Analyzing the Relationship Between Above Ground Biomass and Different Vegetation Indices of Chure Region of Sainamaina Municipality, Nepal

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ABSTRACT

For REDD+ (reducing emissions from deforestation and forest degradation), sustainable management of forests, and protection and enhancement of forest carbon stocks procedures to be successful, accurate measurement of forest above-ground biomass (AGB) are essential. Sentinel imaging that was launched since 2014 provides an opportunity for mapping and monitoring AGB in forests. The aim of this study is to analyze the relationship between AGB and vegetation indices (VIs) derived from Sentinel-2 imagery in the Chure region of Sainamaina municipality. For this, we used 72 sample plots and 7 different VIs. The ARVI (Atmospherically Resistant Vegetation Index) and EVI2 (Enhanced Vegetation Index - 2) shows strong correlation (i.e. r = 0.861 and 0.861) and coefficient of determination value (R2=0.7414 and 0.7415) respectively. Overall, Sentinel-2 multispectral images vegetation indices can produce good results for reporting the AGB.

Keywords: AGB, VIs, Sentinel-2, ARVI, and EVI2

INTRODUCTION

“Forests have a crucial function in reducing CO2 levels in the atmosphere and the global climate system”(Alkama and Cescatti 2016; Pan et al., 2013, Nunes et al 2020). As carbon plays a vital part in the earth's carbon cycle, biomass and carbon stock assessment in tropical forests have recently received wider interests(Basuki et al., 2009). In order to quantify the contributions of forests as carbon sources or sinks and to promote sustainable forest management, estimation of forest biomass and carbon stock is crucial. The quantification of forest biomass and carbon stock is crucial in assessing the contributions of forests as carbon sources or sinks and in promoting sustainable forest management practices. (Mauya et al., 2015; Temesgen et al., 2015)

One way to assess biomass involves a conventional technique that involves destructively measuring aboveground biomass (AGB) by
removing trees. While this approach offers relatively accurate results, it is costly and time-consuming due to the need for extensive fieldwork (Attarchi and Gloaguen 2014). The alternative way is to employ a non-destructive technique of data collection like Remote Sensing (RS) to estimate biomass from spectrally recorded information (Kumar et al., 2015). Due to the accessibility and accuracy of high-resolution images, RS data now plays a crucial role in the calculation of biomass across large parts of tropical areas (Wahlang & Chaturvedi, 2020). Remote sensing (RS) technology nowadays is a widely used tool for biomass assessment (Kankare et al., 2013; Maynard et al., 2007; Wannasiri et al., 2013). Based on repetitive data gathering with little effort, RS may obtain forest information over broad areas at an affordable price and with satisfactory precision (Lu 2006).

The interpretation of biomass and land cover involves utilizing mathematical transformations of the original spectral reflectance, which are commonly referred to as vegetation indices (VIs) (He et al., 2005; Rahman et al., 2003). Satellite-based vegetation indices (VIs) are frequently used in numerous studies to estimate biomass (Foody et al., 2003; Hurcom & Harrison 1998; Li, Zhou, & Xu 2021; Lourenço 2021; Pandit et al., 2018; Schlerf et al., 2005 Sch; Utari et al., 2020). Some studies suggest that there exists a noteworthy positive correlation between vegetation indices (VIs) and biomass (Boyd, 1999; Das & Singh 2012; Heiskanen, 2006; Hurcom & Harrison 1998; Steininger, 2000). However, other studies have demonstrated unsatisfactory outcomes (Foody et al., 2003; Schlerf et al., 2005).

The European Space Agency’s Copernicus program was launched in 2014 with additional significant advancements in radiometric, geographical, and temporal resolution to the global repository of open access data (Astola et al., 2019; Li et al., 2021). For instance, the operational actors notice a significant difference when the spatial resolution is increased from 30 m of Landsat 8 to 10 m of Sentinel-2, which permits calculation of variables (such AGB per ha) at the lower scale levels of forest plots and stands. In comparison to Landsat-8, Sentinel-2 (especially A and B) includes more spectral bands, including three Vegetation Red Edge (VRE) and one Narrow Near Infrared (NNIR) band (13 Sentinel-2 vs. 7 bands) (Biswas et al. 2020; Forkuor et al., 2017). It is anticipated that the VRE bands will help with better AGB estimation and mapping (Qiu et al., 2017).

Limited research has been undertaken in Nepal regarding the utilization of remote sensing (RS) technologies, particularly in estimating aboveground biomass (AGB) with few detailed ground-
based quantifications of biomass. There is paucity of knowledge on forest biomass in the Chure region due to its geological fragility to undertake destructive methods. Further, application of satellite data with ground data is yet at early stage in Nepal and Cure region is not an exception. Thus, the goal of this study is to analyze the relationship between AGB and different VIs (derived from Sentinel-2 images) of forest of Chure region, Nepal

**MATERIALS AND METHODS**

**Study area:**

This study was conducted in Sainamaina Municipality (Fig.1). It is an area located in Chure region of Lumbini province in Rupandehi district of Nepal. The geographical location of study area is 83015'44" E to 83021'01" E longitude and 27038'48" N to 27046'05" N latitude. Area of Chure region of Sainamaina municipality is 9235.11 ha. The research area includes undulating topography and typical of tropical forests. Major species of this region are “Shorearobusta, Syzygiumcumini, Lagerstroemia parviflora, Mallotusphilippinensis, Anogeissus latifolia” (Poudel et al., 2023). The terrain slope of the study area ranges from flat land (00) to steep slopes (upto 65.70) with an elevation ranging from 95 meter to 980m above mean sea level. The average annual precipitation of 2600 mm of which 80% occurs during monsoon period). The mean maximum and minimum temperatures of the research areas has been recorded as 42.5°C and 7.5°C respectively (Thapa & Poudel, 2018).

**Sampling strategy and field data collection**

The total area of the study site is 9235.11 ha which was divided into parts within a 2 * 2 km grid Fig. 2 using ArcMap functionality. The grids were selected such that the selected grids (area 3622 ha) represented the overall vegetation of the study area. For the study, the area to be sampled was calculated using Equation 1, and the total number of sample plots to be surveyed was 72 plots which was calculated using Equation 2. Field information was gathered between the month of August and September.
of 2021. Circular plots of 500m$^2$ (12.62m radius) was employed to obtain the tree data from sample plots. Sample plots were laid in each selected grid and stratified random sampling was adopted to distribute the plots with each grid. Due to inaccessibility, some of the sample plots were shifted to new coordinates. The species name, diameter and height of each tree with DBH 8 cm in each sample plot was measured using diameter tape and clinometer. The diameter was measured at 1.3 meters above the ground. (Askar et al., 2018; Maas et al. 2008).

\[
SI = \frac{a}{A} \times 100
\]

\[
n = \frac{a}{500}
\]

Where $n =$ number of sample plots to be surveyed, $a =$ Area to be surveyed, 500m$^2$ is the area of the sample plot, $S.I =$ Sampling Intensity (0.1%), and $A =$ Total area of the study site.

![Sample Plot of Study Area](image)

*Figure 2: Grid selection and location of sample plot*

**Field data analysis of AGB**

In this study, the aboveground biomass (AGB) was estimated using an enhanced and updated allometric equation developed by Chave et al. (2014) specifically for tropical forest trees. Chave et al. (2014) used an equation that incorporated diameter, height, and specific density of wood for biomass estimation. Height and diameter were measured on-site, whereas the specific wood density was determined through a number of literatures. Species with their default specific values ($\rho$) given by Khanna & Chaturvedi (1982); Thakur (2003) was used to determine tree level...
biomass. When specific values were unavailable, a general value ($\rho = 0.674$) was utilized (Pandit et al., 2018). The calculation of individual biomass and subsequent aggregation was done to obtain individual plot-level AGB.

$$\text{AGB}_{\text{est}} = 0.0673 \times (\rho \times D^2 \times H)^{0.976}$$

Where $\text{AGB}_{\text{est}}$ is AGB estimated in kilogram, $D$ is DBH in cm, $H$ is height in meter, $\rho$ is wood density in g/cm$^3$, 0.0673 and 0.976 are constants.

Vegetation indices and extraction of pixel values

Vegetation indices (VIs) are mathematical formulas that utilize specific spectral bands to emphasize the spectral characteristics of green plants, enabling their differentiation from other features or characteristics. (Adan, 2017). It is calculated by adding up the red spectral band (Chlorophyll absorbent) with the near-infrared band (non-absorbent). Some indices include the Short Wave Infra-Red (SWIR) band as well (Njoku, 2014). The computation is achieved by creating a linear combination of the band through the process of ratioing, differencing, and summing while also considering the ratio of differences (Hanes, 2013). A spectral transformation comprising at least two bands is used to boost the contribution of an image’s vegetation features. Seven different vegetation indices were used in this study. They are Normalized Difference Vegetation Index (NDVI), Simple Ratio (SR), Soil-Adjusted Vegetation Index (SAVI), Enhanced Vegetation Index-2 (EVI2), Atmospherically Resistant Vegetation Index (ARVI), Normalized Difference Water Index (NDWI), and Normalized Difference Index 45 (NDI45) as presented in Table 5. Using the raster calculator tool in ArcGIS 10.5 software, indices were calculated incorporating image spectral bands. Using the buffer tool, a sample plot position (latitude, longitude) was exported as a 12.62 m circular plot.
Using zonal statistics and a buffered circular plot position, the pixel values for all VIs were retrieved, and the data was exported in CSV format for additional analysis.

Table 1: VIs with their formula and authors

<table>
<thead>
<tr>
<th>s.No.</th>
<th>VIs</th>
<th>Authors</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>( \text{NDVI} = \frac{\rho_{\text{NIR}} - \rho_{\text{RED}}}{\rho_{\text{NIR}} + \rho_{\text{RED}}} )</td>
<td>(Gitelson &amp; Merzlyak, 1997)</td>
</tr>
<tr>
<td>2</td>
<td>( \text{SR} = \frac{\rho_{\text{NIR}}}{\rho_{\text{RED}}} )</td>
<td>(Jordan 1969)</td>
</tr>
<tr>
<td>3</td>
<td>( \text{NDI45} = \frac{\rho_{\text{RED}} - 1 - \rho_{\text{RED}}}{\rho_{\text{RED}} - 1 + \rho_{\text{RED}}} )</td>
<td>(Delegido et al. 2011)</td>
</tr>
<tr>
<td>4</td>
<td>( \text{SAVI} = 1.5 \times \frac{\rho_{\text{NIR}} - \rho_{\text{RED}}}{\rho_{\text{NIR}} + \rho_{\text{RED}} + 0.5} )</td>
<td>(Huete, 1988)</td>
</tr>
<tr>
<td>5</td>
<td>( \text{NDWI} = \frac{\rho_{\text{G}} - \rho_{\text{NIR}}}{\rho_{\text{G}} + \rho_{\text{NIR}}} )</td>
<td>(McFeeters 1996)</td>
</tr>
<tr>
<td>6</td>
<td>( \text{ARVI} = \frac{\rho_{\text{NIR}} - \rho_{\text{RED}} - (\rho_{\text{RED}} - \rho_{\text{BLUE}})}{\rho_{\text{NIR}} + \rho_{\text{RED}} + (\rho_{\text{RED}} - \rho_{\text{BLUE}})} )</td>
<td>(Kaufman and Tanre 1992)</td>
</tr>
<tr>
<td>7</td>
<td>( \text{EVI2} = 2.5 \times \frac{\rho_{\text{NIR}} - \rho_{\text{RED}}}{\rho_{\text{NIR}} + 2.4 \times \rho_{\text{RED}} + 1} )</td>
<td>(Jiang et al. 2008)</td>
</tr>
</tbody>
</table>

NIR (Near Infrared), G (Green)

**Statistical analysis**

SPSS and Microsoft Excel were used for statistical analysis. The relationship between each VI and AGB was calculated using linear regression models. AGB was used as the dependent variable \((y)\) and VI was used as the independent variable \((x)\) to determine the change in AGB as a change in VI and the value of \(r\) (correlation coefficient) and \(R^2\) (coefficient of determination) was obtained. The indices with a high value of \(r\) and \(R^2\) indicate high relation between AGB and VIs.

\[ Y = a + bX, \]

Where, \(Y\) is AGB in \(\text{t h-1}\), \(X\) is VIs and, \(a\) and \(b\) are parameters.

**RESULTS**

**Descriptive statistics of field data**

In the field, species enumeration and identification were also done. The results of 72 sample plots revealed a total of 929 trees. The most frequent tree species included Shorearobusta (34.33%), Bauchanania latifolia (12.80%), Anogeissus latifolia (10.22%), Terminalia alata (10.87%), Lagerstroemia parviflora (4.41%), Semecarpus anacardium (3.87%), Acacia catechu (2.47%), Mallotusphilippinensis (2.36%), and Syzygiumcumini (2.26%). The average height, DBH and AGB and CS of 929 trees was found to be 11.40 ± 0.15 meter, average = 24.20 ± 0.49
cm, 11.08 ± 0.68 t h⁻¹, 81.26, average = 5.17 ± 0.32 t h⁻¹ respectively. Table 2 presents species with lowest and highest AGB t h⁻¹. Total AGB from all 72 different sample plots was found 10226.410 t h⁻¹.

<table>
<thead>
<tr>
<th>Five species with lowest AGB t h⁻¹</th>
<th>Five species with highest AGB t h⁻¹</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Species</strong></td>
<td><strong>Species</strong></td>
</tr>
<tr>
<td>Diospyros malabarica</td>
<td>Shorearobusta</td>
</tr>
<tr>
<td>Bridelia retusa</td>
<td>Terminalia alata</td>
</tr>
<tr>
<td>Bombax cebia</td>
<td>Anogeissus latifolia</td>
</tr>
<tr>
<td>Woodfordia fruticosa</td>
<td>Buchanania latifolia</td>
</tr>
<tr>
<td>Azadirachta indica</td>
<td>Lagerstroemia parviflora</td>
</tr>
<tr>
<td>AGB t h⁻¹</td>
<td>AGB t h⁻¹</td>
</tr>
<tr>
<td>1.066</td>
<td>5903.830</td>
</tr>
<tr>
<td>1.123</td>
<td>1890.237</td>
</tr>
<tr>
<td>1.755</td>
<td>771.249</td>
</tr>
<tr>
<td>1.838</td>
<td>337.081</td>
</tr>
<tr>
<td>1.915</td>
<td>267.301</td>
</tr>
</tbody>
</table>

**Comparative r and R² analysis between AGB and VIs**

Comparative analysis between AGB and 7 different VIs revealed the following result as shown in Table 3. The table reveals that all Vis show positive and significant correlation between spectral indices and observed biomass (p = 0 < 0.05). Linear model with high significant was ARVI and EVI2 model with the R² value of 0.7414 and 0.7415 respectively. The R² value indicates that about 74.14% and 74.15% of AGB per hectare was explained by linear model of model ARVI and EVI2 and that remaining about 26% was explained by other variables not introduced in the model. NDWI shows the low correlation coefficient with R² of 0.5539. Similarly, NDVI, SR, NDI45 and SAVI shows R² of 0.7122, 0.7361, 0.699 and 0.7122 respectively.

<table>
<thead>
<tr>
<th>VIs with their value of r and R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>AGB Correlation</td>
</tr>
<tr>
<td>Pearson Correlation</td>
</tr>
<tr>
<td>Sig. (2-tailed)</td>
</tr>
<tr>
<td>R²</td>
</tr>
</tbody>
</table>
Discussion

From this study, comparative analysis between the AGB and different VIs revealed that ARVI and EVI2 has strong correlation and coefficient of determination. Values of r and $R^2$ are 0.861 and 0.7414 respectively for ARVI while the respective value for EVI2 was 0.861 and 0.7415 at the 5% level of significance for linear regression model. The result shows that AGB and all the VIs have strong correlation which is highly significant.
So, AGB predictive model on linear regression equation $Y = 142.55x + 0.5469$ for ARVI and $Y = 65.03x - 17.537$ for EVI2 can be suggested for predicting of AGB in Chure region.

Nakano et al. (2013) in their study computed 7 VIs which are SR, NDVI, EVI, SAVI, OSAVI, LSWI and GR from reflectance data of MODIS and the result reveals that all of the vegetation indices showed significant positive correlation with measured data of AGB. Linear regression analysis indicated that SR, NDVI and OSAVI showed high correlation with AGB with $R^2 = 0.777$, $R^2 = 0.861$ and $R^2 = 0.845$ respectively. Joshi et al. (2019) in their study used slope-based vegetation indices like NDVI, Ratio, TVI and CTVI and the result showed the correlation between the VIs and AGB with correlation coefficient more than 0.7 of which NDVI had relatively higher correlation ($r=0.734$). The study further revealed that NDVI was relatively more significant ($r = 0.734$, $R^2 = 0.5388$ and adjusted $R^2 = 0.5248$) for P. roxburghi studies. Pandit et al. (2018) gained $R^2$ value for SAVI, NDVI were 0.81 and 0.70 respectively while estimating the AGB in sub-tropical buffer zone community forest. Correlation value of 0.89 and 0.81 for the indices NDI45 and NDVI was obtained by (Nuthammachot et al. 2020) in private forest in Indonesia. Similarly, Askar et al. (2018) gained $R^2$ value of NDI45, NDVI to be 0.79 and 0.65 respectively on private forest in Indonesia using Sentinel-2. (Priatama et al. 2022) calculated correlation value of NDVI and SAVI to be 0.73 and 0.80 using Landsat imagery in post-mining area.

NDI45 has shown higher value of $r$ and $R^2$ than of NDVI which might be due to the use of red-edge region, centered at 705 (band 5), 740 (band 6), 783 (band 7), and 865 nm (band 8a). These bands have a lot of potential for monitoring various vegetation features (Shoko and Mutanga 2017). Furthermore, studies such as Askar et al. (2018); Fernández-Manso et al. (2016); Guo et al. (2017); Nuthammachot et al. (2020); Padilla et al. (2017) have demonstrated that red-edge VIs diminishes saturation, particularly in complex vegetation structures (Adan 2017). Saturation occurs, particularly when vegetation reaches maturity in the case of crops (Mutanga & Skidmore, 2004; Wang et al., 2016) while in many cases it is because of complex forest structure (Das & Singh, 2012; Lu et al., 2016; Sinha et al., 2016) causing issues in predicting forest AGB (Wernick et al. 2021). In such a case, the VIs is unable to detect any further increases in biomass because saturation occurs when vegetation completely covers the land, which is frequently expressed as full leaf area coverage. In this case, the biomass continues to grow while the indices remain unchanged (Adan, 2017). Steininger (2000) reported saturation at around 150 t h$^{-1}$. This study concludes the average AGB from the field data to be 142.90 t h$^{-1}$ which
is lower than saturation amount. Thus, data saturation problem is eliminated in this study area due to lower canopy and the AGB can be predicted using the VIs consisting of the NIR, Blue and Red band i.e. ARVI and EVI2.

The degree of the relationship between VIs and AGB varies on a number of elements, including plant species and their surroundings, thus, it is possible to explain the inconsistency in the relationship between VIs and AGB to the variation in biophysical conditions of the research area (Anderson and Hanson, 1992; Mundava et al., 2014). As a result, depending on the local environment, one species exhibits higher connection on one VI while another on another (Joshi et al., 2019).

CONCLUSION

Generally, in this study Sentinel-2 VIs as ARVI and EVI2 shows potential in biomass estimation than other VIs used in this study. This study emphasizes the value of VIs in forestry-related research. Applications for this technique include management of forest resources and conservation-related projects. The use of RS techniques has made it possible to estimate biomass more quickly, more effectively, and in a timely manner for the scientific management of forest resources as opposed to the conventional methodology, which is labor-intensive, complicated, and time-consuming. Thus, freely available multispectral Sentinel-2 data with high spatial, temporal resolution are suitable for calculating AGB at a small scale over wide areas.

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