Estimation of Aboveground Carbon Stocks of Kudremukh National Park in the Western Ghats of India using Multi-sensor Remote Sensing Data and Machine Learning Approach

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ABSTRACT

The Western Ghats of India, a UNESCO World Heritage site and one of the world’s eight ‘hottest hotspots’ of biological diversity, are recognized for their highly productive and characteristic montane forest ecosystems. High-resolution and geographically large coverage mapping of forest carbon stocks is valuable to adapt and effectively implement large-scale forest management strategies. Previous approaches to producing maps of carbon stocks at a regional scale have considered limited areal extant and have relied on knowledge-based stratification and regression of plot-level measurements and low-resolution forest vegetation maps derived from active or passive remote sensing data. With an overall aim of near-future applicability to the entire Western Ghats of India, this study investigated the application of a multi-sensor remote sensing technique to estimate aboveground carbon stocks (AGCS) at high spatial resolution in Kudremukh National Park in the Western Ghats. Implementing a feature-fusion-based integration of satellite-based LiDAR (GEDI), SAR (Sentinel-1), multispectral (Sentinel-2) and DEM (SRTM) datasets in a Randorm Forests machine learning framework, the study proposes a scalable method to map AGB densities and derive carbon stock estimates. The maps are validated using hold-out field inventory data. The study reveals that AGB ranges from 13 to 300 Mg/ha, with a mean of 93.69 Mg/ha, primarily concentrated in grasslands (below 1000 meters). The aboveground biomass density point cloud from GEDI LiDAR data, modelled and upscaled using multi-sensor remote sensing datasets, reveals biomass density patterns and tree species dynamics conforming to the regional patterns. The

findings underscore the importance of elevation and forest cover type in hosting dominant portions of AGCS in Kudremukh National Park. This work offers valuable insights into carbon stock assessment and ecosystem dynamics, benefiting policy decisions related to climate change mitigation and biodiversity conservation efforts.

Keywords: Biomass, Above-Ground Carbon Stocks (AGCS), LiDAR, SAR, Multispectral data, Machine Learning, Random Forests, Western Ghats, Biodiversity

1 INTRODUCTION

Forests are vital as wildlife habitats, clean water, sources of materials and commodities, as well as carbon sinks.[1] Carbon storage and sequestration are among the most important services forest ecosystems provide, which are important factors for climate change mitigation and adaptation. However, their value is not always adequately recognized, with people often taking for granted the benefits of the forest ecosystems.[2,3] Studies have estimated that up to 20% of annual greenhouse gas emissions are caused by the loss of forests due to natural and anthropogenic disturbances worldwide.[4] Therefore, accurately estimating carbon levels is crucial for biodiversity conservation and climate mitigation efforts. Concerns about the effects of increasing atmospheric carbon dioxide on climate have spurred an international initiative aimed at reducing forest-related emissions, notably in the tropics, where the bulk of global deforestation occurs.[5] The implementation of Reducing Emissions from Deforestation and Forest Degradation (REDD+) hinges on the ability to monitor forest carbon stock and dynamics across spatial scales, ranging from entire countries down to the localized scales where deforestation and degradation processes occur.[6]

The Western Ghats is a global biodiversity hotspot for numeric endemic species and a wide variety of habitats including as streams, wet evergreen forests, grasslands, scrub forests, savannas, peat bogs, Myristica swamps, and man-made habitats.[7,8] It serves as a significant carbon reservoir, actively sequestering atmospheric CO_2 and mitigating climate change. Encompassing 36% of the protected areas in India, the Western Ghats harbour diverse forest ecosystems, including tropical rainforests, evergreen, and deciduous forests, with an estimated vegetation carbon stock of 1.23 Gt (billion gigagrams).[9] Functionally relevant and high-resolution mapping of the carbon sequestration potential of the Western Ghats is crucial for understanding the localized patterns of climate change, water, and food security in peninsular India.[9,10] The Kudremukh National Park (KNP), one of the UNESCO World Heritage sites in Western Ghats,[11] is considered representative of the gross ecological and biodiversity characteristics of the Western Ghats. It is an indicator of substantial tropical biological diversity with a high rate of endemism and is the region of the origin of three major rivers - Tunga, Bhadra, and Netravathi rivers. The distinctive evergreen ecosystem within the park plays a crucial role in executing various regulatory functions, particularly regarding biogeochemical cycles. This unique ecological system efficiently manages and influences the flow of essential elements, demonstrating its significance in maintaining ecological balance and sustainability. The records of the forest department of the Government of Karnataka[12] illustrate that the landscape of Kudremukh National Park has undergone considerable changes during the last four decades. Holding the world's largest iron ore deposits, mining activities were initiated from 1980 identifying mineralized areas of about 500 ha. In the process of establishing the unit, the entire landscape of the area was modified with a huge township and other infrastructure facilities. The environmental impact assessment of mining, which was carried out 20 years after the establishment of iron ore mining and processing factor, has highlighted several adverse impacts of mining on the local ecology[13] and eventually led to the declaration of it a protected national park in 1987 and banning of mining activities in 2005.[14]

The forest department, mining authorities, and a number of other corporates involved in the mining and plantation businesses have carried out extensive plantations using exotic trees such as *Eucalyptus tereticornis, Acacia auriculiformis, Grevillea robusta* and *Casuarina equisetifolia*. [12,15] Nevertheless, Kudremukh National Park structurally is heterogeneous and has exceptionally high biological diversity. The degree of endemism is very high[16] in Kudremukh National Park, which includes *Poeciloneuron indicum, Myristica dactyloides, Litsea floribunda* and many other species, and has the characteristics of relics. An accurate estimation of forest aboveground biomass (AGB) is required to provide the baseline carbon stocks and quantify the anthropogenic emissions caused by deforestation and forest degradation in the context of Climate change.[17] In addition, accurate estimation of forest AGB density is critical for implementing cost-effective carbon emission mitigation strategies. The conventional approach of AGB estimation relies on the allometric equations developed based on limited field sampling of tree structural parameters such as height and diameter at breast height (DBH).[18,19] This conventional approach is valuable to a certain extent; however, it is expensive and time-consuming over a vast forest area, limiting scalability. Furthermore, field-based inventory and destructive biomass sampling approaches can introduce substantial sampling and upscaling distortions.[20]

Remote sensing data allows large-scale assessments of the forest ecosystem, structure, and functionality. Various studies have demonstrated the potential of estimating biomass and other structural metrics of forest stands using data from optical,[21,22] SAR,[23] and LiDAR[24,25,26,27,28] sensors mounted on ground-based, airborne, and space-borne platforms. A range of methods, - statistical regressions,[21] machine learning,[29] and deep learning,[30,31] have also been used for estimating the forest biomass. While optical imagery proves proficient in delineating biomass variations, it reaches a point of saturation beyond which it is unable to discern further biomass fluctuations.[32] Conversely, LiDAR exhibits promise in generating AGB density points; however, its sparse distribution of data points renders it inefficient for comprehensive AGB density mapping across extensive areas due to its inherent limitations.[21] Even though many studies have adopted integrated or data fusion methods to overcome the limitations of using a single remote sensing datatype, the forest landscapes that represent the data extents are often limited in spatial extent, and the forest landscapes are predominantly homogeneous with similar terrain and ecological conditions across the length and breadth of imagery coverage.[27,33,34] Application of these studies to complex mosaics of landscapes like Western Ghats is very limited. These constraints often limit the generalization or inference of model suitability for carbon estimations over expansive areas in highly diversified forest landscapes in tropical countries such as the Western Ghats of India. Except for the global or biome-level maps of carbon estimates produced from coarse-resolution satellite data,[23,31,35] there are very limited attempts at assessing the methodological implementations and application of multi-sensor remote sensing data for AGB estimation over a large area - encompassing the full range of forest ecosystems and heterogeneity typical of the Western Ghats of India and thereby serving as operational reference estimations of AGB.[36,37] Leveraging LiDAR and SAR data addresses saturation concerns, whereas optical imagery facilitates scaling the data from regional to broader spatial scales. The objective of this study is to estimate the AGB of a complex and heterogeneous forest landscape of the Western Ghats of India by fusing optical, SAR, and LiDAR data in a machine-learning methodological framework. Considering the space-borne LiDAR-based discrete estimates of biomass as seed measurements, spatially continuous raster data from SAR and multispectral satellite data were modelled by implementing a non-parametric ML approach, Random Forest regression, for the generation of a spatially continuous and high-resolution AGB map that encompasses the entire Kudremukh National Park of the Western Ghats of India. The AGB estimates validated against field inventory values demonstrate consistent and reasonably high accuracy in AGB mapping across varied spatial and ecological contexts.

2 MATERIALS AND METHODS

2.1 Study Area

Within the broader context of generating AGB maps covering the entire geographical extent of the Western Ghats, we have chosen a study site, Kudremukh National Park, which represents geographical and ecological diversity of Western Ghats. The location map of the study area is depicted in Figure 1. Kudremukh National Park extends between 75^{o} 01' to 75^{o} 25' E longitude and 13^{o} 01' to 13^{o} 29' N latitudes; found at an altitude of 1892 m above sea level, encompassing forests of hilly terrain, in an area of 736.28 km^{2} in the Western Ghats, India. It includes Tungabhadra State Forest in the Chikkamagaluru Revenue District, the Naravi reserve forest in the Dakshina Kannada district and the Andar reserve forest in the Udupi District. The Kudremukh National Park has highland and lowland tropical evergreen forests, shola, grassland, savannah, and mosaics of mixed semi-evergreen forest and plantations in the peripheral area (Swamy and Procter, 1994; Krishnamurthy, 2003). The climate is typically tropical, with annual rainfall ranging from 600 to 800 cm. The maximum temperature varies from 21^{o}C to 34^{o}C during April–July, while the minimum temperature ranges from 12^{o}C to 18^{o}C between January and May.[15,38]

The landscape is a mosaic of several unique geographical, ecological, and social attributes with changing elevations. The central, northern, and eastern parts of the study area comprise a formation of rolling hills with a mosaic of grasslands and montane evergreen forests.[39] The forest formation in the western slopes below 300 m are semi-evergreen in nature and are influenced by anthropogenic activities. Below 200 m, a mosaic of landscape element types replaces natural vegetation, with various types of plantations particularly, Arecanut (Areca catechu) dominating this terrain.[40] Primary forest species are *Myristica dactyloides*, *Palaquium ellipticum*, *Garcinia gummi-gutta*, and *Poeciloneuron indicum* play crutial role in maintaining forest ecosystem stability and enhansing the provision of forest ecosystem services.[38]

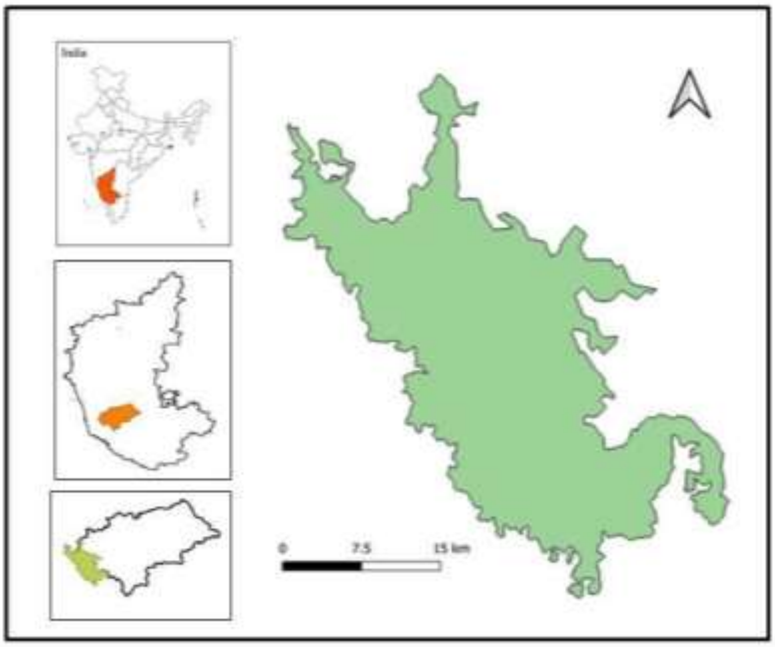

Figure 1. Study Area: location and administrative boundary of the Kudremukh National Park, Western Ghats.

2.2 Data Sources

The study used field inventory data and remote sensing data from different sensors. Aboveground Biomass Density (AGBD) data points from GEDI, a satellite-based LiDAR sensor, backscattering data from microwave RS satellite, multispectral satellite imagery and DEM data form the primary RS datasets. Plot inventory data matching acquisition time and geographical locations of the multi-sensor RS data considered were extracted from the series of plot inventory data acquisitions carried out periodically under the National Carbon Sequestration Mission, India. Below is a brief description of the sources of remote sensing data used.

2.2.1 Discrete measurements of aboveground biomass density (AGBD) from LiDAR

The Global Ecosystem Dynamics Investigation (GEDI) was a LiDAR mission launched by NASA mounted on the International Space Station in 2018. This sensor was specifically designed to retrieve vegetation structure within a novel, theoretical sampling design that explicitly quantifies biomass and its uncertainty across various spatial scales.[41,42] The GEDI mission collected waveform LiDAR data with a dense sampling rate of ~25m footprint along ground tracks paralleling the orbit of the International Space Station (ISS).[43] It provided 1 km x 1 km estimates of mean aboveground biomass density (Mg ha^{-1}) based on observations from mission week 19 starting 2019-04-18 to mission week 138 ending on 2021-08-04. The GEDI L4A Footprint Biomass product converts each high-quality waveform to an AGBD prediction. The L4B product uses the sample present within the borders of each 1 km cell to statistically infer mean AGBD.[44] The mean aboveground biomass density layer of GEDI L4B product was used in the study.

2.2.2 Multispectral and SAR Data and the computation of spectral indices

The study used spatially continuous raster data from satellites - multispectral imagery from Sentinel-2, SAR imagery from Sentinel-1 and elevation data from SRTM DEM. The cloud-free imagery of Sentinel-2 and the corresponding Sentinel-1 data were procured for the year 2021. The SAR data acquired from the Sentinel-1 are generally provided as Level-1 Ground Range Detected (GRD) products.[45] Using the SNAP toolbox provided by the European Space Agency,[46] the SAR data were processed for retrieving the geo-referenced backscatter coefficient (σ°) in decibels (dB). Surface reflectance products from Sentinel-2 L2A images were composited as the S2 mosaic after the cloud and noise removal.[47,48] To calculate topographic indicators SRTM DEM products were used.[49] Bringing to the desirable spatial resolution of 10m common in some spectral bands of Sentinel-2 and multiple spatial resolutions in Sentinel-1, the spatial resolution of the multispectral and SAR data was resampled to a uniform grid size of 10m. To match point-to-point elevation values, the DEM product was up-sampled from 30 m to 10m using the nearest neighbourhood approach. The data sets, and various products and indices generated for the study are listed in Table 1.

Table 1. Multi-sensor variables used for Above Ground Biomass modelling.

Sl. No.	**Images**	**Features**		**Description**
1	S1 mosaic	Backscatter	VV	Single co-polarisation, vertical transmit/vertical receive (in dB)
			VH	Dual-band cross-polarisation, vertical transmit/horizontal receive (in dB)
2	S2 mosaic	Multispectral Bands	B2*	Blue, 490 nm
			B3*	Green, 560 nm
			B4*	Red, 665 nm
			B5*	Red Edge 1/Visible and Near Infrared (VNIR), 705 nm
			B6	Red Edge 2/Visible and Near Infrared (VNIR), 740 nm
			B7	Red Edge 3/ Visible and Near Infrared (VNIR), 783 nm
			B8	Visible and Near Infrared (VNIR), 842 nm
			B8A	Visible and Near Infrared (VNIR), 865 nm
			B11*	Short Wave Infrared (SWIR), 1610 nm
			B12*	Short Wave Infrared (SWIR), 2190 nm
		Vegetation indices	RVI*	Ratio vegetation index, B8/B4
			DVI	Difference vegetation index, B8 − B4
			NDVI*	Normalised difference vegetation index, (B8 − B4)/(B8 + B4)
			EVI*	Enhanced vegetation index, 2.5 × (B8 − B4)/(B8 + 6 × B4 − 7.5 × B2 + 1)
			S2REP	Sentinel-2 red-edge position index, 705 + 35 × [(B4 + B7)/2 − B5] × (B6 − B5)
			REIP*	Red-edge inflection point index,

				700 + 40 × [(B4 + B7)/2 − B5]/(B6 − B5)
			SAVI*	Soil adjusted vegetation index, 1.5 × (B8 − B4)/8 × (B8 + B4 + 0.5)
			MTCI*	Meris terrestrial chlorophyll index, (B6 − B5)/(B5 − B4)
			MCARI*	Modified chlorophyll absorption ratio index, [(B5 − B4) − 0.2 × (B5 − B3)] × (B5 − B4)
			NDVI45*	Normalised difference vegetation index with bands 4 and 5, (B5 − B4)/(B5 + B4)
			NDVI56*	Normalised difference vegetation index with bands 5 and 6, (B6 − B5)/(B6 + B5)
			NDVI57	Normalised difference vegetation index with bands 5 and 7, (B7 − B5)/(B7 + B5)
			NDVI58a	Normalised difference vegetation index with bands 5 and 8a, (B8a − B5)/(B8a + B5)
			NDVI67*	Normalised difference vegetation index with bands 6 and 7, (B7 − B6)/(B7 + B6)
			NDVI68a	Normalised difference vegetation index with bands 6 and 8a, (B8a − B6)/(B8a + B6)
			NDVI78a	Normalized difference vegetation index with bands 7 and 8a, (B8a − B7)/(B8a + B7)
3	SRTM	Topographic Indicators	Elevation*	Elevation in m
			Slope (β)*	Slope
			Aspect	Aspect
			Surface roughness	Surface roughness, 1/cos β

*Filtered predictor variables based on Random Forest variable importance,

2.2.2 Ground truth data

The reference field biomass estimates were obtained using the volume and wood density of each tree species by substituting tree diameter values from 2018 to 2020 following the method suggested by the Forest Survey of India.[50] A plot measuring 1ha (100m x100m), sub-divided into 25 quadrants of 0.04 ha each, was established as the standard measurement unit. The plot's direction was set to true north and was precision geo-located using a differential global navigation satellite system (DGNSS) receiver. Total station was used for marking 20x20 meter quadrant on the ground, and measurements were acquired in 10 quadrants within each plot. The Quadrants were identified based on stratified random sampling and accessibility. Plot-level biomass measurements were derived by upscaling the sampled quadrants. The list of parameters measured in each quadrant are listed in Table 2. For several sampling plots, Terrestrial Laser scanning (TLS) derived tree measurements were generated to account for the non-availability of a few tree-specific parameters and to calibrate local allometric equations. At each site, multiple scans-based TLS measurements were conducted over four circular plots with a radius of 20m. To ensure inter-comparison and calibration of the estimations, TLS scans were undertaken at some sites were full tree measurements and equations are available. Estimations of tree parameters from TLS modelling[36] are considered field data equivalent. Distributed across the range of AGB variability in the study area, reference data on AGB and other tree parameters were acquired at 100 measurement plots.

Table 2. Summary of the parameters measured at reference plots during ground truth data acquisitions.

Sl. No.	Parameter	Instrument
1	Height	Leica Distometer S910
2	Diameter at Breast Height (DBH)	Meter tape
3	Leaf Area Index (LAI)	Licor LAI Meter2200
4	Fraction of Photosynthetically Active Radiation (fPAR)	Quantum Sensor
5	Species name/family	Taxonomist
6	Frequency	Manual counting
7	Bark/stem Sampling (FSI volume equations)	As permitted; manually chopping off selected pieces of stem/ Collection from a nearby timber depot

2.3 Method for the Estimation of AGBD and Carbon Stocks and Validation

The overall methodological framework used to estimate Above Ground Biomass Density (AGBD) and Carbon stock is given in Figure 2. For the complementary feature level fusion of remote sensing data from different sensors and for calibrating a model for estimating AGB, we used the Random Forests machine learning (ML) algorithm in the regression mode. Numerous ML algorithms are available in the literature,[51,52] differentiated for their computational performance, ability to handle random and categorical variables, level of expert involvement, etc. Based on the relevant literature and our pre-implementation experiments for the selection of an appropriate ML algorithms, Random Forests (RF), amongst a host of ML algorithms such as Support Vector Machines (SVM), Multinomial Logistics Regression (MLR), Naive Bayes, K-Nearest Neighbours, Gradient Boosting (GB), AdaBoosting (AB) has offered consistently higher performance. We, therefore, chose the RF algorithm for non-parametric integration and modelling of biomass using field inventory and multi-source remote sensing data.

From the GEDI L4B dataset, 1,000 AGB density points were sampled, which were used for machine learning model training and map visualisation. Further, the training data were split into training and validation sets. The training dataset was partitioned into training (70%) and validation (30%). Further, to train and evaluate the RF algorithm, the model parameter “number of trees” was defined as 500 to make the model statistically robust. Then, the RF algorithm was executed in regression mode, considering the predictor variables, including Sentinel-1 and Sentinel-2 mosaic and SRTM data, targeting the mean aboveground biomass obtained from the GEDI L4B dataset. To analyse the model's performance, a variable importance test was performed to understand whether the predictors had more influence on the model. The correlation was assessed between predicted and observed data and Root-Mean Square Error (RMSE) was computed. To optimize the model further, the predictor variables having the least significance were filtered out based on the Gini Index[53] (Figure 3) and the model was re-calibrated. The prediction model thus optimized was validated using hold-out ground truth measurements and the spatially continuous AGBD map was generated.

Calculating carbon stock as biomass consists of multiplying the total biomass by a conversion factor representing the average carbon content in biomass. It is not possible to separate the different biomass components to account for variations in carbon content as a function of the biomass component. Therefore, the coefficient of 0.55 for the conversion of biomass to C offered by Ref[54] is generalised here to conversions from biomass to carbon stock: C = 0.55 × biomass (Mg/ha).[55] Further, to understand the distribution of carbon across the study area, its variation was studied across different land use classes and elevation gradients.

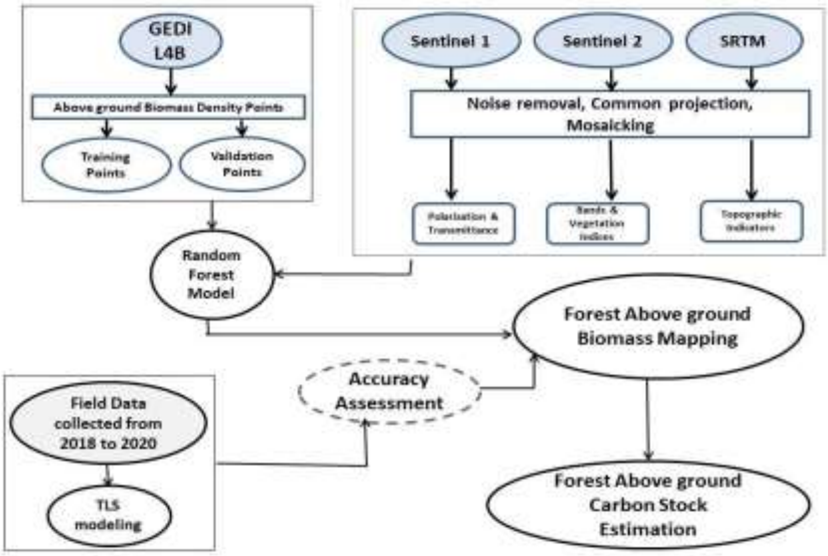

Figure 2. Methodological framework for estimating aboveground biomass (AGB) and carbon stock using multi-sensor remote sensing data.

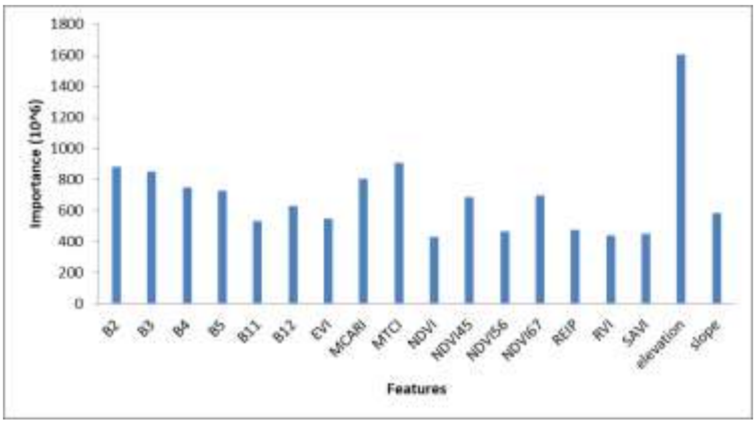

Figure 3. The importance feature evaluation computed based on the Gini Index for implementing the Random Forests algorithm for the multi-sensor remote sensing data used in the AGB estimation (the features are abbreviated in Table 1).

3 Results, Analysis, and Discussion

The validated results of AGB estimation are shown in Figures 4 and 5. The overall AGB of Kudremukh National Park varies between 261.68 to 48.94 Mg/ha (Figure 4), with a mean

AGB of 149.18 Mg/ha. A strong correlation is observed between the estimated and measured AGB, wherein the goodness of fit (R^2) is 0.86 (Fig. 5) with an RMSE value of 12.94 Mg/ha, less than 10% of the mean value. These estimates are good considering the study site's vast geographical area and diversity. The estimates provided by the model are not random, as confirmed by the F-test, and are statistically significant at a confidence level of 95%. To understand the response of the model developed to various levels of AGB, the residual plot is shown in Figure 6. As evident, the points are randomly dispersed, and there is no systematic pattern in the variations of the AGB residuals, suggesting no generic overestimation or underestimation in the model. Even Though there is a substantial underestimation of biomass at higher AGB levels, this pattern appears to be a random feature, as evident from the much higher-level biomass.

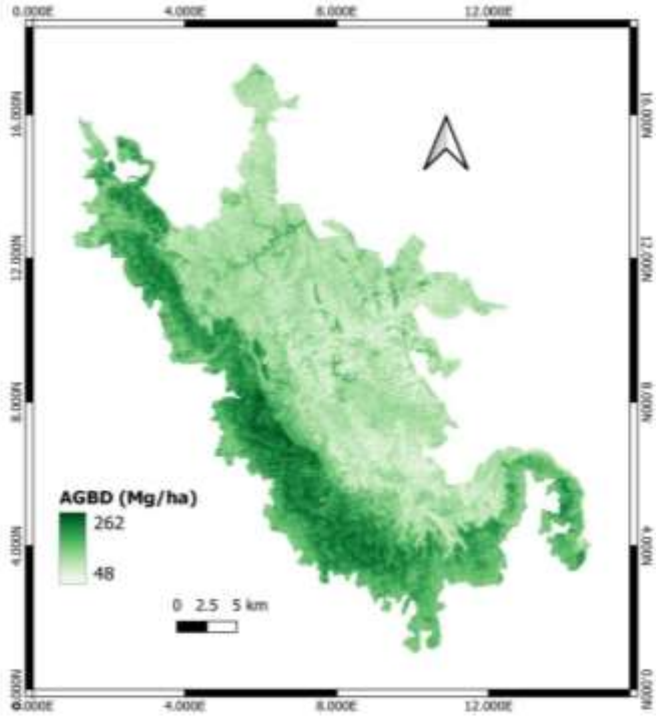

Figure 4. Aboveground Biomass (AGB) map of the Kudremukh National Park, Western Ghats, India, obtained from the ML-based modelling of multi-sensor remote sensing and field inventory data.

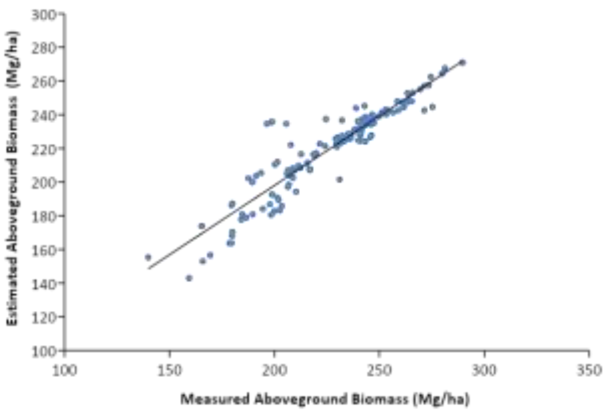

Figure 5. Comparison of the estimated and measured AGB of the Kudremukh National Park, Western Ghats, India.

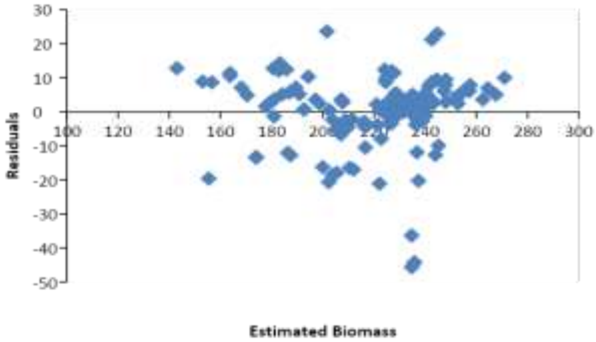

Figure 6. Residual plot of the AGB generated from the paired differences between the estimated and measured AGB values.

The ML-based estimations reveal that the Aboveground Carbon stock (AGCS) ranges from 150 to 50 Mg/ha (Figure 6) with a mean of 93.69 Mg/ha. It can be observed that a major portion of the protected area's AGCS ranges between 50.32 and 73.72 Mg/ha (37.93%), which is majorly composed of grasslands. About 79.89% of the AGCS lies at less than 1000m elevation (Table 3). This is because the lower elevation has many denser and continuous patches of forests consisting of moist evergreen, semi-evergreen, moist deciduous and dry deciduous forests. As one moves towards higher elevations, the forests become patchier and stunted in adapting to the harsh climatic conditions in higher elevations. Also, the shallow soil profile in the higher elevations acts as one of the regulatory agents for tree growth. Most land covers in higher elevations are grassland or rocky outcrops.

Table 3. Elevation-wise distribution of aboveground carbon stock across the Kudremukh National Park, Western Ghats, India.

Sl. No	**Elevation (m)**	**Area(ha)**	**Carbon Stock (Mg)**	**Carbon Stock (Mg/ha)**	**Carbon Stock (%)**
1	<=1000	60352.76	5913361.47	97.98	79.89
2	1000-1200	11205.97	900189.22	80.33	12.16
3	1200-1400	5230.33	401859.89	76.83	5.43
4	1400-1600	1517.38	125283.72	82.57	1.69
5	>1600	693.56	61191.63	88.23	0.83
Total		79000	7401885.94	93.69	100

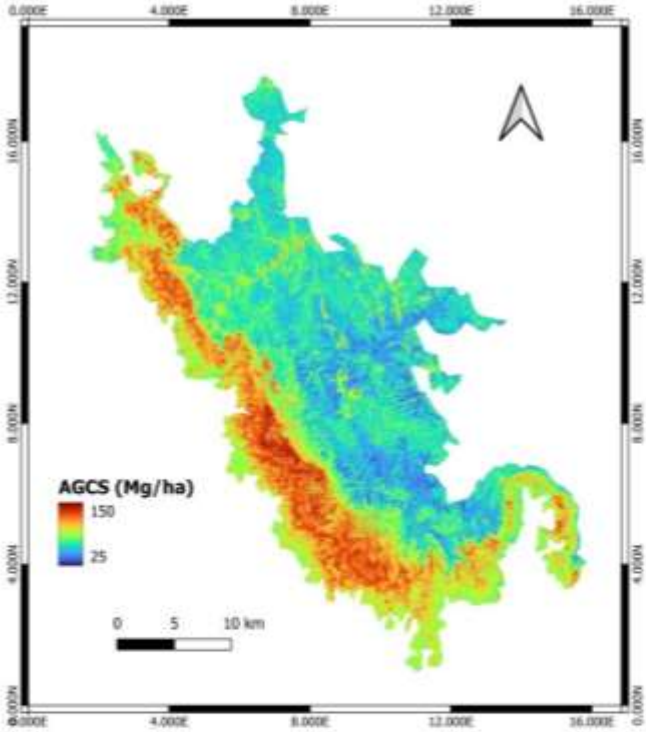

Figure 6. Spatial distribution of the estimated Aboveground Carbon Stock (AGCS) across the Kudremukh National Park, Western Ghats, India.

The important wet evergreen forest species in high-altitude (above 1400m) include *Litsea floribunda*, *Symplocos racemosa*, *Wendlandia thyrsoidea* and others, contributing less than 3% of the carbon stock of the entire landscape. On the other hand, the low-altitude wet evergreen forest (under 1200 m) hosts species such as *Syzygim hemisphericum*, *Hopea canarensis, Myristica dactyloides, Persia macrantha, Palaquium ellipticum, Poeciloneuron indicum*, *Garcinia gummi-gutta.*, contributing 92.05% of the total aboveground carbon stocks of Kudremukh National Park (Table 4). Much of the landscape is covered by forest (66.26%) and grasslands (23.41%) which contribute to 71.30% and 18.64% of AGCS, equivalent to 5302990.96 Mg (101.14 Mg/ha) and 1383075.78 Mg (74.68 Mg/ha) of the carbon stock respectively. Plantations and croplands, with ~4% of the land cover, account for 212120.45 Mg (99.41 Mg/ha) and 62559.63 (89.47 Mg/ha), respectively. Other land uses, including rocky outcrops, built-up, and waterbodies, contribute to 6.75% of the area. The vegetation in this land use class contributes to 472066.9 Mg (85.13 Mg/ha) (Table 4).

Table 4. Land use/land cover (LULC) wise distribution of aboveground carbon stock across the Kudremukh National Park, Western Ghats, India.

Sl. No.	LULC	Area		Carbon stock		
		ha	**%**	**Mg**	**Mg/ha**	**%**
1	Forest	52304.53	66.26	5290273.24	101.14	71.30
2	Grassland	18520.73	23.41	1383075.78	74.68	18.64
3	Plantation	2133.70	2.70	212120.45	99.41	2.86
4	Cropland	699.25	0.88	62559.63	89.47	0.84
5	Rocky outcrop	372.60	0.47	31404.53	84.29	0.42
6	Built up	1497.00	1.89	116281.66	77.68	1.57
7	Waterbody	3472.21	4.39	324380.71	93.42	4.37

Total	79000.00	100	7420096.00	93.94	100

The earliest studies by Ref [56] have identified that the climax vegetation of these forests is tropical evergreen with poorer localities of semi-evergreen as a sub-type and rare richer localities with *Poeciloneuron indicum* as the principal outcrop. Physiognomic stages, such as scrub, savanna, etc., are also seen. Three important forest types, viz., pre-montane, low-altitude evergreen and semi-evergreen, are also discernible. The difference in the AGCS of tree cover can be attributed to different forest types, elevation, forest age and historical disturbances such as selective felling or logging, forest fires, mining, and other anthropogenic activities. The spatial distribution of AGCS acts as a potential indicator for understanding the ecosystem services offered by the forest landscapes. The total carbon stock of Kudremukh National Park is 7401885.94 Mg.

Geographically large-scale and high-resolution maps of carbon stocks are invaluable baseline information products for understanding the contributions and status of the dynamics of carob-source sinks in ecologically fragile and geographically diverse biodiversity hotspots. Rich in biodiversity and exhibiting the extremes of species heterogeneities by various factors of forest landscape systems, global biodiversity hotspots have undergone unprecedented anthropogenic disturbances and biological transformations. Traditional field inventory and remote sensing data-based methods have been widely used for estimating proxy variables of carbon stock, such as biomass, canopy density, tree height, etc. Even though good accuracy is reported, most studies have considered either coarse resolution or limited geographical extents in the implementations. Thus, the model results and inferences are often not applicable to full-scale and highly heterogeneous forest ecosystems such as the Western Ghats of India. Aimed at contributing to the global research efforts of developing and demonstrating methods for large areas but sensitive to localised interactions of carbon estimations in forest ecological systems, we have undertaken this research assessing and demonstrating the potential of an ML-based multi-source remote sensing data approach for the aboveground carbon stock (AGCS) estimation over an entire national park (Kudremukh National Park), a functional representative of the Western Ghats of India. The study employed a comprehensive methodology integrating field inventory data with remote sensing data from various sensors to estimate the aboveground biomass (AGB) and carbon stocks in Kudremukh National Park. Utilising data from LiDAR (GEDI), SAR (Sentinel-1), multispectral imagery (Sentinel-2), DEM (SRTM), field-inventory measurements, and adopting an appropriate ML algorithm, the study has successfully demonstrated the prospect of generating high-resolution maps of AGB. The AGB estimates of the Kudremukh National Park range from 261.68 to 48.94 Mg/ha, with a mean of 149.18 Mg/ha. The estimation of AGCS reveals values ranging from 150 to 50 Mg/ha, with a mean of 93.69 Mg/ha.

The study highlighted notable trends in carbon distribution, with most carbon stocks concentrated in forests below 1000m elevation, dominated by wet evergreen species. Forests at higher elevations exhibit lower carbon stocks due to patchier vegetation and harsher climatic conditions. Additionally, anthropogenic activities such as selective felling, logging, and mining contribute to the variations in the carbon stocks across different forest types and elevations. The results underscore the importance of understanding ecosystem services provided by forest landscapes, with carbon stock distribution as a crucial indicator. The total carbon stock estimation of 7,401,885.94 Mg offers valuable insights for conservation and management strategies in Kudremukh National Park.

Despite the study's merits in providing accurate carbon stock estimates across varied spatial and ecological contexts, it has limitations. These limitations include potential biases in field inventory data, uncertainties in remote sensing data compatibilities, and generalising conversion factors for biomass to carbon estimations. Nevertheless, the study's integrated approach demonstrates its significance in advancing our understanding of forest carbon dynamics. It underscores the importance of utilising multi-sensor remote sensing techniques for comprehensive ecosystem assessments.

4 CONCLUSIONS

Large-area and high-resolution estimation and mapping of aboveground carbon stocks (AGCS) of highly productive and ecological heterogeneous forest ecosystems is an invaluable methodological and information resource for functional forest management. Geographically covering an entire protected national park in the Western Ghats of India, this study has implemented and analysed a method for AGCS estimation at 10m spatial resolution by feature-level fusion of data from multiple but complementary remote sensors (LDAR, SAR and multispectral sensors) in a machine learning methodological framework. Considering biomass as the proxy variable, the distribution of AGCS across the landscape addresses diversity, disturbance, and distribution of the tree species. Has also been analysed. Integrated by the RF machine learning algorithm, the primary predictor variable, discrete records of biomass density obtained from the space-borne LIDAR (GEDI L4b) datasets blend seamlessly with other remote sensing datasets and appear as a viable alternative to traditional field-based inventory methods. Compared with field inventory values, the estimates of AGB from the methodology adopted are 86% accurate. They are responsive to the variation of AGCS across heterogeneous landscapes with varied elevation, ecology, and geological features. The study contributes valuable insights to carbon stock assessment and ecosystem dynamics and recommends adapting the integration of GEDI LiDAR, Sentinel-1, Sentinel-2, and SRTM datasets to generate detailed AGB maps and carbon stock estimates. The study also recommends promoting interdisciplinary collaboration between forest researchers, remote sensing experts, and policymakers to facilitate the translation of scientific findings into practical applications for climate change mitigation and biodiversity conservation efforts.

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CRediT authorship contribution statement:

Kavana R : Writing – original draft, review & editing, Methodology, Conceptualization, Data Curation, Formal Analysis. Rao Rama Nidamanuri: Writing – review & editing, Methodology, Conceptualization, Formal Analysis, Data Curation. B C Nagaraja: Writing – review & editing, Conceptualization. Shrinidhi Ambinakudige: Writing – review & editing, Conceptualization. All authors reviewed the manuscript

Code and Data Availability Statement

Data sharing is not applicable to this article, as no new data were created or analysed.

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