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REVIEW ARTICLE

A critical review of exploring the recent trends and technological advancements in forest biomass estimation

V Kabinesh[1], D Suwethaasri[1], K Baranidharan[1*], R Ravi[1], M Tilak[1], M Kalpana[2], KP Ragunath[2], S Vennila[1], P Hemalatha[1], M Vijayabhama[1], S Bargavi[1], A Eniya[1]

[1]Forest College and Research Institute, Tamil Nadu Agricultural University, Mettupalayam 641 305, Tamil Nadu, India
[2]Tamil Nadu Agricultural University, Coimbatore 641 003, Tamil Nadu, India

*Email: baranidharan.k@tnau.ac.in

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Abstract

Biomass estimation is pivotal in understanding and managing global carbon stocks, offering vital insights into climate change and environmental ecology. It serves as a critical tool for evaluating carbon sequestration potential, a natural mechanism for regulating atmospheric carbon dioxide levels. Accurate estimation of forest biomass not only aids in quantifying carbon stocks but also provides a basis for sustainable forest management, conservation efforts, and policymaking to mitigate climate change impacts. This article provides a comprehensive review of various biomass estimation methods, including ground-based measurements, remote sensing technologies, and hybrid approaches. Each method's strengths, limitations, and practical applications are critically examined, highlighting their suitability for different spatial scales and ecological contexts. Traditional methods, while precise at small scales, are often labour-intensive and limited in coverage. In contrast, remote sensing technologies such as LiDAR, RADAR, and hyperspectral imaging have revolutionized biomass estimation by enabling large-scale and high-resolution assessments. Additionally, recent advancements in machine learning, data fusion, and satellite-based monitoring systems are transforming the field, offering unprecedented accuracy and efficiency. By presenting these trends and innovations, this article provides valuable insights for researchers, practitioners, and policymakers, emphasizing the importance of integrating advanced technologies into biomass estimation for sustainable development and climate resilience.

Keywords

carbon; challenges; climate change; forest biomass estimation; remote sensing

Introduction

The forest is a complex ecosystem that supports a wide range of living organisms like plants, trees, and animals etc., Forest ecosystems contain a significant quantity of biomass and hence play an important role in carbon sequestration and global climate regulation. Woody biomass is the accumulated mass of above and below ground like roots, wood, bark, and leaves of living and dead woody shrubs and trees. It is considered one of the best forms of natural carbon sequester (1). Carbon is an important greenhouse gas because of its global warming influences. Carbon sequestration is the process of capture (through photosynthesis) and long-term storage of atmospheric carbon dioxide (CO_2) (2). Carbon sequestration refers to the provision of long-term storage of carbon in terrestrial, underground, and oceans in the atmosphere. Terrestrial carbon stock mapping is important for the successful implementation of climate change mitigation policies (3).

Forests and soils sequester atmospheric CO_2 within their biomass or in organic matter that is stored in the ground. Forest and soil play an important role in the storing of atmospheric CO_2. Currently, standing forests and soils sequester approximately two-thirds of terrestrial carbon. Biomass production in different forms plays an important role in carbon sequestration in trees (4). Concerns about climate change and global warming are increasingly centered on the extensive buildup of atmospheric greenhouse gases (GHGs). It can stabilize atmospheric CO_2 concentrations by sequestering 2-4 Gt of atmospheric carbon per year. (5).

However, prolonged forest degradation and deforestation will result in a loss of forest biomass or carbon stock, exacerbating the negative effects of global climate change (6). As a result, contemporary concerns about global change and ecosystem functioning need precise biomass measurement and analysis of its dynamics, which is critical for quantifying carbon stock and sequestration rates, as well as analysing possible impacts from climate change (7).

Atmospheric carbon concentration was around 280 ppm at the beginning of the Industrial Revolution, and it has crossed 420 ppm currently. Scientists project that, following current trends, atmospheric carbon levels could reach up to 700 ppm by 2080. Due to climate change, it causes various carcinogenic diseases. It is projected to maintain below 1.5C global mean annual temperature. Carbon stock (CS) estimation studies are essential to understand its overall potential in the forest system. About 30% of the worldwide land surface is covered with forests, the most important providers of ecosystem services and human well-being (8,9).

The Intergovernmental Panel on Climate Change (IPCC) has categorized biomass estimation methods into three distinct tiers: Tier-1, Tier-2, and Tier-3. Each tier represents a different level of methodological complexity in estimating biomass (10). However, continued forest degradation and deforestation will result in the loss of forest biomass or carbon stock. Notwithstanding, the growing biomass can remove carbon dioxide from the atmosphere and store it for an extended period. It can play a critical role in limiting the rise in global temperature (11). Hence, current concerns for global change and ecosystem functioning, require accurate biomass estimation and examination of its dynamics.

Dynamics of research topic based on journals

The bibliographic graph provides an overview of the distribution of journal articles and the thematic evolution of keywords related to biomass estimation methods across various journals and databases. A total of 100 various research and review articles related to the topics from various journals have been analysed and reviewed for the current analysis. Numerous keywords are used for searching and finding out the related articles relevant to the topics, which is represented as the thematic evolution of keywords. The Web of Science contributes the largest number of articles, indicating that it is a significant source of publications on biomass estimation in India. Indian Journals also show a substantial contribution, which reflects a strong local interest and research focus on biomass estimation methods. Wiley comes next, showcasing its prominence as a source of international publications in this area. Taylor and Francis, and Springer have a smaller share, indicating moderate coverage of the topic. Others include various smaller or less prominent journals, showing a diversity of sources beyond the main publishers.

In conclusion, the research on biomass estimation methods is well-represented in both local and international journals, with Web of Science, Indian Journals, and Wiley being the leading sources of publications. This suggests that there is a balanced interest in the subject both within India and globally (Fig. 1&2).

Importance of biomass estimation

Accurately measuring and mapping biomass is crucial for quantifying carbon stocks, assessing climate change impacts, determining suitable locations for bioenergy processing plants, evaluating forest fire fuel, and appraising commercial timber. Although above-ground biomass encompasses both live and dead plant material, recent research has predominantly concentrated on the live component, specifically live trees, due to its significance. Accurate biomass estimates are essential to a better understanding of how deforestation and environmental degradation affect climate change. Interest in biomass studies has increased globally due to its importance as a source of food, energy, and fibre (12,13).

The Intergovernmental Panel on Climate Change (IPCC) identifies five terrestrial ecosystem carbon pools involving biomass: above-ground biomass, below-ground biomass, litter, woody debris, and soil organic matter (14). Among these, above-ground biomass stands out as the most visible, dominant, dynamic, and significant pool, making up approximately 30% of the total terrestrial ecosystem carbon pool. In recent decades, the estimation of biomass, particularly in forests, has garnered significant attention due to growing awareness of climate change and the crucial role that forest biomass plays in both carbon sequestration and the release of greenhouse gases through deforestation (15).

Estimates of biomass are fundamental for carbon inventories and are central to most international carbon trading negotiations. Carbon trading markets depend on long-term data on carbon stocks, especially the above-ground 'live' biomass, as it is the most dynamic, changeable, and manageable component among all biomass pools. This live biomass is considered the 'merchantable' portion of the biomass.

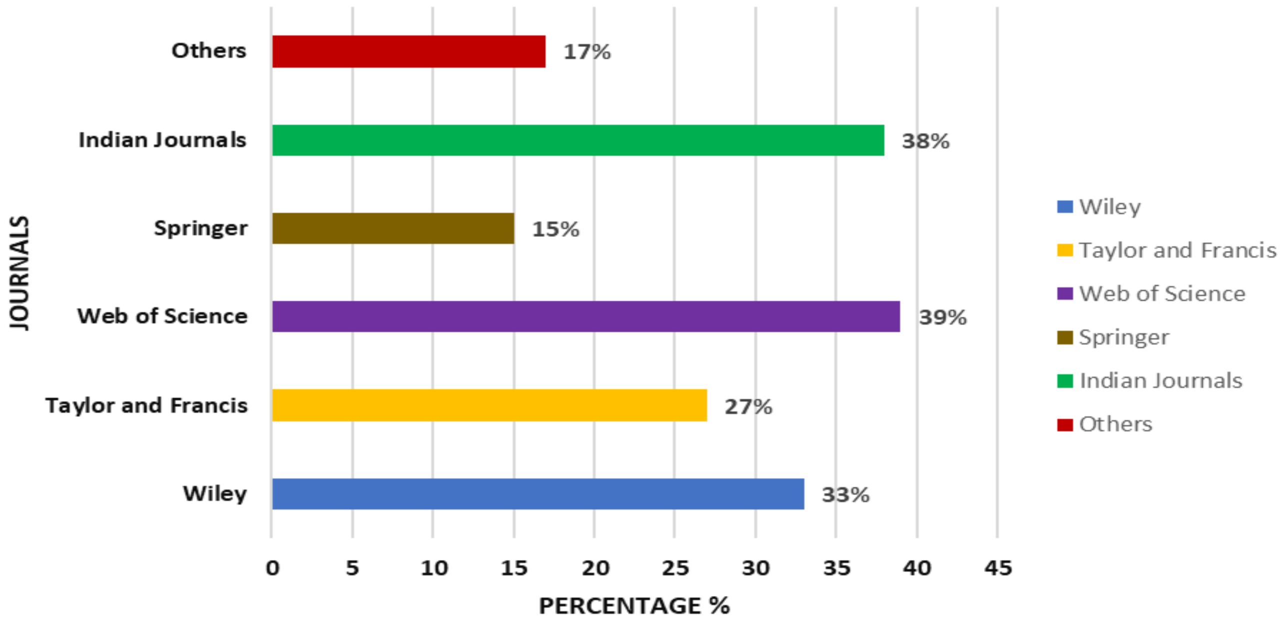

Fig. 1. Dynamic of research topic based on journals.

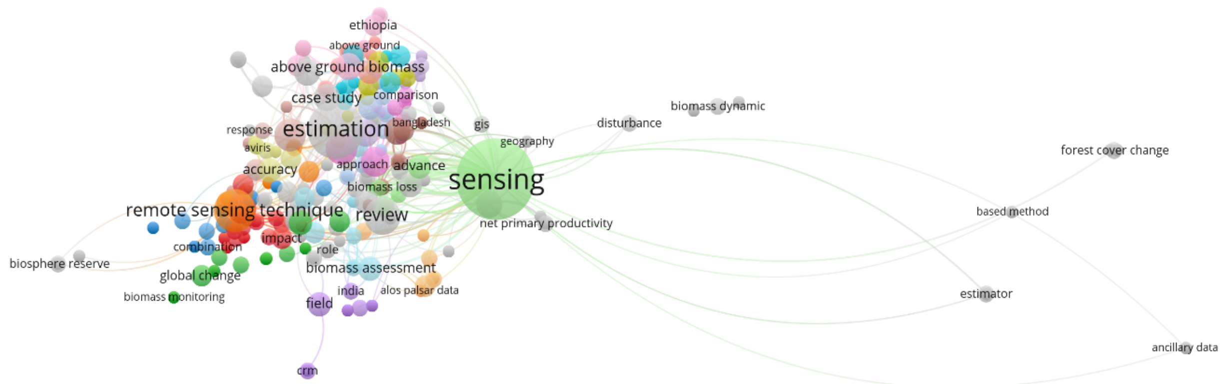

Fig. 2. Thematic evolution of the keywords.

Above-ground forest biomass represents 70% to 90% of the total forest biomass. Globally, soil organic matter contains two to three times more carbon than biomass; however, soil carbon is generally more stable and less prone to oxidation. In contrast, biomass is highly dynamic, influenced by factors such as fire, logging, storms, and land use changes, significantly contributing to atmospheric carbon fluxes. Consequently, it is of greater interest and importance. Given this variability, continuous biomass monitoring is essential, rather than relying on one-time measurements.

Accurate biomass estimations are vital for precise carbon accounting, yet reliable methods are limited. Since biomass, as dry weight, is approximately 50% carbon, accurate measurements are essential for improving carbon flux models and making more accurate climate change projections. Programs such as Reducing Emissions from Deforestation and Forest Degradation (REDD) and its extension, REDD+, rely heavily on precise above-ground biomass estimates. REDD+ integrates financing mechanisms and incentives to combat climate change by reducing deforestation and forest degradation, promoting sustainable forest management, and conservation, and enhancing carbon stocks. Countries participating in REDD+ are required to provide accurate estimates of their forest carbon stocks and monitor changes over time to meet their commitments effectively (16,17).

Wildfire management and fuel control are becoming increasingly integral to forest management strategies. Forest biomass, particularly crown biomass and dry litter, play a crucial role in fire modelling. Traditionally, crown biomass received less attention compared to commercial tree components, but with fire's growing significance in environmental planning, this biomass aspect has gained importance.

Biomass is also a plentiful energy source widely utilized worldwide due to its renewable nature. However, biomass resources are dispersed across vast geographical areas, with their suitability for energy production varying over time and space. Moreover, these resources often exist far from energy generation centres. Given this spatial and temporal distribution challenge and its connection to energy demand centres, it's crucial to have accurate and consistent methods for biomass measurement to assess its feasibility for energy production.

Different methodologies have been used to estimate forest biomass

There are different methodologies available for forest biomass estimation. Every methodology has its pros and cons. This review will let us know about the different methodologies in detail: i) Field measurements; ii) Remote sensing.

Field measurements are the most reliable way to estimate forest biomass, but they are time-consuming and labour-intensive, and they cannot cover enormous areas (18,19). Remote sensing allows for the assessment of forest biomass at several scales, with extensive spatial and temporal coverage. It provides an efficient and affordable method for monitoring AGB by facilitating forest type and canopy density stratification, which substantially aids in field inventory (20). A significant source of inaccuracy in field measuring methods comes from sampling selection, measurement, and statistics or models (21). The cause of mistakes in remote sensing systems is knowledge and competence in image processing software and models (22). RADAR and LiDAR remote sensing, which can detect forest structures, are now being used to assess forest biomass. However, there are limitations in the usual study regions, and they have not been deployed extensively to large-scale investigations because of financial constraints, saturation problems, and environmental concerns (23) (Table 1).

Table 1. Different biomass estimation methods with recent technological advancements

CLASSIFICATION	METHODS	DATA USED	CHARACTERISTICS	REFERENCE
Field measurement-based methods	Destructive method	Sample trees	Individual trees	(75)
	Non-destructive method	Sample trees	Individual trees	(76)
	Allometric equations	Sample trees	Individual trees	(77)
	Conversion from volume to biomass	Volume from sample trees or stands	Individual trees or vegetation stands	(78)
GIS Method	Methods based on ancillary data	Elevation, slope, soil, precipitation, etc.	Per-pixel level, or per field level	(79)
Optical sensor data	Spectral features		Spectral bands, vegetation indices, and transformed images	(80)
	Spatial features		Textural images and segments from the spectral bands	(81)
	Subpixel features		Fractional features such as green vegetation and NPV by unmixing the multispectral image	(82)
	Combination of spectral and spatial features		Combination of images such as spectral bands, vegetation indices, and textural images as extra bands	(81,83)
Active sensor data	Radar		Backscattering coefficients, textural images, interferometry SAR, and Polarimetric SAR interferometry can be used as variables	(4,84)
	Lidar		Lidar metrics based on statistical measures of point clouds or estimated products (e.g. CHM or individual trees) can be used as variables	(85)
	Combination of radar and lidar data		For mapping biomass over large areas where field plots are scarce, lidar samples (e.g. strips) can be taken. Lidar-derived biomass calibrated by field data is then used as the dependent variable, and radar data are used as independent variables for developing biomass estimation models. Lidar-derived biomass serves as “virtual” field data to create a spatially representative biomass “truth” dataset for mapping biomass wall-to-wall using radar data.	(54,86)
Integration of option and/or active sensor data	Fusion of different sensor data e.g. optical and radar data		Fusion of Landsat and radar data to generate an enhanced multispectral image using different techniques such as wavelet-merging.	(87)
	Combination of optical and radar or lidar as extra variables		Lidar and/or radar data are combined with optical-sensor multispectral bands as extra variables	(88)
Remote sensing-based method	Methods based on fine spatial resolution data	Aerial photographs, IKNOS	Per-pixel level	(89,90)
	Methods based on medium spatial resolution data	Landsat TM/ETM+, SPOT	Per-pixel level	(91,81)
	Methods based on coarse spatial resolution data	IRS-IC WiFS, AVHRR	Per-pixel level	(92)
	Methods based on radar data	Radar, lidar	Per-pixel level	(93)

Destructive (direct) methods

The biomass estimation method is a destructive or harvest method also known as the direct method for estimation of Above-ground biomass (AGB) and Carbon stock (19). The destructive estimation method includes harvesting all the trees in the given area and measuring the weight of the various components of the harvested trees like tree trunks, leaves, and branches. Sometimes also known as the harvest method, drying them, and weighing the biomass. It comprises field (site preparation, measurement of felled trees, weighing of logs and sampling for laboratory) and laboratory (dry biomass, density and volume) measurement Operations (24,25). This method of biomass estimation is restricted to small areas or tree sample sizes. Although this method reliably determines biomass for a specific area, it is time-consuming, resource-intensive, damaging, and expensive, making it unsuitable for large-scale investigation. This method is challenging, and only applicable to small areas not relevant to threatened, endangered species, vulnerable forest species and degraded forests. As a result, it is often used for specific research purposes and for developing biomass equations for estimating biomass on a large scale (26) for deriving allometric equations, a non-destructive method is used (4).

Non-destructive (indirect) methods

The non-destructive method is also known as the indirect method which aims to construct a functional relationship between the tree biomass and other tree dimensions, such as stem diameter, height and wood density, through regression analysis (27). It applies to ecosystems with rare or protected tree species were harvesting of such species is not practical or feasible (4). The harvest method is typically impractical or unsuitable for forest studies. As per the Forest Policy, 1988 trees inside the forest are prohibited to cut, so destructive is not suitable and we can adopt only non-destructive methods in the forest. To calculate the carbon estimation. Estimating the above-ground forest biomass by the non-destructive method is by climbing the tree to measure the various parts or by simply measuring the diameter at breast height, height of the tree, volume of the tree and wood density (28). As a result, allometric methods have been developed to estimate total biomass in a non-destructive manner in which height and diameter are at breast height.

The forest biomass/carbon has been estimated by several methods and techniques based on inventory and stock tables. By using the non-destructive method biomass estimation is an essential aspect of studies of carbon stocks as it directly relates to the carbon sequestration on the global carbon balance (4). The non-destructive method was used for the determination of the above-ground weight (total green) dry weight, and Carbon Sequestration (kg), and the total organic carbon of each tree species was evaluated (29). According to Montes, findings using non-destruction methods for biomass estimation can lead to 2.5-7.5 % per tree error (4). In Ethiopia, different researchers used non-destructive methods. However, these methods can also involve a lot of labour, and time and climbing can be troublesome.

A. Challenges of field measurement methods

Numerous academics have pointed out that variations in tree features like wood density and crown architecture, sample plots, and tree errors might impact the calculation of forest biomass. In general, there are three types of sources of errors: measurement error, statistical or model error, and sampling error (21,30).

Sample mistakes can be classified into two phases: the first phase and the second phase, Uncertainty in the biomass estimate is introduced in the first phase when sample plots are chosen using satellite or aerial photos. The ambiguity in the biomass estimate is also caused by the second phase's choice of sampled trees that are measured to create the biomass equation. The inherent variability of the variable of interest, estimation technique, sample size, and sampling scheme all have an impact on sampling error (31,32) and found that the sampling error varied between 2.51% and 22.63% per tree, or 2.65% of the total biomass, in this regard.

The second reason for errors emerged during the measurement of the tree variables, including DBH, height, and weight, which were determined using a calliper, measuring tape, and weighing scale, in that order. Measurement errors can arise from several sources, such as inaccurate equipment, inaccurate data entry, and errors resulting from the irregular shape of the object being measured (33).

Selecting the wrong model to explain the relationship between biomass and tree factors is the third source of inaccuracy (34-36). The literature contains several biomass equations in various model formats. One would expect multiple parameter estimations when various modelling forms are applied to the same data set.

B. General formulas used for biomass and carbon stock estimation

The Above Ground Biomass (AGB) of tree species has been calculated by multiplying the volume of biomass and wood density (37).

AGB (g) = volume of biomass (cm3) * wood density (g cm^{-3}) (Eqn 1)

The Below Ground Biomass (BGB) has been calculated by multiplying Above Ground Biomass taking 0.26 as the root shoot ratio (38,39).

BGB (g) = 0.26 X above ground biomass (ton) (Eqn 2)

Total Biomass (TB) = Above Ground Biomass + Below Ground Biomass (Eqn 3)

C. Estimation of carbon from biomass:

Total carbon = Dry matter biomass × carbon fraction (Eqn 4)

Total carbon = Dry matter biomass × 0.47 (40) (Eqn 5)

Allometric Equations for Biomass Estimation

Allometric equations are the most popular method for determining the biomass of a forest. To evaluate the biomass and carbon stocks of forests, allometric equations are created and applied to information gathered from forest inventories. Generalized biomass prediction equations for various forest types and tree species have been developed by numerous researchers (41-43).

The allometric equations for biomass estimation are developed by establishing a relationship between the various physical parameters of the trees such as the diameter at breast height, height of the tree trunk, total height of the tree, crown diameter, tree species, etc. Equations developed for single species and a mixture of species give the estimate of biomass for specific sites and for large-scale global and regional comparisons.

The forest carbon stocks are widely estimated from the allometric equations for forest biomass. Generally, the carbon concentration of the different parts of a tree is assumed to be 50% of the biomass (44) or 45% of the biomass (27). However, the study estimated the carbon concentration of the dry bole sample to be approximately 48% of the dry bole biomass. The biomass estimation of the forest can be worked out using any of the methods or in combination of the methods mentioned. At the same time, while choosing a method for biomass estimation one should keep in mind the applicability or the suitability of that method for the area or forest type or tree species. The allometric equations and regression models, for biomass estimation, also should not be used beyond their range of validity (45) (Table 2).

The generalized allometric models used to predict total above-ground biomass (kg dry weight) in individual trees were: (Eqn 6 to 11).

Table 2. General Allometric equation for dry and wet tropical forest

Wet tropical forest	M=e [-2.409+0.952 ($\rho w D^2 H$)]	(94)
Dry tropical forest	M=34.47-8.0671D + 0.6589D^2	
Moist tropical forest	M=e (2.134 + 2.53 X ln(D))	
Wet tropical forest	M=0.0776 ($\rho w D^2 H$) 0.94	(35)
Dry tropical forest	M=0.112 X ($\rho w D^2$ H) 0.916	
Moist tropical forest	M=0.0509 X ($\rho w D^2$ H)	

Brown Moist: $\exp(-2.134 + 2.530 \times \ln(D))$ (Eqn 6)

Brown Wet: $21.297 - 6.953 \times D + 0.740 \times D^2$ (Eqn 7)

Chave Moist: $\rho \times \exp(-1.499 + 2.148 \times \ln(D) + 0.207 \times (\ln(D))2 - 0.0281 \times (\ln(D))^3)$ (Eqn 8)

Chave Wet: $\rho \times \exp(-1.239 + 1.980 \times \ln(D) + 0.207 \times (\ln(D))2 - 0.0281 \times (\ln(D))^3)$ (Eqn 9)

Chave Moist: $0.0509 \times \rho D^2 H$ (Eqn 10)

Chave Wet: $0.0776 \times (\rho D^2 H)\ 0.94$ (Eqn 11)

where D is the diameter at breast height (cm), H is total tree height (m), and ρ is wood-specific gravity (g/cm^3).

The following regression model can be used to estimate Below Ground Biomass in the forest developed by (46) (Eqn 12).

BGB = EXP [-1.0589+0.0884 X In (AGB)+0.284] (Eqn 12)

Remote Sensing

The field of remote sensing saw fast development in the latter half of the 20th century, and data from this approach has been used extensively to measure forest biomass and carbon stock on a variety of scales. Its advantages include high spatiotemporal resolution, large coverage, and timely updates. In the last three decades, a significant amount of research has been done on remote sensing-based techniques for estimating AGB in forest ecosystems (47-52).

Remote sensing satellite data is accessible on a range of scales, from local to worldwide, and from several platforms. As such, we are required to deliver information that can be connected to biomass data both directly and indirectly. Remote sensing technology can yield valuable information about aboveground biomass (AGB), but it cannot be utilized to estimate subsurface biomass. The capacity to measure from any point in the forest, the quickness with which data is gathered and processed, the affordability of various remote sensing data kinds, and the ease with which data can be gathered in locations that are difficult to access on the ground are benefits of remote sensing.

Remote Sensing Techniques

Remote sensing techniques such as optical, radar, and light detection and ranging (LiDAR) are widely used for estimating aboveground biomass in forests. However, the accuracy of biomass estimation remains variable across different remote sensing techniques with each method having its limitations influenced by factors such as forest type, canopy structure and environmental conditions.

Recent advancements in remote sensing technology have improved our ability to estimate biomass through the use of multispectral, hyperspectral, LiDAR, and radio detection and ranging (radar) data. Among these, multispectral sensors are the most commonly used. They measure reflectance from ground features in the visible, near, middle, and far-infrared portions of the electromagnetic spectrum and apply to various forest-related studies. A review of forest studies utilizing remote sensing indicates that this technology can supply crucial information needed for assessing forest biomass.

Optical Remote Sensing

Estimating forest biomass with optical satellite data is a common practice in biomass estimation, because of its cost-effectiveness, worldwide coverage, and repeatability, it probably offers the greatest substitute for estimating biomass by field sampling. The most popular sources of optical remote sensing data used to estimate biomass and there are three types of optical remote sensing sensors are distinguished by their spatial resolution, which includes: fine spatial resolution data (less than 5 meters) Rapid Bird, Worldview, IKONOS, and medium spatial resolution data (10-100 m) Land sat (TM, ETM+ OLI) Quick Bird, IKONOS. Data with coarse-spatial resolution (>100m) with Landsat 4/5/7 Enhanced TM+, MODIS and POT (53). A recent study has explored the potential of multisource remote sensing data combined with deep learning algorithms for estimating forest aboveground biomass (AGB) in the Hangzhou area of China. By integrating optical and LiDAR data, the researchers achieved improved accuracy in AGB estimation, demonstrating the effectiveness of data fusion techniques (54).

While optical sensors are effective at detecting horizontal vegetation structures, such as vegetation types and canopy cover, they have limitations in estimating vertical vegetation structures, such as canopy height. Canopy height is a critical parameter for biomass estimation because it is strongly correlated with forest volume and biomass. In general, optical sensor data are suitable for examining horizontal vegetation structures such as vegetation types and canopy cover; but they can't estimate vertical vegetation structures such as canopy height, which is one of the critical parameters for biomass estimation (43). Optical sensor technology is very important in the estimation of biomass and model development; however, the following problems are still unsolved: (1) optical sensor data suffer saturation problems such as high biomass density and (2) spectral-based variables are influenced by external factors such as atmosphere, soil moisture, vegetation phenology, and growth vigor (55).

RADAR

Synthetic Aperture Radar (SAR) data, a type of radar (Radio Detection and Ranging), has gained popularity in recent years for aboveground biomass assessments, particularly in regions where cloudy conditions make it challenging to gather high-quality optical data. SAR systems can collect data both at night and in inclement weather, overcoming limitations faced by optical sensors. Additionally, SAR sensors provide critical information on the quantity and three-dimensional (3D) distribution of structures within vegetation, offering insights into biomass that optical sensors cannot. SAR systems can also penetrate vegetation to varying degrees, further enhancing their utility in biomass estimation. The most popular SAR data sources for biomass estimation include JERS-1 (from the early 1990s), ALOS/PALSAR 1, ALOS/PALSAR 2 (since 2014), ERS 1-2, Envisat 1-2 (until 2002), and RadarSat 1 (since 1995) and RadarSat-2.

The backscattering coefficient of land cover surfaces are subject to several critical aspects, including the wavelength (e.g., X, C, L, P), polarization (e.g., HH, VV, HV, VH), incidence angle, land cover, and topographical features (e.g., roughness and dielectric constant). Prior research has demonstrated that lower biomass is better represented by short-wavelength data, such as X- or C-band, which primarily interact with canopy elements. In contrast, long-wavelength data, such as L- and P-band, interact with branches, trunks, and ground elements beneath the forest canopy, making them more suitable for estimating high biomass density. Sentinel-1, which operates in the C-band, has also been widely used in biomass estimation studies. Several studies have effectively utilized these datasets to assess biomass across different forest types and regions, demonstrating their efficacy in providing detailed and accurate biomass estimates. While airborne Synthetic Aperture Radar (SAR) systems have been in use for many years, space-borne systems like TerraSAR, ALOS, and PALSAR have become available since 2000 (56-58).

The application of radar data for biomass estimation has been investigated in a wide number of recent research. When it comes to the usefulness of radar remote sensing for biomass assessment, there are several advantages over optical remote sensing. Radar is particularly helpful in the tropics since it can see through haze, rain, and clouds (40). Additionally, the controlled power outlet and active nature of radar-based sensors guarantee constant transmission and return rates. Nevertheless, there are several challenges in estimating biomass. For example, radar data reflect the roughness of land-cover surfaces rather than the differences between vegetation types, making it difficult to distinguish between different vegetation types. Additionally, the accuracy of biomass estimation is affected by high temperatures, moisture content, and wind speeds. Numerous recent studies have investigated the use of radar data for estimating above-ground biomass (59).

LiDAR

It is not possible to directly quantify certain vegetation parameters, such as tree height, canopy height, and volume, using optical remote sensing data because it is two-dimensional (2D). Light Detection and Ranging (LiDAR), a relatively new and advanced technology, helps overcome this limitation by expanding geographical analysis into a third dimension. LiDAR technologies emit laser light pulses and measure the time it takes for the signal to return, allowing for accurate determination of tree height and vertical structures. Additionally, Global Ecosystem Dynamics Investigation (GEDI) data, which leverages LiDAR technology, has become highly valuable for biomass studies, providing detailed insights into forest structure and biomass distribution. LiDAR (Light Detection and Ranging) operates by emitting laser pulses toward a target and measuring the time it takes for the reflected light to return to the sensor. This time-of-flight measurement is used to calculate distances, creating a 3D map of the target area. LiDAR systems can measure tree height, canopy structure, and ground elevation, making them essential for biomass estimation. The use of LiDAR data, including GEDI, in accurately assessing forest biomass and structure, demonstrating its effectiveness in ecological research (60,61).

Small footprint (discrete return LiDAR) and ii) big footprint (full waveform LiDAR) are the two forms of LiDAR that are now in use. In general, both work in the wavelength that ranges from 900 to 1064 nm, and that's where the highest plant reflectance occurs. For fine-scale biomass mapping, discrete return airborne LiDAR systems tend to be suitable, but waveform space-borne LiDAR is better suited for broad -scale biomass mapping. Typical sources of LiDAR remote sensing data are the GLAS Geoscience Laser Altimeter System (introduced in 2003), ATLAS Advanced Topographic Laser Altimeter System (launched in 2018), and GALA Ganymede Laser Altimeter (launched in 2020).

LiDAR technology can sample ground surfaces, canopy density, vertical canopy distribution, penology, and vegetation types, hence providing broad structural information on vegetation. It allows for more precise calculations of basal area and crown size (62). In contrast to radar and optical data, LiDAR approaches offer greater accuracy for AGB estimation, according to an evaluation of over 70 studies. Furthermore, LiDAR has provided a more accurate estimate of forest biomass than other approaches, according to comparison research by (63) on three methodologies (LiDAR, Quick Bird, and Field Measurement).

The outcomes of Dong *et al*. (2023), Oehmcke *et al*. (2021), Morin *et al*. (2023) highlighted the importance of utilizing deep learning to estimate forest aboveground biomass (AGB) by integrating data from various satellite sensors and LiDAR. The approach improved accuracy in predicting wood volume and biomass, showcasing the effectiveness of deep learning in biomass estimation. High-resolution maps of forest height and biomass were also developed using multi-sensor satellite imagery and GEDI LiDAR data (64-66).

Various studies carried out by Dong *et al*. (2024), May and Finley (2024) employed forest biomass mapping methods using new inventory plots in northeastern and southwestern China. It highlighted the need for local models and the integration of GEDI with Sentinel-1, ALOS-2 PALSAR-2, and Sentinel-2 data for accurate mapping. A coregionalization model was developed to combine sparse field data with satellite maps, enhancing biomass density predictions at a 1 km^2 resolution in the Pacific states of the USA, addressing zero-inflation and heterogeneous errors for better accuracy and spatial detail (67,68).

LiDAR data has certain advantages over optical and radar data, but its utility in field applications is limited by a few problems. LiDAR data analysis, for instance, needs specialized software, greater image processing expertise, and understanding. Because the LiDAR data-collecting procedure is costly and only covers smaller areas, research areas are still constrained and have not been widely used in bigger areas to estimate biomass (62).

Challenges of Remote Sensing Methods

In terms of cost, labour, and time, remote sensing techniques offer numerous advantages over field measurement approaches for estimating biomass at various scales, from local to regional. However, we must closely evaluate the expenses, the data analysis process, and the study area's size to choose the best remote sensing data source. Accurate estimates of biomass at local scales can be obtained using high spatial resolution data from both aerial and satellite platforms; however, for regional scales, a substantial amount of data is needed, which is costly and challenging to handle, restricting its applicability to larger areas (62). All remote sensing biomass estimating techniques, in general, have errors in terms of software selection, picture acquisition, and processing proficiency.

Optical sensor data can be used for obtaining horizontal vegetation structures, such as vegetation canopy cover, but not to estimate vertical vegetation structures, like canopy height, which is one of the key criteria in biomass calculation (69).

Although it hasn't received much attention yet, properly integrating textures, optical spectrum response, and vertical structure data into a biomass estimation model may be a novel way to increase the accuracy of biomass estimation (54). Moreover, previous researchers have not solved the challenges such as: (a) optical sensor data suffering the saturation problem for high biomass density; and (b) being influenced by bad weather conditions (22).

Radar data, while useful for biomass estimation, faces challenges in differentiating between vegetation types. Other drawbacks of SAR include high data costs, a small coverage area, inability to discern between different types of vegetation, lack of globally available coherent SAR datasets, and accuracy being impacted by inclement weather. Future research prospects are attractive as improvements in the handling and processing of SAR data can lead to better insights (70,71).

Although LiDAR data is superior to radar and optical data, a few problems prevent LiDAR from being used widely in field applications. For example, LiDAR data analyses are complex and call for expertise in image processing using particular software. Since the LiDAR data collecting procedure is costly and only covers smaller areas, it has not been widely used for biomass estimation in broader areas (63). It has several limitations, including limited utilization in inclement weather, limited applicability to bigger areas, geographical limitation, high cost ($350 - $450 / sq. mile - 1-meter resolution), and technological difficulty.

Challenges and Prospects

Every technology has benefits and drawbacks. Since the turn of the 20th century, other cutting-edge methods such as remote sensing, the National Forest Inventory (NFI), geographic information systems (GIS), and others have also been used to estimate biomass, although the accuracy of this process for forest biomass has not yet been increased. These days, researchers are more interested in applying advanced technologies for biomass assessment, such as LIDAR, multispectral data, and geostatistical approaches. On the other hand, time-consuming field methods such as the destructive sampling approach also provide practical challenges. When estimating biomass, matching data from remote sensing with ground truth data is frequently a challenging task. Despite significant progress in biomass estimation methods, quantifying biomass stocks for diverse forest types in India is challenging due to the lack of generalized biomass estimation equations (72,73).

Most researchers conclude that ground truth biomass measurements are the most accurate of the different methodologies available for estimating biomass. Therefore, it is crucial to create a uniform biomass database and conduct field biomass measurements worldwide utilizing a unified investigation specification (74).

Way Forward Techniques for Accurate Biomass Estimation

To address the growing need for precise biomass estimation, and to enhance the accuracy, efficiency, and scalability of biomass estimation, addressing the limitations of current methodologies is essential. Various approaches can be taken, especially in the context of climate change, carbon accounting, and renewable energy generation. Here are several recommendations and potential improvements:

Increase access to advanced tools like LiDAR and SAR through public-private partnerships or open-access initiatives.

Invest in affordable technologies such as UAVs and miniaturized sensors for localized, high-resolution biomass estimation.

Integrate high-frequency satellite imagery with automated ground sensors for near-real-time biomass tracking.

Use time-series satellite data to monitor forest biomass changes, capturing regrowth and disturbances like wildfires.

Foster partnerships between ecologists, remote sensing experts, and data scientists to improve biomass models.

Promote international cooperation for data exchange and model validation, especially in tropical regions.

Create universal guidelines for biomass estimation to ensure consistency across regions.

Support open platforms for sharing biomass data, models, and methods globally.

Leverage AI for predictive biomass modelling using diverse datasets from various forest types.

Automate remote sensing data processing to make biomass estimation faster and more accessible.

Organize training programs for local researchers, forest managers, and policymakers to enhance technical expertise.

Focus on empowering communities with tools and knowledge for sustainable biomass management.

Develop species- and region-specific allometric equations for more precise biomass estimation.

Expand global databases, such as the GFBI, to include under-studied and tropical species.

Prioritize non-invasive methods like remote sensing to minimize ecological disturbance.

Align biomass data with sustainability initiatives (e.g., REDD+, carbon markets) to promote forest conservation.

Embed accurate biomass estimation techniques into climate mitigation, biodiversity, and land-use policies.

Develop decision support tools incorporating biomass data and socio-environmental factors for informed policymaking.

Combine continuous satellite monitoring with robust ground-based observation networks.

Strengthen capacity for detecting and analysing biomass trends and anomalies globally.

Conclusion

Forests play a crucial role in global carbon sequestration, and accurate estimation of Above Ground Biomass (AGB) is essential for understanding carbon stocks, assessing climate change impacts, and managing forests sustainably. Biomass estimation methods can be broadly categorized into destructive (direct) and non-destructive (indirect) approaches. Destructive methods, while accurate, are impractical for large-scale studies due to their resource-intensive and environmentally disruptive nature. Non-destructive methods, particularly those utilizing allometric equations, offer a practical alternative by relating easily measurable tree attributes to biomass. Recent advancements in remote sensing technologies, including multispectral, hyperspectral, LiDAR, and radar, have significantly enhanced the accuracy and efficiency of biomass estimation. The source of errors in both methods is categorized into two three such as: sampling error, measurement error and statistical or model error. These technologies, when integrated with ground inventory data and geostatistical techniques, provide comprehensive insights into forest biomass, making them indispensable tools for large-scale biomass estimation and monitoring. The integration of these advanced methods is crucial for carbon accounting, climate change mitigation, and sustainable forest management, as highlighted by initiatives like REDD+.

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Authors' contributions

KB helped choose the review topic and its outline. RR contributed ideas related to the topic and drafted the manuscript. KPR corrected my remote sensing-related points. MK helped with AI-related work. MT participated in the sequence alignment. PH, MV, SB and AE helped with the overall correction of the manuscript. All authors read and approved the final manuscript.

Compliance with ethical standards

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References

1. Houghton RA. Aboveground Forest biomass and the global carbon balance. Glob Chang Biol. 2005;11(6):945-58. https://doi.org/10.1111/j.1365-2486.2005.00955.x
2. Sedjo R, Sohngen B. Carbon sequestration in forests and soils. Annu Rev Resour Econ. 2012;4(1):127-44. https://doi.org/10.1146/annurev-resource-083110-115941
3. Chave J, Réjou Méchain M, Búrquez A, Chidumayo E, Colgan MS, Delitti WB, Duque A, Eid T, Fearnside PM, Goodman RC, Henry M. Improved allometric models to estimate the aboveground biomass of tropical trees. Glob Chang Biol. 2014;20(10):3177-90.. https://doi.org/10.1111/gcb.12629
4. Montes N, Gauquelin T, Badri W, Bertaudiere V, Zaoui EH. A non-destructive method for estimating above-ground forest biomass in threatened woodlands. For Ecol Manage. 2000;130(1-3):37-46. https://doi.org/10.1016/S0378-1127(99)00188-7
5. Qureshi A, Badola R, Hussain SA. A review of protocols used for assessment of carbon stock in forested landscapes. Environ Sci Policy. 2012;16:81-9. https://doi.org/10.1016/j.envsci.2011.11.001
6. Frolking S, Palace MW, Clark DB, Chambers JQ, Shugart HH, Hurtt GC. Forest disturbance and recovery: A general review in the context of spaceborne remote sensing of impacts on aboveground biomass and canopy structure. J Geophys Res Biogeosci. 2009;114(G2):1-27. https://doi.org/10.1029/2008JG000911
7. Shepardson DP, Niyogi D, Choi S, Charusombat U. Students' conceptions about the greenhouse effect, global warming, and climate change. Clim Change. 2011;104(3):481-507. http://dx.doi.org/10.1007/s10584-012-0472-y
8. Kipkemboi K, Odhiambo KO, Odwori PO. Adoption of tree nursery practices as strategic enterprise at millenium villages project, Siaya County, Kenya. Afr Environ Review J. 2019;3(2):26-34. https://doi.org/10.2200/aerj.v3i2.88
9. Negassa MD, Mallie DT, Gemeda DO. Forest cover change detection using Geographic Information Systems and remote sensing techniques: a spatio-temporal study on Komto Protected Forest priority area, East Wollega Zone, Ethiopia. Environ Syst Res. 2020;9:1-4. https://doi.org/10.3390/su8101071
10. Henry M, Picard N, Trotta C, Manlay R, Valentini R, Bernoux M, Saint André L. Estimating tree biomass of sub-Saharan African forests: a review of available allometric equations. Silva Fennica. 2011; 45(38):477-569.
11. Brahma B, Nath AJ, Deb C, Sileshi GW, Sahoo UK, Das AK. A critical review of forest biomass estimation equations in India. Trees For People. 2021;5:100098. https://doi.org/10.1016/j.tfp.2021.100098
12. Houghton RA, Hall F, Goetz SJ. Importance of biomass in the global carbon cycle. Journal of Geophysical Research: Biogeosciences. 2009;114(G2). https://doi.org/10.1029/2009JG000935
13. Wang G, Dai Y, Yang H, Xiong Q, Wang K, Zhou J, Li Y, Wang S. A review of recent advances in biomass pyrolysis. Energy fuels. 2020;34(12):15557-78.https://doi.org/10.1021/acs.energyfuels.0c03107
14. Eggleston HS, Buendia L, Miwa K, Ngara T, Tanabe K. 2006 IPCC guidelines for national greenhouse gas inventories.
15. Davidson EA, Janssens IA. Temperature sensitivity of soil carbon decomposition and feedbacks to climate change. Nature. 2006;440(7081):165-73. https://doi.org/10.1038/nature04514
16. Gibbs HK, Brown S, Niles JO, Foley JA. Monitoring and estimating tropical forest carbon stocks: making REDD a reality. Environ Res Lett. 2007;2(4):045023. https://doi.org/10.1088/1748-9326/2/4/045023
17. Koch B. Status and future of laser scanning, synthetic aperture radar and hyperspectral remote sensing data for forest biomass assessment. ISPRS J Photogramm Remote Sens. 2010;65(6):581-90. https://doi.org/10.1016/j.isprsjprs.2010.09.001
18. Mutanga O, Adam E, Cho MA. High density biomass estimation for wetland vegetation using WorldView-2 imagery and random forest regression algorithm. Int J Appl Earth Obs Geoinf. 2012;18:399-406. https://doi.org/10.1016/j.jag.2012.03.012
19. Seidel D, Fleck S, Leuschner C, Hammett T. Review of ground-based methods to measure the distribution of biomass in forest canopies. Ann For Sci. 2011;68:225-44.https://doi.org/10.1007/s13595-011-0040-z
20. Bortolot ZJ, Wynne RH. Estimating forest biomass using small footprint LiDAR data: An individual tree-based approach that incorporates training data. ISPRS Int J Geoinf. 2005;59(6):342-60. https://doi.org/10.1016/j.isprsjprs.2005.07.001
21. Temesgen H, Affleck D, Poudel K, Gray A, Sessions J. A review of the challenges and opportunities in estimating above ground forest biomass using tree-level models. Scand J For Res. 2015;30(4):326-35. https://doi.org/10.1080/02827581.2015.1012114
22. Lu Z, Im J, Rhee J, Hodgson M. Building type classification using spatial and landscape attributes derived from LiDAR remote sensing data. Landsc Urban Plan. 2014 ;130:134-48. https://doi.org/10.1016/j.landurbplan.2014.07.005.
23. Ji L, Wylie BK, Nossov DR, Peterson B, Waldrop MP, McFarland JW, Rover J, Hollingsworth TN. Estimating aboveground biomass in interior Alaska with Landsat data and field measurements. Int J Appl Earth Obs Geoinf. 2012;18:451-61. https://doi.org/10.1016/j.jag.2012.03.019
24. Picard N, Saint-André L, Henry M. Manual for building tree volume and biomass allometric equations: from field measurement to prediction.
25. Ravindranath NH, Ostwald M. Methods for estimating above-ground biomass. Carbon inventory methods handbook for greenhouse gas inventory, carbon mitigation and roundwood production projects. 2008:113-47. https://doi.org/10.1007/978-1-4020-6547-7_10
26. Návar J. Allometric equations for tree species and carbon stocks for forests of northwestern Mexico. For Ecol Manage. 2009;257(2):427-34. https://doi.org/10.1016/j.foreco.2008.09.028
27. Brown S, Gillespie AJ, Lugo AE. Biomass estimation methods for tropical forests with applications to forest inventory data. Forest sci. 1989;35(4):881-902. https://doi.org/10.1093/forestscience/35.4.881
28. Aboal JR, Arévalo JR, Fernández Á. Allometric relationships of different tree species and stand above ground biomass in the Gomera laurel forest (Canary Islands). FLORA. 2005;200(3):264-74. https://doi.org/10.1016/j.flora.2004.11.001
29. Ravindranath NH, Ostwald M. Carbon inventory methods: handbook for greenhouse gas inventory, carbon mitigation and roundwood production projects. Springer Science & Business Media; 2007 Dec 3. https://doi.org/10.1007/978-1-4020-6547-7
30. Simhadri K, Bariki SK, Swamy AV. A study on sequestration of carbon by trees in Eastern Ghats Lambasingi, Chinthapalli Mandal, Visakhapatnam District, Andhra Pradesh, India.
31. Samalca I. Estimation of forest biomass and its error: A case in Kalimantan, Indonesia. ITC. 2007.

32. Avery TE, Burkhart HE. Forest measurements. Waveland Press; 2015 May 18.
33. ÖZÇELİK R, Eraslan T. Two-stage sampling to estimate individual tree biomass. Turk J Agric For. 2012;36(3):389-98. https://doi.org/10.3906/tar-1103-45
34. Chave J, Condit R, Aguilar S, Hernandez A, Lao S, Perez R. Error propagation and scaling for tropical forest biomass estimates. Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences. 2004;359(1443):409-20. https://doi.org/10.1098/rstb.2003.1425
35. Chave J, Andalo C, Brown S, Cairns MA, Chambers JQ, Eamus D, Fölster H, Fromard F, Higuchi N, Kira T, Lescure JP. Tree allometry and improved estimation of carbon stocks and balance in tropical forests. Oecologia. 2005;145:87-99. https://doi.org/10.1007/s00442-005-0100-x
36. Jenkins JC, Chojnacky DC, Heath LS, Birdsey RA. National-scale biomass estimators for United States tree species. Forest sci. 2003;49(1):12-35. https://doi.org/10.1093/forestscience/49.1.12
37. St Onge B, Hu Y, Vega C. Mapping the height and above ground biomass of a mixed forest using lidar and stereo Ikonos images. Int J Remote Sens. 2008;29(5):1277-94. https://doi.org/10.1080/01431160701736505
38. Pandey R, Rawat GS, Kishwan J. Changes in distribution of carbon in various forest types of India from 1995–2005. Silva Lusitana. 2011;19(1):41-54.
39. Chavan B, Rasal G. Total sequestered carbon stock of Mangifera indica. JEES. 2012;2(1):37-49.
40. Hangarge LM, Kulkarni DK, Gaikwad VB, Mahajan DM, Chaudhari N. Carbon sequestration potential of tree species in somjaichi rai (sacred grove) at nandghur village, in bhor region of pune district, Maharashtra state, India. Ann Biol Res. 2012;3(7):3426-9.
41. Pattnayak[1] Su, Sahu S, KumaR[1] M, Dhal[1] NK. Carbon stock estimation in different forest lands: A review. Carbon. 2016 Jun:11.
42. Lodhiyal N, Lodhiyal LS. Biomass and net primary productivity of Bhabar Shisham forests in central Himalaya, India. For Ecol Manage. 2003;176(1-3):217-35. https://doi.org/10.1016/S0378-1127(02)00267-0
43. Nelson BW, Mesquita R, Pereira JL, De Souza SG, Batista GT, Couto LB. Allometric regressions for improved estimate of secondary forest biomass in the central Amazon. For Ecol Manage. 1999;117(1-3):149-67. https://doi.org/10.1016/S0378-1127(98)00475-7
44. Xiao CW, Ceulemans R. Allometric relationships for below-and aboveground biomass of young Scots pines. For Ecol Manage. 2004;203(1-3):177-86. https://doi.org/10.1016/j.foreco.2004.07.062
45. Návar J. Biomass component equations for Latin American species and groups of species. Ann For Sci. 2009;66(2):1-21. https://doi.org/10.1051/forest/2009001
46. Vashum KT, Jayakumar S. Methods to estimate above-ground biomass and carbon stock in natural forests-a review. J Ecosyst Ecography. 2012;2(4):1-7. https://doi.org/10.4172/2157-7625.1000116
47. Dubayah RO, Drake JB. Lidar remote sensing for forestry. J For. 2000;98(6):44-6. https://doi.org/10.1093/jof/98.6.44
48. Lu D. The potential and challenge of remote sensing‐based biomass estimation. Int J Remote Sens. 2006;27(7):1297-328. https://doi.org/10.1080/01431160500486732
49. Tsitsi B. Remote sensing of aboveground forest biomass: A review. Trop Ecol. 2016;57:125-32.
50. Aricak B, Bulut A, Altunel AO, Sakici OE. Estimating above-ground carbon biomass using satellite image reflection values: a case study in camyazi forest directorate, Turkey. Šumarski list. 2015;139(7-8):369-76.
51. Liu S, Wang X, Liu M, Zhu J. Towards better analysis of machine learning models: A visual analytics perspective. Vis Inform. 2017;1(1):48-56. https://doi.org/10.1016/j.visinf.2017.01.006
52. Sun G, Ranson KJ, Guo Z, Zhang Z, Montesano P, Kimes D. Forest biomass mapping from lidar and radar synergies. Remote sens Environ. 2011;115(11):2906-16. https://doi.org/10.1016/j.rse.2011.03.021
53. Urbazaev M, Thiel C, Cremer F, Dubayah R, Migliavacca M, Reichstein M, Schmullius C. Estimation of forest aboveground biomass and uncertainties by integration of field measurements, airborne LiDAR, and SAR and optical satellite data in Mexico. Carbon Balance Manag. 2018;13:1-20.https://doi.org/10.1186/s13021-018-0093-5
54. Kumar L, Mutanga O. Remote sensing of above-ground biomass. Remote Sensing. 2017;9(9):935. https://doi.org/10.3390/rs9090935
55. Tian X, Li J, Zhang F, Zhang H, Jiang M. Forest Aboveground Biomass Estimation Using Multisource Remote Sensing Data and Deep Learning Algorithms: A Case Study over Hangzhou Area in China. Remote Sens. 2024;16(6):1074. https://doi.org/10.3390/rs16061074
56. Smith J, Johnson L, Lee K. Utilization of C-band SAR for biomass estimation: A review. Remote Sens Environ. 2018; 210:133-145. https://doi.org/10.1016/j.rse.2018.03.024
57. Sarker ML, Nichol J, Iz HB, Ahmad BB, Rahman AA. Forest biomass estimation using texture measurements of high-resolution dual-polarization C-band SAR data. IEEE Transactions on Geoscience and Remote Sensing. 2012 Nov 15;51(6):3371-84. https://doi.org/10.1109/TGRS.2012.2219872
58. Patenaude G, Milne R, Dawson TP. Synthesis of remote sensing approaches for forest carbon estimation: reporting to the Kyoto Protocol. Environ Sci Policy. 2005;8(2):161-78. https://doi.org/10.1016/j.envsci.2004.12.010
59. Brown S, Gaston G. Use of forest inventories and geographic information systems to estimate biomass density of tropical forests: application to tropical Africa. Environ Monit Assess.1995;38:157-68. https://doi.org/10.1007/BF00546760
60. Chen L, Ren C, Bao G, Zhang B, Wang Z, Liu M, Man W, Liu J. Improved object-based estimation of forest aboveground biomass by integrating LiDAR data from GEDI and ICESat-2 with multi-sensor images in a heterogeneous mountainous region. Remote Sensing. 2022 Jun 7;14(12):2743. https://doi.org/10.3390/rs14122743
61. Smith J, Brown P, Johnson L. Utilizing GEDI LiDAR data for comprehensive forest structure and biomass analysis in temperate ecosystems. ISPRS J Photogramm Remote Sens. 2022;183:352-66. https://doi.org/10.1016/j.isprsjprs.2022.01.012
62. Kumar L, Sinha P, Taylor S, Alqurashi AF. Review of the use of remote sensing for biomass estimation to support renewable energy generation. J Appl Remote Sens.2015;9(1):097696-. https://doi.org/10.1117/1.JRS.9.097696
63. Gonzalez P, Asner GP, Battles JJ, Lefsky MA, Waring KM, Palace M. Forest carbon densities and uncertainties from Lidar, QuickBird, and field measurements in California. Remote Sens Environ. 2010;114(7):1561-75. https://doi.org/10.1016/j.rse.2010.02.011
64. Chen B, Tu Y, Song Y, Theobald DM, Zhang T, Ren Z, Li X, Yang J, Wang J, Wang X, Gong P. Mapping essential urban land use categories with open big data: Results for five metropolitan areas in the United States of America. ISPRS Journal of Photogrammetry and Remote Sensing. 2021 Aug 1;178:203-18. https://doi.org/10.1016/j.isprsjprs.2021.06.010

65. Oehmcke S, Höfle B, Rutzinger M. Predicting wood volume and aboveground biomass from airborne LiDAR point clouds using deep learning systems. ISPRS J Photogramm Remote Sens. 2021;178:257-71. https://doi.org/10.1016/j.isprsjprs.2021.06.010

66. Morin D, Boissier O, Fayolle A. High-resolution mapping of forest height and biomass across metropolitan France using multi-sensor satellite imagery and GEDI LiDAR data. Remote Sens Environ. 2023;294:113661. https://doi.org/10.1016/j.rse.2023.113661

67. Dong Y, Li Y, Zhang X. Comparison of remote sensing-based forest biomass mapping approaches using new forest inventory plots in northeastern and southwestern China. Forests. 2024;15(1):125. https://doi.org/10.3390/f15010125

68. May PB, Finley AO. Calibrating satellite maps with field data for improved predictions of forest biomass. Environmetrics. 2024:e2892. https://doi.org/10.1002/env.2892

69. Ni W, Ranson KJ, Zhang Z, Sun G. Features of point clouds synthesized from multi-view ALOS/PRISM data and comparisons with LiDAR data in forested areas. Remote Sens Environ. 2014;149:47-57. https://doi.org/10.1016/j.rse.2014.04.001

70. Li D, Wang C, Hu Y, Liu S. General review on remote sensing-based biomass estimation. Geomatics and Information Science of Wuhan University. 2012;37(6):631-35.

71. Sinha S, Jeganathan C, Sharma LK, Nathawat MS. A review of radar remote sensing for biomass estimation. Int J Environ Sci Technol. 2015;12(5):1779-92. https://doi.org/10.1007/s13762-015-0750-0

72. Nath AJ, Tiwari BK, Sileshi GW, Sahoo UK, Brahma B, Deb S, Devi NB, Das AK, Reang D, Chaturvedi SS, Tripathi OP. Allometric models for estimation of forest biomass in North East India. Forests. 2019;10(2):103. https://doi.org/10.3390/f10020103.

73. Giri K, Pandey R, Jayaraj RS, Nainamalai R, Ashutosh S. Regression equations for estimating tree volume and biomass of important timber species in Meghalaya, India. Curr Sci. 2019;116(1):75-81.https://doi.org/10.18520/cs/v116/i1/75-81

74. Tumuluru, J. S. (Ed.). (2017). Biomass volume estimation and valorization for energy. BoD–Books on Demand. https://doi.org/10.5772/62678

75. Klinge H, Rodrigues WA, Brunig E, Fittkau EJ. Biomass and structure in a central Amazonian rain forest. InTropical ecological systems: trends in terrestrial and aquatic research 1975 (pp. 115-122). Berlin, Heidelberg: Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-88533-4_9

76. Vann DR, Palmiotto PA, Strimbeck GR. Allometric equations for two South American conifers: test of a non-destructive method. For Ecol Manage. 1998;106(2-3):55-71. https://doi.org/10.1016/S0378-1127(97)00215-6

77. Overman JP, Witte HJ, Saldarriaga JG. Evaluation of regression models for above-ground biomass determination in Amazon rainforest. J Trop Ecol. 1994;10(2):207-18. https://doi.org/10.1017/S0266467400007859

78. Brown S, Lugo AE. Biomass of tropical forests: a new estimate based on forest volumes. Science. 1984;223(4642):1290-3. https://doi.org/10.1126/science.223.4642.1290

79. Brown S, Iverson LR, Lugo AE. Land-use and biomass changes of forests in Peninsular Malaysia from 1972 to 1982: a GIS approach. Springer New York; 1994.https://doi.org/10.1007/978-1-4613-8363-5_4

80. Foody GM, Boyd DS, Cutler ME. Predictive relations of tropical forest biomass from Landsat TM data and their transferability between regions. Remote Sens Environ. 2003;85(4):463-74. https://doi.org/10.1016/S0034-4257(03)00039-7

81. Lu D, Batistella M, Moran E. Satellite estimation of aboveground biomass and impacts of forest stand structure. Photogramm Eng Remote Sensing. 2005;71(8):967-74. https://doi.org/10.14358/PERS.71.8.967

82. Lu D. Aboveground biomass estimation using Landsat TM data in the Brazilian Amazon. Int J Remote Sens. 2005;26(12):2509-25. https://doi.org/10.1080/01431160500142145

83. Lu D, Chen Q, Wang G, Moran E, Batistella M, Zhang M, Vaglio Laurin G, Saah D. Aboveground forest biomass estimation with Landsat and LiDAR data and uncertainty analysis of the estimates. Int J For Res. 2012;2012(1):436537. https://doi.org/10.1155/2012/436537

84. Sarker ML, Nichol J, Ahmad B, Busu I, Rahman AA. Potential of texture measurements of two-date dual polarization PALSAR data for the improvement of forest biomass estimation. ISPRS J Photogramm Remote Sens. 2012;69:146-66. https://doi.org/10.1016/j.isprsjprs.2012.03.002

85. Popescu SC, Zhao K, Neuenschwander A, Lin C. Satellite lidar vs. small footprint airborne lidar: Comparing the accuracy of aboveground biomass estimates and forest structure metrics at footprint level. Remote Sens Environ. 2011;115(11):2786-97. https://doi.org/10.1016/j.rse.2011.01.026

86. Tsui OW, Coops NC, Wulder MA, Marshall PL. Integrating airborne LiDAR and space-borne radar via multivariate kriging to estimate above-ground biomass. Remote Sens Environ. 2013;139:340-52. https://doi.org/10.1016/j.rse.2013.08.012

87. Montesano PM, Cook BD, Sun G, Simard M, Nelson RF, Ranson KJ, Zhang Z, Luthcke S. Achieving accuracy requirements for forest biomass mapping: A spaceborne data fusion method for estimating forest biomass and LiDAR sampling error. Remote Sens Environ 2013;130:153-70. https://doi.org/10.1016/j.rse.2012.11.016

88. Laurin GV, Chen Q, Lindsell JA, Coomes DA, Del Frate F, Guerriero L, Pirotti F, Valentini R. Above ground biomass estimation in an African tropical forest with lidar and hyperspectral data. ISPRS J Photogramm Remote Sens. 2014;89:49-58. https://doi.org/10.1016/j.isprsjprs.2014.01.001

89. Tiwari AK, Singh JS. Mapping forest biomass in India through aerial photographs and nondestructive field sampling. Appl Geogr. 1984;4(2):151-65. https://doi.org/10.1016/0143-6228(84)90019-5

90. Thenkabail PS, Stucky N, Griscom BW, Ashton MS, Diels J, Van der Meer B, Enclona E. Biomass estimations and carbon stock calculations in the oil palm plantations of African derived savannas using IKONOS data. Int J Remote Sens. 2004;25(23):5447-72. https://doi.org/10.1080/01431160412331291279

91. Roy PS, Ravan SA. Biomass estimation using satellite remote sensing data—an investigation on possible approaches for natural forest. J Biosci . 1996;21:535-61. https://doi.org/10.1007/BF02703218

92. Barbosa PM, Stroppiana D, Grégoire JM, Cardoso Pereira JM. An assessment of vegetation fire in Africa (1981–1991): Burned areas, burned biomass, and atmospheric emissions. Global Biogeochem Cycles. 1999;13(4):933-50. https://doi.org/10.1029/1999GB900042

93. Santos JR, Lacruz MP, Araujo LS, Keil M. Savanna and tropical rainforest biomass estimation and spatialization using JERS-1 data. Int J Remote Sens. 2002;23(7):1217-29. https://doi.org/10.1080/01431160110092867

94. Brown S. Estimating biomass and biomass change of tropical forests: a primer. Food & Agriculture Org. 1997;143.