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Relationship between Above-ground Biomass and Different Vegetation Indices of Tea Plantation of Alipurduar District, West Bengal, India

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Authors' contributions

This work was carried out in collaboration among all authors. Author RHR spearheaded the study, conceptualized the primary idea and crafted the research framework. Additionally, they played a pivotal role in developing the materials and methods section. Author MKD on the other hand made significant contributions to data arrangement, meticulously organizing and structuring the research content. Author PB provided invaluable support throughout the research process. Their expertise ensured the coherence and clarity of the study while author DSG actively participated in data analysis, offering critical insights and consistent assistance across various project aspects. Together, the collaborative efforts of all four authors enriched the quality and depth of this research. All authors read and approved the final manuscript.

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ABSTRACT

This study investigates the relationship between above-ground biomass (AGB) and various vegetation indices in the tea plantations of Alipurduar District, West Bengal, India. The research was conducted in three major tea estates: Kumargram, Sankos and Newlands, using stratified random sampling across 36 plots. Field measurements of trees, shrubs and herbs were taken and AGB was estimated using allometric equations. Sentinel-2 satellite data was utilized to derive vegetation indices such as NDVI, GNDVI, SAVI, MSAVI, EVI-1, EVI-2, $NDVI_{RE}$, RDVI, DVI, OSAVI and ARVI. The study found significant variation in AGB, ranging from 31.40 Mg ha^{-1} to 68.84 Mg ha^{-1}, with an average of 47.22 Mg ha^{-1}. Strong positive correlations were observed between AGB and indices like GNDVI (r=0.96) and EVI-2 (r=0.96), indicating their effectiveness in biomass prediction. The integration of remote sensing technologies enhances the scalability and precision of biomass estimation, providing valuable insights into the carbon storage potential and ecological health of tea plantations. These findings have implications for sustainable management and climate change mitigation in agroforestry systems.

Keywords: Above-ground biomass; sentinal-2; vegetation indices; tea garden.

1. INTRODUCTION

Tea, scientifically known as *Camellia sinensis* (L.) O. Kuntze, is a perennial evergreen plant typically cultivated in shrub form to encourage the growth of young shoots. It ranks among the most widely consumed beverages worldwide, with a particularly strong presence in Asia, Africa and the Near East [1]. The increasing demand for tea makes it a vital part of the global beverage market, though its cultivation is confined to areas with specific climates and soil conditions. Tea is a significant source of national pride for India, contributing substantially to the country's foreign exchange earnings and Gross National Product (GNP). India is a global leader in tea production, consumption and export, accounting for 25% of the world's total production. The primary tea-producing regions in India include Assam, West Bengal, Himachal Pradesh, Kerala, Karnataka and Tamil Nadu. These plantations cover more than 5,640 km^2 of agricultural land and produce over 1.209 Tg of tea annually [2,3]. Tea plantations are a significant component of the agricultural landscape in many parts of the world, particularly in regions like the Alipurduar District in West Bengal, India [4]. The region is home to several notable tea estates, such as the Aryaman Tea Estate and the Kumargram and Sankos Tea Estates. The tea industry not only contributes substantially to the local economy but also plays a crucial role in the socio-cultural fabric of the region. The management and sustainability of these plantations are of paramount importance, necessitating accurate and efficient methods for monitoring various agronomic parameters, including above-ground biomass (AGB) [5]. The sustainability and management of these tea plantations are crucial, especially in terms of monitoring agronomic parameters like AGB [6]. Accurate estimation of AGB is essential for assessing the health and productivity of the plantations, which in turn impacts the overall sustainability of the tea industry [7].

Estimating AGB is essential to the long-term sustainability of tea plantation management. It offers insightful information about the productivity, health and capacity of tea plants to sequester carbon [8]. Conventional techniques, such as destructive sampling, are labour and time-intensive, making them unsuitable for large-scale applications. As a result, there is increased interest in non-destructive techniques, especially those that make use of allometric equations. Tree diameter at breast height (DBH), height and wood density are easily observable factors that can be used to estimate AGB using allometric equations [9]. These equations can be used over wide areas without the requirement for destructive sampling because they are derived from statistical correlations acquired from field data [10]. The efficiency and precision of AGB estimation are improved when allometric equations are used in conjunction with remote sensing technology, such as satellite images. Allometric models paired with spatially extended data from remote sensing can yield detailed maps of biomass [11]. This strategy is especially helpful for tea plantations, since traditional approaches are difficult due to the consistent planting patterns and deep canopy. Plantation managers may more effectively monitor the growth dynamics and production potential of tea plants by employing non-destructive approaches.

This allows for timely interventions and improved resource management. Furthermore, by measuring the amount of carbon stored in tea plantations, precise AGB estimation supports efforts to mitigate climate change and account for carbon emissions [12].

The evaluation of AGB in tea plantations necessitates the application of vegetation indices (VIs), which offer detailed insights into plant health, productivity and biomass accumulation [13]. The Normalized Difference Vegetation Index (NDVI) is favoured for its ease of use and reliability in measuring green biomass through the differential reflectance of red and near-infrared light. The Enhanced Vegetation Index (EVI) is particularly beneficial for dense tea plantations as it minimizes atmospheric effects and enhances sensitivity in areas with high biomass [14]. Meanwhile, the Optimized Soil Adjusted Vegetation Index (OSAVI) increases accuracy in areas with varying soil conditions by compensating for soil brightness. Moreover, the Green Normalized Difference Vegetation Index (GNDVI) is attuned to chlorophyll levels, simplifying the monitoring of health and yield in tea plantations. Indices derived from satellite imagery enable precise AGB estimation, leading to better resource management, timely interventions and carbon sequestration efforts, all contributing to climate change mitigation. By incorporating these Vegetation Indices (VIs) with remote sensing data, plantation managers can promote sustainable practices, monitor growth patterns and optimize resource allocation in tea plantations [15]. Vegetation indices (VIs) are employed to mitigate variations in spectral reflectance measurements that arise from factors such as soil background, sun-view angles and atmospheric conditions when assessing biophysical properties. Numerous studies have demonstrated a significantly positive relationship between biomass and vegetation indices [4,16,17]. This study aims to investigate the relationship between biomass and vegetation indices (VIs) in the tea plantations of Alipurduar District, a crucial part of West Bengal’s tea industry. Given the region’s sensitivity to climate change and human activities, the study seeks to identify the VIs or band ratios that best correlate with biomass.

2. MATERIALS AND METHODS

2.1 Study Area

This study focuses on the tea-growing areas of the Alipurduar District (Fig. 1), which lies between latitudes 26°40’20.10" N and 26°38’42.95" N and longitudes 89°47’28.23" E and 89°52’06.82" E. We conducted our research in three major tea estates: Kumargram, Sankos and Newlands. These estates are in the Kumargram Community Development Block of Alipurduar District, West Bengal. Kumargram is situated in the eastern part of the district and is part of the Sub-Himalayan range. The northern fringe of the Dooars Region is ideal for tea cultivation due to its favorable climate and topography, providing large-scale employment opportunities [18]. The region experiences three primary seasons: summer, monsoon and post-monsoon (winter). Generally, temperatures range from a maximum of 33°C to a minimum of 10°C. The majority of the annual rainfall, averaging around 3411 mm, occurs between May and September [4]. The Sanaka River runs along the eastern boundary of Kumargram. The area is bordered by the Chukha District in Bhutan to the north, the Gossaigaon Revenue Circle in Kokrajhar District (Assam) to the east, the Tufanganj II CD Block in Cooch Behar District to the south and the Alipurduar II and Kalchini CD Blocks to the west.

2.2 Field Assessment of Above-ground Biomass

In the present study, stratified random sampling was used for biomass estimation, with 36 plots laid out in different homogeneous strata based on the accessibility of the locations. Trees, shrubs and herbs were sampled using a stratified random nested method. The main quadrat was 20 m x 20 m, with two 5 m x 5 m quadrats marked at diagonal corners for shrubs. For herbs, five 1 m x 1 m plots were marked at all corners and one at the center of the main quadrat. The stem diameter at DBH of all the trees in the quadrate will be measured separately. For shade trees in the tea gardens, a logarithmic equation by Brown *et al*. (1997) was adopted [19].

$$Y = 21.297 - 6.953D + 0.740D^2$$

where Y is the AGB of the tree and D is the diameter of the tree at breast height. The coefficient of determination (R^2) value for the original equations is 0.87. The AGB of tea will be estimated using the allometric equation suggested by Kalita *et al*. (2016).

$$Y = aX^b$$

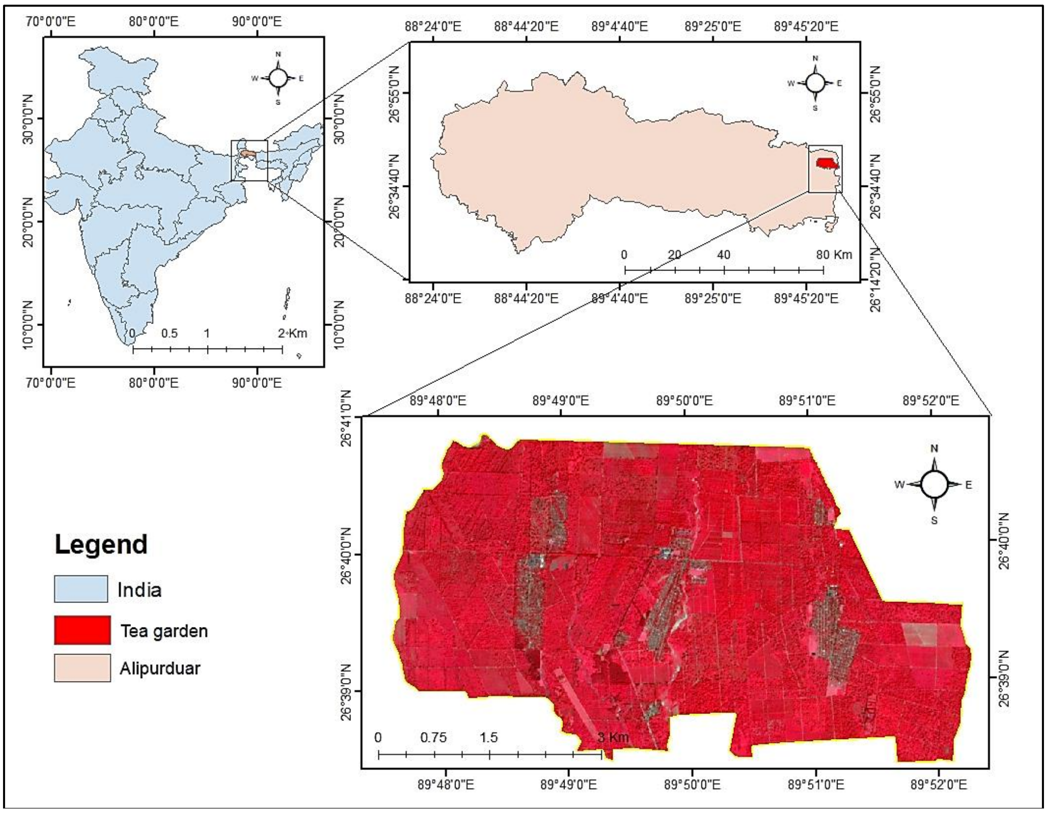

Fig. 1. Geographical Map of the study area in West Bengal, India

Table 1. List of Vegetation indices derived from Sentinal-2 imagery

Vegetation indices	Definition
NDVI (Normalized Difference Vegetation Index)	$\frac{(Band8 - Band4)}{(Band8 + Band4)}$
SAVI (Soil Adjusted Vegetation Index)	$\frac{(Band8 - Band4)}{(Band8 + Band4 + 0.5)} \times 1.5$
MSAVI (Modified Soil Adjusted Vegetation Index)	$2Band8 + \frac{1 - \sqrt{(2Band8 + 1)^2} - 8(Band8 - Band4)}{2}$
NDVI$_{RE}$ (Normalized Difference Vegetation Index with bands 4 and 5)	$\frac{(Band5 - Band4)}{(Band5 + Band4)}$
GNDVI (Green normalized difference vegetation index)	$\frac{(Band7 - Band3)}{(Band7 + Band3)}$
EVI-1 (Enhanced Vegetation Index 1)	$2.5 \times \frac{(Band8 - Band4)}{(Band8 + 6 \times Band4 - 7.5 \times Band2 + 1)}$
EVI-2 (Enhanced Vegetation Index 2)	$2.5 \times \frac{(Band8 - Band4)}{(Band8 + 2.4 \times Band4 + 1)}$
OSAVI (Optimized Soil Adjusted Vegetation Index)	$\frac{(Band8 - Band4)}{(Band8 + Band4 + 0.16)}$
ARVI (Atmospherically Resistant Vegetation Index)	$\frac{(Band8 - (Band4 - \Upsilon \times (Band4 - Band2)))}{(Band8 + (Band4 - \Upsilon \times (Band4 - Band2)))}$
DVI (Difference Vegetation Index)	$Band8 - Band4$
RDVI (Renormalized Difference Vegetation Index)	$\frac{(Band8 - Band4)}{\sqrt{Band8 + Band4}}$

where Y is the biomass component kg per stem, X represents stem diameter (cm) at 5 cm height and a and b stand for coefficient and the allometric constant respectively. For AGB, the values of a and b will be 0.047 and 1.878 respectively [20].

The study utilized Sentinel-2 Level 2A satellite data from November 2023. Since the data was atmospherically corrected surface reflectance, no pre-processing was necessary. The LULC map was created using the maximum likelihood classifier in ArcGIS software (version 10.8.1) [21]. A point shapefile of the sampling sites was generated and overlaid on the corrected image to verify the alignment of plot positions with the ground.

2.3 Vegetation Indices

In the estimation of AGB in tea gardens, various vegetation indices offer unique advantages and insights, making them essential tools for accurate assessment. These indices, derived from Sentinel-2 Level 2A satellite data, provide critical insights into vegetation health and biomass estimation. The indices used include NDVI, GNDVI, SAVI, MSAVI, EVI-1, EVI-2, $NDVI_{RE}$, RDVI, DVI, OSAVI and ARVI (Table 1). Each index has its unique history and significance, contributing to a comprehensive understanding of vegetation dynamics.

The Normalized Difference Vegetation Index (NDVI), a widely used index, measures the difference between near-infrared and red light, providing a basic yet effective measure of plant health [22]. Green Normalized Difference Vegetation Index (GNDVI), a variation using green light, is particularly useful for detecting chlorophyll content and assessing plant vigour [23]. Soil-Adjusted Vegetation Index (SAVI) and its improved version, Modified SAVI (MSAVI), minimize soil brightness effects, making them ideal for areas with sparse vegetation [24]. Enhanced Vegetation Index (EVI-1) and its simplified counterpart, EVI-2, optimize vegetation signals with improved sensitivity in high biomass regions and better atmospheric correction, enhancing canopy structural analysis [25,26]. The Red-Edge NDVI ($NDVI_{RE}$), utilizing the red-edge band, is sensitive to chlorophyll changes and plant stress, crucial for early stress detection. The renormalized Difference Vegetation Index (RDVI) combines NDVI's simplicity with the sensitivity of the Ratio Vegetation Index (RVI), enhancing vegetation signals for biomass estimation. Difference Vegetation Index (DVI) and RVI provide straightforward measures of vegetation health and density, respectively. Optimized SAVI (OSAVI) offers better performance in moderate vegetation cover areas by reducing soil noise. Lastly, the Atmospherically Resistant Vegetation Index (ARVI), with its blue band correction, ensures reliability under varying atmospheric conditions [27,28,29]. Each index contributes uniquely to the comprehensive estimation of AGB, with their combined use providing a robust methodology for monitoring and assessing biomass in tea gardens.

3. RESULTS AND DISCUSSION

3.1 Estimation of Above Ground-biomass

The assessment of above-ground biomass was meticulously carried out using field inventory data, leveraging allometric equations tailored for different plant types. Specifically, the equations developed by Brown *et al*. (1997) were utilized for shade trees, while those by Kalita *et al*. (2016) were applied to tea bushes. In each of the individual field plots, detailed measurements were taken for tea bushes of *Camellia sinensis* and various parameters of shade trees, including tree heights and DBH. There is a rich diversity of shade tree species within the plots, including *Albizia lebbeck*, *Acacia auriculiformis*, *Albizia chinensis*, *Albizia odoratissima*, *Dalbergia sissoo*, *Erythrina indica, Albizia procera* and *Neolamarckia cadamba*. These species contribute significantly to the overall biomass and ecological balance of the area [30].

From the field measurements conducted across 36 sampling points, the estimated above-ground biomass varied significantly, ranging from 31.40 Mg ha^{-1} to 68.84 Mg ha^{-1} .This variation reflects the heterogeneity in tree density and species composition across different plots. On average, the AGB was calculated to be approximately 47.22 Mg ha^{-1} (Table 2), providing a valuable benchmark for understanding the carbon storage potential and ecological health of the region.

Table 2. Descriptive statistics of observed above-ground biomass and derived vegetation indices

Statistic	AGB	NDVI	GNDVI	SAVI	MSAVI	EVI-1	EVI-2	$NDVI_{RE}$	RDVI	DVI	OSAVI	ARVI
Mean	47.22	0.69	0.66	0.44	0.40	0.46	0.45	0.27	0.45	0.28	0.68	0.76
Std	10.68	0.04	0.05	0.06	0.07	0.03	0.04	0.06	0.05	0.05	0.07	0.07
Min	31.40	0.61	0.56	0.33	0.25	0.40	0.37	0.15	0.36	0.20	0.46	0.59
First quartile	41.37	0.67	0.64	0.38	0.32	0.43	0.42	0.23	0.43	0.25	0.65	0.72
Median	50.57	0.70	0.67	0.44	0.40	0.46	0.45	0.27	0.46	0.30	0.69	0.78
Third Quartile	56.57	0.74	0.69	0.50	0.45	0.49	0.47	0.33	0.51	0.32	0.72	0.83
Max	68.84	0.79	0.76	0.57	0.49	0.63	0.57	0.37	0.55	0.38	0.76	0.86

Table 3. Correlation between field-measured above-ground biomass and selected vegetation index

	AGB	NDVI	GNDVI	SAVI	MSAVI	EVI-1	EVI-2	$NDVI_{RE}$	RDVI	DVI	OSAVI	ARVI
AGB	1.00											
NDVI	0.78**	1.00										
GNDVI	0.96**	0.70	1.00									
SAVI	0.58**	0.53	0.53	1.00								
MSAVI	0.33	0.36	0.20	0.34	1.00							
EVI-1	0.76**	0.65	0.69	0.58	0.24	1.00						
EVI-2	0.96**	0.73	0.98	0.56	0.17	0.74	1.00					
$NDVI_{RE}$	0.06	-0.09	0.13	0.06	-0.09	-0.09	0.12	1.00				
RDVI	0.27	-0.01	0.31	0.15	0.09	0.22	0.28	0.33	1.00			
DVI	0.03	-0.19	0.19	0.08	-0.24	-0.12	0.18	0.35	0.00	1.00		
OSAVI	0.40*	0.16	0.49	0.11	-0.26	0.15	0.47	0.18	0.29	0.28	1.00	
ARVI	0.02	-0.02	0.06	-0.14	-0.04	-0.05	-0.02	0.12	-0.17	0.03	0.12	1

*** and *indicate p-value ≤0.01 and ≤ 0.05 respectively*

3.2 Comparative Correlation Analysis between Above-ground Biomass and Vegetation Indices

The Table 2 provides a comprehensive summary of descriptive statistics for AGB and various vegetation indices such as NDVI, GNDVI, SAVI, MSAVI, EVI-1, EVI-2, $NDVI_{RE}$, RDVI, DVI, OSAVI and ARVI. The mean values indicate the average levels of these indices, with ARVI having the highest mean (0.76) and $NDVI_{RE}$ the lowest (0.27). The standard deviation values show the variability in the data, with ARVI again showing the highest variability (0.073) and EVI-1 the lowest (0.034). The range of values, from minimum to maximum, highlights the spread of data, with AGB ranging from 31.40 to 68.84 Mg ha^{-1}. Quartile values provide insights into the distribution, with the first quartile, median and third quartile values showing the central tendency and spread of the data. This statistical summary is crucial for understanding the variability and distribution of biomass and vegetation indices in the study area.

The box plot analysis reveals several key insights into the vegetation indices (Fig. 2). NDVI and GNDVI exhibit a tight range with medians around 0.65, indicating consistent vegetation productivity, though outliers suggest some variability. SAVI and MSAVI show greater spread, particularly MSAVI, hinting at diverse vegetation types or growth stages. EVI-1 and EVI-2 display similar trends in vegetation density, with outliers marking regions of varying vigour. $NDVI_{RE}$'s wider distribution captures subtle canopy differences, possibly due to species or health variations. RDVI's outliers point to areas of extreme vegetation density, while DVI's balanced distribution highlights variability. OSAVI's broad spectrum reflects its sensitivity to vegetation cover variations.

The correlation matrix in Table 3 and Fig. 3. reveals significant relationships between AGB and various vegetation indices. AGB shows a very strong positive correlation with GNDVI (0.96) and EVI-2 (0.96), indicating these indices are highly effective in predicting biomass. NDVI (0.78) and EVI-1 (0.76) also exhibit strong positive correlations with AGB, suggesting their relevance in biomass estimation. SAVI (0.58) and OSAVI (0.40) have moderate correlations, reflecting some predictive capability but are less robust than GNDVI or EVI-2. Conversely, indices like $NDVI_{RE}$ (0.06), RDVI (0.27), DVI (0.03) and ARVI (0.02) show weak correlations, indicating limited utility in estimating AGB. These insights are crucial for selecting appropriate indices for accurate biomass estimation in tea plantations.

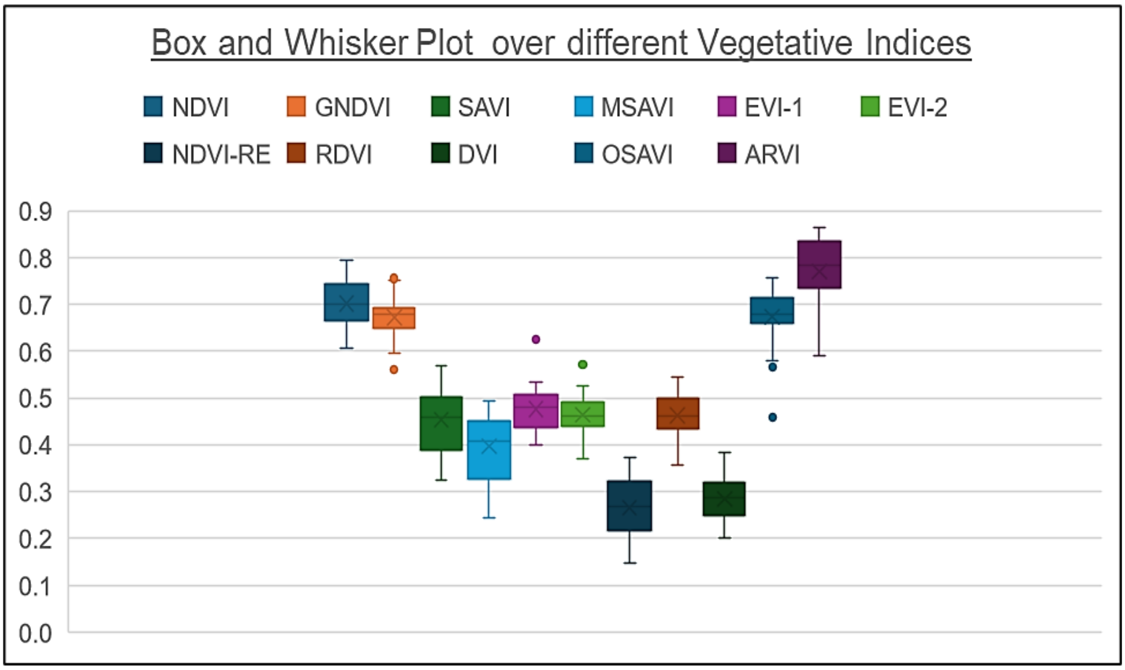

Fig. 2. Box and Whisker plot over different Vegetation Indices

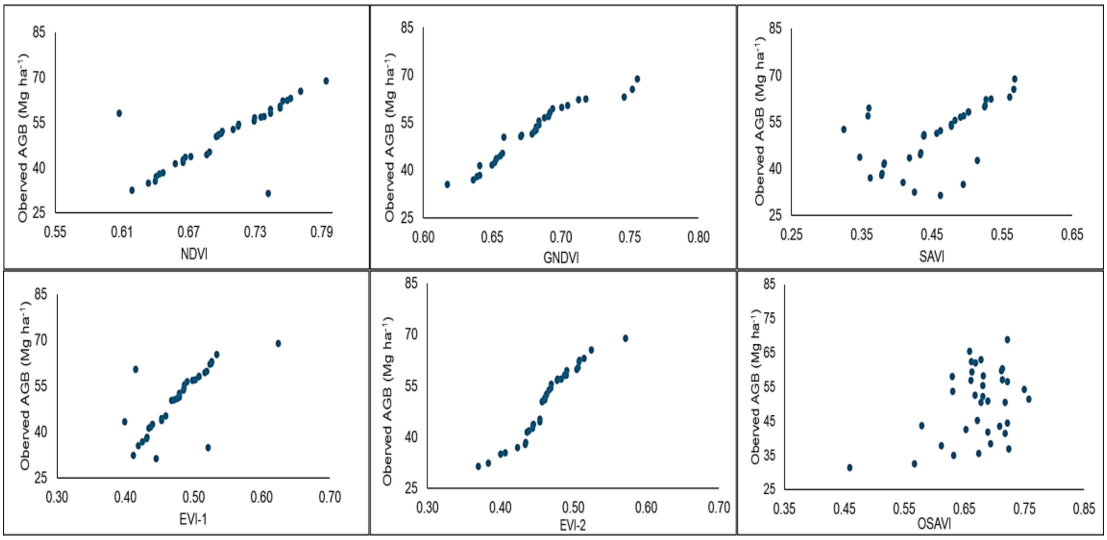

Fig. 3. Scatter Plots showing person correlation co-efficient between AGB and VI's which are significant

4. CONCLUSION

The research provides valuable insights into estimating AGB in tea plantations by leveraging allometric equations and correlating field measurements with vegetation indices. The significant variation in AGB, ranging from 31.40 Mg ha^{-1} to 68.84 Mg ha^{-1} across different plots, underscores the heterogeneity in species composition and tree density. The strong positive correlations of AGB with GNDVI and EVI-2 suggest these indices are highly effective for biomass prediction in such agroforestry systems. The integration of remote sensing technologies, such as satellite imagery and UAV-based sensors, enhances the scalability and precision of biomass estimation by allowing for continuous monitoring across large areas, reducing the need for labour-intensive field measurements. These technologies also provide a more comprehensive understanding of the spatial and temporal dynamics of vegetation. The findings contribute to understanding the carbon storage potential of tea plantations, with implications for sustainable management and climate change mitigation. Future research could explore integrating additional remote sensing techniques, refining models with larger datasets and assessing temporal changes in AGB to further enhance biomass estimation accuracy and ecological health monitoring.

DISCLAIMER (ARTIFICIAL INTELLIGENCE)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc) and text-to-image generators have been used during writing or editing of manuscripts.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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