Original Research Article

Geoinformatics and Modeling Approaches for Estimating Above-Ground Biomass in the Moist Deciduous Forests of Uttara Kannada, Karnataka, India

Abstract:

The present study aims to estimate Above-Ground Biomass (AGB) in the moist deciduous forests of Mundgod Taluk, Uttara Kannada district, Karnataka, India using a combination of field sampling and remote sensing techniques. AGB was assessed using Sentinel-2A satellite imagery with a spatial resolution of 10 meters. Field data were collected using the Point-Centered Quarter (PCQ) method, it includes measuring tree girth at breast height (GBH), tree height, and canopy density. AGB was calculated using artificial form factor and specific gravity of tree species and further modelled using the Normalized Difference Vegetation Index (NDVI) derived from satellite data. The results showed a significant correlation between canopy density and biomass, with very dense forests exhibiting the highest AGB values. The field-measured AGB was 436.96 t/ha for very dense forests, 259.89 t/ha for moderately dense forests, and 161.67 t/ha for open forests. A linear regression model developed between AGB and NDVI showed a high R^2 value of 0.91 for open forests, 0.87 for moderately dense forests, and 0.85 for very dense forests. The total area-weighted biomass for the study area was estimated at 8.87 million tons, with 4.79 million tons in very dense forests, 3.44 million tons in moderately dense forests, and 0.76 million tons in open forests. The regression model validation indicated low Root Mean Square Error (RMSE) values, with the moderately dense forests 8.81 t/ha and the in very dense forests 7.54 t/ha. This study highlights the effectiveness of integrating field measurements with remote sensing for rapid, reliable AGB estimation. The approach offers valuable insights into biomass distribution and carbon sequestration potential, providing a scalable method for carbon inventories at state and national levels, contributing to forest management and climate change mitigation efforts

Keywords: Above ground biomass, NDVI,optical data, Regression equation model.

Introduction

Forest biomass represents the total dry weight of all living components of trees within a given area, encompassing both aboveground parts (leaves, branches, and stems) and belowground components (fine and coarse roots) (Song, 2013). Forest Aboveground Biomass (FAGB) refers specifically to the biomass of the aboveground components, excluding the belowground roots, which typically require labour-intensive excavation for accurate quantification (Zhai et al., 1992). Due to its ease of measurement, FAGB is often preferred over total biomass in ecological studies. The most accurate method for ground-based biomass estimation involves destructive sampling, wherein selected trees are felled, and their biomass is measured by drying samples from the fresh components (e.g., leaves, branches, and stems). This process allows for the derivation of species-specific allometric equations based on parameters such as tree height and diameter at breast height (DBH). These allometric models are then applied to the remaining trees in a sampling plot to estimate their biomass, and the cumulative biomass of all trees within the plot provides a reliable, area-based estimate (Song, 2013).

Over the years, extensive research has focused on developing species-specific allometric equations for various forest types (Jenkins, 2004), which are essential for biomass estimation at local scales.However, despite the existence of allometric equations for most dominant tree species across different countries, these equations are limited in their applicability over large areas. This limitation arises because variables such as DBH, height, and species type cannot be spatially and continuously measured for each individual tree across extensive regions. Although remote sensing (RS) data cannot directly utilize these equations, the variables used in allometry (e.g., DBH and height) can guide the selection of remote sensing-derived features for accurate biomass estimation over broad landscapes.Several global and regional biomass products have been developed using remote sensing techniques (Blackard et al., 2008; Saatchi et al., 2011; Nelson et al., 2017), yet many do not incorporate species-specific allometric considerations, leading to uncertainties in biomass estimates (Lu et al., 2016). Thus, precise estimation of forest biomass over large areas remains a challenging task.

This study aims to estimate Above-Ground Biomass (AGB) in the moist deciduous forests of Mundgod Taluk in Uttara Kannada district using an optical remote sensing technique. This approachwill be used to develop a regression model tailored to the moist deciduous forests. Once validated, the regression model will facilitate AGB prediction in similar forest types across different geographic regions.Accurate estimation of forest biomass is critical for ecological research, carbon budgeting, and sustainable forest management, as well as for supporting national development strategies (Kumar and Mutanga, 2017). Biomass estimation plays a vital role in understanding the global carbon cycle, especially in the context of climate change and greenhouse gas (GHG) dynamics. Forest biomass data have been increasingly used to estimate GHG pools and fluxes from terrestrial ecosystems, particularly under changing land use and land cover conditions. The Kyoto Protocol underscores the significance of terrestrial vegetation and soils as vital carbon sinks (Wani et al., 2010).

Forests, through photosynthetic processes, capture atmospheric carbon dioxide and store it in their biomass. The evaluation of biomass typically involves three primary approaches: field measurements, remote sensing, and Geographic Information Systems (GIS) (Hu et al., 2020). While field measurements offer high accuracy, they are cost-prohibitive and time-consuming for large-scale applications. In contrast, RS and GIS technologies provide opportunities for efficient and reliable biomass estimation and monitoring at multiple spatial scales.Satellite platforms such as NOAA AVHRR, SPOT, MODIS, and ASTER are well-suited for estimating terrestrial biomass and carbon stocks over extensive areas. Vegetation indices, particularly the Normalized Difference Vegetation Index (NDVI), serve as reliable indicators of the Leaf Area Index (LAI), which is strongly correlated with biomass and productivity (Roy and Ravan, 1996). Previous studies, such as that by Dadhwal et al (2009), have utilized state-based remote sensing data combined with field inventory data to estimate India’s phytomass carbon pool (4,017 Tg C) and phytomass carbon density (63.6 Mg C ha^{-1}).

The present study focuses on estimating AGB across different canopy density classes in the moist deciduous forests of Mundgod Taluk using an integrated approach of satellite-based remote sensing and ground-based field measurements. The primary objective is to develop a robust regression model that integrates remotely sensed metrics with field-derived biomass data to generate a geospatial distribution of biomass for the region. The resulting model will serve as a reliable tool for AGB estimation and carbon stock assessment in similar ecosystems, contributing to a better understanding of forest carbon dynamics and supporting climate change mitigation strategies.

Material and methods

Study Area

The study was conducted in the moist deciduous forests of Mundgod Taluk, located in the Uttara Kannada district of Karnataka, India in the year 2022. The study area is geographically positioned between 14°41'45" N to 15°01'30" N latitudes and 74°51'45" E to 75°05'00" E longitudes, encompassing an area of 39,142.54 hectares, with an average elevation of 564 meters above mean sea level (MSL). The spatial extent of the study area is depicted in Figure 1.

Climatic Conditions

The climate of the study area is characterized by four distinct seasons: Summer (March to May): Characterized by rising temperatures. South-West Monsoon (June to September): Dominated by heavy rainfall, particularly over the Western Ghats and Malnad regions. Post-Monsoon Season (October to November): A transitional phase with diminishing rainfall. Winter (December to February): Marked by low humidity and cooler temperatures. The average rainfall of 11.2 - 13.4 inches.

Forest Types and Major Flora

Based on the classification by Champion and Seth (1968), the study area comprises three primary forest types:

1. Southern Moist Mixed Deciduous Forests (3B/C2),
2. Southern Secondary Moist Mixed Deciduous Forests (3B/C2/2S1), and
3. Moist Teak-Bearing Forests (3B/C1).

These moist deciduous forests are dominated by various tree species, including *Tectona grandis*, *Terminalia alata*, *Lagerstroemia lanceolata*, *Lannea coromandelica*, *Pterocarpus marsupium*, *Dalbergia latifolia*, *Anogeissus latifolia*, *Mitragyna parviflora*, *Terminalia bellarica*, *Bombax ceiba*, *Grewia tiliaefolia*, *Terminalia paniculata*, *Madhuca spp*., *Schleichera oleosa*, *Adina cordifolia*, *Xylia xylocarpa*, *and Diospyros spp*., among others.

Ancillary Data

The primary reference data included Survey of India (SOI) toposheets (numbers: 48I/16, 48M/4, 48N/1, 48J/13, 48J/14, and 48N/2) at a scale of 1:50,000, and a forest cover map of moist deciduous forest of Mundgod was developed by Ramachandra et al. (2016).

Field data collection

Field sampling was carried out using randomly laid transects across the entire study area. Within each transect, the Point-Centered Quarter (PCQ) method was employed (Kumarathunge et al., 2011). Each transect was 100 meters long, with sampling points established at 25-meter intervals (i.e., at 0 m, 25 m, 50 m, 75 m, and 100 m). At each of these five sampling points, four trees (one in each quarter) were measured, totalling 20 trees per transect.

Only trees with a diameter at breast height (DBH) of ≥30 cm were included in the measurements. The parameters recorded at each sampling point included tree species, girth at the base (10cm above ground level), girth at breast height (GBH, 1.37 m above the ground), and height (in meters). A girth tape was used for measuring GBH, while height was determined using a hypsometer. Additionally, geographical coordinates (latitude, longitude, and elevation) were documented using a Garmin eTrex 10 GPS device.

Canopy Density Classification

Forest types with canopy cover greater than 10% were selected for sampling based on measurements using a spherical crown densiometer. The canopy density classes were categorized as follows(Anon, 2021):

- Very Dense Forest: Canopy density >70%.
- Moderately Dense Forest: Canopy density between 40-70%.
- Open Forest: Canopy density between 10-40%.

For each canopy class, fifteen sampling plots were enumerated. In those 10 plots was used for testing and 5 plots for the validation. The mean distance of trees within each PCQ transect was calculated, and the area of each transect was computed as the square of the mean distance multiplied by 20. This calculated area was then used to determine biomass estimates for each class.

Above ground Biomass Estimation

Field data was used to estimate Above-Ground Biomass (AGB) by applying artificial form factor and specific gravity. Area-weighted AGB was calculated by multiplying the biomass of each canopy density class by the area it occupies within the forest. These values was then aggregated to determine the total AGB for the study area, providing a spatial distribution of biomass across different canopy density classes within the study area.

The biomass estimates, combined with remote sensing data, were used to develop a regression model for predicting AGB in similar moist deciduous forests. This model contributes to a better understanding of biomass distribution and carbon sequestration potential, aiding in forest management and climate change mitigation efforts.

Volume (m^3) = Basal area (m^2) ×Height (m) × Artificial form factor

Basal area (m^2) $=\pi d^2/4$

Where d is the diameter at breast height

Artificial form factor = $\frac{(\text{girth at base})2}{(\text{girth at the breast height})2}$

Biomass (t) = Volume (m^3) × Specific gravity

The specific gravity of different trees was obtained from the list given by Forest Research Institute (FRI), Dehradun

Regression models were developed to estimate biomass using satellite-derived parameters, including red and infrared band reflectance, as well as the Normalized Difference Vegetation Index (NDVI). A Sentinel-2A surface reflectance image was utilized for this analysis. In ArcGIS, an NDVI map of the entire moist deciduous forest of Mundgod was generated using raster tools. NDVI reflectance values were then recorded for each ground truth location across different canopy density classes(Figure 2).

Spectral modeling was performed using a satellite image from January 2022 to establish a regression relationship between area-weighted biomass and satellite-derived parameters. The best-fit model was selected based on the coefficient of determination (R^2). The regression analysis was conducted between the NDVI value of each canopy density class and the corresponding above-ground biomass (t/ha), following methods outlined by Devagiri et al. (2013). The final best-fit model was applied to estimate biomass for the entire study area.The linear regression equation for optical data is: -

$$Y= a+bx$$

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

The NDVI was calculated using the formula given by Jensen (2005).

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

Where NIR is the reflectivity of the near-infrared band and RED is the reflectivity of the red band.

The 5 plots were used to validate the linear regression equation model.The RMSE and R^2 were used to evaluate the equation (Anup *et al*., 2016).

Results and discussion

The tree density in the moist deciduous forests of Mundgod Taluk, Karnataka, varied significantly across different canopy density classes. In very dense forests, tree density was 451 stems ha^{-1}, while in moderately dense forests it was 363 stems ha^{-1}, and in open forests, it dropped to 125 stems ha^{-1}. These values are consistent with those reported by Verghese and Menon (1998), who documented tree density of 535 stems ha^{-1} in the moist deciduous forests of the Agastyamalai region in Kerala. The field-measured wood biomass was 436.96 t ha^{-1} for very dense forests, 259.89 t ha^{-1} for moderately dense forests, and 161.67 t ha^{-1} for open forests (Table. 1). The total biomass, calculated as area-weighted biomass, was estimated at 4.79 million tons for very dense forests, 3.44 million tons for moderately dense forests, and 0.76 million tons for open forests, resulting in a total biomass estimate of 8.99 million tons (Table.1) for the entire study area. These biomass estimates are comparable to those reported by Hojas et al. (2019) for tropical forests in Malaysia, where very dense forests ranged from 427 to 569 t ha^{-1}, moderately dense forests ranged from 168 to 414 t ha^{-1}, and open forests ranged from 130 to 155 t ha^{-1}.

The NDVI values, derived from Sentinel-2A satellite data, varied across canopy density classes, ranging from 0.32 to 0.73. Higher NDVI values were recorded in very dense forests, corresponding to higher biomass estimates, whereas lower NDVI values in open forests aligned with lower biomass estimates. These results demonstrate a clear relationship between NDVI, forest type, and biomass. Similar findings were reported by Koppad et al.

(2020) for the Joida region of Uttara Kannada district, where NDVI values ranged from 0.64 to 0.74 for very dense forests, 0.54 to 0.64 for moderately dense forests, 0.46 to 0.54 for sparse forests, and 0.39 to 0.46 for scrub forests (Table. 2). Additionally, Hashim et al. (2019) reported NDVI values from -1 to 0.199 for non-vegetated areas, 0.2 to 0.5 for low vegetation areas, and 0.50 to 1 for high vegetation areas, consistent with this study's findings.

The predicted AGB for very dense forests was 434.87 t ha^{-1}, for moderately dense forests was 253.1 t ha^{-1}, and for open forests was 159.50 t ha^{-1}. The regression analysis between NDVI and AGB yielded the highest R^2 value (0.91) for open forests, followed by moderately dense forests ($R^2 = 0.87$) and very dense forests ($R^2 = 0.85$) (Table. 4). The Root Mean Square Error (RMSE) values were highest in moderately dense forests (8.81 t ha^{-1}), followed by open forests (7.87 t ha^{-1}), with the lowest RMSE observed in very dense forests (7.54 t ha^{-1}). These results are in agreement with Askar et al. (2018), who estimated AGB using Sentinel-2 imagery and found an R^2 value of 0.74 in their regression analysis between observed and predicted AGB. The differences in biomass estimates between observed and predicted values may be attributed to variations in crown density, tree phenology, and vegetation types, as remote sensing data are highly sensitive to seasonal changes, phenological characteristics, and canopy closure (Dadhwal et al., 2009).

The analysis of validation results for Above Ground Biomass for three forest density classes as follows. For Very Dense Forest: The observed AGB ranged from 436.5 t/ha to 509.1 t/ha, with a mean of 455.94 t/ha and a standard deviation of 29.94 t/ha. Predicted AGB values averaged 444.78 t/ha (SD = 27.83 t/ha). The mean difference was 11.14 t/ha, and the mean percentage difference was 2.42%, indicating slight underestimation by the model. For Moderate Dense Forest Observed AGB values ranged from 228.3 t/ha to 265.7 t/ha, with a mean of 250.54 t/ha (SD = 15.86 t/ha). Predicted values averaged 257.25 t/ha (SD = 20.98 t/ha). The mean difference was -6.71 t/ha, and the mean percentage difference was -2.59%, suggesting slight overestimation by the model. Open Forest: Observed AGB values ranged from 153.8 t/ha to 198.8 t/ha, with a mean of 179.64 t/ha (SD = 17.00 t/ha). Predicted AGB values averaged 179.89 t/ha (SD = 15.53 t/ha). The mean difference was -0.27 t/ha, and the mean percentage difference was -0.03%, (Table 4) indicating a close match between observed and predicted values.

Overall, this study demonstrates that remote sensing, when integrated with field data, provides an efficient and reliable method for estimating vegetation biomass and carbon stocks over large areas. The alignment between predicted and observed AGB values underscores the potential of spectral modeling for biomass estimation. However, the discrepancies between predicted and observed values highlight the importance of accounting for differences in crown density and phenological conditions when interpreting remote sensing data.

Conclusion

This study aimed to estimate Above-Ground Biomass (AGB) in the moist deciduous forests of Mundgod Taluk, Uttara Kannada district, Karnataka, using a combination of field data and remote sensing techniques. The study demonstrated the effectiveness of integrating satellite-derived indices such as NDVI with field measurements to predict biomass across different canopy density classes. The results revealed a clear relationship between canopy density and biomass, with very dense forests showing the highest AGB and corresponding NDVI values, while open forests exhibited lower biomass and NDVI values.The regression models developed using Sentinel-2A surface reflectance data provided a robust method for predicting AGB across the study area, with high R^2 values, particularly for open forests (R^2 = 0.91). The model validation indicated a relatively low Root Mean Square Error (RMSE) across all canopy density classes, further confirming the reliability of the predictions. Moreover, the area-weighted biomass estimates revealed that the Mundgod moist deciduous forests harbor significant biomass, totaling approximately 8.99 million tons.Remote sensing proved to be a valuable tool for large-scale biomass estimation and carbon assessment, offering rapid, cost-effective, and reliable results. The study highlighted the critical role of forest density in influencing biomass distribution and underscored the utility of spectral modeling in understanding forest structure and function. These findings contribute to broader efforts aimed at quantifying biomass and carbon sequestration potential in tropical forests, providing essential data for forest management, conservation, and climate change mitigation strategies.The integration of geospatial techniques with field data can help improve the accuracy and scalability of biomass estimation, making it a valuable approach for similar studies in other forest types.

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Tables and figures

Table 1: Predicted AGB based on NDVI value in different canopy density classes of moist deciduous forest

Sl. No	Latitude	Longitude	NDVI value	Observed AGB (t/ha)	Predicted AGB (t/ha)
Very dense forest					
1	14°50'17"N	74°58'19"E	0.455	405.5	412.77
2	14°48'06"N	75°01'04"E	0.458	408.7	413.79
3	14°52'18"N	74°56'17"E	0.487	414.5	423.71
4	14°55'32"N	74°55'34"E	0.480	417.5	421.32
5	14°42'07"N	74°59'06"E	0.492	427.1	425.42
6	14°44'03"N	75°00'19"E	0.489	427.8	424.40
7	14°49'08 "N	75°01'04"E	0.508	430.2	430.90
8	14°45'53"N	74°58'57"E	0.510	430.8	431.58
9	14°47'58"N	75°01'20"E	0.513	443.7	432.61
10	14°54'33"N	74°56'22"E	0.660	467.0	482.89
Mean			0.51	427.28	424.06
S. D			0.06	18.10	7.24
Moderate dense forest					
1	14°42'30"N	74°59'45"E	0.377	221.6	221.10
2	15°00'49"N	74°53'50"E	0.380	225.3	223.92
3	14°42'27"N	74°59'02"E	0.387	228.3	230.51
4	14°50'23"N	75°00'53"E	0.388	229.4	231.45
5	14°55'16"N	74°55'50"E	0.396	239.6	238.98
6	14°46'24"N	74°59'24"E	0.416	242.2	257.82
7	14°52'44"N	74°58'53"E	0.427	259.2	268.17
8	14°53'01"N	74°57'30"E	0.436	265.7	276.65
9	14°52'07"N	74°58'15"E	0.439	272.2	279.47
10	14°55'48"N	75°00'04"E	0.442	298.7	282.30
Mean			0.41	248.22	251.04
S. D			0.03	25.04	24.41
Open forest					
1	14°47'05"N	75°00'31"E	0.281	115.6	116.09
2	15°00'32 "N	74°53'26"E	0.293	117.7	129.21
3	14°56'22"N	74°57'31"E	0.295	121.7	131.23
4	14°56'13"N	74°57'21"E	0.305	146.0	141.33
5	14°58'49"N	74°56'11"E	0.318	147.6	154.45
6	14°55'01"N	74°57'06"E	0.320	150.7	156.47
7	14°50'03"N	75°01'28"E	0.325	162.8	161.52
8	14°52'11"N	75°01'28"E	0.327	174.3	163.54

9	14°59'08"N	74°53'52"E	0.333	182.8	169.59
10	14°56'54"N	74°57'21"E	0.350	185.0	186.76
Mean			0.31	150.42	151.02
S. D			0.02	26.04	21.37

Table 2. Validation of a model for SAR-derived above-ground biomass

Sl.no	**Latitude**	**Longitude**	**Observed AGB (t/ha)**	**Predicted AGB(t/ha)**	**Difference (t/ha)**	**% Difference**
Very dense forest						
1	14°47'58"N	75°01'20"E	443.7	422.34	21.34	4.81
2	14°54'05"N	74°56'13"E	509.1	492.47	16.59	3.26
3	14°47'42"N	74°56'03"E	444.5	436.71	7.74	1.74
4	14°47'47"N	74°56'06"E	436.5	428.84	7.63	1.75
5	14°46'11"N	75°01'25"E	445.9	443.55	2.38	0.53
Mean			455.94	444.78	11.14	2.42
S. D			29.94	27.83	7.65	1.65
Moderate dense forest						
1	14°53'01"N	74°57'30"E	265.7	276.65	-10.99	-4.14
2	14°42'27"N	74°59'02"E	228.3	230.51	-2.21	-0.97
3	14°45'20"N	74°53'25"E	259.9	271.94	-12.04	-4.63
4	14°52'44"N	74°58'53"E	259.2	268.17	-8.96	-3.46
5	14°55'16"N	74°55'50"E	239.6	238.98	0.64	0.27
Mean			250.54	257.25	-6.71	-2.59
S. D			15.86	20.98	5.61	2.13
Open forest						
1	14°53'38"N	75°01'21"E	198.8	199.88	-1.11	0.56
2	14°52'24"N	75°00'45"E	182.5	175.65	6.83	3.74
3	14°55'29"N	75°00'11"E	174.3	172.62	1.72	0.99
4	14°52'23"N	74°58'13"E	153.8	160.51	-6.75	-4.39
5	14°53'15"N	75°01'04"E	188.8	190.79	-2.02	-1.07

Mean	179.64	179.89	-0.27	-0.03
S. D	17.00	15.53	5.00	2.99

Table 3. MLR models developed for the different canopy density classes using optical data

Canopy density classes	Regression equation model	R^2	RMSE(t/ha)
Very dense forest	Y=257.12+342.08×X	0.85	7.54
Moderate dense forest	Y=-133.869+941.55×X	0.87	8.81
Open forest	Y=-166.57+1009.5×X	0.91	7.54

Table 4. Observed and predicted above-ground biomass from different density classes of moist deciduous forest of Mundgod taluk from optical data

Classes	Observed biomass (t/ha)	Predicted AGB(t/ha)	Area(ha)	Area weighted Observed biomass (Million tons)	Area weighted predicted biomass (Million tons)
Very dense forest	436.96	434.87	10983.76	4.79	4.77
Moderate dense forest	259.89	253.10	13237.47	3.44	3.35
Open forest	161.67	159.50	4713.18	0.76	0.75
			Total	**8.99**	**8.87**

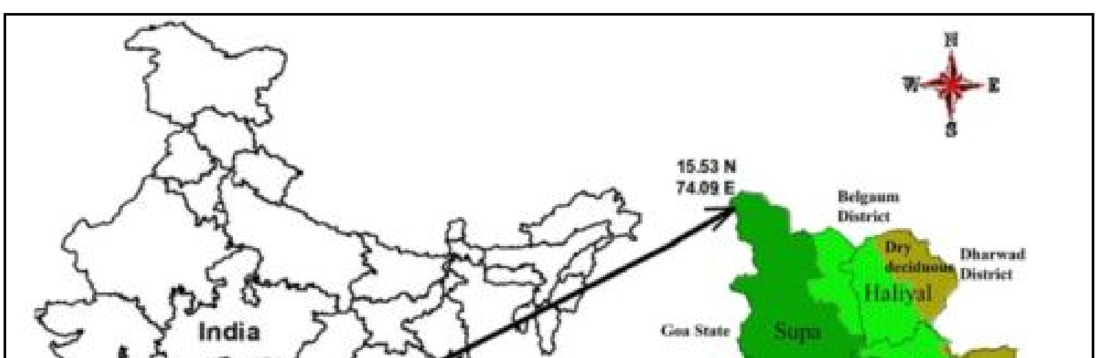
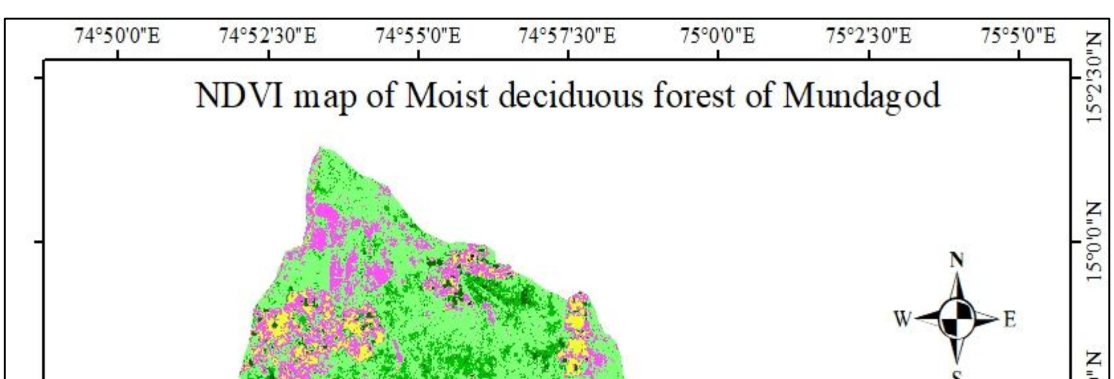


Fig 1. Study area- a moist deciduous forest of Mundgod taluk



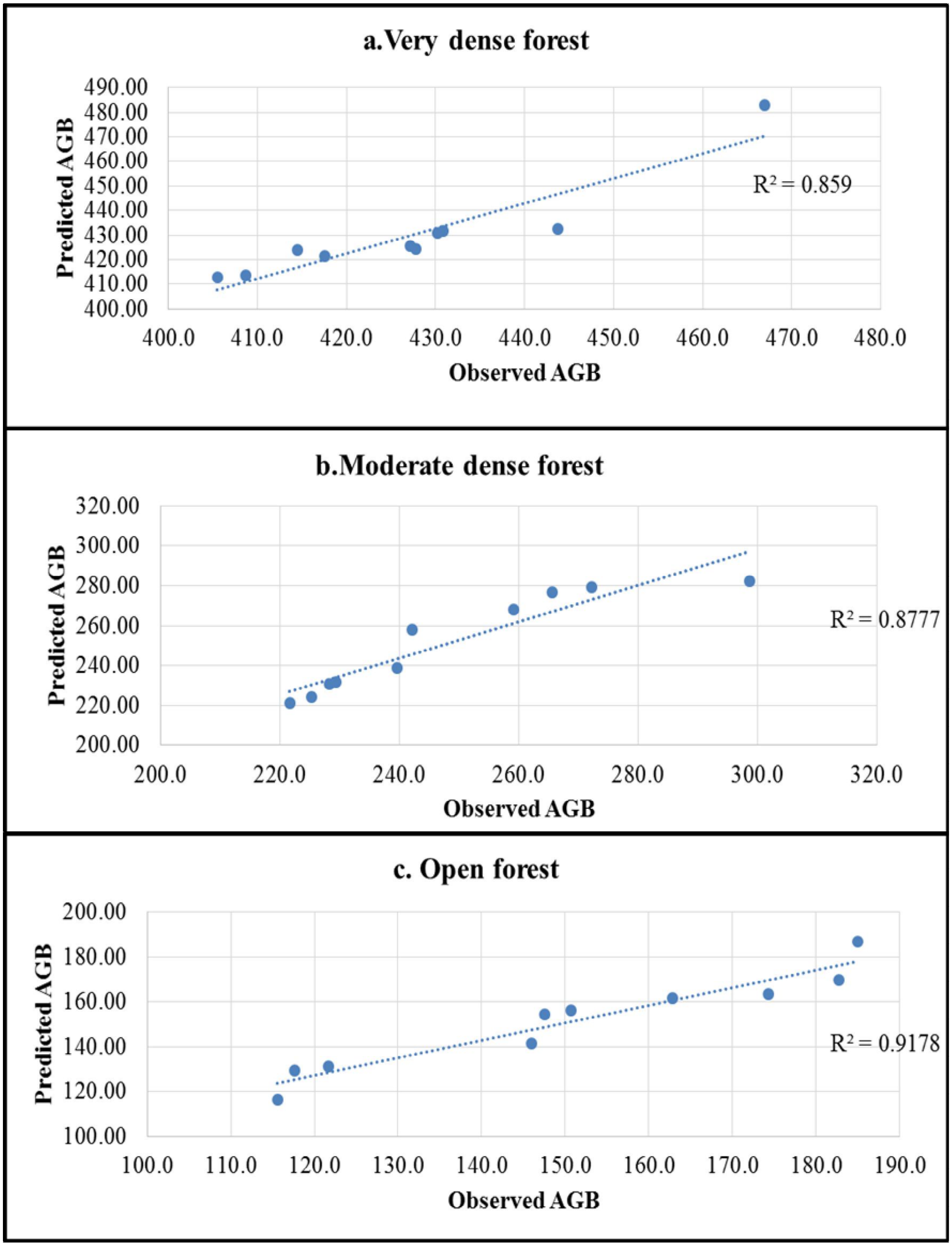


Fig 3: Relationship between optical predicted biomass plotted against field measured biomass a. Very dense forest, b) Moderate dense forest c) open forest