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Assessment of above-ground biomass carbon using optical and microwave remote sensing data

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Abstract
Forests are nature's most attractive and versatile renewable resources, providing a wide range of social, economic, environmental services and benefits. The modeling of carbon balance depends heavily on forests, as they are considered as carbon reservoir. Accurate measurements of biomass and other forest bio physical parameters are necessary to better understand the global carbon cycle. Remote sensing (RS) based AGB estimation approaches have become increasingly popular as non-destructive means of biomass estimation but constitute limited applications, since the green felling in natural forests and plantations is prohibited. The primary sources for AGB estimation are optical data, radio detection and ranging (RADAR) and light detection and ranging (LIDAR) systems. In this context the study was carried out in the Dubare forest of moist deciduous vegetation type of Kushalnagar taluk, Kodagu district to assess the above-ground biomass carbon using optical and microwave remote sensing data. Totally 25 field sampling plots were randomly used for field data collection. Previously developed relevant allometric equations were used to estimate above- ground tree biomass (AGTB) using GBH and height in each plot. The results revealed that the AGTB ranged from 129.05 Mg ha^{-1} to 355.54 Mg ha^{-1}, total carbon stocks ranged from 60.65 Mg ha^{-1} to 167.11 Mg ha^{-1}, while CO2e was found to be ranging from 222.4 Mg ha^{-1} to 612.7 Mg ha^{-1}. The regression model obtained between above-ground tree biomass and Synthetic Aperture Radar (SAR) backscatter value performed well with VH polarization than VV polarization with an R^2 value of 0.69 and RMSE of 31.87 Mg ha^{-1}. The best fit regression model was obtained between above-ground tree biomass and Normalized Difference Vegetation Index (NDVI) with the highest R^2 value of 0.75 and a low RMSE value of 28.20 Mg ha^{-1}.

Keywords: Above-ground tree biomass, remote sensing, synthetic aperture radar, normalized difference vegetation index

Introduction
Forests are nature's attractive and versatile renewable resources, providing a wide range of social, economic, cultural and environmental services. Forests play a significant part in creating a healthy ecosystem and reducing environmental pollutants. In India, forests cover almost 21.71 percent of the country's total land area (Singh *et al*., 2021) [35]. Forests play an important role in regional and global carbon cycles as they store large quantities of carbon in vegetation and soil. Around 80 percent of the world's terrestrial above-ground carbon stores (biomass) are found in forests, which also play a significant role in the global carbon cycle.
The measurement of biomass and subsequent carbon is currently a key part of the REDD+ projects. REDD+ is a set of finance instruments and incentives designed to slow down deforestation and forest degradation in order to combat climate change. Due to deforestation, carbon dioxide, more greenhouse gases remain in the atmosphere. Therefore, accurate measurements of biomass and other forest biophysical parameters are essential for better understand the global carbon cycle and global warming. Biomass estimation is done by using a destructive method and a non-destructive method. A non-destructive method is mainly based on regression equations which are derived from measurable tree parameters like diameter at breast height (dbh), basal area and tree height.

There is a need for global, high temporal resolution forest biomass monitoring techniques, possibly using remote sensing. Optical remote sensing has been successful in forest biomass studies but over limited geographical regions. In areas where cloud cover problem is predominant, it could not be really used. In these conditions, microwave remote sensing provides the best solution as it has several advantages over optical remote sensing in all weather, day and night conditions, penetration through clouds, vegetation, dry soil, sand and dry snow. It is sensitive to surface roughness, dielectric properties, moisture content, polarization, frequency and imaging possibility from different types of polarized energy (HH, VV, HV, and VH). By the late 1970s and 1980s Synthetic aperture radar (SAR) remote sensing emerged as a solution to the limitations faced by traditional optical sensors. SAR sensors on account of their much longer wavelengths (1 mm to 1m) have not only cloud penetrating capability but also the waves can penetrate the atmospheric moisture as well as the upper vegetation layer of the forest canopy and waves are scattered by leaves, twigs, branches and stem. In this context, the present study aimed at using optical and SAR data to assess and model the forest above-ground biomass.

Materials and Methods

Study area

The study was carried out in the moist deciduous forest of Kushalnagar taluk, Kodagu district, in the Central Western Ghats of Karnataka. The Kodagu district lies between 11° 56' and 12° 52’ N at Northern latitudes and Eastern longitudes of 72° 22' and 76° 12’ E. The study area has a tropical humid environment, the elevation ranges from 50 to 1750 m above sea level (MSL), with rainfall ranging from 1500 to 3500 mm in a year.

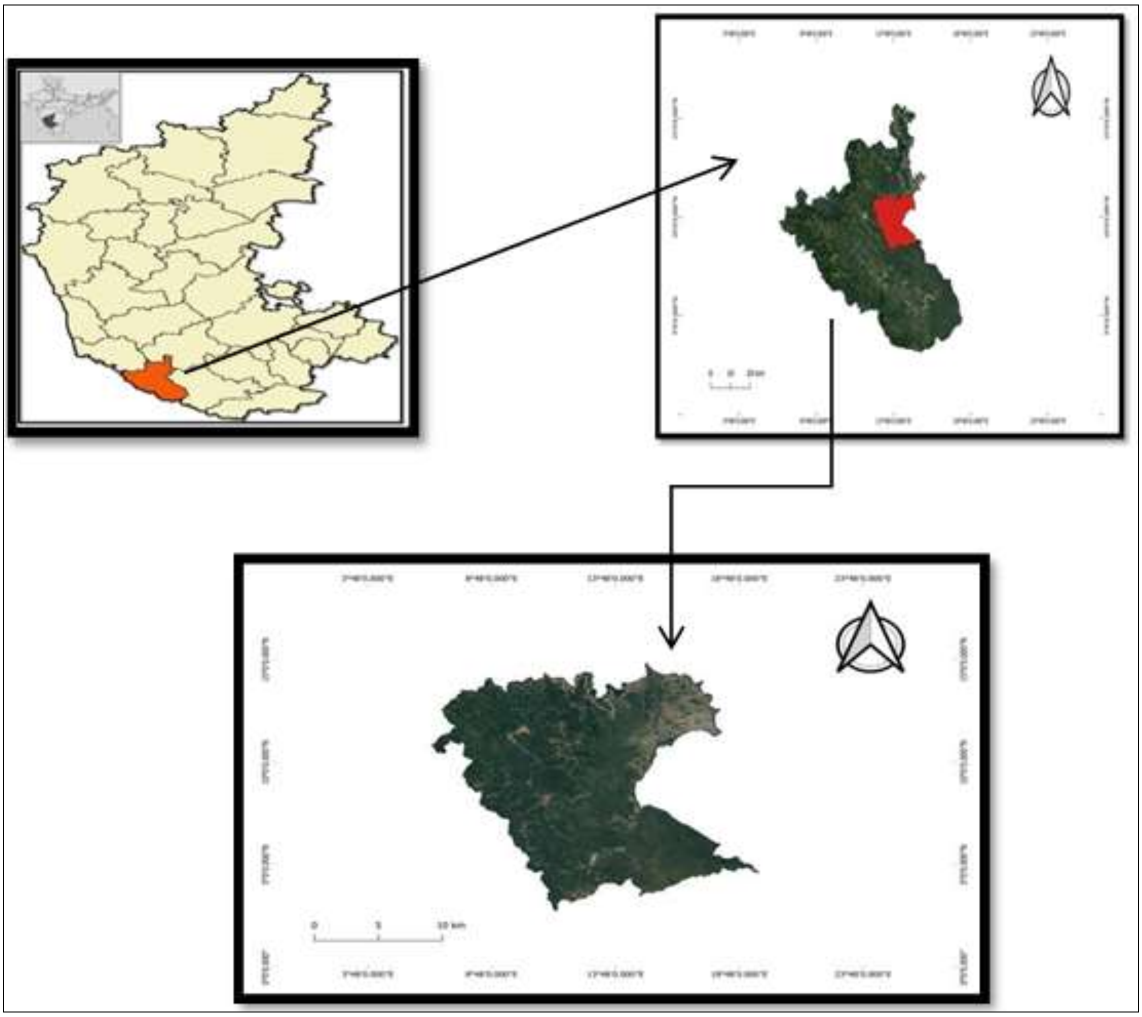

Fig 1: Diagram showing the study area

Methods

Random sampling method was followed for field inventory in the study area. Five super plots of 100 m × 100 m were laid randomly in the study area. Main plots of size of 20 m × 20 m each at the corners and one in the Centre of main plot were laid in main super plots for each to assess the biomass. The observations were recorded are GPS readings of the location, species name, girth (m) at breast height of trees
≥30cm girth and height (m) in each sample plot. The observations like GPS readings (Latitude, longitude, altitude and slope %), were recorded in each of the sample plot.

Estimation of Above-ground Tree biomass (AGTB) and Carbon stock

1. The volume of each standing tree was calculated using the species specific volume equations
2. AGTB was estimated by multiplying the individual tree volume with species specific wood gravity values

Volume = Species specific volume equation

Aboveground tree biomass (AGTB) = Volume of the species × Species-specific gravity

The above-ground tree biomass carbon stock was calculated by using the formula prescribed by Intergovernmental Panel on Climate Change (IPCC 2007).
Total carbon = Biomass (Mg ha^{-1}) × 0.47 CO_2= Carbon stock (Mg ha^{-1}) × 44/12

Optical Satellite data
Satellites having optical sensors that capture images of the Earth's surface using visible, near-infrared and shortwave infrared light are said to be optical satellite data. These sensors can detect, record information about the reflectance and absorption of light across various wavelengths, allowing for the analysis of different features and properties of the Earth's surface.

Sentinel-2:Sentinel-2 is a satellite mission developed by the European Space Agency (ESA) as part of the Copernicus program, which is a joint initiative with the European Union. The primary goal of the Sentinel-2 mission is to provide comprehensive and frequent high-resolution optical imagery of the Earth's land and coastal regions

Normalized Difference Vegetation Index (NDVI): NDVI is one of the most successful methods for quickly identifying vegetated areas and their condition. It quantifies vegetation by measuring the difference between near-infrared and red light. Healthy vegetation absorbs most of the visible light that hits it and reflects a large portion of the NIR band. Unhealthy or sparse vegetation reflects less visible light and less infrared light.

SAR Satellite data
SAR (Synthetic Aperture Radar) satellite data is the data collected by satellites equipped with SAR sensors. SAR is a remote sensing technology that uses radar to create high-resolution images of the Earth's surface. Unlike optical sensors that rely on sunlight, SAR sensors can operate day and night and are not affected by cloud cover. SAR satellites emit microwave signals towards the Earth's surface and measure the time it takes for the signals to bounce back. SAR satellite data is typically processed to generate images, interferograms (for measuring ground deformation) and other derived products. Several space agencies and commercial companies operate SAR satellites, such as the European Space Agency's Sentinel-1 mission and commercial providers like RADARSAT and COSMO-SkyMed.

Sentinel-1: Sentinel-1 is a satellite mission operated by the European Space Agency (ESA) as part of the Copernicus program, which is the European Union's Earth observation initiative. It is a constellation of two radar satellites, Sentinel-1A and Sentinel-1B, launched in 2014 and 2016. Sentinel-1 satellites are equipped with C-band synthetic aperture radar (SAR) sensors, which operate in the microwave range of the electromagnetic spectrum.

Recording backscatter value from the earth features: In SNAP software the σ0 HH and σ0 HV polarisation map of the entire moist deciduous forest of Dubare was opened in the RGB window simultaneously, and then the backscatter value in decibels for each ground truth location was recorded for both the polarization. Field data from all the plots were used to establish the regression equation for biomass versus backscattering of SAR data in VH and VV polarization. The predicted biomass for all the backscatter was determined and a regression equation for mono and dual polarized (VV and VH) SAR data was established for predicting the forest biomass for a moist deciduous forest.

Development of spectral model and AGB Mapping
Satellite data: The establishment of the Regression equation model for predicting AGB was done using Sentinel-1A of SAR data and Sentinel-2A of optical data of the same area using SNAP and ArcGIS software.

Regression analysis: Regression analysis is a set of statistical methods used for the estimation of relationships between a dependent variable and independent variables. Assessing the strength of the relationship between variables and for modelling the future relationship between them. The basic concept of regression analysis involves fitting a regression model to a set of data points and estimating the parameters that define the relationship between the variables. The dependent variable, also known as the response variable or outcome variable, is the variable that is being predicted or explained. The independent variables, also known as predictor variables or explanatory variables, are the variables that are believed to influence or explain the variation in the dependent variable.

Linear regression equation model: It attempts to model the relationship between two or more explanatory variables and a response variable by fitting a linear equation to observed data. Every value of the independent variable x is associated with a value of the dependent variable y.
Using the data analysis toolpak, creating a regression output in excel is followed by the steps mentioned here. By selecting data from the toolbar. The data menu displays the data analysis - analysis tools dialog box displays. From the menu, by selecting regression, in the regression dialog box select the dependent variable data(biomass) in the input Y range. In the input X range select the independent variable data (NDVI value or HH, HV polarisation value). The obtained intercept was used to establish the regression equation.

The linear regression equation for SAR data is: -
Y= a+bx and Y= a+bx1 Where a, b are model parameters
x and x1 are VH and VV backscatter polarization respectively.
The linear regression equation for optical data is:
Y= a+bx

Where a, and b are constants and x is the NDVI value

The NDVI was calculated using the formula given by Jensen (2000) [39].

$$\text{Normalized Difference Vegetation Index} = \frac{\text{NIR - RED}}{\text{NIR + RED}}$$

The equation was validated using ground truth data of 25 plots. The RMSE and R^2 were used to evaluate the equation (Anup *et al.*, 2016) [3].

Results and Discussion
The above-ground biomass and carbon stock of the forest were estimated using plot-wise volume calculations. After estimating the volume calculations of all plots, the above-ground tree biomass of the forest and the total quantity of carbon sequestered for the moist deciduous forest of the Kushalnagar taluk, Kodagu district were estimated. The following result of experiments on above-ground tree biomass and carbon stock are

presented

Assessment of AGTB using optical data

The results of the present study revealed that out of the total 25 plots, the ground-based volume observed in the study area ranging from 234.85 m^3 ha^{-1} to 517.81 m^3 ha^{-1}. Similarly, above-ground tree biomass was observed in the study area, which varied between 129.05 Mg ha^{-1} and 355.54 Mg ha^{-1}. A variation in the number of trees, their height, and gbh was attributed for the variation in above-ground tree biomass and volume.

The carbon stock in the study area ranged from 60.65 Mg ha^{-1} to 167.11 Mg ha^{-1} and the area's total carbon dioxide equivalent (CO2e) was found to be 222.4 Mg ha^{-1} to 612.7 Mg ha^{-1}. The fewer trees in the open forest contributed significantly to its lower carbon stock. The results further indicate that there is more room for expanding plantations in open forests and relying more on carbon sequestration.

Using Sentinel-2 satellite images from QGIS software, the Normalized Difference Vegetation Index (NDVI) values for the study area were retrieved. According to the findings, the NDVI values for each plot ranged from 0.28 to 0.56, while the predicted above-ground tree biomass ranged from 145.49Mg ha^{-1} to 336.31 Mg ha^{-1}.

Assessment of AGTB using SAR data

The quickest and most practical way for estimating aboveground- biomass is to relate field measurements of biomass to backscatter values. Synthetic aperture radar (SAR) sensors are active sensors that radiate microwave energy and detects backscatter radiation from the surface. Due to their ability to work day and night and record backscattering from the upper canopy and woody biomass component of the forest, SAR data is widely employed in the assessment of forest stand parameters. The polarisation of the SAR signals is a crucial component of the SAR data (Ghasemi *et al.,* 2011) [15]. Most microwave sensors produce signals that are either horizontally or vertically polarised. Longer wavelengths (L and P band) with VV and VH polarisations have been shown to produce better results than short wavelengths. The results of the current study revealed that SAR backscatter values ranged from -10.87 dB to -21.74 dB, while the predicted above-ground tree biomass ranged from 143.63 Mg ha^{-1} to 348.68 Mg ha^{-1} for VH polarisation. Similarly, SAR backscatter values with VV polarisation ranged from -6.81 dB to -18.12 dB and predicted above- ground tree biomass values ranged from 143.63 Mg ha^{-1} to 348.68 Mg ha^{-1}. The results differ because they rely on signal saturation, which is a function of wavelength, polarization and the characteristics of the vegetation cover which is also associated with roughness, geometry, dielectric properties as well as of the difficulties caused by the specific properties of the ground such as slope and aspect.

Development of spectral model and AGB Mapping

Regression equation model for above-ground biomass with backscatters of SAR data

The regression (Linear) model was obtained between above-ground tree biomass and SAR backscatter values in the study area. The VH polarisation had an R^2 value of 0.69, which was best and followed by the VV polarisation with the lowest R^2 value of 0.65. VV polarisation had a higher RMSE value at 33.87 Mg ha^{-1}, while VH polarisation had 31.87 Mg ha^{-1}. The linear regression equation is validated with 25 plots of ground truth data which shows a percent difference of biomass values from - 20.20% to 69.43% in the VH polarisation followed by -27.31% to 22.84% in VV polarisation. The model is most suitable for VH polarisation followed by VV polarisation. The direct relationship between microwave backscatter values and plot- wise above-ground tree biomass was observed comparatively low due to variation in errors present in the high biomass region i.e., >200 t/ha. This could be attributed to two types of uncertainties, 1) the exclusion of small trees (< 30 cm) GBH and 2) the saturation of SAR signal at high biomass regions and topographic effects of the study area. The polarimetric-interferometry SAR (PolInSAR) approach or P-band SAR data can be used to solve the saturation problem with SAR data (Das *et al*., 2016) [9]. The validation result and regression tests indicate that Sentinel-1 microwave data can be applied for AGTB calculation, but with varying degrees of accuracy.

Regression equation model for above-ground biomass with NDVI of optical data

Regression analysis is a suitable statistical method for examining the relationship between two continuous variables, such as NDVI values and forest biomass. The regression analysis between NDVI and ground-based AGB showed that the highest R^2 value of 0.75 and a low RMSE value of 28.20 Mg $ha^{-1.}$ The regression model was validated using actual biomass values and the results revealed that there was a difference in biomass values up to the extent of -18.70% to 30.70% in the study area. The model is most suitable for moist deciduous forest. It enhances the accuracy of GIS and remote sensing methods for estimating the volume and biomass of forested areas. The variation in crown density and phenological states of the trees or vegetation types present in the study area may be the cause of the discrepancy between projected and observed biomass estimates. Season, tree phenological characteristics and degree of crown closure are the factors that affect remote sensing data the most (Singh *et al*., 2011) [34].

Table 1: Linear regression models developed for the study area using SAR and optical data

Sl. No.	Data type	Regression equation model	R2	RMSE (Mg ha-1)
1	SAR (VH polarization)	Y=553.54+18.85×x	0.69	31.87
2	SAR (VV polarization)	Y=464.44+18.15×x1	0.65	33.87
3	Optical	Y=-58.09 + 708.2×x2	0.75	28.20

Where x- backscatter values of VH polarization
x1- backscatter values of VV polarisation
x2- NDVI value , Y - Predicted above-ground tree biomass

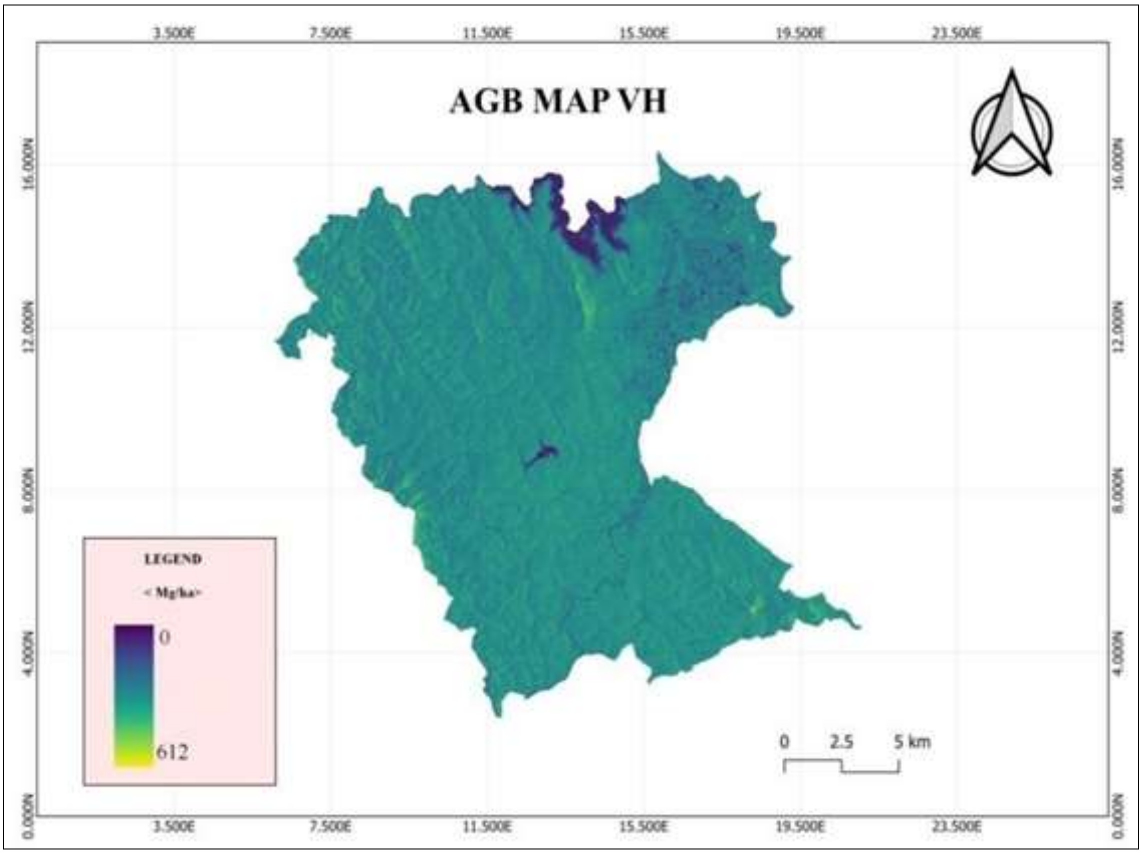

Fig 2: AGB map of the study area from VH polarization

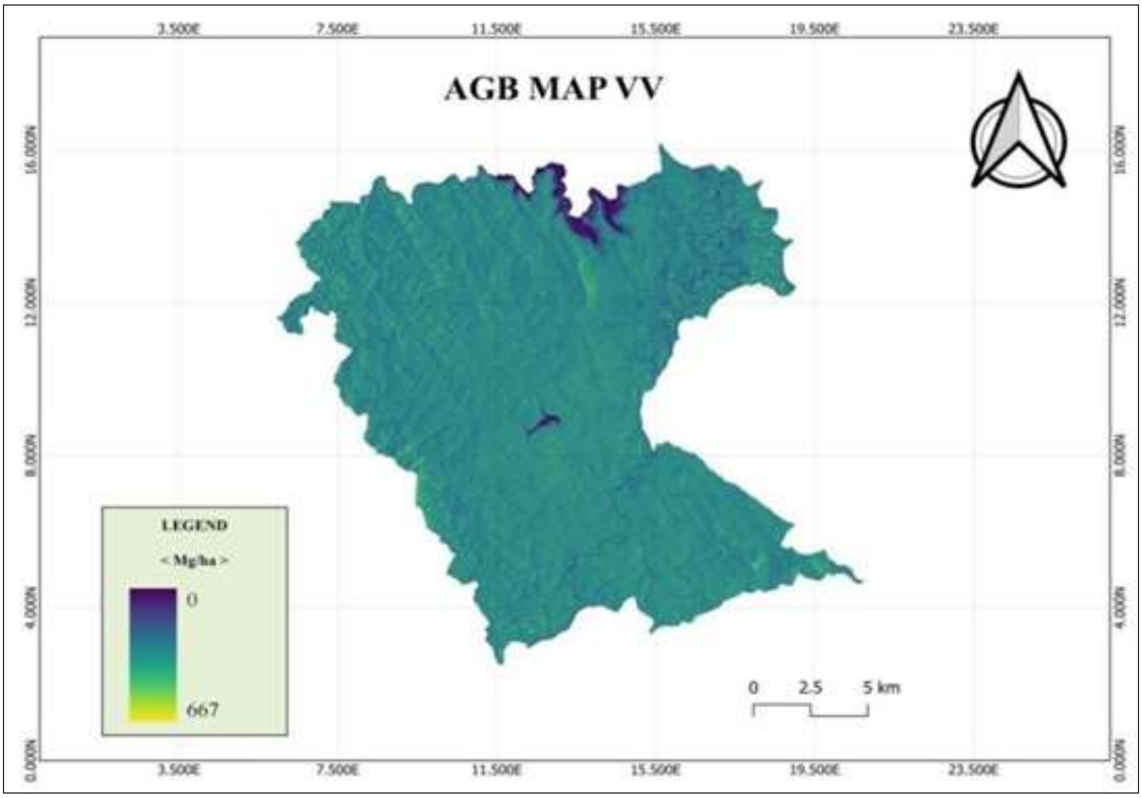

Fig 3: AGB map of the study area from VV polarisation

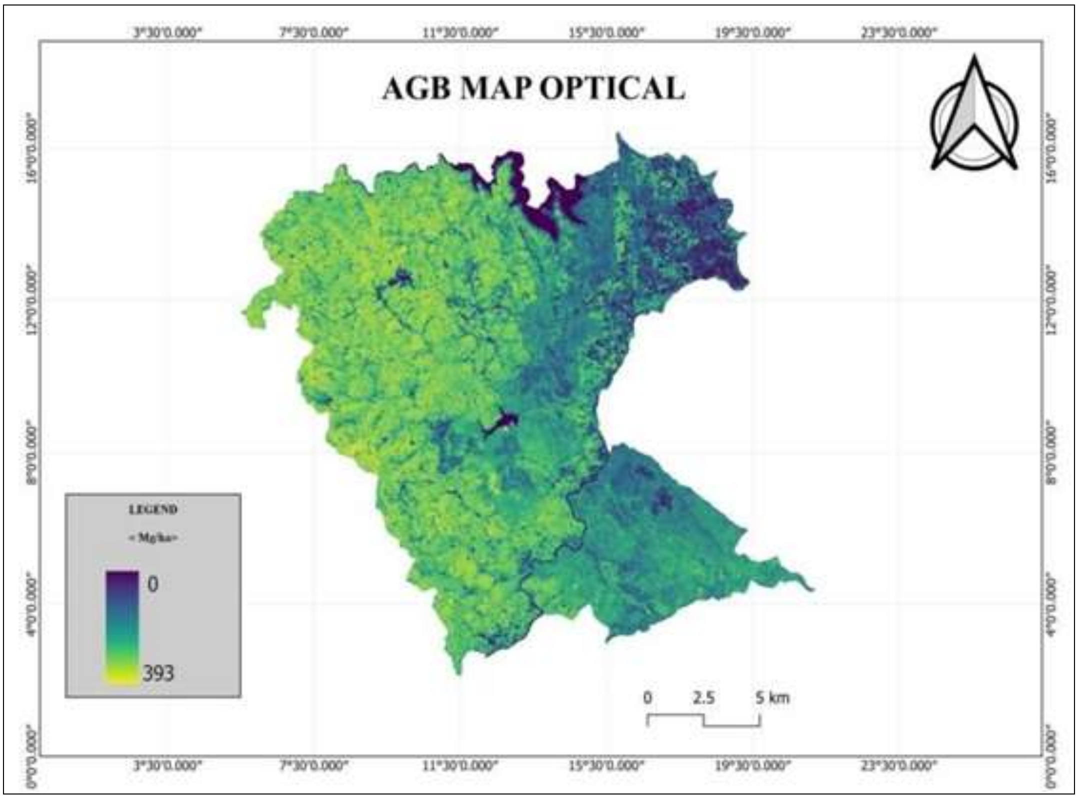

Fig 4: AGB map of the study area from optical data

Conclusion

Forests are managed to meet emission targets and the total amount of biomass they produce determines amount of carbon they will trap in the atmosphere or on the land. A key indication of carbon storage, productivity, and the sequestration of carbon in forests is aboveground biomass. Comparing the structural and functional characteristics of forest ecosystems across a variety of environmental conditions is accomplished by estimating AGB. The traditional methods of estimating AGB rely on measures taken in the field, like diameter at breast height and tree height, etc. These techniques are expensive, labour-intensive and susceptible to bias while choosing representative samples.

As remote sensing can monitor an area of interest on a regular basis, it is an accurate method for studying biomass. GIS and remote sensing technology offer new tools for advanced ecological management. The information they produce is intended to present average timber volumes connected to administrative regions, but because it does not account for spatial variability and generates a bias in carbon measurement. SAR technology is becoming increasingly suitable for forestry studies that can support decision-making to ensure sustainable forest management practises, due to advances in remote sensing technology and the increasing availability of many new air or space-borne satellite systems with fine spatial and spectral resolutions. AGB estimation has made use of SAR data with various wavelengths and polarisations. SAR can record vertical forest structural elements, which makes it useful for estimating biomass, but its inability to differentiate between vegetation kinds has an impact on the accuracy of AGB calculation.

With the use of the optical and SAR data, the current study sought to estimate Above-ground tree biomass. The findings of the study showed that the use of optical remote sensing model exhibits a robust ability to estimate Aboveground Tree Biomass with the highest accuracy. The SAR data model demonstrated as an excellent tool for biomass estimation by utilizing the strength and its capacity. The regression model obtained between above-ground tree biomass and SAR backscatter value performed well with VH polarization than VV polarization. The regression model developed from above ground biomass and NDVI was found to be better with R^2 value of 0.75. For precise global AGB estimation, it is possible to integrate multisource data, which entails the efficient integration of remote sensing including optical and microwave data from medium spatial resolution datasets like SAR and Landsat, to high spatial resolution datasets like LIDAR and Quickbird

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