Research Article

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Forest biomass assessment combining field inventorying and remote sensing data

Abstract: Forests offer high potential for the fight against climate change. However, forests are faced with increased deforestation. REDD+ is a financial mechanism that offers hope to developing countries for tackling deforestation. Aboveground (AGB) estimation, however, is necessary for such financial mechanisms. Remote sensing methods offer various advantages for AGB estimation. A study, therefore, was conducted for the estimation of AGB using a combination of remote sensing Sentinel-1 (S1) and Sentinel-2 (S2) satellite data and field inventorying. The mean AGB for Sub-tropical Chir Pine Forest was recorded as 146.73 ± 65.11 Mg ha⁻¹, while for Sub-tropical Broadleaved Evergreen Forest it was 33.77 ± 51.63 Mg ha⁻¹. Results revealed weak associations between the S1 and S2 data with the AGB. Nonetheless, S1 and S2 offer advantages such as free data resources that can be utilized by developing countries for forest biomass and carbon monitoring.

Keywords: forests, biomass, carbon, remote sensing, climate change

1 Introduction

Forests have the potential to greatly affect the global carbon cycle which can influence the greenhouse effect. They account for 80% of terrestrial carbon and thus play an essential role in climate change mitigation [1]. They are spread over 31% of the earth’s surface, which makes up 4.06 billion hectares (ha) of the land surface [2]. Moreover, they are an essential source of income and livelihood for 1.6 billion people in the world and, therefore, can significantly affect human lives [3]. They also provide a range of ecosystem services and harbor immensely rich biodiversity [4].

According to the Food and Agriculture Organization, Pakistan has a forest area of 4.6% [2]. Forest per capita in Pakistan is only 0.03 compared to the global average of 1 ha [5]. Despite this low forest resource, Pakistan is facing one of the world’s highest deforestation rates of 0.94% annually (from 2010 to 2020) [2]. The "reducing emissions from deforestation and forest degradation and the role of conservation of forest carbon, sustainable management of forests and enhancement of forest carbon stocks" (REDD+) is a result-based financial incentive for developing countries for countering deforestation [6]. However, for REDD+, forest carbon stock assessment is one of the main requirements.

Due to various advantages such as large area coverage and less time consumption, remote sensing has emerged as the most popular method for aboveground (AGB) estimations [7,8]. Amongst different sensors, passive sensors/optical remote sensing have been used widely by numerous researchers for AGB estimation [9,10]. These sensors have been the most preferred because of the high correlations between the spectral bands and/or vegetation indices (VIs) with the AGB [11,12]. Passive sensors utilize the energy from the sun and cannot operate without sunlight [13]. The spatial resolutions for the passive sensors vary from less than one meter to hundreds of meters [10]. The passive sensors have been available and operating for a very long time and provide rich data archives [14,15]. For instance, Landsat and the National Oceanic and Atmospheric Administration Advanced Very High-Resolution Radiometer (AVHRR) missions have been operating for the last 40 years and more [14–16]. Some of the passive sensors include: coarse spatial resolution (>100 m): Moderate Resolution Imaging Spectroradiometer, AVHRR, Meteosat, and SPOT vegetation; medium spatial resolution (10–100 m): Sentinel-2 (S2), Thematic Mapper (TM), Enhanced Thematic Mapper Plus, Operational Land Imager (OLI), and SPOT; fine/high spatial resolution (<5 m): QuickBird, WorldView-2, and IKONOS [15].
Radio detection and ranging (Radar) is another important sensor used for remote sensing. It is an active sensor and can acquire satellite data irrespective of cloud covers, weather, and light conditions [16]. Some other characteristics of the Radar sensors include penetration through the vegetation, soil, and to a certain degree in dry snow; sensitivity to surface roughness, dielectric properties and moisture, wave polarization, and frequency; and volumetric analysis [12]. The dielectric properties are an essential component of a material that describes its interaction with an electrical field [17,18]. Polarization of the electromagnetic waves refers to the orientation of the electric field intensity [19].

Synthetic Aperture Radar (SAR) is a technique/system of Radar that uses signal processing for improving the spatial resolution beyond the limitation of physical antenna aperture [20]. SAR uses the forward motion of an actual antenna for synthesizing a very long antenna which allows the use of longer microwave wavelengths and obtaining good spatial resolution beyond the limitation of physical antenna aperture [21]. The energy utilized by the SAR for remote sensing falls in the electromagnetic microwave domain which ranges from 1 mm to 1 m in wavelengths or 0.3–300 GHz in terms of frequency [22]. The most common microwave bands used in SAR remote sensing include X-band (2.4–3.8 cm wavelength), C-band (3.8–7.5 cm wavelength), L-band (15–30 cm wavelength) and some experiments have also used S-band (7.5–15 cm), P-band (30–100 cm wavelength), and very high frequency band (>1 m wavelength) [19,23]. In SAR, the reflection of the energy from the objects back to the sensor is termed a backscatter and the earth features that interact with the transmitted energy are termed scatterers [24]. Various researchers have demonstrated the potential of SAR sensors for estimating AGB [25,26].

The SAR sensors generally emit signals in horizontal (H) or vertical (V) polarizations [12]. The four general polarization combinations for SAR sensors include (1) HH: the emitted signal has horizontal polarization and the received backscatter also has horizontal polarization, (2) HV: the emitted signal has horizontal polarization and the received backscatter has vertical polarization, (3) VH: the emitted microwave signal has a vertical polarization and the received backscatter energy has a horizontal polarization, and (4) VV: the emitted signal has a vertical polarization and the received signal will also be in vertical polarization [27]. HH and VV are co- or like polarized and HV and VH are cross-polarized signals [28]. The cross-polarized microwave signals are more sensitive to the AGB [12]. Sentinel-1 (S1), Advance Land Observing Satellite-2, RADARSAT 2, RADARSAT constellation mission, TerraSAR-X, TerraSAR-X add-ons for Digital Elevation Measurements, etc. are some of the SAR satellite missions.

To utilize the advantages of free available remote sensing resources for the overall management of the Margalla Hills National Park (MHNP), Pakistan, this study was conducted where AGB was estimated using a combination of field inventory with S1 and S2 data.

2 Materials and methods

2.1 Study area

MHNP is spread over an area of 17,386 ha [29] (Figure 1). The elevation of the MHNP is between 1,347 and 3,907 ft. The MHNP consists of three zones, i.e., Margalla hills, Shakar Parian, and Rawal Lake. The Margalla hills zone, however, forms most of the MHNP and is the extension of the Himalayan range. The MHNP has a rough topography with some steep slopes and various gullies.

The MHNP is adjoined with the Federal Capital City of Pakistan, Islamabad, highlighted in yellow (Rawal Lake and Shakar Parian are located within the city, and the Margalla Hills are located to the north of the city), and it is also extended to the Khyber Pakhtunkhwa Province. The MHNP was declared a National Park on 27 April 1980 under Section 21(I) of the Islamabad Wildlife (Protection, Conservation, and Management) Ordinance, 1979 [30]. Before 1960, much of the area was classified as a “Reserve Forest.” Later, however, the area was declared a “Wildlife Sanctuary” under the West Pakistan Wildlife Protection Ordinance, 1959 [30].

The climate of the area is subtropical semi-arid. The MHNP lies in the monsoon belt, and it experiences two rainy seasons: winter rains from January to March, whereas summer rains from July to September. The soil of MHNP is mainly composed of limestone [31]. The flora of the MHNP includes 101 families, 548 genera, and 608 species [32]. The MHNP is composed of two types of forests, i.e., Sub-tropical Broadleaved Evergreen Forest (SBEF) and Sub-tropical Chir Pine Forest (SCPF) [29]. Figure 2 shows the natural color composite of the S2 image for the study area (combination of bands 4, 3, and 2), and Figure 3 shows the near-infrared (NIR) composite of the S2 image of the study area (combination of bands 8, 4, and 3).

2.2 AGB inventory and estimation

There were 46 sampling plots laid in SCPF, and 31 sampling plots were laid in SBEF of the MHNP randomly. The circular plots of a 17.84 m radius were used for sampling [33]. The diameter at breast heights (DBHs) of all the trees above 5 cm were measured in the sampling plots, with the help of
a DBH tape, at a height of 1.3 m above the ground level [34]. The heights were recorded using the Vertex IV instrument. The heights of all the trees from the sampled plots were measured. It included 640 trees from the SCPF and 443 trees from the SBEF. The Geographic Information System coordinates were collected at the center of the plots using Garmin's handheld Global Positioning System receiver, which can have an error range of 8–10 m.

For AGB estimation, first, the tree volume was estimated by using the following equation [35]:

\[ V = \frac{\pi}{6} D_{\text{DBH}}^3 \]

where \( V \) is the tree volume, and \( D_{\text{DBH}} \) is the diameter at breast height.

Figure 1: (a) Location of the study area in Pakistan and (b) study area.

Figure 2: Natural color composite of S2 image of the study area.
Tree volume \( m^3 = \frac{\pi}{4} \times DBH^2 \times H \times FF \) \( (1) \)

where \( H \) is the height of a tree and FF is the form factor. A form factor of 0.45 was used for \( P. roxburghii \), and a form factor of 0.59 was used for broadleaved species [36]. Afterward, the AGB was estimated using the following equation [37,38]:

\[
AGB(\text{kg}) = \text{Volume}(m^3) \times \text{Wood density}(kg \ m^{-3}) \times BEF, 
\]

where \( BEF \) is the biomass expansion factor.

\( BEF \) of 1.51 was used for \( P. roxburghii \) and 1.59 was used for the broadleaved tree species [39]. Wood densities for trees were sourced from various literature (Table 1). AGB (kg)" was converted to “AGB Mg (megagram)” by dividing by 1,000. The AGB was converted to aboveground carbon (AGC) by using the carbon conversion factor of 0.5 [47]. AGB and AGC values were scaled up to ha by dividing them by 0.1 [48].

\[ 2.3 \] S2 data acquisition and processing

S2 was used for this research. The S2 constellation mission has two satellites, the first is S2A which was launched on June 23, 2015, and the second satellite is S2B, which got launched on March 7, 2017 [49]. The S2 data can be found in three spatial resolutions of 10, 20, and 60 m. In this study, the spatial resolution of 10 m was used to ensure consistency and for utilizing the higher resolution. The S2 data have been utilized in various vegetation-related studies [50]. The details of the various spectral bands of S2 have been provided by Lamquin et al. [51].

Two images of S2 Level-1C were downloaded for this study, i.e., the first image was for August 19, 2019, with a cloud cover of 0.4%, and the second image was also for the same date, August 19, 2019, with a 0.05% of cloud cover. The Semi-Automatic Classification Plugin (SCP) [52] of the QGIS [53] was used for downloading the imageries [54]. As mentioned above, bands 2, 3, 4, and 8 with 10 m resolution were used for this research. The DOSI algorithm of the SCP by Congedo [52] was used for the conversion of the image into BoA reflectance [54]. The merging and sub-setting (clipping) were done in RStudio software [55].

Table 1: Wood densities of trees

<table>
<thead>
<tr>
<th>Sr. no.</th>
<th>Species</th>
<th>Wood density (g cm(^{-3}))</th>
<th>Sources</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>( P. roxburghii ) Sarg.</td>
<td>0.49</td>
<td>[40]</td>
</tr>
<tr>
<td>2</td>
<td>( Bombax ceiba ) L.</td>
<td>0.33</td>
<td>[41]</td>
</tr>
<tr>
<td>3</td>
<td>( Bauhinia variegata ) L.</td>
<td>0.67</td>
<td>[41]</td>
</tr>
<tr>
<td>4</td>
<td>( Eucalyptus camaldulensis ) Dehnh.</td>
<td>0.681</td>
<td>[42]</td>
</tr>
<tr>
<td>5</td>
<td>( Ficus palmata subsp. virgata ) Forssk.</td>
<td>0.39</td>
<td>[41]</td>
</tr>
<tr>
<td>6</td>
<td>( Acacia modesta ) Wall.</td>
<td>0.809</td>
<td>[42]</td>
</tr>
<tr>
<td>7</td>
<td>( Grewia optiva ) J. R. Drumm. ex Burret</td>
<td>0.68</td>
<td>[43]</td>
</tr>
<tr>
<td>8</td>
<td>( Mallotus philippensis ) (Lam.) Muell. Arg.</td>
<td>0.64</td>
<td>[41]</td>
</tr>
<tr>
<td>9</td>
<td>( Cassia fistula ) L.</td>
<td>0.71</td>
<td>[41]</td>
</tr>
<tr>
<td>10</td>
<td>( Broussonetia papyrifera ) (L.) L’Herit ex Vent.</td>
<td>0.507</td>
<td>[44]</td>
</tr>
<tr>
<td>11</td>
<td>( Celtis australis ) L.</td>
<td>0.44</td>
<td>[45]</td>
</tr>
<tr>
<td>12</td>
<td>( Albizia lebbeck ) (L.) Benth</td>
<td>0.55</td>
<td>[41]</td>
</tr>
<tr>
<td>13</td>
<td>( Ziziphus mauritiana ) Lam.</td>
<td>0.76</td>
<td>[41]</td>
</tr>
<tr>
<td>14</td>
<td>( Ficus benghalensis ) L.</td>
<td>0.39</td>
<td>[41]</td>
</tr>
<tr>
<td>15</td>
<td>( Flacourtia indica ) (Burm. f.) Merr.</td>
<td>0.55</td>
<td>[46]</td>
</tr>
</tbody>
</table>
2.4 S1 data acquisition and processing

The S1 mission carries two satellites that are 180° apart [56]. It contains a constellation of two identical satellites, S1A and S1B, which have been launched separately. The satellites are equipped with the C-band SAR instrument which is operating at a center frequency of 5.405 GHz [56]. It includes four imaging modes, i.e., Strip Map (SM), Interferometric Wide swath (IW), Extra-Wide Swath (EW), and Wave (WV), having different resolutions (that is down to 5 m) and a coverage of up to 400 km with a capability of dual polarization (HH + HV, VV + VH) [57]. Each mode is intended for use in different applications. The mission provides free data to the public for use.

A dual polarization (VV + VH), S1 IW Ground Range Detection Level-1 scene was downloaded from the ESA Copernicus Open Access Hub (https://scihub.copernicus.eu/). The C-band SAR product was downloaded for the date of August 24, 2019. The IW mode of acquisition has a 250 km swath width at a spatial resolution of 5 m × 20 m spatial resolution (single look) and an incidence angle between 29.1° and 46.0° [58]. The IW mode of acquisition is suitable for land surface studies [59]. The pre-processing was done following the study of Filipponi [60]. It was conducted in the Sentinel Application Platform software version 8.0 of the ESA [61]. Pre-processing of the satellite images was done after Filipponi [60].

2.5 Extraction of variables from satellite data

VIs are the combination of different spectral bands in visible and NIR regions of the electromagnetic spectrum [62]. These VIs are a simple way to extract information regarding vegetation characteristics from a large set of remote sensing data [63]. They are a useful measure for determining the vigor and productivity of the vegetation [64]. VIs have also been used for AGB estimation and have also demonstrated significant statistical relationships [65]. Some of the causes for this relationship include chlorophyll, water content, canopy structure, leaf angle, density, etc. [66]. Several types of VIs exist which can be categorized into broadband and narrowband [67]. Abdou et al. [68], for instance, reviewed around 35 VIs for their study. Similarly, Agapiou et al. [67] reported 71 different VIs in their study.

For this research, the Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) have been used because of their relatively higher use due to significant correlations with the AGB [69].

NDVI is one of the most preferred indices for comparing vegetation and non-vegetation areas [38]. Since the healthier and greener vegetation absorbs more visible light and reflects a higher infrared light compared to the unhealthy and sparse vegetation, this characteristic is utilized by the NDVI for indicating these differences and changes [70]. The NIR zone is 0.75–1.3 μm and the red zone is 0.62–0.75 μm within the electromagnetic spectrum [70]. The red portion of the visible light is absorbed by the leaves due to the presence of chlorophyll and the NIR portion is reflected which also depends on the leaf and canopy structures [71]. The NDVI ranges from −1 to +1. The negative values portray water bodies, the values that are slightly above 0 represent bare grounds, values which are between 0.2 and 0.8 are representative of the spread and sparse vegetation and the values greater than 0.8 portray greener vegetation and the values which are close to 1 are representatives of lush forests [70]. The equation for the NDVI estimation is as follows [72]:

\[
\text{NDVI} = \frac{(\text{NIR} - \text{RED})}{(\text{NIR} + \text{RED})}. \tag{3}
\]

The estimation and mapping of NDVI were done using QGIS software. EVI is also one of the most used indices mainly because of its simplicity, availability, and its utility in various kinds of ecosystems [73]. EVI is also a ratio that contains the red and NIR bands of the electromagnetic spectrum which are correlated to the “greenness” of the vegetation canopy [73]. Amongst the two VIs, NDVI and EVI, the EVI is more sensitive to the canopy structure, while NDVI is more sensitive to the chlorophyll [74]. Both of these indices complement each other in vegetation-related studies [75]. The value of the EVI also ranges from −1 to 1. The following equation was used for the EVI estimation [75]:

\[
\text{EVI} = 2.5(\text{NIR} - \text{RED})/(\text{NIR} + 6 \times \text{RED} - 7.5 \times \text{Blue} + 1). \tag{4}
\]

The estimation and mapping of EVI were done using QGIS software.

2.6 Statistical analysis

Linear regression was performed using extracted values of NDVI, EVI, VH, and VV, from QGIS software, against the AGB obtained from the field plots. The coefficient of determination \( R^2 \) was used for assessing the strength of the statistical linear relationship between the two variables. It is a useful measure for assessing the statistical linear strength between the two variables [76]. It has also been a common measure that has been used in AGB estimation studies [77]. The evaluation of the strengths of \( R^2 \) was based on the following: (1) 0.19 (weak), (2) 0.33 (moderate), and (3)
0.67 (substantial/significant) [78]. The negative sign implies the negative statistical relationship between the two variables.

Mean and standard deviations were calculated for all the variables (mean ± SD). The data were checked for the normality distribution, for which Shapiro–Wilk test was used. Since the data were not normally distributed, the Wilcoxon Rank Sum Test was used for probing the statistical difference between the two variables. A significance level of 0.05 was used for the statistical tests and analysis. The statistical analysis was performed in RStudio, and the respective graphs were generated. Figure 4 provides a visual representation of the methodological workflow of this study.

3 Results

The mean AGB for SCPF was recorded as 146.73 ± 65.11 Mg ha⁻¹, whereas the mean AGB for SBEF was recorded as 33.77 ± 51.63 Mg ha⁻¹ (Table 2). The mean AGC for SCPF was 73.36 ± 32.55 Mg C ha⁻¹ and the mean AGC for SBEF was 16.88 ± 25.81 Mg C ha⁻¹. There was a significant difference recorded between the mean AGC of the two forests (W = 43, p < 0.05). A significant difference was also recorded between the AGB of the two forests (W = 43, p < 0.05).

The NDVI ranged from −0.34 to 0.80 (Figure 5). The minimum NDVI value was recorded as −0.34 and the highest value was recorded as 0.80. The mean NDVI for the MNHP was recorded as 0.60 ± 0.19. The NDVI distribution of the MNHP is left-skewed (panel 1 in Figure 7). The highest values of NDVI were recorded in the class interval 0.6–0.8 which was 69.82%, followed by 0.4–0.6 which was recorded as 21.22% (Table 3).

The EVI values ranged from −0.11 to 0.89 (Figure 6). The minimum EVI was recorded as −0.11 and the highest EVI was recorded as 0.89. The mean value for EVI for the MNHP was recorded as 0.45 ± 0.16. The EVI shows a bimodal type of distribution for MNHP (panel B in Figure 7). The highest percentage of EVI values was recorded for the interval 0.4–0.6 which was 54.19%, followed by 0.2–0.4 which recorded 23.004% of the total values (Table 4).

Regression analysis between the NDVI and the AGB had shown a weak association between the two variables (R² = 0.009; panel A in Figure 8). There was no significant statistical relationship observed between the two variables of NDVI and the AGB of the SCPF (p > 0.05). There were 46 observations used for each of the variables for the regression analysis. The linear regression equation of “y = 77.24 + 108.05x” was obtained from the analysis.

Table 2: Structural characteristics of forests of MNHP

<table>
<thead>
<tr>
<th>Forests</th>
<th>Mean AGB (Mg ha⁻¹)</th>
<th>Mean AGC (Mg ha⁻¹)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SCPF</td>
<td>146.73 ± 65.11</td>
<td>73.36 ± 32.55</td>
</tr>
<tr>
<td>SBEF</td>
<td>33.77 ± 51.63</td>
<td>16.88 ± 25.81</td>
</tr>
</tbody>
</table>

Figure 4: Methodological workflow.
Forest biomass assessment combining field inventorying and remote sensing data

Figure 5: NDVI for MHNP.

Figure 6: EVI for MHNP.
The regression analysis between the EVI and AGB of the SCPF of MHNP showed a weak association \( \left(R^2 = 0.0002; \right. \) panel B in Figure 8). Statistically, no significant relation was also revealed between the two variables \( \left(p > 0.05 \right. \). There were 46 observations used for each of the variables for performing the regression analysis. The linear regression equation obtained from the analysis was “\( y = 141.65 + 12.23x \).”

The linear regression analysis between the VH polarization and the AGB of the SCPF has revealed a weak association \( \left(R^2 = 0.07; \right. \) panel C in Figure 8). There was no significant statistical relationship recorded between the two variables \( \left(p > 0.05 \right. \). The linear regression equation for these two variables was recorded as “\( y = 7.527 - 8.538x \).”

The linear regression analysis between the VV polarization (predictor variable) and AGB of the SCPF has revealed a weak association \( \left(R^2 = 0.01; \right. \) panel D in Figure 8). There was no significant statistical relationship recorded between the two variables \( \left(p > 0.05 \right. \). The linear regression equation for these two variables was recorded as “\( y = 108.953 - 3.711x \).”

The regression analysis between the NDVI and AGB for the SBEF at the MHNP showed a weak association between the two variables \( \left(R^2 = 0.13; \right. \) panel E in Figure 8). However, a significant statistical relation was revealed between the two variables \( \left(p < 0.05 \right. \). There were 31 observations used for each of the variables for the regression analysis. The linear regression equation of “\( y = 462.1 - 595.8x \)” was obtained from the analysis.

The regression analysis between the EVI and AGB for the SBEF of the MHNP had shown a weak association \( \left(R^2 = 0.09; \right. \) panel F in Figure 8). There was also no significant statistical relation revealed between the two variables \( \left(p > 0.05 \right. \). There were 31 observations used for each of the variables for the regression analysis. The linear regression equation of “\( y = 136.48 - 186.13x \)” was obtained from the analysis.

The linear regression analysis between the VH polarization and AGB of the SBEF has revealed a weak association \( \left(R^2 = 0.001; \right. \) panel G in Figure 8). There was no significant statistical relationship recorded between the two variables \( \left(p > 0.05 \right. \). The linear regression equation for these two variables was recorded as “\( y = 44.28 + 0.69x \).”

A weak linear regression association has been revealed between the VV polarization (predictor variable) and AGB (outcome variable) of the SBEF \( \left(R^2 = 0.01; \right. \) panel H in Figure 8). There was no statistically significant relationship recorded

<table>
<thead>
<tr>
<th>Sr. no.</th>
<th>NDVI index class interval</th>
<th>Percentage of total pixels</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>−0.4 to −0.2</td>
<td>2.53</td>
</tr>
<tr>
<td>2</td>
<td>−0.2 to 0</td>
<td>0.49</td>
</tr>
<tr>
<td>3</td>
<td>0−0.2</td>
<td>1.56</td>
</tr>
<tr>
<td>4</td>
<td>0.2−0.4</td>
<td>4.35</td>
</tr>
<tr>
<td>5</td>
<td>0.4−0.6</td>
<td>21.22</td>
</tr>
<tr>
<td>6</td>
<td>0.6−0.8</td>
<td>69.82</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Sr. no.</th>
<th>EVI index class interval</th>
<th>Percentage of total pixels</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>−0.15 to 0</td>
<td>3.05</td>
</tr>
<tr>
<td>2</td>
<td>0−0.2</td>
<td>2.77</td>
</tr>
<tr>
<td>3</td>
<td>0.2−0.4</td>
<td>23.004</td>
</tr>
<tr>
<td>4</td>
<td>0.4−0.6</td>
<td>54.19</td>
</tr>
<tr>
<td>5</td>
<td>0.6−0.8</td>
<td>16.73</td>
</tr>
<tr>
<td>6</td>
<td>0.8−1</td>
<td>0.24</td>
</tr>
</tbody>
</table>

Figure 7: (a) NDVI distribution of MHNP and (b) EVI distribution of MHNP.
between the two variables \( (p > 0.05) \). The linear regression equation for these two variables was recorded as “\( y = 17.209 - 1.876x \).”

4 Discussion

4.1 NDVI comparison

The NDVI for the study region ranged from \(-0.34\) to \(0.80\) (Figure 5). A similar result was reported by Mannan et al. [29] for the same study region ranging from \(-0.26\) to \(0.85\) for the year 1990, but for the year 2017 slight differences were noted, as the values were reported from \(-0.67\) to \(0.62\). They used the LANDSAT 5 TM data for 1990 and LANDSAT 8 OLI for 2017, where both have a spatial resolution of 30 m. They attributed their lower NDVI values for 2017 to the deforestation caused by the local people for fuelwood extraction, livestock grazing, and frequent forest fires. Slight differences were also noticed by Naeem et al. [79] who reported NDVI values between \(-0.87\) and \(0.69\) for the SCPF near Ghora Gali, Murree, Pakistan. They used the SPOT-5 data with a 2.5 resolution from 2013. Almost similar results were obtained by Mannan et al. [80] who reported NDVI values for the foothills of the Himalayan mountains of northern Pakistan from \(-0.34\) to \(1\) (1998), \(-0.14\) to \(0.89\) (2008), and \(-0.52\) to \(0.83\) (2018) using LANDSAT 5 TM for 1998 and 2008 and LANDSAT 8 OLI for 2018. Mallick et al. [81] reported NDVI values, for 2004, ranging from \(0.15\) to \(0.528\) for the SBEF and SCPF located in the foothills of the Himalayan in northern India. They used the satellite data from the Indian Remote-Sensing Satellite-P6 Linear Imaging Self-Scanning Sensor-4. The NDVI values range between \(-1\) and \(1\) where barren lands and residential built areas usually have values below \(0.1\) [82]. The water bodies such as lakes, etc. have values below \(0\) or in the minus range, as such is the case in this study where the water body, i.e., Rawal Lake had recorded the NDVI values in the minus range [83,84]. The values for the green vegetation typically range from \(0.2\) to \(0.8\) [85].

4.2 NDVI-AGB comparison

In this study, the NDVI had recorded a weak association with the AGB of the SCPF \((R^2 = 0.009; \ p > 0.05)\) (panel A in Figure 8) and similarly also recorded a weak association with the AGB of SBEF \((R^2 = 0.13; \ p < 0.05)\) (panel E in Figure 8). The association between the two variables, NDVI and AGB, was however slightly better in the case of SBEF. The weak association between the AGB and NDVI in this study

![Figure 8](image-url): (a) NDVI–AGB regression of SCPF, (b) EVI–AGB regression of SCPF, (c) VH polarization–AGB regression of SCPF, (d) VV polarization–AGB regression of SCPF, (e) NDVI–AGB regression of SBEF, (f) EVI–AGB regression of SBEF, (g) VH polarization–AGB regression of the SBEF, and (h) VV polarization–AGB regression von SBEF.
is in agreement with Imran et al. [86] who also claimed a relatively weak non-linear association between the two for a study site in Muzaffarabad District, AJK, Pakistan. Similarly, Alam et al. [87] also reported a weak association of the NDVI and AGB ($R^2 = 0.19$), using S2 satellite data, for the invasive tree species, *Broussonetia papyrifera*, found in the MHNPs. Ali et al. [88], however, reported a significant non-linear association between the two variables ($R^2 = 0.81$), using S2 satellite data, for the Khanpur Range, Khyber Pakhtunkhwa, Pakistan. Naeem et al. also reported a significant linear association between AGB and NDVI ($R^2 = 0.7$), using SPOT-5 satellite data, for study sites in Murree and Abbottabad, Pakistan. Similarly, strong associations have also been reported between the two variables by previous studies [89–91]. On the contrary, various researchers [92,93] have also reported a weak association between the two variables.

Some of the drawbacks associated with NDVI also include saturation, which means that the increase in forest biomass is not gauged by the NDVI [94]. The saturation can either be due to the maturity of the forest crop [95] or because of the complex forest canopy structure [96,97]. In the case of this study, the complex canopy structure along with the understorey vegetation seems to have played a significant role. In SBEF for instance, multi-layer spreading crowns were observed along with the dense understorey vegetation, i.e., shrubby growth, etc., which may have accounted for an increase in the vegetated area [92,98]. This would have increased the NDVI values since the light would have been reflected from these vegetated surfaces and would not have accounted for the heights and DBHs of the trees which are strongly correlated with the AGB [99]. This could be one of the reasons that increasing AGB may not have been reflected by the increasing NDVI. Nonetheless, the DBHs and heights of trees can also not be directly recorded by the optical satellite sensors [87]. The SCPF had recorded a mean NDVI (per plot) of 0.64 ± 0.06 compared to the mean NDVI (per plot) of SBEF which was 0.71 ± 0.03. This also corroborates the presence of more vegetated areas in the sampled plots of the SBEF mainly due to the spreading crowns and the understorey vegetation in the form of shrubs, etc. The understorey vegetation was not considered in carbon stock calculations because of its negligible contribution to the overall carbon stocks [100,93,80]. Understorey vegetation was mostly absent in the SCPF, which again substantiates the reason for higher NDVI values in the SBEF [101]. The other reasons for the weak association between the NDVI and the AGB could be due to the shadow since the study area is a hilly region, and the mixed spectral response [102,93]. The satellite data were atmospherically corrected, but shadows still may have existed affecting the NDVI values [87,82]. Mixed spectral response in a pixel, similarly, may have been recorded due to the combined effects of soil and shadow, etc. [87,103].

### 4.3 EVI comparison

The EVI is considered an improved version of NDVI and was developed to optimize vegetation signals for improving sensitivity in high biomass regions and for improved vegetation monitoring by de-coupling of canopy background signals and attenuation of atmospheric effects [75,104]. The values for EVI also range from −1 to 1 [105]. The EVI from this study ranged from −0.11 to 0.89 with a mean of 0.45 ± 0.16 (Figure 6). The EVI (per plot) for SCPF ranged from 0.24 to 0.59 with a mean (per plot) of 0.41 ± 0.08 and the EVI (per plot) for SBEF ranged from 0.33 to 0.68 with a mean (per plot) of 0.55 ± 0.08. This study has shown a weak statistical association between the two variables, EVI and AGB, for both forests. Similar results were also shown by the researchers of previous studies [106,83,92,107]. Various other researchers, however, have recorded a significant association between the two [108–110]. The EVI is more sensitive to topographic variations compared to NDVI, which could be one of the reasons for the weak association between the EVI and AGB [111,83,73]. The second reason could be related to the canopy structure, as EVI is also known to be sensitive to canopy structures [74,75].

### 4.4 C-band SAR-AGB comparison

The C-band SAR data for this study showed a weak association with the AGB of both forests (panels C, D, G, H in Figure 8). The result is in agreement with the previous studies [112–115]. Few researchers have also reported a strong association between the AGB and C band SAR data [116,117]. The backscatter approach based on SAR data has been widely used for AGB mapping [25], and SAR sensors have been utilized in this context of AGB and AGC estimation for over three decades [118–120]. The backscatter is the energy received by the sensor after the transmission which is subsequently related to the AGB measurements recorded during the field inventories [112]. The backscattering coefficient, similarly, is the function of various systems and target parameters [19]. Microwave remote sensing uses radar signals of various wavelengths (1 mm to 1 m) for illuminating the area of interest and measures the backscattering from the same targets [113]. The C-band
(3.8–7.5 cm wavelength) is sensitive to leaves and smaller branches of tree crowns [121]. The C-band signals can penetrate 1–2 m deep into the canopy [122,123]. Unlike the shorter wavelengths such as C-band and X-band (2.4–3.8 cm wavelength), the L-band (15–30 cm wavelength) and P-band (30–100 cm wavelength) penetrate deeper into the canopy and are sensitive to bigger branches and stems, which store the highest biomass [14,124,125]. The C-band saturates at a biomass level of 20 Mg ha\(^{-1}\) [122,126,127]. It is therefore favored for low biomass areas such as regeneration sites [12,27]. The L-band saturates, for biomass, between 150 and 200 Mg ha\(^{-1}\) [128,129]. And, the P-band saturates at around 300 Mg ha\(^{-1}\) [130,131]. Working, however, with the longer wavelength SAR data is not always feasible due to higher costs and lesser availability of operational satellites [132]. There is also no P-band SAR satellite currently available either [114].

The C-band SAR data from the ESA S1 mission are however freely available [132,114]. This can, nonetheless, serve as an opportunity for developing countries, where the requisite funding for satellite imageries is lacking, to regularly monitor their forest biomass potentials [117,132]. In this study, therefore, the penetration level and saturation could be the reasons for the weak association between the C-band SAR data and the AGB of both forests [112,126,113,120].

### 4.5 Implications for forest managers

The study design can be adopted in other mountainous areas in the region for forest carbon monitoring where often accessibility is an issue. Similarly, the use of freely available remote-sensing satellite images can help forest managers for reporting larger areas for forest inventorying exercises. It also helps in the reduction of the costs involved in forest inventorying, especially in developing countries where the forest management budget is already minimal to none. However, forest managers should be equipped with the necessary skills for carrying out remote sensing studies. For this matter, adequate capacity development programs should be conducted by the relevant departments. Forest carbon monitoring has become an essential part of forest planning and management concerning climate change impacts and increasing pressures on forestry resources. It is, therefore, increasingly being employed by forest managers working in various capacities in different enforcement and government departments. Adoption of such studies can also assist concerned forest managers to develop suitable forest management strategies and plans for their respective areas.

### 4.6 Recommendations

It is recommended that the S2 and S1 data should be used for forest carbon monitoring due to the free access in the study area in the future and also in other mountainous areas in the region. Moreover, studies including the longer SAR microwave bands should also be integrated into future research studies of the MHNP for a comprehensive understanding of their interaction with the forest biomass of the study area. The free available satellite resources will be useful in drawing suitable sustainable forest management strategies for the MHNP.

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