**Title:** Modelling and Estimation of Above Ground Biomass and Carbon Stock of *Pinus Roxburghii* Dominated Forest Using Sentinel-2 Imagery in Shreenagar Hill, Nepal

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**Abstract**

Proper methods for the estimation of above ground biomass (AGB) are essential as it helps in the calculation of forest carbon stock (CS).

In this study, field data were collected from a total of 26 sample plots and sentinel-2 satellite imagery was used to generate 11 different vegetation indices (VIs). Field-measured AGB at 18 randomly chosen sample plots (70%) were used to generate the model. Five different regression models (i.e. linear, logarithmic, quadratic, power and exponential) were applied to find the relationship between dependent variable (AGB) and independent variable (Vegetation indices- VIs). Fit statistics of each model were evaluated to shortlist the good model. Remaining 8 sample plots (30%) were used for validation of developed model.

Quadratic regression model developed from normalized difference vegetation index (NDVI) with correlation coefficient (R = 0.92), coefficient of determination ( = 0.86), Akaike information criterion (AIC = 161.13) & Bayesian information criterion (BIC = 164.69) was found as the best model. During model validation of the best model, root mean square error (RMSE = 13.36 t.ha-1), (R = 0.96) & (= 0.92) were found. The validated model predicted the average value of AGB & CS (including no vegetation area) for total study area as 192.40 & 90.43 t.ha-1 respectively.

Results from this study shows the benefits, possibilities, and effectiveness of combining Sentinel-2 VIs with field data to forecast biomass. This research offers a significant and pertinent addition to the field of carbon sequestration policy-making.

**Introduction**

The usage of remote sensing is wide in different domains. [1] used moderate resolution imaging spectro-radiometry images in order to detect and investigate changes in LULC patterns in Gilgit-Baltistan, Pakistan, for a period between 2008 and 2017. Using the land surface temperature data of MODIS for years 2006 to 2020, [2] quantified the temporal trends (Day and night time), surface urban heat island intensity (SUHII) trend in six major cities of the Punjab province of Pakistan and estimated the future SUHII for the year 2030 using the ARIMA model. [3] used artificial intelligence (AI) & long- short-term memory recurrent neural network method in order to explore & forecast future urban–rural vegetation disparities in Pakistan’s six megacities using MODIS EVI data. By processing RS data on Google Earth Engine (GEE), [4] compared the performance of CART RF (Random Forest), SVM (Support Vector Machine) and (Classification and Regression Tree) for LULC estimation.

The global climate system depends heavily on forests, which sequester a significant quantity of carbon [5]. As AGB is used to generate bioenergy, regulates ecosystem productivity, and serves as a carbon sink during photosynthesis, the Global Climatic Observing System (GCOS) has classified it as one of the essential climatic variables (ECV) [6]. An evaluation of AGB facilitates calculation of terrestrial carbon and helps scientists, foresters and managers comprehend and track ecosystem responses and contributions to the climate change and global carbon cycle [7,8]. Remote sensing (RS) and traditional field-based methods are the two main ways to estimate the forest biomass. Traditional field-based methods can be categorized into destructive and non-destructive methods. The destructive approach is precise [9,10], but it takes a lot of time, effort, and money, and it poses environmental risks because it involves cutting down the tree. The non-destructive approach, which is frequently employed in plantations or natural forests, involves estimating AGB without harvesting the tree [11,12]. Compared to conventional methodologies, RS techniques provide an option for quantifying biomass and CS [13]. Researchers now acknowledge the application of RS in height [14] and AGB estimation [15,16] due to its capacity to estimate spatial distribution of AGB at a fair price with acceptable accuracy. Even though it is impossible to detect biomass directly from space, field-based observations paired with spectrally-derived factors from sensor reflectance (bands) boost the accuracy of biomass prediction [17]. National forest monitoring systems should employ remote sensing (RS) technology for inventory in order to monitor forest cover, evaluate forest carbon reference, and assess forest degradation, according to recommendations made by the United Nations joint program on REDD (UN-REDD). Improved methods for integrating data are also necessary to get precise and spatially explicit estimates of forest AGB [18].

Because Landsat images have a medium spatial resolution and are widely accessible, they have been the primary source of forest AGB calculation for the past thirty years [19–21]. Nonetheless, a prevalent issue with Landsat imagery is data saturation; it has been observed that a rise in biomass causes spectral saturation issues, which typically result in an underestimation of biomass [22]. Sentinel-2, a sensor fitted with a multi-spectral instrument (MSI), offers a noteworthy enhancement in terms of spectral coverage, temporal frequency and spatial resolution when compared to the present generation of Landsat sensors [23,24]. The sensor from sentinel-2 has a significant potential for mapping different vegetation properties due to the presence of four bands inside the red-edge region, which are centered at 705 nm (band 5), 740 nm (band 6), 783 nm (band 7), and 865 nm (band 8a) [25].

In the southern coast of Honda Bay, Pureto Princesa City, Philippines, [26] used Sentinel imagery (Sentinel-1 (SAR) & sentinel-2 (Multispectral)) for estimation and mapping of AGB of mangrove and their replacement land uses. [25] tested the potential of Sentinel-2 MSI sensor in detecting and discriminating between Festuca (C3) and Themeda (C4) grass species at Drakensberg mountains, South Africa. In the Sub-Tropical Buffer Zone Community Forests of Parsa National Park, Nepal, [27] developed a new AGB estimation approach and demonstrated the possibility of medium resolution Sentinel-2 Multi-Spectral Instrument (MSI) data use as an alternative to hyper-spectral data. [23] compared Sentinel-2 and Landsat-8 imagery for prediction of forest variable (stem volume, stem diameter, tree height & basal area and species wise components for pine, spruce and broadleaved trees) in the boreal forest of southern Finland. Using field-measured biomass and Sentinel-2 satellite data, [28] used a machine learning regression approach called Random Forest (RF) to estimate the aboveground biomass (AGB) of the forest in Yok Don National Park, Vietnam. In the Shengjin Lake wetland (a Ramsar site), [29] investigated the potential of spectral and textural features from the Sentinel-2 Multispectral Instrument (MSI) for modeling grassland AGB using random forest (RF) and extreme gradient boosting (XGBoost) algorithms. [30] used Sentinel-2 imagery to model and map the aboveground biomass and carbon stock in the Chure area of Sainamaina municipality, Nepal.

However calculation and prediction of AGB & CS by the inventory of forest with field based measurement is quite common in Nepal, the research related to estimation of AGB and CS using remote sensing data with field measurement data is very limited. Majority of research related to AGB & CS estimation in Nepal using Sentinel-2 combined with field measurements were carried out in terai and chure regions of Nepal. To the best of our knowledge, till date, AGB & CS estimation using Sentinel-2 combined with field measurements are not carried out in a pure *Pinus roxburghii* dominated hill forest in Nepal. Therefore, this study aims to i) Find the best regression model for estimation ii) Estimate and map AGB & CS of *Pinus Roxburghii* dominated forest using sentinel-2 spectrally derived indices with plot level AGB data in Shreenagar hill of Tansen municipality.

**Materials and Methods**

**Study Area**

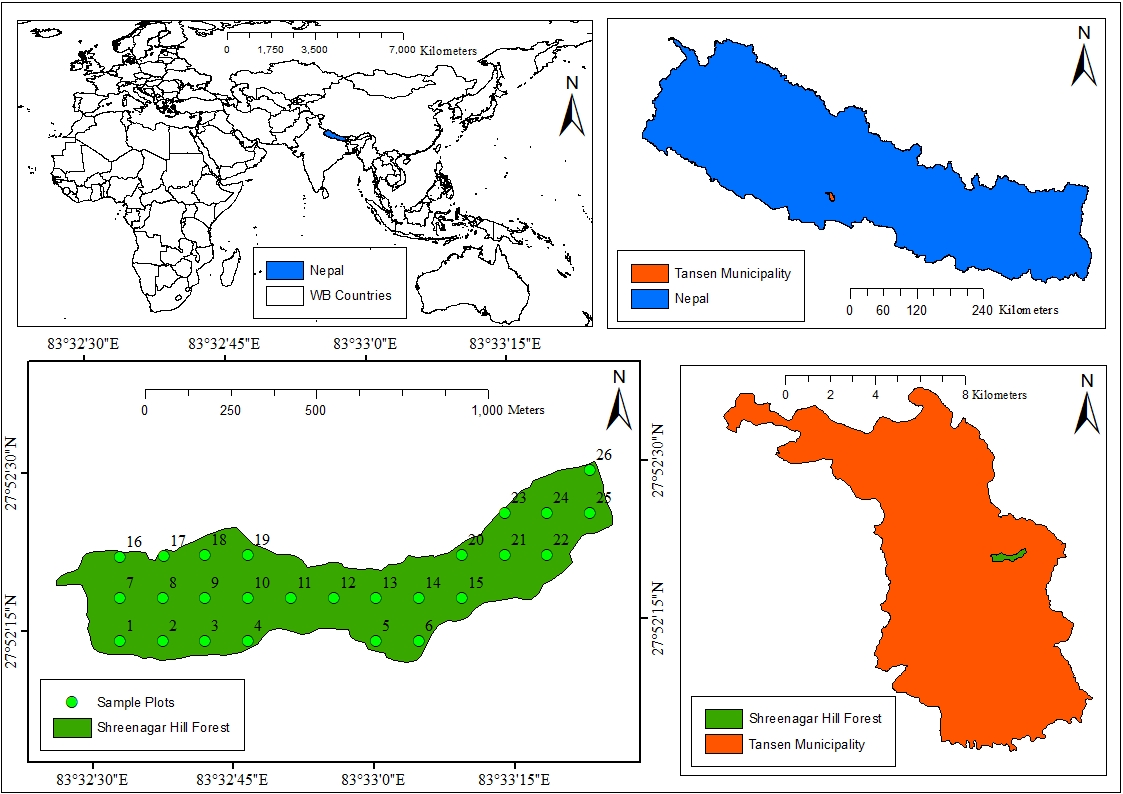
This study was conducted in Shreenagar hill of Tansen municipality as shown in the figure (1), which is located in Palpa District, Lumbini Province, Nepal. Geographically, the study area lies in between latitude 27°52′10″N to 27°52′30″N, longitude 83°32′25″E to 83°33′30″E with the altitude ranging from 1369 to 1498 meter from mean sea level (MSL). It covers an area of 41.10 ha with slope ranging from 19° to 358°, aspect towards the south (majority of area) and has characteristics of sub-tropical forest. From 1971 to 2014, [ 31] reported that the average annual precipitation, annual maximum temperature and annual minimum temperature of Palpa district were 1680.5mm, 26.10°C and 14.80°C respectively. Palpa district has a humid subtropical, dry winter climate. *Pinus roxburghii* (Local name: Khote Salla) is the major dominant forest species followed by *Schima wallichii* (Local name: Chilauni) forest species in the study area. 

Figure (1): Map showing the study area with sample plots

**Research Design Flowchart**

Mapping and Estimation of AGB and CS

Site Selection, Determination of Sampling Intensity & Plot to Plot Distance

Overlaying of Fishnet, Determination of Number of Sample Plots

Sample Plot Location, Forest Inventory, Estimation of Plot Level AGB

Sentinel-2 Image Acquisition

Derivation of Vegetation Indices (VIs)

Extraction of Plot Level Pixel Values of VIs

Development of Regression Models (Linear, Logarithmic, Quadratic, Power, and Exponential) between Dependent Variable (AGB) & Independent Variable (VIs=11),

Evaluation of Shortlisted Regression Models (Based on Adjusted , AIC & BIC)

Shortlisting of Regression Models ()

Development of Regression between Observed AGB & Predicted AGB of 8 Sample Plots

Validation of Best Model (Based on RMSE, & R)

**Sample design and field data collection**

In order to collect the field data of vegetation, temporary circular sample plots, each with an area of 500 m2 (r = 12.62 m) were laid over the entire study area using systematic sampling method in ArcGIS 10.8. The sampling intensity for the study was chosen purposively as 3%. Following the equations (1), (2) & (3) provided by [32] of Nepal, the sample plot area, number of sample plots and plot to plot distance were calculated as 1.23 ha., 25 (rounding up for 24.60) and 125 m (rounding up for 123.38 m purposively) respectively.

………. (1) ………… (2) ………… (3)

Where, a is a total area of sample plots (ha.); SI is sampling intensity; A is total study area (ha.); n is a number of sample plots; p is area of single sample plot (ha.); d is plot to plot distance

While overlaying fishnet with cell size width & height of 125 meters over the study area, a total of 28 sample plots were found inside the boundary line of study area. The increase in sample plots was due to the irregular shape of the boundary line. Two of the sample plots which were too close (< 2 m) to boundary line were removed and three of the sample plots which were at location greater than 10 m but less than 12.62 m from the boundary line were pulled away additionally up to the range between 2 to 5 m from original position in order to establish a complete circular plot of radius 12.62 m within boundary line.

In each plot, forest parameters namely, diameter at breast height (DBH) (1.30 m above the ground) and tree height (H) were measured. Measurements of trees with DBH ≥ 5 cm [27] were only recorded. The X-Y coordinates of twenty-six (26) sample plots which were fixed from fishnet overlaying were searched & located in the field using Garmin GPSMAP 65. DBH of trees were measured using Million Diameter Tape and the trees' height were measured using Apresys Laser Range Finder Powerline 660. In all 26 sample plots as shown in the figure (1), the species name of every tree was also recorded.

**Sentinel-2 Image Acquisition**

The satellite image of Sentinel-2 level-2A with sensing date of 10 May, 2023 and cloud coverage 3.32% was downloaded from the website of Copernicus Open Access Hub. The downloaded tile of Sentinel-2 with an area of 100\*100 km2 was clipped with the shape file of the study area.

**Estimation of Plot Level AGB and CS**

Species specific allometric equation developed by [33]was used for above ground biomass estimation. This equation is based on climate and forest types. The value of specific gravity (density of wood) (ρ) was given by Jackson [34], which was used as a reference by [35] to calculate tree level biomass. A general value (ρ = 0.674), was used in the absence of specific values [27].

…………. (4)

= 0.0509 \* ρH

Where, is above ground biomass estimated in kilograms (kg); ρ is a specific gravity (wood density) in g.cm−3; D is diameter at breast height (DBH) in centimeters (cm); H is height in meter (m); 0.0509 is constant obtained from the literature [33].

Each tree biomass within the plot was calculated using the equation (4) and then it was summed up, to obtain the total biomass of each plot level. Then, it was standardized to tonnes per hectare (t.ha-1) (1 tonne = 1,000 kg). With the formula from equation (5) i.e. using the conversion factor, the amount of CS was computed from the AGB.

CS = AGB \* 0.47 ……………. (5)

Where, CS is the carbon stock in tonnes; AGB is the above ground biomass and 0.47 is a conversion factor or carbon fraction in AGB.

**Deriving VIs from Sentinel-2 Satellite Image**

From sentinel-2 satellite imagery, four bands: band-2 (blue), band-3 (green), band-4 (red) and band-8 (NIR) having spatial resolution of 10 m were used to create various eleven vegetation indices (VIs) following various literature as mentioned in the table (1). Those 11 vegetation indices were chosen based on their effectiveness in earlier biomass estimation research.

Table 1: Formula of VIs with their authors

|  |  |  |  |
| --- | --- | --- | --- |
| S.N. | VIs | Equations | Authors |
| 1. | NDVI | (NIR-Red)/(NIR+Red) | [36–38] |
| 2. | SR | NIR/Red | [39] |
| 3. | DVI | NIR-Red | [38] |
| 4. | NDWI | (Green-NIR)/(Green+NIR) | [40,41] |
| 5. | RDVI |  | [42] |
| 6. | WDRVI | ((0.1\*NIR)-Red/(0.1\*NIR)+Red) | [43] |
| 7. | VARI | (Green-Red)/(Green+Red-Blue) | [44] |
| 8. | EVI | 2.5\*(NIR-Red)/(NIR+6\*Red-7.5\*Blue)+1 | [45,46] |
| 9. | IPVI | NIR/(NIR+Red) | [47] |
| 10. | NLI | / | [48] |
| 11. | GNDVI | (NIR-Green)/(NIR+Green) | [49,50] |

NDVI: Normalized Difference Vegetation Index; SR: Simple Ratio; DVI: Differenced Vegetation Index; NDWI: Normalized Difference Water Index; RDVI: Renormalized Difference Vegetation Index; WDRVI: Wide Dynamic Range Vegetation Index; VARI: Visible Atmospherically Resistant Index; EVI: Enhanced Vegetation Index; IPVI: Infrared Percentage Vegetation Index; NLI: Non-Linear Vegetation Index; GNDVI: Green Normalized Vegetation Index.

**Extraction of plot level pixel values of VIs**

Buffer tool was used to create the circular buffer region (r = 12.62 m) around the center from each sample plot location (latitude and longitude). Zonal Statistics as Table tool was used to extract the pixel value of each of 12.62 m circular sample plots. It provides geo-database table which was exported to excel for further analysis. For 12.62 meters circular plot, zonal statistics provides an average of multiple pixels value by calculating the nearest neighbor pixel values when the sample plot's area is spread across many pixels.

**Statistical Analysis**

IBM SPSS Statistics and Microsoft Excel were used for statistical analysis. Five different functions, i.e., linear, logarithmic, quadratic, power, and exponential regression models were used for assessing the relationship between AGB and each of 11 VIs. In all five functions, AGB was used as the dependent variable (y) and each VI was used as an independent variable (x) in order to determine the change in AGB with the change in VI. Out of 26 total sample plots, 18 were used for examining the relationship & development of model while 8 were used for validation of model. Equations (6) to (10) represent the general form of five different functions.

………… (6)

………… (7)

………… (8)

………….. (9)

…………… (10)

Where, Y is aboveground biomass (t.ha-1); VI is vegetation index value; and are parameters of the respective regression equations.

**Evaluation of Models**

In case of all 55 (5\*11) different regression models, the relationship between AGB (t.ha-1) and different VIs were compared by analyzing the value of the coefficient of determination (). Evaluation, selection and short-listing of better model among various regression models looking at their higher value of is effective as done in various forest biomass estimation study [30,51–53]. Regression models with were shortlisted purposively in this study. Along with other parameters for model selection, [53] have used AIC & BIC and [30] have used , AIC & BIC and both the literatures have selected the model with higher , lowest AIC & BIC value as best model. Therefore, shortlisted regression models were further compared with three statistical parameters: Adjusted ), Akaike information criterion (AIC) & Bayesian information criterion (BIC) as mentioned in equation (11), (12) and (13) respectively to find the best model for AGB estimation in this study.

……….. (11)

Where, N = number of samples, p= number of predictor values, and is the coefficient of determination

………….. (12)

……….. (13)

Where, n = number of sample plots, SEE = sum of squares due to errors, and k = number of parameters.

**Validation of Model**

Among shortlisted models, best model/s with closest values of AIC & BIC were selected for validation purpose. The observed data of AGB from eight sample plots at field level which were independent to the model development process were used for model validation. The relations between observed AGB and predicted AGB data for those eight sample plots were discovered by calculating the value of RMSE, and R. For validation purpose, [27,28,30] have used RMSE & and selected the best model with lower RMSE and higher value. Following these literatures, RMSE, and R were calculated for selected model/s using equations (14), (15) and (16) respectively.

….….. (14) ….….. (15)

……... (16)

Where, n = number of sample plots (8), = observed AGB and = predicted AGB value for the plot i in t.ha-1.

**Mapping and Estimation of AGB and CS**

From best model among selected, AGB & CS mapping of whole study area was carried out. The regression equation of the best fit model was supplied in the algebra map expression in raster calculator with the estimated value of respective statistical parameters and VI. Then, each pixel value of VI gets converted into biomass value. Zero value was provided to pixels with no vegetation/biomass. Estimation map of CS was prepared by multiplying the estimation map of AGB with 0.47 as CS is 47% of AGB [54]. Thus, prepared estimation map of AGB & CS was further reclassified into 5 different classes. Per pixel value of AGB & CS was also extracted and total value (t.ha-1) for the whole study area was computed.

**Results**

**Field measurement and record**

The total number of trees measured in 26 plots were 389 in numbers. Six species of trees that were identified in measured plot with their occurrence are: *Pinus roxburghii* (79.43%), *Schima wallichii* (18.25%), *Diospyros malabarica* (1.03%), *Sapium insigne* (0.51%), *Myrica esculanta* (0.51%), *Castanopsis indica* (0.26%). Various descriptive statistics of total measured trees i.e. DBH (centimeter) (min = 5, max = 51, average = 29.7 ± 0.505), height (meter) (min = 4, max = 25, average = 17.73 ± 0.244), AGB (t.ha-1) (min = 29.88, max = 234.25, average = 192.80) and CS (t.ha-1) (min = 14.04, max = 110.10, average = 90.61).

**Correlation Coefficient and Coefficient of Determination**

All of the vegetation indices (VIs) that were used as an independent variable showed a good correlation with the dependent variable: above ground biomass (AGB) at plot level, with less than 5 % level of significance. Out of total 55 models (5 models \* 11 VIs) that were evaluated using the value of plot level biomass (t.ha-1) and vegetation indices (VIs), 6 models having value of , were selected and shortlisted as shown in the table (3). value for overall models are as shown in the table (2).

Table (2): Coefficient of determination ( between AGB and VIs (5 different models)

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **S.N.** | **VIs** |  | | | | |
| **Linear** | **Logarithmic** | **Quadratic** | **Power** | **Exponential** |
| 1 | NDVI | 0.58 | 0.67 | **0.86** | 0.49 | 0.40 |
| 2 | SR | 0.48 | 0.55 | **0.77** | 0.37 | 0.31 |
| 3 | DVI | 0.40 | 0.48 | 0.66 | 0.32 | 0.25 |
| 4 | NDWI | 0.49 | - | 0.69 | - | 0.38 |
| 5 | RDVI | 0.44 | 0.48 | 0.69 | 0.32 | 0.28 |
| 6 | WDRVI | 0.50 | - | **0.79** | - | 0.33 |
| 7 | VARI | 0.52 | - | **0.71** | - | 0.31 |
| 8 | EVI | 0.55 | 0.65 | **0.77** | 0.45 | 0.34 |
| 9 | IPVI | 0.57 | 0.59 | **0.85** | 0.41 | 0.39 |
| 10 | NLI | 0.45 | 0.45 | 0.45 | 0.28 | 0.28 |
| 11 | GNDVI | 0.49 | 0.53 | 0.69 | 0.42 | 0.38 |

Note: Values of greater than 0.70 are highlighted (bold)

Table (3): Parameter estimates and fit statistics of shortlisted model

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **VIs** | **Parameter estimates** | | | **Forms of  Equation** | **Fit Statistics** | | | |
|  |  |  |  |  | **AIC** | **BIC** |
| NDVI | -764.25 | 5143.02 | -6627.85 | Quadratic | 0.86 | 0.84 | 161.13 | 164.69 |
| SR | -1253.75 | 1275.19 | -272.05 | Quadratic | 0.77 | 0.74 | 169.34 | 172.90 |
| WDRVI | -5455.82 | -18310.26 | -14718.24 | Quadratic | 0.79 | 0.77 | 167.67 | 171.23 |
| VARI | 228.85 | 320.56 | -6228.48 | Quadratic | 0.71 | 0.67 | 173.91 | 177.47 |
| EVI | -245.15 | 575.00 | -173.10 | Quadratic | 0.77 | 0.74 | 169.45 | 173.02 |
| IPVI | -11553.02 | 33824.63 | -24265.76 | Quadratic | 0.85 | 0.83 | 162.37 | 165.93 |

**Evaluation, Development and Validation of Model**

Fit statistics (,, AIC & BIC) value of six shortlisted quadratic regression models showed that, quadratic regression models developed with VIs: NDVI & IPVI described the strong relationship with AGB observed at the field. Higher value of and lower value of AIC & BIC were considered as the criteria for the evaluation of goodness of fit of models. The fit statistics value of both quadratic regression models with strong relationships with AGB are quite close to each other. Therefore, both models were further selected for validation.

Remaining 8 sample plots data for AGB which were not used in model development were used for validation purpose. Those 8 sample plot data were used as observed AGB at field and predicted values of AGB for the same sample plots were calculated using their respective parameters (, , ) & VIs value. The accuracy level between 2 selected quadratic regression models was assessed by calculating the R, and RMSE value from observed AGB & predicted AGB of eight sample plots. The R, and RMSE values of the quadratic regression models: i.e. NDVI & IPVI are as shown in the table (4) along with their scatter plot diagram in the figure (2).

Table (4): Parameters for validation of 2 quadratic regression models

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **VIs** | **Form of Equation** | **R** |  | **RMSE** |
| NDVI | Quadratic | 0.96 | 0.92 | 13.36 |
| IPVI | Quadratic | 0.93 | 0.87 | 14.53 |

Figure (2): Scatterplot diagram of observed & predicted AGB for quadratic model of NDVI and IPVI.

The validation & selection of the model was based on criteria such as: higher R, higher, and lower RMSE. The quadratic regression model developed using NDVI as VI was found more valid and accurate as the values of R (0.96>0.93) and (0.92>0.87) are higher and RMSE (13.36<14.53) is lower in comparison to the quadratic regression model developed using IPVI as VI. 93.43% of observed AGB at the field was justified by the predicted AGB which was predicted from the quadratic regression model of NDVI. Hence, the quadratic regression model of NDVI was selected as the best fit model. The developed & validated equation for the AGB estimation of this study is as shown in equation (18) which is based on the general form of quadratic function's equation as shown in equation (17).

……. (17)

Where, Y is estimated biomass, is y-intercept which is -764.25 and & are slopes which are 5143.02 & -6627.85 respectively, and X is NDVI.

Y= (-764.25) + 5143.02 \* NDVI + (-6627.85) \* …….. (18)

**Mapping & Estimation of AGB and CS**

The prepared estimation map of AGB & CS as shown in the figure (3) shows that the value of AGB & CS range from 0 to 233.45 & 0 to 109.72 t.ha-1 respectively. The average value of AGB & CS (including no vegetation area) for total study area wasfound 192.40 & 90.43 t.ha-1 respectively. Similarly, the average value of AGB & CS (excluding no vegetation area) for total study area was found 193.49 & 90.94 t.ha-1 respectively. A total of 23 pixels (0.23 ha) were found without vegetation/biomass. Figure (3) clears that most of the AGB & CS of forest is within the class range of 176.21 to 233.45 t.ha-1.

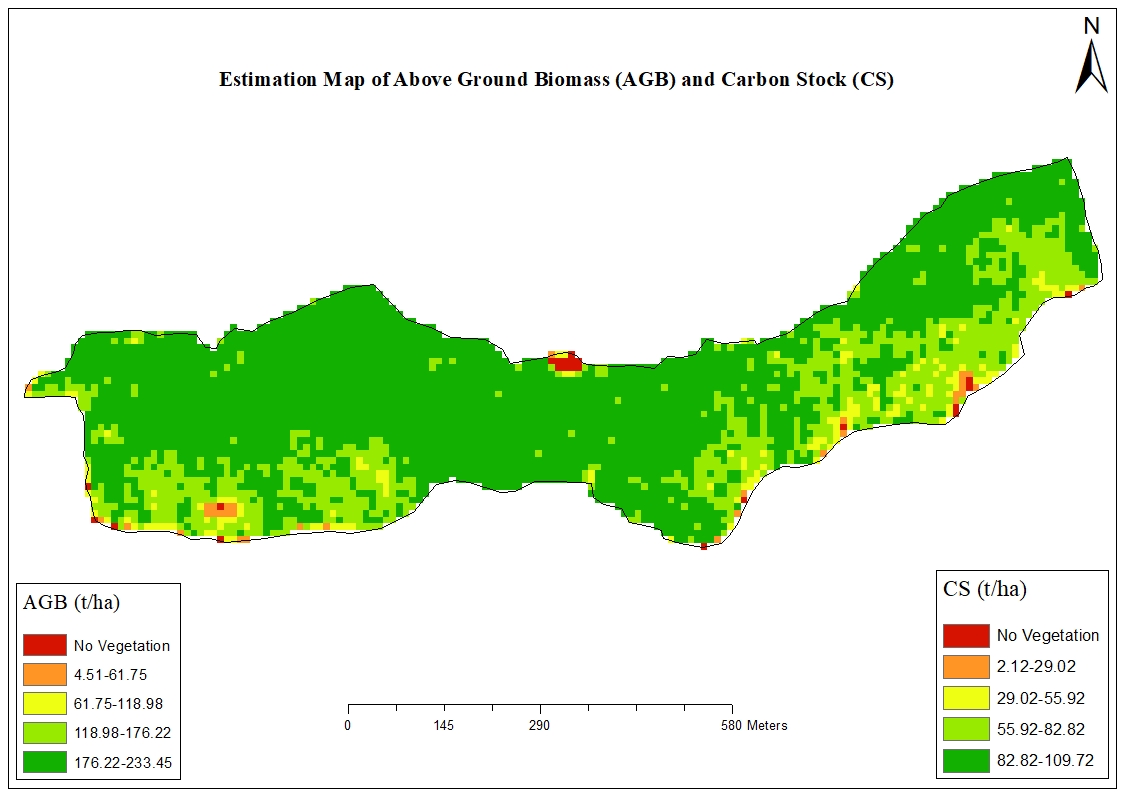


Figure (3): Estimation map of above ground biomass (AGB) and carbon stock (CS)

This research is carried out in a small geographical area which caused for the selection of low number of sample plots. In order to reduce the estimation error & make wider application of research, a very large sample size should be chosen. This is the matter of concern for upcoming researchers in the same scope of the research field.

**Discussion**

All of the vegetation indices which were used as an independent variable in regression models showed the positive correlation with AGB. NLI & DVI showed the minimum value of correlation whereas NDVI and IPVI showed the maximum value of correlation and coefficient of determination. Quadratic regression model developed using two of the VIs i.e., NDVI (R² = 0.86, AIC = 161.13 & BIC = 164.69) & IPVI (R² = 0.85, AIC = 162.37 & BIC = 165.93) showed a good fit statistics & closer value to each other during the development of regression model which were yet to be validated. Maximum value of R² and minimum value of AIC & BIC means VIs have justified the value of AGB in good manner. Similarly, during the model development, [30] found that the quadratic regression model of ARVI (R² = 0.78, AIC = 313.78 & BIC = 320.85), NDVI (R² = 0.78, AIC = 313.60 & BIC = 320.65) & SAVI (R² = 0.78, AIC = 313.62 & BIC = 320.67) showed a good fit statistics & closer value to each other during the development of regression model which were yet to be validated. Model development of both study was done by parametric test but the fit statistics (R², AIC & BIC) for NDVI of [30] is slightly lower than our study. This may be due to the different geographical location of forest, differences in forest type & their reflectance value, differences in the formula for the calculation of AGB. Similarly, [55] used Sentinel-2 to obtain an R² value of 0.79, 0.65, and 0.19 for NDI45, NDVI, and S2REP in Indonesian private forests which is contradictory to our findings. The red-edge region from the formula may have contributed to the NDI45 and S2REP's higher values of r and R2 than the value for NDVI. This region offers the sensor a great deal of possibilities for monitoring different vegetation features [25]. Our study's findings are at odds with those of [56], they estimated the NDVI using optical image spectral bands and found a weak association with biomass (R2 of 0.29). This could be because of saturation problems in tropical forests. They used a combination of Landsat TM and ALOS, PALSAR data for biomass estimation in tropical forests. But, it is good, not to compare with other studies using various combination of RS & models to estimate the biomass as different methodologies of estimating AGB differs from the results.

In many cases, saturation is caused by the complex forest structure [56–58], which brings difficulties in the estimation of forest AGB [59]. Since saturation happens when vegetation fully covers the land which is often referred to as full leaf area coverage. In such a scenario, the VIs are unable to detect any further increases in biomass. The indices don't change in this instance, yet the biomass keeps increasing. VIs function more well in simple structure woods than in dense forests [60]. Numerous conifer species, including Pinus, have been documented to have allelopathic effects on other species [61–65]. It has been found by [66] that conifer leaf and litter extracts reduce the germination of target species. [67] found that out of three types of extracts i.e. green needle extract, needle litter extract and bark extract of *Pinus roxburghii*, allelochemical emission is thought to mostly originate from the bark extract as it was found more toxic. But, [68] found that the allelochemical emission mostly originates from the decomposition of litter. The forest floor of *P. roxburghii* is distinguished by a carpet of dropped needles. The understorey of chir pine woods is characterized by scant flora, which may be at least partially caused by allelopathic action [67]. Similar might be the case in our study that, due to the allelopathic nature of pine, there are no other vegetation or very little vegetation around the pine tree/forest except its fallen needle leaves. Due to which most of the plots with field measured data were showing AGB values directly proportional to the NDVI. This clears that either this study is free from saturation problem or is present in minimal negligible amount. Therefore, AGB was estimated with NDVI which is derived from the red band and NIR.

During the Forest Resource Assessment (FRA) Nepal (2010-14), [69] reported that the tree component contributed 82.13 t.ha-1 of CS from the forest of Middle Mountain. As per [54]**,** CS is just 47% of AGB. Therefore, converting the tree component CS into AGB, it was found 174.74 t.ha-1. The data from the report of [69] is slightly lower to our study as the average value of AGB & CS (including no vegetation area) for total study area were found 192.40 & 90.43 t.ha-1 respectively. The value of AGB and ultimately CS in our study is slightly more than that of FRA (2010-14) because of two main reasons: First, the AGB calculation method of our study is based on [33] whereas the volume calculation method of FRA (2010-14) is based on [70]. Second, we were conducting our research in such a forest area which was nearly fully occupied by forest trees as there in minimal negligible no vegetation area but it may not be the similar case for [69] during FRA Nepal (2010-14).

In this study, the quadratic regression model developed using NDVI was found the best fitted model with R² = 0.92 & RMSE = 13.36 t.ha-1 for the estimation of total AGB & CS of forest. With some similarity in result, [30] also found quadratic regression model developed using NDVI as the best fitted model with R² = 0.83 & RMSE = 10.77 t.ha-1. Compared to this study, there is slight difference in R² and RMSE which may be due to the different geographical location of forest, differences in forest type & their reflectance value, differences in the formula for the calculation of AGB. When an AGB map was created utilizing the best predictor variables from the final model generated, [27] discovered R² = 0.81 and RMSE = 25.57 t.ha-1. But, [27] generated the final model by using RF algorithm which contradicts to the methodology of our study. Our research used parametric technique, whereas random forest (RF) algorithm used by [27] is a non-parametric technique. Machine learning methods including support vector machines (SVMs), ANNs, and random forests (RF) have gained popularity in the past few years for estimating forest AGB [71]. Because these machine learning techniques haven't predefined model structures and instead base the model structure on the data, they are a more reliable way for estimating AGB [72]. Studies such as [73–75] have also provided support for the notion that nonparametric models, as opposed to parametric models, are more appropriate for capturing the heterogeneity of forest AGB. Our study finds parametric technique as a reliable way of estimation of AGB. This is contradictory to studies [73–75]. This might be the reason that our study area forest is more homogenous in terms of forest species density and covers a small geographical area.

This study is mainly focused in estimation of AGB & ultimately CS of the *Pinus roxburghii* dominated hill forest with the help of development of best fit regression model. After proper evaluation of the result from this study, the same methodology can be replicated to other study area with similar geographical conditions & forest types. There is no any compulsion to stick to the same methodology which we have used in this study for AGB & CS estimation. Different methods have their own strength and weakness. Comparison of results from different methods is not worthful. Hence, appropriate methods can be followed for estimating the AGB & CS of the forest.

**Conclusion**

This study developed the best fit regression model for the estimation of AGB & CS of *Pinus roxburghii* dominated shreenagar hill forest of Tansen Municipality, Nepal with the help of Sentinel-2 imagery. After comparing field observed AGB (t.ha-1) with 11 different vegetation indices along five different regression model, the quadratic regression model developed using NDVI & IPVI were selected and shortlisted as their R², AIC & BIC values were best among other models. While comparing the field observed plot level values of AGB and the predicted values of AGB from these two models, NDVI with best fit values of R² (0.92) and RMSE(13.36 t.ha-1) was found validated for estimation of AGB & CS. The average value of AGB & CS (including no vegetation area) for total study area was found 192.40 & 90.43 t.ha-1 respectively. Overall, the results from this study demonstrate the usefulness, potential, and strength of using Sentinel-2 VIs in conjunction with field data to predict biomass. Sentinel-2 is a good choice for scientists and environmentalists looking for free, open-access, and inexpensive satellite sensor data for accurate and dependable AGB and CS monitoring using non-destructive sampling techniques. This research helps to provide data on sequestrated carbon & its linkage to climate change mitigation, sustainable forest management, land use planning and biodiversity conservation. This approach is quite straightforward and can be applied to other hilly regions with comparable biophysical patterns.

The findings of this study indicate that spectral texture indices should be used to assess future work, including the application of this data to other physiographical vegetation zones in various contexts. We also recommend using a very large number of sample size when using this methodology to see if it lowers the estimation error.

**Acknowledgements**

We really appreciate the Forest Officer, Upendra Aryal from Division Forest Office, Palpa, for providing the necessary equipments that were used in the field during data collection. We are also thankful to Akikrit Shreenagar Parya-paryetan Community Forest User Groups' President, Sunita Sharma for her consistent field guidance during the field work.

**Conflict of Interest**

The authors declare that they do not have any conflict of interest(s).

**Data Availability Statement**

All the data required to assess the conclusions for this study are shared in public repository through GitHub.com. Through the following link all the data can be accessed.

<https://github.com/bashyalsagar95/Modelling-and-Estimation-of-AGB-and-CS>

**References**

1. Zafar, Z.; Mehmood, M.S.; Ahamad, M.I.; Chudhary, A.; Abbas, N.; Khan, A.R.; Zulqarnain, R.M.; Abdal, S. Trend Analysis of the Decadal Variations of Water Bodies and Land Use/Land Cover through MODIS Imagery: An in-Depth Study from Gilgit-Baltistan, Pakistan. *Water Supply* **2021**, *21*, 927–940, doi:10.2166/ws.2020.355.

2. Mehmood, M.S.; Zafar, Z.; Sajjad, M.; Hussain, S.; Zhai, S.; Qin, Y. Time Series Analyses and Forecasting of Surface Urban Heat Island Intensity Using ARIMA Model in Punjab, Pakistan. *Land* **2022**, *12*, 142, doi:10.3390/land12010142.

3. Zafar, Z.; Sajid Mehmood, M.; Shiyan, Z.; Zubair, M.; Sajjad, M.; Yaochen, Q. Fostering Deep Learning Approaches to Evaluate the Impact of Urbanization on Vegetation and Future Prospects. *Ecol. Indic.* **2023**, *146*, 109788, doi:10.1016/j.ecolind.2022.109788.

4. Zafar, Z.; Zubair, M.; Zha, Y.; Fahd, S.; Ahmad Nadeem, A. Performance Assessment of Machine Learning Algorithms for Mapping of Land Use/Land Cover Using Remote Sensing Data. *Egypt. J. Remote Sens. Space Sci.* **2024**, *27*, 216–226, doi:10.1016/j.ejrs.2024.03.003.

5. Pan, Y.; Birdsey, R.A.; Phillips, O.L.; Jackson, R.B. The Structure, Distribution, and Biomass of the World’s Forests. *Annu. Rev. Ecol. Evol. Syst.* **2013**, *44*, 593–622, doi:10.1146/annurev-ecolsys-110512-135914.

6. Duncanson, L.; Armston, J.; Disney, M.; Avitabile, V.; Barbier, N.; Calders, K.; Carter, S.; Chave, J.; Herold, M.; Crowther, T.W.; et al. The Importance of Consistent Global Forest Aboveground Biomass Product Validation. *Surv. Geophys.* **2019**, *40*, 979–999, doi:10.1007/s10712-019-09538-8.

7. Chinembiri, T.S.; Bronsveld, M.C.; Rossiter, D.G.; Dube, T. The Precision of C Stock Estimation in the Ludhikola Watershed Using Model-Based and Design-Based Approaches. *Nat. Resour. Res.* **2013**, *22*, 297–309, doi:10.1007/s11053-013-9216-6.

8. Güneralp, İ.; Filippi, A.M.; Randall, J. Estimation of Floodplain Aboveground Biomass Using Multispectral Remote Sensing and Nonparametric Modeling. *Int. J. Appl. Earth Obs. Geoinformation* **2014**, *33*, 119–126.

9. Basuki, T.M.; Van Laake, P.E.; Skidmore, A.K.; Hussin, Y.A. Allometric Equations for Estimating the Above-Ground Biomass in Tropical Lowland Dipterocarp Forests. *For. Ecol. Manag.* **2009**, *257*, 1684–1694.

10. Gibbs, H.K.; Brown, S.; Niles, J.O.; Foley, J.A. Monitoring and Estimating Tropical Forest Carbon Stocks: Making REDD a Reality. *Environ. Res. Lett.* **2007**, *2*, 045023, doi:10.1088/1748-9326/2/4/045023.

11. Brown, S.; Lugo, A.E. Biomass of Tropical Forests: A New Estimate Based on Forest Volumes. *Science* **1984**, *223*, 1290–1293, doi:10.1126/science.223.4642.1290.

12. Methods for Estimating Above-Ground Biomass. In *Carbon Inventory Methods Handbook for Greenhouse Gas Inventory, Carbon Mitigation and Roundwood Production Projects*; Ravindranath, N.H., Ostwald, M., Eds.; Advances in Global Change Research; Springer Netherlands: Dordrecht, 2008; pp. 113–147 ISBN 978-1-4020-6547-7.

13. Rosillo-Calle, F.; Woods, J. *The Biomass Assessment Handbook*; Routledge, 2012;

14. Tiwari, K.; Narine, L.L. A Comparison of Machine Learning and Geostatistical Approaches for Mapping Forest Canopy Height over the Southeastern US Using ICESat-2. *Remote Sens.* **2022**, *14*, 5651.

15. Lu, D. The Potential and Challenge of Remote Sensing‐based Biomass Estimation. *Int. J. Remote Sens.* **2006**, *27*, 1297–1328, doi:10.1080/01431160500486732.

16. Murthy, M.S.R.; Wesselman, S.; Gilani, H. *Multi-Scale Forest Biomass Assessment and Monitoring in the Hindu Kush Himalayan Region: A Geospatial Perspective.*; International Centre for Integrated Mountain Development (ICIMOD), 2015;

17. Dong, J.; Kaufmann, R.K.; Myneni, R.B.; Tucker, C.J.; Kauppi, P.E.; Liski, J.; Buermann, W.; Alexeyev, V.; Hughes, M.K. Remote Sensing Estimates of Boreal and Temperate Forest Woody Biomass: Carbon Pools, Sources, and Sinks. *Remote Sens. Environ.* **2003**, *84*, 393–410.

18. Nandy, S.; Ghosh, S.; Kushwaha, S.P.S.; Senthil Kumar, A. Remote Sensing-Based Forest Biomass Assessment in Northwest Himalayan Landscape. In *Remote Sensing of Northwest Himalayan Ecosystems*; Navalgund, R.R., Kumar, A.S., Nandy, S., Eds.; Springer Singapore: Singapore, 2019; pp. 285–311 ISBN 9789811321276.

19. Foody, G.M.; Boyd, D.S.; Cutler, M.E. Predictive Relations of Tropical Forest Biomass from Landsat TM Data and Their Transferability between Regions. *Remote Sens. Environ.* **2003**, *85*, 463–474.

20. Lu, D. Aboveground Biomass Estimation Using Landsat TM Data in the Brazilian Amazon. *Int. J. Remote Sens.* **2005**, *26*, 2509–2525, doi:10.1080/01431160500142145.

21. Powell, S.L.; Cohen, W.B.; Healey, S.P.; Kennedy, R.E.; Moisen, G.G.; Pierce, K.B.; Ohmann, J.L. Quantification of Live Aboveground Forest Biomass Dynamics with Landsat Time-Series and Field Inventory Data: A Comparison of Empirical Modeling Approaches. *Remote Sens. Environ.* **2010**, *114*, 1053–1068.

22. Steininger, M.K. Satellite Estimation of Tropical Secondary Forest Above-Ground Biomass: Data from Brazil and Bolivia. *Int. J. Remote Sens.* **2000**, *21*, 1139–1157, doi:10.1080/014311600210119.

23. Astola, H.; Häme, T.; Sirro, L.; Molinier, M.; Kilpi, J. Comparison of Sentinel-2 and Landsat 8 Imagery for Forest Variable Prediction in Boreal Region. *Remote Sens. Environ.* **2019**, *223*, 257–273.

24. Castro Gomez, M.G. Joint Use of Sentinel-1 and Sentinel-2 for Land Cover Classification: A Machine Learning Approach. *Lund Univ. GEM Thesis Ser.* **2017**.

25. Shoko, C.; Mutanga, O. Examining the Strength of the Newly-Launched Sentinel 2 MSI Sensor in Detecting and Discriminating Subtle Differences between C3 and C4 Grass Species. *ISPRS J. Photogramm. Remote Sens.* **2017**, *129*, 32–40.

26. Castillo, J.A.A.; Apan, A.A.; Maraseni, T.N.; Salmo III, S.G. Estimation and Mapping of Above-Ground Biomass of Mangrove Forests and Their Replacement Land Uses in the Philippines Using Sentinel Imagery. *ISPRS J. Photogramm. Remote Sens.* **2017**, *134*, 70–85.

27. Pandit, S.; Tsuyuki, S.; Dube, T. Estimating Above-Ground Biomass in Sub-Tropical Buffer Zone Community Forests, Nepal, Using Sentinel 2 Data. *Remote Sens.* **2018**, *10*, 601.

28. Dang, A.T.N.; Nandy, S.; Srinet, R.; Luong, N.V.; Ghosh, S.; Kumar, A.S. Forest Aboveground Biomass Estimation Using Machine Learning Regression Algorithm in Yok Don National Park, Vietnam. *Ecol. Inform.* **2019**, *50*, 24–32.

29. Li, C.; Zhou, L.; Xu, W. Estimating Aboveground Biomass Using Sentinel-2 MSI Data and Ensemble Algorithms for Grassland in the Shengjin Lake Wetland, China. *Remote Sens.* **2021**, *13*, 1595.

30. Poudel, A.; Shrestha, H.L.; Mahat, N.; Sharma, G.; Aryal, S.; Kalakheti, R.; Lamsal, B. Modeling and Mapping of Aboveground Biomass and Carbon Stock Using Sentinel-2 Imagery in Chure Region, Nepal. *Int. J. For. Res.* **2023**, *2023*.

31. DHM *Observed Climate Trend Analysis of Nepal (1971-2014)*; Ministry of Population and Environment, Department of Hydrology and Meteorology: Kathmandu, Nepal, 2017; p. 87;.

32. DOF Guideline for Inventory of Community Forests 2004.

33. Chave, J.; Andalo, C.; Brown, S.; Cairns, M.A.; Chambers, J.Q.; Eamus, D.; Fölster, H.; Fromard, F.; Higuchi, N.; Kira, T.; et al. Tree Allometry and Improved Estimation of Carbon Stocks and Balance in Tropical Forests. *Oecologia* **2005**, *145*, 87–99, doi:10.1007/s00442-005-0100-x.

34. Jackson, J.K. *MANUAL OF AFFORESTATION IN NEPAL*; 2nd ed.; Forest Research and Survey Center, Ministry of Forests and Soil Conservation: Kathmandu, Nepal, 1994; Vol. 2;.

35. GON Forest Carbon Measurement Guideline, 2011 2011.

36. Gitelson, A.A.; Merzlyak, M.N. Remote Estimation of Chlorophyll Content in Higher Plant Leaves. *Int. J. Remote Sens.* **1997**, *18*, 2691–2697, doi:10.1080/014311697217558.

37. Rouse, J.W.; Haas, R.H.; Schell, J.A.; Deering, D.W. Monitoring Vegetation Systems in the Great Plains with ERTS. *NASA Spec Publ* **1974**, *351*, 309.

38. Tucker, C.J. Red and Photographic Infrared Linear Combinations for Monitoring Vegetation. *Remote Sens. Environ.* **1979**, *8*, 127–150.

39. Jordan, C.F. Derivation of Leaf‐Area Index from Quality of Light on the Forest Floor. *Ecology* **1969**, *50*, 663–666, doi:10.2307/1936256.

40. Gao, B. NDWI—A Normalized Difference Water Index for Remote Sensing of Vegetation Liquid Water from Space. *Remote Sens. Environ.* **1996**, *58*, 257–266, doi:10.1016/S0034-4257(96)00067-3.

41. McFEETERS, S.K. The Use of the Normalized Difference Water Index (NDWI) in the Delineation of Open Water Features. *Int. J. Remote Sens.* **1996**, *17*, 1425–1432, doi:10.1080/01431169608948714.

42. Roujean, J.-L.; Breon, F.-M. Estimating PAR Absorbed by Vegetation from Bidirectional Reflectance Measurements. *Remote Sens. Environ.* **1995**, *51*, 375–384.

43. Gitelson, A.A. Wide Dynamic Range Vegetation Index for Remote Quantification of Biophysical Characteristics of Vegetation. *J. Plant Physiol.* **2004**, *161*, 165–173.

44. Gitelson, A.A.; Kaufman, Y.J.; Stark, R.; Rundquist, D. Novel Algorithms for Remote Estimation of Vegetation Fraction. *Remote Sens. Environ.* **2002**, *80*, 76–87.

45. Bannari, A.; Morin, D.; Bonn, F.; Huete, A.R. A Review of Vegetation Indices. *Remote Sens. Rev.* **1995**, *13*, 95–120, doi:10.1080/02757259509532298.

46. Huete, A.; Didan, K.; Miura, T.; Rodriguez, E.P.; Gao, X.; Ferreira, L.G. Overview of the Radiometric and Biophysical Performance of the MODIS Vegetation Indices. *Remote Sens. Environ.* **2002**, *83*, 195–213.

47. Crippen, R.E. Calculating the Vegetation Index Faster. *Remote Sens. Environ.* **1990**, *34*, 71–73.

48. Goel, N.S.; Qin, W. Influences of Canopy Architecture on Relationships between Various Vegetation Indices and LAI and Fpar: A Computer Simulation. *Remote Sens. Rev.* **1994**, *10*, 309–347, doi:10.1080/02757259409532252.

49. Gitelson, A.A.; Kaufman, Y.J.; Merzlyak, M.N. Use of a Green Channel in Remote Sensing of Global Vegetation from EOS-MODIS. *Remote Sens. Environ.* **1996**, *58*, 289–298, doi:10.1016/S0034-4257(96)00072-7.

50. Gitelson, A.A.; Merzlyak, M.N. Remote Sensing of Chlorophyll Concentration in Higher Plant Leaves. *Adv. Space Res.* **1998**, *22*, 689–692.

51. Jachowski, N.R.; Quak, M.S.; Friess, D.A.; Duangnamon, D.; Webb, E.L.; Ziegler, A.D. Mangrove Biomass Estimation in Southwest Thailand Using Machine Learning. *Appl. Geogr.* **2013**, *45*, 311–321.

52. Li, Y.; Li, M.; Li, C.; Liu, Z. Forest Aboveground Biomass Estimation Using Landsat 8 and Sentinel-1A Data with Machine Learning Algorithms. *Sci. Rep.* **2020**, *10*, 9952.

53. Pham, T.D.; Yoshino, K.; Bui, D.T. Biomass Estimation of *Sonneratia Caseolaris* (l.) Engler at a Coastal Area of Hai Phong City (Vietnam) Using ALOS-2 PALSAR Imagery and GIS-Based Multi-Layer Perceptron Neural Networks. *GIScience Remote Sens.* **2017**, *54*, 329–353, doi:10.1080/15481603.2016.1269869.

54. IPCC CHAPTER 4: FOREST LAND. In *IPCC Guidelines for National Greenhouse Gas Inventories*; IPCC, 2006; Vol. 4 ISBN 4-88788-032-4.

55. Askar; Nuthammachot, N.; Phairuang, W.; Wicaksono, P.; Sayektiningsih, T. Estimating Aboveground Biomass on Private Forest Using Sentinel-2 Imagery. *J. Sens.* **2018**, *2018*, 1–11.

56. Sinha, S.; Jeganathan, C.; Sharma, L.K.; Nathawat, M.S.; Das, A.K.; Mohan, S. Developing Synergy Regression Models with Space-Borne ALOS PALSAR and Landsat TM Sensors for Retrieving Tropical Forest Biomass. *J. Earth Syst. Sci.* **2016**, *125*, 725–735, doi:10.1007/s12040-016-0692-z.

57. Das, S.; Singh, T.P. Correlation Analysis between Biomass and Spectral Vegetation Indices of Forest Ecosystem. *Int J Eng Res Technol* **2012**, *1*, 1–13.

58. Lu, D.; Chen, Q.; Wang, G.; Liu, L.; Li, G.; Moran, E. A Survey of Remote Sensing-Based Aboveground Biomass Estimation Methods in Forest Ecosystems. *Int. J. Digit. Earth* **2016**, *9*, 63–105, doi:10.1080/17538947.2014.990526.

59. Wernick, I.K.; Ciais, P.; Fridman, J.; Högberg, P.; Korhonen, K.T.; Nordin, A.; Kauppi, P.E. Quantifying Forest Change in the European Union. *Nature* **2021**, *592*, E13–E14.

60. Lu, D.; Chen, Q.; Wang, G.; Moran, E.; Batistella, M.; Zhang, M.; Vaglio Laurin, G.; Saah, D. Aboveground Forest Biomass Estimation with Landsat and LiDAR Data and Uncertainty Analysis of the Estimates. *Int. J. For. Res.* **2012**, *2012*.

61. Gallet, C. Allelopathic Potential in Bilberry-Spruce Forests: Influence of Phenolic Compounds on Spruce Seedlings. *J. Chem. Ecol.* **1994**, *20*, 1009–1024, doi:10.1007/BF02059738.

62. Kil, B.-S.; Kim, D.-Y.; Kim, Y.-S.; Lee, S.-Y. Phytotoxic Effects of Naturally Occurring Chemicals from Pinus Koraiensis on Experimental Species. *Korean J. Ecol.* **1991**, *14*, 149–157.

63. Lodhi, M.A.K.; Killingbeck, K.T. Effects of Pine-Produced Chemicals on Selected Understory Species in aPinus Ponderosa Community. *J. Chem. Ecol.* **1982**, *8*, 275–283, doi:10.1007/BF00984023.

64. Refifa, T.; Chahdoura, H.; Flamini, G.; Adouni, K.; Achour, L.; Helal, A. Allelopathic Potential of Pinus Halepensis Needles. *Allelopath J* **2016**, *38*, 193–214.

65. Singh, H.P.; Kohli, R.K.; Batish, D.R.; Kaushal, P.S. Allelopathy of Gymnospermous Trees. *J. For. Res.* **1999**, *4*, 245–254, doi:10.1007/BF02762256.

66. Jobidon, R. Allelopathic Potential of Coniferous Species to Old-Field Weeds in Eastern Quebec. *For. Sci.* **1986**, *32*, 112–118.

67. Sharma, N.K.; Batish, D.R.; Singh, H.P.; Kohli, R.K. Allelopathic Effect of Pinus Roxburghii on an Understorey Plant, Bidens Pilosa. *Ann Plant Sci* **2016**, *5*, 1446–1450.

68. Reigosa, M.J.; Souto, X.C.; Gonzalez, L. Allelopathic Research: Methodological, Ecological and Evolutionary Aspects. *Allelopathy Field Obs. Methodol.* **1996**, 213–231.

69. *Middle Mountains Forests of Nepal*; DFRS, Ed.; Government of Nepal, Ministry of Forests and Soil Conservation, Department of Forest Research and Survey, Forest Resource Assessment Nepal: Kathmandu, Nepal, 2015; ISBN 978-9937-8896-2-9.

70. Sharma, E.; Pukkala, T. Volume Equations and Biomass Prediction of Forest Trees in Nepal. *For. Surv. Stat. Div.* **1990**, *47*, 1–16.

71. Fassnacht, F.E.; Hartig, F.; Latifi, H.; Berger, C.; Hernández, J.; Corvalán, P.; Koch, B. Importance of Sample Size, Data Type and Prediction Method for Remote Sensing-Based Estimations of Aboveground Forest Biomass. *Remote Sens. Environ.* **2014**, *154*, 102–114.

72. Vafaei, S.; Soosani, J.; Adeli, K.; Fadaei, H.; Naghavi, H.; Pham, T.D.; Tien Bui, D. Improving Accuracy Estimation of Forest Aboveground Biomass Based on Incorporation of ALOS-2 PALSAR-2 and Sentinel-2A Imagery and Machine Learning: A Case Study of the Hyrcanian Forest Area (Iran). *Remote Sens.* **2018**, *10*, 172.

73. Morin, D.; Planells, M.; Guyon, D.; Villard, L.; Mermoz, S.; Bouvet, A.; Thevenon, H.; Dejoux, J.-F.; Le Toan, T.; Dedieu, G. Estimation and Mapping of Forest Structure Parameters from Open Access Satellite Images: Development of a Generic Method with a Study Case on Coniferous Plantation. *Remote Sens.* **2019**, *11*, 1275.

74. Ou, G.; Li, C.; Lv, Y.; Wei, A.; Xiong, H.; Xu, H.; Wang, G. Improving Aboveground Biomass Estimation of Pinus Densata Forests in Yunnan Using Landsat 8 Imagery by Incorporating Age Dummy Variable and Method Comparison. *Remote Sens.* **2019**, *11*, 738.

75. Zhao, P.; Lu, D.; Wang, G.; Liu, L.; Li, D.; Zhu, J.; Yu, S. Forest Aboveground Biomass Estimation in Zhejiang Province Using the Integration of Landsat TM and ALOS PALSAR Data. *Int. J. Appl. Earth Obs. Geoinformation* **2016**, *53*, 1–15.