Original Research Article

Assessment of above-ground biomass of moist deciduous forest in Mundgod taluk of Uttara Kannada district from geo-informatics using a modelling technique

Abstract: A remote sensing and GIS-based technique were utilised to estimate above-ground biomass in themoist deciduous forest ofMundgod taluk. The study area is located at 14°41'45" N to 15°01'30" N. latitude and 74°51'45"E to 75°05'00" E longitude with an area of 39143 ha. The current study integrates field-measured above-ground biomass with spectral responses Sentinel 2A with a spatial resolution of 10 m. Area-weighted biomass was estimated for the forest by employing the PCQ method by recording tree height and girth at base and dbh. The field-measuredAGB in the very dense forest was 436.96 t/ha, for the moderately dense forest was 259.89 t/ha and for the open forest was 161.67 t/ha.The best-fit regression equation was derived between area-weighted AGB and NDVI for the study area.10 plots of ground truth NDVI value were recorded from theNDVI image. The 5 plots were used to validate the linear regression equation model. The results indicated that the predicted AGB for the very dense forest was 434.87 t/ha, for the moderately dense forest was 253.1 t/ha and the biomass for the open forest was 159.50 t/ha.In the entire region, the total AGB was estimated to be 8.87Mt. The regression (linear) model was obtained between area-weighted above-ground biomass for an open forest with the highest R^2 value (0.91) followed by moderate dense forest (0.87) and a minimum observed in dense forest (0.85). RMSE value higher in the moderate dense forest was 8.81 t/ha followed by the open forest was 7.87 t/ha and the minimum was observed in the dense forest 7.54 t/ha.The current study found that combining remote sensing with field sampling provides quick and reliable estimates of above-ground biomass. Suchan approach could be used more conveniently for carbon inventories at the State and National levels.

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

Introduction

Assessment of biomass is important for scientific research on ecosystem productivity, carbon budgets, and other issues as well as for planning national development strategies (Kumarand Mutanga,2017). In particular, carbon sequestration, and biomass analysis is essential to the carbon cycle. In recent years, biomass has been employed more and more to estimate the pools and fluxes of greenhouse gases (GHG) from the terrestrial biosphere related to changes in land use and land cover. The Kyoto Protocol highlights the significance of terrestrial vegetation and soil as key sinks of atmospheric CO_2 and its various derivatives (Wani *et al*., 2010). Forest ecosystems, particularly vegetation, store carbon in the biomass through a photosynthetic mechanism, sequestering carbon dioxide that would otherwise be released into the atmosphere.Numerous researchers have estimated the biomass and carbon stocks found in India's forests.

Field measurements, remote sensing (RS), and geographic information systems (GIS) are the three basic approaches to biomass evaluation (Hu, 2020). The field measurement is considered to be accurate, but it is costly and time-consuming. Modern tools like RS and GIS have opened up new opportunities for quick and reliable assessments as well as monitoring of aboveground biomass and carbon pools. Satellite data from NOAA AVHRR, SPOT, MODIS and ASTER have enormous potential for assessing terrestrial biomass and carbon pools. Vegetation indices, particularly NDVI, are an accurate indicator of leaf area index (LAI), which is positively related to biomass and productivity (Roy and Ravan, 1996). Dadhwal and Shah (1997) estimated phytomass carbon pool (4,017 Tg C) and phytomass carbon density (63.6 Mg C ha^{-1}) for India's forests using state-based remote sensing-based forest area, field inventory-based growing stock, and crown density-based biomass expansion factor.The present studyaims to estimate the above-ground biomass in different canopy density classes of moistdeciduous forest of Mundgod taluk of Uttara Kannada district reusing satellite data combined with field measurements. The other important objective was to develop a regression model to generate a geospatial distribution of biomass in the region.

Material and methods

The present study was carried out in the moist deciduous forest of Mundgod taluk, Uttara Kannada district (Fig 1). The study area is located at 14°41'45" N to 15°01'30" Nlatitude and 74°51'45"E to 75°05'00" E longitude with an area of 39143 ha.Moist deciduous forests contain *Tectonagrandis, Terminalia alata, Lagerstroemia lanceolata,Anogeissuslatifolia, Mitragyna parviflora, Terminalia bellarica, Grewiatiliaefolia, Terminalia paniculata, Madhuca species, Schliecheraoleosa, Adina cardifolia, Xyliaxylocarpa*etc.

The transects were laid out randomly over the entire area. In each transect, point centred quarter (PCQ) technique was used. A transect of 100 m was laid in the forest. At every 25 m, 4 trees near the centre point were measured with tape one tree in each quarter. Only one tree having ≥30 cm diameter was measured in each of the quarters and parameters like tree species, girth (m) at base and GBH and height (m) were recorded. Such points are laid at every 25 m interval; thus, at the end of 100 m, five points were selected and 20 trees were recorded. The observations like GPS readings (Latitude, longitude, and altitude), were recorded in each of the PCQ. The forest types having more than 10 per cent canopy density were selected randomly over the entire Mundgod moist deciduous forest area based on the spherical crown densiometer. Very dense forest refers to a forest area having a canopy density is more than 70%, moderately dense forest refers to a forest area which comprises 40-70 cent of the canopy density and open forest refers to a forest area with a canopy density of less than 40 per cent and more than 10 per cent (Anon, 2021). Under each canopy class, fifteen plots were laid. The mean distance of trees for the entire PCQ transect was calculated. Each transect area is equal to the square of the mean distance multiplied by 20. The data thus collected was used for biomass estimations. Area-weighted above-ground biomass was calculated by multiplying the area of each class with the biomass of that particular class.

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

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

Where d is the diameter at breast height

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

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

Regression models were developed for biomass as a function of satellite-derived parameters viz., red and infrared reflectance and NDVI. For modelling biomass, a Sentinel 2A surface reflectance image was used. In ArcGIS software, the NDVI map of the entire moist deciduous forest of Mundgod was prepared using a raster tool and the same map is used to record the NDVI reflectance value for each ground truth location for different canopy density classes was recorded. The spectral modelling was done using an image (December 2021) for the establishment of regression between area-weighted biomass and satellite-derived parameters. The best fit model was selected based on R^2. The database created during the study was organized and analysed in MS Excel (Lumbierres*et al.*, 2017).Remote sensing and GIS-based software (Arc GIS 10.2) were used for spectral modelling.The best fit model thus obtained was used to model biomass for the entire area.

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).

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.

Results and discussion

Across different canopy density classes, tree density varied considerably, the tree density in a very dense forest was 451 stems ha^{-1}, in a moderately dense forest it was 363 stems ha^{-1}and tree density in an open forest was 125 stems ha^{-1}.These values are in line with tree density in the moist deciduous forest (MDF) ranging between 72 to 265 stems ha^{-1}asreported by Lumbierreset *al.*(2017). These results are similar to the tree density (535 stems ha^{-1}) reported by Verghese and Menon (1998) for the MDF of the Agastyamalai region in Kerala.

Field-measured wood biomass for the very dense forest was 436.96 t/ha, for the moderately dense forest was 259.89 t/ha and the wood biomass for the open forest was 161.67 t/ha.The total biomass or area-weighted biomass for a very dense forest was 4.79 million tons. The moderately dense forest was 3.44 million tons, and the open forest's total biomass was 0.76 million tons.The total area-weighted biomass in the moist deciduous forest of Mundgod taluk was 8.99 million tons(Table 4).These estimates are within the range reported for the AGB estimates for the Katerniaghat wildlife sanctuary 290.82-455.99 tons/ha in low-density to high-density forests respectively as reported by Behera *et al*. (2016). The highest quantities of biomass were found in very dense forests ranging from 427 to 569 t/ha, in moderate dense forests with 168-414 t/ha, followed by 130-155 t/ha in the open forest in Malaysia as reported by Hojas *et al*. (2019).

The NDVI values varied across the canopy density classes ranging from 0.32 to 0.73.Pursual of these results indicates that there is a relationship between NDVI and forest type and in turn with biomass. Higher NDVI values were recorded for the very dense forest where the area-weighted biomass was also maximum. The lower NDVI values in open forest types coincided with relatively low biomass. To understand this relationship, regression analysis was carried out between NDVI and the area-weighted biomass obtained across the canopy density classes. The results indicated a significant linear relationship between satellite data and field observations (Fig. 2).Similarly, the NDVI value for the very dense forest ranged from 0.64 -0.74, moderately dense forest between 0.54 - 0.64, sparse forest between 0.46 - 0.54 and scrub forest between 0.39 - 0.46 in Joida of Uttara Kannada district was reported by Koppad*et al.* (2020).Similar results reported NDVI values ranging from -1 to 0.199 for the non-vegetation area (barren lands, build-up area) from 0.2 to 0.5 for low vegetation area (shrub and grassland) and from 0.50 to 1 for the high vegetation area (temperate and tropical urban forest) were reported by Hashim *et al.* (2019).Plot-wise predicted AGB based on backscatter value in the moist deciduous forest was shown in table 1. The linear regression equation model was developed for 10 plots of ground truth data for each of the canopy density classes (Table 3). The above-ground biomass was predicted based on the multilinear regression equation. The predicted AGB for the very dense forest was 434.87 t/ha, for the moderately dense forest was 253.1 t/ha and the biomass for the open forest was 159.50 t/ha

The best fit regression (linear) model was obtained between area-weighted above-ground biomass for an open forest with the highest R^2 value of 0.91 followed by moderate dense forest 0.87 and minimum was observed in dense forest 0.85. And RMSE value higher in the moderate dense forest was 8.81 t/ha followed by the open forest was 7.87 t/ha and the minimum was observed in the dense forest 7.54 t/ha (Table 3). The results are in agreement with those of Lumbierres*et al.* (2017) as they reported a significant relation between area weighed AGB and NDVI with an R^2 value of 0.807 from a study made to estimate AGB and carbon pool of southwestern parts of Karnataka. Similarly, Nuthammachot *et al.* (2018) estimated the AGB of a forest using Sentinel-2 imagery. The regression analysis between observed and predicted AGB revealed an R^2 value of 0.74. The difference in biomass estimates between predicted and observed could be due to the differences in crown density and the different phenological conditions of the trees or vegetation types in the study area.

Remote sensing data are most sensitive to season, tree phenological characters and degree of crown closure (Dadhwal*et al.*, 2009).

Remote sensing, being an advanced technology, is quite useful for quick and reliable estimations of vegetation biomass and carbon over large areas. The predicted above-ground biomass and carbon estimates obtained by spectral modellingwere comparable with the observed values which signifies the soundness of this new technique. The difference in the biomass estimates between the predicted and observed values was possibly due to the differences in the crown density and phenological conditions of the trees or vegetation types existing in the study area. Remote sensing data are most sensitive to season, tree phenological character and degree of crown closure.

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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
Moderate dense forest					
11	14°42'30"N	74°59'45"E	0.377	221.6	221.10
12	15°00'49"N	74°53'50"E	0.380	225.3	223.92
13	14°42'27"N	74°59'02"E	0.387	228.3	230.51
14	14°50'23"N	75°00'53"E	0.388	229.4	231.45
15	14°55'16"N	74°55'50"E	0.396	239.6	238.98
16	14°46'24"N	74°59'24"E	0.416	242.2	257.82
17	14°52'44"N	74°58'53"E	0.427	259.2	268.17
18	14°53'01"N	74°57'30"E	0.436	265.7	276.65
19	14°52'07"N	74°58'15"E	0.439	272.2	279.47
20	14°55'48"N	75°00'04"E	0.442	298.7	282.30
Open forest					
21	14°47'05"N	75°00'31"E	0.281	115.6	116.09
22	15°00'32 "N	74°53'26"E	0.293	117.7	129.21
23	14°56'22"N	74°57'31"E	0.295	121.7	131.23
24	14°56'13"N	74°57'21"E	0.305	146.0	141.33
25	14°58'49"N	74°56'11"E	0.318	147.6	154.45
26	14°55'01"N	74°57'06"E	0.320	150.7	156.47
27	14°50'03"N	75°01'28"E	0.325	162.8	161.52
28	14°52'11"N	75°01'28"E	0.327	174.3	163.54
29	14°59'08"N	74°53'52"E	0.333	182.8	169.59
30	14°56'54"N	74°57'21"E	0.350	185.0	186.76

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
Moderate dense forest						
6	14°53'01"N	74°57'30"E	265.7	276.65	-10.99	-4.14
7	14°42'27"N	74°59'02"E	228.3	230.51	-2.21	-0.97
8	14°45'20"N	74°53'25"E	259.9	271.94	-12.04	-4.63
9	14°52'44"N	74°58'53"E	259.2	268.17	-8.96	-3.46
10	14°55'16"N	74°55'50"E	239.6	238.98	0.64	0.27
Open forest						
11	14°53'38"N	75°01'21"E	198.8	199.88	-1.11	0.56
12	14°52'24"N	75°00'45"E	182.5	175.65	6.83	3.74
13	14°55'29"N	75°00'11"E	174.3	172.62	1.72	0.99
14	14°52'23"N	74°58'13"E	153.8	160.51	-6.75	-4.39
15	14°53'15"N	75°01'04"E	188.8	190.79	-2.02	-1.07

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**

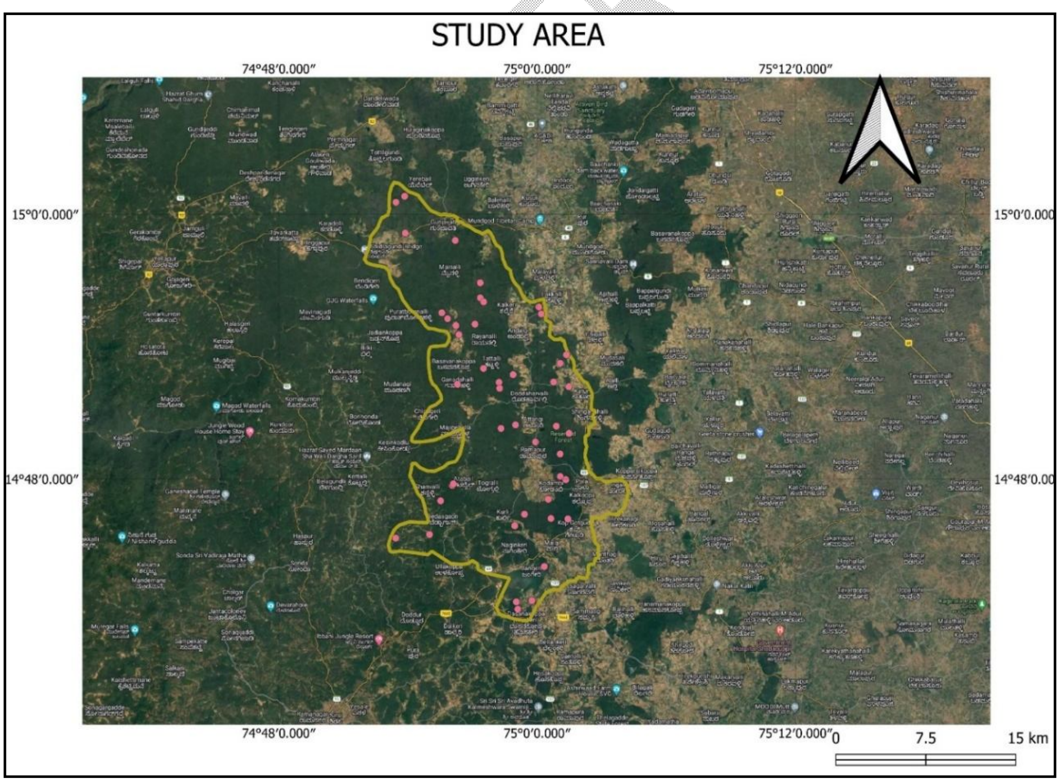

Fig 1. Study area- a moist deciduous forest of Mundgod taluk

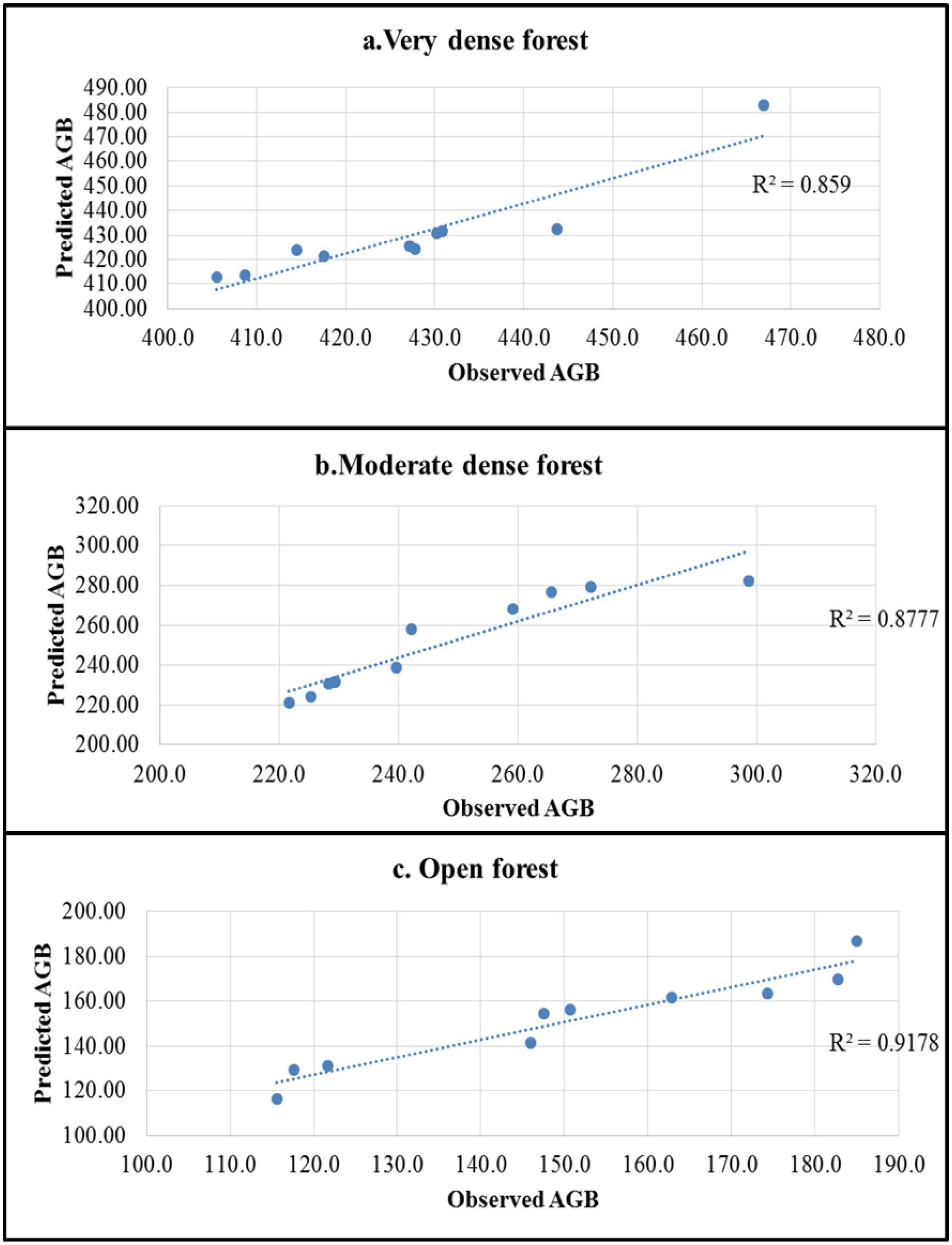

Fig 2: Relationship between optical predicted biomass plotted against field measured biomass a. Very dense forest, b) Moderate dense forest c) open forest