Environment and Ecology 38 (3B) :715—724, July—September 2020
ISSN 0970-0420

The Potential of Radar Remote Sensing in Estimation and Mapping of Forest above Ground Biomass in Sub-Tropical Forest (Kempti Forest Range) in the Himalayas

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Received 6 June 2020; Accepted 22 July 2020; Published on 8 August 2020

ABSTRACT

India is seventh largest country in the world with an area of 328.74 million hectares (Mha) and ranks 10th in the list of most forested nations in the world (FAO 2015) with 80.20 Mha of forest and tree cover. India's forest and tree cover accounts for about 24.56% of the total geographical area of the country (ISFR 2019). The forests across the world are under the immense impacts of climate change which varied across the continents with some forest types being more vulnerable than other (Lucier et al. 2009, Fishlin et al. 2009). Forest plays a crucial role in maintaining global climate change through carbon cycle. This paper investigates the potential of ALOS PALSAR-2 data for the assessment of forest above ground biomass in sub-tropical forest of Uttarakhand. The study explores the retrieval of AGB in sub-tropical forests using non-parametric method, field data and three sets of ALOS PALSAR-2. The non-parameterc method has resulted that the plot level AGB in sub-tropical forest (Kempti Forest Range) ranged from 2.35 t/ha for open forest to 317.99 t/ha for mature forests. In the sub-tropical forest the obtained regression equation y =2.724ln (x)-28.725 derived from biophysical parameters and backscatter coefficients of L-banf HV polarization was used for modeling of AGB due to highest coefficient of determination and least RMSE (R^2 = 0.85, RMSE = 57.41 t/ha). The modeled AGB ranged from 1.02 t/ha to 252.31 t/ha, with an average of 95.73 t/ha. It is concluded that microwave data is significantly able to map and estimate forest above ground biomass operatively over sub-tropical forests.

Keywords Forest, Biomass, Backscatter, ALOS PALSAR-2, Polarization.

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INTRODUCTION

Forest plays a crucial role in maitaining global climate change through carbon cycle. the amount of carbon present in the forests depends upon the biomass per unit area. The biomass is defined as the total amount of above ground living organic matter in trees expressed as oven dry tons per unit area (FAO). The accurate quantification of biomass in required to understand the global carbon pool changes, sustainability and the productivity of the forests (Whittaker and Woodwll 1969, Anderson 1971, Esser 1984, claturvedi and Singh 1987, Rawat and Singh 1988, Malhi et al. 2004, Goetz et al. 2009). The estimation gives us a statistics about the amount of Carbon dioxide sequestered from the atmosphere by the forests and the amount eimitted due to deforestation and forest fire. It is important to know the distribution of biomass from local to global levels, for calculating the sources and sink of carbon and to monitor the change through time. There are a number of ways to estimate and monitor forest above ground biomass (Brandeis et al. 2006, Soenen et al. 2010, FAO 2015). Now, the need for estimation has realized but onne of the method has developed which estimates the accurate amount of biomass.

In earlier days destructive method was adopted which was also known as the harvest method. According to Gibbs et al. (2007) this method was the most direct method for the estimation of above ground biomass and the carbon stocks stored in theforest ecosystem. although this method is limited to small area but it determines the biomass accurately for that particular area. This method is time and resource consuming, strenuous, destructive, expensive and thus not applicable for large-scale analysis. This method is used for development of location and species-specific allometric equations used for accessing biomass on large scale (Navar 2009, Segura and Kanninen 2005). The allometric equations are the most widely used method for the estimation of biomass (Chaturvedi and Singh 1987, Rawat and Singh 1988, Saldarriaga et al. 1988, Uhl et al. 1988, Rana et al. 1989, Adhikari 1992, Fearnside and Guimaraes 1996, Alves et al. 1997, FAO 1997, Chave et al. 2005, IPCC 2006). The Allometric method is based on the principle that every components of trees shows relationship with each other. It is a non-destructive method for the estimation of biomass without felling and thus widely used.

Observations and measurements by satellites have nowadays become the primary source for estimating AGB in tropical forests (Lu 2006). The science of Remote Sensing has played an important role in the mapping and monotoring of frest biomass and carbon due to its synoptic view of forest and surrounding areas. Since no remote sensing instrument can directly measure either biomass or carbon content, additional *in-situ* data is required for establishing a relationship between the remote sensing signal and the biomass (Dong et al. 2003, Rosenqvist et al. 2003). Biomass estimation using optical remote sensing data is usually realized by revealing the correlation between biomass and spectral responses and/or vegetation indices derived from multispectral images (Sader et al. 1989, roy and Ravan 1996, Fazakas et al. 1999, Nelson et al. 2000, Steininger 2000, Mickler et al. 2002, Foody et al. 2003, Phua and Saito 2003, Calvao and Palmeirin 2004, Zheng et al. 2004, Lu 2005, Chiesi et al. 2005, Gibbs et al. 2007, Mycong et al. 2006, Tan et al. 2007, Bastin et al. 2014). The earlier studies had integrated the vegetation index directly to vegetation amount (above ground biomass) and primary productivity (Tucker et al. 1983, Goward and Dave 1987, Huete et al. 2002, Nakaji et al. 2008). Optical remote sensing technologies, theoretically, have limited capability to predict forest biomass since the recorded spectral responses in optical images are mainly related to the interaction between the sun radiance and forest stand canopies. Thus, the correlation between forest biomass and spectral responses or vegetation indices is usually poor, especially for mature forests inwhich spectral responses become saturated and lose sensitivity to trunk and branch biomass. However, frequent cloud coverage in the inner tropics often hampers the acquisition of high quality data. Another major disadvantage is the low saturation level of the spectral bands and the derived spectral indices regarding the biomass estimation (Gibbs et al. 2007, Nichol and Sarker 2011).

Most of the studies with optical sensors have estimated biomass indirectly because of the several inherent limitations of optical data such as: Inability to penetrate the vegetation canopy, insufficient sensitivity to forest structure and above ground biomass, inadequate temporal frequency because of persistent clond cover. It is proposed to evolve methods to improve the assessment of phytomass/Carbon using optical and Microwave remote sensing data in different representative test sites in different ecosystems across the Uttarakhand state and suggest method for impovements in estimates of biomass. It has been demonstrated that there is a strong relationship between backscatter coefficients and above ground biomass within a particular forest types (Baker etal. 1994, Le Toan et al. 1992, Dobson et al. 1992, Imhoff 1995). Taking the advantage of the deeper penctration of longer wavelength and greater saturation (dobson et al. 1992, Kasischke et al. 1997, Luckman et al.

1998, Hoekman and Quinones 2000, Luckman et al. 2000, Saatchi et al. 2007, Mitchard et al. 2014) in the forest canopy, an attempt will be made to develop empirical relationship between Microwave backscatter from satellite and airbome platforms and the biomass levels so as to estimate the forest biomass of the study area.

Studu area

The study lies on the outermost ridge of the Himalayas. slopes are mostly steep to precipitous. The altitude of these forests vary from about 1500m to 2330 m above sea level. The Mussoorie forest division is a longitudinal depression in the north-western complex of the Himalayan range, and thus constitutes an important relief feature of geographic significance. Vegetation of the study area is climatic climax and falls under 12/C-Himalayan moist temperate and moist deciduous forest. Predominant species of this area are *Cedrus deodara, Quercus leucotrichophora, Rhododendron arboreum, Shorea robusta, Mallotus phillippensis, Nyctanthesarbortristis. Lanneacoromandalica, bauhinia purpurea, Toonaciliata, Adinacordifolia, Boehmariarugulosa* mixed with trees of *Qugeiniaoogenensis, Terminaliatomentosa, Cassia fistula* and *Acacia catechu.*Undergrowth mainly consists of *Murrayakoenigii, Colebrookiaoppositifolia, Woodfordiafruticosa, Adhatodavasica. Lantana camara* and *Eupatorium adenophorum.* The figure represents the distribution of forest inventory plots used in the study.

MATERIALS AND METHODS

The L-band ALOS PALSAR-2 data were used in the study. The data were acquired over different forest types of Uttarakhand is the month of February, March and April. The polarization of data varies from Single polarization to Quad polarization. The incidence angle of the data ranges between 32.9^0 to 35.8^0. The rediometric calibration, multilooking, speckle filtering, geocoding and backscatter image processing have been carried out for every data set. Different set of images were produced to know the best possible image for selection of sample plots.

In the current study a plot size of 25m×25m was selected for the measurement of parameters. The size of the plot was selected in such a manner that it resembles the pixel size of the stellite data. The inventories carried out by Forest departments, Forest survey of India, Forest Research Institute,HRS in biodiversity characterization project have taken a plot sizeof 0.1 ha i.e. 31.62 m × 31.6 m for growing stock, volume and biomass estimation. But, in this study the size was selected so because the in-situ interpolation of 0.09 ha to 0.1 ha lead to uncertainty addition in forest biomass estimation. Atotal of 62 plots were laid in the forest area, out of which 40 plots were used for modelling and 22 plots were left for the validation of the model. The samples were laid out inthe region which were least affected by the topographic distortions. It saves the energy as well as time to carry out thefield inventory. Thederived image variables were found to beefficient in discriminating different forest density. This indicates that polarization manipulation techniques can be considered as an image enhancement technique that is useful for identifying forest growth levels. It helps in laying of sample plots in the study area.

RESULTS AND DISCUSSION

The field inventory data were collected in Kempti Forest Range for 62 forest plots using stratified random sampling. The stand structure defines thedistribution and representation of size class of trees in a stand. The number of trees within a sample plot ranges from a minimum of 1 to a maximum of 95. The average number of trees within a sample plot were found to be 30. The top height within theplots eanged from a minimum of 6m to a maximum of 35m. The average height was found to be 23m. The basal area ranged from a minimum of 0.02 m^2 to a maximum of 4.07 m^2. The average basal area was found to be 1.59 m^2. The stem volume ranged from a minimum of 0.1 m3 to a maximum of 37.96 m^3. The stem volume was found to be 13.45 m^3 The plot level biomass ranged from a minimum of 2.35 t/ha to a maximum of 317.99 t/ha. The average biomass was found to be 113.23 t/ha. The regression analysis has been carried out to understand the amount of change in one variable hat is associated with change in other variable. The aim of this model is to determine the straight line relationship that connects basal area and biomass. Based

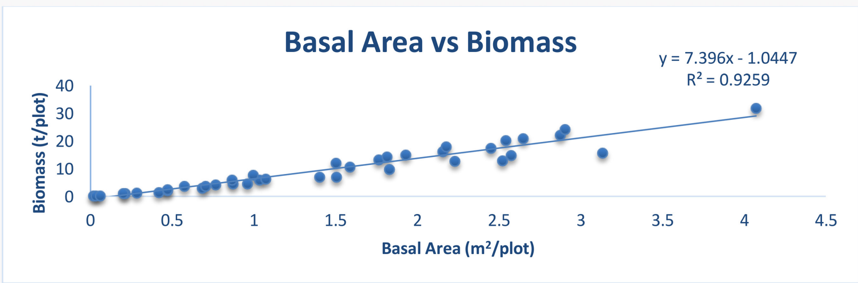

Fig. 1. Relationship between basal area Biomass in sub-tropical forest.

on the scatter diagram of Fig.1, there appears to be a definite relationship between basal area and biomass. A significant coefficient of determination ($R^2 = 0.90$) has been observed between both the variables. An R^2 of 0.90 means that 90% of the variation in the biomass can be explained by the regression line.

Biomass modeling and estimations in sub-tropical forest

The ALOS PALSAR-2 processing was carried out using SNAP software as well as SARScape. The dependence of the backscatter upon weather conditions strongly depends on the scattering mechanisms occurring in a forest. In sparse forests, where the canopy covers only a small fraction of the forest floor, the ground contribution to the backscatter is dominant. In dense, i.e. mature, forests instead the canopy covers most of the ground, therefore, the volume secattering within the vegetation layer makes the ground contribution less important. The backscatter trend can be expected to depend on the imaging conditions and the forest structural characteristics. The backscatter coefficients (σ^0) for the HH, HV and VV components were derived. The responses of all the three variables were different to biomass. The spread in the data depends on several factors. First, the small size of the forest plots and the errors in geolocation can often cause errors in extracting the exact backscatter values. Second, speckle in high-resolution radar imagery can introduce variations in backscatter measurements over forests with similar AGB values. Finally, depending on the canopy architecture (branch and leaf orientation), canopy moisture content, spatial distribution of trees, soil roughness and moisture, and topography, the backscattering coefficients may vary for forests with similar above ground biomass. Moreover, the errors associated with the field data and allometric equations also contribute to the variations shown in backscatter plots.

Correlation analysis is widely used as a statistical analysis technique to study and model the relationship between two continuous variables such as forest biomass and radar backscatter. To apply the correlation analysis, the pixel values of the PALSAR image and the variables at corresponding locations on the ground were extracted. In this case, the backscatters of HH, HV and VV polarizations as well as pixels values of all the variables derived were directly used as the predictors for the measured AGB of the sampling plots. The variable of each plot were correlated to produce empirical functions or models in which the best correlation was selected and used for AGB prediction for the whole study area. The predicted AGB was presented in a thematic layer showing the distribution of AGB t/ha over the study area. The AGB values ranges from 2.35 t/ha for open forest to 317.99 t/ha for mature forests. All the variables were then correlated with AGB that was obtained from the sample plots. The HH backscatter of all corresponding plots in the study area ranged from –20.01 to –4.81 dB, with a mean of –11.6 dB. The HV backscatter of all corresponding plots in the study area ranged from – 25.5 to –10.41 dB, with a mean of –14.73 dB. The VV backscatter of all corresponding plots in the study area ranged from – 24.23 to – 7.21 dB, with a mean of –12.96 dB.

Table 1. Longarithmic correlation and coefficient of determination of AGB and derived image variables from L-band PLASAR polarizations.

Variable	Model	R	R^2	Adjusted K^2	Standard error	RMSE (h/ka)
HH	$y = 2.2929\ln(x)-20.447$	0.814	0.663	0.654	46.083	69.18
BV	$y = 2.7241\ln(x)-28.725$	0.854	0.73	0.723	41.226	57.41
VV	$y = 3.6631\ln(x)-35.513$	0.738	0.546	0.539	39.976	92.33

All the polarization were used independently to find the best fit model for biomass using 42 field inventory plots. The VV was found to be least significant and can only explain about 54% ($R^2 = 0.54$) of the variations in the biomass. It was followed by HH polarization which has explained nearly 66% (R^2=0.66) of the variations in the biomass. HH-polarized data are known to be less sensitive to biomass. It is commonly believed that HV polarized SAR data have better sensitivity for biomass estimation.

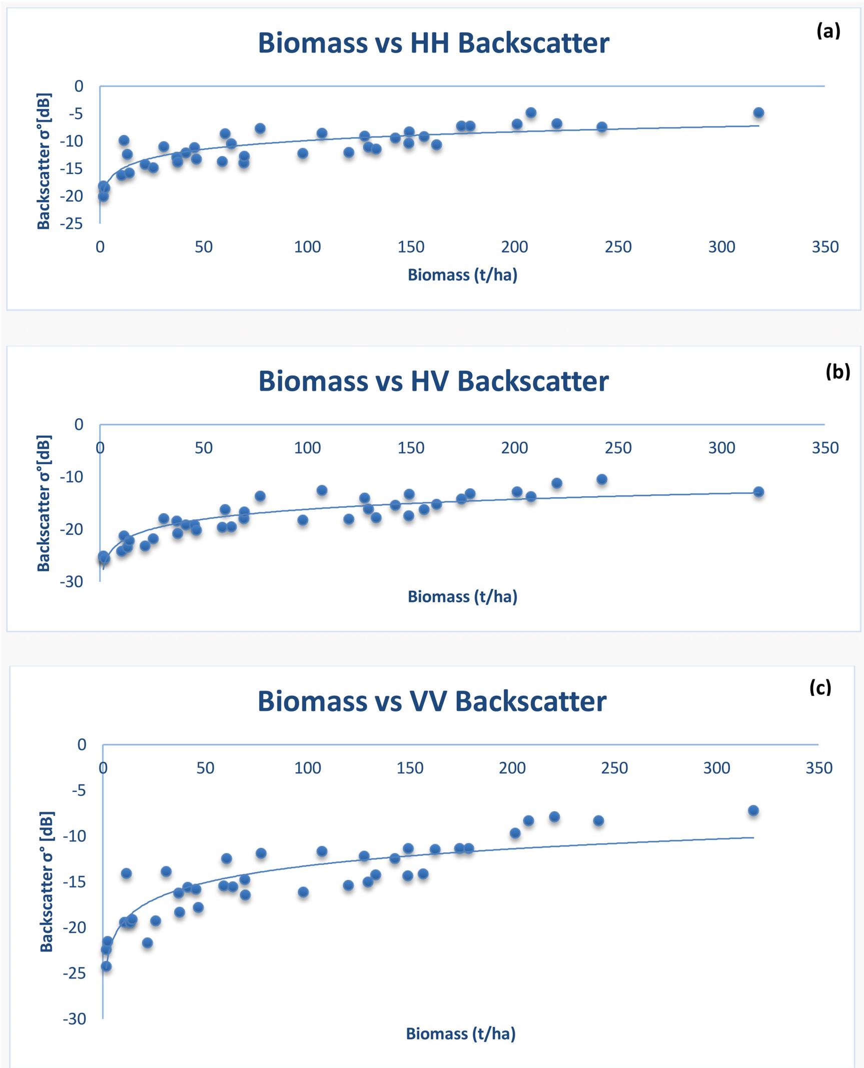

Fig. 2. Relationship between above ground biomass (t/ha) and backscatter intensity: (a) HH (σo, dB); (b) HV (σo, dB; (c) VV (σo, dB).

The goodness of fit was found to be maximum with the cross polarized HV backscatter image. It has explained about 73% of variability in the biomass of sub-tropical forests. This rells us that HV-polarized SAR data have the maximum potential to predict biomass. It was evident that adding more and more parameters using different processing techniques was unable to significantly improve the sensitivity of differently polarization data. Overall, the results showed that the correlation were of high significance for the estimation of biomass in the forest.Based on the correlation analysis, highest correlation with the coefficient of determination (R^2) of 0.73 was observed with the backscatter of HV polarizations, thus the model was scICcted as the AGB prediction model as it gave the best R2 compared to the other variables. The trend line indicates that the biomass component has a logarithmic correlation to the backscatter. The relationship is asymptotic, increasing rapidly at lower AGB levels (i.e. up to 100 t/ha) but decreasing towards higher AGB levels. The scatterplots showing the correspondences of AGB with all the variables are shown in Fig. 2 and the summary of all the model produced is listed in Table 1. The correlation analysis indicates that the above ground biomass has a logarithmic relationship with the variables.

The relationship between backscatter coefficient and per plot biomass for each polarization is shown Fig. 3. The dynamic range of the L-band HV response is larger than that of the co-polarized response and the absolute level is lower because of the relatively weaker mechanisma that given rise to cross polarized backscatter.

The relationship between field biomass and simple radar intensity (HH, HV, VV) is well defined using 40 model plots (Fig.3), but the HV intensity data showed batter performance (adjusted $R^2 = 0.723$) than any other single-polarization data. The poor result can be explained by the speckle noise in the raw (intensity) SAR data compounded by the complex forest structure and rugged topography of the study area.

As the biomass changes from 1 t/ha to about 50 t/ha, there is an about 9 dB increase in HH backscatter. When the biomass is > 50 t/ha, the HH backscatter gets saturated. The modeled HH backscatter shows a similar pattern as the HH SAR backscatter. Because there is about 5 dB dynamic range in HH backscatter, and because the model predicts that the backscatter is mainly from the trunk-ground, the HH SAR backscatter may be linked to the trunk ground. The model also predicts that there is some contribution from canopy volume scattering, but its contribution is small. The contribution from surface backscatter and multiple path interaction of canopy-ground to the total backscatter are insignificant.

There is only an approximately 7 dB increase in VV backscatter when the biomass changes from 1 t/ha to about 50 t/ha. When the biomass is >50 t/

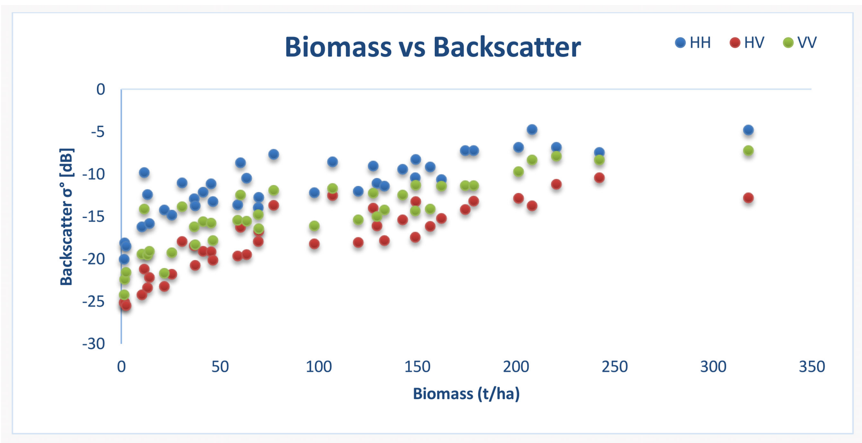

Fig. 3. Relationship between AGB and different backscatter coefficients derived from sub-tropical forest.

ha, the VV backscatter gets saturated. Therefore, VV backscatter are not significantly used in modelling. The backscatter has a mixed contribution from canopy volume scattering, trunk-ground term and surface scattering. Because of the mixed contribution of three components, it will be difficult to isolate the scattering components.

In case of HV polarization, total backscatter is exclusively from thecanopy volume scattering. The saturation limit is too wide at this polarization, and thusit helps to design the algorithm to derive the forest biomass and carbon.

Referring to Table 1, the root mean square error (RMSE) of each estimating model was calculated based on the validation plots that were established in the study area. A total of 22 validation plots, were used to validate the estimates.

Model with variable VV describes 54% of variability of forest AGB in the study area with the RMSE of 92.33 t/ha, which adds the uncertainty in predicting the biomass. It was reduced to 69.18 t/ha, with HH polarization as an input to the model. A large dip in Ramse (57.41 t/ha) has been observed with HV model. In hetrogeneeous forests, the HV polarizations are more sensitive to the canopy structure than HH and VV, therefore they correlate better with biomass.

Aboveground biomass distribution in sub-tropical forest

The obtained regression equation y = 2.7241ln (x)-28.725 derived from biophysical parameters and backscatter coefficient of L-band HV polarization was used for modeling of AGB due to highest coefficient of determination and least RMSE (R^2=0.85; RMSE = 57.41 t/ha). The biomass map represented a modeled biomass map of the region. The results show that with an increase in biomass levels, backscatter coefficient also increases. As the biomass increases, backscatter coefficient also increases and subsequently attains saturation. The scattering mechanism at L.band in a forest canopy are mainly volume scattering in the canopy,double bounce scattering between trunks and the ground, and surface scattering from the forest floor. The study indicates that the variations in the above ground biomass in the study area were closely related to the canopy density of the forest as well as age of the forest stand.The AGB ranged from 1.02 t/ha to 252.31 t/ha, with an average of 95.73 t/ha. The spatial biomass map was classified on the basis of forest density. The open forests (OF) wre categorized with biomass ,50 t/ha and represented in yellow. The Moderately dense forest (MDF) were categorized in the range of biomass from 50-150 t/ha and represented in green. The Very dense forest (VDF) have blomass > 150 t/ha and represented in dark green. The spatial distribution pattern of AGB in the Kempti forest range explicity shows that majority of the area was at the range of<150 t/ha (VDF), followed by biomass range below 50 t/ha (OF) and least were fall under the category of MDF (50-150 t/ha) This has also been observed through ground data too. The total AGB of the study area wasthen calculated based on this distribution. The areas of different forest density classed were extracted (Table 2) The total AGB in a prticular forest class was calculated by multiplying the average biomass with the area. The average biomass for Open Forest was found to be 1920 t/ha, whereas it was 110.37 t/ha MDF and 163.23 t/ha for VDF. The modeled biomass shows a different story in that area. It has been observed from the map (Fig. 4) that most of the area falls under the VDF category. But,it was

Table 2. Basic statistics of AGB and carbon in the study area extracted from the thematic map produced.

Forest Density Class	Total Area (ha)	Modelled Biomass (tonnes)	Modelled Carbon (tonnes)	Carbon sequestration Potential (tonnes carbon)
Open Forest (<50t/ha)	2509.30	48203.63	22655.71	81560.54
MDF (50-150 t/ha)	1462.77	161446.05	75879.65	273166.72
VDF(>150 t/ha)	2612.44	426428.66	200421.47	721517.29
Nf	2190.52	0.00	0.00	0.00
Total	8775.03	636078.35	298956.83	1076244.55

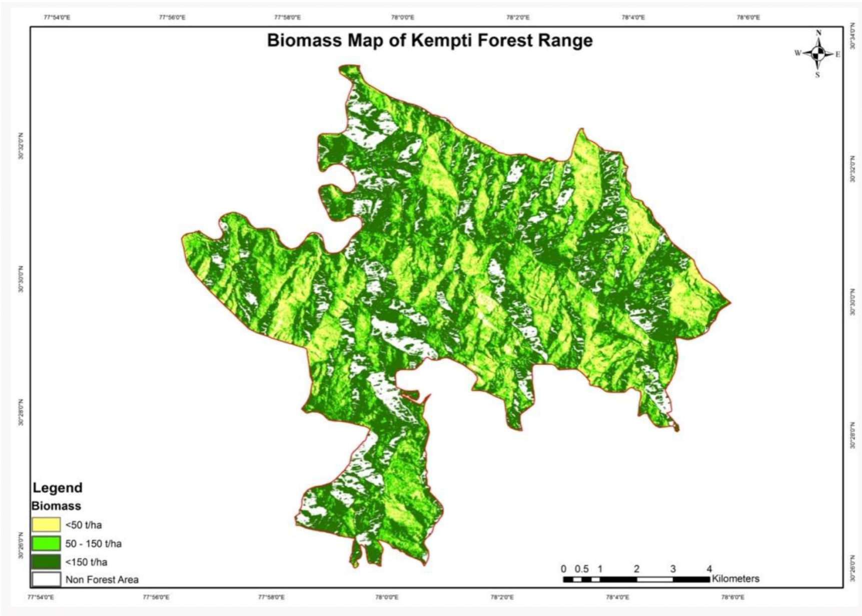

Fig. 4. Biomass map of Kempti Forest Range.

observed from the field that very small area under falls under the category of VDF. It was then verified and concluded that the backscatter coefficient of steep slopes facing the sensor are appeared to be high and due to this the estimated AGB is also observed to the high. The phenomenon of foreshortening and layover is dominant in the hilly terrain. The total AGB in Kempti Forest Range is about 0.63 million tonnes. The carbon calculation from the biomass has been done bymultiplying the biomass by the factor of 0.46 (IPCC). The amount of carbon stored in the forest is found to be about 0.29 million tonnes. The details of forest area under different forest types, modeled biomass, modeled carbon and the sequestration potential are shown in Table 2.

The forest ecosystem captures and retain large volume of carbon over long periods, thus develop a large biomass and carbon pool. The young trees are sequestering large amount of carbon, whereas an old mature trees acts as a reservoir holding large volume of carbon even it is not experiencing net growth. Thus, a young forest holds less carbon, but it is sequestering additional carbon over time. The carbon present in the biomass is converted to CO_2, the lonnes of carbon are multiplied by the ratio of the molecular weight of carbon (44/12).

The open forest in Kempti Forest Range holds 22655.7 1 tonnes of carbon which has potential to sequester 81560.54 tonnes of Carbon dioxide equivalent from the atmosphere. The MDF in Kempti Forest Range holds 75870. 65 tonnes of carbon which has potential to sequester 273166.72 tonnes of Carbon dioxide equivalent from the atmosphere. The VDF has the potential to sequester 717935.27 tonnes of Carbon dioxide equivalent from the atmosphere. A total of 1076244.55 tonnes of Carbon dioxide equivalent is stored from the atmosphere in the Kempti Forest Range.

CONCLUSION

Thisstudy demonstrates that L-band ALOS PALSAR data can be utilized delineate the spatial distribution of the AGB for the whole extent of the Kempti Forest Range. Empirical functions. were derived from the relationship between the AGB measured on the ground sample plots and several image variable derived from L-band ALOS PALSAR polarizations. Among the different variables, backscatter from HV polarization was found to be the best predictor with the highest R^2 when regressed independently. Overall, the simulated AGB in the forest was estimated to range from 1.02 t/ha to 252.31 t/ha , with anaverage of 95.73 t/ha. The estimates were then used to produce a spatially distributed thematic map showing the spatial pattern of AGB for the whole study area. The heterogeneity of the foret structure, a consequence of good management and efficient silviculture practices, has resulted in a forest that has different vegetation density, that can be captured by L-band SAR system. Results also indicated that despite the limitations, which resulted indata saturation about 150 t/ha levels, the use of L-band SAR can provide an alternative that allows rapid assessment of AGB in large areas where access is limited. The errods associated with the prediction model were also observed to increase largely as the AGB exceeded 150 t/ha. The uncertainty caused in the estimation of overall biomass can be reduced by the application of SAR simulation. The invalid pixels due to noice i.e. layover, foreshortening and shadow can be handled by using multi temporal data sets, The data sets with different incident angles plays an important role in the accurate estimation of biomass. The approach described can be used as a practical technique for areas infused with noise.

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