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Assessment of landuse change implication on carbon stock of subtropical forests of East Khasi hills, Meghalaya

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Abstract: The study was carried out with an aim to enumerate the community characteristics, above ground biomass (AGB) and validation of field based biomass with the calculated AGB values using remote sensing and GIS. The study was carried out for East Khasi hills district of Meghalaya using random field sampling in selected land use. Sampling plots were selected in replicate keeping in account altiudinal variations and site characteristics. Soil samples were collected from two depths and anlyzed using sandard methods. The species richness was more in subtropical broad-leaved (SBL) forest than the pine forest (PF). However, stand density and basal cover was more in pine forest primarilly due to large number of individuals having more girth. Total tree biomass estimated in the SBL and PF were 300.5 t ha^{-1} and 195.89 t ha^{-1}, respectively. However predicted AGB was 232.77 t ha^{-1} in the SBL stand and 152.08 t ha^{-1} in PF stand. However, calculated AGB was 300.28 t ha $^{-1}$ in SBL forest and 215.8 t ha^{-1} in PF. Finally, spatial carbon stock map of the selected forest type was prepared and the average biomass carbon was 128.02 t ha^{-1} in SBL and 107.9 t ha^{-1} in pine forest. Total carbon stock was calculated by summing the carbon stock of different pool i.e., tree, litter and soil. Implication of the land use change revealed that an amount of 86.36% carbon will be emitted in the situation when SBL is converted into abandoned land. However, an amount of 82.67% carbon will be emitted when PF are converted into abandoned land.

Keywords: LULC, Soil, Carbon, GIS, Emission

1. Introduction

Climate is one among the vital basis of vegetation composition globally and having important stimulus on species distribution and structural and functional aspect of the forests. It has been reported that landscape plant composition and soil acts as a noteworthy sink of atmospheric carbon dioxide (CO_2) (Wani et al., 2010). About 6.22 and 2.1 Gt CO_2 were released annually through deforestation and forest degradation, respectively (Pearson et al., 2017). About 80% of the above-ground terrestrial carbon and 40% of below-ground terrestrial carbon is stored in the forests (Olson et al., 1983; Dixon and Turner, 1991). Worldwide it has been recognized that deforestation and forest degradation requisite effective management for minimizing greenhouse gas emissions (GHGs). Changes in forest management generally results in less carbon sequestration (Lal and Singh, 2000). Global warming is viewed as increment in normal temperature of the Earth's surface and seas in late decades and its anticipated continuation. The Intergovernmental Panel on Climate Change (IPCC, 2007) anticipates that worldwide temperatures are probably going to rise by 1.1 to 6.4 °C between 1990 and 2100. The CO_2 is the specific constituent of photosynthesis hence influencing plant effectiveness while it is also the key members of ozone harming substances. Hence it is wise to acknowledge that alterations in climate scenario would also alter the functioning system of biological community. Other than carbon in the soil, forests also store a lot of carbon in the biomass (Freibauer et al., 2004). The biomass is by and large progressively used to measure pools and fluxes of GHGs along with land use changes (Cairns et al., 2003). To know the role of vegetation in carbon cycle, biomass and productivity estimations are the transitional steps (Kale et al., 2002). The measure of carbon sequestered by forests can be evaluated from biomass and is roughly 50% of forest dry biomass weight comprises carbon (Cairns et al., 2003; MacDicken, 1997). Researchers have developed a number of allometric equations for biomass estimation and were used at national level aboveground biomass studies (Chave et al., 2005). Further geospatial approaches, recently become more important and play a crucial role in mapping and monitoring forest degradation of large area with very minimum effort and time. Remote sensed images have shown high correlation between spectral bands and vegetation parameters like above ground biomass for the large area (Roy and Ravan, 1996; Lu, 2005).

Many studies reveal that satellite derived spectral vegetation indices such as simple ratio (SR), normalized difference vegetation index (NDVI) and enhanced vegetation index (EVI) have very strong relationship with biomass and plant productivity (de Fries et al., 1995; Kale et al., 2002; Roy and Ravan ,1996). Gupta and Sharma (2014) carried out a study on estimation of biomass and carbon sequestration of trees in protected area of Rajouri, India and reported 34.52 tons of carbon in its standing biomass. Bordoloi et al. (2017) had applied non-destructive approach and estimated AGB of 269.65 Mg Ha^{-1} and 206.03 Mg Ha^{-1} for *Tectona grandis* and *Gmelina arborea* plantations, respectively in Papum Pare districts of Arunachal Pradesh. Devagiri et al. (2013) carried out a remote sensing based approach to estimate AGB and carbon pool and reported 7.25 to 287.047 Mg ha^{-1} AGB from south western part of Karnataka. Kashung et al. (2018) had applied vegetation indices based approach in different landuse sector and reported 84.94 to 218.21 Mg ha^{-1} AGB from West Kameng district

Arunachal Pradesh. The aim of current study was to predict biomass and carbon stock in different forest type and effect of landuse implication on carbon stock of the study area.

2. Study area

The East Khasi Hills district is situated in south-central part of state of Meghalaya having a border with Bangladesh in the south. The district occupies a total geographical area of 2,748 km^2 (Figure 1) and is situated between 25°07″ and 25°41″ N latitude and 91°21″and 92°09″ E longitude. The climate of the district varied from tropical to temperate and weather is humid for major portion of the year excluding fairly dry period during December and March. The district is influenced by the south-west monsoon and receives heavy rainfall.

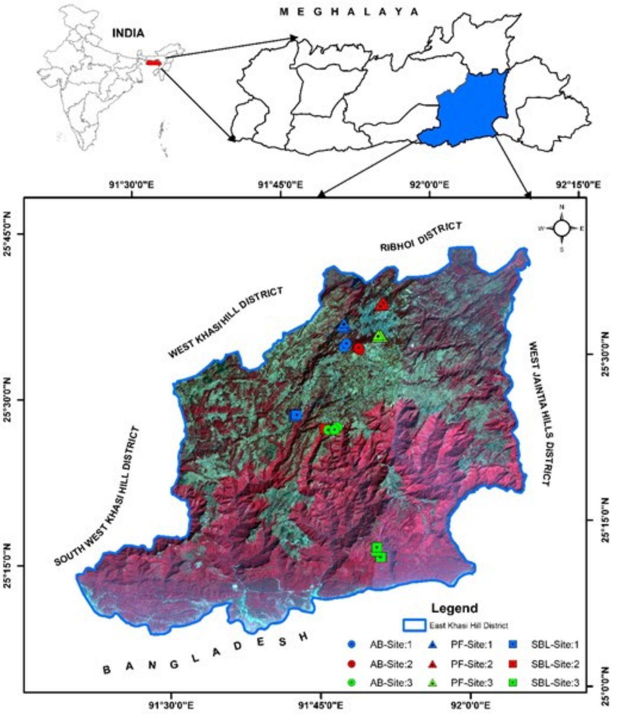

Figure 1: Location map of the study area

3. Materials and Methodology

The study has three phase work which include primary data collection, spatial and non-spatial database creation and spectral modelling. The field measurement was carried out in three different landuse types viz., subtropical broad-leaved forest (SBF), Pine forest (PF) and abandoned lands (AL). Altogether 45 quadrats (0.1 ha) were laid in selected forest patches using non-destructive approach. All the individual (dbh ≥10cm) encountered in the quadrats were measured with their height and diameter at breast height (1.37m above ground level). For litter carbon estimation, litter samples were collected from 1m x 1m qudrat from each sample plot in replicates and were brought to laboratory for further analysis. Soil samples were collected from each plot from two soil depths (0-25 cm and 25-50 cm). Soil pH, moisture content, bulk density and soil carbon were determined following standard methodology (Allen et al., 1974; Anderson and Ingram, 1993). The tested quadrat of the study area is covered by 3 sets of Landsat operational Land Imager (OLI) satellite data with 30m spectral resolution (path/row:136/42,136/43, and 137/42) downloaded from Earth Explorer. All these tiles have undergone the preprocessing operations viz., band-wise radiometric calibration for removal of spurious digital number in raw satellite data, which converted the DN values to at sensor radiance and conversion to surface reflectance following USGS (2019), layer stacking of bands to get false colour composite (FCC) image and re-projection to Universal Transverse Mercator projection system with zone 46 north. All the images were then mosaicked, study area was extracted and followed by land use and land cover classification using supervised approach (Figure 2).

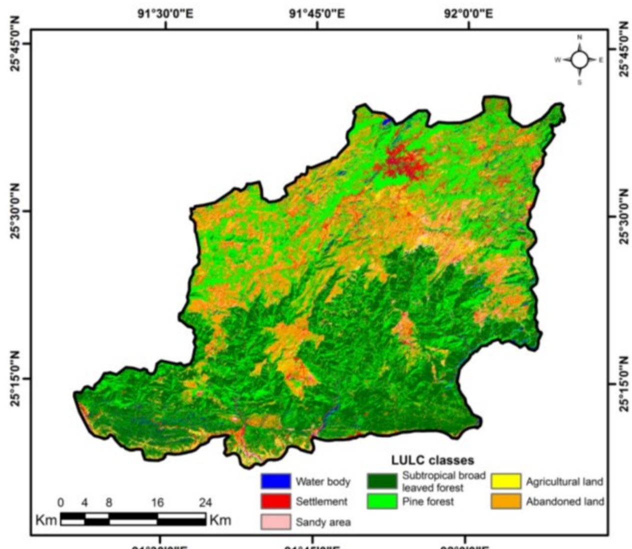

Figure 2: LULC map of the study area

The study area was classified into seven category namely waterbody, settlement, sandy area, subtropical broad-leaved forest, pine forest, agricultural land, and abandoned land (includes barren and degraded forest). The species-specific volumetric equations along with specific gravity or wood density were applied for calculating the volume of each individual tree. Tree alometric equations for many species were not available, hence general equation of the state were used. A fraction of 0.55 of biomass was used for estimating AGB carbon stock while below ground biomass (BGB) was estimated by taking 0.26 fraction of AGB (IPCC, 2003). The total carbon stock was calculated by summing the carbon stock of different pools viz. tree, litter and soil carbon. The prediction of biomass was carried out for selected landuse with the help of satellite data using Normalized Difference Vegetation Index (NDVI) Rouse et al. (1974) and Soil Adjusted Vegetation Index (SAVI), Huete (1988). A linear regression analysis was applied to find out the correlation between different vegetation indices and observed AGB. The resultant best-fit model was then used for spectral modeling of biomass and carbon stock of selected land use. Satellite derived vegetation indices were applied to the image of study area and based on location of sample plot, values of vegetation indices were extracted for each plot. Linear regression model was applied to extracted vegetation indices value against the plot biomass based on field inventory data.

4. Results

4.1 Soil characteristics

Bulk density value of the SBL ranged from 0.70 g cm^3 while the values were 1.27 g cm^3 and 1.06 g cm^3 in the pine forest and abandoned lands, respectively. Arunachalam and Arunachalam (2000) have reported BD of 1 gcm^3 from sacred forest, Mawphlang forests, Meghalaya. The soil moisture content was greater (55.93% to 19.86%) in the upper soil layer than the lower soil layer (15.99% to 45.78 %). The moisture content in abandoned land was unusually higher than the rest of the sites which could be mainly due to dense ground growth. The pH of soil was acidic and values varied from 3.89 to 6.60 in upper soil depth and 4.25 to 6.96 in the lower soil depth. Soil pH was higher in PF followed by AL and SBL. In SBL forest, the upper soil layer showed lower pH than the lower soil depth which could be associated to lower levels of organic matter and greater extent of leaching of a few nutrient elements. The SOC is the organic fraction of soil exclusive of non-decomposed plant and animal residues and is an important indicator of soil health, mitigation and adaptation to climate change. Percentage of SOC ranged from 1.14% to 2.87 % in the upper layer and 0.82% to 2.13% in lower soil depth which shows vertical variability of SOC distribution (Table 1). In upper soil depth Site-2 of SBF had the greater percentage of SOC in both the soil depths while more organic carbon in lower soil depth was in Site-2 of SBL forests. High SOC provides nutrients to plants, enhances soil fertility and improves the water availability. The upper soil depth had greater SOC than the loer soil depth in all the landuse sectors.

4.2. Above ground biomass and carbon

Altogether, 71 tree species were recorded from the SBL and pine forest and the broad-leaved forests recorded maximum species richness (63 species) than the pine forest. Stand density did not differ much and ranges between 558 stems ha^{-1} and 585 stems ha^{-1} with basal area of 34.43 m^2 ha^{-1} to 38.10 m^2 ha^{-1} in the former and later forest stands. The litter carbon was lower (0.82 t ha^{-1} to 2.33 t ha^{-1}) in the SBL than the pine forest which could be attributed due to slow decomposition of pine needles. The SOC ranged from 21.25 t ha^{-1} to 41.53 t ha^{-1} in the SBL and 46.04 t ha^{-1} to 69.22 t ha^{-1} in the PF and 28.89 t ha^{-1} to 47.33 t ha^{-1} in abandoned land. The plot wise (0.1 ha) total biomass for the study area ranged from 10.67 to 62.76 t. The total biomass estimated in SBL forest was 300.5 t ha^{-1} where in the pine forest it was 195. 89 t ha^{-1}. Plot wise total biomass in SBL forest ranged from 13.21 t to 62.76 t and 10.69 to 27.58 t in Pine forest. The total carbon stock estimated were 165.28 t ha^{-1} for SBL forest and 107.74 t ha^{-1}in the Pine forest (Table 3). Pala et al. (2013) reported much higher biomass (1159.900 Mg ha^{-1}) and carbon density (587.190 Mg ha^{-1}) from sacred groves of Garhwal Himalaya. Waikhom et al. (2018) reported AGB from 962.94 to 1130.79 Mg ha^{-1} from sacred groves of Manipur. However, Sundarapandian et al. (2012) reported lower biomass (74.8 mt ha^{-1}) and carbon (47.13 mt ha^{-1}) density. Simalarily Devagiri et al. (2013) had reported lower biomass (70 t ha^{-1}) and carbon stock (33 t ha^{-1}). Correlation was established between plot biomass (t/ha) and basal area for each site and higher coefficient value was observed in Pine forest (R^2 = 0.97) than the SBL (R^2 = 0.95).

4.3. Regression analysis between vegetation indices and plot-based biomass

Satellite derived vegetation indices were extracted for each plot and linear regression model was applied to extracted vegetation indices against the field-based plot biomass. The reflectance based NDVI ranged between -0.74 and 0.84 (Figure 3a) and the negative values of NDVI correspond to waterbodies/lakes. NDVI value of SBL forest ranged from 0.27 to 0.73, in pine forest from 0.35 to 0.54 and 0.22 to 0.35 in the abandoned land. The NDVI and plot based correlation coefficient was low (R^2=0.47). The advantage of SAVI is that it the soil background effect and results are better than the NDVI. The SAVI value ranged from -0.22 to 0.63 while plot wise values varies between 0.09 and 0.44 (Figure 3b). The plot wise SAVI values (0.18 to 0.44) of SBL forest was more than the pine forest (0.14 to 0.25) and abandoned land (0.09 to 0.22). When linear regression model was applied to the extracted values of SAVI and biomass it showed greater correlation coefficient value (R^2=0.71) than the NDVI mainly could be because it considers the soil brightness factor and minimized the effects **(**Table 2**).** Linear regression analysis between field based estimated AGB and satellite derived vegetation indices were carried out to comprehend their associations. The observed correlation coefficient can be compared with the values of R^2=0.73, 0.70 and 0.68 as reported by Devagiri et al. (2013), Das et al. (2017) and Kashung et al. (2018).

4.4 Biomass and carbon stock modelling

The SAVI based model derived from linear regression analysis among the different vegetation indices and field based biomass was applied for modeling of total biomass of selected land use. The predicted total AGB for the study area was 199.91 t ha^{-1} (Figure 4). However, predicted biomass was 232.77 t ha^{-1} and 152.08 t ha^{-1} for SBL and Pine forest (Table 3). The mean total carbon stock for study area was 109.95 t ha^{-1}. The maximum total biomass carbon stock predicted for the SBL forest was 128.02 t ha^{-1} and for Pine forest was 107.90 t ha^{-1}. The predicted spatial carbon stock in different forest type is given in Figure 4. Carbon is among the larger constituents of the biomass and to assess carbon stock from biomass. We have used coefficient of 0.55 for calculating total biomass carbon of the area and total carbon. SBF stores greater carbon stock than the Pine forest followed by the abandoned land. Further PF accumulate greater carbon in the soil than the other two landuse (Table 4). Implication of the landuse change revealed that an amount of 86.36% carbon will be emitted in the situation when SBL forest is being converted into abandoned land. However, an amount of 82.67% carbon will be emitted in the situation when PF is being converted into AL. However once AL is converted into broad-leaved forest through management about 7.33 times carbon will be captured and stored while 5.77 times carbon will be stored in case of Pine forest.

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Table 1: Soil organic carbon (%) in selected landuse types of East Khasi hills district, Meghalaya

Sites/ Soil depths (cm)	SBL		PF		AL	
	0-25cm	25-50cm	0-25cm	25-50cm	0-25cm	25-50cm
Site-1	2.2±0.15	1.75±0.05	1.39±0.07	1.24±0.02	1.77±0.01	1.386±0.02
Site-2	2.87±0.15	2.04±0.11	2.13±0.04	1.82±0.03	1.54±0.03	1.32±0.02
Site-3	1.33±0.16	0.82±0.08	1.72±0.03	1.44±0.006	1.14±0.04	0.94±0.09

Table 2: Coefficient for R^2 for biomass and different vegetation indices

Vegetation Indices	Equation	R^2
Normalize Difference vegetation Index (NDVI)	y = 42.325x – 3.6739	0.47
Soil adjusted vegetation Index (SAVI)	y = 78.895 x– 1.512	0.71

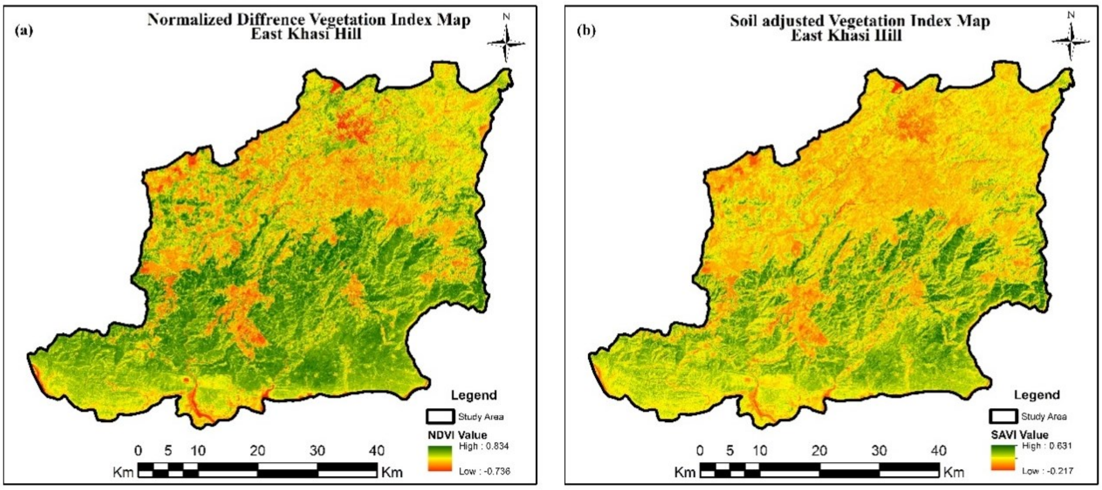

Figure 3: (a) NDVI (b) SAVI map of the study area

Table 3: Predicted and observed AGB and AGB carbon

AGB and carbon stock (t ha^{-1})	Average entire study area	SBL Forest	Pine Forest
Total Estimated biomass	256.91	300.50	195.88
Total Predicted biomass	199.91	232.77	152.08
Total Estimated carbon stock	141.30	165.28	107.74
Total Predicted carbon stock	109.95	128.02	107.90

Table 4: Carbon stock (t/ha) in different pool of selected landuse

Carbon stock	Broad-leaved forest	Pine forest	Abandoned land
AGB	165.28	107.74	-
BGB (root)	90.90	59.25	-
Litter	1.79	2.56	-
Soil	30.09	57.15	39.28
Total	288.06	226.70	39.28

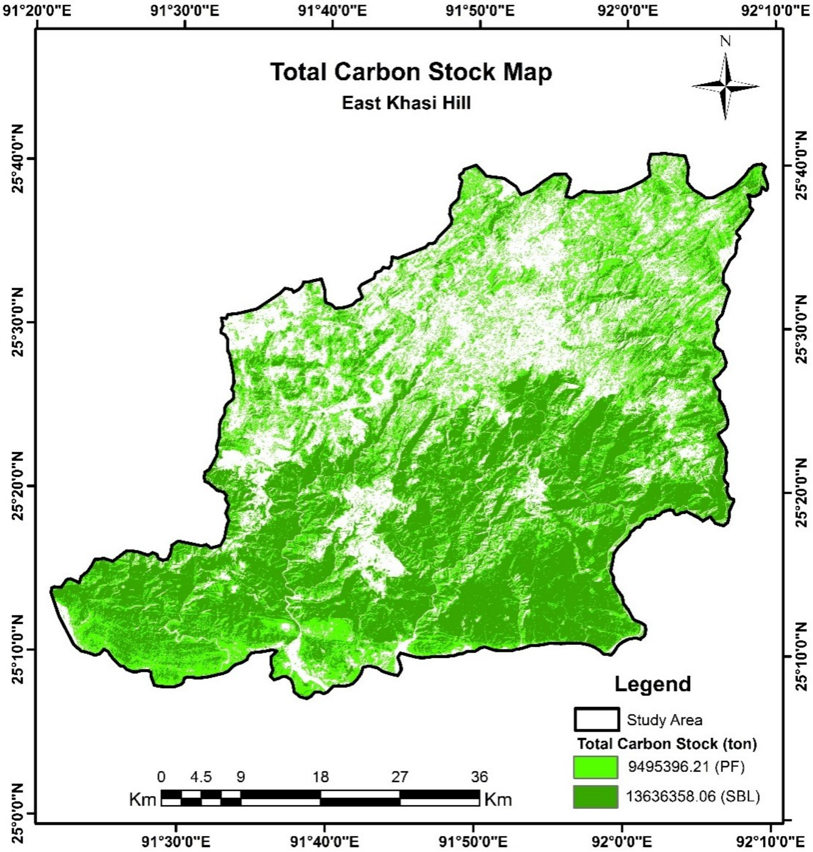

Figure 4: Predicted Carbon stock map for the study area

5. Conclusion

All together 71 tree species were recorded from study area and species richness was more in SBL forest the pine forest. Soil was acidic in nature and acidity was more in Pine forest. Acidity decreases with increase in soil depth mainly due to leaching and precipitation. Soil was sandy in nature. AGB was found to be greater in SBL forest than the pine forest and similar trend was obtained for carbon. Satellite derived biomass and carbon of selected landuse was also calculated using NDVI and SAVI indices. SAVI has resulted better correlation with the observed carbon values. Spatial maps of biomass and carbon was prepared using SAVI regression equation which will be useful for formulating suitable strategic plan for future enhancement of carbon stock of the study area. Total geographical area under subtropical broad-leaved and Pine forests in East Khasi hills district is 106517 ha and 88001 ha, respectively. Total estimated AGB for former forest was 17596675 tonnes and 9433795 tonnes for later forest with an average of 165.2 tones/ha and 107.2 tones/ha, respectively. Subtropical broad-leaved forest stores greater carbon stock than the Pine forest followed by the abandoned land. However, Pine forest accumulates more carbon in the soil than the other two land use. Implication of the land use change revealed that an amount of 86.36% carbon will be emitted in the situation that SBL forest is being converted into abandoned land. However, 82.67% carbon will be emitted in the situation when pine forests are being converted into abandoned land.

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