Chapter 16

From Field to Map: A Review of State-of-the-art Approaches to Estimate Above-Ground Biomass Integrating Remote Sensing Techniques

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ABSTRACT

Remote sensing offers opportunities for mapping forest biomass at a lower cost, faster speed and at a wider scale than field measurements. Aboveground biomass is estimated using remote sensing data acquired over a broad electromagnetic wavelength range from visible to microwave region. The use of remote sensing data to estimate forest aboveground biomass is of great importance for understanding terrestrial carbon dynamics and making forest management policies. The integration of biophysical characteristics of vegetation with remote sensing datasets enables the quantification of biomass stocks across extensive spatial scales. Tropical forests, being the most carbon-rich and structurally complex ecosystems, tend to cause the optical data to saturate quickly when interacting with them. Active remote sensing technologies like SAR and LiDAR present alternative methods for retrieving tree and

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canopy height and estimating aboveground biomass. These technologies can surpass the limitations inherent in optical remote sensing data. By combining these methods, remote sensing serves as a powerful tool for extending field plot-based inventories to a regional level, thus offering a comprehensive understanding of forest biomass.Stateoftheart approaches have demonstrated the potential for accurate and spatially explicit biomass mapping. These methodologies, supported by machine learning, data fusion, and advanced validation techniques provide a robust framework for solving biomass estimation problems.

Keywords: Remote sensing; forest; height; vegetation indices; LiDAR

INTRODUCTION

The biomass is the mass of living biological organisms in a given area or ecosystem at a given time. The Intergovernmental Panel on Climate Change (IPCC) has listed five terrestrial ecosystem carbon pools involving biomass: above-ground biomass, below-ground biomass, litter, woody debris and soil organic matter. Of these five, above-ground biomass is the most visible, dominant, dynamic and important pool of the terrestrial ecosystem, constituting around 30% of the total terrestrial ecosystem carbon pool (Eggleston et al. 2006).Above Ground Biomass (AGB) is all living biomass above the soil including stem, stump, branches, bark, seeds and foliage (Seibel, 2005). It is measured in units of tons of carbon per unit area by oven drying the total mass of organic living plant matter. Forest aboveground biomass is one of the critical parameters for assessing the productivity and health status of forest ecosystems.

Forest aboveground biomass is mainly estimated either by field measurements or by remote sensing methods and this chapter specifically attempts to provide a comprehensive review of the same. An advanced search of scholarly literature in Scopus, covers journal papers, books and conference papers. The search within article title, abstract and keywords of ‘forest’, and ‘biomass’ and ‘remote sensing’ reveals 3598 published documents are related to remote sensing of forest biomass from 1983 to 2022. The increasing number of published documents is connected to the growing interest of the science in studying the biomass of forests (https://www.scopus.com/).

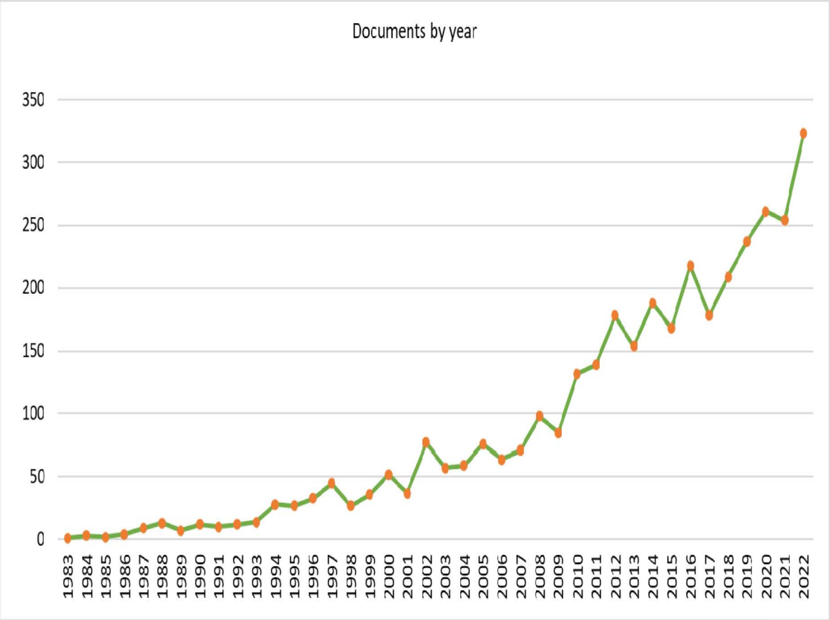

Figure 1. The number of documents on remote sensing of forest biomass published in the last 40 years (https://www.scopus.com/)

2. Traditional methods of biomass estimation

Traditional methods of biomass estimation include direct and indirect sampling methods (Murali et al., 2005). The first method is destructive sampling, which involves the complete harvesting of vegetation in plots and subsequent extrapolation to a unit area of hectare (Klinge et al., 1975). The second method was developed based on the functional relationship that approximates the biomass of the tree component or the total biomass of single trees according to an easily measured variable - diameter at breast height (DBH) or height (Chave et al., 2005). AGB for a specific tree can be expressed as a function of DBH, tree height (H), and/or wood density (S). For a small forest stand, the AGB calculation is more accurate when based on actual field measurements. Biomass estimation equations, also known as allometric equations or regression models, are used to estimate the biomass or volume of aboveground tree components based on DBH and height data. These equations are derived based on measured values of tree weight related to its DBH and height from sample trees. Using biomass equations is a common and cost-effective method to estimate biomass of tree species present in a forest or plantation(Kebede & Soromessa, 2018).

One notable allometric equation in this domain is the Chave et al. (2014) equation, designed specifically for estimating the aboveground biomass of tropical trees. This equation takes the form $Y = b_1 D^2 H$, with Y representing aboveground biomass in kilograms, D as the diameter at breast height in centimetres, H denoting total tree height in meters, and b_1 serving as a species and environment-dependent scaling factor.

Given here is the allometric equation as detailed by Chave et al. (2014),

$$A = 0.0673(\rho D^2 H)^{0.976}$$

Where, ñ = wood density; D = diameter at breast height; and

H = height of the tree.

Once the allometric equations are derived, non-destructive methods can be followed to determine the aboveground biomass. AGB values are converted to carbon by multiplying by a factor of 0.47. It is possible to determine Belowground biomass (BGB) also by multiplying AGB by a factor of 0.26 based on the root-to-shoot ratio relationship (Ravindranath and Ostwald 2008).

3. Remote sensing for aboveground biomass (AGB) estimation

In remote sensing, the sensors are not in direct physical contact with objects or events being observed. The process of acquiring information about earth surface features, from orbiting satellite is known as satellite remote sensing. Its unique characteristics for data acquisition, large coverage and digital format, make it a primary data source for large scale biomass estimation (Lu et al., 2012). A variety of optical passive multispectral and hyperspectral images, Synthetic Aperture Radar (SAR) and Light Detection and Ranging (LiDAR) data are now available for forest biomass studies. Optical sensor data have various spatial, spectral, radiometric, and temporal resolutions. Optical datasets are classified as fine resolution (below 10 m), medium resolution (10-100 m) and coarse resolution. Medium and coarse resolution datasets are useful in discriminating largely differing biomass classes. Different types of optical sensor data, such as Landsat, SPOT, Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), China–Brazil Earth Resources Satellite program (CBERS), QuickBird, Moderate Resolution Imaging Spectroradiometer (MODIS), and Advanced Very High Resolution Radiometer (AVHRR) can be used for biomass estimation (Lu et al., 2012).

Remote sensing systems relying on optical data (visible and infrared) are further limited in the tropics by cloud cover, but newer technologies, such as radar systems, can penetrate clouds and provide data day and night (Asner, 2001). Year-to-year changes in biomass are quite small, about two orders of magnitude smaller than the biomass pool, unlike year-to-year changes in greenness, which can vary 5 – 10% relatively to the seasonal average due to climatic variability (Rosenqvist et al., 2003). The forest carbon stock can be indirectly estimated by using statistical relationships between vegetation indices and ground-based measurements. But this method tends to underestimate carbon stocks in tropical forests where optical satellites are less effective due to dense canopy closure and has been unsuccessful in generating transferable relationships (Waring et al., 1995). Nonetheless, optical remote sensing systems are operational at the global scale and some satellite systems (Landsat and AVHRR) provide a globally consistent record for the last 30 years. Optical sensor data are suitable for the retrieval of horizontal vegetation structures such as vegetation types and canopy cover, but it is not suitable for estimation of vertical vegetation structures such as canopy height, which is one of critical parameters for biomass estimation.

Airborne LiDAR is known for its precise biomass estimation but is costly. It can measure vegetation's three-dimensional structure, distinguishing it from traditional sensors, and has been used in both airborne and satellite systems. Although Airborne Laser Scanning (ALS) offers accurate data in certain zones, its high cost makes it impractical for larger areas. The only globally available satellite system, ICESat's GLAS, has limitations such as a large footprint and terrain sensitivity. Missions like ICESat-2, launched in 2017, and the Global Ecosystem Dynamics Investigation (GEDI) in 2019, aim to overcome these limitations by providing smaller footprints and detailed 3D mapping capabilities. Since no LiDAR mission is currently operational, SAR sensors are anticipated to be the next best solution to provide accurate biomass estimates (Patenaude et al., 1995).

SAR sensors are capable of day-and-night imaging, penetrating clouds and vegetation, obtaining information on the internal structure of forests, and is unaffected by meteorological conditions and sunlight levels. SAR sensitivity to AGB changes with wavelength, affecting the penetration and scattering of microwave signals in the canopy. The microwaves interact with objects that are the same size or larger than its wavelength, leaving smaller objects without influencing the backscatter.

So the longer-wavelength SAR signals can penetrate through leaves and branches in the forest's upper canopy, providing more details about substantial woody parts such as stems and large branches. As these larger components constitute the majority of above-ground biomass in forests, longer-wavelength signals are more suitable for AGB estimation. Many studies have shown correlations between SAR backscatter and AGB at various frequencies, with L-band cross-polarization (L-HV) found to be the best option for low-biomass forests. Earlier research revealed rapid saturation in high biomass forests, with C- & S- bands saturating below 50 t/ha, and L-, P-bands at or below 100 t/ha and 200 t/ha of biomass, respectively (Le Toan et al., 1992; Imhoff, 1995; Luckman et al., 1997; Ningthoujam et al., 2017; Schlund & Davidson, 2018).

3.1. Remote sensing approaches for biomass estimation

Measuring forest biomass at a regional scale using field methods is not feasible because it requires enormous resources and consumes too much time. Remote sensing systems, both optical and active sensors, have proven to be an effective alternative for measuring and monitoring forest biomass at different scales and landscape areas. Studies have implemented deterministic modelling and stochastic modelling, to this effect. Deterministic modelling was to interpolate point information using similarities between measured points (inverse distance weighted (IDW) interpolation), and fitting a smoothing curve along the measured points (polynomial interpolation). In stochastic modelling, ordinary kriging (OK) was employed using parameters derived from semivariograms (Joseph et al., 2010). Aboveground biomass (AGB) can be estimated using linear regression (simple linear regression, multiple linear regression), geostatistical techniques and/or by employing machine learning algorithms. There are mainly three approaches for AGB estimation using remote sensing data, i.e., direct remote sensing approach, stratify & multiply approach, and combine & assign approach.

In the direct remote sensing approach, inputs are field measurements, spectral vegetation indices or backscatter values from remote sensing data. Dependent variable is biomass.

$$Biomass = f(NDVI,\ Backscatter\ etc.,)$$

Direct remote sensing approach for biomass estimation includes both regression models that have been widely used in the past few decades and machine learning techniques that have rapidly developed recently. It is important to effectively employ suitable techniques to extract variables for biomass estimation modeling. Many techniques, such as vegetation indices, image transform algorithms (*e.g.,* principal component analysis (PCA)), minimum noise fraction transform and tasseled cap transform, texture measures, and spectral mixture analysis, which have been used to produce new variables from optical multispectral data (Lu, 2006). Remote sensing provides valuable inputs, such as land cover maps, Leaf Area Index (LAI), phenology, stand age, forest structure, and an estimate of the net and gross primary productivity (Abbas et al. 2020). Vegetation indices, particularly NDVI, are good indicators of leaf area index (LAI), and are positively correlated with biomass and productivity. Many studies report significant positive relationship between vegetation indices and above ground biomass (Zheng et al., 2004). Regression models are applied between spectral reflectance or vegetation indices and field inventory data to estimate above ground biomass (Lu et al., 2004).

Regression model-based methodologies consist of three major steps: biomass estimation based on fieldwork, establishment of regression model between field biomass and satellite information of corresponding pixels, and the use of regression models to generate a biomass image with the spatial prediction (Pizaña et al. 2016). Like regression models, nonparametric algorithms are based on the use of different sensor data, for example, spectral, radar, and LiDAR using many of these models in the forest attributes estimation. They are a framework for creating complex nonlinear biomass models based on the use of remote sensing variables. Recent AGB mapping research in forest landscapes uses diverse predictor data fusion and advanced machine learning models (Fararoda et al. 2021; Behera et al. 2023). The study by Behera et al. (2023) concluded that combinations of texture and spectral variables derived from Sentinel-2 optical imagery along with physical variables are found effective in AGB mapping.Common nonparametric algorithms include k-nearest neighbor (k-NN), artificial neural network (ANN), random forest, support vector machine (SVM), naïve bayes and maximum entropy (Max Ent).

In the stratify & multiply approach, forest plots are stratified in to different forest cover & density classes. For each class, total biomass is estimated as the average of plot biomass x Area.

$$Biomass = \sum_{i=1}^{n} (Plot\ Avg\ Biomass\ ) * (Forest\ Area)$$

The study by Reddy et al. (2016) characterized carbon in aboveground biomass at 5 km grid level in Indian forests using remote sensing, historical archives and field inventory data over eight decades. The study has highlighted the differences in forest canopy density and carbon in forest biomass across India using stratify and multiply approach (Reddy et al. 2016).

The combine & assign approach is another method for mapping biomass with remote sensing. It combines satellite and other spatial data with field biomass data to assign biomass values to each pixel. Combine & assign approach uses several parameters to relate to plot biomass at multi-level stratification using data mining approaches. The random forest regression framework for AGB estimation can be used with both direct remote sensing and combine & assign approach. Potential variables generally used in a biomass estimation procedure are presented in table 1.

Table 1. Potential variables used in a biomass estimation procedure (Lu et al. 2016)

Category	Variables	Description
Optical sensor data	Spectral features	Spectral bands, vegetation indices and transformed images
	Spatial features	Textural images and segments from the spectral bands
	Subpixel features	Fractional features such as green vegetation by unmixing the multispectral image
	Combination of spectral and spatial features	Combination of images such as spectral bands, vegetation indices and textural images as extra bands
Active sensor data	Radar	Backscattering coefficients, textural images, interferometry SAR and Polarimetric SAR
	Lidar	Lidar metrics based on statistical measures of point clouds or estimated canopy height models
Integration of optical and active sensor data	Fusion of different sensor data	Fusion of Landsat and radar data to generate an enhanced multispectral image using different techniques
	Combination of optical and radar or lidar as extra variables	Lidar and radar data are combined with optical sensor bands as extra variables

The advantage of Synthetic Aperture Radar (SAR) is that the signal is less prone to saturation with AGB than optical reflectance. Not all SAR bands are equally suitable: SAR backscatter in the P and L bands has a much stronger correlation with forest AGB than the C and X bands. The L-band has proven particularly valuable for AGB estimation (Tian et al. 2012). The combination of spectral responses and image textures improves the performance of biomass estimation. Estimating forest Above Ground Biomass (AGB) from SAR backscatter utilizes a variety of methods, classified into three primary groups by Santoro et al., 2018: empirical regression models, non-parametric models, and semi-empirical or physically-based models. Empirical models, such as linear models, link AGB with SAR backscatter but may lead to under- or overestimation of AGB. Non-parametric models use algorithms to learn from data, but optimal performance needs substantial training data, often a limitation for large-scale mapping. Physically-based models describe forest backscattered intensity with increased reproducibility by considering scattering mechanisms within the forest, expressed as a function of structural properties and microwave interactions (Sainuddin et al., 2021).

One of the most promising techniques in active remote sensing is airborne laser scanning (ALS). LiDAR (Light Detection and Ranging) has revolutionized the study of forest structure by providing simultaneous high-resolution information on three-dimensional (3D) canopy height (stand height), vertical canopy structure, and elevation. A typical lidar sensor emits pulsed light waves into the surrounding environmentThese pulses bounce off surrounding objects and return to the sensor.The sensor uses the time it took for each pulse to return to the sensor to calculate the distance it travelled. Repeating this process millions of times per second creates a precise, real-time 3D map of the environment. The study of Singhal et al. (2021) destructively measured 12 trees for their carbon stock value and the same was estimated using Terrestrial Laser Scanning technique, local allometric equations and global allometric equations. The carbon content estimates from terrestrial Laser Scanning method (26.01% RMSE relative to mean) were consistently closer to destructive measurements as compared to local allometric equations (42.58%-101.88% RMSE relative to mean) and global allometric equations (38.8%-50.69% RMSE relative to mean).

From Field to Map: An Approach to Estimating Above-Ground Biomass Integrating Remote Sensing and GIS

Estimating forest biomass using remote sensing techniques and Geographic Information System (GIS) involves a multi-step process that combines satellite data, field measurements, and spatial analysis. Combining field data, remote sensing and GIS offers a comprehensive approach to biomass estimation. Here is a general outline of the steps involved in estimating biomass:

1. Data collection and preparation: Measure individual plant parameters (e.g., diameter, height) and collect biomass samples from a representative sample of the population. Select appropriate remote sensing data based on your study area, objectives and available sensors. Preferably obtain high-resolution satellite imagery with relevant spectral bands (e.g., optical, near-infrared, and radar) that cover the study area. Prepare the remote sensing data by correcting for atmospheric effects, radiometric calibration, and geometric correction to ensure consistent data.

2. Biomass estimation models: Develop or select appropriate biomass estimation models. Common models include allometric equations, regression models, and machine learning algorithms. For allometric equations, derive relationships between field-measured parameters and biomass. These equations can be species-specific or generalized.

3. Calibration and regression:

   Ground-based data, such as tree diameter and height measurements, species identification, and plot-level biomass sampling, contribute to the calibration of remote sensing-derived models. Create a dataset that includes field-measured biomass, spectral indices from satellite imagery, and other relevant variables. Apply the calibrated model to the satellite-derived spectral indices to estimate biomass across the entire study area. Another remote sensing-based method is to conduct spatial interpolation techniques (e.g., kriging, inverse distance weighting) to generate continuous biomass maps from discrete field measurements. Utilize airborne or spaceborne lidar data to assess canopy height and vertical structure.

4. Model validation: Validate the accuracy of the remote sensing-based biomass estimates using an independent dataset of ground truth that were not used for model calibration. This step helps ensure the accuracy and reliability of the model. Calculate statistical metrics such as RMSE (Root Mean Square Error) and R-squared to assess the model's performance.

5. Biomass estimation: Once you have a validated model, apply it to the entire remote sensing data set to estimate biomass in the study area. The model converts remote sensing data values into biomass estimates.

6. Fusion of data: To improve the accuracy, combine field data with various remote sensing data types, including spectral, spatial, and structural data from satellites, UAV, and ground-based sensors. Integrating multiple data sources can improve the accuracy of biomass estimation.

7. Interpretation: Interpret biomass estimates in the context of your study objectives and the ecological conditions of the study area.

8. Integration with GIS: Import the biomass maps into GIS software to overlay them with other spatial data layers, such as land cover, roads, and administrative boundaries. Conduct spatial analyses to identify biomass distribution patterns, hotspots, and correlations with environmental factors.

9. Reporting: Create maps and visualizations that depict the spatial distribution of forest biomass. Use colour symbols to represent biomass levels. Generate reports summarizing the methodology, accuracy assessment, and spatial patterns.

Challenges and future directions

Despite remarkable advancements, challenges persist. One of the challenges in biomass estimation lies in capturing spatial variability accurately. Integrating data from diverse sensors, addressing scale disparities, and accounting for complex forest structures are ongoing concerns. It has underscored the current challenges, particularly in areas with higher biomass where optical remote sensing data lack accuracy due to saturation effects. While many studies have concentrated on live woody forest biomass, dead biomass and soil carbon remain less explored. Modern biomass estimation techniques harness the power of machine learning algorithms to fuse remote sensing data with ground-based observations. Random Forest, Support Vector Machines, and neural networks are being employed to develop predictive models that consider intricate relationships between various remote sensing parameters and biomass. These techniques also enable the integration of data from multiple sources, resulting in more robust and accurate estimations. The validation of biomass estimates remains critical for evaluating model performance. Advanced validation techniques include ground-truthing through high-precision LiDAR scans and direct field measurements. Moreover, state-of-the-art approaches have placed emphasis on quantifying uncertainty in biomass estimates, enabling researchers and policymakers to make informed decisions based on the reliability of the data. The continuous refinement of algorithms, better integration of multi-source data, and improved uncertainty quantification are key areas for future research.

CONCLUSIONS

This chapter has provided an overview of the existing methods used to estimate Above-Ground Biomass (AGB) through both passive and active space-borne remote sensing technologies. The utility of various sensors to overcome the challenges is emerging, with techniques like PolInSAR and TomoSAR showing promising results at smaller scales. With technological advancement, uncertainties in AGB estimation are anticipated to decrease. The new generation of sensors, such as LiDAR (ICESat-2, GEDI, MOLI) and SAR (NISAR, BIOMASS, ALOS-2), promises unprecedented accuracy and resolution in AGB estimation. The integration of data from multiple sources, driven by varying accuracy levels, also highlights the potential for a multi-sensor approach to transcend the limitations of single sensor data. Further innovation and collaboration will pave the way for more refined biomass estimation techniques.However, regular monitoring and better integration methods are still needed to fully capture the spatial patterns of biomass accumulation or loss.

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