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Estimation of Above Ground Biomass Using Support Vector Machines and ALOS/PALSAR data

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ABSTRACT

L-band Synthetic aperture radar (SAR) data has been extensively used for forest aboveground biomass (AGB) estimation due to its higher saturation level. However, SAR backscatter is highly influenced by the topography characteristics along with the bio-geophysical properties of vegetation and underneath soil characteristics. This has limited the accuracy of directly relating the SAR backscatter with above ground biomass in highly undulated terrain. In this study, it has been observed that terrain degree of slope and aspect plays a vital role in influencing the SAR backscatter in addition with AGB. Because of this, the degree of slope and aspect along with SAR backscatter in HH (transmit and receive polarizations are horizontal) and HV (transmit horizontal and receive vertical) polarizations have been considered as inputs for Support Vector Machine (SVM) to improve the biomass retrieval accuracy. Our results demonstrate that the accuracy of AGB estimation over hilly terrain can be significantly improved by considering topographical characteristics in addition to L-band backscatter.

Keywords: Synthetic aperture radar; ALOS-2; PALSAR-2; above ground biomass; support vector machines.

1. Introduction

Precise estimation of spatio-temporal biomass is a vital component of carbon stock quantification and understanding sources and sinks. Forests are the dominant terrestrial ecosystem which contains approximately 80% of the Earth's plant biomass (Pan, et al., 2013). Forest biomass includes above ground and below ground components. Above ground biomass (AGB) contributes an amount of 70% to 90% of the total forest biomass (Cairns et al., 1997). Furthermore, AGB is in a continuous state of flux due to wildfires, logging, land use dynamics (which include shifting cultivation) etc., and thus contributes to atmospheric carbon. Several initiatives such as Reducing Emissions from Deforestation and Forest Degradation (REDD) and REDD+ also rely heavily on AGB information (Koch, 2010). Because of importance and dynamism of AGB, it is necessary for accurate estimation and continuous monitoring.

To assess forest biomass, several approaches are followed which include field measurements and developing allometric equations. However these methods provide

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more accurate estimations, but are not effective for large area monitoring due to the time, cost and labour involved. Whereas, remote sensing provides synoptic temporal coverage from local to global scales and is more reliable for regional level as well as global biomass monitoring. There are different types of data, such as optical, radar and LiDAR, with each one having certain advantages over the others. In recent days, Synthetic Aperture Radar (SAR) data has gained prominence over other datasets for AGB estimation due to its all-weather capability and its sensitivity towards bio-geophysical vegetation parameters (Thumaty et al., 2016; Sivasankar et al., 2018). The return signal to the radar is sensitive towards sensor parameters such as frequency of operation, polarization and incidence angle as well as target parameters such as geometrical, structural and dielectric properties of vegetation cover and underneath soil moisture (Henderson and Lewis, 1998; Srivastava et al., 2018). So, a legitimate choice of optimum sensor parameters is critical to improve the sensitivity of SAR data for a particular application.

Numerous researchers have analyzed the sensitivity of the SAR sensor parameters such as frequency, polarization and incidence angle towards AGB estimation (Harrell, et al., 1995; Huang et al., 2015; Sivasankar et al., 2018). Previous studies observed that the radar backscatter saturates when the signal passes through a certain biomass level, which is influenced by the SAR sensor parameters and topography characteristics (Imhoff, 1993; Srivastava, et al., 2011; Lone et al., 2017). Imhoff (1993) analyzed the C-, L- and P-band quadpol. SAR data acquired between 40° and 50° incidence angle for biomass saturation limits and observed that C-band saturates at~ 20 tons/ha; L-band at ~40 tons/ha; and P-band at ~100 tons/ha. It is also identified that the saturation levels vary with the polarization as well. Srivastava et al., (2011) analyzed the two-way attenuation in radar backscatter from soil due to crop cover using water cloud model. It was observed that the attenuation increases with the increase in incidence angle due to increase in signal propagation length through vegetation cover. It is well-known that each microwave frequency band has saturation limit, with this it is understood that the higher incidence angle SAR data gets early saturation than lower incidence angle (Srivastava, et al., 2011). Lone et al. (2017) observed the early saturation of backscatter in SAR shadowing aspects due to increase in propagation length through vegetation than from aspects facing towards sensor. It was also observed that the HV backscatter can estimate AGB with higher accuracy than HH backscatter. Due to this complex function of radar backscatter with several factors such as sensor parameters as well as topography characteristics, this is still a challenging task to precisely retrieve AGB from SAR data.

Several researchers have attempted to retrieve AGB using SAR data (Sivasankar et al., 2018; Baig et al., 2017; Baghdadi et al., 2015). Baig et al. (2017) estimated AGB of Dalbergia sissoo forest plantation from dual-polarized (HH and HV) ALOS-2 PALSAR data using non-linear regression analysis by training AGB model through ground-based AGB measurements and SAR backscatter. The study observed reasonable coefficient of determination (R^2) values of 0.47 and 0.55 for HH and HV backscatters respectively. Baghdadi et al., (2015) analyzed the sensitivity of L-band ALOS/PALSAR data to forest biomass for Eucalyptus plantations. Non-linear regression results found the R^2 of less than 0.5 and RMSE higher than 46.7 ton/ha. However, the accuracy of AGB estimation using nonlinear nonparametric regressions based Random Forest algorithm was improved slightly with R^2 increased from 0.88 to 0.92 and RMSE decreased from 22.7

to 18.9 ton/ha by considering plantation age along with backscatter. Due to the complexity to retrieve AGB from backscatter alone, several researchers have also attempted using multi-sensor remote sensing data for this purpose. Omar, et al. (2017) has used L-band PALSAR-2 (HH and HV) and C-band Sentinel-1A (VV and VH) SAR data for AGB estimation in Dipterocarpus forest of Malaysia. The study used simple linear and multiple linear regression analysis and observed that the combination of all polarizations from both PALSAR-2 and Sentinel-1A SAR data were able to increase the accuracy and reduced the RMSE up to 14 Mg/ha compared to the estimation from single polarization. Shao & Zhang (2016) estimated forest AGB by combining optical and SAR data in Genhe, Inner Mongolia, China. The study has proposed a new passive optical and active microwave integrated vegetation index based on observations from both in-situ measurements and satellite (Landsat-8 Operational Land Imager and RADARSAT-2 SAR data). It can be found from these researches that the integrated use of both optical and SAR data significantly improves AGB estimation than the individual sources only.

In this study, the main objective is to evaluate the influence of the topography characteristics (such as aspect and degree of slope) on SAR backscatter for forest AGB estimation. In addition, support vector machine (SVM), a popular machine learning technique, optimized by evolutionary algorithm, was applied to retrieve AGB using ALOS-2 PALSAR-2 data and SRTM derived aspect and degree of slope. Nongkhyllem wildlife sanctuary and reserve forest located in the state of Meghalaya, India was taken into account for the study area as there has been very limited study on quantifying forest AGB using SAR data in northeast India. Further, the approaches of quantifying forest AGB in other parts of India cannot be exclusively followed in northeast part of India due to its different topographical characteristics. Thus, it is imperative to undertake this study to quantify forest AGB using SAR considering topographical characteristics.

2. Materials and Methods

2.1. Study Area

This study was conducted in Nongkhyllem wildlife sanctuary and reserve forest located in the state of Meghalaya, India (Fig. 1). The area consists of undulating plains to low hills which are part of the Archaean Meghalaya Plateau, having elevation between 200m to 950 m asl while slope ranges from 0 to 49.85 degrees. Most part of the study area is covered by dense tropical evergreen forest with patches of tropical moist deciduous forest, Assam sub-tropical pine forest, semi evergreen forest, Khasi sub-tropical wet hill forest, Khasi hill sal and some jhum cultivation. The important tree species are *Schima wallichi* (8.26%), *Shorea robusta* (5.37%), *Tectona grandis* (4.82%), *Sterculia villosa* (4.36%), *Castanopsis spp.* (4.11%), *Bauhenia spp.* (4.00%), *Tetramales nudiflora* (3.85%), *Artocarpus loocha* (3.70%), *Albizzia procera* (3.53%), *Michelia champaca* (3.46%), *Callicarpa arborea* (3.42%) and *Miscellaneous spp.* (51.12%) (Source: Forest and Environment Department, Govt. of Meghalaya). Roy et al. (2015) have recorded a steady decrease in forests of northeast India mainly due to logging, shifting cultivation and mining. There has been very limited study on quantifying forest AGB using SAR data in northeast India. Further, the approaches of quantifying forest AGB in other parts of India cannot be exclusively followed in northeast part of India due to its different topographical characteristics. Thus, it is imperative to undertake this study to quantify forest AGB using SAR considering topographical characteristics.

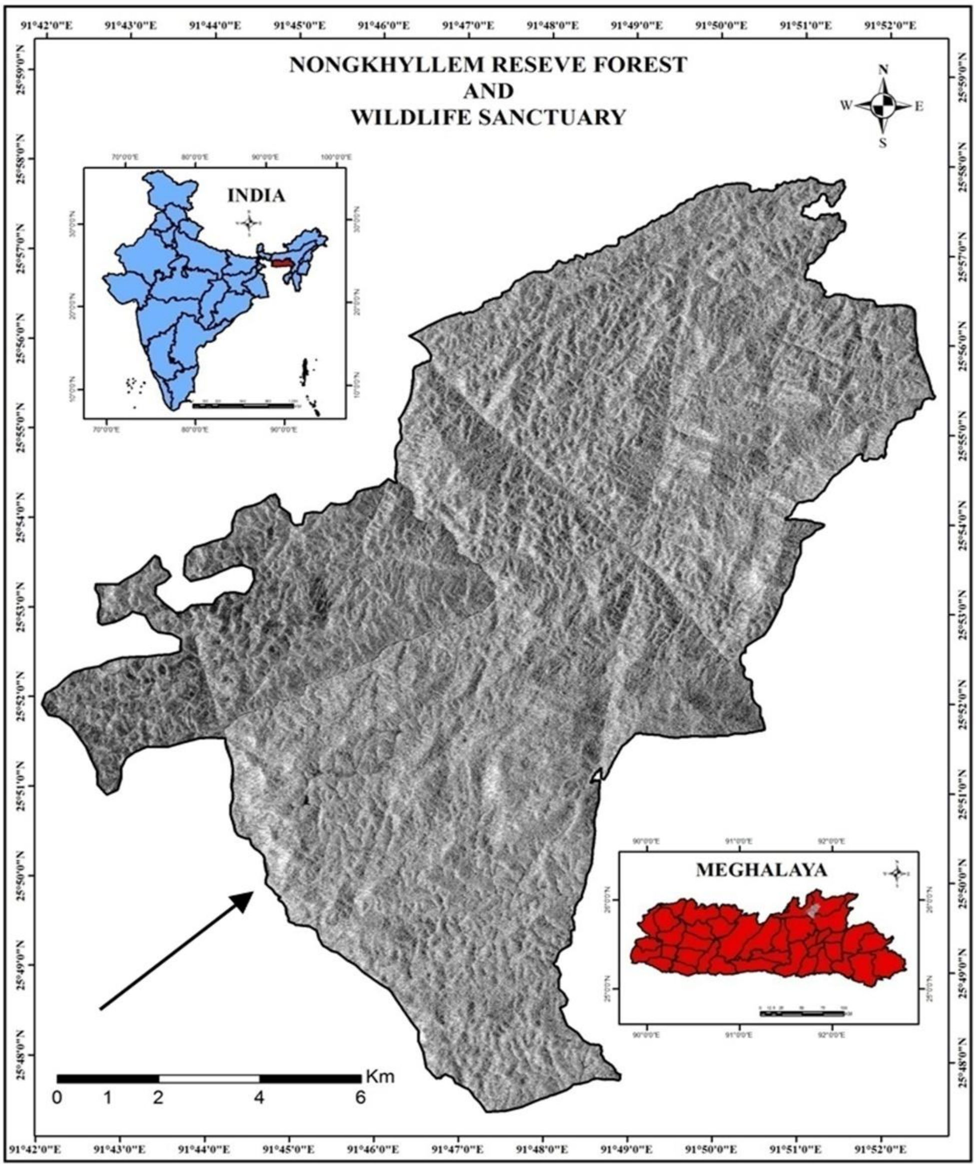


Figure 1. Location of the study area

2.2. Datasets used

Fine beam dual polarized (HH and HV) L-band ALOS-2 PALSAR-2 data with spatial resolution of 9.1 m × 5.3 m (Range × Azimuth), 24 cm radar wavelength and incidence angle of 36.2° captured on November 14th 2014 has been acquired from the Japan Aerospace Exploration Agency (JAXA) for this study. The PALSAR data used in this study is looking towards North-East (NE) direction during data acquisition. Shuttle Radar Topography Mission (SRTM) 30m DEM was used to generate slope, aspect information of the study and also for terrain correction of the PALSAR 2 image. The data was processed in Sentinel Application Platform (SNAP) toolbox provided by European Space Agency (ESA).

Data from 150 sampling plots of one-hectare size from the Meghalaya Forest and Environment Department (MFED) inventory database was used to estimate plot level AGB. The field data acquired from MFED included individual tree based measured parameters of tree height, girth at breast height (GBH) and species type information of 1 ha plot size with 150 sampled plots. The estimated volume or growing stock using the derived volumetric equations was converted into dry biomass by using specific gravity or wood density as the product of specific gravity and volume (Rajput et al., 1996; Mitchard et al., 2012). These sampling plots have requisite size to be considered for target parameters retrieval using PALSAR-2 fine beam mode data (Patel and Srivastava, 2013). Due to the limitations of range Doppler terrain correction, in resolving layover and shadowing, proper care has been taken in choosing the sampling locations for this study. Since the SAR data used in the present study is of 36.2° incidence angle, the ground-truth samples from terrain with slope less than 36.2° are considered to minimize the effect of geometrical errors in SAR data processing of range Doppler terrain correction (Jensen, 2007).

2.3. Support Vector Machine (SVM)

The SVM is a machine learning technique using a high dimensional feature space. Initially, the SVM was developed for optical character recognition and object recognition tasks (Schölkopf et al., 1998). The SVM and Random Forest has produced better results than other machine learning methods like Neural Network (Attarchi & Gloaguen, 2014). It yields prediction functions that are expanded on a subset of support vectors. One of the principle characteristics of the SVM is that instead of reducing the observed training error, the SVM endeavors to decrease the generalized error in order to achieve generalized performance. This generalization error bound is the combination of the training error and a regularization term that controls the complexity of the hypothesis space (Basak, Pal, & Patranabis, 2007). The SVM essentially transforms the nonlinear regression problem into a linear one by using kernel functions to map the original input space into a new feature space with higher dimensions (Cristianini, & Taylor, 2000). Common kernel functions include linear, polynomial, radial bias function (RBF) and hyperbolic tangent, among which, RBF is widely used for various applications due to its typically better performance and smaller number of input parameters (Gao, et al., 2012).The RBF kernel is defined as

$$K_{RBF}(\mathrm{x},\mathrm{x}') = e^{[-\gamma\|\mathrm{x}-\mathrm{x}\prime\|^2]} \quad (1)$$

Where, γ is kernel parameter

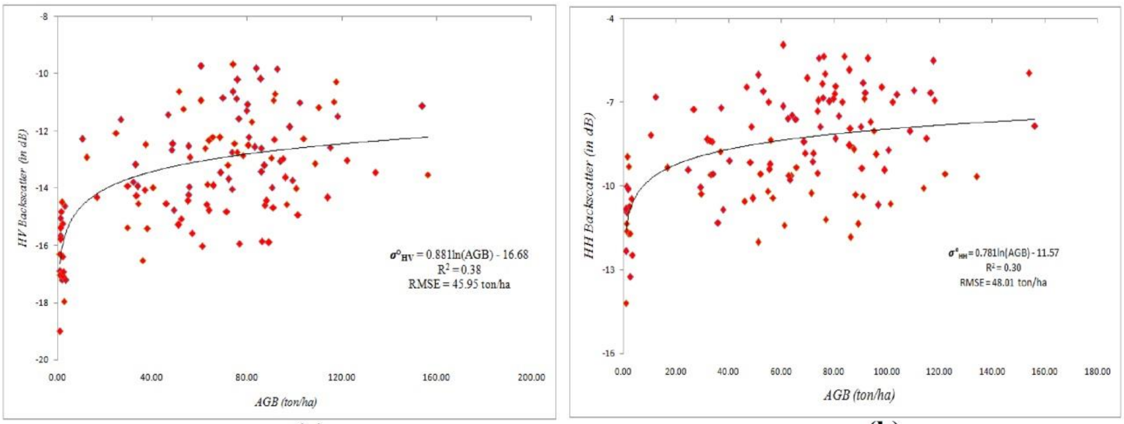
The SVM calculates the difference between the estimated and the actual values, and if the error is less than the ε (tolerated training error i.e., ε-insensitive loss), the regression function is considered to be most desirable and accurate (Samola and Schölkopf, 2004). Consequently, the performance of an SVM model is highly related to the values of the three parameters: C (indicates the tradeoff between the tolerated training error and the model complexity), ε and γ (kernel parameter). To optimize their selection, Evolutionary algorithm (Friedrichs and Igel, 2005) was used in the present study. Coefficient of determination (R^2) and RMSE (as given in Eq. 2) have been used to analyze the AGB retrieval model performance.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(AGB\_est_i - AGB\_obs_i)^2}{n}} \quad (2)$$

Where, AGB_est_i is the i^{th} plot estimated AGB; AGB_obs_i is the i^{th} plot observed AGB; and n denotes the total number of plots.

3. Results and Discussion

The total 150 samples have been segmented into two independent sets of 120 (80%) and 30 (20%) to model non-linear regression relationship of backscatter with in-situ AGB and validate the same respectively. Fig. 2 shows the relationship between the backscatter coefficients in HH and HV polarization with in-situ AGB. As anticipated from previous research works, the backscatter is best fitted with logarithmic relationship and HV backscatter yields higher R^2 and low RMSE than HH backscatter (Thumaty et al., 2016; Morel et al., 2011; Patel and Srivastava, 2013). The results show that HH backscatter was of lower significance with R^2 and RMSE of 0.30 and 48.01 ton/ha respectively; HV backscatter was of higher significance with R^2 and RMSE of 0.38 and 45.95 ton/ha respectively. Thumaty et al., (2016) observed the R^2 of 0.395 and 0.509 for HH and HV backscatter respectively, which was carried over central Indian deciduous forests using ALOS PALSAR L-band data. This lower significance may be due to the highly undulated terrain of the study area. The changes in topographic characteristics such as aspect and degree of slope leads to the change in local incidence angle which intern influence the backscatter. So, this study has continued to analyze the influence of aspect and degree of slope on SAR backscatter in context to the AGB estimation.



(a) (b)

Figure 2. Relationship of backscatter with AGB

The accuracy of forest AGB estimation using ALOS PALSAR data have been observed greater than 10 ton/ha in the previous studies. For example, (Peregon and Yamagata, 2013; Hamdan, et al., 2014) have observed the RMSE of 51 ton/ha in Western Siberia using ALOS PALSAR data and 33.90 ton/ha over Matang Mangroves, Malaysia respectively. Because of this, the backscatter from the sampled locations with 70 ± 10 ton/ha (which ranges from 60 ton/ha to 80 ton/ha) have been considered to understand the influence of the aspect and degree of slope. The mean HH and HV backscatter of having AGB in the range 70 ± 10 ton/ha samples from each aspect have been given in the Fig. 3. The results clearly show that the backscatter varies with the change in topography aspect in spite of having the nearly equal AGB. Higher backscatter was observed from the South (S), South-West (SW) and West (W) aspects facing towards the sensor; lower backscatter from the shadowing aspects which are North (N), NE and East (E); and moderate backscatter from North-West (NW) and South-East (SE) aspects, which are facing perpendicular to the sensor look direction.

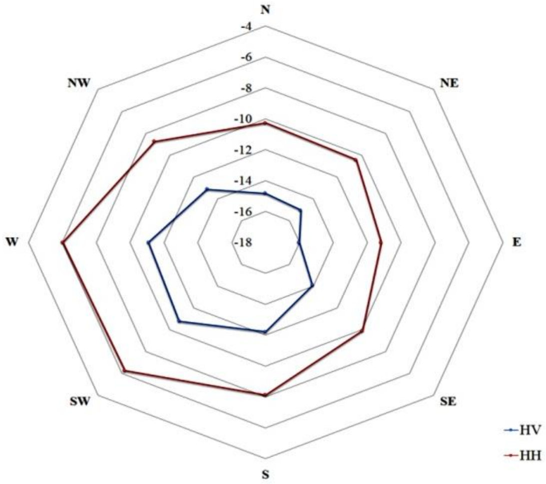


Figure 3. Mean HH and HV backscatter from the sampled plots having 70 ± 10 ton/ha

The trend of the mean HH and HV backscatter from sampled locations having 70 ± 10 ton/ha with changes in degree of slope for all the three grouped cases is given in Fig. 4. It is observed that the HH and HV backscatters have similar behavior. It is identified that the backscatter increases with increase in degree of slope over the aspects facing towards the SAR sensor. Whereas, backscatter decreases with increase in degree of slope over the shadowing aspects (N-NE-E). However, the backscatter has little increased with increase in degree of slope over the aspects facing perpendicular to the SAR look direction. The results from Fig. 3 and 4 indicate that the aspect and degree of slope are vital to be considered for AGB estimation using SAR backscatter.

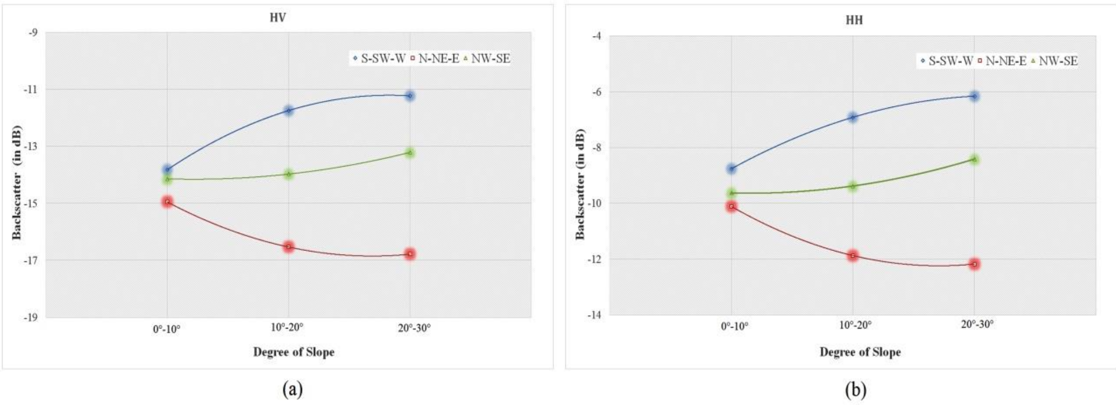


Figure 4. Backscatter trend at various degree of slope (a) HV backscatter (b) HH backscatter

An attempt has been made to consider aspect and degree of slope in addition to L-band SAR backscattering coefficient as the SVM model inputs for AGB retrieval. A total of three models have been calibrated and validated using 120 and 30 independent samples respectively as given in Table 1. The results indicated that the inclusion of aspect and degree of slope information has significantly improved the AGB estimation accuracy. The SVM model with HH backscatter observed R^2 and RMSE of 0.83 and 24.32 ton/ha, whereas the HV backscatter observed R^2 and RMSE of 0.89 and 20.56 ton/ha. As anticipated from previous studies, the HV backscatter model has shown better performance than HH backscatter for AGB retrieval. It is also identified that the use of both HH and HV backscatter has improved R^2 and RMSE of 0.02 and 2.35 ton/ha respectively than HV backscatter alone.

Table 1. AGB retrieval results using SVM

Backscatter used in addition with Degree of slope and Aspect	Model development		Model validation	
	R^2	N	RMSE (ton/ha)	N
HH	0.83	120	24.32	30
HV	0.89	120	20.56	30
HH and HV	0.91	120	18.21	30

4. Conclusions

The present study has shown the influence of terrain aspect and degree of slope for AGB retrieval using L-band SAR data. It has been observed that aspects facing towards the SAR sensor have higher backscatter than from shadowing aspects in spite of having nearly same AGB. It is also identified that the SAR backscatter increases with the increase in degree of slope over aspect facing towards SAR sensor, whereas decreases with the increase in degree of slope over shadowing aspects. This indicates that the topography characteristics such are aspect and degree of slope play a vital role in AGB retrieval using SAR backscatter. In this study, the degree of slope and aspect along with SAR backscatter in HH and HV polarizations have been considered as inputs for SVM to improve the biomass retrieval accuracy. RMSE and R2 have been used to validate the accuracy of the SVM. The results observed that the R^2 and RMSE of 0.30 and 48.01 ton/ha respectively with HH backscatter, whereas 0.38 and 45.95 ton/ha with HV backscatter using non-linear regression approach. As anticipated from previous studies, HV backscatter has shown better performance for AGB estimation than HH backscatter due to the multiple scattering of illuminated microwave signal. Since the degree of slope and aspect have effect on L-band backscatter in addition to AGB, an attempt has been made to train SVM for AGB retrieval using both L-band SAR backscatter and topography characteristics. The use of topography characteristics such are aspect and degree of slope in addition to ALOS-2 backscatter has significantly improved the accuracy, R^2 of 0.83 and 0.89 are observed with HH and HV backscatter respectively. The use of both HH and HV backscatter has slightly increased AGB retrieval accuracy to R^2 and RMSE of 0.91 and 18.21 ton/ha respectively.

Acknowledgements

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References

Attarchi S., Gloaguen R., 2014. Classifying complex mountainous forests with L-Band SAR and landsat data integration: A comparison among different machine learning methods in the Hyrcanian forest. Remote Sensing, 6(5), 3624–3647. https://doi.org/10.3390/rs6053624

Baghdadi N., et al., 2015. Evaluation of ALOS/PALSAR L-band data for the estimation of Eucalyptus plantations above-ground biomass in Brazil. IEEE Journal of Selected Topics in Applied Earth Observation and Remote Sensing, 8(8), 3802–3811.

Baig S., Qazi W.A., Akhtar A.M., Waqar M.M., Ammar A., Gilani H., Mehmood S.A., 2017. Above Ground Biomass Estimation of Dalbergia sissoo Forest Plantation from Dual-Polarized ALOS-2 PALSAR Data. Canadian Journal of Remote Sensing, 43(3), 297–308. https://doi.org/10.1080/07038992.2017.1330143

Basak D., Pal S., Patranabis D.C., 2007. Support Vector Regression. Neuronal Information Processing-Letters and Reviews, 11(10), 203–224. https://doi.org/10.4258/hir.2010.16.4.224.

Cairns M.A., et al., 1997. Root Biomass Allocation in the World's Upland Forests. Oecologia, 111(1), 1–11. https://doi.org/10.1007/s004420050201.

Cristianini N., Taylor J.S., 2000. An introduction to support vector machines and other kernel-based learning methods, Cambridge University Press, 2000.

Friedrichs F., Igel C., 2005. Evolutionary tuning of multiple SVM parameters. Neurocomputing, 64, 107–117.

Gao X., et al., 2012. Classification of hyperspectral image based on SVM optimized by a new particle swarm optimization. In Proc. 2nd International Conference on Remote Sensing, Environment and Transportation Engineering, https://doi.org/10.1109/RSETE.2012.6260436.

Hamdan O., Khali Aziz H., Mohd Hasmadi I., 2014. L-band ALOS PALSAR for biomass estimation of Matang Mangroves, Malaysia. Remote Sensing of Environment, 155, 69–78. https://doi.org/10.1016/j.rse.2014.04.029.

Harrell P.A., Bourgeau-Chavez L.L., Kasischke E.S., French N.H.F., Christensen N.L., 1995. Sensitivity of ERS-1 and JERS-1 radar data to biomass and stand structure in Alaskan boreal forest. Remote Sensing of Environment, 54(3), 247–260. https://doi.org/10.1016/0034-4257(95)00127-1.

Henderson, F.M., Lewis, A.J., 1998. Manual Of Remote Sensing, Principles and Applications Of Imaging Radar, ASPRS, John Wiley, New York.

Huang W., Sun G., Ni W., Zhang Z., Dubayah R., 2015. Sensitivity of multi-source SAR backscatter to changes in forest aboveground biomass. Remote Sensing, 7(8), 9587–9609. https://doi.org/10.3390/rs70809587.

Imhoff M.L., 1993. Radar Backscatter Biomass Saturation - Observations and Implications for Global Biomass Assessment. Igarss'93: Better Understanding of Earth Environment, I–Iv, 43–45.

Koch B., 2010. Status and future of laser scanning, synthetic aperture radar and hyperspectral remote sensing data for forest biomass assessment. ISPRS Journal of Photogrammetry and Remote Sensing, 65(6), 581–590.

Jensen J.R., 2007. Remote sensing of environment: An Earth resources perspective, 2nd ed., Prentice Hall: Upper Saddle River, NJ-07458, ISBN: 0-13-188950-8.

Lone J.M., Sivasankar T., Sarma K.K., Qadir A., Raju P.L.N., 2018. Influence of slope aspect on above ground biomass estimation using ALOS-2 data. International Journal of Science and Research, 6(6), 1422–1428.

Mitchard E.T.A., Saatchi S.S., White L., Abernethy K., Jeffery K.J., Lewis S.L., Collins M., Lefsky M.A., Leal M.E., Woodhouse I.H., Meir P., 2012. Mapping tropical forest biomass with radar and spaceborne LiDAR in Lope National Park, Gabon: overcoming problems of high biomass and persistent cloud, Biogeosciences, 9(1), 179–191. https://doi.org/10.5194/bg-9-179-2012.

Morel A.C., Saatchi S.S., Malhi Y., Berry N.J., Banin L., Burslem D., Nilus R., Ong R.C., 2011. Estimating aboveground biomass in forest and oil palm plantation in Sabah, Malaysian Borneo using ALOS PALSAR data. Forest Ecology and Management, 262(9), 1786–1798. https://doi.org/10.1016/j.foreco.2011.07.008.

Omar H., Misman M.A., Kassim A.R., 2017. Synergetic of PALSAR-2 and Sentinel-1A SAR Polarimetry for Retrieving Aboveground Biomass in Dipterocarp Forest of Malaysia. Applied Sciences, 7(7), 675. https://doi.org/10.3390/app7070675.

Pan Y., Birdsey R.A., Phillips O.L., Jackson R.B., 2013. The Structure, Distribution, and Biomass of the World's Forests. Annual Review of Ecology, Evolution, and Systematics, 44(1), 593–622. https://doi.org/10.1146/annurev-ecolsys-110512-135914.

Patel P., Srivastava H.S., 2013. Ground truth planning for synthetic aperture radar (SAR): Addressing various challenges using statistical approach. International Journal of Advancement in Remote Sensing, GIS and Geography, 1(2), 1–17.

Patel P., Srivastava H.S., 2013. RADARSAT-2 announcement of opportunity project on soil moisture, surface roughness and vegetation parameter retrieval using SAR polarimetry. SAC/EPSA/MPSG/CVD/TDPR&D/01/13, Soar International Closing and Reporting-2013, Final Report Submitted to Canadian Space Agency (CSA) through MDA, Canada, Indian Space Research Organization (ISRO), India, 01–81.

Peregon A., Yamagata Y., 2013. The use of ALOS/PALSAR backscatter to estimate above-ground forest biomass: A case study in Western Siberia. Remote Sensing of Environment, 137, 139–146.

Rajput S.S., Shukla N.K., Gupta V.K., Jain J.D., 1996. Timber mechanics: Strength classification and grading of timber. ICFRE Publication-38, ICFRE, Dehradun, 103.

Roy P.S., et al., 2015. Development of decadal (1985-1995-2005) land use and land cover database for India. Remote Sensing, 7(3), 2401–2430. https://doi.org/10.3390/rs70302401.

Schölkopf B.L. Bartlett P., Smola A., Williamson R., 1998. Support vector regression with automatic accuracy control. Perspectives in Neural Computing: Proceedings of the 8th International Conference on Artificial Neural Networks (ICANN'98), 111–116.

Shao Z., Zhang L., 2016. Estimating forest aboveground biomass by combining optical and SAR data: A case study in genhe, inner Mongolia, China. Sensors (Switzerland), 16(6). https://doi.org/10.3390/s16060834.

Sivasankar T., Lone J.M., Sarma K.K., Qadir A., Raju P.L.N., 2018. The potential of multi-frequency multi-polarized ALOS-2/PALSAR-2 and Sentinel-1 SAR data for aboveground forest biomass estimation. International Journal of Engineering and Technology, 10(3), 797–802.

Smola A.J., Schölkopf B., 2004. A tutorial on support vector regression. Statistics and Computing, 14, 199–222.

Srivastava H.S., et al., 2011. A semi-empirical modeling approach to calculate two-way attenuation in radar backscatter from soil due to crop cover. Current Science, 100(12), 1871–1874.

Srivastava H.S., Sivasankar T., Patel P., 2018. An insight into the volume component generated from RISAT-1 hybrid polarimetric SAR data for crop biophysical parameters retrieval. ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, IV-5, 209–214.

Thumaty K.C., Fararoda R., Middinti S., Gopalakrishnan R., Jha C.S., Dadhwal V.K., 2016. Estimation of above ground biomass for central Indian deciduous forests using ALOS PALSAR L-band data. Journal of the Indian Society of Remote Sensing, 44(1), 31–39. https://doi.org/10.1007/s12524-015-0462-4.