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# Rapid assessment of above ground biomass in forest of Papum Pare district of Arunachal Pradesh: A geospatial approach

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## ABSTRACT

Present study aims to analyze tree composition and above ground biomass (AGB) through geospatial approach using field-based data. Different satellite derived vegetation indices were used for predicting AGB and to select the most appropriate predictive model for spatial mapping. Basal area ranged from 9.1 to 114.7 $m^2$/ha and plot based AGB ranged between 29 and 588.8 t/ha with mean value of 172.36 t/ha. Estimated AGB in mixed dense, plantation and degraded forests are 186 t/ha, 174 t/ha and 81.41 t/ha, respectively. Correlation coefficient ($r^2$) between AGB and vegetation indices such as NDVI, SAVI and ARVI are 0.26, 0.7o and 0.39, respectively. As SAVI resulted greater correlation than the other indices hence was considered best-fit for prediction modeling of AGB. Average predicted AGB for mixed dense forest was 191.16 t/ha followed by plantation (157.61 t/ha) and degraded forest (96.76 t/ha). Predicted AGB of the total forested area of Papum Pare district was 0.072 Pg. Comparative analysis showed that predicted model showed about 27.63 percent greater biomass than the estimated values which could be mainly associated with the number of sampling plots used for spatial modeling. However, present model result good-fit for biomass estimation under limited sampling point conditions.

***Keywords***: Landsat-OLI, allometric equation, above ground biomass, regression, modelling

## 1. INTRODUCTION

Human civilizations are heading to more modernized world than previous traditional society by overpowering nature's gift in the recent past. They deliberately destroyed the ecosystem and its services to achieve their substantial need. Amount of damage they have set leading to various environmental problem for future civilization is also being overlooked. Forests are the store house of biological activities and diversity and also a great role in human life because of having ecological, environmental and aesthetic characteristics. However, a continuous anthropogenic activity creates pressure on forest ecosystems and resulted in reduction in forest product and services. Nabuurs et al. [1] reported that forests are considered as a vital part of global carbon cycle and a large reservoir of carbon which helps in moderating the effect of climate change.

Forest biomass is an indicator in carbon cycle mainly for carbon stock and carbon sequestration. Forest ecosystem regarded as carbon sink mainly because it fixes atmospheric $CO_2$ and sequesters it as a biomass in its different tree component. Pan et al. [2] stated that forest biomass contributes about 44 per cent of global carbon pool. Mooney et al. [3] estimated the tree biomass and documented that nearly 90% of the carbon is stored in tree biomass. Approximately 50% of plant dry biomass was considered as carbon. Therefore, quantification of forest biomass is considered a major assignment as it play vital role in mitigating climate change. The research in biomass estimation and prediction helps in scientific developmental activities, ecosystem services and carbon budget [4, 5, 6]. Different approaches were adopted in the recent past for the estimation of above ground biomass (AGB). Among them, in-situ measurement with traditional techniques was considered to be the most reliable way of assessing biomass data but, they were hardly representing biomass distribution in large extent [7, 8, 9, 10]. In the recent past, geospatial approaches become more important and play a crucial role in mapping and monitoring forest degradation of large area with minimum effort and time. Remote sensed images have shown high correlation between spectral bands and vegetation parameters and made it the important source for estimation above ground biomass for the large area [4, 11, 12, 13, 14, 15, 16].

Different approaches were adopted to estimate AGB from remotely sensed images. Several vegetation indices have proved reliable and widely used by the researchers around the world to estimate the biomass. Several studies used satellite derived indices such as spectral vegetation index (SVI), simple ratio (SR), normalized difference vegetation index (NDVI), enhanced vegetation index (EVI) and have reported positive correlation with biomass and productivity in different forests [11, 17, 18, 19, 20]. AGB is also often calculated by models derived from linear and non-linear regression analysis of species with field measurements [21, 22]. Recent studies suggest that such relations varied temporally and spatially; however estimation of biomass at landscape level are necessary for understanding current processes of the targeted landscapes and gives baseline data for future studies [14, 23] hence present study was undertaken to fulfill the data gap on forest biomass in the state of Arunachal Pradesh, Northeast India.

## 2. MATERIALS AND METHODS

### *2.1. Study area*

The study was conducted in Papumpare district of Arunachal Pradesh and is characterized by hilly ridges, mountains and valley covered with lush green vegetation throughout the year. Study area is located between $26^0$ 55’N and $28^0$40’N latitude and between $92^0$40’E and $94^0$21’E longitude. It is bounded by Kurung Kumey district in the north, Assam in the south, Lower Subansiri district in east and East Kameng in the west (Fig. 1). Altitudinal variation of the study area ranges from 55 to 4175 m asl. The major rock formation in the district can be grouped into tertiary, gondwana, unfossiliferrous sedimentary and metamorphites. The hilly region comprises shale, sandstones, phyllites, qurttzites and others. The valley and low lands have dominantly colluvial and alluvial materials. Major part of the study area is covered by thick forest which has sub-tropical evergreen, deciduous and humid type of vegetation. Climatic condition of the district is of moderate type. Nyishis are the local inhabitants of the district and believed to belong to Tibetan-Mongoloid stocks.

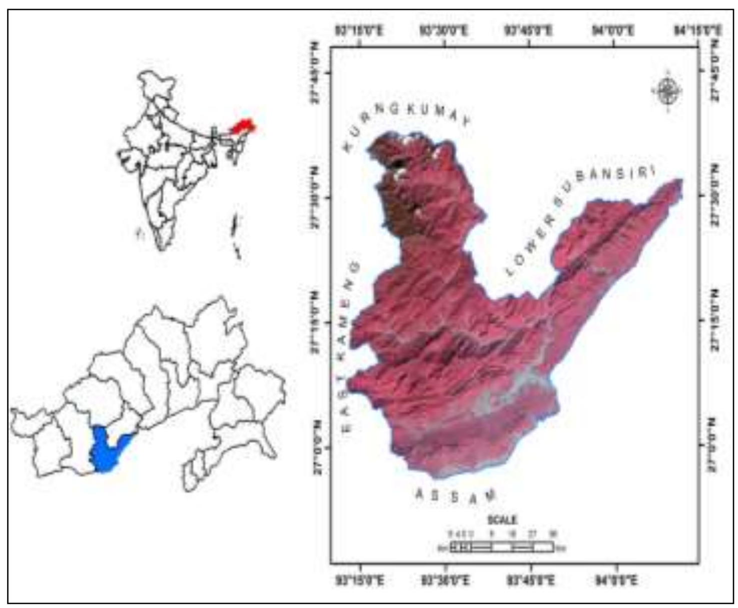


**Figure 1.** Location map of the study area

### *2.2. Field sampling and AGB estimation*

A non-destructive sampling approach was adopted for estimation of AGB of the study area. Total forty three plots having size of 31.6 m x 31.6 m (0.1 ha) were surveyed across the study area. Number of sampling plots varies among the selected land cover mainly due to its coverage in the study area. The diameter of each tree (DBH ≥ 10cm) at breast height (1.37m from ground) was measured with help of measuring tape and height of tree was measured with help of clinometer. All the tree species were identified with the help of regional flora and other published literatures. Community characteristics were calculated using standard methodologies. The volume of each tree was calculated using species-specific allometric equations developed by Forest Survey of India [24]. After volume calculation, resultant value was multiplied by the specific gravity (Indian woods: I-VI, FRI) to estimate the individual tree biomass. The biomass obtained from all sample plots (each in 0.1 ha) were summed up to obtained total estimated AGB.

### *2.3. Satellite data and spectral modeling*

Current study involves biomass estimation from forest inventory as well as satellite data though regression model developed between field-based biomass and spectral band ratio of satellite data. Landsat Operational land imager (OLI) satellite images (30m spatial resolution) were downloaded from Earth explorer. Study area was covered by two image scene of path/row 135/41 and 136/41. Cloud free images for same month were collected although the study area comprised of hilly terrain. These images were radiometrically calibrated to top of atmosphere surface reflectance following Fig. 2. Further, processing of images involves several image processing techniques such as geometric correction, mosaicking and extraction of study area. Radiometric correction of each band was done through ERDAS imagine 9.1 following Landsat OLI user handbook. After radiometric correction all the images were re-projected to Universal Transverse Projection system followed by delineation of study area. Land use and land cover map was prepared using unsupervised classification through ERDAS. Based on the accessibility altogether 43 plots (31.6m x 31.6m) were selected and surveyed in the study area.

Three most widely used vegetation indices *i.e.*, normalized difference vegetation index (NDVI), atmospheric resistant vegetation index (ARVI) and soil adjusted vegetation index (SAVI) were applied in present study of biomass assessment [25, 26, 27]. NDVI is the ratio between the red wavelength with maximum absorption and infrared wavelength with maximum reflectance [25, 28]. SAVI is very much alike to the NDVI but it uses soil brightness correction factor which minimize the soil brightness factor. ARVI suppress the limitation of the NDVI and minimizes the atmospheric influences due to presence of aerosols and gas particle in atmosphere.

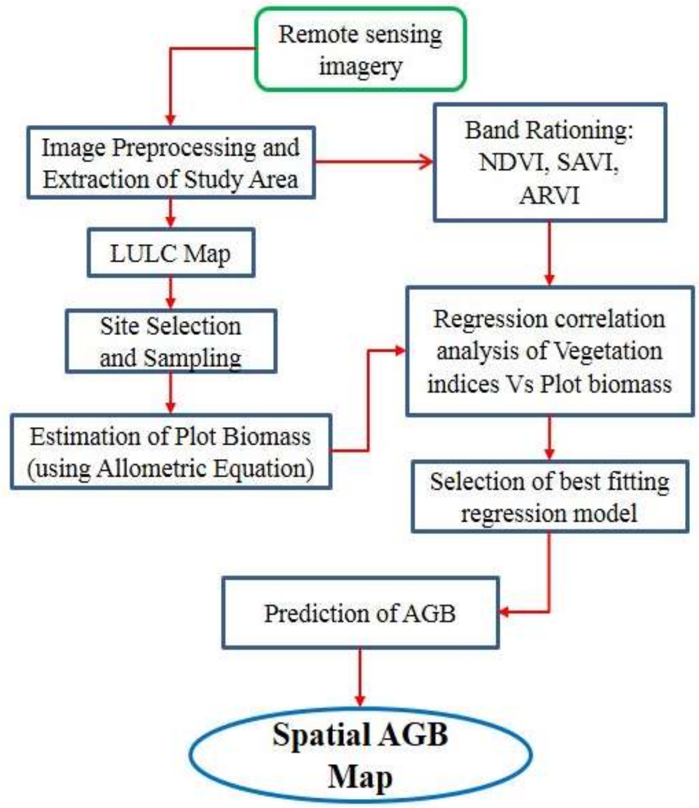


**Figure 2.** Flow chart of methodology followed in current study

Spatial distribution map of biomass and carbon was prepared by spectral modeling and up-scaling of plot observation into regional level. Developed regression model for biomass was the function of satellite derived vegetation indices. Landsat OLI surface reflectance was used for spatial modeling of biomass and carbon. The spectral modeling was done using cloud free satellite image of 2016 for setting up regression between biomass and different indices derived from satellite image of the region. Linear regression model relating biomass to different vegetation indices was carried out. The resultant regression model with high $R^2$ value was considered to be best-fit model and selected for the modeling of spatial distribution of biomass and carbon for the study area.

## 3. RESULTS

### *3.1. Tree composition and dominance*

All together 2350 individual from 186 species and 69 families were recorded from the studied area (43 sampled plots). Among these, maximum diversity was recorded in mixed dense forest followed by degraded and plantation forest. Forests canopy were exclusively composed of species like *Aquilaria malaccensis*, *Bischofia javanica*, *Bombax ceiba*, *Cinnamomum* sp., *Duabanga grandiflora*, *Dysoxylum binectariferum*, *Gmelina arborea*, *Macaranga denticulate*, *Terminalia alata*, *T. myriocarpa*, *Tectona grandis*. Based on the species richness and density, families such as Meliaceae, Myrtaceae, Moraceae and Thymelaeaceae were among the dominant in mixed dense forest. Families such as Lamiaceae, Verbenaceae and Moraceae in degraded forest and Lamiaceae, Rutaceae and Verbanaceae in plantation forest were among the most dominant families. Large numbers of families were represented by single species.

Plantation forest recorded highest stand density (612 stems/ha) followed by mixed dense (548 stems/ha) and degraded (402 stems/ha) forest. Similar to the stand density, plantation forest recorded highest basal area (46.88 $m^2$/ha) and was lowest in degraded forest (22.47 $m^2$/ha). Classified forest map of the study area revealed that total forest cover is about 309553 ha of which maximum spatial forest cover is occupied by dense forest (85%) followed by the open (42132 ha) and plantation (4351 ha) forests. Similar to forest cover, maximum AGB, BGB and total woody biomass (87%) was contributed by the dense forest followed by the open and plantation forests (Table 1).

**Table 1.** Community characteristics of the selected forest types

| Parameter | Dense forest | Plantation forest | Degraded forest |
|---|---|---|---|
| Species richness | 147 | 16 | 23 |
| Family diversity | 40 | 15 | 14 |
| Plot sampled | 28 | 10 | 5 |
| Stand density | 548±20.93 | 612±28.51 | 402±17.13 |
| Basal area ($m^2$/ha) | 42.71±1.42 | 46.88±2.74 | 22.47±1.87 |
| Estimated AGB (t/ha) | 186.73±7.54 | 174.83±3.89 | 81.41±2.78 |

### 3.2. Estimated, predicted AGB and spectral modeling

Estimated AGB values range between 29.02 and 588.77 t/ha with an average 172.38 t/ha. The average AGB for the mixed dense forest was 186 t/ha followed by plantation (174 t/ha) and degraded forest (81.41 t/ha). Species-wise AGB contribution showed that *Terminalia myriocarpa* (52.75 t/ha) followed by *Duabanga grandiflora* (24 t/ha), *Gmelina arborea* (14.64 t/ha) were among the dominant contributors in mixed dense forest. In the plantation area, maximum AGB was contributed by *Tectona grandis* (79.73 t/ha), *Citrus sinessis* (26.36 t/ha), *G. arborea* (22.82 t/ha) while *G. arborea* (18.32 t/ha), *Cinnamomum glucescens* (14.65 t/ha) and *Dillenia indica* (11.55 t/ha) were in the degraded forest. Five most dominant species have contributed about 61%, 76% and 66% of the total AGB in mixed dense, plantation and degraded forests, respectively while many species contributed only to the least AGB in the forest (Table 2).

Geospatial approach was used for modeling and prediction of above ground biomass and correlation between satellite derived vegetation indices and estimated biomass is presented in Table 3. Among the selected vegetation indices in spectral based analysis it was found that the SAVI showed higher correlation ($r^2$ = 0.70) coefficient in AGB prediction than the other indices. Hence the equation developed in correlation analysis between SAVI and plot based biomass was considered as best-fit and applied for predicting AGB of the whole study area. Predicted AGB of the study area was 172.38 t/ha (Fig. 3).

Maximum predicted AGB was recorded in mixed dense forest (191.16 t/ha) followed by plantation (157.61 t/ha) and degraded forest (96.76 t/ha). Spatial map showed that maximum AGB was observed in the area which were inaccessible and having remote location while central part of the district which is densely populated showed low AGB contribution. Total predicted AGB of the forested area was 0.0722 Pg in relation to field based estimated value of 0.057 Pg. Predicted AGB showed about 27.63 percent greater biomass values than the estimated values which could be mainly associated with the number of sampling plots used for spatial modeling. However, present model result good-fit for biomass estimation under limited sampling point conditions.

**Table 2.** AGB contribution of five dominant species in selected forest type

| Forest Type | Species | AGB (t/ha) |
|---|---|---|
| Mixed dense forest | *Terminalia myriocarpa* | 52.76 |
| | *Duabanga grandiflora* | 24.36 |
| | *Gmelina arborea* | 14.61 |
| | *Canarium bengalensis* | 12.57 |
| | *Castanopsis* sp. | 11.36 |
| Plantation forest | *Tectona grandis* | 79.73 |
| | *Citrus sinensis* | 26.36 |
| | *Gmelina arborea* | 22.82 |
| | *Bischofia javanica* | 2.27 |
| | *Michelia champaca* | 2.10 |
| Degraded Forest | *Gmelina arborea* | 18.32 |
| | *Cinnamomum glaucescens* | 14.65 |
| | *Dillenia indica* | 11.56 |
| | *Terminalia myriocarpa* | 6.29 |
| | *Sygzium cumini* | 3.94 |


**Figure 3.** Spatial distribution of biomass in the study area

**Table 3.** Correlation analysis between vegetation indices and estimated plot biomass

| Vegetation Indices | $r^2$ | Equation |
|---|---|---|
| Normalize Differential Vegetation index (NDVI) | 0.26 | $Y = 78.52x - 29.51$ |
| Soil adjusted vegetation Index (SAVI) | 0.70 | $Y = 188.34x - 50$ |
| Atmospheric Resistant Vegetation Index (ARVI) | 0.39 | $Y = 164.26x - 45.83$ |

## 4. DISCUSSION

Forests are a vital home of biodiversity, food, and carbon storing. Tropical forests comprise the largest proportion of the world's forests hence have a significant function in the global carbon cycle. Literatures revealed that forest clearance, loss and degradation significantly contributing to global carbon emissions. Gullison [29] reported that tropical deforestation releases 1.5 Gt of carbon into the atmosphere each year. Carbon stock and sequestration monitoring and assessment are the key factor and support decision maker in the process of climate change mitigation. It required estimating the forest biomass carbon as forests play a significant contribution in carbon cycle. The estimation of biomass of forest also helps in better understanding of forest cover change over the period. Various approaches were adopted for estimating forest biomass. Recent studies have shown that combination of forest inventory and geospatial approach considered to be better as it can be also applied for large. Stand densities and basal cover of current study can be compared with the values reported by various researchers for similar land cover from different parts [30, 31, 32, 33, 34, 35, 36]. Swamy et al. [37] had reported 664 stems /ha from tropical evergreen forest of Western Ghat, Karnataka. Stand density and basal area of present study can also be corroborated with the findings of different tropical and subtropical forest of India.

Present AGB values was higher than the values (32.78 – 261.64 t/ha) reported by Borah et al. [38] from forest of Cacher district, Assam. Several reporters have reported lower AGB values (7.25 – 287.05 t/ha) from tropical forests than the current study [34, 39, 40]. Mensah et al. [41] reported higher

(358.1 t /ha) AGB for the South African Mistbelt forest and Cummings et al. [42] found (377 t/ha) in mixed dense forest and (313 t/ha) in open forest of southwestern Brazilian Amazon rainforest. The predicted AGB of the study area was lower than the value (230 t/ha) reported by Devagiri et al. [34] for the forest of Karnataka and forest of Northern Guangdong, China (65.38 t/ha) by the Shen et al. [43]. Avitabile et al. [44] studied the AGB for the forest of Uganda and documented 382 t/ha.

Satellite derived vegetation indices are the indicator of greenness of vegetation canopy hence were used to quantify the vegetation volume. Vegetation indices are better representative of biomass and most of the vegetation indices derived taking ratio of Near Infrared (NIR) and Red (R) bands. Hence these vegetation indices were used in present study along with forest inventory data to establish the best-fit model for predicting forest AGB of Papum Pare district. Present study reported that SAVI showed high correlation with AGB; however, NDVI was widely used index for estimating biomass while it showed poor relationship. This may be due to index sensitivity to soil brightness effect of forest cover. As ARVI uses three spectral bands which minimizes scattering effect in the atmosphere could be responsible for slightly better relationship than the NDVI. Data saturation also affects the precise estimation of forest AGB due to composite stand structure and closed forest canopy [44, 45]. As SAVI minimizes the soil brightness effect of forest cover hence gave better relationship in current study. Other physiographic factor such as slope, aspect and elevation as well as shadow effect was not taken in to consideration which might also affect the AGB estimation by limiting the spectral reflectance of forest canopy. Literature revealed that these indices were subjected to potential error due to topographic effect which might gave diverse illumination from terrain effect. To minimize these effect processes of topographic normalization of satellite data was required but it was not considered in current study might be other probable reason for meager correlation.

## 5. CONCLUSION

Study showed that selected land use support large number of tree species from different families. Maximum stand density and basal area was recorded from plantation forest mainly due to management practices and it was observed minimum in degraded forest. Estimated Average estimated AGB was 172.38 t/ha (29-589 t/ha). Correlation between SAVI and plot based biomass was considered as best-fit equation and applied for predicting AGB of the whole study area. Predicted AGB was recorded highest in mixed dense forest followed by plantation and degraded forest. Total predicted AGB of the study area was 0.0722 Pg in relation to field based estimated value of 0.057 Pg. Vegetation indices were also affected by geographic factors hence it is good to use topographic normalization of the satellite data. Present study was based on one time data for the estimation and prediction AGB for the study while it is better to use satellite image of different growing season as it will gave better precise prediction. Apart from these indices, Tassel cap index, enhanced vegetation index, modified SAVI can also be used. Microwave data can also be used as these were free from atmospheric effect of aerosols and cloud cover for better prediction.

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## Conflicts of Interest

There are no conflicts of interest.

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