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Biomass Estimation through Vegetation Structure Analysis and Ecological Trails of Almora District, Uttarakhand using Geospatial Technology

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ABSTRACT

Tropical forests store over 40% of the terrestrial carbon and play a major role in the global carbon cycle. A large part of this carbon is sequestered in aboveground biomass (hereafter referred to as AGB or biomass), contributing towards climate regulation. Accurate and reliable forest biomass stock estimation is critical in understanding forest role to regional carbon cycles. So far, the total biomass in Almora District ecosystems is often under-estimated. This study develops to model the relationship between the biomass and the NDVI using both ground based and geospatial technology methods. To achieve this objective, NDVI, were computed from the newly launched Landsat 8 OLI satellite data and used in this study. Results showed a significant relationship ($\alpha = 0.05$) between biomass NDVI. On the contrary, no significant ($p > 0.05$) relationship was established between remotely sensed vegetation indices and the biomass. These findings imply that aboveground woody biomass stocks can be used as a proxy to estimate biomass in tropical forest. Overall, these findings underscore the potential and significance of remote sensing data in understanding Almora District ecosystems contribution to the global carbon cycle.

Keywords: vegetation indices, woody biomass, satellite data

INTRODUCTION

Forest ecosystems are the precious resource providing wildlife habitat and daily supplies such as medicinal ingredients. The tropical forest loss and fragmentation is one of the greatest threats to the world's biological diversity (Choudhary *et al.*, 2019; Palmer, 1992). In 1992, the convention on bio-diversity (CBD) highlighted some measures that must implement to conserve natural ecosystems. Specially for tropical forests, one inhabiting many species contributing to the high species richness in any of the ecosystems on earth. The forest is a plant community naturally formed or both grown and mixed. Deforestation increases atmospheric CO_2 and other trace-gases, ultimately changing climatic behavior, because the absorption of carbon is higher in forest region than in the other terrestrial regions which replace it (Gash and Shuttleworth, 1991).

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Anthropogenic activities, particularly fossil fuel combustion, industrialization and more importantly deforestation have resulted in increased concentration of CO_2 and other GHGs in the atmosphere (IPCC, 2012). These GHGs are responsible for the prevalence of the greenhouse effect and global warming. In that regard, a need has arisen to identify strategies for mitigating the effects of global warming, this is one of the major drivers of climate change. Two main strategies have been proposed to mitigate the negative effects of climate change and these include reducing the emission of GHGs and the capture and storage of CO_2 from the atmosphere (Milne *et al.,* 2013).

The terrestrial ecosystem plays a pivotal role in the capture and storage of atmospheric CO_2. So far, a total of five major carbon sinks have been identified in terrestrial ecosystems. These are the aboveground biomass, below ground biomass, litter, woody debris and soil organic matter (Vashum and Jayakumar, 2012). Among all these carbon pools, aboveground biomass constitutes the largest component, hence its potential contribution to climate change mitigation has been widely researched (Henry *et al.,* 2009; Shackleton and Scholes, 2011; Tian *et al.,* 2012; Carreiras *et al.,* 2013) at the expense of other components of the carbon pool, especially soil organic carbon (SOC). The role played by other carbon pools, particularly the soil carbon has received less research attention yet globally soils contain almost twice the amount carbon found in aboveground biomass (Stockmann *et al.,* 2013).

The advancement of remote sensing technology, mainly optical, helps in facilitating the studies related to assessment and monitoring of forest cover changes (Lu *et al*., 2004). However, other remote sensing data sources like aerial photographs have been used extensively to carry out research along with space-borne Indian satellite (IRS 1A or 1B) data. It helps in achieving higher accuracy and more comprehensive results for classifications. Remote sensing applications have used in wider ranges for earth surface monitoring as well as forest monitoring for deforestation and degradation (Ryu *et al*., 2004; Brown *et al*., 1999; Alban *et al*., 1978; Crow, 1978). For the assessment of the vegetation, some quantifying changes in the greenness level of vegetation cover are studied. Current scientific understanding of soil carbon dynamics in Almora District is poorer than that of aboveground carbon dynamics. This knowledge mismatch arises because most studies on carbon dynamics target aboveground biomass, which is relatively easy to measure (Ribeiro *et al.,* 2008), when compared to the biomass pool.

The objective of this study is to quantify the relationship between aboveground woody carbon stocks and forest biomass stock in Almora District ecosystem and assess the potential of remote sensing for direct estimation of forest biomass stocks.

STUDY AREA

The state of Uttarakhand in the Northern part is lying between 30.33^0 N 78.06^0 E covering an area of about 20,650 sq.km (Fig. 1). The study area, *viz.,* Almora town in Uttarakhand, India extends between 29°05’16” N to 29°17’28” N latitudes and 79°24’07” E to 79°37’05" E longitudes and encompasses an area of 7.27 km². Almora is situated on a ridge at the southern edge of the Kumaon Hills of the Central Himalaya range in the shape of a horse saddle shaped hillock. The average height of the town stands at 1,651 meters above mean sea level. Almora town enjoys the cool temperate climatic conditions. The climate of Almora is characterized by relatively high temperatures and evenly distributed precipitation throughout the year. The main seasons are summer from March to June, the monsoon season from July to November and winter from December to February.

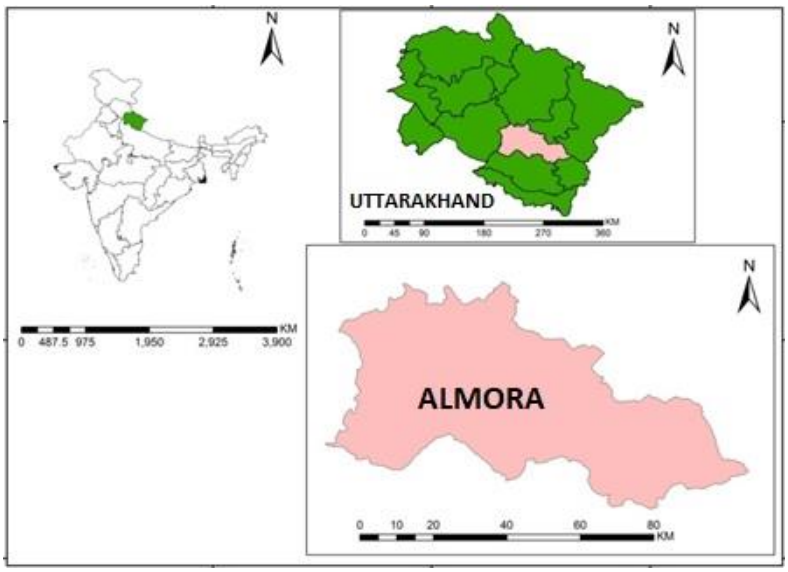


Fig. 1: Study area.

MATERIAL AND METHODS

LANDSAT OLI sensor satellite data for 2015 and 2017 were used to analysis of biomass estimation from the earth explorer website. After download the satellite data it incorporated to ILWIS GIS software for further processing and digital analysis.

Software Used

In this study ERDAS IMAGINE is basic software to use the various analysis to find out the biomass estimation through geospatial technology (Kumar *et al*., 2012; Kumar *et al*., 2018). ERDAS aimed to primarily develop at geospatial raster data processing with respect to various thematic mapping data base to enhance digital image.

Data acquisition

This step is divided into two parts, in which first we have to download vector file (.shp) format of the study area. Then we have to download the satellite imagery of the study area from USGS. In this study we had taken satellite imagery of Landsat 8 of year 2015 and 2017.

Sampling

The precision of sample estimate of population depends not only upon the size of sample, but also on the variability in the population is very high, sampling variance can be reduced by dividing the population into the number of homogeneous groups and then selecting random sampling from these groups of population independently (Kumar *et al.,* 2019; Kumar *et al*., 2014; Chacko, 1965). The homogenous group in which the population is divided is called strata and the procedure of sample selection is called stratified random sampling (Fig. 2).

The use of stratification is possible only when the complete frame for all strata and size are variable. Effectiveness of stratification can be investigated by the analysis of variance. The variance of total population is made up of the variance within individual strata and of variance within the strata. Assessing forest biomass in various sample plots, it is necessary to develop the statistical database for further tree counting in sample plot (Ringrose *et al.,* 1998). In each plot, was taken from chakos formula to calculate total number of sampling to measurement of forest biomass is which consists of mixing of various tree samples from different sample plots.

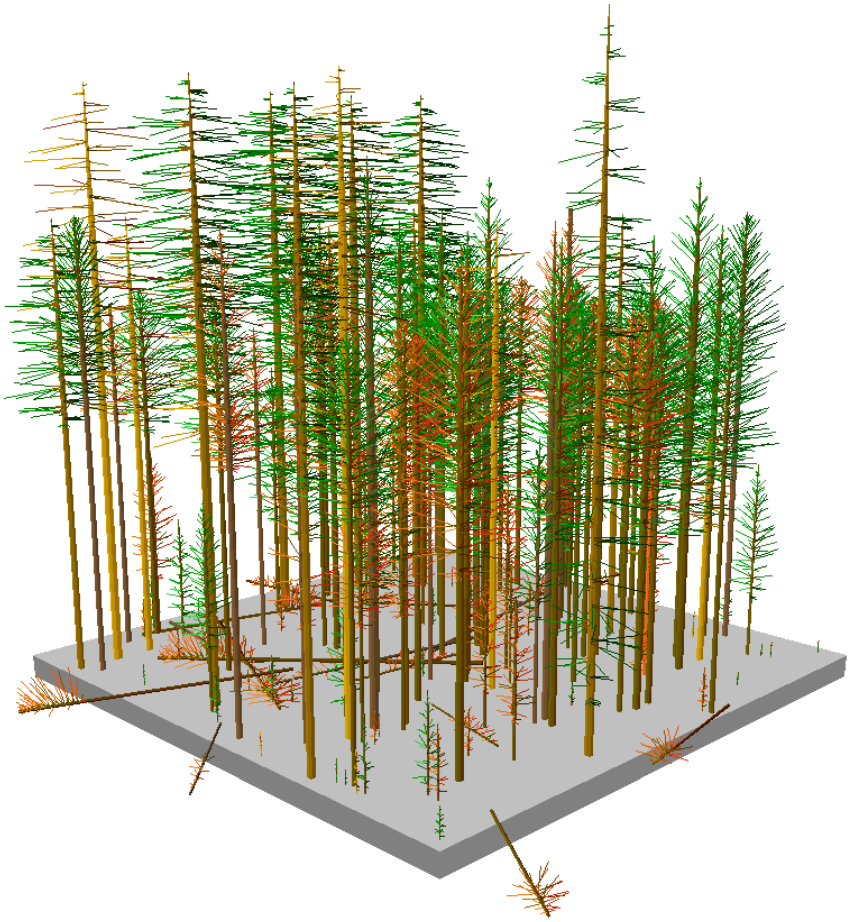


Fig. 2: Plot layout design**.**

Image acquisition and pre-processing

Landsat 8 Operational Land Imager (OLI) satellite images were downloaded from the online Landsat data series archive and imported into ILWIS 3.3 GIS software for processing (Kumar et al., 2018). Prior to calculating vegetation indices, the Digital Numbers (DN) were converted to radiances and then to Top of Atmosphere (TOA) reflectance using radiometric rescaling coefficients provided in the product metadata file (MTL file). The process was done using the following formulae (USGS, 2013):

$$\rho\lambda' = M_\rho Q_{cal} + A_\rho$$

where:

$\rho\lambda'$ = TOA planetary reflectance, without correction for solar angle.
M_ρ = Band-specific multiplicative rescaling factor from the metadata
A_ρ = Band-specific additive rescaling factor from the metadata
Q_{cal} = Quantized and calibrated standard product pixel values (DN)

Reflectance with a correction for the sun angle was calculated as:

$$\rho\lambda = \frac{\rho\lambda'}{\cos(\theta_{SZ})} = \frac{\rho\lambda'}{\sin(\theta_{SE})}$$

where:

$\rho\lambda$ = TOA planetary reflectance
θ_{SE} = Local sun elevation angle
θ_{SZ} = Local solar zenith angle; $\theta_{SZ} = 90° - \theta_{SE}$

Remotely sensed vegetation indices

To assess whether soil carbon stocks can be estimated indirectly from satellite imagery, three selected remotely sensed vegetation indices were calculated from Landsat 8 OLI images. These include NDVI. The indices were computed as following:

$$NDVI = \frac{NIR - R}{NIR + R}$$

Where NIR is Reflectance in the Near Infra-red and R is Reflectance in the Red Band. These indices were selected and used in this study based on their performance in previous studies (Thenkabail *et al*., 2013).

Biomass estimation

The biomass can be estimated by two approaches *i.e.,* volume method and direct biomass estimate method. The volume method is processed through measuring volume estimate of converted biomass (tonnes/ha). The second method *i.e.,* direct method is followed by using biomass allometric equations *i.e.* functions that relate oven-dry biomass per tree as a function of a single or a combination of tree dimensions (Brown, 1999). The inputs of tree biomass equations are same as of tree volume equations which can be tree diameter at breast height (DBH) as an independent variable, often with tree height (H) and other variables. Total tree volume (V_{tot}) is calculated as the sum of each component volume of the tree as follows:

$$V_{tot} = V_{stem} + V_L\text{-branch} + \text{Vs-branch}$$

V_{stem} is total tree volume,
V_L-branch is volume of large branches
Vs-branch is volume of small branches

However, more generally, standard models are used to estimate merchantable or bole volume (up to the point of first branch or defect) and total tree volume. Philip (1994) describes three such models: (i) The Smalian's model, (ii) Huber's model and (iii) Newton's model. Volume estimates are then multiplied by specific wood density values to derive biomass estimates. Specific wood density (SWD) refers to oven-dry mass per unit of green wood volume (t/m^3 or g/cm^3). Where there is inadequate wood density data, an estimate of a weighted mean wood density can be made from known species by applying the arithmetic mean for known species to unknown species. Biomass estimates are then subjected to biomass expansion factors to account for tree components whose volume or biomass are not measured, such as minor branches and twigs. In general, the expansion factor (ExpF) is used to calculate total aboveground volume or biomass where there is partial aboveground volume or biomass data and can be applied to both tree and plot data (Somogyi *et al.,* 2008). Thus, biomass from volume data can be expressed as:

Aboveground biomass = Estimated volume over bark x SWD x ExpF

1. Deodar (*Cedrus deodara*): $V = -0.087+0.289\times D^2 \times H$
2. Banj (*Quercus leucotrichophora*): $V= 0.014796+0.319061\times D^2\times H$
3. Buransh (*Rhododendron arboreum*): $V= 0.06007-0.21874\sqrt{D}+3.63428\times D^2$
4. Moru (*Quercus floribunda*): $V= 0.01480+0.31906\times D^2\times H$
5. Anyar (*Lyonia ovalifolia*): $V= 0.03468-0.56878\times D+4.72282\times D^2$

Where:

V= volume; D = diameter at breast height.

The above ground biomass was worked out by multiplying the calculated volume with the specific gravity of the tree. Species wise specific gravity (Deodar-0.497, Banj-0.826, Buransh-0.600, Moru-0.600, Kafal-0.600, Anyar-0.600, Utis-0.319, Chir-0.537, Kaill-0.600 (FSI, 2017).

Biomass (B) = Volume (V)* Specific Gravity (SG)

RESULT AND DISCUSSION

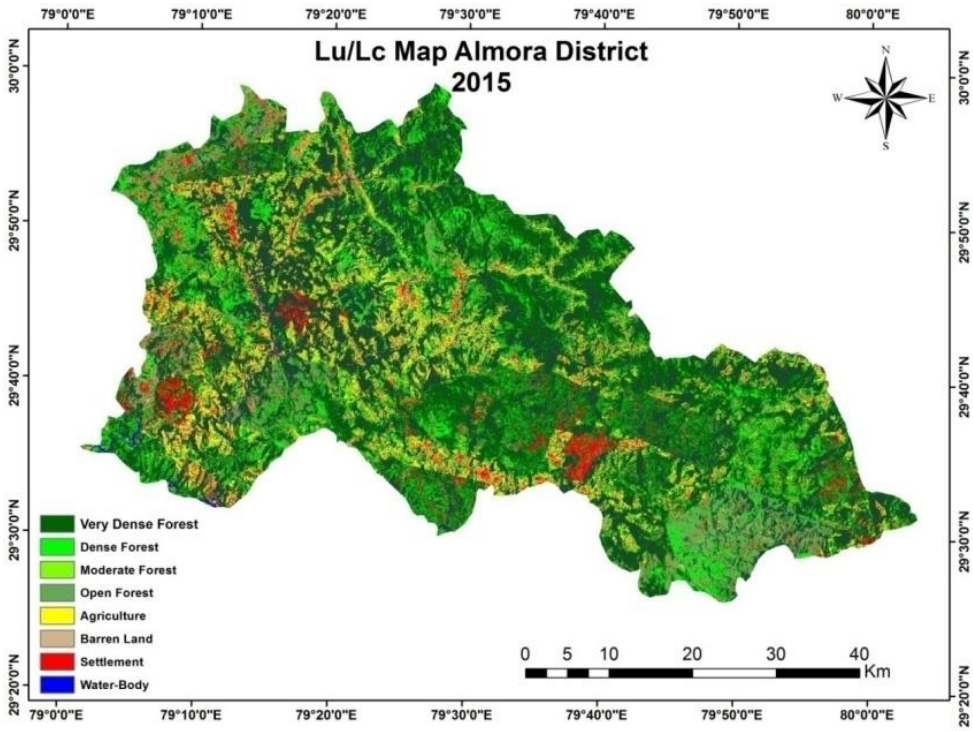
Forest biomass in the upper soil layer (0-15 cm) was positively correlated with aboveground woody carbon and this relationship was significant (r = 0.678; P<0.01) aboveground carbon. However, there were no significant correlations (r = -0.11, P> 0.05) and aboveground woody biomass.

Land use/Land cover

The terms land use and land cover is often used interchangeably, but each term has its own unique meaning. Land cover–refers to the characteristics and surface cover of Earth's surface, as represented by natural elements like vegetation, water, bare earth, impervious surface and other physical features of the land. Identification of land cover establishes the baseline information for activities like thematic mapping and change detection analysis. Land use–refers to the activity, economic purpose, intended use, and/or management strategy placed on the land cover type(s) by humans or land managers. It is important to distinguish this difference between land cover and land use, and the information that can be ascertained from each. The properties measured with remote sensing techniques relate to land cover, from which land use can be inferred, particularly with ancillary data or a priori knowledge. LU/LC map were produce for 2015 and 2017 satellite data with help of ground truth survey. According to the land use/cover map (Fig. 3), forest area is predominantly covered by agriculture, water bodies and barren land in which human activities are relatively less intense. Barren land is commonly contacted with crop land (Elvidge *et al.,* 2019; Kumar *et al.,* 2018; Tripathy *et al.,* 2018; Kumar et al., *2017*).

Estimation of biomass

Exploring whether remote sensing may enhance the accurate estimation of biomass for 2015 (Fig. 4) and this technology overcomes some of the limitations of field-based methods. The findings of this study indicate that vegetation indices derived from optical bands had a weak relationship with NDVI. These results suggest that multi-spectral optical remotely sensed data poorly performs in estimating biomass stocks in Almora ecosystems. These results underscore the aforementioned challenges encountered in the utilization of remotely sensed data in mapping.



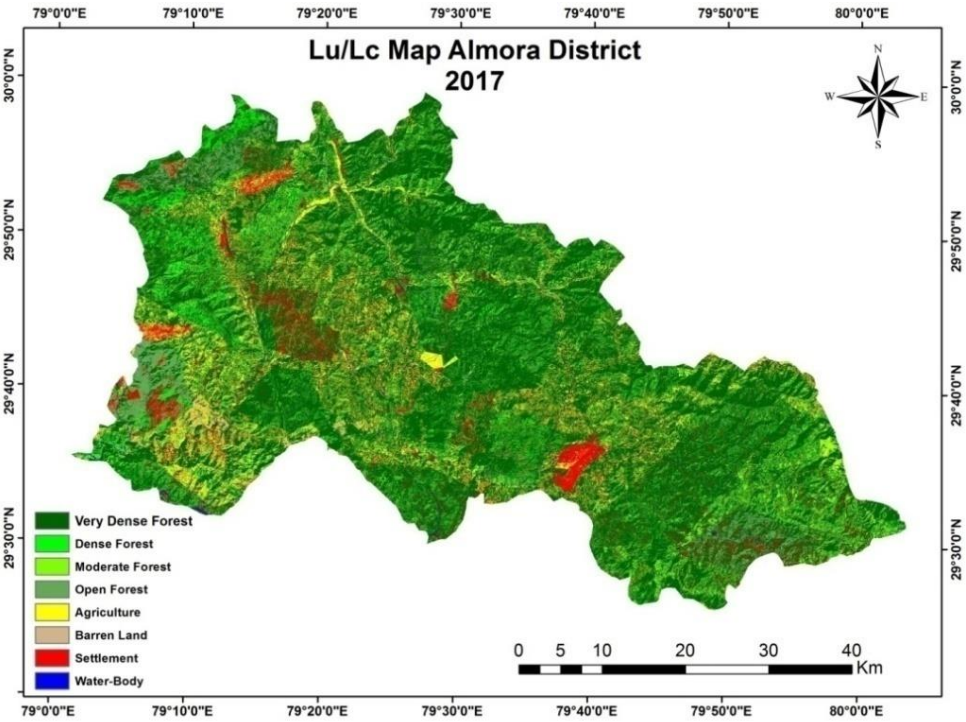


Fig. 3: LU/LC Classified Map of Almora district 2015 and 2017.

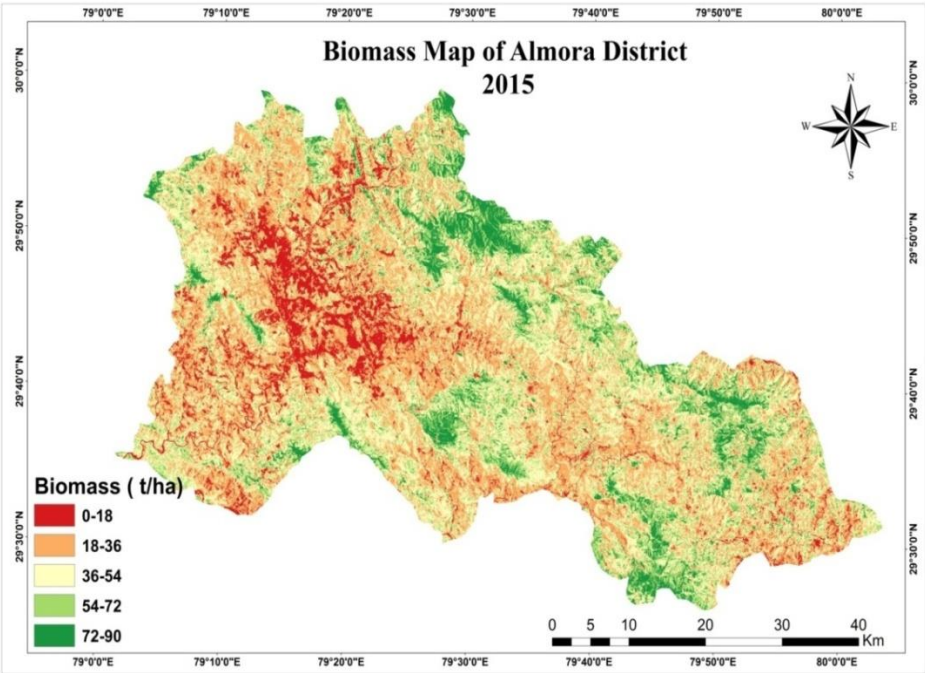


Fig. 4: Biomass map of Almora district (2015).

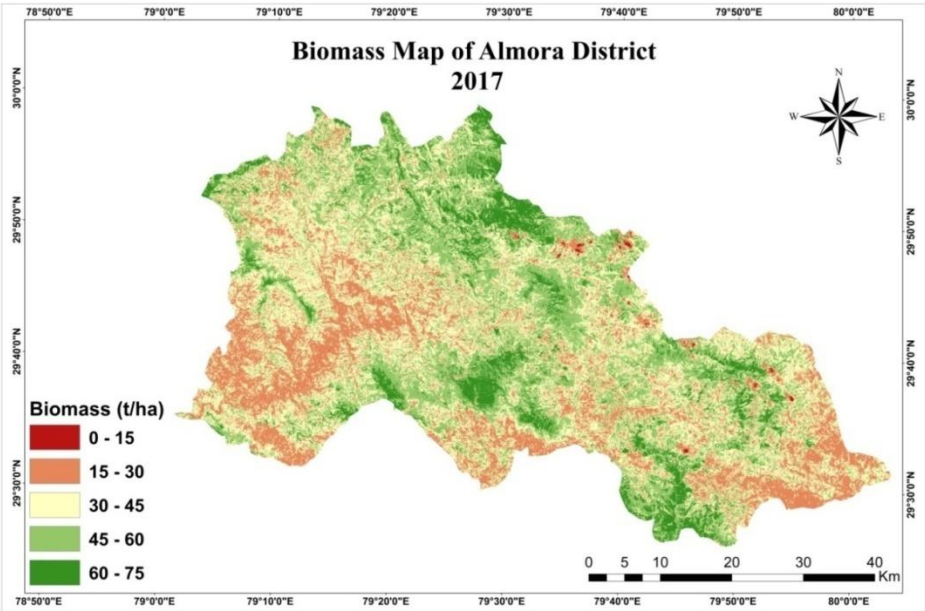


Fig. 5: Biomass map of Almora district (2017).

The DBH and height for each tree species were used for regression analysis to get an estimate of biomass (Kumar *et al.*, 2018). Tree biomass at (90.45 t/ha) was Maximum at Pithaoragarh, Uttarakhand. However, minimum biomass was recorded at (18.71 t/ha), at centre city of Almora for 2015. Tree biomass at (50.50 t/ha) was maximum at Pithaoragarh. However, minimum biomass was recorded at Bageshwer (9.75 t/ha) for 2017 (Fig.5).

CONCLUSION

The objective of this study was to quantify the relationship between NDVI and forest biomass to assess the potential of utilizing remotely sensed for estimation biomass stocks stock in a dry Almora ecosystem. The results of this study indicate that aboveground woody biomass stocks, which can be estimated from space offers a promising avenue to estimate SOC in the upper soil layer (0-15 cm) in Almora ecosystems of Uttarakhand. However, direct estimation of biomass from space relying on satellite remote sensing is still difficult and more research using non-optical regions of the electromagnetic spectrum is needed to address this gap. In that regard the results of this study a foundation for evaluating other remotely sensed datasets in estimating biomass.

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