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EDITORIAL

Forest Biomass Assessment Using Multisource Earth Observation Data: Techniques, Data Sets and Applications

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Introduction

Forests cover around one-third of the Earth's surface (Pan et al., 2013), offering a myriad of ecosystem services crucial for sustaining life on our planet. Among these, a pivotal service is their ability to sequester carbon, thereby mitigating the impacts of emissions from fossil fuels and associated global warming (Tian et al., 2022). An essential parameter in this process is forest biomass, recognized as the essential climate variable. Aboveground biomass (AGB) in forests serves as a fundamental indicator of ecosystem productivity, biodiversity, and carbon storage (Ma et al., 2024). Although traditional methods such as site-level studies, national forest inventories, and regional synthesis have yielded significant insights, there is now widespread recognition of the need to address gaps in spatial carbon capture. Identifying carbon sink areas and predicting future sink capacities under varying climate and policy scenarios have become critical aspects of climate change mitigation strategies.

Remote sensing (RS) derived forest biomass density mapping with low uncertainty is very crucial. Forests, with their phytomass and soil organic carbon reservoirs, constitute the primary terrestrial carbon repositories, thus exerting a significant influence on the global carbon budget (Pan et al., 2011). Therefore, accurately quantifying forest AGB is indispensable for understanding the global carbon cycle and discerning the response of forest ecosystems to climate change (Tian et al., 2023).

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RS-Forest Biomass: Current Status

The integration of field inventory with RS data presents an efficient and dependable approach for estimating and mapping forest biomass across large areas (Nandy et al., 2019; Zhang et al., 2019). With the availability of earth observation (EO) data, quantifying forest carbon stocks from local to global scales has become feasible. Various optical passive multispectral and hyperspectral images, as well as active sensors such as Radio Detection And Ranging (RADAR) and Light Detection and Ranging (LiDAR) data, are now accessible for forest biomass assessments. Predictor variables derived from RS data are empirically linked to field-measured biomass through diverse approaches ranging from simple linear regression, geostatistical techniques to advanced machine learning algorithms (Dang et al., 2019; Kushwaha et al., 2014; Yadav & Nandy, 2015). Concurrently, endeavors persist in utilizing EO-derived tree parameters for modelling tree growth.

Furthermore, efforts are underway to explore very high-resolution and LiDAR data from space to Unmanned Aerial Vehicles (UAVs) for large-scale forest biomass mapping up to the tree-level. The integration of data from multiple EO sources, each with varying accuracies, has driven the development of a multi-sensor approach. However, the regular monitoring of forest biomass to capture spatial patterns of biomass accumulation or loss is still to be fully demonstrated. By employing improved methods of integration, the multi-sensor approach has the potential to overcome the limitations associated with single sensor data (Nandy et al., 2021; Yadav et al., 2019).

Accurate forest biomass maps are crucial for effective forest management and planning, carbon accounting, understanding carbon dynamics, and forest productivity modeling. Therefore, it is imperative to devise reliable methods for forest biomass mapping and monitoring to address these issues comprehensively. Examining long-term trends and spatial variability in forest carbon sink strength is essential for enhancing our understanding of the carbon-climate feedback. From a practical standpoint, advancements in this field of research hold significant implications for various applications.

RS-Forest Biomass: Indian Scenario

RS has been instrumental in estimating forest AGB in Indian forests for several decades. Various RS data and methodologies have been employed for AGB estimation in India, sourced from diverse platforms and sensors including passive optical, microwave, and LiDAR data. RS data derived spectral, texture, topographic variables, and forest canopy height were integrated with field inventory data using a range of modeling approaches, from simple linear regression (Kushwaha et al., 2014) to advanced machine learning techniques (Nandy et al., 2021).

Optical RS images with differing spatial, spectral, and temporal resolutions have been extensively utilized for AGB estimation across various scales (Nandy & Kushwaha, 2021). Coarse-resolution RS data like MODIS have proven successful for regional to national-scale AGB estimation (Fararoda et al., 2021; Pandey et al., 2019). Nationwide and regional studies have also been carried out to systematically analyse multi-decade carbon stocks changes in aboveground forest biomass at a 5 km grid resolution, as influenced by forest fraction in each grid. These efforts utilized multi-source datasets, drawing upon historical archives, field inventory data, and employed stratify and multiply approach (Reddy et al., 2016, 2015a, 2015b). Medium-resolution optical satellite data such as Landsat, IRS LISS-III, and Sentinel-2 have been effective in estimating AGB in diverse forests and agroforestry systems in India (Kalita et al., 2022; Kumar et al., 2021; Nandy et al., 2017; Yadav & Nandy, 2015). High-resolution optical satellite data like IRS LISS-IV (Heyojoo & Nandy, 2014; Manna et al., 2014) and very high-resolution data like Worldview-2 and Cartosat (Pandey et al., 2020; Pargal et al., 2017) have been employed for AGB estimation in forests as well as tree outside forests at both forest stand and tree levels. Microwave data, including synthetic aperture radar (SAR), interferometric SAR (InSAR), and polarimetric InSAR (PolInSAR) data, have also been utilized for AGB estimation across various scales (Ghosh & Behera, 2021; Mukhopadhyay et al., 2022).

Moreover, LiDAR data from terrestrial and spaceborne platforms have proven highly effective in accurately estimating AGB across various forest types in India (Dhanda et al., 2017; Mohite et al., 2024; Nandy et al., 2021; Singh et al., 2023; Singhal et al., 2021). Integration of multi-sensor data, including passive optical, SAR, and LiDAR data, has demonstrated superior AGB estimation compared to single sensor data (Fararoda et al., 2021; Malhi et al., 2022; Nandy et al., 2021). The synergistic use of RS data from multiple sources employing machine learning techniques emerges as a promising strategy for AGB estimation. Furthermore, UAVs have emerged as valuable RS tools, showing enhanced applications in forest AGB estimation. RS is expected to continue playing a crucial role in future forest AGB estimation and carbon cycle studies in India.

RS-Forest Biomass: Special Issue

In the above context, a special issue titled "Forest Biomass Assessment using Multisource Earth Observation Data: Techniques, Data Sets, and Applications" was compiled. This issue comprises 17 articles, all focusing on Indian sites as study regions and encompassing various forest types, including two studies on mangroves. These articles can be broadly categorized as: (a) Forest biomass estimation using optical sensors, with attention to very high resolution and hyperspectral data (Pardeshi et al., 2024; Pasha & Dadhwal, 2024; Singh et al., 2024; Verma et al., 2024), (b) Utilization of SAR sensors, including polarimetric data, for biomass estimation (Ali & Khati, 2024; Bhavsar et al., 2024; Hati et al., 2024; Singhal et al., 2024), (c) Application of LiDAR sensors, both terrestrial and spaceborne, for biomass estimation (Bhandari & Nandy, 2024; Rodda et al., 2024a, 2024b), (d) Integration of multi-sensor EO data for biomass estimation (Behera et al., 2024; Bhandari et al., 2024; Prakash et al., 2024; Sainuddin et al., 2024; Sanam et al., 2024), and (e) Biomass product validation, regional studies, and application-focused research (Bhat et al., 2024).

A common thread among these articles is the widespread adoption of recent analytical methods, particularly machine learning. Apart from offering valuable insights into techniques and applications of remote sensing data for forest biomass mapping, these articles also highlight areas that warrant further investigation, as summarized in a later section.

Forest Biomass Estimation Using Optical Sensors

Pasha and Dadhwal (2024) estimated the AGB and carbon (C) stock of natural rubber (*Hevea brasiliensis*) plantations in Tripura. They utilized a multi-year satellite data-based rubber plantation age-class map along with field AGB data to generate age-based rubber AGB and C-stock maps with 5-year interval age classes. Their analysis revealed a total carbon storage of 2.8 Tg across all age group rubber plantations. The developed approach demonstrates practical applicability for accurate C-stock accounting in other managed forests.

Singh et al. (2024) employed object-based image analysis (OBIA) of WorldView-2, a very high resolution satellite imagery (VHRS), to map the tree aboveground carbon stock of sal (*Shorea robusta*) forests in the Doon valley, Uttarakhand. Utilizing OBIA for image segmentation and classification enabled the delineation of tree crowns and calculation of canopy projection area (CPA). Their study unveiled a strong relationship between diameter at breast height (dbh) and tree CPA, as well as CPA and tree carbon. The research highlighted the efficiency of OBIA of VHRS imagery coupled with field inventory for quantifying and mapping tree carbon stock.

Pardeshi et al. (2024) developed an empirical model using ground-based tree biomass and satellite-based indices to estimate AGB for mangroves in Maharashtra. They observed the strongest correlation of AGB with maximum NDVI, which was used in regression analysis to estimate AGB and carbon. Their study estimated carbon sequestration by determining the difference in total carbon content, confirming the role of mangroves as a carbon sink.

Verma et al. (2024) evaluated the potential of the spaceborne hyperspectral sensor, PRISMA, for estimating AGB in a tropical dry deciduous forest of Gujarat. Their findings underscored the significant impact of vegetation indices and phenological conditions on AGB prediction. The study emphasized the influence of phenological variations on AGB estimation, highlighting the utility of narrowband indices in such analyses.

Forest Biomass Estimation Using SAR Sensors

Hati et al. (2024) estimated AGB using SAR data in the intricate mangrove assemblage of Lothian Island, Indian Sundarbans. They performed a comparative analysis of SAR datasets to assess the advantages of the L band in ALOS-PALSAR-2 data over the C band in RISAT-1 and Sentinel-1 data. Backscatter generated from RISAT-1 RH, Sentinel VH, and ALOS-PALSAR-2 HV and VH exhibited the best performance when regressed with field observations. This study provides valuable input for carbon mapping and serves as a baseline report of blue carbon stock availability in the Sundarbans.

Ali and Khati (2024) utilized L-band ALOS-2/PALSAR-2 SAR data along with multi-parameter linear regression (LR) and Random Forest (RF) regression for forest biomass estimation in Haldwani Forest Range, Uttarakhand. The study demonstrated a significant improvement in biomass prediction accuracy with the RF model compared to the LR model. Input parameters to the RF algorithm included backscatter, decomposition powers, and species information. This approach offers an effective means of estimating forest AGB and height using L-band SAR data and machine learning algorithms, promising accurate and cost-effective estimates.

Singhal et al. (2024) showcased the applications of Earth Observation Satellite-04 (EOS-04), a C-band SAR data, in forest phenological studies and biomass estimation across varied vegetation conditions. EOS04 data were synergistically used with L-band ALOS PALSAR data for forest biomass estimation, enhancing estimation accuracy. This study successfully demonstrated the utility of EOS-04 for tracking land surface phenology and estimating AGB.

Bhavsar et al. (2024) utilized HH/HV dual-polarization SAR data from EOS-04 (C-band) and ALOS-2 PALSAR-2 (L-band) satellites to estimate AGB. They developed a multiple linear regression-based statistical model for AGB prediction, considering the best-suited frequency and polarization data for different forest density classes. Strong correlation between AGB and HV backscatter from both frequencies was observed. The study highlights the potential of using multi-frequency SAR data to reduce errors in AGB prediction by incorporating forest categorization into the prediction model.

Forest Biomass Estimation Using LiDAR Sensors

Bhandari and Nandy (2024) employed an integrated approach to predict forest AGB in Barkot Reserve Forest, Uttarakhand, by incorporating Terrestrial Laser Scanning (TLS) data, Landsat-8 OLI data-derived forest canopy density (FCD), and spectral indices. AGB was estimated using TLS-derived dbh and height, modeled in relation to Landsat-8 OLI-derived FCD classes and spectral indices. Utilizing a multiple linear model, the study successfully predicted the average AGB and total AGB of the study area. The research underscores the efficacy of combining TLS and satellite data-derived FCD and spectral indices as a rapid and accurate method for forest AGB prediction.

Rodda et al. (2024a) utilized 3D point clouds from TLS to model individual trees, extracting tree volumes to develop local allometric equations in tropical dry deciduous forests of Betul, Madhya Pradesh. TLS-based allometry models demonstrated superior predictions with lower error estimates compared to traditionally used volume equations. The findings suggest that TLS data can expand the range and sampling size of allometric equations through non-destructive volume estimation, thereby enhancing traditional allometric models and reducing uncertainty in landscape-level biomass estimates.

Rodda et al. (2024b) conducted a comprehensive accuracy assessment of ATL08 (ICESat-2) and L2A (GEDI) height data products over tropical dry deciduous forests in the Central Indian region during leaf-off and leaf-on seasons, using reference airborne LiDAR data. The study validated the GEDI L4A (above-ground biomass density—AGBD) product against a reference AGBD map derived from field estimates and canopy height model from airborne LiDAR. Despite variations in leaf condition, the study found that strong beams during nights from both systems (GEDI and ICESat-2) effectively retrieved terrain height. However, substantial discrepancies were observed between GEDI-AGBD estimates and the reference AGBD map.

Forest Biomass Estimation Using Multi-sensor Earth Observation Data

Bhandari et al. (2024) mapped forest canopy height and AGB in Pauri Garhwal district of Uttarakhand, by integrating Global Ecosystem Dynamics Investigation (GEDI) and Sentinel data using the RF algorithm. They found that a combination of LiDAR and SAR variables efficiently predicted forest canopy height. AGB was mapped by integrating field-measured AGB with Sentinel-2 data-derived spectral and texture variables, and modelled forest canopy height derived from GEDI and Sentinel-1 data using the RF model. The study highlighted the effectiveness of a synergistic approach involving multi-sensor data in predicting forest canopy height and AGB, showcasing the utility of machine learning algorithms in mapping forest biophysical parameters.

Prakash et al. (2024) estimated the AGB of Sikkim state, by employing machine learning (ML) techniques such as RF and categorical boosting algorithm (CatBoost) and integrating multi-sensor satellite data including Sentinel-1, Sentinel-2, and ALOS2 PALSAR2. They observed that the RF model slightly outperformed the CatBoost model, with SAR variables emerging as significant predictors due to their contribution to plant structural properties. This study underscored the importance of multi-sensor data integration and ML models in AGB estimation, highlighting their potential applications in forest management and climate change mitigation efforts in the Himalayan mountainous region.

Sainuddin et al. (2024) integrated SAR and multispectral imagery with in-field observations to estimate AGB in the Purna regional landscape of northern Western Ghats, utilizing satellite data/products such as Sentinel-1, Sentinel-2, SRTM DEM, and global canopy height products. They applied machine learning algorithms including RF, Extreme Gradient Boosting (XGB), and Boosted Regression Trees (BRT) to effectively predict AGB. The study demonstrated the potential of integrating SAR and multispectral data for enhanced AGB estimation, suggesting that ML models, particularly algorithms like RF, XGB, and BRT, can effectively address the complex relationships between AGB and satellite-derived variables.

Sanam et al. (2024) aimed to model the AGB of mangroves in Bhitarkanika, Odisha using a multi-sensor approach integrating Sentinel-2, Landsat-8, and hyperspectral Airborne Visible Infra-Red Imaging Spectrometer-Next Generation (AVIRIS-NG) datasets. They found that combining textural features yielded better prediction models than independent sets of features, with genetic algorithm (GA) and recursive feature elimination CV (RFECV) proving to be effective feature selectors. The study concluded that incorporating structural information of vegetation canopy obtained from textural parameters of different input bands improved regression models for biomass prediction.

Behera et al. (2024) utilized texture and spectral variables derived from Sentinel-2 data, along with topographic variables and GEDI-Landsat tree height product, to estimate forest AGB in Eastern Ghats. Their model explained AGB variability significantly with relatively low uncertainty, highlighting the effectiveness of combinations of texture and spectral variables along with physical variables in AGB mapping. The study's method and results were promising, suggesting potential replicability for building a generalized AGB model.

Biomass Product Validation, Regional & Application Studies

Recent AGB global products like ESA-CCI and GlobBiomass play a crucial role in carbon sequestration, emission, and climate change studies. Although these products have been developed and tested using global field datasets, there has been limited utilization of Indian field measurements for validation purposes. Bhat et al. (2024) compiled a database of field measurements from published literature to validate ESA-CCI 2018 & 2010 and Santoro-2010 datasets. Overall, all products showed saturation and failed to accurately capture AGB of plots exceeding 250 Mg ha^{-1}, while also underestimating the mean AGB for large areas. The study recommends expanding Indian datasets for the development and validation of AGB models and updating global datasets with Indian observations using new data integration approaches.

RS-Forest Biomass: Challenges & Way Forward

(a) Enlarging and continuous expansion of field inventory data: There is a need to collect field data over unrepresented areas as well as continue further field data collection to investigate new sensors and parameters that are either being specially designed for forest biomass (e.g., BIOMASS) or can provide parameters and proxies for forest biomass modelling (e.g., NISAR). Rapid and accurate field data collection with TLS could play an important role and additional ground and UAV-based techniques for rapid field estimation are important. Additionally, more of the field data should be in an open access domain to make rapid progress. Recent publication of TLS-based open map data for biomass (Rodda et al., 2024c) needs to be replicated over wider regions and time periods to support AGB retrieval and mapping.

(b) Standardization of protocols for plot, local, and regional biomass from field studies: The majority of Indian studies have used 0.1 ha plots for their ground verification data collection. The uncertainty of field-level biomass at this plot size has been estimated to exceed 30 percent. Use of this data is likely to introduce errors in the developed models also. Thus, either use of a larger plot size (e.g. 1 ha) or a mean of 0.1 ha plots which was adopted in the Vegetation Carbon Project of the National Carbon Project (Dadhwal et al., 2009) and provided the only state-level forest biomass map of state of Madhya Pradesh, India using ALOS data (Thumaty et al., 2016), optical sensor based national biomass map (Rajashekar et al., 2018) as well as multi-sensor national forest biomass map developed with Indian field plot data (Fararoda et al., 2021) or any comparable approach needs to be adopted.

(c) Exploring new indices and parameters from RS: Recent studies on SAR tomography, polarization, and structural patterns from high resolution are promising. Generation of large datasets and the study of the increase in prediction accuracy due to their inclusion needs to be pursued.

(d) Independent estimation of biomass change and degradation: Current RS estimated biomass has significant errors at pixel level and may not reliably estimate change in biomass or biomass degradation. Development of such models will improve the assessment of biomass change. New parameters being explored such as VODCA from passive microwave also have large RMSE.

(e) Multi-sensor EO-based forest biomass: It needs to use layers characterizing forest type, forest age, and forest management, which capture the structure, phenology, composition as well as the dominant drivers of forest biomass variability. This is different from the canopy density classification more widely adopted by the Forest Survey of India (FSI) which includes all plantations also as forest. Open access to forest type maps of FSI and revision and update of vegetation type maps such as Reddy et al. (2013) with the inclusion of forest age, especially for plantations would enhance the usefulness of RS-forest biomass models.

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