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ESTIMATING ABOVE-GROUND BIOMASS OF AGROFORESTRY TREE SPECIES IN BHADADRI KOTHAGUDEM DISTRICT, TELANGANA, INDIA, USING SENTINEL-2 SATELLITE DATA

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ABSTRACT

This study investigates the relationship between Above Ground Biomass (AGB) and Vegetation Indices (VIs) derived from Sentinel-2 satellite data for Eucalyptus, Subabul and Oil palm-based agroforestry systems (AFS) in Bhadradri Kothagudem District, Telangana state, India. Field measurements were collected and above-ground biomass (AGB) was estimated using allometric equations. The vegetation indices derived for this study area were Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Soil Adjusted Vegetation Index (SAVI) and Modified Soil Adjusted Vegetation Index (MSAVI). In this study, Linear regression model was fitted to establish the relationship between AGB and VIs. Among the VIs, strongest positive correlation was observed for EVI with correlation coefficient (r) of 0.94 and coefficient of determination (R^2) value of 0.88 compared to another VIs. The mean AGB estimated for Eucalyptus (3years old) was 42 t ha^{-1}, Subabul (3 years old) was 66 t ha^{-1} and Oil palm (up to 21 years) was 152 t ha^{-1} for the study area. The lowest Root mean square error (RMSE) value from predicted and observed AGB was 24 t ha^{-1}for EVI. Thus, it was concluded that the Enhanced Vegetation Index (EVI) is the most suitable index for estimating the above-ground biomass (AGB) of Eucalyptus, Subabul, and Oil Palm-based agroforestry systems. The yield model developed incorporating EVI was utilized to estimate the AGB of these species in this study.
Keywords: Above Ground Biomass, Agroforestry Systems, Sentinel-2, Vegetation Indices

Introduction

All living biomass above the soil including stem, stump, branches, bark, seeds and foliage is termed as Above Ground Biomass. The Intergovernmental Panel on Climate Change (IPCC) recognizes five carbon pools in terrestrial ecosystems that comprise above-ground biomass (AGB), below-ground biomass (BGB), litter, woody debris, and soil organic matter (SOM). Among these pools, AGB is the most visible, dynamic and crucial component, accounting for approximately 30% of the total carbon pool in the terrestrial ecosystem (Kumar and Mutanga 2017). Accurate quantification of aboveground carbon in AFS is vital for comprehending the carbon storage potential of these systems and facilitating trading Malhi *et al.* (2008). Quantification of (AGB) of tree species is very important for carbon flux monitoring, carbon budget accounting and supporting climate change modelling studies.

The AGB can be estimated through both destructive and non-destructive methods. Destructive methods involve cutting down trees and weighing them, but these are limited to small areas due to their destructive nature, as well as the time, expense, labor intensive and loss of biodiversity. Furthermore, they are not suitable in areas where threatened flora and fauna may be present. Non-destructive methods include estimating biomass using allometric equations or through remote sensing Kumar and Mutanga. (2017). Nowadays, a common method for evaluating biomass is remote sensing technology Kankare *et al.* (2013) and Wannasiri *et al.* (2013). Several studies have regularly employed satellite-based VIs to estimate biomass Pandit *et al.* (2018); Joshi *et al.* (2019); Utari *et al.* (2020); Poudel *et al.* (2022); Joshi *et al.* (2019); Rajani *et al.* (2024). Allometric equations were developed based on three dimensions such as height and diameter at breast height (DBH) Kumar and Mutanga. (2017). The combination of field-measured and remote sensing data is useful for the assessment of AGB, carbon stock, and their changes over extensive coverage areas Kiyono *et al.* (2011).

Satellite based VIs models are the most commonly used models for estimation of biomass. Vegetation index models use the popular red and near infrared wavelengths to emphasize the difference between the strong absorption of red electromagnetic radiation and the strong scatter of near infrared radiation in knowing the vegetation characteristic. VIs are used to remove the variations caused in spectral reflectance measurement while measuring biophysical properties caused due to soil background, sun view angles and atmospheric conditions. Many previous studies have shown significantly positive relationship between biomass and VIs Das and Singh. (2012), Wahlang and Chaturvedi. (2020), Singh *et al.* (2024). Hence, a study was conducted to examine the relation between AGB of Agroforestry tree species and VIs in Bhadradri Kotthagudem district, Telangana. This study was executed to identify the best yield model using the vegetation index that can correlate with the biomass.

Materials and Methods

Study area

The study area conducted was the Bhadradri Kotthagudem district shown in fig.1, which covers a geographical area of 7483 sq. km and it is located between 18° 13' and 17° 13' of Northern Latitude and 80° 12' and 81° 18' of the Eastern Longitude. Area under forest is 4287 sq.kms. Major agricultural crops grown in this region are rice, cotton, maize and chillies. The Plantation crops, that are larger number are oil palm, coconut, cocoa, cashewnut, areca nut and fruits trees like mango, papaya, guava, banana and acid lime. Eucalyptus, Subabul, Oil palm, Mango and Cashewnut based AFS are mostly followed in this district. This district recorded an annual mean maximum temperature of 35.07ºC and mean minimum temperature of 22.65ºC with an average annual rainfall of 147.76 mm.

Field assessment of Above Ground Biomass (AGB)

In the present study random sampling method was used to estimate the Above ground biomass. The locations of the sampling sites were recorded by using GNSS app in the mobile. The data collected from the field was height and DBH of the tree species. Further biomass of trees was computed by multiplying volume with density of a particular tree species taking into consideration of radius and tree height

Tree volume was computed using volumetric equation

i.e. $V= \pi r^2 h$ Keerthika and Parthiban. (2022)

Here: V= volume in m^3

r^2= radius of the tree at 1.37 m above the ground = DBH/2

h= height of the tree in meter

Satellite data

In this study, Sentinel-2 Level 2A satellite imagery was used for species identification, the data for 5th January 2024 was downloaded from Copernicus website. All the bands were layer stacked using ERDAS IMAGINE 2018 software. The obtained tiles (paths/rows) were mosaicked and the study area was extracted using the area of interest. A point file representing the sampling sites was generated and overlaid on the corrected image to verify the alignment of the plots with the ground-truth data. Agroforestry species classification was conducted using E-Cognition software after excluding forest areas. The FCC image was clipped to focus on the agroforestry region, and vegetation indices (VIs) such as NDVI, EVI, SAVI, and MSAVI were generated. Correlation analysis was then performed between these indices and the biomass.

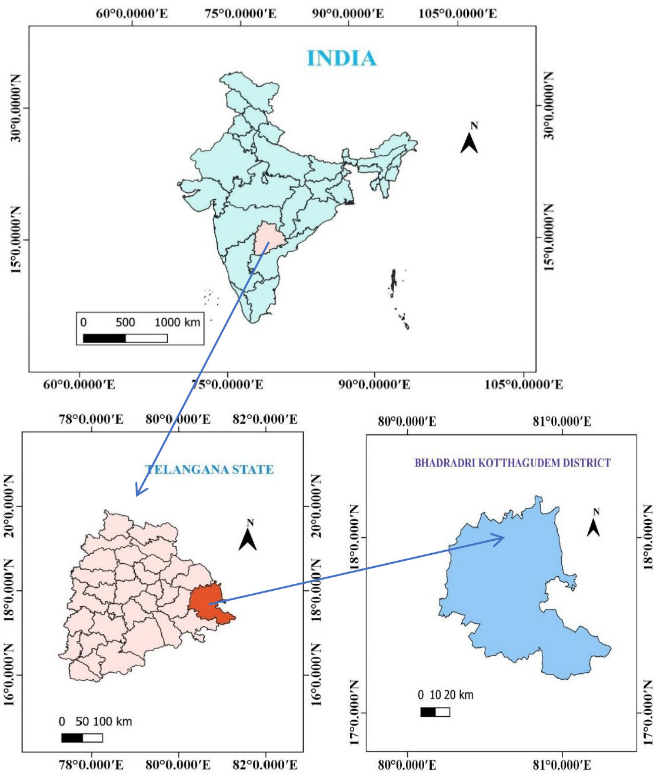

Fig. 1 : Location map of the study area

Vegetation indices (VIs)

Vegetation indices (VIs) are the mathematical formulas that use specific spectral bands to highlight the spectral properties of green plants, allowing them to be distinguished from other features or characteristics Poudel *et al.* (2023). The Normalized Difference Vegetation Index (NDVI), as introduced by Rouse *et al.* (1974), is one of the most commonly used vegetation indices in forestry-related studies due to its wide applicability across various remote sensing applications. It is the ratio between the maximum absorption of red wavelengths by chlorophyll pigments and the maximum reflectance of infrared wavelengths due to the leaf's cellular structure Wahlang and Chaturvedi. (2020).

The Soil Adjusted Vegetation Index and its improved version, the Modified Soil Adjusted Vegetation Index are designed to reduce the influence of soil background reflectance and making them more suitable for areas with spare vegetation Ragini *et al.* (2024).

The Enhanced Vegetation Index (EVI) is an "optimized" Vegetation Index, developed to enhance the vegetation signal by increasing sensitivity in high-biomass regions. It also improves vegetation monitoring by decoupling the canopy background signal and reducing atmospheric influences Shibani *et al.* (2023). The Enhanced Vegetation Index (EVI), using coefficients L = 1, C1 = 6, C2 = 7.5, and G (gain factor) = 2.5, offers a reliable estimate of vegetation, which can be useful for forecasting primary production. However, ecosystem models based on EVI data or other crop indicators are frequently constrained by the limited availability of satellite data records Gurung *et al.* (2009). The indices were generated using the QGIS Software. A sample plot located at a specific latitude and longitude was exported as a 10m circular plot. Using zonal statistics and a buffered circular area around the plot position, pixel values for all vegetation indices (VIs) were extracted. The equations of NDVI, EVI, SAVI and MSAVI are given in Table.1

Table 1: Vegetation Indices used in this study.

Sr. no	Vegetation index	Equation	Reference
1	NDVI	$R_{NIR-RED}/R_{NIR+RED}$	Rouse *et al.* (1974)
2	SAVI	1.5*(NIR-RED)/(NIR+RED*0.5)	Huete (1988)
3	MSAVI	= 1/2 [2 NIR + 1 – √ (2 NIR + 1) 2 – 8 (NIR – RED)]	Qi *et al.* (1994)
4	EVI	EVI=G×NIR−RED/NIR+(C1×RED−C2×BLUE) + L	Huete *et al.* (2002)

Statistical Analysis

Statistical analysis was conducted using SPSS and Microsoft Excel to evaluate the relationship between vegetation indices (VIs) and above-ground biomass (AGB). Different regression models were tested, with AGB as the dependent variable (y) and VI as the independent variable (x). These models quantified how variations in VIs influenced AGB, using the correlation coefficient (r) and the coefficient of determination (R^2) to measure the strength of the relationship. The linear model yielded higher r and R^2 values, indicating a stronger correlation.

The linear regression equation used in the analysis was:

$$Y = a + bx$$

where Y represents AGB in t ha^{-1}, X is the vegetation index (VI), and

a is the Y intercept and b is the slope of the line.

Results and Discussion

Estimation of Above Ground Biomass (AGB)

The biomass assessment was done based on the field inventory data collected across 30 ground truth points in 13 villages covers 5 mandals of Bhadradri Kothagudem district. Tree volume was multiplied by the specific gravity of each tree species to calculate the biomass.

Analysis of field data reveled that, the highest mean observed AGB was recorded in Oil palm based AFS followed by Subabul and Eucalyptus. The average AGB recorded for Eucalyptus (3-year-old) was 42t ha^{-1}, Subabul (3-year-old) was 66 t ha^{-1} and Oil palm (21-year-old) was 152 t ha^{-1}. Singh and Toky (1995) recorded an AGB of 95.59 t ha^{-1} for eucalyptus species at 4-year age, 111t ha^{-1} for subabul in arid India. Kumar *et al.* (2017) reported that the total biomass of ten-year-old oil palm under irrigated conditions as 72.5 ± 5.0 t ha^{-1}.

Relationship between Above Ground Biomass and Vegetation Indices

A comparative correlation analysis was conducted to examine the relationship between vegetation indices and biomass data measured in field. In this study Linear regression model was fitted to establish the relationship between AGB and VIs. The results presented in fig.1 shows that, all the vegetation indices NDVI, EVI, SAVI and MSAVI exhibit a positive correlation with AGB. Similar results were obtained for many researches. Nakano *et al.* (2013) in their study computed 7 VIs *viz.*, SR, NDVI, EVI, SAVI, OSAVI, LSWI and GR from MODIS data. The results revealed that all of the VIs showed significant positive correlation with measured data of AGB.

In this study, linear regression model showed higher positive correlation and among the VIs, strongest positive correlation was observed for EVI with correlation coefficient (r) of 0.94 and coefficient of determination (R^2) value of 0.88 and low RMSE (24 t ha^{-1}) as shown in Table.2 The strong correlation between EVI and AGB may be due to EVI's sensitivity to changes in vegetation density and canopy structure, as well as its ability to minimize the influence of factors like soil background and atmospheric conditions, making it particularly reliable in the dense and heterogeneous environments typical of agroforestry systems Xue and Su. (2017). Poudel *et al.* (2023) in their study, also concluded that ARVI and EVI-2 showed strong correlation (r = 0.861) and coefficient of determination (R^2= 0.7414 and 0.7415) with AGB in Chure region of Sainamaina Municipality, Nepal. The next closest fit was obtained for NDVI with r = 0.85, R^2 = 0.73 and RMSE was 37 t ha^{-1}. Similar results were also obtained for SAVI and MSAVI with r = 0.79 and 0.78, R^2 = 0.62 and 0.61. The highest RMSE (45 t ha^{-1}) was observed for MSAVI.

Table 2: Statistical summary of regression analysis between AGB and VIs

Vegetation index	Model	Multiple R	R^2	Adjusted R	RMSE
NDVI	Y = 1045*NDVI-365	0.85	0.73	0.71	37
EVI	Y = 798*EVI-597	0.94	0.88	0.88	24
SAVI	Y = 613*SAVI-306	0.79	0.62	0.61	44
MSAVI	Y = 905*MSAVI-453	0.78	0.61	0.59	45

In a study conducted by Joshi *et al*. (2019), NDVI showed highest correlation with AGB for *Pinus roxburghii* (r= 0.76, R^2=0.53, adjusted r= 0.52) compared to other indices. Similarly, Askar *et al*. (2018) found higher R^2 value for NDI45, NDVI to be 0.79 and 0.65 respectively on private forest in Indonesia using Sentinel-2.

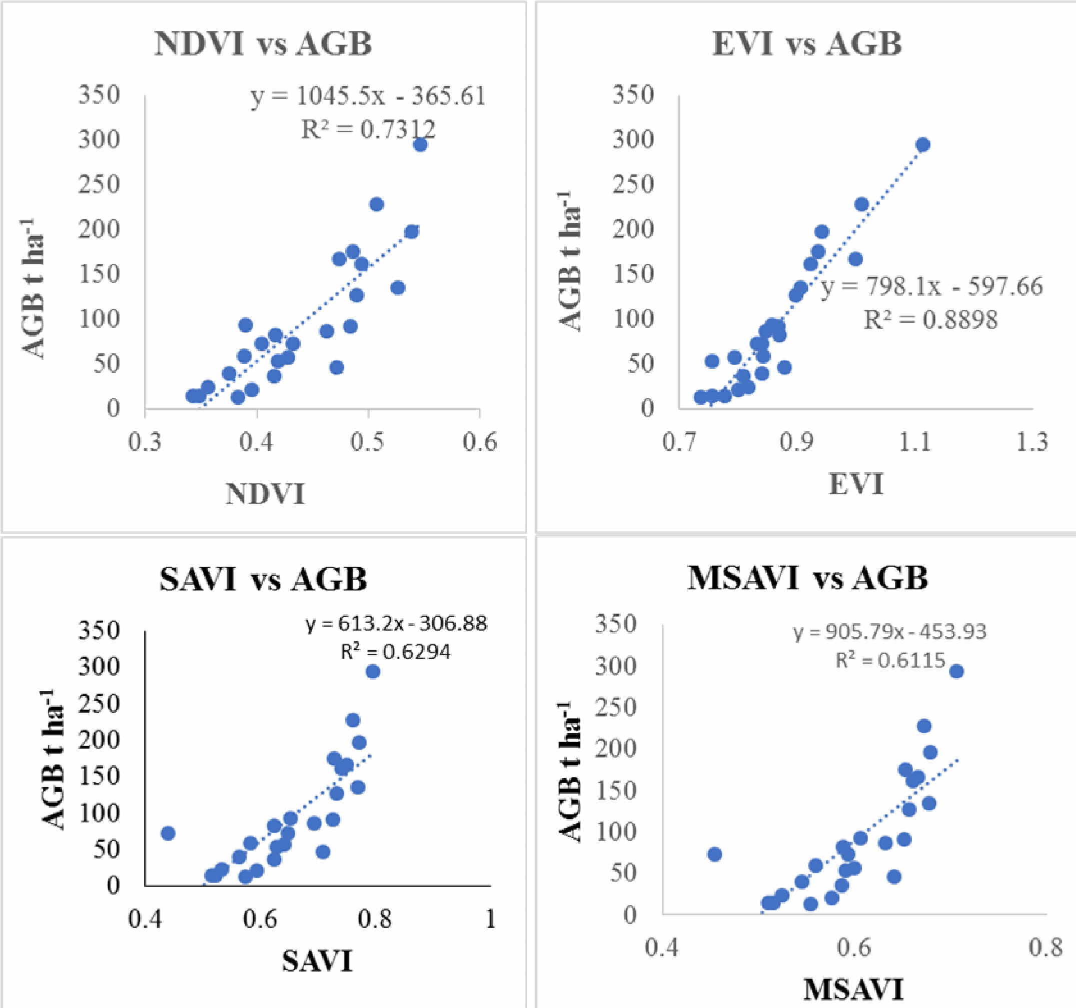

Fig. 2 : Scatter plots showing correlation between AGB and VIs

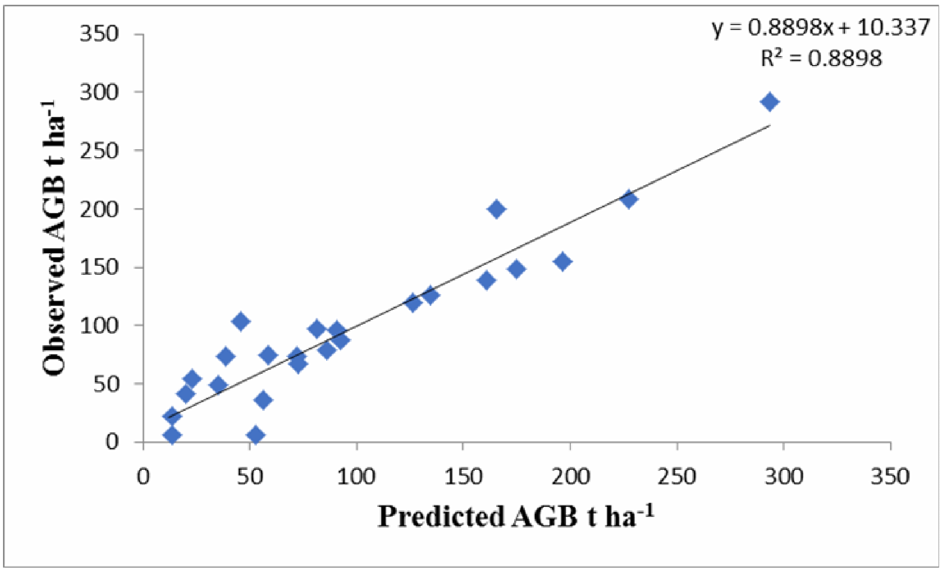

Fig. 3: Comparision of observed and predicted AGB

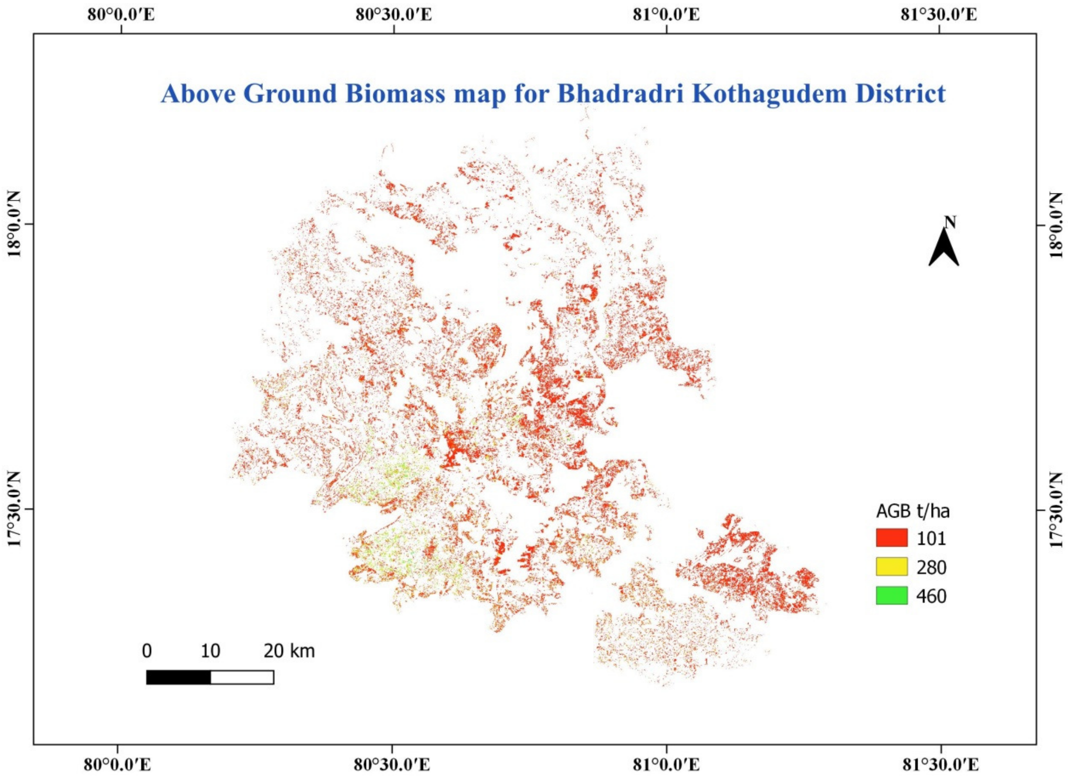

Fig. 4: AGB (t ha^{-1}) of the Agroforestry tree species for Bhadradri Kothagudem district, Telangana

Conclusion

In this study, it was concluded that among the vegetation indices (VIs) analysed, the Enhanced Vegetation Index (EVI) demonstrated the strongest correlation with above-ground biomass (AGB), with r=0.94, R^2=0.88 and adjusted R^2 = 0.88. EVI proved to be the most suitable VI for estimating AGB in agroforestry systems. A linear regression model was successfully applied to estimate the AGB of agroforestry tree species in Bhadradri Kothagudem district, Telangana state. The use of remote sensing (RS) techniques significantly enhanced the efficiency, accuracy and timeliness of biomass estimation compared to conventional methods, which are labour-intensive, complex and time-consuming. Freely available multispectral Sentinel-2 data, with its high spatial and temporal resolution, provides a reliable and scalable solution for large-scale AGB estimation.

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