Article

Estimating above and below ground carbon stock of forest using field inventory and vegetation indices: A case study of Godebie National Park, Ethiopia

Adamsew Marelign[1], **Muhabaw Taju**[2], **Ebrahim Esa**[3], **Asrat Akele**[1], **Temesgen Mekonen**[1], **Birara Fentahun**[4], **Kindie Gebeye**[4], **Habtamu Tekeba**[1]

[1]Department of Natural Resource Management, College of Agriculture and Environmental Sciences, University of Gondar, P.O Box 179 Gondar, Ethiopia

[2]Department of Forestry, College of Agriculture and Environmental Sciences, University of Gondar, Gondar, Ethiopia

[3]Department of Geography and Environmental Studies, College of Social Science and Humanities, University of Gondar, P.O Box 179 Gondar, Ethiopia

[4]Department of Plant Sciences, College of Agriculture and Environmental Sciences, University of Gondar, Gondar, Ethiopia

E-mail: adamsewmarelign@gmail.com

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Abstract

Forests are the potential source for managing carbon sequestration and balancing universal carbon equilibrium between sources and sinks. In view of the importance of biomass, this study makes an attempt to estimate temporal and spatial carbon stock of Godebie National Park, Ethiopia, using Moderate Resolution Imaging Spectro radiometer (MODIS), normalized difference vegetation index (NDVI), enhanced vegetation index (EVI) and the field inventory data through geospatial techniques. A model was developed for establishing the relationship between forest carbon, EVI, and NDVI in the selected study site. The correlation value between estimated carbon stock with EVI were found as 0.69, while with NDVI, the values were obtained as 0.87 respectively. The regression model of measured biomass with NDVI and EVI was developed for the data obtained during the period 2020-2021. The R^2 values obtained were 0.81 for the regression model between estimated carbon stock and EVI, and 0.77 for the regression model between NDVI and estimated carbon stock. The results indicate that the methodology adopted in this study can help in selecting best fit model for analyzing relationship between carbon stock and NDVI/EVI and for estimating biomass and carbon stock using allometric equation at various spatial scales. The produced output map and allometric equation revealed carbon stock distribution of 5.88 t/ha up to 900 t/ha, with an average value of 406.67. Generally, the approaches used on this study can be used by the forest planners, policy makers, and government officials for conservation and protection of the forest ecosystem.

Keywords carbon stock; remote sensing; vegetation index; Godebie; regression.

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1 Introduction

Climate change has been proven by scientific data and unmistakably recognized as a global issue of concern by the global community. The combustion of fossil fuels, and hence the destruction of forests, has led heat-trapping Green House Gases (GHGs) to increase greatly in our atmosphere since the industrial revolution, at a rate and magnitude far greater than natural variations would suggest. The Earth's surface average temperature will climb by 1.8 to 4°C by the end of the century if GHG concentrations in the atmosphere continue to rise. (IPCC, 2007a). Thus, the rapid increase in global surface temperature is especially because of the increase within the amount of CO_2 within the atmosphere primarily because of anthropogenic activities (Broadmeadow and Robert, 2003). As a result of change in global climate there has been a widespread and growing concern that has led to extensive international discussions and negotiations. In seeking solutions for this, the overwhelming priority is to scale back emissions of GHGs and to increase rates of carbon sequestration. The concerns have led to efforts of reducing emissions of GHGs, especially CO_2, and measuring carbon absorbed by and stored in forests, soils, and oceans. To hamper the increase of GHGs concentrations within the atmosphere, and thus possible climate change, is to increase the amount of carbon removed by and stored in forests (IPCC, 2007b; Jandl et al., 2006).

As a natural solution, the role of trees and forests within the process of carbon cycle is sort of significant because it stores more carbon among the terrestrial ecosystems (Sundquist et al., 2008; van Deusen, 2010). This may make forest ecosystems to be the most significant terrestrial carbon sink on the planet. Protected areas (National parks), with their all and diverse ecosystems including forests are vital systems to to trap and store carbon from the atmosphere, as well as to assist people and ecosystems in adapting to the effects of global warming (MacKinnon et al., 2011).

Ethiopia, being party to the United Nations Environmental Program and signatory to its treaties and protocols, is striving to contribute to the international effort of global climate change adaptation and mitigation. It's adjusted its development strategy aiming at meeting net zero emissions by 2030 and developed climate resilient green economy (CRGE) strategy. Conserving and enriching existing forests, establishing new forests, enhancing of the prevailing protected areas and establishing new ones are a number of the measures undertaken by the government.

However, huge deforestation is taken place within the national park of Ethiopia for the aim of investments and finding of fuel wood by the local communities. This Park (Godebie National Park) should require sustainable management plan for the carbon storage sustainably and conserve the biodiversity. It has no information about the carbon potential of Godebie Park for further perform research or financing by carbon trading consistent with REDD+ mechanism (Ewunetie, 2021). The role of forests to capture and store carbon from the atmosphere has been studied by several researchers (Girma et al., 2014; Simegn et al., 2014; Assaye, 2016; Andargie et al., 2018). However, these studies were done through field inventory based allometric equation or non-destructive sampling method and difficult to use on a large-scale area.

Remote sensing techniques help in the forest biomass and carbon estimation and it has an excellent advantage for acquiring ground data at multiple scales with a synoptic and temporal coverage at species level (Kerr and Ostrovsky, 2003; Pandey et al. 2019). Spatial biomass is often estimated through regression analysis between estimated biomass and spectral reflectance of varied bands of remotely sensed datasets. However, it remains a challenge to determine the correlation due to the complexity of canopy characteristics, landscape heterogeneity, and the uncertainty of remote sensing information (Lu et al., 2016; Li et al., 2023).

This study makes an effort to estimate forest carbon in Godebie National Park Forest using field inventory data and geospatial techniques. The linear and nonlinear algorithms for carbon estimation using MODIS products were developed and performance assessment of the developed models using different statistical measures was performed. Moreover, through this study, a summary on the present situation of forest carbon (above and below ground carbon), Normalized difference vegetation index (NDVI), enhanced vegetation index (EVI), and their correlation were presented and discussed.

2 Materials and Methods

2.1 Description of the study area

Godebie national park is found in West Armachiho District of West Gondar Administrative Zone, in Amhara National Regional state, North West, Ethiopia. Godebie national park is bordered with six rural kebeles from West Armachiho and Metema districts. Godebie National Park is part of the Dirmaga watershed (Marelign and Mekonen, 2022). Geographically, it is located on 13012'20.51" to 13023'18.10" N and 36013'56.73" to 36028'04.63" East (Fig. 1) with an altitudinal range of 718 m to 1229 m above sea level.

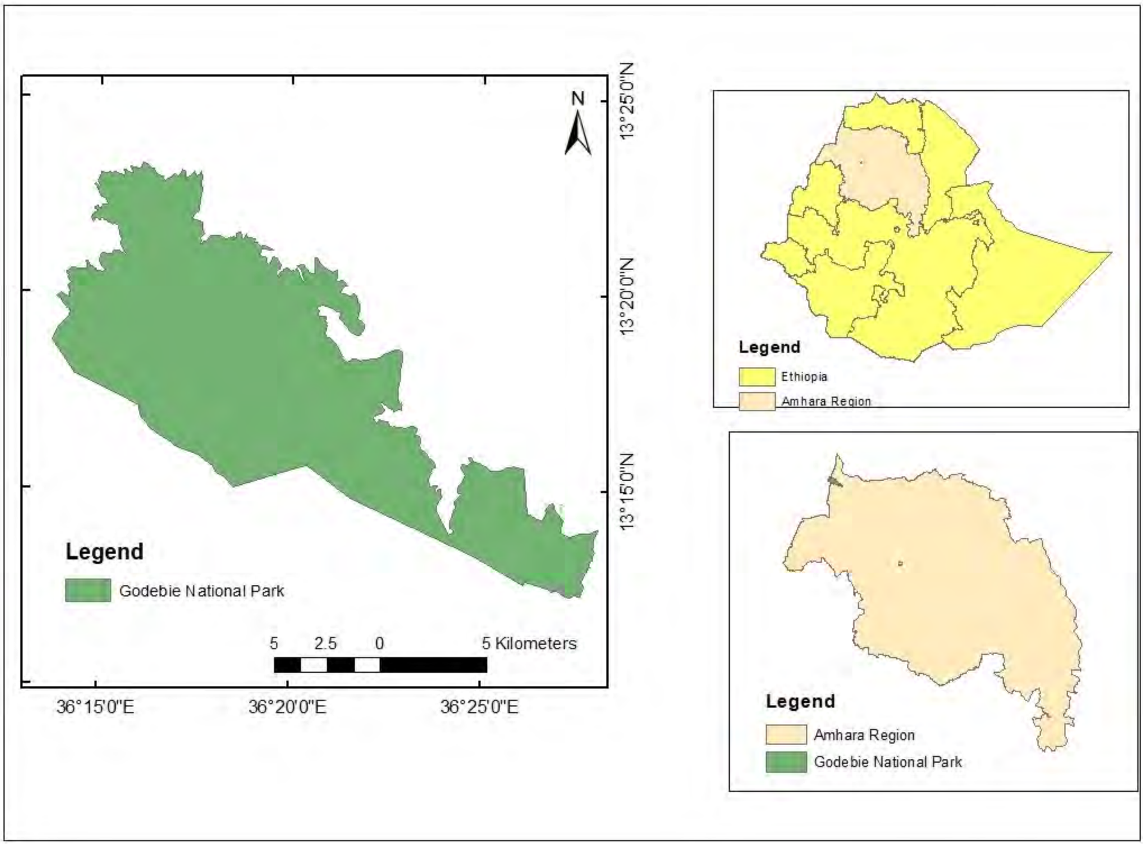

Fig. 1 Map of the study area.

According to the information obtained from west Armachiho office of Agriculture, Godebie National Park Forest is situated under 'Kolla' agro ecological zones. The area is hotter throughout the year having annual temperature range of 38-48°C and the area receives 600-1100mm annual rainfall stayed from June – August (NMA, 2007). The temperatures range from 15.1°C to 40°C with mean annual temperature of 27.1°C. Interms of topography, about half (54.5%) of the study area is plain and the remaining area were (45.5%) slopy area. The major soil types of the area are Eutric nitisols, Chromic vertisol, and Orthic luvisols. The Park is home of different mammals and bird's species. Based on vegetation classification of Ethiopia (Friis and van, 2010). Godebie National Park Forest communities are broadly categorized as Combretum-Terminalia woodland and wooded grassland with Terminalia brownii, Anogeissus leiocarrpa and Dalbergia melanoxylon as frequent species; Acacia-Commiphora woodland and bushland proper with dominant Acacia seyal, Acacia polycantha and Balanites aegyptiaca species; and riparian/riverine forest with Adansonia digitata, Diospyros mespiliformis and Tamarindus indica as dominant species.

2.2 Field inventory–based carbon estimation

The development of field inventory was carried out for the study sites in the months of January and February during the years 2020-2021. Prior knowledge of the biophysical parameter of vegetation gathered during field surveys is an important component for studying the region using remote sensing analysis. A total of 44 plots were laid in a forest area of Godebie National Park, North West Ethiopia, over two years, with a one-hectare permanent plot (100 m x 100 m) established in each of the 44 sites and sub-gridded into 5 sub-plots of size 100 (10 m x 10 m) (Pandey et al., 2019) quadrats for forest inventories to quantify the physical parameters (Fig. 2). Systematic sampling was employed for vegetation data collection to ensure that sufficient representative samples of vegetation from all gradient levels (Kent, 2012). Following the procedure used in (Senbeta and Teketay, 2001; Fisaha et al., 2013). Five transect lines were laid in the forest following vegetation distribution that may include the Combretum-Terminalia woodland community, the Acacia-Commiphora woodland, and bushland community, and the Riparian/ riverine vegetation community following the methodology used by (Temesgen 2020). Based on the above principles 44 square sample quadrats with a size of 10 m x 10 m were laid down alternatively along the line transects at 500 m intervals along the linear transects using GPS and Compass.

Carbon in the AGB was assessed through measurement of standing trees and shrubs using proper mensuration techniques. DBH and height of trees were measured according to their size class in the respective subplots. Therefore, species type, diameter at breast height (DBH) and height of trees (H) were the interest of measurement for trees. GPS was used to identify the location of plots. DBH was measured with caliper/diameter tape depending on the size of the tree. Tree height was measured using haga hypsometer, and slope was measured with suunto clinometer to adjust the size of the plots to proper size. Natural Database for Africa (NDA) virsion 2.0, August 2011 CD-Rom was also used for species identification. For species that was difficult to identify in the field, their local names were recorded, herbarium specimens were collected, pressed and dried properly using plant presses and identified in the office helped by botanists.

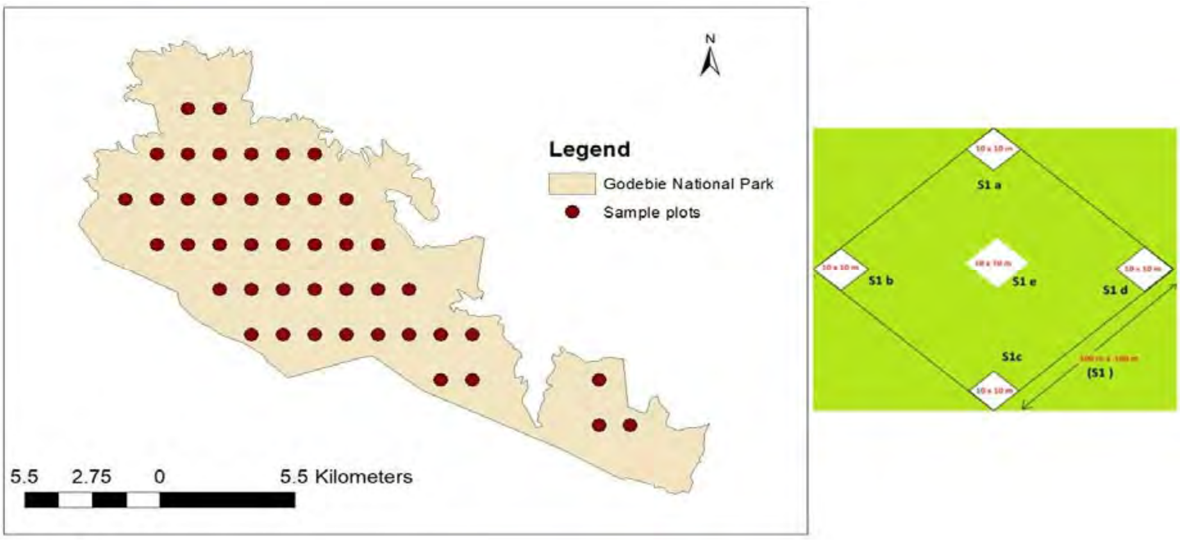

Fig. 2 Field sample location points for the study site (left) and Field sampling plot size (right).

Carbon stock has been assessed in above and below ground carbon pools, which is in accordance with the methodology adopted (Ewnetie et al., 2021). Hence, the major activities of carbon measurement during the field data collection were focused on above-ground biomass and below-ground biomass.

Carbon stock assessments in Africa are highly variable and have high degree of uncertainty due to lack of consistency in techniques of inventory and lack of site and species specific allometric equations. There are few species specific allometric equations developed in Africa, and most of the carbon stock assessments used general allometric equations. but this causes the high degree of variability in site growth conditions and growth characteristics of species as well as it cannot estimate the correct biomass and carbon. Therefore, Species-specific allometric equations are very important and, in this regard, there are allometric models (Andargie et al., 2018) which are appropriate for improving aboveground biomass (AGB) and carbon (AGC) estimations in woodland ecosystems in Ethiopia and near to study area in Particular. Thus, this study used the following equation developed by Andargie et al. (2018) as follows:

$$\ln(AGB) = -2.965 + 1.820\ln(DBH) + 1.157\ln(H) \ldots\ldots(1)$$

where H is total height; DBH is diameter at breast height; AGB is aboveground biomass; and ln is natural logarithm. The above-ground carbon (AGC) and above-ground biomass CO_2 equivalent (AGB CO_2 eq) sequestrated in the study area was calculated by the principles of (Pearson, 2005) as follows:

$$AGC = AGB * 0.5) \ldots\ldots(2)$$

$$AGB\ CO2eq = AGC \times 3.67 \ldots\ldots(3)$$

According to (Pearson, 2005; MacDicken, 1997), standard methods of estimating belowground biomass (BGB) and belowground carbon (BGC) can be obtained as 20% (AGB*0.2) and 10% (AGC*0.5) of above-ground tree biomass, respectively.

The total carbon stock density of the study area was calculated using the equation of (Subedi et al., 2010) by summing up the carbon stock densities of the individual carbon pools of the study area:

$$TC = AGC + BGC \ldots\ldots(4)$$

Where TC = carbon stock density for all carbon pools (t/ha), AGC = carbon in above-ground tree and shrub biomass (t/ha), BGC = carbon in below-ground tree and shrub biomass (t/ha),

2.3 Satellite image based forest carbon estimation

2.3.1 Satellite data sources and acquisition

The present study has utilized Moderate Resolution Imaging Spectroradiometer (MODIS) data: MYD13Q1 for the analysis of vegetation. The satellite data of Godebie National Park is acquired from National Aeronautics and Space Administration (available at https://earthdata.nasa.gov/). The MODIS satellite data is acquired in respect to the ground sampling date. The MYD13Q1 data is generated on 16-day intervals and at multiple spatial and temporal resolutions providing consistent spectral vegetation indices (Table 1).

This section deals with the NDVI, EVI, and their estimation using the MODIS datasets. The description of the satellite datasets along with the scale factor for NDVI and EVI has been provided 0.0001 (Myneni et al., 2003). NDVI is considered as one of the most preferred spectral indices to differentiate vegetated regions from non-vegetated regions (Tucker, 1979). The NDVI is a term which indicates the photosynthetically active radiation for vegetation (Rani et al., 2018). That is strongly affected by climatic conditions, and surrounding factors such as soil and geomorphology as well as physio-chemical characteristics of plant and leaf texture.It transforms the image of NIR and Red channels into a single band image with values ranging between − 1 and + 1.

Table 1 Descriptions of satellite datasets used in the study.

Satellite Data	MODIS MYD13Q1 (NDVI, EVI)
Path /horizontal tile number	21
Row/ vertical tile number	7
Spatial Resolution	250 m
years	January 2020, January 2021 and February 2021

The values of NDVI indicate the amount of chlorophyll content present in vegetation, where higher NDVI value indicates dense and healthy vegetation and lower value indicates sparse vegetation/bare soil. Thus, regions assigned for higher NDVI values are because of relatively higher reflectance value in NIR and lower in the red band (Tomar et al., 2013). to monitor vegetation health, changes, types, amount, and condition.(Pandey et al. 2019) To identify and assess the relationship between NDVI and EVI of the study sites, regression analysis is employed in the study. To obtain the pixel values associated with carbon of the forest, the NDVI equation was used:

$$NDVI = \frac{NIR - Red}{NIR + Red} \quad \text{………..(5)}$$

NDVI: Normalized Difference Vegetation Index, NIR: Near Infrared Band, Red: Red Band Similarly, to compare the indexes distribution values for the research area, the EVI index equation was utilized (Huete, 1999):

$$EVI = 2.5 * \frac{(NIR - Red)}{(NIR + C1xRed - C2xBlue + L} \quad \text{………..(6)}$$

EVI is Enhanced Vegetation Index, NIR is Near Infrared Band, Red is Red Band, Blue is Blue Band, C1 means values as coefficients for atmospheric resistance Value 6, C2 means values as coefficients for atmospheric resistance Value 7, L is value to adjust for canopy background.

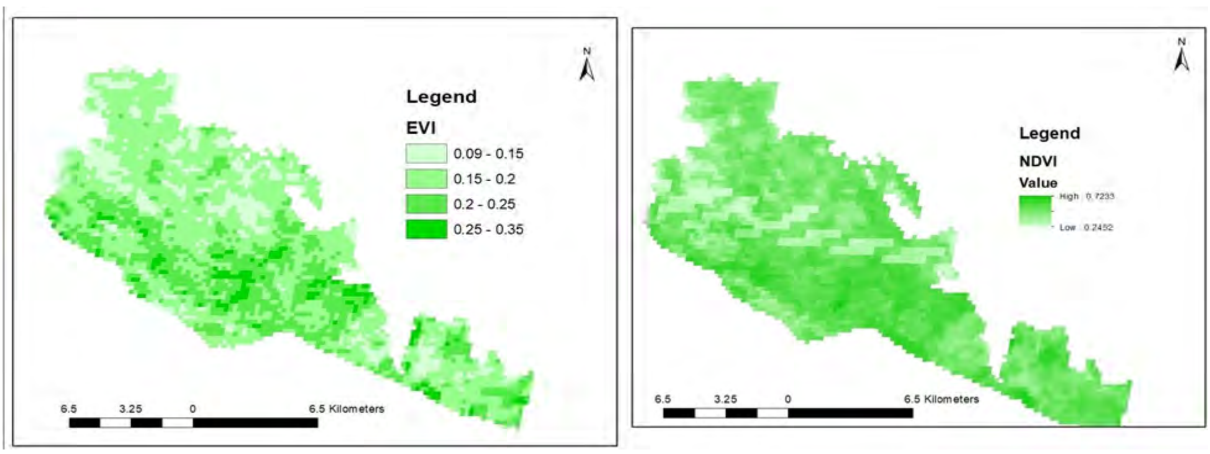

Fig. 3 Enhanced vegetation index (left) and Normalized deference vegetation index (right) of the study area.

2.3.2 Forest carbon estimation

To estimate the forest carbon, primarily, the NDVI and EVI values were extracted from the MODIS data. The exact geographic coordinates of the sampling plots were obtained with the help of GPS. Ground truth points were imported to generate vector data (point) in Arc GIS environment and the resulting vector data was overlaid on the NDVI and EVI products to extract the NDVI and EVI values. The extracted NDVI and EVI values were regressed with the field measured forest carbon values for statistical analysis. The linear equation thus obtained was used to generate the final estimated biomass map of the area.

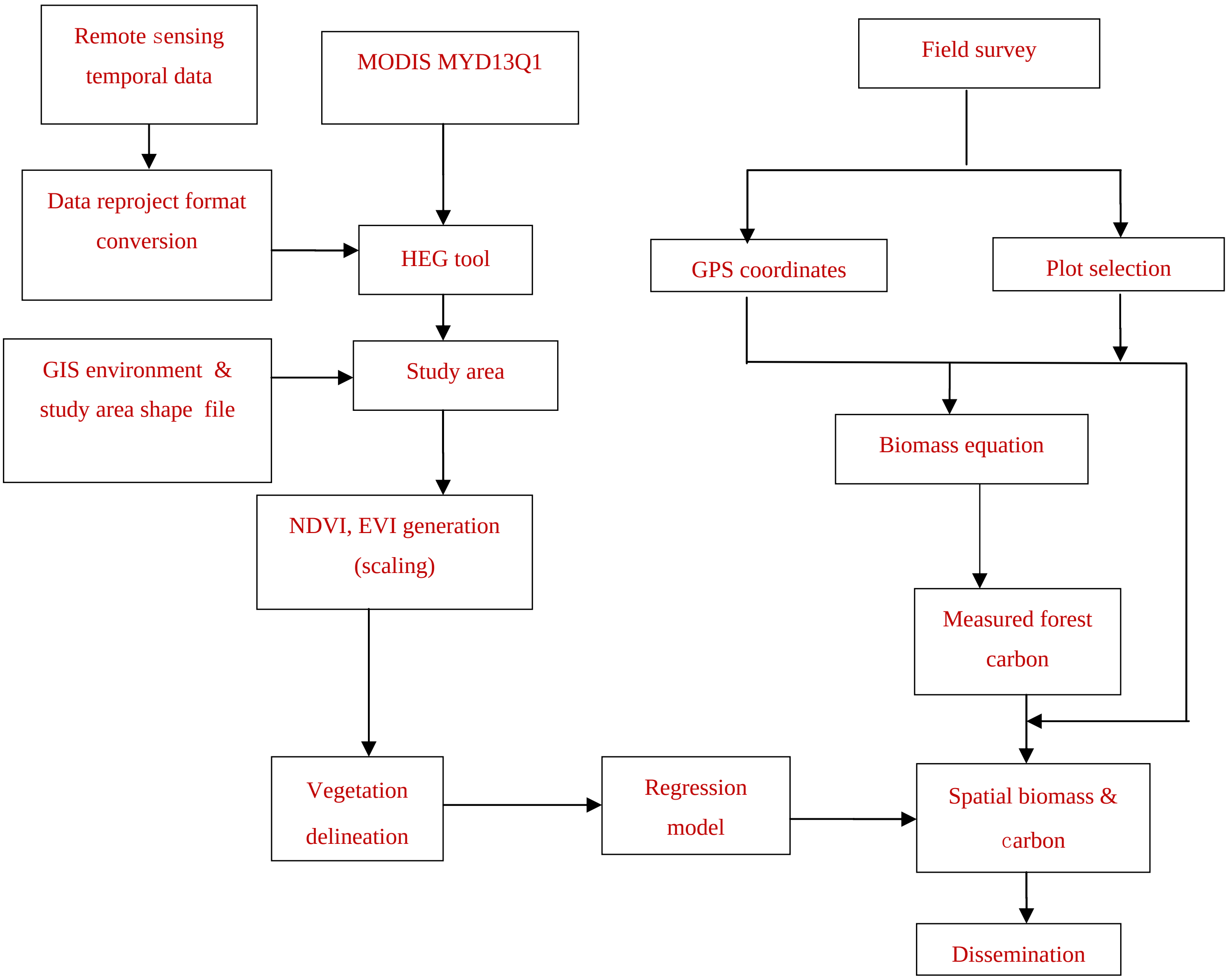

Fig. 4 Schematic Methodology adopted for this study.

The linear regression model between field measured forest carbon and NDVI generated an equation: $y = 1349.5x - 204.24$, at $p < 0.05$, where y = estimated forest carbon, 1349.5 and 204.24 are regression coefficients, and x is NDVI value. Similarly, other regression model between field measured forest carbon and EVI generated an equation: $y = 3864.2x – 339.21$, at $p < 0.05$, where y = predicted forest carbon, 3864.2 and 339.21 are regression coefficients, and x is EVI value. The regression models include field-based forest carbon measurements, NDVI and EVI values, to develop the equations. The derived equation is then utilized to estimate vegetation carbon. After that, estimated forest carbon and measured forest carbon are compared to each other. Vegetation carbon of each year (2020-2021) was generated from the MODIS datasets. Additionally, in this study, the specific vegetation inventory was conducted for the mentioned period and the similar time period satellite datasets were employed to derive the forest biomass in order to maintain the consistency in the spatial as well as temporal datasets. This enables to have field and satellite-derived forest carbon for comparison and validation. This also provides a comparable idea of the spatial distribution of forest carbon over the study site.

3 Results and Discussion

This study makes an effort to estimate forest biomass in Godebie National Park using field inventory data and satellite data based geospatial techniques. Models were developed for establishing the relationship between vegetation indices (NDVI and EVI) and field inventory-based forest carbon.

3.1 NDVI and EVI derived from the satellite dataset

NDVI map generated using satellite data is shown in Fig. 3, while the final EVI map generated values ranges from 0.09 (low) to 0.35 (high) as shown in Fig. 3. The relationship between estimated forest carbon (AGC & BGC) with EVI is found to be 0.81 and 0.74 for the years 2020 and 2021 respectively, while for forest carbon (AGC & BGC) and NDVI, R^2 values were found to be 0.776 and 0.679 for the year 2020 and 2021 respectively.

3.2 Field inventory-based biomass and carbon stock

The average above ground biomass of the trees measured during the field survey is found to be 721.048 t/ha (Table 2), while spatial variation of biomass value over different locations varies from 10.429 to 1530.851 t/ha. Based on field data and allometric equation, the maximum and minimum above-ground carbon of the study area was found to be 719.5 and 4.902t/ha respectively. Similarly, the maximum and minimum below-ground carbon was also 180.50 and 0.98 t/ha (Table 2). The mean above-ground and below ground carbon stock in trees and shrub species of the study area was estimated to be 338.893±4.5 t/ha and 67.779±2.5 t/ha, respectively. Accordingly, a mean of 1904.07 t/ha CO_2eq was sequestrated in the above-ground and below ground biomass of trees and shrubs of the study area.

Table 2 Descriptive statistics of above and below ground biomass, carbon stock and carbon dioxide equivalent.

	Above ground			**Below ground**		
	AGB(t/ha)	AGC(t/ha)	CO_2 eq(t/ha)	BGB(t/ha)	BGC(t/ha)	CO_2 eq(t/ha)
N of plots	44	44	44	44	44	44
Mean	721.048	338.893	1243.735	144.210	67.779	248.747
Max	1530.851	719.5	2638.406	384.043	180.50	661.89
Min	10.429	4.902	17.989	2.086	0.980	3.598
Median	129.781	60.997	223.859	25.956	12.199	44.772

Table 3 Average value of above and below ground carbon and carbon dioxide equivalent.

	AGC	**BGC**	**Total Carbon**
Mean Carbon (t/ha)	338.89±6.5	67.78±2.3	406.67±4.2
Mean CO_2 eq (t/ha)	1243.74±12.99	248.747±4.75	1904.068±8.74

3.3 Regression models for estimated forest carbon using NDVI and EVI

The field-estimated carbon (AGC & BGC) value ranges from 5.88 t/ha to 900.0 t/ha (Table 2) while the average carbon (AGC & BGC) is 406.67 t/ha (Table 3). EVI value ranging from 0.09 to 0.35 is obtained from satellite data; the correlation (r = 0.87) between estimated carbon and NDVI is generated with the R^2 value of 0.77. Similarly, the relationship between EVI and estimated carbon is statistically correlated (r = 0.69) with R^2 value of 0.81 as shown in Figure 5. Carbon stock map at pixel level was prepared using the best fit regression analysis using EVI and NDVI data. Forest carbon stock map was prepared by taking the average values of a, b, and c coefficient values of equations and smaller root mean square error (RMSE) of best fitted regression analysis in the study site.

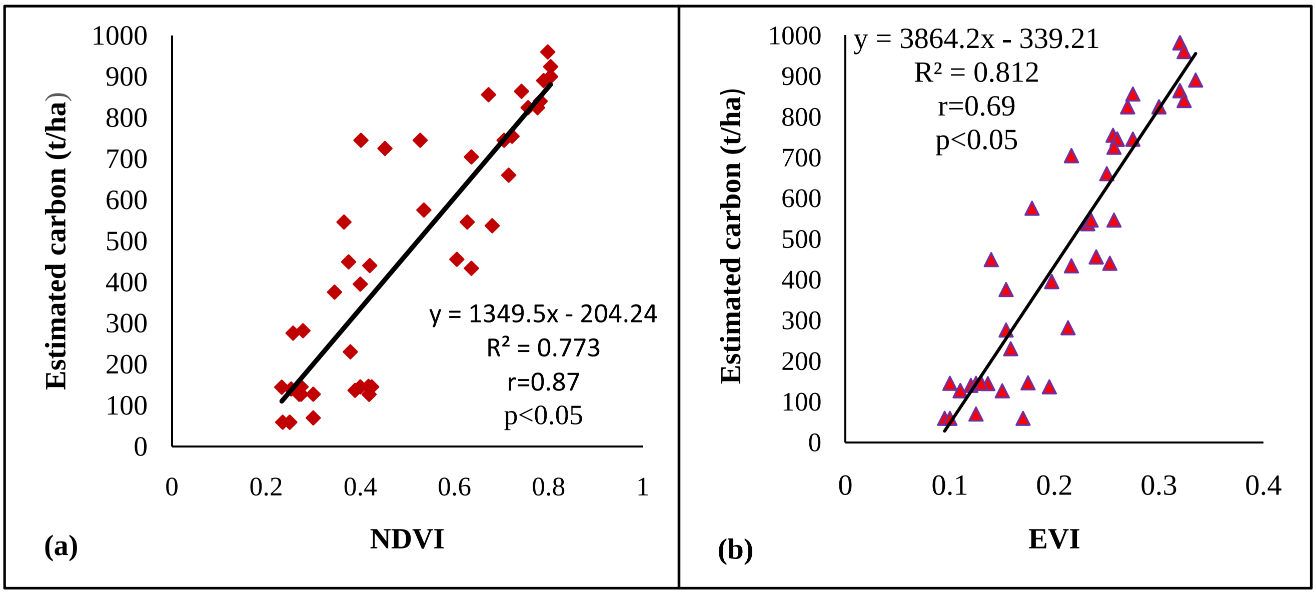

Fig. 5 Linear regression between NDVI and estimated carbon (a) and relationship between enhanced vegetation index (EVI) and estimated carbon (b).

Estimated carbon stock was validated using field measured carbon stock values in 2021 G.C to assess the accuracy of the model. Regression coefficients and root mean square error for EVI (R^2 = 0.815 and RMSE =315.89) and for NDVI (R^2 = 0.776 and RMSE =178.83) are presented in Table 4. The graphical representation of the relationship obtained is shown in Figure 6 for the period of January 2020, January 2021 and February 2021. NDVI and forest carbon were taken as independent and dependent variables in the linear regression model, respectively.

This finding also tried to contributes to assess the performance of MODIS vegetation indices (NDVI and EVI) for estimating carbon stock using best fit regression model. The spatial distribution of NDVI shows a significant good amount of area is under vegetation cover; NDVI value reflects the distribution of healthy and dense vegetation in the study area. Most of the areas are having higher EVI and NDVI values (Fig. 2), which indicates that EVI and NDVI are correlated. Similarly, the correlation between estimated carbon with EVI was obtained as 0.69, while the correlation with NDVI was found to be 0.87 respectively.

Table 4 Equations and goodness of fit statistics for the model developed from vegetation indices.

	Model	Coefficient	R^2	RMSE	sig
NDVI	Y=1349.5(NDVI)-204.24	1349.5	0.7761	178.83	0.0001
EVI	Y=3864.2(EVI)-339.21	3864.2	0.815	315.69	0.0002

Y represents forest carbon (above and below ground carbon).

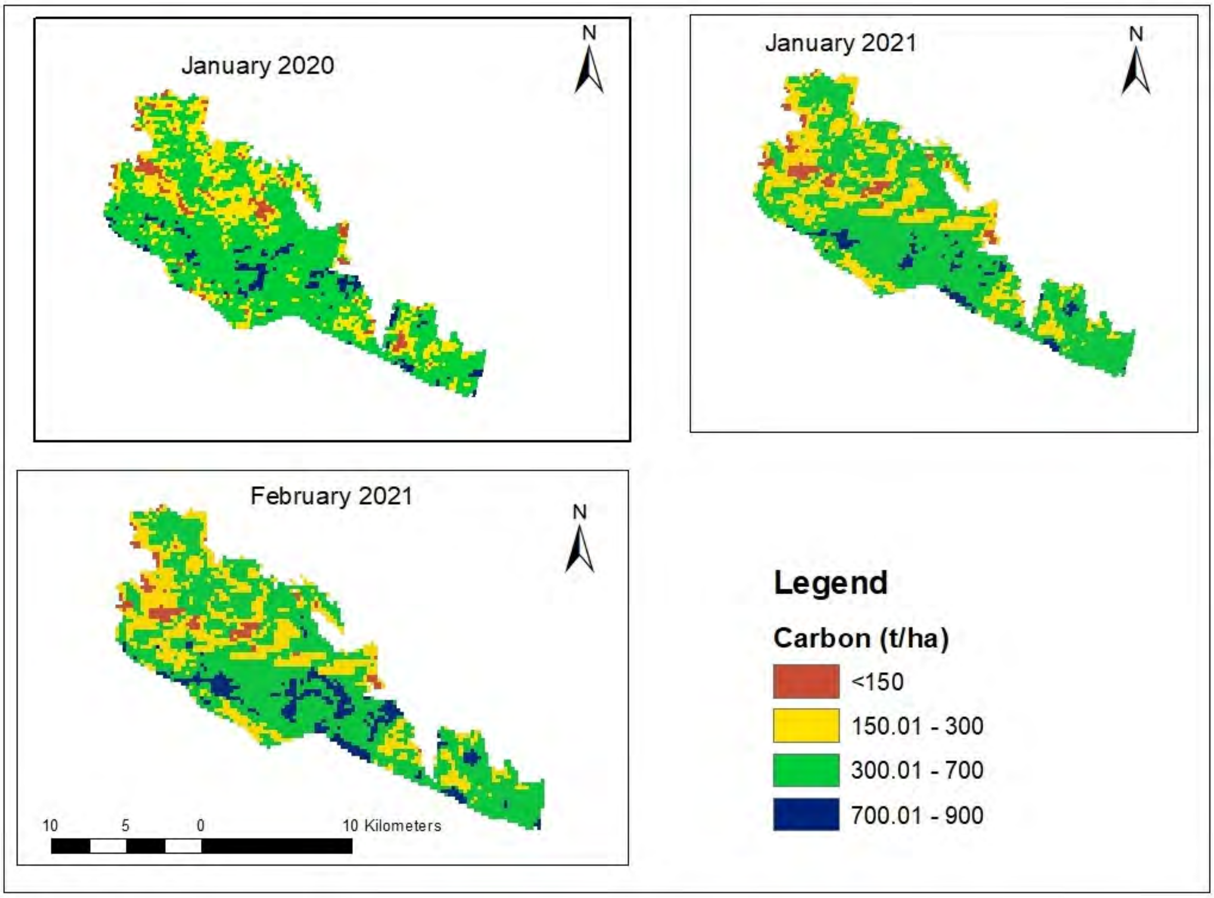

Fig. 6 Spatial carbon distribution map of Godebie National Park (2020-2021).

Generally satellite particularly MODIS based vegetation indices were significant in estimating the above ground forest biomass and carbon stocks. Study conducted by Gashu and Marelign (2022) revealed that MODIS Derived NDVI and EVI showed good performance for the estimation of Above ground biomass and carbon stock of Tru-Selam forest in central Ethiopia. Similarly, Marelign and Mekonen (2022) investigated that NDVI drived from Landsat 8 revealed good performance with R^2 and RMSE value of 0.7459 and 24.33 respectively for estimating woodland above ground carbon in Dirmaga Watershed.

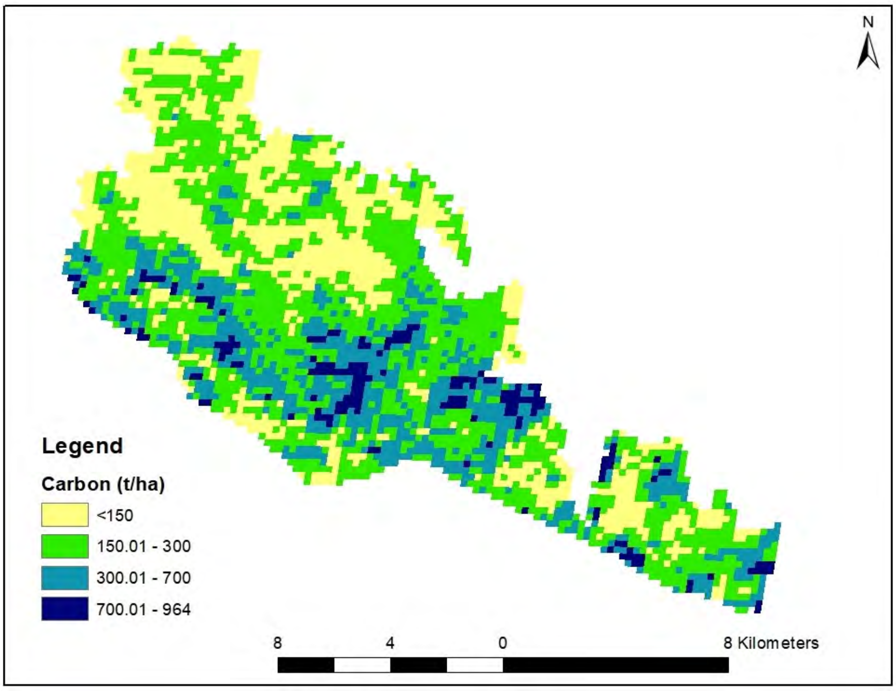

Fig. 7 Spatial distribution of average carbon during 2020-2021.

The forest carbon results indicated that the average vegetation biomass in Godebie National Park is 406.67 t/ha. Temporal spatial distribution of the forest carbon in Godebie National Park is shown in Fig. 6 and the average forest carbon is shown in Figure 7. This map revealed the presence of maximum forest carbon in the middle part and southern part of the study area.

3.4 The total carbon stock and climate change mitigation potential of Godebie National Park

The total mean carbon stock potential of Godebie National Park was calculated by summing up all the carbon Pools of the study area namely: The average AGC and BGC was 338.893 and 67.779 t/ha, respectively. Which gave a total carbon stock potential of 406.67 t/ha (Table 2). The carbon pools of above-ground biomass and belowground biomass, had a capacity of removing 2835.519 and 567.104 t/ha CO_2 equivalent, respectively, with a total global climate change mitigation potential of 2276.83 t/ha CO_2 equivalents (Table 3).

4 Conclusion and Recommendation

Remote sensing and geospatial technology are widely used for reliable estimation of vegetation carbon and biomass over a large-scale region. The estimation of aboveground carbon can be obtained by satellite data and regression modeling. The relationship of MODIS NDVI and EVI with the estimated forest carbon was statistically significant with R^2 value of 0.77 and 0.81 respectively. Based on the field inventory and MODIS NDVI and EVI estimation, the average carbon of the study area is 406.67 t/ha with a carbon dioxide sequestration potential of 1904.07 t/ha CO_2 equivalent. Therefore, the findings of this study showed that the remote sensing technology integrated with field inventory can be used for AGB and AGC estimation and thus valuable for forest monitoring and management of a large spatial region. Generally, the methods implemented in this study can be used by the forest planners, policy makers, and government officials for conservation and protection of the forest ecosystem and effective management of the Godebie National Park Forest.

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