International Journal of Science and Research (IJSR)
ISSN: 2319-7064
SJIF (2019): 7.583

Application of Remote Sensing for Above-Ground Biomass Estimation

Harsimran Singh Sodhi

Forest Research Institute, Dehradun, Uttarakhand, India
Email: *harsimransodhi94[at]gmail.com*

Abstract: ***Forests are considered carbon reservoirs and plays a critical role in modeling carbon balance. The total amount of above-ground and below-ground organic matter of plant parts is called biomass. The forest aboveground biomass (AGB) estimation is important for climate change mitigation programs. Remote sensing (RS) based AGB estimation methods have gained importance and substantial research has been conducted in the past thirty years. This review paper provides a survey of aboveground biomass estimation methods using RS and demonstrates the benefits of RS over traditional methods. Optical data, Radio Detection and Ranging (RADAR), and Light Detection and Ranging (LIDAR) systems are the primary sources for AGB estimation. The literature review demonstrates the importance of biomass, description of various methods used for above-ground biomass estimation, and also reviews various attempts made by Indian researchers for estimating aboveground biomass using RS. This review has indicated the limitations of using single sensor data and the importance of integrating multi-sensor data to produce accurate results. More research is needed to reduce the data saturation problem through the use of advanced image processing technologies.***

Keywords: aboveground biomass; LIDAR; Optical; RADAR; remote sensing.

1. Introduction

The rapid rates of deforestation and industrialization in recent years have led to a sudden increase in carbon dioxide (CO_2) in the atmosphere from the preindustrial era. Different ecosystems act as carbon(C) sinks and absorb CO_2 in varying capacities. Currently, Earth's CO_2 level is 415ppm which surpassed the dangerous critical threshold of 400ppm, in comparison to the safe level of 350ppm (Sinha et al. 2020; Raha et al. 2020). Forests are a significant source of carbon sink on Earth as 80% of the terrestrial aboveground C stocks are contained in them, and also exchange large quantities of C with the atmosphere through respiration and photosynthesis playing a crucial role in the global carbon cycle (Rajashekar et al. 2018). Biomass and C stocks in forests vary with forest type, age, canopy cover, stand structure, and altitude (Srinivas and Sundarapandian 2019; Raha et al. 2020). Therefore, forest biomass is considered as a complex property that is influenced by forest structure, distribution, ecological processes, composition, and architectural attributes (Raha et al. 2020).

Quantification of forest aboveground biomass (AGB) is important for carbon flux monitoring, carbon budget accounting, and supporting climate change modeling studies (Zhu and Liu 2015; Dang et al. 2019). The frequently used methods for estimating forest aboveground biomass are through the use of field plots (Zhu and Liu 2015). The accurate method to calculate AGB is based on field measurements, but the collection of field data is labor-intensive and time-consuming (Lu et al. 2016). Alternatively, non-destructive allometric equations can be used to accurately estimate forest biomass, because once the equations have been developed, it is possible to investigate large study regions, and disturbances like the destruction of a forest stand are avoided (Kenzo et al. 2009). Apart from the traditional methods of aboveground biomass estimation, remote sensing based methods have extensively been used due to their comprehensive temporal and spatial coverage, and time and cost-effectiveness (Nandy et al. 2017). Field inventory data integrated with remote sensing data have been extensively used for estimating forest biomass (Muukkonen and Heiskanen 2005; Hu et al. 2016; Su et al. 2016). The United Nations collaborative program on REDD has also recommended that there should be the use of RS technology in national forest monitoring systems for conducting an inventory to monitor forest cover, evaluate forest carbon reference, and assess forest degradation (Dang et al. 2019). By linking field inventory data, forest biomass can be estimated from RS datasets using statistical models. Generally, optical remote sensing [e.g., Landsat Thematic Mapper (TM) and Moderate Resolution Imaging Spectroradiometer (MODIS)] and radar techniques have become principal data sources for estimating AGB, because of their availability (Su et al. 2016). At a global level mapping, the medium and coarse resolution optical sensors, such as MODIS and NOAA AVHRR, are mostly used due to their frequent temporal coverage, while finer resolution instruments, such as ASTER, SPOT, and Landsat sensors are required for quantifying change at local to the regional level (Muukkonen and Heiskanen 2005).

2. The Biomass

Biomass is produced by green plants through the process of photosynthesis. Humans have exploited the energy stored in the biomass, by burning it as a fuel (McKendry 2002). Biomass energy generates less pollution than fossil fuels (such as coal, petrol), decreases dependence on foreign oil, reduces waste material, and creates employment opportunities (Demirbas 2004). Biomass consists of the aboveground and below ground living mass (trees, shrubs, and roots) and the dead mass of litter (Lu 2006). AGB is a crucial indicator of carbon storage and forest productivity (Calders et al. 2015).

Above ground biomass is an important aspect of carbon stocks and carbon sequestration studies on the global level.

Estimation of the AGB is useful for comparing functional and structural attributes of forest (Mani and Parthasarathy 2007).

The biomass determines the C that will be released in the atmosphere in the form of carbon monoxide (CO) and carbon dioxide (CO_2). The term carbon and biomass are used in similar meanings for biomass studies as half the amount of biomass is approximately equal to the carbon (Yaklaşımlar 2012).

3. Remote sensing based approaches for the estimation of aboveground biomass

In 1930s preliminary studies on biomass were conducted to estimate AGB by tree species. Harvest methods were used in these studies which included harvesting the trees and weighing them after oven drying. This type of method becomes difficult if below-ground biomass is included and could overestimate biomass density if they include large trees. Generally, the harvest method is not practical in high biomass density areas, and repeating these measurements is not feasible. To solve these problems, researchers have developed indirect methods of biomass estimation.

The application of remote sensing is a cost-effective and practical approach to analyze data over large areas (Yaklaşımlar 2012). The terrestrial ecosystem of India is broadly studied for estimation of point biomass and productivity but the application of these observations has limitations using conventional methods (Roy and Ravan 1996). Observations of vegetation through satellite provide worldwide coverage with a high spatial resolution (Dong et al. 2003). Remote sensing technology enables rapid assessment of aboveground biomass at low cost (Kumar et al. 2015).

For biomass estimation, remote sensing technologies can be classified into three: Optical, RADAR, and LIDAR.

3.1. Optical system

Two-dimensional representation of land surface vegetation is provided by optical remote sensors and its reflectance properties are indirectly related to biophysical parameters (Fatoyinbo 2012). Optical sensor data is sufficient for the estimation of horizontal vegetation structures such as canopy cover and vegetation types, but it is not relevant for the estimation of vertical vegetation structures (Lu et al. 2016). Medium to high spatial resolution optical data is useful for studies at local to regional scale, while medium to coarse resolution data provides information on a regional to continental scale (Eisfelder et al. 2012). These optical sensors depend on sunlight as the light source and measure the amount of sunlight reflected by the crop. The reflectance properties of plants are related to the physiological status and growth of the crop (Erdle et al. 2011).

3.2. RADAR systems

Synthetic aperture radar (SAR) sensors are the active sensors, sending microwave radiation, and detecting the backscatter radiation by the surface (Mitchard et al. 2009). RADAR data is widely used in the estimation of forest stand parameters as they can operate day and night and record backscattering from the upper canopy and woody biomass component of the forest (Yaklaşımlar 2012). Based on the backscattering amplitude, the regression technique and the interferometry technique are commonly used in biomass estimation (Lu et al. 2016).

In general, the RADAR transmitted energy at low frequency in the form of electromagnetic wave, penetrates the forest canopy and is reflected from forest components like foliage, branches, stems, and soil. Knowing the value of transmitted and received energy, a relationship has been developed so that the ratio of these energies is related to properties of the forest (Saatchi et al. 2011). SAR data is obtained in X, C, L, and P bands. To extract details about the surface layer of trees X band is suitable as it is scattered by leaves and canopy cover surface. The C band penetrates through leaves and is scattered by small branches and lower layer elements. The L band is scattered by the trunk and main branches. The P band penetrates canopy cover and greater part backscattering of P band is caused by trunk and ground. For aboveground biomass estimation SAR L band data have been proven valuable (Yaklaşımlar 2012).

An important parameter of the SAR data is the polarization of the SAR signals. The polarization of electromagnetic waves depends upon the interaction between signals and reflectors. Most of the microwave sensors emit signals in horizontal or vertical polarization. The SAR data may have four polarizations: HH, HV, VH, VV. HV polarization is most sensitive to aboveground biomass estimation (Sinha et al. 2015).

In the RADAR data saturation problem is also common. The saturation level depends upon polarization, wavelengths, ground conditions, and characteristics of vegetation stand structure. L-band backscatter is suitable in tropical regions for estimating biomass of regenerating forests (Lu 2006).

For distinguishing vegetation types it is difficult to use radar data because it reflects roughness of land surface instead of distinction between vegetation types. Another problem is speckle in radar data. Proper employing filtering methods to lessen outliers and noise in Interferometric Synthetic Aperture Radar (InSAR) data are required to improve performance in vegetation height estimation, (Lu et al. 2016).

3.3. LIDAR systems

LIDAR is an active RS technology (Lim et al. 2003). The instrument positioned on a platform emits laser pulses towards a target for example woodland (Fatoyinbo 2012) and measures reflected energy and time difference between pulse emission and reception (Yaklaşımlar 2012). The LIDAR ‘footprint’ is the area illuminated by the laser pulse and the size of the footprint is determined by laser divergence and distance from the target of the LIDAR system. Interactions of laser pulse with vegetation are depended upon the wavelength of emitted pulse, reflectance, transmittance, rates of absorption for each foliage, bark, and background type (Fatoyinbo 2012).

Paper ID: SR21403150310 DOI: 10.21275/SR21403150310

LIDAR systems can be divided into two: discreet return and full-waveform systems (Laurin et al. 2014). The difference between the full-waveform and discrete return systems is that former records the entire backscattered signal which is above noise threshold while the latter records first and last returns or sometimes, several intermediate points (Rosette et al. 2012). The discreet return system evaluates the distance between the target and the sensor while the Full-waveform system records the shape and intensity of the pulse reflected from targets, which allows retrieval of the three-dimensional distribution of tree canopy (Yang et al. 2013).

The investigation of full-waveform data has improved enhanced point extraction, height estimations, and additional target information. The full-waveform LIDAR system has also been used in forestries such as single tree detection, estimation of forest structure characteristics, and tree species classification (Cao et al. 2014). The laser penetration indices that are derived from discreet-return LIDAR data are frequently used to estimate biomass of forest but the disadvantage of the discreet-return LIDAR system is that they record several limited returns, so canopy cover cannot be determined accurately (Nie et al. 2017).

4. The current state of remote sensing applications for aboveground biomass estimation in India.

Several methods have been used for the estimation of forest biomass such as by harvest method, by using allometric equations. This section elaborates on the various attempts made by Indian researchers for estimating aboveground biomass using remote sensing. The various available literature on biomass estimation is also summarised in table 1.

Madugundu et al. (2008) demonstrated the potential of the IRS P6 LISS-IV sensor for the aboveground biomass (AGB) estimation. They conducted their study in Haliyal and Yellapur forest divisions, Western Ghats of Karnataka, India. In their study, they derive regression equations describing the relationship between Normalized Difference Vegetation Index (NDVI) and Estimated Leaf Area Index (ELAI) and Estimated aboveground biomass (EAGB). Based on a regression equation between NDVI and ELAI remote sensing data based Predicted Leaf Area Index (PLAI) was generated. Further, the Predicted Aboveground Biomass (PAGB) image was generated based on the regression equation between PLAI and EAGB.

Bijalwan et al. (2010) conducted a study in the Raipur district of Chhattisgarh to characterize carbon status and land use of the tropical forest using GIS (Geographic Information System) and RS techniques. The highest AGB was found in the mixed forest and lowest in degraded forests.

Suresh et al. (2014) used ALOS PALSAR data along with field inventory data to estimate aboveground biomass over Odisha state, India. They used linear regression models by using log transformations of field biomass data for establishing a relationship between the backscattering coefficient of ALOS PALSAR and field AGB.

Yadav and Nandy (2015) attempted to map aboveground woody biomass (AGWB) using forest inventory, remote sensing, and geostatistical techniques. The study was conducted in the Bhabar-dun sal forest (Uttarakhand, India). IRS P6 LISS-III satellite data (December 1, 2012) was used. The study compared geostatistical techniques that are Direct Radiometric Relationships (DRR), CoKriging (CoK), and K-Nearest Neighbour (k-NN). For DRR, the spectral bands and vegetation indices (independent variables) were regressed with AGWB values (dependent variable). Using the best relationship between independent variables and dependent variables a biomass map was generated. For the k-NN technique, the same variables were used to create a biomass map using k-NN Forest software. For CoK Gaussian, exponential and circular semivariograms were examined for the best fit. The k-NN method with Mahalanobis distance was considered to be the best technique for biomass mapping.

Thumaty et al. (2016) used ALOS PALSAR L-Band data to estimate AGB for Central Indian Deciduous Forests. The study was conducted in Madhya Pradesh, India. The data of 415 sampling plots was used which was collected over the study area during 2009-2010. By using volume equations plot-level AGB estimates were computed using field inventory data. The plot-level aboveground biomass estimates were modeled with PALSAR backscatter information in HV, HH. The total AGB of the study area was estimated to be 367.4Mt.

Nandy et al. (2017) estimated forest biomass by integrating field inventory data and RS satellite data using an artificial neural network (ANN) technique. For field data collection stratified random sampling was adopted to lay out sample plots in different strata. The volume of trees in the plots was calculated using species-specific volumetric equations developed by Forest Survey of India (FSI) for the same locality. The AGB was calculated by multiplying volume by specific gravity and biomass expansion factor (BEF). Multivariable linear regression (MLR) was carried out with top texture and spectral variables for estimating biomass.

Reddy et al. (2017) estimated AGB using texture derived information from IRS Cartosat-1 data in the evergreen forests of Western Ghats. In their study, plot-level estimated aboveground biomass from 15 plots was used to relate with texture derived metrics from IRS Cartosat-1 data. Using Cartosat-F (viewing angle = 26^{o}) imagery the effect of viewing geometry on the relationship was measured.

Sivasankar et al. (2018) used SAR data from Sentinel-1 and ALOS-2/PALSAR data for biomass estimation. The field data collected from the Environment department and Meghalaya Forest was used in the study. Tree volume was calculated using species-specific volumetric equations and biomass was estimated by multiplying volume with specific gravity. Regression analysis was executed between aboveground biomass and backscattering coefficients of L-band and C-band separately.

Paper ID: SR21403150310 DOI: 10.21275/SR21403150310

Table 1: A brief description for selected research in India for estimation of AGB using remote sensing

Study region	Use of remote sensing data	Methodology	Reference
Haliyal and Yellapur Forest divisions in Western Ghats (Karnataka)	IRS P6 LISS-IV	1) In the study area 30 plots were distributed using the randomizer function of ERDAS Imagine software and in each plot, all adult trees were measured for girth at breast height (GBH), 2) The allometric regression model (Murali et al. 2005) was used for EAGB estimation, 3) IRS P6 LISS-IV image processing, 4) All 8 vegetation classes were delineated based on their spectral signature, 5) Integration of EAGB and RS based PLAI.	Madugundu et al.(2008)
Balamadi watershed (part of Barnawapara sanctuary, Raipur districts in Chattisgarh)	IRS 1D LISSIII	1) Delineation of vegetation types and different land use by digitally analyzing RS satellite data, 2) Generation of NDVI map and color-coded map, 3) Preparation of contour and drainage maps, 4) Laying of sample plots in different forest types using a stratified random sampling approach, 5) Use of species-specific volume equations published by Forest Survey of India (FSI), 6) Volume of every tree in each quadrat was multiplied with its mean density to obtain stem biomass, which was further multiplied with biomass expansion factor to obtain AGB.	Bijalwan et al.(2010)
Odisha	ALOS PALSAR 50m	1) By using the allometric equation and wood densities, tree-level measurements (collected during field inventory data in 2009-2010) were converted to biomass density, 2) Integration of field inventory based biomass estimation and ALOS-PALSAR backscatter coefficients to obtain spatial forest AGB, 3) SVM based Radial Basis Function classification was used to carry out binary classification using field inventory data and ALOS-PALSAR HV and HH backscatter coefficient images	Suresh et al.(2014)
Bhabar-dun Sal Forest	IRS P6 LISS-III	1) Collection of biophysical data using Stratified random sampling, 2) Species-specific volumetric equations were employed to calculate volume, further multiplying volume by specific gravity to get biomass, 3) 3 forest-type density classes of Shorea robusta and 4 non-forest classes were delineated from IRS P6 LISS-III imagery, 4) Vegetation indices and spectral bands were used as independent variables while, biomass as the dependent variable for comparing DRR, CoK, and k-NN.	Yadav and Nandy(2015)
Madhya Pradesh	ALOS PALSAR L-Band	1) Allometric volume equations and miscellaneous volume equations were used to compute tree volume, 2) The DN data of PALSAR HV and HH mosaics were converted to Normalized Radar Cross Section (NRSC), 3) The plot-level aboveground biomass estimates were empirically modeled with PALSAR information in HV, HH and their ratios from various forest types.	Thumaty et al.(2016)
Barkot forest, Uttarakhand	Resourcesat-1 LISS-III	1) LISS-III satellite data was used and the digital numbers of all bands of this data were converted into reflectance image, 2) The image was geometrically referenced and subset image of the study area was extracted, 3) Spectral variables were extracted, 4) GLCM (Gray level co-occurrence matrix) method was used to derive texture variables, 5) Optimum kernel size was determined for the extraction of all the texture variables, 6) False color composite (FCC) was used for stratification of different vegetation types and canopy density categories, 7) For field data collection, stratified random sampling was applied for laying sample plots in different strata, 8) Using volumetric equations volume of trees of sample plots was calculated and AGB was determined by multiplying volume by specific gravity and BEF, 9) Below ground biomass (BGB) was calculated using root shoot ratio, 10) Total shrub, herb and litter biomass per plot was calculated by drying the sample in oven at 80^{o}C, 11) Total biomass per plot was calculated by adding AGB, BGB, shrub biomass, herb biomass and litter biomass, 12) Multi layer perceptron (MLP) was used considering biomass as dependent variable, spectral and textural variables as independent variables, 13) ANN model was used to optimize independent variables, 14) MLR was run between biomass, spectral and textural variables separately to determine stabilized R^2 value, 15) Using coefficients for selected variables empirical equation was established for biomass estimation.	Nandy et al. (2017)
Uppangala, near Pushpagiri Wildlife sanctuary, Western Ghats	IRS Cartosat-1, IKONOS	1) Total of 15 plots was laid in the accessible zones possessing homogenous canopy texture and from each plot, field measurements were obtained, 2) AGB was determined using regional allometric model, 3) Satellite image of the study area was divided into 125 X 125 m contiguous unit windows, 4) On each unit window, 2D Fast Fourier Transformation (FFT) was applied and r-spectra was generated, 5) Using z-score normalization r-spectra was standardized over all windows over the entire image, 6) Principal component analysis (PCA) was performed on r-spectra, 7) The first three PC axes were used as texture indices, 8) These texture indices were related to AGB of 15 plots using multivariate linear regression.	Reddy et al. (2017)
Nongkhyllem Wildlife Sanctuary and Reserve Forest, Meghalaya	Sentinel-1, ALOS-2/PALSAR-2	1) Species-specific volumetric equations were used for estimating tree volumes of sample plots and it was converted into AGB by multiplying volume with specific gravity using species-specific gravity, 2) SAR data from Sentinel-1 and PALSAR-2 were calibrated using SNAP for generating backscattering coefficients, 3) Refined Lee filter was used for speckle noise reduction, 4) The extracted backscatter signatures of C-band VV, VH polarization, and L-band HH, HV polarizations were correlated with AGB, 5) SVM technique was adopted to obtain a relation between SAR backscatter and AGB.	Sivasankar et al. (2018)

5. Conclusion

Aboveground biomass is an important indicator of C storage, forest productivity, and sequestration of forests (Calders et al. 2015). Estimating AGB is useful for comparing functional and structural attributes of forest ecosystems across a broad range of environmental conditions (Mani and Parthasarathy 2007).

Traditional methods of AGB estimation depend upon field measurements such as diameter at breast height, tree height, etc. These methods are costly and labor-intensive. The limitation of the traditional method is the biasness in the selection of representative samples. However, the application of RS methods is the most economical and practical alternative to retrieve data over large areas. Remote sensing is an accurate tool for biomass studies because of its ability to periodically measure the area of interest. AGB estimation using RS is a complex process in which many factors, like atmospheric conditions, data saturation, mixed pixels, extracted remote sensing variables, insufficient sample data, and selected algorithms may affect the performance of AGB estimation (Lu 2006).

Radar data are an important source of data for aboveground biomass estimation. Radar is suitable for biomass estimation because of its ability to capture vertical forest structure features, but its inability to distinguish vegetation types affect AGB estimation accuracy.

Integration of multiscale data from medium spatial resolution datasets, like RADAR and Landsat, high spatial resolution datasets, such as LIDAR and Quickbird, and coarse spatial resolution datasets, like MODIS, may be used for global biomass estimation (Lu et al. 2016).

Optical sensor data can be used for developing a horizontal vegetation structure instead of a vertical structure. The stereo-viewing capability in optical sensor data like Terra ASTER, ALOS/PRISM can provide vertical vegetation structure. So, proper integration of optical spectral response and this vertical structure features in a biomass estimation model can be used to improve biomass estimation accuracy (Lu et al. 2016).

References

[1] Bijalwan A, Swamy SL, Sharma CM, et al (2010) Land-use, biomass and carbon estimation in dry tropical forest of Chhattisgarh region in India using satellite remote sensing and GIS. J For Res 21:161–170
[2] Calders K, Newnham G, Burt A, et al (2015) Nondestructive estimates of above-ground biomass using terrestrial laser scanning. Methods Ecol Evol 6:198–208
[3] Cao L, Coops N, Hermosilla T, et al (2014) Using small-footprint discrete and full-waveform airborne LiDAR metrics to estimate total biomass and biomass components in subtropical forests. Remote Sens 6:7110–7135
[4] Change IPOC (2006) 2006 IPCC guidelines for national greenhouse gas inventories. 2013-04-28]. http//www. ipcc-nggip. iges. or. jp./public/2006gl/index. html
[5] Dang ATN, Nandy S, Srinet R, et al (2019) Forest aboveground biomass estimation using machine learning regression algorithm in Yok Don National Park, Vietnam. Ecol Inform 50:24–32
[6] Demirbas A (2004) The importance of biomass. Energy sources 26:361–366
[7] Dong J, Kaufmann RK, Myneni RB, et al (2003) Remote sensing estimates of boreal and temperate forest woody biomass: carbon pools, sources, and sinks. Remote Sens Environ 84:393–410
[8] Eisfelder C, Kuenzer C, Dech S (2012) Derivation of biomass information for semi-arid areas using remote-sensing data. Int J Remote Sens 33:2937–2984
[9] Erdle K, Mistele B, Schmidhalter U (2011) Comparison of active and passive spectral sensors in discriminating biomass parameters and nitrogen status in wheat cultivars. F Crop Res 124:74–84
[10] Fatoyinbo L (2012) Remote Sensing of Biomass: Principles and Applications. BoD–Books on Demand
[11] Hu T, Su Y, Xue B, et al (2016) Mapping global forest aboveground biomass with spaceborne LiDAR, optical imagery, and forest inventory data. Remote Sens 8:565
[12] Kenzo T, Furutani R, Hattori D, et al (2009) Allometric equations for accurate estimation of above-ground biomass in logged-over tropical rainforests in Sarawak, Malaysia. J For Res 14:365–372
[13] Kumar L, Sinha P, Taylor S, Alqurashi AF (2015) Review of the use of remote sensing for biomass estimation to support renewable energy generation. J Appl Remote Sens 9:97696
[14] Laurin GV, Chen Q, Lindsell JA, et al (2014) Above ground biomass estimation in an African tropical forest with lidar and hyperspectral data. ISPRS J Photogramm Remote Sens 89:49–58
[15] Lim K, Treitz P, Wulder M, et al (2003) LiDAR remote sensing of forest structure. Prog Phys Geogr 27:88–106
[16] Lu D (2006) The potential and challenge of remote sensing-based biomass estimation. Int J Remote Sens 27:1297–1328
[17] Lu D, Chen Q, Wang G, et al (2016) A survey of remote sensing-based aboveground biomass estimation methods in forest ecosystems. Int J Digit Earth 9:63–105
[18] Madugundu R, Nizalapur V, Jha CS (2008) Estimation of LAI and above-ground biomass in deciduous forests: Western Ghats of Karnataka, India. Int J Appl Earth Obs Geoinf 10:211–219
[19] Mani S, Parthasarathy N (2007) Above-ground biomass estimation in ten tropical dry evergreen forest sites of peninsular India. Biomass and Bioenergy 31:284–290
[20] McKendry P (2002) Energy production from biomass (part 1): overview of biomass. Bioresour Technol 83:37–46
[21] Mitchard ETA, Saatchi SS, Woodhouse IH, et al (2009) Using satellite radar backscatter to predict above-ground woody biomass: A consistent relationship across four different African landscapes. Geophys Res Lett 36:
[22] Murali KS, Bhat DM, Ravindranath NH (2005)

Biomass estimation equations for tropical deciduous and evergreen forests. Int J Agric Resour Gov Ecol 4:81–92
[23] Muukkonen P, Heiskanen J (2005) Estimating biomass for boreal forests using ASTER satellite data combined with standwise forest inventory data. Remote Sens Environ 99:434–447
[24] Nandy S, Singh R, Ghosh S, et al (2017) Neural network-based modelling for forest biomass assessment. Carbon Manag 8:305–317
[25] Nie S, Wang C, Zeng H, et al (2017) Above-ground biomass estimation using airborne discrete-return and full-waveform LiDAR data in a coniferous forest. Ecol Indic 78:221–228
[26] Raha D, Dar JA, Pandey PK, et al (2020) Variation in tree biomass and carbon stocks in three tropical dry deciduous forest types of Madhya Pradesh, India. Carbon Manag 1–12. https://doi.org/10.1080/17583004.2020.1712181
[27] Rajashekar G, Fararoda R, Reddy RS, et al (2018) Spatial distribution of forest biomass carbon (Above and below ground) in Indian forests. Ecol Indic 85:742–752
[28] Reddy RS, Rajashekar G, Jha CS, et al (2017) Estimation of above ground biomass using texture metrics derived from IRS Cartosat-1 panchromatic data in evergreen forests of Western Ghats, India. J Indian Soc Remote Sens 45:657–665
[29] Rosette J, Suárez J, Nelson R, et al (2012) Lidar remote sensing for biomass assessment. Remote Sens Biomass—Princ Appl 24:3–27
[30] Roy PS, Ravan SA (1996) Biomass estimation using satellite remote sensing data—an investigation on possible approaches for natural forest. J Biosci 21:535–561
[31] Saatchi S, Marlier M, Chazdon RL, et al (2011) Impact of spatial variability of tropical forest structure on radar estimation of aboveground biomass. Remote Sens Environ 115:2836–2849
[32] Sinha S, Jeganathan C, Sharma LK, Nathawat MS (2015) A review of radar remote sensing for biomass estimation. Int J Environ Sci Technol 12:1779–1792
[33] Sinha S, Mohan S, Das AK, et al (2020) Multi-sensor approach integrating optical and multi-frequency synthetic aperture radar for carbon stock estimation over a tropical deciduous forest in India. Carbon Manag 11:39–55. https://doi.org/10.1080/17583004.2019.1686931
[34] Sivasankar T, Lone JM, Sarma KK, et al (2018) The potential of multi-frequency multi-polarized ALOS-2/PALSAR-2 and Sentinel-1 SAR data for aboveground forest biomass estimation. Int J Eng Technol 10:797–802
[35] Srinivas K, Sundarapandian S (2019) Biomass and carbon stocks of trees in tropical dry forest of East Godavari region, Andhra Pradesh, India. Geol Ecol Landscapes 3:114–122. https://doi.org/10.1080/24749508.2018.1522837
[36] Su Y, Guo Q, Xue B, et al (2016) Spatial distribution of forest aboveground biomass in China: Estimation through combination of spaceborne lidar, optical imagery, and forest inventory data. Remote Sens Environ 173:187–199
[37] Suresh M, Chand TRK, Fararoda R, et al (2014) Forest above ground biomass estimation and forest/non-forest classification for Odisha, India, using L-band Synthetic Aperture Radar (SAR) data. Int Arch Photogramm Remote Sens Spat Inf Sci 651–658
[38] Thumaty KC, Fararoda R, Middinti S, et al (2016) Estimation of above ground biomass for central Indian deciduous forests using ALOS PALSAR L-band data. J Indian Soc Remote Sens 44:31–39
[39] Yadav BK V, Nandy S (2015) Mapping aboveground woody biomass using forest inventory, remote sensing and geostatistical techniques. Environ Monit Assess 187:308
[40] Yaklaşımlar TÜBBG (2012) Recent approaches in above ground biomass estimation methods. Aegean Geogr J 21:39–51
[41] Yang X, Strahler AH, Schaaf CB, et al (2013) Three-dimensional forest reconstruction and structural parameter retrievals using a terrestrial full-waveform lidar instrument (Echidna®). Remote Sens Environ 135:36–51
[42] Zhu X, Liu D (2015) Improving forest aboveground biomass estimation using seasonal Landsat NDVI time-series. ISPRS J Photogramm Remote Sens 102:222–231