REVIEW ARTICLE

# Forest Biomass Assessment Integrating Field Inventory and Optical Remote Sensing Data: A Systematic Review

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## Abstract

Forests are the main reservoir of terrestrial carbon and thus play a significant role in the global carbon budget. To quantify the forest carbon stock, it is essential to assess the forest biomass. The regular monitoring of forest biomass is necessary to understand the carbon source/sink nature of the forests. Integration of field inventory with remote sensing (RS) data offers an efficient and reliable method for large-area forest aboveground biomass (AGB) estimation and mapping. The availability of the Earth observation data has made it feasible to quantify forest carbon stocks from local to global scales.The availability of optical satellite data for the past five decades has led to its extensive use in forest biomass studies. Spectral reflectance and spectral indices derived from optical RS data are used as predictor variables for AGB estimation. However, cloud cover and saturation of spectral values limit the use of optical RS data in AGB studies. Despite the limitations, optical RS data has been extensively tested and used for forest biomass/carbon assessment from local to global levels due to its long legacy. In this context, the present review highlights the utility of optical RS data in forest AGB estimation using various approaches.


**Keywords:** Aboveground biomass, Forest, Modelling, Optical satellite data, Remote sensing.

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## Introduction

Forests provide a plethora of ecosystem services that are key for the survival of life on the planet Earth. One of the significant roles played by the forests is balancing the atmospheric $CO_2$ and thus regulating the global climate and mitigating global warming. Forests are the main reservoir of terrestrial carbon and thus, play a vital role in the global carbon budget (Li *et al*., 2020; Nandy *et al*., 2021). The carbon is stored in the forest as biomass, which is the total amount of above- and belowground organic matter of living as well as the dead plant parts (FAO, 2005). The accumulated carbon is stored in five different pools in the forest ecosystem: aboveground biomass, belowground biomass, deadwood, litter, and soil organic matter. The major factors which influence the amount of carbon in these pools are age, species composition, disturbances, and soil characteristics. The assessment of forest biomass is essential to quantify the carbon stock. To understand the carbon source/sink nature of the forests it is necessary to monitor biomass at regular intervals varying from months to years (Nandy *et al*., 2019).

Biomass can be assessed by various methods, viz., harvest, field inventory, and integration of field inventory and remote sensing (RS) data (Kushwaha *et al*., 2014). The assessment of aboveground biomass (AGB) requires extensive field inventory. It is laborious and inapt for inaccessible are asandhence, practicable only in relatively smaller and accessible areas. Conversely, integrating field inventory with RS data offers a competent and reliable method of AGB estimation and mapping (Kushwaha *et al*., 2014; Lu *et al*., 2014; Manna *et al*., 2014; Heyjoo and Nandy, 2014; Yadav and Nandy, 2015). RS has played a vital role in quantifying carbon stocks during the last five decades.The availability of the Earth observation data has made it feasible to quantify forest carbon stocks from local to global scales. A variety of passive optical multispectral and hyperspectral images and active sensors like Radio Detection and Ranging (RADAR) and Light Detection And Ranging (LiDAR) data are nowadays available for AGB studies. However, due to the availability of optical satellite data for the past five decades, it has been widely used for forest biomass studies.

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### Optical Remote Sensing Data and Its Derived Variables used for Forest Biomass Estimation

Due to its various advantages, such as synoptic view, large-area coverage, availability of long-term temporal data, and accessibility to remote areas,optical RS data have been extensively used for AGB estimation globally (Muukkonen and Heiskanen, 2007; Kushwaha *et al*., 2014; Manna *et al*., 2014; Heyojoo and Nandy, 2014; Yadav and Nandy, 2015). Spectral reflectance and spectral indices derived from optical RS data are used as predictor variables for AGB estimation (Nandy *et al*., 2019). However, cloud cover and saturation of spectral values limit the use of optical RS data in AGB studies. Despite the limitations, optical RS data has been extensively tested and used for forest biomass/carbon assessment from local to global levels due to its long legacy.

Optical sensors acquire images in the visible, near-infrared, and shortwave regions of the electromagnetic spectrum. In addition to the spectral variables, texture variables derived from the optical data are also used as predictor variables for biomass/carbon estimation. Spectral indices have been widely used for generating empirical relationships of biomass estimates. Table 1 shows the most frequently used spectral indices for biomass/carbon estimation. Normalized difference vegetation index (NDVI), enhanced vegetation index (EVI), soil-adjusted vegetation index (SAVI), and modified soil-adjusted vegetation index (MSAVI) are some of the vegetation indices that have been used extensively for forest biomass studies (Nandy *et al*., 2019).

## Field Inventory for Biomass Estimation

For RS-based forest AGB assessment, field inventory data forms an integral part. In this approach, the field-measured biomass is considered as the dependent variable and the RS data-derived variables are considered as the independent variables. Hence, the identification of appropriate RS data-derived variables are essential for finding their relationship with the field-estimated biomass. By linking the dependent and independent variables, various models were developed for biomass estimation. The model output needs to be validated to evaluate the model's performance. Validation is done using field-measured biomass. Usually, 70% of the field-measured biomass data is randomly identified as a training set and the remaining 30% of data is used as a validation set. The uncertainty analysis of the prediction is also carried out. Hence, accurate field-measured biomass data is crucial for spatial biomass estimation using RS.

**Table 1:** Spectral indices widely used as predictor variables for forest biomass/carbon estimation.

| *Sl. No.* | *Spectral indices* | *Formula* | *Reference* |
|---|---|---|---|
| 1. | Simple Ratio(SR) | $\frac{NIR}{Red}$ | Birth and McVey, 1968 |
| 2. | Moisture Stress Index (MSI) | $\frac{SWIR}{NIR}$ | Hunt and Rock, 1989 |
| 3. | Land Surface Water Index (LSWI) | $\frac{NIR - SWIR}{NIR + SWIR}$ | Xiao *et al*., 2002 |
| 4. | Normalised Difference Vegetation Index (NDVI) | $\frac{NIR - Red}{NIR + Red}$ | Rouse *et al*., 1974 |
| 5. | Wide Range Vegetation Index (WDRVI) | $\frac{a * NIR - Red}{a * NIR + Red}$ (*a* has a value of 0.1– 0.2) | Gitelson, 2004 |
| 6. | Enhanced Vegetation Index (EVI) | $\frac{2.5 * (NIR - Red)}{NIR + 6 * Red + 7.5 * Blue + 1}$ | Huete *et al*., 2002 |
| 7. | EVI2 | $\frac{2.5 * (NIR - Red)}{NIR + 2.4 * Red + 1}$ | Jiang *et al*., 2008 |
| 8. | Visible Atmospherically Resistant Index (VARI) | $\frac{Green - Red}{Green + Red - Blue}$ | Gitelson *et al*., 2002 |
| 9. | Global Vegetation Moisture Index (GVMI) | $\frac{(NIR + 0.1) - (SWIR + 0.02)}{(NIR + 0.1) + (SWIR + 0.02)}$ | Ceccato *et al*., 2002 |
| 10. | Soil-Adjusted Vegetation Index (SAVI) | $\frac{(1 + L)(NIR - Red)}{(L + NIR + Red)}$ | Huete, 1988 |
| 11. | Optimized Soil Adjusted Vegetation Index (OSAVI) | $\frac{NIR - Red}{NIR + Red + 0.16}$ | Rondeaux *et al*., 1996 |
| 12. | Renormalized Difference Vegetation Index (RDVI) | $\frac{NIR - Red}{(NIR + Red)^{0.5}}$ | Roujean and Breon, 1995 |
| 13. | Perpendicular Vegetation Index (PVI) | $\frac{NIR - \alpha * Red - b}{1 + \alpha^2}$ $NIR_{Soil} = \alpha * Red_{Soil} + b$ | Richardson and Wiegand, 1977 |
| 14. | Transformed Soil Adjusted Vegetation Index (TSAVI) | $\frac{\alpha * (NIR - \alpha * Red - b)}{Red + \alpha * NIR - \alpha b + 0.08(1 + \alpha^2)}$ | Baret and Guyot, 1991 |
| 15. | Modified Soil Adjusted Vegetation Index (MSAVI) | $(2 * NIR + 1 - ((2 * NIR + 1)^2 - 8(NIR - Red)^{0.5})/2$ | Qi *et al*., 1994 |
| 16. | Difference Vegetation Index (DVI) | $NIR - Red$ | Tucker,1979 |

Biomass is calculated from the field inventory data by using species as well as site-specific allometric and volumetric equations. However, in many cases in India, allometric equations are not available. In such cases, species and site-specific volumetric equations are generally used for AGB calculation.

The stratified random sampling approach is generally used for field inventory associated with RS-based forest biomass studies in heterogeneous forests. In this case, forest type and forest canopy density are considered as stratum (Yadav and Nandy, 2015; Nandy *et al.*, 2017).Sample plots of 0.1 ha (31.62 mx31.62 m) are laid down in different strata based on probability proportional sampling. First of all, a pilot study is carried out for finding out the total number of sample plots to be laid in the whole area using equation 1 (Chacko, 1965):

$$N = \frac{t^2 \times CV^2}{(SE\%)^2} \tag{1}$$

where, N is the total number of sample plots, t is the statistical value at 95% significance level, CV is the coefficient of variation and SE% is the standard error percentage.

The total numbers of sample plots are proportionally distributed in the different strata using equation 2 (Cochran, 1963):

$$n_h = \frac{N_h}{N} \times n \tag{2}$$

Where, $n_h$ is the number of samples in $h$ stratum, $N_h$ is the size of $h$ stratum, $N$ is the total population size, and n is the total number of samples.

The field inventory design is depicted in Fig. 1. In different strata, sample plots of 0.1 ha (31.62m x 31.62m) are laid and the geographical coordinates of each plot are noted down. For tree biomass assessment, in each plot, the name of the tree species, its girth at breast height (*gbh*) (1.37m above ground) and height are measured. For shrubs, including saplings, two sample plots of 5 m x 5 m are laid at the opposite corners of the 0.1 ha plot. In the same 0.1 ha plot, 5 sample plots of 1 m x 1 m at four corners and one 1 m x 1 m at the center were laid for herbs and litter. The volume of individual trees of the sample plot is usually calculated using diameter at breast height (dbh) value in the species and site-specific volumetric equations (FSI, 1996). The AGB of the tree species is calculated by multiplying the tree volume with the species and site-specific wood density(FRI, 2002) and further multiplying it by biomass expansion factor (BEF) (Haripriya, 2000). Below ground biomass (BGB) is calculated using the root-shoot ratio. However, there is a scarcity of BGB values of trees of India. For shrubs, the individuals of each species inside the 5 m x 5 m plot are counted. Small portions of the shrub species are collected and the fresh weight is taken. For herbs and litter, fresh weights of all the materials inside the 1 m x 1 m plot are taken and a small portion of it is collected. The representative samples of shrubs, herbs, and litter are then kept in a hot air oven at 80°C for drying till constant weight. Finally the total biomass of the 0.1 ha plot is calculated by adding AGB, BGB, shrubs, herbs, and litter biomass. Total carbon stock is estimated by multiplying the total biomass by 0.47 (IPCC, 2006). This inventory process is repeated for all the 0.1 ha plots laid in different strata.

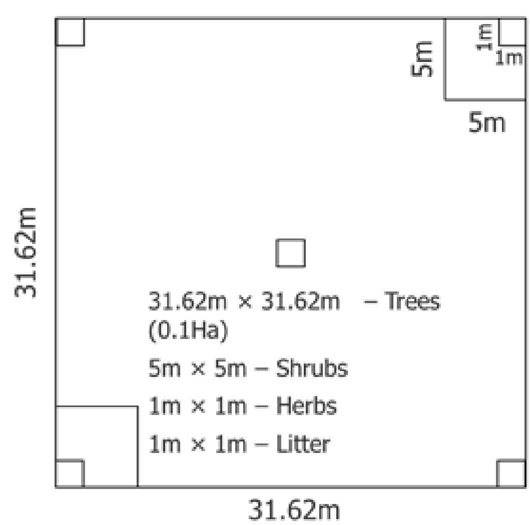


**Fig. 1:** Sampling design.

## Approaches for RS-based Forest Biomass Estimation

To map the spatial distribution of biomass, a relationship is established between the satellite data-derived variables and field-measured biomass. Fig. 2 shows the general approach used for mapping the spatial distribution of AGB.

The following approaches are generally used for mapping the spatial distribution of AGB using optical satellite data.

## Regression Modelling

In regression modelling, simple linear regression (SLR) and multiple linear regression (MLR) modelling techniques are widely used. In these modelling approaches, the spectral variables are considered as independent variables whereas the field-measured biomass is the dependent variable. In these modelling techniques, the basic assumption is that the spectral variables are correlated with biomass and there is a limited correlation among the independent variables (Lu *et al.*, 2004). In SLR, only one independent variable is correlated with the dependent variable, whereas in MLR more than one independent variable is considered to estimate biomass. These modelling approaches were frequently used earlier. However, these kinds of modelling approaches are not effective in high biomass areas.

Kushwaha *et al.* (2014) assessed the growing stock and woody biomass in Asola-Bhatti Wild life Sanctuary, Delhi, India. In this study, merged data of IRS-P6 LISS-IV and Cartosat-1 PAN was used. An SLR was established between NDVI and field-

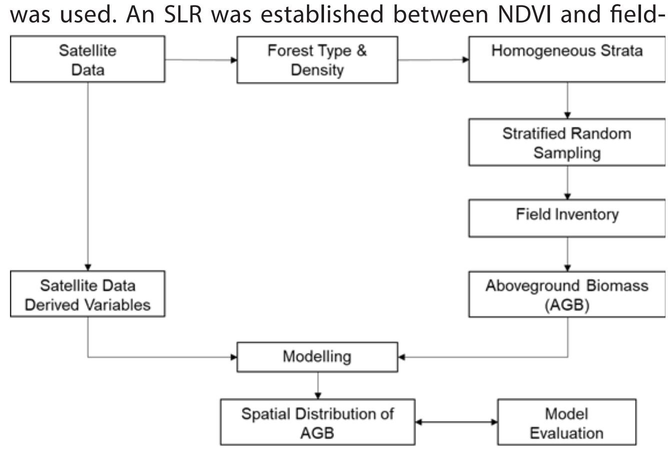


**Fig. 2:** The general approach used for mapping the spatial distribution of AGB.

measured growing stock and biomass. They observed a strong correlation between the NDVI and the growing stock ($R^2$=0.84) as well as with biomass ($R^2$=0.88). This study demonstrated that growing stock and woody biomass could be effectively estimated with high accuracy using optical remote sensing data in low biomass areas.

AGB was estimated in a 5-year-old *Avicennia marina* lantation of Indian Sundarbans by Manna *et al*. (2014) using IRS LISS-IV satellite data and field-measured AGB. The band reflectance values and the vegetation indices, *viz.,* NDVI, optimized soil adjusted vegetation index (OSAVI), and transformed difference vegetation index (TDVI) were correlated with the AGB. OSAVI showed the strongest positive linear relationship with the AGB ($R^2$= 0.72) as it is known to nullify the background soil reflectance effect added to vegetation reflectance. The study highlighted that this approach can be effective for monitoring and management of young mangrove plantations in a time and cost-effective manner. Heyojoo and Nandy (2014) estimated AGB of trees outside forests in Bijnor district of Uttar Pradesh, India using IRS P6 LISS-IV satellite data coupled with field inventory. In this study, spectral models of AGB with different bands and indices were established and the best linear relationship with the red band was observed ($R^2$ = 0.55). Using this relationship, the spatial distribution of AGB was mapped.

Aboveground woody biomass (AGWB) was mapped by Yadav and Nandy (2015) in Timli Forest Range of Uttarakhand, India using IRS P6 LISS-III and field inventory data. A stratified random sampling approach was used to collect the field inventory data. A positive relationship was found between NDVI and AGWB, though it was very low. A biomass map was prepared using NDVI with a root mean square error (RMSE) of 67.17 Mgha$^{-1}$. Thestudy did not find any significant relationships between individual spectral bands and AGWB as the values of spectral bands was saturated in high biomass areas. This is well-established that passive optical RS-based biomass models perform better in low biomass regions (Anaya *et al*., 2009; Kushwaha *et al*., 2014; Manna *et al*., 2014).

## Geostatistical Modelling

The regression modelling fails in many cases as the independent spectral variables are often found to be linearly correlated (Lu, 2005) which may have non-linear relationships with the biomass (Li, 2010). Non-parametric geostatistical approaches, like k-Nearest Neighbour (k-NN). Ordinary Kriging (OK), Universal Kriging (UK), Co-Kriging (CoK) and Regression Kriging (ReK)can be used effectively to address this limitation. Yadav and Nandy (2015) mapped AGWB in the Timli Forest Range, Uttarakhand, India using k-NN and CoK. k-NN using Mahalanobis distance showed the best result (RMSE=42.25 Mgha$^{-1}$), followed by fuzzy distance (RMSE=44.23 Mgha$^{-1}$) and Euclidean distance (RMSE=45.13 Mgha$^{-1}$), whereas using CoK technique, the RMSE was found to be 52.2 Mgha$^{-1}$. The study emphasized that the integration of field-measured biomass, RS data, and non-parametric methods, like k-NN and CoK are effective in AGB mapping, especially in high biomass regions.

Watham *et al*. (2016) used field-measured AGB, Landsat 8 OLI derived variables and geostatistical tools for AGB mapping in Barkot Flux Tower site, Uttarakhand, India. AGB prediction maps were prepared using OK, UK, CoK, and ReK methods. CoK with Land Surface Water Index had the lowest RMSE of 58.77 Mg ha$^{-1}$ ($R^2$=0.63). LSWI performed best because of its sensitivity to leaf moisture. This study also highlighted the utility of geostatistical modelling in AGB mapping.

## Object-based Image Analysis

For assessing the carbon stocks of individual trees, very high-resolution satellite (VHRS) imagery is used. Object-based image analysis (OBIA) technique is used for extracting individual tree crowns and the canopy projection area (CPA) from the VHRS imagery and by developing a relationship between CPA and dbh of the tree, the carbon stock can be quantified and mapped. Singh (2014) quantified and mapped the aboveground carbon stock of sal (*Shorear obusta*) forests of Doon valley, India using WorldView-2 satellite imagery and field data. OBIA was used for image segmentation (accuracy - 72.12%) and classification (accuracy - 84.82%). It facilitated the delineation of individual tree crowns and CPA calculation. This study revealed a strong relationship between dbh and CPA of trees and, hence, CPA and tree carbon. It also highlighted that VHRS imagery coupled with OBIA can be effectively used to quantify and map the tree carbon stock. Pandey *et al*. (2020) assessed and mapped the aboveground tree carbon stock using WorldView-2 satellite imagery in the Barkot forest of Uttarakhand, India. OBIA was carried out for image segmentation and classification. The segmented image was classified into sal, teak and shadow. The multi-resolution image segmentation and the classification accuracy were found to be 74% and 83%, respectively. Using the relationship between CPA and carbon, the carbon stock of individual trees was mapped. The study highlighted the utility of OBIA and VHRS imagery for high resolution carbon stock mapping of forest.

## Machine Learning-based Modelling

The machine-learning algorithms, such as random forest (RF) (Breiman, 2001), support vector machine (SVM) (Vapnik *et al*., 1997),and Artificial Neural Network (ANN)(Haykin, 1994) can be effectively used for variable optimization and also for modelling the spatial distribution of AGB. Nandy *et al*. (2017) estimated forest biomass by incorporating Resourcesat-1 LISS-III data with field-measured biomass using ANN in Barkot forest, Uttarakhand, India. The spectral and textural variables were ranked with respect to the dependent variable forest biomass using ANN. The top ten variables were used to generate an MLR model for predicting the spatial distribution of biomass with an $R^2$=0.70 and RMSE= 93.41 Mgha$^{-1}$. The study revealed the capability of the ANN technique for optimizing the independent variables and predicting the AGB with an optimum number of independent variables.

Dang *et al*. (2019) used Sentinel-2 satellite imagery combined with field-measured AGB to estimate and map forest AGB in Yok Don National Park, Vietnam using RF algorithm. They extracted 132 spectral and textural variables from Sentinel-2 imagery for predicting the AGB and found that a combination of spectral and texture variables could effectively predict AGB. RF was further used to optimize the number of variables. A combination of 11 spectral and textural variables was used to develop a model for estimating AGB with high accuracy ($R^2$ = 0.81, RMSE = 36.67 Mg $ha^{-1}$and %RMSE of 19.55%). The study demonstrated that Sentinel-2 imagery in conjunction with RF has the potential to effectively predict the spatial distribution of forest AGB with high accuracy.

## Conclusion

Forests play a crucial role in the carbon cycle, and hence, timely mapping and monitoring of forest carbon stock can act as a vital indicator of climate change. Forest biomass maps are important for forest management and planning, carbon accounting, carbon dynamics analysis, and forest productivity modelling. The reliable estimates of forest biomass are essential to address these issues effectively. The RS applications provide reasonable AGB estimates compared to labour-intensive, economically expensive, and time-consuming traditional techniques. The long legacy of the optical RS data provides means to monitor the forest AGB in combination with the *in-situ* biomass inventory. The abundantly available optical RS data has led to the mapping and modelling forest AGB from local to global scales. Various modelling approaches ranging from simple and multiple regression methods to machine learning algorithms have been utilized to map the spatial distribution of forest AGB at varying temporal scales. The optical RS data perform well in the low biomass density forests. The problems of spectral values saturation in high biomass areas and cloud cover may limit their use for AGB studies in high biomass forests. In synergy with various active sensor data, the optical RS data will continue to further contribute to the mapping and monitoring of the forest AGB.

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