published by

EQA - International Journal of Environmental Quality
ISSN 2281-4485 - Vol. 43 (2021): 47-64
Journal homepage: https://eqa.unibo.it/

Geospatial assessment of carbon stock inventory by vegetation indices in Pai Forest, Sindh, Pakistan

Tayyab Shafique [1]*, Muhammad Hashim Zuberi [1], Zafar Iqbal Shams [2]

[1] Department of Environmental Sciences, Sindh Madressatul Islam University, Karachi, Pakistan
[2] Institute of Environmental Studies, University of Karachi, Pakistan

*Corresponding author e-mail: tayyabshafique707@gmail.com

Article info
Received 11/1/2021; received in revised form 8/2/2021; accepted 25/2/2021.
DOI: 10.6092/issn.2281-4485/12203

Abstract
Ranking 5th at global Climate Vulnerability Index, Pakistan is facing massive decline in the forest cover. Therefore, carbon stock of Pai Forest has been in-vestigated which is converted from a *riverine-to-irrigated* forest. This study in-corporates the direct and indirect carbon stock inventory development in 2018 and 2020, respectively, using geospatial assessments for which field-based carbon stock of nine tree species (232 individuals) is calculated in 2018 using allometric models which is then statistically correlated with the Remote Sensing (RS) and Geographic Information System (GIS) using Landsat-8 satellites. Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation In-dex (EVI) were calculated for 2018 and 2020 from 8 quadrats of the forest (each of 800m × 800m) and a regression model was developed using SPSS. Using this model, the indirect estimation of carbon stock was conducted to find out carbon stock of the forest in 2020. *Dalbergia sissoo* demonstrates the highest potential for carbon sequestration. The results revealed that both NDVI and EVI carbon stock are also declined during in the forest. This carbon stock inventory of Pai Forest will be useful for policymakers to adopt geospatial monitoring assessments while planning sustainable forest management strate-gies to achieve Sustainable Development Goal 13: Climate Action.

Keywords
carbon Stock, NDVI, EVI, Remote Sensing, Geographic Information System, Pai Forest

Introduction

Carbon stocks in the form of forests are the most environmentally sustainable and economically viable corridors in the tropics to combat climate change (Jantz et al. 2014). However, the increase in the concentration of atmospheric carbon dioxide (Field et al. 2014). particularly due to excessive fossil fuel burning and deforestation is contributing towards the loss of carbon sinks and ultimately to global climate change (Bullock & Woodcock 2020). Considering these aspects, the world has recognized climate change, while United Nations has defined a list of 17 Sustainable Development Goals (UN-SDGs) in 2015, which are strongly connected with its Goal 13, the Climate Action (Nerini et al. 2019). Considering climate change mitigation through forest carbon stock, another important Goal 15: Life on Land in combination with SDG 13 is providing a pool of strategies to achieve forest conservation. Pakistan has been blessed with enormous natural resources including forests. Unfortunately, it has been confronted with achieving sustainability due to capacity development challenges (Khan & Ali 2019) while ranking 5th in terms of global climate vulnerability index (Eckstein et

DOI: 10.6092/issn.2281-4485/12203

al. 2019). According to the first remote sensing-based assessment in Pakistan in 1992, the country had 4.1% forested area (Qamer et al. 2016). In addition, World Bank reported in 2016 that the forest area in the country has declined from 3.28% to 1.85% for the duration of 1990-2016, largely due to deforestation (World Bank 2016). However, according to the Sustainable Development Report 2020, Pakistan has recently demonstrated better performance in achieving Goal 13 among all 17 goals (Sachs et al. 2020). Progressing towards the SDGs achievement particularly Goal 13 (Climate Action), more efforts are required to restore the forest carbon stocks (Hiratsuka et al. 2019). Prior to this, a baseline investigation regarding the existing forest carbon stock is necessary to be conducted, which can be used to forecast future trends for the assessment of forest carbon dynamics. Beyond the applications of conventional tools for direct measures of carbon stock assessment which involves tree destruction (Vieilledent et al. 2012), Remote Sensing (RS) and Geographic Information System (GIS) technologies can be integrated with allometric models (Situmorang et al. 2016) to indirectly assess existing forest carbon stock by non-destructive methods (Ajani & Shams 2016) over a comparatively larger area, high accuracy, low cost, and minimum manpower.

Similarly, the forest in Sindh, which is spread across the province, has declined over the last few decades. The Pai Forest, which was once a riverine forest, has now been converted into an irrigated forest due to substantial reduction of freshwater supply from the mighty Indus River, which resulted in the loss of its forested area. Other anthropogenic and natural factors are also affecting this ecosystem including soil salinization (Siyal et al. 2016). This study has combined the field as well as remote efforts to monitor and analyze the carbon stock and vegetation indices in a forested ecosystem and also to forecast its future scenario by geospatial assessment and monitoring. Using vegetation indices i.e., Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI). Moreover, the application of the current study can potentially provide temporal variations across multiple geospatial ecosystems at both the small- and large-scale circumstances. Statistical analysis-based results of this study have the potential to introduce such innovative methods in national forest policy development and decision making.

Methodology

Study Area

Because of its ecological importance, the Sindh Wildlife Department has declared the Pai Forest as a protected area (Game Reserve) for conservation and sustainable management of wildlife and its habitat. It covers an area of 1933 hectares and is located in Sakrand *taluka* of district Shaheed Benazirabad (formerly Nawabshah) between 68°12’20” to 68°17’04” E longitudes, and 26°04’50” and 26°07’40” N latitudes at the left bank of the Indus River (Fig. 1).

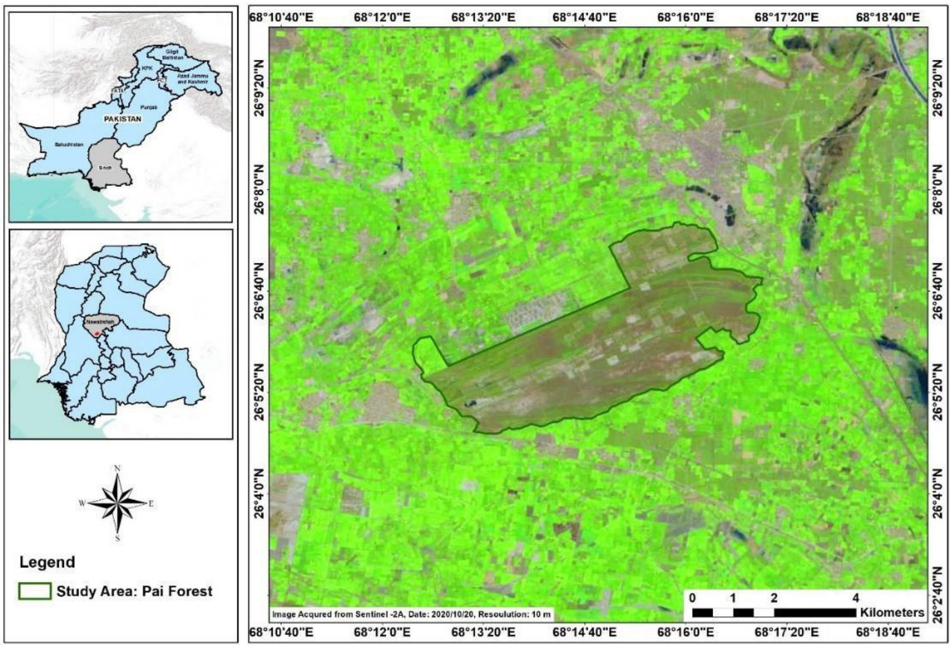

Figure 1. *Study Area.*

DOI: 10.6092/issn.2281-4485/12203

Pai Forest lies at an elevation of 4 to 33 m above sea level. The soil of the Pai Forest is sandy loam in texture having a pH range of 8 to 8.4. The moisture content in the soil is approximately 10% (WWF 2008). The climatic conditions of the forest are hot and arid in nature. The maximum temperature remains high from April to July and sometimes reaches up to 45°C in May and June. The minimum temperature usually reached up to 28°C in June and July. The mean annual precipitation has significantly declined from 2015 to 2018. The district experienced only 6.3 mm of mean annual precipitation in 2018. Relative Humidity remains high from July to September and sometimes experiences the mean monthly relative humidity up to 52%. The forest lives through the highest wind velocity during June, July, and August.

Diverse ecological resources including flora and fauna are found in the forest. Among large mammals, *Canis aureus* (Asiatic Jackal), *Felis chaus* (Jungle Cat), and *Axis porcinus* (Hog Deer) are very common. Resident birds in the forest include *Streptopelia decaocto* (Eurasian collared dove), *Psittacula krameri* (Parakeet), *merops orientalis* (Green bee-eater). Commonly found trees species are *Eucalyptus camaldulensis* (Sufaida or Baid Mushk), *Dalbergia sissoo* (Taali/Sheesham), *Ziziphus jujube* (Jujube), *Azadirachta indica* (Neem), *Acacia nilotica* (Baber), *Prosopis cineraria* (Kandi), *Salvadora persica* (Khabber), *Tamarix aphylla* (Lao) and *Salvadora oleoides* (Jaar/Peroon) (WWF 2008).

The area has a total of 22 villages, which are dependent on the forest include Palyo Bhutto, Mari Sabki, Mari Alam, Mari Jalbani, Ghulam Faqeer Zardari, Murad Kerio, Majeed Kerio, Gul Sher Machi, Ghulam Hyder Bhutto, Nazar Bhatti, Mehmood Kerio, Rahmo Kerio, Rasoolabad, Khan Muhammad Chowhan, Haji Kerio, Jaffar Jamali, Talli, Doud Gudaro, Ghulam Jatoi, Punhoon Gudaro, Morio Lakho and Nangar Chandio (Faruqi 2011).

Data Collection

Preliminary Survey. Before data collection, a preliminary survey of the study area was conducted to investigate the sites of the forests, which are suitable for field data collection and can potentially be helpful for serving as representative samples of the entire Pai Forest. The fishnet tool was applied using ArcGIS 10.1 before data collection, in order to get the quadrats of 800 m x 800 m. A total of 54 quadrats were obtained after the processing of Fishnet tool. Then, only those quadrats were selected whose boundaries are completely within the limits of the Pai Forest (Fig. 2).

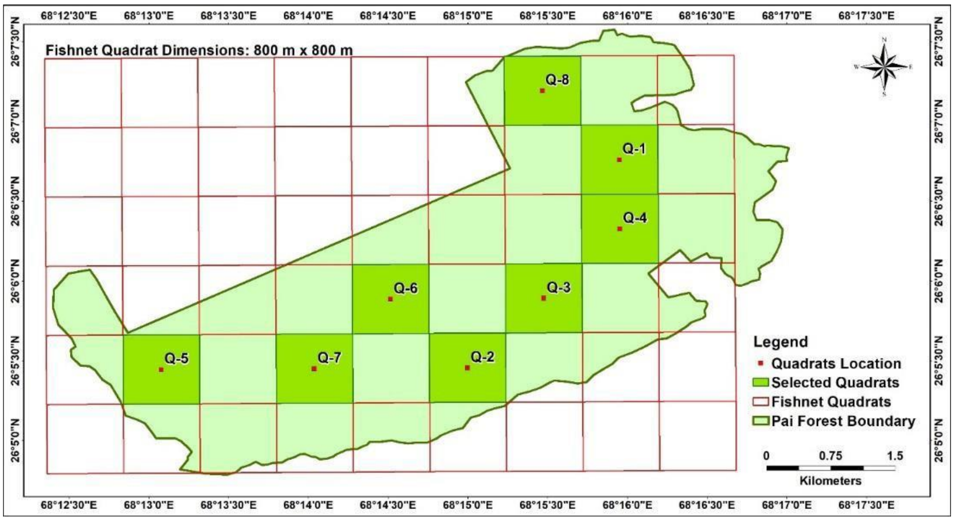

Figure 2. *Selected Quadrats.*

Field Data Collection. A field survey was conducted in March and April 2018 and a total of 232 individual trees from 9 tree species belonging to 7 families are selected to estimate the carbon stock.

RS and GIS Data Collection. Landsat-8 OLI/TIRS (Operational Land Imager/Thermal Infrared Scanner) imageries were acquired for the year 2018 and 2020 from https://earthexplorer.usgs.gov/. Landsat is a multispectral, sun-synchronous polar orbit, with a temporal and spatial resolution of 15 days and 30m respectively. Image processing was done by radiometric corrections for the Landsat image (Situmorang et al. 2016) which was then used to calculate NDVI and EVI. A detailed inventory of the satellite data is shown in Table 1.

DOI: 10.6092/issn.2281-4485/12203

Table 1. *Satellite Data Specifications.*

Date of Acquisition	April 19th, 2018	February 4th, 2020
Time of Acquisition (Zulu Time Zone)	05:50:42	05:56:47
Satellite	Landsat-8	Landsat-8
Sensor	OLI/TIRS	OLI/TIRS
Path/Row (WRS-2)	152/042	152/042
Number of Bands	11	11
Band Resolution (m)	30 (B1-B9), 100 (B10-B11)	30 (B1-B9), 100 (B10-B11)
Bands required for NDVI	B4 and B5	B4 and B5
Bands required for EVI	B2, B4 and B5	B2, B4 and B5
Cloud Cover (%)	0.39	0.51
Sun Elevation Angle (degrees)	63.80°	40.49°

Data Analysis

Field Data Analysis. Carbon sequestered by a tree is one-half of its biomass (Ajani & Shams 2016), since the trees on an average contain 50% carbon in different parts of their biomass (Chavan & Rasal 2011, 2012). In this study, quadrat wise analysis of the field data was performed. The biomass of all the individual trees in each quadrat was calculated by adopting the method suggested by a study (Ajani & Shams 2016). The height of the trees was calculated by using the Eq. [1].

$$\text{Tree height (m)} = \text{Tree shadow} \times \frac{\text{Your height}}{\text{Your shad}} \quad [1]$$

The tree trunk diameter at breast height (DBH) was taken at 1.3m for the calculation of Above Ground Biomass (A_{GB}). In Eq. [2], tree volume is denoted by V while Wood Density (W_D) is acquired from Global Wood Density Database (Zanne et al. 2009).

$$A_{GB} = V \times W_D \quad [2]$$

In Eq. 3, "r" is the tree trunk radius at breast height, and "H" is the height of tree.

$$V = \pi r^2 H \quad [3]$$

The Above Ground Biomass is multiplied by 0.26 [4] to obtain the Below Ground Biomass (B_{GB}) since the Below Ground Biomass of trees on an average is 26% of their Above Ground Biomass [5].

///

$$B_{GB} = A_{GB} \times 0.26 \quad [4]$$

$$T_B = A_{GB} \times B_{GB} \quad [5]$$

The Total Biomass (T_B) was calculated by adding the Above Ground Biomass and Below Ground Biomass. Carbon Stock (CS) was calculated by using Eq. [6].

$$CS = \frac{T_B}{2} \quad [6]$$

RS and GIS Data Analysis. Image processing was performed for the acquired satellite images. Before the calculation of NDVI, it is necessary to convert Digital Number (DN) values to Top of Atmosphere (ToA) Reflectance data. Therefore, individual bands of OLI were subjected to extract the study area using the masking tool, and then radiometric correction of each band was done separately (Table 2) using Eq. 7 and Eq. 8 (Situmorang et al. 2016); where, "$\rho\lambda$" is ToA reflectance, "Mρ" is Band-specific multiplicative rescaling factor, "Aρ" is Band-specific additive rescaling factor (provided in the metadata, "Qcal" is Quantized and calibrated standard product pixel values (DN) for each band, "θ_{SZ}" is Sun Zenith Angle and "θ_{SE}" is Sun Elevation Angle.

$$\rho\lambda = \frac{M\rho Qcal + A\rho}{\cos(\theta_{SZ})} \quad [7]$$

///

$$\theta_{SZ} = 90 - \theta_{SE} \quad [8]$$

DOI: 10.6092/issn.2281-4485/12203

Table 2. *OLI Specifications for radiometric corrections (2018 and 2020).*

Variables	Band 4 (Red) and Band 5 (NIR) of Landsat OLI	
	April 19th, 2018	February 4th, 2020
M_ρ	2×10^{-05}	2×10^{-05}
A_ρ	-0.1	-0.1
θ_{SE}	63.80815295°	40.49986490°
θ_{ZE}	26.19184705°	49.5001351°
Cos (θ_{ZE})	0.48965192802	0.72114175604

a) Normalized Difference Vegetation Index (NDVI)

The biomass of the tree species of the forest was obtained as pixel values and the NDVI was calculated by the following equation (Zhu & Liu 2015); where, NDVI is Normalized Difference Vegetation Index; NIR is Near Infrared Band and RED is Red Band, as:

$$NDVI = \frac{NIR - RED}{NIR + RED} \quad [9]$$

b) Enhanced Vegetation Index (EVI)

To compare the distribution of Index, EVI was calculated by using the following equation (Bannari et al. 1995); where EVI is Enhanced Vegetation Index, BLUE is Blue Band; C1 is values as coefficients for atmospheric resistance (Value 6); C2 is values as coefficients for atmospheric resistance (Value 7) and L is Value to adjust for canopy background, as:

$$EVI = 2.5 \times \frac{NIR - RED}{NIR + C1 \times RE - C2 \times BLUE + L} \quad [10]$$

Statistical Analysis

Correlation Model. During the above procedures, we calculated *Carbon* Stock using field-based analysis and NDVI using RS and GIS based analysis. Now, the basic purpose for statistical analysis is to find the correlation between Carbon Stock and NDVI and then to develop a regression equation for the sampled quadrats in the form linear regression equation. Person's Correlation Model, also called zero-order correlation (Ruigar & Golian 2015) was applied in this study using the following equation; where, "r_{xy}" is Pearson r correlation coefficient between x (NDVI) and y (CS), "n" is a number of quadrats, "x_i" is the value of x (NDVI) (for i^th quadrat) and "y_i" is value of y (CS) (for i^th quadrat).

$$r_{xy} = \frac{n\sum x_i y_i - \sum x_i \sum y_i}{\sqrt{\left[n\sum x_i^2 - \left(\sum x_i\right)^2\right]\left[n\sum y_i^2 - \left(\sum y_i\right)^2\right]}} \quad [11]$$

Regression Model. The obtained linear regression equation, as shown below, was then manipulated to quantify the Carbon Stock (dependent variable) across whole Pai Forest by calculating the NDVI (independent variable) through RS and GIS based analysis. Where, "y" is dependent variable (CS), "x" is independent variable (NDVI), "a" is Constant for Carbon Stock (CS) and "b" is intercept for NDVI and both were calculated using IBM SPSS version 22.

$$y = a + bx \quad [12]$$

////

$$CS = a + bNDVI \quad [13]$$

Data Validation

Data validation was done by calculating the standard deviation, skewness, and kurtosis of the mean values of each parameter, i.e., carbon stock, NDVI, and EVI for 2018 (Panda & Sahu 2019; C. Sharma & Ojha 2020). Skewness and kurtosis play a very significant role in forest research since both have the ability to describe the distribution of the selected parameters over the entire forest in a simplified manner (Duan et al. 2013). Moreover, in modeling-based analysis, such as this study has attempted to forecast the carbon stock of Pai Forest in the future using the RS and GIS-based technology, skewness and kurtosis helped to improve the regression analysis and R^2 values. Data validation was conducted using the following equations (Ghani & Ahmad 2010); where "N" is a number of quadrats selected, "σ" is Standard Deviation, "x_i" is i = 1, 2, 3, . . . , x, "N" is the series of quadrats (Q-1, Q-2, …Q-N), and "μ" is mean of observations.

DOI: 10.6092/issn.2281-4485/12203

$$\sigma=\frac{1}{N}\sum_{i=1}^{N}(x_i-\mu)^2 \quad [14]$$

//

$$\text{Skew}=\frac{N}{(N-1)(N-2)}\sum_{i=1}^{N}\left(\frac{x_i-\mu}{\sigma}\right)^3 \quad [15]$$

//

$$\text{Kurt}=\frac{N(N+1)}{(N-1)(N-2)(N-3)}\sum_{i=1}^{N}\left(\frac{x_i-\mu}{\sigma}\right)^4-\frac{3(N-1)^2}{(N-2)(N-3)} \quad [16]$$

Results and Discussion

Species specific carbon stock

Across the eight quadrats, a total of 232 trees representing 9 tree species belonging to 7 families were selected from Pai Forest during 2018. Results of Basal Area, Total Biomass (T_B), and Carbon Stock (CS) in the different tree species are placed in Table 3. Among all individuals, the Basal Area varied between 1.22 to 19.74 m^2, whereas T_B and CS varied between 8.417 to 426.405 metric ton and 4.208 to 213.202 metric ton, respectively.

Carbon Stock in all the individuals of all species (n=232) is 557.073 metric ton and on an average, the individual tree has 61.897 metric ton carbon. In this study, *Dalbergia sissoo* (n=26) demonstrated the greatest carbon stock (208.727 metric ton) among the selected species. *D. sissoo* also showed the highest mean carbon stock per tree (8.027 Mt/tree), which was followed by *Eucalyptus camaldulensis* (n=29, 7.351 Mt/tree) while *Salvadora oleoides* revealed the lowest mean carbon stock per tree (n=24, 0.175 Mt/tree). The literature divulges that the attained results for *D. sissoo* in Pai Forest are the uppermost value of Carbon Stock throughout the Asian Sub-continent (Kaur et al. 2002; C. M. Sharma et al. 2011) due to low disturbances. In contrast, a Brazilian study showed 13.45 to 17.55 Mt (Bernardo et al. 1998) for *E. camaldulensis* which is higher than this study. However, a study (Zhang et al. 2012) revealed Carbon Stock ranging from 1.33 to 3.932 Mt. Pakistan and Brazil located close to the equator compared to China, although China and Pakistan are South Asian countries. Altitudinal variation contributes significantly to the Carbon Stock in tree species as the carbon stocking potential of trees decreases with increasing altitude (Sheikh et al. 2009). The overall trend followed by the 9 species for the carbon stock is: *D. sissoo E.* > *camaldulensis* > *Z. jujube* > *A. nilotica* > *A. indica* > *S. persica* > *P. cineraria* > *T. aphylla* > *S. oleoides.*

Table 3. *Carbon Stock (CS) in Metric ton (Mt) of selected 9 tree species of Pai Forest.*

Families	Species	Number of individuals of a species	Basal Area (m^2)	T_B of all individuals of the species (Mt)	T_B/tree (Mt/tree)	CS of all individuals of the species (Mt)	CS/tree (Mt/tree)
Myrtaceae	*Eucalyptus camaldulensis*	29	11.07	426.405	14.703	213.202	7.3518
Fabaceae	*Dalbergia sissoo*	26	19.74	417.455	16.055	208.727	8.027
Rhamnaceae	*Ziziphus jujube*	22	8.28	85.995	3.9088	42.997	1.954
Meliaceae	*Azadirachta indica*	28	3.12	49.187	1.756	24.593	0.878
Mimosaceae	*Acacia nilotica*	22	2.87	49.130	2.233	24.565	1.116
Mimosaceae	*Prosopis cineraria*	29	4.14	32.514	1.121	16.257	0.560
Salvadoraceae	*Salvadora persica*	27	5.95	31.930	1.182	15.965	0.591
Tamaricaceae	*Tamarix aphylla*	25	1.22	13.109	0.524	6.554	0.262
Salvadoraceae	*Salvadora oleoides*	24	1.71	8.417	0.350	4.208	0.175
Total		232	58.1	1114.145	41.837	557.073	20.918
Mean			6.455	123.793	4.648	61.897	2.324
Min			1.22	8.417	0.350	4.208	0.175
Max			19.74	426.405	16.05	213.202	8.027

DOI: 10.6092/issn.2281-4485/12203

Correlation Matrix

Correlation Matrix between Carbon Stock, A_{GB} and B_{GB}. The present study discloses that the increase in biomass either above or below the ground is directly related to the increase in the carbon stock potential of the 9 selected tree species (Table 4). Similar results have also been produced by a study conducted over 229 territories and countries across the world (Kindermann et al. 2008).

Table 4. *Correlation matrix between carbon stock, A_{GB} and B_{GB}.*

Parameters	Carbon Stock	A_{GB}	B_{GB}
	Pearson's Correlation		
Carbon Stock	1		
A_{GB}	1.000**	1	
B_{GB}	1.000**	1.000**	1

**. Correlation is significant at 0.01 level ($p < 0.01$)

Correlation among all parameters involved in carbon stock estimation of selected species. The findings of the study show that the correlation among all the parameters involved in the carbon stock estimation of 9 selected species is statistically significant ($p<0.01$) (Table 5). Similar to our study, another study reported that the correlation between DBH, basal area, and tree volume was highly significant and the same study has concluded that *D. sissoo* is the most efficient tree to stock carbon and to sequester it for longer-term (Bohre et al. 2012).

Table 5. *Correlation among parameters involved in carbon ctock cstimation of selected species.*

Parameters	Carbon Stock	Circum-ference	DBH	Basal Area	Radius	Height	Wood Density	A_{GB}	B_{GB}
	Pearson's Correlation								
Carbon Stock	1								
Circumference	.827**	1							
DBH	.827**	1.000**	1						
Basal Area	.878**	.975**	.975**	1					
Radius	.878**	.975**	.975**	1.000**	1				
Height	.597**	.269**	.269**	.270**	.270**	1			
Wood Density	.536**	.656**	.656**	.644**	.644**	.275**	1		
A_{GB}	1.000	.827**	.827**	.878**	.878**	.597**	.536**	1	
B_{GB}	1.000	.827**	.827**	.878**	.878**	.597**	.536**	1.000**	1

**. Correlation is significant at 0.01 level ($p < 0.01$)

Geospatial Trends of NDVI and EVI in Pai Forest

In 2018, the ground-based analysis to calculate carbon stock and RS and GIS-based analysis to calculate NDVI and EVI show that Quadrat-1 (Q-1) demonstrated the highest NDVI and EVI values among all quadrats (Table 6). The spatial distribution of the NDVI and EVI of the sampled quadrats is geographically illustrated in Figure 3.

DOI: 10.6092/issn.2281-4485/12203

Table 6. *NDVI and EVI of Selected Quadrats in 2018*

Quadrats	2018								
	NI VI				E I				Calculated CS (Metric Tons)
	Min	Max	Mean	SD	Min	Max	Mean	SD	
Q-1	0.21	0.59	0.47	0.07	0.31	1.31	1.03	0.18	125.085
Q-2	0.25	0.55	0.44	0.06	0.44	1.19	0.89	0.15	93.799
Q-3	0.15	0.57	0.43	0.11	0.25	1.25	0.89	1.25	84.012
Q-4	0.16	0.58	0.46	0.10	0.29	1.28	0.96	0.23	121.461
Q-5	0.17	0.56	0.41	0.07	0.28	1.20	0.82	0.17	68.999
Q-6	0.15	0.59	0.42	0.11	0.27	1.29	0.86	0.27	70.467
Q-7	0.14	0.56	0.32	0.10	0.23	1.21	0.62	0.23	31.368
Q-8	0.15	0.56	0.43	0.09	0.26	1.23	0.86	0.23	83.999
Pai Forest	0.07	0.62	0.41	0.11	0.11	1.41	0.84	0.27	84.898

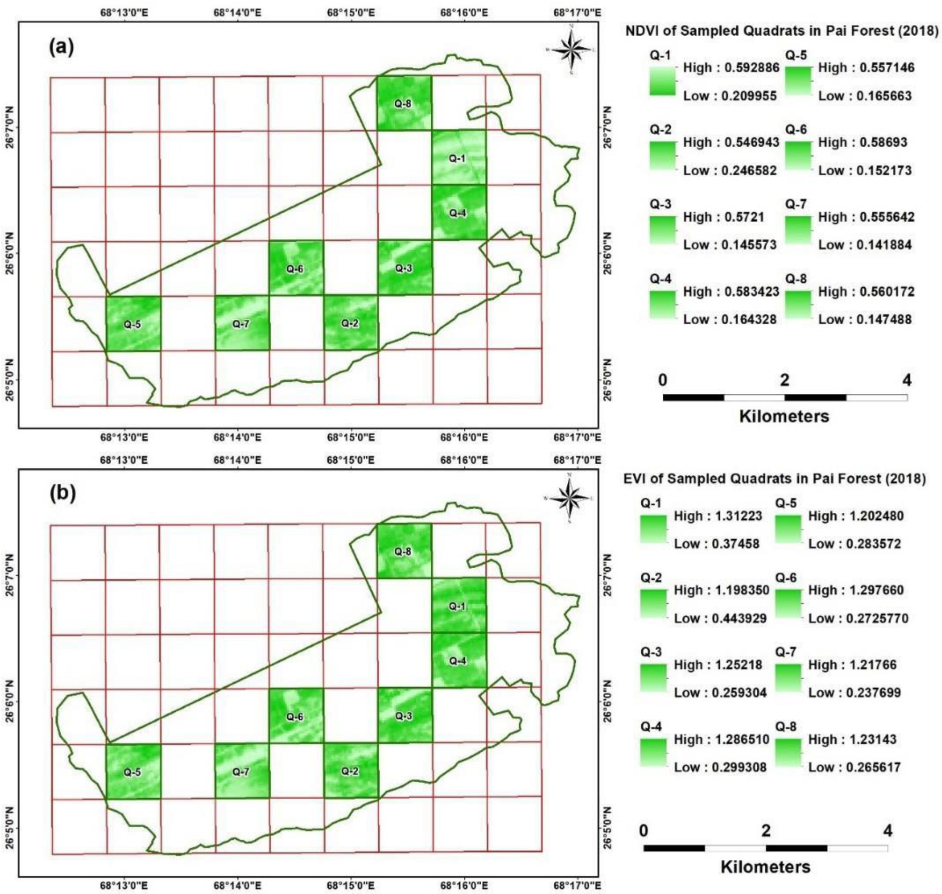

Figure 3. *NDVI and EVI of Sampled Quadrats in 2018.*

DOI: 10.6092/issn.2281-4485/12203

The interpolation-based geospatial distribution of the NDVI and EVI of the sampled quadrats is illustrated in Fig. 4. It was found that the highest mean NDVI in 2018 was observed in Q-1 (0.47) and the lowest in Q-7 (0.32) (Table 6), ranging from 0.21 to 0.59 and 0.14 to 0.56 respectively (Fig. 3a). However, the highest mean EVI in 2018 was also occurred in Q-1 (1.03) and the lowest in Q-7 (0.62) (Table 6), ranging from 0.23 to 1.21 and 0.31 to 1.31, respectively (Fig. 3b).

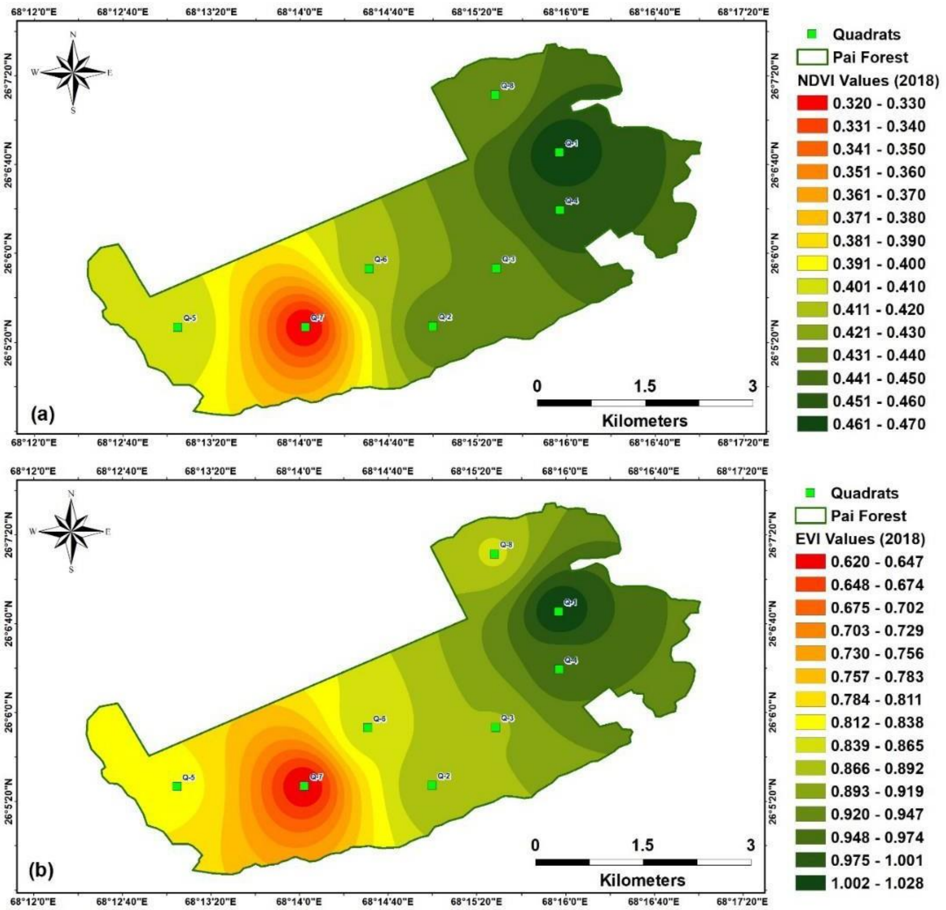

Figure 4. *Quadrat-wise NDVI and EVI in 2018.*

The results of *Raster Calculator* from *Spatial Analyst Tool* in ArcGIS 10.1 showed that in 2018, NDVI ranges from 0.07 to 0.62, and for EVI the entire Pai Forest has the value ranging from 0.1 to 1.4 (Fig. 5). Results produced in a study on spatial and temporal vegetation dynamics in Pai Forest are also indicating that the values of NDVI have declined from -0.030303 to 0.585586 in 1987 to -0.0148 to 0.4331 in 2014 (Siyal et al. 2016). In 2020, the lowest NDVI was observed in Q-3 (0.27) and the highest in Q-5 (0.42) (Table 7) ranging from 0.14 to 0.49 and 0.18 to 0.63, respectively (Fig. 6a). In 2020, the lowest EVI was observed in Q-2 (0.47) and highest in Q-5 (0.74) (Table 7) ranging from 0.05 to 0.16 and 0.07 to 0.18, respectively (Fig. 6b).

DOI: 10.6092/issn.2281-4485/12203

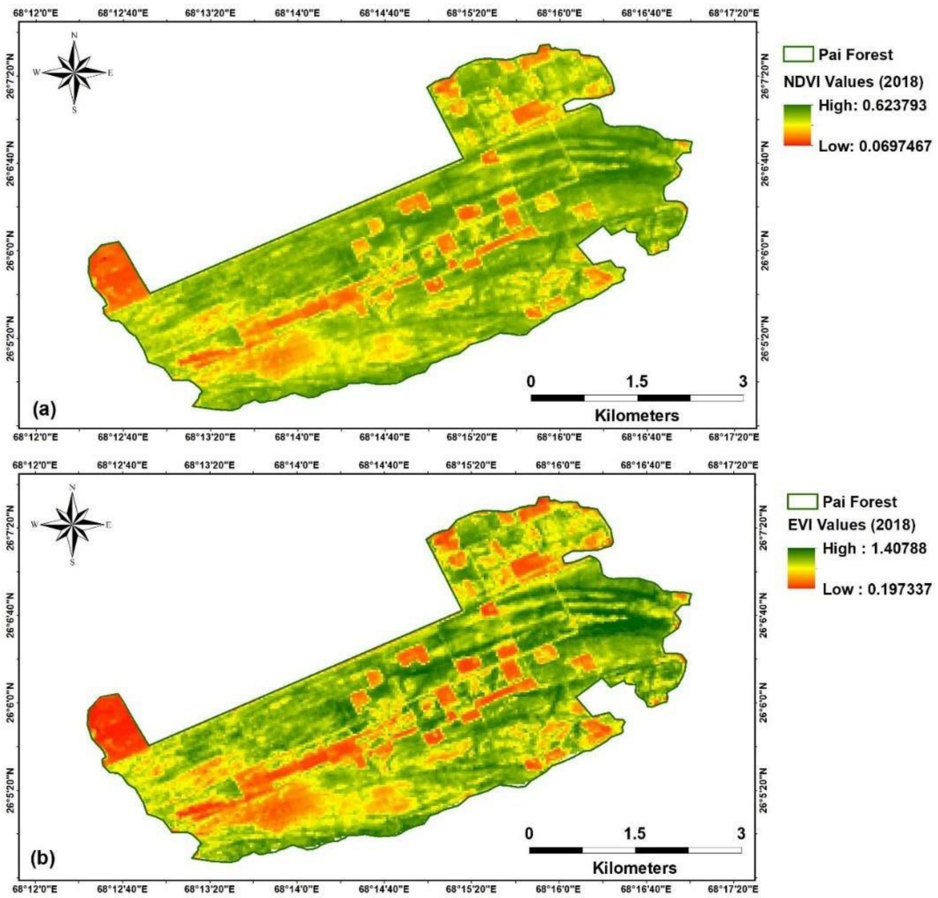

Figure 5. *NDVI and EVI of Pai Forest in 2018*

Table 7. *NDVI and EVI of Selected Quadrats in 2020*

2020										
Quadrats	Calculated								Estimated	
	NDVI				EVI				CS (Mt) on the basis of NDVI	CS (Mt) on the basis of EVI
	Min	Max	Mean	SD	Min	Max	Mean	SD		
Q-1	0.17	0.53	0.4	0.07	0.16	0.52	0.36	0.07	70.6	106.48
Q-2	0.18	0.5	0.29	0.05	0.16	0.47	0.24	0.05	2.51	29.32
Q-3	0.14	0.49	0.27	0.06	0.14	0.49	0.23	0.06	1.5	22.89
Q-4	0.19	0.52	0.36	0.07	0.17	0.51	0.32	0.07	45.84	80.76
Q-5	0.18	0.63	0.42	0.07	0.18	0.74	0.39	0.07	82.98	125.77
Q-6	0.16	0.55	0.34	0.08	0.16	0.56	0.31	0.09	33.46	74.33
Q-7	0.17	0.53	0.3	0.08	0.16	0.53	0.27	0.08	8.7	48.61
Q-8	0.17	0.5	0.36	0.08	0.17	0.48	0.32	0.08	45.84	48.61
Pai Forest	-0.18	0.75	0.36	0.1	-0.12	1.01	0.33	0.12	36.42	67.09

DOI: 10.6092/issn.2281-4485/12203

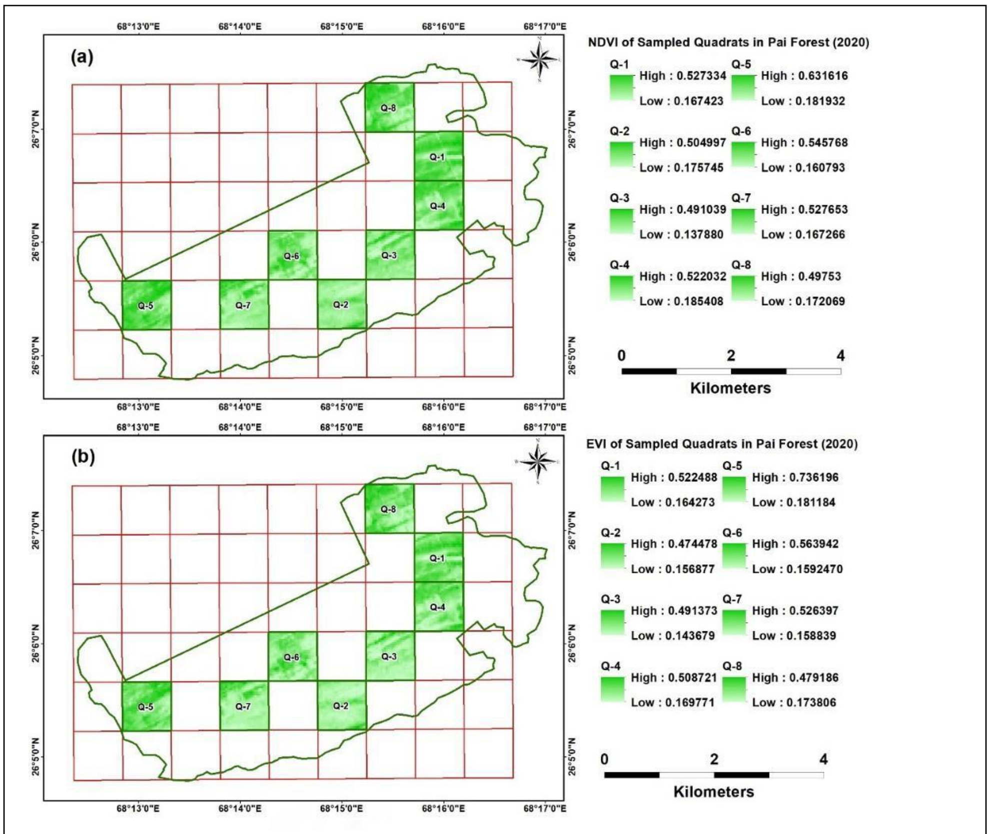

Figure 6. *NDVI and EVI of Sampled Quadrats in 2020*

The interpolation based geospatial distribution analysis of both the vegetation indices shows that the highest NDVI and EVI are found along the extreme eastern and western side of the forest (Fig. 7).

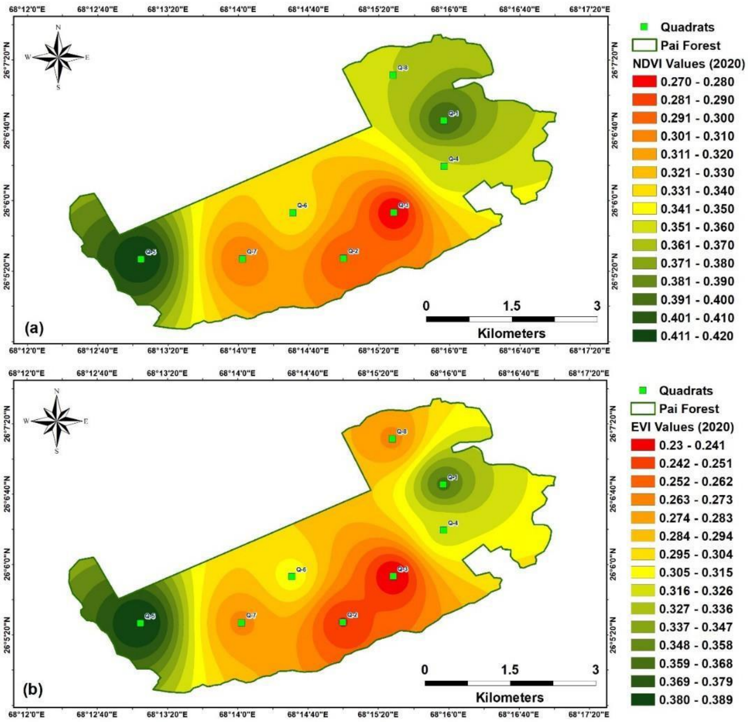

Figure 7. *Quadrat-wise NDVI and EVI in 2020.*

DOI: 10.6092/issn.2281-4485/12203

However, the confined area of low values of NDVI and EVI in the southwestern part of the forest in 2018 (Fig. 4), has further expanded towards the central part of the forest in 2020 (Fig. 7). Thus, it is clearly indicating that according to both the vegetation indices, vegetation has declined in the Pai Forest and the central part of the forest is largely affected.

Using *Raster Calculator* from *Spatial Analyst Tool* in ArcGIS 10.1, the NDVI and EVI of the entire Pai Forest were calculated on the pixel-wise data. The analysis revealed that NDVI ranges from -0.18 to 0.75 (Fig. 8) and for EVI has a value ranging from -0.12 to 1.01 in the Pai Forest.

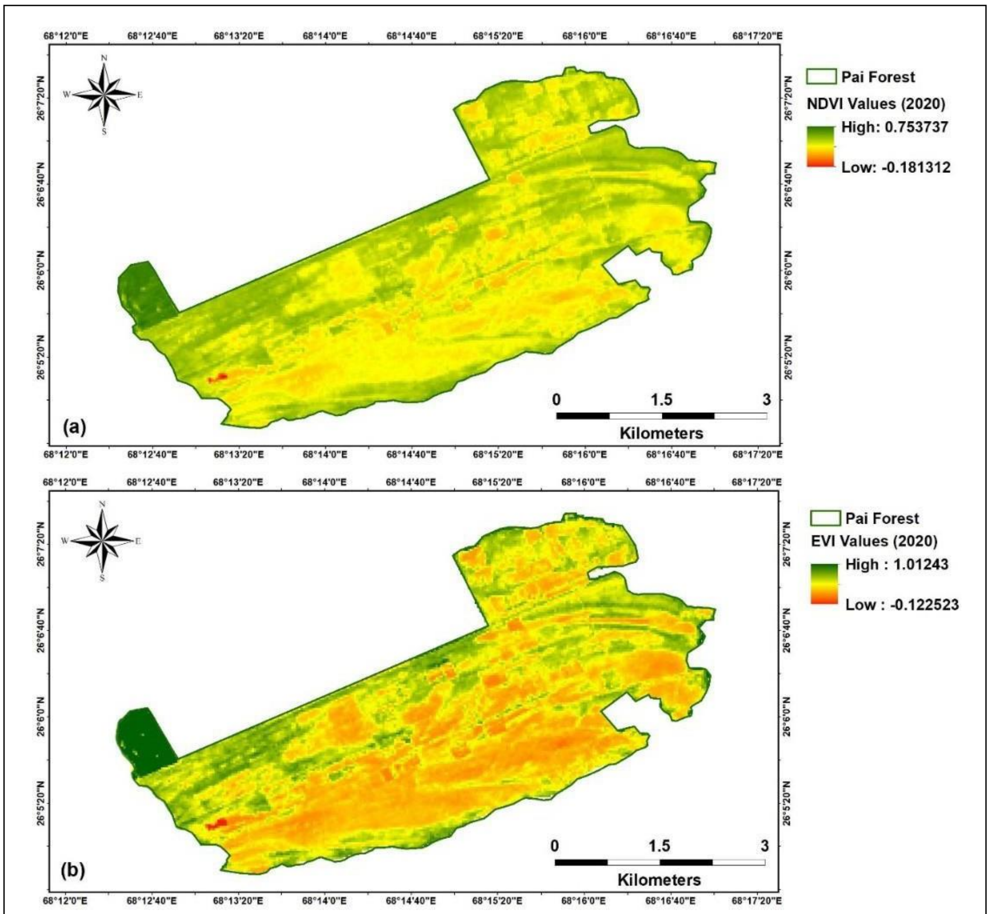

Figure 8. *NDVI and EVI of Pai Forest in 2020.*

Calculated Carbon Stock in 2018. The calculated carbon stock of Pai Forest in 2018 is illustrated in Table 8 indicating that the Carbon Stock in the forest ranges from 31.368 Mt to 121.461 Mt. These results were achieved using the field data. These values were then shown geographically using the interpolation tool as represented in Fig. 9. The geospatial distribution of Carbon Stock depicts that the central part of the forest has minimum carbon stock around Q-7. Whereas, on eastern and western extremes, the carbon stock was detected at higher values. Carbon stock calculation on ground level has been widely conducting all over the world aiming to develop a strong statistical correlation between the carbon stock and vegetation indices. Then, this statistical correlation can be used to remotely detect the carbon stock of any ecosystem with the help of satellite imageries without conducting a survey. Similarly, a number of studies have adopted this methodology. Therefore, the interest in carbon stock estimation has largely affected forest studies in a positive manner which has opened a window towards the wide application of RS and GIS in the forestry sector (Situmorang et al. 2016).

DOI: 10.6092/issn.2281-4485/12203

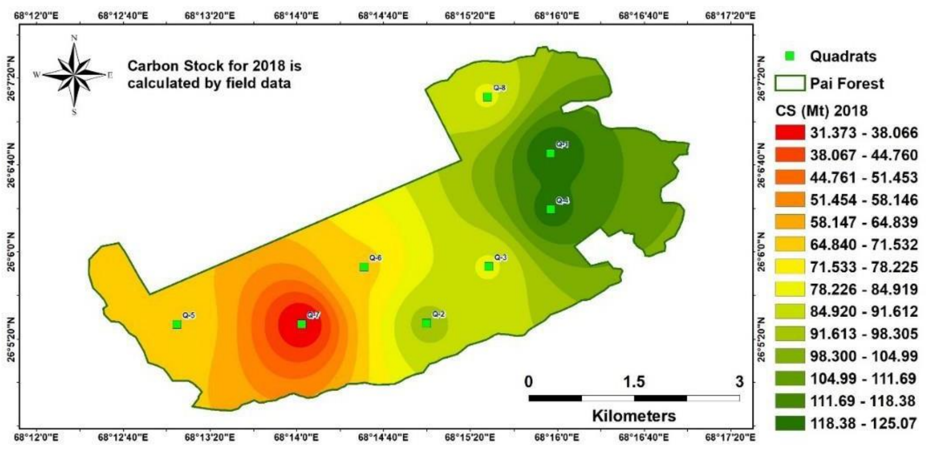

Figure 9. *Carbon Stock in 2018*

Estimated Carbon Stock in 2020. Based on the statistical analysis for finding the correlation and regression between NDVI and EVI of 2018 with the calculated carbon stock of Pai Forest in 2018, a statistical equation was developed. According to the statistical and RS and GIS-based analysis, carbon stock in 2020 was indirectly estimated for the year 2020 using the NDVI and EVI values of the same year (Table 8).

Table 8. *Calculated and estimated carbon stock in Pai Forest in 2018 and 2020.*

Carbon Stock in 2018 (Calculated)				
Quadrats	Mean NDVI	Mean EVI	Calculated CS (Metric Tons)	
Q-1	0.47	1.03	125.085	
Q-2	0.44	0.89	93.799	
Q-3	0.43	0.89	84.012	
Q-4	0.46	0.96	121.461	
Q-5	0.41	0.82	68.999	
Q-6	0.42	0.86	70.467	
Q-7	0.32	0.62	31.368	
Q-8	0.43	0.86	83.999	
Pai Forest	0.41	0.84	84.89875	
Carbon Stock in 2020 (Estimated)				
Quadrats	Mean NDVI	Mean EVI	CS (Metric Tons) using NDVI	CS (Metric Tons) using EVI
Q-1	0.4	0.36	70.6	106.48
Q-2	0.29	0.24	2.51	29.32
Q-3	0.27	0.23	1.5	22.89
Q-4	0.36	0.32	45.84	80.76
Q-5	0.42	0.39	82.98	125.77
Q-6	0.34	0.31	33.46	74.33
Q-7	0.3	0.27	8.7	48.61
Q-8	0.36	0.27	45.84	48.61
Pai Forest	0.36	0.33	36.42	67.09

DOI: 10.6092/issn.2281-4485/12203

Correlation and Regression Modeling

It corresponds to the *Indirect Carbon Stock Estimation using NDVI and EVI*. The results show that for the 8 selected quadrats in Pai Forest in 2018, a positive correlation has been found among carbon stock, mean NDVI, and mean EVI values. All the correlation coefficients were found statistically significant ($p < 0.01$) (Table 9). Similarly, a study (Vicharnakorn et al. 2014) has also performed correlation and regression analysis in various types of forests including Dry Dipterocarp Forest (DDF), Dry Evergreen Forest (DEF), Disturbed Forest (DF), Mixed Deciduous Forest (MDF), and Paddy Fields (PFi). This study was conducted in the tropical forest region of Savannakhet Province of Laos in the Asian continent over 81 plots of 40 × 40 m dimensions. This study concludes that the strongest correlation was found in the Mixed Deciduous Forest (MDF) among vegetation indices and above-ground biomass. In Pai Forest, a strong correlation also found among carbon stock when compared with both the vegetation indices; NDVI, and EVI.

Table 9. *Correlation between calculated carbon stock with NDVI and EVI of Pai Forest, 2018.*

Parameters	Mean CS 2018	Mean NDVI 2018	Mean EVI 2018
	Pearson's Correlation		
Mean CS 2018	1		
Mean NDVI 2018	0.944**	1	
Mean EVI 2018	0.962**	0.983**	1

**. Correlation is significant at 0.01 level ($p < 0.01$)

Estimation of Carbon Stock on the basis of NDVI and EVI

The regression model was incorporated to indirectly estimate the carbon stock in the Pai Forest for the year 2020. Using this model, NDVI values were correlated with the carbon stock of the year 2018 and then used for the estimation of carbon stock in 2020 on the basis of slope and intercept. Using the regression model for NDVI and Carbon Stock in 2018, the estimated carbon stock in 2020 on the basis of NDVI is shown in Figure 10a. The value of R^2 is illustrated with the NDVI and Carbon Stock relation in Figure 11a. Similar to NDVI, the regression model was incorporated to indirectly estimate the Carbon Stock in the Pai Forest for the year 2020. Correlation of the EVI values was found with the Carbon Stock of the year 2018 which is then used for the estimation of Carbon Stock in 2020 on the basis of slope and intercept. The value of R^2 is illustrated with the EVI and Carbon Stock relation in Figure 10b. Using the regression model for EVI and Carbon Stock in 2018, the estimated carbon stock in 2020 on the basis of EVI is shown in Figure 11b.

$$CS = -177 + 619\ NDVI \quad [17]$$

$$CS = -125 + 243\ EVI \quad [18]$$

Model summary, Analysis of variance (ANOVA) and Coefficient constants for carbon stock with NDVI and EVI in 2018 are represented in Table 10.

DOI: 10.6092/issn.2281-4485/12203

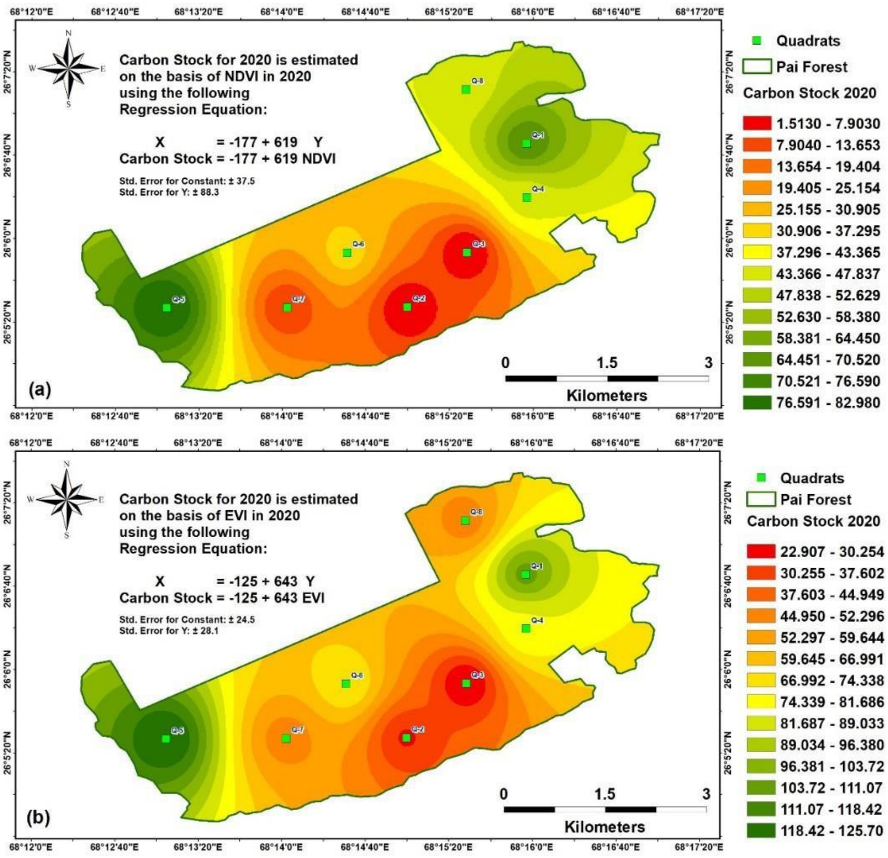

Figure 10. *(a) NDVI and (b) EVI based Carbon Stock in 2020.*

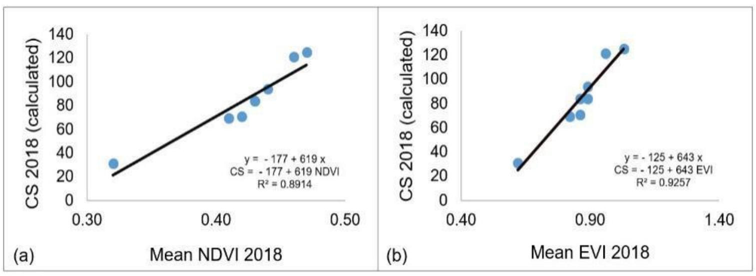

Figure 11. *R^2 of (a) NDVI and (b) EVI with Carbon Stock in 2018.*

DOI: 10.6092/issn.2281-4485/12203

Table 10. *Model Summary, ANOVA and Coefficients of NDVI and EVI*

Model Summary[a]						
Parameters		**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**	
NDVI		0.944[b]	0.891	0.873	10.727556	
EVI		0.962[c]	0.926	0.913	8.87726	
ANOVA[a]						
Model		**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
NDVI	Regression	5668.693	1	5668.693	49.259	0.000[b]
	Residual	690.483	6	115.080	-	-
	Total	6359.176	7	-	-	-
EVI	Regression	5886.327	1	5886.327	74.694	0.000[c]
	Residual	472.835	6	78.806	-	-
	Total	6359.162	7	-	-	-
Coefficients[a]						
Model		**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**
		B	**Std. Error**	**Beta**		
NDVI	Constant	-177.023	37.511	-	-4.71	0.003
	Mean NDVI 2018	619.934	88.329	0.944	7.01	0.000
EVI	Constant	-125.704	24.569	-	-5.116	0.002
	Mean EVI 2018	243.119	28.130	0.962	8.643	0.000

(a) Dependent Variable: Mean Carbon Stock 2018, (b) Predictors: Constant, Mean NDVI 2018 and (c) Predictors: Constant, Mean EVI 2018

Conclusions

The carbon stock inventory of the Pai Forest was directly and indirectly developed for the years 2018 and 2020 respectively, by means of NDVI and EVI using field data and geospatial assessments. The results showed that for the 8 selected quadrats in Pai Forest in 2018, a positive correlation has been found among carbon stock based on the selected tree species, mean NDVI, and mean EVI values. All the correlation coefficients were found significant ($p < 0.01$). The geospatial results and indirect estimation of carbon stock in 2020 using correlation and regression model highlighted that the central part of the forest has lost the carbon stock at an alarming rate and has lesser NDVI and EVI values compared to the quadrats located at the periphery of the forest. The results of this study are statistically significant and the adopted methodologies can be further explored for detailed studies on forest carbon dynamics and inventory preparation. The regression models of NDVI and EVI in correlation with carbon stock can successfully be implemented on any forested ecosystem once the baseline carbon stock data would be taken for the particular tree species. The integration of RS and GIS, satellite data, and statistical analysis with ground-based carbon stock data is an innovative method that can aid carbon stock inventory development of historic times and for future forecasting of carbon stock dynamics.

DOI: 10.6092/issn.2281-4485/12203

Acknowledgement
The authors are thankful to the REDD+ and Ministry of Climate Change, Pakistan, to facilitate this research in Implementing REDD+ Readiness Preparation Proposal with the financial support of the Forest Carbon Partnership Facility of the World Bank.

References

AJANI A., SHAMS Z. I. (2016) Comparative status of sequestered carbon stock of Azadirachta indica and Conocarpus erectus at the University of Karachi Campus, Pakistan. International Journal of Environment, 5(2):89–97. https://doi.org/10.3126/ije.v5i2.15009

BANNARI A., MORIN D., BONN F., HUETE A. R. (1995) A review of vegetation indices. Remote Sensing Reviews, 13(1–2):95–120. https://doi.org/10.1080/02757259509532298

BERNARDO A.L., REIS M.G.F., REIS G.G., HARRISON R.B., FIRME D.J. (1998) Effect of spacing on growth and biomass distribution in Eucalyptus camaldulensis, E. pellita and E. urophylla plantations in southeastern Brazil. Forest Ecology and Management, 104(1–3):1–13. https:doi.org/10.1016/S0378-1127(97)00199-0

BOHRE P., CHAUBEY O.P., SINGHAL P.K. (2012) Biomass accumulation and carbon sequestration in Dalbergia sissoo Roxb. International Journal of Bio-Science and Bio-Technology, 4(3):29–44.

BULLOCK E.L., WOODCOCK C.E. (2020) Carbon loss and removal due to Forest disturbance and regeneration in the Amazon. Science of The Total Environment, 142839. https://doi.org/10.1016/j.scitotenv.2020.142839

CHAVAN B.L., RASAL G.B. (2011) Sequestered carbon potential and status of Eucalyptus tree. International Journal of Applied Engineering and Technology, 1(1):41–47.

CHAVAN B.L., RASAL G. B. (2012) Comparative Status of Carbon Dioxide Sequestration in Albizia Lebbek and Delonix Regia. Universal Journal of Environmental Research & Technology, 2(1):85–92.

DUAN A., ZHANG J., ZHANG X., HE C. (2013) Stand diameter distribution modelling and prediction based on Richards function. PLoS One, 8(4), e62605. https://doi.org/10.1371/journal.pone.0062605

ECKSTEIN D., KÜNZEL V., SCHÄFER L., WINGES M. (2019) Global Climate Risk Index (2020) Who Suffers Most from Extreme Weather Events? Weather-Related Loss Events in 2018 and 1999 to 2018. Germanwatch. https://germanwatch.org/en/cri - Accessed on 2 February, 2020.

FARUQI S. (2011) Into the Pai Forest. Dawn. https://www.dawn.com/news/680945/into-the-pai-forest - Accessed on 7 December, 2018.

FIELD C.B., BARROS V.R., DOKKEN D.J., MACH K.J., MASTRANDREA M. D., BILIR T.E., CHATTERJEE M., EBI K.L., ESTRADA Y.O., GENOVA R.C., (2014) IPCC 2014: Summary for policymakers in Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Contrib. Work. Gr. II to Fifth Assess. Rep. Intergov. Panel Clim. Chang:1–32. https://epic.awi.de/id/eprint/37531/

GHANI I.M.M., AHMAD S. (2010) Stepwise multiple regression method to forecast fish landing. Procedia-Social and Behavioral Sciences, 8:549–554. https://doi.org/10.1016/j.sbspro.2010.12.076

HIRATSUKA M., NAKAMA E., SATRIADI T., FAUZI,H., ARYADI M., MORIKAWA Y. (2019) An approach to achieve sustainable development goals through participatory land and forest conservation: a case study in South Kalimantan Province, Indonesia. Journal of Sustainable Forestry, 38(6):558–571. https://doi.org/10.1080/10549811.2019.1598440

JANTZ P., GOETZ S., LAPORTE N. (2014) Carbon stock corridors to mitigate climate change and promote biodiversity in the tropics. Nature Climate Change, 4(2):138–142. https://doi.org/10.1038/nclimate2105

KAUR B., GUPTA S.R., SINGH G. (2002) Carbon storage and nitrogen cycling in silvopastoral systems on a sodic in northwestern India. Agroforestry Systems, 54(1):21–29. https://doi.org/10.1023/A:1014269221934

KHAN A.J., ALI W. (2019) Capacity Development Challenges in the way of SDGs implementation in Pakistan. Sustainable Development Policy Institute. https://think-asia.org/bitstream/handle/11540/9713/W-166.pdf?

KINDERMANN G., MCCALLUM I., FRITZ S., OBERSTEINER M. (2008) A global forest growing stock, biomass and carbon map based on FAO statistics. Silva Fennica, 42(3):387–396. https://doi.org/10.14214/sf.244

NERINI F.F., SOVACOOL B., HUGHES N., COZZI L., COSGRAVE E., HOWELLS M., TAVONI M., TOMEI J., ZERRIFFI H., MILLIGAN B. (2019) Connecting climate action with other Sustainable Development Goals. Nature Sustainability, 2(8):674–680. https://doi.org/10.1038/s41893-019-0334-y

DOI: 10.6092/issn.2281-4485/12203

PANDA A., SAHU N. (2019) Trend analysis of seasonal rainfall and temperature pattern in Kalahandi, Bolangir and Koraput districts of Odisha, India. Atmospheric Science Letters, 20(10), e932. https://doi.org/10.1002/asl.932

QAMER F.M., SHEHZAD K., ABBAS S., MURTHY M.S.R., XI C., GILANI H., BAJRACHARYA B. (2016) Mapping deforestation and forest degradation patterns in western Himalaya, Pakistan. Remote Sensing, 8(5):385–401. https://doi.org/10.3390/rs8050385

RUIGAR H., GOLIAN S. (2015) Assessing the correlation between climate signals and monthly mean and extreme precipitation and discharge of Golestan Dam Watershed. Earth Sciences Research Journal, 19(1):65–72. https://doi.org/10.15446/esrj.v19n1.40996

SACHS J., SCHMIDT-TRAUB G., KROLL C., LAFORTUNE G., FULLER G., WOELM F. (2020) Sustainable Development Report 2020. The Sustainable Development Goals and COVID-19. Cambridge University Press Development Report. https://sdgindex.org/reports/sustainable-development-report-2020/ - Accessed on 7 August, 2020

SHARMA C.M., GAIROLA S., BADUNI N.P., GHILDIYAL S.K., SUYAL S. (2011) Variation in carbon stocks on different slope aspects in seven major forest types of temperate region of Garhwal Himalaya, India. Journal of Biosciences, 36(4):701–708. https://doi.org/10.1007/s12038-011-9103-4

SHARMA C., OJHA C.S.P. (2020) Statistical parameters of hydrometeorological variables: standard deviation, SNR, skewness and kurtosis. In Advances in Water Resources Engineering and Management:59–70. Springer. https://doi.org/10.1007/978-981-13-8181-2_5

SHEIKH M.A., KUMAR M., BUSSMANN R.W. (2009) Altitudinal variation in soil organic carbon stock in coniferous subtropical and broadleaf temperate forests in Garhwal Himalaya. Carbon Balance and Management, 4(1):6. https://doi.org/10.1186/1750-0680-4-6

SITUMORANG J. P., SUGIANTO S., DARUSMAN D. (2016) Estimation of Carbon Stock Stands using EVI and NDVI vegetation index in production forest of lembah Seulawah sub-district, Aceh Indonesia. Aceh International Journal of Science and Technology, 5(3):126–139. https://doi.org/10.13170/aijst.5.3.5836

SIYAL A.A., SIYAL A.G., MAHAR R.B. (2016). Spatial and temporal dynamics of Pai forest vegetation in Pakistan assessed by RS and GIS. Journal of Forestry Research, 28(3):593–603. https://doi.org/10.1007/s11676-016-0327-x

VICHARNAKORN P., SHRESTHA R.P., NAGAI M., SALAM A.P., KIRATIPRAYOON S. (2014) Carbon stock assessment using remote sensing and forest inventory data in Savannakhet, Lao PDR. Remote Sensing, 6(6):5452–5479. https://doi.org/10.3390/rs6065452

VIEILLEDENT G., VAUDRY R., ANDRIAMANOHISOA S.F.D., RAKOTONARIVO O.S., RANDRIANASOLO H.Z., RAZAFINDRABE H.N., RAKOTOARIVONY C.B., EBELING J., RASAMOELINA M. (2012) A universal approach to estimate biomass and carbon stock in tropical forests using generic allometric models. Ecological Applications, 22(2):572–583. https://doi.org/10.1890/11-0039.1

WORLD BANK (2016) World Development Indicators Database, Forest Area. World Bank. https://data.worldbank.org/indicator/AG.LND.FRST.ZS?locations=PK - Accessed on 14 June 2019

WWF. (2008). Natural Vegetation Assessment. In S. Khatoon & G. Akbar (Eds.), Indus for All Programme, WWF Pakistan.
ZANNE, A. E., LOPEZ-GONZALEZ, G., COOMES, D. A., ILIC, J., JANSEN, S., LEWIS, S. L., MILLER, R. B., SWENSON, N. G., WIEMANN, M. C., & CHAVE, J. (2009). Global Wood Density Database. http://db.worldagroforestry.org/

ZHANG, H., GUAN, D., & SONG, M. (2012). Biomass and carbon storage of Eucalyptus and Acacia plantations in the Pearl River Delta, South China. Forest Ecology and Management, 277:90–97. https://doi.org/10.1016/j.foreco.2012.04.016

ZHU, X., & LIU, D. (2015). Improving forest aboveground biomass estimation using seasonal Landsat NDVI time-series. ISPRS Journal of Photogrammetry and Remote Sensing, 102:222–231. https://doi.org/10.1016/j.isprsjprs.2014.08.014