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Estimation of above ground biomass in tropical heterogeneous forests in India using GEDI

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A B S T R A C T

Quantifying above ground biomass (AGB) and its spatial distribution can significantly contribute to monitor carbon stocks as well as the carbon storage dynamics in forests. For effective forest monitoring and management in the case of complex tropical Indian forests, there is a need to obtain reliable estimates of the amount of carbon sequestration at regional as well as national levels, but the estimation of biomass is quite challenging. The main objective of the study is to validate the usefulness of the gridded above ground biomass density (AGBD) estimates (ton/ha) of the spaceborne LiDAR Global Ecosystem Dynamics Investigation data (GEDI L4B, Version 2) across two tropical heterogeneous forests in India, Betul and Mudumalai forests. Methodology includes, for each forest area, a linear regression model which predicts AGB from Sentinel-2 MSI data was developed using ground reference data and comparing it with the GEDI AGBD values. The AGB model for the Betul forests in Central India had a RMSE of 13.9 ton/ha, relative RMSE = 8.7% and a R^2 of 0.88, with a bias of −0.28 ton/ha, and a comparison between modelled AGB and GEDI gridded AGBD at 1 km resolution show a relatively strong correlation (0.66) and no or little bias. It also found that GEDI AGBD footprint value is underestimated compared to the AGB according to the Sentinel-2 model. For the Mudumalai forest in southern India, the AGB model had an RMSE of 29.1 ton/ha, relative RMSE = 10.8%, and an R^2 of 0.79 and a bias of −0.022. The correlation between modelled AGB and gridded GEDI AGBD was 0.84, and GEDI AGBD is underestimated compared to AGB from the Sentinel-2 model. The field values of AGB of Betul lies between 42.2 ton/ha and 238.8 ton/ha and for the Mudumalai forests, the AGB lies between 75.9 ton/ha and 353.6 ton/ha. The results indicates that the GEDI gridded AGBD underestimates AGB, and that the model used to produce the gridded AGBD product needs to be adjusted to provide reliable information on the carbon balance and its changes over time for the type of Indian forests that exists in the two test areas.

1. Introduction

Accurate predictions of above ground biomass (AGB) is useful for comparing structural and functional attributes of forest ecosystem (Barbosa et al., 2014; Hall et al., 2006; Li et al., 2020; Mitchard, 2018; Palma et al., 2021). The impact of carbon loss due to deforestation and forest degradation and the effect of ecosystem functional characteristics can be obtained by understanding the regional as well as global changes in AGB (Feng et al., 2022; Houghton, 2005; Jung et al., 2021; Li et al., 2020). Information on the spatial distribution of AGB can potentially contribute in forest management, carbon source and sink investigations, and is critical to understand implications of climate change on forest structure (Baccini et al., 2017; Piao et al., 2022; Slik et al., 2013; Wulder et al., 2020). Various approaches are there for the estimation of AGB, in which field measurements are most accurate but it is quite challenging due to the unavailability of suitable data sets, varying localities and difficulties in accessibility (Basuki et al., 2009; Lu et al., 2016; Mutanga et al., 2012; Torre-Tojal et al., 2022).

In India, estimates of carbon stocks for whole states and the entire country has regularly been made by the Forest Survey of India (FSI) an organisation under the ministry of environments and forests, government of India (Ravindranath et al., 2008; Wani et al., 2012). FSI launched the Indian National Forest Inventory (NFI) in 2003 with the aim to provide reliable estimates of growing stock in forest and for trees outside forest (Tewari et al. (2016); Thakur, 2018). The primary objective of the NFI is to assess growing stock of trees, number of trees, bamboo, soil carbon, carbon stock in India's forests, invasive species and other parameters depicting forest health and growth using a grid-based

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sampling scheme (FSI, 1996;Thakur, 2018). FSI estimates carbon stock in different pools at the national and state level using the NFI data following the methodology of Good Practices Guidance (GPG) developed by Intergovernmental Panel on Climate Change (IPCC), 2001 (Forest Survey of India, 2021). The forest carbon stock in Indian forests for 2021 has been estimated to 7204.0 Million tonnes and very dense and dense forest constitute 57% of the total forest cover (India State of Forest Report (ISFR), 2021).

The use of remote sensing has the potential to provide cost-effective estimates of biomass compared to the labour intensive, costly and time-consuming traditional techniques (Couteron et al., 2012; Timothy et al., 2016). Remote sensing also has the advantage to cover inaccessible areas and it might be a cost-efficient way to get estimates of biomass across countries such as India. Various studies have estimated forest AGB in India using optical satellite data (Devagiri et al., 2013; Ghosh et al., 2021; Ghosh and Behera, 2018; Jha et al., 2015; Nandy et al., 2019; Pargal et al., 2017; Singh et al., 2024) and Synthetic Aperture Radar (SAR) data (Ali and Khati, 2024; Kumar et al., 2019; Thumaty et al., 2016). Some studies have used the combination of Optical and SAR data for the estimation of AGB (Prakash et al., 2024; Sinha et al., 2019). Several studies on carbon pools, AGB and carbon density (Chhabra et al., 2002; Dadhwal et al., 2009;Haripriya, 2000; Jha et al., 2015;Pargal et al., 2017; Raha et al., 2020; Ravindranath et al., 1997; Ravindranath et al., 2008; Vashum and Jayakumar, 2012) were utilized for both national and international reporting of India's total carbon stock (Sodhi (2021). Several of these studies are limited to a particular methodology and are region specific (Bijalwan et al., 2010; Kale et al., 2009; Ramachandran et al., 2007; Ravindranath and Ostwald, 2008; Salunkhe et al., 2018). Airborne (Light Detection and Ranging) LiDAR is a remote sensing technique that can be used to produce map with estimated forest variables such as AGB across large areas (Gao et al., 2022; Georgopoulos et al., 2023; Nilsson et al., 2017, Packalén and Maltamo, 2007). LiDAR has already been used in India to retrieve certain forest structural parameters such as AGB (Mangla et al., 2016; Véga et al., 2015), diameter at breast height (dbh) (Reddy et al., 2018), tree volume (Mayamanikandan et al., 2019) as well as tree height (Bhattacharjee et al., 2019). Several studies demonstrates the potential of using data from the second generation of the Ice, Cloud,and land Elevation Satellite (ICESat-2) and the Global Ecosystem Dynamics Investigation (GEDI) to estimate forest stand height and AGB in India (e.g., Musthafa and Singh, 2022; Nandy et al., 2021). GEDI provides an unprecedented sampling density of forest structural properties (Dubayah et al., 2020; Guo et al., 2023; Liang et al., 2023; Potapov et al., 2021). It has, for example been shown that GEDI L2A data can be used to estimate AGB on a stand level with an root mean square error (RMSE) of 27.26% in northern India, but the GEDI AGB estimates was generally lower than the field observed (Musthafa and Singh, 2022).

The biomass estimation by application of high resolution characterisation of vertical canopy structure using LiDAR data as well as time series remote sensing data through novel modelling approaches are a prerequisite for effective forest monitoring and management in the case of complex and partly inaccessible tropical forests in India. The Sentinel-2 Multi-Spectral Instrument (MSI) have potential applications in estimating or classifying forest biophysical variables such as tree cover (e.g., Godinho et al., 2018), AGB (e.g., Majasalmi and Rautiainen, 2016; Pandit et al., 2018; Persson et al., 2021), AGB change (Puliti et al., 2021), growing stock volume (e.g., Chrysafis et al., 2017; Mura et al., 2018), tree species (e.g., Grabska et al., 2019), and riparian vegetation (Daryaei et al., 2020). Spectral band values and spectral-derived vegetation indices from Sentinel-2 can also be used for accurate and timely estimation of AGB in sub-tropic (Nuthammachot et al., 2018, 2020; Pandit et al., 2018) and tropical forests (Malhi et al., 2022). The spaceborne LiDAR data are not spatially continuous and therefore we need the integration of LiDAR metrics with continuous spectral time series remote sensing data for obtaining comprehensive and continuous AGB spatial distribution (Jiang et al., 2021; Jiang et al., 2022; Li et al., 2020). Sentinel 2 spectral data provides the possibility to continuously map and monitor AGB across Indian forests and GEDI enables access to LiDAR data for assessing forest structural properties at larger spatial scales and shorter temporal resolution previously attainable only from optical satellite-based data. Certain studies have utilized combination of spectral variables from Sentinel-2 and ICESat-2 data (Nandy et al., 2021) to provide improved estimate of forest height and AGB in sub-tropical forests, but studies utilising optical and spaceborne LiDAR for forest AGB estimation in highly biodiverse tropical forest regions is very limited (Musthafa and Singh, 2022). It is also evident that applicability of GEDI to capture vegetation structure across large spatial extents is limited as GEDI consists of footprints of discrete laser beams representing a point sample, which specifies the need to be combined with other sources of information (Xi et al., 2022). There are also other studies which emphasised the significance of multisource data integration for improved biomass estimation (Shendryk (2022); Yang et al., 2023).

There is a need to evaluate the potential of GEDI in combination with spectral data sets to improve AGB estimation and for effective forest monitoring and management in the case of complex inaccessible tropical forests in India. However, we can therefore utilise reliable AGB estimates from GEDI products, especially the gridded (preferably in combination with field data and time series spectral data in a statistical approach) to improve the quality of the carbon data used for, for example international reporting. The main objective of this study was thus to investigate the possible use of the GEDI above ground biomass density (AGBD) data to assess the total amount of AGB in Indian tropical forests, where AGB is the mass (e.g., ton) and AGBD is the mass per unit area (e.g. ton/ha). Our approach was to first create a model estimating AGB using Sentinel 2 spectral data as independent variables and then, in a second step, compare the GEDI footprint AGBD and the gridded (1 km × 1 km) AGBD product with AGBD values from the model developed.

2. Materials and methods

2.1. Study area

India possesses extremely diverse and heterogeneous forest ecosystems whose forests accounts for one fifth of the geographical area and the vegetation types varies from Himalayas in the north to Western Ghats in south (Reddy et al., 2015). Betul forests, located in the central part of India, and the Mudumalai forest in southern India was selected as study areas (Fig. 1). Betul forest lies between 21°22′ and 22°24′ N longitude and 77°04′ and 78°33′ E latitude in the state of Madhya Pradesh, with strong seasonality during monsoon and winter and the leaf-off season from April–May. The elevation varies from 442 m to 1133 m above mean sea level and the forest soils include black cotton soil, stiff clayey soil and the average rainfall varying from1959 mm to 1301 mm. Betul forest comprises of mixed deciduous forests (dominated by teak), tropical dry deciduous forests, moist deciduous teak forests (with or without bamboo), dry deciduous teak forests (with or without bamboo), bamboo forests, Southern tropical moist deciduous teak forests, southern tropical dry deciduous forests, dry teak forests, Boswellia forests, and tropical thorn forests (Kumar and Khanna, 1998; Lale et al., 2020; Singh and Moharir, 2003). The tree species mainly seen are Terminalia crenulata, Ougeinia oojeinensis, Adina cordifolia, *Anogeissus latifolia*, Gardenia latifolia and *Tectona grandis* (Jha et al., 2013; Mayamanikandan et al., 2019) with an average stand height about 22 m (Jha et al., 2013; Rodda et al., 2023). The Mudumalai forest is a part of the Western Ghats that covers an area of 321 km^2, located (11°30′55.95"N, 76°13′34.63″E and 11° 4′11.38"N, 76°22′40.95″E) in the state of Tamilnadu with leaf less stages during December–February and leaf expansion stages from May–July (Suresh and Nanda, 2021). The elevation of Mudumalai forest is ranging from 300 m to 1200 m at sea level with undulating topography with red and black soils having different proportions of clay and sand. It comprises of mainly tropical dry deciduous

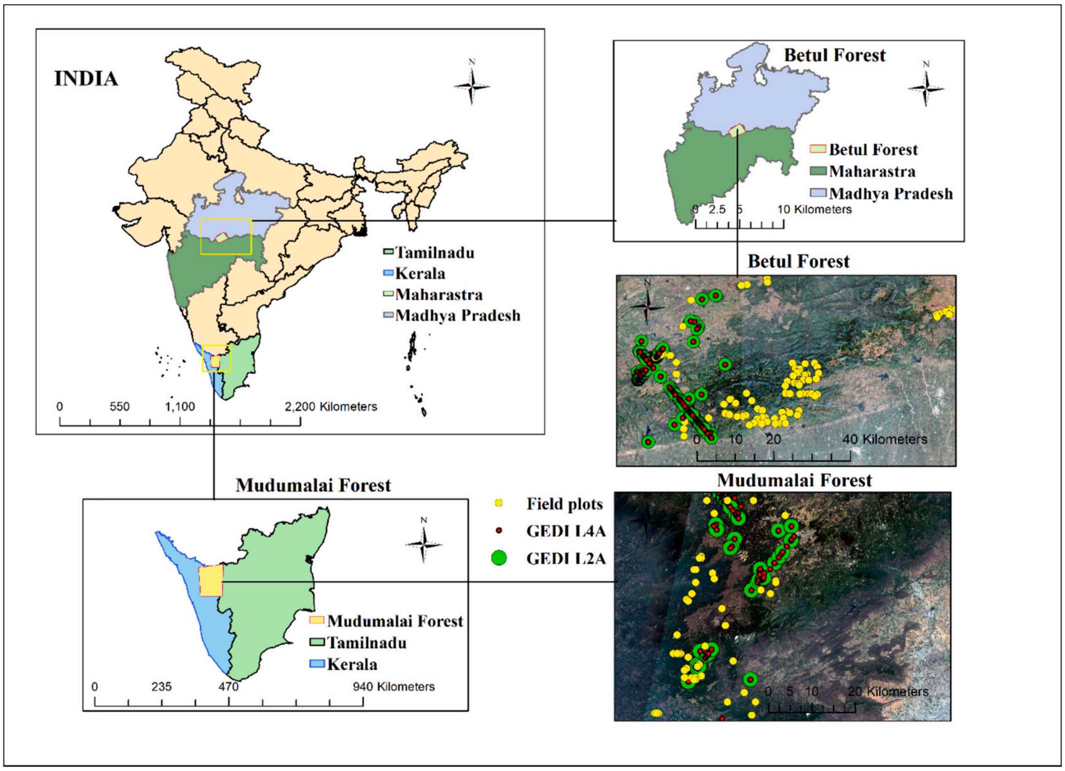

Fig. 1. Study areas, the field plots locations and the GEDI L4A and L2A footprints distribution across Betul forest and Mudumalai Forest, including the used Sentinel 2 images.

forests, tropical deciduous forests, tropical moist deciduous forests, dry thorn forests, tropical semi-evergreen forests, moist bamboo brakes, and riparian forests, with an average stand height of 20 —25 m (Champion and Seth, 1968). The average annual rainfall is approximately 900 to 1600 mm, received mainly between May and November (Kishore et al., 2024; Murali and Sukumar, 1994; Nath et al., 2006; Sukumar et al., 1992).

2.2. Data sets used

As mentioned above, GEDI L4B gridded AGBD data and L4A footprint AGBD data were compared with AGBD estimated using Sentinel-2 spectral data as independent variables (Table 1). We also examined and compared the relationship between forest height and AGBD for GEDI and our field measurements.

Table 1
Data sets used in the study.

Data sets used	Details
GEDI L2A	Relative Height (RH, m) of 2019 Spatial Resolution: Footprints ~25 m in diameter Temporal Resolution: Varies
GEDI, L4AGEDI, L4B	Above Ground Biomass Density, Ton/ha) data (GEDI L4A Published on 2019-04-18) at the scale of individual footprints Spatial Resolution: Footprints ~25 m in diameter Temporal Resolution: One-time estimate AGBD (Ton/ha) 1 km gridded- mean AGBD (GEDI L4B Published on 2022-03-29) Spatial Resolution: 1 km Temporal Resolution: One-time estimates
Sentinel-2	Spectral data of 2019 (Level 2A November 28, 2019 for Betul Forest, Level-1C tile from February 23, 2019 for Mudumalai Forest) Spatial Resolution: 10 to 60-m pixel size Temporal Resolution: 5 days
Field data	Plot level (100 m × 100 m) AGBD(Ton/ha), collected March – October 2019

2.2.1. Field data

The field data which was collected during March–October 2019 is provided by the Indian Institute of Space Science and Technology (IIST). Available field data consists of biomass values of 112 square sized plots (100 m × 100 m) for Betul forests and 52 plots for Mudumalai forests. All plots were geo-located using DGPS. Each plot was sub-divided into 25 quadrants of 0.04 ha (20 × 20 m) and measurements were taken in 10 randomly selected quadrants in each plot. A total station was used to delineate and mark the boundaries of the selected quadrants (Mayamanikandan et al., 2022; Rajashekar et al., 2018). In each quadrant, diameter, and height, were measured, species or family name were registered and volume was estimated using species specific allometric functions using diameter as independent variable (FSI, 1996). AGB was estimated for all trees by multiplying tree volume by wood density (FSI, 1996) using a diameter threshold of dbh $\geq$ 10 cm for stems and 5 cm for branches. Quadrant level AGBD was estimated as the sum of AGB for all individual trees within each quadrant divided by the quadrant size (0.04 ha).

The forest AGBD in the study area Betul lies between 42.2 ton/ha and 238.8 ton/ha according to the field survey, with an average value of 139.4 ton/ha (Table 2). For Mudumalai forests, the AGBD lies between 75.9 ton/ha and 353.6 ton/ha, and the average value of 268.6 ton/ha. The distribution of AGBD for two regions are shown in the histogram (Fig. 2).

2.2.2. GEDI data

GEDI was launched by National Aeronautics and Space Administration (NASA) on December 5, 2019 and it is the first spaceborne full waveform LiDAR with a high resolution ranging instrument which produces the 3D structure of the Earth between 51.6° N and 51.6° S (Dubayah et al., 2022; Duncanson et al., 2020). GEDI height data is in 25 m resolution and GEDI also provides data related to quantitative, global, and transparent assessments of the spatial distribution of carbon stocks in the world's forests at both foot print level and for 1 km grid

Table 2
Descriptive statistics of GEDI data and field data of Betul and Mudumalai Forests.

Forest	Data sets	Variable	No of shots or plots	Minimum	Maximum	Mean	Standard deviation
	GEDI L4A	AGBD (Ton/ha)	141*	0.8	356.8	88.1	70.9
	GEDI L2A	Relative height (m)	141*	3.4	37.9	17.0	7.0
Betul Forest	GEDI L4B	Gridded aboveground biomass density (AGBD) (Ton/ha) (1 km)	–	6.5	194.17	71.3	17.2
	Betul Forest field measurements	AGBD (Ton/ha)	112	42.2	238.8	139.4	44.2
	GEDI L4A	AGBD (Ton/ha)	241*	8.0	889.8	148.0	216.9
Mudumalai Forest	GEDIL2A	Relative height (m)	241*	3.25	36.8	12.7	11.3
	GEDIL4B	Gridded aboveground biomass density (AGBD) (Ton/ha) (1 km)	–	12.2	429.7	160.4	94.2
	Mudumalai Forest field measurements	AGBD (Ton/ha)	52	94.4	353.6	290.1	71.9

* Number of available shots with acceptable uncertainty (GEDI L4A beam sensitivity threshold = 0.98 and, GEDI L2A beam sensitivity threshold = 0.95).

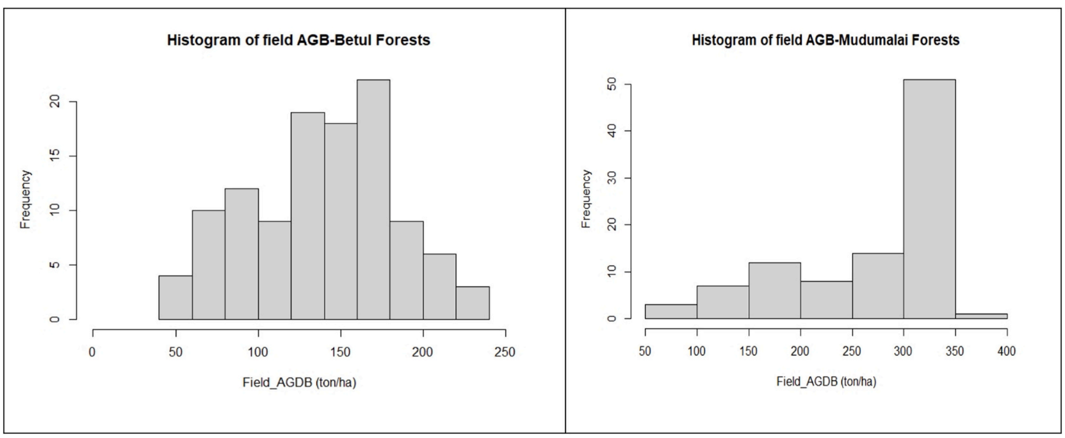

Fig. 2. Field AGBD distribution across Betul and Mudumalai forests.

cells along with associated uncertainties (Dubayah et al., 2022).

The GEDI instrument comprises of 3 lasers that emits pulses along 8 parallel tracks and each pulse or footprint is separated by 60 m along track and 600 m across track with a footprint diameter of 25 m. The main data used includes AGBD at the scale of individual footprints (GEDI L4A) and the 1 km × 1 km (1 km, hereafter) gridded GEDI L4B AGBD, both from ORNL DAAC, and Relative Height (RH_99 of L2 A GEDI) from the Land Processes Distributed Active Archive Center (LP DAAC). In GEDI, a sophisticated post-processing algorithm is available to the received waveforms from the GEDI instrument to detect weaker waveform signals. The "algorithm setting group" is defined as the specific set of parameters used in an algorithm run which includes six (i.e., 1, 2, 3, 4, 5, 6, and 10) defined groups (A value of 10 indicates algorithm setting group 5 has been used, but that the lowest detected mode is likely a noise detection and when this occurs, a higher mode has been used to calculate RH metrics) (Hofton et al., 2020). The geolocation group and the agbd_prediction group of GEDI L4A have footprint data for each "algorithm setting group" and the variables are *_aN, where N is 1, 2, 3, 4, 5, 6, or 10. GEDI L4A models are stratified into five plant functional types (PFTs) PFTs including ENT: evergreen needle leaf trees, EBT: evergreen broadleaf trees), DBT: deciduous needleleaf trees, DNT: deciduous broadleaf trees, GSW: grasses, shrubs and woodlands). The selected study areas belongs to PFTs DBT and EBT. For the different geographic strata, there will be considerable variability in model performance (Duncanson et al., 2022).

In total, 16 granules of GEDI L2 A data containing ground elevation, canopy top height, relative height (RH) metrics, quality flags, and sensitivity values (Dubayah et al., 2021; GEDI, 2021) and AGBD data from 18 GEDI L4A granules were downloaded for the Betul test area (Fig. 1). RH is the height at which a certain quantile returned energy is reached relative to the ground, and canopy top height is computed by subtracting the elevation of the highest detected return from the ground (Dubayah et al., 2020; Hofton et al., 2002). The GEDI finder tool was utilized to find the specific granules from 2019 intersecting the Betul test site, and the GEDI_subsetter.py tool was used to download the L2A granules from the LP DAAC data user resources repository and to convert them to GeoJSON format. The GEDI L4A data were downloaded in the Hierarchical Data Format (HDF5) for the year 2019 and converted to shapefiles using a Python script.

A model calibration method using simulated GEDI waveforms and a cross validation framework has been developed to ensure geographic transferability of AGBD (Hancock et al., 2019; Kellner et al., 2017). The L4A products are footprint level predictions of aboveground biomass density for individual footprints obtained by parametric models that linearize the relationship between L2A relative height metrics with field plot estimates of AGBD (Dubayah et al., 2020). Other than AGBD, the GEDI L4A datasets also includes variables such as the associated uncertainty metrics, quality flags, and model inputs including the scaled and transformed GEDI L2A RH metrics and footprint geolocation variables (GEDI L4A Footprint Level AGBD, Version 1 (ornl.gov)).

GEDI L4B product is also used in the study which contains estimates of mean AGBD (1 km) based on observations from GEDI mission (Dubayah et al., 2022). The data is available in GeoTIFF format in which each file provides estimates of mean AGBD. The GEDI L4B gridded AGBD used hybrid estimation to create an exhaustive coverage of non-overlapping 1 km × 1 km mean AGBD estimates (Dubayah et al., 2022), together with the corresponding estimated standard error. The estimated standard errors accounts for both model uncertainty and uncertainty related to the GEDI sample within a single grid cell. AGBD from the GEDI data, RH and the field observed AGBD are shown in Table 2.

Similarly, for Mudumalai forest 25 GEDI L4A granules and 25 GEDI L2A granules were downloaded in the Hierarchical Data Format (HDF5) for the year 2019, and converted to shapefiles using Python script. We also downloaded GEDI L4B AGBD gridded data for the given study area which is in the GeoTiFF format.

The sample plot locations and the spatial distribution of the GEDI granules across the Betul and Mudumalai forests are presented in the Fig. 1. In the figure, only filtered GEDI AGBD values are shown, since GEDI shots which are no data values and the footprints located outside forest masks were excluded. The GEDI L4A and L2A footprints are represented differently as red dots for L4A and green for L2A foot prints.

2.2.3. Filtering and selection of appropriate GEDI data

A flow chart depicting the methods used is shown in the Fig. 3. In the GEDI L4A footprint data, AGBD is reported for each algorithm setting group AGBD 1, 2, 3, 4, 5, 6, or 10. The l4_quality_flag uses a beam sensitivity threshold of 0.95, which is an estimate of the maximum canopy cover that can be penetrated considering the signal-to-noise ratio of the waveform. For dense tropical forests, Dubayah et al. (2021) concludes that the beam sensitivity threshold should be higher to minimize measurement error in the RH metrics. Thus, we filtered the GEDI data of both forests based on the beam sensitivity threshold of 0.98, meaning that shots with a beam sensitivity below the value were discarded. The shots having no data values (−9999) of AGBD values were also discarded. We selected only the footprints located on forestland for the study utilising google satellite imagery with CRS EPSG: 3857 - WGS 84 (Map data ©2015 Google) from QuickMapServices plugin in QGIS.

2.2.4. Sentinel-2 data

European Space Agency's Sentinel-2 satellites (Sentinel-2 A launched in June 2015 and Sentinel-2B in March 2017) provide medium to high spatial resolution images, both carry the MSI. The mission have wide applications including monitoring of forests and vegetation, soils and water cover and have high revisit frequency (5 days). A Sentinel-2 MSI Level-2 A tile (cloud free) from November 28, 2019 for Betul forests was downloaded from Copernicus open access hub using QGIS Semi-Automatic Classification Plugin (SCP) (Congedo, 2021). Sentinel-2 MSI has 13 spectral bands ranging from 10 to 60-m pixel size. In the study, we used the blue (B2), green (B3), red (B4) and near infrared (B8) channels that have 10-m resolution and the red edge (B5), near-infrared NIR (B6, B7 and B8A) and short-wave infrared SWIR (B11 and B12) channels that have a ground sampling distance of 20 m. The preprocessing includes a simple atmospheric correction using the Dark Object Subtraction 1 (DOS1) method. Spectral (reflectance) values for all bands were extracted for all field plots and GEDI L4A footprints within the study area. We also downloaded a Sentinel-2 MSI Level-1C product from February 23, 2019 for Mudumalai forest directly from the Copernicus open access hub, and the pre-processing and extraction of spectral data for all field plots was made using the same process as used in the Betul area. We resampled all Sentinel-2 bands to100m to match the size of the field plots. Spectral values were calculated as mean values of the original 10 m or 20 m pixels.

2.3. Extraction of spectral data from Sentinel-2 imagery for GEDI footprints

Spectral values for all 100 m resolution Sentinel-2 bands were extracted to the GEDI footprints the using bilinear interpolation method in which we done taking the weighted average determined by the value of the four nearest 100 m pixels and their relative position or weighted distance adjusted to account for their distance from the centre of the GEDI footprint. By resampling Sentinel-2 images to the size of the field plots (100 m × 100 m) we lose valuable details which might have an negative influence on our AGBD model.

A regression model estimating AGBD was constructed using Sentinel-2 spectral data of 100 m (all spectral bands except bands 1, 9 and 10) and the available field data (Eq. (1)).

$$AGB = \beta_0 + \beta_1 B_1 + \beta_2 B_2 + \ldots + \beta_{10} B_{10} + \varepsilon \tag{1}$$

Where B_i is band 2, 3, 4, 5, 6, 7, 8, 8 A, 11, and 12. The explanatory variables were selected using regsubsets in the R package leaps (Lumley and Lumley, 2013). The best model was selected, by setting the maximum number of explanatory variables (spectral bands) to incorporate in the model to 9 (nvmx = 9). Based on the adjusted R^2, we selected the B2, B5 and B6 as predictors for Betul forest. Adding more independent variables did only have a marginal effect on the adjusted R^2. An AGBD map with a cell size of 100 m was constructed by applying the AGBD model to all 100 m pixels in the resampled Sentinel-2 image. Mean values were calculated for each 1 km grid cell in the GEDI L4B dataset based on the cell values in the 100 m-resolution AGBD map. Only 1 km-cells that were entirely located on forestland according to the

Table 3
Sentinel 2 bands used in the study.

Forest name	Sentinel 2 bands	Best bands selected
Betul Forest	20 m spatial resolution bands: B5 (705 nm), B6 (740 nm), B7 (783 nm), B8A (865 nm), B11 (1610 nm) and B12 (2190 nm)	B2, B5 and B6
Mudumalai forest	10 m spatial resolution bands: B2 (490 nm), B3 (560 nm), B4 (665 nm) and B8 (842 nm)	B3, B4 and B8A

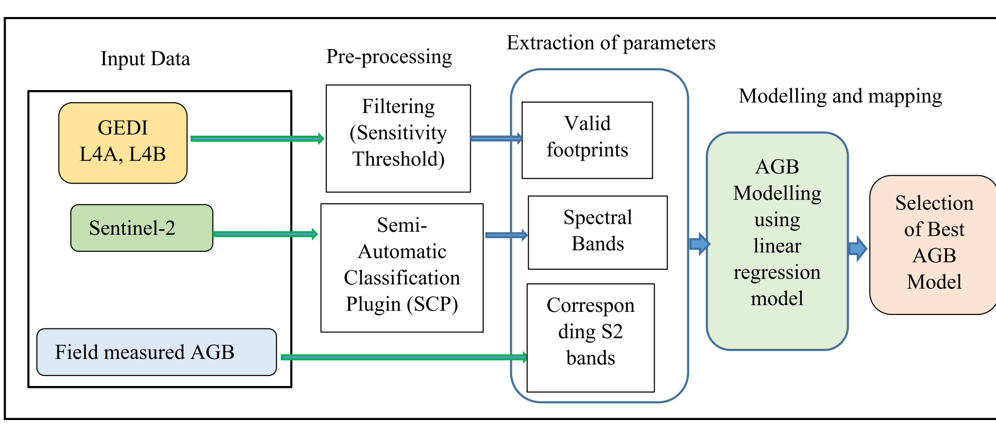

Fig. 3. Flow chart depicting the methodology.

Google satellite map was used (Fig. 5). Similarly, we selected the B3, B4 and B8A as the best predictors for Mudumalai forest (Table 3). We tested the study using random forest and robust regression also, but linear regression model found to be the best model for the given study.

We evaluated the model performance utilising leave-one-out cross-validation, (LOOCV) approach. In the LOOCV approach, one observation at a time is extracted from the dataset and the model parameters are estimated using the remaining (n-1) observations. The model is then applied to the extracted observation.

3. Results

The GEDI data and the available field data did not coincide geographically or in size. Thus, we have compared the GEDI L4A AGBD footprint values with AGBD estimated from the Sentinel-2 models. We also compared the relationship between tree height and AGBD for field data and GEDI data, respectively to understand the relationship between GEDI AGBD and height with respect to the corresponding field based values at the two study area.

3.1. The relationship between tree height and AGBD for GEDI and field data

The relationship between tree height and AGBD was examined for both the field measurements and the GEDI data for the Betul forest. For selecting the best data, we are using the sensitivity metric and quality flag value of 1, which indicates the cover and vertical profile metrics represent the land surface and meet criteria based on waveform shot energy, sensitivity, amplitude, and real-time surface tracking quality, and the quality of extended Gaussian fitting to the lowest mode. We filtered the GEDI L2A data based on the quality_flag value (we removed all shots where the quality_flag was set to 0) and sensitivity threshold (0.95). We compared the relationship between GEDI relative height (RH) from L2A data and AGBD from L4A data as well as tree height and AGBD from the field survey data. As can be seen in Fig. 4, the relationship between tree height and AGBD is almost linear for the field measurements. For GEDI, the relationship seems to be non-linear, especially for biomasses below approximately 100 t/ha. For higher AGBD values, the relationship seems to be almost linear also for the

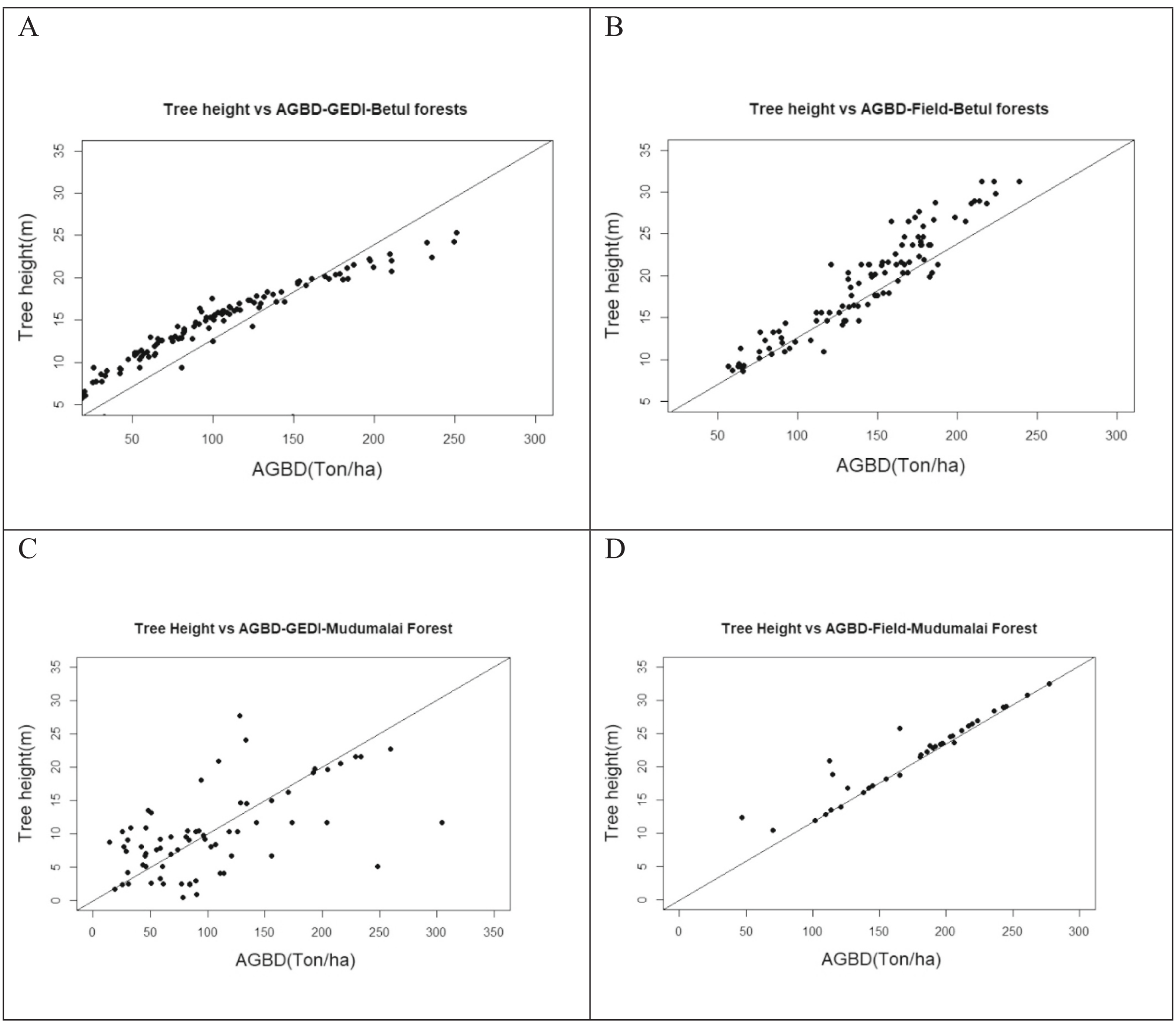

Fig. 4. (4A) Tree heights (RH) versus AGBD-GEDI, (4B) tree height (field measured) versus AGBD-field for Betul forests and (4C) the tree heights (RH) versus AGBD-GEDI, (4D) tree height (field measured) versus AGBD-field of Mudumalai Forest.

GEDI data. GEDI tree heights are influenced by the topography of the study area, at least for steep slopes (slope > 20%). It is evident that GEDI AGBD and the field AGBD, varies for the values below 50 Ton/Ha. GEDI have biomass values below 50 (Ton/Ha) and the variation between the tree height and AGBD is different from the variation between the field AGBD and height. In the case of Mudumalai forest, the variation is comparatively high, which might be an effect of that GEDI tree heights are influenced by the undulating topography and that RH metrics may be biased in very dense canopy conditions due to the weak terrain-reflected signal received by GEDI sensors. RH metrics might also be biased in areas that they have not been calibrated for. There is relatively few usable GEDI footprints in the two sites as seen in Fig. 4. Minimum and maximum values are different form the values in Table 2 as we have excluded the GEDI values that are outside the forests for the comparison in Fig. 4. Note that the two scatterplots show two different datasets from the Betul test area and that Fig. 4 A and Fig. 4C only includes observations that are entirely located on forestland.

3.2. Modelling AGBD using Sentinel-2 data

We used linear regression to model AGBD (field measured) as a function of Sentinel-2 spectral data in both test areas. As mentioned above, the selected model in the Betul area included bands 2, 5 and 6 (B2, B5 and B6), and had a root mean square error (RMSE) of 11.27 ton/ha and an R^2 of 0.90. Inspections of residual plots indicate that the model is good and the validation of the model using a leave-one-out cross-validation (LOOCV) approach show an RMSE of 13.93 ton/ha, an R^2 of 0.88, a mean absolute error (MAE) of 10.77 and a bias of −0.28. The selected bands B2, B5 and B6 have been successfully used in recent studies to estimate forest biomass (Chen et al., 2021; Xi et al., 2022).

The model was used to estimate AGBD for all pixels in the resampled (100 m) Sentinel-2 image and the estimates were compared with GEDI L4A footprint (25 m) AGBD (Fig. 5B1). It was found that the correlation between the estimates was strong with $r = 0.98$ (Fig. 5B1) and that GEDI L4A AGBD estimates generally were lower than the estimates from the Sentinel-2 model. The GEDI L4B gridded AGBD was plotted against AGBD from a 1 km-resolution map with aggregated estimates from the 100 m Sentinel-2 map. As shown in Fig. 5A1, we obtained a relatively

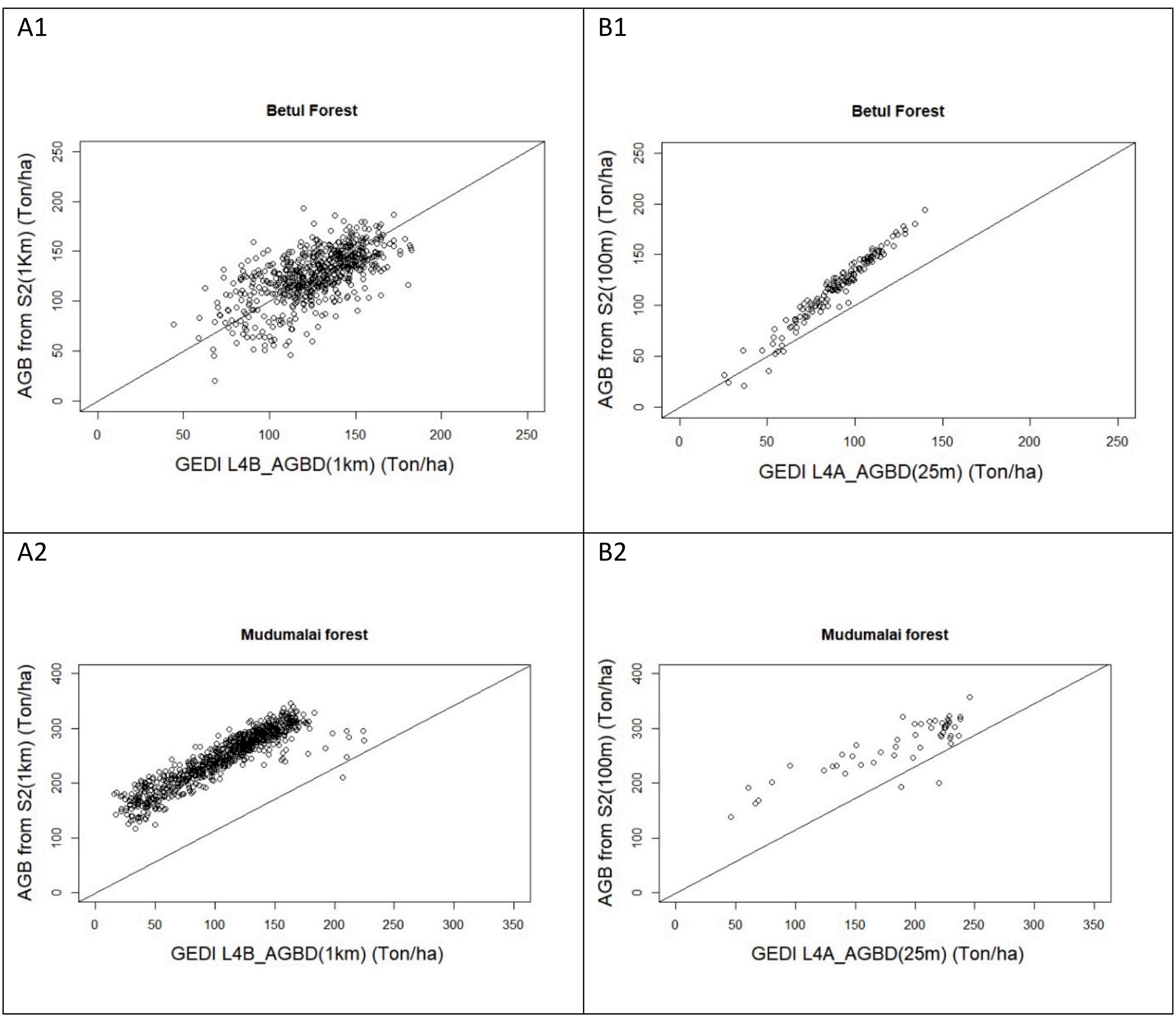

Fig. 5. Scatterplot of GEDI L4B AGBD (1 km) versus estimates of AGBD from Sentinel-2 bands, 2, 5 and 6 (A1, A2) and GEDI L4A AGBD (25 m) versus predictions of AGBD from Sentinel-2 bands, 3, 4 and 8 A (B1, B2) for Betul and Mudumalai forests respectively.

strong correlation (r = 0.66) between AGBD from the 1 km GEDI data and AGBD from the 1 km Sentinel-2 map.

For Mudumalai forest, we included bands 3, 4 and 8 A (B3, B4 and B8 A), and obtained an RMSE of 12.24 ton/ha and an R2 of 0.811. These selected bands performs well for biomass estimation as the band 3 (Green) relate to the presence of chlorophyll in the vegetation and the band 4 (Red) is useful for identifying vegetation types and is strongly affected by dead foliage and the band 8 A (red edge) perform well for vegetation classification. These optical spectral bands have been successfully used to estimate forest biomass in recent studies (Chen et al., 2021, Xi et al., 2022). The red-edge bands are highly related to vegetation properties, such as leaf area index, biomass, and structural carbohydrates (Martin-Gallego et al., 2020). The model is validated using a leave-one-out cross-validation (LOOCV) approach show an RMSE of 29.11 ton/ha, an R^2 of 0.80, a MAE of 18.73 and a bias of (−0.022).

We obtained a relatively strong correlation ($r = 0.72$) between AGBD from the L4A GEDI data and AGBD from the 100 m Sentinel-2 map (Fig. 5B2) and the correlation obtained between GEDI 1 km gridded and Sentinel-2 map is $r = 0.84$ as shown in Fig. 5A2. The raster maps of both forests are developed for the AGBD estimates from Sentinel-2 (100 m and 1 km) and GEDI AGBD for both forests and are shown in Fig. 6.

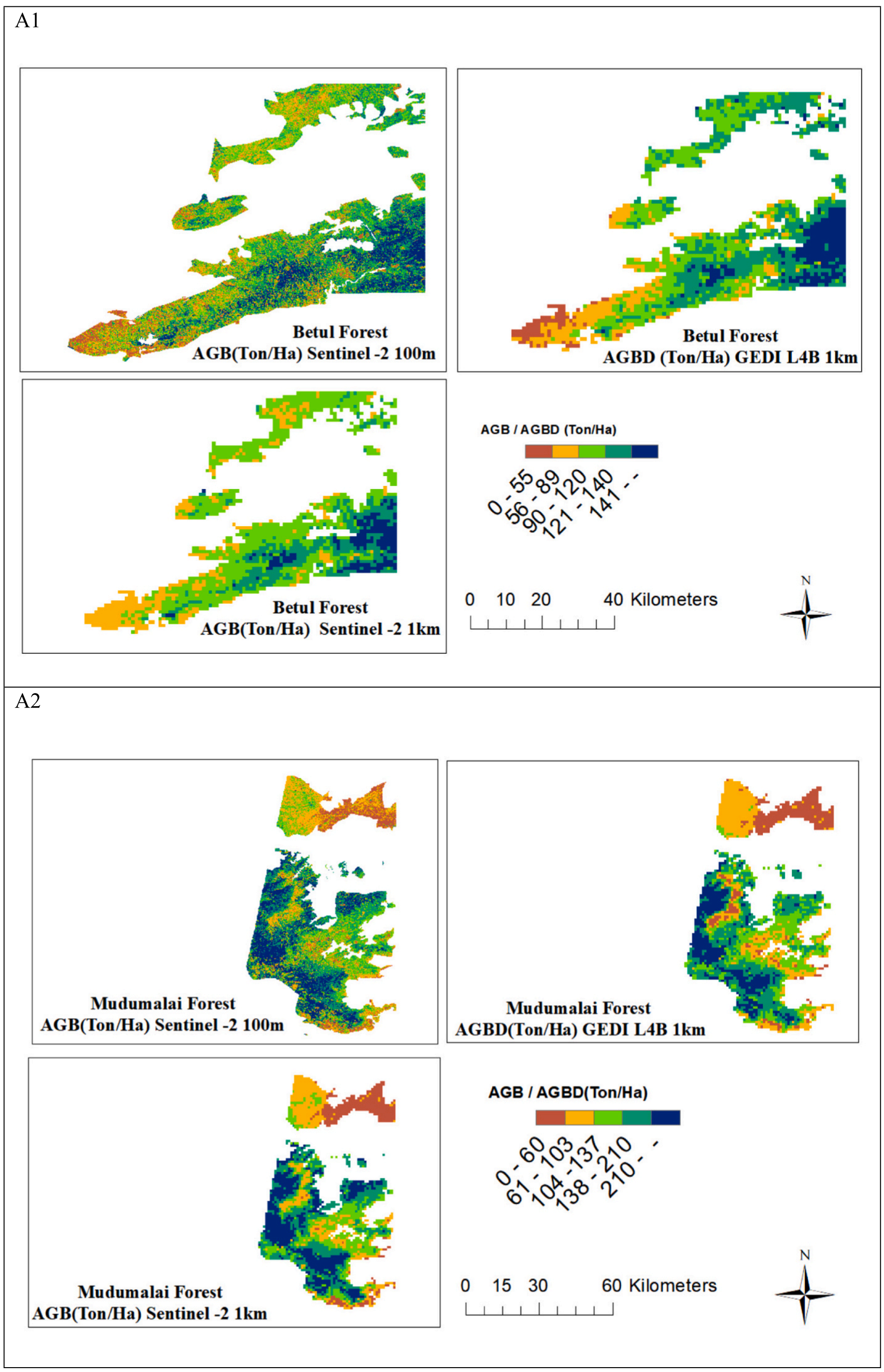

Fig. 6. Raster maps with estimated AGBD from Sentinel-2 (cell size = 100 m), aggregated estimates of AGBD from Sentinel-2 (cell size = 1 km), and GEDI L4B gridded AGBD (cell size = 1 km) for Betul (A1) and Mudumalai (A2) forest.

Our results show that the correlations between AGBD from GEDI (L4A and L4B) and the Sentinel-2 model was relatively high. However, the AGBD values from the Sentinel-2 model are found to be higher than the GEDI L4A values for both test areas. It is also found that Sentinel-2 model gave higher AGBD values than GEDI L4B in the Mudumalai forest, and that there were no significant difference between the AGBD values from GEDI L4B and the Sentinel-2 model in the Betul forest.

Sentinel-2 alone cannot provide vertical forest stand structure information and the data saturation is an important factor resulting in a relatively low AGBD estimation performance (Lu, 2006; Zhao et al., 2016) and insensitivity to large AGBD variations (Lu et al., 2012). The Sentinel-2 model might also be affected by uncertainties of the field observations such as small differences in the geolocation between field measurements and Sentinel-2 pixels. Data saturations often cause low accuracy for estimating the AGBD in high biomass or high canopy density areas which can be solved by the combined use of spectral data and structural data (Basuki et al., 2013; Luo et al., 2017; Vafaei et al., 2018).

4. Discussion

The main goal of the work is to evaluate the performance of GEDI above ground biomass estimation across the two forests sites of India. The study helps to better understand forest AGBD distribution and spatial changes in terrestrial carbon fluxes and to assess the main capabilities of the GEDI sensor for estimating AGBD in Indian tropical forests. The study thus shows the potential to improve the estimation of terrestrial carbon storage and better understand forest ecosystem processes across larger areas.

Our results indicate that AGBD estimates from gridded GEDI L4B data and footprint based GEDI L4A data potentially could be used to map and monitor AGBD in Indian tropical forests. However, this would require that the estimates are calibrated, for example using field data from an independent sample. It has been recommended to use airborne LiDAR data in combination with field observations when calibrating and validating GEDI data (Dubayah et al., 2020; Dubayah et al., 2021; Dubayah et al., 2022; Duncanson et al., 2020).

In Indian forests, the availability and accessibility of airborne LiDAR data are unfortunately limited. Better AGB estimates can be obtained using generic equations based on trees harvested for several sites (Chave et al., 2005; Chave et al., 2014; Cifuentes Jara et al., 2015) or using locally developed models which provides less uncertainty (Chave et al., 2014). The estimation of AGB in the varying and diverse forests of India is quite challenging due to the lack of AGB estimation equations (Giri et al., 2019; Nath et al., 2019; Salunkhe et al., 2018) and due to the unavailability of systematic data sets, varying localities and inaccessibility of diverse forests. Also, the development of allometric biomass models is important process in biomass estimation and the relationships vary among specific species (Lin et al., 2016). The lack of adequate equations for predicting biomass for every species can cause substantial bias in the biomass estimation. Tree species grouping method to develop biomass models could help to reduce the uncertainty in forest biomass estimation (Kebede and Soromessa, 2018; Xing et al., 2019). For the accurate estimation of forest biomass and reducing uncertainty, it is important to have species- and site-specific allometric equations for biomass estimation rather than utilising generalized models which produces biased estimates (Xiang et al., 2016). In India, equations combining variables such as tree height, diameter at breast height, and wood density to total tree biomass (Chave et al., 2005) and multispecies pan tropical equations (Chave et al., 2005, 2014; Nath et al., 2019; Vashum and Jayakumar, 2012) can be used to estimate biomass (Brahma et al., 2021), but quantifying biomass depends on factors such as the data set used, size of the field inventory, and result validation. This indicates the need for the development of suitable and robust equations (Brahma et al., 2021; Weiskittel et al., 2015).

Another finding is that Sentinel-2 provide data that can be used to estimate AGB in the type of forests that exists in both the Betul and the Mudumalai test area. Several studies have successfully investigated the application of Sentinel-2 data (Kumar et al., 2021) and other optical sensors (Dhanda et al., 2017; Sinha et al., 2019) for AGB estimation across India. Nandy et al. (2021) utilized Sentinel-2 and ICESat data across Indian forests showed that integrating forest canopy height in the forest AGBD model improved the accuracy of the AGBD estimates. Many studies emphasise the integrated use of different remote sensing data for better estimation of AGB in Indian tropical forests (Khan et al., 2020; Sinha et al., 2019). For example Malhi et al. (2022) integrate Sentinel-2 with Sentinel-1 SAR data for the estimation of AGBD with machine learning techniques. Certain studies use optical and SAR data for the estimation of AGBD across Indian forests (Prakash et al., 2024, Behera et al., 2016, Ali and Khati (2024).

Underestimation of GEDI AGBD is evident in this study which might be due to the geolocation uncertainty in GEDI measurements in highly multi-layered forests (Dorado-Roda et al., 2021; Duncanson et al., 2022). Forests with high horizontal heterogeneity and high vertical complexity of mature dense forests leads to an increase in AGBD error (Jia et al., 2023; Wang et al., 2022)which might explain why the accuracy of GEDI data varied between the two test areas. Topographic slope which results in substantial variation among tree heights and its influence on GEDI waveform cannot be neglected (Campbell et al., 2021; Jia et al., 2023; Shendryk, 2022) and the uncertainties can also be caused by the forest-type-specific and geography-specific factors (Dubayah et al., 2022; Duncanson et al., 2022; Mohite et al., 2024) which highlights the value of regional field data and models. Several studies showed that quality assessment of GEDI data for a specific region needs to be done before using the data for AGBD estimation (Mohite et al., 2024) and uncertainties exist associated with the quality issues. Jia et al., 2023 showed the GEDI L4A severely underestimated the AGBD of coniferous forests which specifies that relatively low accuracy of GEDI L4A due to canopy heterogeneity in dense forests with high biomass. The comparison between AGBD from the Sentinel-2 model and GEDI L4A footprint data indicates that the GEDI AGBDs are underestimated. Our study indicate that there is relatively few usable GEDI footprints in the Betul test area and similar is the case for Mudumalai forest. Altogether, this shows the importance of not relying entirely on GEDI data, uncertainties exist, possibly influencing the accuracy of AGBD predictions. Thus, it is interesting to consider methods where GEDI data are combined with other types of data in an efficient, for example in a model-assisted framework (e.g., Ståhl et al., 2016) or hierarchical modelling (e.g., Saarela et al., 2016, 2018).

5. Conclusion

GEDI provide AGBD estimate that, if properly calibrated, can potentially be used to quantifying the amount of carbon stored in the Indian forests and thereby help to calculate the carbon sequestration potential of forests under future climate and land-use scenarios. In this study, we have compared both GEDI L4A foot print and gridded GEDI L4B AGBD with AGBD estimated from Sentinel-2 data. The estimates of GEDI AGBD across the tropical forests in India have a relatively strong correlation ($r = 0.66$ for Betul and $r = 0.84$ for Mudumalai forests) with AGBD estimates from Sentinel-2. It was also found that the GEDI AGBDs are under-estimated compared to the Sentinel-2 AGBD estimates. This indicates that GEDI AGBD preferably should be combined with other types of data to ensure that estimate for a certain geographic area is unbiased. GEDI AGBD when utilized with model assisted statistical or modelling frameworks and combined with other types of data, thus, has the potential to support intergovernmental policy initiatives such as REDD, UNFCC and Kyoto Protocol in which India is involved in Clean Development mechanism (CDM) by giving information for climate adaptation and mitigation, sustainable land use and conservation of biodiversity.

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CRediT authorship contribution statement

Indu Indirabai: Writing – original draft, Visualization, Validation, Software, Formal analysis, Data curation. **Mats Nilsson:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software.

Declaration of competing interest

The authors declare no conflict of interest.

Data availability

The GEDI L4A, GEDI L2A and GEDI L4B are available online. (Access - GEDI (umd.edu)) https://daac.ornl.gov/GEDI/guides/GEDI_L4A_AGB_Density.html

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References

Ali, N., Khati, U., 2024. Forest aboveground biomass and forest height estimation over a sub-tropical forest using machine learning algorithm and synthetic aperture radar data. J. Indian Soc. Remote Sens. 1–16.

Baccini, A., Walker, W., Carvalho, L., Farina, M., Sulla-Menashe, D., Houghton, R.A., 2017. Tropical forests are a net carbon source based on aboveground measurements of gain and loss. Science 358 (6360), 230–234.

Barbosa, J.M., Broadbent, E.N., Bitencourt, M.D., 2014. Remote sensing of aboveground biomass in tropical secondary forests: A review. Int. J. For. Res. 1–14.

Basuki, T.M., Van Laake, P.E., Skidmore, A.K., Hussin, Y.A., 2009. Allometric equations for estimating the above-ground biomass in tropical lowland dipterocarp forests. For. Ecol. Manag. 257 (8), 1684–1694.

Basuki, T.M., Skidmore, A.K., Hussin, Y.A., Van Duren, I., 2013. Estimating tropical forest biomass more accurately by integrating ALOS PALSAR and Landsat-7 ETM+ data. Int. J. Remote Sens. 34 (13), 4871–4888.

Behera, M.D., Tripathi, P., Mishra, B., Kumar, S., Chitale, V.S., Behera, S.K., 2016. Above-ground biomass and carbon estimates of Shorea robusta and Tectona grandis forests using QuadPOL ALOS PALSAR data. Adv. Space Res. 57 (2), 552–561.

Bhattacharjee, R., Nandy, S., Sett, T., Gupta, A., 2019. Tree Parameters Retrieval and Volume Estimation Using Terrestrial Laser Scanner: A Case Study on Barkot Forest.

Bijalwan, A., Swamy, S.L., Sharma, C.M., Sharma, N.K., Tiwari, A.K., 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.

Brahma, B., Nath, A.J., Deb, C., Sileshi, G.W., Sahoo, U.K., Das, A.K., 2021. A critical review of forest biomass estimation equations in India. Trees For. People 5, 100098.

Campbell, E.M., Magnussen, S., Antos, J.A., Parish, R., 2021. Size-, species-, and site-specific tree growth responses to climate variability in old-growth subalpine forests. Ecosphere 12 (5), e03529.

Champion, H.G., Seth, S.K., 1968. A Revised Survey of the Forest Types of India. Manager of Publications.

Chave, J., Andalo, C., Brown, S., Cairns, M.A., Chambers, J.Q., Eamus, D., Yamakura, T., 2005. Tree allometry and improved estimation of carbon stocks and balance in tropical forests. Oecologia 145, 87–99.

Chave, J., Réjou-Méchain, M., Búrquez, A., Chidumayo, E., Colgan, M.S., Delitti, W.B., Vieilledent, G., 2014. Improved allometric models to estimate the aboveground biomass of tropical trees. Glob. Chang. Biol. 20 (10), 3177–3190.

Chen, Y., Guerschman, J., Shendryk, Y., Henry, D., Harrison, M.T., 2021. Estimating pasture biomass using sentinel-2 imagery and machine learning. Remote Sens. 13 (4), 603.

Chhabra, A., Palria, S., Dadhwal, V.K., 2002. Growing stock-based forest biomass estimate for India. Biomass Bioenergy 22 (3), 187–194.

Chrysafis, I., Mallinis, G., Siachalou, S., Patias, P., 2017. Assessing the relationships between growing stock volume and Sentinel-2 imagery in a Mediterranean forest ecosystem. Remote Sens. Lett. 8 (6), 508–517.

Cifuentes Jara, M., Henry, M., Réjou-Méchain, M., Wayson, C., Zapata-Cuartas, M., Piotto, D., Westfall, J., 2015. Guidelines for documenting and reporting tree allometric equations. Ann. For. Sci. 72 (6), 763–768.

Congedo, L., 2021. Semi-automatic classification plugin: A Python tool for the download and processing of remote sensing images in QGIS. J. Open Source Softw. 6 (64), 3172.

Couteron, P., Barbier, N., Proisy, C., Pélissier, R., Vincent, G., 2012. Linking remote-sensing information to tropical forest structure: the crucial role of modelling. Earthzine 4, 1–4.

Dadhwal, V.K., Singh, S., Patil, P., 2009. Assessment of phytomass carbon pools in forest ecosystems in India. NNRMS Bull. 41.

Daryaei, A., Sohrabi, H., Atzberger, C., Immitzer, M., 2020. Fine-scale detection of vegetation in semi-arid mountainous areas with focus on riparian landscapes using Sentinel-2 and UAV data. Comput. Electron. Agric. 177, 105686.

Devagiri, G.M., Money, S., Singh, S., Dadhawal, V.K., Patil, P., Khaple, A., Hubballi, S., 2013. Assessment of above ground biomass and carbon pool in different vegetation types of south western part of Karnataka, India using spectral modeling. Trop. Ecol. 54 (2), 149–165.

Dhanda, P., Nandy, S., Kushwaha, S.P.S., Ghosh, S., Murthy, Y.K., Dadhwal, V.K., 2017. Optimizing spaceborne LiDAR and very high resolution optical sensor parameters for biomass estimation at ICESat/GLAS footprint level using regression algorithms. Prog. Phys. Geogr. 41 (3), 247–267.

Dorado-Roda, I., Pascual, A., Godinho, S., Silva, C.A., Botequim, B., Rodríguez-González, P., Guerra-Hernández, J., 2021. Assessing the accuracy of GEDI data for canopy height and aboveground biomass estimates in Mediterranean forests. Remote Sens. 13 (12), 2279.

Dubayah, R., Blair, J.B., Goetz, S., Fatoyinbo, L., Hansen, M., Healey, S., Silva, C., 2020. The global ecosystem dynamics investigation: high-resolution laser ranging of the Earth's forests and topography. Sci. Remote Sens. 1, 100002.

Dubayah, R.O., Armston, J., Kellner, J.R., Duncanson, L., Healey, S.P., Patterson, P.L., Hancock, S., Tang, H., Hofton, M.A., Blair, J.B., Luthcke, S.B., 2021. GEDI L4A Footprint Level Aboveground Biomass Density, Version 1.

Dubayah, R.O., Armston, J., Healey, S.P., Yang, Z., Patterson, P.L., Saarela, S., Kellner, J. R., 2022. GEDI L4B Gridded Aboveground Biomass Density, Version 2. ORNL DAAC.

Duncanson, L., Neuenschwander, A., Hancock, S., Thomas, N., Fatoyinbo, T., Simard, M., Dubayah, R., 2020. Biomass estimation from simulated GEDI, ICESat-2 and NISAR across environmental gradients in Sonoma County, California. Remote Sens. Environ. 242, 111779.

Duncanson, L., Kellner, J.R., Armston, J., Dubayah, R., Minor, D.M., Hancock, S., Zgraggen, C., 2022. Aboveground biomass density models for NASA's global ecosystem dynamics investigation (GEDI) lidar mission. Remote Sens. Environ. 270, 112845.

Feng, Y., Zeng, Z., Searchinger, T.D., Ziegler, A.D., Wu, J., Wang, D., Zheng, C., 2022. Doubling of annual forest carbon loss over the tropics during the early twenty-first century. Nat. Sustain. 5 (5), 444–451.

Forest Survey of India, 2021. India State of Forest Report-2021. Forest Survey of India, Dehradun.

FSI, 1996. Volume Equations for Forests of India, Nepal and Bhutan.

Gao, L., Chai, G., Zhang, X., 2022. Above-ground biomass estimation of plantation with different tree species using airborne lidar and hyperspectral data. Remote Sens. 14 (11), 2568.

GEDI, 2021. L4A Footprint Level Aboveground Biomass Density, Version 1 (ornl.gov). https://daac.ornl.gov/GEDI/guides/GEDI_L4A_AGB_Density.html (accessed 29 th sept 2021).

Georgopoulos, N., Gitas, I.Z., Korhonen, L., Antoniadis, K., Stefanidou, A., 2023. Estimating crown biomass in a multilayered fir forest using airborne LiDAR data. Remote Sens. 15 (11), 2919.

Ghosh, S.M., Behera, M.D., 2018. Aboveground biomass estimation using multi-sensor data synergy and machine learning algorithms in a dense tropical forest. Appl. Geogr. 96, 29–40.

Ghosh, S.M., Behera, M.D., Jagadish, B., Das, A.K., Mishra, D.R., 2021. A novel approach for estimation of aboveground biomass of a carbon-rich mangrove site in India. J. Environ. Manag. 292, 112816.

Giri, K., Pandey, R., Jayaraj, R.S.C., Nainamalai, R., Ashutosh, S., 2019. Regression equations for estimating tree volume and biomass of important timber species in Meghalaya, India. Curr. Sci. 116 (1), 75–81.

Godinho, S., Guiomar, N., Gil, A., 2018. Estimating tree canopy cover percentage in a mediterranean silvopastoral systems using sentinel-2A imagery and the stochastic gradient boosting algorithm. Int. J. Remote Sens. 39 (14), 4640–4662.

Grabska, E., Hostert, P., Pflugmacher, D., Ostapowicz, K., 2019. Forest stand species mapping using the Sentinel-2 time series. Remote Sens. 11 (10), 1197.

Guo, Q., Du, S., Jiang, J., Guo, W., Zhao, H., Yan, X., Xiao, W., 2023. Combining GEDI and sentinel data to estimate forest canopy mean height and aboveground biomass. Eco. Inform. 78, 102348.
Hall, R.J., Skakun, R.S., Arsenault, E.J., Case, B.S., 2006. Modeling forest stand structure attributes using Landsat ETM+ data: application to mapping of aboveground biomass and stand volume. For. Ecol. Manag. 225 (1–3), 378–390.
Hancock, S., Armston, J., Hofton, M., Sun, X., Tang, H., Duncanson, L.I., Dubayah, R., 2019. The GEDI simulator: a large-footprint waveform lidar simulator for calibration and validation of spaceborne missions. Earth Space Sci. 6 (2), 294–310.
Haripriya, G.S., 2000. Estimates of biomass in Indian forests. Biomass Bioenergy 19 (4), 245–258.
Hofton, M.A., Rocchio, L.E., Blair, J.B., Dubayah, R., 2002. Validation of vegetation canopy lidar sub-canopy topography measurements for a dense tropical forest. J. Geodyn. 34 (3–4), 491–502.
Hofton, M., Blair, J.B., Story, S., Yi, D., 2020. Algorithm Theoretical Basis Document (ATBD).
Houghton, R.A., 2005. Aboveground forest biomass and the global carbon balance. Glob. Chang. Biol. 11 (6), 945–958.
India State of Forest Report (ISFR), 2021. Forest Survey of India, Dehradun.
Intergovernmental Panel on Climate Change (IPCC), 2001. Climate Change 2001: The Scientific Scenario. Contributions of Working Group I to the Third Assessment Report of the IPCC. Cambridge University Press, Cambridge.
Jha, C.S., Thumaty, K.C., Rodda, S.R., Sonakia, A., Dadhwal, V.K., 2013. Analysis of carbon dioxide, water vapour and energy fluxes over an Indian teak mixed deciduous forest for winter and summer months using eddy covariance technique. J. Earth Syst. Sci. 122 (5), 1259–1268.
Jha, C.S., Fararoda, R., Rajashekar, G., Singh, S., Dadhwal, V.K., 2015. Spatial distribution of biomass in Indian forests using spectral modelling. In: Geospatial Information Systems for Multi-Scale Forest Biomass Assessment and Monitoring in the Hindu Kush Himalayan Region, p. 139.
Jia, M., Wang, Z., Mao, D., Ren, C., Song, K., Zhao, C., Wang, Y., 2023. Mapping global distribution of mangrove forests at 10-m resolution. Science Bulletin 68 (12), 1306–1316.
Jiang, F., Kutia, M., Ma, K., Chen, S., Long, J., Sun, H., 2021. Estimating the aboveground biomass of coniferous forest in Northeast China using spectral variables, land surface temperature and soil moisture. Sci. Total Environ. 785, 147335.
Jiang, F., Deng, M., Tang, J., Fu, L., Sun, H., 2022. Integrating spaceborne LiDAR and Sentinel-2 images to estimate forest aboveground biomass in Northern China. Carbon Balance Manag. 17 (1), 1–13.
Jung, M., Arnell, A., De Lamo, X., García-Rangel, S., Lewis, M., Mark, J., Visconti, P., 2021. Areas of global importance for conserving terrestrial biodiversity, carbon and water. Nat. Ecol. Evol. 5 (11), 1499–1509.
Kale, M.P., Ravan, S.A., Roy, P.S., Singh, S., 2009. Patterns of carbon sequestration in forests of Western Ghats and study of applicability of remote sensing in generating carbon credits through afforestation/reforestation. J. Ind. Soc. Remote Sens. 37, 457–471.
Kebede, B., Soromessa, T., 2018. Allometric equations for aboveground biomass estimation of *Olea europaea* L. subsp. cuspidata in Mana Angetu Forest. Ecosyst. Health Sustain. 4 (1), 1–12.
Kellner, J.R., Armston, J., Blair, J.B., Duncanson, L., Hancock, S., Hofton, M.A., Dubayah, R., 2017, December. Algorithm theoretical basis for GEDI level-4A footprint above ground biomass density. In: AGU Fall Meeting Abstracts, 2017 pp. B11H-03.
Khan, K., Iqbal, J., Ali, A., Khan, S.N., 2020. Assessment of sentinel-2-derived vegetation indices for the estimation of above-ground biomass/carbon stock, temporal deforestation and carbon emissions estimation in the moist temperate forests of Pakistan. Appl. Ecol. Environ. Res. 18 (1).
Kishore, B.S.P.C., Kumar, A., Saikia, P., 2024. Understanding the invasion potential of *Chromolaena odorata* and *Lantana camara* in the Western Ghats, India: an ecological niche modelling approach under current and future climatic scenarios. Eco. Inform. 79, 102425.
Kumar, A., Khanna, K.K., 1998. Studies on the flora of Betul district, Madhya Pradesh. J. Econ. Taxon. Bot. 22, 495–516.
Kumar, A., Kishore, B.S.P.C., Saikia, P., Deka, J., Bharali, S., Singha, L.B., Khan, M.L., 2019. Tree diversity assessment and above ground forests biomass estimation using SAR remote sensing: a case study of higher altitude vegetation of north-East Himalayas, India. Phys. Chem. Earth Parts A/B/C 111, 53–64.
Kumar, R., Rai, A., Mishra, V., Diwate, P., Arya, V., 2021. Performance evaluation of supervised classifiers for land use and land cover mapping using Sentinel-2 MSI image. J. Geosci. Res. 6 (231), 241.
Lale, S.K., Chandra, R., Ratha, C., et al., 2020. Important medicinal plants of Betul (west) forest division of Madhya Pradesh, India. J. Drug Res. Ayurvedic Sci. 5 (4), 203–214.
Li, Y., Li, M., Li, C., Liu, Z., 2020. Forest aboveground biomass estimation using Landsat 8 and sentinel-1A data with machine learning algorithms. Sci. Rep. 10 (1), 9952.
Liang, M., González-Roglich, M., Roehrdanz, P., Tabor, K., Zvoleff, A., Leitold, V., Duncanson, L., 2023. Assessing protected area's carbon stocks and ecological structure at regional-scale using GEDI lidar. Glob. Environ. Chang. 78, 102621.
Lin, D., Anderson-Teixeira, K.J., Lai, J., Mi, X., Ren, H., Ma, K., 2016. Traits of dominant tree species predict local scale variation in forest aboveground and topsoil carbon stocks. Plant Soil 409, 435–446.
Lu, D., 2006. The potential and challenge of remote sensing-based biomass estimation. Int. J. Remote Sens. 27 (7), 1297–1328.
Lu, D., Chen, Q., Wang, G., Moran, E., Batistella, M., Zhang, M., Saah, D., 2012. Aboveground forest biomass estimation with Landsat and LiDAR data and uncertainty analysis of the estimates. Int. J. For. Res. 2012.
Lu, D., Chen, Q., Wang, G., Liu, L., Li, G., Moran, E., 2016. A survey of remote sensing-based aboveground biomass estimation methods in forest ecosystems. Int. J. Digit. Earth 9 (1), 63–105.
Lumley, T., Lumley, M.T., 2013. Package 'leaps'. Regression subset selection. In: Thomas Lumley Based on Fortran Code by Alan Miller. Available online. http://CRAN.R-project.org/package=leaps (Accessed on 18 March 2018).
Luo, S., Wang, C., Xi, X., Pan, F., Peng, D., Zou, J., Qin, H., 2017. Fusion of airborne LiDAR data and hyperspectral imagery for aboveground and belowground forest biomass estimation. Ecol. Indic. 73, 378–387.
Majasalmi, T., Rautiainen, M., 2016. The potential of Sentinel-2 data for estimating biophysical variables in a boreal forest: a simulation study. Remote Sens. Lett. 7 (5), 427–436.
Malhi, R.K.M., Anand, A., Srivastava, P.K., Chaudhary, S.K., Pandey, M.K., Behera, M.D., Kiran, G.S., 2022. Synergistic evaluation of sentinel 1 and 2 for biomass estimation in a tropical forest of India. Adv. Space Res. 69 (4), 1752–1767.
Mangla, R., Kumar, S., Nandy, S., 2016, May. Random forest regression modelling for forest aboveground biomass estimation using RISAT-1 PolSAR and terrestrial LiDAR data. In: Lidar Remote Sensing for Environmental Monitoring XV, vol. 9879. SPIE, pp. 109–119.
Martin-Gallego, P., Aplin, P., Marston, C., Altamirano, A., Pauchard, A., 2020. Detecting and modelling alien tree presence using Sentinel-2 satellite imagery in Chile's temperate forests. For. Ecol. Manag. 474, 118353.
Mayamanikandan, T., Reddy, R.S., Jha, C.S., 2019, October. Non-destructive tree volume estimation using terrestrial lidar data in teak dominated central Indian forests. In: 2019 IEEE Recent Advances in Geoscience and Remote Sensing: Technologies, Standards and Applications (TENGARSS). IEEE, pp. 100–103.
Mayamanikandan, T., Reddy, S., Fararoda, R., Thumaty, K.C., Praveen, M.S.S., Rajashekar, G., Gummapu, J., 2022. Quantifying the influence of plot-level uncertainty in above ground biomass up scaling using remote sensing data in central Indian dry deciduous forest. Geocarto Int. 37 (12), 3489–3503.
Mitchard, Edward T.A., 2018. The tropical forest carbon cycle and climate change. Nature 559 (7715), 527–534.
Mohite, J., Sawant, S., Pandit, A., Sakkan, M., Pappula, S., Parmar, A., 2024. Forest aboveground biomass estimation by GEDI and multi-source EO data fusion over Indian forest. Int. J. Remote Sens. 45 (4), 1304–1338.
Mura, M., Bottalico, F., Giannetti, F., Bertani, R., Giannini, R., Mancini, M., Chirici, G., 2018. Exploiting the capabilities of the Sentinel-2 multi spectral instrument for predicting growing stock volume in forest ecosystems. Int. J. Appl. Earth Obs. Geoinf. 66, 126–134.
Murali, K.S., Sukumar, R., 1994. Reproductive phenology of a tropical dry forest in Mudumalai, southern India. J. Ecol. 759–767.
Musthafa, M., Singh, G., 2022. Forest above-ground woody biomass estimation using multi-temporal space-borne LiDAR data in a managed forest at Haldwani, India. Adv. Space Res. 69 (9), 3245–3257.
Mutanga, O., Adam, E., Cho, M.A., 2012. High density biomass estimation for wetland vegetation using WorldView-2 imagery and random forest regression algorithm. Int. J. Appl. Earth Obs. Geoinf. 18, 399–406.
Nandy, S., Ghosh, S., Kushwaha, S.P.S., Senthil Kumar, A., 2019. Remote sensing-based forest biomass assessment in northwest Himalayan landscape. Remote Sens. Northw. Himalayan Ecosyst. 285–311.
Nandy, S., Srinet, R., Padalia, H., 2021. Mapping forest height and aboveground biomass by integrating ICESat-2, Sentinel-1 and Sentinel-2 data using random forest algorithm in northwest Himalayan foothills of India. Geophys. Res. Lett. 48 (14), e2021GL093799.
Nath, C.D., Dattaraja, H.S., Suresh, H.S., Joshi, N.V., Sukumar, R., 2006. Patterns of tree growth in relation to environmental variability in the tropical dry deciduous forest at Mudumalai, southern India. J. Biosci. 31 (5), 651–669.
Nath, A.J., Tiwari, B.K., Sileshi, G.W., Sahoo, U.K., Brahma, B., Deb, S., Gupta, A., 2019. Allometric models for estimation of forest biomass in north East India. Forests 10 (2), 103.
Nilsson, M., Nordkvist, K., Jonzén, J., Lindgren, N., Axensten, P., Wallerman, J., Olsson, H., 2017. A nationwide forest attribute map of Sweden predicted using airborne laser scanning data and field data from the national forest inventory. Remote Sens. Environ. 194, 447–454.
Nuthammachot, N., Phairuang, W., Wicaksono, P., Sayektiningsih, T., 2018. Estimating aboveground biomass on private forest using Sentinel-2 imagery. Journal of Sensors 2018.
Nuthammachot, N., Askar, A., Stratoulias, D., Wicaksono, P., 2020. Combined use of Sentinel-1 and Sentinel-2 data for improving above-ground biomass estimation. Geocarto Int. 1–11.
Packalén, P., Maltamo, M., 2007. The k-MSN method for the prediction of species-specific stand attributes using airborne laser scanning and aerial photographs. Remote Sens. Environ. 109 (3), 328–341.
Palma, A.C., Goosem, M., Fensham, R.J., Goosem, S., Preece, N.D., Stevenson, P.R., Laurance, S.G., 2021. Dispersal and recruitment limitations in secondary forests. J. Veg. Sci. 32 (1), e12975.
Pandit, S., Tsuyuki, S., Dube, T., 2018. Estimating above-ground biomass in sub-tropical buffer zone community forests, Nepal, using Sentinel-2 data. Remote Sens. 10 (4), 601.
Pargal, S., Fararoda, R., Rajashekar, G., Balachandran, N., Réjou-Méchain, M., Barbier, N., Couteron, P., 2017. Inverting aboveground biomass–canopy texture relationships in a landscape of Forest mosaic in the Western Ghats of India using very high resolution Cartosat imagery. Remote Sens. 9 (3), 228.
Persson, H.J., Jonzén, J., Nilsson, M., 2021. Combining TanDEM-X and Sentinel-2 for large-area species-wise prediction of forest biomass and volume. Int. J. Appl. Earth Obs. Geoinf. 96, 102275.

Piao, Y., Lee, D., Park, S., Kim, H.G., Jin, Y., 2022. Forest fire susceptibility assessment using google earth engine in Gangwon-do, Republic of Korea. Geomat. Nat. Haz. Risk 13 (1), 432–450.

Potapov, P., Li, X., Hernandez-Serna, A., Tyukavina, A., Hansen, M.C., Kommareddy, A., Hofton, M., 2021. Mapping global forest canopy height through integration of GEDI and Landsat data. Remote Sens. Environ. 253, 112165.

Prakash, A.J., Mudi, S., Paramanik, S., Behera, M.D., Shekhar, S., Sharma, N., Parida, B. R., 2024. Dominant expression of SAR backscatter in predicting aboveground biomass: integrating multi-sensor data and machine learning in Sikkim Himalaya. J. Indian Soc. Remote Sens. 1–13.

Puliti, S., Breidenbach, J., Schumacher, J., Hauglin, M., Klingenberg, T.F., Astrup, R., 2021. Above-ground biomass change estimation using national forest inventory data with Sentinel-2 and Landsat. Remote Sens. Environ. 265, 112644.

Raha, D., Dar, J.A., Pandey, P.K., Lone, P.A., Verma, S., Khare, P.K., Khan, M.L., 2020. Variation in tree biomass and carbon stocks in three tropical dry deciduous forest types of Madhya Pradesh, India. Carbon Manag. 11 (2), 109–120.

Rajashekar, G., Fararoda, R., Reddy, R.S., Jha, C.S., Ganeshaiah, K.N., Singh, J.S., Dadhwal, V.K., 2018. Spatial distribution of forest biomass carbon (above and below ground) in Indian forests. Ecol. Indic. 85, 742–752.

Ramachandran, A., Jayakumar, S., Haroon, R.M., Bhaskaran, A., Arockiasamy, D.I., 2007. Carbon sequestration: estimation of carbon stock in natural forests using geospatial technology in the eastern Ghats of Tamil Nadu, India. Curr. Sci. 323–331.

Ravindranath, N.H., Ostwald, M., 2008. Modelling for Estimation and Projection of Carbon Stocks in Land-Use Systems. Carbon Inventory Methods Handbook for Greenhouse Gas Inventory, Carbon Mitigation and Roundwood Production Projects, pp. 201–215.

Ravindranath, N.H., Somashekhar, B.S., Gadgil, M., 1997. Carbon flow in Indian forests. Clim. Chang. 35 (3), 297–320.

Ravindranath, N.H., Chaturvedi, R.K., Murthy, I.K., 2008. Forest conservation, afforestation and reforestation in India: implications for forest carbon stocks. Curr. Sci. 216–222.

Reddy, C.S., Jha, C.S., Diwakar, P.G., Dadhwal, V.K., 2015. Nationwide classification of forest types of India using remote sensing and GIS. Environ. Monit. Assess. 187, 1–30.

Reddy, R.S., Jha, C.S., Rajan, K.S., 2018. Automatic tree identification and diameter estimation using single scan terrestrial laser scanner data in central Indian forests. J. Indian Soc. Remote Sens. 46 (6), 937–943.

Rodda, S.R., Nidamanuri, R.R., Mayamanikandan, T., Rajashekar, G., Jha, C.S., Dadhwal, V.K., 2023. Non-destructive Allometric modeling for tree volume estimation in tropical dry deciduous forests of India using terrestrial laser scanner. J. Indian Soc. Remote Sens. 1–15.

Saarela, S., Holm, S., Grafström, A., Schnell, S., Næsset, E., Gregoire, T.G., Ståhl, G., 2016. Hierarchical model-based inference for forest inventory utilizing three sources of information. Ann. For. Sci. 73 (4), 895–910.

Saarela, S., Holm, S., Healey, S.P., Andersen, H.E., Petersson, H., Prentius, W., Ståhl, G., 2018. Generalized hierarchical model-based estimation for aboveground biomass assessment using GEDI and landsat data. Remote Sens. 10 (11), 1832.

Salunkhe, O., Khare, P.K., Kumari, R., Khan, M.L., 2018. A systematic review on the aboveground biomass and carbon stocks of Indian forest ecosystems. Ecol. Process. 7, 1–12.

Shendryk, Y., 2022. Fusing GEDI with earth observation data for large area aboveground biomass mapping. Int. J. Appl. Earth Obs. Geoinf. 115, 103108.

Singh, I.J., Moharir, S., 2003. Forest management using remote sensing and GIS in Barbatpur range, Betul forest division. J. Indian Soc. Remote Sens. 31 (3), 149–156.

Singh, R.K., Biradar, C.M., Behera, M.D., Prakash, A.J., Das, P., Mohanta, M.R., Rizvi, J., 2024. Optimising carbon fixation through agroforestry: estimation of aboveground biomass using multi-sensor data synergy and machine learning. Eco. Inform. 79, 102408.

Sinha, S., Santra, A., Das, A.K., Sharma, L.K., Mohan, S., Nathawat, M.S., Jeganathan, C., 2019. Regression-based integrated bi-sensor SAR data model to estimate forest carbon stock. J. Indian Soc. Remote Sens. 47, 1599–1608.

Slik, J.F., Paoli, G., McGuire, K., Amaral, I., Barroso, J., Bastian, M., Zweifel, N., 2013. Large trees drive forest aboveground biomass variation in moist lowland forests across the tropics. Glob. Ecol. Biogeogr. 22 (12), 1261–1271.

Sodhi, H., 2021. Application of remote sensing for above-ground biomass estimation. Int. J. Sci. Res. (IJSR) 10 (4), 182–187.

Ståhl, G., Saarela, S., Schnell, S., Holm, S., Breidenbach, J., Healey, S.P., Gregoire, T.G., 2016. Use of models in large-area forest surveys: comparing model-assisted, model-based and hybrid estimation. For. Ecosyst. 3, 1–11.

Sukumar, R., Dattaraja, H.S., Suresh, H.S., Radhakrishnan, J., Vasudeva, R., Nirmala, S., Joshi, N.V., 1992. Long-term monitoring of vegetation in a tropical deciduous forest in Mudumalai, Southern India. Curr. Sci. 608–616.

Suresh, H.S., Nanda, A., 2021. Comparative phenologies of two tropical dry forests in southern India. J. Glob. Ecol. Environ. 13 (1), 36–57.

Tewari, A., Bhatt, J., Mittal, A., Singh, N., Tamta, K.K., 2016. Regeneration issues and indicators of seed maturity in Mallotus phillipensis Muel. Arg. In the tropical forests of Uttarakhand. Ecol. Environ. Conserv. 22 (2), 767–773.

Thakur, T.K., 2018. Diversity, composition and structure of understorey vegetation in the tropical forest of Achanakmaar Amarkantak biosphere reserve, India. Environ. Sustain. 1 (3), 279–293.

Thumaty, K.C., Fararoda, R., Middinti, S., Gopalakrishnan, R., Jha, C.S., Dadhwal, V.K., 2016. Estimation of above ground biomass for central Indian deciduous forests using ALOS PALSAR L-band data. J. Indian Soc. Remote Sens. 44 (1), 31–39.

Timothy, D., Onisimo, M., Riyad, I., 2016. Quantifying aboveground biomass in African environments: a review of the trade-offs between sensor estimation accuracy and costs. Trop. Ecol. 57 (3), 393–405.

Torre-Tojal, L., Bastarrika, A., Boyano, A., Lopez-Guede, J.M., Grana, M., 2022. Above-ground biomass estimation from LiDAR data using random forest algorithms. J. Comput. Sci. 58, 101517.

Vafaei, S., Soosani, J., Adeli, K., Fadaei, H., Naghavi, H., Pham, T.D., Tien Bui, D., 2018. Improving accuracy estimation of Forest aboveground biomass based on incorporation of ALOS-2 PALSAR-2 and sentinel-2A imagery and machine learning: a case study of the Hyrcanian forest area (Iran). Remote Sens. 10 (2), 172.

Vashum, K.T., Jayakumar, S., 2012. Methods to estimate above-ground biomass and carbon stock in natural forests-a review. J. Ecosyst. Ecograph. 2 (4), 1–7.

Véga, C., Vepakomma, U., Morel, J., Bader, J.L., Rajashekar, G., Jha, C.S., Dadhwal, V.K., 2015. Aboveground-biomass estimation of a complex tropical forest in India using lidar. Remote Sens. 7 (8), 10607–10625.

Wang, J., Wang, X., Ji, Y., Gao, J., 2022. Climate factors determine the utilization strategy of forest plant resources at large scales. Front. Plant Sci. 13, 990441.

Wani, A.A., Joshi, P.K., Singh, O., Pandey, R., 2012. Carbon inventory methods in Indian forests-A review. Int. J. Agric. For. 2 (6), 315–323.

Weiskittel, A.R., MacFarlane, D.W., Radtke, P.J., Affleck, D.L., Temesgen, H., Woodall, C. W., Coulston, J.W., 2015. A call to improve methods for estimating tree biomass for regional and national assessments. J. For. 113 (4), 414–424.

Wulder, M.A., Hermosilla, T., White, J.C., Coops, N.C., 2020. Biomass status and dynamics over Canada's forests: disentangling disturbed area from associated aboveground biomass consequences. Environ. Res. Lett. 15 (9), 094093.

Xi, Y., Tian, Q., Zhang, W., Zhang, Z., Tong, X., Brandt, M., Fensholt, R., 2022. Quantifying understory vegetation density using multi-temporal Sentinel-2 and GEDI LiDAR data. GISci. Remote Sens. 59 (1), 2068–2083.

Xiang, W., Zhou, J., Ouyang, S., Zhang, S., Lei, P., Li, J., Forrester, D.I., 2016. Species-specific and general allometric equations for estimating tree biomass components of subtropical forests in southern China. Eur. J. For. Res. 135, 963–979.

Xing, D., Bergeron, J.C., Solarik, K.A., Tomm, B., Macdonald, S.E., Spence, J.R., He, F., 2019. Challenges in estimating forest biomass: use of allometric equations for three boreal tree species. Can. J. For. Res. 49 (12), 1613–1622.

Yang, Q., Niu, C., Liu, X., Feng, Y., Ma, Q., Wang, X., Guo, Q., 2023. Mapping high-resolution forest aboveground biomass of China using multisource remote sensing data. GISci. Remote Sens. 60 (1), 2203303.

Zhao, P., Lu, D., Wang, G., Wu, C., Huang, Y., Yu, S., 2016. Examining spectral reflectance saturation in Landsat imagery and corresponding solutions to improve forest aboveground biomass estimation. Remote Sens. 8 (6), 469.