International Journal of Botany Studies
www.botanyjournals.com
ISSN: 2455-541X
Received: 12-06-2026, Accepted: 12-07-2026, Published: 27-07-2026
Volume 11, Issue 3, 2026, Page No. 210-218

Remote sensing-based assessment of *musa* spp. cover and carbon sequestration potential in dima hasao district, assam

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DOI: https://doi.org/10.66856/ijbs.2026.11.3.11196

Abstract
Anthropogenic CO_2 emissions since the Industrial Revolution have accelerated atmospheric carbon accumulation, necessitating precise quantification of terrestrial carbon sinks. Plant biomass remains a critical component of global carbon cycling, and remote sensing offers a scalable approach to above-ground biomass (AGB) estimation. This study employed Sentinel-2 Level-2A multispectral imagery and vegetation indices, processed in QGIS with the Orfeo Toolbox, to quantify banana (Musa sp.) biomass in Dima Hasao district, India. A random forest classifier achieved 92.1% overall accuracy in land cover classification, subsequently refined through manual digitization in Google Earth Pro. Across 1,221.53 ha of banana cover, carbon storage was estimated at 3.559±1.472ton C ha^{-1}. These findings demonstrate the robustness of freely available Sentinel-2 data combined with machine learning classifiers for reliable, cost-efficient biomass assessment in heterogeneous landscapes.

Keywords: Carbon sequestration, above-ground biomass (AGB), sentinel-2 imagery, remote sensing, banana (Musa sp.) plantations

Introduction

The emission of greenhouse gases, especially carbon dioxide (CO_2), into the atmosphere is one of the main causes of global warming, and making their mitigation one of the urgent priorities to address climate change. Out of estimated 870±61 PgC stored in global forest ecosystem, approximately 43% is contained in the living biomass (Pan *et al*., 2024) [54] and plays a significant role in the sequestration of atmospheric carbon dioxide and mitigating climate change (Pan *et al*., 2011 Poudel *et al*., 2023) [53, 56]. However, anthropogenic activities, such as deforestation and unsystematic agriculture, reduce carbon sequestration capacity of forest while increase carbon in the atmosphere, thereby exacerbating ecosystem degradation and climate change. The impact of greenhouse gas emissions has reached to a level, that climate change has become a global challenge implicating agriculture, forest ecosystems, health care, etc. (Sharma *et al*., 2016) [64].

Reducing Emissions from Deforestation and Forest Degradation (REDD+) was established by the United Nations Framework Convention for Climate Change (UNFCCC) to reduce carbon emissions by promoting sustainable forest management, conservation, and reforestation initiatives. Under UNFCCC framework the members are required to report on carbon emissions and sinks through greenhouse gas inventories (Curiel-Esparza *et al*., 2015 [15] Deo *et al*., 2017) [19]. REDD+ aims to increase carbon stock through sustainable forest management and forest conservation, and restoration of degraded forest (Khan *et al*., 2020). Through this mechanism, developing countries that successfully reduce greenhouse gas emissions and increase carbon sequestration through reforestation and improved forest management practices can receive financial incentives and performance-based compensation under the REDD+ framework (Le Toan *et al*., 2011 [41] Sessa & Dolman, 2008 [63] Khan *et al*., 2020).

Above-ground biomass plays an important role in carbon sequestration, and represents one of the main terrestrial carbon stocks, which holds approximately 40% of terrestrial carbon (Canadell & Raupach, 2008 [12] Muhe & Argaw, 2022) [47]. Effective Managing terrestrial biomass through different management plans is therefore required for successful implementation of REDD+ objectives. Assessing of above-ground biomass gives valuable insight into the terrestrial carbon stock, forest succession, and ecosystem dynamic thereby supporting sustainable forest management and conservation planning (Askar *et al*., 2018 [5] Gallaun *et al*., 2010) [22]. Above-ground biomass (AGB) can be determined either uising destructive method or non-destructive method (Muhe & Argaw, 2022) [47]. In the destructive method, in involves harvesting vegetation and determining biomass from its oven dried weight whereas non-destructive approaches, particularly allometric models, are widely used for large-scale assessments and in protected areas where tree harvesting is not feasible. Although the destructive method generally provides the highest estimation accuracy, it is labour-intensive, time-consuming, and often impractical for extensive or conservation-sensitive areas (Brown, 1993 Hughes *et al*., 1999) [11, 32] Hughes.

Estimation of AGB for a larger area or restricted area: the destructive method becomes impartial, making non-destructive primary means of estimating AGB. In recent times remote sensing technology has been widely used for the estimation of AGB through the analysis of multispectral images captured by satellites or unmanned aerial vehicles (UAVs). There are various methods to study carbon sequestration through estimation of biomass by remote sensing technology. The most common methods applied in remote sensing are the allometry method, machine learning, physical/radioactive transfer models (Isbaex *et al*., 2021) [33], data fusions (LiDAR + SAR) (Chen *et al*., 2023), stratification and lookup tables (Fan *et al*., 2022 [20] Gibbs *et al*., 2007) [24], the stratify and multiply method, etc. (Avitabile *et al*., 2011) [6]. These indirect methods of measuring biomass have many advantages in decision-making for vegetation study, environmental assessment, management, conservation, etc. (Zhu & Liu, 2015) [71].

Various remote sensing data are available from different organizations that use sensors like optical sensors, Synthetic Aperture Radar (SAR), and Light Detection and Ranging (LiDAR) (Kelsey & Neff, 2014) [39]; however, there are limitations for extensive use due to various reasons like restricted accessibility, high cost, and low resolution (Lu, 2006 [43] Muhe & Argaw, 2022). Medium resolution image provided by Landset and sentinel [47] is commonly used to study vegetation and estimation of Biomass. Landset and Sentinel image are freely available which is provided by United States Geological survey and European space Agency respectively (Zhu & Liu, 2015; Askar *et al*., 2018) [5, 71].

Through Geographical information systems and remote sensingwe can effectively evaluate carbon stock and biomass mapping at regional and global scale (Khan *et al*., 2020). Mapping of plant biomass through spatial distribution plays a remarkable role in management efficiency and decision making on landscapes especially of large forest with high diversity of plants species and where accessibility is difficult through ground visit (Foody & Cutler, 2006 [21] Arekhi *et al*.,2017) [4]. Data provided by Geospatial sensing tools can be use to classify plant species accurately and estimate biomass in nondestructive way (Singh *et al*., 2014; Odindi *et al*., 2014; Chen *et al*., 2021) [13, 49, 66].

With the launching of Sentinel-2 imagery by the European Space Agency in 2015, it is widely used in research of vegetation studies, like species diversity, vegetation mapping, biomass mapping, etc. It is freely available and provides better resolution than Landsat imagery. Sentinel-2 has two satellites phased at 180 to each other, placed in a sun-synchronous orbit at an altitude of 786 km that operate simultaneously. The sensor on the satellite provides images with 13 spectral bands with a 290 km swath with different resolutions. The four visible to near-infrared bands are provided with 10 m resolution, and the red edge and shortwave infrared wavelengths are provided with 20 m resolution (Chen *et al*., 2021) [13].

Musa spp. Both wild and cultivar are important plant species to human culture. India is the largest producer of *Musa* spp. cultivars, and it is exported to countries, especially those of the Middle East and Nepal (Kumar *et al*., 2013) [40]. When bananas are harvested, huge residue is generated, mostly left to decompose, which ultimately releases a huge amount of GHG (Ortiz-Ulloa *et al*., 2021) [50, 51]. *Musa plants* absorb CO_2 more than one-third of their dry mass during their life cycle (Sage & Zhu, 2011) [61, 71], which shows *Mus*a spp. potentiality in carbon sequestration. Earlier studies have been made by several researchers to determine the AGB of *Musa* and its carbon sequestration using the allometric method by Ortiz-Ulloa *et al*. (2021) [50, 51], Temjen *et al*. (2022), and Danarto & Hapsari (2015) [16, 68]. Mapping of banana cultivar distribution through analysis of multispectral data on GIS tools has also been done by few researchers. Karthikkumar *et al*. (2019) [37] mapped bananas using Sentinel 1 imagery in Tamil Nadu, India, and Alabi *et al*. (2022) [3] mapped bananas from multispectral images taken from a UAV. This paper aims to estimate the above-ground biomass (AGB) of *Musa* spp. in order to evaluate their carbon sequestration potential. In addition, a biomass distribution map is generated using Sentinel-2 satellite imagery and processed within the QGIS platform and digitized using a Google Earth Pro image as a reference.

Materials and Method

1. Study area

Dima Hasao district earlier known as North Cachar Hills District of Assam lies between 25º 3′ and 25º47′ N Latitude and between 92º37′ and 93º17′ E Longitude with total area of 4888 Km^2. It is on the southern part of the state of Assam, between the Barak valley and the Brahmaputra valley. The district is mostly hilly due to the Borail range, although low-lying plains are also present. The elevation of the study area ranges from 19 m to 1866 m, and it is part of the Eastern Himalayan region and some part of the Shillong Plateau in the western zone (Government of Assam, 2025) [28]. The mixture of both plains and hills gives a diverse variation in vegetation and microclimate. The highest peak of the state lies in the district known as Siekel Peak under Thumjang Village. According to the Indian State of Forest Report (ISFR) assessment of 2023 published by the Ministry of Environment, Govt. of India (2024) [46], 82.68% of the total area of the district is covered by forest, of which, out of the total forest area, 7.34% is dense forest, 34.8% is moderately dense forest, and 57.86% is open forest.

During winter, the temperature ranges from 6° to 14°C, and during summer, it ranges from 14° to 33°C. Average annual rainfall is 1145 mm, and the majority of rainfall occurs during the monsoon, i.e., June to September (Hazarika *et al*., 2024) [30]. The soil type of the study area is mostly laterite and lateritic.

2. Field data collection

2.1. Data collection for AGB

Field data was collected between April 2024 and April 2025. Following the stratified random method, a total of 30 plots measuring 20 m² were set up. The plots were taken in squares so as to be compatible with remote sensing data, which is permitted under IPCC 2006 (Scheuschner, 2007) [62] guidelines. Diameter at breast height (DBH) that is 1.3 m above the ground of all the plants taller than 1.5 m within the plot was measured (Aeberli *et al*., 2023) [1]. Based on the DBH, the total biomass of the banana plant within the plot was calculated using the allometric method (eqn. 4).

2.2. Sampling of class polygon

During the field data collection, a polygon sample was collected for the banana cover and other vegetation by the Google Earth Pro app, where 214 polygons were collected for each class. Google Earth Pro is a free remote sensing tool for sample collection, which can be used for reference and validation of data. In the recent research this tool is commonly used for sample collection (Biswas *et al*., 2023 [9] Matarira *et al*., 2022 [44] Padma *et al*., 2022) [52] and provides satellite imagery in different resolutions based on the image provider.

2.3. Multispectral imagery data collection

For the generation of *Musa* spp. cover, the most recent Sentinel-2 Level 2A image near to the field data collection date with Cloud free was downloaded from the Copernicus

Data Space System website (https://dataspace.copernicus.eu). Sentinel 2 Level 2A imagery is cost-free and provides medium resolutions of 10, 20, and 60. It is widely used in various remote sensing studies, and biomass estimation is one of them. The Sentinel 2 L2A image comes with atmospheric correction; therefore, there is no further atmospheric correction required. The raster downloaded was merged and extracted using the study area map, which was then used for calculating vegetation indices.

The Dima Hasao district administrative boundary, i.e., the study area shapefile, was extracted from the Indian shapefile downloaded from the open-source shapefile site https://diva-gis.org. All the bands used for calculation of vegetation index (VI) were reprojected to EPSG:32646-WGS 84/UTM zone 46N. Imagery with 60m pixels was resampled to 10m pixels and extracted. After extraction all rasters were aligned, and vegetation indices were calculated. Vegetation indices calculated are mentioned in Table 1.

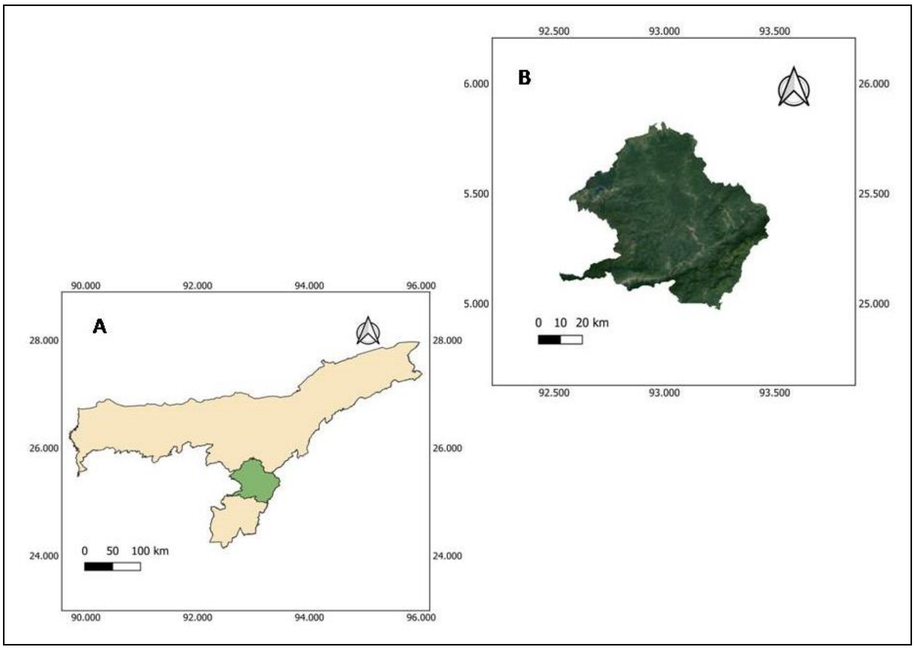

Fig 1: A; Assam map showing the location of Study area. B; Study area showing vegetation and topography, on the southern part with more altitude hills and northern side with plane region and less thickness in vegetation.

2.4. Rationale for methodology

Mapping of species cover through regression models is widely used in remote sensing, as it gives high accuracy. But this regression model is only suitable when the study area is homogeneous and it is easy to get a linear, pure pixel of the specimen. These methods become unsuitable when the study area is highly heterogeneous, has high spectral variation, has the presence of shadows, or has variation in topography which creates difficulty in regression modelling (Lu, 2006) [43]. This method is site-specific and has the biggest drawback when the study area is nonlinear and complex; therefore, patterns cannot be applied in a highly heterogeneous site (Chen *et al.*, 2021) [13]. The present study area is highly heterogeneous, and topography also varies significantly, which gives differences in microclimate. The study area contains both plain and hilly regions which have varied humidity and average temperature. Wild *Musa* sp. are found widely mixed with other species, while the cultivated *Musa* sp. is low density, only 702.5 plants/ha, and they are intercropped with other horticultural crops like oranges, betel nuts, pineapples, etc. In most cases, this creates difficulty in getting pure pixels due to high spectral variation. This high variation results in low correlation in field AGB, which becomes unsuitable for regression models.

The study adopts the Stratify and multiply method using on-screen digitisation, which is simple and suitable for the vegetation in the present study area. Earlier studies done by Avitabile *et al.* (2011) [6] have been successful using this method. The other reason is that *Musa* spp. can be identified in Google Earth Pro images; therefore, it becomes easy to digitalise *Musa* spp. using the classified raster and Google Earth imagery as a reference layer, followed by ground validation.

Table 1: Vegetation indices used for the study

Indices	Formula	Reference
ARVI	(NIR-(2Red-Blue))/(NIR+(2Red-Blue))	Kaufman & Tanre (1992) [38]
AVI	$\sqrt[3]{(NIR(1-Red)(NIR-Red))}$	Plummer (1994) [55]
CIg	$\left(\frac{NIR}{Green}\right)-1$	Gitelson & Merzlyak (2003) [26]
CIre	$\left(\frac{NIR}{Red}\right)-1$	Gitelson & Merzlyak (2003) [26]
DVI	$NIR-Red$	Tucker (1997)

EVI	$2.5(NIR-Red)/(NIR+6Red-7.5Blue+1)$	Heute *et al* (2002)
EVI2	$(2.5NIR-Red)/(NIR+2.4Red+1)$	Jiang *et al* (2008) [34]
ENDVI	$(NIR-Green)/(NIR+Green)$	Gitelson & Merzlya (1998) [25]
IRECI	$(NIR-Red)/(RE1-RE2)$	Daughtry *et al* (2000) [17]
MSAVI	$(2NIR+1-\sqrt{(NIR+1)^2}-8(NIR-Red))/2$	Qi *et al* (1994) [57]
NDII	$(NIR-SWIRI)/(NIR+SWIRI)$	Hardisky & Smart (1983) [29].
NDIIswir2	$(NIR-Swir2)/(NIR+Swir2)$	Hardisky & Smart (1983) [29].
NDVI	$(NIR-Red)/(NIR+Red)$	Rouse *et al* (1974) [59]
NDVIre3	$(NIR-Re3)/(NIR+Re3)$	Delegido *et al*(2011) [18]
NDWI	$(Green-NIR)/(Green+NIR)$	McFeeter (1996)
RENDVI	$(NIR-Re)/(NIR+Re)$	Tucker (1997)
RENDVI705	$(NIR-Red1)/(NIR+Red1)$	Puletti *et al* (2018)
RERVI	NIR/Re	Kanke *et al* (2016)
SAVI	$((1.5(NIR-Red))/(NIR+Red+0.5)$	Huete *et al* (2002) [31]
SQSR	$\sqrt{NIR}/Red$	Daughtry *et al* (2000) [17]
SR	NIR/Red	Jordan (1969) [36]
SRre	NIR/RE	Sims & Gamon (2002) [65]
TNDVI	$\sqrt{(NDVI+0.5)}$	Jin *et al* (2023) [35]
TVI2	$\sqrt{200.(NIR-Green)}-(Red-Green)$	Bannariet a (1995) [7]
VARIg	(Green-Red)/(Green+Red-Blue)	Gitelson*et al* (2002) [27]

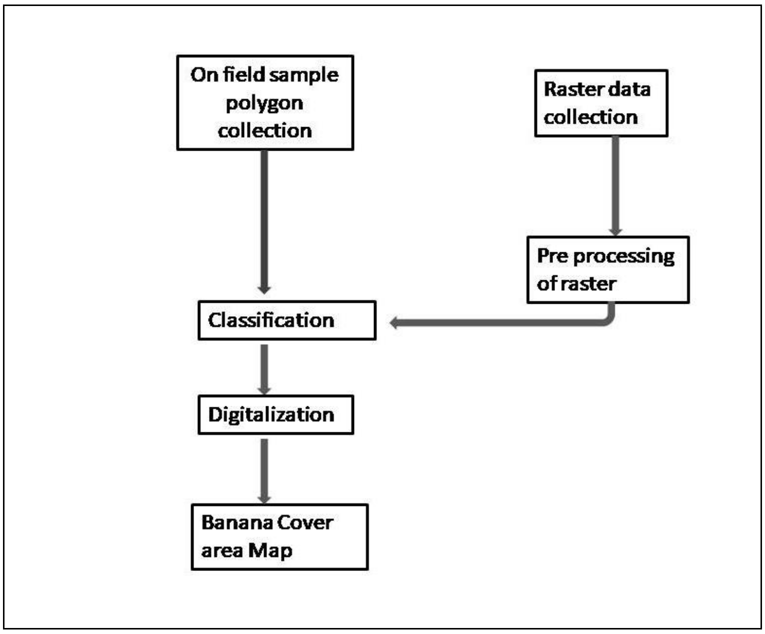

Fig 2: Flow chart of Banana covers area Map creation

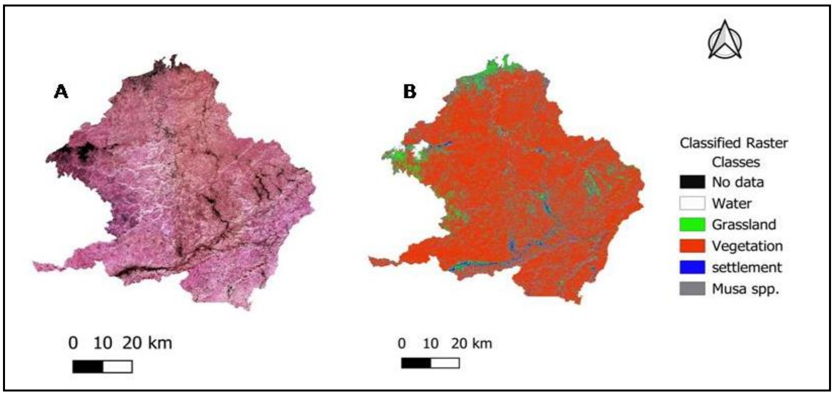

Fig 3: A stacked raster of Different Vegetation Indices, B: Classified raster

Fig 4.1: Field-verified banana plantation, Fig.4.2. Google Earth Pro imagery of fig.4.1

2.5. Image classification

A total of 214 samples were collected for each land cover class; these samples were randomly divided into training and validation datasets within the QGIS attribute table for independent accuracy assessment. An optimized parameter was used for balance accuracy, where 161 training samples and 53 validation samples for each class were set for balance representation. Image classification was carried out using the Orfeo Toolbox (OTB) plugin in QGIS, which is widely applied for both pixel-based and object-based classification (Teodoro & Araujo, 2016) [69]. Random forest was used to classify, which is a powerful classifier that can handle high-dimensional data and can distinguish multicollinearity of vegetation indices that shows effectiveness when classes have less correlation with vegetation index values. For stable prediction, the number of trees was set to 100, and maximum tree depth was limited to 8 to prevent over-fitting. Additionally, to reduce inter-tree correlation and improve model robustness, a subset of 5 features was chosen at each node. The classified raster was converted into a KMZ file and imported into Google Earth Pro. Using the classified layer along with Google Earth Pro satellite imagery as reference, banana cover was manually digitized. Finally, a banana area cover map was generated from the manually digitized shapefile.

Result

1. Accuracy assessment and validation of banana cover classification

Accuracy of the classification can be depicted by the confusion matrix and kappa coefficient. The confusion matrix was constructed by the OTB plugin during the random forest model creation from the training and validation samples. Training and validation samples are independent samples that were randomly separated from the total sample collected in the attribute table of QGIS. The Kappa coefficient also gives the validity of the classification. It evaluates how the training sample agrees with the reference sample, which can be calculated from the confusion metrics. The OTB plugin read the sample based on pixels, and the confusion matrix was computed on the effective number of pixels read during model creation.

The overall accuracy obtained in the classification of the multispectral Sentinel-2 imagery is 92.1%. The overall user and producer accuracy of the model is 92.32% and 92.08%, respectively. The producer accuracy of bananas is 81.3%, and users' accuracy is 89.7%. Bananas are misclassified as vegetation in some cases, as bananas are mixed-grown with other species. The confusion matrix is given in table 1. The Kappa coefficient calculated from the confusion matrix is 0.90, which signifies that the model and classification have strong agreement. The formula used for the calculation of the kappa coefficient given by Cohen (1960) [14] is given below.

$$k = (Po - Pe)/(1 - pe) \qquad \text{eq1}$$

$$\mathrm{Po} = (\textstyle\sum_{i=1}^{k} \mathrm{xii})/\mathrm{N} \qquad \text{eq2}$$

$$\mathrm{Pe} = (\textstyle\sum_{i=1}^{k} (\mathrm{Ri.\,Ci}))/\mathrm{N}^2 \qquad \text{eq3}$$

Where, k=kappa coefficient
Po=overall accuracy
Pe=Expected agreement by chance
Ri=Row total for reference pixel of class i
Ci=Column total of classified pixel for class i
N=total number of sample

In the study area, in most of the cases banana is cultivated along with other crops and the wild variety are mixed with other plant species therefore getting the pure pixel of banana plant was difficult, which is why banana is often misclassified as vegetation in the validation of classification. There fore manual digitalization was done for better accuracy and representation of banana cover. Banana leaves are large and elongated which gives broad surface area and form cluster at the top that make it easy to identify in Google earth pro. The classified raster was converted into kmz file and loaded in Google earth pro and digitalization was done which was followed by field verification. Through digitalization the *Musa* spp. cover is found to be 1221.53 hectare.

Table 3: Confusion matrix

Reference/Predicted	Water	Grassland	Forest	Settlement	Banana
Water	92	2	0	2	0
Grassland	0	90	3	3	0
Forest	0	0	88	0	8
Settlement	0	1	0	94	1
Banana	0	2	16	0	78

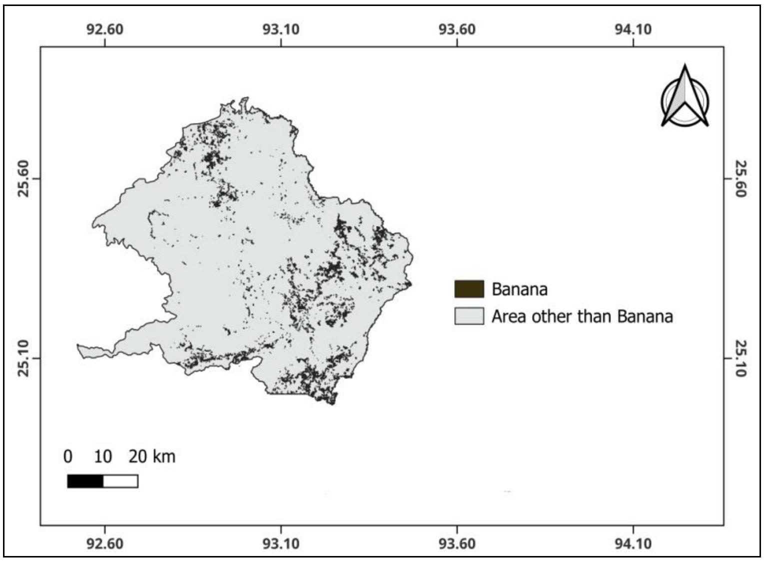

Fig 4.3: Banana cover area map in Dima Hasao District (Assam)

Carbon sequestration potential

Above ground biomass was calculated by allometric equation (eq4), given by Kurniawan *et al* (2010). Total carbon stored in biomass was calculated by eqn5 given by Hairiah *et al*. (2001) The above ground biomass calculated through allometric method is found to be 7.738±3.2 ton/ha and the total biomass under banana cover is 9449.3±3908.9 ton Therefore the total carbon stored is 3.559±1.472ton C ha^{-1} which is 13.06±1.4772ton CO_{2eq}/ha.

AGB=0.0303 X $D^{2.1345}$ eq4

Where, AGB= above ground biomass, D=DBH

Total Carbon= A X 0.46 eq5

Where A is Biomass.

Table 4: Comparative Carbon storage with other similar studies.

Species	Plant/ha	AGB (ton/ha)	C ton/ha	Reference
Musa spp (Ecuador)	984-1490	10.99-15.27	3.16-6.24	Ortiz-Ulloa *et al*., 2021 [50, 51]
Musa spp (Indian Average)	2267-4440	5.71-11.19	4.085-6.194	Ganeshamurth,2023
Musa spp (This study)	400-1400	4.538-10.938	2.087-5.031	

The carbon stored in the standing AGB of *Musa* spp. of the present study it is comparatively lower than other previous studies done in Ecuador and India.Compared to the other studies, in the present study the density is substantially lower (400-1400 plants ha^{-1}) where in Ecuador the density is 984-1490 plants ha^{-1} while the density studied in the Indian commercial cultivated Banana the density is relatively high (2267-4440 plants ha^{-1}). This lower density contributed to lower biomass (4.538-10.938ton ha^{-1}) and carbon storage (2.087-5.031 C ton ha^{-1}) but still it is within the range of Indian average.

Discussion

According to the assessment done by the Department of Agriculture, Dima Hasao District, during 2023-2024, the total area of banana cultivation was 1,673 hectares. Communication was done with the area executive assistant (AEA) to enquire about the assessment method. The significant difference in the banana area cover may be due to the difference in the method of data collection. The AEA ground data collectors have followed a random questionnaire under their circle. During the sample collection of the present study, it was rarely observed that farmers followed the scientific method of cultivation, and irrigation was completely dependent on rain, as mentioned earlier. Wild *Musa* spp. grows in patches mixed with other species. Due to unscientific farming, and in most casesit is non-commercial and intermixed with other species, it caused low density (702.5 plants/ha^{-1}).

The pseudostem of *Musa* spp. is annual, and usually the pseudostem is discarded and left to rot. Several studies have been made on the use of pseudo-stem in different value-added processing. The pseudostem is rich in biochemicals, fibres, pharmaceutical compounds, etc. (Munishamanna *et al*., 2020) [48]. Studies done on the applicability of pseudo-stems in textiles showed promising results. Softening treatments like alkalisation, bleaching, and oil-water emulsification of pseudo-stem fibre increase its softness and spinability into yarns; the fabrics are lightweight, and their tensile strength is comparable to natural fibres (Akubueze *et al*., 2015 [2] Barreto *et al*., 2010 [8] Brindha *et al*., 2012) [10]. *Musa* spp. pseudostem being annual, in some cases less than one year, and considering biomass production of 3.559±1.472 tonnes C ha^{-1} yr^{-1}, can contribute significantly to carbon sequestration within the range of young tropical forests of about 4.45 tonnes C ha^{-1} yr^{-1} (Loh *et al*., 2022) [42]. Although there are fast-growing species that sequester much higher amounts, like eucalyptus plantations, which can sequester about 9.8 to 21 tonnes of C per hectare per year based on the availability of water (Ryan *et al*., 2010) [60]

Conclusion

Scientific cultivation through proper irrigation and spacing techniques that fully use the available space for banana cultivation will increase the productivity of fruit and AGB. *Musa* spp., being fast-growing plants, can potentially be employed for carbon sequestration and at the same time generate economic benefit through properly and sustainably utilising the plant. Harvesting mature pseudostems from both wild and cultivars and processing them into other economical products like fibres in textile industries, paper, biochemical compounds, manure, etc. could significantly contribute to forest management, conservation and sustainable agriculture to attain the objectives of REDD+, thereby contributing to carbon sequestration with the additional economical benefit.

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