ASSESSMENT OF LANDSAT-8 AND SENTINEL-2 IMAGERY FOR ESTIMATION OF ABOVEGROUND BIOMASS AND CARBON STOCKS IN CHURE FORESTS OF NEPAL

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ABSTRACT

Forests play a crucial role in global carbon cycles and biodiversity conservation. Quantifying forest aboveground biomass (FAGB) helps in assessing carbon emission and sequestration and can reduce uncertainty in monitoring global carbon cycles and climate change. Remote sensing techniques have proved to be a cost-effective way to estimate FAGB with timely and repeated observations and recommended by United Nations Framework on Climate Change (UNFCC) to assess FAGB and carbon stock for Reduction of Emissions from Degradation and Deforestation Program (REDD+). This research presents an assessment of freely available Landsat-8 and Sentinel-2 imagery for estimating FAGB in the Chure forests of Nepal using Multiple Regression Analysis. Sentinel-2 and Landsat 8 missions are similar, but Sentinel-2 has higher spatial resolution and collects data from the red-edge region of the electromagnetic spectrum while Landsat has one of the largest temporal ranges of imagery range from 1970s. Twelve variables derived from Landsat-8 and fifteen variables derived from Sentinel-2 imageries were used in the study. Forest inventory data of 225 plots collected by the Forest Research and Training Centre (FRTC) in 2017 and 2018 through field measurements, were used to train and validate the model. The correlation of FAGB measured in each plot and variables extracted from the Landsat-8 and Sentinel-2 optical imageries were assessed by the Pearson correlation coefficients. Multiple Linear Regression was applied based on chosen variables to develop the models for estimating FAGB for the whole study area. The R-squared values of 0.78 and 0.68 and standard error of estimate 45.98 and 40.29 were obtained respectively for the Sentinel-2 and Landsat-8 based estimation models. The estimated results were validated by considering R^2 and RMSE values between observed and estimated FAGB. The values of R^2 and RMSE between observed and estimated FAGB were 0.70 and 45.02 tons/ha and 0.77 and 34.33 tons/ha for Landsat-8 and Sentinel-2 images respectively. The results of the study showed that both Sentinel-2 and Landsat-8 imageries are viable for FAGB and carbon stocks estimation. However, with high R2 and low RMSE value Sentinel-2 based model outperforms the Landsat-8 based model and it seems to be better suited for FAGB estimation in Chure area for the studied year. Overall, the research highlights the potential of Sentinel-2 and Landsat-8 imagery for FAGB estimation and emphasizes the importance of utilizing multi-source data and advanced modelling techniques for accurate and reliable FAGB mapping. The study also revealed that Chure forests are of considerable significance as they store substantial amounts of carbon despite disturbance from different anthropogenic activities.

KEYWORDS: Forest Above Ground Biomass, Landsat-8 Imagery, Sentinel-2 imagery, Carbon stock, Chure Forests, Vegetation Indices, Multiple Regression Analysis

1. INTRODUCTION

Climate change is a critical issue that the world is currently facing(Shrestha et al., 2025). The main cause of this problem is changes in land use due to increased human activities such as deforestation, burning fossil fuels, and expanding industries(Ning et al., 2023). These activities result in high levels of carbon dioxide (CO_2) in the atmosphere, along with other greenhouse gases (GHG), which trap thermal energy(Nunes, 2023). This global warming phenomenon causes climate change and, as a result, can lead to natural disasters such as earthquakes, floods, droughts, wildfires, high temperatures, and other related events(Hassan, 2024). Forests play a crucial role in mitigating atmospheric CO_2 levels(Alkama & Cescatti, 2016; Psistaki et al., 2024)

Approximately 40% of the Earth's terrestrial carbon is stored in tropical rainforests, making them a significant contributor to the global carbon cycle (Mauya et al., 2015). However, rapid deforestation threatens this vital function, resulting in 12-20% of total anthropogenic CO_2 emissions despite their ecological importance (Collins, 2015). The United Nations Framework Convention on Climate Change (UNFCCC) had introduced an initiative named the Reduction of Emissions from Degradation and Deforestation Program (REDD+) which provides financial incentives to developing countries to conserve and manage forests in their countries that effectively reduce emissions resulting from anthropogenic activities (Mermoz et al., 2015). Such initiatives require transparent, comprehensive, steady, comparable, and precise national and subnational measurement, reporting, and verification (MRV) systems to monitor and evaluate the forest biomass /carbon stock and the resulting carbon emissions (Lallo et al., 2017).

Forest above-ground biomass (FAGB) represents the largest carbon pool in forest ecosystems (Güneralp et al., 2014). However, human activities such as deforestation can lead to a reduction in forest area, which can cause the deterioration of the FAGB, carbon stock (CS), which not only diminishes CO_2 sequestration but also results in the release of stored carbon back into the atmosphere thereby, aiding to the global warming (Chinembiri et al., 2013). Precise measurement of FAGB is essential for effective forest management, climate change mitigation through REDD+, sustainable forest management, and efforts to conserve and enhance forest carbon stocks. Therefore, it is essential to rapidly and accurately estimate and monitor FAGB across diverse spatial and temporal scales. This is crucial for significantly reducing uncertainties in carbon stock assessments and providing valuable insights for strategic forest management plans (Pan et al., 2013).

Nepal possesses abundant forest resources, covering around 44.74 % of its total land area, equivalent to 6.2 million hectares (DFRS, 2018). According to a report by the Food and Agriculture Organization (FAO) in 2015, the estimated amount of living biomass in Nepalese forests was 484 million tons. This comprises 359 million tons of FAGB and 126 million tons of below-ground biomass (BGB). However, these figures are presented at a national scale and lack the necessary granularity for effective planning (FAO, 2015).

In general, FAGB can be estimated through three available methods: model-based simulations, measurements from traditional ground inventories, and retrievals from remote-sensing datasets(Su et al., 2016). Model-based simulation methods usually provide FAGB estimations from local to global scales based on model inputs (e.g., radiation, climate surfaces, and elevations) instead of the actual FAGB distribution (Li et al., 2022). Traditional forest inventory methods (e.g., direct harvest methods and indirect allometric modelling methods) can provide reliable information on biomass at local or regional scales (Torre-Tojal et al., 2022). However, taking ground measurements is labor- intensive and expensive when used for large areas, and is time-consuming for a nationwide forest survey. Compared with the forest inventory approach, remote-sensing techniques significantly improve the efficiency of FAGB mapping in large areas and areas that are difficult to access (Ehlers et al., 2022). By linking with ground inventory data, FAGB can be estimated from remote sensing datasets using statistical models. Typically, passive optical remote sensing [e.g., Moderate Resolution Imaging Spectroradiometer (MODIS) of 250m resolution, Landsat Thematic Mapper (TM) of 30m resolution and radar techniques [e.g., phased array L-band synthetic aperture radar (PALSAR) of 10m resolution and Shuttle Radar Topography Mission (SRTM) of 30m resolution] have become primary data sources for estimating FAGB, because of their availability(Su et al., 2016).

In the past three decades, Landsat images have been mostly used for forest AGB estimation mainly because of the freely accessible long archive images with medium spatial resolution (Nguyen et al., 2020). Landsat 8 is a multispectral imagery with medium spatial resolution which is one of the most suitable open-source sensors for extracting land cover and forestry applications. Landsat 8 has a fine spectral resolution, high resolution (15 meters) in the panchromatic band, 30 meters in multispectral imagery, and a radiometric resolution of 12 bits (Ke et al., 2015). Karlson (2015) evaluated the utility of Landsat images in Sudano-Sahelian Woodlands for Tree Canopy Cover and biomass assessment. Gizachew et. al. (2016) reported that applications of Landsat satellite products are boundless and are used most extensively for biomass and vegetation analysis due to their free data availability, spatial coverage, and high temporal resolution. Many previous studies have used Landsat products for biomass estimation by developing relationships between field data and different vegetation indices (Ou et al., 2019; Priatama et al., 2022; Turgut & Günlü, 2022; Zhang et al., 2023). Many researchers worked on Landsat data and explored the behavior of various spectral indices such as the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Soil Adjusted Vegetation Index (SAVI), and Modified Soil Adjusted Vegetation Index (MSAVI) (Imran & Ahmed, 2018a; Qiu et al., 2020; Tang et al., 2022).

Sentinel-2 is a polar-orbiting satellite equipped with a multi-spectral instrument, MSI sensor, launched on 23 June 2015 by the European Space Agency (ESA), provides a significant improvement in spectral coverage, spatial resolution, and temporal frequency over the current generation of Landsat sensors(Castro Gómez, 2017). The spectral configuration of Sentinel-2 is comparable to some commercial satellite data, such as Worldview-2 and RapidEye, because of the presence of the red-edge band, but is further improved by incorporating shortwave infrared bands (SWIR). The unique characteristics of Sentinel-2 as compared to commercial satellites is the only inclusion of the red edge band, which is important for vegetation assessment and monitoring (Ramoelo et al., 2015).

While various studies have highlighted the utility of both Sentinel-2 and Landsat-8 data for forest assessments across diverse ecosystems, there exists a critical knowledge gap regarding their comparative effectiveness in estimating forest aboveground biomass and carbon stocks in the distinctive context of Nepal's Chure Forests. The Chure region is characterized by its ecological complexity, ranging from subtropical to temperate forests, and is located at the foothills of the Himalayas. These forests are essential components of Nepal's landscape, influencing climate regulation, water resources, and biodiversity conservation. However, they are also vulnerable to anthropogenic pressures such as deforestation, land use changes, and degradation.

This research aims to bridge the aforementioned research gap by conducting a comprehensive assessment of Landsat-8 and Sentinel-2 imageries for estimating forest aboveground biomass and carbon stocks within the Chure Forests of Nepal. This study uses multiple regression analysis techniques to derive the relationships between variables derived from Landsat-8 and Sentinel-2 imageries and FAGB calculated from field plots and hence calculates FAGB and carbon stocks in the entire region. By exploring the capabilities of these satellite imageries, this study provides insights into their applicability, accuracy, and limitations in this unique forest ecosystem. The findings of this study will contribute valuable information to guide forest management strategies, inform policy decisions, and support Nepal's commitment to sustainable development and climate change mitigation.

2. MATERIALS AND METHODS

2.1 Study Area

The study was conducted in the Chure region of Nepal. The geographical location of the study area is 80° 09' 25"E to 88° 11' 16"E longitude and 26° 37' 47"N to 29° 10' 27"N latitude (Subedi et al., 2022) as illustrated in Figure 1. The area of the Chure region is about 1,898,263 hectares and occupies 12.80% of the area of the entire country (DFRS, 2014; Thapa et al., 2023). It extends in an east-west direction, covering 37 of the 77 districts in the country. Forests cover the highest proportion of the total area of the Chure region (72.37%; 1,373,743 ha) (DFRS, 2014). The study area has a typical tropical forest with undulating topography. Major species of this region are Sal, Pine, Khair, and Sissoo (DFRS, 2014a). The Chure region has a sub-tropical to warm temperate climate that is characterized by hot and sub-humid summers, intense monsoon rain, and cold dry winters (DFRS, 2014). The average annual minimum temperature in this region ranges from 12°C to 19°C, while the average annual maximum temperature ranges from 22°C to 30°C (DFRS, 2014). The precipitation pattern in the Chure region is variable, with the highest annual rainfall occurring in the Koshi and Bagmati provinces. The total annual rainfall varies from a minimum of 1,138 mm to a maximum of 2,671 mm (DFRS, 2014b).

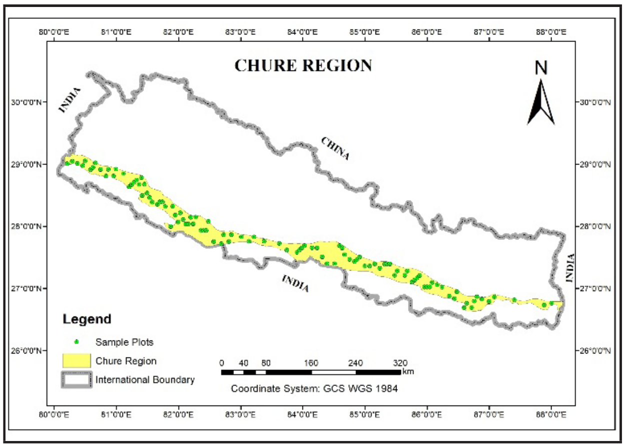

Figure 1. Study Area Map

2.2 Data and Software

The study utilized two types of secondary data - satellite imagery and forest inventory data. The multitemporal time series of Landsat-8 and Sentinel-2 images from 2017 to 2019 were obtained from Google Earth Engine (GEE). The multitemporal time series data were used as the data over whole Chure region was collected during this time period. Further, the multitemporal time series image helps to minimize the errors due to the effect of cloud and shadows in individual images (Chen et al., 2021; Qi et al., 2022). Forest cover map of ESA was used for masking the forest area. In addition, the Forest Research and Training Centre (FRTC) provided forest inventory data for field sample plots. This data included information on tree height and Diameter Breast Height (DBH), which allowed for the calculation of FAGB for the sample plots. More details on the satellite images used are given in Table 1.

Table 1. Specifications for Satellite Imagery

SN	Satellite Image	Number of Bands Used	Spatial Resolution (m)	Cloud Cover (%)	Time
1.	Landsat-8	2,3,4,5,6,7	30m	Less than 3 %	Multitemporal (2017 to 2019)
2.	Sentinel-2	2,3,4,5,6,7,8	10m and 20m	Less than 3 %	Multitemporal (2017 to 2019)

Table 2 shows the software and tools used for image download, processing, analysis and mapping.

Table 2. Software and Tools Used in the Study

Software/Platform	Purpose
Google Earth Engine	For image download, image processing and extracting vegetation indices
QGIS	Mapping and Analysis
SPSS	For Statistical Analysis

2.3 Methods

The amount of FAGB and carbon stocks in the study area were estimated and mapped using field data and information from remote sensing data, particularly Landsat-8 and Sentinel-2 imagery. The imagery was obtained from GEE, and its pre-processing and processing were also performed in GEE.

Vegetation indices such as NDVI, EVI, GDVI, GNDVI, NDWI, RGR, SAVI, and SLAVI and Tasselled Cap Brightness, Greenness and Wetness indices were derived from Landsat 8 image. The vegetation indices derived from the Sentinel-2 image were NDVI, EVI, GDVI, GNDVI, IRECI, RGR, SAVI, NDI45, SR, Red Edge 1 NDVI, Red Edge 2 NDVI and Red Edge 3 NDVI and Tasselled Cap Brightness, Greenness and Wetness indices.

First, the statistical correlation tests were performed between FAGB and variables derived from Landsat-8 and Sentinel-2 imagery. The variables combination that had a high coefficient of determination and low standard error of estimate were selected as the final estimation variables. Further, variables with high multicollinearity were excluded to ensure the most accurate and reliable results. Models were developed for each of the imageries, i.e., Landsat-8 and Sentinel-2, by considering the coefficient of selected variables and constant values from multiple linear regression analysis. The developed model was used to estimate the productivity of FAGB and carbon stocks in the study area. Figure 2 presents summary of the methodology adopted for the estimation of FAGB in the study area.

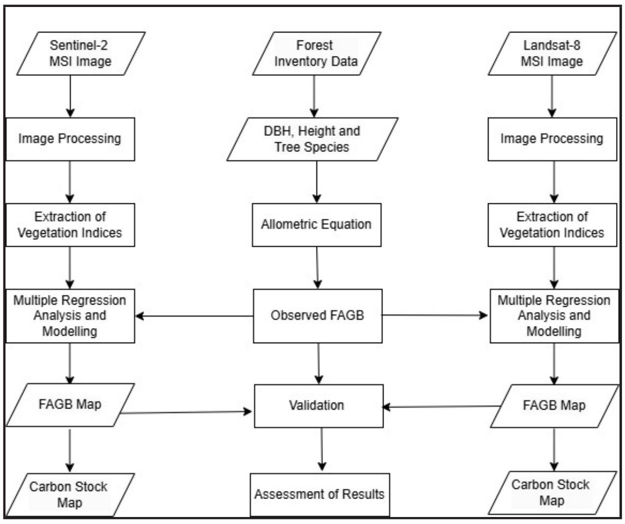

Figure 2. Methodological flowchart of Study

2.3.1 Image Pre-processing: Landsat-8 and Sentinel-2 atmospherically corrected surface reflectance imageries were pre-processed and processed in GEE. The pre-processing of image included masking out cloud and cloud shadows, masking saturated pixels and scaling the bands. The resolution of all Landsat-8 bands was 30m while bands of 10m and 20m were used in case of Sentinel-2 image. The 10m resolution bands were resampled to 20m before analysis to maintain consistency in data. The image was clipped to the shape of the study area.

2.3.2 Vegetation Indices: The vegetation indices layers were derived using pre-processed Landsat-8 and Sentinel-2 bands in GEE. Twelve indices were selected based on their performance in previous studies (Koju et al., 2019; Nguyen et al., 2020; Tian et al., 2023). Table 8 shows all the vegetation indices derived from Landsat-8 bands.

Table 3. Landsat 8 Bands, Vegetation Indices and Tasselled Cap Indices

Estimation Variables	Formula/Description	Reference
Vegetation Indices		
NDVI	(B5-B4)/(B5+B4)	(Pettorelli et al., 2005)
RGR	B4/B3	(Sims & Gamon, 2002)
GDVI	$(B5^2 - B4^2)/(B5^2 + B4^2)$	(Karlson et al., 2015)
GNDVI	(B5- B3) / (B5+ B3)	(Wang et al., 2007)
EVI	{2.5*(B5-B4)}/{B5+(6*B4-7.5* B2) +1}	(Hasanah et al., 2020)
SAVI	1.5*(B5 - B4)/(B5 + B4+0.5)	(Huete, 1988)
SR	B5/ B4	(Bannari et al., 1995)
NDWI	(B5- B7)/(B5+ B7)	(Jackson et al., 2004)
SLAVI	B5/(B4+ B7)	(Karlson et al., 2015)
Tasseled Cap Indices		(Samarawickrama et al., 2017)
Brightness		
(0.3029 * B2) + (0.2786 * B3) + (0.4733 * B4) + (0.5599 * B5) + (0.5080 * B6) + (0.1872 * B7)		
Wetness		
(0.151 * B3) + (0.197 * B4) – (0.328 * B5) + (0.340 * B6) – (0.711 * B7)		
Greenness		
(0.6685 * B4) – (0.2848 * B3) – (0.0002 * B5) – (0.0721 * B6) – (0.5020 * B7)		

Table 4. Sentinel-2 Bands, Vegetation Indices and Tasselled Cap Indices

Estimation Variables	Formula/Description	Reference
Vegetation Indices		
NDVI	(B8-B4)/(B8+B4)	(Gitelson & Merzlyak, 1997)
RGR	B4/B3	(Sims & Gamon, 2002)
NDI45	(B5-B4)/B5+B4)	(Frampton et al., 2013)
GDVI	$(B8^2-B4^2)/(B8^2+B4^2)$	(Karlson et al., 2015)
GNDVI	(B8-B3)/(B8+B3)	(Wang et al., 2007)
IRECI	(B7-B4)/(B5/B6)	(Frampton et al., 2013)
EVI	{2.5*(B8-B4)}/{B8+(6*B4-7.5*B2) +1}	(Hasanah et al., 2020)
SAVI	1.5*(B8-B4)/(B8+B4+0.5)	(Karlson et al., 2015)
SR	B8/B4	(Karlson et al., 2015)
RE1 NDVI	(B8-B5)/(B8+B5)	(Fernández-Manso et al., 2016)
RE2 NDVI	(B8-B6)/(B8+B6)	
RE3 NDVI	(B8-B7)/(B8+B7)	
Tasseled Cap Indices		(Samarawickrama et al., 2017)
Brightness		
(0.3029 * B2) + (0.2786 * B3) + (0.4733 * B4) + (0.5599 * B8) + (0.5080 * B11) + (0.1872 * B12)		
Wetness		
(0.151 * B3) + (0.197 * B4) –(0.328 * B8) + (0.340 * B11) – (0.711 * B12)		
Greenness		
(0.6685 * B4) – (0.2848 * B3) – (0.0002 * B8) – (0.0721 * B11) – (0.5020 * B12)		

2.3.3 Extract Pixel Values of Explanatory Variables

The pixel values for each variable derived from Landsat-8 and Sentinel-2 were extracted in GEE and exported in CSV format. The field plot locations (latitude, longitude) were used as a reference while extracting the values of indices. The value of the indices within the radii of 20m was taken into consideration to maintain consistency with FAGB values of ground sample plots. Buffer of 20m radius was created for each point representing the plot locations. The minimum, maximum and mean values of indices within the plot were extracted. But the mean values of indices were used as it produced results with highest accuracy.

2.3.4 Statistical Analysis

Statistical analysis was carried out using SPSS software. Correlation analyses were made before model development to know the relation between estimation variables and observed FAGB. The relation between independent variables(indices) and dependent variable (observed FAGB) was assessed based on the value of correlation coefficient. Further, scatter plot was made between each of the independent variables (indices) and dependent variable (observed FAGB). Multicollinearity between variables was tested based on the tolerance value, Eigen value and Variation Inflation Factor (VIF). The variables with tolerance value greater than 0.2 and VIF less than 5 were chosen for the multiple linear regression and variables not satisfying the condition were excluded from the analysis (Shrestha, 2020; Tranmer et al., 2020).

2.3.5 Model Development using Regression Analysis

The objective of regression analysis is to quantify the relationship between a dependent variable and one or more independent variables (Shrestha, 2020). Regression implies a cause-and-effect relationship in which a change in the value of an independent variable will result in an expected average change in the dependent variable. The quantitative relationship is expressed by an equation and its graphic representation. The square value of the correlation coefficient (R^2) is called the coefficient of determination. It can be interpreted as indicating the percentage of variation in one variable that is associated with other variables.

Multiple Linear regression models were developed on SPSS software to assess the relationship between each VIs and observed FAGB. The model was evaluated based on the values of coefficient of determination (R2) and standard error of estimate. The best model was developed by integrating those variables with high R2 and a lower standard error value. The equation obtained from the multiple linear regression model was then used to estimate FAGB. The R2 was preferred since it has a standard measure with values ranging from 0 to 1. The R2 also shows the percentage of the variability explained by the model. Thus, making it easy to understand the relationship between the independent and dependent variables (Ji & Peters, 2007). The equation obtained from the multiple regression model was then used to estimate FAGB.

2.3.6 Validation of Estimated FAGB

The FAGB estimated from the developed model was validated by using validation data comprising of FAGB of ground sample plots. Observed FAGB of 33 plots was used for validation of the results. RMSE between observed and estimated FAGB was computed to determine the effectiveness of the models by using the formula given in Equation 1. A model with low RMSE error is considered suitable for FAGB prediction.

$$\text{RMSE} = \sqrt{\sum_{i=1}^{n} (FAGB_o - FAGB_e)^2 / n} \quad (1)$$

where, $FAGB_o$ is Observed FAGB Value (Dependent Variable), $FAGB_e$ is estimated FAGB Value (Independent Variable), n is number of samples.

3. RESULTS AND DISCUSSION

3.1 Observed FAGB

Based on field data different tree species were found in the forest. Altogether data of 225 plots were used for the study. There were 44 trees on average on a plot of 1256.63 m2. The maximum number of trees recorded was 136 and the minimum was 8. Similarly, the average tree height was 12m with a maximum of 43 m and a minimum was 4 m. From the observed field data, an average FAGB of 209.73 tons/ha, a minimum FAGB of 27.77 tons/ha and, the maximum FAGB OF 402.15 tons/ha was found. The descriptive statistics of the field plot data is given in Table 5.

Table 5: Descriptive Statistics of Observed FAGB

No. of Plots	Mean	Minimum	Maximum	Standard Deviation
225	209.73	27.77	402.15	80.04

3.2 Model Development for FAGB Prediction

3.2.1 Model Development for FAGB Estimation using Landsat-8 Variables: The model was developed using SPSS software based on variables that have a good correlation with the observed FAGB using multiple regression analysis. The estimation model has an R^2 value of 0.68 and the standard error of the estimate was 45.98. Only two variables were selected to develop the model and others were excluded due to multicollinearity. A multicollinearity test was done and variables having multicollinearity effect were discarded by the model based on the values of Variation Inflation Factor (VIF), tolerance values, and eigen values (Shrestha, 2020; Tranmer et al., 2020). The estimation variables selected for model development are NDVI and Greenness. Many studies have found that NDVI and Greenness have good correlation with FAGB and are the most important estimation variables for FAGB estimation (Dube & Mutanga, 2015; Imran & Ahmed, 2018; Koju et al., 2019; Turgut & Günlü, 2022). The results of the multiple regression analysis are shown in Table 11 and Table 12. The evaluation metrics of the estimated model are consistent with the study by Koju et. al. 2019 in which the R^2 value of the models for FAGB estimation ranged from 0.65 to 0.72 (Koju & Zhang, 2019).

3.2.2 Model Development for FAGB Estimation using Sentinel-2 Variables:

The model was developed using SPSS software based on variables that have a good correlation with the observed FAGB using multiple regression analysis. The estimation model has an R^2, adjusted R^2, and standard error of estimate values of 0.78, 0.77, and 40.29 respectively. Only five variables were selected to develop the model and others were excluded because of their lower coefficient of determination values and multicollinearity. The process of the multicollinearity test was similar to the one mentioned in section 4.3.1 (Shrestha, 2020; Tranmer et al., 2020). The variables selected for model development are Red to Green Ratio, NDVI, RE3NDVI, Greenness, and Brightness. The results of multiple regression analysis are shown in Table 13 and Table 14. The measures of assessment for the estimation model comply with the research done by Singh et. al. 2023 in Sal Forest of Western Terai, Nepal where the R^2 value of the estimation models ranged from 0.72 to 0.77 for different estimation variables (Singh et al., 2023).

3.3 Mapping FAGB and Carbon Stock

3.3.1 Mapping FAGB and Carbon Stock Using Landsat-8 Model

The estimated FAGB map was produced by using equation 2 obtained from multiple regression analysis.

$$FAGB_{L8} = 603.292*NDVI + 1346.431*Greenness - 146.167 \quad (2)$$

The forest area extracted from the land cover map was considered (ESA, 2019). The estimated FAGB map for the study area is shown in Figure 3. From the FAGB distribution in the map, it can be seen that over the area the FAGB was mostly from 100 to 300 tons/ha. However, in some areas that are close to built-up and agricultural areas, the FAGB of less than 100 tons/ha was found due to anthropogenic activity. In a few areas with dense forest which are far from anthropogenic activities and difficult to access, an FAGB of greater than 300 tons/ha was found. An average FAGB of 219.55 tons/ha was found in the study area.

Finally, a carbon stock map was produced by multiplying FAGB with carbon conversion factor of 0.47 (IPCC, 2003). Figure 4 presents the map of carbon stocks calculated from the FAGB map. Because this map was produced based on FAGB, it has a similar trend in the carbon stocks distribution. The area that has difficulties in accessibility has the largest carbon stocks with the amount higher than 150 tons/ha. The carbon stocks with the amount of less than 50 tons/ha were found in the easily accessible area that was near the road and other land cover types.

3.3.2 Mapping FAGB and Carbon Stock using Sentinel-2 Model

The estimated FAGB map was produced by using equation 3 obtained from multiple regression analysis.

$$FAGB_{S2}=634.846*NDVI-348.090*RE3NDVI-69.298*RGR+150.578*BRIGHTNESS+902.941*GREENNESS–74.685 \quad (3)$$

The forest area extracted from the land cover map was considered (ESA, 2019). The estimated FAGB map for the study area is shown in Figure 5. From the FAGB distribution in the map, it can be seen that over the area the FAGB was mostly from 100 to 300 tons/ha. However, in some areas that are close to built-up and agricultural areas the FAGB of less than 100 tons/ha was found due to anthropogenic activity. In a few areas with dense forests which are far from anthropogenic activities and difficult to access, an FAGB of greater than 300 tons/ha was found. An average FAGB of 212.96 tons/ha was found in the study area.

Finally, a carbon stock map was produced by multiplying FAGB with the carbon conversion factor of 0.47 (IPCC, 2003). Figure 6 presents the map of carbon stocks in the forest calculated from the FAGB map. Because this map was produced based on FAGB, it has a similar trend in the carbon stocks distribution.

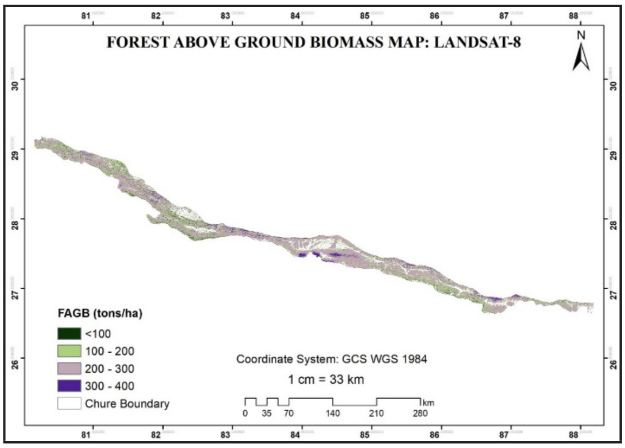

Figure 3. FAGB Map of Chure Forests using Landsat-8 Model

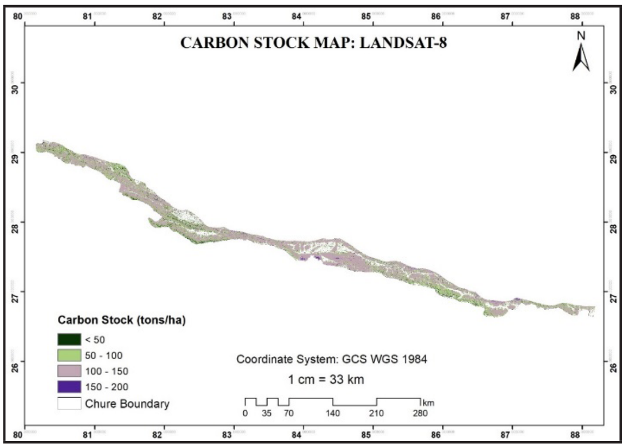

Figure 4. Carbon Stock Map of Chure Forests Based on Landsat-8 Model

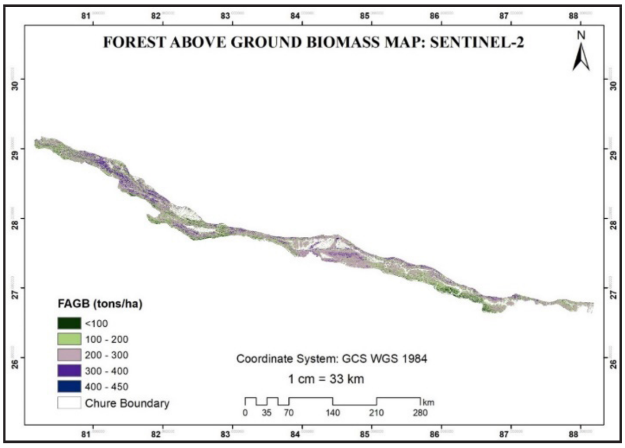

Figure 5. FAGB Map of Chure Forests using Sentinel-2 Model

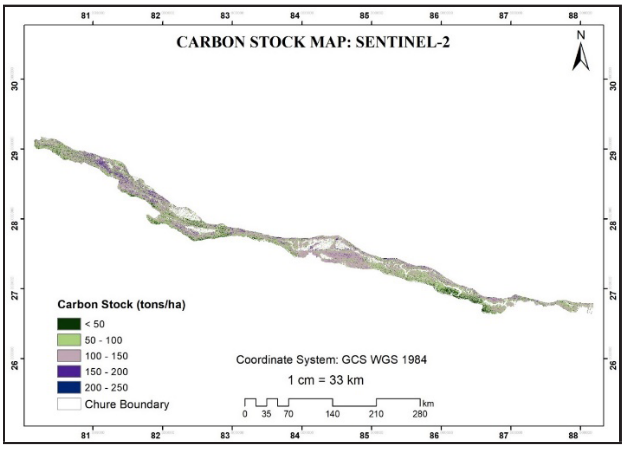

Figure 6. Carbon Stock Map of Chure Forests Based on Sentinel-2 Model

3.4 Validation of Estimated FAGB

3.4.1 Validation of FAGB Estimated from Landsat-8 Explanatory Variables: 15% of total sample plots i.e., 33 plots were used for validation of the estimated FAGB from the model. Estimated FAGB for these thirty-three plots were extracted and correlated with observed FAGB. The dependent (observed FAGB) and independent (estimated FAGB) variables have a good correlation with coefficient of determination 0.70 indicating approximately 70% of the observed FAGB is explained by the estimated FAGB. Since they have a good correlation, it was selected to map the final FAGB and carbon stock. The scatter plot diagram of estimated FAGB versus observed FAGB is shown in Figure 7. The RMSE error between observed and estimated FAGB was found 45.02 tons/ha. The validation results of the model are close to that of the study by Koju et. al. 2019 where the values of R^2 and RMSE error were 0.79 and 63 tons/ha respectively (Koju & Zhang, 2019). The results of our study show that the FAGB can be estimated within acceptable accuracy limits using Landsat-8 imagery.

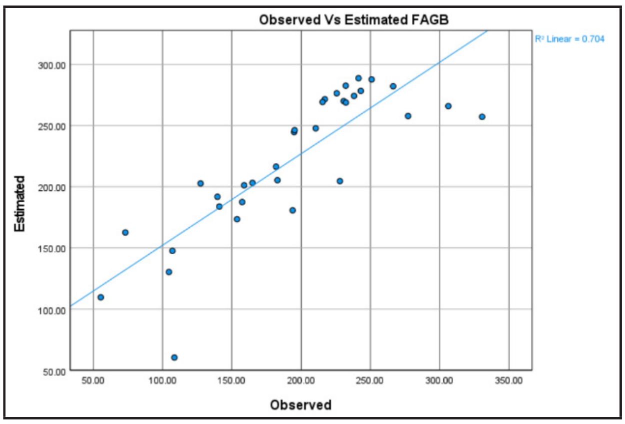

Figure 7. Scatter Plot of Observed Vs Landsat-8 Estimated FAGB

3.4.2 Validation of FAGB Estimated from Sentinel-2 Explanatory Variables: Estimated FAGB for these thirty-three plots were extracted and correlated with observed FAGB. The dependent (observed FAGB) and independent (estimated FAGB) variables have a good correlation with a coefficient of determination of 0.77. It indicates that approximately 77% of the observed FAGB was explained by the estimated model. Since they have a good correlation, it was selected to map the final FAGB and carbon stock. The RMSE error between observed and estimated FAGB was found 34.33 tons/ha. The scatter plot between observed and estimated FAGB is shown in Figure 8. The R^2 and RMSE values are in agreement with that of the research by Askar et. al. 2018 where the R^2 and RMSE values were 0.74 and 27 tons/ha respectively (Askar et al., 2018).

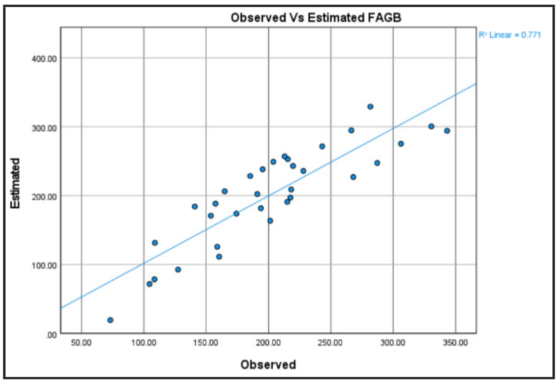

Figure 8. Scatter Plot of Observed Vs Sentinel-2 Estimated FAGB

4. CONCLUSION

This study has been conducted to develop and evaluate remote sensing-based models for estimating FAGB and carbon stocks in Chure forests of Nepal using variables derived from Sentinel-2 and Landsat-8 satellite imagery. Vegetation indices and Tasseled Cap indices from both imageries were combined with field data of 225 plots to assess the effectiveness of each dataset in estimating FAGB. The R-squared values of 0.78 and 0.68 and standard error of estimate 45.98 and 40.29 were obtained respectively for the Sentinel-2 and Landsat-8 estimation models.

The average FAGB productivity in the Chure forests from this study is 219.55 tons/ha and 212.96 tons/ha for Landsat-8 and Sentinel-2 based models respectively. The models were validated by using observed FAGB data of 33 ground sample plots. The value of R^2 obtained from the scatter plot between observed and estimated FAGB were 0.70 and 0.77 for Landsat-8 and Sentinel-2 based data respectively. Further, the RMSE error between observed and estimated FAGB were 45.02 tons/ha and 34.33 tons/ha respectively indicating estimation models developed from both imageries are viable for FAGB estimation. However, with high R^2 and low RMSE value Sentinel-2 based model outperforms the Landsat-8 based model and it seems to be better suited for FAGB estimation in Chure area for studied year. The finer spatial and spectral resolution of Sentinel-2 allows for a more detailed characterization of forest structure and biomass distribution, leading to more accurate estimations. However, in some scenarios where temporal trend of FAGB over decades is needed, Landsat image could be more useful.

Overall, this study highlights the potential of Sentinel-2 and Landsat-8 imagery for FAGB estimation and emphasizes the importance of utilizing multi-source data and advanced modelling techniques for accurate and reliable FAGB estimation and mapping. The study also revealed that Chure forests are of considerable significance as they store suitable amounts of carbon despite disturbance from different anthropogenic activities. These insights can contribute to REDD+ initiatives by supporting efforts to quantify carbon stocks, reduce emissions from deforestation, and promote sustainable forest management practices in the Chure forests of Nepal, aligning with global climate change mitigation goals. Further research and validation efforts are necessary to improve the robustness and applicability of remote sensing-based approaches in FAGB estimation.

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