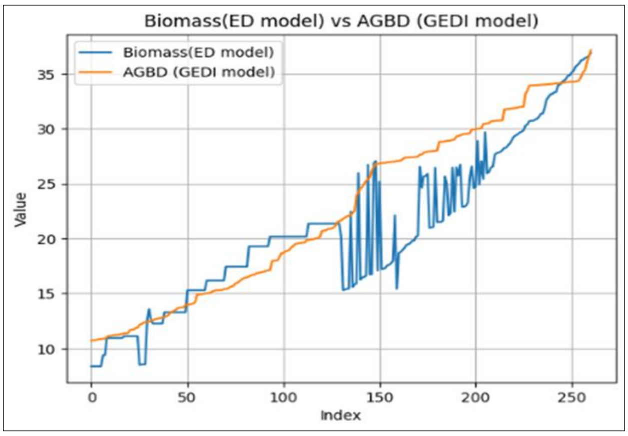


Figure 4. AGBD verification for Acadia Forest using Utla et al. (2025b) method.

The results highlight the contribution of a parametric model for biomass estimation without ground truth data, traditionally used in past studies (Duncanson et al., 2022; Francini et al., 2022; Musthafa and Singh et al., 2022; Mohite et al., 2024; Ni et al., 2021; Silleos et al., 2006; Tamiminia et al., 2024). This study demonstrates the model's robustness and applicability by achieving comparable accuracy across two ecologically distinct boreal forest sites.

5. Conclusion

This study emphasizes the potential of global open-source remote sensing datasets for biomass estimation in large boreal forests, particularly in challenging terrains where ground truth data collection is impractical. The proposed parametric model integrates GEDI Level 4A data, Sentinel-2 L2A imagery, and SRTM 30m DEM to estimate AGB for Acadia and Taiga forests, assessing its accuracy using Random Forest and k-Nearest Neighbour regression techniques. These methods support variable selection and ensure efficient parameter estimation, with minimal human intervention for training data. The model showed consistent AGBD predictions from May to September 2021-2022, utilizing fewer features and reduced human input due to visible vegetation and no snow cover. The Random Forest algorithm outperformed KNN in capturing non-linear relationships, reducing overfitting, and improving generalization, especially with high-dimensional data. It also identified variable importance as weights in the model. Overall, the study demonstrates the effectiveness of using remote sensing data alone for biomass mapping in inaccessible regions, offering a practical solution for large-scale studies. The authors anticipate broad applicability of the developed model for forest management and conservation strategies, leveraging various sensors.

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